UNIVERSIDAD AUTÓNOMA DE MADRID

ESCUELA POLITÉCNICA SUPERIOR

Ph.D. Thesis

Quality of Service Analysis of Internet Links with Minimal Information

Author:
Felipe Mata Marcos

Supervisor:
Prof. Javier Aracil Rico

Madrid, 2012

DOCTORAL THESIS:	Quality of Service Analysis of Internet Links with Minimum Information
AUTHOR:	Felipe Mata Marcos
SUPERVISOR:	Prof. Javier Aracil Rico

The committee for the defense of this doctoral thesis is composed by:

PRESIDENT:	Prof. TBA
MEMBERS:	Dr. TBA
	Dr. TBA
	Prof. TBA
SECRETARY:	Dr. TBA

To my parents

Summary

Monitoring the Quality of Service (QoS) of Internet links is of paramount importance for Network Operators and Service Providers (NOSP), and consequently has received great attention from the research community. To monitor QoS, practitioners leverage on network traffic measurements and, by means of practical models and statistical techniques, make predictions and detect outliers that allow the planning of telecommunication networks and the detection of abnormal behavior, respectively.

However, obtaining detailed measurements from Internet links at current network speeds is very challenging, mainly because memory accesses' speeds have increased at a smaller pace than Internet links' speeds. Moreover, the amount of resources required to properly storage detailed network measurements make unfeasible to perform long measurement campaigns. These facts have motivated the application of different techniques to gather information from the network, such as collecting subsets of network traffic by applying sampling techniques in the packet capture process, or just collecting summarized statistics of the number of bytes transferred, such as those used in Multi Router Traffic Grapher (MRTG), where the maximum and average transfer speeds are recorded at non-overlapping time intervals of a given length. These techniques make network traffic monitoring less demanding and allow performing longer measurement campaigns.

Accordingly, this thesis proposes two methodologies to perform QoS analysis of Internet links leveraging on summarized statistics of network traffic. Each methodology relies on a network traffic model, validated using actual network traffic measurements, on which sound statistical methodologies are used on attempts of detecting relevant events that either require action from the network managers or may be related with degradations of the provided QoS.

The first methodology is designed to detect shifts in users' behavior, and consequently the detected events may entail capacity planning decisions. It builds on modeling the network traffic during a day using a multivariate fairly Gaussian distribution, from which changes in the parameters are detected at timescales of weeks. The change point instants are detected using clustering techniques and validated through the application of the Multivariate Behrens-Fisher Problem (MBFP). The proposed methodology is applied to real network measurements obtained from the Spanish academic network RedIRIS, showing satisfactory performance and entailing large Operational Expenditures (OPEX) reduction to NOSP in the management process of large-scale networks.

The second methodology performs anomaly detection through trend removal of network traffic measurements. It is tailored for Voice over IP (VoIP) traffic data, which is one of the most popular services provided through Internet nowadays. The methodology takes as input call count measurements of the VoIP service exhibiting seasonal trends, and outputs stationary residuals, which are used to detect anomalies by means of the application of unsophisticated statistical assumptions. Moreover, we propose a measurement alternative for monitoring VoIP systems. This alternative yields smaller correlations between the obtained measurements when some assumptions are met, which we showed to be satisfied in actual measurements we analyzed.

Resumen

Monitorizar la Calidad de Servicio (QoS, de sus siglas en inglés) de enlaces de Internet es de vital importancia para Operadores de Red y Proveedores de Servicio (NOSP, de sus siglas en inglés), y por tanto ha recibido gran atención por parte de la comunidad científica. Para monitorizar la QoS, los expertos usan medidas del tráfico de red y, mediante la aplicación de modelos prácticos y técnicas estadísticas, hacen predicciones y detectan valores atípicos que permiten el dimensionado de redes de telecomunicaciones y la detección de comportamiento anómalo, respectivamente.

Sin embargo, obtener medidas detalladas de enlaces de Internet a las velocidades de red actuales es muy exigente, principalmente porque las velocidades de acceso a memorias han crecido a menor ritmo que las velocidades de los enlaces de Internet. Además, la cantidad de recursos requerida para almacenar apropiadamente medidas de red detalladas hace imposible realizar largas campañas de medidas. Estos hechos han motivado la aplicación de diferentes técnicas para recolectar información de la red, tales como recopilar subconjuntos del tráfico de red mediante la aplicación de muestreo en el proceso de captura de paquetes, o simplemente la recopilación de estadísticos resumidos del número de bytes transferidos, como los usados en Multi Router Traffic Grapher, donde la tasa de transmisión máxima y media son recogidas en intervalos disjuntos de una longitud dada.

Por consiguiente, esta tesis propone dos metodologías para realizar análisis de QoS en enlaces de Internet usando estadísticos resumidos del tráfico de red. Cada metodología se basa en un modelo del tráfico de red, validado con medidas de tráfico de red reales, sobre los cuales técnicas estadísticas fiables son aplicadas con el objetivo de detectar eventos relevantes que o bien requieren actuación por parte de los gestores de red o quizá estén relacionados con degradaciones de la QoS provista.

La primera metodología está diseñada para detectar variaciones en el comportamiento de los usuarios, por lo que los eventos detectados pueden conllevar decisiones de dimensionado de red. Primero modelamos el tráfico de red a lo largo de un día usando una distribución multivariante prácticamente Gaussiana, mediante la cual cambios en sus parámetros son detectados en escalas de tiempo de semanas. Los instantes de cambio se detectan usando técnicas de clustering y son validados mediante la aplicación del Problema de Behrens-Fisher Multivariante. La metodología propuesta se ha aplicado a medidas reales de tráfico de red obtenidas de la red académica española RedIRIS, demostrando un rendimiento satisfactorio y conllevando para los NOSP grandes reducciones de los gastos operacionales en el proceso de gestión de redes de gran escala.

La segunda metodología realiza detección de anomalías mediante la eliminación de la tendencia existente en medidas del tráfico de red. Está específicamente diseñada para tráfico de Voz sobre IP (VoIP, de sus siglas en inglés), que es uno de los servicios más populares ofrecidos a través de Internet hoy en día. La metodología utiliza medidas de la cantidad de llamadas en el servicio VoIP que exhiben tendencias periódicas, y las transforma en residuos estacionarios que son usados para detectar anomalías mediante la aplicación de asunciones estadísticas poco sofisticadas. Además, también proponemos una forma alternativa de monitorizar sistemas de VoIP. Esta alternativa produce menores correlaciones entre las medidas obtenidas cuando algunas asunciones se cumplen, las cuales son satisfechas concretamente en las medidas de tráfico real que hemos analizado.

Acknowledgments

It is difficult to write technical papers clear and concisely (moreover if you have to write them in a foreign language), but it is more difficult to properly write an acknowledgment, being fair with all the people that helped you, either by directly working side by side, or by supporting and understanding your situation externally. Therefore, I would like to explicitly thank those people, whose help has mainly impacted my researching career and my whole life, apologizing to those ones not mentioned. This work is dedicated to all of them.

Firstly, I would like to thank my family for their support and understanding every time, although I have not been able to spend as much time with them as I desire—however, I expect this situation to change from now on. Their protection and upbringing have made up the man that I am nowadays—well, not completely, they are only responsible for those good things I sometimes do.

Although my friends' contribution to this work is arguable (sorry dudes, but you are better for wasting time ;-]!), they also merit to be acknowledged, because taking the most of the spare time helps me to be productive during working hours. Maybe since I started the PhD my free time is reduced and I am not able to see you frequently, but it does not mean our relationship is worse, it just changed. Nobody could snatch me the memories of the good moments we have spent together.

A special acknowledgment is dedicated to my supervisor, Javier Aracil, for his close collaboration and good advise, the fruitfulness of this work and the forthcoming ones is mainly your duty. Thank you for allowing me to start my researching career here. In the same way, I would like to thank my colleagues from the Networking Research Group: Javier Ramos, Pedro Santiago, Jaime Garnica, Víctor Moreno, David Muelas, Santiago Pina, Germán Retamosa, David Madrigal, Jorge López de Vergara, Sergio López, Paco Gómez, Iván González, Luis de Pedro, Gustavo Sutter, and those that are no longer here: Víctor López, Bas Huiszoon, Alfredo Salvador, José Alberto Hernández, Diego Sánchez, Jaime Fullaondo and Walter Fuertes. A singular mention is deserved to José Luis García, from whom I learned so much. Thank you for all this time at the laboratory and all the good moments we have shared. This also definitely includes my other colleagues from the laboratory Pedro Gómez, Álvaro García and Miguel Cubillo. All my work would not have been possible without the support of the Universidad Autónoma de Madrid and the Departamento de Tecnología Electrónica y de las Comunicaciones (former Departamento de Informática) of the Escuela Politécnica Superior.

In addition, I would also like to express my gratitude to RedIRIS for providing us with traffic measurements that have been fundamental to this thesis, to the Spanish Ministry of Education and Science that has funded this research under the F.P.U. fellowship program, and the COST TMA action that has helped me to grow as a researcher. Specially related to the TMA action, I would like show my gratefulness to Raimund Schatz and Michel Mandjes for hosting me in Wien and Amsterdam, respectively.

My stay in Wien was very constructive. I learned a lot in the topic of Quality of Experience, which I think is going to be one of the most fertile field of research in networking. I would like to thank Peter Fr´'ohlich and Michal Ries for their comprehension and patience with me. This includes all the members of The Telecommunications Research Center Vienna (FTW), in particular the Settanni twins.

From my TMA STSM in Amsterdam I retain great memories. Furthermore, it was very productive. This stay helped me to grow up, both as a researcher and as a person. Moreover, I learned a lot with the discussions with Michel, and working side by side with Piotrek Żuraniewski, who in addition helped me a lot to integrate in Universiteit van Amsterdam's lifestyle and feel less lonely. This absolutely includes all the staff and other students from the Korteweg-de Vries Institute for Mathematics, specially Ricardo Reis. Although not in person, I also had the chance to work with Marco Mellia during my STSM at Amsterdam. Furthermore, our achievements would not have been possible without the VoIP traffic traces that Marco kindly shared with us. I would like to sincerely express my gratitude to Marco and Telecommunication Network Group of Politecnico di Torino members for allowing me the use of such data in this thesis.

Last, but for sure not the least, Cristina, I dedicate this work to you. Your company, support and understanding are invaluable. Thank you for being by my side, we have to celebrate this! (yes yes, I pay...;-])

Contents

List of Figures

List of Tables

Acronyms

ACO Ant Colony Optimization. 41

AE All Equal. 115, 118, 119, 121

AID Anomaly-based Intrusion Detection. 14–48, 50–81, 83–92, 167

AIDS Anomaly-based Intrusion Detection System. 14–17, 24, 48, 74

AIS Artificial Immune System. 27–30, 64

ANN Artificial Neural Network. 46–49

API Application Programming Interface. 8

ARIMA Auto Regressive Integrated Moving Average. 116

BN Bayesian Network. 50

BSM Basic Security Mode. 86

CAPEX Capital Expenditures. 132

CCDF Complementary Cumulative Distribution Function. 140–142

CD Change Detection. 80–82

CDF Cumulative Distribution Function. 157

CHT Call Holding Times. 140, 152, 155, 166

CI Computational intelligence. 26, 30, 40

DAG Directed Acyclic Graph. 50

DC Dendritic Cells. 30

DDoS Distributed Denial of Service. 43, 49, 62, 81, 82

DiffServ Differentiated Services. 1, 2

DoS Denial of Service. 48, 74, 76, 79, 81, 95

EC Evolutionary Computation. 30

ECDF Empirical Cumulative Distribution Function. 231

EoC Ensemble of Classifiers. 53

FP False Positive. 114

FPR False Positives Ratio. 115, 116, 118, 121

FS Fuzzy System. 35

FSM Finite State Machine. 38

GA Genetic Algorithm. 31–33, 37

GoF Goodness of Fit. 140, 141, 145

GP Genetic Programming. 33, 34

GPL General Public License. 11

GPU Graphic Processing Unit. 91

HIS Human Immune System. 27, 29

HMM Hidden Markov Model. 69–71

HP Honeypot. 92

HTML HyperText Markup Language. 11

ICMP Internet Control Message Protocol. 28

ID Intrusion Detection. 13, 20, 21, 30, 32, 33, 37, 46, 53, 62, 75, 76, 87, 90, 91

IDOC Intrusion Detection Operating Characteristic. 87

IDS Intrusion Detection System. 13–15, 17, 18, 31–33, 35–37, 41, 46, 48–50, 52, 53, 57, 75, 77, 85–87, 90

IntServ Integrated Services. 1

IP Internet Protocol. 9, 17, 79, 82, 137

ISP Internet Service Provider. 98

KBS Knowledge-Based System. 38

KS Kolmogorov-Smirnov. 105, 139–142, 231

LGP Linear Genetic Programming. 34

M Means. 115

MBFP Multivariate Behrens-Fisher Problem. viii, 4, 96, 97, 110–113, 119–121, 126–128, 234, 237

MI Monthly Increments. 117

MIB Management Information Base. 9, 11, 17, 48, 58, 74, 81

MIDS Misuse-based Intrusion Detection System. 14, 16

MLE Maximum Likelihood Estimate. 141

MRTG Multi Router Traffic Grapher. vii, 8, 10–12, 98, 99, 143

MSE Mean Squared Error. 144

MV Mean-Variances. 115

MVN Multivariate Normality. 105–107, 109, 110, 112, 113

NBC Naive Bayes Classifier. 55

NN Nearest Neighbor. 44–46, 75

NOSP Network Operators and Service Providers. vii, viii, 4, 132, 137, 164, 166

NS Negative Selection. 27–29

OD Origin-Destination. 94, 95

OID Object IDentifier. 11

OPEX Operational Expenditures. viii, 5, 96, 122, 128, 129, 132, 164

P2P Peer-to-Peer. 125

PCA Principal Component Analysis. 75–79, 89

PCAP Packet Capture. 8

PoP Point of Presence. 94, 98, 137

PSO Particle Swarm Optimization. 41

Q-Q Quantile-Quantile. 145, 146

QI Quarterly Increments. 117

QoE Quality of Experience. 132

QoS Quality of Service. vii, viii, 1–4, 7, 12–14, 94–96, 129, 132, 163, 166, 167

RB Rule-Based. 39

RBF Radial Basis Function. 32, 49, 56

ROC Receiver Operating Characteristic. 87, 91

RSVP Resource Reservation Protocol. 1

SACF Sample Autocorrelation Function. 123, 125, 126

SCTP Stream Control Transmission Protocol. 10

SI Swarm Intelligence. 40, 41

SLA Service-level Agreement. 1, 129

SNMP Simple Network Management Protocol. 9, 11, 17, 58, 95, 98, 101, 102

SOM Self-Organizing Map. 62–65

SVD Singular Value Decomposition. 136

SVM Support Vector Machine. 56–58, 61

SXCF Sample Cross-correlation Function. 125, 126

TCP Transmission Control Protocol. 9, 28, 38, 63, 70, 81

TE Traffic Engineering. 1, 2

ToS Type of Service. 9

TSF Time Series Forecasting. 83

UAM Universidad Autónoma de Madrid. 10

UDP User Datagram Protocol. 9, 10, 28

V Variances. 115

VoIP Voice over IP. viii, 5, 83, 131–135, 137, 138, 140, 151, 152, 162, 165, 166, 168

Chapter 1

Introduction

This chapter provides an overview of this Ph.D. thesis and introduces its motivation, presents its objectives and hypothesis, and finally describes its main contributions outlining its organization.

1.1 Overview and Motivation

Quality of Service (QoS) refers to the delivery of data over communication networks attending to special requirements. Particularly in computer networks, QoS refers to the guarantee of certain levels of performance to data delivery by means of Traffic Engineering (TE) tasks. Such levels of performance are commonly agreed in a contractual document signed by both the provider and the consumer, namely the Service-level Agreement (SLA). A SLA defines the performance of the service being offered in terms of some measurable network indicators, such as throughput, latency or jitter. Network managers and operators monitor their network with the aim of timely detecting QoS degradations. The TE tasks they make use for QoS control can be divided into two main classes: system based and measurement based approaches. The former class is basically formed by two architectures that provide frameworks for ensuring QoS, namely Integrated Services (IntServ) and Differentiated Services (DiffServ). IntServ implements a parametrized approach where applications use the Resource Reservation Protocol (RSVP) to request and reserve resources through a network, whereas DiffServ implements a prioritized model by marking packets according to the type of service they desire and applying different queueing strategies to tailor performance to expectations.

On the other hand, the measurement based approaches leverage on network traffic measurements and, by means of practical models and statistical techniques, make predictions to plan telecommunication networks and detect abnormal behavior. This second alternative for QoS provisioning is commonly used in practice, as there are studies pointing out that improving QoS by investing in capacity is more profitable than investing in provision of multiple service classes [Odl99]. Consequently, this Ph.D. thesis focuses on this latter class, and provides useful network traffic models and the corresponding algorithms leveraging on them to develop TE tasks on large-scale networks.

In order to accurately perform TE tasks, it has traditionally been of paramount importance to have detailed descriptions about what is happening in the network. For this reason, there are a lot of measurement techniques existing in the literature (active and passive), most of them being implemented by network managers, allowing them to tackle incidences in the network. For instance, network operators can track malicious traffic to prevent their users for being target of security attacks [Den87, CLC04, MR04, SSS$^+$10], assess QoS [vdBMvdM$^+$06, MPM05] or specially bill high consuming clients [EV02]. This increasing interest in network measurements by network operators has been reflected in the research community. There have been many contributions involving network measurements to characterize the Internet traffic [RK96, BM01, BC02, NAR$^+$04, DPV06a, MGDLdVA12], or even to characterize specific applications [BS06, SFKT06, PGDM07, PM07, ZSGK08].

All these studies demonstrate the importance of network measurements for network research and operation, however, collecting accurate network measurements has become an arduous task because links' speeds have increased at a larger pace than memory accesses' speeds [Rob00], making it unfeasible to monitor all the network traffic. This fact has motivated the development of new techniques to substitute the previously used ones, such as the application of sampling to network traffic measurement [CPB93, Coc97, LG08]. Sampling allows longer measurement campaigns; however, it entails a reduction of the available information. Therefore, the application of statistical inference and digital signal processing techniques have gained importance, allowing to obtain information of interest. One of the most common ways for gathering this information is by extracting patterns or footprints that are easily detectable and then characterize in an accurate manner the measured traffic [MC00], even measuring these footprints at different time resolutions [PTZD05]. Once the footprints are detected, statistical methodologies are applied to corroborate whether the conclusions obtained from them can be extrapolated or they are just a particular case of the study [KN02].

This constraint in the amount of information possible to gather and analyze from the network has fostered the development of techniques able to identify abnormal behavior [ACP09] or pattern shifts with minimal information [MGDA12]. The ability to infer different networks status with minimal information makes these techniques also useful for real-time monitoring. Consequently, network managers and operators are still capable of control their networks and take action timely to resolve security breaks and capacity shortages even though the information they can gather from the network is a subsample of what really the network is transmitting.

1.2 Objectives and Hypothesis

This thesis presents the analysis of different measurement datasets of Internet links with the aim of detecting degradations of the QoS in the network. The analyzed datasets contain minimal information, in the sense that they contain summarized statistics instead of having detailed records of each event in the network.

We make two common assumptions for developing models of the analyzed traffic. First, we assume that *network traffic is short-term stationary*—i.e., the statistics of the traffic distribution, and consequently its corresponding parameters, slowly vary with time. Second, we assume that *network traffic exhibits a normal baseline under benign and without problems usage*, and deviations from such baseline may evidence the presence of attacks or pattern shifts, which we term as anomalous events. This anomalous events, which may pose QoS degradations to the network customers, may be detected through deviations from the proposed models.

Consequently, our objective is *to provide the necessary machinery to detect such anomalous events in a timely fashion with statistical foundation of their relevance*, which is of paramount interest for Network Operators and Service Providers (NOSP). This machinery places alerts of the detected events to the network managers, allowing them to take appropriate responses on attempts of diminishing the impact of such events in the level of QoS in the network. To this end, we build network traffic models that are useful for tracking the network traffic behavior at the timescales of interest, which are given by the relevant events we aim to detect with the model. This models constitute the normal baseline from which deviations are flagged as anomalous, which are detected using sound statistical techniques.

1.3 Thesis Structure

The rest of the present document is structured as follows. First, Chapter 2 describes the state of the art. The first section presents a description of the main formats of storing information captured from network links, whereas the second one is devoted to survey the different approaches proposed in the literature for the detection of anomalies, providing a taxonomy for classifying the surveyed techniques.

Then, Chapter 3 presents a methodology for detecting change points at large timescales which may evidence shifts in users' behavior. The methodology leverages on a multivariate model for representing the network traffic along a day, and change points are detected by inspecting the evolution through time in the mean vector of the model. The change point instants are detected using clustering techniques and validated through a sound statistical technique, namely the Multivariate Behrens-Fisher Problem (MBFP). This technique contrast the null hypothesis of stationary mean against the alternative hypothesis of a mean shift. The proposed methodology is applied to real network measurements obtained from the Spanish academic network RedIRIS, showing satisfactory performance. Finally, we propose a framework for applying the described methodology to perform network management of large-scale networks. This framework allows the visualization of the detected anomalous events in a network weather map, which entails a large reduction of the Operational Expenditures (OPEX).

Chapter 4 describes a methodology for removing the inherent trend in actual measurements due to the well-known day-night traffic pattern. This methodology is specifically tailored for Voice over IP (VoIP) traffic data, which is one of the most popular services provided through Internet nowadays. The methodology takes as input call count measurements of the VoIP service exhibiting a seasonal trends, and outputs stationary residuals, which are used to detect anomalies by means of unsophisticated statistical assumptions. Moreover, we propose in this chapter a measurement alternative for monitoring VoIP systems. This alternative yields smaller correlations between the obtained measurements when some assumptions are met, which we showed to be satisfied in the actual measurements from an Italian operator that we analyzed.

Finally, Chapter 5 concludes this thesis and outlines future steps continuing the work presented in Chapter 3 and Chapter 4.

Chapter 2

State of the Art

This chapter provides the background and revises the most relevant works related to the topic of this thesis. The structure of the chapter is as follows. First, the different kinds of usually available network measurements are described in Section 2.1. Then, the concept of Quality of Service (QoS), that is, the quality that the service provider is offering to its customers, is reviewed from the viewpoint of anomaly detection in Section 2.2. Anomalies are network events that deviate from the normal pattern and may be related to degradations in the performance of Internet systems and host, thus influencing the QoS. In the survey of Section 2.2 we include two approaches to anomaly detection that are used in this thesis: change point detection of time series data (Chapter 3) and time series prediction for detecting deviations from normal behavior that may be closely related with service degradation (Chapter 4). In any case, a more detailed revision of the related work of these and different topics will be presented in the corresponding chapters when required.

2.1 Network Measurements

Network managers are in charge, among other tasks, of keeping network performance under reasonable levels. For this reason, production networks are continuously monitored, exporting the obtained measurements for further processing. However, the amount of network traffic generated at large-scale networks is humongous, so it is very challenging to handle it in an efficient way. These challenges appear since traffic traversing network links at ever-increasing speeds has to be monitored in a timely fashion. For this reason, different kinds of network traffic monitors have been developed. In this chapter we describe the most common network monitoring tools and the characteristics of the measurement data that they output. These measurement data has been deeply analyzed in this study, so it is strongly necessary to understand their advantages and their drawbacks, e.g., the information that can or cannot be extracted from them, their computational costs, etc. The remaining of the chapter is structured as follows. Section 2.1.1 describe packet captures measurements. Following, the NetFlow records and the definition of network flow are presented in Section 2.1.2. Finally, Section 2.1.3 describes the information available in Multi Router Traffic Grapher (MRTG) records, and how it is obtained.

2.1.1 Packet Captures

Packet capture is the process whereby each packet traversing a link is copied to output files, which are commonly referred as packet traces. This measurement process reproduces exactly the status of the link within the measurement period. The most common format for these packet traces is the one obtained through the Packet Capture (PCAP) [JLM93] Application Programming Interface (API), which is used and supported by a variety of network sniffers and packet analyzers.

The advantage of packet captures is that all the available network information is included in the packet traces, i.e., both the payloads and headers. This, however, leads to an important drawback regarding storage requirements. As packet traces contain all the information within a packet, this means that the packet trace size will be equal to the number of bytes of the captured packets. As the speeds of networks are continuously increasing [Rob00], the size of the packet traces is growing at the same rate for a fixed measurement period. This fact makes long packet capture measurement campaigns unfeasible, and it is common to have them split into one hour intervals within one day.

Another negative aspect of packet traces is that packet traces of production networks are very hard to find. The reason for this is related to privacy concerns regarding the personal information that is sent and received in the Internet Protocol (IP) packets, including the IP addresses. Techniques to circumvent these legal aspects are mainly based on anonymization of IP addresses and removal of packet payloads. Even taking into account these limitations, there are few packet traces publicly available in the Internet.

These sources of traffic are not used in this thesis, as they are not considered to contain *minimal information* about the network status.

2.1.2 NetFlow Records

A flow is defined as a sequence of packets that share the same source and destination IP addresses, port numbers and transport protocol identification. The information that NetFlow stores for each flow entry in its memory includes traffic volume (in bytes and packets), port numbers, source and destination IP addresses, Type of Service (ToS), input and output interfaces indexes (as per Simple Network Management Protocol (SNMP) Management Information Base (MIB)), together with timestamps for the flow beginning and end..

NetFlow is a proprietary format developed by Cisco Systems that runs in their routers and it is implemented by other vendors as well. This protocol is used to monitor the traffic that traverses a router and to keep performance statistics. Cisco defines a flow as a unidirectional sequence of packets sharing all the following 7 values, commonly referred as 7-tuple: Source and Destination IP addresses, IP protocol, Source and Destination ports in case that the IP protocol is Transmission Control Protocol (TCP) or User Datagram Protocol (UDP), Ingress interface and IP ToS.

NetFlow updates the NetFlow record for a flow when a new packet belonging to that flow is sampled, until a timeout counter expires, i.e., when no packets belonging to that flow are sampled for more than *timeout* units of time, or when it samples a packet that finalizes a TCP session, i.e., it samples a packet with either the FIN flag or the RST flag set. The NetFlow sampling method is a deterministic sampling method, i.e., for every N packets it sees, NetFlow samples the first packet and does nothing with the remaining ones.

The NetFlow record contains a wide variety of statistics about the flow, where the most important ones are the timestamps for the flow start and finishing times, number of bytes and packets observed in the flow (that are actually estimations of the real value by taking into account the sampling ratio), as well as the 7-tuple (see [Cla04] for more detailed description of NetFlow records).

Each router with NetFlow capabilities generates NetFlow records, which are exported from the router using UDP or Stream Control Transmission Protocol (SCTP) packets to a NetFlow collector. In the RedIRIS scenario of Figure 2.1, the autonomic routers are routers with NetFlow capabilities that export the NetFlow records to the NetFlow collector located at Universidad Autónoma de Madrid (UAM)'s premises. This scenario is also used for the reporting of MRTG network measurements (Section 2.1.3).

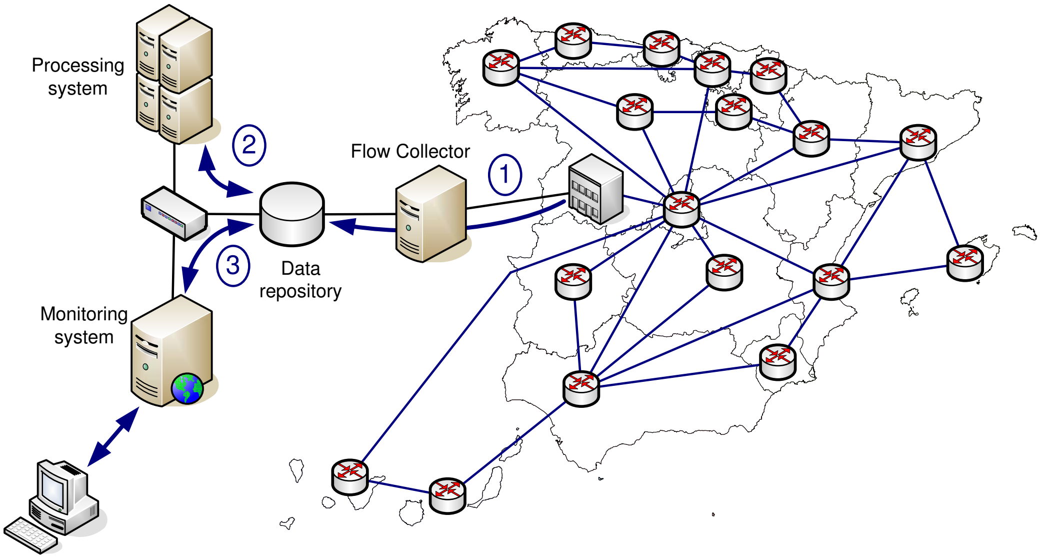


Figure 2.1: RedIRIS Points of Presence.

2.1.3 MRTG Records

MRTG [OR98] is a software tool distributed under GNU General Public License (GPL) freely available from the MRTG web page[1]. In its origins it was developed as a software to monitor and measure traffic load on network links, graphing the information and showing statistics as maximum, minimum and mean values, but it has evolved to allow the user to visualize almost any kind of information. It is written in Perl, and is available for several operating systems, including Windows, Linux and Mac.

It uses SNMP to send requests to the monitored device. SNMP is an application layer protocol that facilitates the exchange of information between network devices (where a SNMP agent must be running) using MIBs to define hierarchically what information is available to be monitored.

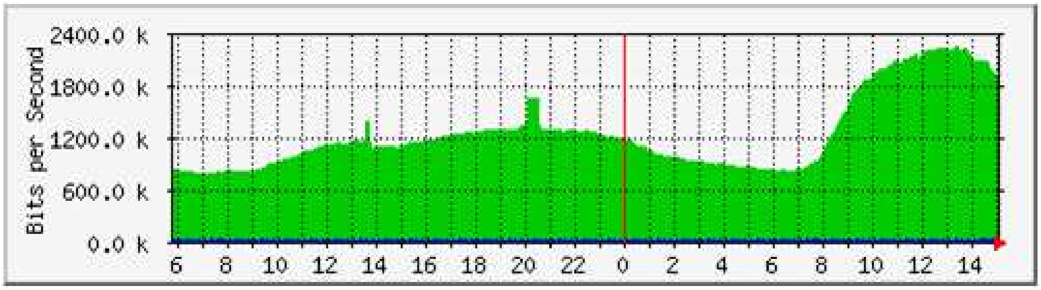


Figure 2.2: Sample one-day MRTG monitoring.

The requests that MRTG sends to a device contain the Object IDentifier (OID) of the resource that it wants to get information about. The SNMP agent of the device looks up the OID in its MIB and response the MRTG with the corresponding data encapsulated in SNMP protocol. MRTG then gathers all the information received in an incremental database and creates a HyperText Markup Language (HTML) document containing graphs of the received information, as shown in Figure 2.2.

MRTG measures two values per target, the input value and the output value. The input value is plotted as a solid green area and the output one as a blue line, as can be seen in the figure. It collects the data every five

[1] http://oss.oetiker.ch/mrtg

minutes for daily graphs, and greater time spans for weekly, monthly and yearly graphs. Furthermroe, MRTG features automatic scaling of the Y-axis to fit the graph to the information area and it also reports the maximum, average and current values for both input and output data, as is shown in Table 2.1.

Table 2.1: Sample statistics for the input and output of the target

Direction	**Max**	**Average**	**Current**
In	2.23 Mb/s (22.3%)	1.23 Mb/s (12.3%)	1.89 Mb/s (18.9%)
Out	880.0 b/s (0.0%)	16.0 b/s (0.0%)	312.0 b/s (0.0%)

MRTG measurements will form the information basis for the thesis, as they are regarded as the minimum source of network information for management purposes.

2.2 Anomaly Detection

The Internet has opened new avenues for information accessing and sharing. However, the widespread use of the Internet also presents an opportunity for hackers and enemies to attack unprotected hosts in order to control them, gain access to their sensitive information or discontinue its availability for a certain period of time. This kind of activities impose severe losses to the targets of the attacks, in the order of billions of U.S. dollars. In addition, they may affect the QoS that the service providers offer to their customers in several ways. Consequently, there is an increasing interest in preventing, detecting and responding to such attacks in a timely fashion, which is commonly denoted as intrusion detection in the networking community. Intrusion detection is accomplished by means of misuse detection systems, based on well-known attack signatures, or anomaly detection systems, with the ability of discover unknown kinds of attacks. In this section, we survey the proposed taxonomies of anomaly intrusion detection systems, and propose a new one that embraces them. Furthermore, we present the most comprehensive survey of anomaly intrusion detection techniques to date, based on the structure given by the proposed taxonomy. Finally, we discuss the main problems related to the anomaly intrusion detection paradigm, and the open roads for future research that we envisage as of paramount importance for the success of the field.

2.2.1 Introduction

The Internet has brought about numerous benefits, representing nowadays one of the biggest avenues for information accessing and sharing. This entails the development of complex corporate networks and a diversity of web services, at which there is an important ensemble of data (customers personal information, financial corporate data, etc.) and resources that must not be accessed, modified nor compromised by external entities. However, the widespread use of the Internet also presents an opportunity for hackers and enemies to attack unprotected hosts in order to control them, gain access to their sensitive information or discontinue its availability for a certain period of time, thus reducing their QoS. This kind of activities impose severe losses to the targets of the attacks, in the order of billions of U.S. dollars [Com08]. Consequently, there is an increasing interest in preventing, detecting and responding to such attacks in a timely fashion, which is commonly denoted as Intrusion Detection (ID) in the networking community.

Dating back more than twenty years, the bases for ID in networked systems were established in the works of Anderson [And80] and Denning [Den87]. The assumptions posed by these works for ID state that *exploitation of system's vulnerabilities involves abnormal use of the system*, and therefore *security violations could be detected from abnormal patterns of system usage* [Den87]. Since then, myriads of studies and proposals have been published presenting different alternatives to tackle the ID problem, namely IDSs. IDSs are the *burglar alarm* of the computer security field, making *noise* when an intruder is detected to alert the *security officer*, which can respond to with it an appropriate *action*. The performance of IDSs is measured in terms of the *detection accuracy* and *false positives rate*. The detection accuracy is the percentage of correct detected intrusions (*true positives*) out of the total number of intrusions, the higher the better. On the contrary, false positives rate is the percentage of incorrect alerts placed by the Intrusion Detection System (IDS) out of the total number of alerts generated, the lower the better.

Traditionally, IDSs are classified as *misuse-based intrusion detection systems* or *anomaly-based intrusion detection systems*. A combination of both is termed *hybrid intrusion detection system*. MIDSs, also denoted as signature-based intrusion detection systems, aim at finding a match between the activities in the system and a set of predefined malicious activity patterns, similar to *fingerprint identification* against a *criminal fingerprint database* in dactyloscopy. MIDSs have large detection accuracy for known attacks with a low false positive rate. This makes them suitable for taking response actions to the detected attacks. However, they are not able to detect new kinds of attacks, or variants of existing ones, and the process of generating signatures is a time-consuming task that must be performed continuously because new classes of attacks are developed everyday.

On the contrary, AIDSs define a *normal* baseline, flagging deviations from such normal profile as abnormal behavior, with the assumption that anomalies are scarce compared to the normal behavior. It is like finding *metals* buried in the *beach sand*, where the Anomaly-based Intrusion Detection System (AIDS) is the *metal detector* that points to possible metals. When an AIDS places an alert, we either find a *priced treasure* (true positive) or a *worthless item* (false positive). AIDSs are capable of pointing to new unknown kind of attacks such as *zero-day attacks*. Nonetheless, they place a high volume of false positive alerts, which prevents its autonomous deployment and forces the network manager to spend a significant amount of time discarding irrelevant events. For this reason, AIDSs are not commonly deployed in real networks under production, and MIDSs are used instead. Per contra, this room for improvement has made AIDSs a fertile field of research in the last years.

Motivated by the vast amount of research on AIDSs and its relevance to QoS, this work aims at providing a comprehensive survey of the state of the art in Anomaly-based Intrusion Detection (AID) techniques presented in the literature over the period 2000-2012, including a survey of the proposed taxonomies.

We organize the rest of this article as follows. In Section 2.2.2 we survey the taxonomies of AID techniques proposed in the literature and propose a new one. Then, we review the proposed AID techniques in Section 2.2.3. We leverage in this section on the taxonomy presented in Section 2.2.2, grouping the existing techniques into the different categories in the taxonomy based on the underlying detection paradigm they adopt. Section 2.2.4 discusses the main problems when developing an AIDS, whereas Section 2.2.5 deliberates on the future trends on AID. Finally, Section 2.2.6 concludes the section.

2.2.2 Anomaly Intrusion Detection Taxonomy

This section is devoted to review the taxonomies proposed in the literature for AID techniques. In addition, we will propose a new taxonomy based on the most important characteristics of the surveyed taxonomies.

Taxonomies Proposed in the Literature

There have been several studies surveying AID systems and techniques in the recent past years, and some of them have proposed taxonomies to classify such techniques. In addition, there exist taxonomies for AID that do not only focus on classifying the different techniques used for AID, but also include classifications based on other features of AIDSs—that also apply to IDSs in general. Consequently, we divide this section into two parts, one dealing with the taxonomies of AIDSs based on their features excepting the taxonomy of the AID techniques, which is treated in the second part. The reason for such splitting is because the first part applies generally to IDSs and there is a high grade of consensus on it, while the taxonomies for AID techniques vary considerably depending on the authors, and consequently deserve more discussion.

Taxonomies of AIDSs AIDSs own a wide range of characteristics that allow their classification. Although not all the authors providing taxonomies

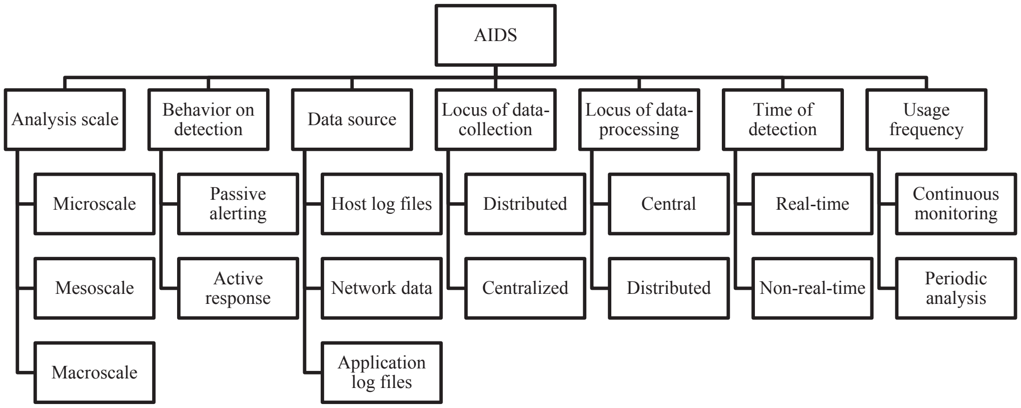


Figure 2.3: General taxonomy of AIDSs that is applicable to MIDSs. The classification of AID techniques is deferred to Section 2.2.2.

for AIDSs include all these characteristics, there is a high grade of acceptance on the ability of such characteristics to allow AIDSs differentiation, which are also applicable to MIDSs. Such characteristics are summarized in Figure 2.3 and will be described in the following paragraphs.

Analysis Scale: Analysis scale ([ETGTDV04]) refers to the granularity, either in terms of the parts of the system analyzed or in terms of the time scale, used in the detection of anomalous events.

- *Microscale*: Methods based on the analysis of low-level features, such as analysis of individual packets, traffic analysis over short periods of time (in the order of seconds) or the analysis of specific services or applications.

- *Mesoscale*: Methods based on the analysis of medium-level features, such as analysis of connections or flows, traffic analysis over medium periods of time (in the order of minutes) or the analysis of the traffic destined to a specific host or subsets of hosts.

- *Macroscale*: Methods based on the analysis of high-level features, such as network-wide analysis [LCD04b], traffic analysis over long periods of time (in the order of hours or days) or the analysis of all the host within the network.

Behavior on Detection: Behavior of detection ([DDW00]) refers to the action the IDS takes when an anomaly is detected.

- *Passive alerting*: Passive alerting is the usual approach used by AIDSs given the high number of false alarms such systems usually place. Consequently, AIDSs just signal an alert to the system manager in order to alert for the discovered event, instead of taking actions that may degrade the performance of the system to benign users.

- *Active response*: Some IDSs have an active response to the detected events. These responses may be of the form of closing the connections related to the attack, banning the remote IP address from which the attack is launched or restoring the files modified by the suspicious user.

Data Source: Data source ([DDW00]) refers to the origin of the data used to detect anomalies.

- *Host-based*: Host-based IDSs collect audit data from the host that is under protection. The sources of the audit data may be Unix commands providing snapshots of information on what is happening in the host, such as *ps, pstat, vmstat, getrlimit, ...*, accounting information of the usage of host's resources, or the *syslog* of system calls.

- *Network data*: Network-based IDSs collect information from the network to perform the AID. The sources of such data may be information contained in MIB repositories accessed through SNMP, flow summaries gathered from routers implementing NetFlow or its variants, or network packets captured at the network interface card (see Section 2.1).

- *Application log files*: Application log files are log files generated by the designer of the application, and are gaining importance lately given the trend towards application servers. They have the advantage of being more accurate and complete, but some kinds of attacks may prevent the writing in such logs or may be targeted to lower levels of the system stack making such sources worthless.

Locus of Data-Collection: Locus of data-collection ([Axe00]) refers to the number of sources of the data. It can be collected from many different sources in a *distributed* fashion or from a single point using the *centralized* approach.

Locus of Data-Processing: Locus of data-processing ([Axe00]) refers to the way the data is processed after collection. It can be processed in a *central* location or in a *distributed* fashion.

Time of Detection: Time of detection ([Axe00]) refers to the time required to verify new data instances for anomalies. An IDS can detect intrusions in *real-time* or *off-line*, in a forensic manner.

Usage Frequency: Usage frequency ([DDW00]) refers to the way IDSs monitors the system. It can either *continuously* monitor the system or it can wake-up *periodically* to perform the analysis.

Taxonomies of AID techniques There have been proposed several taxonomies for AID techniques that may vary considerably from one to another. In order to survey such taxonomies in an organized manner, we review them in chronological order. The description of the different classes in the taxonomies is deferred to Section 2.2.3.

We begin the survey of taxonomies with the technical report from 2000 of Axelsson [Axe00]. This was one of the first works to provide a taxonomy of IDSs. The AID principles are divided into self-learning and programmed principles (see Figure 2.4). The self-learning principles are divided depending on whether they leverage on temporal information or not. On the other hand, the programmed principles are either based on descriptive statistics or they model the behavior through state series. The taxonomy proposed by McHugh in 2001 [McH01] is basically the same proposed by Axelsson, but he added immune inspired methods into the time series models.

Also in 2000, Debar *et al.* [DDW00] presented a revision of a previously authored taxonomy [DDW99]. In such taxonomy, they divide the AID tech-

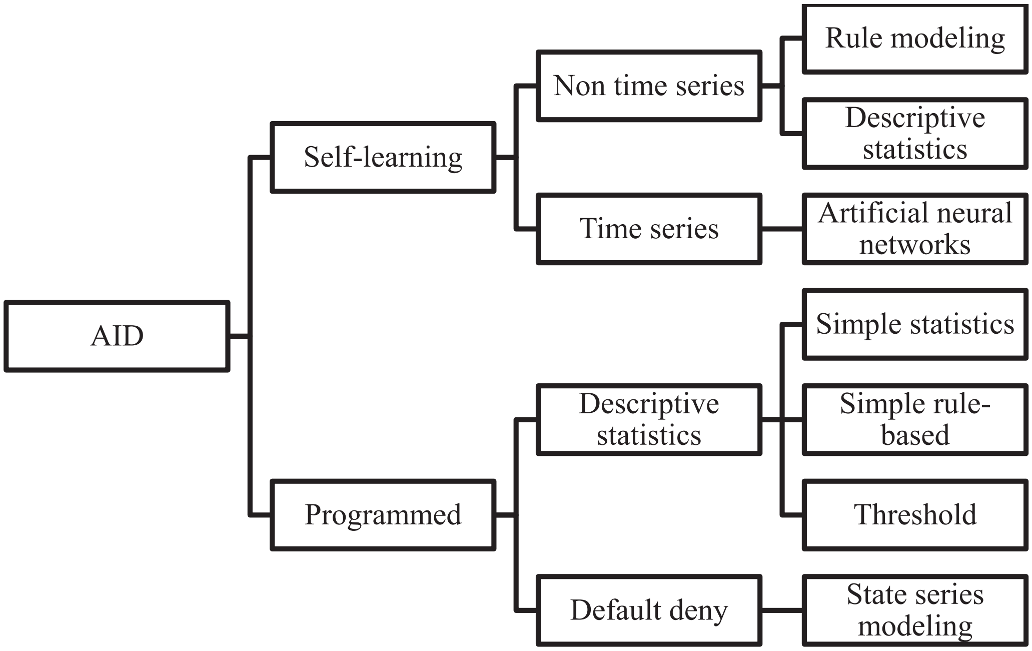


Figure 2.4: Taxonomy of AID principles proposed by Axelsson [Axe00].

niques into five classes: Statistics, Expert systems, Neural networks, User intention identification, and Computer immunology. User intention identification is better known as *profile-based*, as denoted in other works.

Later in 2002, Verwoerd and Hunt [VH02] proposed a more detailed taxonomy, as shown in Figure 2.5. From the proposed classes, File and Taint checking are already implemented in many operative systems and programming languages.

In 2004, Estevez-Tapiador *et al.* [ETGTDV04] proposed a simple taxonomy, where the AID techniques are classified into Learnt-models and Specification-based models. Then, Learnt models are later splitted into Statistical and Rule-based. Similarly simple taxonomies were proposed by Kabiri and Ghorbani in [KG05] and Sobh in [Sob06]. The taxonomy of Kabiri and Ghorbani consists of four classes: Artificial intelligence, Embeded programming, Agent based, and Software engineering; but no subclasses were proposed. Similarly, the taxonomy proposed by Sobh divides AID techniques into three classes: Statistical analysis, Data mining, and Rate limiting. These

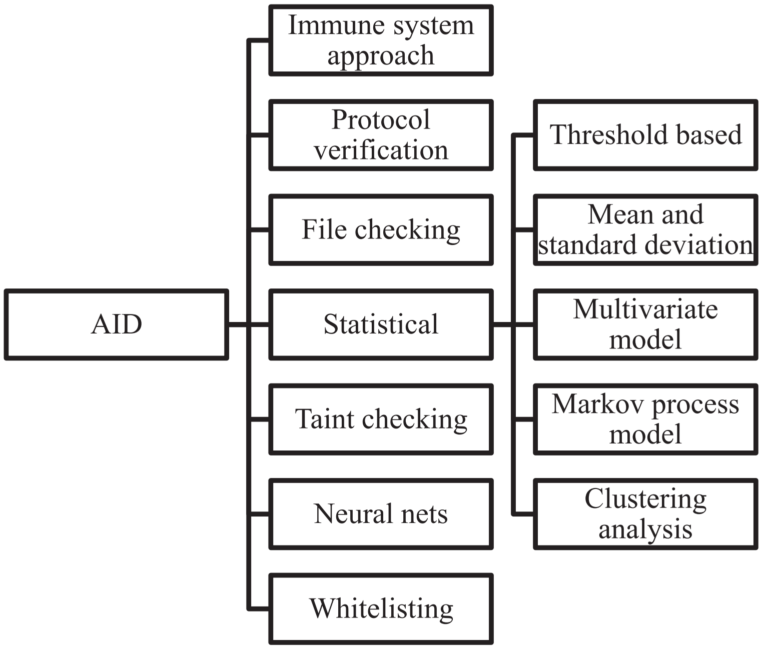


Figure 2.5: Detailed taxonomy of AID principles proposed by Verwoerd and Hunt [VH02].

taxonomies are very simple and lack some very important AID techniques' classes.

Patcha and Park in [PP07] and García-Teodoro *et al.* in [GTDVMFV09] propose other taxonomies based also in three main classes. However, such classes are later divided into subclasses, providing more fine-grained taxonomies—see Figure 2.6 for Patcha and Park's taxonomy and Figure 2.7 for the taxonomy of García-Teodoro *et al.*

Finally, the most comprehensive taxonomy we have found in the literature is that proposed by Chandola *et al.* in [CBK09]. Chandola *et al.* provided an exhaustive survey of anomaly detection techniques not limited only to those applied to ID, but also surveyed those applied to other fields such as fraud detection or image processing. However, the taxonomy perfectly applies to AID techniques, as shown in Figure 2.8.

As can be seen from the surveyed taxonomies, there is some kind of consensus in the classes proposed in the literature to classify the different

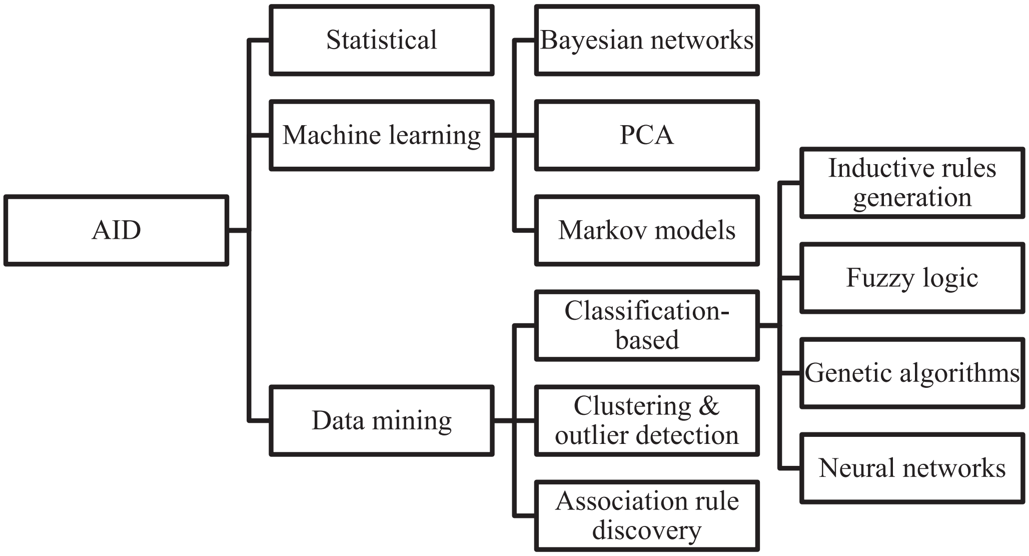


Figure 2.6: Fine-grained taxonomy of AID principles proposed by Patcha and Park [PP07].

techniques, being the principal differences related to the grouping of techniques and the granularity of the description of the different branches in the trees.

Finally, there are some other taxonomies of AID techniques restricted to specific scientific disciplines. In this light, Kim *et al.* in [KBA$^+$07] provide a survey and taxonomy of immune system approaches to ID. The immune system approaches may be divided into two main classes: Negative selection and Danger theory. Artificial immune systems are a class of computationally intelligent systems inspired by the principles of the human immune system. The use of computational intelligence in intrusion detection systems was studied by Wu and Banzhaf in [WB10], who proposed a taxonomy for such systems as shown in Figure 2.9.

Taxonomy Proposal

In this section we propose a new taxonomy to classify the AID techniques. This taxonomy is based on the surveyed taxonomies and on the review of the existing literature that is presented in Section 2.2.3. The taxonomy

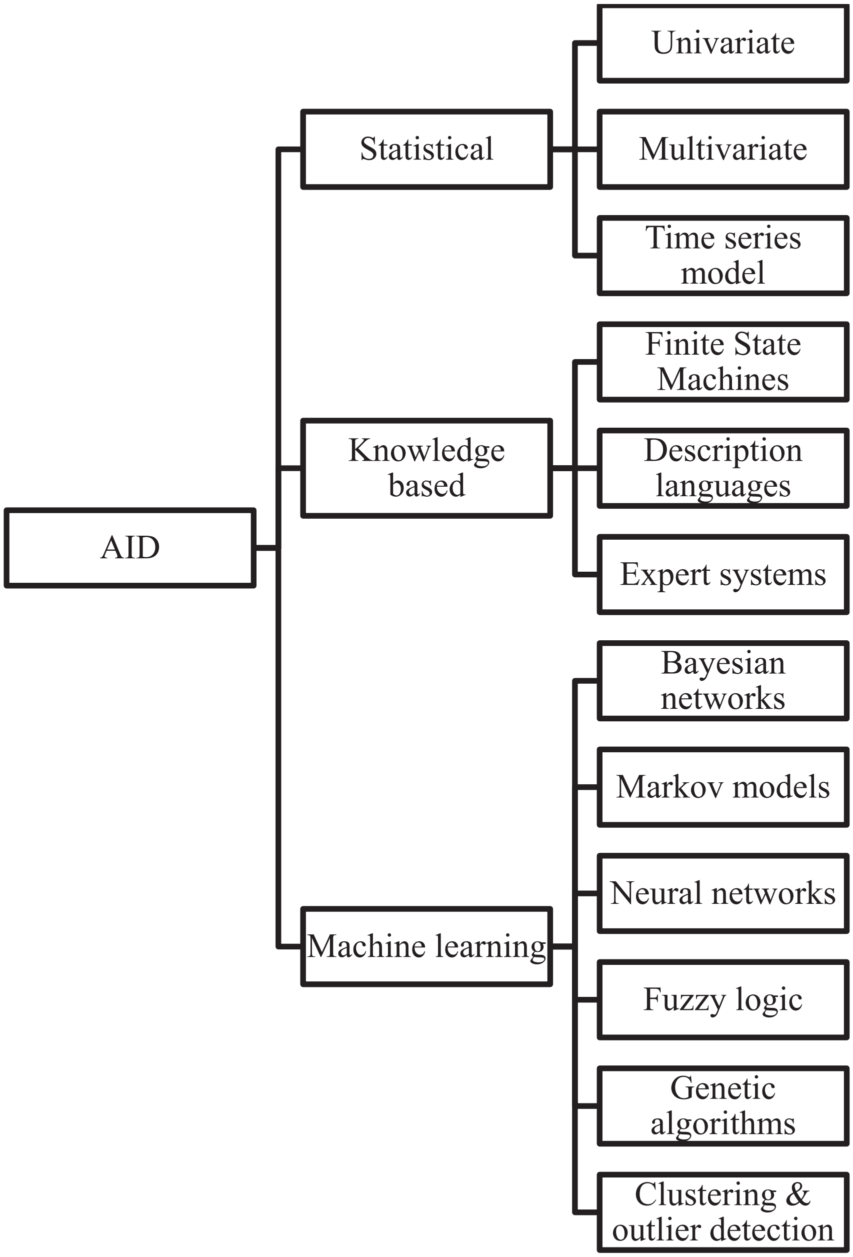


Figure 2.7: Fine-grained taxonomy of AID principles proposed by García-Teodoro *et al.* [GTDVMFV09].

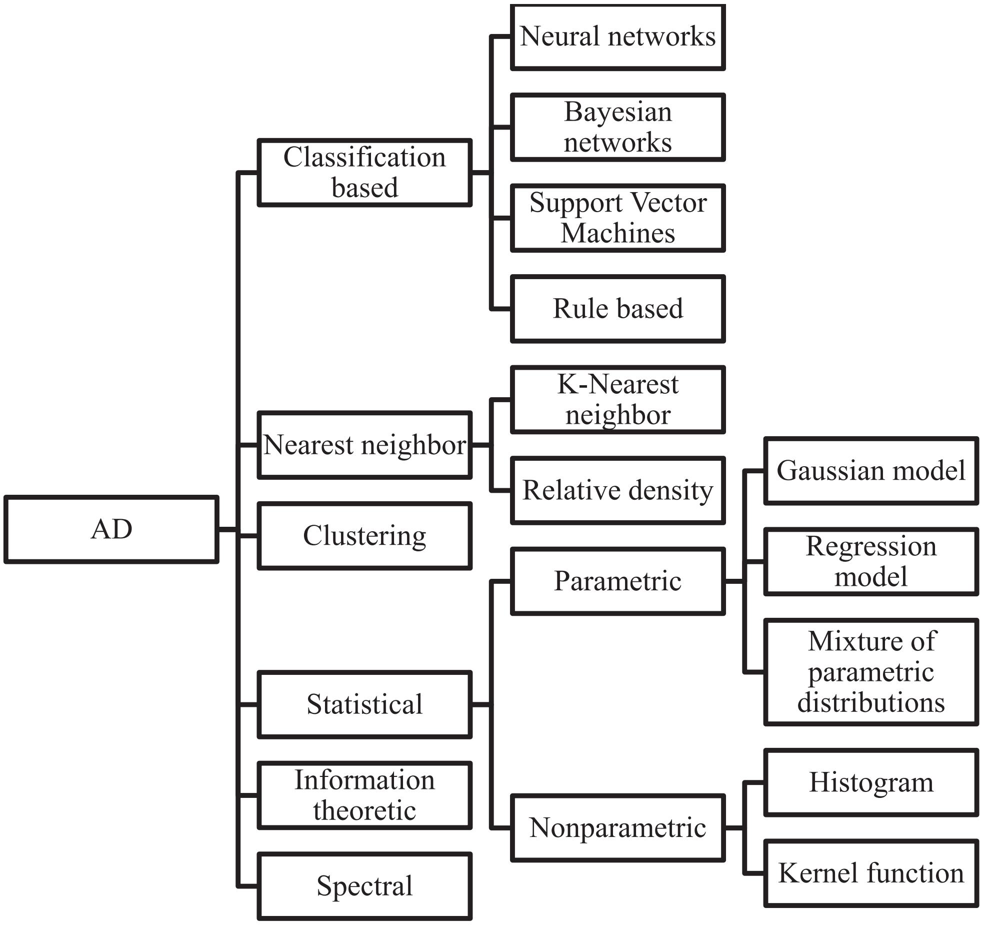


Figure 2.8: Exhaustive taxonomy of AID principles proposed by Chandola *et al.* [CBK09].

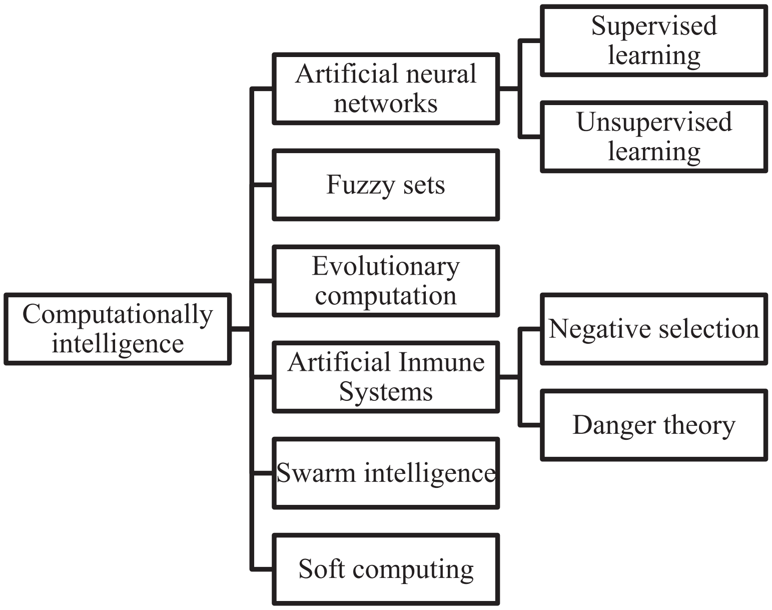


Figure 2.9: Taxonomy of computational intelligence systems applied to AID proposed by Wu and Banzhaf [WB10].

is presented in Figure 2.10. It is a more detailed taxonomy divided into five main classes: Computational intelligence, Information theory, Machine learning, Statistical and Time series analysis.

Computational intelligence is a set of Nature-inspired computational methodologies and approaches to address complex problems of the real world, applications to which traditional methodologies and approaches are ineffective or infeasible. Information theory is a branch of applied mathematics and electrical engineering involving the quantification of information. Machine learning is a scientific discipline concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases. Although it is conceived as a branch of computational intelligence, we have separated it as another class given the prolific contribution of AIDSs belonging to machine learning. Statistical methods are based on statistics, which is the study of the collection, organization, analysis, and interpretation of data. Finally, time series analysis comprises methods for analyzing time series data in order to

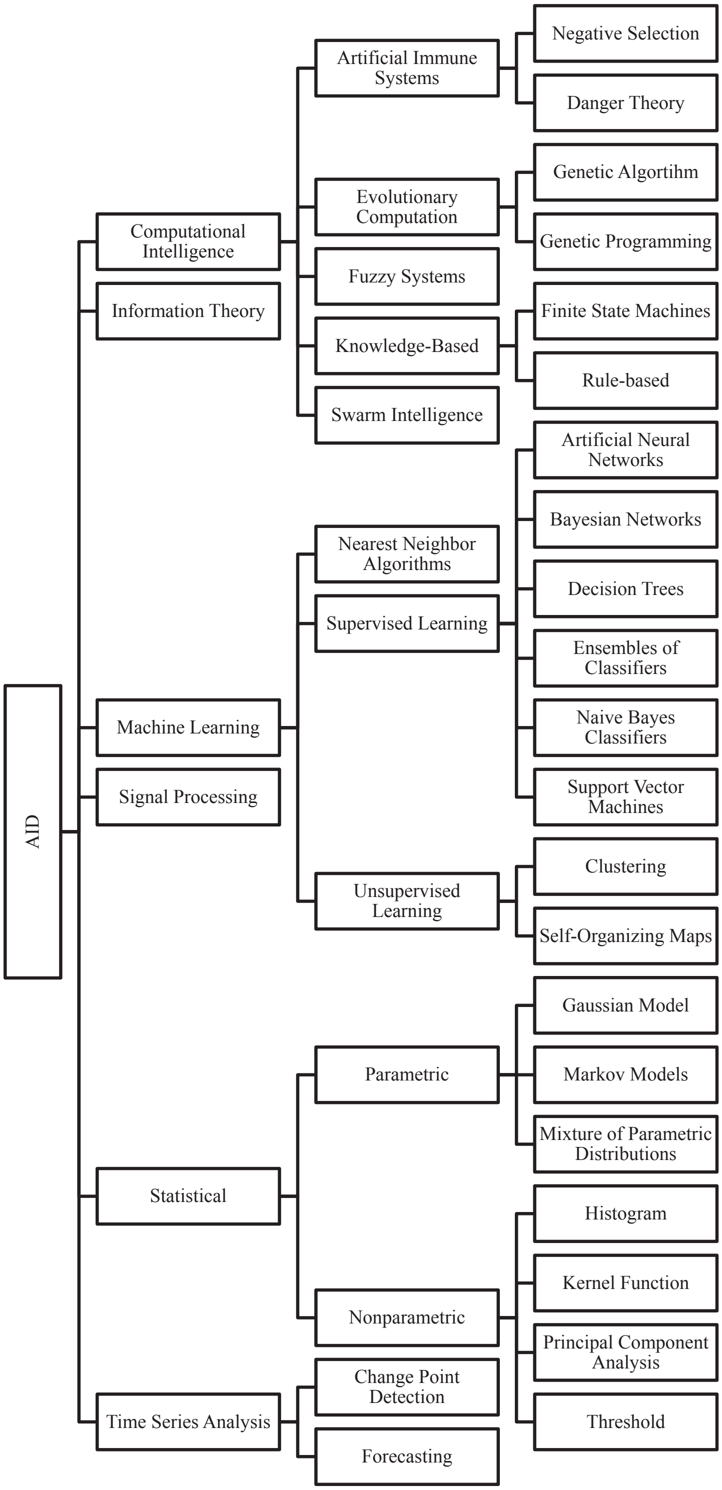


Figure 2.10: Taxonomy proposal of AID techniques.

extract meaningful statistics and other characteristics of the data. Although it can be groped inside statistical, we have decided to locate it in a separate branch because the viewpoint taken for AID may not be based on statistical methods.

2.2.3 Anomaly Intrusion Detection Techniques

This section is devoted to provide a survey of the proposed techniques in AID. Since the majority of the techniques rely on existing detecting paradigms as presented in the taxonomy of Figure 2.10 and apply variations to them, we will follow in this section the aforementioned classification and describe each basic technique for each category, finally summarizing the different variations proposed in the literature.

All these techniques are divided into two main steps. In the first step, commonly denoted as the training phase, the AID technique builds a model of the normal behavior based on training data. Then, in the second step, anomalies are detected, and usually given an anomaly score, based on a similarity measure of the test instances with the normal trained baseline. This second step is denoted in the literature as testing phase.

Computational Intelligence

Computational intelligence (CI) is a fairly new research field of Nature-inspired computational methodologies and approaches to address complex problems of the real world applications. Although there is not yet full agreement on what CI exactly is, there is a widely accepted view on which areas belong to CI, which will be described next. The most accepted definition of CI is given by Bezdek in [Bez92]:

> A system is computational intelligent when it: deals with only numerical (low-level) data, has pattern recognition components, does not use knowledge in the artificial intelligence sense; and additionally when it (begins to) exhibit (i) computational adaptivity, (ii) computational fault tolerance, (iii) speed approaching

human-like turnaround, and (iv) error rates that approximate human performance.

Artificial Immune Systems AISs try to mimic the Human Immune System (HIS), which is capable of protecting the body against damage from an extremely large number of harmful pathogens without prior knowledge of the structure of these pathogens [KBA$^+$07].

Negative Selection: Negative Selection (NS) algorithms are based on one specific aspect of the HIS: NS in the T-cell maturation process. NS eliminates inappropriate T-cells that bind to self antigens. This allows the HIS to detect non-self antigens without mistakenly detecting self antigens. NS algorithms consist of the following three steps: defining self, generating detectors and monitoring the occurrence of anomalies. The self is defined as the normal behavior of analyzed patterns in the monitored system. Secondly, the algorithm generates a number of random patterns that are compared to the self patterns. In the case of a pattern matching a self-pattern, such pattern is not a useful detector and thus it is eliminated. Otherwise, it becomes a detector. Finally, in the monitoring stage, when any of the detector patterns match a monitored pattern, the monitored system is considered to be under risk and an alert is placed [KBA$^+$07].

NS-based methods entail a number of features that make them suitable for AID. First, no prior knowledge of intrusions is required, which allows to detect new kinds of anomalies. Second, the detection rate is tunable by setting the number of generated detectors. Finally, detection is distributable, which means that each detector can detect anomalies independently and without communication with other detectors [DFH96].

Table 2.2 summarizes different approaches to AID based on NS algorithm.

Table 2.2: Negative selection approaches to AID.

Technique	Comments
Hofmeyr and Forrest [HF00]	They present LISYS, an architecture for detecting anomalies using NS algorithm for binary detection generation.
González *et al.* [GDK02]	They present a technique to detect anomalies using negative selection and classification.
Harmer *et al.* [HWGL02]	NS applied to detect anomalies based on 28 TCP packet header features and 16 features of UDP and Internet Control Message Protocol (ICMP) packet headers.
Dasgupta and González [DG02]	They present two Artificial Immune System (AIS)-based methods to detect anomalies: negative and positive characterization.
González and Dasgupta [GD02b]	They propose a two-step approach for AID. First, a NS algorithm is used to generate abnormal samples, that are used jointly with normal ones in the training of an artificial neural network. The proposed method is compared with a self-organizing map.
González and Dasgupta [GD03]	Network-based anomaly detection technique.
Gómez *et al.* [GGD03]	They present a new technique for generating a set of fuzzy rules that can characterize the non-self space (abnormal) using only self (normal) samples.
Esponda *et al.* [EFH04]	They present a framework to evaluate positive and negative selection schemes.

Continued on next page

Table 2.2 – continued from previous page

Technique	Comments
Sarafijanović and Le Boudec [SLB05]	They investigate the use of an AIS to detect node misbehavior in a mobile ad hoc network using dynamic source routing.
Powers and He [PH08]	They propose a two-component hybrid model. The first one uses an AIS to detect anomalies. The second one uses self-organizing maps to classify the anomalies detected by the AIS.
Greensmith *et al.* [GFA08]	They present an AIS-based AID focused on the detection of port scanning using SYN packets.
Schmidt *et al.* [SPL+09]	They present a framework to monitor smartphones and remotely detect anomalies using self-organizing maps and AIS techniques.

Danger Theory: In 1998, Burgess [Bur98] claimed that the self and non-self distinction on which the NS algorithms are based was too simple to model the whole HIS mechanism. Consequently, he proposed to use the Danger theory [Mat94].

Danger theory argues that there must be discrimination beyond the self and non-self distinction because the HIS only discriminates the self from the non-self partially. As a consequence, Danger theory posits that it is not the *foreignness* of the antigens what is important for immune detection, but instead the relative *danger* of these antigens. In this way, the Danger theory suggests that foreign invaders which are dangerous will induce the generation of cellular molecules (*danger signals*) by initiating cellular stress or cell death. Finally, this danger signal triggers the evaluation of potential antigens through negative selection. Aickelin *et al.* in [ABC$^+$03] present the first in-depth discussion on the application of Danger theory to ID.

Table 2.3 summarizes different approaches to AID based on Danger theory.

Table 2.3: Danger theory approaches to AID.

Technique	**Comments**
Burgess [Bur00]	Cfengine: Open source configuration management platform.
Begnum and Burgess [BB03]	Combine process homeostasis with Cfengine positive and negative selection schemes.
Sarafijanović and Le Boudec [SLB04]	They present an AID system for wireless ad hoc networks that considers packet losses as a danger signal.
Greensmith *et al.* [GAC05]	They employ DCs within AIS that coordinated T-cell immune responses.
Kim *et al.* [KWAM05]	They discuss T-cell immunity and tolerance for computer worm detection.
Kim *et al.* [KGTA05]	The artificial tissue, the Dendritic Cells (DC) algorithm and T-cell algorithm were combined and presented as a different version of the danger theory inspired AISs.

Evolutionary Computation Evolutionary Computation (EC) is a subfield of CI that involves combinatorial optimization problems. EC uses iterative progress, such as growth or development in a population. This population is then selected in a guided random search using parallel processing to achieve the desired end. Such processes are often inspired by biological mechanisms of evolution [WB10].

Genetic Algorithm: A Genetic Algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to search problems, such as finding anomalies buried in the background traffic. GA is used in IDSs as optimization components, for automatically modeling structure design or as classifiers [WB10].

In a GA, a population which encode candidate solutions to the target problem evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population based on their fitness, and modified (mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. Consequently, a GA requires a genetic representation of the solution and a fitness function to evaluate it.

Table 2.4 summarizes different approaches to AID based on GAs.

Table 2.4: Genetic algorithm approaches to AID.

Technique	Comments
Mischiatti and Neri [MN00]	They learn network models using GAs, and compare for discrepancies.

Continued on next page

Table 2.4 – continued from previous page

Technique	Comments
Balajinath and Raghavan [BR01]	They use GAs to learn the individual user behavior and detect anomalies by predicting current user behavior based on past observations.
Gomez and Dasgupta [GD02a]	They present a methodology that allows the application of fuzzy classifiers and genetic algorithms to AID.
Gómez *et al.* [GDNG02]	The authors propose a new linear representation scheme for evolving fuzzy rules using the concept of complete binary tree structures and apply it to detect network-based anomalies.
Hofmann *et al.* [HSS03]	They use a GA to learn the structure of Radial Basis Function (RBF) nets.
Pillai *et al.* [PEV04]	They introduce the application of GAs, in order to improve the effectiveness of IDSs.
Liu *et al.* [LCLZ04]	They use genetic clustering to automatically establish clusters and detect intruders by labeling normal and abnormal groups.
Leon *et al.* [LNG04]	They apply clustering to detect anomalies. The number of clusters is automatically determined by a GA.
Li [Li04]	The author describes a technique of applying GAs to network ID. The implementation considers both temporal and spatial information of network connections.
Lu and Traore [LT05]	They applied a GA to decide the number of clusters based upon Gaussian mixture models.
Zhao *et al.* [ZZL05]	They apply k-means to decide potential cluster centers and a GA subsequently refined the centroids.

Continued on next page

Table 2.4 – continued from previous page

Technique	Comments
Gong *et al.* [GZA05]	A GA is employed to derive a set of classification rules from network audit data, and the support-confidence framework is utilized as fitness function to judge the quality of each rule.
Stein *et al.* [SCWH05]	The authors propose an IDS that uses a GA to select a subset of input features for decision tree classifiers, thus improving the classification performance.
Abadeh *et al.* [AHL07]	They propose an AID system based on fuzzy learning using GAs.
Abadeh *et al.* [SAHBS07]	They propose a method based on GAs to find fuzzy rules.
Toosi and Kahani [TK07]	They present a method to detect anomalies based on three layers. One of them is based on GAs.
Özyer *et al.* [ÖAB07]	The authors propose an intelligent IDS that uses fuzzy association rules mining to select classification rules that are later used by a genetic fuzzy classifier.
Tsang *et al.* [TKW07]	The authors present a novel ID approach that evolves fuzzy-rules using GAs to detect network-based intrusions.

Genetic Programming: Genetic Programming (GP) is a specialization of GAs where each individual is a computer program. It is used to optimize a population of computer programs according to a fitness landscape determined by a program's ability to perform a given computational task.

GP evolves computer programs, traditionally represented in memory as tree structures, which can be easily evaluated in a recursive manner. Every tree node has an operator function and every terminal node has an operand, making mathematical expressions easy to evolve and evaluate. Non-tree representations have been suggested and successfully implemented, such as Linear Genetic Programming (LGP).

Table 2.5 summarizes different approaches to AID based on GP.

Table 2.5: Genetic programming approaches to AID.

Technique	**Comments**
Song *et al.* [SHZH03]	They propose page-based LGP with two-layer Subset Selection to address a two-class intrusion detection classification problem.
Lu and Traore [LT04]	They present a rule evolution approach based on GP for detecting novel attacks on networks.
Mukkamala *et al.* [MSA04]	They present an AID approach based on LGP.
Song *et al.* [SHZH05]	They present a methodology to filter features of a dataset to its application to genetic programming.
Grosan *et al.* [GAH05]	They present an AID system based on Multi-Expression Programming.
Yin *et al.* [YTHH05]	They present a GP-based rule learning approach for detecting attacks on network.
Folino *et al.* [FPS05]	They present an intrusion detection algorithm based on GP ensembles.
Abraham *et al.* [AGMV07]	They present three variants of GP techniques to AID.

Continued on next page

Table 2.5 – continued from previous page

Technique	Comments
Chen *et al.* [CAY07]	The authors present an IDS using a flexible multi-layer Artificial Neural Network, which is evolved using the probabilistic incremental program evolution algorithm and whose features are selected using Particle Swarm Optimization.

Fuzzy Systems FSs are based on fuzzy logic. Fuzzy logic, dealing with the vague and imprecise, analyzes analog input values in terms of logical variables that take on continuous values between 0 and 1, in contrast to digital logic, which operates on discrete values of either 1 or 0 (true or false respectively).

The input variables in a Fuzzy System (FS) are in general mapped into by sets of membership functions, known as *fuzzy sets*. The process of converting a crisp input value to a fuzzy value is called *fuzzification*. The microcontroller makes decisions for what action to take based on a set of *rules* involving fuzzy sets.

FSs consist of an input stage, a processing stage, and an output stage. The input stage maps inputs to the appropriate membership functions and truth values. The processing stage invokes each appropriate rule and generates a result for each, then combines the results of the rules. Finally, the output stage converts the combined result back into a specific control output value.

Table 2.6 summarizes different approaches to AID based on FSs.

Table 2.6: Fuzzy system approaches to AID.

Technique	Comments
Dickerson and Dickerson [DD00]	They present FIRE, an anomaly-based IDS that uses fuzzy logic to assess whether malicious activity is taking place on a network.
Bridges and Vaughn [BV00]	They propose the use of fuzzy association rules and fuzzy sequential rules to mine normal patterns from audit data.
Luo and Bridges [LB00]	They build an AID system by comparing fuzzy rules mined in the training phase with those mined from new audit data.
Zhu *et al.* [ZPZC01]	They present a comparison of three data mining techniques for AID. They conclude that fuzzy sets provide the best accuracy, followed by artificial neural networks and rule-based techniques.
Florez *et al.* [FBV02]	They propose a fuzzy rules comparison algorithm that is amenable to on-line application.
Gómez *et al.* [GDNG02]	The authors propose a new linear representation scheme for evolving fuzzy rules using the concept of complete binary tree structures and apply it to detect network-based anomalies.
Gómez and Dasgupta [GD02a]	They present a methodology that allows the application of fuzzy classifiers and genetic algorithms to AID.
Shah *et al.* [SUJ03]	They present a fuzzy clustering (C-Mediods) approach to AID.

Continued on next page

Table 2.6 – continued from previous page

Technique	Comments
Gómez *et al.* [GGD03]	They present a new technique for generating a set of fuzzy rules that can characterize the non-self space (abnormal) using only self (normal) samples.
Chavan *et al.* [CSD+04]	The authors propose an IDS using artificial neural networks and fuzzy inference system.
El-Semary *et al.* [ESEGP05]	They propose an AID based on a fuzzy inference engine to compare rules.
Chimphlee *et al.* [CANMS+06]	They present a fuzzy clustering (C-Means) approach to AID.
Abadeh *et al.* [AHL07]	They propose an AID system based on fuzzy learning using genetic algorithm.
Abadeh *et al.* [SAHBS07]	They propose a method based on GAs to find fuzzy rules.
Toosi and Kahani [TK07]	They present a method to detect anomalies based on three layers. One of the is based on fuzzy logic.
Abraham *et al.* [AJTH07]	They present a distributed AID system using fuzzy classifiers.
Özyer *et al.* [ÖAB07]	The authors propose an intelligent IDS that uses fuzzy association rules mining to select classification rules that are later used by a genetic fuzzy classifier.
Tsang *et al.* [TKW07]	The authors present a novel ID approach that evolves fuzzy-rules using genetic algorithms to detect network-based intrusions.

Knowledge-Based A Knowledge-Based System (KBS) is a computer system that emulates the decision-making ability of a human expert. KBSs are designed to solve complex problems by reasoning about knowledge, like an expert, and not by following the procedure of a developer as is the case in conventional programming.

Finite State Machines: A Finite State Machine (FSM) is a mathematical model used to design computer programs and digital logic circuits. It is conceived as an abstract machine that can be in one of a finite number of states. The machine is in only one state at a time (*current state*). It can change from one state to another when initiated by a triggering event or condition (*transition*). A particular FSM is defined by a list of the possible transition states from each current state, and the triggering condition for each transition.

Table 2.7 summarizes different approaches to AID based on FSMs.

Table 2.7: Finite state machines approaches to AID.

Technique	**Comments**
Ghosh *et al.* [GMS00]	They present two methods to detect anomalies. The methods are based on artificial neural networks and FSMs.
Sekar *et al.* [SGF$^+$02]	They present a method to detect anomalies based on protocol modeling with FSMs.
Estevez-Tapiador *et al.* [ETGTDV03]	They present a FSM model for TCP which is useful for detecting anomalies through the use of Markov chains.
Treurniet [Tre11]	The author presents a method to monitor Internet traffic sessions using FSMs of the main protocols.

Rule-Based: Rule-Based (RB) AID techniques learn rules that capture the normal behavior of a system. A test instance that is not covered by any such rule is considered as an anomaly. A basic RB technique consists of two steps. The first step is to learn rules from the training data using a rule learning algorithm. Each rule has an associated confidence value that is proportional to the ratio of correctly classified training instances. The second step is to find, for each test instance, the rule that best captures the test instance. The inverse of the confidence associated with the best rule is the anomaly score of the test instance.

Table 2.8 summarizes different approaches to AID based on RB.

Table 2.8: Rule-based approaches to AID.

Technique	**Comments**
Lee *et al.* [LSM00]	They propose to use the association rules and frequent episodes computed from audit data to detect anomalies.
Barbará *et al.* [BCJW01]	They propose a system that implements several data mining techniques to detect anomalies.
Zhu *et al.* [ZPZC01]	They present a comparison of three data mining techniques for AID. They conclude that fuzzy sets provide the best accuracy, followed by artificial neural networks and rule-based techniques.
Mahoney and Chan [MC02]	They present a method that learn rules from attack-free network traffic.
Mahoney and Chan [MC03]	They present an algorithm (LERAD) that learns rules for finding rare events in nominal time-series data with long range dependencies.

Continued on next page

Table 2.8 – continued from previous page

Technique	Comments
Han and Cho [HC03]	They present a rule-based model to integrate different AID approaches.
Chan *et al.* [CMA03]	They explore two methods for anomaly detection based on past behavior. The first method is a rule learning algorithm. The second method uses a clustering algorithm to identify outliers.
Otey *et al.* [OPG$^+$03]	They present and evaluate a NIC-based network intrusion detection system. The AID system is rule-based.
Gómez *et al.* [GGD03]	They present a new technique for generating a set of fuzzy rules that can characterize the non-self space (abnormal) using only self (normal) samples.
Qin and Hwang [QH04]	They propose a new Internet trace technique for generating frequent episode rules to characterize Internet traffic events.
Tandon and Chan [TC07]	They propose the use of weights in the learned rules to enhance LERAD.
Brauckhoff *et al.* [BDWS09]	They propose the use of association rule mining to find and summarize the flows related with the detected anomalies.

Swarm Intelligence Swarm Intelligence (SI) is an CI technique involving the study of collective behavior in decentralized systems. It computationally emulates the emergent behavior of *social insects* or *swarms* in order to simplify the design of distributed solutions to complex problems.

Generally speaking, SI models are population-based. Individuals in the population are potential solutions. These individuals collaboratively search for the optimum through iterative steps. Individuals change their positions in the search space, however, via direct or indirect communications, rather than the crossover or mutation operators in evolutionary computation. Among the SI methods, there are two that outstand: Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [WB10].

Table 2.9 summarizes different approaches to AID based on SI.

Table 2.9: Swarm intelligence approaches to AID.

Technique	**Comments**
Ramos and Abraham [RA05]	They present an ant-based clustering algorithm to detect intrusion in a network infrastructure.
Tsang and Kwong [TK05]	They propose an improved version of the basic ant-based clustering algorithm.
Abadeh *et al.* [AHA06]	They embedded a standard PSO into their fuzzy genetic algorithm.
Guolong *et al.* [GQW07]	They propose the use of PSO to learn classification rules.
He *et al.* [HLC07]	They present an ant-classifier algorithm for discovering classification rules.
Chen *et al.* [CAY07]	The authors present an IDS using a flexible multi-layer Artificial Neural Network, which is evolved using the probabilistic incremental program evolution algorithm and whose features are selected using PSO.

Information Theory

Information theory is a branch of applied mathematics and electrical engineering involving the quantification of information. A key measure of information, known as entropy, was proposed by Claude E. Shanon in 1948. Entropy quantifies the uncertainty involved in predicting the value of a random variable, and it has been applied to AID since, by hypothesis, anomalies in data induce irregularities in the information content of the data set. Consequently, measuring the information content in anomaly-free data and comparing it to the entropy of test data is able to detect potential anomalies.

Table 2.10 summarizes different approaches to AID based on information theory.

Table 2.10: Information theory approaches to AID.

Technique	**Comments**
Lee and Xiang [LX01]	They propose to use several information-theoretic measures, namely, entropy, conditional entropy, relative conditional entropy, information gain, and information cost for anomaly detection.
Gu *et al.* [GMT05]	They introduce the detection of anomalies using the maximum entropy which detect changes that point to anomalies.
Lakhina *et al.* [LCD05]	They present a method to detect anomalies in large datasets through sample entropy.
Xu *et al.* [XZB05]	They present a model to profile backbone traffic using clustering and entropy.
Wagner and Plattner [WP05]	They present an application of entropy to detect worms in the Internet.

Continued on next page

Table 2.10 – continued from previous page

Technique	Comments
Żuraniewski and Rincón [ŻR06]	They propose two methods for detecting change points in the network traffic fractality. The first one is based on a cumulated sum (CUSUM) technique while the second uses the Schwarz Information Criterion.
Nychis *et al.* [NSA$^+$08]	They evaluate entropy-based AID techniques. They found that port and address distributions are highly correlated.
Ashfaq *et al.* [ARM$^+$08]	They present a comparison of eight AID systems focused on detecting portscans. The best performance is exhibited by entropy-based and threshold random walk techniques.
Lee *et al.* [LKK$^+$08]	They propose a method for proactive detection of Distributed Denial of Service (DDoS) attacks using entropy and clustering. The method is able to detect the attacks in their initial stages.
Androulidakis *et al.* [ACP09]	They present a study of how to improve the sampling process to reduce its impact on AID. They illustrate their results with an entropy-based AID.
Burkhart *et al.* [BSMD10]	They propose SEPIA, a library for multiparty computation that allows preserving privacy when aggregating multi-domain network events and statistics. They illustrate the framework detecting anomalies using entropy and thresholds.

Machine Learning

Machine learning is a scientific discipline concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data. A learner can take advantage of examples (data) to capture characteristics of interest of their unknown underlying probability distribution. A major focus of machine learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on data. Hence the learner must generalize (perform accurately on new, unseen examples after training on a finite data set) from the given examples, so as to be able to produce a useful output in new cases. Quoting Tom M. Mitchell:

> A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E [Mit97].

Nearest Neighbor Algorithms Nearest Neighbor (NN) algorithms are based on the assumption that normal data instances are *far* from anomalous data instances. Consequently, NN-based AID techniques require a distance or similarity measure. For continuous attributes, Euclidean distance is a popular choice.

The most popular algorithm uses the distance to the k^{th} nearest neighbor (k-NN). In this technique, an anomaly score proportionally inverse to the distance to its k^{th} nearest neighbor is assigned to new data instances. Finally, a threshold, based either on the anomaly score or given by the m^{th} largest score, is used to determine which instances of the dataset are considered to be anomalous.

Table 2.11 summarizes different approaches to AID based on nearest neighbor algorithm.

Table 2.11: Nearest neighbor algorithm approaches to AID.

Technique	Comments
Eskin *et al.* [EAP$^+$02]	They present three methods to detect anomalies, based on nearest neighbors, clustering and support vector machines, respectively.
Liao and Vemuri [LV02b]	They present a method to detect intrusions by monitoring executing programs. They use k-NN to detect deviations of programs' behavior.
Liao and Vemuri [LV02c]	They present a new approach, based on the k-NN classifier, to classify program behavior as normal or intrusive.
Dokas *et al.* [DEK$^+$02]	They present three methods to detect anomalies, based on nearest neighbors, density based local outliers and support vector machines, respectively.
Hu *et al.* [HLV03]	They compare the performance of robust support vector machines with that of conventional support vector machines and NN classifiers.
Lazarevic *et al.* [LEK$^+$03]	They compare different AID techniques, among which they use k-NN.
Hautamaki *et al.* [HKF04]	They present an outlier detection using indegree number algorithm that utilizes k-NN graph.
Patwari *et al.* [PHIP05]	They use k-NN to reduce dimensionality of network measurements to two dimensions thus providing a mean for visualization of the relationships existing in the data.

Continued on next page

Table 2.11 – continued from previous page

Technique	Comments
Ahmed *et al.* [AOC07]	They investigate the use of the block-based One-Class Neighbor Machine and the recursive Kernel-based Online Anomaly Detection algorithms for network ID.
Sharma *et al.* [SPP07]	They present an IDS based on system call sequences using text processing techniques. As similarity measure a kernel function is used, and k-NN classify the processes as either normal or abnormal.
Li and Guo [LG07]	The authors propose a novel supervised network ID method based on transductive confidence machines for k-NN.

Supervised Learning Supervised learning is the machine learning task of inferring a function from supervised (*labeled*) training data. The training data consist of a set of training examples and a desired output value. A supervised learning algorithm analyzes the training data and produces an inferred function. The inferred function should predict the correct output value for any valid input object. Supervised learning techniques have been numerously applied to AID, although it is hard to properly label training data. Typically, attack-free data are used for the training phase, and the paradigms flag unseen patterns as anomalous.

Artificial Neural Networks: An Artificial Neural Network (ANN) is a mathematical model that is inspired by the structure and functional aspects of biological neural networks. An ANN consists of an interconnected group of artificial neurons, which changes its structure based on information that flows through the network during the learning phase. They are typically used to model complex relationships between inputs and outputs or to find patterns in data.

A basic ANN operates in two steps. First, an ANN is trained on the normal training data to learn the normal classes. Second, each test instance is provided as an input to the ANN. If the ANN accepts the test input, it is normal and it is an anomaly on the contrary.

Table 2.12 summarizes different approaches to AID based on artificial neural network.

Table 2.12: Artificial neural network approaches to AID.

Technique	**Comments**
Ghosh *et al.* [GMS00]	They present two methods to detect anomalies. The methods are based on ANNs and finite state machines.
Lee and Heinbuch [LH01]	They present a method to detect protocol misuse using hierarchical neural networks.
Zhu *et al.* [ZPZC01]	They present a comparison of three data mining techniques for AID. They conclude that fuzzy sets provide the best accuracy, followed by ANNs and rule-based techniques.
Manikopoulos and Papavassiliou [MP02]	They present a method to detect anomalies using a distribution comparator. The comparisons are joined with a neural network.
González and Dasgupta [GD02b]	They propose a two-step approach for AID. First, a negative selection algorithm is used to generate abnormal samples, that are used jointly with normal ones in the training of an ANN. The proposed method is compared with a self-organizing map.

Continued on next page

Table 2.12 – continued from previous page

Technique	Comments
Mukkamala *et al.* [MJS02]	They describe two approaches to AID, one using support vector machines and other using ANNs. In addition, they show an approach for data reduction, exhibiting its performance with the proposed models.
Sung and Mukkamala [SM03]	They perform experiments to identify which are the most interesting features of DARPA datasets (§2.2.4) for the identification of the different traffic kinds.
Joo *et al.* [JHH03]	They propose a method that uses the neural network model for AID but consider the cost ratio of false negative errors to false positive errors to enhance the effectiveness of the intrusion detection.
Li and Manikopoulos [LM03]	The authors present MAID, a histogram-based AIDSs that uses ANN classifiers to detect Denial of Service (DoS) attacks using MIB traffic parameters.
Moradi and Zulkernine [MZ04]	They present a a model to classify anomalies in three classes (one of them is normal traffic) using a multilayer neural network.
Chavan *et al.* [CSD$^+$04]	The authors propose an IDS using ANN and fuzzy inference system.
Corchado *et al.* [CHS05b]	They present a method to detect anomalies by projecting features using neural networks.
Chen *et al.* [CHS05a]	They compare ANNs and support vector machines to detect anomalies on business service management audit data. They conclude that support vector machines outperform ANNs.

Continued on next page

Table 2.12 – continued from previous page

Technique	Comments
Zhang *et al.* [ZJK05]	They present two hierarchical frameworks to detect intrusions based on modular neural networks trained with RBFs.
Mukkamala *et al.* [MSA05]	They present three methods to detect anomalies based on artificial neural networks, support vector machines and multivariate adaptive regression splines. Then they build a new detector joining the previous ones, which outperforms them.
Gavrilis and Dermatas [GD05]	They present and evaluate a RBF neural network detector for DDoS attacks in public networks based on statistical features estimated in short-time windows of the incoming data packets.
Han and Cho [HC06]	They use evolutionary neural networks to detect anomalies.
Amini *et al.* [AJS06]	They present a framework to detect intrusions using different kinds of neural networks.
Florez-Larrahondo *et al.* [FLLD$^+$06]	They propose the integration of intelligent anomaly detection agents for distributed monitoring. They monitor operating system calls with neural network models and function calls with hidden Markov models.
Faraoun and Boukelif [FB07]	They present a method to detect anomalies using neural networks that uses k-means clustering to improve the training phase.
Chen *et al.* [CAY07]	The authors present an IDS using a flexible multi-layer ANN, which is evolved using the probabilistic incremental program evolution algorithm and whose features are selected using Particle Swarm Optimization.

Continued on next page

Table 2.12 – continued from previous page

Technique	Comments
Liu *et al.* [LYY07]	The authors propose a hybrid IDS using principal component analysis neural networks.
Corchado and Herrero [CH11]	They present a methodology to visualize network traffic that is able to expose the anomalies present in such traffic.

Bayesian Networks: A Bayesian Network (BN) is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a Directed Acyclic Graph (DAG). The nodes of such DAG represent random variables in the Bayesian sense. Edges represent conditional dependencies—nodes which are not connected represent variables which are conditionally independent of each other. Each node is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node.

Given a test data instance, the model estimates the posterior probability of the test instance belonging to the normal and anomaly classes, based on the training data. The class with the largest posterior probability is chosen as the predicted class for the given test instance.

Table 2.13 summarizes different approaches to AID based on Bayesian networks.

Table 2.13: Bayesian networks approaches to AID.

Technique	Comments
Valdes and Skinner [VS00]	They present an adaptive, model-based technique for attack detection, using Bayes networks technology to analyze bursts of traffic.
Ye *et al.* [YXE00]	They present a method based on Bayesian probabilistic network to detect network anomalies.
Barbara *et al.* [BWJ01]	They propose a method based on a technique called pseudo-Bayes estimators to enhance an anomaly detection systems ability to detect new attacks while reducing the false alarm rate as much as possible.
Bronstein *et al.* [BDD+01]	They propose a general architecture and implementation for the autonomous assessment of health of arbitrary service elements using Bayesian networks.
Sebyala *et al.* [SOS02]	They present the application of Bayesian technology in the development of an anomaly detection system for proxylets.
Kruegel *et al.* [KMRV03]	They present a method to detect anomalies based Bayesian classifiers aggregated in a Bayesian network.
Mutz *et al.* [MVVK06]	They present a host-based AID system based on several models of system call arguments. The different models are joined using a Bayesian network.

Decision Trees: A Decision tree is a decision support tool that uses a tree-like graph of decisions and their possible consequences. Decision tree learning uses a decision tree as a predictive model which maps observations about an instance to conclusions about the instance's target value. In these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels.

Table 2.14 summarizes different approaches to AID based on decision trees.

Table 2.14: Decision trees approaches to AID.

Technique	**Comments**
Li and Ye [LY01]	They present a model to detect anomalies based on decision trees. The trees are trained using past data with anomalies.
Amor *et al.* [ABE04]	They present two models and compare their performance using DARPA datasets(§2.2.4). The methods are naive Bayes classifier and decision trees.
Peddabachigari *et al.* [PAT04]	The authors compare IDSs based on decision trees and support vector machines. They show that decision trees give better overall performance than support vector machines.
Kang *et al.* [KFH05]	They present a new model for representing system calls and test its efficiency when applied to AID.
Depren *et al.* [DTAC05]	They present a hybrid model for intrusion detection. A self-organizing map and a decision tree are joined with a rule-based decision support system.
Stein *et al.* [SCWH05]	The authors propose an IDS that uses a genetic algorithm to select a subset of input features for decision tree classifiers, thus improving the classification performance.

Continued on next page

Table 2.14 – continued from previous page

Technique	Comments
Gaddam *et al.* [GPB07]	They present a two-step method to detect anomalies. First they apply k-means clustering to cluster the data, and then they apply ID3 decision to detect subgroups within each cluster.
Peddabachigari *et al.* [PAGT07]	They present four different methods based on different intelligent system approaches to detect anomalies.
Xiang *et al.* [XYM08]	They propose a multiple-level hybrid classifier for ID that combines tress classifiers and Bayesian clustering.

Ensemble of Classifiers: Ensemble of Classifiers (EoC) methods use multiple models to obtain better predictive performance than could be obtained from any of the constituent models. The objective is to combine the different models in order to enhance their benefits while diminishing their drawbacks. In addition, different models can provide complementary information about the patterns to be classified.

Table 2.15 summarizes different approaches to AID based on ensembles of classifiers.

Table 2.15: Ensembles of classifiers approaches to AID.

Technique	Comments
Bass [Bas00]	The author surveys IDSs requirements. He points that future IDSs would base their decisions on data fusion.

Continued on next page

Table 2.15 – continued from previous page

Technique	Comments
Manikopoulos and Papavassiliou [MP02]	They present a method to detect anomalies using a distribution comparator. The comparisons are joined with a neural network.
Han and Cho [HC03]	They present a rule-based method to integrate different anomaly detection models. The final system is more robust to false positives.
Siaterlis and Maglaris [SM04]	They present a method to integrate different denial of service attack detection mechanisms.
Mukkamala *et al.* [MSA05]	They present three methods to detect anomalies based on artificial neural networks, support vector machines and multivariate adaptive regression splines. Then they build a new detector joining the previous ones, which outperforms them.
Shifflet [Shi05]	The author presents a model, independent of the AID techniques, to fusion alerts and information.
Mutz *et al.* [MVVK06]	They present a host-based AID system based on several models of system call arguments. The different models are joined using a Bayesian network.
Peddabachigari *et al.* [PAGT07]	They present four different methods based on different intelligent system approaches to detect anomalies. The ensemble of all the methods has the best performance.
Zhou *et al.* [ZHR$^+$07]	They propose a method to fusion alerts from different intrusion detection systems.

Continued on next page

Table 2.15 – continued from previous page

Technique	Comments
Giacinto *et al.* [GPDRR08]	They present a method to detect anomalies by creating a classifier for each traffic kind and fusing the information of such classifiers.

Naive Bayes Classifiers: A Naive Bayes Classifier (NBC) is a simple probabilistic classifier based on applying Bayes' theorem with strong (*naive*) independence assumptions. This means that a NBC assumes that the presence/absence of a particular feature of a class is unrelated to the presence/absence of any other feature, given the class variable.

An advantage of the NBCs is that it only requires a small amount of training data to estimate the parameters necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix. Despite of its simplicity, NBCs have shown remarkable performance in complex problems.

Table 2.16 summarizes different approaches to AID based on naive Bayes classifier.

Table 2.16: Naive Bayes classifier approaches to AID.

Technique	Comments
Schultz *et al.* [SEZS01]	The authors propose a method for detecting new malicious executables using different classifiers. The best performance is obtained through NBCs.
Kruegel *et al.* [KMRV03]	They present a method to detect anomalies based Bayesian classifiers aggregated in a Bayesian network.

Continued on next page

Table 2.16 – continued from previous page

Technique	Comments
Axelsson [Axe04]	The author presents a method to detect anomalies using a Bayesian classifier with interactive training for reducing the false positive rate.
Amor *et al.* [ABE04]	They present two models and compare their performance using DARPA datasets(§2.2.4). The methods are naive Bayes classifier and decision trees.
Kang *et al.* [KFH05]	They present a new model for representing system calls and test its efficiency when applied to AID.

Support Vector Machines: A Support Vector Machine (SVM) is a concept in statistics and computer science for a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the input, making SVMs a non-probabilistic binary linear classifier. Given a set of attack-free training examples, an SVM training algorithm builds a model that determines whether new examples lie within the learned region or outside its boundaries. Kernels, such as RBF kernel, can be used to learn complex regions.

Table 2.17 summarizes different approaches to AID based on support vector machines.

Table 2.17: Support vector machines approaches to AID.

Technique	**Comments**
Dokas *et al.* [DEK$^+$02]	They present three methods to detect anomalies, based on nearest neighbors, density based local outliers and SVMs, respectively.
Eskin *et al.* [EAP$^+$02]	They present three methods to detect anomalies, based on nearest neighbors, clustering and SVMs, respectively.
Mukkamala *et al.* [MJS02]	They describe two approaches to AID, one using SVMs and other using artificial neural networks. In addition, they show an approach for data reduction, exhibiting its performance with the proposed models.
Hu *et al.* [HLV03]	They compare the performance of Robust SVMs with that of conventional SVM and nearest neighbors classifiers.
Lazarevic *et al.* [LEK$^+$03]	They compare different AID techniques, among which they use SVMs.
Heller *et al.* [HSKS03]	They present a host-based IDS that monitors accesses to the Microsoft Windows Registry using SVMs.
Sung and Mukkamala [SM03]	They perform experiments to identify which are the most interesting features of DARPA datasets (§2.2.4) for the identification of the different traffic kinds.
Kim and Park [KP03]	They propose and evaluate a network-based IDS using SVMs.
Laskov *et al.* [LSK04]	They propose a novel formulation of a one-class SVM specially designed for typical IDSs data features.

Continued on next page

Table 2.17 – continued from previous page

Technique	Comments
Peddabachigari *et al.* [PAT04]	The authors compare IDSs based on decision trees and SVMs. They show that decision trees give better overall performance than SVMs.
Chen *et al.* [CHS05a]	They compare artificial neural networks and SVMs to detect anomalies on business service management audit data. They conclude that SVMs outperform artificial neural networks.
Kang *et al.* [KFH05]	They present a new model for representing system calls and test its efficiency when applied to AID.
Zhang and Shen [ZS05]	They present modifications to SVMs that allow optimizing their training time and its application on real-time.
Mukkamala *et al.* [MSA05]	They present three methods to detect anomalies based on artificial neural networks, support vector machines and multivariate adaptive regression splines. Then they build a new detector joining the previous ones, which outperforms them.
Khan *et al.* [KAT07]	They present a method to enhance the training efficiency of SVMs using hierarchical clusters.
Peddabachigari *et al.* [PAGT07]	They present four different methods based on different intelligent system approaches to detect anomalies.
Yu *et al.* [YLKP08]	They propose to detect traffic flooding attacks using MIB data accessed through SNMP. For attack detection and classification they use different SVMs.

Unsupervised Learning Unsupervised learning refers to the problem of trying to find hidden structure in unlabeled data. Since the examples given to the learner are unlabeled, there is no *ground-truth* to evaluate a potential solution. This distinguishes unsupervised learning from supervised learning and reinforcement learning.

Clustering: Clustering is the task of assigning a set of objects into groups so that the objects in the same cluster are more similar to each other than to those in other clusters.

Clustering can be achieved by various algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find them. Popular notions of clusters include groups with low distances among the cluster members, dense areas of the data space, intervals or particular statistical distributions.

To detect anomalies using clustering, a clustering algorithm and a similarity measure must be chosen. The most popular similarity measure is the Euclidean distance. The clustering algorithm builds the clusters based on the similarity distance. The anomalies are determined by the instances that do not belong to any cluster, the instances that are *far* from their cluster centroids, or data instances that belong to small or sparse clusters. The interested reader is deferred to [CBK09, Section 6.1] for a discussion of the differences between nearest neighbor and clustering paradigms.

Table 2.18 summarizes different approaches to AID based on clustering.

Table 2.18: Clustering approaches to AID.

Technique	**Comments**
Portnoy *et al.* [PES01]	They present a method to detect anomalies based on clustering.
Ye and Li [YL01]	They present a method based on clustering and classification to recognize intrusion signatures.

Continued on next page

Table 2.18 – continued from previous page

Technique	Comments
Taylor and Alves-Foss [TAF02]	They evaluate with real data an network-based AID system based on clustering.
Eskin *et al.* [EAP$^+$02]	They present three methods to detect anomalies, based on nearest neighbors, clustering and support vector machines, respectively.
Sequeira and Zaki [SZ02]	They present a host-based anomaly detection model which uses clustering to detect anomalous events.
Gómez *et al.* [GDN03]	The authors present a novel unsupervised robust clustering technique based on the Gravitational Law and the second Newton's motion Law and apply it to network-based AID.
Zanero and Savaresi [ZS04]	They present a two-tier architecture to detect anomalies. The first layer summarizes the packet payload information, whereas the second layer detects and signals anomalies.
Liu *et al.* [LCLZ04]	They use genetic clustering to automatically establish clusters and detect intruders by labeling normal and abnormal groups.
Lakhina *et al.* [LCD05]	They present a method to detect anomalies in large datasets through sample entropy. The detected anomalies are classified using clustering.
Xu *et al.* [XZB05]	They present a model to profile backbone traffic using clustering and entropy.
Kang *et al.* [KFH05]	They present a new model for representing system calls and test its efficiency when applied to AID.

Continued on next page

Table 2.18 – continued from previous page

Technique	Comments
Leung and Leckie [LL05]	They present a method to detect anomalies using density and grid-based clustering.
Jiang *et al.* [JSW$^+$06]	They present CBUID, a clustering-based method for the unsupervised intrusion detection.
Khan *et al.* [KAT07]	They present a method to enhance the training efficiency of SVMs using hierarchical clusters.
Faraoun and Boukelif [FB07]	They present a method to detect anomalies using neural networks that uses k-means clustering to improve the training phase.
Gaddam *et al.* [GPB07]	They present a two-step method to detect anomalies. First they apply k-means clustering to cluster the data, and then they apply ID3 decision to detect subgroups within each cluster.
Zhong *et al.* [ZKS07]	They investigate multiple unsupervised clustering algorithms for AID: k-means, mixture of spherical Gaussians and self-organizing map among others.
Lee *et al.* [LKK$^+$08]	They propose a method for proactive detection of DDoS attacks using entropy and clustering. The method is able to detect the attacks in their initial stages.
Xiang *et al.* [XYM08]	They propose a multiple-level hybrid classifier for ID that combines tress classifiers and Bayesian clustering.

Self-Organizing Maps: A Self-Organizing Map (SOM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional, discretized representation of the input space of the training samples, called a map. This makes SOMs useful for visualizing low-dimensional views of high-dimensional data, akin to multidimensional scaling. The model was first described as an artificial neural network by the Finnish professor Teuvo Kohonen, and therefore it is sometimes called a Kohonen map [Koh82].

Like most artificial neural networks, SOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector.

Table 2.19 summarizes different approaches to AID based on self-organizing maps.

Table 2.19: Self-organizing maps approaches to AID.

Technique	**Comments**
Rhodes *et al.* [RMC00]	They use SOMs to recognize anomalies in computer network data stream.
Lichodzijewski *et al.* [LZHH02a]	They present an AID system based on a SOM.
Lichodzijewski *et al.* [LZHH02b]	They present a host-based unsupervised AID method using a SOM on user session's information.
Labib and Vemuri [LV02a]	They present a method to detect anomalies based on a SOM that allows results visualization.
González and Dasgupta [GD02b]	They propose a two-step approach for AID. First, a negative selection algorithm is used to generate abnormal samples, that are used jointly with normal ones in the training of an artificial neural network. The proposed method is compared with a SOM.

Continued on next page

Table 2.19 – continued from previous page

Technique	Comments
Kayacik *et al.* [KZHH03]	They present a method based on 6 SOMs, one for each analyzed feature, to detect anomalies.
Ramadas *et al.* [ROT03]	They present an AID model based on a SOM and apply it to a six-tuple of network features.
Zanero and Savaresi [ZS04]	They present a two-tier architecture to detect anomalies. The first layer summarizes the packet payload information, whereas the second layer detects and signals anomalies.
Zanero [Zan05]	They present a method to detect anomalies by monitoring TCP traffic patterns using a SOM.
Sarasamma *et al.* [SZH05]	They present an AID system using a hierarchical SOM.
Depren *et al.* [DTAC05]	They present a hybrid model for intrusion detection. A SOM and a decision tree are joined with a rule-based decision support system.
Vokorokos *et al.* [VBC06]	They present an AID system using a SOM.
Bolzoni *et al.* [BEH06]	They present a two-tier AID system. The first layer uses a SOM to classify network traffic while the second uses PAYL [WS04] to detect the anomalies.
Amini *et al.* [AJS06]	They present a framework to detect intrusions using different kinds of neural networks.
Wang *et al.* [WGZY06]	They present two methods for host-based anomaly detection by creating application profiles. The first method is based on hidden Markov models while the second is based on a SOM.

Continued on next page

Table 2.19 – continued from previous page

Technique	Comments
Kayacik *et al.* [KZHH07]	They present an AID system using a hierarchical SOM.
Zhong *et al.* [ZKS07]	They investigate multiple unsupervised clustering algorithms for AID: k-means, mixture of spherical Gaussians and SOMs among others.
Greensmith *et al.* [GFA08]	They present an AIS-based AID focused on the detection of port scanning using SYN packets, and compare it with a solution based on a SOM.
Powers and He [PH08]	They propose a two-component hybrid model. The first one uses an artificial immune system to detect anomalies. The second one uses SOMs to classify the anomalies detected by the artificial immune system.
Zanero and Serazzi [ZS08]	They present a two-tier AID system. The first layer uses a SOM to classify network traffic while the second uses outlier detection to detect the anomalies.
Schmidt *et al.* [SPL$^+$09]	They present a framework to monitor smartphones and remotely detect anomalies using a SOM and artificial immune system techniques.

Signal Processing

Signal processing deals with operations on or analysis of signals, in either discrete or continuous time. Signals of interest can include sound, images, time-varying measurement values and sensor data. Signals are analog or digital electrical representations of time-varying or spatial-varying physical quantities.

The most applied signal processing technique to detect anomalies is based on the wavelet transform. The wavelet transform is a representation of a signal by a combination of square-integrable functions, which is very useful for detecting abrupt changes in the analyzed signals.

Table 2.20 summarizes different approaches to AID based on signal processing.

Table 2.20: Signal processing approaches to AID.

Technique	**Comments**
Barford and Plonka [BP01]	They present their intention to build a framework to obtain and analyze anomalies based on flow-level network traces, and present their main characteristics.
Thottan and Ji [TJ03]	They present a method to detect anomalies based on statistical signal processing technique based on abrupt change detection.
Zhang *et al.* [ZGGR05]	They introduce the term anomography, which is the union of anomaly detection using tomographic data. They present and compare different techniques.
Dainotti *et al.* [DPV06b]	They propose a two-tier architecture to detect anomalies. In the first layer two conservative are used to point to possible anomalies. In the detectors second layer, a continuous wavelet transform is used to determine the time instant of the anomaly and its duration.
Zheng and Hu [ZH06]	They present a method based on vector quantization, a technique used in image compression.
Kyriakopoulos and Parish [KP07]	They use the wavelet transform to detect anomalies at different timescales. Anomalies are detected as abrupt signal changes.

Continued on next page

Table 2.20 – continued from previous page

Technique	Comments
Lu and Ghorbani [LG09]	They propose an AID system using wavelets and Gaussian mixture models. They define 15 network features that are able to model the normal network situation. Then, using wavelets and an autoregressive model they fit the time series of the characteristics. The residuals of the regression are used to detect the anomalies.
Silveira *et al.* [SDTG10]	They propose ASTUTE, a threshold-based AID technique focused on detecting correlated flows. They compare the performance of ASTUTE with two alternate anomaly detectors based on Kalman filters and wavelets.

Statistical

Statistical AID methods rely on statistics to detect anomalous events. Statistics is the study of the collection, organization, analysis, and interpretation of data. The underlying principle of any statistical anomaly detection technique is, quoting Anscombe and Guttman [AG60]:

> An anomaly is an observation which is suspected of being partially or wholly irrelevant because it is not generated by the stochastic model assumed.

Statistical techniques fit a statistical model (usually for normal behavior) to the given data and then apply a statistical inference test to determine if an unseen instance belongs to this model or not.

Parametric Parametric statistics is a branch of statistics that assumes that the data have come from a type of probability distribution and makes inferences about the parameters of the distribution. Parametric methods establish more assumptions than non-parametric methods. If those extra assumptions are correct, parametric methods can produce more accurate and precise estimates. However, if those assumptions are incorrect, parametric methods can be very misleading.

Gaussian Model: The Gaussian distribution is a two-parameter continuous probability distribution that has a bell-shaped probability density function. The Gaussian distribution is considered the most prominent probability distribution in statistics: it is very tractable analytically, arises as the outcome of the central limit theorem and the *bell* shape of the normal distribution makes it a convenient choice for modeling a large variety of random variables encountered in practice.

Gaussian model-based techniques fit a Gaussian distribution to anomaly-free data. The parameters are commonly estimated using maximum likelihood estimation [Ald97]. The anomaly score for a data instance is the inverse of the probability of that instance being generated by the fitted model, and a threshold is set to determine the anomalies.

Table 2.21 summarizes different approaches to AID based on Gaussian models.

Table 2.21: Gaussian model approaches to AID.

Technique	**Comments**
Yamanishi and Takeuchi [YT01]	They propose an AID method that uses a Gaussian mixture model as a statistical representation of normal behaviors.
Ye *et al.* [YECV02]	They present an AID system based on a multivariate Gaussian model. They use the Hotelling's T^2 test to detect mean-shift anomalies.

Continued on next page

Table 2.21 – continued from previous page

Technique	Comments
Mutz *et al.* [MVVK06]	They present a host-based AID system based on several models of system call arguments. The different models are joined using a Bayesian network.
Robertson *et al.* [RVK$^+$06]	They use different AID models to develop an AID system. One of the methods uses a Gaussian distribution to model attribute length. The system is applied to detect web-based attacks.
Zhong *et al.* [ZKS07]	They investigate multiple unsupervised clustering algorithms for AID: k-means, mixture of spherical Gaussians and self-organizing map among others.
Chhabra *et al.* [CSKC08]	They present a method to detect network-wide anomalies with sparse communication between monitors. The method is based on the quantiles of traffic distributions after Gaussian modeling.
Lu and Ghorbani [LG09]	They propose an AID system using wavelets and Gaussian mixture models. They define 15 network features that are able to model the normal network situation. The, using wavelets and an autoregressive model they fit the time series of the characteristics. The residuals of the regression are used to detect the anomalies.

Markov Models: A Markov model is a stochastic model that assumes the Markov property. A stochastic process has the Markov property, also known as memoryless property, if the conditional probability distribution of future states of the process (conditional on both past and present values) depends only upon the present state; that is, given the present, the future does not depend on the past.

The most popular Markov models are Markov chains and HMMs. A Markov chain is a mathematical system that undergoes transitions from one state to another, between a finite or countable number of possible states. It is a random process characterized by the Markov property. A Hidden Markov Model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (*hidden*) states. In a regular Markov model, the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a HMM, the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by a HMM gives some information about the sequence of states.

Table 2.22 summarizes different approaches to AID based on Markov models.

Table 2.22: Markov model approaches to AID.

Technique	**Comments**
Lane and Brodley [LB03]	They introduce two approaches to AID: one employing instance-based learning and the other using HMMs.
Estevez-Tapiador *et al.* [ETGTDV03]	They present a finite state machine model for TCP which is useful for detecting anomalies through the use of Markov chains.
Yeung and Ding [YD03]	They present two methods to detect host-based anomalies. System calls are modeled using a HMM or frequency distributions (histograms).
Wang *et al.* [WGZ04b]	They present a model for detecting anomalies by analyzing system call logs using HMMs.

Continued on next page

Table 2.22 – continued from previous page

Technique	Comments
Ye *et al.* [YZB04]	They present the application of Markov chains to anomalies by building a model for system activity transitions.
Estevez-Tapiador *et al.* [ETGTDV05]	They present a method based on the monitoring of incoming HTTP request to detect attacks against web servers. The detection is accomplished through a Markovian model.
Khanna and Liu [KL06]	They present a method to detect anomalies on mobile ad-hoc networks using a HMM.
Wang *et al.* [WGZY06]	They present two methods for host-based anomaly detection by creating application profiles. The first method is based on HMMs while the second is based on a self-organizing map.
Mutz *et al.* [MVVK06]	They present a host-based AID system based on several models of system call arguments. The different models are joined using a Bayesian network.
Florez-Larrahondo *et al.* [FLLD$^+$06]	They propose the integration of intelligent anomaly detection agents for distributed monitoring. They monitor operating system calls with neural network models and function calls with HMMs.
Paschalidis and Smaragdakis [PS09]	They propose two methods to on-line spatial AID. One is model-based using a Markov modulated process whereas the other is model-free.

Mixture of Parametric Distributions: A mixture model is a probabilistic model for representing the presence of subpopulations within an overall population, without requiring that an observed dataset should identify the subpopulation to which an individual observation belongs. Generally, mixture models are used to make statistical inferences about the properties of the subpopulations given only observations on the pooled population, without subpopulation-identity information.

There are two possible approaches using mixture models. The first one use a set of distributions to model the normal behavior, while using a different set of distributions to model the anomalous behavior. Then, new data instances are assigned to any of the distributions based on their likelihood, and in the case such distribution is used to model the anomalous behavior, data instances are flagged as anomalous. The second approach only models the normal instances as a mixture of parametric distributions, and the data instances that have low likelihood of belonging to the any of the distributions are reported as anomalous.

Table 2.23 summarizes different approaches to AID based on mixtures of parametric distributions.

Table 2.23: Mixture of parametric distributions approaches to AID.

Technique	**Comments**
Eskin [Esk00]	They present a method to detect anomalies using a mixture model for explaining the presence of anomalies in the data.
Yamanishi and Takeuchi [YT01]	They propose an AID method that uses a Gaussian mixture model as a statistical representation of normal behaviors.
Yamanishi *et al.* [YTWM04]	They propose a method to detect anomalies using a finite mixture model.

Continued on next page

Table 2.23 – continued from previous page

Technique	Comments
Zhong *et al.* [ZKS07]	They investigate multiple unsupervised clustering algorithms for AID: k-means, mixture of spherical Gaussians and self-organizing map among others.
Lu and Ghorbani [LG09]	They propose an AID system using wavelets and Gaussian mixture models. They define 15 network features that are able to model the normal network situation. The, using wavelets and an autoregressive model they fit the time series of the characteristics. The residuals of the regression are used to detect the anomalies.

Nonparametric Nonparametric statistics refer to statistical techniques that either do not rely on data belonging to any particular distribution or do not assume that the structure of a model is fixed. Such techniques typically make fewer assumptions regarding the data when compared to parametric techniques.

Histogram: A histogram is a graphical representation showing a visual impression of the distribution of data. It is an estimate of the probability distribution of a random variable and was first introduced by Karl Pearson [Pea95]. A histogram consists of tabular frequencies, shown as adjacent rectangles, erected over discrete intervals (*bins*), with an area equal to the frequency of the observations in the interval. A histogram may also be normalized displaying relative frequencies.

Histogram-based AID techniques build histograms of the analyzed data to maintain a profile of the normal data. The histogram is build using attack-free data, and new data instances are labeled as anomalous if they do not fall in any of the histogram bins.

Table 2.24 summarizes different approaches to AID based on histograms.

Table 2.24: Histogram-based approaches to AID.

Technique	Comments
Eskin [Esk00]	They present a method to detect anomalies using a mixture model for explaining the presence of anomalies in the data.
Yamanishi and Takeuchi [YT01]	They propose an AID method that uses a Gaussian mixture model as a statistical representation of normal behaviors.
Sekar *et al.* [SGF$^+$02]	They present a method to detect anomalies based on protocol modeling with finite state machines.
Krügel *et al.* [KTK02]	They present a method to detect anomalies based on packet payload modeling. Then they use histograms and a variation of χ^2 test to detect deviations.
Yeung and Ding [YD03]	They present two methods to detect host-based anomalies. System calls are modeled using a hidden Markov model or frequency distributions.
Li and Manikopoulos [LM03]	The authors present MAID, a histogram-based AIDS that uses artificial neural network classifiers to detect DoS attacks using MIB traffic parameters.
Yamanishi *et al.* [YTWM04]	They propose a method to detect anomalies using a finite mixture model.
Mutz *et al.* [MVVK06]	They present a host-based AID system based on several models of system call arguments. The different models are joined using a Bayesian network.

Kernel Function: Kernel functions are used to estimate probability density distributions. Although kernel-based techniques are nonparametric, anomaly detection techniques based on kernel functions are similar to the parametric methods aforementioned. The only difference is how the density is estimated.

Table 2.25 summarizes different approaches to AID based on kernel functions.

Table 2.25: Kernel function-based approaches to AID.

Technique	**Comments**
Yeung and Chow [YC02]	They present a method to detect anomalies using Parzen windows with Gaussian kernels.
Ahmed *et al.* [ACL07]	They present a kernel-based method to detect anomalies that is amenable for on-line deployment.
Ahmed *et al.* [AOC07]	They investigate the use of the block-based One-Class Neighbor Machine and the recursive Kernel-based Online Anomaly Detection algorithms for network ID.
Sharma *et al.* [SPP07]	They present an IDS based on system call sequences using text processing techniques. As similarity measure a kernel function is used, and k-NN classify the processes as either normal or abnormal.

Principal Component Analysis: Principal Component Analysis (PCA) is an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables.

The assumption of PCA-based AID techniques is that data can be embedded into a subspace of lower dimensionality where normal and anomalous instances differ significantly.

Table 2.26 summarizes different approaches to AID based on principal component analysis.

Table 2.26: Principal component analysis based approaches to AID.

Technique	Comments
Shyu *et al.* [SCSC03]	They present a method to detect anomalies based on outlier detection using PCA.
Lakhina *et al.* [LCD04b]	They use PCA to decompose network traffic in regular (anomaly-free) and noisy components which contain spikes that point to anomalies.
Bouzida *et al.* [BCCBG04]	They use PCA to alleviate the decision process of decision trees and nearest neighbor based AID techniques.
Lakhina *et al.* [LCD04a]	They extend their work presented in [LCD04b] applying it to origin-destination flows. Moreover, they perform a manual classification of the detected anomalies.
Labib and Vemuri [LV04]	They present a PCA-based method to detect anomalies focused on DoS attacks.
Oka *et al.* [OOAK04]	They present a method to detect anomalies using system information and eigen co-occurence matrix, which is a technique close to PCA.
Wang *et al.* [WGZ04a]	They present a ID method based on PCA with low overhead and high efficiency.

Continued on next page

Table 2.26 – continued from previous page

Technique	Comments
Zhang *et al.* [ZGGR05]	They introduce the term anomography, which is the union of anomaly detection using tomographic data. They present and compare different techniques.
Li *et al.* [LBC+06]	They present an improvement to network-wide PCA-based AID by using sketches.
Huang *et al.* [HGH+06]	They present a framework to distributed AID by using sophisticated thresholds. Moreover, they use PCA to separate the network traffic in regular and noisy components.
Wang and Battiti [WB06]	They present novel method for intrusion identification in computer networks based on PCA.
Huang *et al.* [HNG+07a]	The authors build a method to detect network-wide anomalies based on the method proposed in [LCD04b], but using less communication with the coordinator node.
Ringberg *et al.* [RSRD07]	The authors evaluate the application of PCA to detect anomalies. They show that using PCA-based AID techniques is harder because of the parameter tuning.
Huang *et al.* [HNG+07b]	They present a framework to detect network-wide anomalies in a distributed but coordinated fashion.
Huang *et al.* [HFLX07]	They present a method to analyze BGP announcements in large-scale networks. Using PCA they manage to detect events that cause network problems.
Liu *et al.* [LYY07]	The authors propose a hybrid IDS using PCA neural networks.

Continued on next page

Table 2.26 – continued from previous page

Technique	Comments
Wang *et al.* [WGZ08]	They present a method to detect anomalies that is applicable to large datasets. It is based on PCA using system call registries.
Schmidt *et al.* [SPL+09]	They present a framework to monitor smartphones and remotely detect anomalies using self-organizing maps and artificial immune system techniques. The features are selected using PCA.
Xu *et al.* [XHF+09]	They present a method to extract useful information from system logs and use it for PCA-based AID.
Brauckhoff *et al.* [BSM09]	They analyze the problems of using PCA for AID and propose the Karhunen-Loeve expansion to solve them.
Rubinstein *et al.* [RNH+09]	They evaluate poisoning techniques to evade attack detection in AID systems and propose an antidote using robust statistics on the PCA-subspace method.

Threshold: Threshold-based techniques for AID detection are the simplest statistical process control [SRRW00] mechanisms. Usually, the thresholds are predefined based on heuristics or experience of the manager. The thresholds may be upper or lower bounds that when surpassed provide evidence of an attack. When the system has collected the sufficient enough statistics, the thresholds establish when to place an alarm.

Table 2.27 summarizes different approaches to AID based on thresholds.

Table 2.27: Threshold based approaches to AID.

Technique	Comments
Staniford *et al.* [SHM02]	They present SPADE, a statistical packet anomaly detection engine to detect portscans.
Williamson [Wil02]	They present a method to detect virus on the Internet. They use a threshold-based technique to detect new outgoing connections of infected hosts.
Jung *et al.* [JPBB04]	They present a method to detect portscans based on thresholds and sequential reasoning.
Wu *et al.* [WVGK04]	They present a method to detect worms based on checking which hosts are attempting connections to unassigned IP addresses. They confirm the infection by setting thresholds in different network statistics.
Borders and Prakash [BP04]	They present a method to detect malicious outgoing connections. The detection is targeted to already infected hosts, and is based on thresholds over outgoing connections' data.
Xu *et al.* [XZB05]	They present a model to profile backbone traffic using clustering and entropy.
Siris and Papagalou [SP06]	They present two algorithms to detect anomalies, specifically SYN flooding DoS attacks. The proposed algorithms are based on threshold and CUSUM [Pag54].
Huang *et al.* [HGH$^+$06]	They present a framework to distributed AID by using sophisticated thresholds. Moreover, they use PCA to separate the network traffic in regular and noisy components.

Continued on next page

Table 2.27 – continued from previous page

Technique	Comments
Agosta *et al.* [ADWCL07]	They propose the use of a supervised classifier trained as a traffic predictor to control a time-varying detection threshold for the detection of worms in a distributed fashion.
Ashfaq *et al.* [ARM$^+$08]	They present a comparison of eight AID systems focused on detecting portscans. The best performance is exhibited by entropy-based and threshold random walk techniques.
Silveira *et al.* [SDTG10]	They propose ASTUTE, a threshold-based AID technique focused on detecting correlated flows. They compare the performance of ASTUTE with two alternate anomaly detectors based on Kalman filters and wavelets.
Burkhart *et al.* [BSMD10]	They propose SEPIA, a library for multiparty computation that allows preserving privacy when aggregating multi-domain network events and statistics. They illustrate the framework detecting anomalies using entropy and thresholds.

Time Series Analysis

A time series is a sequence of data points, measured typically at successive time instants spaced at uniform time intervals. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data.

Change Detection Change Detection (CD) is a statistical analysis tool that tries to identify changes in the probability distribution of a stochastic process or time series. In general the problem concerns both detecting whether or not a change has occurred, or whether several changes might have occurred, and identifying the times of any such changes. AID techniques based on CD assume that any change in the modeled process is related with an anomaly. In Chapter 3 we present an example of a CD technique to detect sustained changes in large-scale networks.

Table 2.28 summarizes different approaches to AID based on change detection.

Table 2.28: Change detection based approaches to AID.

Technique	Comments
Choi *et al.* [CPZ02]	They present a method to detect change points in network traffic volume by detecting non-stationarities.
Cabrera *et al.* [CLQ$^+$02]	The authors propose the detection of DDoS attacks by modeling the rate of change of key MIBs variables.
Thottan and Ji [TJ03]	They present a method to detect anomalies based on statistical signal processing technique based on abrupt change detection.
Schweller *et al.* [SGPC04]	They present a method to detect change points based on sketches (reverse hashing).
Siris and Papagalou [SP06]	They present two algorithms to detect anomalies, specifically SYN flooding DoS attacks. The proposed algorithms are based on threshold and CUSUM [Pag54].
Chen and Hwang [CH06]	They present a method to detect DDoS attacks by using change aggregation trees at each router.

Continued on next page

Table 2.28 – continued from previous page

Technique	Comments
Tartakovsky *et al.* [TRBK06a]	They present three methods to detect anomalies based on CUSUM and applied to detect TCP SYN flooding attacks.
Żuraniewski and Rincón [ŻR06]	They propose two methods for detecting change points in the network traffic fractality. The first one is based on a cumulated sum (CUSUM) technique while the second uses the Schwarz Information Criterion.
Tartakovsky *et al.* [TRBK06b]	They present two CD methods to detect anomalies. The methods differ in the training step, and are applied to network traffic.
Scherrer *et al.* [SLO$^+$07]	They present a model for Internet traffic at different aggregation levels using a non-Gaussian process. Based on such model, they present a method to detect anomalies based on change detection on the parameters of the model.
Dewaele *et al.* [DFB$^+$07]	They present a method to detect anomalies at a single point in the network. To that end, sketches are used to condense the information on similar groups. Then, each group is modeled with a multiresolution non-Gaussian process that is used to detect the anomalies.
Chen *et al.* [CHK07]	They present an architecture to detect DDoS attacks using CD in the traffic volumes of different routers.
Schweller *et al.* [SLC$^+$07]	They propose the detection of volume-based anomalies through change detection, using prediction and reversible sketches.

Continued on next page

Table 2.28 – continued from previous page

Technique	Comments
Rebahi *et al.* [RSM08]	They present a CD method to detect attacks against IP multimedia subsystems based on CUSUM.
D'Alconzo *et al.* [DCRM10]	They present a method to detect anomalies on 3G mobile traffic. The method is based on detecting changes on traffic distributions.
Mandjes and Żuraniewski [MŻ11]	They propose the use of CUSUM-type change point detection techniques for detecting overload periods in network links in a setting in which each connection roughly consumes the same amount of bandwidth.

Forecasting Time Series Forecasting (TSF) is the use of a model to predict future values based on previously observed values. Typically, the predicted values are given along with a confidence interval. Consequently, the AID techniques based on TSF flag as anomalous any data instance that lie outside the confidence interval provided on their prediction. In this section we can also include regression models, where the residuals for the test instances are used to provide anomaly scores. In Chapter 4 we provide an example of a TSF technique for the detection of anomalies in Voice over IP (VoIP) call count data.

Table 2.29 summarizes different approaches to AID based on forecasting.

Table 2.29: Forecasting approaches to AID.

Technique	Comments
Brutlag [Bru00]	The author propose a method to detect aberrant behavior using the Holt-Winters prediction method.
Eskin *et al.* [ELS01]	They present the use of dynamic windows in the detection of system-call anomalies. They use prediction to detect whether a sequence is probable or not.
Balajinath and Raghavan [BR01]	They use genetic algorithms to learn the individual user behavior and detect anomalies by predicting current user behavior based on past observations.
Dagon *et al.* [DQG+04]	They present a method to detect worms by using honeypots (§ 2.2.5). They use logit regression to detect clusters of relevant events.
Ye *et al.* [YCB04]	They present two models for forecasting system calls and detect anomalies when the χ^2 distance to the prediction is high.
Kang *et al.* [KFH05]	They present a new model for representing system calls and test its efficiency when applied to AID.
Zhang *et al.* [ZGGR05]	They introduce the term anomography, which is the union of anomaly detection using tomographic data. They present and compare different techniques.
Schweller *et al.* [SLC+07]	They propose the detection of volume-based anomalies through change detection, using prediction and reversible sketches.

Continued on next page

Table 2.29 – continued from previous page

Technique	Comments
Agosta *et al.* [ADWCL07]	They propose the use of a supervised classifier trained as a traffic predictor to control a time-varying detection threshold for the detection of worms in a distributed fashion.
Lu and Ghorbani [LG09]	They propose an AID system using wavelets and Gaussian mixture models. They define 15 network features that are able to model the normal network situation. The, using wavelets and an autoregressive model they fit the time series of the characteristics. The residuals of the regression are used to detect the anomalies.
Silveira *et al.* [SDTG10]	They propose ASTUTE, a threshold-based AID technique focused on detecting correlated flows. They compare the performance of ASTUTE with two alternate anomaly detectors based on Kalman filters and wavelets.

2.2.4 Problems of Anomaly Intrusion Detection

The application and development of AID systems is problematic in many ways. First, the evaluation of new proposed AID systems lacks of properly labeled data. This situation also obstruct the comparison of different AID systems in order to select the system which better fits the needs of the manager. Second, current network monitoring approaches are based on sampling to cope with the ever-increasing communication speeds. This entails a information reduction that may spoil the AID techniques applied in current IDSs. However, despite of the traffic sampling, the amount of data to be analyzed by an IDS is humongous, and usually is high-dimensional. Working with such large datasets make the training and testing phases of AID systems very time consuming, and it may even prevent some AID systems to be deployed in an on-line fashion. Moreover, the presence of none-relevant features in such data sets may also reduce the detection accuracy of some AID systems. Consequently, feature selection has gained interest in the recent years in order to work only with the most relevant features to detect the target intrusions. Finally, the fact that AID systems place large number of false alarms is vox populi. Such large number of false positives is the reason for the limited deployment of AID systems in real networks under production, because the network manager has to manually inspect all the raised alarms in order to filter those that were not related with a security compromise, and automated responses to detected attacks cannot be applied, because they may lead to self-imposed denials of service. We further analyze these problems related with AID in what follows.

Evaluation of IDSs

Evaluating IDSs requires that the datasets used for testing have properly labeled the data instances as normal or anomalous. This is also a requirement for the training datasets in supervised learning techniques. However, labeling audit data is a very challenging and time consuming task. Such difficulty is observed by the scarce availability of free datasets for testing IDSs. The most popular, and almost the only, labeled datasets for evaluating IDSs were provided by the Lincoln Laboratory at MIT under the DARPA sponsorship. Such laboratory provided two datasets ([LFG^{+}00] and [LHF^{+}00]) for off-line evaluation of IDSs, but the process was discontinued, mainly because of the mentioned difficulties in generating such datasets. The datasets were generated in a controlled private network, with a mix of real and simulated machines using custom software automata that generated background traffic, while the 32 different attack types were targeted to the real machines. There were four different sources for the datasets: sniffed network traffic, Solaris Basic Security Mode (BSM) audit data, Windows NT audit data (added in [LHF^{+}00]), and file-system snapshots; and two datasets were provided for evaluation, one with labeled attacks for training purposes, and an unlabeled one for fairly testing the different AID approaches. Later, Stolfo et al. extracted basic features and derived secondary features from these original data and created the KDD Cup 1999 data[2] that was used for the Third International Knowledge Discovery and Data Mining Tools competition.

However, despite the impressive undertaking of the Lincoln Lab evaluation program, it has raised criticism regarding the methodologies used in the evaluation and the generation of the datasets [McH00]. McHugh stressed the lack of documentation of the experimental approach and the relative poor basis for characterizing IDSs that the measures used in the evaluation provide. Such measures were the operating points of the different algorithms tested. Receiver Operating Characteristic (ROC) techniques analyze the trade-off between false alarm and detection rate for detection systems, and were originally developed in the field of signal detection. McHugh criticizes that ROC analysis is not a constructive measure, claim raised by some of the participants in the evaluation as well. This has motivated the development of more specific measures for evaluating IDSs. For instance, Cárdenas *et al.* [CBS06] propose Intrusion Detection Operating Characteristic (IDOC) curves as a new IDS performance trade-off which combines in an intuitive way the variables that are more relevant to the ID evaluation process. Ringberg *et al.* [RRR08] present the basic needs for evaluating AID systems, claiming that the field deserves more rigor and an universal framework that permits performance comparisons. They propose to use anomaly simulation and background traffic in addition to labeled datasets to enhance IDSs evaluation.

Finally, despite of the shortcomings pointed out by McHugh, there is a large amount of research on IDSs that have used the DARPA datasets to evaluate their proposals. We would like to note that these datasets are too old for being useful for evaluation, and comparing the performance of new developed techniques for AID with those evaluated in DARPA competitions is extremely unfair.

[2] The dataset is available at `http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html`

Sampling

With the ever-increasing speeds of communication channels, sampling is a *must* rather than an option in network traffic measurement. Sampling procedures are applied in several monitoring systems, such as NetFlow, and basically selects *individuals* (e.g., packets, flows, etc.) from within a population (i.e., the network traffic) to estimate characteristics of the whole population when observing the whole population is infeasible. However, despite of its necessity, there have been several works pointing out the drawbacks that sampling entails for AID ([BTW$^+$06, MCS$^+$06, MSC$^+$06]).

These works have evaluated the impact of sampling on anomaly detection metrics and whether sampled data is sufficient for anomaly detection. The authors of [BTW$^+$06] have observed that simple random sampling, which is the most typically applied sampling technique, does not severely affect the distributions of the number of bytes and packets, whereas the sampled flow distribution significantly differs from the population counterpart. As a consequence, the AID approaches leveraging on the amount of bytes or packets work almost perfectly on sampled data, but flow-based AID techniques [SSS$^+$10] experience a decrement in their performance. Furthermore, they found out that sampling affect the most the volume-based techniques, whereas entropy-based alternatives maintain almost all their properties unaltered, thus recommending their use when using sampled data.

There exist other sampling methods proposed in the literature, and some of them are evaluated by Mai *et al.* [MCS$^+$06]. Specifically, they compare the simple random sampling with smart sampling [DLT03], flow-sampling [DLT04] and sample-and-hold [EV03]. Among these techniques, the best performance is observed with flow-sampling because it maintain higher accuracy at the flow level. On the other hand, smart sampling and sample-and-hold are focused on detecting large flows (*heavy-hitters*), which makes them irrelevant for AID because AID techniques focus typically on small flows.

To solve the problems that come along with sampling network traffic, Androulidakis *et al.* [ACP09] present an study on how network traffic sampling may be improved in order that not only the impact of the sampling process on AID techniques is reduced, but also AID gets improved after the sampling process. To this end, they propose selective sampling, that is able to remove not interesting network data by opportunistically and preferentially sampling traffic data with the aim of achieving a magnification of the appearance of anomalies within the sampled data set.

Feature Selection and Reduction

Reducing the number of features used in an AID system reduces the training and detection times. This is very advantageous, specifically reducing the detection times, as it enable the deployment of the AID system to work in an on-line fashion. Consequently, selecting an appropriate number of features on which the AID approach is designed enhances the detection system, and may also improve the system's performance in a similar way that does selective sampling [ACP09].

The problem of feature selection is of paramount importance in genetics, where the number of features is overwhelming. It focuses on removing irrelevant features (those that not contribute to differentiate the instances in the classification problem) and redundant features (those whose information is contained or can be derived from other features). Many feature selection techniques have been developed, and the interested reader is referred to the survey of Chen *et al.* [CLCG06] for a detailed review of the state of the art.

An alternative to feature selection is feature transformation. Examples of feature transformation are singular value decomposition and PCA, which is one of the reasons for this technique being so popular for AID (see Section 2.2.3).

False Positives

Current AID systems are popular for placing large number of false alarms. Such false alarms appear as a result of the lack of interpretation of the discovered suspicious events—an AID system classify audit data as normal or anomalous, but do not provide detailed information regarding the nature of the abnormality. False positives reduce the performance of AID system for several reasons. First of all, there is a very high cost of errors, specially when compared to other fields where anomaly detection is applied [SP10]. A false positive forces the manager to spend time examining the reported incident to ensure that the flagged event is malicious, discovering eventually that it is benign. On the other hand, false negatives entail a compromise of the monitored system, which may cause serious damage to an organization. Furthermore, the high number of false positives prevent AID systems to take automated response to the discovered events. Blocking an attack by dynamically reconfiguring a firewall to drop packets from the intruder-flagged connection may result in an undesired denial of service to a benign user if it is done in response to a legal network action wrongly identified as an attack.

For this reason, there have been studies to reduce the number of false positives. Noel *et al.* [NWY02] propose a framework to characterize ID activities: degree of attack guilt. This framework allows to assign a confidence score to reported alarms and share such scores in order to reduce the false positives rate. Kruegel *et al.* [KMRV03] identified two reasons for the large number of false alarms, namely the simplistic aggregation of model outputs in the decision phase and the lack of integration of additional information into the decision process, and proposed an event classification scheme to mitigate such shortcomings. The event classification scheme is based on Bayesian networks, which improve the aggregation of different model outputs and the incorporation of additional information. Their experimental results show that the accuracy of the event classification process is significantly improved. Later, Axelsson [Axe04] proposed to use a visualization process to interact with the training of a Bayesian classifier, in order to reduce the false positives rate by adjusting the model parameters. More recently, Gil Pérez *et al.* [GPGMMPSG12] proposed to assign a reputation score to each IDS within a network, where the different IDSs collaborate to detect distributed attacks. The reputation score is used to discard alarms from low reputation IDSs, thus lowering the number of false alarms. Such reputation score is based on previous interactions and alerts placed by each IDS.

2.2.5 Future Trends in Anomaly Intrusion Detection

Future trends in AID have to focus on solving the problems pointed out in the previous section, principally those related with evaluation of IDSs and reduction of false positives rate. Regarding the former, more effort is needed to develop ground-truth datasets, where the behavior-deviating patterns are properly labeled and hence practitioners may evaluate their proposals to be aware of their shortcomings. In addition, a fair comparison metric for comparing different AID solutions is still missing. Those metrics proposed as alternative to ROC analysis lack of generality, as the parameters values they use (such as the cost associated with false positives/negatives) are system dependent.

Regarding the false positives rate, we believe that reducing it is the main open challenge in AID. One intermediate step could be the reduction of manager's analysis time spent in checking the reported alarms. To accomplish such time reduction, we propose to use clustering techniques in order to inspect groups of alarms instead of reviewing them individually. If an appropriate clustering is obtained, then the manager would be able to inspect only several alarms from a cluster in order to decide whether a given alarm cluster constitutes a real threat or is a false alarm, thus saving great amount of expensive manager time.

Another field of further investigation is to find ways to keep pace with current networks' increased size, speed, and dynamics. Paxson *et al.* [PAD$^+$06] propose to rethink hardware support for network analysis and ID. In this light, the use of Graphic Processing Unit (GPU) acceleration to design high-performance software, such as PacketShader [HJPM10] (a software router framework for general packet processing with GPU acceleration) may open new avenues for improving AID systems' performance.

We would also like to note that, after the exhaustive revision of the literature provided, we have observed that the number of spatial-based AID systems is surprisingly scarce. It is our belief that spatial-based AID systems would gain interest by practitioners given the benefits that such approaches may imply for the management of large-scale networks. Spatial analysis of the anomalies may in addition detect different kinds of attacks that go unnoticed when observed at a single network point, by taking into account correlations of the observed values at different network points and not only its marginal distributions.

Finally, we believe that there is still a large gap to fill in the intrusion security area based on detection of anomalies in order to be deployed in real systems under production. Current approaches are based on hybrid system, where a misuse intrusion detection components are used to detect well-known attacks at high detection rates with the support of AID components to quarantine unknown kind of attacks. Such systems would benefit the usage of HPs in addition. A Honeypot (HP) is a trap set to detect, deflect, or in some manner counteract attempts of unauthorized use of information systems. Generally it consists of a computer, data, or a network site that appears to be part of a real network, but is actually isolated and monitored, and which seems to contain information or a resource of value to attackers. Consequently, any connection attempt to the HP is highly probable of being a malicious activity. In this way, HPs may be regarded as a *surveillance system* using *cameras* that *record* the intruder when trying to open a *safeguard* that allow observing the intruder's techniques to evade the systems security. Furthermore, HPs will keep the attacker busy leaving more time for the system manager to take response, and, as a consequence, HPs may waste attackers' time and force them to gave up promptly after failing to reach their objectives.

2.2.6 Conclusions

This section presented a survey of the state of the art of anomaly intrusion detection, focusing on the period 2000-2012. During this period, numerous studies have presented research in new ways of discovering abnormal events using network or host data. We believe this is the more comprehensive survey on AID systems to date. We have presented in addition a survey of the proposed taxonomies to classify the existing AID techniques, and proposed a new comprehensive one. The taxonomy allowed us to present the main techniques applied in AID in an structured manner.

Furthermore, we have analyzed the main problems affecting the AID paradigm, and which future trends should be addressed in order to solve them. We hope that this work can serve as a useful guide through the maze of the literature, enabling the understanding of the different approaches to allow new practitioners focusing on the AID techniques that are prone to provide higher performance given their specific requirements.

Chapter 3

Detection of Traffic Changes in Large-Scale Backbone Networks

Network management systems produce a huge amount of data in large-scale networks. For example, the Spanish academic network features hundreds of access and backbone links, each of which produces a link utilization time series. For the purpose of detecting relevant changes in traffic load a visual inspection of all such time series is required. As a result, the operational expenditure increases. In this chapter, we present an on-line change detection algorithm to identify the relevant change points in link utilization, which are presented to the network manager through a graphical user interface. Consequently, the network manager only inspects those links that show a stationary and statistically significant change in the link load. These changes may call for link's capacity upgrade in order to maintain desired levels of Quality of Service.

3.1 Introduction

In large-scale networks, the amount of information provided by management systems is huge. For example, time series of traffic volume or network link load may be provided per each access link. Network managers face with visual inspection of far too many graphs, which motivates automated procedures that basically pinpoint which are the links that deviate from a typical behavior and demand intervention from the manager, out of the many links present in the network. We propose a load model for network links that is capable of efficiently tracking sustained load changes in network links. These sustained changes may call for link's capacity upgrade in order to maintain a desired level of Quality of Service (QoS). Our model is suitable for any network link with high aggregation—e.g., backbone links and access links of large institutions. It is aimed at facilitating network-wide monitoring of large-scale networks, by clearly identifying network links with a varying traffic behavior. Moreover, forensic data for each link can be later analyzed off-line, in order to spot possible correlations that serve to understand how the detected load changes in one link have impacted the performance of the rest of the network.

Previous approaches to network-wide traffic analysis use point-to-point [BDTJ02, LPC$^+$04] or point-to-multipoint [FGL$^+$01] models for analyzing the demands in backbone networks. The key concept in these works is the Origin-Destination (OD) flow. An OD flow is a time series that comprises all the traffic that enters the backbone in a given Point of Presence (PoP) and leaves in another PoP. Therefore, the analysis of the backbone demands is divided into n^2 time series, each representing an OD flow, being n the number of PoPs in the backbone network. To compute the OD flow time series, the authors of these works leverage on flow level measurements to find the amount of traffic entering the network at each PoP and routing information measurements to determine the egress point of each measured flow. Our approach to network-wide traffic analysis reduces the complexity of the aforementioned methodologies leveraging on link time series. Network topologies in backbone networks are usually far from being a completely meshed topology. Thus, the number of links in a backbone network is considerably lower than the square of the number of nodes. In our case study, the Spanish academic network RedIRIS[1] comprises 18 PoPs and only 30 backbone links.

[1] `http://www.rediris.es/index.php.en`

Therefore, our network-wide traffic analysis approach accounts for only 60 elements to monitor (because the links are bidirectional), considerably less than the $18^2 = 324$ different OD flows with the RedIRIS topology. Moreover, our model is fed only with average load measurements at high granularity (90 minutes intervals), which can be easily obtained from Simple Network Management Protocol (SNMP) measurements [Sta98]. This also entails a complexity reduction compared with the other network-wide traffic analysis approaches existing in the literature. Our model needs simpler measurements and simpler post-processing steps for the measurements, which makes it amenable for on-line application and enables its utilization in a broader set of network links.

We think this work is relevant to network operators and the research community. On one hand, network operators are aware of the importance of detection of traffic changes, which are relevant at different timescales. Load changes at short timescales are relevant for attack detection, where a sudden change in the load may be related with flash crowds or Denial of Service (DoS) attacks [BKPR02, CH06, KSZC03, SGPC04]. On the contrary, load changes at long timescales (in the scale of days or weeks) should be taken into account for traffic engineering task such as load balancing and capacity planning in order to guarantee some predefined levels of QoS [PTZD05, FGL$^+$00]. To the best of our knowledge, there is little existing work in the literature regarding traffic engineering procedures based on the detection of statistically significant sustained changes, and the more relevant approaches are normally based on simple time series forecasting techniques [Bru00] focused on short-term changes. In those cases, a prediction of the load is used to compute confidence bands, where the actual value of the load should lie in under normal network performance. However, this methodology is not able to determine whether the change is stationary (i.e., the changed value is maintained over several time periods) and therefore the traffic behavior has changed. Consequently, in practice, the network manager should visually inspect the different link load plots to make such decision. In contrast, our methodology focuses only on sustained changes that may imply a shift in users' behavior, and the network manager should take action in response to such shift in order to maintain the offered QoS on the network.

In this chapter, we provide techniques that allow the network manager to focus only on those links that show stationary load changes. The case study is the Spanish Academic Network RedIRIS. We note that RedIRIS features 30 bidirectional backbone links and hundreds of connections to large institutions, and it is not feasible to analyze all of the corresponding time series separately from an Operational Expenditures (OPEX) point of view. Consequently, our proposed technique filters out those links which do not show statistically significant changes in the traffic behavior. As a result, the OPEX is largely reduced, because the traffic engineering tasks are only performed on a reduced subset of links. To identify such changes, we developed an on-line algorithm that uses clustering techniques and statistically sound methodologies to determine the location and statistical significance of the change points. In addition to providing valuable techniques to discriminate load-changing links, which have a direct impact in OPEX reduction, our findings also serve to gain insight about the dynamics of load change in large-scale networks. Is the load change continuous or showing sudden change in mean? How frequent are load changes in a large network? Our analysis serves to address these issues with a dataset that is three-year long and comprises the whole Spanish academic network—i.e., more than one million users.

Our proposed algorithm is based on a fairly multivariate Gaussian vector that models the daily traffic pattern of links with large aggregation level. Such model splits the 24 hour day period into 16 non-overlapping intervals of 90 minutes starting at midnight, each of which is a vector component. We have validated our fairly Gaussian model with real network measurements obtained also from the RedIRIS network, showing evidence that the significance of the normal theory tests of mean vectors and covariance matrices is not severely affected by the deviations from normality existing in actual data. This result allows us to apply multivariate normal inference to the mean vector, namely the Multivariate Behrens-Fisher Problem (MBFP) procedure, to determine if there is a statistically significant difference in the mean vectors of two consecutive time series. Therefore, when there is evidence of a change in the load time series, we alert the network managers, allowing them to take the appropriate action as a response to that change.

After assessing the performance of the load change detection algorithm, we have applied it to such real network measurements, showing the efficiency in reducing the number of times the network needs supervision. We have analyzed more than 300 days worth of data, and in average, we have placed around 11 alerts per link. This supposes that a network manager would have receive an alert for a statistically significant and sustained change less than 4% of the days. In the remaining days, the network is considered stable and no action is required.

A distinguishing feature of the MBFP procedure to detect changes is that it evaluates the difference in the mean vectors taking all the vector components into account at the same time. This may result in changes that are due to either small differences in several vector components or large differences in a single vector component. In addition, as the vector components represent time intervals, the relevance of a change may be different depending on the vector component that caused the change detection. For instance, changes at night-time may not be relevant compared to those at the busy hours. Consequently, we devise an alert color code to categorize the change points located by our algorithm. Such color code is used to create weather maps of the network, allowing to visually inspect the relevant events happening in the network in an straightforward manner.

The rest of the chapter is organized as follows: Section 3.2 is devoted to present the measurement dataset. Section 3.3 describes the load model and presents the methodology and results of its validation process. Section 3.4 presents the on-line load change detection algorithm and the assessment of its performance with synthetic data. Section 3.5 provides the results of the application of the algorithm to actual network measurements and Section 3.6 shows how the proposed methodology could be applied to monitor a large-scale network like RedIRIS. Finally, Section 3.7 concludes the chapter.

3.2 Measurement Dataset

This section is devoted to present an overview of the network traffic measurements used in this chapter. As we noted in the previous section, our algorithm is fed by average load measurements computed at non-overlapping intervals of 90 minutes length. A simple averaging process of SNMP measurements obtained at 5 minutes granularity is enough to obtain such data. We gather network measurements at such resolution from Multi Router Traffic Grapher (MRTG) tools [OR98] installed on the network equipments of the Spanish academic network RedIRIS (see Section 2.1.3 for a detailed description of MRTG). In what follows, we present a description of the dataset and the network from which we obtained such measurements, and an overview of the daily and weekly traffic patterns that characterize the links in the network.

3.2.1 Description of the Measurement Dataset

The RedIRIS network comprises 18 PoPs spread along the Spanish country (Figure 3.1 shows the backbone network topology), and provides Internet access to more than 350 institutions, mainly universities and public research centers, which make up a grand total of more than a million users. In addition, it has several Internet exchange points with the European Research and Education Network GEANT, and with other ISPs (Telia, Global Crossing, etc.). RedIRIS provided us with MRTG records and flow summaries of the PoPs in Figure 3.1 and from an extensive set of universities and exchange points. We have selected 18 links out of the total to make this study, which transport large amounts of data and are representative of the variety of links that are present in the network. Our dataset includes 10 university links, 5 backbone links of the RedIRIS core network and 3 links that provide connection with exchange points or the European academic network GÉANT[2]. For privacy concerns, we label the University links as $U_1, U_2, \ldots, U_{10}$. We do the same with the Backbone links, $B_1, B_2, \ldots, B_5$, and the eXchange point

[2] http://www.geant.net/

links, X_1, X_2 and X_3.

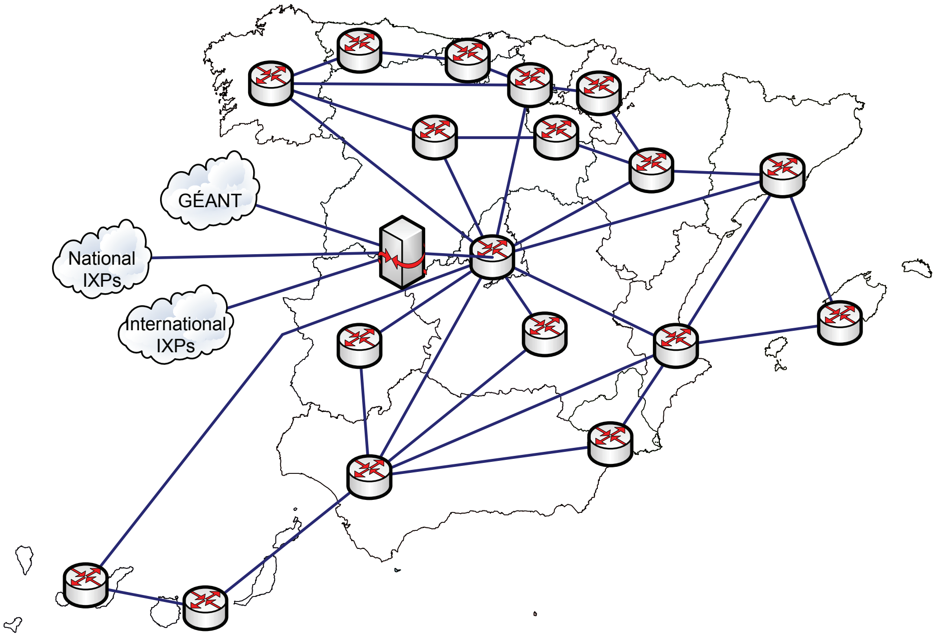


Figure 3.1: RedIRIS network architecture.

In total, we have collected and analyzed three-years worth of MRTG records (2007, 2008 and 2009). MRTG have been configured with measurement intervals of 5 minutes—i.e., there is a new record every five minutes. With this time granularity, we have 288 records for each day and direction (incoming/outgoing) in every link. Our measurements span from the 2^{nd} of February 2007 to the 10^{th} of March 2009, namely we collect more than 750 days worth of data per link. Such MRTG records contain five different fields: the UNIX timestamp of the measurements (which will play an special role in the measurements preprocessing step) and the average and maximum transfer rates, in bps, for both interfaces in the last measurement interval. We summarize some relevant information about the links present in the dataset in Table 3.1.

Table 3.1: Relevant data from the links contained in the dataset (Incoming/Outgoing).

Link type	Average load (Mbps)	Average no. of users
University	31.51/19.20	19,346
Backbone	437.34/344.61	171,988
eXchange	1101.40/818.17	1,000,000

3.2.2 RedIRIS Daily and Weekly Traffic Patterns

As RedIRIS is an academic network, its traffic pattern slightly differs from that of residential networks previously reported in the literature [TMW97, TRA08, FCE05]. Therefore, instead of having its maximum peak after 8 p.m., when residential users come back home, the RedIRIS peak hour happens around mid-day. We also observe a clear daily traffic pattern for weekdays, which is very similar among the different analyzed links. However, greater differences appear when considering weekends, which show a nearly flat traffic pattern, mainly composed by traffic that is sent without user interaction. Such differences are shown in Figure 3.2, where the solid line corresponds to the traffic of the outgoing direction (traffic sourced in RedIRIS and destined to the Internet) and the dashed line corresponds to the incoming traffic (traffic sourced in the Internet and destined to RedIRIS), of one week for one of the backbone links, which we have found to be representative of the phenomenon.

In Figure 3.2 we have plotted the link utilization, instead of bandwidth consumption. Note that such values are linearly related by the capacity of the link, i.e., $utilization = bandwidth/capacity$. Plotting utilization values facilitates the comparison between different days and universities. In addition, it provides evidence that the utilization values are always under reasonable thresholds (say 30% [NP08]). Therefore, the links are not congested, which means our analysis is not influenced by *clipping* of traffic peaks reaching the link capacity. Therefore, we safely work under the *free traffic* hypothesis [Nor95], which allows unbiased characterization irrespective of the link capacity. Consequently, assuming such an initial state when we deploy our

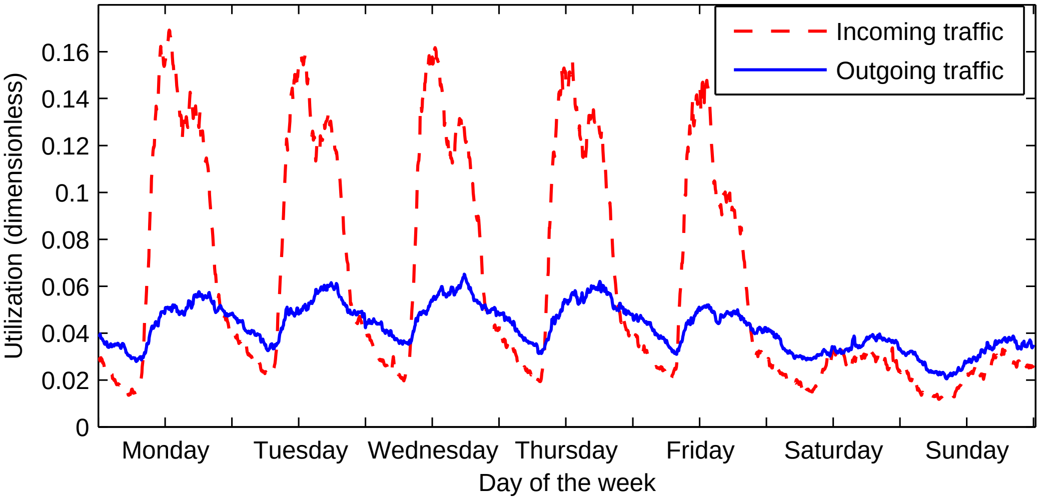


Figure 3.2: Time Series representation of the utilization of a RedIRIS link for a whole week.

proposed methodology in a network and that the manager takes into consideration the alerts placed by the algorithm, the network should not present saturation during long periods of time and the free traffic hypothesis should remain valid.

3.3 Multivariate Normal Model for Daily Traffic

In this section, we present our multivariate model for network daily traffic load, and show practical evidence of its applicability. We assume that the network measurements to model come from SNMP reports at 5 minutes granularity due to its popularity, or instead come from another measurement methodology but using the same format. This model takes advantage of the apparently invariance of the daily traffic pattern shape for working days presented in Section 3.2.2. The methodology for the model validation is presented in Section 3.3.2, and the corresponding results can be found in Section 3.3.3. Finally, a discussion of the results concludes this section.

3.3.1 Description of the Multivariate Normal Model

From the overview of the RedIRIS daily traffic pattern, we can clearly differentiate between weekdays and weekends. The former have a clear day-night pattern, which is influenced by the number of users being active (sending or receiving traffic) at the different times of the day. On the contrary, the weekends have a nearly flat, less utilized daily pattern, which supports the hypothesis that such traffic is mainly due to standalone applications, with no user interaction. Accordingly, we remove weekends, summer & Christmas holidays, national & regional holidays and eventually examination periods. Thus, we only consider working days, which are more interesting for traffic engineering purposes.

The model assumes that measurements of the same interval during different days come from the same (at first hand unknown) probability distribution. We base such an assumption in the fact that the shape of the traffic pattern does not show significant variation with time. Consequently, the differences between the measurements in the same measurement interval of different days should be small (if there is no change in the users' behavior). However, such probability distribution does not have the same parameters between different measurement intervals of the same day, for instance at 12:00 a.m. and at 12:00 p.m. Therefore, a multivariate distribution to model the daily network load seems to be reasonable, with each measurement interval having its own parameters.

However, the number of different measurement intervals per day with the default SNMP time granularity of the reports (5 minutes, which results in 288 measurements per day) is too large. Actually, a 288-variate model is not analytically tractable [Don00]. In order to make the model more manageable, we averaged the load values into 16 disjoint intervals of 90 minutes (i.e., we average $90/5 = 18$ SNMP samples to form each of the vector components). The reasons to choose such averaging period are manifold: first, we need the averaging period to be a multiple of the measurement granularity and a divisor of the number of minutes in a day; second, chances are that data are missing in the five minutes timescale, but having 18 consecutive five-minutes interval samples missing is unlikely. Note that if all measurements from an averaging interval are missing, we place an alert to the network manager (the link may be down), and then remove the whole day from the sample, because the Gaussian vector is incomplete[3]; third, the different measurement points may not be synchronized. A timescale of 90 minutes is coarse enough to circumvent this problem, as stated in [PTZD05]; fourth, the averaging process reduce the bias that outliers and measurement errors introduce to the results; last, but not the least, the assumption of fairly Gaussian Internet traffic holds when there is enough temporal aggregation of the measurements [KN02, vdMMP06, vdBMvdM$^+$06]. Consequently, in addition to simplifying the model, we obtain a reasonable distribution for the averaged samples (however, we take the fairly normal distribution only as an hypothesis, and show practical evidence of the validity of such assumption in the remaining of the section).

After the preprocessing step, which removes the holidays and incomplete day-vectors, the dataset contains more than 300 samples per link and direction, each of them representing a day worth of traffic data that we model with a 16-variate Gaussian distribution. Note that this preprocessing step can be done in an on-line fashion, because the days to be removed are known in advance. Finally, Figure 3.3 shows the time series of the average daily utilization pattern of the RedIRIS network with the 16 selected intervals presented in Table 3.2.

To summarize, we present the assumptions relevant to the model in the following bullet list:

- The daily traffic-pattern shape can be regarded as short-term invariant.
- The utilization of the links is always below critical levels, e.g., 60%. That means that we safely work under the free traffic hypothesis.
- Measurements from the same interval during different days come from the same probability distribution.

[3] Alternatively, the network manager could decide to apply missing value techniques such as replacing with the mean value of such vector component of the cluster [AH08, Chapter 13].

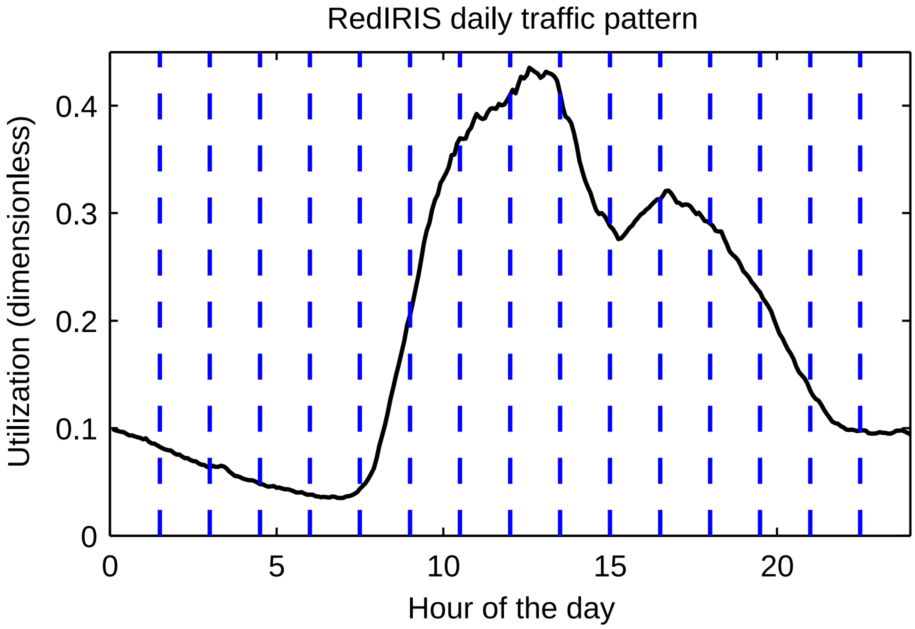


Figure 3.3: Time Series representation of the average utilization pattern of the RedIRIS network (solid line) and time divisions according to the multivariate model (vertical dashed lines).

Table 3.2: Correspondence between vector components and time of day.

Vector component	**Time interval**	**Vector component**	**Time interval**
1	00:00-01:30	9	12:00-13:30
2	01:30-03:00	10	13:30-15:00
3	03:00-04:30	11	15:00-16:30
4	04:30-06:00	12	16:30-18:00
5	06:00-07:30	13	18:00-19:30
6	07:30-09:00	14	19:30-21:00
7	09:00-10:30	15	21:00-22:30
8	10:30-12:00	16	22:30-00:00

- The parameters of such distribution depend on the actual interval of measurement.
- The Gaussian distribution is appropriate for modeling the average load in such intervals (this assumption is validated in Section 3.3.3).

3.3.2 Methodology

To validate the applicability of the model to network traffic inferences, we have performed several verifications of the fairly Gaussian assumption. More specifically, we have adopted the methodology used in [vdMMP06] to verify the fair normality of the marginal distributions of our multivariate model. In addition to this, we have also tested for Multivariate Normality (MVN). This is necessary because the fact that several variables have univariate normal distributions does not imply that they jointly have normal distribution [Kow73]. In what follows, we briefly describe the normality tests applied for both univariate marginal and the joint multivariate distributions.

Van de Meent et al. [vdMMP06] have shown that the linear correlation coefficient γ between the order statistics of the sample and the corresponding normal quantiles of the model distribution (i.e., a normal distribution with parameters estimated from the sample) is, roughly speaking, equivalent to the Kolmogorov-Smirnov (KS) test for testing univariate normality, i.e., if $\gamma > 0.9$, then the null hypothesis of normality cannot be rejected by the KS test at significance level 0.05 (see Appendix A for further description of the KS test). We have followed such approach and calculated the coefficient γ for each of the 16 univariate normal distributions according to our model. To compute γ, let $x_1, x_2, \ldots, x_n$ be a univariate sample of size n. Let $\bar{x}$ and s^2 be the unbiased estimates for the sample mean and the sample variance, i.e., $\bar{x} = n^{-1}\sum_{i=1}^{n} x_i$ and $s^2 = (n-1)^{-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$. Define $x_{(i)}, i = 1, 2, \ldots, n$ as the order statistics of the sample, i.e., $x_{(1)} < x_{(2)} < \ldots < x_{(n)}$, and q_i their corresponding quantiles given by $q_i = \Phi^{-1}(\frac{i}{n+1})$, where Φ^{-1} is the inverse of the normal cumulative distribution function with mean $\bar{x}$ and variance s^2. Denote by $\bar{q}$ the mean of the quantiles, then the linear correlation coefficient γ is given by:

$$\gamma = \frac{\sum_{i=1}^{n}(x_{(i)} - \bar{x})(q_i - \bar{q})}{\sqrt{\sum_{i=1}^{n}(x_{(i)} - \bar{x})^2 \sum_{i=1}^{n}(q_i - \bar{q})^2}}. \tag{3.1}$$

Regarding MVN, we have selected Mardia's multivariate skewness and kurtosis coefficients $b_{1,p}$ and $b_{2,p}$ [Mar70] to measure deviations from MVN. The main reasons to select these statistics are their affine invariance property and tractability. Moreover, Mardia has shown that the significance of the normal theory tests of mean vectors and covariance matrices is adversely affected by skewness [Mar75] and kurtosis [Mar74], respectively, i.e., having a large skewness (kurtosis) deviation from multinormality adversely affects the false positive rate of normal theory tests applied to the mean vector (covariance matrix). Therefore, we can assess fairly MVN by using these tests and, in addition, this can shed light on the suitability of our multivariate model for making inferences about the mean vector and the covariance matrices—the methodology we apply in Section 3.4 for change detection makes inference about the mean vector. Let $\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n$ be a p-dimensional random sample of size n, then Mardia's multivariate coefficients for skewness and kurtosis are given, respectively, by:

$$b_{1,p} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} r_{ij}^3 \quad \text{and} \quad b_{2,p} = \frac{1}{n}\sum_{i=1}^{n} r_i^4, \tag{3.2}$$

where $n > p$ and

$$r_{ij} = (\mathbf{y}_i - \bar{\mathbf{y}})^T \mathbf{S}_n^{-1} (\mathbf{y}_j - \bar{\mathbf{y}}), \qquad r_i^2 = (\mathbf{y}_i - \bar{\mathbf{y}})^T \mathbf{S}_n^{-1} (\mathbf{y}_i - \bar{\mathbf{y}}), \tag{3.3}$$

$$\bar{\mathbf{y}} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{y}_i, \qquad \mathbf{S}_n = \frac{1}{n}\sum_{i=1}^{n} (\mathbf{y}_i - \bar{\mathbf{y}})(\mathbf{y}_i - \bar{\mathbf{y}})^T, \tag{3.4}$$

where $\mathbf{x}^T$ is the transpose vector of $\mathbf{x}$. For convenience of applying existing statistical tables, the following standardized forms are used in practice [Mar70]:

$$sb_{1,p} = \frac{nb_{1,p}}{6} \xrightarrow{d} \chi^2_{df}, \quad sb_{2,p} = \frac{b_{2,p} - p(p+2)(n-1)/(n+1)}{\sqrt{8p(p+2)/n}} \xrightarrow{d} \mathcal{N}(0,1), \tag{3.5}$$

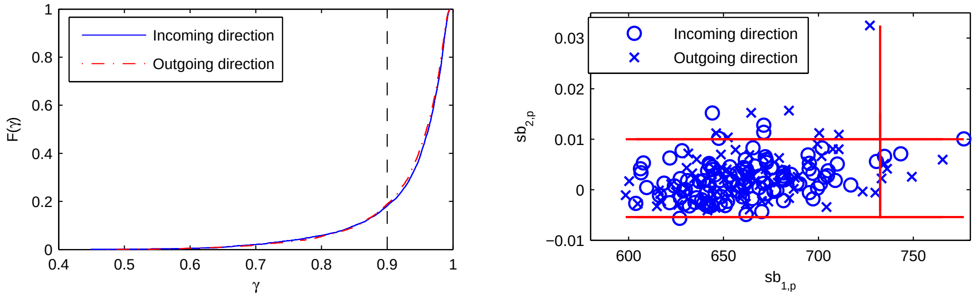
where $df = p(p+1)(p+2)/6$ are the degrees of freedom of the χ^2 distribution and $\xrightarrow{d}$ means convergence in distribution ($n \to \infty$). Therefore, large values of $b_{1,p}$ and $|b_{2,p}|$ (because this second test is two-sided) indicate non-MVN.

3.3.3 Results of the Model Validation

To apply the above-mentioned techniques, we have preprocessed the data set described in Section 3.2.1 according to the restrictions presented in Section 3.3.1 (removal of holidays and incomplete day-vectors).

We have then computed the linear correlation coefficient γ using all the measurement campaign samples in each direction of each link. The results were very poor, and the univariate normality was rejected for all the marginal distributions. However, this does not imply that the model is inappropriate, but that the parameters may be changing with time, i.e., the sample is non-stationary. In spite of this, we can assume that the traffic is short-term stationary [GDHA+11], i.e., that the parameters of the underlying distribution remain nearly stable for a short period of time, say 20-30 days, and accordingly apply the normality tests to subsamples of that size. For this reason, we have divided our sample into subsamples of size $n = 20$ day-vectors, which is equivalent to a period of 25-28 natural days—that is because we rule out holidays. Consequently, we computed the γ coefficient for each subsample marginal distribution, and the results are shown in Figure 3.4(a), where we have plotted the cumulative distribution function of the γ value of such marginal subsamples.

With regard to MVN, it is well-known that if non-normality is indicated for one or more of the marginals, MVN can be rejected [JW92, p. 133]. Hence, we do not verify MVN neither for the whole dataset nor for those of the above-mentioned subsamples in which any of the marginal distributions was deemed non-Gaussian. To properly apply the corresponding standard-



(a) (b)

Figure 3.4: Normality test results: (a) Univariate normality results. (b) Multivariate normality results.

ized values of the statistics for testing multivariate skewness and kurtosis, we cannot use the corresponding limiting distributions, because the size of our samples is small. Therefore, we ran $N = 100,000$ Monte Carlo simulations on N independently generated samples $\mathbf{Z} \sim \mathcal{N}_p(\mathbf{0}, \mathbf{I}_p)$ of size $n = 20$ to estimate the critical values of the standardized forms of the statistics, where $\mathbf{0}$ is a vector of 16 components all equal to 0, and $\mathbf{I}_p$ is the identity matrix of rank $p = 16$. These critical values are summarized in Table 3.3 for three different significance levels.

Table 3.3: Critical values for the statistical tests for multivariate skewness and kurtosis.

Significance level (α)	$\boldsymbol{cv_{sb_{1,p}}}$	$\boldsymbol{cv_{sb_{2,p}}}$	
		lower	***upper***
0.10	695.7828	−0.0040	0.0054
0.05	708.6464	−0.0046	0.0069
0.01	732.4614	−0.0054	0.01

In this table, $cv_{sb_{1,p}}$ refers to the critical value for the standardized value of $b_{1,p}$. Values of $sb_{1,p}$ larger than $cv_{sb_{1,p}}$ indicate skewness in the sample. On the other hand, $cv_{sb_{2,p}}lower$ and $cv_{sb_{2,p}}upper$ are the critical values for the two-tailed test for kurtosis. Values of $sb_{2,p}$ smaller than $cv_{sb_{2,p}}lower$ or greater than $cv_{sb_{2,p}}upper$ indicate kurtosis in the sample.

We have presented in Figure 3.4(b) the results of the statistical tests when applied to our dataset. We show in the x-axis the value of $sb_{1,p}$ whereas in the y-axis we can find the values of $sb_{2,p}$. Each subsample is represented by a $\circ$ symbol for the incoming direction or by a $\times$ symbol for the outgoing direction. We have represented with straight lines the thresholds given by the critical values at the significance level $\alpha = 0.01$. The percentage of tests indicating rejection of the null hypothesis are presented in Table 3.4, where we show the results of the Skewness test, the Kurtosis test and the combination of both.

Table 3.4: Percentage of rejection of the multivariate skewness and kurtosis tests.

Direction	**Rejection ratio**		
	Skewness test	**Kurtosis test**	**Either Skewness or Kurtosis**
Incoming	2.80%	4.60%	6.54%
Outgoing	5.88%	8.24%	14.12%
Both	4.17%	6.25%	9.90%

3.3.4 Discussion of the Results

The results for the univariate normality test shown in Figure 3.4(a) give evidence that the performance in the incoming and outgoing directions is nearly the same, as the corresponding lines for each direction are partially superimposed. In both of them, it can be seen that for more than 80% of the cases studied, the goodness-of-fit measure γ was above the threshold 0.9. Such results are close similar to those of [vdMMP06], so we can obtain a similar conclusion, i.e., the 16-variate traffic load vector components, when considered separately, can be deemed as fairly Gaussian.

Regarding MVN, Table 3.4 shows that the model fits better to the incoming direction of traffic. This is a consequence of the larger aggregation of the incoming traffic, as shown in Table 3.1. When taking both directions into account, Table 3.4 shows that MVN can be rejected for approximately 10% of the cases. Although we cannot assume that the multivariate model is totally accurate, there is an evidence based on the results that fairly MVN can be accepted. Moreover, we can see from such results that our model is suitable for applying multinormality inference to the mean vector (e.g., the MBFP procedure), because the percentage or rejections for the skewness tests (4.17%) is small and therefore the significance of the multinormality theory tests for mean vectors [Mar75] will not be severely affected. The same conclusion can be drawn by having a look at the percentage of rejections for the kurtosis tests (6.25%), which in turn evidences that the significance of multinormality theory tests for covariance matrices [Mar74] will not be affected drastically.

With regards to outstanding peaks or non sustained congestions, e.g., *flash crowds*, that may spoil the normality of the data, we note that the effect of such undesirable situations is absorbed by the averaging process applied in the preprocessing step of the model.

All in all, we note that the fair normality assumption cannot be rejected for the majority of the subpopulations in the univariate case, and the fair MVN assumption also seems to be correct, so the fair MVN hypothesis of the proposed model can be accepted.

3.4 On-line Load Change Detection Algorithm

In the validation of the multivariate model we confirmed that the whole dataset does not follow a normal distribution, whereas small subsamples of it actually do. This fact suggest that the parameters of the normal distribution may be changing slowly with time—i.e., short-term stationarity. This section presents an on-line load change detection algorithm, aimed at identifying changes in traffic loads when monitoring Internet links. Such algorithm produces an alert when a sustained and statistically significant change has been detected. Then, the network manager verifies the change and takes action if the change is truly relevant. Our algorithm uses a two-step approach to detect the change points: first, a clustering technique for selecting potential change points is applied; then a sound statistical methodology is used to determine whether changes are casual or they define a breakpoint between stationary regions. Before describing the proposed algorithm in Section 3.4.2, we introduce the applied methodology in Section 3.4.1. Then, we validate the behavior of the algorithm with synthetically generated time series, showing the results in Section 3.4.3.

3.4.1 Methodology

In this section, we first present the clustering technique that has been adopted and then provide a brief introduction to the statistical methodology, namely the Behrens-Fisher problem. The selected clustering algorithm is k-means [DHS01], which is a two-step iterative algorithm that finds the clusters by minimizing the sum of the squared distances to a representative, which is called *centroid*. The input to the algorithm is the number of clusters k existing in the dataset—in our algorithm we always look for two clusters. The choice of k-means for our on-line algorithm is due to the ease of adding a new instance to an existing model. To do so, it is only necessary to compute the distance from the new instance to the existing centroids, and then recompute the centroid for the cluster the new instance is assigned to. Finally, if the centroids have changed, k-means is applied again from a quasi-optimal solution, so the algorithm finds the new centroids faster than the first time. On the other hand, in order to obtain clusters that are adjacent in time (i.e., all samples of the cluster being sequential in time and not out of order), the UNIX initial timestamp of the last sample of the day is included as an additional vector component.

In order to verify that the obtained clusters are actually different, we have applied the MBFP. The MBFP is the statistical problem of testing whether the mean vectors of two multivariate Gaussian distributed populations ($\mathbf{X}^{(1)}, \mathbf{X}^{(2)}$) are the same (null hypothesis H_0), for the case of unknown covariance matrices. Assuming homogeneity of the covariance matrices would allow applying simpler models, such as MANOVA. However, the homogeneity of covariance matrices is a strong assumption that indeed is not verified by the data. This motivates the application of the MBFP whose sole assumptions are that $\mathbf{X}^{(i)} \sim \mathcal{N}_p(\boldsymbol{\mu}^{(i)}, \boldsymbol{\Sigma}^{(i)}), i = 1, 2$; i.e., the samples of population i come from a p-variate normal distribution with mean vector $\boldsymbol{\mu}^{(i)}$ and covariance matrix $\mathbf{\Sigma}^{(i)}$. To solve this problem, the Hotelling's T^2 statistic given by

$$T^2 = n\frac{\mathbf{Y}\mathbf{S}_y^{-1}\mathbf{Y}^T}{n-1}\frac{n-p}{p} \sim \mathcal{F} \tag{3.6}$$

is used, where $\mathbf{Y}$ is a p-dimensional vector $\mathbf{Y} = (y_1, y_2, \ldots, y_p)$ of the means of the differences between both populations $(\mathbf{X}^{(1)}, \mathbf{X}^{(2)})$, assuming both populations are of equal size n [And58], and $\mathbf{S}_y$ is the unbiased estimation of its covariance matrix as given by (3.4). This statistic follows a $\mathcal{F}$-distribution with p and $n-p$ degrees of freedom under H_0. However, when the sample sizes are not the same, a transformation is needed before computing the T^2 statistic [And58, Section 5.6]. The interested reader is referred to Appendix B.2 for further description of the MBFP procedure. We note that such test is suitable when using our multivariate model because we have shown, in Section 3.3, that the skewness of our sample (which is the deviation from normality that mostly affects hypothesis testing procedures for normal mean vectors) is typically under the bounds allowed by the statistical test.

The MBFP assumes that the data comes from multivariate normal distributions. In order to trust in the results of the MBFP test, we have to make sure that our data is multivariate normal. Although we have assessed the MVN of our model in the previous section, it was shown that in some cases such assumption could be rejected. Consequently, we apply the same analytical tests described in Section 3.3.2 to both clusters before applying the MBFP. Although it is necessary to test the MVN assumption before each application of the MBFP test, these tests are lightweight and can be performed on-line very fast. If the MVN condition does not hold, the distribution of the T^2 statistic under the null hypothesis may differ from the central $\mathcal{F}$-distribution, and thus the probability of rejecting the null hypothesis when it is actually true would be different—Type I error. Therefore, we warn the network manager whenever this happens, in order not to blindly trust the output of the algorithm.

3.4.2 Description of the Algorithm

Our on-line load change detection algorithm aims at identifying whether the detected change point represents a breakpoint between two different stationary behaviors of the link load. More specifically, we wish to assess if a change in the mean vector has occurred. Once detected, the change points are reported to the network managers to let them know that potential anomalies may have happened. The first step in our algorithm is to preprocess the measurements in order to obtain daily samples according to the multivariate model presented in Section 3.3.1.

We do such preprocessing in an on-line fashion, obtaining a day-sample after all the measurements of a day have been collected, which we add to the sample set $\mathcal{S}$. When we have enough day-samples ($\#\mathcal{S} \geq 34$), we apply the k-means technique looking for two clusters. If the reported clusters are suitable for the algorithm, i.e., each one with at least 17 samples (meaning two potential sustained change-free regions), we mark as a potential change point between the reported clusters. Once a potential change point is found, we apply the MBFP statistical hypothesis testing procedure to the reported clusters after testing for MVN. Even if the MVN assumption does not hold (i.e., the MVN tests reject the null hypothesis) the algorithm continues to the following step, and applies the MBFP test to the populations. However, the network manager is warned about this fact to be aware of the potential inaccuracy. Finally, if the MBFP test rejects the null hypothesis of equality of means, an alert is placed to the network manager that indicates a sustained and statistically significant change point, and the oldest cluster is removed from the sample set. The flowchart of Figure 3.5 summarizes the work-flow of the algorithm.

3.4.3 Validation of the Algorithm

To assess the performance of the load change detection algorithm, we have tested it with synthetically generated data. Such data allow us to verify whether the algorithm is detecting the changes properly, because we know beforehand where the changes are located. The synthetic datasets generated

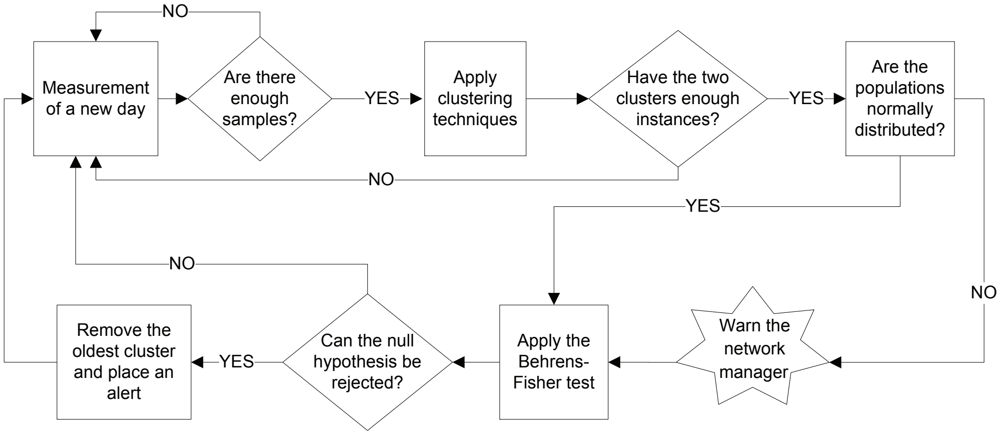

Measurement of a new day
Are there enough samples?
NO
YES
Apply clustering techniques
Have the two clusters enough instances?
YES
NO
Are the populations normally distributed?
YES
NO
Warn the network manager
Apply the Behrens-Fisher test
Can the null hypothesis be rejected?
NO
YES
Remove the oldest cluster and place an alert

Figure 3.5: Work-flow of the on-line algorithm. The starting point is defined in the "Measurement of a new day" box.

to test the algorithm can be classified into two different groups, depending on whether they have changes or not. In what follows we describe the datasets and show the results of the performance evaluation. The datasets are N 16-dimensional normal distributed vectors[4], with $N = 9000$, which is large enough to assess the validity of the obtained results—note that a sample of $N = 9000$ is equivalent to analyzing approximately 25 years of data in our algorithm.

Datasets with no Changes

We have generated four datasets with no changes—i.e., all the samples in the dataset have the same mean vector. Even in this case, there is always the chance of detecting a change anyway, thus having False Positive (FP) alarms. These FPs can be controlled with the significance level α, which is the probability of rejecting the null hypothesis (that is, detecting a change) even though there is no change in the data—Type I Error. The purpose of these datasets is to evaluate the FP rate under no changes, which asymptotically

[4] all the vector components are independent of each other

must approach the probability of Type I Error, namely

$$\mathrm{P}(\text{Type I Error}) = \mathrm{P}(\text{reject } H_0 | H_0 \text{ is true}) = \alpha = \lim_{M\to\infty} \frac{\#\text{ of rejections}}{M}, \tag{3.7}$$

where M is the total number of tests performed in datasets that fulfill H_0.

Description of the Datasets These datasets are obtained through four different affine transformations on four different random samples of size N distributed according to a standard 16-variate normal distribution. The applied transformations have been chosen in order to obtain: *(i)* a sample where all the vector components have the same mean and variance: All Equal (AE) dataset; *(ii)* a sample where each vector component has a different mean, but their variances are the same: Means (M) dataset; *(iii)* a sample where each vector component has the same mean but a different variance: Variances (V) dataset; and *(iv)* a sample where each vector component has different values for the mean and variance: Mean-Variances (MV) dataset. Matlab code for generating these affine transformations is provided in Appendix D. Even though different vector components may have different values for the mean and/or the variance, such values are held for all the N realizations of such vector components.

Results We have measured the False Positives Ratio (FPR) given by (3.7) for different significance levels α—see Figure 3.6. The results show that the FPR of each dataset is always below the significance level used in the tests. Such FPR remains almost negligible for significance levels smaller than $\alpha = 0.06$. Thus, we have a large interval of possible significance levels with good performance. Significance levels above 0.06 experiment an increase in the FPR, but also the FPR range remains smaller than the theoretical one. The differences in the performance of the algorithm for the four different datasets are not relevant, because these differences are mainly due to random number generation issues—we have confirmed this by applying different transformations to the same random sample.

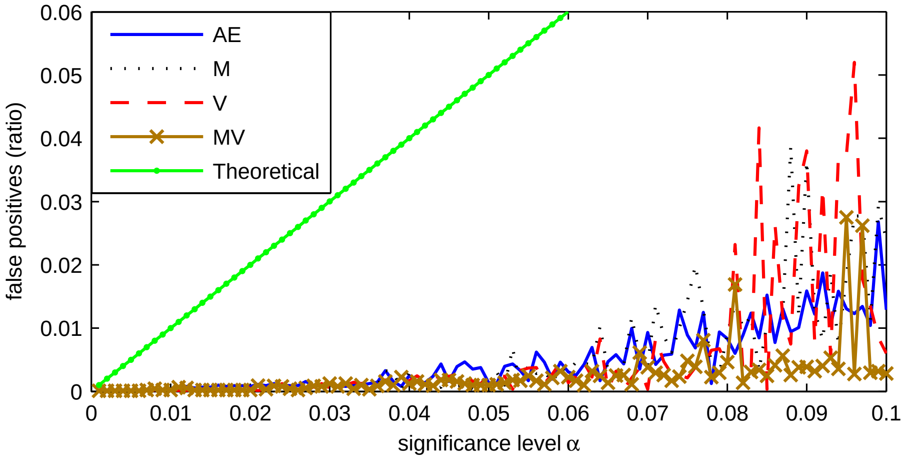


Figure 3.6: FPR in datasets with no changes.

Datasets with Staggered Increments

As the aim of the algorithm is to detect changes in the load, and after confirming that there is a low FPR, a validation with controlled changes follows. Consequently, we have generated two different datasets with staggered increments of duration one and three months, i.e., the distribution of the samples remains the same for one (three) month(s), after which the mean is increased. We note that this kind of growth is the most significant for the capacity planning task [dFV02], because linear increments are easily tracked by classical time series analysis [BD91], consequently a forecast of upgrading times when there is linear tendency is straightforward. This can be accomplished by fitting a time series model to the data (for instance an Auto Regressive Integrated Moving Average (ARIMA) model [PTZD05]) and then predicting when the time series will be above a given threshold [Bru00]. However, the staggered increments represent a sudden change of load that is worth being investigated by the network manager.

Description of the Datasets The growth rate for the monthly staggers is chosen such that effective annual growth is around 90%, which is in accordance with popular reports about the Internet traffic growth [Odl03]. Hence, the monthly growth is approximately 6%. The quarterly growth has also been set to approximately 6%, on attempts to make the obtained results comparable, i.e., we have longer periods without changes in the quarterly growth dataset, but the size of the staggers (which is relevant for our algorithm) are the same in both time series. Accordingly, the theoretical number of changes that should be detected with the algorithm in the Monthly Increments (MI) dataset is 300 and in the Quarterly Increments (QI) dataset is 100.

Results In Figure 3.7(a), we show the number of detected changes on the MI data as a function of the significance level of the performed tests. Note that an increase in the significance level implies that the test is comparatively less restrictive and the critical region is larger, resulting in more detected changes. This figure shows very promising results, because the number of detected changes is in the range 295-310, while the correct value is 300. In addition, the number of false negatives is small for all the significances tested.

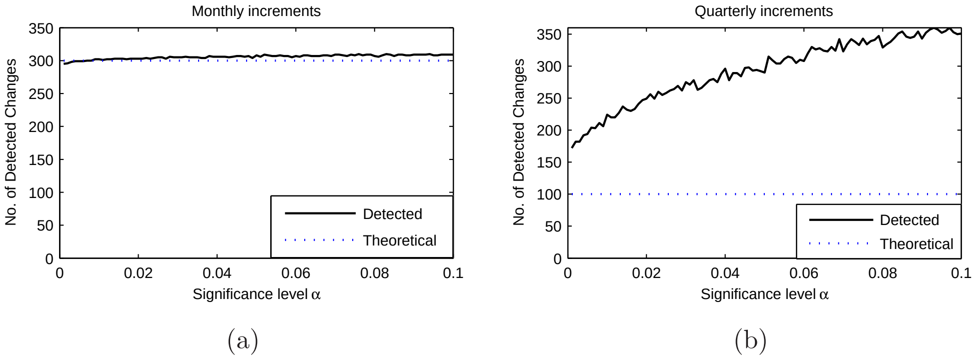


Figure 3.7: Detected changes in the staggered increments dataset: (a) Monthly Increments dataset; (b) Quarterly Increments dataset.

Figure 3.7(b) presents the same information but for the QI data. We note that the algorithm performance decreases. There is no significance level at which we detect exactly the same number of changes that are theoretically in the dataset. In addition, the false positives have enlarged, being now greater than 50. With significance values larger than 0.06 we detect more than 300 changes, meaning that for every theoretical change, we alert for 3 detected changes. We will shed light on the causes of this misidentification in the following paragraph by inspecting the results at a fixed significance level.

Analysis at Fixed Significance Level

We now further inspect the results of the validation, but with a fixed value for the significance level. The value selected for the significance level is $\alpha = 0.05$, as it is the most commonly used value. By making the significance level fixed, we can apply the analysis of the Hotelling's T^2 statistic presented in Appendix C. In addition, we can present graph plots of the clusters found and inspect the reported change points. On those graphs, we plot the values of the projection in one vector component, using different color and marker combinations to differentiate the change-free regions according to the results of the algorithm. Furthermore, we mark with a straight horizontal line the mean of all the values within a change-free region, which makes it for judging the validity of the reported change points. As the amount of points generated for each vector component is huge, we will focus on certain regions of the plots that we have found to be relevant for the validation.

Datasets with no Changes To analyze the reported changes when the input dataset has no changes in theory, we focus on the AE dataset.

In Figure 3.8(a), we show the change-free regions found by the algorithm using different color-marker schemes in the first 300 samples of the AE dataset. Although the samples are concentrated around the true mean (100), the algorithm detected some change points. This happens because we are applying a statistical test, whose confidence level can be interpreted as the FPR in the limit.

The change points reported by the algorithm in this dataset can be due to the following reasons: *(i)* The algorithm found one cluster with mean above the theoretical value followed by a cluster with mean under the theoretical value (or vice versa). This can be easily seen between the first two change-free regions in Figure 3.8(a); *(ii)* the weighted sum of the differences in all the vector components is above $F^{1-\alpha_0}_{p,N-p}$ (Appendix C). To illustrate this fact, we present in Figure 3.8(b) the same zoom area for vector component 2. The

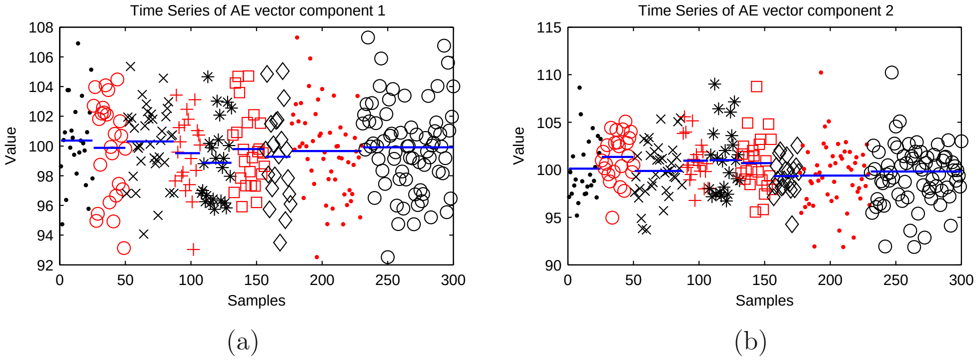
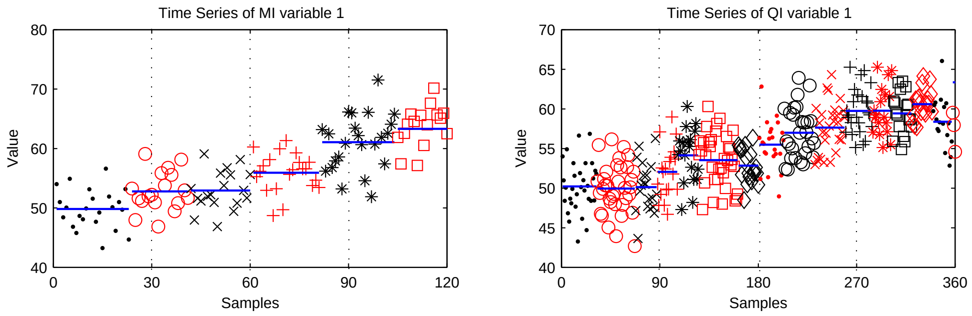


Figure 3.8: Time Series representation of the change-free regions for the first 300 samples: (a) 1^{st} vector component of the AE dataset; (b) 2^{nd} vector component of the AE dataset.

differences between the last two change-free regions on Figure 3.8(a)–(b) (the dots ($\cdot$) around sample 200 and the circles ($\circ$) on its right) are very small, but the addition of these differences through all the variables produces a change point—this is in fact an advantage of the statistical procedure used in our algorithm: MBFP tests for differences in the mean taking into account the variations in all the vector components at the same time.

Datasets with Staggered Increments These datasets are designed to be invariant both in mean and variance for a fixed period of time, after which the value of the mean is increased. Consequently, in these regions without changes we are in the same case as in the AE dataset. We therefore inspect each stair of the dataset from the point of view used for the dataset with no changes.

The clusters in the final samples of the MI and QI datasets (sample 8000 and above) are easily identified by the algorithm, as the differences between those clusters are large enough due to the increment by percentage in each theoretical change point. Therefore, we will zoom in the beginning of the datasets and focus on the first samples—the four first change-free regions. Such regions are depicted in Figure 3.9(a) for the MI dataset and Figure 3.9(b) for the QI dataset, where we have placed vertical lines in the time instants where the theoretical change points are located.



(a)

(b)

Figure 3.9: Zoom to the first four change-free regions of the 1^{st} vector component with delimitation lines for the theoretical change points: (a) MI dataset; (b) QI dataset.

As can be seen in the figures, the variance of the samples is large enough (compared to the mean value) to make samples in different theoretical change-free regions (therefore with different means) to be indistinguishable in some cases. For instance, consider the first change-free region (under sample 30) of Figure 3.9(a). The circle ($\circ$) samples in this region are generated with the same mean as the dot ($\cdot$) ones. However, these circle samples resemble more to those circle samples in the second change free region (between samples 30 and 60) than to the dot ones with the same theoretical mean. This is detected by the algorithm through the clustering technique, which divides the first region before the theoretical change. As the difference between the means is truly significant, the MBFP procedure detects it and a change point is reported between these clusters. That is a visual example that shows how the algorithm misses the true location of the change point between those regions, which we have also observed in other instants of the dataset. This rationale explains all the false positives detected by the algorithm, that under small variance samples or with a more restrictive significance value would have been detected in the right time instant. However, if we pay attention to the second change-free region, we find that there are no significant differences between the two clusters found by the algorithm when inspecting them visually. Note from C that the detected change point between these two clusters is also due to the differences in the means of the remaining vector components, although apparently in this component there is no change.

In the QI dataset (Figure 3.9(b)), in each theoretical change-free region our algorithm reported several change points. The reason for the detection of these extra change points is the same pointed out for the AE dataset, as the extra change points are detected within a theoretical change-free region, where the mean and the variance remain constant. On the other hand, there are some theoretical change points not reported by the algorithm—for instance the one in sample 270. The explanation for this misidentification is the same as in the MI dataset—i.e., the variance of the samples is high compared to their mean.

Consequently, if we focus on the detected change points that cannot be attributed to the inherent FPR of the statistical test given by its significance, the performance of our algorithm with different kinds of datasets is satisfactory because the number of change points detected is approximately the same than in our ground truth datasets. There is still a little deviation in the location of the change points, but such deviation is small enough compared to the length of the change-free regions (we have location errors smaller than 5 days, whereas the change-free regions are larger than 25 days in average), and therefore its effect is not truly relevant for traffic engineering tasks performed by network managers. Actually, the aim of our change point detection technique is to identify links with a changing stationary traffic behavior and not sudden load increases, which are usually detected with threshold-based management systems.

3.5 Change Point Analysis with Real Network Measurements

In this section, we present the results of applying our change point detection methodology (Section 3.4) to the real network measurements of Section 3.2.1. Table 3.5 summarizes the number of tests performed and alerts generated by our algorithm when applied to such dataset, which is three-year long. The second column shows the number of times the MBFP testing methodology was applied. This is the number of times that the clustering algorithm found potential change points. The third column shows the number of times an alert was generated—i.e., the number of times the null hypothesis of equality of means was not satisfied. The values on the left of the slash refer to the incoming direction, and the ones on the right to the outgoing direction.

Table 3.5: Results of the on-line algorithm (Incoming/Outgoing).

Link	**Number of tests**	**Number of alerts**	**Link**	**Number of tests**	**Number of alerts**
U_1	68/130	12/9	U_2	112/75	10/12
U_3	64/84	11/11	U_4	79/59	10/12
U_5	62/75	13/11	U_6	108/61	10/11
U_7	86/57	10/11	U_8	73/84	10/10
U_9	68/76	13/11	U_{10}	82/94	11/13
B_1	85/89	11/10	B_2	98/85	8/9
B_3	56/76	11/12	B_4	59/57	12/11
B_5	123/88	10/11	X_1	65/102	11/12
X_2	67/67	11/12	X_3	103/75	9/11

The advantage of our on-line algorithm to network load detection is that it decreases the OPEX by reducing the human supervision. We remark that our algorithm produces an alert only in case a stationary change in the load happens. The rest of the time the link is considered normal and no intervention from the network manager is required. Taking into account the duration of the measurement campaign, our algorithm placed less than 13 network load change alerts requiring human supervision in a period of more than 750 days (including holidays), which means a load change nearly every two months in average. We also show in Table 3.6 the average values for both the number of tests and the number of alerts in both directions, when grouped by link type, and the total average of such quantities.

To illustrate these results, we present in Figure 3.10 the obtained clusters using the color-markers scheme of Section 3.4.3 for different links. More specifically, we show the results for the time interval 10:30-12:00 (variable 8), because it is the busiest interval. Figure 3.10(a)-(b) show the results for U_1 for the incoming-outgoing direction, respectively. Figure 3.10(c)-(d) show

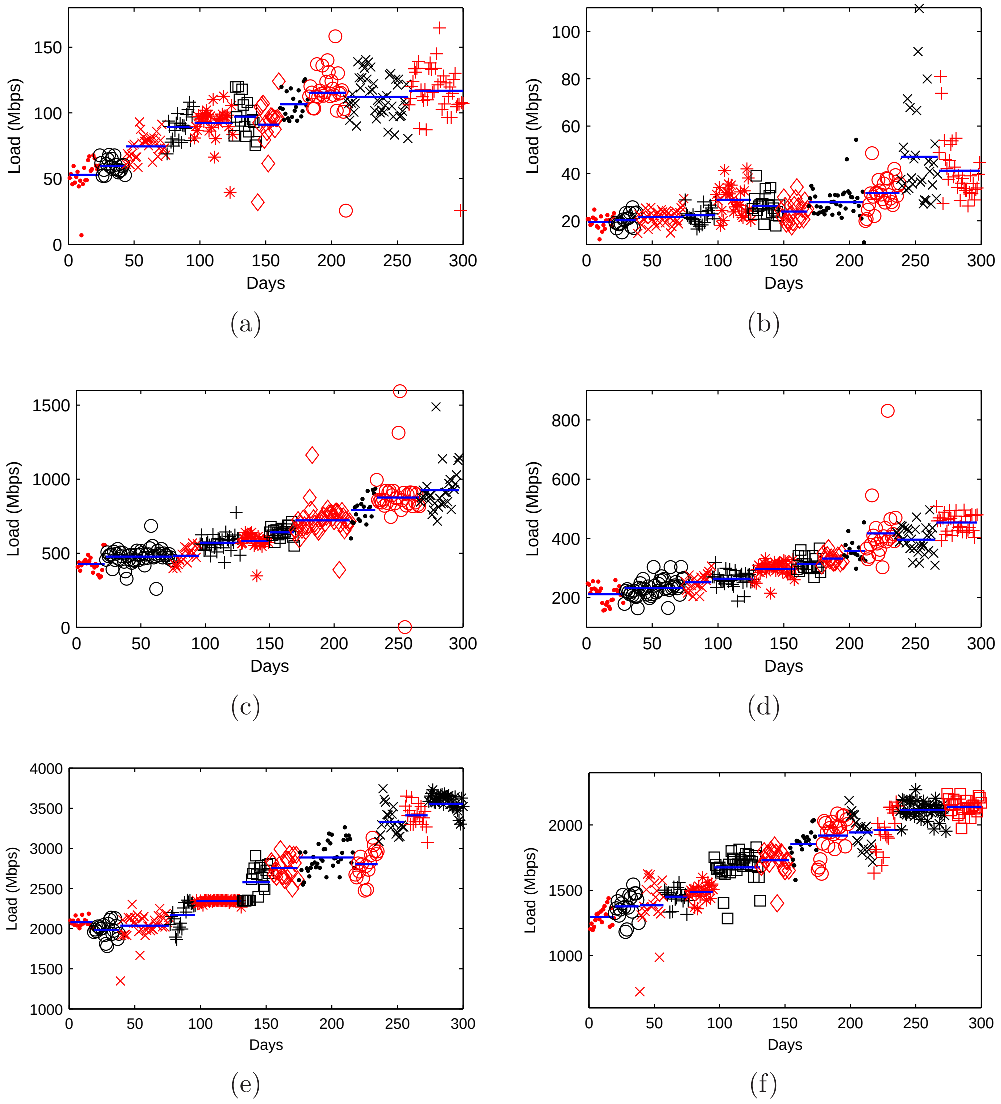
Table 3.6: Average of the on-line algorithm results (Incoming/Outgoing).

Link type	**Number of tests**	**Number of alerts**
University	80.20/79.50	11.00/11.09
Backbone	84.20/79.00	10.40/10.60
eXchange	78.33/81.33	10.33/11.66
Total	80.94/79.67	10.72/11.06

the results for B_1 and finally Figure 3.10(e)-(f) show the obtained clusters for the X_1. We have selected these links because we have found them to be representative.

As it turns out, nearly all the clusters obtained by the algorithm and shown in the figures are reasonable. However, there are some reported clusters that do not seem to have been properly detected. It is worth recalling the rationale followed in the validation of the algorithm, i.e., that a reported change point can be due to differences in different variables than the one shown.

To further analyze the results of the change detection algorithm, we created a binary time series with the change points reported by the algorithm for each direction of each university link. Such time series has a 0 value during a change-free region (where we have also included holidays), whereas the change point instant is marked with a 1. For each of these time series, we have computed the Sample Autocorrelation Function (SACF) to find possible periodicities. Furthermore, in order to assess whether an autocorrelation coefficient ac at a given lag l_0 is significant, we have also delimited the 99% confidence interval for the null hypothesis $H_0 : ac(l_0) = 0$ with horizontal straight lines. Therefore, those lags l with $ac(l)$ outside this region significantly differ from 0. We show in Figure 3.11(a) an example of the results from link U_1, as we have found it to be representative of the set of SACF. In that figure, we see that there is some periodicity in the binary change point time series, because there are significant autocorrelation coefficients at lags approximately multiple of 50. However, such periodicity does not mean that the changes in the load are periodic, but that the restrictions of the



(a)

(b)

(c)

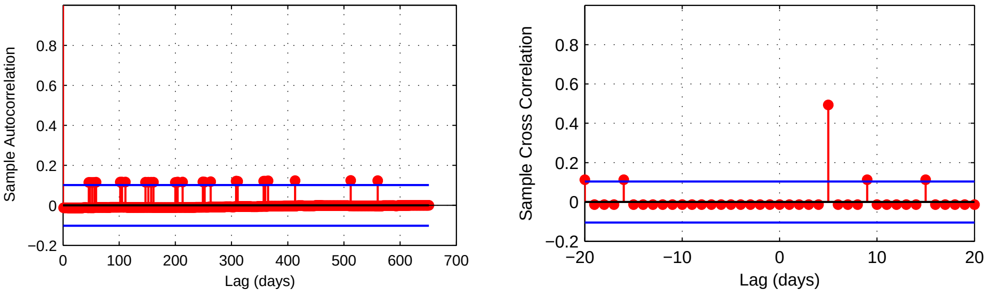
(d)

(e)

(f)

Figure 3.10: Change points found by the on-line algorithm on the time interval 10:30-12:00: (a) Incoming direction of link U_1. (b) Outgoing direction of link U_1. (c) Incoming direction of link B_1. (d) Outgoing direction of link B_1. (e) Incoming direction of link X_1. (f) Outgoing direction of link X_1.

algorithm (i.e., that the changes must be sustained for more than two weeks) affect the randomness of the time between change points. Therefore, we can conclude that the changes in the load are not subjected to certain relevant events, like the change between months or academic seasons.



(a)

(b)

Figure 3.11: Correlations functions of the binary time series (including holidays): (a) Sample Autocorrelation Function (SACF) of the outgoing direction of U_1. (b) Sample Cross-correlation Function (SXCF) between the incoming and outgoing direction of U_1.

In addition, we also computed the Sample Cross-correlation Function (SXCF) between the incoming and outgoing directions of each university link. The results show that only 3 out of the 18 total links have no significant cross-correlation coefficient xc within 5 lags, determined by the same criteria used with the SACF. This means that the changes in the loads of the incoming and outgoing directions of the same link are usually correlated, and are detected by the algorithm within a small difference of days. Such result is expected, as the main important facts impacting the load of a link are traffic engineering tasks, such establishing/changing routes or upgrading link capacities, and variations in the number of users accessing the network or in the intensity of usage. On the other hand, we envisage that when the changes are asymmetric (i.e., there appears a change in one direction but not in the other one), such changes are mainly due to shifts in the way the users access the network or their preferred applications—behavioral changes. For instance, some Internet users are gradually moving from Peer-to-Peer (P2P) applications, where received and sent traffic are approximately in the same order of magnitude, to one-click hosting services, where large amounts of traffic are downloaded whereas the uploaded traffic is negligible for the most of the users [AMD09]. An example of the SXCF is shown in Figure 3.11(b) again for university U_1. We show in that figure only the range of ±20 lags from the origin, which is enough given the periodicity exhibited by the SACF shown in Figure 3.11(a).

3.6 Network Management Based on Relevant Events

In this section we present a network management system that uses the change point detection algorithm—i.e., it shows the relevant events that potentially need action by the network manager. We develop an alert color code to differentiate the importance of the detected changes, which allows us to create weather maps of the operator's network showing the most conflictive links that may be eligible for capacity planning and traffic engineering tasks. As it turns out, when the algorithm detects a change point, it only reports its location, but not any measure of its relevance. Obviously, the impact of a change in the load in the busy hour is not the same as if the change is produced in the midnight. To differentiate such changes, once our algorithm has detected a change point, we apply a univariate normality test for the differences in the means of each variable of the reported clusters. We do so because the MBFP methodology does not distinguish between variables, but takes the overall effect into account. As a consequence of the multiple testing, we apply the Bonferroni correction [Hay05, page 386] to maintain the familywise error rate, thus setting the corrected significance level to $\alpha_c = \alpha/p$, where α is the desired probability of Type I Error and p is the number of tests, which in our case equals the dimension of the distribution. For those univariate tests, we use the Welch's t test [Wel38], which is the most widely used approximation to the Behrens-Fisher problem in the univariate case. These multiple tests determine which of the variables has experienced a change. Consequently, we can establish an alert color code, depending on which variables are known to have a change in their means and taking into account the daily pattern of the link (Figure 3.2).

The alert color code contains five different colors. The variables and time intervals such colors are related to are presented in Table 3.7. Consequently, when we detect a change point, and this is motivated by a change in the variables where the load is higher, we mark such link with red color, we do the same using orange when the change is in a medium load variable, and using yellow when the load is low—during nighttime. Finally, if there is no change point, we mark the link as green, meaning that it remains stable. When we encounter a conflict, i.e., changes happening in two or more variables with different color codes, we mark the link with the most restricting color—i.e., we use the color assigned to the change in the variable with higher load. In addition, chances are that no significant change is detected by the Welch's t test with the Bonferroni correction—for instance, if the change where due to small differences in all the vector components. If this happens, we mark the link using a blue color.

Table 3.7: Alert color code for network surveillance.

Color	**Meaning**	**Variables**	**Time period**
Red	Change in a high load variable	7-9	09:00-13:30
Orange	Change in a medium load variable	10-13	13:30-19:30
Yellow	Change in a low load variable	1-6, 14-16	19:30-09:00
Blue	Change detected by the MBFP not found by the multiple comparisons	-	-
Green	No change detected by the MBFP	-	-

Note that the links marked with a color different than green would require human supervision. Once the network manager becomes aware of the alert, it can be disabled because either the change is not considered relevant enough to take any action or the actions have already been carried out. To illustrate the alert based system, an example of such map is presented in Figure 3.12 using the RedIRIS network architecture showed in Figure 3.1. In this example, one link is marked with red color, meaning that in the corresponding link, a change in a variable with high load was detected. We also have two links marked with orange color, corresponding to changes in medium load variables, and two other links marked with yellow color corresponding to changes in low load variables. Remember that in the link marked with red color, chances are that there were changes also in other variables, but the red alert prevails because it is the most important. In addition, there are two links marked with blue color. In such links, a change in the load was detected by the MBFP procedure. However, such change was due to small contributions of the differences in all the vector components, and no change was found by the Welch's t test. Finally, the remaining links are marked with green color, meaning that there is no change detected in those links, which are then considered to remain stable.

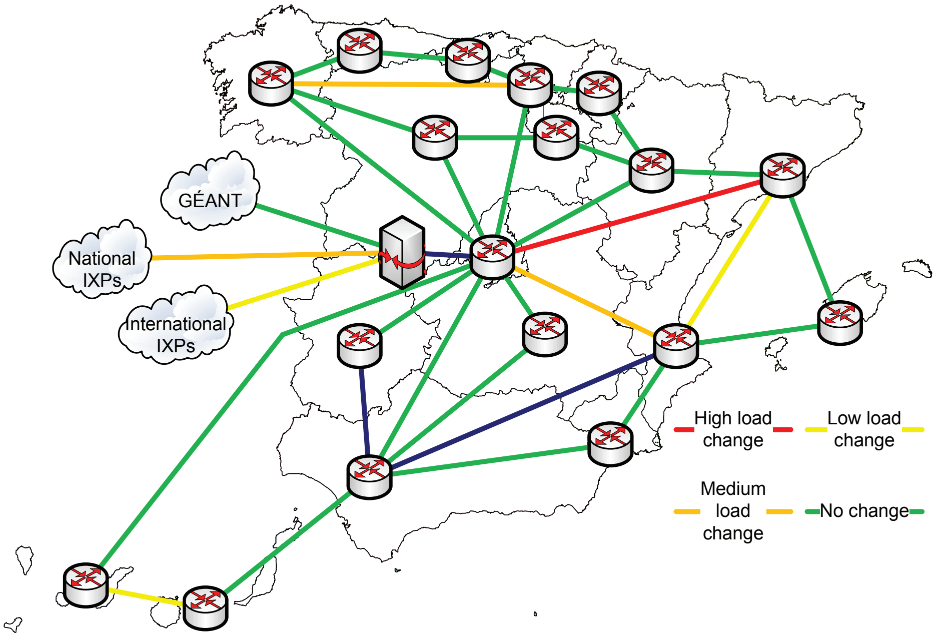


Figure 3.12: Sample weather map of the RedIRIS network, with some links needing the network manager attention.

This way of visualizing the relevant events in the whole network facilitates large-scale network operators the surveillance of the network, allowing them to reduce the OPEX expenditures or to move staff from the network supervision center to link locations, in order to take action to respond to the relevant events in a faster way.

3.7 Summary and Conclusions

In this chapter, we have presented an on-line load change detection algorithm, which uses clustering and statistical techniques to identify statistically significant load changes. The algorithm is based on a multivariate fairly normal model, which keeps track of the well-known daily pattern of the network, in order to make the statistical inference. We have validated the suitability of that distribution to model the daily pattern and make inferences about the means of the distribution.

The application of our methodology to real network measurements available from the Spanish academic network shows promising results, allowing the network operator saving OPEX expenditures by reducing the visual inspection of the traffic time series. Finally, we have presented an alert color code scheme that allows to manage the network focusing only on the relevant events detected by the algorithm. To facilitate this task, visual maps of the network are used as visualization tool of the algorithm's output. This efficient way of network-wide monitoring permit the service providers to guarantee the required levels of QoS, as established in the corresponding Service-level Agreement (SLA).

Chapter 4

Weekly Pattern Timeseries Detrending: The Case of VoIP

Quality of service and of experience are very important and have consequently attracted a lot of attention from the research community, specially for Voice over IP (VoIP) services. The most impacting performance degradation for VoIP comes from packet losses, which are mainly due to overload periods. Consequently, timely detection of overload periods is crucial for management of VoIP services and allows a reduction of expenses. The monitoring of actual measurements for detecting overload periods lacks the existence of detrending models that remove the non-stationarity from the data. In this chapter, we propose a detrending methodology tailored for VoIP services that removes the trend from actual measurements and permits the application of the broad family of statistical techniques that assume stationary data. To show the performance of the methodology, we have designed an outlier-friendly anomaly detection algorithm that signals anomalies after outlier removal. Furthermore, as the residuals of the detrending methodology exhibit large correlations, we have proposed an alternative measurement methodology to monitor Poisson-nature arrival processes, such as the process of call arrivals in a VoIP system. The proposed technique outperforms the traditional one for heavy-tailed service times, which we have demonstrated to be the case of the actual measurements analyzed in this chapter.

4.1 Introduction

Quality of Service (QoS) and Quality of Experience (QoE) are very important for Network Operators and Service Providers (NOSP), and have consequently attracted a lot of attention from the research community [SJ11, MA06]. This is specially the case of VoIP services, for which low values of QoS related metrics (latency, packet loss and jitter) are crucial in order to enable its deployment [KP09]. Furthermore, the users perception of these network characteristics may foster the usage of the service, thus increasing service providers revenue. With regards to the VoIP service, which we take as leading example in this chapter, the most impacting performance degradation comes from packet losses [BMPR10]. Packet losses are mainly due to overload periods—i.e., time periods where the network devices are not able to cope with the amount of load injected into the system. Furthermore, overload periods also have an impact on the latency and jitter, increasing the values that may be observed during low occupancy periods. Consequently, timely detection of overload periods is crucial for the management of VoIP services [MŻ11]. Timely detection of overload periods allows anticipation of quality degradations and enables proactive network management [CCM+11]. To this end, NOSP are investing large amounts of money in capital and operational expenditures. Capital Expenditures (CAPEX) are in the form of new network devices capable of coping with the ever increasing speed in network links, mainly in the form of active and passive probes that gather network traffic measurements at different points in the network [CCM+11], and high performance servers able to analyze the gathered measurements in a centralized way [CMGD+11]. On the other hand, Operational Expenditures (OPEX) are devoted to maintain such network devices and to hire network managers capable of detecting and troubleshooting network problems. Given this large investment, we have proposed an automated technique to reduce OPEX by supporting the network monitoring tasks in Chapter 3. In order to provide this support, the automated technique relies on the statistical analysis of network traffic measurements. However, network traffic measurements are not stationary. Instead, there is typically a day-night pattern, at which traffic loads are large during daytime and decrease at nighttime. This traffic patterns are a consequence of users' behavior, whose activity is reflected in the amount of traffic observed in the network.

The lack of stationarity in network measurements, which is a common assumption in the main statistical techniques, is a serious disadvantage when analyzing network traffic measurements. As a consequence, direct application of such statistical techniques to network traffic measurements may lead to erroneous conclusions [DG06], such as large amounts of false positives/negatives. Therefore, we propose an unsophisticated methodology for removing the inherent daily pattern in network traffic measurements, tailored for VoIP call counts data. The methodology is based on some properties of the call arrival process, which we prove to be time-varying Poisson in our case study. The idea behind the proposed technique is simple. We compute an estimate of the average daily pattern by means of a moving average procedure. Such procedure has been proved to be fairly accurate for prediction purposes [Tay08]. After the average daily pattern is computed, it is subtracted from the actual measurements. In the end, we standardize the result dividing the difference by the square root average pattern—which is the standard deviation of the measurements given the Poisson nature of the process. The output of the methodology are standardized samples (i.e., zero mean and unit variance) that follow a normal distribution in the case the amount of load in the network is considerable. Accordingly, we have observed that the performance of the methodology improves when the night periods are removed from the original sample. The night period removal has no unfavorable consequences for our goals because the chances that an overload period happens during night are negligible. However, we observed that there are large correlations between the output samples, which evidences lack of independence. As independence is typically an assumption for many statistical techniques as well, such large correlation may spoil the results of the statistical analysis applied. We investigated further such correlations, and designed an alternative measurement methodology that yields smaller correlations in some cases, which depend on the nature of the call holding time distribution, than the traditional measurement methodology for Poisson processes. Specifically, we show that when the call holding time distribution follows a Pareto or log-normal distribution, there is a high probability that our proposal outperforms the traditional one, which eventually depends on the actual parameters of such distributions. Furthermore, we show that the best fitting model for the call holding times is a mixture of two log-normals and a Pareto distribution in our dataset. In addition, we present a numerical evaluation which shows that the proposed alternative outperforms the traditional measurement methodology in terms of correlations if the call holding time is distributed accordingly to the best fitting model.

On attempts to show the performance of the proposed trend removal technique, we propose an on-line *oulier-friendly* anomaly detection algorithm. The algorithm removes outliers before signaling anomalies taking into account the likeliness of each model's residual. The algorithm is able to detect both shortages and overload periods, as well as shifts in users' behavior.

The structure of the rest of the chapter is as follows: Section 4.2 presents the related work. Mainly, we surveyed the forecasting techniques that have been proposed for predicting call count measurements, and summarize the models suggested in the literature to fit the arrival process and holding time distribution of VoIP calls. Afterwards, a description of the dataset and its daily pattern is presented in Section 4.3, along with the results of modeling the call arrival process and its duration distribution. After describing in detail the proposed methodology to remove the trend from VoIP call count measurements and assessing the validity of its theoretic assumptions in Section 4.4, we propose the alternative measurement technique and present its evaluation in Section 4.5. Next, we provide in Section 4.6 a description of the anomaly detection methodology and the results of its application to the measurement dataset after the seasonality is removed. Finally, Section 4.7 concludes the chapter.

4.2 Related Work

The traffic patterns in telecommunication systems have been analyzed for more than a decade [TMW97], and even its evolution throughout time has been studied [Hee07]. Such patterns appear as a response to users' behavior, and are commonly referred in the literature with the term *daily pattern*. The daily pattern varies depending of the kind of users that access the network, although it can be deemed as invariant (i.e., having a similar shape from day to day) when the kind of users is fixed. These users can be divided into two main groups. On one hand, we have enterprise users—users that access the network in their workplaces. The daily pattern that they produce is directly related to the office working hours, i.e., the load is larger during working hours, and usually there appear two clearly distinguishable peaks—before and after lunchtime. A study of this kind of daily pattern can be found in [MGDA10] for the Spanish Academic Network RedIRIS[1] and was briefly presented in Section 3.2.2. On the other hand, we have domestic users—users that access the network from their residence. This pattern is also influenced by the working hours, but in an opposite way: the load is larger after usual working hours, when users come back from their workplaces. Such usage pattern has been studied within the TRAMMS European project [ALK+09, ALS+10].

This shape invariance of the network traffic measurements is also observed at different timescales. For instance, if we compare measurements in a weekly basis, we can observe that the shape of the pattern is approximately the same from Monday to Thursday. On Fridays, we observe a scaled version of the other working days pattern—i.e., the shape is the same, but the load is usually smaller. Finally, on weekends and holidays, we found almost flat patterns when dealing with enterprise measurements. The main reason for this flat pattern is that the traffic during weekends is principally due to applications that are left running and generate traffic without user interaction.

A similar traffic pattern can be observed when taking into account only VoIP traffic [BMPR10, Hee07]. However, the studies of VoIP traffic have put more effort on analyzing the call characteristics, namely the call arrival process and the call holding time distribution, rather than focusing on the daily or weekly patterns. Regarding the call arrival process, it is widely accepted

[1] http://www.rediris.es/index.php.en

that it is fairly well modeled by a time-inhomogeneous Poisson process, which can be considered stationary at short timescales, ranging from scores of minutes to hours [Hee07, BMS+04, BGM+05]. In this line, there have been studies in the literature proposing methods for estimating the parameters of such processes [MPW96], assessing the validity of such assumption by means of statistical tests [BGM+05, BMS+04, BZ02], and even adapting traditional queing-theoretic models to this arrival process [Mas02]. In our study, we use the test presented in [BGM+05] to validate the time-inhomogeneous Poisson arrival process assumption in our dataset. The details of the test are described in Section 4.3.2. Conversely, there is no consensus in which model provides the best fit to the call holding time distribution. However, the fact that the holding times are no longer appropriately modeled by means of exponential distributions has been widely proved. The distributions proposed in the literature are manifold. Examples of this are the hyper-exponential distribution [Hee07], the inverse Gaussian distribution [BMPR10], the Weibull distribution [CK02], the Pareto distribution [DSM04], and the log-normal distribution [CHL07]. In our case study presented in Section 4.3.3 we show that the best modeling distribution is the log-normal distribution, although higher goodness-of-fit is achieved by a mixture model composed of two log-normal and one Pareto components.

On the context of call centers, the main research efforts have focused on providing an accurate forecast of the time series of call arrivals [ADL04, SH05, SH08a, SH08b, Tay08]. Avramidis et al. [ADL04] propose three different models for this task. The proposed models are parsimonious, in the sense that the number of parameters is small, which make them useful for on-line methodologies. However, the timescale of prediction is larger than two weeks which is useful for staffing of call centers, because the agents must know their assignment two weeks or more ahead, but not for our purposes—we work with complete weeks, or the weekly pattern, and require one-week lead time forecasts. Shen and Huang [SH08b, SH05, SH08a] apply Singular Value Decomposition (SVD) to reduce dimensionality and denoise the time series before forecasting, by leveraging on the significant singular values. The SVD is also useful for anomaly detection as showed in Section 2.2. However, such anomaly detection is achieved through visual inspection of the singular values, which makes it useless for application in automated detection methodologies, and the timescale of detection is in the range of days, which is useful for forensic network analysis, but not for on-line and timely reaction. In [SH08b], Shen and Huang improve the forecasting methodology by dynamically updating the forecast with intraday information. Such updates reduce the prediction error, but at the expense of larger model complexity. A comparison of univariate time series methods is presented in [Tay08]. This comparison includes naive methods such as moving average—which is the approach we follow in our methodology.

All in all, the more complex methods achieve the smaller prediction error in few-days ahead forecasting, but simpler methods such as moving average achieve similar prediction errors for one week lead times and are computationally more tractable.

4.3 Measurement Dataset

Experiments in this chapter are using actual traffic traces collected from an operational network. Using Tstat [FMM$^+$11], Internet Protocol (IP) traffic exchanged by customers was measured in a large Point of Presence (PoP) of an NOSP in Italy where VoIP is deployed. A total of 22,000 customers were continuously monitored for more than 4 months, starting from November 2010. Tstat is used to identify VoIP flows, i.e., voice calls, and to extract several performance indexes for each call [BMPR10]. The measurements were kindly donated by the Telecommunication Network Group of Politecnico di Torino, in compliance with data privacy preserving regulations.

In particular, in the context of the present chapter we are interested in the call arrival process and call holding time distribution. The resulting dataset contains the log of the call arrival epochs and the corresponding durations. Later in this chapter, we statistically analyze these, and use the resulting processes/distributions to assess the performance of our methodology. This dataset containing start and end times of the calls will be referred to as *detailed* below. On the other hand, the dataset containing the count process of the number of calls being active is referred to as *summarized* in what follows. It is used to estimate the average pattern, apply our proposed detrending model and analyze the residuals for deviations of normality that may signal anomalies in the network.

4.3.1 Daily and Weekly Patterns

In this section we present the average daily and weekly patterns of the VoIP measurements we use in the following sections. As can be seen in Figure 4.1, the daily and weekly patterns are very much alike to those of the RedIRIS network presented in Section 3.2.2. The daily pattern exhibits two peaks, before and after lunchtime, typical of enterprise networks. Although the measurements come from residential networks, such behavior is expected in VoIP data. Regarding the weekly patter, we again observe the typical pattern of enterprise networks, having working days similar shape among them. However, the weekends have an scaled version of the weekday pattern instead of having a flat pattern such as the observed in enterprise networks.

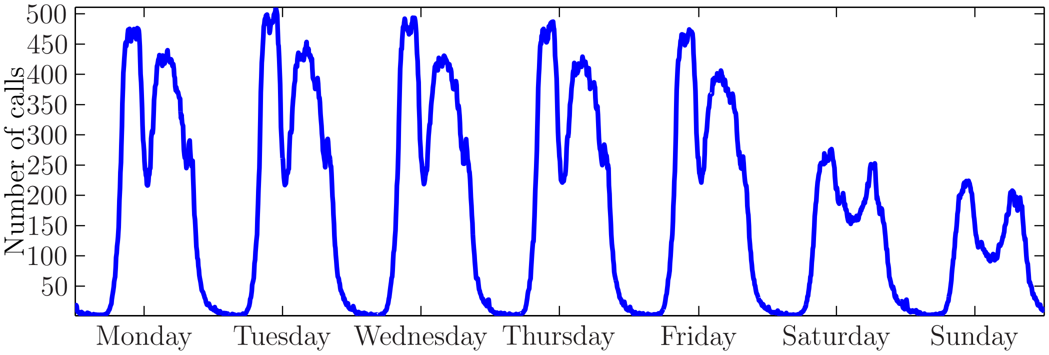


Figure 4.1: Average weekly pattern of the analyzed dataset.

4.3.2 Call Arrival Process

Classical theoretical models for voice traffic posit that the call arrival process is Poisson distributed. Such process results when there is a large number of users generating calls independently of each other. However, this simple model does not usually apply to actual measurements, commonly explained because the users' behavior varies during the day. To cope with such users' behavior variation, non-homogeneous Poisson processes are used instead—in which the intensity of call arrivals is time dependent. In practice, this time-varying condition is relaxed, and the process rate is assumed to remain constant for blocks of time—i.e., the process is considered to be short-term stationary. We conjecture that the arrival process in our dataset is time-varying Poisson in this sense, and thus the intensity remains constant for time-blocks of length L. In our particular case, we need $L \geq 300$ seconds to prove the validity of equation (4.4).

To assess the correctness of our model, we apply to our detailed dataset a test presented by Brown *et al.* in [BGM+05] specifically designed to statistically prove whether the arrival rate is constant within each given time block. To construct the test, the interval of a day is split into disjoint blocks of length L, resulting in a total of I blocks. With this setup, let T_{ij} be the j^{th} ordered arrival time in the i^{th} block. Denoting with $J(i)$ the total number of arrivals within the i^{th} block, we then define $T_{i0} = 0$ and

$$R_{ij} = (J(i)+1-j)\Big(-\log\Big(\frac{L - T_{ij}}{L - T_{i,j-1}}\Big)\Big), \;\; j = 1, \ldots, J(i); i = 1, \ldots, I. \quad (4.1)$$

The $\{R_{ij}\}$ will be independent standard exponential variables under the null hypothesis that the arrival rate is constant within each block. We note that the null hypothesis does not assume that the arrival rates of different blocks have any pre-specified relationship, and refer the interested reader to the original publication [BGM+05] for a proof of the test.

In Table 4.1 we present the results of applying the test to different block sizes L. We use the Kolmogorov-Smirnov (KS) test to verify the null hypothesis at 5% significance level—see Appendix A for a brief description of the KS test. The results presented in the table show that the arrival process can be regarded as fairly time inhomogeneous Poisson only at very short timescales, say less than 10 minutes, which is enough to justify such an assumption in our methodology.

Table 4.1: Results of the inhomogeneous Poisson arrival process assessment.

Block length L **(min)**	**Rejection %**	**Block length** L **(min)**	**Rejection %**
90	73.93	30	35.32
75	69.24	25	27.04
60	61.34	20	19.09
45	49.55	15	14.08
40	43.88	10	9.39
35	38.94	5	6.90

4.3.3 Call Holding Time Distribution

In this section we study the Call Holding Times (CHT) in our sample, aiming at finding the model which best fits the service-time duration distribution. The literature posits that the CHT distribution is no longer appropriately modeled by an exponential distribution, and several alternatives have been proposed. The majority of them are heavy-tailed distributions for the VoIP service, which may be explained given the low (usually flat) rates at which the service is commercialized. After a visual inspection, it turns out that a heavy-tailed distribution is the more likely distribution to fit our detailed dataset as well. In this visual inspection, we have used *log-log* plots of the empirical Complementary Cumulative Distribution Function (CCDF) of the sample, which allow us to gain insight in the tail of the distribution. Consequently, we particularly restrict in our Goodness of Fit (GoF) assessment to heavy-tailed distributions, in the sense that the distribution has heavier tails than the normal distribution. To measure the GoF we use again the KS statistic, although in this case testing for the null hypothesis that the sample comes from the hypothesized distribution is not possible. As we are estimating the parameters of the hypothesized models from the sample, the critical values determined in this way are invalid [Dur73]. However, we still can use the KS statistic as a measure of model discrepancy, which will allow us to select the best fitting model.

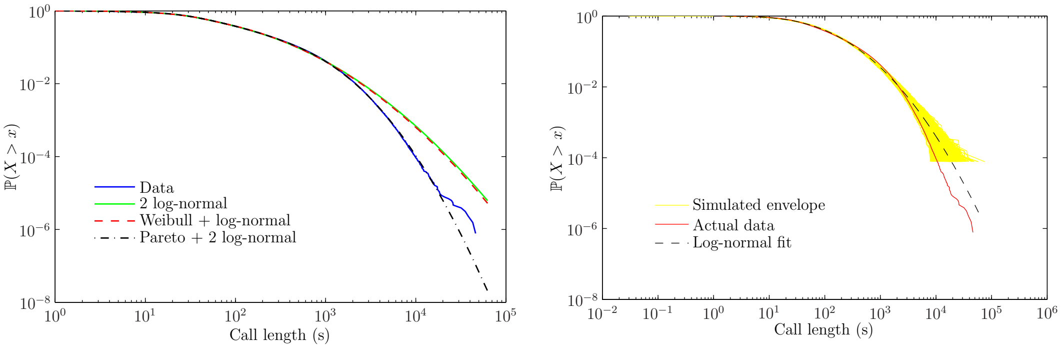
Table 4.2 summarizes the results of the GoF study. In that table, we present the models which evidenced better fit to the data sorted by the value of the KS statistic (the shorter the better), along with the MLEs of the corresponding parameters.

Table 4.2: GoF results for different fitting models.

Distribution	**Parameters**			**KS statistic**
	Pareto	Log-normal$_1$	Log-normal$_2$	
Pareto	$p = 0.6793$	$p = 0.2023$	$p = 0.1184$	0.0046
+	$k = 0.2749$	$\mu = 6.0857$	$\mu = 3.5410$	
2 log-normal	$\sigma = 63.1607$	$\sigma = 0.9523$	$\sigma_3 = 0.5201$	
	Log-normal$_1$	Log-normal$_2$	–	
	$p = 0.1089$	$p = 0.8911$		
2 log-normal	$\mu = 3.6421$	$\mu = 4.2926$		0.0074
	$\sigma = 0.4810$	$\sigma = 1.5528$		
	Weibull	Log-normal	–	
Weibull	$p = 0.0968$	$p = 0.9032$		0.0075
+	$\lambda = 42.7199$	$\mu = 4.2964$		
log-normal	$k = 2.4978$	$\sigma = 1.5385$		
	Log-normal	–	–	
	$p = 1$			
Log-normal	$\mu = 4.2218$			0.0246
	$\sigma = 1.4882$			

Figure 4.2(a) shows the *log-log* plot of the empirical CCDF of the data along with the models presented in Table 4.2. Accordingly with the quantitative results, we can observe in the figure that the best fit is provided by the mixture of two log-normal and one Pareto distributions. This mixture model is capable of fitting the whole body of the data, but there is a lack of fit in the very end of the tail. Furthermore, we can observe a small oscillation in the data tail, which is not captured by any of the fitting models. However, this can be just an artifact provoked by the sample size. Although the number of samples is large (>1 million of samples) for usual purposes, it may not be enough to accurately estimate the probabilities in the tail, since those events are rather unlikely. To shed light to this fact, we computed a distributional envelope for the log-normal fitting model, which shows the high variability that the log-normal distribution can have in the tail. Concretely, we gen-

erated $N = 1000$ populations of size s =100K samples from a log-normal distribution with the same parameters that provide the best fit. We computed the empirical CCDFs of these populations, and plotted them jointly with the data and the log-normal best fitting model in Figure 4.2(b). In that figure we can observe that the actual measurements lie within the simulated envelope. Consequently, we can conclude that the actual measurements are a plausible realization of the best log-normal fitting. We note that in fact, according to Table 4.2, there are models that provide even better fit to the actual data. This means that the situation is even better if other models are taken into account.



(a) (b)

Figure 4.2: *Log-log* plots of the data: (a) *log-log* plot of the data and the best fitting models according to the KS statistic value; (b) *log-log* plot of the data along with the best log-normal fit and its simulation envelope.

4.4 Detrending Methodology

In this section, we provide a methodology to remove the inherent seasonality that exists in network traffic measurements. After its description and justification, we present an analysis of its performance and the achievement of the expected results.

4.4.1 Methodology Description and Expected Results

Our methodology exploits the practical invariance of the weekly pattern to estimate and remove the seasonality from the measurements. We assume a set-up where the measurements are time series of traffic counters (byte counts, number of active calls, etc.) at a given time granularity. In our analysis, we will use a five-minute time granularity, because it is the usual timescale for many tools that output network traffic measurements—e.g., the Multi Router Traffic Grapher (MRTG) tool [OR98]. We denote the network traffic measurements as x_i^n, being $i = 0, 1, 2, \ldots, 2015$ the number of the 5-minute interval within the week, starting on Monday midnight, and n denoting the week number within the dataset, out of a total of $N = 12$ weeks. The purpose of the methodology is to provide a good estimate $\mathbf{y}^n$ for the measurement vector of week n, $\mathbf{x}^n$, using the available information from previous weeks, $\mathbf{x}^j$, $j < n$.

We assume that the differences from week to week in the weekly pattern are due to random deviations from an average network usage pattern, and therefore propose the following model for the measurements

$$\mathbf{x}^n = \boldsymbol{\alpha} + \boldsymbol{\varepsilon}^n, \tag{4.2}$$

where $\boldsymbol{\alpha}$ denotes the average fixed pattern and $\boldsymbol{\varepsilon}^n$ are the random deviations from such pattern. We assume that this deviations are normally distributed with zero mean and heteroscedastic variance $\boldsymbol{\sigma}^2$.

The simpler approach for estimating the average pattern is to set the prediction vector $\mathbf{y}^n$ to a windowed average $\bar{\mathbf{x}}^n(w)$ of the measurements in the previous weeks, assigning different weights W_j to different week lags, being w the length of the window in weeks:

$$\mathbf{y}^n = \hat{\boldsymbol{\alpha}}^n = \bar{\mathbf{x}}^n(w) = \sum_{j=1}^{w} \frac{1}{W_j} \mathbf{x}^{n-j}. \tag{4.3}$$

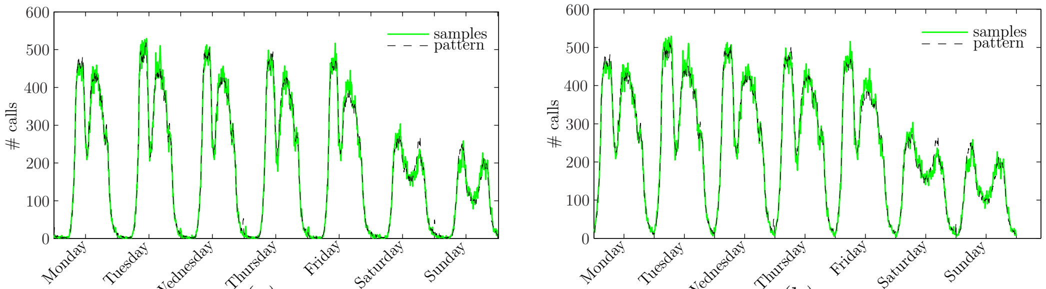
The proposed estimation uses the arithmetic average of the measurements in a window of size $w = 5$. We use this window size because it represents a trade-off between model accuracy and robustness to pattern shifts—meaning that the model would be able to track variations with time on the pattern shape. On the other hand, we use the arithmetic mean (all the weights W_j equal to the window size w) because it minimizes the Mean Squared Error (MSE) of the estimator. Nonetheless, we have also tested different averaging processes (for instance exponentially decreasing or increasing weights), and the differences in performance are negligible.

We can then remove the estimated pattern from the actual measurements, obtaining theoretically zero mean residuals. However, as the errors in the model are assumed to be heteroscedastic, so will be the residuals computed after trend removal. This would suppose a drawback, because many of the main statistical tools assume homoscedasticity besides stationarity, and therefore calls for standardization. Such standardization implies dividing each residual by its standard deviation. Consequently, we would need to design another model for estimating the pattern standard deviation. Instead, we exploit the distributional properties of the measurement process to circumvent this computation. Concretely, we showed in Section 4.3.2 that the arrival process is time inhomogeneous Poisson. As a consequence, we can use the property relating the mean and the variance of a Poisson process to estimate the standard deviation—for a Poisson process, the mean equals the variance. Hence, we obtain standardized residuals $\boldsymbol{r}^n$ by removing the average pattern from the actual measurements, and then dividing by its square root:

$$\boldsymbol{r}^n = \frac{\boldsymbol{x}^n - \boldsymbol{y}^n}{\sqrt{\boldsymbol{y}^n}}. \tag{4.4}$$

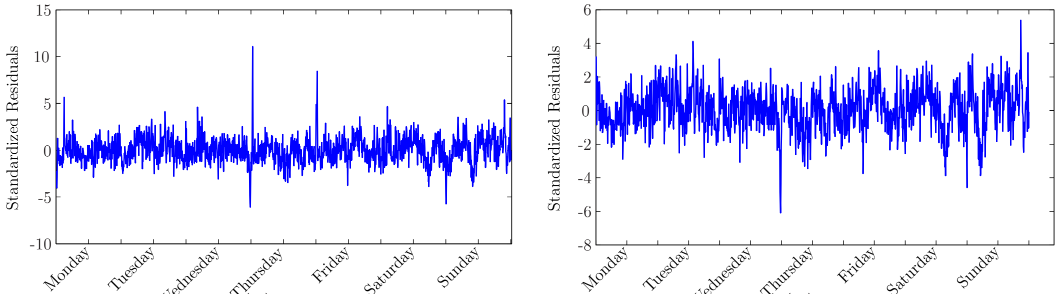
4.4.2 Model Performance Results

We have estimated the seasonality according to equation (4.3) in our summarized dataset, and computed the corresponding residuals using equation (4.4). For the shake of brevity, we only show the results for one week, which we have found to be representative of the performance of the model. Figure 4.3(a) shows the estimated pattern, computed from previous weeks samples, superimposed on the actual samples of the week under study. It shows the GoF of the estimated pattern to the actual measurements, mainly due to the high stability of the weekly pattern in this kind of data. The main differences appear at the peaks of the weekly pattern, at which the samples show abrupt variations. The corresponding residuals are shown in Figure 4.4(a). The variance of the residuals seems to be higher than expected, even appearing very large deviations from its mean—higher than 5σ. This can be better observed in the corresponding Gaussian Quantile-Quantile (Q-Q) plot, shown in Figure 4.5(a), at which there appears deviations in the tails from the straight line that indicate non-normality.



(a) (b)

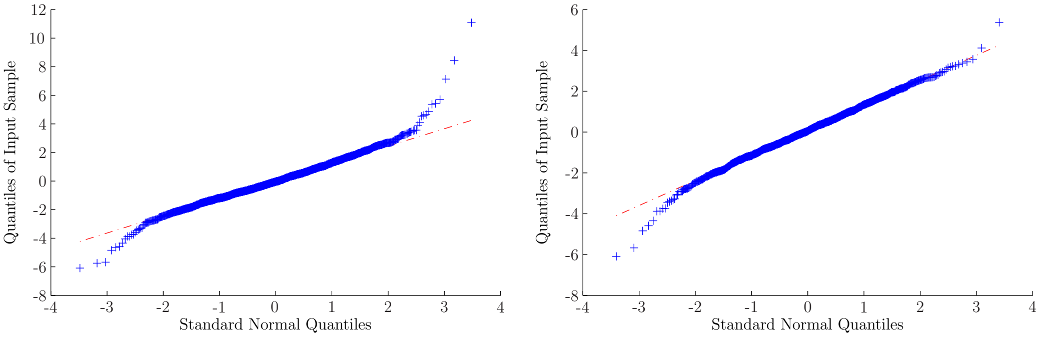
Figure 4.3: Data samples for the week under study and estimated pattern based on previous weeks data samples: (a) nights included; (b) nights removed.



(a) (b)

Figure 4.4: Residuals obtained after standardization with the estimated pattern: (a) nights included; (b) nights removed.

The reason behind such large deviations from the hypothesized distribution is related with the night periods. During the night, the load decreases



(a) Deviations from a straight line appear in the tail evidencing non-normality.

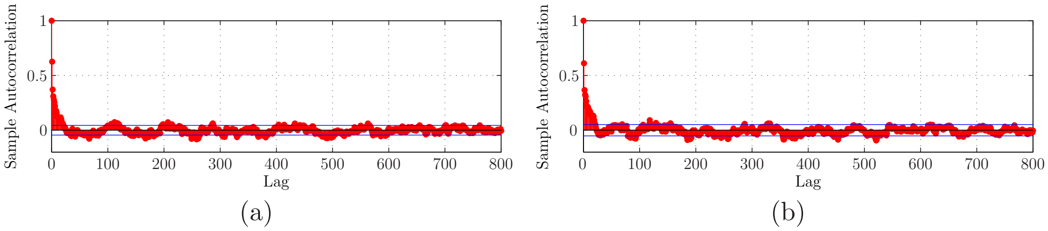
(b) Smaller deviations appear when nights are removed.

Figure 4.5: Gaussian Quantile-Quantile plots of the residuals: (a) nights included; (b) nights removed.

drastically, being nearly zero for several hours—when the majority of the users sleep. The estimated pattern captures this behavior and causes the residual computation to explode in the standardization step—when dividing by the square root of the estimated pattern. To circumvent this numerical problem, we decided to remove the night periods from the sample. Note that for the final purpose of our methodology (i.e., detecting overload periods that may cause system performance degradation) nights are practically irrelevant, given that the amount of traffic is low and therefore it is difficult that sudden changes might have an impact on the network performance.

We define the night period from midnight to 6 a.m., and remove the related samples from the dataset—we filter out a total of 72 samples per day. The corresponding estimated pattern and residuals are shown in Figure 4.3(b) and Figure 4.4(b), respectively. We can observe that without nights the variance of the residuals has been reduced. This is shown also in Figure 4.5(b), where the Gaussian Q-Q plot of the residuals without nights is presented. As it can be observed, now the deviations in the tails are not so large, and consequently fairly normality cannot be rejected.

However, we have observed that there is some periodical trends in the residuals—see Figure 4.4. This may imply that there exists correlation between the residuals, violating the assumption of independence that is used in most of the sound statistical procedures. To gain insight into this effect, we present in Figure 4.6 the autocorrelations of the residuals for both cases: including and without including nights in the sample. Such figures confirm that there is some periodic component in the residuals, because the autocorrelation plots show some kind of oscillation. This turns out in a non-negligible correlation, having more than 9% of the samples outside the 5% confidence interval when nights are included and more than 7.5% when night periods are filtered out. Although such values may not appear to be very large, it is worth noting that such values are computed over the whole week, and therefore include large timescales that are not interesting in terms of correlations. The corresponding values when taking into account only 2 hours (first 24 lags), are considerably larger. For the case including nights, we found that approximately 85% of the samples are outside the 5% confidence interval, whereas in the case without nights this value is reduced to approximately 80%.



(a)

(b)

Figure 4.6: Autocorrelations of the residuals: (a) nights included; (b) nights removed.

These results evidence the high correlation in the residuals, which may imply a performance degradation when used as input for a methodology assuming independence. We envisage that the reason behind such large correlation in the residuals is due, among others, to the simplicity of our trend estimation model, which is not able to adapt dynamically (i.e., in a short timescale, say hours) to deviations from the pattern. As a consequence, when actual measurements are above the estimated pattern from previous weeks, there is a high probability that this situation would remain the same for the next samples, and vice versa, resulting in the observed trend in the residuals. Nonetheless, we have decided to keep the model as simpler as possible at the expense of small performance degradations.

4.5 Measurement Alternative

In Section 4.4 we presented and analyzed the performance of our seasonality removal methodology. Such methodology removes the seasonal trend from call count measurements and transform the data into correlated fairly standard-normal samples. Such correlation is a serious drawback for the methodology, because most of the sound statistical techniques relies on independent samples. We believe that such high correlations are due to several reasons, mainly *(i)* the simplicity of the detrending model of Section 4.4; *(ii)* the potential existence of call centers in our dataset, which may group different calls being active within a time interval into a unique network flow, increasing the correlation between measured samples; *(iii)* the discrete support of the data, as we are considering number of calls instead of bytes transferred; and *(iv)* the way the measurements are obtained. Traditionally, these systems are measured counting the number of calls N present in the system at regular time instants (e.g., $N_0, N_t, N_{2t}, \ldots$). In this section we analyze an alternative to measure call counts, and compare its performance in terms of correlation with the traditional one. More precisely, we define

$$H_a = \{\#\text{calls that have been present in the system during the interval } [a, a+t]\}.$$

4.5.1 Alternative Proposal

To evaluate the performance of this alternative, we compute the correlation between two measurements at different time instants—e.g., H_0 and H_{kt}. To simplify the computations, we will assume in what follows that the arrival process is Poisson with constant arrival rate—i.e., the analysis presented here is of practical application in the timescales where the arrival rate can be deemed invariant, as reported in Section 4.3.2. Consequently, we obtain

$$Corr(H_0, H_{kt}) = \frac{Cov(H_0, H_{kt})}{std(H_0) \cdot std(H_{kt})} = \frac{Cov(H_0, H_{kt})}{Var(H_0)} = \frac{Cov(H_0, H_{kt})}{\mathbb{E}[H_0]}, \tag{4.5}$$

where in the second equality we have used the stationarity assumption, whereas in the last equality we have used the fact that H_0 is a sum of (inde-

pendent) Poisson processes, and consequently, it is Poisson and the variance and the mean are equal. To compute equation (4.5), we split such processes in the following Poisson processes:
$A_a =$ # arrivals up to time a that depart in $[a, a+t]$.
$B_a =$ # arrivals in $[a, a+t]$ that depart in $[a, a+t]$.
$C_a =$ # arrivals in $[a, a+t]$ that are still present at time $a+t$.
$D_a =$ # arrivals up to time a that are still present at time $a+t$.

Therefore, we obtain the following identity:

$$H_a = A_a + B_a + C_a + D_a, \quad \forall a \in \mathbb{R} \tag{4.6}$$

However, for the correlation computation, we can simplify further, as not all the subprocesses are dependent. On one hand, for the first count interval, only those calls that are still present at the end of the interval can still be there in the beginning of the latest count interval. Therefore, we can take only into account such processes (C_0 and D_0) and the result will not vary. On the other hand, for the latest count interval, only those calls that arrived before the beginning of the interval can interact, so we can apply the same reasoning and take only into account such processes (A_{kt} and D_{kt}). Consequently, equation (4.5) can be rewritten as follows:

$$Corr(H_0, H_{kt}) = \frac{Cov(C_0 + D_0, A_{kt} + D_{kt})}{\mathbb{E}[A_0 + B_0 + C_0 + D_0]} \tag{4.7}$$

We could now use the bilinearity property of the covariance function to split the covariance in equation (4.7) and simplify the computation. However, it can be shown that the following two identities hold for all $a \in \mathbb{R}$:

$$C_a + D_a = N_{a+t}, \tag{4.8}$$

$$A_a + D_a = N_a. \tag{4.9}$$

Therefore,

$$Cov(C_0 + D_0, A_{kt} + D_{kt}) = Cov(N_t, N_{kt}) = \rho\mathbb{P}(S_e > (k-1)t), \tag{4.10}$$

where in the last identity we have defined $\rho = \lambda\mathbb{E}[S]$, being S the service time distribution, and S_e its excess lifetime. This last result is well-known from queueing systems theory. It is also true that $B_a + C_a = F_a$ is the number of arrivals in the interval $[a, a+t]$. This can be used to compute the mean of H_a for all $a \in \mathbb{R}$:

$$\mathbb{E}[H_a] = \mathbb{E}[A_a + B_a + C_a + D_a] = \mathbb{E}[N_{a+t} + F_a] = \rho + \lambda t = \rho\Big(1 + \frac{t}{\mathbb{E}[S]}\Big). \quad (4.11)$$

Finally, using equations (4.10) and (4.11), we obtain the result for equation (4.5):

$$Corr(H_0, H_{kt}) = \frac{\rho\mathbb{P}(S_e > (k-1)t)}{\rho(1 + \frac{t}{\mathbb{E}[S]})} = \frac{\mathbb{P}(S_e > (k-1)t)}{1 + \frac{t}{\mathbb{E}[S]}}. \quad (4.12)$$

It is worth noticing that in the previous computations we did not make any assumption regarding the service time distribution, which means that equation (4.12) holds for any kind of service time distribution given that the arrival process is Poisson.

4.5.2 Correlations Study: Dependence on the Service Time Distribution

We now proceed to evaluate the performance of our proposed alternative by comparing the correlation appearing from our proposal versus the correlation of the traditional call count process N_t. We make this comparison assuming three kinds of service time distributions, namely exponential, Pareto and log-normal. To this end, we use the following well-known result from the queuing systems theory:

$$\mathbb{P}(S_e > y) = \frac{1}{\mathbb{E}[S]} \int_y^\infty \mathbb{P}(S > \tau) d\tau. \quad (4.13)$$

Concretely, we want to assess whether $Corr(H_0, H_{kt})$ is smaller than $Corr(N_0, N_{kt})$ in any situation.

Exponential Distribution

In this subsection we assume that the call service time S is exponentially distributed with parameter μ, i.e.,

$$\mathbb{P}(S \leq s) = \Big(1 - e^{-\mu s}\Big) u(x), \tag{4.14}$$

where $u(x)$ is the heaviside step function [AS72].

Consequently, the excess lifetime distribution is as follows:

$$\mathbb{P}(S_e > y) = \frac{1}{\mathbb{E}[S]} \int_y^\infty \mathbb{P}(S > \tau) d\tau = e^{-\mu y}. \tag{4.15}$$

With this result, we obtain the following inequality:

$$\begin{aligned} Corr(H_0, H_{kt}) &< Corr(N_0, N_{kt}) && (4.16)\\ e^{\mu t} &< 1 + \mu t. && (4.17)\\ & && (4.18) \end{aligned}$$

It is easy to verify that the inequality (4.18) is never satisfied—for instance using the series expansion of the exponential. Therefore, there is no situation where the correlations of interval counts are smaller, so the number of calls present in the system measurements is preferred for exponential service times. However, although this distribution was widely accepted to model the service times for the traditional voice service, it has been proved that it is not suitable for VoIP systems—Section 4.2.

Pareto Distribution

In this subsection we assume that the call service time S is Pareto distributed with parameter α, as follows:

$$\mathbb{P}(S \leq s) = [1 - (1 + s)^{-\alpha}] u(s). \tag{4.19}$$

The corresponding excess lifetime distribution is as follows:

$$\mathbb{P}(S_e > y) \;=\; \frac{1}{\mathbb{E}[S]}\int_y^{\infty}\mathbb{P}(S > \tau)d\tau = (1+y)^{1-\alpha}, \tag{4.20}$$

so we obtain:

$$\begin{aligned} Corr(H_0, H_{kt}) &< Corr(N_0, N_{kt}) \\ f(t) = \Big(1 - \frac{t}{1+kt}\Big)^{1-\alpha} &< 1 + (\alpha - 1)t = g(t). \end{aligned} \tag{4.21}$$

To find a sufficient solution for this new inequality, we will use the fact that, if $f(0) \leq g(0)$, then $f(t) \leq g(t)$ if and only if $f'(t) \leq g'(t)\ \forall t > 0$. After applying this reasoning for three times, we obtain the following sufficient condition

$$Corr(H_0, H_{kt}) < Corr(N_0, N_{kt}) \tag{4.22}$$

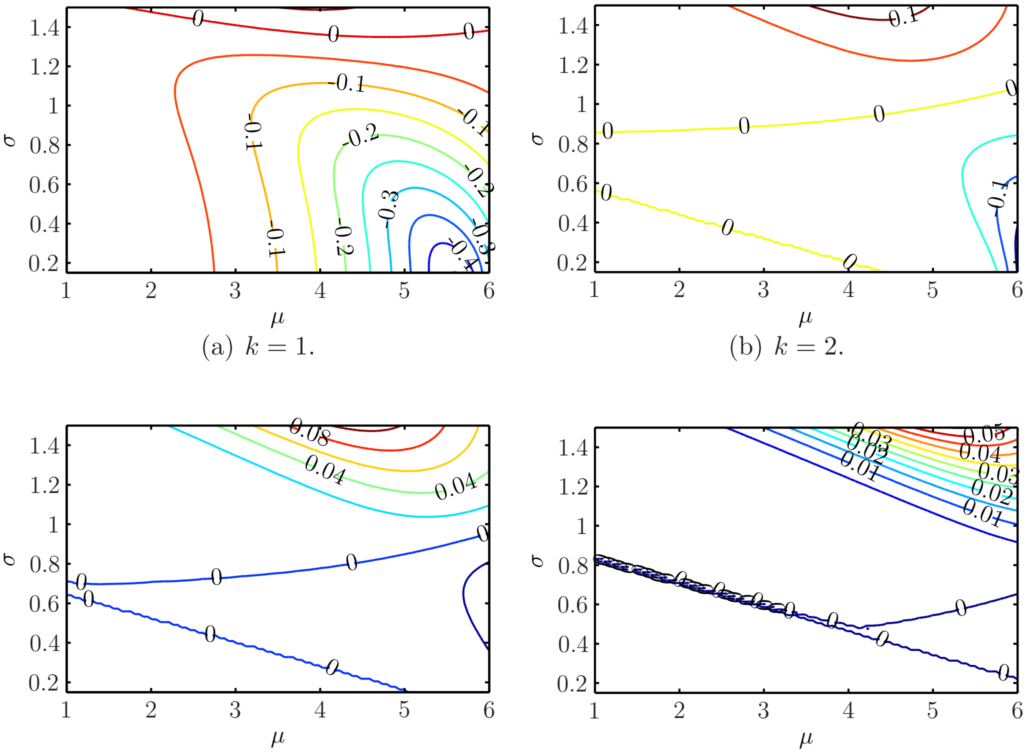
$$k > \frac{\alpha}{2}. \tag{4.23}$$

However, we observed by numerical analysis that the condition is even less restrictive, and there are some cases where $k < \frac{\alpha}{2}$ and the inequality we want to assess still holds for the Pareto distribution.

Log-normal Distribution

In this subsection we present the comparison of the correlations when the service time distribution is assumed to be log-normal. Owing to its analytical intractability, we will not present an analytical study of this case analogous to the ones presented before. In contrast, we use a numerical approach to study this distribution, because it is, in addition to the Pareto distribution, the most common distribution used in practice for modeling CHT of VoIP systems—Section 4.2.

We have used numerical integration to obtain the excess lifetime probability for different values of the log-normal parameters μ and σ at different time lags k. We use this results to compute surface plots of the differences in the correlations using the two measurement alternatives, concretely $Corr(N_0, N_t) - Corr(H_0, H_t)$. Such surface plots are presented in Figure 4.7 for the most representative values of k.



(a) $k = 1$.

(b) $k = 2$.

(c) $k = 3$.

(d) $k = 10$.

Figure 4.7: Contour plots showing the isopleths of comparing the correlations computed using both measurement alternatives ($Corr(N_0, N_t) - Corr(H_0, H_t)$) when the service time distribution is assumed to be log-normal. Different values of the time lag k are reported in the figures.

As we can see in Figure 4.7, there is a clear benefit when using the traditional approach for large values of μ but small of σ at the first lags—k=1 in Figure 4.7(a) and $k = 2$ in Figure 4.7(b). Concretely, for $k = 1$ the performance of both alternatives is almost the same, being the difference nearly zero for all the pairs (μ, σ) except the ones mentioned above. However, as we move to larger lags, the situation improves for the proposed alternative.

In Figure 4.7(b) it can be observed a region at which the proposed alternative clearly outperforms the classical alternative—for medium values of μ and large values of σ. In addition, there is no region where the performance of the traditional alternative improves—a region at which the difference is more negative. In contrast, the differences in the region at which the traditional alternative outperforms the proposed one for $k = 1$ are smaller as larger values of k are taken into account. Concretely, for $k = 3$ (Figure 4.7(c)) such differences are almost negligible. On the contrary, the region where the proposed alternative outperforms the traditional is wider, although the differences have decreased—this is because the correlations decrease with larger lags. Finally, in Figure 4.7(d) we can see that the proposed alternative still outperforms the traditional one for $k = 10$, but now in a narrowed region—at which, in fact, the differences are decreasing. In contrast, the region where there is no difference between the alternatives has got larger, because now there are more pairs (μ, σ) at which both correlations are equal to zero.

All in all, we can see from Figure 4.7 that there is an overall benefit from switching from the traditional alternative to the proposed one. This is not only because there is a larger region at which the proposed alternative outperforms the traditional one, but also because such difference in performance is not negligible, and will turn out in smaller correlations, as desired. However, we can see that there exist some regions where the traditional alternative would be preferable, although for the cases analyzed these regions are smaller than the regions at which the alternative proposal is better.

Numerical Correlation Study

Up to now, we have show that the proposed alternative methodology for measuring call counts may outperform the traditional one in terms of correlations, depending on the distribution that models the call holding time distribution. This means that there are some cases where $Corr(H_t, H_{kt})$ is smaller than $Corr(N_t, N_{kt})$. Consequently, one should analyze the service time distribution in depth before deciding which kind of measurements capture from the network.

In this subsection, we provide a in-depth comparison of both measurement alternatives, assuming as CHT distributions the best fitting models obtained in Section 4.3.3. Concretely, we will restrict ourselves to the simple log-normal fit and the mixture with two log-normal and one Pareto components. In Figure 4.8 we show the results for both models. The figure shows that assuming these call holding time distributions, the proposed measurement alternative outperforms the traditional one at every time lag. The difference between both correlations reach its maximum at the first lags, which is the timescale of interest for the purposes of the methods presented in this paper. Consequently, we have found practical evidence using actual network measurements that the proposed measurement alternative would enhance models performance in terms of yielding lower correlations.

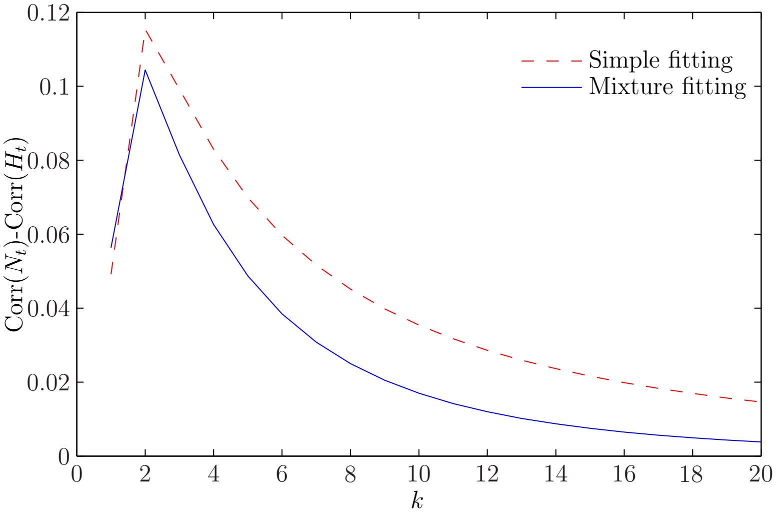


Figure 4.8: Correlation comparison of both measurement alternatives assuming the call holding time is distributed accordingly to the two best fitting models as presented in Section 4.3.3.

4.6 Anomaly Detection Algorithm

In this section we present an on-line *outlier-friendly* algorithm to detect deviations from the model in the residuals. Basically, the algorithm computes the likeliness of observing a sample deviating more than s_{lower} times σ, the standard deviation of the residuals, expressed in terms of the number m of samples one would have to generate from the hypothesized distribution (standard normal in our case) in order to observe such a deviating sample. Then the algorithm looks back to the m samples previous to the sample under test, and decides whether the test sample is an outlier or an anomaly depending on the number of observed samples within that interval that deviates as much as the sample under test. That is the reason because we call our algorithm outlier-friendly. Instead of fixing a confidence band, our algorithm takes into account that although samples outside the confidence band are strange, there is high likeliness of having them in small frequency for large datasets. Consequently, if the algorithm has not observed samples outside the confidence band for a *large enough* history interval, the next sample outside the confidence band will be regarded as an outlier, and no alert will be generated. In our case, the length of the history interval is determined by the likeliness of observing such a deviating sample. A more detailed description of the algorithm is presented in Section 4.6.1. Finally, Section 4.6.2 presents the results of applying the algorithm to the summarized dataset of Section 4.3.

4.6.1 Description of the Algorithm

The on-line *outlier-friendly* algorithm that we propose aims at detecting residuals deviating more than s_{lower} times σ, the standard deviation of the residuals, but taking into account the possibility of a sample being an outlier as a consequence of being isolated—i.e., it is the only sample outside the confidence band given by s_{lower} within a *reasonable* interval. The length of the interval m is determined as a function of the likeliness of observing such a deviating sample, and it is only considered backwards, as we cannot anticipate the future when applying our algorithm on-line. However, if we could consider future samples as well, chances are that there is an interval of length m containing the sample under test as the only sample outside the confidence band, although within the $m-1$ previous samples to the sample under test (our available history when applying the algorithm on-line) there is at least one outside the confidence band. For this reason, we set the algorithm to only inspect a fraction q of the interval m backwards, and give a free interval of length $(1 - q) \cdot m$ in the future direction to compensate for the unavailability of such data.

In addition, we mark all the samples deviating more than s_{upper} times σ automatically as anomalous. This upper threshold is set in order to determine the maximum amount of history samples the algorithm has to store. The likeliness l of a sample under test t is $l(t) = 2\phi(-|t|)$, where the factor 2 comes from the two tailed nature of the normal distribution and ϕ denotes the standard normal Cumulative Distribution Function (CDF). The length of the backward history interval m is computed as the inverse of this likeliness, as shown in equation (4.24).

$$m(t) = round\Big(\frac{1}{2\phi(-|t|)}\Big), \tag{4.24}$$

where we have rounded the result to the nearest integer in order to consider only integer-length intervals. With this relation, the thresholds s_{lower} and s_{upper} translate into intervals of length m_{min} and m_{max}, respectively.

With these parameters set, the algorithm proceeds as follows:

1. Draw the next sample under test t and compute the length of the interval $m(t)$ using (4.24) and proceed to step 2.

2. If $m(t) \geq m_{max}$, place an alert and proceed to step 1, else, proceed to step 3.

3. If $m(t) < m_{min}$, the sample is normal: do not place an alert and proceed to step 1. Else, proceed to step 4.

4. Inspect the $q \cdot m(t)$ samples previous to t. If there is at least one sample r such that $|r| \geq |t|$ within such interval, then place and alert. On the contrary, the sample is not anomalous, it is just an outlier, and no alert is placed. In any case, proceed back to step 1.

Table 4.3: Parameters of the on-line algorithm for detecting anomalies in the residuals.

Parameter	Value
s_{lower}	3
s_{upper}	4
q	0.75
m_{min}	370
m_{max}	15,787

4.6.2 Anomaly Detection in VoIP Data

In this section we present the results of applying our algorithm described in the previous section to the summarized dataset of Section 4.3. The parameters used in the application of the algorithm are presented in Table 4.3.

We present the results of the application of the algorithm for two different weeks of the dataset in Figure 4.9. We have selected these weeks as considering them representative of the performance of the algorithm. Figure 4.9(a) is the same week presented in the figures of Section 4.4.2, whereas Figure 4.9(b) shows the next week in the dataset, at which one sample was regarded as an outlier instead of an anomaly despite of being outside the confidence band given by s_{lower}. In the figures, the residuals are plotted using a solid green line, whereas the confidence bands given by s_{lower} are plotted using horizontal dashed blue lines. Samples flagged as anomalous by the algorithm are plotted using black asterisks ($*$) symbols, whereas samples outside the confidence band but not flagged as anomalous (outliers) are plotted using red asterisks symbols. There is one of such ouliers on Tuesday of Figure 4.9(b). Such sample is labeled as an outlier instead of an anomaly because it is the only sample outside the confidence band given by s_{lower} since the beginning of the week, and its deviation is not very large.

As can be seen in the figures, the anomalies are not mainly related to day changes as a consequence of the night removal, however, there is a large amount of them in such instants—this is better observed in figures 4.10 and 4.11 that will be described later. A more conservative (*larger*) night period could be considered in order to remove some of the alerts generated in day

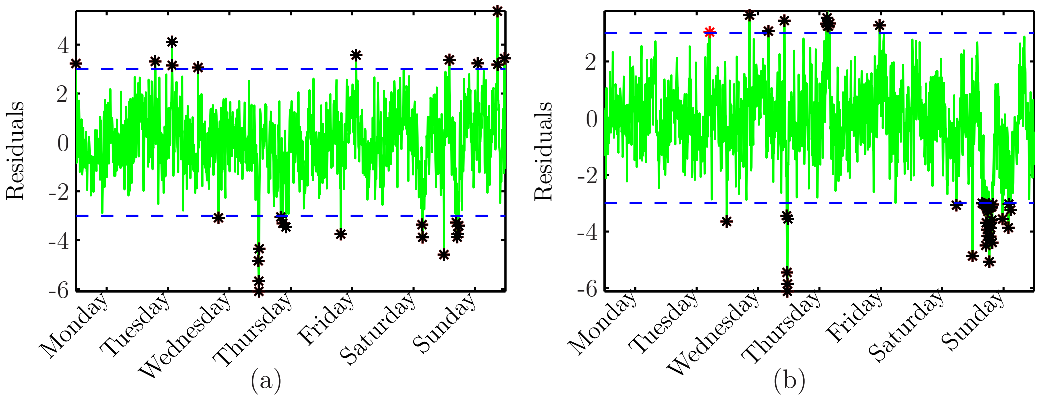


Figure 4.9: Results of applying the anomaly detection algorithm to the residuals obtained from the model presented in Section 4.4 (the ticks refer to the middle of each day): (a) all the samples outside the 3σ confidence band are reported as anomalies; (b) one sample outside the 3σ confidence band is not reported as anomalous.

changes.

It may also be observed that some of the anomalies from one week are still present in the next one—remember that 4.9(b) is next in time to 4.9(a). This fact can be observed on the anomalies between Wednesday and Thursday and some of the ones on Sunday. On the contrary, another anomalies are only present in just one week, such as those on Monday and Tuesday. The reason for this is related with the *unlikeliness* of the anomaly and the way the average pattern is computed. Larger anomalies (i.e., anomalies that deviate the most) take a larger impact on the average pattern as its effect is proportional to the distance to the pattern, whereas smaller anomalies are absorbed by the averaging process when computing the average pattern. Consequently, larger anomalies modify the pattern, and affect the average patterns where them are included, causing to wrongly flag as anomalous samples that are indeed following the normal pattern—i.e., false positives. In addition, they may hinder the detection of another anomalies that *hide* behind the deviated pattern, thus provoking false negatives.

The solution to this would be to take into account the size of the anomalies detected when computing the pattern, removing those whose deviation is *large* from the pattern computation. As a side-effect of this measure, the model would not be able to cope with abrupt changes in the pattern, as those are filtered out as a consequence of the anomalies they entail. To reduce this side-effect, the model would have to decide to either compute the pattern from the previous samples at which the anomalies are filtered out (in the case the density of the anomalies is low in the previous weeks), or instead forget what used to be *normal* and use the samples flagged as anomalous, because it now considers that the pattern has changed abruptly, maybe as a consequence of a shift in users' behavior—such as those changes inspected in Chapter 3. We would like to note that this consideration could be taken sample by sample (i.e., for each of the 2016 samples within a week, 1512 if nights are removed) instead of for whole weeks, which may make the pattern estimation and anomaly detection more robust to changes in the pattern.

We observe a large density of anomalies on Sunday of Figure 4.9(b). This is not directly related to the anomalies on the same period in the previous week, as those anomalies are more isolated. On the contrary, we think such high density of anomalies may evidence a shortage (given that the actual week is below the pattern) or a shift in users' behavior, but given the anomalies in the previous week in the same period we believe the shift in users' behavior is more likely.

Finally, although Figure 4.9 is useful for analyzing the performance of our algorithm, in order to present the results to the network manager, plots of the actual measurements are more practical. We can use our model to detect anomalies without computing the residuals, but translating the confidence bands in the residuals to confidence bands for the actual measurements. These are just plots at distances $\pm s_{lower} \cdot \sigma$ from the average pattern, where σ, as shown in Section 4.4.1, is approximated with the square root of the pattern. Examples of these plots are shown in Figure 4.10 and Figure 4.11 for the two weeks of Figure 4.9.

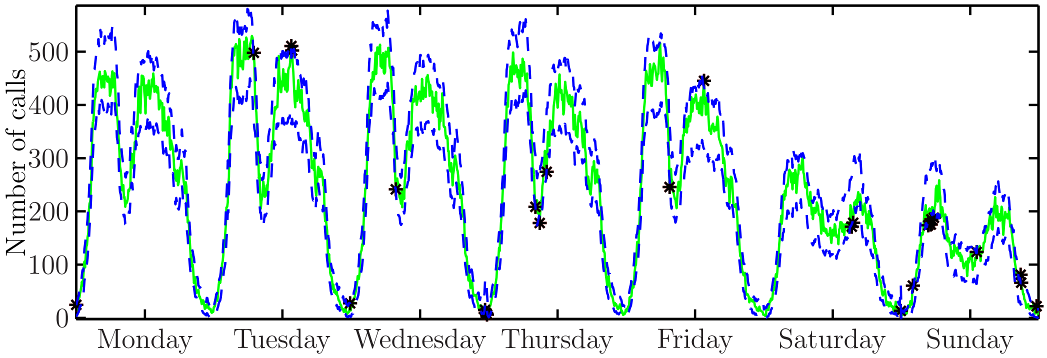


Figure 4.10: Actual measurements of Figure 4.9(a) with confidence bands.

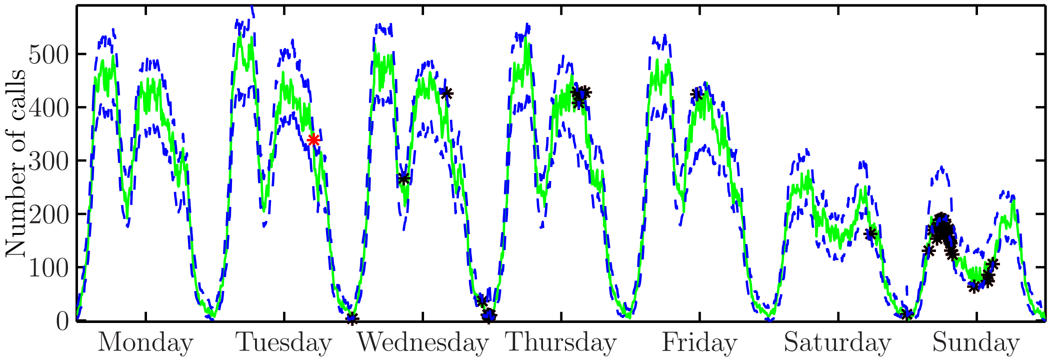


Figure 4.11: Actual measurements of Figure 4.9(b) with confidence bands.

4.7 Summary and Conclusions

In this chapter, we have presented a model to detect short-term volume anomalies (i.e., anomalies that have an impact in short time periods of aggregate data) of VoIP measurements. The model uses an estimation of the average weekly pattern to compute residuals from the model fitting that are distributed as a standard normal distribution. Anomalies are detected taken into account the likeliness of a high deviating residual and the amount of residuals with such high deviation in the previous samples. Such model is able to detect both shortages and overload periods, as well as shifts in users' behavior. However, a considerable amount of false positives/negatives comes as a result of not feeding the average weekly pattern estimation with the discovered anomalies—i.e, anomalies are not filtered out when detected, and are used also to estimate the patterns. We believe that this may be one of the reasons for having very large correlations in the residuals, in addition to the ones mentioned throughout the chapter. To reduce the correlations in the residuals, we proposed an alternative measurement technique to monitor Poisson-nature arrival processes, such as the process of calls arriving at a VoIP system. Such alternative yields smaller correlations in the case the service times of the calls in the system are heavy-tailed distributed, which is the case for the analyzed dataset and other studies presented in the literature. Finally, the future work we envisage comprises the inclusion of feedback from the anomaly detector module into the pattern estimation one, in order to filter anomalies and improve the robustness of the pattern estimation to enhance the proposed system.

Chapter 5

Conclusions

This chapter is devoted to summarize the main results of this Ph.D. thesis (Section 5.1) and outline the envisaged directions for future work and new research lines for continuing the contributions presented in this document (Section 5.2).

5.1 Main Contributions

This thesis addressed the analysis of Internet link's Quality of Service (QoS) leveraging on minimal information measurements. Specifically, the source of network information was count processes of network data or call counts, which contain coarse-grained summarized statistics of the network status. To achieve this objective, two contributions enshrined in the anomaly detection context were proposed that accomplished the goal at different timescales: detection of sustained load changes that provide useful information for capacity planning and detection of mid-term pattern deviations that provide useful information for abnormal behavior detection and troubleshooting. The main conclusions from these contributions are presented at the end of their respective chapters in this thesis. However, we outline them in the following list.

1. **Sustained load changes are detectable in large-scale networks with statistical foundation by leveraging on coarse grained**

network link measurements: Chapter 3 demonstrated that using an appropriate model for byte count measurements of router links it is possible to apply sound statistical methodologies for the detection of sustained load changes with statistical foundation. These changes may be related with shifts in users' behavior or may come as a result of traffic engineering decisions that modify the network topology or routing architecture. Consequently, the detection of this kind of load changes is useful for network capacity management and planning. Furthermore, the usage of the proposed methodology significantly reduces the dedication of network managers to network measurement time series inspection which, as it turns out, entails a large reduction of the Network Operators and Service Providers (NOSP) Operational Expenditures (OPEX), thus increasing the providers' revenue. Other contributions of this chapter are summarized in the following bullet list:

- A multivariate fairly-Gaussian distribution is able to model the day-night traffic pattern of sufficiently large aggregated measurements using 16 components each representing 90-minutes disjoint intervals (Section 3.3).
- An automated algorithm is able to work with the proposed model in a on-line fashion to detect potential change points on coarse grained measurements and assess their statistical significance (Section 3.4).
- Change points are independent for a fixed network link, but the change points in the incoming and outgoing directions of a given network link are highly correlated (Section 3.5).
- Leveraging on the proposed model and detection algorithm, we contributed with a visualization framework for the relevant discovered events using a network weather map (Section 3.6).

Finally, the contributions in this chapter have led to the following publications (presented in chronological order):

- F. Mata, J. Aracil, and J. L. García-Dorado, "Automated Detection of Load Changes in Large-Scale Networks," in *Proceedings of International Workshop on Traffic Monitoring and Analysis,* Aachen (Germany), May 2009, pp. 34–41.

- F. Mata and J. Aracil, "Performance evaluation of an Online Load Change Detection Algorithm," in *Proceedings of International Conference on Computer and Automation Engineering, vol. 1,* Singapore (Republic of Singapore), February 2010, pp. 261–266.

- F. Mata, J. L. García-Dorado and J. Aracil, "On the Suitability of Multivariate Normal Models for Statistical Inference Based on Traffic Measurements," in *Passive and Active Measurement conference,* Zurich (Switzerland), April 2010, Poster Session.

- F. Mata, J. L. García-Dorado, and J. Aracil, "Multivariate Fairly Normal Traffic Model for Aggregate Load in Large-Scale Data Networks," in *Proceedings of Wired/Wireless Internet Communications,* Luleå (Sweden), June 2010, pp. 278–289.

- F. Mata, J. L. García-Dorado, and J. Aracil, "Caracterización temporal de las demandas de ancho de banda en enlaces con alta agregación mediante un modelo normal multivariante," in *Actas de las IX Jornadas de Ingeniería Telemática,* Valladolid (Spain), October 2010.

- F. Mata, J. L. García-Dorado, and J. Aracil, "Detection of traffic changes in large-scale backbone networks: The case of the Spanish academic network," *Computer Networks*, **56** (2) (2012), pp. 686–702.

2. **Mid-term volume-based anomalies are detectable using prediction in time series with trends leveraging on history data:** Chapter 4 demonstrated that it is possible to remove the inherent trend existing in time series data of Voice over IP (VoIP) service measurements leveraging on history data and apply statistical inference to

detect volume-based anomalies that may be related with shortage or overload periods. This kind of anomalies reduce the QoS of the service drastically, so timely detection of such anomalies is of paramount importance for NOSP, as it prevents the degradation of the customers' perception of the service, thus fostering its usage. Other contributions of this chapter are summarized in the following bullet list:

- The call arrival process in a VoIP service may be modeled using a time-inhomogeneous Poisson process (Section 4.3.2).
- The call holding time distribution in a VoIP service is no longer appropriately modeled by exponential distributions, and more accurate models are provided by mixtures of heavy-tailed distributions (Section 4.3.3).
- The Poissonian nature of the call arrival process allows removing the inherent trend of VoIP call count measurements yielding standard normal residuals (Section 4.4).
- Given the distributions of the call arrival process and Call Holding Times (CHT), measuring the number of calls that have been present in the system during uniformly spaced time intervals generates lower correlated processes than measuring the number of calls present in the system at the end of the uniformly spaced time intervals (Section 4.5).
- Leveraging on the proposed trend removal methodology, we contributed with a *outlier-friendly* anomaly detection algorithm that removes outliers from the residuals before signaling large-deviating samples as anomalous (Section 4.6).

Finally, the contributions in this chapter have led to the following publication:

- F. Mata, P. Żuraniewski, M. Mandjes and M. Mellia, "Anomaly Detection in VoIP Traffic with Trends," accepted for its publication in *Proceedings of 24th International Teletraffic Congress,* Krakow (Poland), September 2012.

In addition to these contributions, we also presented a comprehensive survey of Anomaly-based Intrusion Detection (AID) systems. The survey focused on the period 2000-2012. During this period, numerous studies presented research in new ways of discovering abnormal events using network or host data. We believe this is the more comprehensive survey on AID systems to date. We have presented in addition a survey of the proposed taxonomies to classify the existing AID techniques, and proposed a new one embracing them (Section 2.2.2). The taxonomy allowed us to present the main techniques applied in AID in an structured manner (Section 2.2.3).

Furthermore, we analyzed the main problems affecting the AID paradigm (Section 2.2.4), and which future trends should be addressed in order to solve them (Section 2.2.5). We hope that this work can serve as a useful guide through the maze of the literature, enabling the understanding of the different approaches to allow new practitioners focusing on the AID techniques that are prone to provide higher performance given their specific requirements.

5.2 Future Work

The results presented in this thesis open new research lines for future work in QoS analysis with minimal information. In what follows, we suggest some future research topics in this field:

- **Load variance change detection:** In this thesis we focused on the detection of changes in the load mean. Detecting changes in the load mean is useful for capacity management and planning, as a consequence of the naive rule of thumb typically used to over-provision current network links—this rule of thumb set the required link capacity to the mean value of the load plus some guard band to prevent overload periods. Consequently, a change in the mean load may require the upgrade of a link's capacity following this rule of thumb. However, if smarter dimensioning rules are used (e.g., [PNvdMM09, vdMMP07]), changes in the load variance may also trigger the upgrade of a link's capacity, as these smarter dimensioning rules set the required link capacity to the mean value plus some standard deviations, in addition to the guard band.

- **Include feedback from the anomaly detector in the pattern estimation and residual computation to enhance robustness:** As was mentioned in Chapter 4, the proposed methodology to remove the trend was not informed of the anomalies detected by the anomaly detection algorithm. This lack of feedback has the consequence of using abnormal values to estimate the pattern, which may provoke the classification of normal instances as anomalous, in addition to allow some anomalies to hide within the wrongly estimated pattern. Consequently, a correct management of the detected anomalies may enhance the robustness of the proposed methodology and, moreover, it may allow the detection of pattern shifts if large densities of anomalies are observed in the recent history.

- **Test new regression models for VoIP call count data:** In our contribution in Chapter 4, we restricted ourselves to an unsophisticated methodology to remove the trend from the measurements, with the objective of having high results interpretation and low system complexity to enable its on-line deployment. However, other regression models may be used to accomplish similar objectives, and the performance of the different solutions may be compared. Specifically, given the Poissonian nature of the call arrival process, Poisson regression seems to be a very promising alternative to the proposed trend removal methodology.

- **Trend removal of multi-service measurements:** The proposed trend removal methodology presented in Chapter 4 is tailored to call count data of VoIP services. This trend removal methodology exploits the properties of the Poissonian nature of the call count process, which is not typically observed in multi-service measurements. Therefore, new trend removal methodologies must be designed in order to obtain satisfactory results when removing the trend from multi-service traffic measurements.

Conclusiones

Este capítulo está dedicado a resumir los principales resultados de esta tesis y a dar una visión general de las direcciones previstas para el trabajo futuro para continuar con las contribuciones presentadas en este documento.

Contribuciones Principales

Esta tesis trata el análisis de Calidad de Experiencia (QoS, de sus siglas en inglés) de enlaces de Internet utilizando medidas de red con información mínima. Concretamente, la fuente de información de red fueron procesos de conteo de datos de red o conteo de llamadas, que contienen estadísticos resumidos con baja granularidad del estado de la red. Para alcanzar este objetivo, se han propuesto dos contribuciones enmarcadas en el contexto de detección de anomalías, las cuales alcanzan el objetivo propuesto a diferentes escalas de tiempo: detección de cambios sostenidos en la carga que provee información útil para el dimensionado de la red y la detección de desviaciones sobre el patrón a media escala que suministra información útil para la detección y solución de comportamientos anómalos. Las principales conclusiones de estas contribuciones se han presentado al final de sus respectivos capítulos, sin embargo, son resumidas en la siguiente lista.

1. **Cambios sostenidos en la carga son detectables con base estadística en redes con numerosos enlaces mediante el uso de medidas de enlaces de red con baja granularidad:** El Capítulo 3 demostró que usando un modelo apropiado para medidas de conteo de bytes de enlaces de routers es posible aplicar técnicas estadísticas

fiables para la detección con base estadística de cambios sostenidos en la carga. Estos cambios pueden estar relacionados con cambios en el comportamiento de los usuarios o pueden ser resultado de decisiones de ingeniería de tráfico que modifican la topología de red o la arquitectura de enrutado. Consecuentemente, la detección de este tipo de cambios en la carga es útil para la gestión y el dimensionado de redes. Además, el uso de la metodología propuesta reduce significativamente la dedicación que los gestores de red han de dedicar a la inspección de series temporales del tráfico, lo que conlleva una gran reducción de los Gastos Operativos (OPEX, de sus siglas en inglés) de los Proveedores de Servicios y Operadores de Red (NOSP, de sus siglas en inglés), y por tanto incrementa sus ingresos. Otras contribuciones de este capítulo se resumen en la siguiente lista de viñetas:

- Una distribución multivariante prácticamente Gaussiana es capaz de modelar el patrón de tráfico día-noche de medidas de red suficientemente agregadas usando 16 componentes, cada una representando intervalos disjuntos de 90 minutos de duración (Sección 3.3).
- Un algoritmo automático es capaz de trabajar con el modelo propuesto en tiempo real para detectar puntos de cambio potenciales en medidas de red con baja granularidad y verificar su significancia estadística (Sección 3.4).
- Los puntos de cambio son independientes entre sí para un enlace de red fijo, pero los puntos de cambio en los sentidos ascendente y descendente de un enlace de red dado están altamente correlados (Sección 3.5).
- Usando el modelo y algoritmo de detección propuestos, hemos contribuido con un marco de visualización para los eventos relevantes descubiertos usando un mapa del tiempo de la red (Sección 3.6).

Finalmente, las contribuciones de este capítulo han dado lugar a las siguientes publicaciones (presentadas en orden cronológico):

- F. Mata, J. Aracil, and J. L. García-Dorado, "Automated Detection of Load Changes in Large-Scale Networks," in *Proceedings of International Workshop on Traffic Monitoring and Analysis,* Aachen (Germany), May 2009, pp. 34–41.
- F. Mata and J. Aracil, "Performance evaluation of an Online Load Change Detection Algorithm," in *Proceedings of International Conference on Computer and Automation Engineering, vol. 1,* Singapore (Republic of Singapore), February 2010, pp. 261–266.
- F. Mata, J. L. García-Dorado and J. Aracil, "On the Suitability of Multivariate Normal Models for Statistical Inference Based on Traffic Measurements," in *Passive and Active Measurement conference,* Zurich (Switzerland), April 2010, Poster Session.
- F. Mata, J. L. García-Dorado, and J. Aracil, "Multivariate Fairly Normal Traffic Model for Aggregate Load in Large-Scale Data Networks," in *Proceedings of Wired/Wireless Internet Communications,* Luleå (Sweden), June 2010, pp. 278–289.
- F. Mata, J. L. García-Dorado, and J. Aracil, "Caracterización temporal de las demandas de ancho de banda en enlaces con alta agregación mediante un modelo normal multivariante," in *Actas de las IX Jornadas de Ingeniería Telemática,* Valladolid (Spain), October 2010.
- F. Mata, J. L. García-Dorado, and J. Aracil, "Detection of traffic changes in large-scale backbone networks: The case of the Spanish academic network," *Computer Networks*, **56** (2) (2012), pp. 686–702.

2. **Anomalías a media escala basadas en volumen son detectables usando predicción en series temporales con tendencias basándose en datos históricos:** El Capítulo 4 demostró que es posible eliminar la tendencia inherente que existe en series temporales de datos

del servicio de voz sobre IP (VoIP, de sus siglas en inglés) basándose en datos históricos y aplicando inferencia estadística para detectar anomalías basadas en volumen, que pueden estar relacionadas con periodos con cortes o sobrecargas de tráfico. Este tipo de anomalías reduce la QoS drásticamente, por lo que la detección oportuna de estas anomalías es de primordial importancia para los NOSP, ya que previene la degradación de la imagen que los clientes tienen del servicio, fomentando así su uso. Otras contribuciones de este capítulo se resumen en la siguiente lista de viñetas:

- El proceso de llegadas en el servicio de VoIP puede ser modelado usando un proceso de Poisson de tasa no homogénea (Sección 4.3.2).
- La distribución del tiempo de servicio en el servicio de VoIP ya no es correctamente modelada con distribuciones exponenciales. Modelos más precisos se obtienen mediante combinaciones de distribuciones con cola pesada (Sección 4.3.3).
- La naturaleza Poissoniana del proceso de llegadas de llamadas permite eliminar la tendencia inherente en medidas de conteo de llamadas de VoIP, dando lugar a residuos con distribución normal estándar (Sección 4.4).
- Dadas las distribuciones del proceso de llegadas de llamadas y del tiempo de servicio, medir el número de llamadas que han estado presentes en el sistema durante intervalos de tiempo equiespaciados genera procesos menos correlados que medir el número de llamadas presentes en el sistema al final de dichos intervalos de tiempo (Sección 4.5).
- Utilizando la metodología propuesta para eliminación de tendencias, hemos contribuido con un algoritmo de detección de anomalías que elimina los valores atípicos de los residuos antes de señalizar muestras con grandes desviaciones como anómalas (Sección 4.6).

Finalmente, las contribuciones de este capítulo han dado lugar a la siguiente publicación:

- F. Mata, P. Żuraniewski, M. Mandjes and M. Mellia, “Anomaly Detection in VoIP Traffic with Trends,” aceptado para su publicación en *Proceedings of 24th International Teletraffic Congress,* Krakow (Poland), September 2012.

Además de estas contribuciones, también hemos presentado una exhaustiva revisión de sistemas de detección de anomalías. Esta revisión se centró en el periodo 2000-2012. Durante este periodo, numerosos estudios presentaron investigación sobre nuevas maneras de descubrir eventos anormales usando datos de red o de equipos. Creemos que esta es la revisión más exhaustiva sobre sistemas de detección de anomalías presentada hasta la fecha. Además, hemos presentado una revisión de las taxonomías propuestas para clasificar las técnicas existentes de detección de anomalías, y propusimos una nueva que embarca a las anteriores (Sección 2.2.2). Esta taxonomía nos permitió presentar las principales técnicas aplicadas en detección de anomalías de manera estructurada (Sección 2.2.3).

Además, hemos analizado los principales problemas que afectan el paradigma de detección de anomalías (Sección 2.2.4), y qué tendencias futuras se deben tratar para resolverlas (Sección 2.2.5). Esperamos que este trabajo pueda servir como una guía útil a través de la vasta literatura, posibilitando la comprensión de los diferentes enfoques para permitir a los nuevos profesionales centrarse en las técnicas de detección de anomalías que son propensas a obtener mayores rendimientos dados unos requerimientos específicos.

Trabajo Futuro

Los resultados presentados en esta tesis abren nuevas líneas de investigación para trabajo futuro en el análisis de QoS usando información mínima. En lo que sigue, sugerimos algunos temas de investigación futura en este área:

- **Detección de cambios en la varianza de la carga:** En esta tesis nos hemos centrado en la detección de cambios en la media de la carga. Detectar estos cambios es útil para el dimensionado de redes, como consecuencia de las reglas simples utilizadas para sobredimensionar los enlaces de red actuales (estas reglas simples establecen el ancho de banda requerido por un enlace al valor medio de la carga más un extra como banda de guarda para evitar periodos de sobrecarga). Por consecuencia, un cambio en la carga media puede requerir la actualización de la capacidad de un enlace siguiendo estas reglas. Sin embargo, si reglas de dimensionado más inteligentes son utilizadas (por ejemplo [PNvdMM09, vdMMP07]), los cambios en la varianza de la carga pueden también provocar la actualización de un enlace, ya que estas reglas de dimensionado más inteligentes establecen el ancho de banda requerido por un enlace al valor medio de la carga más varias desviaciones estándar, además de la banda de guarda.

- **Incluir retroalimentación desde el detector de anomalías al estimador de patrones y computador de residuos para incrementar la robustez del sistema:** Como fue mencionado en el Capítulo 4, la metodología propuesta para eliminar la tendencia no tenía en cuenta las anomalías detectadas por el algoritmo de detección de anomalías a la hora de calcular el patrón medio. La falta de esta retroalimentación tiene como consecuencia el uso de valores anormales a la hora de estimar el patrón, lo que puede provocar la clasificación errónea de instancias normales como anómalas, y además puede permitir a algunas anomalías esconderse detrás del patrón mal estimado. Por consecuencia, una correcta gestión de las anomalías detectadas puede mejorar la robustez de la metodología propuesta y, además, puede permitir la detección de variaciones en el patrón si una gran densidad de anomalías se observan entre las muestras recientes.

- **Probar nuevos modelos de regresión para datos de VoIP:** En nuestra contribución en el Capítulo 4, nos restringimos a una metodología simple para eliminar la tendencia de las medidas con el objetivo de tener una mayor interpretación de los resultados y menor complejidad en el sistema para posibilitar su funcionamiento en tiempo real. Sin embargo, otros modelos de regresión pueden ser usados para conseguir objetivos similares y el rendimiento de las diferentes soluciones puede compararse. Concretamente, dada la naturaleza Poissoniana del proceso de llegadas de llamadas, la regresión de Poisson parece ser una alternativa prometedora para la metodología de eliminación de tendencias propuesta.

- **Eliminación de tendencias en medidas multi-servicio:** La metodología para eliminar tendencias propuesta en el Capítulo 4 está específicamente diseñada para datos de conteo de llamadas de servicios de VoIP. Esta metodología explota las propiedades Poissonianas del proceso de llegada de llamadas al sistema, que no se dan en medidas de otro tipo de servicios. Por tanto, nuevas metodologías de eliminación han de ser diseñadas para obtener resultados satisfactorios cuando se elimina la tendencia de medidas de tráfico multi-servicio.

References

[ABC$^+$03] U. Aickelin, P. Bentley, S. Cayzer, J. Kim, and J. McLeod, *Danger theory: The link between AIS and IDS?*, Artificial Immune Systems (2003), 147–155. 30

[ABE04] N.B. Amor, S. Benferhat, and Z. Elouedi, *Naive bayes vs decision trees in intrusion detection systems*, Proceedings of 2004 ACM symposium on Applied computing, ACM, 2004, pp. 420–424. 52, 56

[ACL07] T. Ahmed, M. Coates, and A. Lakhina, *Multivariate online anomaly detection using kernel recursive least squares*, Proceedings of 26th IEEE International Conference on Computer Communications, IEEE, 2007, pp. 625–633. 74

[ACP09] G. Androulidakis, V. Chatzigiannakis, and S. Papavassiliou, *Network anomaly detection and classification via opportunistic sampling*, IEEE Network. **23** (2009), no. 1, 6–12. 3, 43, 87, 88

[ADL04] A.N. Avramidis, A. Deslauriers, and P. L'Ecuyer, *Modeling daily arrivals to a telephone call center*, Manage. Sci. (2004), 896–908. 136

[ADWCL07] J.M. Agosta, C. Diuk-Wasser, J. Chandrashekar, and C. Livadas, *An adaptive anomaly detector for worm detection*, Proceedings of 2nd USENIX workshop on Tackling computer systems problems with machine learning techniques, USENIX Association, 2007, pp. 3–9. 79, 84

[AG60] F.J. Anscombe and I. Guttman, *Rejection of outliers*, Technometrics (1960), 123–147. 66

[AGMV07] A. Abraham, C. Grosan, and C. Martin-Vide, *Evolutionary design of intrusion detection programs*, Int. J. Netw. Secur. **4** (2007), no. 3, 328–339. 34

[AH08] H.J. Ader and DJ Hand, *Advising on research methods: a consultant's companion*, Johannes van Kessel Publ., 2008. 103

[AHA06] M.S. Abadeh, J. Habibi, and S. Aliari, *Using a particle swarm optimization approach for evolutionary fuzzy rule learning: a case study of intrusion detection*, Proceedings of Information Processing and Management of Uncertainty in Knowledge Based Systems, 2006, pp. 2–7. 41

[AHL07] M.S. Abadeh, J. Habibi, and C. Lucas, *Intrusion detection using a fuzzy genetics-based learning algorithm*, J. Netw. Comput. Appl. **30** (2007), no. 1, 414–428. 33, 37

[AJS06] M. Amini, R. Jalili, and H.R. Shahriari, *Rt-unnid: A practical solution to real-time network-based intrusion detection using unsupervised neural networks*, Comput. Secur. **25** (2006), no. 6, 459–468. 49, 63

[AJTH07] A. Abraham, R. Jain, J. Thomas, and S.Y. Han, *D-scids: Distributed soft computing intrusion detection system*, J. Netw. Comput. Appl. **30** (2007), no. 1, 81–98. 37

[Ald97] J. Aldrich, *Ra fisher and the making of maximum likelihood 1912-1922*, Statistical Science **12** (1997), no. 3, 162–176. 67

[ALK$^+$09] A. Aurelius, C. Lagerstedt, M. Kihl, M. Perényi, I. Sedano, and F. Mata, *A Traffic Analysis in the TRAMMS Project*, Telekomunikacije **4** (2009), 29–37. 135

[ALS$^+$10] A. Aurelius, C. Lagerstedt, I. Sedano, S. Molnar, M. Kihl, and F. Mata, *TRAMMS: Monitoring the evolution of residential broadband Internet traffic*, Future Network and Mobile Summit, 2010, pp. 1–9. 135

[AMD09] D. Antoniades, E. P. Markatos, and C. Dovrolis, *One-click hosting services: a file-sharing hideout*, Proceedings of ACM SIGCOMM Internet Measurement Conference (Chicago, USA), 2009, pp. 223–234. 126

[And58] T. W. Anderson, *An introduction to multivariate statistical analysis*, Wiley New York, 1958. 112, 234, 235, 236

[And80] J.P. Anderson, *Computer security threat monitoring and surveillance*, Tech. report, James P. Anderson Company, Fort Washington, Pennsylvania, 1980. 13

[AOC07] T. Ahmed, B. Oreshkin, and M. Coates, *Machine learning approaches to network anomaly detection*, Proceedings of 2nd USENIX workshop on Tackling computer systems problems with machine learning techniques, USENIX Association, 2007, p. 7. 46, 74

[ARM$^+$08] A. Ashfaq, M. Robert, A. Mumtaz, M. Ali, A. Sajjad, and S. Khayam, *A comparative evaluation of anomaly detectors under portscan attacks*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 5230, Springer Berlin / Heidelberg, 2008, pp. 351–371. 43, 79

[AS72] M. Abramowitz and I. A. Stegun (eds.), *Handbook of mathematical functions with formulas, graphs, and mathematical tables*, Dover, 1972. 151

[Axe00] S. Axelsson, *Intrusion detection systems: A survey and taxonomy*, Tech. report, Chalmers University of Technology, 2000. 18, 19

[Axe04] ______, *Combining a bayesian classifier with visualisation: Understanding the IDS*, Proceedings of 2004 ACM workshop on Visualization and data mining for computer security, ACM, 2004, pp. 99–108. 56, 89

[Bas00] T. Bass, *Intrusion detection systems and multisensor data fusion*, Communications of the ACM **43** (2000), no. 4, 99–105. 53

[BB03] K.M. Begnum and M. Burgess, *A scaled, immunological approach to anomaly countermeasures: Combining ph with cfengine*, Proceedings of IFIP/IEEE Eighth International Symposium on Integrated Network Management, 2003, pp. 31–42. 30

[BC02] N. Brownlee and K. C. Claffy, *Understanding Internet traffic streams: dragonflies and tortoises*, IEEE Communications Magazine **40** (2002), no. 10, 110–117. 2

[BCCBG04] Y. Bouzida, F. Cuppens, N. Cuppens-Boulahia, and S. Gombault, *Efficient intrusion detection using principal component analysis*, Proceedings of 3ème Conférence sur la Sécurité et Architectures Réseaux, 2004. 75

[BCJW01] D. Barbará, J. Couto, S. Jajodia, and N. Wu, *Adam: a testbed for exploring the use of data mining in intrusion detection*, ACM SIGMOD Record **30** (2001), no. 4, 15–24. 39

[BD91] P. J. Brockwell and R. A. Davis, *Time series: theory and methods*, Springer Series in Statistics, Springer, 1991. 116

[BDD$^+$01] A. Bronstein, J. Das, M. Duro, R. Friedrich, G. Kleyner, M. Mueller, S. Singhal, and I. Cohen, *Self-aware services: Using bayesian networks for detecting anomalies in internet-based services*, Proceedings of IEEE/IFIP International Symposium on Integrated Network Management, IEEE, 2001, pp. 623–638. 51

[BDTJ02] S. Bhattacharyya, C. Diot, N. Taft, and J. Jetcheva, *Geographical and temporal characteristics of inter-PoP flows: View from a single PoP*, European Transactions on Telecommunications **13** (2002), no. 1, 5–22. 94

[BDWS09] D. Brauckhoff, X. Dimitropoulos, A. Wagner, and K. Salamatian, *Anomaly extraction in backbone networks using association rules*, Proceedings of 9th ACM SIGCOMM Internet measurement conference, ACM, 2009, pp. 28–34. 40

[BEH06] D. Bolzoni, S. Etalle, and P. Hartel, *Poseidon: a 2-tier anomaly-based network intrusion detection system*, Proceedings of Fourth IEEE International Workshop on Information Assurance, IEEE, 2006, pp. 156–166. 63

[Bez92] J.C. Bezdek, *On the relationship between neural networks, pattern recognition and intelligence*, Int. J. Approx. Reasoning **6** (1992), no. 2, 85–107. 26

[BGM$^+$05] L.D. Brown, N. Gans, A. Mandelbaum, A. Sakov, H. Shen, S. Zeltyn, and L.H Zhao, *Statistical analysis of a telephone call center: A queueing science perspective*, J. Am. Stat. Assoc. **100** (2005), 36–50. 136, 139

[BKPR02] P. Barford, J. Kline, D. Plonka, and A. Ron, *A signal analysis of network traffic anomalies*, Proceedings of ACM SIGCOMM Workshop on Internet Measurement (Marseille, France), 2002, pp. 71–82. 95

[BM01] N. Brownlee and M. Murray, *Streams, Flows and Torrents*, PAM Workshop, 2001. 2

[BMPR10] R. Birke, M. Mellia, M. Petracca, and D. Rossi, *Experiences of VoIP traffic monitoring in a commercial ISP*, Int. J. Netw. Manag. **20** (2010), no. 5, 339–359. 132, 135, 136, 137

[BMS$^+$04] L.D. Brown, A. Mandelbaum, A. Sakov, H. Shen, S. Zeltyn, and L. Zhao, *Multifactor Poisson and Gamma–Poisson models for call center arrival times*, Tech. report, University of Pennsylvania, 2004. 136

[BP01] P. Barford and D. Plonka, *Characteristics of network traffic flow anomalies*, Proceedings of 1st ACM SIGCOMM Workshop on Internet Measurement, ACM, 2001, pp. 69–73. 65

[BP04] K. Borders and A. Prakash, *Web tap: detecting covert web traffic*, Proceedings of 11th ACM conference on computer and communications security, ACM, 2004, pp. 110–120. 78

[BR01] B. Balajinath and SV Raghavan, *Intrusion detection through learning behavior model*, Comput. Commun. **24** (2001), no. 12, 1202–1212. 32, 83

[Bru00] J. Brutlag, *Aberrant behavior detection in time series for network monitoring*, Proceedings of USENIX Conference on System Administration, 2000, pp. 139–146. 83, 95, 116

[BS06] S. A. Baset and H. Schulzrinne, *An Analysis of the Skype Peer-to-Peer Internel Telephony Protocol*, IEEE Infocom, 2006. 2

[BSM09] D. Brauckhoff, K. Salamatian, and M. May, *Applying PCA for traffic anomaly detection: Problems and solu-*

tions, Proceedings of The 28th Annual IEEE International Conference on Computer Communications, IEEE, 2009, pp. 2866–2870. 77

[BSMD10] M. Burkhart, M. Strasser, D. Many, and X. Dimitropoulos, *Sepia: privacy-preserving aggregation of multi-domain network events and statistics*, Proceedings of 19th USENIX conference on Security, USENIX Association, 2010, pp. 15–32. 43, 79

[BTW$^+$06] D. Brauckhoff, B. Tellenbach, A. Wagner, M. May, and A. Lakhina, *Impact of packet sampling on anomaly detection metrics*, Proceedings of 6th ACM SIGCOMM conference on Internet Measurement, ACM, 2006, pp. 159–164. 87

[Bur98] M. Burgess, *Computer immunology*, Proceedings of the 12th USENIX conference on System administration, USENIX Association, 1998, pp. 283–298. 29

[Bur00] ______, *Evaluating cfengine's immunity model of site maintenance*, Proceeding of 2nd SANE System Administration Conference, 2000. 30

[BV00] S.M. Bridges and R.B. Vaughn, *Fuzzy data mining and genetic algorithms applied to intrusion detection*, Proceedings of 23rd National Information Systems Security Conference, vol. 19, 2000, pp. 13–31. 36

[BWJ01] D. Barbará, N. Wu, and S. Jajodia, *Detecting novel network intrusions using bayes estimators*, Proceedings of first SIAM Conference on Data Mining, 2001. 51

[BZ02] L.D. Brown and L.H. Zhao, *A test for the Poisson distribution*, Sankhyā Ser. A **64** (2002), no. 3, 611–625. 136

[CANMS$^+$06] W. Chimphlee, A.H. Abdullah, M. Noor Md Sap, S. Srinoy, and S. Chimphlee, *Anomaly-based intrusion detection using fuzzy rough clustering*, Proceedings of International Conference on Hybrid Information Technology, vol. 1, IEEE, 2006, pp. 329–334. 37

[CAY07] Y. Chen, A. Abraham, and B. Yang, *Hybrid flexible neural-tree-based intrusion detection systems*, International Journal of Intelligent Systems **22** (2007), no. 4, 337–352. 35, 41, 49

[CBK09] V. Chandola, A. Banerjee, and V. Kumar, *Anomaly detection: A survey*, ACM Comput. Surv. **41** (2009), no. 3, 15. 20, 23, 59

[CBS06] A.A. Cárdenas, J.S. Baras, and K. Seamon, *A framework for the evaluation of intrusion detection systems*, Proceedings of IEEE Symposium on Security and Privacy, IEEE, 2006, pp. 15–pp. 86

[CCM$^+$11] A. Cuadra, M. M. Cutanda, R. M. Martínez, O. Fernández, S. Prieto, S. Serrano, and J. C. Barbadillo, *OMEGA-Q: A platform for measuring, troubleshooting and monitoring the quality of IPTV services*, Proceedings of International Symposium on Integrated Network Management (Dublin, Ireland), 2011, pp. 878–891. 132

[CH06] Y. Chen and K. Hwang, *Collaborative change detection of DDoS attacks on community and ISP networks*, Proceedings of IEEE Symposium on Collaborative Technologies and Systems, 2006, pp. 401–410. 80, 95

[CH11] E. Corchado and Á. Herrero, *Neural visualization of network traffic data for intrusion detection*, Appl. Soft. Comput. **11** (2011), no. 2, 2042–2056. 50

[CHK07] Y. Chen, K. Hwang, and W.S. Ku, *Collaborative detection of ddos attacks over multiple network domains*, IEEE T. Parall. Distr. **18** (2007), no. 12, 1649–1662. 81

[CHL07] W.E. Chen, H.N. Hung, and Y.B. Lin, *Modeling VoIP call holding times for telecommunications*, IEEE Netw. **21** (2007), no. 6, 22–28. 136

[CHS05a] W.H. Chen, S.H. Hsu, and H.P. Shen, *Application of SVM and ANN for intrusion detection*, Computers & Operations Research **32** (2005), no. 10, 2617–2634. 48, 58

[CHS05b] Emilio Corchado, Álvaro Herrero, and José Sáiz, *Detecting compounded anomalous SNMP situations using cooperative unsupervised pattern recognition*, Artificial Neural Networks: Formal Models and Their Applications, Lecture Notes in Computer Science, vol. 3697, Springer Berlin / Heidelberg, 2005, pp. 750–750. 48

[CK02] C.N. Chuah and R.H. Katz, *Characterizing packet audio streams from Internet multimedia applications*, Proceedings of International Conference on Communications (New York, USA), vol. 2, 2002, pp. 1199–1203. 136

[Cla04] B. Claise, *RFC 3954: Cisco Systems NetFlow Services Export Version 9*, 2004. 10

[CLC04] L.C. Chen, T.A. Longstaff, and K.M. Carley, *Characterization of defense mechanisms against distributed denial of service attacks*, Comput. Secur. **23** (2004), no. 8, 665–678. 2

[CLCG06] Y. Chen, Y. Li, X.-Q. Cheng, and L. Guo, *Survey and taxonomy of feature selection algorithms in intrusion detection system*, Information Security and Cryptology, Lecture Notes in Computer Science, vol. 4318, Springer Berlin / Heidelberg, 2006, pp. 153–167. 88

[CLQ+02] J.B.D. Cabrera, L. Lewis, X. Qin, W. Lee, and R.K. Mehra, *Proactive intrusion detection and distributed denial of service attacksa case study in security management*, Journal of Network and Systems Management **10** (2002), no. 2, 225–254. 80

[CMA03] P.K. Chan, M.V. Mahoney, and M.H. Arshad, *A machine learning approach to anomaly detection*, Tech. report, Department of Computer Sciences, Florida Institute of Technology, Melbourne, 2003. 40

[CMGD+11] A. Cuadra, F. Mata, J.L. García-Dorado, J. Aracil, J. de Vergara, F. Cortés, P. Beltrán, E. de Mingo, and A. Ferreiro, *Traffic monitoring for assuring quality of advanced services in Future Internet*, Proceedings of International Conference on Wired/Wireless Internet Communications, 2011, pp. 186–196. 132

[Coc97] W. G. Cochran, *Sampling techniques*, Wiley and Sons, NY, 1997. 3

[Com08] Computer Economics, *2007 malware report: The economic impact of viruses, spyware, adware, botnets, and other malicious code*, July 2008. 13

[CPB93] K. C. Claffy, G. C. Polyzos, and H.-W. Braun, *Application of sampling methodologies to network traffic characterization*, SIGCOMM Comput. Commun. Rev. **23** (1993), no. 4, 194–203. 3

[CPZ02] B.Y. Choi, J. Park, and Z.L. Zhang, *Adaptive random sampling for load change detection*, ACM SIGMETRICS Performance Evaluation Review **30** (2002), no. 1, 272–273. 80

[CSD$^+$04] S. Chavan, K. Shah, N. Dave, S. Mukherjee, A. Abraham, and S. Sanyal, *Adaptive neuro-fuzzy intrusion detection systems*, Proceedings of International Conference on Information Technology: Coding and Computing, vol. 1, IEEE, 2004, pp. 70–74. 37, 48

[CSKC08] P. Chhabra, C. Scott, E.D. Kolaczyk, and M. Crovella, *Distributed spatial anomaly detection*, The 27th Annual IEEE International Conference on Computer Communications, IEEE, 2008, pp. 1705–1713. 68

[DCRM10] A. D'Alconzo, A. Coluccia, and P. Romirer-Maierhofer, *Distribution-based anomaly detection in 3g mobile networks: from theory to practice*, International Journal of Network Management **20** (2010), no. 5, 245–269. 82

[DD00] J.E. Dickerson and J.A. Dickerson, *Fuzzy network profiling for intrusion detection*, Proceedings of 19th International Conference of the North American Fuzzy Information Processing Society, 2000, pp. 301–306. 36

[DDW99] H. Debar, M. Dacier, and A. Wespi, *Towards a taxonomy of intrusion-detection systems*, Comput. Netw. **31** (1999), no. 8, 805–822. 18

[DDW00] ______, *A revised taxonomy for intrusion-detection systems*, Ann. Telecommun. **55** (2000), no. 7, 361–378. 17, 18

[DEK$^+$02] P. Dokas, L. Ertoz, V. Kumar, A. Lazarevic, J. Srivastava, and P.N. Tan, *Data mining for network intrusion detection*, Proceedings of NSF Workshop on Next Generation Data Mining, 2002, pp. 21–30. 45, 57

[Den87] D.E. Denning, *An intrusion-detection model*, IEEE Trans. Softw. Eng. (1987), no. 2, 222–232. 2, 13

[DFB$^+$07] G. Dewaele, K. Fukuda, P. Borgnat, P. Abry, and K. Cho, *Extracting hidden anomalies using sketch and non gaussian multiresolution statistical detection procedures*, Proceedings of 2007 workshop on Large scale attack defense, ACM, 2007, pp. 145–152. 81

[DFH96] P. D'haeseleer, S. Forrest, and P. Helman, *An immunological approach to change detection: Algorithms, analysis and implications*, Proceedings of IEEE Symposium on Security and Privacy, IEEE, 1996, pp. 110–119. 27

[dFV02] Y. d'Halluin, P.A. Forsyth, and K.R. Vetzal, *Managing capacity for telecommunications networks under uncertainty*, IEEE/ACM Trans. Netw. **10** (2002), no. 4, 579 – 587. 116

[DG02] D. Dasgupta and F. González, *An immunity-based technique to characterize intrusions in computer networks*, IEEE Trans. Evol. Comput. **6** (2002), no. 3, 281–291. 28

[DG06] E.B. Dagum and S. Giannerini, *A critical investigation on detrending procedures for non-linear processes*, J. Macroecon. **28** (2006), no. 1, 175–191. 133

[DHS01] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern classification*, Wiley New York, 2001. 111

[DLT03] N. Duffield, C. Lund, and M. Thorup, *Estimating flow distributions from sampled flow statistics*, Proceedings of 2003 conference on Applications, technologies, architectures, and protocols for computer communications, ACM, 2003, pp. 325–336. 87

[DLT04] ______, *Flow sampling under hard resource constraints*, SIGMETRICS Perform. Eval. Rev. **32** (2004), no. 1, 85–96. 87

[Don00] D.L. Donoho, *High-dimensional data analysis: The curses and blessings of dimensionality*, AMS Math Challenges Lecture (2000), 1–32. 102

[DPV06a] A. Dainotti, A. Pescape, and G. Ventre, *A Packet-level Characterization of Network Traffic*, 11th Intenational Workshop on Computer-Aided Modeling Analysis and Design of Communication Links and Networks, 2006, pp. 38–45. 2

[DPV06b] A. Dainotti, A. Pescapé, and G. Ventre, *Wavelet-based detection of DoS attacks*, Proceedings of IEEE Global Telecommunications Conference, 2006, pp. 1–6. 65

[DQG$^+$04] D. Dagon, X. Qin, G. Gu, W. Lee, J. Grizzard, J. Levine, and H. Owen, *Honeystat: Local worm detection using honeypots*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 3224, Springer Berlin / Heidelberg, 2004, pp. 39–58. 83

[DSM04] T.D. Dang, B. Sonkoly, and S. Molnár, *Fractal analysis and modeling of VoIP traffic*, Proceedings of International Telecommunications Network Strategy and Planning Symposium (Vienna, Austria), 2004, pp. 123–130. 136

[DTAC05] O. Depren, M. Topallar, E. Anarim, and M.K. Ciliz, *An intelligent intrusion detection system (IDS) for anomaly and misuse detection in computer networks*, Expert systems with Applications **29** (2005), no. 4, 713–722. 52, 63

[Dur73] J. Durbin, *Weak convergence of the sample distribution function when parameters are estimated*, Ann. Stat. (1973), 279–290. 140, 232

[EAP$^+$02] E. Eskin, A. Arnold, M. Prerau, L. Portnoy, and S. Stolfo, *A geometric framework for unsupervised anomaly detection: Detecting intrusions in unlabeled data*, Proceedings of Conference on Applications of Data Mining in Computer Security, vol. 6, Kluwer Academics, 2002, pp. 77–102. 45, 57, 60

[EFH04] F. Esponda, S. Forrest, and P. Helman, *A formal framework for positive and negative detection schemes*, IEEE Trans. Syst. Man Cybern. Part B-Cybern. **34** (2004), no. 1, 357–373. 28

[ELS01] E. Eskin, W. Lee, and S.J. Stolfo, *Modeling system calls for intrusion detection with dynamic window sizes*, Proceedings of DARPA Information Survivability Conference & Exposition II, vol. 1, IEEE, 2001, pp. 165–175. 83

[ESEGP05] A. El-Semary, J. Edmonds, J. González, and M. Papa, *A framework for hybrid fuzzy logic intrusion detection systems*, Proceedings of 14th IEEE International Conference on Fuzzy Systems, IEEE, 2005, pp. 325–330. 37

[Esk00] E. Eskin, *Anomaly detection over noisy data using learned probability distributions*, Proceedings of International Conference on Machine Learning, 2000. 71, 73

[ETGTDV03] J.M. Estevez-Tapiador, P. García-Teodoro, and J.E. Díaz-Verdejo, *Stochastic protocol modeling for anomaly based network intrusion detection*, Proceedings of First IEEE International Workshop on Information Assurance, IEEE, 2003, pp. 3–12. 38, 69

[ETGTDV04] J. M. Estevez-Tapiador, P. García-Teodoro, and J. E. Díaz-Verdejo, *Anomaly detection methods in wired networks: a survey and taxonomy*, Comput. Commun. **27** (2004), 1569–1584. 16, 19

[ETGTDV05] J.M. Estevez-Tapiador, P. García-Teodoro, and J.E. Díaz-Verdejo, *Detection of web-based attacks through markovian protocol parsing*, Proceedings of 10th IEEE Symposium on Computers and Communications, IEEE, 2005, pp. 457–462. 70

[EV02] C. Estan and G. Varghese, *New directions in traffic measurement and accounting*, ACM SIGCOMM , 2002, pp. 323–336. 2

[EV03] ______, *New Directions in Traffic Measurement and Accounting: Focusing on the Elephants, Ignoring the Mice*, ACM Transactions on Computer Systems **21** (2003), no. 3, 270–313. 87

[FB07] K.M. Faraoun and A. Boukelif, *Neural networks learning improvement using the k-means clustering algorithm to detect network intrusions*, International Journal of Information and Mathematical Sciences **3** (2007), no. 2, 161–168. 49, 61

[FBV02] G. Florez, SA Bridges, and R.B. Vaughn, *An improved algorithm for fuzzy data mining for intrusion detection*, Proceedings of 2002 Annual Meeting of the North American Fuzzy Information Processing Society, IEEE, 2002, pp. 457–462. 36

[FCE05] K. Fukuda, K. Cho, and H. Esaki, *The impact of residential broadband traffic on Japanese ISP backbones*, Comput. Commun. Rev. **35** (2005), no. 1, 15–22. 100

[FGL$^+$00] A. Feldmann, A. Greenberg, C. Lund, N. Reingold, and J. Rexford, *Netscope: Traffic engineering for IP networks*, IEEE Network. **1** (2000), no. 9, 11–19. 95

[FGL$^+$01] A. Feldmann, A. Greenberg, C. Lund, N. Reingold, J. Rexford, and F. True, *Deriving traffic demands for* *operational IP networks: methodology and experience*, IEEE/ACM Trans. Netw. **9** (2001), no. 3, 265–280. 94

[FLLD+06] G. Florez-Larrahondo, Z. Liu, Y.S. Dandass, S.M. Bridges, and R. Vaughn, *Integrating intelligent anomaly detection agents into distributed monitoring systems*, Journal of Information Assurance and Security **1** (2006), no. 1, 59–77. 49, 70

[FMM+11] A. Finamore, M. Mellia, M. Meo, M.M. Munafo, and D. Rossi, *Experiences of internet traffic monitoring with tstat*, IEEE Network. **25** (2011), no. 3, 8–14. 137

[FPS05] G. Folino, C. Pizzuti, and G. Spezzano, *GP ensemble for distributed intrusion detection systems*, Pattern Recognition and Data Mining, Lecture Notes in Computer Science, vol. 3686, Springer Berlin / Heidelberg, 2005, pp. 54–62. 34

[GAC05] J. Greensmith, U. Aickelin, and S. Cayzer, *Introducing dendritic cells as a novel immune-inspired algorithm for anomaly detection*, Artificial Immune Systems (2005), 153–167. 30

[GAH05] C. Groşan, A. Abraham, and S. Y. Han, *Mepids: Multi-expression programming for intrusion detection system*, Artificial Intelligence and Knowledge Engineering Applications: A Bioinspired Approach, Lecture Notes in Computer Science, vol. 3562, Springer Berlin / Heidelberg, 2005, pp. 167–210. 34

[GD02a] J. Gómez and D. Dasgupta, *Evolving fuzzy classifiers for intrusion detection*, Proceedings of the 2002 IEEE Workshop on Information Assurance, vol. 6, New York: IEEE Computer Press, 2002, pp. 321–323. 32, 36

[GD02b] F. González and D. Dasgupta, *Neuro-immune and self-organizing map approaches to anomaly detection: A comparison*, Proceedings of First International Conference on Artificial Immune Systems, 2002, pp. 203–211. 28, 47, 62

[GD03] F.A. González and D. Dasgupta, *Anomaly detection using real-valued negative selection*, Genet. Program. Evol. Mach. **4** (2003), no. 4, 383–403. 28

[GD05] D. Gavrilis and E. Dermatas, *Real-time detection of distributed denial-of-service attacks using RBF networks and statistical features*, Comput. Netw. **48** (2005), no. 2, 235–245. 49

[GDHA$^+$11] J. L. García-Dorado, J. A. Hernández, J. Aracil, J. E. López de Vergara, and S. López-Buedo, *Characterization of the busy-hour traffic of IP networks based on their intrinsic features*, Comput. Netw. **55** (2011), no. 9, 2111 – 2125. 107

[GDK02] F. González, D. Dasgupta, and R. Kozma, *Combining negative selection and classification techniques for anomaly detection*, Proceedings of Congress on Evolutionary Computation, vol. 1, IEEE, 2002, pp. 705–710. 28

[GDN03] J. Gómez, D. Dasgupta, and O. Nasraoui, *A new gravitational clustering algorithm*, Proceedings of Third SIAM International Conference on Data Mining, vol. 3, 2003, pp. 83–94. 60

[GDNG02] J. Gómez, D. Dasgupta, O. Nasraoui, and F. Gonzalez, *Complete expression trees for evolving fuzzy classifier systems with genetic algorithms and application to network intrusion detection*, Proceedings of Annual Meeting of the North American Fuzzy Information Processing Society, IEEE, 2002, pp. 469–474. 32, 36

[GFA08] J. Greensmith, J. Feyereisl, and U. Aickelin, *The DCA: SOMe comparison*, Evolutionary Intelligence **1** (2008), no. 2, 85–112. 29, 64

[GGD03] J. Gómez, F. González, and D. Dasgupta, *An immuno-fuzzy approach to anomaly detection*, Proceedings of 12th IEEE International Conference on Fuzzy Systems, vol. 2, IEEE, 2003, pp. 1219–1224. 28, 37, 40

[GMS00] A. Ghosh, C. Michael, and M. Schatz, *A real-time intrusion detection system based on learning program behavior*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 1907, Springer Berlin / Heidelberg, 2000, pp. 93–109. 38, 47

[GMT05] Y. Gu, A. McCallum, and D. Towsley, *Detecting anomalies in network traffic using maximum entropy estimation*, Proceedings of 5th ACM SIGCOMM conference on Internet Measurement, USENIX Association, 2005, pp. 32–32. 42

[GPB07] S.R. Gaddam, V.V. Phoha, and K.S. Balagani, *K-means+ id3: A novel method for supervised anomaly detection by cascading k-means clustering and id3 decision tree learning methods*, IEEE Trans. Knowl. Data Eng. **19** (2007), no. 3, 345–354. 53, 61

[GPDRR08] G. Giacinto, R. Perdisci, M. Del Rio, and F. Roli, *Intrusion detection in computer networks by a modular ensemble of one-class classifiers*, Information Fusion **9** (2008), no. 1, 69–82. 55

[GPGMMPSG12] M. Gil-Pérez, F. Gómez-Mármol, G. Martínez-Pérez, and A. Skarmeta-Gómez, *Repcidn: A reputation-based collaborative intrusion detection network to lessen the impact of* *malicious alarms*, Journal of Network and Systems Management **20** (2012), 1–40. 89

[GQW07] C. Guolong, C. Qingliang, and G. Wenzhong, *A pso-based approach to rule learning in network intrusion detection*, Fuzzy Information and Engineering, Advances in Soft Computing, vol. 40, Springer Berlin / Heidelberg, 2007, pp. 666–673. 41

[GTDVMFV09] P. García-Teodoro, J. Díaz-Verdejo, G. Macia-Fernandez, and E. Vázquez, *Anomaly-based network intrusion detection: Techniques, systems and challenges*, Comput. Secur. **28** (2009), no. 1-2, 18–28. 20, 22

[GZA05] R.H. Gong, M. Zulkernine, and P. Abolmaesumi, *A software implementation of a genetic algorithm based approach to network intrusion detection*, Proceedings of Sixth International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing and First ACIS International Workshop on Self-Assembling Wireless Networks, IEEE, 2005, pp. 246–253. 33

[Hay05] A.F. Hayes, *Statistical methods for communication science*, Taylor & Francis, 2005. 126

[HC03] S.J. Han and S.B. Cho, *Detecting intrusion with rule-based integration of multiple models*, Comput. Secur. **22** (2003), no. 7, 613–623. 40, 54

[HC06] ______, *Evolutionary neural networks for anomaly detection based on the behavior of a program*, IEEE Trans. Syst., Man, Cybern. B **36** (2006), no. 3, 559–570. 49

[Hee07] P.E. Heegaard, *Evolution of traffic patterns in telecommunication systems*, Porceedings of International Conference on Communications and Networking in China (Shanghai, China), 2007, pp. 28–32. 135, 136

[HF00] S.A. Hofmeyr and S. Forrest, *Architecture for an artificial immune system*, Evolutionary computation **8** (2000), no. 4, 443–473. 28

[HFLX07] Y. Huang, N. Feamster, A. Lakhina, and J. Xu, *Diagnosing network disruptions with network-wide analysis*, SIGMETRICS Perform. Eval. Rev. **35** (2007), no. 1, 61–72. 76

[HGH$^+$06] L. Huang, M. Garofalakis, J. Hellerstein, A. Joseph, and N. Taft, *Toward sophisticated detection with distributed triggers*, Proceedings of 2006 SIGCOMM workshop on Mining network data, ACM, 2006, pp. 311–316. 76, 78

[HJPM10] S. Han, K. Jang, K. Park, and S. Moon, *Packetshader: a GPU-accelerated software router*, SIGCOMM Comput. Commun. Rev. **40** (2010), no. 4, 195–206. 90

[HKF04] V. Hautamaki, I. Karkkainen, and P. Franti, *Outlier detection using k-nearest neighbour graph*, Proceedings of 17th International Conference on Pattern Recognition, vol. 3, IEEE, 2004, pp. 430–433. 45

[HLC07] J. He, D. Long, and C. Chen, *An improved ant-based classifier for intrusion detection*, Proceedings of Third International Conference on Natural Computation, vol. 4, IEEE Computer Society, 2007, pp. 819–823. 41

[HLV03] W. Hu, Y. Liao, and V.R. Vemuri, *Robust anomaly detection using support vector machines*, Proceedings of international conference on machine learning, 2003, pp. 282–289. 45, 57

[HNG$^+$07a] L. Huang, X.L. Nguyen, M. Garofalakis, J.M. Hellerstein, M.I. Jordan, A.D. Joseph, and N. Taft, *Communication-efficient online detection of network-wide anomalies*, Proceedings of 26th Annual IEEE International Conference on Computer Communications, IEEE, 2007, pp. 134–142. 76

[HNG$^+$07b] L. Huang, X.L. Nguyen, M. Garofalakis, M.I. Jordan, A. Joseph, and N. Taft, *In-network PCA and anomaly detection*, Advances in Neural Information Processing Systems **19** (2007), 617–630. 76

[HSKS03] K.A. Heller, K.M. Svore, A.D. Keromytis, and S.J. Stolfo, *One class support vector machines for detecting anomalous windows registry accesses*, Proceedings of workshop on Data Mining for Computer Security, 2003. 57

[HSS03] A. Hofmann, C. Schmitz, and B. Sick, *Rule extraction from neural networks for intrusion detection in computer networks*, Proceedings of IEEE International Conference on Systems, Man and Cybernetics, vol. 2, IEEE, 2003, pp. 1259–1265. 32

[HWGL02] P.K. Harmer, P.D. Williams, G.H. Gunsch, and G.B. Lamont, *An artificial immune system architecture for computer security applications*, IEEE T. Evolut. Comput. **6** (2002), no. 3, 252 –280. 28

[JHH03] D. Joo, T. Hong, and I. Han, *The neural network models for IDS based on the asymmetric costs of false negative errors and false positive errors*, Expert Systems with Applications **25** (2003), no. 1, 69–75. 48

[JLM93] V. Jacobson, C. Leres, and S. McCanne, *pcap-Packet Capture library*, 1993. 8

[JPBB04] J. Jung, V. Paxson, A.W. Berger, and H. Balakrishnan, *Fast portscan detection using sequential hypothesis testing*, Proceedings of IEEE Symposium on Security and Privacy, IEEE, 2004, pp. 211–225. 78

[JSW^{+}06] S.Y. Jiang, X. Song, H. Wang, J.J. Han, and Q.H. Li, *A clustering-based method for unsupervised intrusion detections*, Pattern Recognition Letters **27** (2006), no. 7, 802–810. 61

[JW92] R. A. Johnson and D. W. Wichern, *Applied multivariate statistical analysis*, Prentice-Hall International Editions, 1992. 107

[KAT07] L. Khan, M. Awad, and B. Thuraisingham, *A new intrusion detection system using support vector machines and hierarchical clustering*, VLDB J. **16** (2007), no. 4, 507–521. 58, 61

[KBA^{+}07] J. Kim, P.J. Bentley, U. Aickelin, J. Greensmith, G. Tedesco, and J. Twycross, *Immune system approaches to intrusion detection–a review*, Natural computing **6** (2007), no. 4, 413–466. 21, 27

[KFH05] D.K. Kang, D. Fuller, and V. Honavar, *Learning classifiers for misuse and anomaly detection using a bag of system calls representation*, Proceedings of Sixth Annual IEEE SMC Information Assurance Workshop, IEEE, 2005, pp. 118–125. 52, 56, 58, 60, 83

[KG05] P. Kabiri and A.A. Ghorbani, *Research on intrusion detection and response: A survey*, Int. J. Netw. Secur. **1** (2005), no. 2, 84–102. 19

[KGTA05] J. Kim, J. Greensmith, J. Twycross, and U. Aickelin, *Malicious code execution detection and response immune sys-*

tem inspired by the danger theory, Proceedings of Adaptive and Resilient Computing Security Workshop, 2005. 30

[KL06] R. Khanna and H. Liu, *System approach to intrusion detection using hidden markov model*, Proceedings of 2006 international conference on Wireless communications and mobile computing, ACM, 2006, pp. 349–354. 70

[KMRV03] C. Kruegel, D. Mutz, W. Robertson, and F. Valeur, *Bayesian event classification for intrusion detection*, Proceedings of Computer Security Applications Conference, IEEE, 2003, pp. 14–23. 51, 55, 89

[KN02] J. Kilpi and I. Norros, *Testing the Gaussian approximation of aggregate traffic*, Proceedings of ACM SIGCOMM Workshop on Internet Measurement (Marseille, France), 2002, pp. 49–61. 3, 103

[Koh82] T. Kohonen, *Self-organized formation of topologically correct feature maps*, Biological cybernetics **43** (1982), no. 1, 59–69. 62

[Kow73] C. J. Kowalski, *Non-normal bivariate distributions with normal marginals*, The American Statistician **27** (1973), no. 3, pp. 103–106. 105

[KP03] D. Kim and J. Park, *Network-based intrusion detection with support vector machines*, Information Networking, Lecture Notes in Computer Science, vol. 2662, Springer Berlin / Heidelberg, 2003, pp. 747–756. 57

[KP07] K. G. Kyriakopoulos and D. J. Parish, *Automated Detection of Changes in Computer Network Measurements using Wavelets*, Proceedings of 16th International Conference on Computer Communications and Networks, 2007, pp. 1223–1227. 65

[KP09] S. Karapantazis and F.N. Pavlidou, *VoIP: A comprehensive survey on a promising technology*, Comput. Netw. **53** (2009), no. 12, 2050–2090. 132

[KSZC03] B. Krishnamurthy, S. Sen, Y. Zhang, and Y. Chen, *Sketch-based change detection: methods, evaluation, and applications*, Proceedings of ACM SIGCOMM Conference on Internet Measurement (Miami, USA), 2003, pp. 234–247. 95

[KTK02] C. Krügel, T. Toth, and E. Kirda, *Service specific anomaly detection for network intrusion detection*, Proceedings of 2002 ACM symposium on Applied computing, ACM, 2002, pp. 201–208. 73

[KWAM05] J. Kim, W. Wilson, U. Aickelin, and J. McLeod, *Cooperative automated worm response and detection immune algorithm (cardinal) inspired by t-cell immunity and tolerance*, Artificial Immune Systems (2005), 168–181. 30

[KZHH03] H.G. Kayacik, A.N. Zincir-Heywood, and M.I. Heywood, *On the capability of an SOM based intrusion detection system*, Proceedings of International Joint Conference on Neural Networks, vol. 3, IEEE, 2003, pp. 1808–1813. 63

[KZHH07] H. G. Kayacik, A. N. Zincir-Heywood, and M. I. Heywood, *A hierarchical SOM-based intrusion detection system*, Eng. Appl. Artif. Intell. **20** (2007), 439–451. 64

[LB00] J. Luo and S.M. Bridges, *Mining fuzzy association rules and fuzzy frequency episodes for intrusion detection*, International Journal of Intelligent Systems **15** (2000), no. 8, 687–703. 36

[LB03] T. Lane and C. E. Brodley, *An empirical study of two approaches to sequence learning for anomaly detection*, Machine Learning **51** (2003), 73–107. 69

[LBC$^+$06] X. Li, F. Bian, M. Crovella, C. Diot, R. Govindan, G. Iannaccone, and A. Lakhina, *Detection and identification of network anomalies using sketch subspaces*, Proceedings of 6th ACM SIGCOMM conference on Internet measurement, ACM, 2006, pp. 147–152. 76

[LCD04a] A. Lakhina, M. Crovella, and C. Diot, *Characterization of network-wide anomalies in traffic flows*, Proceedings of 4th ACM SIGCOMM conference on Internet measurement, ACM, 2004, pp. 201–206. 75

[LCD04b] ———, *Diagnosing network-wide traffic anomalies*, Comput. Commun. Rev. **34** (2004), no. 4, 219–230. 16, 75, 76

[LCD05] ———, *Mining anomalies using traffic feature distributions*, ACM SIGCOMM Computer Communication Review, ACM, 2005, pp. 217–228. 42, 60

[LCLZ04] Y. Liu, K. Chen, X. Liao, and W. Zhang, *A genetic clustering method for intrusion detection*, Pattern Recognit. **37** (2004), no. 5, 927–942. 32, 60

[LEK$^+$03] A. Lazarevic, L. Ertoz, V. Kumar, A. Ozgur, and J. Srivastava, *A comparative study of anomaly detection schemes in network intrusion detection*, Proceedings of Third SIAM International Conference on Data Mining, vol. 3, SIAM, 2003, pp. 25–36. 45, 57

[LFG$^+$00] R.P. Lippmann, D.J. Fried, I. Graf, J.W. Haines, K.R. Kendall, D. McClung, D. Weber, S.E. Webster, D. Wyschogrod, R.K. Cunningham, et al., *Evaluating intrusion detection systems: The 1998 darpa off-line intrusion detection evaluation*, Proceedings of DARPA Information Survivability Conference and Exposition, vol. 2, IEEE, 2000, pp. 12–26. 85

[LG07] Y. Li and L. Guo, *An active learning based tcm-knn algorithm for supervised network intrusion detection*, Comput. Secur. **26** (2007), no. 7-8, 459–467. 46

[LG08] W. J. Liu and J. Gong, *Double sampling for flow measurement on high speed links*, Computer Networks **52** (2008), no. 11, 2221–2226. 3

[LG09] W. Lu and A.A. Ghorbani, *Network anomaly detection based on wavelet analysis*, EURASIP Journal on Advances in Signal Processing **2009** (2009), 4. 66, 68, 72, 84

[LH01] S.C. Lee and D.V. Heinbuch, *Training a neural-network based intrusion detector to recognize novel attacks*, IEEE Trans. Syst. Man Cybern. Paart A-Syst. Hum. **31** (2001), no. 4, 294–299. 47

[LHF+00] R. Lippmann, J.W. Haines, D.J. Fried, J. Korba, and K. Das, *The 1999 darpa off-line intrusion detection evaluation*, Comput. Netw. **34** (2000), no. 4, 579–595. 85

[Li04] W. Li, *Using genetic algorithm for network intrusion detection*, Proceedings of United States Department of Energy Cyber Security Group 2004 Training Conference, 2004, pp. 24–27. 32

[Lil67] H. W. Lilliefors, *On the Kolmogorov-Smirnov test for normality with mean and variance unknown*, Journal of the American Statistical Association **62** (1967), no. 318, 399–402. 232

[LKK+08] K. Lee, J. Kim, K.H. Kwon, Y. Han, and S. Kim, *DDoS attack detection method using cluster analysis*, Expert Systems with Applications **34** (2008), no. 3, 1659–1665. 43, 61

[LL05] K. Leung and C. Leckie, *Unsupervised anomaly detection in network intrusion detection using clusters*, Proceedings of Twenty-eighth Australasian conference on Computer Science, vol. 38, Australian Computer Society, Inc., 2005, pp. 333–342. 61

[LM03] J. Li and C. Manikopoulos, *Early statistical anomaly intrusion detection of dos attacks using mib traffic parameters*, Proceedings of Information Assurance Workshop, IEEE, 2003, pp. 53–59. 48, 73

[LNG04] E. Leon, O. Nasraoui, and J. Gomez, *Anomaly detection based on unsupervised niche clustering with application to network intrusion detection*, Proceedings of Congress on Evolutionary Computation, vol. 1, IEEE, 2004, pp. 502–508. 32

[LPC$^+$04] A. Lakhina, K. Papagiannaki, M. Crovella, C. Diot, E.D. Kolaczyk, and N. Taft, *Structural analysis of network traffic flows*, ACM SIGMETRICS Performance Evaluation Review **32** (2004), no. 1, 61–72. 94

[LSK04] P. Laskov, C. Schäfer, and I. Kotenko, *Intrusion detection in unlabeled data with quarter-sphere support vector machines*, Proceedings of International GI Workshop on Detection of Intrusions and Malware & Vulnerability Assessment, 2004, pp. 71–82. 57

[LSM00] W. Lee, S.J. Stolfo, and K.W. Mok, *Adaptive intrusion detection: A data mining approach*, Artificial Intelligence Review **14** (2000), no. 6, 533–567. 39

[LT04] W. Lu and I. Traore, *Detecting new forms of network intrusion using genetic programming*, Computational Intelligence **20** (2004), no. 3, 475–494. 34

[LT05] ______, *An unsupervised anomaly detection framework for network intrusions*, Tech. report, Information Security and Object Technology Group, University of Victoria, 2005. 32

[LV02a] K. Labib and R. Vemuri, *Nsom: A real-time network-based intrusion detection system using self-organizing maps*, Tech. report, Dept. of Applied Science, University of California, Davis, 2002. 62

[LV02b] Y. Liao and V.R. Vemuri, *Use of k-nearest neighbor classifier for intrusion detection*, Comput. Secur. **21** (2002), no. 5, 439–448. 45

[LV02c] ______, *Using text categorization techniques for intrusion detection*, Proceedings of 11th USENIX Security Symposium, USENIX Association, 2002, pp. 51–59. 45

[LV04] K. Labib and V.R. Vemuri, *Detecting and visualizing denial-of-service and network probe attacks using principal component analysis*, Proceedings of Third Conference on Security and Network Architectures, 2004. 75

[LX01] W. Lee and D. Xiang, *Information-theoretic measures for anomaly detection*, Proceedings of IEEE Symposium on Security and Privacy, IEEE, 2001, pp. 130–143. 42

[LY01] X. Li and N. Ye, *Decision tree classifiers for computer intrusion detection*, Journal of Parallel and Distributed Computing Practices **4** (2001), no. 2, 179–190. 52

[LYY07] G. Liu, Z. Yi, and S. Yang, *A hierarchical intrusion detection model based on the pca neural networks*, Neurocomputing **70** (2007), no. 7, 1561–1568. 50, 76

[LZHH02a] P. Lichodzijewski, A.N. Zincir-Heywood, and M.I. Heywood, *Dynamic intrusion detection using self-organizing* *maps*, Proceedings of 14th Annual Canadian Information Technology Security Symposium, 2002. 62

[LZHH02b] ______, *Host-based intrusion detection using self-organizing maps*, Proceedings of 2002 International Joint Conference on Neural Networks, vol. 2, IEEE, 2002, pp. 1714–1719. 62

[MA06] A. Meddahi and H. Afifi, *"Packet-E-model": E-model for VoIP quality evaluation*, Comput. Netw. **50** (2006), no. 15, 2659–2675. 132

[Mar70] K. V. Mardia, *Measures of multivariate skewness and kurtosis with applications*, Biometrika **57** (1970), no. 3, 519. 106

[Mar74] ______, *Applications of some measures of multivariate skewness and kurtosis in testing normality and robustness studies*, Sankhyā: The Indian Journal of Statistics, Series B **36** (1974), no. 2, 115–128. 106, 110

[Mar75] ______, *Assessment of multinormality and the robustness of Hotelling's T 2 test*, Applied Statistics (1975), 163–171. 106, 110

[Mas02] W.A. Massey, *The analysis of queues with time-varying rates for telecommunication models*, Telecommun. Syst. **21** (2002), no. 2, 173–204. 136

[Mat94] P. Matzinger, *Tolerance, danger, and the extended family*, Annu. Rev. Immunol. **12** (1994), no. 1, 991–1045. 29

[MC00] S. McCreary and K. C. Claffy, *Trends in Wide Area IP Traffic Patterns*, Tech. report, The Cooperative Association for Internet Data Analysis (CAIDA), 2000. 3

[MC02] M.V. Mahoney and P.K. Chan, *Learning nonstationary models of normal network traffic for detecting novel attacks*, Proceedings of 8th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM Press, 2002, pp. 376–385. 39

[MC03] ———, *Learning rules for anomaly detection of hostile network traffic*, Proceedings of 3rd IEEE International Conference on Data Mining, IEEE Computer Society, 2003, p. 601. 39

[McH00] J. McHugh, *Testing intrusion detection systems: A critique of the 1998 and 1999 darpa intrusion detection system evaluations as performed by lincoln laboratory*, ACM Transactions on Information and System Security **3** (2000), no. 4, 262–294. 86

[McH01] ———, *Intrusion and intrusion detection*, Int. J. Inf. Secur. **1** (2001), no. 1, 14–35. 18

[MCS$^+$06] J. Mai, C. N. Chuah, A. Sridharan, T. Ye, and H. Zang, *Is sampled data sufficient for anomaly detection?*, Proceedings of 6th ACM SIGCOMM conference on Internet measurement, 2006, pp. 165–176. 87

[MGDA10] F. Mata, J.L. García-Dorado, and J. Aracil, *Multivariate fairly normal traffic model for aggregate load in large-scale data networks*, Wired/Wireless Internet Communications, Lecture Notes in Computer Science, vol. 6074, Springer Berlin / Heidelberg, 2010, pp. 278–289. 135

[MGDA12] ———, *Detection of traffic changes in large-scale backbone networks: The case of the spanish academic network*, Comput. Netw. **56** (2012), no. 2, 686 – 702. 3

[MGDLdVA12] F. Mata, J. L. García-Dorado, J. E. López de Vergara, and J. Aracil, *Factor analysis of Internet traffic destinations from similar source networks*, Internet Research **22** (2012), no. 1, 29–56. 2

[Mit97] T.M. Mitchell, *Machine learning*, McGraw Hill, 1997. 44

[MJS02] S. Mukkamala, G. Janoski, and A. Sung, *Intrusion detection: support vector machines and neural networks*, Proceedings of the IEEE international joint conference on neural networks, 2002, pp. 1702–1707. 48, 57

[MN00] M. Mischiatti and F. Neri, *Applying local search and genetic evolution in concept learning systems to detect intrusion in computer networks*, Proceedings of Workshop about Machine Learning and Data Mining, 2000. 31

[MP02] C. Manikopoulos and S. Papavassiliou, *Network intrusion and fault detection: a statistical anomaly approach*, IEEE Commun. Mag. **40** (2002), no. 10, 76–82. 47, 54

[MPM05] G. M. Muntean, P. Perry, and L. Murphy, *Objective and Subjective Evaluation of QOAS Video Streaming over Broadband Networks*, IEEE eTransactions on Network and Service Management **2** (2005), no. 1, 19–28. 2

[MPW96] W.A. Massey, G.A. Parker, and W. Whitt, *Estimating the parameters of a nonhomogeneous Poisson process with linear rate*, Telecommun. Syst. **5** (1996), no. 2, 361–388. 136

[MR04] J. Mirkovic and P. Reiher, *A taxonomy of DDoS attack and DDoS defense mechanisms*, Comput. Commun. Rev. **34** (2004), no. 2, 39–53. 2

[MSA04] S. Mukkamala, A. Sung, and A. Abraham, *Modeling intrusion detection systems using linear genetic programming* *approach*, Innovations in Applied Artificial Intelligence, Lecture Notes in Computer Science, vol. 3029, Springer Berlin / Heidelberg, 2004, pp. 633–642. 34

[MSA05] S. Mukkamala, A.H. Sung, and A. Abraham, *Intrusion detection using an ensemble of intelligent paradigms*, J. Netw. Comput. Appl. **28** (2005), no. 2, 167–182. 49, 54, 58

[MSC$^+$06] J. Mai, A. Sridharan, C.N. Chuah, H. Zang, and T. Ye, *Impact of packet sampling on portscan detection*, IEEE J. Sel. Area. Comm. **24** (2006), no. 12, 2285–2298. 87

[MVVK06] D. Mutz, F. Valeur, G. Vigna, and C. Kruegel, *Anomalous system call detection*, ACM Transactions on Information and System Security **9** (2006), no. 1, 61–93. 51, 54, 68, 70, 73

[MZ04] M. Moradi and M. Zulkernine, *A neural network based system for intrusion detection and classification of attacks*, Proceedings of 2004 IEEE International Conference on Advances in Intelligent Systems - Theory and Applications, 2004. 48

[MŻ11] M.R.H. Mandjes and P. Żuraniewski, *M/G/infinity transience, and its applications to overload detection*, Performance Evaluation **68** (2011), 507–527. 82, 132

[NAR$^+$04] H. T. M. Neto, J. M. Almeida, L. C. D. Rocha, W. Meira, P. H. C. Guerra, and V. A. F. Almeida, *A characterization of broadband user behavior and their e-business activities*, ACM SIGMETRICS Performance Evaluation Review **32** (2004), no. 3, 3–13. 2

[Nor95] I. Norros, *On the use of fractional brownian motion in the theory of connectionless networks*, IEEE J. Sel. Area. Comm. **13** (1995), no. 6, 953 –962. 100

[NP08] A. Nucci and K. Papagiannaki, *Design, measurement and management of large-scale IP networks*, Cambridge University Press, 2008. 100

[NSA^{+}08] G. Nychis, V. Sekar, D.G. Andersen, H. Kim, and H. Zhang, *An empirical evaluation of entropy-based traffic anomaly detection*, Proceedings of 8th ACM SIGCOMM conference on Internet measurement, ACM, 2008, pp. 151–156. 43

[NWY02] S. Noel, D. Wijesekera, and C. Youman, *Modern intrusion detection, data mining, and degrees of attack guilt*, Applications of Data Mining in Computer Security (2002), 1–31. 89

[ÖAB07] T. Özyer, R. Alhajj, and K. Barker, *Intrusion detection by integrating boosting genetic fuzzy classifier and data mining criteria for rule pre-screening*, J. Netw. Comput. Appl. **30** (2007), no. 1, 99–113. 33, 37

[Odl99] A. M. Odlyzko, *The economics of the internet: Utility, utilization, pricing and quality of service*, Tech. report, University of Minnesota, 1999. 2

[Odl03] A. M. Odlyzko, *Internet traffic growth: sources and implications*, Proceedings of SPIE (Orlando, USA), vol. 5247, 2003, pp. 1–15. 116

[OOAK04] M. Oka, Y. Oyama, H. Abe, and K. Kato, *Anomaly detection using layered networks based on eigen co-occurrence matrix*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 3224, Springer Berlin / Heidelberg, 2004, pp. 223–237. 75

[OPG^{+}03] M. Otey, S. Parthasarathy, A. Ghoting, G. Li, S. Narravula, and D. Panda, *Towards nic-based intrusion de-*

tection, Proceedings of ninth ACM SIGKDD international conference on knowledge discovery and data mining, ACM, 2003, pp. 723–728. 40

[OR98] T. Oetiker and D. Rand, *MRTG: The Multi Router Traffic Grapher*, Proceedings of USENIX Conference on System Administration (Boston, USA), 1998, pp. 141–148. 11, 98, 143

[PAD$^+$06] V. Paxson, K. Asanovic, S. Dharmapurikar, J. Lockwood, R. Pang, R. Sommer, and N. Weaver, *Rethinking hardware support for network analysis and intrusion prevention*, Proceedings of USENIX Hot Security, 2006, p. 11. 90

[Pag54] E.S. Page, *Continuous inspection schemes*, Biometrika **41** (1954), no. 1/2, 100–115. 78, 80

[PAGT07] S. Peddabachigari, A. Abraham, C. Grosan, and J. Thomas, *Modeling intrusion detection system using hybrid intelligent systems*, J. Netw. Comput. Appl. **30** (2007), no. 1, 114–132. 53, 54, 58

[PAT04] S. Peddabachigari, A. Abraham, and J. Thomas, *Intrusion detection systems using decision trees and support vector machines*, International Journal of Applied Science and Computations **11** (2004), no. 3, 118–134. 52, 58

[Pea95] K. Pearson, *Contributions to the mathematical theory of evolution. ii. skew variation in homogeneous material*, Philosophical Transactions of the Royal Society of London. A **186** (1895), 343–414. 72

[PES01] L. Portnoy, E. Eskin, and S. Stolfo, *Intrusion detection with unlabeled data using clustering*, Proceedings of ACM CSS Workshop on Data Mining Applied to Security, 2001, pp. 1–13. 59

[PEV04] M.M. Pillai, J.H.P. Eloff, and H.S. Venter, *An approach to implement a network intrusion detection system using genetic algorithms*, Proceedings of 2004 annual research conference of the South African institute of computer scientists and information technologists on IT research in developing countries, South African Institute for Computer Scientists and Information Technologists, 2004, pp. 221–221. 32

[PGDM07] M. Perenyi, A. Gefferth, T. D. Dang, and S. Molnar, *Skype Traffic Identification*, IEEE Global Telecommunications Conference, 2007, pp. 399–404. 2

[PH08] S.T. Powers and J. He, *A hybrid artificial immune system and self organising map for network intrusion detection*, Information Sciences **178** (2008), no. 15, 3024–3042. 29, 64

[PHIP05] N. Patwari, A.O. Hero III, and A. Pacholski, *Manifold learning visualization of network traffic data*, Proceedings of ACM SIGCOMM workshop on Mining network data, ACM, 2005, pp. 191–196. 45

[PM07] M. Perenyi and S. Molnar, *Enhanced Skype traffic identification*, Proceedings of the 2nd international conference on Performance evaluation methodologies and tools, 2007. 2

[PNvdMM09] A. Pras, L. Nieuwenhuis, R. van de Meent, and M.R.H. Mandjes, *Dimensioning network links: a new look at equivalent bandwidth*, IEEE Network. **23** (2009), no. 2, 5–10. 167, 174

[PP07] A. Patcha and J.M. Park, *An overview of anomaly detection techniques: Existing solutions and latest technological* *trends*, Comput. Netw. **51** (2007), no. 12, 3448–3470. 20, 21

[PS09] I.C. Paschalidis and G. Smaragdakis, *Spatio-temporal network anomaly detection by assessing deviations of empirical measures*, IEEE/ACM Trans. Netw. **17** (2009), no. 3, 685–697. 70

[PTZD05] K. Papagiannaki, N. Taft, Zhi-Li Zhang, and C. Diot, *Long-term forecasting of Internet backbone traffic*, IEEE Transactions on Neural Networks **16** (2005), no. 5, 1110–1124. 3, 95, 103, 116

[QH04] M. Qin and K. Hwang, *Frequent episode rules for internet anomaly detection*, Proceedings of third IEEE International Symposium on Network Computing and Applications, IEEE, 2004, pp. 161–168. 40

[RA05] V. Ramos and A. Abraham, *Antids: Self orga nized ant-based c lustering model for intrusion det ection system*, Soft Computing as Transdisciplinary Science and Technology, Advances in Soft Computing, vol. 29, Springer Berlin / Heidelberg, 2005, pp. 977–986. 41

[RK96] A. Rueda and W. Kinsner, *A survey of traffic characterization techniques in telecommunication networks*, Canadian Conference on Electrical and Computer Engineering (Calgary, Alta., Canada), vol. 2, May 1996, pp. 830–833. 2

[RMC00] B.C. Rhodes, J.A. Mahaffey, and J.D. Cannady, *Multiple self-organizing maps for intrusion detection*, Proceedings of 23rd national information systems security conference, 2000, pp. 16–19. 62

[RNH$^+$09] B.I.P. Rubinstein, B. Nelson, L. Huang, A.D. Joseph, S. Lau, S. Rao, N. Taft, and JD Tygar, *Antidote: understanding and defending against poisoning of anomaly detectors*, Proceedings of 9th ACM SIGCOMM conference on Internet measurement conference, ACM, 2009, pp. 1–14. 77

[Rob00] L. G. Roberts, *Beyond Moore's Law: Internet Growth Trends*, Computer **33** (2000), no. 1, 117–119. 2, 8

[ROT03] M. Ramadas, S. Ostermann, and B. Tjaden, *Detecting anomalous network traffic with self-organizing maps*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 2820, Springer Berlin / Heidelberg, 2003, pp. 36–54. 63

[RRR08] H. Ringberg, M. Roughan, and J. Rexford, *The need for simulation in evaluating anomaly detectors*, Comput. Commun. Rev. **38** (2008), no. 1, 55–59. 86

[RS94] F. J. Rohlf and R. R. Sokal, *Statistical tables*, WH Freeman, 1994. 232

[RSM08] Y. Rebahi, M. Sher, and T. Magedanz, *Detecting flooding attacks against IP Multimedia Subsystem (IMS) networks*, Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, IEEE, 2008, pp. 848–851. 82

[RSRD07] H. Ringberg, A. Soule, J. Rexford, and C. Diot, *Sensitivity of PCA for traffic anomaly detection*, SIGMETRICS Perform. Eval. Rev. **35** (2007), no. 1, 109–120. 76

[RVK$^+$06] W. Robertson, G. Vigna, C. Kruegel, R.A. Kemmerer, et al., *Using generalization and characterization techniques in the anomaly-based detection of web attacks*, Proceedings of 13th Symposium on Network and Distributed System Security, 2006. 68

[SAHBS07] M. Saniee Abadeh, J. Habibi, Z. Barzegar, and M. Sergi, *A parallel genetic local search algorithm for intrusion detection in computer networks*, Engineering Applications of Artificial Intelligence **20** (2007), no. 8, 1058–1069. 33, 37

[SCSC03] M.L. Shyu, S.C. Chen, K. Sarinnapakorn, and L.W. Chang, *A novel anomaly detection scheme based on principal component classifier*, Tech. report, Center for High Assurance Computer Systems, 2003. 75

[SCWH05] G. Stein, B. Chen, A.S. Wu, and K.A. Hua, *Decision tree classifier for network intrusion detection with ga-based feature selection*, Proceedings of 43rd annual Southeast regional conference, vol. 2, ACM, 2005, pp. 136–141. 33, 52

[SDTG10] F. Silveira, C. Diot, N. Taft, and R. Govindan, *Astute: detecting a different class of traffic anomalies*, SIGCOMM Comput. Commun. Rev. **40** (2010), no. 4, 267–278. 66, 79, 84

[SEZS01] M.G. Schultz, E. Eskin, F. Zadok, and S.J. Stolfo, *Data mining methods for detection of new malicious executables*, Proceedings of IEEE Symposium on Security and Privacy., IEEE, 2001, pp. 38–49. 55

[SFKT06] K. Suh, D. R. Figueiredo, J. Kurose, and D. Towsley, *Characterizing and Detecting Skype-Relayed Traffic*, Proceedings of the 25th IEEE International Conference on Computer Communications, April 2006, pp. 1–12. 2

[SGF$^+$02] R. Sekar, A. Gupta, J. Frullo, T. Shanbhag, A. Tiwari, H. Yang, and S. Zhou, *Specification-based anomaly detection: a new approach for detecting network intrusions*, Proceedings of 9th ACM conference on computer and communications security, ACM, 2002, pp. 265–274. 38, 73

[SGPC04] R. Schweller, A. Gupta, E. Parsons, and Y. Chen, *Reversible sketches for efficient and accurate change detection over network data streams*, Proceedings of ACM SIGCOMM Conference on Internet Measurement, 2004, pp. 207–212. 80, 95

[SH05] H. Shen and J.Z. Huang, *Analysis of call centre arrival data using singular value decomposition*, Appl. Stoch. Models. Bus. Ind. **21** (2005), no. 3, 251–263. 136

[SH08a] ______, *Forecasting time series of inhomogeneous Poisson processes with application to call center workforce management*, Ann. Appl. Stat. **2** (2008), no. 2, 601–623. 136

[SH08b] ______, *Interday forecasting and intraday updating of call center arrivals*, M&SOM-Manuf. Serv. Oper. Manag. **10** (2008), no. 3, 391–410. 136, 137

[She04] D. Sheskin, *Handbook of parametric and nonparametric statistical procedures*, CRC Press, 2004. 232

[Shi05] J. Shifflet, *A technique independent fusion model for network intrusion detection*, Proceedings of Midstates Conference on Undergraduate Research in Computer Science and Mathematics, vol. 3, 2005, pp. 13–19. 54

[SHM02] S. Staniford, J.A. Hoagland, and J.M. McAlerney, *Practical automated detection of stealthy portscans*, Journal of Computer Security **10** (2002), no. 1/2, 105–136. 78

[SHZH03] D. Song, M. Heywood, and A. Zincir-Heywood, *A linear genetic programming approach to intrusion detection*, Genetic and Evolutionary Computation, Lecture Notes in

Computer Science, vol. 2724, Springer Berlin / Heidelberg, 2003, pp. 208–208. 34

[SHZH05] D. Song, M.I. Heywood, and A.N. Zincir-Heywood, *Training genetic programming on half a million patterns: an example from anomaly detection*, IEEE T. Evolut. Comput. **9** (2005), no. 3, 225–239. 34

[SJ11] R. Stankiewicz and A. Jajszczyk, *A survey of QoE assurance in converged networks*, Comput. Netw. **55** (2011), no. 7, 1459–1473. 132

[SLB04] S. Sarafijanović and J.Y. Le Boudec, *An artificial immune system for misbehavior detection in mobile ad-hoc networks with virtual thymus, clustering, danger signal, and memory detectors*, Artificial Immune Systems, Lecture Notes in Computer Science, vol. 3239, Springer Berlin / Heidelberg, 2004, pp. 342–356. 30

[SLB05] ______, *An artificial immune system approach with secondary response for misbehavior detection in mobile ad hoc networks*, IEEE T. Neural. Networ. **16** (2005), no. 5, 1076–1087. 29

[SLC$^+$07] R. Schweller, Z. Li, Y. Chen, Y. Gao, A. Gupta, Y. Zhang, P.A. Dinda, M.Y. Kao, and G. Memik, *Reversible sketches: enabling monitoring and analysis over high-speed data streams*, IEEE/ACM Trans. Netw. **15** (2007), no. 5, 1059–1072. 81, 83

[SLO$^+$07] A. Scherrer, N. Larrieu, P. Owezarski, P. Borgnat, and P. Abry, *Non-gaussian and long memory statistical characterizations for internet traffic with anomalies*, IEEE T. Depend. Secure. **4** (2007), no. 1, 56–70. 81

[SM03] A.H. Sung and S. Mukkamala, *Identifying important features for intrusion detection using support vector machines and neural networks*, Proceedings of Symposium on Applications and the Internet, IEEE, 2003, pp. 209–216. 48, 57

[SM04] C. Siaterlis and B. Maglaris, *Towards multisensor data fusion for DoS detection*, Proceedings of 2004 ACM symposium on Applied computing, ACM, 2004, pp. 439–446. 54

[Sob06] T.S. Sobh, *Wired and wireless intrusion detection system: Classifications, good characteristics and state-of-the-art*, Comput. Stand. Interfaces **28** (2006), no. 6, 670–694. 19

[SOS02] A.A. Sebyala, T. Olukemi, and L. Sacks, *Active platform security through intrusion detection using naive bayesian network for anomaly detection*, Proceedings of London Communications Symposium, 2002. 51

[SP06] V.A. Siris and F. Papagalou, *Application of anomaly detection algorithms for detecting syn flooding attacks*, Comput. Commun. **29** (2006), no. 9, 1433–1442. 78, 80

[SP10] R. Sommer and V. Paxson, *Outside the closed world: On using machine learning for network intrusion detection*, Proceedings of IEEE Symposium on Security and Privacy, IEEE, 2010, pp. 305–316. 89

[SPL$^+$09] A.D. Schmidt, F. Peters, F. Lamour, C. Scheel, S.A. Çamtepe, and S. Albayrak, *Monitoring smartphones for anomaly detection*, Mobile Networks and Applications **14** (2009), no. 1, 92–106. 29, 64, 77

[SPP07] A. Sharma, A.K. Pujari, and K.K. Paliwal, *Intrusion detection using text processing techniques with a kernel based* *similarity measure*, Comput. Secur. **26** (2007), 488–495. 46, 74

[SRRW00] Z.G. Stoumbos, M.R. Reynolds, T.P. Ryan, and W.H. Woodall, *The state of statistical process control as we proceed into the 21st century*, J. Am. Stat. Assoc. **95** (2000), no. 451, 992–998. 77

[SSS$^+$10] A. Sperotto, G. Schaffrath, R. Sadre, C. Morariu, A. Pras, and B. Stiller, *An overview of IP flow-based intrusion detection*, IEEE Communications Surveys & Tutorials **12** (2010), no. 3, 343–356. 2, 87

[Sta98] W. Stallings, *SNMP, SNMPv2, SNMPv3, and RMON 1 and 2*, Addison-Wesley Longman Publishing Co., Inc. Boston, USA, 1998. 95

[Ste74] M. A. Stephens, *EDF statistics for goodness of fit and some comparisons*, Journal of the American Statistical Association **69** (1974), no. 347, 730–737. 232

[SUJ03] H. Shah, J. Undercoffer, and A. Joshi, *Fuzzy clustering for intrusion detection*, Proceedings of 12th IEEE International Conference on Fuzzy Systems, vol. 2, IEEE, 2003, pp. 1274–1278. 36

[SZ02] K. Sequeira and M. Zaki, *Admit: anomaly-based data mining for intrusions*, Proceedings of eighth ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2002, pp. 386–395. 60

[SZH05] S.T. Sarasamma, Q.A. Zhu, and J. Huff, *Hierarchical Kohonenen net for anomaly detection in network security*, IEEE Trans. Syst., Man, Cybern. B **35** (2005), no. 2, 302–312. 63

[TAF02] C. Taylor and J. Alves-Foss, *An empirical analysis of nate: Network analysis of anomalous traffic events*, Proceedings of 2002 workshop on New security paradigms, ACM, 2002, pp. 18–26. 60

[Tay08] J.W. Taylor, *A comparison of univariate time series methods for forecasting intraday arrivals at a call center*, Manage. Sci. **54** (2008), no. 2, 253–265. 133, 136, 137

[TC07] G. Tandon and P.K. Chan, *Weighting versus pruning in rule validation for detecting network and host anomalies*, Proceedings of 13th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2007, pp. 697–706. 40

[TJ03] M. Thottan and C. Ji, *Anomaly detection in IP networks*, IEEE T. Signal. Proces. **51** (2003), no. 8, 2191–2204. 65, 80

[TK05] C.H. Tsang and S. Kwong, *Multi-agent intrusion detection system in industrial network using ant colony clustering approach and unsupervised feature extraction*, Proceedings of IEEE International Conference on Industrial Technology, IEEE, 2005, pp. 51–56. 41

[TK07] A.N. Toosi and M. Kahani, *A new approach to intrusion detection based on an evolutionary soft computing model using neuro-fuzzy classifiers*, Comput. Commun. **30** (2007), no. 10, 2201–2212. 33, 37

[TKW07] C.H. Tsang, S. Kwong, and H. Wang, *Genetic-fuzzy rule mining approach and evaluation of feature selection techniques for anomaly intrusion detection*, Pattern Recognit. **40** (2007), no. 9, 2373–2391. 33, 37

[TMW97] K. Thompson, G. J. Miller, and R. Wilder, *Wide-area Internet traffic patterns and characteristics*, IEEE Network **11** (1997), no. 6, 10–23. 100, 134

[TRA08] TRAMMS consortium, *TRAMMS IP Traffic report*, Tech. Report 2, TRAMMS project, 2008, available at `http://projects.celtic-initiative.org/tramms/files/tramms_public_ip_traffic_report_no2.pdf`, last acessed May 2012. 100

[TRBK06a] A.G. Tartakovsky, B.L. Rozovskii, R.B. Blažek, and H. Kim, *Detection of intrusions in information systems by sequential change-point methods*, Statistical Methodology **3** (2006), no. 3, 252–293. 81

[TRBK06b] A.G. Tartakovsky, B.L. Rozovskii, R.B. Blazek, and H. Kim, *A novel approach to detection of intrusions in computer networks via adaptive sequential and batch-sequential change-point detection methods*, IEEE Trans. Signal Process. **54** (2006), no. 9, 3372–3382. 81

[Tre11] J. Treurniet, *A network activity classification schema and its application to scan detection*, IEEE/ACM Trans. Netw. (2011), no. 99, 1396–1404. 38

[VBC06] L. Vokorokos, A. Balaz, and M. Chovanec, *Intrusion detection system using self organizing map*, Acta Electrotechnica et Informatica **6** (2006), no. 1, 1–6. 63

[vdBMvdM$^+$06] H. van den Berg, M.R.H. Mandjes, R. van de Meent, A. Pras, F. Roijers, and P. Venemans, *QoS-aware bandwidth provisioning for IP network links*, Computer Networks **50** (2006), no. 5, 631–647. 2, 103

[vdMMP06] R. van de Meent, M.R.H. Mandjes, and A. Pras, *Gaussian traffic everywhere?*, Proceedings of IEEE International Conference on Communications (Instanbul, Turkey), vol. 2, June 2006, pp. 573–578. 103, 105, 109

[vdMMP07] ______, *Smart Dimensioning of IP Network Links*, 18th IFIP/IEEE International Workshop on Distributed Systems: Operations and Management (DSOM'07), Springer, 2007, pp. 86–97. 167, 174

[VH02] T. Verwoerd and R. Hunt, *Intrusion detection techniques and approaches*, Comput. Commun. **25** (2002), no. 15, 1356–1365. 19, 20

[VS00] A. Valdés and K. Skinner, *Adaptive, model-based monitoring for cyber attack detection*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 1907, Springer Berlin / Heidelberg, 2000, pp. 80–93. 51

[WB06] W. Wang and R. Battiti, *Identifying intrusions in computer networks with principal component analysis*, Proceedings of First International Conference on Availability, Reliability and Security, IEEE, 2006, pp. 8–pp. 76

[WB10] S.X. Wu and W. Banzhaf, *The use of computational intelligence in intrusion detection systems: A review*, Appl. Soft. Comput. **10** (2010), no. 1, 1–35. 21, 24, 31, 41

[Wel38] B. L. Welch, *The significance of the difference between two means when the population variances are unequal*, Biometrika **29** (1938), no. 3, 350–362. 126, 234

[WGZ04a] W. Wang, X. Guan, and X. Zhang, *A novel intrusion detection method based on principle component analysis in computer security*, Advances in Neural Networks, Lecture Notes in Computer Science, vol. 3174, Springer Berlin / Heidelberg, 2004, pp. 88–89. 75

[WGZ04b] W. Wang, X.H. Guan, and X.L. Zhang, *Modeling program behaviors by hidden markov models for intrusion detection*, Proceedings of 2004 International Conference on Machine Learning and Cybernetics, vol. 5, IEEE, 2004, pp. 2830–2835. 69

[WGZ08] W. Wang, X. Guan, and X. Zhang, *Processing of massive audit data streams for real-time anomaly intrusion detection*, Comput. Commun. **31** (2008), no. 1, 58–72. 77

[WGZY06] W. Wang, X. Guan, X. Zhang, and L. Yang, *Profiling program behavior for anomaly intrusion detection based on the transition and frequency property of computer audit data*, Comput. Secur. **25** (2006), no. 7, 539–550. 63, 70

[Wil02] M.M. Williamson, *Throttling viruses: Restricting propagation to defeat malicious mobile code*, Proceedings of 18th Annual Computer Security Applications Conference, IEEE, 2002, pp. 61–68. 78

[WP05] A. Wagner and B. Plattner, *Entropy based worm and anomaly detection in fast IP networks*, Proceedings of IEEE International Workshops on Enabling Technologies: Infrastructure for Collaborative Enterprise, IEEE, 2005, pp. 172–177. 42

[WS04] K. Wang and S. Stolfo, *Anomalous payload-based network intrusion detection*, Recent Advances in Intrusion Detection, Lecture Notes in Computer Science, vol. 3224, Springer Berlin / Heidelberg, 2004, pp. 203–222. 63

[WVGK04] J. Wu, S. Vangala, L. Gao, and K.A. Kwiat, *An effective architecture and algorithm for detecting worms with various scan*, Proceedings of Internet Society Network and Distributed System Security Symposium, 2004. 78

[XHF$^+$09] W. Xu, L. Huang, A. Fox, D. Patterson, and M.I. Jordan, *Detecting large-scale system problems by mining console logs*, Proceedings of ACM SIGOPS 22nd symposium on Operating systems principles, ACM, 2009, pp. 117–132. 77

[XYM08] C. Xiang, P.C. Yong, and L.S. Meng, *Design of multiple-level hybrid classifier for intrusion detection system using bayesian clustering and decision trees*, Pattern Recognition Letters **29** (2008), no. 7, 918–924. 53, 61

[XZB05] K. Xu, Z.L. Zhang, and S. Bhattacharyya, *Profiling internet backbone traffic: behavior models and applications*, SIGCOMM Comput. Commun. Rev. **35** (2005), no. 4, 169–180. 42, 60, 78

[YC02] D.Y. Yeung and C. Chow, *Parzen-window network intrusion detectors*, Proceedings of 16th International Conference on Pattern Recognition, vol. 4, IEEE, 2002, pp. 385–388. 74

[YCB04] N. Ye, Q. Chen, and C.M. Borror, *Ewma forecast of normal system activity for computer intrusion detection*, IEEE T. Reliab. **53** (2004), no. 4, 557–566. 83

[YD03] D.Y. Yeung and Y. Ding, *Host-based intrusion detection using dynamic and static behavioral models*, Pattern Recognit. **36** (2003), no. 1, 229–243. 69, 73

[YECV02] N. Ye, S.M. Emran, Q. Chen, and S. Vilbert, *Multivariate statistical analysis of audit trails for host-based intrusion detection*, IEEE Trans. Comput. **51** (2002), no. 7, 810–820. 67

[YL01] N. Ye and X. Li, *A scalable clustering technique for intrusion signature recognition*, Proceedings of 2001 IEEE

Workshop on Information Assurance and Security, 2001, pp. 1–4. 59

[YLKP08] J. Yu, H. Lee, M.S. Kim, and D. Park, *Traffic flooding attack detection with SNMP MIB using SVM*, Comput. Commun. **31** (2008), no. 17, 4212–4219. 58

[YT01] K. Yamanishi and J. Takeuchi, *Discovering outlier filtering rules from unlabeled data: combining a supervised learner with an unsupervised learner*, Proceedings of seventh ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2001, pp. 389–394. 67, 71, 73

[YTHH05] C. Yin, S. Tian, H. Huang, and J. He, *Applying genetic programming to evolve learned rules for network anomaly detection*, Advances in Natural Computation (2005), 445–445. 34

[YTWM04] K. Yamanishi, J.I. Takeuchi, G. Williams, and P. Milne, *On-line unsupervised outlier detection using finite mixtures with discounting learning algorithms*, Data Mining and Knowledge Discovery **8** (2004), no. 3, 275–300. 71, 73

[YXE00] N. Ye, M. Xu, and S.M. Emran, *Probabilistic networks with undirected links for anomaly detection*, Proceedings of IEEE Systems, Man, and Cybernetics Information Assurance and Security Workshop, 2000, pp. 175–179. 51

[YZB04] N. Ye, Y. Zhang, and C.M. Borror, *Robustness of the markov-chain model for cyber-attack detection*, IEEE T. Reliab. **53** (2004), no. 1, 116–123. 70

[Zan05] S. Zanero, *Analyzing TCP traffic patterns using self organizing maps*, Image Analysis and Processing, Lecture Notes in Computer Science, vol. 3617, Springer Berlin / Heidelberg, 2005, pp. 83–90. 63

[ZGGR05] Y. Zhang, Z. Ge, A. Greenberg, and M. Roughan, *Network anomography*, Proceedings of 5th ACM SIGCOMM conference on Internet Measurement, 2005, p. 30. 65, 76, 83

[ZH06] J. Zheng and M. Hu, *An anomaly intrusion detection system based on vector quantization*, IEICE Transactions on information and systems E series D **89** (2006), no. 1, 201–210. 65

[ZHR$^+$07] J. Zhou, M. Heckman, B. Reynolds, A. Carlson, and M. Bishop, *Modeling network intrusion detection alerts for correlation*, ACM Transactions on Information and System Security **10** (2007), no. 1, 4. 54

[ZJK05] C. Zhang, J. Jiang, and M. Kamel, *Intrusion detection using hierarchical neural networks*, Pattern Recognition Letters **26** (2005), no. 6, 779–791. 49

[ZKS07] S. Zhong, T.M. Khoshgoftaar, and N. Seliya, *Clustering-based network intrusion detection*, International Journal of Reliability Quality and Safety Engineering **14** (2007), no. 2, 169. 61, 64, 68, 72

[ZPZC01] D. Zhu, G. Premkumar, X. Zhang, and C.H. Chu, *Data mining for network intrusion detection: A comparison of alternative methods*, Decision Sciences **32** (2001), no. 4, 635–660. 36, 39, 47

[ŻR06] P. Żuraniewski and D. Rincón, *Wavelet transforms and change-point detection algorithms for tracking network traffic fractality*, Proceedings of 2nd Conference on Next Generation Internet Design and Engineering, IEEE, 2006, pp. 216–223. 43, 81

[ZS04] S. Zanero and S.M. Savaresi, *Unsupervised learning techniques for an intrusion detection system*, Proceedings of 2004 ACM symposium on Applied computing, ACM, 2004, pp. 412–419. 60, 63

[ZS05] Z. Zhang and H. Shen, *Application of online-training svms for real-time intrusion detection with different considerations*, Comput. Commun. **28** (2005), no. 12, 1428–1442. 58

[ZS08] S. Zanero and G. Serazzi, *Unsupervised learning algorithms for intrusion detection*, Proceedings of IEEE Network Operations and Management Symposium, IEEE, 2008, pp. 1043–1048. 64

[ZSGK08] M. Zink, K. Suh, Y. Gu, and J. Kurose, *Watch global, cache local: YouTube network traffic at a campus network: measurements and implications*, Proceedings of SPIE **6818** (2008), 681805. 2

[ZZL05] J.L. Zhao, J.F. Zhao, and J.J. Li, *Intrusion detection based on clustering genetic algorithm*, Proceedings of International Conference on Machine Learning and Cybernetics, vol. 6, IEEE, 2005, pp. 3911–3914. 32

List of Publications

Publications Directly Related to this Thesis

1. Felipe Mata, Javier Aracil, and José Luis García-Dorado, "Automated Detection of Load Changes in Large-Scale Networks," in *Proceedings of International Workshop on Traffic Monitoring and Analysis,* Aachen (Germany), May 2009. Published in Lecture Notes in Computer Science, Vol. 5537, pp. 34–41, Springer Verlag.
   Chapter 3 in this thesis.

2. Felipe Mata and Javier Aracil, "Performance evaluation of an Online Load Change Detection Algorithm," in *Proceedings of International Conference on Computer and Automation Engineering, vol. 1,* Singapore (Republic of Singapore), February 2010, pp. 261–266.
   Chapter 3 in this thesis.

3. Felipe Mata, José Luis García-Dorado, and Javier Aracil, "Multivariate Fairly Normal Traffic Model for Aggregate Load in Large-Scale Data Networks," in *Proceedings of Wired/Wireless Internet Communications,* Luleå (Sweden), June 2010. Published in Lecture Notes in Computer Science, Vol. 6074, pp. 278–289, Springer Verlag.
   Chapter 3 in this thesis.

4. Felipe Mata, José Luis García-Dorado and Javier Aracil, "On the Suitability of Multivariate Normal Models for Statistical Inference Based on Traffic Measurements," in *Passive and Active Measurement conference,* Zurich (Switzerland), April 2010, Poster Session.
   Chapter 3 in this thesis.

5. Felipe Mata, José Luis García-Dorado, and Javier Aracil, "Caracterización temporal de las demandas de ancho de banda en enlaces con alta agregación mediante un modelo normal multivariante," in *Actas de las IX Jornadas de Ingeniería Telemática,* Valladolid (Spain), October 2010.
   Chapter 3 in this thesis.

6. Felipe Mata, José Luis García-Dorado, and Javier Aracil, "Detection of traffic changes in large-scale backbone networks: The case of the Spanish academic network," *Computer Networks*, **56** (2) (2012), pp. 686–702.
   Chapter 3 in this thesis.

7. Felipe Mata, Piotr Żuraniewski, Michel Mandjes and Marco Mellia, "Anomaly Detection in VoIP Traffic with Trends," accepted for its publication in *Proceedings of 24th International Teletraffic Congress,* Krakow (Poland), September 2012.
   Chapter 4 in this thesis.

Publications in Topics Related to this Thesis

8. Felipe Mata, José Luis García-Dorado, Javier Aracil, and Jorge López de Vergara "Factor analysis of Internet traffic destinations from similar source networks," *Internet Research*, **22** (1) (2012), pp. 29-56.

9. Felipe Mata, Roberto González-Rey, José Luis García-Dorado, and Javier Aracil, "On the Real Impact of Path Inflation in Networks Under Production," accepted for its publication in *Proceedings of TRaf-*

fic Analysis and Classification Workshop, Limassol (Cyprus), August 2012.

10. Antonio Cuadra, Felipe Mata, José Luis García-Dorado, Javier Aracil, Jorge López de Vergara, Francisco Javier Cortés, Pablo Beltrán, Eduardo de Mingo, and Ángel Ferreiro, "Traffic monitoring for assuring quality of advanced services in future Internet," in *Proceedings of Wired/Wireless Internet Communications*, Vilanova i la Geltrú (Spain), June 2011. Published in Lecture Notes in Computer Science, Vol. 6649, pp. 186–196, Springer Verlag.

11. Andreas Aurelius, Christina Lagerstedt, Iñigo Sedano, Sándor Molnár, Maria Kihl, and Felipe Mata, "TRAMMS: Monitoring the evolution of residential broadband Internet traffic," in *Proceedings of Future Network and Mobile Summit*, Florence (Italy), June 2010, pp. 1-9.

12. Andreas Aurelius, Christina Lagerstedt, Maria Kihl, Marcell Perényi, Iñigo Sedano, and Felipe Mata, "A Traffic analysis in the TRAMMS project," *Telekomunikacije magazine*, November 2009.

13. Antonio Cuadra, Ángel Ferreiro, Nuria Gómez, Felipe Mata, and Javier Ramos, "Monitorización de tráfico IP para el control de calidad de servicio en entornos convergentes," in *Actas de las XIX Jornadas Telecom I+D*, Madrid (Spain), November 2009.

Appendix A

Kolmogorov-Smirnov Test and Lilliefors' Correction

The Kolmogorov-Smirnov (KS) test is a quite general test to determine the equality of one-dimensional probability distributions. It can be used to compare two samples (two-sample KS test) or to compare a sample with a reference continuous probability distribution (one-sample KS test). In our study we have used the one-sample KS test variant. The hypothesis of the test is that the sample $X = x_1, x_2, \ldots, x_n$ comes from a continuous probability distribution given by $F(x)$. To proceed with the test the following three steps are needed.

1. Order sample values $x_{(1)}, x_{(2)}, \ldots, x_{(n)}$.

2. Compute the Empirical Cumulative Distribution Function (ECDF) $F_n(x)$ as follows
$$F_n(x) = \begin{cases} 0 & \text{if } x < x_{(1)} \\ \frac{r}{n} & \text{if } x_{(r)} \leq x < x_{(r+1)} \\ 1 & \text{if } x \geq x(n) \end{cases}$$

3. Compute the maximum discrepancy between the ECDF $F_n(x)$ and the hypothesized one $F(x)$ with the statistic
$$D_n = max|F_n(x) - F(x)| \tag{A.1}$$

> which distribution, under the null hypothesis, has been tabulated [RS94]. If once fixed α, the computed D_n is greater than the tabulated value, the null hypothesis is rejected.

However, if the theoretical distribution function $F(x)$ is computed by estimating the parameters from the sample, the distribution of D_n is only an approximation, thus the power of the test is reduced [Ste74], and the results of the test are very conservative because the used critical values are invalid—see [Dur73]. The Lilliefors test arises when correcting for this bias in the normal case. So, Lilliefors [Lil67] computed the distribution of D_n when the parameters of the normal distribution (μ, σ^2) are estimated by the sample parameters $(\bar{x}, \hat{s}^2)$ and tabulated it [She04].

Appendix B

Behrens-Fisher Problem

The Behrens-Fisher problem is the statistical problem of testing whether the means of two normally distributed populations ($X^{(1)}, X^{(2)}$) are the same (null hypothesis H_0) or not (alternative hypothesis H_1) when the variances of the populations are unknown—i.e., it cannot be assumed that both variances are equal. In this Appendix, we present the most popular solutions to this problem in the univariate (Section B.1) and multivariate (Section B.2) cases.

B.1 Univariate Behrens-Fisher Problem

A similar problem to the Behrens-Fisher problem, but simpler, is the statistical problem of testing whether the means of two normally distributed populations ($X^{(1)}, X^{(2)}$) are the same *when the variances are equal.* The solution to this problem is well-known and uses the two-sample Student's t-test. The assumptions are that $X^{(i)} \sim \mathcal{N}(\mu^{(i)}, \sigma^{(i)}), i = 1, 2$; i.e. the samples of population i come from a univariate normal distribution with mean $\mu^{(i)}$ and variance $\sigma^{(i)}$. The t statistic to test whether the means are different under the equality of variances assumption can be calculated as follows:

$$t = \frac{\bar{X}^{(1)} - \bar{X}^{(2)}}{s_{X^{(1)}X^{(2)}}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, \tag{B.1}$$

where

$$s_{X^{(1)}X^{(2)}} = \sqrt{\frac{(n_1-1)s^2_{X^{(1)}} + (n_2-1)s^2_{X^{(2)}}}{n_1+n_2-2}} \tag{B.2}$$

and n_i, $\bar{X}^{(i)}$ and $s^2_{X^{(i)}}$ are respectively the sample size, sample mean and sample variance of population $X^{(i)}$, $i = 1, 2$. The statistic (B.1) is distributed according a Student's t-distribution with $\nu = n_1 + n_2 - 2$ degrees of freedom.

The most popular solution to the univariate Behrens-Fisher problem is the approximation proposed by Welch [Wel38]. This approximation, popularly kwnon as Welch's t-test, is an adaptation of Student's t-test, as follows:

$$w = \frac{\bar{X}^{(1)} - \bar{X}^{(2)}}{\sqrt{\frac{s^2_{X^{(1)}}}{n_1} + \frac{s^2_{X^{(2)}}}{n_2}}}, \tag{B.3}$$

which follows a Student's t-distribution with ν' degrees of freedom under the null hypothesis. Unlike in Student's t-test, the denominator is not based on a pooled variance estimate. The degrees of freedom ν' associated with this variance estimate is approximated using the Welch-Satterthwaite equation:

$$\nu' = \frac{\left(\frac{s^2_{X^{(1)}}}{n_1} + \frac{s^2_{X^{(2)}}}{n_2}\right)^2}{\frac{s^4_{X^{(1)}}}{n_1^2(n_1-1)} + \frac{s^4_{X^{(2)}}}{n_2^2(n_2-1)}} \tag{B.4}$$

We use Welch's t-test in Section 3.6 for the evaluation of changes in the mean of each vector component individually. Once the w-statistic is computed, the statistical test at level α proceeds by comparing the obtained w value with the $1-\alpha$ percentile of the Student's t-distribution with ν' degrees of freedom. We denote this percentile by $t^{1-\alpha}_{\nu'}$. Then, the null hypothesis is rejected if $w > t^{1-\alpha}_{\nu'}$.

B.2 Multivariate Behrens-Fisher Problem

The generalization of the Behrens-Fisher Problem to multivariate data is known as the Multivariate Behrens-Fisher Problem (MBFP) [And58], which we use in the methodology presented in Chapter 3. The assumptions are that $\boldsymbol{X}^{(i)} \sim \mathcal{N}_p(\boldsymbol{\mu}^{(i)}, \Sigma^{(i)}), i = 1, 2$; i.e. the samples of population i come from a p-variate normal distribution with mean vector $\boldsymbol{\mu}^{(i)}$ and covariance matrix $\Sigma^{(i)}$, where in our case $p = 16$[1]. To solve this problem the Hotelling's T^2 statistic is used, and two different cases arise depending on the sizes of the populations. If both populations have the same number of samples n, and the numbering of the samples does not depend on the samples themselves, the procedure is to form a new random variable $\boldsymbol{Y}$ that is the difference of the initial populations, i.e. $\boldsymbol{y}_j = \boldsymbol{x}_j^{(1)} - \boldsymbol{x}_j^{(2)}, j = 1, 2, \ldots, n$. For this new random variable (that under the null hypothesis has zero mean) the sample mean vector $\bar{\boldsymbol{Y}}$ and the sample covariance matrix $S_{\boldsymbol{y}}$ are computed. The T^2-statistic in this case is as follows:

$$T^2 = n\frac{\bar{\boldsymbol{Y}} S_{\boldsymbol{y}}^{-1} \bar{\boldsymbol{Y}}^t}{n-1}\frac{n-p}{p}, \tag{B.5}$$

where $\bar{\boldsymbol{Y}}^t$ denotes the transpose vector of $\bar{\boldsymbol{Y}}$. It can be shown (see chapter 5 of [And58]) that under the null hypothesis T^2 follows a noncentral F distribution with p and $n-p$ degrees of freedom and noncentrality parameter

$$\eta = (\boldsymbol{\mu}^{(1)} - \boldsymbol{\mu}^{(2)}) \Sigma_{\boldsymbol{y}}^{-1} (\boldsymbol{\mu}^{(1)} - \boldsymbol{\mu}^{(2)})^t. \tag{B.6}$$

Under the null hypothesis, $\boldsymbol{\mu}^{(1)} = \boldsymbol{\mu}^{(2)}$, so $\eta = 0$. As the noncentrality parameter is zero, the distribution of equation (B.5) turns out to be a Snedecor's $\mathcal{F}$ distribution.

On the other hand, when the sizes of the populations are not equal, a transformation is needed before computing the T^2-statistic. If the sizes of $\boldsymbol{X}^{(1)}$ and $\boldsymbol{X}^{(2)}$ are respectively n_1 and n_2, assuming that $n_1 < n_2$ without loss of generality, we obtain a new random variable $\boldsymbol{Q}$ through the following

[1] We use bold font to denote vectors, and capital letters to denote matrices except for the Hotelling's statistic, that we use a capital letter to indicate that it corresponds to the multivariate version of the problem.

transformation, as follows:

$$\boldsymbol{q}_j = \boldsymbol{x}_j^{(1)} - \sqrt{\frac{n_1}{n_2}}\boldsymbol{x}_j^{(2)} + \frac{1}{\sqrt{n_1 n_2}}\sum_{k=1}^{n_1}\boldsymbol{x}_k^{(2)} - \frac{1}{n_2}\sum_{l=1}^{n_2}\boldsymbol{x}_l^{(2)}, \quad j = 1, \cdots, n_1, \tag{B.7}$$

where $\boldsymbol{x}_k^{(1)}$, $k = 1, 2, \cdots, n_1$, are the samples of $\boldsymbol{X}^{(1)}$ and $\boldsymbol{x}_m^{(2)}$, $m = 1, 2, \cdots, n_2$, are the samples of $\boldsymbol{X}^{(2)}$. As shown by [And58], this new random variable has a mean vector equal to the difference of the mean vectors of the two populations, and the covariance matrix is given by the following equation:

$$Cov(\boldsymbol{q}_k, \boldsymbol{q}_m) = \mathbb{E}[\boldsymbol{q}_k - \mathbb{E}[\boldsymbol{q}_k]] \cdot \mathbb{E}[\boldsymbol{q}_m - \mathbb{E}[\boldsymbol{q}_m]] = \delta_{k,m}(\Sigma^{(1)} + \frac{n_1}{n_2}\Sigma^{(2)}), \tag{B.8}$$

where $\delta_{k,m}$ is the Dirac delta function evaluated in $k - m$ and $\mathbb{E}$ is the Expectation Operator. The T^2-statistic in this case is as follows:

$$T^2 = n_1 \frac{\bar{\boldsymbol{Q}} S_{\boldsymbol{q}}^{-1} \bar{\boldsymbol{Q}}^t}{n_1 - 1} \frac{n_1 - p}{p}. \tag{B.9}$$

As in the previous case, equation (B.9) is distributed under the null hypothesis as a Snedecor's $\mathcal{F}$ distribution with p and $n_1 - p$ degrees of freedom.

Once the T^2 statistic is computed taking into account the case that applies of the above described, the statistical test at level α proceeds by comparing the obtained T^2 value with the $1 - \alpha$ percentile of the Snedecor's $\mathcal{F}$ distribution with the appropriate degrees of freedom. If the degrees of freedom are p and m, we denote this percentile by $F_{p,m}^{1-\alpha}$. Then, the null hypothesis is rejected if $T^2 > F_{p,m}^{1-\alpha}$.

Appendix C

Analysis of Hotelling's T^2 Statistic

In this appendix we present an analysis of Hotelling's T^2 statistic, given by equation (B.5), to further understand why a change is reported using the Multivariate Behrens-Fisher Problem (MBFP), in order to apply our conclusions when we deeply inspect the output of the algorithm at a fixed significance level using synthetically generated input in Section 3.4.3. The statistic follows a $\mathcal{F}$-distribution with p and $n - p$ degrees of freedom under H_0, where we assume that both populations have the same size n to simplify computations.

The term $\mathbf{Y} S_{\boldsymbol{y}}^{-1} \mathbf{Y}^T$ is a quadratic form of the p vector components of the random vector $\mathbf{Y}$. As we are using synthetic data, we can approximate the covariance matrix used to generate the samples as follows. Such matrix has been chosen to be diagonal—remember that the vector components are independent. This implies that the quadratic form is the weighted sum of the square of all the vector components—being the weights given by the elements of the diagonal of the covariance matrix. In the simplest case, all the vector components have the same variance, so the covariance matrix is a multiple of the identity matrix. Assuming all the vector components of $\mathbf{Y}$ are equal to $\hat{y}$, this yields

$$\begin{aligned} T^2 &= n\frac{\mathbf{Y}S_{\boldsymbol{y}}^{-1}\mathbf{Y}^T}{n-1}\frac{n-p}{p} \approx n\frac{\mathbf{Y}\frac{1}{\sigma^2}I_p\mathbf{Y}^T}{n-1}\frac{n-p}{p} = \frac{n}{n-1}\frac{n-p}{p}\sum_{i=1}^{p}\frac{y_i^2}{\sigma^2} \\ &\approx \frac{n}{n-1}\frac{n-p}{p}\frac{p\hat{y}^2}{\sigma^2} = n\frac{n-p}{n-1}\frac{\hat{y}^2}{\sigma^2}. \end{aligned} \tag{C.1}$$

If we set a fixed value for the significance level $\alpha = \alpha_0$, we are comparing the value obtained from (B.5) against a value that is a function of n—given that the dimension of the random vector p is also fixed. This function is the 1-α_0 percentile of Snedecor's $\mathcal{F}$-distribution with p and $n-p$ degrees of freedom—we use $F_{p,n-p}^{1-\alpha_0}$ to denote this percentile. We reject H_0 if the T^2 statistic value is greater than the value of the function evaluated in that n, which is equivalent to

$$\frac{\hat{y}^2}{\sigma^2} > \frac{F_{p,n-p}^{1-\alpha_0}}{n}\frac{n-1}{n-p}. \tag{C.2}$$

However, if we do not assume such simplifications (i.e., that the covariance matrix is not a scaled version of the identity matrix, but it is still diagonal, and all vector components of $\mathbf{Y}$ are not necessarily equal), we reach to a more general version of condition (C.2), given that T^2 satisfies:

$$T^2 = n\frac{\mathbf{Y}S_{\boldsymbol{y}}^{-1}\mathbf{Y}^T}{n-1}\frac{n-p}{p} \approx \frac{n}{n-1}\frac{n-p}{p}\sum_{i=1}^{p}\frac{y_i^2}{\sigma_i^2} = \frac{n}{n-1}\frac{n-p}{p}\sum_{i=1}^{p}w_i y_i^2, \tag{C.3}$$

with the weights of vector component i, w_i, being equal to the inverse of the variance of variable i

$$w_i = \frac{1}{\sigma_i^2}. \tag{C.4}$$

Consequently, the general form of condition (C.2) is as follows:

$$\sum_{i=1}^{p} w_i y_i^2 > \frac{F_{p,n-p}^{1-\alpha_0}}{n}\frac{n-1}{n-p}p = CV. \tag{C.5}$$

If condition (C.5) is satisfied, it is possible that there exists a subset $\mathfrak{I}$ of the set of index I in the summation of the left hand side such that

$$\sum_{i=1}^{p} w_i y_i^2 > \sum_{i \in \mathfrak{I}} w_i y_i^2 > \frac{F_{p,n-p}^{1-\alpha_0}}{n} \frac{n-1}{n-p} p. \tag{C.6}$$

Consequently, it is possible that a change is reported when there are significant changes only in a subset of the vector components, i.e., if we take into account a single variable $i \notin \mathfrak{I}$, chances are that a change is not observable in such subspace, although the test methodology reports a change due to the differences in the vector components $i \in \mathfrak{I}$.

Table C.1: Rejecting values for the quotient between the square of the change in one vector component and its variance.

$\boldsymbol{n}$	$\boldsymbol{n-p}$	$\boldsymbol{CV}$	$\boldsymbol{n}$	$\boldsymbol{n-p}$	$\boldsymbol{CV}$
17	1	231.9660	22	6	0.6240
18	2	9.1768	23	7	0.4775
19	3	2.7449	24	8	0.3835
20	4	1.3880	25	9	0.3188
21	5	0.8769	26	10	0.2719

Finally, we present in Table C.1 the critical values for the first ten suitable values of n—note that $n > p$ is required in order to ensure the matrix $S_{\boldsymbol{y}}$ is invertible.

Appendix D

Affine Transformations

In this appendix, we provide the Matlab code that we used to generate the four different affine transformations applied to generate the controlled datasets used in the validation of the proposed algorithm (Section 3.4.3).

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%   Synthetic data generator
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear all
N = 9000; %Sample size
p = 16; %Vector dimension
X = randn(N,p); %Random sample of standard multinormal

%% all the vector components equally distributed
mu = 100*ones(N,p); %mean vector
sigma = diag(10*ones(1,p)); %covariance matrix
[B,D] = eig(sigma);
A = B*sqrt(D);
allEqual = mu+X * A’; %affine transformation


%% all vector components equally distributed but with
% different means
```

```
mu = ones(N,1)*linspace(50,150,p); %mean vector
sigma = diag(10*ones(1,p)); %covariance matrix
[B,D] = eig(sigma);
A = B*sqrt(D);
means = mu + X * A'; %affine transformation


%% all vector components equally distributed but with
% different variance
mu = 100*ones(N,p); %mean vector
sigma = diag(10*linspace(0.5,1.5,p));%covariance matrix
[B,D] = eig(sigma);
A = B*sqrt(D);
variances = mu +X*A'; %affine transformation


%% all vector components equally distributed but with
% different mean and variance
mu = ones(N,1)*linspace(50,150,p); %mean vector
sigma = diag(10*linspace(0.5,1.5,p));%covariance matrix
[B,D] = eig(sigma);
A = B*sqrt(D);
meansVariances = mu +X*A'; %affine transformation
```

Index