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A Contextual Modeling Approach for Model-based Recommender Systems

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Abstract. In this paper we present a contextual modeling approach for model-based recommender systems that integrates and exploits both user preferences and contextual signals in a common vector space. Differently to previous work, we conduct a user study acquiring and analyzing a variety of realistic contextual signals associated to user preferences in several domains. Moreover, we report empirical results evaluating our approach in the movie and music domains, which show that enhancing model-based recommender systems with time, location and social companion information improves the accuracy of generated recommendations.

Keywords: context-aware recommendation, contextual modeling, model-based recommender systems.

1 Introduction

Recommender Systems (RS) are software tools that provide users with suggestions of items that should be the most appealing based on personal preferences (tastes, interests, goals). Main strategies of RS are *content-based filtering* (CBF), which recommends items similar to those preferred by the user in the past, and *collaborative filtering* (CF), which recommends items preferred in the past by people who are similar-minded to the user. To overcome particular limitations, CBF and CF are commonly combined in the so-called *hybrid filtering* (HF) strategies [3,7].

For any of the above strategies, recommendation approaches can be classified as *heuristic-based* or *model-based* [3,6]. Heuristic-based approaches utilize explicit heuristic formulas that aggregate collected user preferences to compute item relevance predictions. Model-based approaches, in contrast, utilize collected user preferences to build (machine learning) models that, once built, provide item relevance predictions. In this way, model-based approaches lead to faster responses at recommendation time.

In its basic formulation, recommender systems do not take into account the *context* –e.g. time, location, and social companion– in which the user experiences an item. It has been shown, however, that context may determine or affect the user's preferences when selecting items for consumption [9]. Those RS that somehow exploit contextual information are called context-aware recommender systems (CARS). Adomavicius et al. [2,4], classify them as *contextual pre-filtering*, *contextual post-filtering*, and *contextual modeling* approaches. Contextual pre- and post-filtering approaches are based on context-unaware recommendation methods, which are applied on pre-processed preference data, or are used to generate recommendations that are post-adjusted, in both cases according to the user's current context. Contextual modeling, on the contrary, extends the user-item preference relations with contextual information to compute recommendations.

Researchers have shown that CARS provide more accurate recommendations than context-unaware RS [5,11]. Nevertheless, context-aware recommendation is a relatively unexplored area, and still needs a much better comprehension [4]. For instance, analyzing which are the characteristics and values of distinct contextual signals –alone or in combination– that really influence recommendation performance improvements is an important open research issue. Some researchers have conducted studies on context-aware recommendation comparing different approaches [13,14,15], but little work has been done at the contextual signal level. Moreover, in general, reported studies have focused on individual domains, without analyzing the generalization of the proposed approaches for several domains.

A major difficulty to address the above issues is the current lack of available real context-enriched data. A method for obtaining contextual data is to automatically infer the context in which the user experiences an item, e.g. by capturing time and location signals. In general, this approach has been used in CARS research to capture context data (usually timestamps) when users rate items. However, it is important to note that if a system collects ratings instead of consumption/purchase records, the captured contexts do not necessarily correspond to the real contexts that affect or determine the user's (contextualized) preferences for items.

In this paper we present a *contextual modeling* approach for *model-based RS* that integrates both user preferences and contextual signals in a common vector space, and, being a *hybrid recommendation* approach, exploits content-based user preferences in a collaborative filtering fashion. Differently to previous work, we conduct a user study acquiring and analyzing a variety of realistic contextual signals associated to user preferences in several domains. Moreover, we report empirical results evaluating our approach in the movie and music domains, which show that enhancing model-based recommender systems with time, location and social companion information improves the accuracy of generated recommendations.

The remainder of the paper is structured as follows. In Section 2 we discuss related work. In Section 3 we present our contextual modeling approach for integrating user preferences and contextual signals. In Section 4 we describe the user study and analysis performed, and in Section 5 we report the recommendation results obtained. Finally, in Section 6 we provide some conclusions and future research directions for our work.

2 Related work

Quoting Dey [8], "context is any information that can be used to characterize the situation of an entity." In information retrieval and filtering systems, an entity can be a user, an (information) item, or an experience the user is evaluating [5], and any signal –such as device, location, time, social companion, and mood– regarding the situation in which a user interacts with an item can be considered as context.

Context-aware recommender systems exploit contextual information to provide differentiated recommendations according to the user's current situation. Based on how such contextual information is exploited, three types of context-aware recommendation approaches can be distinguished [4]: *contextual pre-filtering approaches* –which prune, split and/or group available user preference data according to the target context, before applying a context-independent recommendation algorithm–, *contextual post-filtering approaches* –which apply a context-independent recommendation algorithm on the original user preference data, and afterwards adapt the generated recommendations according to the target context–, and *contextual modeling* –which incorporate contextual information into the algorithm that generates recommendations.

In this paper we focus on contextual modeling, since it lets effectively extend and exploit the user-item relations with several contextual signals, without the need of discarding (valuable) data or adapting generated recommendations for providing contextualized recommendations.

One of the first contextual modeling approaches was presented in [12], where Oku et al. incorporated several contextual signals –including time, social companion, and weather– into a Support Vector Machine model for restaurant recommendation. Yu et al. [16] modeled situation context (in which the user utilizes/consumes an item) and capability context (in which the current capacity of the utilized device is specified) to provide media recommendations in smart phones. These contexts are incorporated into content-based Bayesian and rule-based recommendation approaches. Abbar et al. [1] proposed a conceptualization of context-aware recommendation based on an architecture composed of various context-based personalization services, including context discovery, binding and matching services. In the proposed architecture, context clusters are formed by analyzing user activity logs to describe regular contexts or situations, such as "at home" and "at work." Koren [11] extended the Matrix Factorization model incorporating temporal context information for movie rating prediction. The time signal was indeed argued as a key factor by the winning team of the well-known Netflix Prize competition. Finally, Karatzoglou et al. [10] used Tensor Factorization to model *n*-dimensional contextual information. The approach was called multiverse recommendation because of its ability to bridge data pertaining to different contexts (universes of information) into a unified model.

In the literature, most of the work on context modeling for recommendation focuses on individual domains, exploits a single contextual signal, and/or evaluates approaches in terms of performance recommendation improvements due to the consideration of contextual signals, without analyzing and characterizing the context values that really determine such improvements. Differently, in this paper we conduct a user study aimed to acquire and evaluate a variety of realistic contextual signals associated to the users' preferences in several domains, and present an analysis of recommendation improvements for the different values of the contextual signals when they are exploited alone or in combination.

3 Contextual Modeling in Model-based Recommender Systems

We address the contextual modeling problem from a machine learning perspective. Specifically, we propose to represent both user preferences and contextual signals in a common vector space. The dimensions of the considered vector space are content-based attributes associated to user preferences and item features, and context-based attributes associated to user-item preference relations. Hence, as shown in Figure 1, a preference relation $p(u,i)$ between user $u \in \mathcal{U}$ and item $i \in \mathcal{I}$ is defined as a pattern:

$$p(u,i) \equiv \langle f_1(u), \dots, f_M(u), g_1(i), \dots, g_N(i), h_1(u,i), \dots, h_K(u,i); r \rangle$$

where $f_m(u): \mathcal{U} \to \mathbb{R}$ gives a numeric value that indicates the preference of user u for (items with) a content attribute a_m; $g_n(i): \mathcal{I} \to \mathbb{R}$ gives a numeric value that indicates the importance of a (content) attribute a_n for describing item i; $h_k(u,i): \mathcal{U} \times \mathcal{I} \to \{0,1\}$ is 1 if a contextual signal c_k is active in the preference of user u for item i, and 0 otherwise; and $r \in \{0,1\}$ is the preference relevance of user u for item i, being 1 if user u prefers/likes item i (for the context values $h_1(u,i), \dots, h_K(u,i)$), and 0 otherwise.

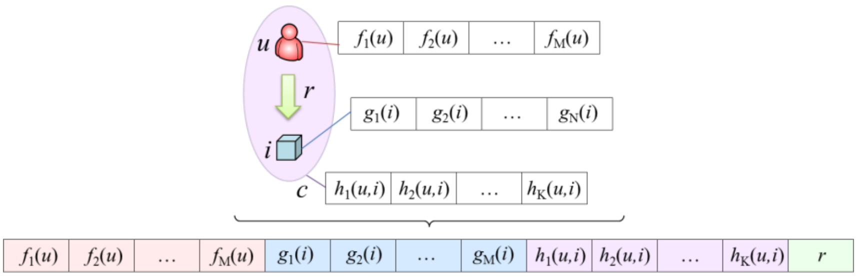

Figure 1. A user-item preference relation as a pattern of content- and context-based attributes.

In the user study presented in this paper, for the movie and music domains, we considered the content- and context-based attributes shown in Table 1. For each user u, the value $f_m(u)$ of a content-based attribute a_m was the number of u's liked/preferred items with a_m. For each item i, the value $g_n(i)$ of a content-based attribute a_n was 1 if i had the attribute, and 0 otherwise.

Table 1. Attributes in the movie and music domains considered in the user study.

Domain	Attribute type	Attributes	
movies	*content-based (f, g)*	a user's preferred/liked genres	action, adventure, animation, comedy, crime, drama, family, fantasy, futuristic, historical, horror, melodrama, musical, mystery, neo noir, parody, romance, sci-fi, thriller, war
		a movie's genres	
	context-based (h)	day of the week	work day, weekend day, indifferent
		time of the day	morning, afternoon, night, indifferent
		social companion	alone, with my partner, with my family, with friends, indifferent
music	*content-based (f, g)*	a user's preferred/liked genres	60s, 70s, 80s, 90s, acoustic, ambient, blues, classical, electronic, folk, hip hop, indie, jazz, latin, metal, pop, punk, rnb, rock, soul
		a musician's genres	
	context-based (h)	day of the week	work day, weekend day, indifferent
		time of the day	morning, afternoon, night, indifferent
		location	at home, at work, at the car/bus, at the bar/disco, indifferent

The set of attribute patterns (collected in the user study) was then used to build and evaluate a number of well-known classifiers, namely Naïve Bayes, Random forest, Multilayer Perceptron, and Support Vector Machine. In this way, preferences of individual users were exploited in a collaborative way, and the classifiers can be considered as model-based hybrid recommender systems.

Analyzing the collected patterns, in Section 4 we present relations existing between user preferences for movie/music genres and the considered contexts. Next, in Section 5 we present an evaluation on the effect of exploiting or discarding contextual information by the recommender systems.

4 Analyzing Contextualized User Preferences

To evaluate our contextual modeling approach with realistic context information associated to user preferences at item consumption time, we built an online evaluation tool[1], where users were presented with sets of movies or musicians (no combinations of both), and were requested to freely provide personal ratings for those movies they had watched and musicians they had listened to. To facilitate the evaluation, the users could select preferred movie and music genres and the language –English or Spanish– of the online evaluation, and skip any item they did not want to evaluate. For both the movie and music domains, 20 genres (shown in Tables 2 and 3) were used as user preferences and item features.

A total of 72 users, recruited via social networking sites, participated in the study, evaluating 178 movies and 132 musicians, generating 713 evaluation cases. In each evaluation case, a target user assigned to an item (movie or musician) an integer rating in the range [1, 10], and specified the context (h attribute values in Table 1) in which she preferred to consume the item. In the offline analysis, the preference relevance $r \in \{0,1\}$ of an evaluation case was set in two ways: a) r was set to 1 if the rating was greater or equal than 7, taking into account that the average ratings of all users (*community*) in the movie and music domains were 7.26 and 7.48, respectively; and b) r was set to 1 if the rating was greater or equal than the target *user*'s average rating.

4.1 Analysis of Contextualized User Preferences in the Movie Domain

Table 2 depicts the distribution of contextualized movie preferences of the users who participated in our study. The table relates the considered 20 movie genres with the time and social companion contexts. Each cell in the table has a numeric value that is the number of users who liked (i.e., assigned a rating greater or equal to 7) a movie belonging to the corresponding genre in a particular context, discarding cases in which a movie genre was preferred by only one user in the given context. The green/red arrows indicate the most/least liked movies in work and weekend days. The circles reflect the relative popularity of the genres in the *time of the day* (morning/ afternoon/night) context.

From the table, interesting observations can be made. Regarding the *day of the week* context, comedy, adventure and fantasy movies are watched in any day,

[1] Online evaluation tool, http://ir.ii.uam.es/emotions

showing the users' majority like for movies evoking positive emotions. In contrast, science-fiction, futuristic and thriller genres are preferred in work days, and family and romance genres are preferred in the weekends (when kids, couples and whole families tend to watch movies together at home or at the cinema). This may mean that people tend to like tense, brainy and sophisticated movies in the work days, and more calm, easy-going and emotional movies in the weekends. Regarding the *time of the day* context, some genres show quite significant differences. Science-fiction and thriller movies are preferred in the morning and afternoon; action and drama movies, in the afternoon; and adventure, musical and romance movies, at night. Finally, regarding the *social companion* context, it is worth noting that the users preferred to watch movies alone in work days, while seem to watch movies with relatives and friends in the weekends. This may be of special interest in the design of time-aware group recommender systems.

Table 2. Summary of the users' preference distribution for movie genres in the considered time and social companion contexts.

MOVIES	action	adventure	animation	comedy	crime	drama	family	fantasy	futuristic	historical	horror	melodrama	musical	mystery	neo noir	parody	romance	sci-fi	thriller	war
Work day	⇨	⇧	⇨	⇧	⇩	⇨	⇨	⇧	⇨	⇩	⇩	⇩	⇩	⇩	⇩	⇩	⇩	⇧	⇨	⇩
Morning	◑	●	◑	◕	○	◔	◑	●	◑	○	○	○	○	○	○	○	○	●	◔	○
Alone	39	58	27	41	2	18	28	48	28	2	5	4	4	7	6	5	12	52	20	4
With my partner	3	3	2	2			2											2		
With my family		11	8	12			10	11								2	4			
With friends		2		3				3	4					2				6	3	
Afternoon	◕	◑	○	◔	◔	◑	○	◑	◕	○	○		○	◔	○		○	●	◕	
Alone	15	20	5	9	11	20	3	18	18		3		2	12	5		4	30	18	
With my partner	4	2		2				4	6		3							6	4	
With my family	5	4	3	3	2	3	3	3											3	
With friends	6	2				5		3	9	2	2			4	3			12	11	
Night	◔	●	◑	◕		○	●	●				○	○			○	○	○		
Alone	6	10	5	6		4	8	11				3	2				2	5		
With my partner				2												2				
With my family		8	6	7			8	8								3	3			
With friends		2		2			2	2												
Weekend day	⇨	⇧	⇨	⇧	⇩	⇩	⇧	⇧	⇩	⇩	⇩	⇩	⇩	⇩	⇩	⇩	⇨	⇩	⇩	⇩
Morning	○	●		○		◔	○	○												
Alone	2	3				3														
With my family		2		2			2	2												
Afternoon	●	●	◔	◕	○	◔	◔	◕	◑	○	○		○	○	○	○	◔	◕	◑	○
Alone	7	9	2	3		6	2	7	5	3	2						2	7	3	3
With my partner	17	18	4	11	2	5	3	16	10	4	5		3	4		2	6	12	8	3
With my family	5	10	6	7			6	6	2									6		
With friends	5	5		6	5	4		4	3					2	2		7	4	7	
Night	○	●	◕	◕	○	○	●	●	○	○		○	◔	○		○	◔	○	○	○
Alone	7	16	6	6		8	8	13	2	6		3	3	2			3	4		6
With my partner	7	30	28	26	2		30	25					10			4	12	3	2	
With my family	4	50	36	43		6	50	45	3	4		4	15			9	18	6		2
With friends		4	3	3			3	4								2	4			

4.2 Analysis of Contextualized User Preferences in the Music Domain

Analogously to Table 2 for the movie domain, Table 3 depicts the distribution of contextualized music preferences of the users who participated in our study. The table relates the considered 20 music genres with the time and location contexts. The meaning of numeric values, arrows and circles is the same as in Table 2.

In the music domain, we can make the following observations. Regarding the *day of the week* context, it can be seen that people stated their music preferences mostly for work days. The diversity of liked music genres is also higher in work days than in the weekends, when 80s-90s, electronic, rock, pop and Latin (American) music genres are the most preferred. Regarding the *time of the day* context, as one may expect, people mostly prefer listen to music during the morning (in work days, at work), and during the afternoon (in the weekends, at home). In general, for a particular music genre, and without taking the listening frequencies into account, no significant preference differences are observed among day time periods. Finally, regarding the *location* context, apart from the fact that people tend to listen to music at work in work days, and at home in the weekends, we could highlight that at a bar/disco, people prefer listening to indie, pop and rock music than other music genres.

Table 3. Summary of the users' preference distribution for music genres in the considered time and location contexts.

MUSIC	60s	70s	80s	90s	acoustic	ambient	blues	classical	electronic	folk	hip hop	indie	jazz	latin	metal	pop	punk	rnb	rock	soul
Work day	⇩	⇨	⇨	⇨	⇩	⇩	⇩	⇩	⇩	⇩	⇩	⇨	⇩	⇩	⇩	⇧	⇩	⇩	⇧	⇩
Morning	○	◔	◑	◕	○	○	○	○	○	○	○	◑	○	◔	○	●	○	○	●	○
At home			3	3								2			2	6	2		6	
At work	7	26	36	39	4	11	15	5	12	2	5	26	5	21	12	61	3	3	60	7
At the car/bus		2	5	5		3			3			3				8		3	4	
At the bar/disco	2		3	7	2	2		6	3			4				9		3	7	
Afternoon	○	◔	○				◔			○		○		○		◑			●	
At home			2											2		2			3	
At work		2					2									3			3	
At the bar/disco	2	4					3			2		3				3			7	
Night		○	○	○			○		○			●	○			◕			●	◔
At work		2										2				2			2	2
At the car/bus												2							2	
At the bar/disco			3	3			2		2			4	2			4			4	2
Weekend day		⇩	⇨	⇧		⇩			⇨		⇩	⇩		⇩		⇧		⇩	⇨	⇩
Afternoon		○	◑	●		○			◑		○	○		◔		●		○	◕	○
At home		5	23	34		7			18		3	3		12		35		7	21	3
At work																2			2	
At the bar/disco						2			2			3				3			3	
Night			○	◔										◔		●			◕	
At the bar/disco			2	3										3		5			4	

5 Evaluating Contextualized Recommendations

In this section we report results from an offline evaluation of a number of machine learning algorithms –namely Naïve Bayes, Random forest, Multilayer Perceptron (MLP), and Support Vector Machine (SVM) classifiers– built with user (movie/music) genre preferences, item (movie/music) genres, and (time, location, social companion) context values integrated by the contextual modeling approach presented in Section 3.

The classifiers were built with patterns associated to user-item preference relations. The attributes of a pattern corresponded to a user's favorite genres, an item's genres, and, in some configurations, the time and/or location/social companion context of the user-item preference relation. The pattern's class label was 1 if the user "liked" the item in the given context, and 0 otherwise, where "liked" means the user assigned to the item a rating equal or greater than 7 (*community average*), or a rating greater or equal than the user's average rating (*user average*).

The tables of this section show the best average (10-fold cross validation) performance values of the classifiers for the distinct user profile types. As commonly done in machine learning, we computed accuracy (percentage of patterns correctly classified) as the main measure for recommendation performance. Additionally, in order to take the pattern's class distribution into account, we also computed the geometric mean $g = \sqrt{acc^{+} \cdot acc^{-}}$ (being acc^{+} and acc^{-} the accuracy values on the majority/like and minority/dislike classes respectively), and the Area Under the ROC Curve (AUC).

5.1 Evaluation of Contextualized Recommendations in the Movie Domain

Table 4 shows the performance results of the recommendation models for the different user profile types in the movie domain. It can be seen that in general incorporating contextual information into the classifiers improves the overall acc and g values. In this case, the time context was the most influential to obtain better performance, and Random Forest was the best performing algorithm.

Table 4. Performance values of the model-based recommender systems built with the different user profile types (attribute configurations) in the movie domain. Global top values are in bold, and best values for each profile type are underlined.

Profile type	**Classifier**	**Community average**					**User average**				
		acc	**acc+**	**acc-**	**g**	**AUC**	**acc**	**acc+**	**acc-**	**g**	**AUC**
-	*Majority class*	71.4	100.0	0.0	0.0	49.3	57.2	100.0	0.0	0.0	49.2
genres	*Naïve Bayes*	73.6	96.3	16.8	40.2	62.8	54.8	83.6	16.3	36.9	50.8
	Random forest	76.9	90.6	42.9	62.3	71.9	59.6	68.5	47.8	57.2	60.7
	MLP	73.3	91.6	27.7	50.4	67.1	53.4	60.5	43.8	51.5	52.1
	SVM	70.4	82.2	41.2	58.2	61.7	55.5	75.6	28.7	46.6	52.1
genres + time contexts	*Naïve Bayes*	73.8	96.3	17.6	41.2	63.5	55.5	81.5	20.8	41.2	52.7
	Random forest	**77.4**	91.2	42.9	**62.5**	**74.5**	**63.9**	70.2	55.6	**62.5**	**66.3**
	MLP	74.0	90.9	31.9	53.9	68.5	57.2	62.2	50.6	56.1	58.1
	SVM	70.7	80.5	46.2	61.0	63.3	55.5	74.8	29.8	47.2	52.3
genres + companion context	*Naïve Bayes*	73.3	96.0	16.8	40.2	62.9	53.6	80.3	18.0	38.0	51.0
	Random forest	74.0	89.2	36.1	56.8	70.9	60.1	69.7	47.2	57.4	61.6
	MLP	72.8	90.2	29.4	51.5	66.7	56.0	60.9	49.4	54.9	57.4
	SVM	69.5	79.1	45.4	59.9	62.3	55.0	73.9	29.8	46.9	51.9
genres + all contexts	*Naïve Bayes*	73.8	95.3	20.2	43.8	63.6	54.8	80.3	20.8	40.8	52.6
	Random forest	75.5	90.6	37.8	58.5	73.6	62.3	67.6	55.1	61.0	61.3
	MLP	73.8	89.9	33.6	55.0	68.1	53.8	61.3	43.8	51.8	54.4
	SVM	71.4	81.1	47.1	61.8	64.1	56.0	74.8	30.9	48.1	52.8

5.2 Evaluation of Contextualized Recommendations in the Music Domain

Table 5 shows the performance results of the recommendation models for the different user profile types in the music domain. Similarly to the movie domain, it can be seen that in general incorporating contextual information into the classifiers improves the overall acc and g values. In this case, location context is more influential than time context to obtain better performance, and is the combination of both contextual signals what leads to the best performance. Random Forest is again the algorithm that achieves the highest performance values.

Table 5. Performance values of the model-based recommender systems built with the different user profile types (attribute configurations) in the music domain. Global top values are in bold, and best values for each profile type are underlined.

Profile type	Classifier	Community average					User average				
		acc	acc+	acc-	g	AUC	acc	acc+	acc-	g	AUC
-	*Majority class*	75.9	100.0	0.0	0.0	46.5	56.0	100.0	0.0	0.0	47.6
genres	*Naïve Bayes*	70.7	82.8	32.6	51.9	53.5	50.3	60.7	36.9	47.3	47.2
	Random forest	73.3	85.5	34.8	54.5	58.7	59.2	66.4	50.0	57.6	60.4
	MLP	72.8	83.4	39.1	57.1	60.8	52.9	55.1	50.0	52.5	50.6
	SVM	73.8	83.4	43.5	60.2	63.5	52.9	58.9	45.2	51.6	52.1
genres + time contexts	*Naïve Bayes*	71.7	83.4	34.8	53.9	55.8	53.9	61.7	44.0	52.1	51.0
	Random forest	75.4	87.6	37.0	56.9	69.8	60.7	60.7	60.7	60.7	62.3
	MLP	74.9	83.4	47.8	63.2	68.8	59.7	59.8	59.5	59.7	58.5
	SVM	75.4	83.4	50.0	64.6	66.7	56.5	58.9	53.6	56.2	56.2
genres + location context	*Naïve Bayes*	71.2	82.8	34.8	53.7	54.3	53.9	61.7	44.0	52.1	49.7
	Random forest	75.9	87.6	39.1	58.5	64.2	61.8	65.4	57.1	61.1	61.0
	MLP	74.3	83.4	45.7	61.7	65.4	56.0	58.9	52.4	55.5	57.4
	SVM	74.3	81.4	52.2	65.2	66.8	63.4	63.6	63.1	63.3	63.3
genres + all contexts	*Naïve Bayes*	70.2	81.4	34.8	53.2	56.3	54.5	62.6	44.0	52.5	52.6
	Random forest	**79.6**	90.3	45.7	**64.2**	**74.4**	**63.9**	64.5	63.1	**63.8**	**65.0**
	MLP	76.4	85.5	47.8	64.0	65.3	60.2	64.5	54.8	59.4	59.9
	SVM	77.5	82.8	60.9	71.0	71.8	59.2	61.7	56.0	58.7	58.8

6 Conclusions and Future Work

On realistic context-enriched user preference data in the movie and music domains, we have analyzed the influence of several (isolated and combined) contextual signals –namely time, location and social companion–, and have empirically shown that a proposed contextual modeling approach lets improve the performance of a number of model-based recommender systems.

In the future we should increase the size of the dataset by collecting additional user evaluations. With a larger dataset we could build heuristic-based collaborative filtering strategies, and integrate them with pre- and post-filtering contextualization approaches. As stated by Adomavicius et al. [4], one of the main current challenges on context-aware recommendation is the investigation and comprehension of which contextualization approaches perform better, and under which circumstances.

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