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Enriching Group Profiles with Ontologies for Knowledge-driven Collaborative Content Retrieval

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Abstract

This paper proposes several strategies for the combination of ontology-based user profiles to generate a shared semantic profile for a group of users. The performance of the strategies is theoretically and empirically evaluated in an existing personalization framework from a knowledge-driven multimedia retrieval system. Early experiments are reported here, which show the benefits of using semantic user preferences representations and providing initial evidence as to which profiles combination strategies are most appropriate for collaborative content retrieval tasks.

1. Introduction

During the last few years, a number of domains have been identified in which personalization has a great potential impact, such as news, education, advertising, tourism or e-commerce. User modeling may encompass large range of personal characteristics. Among them, user interest for topics or concepts (directly observed, or indirectly, via user behavior monitoring followed by system inference) is one of the most useful in many domains, and widely studied e.g. in the user modeling and personalization research community. While the creation and exploitation of individual models of user preferences and interests have been largely explored in this field, group modeling - combining individual user models to model a group - has not received the same attention [1][3][4].

It is very often the case that users do not work in isolation. Indeed, the proliferation of virtual communities, computer-supported social networks, and collective interaction (e.g. several users in front of a Set-top Box), call for further research on group modeling, opening new problems and complexities.

Collaborative applications should be able to adapt to groups of people who interact with the system. These groups may be quite heterogeneous, e.g. age, gender, intelligence and personality influence on the perception and complacency with the system outputs each member of the groups may have. Of course, the question that arises is how can a system adapt itself to a group of users, in such a way that each individual enjoys or even benefits from the results.

Though explicit group preference modeling has been addressed to a rather limited extent, or in an indirect way in prior work in the computing field, the related issue of social choice (also called group decision making, i.e. deciding what is best for a group given the opinions of individuals) has been studied extensively in economics, politics, sociology, and mathematics [5][6]. The models for the construction of a social welfare function in these works are similar to the group modeling problem we put forward here.

Other areas in which social choice theory has been studied are meta-search, collaborative filtering, and multi-agent systems. In meta-search, the ranking lists produced by multiple search engines need to be combined into one single list, forming the well-known problem of rank aggregation in Information Retrieval. In collaborative filtering, preferences of a group of individuals have to be aggregated to produce a predicted preference for somebody outside the group. In multi-agent systems, agents need to take decisions that are not only rational from an individual's point of view, but also from a social point of view.

In this work, we study the feasibility of applying strategies, based on social choice theory [2], for combining multiple individual preferences in a personalization framework from a knowledge-based multimedia retrieval system [7]. Several authors have tackled the problem combining, comparing, or merging content-item based preferences from different members of a group. Here we propose to exploit the expressive power and inference capabilities supported by ontology-based technologies. In the framework user preferences are gathered in ontology semantic concept-based user profiles. Using these profiles, the framework retrieves personalized ranked lists of items and shows them in a graphical interface.

Combining several profiles with the considered group modeling strategies we seek to establish how humans create an optimal multimedia item ranked list for a group, and how they measure the satisfaction of a given item list. The theoretical and empirical experiments performed will demonstrate the benefits of using semantic user preferences and exhibit which semantic user profiles combination strategies could be appropriate for a collaborative environment.

The rest of the paper is organized as follows. An overview of our knowledge-based multimedia retrieval system is given in Section 2. After this, in Section 3, the studied group modeling strategies are described. Section 4 explains the experiments done and analyses the obtained results. Finally, Section 5 summarizes our conclusions and future research lines.

2. Underlying personalization framework

Our research builds upon an ontology-based personalization framework being developed in the aceMedia project (http://www.acemedia.org). In this section we provide an overview of the basic principles in this framework, with a special focus on user profile representation, and the exploitation of the profiles for personalized content retrieval. Further details can be found in previous works [7].

In contrast with other approaches in personalized content retrieval, the aceMedia approach makes use of explicit user profiles (as opposed to e.g. sets of preferred documents). The user preferences are represented as a vector of weights (numbers from 0 to 1), measuring the intensity of the user interest for the concepts corresponding to the different classes and instances of a domain ontology.

Comparing the metadata of multimedia items, and the preferred concepts in a user profile, the system finds how the user may like each element. Based on her preference weights, measures of user interest for content units can be computed, with which it is possible to prioritize, filter and rank contents (a collection, a catalog section, a search result) in a personal way.

The ontology-based representation is richer, more precise, less ambiguous than a keyword-based or item-based model. It provides an adequate grounding for the representation of coarse to fine-grained user interests (e.g. interest for individual items such as *a sport team*, *an actor*, *a stock value*) in a hierarchical way, and can be a key enabler to deal with the subtleties of user preferences. An ontology provides further formal, computer-processable meaning on the concepts (*who is coaching a team*, *an actor's filmography*, *financial data on a stock*), and makes it available for the personalization system to take advantage of. Furthermore, ontology standards, such as RDF and OWL, support inference mechanisms that can are used in the system to further enhance personalization, so that, for instance, a user interested in animals (superclass of *cat*) is also recommended multimedia items about cats. Inversely, a user interested in *lizards*, *snakes*, and *chameleons* can be inferred to be interested in *reptiles* with a certain confidence. Also, a user keen of *UK* can be assumed to like *Manchester*, through the 'locatedIn' relation.

Thus, the system outputs ranked lists of content items taking into account not only the preferences of the current user, but also a semantic spreading mechanism through the user profile and the domain ontology. In fact, previous experiments were done without the semantic spreading process and very poor results were obtained. The profiles were very simple and the matching between the preferences of different users was low. This observation shows a better performance when using ontology-based profiles, instead of keyword-based preference representations.

As a continuation of our work on semantic personalization, we add the system the possibility of integrate individual user profiles in a unique group model. That will be the main goal of this work.

3. Group modeling strategies

In [2] Judith Masthoff discusses several strategies for combining individual user models to adapt to groups. Considering a list of TV programs and a group of viewers, she investigates how humans select a sequence of items for the group to watch, how satisfied people believe they would be with the sequence chosen by the different strategies and how their satisfactions correspond with that predicted by a number of satisfaction functions. These are the three questions we wanted to investigate using semantic user profiles.

In this scenario, because of we have explored the combination of ontology-based user profiles, instead of user rating lists, we had to slightly modify the original strategies described in [1]. For instance, due to multimedia item preference weights have to belong to the range [0,1], the weights obtained for a group profile must be normalized. The following are brief descriptions of the ten selected strategies.

1. **Additive Utilitarian Strategy**. Preference weights from all the users of the group are added, and the larger the sum the more influential the preference is for the group. Note that the resulting group ranking will be exactly the same as that obtained taking the average of the individual preference weights.

2. **Multiplicative Utilitarian Strategy**. Instead of adding the preference weights, they are multiplied, and the larger the product the more influential the preference is for the group. This strategy could be self-defeating: in a small group the opinion of each individual will have too much large impact on the product. Moreover, in our case it is advisable not to have null weights because we would lose valued preferences. So, if this situation happens, we change the weight values to very small ones (e.g. 10^{-3}).

3. **Borda Count**. Scores are assigned to the preferences according to their weights in a user profile: those with the lowest weight get zero scores, the next one up one point, and so on. When an individual has multiple preferences with the same weight, the averaged sum of their hypothetical scores are equally distributed to the involved preferences.

4. **Copeland Rule**. Being a form of majority voting, this strategy sorts the preferences according to their Copeland index: the difference between the number of times a preference beats (has higher weights) the rest of the preferences and the number of times it loses.

5. **Approval Voting**. A threshold is considered for the preferences weights: only those weights greater or equal than the threshold value are taking into account for the profile combination. A preference receives a vote for each user profile that has its weight surpassing the establish threshold. The larger the number of votes the more influential the preference is for the group. In the experiments the threshold will be set to 0.5.

6. **Least Misery Strategy**. The weight of a preference in the group profile is the minimum of its weights in the user profiles. The lower weight the less influential the preference is for the group. Thus, a group is as satisfied as its least satisfied member. Note that a minority of the group could dictate the opinion of the group: although many members like a certain item, if one member really hates it, the preferences associated to it will not appear in the group profile.

7. **Most Pleasure Strategy**. It works as the Least Misery Strategy, but instead of considering for a preference the smallest weights of the users, it selects the greatest ones. The higher weight the more influential the preference is for the group.

8. **Average Without Misery Strategy**. As the Additive Utilitarian Strategy, this one assigns a preference the average of the weights in the individual profiles. The difference here is that those preferences which have a weight under a certain threshold (we used 0.25) will not be considered.

9. **Fairness Strategy**. The top preferences from all the users of the group are considered. We have decided to select only the $N/2$ best ones, where N is the number of preferences not assigned to the group profile yet. From them, the preference that least misery causes to the group (that from the worst alternatives that has the highest weight) is chosen for the group profile with a weight equal to 1. The process continues in the same way considering the remaining N-1, N-2, etc. preferences and uniformly diminishing to 0 the further assigned weights.

10. **Plurality Voting**. This method follows the same idea of the Fairness Strategy, but instead of selecting from the $N/2$ top preferences the one that least misery causes to the group, it chooses the alternative which most votes have obtained.

Some of the above strategies, e.g. the Multiplicative and the Least Misery ones, apply penalties to those preferences that involve dislikes from few users. As mentioned before, this fact can be dangerous, as the opinion of a minority would lead the opinion of the group. If we assume users have common preferences, the effect of this disadvantage will be obviously weaker. For this reason, we shall define the individual profiles with preferences shared by the users in more or less degree. We are aware it will be necessary to automatically determine the users of a group.

In any case, with our semantic user profile representation, we identified two different approaches to applying the explained group modeling strategies. The first one (Figure 1), which we call *profile combination method*, merges individual user profiles to form a common user profile and generate common recommendation according to this new profile.

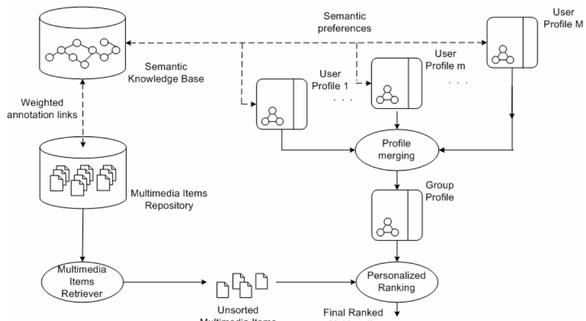

Figure 1. User profile combination method

The second approach (Figure 2) extracts individual user rankings according to individual user profiles, and aggregates them using specific criteria at a later stage. We refer to it as the *ranking combination method*.

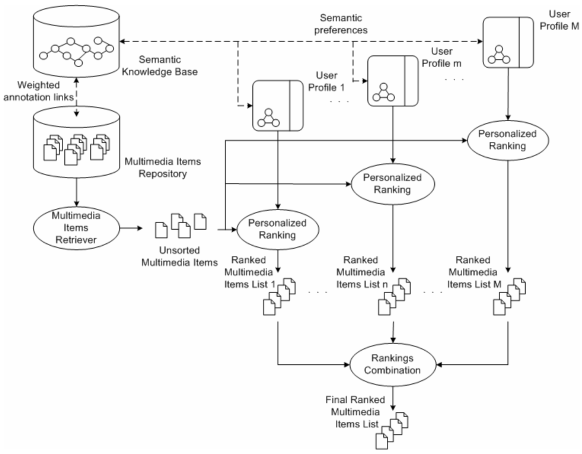

Figure 2. User ranking combination method

At first sight it is not clear which method is going to better perform group profiling in our system. This and other aspects, such as an optimal group modeling strategy, will be investigated in the experiments described in the next section.

4. Experiments

Two different sets of experiments have been done for this work. The first one will try to find the group modeling strategy that best fits the human way of selecting items when personal tastes of a group have to be considered. We shall try to establish the strategy that most satisfaction offers to the members of the group. The second one tackles the problem in the opposite direction. Given a group modeling strategy, we shall try to determine how to measure the satisfaction the strategy offers to the group.

The scenario of the experiments was the following. A set of twenty four pictures was considered. For each picture several semantic-annotations were taken, describing their topics (at least one of beach, construction, family, vegetation, and motor) and the degrees (real numbers in [0,1]) of appearance these topics have on the picture. Ten subjects participated in the experiments. They were Computer Science Ph.D. students of the High Polytechnic School at UAM. They were asked in all experiments to think about a group of three users with different tastes. In decreasing order of preference (i.e., progressively smaller weights): a) User_1 liked *beach*, *vegetation*, *motor*, *construction* and *family*, b) User_2 liked *construction*, *family*, *motor*, *vegetation* and *beach*, and c) User_3 liked *motor*, *construction*, *vegetation*, *family* and *beach*.

The next subsections describe in detail the experiments done and expose the results and conclusions obtained from them.

4.1 Optimal ranking according to human subjects on behalf of a group of users

We have defined two distances that measure the existing difference between two given ranked multimedia items lists. The goal is to determine which group modeling strategies give ranked lists closest to those empirically obtained from several subjects.

Consider Ω as the set of multimedia items stored and retrieved by the system. Let $\tau_{sub} \in [0,1]^{|\Omega|}$ the multimedia items ranked list for a certain subject and let $\tau_{str} \in [0,1]^{|\Omega|}$ the multimedia items ranked list for a given combination strategy. We use the notation $\tau(x)$ to refer the position of the multimedia item $x \in \Omega$ in the ranked list τ. The first defined distance between these two ranked lists is defined as follows:

$$d_1(\tau_{sub}, \tau_{str}) = \sum_{x \in \Omega} \left| \tau_{sub}(x) - \tau_{str}(x) \right| \quad (1)$$

This expression basically sums the differences between the positions of each item in the subject and strategy ranked lists. Thus, the smaller the distance the more similar the ranked lists. The distance might represent a good measure of the disparity between the user preferences and the ranked list obtained from a group modeling strategy. However, in typical information retrieval systems, where many items are retrieved for a specific query, a user usually takes into account only the first top ranked items. In general, he will not browse the entire list of results, but stop at some top k in the ranking. We propose to more consider those items that appear before the k-th position of the strategy ranking and after the k-th position of the subject ranking, in order to penalize more those of the top k items in the strategy ranked list that are not relevant for the user.

With these ideas in mind, the following could be a valid approximation for our purposes:

$$d(\tau_{sub}, \tau_{str}) = \sum_{k=1}^{|\Omega|} P(k) \frac{1}{k} \sum_{x \in \Omega} \left| \tau_{sub}(x) - \tau_{str}(x) \right| \cdot \chi_k(x, \tau_{sub}, \tau_{str})$$

where P(k) is the probability of the user stops browsing the ranked item list at position k, and

$$\chi_k(x, \tau_{sub}, \tau_{str}) = \begin{cases} 1 & \text{if } \tau_{str}(x) \le k \text{ and } \tau_{sub}(x) > k \\ 0 & \text{otherwise} \end{cases}$$

Again, the smaller the distance the more similar the ranked lists.

The problem here is how to define the probability P(k). Although an approximation to the distribution function for P(k) can be taken e.g. by interpolation of data from a statistical study, we simplify the model fixing P(10) = 1 and P(k) = 0 for $k \neq 10$, assuming that users are only interested in those multimedia items shown in the screen at first time after a query. Our second distance is defined as follows:

$$d_2(\tau_{sub},\tau_{str}) = \frac{1}{10}\sum_{x\in\Omega}\left|\tau_{sub}(x)-\tau_{str}(x)\right| \cdot \chi_{10}(x,\tau_{sub},\tau_{str}) \quad (2)$$

Observing the twenty four pictures, and taking into account the preferences of the three users belonging to the group, the ten subjects were asked to make an ordered list of the pictures. With the obtained lists we measured the distances d_1 and d_2 with respect to the ranked lists given by the group modeling strategies. The average results are shown in Figure 3.

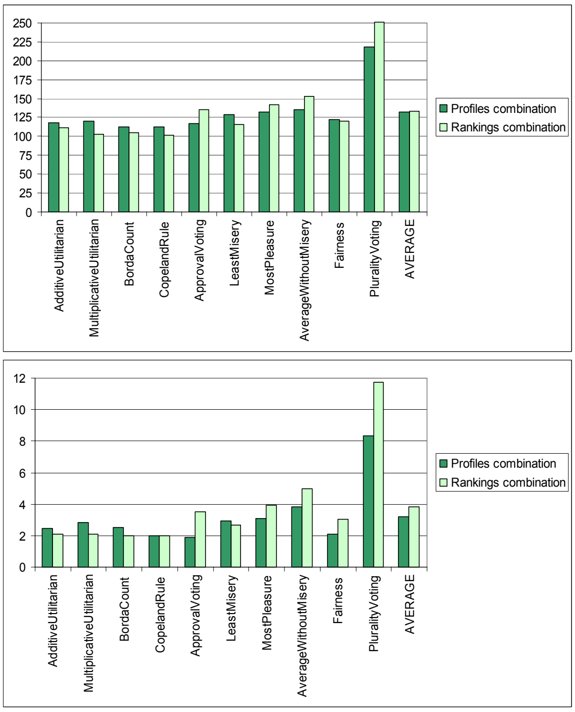

Figure 3. Average distances d_1 and d_2 for subjects profiles and rankings combinations

On one hand, it can be concluded that strategies like *Borda Count* and *Copeland Rule* give lists more similar to those manually created by the subjects, and strategies like *Average Without Misery* and *Plurality Voting* obtained the greatest distances. On the other hand, it seems the profile combination method slightly overcomes the ranking combination method.

The above deductions are founded on an empirical point of view. To obtain more theoretical results we also compared the strategies lists against the lists obtained using semantic user profiles. Figure 4 exposes the results. Surprisingly, they are very similar to the empirical ones. They agree with the strategies that seem to be more or less adequate for group modeling.

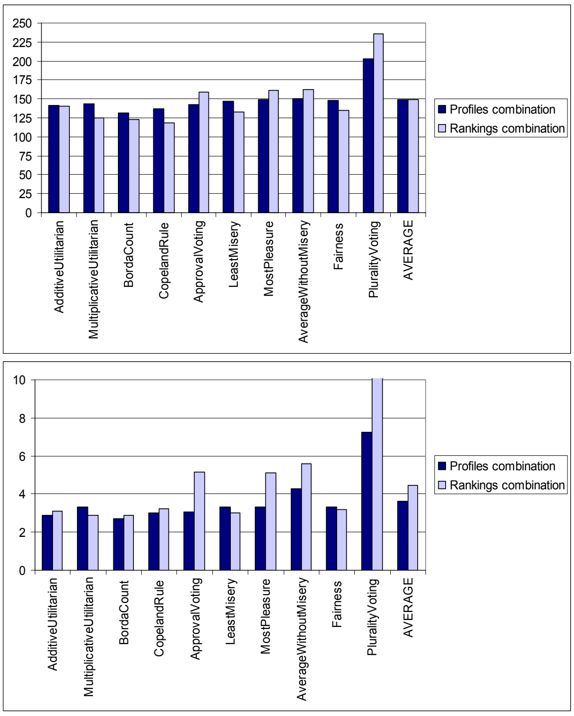

Figure 4. Average distances d1 and d2 for user profiles and ranking combinations

4.2 Human-measured satisfaction for a content ranking on behalf of a group of users

In the previous experiments we tried to find which group modeling strategies generate ranked list most similar to those established by humans and those created from our ontology-based user profiles. The idea behind this search is the assumption that the more similar a ranked list is to that generated from a user profile, the most pleasure causes to the user. In this section we seek the same goal, but directly trying to measure the satisfaction each strategy provide. This time, the top ten ranked items from each strategy with all the combination methods were presented to the subjects. Then they were asked to decide the degree of satisfaction each list offers to each of the three users in the group. Four different satisfaction levels were used: very *satisfied*, *satisfied*, *unsatisfied* and *very unsatisfied*, corresponding to four, three, two and one vote respectively. The normalized sums of the obtained votes for each strategy are shown in Figure 5.

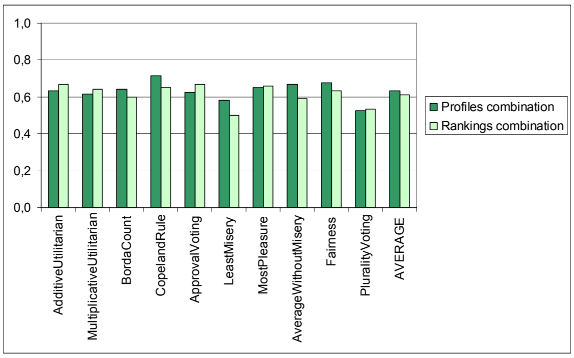

Figure 5. Subject Average Satisfaction

Once more, a theoretical foundation is needed. In [2] three satisfaction functions are presented: a) linear addition satisfaction, b) quadratic addition satisfaction, and, c) quadratic addition minus misery satisfaction. Here, we only study the first one. The quadratic forms are not applicable to our lists because their ratings take values in [0,1], instead of being natural numbers. The way the linear addition satisfaction function measures the pleasure a strategy gives to a specific user is the following. For the k top items of the ranked list τ_{str}, the weights or ratings assigned to these items in the user ranked list are added, and finally normalized:

$$\frac{\sum_{x:\tau_{str}(x)\le k} w_{user}(x)}{\sum_{x\in\Omega} w_{user}(x)}$$

In order to be consistent with the empirical experiments, we established k = 10. Note that it is necessary for our system to use normalization. The values of the rankings are skewed within the strategies: some of them are close to 0 and others provide uniform distributed weights in [0,1]. Thus absolute satisfactions values can not be considered. Figure 6 summarizes the average satisfaction values for each strategy.

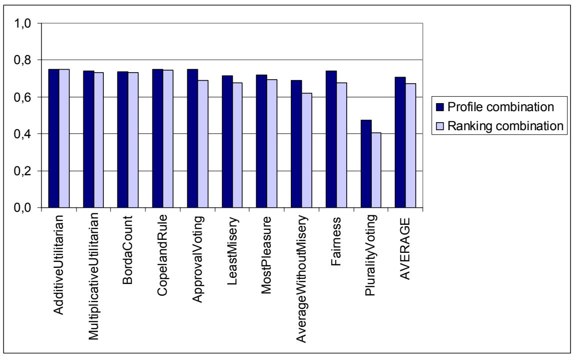

Figure 6. User Normalized Linear Addition Satisfaction

As it can be seen from the figure, the normalized linear addition satisfaction might be a good approximation to real satisfaction values. The satisfaction levels are relatively similar to those obtained from the subjects, especially in the Plurality Voting, where both empirical and theoretical satisfactions are the worst of all the studied strategies. Moreover, it seems there are no significative differences in the satisfaction obtained using profiles and rankings combination methods.

5. Conclusions and further work

In this paper, we have applied several strategies, based on social choice theory, for combining multiple ontology-based user profiles in a multimedia retrieval system. Through early empirical and theoretical experiments we have observed that strategies like *Borda Count* and *Copeland Rule* might be good candidates for the generation of semantic group profiles. However, a more detailed and rigorously experimentation is needed in order to draw more conclusive and statistically significant observations.

In the research, user profiles have been manually defined attempting to share in more or less degree semantic preferences. We are aware an automatic preference acquisition process has to be evaluated.

6. Acknowledgments

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