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Context Dependent Preference Acquisition with Personality-Based Active Learning in Mobile Recommender Systems

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Abstract. Nowadays, Recommender Systems (RSs) play a key role in many businesses. They provide consumers with relevant recommendations, e.g., Places of Interest (POIs) to a tourist, based on user preference data, mainly in the form of ratings for items. The accuracy of recommendations largely depends on the quality and quantity of the ratings (preferences) provided by the users. However, users often tend to rate no or only few items, causing low accuracy of the recommendation. Active Learning (AL) addresses this problem by actively selecting items to be presented to the user in order to acquire a larger number of high-quality ratings (preferences), and hence, improve the recommendation accuracy. In this paper, we propose a personalized active learning approach that leverages user's personality data to get more and better in-context ratings. We have designed a novel human computer interaction and assessed our proposed approach in a live user study - which is not common in active learning research. The main result is that the system is able to collect better ratings and provide more relevant recommendations compared to a variant that is using a state of the art approach to preference acquisition.

Keywords: Recommender Systems, Collaborative Filtering, Personalized Active Learning, Cold start, Mobile

1 Introduction

In the more recent years there has been an explosive growth of the sheer volume of information available through the World Wide Web. For instance, in tourism websites, the amount of travel offers is continuously increasing, making it extremely difficult to select a good hotel or a place to stay, due to the overwhelming number of offers provided and the lack of effective system support. RSs address this "information overload" problem by providing to users recommendations for items that are likely to be appealing to them [1].

Collaborative filtering (CF) is a state-of-the-art technique that generates recommendations by exploiting ratings for items provided by a network of users. A challenging problem of CF is the cold-start problem, i.e., its poor performance on new items and on new users. In fact, CF requires that an adequate number of ratings is provided by the target user (who is requesting a recommendation), which makes the system knowledgeable about the user's preferences, before relevant suggestions can be generated.

The cold-start problem becomes even more severe for Context-Aware Recommender Systems (CARS), i.e., systems that recommend items by exploiting not only the traditional user and item dimensions but also contextual information [2]. In these systems, it doesn't suffice anymore to have enough ratings of several users for many items; the system must have collected a sufficient number of ratings in the various contextual situations as well. For instance, imagine that a CARS for places of interest (POIs) collected from the users many low ratings for a mountain hiking route, and the users tagged these ratings with "rainy weather", to indicate that the item was always experienced under that contextual situation (which influenced the rating). Moreover, assume that no rating for the same route was tagged with "sunny day", which is a contextual condition expected to make that route much more attractive. In this case, that route would not be recommended to any user during a sunny day since the system could not learn yet that in a sunny day the ratings for this item tend to be higher than on a rainy day.

In order to tackle this problem in a CF system (irrespectively whether is context-aware or not), the user-system interaction typically begins with a rating elicitation process (preference elicitation). When a new user registers, the system proposes a set of selected items for her to rate. If the system is context-aware the user must specify not only her ratings but has to tag each rating with the contextual conditions under which the item was experienced (e.g., a rainy or sunny day). In fact, the ratings that a user provides are not all equally informative of her preferences and equally useful for the RS to generate accurate recommendations (for her and also for other users). For this reason, in the most advanced CF systems, the items selected by the system for the user to rate are computed by an Active Learning (AL) strategy aiming at acquiring a better user profile and ultimately generating more accurate recommendations [3–6].

In this paper we illustrate the application of a novel AL strategy for context-aware rating elicitation that uses the personality of the user within a mobile recommender system for places of interest, which is called STS (South Tyrol Suggests). First, the user personality is acquired with a simple questionnaire. Then, using a customised matrix factorisation model, the system predicts the items that the user is familiar with, i.e., items that the user has experienced in the past, and asks the user to rate them. This prediction is crucial because in our application domain, which is tourism, users cannot experience or try an item during the rating elicitation process, as for instance in the music domain, in which users can listen to a music track on the spot and rate it. Moreover, in the selected domain, user needs are dependent on the context of the travel and are not simply based on the long term preference model. Therefore, any user rating should explicitly indicate the contextual situation of the user while she was experiencing the rated item, i.e., must be tagged with as many as possible contextual conditions which correctly describe the experience of the user.

The proposed AL strategy, by exploiting the knowledge of the user personality, aims at maximizing the utility of the recommendations, which is measured by the appropriateness of the suggestions to the user preference and their relevance to the current contextual situation of the user (requesting recommendations). In order to measure the above mentioned properties we have designed a novel evaluation methodology and conducted a user study [7]. We hypothesised that if the recommendation model is trained with the ratings elicited by the proposed AL strategy then it will recommend items that not only "fit the preferences" of the user (ultimate goal of classical RSs), but also are "well-chosen for the situation" of the user (her contextual situation). In fact, our results show that the proposed AL strategy, compared to a state-of-the-art strategy, elicits ratings that make the recommendations more "context-aware", i.e., better suited for the current situation of the user. Moreover, it acquires more and better ratings, i.e., the acquired ratings are tagged by the raters with more contextual conditions.

In conclusion, the main contributions of the paper are the following:

1. Based on the acquired user personality, we have designed a new algorithmic AL strategy that can be used for preference elicitation in CARS.
2. We have designed an easy-to-use HCI that supports user personality acquisition, context-aware rating elicitation and recommendation in a mobile scenario.
3. We have designed a novel online user study to evaluate our proposed AL strategy with respect to the quality of the generated recommendations.
4. We have shown that the proposed AL strategy outperforms a state-of-the-art one in terms of how well-chosen are the recommendations for the current user situation, which indicates that it is more effective in context-aware recommendation scenarios.

The rest of this paper is structured as follow: Section 2 presents the HCI that we have developed for preference elicitation. Section 3 describes the structure of the user study and the obtained results. Section 4 discusses the related works and positions this work with respect to the state-of-the-art in active learning for collaborative filtering. Finally, section 5 summarizes contributions and outlines directions for future work.

2 Human Computer Interaction for Active Learning Preference Elicitation

This section describes the experimental design of the user study and the human-computer interaction with STS (South Tyrol Suggests): our Android-based recommender system that provides users with context-aware recommendations for attractions, events, public services, restaurants, and accommodations (for South Tyrol region in Italy).

2.1 Personality Questionnaire

After the user has registered to the system by specifying her username, password, birthdate and gender, she is asked to fill out the Ten-Item Personality Inventory (TIPI) questionnaire [8], so that the system can assess her Big Five personality traits (openness, conscientiousness, extroversion, agreeableness, neuroticism). Figure 1 (left) shows a screenshot of our application where one of the questionnaire statements is illustrated. The full questionnaire includes the following ten statements, answered on a 7-point Likert scale (from “strongly disagree” to “strongly agree”): I see myself as extraverted, enthusiastic; I see myself as critical, quarrelsome; I see myself as dependable, self-disciplined; I see myself as anxious, easily upset; I see myself as open to new experiences, complex; I see myself as reserved, quiet; I see myself as sympathetic, warm; I see myself as disorganized, careless; I see myself as calm, emotionally stable; I see myself as conventional, uncreative.

2.2 Active Learning Strategies

Using the assessed personality (as illustrated in Figure 1, middle), along with the retrieved age and gender as input to one of the two implemented AL strategies (i.e., either the state-of-the-art log(popularity) * entropy [9] or our proposed personality-based binary prediction [7], depending on the experimental group the user belongs to), the system identifies and prompts the user to rate eight POIs, whose ratings are aimed at best improving the quality of subsequent recommendations. The *log(popularity) * entropy* strategy is considered as a baseline in our evaluation (see section 3). We have used it since previous works have compared it with other approaches and reported its excellent performance [9, 10, 4, 6]. In fact, it has been shown that this strategy (or its variation) is one of the bests [9, 4, 6].

Log(Popularity) * Entropy scores each item i by multiplying the logarithm of the *popularity* of i (i.e., the number of ratings for i in the training set) by the entropy of the ratings for i. Then, the top scored items are proposed to be rated by the user (4 in our experiments). This strategy is a *Balanced* strategy [9] in the sense that it tries to collect many ratings, by highly scoring items that are popular (hence can be rated), but also taking into account their relative informativeness (measured by the ratings' entropy), hence finding a balance between the quantity and quality of the acquired ratings.

Personality-Based Binary Prediction first transforms the rating matrix in a matrix with the same number of rows and columns, by mapping null entries to 0, and not null entries to 1. Hence, this new matrix models only whether a user rated an item or not, regardless of its value. Then, this Boolean matrix is used to train an extended version of the popular matrix factorization algorithm. Our model, which is fully described in [7], is similar to that proposed in [11], and enhances the user representation with additional factor vectors that correspond to each attribute in the set of user-associated attributes, in our case, gender, age group and the discretized scores for the Big Five personality traits.

2.3 Contextual Information Acquisition

The acquisition of rating-in-context is a new feature of the rating elicitation HCI that we have designed. During the rating elicitation process, for each of the POIs selected by the AL strategies, the user can specify her rating as well as the value of up to three randomly selected contextual factors (from a set of 14 context factors [12]) in which the POI was visited. From the GUI design view, three contextual factors can better fit into the mobile device and the random selection allows to sample uniformly the impact of every factor on the ratings. Figure 1 (right) shows the snapshot of the system where the user is presented a POI and is asked to rate it, if she has experienced it, and specify the contextual situation, if she remembers it and is eager to give. For instance, here, the user is asked to specify the travel budget, the crowdedness as well as the duration of the stay. We note that such contextual information could help the system to better figure out the contextual situation when the user experienced a POI, and hence help the system to make better predictions and better recommendations.

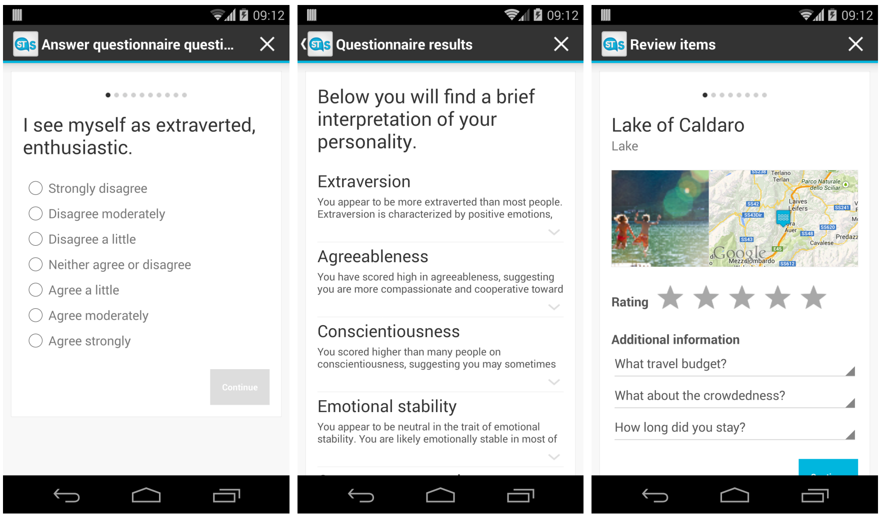

Fig. 1. Personality Questionnaire (left), Big 5 Personality Trait Assessment (centre), and Active Learning (right)

2.4 Recommendation Presentation

After the user has completed this registration procedure (i.e., by filling out the personality questionnaire as well as by rating known POIs), she is finally presented with the suggestions (recommendations) screen, as illustrated in Figure 2 (left). This window provides the user with a list of four POIs that are considered highly relevant taking into account the previously acquired user's ratings as well as the current contextual conditions around the user and the POIs. In order to take into account the current contextual conditions when generating POI recommendations, we use an extended version of Context-Aware Matrix Factorization (CAMF) [13], which, besides the standard parameters (i.e., global average, item bias, user bias and user-item interaction), incorporates baseline parameters for each contextual condition and item pair. This extended version, analogously to our implemented AL strategy, exploits known user attributes to provide accurate recommendations also for users with no or few ratings (more details can be found in [12]). We note that some of the contextual conditions are automatically acquired (e.g., weather conditions, temperature, season and location), whereas others can be specified by the user using a system screen (e.g., mood, budget, means of transport) (Figure 2, middle).

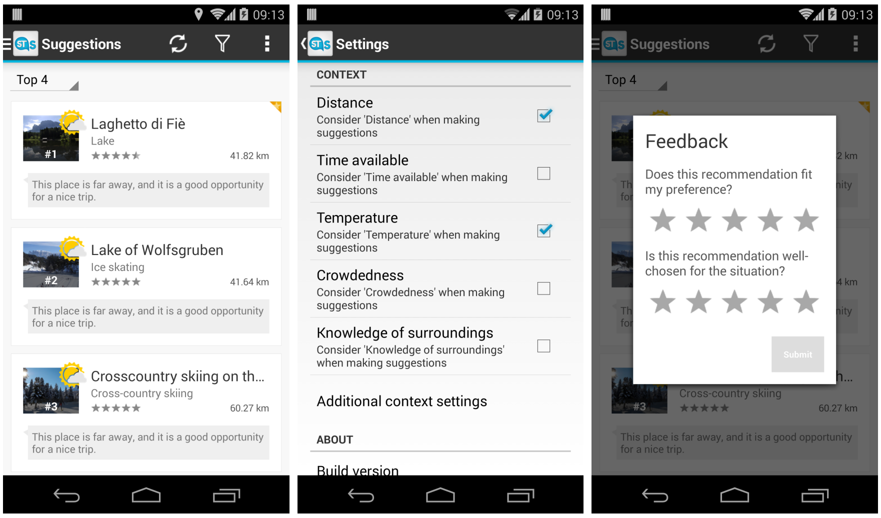

Fig. 2. Context-Aware Suggestions (left), Context Settings (centre), and Feedback on Recommendations (right)

Since we were interested in evaluating the quality of the individual recommendations produced by our recommender, we asked the user to complete a short mobile-based questionnaire (see Figure 2, right) for each of the recommended POIs that popped up after doing a long press on them. The questionnaire contains the following two specific statements to be answered on a five-star rating scale (1 star being the lowest score and 5 stars being the highest score):

- Q1: Does this recommendation fit my preference?
- Q2: Is this recommendation well-chosen for the situation?

These statements are obtained from [14], which provides a standard questionnaire for perceived recommendation quality and choice satisfaction. We chose these statements since they address two important goals of recommender systems, i.e., fitting the preference of the user (general preference) and being well-chosen and relevant (specific preference related to the context).

3 Evaluation Results

The online evaluation methodology presented in the previous section was designed to understand whether the incorporation of human personality into AL can result in eliciting more informative ratings or not. We have formulated the following hypotheses: the proposed personality-based AL strategy (in comparison to the chosen baseline) elicits ratings which result in recommendations that: a) better fit the preference of the user (preference fitting), and, b) are well-chosen for the current situation of the user (context-awareness).

To evaluate these hypotheses we conducted a live user study involving 51 participants who were randomly assigned either to the log(popularity) * entropy strategy group (n = 19) or the personality-based binary prediction item selection strategy group (n = 27). Some users from log(popularity) * entropy strategy group have been excluded because they did not complete the evaluation. Given a particular AL strategy, the (training) rating matrix evolves by including all the ratings entered by users on the training items elicited so far. Using these ratings the RS model is computed and recommendations are generated.

Table 1 summarises the results of the evaluation. It shows the average replies of the users to the two statements mentioned above. Those of the users assigned to personality-based binary prediction Active Learning is 3.56 for Q1 (preference fitting) and 3.31 for Q2 (context awareness). For the log(popularity)* entropy strategy, these numbers are 3.58 (for Q1) and 2.95 (for Q2), respectively. Comparing the results, we observe that both strategies got almost the same average reply to Q1 (no significant difference, $p = 0.43$ for a t-test), while personality-based strategy got a significantly higher average for Q2 ($p = 0.049$). Hence, while both strategies acquired ratings that resulted in recommendations that "fits the preferences" of the users, the proposed personality-based binary prediction strategy outperforms log(popularity) * entropy, by acquiring ratings that result in recommendations that are evaluated to be more "well-chosen".

In [7] we have shown that the proposed active learning strategy acquires significantly more ratings than *log (popularity) * entropy*. Here we want to also compare these strategies in term of how many contextual conditions are entered by the users, in order to describe their POI experience, during the rating elicitation process. The users assigned to the variant using the personality-based active learning strategy, by average, have entered 1.52 contextual conditions (out of 3) vs. 1.01 entered by the users assigned to log(popularity) * entropy strategy variant ($p = 0.001$). This result indicates that the proposed strategy acquires significantly more contextual conditions. We believe that this effect is due to the fact that the personality-based strategy selects POIs that are more familiar

Table 1. Average users reply to recommendations evaluation questions (numbers in bold indicate significant improvement of one strategy vs. the other). "# of contexts" refers to the average number of contextual conditions entered by a user while rating an item.

	AL Strategies	
	log (popularity) * entropy	**personality-based binary pred.**
Q1	3.58	3.56
Q2	2.95	**3.31**
# of contexts	1.01	**1.52**

to the users and hence users may better remember the experience of their visit (and the contextual conditions).

Furthermore, we note that STS was deployed on Google Play on Sep 18, 2013, and until Jan 14, 2014, 465 users have used the system (346 users downloaded it from Google Play). Overall, the system has collected 2,415 ratings and many of the ratings were entered together with a description of the context of the experience. Among the full set of users, 380 (81.72%) have completed the personality questionnaire and 326 (70.1%) went through the active learning phase. This shows that users largely accept to follow the proposed active learning phase to obtain recommendations.

4 Related Works

Most of RSs interactions begin with a sign-up process that includes a preference elicitation phase. In this phase the users are required to enter their preferences, for instance, in the form of ratings to items. After that, the recommender system is able to generate and display a set of personalized recommendations for the user to review or critique. The more informative about the user preferences the available ratings are the higher the recommendation quality is. This is because the ratings given by the users are not all equally useful for the system and informative of the users' preferences and tastes. Indeed, the need to implement more effective sign up processes is one of the main motivations of the research on Active Learning (AL) for recommender systems.

Several AL strategies have been proposed and evaluated [15, 3, 10, 9, 4, 16]. Two methodologies have been used for evaluating AL strategies: either based on conducting *online* or *offline* studies. In the first case, the active learning system interacts with real users and acquires their preferences (ratings) by means of a customary designed user interface. This requires to access an up-and-running recommender system, preferably with a large network of active users. Conversely, in offline evaluations, a pre-collected rating dataset is used to simulate the behaviour of users interacting with the system. However, since the online evaluation is expensive and time consuming, the majority of previous works have focused on offline evaluations [15, 3, 16], while only a few of them have tackled online evaluations [10, 9, 4].

One of these few works which conducted an online evaluation, as a follow up to a preliminary offline study, is [9]. The authors considered six AL strategies: *entropy*, where items with the largest rating entropy are preferred; *random* request; *popularity*, which is measured by the number of ratings for an item, and hence the most frequently rated items are selected; $log(popularity) * entropy$ where items that are both popular and have diverse ratings are selected; and finally *item-item personalized*, where random items are proposed until the user rates one. Then, a recommender is used to predict what items the user is likely to have seen based on the ratings already provided by the user. These predicted items are requested to the user to rate. In online evaluation, every new user who registers to the system (MovieLens), was presented with a number of movies (10 movies per webpage) selected by one of the active learning strategies described before. This process continued until the user rated 10 or more movies. Then the strategies were compared in terms of the number of pages the users had seen. The authors considered this measure as an indication of "the effectiveness of the signup process". In their results, they have shown that overall the $log(popularity) * entropy$ strategy got the best prediction accuracy while popularity and item-item were the best in terms of the effectiveness of the signup process. It is important to note that there are several differences between their work and ours. First of all, they have not compared the strategies with respect to the recommendation quality (fitting to the user preference, and context-awareness) or the number of acquired contextual conditions. Instead, they focused on the number of pages the users see during the rating elicitation process. Moreover, their RS uses only the ratings while our system uses the users' personality together with their ratings, and hence, can generate personalized recommendations even if the user has not provided any rating. Finally, their system recommends movies through a web interface, while, our system recommends POIs through a mobile interface, which is totally different (due to the limited interaction capabilities in the mobile devices). For instance, the mobile screen size is small and this makes it infeasible to present properly 10 items in a page (as they have done in their work).

In [4] the authors followed up their early work [9] by proposing an AL strategy, called $IGCN$, which is based on decision trees. According to the user rating entered for the asked item a different branch is followed, and a new node, which is labelled with another item to rate, is determined. They also considered two alternative strategies. The first one is $entropy0$ that differs from the classical entropy strategy, which we mentioned above, because the missing value is considered as a possible rating (category 0). The second one is called $HELF$, where items with the largest harmonic mean of entropy and popularity are selected. They have evaluated their strategies in an online study after a preliminary offline analysis: for every new user who registered to the RS (MovieLens), a number of movies selected by one of the AL strategies, was shown. After the user had rated 20 movies she took a brief optional survey that collects the users' opinions about the signup process. Then the RS was trained on the ratings entered by the user during the signup process (train set) and generated a set of recommendations to the user. After that, the user could provide any rating whenever she wanted, either by searching movies or using the “rate more movies” feature that presents random movies. Finally, the ratings entered by the user, after the signup process, were used as test set to evaluate the accuracy of the RS. The authors have concluded that, overall, Entropy0 and IGCN performed the best among the considered strategies. It is worth noting that this work has also several differences compared to ours. First of all, they have not asked the users whether the recommendations are well-chosen for the user’s contextual situation or not. Moreover, they have asked the users to rate any movie any time they want. In this way, the users were more likely to rate the movies that they like, while we asked the users to evaluate only the recommended items even if they don’t like them, hence we better measured the true performance of the RS. Another difference is that, in this work, the users completed a survey in order to globally evaluate the AL items and the sign-up process. We instead asked the users to evaluate, one by one, the recommended items.

We must note that the AL approach illustrated in this paper was originally proposed in [7]. It exploits user’s personality information - using the Five Factor Model (FFM) - in order to identify a list of items that are not only useful to rate but also expected to be experienced by the user. Personality is a predictable and stable factor that forms human behaviours. It has been shown that there are direct relations between personality and tastes / interests [17]: people with similar personality factor usually share similar interests and tastes. Earlier studies conducted on the user personality characteristics support the possibility of using this information in collaborative filtering based recommender systems [18]. However, to the best of our knowledge, no previous research work has incorporated the personality of the user in AL for RS. In [7] we showed that the proposed personality-based AL technique increases the number of ratings elicited from the users as well as the recommendation accuracy, measured in terms of Mean Absolute Error (MAE), i.e., the average absolute deviation of the predicted ratings from the true ratings in a randomly selected test set. In this paper, instead, we evaluate the quality of the recommendation list rather than the system accuracy on a random list of items, and we show that there is a positive effect on the “context awareness” dimension of the recommendations.

5 Discussion and Future Work

In this paper, we have proposed a novel AL strategy based on collecting the user personality. We have applied this strategy in the mobile recommender system to elicit context-aware ratings. Also, an easy-to-use HCI has been designed for our application. Using this application, we have conducted an online user study to evaluate our proposed AL strategy with respect to the quality of recommendations. Our results have shown that our proposed AL strategy outperforms a state-of-the-art strategy and it is more effective in context-aware RSs.

We want to finally discuss a number of issues and implications of our research. Most of the current active learning approaches for collaborative filtering implement the *Standard Interaction Model* [3], i.e., the system selects and proposes a set of items to the user to rate only in the sign up process, until she rates a sufficient number of items. An alternative interaction model is the *Conversational and Collaborative Model* [3], which, in addition to allow the user to rate items in the sign-up process, it proposes to rate some additional items whenever the user is motivated to provide more ratings. For instance, in a tourism scenario the system may ask the user to rate a POI when she is visiting it. We call this feature *Proactivity*, and a proactive system asks the user to rate an item when the user is in a better position to provide a reliable rating. For instance, our mobile platforms can help users to rate their experienced items in a ubiquitous manner. In a future work we want to extend the current active learning strategy to become even more proactive, i.e., the system should evaluate the items and select the most useful and appropriate for rating elicitation, not only in the sign-up process, but also in the full operational usage of the system.

Moreover, while there are several types of contextual data that can be automatically obtained from sensors (e.g., weather, temperature, location, daytime, season, and weekday) there are contextual information that can only be provided by the user (e.g., budget, companion, mood, and transport mean). However, not all the contextual factors are equally useful for the system to improve the accuracy. For instance, may not be useful to know the transportation mean of the travel when the user is rating a visit to a museum. In other words, the transportation mean may not have any impact on the experience of the museum and hence should not be used in the predictive model that evaluates if a museum is worth recommending to a user. Moreover, actively selecting the contextual factors that are more informative and relevant to the item is an feature that can also ease the user-system interaction (more meaningful requests are made to the user).

Another issue in active learning for recommender systems concerns the sequential nature of preference elicitation. Although we have shown that identifying a list of well selected items for the user to rate can increase the system performance (number of ratings elicited and recommendation accuracy), this approach may fail to correctly react to the first users entered ratings and may not immediately adapt the remaining rating requests to the user. Hence, sequential AL algorithm in which the items to be rated are selected incrementally by choosing each successive item to be rated based on the users ratings provided to the previously requested items is an interesting area of future research.

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