On the impact of neighborhood selection strategies for recommender systems in LBSNs

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Abstract. Location-based social networks (LBSNs) have emerged as a new concept in online social media, due to the widespread adoption of mobile devices and location-based services. LBSNs leverage technologies such as GPS, Web 2.0 and smartphones to allow users to share their locations (check-ins), search for places of interest or POIs (Point of Interest), look for discounts, comment about specific places, connect with friends and find the ones who are near a specific location. To take advantage of the information that users share in these networks, Location-based Recommender Systems (LBRSs) generate suggestions based on the application of different recommendation techniques, being collaborative filtering (CF) one of the most traditional ones. In this article we analyze different strategies for selecting neighbors in the classic CF approach, considering information contained in the users' social network, common visits, and place of residence as influential factors. The proposed approaches were evaluated using data from a popular location based social network, showing improvements over the classic collaborative filtering approach.

1 Introduction

The great explosion of cell phone use, the easiness to acquire the geographical location of people, and the development of wireless communications, has allowed the creation of social services whose main feature is the geographical location of users. Foursquare[1] is the most popular social network among these services, allowing users to easily share their geographical location as well as contents related to that location in an online way. The user location is a new dimension in social networks that narrows the gap between the physical world and online social networking services, creating new opportunities and challenges for traditional recommendation systems. These systems are an alternative to deal with the problem of information overload that users face while seeking information about items of interest in vast amounts of knowledge. Traditional methods such as collaborative filtering (CF), content-based recommendation (CB) and hybrid methods [14] process information derived from the ratings provided by users and the characteristics of the items involved to generate a list of recommendations.

[1] `http://es.foursquare.com/`

However, in social networks there is additional information that recommendation methods should take into account, such as users' behavior and relations of friendship between them [20].

Regarding location based social networks (LBSNs), geo-localized data is a physical dimension that traditional social networks do not possess. In this new era, users can benefit from obtaining a pervasive and ubiquitous access to location-based services from anywhere through mobile devices. In a LBSN, there are relationships of various types, such as the User-User relationship, showing the friendship between two users or coincidence in places visited by these users; the User-Place relationship showing that a user visited a given place; the Place-Place relationship, which shows distance relationships or categorical membership. In addition to these relationships, users generate content-based relations, such as comments after visiting a place.

In this context, location based recommender systems have emerged [16] as a means to exploit geographical properties as an auxiliary source for recommending friends [11,15], places [10], activities [21,5] and events [12,9]. The heterogeneity of the data produced by location-based social networks creates the need for new approaches in recommendation systems, using different data sources and methodologies for enhancing recommendation. The Collaborative Filtering (CF) approach, for example, relates users to items through ratings or opinions, so that it can be straightforwardly applied to the construction of LBRSs. However, traditional CF approach lacks of the geo-localization dimension.

In this work, we propose different strategies for including the additional dimensions available in LBSNs in the context of user-based collaborative filtering for recommending locations. User-based approaches recommend items (e.g. places) based on an aggregation of the preferences of similar users or neighbors, i.e. users with similar tastes. As user-based CF trusts neighbors as information sources, the quality of recommendations are a direct consequence of the selected neighborhood. Our main hypothesis is that location-based social networks provide rich information for establishing relations beyond similarity, which can improve the selection of potential neighbors and, therefore, improve the estimation of preferences during the recommendation process.

The rest of the article is organized as follows. In Section 2 we describe related works. In Section 3, we present the different neighborhood selection strategies proposed and evaluated in this work. In Section 4, we describe the experimental results we carried out to analyze these strategies. Finally in Section 5 we present our conclusions and outline some future works.

2 Related work

Location-based social networks (LBSNs) allow users to build connections with their friends, share their locations via check-ins for points of interests (POIs) (e.g., restaurants, tourist spots, and stores) as well as location-related contents (e.g., geo-tagged photos and comments). In addition to provide users a social interaction platform, LBSNs are a rich source of information (containing social relationships, check-in history and tips) to mine users' preferences. Thus, location-based social networks open new possibilities for recommender systems [3], which can suggest different types of items such as: friends, places or points of interest (POI), activities and events.

Location-based recommender systems use the geographical property of LBSNs as an auxiliary source to improve recommendations of places or activities in which a target user may be interested in. Recent studies show the importance of location in generating new friendship relations. For example, in [15] the problem of friend recommendation was studied and it was concluded that about 30% of new links are chosen from users who visited the same places. In [7] the authors propose an approach for recommending friends who have similar interests as well as real-life location and dwell time with the target user. Geographic-Textual-Social Based Followee Recommendation (GTS-FR) approach is proposed in [18] for followee recommendation in LBSNs by exploring geographic, textual and social properties simultaneously.

Point-of-Interest (POI) recommender systems play an important role in LBSNs as they can help users explore attractive locations. Traditional CF relies on explicit ratings for items for generating recommendations. Although ratings are not available in LBSNs, the frequencies of check-ins recorded by LBSNs implicitly reflect the users' preferences for a given POI. Hence, several works [17,5,6] applied user-based CF approaches starting from mining the check-in patterns of users. In [17], the authors argue that geographical influence between POIs plays an important role in the behavior of users' check-ins and propose a framework for POI recommendation that merges user preferences as well as social and geographical influence. In [5], the authors propose an approach for detecting the current user context, inferring possible leisure activities and recommend appropriate content on the site (shops, parks, movies). Berjani et al. [6] applied a Regularized Matrix Factorization (RMF) technique for CF-based personalized recommendation of potentially interesting spots. Within the CF framework, [8] uses highly available GPS trajectories to enhance visitors with context-aware POI recommendations, [23] extract the user travel experience in the target region to reduce the range of candidate POIs. [19] introduce the temporal behavior of users into a time-aware POI recommendation and [22] propose an opinion-based POI recommendation framework taking advantage of the user opinions on POIs expressed as text-based tips. Differently from these works, the strategies presented in this paper aim to explore how to better select neighbors in CF-based POI recommendation by introducing the different elements available in LBSNs, such as friend relationships and geo-located checkins.

3 Neighborhood Selection Strategies

In a traditional CF scenario, there are m users $U{=}u_1, u_2, ..., u_m$, and a list of n items $I{=}i_1, i, ..., i_n$, that can be recommended to users. Each user has expressed her opinion about a set of items $I_{u_i} \subseteq I$, generally in an explicit way with a rating or value in a given numerical scale. This information is stored in a user-item matrix M of size $m \times n$, such that the value of each cell in M represents the preference score (rating) given by user i to item j. Memory-based CF approaches make predictions based on the user-item matrix in two ways, based on users or based on items [1]. Given an active user who requires a prediction for an item without rating, CF algorithms measure the similarities between the active user and other users (user-based approach), or between the item and the remaining items (item-based approach). Therefore, a rating is predicted by an aggregation of the ratings that the item received from similar users in the first case, or ratings given by the active user to similar items in the second case.

The classic user-based CF model is then defined as in Equation 1 [13]:

$$\tilde{r}(u,i) = \bar{r}(u) + C_o \sum_{v \in N_k(u,i)} sim(u,v)\left(r(v,i) - \bar{r}(v)\right) \tag{1}$$

where $r(v,i)$ is the rating given by user v to item i, $\tilde{r}$ is the rating prediction (different from the observed rating r), $N_k(u,i)$ is the set of k most similar users to u and $sim(u,v)$ is the function that determines the similarity between users u and v. C_o is a normalizing factor. The preference of user u for an item i is predicted according to the average rating $\bar{r}(u)$, the sum of deviations of the ratings given by the neighbors v to item i and the average ratings $\bar{r}(v)$, weighting by the similarity with neighbors.

User-based approaches assume that not all users are equally useful in the prediction for a given user, thus two main problems emerge: (1) selecting neighbors for a user to generate recommendations; (2) how to use properly the information provided by those neighbors in the generation of recommendations. Usually, the selection of neighbors is based on their similarity to the active user, while a common practice is to define a maximum number of users to narrow the neighborhood. Once the neighborhood is defined, the contribution of each neighbor to the prediction is weighted based on their distance from the active user. For example, a widely used alternative is a linear combination of the ratings weighted by the similarity with the neighbors. However, there are other factors that may be valuable for selecting neighbors. For example, in the case of this work the users' history of visits can be considered relevant beyond the ratings similarity.

To properly separate the two problems, the selection of neighbors on one hand and the weighting of their opinions on the other, [4] propose a modification the classic formula. This new formula considered an allocation score function (scoring) depending on the active user u, a neighbor v and an item i, or some combination thereof. This function gives a higher value when the triplet of user-neighbor-item is more valuable or expected to work better in predicting a rating according to the available information. Eq. 1 is then generalized as Equation 2:

$$\tilde{r}(u,i) = \bar{r}(u) + C_o \sum_{v \in g(u,i;k;s)} f\left(s(u,i,v), sim(u,v)\right) * \left(r(v,i) - \bar{r}(v)\right) \tag{2}$$

where g is the function that selects neighbors and f is an aggregation function that combines the outcomes of the scoring function s and $sim\,(u, v)$ the similarity between users.

The selection of neighbors involves the determination of the similarity of users to the target user, by making a comparison with all the users in the database. So any user that is similar to the target user may contribute to the preference estimation. The function g (selection of neighbors) may be influenced by relations present in a LBSN. Thus, restricting with some criteria the potential neighborhood of a target user by exploiting the information generated in LBSN, we can reduce the number of comparisons and, at the same time, improve the preference estimation. In this context, we present different approaches to the selection of potential neighbors.

In this paper we propose four different strategies for selecting neighbors in a user-based CF approach for recommendation based on the following information extracted from the LBSN: (1) friend relationships established by users, (2) common places visited by users, (3) area of residence, and (4) visiting area of users. These four strategies are used for defining the function g in Equation 2, i.e. the way in which neighbors are selected, whereas the rest of the formula remains unchanged. Then, once neighbors are selected based on a given strategy, the similarity of their preferences is assessed.

The first approach consists in using information from the actual social network created by users in the system. In this strategy, the set of neighbors that can contribute to the preference estimation of a target user is restricted to those that relate socially with this user (see Figure 1(a)). These relationships can be direct relationships (direct friends) or indirect relationships (friends of friends). In other words, this strategy searches for the k users most socially similar/related to predict the preferences of the target user by exploring the ego-centric social network of the target user up to a certain level.

In addition to the social relationship mentioned above, users can be related by common visited places. These may be represented in a network as in Figure 1(b), where users are nodes and the edges represent the number of times that users coincided in one place, producing a geo-located relationship. With the same idea as in the social network approach, you can limit the set of users who may be potential neighbors of the target user up to a certain level in the network. Therefore, this strategy seeks for the k most similar users to the target user in the set of users with a geo-localized relation with the target user.

Another way to select potential users to form a given user neighborhood is using the users' demographic information provided by the LBSN. The simplest strategy is grouping users according to the area where they live (see Figure1(c)), with the hypothesis that users of the same district, state, or country are the most appropriate for comparing preferences with, as they have the same customs. So potential neighbors that will contribute to the estimated preference for the target user may be those that have the same place of residence. This strategy looks for the k most similar users in the set of users who live in the same area that the

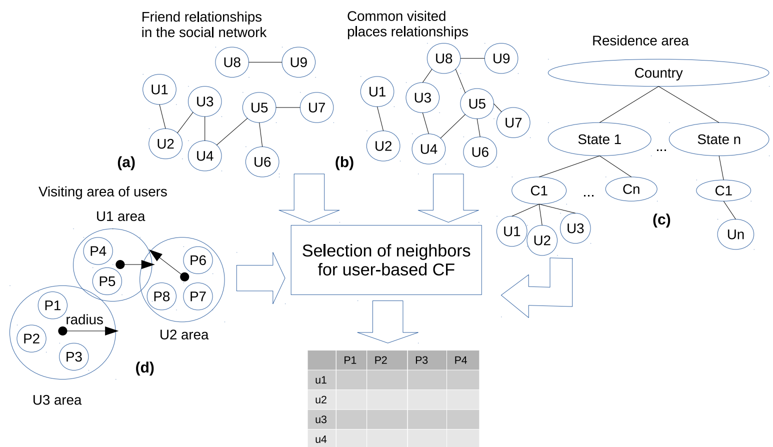


Fig. 1: Overview of the proposed neighbor selection strategies

target users, where area can be defined at different granularity levels, such as country, state, city and county.

Finally, the last strategy is based on the idea that users visiting places in same area are alike (see Figure1(d)). Then, the strategy requires first to identify the area delimiting the places a user visited and, then, to calculate the intersection with the visiting area of other users. It is assumed that the greater the intersection with the target user, the more useful the preferences of the user for predicting the rating of a given item are. Algorithm 1 describes the steps followed to calculate the visiting area of users, with X=1.

4 Experimental Results

This section describes the experiments conducted to evaluate the different approaches for neighborhood selection under the user-based CF approach, and the results obtained.

4.1 Experimental design

In order to evaluate the proposed strategies for selecting neighbors in the collaborating filtering method within LBSNs, several experiments were run and compared in their performance at recommending places. For these experiments different neighborhood sizes were considered (5, 10, 20, 30, and 50 users), whereas the similarity of preferences is calculated using the standard cosine similarity. For each of the defined strategies several parameters can be configured, the reported experiments were set as follows:

– Strategy 1: Potential neighbors were extracted from the social network considering different levels of friendship relationships (levels 1, 2, 3, 4, 5).

Algorithm 1 Calculation of visiting area for Strategy 4

for all $u \in U$ **do**
  Get all places P_u visited by user u from the user checkins
  for all $p \in P_u$ **do**
    Use $\langle Latitude, Longitude \rangle$ of the place p as the area centroid
    Count the number of visits in a radius of X km, taking into account taking into account all places in P_u
  end for
  Calculate the most dense centroid
end for

- Strategy 2: Potential neighbors were extracted from the network of visits considering different levels of geo-location relationships (levels 1, 2, 3, 4, 5).
- Strategy 3: Potential neighbors were extracted considering their place of residence in the profile considering two levels, county and state level.
- Strategy 4: Potential neighbors were extracted analyzing common patterns in geo-localized behavior.

The defined strategies were compared against the baseline, the traditional user-based CF approach in which the k most similar users are selected by calculating the cosine similarity of preferences between the target user and all users in the system. For the different experiments, we carried out some data processing on the selected dataset, which is detailed in Section 4.2. The performance of the different strategies at predicting the preferences of a user was evaluated using the standard MAE (Mean Absolute Error) metric given by Equation 3, which measures the error in the estimation for the set of user-item pairs T.

$$MAE = \frac{1}{\mid T \mid} \sum_{(u,i) \in T} \mid \overline{r}_{ui} - r_{ui} \mid \tag{3}$$

4.2 Dataset

For the experiments the dataset from [2] was used, containing data collected from one of the most widely used LBSN, *Foursquare*. The dataset contains the following information: *Places*, information about the places visited, *Users*, data of the users using the system, *Tips*, information about check-ins made by users, *Friendship*, information on the social relationship between users and *Categories*; information of the categories of *Foursquare* places. In the dataset there are users from all over the world, but for our experiments only users belonging to the state of New York were considered, as they are greater in quantity. Out of the 47,220 users in the dataset, the 27,000 users from New York were used.

For Strategy 1, we used the social network among users in *Foursquare*, which is an undirected network and it has no weights in the edges. The dataset has a total of 47,220 nodes and 1,192,758 edges. For Strategy 2, the dataset was processed to generate the network of common places visited. In this network a node is a user and the relationship between two users is given by the number of common visits. Relationships based on a single visit in common were eliminated, because they can be just a coincidence. The resulting network of common visits can be categorized as an undirected network, with weighted edges (number of common visits between users).

For Strategy 3, the variable "Home city" from the user profiles was considered to group users from New York in counties (e.g. Manhattan, Brooklyn, Queens). We used the service from Google maps[2] to obtain more information about the place of residence. For Strategy 4, two steps were required. First we obtained the places visited for each user according to the checkins made and calculated the visiting area according to Algorithm 1. Then, the distance between the area visited by two users was calculated using the cosine measure regarding their centroids and considering the earth radius of 6378.1 km.

Finally, visits or checkins were used as as a means to assess the user preferences in the user-item matrix M, because if a person often visits a place we can deduce that he/she liked it. In this context, for generating the preference matrix, we considered a 5 stars scale, where 1 represents "bad", 2 represents "regular", 3 represents "good", 4 indicates "very good", and 5 indicates "excellent". These were mapped to the scale of values as follows, 1 visit is mapped to the value 2, 2 visits to a value of 3, 3 visits to a value 4 and 4 or more visits to a value 5.

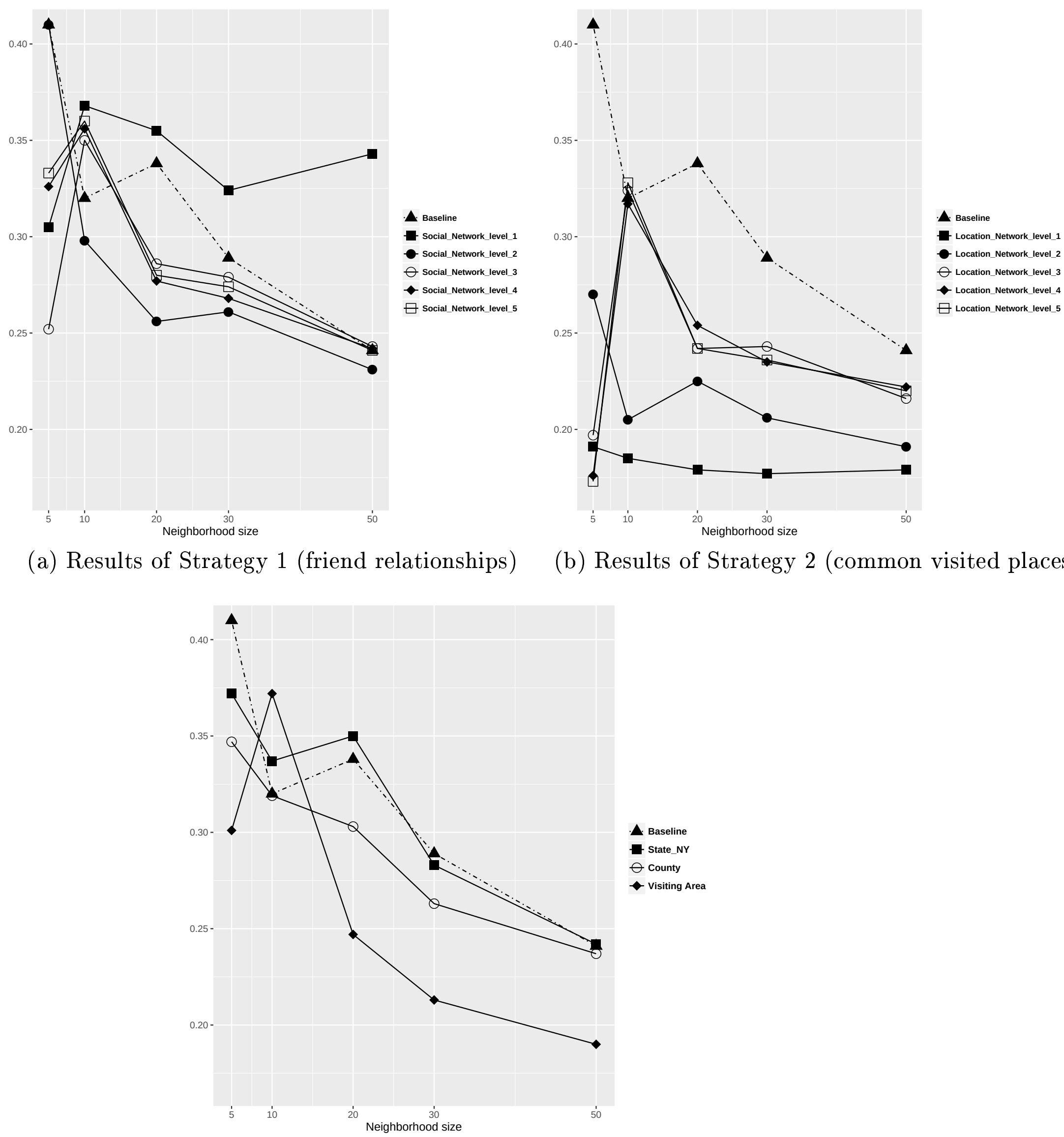
4.3 Results

Figure 2 shows the experimental results obtained for the different strategies. In Figure 2(a) it is possible to observe the results considering different levels of friend relationships according to Strategy 1. The Baseline is the traditional collaborative filtering approach that selects the k most similar users based con the cosine similarity of their preferences exclusively. Considering a single level of relationships, i.e., only the direct friends of the target user, the results obtained are worst than the baseline. However, friend-of-a-friend relationships (the level 2) are the best performing, reducing the MAE considerably with respect to the baseline. If the social graph is further explored, after the second level (level 3 ahead) the error increases, but it is still better than the baseline.

Figure 2(b) shows the results considering the network formed by common visited places defined in Strategy 2. This strategy outperformed the baseline in all its variations. The best performing option was using the direct edges, i.e. users that visit the same places than the target user. Exploring further this network the MAE values grow, even though they are still better than the baseline.

Figure 2(c) reports the results of the strategies concerning with geo-localization (Strategies 3 and 4). Selecting neighbors from the same state reaches comparable results to the baseline. Specializing more the region, i.e., using New York counties, the prediction error is reduced. In addition, Strategy 4 attains an important improvement, reducing the MAE scores significantly. Then, if the influence or

[2] https://developers.google.com/maps/web-services/overview?hl=es



(a) Results of Strategy 1 (friend relationships)

(b) Results of Strategy 2 (common visited places)

(c) Results of Strategy 3 and 4 (visiting areas)

Fig. 2: Experimental results for all the strategies

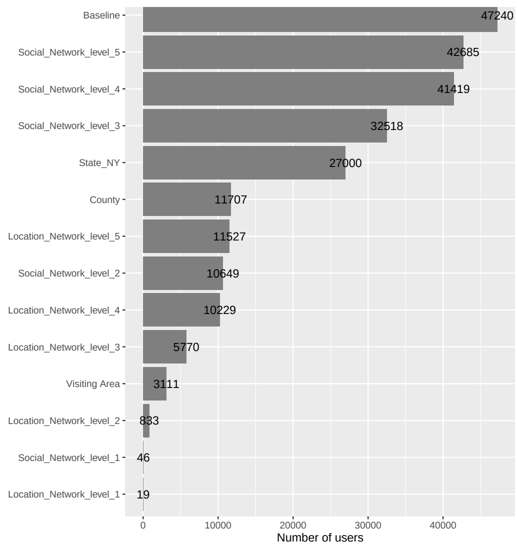


Fig. 3: Number of users compared for selecting the neighborhood

visiting area of users is taken into account, those users hanging around the same places than the target user seem to be the most useful for interest prediction.

In general terms, the proposed strategies for selecting neighbors based on the different elements available in LBSNs achieve better results than the traditional CF approach. An additional advantage of these strategies is the number of users involved in the computation of predictions. User-based CF is based on the similarity computations of the target user with every other user in the dataset, for choosing the k most similar ones. In the proposed strategies, this number of users is reduced. Figure 3 reports the average number each target user needs for determining the neighborhood for each strategy, in decreasing order. The baseline uses all of the 47240 users. If the friend relationships are used, the number increases as more levels of the network are explored. The best performing option, that was friend-of-a-friend (level 2) involves 10649 users (22%). The best performing variation using the network of common visited places (level 1) is based in only 19 users. Also, using the visiting area of users involves 3111 users (6.5%). Naturally, in the case of Strategies 2 and 4, the visiting graph and the visiting area requires previous data calculation and their updating with its consequent computational cost. This effort, however, can be done off-line. Strategies 1 and 3, instead, use data accessible from the profiles in the LBSN (friends and residence).

5 Conclusions

In this article we have proposed different strategies for selecting neighbors in the context of collaborative filtering for the recommendation of places of interest (POI) in LBSNs. The different elements available in these networks, such as the relationships among users and the geo-localization of data, allows us to select users that are potentially more useful for prediction. In this direction, we proposed four strategies, two based on relationships such as friendship and co-located visits, and two using geographical information, such as the place where users live and walk around. The experimental results showed that all of these strategies are capable of improving the baseline, which is the traditional user-based CF approach. Moreover, most of them require less computation in the selection of the neighborhood. The selection based on the friend-of-a-friend network, the users that visit more than a common place, the users in the same county and those visiting places in an intersecting area, were the best alternatives for each of the strategies. All in all, the best performing strategy was to select the neighbors from those that have visited some places in common with the target users. Notably, this strategy not only reduced the error in prediction significantly, but also was the one involving less users in this step of the CF approach. As regards future work, we plan to integrate other elements of LSBNs, such as the text-based tips to estimate the preferences as well as to evaluate functions to weight the selected neighbors for improving prediction.

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