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IMPROVING RECOMMENDATION OF LEISURE ACTIVITY USING SOCIAL FACTOR IN CROSS-DOMAIN APPROACH

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Abstract. In this paper we want to analyze how social factor such as friendship on Facebook can influence cross-domain recommendation results. For this we analyzed preferences of people from several cities around the world about various types of leisure activities, taking into consideration different purposes for which activity is performed.

Keywords: recommender systems; collaborative filtering; cross-domain recommendation; social recommendation.

INTRODUCTION

Nowadays, we see tremendous amount of options when purchasing movies, books or looking for leisure activity. Despite the overwhelming number of options we are exposed to, we are still missing out a plenty of opportunities, but not because we don't want to, but because we are not aware of the possibility. This raises a need for intelligent systems providing personalized service with respect to users' needs and interests, represented by user models. Recommender systems, which become more popular and widespread, can be applied for solving this problem. Collaborative filtering is one of the most popular and widely used recommender systems approaches. In collaborative filtering recommendations are based on users' behaviour, i. e. users are similar if they have similar preferences, if they like the same options. Thus we make decisions using not the content of the available options, but in users' attitude to these options.

Different recommender systems were successfully applied in such well-known digital services as Amazon, Netflix, MovieLens, Last.fm, Pandora.com and many others. There are also a number of online services such as TripAdvisor, Foursquare, Yelp and Evenbrite providing different types of suggestions for activities to perform in leisure time, events or places to visit. Although such services help people to focus attention to a reduced number of events, in most cases people still have the feeling of missing out interesting activities [1]. In recent researches [1, 2] it was shown that taking into consideration social factor such as friendship on Facebook improves performance of leisure activity recommendation in comparison with user based collaborative filtering approach using k-most-similar users. Also it was shown [2] that information about users' preferences in one leisure activity domain can be used to make prediction of users' preferences in another leisure activity domain even without any information of user's preferences in second leisure activity domain, that helps to solve the cold start problem of collaborative filtering and thus provide better recommendations, extending the knowledge-base to different leisure activity domains. In this study we want to find out how social factor influence performance of cross-domain recommendation in comparison with user based collaborative filtering approach using k-most-similar users.

FORMAL EXPERIMENT DEFINITION

Let U be the set of all users and P the set of all places of a possible activity. Let A be the set of all activities like drinking aperitivo in a bar, having dinner at a restaurant, drinking some beer in a pub or dancing in a club. Let G be the set of goals that can be accomplished with an activity. For example, goal can be something like achieving best price/quality ratio [2].

$Liked(u, p, a, g) \in U \times P \times A \times G$ – be all the places user rated positively for a given activity and a given goal.

$Dislked(u,p,a,g) \in U \times P \times A \times G$ – be all the places user rated negatively for a given activity and a given goal.

$$Rated(u,p,a,g) = Liked(u,p,a,g) \cup Disliked(u,p,a,g),$$

$$Known(u,a) = \{p \epsilon P | \exists g \epsilon G, Rated(u,p,a,g)\},$$

$$Unknown(u,a) = P \backslash Known(u,a).$$

In the studies we will consider two relations between users: similarity and friendship.

$FriendOf(u',u) \Leftrightarrow FriendOf(u,u') \Leftrightarrow u$ and u' are Facebook friends.

Similarity is the ratio of similarly rated activities from co-rated set of activities to a number of all co-rated activities. In other words shows how much preferences of one user coincide with preferences of another user [2].

$$sim(u,u',a) = \frac{\|Corated(u,u',a)\|}{\|Known(u,a) \cap Unknown(u,a)\|}.$$

$$Corated(u,u',a) = \{p \epsilon P | g \epsilon G, \\ Liked(u,p,a,g) \cap Liked(u',p,a,g) \cup \\ Disliked(u,p,a,g) \cap Disliked(u',p,a,g)\}.$$

Recommendation of places p to a user u to perform an activity a with a goal g [2]:

1) $Rec(u,a,g,k) \subseteq Unknown(u,a)$.
2) $\|Rec(u,a,g,k)\| = k$.
3) $\forall p \in Rec(u,a,g,k)$ $\forall p' \in \big(Unknown(u,a) \backslash Rec(u,a,g,k)\big)$ $\big(score(Net(u),p,a,g) \geq score(Net(u),p',a,g)\big)$,

where scoring function for a place p on a network $Net(u)$ to perform an activity a with a goal g is defined as average rating of users $u \in Net(u)$:

$$score(p,Net(u),a,g) = \frac{\|Likes(p,Net(u),a,g)\| - \|Dislikes(p,Net(u),a,g)\|}{\|Net(u)\|},$$

$$Likes(p,Net(u),a,g) = \{u' \in Net(u) | Liked(u',p,a,g)\},$$

$$Dislikes(p,Net(u),a,g) = \{u' \in Net(u) | Disliked(u',p,a,g)\}.$$

In this study we focused on understanding whether recommendation across different activities coming from similar friends gives better performance than recommendation coming from similar friends. Thus we defined the networks for similar users $Net_{su}(u)$ and similar friends $Net_{sf}(u)$ for recommendation across different activities:

$$Net_{su}(u) = \{u' \in U | \exists a' \in A, sim(u,u',a') > \delta\},$$

$$Net_{sf}(u) = \{u' \in U | \exists a' \in A, FriendOf(u,u') \cap sim(u,u',a') > \delta\}.$$

INITIAL DATA

Three different cities around the world were considered: Trento (Italy), Asunción (Paraguay) and Tomsk (Russia). In each city ratings were acquired not only for restaurants but also for another activity that is usually done before or after going out for dinner: drinking aperitif in a bar in Trento (Italy), drinking some beer in a pub or bar in Asunción (Paraguay), dancing in a club in Tomsk (Russia). For each place people specified four different marks according to different goals: one mark was dedicated to the price / quality ratio and the other three were related to the different types of companions people can spend their leisure time with, which are tourists, friends and their partner [2]. Also information about friendship on Facebook was obtained. In this study we used data gathered in Trento University with help of service ComeAlong. Gathered data contain a total of 9820 ratings from 162 local people on 353 restaurants and 85 places for second activity (Table 1).

Table 1

Gathered data

	Trento (Italy)	Asunción (Paraguay)	Tomsk (Russia)
Number of people	49	97	16
Number of marks	2700	6100	1020
Number of restau-rants to visit	67	254	32
Number of second activities (bars for aperitif, pubs or bars, clubs)	30	43	12

Table 2

Co-rated activities number for Activity1 (Visiting restaurant)

Number of co-rated activities	Number of users on the average		
	Trento (Italy)	Asunción (Paraguay)	Tomsk (Russia)
0	8	40	2
1	10	25	2
2	6	12	2
3	5	6	1
4	2	3	1
5	1	1	1

We analyzed this data and checked the following:

1) Co-rated activities number for different purposes. We considered number of users on the average co-rated 0, 1, 2, 3, 4, 5 activities (Tables 2 and 3).

2) Users similarity for different activities (Tables 4 and 5). We considered following similarity ranges: (0.6–0.8), (0.8–1.0)

Table 3

Co-rated activities number for Activity 2 (Visiting bars for aperitif, pubs or bars, clubs)

Number of co-rated activities	Number of users on the average		
	Trento (Italy)	Asunción (Paraguay)	Tomsk (Russia)
0	9	10	2
1	11	20	3
2	8	18	1
3	5	9	1
4	3	2	2
5	3	2	2

Table 4

Users similarity for different activities, similarity range 0.6–0.8

	Number of users on the average		
	Trento (Italy)	Asunción (Paraguay)	Tomsk (Russia)
Activity 1 (Visiting restaurant)	3	4	2
Activity 2 (Visiting bars for aperitif, pubs or bars, clubs)	3	4	1

Table 5

Users similarity for different activities, similarity range 0.8–1.0

	Number of users on the average		
	Trento (Italy)	Asunción (Paraguay)	Tomsk (Russia)
Activity 1 (Visiting restaurant)	2	3	0
Activity 2 (Visiting bars for aperitif, pubs or bars, clubs)	2	4	0

EVALUATION OF ALGORITHMS

For each user $u \in U$ we created a dataset without all his ratings for the second activity a' (aperitif in Trento, bars in Asunción, club in Tomsk), thus defining $Known(u, a') = \emptyset$. For each user $u \in U$ we built network of similar friends $Net_{su}(u)$ and network of similar users $Net_{sf}(u)$ based on user preferences for restaurants a. As a result $Net_{su}(u)$ and $Net_{sf}(u)$ is a set of users sharing similar preferences for a (e. g. dinner in a restaurant), since all user ratings for a' (e. g. drinking beer in a bar) were removed. Thus we are recommending places for a', using the network of users with similar taste for a. We have used similarity measure with $\delta \geq 0.7$.

To evaluate performance of two approaches we have used the following definitions of precision and recall:

$$precision = \frac{\|Tp(u)\|}{\|Tp(u)\| - \|Fp(u)\|},$$

$$recall = \frac{\|Tp(u)\|}{\|Tp(u)\| - \|Fn(u)\|},$$

$$Tp(u) = \{p \in Rec(u, a, g) | Liked(u, p, a, g)\},$$
$$Fp(u) = \{p \in Rec(u, a, g) | Disliked(u, p, a, g)\},$$
$$Fn(u) = \{p \in Unknown(u, a) \setminus Rec(u, a, g) | Liked(u, p, a, g)\}.$$

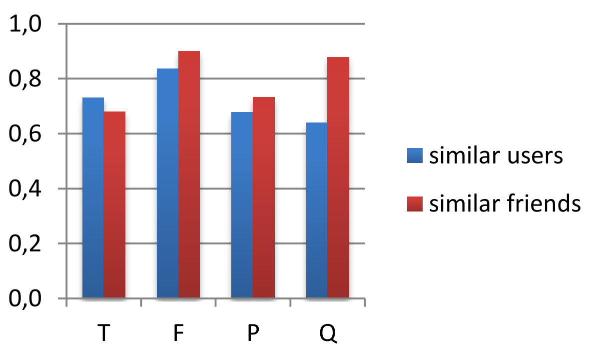

Fig. 1. Precision in Italy (Trento), $k = 10$

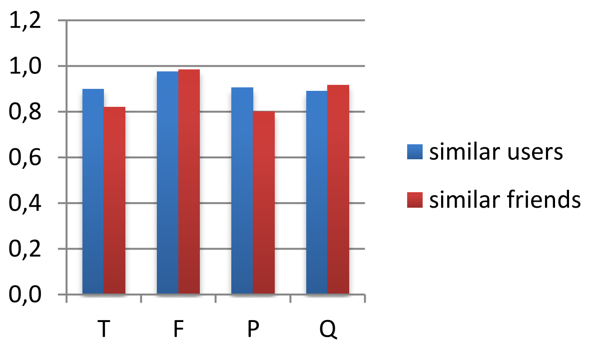

Fig. 2. Recall in Italy (Trento), $k = 10$

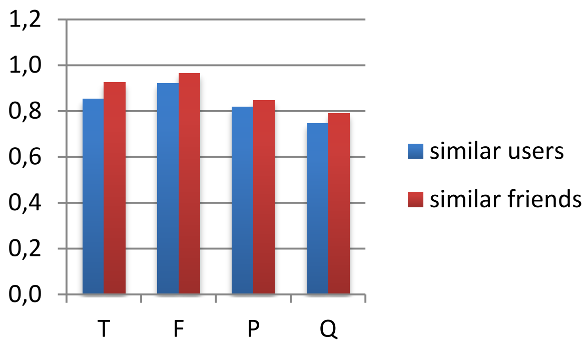

Fig. 3. Precision in Paraguay (Asuncion), k = 10

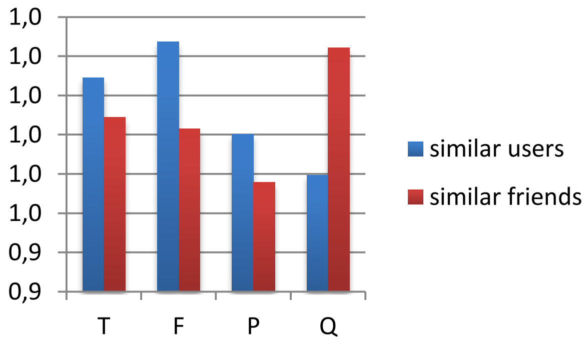

Fig. 4. Recall in Paraguay (Asuncion), k = 10

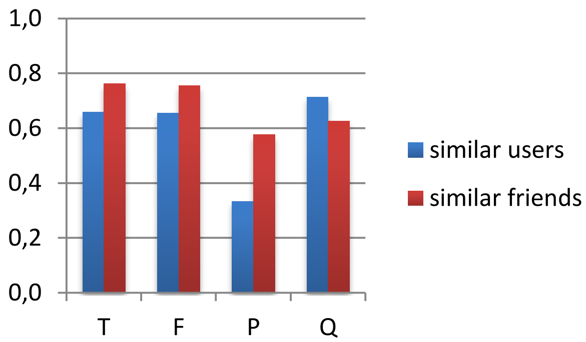

Fig. 5. Precision in Russia (Tomsk), k = all

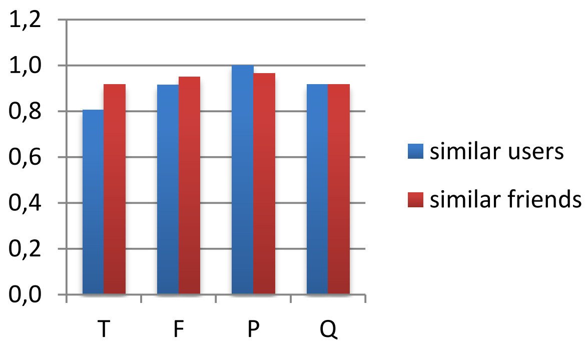

Fig. 6. Recall in Russia (Tomsk), k = all

CONCLUSION

Analyzing the results we can see that in most cases precision of cross-domain recommendation using social factor (Facebook friends) appeared to be better in comparison with cross-domain recommendation using *k*-nearest-neighbours approach (Fig. 1, 3, and 5). What is interesting to mention – is that recall in all cases is the best for the «Price/Quality» goal (Fig. 2, 4, and 6). And in case of Trento (Italy) in Fig. 2 and Tomsk (Russia) in Fig. 6 recall is also better for the «Bringing friends» goal. It is worth mentioning that for cross-domain recommendation it is important that we have high dense matrix for first domain, which we use in order to find users with similar preferences. As we see from our data analyses (Tables 2, 4, and 5) number of users on the average that corated more than four places is equal to one, mostly users corated two or three places, also there are not more than five, seven and two number of users on the average for Trento, Asunción and Tomsk correspondingly that has similarity higher than 0.6.

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МЕТАДАННЫЕ

Заглавие: Повышение качества рекомендации мероприятий путем учета социального фактора в кросс-доменной рекомендации.

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Аннотация: Оценено влияние социальных факторов таких как дружба в Facebook, на качество кросс-доменной рекомендации. Для этого были проанализированы предпочтения людей из нескольких городов в разных странах по поводу различных мероприятий (досуга). При этом учитывались цели с которыми посещались мероприятия (проводился досуг).

Ключевые слова: рекомендательные системы; совместная фильтрация; социальная рекомендация; кросс-доменная рекомендация.

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