Utilizing Online Social Network and Location-Based Data to Recommend Items in an Online Marketplace

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ABSTRACT

Recent research has unveiled the importance of online social networks for improving the quality of recommender systems and encouraged the research community to investigate better ways of exploiting the social information for recommendations. While most of the research focused on enhancing a traditional source of data (e.g., ratings, implicit feedback, or tags) with some type of social information, little is known about how different sources of social data can be combined with other types of information relevant for recommendation. To contribute to this sparse field of research, in this paper we exploit users' interactions along three dimensions of relevance (social, transactional, and location) to assess their performance in a barely studied domain: recommending items to people in an online marketplace environment. To that and we defined sets of user similarity measures for each dimension of relevance and studied them isolated and in combination via hybrid recommender approaches, to assess which one provides the best recommendation performance. Interestingly, in our experiments conducted on a rich dataset collected from SecondLife, a popular online virtual world, we found that recommenders relying on similarity measures obtained from the social network yielded better results than those inferred directly from the marketplace data.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval—*Information filtering*

Keywords

recommender systems; online marketplaces; SNA

1. INTRODUCTION

Research on recommender systems has gained tremendous popularity in recent years. Especially since the hype of the social Web and the rise of social media and networking platforms such as Twitter or Facebook, recommender systems are acknowledged as an essential feature helping people to, for instance, discover new connections between people or resources. Most of the literature that leverages social data for recommendations is focused on recommending users, (e.g., [7, 3]), tags (e.g., [6]) or points-of-interest (e.g, [11]), though some works have exploited social information for item recommendation, being the most important ones model-based. Jamali et al. [9] introduced SocialMF, a matrix factorization model that incorporates social relations into a rating prediction task, decreasing RMSE with respect to previous work. Similarly, Ma et al. [11] incorporated social information in two models of matrix factorization with social regularisation, with improvements in both MAE and RMSE for rating prediction. Among their evaluations, they concluded that choosing the right similarity metric between users plays an important role in making a more accurate prediction. On a more general approach, Karatzoglou et al. [5] use implicit feedback and social graph data to recommend places and items, evaluating with a ranking task and reporting significant improvements over past related methods. Compared to these state-of-the-art approaches, our focus on this paper is at providing a richer analysis of feature selection (similarity measures) with a more comprehensive evaluation than previous works, and in a rarely investigates domain: product recommendation in a social online marketplace. For instance, in Guo et al. [7] or Trattner et al. [16] the authors leveraged social interactions between sellers and buyers in order to predict sellers to customers. Other relevant work in this context is the study of Zhang & Pennacchiotti [17] who showed how top-level categories can be better predicted in a cold-start setting on Ebay by exploiting the user's "likes" from Facebook.

To contribute to this sparse field of research, in this paper we present preliminary results of a research project that aims at understanding how different sources of interaction data can help in recommending items to people in an online marketplace. More precisely, we examined several similarity measures over three dimensions of relevance (social, transactional, and location) as well as their combinations and assessed the results via a more comprehensive set of metrics than previous works. To the best of our knowledge, this is the first study that offers such a comprehensive feature selection and evaluation for product recommendation in online marketplaces. The study was conducted using a large-scale dataset crawled from the virtual world of SecondLife. In this way, we could study the utility of each similarity measure and entity type separately as well as combine them in the form of hybrid approaches to show which combinations, per dimension and globally, provide

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Marketplace Dataset (Market)	
Number of purchases	$39,055$
Mean number of purchases per user	5.56
Number of products	$30,185$
Mean number of purchases per products	1.29
Number of products with categories	$24,276$
Mean number of categories per product	2.86
Number of sellers	$8,149$
Mean number of purchases per seller	3.70
Online Social Network Dataset (Social)	
Number of interactions	$490,236$
Mean number of interactions	69.75
Number of groups	$39,180$
Mean number of groups per user	$9,419$
Number of interests	5.57
Mean number of interests per user	1.34
Location-based Dataset (Location)	
Number of different favorite locations	$10,538$
Mean number of favorite locations per user	5.77
Number of different shared locations	$5,736$
Mean number of shared locations per user	1.94
Number of different monitored locations	$1,887$
Mean number of monitored locations per user	6.52

Table 1: Basic statistics of the SL datasets used in our study.

the best recommendations in terms of recommendation accuracy, Diversity and User Coverage.

2. DATASETS

In our study we relay on three datasets[1] obtained from the virtual world SecondLife (SL). The main reason for choosing SL over real world sources are manifold but mainly rely on the fact that currently there are no other datasets available that comprise marketplace, social and location data of users at the same time. For our study we focused on users who are contained in all three sources of data, which are 7,029 users in total. To collect the data (see Table 1) we crawled the SL platform as described in our previous work [10, 14].

Marketplace Dataset. Similar to eBay, every seller in the SL marketplace[2] owns her own seller's store and publicly offers all of the store's items. Furthermore, sellers can apply meta-data such as price, title or description to their products. In turn, customers are able to provide reviews to products. We extracted 29,802 complete store profiles, with corresponding 39,055 trading interactions, and 2,162,466 products, of which 30,185 were purchased. From the purchased products, 24,276 are described using categories.

Online Social Network Dataset. The online social network MySecondLife[3] is similar to Facebook with regard to postings: users can interact with each other by sharing text messages and commenting or loving (= liking) these messages. From the extracted 7,029 complete user profiles, we gathered 39,180 different groups users belong to, 9,419 different interests users defined for themselves and 490,236 interactions between them.

Location-Based Dataset. Overall, we employed three different sources of location-based data in our experiments: a) Favored Locations: every user of SL can specify up to 10 so-called "Picks" in their profile representing her favourite locations that other users can view in the user's MySecondLife profile. We found that the extracted users picked 40,558 locations from 10,538 unique locations; b) Shared Locations: users in SL can also share information about their current in-world position through in-world pictures called "snapshots", which also include in-world GPS information (similar as Foursquare). Overall, we identified 13,637 snapshots in 5,736 unique locations; and c) Monitored Locations: as in real life, users in SL can create events in the virtual world and publicly announce them in a public event calendar. We collected these events, with an accurate location and start time, and extracted 157,765 user-location-time triples, with 1,887 unique locations.

3. EXPERIMENTAL SETUP

In this section we provide a detailed description of the evaluation methodology, recommender approaches and similarity measures used in our study.

3.1 Similarity Measures

As shown in our previous work (e.g., [14]), similarities between users can be derived in two different ways: either we calculate similarities between users on the content (= meta-data) provided directly by the user profiles or on the network structure of the user profiles interacting with each other. In the following sub-sections we present more details about these ideas.

3.1.1 Content-based Similarity Measures

We define our set of content-based similarity measures based on different types of entities or meta-data information that are directly associated with the user profiles in our data sources. In the case of the marketplace dataset these entities are purchased products, product categories and sellers of the products, in the case of the social network these are groups and interests the users have assigned, and in the case of the location-based dataset these are favored locations, shared locations and monitored locations. Formally, we define the entities of a user u as $\Delta(u)$ in order to calculate the similarity between two users, u and v.

The first content-based similarity measure we induce is based on the entities two users have in common. It is called *Common Entities* and is given by $sim(u,v) = |\Delta(u) \cap \Delta(v)|$. The second similarity measure, *Total Entities*, is defined as the union of two users' entities and is calculated by $sim(u,v) = |\Delta(u) \cup \Delta(v)|$. These two similarity measures are combined by *Jaccard's Coefficient for Entities* as the number of common entities divided by the total number of entities: $sim(u,v) = \frac{|\Delta(u) \cap \Delta(v)|}{|\Delta(u) \cup \Delta(v)|}$.

3.1.2 Network-based Similarity Measures

In our experiments we consider all networks as an undirected graph $G\langle V, E\rangle$ with V representing the user profiles and $e = (u,v) \in E$ if user u performed an action on v (see also [14]). In the case of the social network, these actions are defined as social interactions, which are a combination of likes, comments and wallposts. In the case of the location-based dataset, actions between users are determined if they have met each other in the virtual world at the same time in the same location[4]. Furthermore, the weight of an edge $w_{action}(u,v)$ gives the frequency of a specific action between two users u and v. Finally, this network structure also let us determine the neighbors of users in order to calculate similarities based on this information. We define the set of neighbors of a node $v \in G$ as $\Gamma(v) = \{u \mid (u,v) \in E\}$.

The first network-based similarity measure we introduce, uses the number of *Directed Interactions* between two users and is given

[1] **Note:** The datasets could be obtained by contacting the fourth author of this work.

[2] https://marketplace.secondlife.com/

[3] https://my.secondlife.com/

[4] **Note:** We derived the networks in our study from the location-based dataset only for the monitored locations, since the exact timestamps are not available for the favored nor the shared locations in the datasets.

by $sim(u,v) = w_{action}(u,v)$. In contrast to *Directed Interactions*, the following similarity measures are based on the neighborhood of two users: The first neighborhood similarity measure is called *Common Neighbors* and represents the number of neighbors two users have in common: $sim(u,v) = |\Gamma(u) \cap \Gamma(v)|$. To also take into account the total number of neighbors of the users, we introduced *Jaccard's Coefficient for Common Neighbors*. It is defined as $sim(u,v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}$. Another related similarity measure is called *Neighbourhood Overlap*. Formally, this is written as $sim(u,v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u)| + |\Gamma(v)|}$. A refinement of this measure was proposed as *Adamic Adar*, which adds weights to the links since not all neighbors in a network have the same tie strength: $sim(u,v) = \sum_{z \in \Gamma(u) \cap \Gamma(v)} \frac{1}{log(|\Gamma(z)|)}$. The *Preferential Attachment Score*, first mentioned by Barabasi et al. [1], is another network-based similarity measure with the goal to prefer active users in the network. This score is the product of the number of neighbors of each user and is calculated by $sim(u,v) = |\Gamma(u)| \cdot |\Gamma(v)|$.

3.2 Recommendation Approaches

User-based Collaborative Filtering. As already highlighted, we used a user-based Collaborative Filtering (CF) approach to recommend items to people. The basic idea of this approach is that users who are more similar to each other, e.g., have similar taste, will likely agree or rate on other resources in a similar manner [12]. Out of the different CF approaches we used the non-probabilistic user-based nearest neighbor algorithm where we first find the k-nearest similar users and afterwards recommend the resources of those user as a ranked list of top-N items to the target user that are new to her (i.e., she has not purchased those items in the past).

The similarity values of the user pairs $sim(u,v)$ are calculated based on the measures proposed in Section 3.1 (i.e., constructing the neighborhood). Based on these similarity values, each item i of the k most similar users for the target user u is ranked using the following formula [12]:

$$pred(u,i) = \sum_{v \in neighbors(u)} sim(u,v) \qquad (1)$$

Collaborative Filtering Hybrids. To further explore how to combine our data for recommendation, we investigated different hybridization methods (see also [4]). The hybrid approach chosen in the end is known as *Weighted Hybrid*, where the score of each recommended item is calculated as the weighted sum of the scores for all recommender approaches. It is given by:

$$W_{rec_i} = \sum_{s_j \in S} (W_{rec_i,s_j} \cdot W_{s_j}) \qquad (2)$$

where the combined weighting of the recommended item i, W_{rec_i}, is given by the sum of all single weightings for each recommended item in an approach W_{rec_i,s_j} multiplied by the weightings of the recommender approaches W_{s_j}. We weighted each recommender approach W_{s_j} based on the nDCG value obtained from the individual approaches. We also experimented with two other hybrid approaches, known as *Mixed Hybrid* [4] and *Cross-Source Hybrid* [4]. However, these approaches have not yielded better results than the *Weighted Hybrid*.

Baseline. As baseline for our study, we used a simple MostPopular approach recommending the most popular items in terms of purchase frequency to the users.

All recommender approaches mentioned in this paper have been implemented into our scalable big data social recommender framework *SocRec*, an open-source framework which can be obtained from our Github repository[5].

		Sim. Measure/Entity	$nDCG$@10	P@10	R@10	D	UC
		Most Popular	.0082	.0021	.0122	.5945	100.00%
Market	Content	Common Purchases	.0197	.0063	.0228	.5660	33.55%
		Common Sellers	.0239	.0076	.0313	.5571	54.05%
		Jaccard Sellers	.0248	.0080	.0315	.5332	54.05%
		Total Sellers	.0159	.0045	.0189	.5887	54.05%
		Common Categories	.0079	.0028	.0110	.6542	41.90%
		Jaccard Categories	.0079	.0028	.0108	.5788	41.90%
		Total Categories	.0014	.0005	.0023	.6606	41.90%
Social	Content	Common Groups	.0074	.0014	.0098	.6127	65.24%
		Jaccard Groups	.0077	.0015	.0101	.6154	65.24%
		Total Groups	.0018	.0004	.0028	.6375	65.24%
		Common Interests	.0005	.0002	.0008	.6173	37.76%
		Jaccard Interests	.0008	.0002	.0010	.6123	37.76%
		Total Interests	.0011	.0003	.0012	.6372	37.76%
	Network	Directed Interactions	.0879	.0405	.1603	.4897	30.26%
		Common Neighbours	.1366	.0425	.1388	.4369	55.78%
		Jaccard Common Neighbours	.1490	.0470	.1556	.5500	63.71%
		Neighbourhood Overlap	**.1710**	**.0537**	**.1906**	.5582	63.67%
		Adamic/Adar	.1171	.0385	.1304	.4681	60.90%
		Pref. Attach. Score	.0355	.0142	.0518	.5516	62.31%
Location	Content	Common Favored Locations	.0045	.0010	.0071	.6042	95.08%
		Jaccard Favored Locations	.0045	.0010	.0061	.6065	95.08%
		Total Favored Locations	.0038	.0009	.0052	.6181	95.08%
		Common Shared Locations	.0015	.0004	.0023	.6008	27.23%
		Jaccard Shared Locations	.0018	.0005	.0028	.5927	27.23%
		Total Shared Locations	.0007	.0002	.0016	.5931	27.23%
		Common Monitored Locations	.0030	.0007	.0045	.6250	**97.99%**
		Jaccard Monitored Locations	.0028	.0007	.0041	.6226	**97.99%**
		Total Monitored Locations	.0015	.0004	.0025	.6160	**97.99%**
	Network	Common Neighbours	.0023	.0005	.0032	.6224	35.28%
		Jaccard	.0034	.0007	.0042	.6168	35.28%
		Neighbourhood Overlap	.0023	.0006	.0038	.6233	35.28%
		Adamic/Adar	.0025	.0006	.0035	**.6787**	35.28%
		Pref. Attach. Score	.0005	.0002	.0009	.5962	37.20%

Table 2: Results of the user-based CF approaches based on different similiarity measures.

3.3 Evaluation Method and Metrics

To evaluate the performance of each approach in a recommender setting, we performed a number of off-line experiments. Therefore, we split the SL dataset in two different sets (training and test set) using a method similar to the one described in [10], i.e., for each user we withheld 10 purchased products from the training set and added them to the test set to be predicted. Since we did not use a p-core pruning technique to prevent a biased evaluation, there are also users with less than 10 relevant items. For those users, we considered half of their purchased items for training and the other half for testing. With that method at hand we were able to simulate cold-start users for whom there is no item in the training set and the only relevant item is used in the test set.

To finally quantify the performance of each of our recommender approaches, we used a diverse set of well-established metrics in recommender systems. In particular, we report nDCG@10, P@10 (Precision at '10'), R@10 (Recall at '10'), User Coverage (UC) and Diversity (D) [13, 8]. All performance metrics are calculated and reported based on the top-10 recommended items.

4. RESULTS

In this section we highlight the results of our experiments in terms of algorithmic performance.

Our evaluation has been conducted in two steps: we first compared the different recommender approaches with the corresponding similarity measures and data sources isolated (see Table 2) and then combined these approaches in the form of hybrids (see Table 3) to validate to which extent they can be used to build more robust recommenders. The results for the different recommender ap-

[5]https://github.com/learning-layers/SocRec

Sets		$nDCG@10$	$P@10$	$R@10$	D	UC
Most Popular		.0082	.0021	.0122	.5945	100.00%
Market	Content	.0239	.0073	.0306	.6367	56.17%
Social	Content	.0067	.0015	.0096	.6877	78.67%
	Network	**.1597**	**.0550**	**.2041**	.6316	63.76%
	Combined	.1135	.0390	.1464	.6746	91.04%
Location	Content	.0053	.0014	.0083	**.6928**	99.90%
	Network	.0025	.0007	.0040	.6847	37.20%
	Combined	.0054	.0014	.0081	.6925	99.90%
Combined		.1085	.0363	.1395	.6722	**100.00%**
Combined Top 3		.1168	.0361	.1330	.6620	98.88%

Table 3: Results of the hybrid recommendation approaches.

proaches presented in this paper are calculated in relation to their User Coverage (UC), i.e. only for the users where they were able to produce recommendations (see also [2]).

Table 2 shows the recommender accuracy (nDCG@10, P@10 and R@10), Diversity (D) and User Coverage (UC) for the different user-based CF approaches using content- and network-based similarity measures in the three datasets (marketplace, social and location) along with the Most Popular approach as a baseline. The best results in terms of accuracy are reached by the network-based approaches based on interactions (e.g., loves, comments, wallposts) between the users in the social network. Surprisingly these approaches clearly outperform the user-based CF approaches relying on marketplace data, which implies that social interactions of the users are a better predictor to recommend items to people than marketplace data. Another interesting finding is that the neighborhood-based measures also seem to be better indicators to determine the similarity between users than the direct interactions between these pairs, with the exception of Preferential Attachment Score, which reveals that the individual's taste is driven by the user's peers rather than by the popular users in the SL social network. On the other hand, location data had an unexpected poor performance compared to our previous work on predicting tie strength between users [14]. Despite this drawback, the fact that favored locations yielded better results than shared and monitored might indicate that this variable is far from noise and it actually carries some signal that the user-based CF approach might not be the best to exploit it. Moreover, in the results of the hybrid recommendation approaches in Table 3 we observe that the only one that yields better results than its parts isolated is based on location data, suggesting that there is some additional relevance signal not yet extracted, calling for latent-features approaches to assess their utility before dropping them as unuseful.

Looking next to the hybrid approaches in Table 3, we see again the recommender approaches based on the social network data outperform the ones based on marketplace and location-based data as well as the baseline (Most Popular). Furthermore, when combining all three data sources, the overall recommendation accuracy is decreased to 10.85% with respect to nDCG and 13.95% with respect to Recall, but the User Coverage is increased to the maximum of 100%. This means that the hybrid approach is capable of providing accurate recommendations for all users in the datasets. Another hybrid approach shown in Table 3, combines only the best recommender approaches from each data source (Top 3) reaching higher accuracy than the hybrid that combines all approaches.

5. CONCLUSIONS & FUTURE WORK

In this work we presented preliminary results of a recently started project that tries to utilize various sources of interaction data to recommend items to people in an online marketplace setting. As the results have shown, the user-based Collaborative Filtering approaches that utilize online social network data to calculate the similarities between users performed best, significantly outperforming the other approaches relying on both – marketplace and location-based user data. Furthermore, we have revealed that more robust recommenders for online marketplaces can be constructed utilizing online social network and location-based user data.

Although the results of this study are based on a dataset obtained from the virtual world SecondLife we believe that it bears great potential to create a sequence of interesting studies that may have implications for the "real" world (see e.g., [15]). For instance, one of the potential interesting issues we are currently exploring is predicting categories of products to users in a cold-start setting by a diversity of measures. Other important work we plan is the use of state-of-the-art model-based approaches in order to assess whether the signal extracted from similarity measures in the current analysis can be replicated (in the case of social data) or improved (in the case of location data) for different recommendation tasks.

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