Making Recommendations by Integrating Information from Multiple Social Networks

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Recommendation systems are commonly used by the web-platforms, such as social networks, review web-sites, and e-commerce web-sites, to serve their users. Each platform captures and maintains data related to its users and uses this data to produce recommendations. However, people generally use different web-platforms for different purposes. Integration of information from multiple platforms can widen the perspective of web-platforms and help them to model their users more effectively. Motivated by this, we integrated data collected from multiple platforms and developed a recommendation framework which uses the integrated data. The datasets we collected and anonymized contain information from BlogCatalog, Twitter, Flickr, Facebook, YouTube and LastFm. We used single versus multiple features from a single source versus multiple sources and observed performance of several different types of recommendation methods. The results of the experiments showed that using multiple features from multiple social networks models users' behavior better and leads to better recommendation performance.

CCS Concepts:•**Information systems** → **Social networking sites; Recommender systems;** *Collaborative filtering;* Social recommendation;

General Terms: Information retrieval, Recommender systems, Social networking sites

Additional Key Words and Phrases: Individual modeling, Multiple data sources, Social networks

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1. INTRODUCTION

Recommendation systems are commonly used by the web-platforms, such as social networks, review web-sites, and e-commerce web-sites, to serve their users. For example, LinkedIn, a social-network site for professionals, has a service, named as "Jobs You May Be Interested In", to suggest jobs to its members based on their profiles. Most of these platforms use their own information to model users' preferences [Liu and Maes 2005] which leads to a limited perspective on users. However integrating information from multiple platforms can help these services to widen their perspective and to model the users better.

People generally use different web-platforms for different purposes. For example, even though both LinkedIn and Facebook are social networks, people use LinkedIn for professional connections and Facebook for personal connections [Motoyama and Varghese 2009]. Combining information from various platforms can help systems to model users better [Zafarani and Liu 2013]. The literature on identity resolution and cross-domain recommendation can be used for this purpose. Identity resolution research

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aims to connect identities of a single person across social networks, e.g., [Liu and Maes 2005], [Motoyama and Varghese 2009], [Zafarani and Liu 2013], [Jain et al. 2013], [Tan et al. 2014b]. Jain et al. [Jain et al. 2013] states that identity resoultion solutions can be used by various applications, such as security, privacy and recommendation systems. Some of the researches in recommendation systems aim to make recommendations across domains, e.g., [Tan et al. 2014a], [Zhang 2014], [Kumar et al. 2014]. However, these cross-domain recommendation systems focused on matching items rather than users' preferences across platforms. Inspired from the above-mentioned research in the literature, in our previous work [Ozsoy et al. 2015] we integrated data collected from multiple different social networks, created an integrated model of users' preferences and used this model to make more guided recommendations. To the best of our knowledge, that work is the first work that models users from a a wider global perspective by integrating data from multiple sources. In this work, we expand our previous work by introducing new social networks and more users to our system and by extending our experiments on different use-cases.

In our previous work [Ozsoy et al. 2015] we created our own data-sets, since the existing data-sets used in cross-domain recommendations and identity resolution don't have information on users' preferences/behaviors and information on items at the same time. In that work, we collected information about users from the BlogCatalog website, which lets users to share accounts on other social-platforms. Using the shared account information, we collected information from Flickr and Twitter, whenever the information is publicly available. In this work, we expand the data-set by introducing data from three new social networks, namely Facebook, YouTube and LastFm. Besides, we expend the number of users used during the evaluation and evaluated our system for different purposes, i.e. making recommendation for different platforms. [1]

The contributions of this work can be summarized as follows:

— We integrated data collected from multiple social networks and used the integrated data to model users with a wider perspective. Then, the constructed model is used in the recommendation process.
— We expanded the data-set created in our previous work [Ozsoy et al. 2015]. The previous data-set contains information collected from BlogCatalog, Twitter and Flickr and users are limited to the ones who have accounts in all the three platforms. In the expanded data-set, created for this work, data from three new social networks, namely Facebook, YouTube and LastFm, are included. Besides, not only the sub-group of users but also all the available users are used for the evaluation.
— We implemented several recommendation methodologies to observe the effectiveness of use of single versus multiple features. The used recommendation methodologies are collaborative filtering, multi-objective optimization based recommendation [Ozsoy et al. 2014], hybrid recommendation and social-historical model [Gao et al. 2012] based recommendation methods.
— We compared the performance of the different recommendation methodologies on single feature versus multiple features and on a single source versus multiple sources. Besides, we performed evaluation on two different platforms, such that we aimed to recommend new groups to Flickr users and new following relation to BlogCatalog users.

The rest of the paper is composed of the following sections: The collected and prepared multi-source data-set is described in Section 2. The recommendation methods and the features we used are presented in Section 3. The experimental settings and

[1] We will share the data-set for academic research.

their results are discussed in Section 4. An overview on the related work is presented in Section 5. The paper is concluded in Section 6.

2. MULTI-SOURCE DATA-SET

In our previous work [Ozsoy et al. 2015] we created a data-set using three different social networks, namely BlogCatalog, Twitter and Flickr. In this work, we expand the data-set with other social networks.

In the previous work, we used BlogCatalog web-site as our base platform inspiring from [Zafarani and Liu 2013]. BlogCatalog lets its users to publicly share their accounts on other platforms. After collecting the account information of users on other social networks, we presented the number of users from each social network in Figure 1.

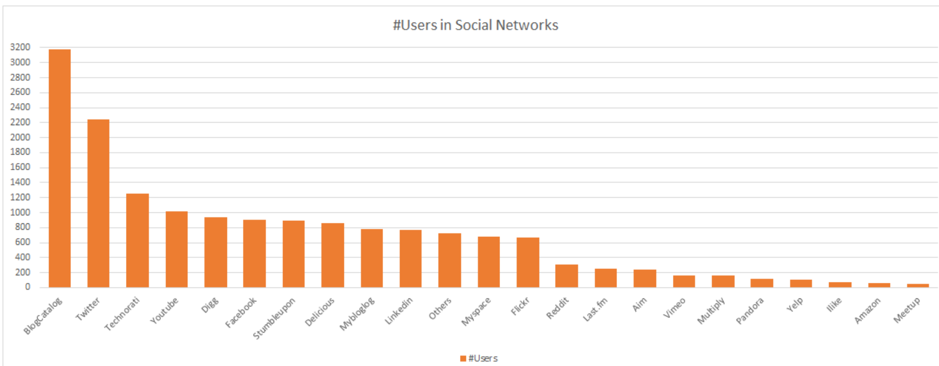

Fig. 1. Number of users on each social network

According to Figure 1, there are three clusters of social networks based on the number of users: The first cluster contains social networks with the highest amount of users. Among them, in the previous work we collected data from BlogCatalog and Twitter. In this work, we attempted to collect data from Technorati, however the platform stopped its previous services on May 2014 and the related data is not reachable anymore. The second cluster contains social networks with average number of users. In the previous work, we collected data only from Flickr, due to its API's ease of use and publicly available data. In this work, we also collected data from YouTube and Facebook. We attempted to collect data from other platforms too, however they either closed their services or they have very restrictive rules on data collection. For example, LinkedIn platform does not allow developers to collect most of the data without users' permission and does not let them to save any collected data for future use. The last cluster contains limited number of users (i.e., less than 300). In the previous work, we did not collect any data from this cluster. In this work, we collected data from LastFm since its API is easy to use and most of the data is publicly available.

The social networks we selected, namely BlogCatalog, Twitter, Flickr, YouTube, Facebook and LastFm, are active platforms, such that the state of the network may change by time. For example, a user may start to follow new users or may become member to new groups. The data we collected represents only the state of those networks on the data collection date. We collected the publicly available data from BlogCatalog, Twitter and Flickr on 19-20 February 2015 and from YouTube, Facebook and LastFm on 3-8 June 2015.

For readers who are not familiar with the platforms we are using, we want to briefly explain them: BlogCatalog is a platform which lets bloggers to share information about themselves and their blogs. Also users can search for blogs of their interest and interact with other bloggers on the forums. Each blogger owns his/her own page in which they can give brief description about themselves, share their hometown, communities and accounts on other platforms. Also the platform provides information on the recent visitors of the bloggers' personal page, the blogs he/she has, the followers, the followees and the reading list. Twitter is an online social network and it provides services to its users to share short messages (tweets) with the public, send or receive directed messages to other users and connect with other users. On their personal pages, users can give brief information on themselves and can share their city information. On this page, there is also information on the tweets a user has written, the followers and followees, favorites and lists. Flickr provides services to its users to share their photographs, label them with tags, titles and descriptions. The photos the user shared, the albums he/she created, and the photos he/she favored can be seen on personal pages. Also, in the web-site users can form groups, share their photos with others, and discuss subjects of their choice.

Facebook is an online social networking platform which provides services to its users to create user profiles, connect to other users, exchange messages, post status updates and photos, and form groups. The publicly available information is chosen by the users themselves. YouTube is a video-sharing website which provides services to users to upload, view and share videos. On the video pages, the number of views, the number of likes and dislikes and the comments are available. Registered users can create their own channels, also they can subscribe to other channels to follow new videos. Description of the channel, the uploaded videos and the play-lists created by the users are available on the channels. LastFm is a music website in which users have their own profile pages. The tracks the users listened to, the top artists and the top albums they like are listed on the profile pages. LastFm uses these information, and many others, to give recommendations on new tracks to listen to or on other users to connect to its registered users. It also provides services to users to form groups and add/search events.

As mentioned before, we used BlogCatalog as our base platform inspiring from [Zafarani and Liu 2013]. On BlogCatalog users can publicly share their accounts on other social networks.Using this information we first found the mapping of user-ids and then we collected data about these users on other platforms by using their APIs. During this process, we found that it is not possible to collect information for all the users of each platform, since they close their accounts or they do not publicly share their information. For example, on BlogCatalog 671 of the users indicate that they have a Flickr account. However, we could not collect any information for 318 of them, since their accounts are unreachable. We collected only publicly available information and anonymized the collected data to avoid privacy issues.

The data from BlogCatalog, Twitter and Flickr are collected and analyzed in our previous work [Ozsoy et al. 2015]. The collected information on these platforms is as follows: From BlogCatalog, we collected user-ids, cities of the users, regions of these cities, e.g., North America, Europe, etc., and followers and followees of the users. From Twitter, we collected user-ids, creation date of the account, verification information of the account, favorites count of the user, friends count of the user, and followers and followees of the user. From Flickr, we collected user-ids, first date of their photo sharing, contacts of the users, photos that the users favored, number of views, favorites, comments and tags of those photos and groups that the user is member of and the count of members, photos and topics of those groups.

In this work, we expand the previous data-set by collecting information from Facebook, YouTube and LastFm. From Facebook, we collected user-ids and last update date of the account. We did not collect other information since either they may cause privacy problem (e.g. the name of the user) or the information is not publicly available. We used the last update date information as a measure to indicate the activity level of the users. In Table I, we present the number of users in the given update date ranges, in terms of year or year-month, their ratio to all of the users and the label we assigned to them. From YouTube we collected user-ids, video, view, comment,and

Table I. Last update dates on Facebook in the given date ranges

Date	Count	Ratio	Label
$<$ 2014 or Unknown	103	0.137	Inactive (0)
2014	161	0.214	Not very active (1)
$<$ 2015 May	242	0.323	Active (2)
2015 May or June	245	0.326	Very active (3)

subscriber count of their account, account publication date, user-ids of the subscribed account (i.e., following), subscription date, (user activity date and type (i.e. Bulletin, PlayListItem, Like, Subscription or Upload) and users topics. On YouTube the topics are related to the Freebase topics, so we collected from Freebase the following information on topics: topic ids, topic names, topic notable ids and topic notable names. The notable topics can be thought to be a upper level representation of the topic. For example both topics "Game show" and "Animated cartoon" have the same notable topic "TV genre". We further created the relation from user topics to Freebase notable topics to make the analysis easier. We used this relation during the experiments we performed. From LastFm we collected user-ids, country, age and gender of the users, users' friends and users' top albums and top artists together with their ranks.

In this work, we prepared two different data-sets that incorporate the above-mentioned data collected from six different social networks. In the first data-set, we expanded the data-set that was used in [Ozsoy et al. 2015] with three new social networks; namely Facebook, YouTube and LastFm. In the previous work the users were limited to the ones which have accounts in the three social networks; namely BlogCatalog, Twitter and Flickr. In the expansion we just considered those users only and expanded the data with new social networks. In the second data-set, we used all the available users from all the six social networks regardless of the level of overlap. Detailed information on the data-sets are as follows:

Dataset 1: In our previous work [Ozsoy et al. 2015], from BlogCatalog we collected information of 22291 users, whose city information is known. However, only 3179 of them explicitly indicate their accounts on other social networks. Among the BlogCatalog users, only 2187 of them publicly share their Twitter accounts and only 671 of them publicly share their Flickr accounts. Even though users share their accounts publicly on BlogCatalog, we are not able to collect all of them; since some of those accounts are closed or private. There are 241 users who have accounts in all of the above mentioned three platforms. In [Ozsoy et al. 2015], these 241 users are used for the experiments. In this work, we added information collected from Facebook, YouTube and LastFm to these selected 241 users, if they have any account on the related platforms. Some information on the selected 241 users are as follows: On BlogCatalog data-set all the 241 users are available and these users are identified to be from 66 different cities, which are located in 6 different regions. Among these users 133 of them have followees and 156 of them have followers. On Twitter data-set all the 241 users are available and 237 of the them have followers and 234 have followees. On Flickr all the 241 users are available and 160 of them have at least one contact. 126 of the 241 Flickr users are members of at least one group. The total number of Flickr groups in the produced data-set is 4802. Finally, 105 of the 241 users have at least one favorite photo, and the total number of distinct photos favored by a member is 5067. These photos have 17611 different tags in total. On Facebook 89 of the selected 241 users are available. Among the selected 89 Facebook users, the number of users having the activity level inactive is 15, not very active is 17, active is 27 and very active is 30. On YouTube 118 of the selected 241 users are available. Among these users 115 of them have at least one kind of activity, only 1 of them has a subscription to other channels and only 1 of them are subscribed by other users. 103 of the 118 YouTube users indicated at least one topic as their interest. The number of distinct topics is 118 and the number of Freebase notable topics is 57. This indicates that even though most of the users have different topic tags as their interest, they mostly share a common taste. On LastFm 53 of the selected 241 users are available. These users indicate that they are from 17 different countries. Among these users 10 of them are females, 30 of them are males and 13 of them did not indicate any gender. Among the selected 53 LastFm users, 37 of them have at least one friend and only 2 of them are friends of others. 19 of the 53 LastFm users indicated their top albums and top artists. There are 14818 different albums and 7846 different artists that are listed in the top albums and top artists lists. 13807 of the albums and 6297 of the artist are listed in top by only a single user. This indicates that the collected LastFm users have mostly unique music taste.

Dataset2: In the second data-set, instead of limiting the users to a subgroup, we used all the available users. There are 22291 users in BlogCatalog who are used as the base in this project. The total number of users whose names are listed in the users, followers or followees lists is 84467. The 22291 base BlogCatalog users are from 94 different cities from 6 different regions. Among these users, 6990 of them follow some other users and 8912 of them are followed by other users. The ones who have following information follow 61621 distinct users. The ones who have follower information are followed by 31476 users. Even though there are 2187 BlogCatalog users who indicate that they have an account of Twitter, we are able to collect information of only 1802 of them, since some of the users have closed their accounts or have private accounts. 1760 of these users have at least one follower and 1738 of them have at least one followee. None of the followers and 884 of the followees are among the base 1802 Twitter users. There are 349 Flickr users who have shared their accounts on BlogCatalog and whose information is publicly accessible. 240 of the 349 Flickr users have at least one contact and 13 of the contacts are among the selected 349 Flickr users. 189 of these users are member of at least one group. The total number of Flickr groups which have at least one member is 7725. 158 of the 349 Flickr users have at least one favorite photo, the total number of distinct photos favored by a member is 7451 and these photos have 24719 distinct tags in total. On Facebook, we were able to collect information of 751 users. Among these users, there are 103 inactive, 161 not very active, 242 active and 245 very active users. There are 822 YouTube users who have shared their account on BlogCatalog and whose information is publicly accessible. 792 of these users have an activity type and only 20 of them are subscribed to a channel. 702 of the 822 YouTube users has at least one topic as their interest. The number of distinct topics and the number of Freebase notable topics that are indicated as interest by these users are 523 and 193, respectively. On LastFm, there are 234 users who have shared their accounts on BlogCatalog and whose information is publicly accessible. These users are from 29 countries. 60 of these users are female, 115 of them are male and 53 of them haven't indicate any gender information. 168 of the 234 LastFm users have at least one friend. 81 of these users have at least one top artist and 78 of them have at least one top album. 19736 artist and 43066 albums are listed in the top-artist or top-albums list of these LastFm users.

We conjecture that the constructed data-sets can be used for several different purposes; such as tag prediction, item recommendation, link prediction, identity prediction and location prediction.

3. RECOMMENDATIONS USING MULTIPLE DATA SOURCES

By having diverse and rich set of features in the data-sets, it is possible to develop a variety of recommendation systems which are capable of serving different purposes. In our previous work [Ozsoy et al. 2015], we aimed to make recommendations to Flickr users about the groups they may join in the future. In this work, we continued with this objective using the first data-set introduced in Section 2. As a second objective, we decided to make recommendations to BlogCatalog users on whom they can follow in the future. For this purpose, we used the second data-set explained in Section 2.

We decided to continue to use collaborative filtering, multi-objective optimization based, hybrid and social-historical model based recommendation methods to observe the effect of using data from multiple data sources, as done in our previous work [Ozsoy et al. 2015].

Collaborative filtering based recommendation: In user-based collaborative filtering, the neighbors are decided based on the similarities of other users to the target user. Then neighbors' past preferences are used to give a recommendation to the target user.

Multi-objective optimization based recommendation: Employing our multi-objective optimization based method proposed in [Ozsoy et al. 2014], we decided on the neighbors by using the Pareto dominance. Then the neighbors' previous preferences are used to make recommendations as it is done in collaborative filtering.

Hybrid recommendation: Item based hybrid approach combines the output of different recommendation methods. Even though several different techniques for hybridization are explained in [Burke 2002], in this work we combined only different collaborative filtering methods. the combination of the results and the rankong of the items are done based on the number of votes that each item received.

Social-historical model based recommendation: We used the method proposed in [Gao et al. 2012] which originally aims to predict next check-in venue. It models check-ins by a language model and combines friendship information as well.

Even though there are various features available from different social networks, in this work we used a subset of the features to demonstrate the effectiveness of integrating information from multiple sources. It is possible to add new features in future experiments. In this work, we kept the features used in the previous work [Ozsoy et al. 2015], i.e., from BlogCatalog, Twitter, Flickr, and expanded it with additional features from the new social networks, namely Facebook, YouTube and LastFm. The features used in this study and their source social network are explained next:

Flickr groups: On Flickr users can join different groups depending on their interests. A recommendation system can use the knowledge about previously joined groups to make predictions on the groups that these users may join in the future.

Flickr contacts: On Flickr users can connect with other members based on their real-world interactions or on similar interests on the web-platform. A recommendation system can use the contacts' past preferences to make predictions, as the contacts most probably share similar interests.

Flickr common contacts: Similar to Flickr contacts, this feature uses past preferences of other similar users. However, for this feature similarity among users are calculated based on the common contacts rather than having direct connection.

Twitter followees: On Twitter, users follow other users who they already know (e.g., friends, family members, etc.) or who they like, admire or support (e.g., political leaders, singers, etc.). Having common followees may indicate that two users are similar to

each other, and this can be used to make recommendations.
BlogCatalog followees: Similar to Twitter followees, users in BlogCatalog follow other users based on similar interests. Information from other users who have similar interests can be used to give recommendations to the target users.
Facebook activity level: The source social network of this feature is Facebook. Some users in our dataset are actively using their Facebook account, and some others are not. As explained in Section 2, we divided the users into four groups based on their activity level. Knowledge on this feature may help to group users together by their activity on social networks. For example, more active users may join more recent groups while others tend to join well-established ones.
YouTube-Freebase topics: On YouTube users indicate their interested topics and on Freebase notable topic, i.e., the upper level representation of the topic, is available. We used the combination of this information and found similarity of users on their Freebase notable topics. We used this similarity to give recommendations to the target users.
LastFm gender: The source social network of this feature is LastFm. Users of different genders may prefer different items to use/follow. This feature can be used for making recommendations.
LastFm top-artists: Based on the mostly listened tracks, LastFm provides a list of top-artists for each user. Having common top-artists may indicate that users have similar music taste, which can be used for making recommendations.

For all the selected features, except Flickr contacts, Facebook activity level and LastFm gender, we calculated the user-user similarity using the Cosine Similarity measure. For Flickr contacts, the similarity between the target user and his/her contacts is assigned the value 1.0, and for others the value assigned is 0.0. Similarly for Facebook activity level is handled as follows: users at the same activity level are assigned the similarity value of 1.0, and otherwise 0.0. Lastly, for LastFm gender users of the same gender are assigned the the similarity value of 1.0, and otherwise 0.0.

4. EVALUATION

For the evaluation, we used precision@k, recall@k and F1-measure, which are commonly used in the recommendation and search literature. These measures are computed as given in Equations 1, 2 and 3.

$$Precision_k = \frac{tp_k}{tp_k + fp_k} \tag{1}$$

$$Recall_k = \frac{tp_k}{tp_k + fn_k} \tag{2}$$

$$F1 - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

In the above equations, k indicates the output list length, tp refers to true positives, i.e., recommended and actually used items, fp is false positives, i.e., recommended but actually not used items, and fn indicates false negatives, i.e., not recommended but actually used items. Here it is worth mentioning that it is common for recommendation methods to have low precision results as the data is very sparse. For instance, in [Zhang and Chow 2015] the authors gave several examples of low precision results, which are in the range [0.030, 0.035], for different data-sets.

Considering the fact that the average precison@k value of a method can be high even though it is able to make recommendations just to a few users, we also calculated the hit-rate of the invoked methods. Hit-rate is the ratio of the users who are given at least one true recommendation. Hit-rate is calculated by Equation 4.

$$HitRate = \frac{\sum_{m \in M} HitRate_m}{|M|} \tag{4}$$

where M is the set of target users, m is one of those users, and $HitRate_m$ is a number whose value is set to 1.0 if the output list contains at least one true recommendation and to 0.0 otherwise.

To create the training and test set we followed the same approach on the two data-sets. For each data-set, we created two disjoint sets on the related feature, one for training and the other for testing. The sets are created by selecting the users with at least 5 items, and we randomly selected 20% of their items from the data-set. The randomly selected items are collected as the test set. The rest of them are used as the training set. For the first data-set, we set our objective as making Flickr group recommendations. In the original data-set there are 126 Flickr users where each of them is a member of at least one group. After creating the training and the test sets, we were left with 126 users in the training set and 86 users in the test set. On average, these users are members of 56.008 groups for the training set and 12.628 groups in the test set. For the second data-set, we set our objective as making BlogCatalog followee recommendations, i.e., whom to follow. In the original data-set there are 6990 BlogCatalog users who follow at least one other BlogCatalog user. After creating the training and test set, the number of users are found to be 6990 and 3670, respectively. The average number of followees on the training and test sets are 39.073 and 17.304, respectively.

As explained in Section 3, we implemented several different methods with a variety of features from the data-set we collected. In Table II, we present the list of methods together with the used features and their abbreviations. These abbreviations will be used in the rest of this paper.

Table II. The abbreviations used in this study

Methods	Abbreviation
Collaborative filtering	CF
Multi-objective optimization	MO
Hybrid	HI
Social-historical	SH
Features	**Abbreviation**
Flickr Groups	FG
Flickr Contacts	FC
Flickr Common Contacts	FCC
Twitter followees	TF
BlogCatalog followees	BCF
Facebook activity level	FbA
YouTube-Freebase topics	YT
LastFm gender	LG
LastFm top-artists	LAr

The details on the evaluation results on recommendations of Flickr groups and recommendations of BlogCatalog followees are given in Sections 4.1 and 4.2, respectively.

4.1. Recommendation of Flickr groups

For the experiments, we need to assign neighbors count (N) and the output list size (k), which can affect the performance of the methods. In the previous work [Ozsoy et al.

2015], we first started with some arbitrary values of these parameters and decided on the method that performs the best. Afterwards, we decided on the best values of N and k using only the selected method. To be fair to the other methods, lastly, we performed the analysis on all the methods using the determined N and k values.

Following our previous work, first, we assigned N and k to 5. We did not want to assign a larger value to N because we only have 126 users. We assigned to k the value 5 based on experience because we observed in our daily life that most recommendation systems prefer to present a small number of items as recommendations to their users. The evaluation results of the methods with the assigned values of N and k are shown in Figure 2, where the method and features combination are reflected in the form $Method - Feature1\_Feature2\_Feature3$. For example, the combination $HI - FG\_TF\_BCF\_LG$ refers to the Hybrid method combined with the features Flickr groups, Twitter followees, BlogCatalog followees and LastFm gender. Also, hitrate has been scaled to its 10% in order to have a better representation together with the other metrics.

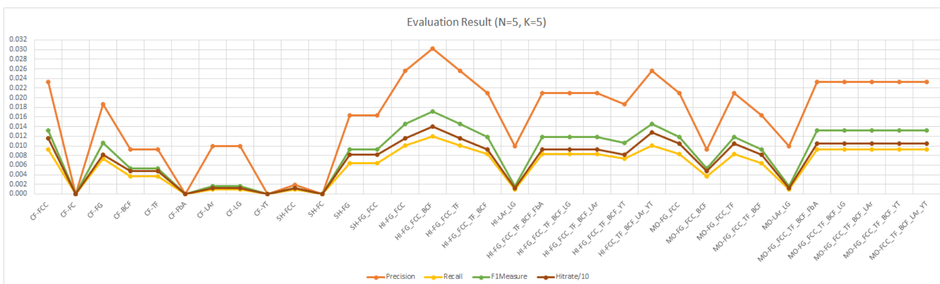

Fig. 2. Evaluation results for N=5 and k=5 (Flickr groups)

In Figure 2, we show both the results of the experiments that were conducted for our previous work [Ozsoy et al. 2015] and the results of the new experiments that use the features collected from the additional social networks. According to the figure, using data from the same social network and same feature does not necessarily lead to better performance. For example, CF_FCC (collaborative filtering using Flickr common contacts) performs better than CF_FG (collaborative filtering using Flickr groups). The methods that use information from a different social network only, such as CF_BCF or CF_LG, don't perform better than the methods that use information from the target social network. This may be related to the fact that people use different web-platforms for different purposes [Motoyama and Varghese 2009] and may behave differently in different social networks. Using the Social-Historical model [Gao et al. 2012] did not show good performance when the output list size is set to 5. Using multiple features at once (HI and MO methods) performs better than using a single feature (CF methods). The hybridization of item recommendations (HI methods) showed the best performance when Flickr groups, Flickr common contacts and BlogCatalog followees are used altogether.

Our multi-objective optimization based recommendation method [Ozsoy et al. 2014] performed the best when Flickr groups, Flickr common contacts or when additionally Twitter followees are used together. Other metrics, namely recall, F1-measure and hitrate, follow similar patterns to the precision results. According to these results, the best performing method is $HI - FG\_FCC\_BCF$. We already used this method to decide on the best N and k values in our previous work [Ozsoy et al. 2015]. In that work, we first decided on the best value of N by keeping $k = 5$ and evaluating the results by setting N values in the range [1,62] with 1 increment. According to the evaluation results, the best N is found to be 16. Afterwards, best k value is decided by using the same method and when N is set to 16. For this purpose k is set to values in the range [1,30] with increments of 1. The results showed that depending on the evaluation metric, different k values perform the best: The best value of k for precision is 4, it is 27 or 28 for recall, and it is 12 for F1-measure. We used these values for the rest of the experiments.

Lastly, we performed the analysis on all the methods with the selected values of the N and k parameters. We discarded Flickr contacts feature since it does not provide any successful recommendations as reflected in Figure 2. The evaluation results of the methods when N is set to 16 and k is set to either 4, 27 or 12 are presented in Figures 3, 4 and 5. When $k = 4$, i.e., the value that produces the highest precision in the previous experiment, the collaborative filtering that uses the target feature, namely the Flickr groups, and the hybridization of item based methods (HI methods) perform best. As observed in the previous work, we observe that the change of the neighbor and output list size affect the performance of the methods, and hence they should be tuned carefully. Mostly, recall, F1-measure and hitrate results follow patterns similar to the precision results. These results confirm that using data from multiple sources (e.g., social networks) improves the recommendation performance. When $k = 27$, i.e., the value that produces the highest recall in the previous experiment, generally precision performance of the methods decreases while recall performance increases. This is the expected behavior, since the increased output list size makes it easier to list true recommendations on the output, however it also leads to include more false recommendations in the output list. According to Figure 4, the best performing methods belong to the social-historical model. However unlike other methods and the results of previous experiments, there is a larger gap between hitrate and recall performance. This may indicate that these methods are able to give better recommendations for certain users as k increases. Besides, the social-historical model based method, the methods that use multiple features at once (HI and MO methods) perform equally good to or better than the methods that use single feature (CF methods). When $k = 12$, i.e., the value that produces the highest F1-measure in the previous experiment, results similar to the previous experiment, ($k = 27$) are observed. There is a decrease in precision and increase in recall and F1-measure compared to the case $k = 4$. As explained previously, longer output list leads to higher recall and F1-measure.

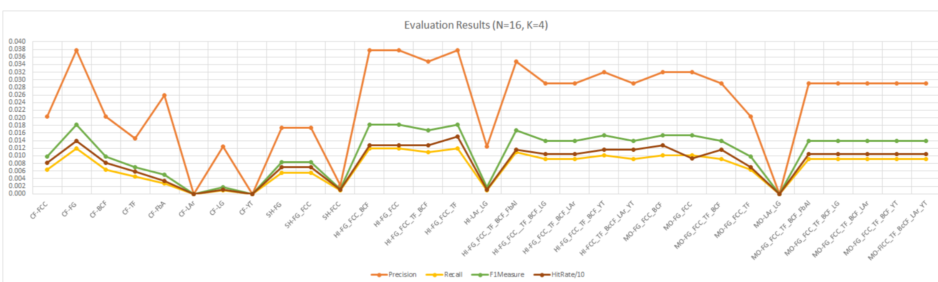

Fig. 3. Evaluation results for N=16 and k=4 (Flickr groups)

Even though we performed experiments that favor each of the metrics, i.e., precision, recall, and F1-measure, it is more important to make true recommendations to as many users as possible, i.e., higher hitrate; and present in the limited length output list one or more items that the user is expected to use in the future, i.e., higher

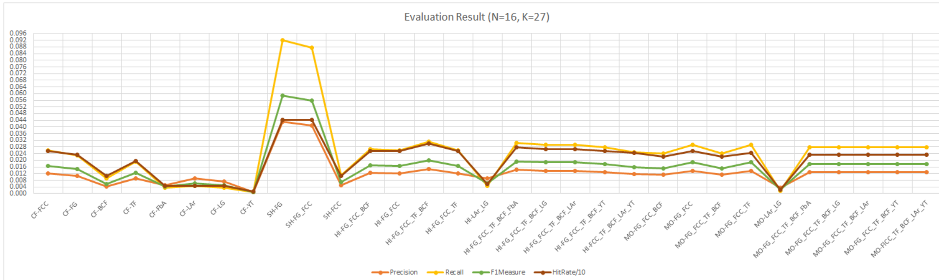

Fig. 4. Evaluation results for N=16 and k=27 (Flickr groups)

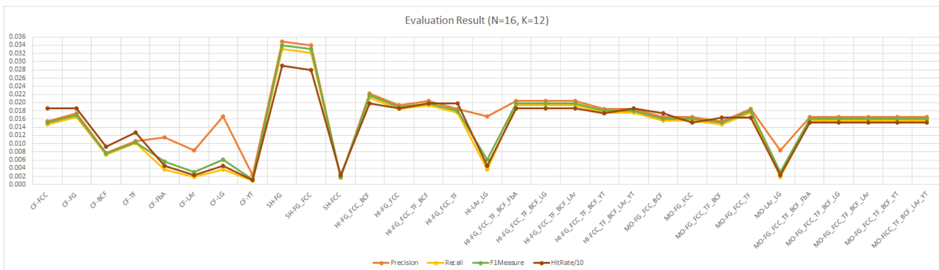

Fig. 5. Evaluation results for N=16 and k=12 (Flickr groups)

precision. Based on our analysis, for shorter outputs lists and when precision and hitrate are considered more important, the best performing method is the hybridization method that combines information from multiple features from multiple social networks. This way the method can model its users with other aspects which are not obvious for a single social network.

4.2. Recommendation of BlogCatalog followees

We modeled suggesting new links, i.e., new followees, as a recommendation problem. Similar to the experiments performed in the previous section, we started with a guess on values of parameters N and k and found the best performing method, then we decided on the best N and k values using the selected method and lastly we conducted experiments on all of the methods with the decided N and k values.

First, we assigned N and k to 5, as we did in the previous experiment. The evaluation results of the methods with our initial assigned values of N and k are shown in Figure 6, with the same naming pattern, i.e., $Method - Feature1\_Feature2\_Feature3$. Similar to the previous figures, hitrate has been scaled to its 10% in order to have a better representation of the other metrics.

According to Figure 6, the best performing methods are collaborative filtering method that use the target feature, i.e., CF_BCF, and methods that use combination of features from multiple social networks. We observed that HI-FG_FCC_TF_BCF_LG; which use hybrid itemization method using Flickr groups, Flickr common contacts, Twitter followings, BlogCatalog followings and LastFm gender features performs slightly better than the other methods. For instance, it performs 0.1% better than others in terms of recall, F1-measure and hitrate. We chose this method to decide on the best N and k values.

Using the HI-FG_FCC_TF_BCF_LG method, first we decided on parameter N by setting its value in the range [1,50] with 1 increment. Even though there are 6990 users,

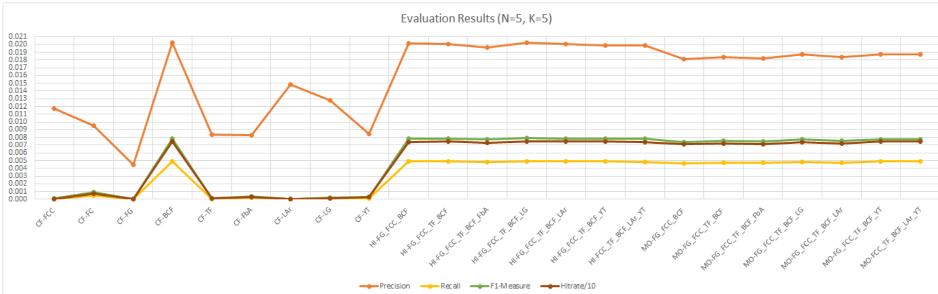

Fig. 6. Evaluation results for N=5 and k=5 (BlogCatalog followees)

we stopped neighbor count at 50. During the experiments we didn't use any parallelization technique, and higher N value required more resources. In the future we will move our implementation to a parallelized implementation to observe the performance with higher N values. The result of the experiment is shown in Figure 7. According to the figure, after increasing N from 1 to 3-4 there is a balance on the performance up until $N = 36$. After $N = 36$, there is a small increase in the performance of the evaluation metrics. However, it is not obviously seen, the hitrate ratio increases as N increase. For example, when $N = 1$ the hitrate is 0.0000012339, when $N = 36$ it is 0.0000022346 and when $N = 50$ it is 0.0000025742. Even though these values are really small, we preferred to set N to 50.

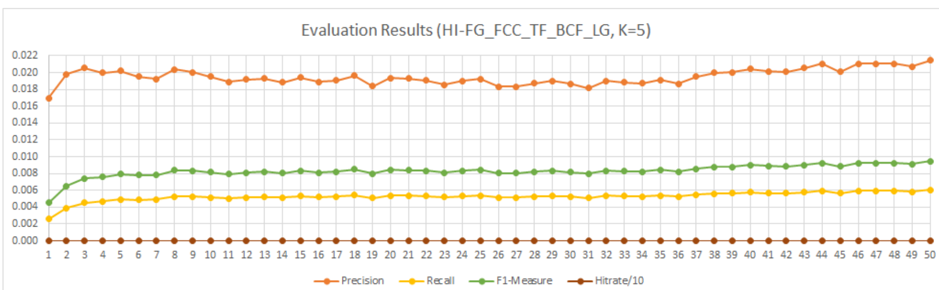

Fig. 7. Evaluation results for the HI-FG_FCC_TF_BCF_LG method and k=5 (BlogCatalog followees)

After deciding on $N = 50$, the next step is to decide on the k value. We conducted experiments using the HI-FG_FCC_TF_BCF_LG method and by setting k values in the range [1,30] with 1 increment. We limited the maximum output list size as 30, since in real life most of the recommendation systems present shorter lists, such as 10 or 15 elements in a page at most. The results of the experiment are shown on Figure 8. According to the figure, the precision performance increases up until $k = 11$ and then stays in balance and after k is around 16 it starts to decrease. The performance of recall, F1-measure and hitrate increase as k increase. As a result of these observations, we decided to set k to 15, which is one of the values that provide the best precision performance, and to 30 which provides the best recall, F1-measure and hitrate performance.

We conducted experiments on all of the methods using the parameters $N = 50$, $k = 15$ or $k = 30$ and the results are presented in Figures 9 and 10, respectively. The figures show that the best performing methods are the collaborative filtering method that uses the BlogCatalog followee feature, i.e., CF_BCF, and methods that use combination of

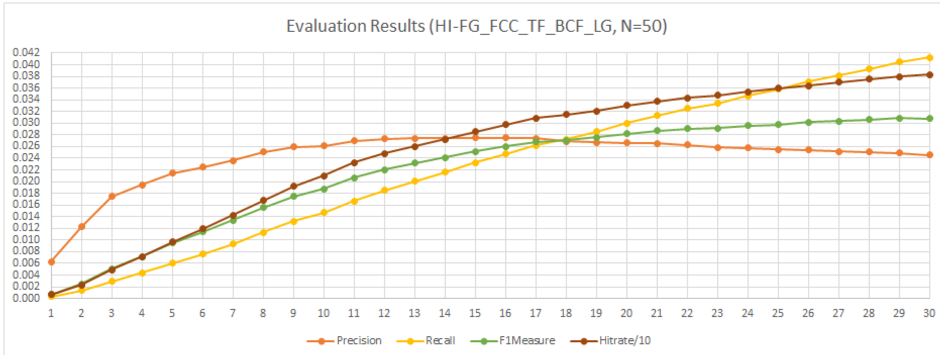

Fig. 8. Evaluation results for the HI-FG_FCC_TF_BCF_LG method and N=50 (BlogCatalog followees)

features from multiple social networks. Multi-objective optimization based methods perform slightly better than others in terms of hitrate when $k = 30$.

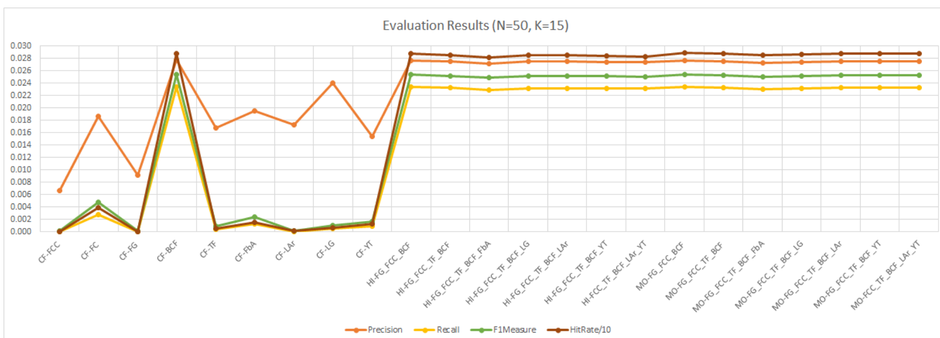

Fig. 9. Evaluation results for N=50 and k=15 (BlogCatalog followees)

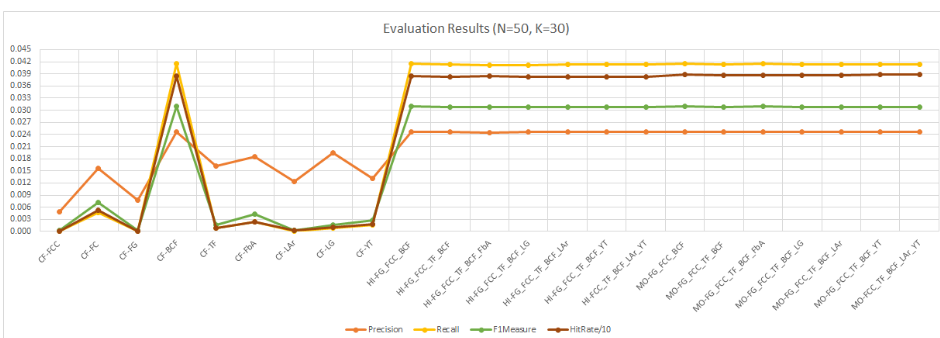

Fig. 10. Evaluation results for N=50 and k=30 (BlogCatalog followees)

From the previous experiments, we observed that collaborative filtering method that use the BlogCatalog followee feature, i.e., CF_BCF, and hybridization of items methods (HI methods) and multi-objective optimization based methods perform equally well. We further analyzed their performance on different types of users. For this purpose, we selected CF_BCF, HI-FG_FCC_BCF and MO-FG_FCC_BCF methods. We compared these methods for $N = 50$ and $k = 15$; similar analysis can be easily performed for other settings too. All of these methods have nearly the same overall precision performance and the later two of them use features from multiple social networks. The analysis results are presented in Tables III and IV.

According to the results, the collaborative filtering method and the hybrid method perform equally well on users whose precision is around 0.440; this means they can perform equally good for users who have on average 6.6 followees in the test set (Found by multiplying k by the average precision, i.e., 15 * 0.440 = 6.6). Also, these methods perform equally well when there are about 74 followees information in the train set. When we further analyzed the case of equal performance, we observed that all of the three methods are unable to make true recommendations for users who have on average 5.3 followees in the test set and about 32 followees on average in the train set. This indicates that these methods perform better for users with more followees in the training and test sets. When we looked at the cases where CF_BCF performs better, we observed that this method performs better for users with 10-12 followees in the test set. On the other hand, both the hybrid (HI) and the multi-objective optimization based (MO) methods are better than the collaborative filtering based method for users with less number of followees in the test set. Also they are able to model the target user better than collaborative the filtering based method when there are less number of followees information in the train set. For example, MO-FG_FCC_BCF performs better than CF_BCF when there are on the average 33 followees in the train set. The analysis shows that using multiple features from multiple social networks helps the system to model users more effectively, especially for users with less information.

Table III. Comparison of methods (CF_BCF vs. HI-FG_FCC_BCF)

Analysis	Avg. prec. upper bound (test set)	Avg. no. of followees on the train set
Perform equally well	0.447	73.771
Perform equally well(At least one true rec.)	0.666	178.875
Perform equally well(No true rec.)	0.359	31.343
CF_BCF performs better	0.850	66.000
HI-FG_FCC_BCF performs better	0.400	21.000

Table IV. Comparison of methods (CF_BCF vs. MO-FG_FCC_BCF)

Analysis	Avg. prec. upper bound (test set)	Avg. no. of followees on the train set
Perform equally well	0.439	39.813
Perform equally well (At least one true rec.)	0.663	105.865
Perform equally well (No true rec.)	0.355	32.319
CF_BCF performs better	0.717	205.292
MO-FG_FCC_BCF performs better	0.562	33.119

5. RELATED WORK

Recommendation systems aim to make recommendations to users based on their interests. Recently, most of the research on recommendation system focus on combining different kinds of information. [Yuan et al. 2013], [Liu et al. 2013], [Hu et al. 2013b], [Gao et al. 2013], [Yuan et al. 2014] and [Tsai and Lai 2015] use temporal information as well as historical preferences of users to make time-aware recommendations. Besides temporal information, location and social network information are used by many recommendation methods. LARS [Levandoski et al. 2012], [Zheng et al. 2010], [Ye et al. 2011], [Cheng et al. 2013] are some examples of systems that use location to improve the performance of their recommendation process. Another set of methods use friendship information to make better recommendations. [Gao et al. 2012], SoCo [Liu and Aberer 2013], [Ye et al. 2010] and [Ma et al. 2011] are some examples of these kinds of systems. These systems mostly use linear combination of features. Some other approaches in the literature use multi-objective optimization methods by combining multiple criteria, e.g., [Lakiotaki et al. 2008], [Manouselis and Costopoulou 2007], [Lee and Teng 2007], [Ortega et al. 2013] and [Ozsoy et al. 2014].

Another set of research focuses on cross-domain recommendation, which models the users in a domain and uses that model in the target domain. [Winoto and Tang 2008], [Tan et al. 2014a], [Zhang 2014], [Kumar et al. 2014], [Hu et al. 2013a] and [Loni et al. 2014] are some of the examples from cross-domain recommendation systems. These systems mostly use item-based matches and do not consider users' identities or they use data from a single source and assume different categories, such as books and movies, as different domains. One of the first research efforts on cross-domain recommendation belong to [Winoto and Tang 2008]. In that work, users were surveyed on category names and ratings they give. The collected data was analyzed both in group and at individual levels. The results showed that multiple information sources for recommendations is promising. [Tan et al. 2014a] found the correlation between objects by using a Bayesian hierarchical approach based on the Latent Dirichlet Allocation (LDA) method by modeling users' interests and objects' topics. The output correlations were used to give recommendations to target users based on their interests. [Zhang 2014] aimed to give recommendations across the web-sites by using browsing information of the users. This idea is similar to ours in the sense that we aim to use multiple social networks and they used multiple browsing history. However, the browsing history of the users may not be always available. [Kumar et al. 2014] used textual information of items to map them across domains. Then these mappings were used to give cross-domain recommendations. [Hu et al. 2013a] modeled users, items and domains together with the assumption that users behave similarly across domains. They evaluated their method on books and movies datasets collected from the Amazon web-site. [Loni et al. 2014] modeled users' preferences separately on each domain using the types of items. Then using factorization machines, they combined the separate models into one. [Li and Lin 2014] identified user and item mapping across the rating matrices and used the out mapping in the recommendation process. In this work, they assumed similar rating behavior of users on both domains, and there were some overlapping users/items. They evaluated their method on a synthetic dataset and Yahoo! Music dataset.

An alternative to cross-domain recommendation can be using identity resolution across domains, such as mapping users on different domains. This approach can be useful to analyze the users' behavior on different domains and the analysis results can be used by other applications, e.g., recommendation systems. [Liu and Maes 2005], [Motoyama and Varghese 2009],[Zafarani and Liu 2013],[Jain et al. 2013] and [Tan et al. 2014b] are some example works that aim to connect identities across social networks, namely identity resolution. They mostly focus on mapping users across domains, but not on their preferences or interactions with the related social network, i.e., they do not make any recommendation. [Liu and Maes 2005] used two different social networks to collect user descriptions. Then using the co-occurrence of the words, the authors built a network which connects interests and identities. They used this network to give recommendations. They did not aim to figure out individual identities but generic groups, such as Dog Lovers. [Motoyama and Varghese 2009] searched and matched users across online social networks. For matching purposes, they used several different attributes of the users; such as age, gender, location, country and name. [Zafarani and Liu 2013] mapped individuals across social media sites by first identifying users' unique behavior patterns, such as using similar names or typing patterns, then constructing features based on the captured behavior, and lastly identifying users using machine learning techniques. [Jain et al. 2013] used content and network features additional to previously used features to map users across Facebook and Twitter. They concluded that using different attributes provides distinct aspects of the identity of the users, and helps to improve the performance of the identity resolution process. [Tan et al. 2014b] proposed a semi-supervised manifold alignment method to map users across social networks. Even though they used social structures only, they stated that names of users can also be used to boost the performance of the system.

6. CONCLUSION AND FUTURE WORK

Today's web-based platforms, such as social networks, review web-sites, e-commerce web-sites are commonly use recommendation systems. Each of these platforms models its users and makes recommendations using only the local information captured by the website [Liu and Maes 2005]. It is known that people tend to use different web-platforms for different purposes [Motoyama and Varghese 2009]. Instead of restricting the analysis to locally captured information, considering information from multiple sources is more beneficial and rewarding. In other words, to have more complete information about each user, it is essential to consider integrated information from multiple social networks [Zafarani and Liu 2013].

In this work, we extended our previous work [Ozsoy et al. 2015] by integrating information collected from multiple different social networks to create integrated model of individuals and to give recommendations to them. To the best of our knowledge, our work is the first work aiming to use integrated information from multiple social networking platforms in the recommendation process. In this paper, the previously prepared dataset which was using data from BlogCatalog, Twitter and Flickr web-sites, is extended with data collected from Facebook, YouTube and LastFm. We created two different datasets: The first one is an extension of the previously created dataset. Previously, we used a subset of the data that contains users who have accounts in all the three websites and their preferences/interactions in each website. In the extension, we used the same users with additional features from the new three social networks. The second dataset contains all of the users collected from all the six social networks.

We used the created datasets to give recommendations to the target people on different platforms, i.e., recommending new groups to follow to Flickr users and recommending other users to follow to BlogCatalog users. We implemented several different types of recommendation methodologies to observe their performance, namely collaborative filtering, multi-objective optimization based recommendation, hybrid and social-historical model based recommendation methods. We compared the performance of these recommendation methodologies while using single versus multiple features from a single versus multiple sources. The conducted experiments showed that using multiple features from multiple sources improved the recommendation performance.

As future work, we want to integrate identity resolution methods into our work and produce an end-to-end recommendation system. We also want to use more features which are not covered in this paper. Finally, we want to try some other recommendation methods to observe their effectiveness while using a multi-source dataset.

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