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Making Recommendations by Integrating Information from Multiple Social Networks

Makbule Gulcin Ozsoy · Faruk Polat · Reda Alhajj

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Abstract Recommendation systems are commonly used by web-platforms, such as social networks, review web-sites, and e-commerce web-sites, to serve their users. Each platform produces recommendations by capturing and maintaining data related to its users. However, people generally use different web-platforms for different purposes. Thus, each platform captures its own data which may reflect certain aspects related to its users. Integrating data from multiple platforms may widen the perspective of the analysis and help in modeling users more effectively. Motivated by this, we developed a recommendation framework which integrates data collected from multiple platforms. For this purpose, we collected and anonymized datasets, which contain information from BlogCatalog, Twitter, Flickr, Facebook, YouTube and LastFm. The constructed and integrated data forms a consolidated repository that may become a valuable source for researchers. We implemented several different types of recommendation methodologies to observe their performance while using single versus multiple features from a single source versus multiple sources. The conducted experiments showed that using multiple features from multiple social networks produces a more concrete and wider perspective of user behavior and preferences leading to improved recommendation outcome.

Keywords Recommendation systems · Individual modeling · Multiple data sources · Social networks · Multiple perspective based analysis

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1 Introduction

Recommendation systems are commonly used by web-platforms, such as social networks, review web-sites, and e-commerce web-sites, to serve their users [1]. For instance, Imdb is a movie review web-site which has a service called "Recommended for you" that gives movie recommendations to registered users. LinkedIn is a social-networking site for professionals and has a service named "Jobs You May Be Interested In" to suggest jobs to members based on their profiles. Most of these platforms use proprietary information to model users' preferences [2, 3], and this leads to a limited perspective related to users. However, integrating information from multiple platforms may help in widening the perspective and hence in modeling users better.

People generally use different web-platforms for different purposes. For example, even though both LinkedIn and Facebook are social networking platforms, people use mostly LinkedIn for professional connections and Facebook for personal connections [4]. Thus, combining information from various platforms can help in modeling users better [5].

Reported research on identity resolution and cross-domain recommendation can be used for this purpose. Identity resolution research aims to connect identities of a single person across social networking platforms, e.g., [2], [4], [5], [6], [7]. The work described in [6] stated that identity resolution solutions can be used by various applications, such as security, privacy and recommendation systems. Some research efforts in recommendation systems concentrate on recommendations across domains, e.g., [8], [9], [10]. However, these cross-domain recommendation systems focused solely on matching items and have not considered users' preferences across platforms. There are also recommendation methods that aim to combine multiple features, such as past preferences on items, social relations among users [11], location and temporal information, e.g., [12], [13], [14], [15], and [16]. To the best of our knowledge, even though these works use multiple features at once, none of them employs data from multiple sources. Recently, in a challenge described in [17], usage of linked data in recommendation systems is introduced as a novel strategy. In the challenge description it is stated that combining diverse information about users, items and their relations can improve recommendation performance. However, the dataset introduced in this challenge contains diverse/linked information on items, but not users. Inspired from the above-mentioned research, in our previous work described in [18], we combined data collected from multiple social networking platforms and created an integrated repository that reflects users' preferences. This may form better basis for more guided and informative recommendations. To the best of our knowledge, our work is the first to construct such kind of data repository which could be used to model users from a wider global perspective by integrating data from multiple sources [19]. In this work, we expand our previous work by introducing new social networks and hence by adding more users to our system.

In our previous work described in [18], we created our own data-sets, since existing data-sets used in cross-domain recommendations and identity resolution don't have information on users' preferences/behavior and items at the same time. For that initial study, we collected information about users from BlogCatalog website, which allows users to share accounts on other social-platforms. Using the shared account information, we collected publicly available information from Flickr and Twitter. In this work, we expand the data-set by introducing data from three new social networking platforms, namely Facebook, YouTube and LastFm. Besides, we expand the number of users considered in the evaluation and we evaluated our system for different purposes, i.e., making recommendation for different platforms[1].

To summarize, contributions of our work described in this paper may be enumerated as follows:

- We collected and integrated data from multiple social networking platforms to model users with a wider global perspective. We used the constructed and populated multi-source data as input to various models to give recommendations to interested people.
- We expanded the data-set created in our previous work [18] to cover more details and more platforms. Our first dataset described in [18] was small and was intended as a proof of concept. It was collected from BlogCatalog, Twitter and Flickr and users are limited to those who have accounts in all the three platforms. In the expanded data-set, utilized for this paper, data from three new social networks, namely Facebook, YouTube and LastFm, has been added. Besides, the evaluation is not limited to only sub-group of users with overlapping accounts; instead the evaluation covers all available users.
- We implemented several recommendation methodologies to observe their performance. We mainly used methods like collaborative filtering, multi-objective optimization based recommendation [16], hybrid recommendation and social-historical model [20] based recommendation.
- We compared the performance of different recommendation methodologies on a single feature versus multiple features and on a single source versus multiple sources. Besides, we performed evaluation on two independent platforms. For instance, we tried to recommend new groups to Flickr users and new following relation to BlogCatalog users.

The rest of the paper is structured as follows: The collected and prepared multi-source data-sets are described in Section 2. The employed methodologies are presented in Section 3. The conducted experiments and their results are discussed in Section 4. Section 5 provides an overview of the related work. Section 6 is conclusions and future work.

2 The Collected Multi-Source Datasets

In our previous work described in [18] we created a dataset from three different social networking platforms, namely BlogCatalog, Twitter and Flickr. For the

[1] We plan to share the collected data-set for academic research.

study described in this paper, we have expanded the dataset by covering other social networking platforms.

For the previous work, we were influenced by [5], and used BlogCatalog as our base platform. BlogCatalog allows its users to publicly share their accounts on other platforms. The number of users collected from each platform is shown in Figure 1.

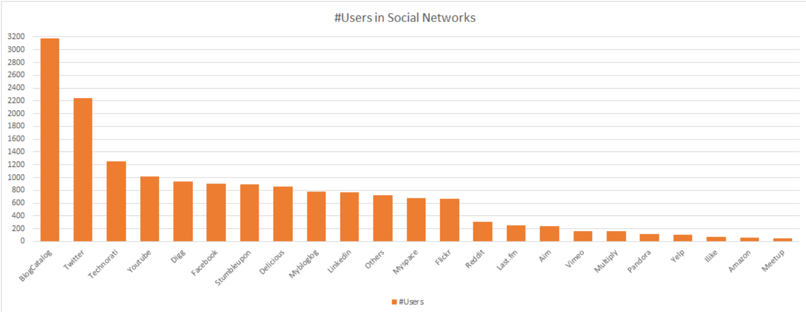

Fig. 1: Number of users from each social networking platform

According to Figure 1, there are three clusters of social networking platforms based on number of users: The first cluster contains platforms with highest number of users. Under this category, in the previous work we collected data from BlogCatalog and Twitter. For the study described in this paper, 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 because of the publicly available data and it is easy to use its API. For this study, 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 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. However, for this study, we collected data from LastFm since it is easy to use its API and most of the data is publicly available.

We mostly selected active social networking platforms, namely BlogCatalog, Twitter, Flickr, YouTube, Facebook and LastFm, where the state of the network may change over 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 for the date it was accessed. We collected publicly available data from BlogCatalog, Twitter and Flickr on 19-20 February 2015 and from YouTube, Facebook and LastFm on 3-8 June 2015.

To help readers to better understand the environment used in this paper, we briefly explain the theme of each of the five platforms used in this study. For instance, BlogCatalog is a platform which allows 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 where he/she may post a brief self description, share own hometown, communities and accounts on other platforms. Also the platform provides information on recent visitors of bloggers' personal pages, owned blogs, followers, followees and reading list. Twitter is an online social networking platform which 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 may post own brief information and city information. This page contains also information about written tweets, followers and followees, favorites and lists. Flickr allows its users to share their photographs, label them with tags, titles and descriptions. Photos shared, albums created, and photos favored can be seen on personal pages. Also, users may 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 platform 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 users are available on the channels. LastFm is a music platform in which users have their own profile pages. The tracks users listened to, top artists and top albums they like are listed on profile pages. LastFm uses this information, and many others, to give recommendations to registered users regarding new tracks to listen to or other users to connect to. It also provides services to users to form groups and add/search events.

Recall that BlogCatalog has been used as our base platform based on the work described in [5]. On BlogCatalog users may publicly share their accounts on other social networking platforms. Using this information we first found the mapping of user-ids, and then we collected data about these users from other platforms by using their APIs. During this process, we realized that it is not possible to collect information about all users of each platform, since some users close their accounts or do not publicly share their information. For example, on BlogCatalog 671 of 3179 users indicate that they have a Flickr account. However, we could not collect any information about 318 of them because their accounts are unreachable. We collected only publicly available information and anonymized the collected data to avoid privacy issues. Another challenge we faced is that each social networking platform structures its data in a different way. However, since we used their APIs, we were able to easily collect the required information related to target users. Afterwards, based on users' mapping across social networking platform as obtained from BlogCatalog, we created our own structure to save the data. The last challenge is related to privacy of the collected data. We anonymized all the data and we assigned our own ids, which are unrelated to the ids assigned by the accessed websites/social networks.

As mentioned earlier, for the study described in this paper, we expanded the dataset created in [18]. The expanded dataset contains data from six different social networking platforms, namely BlogCatalog, Twitter, Flickr, Facebook, YouTube and LastFm. Figure 2 presents all features collected from these social networking platforms.

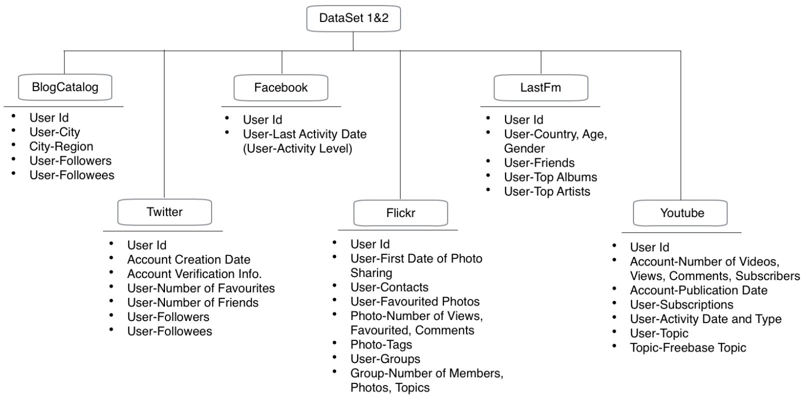

Fig. 2: Characteristics of the collected social networking data

Data from BlogCatalog, Twitter and Flickr were collected and analyzed in our previous work described in [18]. The following information has been collected from these platforms. From BlogCatalog, we collected (1) user-ids, (2) cities of users, (3) regions of cities, e.g., North America, Europe, etc., (4) followers of users, and (5) followees of users. From Twitter, we collected (1) user-ids, (2) account creation date, (3) account verification information, (4) number of favorites of the users, (5) number of friends, (6) followers of the users, and (7) followees of the users. From Flickr, we collected (1) user-ids, (2) first date of photo sharing, (3) contacts, (4) favored photos, (5) number of views, favorites and comments of photos, (6) tags of photos, (7) membership in groups, and (8) number of members, photos and topics of groups.

In this paper, we expanded the previous dataset by collecting information from Facebook, YouTube and LastFm. From Facebook, we collected (1) user-ids and (2) account last update date. We did not collect other information since either they may cause privacy issues (e.g., user name) or the information is not publicly available. We used last update date information as a measure to indicate user's activity level. Table 1 presents number of users in the given update date ranges, in terms of year or year-month, their ratio to all users and the label assigned to them.

Table 1: 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)

From YouTube we collected: (1) user-ids, (2) video, view, comment and subscriber count of accounts, (3) account publication date, (4) user-ids of subscribed accounts (i.e., following) and subscription date to those accounts, (5) user activity date and type (i.e., Bulletin, PlayListItem, Like, Subscription or Upload) and (6) users topics. Topics on YouTube are related to Freebase topics. Consequently, we collected from Freebase the following information on topics: (1) topic ids, (2) topic names, (3) topic notable ids, and (4) topic notable names. Notable topics can be thought of as upper level representation of a topic. For example, both "Game show" and "Animated cartoon" have the same notable topic "TV genre". We further created the relationship from user topics to Freebase notable topics to make the analysis easier. We used this relationship during the conducted experiments. From LastFm, we collected (1) user-ids, (2) country, age and gender, (3) friends, (4) top albums with their ranks, and (5) top artists with their ranks.

For this study, we prepared two different datasets that incorporate the above-mentioned data collected from six different social networking platforms. In the first dataset, we expanded the data-set that we used in [18] by covering three new social networking platforms, namely Facebook, YouTube and LastFm. In the previous work, users were limited to those who have accounts in three social networking platforms; namely BlogCatalog, Twitter and Flickr. In the expansion, we considered those users and expanded the data by covering new social networking platforms. In the second dataset, we used all available users from all the six social networking platforms regardless of the level of overlap. Detailed information related to the datasets is given next:

Dataset 1: In our previous work described in [18], from BlogCatalog we collected information of 22291 users whose city information is known. However, only 3179 users explicitly indicate their accounts on other social networks. Even though users share their accounts publicly on BlogCatalog, we are not able to collect all of them; since some accounts are closed or private. Among BlogCatalog users, only 2187 publicly shared their Twitter accounts and only 671 publicly shared their Flickr accounts. There are 241 users who have accounts in all of the above mentioned three platforms. In [18], these 241 users are used for the experiments. In this work, we added to these selected 241 users when exists their related available information collected from Facebook, YouTube and LastFm. Some information related to the selected 241 users could be expressed as follows:

– There are 241 users available in BlogCatalog dataset; they are from 66 different cities, which are located in 6 different regions. Among them 133 users have followees and 156 have followers.
– In Twitter dataset, there are 241 users available; 237 of the them have followers and 234 have followees.
– In Flickr, there are 241 users available, and 160 of them have at least one contact. Of the 241 Flickr users, 161 are members of at least one group. Total number of Flickr groups in the produced dataset is 4802. Of the 241 users, 105 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.
– Of the selected 241 users, 89 are available in Facebook dataset. Among these 89 Facebook users, only 15 have activity level inactive, 17 are not very active, 27 are active, and 30 are very active.
– In YouTube dataset, 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. Of the 118 YouTube users 103 of them indicated at least one topic as their interest. Number of distinct topics is 118 and number of Freebase notable topics is 57. This indicates that even though most users have different topic tags as their interest, they mostly share a common taste.
– In LastFm dataset, 53 of the selected 241 users are available. These users indicated that they are from 17 different countries; 10 of them are females, 30 are males, and 13 did not indicate any gender. Among the selected 53 LastFm users, 37 have at least one friend and only 2 of them are friends of others. Of the 53 LastFm users, 19 indicated their top albums and top artists. There are 14818 different albums and 7846 different artists listed in the top albums and top artists lists; 13807 albums and 6297 artists 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 dataset, instead of limiting users to a subgroup, we used all available users.

– There are 22291 users in BlogCatalog who are used as base in this project. The total number of names listed as users, followers or followees 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 indicated having Twitter accounts, we were able to collect information about only 1802 of them

because some 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 (but 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. Of the 349 Flickr users, 240 have at least one contact and 13 of the contacts are among the selected 349 Flickr users. 189 of these users are members of at least one group. Total number of Flickr groups which have at least one member is 7725. Of the 349 Flickr users, 150 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. Of the 822 YouTube users, 702 declared interest in at least one topic. Number of distinct topics and number of Freebase notable topics indicated of interest to 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 are male and 53 haven't indicate any gender information. Of the 234 LastFm users, 168 have at least one friend; 81 of these users have at least one top artist and 78 have at least one top album; 19736 artist and 43066 albums are listed in top-artist or top-albums lists of these LastFm users.

Finally, 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. For instance, the behavior of a user in a single network or multiple social networks can be used to predict his/her hometown. Further, this information can be used by researchers and practitioners working on recommendation systems, privacy and security, among other domains.

3 Recommendations Using Multiple Data Sources

Acquiring diverse and rich sets of features from a wide range of data-sources helps in developing alternative recommendation systems capable of serving various purposes. In this paper, we exemplify two alternatives. In our previous work described in [18], we aimed to make recommendations to Flickr users about groups they may join in future. In this paper, we continue with this objective using the first data-set introduced in Section 2. As a second objective, we decided to make recommendations to BlogCatalog users regarding whom they can follow in future. For this purpose, we used the second data-set described in Section 2.

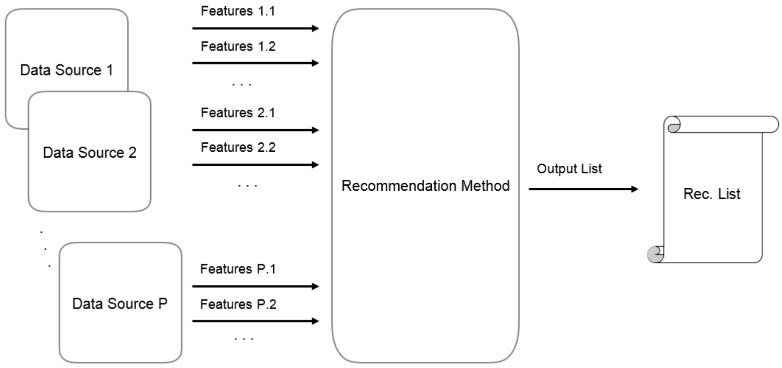

Fig. 3: The general structure of the system

Shown in Figure3 is the general structure of the system which shows how recommendation methods function based on data from multiple data sources with multiple features. Data sources are labeled from 1 to P, and each source is characterized by a non-empty set of features which are used as an input to the recommendation method to produce a list of alternative recommendations. For the study described in this paper, 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 [18].

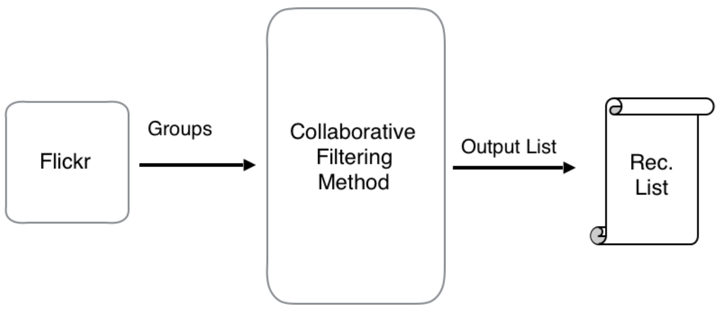

Fig. 4: Collaborative filtering recommendation method

Collaborative filtering based recommendation: We used user-based collaborative filtering. In user-based collaborative filtering, neighbors are decided based on similarities of users to the target user. Users who are most similar to the target user are assigned as neighbors. Then recommended items are decided by using neighbors' past preferences. In this step, different approaches to combine neighbors' preferences can be used: In voting based approach, all neighbors are considered equal and items are chosen based on number of neighbors who have chosen them. In weighted approach, neighbors can be assigned different weights, e.g., based on their similarities, and items are chosen based on number of the neighbors who have chosen items and weights of the neighbors. Other approaches are also possible. In this study, we used voting based approach. The user-based collaborative filtering method uses only a single feature from a single data-source. The structure of the methodology is illustrated in Figure 4, where a single data source, namely Flickr, and a single feature, namely Flickr groups, is used to make recommendations.

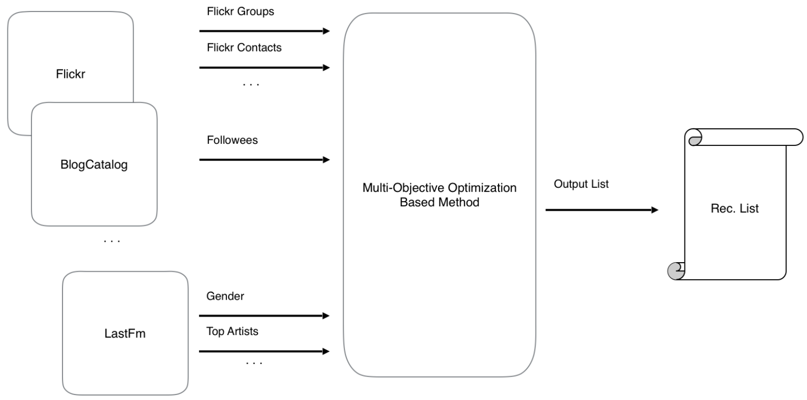

Fig. 5: The multi-objective optimization based recommendation method

Multi-objective optimization based recommendation: We used the multi-objective optimization based method proposed in [16]. This method determines neighbors by employing Pareto dominance method. For this purpose, similarities of users are calculated for each feature. Then based on similarities, non-dominated users are decided based on Pareto dominance results. Users who are non-dominated are assigned as neighbors. If a predefined number of neighbors should be chosen, an iterative process can be employed by removing the already selected ones from the set and re-applying the approach on the new set. After selecting neighbors, past preferences of neighbors are used to make recommendations as it is done in collaborative filtering. In this work, we applied iterative Pareto dominance based process of neighbor selection and voting based item selection. The multi-objective optimization based method proposed in [16] is capable of combining multiple features from a single data-source or from multiple data-sources at once. The overall flow of the method is depicted in Figure 5, where multiple data sources and multiple features are used to make recommendations. For instance, to make Flickr groups recommendations to Flickr users, we used all data from the six social networking platforms mentioned in Section 2. Also, any features can be used from each platform without any limitation on the number of features to be used or on the combination of features.

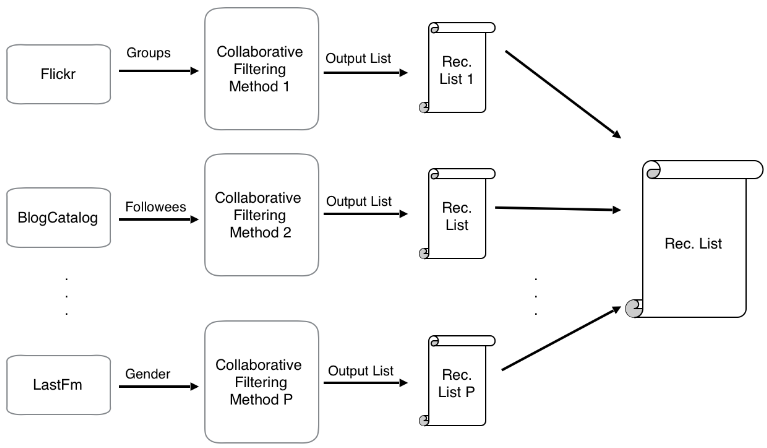

Fig. 6: The hybrid recommendation method

Hybrid recommendation: We used an item based hybrid approach which combines the output of different recommendation methods. Even though several techniques for hybridization are explained in [21], in this study we combined only collaborative filtering methods using different features. The combination of the results and the ranking of items are decided based on the number of votes each item received. This method is capable of combining multiple features once they are decided by a single feature based collaborative filtering method. Since each recommendation method is executed separately, there is no limit on the data-source, i.e., features from single data-source or from multiple data-sources can be used. The overall structure of the methodology is represented in Figure 6, where first multiple collaborative filtering based methods are used, then their output predictions are combined. Each collaborative filtering based method, labeled from 1 to P, uses only one feature from a single social network. The item based hybrid method uses predictions made by each collaborative filtering method to combine and create a prediction list.

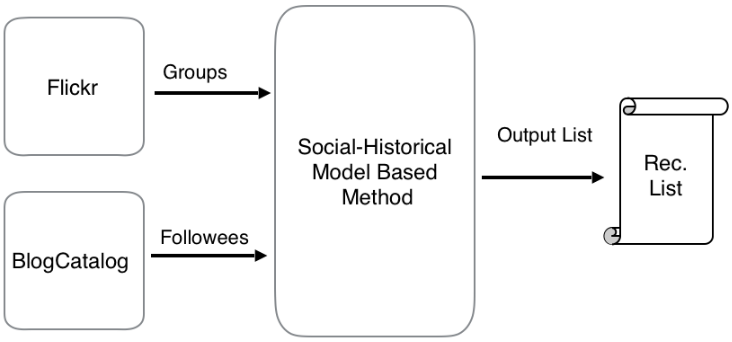

Fig. 7: The social-historical model based recommendation method

Social-historical model based recommendation: We used the method proposed in [20], which is one of the state-of-the-art methods described in the literature. It originally aims to predict next check-in venue by combining users' past check-ins and friendship information in location based social networks. It models check-ins by a language model. The combination of friendship information is performed by a linear model. Also, it is possible to make recommendations using only past check-ins or only friendship information. The social-historical model based recommendation method [20] proposed to combine two features at once. These features do not necessarily need to be from a single data-source, i.e. features from multiple data-source can be used. The structure of the methodology is illustrated in Figure 7, where data from two sources are used to make recommendations. The method is able to combine up to two features. These features may be collected from different social networking platforms as well as a single one.

Even though the dataset contains features from different social networking platforms, 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, in addition to the features used in our previous work [18], i.e., from BlogCatalog, Twitter, Flickr; we expanded the coverage to other features from the new social networking platforms, namely Facebook, YouTube and LastFm. The features used in this study and their source social networking platform are explained next:
Flickr groups: In Flickr users can join different groups depending on their interests. A recommendation system can use knowledge about previously joined groups to make predictions on the groups that these users may join in the future.
Flickr contacts: In 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 contacts' past preferences to make predictions, as 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 similarities among users are calculated based on common contacts rather than having direct connection.
Twitter followees: In Twitter, users mostly 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 target users.
Facebook activity level: The source social networking platform 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 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: In YouTube users indicate their interested topics and 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 target users.
LastFm gender: The source social networking platform 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 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 user-user similarity using Cosine Similarity measure. For Flickr contacts, 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 similarity value of 1.0, and others receive 0.0. Lastly, for LastFm gender, users of same gender are assigned similarity value of 1.0, and others receive 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 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 [22] 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 hit-rate of the invoked methods. Hit-rate is the ratio of 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 applied 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 users with at least 5 items, and we randomly selected 20% of their items from the dataset. The randomly selected items are collected as the test set and the rest are used as the training set.

For the first dataset, we set our objective as making Flickr group recommendations. In the original dataset there are 126 Flickr users where each is a member of at least one group. After creating the training and test sets, we had 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 dataset, we set our objective as making BlogCatalog followee recommendations, i.e., whom to follow. In the original dataset there are

6990 BlogCatalog users who follow at least one other BlogCatalog user. After creating the training and test set, the number of users were found as 6990 and 3670, respectively. The average number of followees in the training and test sets are 39.073 and 17.304, respectively.

As explained in Section 3, we implemented several methods with a variety of features from the collected datasets. In Table 2, 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. Whenever multiple features from a single social networking platform are used, e.g., Flickr groups and Flickr Contacts, the method uses data from a single source, e.g., Flickr, and whenever the features are from different social networking platforms, e.g., Flickr groups and BlogCatalog followees, the method uses data from multiple sources, e.g., from Flickr and BlogCatalog.

Table 2: 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

Details of the evaluation results on our two objectives, namely 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

Our first example recommendation system aims to recommend Flickr groups to users. 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 our previous work [18], 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. Evaluation results of the methods with the assigned values of N and k are shown in Figure 8, 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, hit-rate has been scaled to its 10% in order to have a better representation together with the other metrics.

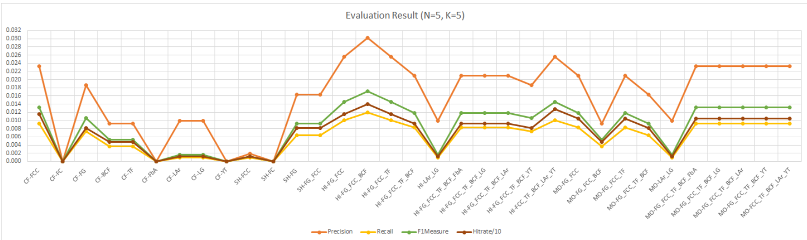

Fig. 8: Evaluation results for N=5 and k=5 (Flickr groups)

In Figure 8, we show results of the experiments that were conducted for our previous work [18] and results of the new experiments that use the features collected from the additional social networking platforms. According to the figure, using data from the same social networking platform and same features do 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). Methods that use information from a different social networking platform only, such as CF_BCF or CF_LG, don't perform better than methods that use information from the target social networking platform. This may be related to the fact that people use different web-platforms for different purposes [4] and may behave differently in different social networks. Using the Social-Historical model [20] 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). Hybridization of item recommendations (HI methods) showed best performance when Flickr groups, Flickr common contacts and BlogCatalog followees are used altogether.

Our multi-objective optimization based recommendation method described in [16] 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 precision results while using different combinations of networks. 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 [18]. 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 methods with the selected values of parameters N and k. We discarded Flickr contacts feature since it does not provide any successful recommendations as reflected in Figure 8. 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 9, 10 and 11. When $k = 4$, i.e., the value that produces the highest precision in the previous experiment, collaborative filtering that uses the target feature, namely Flickr groups, and hybridization of item based methods (HI methods) perform best. As observed in the previous work, we observe that change of 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 precision results while using different methods and features. These results confirm that using data from multiple sources (e.g., social networks) improves 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 10, 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 and methods that use multiple features at once (HI and MO methods) perform equally good to or better than 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.

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 to present in the limited length output list one or more items that the user is expected to use in the future, i.e., higher precision. Based on our analysis, for shorter output lists and when precision and hit-rate are considered more important,

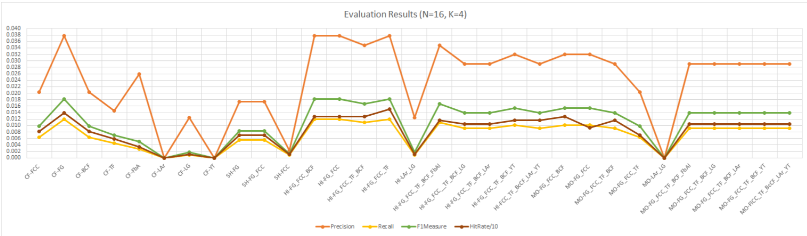

Fig. 9: Evaluation results for N=16 and k=4 (Flickr groups)

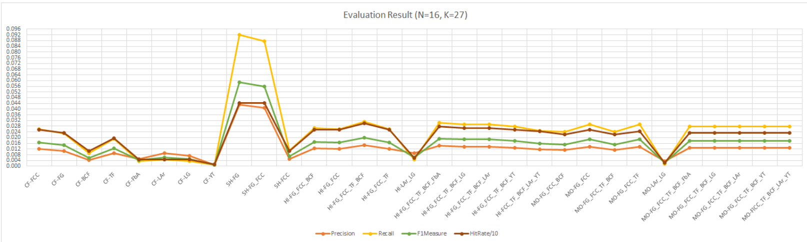

Fig. 10: Evaluation results for N=16 and k=27 (Flickr groups)

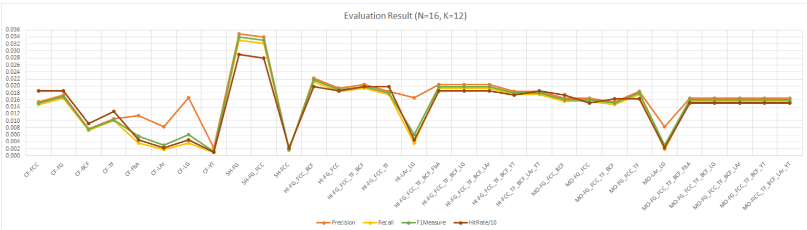

Fig. 11: Evaluation results for N=16 and k=12 (Flickr groups)

the best performing method is the hybridization method which combines information of multiple features from multiple social networking platforms. This way, the method can model its users with other aspects which are not obvious for a single social networking platform.

4.2 Recommendation of BlogCatalog followees

Our second example recommendation system suggests new links, i.e., new followees, to BlogCatalog users. 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 best N and k values using the selected method, and lastly we conducted experiments on all methods with the decided N and k values.

First, we assigned N and k to 5, as we did in the previous experiment. Evaluation results of the methods with our initial assigned values of N and k are shown in Figure 12, 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 12, 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 networking platforms. We observed that HI-FG_FCC_TF_BCF_LG, which is based on hybrid itemization method using Flickr groups, Flickr common contacts, Twitter followings, BlogCatalog followings and LastFm gender features performs slightly better than 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.

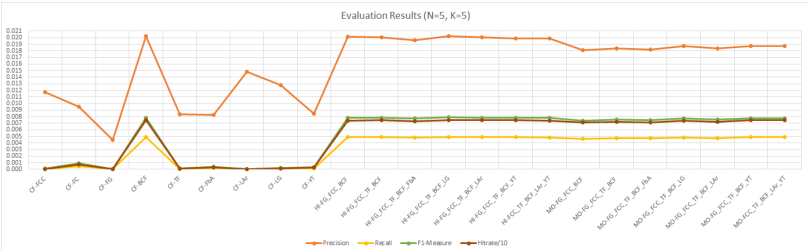

Fig. 12: Evaluation results for N=5 and k=5 (BlogCatalog followees)

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, 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. Results from the experiment are shown in Figure 13. According to the figure, after increasing N from 1 to 3-4 there is a balance on performance up to $N = 36$. After $N = 36$, there is a small increase in performance of the evaluation metrics. However, it is not obviously seen, that hitrate ratio increases as N increases. For example, when $N = 1$ hitrate is 0.0000012339, it is 0.0000022346 when $N = 36$, and it is 0.0000025742 when $N = 50$. Even though these values are really small, we preferred to set N to 50.

After deciding on $N = 50$, the next step is to decide on k value. We conducted experiments using HI-FG_FCC_TF_BCF_LG method and by setting k values in the range [1,30] with 1 increment. We limited maximum output list size to 30, since in real life most recommendation systems present shorter lists, such as 10 or 15 elements in a page at most. Results of the experiment are

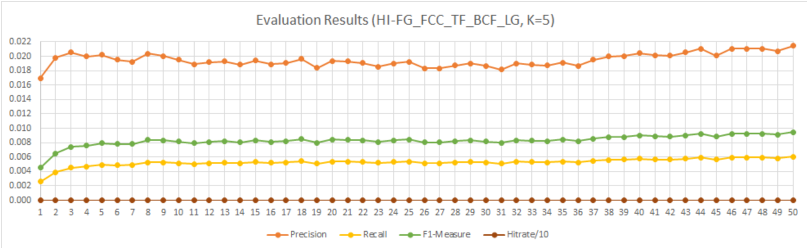

Fig. 13: Evaluation results for the HI-FG_FCC_TF_BCF_LG method and k=5 (BlogCatalog followees)

shown on Figure 14. According to the figure, precision performance increases up to $k = 11$, then it stays in balance, and finally starts to decrease after k is around 16. Performance of recall, F1-measure and hitrate increase as k increases. As a result of these observations, we decided to set k to 15, which is one of the values that provide best precision performance, and to 30 which provides best recall, F1-measure and hitrate performance.

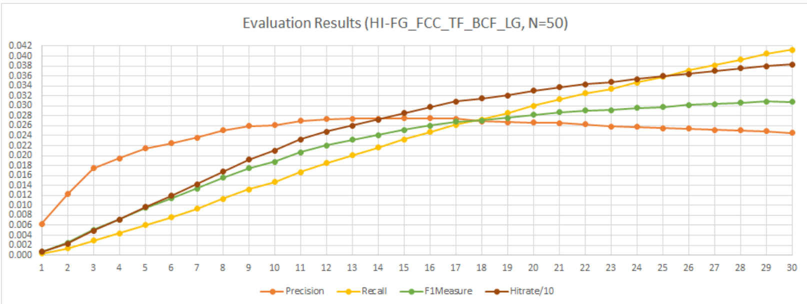

Fig. 14: Evaluation results for the HI-FG_FCC_TF_BCF_LG method and N=50 (BlogCatalog followees)

We conducted experiments on all methods using the parameters $N = 50$, $k = 15$ or $k = 30$. The results are presented in Figures 15 and 16, respectively. The figures show that the best performing methods are collaborative filtering which uses BlogCatalog followee feature, i.e., CF_BCF, and methods that use combination of features from multiple social networking platforms. Multi-objective optimization based methods perform slightly better than others in terms of hitrate when $k = 30$.

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

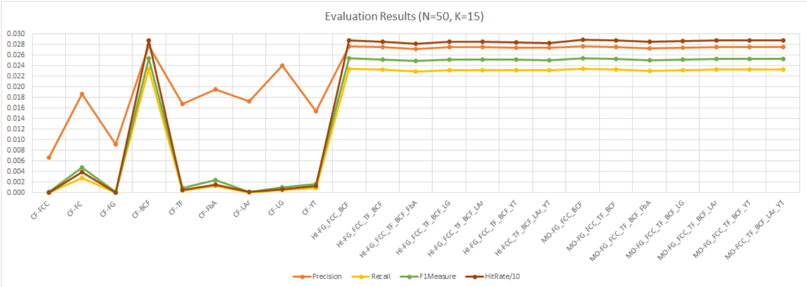

Fig. 15: Evaluation results for N=50 and k=15 (BlogCatalog followees)

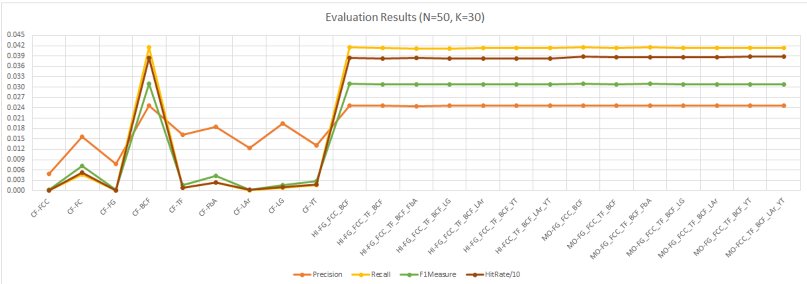

Fig. 16: Evaluation results for N=50 and k=30 (BlogCatalog followees)

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 these methods have nearly the same overall precision performance and the later two of them use features from multiple social networking platforms. Analysis results are reported in Tables 3 and 4.

According to the results, collaborative filtering method and hybrid method perform equally well on users whose precision is around 0.445; this means they can perform equally good for users who have on average 6.7 followees in the test set (Found by multiplying k by average precision, i.e., 15 * 0.445 = 6.7). Also, these methods perform equally well when there are about 74 followees information in the train set. Similarly, comparison of collaborative filtering and multi-objective optimization based method reveals equal performance when there are about 6.6 followees in the test set and around 40 followees in the train set. When we further analyzed the case of equal performance, we observed that all 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 hybrid (HI) and multi-objective optimization based (MO) methods are better than 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 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 average 33 followees in the train set. The analysis shows that using multiple features from multiple social networking platforms helps the system to model users more effectively, especially for users with less information.

Table 3: Comparison of methods (CF_BCF vs. HI-FG_FCC_BCF) when N=50 and k=15

Analysis	Avg. prec. upper bound and avg. #followees (test set)	Avg. #followees on the train set
Perform equally well	0.447 * 15 = 6.705	73.771
Perform equally well (At least one true rec.)	0.666 * 15 = 9.990	178.875
Perform equally well (No true rec.)	0.359 * 15 = 5.385	31.343
CF_BCF performs better	0.850 * 15 = 12.750	66.000
HI-FG_FCC_BCF performs better	0.400 * 15 = 6.000	21.000

Table 4: Comparison of methods (CF_BCF vs. MO-FG_FCC_BCF) when N=50 and k=15

Analysis	Avg. prec. upper bound and avg. #followees (test set)	Avg. #followees on the train set
Perform equally well	0.439 * 15 = 6.585	39.813
Perform equally well (At least one true rec.)	0.663 * 15 = 9.945	105.865
Perform equally well (No true rec.)	0.355 * 15 = 5.325	32.319
CF_BCF performs better	0.717 * 15 = 10.755	205.292
MO-FG_FCC_BCF performs better	0.562 * 15 = 8.430	33.119

5 Related Work

Recommendation systems aim to make recommendations to users based on their interests [23, 24]. Recently, most of the research on recommendation system focus on combining different kinds of information. Works described in [25], [26] [27], [28], [12], [29] and [30] 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. For instance, LARS [31], [32], [13], [33] are some examples of systems that use location to improve performance of the recommendation process. Another set of methods use friendship information to make better recommendations; works described in [20], SoCo [34], [14] and [15] are some examples of this kind of systems. These systems mostly use linear combination of features. Some other approaches described in the literature use multi-objective optimization methods by combining multiple criteria, e.g. [35], [36], [37], [38] and [16]. Even though these works use multiple features at once, none of them use data from multiple data sources. Recently, in a challenge [17] related to recommendation systems, using diverse data from multiple sources is used as the main purpose of the challenge. Methods which ranked higher on different tasks of the challenge used hybridization and ensemble methods [39]. Even though the idea of the challenge is similar to ours, unlike our work it is based on using diverse data from multiple sources about items, not about users.

Another set of research focuses on cross-domain recommendation, which models users in a domain and employs the model in a target domain. Works described in [40], [8], [9], [10], [41] and [42] are some 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 [40]. 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. Results showed that multiple information sources for recommendations is promising. The work described in [8] found correlation between objects by using a Bayesian hierarchical approach based on Latent Dirichlet Allocation (LDA) method by modeling users' interests and objects' topics. Output correlations were used to give recommendations to target users based on their interests. Zhang et al. [9] aimed to give recommendations across web-sites by using browsing information of 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, browsing history of users may not be always available. Kumar el al. [10] used textual information of items to map them across domains. Then these mappings were used to give cross-domain recommendations. Hu et al. [41] 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 Amazon web-site. The work described in [42] modeled users' preferences separately on each domain using types of items. Then using factorization machines, they combined separate models into one. Li el al. [43] identified user and item mapping across rating matrices and used the out mapping in the recommendation process. In their 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 users' behavior on different domains and analysis results can be used by other applications, e.g., recommendation systems. Works described in [2], [4],[5],[6] and [7] 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 el al. [2] used two different social networking platforms to collect user descriptions. Then using co-occurrence of 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. Authors of [4] searched and matched users across online social networking platforms. For matching purposes, they used several different attributes of users; such as age, gender, location, country and name. Zafarani et al. [5] 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. [6] 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 users, and helps to improve performance of the identity resolution process. Finally, Tan et al. [7] proposed a semi-supervised manifold alignment method to map users across social networking platforms. Even though they used social structures only, they stated that names of users can also be used to boost performance of the system.

6 Conclusion and Future Work

Today's web-based platforms, such as social networking platforms, review websites, e-commerce web-sites, etc. commonly use recommendation systems. Each of these platforms models its users and makes recommendations using only local information captured by the website [2]. It is known that people tend to use different web-platforms for different purposes [4]. 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 networking platforms for more comprehensive vision and hence better guidance [5, 44].

In this paper, we extended our previous work described in [18] by integrating information collected from multiple different social networking platforms to create an integrated model of individuals and to give recommendations to them. To the best of our knowledge, our work is the first to construct such kind of data repository and to use in the recommendation process integrated information on individuals from multiple social networking platforms. In this paper, the previously prepared dataset which included 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 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 networking platforms. The second dataset contains information related to users collected from all the six social networks, i.e. without getting a subset of users.

We used the created datasets to make recommendations to target users on different platforms, i.e., recommending to Flickr users new groups to follow, and recommending to BlogCatalog users other users to follow. We implemented several different types of recommendation methodologies to observe their performance. These methods include 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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References

1. J. Bobadilla, F. Ortega, A. Hernando, and A. Gutirrez. Recommender systems survey. *Knowledge-Based Systems*, 46:109 – 132, 2013. ISSN 0950-7051. doi: http://dx.doi.org/10.1016/j.knosys.2013.03.012. URL `http://www.sciencedirect.com/science/article/pii/S0950705113001044`.
2. Hugo Liu and Pattie Maes. Interestmap: Harvesting social network profiles for recommendations. *Beyond Personalization 2005*, page 54, 2005.
3. I-Chin Wu and Yun-Fang Niu. Effects of anchoring process under preference stabilities for interactive movie recommendations. *Journal of the Association for Information Science and Technology*, 66(8): 1673–1695, 2015. ISSN 2330-1643. doi: 10.1002/asi.23280. URL `http://dx.doi.org/10.1002/asi.23280`.
4. Marti Motoyama and George Varghese. I seek you: Searching and matching individuals in social networks. In *Proceedings of the Eleventh International Workshop on Web Information and Data Management*, WIDM '09, pages 67–75, New York, NY, USA, 2009. ACM. ISBN 978-1-60558-808-7.
5. Reza Zafarani and Huan Liu. Connecting users across social media sites: A behavioral-modeling approach. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD

'13, pages 41–49, New York, NY, USA, 2013. ACM. ISBN 978-1-4503-2174-7.
6. Paridhi Jain, Ponnurangam Kumaraguru, and Anupam Joshi. @i seek 'fb.me': Identifying users across multiple online social networks. In *Proceedings of the 22Nd International Conference on World Wide Web Companion*, WWW '13 Companion, pages 1259–1268, Republic and Canton of Geneva, Switzerland, 2013. International World Wide Web Conferences Steering Committee. ISBN 978-1-4503-2038-2.
7. Shulong Tan, Ziyu Guan, Deng Cai, Xuzhen Qin, Jiajun Bu, and Chun Chen. Mapping users across networks by manifold alignment on hypergraph. In *Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence, July 27 -31, 2014, Québec City, Québec, Canada.*, pages 159–165, 2014.
8. Shulong Tan, Jiajun Bu, Xuzhen Qin, Chun Chen, and Deng Cai. Cross domain recommendation based on multi-type media fusion. *Neurocomput.*, 127:124–134, March 2014. ISSN 0925-2312.
9. Yongfeng Zhang. Browser-oriented universal cross-site recommendation and explanation based on user browsing logs. In *Proceedings of the 8th ACM Conference on Recommender Systems*, RecSys '14, pages 433–436, New York, NY, USA, 2014. ACM. ISBN 978-1-4503-2668-1.
10. A. Kumar, N. Kumar, M. Hussain, S. Chaudhury, and S. Agarwal. Semantic clustering-based cross-domain recommendation. In *Computational Intelligence and Data Mining (CIDM), 2014 IEEE Symposium on*, pages 137–141, Dec 2014.
11. Esther Meng-Yoke Tan and Dion Hoe-Lian Goh. A study of social interaction during mobile information seeking. *Journal of the Association for Information Science and Technology*, 66(10):2031–2044, 2015. ISSN 2330-1643. doi: 10.1002/asi.23310. URL http://dx.doi.org/10.1002/asi.23310.
12. Huiji Gao, Jiliang Tang, Xia Hu, and Huan Liu. Exploring temporal effects for location recommendation on location-based social networks. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 93–100. ACM, 2013.
13. Mao Ye, Peifeng Yin, Wang-Chien Lee, and Dik Lun Lee. Exploiting geographical influence for collaborative point-of-interest recommendation. In *Proceeding of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2011, Beijing, China, July 25-29, 2011*, pages 325–334, 2011. doi: 10.1145/2009916.2009962.
14. Mao Ye, Peifeng Yin, and Wang-Chien Lee. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, GIS '10, pages 458–461, New York, NY, USA, 2010. ACM.
15. Hao Ma, Dengyong Zhou, Chao Liu, Michael R. Lyu, and Irwin King. Recommender systems with social regularization. In *Proceedings of the Forth International Conference on Web Search and Web Data Mining, WSDM 2011, Hong Kong, China, February 9-12, 2011*, pages 287–296,

2011. doi: 10.1145/1935826.1935877.
16. Makbule Gulcin Ozsoy Ozsoy, Faruk Polat, and Reda Alhajj. Multi-objective optimization based location and social network aware recommendation. In *10th IEEE International Conference on Collaborative Computing: Networking, Applications and Worksharing, CollaborateCom 2014, Miami, Florida, USA, October 22-25, 2014*, pages 233–242, 2014. doi: 10.4108/icst.collaboratecom.2014.257382.
17. ESWC-14 Challenge. Eswc-14 challenge: Linked open data-enabled recommender systems, March 2014. URL `http://challenges.2014.eswc-conferences.org/index.php/RecSys`.
18. Makbule Gulcin Ozsoy Ozsoy, Faruk Polat, and Reda Alhajj. Modeling individuals and making recommendations using multiple social networks. In *International Symposium on Foundations and Applications of Big Data Analytics*, FAB '15, pages 1–1, 2015.
19. Marcin Maleszka, Bernadetta Mianowska, and Ngoc Thanh Nguyen. A method for collaborative recommendation using knowledge integration tools and hierarchical structure of user profiles. *Knowledge-Based Systems*, 47:1 – 13, 2013. ISSN 0950-7051. doi: http://dx.doi.org/10.1016/j.knosys.2013.02.016. URL `http://www.sciencedirect.com/science/article/pii/S0950705113000890`.
20. Huiji Gao, Jiliang Tang, and Huan Liu. Exploring social-historical ties on location-based social networks. In *Proceedings of the Sixth International Conference on Weblogs and Social Media, Dublin, Ireland, June 4-7, 2012*, 2012.
21. Robin D. Burke. Hybrid recommender systems: Survey and experiments. *User Model. User-Adapt. Interact.*, 12(4):331–370, 2002. doi: 10.1023/A:1021240730564.
22. J. Zhang and C. Chow. Ticrec: A probabilistic framework to utilize temporal influence correlations for time-aware location recommendations (to be published). *Services Computing, IEEE Transactions on*, PP(99):1–1, 2015.
23. Cheng-Lung Huang, Po-Han Yeh, Cheng-Wei Lin, and Den-Cing Wu. Utilizing user tag-based interests in recommender systems for social resource sharing websites. *Knowledge-Based Systems*, 56:86 – 96, 2014. ISSN 0950-7051. doi: http://dx.doi.org/10.1016/j.knosys.2013.11.001. URL `http://www.sciencedirect.com/science/article/pii/S0950705113003511`.
24. Bracha Shapira and Boaz Zabar. Personalized search: Integrating collaboration and social networks. *Journal of the American Society for Information Science and Technology*, 62(1):146–160, 2011. ISSN 1532-2890. doi: 10.1002/asi.21446. URL `http://dx.doi.org/10.1002/asi.21446`.
25. Quan Yuan, Gao Cong, Zongyang Ma, Aixin Sun, and Nadia Magnenat Thalmann. Time-aware point-of-interest recommendation. In *Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '13, pages 363–372, New York, NY, USA, 2013. ACM. ISBN 978-1-4503-2034-4.

26. Lara Quijano-Snchez, Beln Daz-Agudo, and Juan A. Recio-Garca. Development of a group recommender application in a social network. *Knowledge-Based Systems*, 71:72 – 85, 2014. ISSN 0950-7051. doi: http://dx.doi.org/10.1016/j.knosys.2014.05.013. URL http://www.sciencedirect.com/science/article/pii/S095070511400197X.
27. Xin Liu, Yong Liu, Karl Aberer, and Chunyan Miao. Personalized point-of-interest recommendation by mining users' preference transition. In *Proceedings of the 22Nd ACM International Conference on Conference on Information Knowledge Management*, CIKM '13, pages 733–738, New York, NY, USA, 2013. ACM. ISBN 978-1-4503-2263-8.
28. Bo Hu, Mohsen Jamali, and Martin Ester. Spatio-temporal topic modeling in mobile social media for location recommendation. In *Data Mining (ICDM), 2013 IEEE 13th International Conference on*, pages 1073–1078. IEEE, 2013.
29. Quan Yuan, Gao Cong, and Aixin Sun. Graph-based point-of-interest recommendation with geographical and temporal influences. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*, pages 659–668. ACM, 2014.
30. Chieh-Yuan Tsai and Bo-Han Lai. A location-item-time sequential pattern mining algorithm for route recommendation. *Knowledge-Based Systems*, 73:97–110, 2015.
31. Justin J. Levandoski, Mohamed Sarwat, Ahmed Eldawy, and Mohamed F. Mokbel. LARS: A location-aware recommender system. In *IEEE 28th International Conference on Data Engineering (ICDE 2012), Washington, DC, USA (Arlington, Virginia), 1-5 April, 2012*, pages 450–461, 2012. doi: 10.1109/ICDE.2012.54.
32. Vincent Wenchen Zheng, Yu Zheng, Xing Xie, and Qiang Yang. Collaborative location and activity recommendations with GPS history data. In *Proceedings of the 19th International Conference on World Wide Web, WWW 2010, Raleigh, North Carolina, USA, April 26-30, 2010*, pages 1029–1038, 2010. doi: 10.1145/1772690.1772795.
33. Chen Cheng, Haiqin Yang, Michael R. Lyu, and Irwin King. Where you like to go next: Successive point-of-interest recommendation. In *IJCAI 2013, Proceedings of the 23rd International Joint Conference on Artificial Intelligence, Beijing, China, August 3-9, 2013*, 2013.
34. Xin Liu and Karl Aberer. Soco: a social network aided context-aware recommender system. In *22nd International World Wide Web Conference, WWW '13, Rio de Janeiro, Brazil, May 13-17, 2013*, pages 781–802, 2013.
35. Kleanthi Lakiotaki, Stelios Tsafarakis, and Nikolaos F. Matsatsinis. Utarec: a recommender system based on multiple criteria analysis. In *Proceedings of the 2008 ACM Conference on Recommender Systems, RecSys 2008, Lausanne, Switzerland, October 23-25, 2008*, pages 219–226, 2008. doi: 10.1145/1454008.1454043.
36. Nikos Manouselis and Constantina Costopoulou. Experimental analysis of design choices in multiattribute utility collaborative filtering. *IJPRAI*, 21(2):311–331, 2007. doi: 10.1142/S021800140700548X.

37. Hsin-Hsien Lee and Wei-Guang Teng. Incorporating multi-criteria ratings in recommendation systems. In *Proceedings of the IEEE International Conference on Information Reuse and Integration, IRI 2007, 13-15 August 2007, Las Vegas, Nevada, USA*, pages 273–278, 2007. doi: 10.1109/IRI.2007.4296633.
38. Fernando Ortega, José Luis Sánchez, Jesús Bobadilla, and Abraham Gutiérrez. Improving collaborative filtering-based recommender systems results using pareto dominance. *Inf. Sci.*, 239:50–61, 2013. doi: 10.1016/j.ins.2013.03.011.
39. Tommaso Di Noia, Ivn Cantador, and VitoClaudio Ostuni. Linked open data-enabled recommender systems: Eswc 2014 challenge on book recommendation. In Valentina Presutti, Milan Stankovic, Erik Cambria, Ivn Cantador, Angelo Di Iorio, Tommaso Di Noia, Christoph Lange, Diego Reforgiato Recupero, and Anna Tordai, editors, *Semantic Web Evaluation Challenge*, volume 475 of *Communications in Computer and Information Science*, pages 129–143. Springer International Publishing, 2014. ISBN 978-3-319-12023-2.
40. Pinata Winoto and Tiffany Tang. If you like the devil wears prada the book, will you also enjoy the devil wears prada the movie? a study of cross-domain recommendations. *New Generation Computing*, 26(3):209–225, 2008. ISSN 0288-3635.
41. Liang Hu, Jian Cao, Guandong Xu, Longbing Cao, Zhiping Gu, and Can Zhu. Personalized recommendation via cross-domain triadic factorization. In *Proceedings of the 22Nd International Conference on World Wide Web*, WWW '13, pages 595–606, Republic and Canton of Geneva, Switzerland, 2013. International World Wide Web Conferences Steering Committee. ISBN 978-1-4503-2035-1.
42. Babak Loni, Yue Shi, Martha Larson, and Alan Hanjalic. Cross-domain collaborative filtering with factorization machines. In *Advances in Information Retrieval - 36th European Conference on IRResearch, ECIR 2014, Amsterdam, The Netherlands, April 13-16, 2014. Proceedings*, pages 656–661, 2014.
43. Chung-Yi Li and Shou-De Lin. Matching users and items across domains to improve the recommendation quality. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '14, pages 801–810, New York, NY, USA, 2014. ACM. ISBN 978-1-4503-2956-9.
44. Martin Frick. Big data and its epistemology. *Journal of the Association for Information Science and Technology*, 66(4):651–661, 2015. ISSN 2330-1643. doi: 10.1002/asi.23212. URL `http://dx.doi.org/10.1002/asi.23212`.