

Reciprocal Recommendation System for Online Dating

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Abstract—Online dating sites have become popular platforms for people to look for potential romantic partners. Different from traditional user-item recommendations where the goal is to match items (e.g., books, videos, etc) with a user’s interests, a recommendation system for online dating aims to match people who are mutually interested in and likely to communicate with each other. We introduce similarity measures that capture the unique features and characteristics of the online dating network, for example, the interest similarity between two users if they send messages to same users, and attractiveness similarity if they receive messages from same users. A reciprocal score that measures the compatibility between a user and each potential dating candidate is computed and the recommendation list is generated to include users with top scores. The performance of our proposed recommendation system is evaluated on a real-world dataset from a major online dating site in China. The results show that our recommendation algorithms significantly outperform previously proposed approaches, and the collaborative filtering-based algorithms achieve much better performance than content-based algorithms in both precision and recall. Our results also reveal interesting behavioral difference between male and female users when it comes to looking for potential dates. In particular, males tend to be focused on their own interest and oblivious towards their attractiveness to potential dates, while females are more conscientious to their own attractiveness to the other side of the line.

I. INTRODUCTION

Online dating sites have become popular platforms for people to look for potential romantic partners, offering an unprecedented level of access to possible dates that is otherwise not available through traditional means. According to a recent survey¹, 40 million single people (out of 54 million) in the US have signed up with various online dating sites such as Match.com, eHarmony, etc, and around 20% of currently committed romantic relationships began online, which is more than through any means other than meeting through friends.

Many online dating sites provide suggestions on compatible partners based on their proprietary matching algorithms. Unlike in traditional user-item recommendation systems where the goal is typically to predict a user’s opinion towards passive items (e.g., books, movies, etc), when making recommendation of potential dates to a user (referred to as service user) on an online dating site, it is important that not only the recommended users match the user’s dating interest, but also the recommended users are interested in the service user

and thus likely to reciprocate when contacted. A successful online dating recommendation system should match users with mutual interest in each other and hence result in better chances of interactions between them and improved user satisfaction level.

In this paper, we study the reciprocal online dating recommendation system based on a large real-world dataset obtained from a major online dating site in China with a total number of 60 million registered users. In particular, given a user, we seek to identify a set of users who are most likely to be contacted by the service user when recommended and reciprocate when contacted.

The characteristics of the our online dating network present unique opportunities and challenges to the reciprocal recommendation problem. First, there is a rich set of user attributes available in our dataset that can be used in the prediction models. These include a user’s age, gender, height, weight, education level, income level, house ownership, geographic location, occupation, interests/hobbies, number of photos, etc. In addition, there are a variety of online dating specific information including a user’s preference in potential dates (age range, height range, education level, income range, geography location, etc), and his/her dating and marriage plan (when to get married, whether to live with parents and have child after marriage, marriage ceremony style, etc). Moreover, our dataset contains the communication traces between users, i.e., who sent or replied to messages to whom and the associated timestamps. As shown in our earlier paper [2], the communication trace of a user reflects his/her actual dating preference, which may significantly deviate from his/her stated preference and thus should play an important role in the design of the recommendation system.

Due to the heterogeneous dating nature in our recommendation problem (dating is restricted to users of opposite genders on the online dating site in our study), previous approaches designed for friend recommendation in conventional online social networks such as Facebook and LinkedIn cannot be directly applied. For example, the number of common neighbors is often used for friend recommendation for conventional social networks, i.e., the more common friends two users share, the more likely they will become friends and thus should be recommended to each other. On a heterosexual online dating site, however, a user is only interested in contacting other users of opposite gender, resulting in a bipartite network between males and females. There is no common neighbors between a

¹<http://statisticbrain.com/online-dating-statistics>

service user and recommended users since they are of different genders. To this end, we will need to devise appropriate mechanisms that accounts for the special characteristics of the online dating network.

The contributions of this paper are summarized as follows.

We present a recommendation system that aims to match users who are most likely to communicate with each other. We introduce similarity measures that capture the unique features and characteristics of the heterogeneous online dating network. In particular, we build a preference model for each service user based on the attributes of users who have been contacted by the service user. We also characterize the interest similarity between two users if they send messages to same users, and attractiveness similarity if they receive messages from same users. Based on these similarity measures we compute the compatibility between a service user and potential dating candidates and the recommendation list is generated to include candidates with top scores. Using a combination of similarity measures, we construct a set of content-based and collaborative filtering-based algorithms with different measures of compatibility between users.

We evaluate the performance of our proposed algorithms on the real-world online dating dataset that consists of 200,000 users and around two million messages over a period of two months. Our results show that both content-based and collaborative filtering-based recommendation algorithms presented in our paper significantly outperform previously proposed approaches. Also, compared to the content-based algorithms, our collaborative filtering-based algorithms achieve much better performance in both precision and recall.

Our results also reveal interesting behavioral difference between male and female users when it comes to looking for potential dates. Among the collaborative filtering-based algorithms, the best performance for male users is achieved when the recommender captures the attractiveness of recommended users to the service user and interest from the service user in recommended users. On the contrary, the best performance for females is achieved when recommended users are interested in the service user and the service user is attractive to recommended users. The results show that when looking for potential dates, males tend to be focused on their own interest and oblivious towards their attractiveness to potential dates, while females are more conscientious to their own attractiveness to and interest from the other side on the line.

The rest of the paper is organized as follows. Section II describes the related work on reciprocal recommendation as well as reciprocal relation prediction in online social networks. Section III presents the reciprocal recommendation algorithms we proposed. Section IV describes the characteristics of our dataset and presents the performance of our proposed algorithms. Finally, we conclude our paper in Section V.

II. RELATED WORK

A few studies on the analysis of user behavior of online dating sites have provided valuable guidelines to design recommendation system for online dating. In [2], the authors analyze how user's sending and replying behavior correlate

with several important user attributes, such as age, income, education level, and number of photos, etc., and how much a user's actual preference deviates from his/her stated preference. The findings also correspond to the result of [16] that the recommendation system built on user's implicit preference outperforms that built on user's explicit preference.

There exists research that aims to predict user reciprocity in various online social networks. In [17], a machine learning based approach is proposed to find plausible candidates of business partners using firm profiles and transactional relations between them. The authors of [11] propose a Triad Factor Graph model to deal with two-way relation prediction in online social networks. In [3], both user-based and graph-based features are applied in a machine learning framework to predict user replying behavior in online dating networks. A new collaborative filtering approach called *CLiMF* [14] is proposed to learn latent factors of users and items and improves the performance of top-k recommendations for recommending friends or trustees on Epinions and Tuenti. Further, they improve the algorithm by optimizing Expected Reciprocal Rank, an evaluation metric that generalizes reciprocal rank in order to incorporate user feedback with multiple levels of relevance in [15].

There have been recently several studies on the people to people recommendation for online social networks. Both content based algorithm and collaborative filtering method are applied to recommend users to follow in Twitter [10]. A LDA-based method is employed in [13] to discover communities in Twitter-style online social networks, and matrix factorization are applied on each community to provide recommendations.

For online dating recommendations, the authors in [12] and [7] analyzed the characteristics of reciprocal recommendations in detail. In particular, [12] considers both local utility (users' mutual preference) and global utility (overall bipartite network), and proposes a generalized reciprocal recommendation framework for both online dating sites and online recruiting sites. A content based reciprocal algorithm (RECON) proposed in [7] learns the preference of both sides of users and defines a new evaluation metric (success rate) to evaluate the performance of their algorithm. In their following work [8], [9], RECON is extended to consider both positive and negative preference, and collaborative filtering is applied with stochastic matching algorithm. In [4], a hybrid collaborative filtering based algorithm that takes reciprocal links into account is proposed and shown to have good performance in recommending both initial and reciprocal contacts. A recent study of [18] finds that users with similar profiles like and dislike similar people, and are liked and disliked by similar people. This hypothesis is used to build a content-collaborative reciprocal recommender, which is evaluated on a popular online dating dataset. In [6], collaborative filtering algorithms are used to capture the reciprocity in people to people recommendation. The authors in [5] propose a two-side matching framework for online dating recommendations and design a Latent Dirichlet Allocation (LDA) model to learn the user preferences from the observed user messaging behavior and user profile features.

The studies most relevant to our online dating recommendation problem are [7] and [4], in which a content-based algorithm (RECON) and a collaborative filtering-based algorithm (HCF) was presented and shown to outperform other

approaches. In this paper we will compare the performance of our proposed algorithms with these two algorithms.

III. RECOMMENDATION SYSTEM

In this section, we propose a generalized reciprocal recommendation system that aims to match people with mutual interest in each other. We also introduce two previously proposed approaches, namely, a content-based algorithm RECON [7] and a hybrid collaborative filtering algorithm (HCF) [4] for comparison.

A. System Design

The success of a reciprocal recommendation system lies in its ability to recommend users with whom the service user has mutual interest and thus they are likely to communicate with each other. The interaction records between a pair of users are a good indicator of actual interest and attractiveness between the sender and receiver. If a recommended user matches the service user's interest, the service user will be more likely to approach the recommended user. Also, if the service user's attractiveness is compatible with the recommended user's interest, the recommended user will be more likely to reply to the service user when contacted.

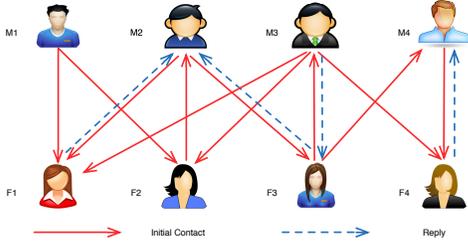


Fig. 1. Example of an online dating recommendation problem

Figure 1 depicts an example of an online dating network. Based on user attributes and their communication traces, our goal is to match users with mutual interest in each other, for example, M3 and F3, M4 and F4. In the following we will describe how to measure the similarity between a pair of users in terms of their dating interest and attractiveness, and how to construct various recommendation algorithms based on these similarity measures.

Our reciprocal recommendation system is comprised of the following four major components.

Extracting User Based Features: When a user registers with the online dating site, he/she needs to provide a variety of profile information including the user's gender, age, current location (city level), home town location, height, weight, body type, blood type, occupation, income range, education level, religion, astrological sign, marriage and children status, photos, home ownership, car ownership, interests, smoking and drinking behavior. Most of these attributes are categorical features, except age, height, weight and number of photos.

Extracting Graph Based Features: The online dating site we study is for heterosexual dating and only allows communications between users of opposite sex. The communication traces

between users can be modeled as a bipartite network between males and females. A collection of graph-based similarity features are extracted from the bipartite graph that represent a user's active level in dating and attractiveness. The detailed definitions of these graph based features are provided in Section III-B.

Compute Reciprocal Scores: Based on both user-based and graph-based features, we use the reciprocal score to measure the mutual interest and attractiveness between a pair of potential dates as described in Algorithm 1.

Algorithm 1 Reciprocal Score(x, y)

Input: service user x , and recommended user y
Output: reciprocal score
begin
 /* initialize compatible scores s^* */
 $s(x, y) = 0.0$
 $s(y, x) = 0.0$
 /* compute compatible scores for both x and y */
foreach u in $Neighbor_1(y)$:
 $s(x, y) = s(x, y) + Similarity_1(x, u)$
end for
foreach v in $Neighbor_2(x)$:
 $s(y, x) = s(y, x) + Similarity_2(y, v)$
end for
 /* normalize compatible scores for both x and y */
 if $|Neighbor_1(y)| > 0$
 $s(x, y) = \frac{s(x, y)}{|Neighbor_1(y)|}$
 if $|Neighbor_2(x)| > 0$
 $s(y, x) = \frac{s(y, x)}{|Neighbor_2(x)|}$
 /* compute reciprocal score */
 if $s(x, y) > 0$ and $s(y, x) > 0$
 return $\frac{2}{(s(x, y))^{-1} + (s(y, x))^{-1}}$
 else
 return 0.0
end

In Algorithm 1, $Neighbor_1()$ and $Neighbor_2()$ represent the neighbor set of a user with different directions in the bipartite network, and their formal definitions are given in equations (6) and (7). $Similarity_1(,)$ and $Similarity_2(,)$ are customizable functions measuring the similarity between two users. We will discuss these functions in the following subsection. Given $Neighbor_1$, $Neighbor_2$, $Similarity_1$ and $Similarity_2$, $s(x, y)$ measures the similarity between user x and user y 's neighbors, while $s(y, x)$ measures the similarity between user y and user x 's neighbors. After computing $s(x, y)$ and $s(y, x)$, the reciprocal score is computed as the harmonic mean of these two similarity scores.

Generate Recommended User List: For a given service user, a recommendation list will be generated by ranking these reciprocal scores. We will present the top-K users in the list to the service user. Note that the reciprocal score may not be symmetric if $Neighbor_1$ and $Neighbor_2$ are set as different functions or $Similarity_1$ and $Similarity_2$ are set as different functions. This is different from the case in RECON where there is a unique reciprocal score for any pair of users.

B. Similarity Functions

1) *Content-based Similarity Functions*: In content-based recommendation system, every recommended user can be represented by a feature vector or an attribute profile. These features can be numeric or nominal values representing some aspect of the user, such as age, height, income, and etc. Let A_x denote the set of known attributes (age, height, income, education level, etc) of user x , i.e.,

$$A_x = \{a : a \text{ is a known attribute of user } x\}.$$

We denote the set of user-based attributes of user x as

$$U_x = \{v_a^x : \text{for } a \in A_x\}, \quad (1)$$

where v_a^x is the value of attribute a of user x .

The first similarity measure based on user attributes follows the work of RECON [7], where the values of the numeric attributes (e.g., age, height, and etc) are grouped into ranged nominal values. For each service user, RECON builds his/her preference model by constructing the distribution of the receivers' user attributes. How much a service user is interested in a recommended user is then measured by comparing the attributes of the recommended user with the preference model of the service user. This is equivalent to computing the similarity between two users as follows:

$$\text{content-similarity}^a(x, y) = \frac{\sum_{a \in A_x \cap A_y} P_a(x, y)}{|A_x \cap A_y|} \quad (2)$$

where

$$P_a(x, y) = \begin{cases} 1, & \text{if } v_a^x = v_a^y \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

In RECON, numerical values are converted into categorical values, for example, users are divided into age groups 20-24, 25-29, 30-34, etc. Note that this method does not capture the numerical attribute information at the boundaries of continuous ranges. For example, a user of age 25 will not be considered to be similar to a user of age 24 as they fall into different age ranges. To avoid the loss of information, we modify the similarity measure defined in equation (2) as follows and use it as our second similarity measure, i.e.,

$$\text{content-similarity}^b(x, y) = \frac{\sum_{a \in A_x \cap A_y} Q_a(x, y)}{|A_x \cap A_y|}, \quad (4)$$

where $Q_a(x, y) = P_a(x, y)$ for the nominal attributes as before; for numeric attributes, we define

$$Q_a(x, y) = \frac{v_a^* - |v_a^x - v_a^y|}{v_a^*}, \quad (5)$$

where $v_a^* = \max_{i \neq j} |v_a^i - v_a^j|$ represents the maximum absolute difference for attribute a among all users. This new similarity measure results in a value between 0 when the attributes of the two users have the maximum difference (i.e., $|v_a^i - v_a^j| = v_a^*$) and 1 when the attributes of the two users are the same (i.e., $v_a^i = v_a^j$). For the above example, the age similarity between a 24-year-old user and a 25-year-old user will be 48/49 (very close to 1), where 49 is the max difference in user ages. It is clear that this new measure can better capture the similarity of numerical attributes between two users than the measure defined in equation (2), and as will be shown in Section IV,

results in better performance in generating the recommendation list.

The above two similarity measures are based on user attributes, and can be used to construct variations of content-based recommendation algorithms.

2) *Graph-based Similarity Functions*: Based on the message traces between users, we define the following two graph-based measures to capture the user's active level and attractiveness:

$$Se(x) = \{y : x \text{ has sent a messages to } y\} \quad (6)$$

$$Re(x) = \{y : x \text{ has received a message from } y\} \quad (7)$$

where $Se(x)$ is defined as the set of out-neighbors of x and its cardinality reflects the activeness of user x ; $Re(x)$ is defined as the set of in-neighbors of x and its cardinality reflects the attractiveness of user x .

Based on the graph-based measures defined in equations (6) and (7), we introduce the following two similarity functions:

Interest similarity: Consider two users of the same gender, x and y . If they both contact a same user, it shows that they share common interest in looking for potential dates. The fraction of users who received messages from both x and y among all users who received messages from either x or y serves as a measure of the similarity between the dating interest of the two users, i.e.,

$$\text{interest-similarity}(x, y) = \frac{|Se(x) \cap Se(y)|}{|Se(x) \cup Se(y)|} \quad (8)$$

Note that we adopt the Jaccard Coefficient in the interest similarity measure as the number of shared receivers from a pair of users is typically far outnumbered by the total number of receivers from the two users [2]. For the example shown in Figure 1, together M1 and M2 contacted three different females among which F2 received messages from both of them. The interest-similarity between M1 and M2 is thus 1/3.

Attractiveness similarity: Consider two users of the same gender, x and y . If they both receive messages from a same user, it shows that they share common attractiveness to potential dates. The fraction of users who sent messages to both x and y among all users who sent messages to either x or y serves as a measure of the similarity between the attractiveness of the two users, i.e.,

$$\text{attractiveness-similarity}(x, y) = \frac{|Re(x) \cap Re(y)|}{|Re(x) \cup Re(y)|}. \quad (9)$$

By the same token we adopt the Jaccard Coefficient in the attractiveness similarity measure. For the example shown in Figure 1, both F1 and F2 received messages from M1 and M3 while F1 also received messages from M2. The attractiveness similarity between F1 and F2 is thus 2/3.

C. Recommendation Algorithms

Based on these four similarity functions, we construct the following two content based algorithms and four collaborative filtering algorithms.

The content based algorithms (CB1 and CB2) are constructed based on the similarity of user attributes, including:

CB1 (RECON): Both $Neighbor_1$ and $Neighbor_2$ in Algorithm 1 are set as out-neighbors $Se()$, and both $Similarity_1$ and $Similarity_2$ are computed using content similarity defined in equation (2). This algorithm is the same as RECON [7].

CB2: Both $Neighbor_1$ and $Neighbor_2$ are set as out-neighbors $Se()$, and both $Similarity_1$ and $Similarity_2$ are computed using content similarity function defined in equation (4), where we do not convert numeric attributes into nominal attributes.

Collaborative filtering-based algorithms make use of the communication history of the service user as well as the decisions made by users with similar interest or attractiveness to help make recommendations. Based on different combinations of users' dating interest and attractiveness, we construct the following four collaborative filtering-based recommendation algorithms (CF1-CF4):

CF1: Both $Neighbor_1$ and $Neighbor_2$ are set as out-neighbors $Se()$, and both $Similarity_1$ and $Similarity_2$ are computed using attractiveness similarity defined in equation (9). Therefore, for Algorithm 1 we have

$$s(x, y) = \frac{1}{|Se(y)|} \sum_{k \in Se(y)} \text{attractiveness_similarity}(x, k)$$

$$s(y, x) = \frac{1}{|Se(x)|} \sum_{k \in Se(x)} \text{attractiveness_similarity}(k, y)$$

In this case, $s(x, y)$ sums up the attractiveness similarity (i.e., contacted by same users) between service user x and users who have been contacted by user y , capturing the attractiveness of the service user x to user y . Similarly, $s(y, x)$ captures the attractiveness of user y to service user x . Putting these two factors together, this algorithm captures the mutual attractiveness between the service user and recommended users. An example of CF1 algorithm is shown in Figure 2(a).

CF2: Both $Neighbor_1$ and $Neighbor_2$ are set as in-neighbors $Re()$. Both $Similarity_1$ and $Similarity_2$ are computed using interest similarity defined in equation (8). In this case, $s(x, y)$ sums up the interest similarity between service user x and users who have contacted user y , capturing the interest from user x to y . Similarly, $s(y, x)$ captures the interest from user y to x . Together, this algorithm captures the mutual interest between the service user and recommended users. An example of CF2 algorithm is shown in Figure 2(b).

CF3: $Neighbor_1$ is set as out-neighbors $Se()$, while $Neighbor_2$ is set as out-neighbors $Re()$. $Similarity_1$ is computed using attractiveness similarity defined in equation (9), and $Similarity_2$ is computed using interest similarity defined in equation (8). This algorithm captures the interest from recommended users in the service user and the attractiveness of the service user to recommended users. An example of CF3 algorithm is shown in Figure 3(a).

CF4: $Neighbor_1$ is set as in-neighbors $Re()$, while $Neighbor_2$ is set as out-neighbors $Se()$. $Similarity_1$ is computed using interest similarity defined in equation (8), and $Similarity_2$ is computed using attractiveness similarity defined in equation (9). This algorithm captures the attractiveness of recommended users to the service user and the interest of

the service user in recommended users. An example of CF4 algorithm is shown in Figure 3(b).

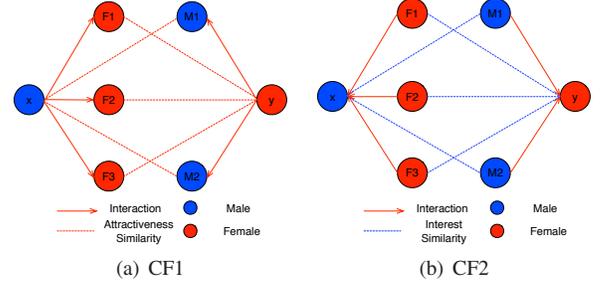


Fig. 2. Example of CF1 and CF2 algorithms.

Figure 2 illustrates the mechanism of CF1 and CF2 algorithms. In the example of CF1 shown in Figure 2(a), service user x sent messages to users $F1$, $F2$ and $F3$. These out-neighbors of service user x share similar attractiveness with user y , i.e., user y and $F1$, $F2$, $F3$ received messages from at least one common user. Also, user y sent messages to users $M1$ and $M2$ who share similar attractiveness of user x . Therefore, CF1 captures the mutual attractiveness between the service user and recommended users. If the reciprocate score between x and y ranks in the top-K position, user y will be included in the recommendation list for service user x . Figure 2(b) shows an example of CF2, which captures the mutual interest between the service user x and user y , i.e., user x 's interest in user y and user y 's interest in service user x . Examples of CF3 and CF4 illustrated in Figure 3 can be interpreted in a similar way.

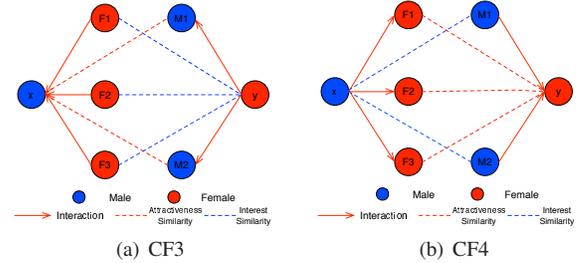


Fig. 3. Example of CF3 and CF4 algorithms.

In addition to the above algorithms, we also implement the content-based algorithm (RECON) proposed in [7] and the hybrid collaborative filtering algorithm (HCF) proposed in [4]. In particular, RECON corresponds to our CB1 algorithm, where the $Neighbor_1$ and $Neighbor_2$ are set as $Se()$ function, and $Similarity_1$ and $Similarity_2$ are computed based on equation (2). HCF extends the baseline collaborative filtering approach by considering both initial and reciprocal contacts to compute the similarity between two users, where reciprocal links are given higher weight than single direction contacts. These two algorithms are most related to our study and have been shown to outperform many other approaches. We will compare the performance of our proposed algorithms with these two algorithms in Section IV.

IV. EVALUATION

A. Dataset Overview

The dataset used in our study is obtained through a collaboration with baihe.com, one of the major online dating sites in China. Our dataset includes the profile information of 200,000 users uniformly sampled from users registered in November of 2011. Of the 200,000 sampled users, 139,482 are males and 60,518 are females, constituting 69.7% and 30.3% of the total number of sampled users respectively. For each user, we have his/her message sending and receiving traces (who contacted whom at what time) in the online dating site and the profile information of the users that he or she has communicated with from the date that the account was created until the end of January 2012. Note that the site is for heterosexual dating and only allows communications between users of opposite sex.

After a user creates an account on the online dating site, he/she can search for potential dates based on information within the profiles provided by the other users including user location, age, etc. Once a potential date has been discovered, the user then sends a message to him/her, which may or may not be replied by the recipient. In this paper we focus on the prediction of whether a user will reply to initial messages sent by other users. Subsequent interactions between the same pair of users do not represent a new sender-receiver pair and can not be used as the only indicator for continuing relationship as users may choose to go off-line from the site and communicate via other channels (e.g., email, phone or meet in person).

TABLE I. DATASET DESCRIPTION

Type	Initial contact links	Reciprocal links (Reply rate)
Male to Sample Female	1,586,059	150,917 (9.5%)
Female to Sample Male	328,645	58,946 (17.9%)

Since we only have eight full weeks' worth of online dating interaction records for our sample users, we will consider the activities of each user during the first eight weeks of his/her membership. Table I describes the characteristics of the dataset. More detailed description and analysis of the dataset can be found in our recent work [1], [2].

B. Experiment Setup

Most of the active users in our dataset are newly registered users. They are usually very active in looking for a potential date in the first one or two weeks after registration [1]. We select the user interactions within 10 days from user registration time as the training data, and interactions in the remaining time as the test set.

We filter the service users by selecting users who have sent or replied at least 5 messages in the training period, and use the interactions between these users in the test period as the test set. For the training set, we count all the interactions initiated, received or replied to by the selected users in the training period, and use these interactions to train our recommendation system. Table II summarizes the experiment dataset.

For RECON (CB1) and CB2, we manually pick 20 features over all 39 features. These selected features include age, height, weight, city, education level, income, house status, marriage status, children status, physical looking, car status,

TABLE II. EXPERIMENT DATASET

Male	Female	# of Messages in Training Set	# of Messages in Test Set
24,602	8,250	730,110	270,294

number of photos, smoking habit, drinking habit, marriage status, parents status, children plan, dating method, and wedding plan. Among these features, age, height, weight, and number of photos are treated as numeric values. For HCF, we performed several experiments to get the optimal weight parameter s in the computation of the success score between two users [4].

C. Evaluation Metrics

For a given service users in our test set, we rank the recommended users by comparing their reciprocal scores, and recommend the top-K users in the list. We evaluate the performance of each algorithm by comparing the top-K users in the recommended list with the receivers contacted by the service user in test set.

For a given service user, we define three set of users: T as the set of users we have recommended to the service user, I as the collections of users who have been contacted by the service user and R as the set of users who have been contacted by the service user and replied to the service user in the test set. We define the following two different evaluation metrics:

$$I\text{-Precision} = \frac{|I \cap T|}{|T|}, \quad I\text{-Recall} = \frac{|I \cap T|}{|I|}, \quad (10)$$

and

$$R\text{-Precision} = \frac{|R \cap T|}{|T|}, \quad R\text{-Recall} = \frac{|R \cap T|}{|R|}, \quad (11)$$

where $I\text{-Precision}$ and $R\text{-Precision}$ measure the ratio of users in the recommendation list who have been contacted by or exchanged messages with the service user, respectively. $I\text{-Recall}$ and $R\text{-Recall}$ measure the ratio of users who have been contacted by or exchanged messages with the service user in the list of recommended users. From another perspective, $I\text{-Precision}$ and $I\text{-Recall}$ measure an algorithm's performance in recommending users that the service user is interested in and thus likely to contact, and $R\text{-Precision}$ and $R\text{-Recall}$ measure an algorithm's performance in recommending users who have mutual interest with the service user and are thus likely to reciprocate when contacted.

D. Evaluation Results

In this subsection, we apply our recommendation algorithms on the experiment datasets, and compare the performance with RECON [7] and HCF [4]. We first report the performance of recommending users that the service user will contact, and then evaluate the performance of recommending users who will reciprocate when contacted by the service user.

1) *I-Precision and I-Recall*: We first examine the performance of these algorithms in recommending users whom the service user is interested in and thus likely to contact.

Figures 4 and 5 show the performance of the two content-based algorithms, namely, CB1(RECON) and CB2. We observe that by preserving the values of numeric attributes in the

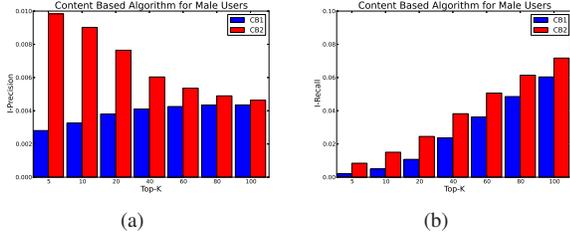


Fig. 4. *I-Precision* and *I-Recall* of content-based algorithms for male users

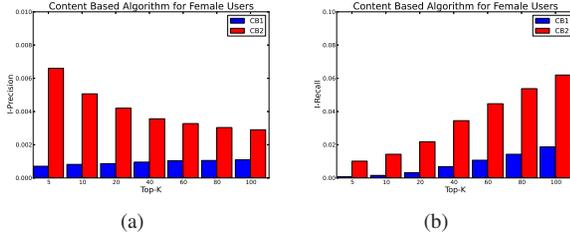


Fig. 5. *I-Precision* and *I-Recall* of content-based algorithms for female users

similarity measure, CB2 significantly outperforms CB1 in both precision and recall. The improvement is more pronounced for females than for males.

Figures 6 and 7 show the *I-Precision* and *I-Recall* of the collaborative filtering based recommendation algorithms for male and female users, respectively. We observe that for both male and female users, the four algorithms proposed in this paper, CF1 to CF4, significantly outperform previously proposed HCF algorithm. For male users, while there are some difference in the performance of CF1, CF2, and CF3, the difference is rather small when compared with CF4, which is much more effective in attracting the service user to contact the recommended users. However, for female users,

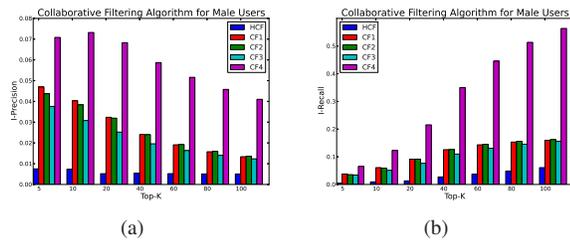


Fig. 6. *I-Precision* and *I-Recall* of collaborative filtering algorithms for male users

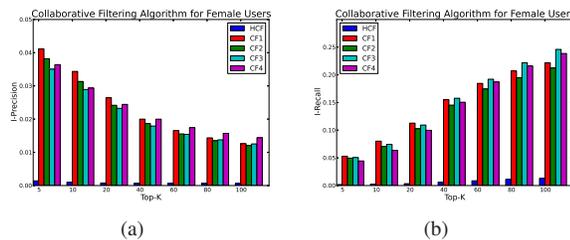


Fig. 7. *I-Precision* and *I-Recall* of collaborative filtering algorithms for female users

the four algorithms (CF1 to CF4) all perform similarly. There is no algorithm significantly outperforming others. Note that the CF4 algorithm captures the interest of the service user in recommended users as well as the attractiveness of the recommended users to the service user. The results indicate that when it comes to looking for potential dates, males tend to be more focused on their own interest and oblivious towards their attractiveness to potential dates, while females do not show such behavior.

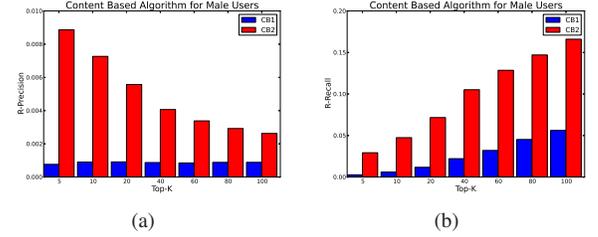


Fig. 8. *R-Precision* and *R-Recall* of content-based algorithms for male users.

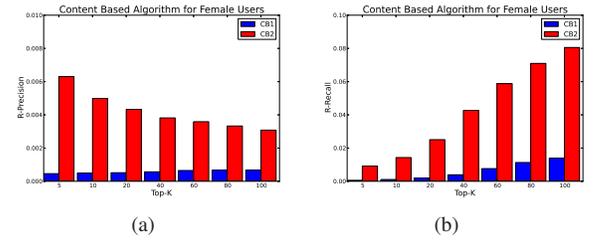


Fig. 9. *R-Precision* and *R-Recall* of content-based algorithms for female users.

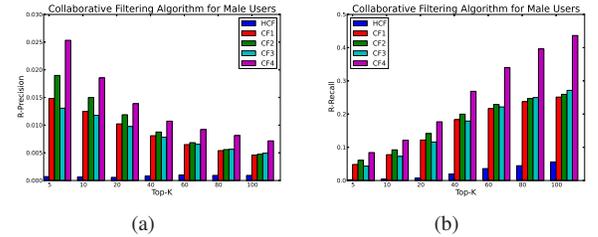


Fig. 10. *R-Precision* and *R-Recall* of collaborative filtering algorithms for male users.

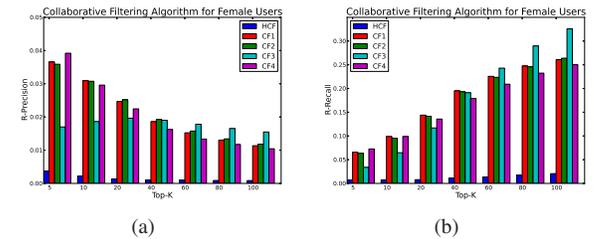


Fig. 11. *R-Precision* and *R-Recall* of collaborative filtering algorithms for female users.

2) *R-Precision* and *R-Recall*: We now examine the performance of these algorithms in recommending users who will be contacted by and exchange messages with the service user.

Figures 8 and 9 show the R -Precision and R -Recall of the two content-based algorithms for male and female users, respectively. Similar to I -Precision and I -Recall, CB2 performs much better than CB1(RECON), as CB2 does not convert numeric attributes into nominal attributes and thus does not lose information of these numeric attributes.

The performance of the collaborative filtering-based algorithms for male and female users are shown in Figures 10 and 11, respectively. The algorithms proposed in our paper (CF1-CF4) still achieve much better results than HCF. For male users, while CF4 still outperforms the other algorithms, the difference is not as pronounced as for I -Precision and I -Recall measures. For female users, CF1 and CF2 show very similar behavior. Recall that CF1/CF2 captures the mutual interest/attractiveness between the service user and recommended users. This shows that learning the mutual interest and mutual attractiveness between two users have similar effects for recommending potential dates for females. Unlike for male users, CF4 does not outperform other algorithms for female users. On the contrary, when the recommendation list (K) becomes large, CF3 starts to outperform the other algorithms. Recall that CF3 is symmetric to CF4, capturing the interest from recommended users in the service user and the attractiveness of the service user to the recommended users. The results indicate that when females look for potential dates, they are more conscientious to their own attractiveness to the other side of the line and the other sides' interest in them.

Note that in our experiments collaborative filtering-based algorithms (CF1-CF4) yield much higher precision and recall than content-based algorithms (CB1, CB2). One main drawback of collaborative filtering-based approach is that it can not address the cold start problem. On the other hand, content-based algorithm RECON [7] provides a feasible solution to the cold start problem by recommending users who are interested to the new service user.

V. CONCLUSIONS

Matching users with mutual interest in each other is an important task for online dating sites. In this paper, we propose a set of similarity based reciprocal recommendation algorithms for online dating. We introduce several similarity measures that characterize the attractiveness and interest between two users, and select most compatible users for recommendations. We evaluate the performance of our proposed algorithms on a large dataset obtained from a major online dating site in China. Our results show that the collaborative filtering-based algorithms achieve much better performance than content-based algorithms in both precision and recall, and both significantly outperform previously proposed approaches. Our results also show that male and female users behave differently when it comes to looking for potential dates. In particular, males tend to be focused on their own interest and oblivious towards their attractiveness to potential dates, while females are more conscientious to their own attractiveness to the other side on the line.

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