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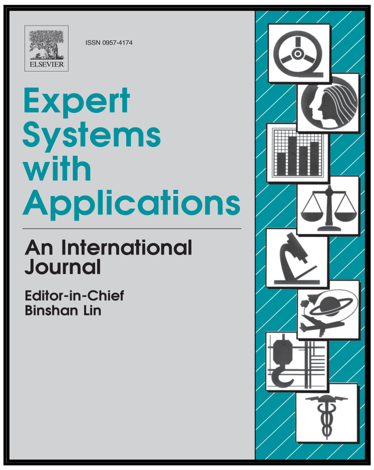


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# Personalized Recommender System based on Friendship Strength in Social Network Services

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Abstract

The rapid growth of social network services has produced a considerable amount of data, called big social data. Big social data are helpful for improving personalized recommender systems because these enormous data have various characteristics. Therefore, many personalized recommender systems based on big social data have been proposed, in particular models that use people relationship information. However, most existing studies have provided recommendations on special purpose and single-domain SNS that have a set of users with similar tastes, such as MovieLens and Last.fm; nonetheless, they have considered closeness relation. In this paper, we introduce an appropriate measure to calculate the closeness between users in a social circle, namely, the friendship strength. Further, we propose a friendship strength-based personalized recommender system that recommends topics or interests users might have in order to analyze big social data, using Twitter in particular. The proposed measure provides precise recommendations in multi-domain environments that have various topics. We evaluated the proposed system using one month's Twitter data based on various evaluation metrics. Our experimental results show that our personalized recommender system outperforms the baseline systems, and friendship strength is of great importance in personalized recommendation.

Keyword

Personalized recommender system, Social network services, Friendship strength, Social behavior, Collaborative filtering (CF)

## 1. Introduction

Recently, considerable real-time data have been generated because of the increase in the use of social network services (SNSs). Through SNSs, users can express their opinions in an unconstrained manner, and share their interests with others. This spontaneous participation of users in SNSs results in the generation of enormous amounts of data with various characteristics, called big social data (Cambria et al., 2013). Big social data have been used in various studies in many research fields because of their massiveness and variety (Manovich, 2011). In these fields, active research on personalized recommender systems has been conducted to provide appropriate information to users according to their demands and preferences (Guy, 2013).

Traditional personalized recommender systems employ mainly a collaborative filtering (CF) algorithm. A CF provides recommendations to users by analyzing their individual characteristics in order to utilize the information of other users who are highly similar to them (Herlocker et al., 1999). Big social data enable us to consider new diverse features to calculate the similarity between users, which cannot be used in traditional personalized recommender systems (Bellogin et al., 2013). These features have three main properties: “Contents generated by users”, “Relationship information” and “Interaction information”. “Contents generated by users” refers to all contents on SNS that are created by the users themselves, and their meta-information, such as tweets on Twitter, posts on blog, posting time of contents and tag information (Bobadilla et al., 2013). “Relationship information” constitutes a social circle representing directly linked or connected relationships among users on SNS, such as the follower-followee relationship on Twitter and, the friends list on Facebook. “Interaction information” refers to messages or contents exchanged between users, such as mention and retweet on Twitter, review sharing on Yelp, and message on Facebook (Nepal et al., 2013). Using these features, we can improve the recommendation quality as compared to that of traditional systems.

In order to calculate the similarity between users, conventional CF methods use similarity measures such as the Pearson correlation coefficient (PCC) (Herlocker et al., 1999) and Jaccard mean squared difference (JMSD) (Bobadilla et al., 2010). However, these measurements are not suitable for big social data-based personalized recommendations. This is because existing similarity measures are suitable for utilizing explicit (e.g., user’s rating) rather than implicit information (e.g., users’ behaviors such as the number of times that the user has listened to a particular song, the number of applications downloaded, and the web pages visited), whereas most big social data comprise implicit information (Chen et al., 2013; Ma, 2013). Further, users trust closely related users’ information in a social circle, and many research studies have verified that their information is useful for upgrading personalized services in practice (Servia-Rodriguez et al., 2014). However, existing similarity measures are not appropriate for calculating the closeness among users in a social circle, because they cannot easily consider the various characteristics of big social data, except for contents generated by users (Bobadilla et al., 2010; Liu & Aberer 2013; Liu et al., 2014a).

Moreover, most personalized recommender systems are based mainly on the relation information among users on SNS. If users are closely connected or linked to each other in their social circle, there is a high probability that they have similar interests and interact with each other actively (Nepal et al., 2013). In many studies, the degree of closeness between users was measured through the big social data. However, most of them provide recommendations using only the data of a single-domain SNS, such as MovieLens and Last.fm (Konstas et al., 2009; Servajean et al., 2014). In other words, they utilize sets of users who have similar tastes for specific domains. Users generate contents about numerous topics and form a relationship with other users who have various interests in a variety of topics. However, existing personalized recommender systems do not consider the number of topics users share with each other, because they are used only in a single topic domain. In addition, little works have been conducted on the multi-domain social circles that are formed by users with various topics and interests.

In this paper, to overcome the limitations of existing research, we propose a novel approach for measuring closeness between users that considers various features of big social data, particularly “Contents generated by users”, “Relationship information” and “Interaction information”. We refer to the closeness measure as friendship strength. Our proposed personalized recommender system can utilize the information of closely connected users; furthermore, this system can recommend appropriate interests or topics on SNSs. In other words, the recommended items in this paper are the interests or topics, especially smartphone, music, movie, and drama in which users might be interested.

The main contributions of this paper are as follows:

(1) The implicit information of big social data, which has not been utilized in the existing similarity measures, such as PCC and JMSD, can be used to calculate friendship strength between users. More specifically, friendship strength is determined by dividing it into interaction, group, and personal similarity, and is calculated by the combination of the three similarities.

(2) The proposed personalized recommender system provides appropriate recommendation results for users by using the information of other users who have a high level of friendship strength with them.

(3) We use data from Twitter, which is a multi-domain rather than a single-domain SNS for measuring performance. Through an extensive experiment, we verify that the performance of our system is high level for multiple domains.

(4) In this study, to evaluate the superiority of our proposed friendship strength-based system, we used various evaluation metrics for personalized recommender systems: precision, recall, F1 measure, mean

absolute error (MAE) and normalized discounted cumulative gain (NDCG). We verify that the performance of our approach is better than that of baselines in all metrics. In addition, friendship strength plays an important role in personalized recommendation.

The remainder of this paper is structured as follows. In Section 2, we describe the existing personalized recommender systems that use big social data, particularly considering the people relationships on an SNS. Section 3 explains our friendship strength-based personalized recommender system, which calculates the closeness among SNS users. Section 4 describes an evaluation framework for evaluating the performance of the proposed system and shows a comparative evaluation and the usage of big social data between the proposed system and the existing systems. In Section 5, we discuss whether our proposed friendship strength is applicable to other recommender system based on SNS and our limitations. Section 6 presents our conclusions and briefly describes the future work directions.

## 2. Related Work

### *2.1. Personalized Recommender System based on Big Social Data*

A personalized recommender system collects information about the preference of its users for items. Using this preference information, it recommends items that its users may wish to acquire. In previous systems, this information could be obtained by using the explicit or implicit information. As a result of using big social data such as follower-followee, friends' lists, tweets, blog posts, and tags, we can acquire more information to enhance personalized recommendations, compared with the recommendations provided by systems that not use such data. Therefore, there has been extensive research on the use of big social data in personalized recommender systems.

Many methods measure the similarity between users by utilizing preference values, particularly explicit ratings like PCC (Herlocker et al., 1999). Liu & Aberer (2013) utilized PCC and extended it to a version that can handle contextual information. Babadilla et al. (2010) proposed JMSD, which combines the Jaccard measure and MSD. They considered the ratio of common ratings as well as the absolute difference of ratings between two users. Liu et al. (2014a) proposed the new heuristic similarity model (NHSM) and calculated similarity by using not only users own ratings, but also the global preference reflected in user behaviors. Zhu et al. (2014) give a weight to popular items in every user to item rating matrix, and use cosine similarity to calculate similarity between users. Then, they predicted the interest of users with respect to them. However, the similarity measures of the above approaches are mainly based on explicit information, although they use public SNS data, such as MovieLens, Netflix, FilmAffinity, and Epinions. Therefore, they do not yield an appropriate similarity measures for big social data-based personalized recommender systems, because it is difficult to utilize implicit information properly.

Big social data include various implicit data, particularly user-generated data, such as tags and profiles, because of their intrinsic nature. Therefore, many researchers utilized these implicit data to improve their recommender systems. Firan et al. (2007) studied personalized track recommendations using data from Last.fm. They analyzed the tag usage statistically and showed that the user profiles based on these tags could produce better recommendations than the conventional ones based on track usage. Li et al. (2008) discovered the common interests shared by groups of users by using the user-generated tags on the social bookmarking site Delicious. Liu et al. (2014b) proposed a personalized tag recommendation system on Flickr, which matched new updated photos with geo specific tags. They used both the tagging history of users and the geographic information to generate recommended tags based on a learning method. Yin et al. (2014 & 2015) proposed user behavior model, namely temporal context aware mixture model (TCAM) and extended TCAM to dynamic temporal context aware mixture model (DTCAM). They observed rating behaviors of users based on two factors: user implicit preferences and temporal attentions of the whole social circle on the SNS. Servajean et al. (2014) tried to find the relevant users set (i.e., cluster) for a specific user in order to provide recommendations. They proposed a new clustering algorithm for recommendations based on their proposed similarity measure, namely usefulness and evaluated it by using MovieLens, Flickr and Last.fm. However, the above approaches are based on the information of unspecified individuals who are very similar to the target users, but are not linked with them. Therefore, they have difficulty reflecting personal tendencies sufficiently and yield a low recommendation accuracy as compared with approaches that consider users' relationship information on SNS for recommendations.

## 2.2. Personalized Recommender System based on People Relationship Information

Relationship information, which is a unique feature of SNSs, is highly appropriate information for improving the performance of personalized recommender systems. For this reason, many research studies on exploiting this information have been conducted. Personalized recommendation using relationships on SNSs is classified as recommended by influentials (Lin et al., 2014) or friends (Guy et al., 2010). Traditional personalized recommender systems recommend items by using information about unspecified individuals who are not connected to the users. However, we can utilize the people relationship information on an SNS to recommend items to users by using information about the acquaintances connected to them. The degree of similarity of the preference between users who are connected to each other on an SNS is higher than that of users who are not connected, and the influence of the connected users on the SNS is an important factor affecting personalized recommendations (Servia-Rodriguez et al., 2014). Many studies have proven that this has significantly improved the performance of personalized recommendation to use the information of the connected users.

### 2.2.1. Influential-based Personalized Recommender Systems

An influential is one who plays an important role in the SNS (Kwak et al., 2010), and influential-based recommendation is processed by the information of experts in their field or area. Hence, influential-based recommendations are used mainly in recommender systems that require expertise, such as those in academic fields or related to news. Zhen et al. (2009) defined a collaborative team as people with expert knowledge and provided recommendations using their information. Tang et al. (2008 & 2012) collected researcher profiles from the web and developed the ArnetMiner system, which recommends experts and papers relevant to users. Lin et al. (2014) defined a person who exerts influence on the news community as an expert. They proposed PRemiSE, which uses their defined expert information and improves the quality of personalized news recommendations. However, people tend to trust the opinions of acquaintances they know directly. According to a report by Harris Interactive (Heckathorne, 2010), the opinion of friends has more credibility than that of an influential, when a person decides to purchase products. Therefore, influential-based recommendation is suitable for knowledge-intensive domains, such as academic fields or news (Tang et al., 2008 & 2012; Zhen et al., 2009; Lin et al., 2014), but not for general domains including taste, interest or hobby, such as movie, music and drama; recently, a few studies have been conducted on general domains, such as Twitter (Bhattacharya et al., 2014). In addition, influence measurement does not consider the closeness among users, but is generally measured by focusing on the impact over the entire network. In other words, influential-based recommendation does not utilize relationship and communication information among users.

### 2.2.2. Friend-based Personalized Recommender Systems

In the case of an SNS, as mentioned previously, it is more efficient to provide recommendations based on the information of friends than that of influentials, because people tend to pay more attention to the opinions of acquaintances and friends than to those of influentials (Heckathorne, 2010). Thus, personalized recommendations have been provided using the information of friends in most of the domains, except in those related to professional or specialized knowledge. Geyer et al. (2008) encouraged user participation through the About You platform that recommends useful contents to users for writing their profiles, particularly using people relationship and user-generated contents. They used a binary score to determine whether the users are connected or not, and gave a weight to the contents of the connected users. Xu et al. (2013) discovered the preference of users on microblog based on the information of their connected users. They focused on filtering out unnecessary connected users to predict the preference of specific user, as opposed to general approaches finding relevant users. The aforementioned research use a relationship with a number of users on SNS, but a connected relationship itself does not guarantee that two users have a friendly relationship. However, the above approaches do not consider the closeness between users on an SNS and treat them all equally. Therefore, most of the studies have provided recommendations only for single-domain SNSs that have a set of users with similar interests and preferences.

In this paper, we call the strength of the connection friendship strength, which is a property for quantifying the closeness between users. Different terms for friendship strength were used in other research studies, such as tie strength (Granovetter, 1973; Servia-Rodriguez et al., 2014), intimacy (Rau et al., 2008; Seol et al., 2015) and trust (Golbeck, 2006; Deng et al., 2014). Recently, several personalized recommender systems that consider the friendship strength have been proposed. Konstas et al. (2009) provided music recommendation based on Last.fm through Random Walk with Restart (RWR) by using users' play count, tag and friendship information. Guy et al. (2010) proposed a hybrid approach that combines CF and content-based filtering to recommend social media considering both people relationships and user-generated tags. Golbeck (2006) presented FilmTrust, a web site using the trust among the users in a web-based SNS to provide predictive movie recommendations. He called this the reliability of users "trust," and assigned a weight to the information of high trust users for recommendations. Servia-Rodriguez et al. (2014) took into account the interaction and the social circle information of users to calculate the tie strength between them. Further, they proposed a personalized model based on the tie strength to enhance social services. Lai et al. (2013) considered three types of influence factors for recommendation: social, interest and popularity. They calculated the social influence by measuring the rate of photo sharing between directly connected users. Yu et al. (2013) considered the interaction between users on social circle, called the users' popularity, to predict the interest of users. Qian et al. (2013) calculated the rating based on the interpersonal influence (i.e., trust relation) and the interest similarity between users, and proposed personalized recommender system on the basis of these two factors along with personal preferences information. In particular, they calculated the similarity measures of multi-level of items to classify their category. Ma et al. (2014) proposed user recommendations on SNS considering both the relationship in the social circle and the topic similarity between users. Through the previous research, personalized recommender systems that consider the friendship strength can provide higher quality recommendations than systems that treat all relations as the same. However, thus far, a multi-dimensional analysis has not been performed on the factors influencing the friendship strength used in existing studies. Not considering the various elements affecting the friendship strength and not combining them appropriately lead to an inappropriate measurement of the closeness between users. Consequently, a new method is required that analyzes the factors affecting the friendship strength appropriately and combines them to calculate friendship strength.

## 3. Friendship Strength Based Personalized Recommender System

The proposed personalized recommender algorithm is based primarily on CF. CF-based recommender systems using people relationships on SNSs provide recommendations to users by using the information of their directly connected users or friends which is very useful for improving the recommendation quality. In particular, the strongly connected users had a greater positive influence on each other than the weakly connected users. In this paper, we consider various implicit data on SNS to calculate similarity which is different from existing similarity measure in CF. We call our similarity friendship strength with the three types of properties namely interaction, group, and personal similarity and propose a friendship strength-based personalized recommender system.

### *3.1. Methodology*

We propose the methodology of personalized recommender system to find relevant interests of users as shown in Fig. 1. The methodology largely consists of three phases: data processing, calculation of friendship strength, and personalized recommendation phase. First, we process raw data for the first phase, and then calculate friendship strength between users. Finally, we find the interests of users to use friendship strength-based personalized recommendation.

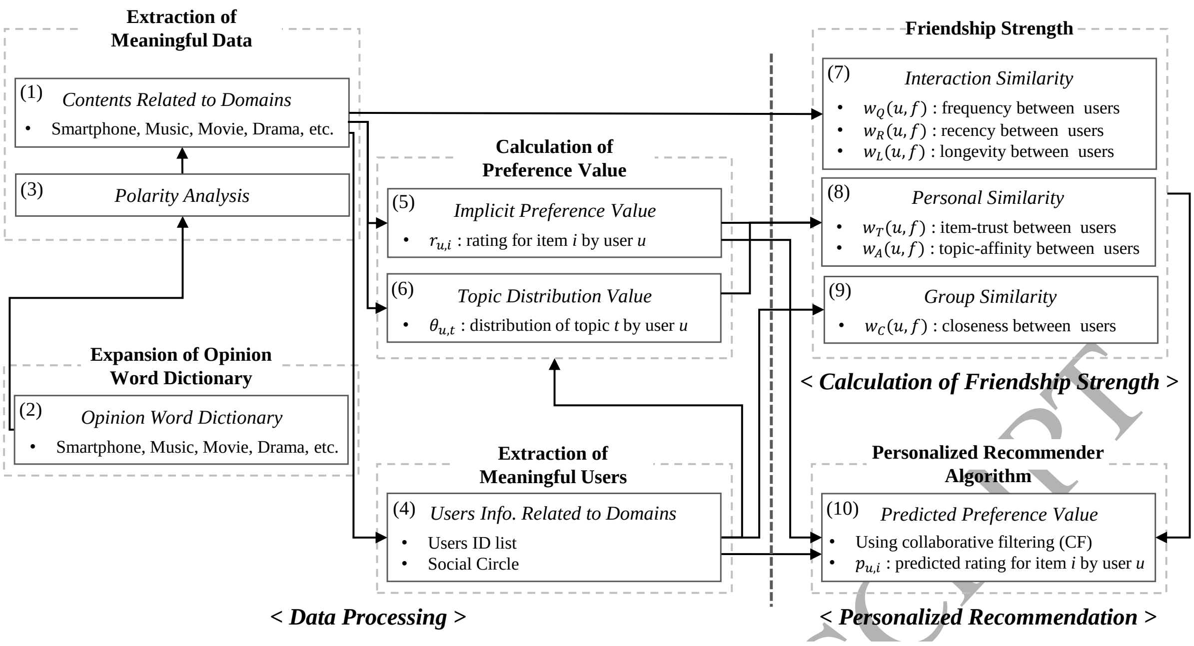


Fig. 1. **Methodology for the proposed personalized recommender system**

In the data processing phase, we process the data necessary for constructing our system. First, we extract data associated with the smartphone, music, movie, and drama domains (Step 1). Second, we extend the opinion word dictionary to add positive and negative words related to the music, movie, and drama domains based on the existing opinion word dictionary related to the dictionary for smartphone and prior research using English opinion word dictionary (Step 2). Third, using the opinion dictionary, we analyze the polarity of user-generated contents, such as tweets on Twitter, posts on Facebook, and reviews on Yelp (Step 3). Then, we extract users associated with the four domains and their relationship information. Using the extracted user information, we store the user's id list and create a user-to-user matrix for forming a social circle (Step 4). Finally, using scores of the polarity analysis of contents and the number of times the users refer to item, we measure the implicit preference value (Step 5) and the topic distribution value (Step 6) used in the proposed friendship strength and personalized recommender system.

In the calculation of friendship strength phase, we calculate the friendship strength between users. First, we calculate interaction similarity using communication information between users such as, retweet and mention in Twitter, contact information in Delicious, reviews on Facebook and Yelp. (Step 7). Second, we measure personal similarity using preference values, which are implicit preference value and topic distribution value (Step 8). And then, we calculate group similarity using users' social circle information on SNS (Step 9).

Finally, using friendship strength between users and implicit preference values, we calculate predicted preference value based on CF algorithm and provide appropriate recommendation results for users (Step 10). The detailed explanations for core steps are discussed in sections below.

## *3.2. Classification on Polarity of Contents (Steps 2 and 3)*

**Table 1**

Opinion Word Dictionary

| Topic | Polarity | |
|---|---|---|
| | Positive # | Negative # |
| Smartphone | 384 | 509 |
| Music | 220 | 182 |
| Movie | 225 | 211 |
| Drama | 227 | 211 |

Users express their emotions or feelings in the contents they post on an SNS. Thus, we should consider the polarity of contents when using the user-generated contents on SNSs for making personalized recommendations. To classify Korean contents' polarity, we utilize a smartphone-related opinion word dictionary provided by

DaumSoft. Further, based on a previous study (Esuli & Sebastiani 2006) using an English opinion word dictionary called SentiWordNet, we find representative words in Korean of negative and positive opinions, and create our Korean opinion dictionary expanded to fit the certain domains (e.g., music, movies, and drama). Our opinion word dictionary includes both negative and positive words, as shown in Table 1.

On the basis of this dictionary, we classify a user-generated content $D$ as positive, neutral or negative by providing a rating of 1, 0.5, or 0, and call it the polarity score of content $D$, defined as equation (1):

$$o_D = \begin{cases} 0 & if \quad D\, is\ negative \\ 0.5 & if \quad D\, is\ neutrality \\ 1 & if \quad D\, is\ positive \end{cases} \tag{1}$$

## 3.3. Calculation of Preference Value of Users (Steps 5 and 6)

Most of the big social data-based personalized recommender systems measure the users' preferences by using implicit information such as user-generated contents. In this paper, to measure preference value of users, we extract keywords (i.e., items) from the user-generated contents and call the domain containing the keywords a topic. Then, we calculate item and topic preference of users respectively. First, we calculate the implicit indicator of item preference based on the polarity of contents and the total number of the user-generated contents. If the polarity of the content $D$ is $o_D$ and the set of the contents about item $i$ by $u$ is $D_{u,i}$, the item preference value $r_{u,i}$ is defined as equation (2):

$$r_{u,i} = \frac{\sum_{D \in D_{u,i}} o_D}{\left| D_{u,i} \right|} \tag{2}$$

We also measure topic distribution value as a topic preference of users. Topic distribution value is a high-level preference of users, and is calculated by using distribution of the total number of the user-generated contents associated with topic $t$. If $D_u$ is the set of the contents by $u$ and $D_{u,t}$ is the set of the contents about topic $t$ by $u$, the topic distribution value $\theta_{u,t}$ is defined as equation (3):

$$\theta_{u,t} = \frac{|D_{u,t}|}{|D_u|} \tag{3}$$

## 3.4. Calculation of Friendship Strength (Steps 7, 8 and 9)

We consider various elements that affect the friendship strength on SNSs to calculate the friendship strength between users suitable for a personalized recommender system. The proposed friendship strength is classified into three types of similarity: interaction, group, and personal. Table 2 provides the definition of the properties of friendship strength.

**Table 2**

Representation and Definition of Friendship Strength

| | Property | Weight | Definition |
|---|---|---|---|
| Interaction Similarity | Frequency | $w_Q(u, f)$ | How much user $u$ communicates with his/her friend $f$ |
| | Recency | $w_R(u, f)$ | How recently user $u$ lasts encountered his/her friend $f$ |
| | Longevity | $w_L(u, f)$ | How long is the contact between user $u$ and his/her friend $f$ |
| Group Similarity | Intimacy | $w_I(u, f)$ | How similar are the social circles of user $u$ and his/her friend $f$ |
| Personal Similarity | Item-Trust | $w_T(u, f)$ | How similar are the interests of user $u$ and $f$ |
| | Topic-Affinity | $w_A(u, f)$ | How many topics have user $u$ and $f$ discussed |

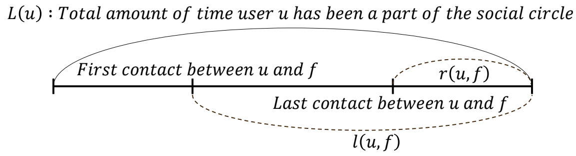


**Fig. 2.** Concept of functions $L(u)$, $r(u, f)$ and $l(u, f)$.

### *3.4.1. Interaction Similarity*

Interaction similarity is measured through "*the breadth and the depth of interaction*" between users (Rau et al., 2008). If two users have similar tastes or preferences, they share information actively (Nepal et al., 2013). Therefore, the interaction similarity between users is an important factor of friendship strength. In the case of Twitter, users share information and communicate with each other using the "mention" or "retweet" function. Similarly, the users of Facebook and Yelp can interact with each other using the reviews. We calculate the interaction similarity to use these functions. In this study, we use the frequency, recency, and longevity properties to measure the interaction similarity.

First, we count the number of times the users communicate with each other on SNSs to measure frequency. As shown in previous research, it is likely that strongly connected users, who communicate actively, exchange more useful information with each other. Thus, frequency should be assigned for personalized recommendations as a weight. This count is based on the number of contacts between users $u$ and $f$, and is defined as $q(u, f)$. Frequency is measured by normalizing $q(u, f)$ in the range between 0 and 1 with a log function, which was applied to a personalized Twitter search by Vosecky et al., (2014), and is defined as equation (4):

$$w_Q(u, f) = \begin{cases} \log_{10}\{1 + q(u, f)\} & if \quad q(u, f) < 10 \\ 1 & if \quad q(u, f) \geq 10 \end{cases} \tag{4}$$

While frequency is a weight related to the number of contacts, recency and longevity are weights related to the contact-time between users. To calculate the latter two weights, we define three functions: $L(u)$, $r(u, f)$ and $l(u, f)$, as shown in Fig. 2. Recency measures how recently the users have contacted or communicated with each other. A considerable amount of real-time data is generated on SNSs, and therefore, the most recent information is very important (Dai & Davison, 2010). Further, recent contact means that the users share a current interest. Therefore, whether the users have contacted each other recently or not is a key factor in measuring the closeness of a relationship. $r(u, f)$ denotes a value that is the measure of how recently users $u$ and $f$ contacted each other, and it is defined as the elapsed time from the last contact to the current time. $L(u)$ represents the total amount of time during which the data of user $u$ were collected. Recency is calculated as the ratio of $r(u, f)$ to $L(u)$, and is expressed as equation (5):

$$w_R(u, f) = \frac{r(u, f)}{L(u)} \tag{5}$$

Longevity measures the duration of the users' contact with each other. The information of a person who communicates with another for a relatively long period of time is more important than that of one who does not (Daly & Haahr, 2009). Where $l(u, f)$ denotes a period of contact between users $u$ and $f$, longevity is defined as equation (6):

$$w_L(u, f) = \frac{l(u, f)}{L(u)} \tag{6}$$

Interaction similarity is calculated by using a weighted sum of frequency, recency and longevity in order to consider all the communication-based friendship strength properties as equation (7):

$$Sim_I(u,f) = \alpha_I w_Q(u,f) + \beta_I w_R(u,f) + \chi_I w_L(u,f) \qquad (7)$$
$$(\alpha_I + \beta_I + \chi_I = 1)$$

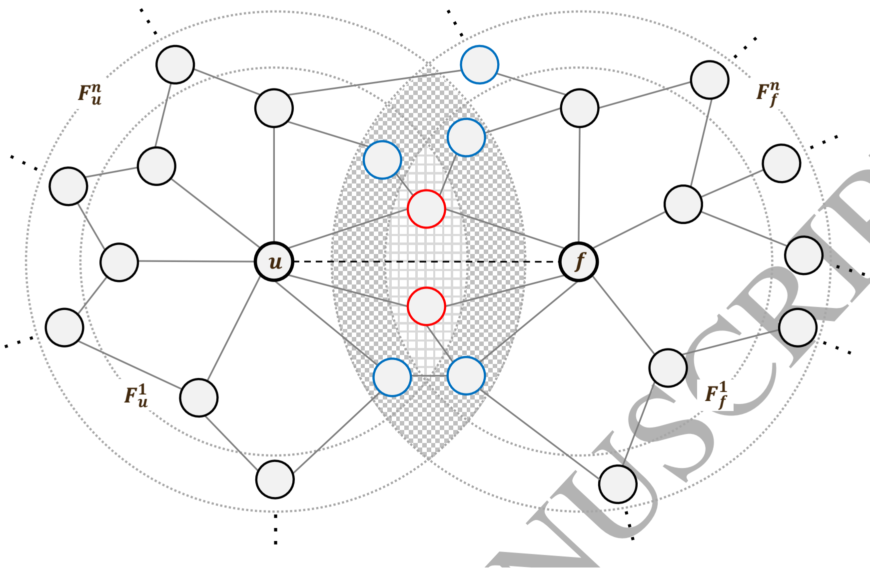


**Fig. 3.** Intimacy (Group Similarity) between User $u$ and his/her friend $f$.

### *3.4.2. Group Similarity*

Group similarity is an element of friendship strength related to the similarity of the social circles to which the users belong on the SNS, and we define it as intimacy. In general, the users' SNS social circles provides important information regarding their tastes or preferences, because they tend to add users who are in close contact with them offline or have similar interests, to their list of friends. In other words, two users with similar friend lists have a high probability of closeness (Lee & Brusilovsky, 2009; Zanda et al., 2012; Seol et al., 2015). Therefore, the proposed intimacy is calculated using the ratio of shared friends between groups of users $u$ and $f$.

The existing intimacy is used for calculating the group similarity between users by using only directly related friends' sets (Seol et al., 2015). However, by taking indirectly related friends into account, we can obtain information and resources beyond those available in the users' own social circle. Further, indirectly connected users play a significant role in the flow of information in the SNS (Granovetter, 1973). Therefore, it is important to consider the information of indirectly related friends. Hence, the proposed intimacy applies the concept of user friend level to make sufficient use of the information of indirectly connected users, as shown in Fig. 3. We define level-one $F_u^1$ as consisting of those users who are directly connected to user $u$, and level-$n$ $F_u^n$ as a set of indirectly connected users, such as friends of friends of user $u$. For example, $F_u^2$ denotes a set of users who are connected within two edges to user $u$. In this study, we set $n$ as six because almost all users on an SNS are connected within six edges (Kwak et al., 2010).

A intimacy that consider both directly and indirectly connected groups of users $u$ and $f$, who are connected to each other, is used for calculating the group similarity to utilizing the Jaccard measure. It is defined as equation (8):

$$Sim_G(u,f) = w_I(u,f) = \alpha_G \frac{|F_u^1 \cap F_f^1|}{|F_u^1 \cup F_f^1|} + \beta_G \frac{|F_u^n \cap F_f^n|}{|F_u^n \cup F_f^n|} \qquad (8)$$
$$(\alpha_G + \beta_G = 1)$$

### 3.4.3. Personal Similarity

Personal similarity denotes the degree of similarity between user-generated contents on SNSs, and it is calculated by the preference value of items and the distribution of their topics. In this study, we calculate the item-trust, which is the similarity of preference for items, and the topic-affinity, which is the similarity of the distribution of topics based on a classification of user-generated contents.

Measuring the degree of preference similarity between users is important in CF-based personalized services (Bobadilla et al., 2010; Liu & Aberer 2013; Liu et al., 2014a), because SNS users in a relatively intimate relationship with each other have a similar interest. In a personalized recommender system, several similarity measures can be used for calculating the preference similarity between users. Among them, PCC is the most popular measure and is thus the measure mainly used. However, PCC is not appropriate for a big social data-based recommender system that use implicit information, which does not constitute an explicit numerical preference value of items, because it is more suitable for recommender systems that include explicit information such as the ratings for items. Because in an SNS users mention a variety of interests or preferences, in particular on Twitter, the data of which were used for the experiments in this study, it is vital to consider the ratio of common interests rather than to measure only the numerical similarity of preferences. Therefore, we utilize JMSD (Bobadilla et al., 2010), which considers the ratio of common interests as well as the numerical interest similarity, to measure the similarity of the preference value between users. JMSD is calculated as the product of the MSD and the Jaccard measure, which measure the preference similarity and the ratio of common interest, respectively. MSD is the average of the difference between the preference values for an item for users $u$ and $f$. $d_{u,f}^{i}$ denotes the square of the difference between the preference values for item $i$ for users $u$ and $f$; this value is considered only when both users have a preference value for item $i$. Further, $d_{u,f}$ represents a set of $d_{u,f}^{i}$. Then, MSD is defined as equation (9):

$$MSD(u,f) = \frac{\sum_{i \in I} d_{u,f}^{i}}{|d_{u,f}|}$$
$$d_{u,f}^{i} = \begin{cases} (r_{u,i} - r_{f,i})^2 & if \quad r_{u,i} \neq null \wedge r_{f,i} \neq null \\ null & if \quad r_{u,i} = null \vee r_{f,i} = null \end{cases} \tag{9}$$

The Jaccard measure is calculated as the ratio of common mentioned item on SNSs. If $r_u$ and $r_f$ denote a set of preference value for users $u$ and $f$, respectively, then the Jaccard measure is defined as equation (10):

$$Jaccard(u,f) = \frac{|r_u \cap r_f|}{|r_u \cup r_f|} = \frac{|d_{u,f}|}{|r_u| + |r_f| - |d_{u,f}|} \tag{10}$$

SNS users can generate a large number of contents related to various topics, such as music, movies, and books etc. The more intimate the relationship between the users, the wider is the range of topics exchanged among the users. In addition, the similarity of topics between users on SNSs is one of the main elements of a personalized Twitter search with the frequency providing the appropriate retrieval result in accordance with the individual’s propensity (Vosecky et al., 2014). Therefore, we should consider the number of topics that the users share, which is different from previous research that measured only the item-trust, to provide high quality of recommendations in multi-domains. Therefore, in this study, the proposed personal similarity considers not only item-trust but also the similarity of topics, and we call it topic-affinity. To measure topic-affinity, we compute the distribution of specific topic $t$ in all of the users’ contents as $\theta_{u,t}$. After the measurement of the distribution of topics for each user is completed, the topic-affinity between users $u$ and $f$ is calculated by using the Kullback-Leibler divergence (Vosecky et al., 2014), which can measure the difference between two distributions. We define the set of topics as $T$. Then, the topic-affinity is calculated as equation (11):

$$w_A(u,f) = \frac{1}{KL(\theta_{u,t} \parallel \theta_{f,t}) + 1}$$
$$KL(\theta_{u,t} \parallel \theta_{f,t}) = \sum_{t \in T} \theta_{u,t} \frac{\theta_{u,t}}{\theta_{f,t}} \tag{11}$$

Personal similarity is calculated as a weighted sum of both the item-trust and the topic-affinity, which denote the similarity of the item and the topic mentioned by users; and it is defined as equation (12):

$$Sim_P(u,f) = \alpha_P w_T(u,f) + \beta_P w_A(u,f)$$
$$(\alpha_P + \beta_P = 1) \tag{12}$$

The range of the values of the properties defined above is 0 to 1 for all six, but the mean, standard deviation, and distribution of numerical values of each type of property are different. Therefore, all properties of similarity, $w_n(u,f)$, are normalized as follows: $\{w_n(u,f) - \overline{X}\}/s$, where $\overline{X}$ and $s$ represent the mean and the standard deviation of the similarities between a user $u$ and $f$.

$w(u,f)$ denotes friendship strength and is calculated by a combination of the elements, such as $Sim_I(u,f)$, $Sim_G(u,f)$, and $Sim_P(u,f)$. When $\sigma^T$ is a weighted vector that provides the difference in the weight value according to the importance of each element, $w(u,f)$ is calculated as equation (13):

$$w(u,f) = \sigma^T \begin{pmatrix} Sim_I(u,f) \\ Sim_G(u,f) \\ Sim_P(u,f) \end{pmatrix} \tag{13}$$

### 3.5. *Personalized Recommendation (Step 10)*

The proposed personalized recommender algorithm based on friendship strength recommends items (i.e., interests) to users by considering their tendency. We calculate the friendship strength by applying various characteristics of big social data on SNSs and use it as the similarity measure between users. Furthermore, the information of connected users who are linked in their social circle is more important than that of the not connected users. Therefore, we use only the information of directly or indirectly connected users. The predicted preference value of user $u$ for item $i$ is defined as equation (14), where $\overline{r_u}$ and $\overline{r_f}$ denote the mean preferences of users $u$ and $f$ for all items, respectively.

$$p_{u,f} = \overline{r_u} + \frac{\sum_{f \in F_u^1 \cup F_u^n} (r_{f,i} - \overline{r_f}) w(u,f)}{\sum_{f \in F_u^1 \cup F_u^n} w(u,f)} \tag{14}$$

## 4. Experiment and Evaluation

### 4.1. *Data Set*

In this study, we used the data of 120 million crawled Korean contents and 160 million users on Twitter provided by DaumSoft[1] for the period from July 1, 2012, to July 30, 2012. We briefly describe the provided raw data. The raw data is categorized as tweet related information, user relationship information, and opinion word dictionary for smartphones. The tweet data set is divided into information about tweets and the user information

[1] http://www.daumsoft.com/

related to the tweets. The former consists of the tweet document id, user-generated tweets, parsed tweet contents, the posting time of the tweets, and the retweeted tweet document id, and the latter consists of the user id and mentioned user id. The information of user relationship consists of a list of user ids identifying each user and sets of the user's followees. The provided opinion word dictionary consists of positive and negative words lists for smartphones to determine the polarity of tweets related to smartphone.

In order to verify whether the recommendation performance is improved in multi-domains by using our friendship strength-based personalized recommender system, we extracted 933,499 tweets and 308,155 users related to the smartphone, music, movie, and drama domains from the provided data. Further, we used only the data of 6,318 active users who mentioned all four domains to ensure a precise experiment. In the case of the smartphone domain, we chose 11 smartphone devices that were on the market during the study period. In the case of the music domain, 11 songs, which were ranked in the top 10 on South Korea's music streaming web sites, Bugs Music[2], were selected. In the case of the movie domain, we chose 4 Korean movies and 4 foreign movies screened in Korea during the study period. In the case of the drama domain, we chose 9 dramas that were aired by Korean terrestrial television companies, such as KBS, MBC, and SBS. All the data sets used in our experiments are shown in Table 3.

**Table 3**

Data Set for Experiment

| | Topic | | | |
|---|---|---|---|---|
| | Smart Phone | Music | Movie | Drama |
| #Item | 11 | 11 | 8 | 9 |
| #Tweets | 324,991 | 78,148 | 284,084 | 246,276 |
| #Users | 89,036 | 47,221 | 89,372 | 82,526 |
| #Active Users | 6,318 | | | |
| #All Tweets | 933,499 | | | |
| Time Span | 2012 - 07 - 01 ~ 2012 - 07 - 31 | | | |

## *4.2. Evaluation Process*

In this study, we conducted a *cross validation* based on the processing data provided by DaumSoft to evaluate the proposed personalized recommender system. The framework of our evaluation is shown in Fig. 4.

In the validation step, we conducted *cross validation* for the experiment based on data processing. First, we divided the data into a test set and a training set. In the case of the set of users, we considered 20% of the active users as the test users and 80% as the training users. After building a user-to-user friendship strength matrix for the experiment, we found that the density of the interaction similarity (*density:* $2.85\times10e^{-4}$) was smaller than the density of the personal (*almost 1*) and the group similarity (*density:* $2.5\times10e^{-3}$ *if* $n=1$, *density:* $6.5\times10e^{-1}$ *if* $n\leq6$). Therefore, we considered 20% of the active users who interact actively with other users to be test users in order to reflect the influence of interaction similarity. In the case of the set of items, it was not suitable to use *n-fold cross validation* as for the set of users. In our data set, there were 39 items used in the experiments; however, the mean of the number of the items mentioned by active users was roughly 10. Therefore, we used the *leave-one-out cross validation* for the set of items. After the separation of the test set and the training set, we calculated the friendship strength for the test users. The interaction and the group similarity were measured by using the user-

[2] http://www

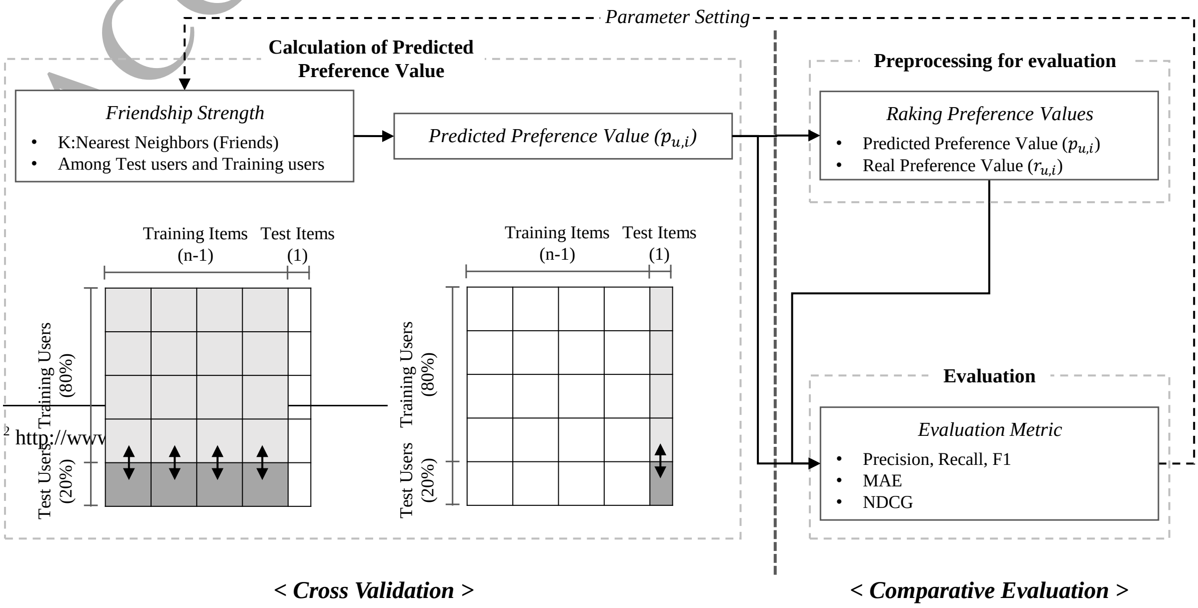


**Fig. 4.** Evaluation Framework.

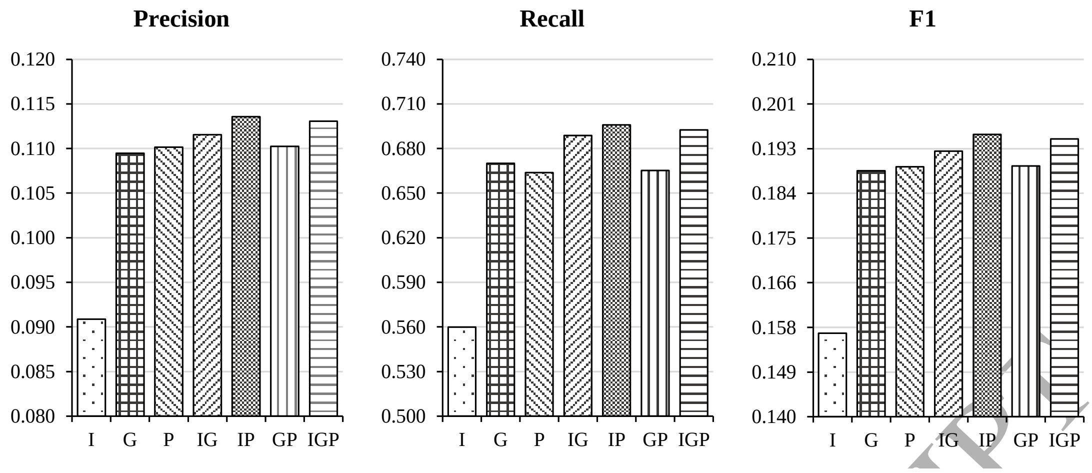


Fig. 5. Results of the combination of friendship strength elements.

to-user friendship strength matrix, and the personal similarity was calculated using the preference value and the topic distribution value of training items between test users and training users.

In the evaluation step, we validated the superiority of the proposed friendship strength-based personalized recommender system using a comparative evaluation. First, we determined the friendship strength of the k-nearest neighbors (i.e., k-friends close to the test users) and then, calculated the predicted preference value ( $p_{u,i}$ ) of test users according to the proposed system based on the information of k-nearest neighbors. Second, we determined the weighted value of three friendship strength elements ( $\alpha_I$ , $\beta_I$ , $\chi_I$ , $\alpha_G$ , $\beta_G$ , $\alpha_P$ , and $\beta_P$ ) and the weighted vector ( $\sigma^T$ ) by adjusting it to use the predicted preference value. Finally, we conducted a comparative evaluation to verify the performance of the proposed system using various metrics such as precision, recall, F1 measure, MAE, and NDCG.

### *4.3. Decision of the best combination of Friendship Strength Elements*

We measured the similarity between users through the combination of three friendship strength elements: interaction similarity (I), group similarity (G), and personal similarity (P). There are seven combinations, namely I, G, P, IG, IP, GP, and IGP, and we need to pre-determine which combination exhibits the best performance. Therefore, before the comparative evaluation with baselines, we conducted an experiment to find the combinations with the highest performance by using precision, recall, and F1 measure shown in Fig. 5.

When we used I, G and P as a single element of friendship strength, the performance of I was inferior to the performance of G or P. This is because the user-to-user friendship strength matrix density of I is less than that of the other elements. However, we can confirm that I has a greater effect on the performance improvement when used together with G and P than when used alone. From Fig. 5, we can infer that G and P show a similar performance, which is better than the performance of I when used as a single element of the friendship strength; however, when they are used in combination with the other elements, their effect is less than that of I. Among all the combinations, the combination of I and P (IP) shows the best performance; its performance is better than the performance of the combination of all elements (IGP). Therefore, in this study, we set IP as the friendship strength.

### *4.4. Experimental Results*

To prove the quality of the recommendation generated by the proposed friendship strength-based personalized recommender system, we evaluated the performance of the proposed system and compared it with that of baselines. The baselines used for the comparative evaluation were CF based on PCC and JMSD. CF has been used widely for personalized recommender system, both academically and commercially. In practice, many web services such as Amazon, Reddit, and YouTube, are based on CF (Saleem, 2008; Ekstrand et al., 2011); furthermore, SNS such as Last.fm, Facebook, and LinkedIn use CF to recommend items or friends (Ekstrand et al., 2011; Victor et al., 2011). We chose PCC for a baseline because it is the most popular with CF-based personalized recommender systems (Herlocker et al., 1999; Golbeck, 2006; Liu & Aberer, 2013). For instance,

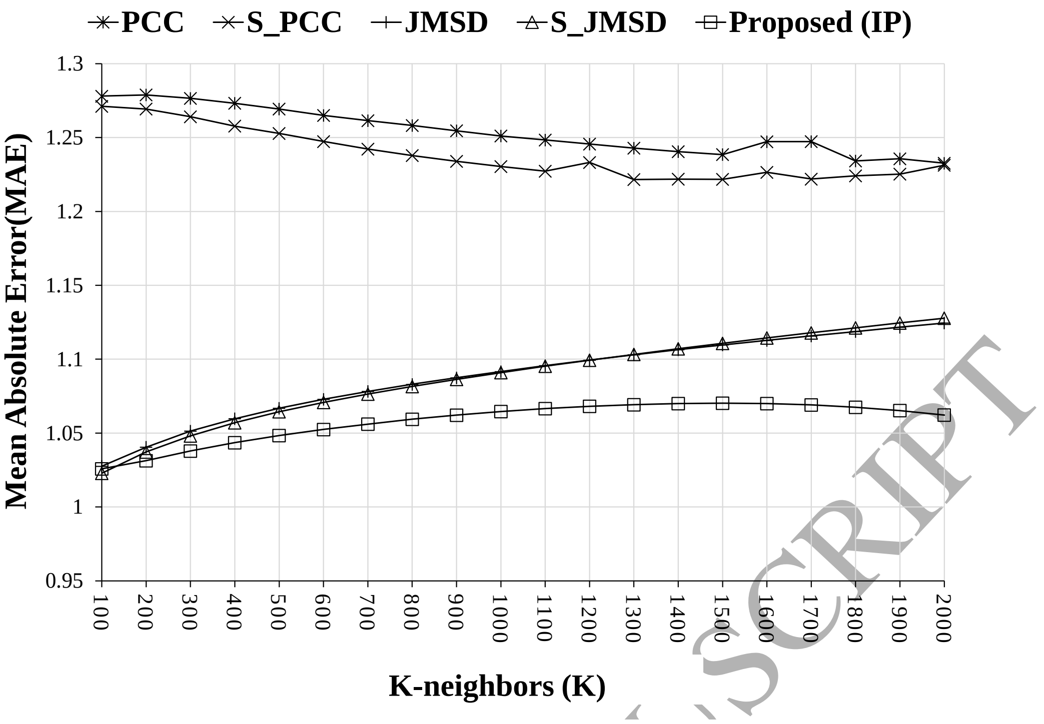


Fig. 6. Comparative evaluation to measure predicted value's quality

Ringo (music), BellCore (movie), and FilmTrust (movie) are all based on PCC (Golbeck, 2006; Ekstrand et al., 2011). JMSD is chosen because it can consider the ratio of common interest. Therefore, JMSD is more suitable for Twitter-based recommender systems than other numerical value-based similarity measures. JMSD-based recommender systems do not exist in practice, but their effectiveness has been proven using real recommender system databases, such as Movielens, FilmAffinity, and Netflix (Bobadilla et al., 2010). The proposed system utilizes the information of users who are connected directly or indirectly on the SNS, whereas the baselines provide recommendations for users using the data of unspecified individuals. Thus, we needed to verify whether the information of connected users is helpful in the case of using PCC and JMSD. To prove this, we measured the performance of the baselines based on PCC and JMSD by using the information of connected users (S_PCC and S_JMSD), and compared it with that of the baselines using the information of unspecified individuals and the proposed system. We validated the quality of recommendation made by the proposed system using MAE, precision, recall, F1-measure, and NDCG which are the main metrics used for measuring the performance of the personalized recommender systems.

First, we calculated the difference between the predicted preference value and the actual user's preference value to evaluate the accuracy of the predicted value generated by the personalized recommender systems (Bobadilla et al., 2013). MAE is mainly used for the error measurement of predicted values and is defined as equation (15):

$$MAE = \frac{1}{|I|}\sum_{i \in I}\left\{\frac{1}{|O_{u,i}|}\sum_{u \in O_{u,i}}\left|p_{u,i} - r_{u,i}\right|\right\} \qquad (15)$$
$$O_{u,i} = \{u \in U \mid p_{u,i} \neq null \wedge r_{u,i} \neq null\}$$

$O_{u,i}$ denotes the set of users, the $p_{u,i}$ and $r_{u,i}$ of whom are both not null values in the test users' set $U$. The error of the $p_{u,i}$ is calculated as the absolute value of the difference between $p_{u,i}$ and $r_{u,i}$. The results of MAE for the comparative evaluation are shown in Fig. 6; in this case, the range of k-neighbors ($K$) is 100 to 2,000.

As shown in Fig. 6, the proposed friendship strength-based system has a lower error rate than PCC and JMSD. The figure shows that the performance of the predicted preference value's accuracy is significantly improved by

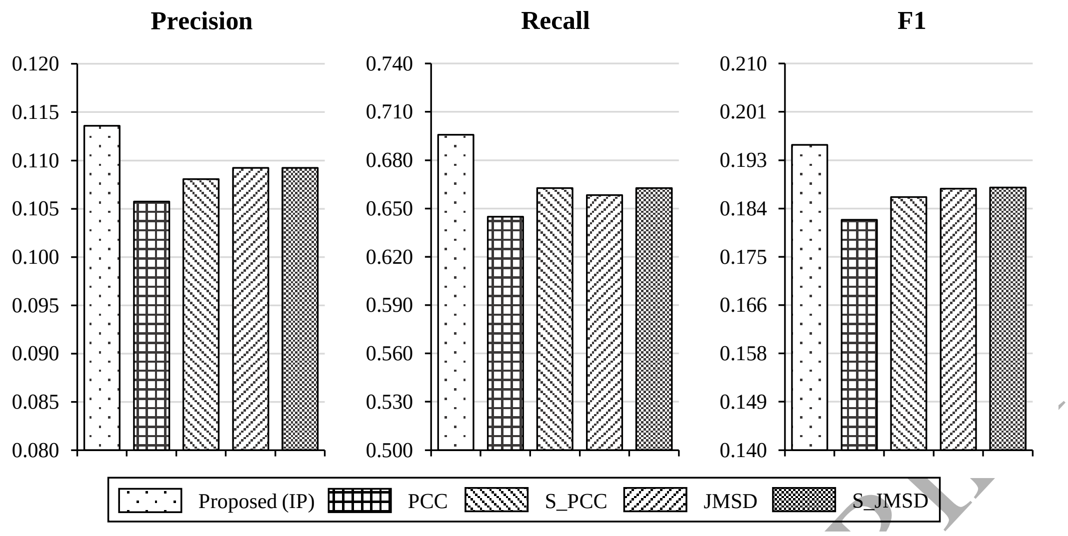


Fig. 7. Comparative evaluation to measure the quality of the set of recommendations

15 to 20% and 13 to 19% as compared to that of the PCC and S_PCC, respectively, in the overall range. As compared with the JMSD and S_JMSD, its performance is nearly the same or slightly better until the number of $K$ reaches 1,000. However, when the number of neighbors is greater than 1,000, the performance is improved by approximately 5%. Further, the larger the number of $K$, the higher is the performance improvement. The comparison results for PCC and JMSD show that the accuracy of the JMSD is higher, but the range of performance improvement decreases with the increase in the number of $K$. Finally, we find that the information of connected users affects the accuracy of the predicted preference value more than that of unspecified users in the existing JMSD- and PCC-based personalized recommender systems. S_PCC and S_JMSD which use the information of the connected users exhibit better quality than PCC and JMSD, even when S_JMSD is almost similar to JMSD, but slightly better as a whole.

Users' reliance on the recommendation results received through personalized services is not determined by the accuracy of the predicted values. MAE may be a good metric to measure the performance of the recommender algorithms. However, it cannot measure the satisfaction with the recommendation results that the users feel. Users trust results (i.e., recommended item lists) obtained through personalized recommender systems if they are in fact satisfied with these results. Therefore, it is necessary to measure the users' satisfaction with the recommended results; This is calculated by determining whether the result is relevant to the user or not. Precision, recall, and F1 measure are representatively used for measuring the effectiveness of the personalized recommendation's results (Bobadilla et al., 2013). They are defined as equations (16), (17) and (18), where $Z_u$ denotes a set of $N$ recommended items provided by users and $\vartheta$ represents the threshold value.

$$precision = \frac{1}{|U|}\sum_{u \in U}\frac{\left|\{i \in Z_u \mid r_{u,i} \geq \vartheta\}\right|}{|N|} \tag{16}$$

$$recall = \frac{1}{|U|}\sum_{u \in U}\frac{\left|\{i \in Z_u \mid r_{u,i} \geq \vartheta\}\right|}{\left|\{i \in I \mid r_{u,i} \geq \vartheta\}\right|} \tag{17}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{18}$$

First, to measure the precision, recall and F1 measure, we not only ranked the lists of the recommended items according to the high predicted preference value but also determined the threshold for judging the relevance of the recommended items. In this paper, the $r_{u,i}$ is defined as from 0 to 1. If $r_{u,i}$ is higher than 0.5, user $u$ has given a positive opinion about item $i$ more than once in all his/her tweets. Therefore, we set the threshold value as 0.5, because it can be judged that recommended item $i$ is relevant if $r_{u,i}$ is higher than 0.5.

As shown in Fig. 7, in terms of the metrics for the set of recommendations, such as precision, recall and F1 measure, the proposed system achieves a higher value than the baselines. In terms of precision, the proposed system exhibits an improvement of about 7% and 5% as compared to PCC and S_PCC, respectively. The system is also shown to enhance performance by approximately 4% as compared to JMSD and S_JMSD. In terms of recall, the proposed system exhibits a performance improvement of about 8% as compared to PCC and of about 6% as compared to JMSD. As compared with S_PCC and S_JMSD, it exhibits a performance improvement of about 5%. For the F1 measure, the results are similar to those obtained for precision. The proposed system exhibits a performance that is approximately 7% better than that of PCC, 5% than that of S_PCC, and 4% than that of JMSD and S_JMSD.

In personalized recommender systems, we consider mainly the relevance of high ranked items because users tend to look only at the top ranked results among all the recommended items to find the relevant items (Baltrunas et al., 2010). Therefore, if $N$ items are recommended to users, the first recommended item has the highest importance. Furthermore, when the high ranked items are incorrect or not relevant to users, a more serious error is generated than when the low ranked items are incorrect or not relevant. On the basis of these assumptions, DCG and Ideal DCG (IDCG) are calculated according to equations (19) and (20). NDCG (Baltrunas et al., 2010) is the value of DCG divided by IDCG, as defined in equation (21).

$$DCG = \frac{1}{|U|}\sum_{u \in U}\left\{ r_{u,p_1} + \sum_{i=2}^{k} \frac{r_{u,p_i}}{\log_2 i} \right\} \tag{19}$$

$$IDCG = \frac{1}{|U|}\sum_{u \in U}\left\{ r_{u,r_1} + \sum_{i=2}^{k} \frac{r_{u,r_i}}{\log_2 i} \right\} \tag{20}$$

$$NDCG = \frac{DCG}{IDCG} \tag{21}$$

$p_1, \ldots, p_n$ and $r_1, \ldots, r_n$ denote the list of ranked items according to the predicted preference value and the actual preference value provided by the users, respectively. $r_{u,p_i}$ and $r_{u,r_i}$ represent the preference value of the $p_i$ th and $r_i$ th items actual preference value given by user $u$, respectively. In this study, we conducted a comparative evaluation using NDCG when $k$, which is the number of all recommended items, was set at 5, 10, or 20. Table 4 shows the results of NDCG for the proposed system and the baselines.

As for the measurement of the quality of the ranked results as shown in Table 4, the difference in NDCG between the proposed system and the baselines is not very large. Nevertheless, in all cases, when k is 5, 10, or 20, the proposed system's NDCG is higher than that of the baselines.

**Table 4**
Comparative evaluation to measure user satisfaction with ranked list

| | NDCG@k | | |
|---|---|---|---|
| | k=5 | k=10 | k=20 |
| PCC | 0.7978 | 0.8588 | 0.8779 |
| S_PCC | 0.7963 | 0.8578 | 0.8771 |
| JMSD | 0.7963 | 0.8576 | 0.8736 |
| S_JMSD | 0.7986 | 0.8584 | 0.8752 |
| Proposed (IP) | **0.8039** | **0.8607** | **0.8784** |

We evaluated our friendship strength-based personalized recommender system by using various metrics: MAE, precision, recall, F1 measure, and NDCG. The results show that the proposed system exhibits a better performance than the baselines in terms of all the metrics. The proposed system based on the friendship strength provides recommendations for users by using the information of other users who are closely connected with them on the SNS; therefore, its recommendations are more valuable for users than those of the baselines based on PCC and JMSD, which use the information of unspecified users. Further, the performance of S_PCC and

S_JMSD is better than that of PCC and JMSD, respectively, except that PCC's NDCG and recall values are higher than S_PCC's. That is, the use of the information of connected users' results in better recommendations than does that of the information of not connected users. Consequently, we verify that it is very efficient to use the information of connected users in personalized recommender systems based on people relationship information. Finally, the performance of proposed system is superior to S_PCC and S_JMSD. This result reveals that the measurement of the proposed friendship strength appropriately represents the closeness between users with respect to their relationship and the proposed personalized recommender system based on friendship strength is useful for improving the accuracy of recommendations.

**Table 5**

Comparison of the usage of big social data on personalized recommender system

| | Category | Interaction information | | | Group information | Personal information | | Data set (Experiment domain) |
|---|---|---|---|---|---|---|---|---|
| | | Frequency | Recency | Longevity | | Item similarity measure | Topic similarity measure | |
| Bobadilla et al. (2010) | Unspecified individuals | Not support | Not support | Not support | Not Support | JMSD | Not support | MovieLens (Movie), NetFlix (Movie), FilmAffinity (Movie) |
| Liu et al. (2014a) | Unspecified individuals | Not support | Not support | Not support | Not Support | New Heuristic Similarity Model (NHSM) | Not support | MovieLens (Movie), Epinions (Multi-domain) |
| Zhu et al. (2014) | Unspecified individuals | Popularity of items (in a whole network) | Not support | Not support | Not support | Cosine | Not support | MovieLens (Movie) |
| Firan et al. (2007) | Unspecified individuals | Not support | Not support | Not support | Not support | Cosine | Not support | Last.fm (Music) |
| Li et al. (2008) | Unspecified individuals | Not support | Not support | Not support | User clusters for topics | Similarity of intra- and inter-topics (based on cosine) | Not support (do not exist higher level of topic) | Delicious (URLs) |
| Liu et al. (2014b) | Unspecified individuals | Not support | Not support | Not support | Not support | Gaussian kernel, Cosine | Not support | Flickr (Geo-Specific Tag) |
| Yin et al. (2014 & 2015) | Unspecified individuals | Not support | Temporal context (recent interests in a whole network) | Not support | Not support | Vector Space Similarity (VSS), Jaccard, PCC | Not support (topic is higher level of item, but do not exist topic similarity) | Digg (News) MovieLens (Movie) Douban Movie (Movie) Delicious (URLs) |
| Servajean et al. (2014) | Unspecified individuals | Not support | Not support | Not support | Not support | Usefulness score (based on Jaccard) | Not support | MovieLens (Movie) Flickr (Photo) Last.fm (Music) |
| Zhen et al. (2009) | Influentials | Not support | Not support | Not support | Collaborative team (a set of influentials) | Relationship Similarity Coefficient (RSC), Influence Coefficient (InfC) | Not support | The environment of a manufacturing enterprise (Enterprise knowledge) |
| Tang et al. (2008 & 2012) | Influentials | Not support | Not support | Not support | Random Walk with Restarts (RWR) | Cross-domain Topic Learning (CTL) | Not support | Aminer (Academic items) |
| Lin et al. (2014) | Influentials | Not support | Not support | Not support | Expert model (a way to find implicit influentials) | Cosine | Not support | Google News (News) |
| Bhattacharya et al. (2014) | Influentials | Not support | Not support | Not support | Topic experts (based on list meta-data) | Interest vector | Not support | Who Likes What (Multi-domain) |
| Geyer et al. (2008) | Connected Users | Not support | Not support | Not support | Relationship strength (based on binary score) | Candidate relevance score | Not support (do not exist higher level of topic) | About You (Topics for user profile) |
| Xu et al. (2013) | Connected users | Not support | Decay factor (weight of posting time) | Not support | Followee Influence (based on PageRank) | Not support (item is lower level of topic, but do not exist item similarity) | Cosine | Sina Weibo (Multi-domain) |
| Konstas et al. (2009) | Friends | Not support | Not support | Not support | RWR | RWR | Not support | Last.fm (Music) |
| Guy et al. (2010) | Friends | Not support | Not support | Not support | Familiarity relationship score | Similarity score (based on Jaccard) | Not support | SaND (Social media items) |
| Golbeck (2006) | Friends | Not support | Not support | Not support | Trust value | PCC | Not support | FilmTrust (Movie) |
| Lai et al. (2013) | Friends | Social influence (the ratio of the sharing favorite photo between friends) | Time factor (weight of posting time) | Not support | Popularity influence (the total count of photo in a whole network) | Interest influence (interest similarity) | Not support | Flickr (Photo) |
| Yu et al. (2013) | Friends | Users popularity (based on cosine) | Decay factor (weight of posting time) | Not support | Not support (but using direct friends info.) | Distance similarity measure | Not support (do not exist higher level of topic) | Sina Weibo (Multi-domain) |
| Qian et al. (2013) | Friends | Not support | Not support | Not support | Interpersonal influence, Trust value | Interpersonal interest similarity (Second level of category, based on cosine) | Interpersonal interest similarity (First level of category, based on cosine) | Yelp (Restaurant) MovieLens (Movie) Douban Movie (Movie) |
| Ma et al. (2014) | Friends | Not support | Not support | Not support | Trust relations | Topic similarity (based on cosine) | Not support (do not exist higher level of topic) | Sina Weibo (Users) |
| Proposed model | Friends | Frequency | Recency | Longevity | Intimacy (based on Jaccard) | Item-trust (based on JMSD) | Topic-affinity (based on KL-divergence) | Twitter (Multi-domain) |

Finally, we compare the proposed system with previous personalized recommender systems, based on the method of using big social data shown in Table 5. We mainly categorized recommender systems based on whether they used the people relationship information or not, as described in Section 2.

Calculating the item similarity between users based on big social data appropriately is a prerequisite condition for all personalized recommender systems. However, some studies (Firan et al., 2007; Li et al., 2008; Bobadilla et al., 2010; Liu et al., 2014a; Liu et al., 2014b; Servajean et al., 2014; Zhu et al., 2014; Yin et al., 2014 & 2015) only consider item similarity, and their systems are based on the information of unspecified individuals highly similar to the target users. They do not consider the connections between users in a social circle, but form the clusters based on a set of unspecified individuals with similar interests. A few studies (Zhu et al., 2014; Yin et al., 2014 & 2015) consider the information of an entire social circle, but this is not the information between connected users.

Most big social data-based personalized recommender systems consider the connectivity among users on SNS (i.e., group information). However, influential-based recommendations (Zhen et al., 2009; Tang et al., 2008 & 2012; Lin et al., 2014) only find the expert users in an entire network. They do not consider the connection or relationship between two users. Therefore, the information of friends is important for a big social data-based personalized recommender system; furthermore, the measurement of friendship strength between users is a key factor. A few studies (Geyer et al., 2008; Xu et al., 2013) just use the connection relationship between users without considering the distance between them; in other words, they do not consider friendship strength. Group information is mainly used to calculate the friendship strength in many studies (Golbeck, 2006; Konstas et al., 2009; Guy et al., 2010; Qian et al., 2013; Ma et al., 2014). They assign a weight to intimate friends, based on their measurement of the closeness between users, to use the group information. For example, they calculate group similarity to use RWR (Konstas et al., 2009) or call it familiarity relationship score (Guy et al., 2010), trust relationship (Golbeck, 2006; Qian et al., 2013; Ma et al., 2014), or interpersonal influence (Qian et al., 2013). However, there are few friendship strength measurements to use interaction information. Yu et al. (2013) and Lai et al. (2013) considered frequency for calculating friendship strength, but most studies using interaction information simply consider the interests of an entire social circle (Yin et al., 2014 & 2015; Zhu et al., 2014), or weight recently posted items (Xu et al., 2013; Yu et al., 2013). Our system is different from other studies in that we consider the interaction information between users to calculate the friendship strength divided by frequency, recency, and longevity.

Further, most works do not calculate the similarity of higher level of items (i.e., topics), except one (Qian et al., 2013). Therefore, most existing studies validate their methods using special purpose SNSs, such as movie and music; few works (Yu et al., 2013; Liu et al., 2014a; Bhattacharya et al., 2014) have been conducted on the multi-domain environment. Some research (Geyer et al., 2008; Li et al. 2008; Yu et al., 2013; Ma et al., 2014) measures topic similarity, but their methods do not consider a higher or lower level of topic. A few studies (Qian et al., 2013; Yin et al., 2014 & 2015) classify items and topic levels. However, Yin et al. (2014 & 2015) do not consider the topic similarity, and Qian et al., (2013) only calculate both item and topic similarity. We define the higher level of items as a topic, and calculate both item and topic similarity between users.

The comparison of the usage of big social data on personalized recommender systems shows that we consider various factors of big social data to calculate friendship strength as compared to others. Therefore, our measurement is a more appropriate measurement of friendship strength between users for personalized recommender system rather than existing research.

## 5. Discussion

From the viewpoint of whether friendship strength applies to other recommender systems based on SNS, our proposed friendship strength can be utilized in any system provided they have interaction data among users, friend list information or items having several levels. For example, Delicious has contact information among users, and Facebook and Yelp have review information among users. These contact and review information can calculate interaction similarity of our friendship strength. In addition, we can calculate personal similarity to use MovieLens, which has movie (i.e., item) and genre (higher level of movies, i.e., topic) data. Finally, group similarity is also calculated in all recommender systems having friend list or connection relationship. Most recommender systems based on SNSs have at least two characteristics to calculate friendship strength. Therefore, friendship strength can be used by any system.

We evaluate our proposed system to utilize various metrics, such as MAE, precision, recall, F1-measure, and NDCG. However, the improvement in our proposed system is not significant, except that the MAE of the proposed system is higher by 15 to 20% and by 13 to 19% from that of PCC and S_PCC, respectively. This is because of our experimental environment. In our experiments, the number of item is smaller than other recommender systems' data. This environment bring about small improvement in performance, because the recommended items for all recommender systems including those for the proposed system are not clearly different. Therefore, the difference in the quality of recommendation is not significant. However, it is a noteworthy result that our proposed system is the highest in all metrics, because it is difficult to improve all metrics having different characteristics.

## 6. Conclusion

In this paper, we proposed a friendship strength-based personalized recommender system. The proposed friendship strength considers various characteristics of big social data in order to measure the closeness between users on SNS. Our personalized recommender system grants a weight to those users who are closely connected in their social circle based on friendship strength in order to recommend the topics or interests in which users might be interested. We conducted comparative experiments using one month's Twitter data, which is multi-domain SNS and verified the proposed algorithm using various metrics: precision, recall, f1 measure, MAE, and NDCG. The experimental results verified that the use of the information of connected users on the SNS is better than that of the information of unspecified users for big social data-based personalized recommendations. Further, and more importantly, the proposed friendship strength determines the degree of closeness between users appropriately and helps to improve personalized recommendations in a multi-domain environment as compared to other measures.

In future work, we intend to validate that the proposed friendship strength is effective in various personalized services such as personalized retrieval, micro blog search, and semantic web. Further, we intend to conduct a study focusing on the accuracy of the personalized recommendations through the pre-crawled data provided by DaumSoft. We need to optimize the computation time of recommendations to efficiently process the large amount of big social data generated in real time, and develop personalized recommender systems to handle these data.

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