SimTrust: A New Method of Trust Network Generation

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Abstract—Trust can be used for neighbor formation to generate automated recommendations. User assigned explicit rating data can be used for this purpose. However, the explicit rating data is not always available. In this paper we present a new method of generating trust network based on user’s interest similarity. To identify the interest similarity, we use user’s personalized tag information. This trust network can be used to find the neighbors to make automated recommendation. Our experiment result shows that the precision of the proposed method outperforms the traditional collaborative filtering approach.

Keywords—trust network; interest similarity; recommender; rating; tag

I. INTRODUCTION

Traditional collaborative filtering recommender systems generate recommendations based on similar users’ opinions. Recently, incorporating trust models into recommender systems attracts attention of many researchers. Trust based recommender systems generate recommendations based upon trust peers opinion, instead of similar users’ opinion. To overcome the well known cold-start problem is the main reason for this. In such a system, trust is used for neighborhood formation. Trust could be used as supplementary or replacement method of widely used collaborative filtering [1, 2]. Ziegler [3] has conducted analysis on the correlation between interpersonal trust and interest similarity. Their investigation suggested that the relationship between users’ trust and similarity is positive. In their work; it is assumed that if two people have similar interests, they most likely trust each other. In a recent work, Bhuiyan [4] presents a survey on the relationship between trust and interest similarity in a social network. The results of the survey also support Ziegler’s hypothesis strongly. Based on these findings, we propose to use users’ interest similarity to form the trust network among the users irrespective of personal relationship. Moreover, we also propose a new method to calculate user interest similarity by using user generated tag information.

Even though a significant effort has been made by the research community to improve recommendation quality and alleviate cold-start problem, it is still a challenging research problem. There are many different techniques and systems have already been developed and implemented in different domains of recommender systems. However, most of the existing research on recommender systems focuses on developing techniques to better utilize the available information resources to achieve better recommendation quality. Because of the unavailability of sufficient data and information, these techniques have achieved only limited improvements to overall recommendation quality [1]. The existing trust based recommender works have assumed that the trust network already exists. In this work, we propose to use trust as an alternative method in the absence of explicit rating data to find the neighbors and replace the first step of traditional collaborative filtering system where it finds the neighbors based on overlapped or common previous ratings data. Based on the results obtained from the experiment conducted in this work, it has been found that the proposed techniques have achieved promising improvement in the overall recommendation making in terms of correct recommendation.

The rest of the paper is organized in following ways. In section 2, we discuss other related work. Section 3 describes the traditional approach of making recommendation. Section 4 presents the proposed algorithm for trust estimation. Section 5 explains the dataset and experiment setup. Section 6 presents the experiment results and discussed about the findings and the paper concludes in section 7.

II. RELATED WORK

To deal with the ever-growing information overload in the Internet, recommender systems are widely used online to suggest potential customers’ items they may like or find useful. There are many popular sites such as Amazon, eBay, Epinions etc. has successfully implemented online recommender system. Collaborative filtering is the most popular techniques for recommender systems which collects opinions from customers’ in the form of ratings on items, services or service providers’. Early recommender systems mostly utilized collaborative and content-based heuristics approach. But over the past several years a broad range of statistical, machine learning, information retrieval and other techniques are used in recommender systems [5]. The task in collaborative filtering is to predict the utility of items to a particular user based on a database of user votes from a sample or population of other users. Because of the different taste of different people, they rate differently according to their subjective taste. If two people rate a set of items similarly, they share similar tastes. In the recommender system, this information is used to recommend items that one participant likes, to other persons in the same cluster. But the collaborative filtering system performs poor when
there is not sufficient previous common rating available between users. To overcome the cold-start problem and with the dramatic growth of online social networks, trust based approach to recommendation has emerged. This approach assumes a trust network among users and makes recommendations based on the ratings of the users that are directly or indirectly trusted by the target user [6].

There are very few sites such as www.epinions.com, www.allconsuming.net, http://trust.mindswap.org/film trust, http://www.rummble.com etc. allow members to express which other agents they trust, by which the explicit trust value is collected. But most of the social network does not collect explicit rating about trust among the user [7]. In such a situation, a trust network needs to build before using trust value to improve the recommendations. For developing trust network, we use the users’ interest similarity based on the tag information. For assigning a label or organizing items, users may provide one or more keywords as a tag in any web site associated with Web 2.0. It is a non-hierarchical keyword or term assigned to a piece of information such as an internet bookmark or a file name. This kind of metadata helps describe an item and allows it to be found again by browsing or searching. Tags are chosen informally and personally by the item's creator or by its viewer, depending on the system. However, user tag can be regarded as users’ personal opinion expression or considered as implicit rating on the tagged item. Thus tagging information could be useful while making recommendation [8].

Though there are a good number of works that are available in the field of recommender systems using collaborative filtering, very few researchers consider using tag information to make recommendation [9-13]. Tso-Sutter [9] used tag information as a supplementary source to extend the rating data. They did not use it as the replacement of the explicit rating information. Liang et.al [11] proposed to integrate social tags with item taxonomy to make personalized user recommendations. Other recent works include integrating tag information with content based recommender systems [10], extending the user-item matrix to user-item-tag matrix to collaborative filtering item recommendations [11], combining users’ explicit ratings with the predicted users’ preferences’ for items-based on their inferred preferences for tags [14] etc. However, using tags for recommender system is still in demand [11, 14].

III. TRADITIONAL APPROACH

Collaborative filtering recommender systems try to predict the utility of items for a particular user based on the items previously rated by other users [5]. More formally, the utility \( u(c,s) \) of item \( s \) for user \( c \) is estimated based on the utilities \( u(c_j,s) \) assigned to item \( s \) by those users \( c_j \in C \) who are “similar” to user \( c \). According to Breese et al. [15], algorithms for collaborative filtering recommendations can be grouped into two general classes: memory based and model based. Memory based algorithms are heuristics that make rating predictions based on the entire collection of previously rated items by the users. The value of the unknown rating \( r_{c,s} \) for user \( c \) and item \( s \) is usually computed as an aggregate of the ratings of some other users for the same item \( s \):

\[
r_{c,s} = \text{agg}(r_{c,j}, c' \in C)
\]

Where \( C \) denotes the set of \( N \) users that are the most similar to user \( c \) and who have rated item \( s \) (\( N \) can range anywhere from 1 to the number of all users). We use the following aggregation function:

\[
r_{c,s} = k \sum_{c' \in C} \text{sim}(c, c') \times r_{c',s}
\]

Where multiplier \( k \) serves as a normalizing factor and is usually selected as

\[
k = 1 / \sum_{c' \in C} |\text{sim}(c, c')|
\]

In case of binary value (eg. either an item is rated or not), Jaccard’s coefficient is generally used. Jaccard's coefficient measure similarity and Jaccard's distance measure dissimilarity; are measurement of asymmetric information on binary (and also non-binary) variables. For some applications, the existence of \( S \) in Simple Matching makes no sense because it represents double absence. This may happen when the value of positive and negative do not have equal information (asymmetry). For example, if the negative value is not important, counting the non-existence in both objects may have no meaningful contribution to the similarity or dissimilarity. Jaccard's coefficient removes the \( S \) from simple matching coefficient to become Formula

\[
S_y = \frac{p}{p + q + r}
\]

Where;

- \( p = \) number of variables that positive for both objects
- \( q = \) number of variables that positive for the \( i \)th objects and negative for the \( j \)th object
- \( r = \) number of variables that negative for the \( i \)th objects and positive for the \( j \)th object
- \( s = \) number of variables that negative for both objects

IV. SIMTRUST: THE PROPOSED ALGORITHM

To describe the proposed approach, we define some concepts used in this paper as below.

- **Users**: \( U = \{u_1,u_2,...,u_N\} \) contains all users in an online community who have used tags to label and organize items.
- **Items** (i.e., **Products, Resources**): \( P = \{p_1,p_2,...,p_P\} \) contains all items tagged by users in \( U \). Items could be any type of online information resources or products in an online community such as web pages, videos, music tracks, photos, academic papers, documents and books etc.
- **Tags**: \( T = \{t_1,t_2,...,t_T\} \) contains all tags used by users in \( U \). A tag is a piece of textural information given by users to label or collect items.

As mentioned before, we believe the trustworthiness between users is useful for making recommendations.
However, the trust information is not always available, and even available, it may change over time. In this research, we propose to automatically construct the trustworthiness between users based on users’ online information and online behaviour.

Trust is a complex concept. A vast literature on trust has grown in several area of research but it is relatively confusing and sometimes contradictory, because the term is being used with a variety of meaning [16]. Golbeck et al. [17] defines trust as “trust in a person is a commitment to an action based on belief that the future actions of that person will lead to a good outcome”. In reality the way a user decide about trust values in a real setting can depend on many factors, personal subjective tastes or previous experience. Some researchers have found that given some predefined domain and context, people’s interest similarity is a strong predictor of interpersonal trust [18, 19]. Ziegler and Golbeck [20] have investigated the relationship between people’s interest similarity and trust. Their empirical analysis on the correlation of interpersonal trust and interest similarity showed positive mutual interactions between interpersonal trust and interest similarity. That means, people who have similar interests tend to be more trustful to each other. Under this assumption, we propose to construct user trustworthiness based on their interest similarity generated from their tagging information.

The current research on tags is mainly focusing on how to build better collaborative tagging systems, personalize search using tag information [21] and recommending items [9] to users etc. However, tags are free-style vocabulary that users used to classify or label their items. Since there is no restriction, boundary, or pre-specified vocabulary on selecting words for tagging items, the tags used by users lack in standardization and unification and also contain a lot of ambiguity. Moreover, usually the tags are short containing only one or two words, which make it even harder to truly get the semantic meaning of the tags. To solve this problem, we propose an approach to extract the semantic meaning of a tag based on the description of the items in that tag. For each item, we assume that there is a set of keywords or topics which describe the content of the item. This assumption is usually true in reality. For most products, normally there is a product description along with the product. From the product description, by using text mining techniques such as tf-idf method, from the descriptions of the items in $t_{ij}$, we can generate a set of frequent keywords denoted as $W_j = \{w_{i1},...,w_{ik}\}$ to represent the semantic meaning of the tag. The frequency of the keywords, denoted as $v_{ij} = \lt f_1,...,f_k \gt$ where $f_k$ is the frequency of the $k^{th}$ keyword, measures the strength of each keyword in tag $t_{ij}$ to represent the meaning of the tag. Also the vector $v_{ij}$ can be used to calculate the similarity of two tags in terms of their semantic meaning $\forall u_i,u_j \in U$, let $T_j = \{t_{i1},...,t_{ij}\}, T_j = \{t_{i1},...,t_{ij}\} \subseteq T$ be the set of tags which were used by user $u_i$ and $u_j$, respectively. Corresponding to $T_i$ and $T_j$, $W_i = \{w_{i1},...,w_{im}\}$ and $W_j = \{w_{j1},...,w_{jm}\}$ are the collection of keyword sets for the tags in $T_i$ and $T_j$, respectively, and $V_i = \{v_{i1},...,v_{in}\}$ and $V_j = \{v_{j1},...,v_{jn}\}$ are the corresponding vectors of keyword frequency. For example, $w_{ij}$ is the set of keywords derived from the items descriptions in tag $t_{ij}$ and $v_{ij}$ is the vector of frequency of the keywords in $w_{ij}$. Let $\text{sim}(v_{ip},v_{iq})$ be the similarity between $v_{ip}$ and $v_{iq}$, if $\text{sim}(v_{ip},v_{iq})$ is larger than a pre-specified threshold, the two tags $t_{ip}$ and $t_{iq}$ are considered similar.

The aim is to build the conditional probability $p(u_i / u_j)$ estimating the likelihood that user $u_i$ is similar to user $u_j$ in terms of user $u_j$’s information interests. The following equation is defined to calculate how similar user $u_i$ is interested in keyword $k$ given that user $u_j$ is interested in the keyword $k$:

$$p_k(u_i / u_j) = \frac{n_{ij}^k}{n_{ij}}$$

(5)

Where, $n_{ij}^k$ denotes the number of tags in $W_j$ that contain keyword $w_k$, $n_{ij}$ denotes the number of tags in $W_j$ that contain keyword $w_k$ and are similar to tags in $W_i$ that contain keyword $w_k$ as well. After calculating this for every keyword, the average of the probability $p_k(u_i / u_j)$ is used to estimate the probability $p(u_i / u_j)$:

$$p(u_i / u_j) = \left( \sum_{k \in W} p_k(u_i / u_j) \right) / |W|$$

(6)

where, $W=\{w_{i1},...,w_{im}\}$ is the set of all keywords in $W_i$ or $W_j$.

In this paper, we used the conditional probability $p(u_i / u_j)$ to measure the trust from user $u_i$ to user $u_j$. Given $u_i$, the higher the $p(u_i / u_j)$, the higher user $u_i$ trusts user $u_j$ since user $u_i$ has similar interest as $u_j$.

V. EXPERIMENT

We used the traditional collaborative filtering algorithm to make automated recommendations. The traditional collaborative filtering algorithm has two steps. First, it finds the similar neighbors based on the overlap of previous ratings and in the second steps, it calculates to predict an item to recommend to a target user. For all of the


experiment data, we use the same method for the second part of the algorithm. But, we have used our proposed trust network based algorithm to find the neighbors and make recommendations. Then compare those recommendation results with the traditional collaborative filtering method using Jaccard’s coefficient to find the neighbors.

For our experiment, we used the book dataset downloaded from www.amazon.com. User tag data and book taxonomy data, both are obtained from Amazon site. The book data have some significant difference between other data about movies, games or videos. Every published book has a unique ISBN, which makes it easy to ensure interoperability and gather supplementary information from various other sources, e.g., taxonomy or category descriptors from Amazon for any given ISBN. The dataset consists of 2,200 unique users and 18,663 unique books. The tree structure Amazon book taxonomy contains 9,919 unique topics. An example of a small fragment of the book taxonomy extracted from Amazon.com is shown in Fig.1.

The “Precision and Recall” method is used to evaluate the recommendation performance. This evaluation method has been initially suggested by Cleverdon as evaluation metrics for information retrieval systems [22]. Due to the simplicity and the popular uses of these two metrics, they have been also adopted for recommender system evaluations [23-25]. The top-N items are recommended to the users. For comparison, we use N = 5, 10, 15 and 20. Precision and Recall for an item list recommended to user are computed based on the following equations:

\[
\text{Precision} = \frac{|T_i \cap P_i|}{|P_i|} \quad (7)
\]

\[
\text{Recall} = \frac{|T_i \cap P_i|}{|T_i|} \quad (8)
\]

Where \( T_i \) is the set of all items preferred by user \( u_i \), and \( P_i \) is the set of all recommended items generated by the recommender system. Based on the equation 7 and 8, it can be observed that precision and recall are inversely correlated and are dependent on the size of the recommended item list. They should be considered together to evaluate completely the performance of a recommender. F1 Metric, suggested by Sarwar et al. [23] is one of the most popular techniques for combining precision and recall together in recommender system evaluation which can be computed by the formula 8 is used for our evaluation.

\[
F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)
\]

VI. RESULTS AND DISCUSSION

We used the same dataset for making recommendations. We let each of the two techniques to recommend a list of N items to each of these 2,200 users, and different values for N ranging from 5 to 20 are tested. Fig. 2 shows the precision values of recommendation made among our proposed tag-based Similarity Trust approach (ST) and the Jaccard’s coefficient based traditional Collaborative Filtering (CF) approach. The results of the experiment are shown in Fig 2, Fig 3 and Fig 4. It can be observed from the figures that for all three evaluation metrics, the proposed ST technique achieved the best result among the two techniques compared. Among the proposed ST and traditional CF recommender, our proposed ST performed significantly better than the traditional CF method. Both of these methods used the same recommendations techniques but the difference is in the finding neighbors’ technique. The results clearly show that when we use the traditional collaborative filtering approach for finding neighbors, it performed the worst. Our proposed tag-based similarity trust approach performed better than the traditional approach.

Fig 3 shows the Recall values between the same approaches.

Finally in Fig 4, the F Measure based on Precision and Recall of the two approaches is presented.
A new algorithm for generating trust networks based on users’ interest similarity derived from user tagging information was proposed in this paper. Based on users’ trust, the users who have similar interests to the target user can be found. The experiment results showed that this tag-based similarity approach performs better while making recommendations than the traditional collaborative filtering based approach. This proposed technique will be very helpful to deal with cold start problem; even the explicit trust rating data is unavailable. The finding will contribute in the area of recommender system by improving the overall quality of automated recommendation making.

REFERENCES


