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Credibility-based Social Network Recommendation: Follow the Leader

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Abstract

In Web-based social networks (WBSN), social trust relationships between users indicate the similarity of their needs and opinions. Trust can be used to make recommendations on the web because trust information enables the clustering of users based on their credibility which is an aggregation of expertise and trustworthiness. In this paper, we propose a new approach to making recommendations based on leaders' credibility in the "Follow the Leader" model as Top-N recommenders by incorporating social network information into user-based collaborative filtering. To demonstrate the feasibility and effectiveness of "Follow the Leader" as a new approach to making recommendations, first we develop a new analytical tool, Social Network Analysis Studio (SNAS), that captures real data and used it to verify the proposed model using the Epinions dataset. The empirical results demonstrate that our approach is a significantly innovative approach to making effective collaborative filtering based recommendations especially for cold start users.

Keywords

Web-based social networks, social trust, credibility, Follow the Leader, clustering.

INTRODUCTION

Recommender Systems (RS) aim to provide users with recommendations about items that people with similar tastes and preferences have liked in the past. Collaborative Filtering (CF) is the dominant technique (Massa and Avesani 2007) for recommender systems; it relies on the opinions expressed by other users. Most CF based recommender systems build a neighborhood of likeminded customers who appear to have similar preferences (Sarwar, Karypis et al. 2002). The neighborhood formation scheme (clustering) is in fact the model-building or learning process for a recommender system algorithm. The main purpose of neighborhood formation is to produce recommendations that can be of two types: predict an opinion-score of a product for that user, or recommend to the user Top-N products not already purchased (Sarwar, Karypis et al. 2002), (Deshpande and Karypis 2004) and that the user will like the most. Schafer, Frankowski et al. (2007) introduce two different types of nearest neighbor CF algorithms: user-based algorithms to generate predictions based on similarities between users, and item-based algorithms to generate predictions based on similarities between items.

Previous research (Lerman 2006) has shown that people tend to like items their friends like and are attracted to the activities of others in their social circle. User designated friends in social networks, therefore, can be reliable sources of recommendations (Gürsel and Sen 2009). Sinha and Swearingen (2001) compared the quality of recommendations made by recommender systems and by users' friends. They found that users preferred recommendations from friends to those made by recommender systems such as Amazon.com (Liu and Lee 2009).

In daily life, when people seek advice from peers, they consider their past interaction history to locate the right peer, or if advice is received, they utilize these past interactions to judge the advice quality (Gürsel and Sen 2009). Furthermore, users would prefer to receive recommendations from people they trust. In fact, users prefer to receive recommendations from people they trust more. Hence, recommendations are made based on the ratings given by users who are either directly trusted by the current user or indirectly trusted by another trusting user through trust propagation mechanism (Zarghami, Fazeli et al. 2009).

One drawback of CF is that it is unable to distinguish neighbors as friends or strangers with similar tastes (Liu and Lee 2009). While it utilizes neighbors to generate recommendations, it is currently unable to reflect how people seek information using their friends in social networks.

In the early days of the Internet, identifying the close friends of a user was difficult (Liu and Lee 2009). Now, social networking Web sites such as Facebook and MySpace, make gathering social network information easy, allowing one to integrate social network information and CF when generating recommendations. Therefore, the main objective of our paper is to utilize social network information to make recommendations based on the credibility of users drawn from their trustworthiness and expertise.

Social networks have been used in CF, recently (DuBois, Golbeck et al. 2009) trust is used as a basis for forming clusters. Our work is the first that uses a formal "Follow the Leader" model based on web-based social networks and user credibility to generate a cluster of most trustworthy and experienced users in the social network called leaders and then show how leaders act as advisers to other users including cold-start users who do not have enough interactions to capture their similarity.

MOTIVATIONS and CONTRIBUTIONS

Utilizing trust in Web-based social networks (WBSNs) provides a promising approach to make recommendations to other users based on trust propagation in finding a friend or a friend of a friend with similar interests. However, the quality of recommendations can be improved further by incorporating users' expertise because a trusted expert advice will lead to better recommendations.

We believe seeking advice from a trustworthy expert is more feasible than seeking advice from an ordinary trustworthy user. This leads to the question: How do we find trustworthy experts in the WBSN?

Our key contribution in this paper is threefold:

- A user model based on its credibility that captures trust relationships between users.
- A clustering approach based on the "Follow the Leader" model and user credibility.
- An effective means to generate high quality user-based collaborative recommendations based on user credibility and following the leaders.

The rest of this paper is organized as follows: the next section provides a brief overview of some related research work followed by our technical framework. The next two sections report, analyze and evaluate the empirical study of the proposed model. Finally, we conclude by summarizing our findings and our future plans for further work.

RELATED WORKS

Web-Based Social Networks and Trust

Web-based social networks (WBSNs) are online communities (people, organizations or other social entities) (Shekarpour and Katebi 2009) connected by a set of social relationships, such as friendship, co-working or information exchange in varied contexts e.g., entertainment, religion, dating, or business.

Web-Based Social Networks currently play an important role in the life of millions of active Internet users. Over the last few years, interest in social networking websites such as MySpace and Facebook have increased considerably (Gürsel and Sen 2009). In WBSNs users are able to express how much they trust other users. Trust provides users with information about the people they share content with and accept content from. Since most participants do not know each other in real life and have no prior direct interactions with each other on social networking sites, the trust inference mechanism is becoming a critical issue when participants want to establish a new trust relation or measure trust values between connected users (Liu, Wang et al. 2009). The idea here is not to search for similar users as CF does but to search for trustworthy users by exploiting trust propagation over the trust network (Massa and Avesani 2007).

WBSN users are allowed to state how trustworthy they consider other users, in the context of RSs, it relates to the extent that they consider the ratings provided by a certain user as valuable and relevant (Massa and Avesani 2007). This additional information (trust statements) can be organized in a trust network and trust metrics can be used to predict the trustworthiness of other users as well, for example: friends of friends.

Trust-Based Collaborative Filtering (CF)

The connection between user similarity and trust was established in (Ziegler and Golbeck 2007). Using experiments they demonstrate that there exists a significant correlation between the trust expressed by the users and their similarity based on the recommendations they made in the system; the more similar two people are, the greater the trust between them.

Similarity has proved to be a key element for neighbor selection in order to provide accurate recommendations. Neighbor trustworthiness and expertise have also been studied as relevant complementary criteria to select the best possible collaborative advice (Kwon, Cho et al. 2009). Similarity can be interpreted in several ways such as similarity in interests or ratings or opinions. Recently (Golbeck 2009) explored the relationship between trust and profile similarity. They show through surveys and analysis of data in existing systems that when users express trust, they are capturing many facets of similarity with other users. In a system that has a trust component users make direct statements about people they trust, these statements generate a social network.

Empirical results show that using measures of trust in social networks can improve the quality of recommendations. O'Donovan and Smyth (2005) performed an analysis of how trust impacts the accuracy of recommender systems. Using the MovieLens dataset they create trust-values by estimating how accurately a person predicted the preferences of another. Those trust values were then used in connection with a traditional CF algorithm (Breese, Heckerman et al. 1998), and an evaluation showed significant improvement in the accuracy of the recommendations.

Hundreds of millions of people are members of social networks online and many of those networks contain trust data (DuBois, Golbeck et al. 2009). With access to this information, trust has the potential to improve the way recommendations are made. Trust of strangers can be established based on trust propagation (Borzymek, Sydow et al. 2009). This term signifies all mechanisms that contribute to the dynamic extension of a trust relation. A common kind of trust propagation is similarity propagation, whereby a new trust relationship can be established between two sufficiently similar users.

Follow the Leader

As pointed out by social psychology theory (Liu, Wang et al. 2009), the role of a person in a specific domain has significant influences on trust evaluation if the person recommends a person or an object. Thus, the role of the user should also be taken into account in making recommendations.

Follow the leader in dynamic social networks (Goldbaum 2008), is a model of opinion formation with dynamic confidence in agent-mediated social networks where the profiling of agents as leaders or followers is possible. An opinion leader is specified as a highly self-confident agent with strong opinions. An opinion follower is attracted to those agents in which it has more confidence. The "Follow the Leader" model provides a formal probabilistic approach, Goldbaum's (2008) model identifies three types of consumers that seek input from outside experts:

1. The consumer has a fixed set of preferences but imperfect information concerning the available product options. The expert offers information or advice that helps the consumer buy the product that maximizes her exogenous utility.
2. The consumer possesses some innate preferences over the available products, but can be influenced by the opinion of others (peers) and experts. The "expert" may be someone possessing both better information than the general public about the consumer options (as in case 1), but also someone who can provide advice that is consistent with the underlying preferences of a group of consumers.
3. The consumer has no innate preferences. The consumer's tastes are fully fashioned by the influence of peers and experts. In this case, the expert shapes opinion, but need not have any special advantage in evaluating the options.

The expert in all previous cases can be considered as an experienced user who spends time and effort analyzing product features, and finally making her decision to use the product, and giving high quality feedback on that product. Furthermore, she is in a position to strongly recommend the product to her friends if they have similar needs.

According to (Goldbaum 2008), in a social network a member is either a leader or a follower who adopted another leader's opinion or recommendation to use a product. Subsequently this member adopts whatever her best friend adopted, otherwise the member has no active friends and consequently it acts as an independent (leader).

Ramirez-Cano and Pitt (2006), define the relationship between two agents (users) as a confidence function, such that: "an agent (i) increases its confidence in another agent (j) based on how well (j's) opinion meets the criteria specified in i's mind-set. A mind-set represents the set of beliefs, attitudes, assumptions and tendencies that predetermine the way an agent evaluates a received opinion". Subsequently we conclude that user trust is the determinant relationship between two friends.

TECHNICAL FRAMEWORK

In this section we define the following concepts to be used in our model.

In WBSN, let (U) be a set of users, $\boldsymbol{U} = \{\boldsymbol{u_1}, \ldots, \boldsymbol{u_N}\}$, interacting in a set of contexts $\boldsymbol{C} = \{\boldsymbol{c_1}, \ldots, \boldsymbol{c_L}\}$, such as categories in EPINIONS. In each context \ category there is a set of items I, such that: $\boldsymbol{I} = \{\boldsymbol{i_1}, \ldots, \boldsymbol{i_K}\}, where\ I \in C$, K is the number of items in the set I.

Each user *(u ∈ U)* rates a set of items M denoted by: $R_u^I = \{R_u^1, \ldots, R_u^i, \ldots, R_u^M\}, where\ M \leq K$, and (R_u^i) is the rating value of user *(u)* for item *(i)*. The rating value can be any real number, but most often ratings are integers, e.g. in the range [1, 5].

In a trust-aware system, there is also a trust network among users. We define (T_u^v) to be the direct trust between user *(u)* and user *(v)*, trust value is a real number in [0, 1]: (0) means no trust and (1) means full trust between users or a value on a scale in the range [0, 5]. Binary trust networks are the most common trust networks such as Amazon and eBay.

In this model, we are concerned with the following characteristics of trust: (1) Trust is context based (2) Trust is directed from source to target (3) Trust is transitive (4) Trustworthiness is dynamic: since trust can increase and decrease with further experiences (interactions or observation). Trustworthiness can also decay with time (Golbeck 2005), (Jaquet-Chiffelle 2009).

Credibility Based Clustering – Follow the Leader

The "Follow the Leader" model (Goldbaum 2008), provides us with insights to cluster users based on their roles in the WBSN i.e. either leaders or followers. Enriching the "Follow the Leader" model with trust, gives us the potential to analyze WBSN based on user's credibility. Figure 1 shows the basis of our approach. A credibility measure of users reflects their trustworthiness and expertise provides us with means to cluster users in a specific context. Some users can be classified as leaders others can be classified as followers according to their credibility level.

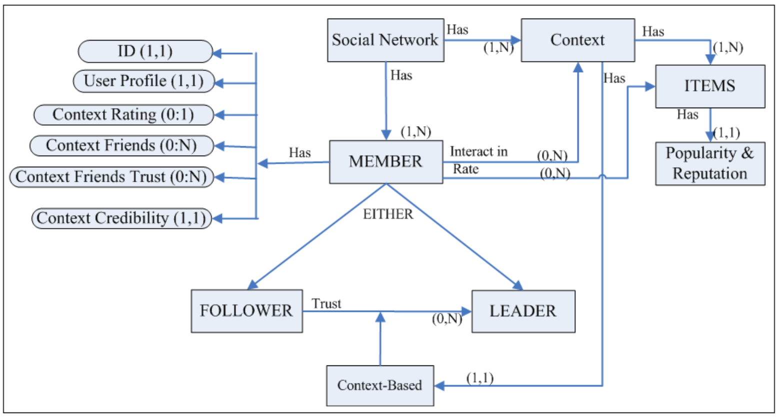

Figure 1: WBSN trust-aware Follow the Leader model

User Credibility

Credibility is a synonym of believability (Andrade, Neves et al. 2005). Credibility of an agent can be measured by its trustworthiness, expertise, and dynamism (Kouzes and Posner 2003). The majority of researchers identify two key components of credibility: trustworthiness and expertise. In evaluating user credibility we address these two components as follows:

Trustworthiness: Barney and Hansen (1994) in (Aquevegue and Ravasi 2006) explicitly differentiate between trust and trustworthiness pointing out "while trust is an attribute of a *relationship* between exchange partners, trustworthiness is an *attribute* of individual exchange partners". Therefore, a trustworthy person is someone in whom we can place our trust without any risk of being disappointed or betrayed" (Jaquet-Chiffelle 2009).

In trust-aware WBSN for a specific context, users act as trustor or trustee. Trustor users provide trust scores for other users (trustee) based on their confidence level that trustee provides reliable ratings for items in a specific context. Consequently trustee's gain reputation for her trustworthiness, hence the more trustors who either directly or indirectly trust a user, the more her credibility increases, formally we represent this relation as follows:

$$\mathrm{Cr}(T_T^u) = f(T_v^u, N_D^u, N_I^u, N_{DMax}, N_{IMax}) \qquad (1)$$

Where $\mathrm{Cr}(T_T^u)$ value is a real number in [0, 1], (T_v^u) is *scaled* trust score of user (v) assigns to user (u) as defined previously, (N_D^u) is the number of *direct friends* who trust (u), (N_I^u) is the number of *indirect friends* of (u) i.e. friends of friends. In order to give the user with max number of followers more weight than others, we consider the user with the maximum direct followers (N_{DMax}) as a reference point, consequently (N_{IMax}) refers to the maximum number of indirect friends in the set.

Scaled trust score is defined as follows: $T_v^u = \frac{T_v^u(Given)}{T_{range}}$, where Trust score range T_{range} = 5.

Credibility from direct followers trust:

Direct followers / friends of a user provide trust scores specifying how much they trust the user. The aggregation of trust scores is a measure of user' trustworthiness, consequently it is a measure of her credibility. Formally, we denote credibility from direct followers / friends trust as: $\mathrm{Cr}(T_D^u)$, and defined it as follows:

$$\mathrm{Cr}(T_D^u) = \frac{1}{N_{DMax}} * \sum_{v=1}^{N_D} T_v^u \qquad (2)$$

Where $\mathrm{Cr}(T_D^u)$ value is a real number in [0, 1], $(\boldsymbol{N_{Max}})$ refers to maximum number of direct followers of a user in the context. The impact of (N_D^u) appears on the aggregation of trust values from direct followers (friends). As can be seen credibility from direct followers is normalized, hence if the most trustworthy user receives a trust score of 5 from all friends then: $\mathrm{Cr}(T_D^u) = 1$, if that user has the maximum number of direct followers.

Credibility from Indirect Followers Trust

Using the trust transitivity feature of trust (Golbeck and Hendler 2006), friends of friends who trust their nearest friend, and also trust their friends next friend, with a trust score of the product of the two scores, formally $\mathrm{Cr}(T_I^u)$ is defined as follows:

$$\mathrm{Cr}(T_I^u) = \frac{1}{N_{IMax}} * \sum_{v=1}^{N_D} \{T_v^u * \sum_{v=1}^{N_I} T_v^u\} \qquad (3)$$

Where $\mathrm{Cr}(T_I^u)$ value is a real number in [0, 1], $(\boldsymbol{N_{IMax}})$ refers to maximum number of indirect followers of a user in the context. (T_v^u) in the first part refers to direct trust of direct followers to the target user N_D, while (T_v^u) in the second part refers to indirect followers trust N_I. Trust aggregation for each direct follower over indirect followers allows us to aggregate the trust associated with all friends of this follower. For example in Figure 2, if F12 trusts F1 with score (4) and F1 trusts U with score (3) on a trust scale of maximum (5), then F12 trusts U with score = (4 * 3) / (5 * 5) = 0.48 in normalized measure or 2.4 in scaled measure of 5.

Example: we provide the following example based on Figure 2 to explain and illustrate the above concepts:

1. To scale trust values we divide each *trust value* by (5), thus trust values (3, 4, 3) for direct followers, are scaled to trust values (0.6, 0.8, 0.6).
2. If user (U) with the maximum number of direct followers and indirect followers in this context then: $N_{DMax} = 3$, and $N_{IMax} = 5$.
3. Credibility from Direct Followers computed as:
   $\mathrm{Cr}(T_D^u) = \frac{1}{3} * (0.6 + 0.8 + 0.6) = 0.667$
4. Credibility from Indirect Followers computed as:

$\mathrm{Cr}(T_I^u) = \frac{1}{5} * \big(0.6 * (1 + 0.8) + 0.8 * (0.4 + 0.6 + 0.6)\big) = 0.472$

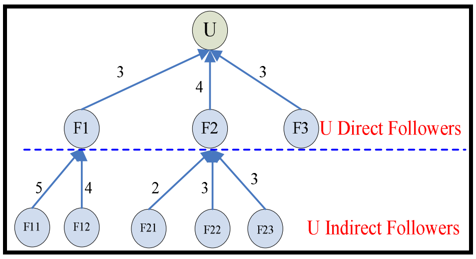

Figure 2: Direct and Indirect Followers

Expertise: Expertise, a key dimension of credibility; it is defined as the degree of a user's competency to provide an accurate ratings and exhibit high activity (Kwon, Cho et al. 2009). The expertise dimension of credibility captures the perceived knowledge and skills of the user in a given context.

If item (i) received ratings from N users, each provide (R_u^i) for that item then the average of ratings of item (i) is given by: $R_{avg}^i = \frac{1}{N} * \sum_{u=1}^{N} R_u^i$ (4)

In order to avoid current user rating influence on (R_{avg}^i) and for small number of raters e.g. (N < 10), we can exclude current user rating from (R_{avg}^i) calculations, this yields:

$$R_{avg1}^i = \frac{1}{N-1} * \{\sum_{u=1}^{N} R_u^i\} - R_u^i \qquad (4.a)$$

Thus user trustworthiness in providing rating (R_u^i) for item (i) is measured by comparing the provided rating (R_u^i) with (R_{avg}^i), the smaller the difference between the two ratings, the higher is the user trustworthiness. So, trustworthiness of one rating is given in the following formula: difference between two ratings is given as:

$$\mathrm{Cr}(R_u^i) = 1 - \frac{|R_u^i - R_{avg}^i|}{\mathrm{R}_{\mathrm{Max}}^i} \qquad (5)$$

Where $\mathrm{R}_{\mathrm{Max}}^i$ is the maximum rating scale. Although other researchers such as (O'Donovan and Smyth 2005) use other approaches to penalize ratings too far from reference rating (R_{avg}^i), we believe this formula works for binary rating and scaled ratings as well, and we show this empirically.

If user (u) provides ratings for (M) items, then accumulated user credibility from rating M items is denoted by $\mathrm{Cr}(R_u)$, where value is a real number in the range [0, 1], formally given by:

$$\mathrm{Cr}(R_u) = \frac{1}{M} * \sum_{i=1}^{M} \mathrm{Cr}(R_u^i) = \frac{1}{M} * \sum_{i=1}^{M} \left\{1 - \frac{|R_u^i - R_{avg}^i|}{\mathrm{R}_{\mathrm{Max}}^i}\right\} \quad (6)$$

In order to differentiate between users who provide more ratings for different items, user credibility increases if the number of ratings increases. To consider this factor, we model user contribution as a weight factor for user ratings credibility; hence users who contribute more than others are rewarded more. So, if we consider the user with the maximum number of ratings over all items (K) as a reference point ($\mathrm{N}_{\mathrm{Max}}^{\mathrm{K}}$), then the user contribution weight = (number of ratings of the user / maximum number of ratings among all users), formally given by:

$$\mathrm{R}_u^{\mathrm{W}} = \frac{\mathrm{M}}{\mathrm{N}_{\mathrm{Max}}^{\mathrm{K}}} \quad (7)$$

Using equation (7) in (6), yields the user credibility from rating component,

$$\mathrm{Cr}(R_u) = \frac{1}{\mathrm{N}_{\mathrm{Max}}^{\mathrm{K}}} * \sum_{i=1}^{M} \left\{1 - \frac{|R_u^i - R_{avg}^i|}{\mathrm{R}_{\mathrm{Max}}^i}\right\} \quad (8)$$

It is clear from the above equation that if the user did not make any rating contributions, then their reward from this component equals zero. The more credible contributions she makes, the more reward she receives.

Computing user Credibility

By aggregating credibility components: trustworthiness (credibility from direct followers and indirect followers) and expertise, we compute user credibility as:

$$\mathrm{Cr}(u) = \alpha * \mathrm{Cr}(R_u) + \beta * \mathrm{Cr}(T_D^u) + \gamma \mathrm{Cr}(T_I^u) \quad (9)$$

Where $\alpha + \beta + \gamma = 1$, and α, β, γ are system tuning parameters represent the importance of each credibility component. In our experiments we use the values (5/9, 3/9, 1/9) respectively.

Clustering Users Based on Credibility

In this model we define a *credibility threshold* from which we identify leaders and followers as follows:

$$\begin{cases} \text{if } \mathrm{Cr}(u) \geq \mathrm{Cr}_{\mathrm{Threshold}}, & \text{then user is Leader} \\ \text{if } \mathrm{Cr}(u) < \mathrm{Cr}_{\mathrm{Threshold}}, & \text{then user is Follower} \end{cases} \quad (10)$$

$\mathrm{Cr}_{\mathrm{Threshold}}$ refers to the *Credibility Threshold,* which is a system parameter that identifies users based on their credibility and it is used to promote enough leaders from the target set.

Leaders usually have the knowledge and power to provide trustworthy advice in recommending the most trustworthy items for other users.

To build a follow the leader hierarchy, we use credibility to identify user's roles i.e. (leaders, followers, independents). Followers usually follow the most credible friend in a given context. Using the confidence relation, if a follower finds her credibility more than the credibility of all her friends, then the user acts as either leader if she qualified as leader, or as an independent. Due to the dynamism of the network created by its natural evolution some leaders may lose their credibility over time if they behave dishonestly or if they stop making contributions or their trustworthiness drops.

Using leaders as potential Top-N recommenders

In order to make recommendations, our approach relies on leaders as the Top-N credible and trustworthy users in a specific context of providing recommendations. The number of leaders is determined by the credibility threshold defined previously.

We compute the predicted rating by user (a) for unknown item (i) using the following formula replacing similarity weight in (Massa and Avesani 2007) with credibility weight:

$$Pred(a,i) = R_a^{Avg} + \frac{\sum_{u=1}^{K} \mathrm{Cr}(u) * (R_u^i - R_u^{Avg})}{\sum_{u=1}^{K} \mathrm{Cr}(u)} \quad (11)$$

where K is the number of leaders who rated item (i), R_u^i represents the rating for item (i) provided by a leader (u), (R_u^{Avg}) represents leader ratings average and R_a^{Avg} represents average ratings provided by user (a).

When the target user (a) does not have ratings or her ratings < 5, i.e. cold start user, then we use the following formula replacing trust weight in (Golbeck and Hendler 2006) by credibility weight Cr(*u*) of a leader:

$$R_{Pred}^i = \frac{\sum_{u=1}^{K} \mathrm{Cr}(u) * R_u^i}{\sum_{u=1}^{K} \mathrm{Cr}(u)} \quad (12)$$

EXPERIMENTS AND RESULTS

To demonstrate the feasibility and effectiveness of an innovative the “Follow the Leader” approach to making recommendations, first we developed a Social Network Analysis Studio (SNAS) to analyze and build Follow the Leader models. In order to test and evaluate our model we captured real data from the Epinions dataset, and used it to verify the proposed model. In this section, we discuss the datasets, experimental design, and the results which demonstrate that the idea of “Follow the Leader” as means to build credibility can improve the accuracy of recommendations.

The Epinions Dataset

For our experiments, we used the Epinions[1] dataset to validate the applicability of our approach, because Epinions provides us with the required information; trust relationships between users and corresponding trust ratings between individuals and Ratings of items by the members of the social network. We used the version of the Epinions data set which has 49,290 users who rated a total of 139,738 different items at least once, writing 664,824 reviews with 487,181 issued trust statements.

To represent a context; our procedure is as follows: (1) we selected 25 items (randomly) from Epinions dataset. (2) We extracted the item ratings from “Ratings data” for all users who rated any of the selected items. (3) All associated trust statements from the “Trust data” were selected. (4) From the (25) items we accumulated the ratings history for each user; items rated and corresponding ratings. (5) We removed self trust statements and duplicated trust statements from the extracted trust data set. (6) Finally we generated three datasets;

1. DataSet-1: includes all users who rated any of the items (106, 515, 698, 18560)
2. DataSet-2: includes all users who rated any of the items (619, 1081, 2164, 3010, 6147)
3. DataSet-3: includes all users who rated any of the (9) items, i.e. includes all users in both data sets.

In order to enrich users with more items ratings history, users’ ratings history of (16) additional items were included. Corresponding ratings for the items (363, 390, 391, 393, 615, 651, 659, 660, 700, 734, 1083, 1109, 2810, 3017, 6114 and 6131) were used in the user rating history who rated them; hence we can consider our datasets refer to any item in the 25 items, which we consider as a context in our approach. Summary of the three datasets is shown in Table 1.

Table 1. Datasets Analysis Summary

DATASET	Rating No	Rating Avg.	Trust Records	SNW Users	LDRS No	FLWRS NO	LDRS-AVG Items Rated	FLWR AVG Items Rated	LDRS AVG Rating\ITM	FLWR AVG Rating\ITM
DATASET-1	596	3.70	419	229	26	203	5.9	2.2	3.50	3.18
DATASET-2	1076	3.88	2424	634	74	560	6.7	2.8	3.97	3.45
DATASET-3	1672	3.81	2883	830	94	736	6.6	2.6	4.02	3.42
TOTAL	3344		5726	1693	194	1499				

Social Network Analysis Studio (SNAS)

We have developed a Social Network Analysis tool utilizing the NetLogo platform (NetLogo 2009) inspired by Goldbaum, (2008) simulation of individual choice and social influence. The user interface is shown in Figure 3 (for DATASET-3). Although NetLogo was used as simulation tool, it has the facility to capture real data. We use it to analyze and evaluate the validity of our approach. Figure 4 shows the “Follow the Leader” Model for social network in item 2164. The black and red color nodes refer to leaders and potential leaders, green nodes refer to followers and the blue nodes refer to independents.

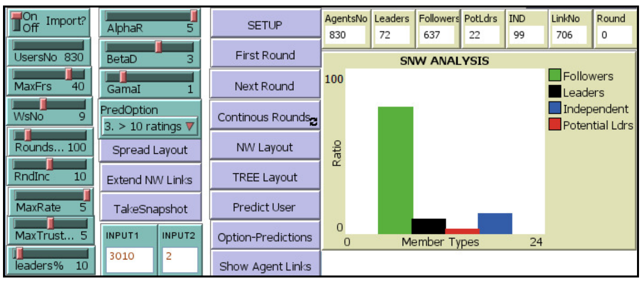

Figure 3: Social Network Analysis Studio (SNAS) – User interface

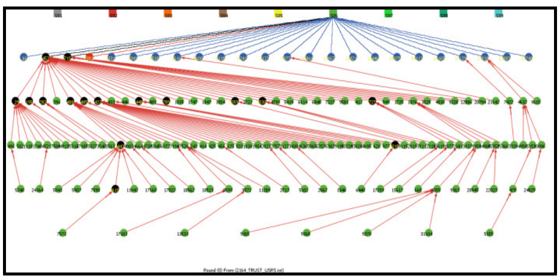

Figure 4: Follow the Leader Model for social network in item 2164

1 http://www.trustlet.org/wiki/Downloaded_Epinions_dataset

Potential leaders are normal followers who have more confidence in themselves than in their friends; their credibility is below the credibility threshold and they usually have an adequate number of followers. Independents are users with self-confidence in themselves higher than confidence in others, but they don't possess enough credibility to be considered as leaders.

Experimental Setup

To validate the hypothesis that using the "Follow the Leader" approach is an applicable approach to improve the accuracy of recommendations, we use ***leave-one-out*** as our testing strategy. Leave-one-out is an approach that can be used on a known dataset and involves hiding one rating and then trying to predict it with a certain algorithm. The predicted rating is then compared with the actual rating and the difference in absolute value is the prediction error. The procedure is repeated for all the ratings and an average of all the errors is computed as the Mean Absolute Error (MAE) given the following formula:

$$MAE(1) = \frac{\sum_{i=1}^{N} |R_u^{Actual} - R_u^{Predicted}|}{N} \quad (13)$$

For consistency, we measure MAE(2) with respect to average item rating by all users who rated it, MAE(2) is given the following formula:

$$MAE(2) = \frac{\sum_{i=1}^{N} |R_i^{Average} - R_u^{Predicted}|}{N} \quad (14)$$

Table 2. Experimental Results of Prediction Algorithms – Cold Start

			MAE-1		MAE-2		
DATASET	Testing Option	No. Test Cases	Cold Start Credibility CF-1C	Cold Start TRUST CF-2C	Cold Start Credibility CF-1C	Cold Start TRUST CF-2C	Coverage (1)
DataSet-1	OPTION-1	200	0.990	0.980	0.291	0.753	59.50%
DataSet-2	Cold Start	488	0.877	0.878	0.276	0.696	76.02%
DataSet-3	< 5 ratings	669	0.934	0.903	0.301	0.709	72.50%
Over-All	Average	452	0.922	0.905	0.291	0.711	71.85%

Table 3. Experimental Results of Prediction Algorithms: Experienced Users

				MAE-1			MAE-2		
DATASET	Testing Option	No. Test Cases	CF-1 Credibility	CF-2 Trust	CF-3 LDrs Similarity	CF-1 Credibility	CF-2 Trust	CF-3 LDrs Similarity	Coverage (1)
DataSet-1		24	1.028	0.900	1.354	0.689	0.748	1.129	41.67%
DataSet-2	OPTION-2	132	0.981	0.940	1.178	0.640	0.650	0.941	56.82%
DataSet-3	5-8 ratings	145	0.959	0.944	1.197	0.605	0.654	0.962	55.86%
DataSet-1		5	0.957	N\A:Leaders	1.525	0.211	N/A	0.694	0.00%
DataSet-2	OPTION-3	14	0.914	0.991	1.160	0.333	0.572	0.606	64.29%
DataSet-3	> 8 ratings	16	0.870	1.092	1.383	0.298	0.701	0.782	62.50%
Over-All	Average	56	0.967	0.948	1.213	0.593	0.658	0.938	55.89%

(1) Coverage here refers to the ratio of returned valid predictions over all predictions for CF-2. This value is (100%) for the CF-1 and CF-3.

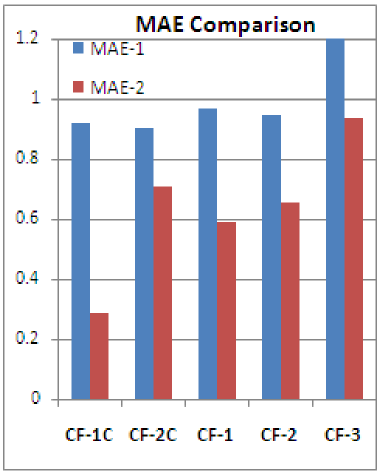

Figure 5. MAE Average for all predictions over all Datasets

We follow the following procedure for each dataset:
1. Generate the "Follow the Leader" model for each dataset.
2. Select users to predict item ratings for them, based on the following test options, number of ratings indicate the expertise level of the customer. It is not necessary that it reflects their credibility.

Option-1: for users who rated 4 items or less, these usually are followers in the model and cold start users.

Option-2: for users who rated 5 items and up to 8 items.

Option-3: for users who rated 9 items or more, those usually are leaders in the model for the selected datasets.

3. Generate a predictive rating for each user for a specific item based on the leave-one-out strategy.

Prediction Algorithms

We use the following algorithms to verify and benchmark our approach prediction accuracy:

1. **CF-Credibility (CF-1)**: based on algorithm – equation (11).
2. **Neighbors TRUST (CF-2):** based on (Golbeck and Hendler 2006) formula, outlined in section 3.1 of the FilmTrust. This algorithm is used as a benchmark to our CF-Credibility (CF-1). "Follow the Leader" model provides the means to identify the nearest neighbors easily.
3. **CF-LDRs Similarity(CF-3)**: this is the conventional CF prediction algorithm outlined in Motivation section – formula (1) of (Massa and Avesani 2007), with consideration that the similarity is based on leaders in our data set. This algorithm is used as benchmark to our CF-Credibility.

CF-1C and CF-2C refer to cold start users case.

RESULTS ANALYSIS and DISCUSSION

1. In a Web based social network, user credibility is the determinant of its behavior; credibility of a user in a specific domain/context is the predictor of their role. Usually users with high credibility act as leaders, while users with lowest credibility act as followers.
2. Leaders can provide recommendations with (100%) coverage in a credibility based prediction algorithm, while the Neighbors Trust algorithm (CF-2, CF-2C) does not, because users in Neighbors Trust do not have sufficient friends to reliably apply the trust algorithm.
3. Cold Start Credibility (CF-1C) algorithm outperforms Neighbor Trust in two dimensions: first the coverage of Cold Start Credibility is (100%) while for Neighbor Trust the average coverage is (72%). Second the quality of recommendations (MAE-2) of Cold Start Credibility is (0.291) while for Neighbor Trust (MAE-2) is (0.711). This result emphasis that normal users (followers) possess less credibility than leaders.
4. CF-Credibility (CF-1) outperforms CF-LDRs Similarity (CF-3) with (25%); this difference emphasis that the credibility based approach provides more accurate results even when using the same leaders to measure the similarity with them.
5. In OPTION-3: for users who rated 9 items or more, we observe that the Neighbor Trust algorithm provided poorer prediction in dataset-1, and predictions are too far from average algorithm performance to be of value because the users in OPTION-3 are almost leaders. Leaders usually do not act as trustors; they are trusted by other users. In other words leaders are not necessarily good judgers of credibility or at developing trust.
6. In OPTION-3: for users who rated 9 items or more, CF-1 (credibility based) outperform other approaches because leaders have enough ratings to compute the average.
7. Increasing the number of users in the social network produced more credible results; it scales well. This behavior is more obvious in option-2 and option-1 for CF-Credibility algorithm. The reason is that when increasing the size of the network, the number of genuine leaders also tends to increase.

CONCLUSIONS

In this paper, we proposed a new approach to making recommendations based on leaders' credibility in the "Follow the Leader" model as Top-N recommenders by incorporating social network information into user-based collaborative filtering. Credibility based clustering approach can be used for recommenders that are embedded in social networks where users' trust statements and items ratings are accessible.

We have evaluated our proposed framework through our Social Network Analysis Studio (SNAS) in a specific context extracted from the widely used Epinions dataset. The results presented in this paper show that our credibility based clustering derived from the "Follow the Leader" model provides a highly effective approach to identify Top-N recommenders, who are leaders in the context with the highest trustworthiness and expertise among all users.

We proved the feasibility of our proposed framework by providing accurate predictions and benchmarking them against the leading algorithms CF-Similarity based (Massa and Avesani 2007) and with Social TRUST (Golbeck and Hendler 2006). The results of the experiments included in this paper show the applicability and performance of the proposed credibility assessment based on "Follow the Leader" Model shows significant measurable enhancements over other approaches.

We have shown that using the "Follow the Leader" model is an effective approach to cluster users based on their credibility which gives high performance predictions. In addition, trust relations can be extracted easily from the model, and user credibility is a valuable parameter in calculating items reputation. Our future plan is to use user credibility to compute items reputation which is an important factor in identifying Top-N items in the context.

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