Reliable Social Trust Management with Mitigating Sparsity Problem

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Abstract

Social networks express the information flows of individuals or groups using actors and relationships. Along with the growth of WWW, interest in large-scaled social networks has grown bigger. However, social networks being applied in diverse areas are facing with sparsity problems resulting from a shortage of actual relations with structural properties. Therefore, in this paper, sparsity problems are solved by creating contents based virtual relations applied with the clustering approach. In addition, a reliable social trust model is presented through combinations of actual relations and virtual relations. In experiments, the performance of the proposed approach will be evaluated using connectivity between nodes and F-measures.

1 Introduction

For quick Problem Statement instructions please skip to Section 2.

Social networks express the concept of psychological and social relationships between individuals or groups as networks in the form of graphs using nodes (actors) and links (relationship) [1, 2, 3]. To analyze this structure of social networks, studies have been repeated for over 50 years in the areas of sociology and computer science etc. Since late 1990s, with the growth of WWW(World Wide Web), Typical social network services(blog, collaborative-filtering systems, online gaming etc.) have created ten billions of user generated contents because the user oriented web was coming [4, 5, 6]. As a result, interest has grown bigger not only in the establishment of large-scaled social networks but also in the optimization of diverse search and recommendation systems [7].

Most studies of social networks focus on analyzing graphs expressed as relational networks [8, 9]. Also, there have been many studies that attempted to specify the degrees of relationships by defining social trust models [7, 10, 11]. Using graph analysis and trust models, many studies have been conducted on visualization [12], relation maintenance [13, 14, 15] and link predictions [16, 17, 18] etc in social networks. In addition, studies intended to apply social networks to diverse areas such as e-mail spam detection [19, 20, 21, 22] and recommendation systems [10, 23, 24] have been actively conducted.

To provide efficient social network services it is important to measure how much they trust someone. In case of Web-based social networks, we need to consider the available personal information (e.g. profiles, users' opinions etc.) because we don't know the history between people and their own background [7]. In addition, the uncertainty and risk of the interactions between people who do not know each other are becoming barriers to reliable trust management [25]. Hence, trust management approaches quantify the trust score with structural property and attribute of actors.

On the other hand, unsupervised learning (or clustering scheme) means partitioning data into many meaningful subgroups (or clusters) using unspecific attributes [26]. This is different from classification

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in that this is a training stage using labeled documents and that category labels are obtained by being driven by data [27, 28]. Therefore, when classifying data with no defined categories like user profiles, the clustering scheme is more useful [29]. The clustering scheme is used diversely not only in the areas of machine learning, artificial intelligence and pattern recognition but also in the area of computer science such as web mining and text document collection and in the area of social science such as sociology and psychology [30]. Clustering can be divided into k-means clustering [31] and hierarchical clustering [32] etc in application depending on the characteristics of data.

As interest in social networks has grown bigger, interest in trust management through social trust models has also grown bigger. One of the major problems in trust management in social networks is a sparsity problem of relations between nodes. Most of the previous approaches in dealing with these problems focused on filtering techniques. But, these approaches have a weakness in missing valuable information. Therefore, in this paper, a reliable trust management approach made through combinations of actual relations and virtual ones will be proposed. Virtual relations are created using contents based clustering approaches and sparsity problems can be solved by extending actual relationships in social networks.

This paper is composed as follows. In Section 2, problem statement is described. In section 3., the proposed relationship extension scheme intended to solve sparsity problems is introduced. In section 4, experimental results are analyzed followed by concluding remarks in the section 5.

2 Problem Statement

Relations between actors in social networks are defined using users' structural properties (co-author information, sending or receiving e-mail messages etc.) or attributes of actors (user profile, user created contents etc.) [18, 33]. If a finite set of n Actors is defined as $A = \{a_1, a_2, a_3, \ldots, a_n\}$, the possible connection(C_{Max}) that can appear among them can be shown as (Eq.1) [34].

$$C_{Max} = \frac{n(n-1)}{2} \tag{1}$$

In fact, the number of actors' relations is limited. As a result, the created sparse social networks become to have problems such as isolated sub-groups and isolated actors. Also, in searches and recommendations etc using social networks, a phenomenon of remarkably decreased connectivity between actors occur due to the shortage of source data.

Recently, studies related with search and recommendation systems utilizing social networks have proposed methods to filter social network information using indirect information. However, these filtering approaches bring about results that add to sparsity problems. Therefore, studies of social networks should focus on solving sparsity problems not only by filtering approaches but also by extending relations in social networks. Existing studies intended to solve sparsity problems create relations by simply using similarity values between actors [35, 36]. However, they have a limitation in that they do not have any clear definition or range of those relations created as such. Therefore, reliable methods to solve sparsity problems should be able to specify the definition and range of those relations inferred from the attributes of actors.

3 Reliable Social Trust Management with Mitigating Sparsity Problem

In this section, a reliable trust management approach that can solve sparsity problems occurring in social trust models will be introduced. To be specific, actors are clustered using the similarity of attribute properties in order to solve sparsity problems and virtual relations are created between actors in these

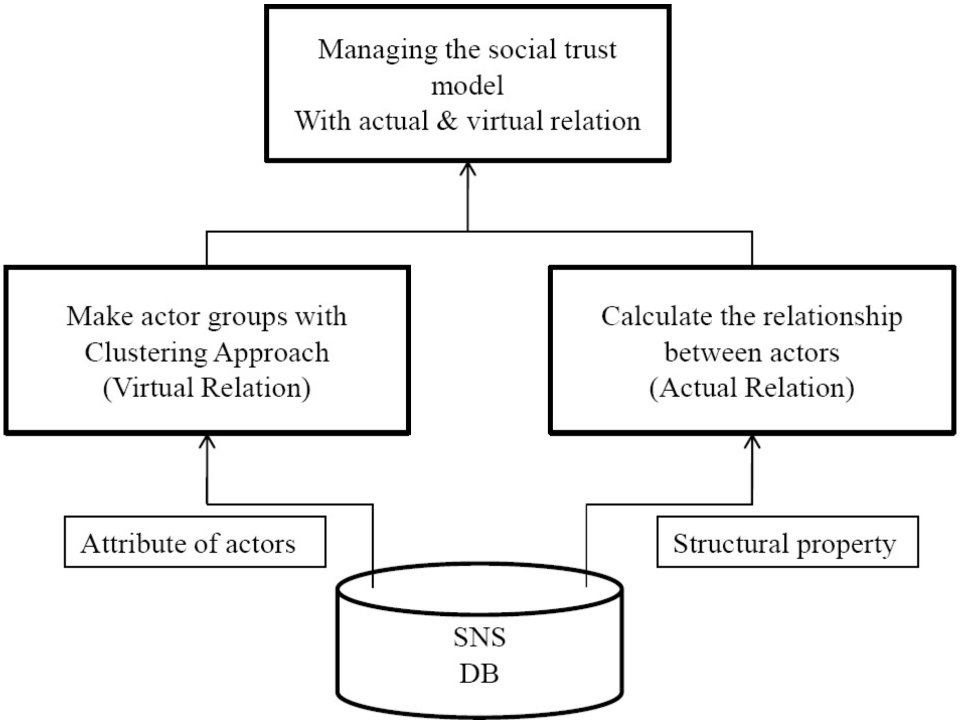

Figure 1: An overview of the proposed approach

groups to enrich relations. Then, a reliable social trust model will be presented by specifying their relationships with actual relations. The proposed approach is divided into an actual relation extraction stage, a virtual relation extraction stage and a trust management stage (Figure 1). In this paper, DBLP data sets [37] are used to establish social networks.

3.1 Actual Relation Extraction Stage

In this section, actors' structural properties are used to extract actual relations. Social Trust Models can be divided into two types based on the types of relations. The first one is cases where relations between actors are made one-way (e.g. tagging in a blog, following in a twitter, sending or receiving e-mail message). Therefore, in these cases, although information flows in one direction, effects in the opposite direction also exist and thus the inverse operations of relations should be considered [38]. The second one is cases where relations between actors are made two-way (e.g. DBLP data set). In these cases, common link areas of actors may be measured to define a trust model.

In this paper, it is assumed that, relationship($TS_{ActualRel}$) between actors are made mutually and the trust model appearing between Actors are determined by the degree of common areas($Degree_{CommonArea}$) of the actual relations maintained by the actors in Figure 2 (Eq. 2) [39]. In this case, if the Trust value is 0, there is no relation. Therefore, in the case of the DBLP data set used in this paper, the number of co-written publications becomes the trust score of actual relations. Actual relations are used to evaluate the clusters made to compose actor groups and finally used to manage social trust together with virtual relations.

$$TS_{ActualRel} = Degree_{CommonArea} \qquad (2)$$

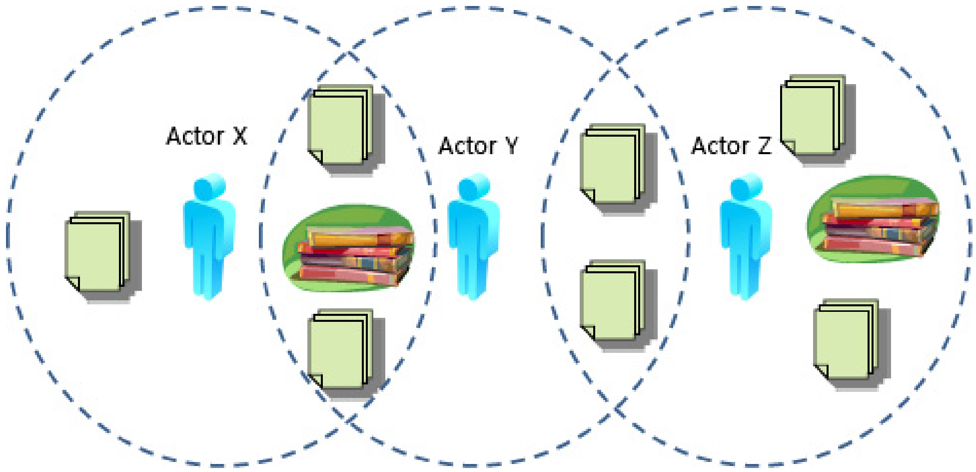

Figure 2: trust Extraction for calculating the actual relation with common interests

3.2 Contents based Clustering Stage for Extracting Virtual Relation

In this section, a Clustering scheme intended to compose actor groups using the attributes of actors. Each Actor has contents with diverse natures. Although contents that have each unified attribute can be represented in the form of sub-objects of the object termed actor, in this paper, they are defined as one object having an integrated attribute. Therefore, as shown in (Eq. 3), Actors(A_i) become to take the form of vectors that have terms(t_k) with different characteristics as attributes.

$$\vec{A_i} = \{t_1, t_2, t_3, \ldots, t_n\} \tag{3}$$

The relational degrees of individual Actors can be calculated using the Cosine Similarity [40] shown in (Eq. 4). They define the weight values owned by individual terms by processing the attributes owned by the actors using the TF-IDF(Term Frequency-Inverse Document Frequency) method.

$$S_{ij} = \cos\alpha = \frac{\vec{A_i} \cdot \vec{A_j}}{\|\vec{A_i}\| \cdot \|\vec{A_j}\|} \tag{4}$$

To compose actor groups, the K-means clustering approach is applied based on similarity values between actors. First, in order to initialize k Clusters, k actors are randomly selected and defined as cluster prototypes(M). Cluster prototypes are values that represent the member nodes of the clusters(C_w). Then, each actor becomes to join the cluster with a similarity value which is the closest to its similarity value (Eq. 5). Once all of the nodes has joined, new cluster prototypes become to be selected because the cluster setting has been changed. To compose optimum clusters, this process is repeatedly implemented until the newly selected Cluster prototypes become the same as the existing cluster prototypes (Table 1).

$$TS_{VirtualRel} = S_{ij} \tag{5}$$

Nodes in the finally selected clusters have the similar attributes and they form actor groups. The nodes positioned in the same actor group become to form virtual relations between each other using the values of similarity between actors as trust scores($TS_{VirtualRel}$). By enriching the actual relations established with structural properties, they not only reinforce the connectivity of the social trust model but also can clarify the range and definition of virtual relations.

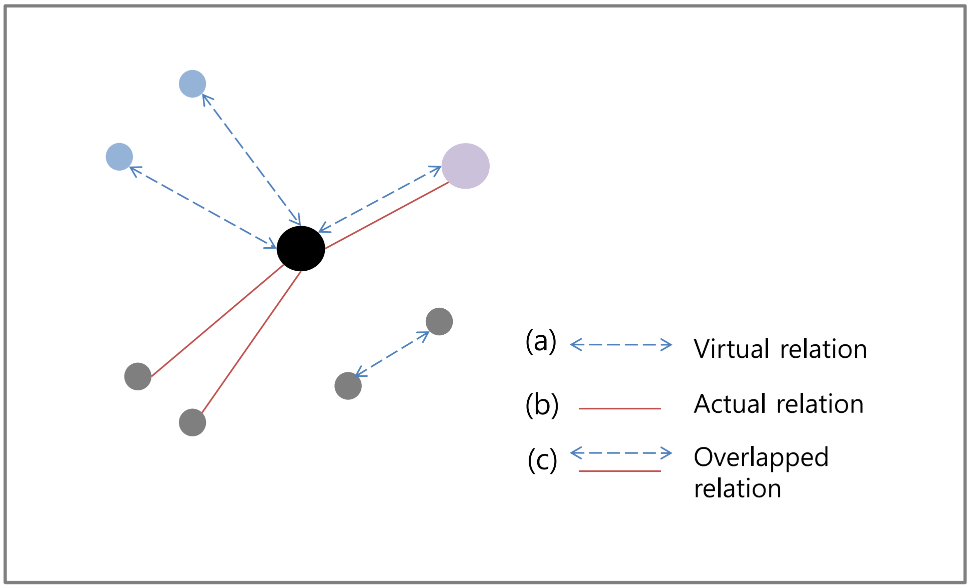

Figure 3: (a) virtual relation with attribute of actors, (b) Actual relation with structural property, (c) overlapped relation

3.3 Trust Management Stage

In this section, a trust model of social networks applied with enriched relationships will be defined. In this paper, relationships arising between actors are divided into actual relations that can be obtained from structural properties and virtual relations extracted from the attributes of nodes. Therefore, the ranges of the two relations are also different. Actual relations become to have 1 or larger integer ranges as the quantity of common contents is measured. On the other hand, virtual relations become to have positive decimals below 1 as they are measured with similarity between actors. Therefore, in the case of virtual relations, trust scores which are always lower than those of actual relations are drawn.

Besides, the trust scores of nodes where both actual relations and virtual relations have been formed simultaneously should be also defined. Overlapped relations should guarantee the minimum actual relation value and the similarity values of attributes should be proportionally reflected by trust scores. Therefore, the proposed approach defines the trust scores of relations($TS_{overlapRel}$) between those nodes

Table 1: Process for organizing the actor groups with K-means clustering algorithm

1) Initialize a K-partition randomly. Calculate the cluster prototype matrix M = [m1, ..., mK].
2) Assign each actor in the data set to the nearest cluster C_W i.e. $\chi_j \in C_W, if \|\chi_j - m_i\|$ $for j = 1, \dots, N, i \neq w, and i = 1, \dots, K.$
3) Recalculate the cluster prototype matrix based on the current partition.
4) Repeat steps 2) – 3) until there is no change for each cluster

that have both actual relations and virtual relations simultaneously using (Eq. 6).

$$TS_{OverlapRel} = TS_{ActualRel} \times (1 + TS_{VertualRel}) \tag{6}$$

We propose the alternative trust calculation for decomposing direct and indirect relation between actors. In case of a direct relation, the three kinds of types are adjusted to Trust Score($TS_{relation}$) which are $TS_{ActualRel}, TS_{VirtualRel}, TS_{OverlapRel}$ (Eq. 7).

$$TS_{relation} = \begin{cases} [TS_{ActualRel}|TS_{VirtualRel}|TS_{overlapRel}] & \text{if relation is direct relation} \\ Indirect_{TS} & \text{indirect relation} \end{cases} \tag{7}$$

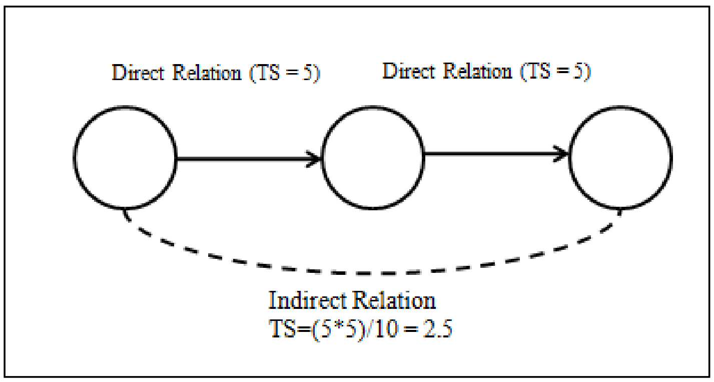

Figure 4: Example of the Trust Inference of indirect connection

In case of direct relation, we can use the primary value simply. For extracting the trust score of an indirect relation, actual and virtual relations have the separated calculation method, however. Because they have the differential ranges of value. The trust score of an indirection relation($InDirect_{TS}$) is accordingly normalized with (Eq. 8). (Figure 4) shows the example of this normalization method. There is an indirect relation which is composed with two actual relations. The inferred trust score of this indirect relation is 2.5. (But, we don't have to consider the calculation which has several duplicate paths.)

$$InDirect_{TS} = \frac{\Pi[TS_{ActualRel}|TS_{VirtualRel}|TS_{overlapRel}]}{10^{k-1}} \tag{8}$$

The proposed approach specifies the definition and range of virtual relations based on contents based clustering. Also, the approach can explicitly define virtual relations' association with existing actual relations too. As a result, the approach can do more reliable trust management compared to approaches [36] that use the similarity values between all existing actors.

4 Experiments

4.1 Experimental setup

In this paper, experiments were conducted based on the DBLP [37] distributed in June 2009. We extracted 1,487 papers and 1,449 actors who are the authors of those papers. To conduct the experiments, two types of information were extracted: (i) relations between the individuals with co-author information, (ii) attribute of the node, it is title of publications. The First information, which represents a set of social relationships and it made the actual relations. The second extracted factors are used to construct vector space model of actors by title of publications. The clusters are organized with similarity between actors.

The Experiments are separated to analyzing the sparsity problem and evaluating the connectivity. We also measured the performance of proposed approach with F-Measure.

4.2 Problem Analysis

In this section, the sparsity problems existing in existing social networks will be analyzed. The social networks characterized by mutually connected relationships used in this experiment become to have the largest number of relations when they theoretically have the nature of complete graphs. Therefore, if it is assumed that a network is composed of n actors, n(n-1)/2 relations will be created at the maximum in the network. As shown in (Table 2), in the case of the experimental data, although around 1 million relations can be created, only around 31,000 actual relations are created. This is only around 2.9% of the number of all possible relations. Furthermore isolated nodes which are publications and authors are 1005, 818, respectively. It shows that the nodes which participated to social networks are under the 50%. Therefore, in the case of search systems intended to communicate information or recommendations, filtering systems using existing social networks are not suitable.

4.3 Experimental Result

The proposed approach is compared with a link based social networks [36]. (Figure 5) and (Figure 6) shows number of relations and fluctuation in each step. Previous approach displayed the steady inclination of the indirect relation. On the other hand, the proposed approach shows a lot more indirect relations with the progress of phase. For example, there are 340,000 relations in two-hop phase. It is 31 times more than the other one. (In theory, 55 billions of maximum relations can be composed in two-hop phase.) In three-hop relations, gap between two approaches are increased 130 times. These data show that the

Table 2: A specification of Data set extracted from DBLP for this experiment

	Data set
A number of Authors	1,449
A number of publications	1,487
An average number of actors per paper	3.3456
An average author of papers per author	3.4334

Table 3: Sparsity problem in a social networks with the number of actual relations

	Experiment data	Ratio(%)
Number of the Actual relation	31,340	2.9
Max number of the relation	1,049,076	100
The isolated nodes (paper)	1005	67.6
The isolated nodes (author)	818	56.6

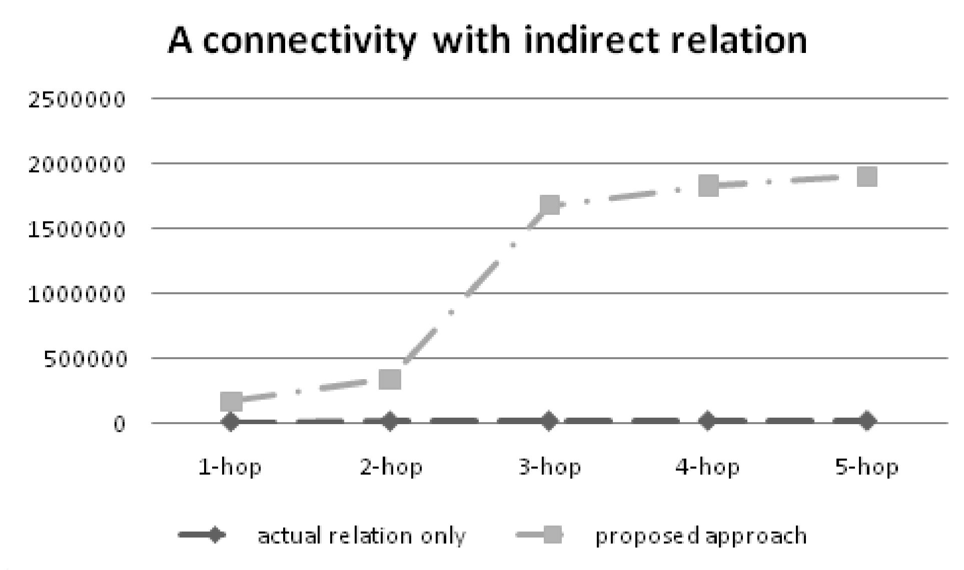

Figure 5: A connectivity with indirect relation

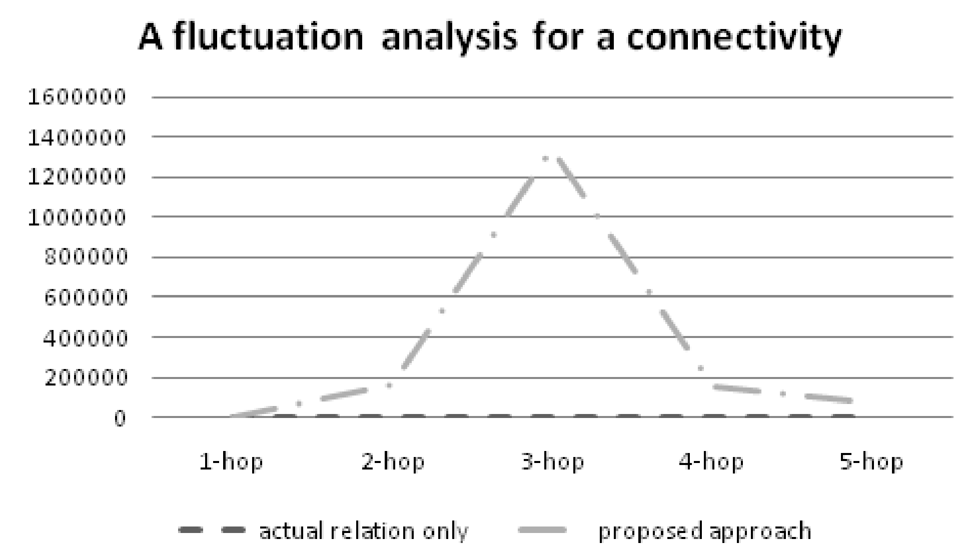

Figure 6: Example of the Trust Inference of indirect connection

sparcity problem of the previous approach was worsening with increasing the degree of composition. On the other hand, the proposed approach mitigates the sparcity problem by generating virtual relations.

F-measure is used to measure the performance of the proposed approach. Precision and Recall are a standard measure for exactness and completeness, respectively [40]. F-measrue(F1) is the harmonic mean of precision and recall. Among other ones, F1 measure in which recall and precision are evenly weighted (Eq. 9) is selected.

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{9}$$

(Figure 7) displays the F-measure is applied to top-k ranks. For a small k number, both approaches show the similar results in F-measure. This is not surprising at all as actual relations are usually in top rank in both approaches. With increasing the number of result data set, gap between the two approaches is widening. As the accessible actors are increasing, precision and recall of the proposed approach are also increasing.

The experimental results show that the proposed approach using virtual relations have a better solution for the sparcity problem. Furthermore, it also improves the performance of the system with a new social trust model.

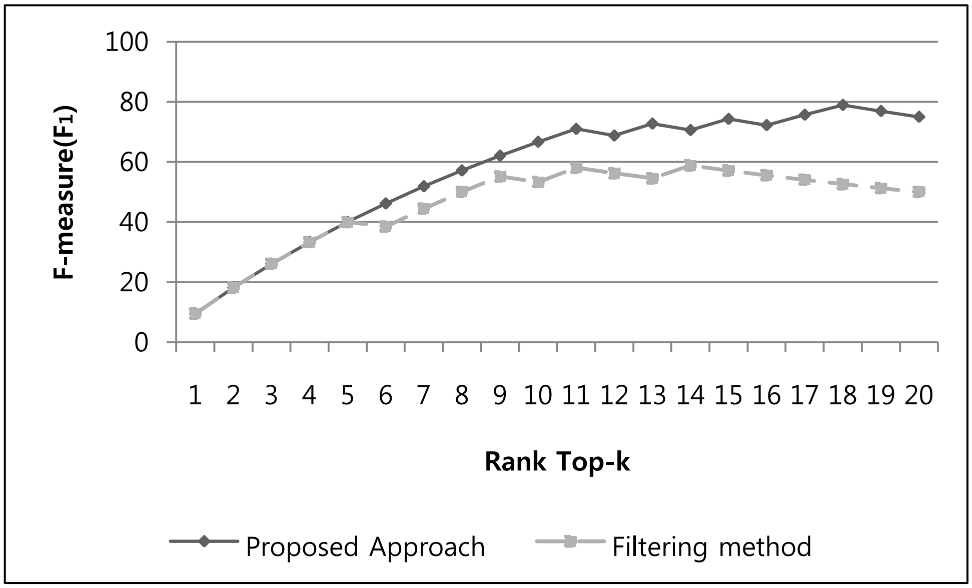

Figure 7: Performance measurement with Precision-Recall and F-Measure

5 Conclusions

As interest in social networks studies has grown bigger along with the development of Web, social network trust management and applications have come into the spotlight. However, search and recommendation systems to which social networks are mainly applied are limited in reliable trust management due to sparsity problems. Therefore, to solve this problem, this paper proposes a reliable social trust model where relations between actors are divided into actual relations and virtual relations in definitions. Virtual relations not only solves sparsity problems by enriching existing actual relations but also are combined with actual relations to specify the definition and range of relations needed in reliable trust management.

Later, for effective social trust management, the diverse collaborations occurring between actors should be analyzed. Besides, solutions for the uncertainty problems occurring in the diverse indirect relations arising in trust management are keenly needed.

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