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A Hybrid Social Network-based Collaborative Filtering Method for Personalized Manufacturing Service Recommendation

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Abstract: Nowadays, social network-based collaborative filtering (CF) methods are widely applied to recommend suitable products to consumers by combining trust relationships and similarities in the preference ratings among past users. However, these types of methods are rarely used for recommending manufacturing services. Hence, this study has developed a hybrid social network-based CF method for recommending personalized manufacturing services. The trustworthy enterprises and three types of similar enterprises with different features were considered as the four influential components for calculating predicted ratings of candidate services. The stochastic approach for link structure analysis (SALSA) was adopted to select top K trustworthy enterprises while also considering their reputation propagation on enterprise social network. The predicted ratings of candidate services were computed by using an extended user-based CF method where the particle swarm optimization (PSO) algorithm was leveraged to optimize the weights of the four components, thus making service recommendation more objective. Finally, an evaluation experiment illustrated that the proposed method is more accurate than the traditional user-based CF method.
Keywords: manufacturing service recommendation, social network, collaborative filtering, SALSA, PSO.

1 Introduction

Given the parallel and almost simultaneous rapid development of both Web 2.0 and global manufacturing resources, a large number of manufacturing enterprises have turned to social network-based resources to improve their core competitiveness. For example, service-oriented architectures (SOAs) [7] and their corresponding web services offer dynamic methods that allow manufacturing enterprises to communicate with their suppliers and customers [4]. However, selecting the most appropriate recommendation technique is still a common challenge among numerous manufacturing enterprises.

Recommender methods have been widely applied to address the information overload problem often encountered in recommending personalized products or services by using the collaborative filtering (CF) [1] method, mostly in the commercial domain, including Amazon and Netflix. The traditional CF-based recommender systems usually face serious drawbacks, such as data sparsity and cold-start, which seriously affect the effectiveness of the service recommendation. To solve data sparsity and cold-start problems, social network information can be explored to leverage service preferences of users, trust relationships among users, and influence of users on others, thus making personalized service recommendations more accurate and objective [6].

Through comparison with and analysis of previous works, this study proposed that the social network-based CF method can also be applied in the area of manufacturing services not only as a solution to the industry's information overload problem but as an alternative to its need for a more accurate and objective personalized recommendation technique. It is assumed that the opinions of trustworthy enterprises have significant influence on the consumers who use social network-based information to access information on required services or products. Apart from trust relationships of enterprises, similarity of consumer enterprises is another important factor for calculating predicted ratings to recommend services, since two enterprises with similar features may have higher similarity of preference ratings on required services.

However, conventional social network-based CF methods still have some serious drawbacks to be explored. First, the traditional trust evaluation methods usually ignore the reputation propagation in social networks. Second, traditional CF recommendation methods basically use single similarity between consumer enterprises (i.e., rating similarity), making the result of service recommendation ineffective. Furthermore, the corresponding weights of influential attributes for calculating predicted ratings are subjectively or averagely determined, resulting in inaccurate manufacturing service recommendation.

To overcome the above barriers, this study proposed a hybrid social network-based CF method to make manufacturing service recommendation more effective and accurate. First, stochastic approach for link structure analysis (SALSA) [15] was leveraged to compute the global reputation values of enterprises in selecting top *K1* trustworthy enterprises by considering reputation propagation in enterprise social network. In addition to the selection of trustworthy enterprises, three types of similar enterprises were selected as influential components for predicting ratings. The types of enterprise similarity include rating similarity, development stage similarity, and category similarity. After the four influential components were selected, the predicted ratings of candidate services were calculated by using an extended user-based CF method where particle swarm optimization (PSO) [12] was leveraged to automatically and objectively obtain the weights of the four influential components. Finally, the manufacturing services with higher predicted ratings can be recommended to the consumer enterprise, by using user-based CF method.

The rest of this paper is organized as follows: Section 2 summarizes several related works. Section 3 further elaborates on the proposed hybrid method. Section 4 presents the experimental evaluation to verify the effectiveness of the proposed method. Lastly, Section 5 gives the conclusion of this paper, as well as suggestions for further research.

2 Related works

2.1 Social network-based recommender method

Social networks derive their name from social associations among people, and model social connections among individuals or objects [20]. In recent years, large amounts of useful information from social networks have been mined and integrated with recommender systems to enhance the quality of recommendation, and consequently, social network-based recommender methods have been broadly applied and extended to various domains.

For instance, Eirinaki et al. [8] presented a trust-aware system for personalized recommendation, employing both implicit trust and explicit trust between users in the social network. Meanwhile, the Liu et al. [17] study proposed a novel recommendation system that considered social relations and item contents into the Bayesian Probabilistic Matrix Factorization (BPMF) [23] to improve the accuracy of recommendation. Additionally, Sun et al. [25] proposed a dynamic competitive approach to overcome the problem of environmental change for social network service recommendation. A previous work [29]-also done by the present writers-presented Quality of Service (QoS)-aware service recommendation by combining social network and CF technology to predict the missing QoS values for manufacturing service recommendation.

However, the previous social network-based recommender methods [8, 17, 23, 25, 29], have not considered reputation propagation between consumer enterprises, which makes the result of manufacturing service recommendation ineffective. Therefore, this study employed SALSA, which is an effective link analysis method to compute global and accurate reputation value of enterprises in a social network.

2.2 Stochastic approach for link structure analysis (SALSA)

SALSA is an effective link analysis method that combines the idea of PageRank with the hub and authority idea of HITS [21] and it is usually used in ranking of web pages.

White et al. [28], for instance, proposed a general framework to estimate the relative importance of nodes in a graph by using SALSA algorithm. Najork et al. [18] proposed some definitions of neighborhood graph to enhance the effectiveness and the efficiency of query-dependent link-based ranking algorithms including SALSA algorithm. Furthermore, Borodin et al. [2] presented an extended SALSA-called popularity SALSA (pSALSA)-to extract useful information about the relative ranking of the web pages. Subsequently, Langville et al. [14] proved that SALSA is the best ranking algorithm for Web information retrieval by comparing HITS and PageRank. We find that the link structure of SALSA is similar with transactions among consumer enterprises in a social network. Therefore, this study adopted SALSA to calculate the global reputation values of trustworthy enterprises in a social network.

2.3 Particle swarm optimization (PSO)

PSO [12] was initially proposed by Kennedy and Eberhart in 1995, and the concept was derived from the foraging behaviors of a swarm of birds to address optimization problems. In the past two decades, PSO has been continually extended to facilitate its application in various domains, including education, economics, and engineering.

For instance, Sobecki [24] proposed five swarm intelligence algorithms in the field of student course recommendation, including ant colony optimization (ACO) [5] and PSO. Specifically, PSO was employed to find the set of the optimal neighborhood of students for further grade prediction. The study of Park et al. [19] presented an improved PSO that combined chaotic sequences with the linearly decreasing inertia weights to enhance the global searching capability to overcome nonconvex economic dispatch (ED) problems. Esfahani et al. [9] provided an optimal control system to enhance power quality-where the fuzzy PSO method was proposed for optimization of proportional-integral-derivative (PID) controller. The Tyagi et al. [26] research utilized the multi-objective PSO-based association rule mining model to objectively obtain minimum support and minimum confidence to extract the useful association rules, so that the collaborative filtering recommendations are obviously enhanced.

According to these aforementioned studies, PSO is a promising stochastic optimization technique for handling multi-objective problems; however, it is rarely employed as an optimal service recommendation in the domain of manufacturing services. In the present study, we takes advantage of the PSO algorithm to automatically and objectively obtain corresponding weights of influential components to recommend the most effective and efficient manufacturing services.

3 The proposed hybrid method

To enhance the quality of manufacturing service recommendation, this paper proposes a hybrid social network-based CF method to modify the traditional user-based CF method. Trustworthy enterprises and three types of similar enterprises with different features can be regarded as influential components for calculating predicted rating. Fig. 1 demonstrates the overview of the proposed method, and it is divided into four parts: (a) selection of top *K1* trustworthy enterprises-considering global reputation propagation in enterprise social network; (b) selection of three types of top K similar enterprises-with different features, including rating similarity, development stage similarity, and category similarity; (c) optimization of four corresponding weights-by means of PSO algorithm; and (d) manufacturing service recommendation-by calculating rating value of required service through extended user-based CF method.

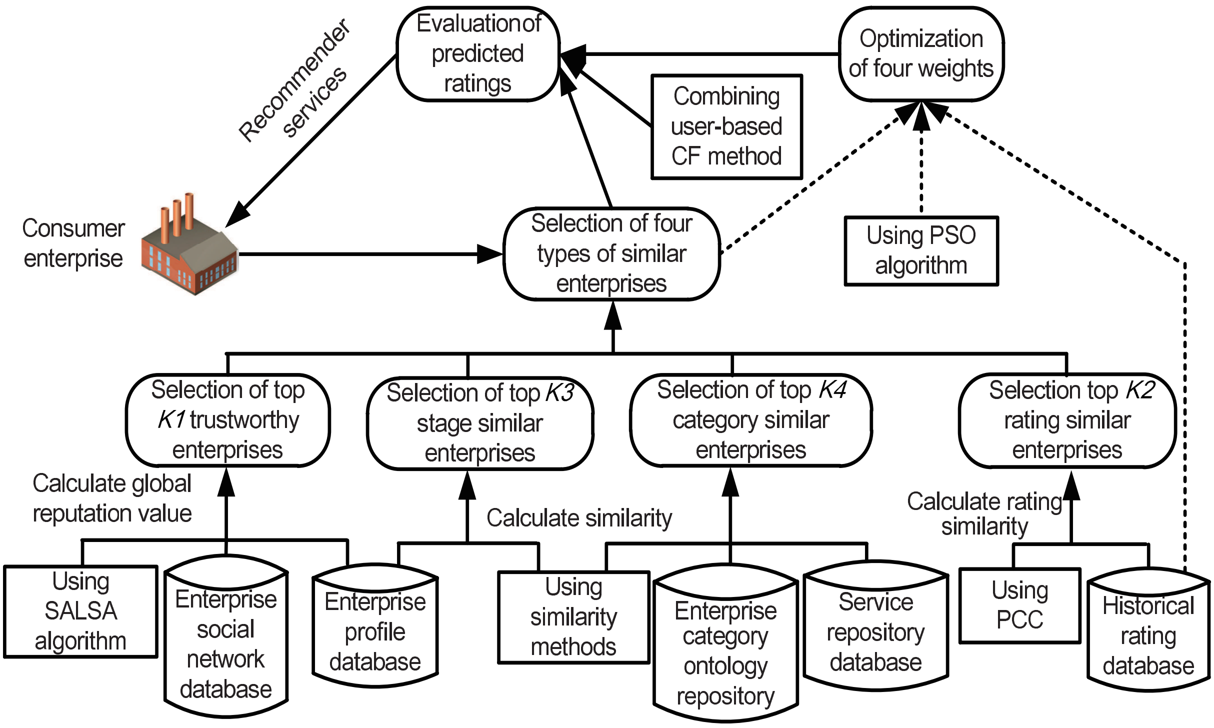

Figure 1: Overview of our proposed method

3.1 Selection of top *K1* trustworthy enterprises by using SALSA

To select the trustworthy enterprises more accurately, first, the relative trust weight based on social network was identified. Then, SALSA was employed to compute the global reputation value by considering reputation propagation in social networks.

Trust weight identification in a social network

Each enterprise was linked with one or several friend enterprises in social networks and each link carried a corresponding trust weight that was first identified. Inspired by a previous work-also conducted by the present writers-in the domain of attention (DOA) [30], it was established that the more number of times that a consumer enterprise has connected with friend enterprises such as visiting home page and inquiring services, the more trust the consumer enterprise has on a friend enterprise. Therefore, this study considered average connection times as trust weight and the formulation is represented as follows:

$$tw_{ij} = \frac{ConnTimes(E_i, E_j)}{\sum_{k=1}^{K} ConnTimes(E_i, E_k)}, \tag{1}$$

where $ConnTimes(E_i, E_j)$ denotes the number of times that enterprise i has connected to enterprise j, and denominator means the total times that enterprise i has connected with all enterprises in social network. The number of connection times can be extracted from the enterprise profile.

Calculation of global reputation value by using SALSA

A large amount of reputation evaluation methods have been widely used to compute reputation value. However, the conventional reputation evaluation methods usually ignore the reputation propagation in enterprise social networks. Largely, SALSA [15] is known as a promising link analysis algorithm, combining advantages of both PageRank [3] and HITS [13]. This study found that the link structure of SALSA is similar to reputation propagation in an enterprise social network, such that it is appropriately adopted to calculate the global reputation values of enterprises based on the trust weight.

In an enterprise social network, the relationships among consumer enterprises can be regarded as a bipartite undirected graph $G = (V_h, V_a, E)$, where V_h and V_a denote a set of hub enterprises (all the enterprises in a social network with out-degree) and a set of authority enterprises (all the enterprises in a social network with in-degree), respectively. E is the set of directed interactions edge between the enterprises. Each edge is arranged with a corresponding trust weight calculated by equation (1). An adjective matrix $\mathbf{M}$ can be built based on the link structure of the social network. The initial $m_{ij} = 1$ if the enterprise i points to enterprise j, otherwise, $m_{ij} = 0$. Each edge is assigned a trust weight, so that $m_{ij} = 1 \times tw_{ij}$ or 0. The equations of hub matrix $\mathbf{H}$ and authority matrix $\mathbf{A}$ are represented as follows [16]:

$$\mathbf{H} = \mathbf{M}_r \mathbf{M}_c^T,\ \mathbf{A} = \mathbf{M}_c^T \mathbf{M}_r, \tag{2}$$

where $\mathbf{M}_r$ and $\mathbf{M}_c$ denote each nonzero row divided by row sum of matrix $\mathbf{M}$ and each nonzero column divided by its column sum, respectively.

This research considered the authority value of SALSA as the reputation value of an enterprise. When G is connected, SALSA assigns each page an authority weight, which is proportional to the sum of weights of its incoming edges [16]. However, if G is not connected, the authority value of enterprise i can be represented as follows [16]:

$$a_i = \frac{|A_j|}{|A|} \times \frac{\sum_{j=1}^{|B(i)|} tw_{ij}}{\sum_{j=1}^{|E_j|} tw_{ij}}, \tag{3}$$

where $|A_j|$ and $|A|$ denote the number of enterprises in jth connected component and total number of enterprises in the set of V_a, respectively; $|B(i)|$ and $|E_j|$, respectively, denote the number of in-degree enterprise i and total number of in-degree enterprises in jth connected component; enterprise i belongs to jth connected component.

An example of trust relationship among enterprises in social networks is shown in Fig. 2.

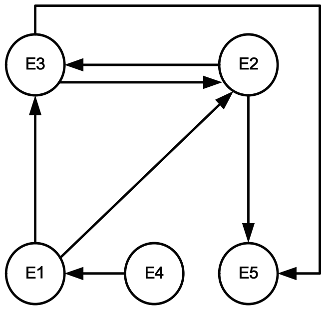

Figure 2: An example of trust relationship in enterprise social network

The connection times among enterprises can be extracted from enterprise profile in table 1.

Table 1: Connection times among enterprises

	E1	E2	E3	E4	E5
E1	0	30	50	0	0
E2	0	0	40	0	10
E3	0	10	0	0	30
E4	10	0	0	0	0
E5	0	0	0	0	0

The trust weights between the enterprises can be computed by using formulation 1, and adjective matrix **M** can be built. The trust relationship in enterprise social network in Fig. 2 can be transformed as bipartite graph in Fig. 3.

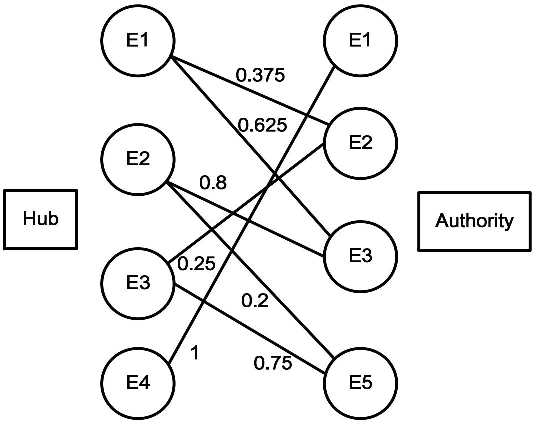

Figure 3: G: bipartite graph of the example

According to the aforementioned formulation 2, we can calculate the hub matrix **H** and authority matrix **A** in the enterprise social network.

$$\mathbf{M} = \begin{array}{c} \\ E1 \\ E2 \\ E3 \\ E4 \\ E5 \end{array} \!\!\begin{array}{c} \begin{array}{ccccc} E1 & E2 & E3 & E4 & E5 \end{array} \\ \begin{bmatrix} 0.000 & 0.375 & 0.625 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.800 & 0.000 & 0.200 \\ 0.000 & 0.250 & 0.000 & 0.000 & 0.750 \\ 1.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \end{bmatrix} \end{array} \quad \mathbf{H} = \begin{array}{c} \\ E1 \\ E2 \\ E3 \\ E4 \\ E5 \end{array} \!\!\begin{array}{c} \begin{array}{ccccc} E1 & E2 & E3 & E4 & E5 \end{array} \\ \begin{bmatrix} 0.629 & 0.278 & 0.094 & 0.000 & 0.000 \\ 0.445 & 0.405 & 0.150 & 0.000 & 0.000 \\ 0.188 & 0.185 & 0.625 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \end{bmatrix} \end{array} \quad \mathbf{A} = \begin{array}{c} \\ E1 \\ E2 \\ E3 \\ E4 \\ E5 \end{array} \!\!\begin{array}{c} \begin{array}{ccccc} E1 & E2 & E3 & E4 & E5 \end{array} \\ \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.344 & 0.469 & 0.000 & 0.188 \\ 0.000 & 0.209 & 0.703 & 0.000 & 0.089 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.188 & 0.200 & 0.000 & 0.613 \end{bmatrix} \end{array}$$

According to the structure of matrix **H** and matrix **A**, G is not connected and the authority value of enterprise i can be calculated by using formulation 3. The result of global reputation values of enterprises can be represented as $[a_1, a_2, a_3, a_4, a_5]^T = [0.250, 0.156, 0.356, 0, 0.238]^T$.

Therefore, this study selected top *K1* trustworthy enterprises in social networks as an influential component of manufacturing service recommendation.

3.2 Selection of three types of similar enterprises

In addition to trustworthy enterprises, this paper considered the similarity of past consumer enterprises to recommend suitable manufacturing service. Conventional user-based CF method usually only considers rating similarity of past consumer enterprises to predict ratings of candidate manufacturing services.

However, other similar features of enterprises also have significant influence on predicting ratings of candidate manufacturing services. This section discusses the three types of top K similar enterprises-chosen for this study-as the additional three influential components of manufacturing service recommendation, including rating similarity, stage similarity, and category similarity.

Selection of top *K2* enterprises with similar ratings

Pearson Correlation Coefficient (PCC) [22] is a popular and effective technology to calculate similarity among users based on the historical ratings. In this section, PCC is also leveraged to calculate the rating similarity of consumer enterprises according to their historical ratings to services, and the equation is presented as follows [29]:

$$Rate\_Sim(E_a, E_b) = \frac{\sum_{i=1}^{I}(r_{a,i} - \overline{r_a}) \times (r_{b,i} - \overline{r_b})}{\sqrt{\sum_{i=1}^{I}(r_{a,i} - \overline{r_a})^2} \times \sqrt{\sum_{i=1}^{I}(r_{b,i} - \overline{r_b})^2}}, \tag{4}$$

where I means the total number of manufacturing services co-rated by consumer enterprise E_a and E_b; $r_{a,i}$ and $r_{b,i}$ denote the rating value of manufacturing service i provided by E_a and E_b, respectively; $\overline{r_a}$ and $\overline{r_b}$ mean the average ratings of E_a and E_b, respectively. The value of $Rate\_Sim(E_a, E_b)$ will be within the interval [-1, 1], and the larger it is, the higher is the similarity between E_a and E_b. We can select top *K2* enterprises with similar ratings.

Selection of top *K3* enterprises with similar development stages

For a manufacturing enterprise, the stage of enterprise development also plays an important role in service selection since the different stages of development have a different focus on manufacturing services. For example, start-up stage enterprises usually pay more attention on price of manufacturing service to reduce costs, while mature enterprise may rather put more emphasis on the quality of manufacturing service to attract more consumers. However, the development stages similarity is usually ignored in the process of manufacturing service recommendation. Therefore, this study considered the development stages of enterprise as an influential factor of manufacturing service recommendation.

According to the lifecycle of enterprise development, each enterprise can be divided into four stages: start-up, growth, maturity, and decline. The stage of each enterprise can be assessed by the Hwang method [11] and we will not repeat here. The equation of stage similarity is shown as follows:

$$Stage\_Sim(E_a, E_b) = 1 - \frac{|E_{a,s} - E_{b,s}|}{dec - start}, \tag{5}$$

where $E_{a,s}$ and $E_{b,s}$ denote the stages of enterprises E_a and enterprise E_b, respectively; *dec* and *start* mean the start-up stage and declining stage, respectively. We define the four stages as real numbers: 1, 2, 3, and 4. The top *K3* enterprises with similar development stage were selected.

Selection of top *K4* enterprises with similar enterprise category

The category of manufacturing enterprise can be divided into three levels, namely broad heading, medium-class, and subclass. The broad heading can be further segmented into 25 types, including food manufacturing, tobacco manufacturing, and medical manufacturing. It can be further decomposed into medium-class and subclass. The semantic similarity of enterprise category is an indispensable factor for recommending manufacturing service. Food manufacturing enterprise, for instance, and medical manufacturing enterprise have completely different demands in terms of manufacturing services.

A previous work [4]-by these writers-explored a rich body of OWL-based manufacturing service ontologies, and it was referenced to develop the ontology of enterprise category to calculate the semantic similarity of this category. The particle of the ontology is illustrated in Fig. 4. The formulation of the semantic similarity of enterprise category can be represented as follows [4]:

$$\begin{aligned} Category\_Sim = \mu \frac{n(C_{super}(E_a, O) \cap C_{super}(E_b, O))}{n(C_{super}(E_a, O) \cup C_{super}(E_b, O))} \\ + \nu \frac{n(C_{midd}(E_a, O) \cap C_{midd}(E_b, O))}{n(C_{midd}(E_a, O) \cup C_{midd}(E_b, O))} + \lambda \frac{n(C_{sub}(E_a, O) \cap C_{sub}(E_b, O))}{n(C_{sub}(E_a, O) \cup C_{sub}(E_b, O))}, \end{aligned} \tag{6}$$

where $n(C_{super}(E_a, O) \cap N_{super}(E_b, O))$ means the number of the broad heading to which both enterprise a and enterprise b belong within ontology. $n(C_{super}(E_a, O) \cup N_{super}(E_b, O))$ denotes the number of the broad heading to which either enterprise a or enterprise b belongs within ontology. By that analogy, the similarity of the medium-class and subclass of enterprise category can be computed, and $\mu + \nu + \lambda = 1$. According to the result of semantic similarity of manufacturing enterprise category, the top $K4$ enterprises with similar location were selected.

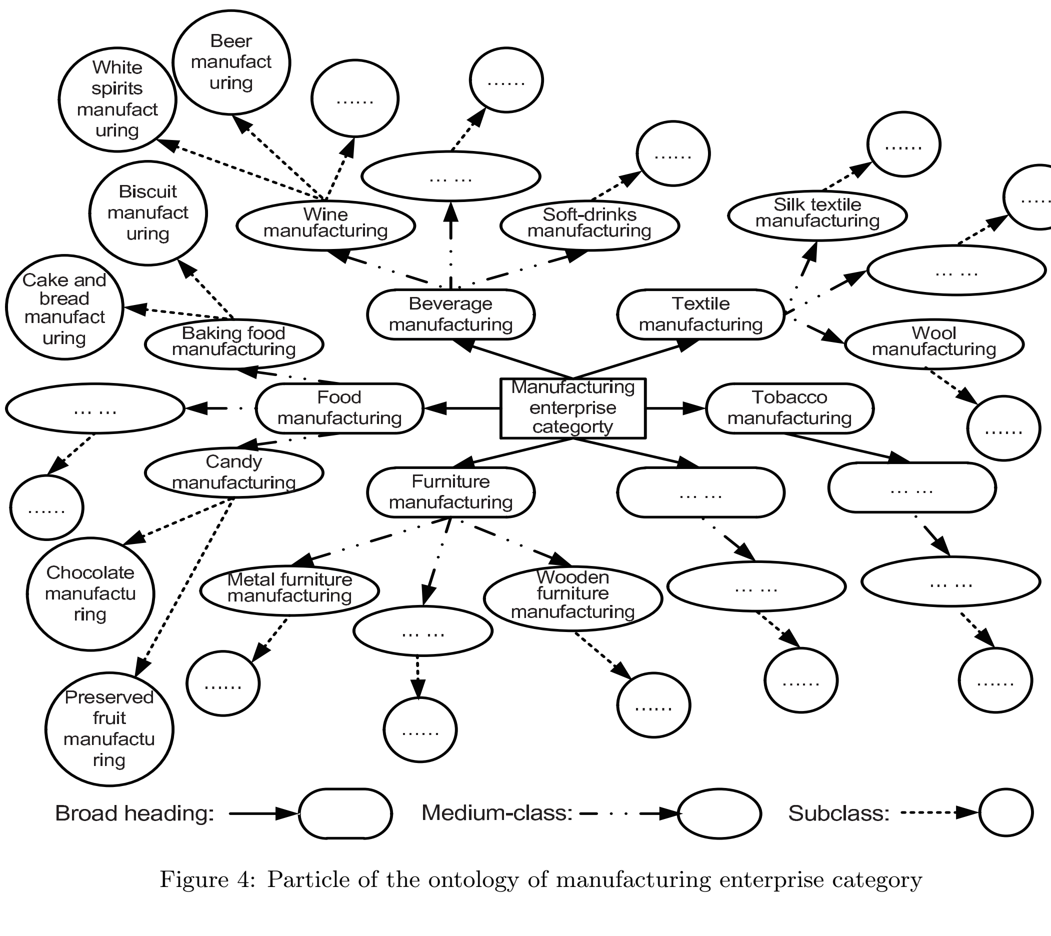

Figure 4: Particle of the ontology of manufacturing enterprise category

3.3 Four weights optimization by using PSO

The weight optimization of the four influential components is inspired by genetic algorithm (GA)-based learning method [10], which was employed to determine the degree of importance of corresponding criteria of electronic service of Internet banking.

However, PSO algorithm is more efficient than GA, since PSO has no complicated operators, including selection, crossover, and mutation. Therefore, the study adopted the PSO algorithm to determine the objective weights of the four influential components to calculate the predicted ratings of target manufacturing services.

Fitness function

Based on the principle of PSO algorithm, the study first constructed the fitness function to judge the performance of positions of particles. The main ideology behind constructing a fitness function is to compare actual average rating of services, which the query enterprise has consumed and rated, with predicted rating of past consumer enterprises. The actual average rating of J services that was rated by consumer enterprise is denoted as $\overline{R_a}$. The equation for predicted average rating of J services rated by consumer enterprise is represented as follows:

$$PAR_J = \frac{1}{J} \times \sum_{j=1}^{J} PR(E_a, S_j), \tag{7}$$

where J means total number of services rated by enterprise E_a. $PR(E_a, S_j)$ denotes the predicted rating of the jth service using user-based CF, and it can be calculated as following formulation:

$$PR(E_a, S_j) = \sum_{i=1}^{4} a_i \times \frac{\sum_{ki=1}^{Ki} R(E_{ki}, S_j) \times comp_i(E_a, E_{ki})}{\sum_{ki=1}^{Ki} comp_i(E_a, E_{ki})}, \tag{8}$$

where Ki means ith set of top K enterprises (i.e., *K1*, *K2*, *K3* and *K4*); $comp_i(E_a, E_{ki})$ is expressed as ith component calculated by the four equations (3-6); $R(E_a, S_j)$ is the rating provided by kith enterprise E_{ki} in top Ki enterprises; and α_i denotes corresponding weight which will be optimized.

Through comparison of actual average rating and predicted average rating, the distance between them seems closer; hence, the performance of the position of the particle is better. The final fitness function was constructed as follows:

$$fv_a = \frac{1}{1 + |\overline{R_a} - PAR_J|}, \tag{9}$$

where fv_a denotes the fitness value of the four weights, and $\overline{R_a}$ means average rating of services that the consumer enterprise has rated.

Identification of optimal weights of each influential component

The four influential components are regarded as four particles in corresponding four-dimensional space and the range of each axis was set on interval [0, 1]. Each particle has a velocity to update its position in its corresponding dimensional space. The position of the particle with highest fitness value was set as the global best position (gd) in each iteration. The ith particle kept its best personal position (p_{id}) which was visited in the corresponding dth dimension of search space. The velocity and position of each particle were updated as follows [27]:

$$v_{id}^{t+1} = \omega v_{id}^{t+1} + c_1 r_1 (p_{id}^{t} - x_{id}^{t}) + c_2 r_2 (p_{gd}^{t} - x_{id}^{t}), \tag{10}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}, \tag{11}$$

where ω means a random inertia weight between 0 and 1; v_{id}^t denotes the velocity of ith particle in generation t; c_1 and c_2 are two positive constants; r_1 and r_2 are two random numbers among 0 and 1; and x_{id}^t means the current position of ith particle in generation t.

Through multiple iterations, the best personal positions of the four particles in their corresponding dimensional spaces were obtained. The weights of four influential components were normalized as follows:

$$\alpha_i = \frac{x_{id}}{\sum_{i=1}^{4} x_{id}}, \tag{12}$$

where x_{id} denotes the best personal position of ith particle in corresponding dth space.

3.4 Manufacturing service recommendation

The missing rating of manufacturing service Sr which consumer enterprise Ea needs can be predicted using a user-based CF method. The final equation of manufacturing service recommendation can be referred to equation (8), and the corresponding weight α_i was objectively obtained through the optimization process that is illustrated in sub-section 3.3 in detail. Accordingly, the predicted missing ratings of various manufacturing services, the top k manufacturing services with higher predicted ratings, can be recommended to the consumer enterprise.

4 An evaluation experiment

In this section, a comparison experiment to evaluate the quality of manufacturing service recommendation was conducted through the use of the study's proposed hybrid method. Evaluation metric of mean absolute error (MAE) was employed to evaluate the accuracy of our proposed hybrid method. The formulation is expressed as follows [29]:

$$MAE = \frac{\sum_{t=1}^{T} |p_t - a_t|}{T}, \tag{13}$$

where T means the total number of predictions, and p_t and a_t denote the tth predicted rating and tth actual rating, respectively.

4.1 Comparative methods

Two recommender methods were selected to compare with the proposed hybrid method of the study to demonstrate the accuracy of the method. These are:

(1) Traditional user-based CF method, which only considers rating similarity between past consumer enterprises to predict ratings of candidate services.

(2) Combined social network and CF method [29], which is an effective method for manufacturing service recommendation, while it has not considered reputation propagation in enterprise social network, and only subjectively assigned relative weights of the influential components.

4.2 Comparison results

In the historical rating registry, there are 8796 ratings of 372 manufacturing services provided by 156 consumer enterprises with their relative trust information and profiles. The ratings varied from 1 to 5, and 80% of the rating data were randomly selected to act as training set and the rest were represented as testing set.

Fig. 5 demonstrates the three sets of MAE values calculated by using three recommender methods with different sizes of neighbors from 5 to 17. According to the results of experiments, the MAE values calculated by our proposed method are lower than the other two methods. Therefore, our proposed method in this study is more accurate than traditional user-based CF method and the combination of the social network and CF method. The results also reveal that the performance of our proposed method is the best at the point of 11 in neighbor size.

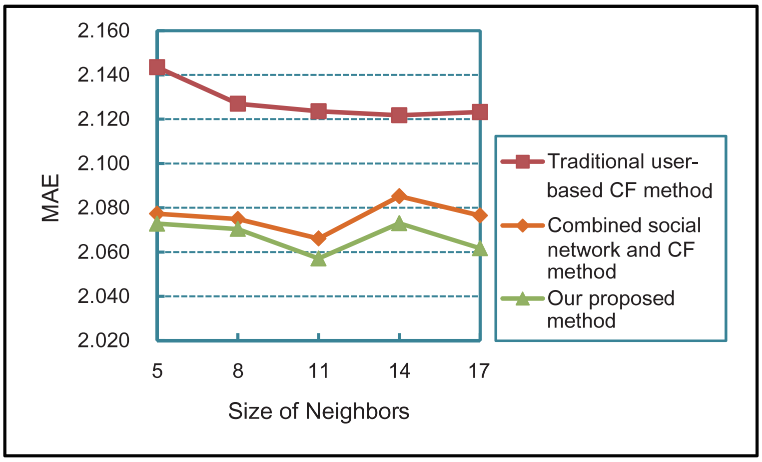

Figure 5: Comparison of MAE values of three methods

5 Conclusion

In this paper, a hybrid social network-based CF method is proposed to make manufacturing service recommendation more accurate and objective. The result of the evaluation experiment illustrates that the proposed hybrid method is more accurate than the other traditional recommender methods.

To sum up, the major contributions of this paper are as follows: first, trustworthy enterprises are obtained by identifying trust weight and leveraging SALSA that considers reputation propagation based on social network in the process of calculating reputation value; second, the trustworthy enterprises and three types of similar enterprises with different features are considered as four influential components for calculating predicted ratings of candidate services to enhance the quality of manufacturing service recommendation; third, personalized manufacturing service can be recommended by using an extended user-based CF method where PSO algorithm is employed to automatically and objectively obtain the weights of four influential components.

Still, this paper has some limitations, which can be further explored in future research. For instance, more useful information on enterprise social networks can be mined to enhance the accuracy of manufacturing service recommendation.

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