

A Decision Making Method Based on TOPSIS and Considering the Social Relationship

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Abstract— With the rapid development of social networks, the decision-making of users is deeply influenced by online ratings, and suggestions from friends and relatives, and they have become important references for consumers to make decisions. However, the multi-sources information makes it difficult for users to make efficient decisions. In order to overcome this difficulty, our research lays a basis on helping consumers to make decisions. We consider the impacts from both friends in social networks such as Facebook and online buyers of online shopping websites such as Amazon. Furthermore, for generating the impact weights of friends, we utilize the Hawks process to simulate the interaction process with three typical interactive behaviors. For making a higher accuracy of product ratings, we filter online buyers and adopt the ratings from the buyers who had similar interests with a target individual. At last according to friends' suggestions, online ratings, and the weights generated formerly, we provide the option preference by the TOPSIS (Technique for order preference by similarity to an ideal solution) method. The training results analysis of the parameters involved in our research is provided as well as the decision making results evaluation. Compared with the state-of-art methods, our method can provide more accurate results. The architecture and algorithms we provided also can be applied to other kinds of social network based decision-making processes.

Keywords—Social Computing; TOPSIS; Decision Making; Hawks Process; Relationship Strength; User Based Collaborative Filtering

I. INTRODUCTION

The social network has changed individuals' decision-making behaviors greatly. Considering a typical purchasing process, an individual would first ask her/his friends' opinions through social software, then check the comments (rating) of other buyers on web pages, and at last make a decision. As a result, the research on using social network analysis to support collective decision-making process is needed urgently[1]. However, the explosion of social network information creates a wealth of ratings and comments. This makes it difficult for individuals to make decisions, such as consumption decisions, as the individuals don't know which comments are suitable for their own decision. So, it is very important to analyze how to use the information provided by other individuals to improve the efficiency and accuracy of decision making. In addition, in a social

relationship, whether the decisions are better also measured by the interaction influences the decisions created, such as the influences among reference group [2]. Keeping the social relationship such as maintaining the friendship is also an important purpose of individuals. That is why friends' suggestions usually impact individuals significantly. However, friends' relationships are dynamically changed. As a consequence, an accurate dynamical social relationship calculation based decision-making method needs to be provided.

Making decisions based on multiple views (attributes) is a typical group decision-making problem. Usually, it needs group members (reviewers) to give evaluations to different schemes. Techniques for order preference by similarity to an ideal solution (TOPSIS) based methods are often adopted to generate the orders according to the evaluations [3-5]. However, if the number of reviewers is too large, there would be a dimension disaster. In addition, reviewers' interests are somehow different. So, the reviewer filtering or weight calculation is a key point of this kind of problems. Usually, the interaction strength is adopted to generate the friend filter [6-8], however, the impact of the interaction behaviors is difficult to simulate. Another key point is that the existing related algorithms are based on the interaction with trusted friends. However, not all the trusted friends are familiar with the products that the current decision is based on. This results in the decision making to be a sparse problem. As a result, the buyers' ratings need to be integrated into a decision making process. In order to address these challenges, we use friends' suggestions and online buyers' comments, separately. We use social media system to get the individual's relationship, most importantly, the friends are different of the online buyers. As a consequence, friends are independent from the topic and we ask friends to give suggestions directly. In order to address these challenges,

- i. We construct the relationship strength by both personal information similarity and interaction strength to generate the weights of trusted friends as reviewers, as shown in Fig. 1(1-1) and (1-2). The bigger the circle is, the more important the friend is. We exploit the Hawkes point process to simulate

the behavioral impact of the interaction strength, as shown in Fig. 1(2-1).

- ii. Then we filter the online buyers based on their comments within one product with the Singular Value Decomposition (SVD) method [9], and calculate their opinions according to ratings and consumption ranks on the web page, which is represented in Fig. 1(2-2), the ellipse denotes the

online buyers who had similar interests with the individual.

- iii. We model the weights of the trusted friend part and the buyers part by the Gaussian distribution and frequency separately, which are shown in Fig. 1(3-1) and (3-2). We make proper decisions using a TOPSIS based method according to the weights and refresh the weights by the user's decision, which can be found in Fig. 1(4).

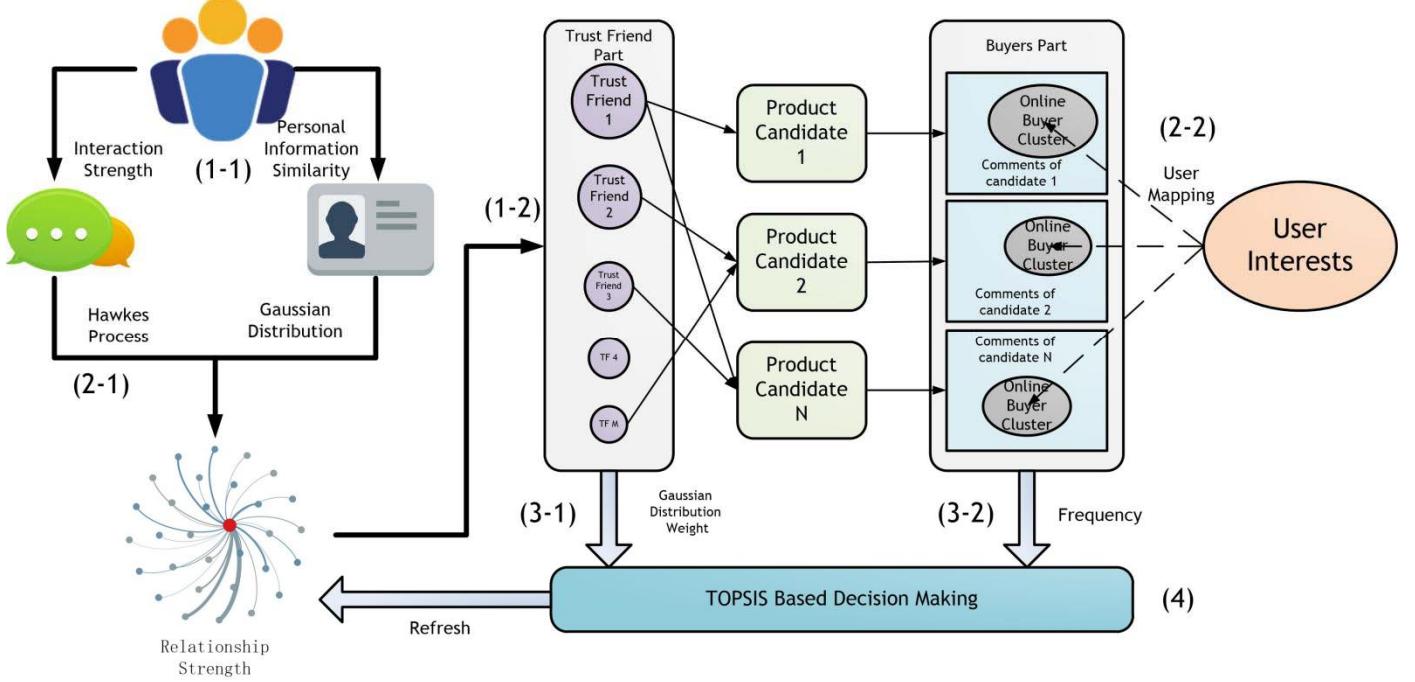


Fig. 1 Processing pipeline

Different from the personal recommendation, our research does not focus on the individuals' experiences, but on finding useful and concise information for individuals from their online friends and helping make decisions. Similar to the trust prediction problem, our approach needs to establish the interaction relationship first; however, we do not make trust prediction but make decisions according to both the trusted friends and online buyers.

Compared with existing methods, our contributions include: (1) making decisions not only according to online buyers but also the trusted friends which is similar to the natural decision making process and helpful for strengthening the social relationship; (2) improving the user based collaborative filtering algorithm with TOPSIS by integrating friends' suggestions so that the sparsity problem could be solved.

This paper is organized as follows: in Section 2 we introduce the related works and compare them with our approach. Section 3 presents the generation loops of the approach. Experiments and discussions appear in Sections 4. Finally, in Section 5 we summarize the main contributions of our paper and discuss possible future works.

II. BACKGROUND

TOPSIS based methods are usually adopted to solve the multi-criteria group decision-making problem [3]. The main concept of this kind of methods is to construct an N dimensional space with N indicators (corresponding attributes or reviewers), so that, according to the value of each indicator of an option, the option can be treated as a point in the N dimensional space. Then using the best indicator values to set the optimal point and worst indicator values to set the worst

point, the option could be evaluated by the weighted distances from the two points to the evaluation point.

Then identifying the weights is critical for this kind of methods. As decision making is based on the trusted friends' suggestions, the relationship strength is adopted to generate weights. The former relationship strength generation algorithm only used static information such as in Panovich's work [6]. Srba [7] weighted multiple user interaction behaviors and analyzed the evolution of the relationship strength. The current interaction behaviors were adopted in Xiang's research [8] to provide a latent factor relationship strength model (LRS). However, the impacts of individuals' past interaction behaviors were not considered. In Xiong's works [9], the co-occurrence of user names was adopted as a useful feature. Here we improve their method by utilizing the Hawkes process [10] to simulate the impact of interactive behaviors to the interaction strength and we believe the co-occurrence of user names is involved in the interaction behaviors.

In the buyer rating filter part, we adopt the SVD method [11] which is a typical principle component analysis method. This method was usually utilized in collaborative filtering and relational learning [12-13] as it can efficiently analyze the contents such as user profiles and micro-blogs. Probabilistic theories were also integrated into SVD, such as DMF and the Bayesian model [14, 15], to improve its performance. However, the sparsity problem needs to be overcome.

In the decision-making area, compared with VIKOR and ELECTRE kinds of methods [17-18], TOPSIS based methods are easier to implement, however, the value of each indicator is hard to quantify from comments. Then the fuzzy theory was adopted to solve this problem in Boran and Zhang's works [4-5]. Fortunately, we do not need to use this kind of complex algorithms, as the comments on the social network are often accompanied by ratings which are quantitative values. But we still need to find out whose ratings should be adopted.

III. DECISION MAKING PROCESS

A. Adopt Hawkes Process to Simulate Interaction Process

It's easy to know that individuals' relationship strengths are affected by the interaction strengths which change dynamically. Hawkes process is a special linear self-excited process formed by the linear superposition of point processes, as shown in Fig. 2. Based on the condition that the probability of the current event, represented as λ_t , is affected by the similar past events, represented as t_i , a relationship is established between

the past events and the current event with weights β_i . In our research, the interaction process of individuals is treated as a point process, as a consequence, the interaction strength can be treated as the probability of a point process and then the Hawkes process can be utilized to calculate the probability.

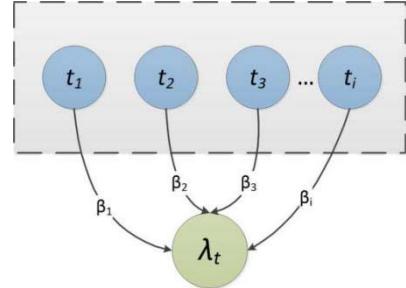


Fig. 2. Hawkes process.

B. Relationship Strength Construction

As shown in Fig. 3, the relationship strength $R(i,j)$, represented as R_t , is the weighted sum of the individuals' interaction strength $I(i,j)$, represented as I_m , and the personal information (PI) similarity $S(i,j)$, represented as S . In our method, the interaction strength $I(i,j)$ is generated by three most important interaction behaviors that are commenting, re-posting and quoting[19]. And $S(i,j)$ is a vector with N elements as the distance of N PI attributes which refer to Xiang's work[8] shown in Table 1.

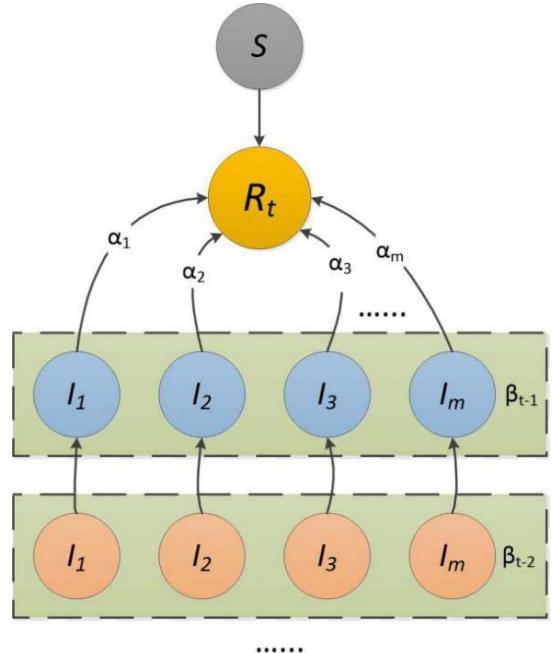


Fig. 3. Interaction similarity and behaviors.

$$I(i,j) = \begin{cases} 1, & \text{mutual interaction} \\ 1/2, & \text{one side interaction} \\ 0, & \text{no interaction} \end{cases} \quad (1)$$

$$S(i,j) = (\|attr_n(i) - attr_n(j)\|), n \in N \quad (2)$$

Table 1. PI attributes

S_1	Same district $S_1=1$, same city $S_1=2/3$, others 0.
S_2	Stu: Same class $S_2=1$, Same college $S_2=2/3$, others 0. Worker: Same room $S_2=1$, same department $S_2=2/3$, others 0.
S_3	Same education background $S_3=1$, adjacent level $S_3=2/3$, 2 level difference $S_3=1/3$, others 0.
S_4	Same sex $S_4=1$, other 0.
S_5	Similarity of personal introduction with cosine distance

Assuming $I(i,j)$ and $S(i,j)$ are independent, the relationship strength $R(i,j)$ can be represented as follows:

$$\begin{aligned} p(R(i,j) | S(i,j), I(i,j)) \\ = p(R(i,j) | S(i,j)) \times p(R(i,j) | I(i,j)) \end{aligned} \quad (3)$$

Inspired by Junchen's work [19], we adopt the Gaussian distribution to represent the similarity distribution and Hawkes process to simulate the interaction process as follows:

$$p(R(i,j) | S(i,j)) = N(\Omega \cdot S(i,j), \sigma^2) \quad (4)$$

$$p(\Omega) \propto e^{-1/2\Omega^T \Omega} \quad (5)$$

$$p(R(i,j) | \sum_{n=1}^{k-1} I(i,j)) = \lambda_0(k) + \sum_{n=1}^{k-1} \sum_{m=1}^M \alpha_m e^{-\beta_m(k-n)} \quad (6)$$

where Ω , to be estimated, denotes the weight vector for $I(i,j)$, σ^2 is the variance and initialized as 0.5, $\lambda_0(k)$ is the basic strength and k is the time period, β_m denotes the decay coefficient and α_m means the weight of behavior m . α_m and β_m can be estimated by the maximum likelihood estimation [10]. Then probability of $p(R(i,j) | S(i,j))$ is represented as $\varphi(i,j)$:

$$\varphi(i,j) = \prod \exp\left(-\frac{1}{2\delta^2}(\Omega^T \cdot S(i,j) - R(i,j))^2\right) \quad (7)$$

The ln-likelihood of $\varphi(i,j)$ would be:

$$\ln(\varphi) = \sum \left(-\frac{1}{2\delta^2}(\Omega^T \cdot S(i,j) - R(i,j))^2\right) \quad (8)$$

Set $\lambda(k) = \lambda_0(k) + \sum_{n=1}^{k-1} \sum_{m=1}^M \alpha_m e^{-\beta_m(k-n)}$, then deriving from reference [20], ln-likelihood of probability for $\lambda(k)$ is represent as:

$$\ln(\lambda) = \sum_{i=1}^n \ln(\lambda(t_i)) - \int_0^T \lambda(t) dt \quad (9)$$

Let's take partial derivative to a , β and Ω using the Newton-Raphson method and set formula (10). Then the parameters could be calculated. And the weights of friends as reviewers can be generated directly from the relationship strength.

$$\begin{cases} \frac{d\lambda(t)}{d\alpha} = 0, \frac{d\lambda(t)}{d\beta} = 0 \\ \frac{d \ln(\varphi)}{d\Omega} = 0 \end{cases} \quad (10)$$

C. Online Buyers Filtering

After getting the weights of individuals' friends, we need to filter the online buyers by their comments. Here we adopt the user based CF and user comments to generate user preference. We firstly make a clustering analysis to the buyer comment keyword vectors through SVD, then map a user into the cluster space by checking the similarity between the individual and buyers by the individual's interest keyword vector, and at last select the nearest buyers as the experts. We manually choose the common user interest points as the initial keyword vector. We assume that users who have the similar interests would have similar comment keywords. Let A be the matrix composed of buyers' comment keyword vectors such that the row represents whose comments the keyword appears in and the column indicates which keywords appear in the buyer's comments, as shown in table 2.

Table 2. Matrix to be decomposed

Keywords	Buyer1	Buyer2	Buyer3	...	BuyerN
price	1				1
quality		1			
looks			1		
brand		1	1		
function	1		1		

Then we can make clustering according to the comment keywords with formula (11).

$$A_{m \times n} = K_{m \times r} \Sigma_{r \times r} B_{r \times n}^T \quad (11)$$

$$\tilde{B} = \{b_i \mid S(i, b_i) < \sigma, i \leq n\} \quad (12)$$

Where $K_{m \times r}$ is a matrix that contains m rows r -dimensional vectors and these vectors denote the positions of keywords in cluster space. Σ is the singular value matrix. $B_{r \times n}$ contains n columns r -dimensional vectors which can be treated as the positions of buyers in the cluster space. Then r is the number of singular values and also is the cluster space dimension. Consequently, it is very important for reducing computing consumption and is usually set to be 3. After mapping individual's interests keyword vector into the cluster space, $S()$ denotes the Euclidean distance from the individual i to buyer b_i . σ is the threshold, here we set 0.1. \tilde{B} denotes the buyer cluster we adopt. Then the weighted sum of the ratings of buyer clusters in \tilde{B} can generate the general buyer rating. Buyer rating for all the product candidates could be calculated in this way.

D. Weight Setting

For the trusted friends and online buyers views, we need to set their weights w_f and w_e .

$$\sum_{i=1}^M w_f^i + \sum_{j=1}^N w_e^j = 1 \quad (13)$$

where M is the number of friends and N is the number of online buyer groups (equal to the number of product candidates). As the individual could either adopt the trusted friends' opinion or not, according to the law of large numbers as shown in (14), we adopt frequency w_f^* to estimate the probability distribution of w_f ,

$$\lim_{n \rightarrow \infty} P\left\{ \left| \frac{k}{n} - p \right| < \varepsilon \right\} = 1 \quad (14)$$

$$w_f^* = \frac{1}{M} \sum_{i=1}^M x_i \quad (15)$$

where $x_i=1$ when an individual adopts the trusted friends' suggestion, otherwise, $x_i=0$. When the total weight of friends w_f is generated, w_f^i is easy to get according to the interaction strength. Let every candidate has the same weight, then:

$$w_e^j = w_e / N = (1 - w_f) / N \quad (16)$$

E. TOPSIS Based Decision Making

TOPSIS based methods are usually adopted to solve multiple criteria decision making problems. In our case, the decision making matrix consists of trusted friends'

opinions (TFs) and general buyer ratings (GBRs). Note that one trusted friends can give more than one suggestions and these suggestion strengths are measured as weak 0.4, normal 0.7 and strong 1.0. In addition, the number of online buyer ratings is equal to the number of the product candidates (PC) and each GBR has only one rating value, as we cluster the users of each product candidate as online buyers and generate the cluster's rating for each product candidate. It's easy to observe that the optimal product should have the attribute vector with all elements equal to 1. We calculate the weighted distances from each PC to optimal product $D_{optimal}$ and the worst product D_{worst} . Then, the candidate can be evaluated with the following formula:

$$B = \frac{D_{optimal}}{D_{optimal} + D_{worst}} \quad (17)$$

According to B , we can get the preference. As we utilize both trusted friend suggestions and online buyer ratings, the sparsity problem is solved as long as either the friends give one suggestion or the buyers give their ratings.

F. Weights Update

After individual's giving a decision, we can refresh the weights of trusted friends w_f and online buyers w_e by formula (15). M denotes the decision times. Let x_i be the decision. $x_i=1$ when an individual choose friends' recommendations which means he or she does not choose the top GBR product, while $x_i=0$ in the opposite case. $x_i=0.5$ when an individual choose neither the top GBR nor the top friend recommended product, or the product is recommended by both GBR and trusted friends.

IV. SIMULATION RESULTS & ANALYSIS

A. For the relationship strength generation.

As we need to compare the strength generation result with the ground truth which is subjectively evaluated by users and no such data are available currently, then we crawl user data from three widely used social networks, Twitter, Facebook and QQ to test the algorithm. We use the computer with I7 CPU and 8G memory to train the parameters α and β . Fig. 4 shows a training example. The top image is derived from QQ user interaction data for 30 days about 32k and divided into 60 parts. For the purpose of showing the parameter impact, we eliminate comment data from the first five days, re-posting data from the second five days, quoting data from the third five days, and all the data from fifth

five days. Then we ask users to evaluate the relationship part by part without considering the eliminated interactions. For example, we ask them if you did not write comments in the first five days, then please rate your relationship. The bottom left shows the results of the β evaluation, in which we adopt 5 days, 15 days until

30 days as the time period and 24 hours and 48 hours as the time step. It can be clearly seen from the figure that the comment impact decays slower than the other two behaviors; the smaller β is the slower it decays. Besides, although we use different days as the time period to train the parameters, the values vibrate in a certain range.

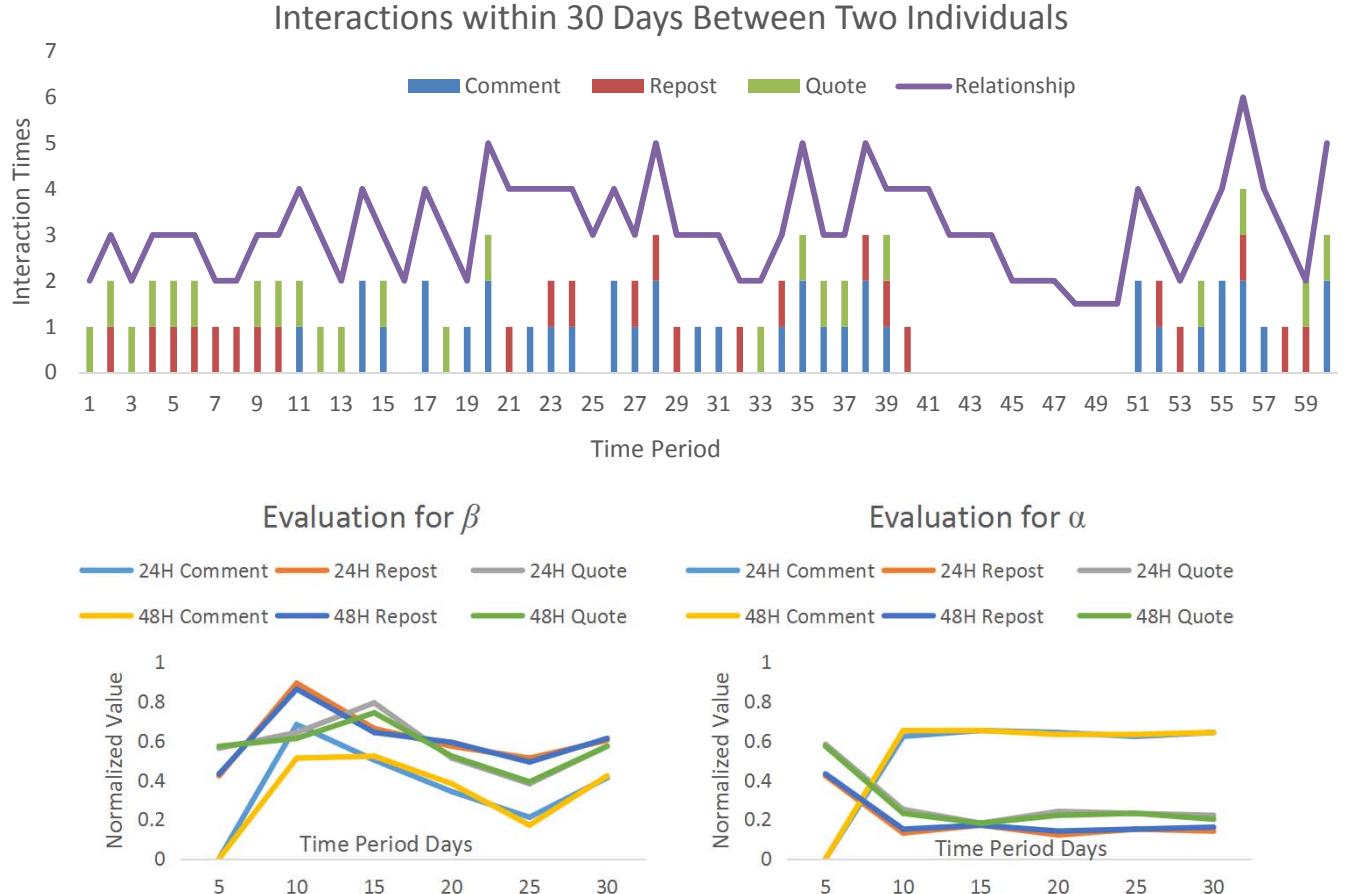


Fig. 4. The parameter training results.

As a consequence, we can draw the conclusion that the interactions between two individuals are stable. When the interactive data change significantly the user rating is still above 1.5, such as in the fifth five days. And this makes the β of each behavior smaller. When using 48 hours and the time step, the curves are smoother than the 24 hours curves. The bottom right figure shows the α evaluation. It is easy to know that the weight of comment is bigger than the quoting weight, and the quoting weight is bigger than the re-posting weight, such as the average of the second five day relationship is bigger than the average of the first five day relationship, and the average of the third five day relationship is bigger than the average of the second five day relationship. Although the data are eliminated from the fifth five days, the relationship remains, such that, the

weights of each behavior do not change too much compared with third five days. From these three figures we can find that, because of the stability of interactive parameters, the 30 days are suitable as the time period to generate the relationship strength.

According to Table 1, we can calculate the values of $S(i,j)$, and then the parameter Ω is relatively easier to be estimated by the MLE method with the Gaussian distribution. The normalized vector in this case is (0.1, 0.35, 0.3, 0.05, 0.2).

Individuals' average evaluation to relationship strength algorithms is shown in Fig. 5, where we randomly select 45 users without the background knowledge from 3 groups in terms of age. Each group

contains 5 Twitter users, 5 Facebook users, and 5 QQ users. Users give their strength ratings to their online friends. We also generate the strength graph by the Xiang's method, Panovich's method, Xiong's method and ours. We set 20 nodes, which means we generate 19 friends' relationship strengths with the individual. The time period is during 2016 July 15th to 2017 Jan 15th and we use one month to train the parameters. We adopt mean absolute error (MAE) to evaluate the performance. From these images, we can see that the errors of Panovich's method are big especially in calculating the relationship with seldom contacted friends. Xiang's method is better than Panovich's as they take friends' static information into consideration. Xiong's method is even better than Xiang's because they integrate the dynamic interaction behavior and co-occurrence of user names, however, they do not distinguish the differences among different behaviors. Furthermore, Xiong's method focuses on generating the strength graph for all the users involved in the circle, while ours focuses on constructing the star graph. For teenage and twenties, the Xiang's method is better than the Panovich's, as Xiang took the dynamic interaction into consideration. However, as some thirties do not use social softer ware frequently, static information impacts more than dynamic interactions, so the Xiong's and Panovich's methods are relatively better.

User Evaluation for Strength



Fig. 5. User evaluation for relationship strength by average accuracy of each method.

B. For the buyer filter part.

We adopt comments in Epinion and comments in Amazon including 548,552 nodes from SNAP [21]. We cluster the comments and keywords and map the clusters to the two-dimensional space. Then we also can map individuals into the two-dimensional space by their interest keywords. Furthermore, it is easy to select similar buyers by calculating Euclidean distances from the two-dimensional mapping space.

C. For the option preference providing part.

Compared with Luo [12], Zhang [14], and Hernando [15], we exploit trusted friend suggestions based on the online review data so that the option preference can be generated without buyer ratings. We select 5 typical social recommended systems [22-26], including user based CF systems using matrix factorization or factorization machines which are similar to our method to generate a sequence of 5 products. And compare these with our method, using normalized distance-based performance measure (NDMP) [27] and rank-based precision (RBP) [28] evaluation metrics. The average of 50 comparison results on Amazon data set [21] can be found in table 3. When calculating RBP, the probability is set as 0.5. Compared with the other social recommendation algorithms, the use of Hawks process can generate more accurate interactive relationship prediction and is more in line with the user habits. Furthermore, we adopt the way that friends directly recommend products to solve the cold start problem.

Table 3. Recommended system comparison

	Ours	Ma	Noel	Yang	Rendle	Liang
NDMP	0.22	0.44	0.45	0.37	0.38	0.29
RBP	0.93	0.73	0.75	0.72	0.88	0.89

V. CONCLUSION

An online shopping based decision-making method in a social network environment is provided in our paper. This method can generate preferences to purchasing options according to both friends suggestions and buyers ratings, which is different from the typical recommendation system. Consequently, the sparsity problem can be overcome as long as either the friends have suggestions or online buyers have ratings. However, when the friends did not give suggestions, our algorithm became a user based collaborative filtering algorithm. Then the social relationships play important role in decision making. The dynamic user interaction and personal information are simulated by the Hawks process for generating the relationship strength as the user weights, furthermore, the buyer ratings are filtering by the SVD method for improving the rating accuracy according to user interests. However, if the buyer comments are too few to filter the buyers, then the general buyer ratings become the average ratings. In addition, for some newly sold product without reviews, the friend suggestions will impact the decision independently. Besides, user interactions do not always

reflect the user relationship strength, most important, the ground truths are generated by the user themselves. Then how to establish the ground truth in a more scientific and systematic way and enhance the accuracy for predicting the relationship should be our future works.

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REFERENCES

- [1] Jannach D, Adomavicius G. Recommendations with a Purpose[C]// ACM Conference on Recommender Systems. ACM, 2016:7-10.
- [2] Wu J, Xiong R, Chiclana F. Uninorm trust propagation and aggregation methods for group decision making in social network with four tuple information[J]. Knowledge-Based Systems, 2016, 96(2):29-39.
- [3] Lourenzutti R, Krohling R A. A generalized TOPSIS method for group decision making with heterogeneous information in a dynamic environment[J]. Information Sciences, 2016, 330:1-18.
- [4] Boran F E, Genç S, Kurt M, et al. A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method[J]. Expert Systems with Applications, 2009, 36(8):11363-11368.
- [5] Zhang X, Xu Z. Extension of TOPSIS to Multiple Criteria Decision Making with Pythagorean Fuzzy Sets[J]. International Journal of Intelligent Systems, 2014, 29(12):1061-1078.
- [6] Panovich, K., Miller, R., and Karger, D. Tie strength in question & answer on social network sites. Proc. of CSCW, ACM (2012), 1057-1066.
- [7] Srba I, Bielikova M. Tracing Strength of Relationships in Social Networks[C]//International Conference on Web Intelligence and Intelligent Agent Technology. IEEE, 2010:13-16.
- [8] Xiang R, Neville J, Rogati M. Modeling relationship strength in online social networks[C]// International Conference on World Wide Web, WWW 2010, Raleigh, North Carolina, USA, April. DBLP, 2010:981-990.
- [9] Xiong L, Lei Y, Huang W, et al. An estimation model for social relationship strength based on users' profiles, co-occurrence and interaction activities[J]. Neurocomputing, 2016, 214:927-934.
- [10] Ozaki T. Maximum likelihood estimation of Hawkes' self-exciting point processes[J]. Annals of the Institute of Statistical Mathematics, 1979, 31(1):145-155.
- [11] Shlens J. A Tutorial on Principal Component Analysis[J]. Eprint Arxiv, 2014, 51(3):219-226.
- [12] Luo X, Zhou M, Xia Y, et al. An Efficient Non-Negative Matrix-Factorization-Based Approach to Collaborative Filtering for Recommender Systems[J]. IEEE Transactions on Industrial Informatics, 2014, 10(2):1273-1284.
- [13] Singh A P, Kumar G, Gupta R. Relational learning via collective matrix factorization[C]// ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Las Vegas, Nevada, USA, August. 2008:650-658.
- [14] Zhang Z, Liu Y, Xu G, et al. Recommendation using DMF-based fine tuning method[J]. Journal of Intelligent Information Systems, 2016:1-14.
- [15] Hernando A, Bobadilla J, Ortega F. A non negative matrix factorization for collaborative filtering recommender systems based on a Bayesian probabilistic model[J]. Knowledge-Based Systems, 2016, 97(C):188-202.
- [16] Allen S M, Chorley M J, Colombo G B, et al. Exploiting user interest similarity and social links for micro-blog forwarding in mobile opportunistic networks[J]. Pervasive & Mobile Computing, 2011, 11(2):106-131.
- [17] Devi K, Yadav S P. A multicriteria intuitionistic fuzzy group decision making for plant location selection with ELECTRE method[J]. The International Journal of Advanced Manufacturing Technology, 2013, 66(9):1219-1229.
- [18] Roostaei R, Izadikhah M, Lotfi F H, et al. A Multi-Criteria Intuitionistic Fuzzy Group Decision Making Method for Supplier Selection with VIKOR Method[J]. International Journal of Fuzzy System Applications, 2012, 2(1):1-17.
- [19] Sumeng D. Study on Individual Interaction Behavior and Evolutionary Mode in Social Networks [D]. Beijing Jiaotong University, 2016.
- [20] Juncen L, Sheng G, Yu Z, et al. Inferring links in cascade through hawkes process based diffusion model[C]// IEEE International Conference on Network Infrastructure and Digital Content. IEEE, 2014:471-475.
- [21] Leskovec J and and Sosic R. SNAP: A General-Purpose Network Analysis and Graph-Mining Library[J]. ACM Transactions on Intelligent Systems and Technology (TIST), 2016, 8(1):1.
- [22] Ma H, King I, Lyu M R. Learning to recommend with social trust ensemble[C]// International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2009:203-210.
- [23] Noel J, Sanner S, Tran K N, et al. New objective functions for social collaborative filtering[M]. ACM, 2012.
- [24] Yang X, Steck H, Guo Y, et al. On top-k recommendation using social networks[C]// ACM Conference on Recommender Systems. ACM, 2012:67-74.
- [25] Liang D, Altosaar J, Charlin L, et al. Factorization Meets the Item Embedding: Regularizing Matrix Factorization with Item Co-occurrence[C]// ACM Conference on Recommender Systems. ACM, 2016:59-66.
- [26] Rendle S. Social network and click-through prediction with factorization machines[J]. KDD, 2012.
- [27] Yao Y Y. Measuring retrieval effectiveness based on user preference of documents[J]. Journal of the Association for Information Science and Technology, 1995, 46(2):133-145.
- [28] Moffat A, Zobel J. Rank-biased precision for measurement of retrieval effectiveness[J]. Acm Transactions on Information Systems, 2008, 27(1):2.