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Cluster Analysis Research on Consumers' Perceived Recommendation Trust

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Abstract

Emerging social commerce relies on social media and is a new growth point for the development of e-commerce. However, it is difficult to cluster the recommendation information to reflect the subjectivity of consumers and the relationship between subjects. This paper constructs a clustering method based on consumer perception recommendation trust in the context of large-scale social networks and improves on subjective logic methods. Integrate trust characteristics into subjective logic trust transfer algorithm. Transform objective recommendation information into consumer subjective and differentiated perceived trust. Extract the similarity of perceptual recommendation trust and relationship intimacy from social networks to generate a normal matrix, and divide it by the method of spectral halving. A consumer perception trust network is extracted from social networks, a clustering method for consumer perception trust in social business is proposed from the perspective of complex network division, and a clustering center identification and update mechanism is designed for the high dynamic characteristics of social networks. The experimental results prove that: social business merchants and platforms quickly identify consumer perception of trust orientation, and provide methodological support for merchants to formulate trust-based precision marketing strategies for social business.

Keywords: *Social business, Perceived trust, Recommendation information, Clustering method*

1. Introduction

Emerging social commerce is based on social media [1][2]. It has just started but is booming with rapid momentum, becoming a new growth point in the development of e-commerce. However, due to the virtuality and high risk of online transactions, a trust crisis has always been a problem that plagues online transactions. The social relationship and interactivity between subjects in social commerce is an important difference between social commerce and e-commerce. In social commerce, Online Word-of-Mouth (Online Word-of-Mouth) has become the main way for consumers to build trust [3]. Compared with traditional e-commerce, consumers' perception of trust is more dependent on user-generated content as a carrier. Recommended by others [4]. For social commerce platforms, how to predict consumers' perceived trust based on these recommendations is the primary issue in formulating precision marketing strategies [5]. For example, a social commerce platform recommends a debugging-free hearing aid for a consumer based on his browsing history. There is a wide range of hearing

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aids sold by various brands and different businesses on the platform, and there are also many user-experienced generated content about the hearing aid. According to the content of the recommended information and the intimacy between the information publisher, that is, the recommender and the consumer, it is possible to predict the perceived trust that consumers may have in different businesses and various types of hearing aids, to provide consumers with accurate recommendations and promote them. purchase behavior. This is significantly different from the traditional e-commerce recommendation strategy based on the similarity of consumers' browsing products and the reputation of merchants, and it is a new problem faced by social commerce platforms.

Clustering a large number of user-generated content is an effective way to solve this problem, but the clustering method cannot reflect the structure of social networks, and it is difficult to reflect the influence of online social relationships on consumer perception and trust. This is a unique background belt of social commerce. New questions coming. A series of characteristics of social commerce also pose new challenges to the clustering method:

(1) The high interaction characteristics of social commerce: the interpersonal relationship of social networks significantly affects consumers' perceived trust [6], which is also social commerce. An important source of consumer perception trust in China, clustering methods represented by K-means, K-center, and neural network algorithms can only cluster recommended information, but cannot integrate the intimacy of inter-subject relationships, causing clustering difficulties.

(2) The personalization of consumers in social commerce is significant: The formation of consumer perceived trust is highly subjective. Different consumers may have different perceived trust for the same recommendation information. How to describe the subjective perception of consumer trust It is difficult to accurately analyze consumers' perceived trust and formulate precision marketing strategies.

(3) The scale of social networks is huge, and user-generated content is quantified: A large number of new user-generated content appears in social networks at all times, and its real-time and dynamic characteristics further deepen the complexity of the problem.

Therefore, the essential problem to be solved in this paper is "the clustering problem of the relationship-oriented perception recommendation trust considering the differences of consumers". The two difficult issues are: First, how to characterize consumers' subjective perception of trust. Second, how to integrate the differences of consumers. Third, how the social network structure clusters the perceived recommendation trust. Aiming at the above difficult problems, this paper will consider the perceptual recommendation trust clustering problem of the network structure and transform it into a composite network partition problem, using subjective logic methods to describe consumers' subjective perceptual trust, and introducing trust tendency coefficient adjustments to improve subjective logic methods to calculate consumers Differentiated perceptual recommendation trust combines the relationship strength network with the perceptual recommendation trust similarity network, and divides the composite network using the spectrum halving method, and builds a clustering method of consumer perception trust from the perspective of complex networks. Finally, according to the highly dynamic characteristics of the network, a clustering comprehensive opinion space calculation and update strategy is proposed.

Establishing trust through word of mouth is a typical trust transmission problem. The trust transfer model originated from the field of computer network security. The subjective logic method is the classic method of trust transfer calculation in this field. However, its research subject is computer network nodes and does not consider human subjectivity and difference [7], so it is difficult to apply to subjects' human social business background. Therefore, the two key issues to be solved in this paper are: (1) The calculation of consumer heterogeneous perception trust. (2) The generation and division of composite networks. The specific research methods are as follows: (1) Introduce the trust tendency coefficient to improve the subjective logic method, so that it can reflect the heterogeneity of consumers, expand the application range of subjective logic method, and propose new descriptions and measures for consumers' perception of recommendation trust method. (2) The normal matrix-based spectral bisector method is used to divide the network. This method does not need to specify the cluster center or the number of clusters in advance, and the result of the division is more accurate and objective. The normal matrix generation is the primary problem that this method needs to solve. In this paper, an improved subjective logic method is used to calculate the heterogeneous perceptual recommendation trust, and the perceptual recommendation trust similarity and relationship intimacy are combined to generate a composite network. On this basis, a normal matrix is generated and further divided to provide a composite network partition new idea.

2. Theoretical basis

2.1. The key influencing factors of consumer perception of trust in social commerce

With the rise of social commerce, the issue of consumer trust in social commerce has attracted widespread attention from scholars at home and abroad [8]. Because of the virtual nature of transactions, consumers' perceived risks are high, and trust is particularly important for social commerce businesses. Social commerce is built based on social networks. The relationship between people and word-of-mouth behavior are important differences between social commerce and traditional e-commerce, and it is an important factor in consumers' perception of trust. Sanghyun Kim [9] analyzed the influence of social commerce characteristics on consumers' perceived trust, and the influence of trust perception on purchase intention and word-of-mouth intention, which proved through empirical analysis Information quality, transaction security, human-to-human communication, and word-of-mouth referrals are key influencing factors that affect consumers' perceived trust, and perceived trust significantly affects consumer purchases and word-of-mouth referrals Intent. Mahamood Hajli [10] researched the adoption of social commerce. Based on the TAM model, he added consumer-specific user-generated content and interactive behaviors in social networks, proving that relationship-based recommendation, introduction, and perceived usefulness affect consumption. Consumers perceive the key influencing factors of trust, and trust further promotes the formation of consumers' purchase intentions. Scholars such as Jacob Weisberg [11] used social presence as an intermediary variable to study the relationship between purchase experience and purchase intention, proving the positive influence of perceived trust on purchase intention.

Relationship intimacy is an important indicator to measure the influence of recommended information [12]. There are a large number of real-time updated user-generated content in social networks, and the recommendation information provided by friends of different intimacy levels often has different effects on consumers. The results of the past research conducted by word-of-mouth show that the more intimate the relationship plays in the recommendation process, the more obvious the role, the more intimate the relationship, the more people feel at ease and reliable [13], which is easier to promote the formation of trust transmission [14]. And the recommendation information obtained through the relationship with high intimacy has a greater impact on the purchase decision of consumers [15]. According to the relevant research conclusions of complex networks, relationships breed similarity [16], indicating that relationships play an important role in the judgment of recognition and similarity between subjects.

Consumers forming subjective perception trust based on the recommendation information in social networks is a complex psychological process. For the same recommendation information, different consumers often have different perceptions of trust [17]. Compared with traditional e-commerce, the information obtained by consumers in social commerce is more comprehensive, and the influencing factors of perceived trust are more complex than in traditional e-commerce, so it has strong subjectivity and different characteristics. The fundamental reason for the differentiation of perceived trust is the unique trust tendency of the subject [18][19]. The formation of trust tendencies is often determined by the subject's experience, personality, and other factors, and is a unique personality trait of the subject. This personal trait can be characterized by two dimensions: trust disposition and distrust disposition [17][20]: People with high trust tend to believe in others and things, but have high distrust tendencies. On the contrary, the two tendencies can significantly reduce the uncertainty of the subject's perception of trust.

Consumer trust in social commerce has become a research hotspot for scholars at home and abroad. A large number of studies have been conducted around the formation of consumer perceived trust and the relationship between perceived trust and transaction decisions. A large number of empirical studies have shown that consumers' perceived trust is the prerequisite for transaction decision-making in the context of social commerce, and consumers' trust tendencies are the characteristics of the subject itself, which play a decisive role in the formation of perceived trust. The intimacy between subjects is the key factor that affects the importance of recommended information, and it plays a moderating role in the judgment of similarity between subjects.

2.2. Subjective logic method

The subjective logic method (Trust Network Analysis with Subjective Logic, TNA-SL) [21] is often used in the research of trust transfer in the network. The research of trust transfer originated in the research field of P2P network security and is used for computing distributed networks without a central processing mechanism. The credibility of the mid-node. The subjective logic method expresses the subject's trust in the opinion space and adds the dimension of "uncertainty" to portray the ambiguity of people's subjective consciousness [22], breaking the traditional expression method that only has two dimensions of trust and distrust, and is closer to people's thinking. Way. This method uses opinion space triples $\omega = \{a，d，u\}$ to represent consumers' perceived trust, where b represents trust belief, d represents distrust belief, and u represents perceived distrust. Uncertainty, and $b + d + u = 1$. The method consists of two main parts. One is the calculation of trust transfer between subjects, which is an iterative calculation method of trust transfer between multiple subjects on a trust chain, and the second is the trust fusion calculation on multiple recommended paths.

2.3. Related research on clustering methods and network partitioning methods

Due to the large scale of social networks, dynamic and complex characteristics, the high-quantity characteristics of recommended information are prominent, and clustering of recommended information is one of the ways to solve this problem. Scholars at home and abroad have conducted a lot of research on clustering methods. Common clustering methods include heuristic K-means algorithm, K-center point algorithm, neural network algorithm, and so on. However, merely clustering information does not reflect the trust relationship between people in social commerce, and it breaks away from the background of social commerce. The complex network division method starts with the network structure and divides the network graph into clusters, which can preserve the interpersonal relationships in social networks, and is more suitable for social business backgrounds. The spectrum bisection method is one of the common methods for complex network division.

Most of the spectral halving methods require the number of communities to be specified in advance, and the accuracy of the number of communities specified in advance seriously restricts the accuracy of clustering. Capocci proposes a normal matrix-based spectral halving method based on the spectrum halving method, which divides the nodes in the network into multiple clusters by calculating the eigenvector of the matrix. This method does not need to specify the number of clusters in advance, and the division of clusters is more objective and accurate. Among them, the construction of the Normal matrix is the research focus of the spectrum halving method.

The spectrum bisector method can be clustered and divided from the perspective of network structure, but in social commerce, word of mouth among consumers is the prerequisite to promoting the formation of perceived trust. The spectrum bisector method cannot incorporate recommendation information while dividing the network structure. How to integrate the characteristics of the subject, the recommendation information, and the relationship between the subjects to construct the Normal matrix is the key problem to solve the consumer perception and trust clustering in social commerce.

Clustering consumer perception trust in social networks can help businesses analyze the orientation of consumers' perception of trust and formulate relevant marketing strategies accordingly. It can also meet the large-scale and highly dynamic characteristics of social networks, but it is difficult to integrate the network structure. The problem of difficult integration of information and recommended information. Consumers' perception of trust is highly subjective, and individual differentiation is significant, which further deepens the complexity of the problem. In the context of emerging social commerce, the clustering of perceived recommendation trust is a new problem faced by social commerce merchants, and it is also an important development direction for the research on the perceived trust of social commerce consumers.

Perceived recommendation trust is the subjective feeling produced by consumers based on the recommendation information of others, which has the characteristics of vagueness and uncertainty. The subjective logic method abstracts perceived trust into trust beliefs, distrust beliefs, and perceived uncertainty, which can well reflect the ambiguity and uncertainty of consumer perception, and is therefore very suitable for the expression of perceived trust, and the relationship between subjects is close. The degree is not only the carrier of trust transmission but also regulates the judgment of similarity between subjects. Therefore, this paper combines the subjective logic method with the normal matrix-based spectrum halving method to construct a perceptual recommendation trust clustering method. First, add the consumer trust propensity coefficient to improve the subjective logic calculation method to calculate the consumer's differentiated perceived recommendation trust; then, use the frequency of interaction to measure the strength of the relationship between recommenders, and adjust the perceived recommendation trust similarity, thereby the similarity of perceived recommendation trust is combined with the relationship intimacy network, then the normal matrix is constructed, and the spectrum halving method is applied to cluster the network, to integrate the relationship between subjects and the recommendation of others at the same time, and on this basis, the perception Recommend trust for clustering; Finally, due to the highly dynamic nature of social networks, this paper proposes a method for identifying cluster centers and an update strategy for clustering centers based on the high dynamic characteristics of the network.

3. Clustering method of consumer perception of recommendation trust

Online word of mouth is the main way for consumers to establish perceived trust in social networks. The establishment of differentiated perceived recommendation trust by consumers based on the recommendation information in social networks has transformed objective to subjective. This paper first calculates the consumer's perceived recommendation trust based on the recommender's trust tendency, then combines the perceived recommendation trust similarity with social networks, extracts the similarity and intimacy network, and finally considers the consumer's herd mentality to gather the perceived recommendation trust. kind.

3.1. Calculation of consumer perception of recommendation trust in social commerce

The main body that provides recommendation information in the social network is the recommender, and the decision-making body is called the consumer. Consumers subjectively process the recommendation information and establish perceived recommendation trust based on the recommendation information of the recommender, the degree of trust in the recommender, and their trust tendency.

Definition 1. Suppose there are n online social relationships between recommenders and consumers in the network, and the recommended information provided by the recommenders expresses the subject's opinion on whether the goods or services that have been purchased are credible, and abstract it as an opinion space 3. Tuple $\omega_i = \{b_i, d_i, u_i\}, i \in [1, n]$, where b_i is trust belief, d_i represents distrust belief, u_i represents the uncertainty of perception, then: $b_i + d_i + u_i = 1, 0 \leq b_i, d_i, u_i \leq 1$.

Definition 2. Suppose the consumer's trust opinion space for the recommender is $\xi_i = \{t_i, g_i, h_i\}, i \in [1, n]$, where t_i represents the consumer's belief in the i-th recommender, and g_i represents distrust Belief, h_i represents uncertainty, there are: $t_i + g_i + h_i = 1, 0 \leq t_i, g_i, h_i \leq 1$.

Definition 3. Suppose the consumer's trust tendency coefficient is δ, and $\delta \in (-1,1)$ When $\delta < 0$, it means that the consumer has a distrust tendency, and when $\delta > 0$, it means that the consumer has a trust tendency. δ can be characterized by the deviation degree of the transaction evaluation in the past transaction records. Let the consumer have k transaction records on a shopping website, where the evaluation value of the rth transaction is p_r, and all the goods purchased on the rth exchange the average customer's total evaluation value is p, then the perceived trust tendency coefficient δ is:

$$\delta = \frac{1}{k}\sum_{r=1}^{k} \frac{p_r - \overleftarrow{\overline{p}}_r}{\overleftarrow{\overline{p}}_r} \tag{1}$$

Calculating the trust tendency coefficient of consumers based on the evaluation deviation degree of past multiple transaction records can more objectively describe the subjective trust tendency of consumers. If the evaluation given by the consumer in the past multiple transaction records is often higher than the average evaluation value, it indicates that the consumer has a tendency to trust, $\delta \in (0，1)$, and if the consumer's evaluation is often lower than the average evaluation value, it means consumption People tend to distrust, with $\delta \in (-1, 0)$. When $\delta = 0$, it means that consumers have no obvious trust tendency.

Definition 4. Suppose that the perceptual trust opinion space that consumers want to establish based on the recommendation letter of recommender i is $TR_i = \{\alpha_i, \beta_i, \gamma_i\}$,$i \in [1, n]$, where α_i represents the direction of perception of trust, β_i represents Do not believe in any direction, γ_i represents uncertainty.

Incorporating consumer trust tendencies into the subjective logic transfer calculation method, the improved perceived recommendation trust value is:

$$TR_i = \{\alpha_i, \beta_i, \gamma_i\} = \xi_i \times \omega_i \tag{2}$$

When $\delta \geq 0$, consumers tend to trust and are optimistic about others' recommendations, and the perceived recommendation trust opinion space is:

$$\begin{cases} \alpha_i = t_i(b_i + \delta u_i) \\ \beta_i = t_i d_i \\ \gamma_i = g_i + h_i + (1 - \delta) t_i u_i \end{cases} \tag{3}$$

When $\delta < 0$, consumers tend to distrust, and they have a negative attitude toward others' recommendations. The perceived recommendation trust opinion space is:

$$\begin{cases} \alpha_i = t_i b_i \\ \beta_i = t_i(d_i - \delta u_i) \\ \gamma_i = g_i + h_i + (1 + \delta) t_i u_i \end{cases} \tag{4}$$

Use the trust propensity coefficient to adjust the perceptual trust opinion space TR_i, and when $\delta \in (0,1)$, the belief in the perceptual trust opinion space increases to the value of α_i, and the unbelief arbitrary to β_i decreases correspondingly, while the uncertainty remains unchanged γ_i, when $\delta \in (-1,0)$, the perceptual trust opinion space is adjusted backward, and when $\delta = 0$, the formula (2) degenerates to the subjective logic trust transfer calculation method.

3.2. Perceptual recommendation trust clustering method based on spectrum bisector method

Extract the similarity network of perceived recommendation trust from social networks, and modify the network with the strength of the inter-subject relationship, thereby fusing the perceived recommendation trust of the subject with the inter-subject relationship, and on this basis, generate a normal matrix and divide the network using the spectrum halving method.

(1) Perception recommendation trust similarity network extraction

Taking the subject's perceptual recommendation trust as the node, and the similarity between perceptual recommendation trust as the edge, the perceptual recommendation trust similarity network is extracted from the social network.

Definition 5 Suppose the similarity between any two-perception recommendation trust three-dimensional vectors TR_i and TR_j is sr_{ij}, and the cosine angle value is used to measure the similarity of the perception recommendation trust three-dimensional opinion space sr_{ij}:

$$sr_{ij} = cos\,\theta_{ij} = \frac{\alpha_i\alpha_j + \beta_i\beta_j + \gamma_i\gamma_j}{\sqrt{\alpha_i^2 + \beta_i^2 + \gamma_i^2}\sqrt{\alpha_j^2 + \beta_j^2 + \gamma_j^2}} \tag{5}$$

The perceptual recommendation trust similarity matrix is obtained as SR:

$$SR = \begin{pmatrix} 1 & sr_{12} & sr_{13} & \cdots & sr_{1n} \\ & 1 & sr_{23} & \cdots & sr_{2n} \\ & & 1 & \cdots & sr_{3n} \\ & & & O & M \\ & & & & 1 \end{pmatrix} \tag{6}$$

(2) Extraction of similarity and relationship intimacy network

Therefore, this paper uses the frequency of communication to measure the strength of the relationship between recommenders and modifies the perceptual recommendation trust similarity matrix SR accordingly.

Definition 6 Let the social network formed by all recommenders be the weighted network $G =< V, E >$, the edge weight φ_{ij} is the number of interactions between subjects in the social network. Then the adjacency matrix of the weighted network G is a dimensional symmetric matrix,$n = |V|$. The number of non-zero elements in the matrix is |E|.

Definition 7 Let the relationship intimacy matrix be F

$$F = \begin{pmatrix} 0 & f_{12} & f_{13} & \cdots & f_{1n} \\ & 0 & f_{23} & \cdots & f_{2n} \\ & & 0 & \cdots & f_{3n} \\ & & & 0 & M \\ & & & & 0 \end{pmatrix} \tag{7}$$

$$f_{ij}\left(\varphi_{ij}\right) = \frac{\varphi_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \varphi_{ij}} \tag{8}$$

The perceptual recommendation trust similarity and relationship intimacy matrix are superimposed into the similarity and intimacy matrix C: $C = SR + F$, then the elements in matrix C are:

$$\begin{cases} c_{ij} = sr_{ij} + f_{ij}\left(\varphi_{ij}\right) & sr_{ij} + f_{ij}\left(\varphi_{ij}\right) \leq 1 \\ c_{ij} = 1 & sr_{ij} + f_{ij}(\theta_{ij}) > 1 \end{cases} \tag{9}$$

The similarity and intimacy matrix C contains the information of perceptual recommendation trust similarity and relationship intimacy, which can be regarded as the enhancement of relationship intimacy to similarity, which is consistent with the social psychology research conclusion: connection breeds similarity.

(3) Generation of Normal Matrix

In social networks, the network scale is large, the network dynamics are high, and the user-generated content has the characteristics of globalization. To improve the calculation speed, the similarity and relationship intimacy network is simplified to a certain extent. If two perceived recommendation trust similarities are very low and the intimacy between subjects is also very low, it can be intuitively considered that the two are not similar or the social relationship is not close. Therefore, the threshold η is set to remove the edges with small similarities to simplify the network. The simplified similarity and relationship intimacy matrix are C, and the elements in the matrix are:

$$c_{ij}^{'}=\begin{cases}0, c_{ij}<\eta \\ c_{ij}, c_{ij}\geq\eta\end{cases} i,, j\in[1,n] \tag{10}$$

(4) Generation of Normal Matrix

First, convert the corrected similarity and relationship intimacy matrix C into Laplace matrix L, and the elements in matrix L

$$l_{ij}=\begin{cases}deg(i), & i=j \\ c_{ij}^{'} & i\neq j\end{cases} \tag{11}$$

The transformed Laplace matrix is:

$$L=\left(l_{ij}\right)_{n\times n}=\begin{pmatrix}deg(1) & -c_{12}^{\circ} & -c_{13}^{\circ} & \cdots & -c_{1n}^{\circ} \\ & deg(2) & -c_{23}^{\circ} & \cdots & -c_{2n}^{\circ} \\ & & deg(3) & \cdots & -c_{3n}^{\circ} \\ & & & 0 & M \\ & & & & deg(i)\end{pmatrix} \tag{12}$$

Where, $L=K-A$, so there are:

$$K=diag\left(d(1),d(2),\cdots,d(i)\right) \tag{13}$$

$$A=\begin{pmatrix}0 & sr_{12}^{\circ} & sr_{13}^{\circ} & \cdots & sr_{1n}^{\circ} \\ & 0 & sr_{23}^{\circ} & \cdots & sr_{2n}^{\circ} \\ & & 0 & \cdots & sr_{3n}^{\circ} \\ & & & 0 & M \\ & & & & 0\end{pmatrix} \tag{14}$$

Further transformed into Normal matrix N:

$$N=K^{-1}A \tag{15}$$

Solve the first or second eigenvalues and eigenvectors of the Normal matrix. If the eigenvectors are distributed in steps, then each step corresponds to a cluster, and the clusters in the network can be divided into each cluster. The recommended information provided by the recommenders is similar or the relationship between the recommenders is relatively close. Through the cluster division of similarity and relationship intimacy networks, social relationships are integrated into the clusters of perceived recommendation trust.

3.3. Calculation and update mechanism of cluster centers

Replacing the opinion space of the whole cluster with the cluster center can achieve the purpose of simplifying the massive information. Due to the high dynamic characteristics of social networks, the nodes in the network enter very frequently. Computing the clustering center and designing the update mechanism of the clustering center can meet the requirements of network dynamics.

(1) Identification of cluster centers

Sociological related research shows that nodes with high degrees in the network tend to have higher influence [2]. The influence of star nodes is an important factor in consumer perception of trust, so the clustering center is calculated based on the degree of the main body in the network.

Suppose the network of similarity and relationship intimacy can be divided into v clusters, then the sub-network formed by the u-th cluster is $G_{\mathrm{u}} =< V_{\mathrm{u}}, E_{\mathrm{u}} >$, then the v clusters divided out are v perceptual recommendation trusts Clustering.

Definition 8 Suppose the opinion space of the u-th cluster center is T_u,$1 \leq u \leq v$, then:

$$T_u = \{\rho_u, \tau_u, \varepsilon_u\} = \frac{\sum_{p=1}^{|V|} deg(v_p^u) TP_p^u}{\sum_{p=1}^{|V|} deg(v_p^u)} \tag{16}$$

Where, v_p^u represents the p-th node in the sub-network $G_u = \langle V_u,, E_u >$ formed by the u-th cluster.

(2) Classification of newly entered nodes

When a new recommender enters the network, set the recommendation information of the new recommender as $\omega_{\mathrm{new}} = \{b_{\mathrm{neu}}, d_{\mathrm{new}}, u_{\mathrm{new}}\}, b_{\mathrm{neew}}, d_{\mathrm{new}}, u_{\mathrm{new}} \in [0,1]$ and $b_{\mathrm{new}} + d_{\mathrm{new}} + u_{\mathrm{new}} = 1$. Consumers' trust opinion space for new recommenders is $\xi_{\mathrm{new}} = \{t_{\mathrm{new}}, g_{\mathrm{new}}, h_{\mathrm{neu}}\}$, then the similarity $s^{\mathrm{new}}u$ between the entry node and the opinion space of each cluster center is:

$$s_u^{\mathrm{new}} = \frac{t_{\mathrm{new}}\, \rho_u (b_{\mathrm{new}} + \delta u_{\mathrm{new}}) + t_{\mathrm{new}}\, \tau_u (d_{\mathrm{new}} - \delta u_{\mathrm{new}}) + \tau_u (g_{\mathrm{new}} + h_{\mathrm{new}} + t_{\mathrm{new}}\, u_{\mathrm{new}})}{\sqrt{b_{\mathrm{new}}^2 + d_{\mathrm{new}}^2 + u_{\mathrm{new}}^2} \cdot \sqrt{t_{\mathrm{new}}^2 (b_{\mathrm{new}} + \delta u_{\mathrm{new}})^2 + t_{\mathrm{new}}^2 (d_{\mathrm{new}} - \delta u_{\mathrm{new}})^2 + (g_{\mathrm{new}} + h_{\mathrm{new}} + t_{\mathrm{new}}\, u_{\mathrm{new}})^2}} \tag{17}$$

According to the calculation result of the similarity s_u^{new}, the new entry subject new is classified into the cluster arg max (s_u^{new}).

(3) The update strategy of cluster centers

Large-scale social network entities enter very frequently, and every time a new entity enters, it will bring a large amount of calculation to update the cluster center. Therefore, this paper proposes an updated strategy for clustering centers based on the influence of newly entered nodes:

Definition 9 Let deg(new) denote the degree of the newly entered subject, $\overline{\mathrm{deg}_u}$ denotes the average degree of the social network in the u-th cluster, then:

$$\overline{deg_u} = \frac{\sum_{p=1}^{|V|} deg(v_p)}{|V_u|} \tag{18}$$

Let S_p^u denote the similarity between the perceptual recommendation trust opinion space of any node p in the u-th cluster and the cluster center opinion space T_u, then the cluster opinion space update strategy is:

$$s_u^{new} \leq min S_p^u, p \in [1, |V_u|] \Rightarrow T_u^{'} = T_u \tag{19}$$

$$\left(s_u^{new} > min S_p^u\right) \wedge \left(deg(new) < \overline{deg_u}\right), p \in [1, |V_u|] \Rightarrow T_u^{'} = T_u \tag{20}$$

$$\left(s_u^{new} > min S_p^u\right) \wedge \left(deg(new) > \overline{deg_u}\right), p \in [1, |V_u|] \Rightarrow T_u' = \frac{|V_u| \overline{deg_u} \cdot T_u + deg(new)\, \omega_{new}}{|V_u| \overline{deg_u} + deg(new)} \tag{21}$$

Equation (19) indicates that when the similarity between the new entry node and the cluster center is less than or equal to the minimum similarity between other nodes in the cluster and the cluster center, the cluster center is not updated; Equation (20) indicates that when the new entry node and the cluster center are similar When the similarity of the cluster center is greater than the similarity of other nodes in the cluster and the cluster center, and the degree of the new entry node is lower than the average degree of the node in the cluster, the cluster center is not updated; formula (21) indicates that when the new entry The similarity between the node and the cluster center is greater than the similarity between other nodes in the cluster and the cluster center, and the cluster center is updated when the degree of the newly entered node is higher than the average degree of the nodes in the cluster. The cluster center update strategy considers the opinion space of perceived recommendation trust and the social influence of new entrants.

4. Experiment

4.1. Experimental procedure

Suppose that for a certain product, there are a large number of comments about the product in the social network of a social commerce platform. To analyze and predict the perceived trust of a certain consumer, the platform gathers the perceived recommendation trust obtained by the consumer. Class analysis, and on this basis, formulate corresponding marketing strategies or provide precise product recommendations.

Simulation initialization: Initial social network: Suppose there are a total of 300 recommenders in the network, with an average degree of 30, which is 1/10 of the number of nodes. Recommendation information: Initially assign the recommendation information. It is assumed that there are three types of recommendation information opinion space: 1. Trust beliefs are greater than distrust beliefs. 2. Trust belief is less than distrust belief. 3. Trust belief and distrust belief are similar. The number of recommenders in the three categories is 150, 120, and 30, respectively, and the overall preference is to believe in any direction. Trust propensity coefficient: The values of the trust propensity coefficient are 0.1, 0.3, 0.7, -0.1, -0.3, and -0.7 as examples to carry out simulation experiments and compare and analyze the simulation results. The simulation steps are as follows:

Step 1 Randomly assign values to the relationship and the number of interactions between 300 nodes to generate an initial social network;

Step 2 Randomly assign values to the recommended information opinion space provided by 300 recommenders according to the above three classification rules, and randomly assign values to consumers' perceived trust opinion space of all recommenders;

Step 3 Calculate the consumer's perceived recommendation trust. According to formula (3) (4), the recommendation information is transformed into consumer perception recommendation trust;

Step 4 The extraction of perceptual recommendation trust similarity network. According to the similarity calculation formula (5) (6), calculate the similarity of the perceived recommendation trust opinion space among all subjects in the network, and obtain the similarity matrix SR;

Step 5 The extraction of similarity and intimacy network. Calculate the communication frequency matrix F according to formula (7) (8), and compound the similarity matrix SR with the communication frequency matrix F according to formula (7) to generate the revised similarity and intimacy matrix C;

Step 6 Divide the revised similarity and intimacy network. Calculate and generate Laplace matrix according to formula (11) (12), and finally generate Normal matrix according to (11 ~ 13);

Step 7 Solve the eigenvalues and eigenvectors of the Normal matrix, and divide the similarity and relationship intimacy network;

Step 8 Calculate the cluster center opinion space according to formula (16).

4.2. Experimental results

According to the experimental process in 4.1, divide the generated similarity and intimacy network, and calculate the clustering division under different trust propensity coefficients, and the average value of the 300 nodes' perception and recommendation trust opinion space, as shown in [Table 1] and [Table 2].

Table 1 Classification of clusters under different trust propensity coefficients

δ	Cluster number	Number of nodes in the cluster	Cluster center opinion space	δ	Cluster number	Number of nodes in the cluster	Cluster center opinion space
0.1	1	84	{0.695,0.042,0.263}	−0.1	1	86	{0.687,0.054,0.259}
	2	71	{0.078,0.658,0.264}		2	72	{0.069,0.662,0.269}
	3	145	{0.441,0.268,0.291}		3	142	{0.434,0.276,0.290}
0.3	1	91	{0.712,0.037,0.250}	−0.3	1	70	{0.682,0.067,0.250}
	2	54	{0.088,0.677,0.235}		2	92	{0.066,0.678,0.256}
	3	155	{0.431,0.291,0.277}		3	138	{0.431,0.295,0.274}
0.7	1	102	{0.768,0.039,0.193}	−0.7	1	53	{0.676,0.092,0.213}
	2	40	{0.107,0.697,0.196}		2	104	{0.060,0.719,0.220}
	3	158	{0.450,0.301,0.249}		3	143	{0.425,0.328,0.247}

Table 2 The average value of 300 perceived recommendation trust opinion spaces under different trust propensity coefficients

δ	Perceived recommendation trust opinion space average	δ	Perceived recommendation trust opinion Spatial average
0.1	{0.426,0.297,0.277}	−0.1	{0.419,0.305,0.276}
0.3	{0.455,0.284,0.261}	−0.3	{0.378,0.359,0.263}
0.7	{0.513,0.265,0.223}	−0.7	{0.343,0.422,0.235}

Suppose, in the case of $\delta = 0.1$, the recommendation information opinion space of the new recommender is $\omega_{new} = \{0.8, 0.05, 0.15\}$, the degree of the subject is 100, according to 3. In section 3 (2) the classification of the new entry node, the new entry recommender should be classified into the first category. The average degree of each cluster is approximately equal to the average degree of the entire network 30, according to 3. In Section 3.3 the update strategy of the cluster center, the center opinion space of the first cluster after the update is:

$$\begin{aligned} T_1' &= \frac{|V_1|\overline{deg}_1 \cdot T_1 + deg(new)\,\omega_{new}}{|V_1|\overline{deg}_1 + deg(new)} \\ &= \frac{84 \times 30 \times \{0.695,0.042,0.263\} + 100 \times \{0.8,0.05,0.15\}}{84 \times 30 + 100} = \{0.699,0.042,0.259\} \end{aligned} \quad (22)$$

The recommendation information provided by the newly entered node has a strong belief and direction and has a high influence. The entry of the new node prompts a slight increase in the letter directly in the opinion space of the first cluster center.

4.3. Analysis of experimental results

It can be seen from [Table 1] that the clustering method proposed in this paper can identify three different types of recommendation information. The difference between trust and distrust in the third cluster is small, and the classification is the same as that of the initial recommendation information opinion space. The nodes in the cluster are more concentrated in the third category. The trust and distrust of this type of opinion space are similar, and the inclination is not clear. The intuitive result of word-of-mouth behavior.

(1) Judging from the number of nodes in the 6 clustering results in [Table 1], when $\delta > 0$, the larger the δ, the more the number of nodes in the first cluster, and the less the number of nodes in the second cluster; When $\delta < 0$, the smaller the δ, the more the number of nodes in the second cluster, and the less the number of nodes in the first cluster. It reflects that for the same recommendation information, the difference between perceived recommendation trust is established when consumers have different trust tendencies. When consumers tend to trust, the more obvious the tendency to trust, the higher the degree of confidence in the recommendation information of others, and the correspondingly optimistic attitude towards negative recommendation information. When consumers tend to distrust, the more serious their distrust tendency is, the more difficult it is to establish a positive perception of recommendation trust. On the contrary, they have a negative perception of certain positive recommendation information.

(2) From the point of view of the cluster center opinion space, when $\delta > 0$, the larger δ is, the higher the letter arbitrary direction in the cluster center opinion space is. On the contrary, when $\delta < 0$, the smaller δ is in the cluster center opinion space. Judging from the average value of the perceived recommendation trust opinion space in the case of the six trust propensity coefficients in Table 2, except when δ = -0.7, the belief arbitrary direction in the average opinion space is higher than the unbelieving arbitrary direction, which is the same as the overall intention of the recommendation information. When δ = -0.7, consumers have a very strong distrust tendency, and the average value of the opinion space tends to distrust. When $\delta > 0$, the larger δ is, the higher the average value of the perceptual recommendation trust opinion space is, the higher the arbitrary direction of disbelief, and the lower the arbitrary direction of unbelief. When $\delta < 0$, the smaller the value of δ, the lower the arbitrary direction of disbelief, and the higher the arbitrary direction of unbelief. As $|\delta|$ increases, the degree of hesitation in the average opinion space decreases.

Simulation experiments prove the effectiveness of the clustering method proposed in this paper. The experimental results reflect the positive correlation between trust propensity and consumer perception of the recommended trust opinion space, and also reflect the correlation between trust propensity and the number of nodes in the cluster. The clustering method proposed in this paper can identify the consumer's subjective perception and recommendation trust clustering based on considering the relationship between social network subjects and the consumer's trust tendency, and the trust tendency coefficient plays a significant role in regulating. The cluster center update strategy is in progress.

5. Conclusion

This article constructs a clustering method for consumer perception recommendation trust in the context of large-scale social networks, improves on subjective logic methods, integrates trust characteristics into subjective logic trust transfer algorithms, and transforms objective recommendation information into consumer subjective and differentiated Perceived trust;

extract the perceptual recommendation trust similarity and relationship intimacy network from the social network to generate a Normal matrix, and divide it with the spectral bisector method, extract the consumer perception trust network from the social network, and propose society from the perspective of complex network division The clustering method of commercial consumers' perception of trust is optimized, and the identification and update mechanism of clustering centers is designed according to the high dynamic characteristics of social networks. Finally, the feasibility of this method is verified by simulation experiments. The clustering method proposed in this paper can cluster the recommended information while considering the social relationship of social networks and can integrate the characteristics of consumers' trust tendency to better characterize the subjectivity of consumers' perception of trust. The clustering method proposed in this paper can adapt to the social network environment with large-scale, quantified, and dynamic user-generated content, and provides a new perspective for consumer perception and trust-oriented analysis in emerging social commerce. Quickly identify consumer perception of trust orientation for social commerce merchants and platforms, and provide method support for merchants to formulate trust-based precision marketing strategies for social commerce.

References

[1] T. S. Andrew and T. Olivier, “Deriving value from social commerce networks,” Social Science Electronic Publishing, vol.47, no. 2, pp.215-228, **(2010)**

[2] C. Renata and P. Zhang, “Social commerce: Looking back and forward,” Proceedings of the American Society for Information Science and Technology, vol.48, no.1, pp.1-10, **(2012)**

[3] M. Hassan, Z. Iqbal, and B. Khanum, “The role of trust and social presence in social commerce purchase intention,” Pakistan Journal of Commerce and Social Sciences (PJCSS), vol.12, no.1, pp.111-135, **(2018)**

[4] R. B. Lount Jr., “The impact of positive mood on trust in interpersonal and intergroup interactions,” Journal of Personality and Social Psychology, vol.98, no.3, pp.420, **(2010)**

[5] Y. Su-Rong, Z. Xiao-Lin, Y. W. William, W. Song, and W. Y. Zhang,” A graph-based comprehensive reputation model: Exploiting the social context of opinions to enhance trust in social commerce,” Information Sciences, vol.318, pp.51-72, **(2015)**

[6] J. B. Johnson and H. P. Reingen, “Social ties and word-of-mouth referral behavior,” Journal of Consumer Research, vol.14, no.3, pp.350-362

[7] Y. Jin and P. H. Xiang, “A trust transitivity model of farmers for purchasing agricultural means of production online,” Icic Express Letters, vol.8, no.3, pp.927-933, **(2014)**

[8] Z. Lina, Z. Ping, and Z. Hans-Dieter, “Social commerce research: An integrated view,” Electronic Commerce Research and Applications, vol.12, no.2, pp.61-68, **(2013)**

[9] K. Sanghyun and P. Hyunsun, “Effects of various characteristics of social commerce (s-commerce) on consumers’ trust and trust performance,” International Journal of Information Management, vol.33, no.2, pp.318-332, **(2013)**

[10] H. Nick and H. Mahmood, “A research framework for social commerce adoption,” Information Management and Computer Security, vol.21, no.3, pp.144-154, **(2013)**

[11] J. Weisberg, D. Te’ Eni, and L. Arman, “Past purchase and intention to purchase in e-commerce: The mediation of social presence and trust,” Internet Research Electronic Networking Applications and Policy, vol.21, no.1, pp.82-96, **(2011)**

[12] S. Dong-Hee, “User experience in social commerce: In friends we trust,” Behaviour and Information Technology, vol.32, no.1, pp.52-67, **(2013)**

[13] J. Berger, “Word of mouth and interpersonal communication: A review and directions for future research,” Journal of Consumer Psychology, vol.24, no.4, pp.586-607, **(2014)**

[14] Y. Su-Rong, Z. Xiao-Lin, W. Yan, S. William Wei, and Z. Wen Yu, “A graph-based comprehensive reputation model: Exploiting the social context of opinions to enhance trust in social commerce,” Information Sciences, vol.318, pp.51-72, **(2015)**
[15] M. Granovetter and R. Soong, “Threshold models of interpersonal effects in consumer demand,” Journal of Economic Behavior and Organization, vol.7, no.1, pp.83-99
[16] A. Capocci, V. D. P. Servedio, G. Caldarelli, and F. Colaiori, “Detecting communities in large networks,” Physica A Statistical Mechanics and its Applications, vol.352, pp.2-4, pp.669-676, **(2005)**
[17] D. H. Mcknight, C. J. Kacmar, and V. Choudhury, “Dispositional trust and distrust distinctions in predicting high-and low-risk Internet expert advice site perceptions,” e-Service Journal, vol.3, no.2, pp.35-58, **(2004)**
[18] W. Guohua, H. Xiaorui. W. Yuhong, “Effects of perceived interactivity, perceived web assurance and disposition to trust on initial online trust,” Journal of Computer-mediated Communication, vol.16, no.1, pp.1-26, **(2010)**
[19] R. Saadi, O. Hasan, J. M. Pierson, and L. Brunie, “Establishing trust beliefs based on a uniform disposition to trust,” International IEEE Conference on Signal-Image Technologies and Internet-Based System, **(2017)**
[20] W. W. Stephen, N. Waros, and H. Chia-Hung, “Trust disposition, trust antecedents, trust, and behavioral intention,” Service Industries Journal, vol.35, no.10, pp.555-572, **(2015)**
[21] A. J. Jeang, “The consensus operator for combining beliefs,” Artificial Intelligence, vol.141, no.1, pp.157-170, **(2002)**
[22] A. J. Jesang, E. Gray, and M. Kinateder, “Simplification and analysis of transitive trust networks,” Web Intelligence and Agent Systems: An International Journal, vol.4, no.2, pp.139-161, **(2006)**

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