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Meiguang Zheng
Central South University
Yi Li
Other Press
Zhengfang He
Other Press
Yu Hu
Central South University
Jie Li
Central South University
Liu Yang (yangliu@csu.edu.cn)
Central South University https://orcid.org/0000-0001-7431-3462

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RESEARCH

Context-aware POI Recommendation using Neutrosophic Set for Mobile edge computing

Meiguang Zheng[1], Yi Li[2], Zhengfang He[3], Yu Hu[1], Jie Li[1] and Liu Yang[1*]

*Correspondence: yangliu@csu.edu.cn
[1]School of Computer science and Engineering, Central South University, ChangSha 410083, China
Full list of author information is available at the end of the article

Abstract

With the rapid development of mobile communication technology, there is a growing demand for high-quality point of interest(POI) recommendation. The POIs visited by users only account for a very small proportion. Thus traditional POI recommendation method is vulnerable to data sparsity and lacks a clear and effective explanation for POI ranking result. The POI selection made by the user is influenced by various contextual attributes. The challenge lies in representing accurately and aggregating multiple contextual information efficiently. We transform the POI recommendation into a contextual multi-attribute decision problem based on the neutrosophic set (NS) which is suitable for representing fuzzy decision information. We establish a unified framework of contextual information. Firstly, we propose a contextual multi-attribute NS transformation model of POI, including the NS model for single-dimensional attributes and the NS model for multi-dimensional attributes. And then through the aggregation of multi attribute NS, the POI that best conforms to user's preferences is recommended. Finally, the experimental results based on the Yelp dataset show that the proposed strategy performs better than the typical POI recommendation method in NDCG, accuracy, and recall rate.

Keywords: POI recommendation; neutrosophic set; multi-criteria decision; context-aware; user preference

1 Introduction

Nowadays, 5G technology has the characteristics of high capacity, high speed, low latency and high mobility, which can provide the communication foundation for mobile edge computing (MEC). A typical application of MEC is location-based social networks (LBSN), where users are increasingly posting their actual location, visit time and evaluation of their POI in the form of check-in records [1]. Typical LBSN sites include Foursquare, Yelp, Gowalla, Dianping, and so on. People can use a LBSN to discover the POI that they are interested in, check in to it and share their check-in information and experience with friends. When users are faced with a large amount of information in LBSN, the recommendation system should use users' check-in data and the large amount of valuable information contained in the POI to help users discover potentially interesting POI and make a satisfactory recommendation.

Traditional POI recommendation methods include memory-based collaborative filtering [2, 3] and model-based collaborative filtering [4, 5]. On one hand, the memory-based method relies heavily on the user check-in data. Compared with the large number of POIs in LBSNs, the POIs visited by users only account for a very small proportion and thus the memory-based collaborative filtering POI recommendation method is vulnerable to data sparsity [6]. On the other hand, the model-based method obtains results from training data, which lacks a clear and effective explanation for POI ranking.

In fact, the contextual information of POI will have an important impact on users' decision behavior. For example, people may go to restaurants or shops nearby after visiting a museum, so POIs that are closer to the user's check-in record are more geographically relevant than those that are further away, and the probability of access is higher. Studies have shown that users' check-in behaviors are geographically clustered [2], and such contextual information can assist decision making. Meanwhile, the data sparsity of POI recommendation makes it necessary to aggregate multiple contextual information. There are many difficulties in context-aware POI recommendation, which are mainly reflected in the following aspects:(1) Due to the heterogeneity of the various POI contextual data, it is difficult to design a unified framework to integrate multiple context attributes. (2) The check-in behavior of users is a complex decision process. It is necessary to reasonably model the influence of the contextual information on user decisions.(3) Most of the current POI recommendation studies are not comprehensive enough to consider the attributes that affect user selection and cannot effectively integrate them.

In order to solve the above problems and improve the interpretability of POI recommendation while avoiding the sparsity of check-in data, we propose a context-aware POI recommendation method based on neutrosophic set in edge computing. It transforms the POI recommendation problem into a multi-criteria decision making (MCDM). The neutrosophic set (NS) [7] is an extension of the fuzzy set. It uses truth-membership, indeterminacy-membership, and falsity-membership to represent fuzzy decision information, which can describe the fuzzy nature of objective things in a delicate and accurate way. It is suitable for solving MCDM problems [8, 9]. Our POI recommendation method is belong to a content-based solution, which is an important means to alleviate the problem of data sparsity [10]. At the same time, the method based on the neutrosophic set in this paper can clearly obtain the membership degree, non-membership degree and uncertainty of each attribute of a POI, which can effectively explain the POI ranking results.

Our contributions include theoretical analyses and experimental results:

(1) We provide a novel unified framework to represent and fully mine the user check-in context information, in which the context attributes are represented by the single-dimensional attribute NS model or by the multi-dimensional attribute NS model.

(2) We design an objective mechanism to measure the degree of a user's individual attribute preference and use the aggregation operator of NS to generate the final recommendation list.

(3) We conduct experiments on the Yelp dataset. The results show that the proposed model could effectively recommend POIs which meet user preferences.

2 Related work

2.1 POI recommendation

Memory-based collaborative filtering and model-based collaborative filtering are common methods for POI recommendation. In memory-based collaborative filtering technologies, such as user-based collaborative filtering and item-based collaborative filtering, the check-in data are used to calculate the similarity between users or places to recommend POIs that similar users have visited or similar places that have been visited [2]. Zhu et al. [3] integrated user similarity, geographical location similarity and trust relationships to improve the accuracy of the recommendation system in the user-based collaborative filtering model. However, user check-in data will seriously affect the effectiveness of memory-based collaborative filtering method. It is vulnerable to data sparsity because the check-in data of POIs are highly sparse. Therefore, memory-based collaborative filtering technology cannot effectively recommend POIs. Compared with the traditional collaborative filtering recommendation method, content-based recommendation method can alleviate data sparseness. Content-based Method is not only based on explicit or implicit scoring data, but also based on the external information of the scoring matrix to help filter similar users, thereby alleviating data sparsity. The multi-attribute integration method based on NS in this paper is a content-based solution.

Model-based collaborative filtering techniques are also applied to POI recommendations. It assumes that users form clusters based on their similar behaviors and uses machine learning techniques such as clustering algorithms and Bayesian networks to learn the model according to the users' behaviors. For example, Gao et al. [11] designed a model based on matrix decomposition to improve the quality of POI recommendations and combined social information with geographic information for recommendations. Liu et al. [4] applied the adaptive multi-order Markov model to predict the user's next check-in POI according to the user's historical check-in data. Liu et al. [5] believed that the user's check-in behavior was jointly determined by user preference, geographical influence and user movement behavior. To comprehensively analyze the joint effect of the above attributes, a Bayesian nonnegative matrix factorization model was constructed to calculate the user preferences for candidate POIs. Model-based methods get results from training data. A high POI ranking cannot clearly explain why it ranks high. The membership degree, non-membership degree and uncertainty of each attribute of each POI can be clearly obtained by using the NS, which can effectively interpret the POI ranking results.

At present, personalized POI recommendations based on LBSNs have been widely studied. When users check in on LBSNs, specific location information is needed to submit to the edge server, the trajectory involved in users'check-in data may reveal users'privacy. Kuang et al. propose to protect edge users'location information by a weighted noise injection method.Then model users'check-in sequences with their latent states based on HMM, and EM algorithm is used to estimate the parameters of the model [12]. Many current studies have considered some related attributes to improve the effect of POI recommendation. Such as geographic location [13, 14], interest topics [15, 16], popularity [17, 18], social relationships [19, 14], etc. Considering the above attributes alone can improve the effect of POI recommendation, but the improvement effect is limited. The current research has a development trend that combines multiple related attributes. Ye et al. [2] proposed a linear integration framework by combining user preferences, social influences, and geographical influences, and designed a probability prediction model for a given user checking in a POI. However, this method only considers aforementioned three contextual information and simply carried out linear combination. Zhang et al.[20] proposed a POI recommendation method called GeoSoCa that exploits geographical, social and categorical correlations among users and POIs. The method separately models each type of information, and then takes the product of the three scores as the final recommendation score. In addition, it is also common to use some mature models to integrate multiple factors, such as probability models. Liu et al. [21] proposed a general probabilistic latent factor model that takes user preferences, geographical influence, and user mobility into consideration during the recommendation process, and uses Poisson probability matrix decomposition to obtain implicit feedback of user check-in data to get better recommendations. However, due to the implicit nature of the variables, it is difficult to explain the POI ranking results to users. Recommendations that lack interpretability cannot allow users to fully trust the recommendation results, which may make users tend to think that the recommended items are just advertisements for commercial benefits, thereby reducing the credibility of the recommendation results. Compared with the model-based method, our method based on neutrosophic set has a significant advantage in terms of interpretability, which is mainly reflected in the fact that its structure and parameters can have obvious physical meanings, which facilitates users' understanding of the implications.

2.2 Neutrosophic set theory

Neutrosophic set has been widely used in image processing [22, 23], pattern recognition [24] and medical diagnosis [25, 26, 8]. Neutrosophic set is widely used to solve MCDM problems because it can represent fuzzy decision information in multiple dimensions. For example, Zhang et al. [9] used neutrosophic set to represent the user's comments on restaurants, which can consider the active, neutral and passive information in online reviews all at once, and solve the problem of fuzzy and uncertain information loss caused by using real numbers to represent text reviews, so as to provide decision support for the user to select a restaurant. Ma et al. [27] integrated the assessment data of cloud services and the user's application requirements and transformed them into neutrosophic set to measure the uncertainty of cloud environment, so as to recommend the most cost-effective cloud services to users. Transforming various attributes that affect POI selection into a neutrosophic set can provide us with an efficient model to study POI recommendation problem.

3 Problem definition and overall framework

In this section, we first introduce the context information considered in this paper, then introduce some basic representations and operations of the neutrosophic set, which is necessary to further understand our model, and finally illustrate our framework.

3.1 Context information for POI recommendation

Context information is any kind of information that characterizes an entity in a specific domain [28]. In our context-aware POI recommendation, four context attribute parameters including geographic location, interest topic, popularity, and social relationship are considered.

Geographic location. Among the multiple attributes that affect users decision-making, the first consideration is that the geographical location of the POI often affects users' decision behavior, which is also the greatest difference between POI recommendation and traditional recommendation [29]. Users tend to visit POIs that are close to the previous check-in location.

Interest topic. Users may be attracted by some topic appeared in the introduction and comments of POI, resulting in the check-in behavior. Considering the text information related to the POI, the sparsity of check-in data could be alleviated to some extent. To better understand the pattern of LBSN and improve its services, it is an appropriate approach to explore the topic feature information contained in the text information.

Popularity. Usually, the decision of a person to check in to a POI is largely influenced by the public reputation, which can be expressed as the popularity of the POI [5]. The popularity of the POI reflects the quality of the services and products provided by POI. Popularity largely affects user check-in behaviors.

Social relationship. Friends are more likely than strangers to have common preferences, and the use of users' social relationships can improve the quality of POI recommendations based on LBSNs. In the current research on the influence of social relationships on POI recommendation, the similarity is usually obtained from whether the check-in POI coincide with each other, without considering the evaluation of the user's friends on the POI. When a user's friends check in a POI, they may give good or bad comments, and this has a very different impact on the user. It is not enough to simply consider whether a friend checks in or not.

For the fuzzy and uncertain features of the user's preferences for the different attributes reflected in the contextual information, we considers the POI recommendation problem as an MCDM problem from the perspective of user decision-making. The decision criteria for the users to choose POIs are geographical location, interest topic, popularity and social relationship. To model the influence of the contextual information on the user's choice of POI and effectively aggregate them, we propose a context-aware POI recommendation method based on the neutrosophic set.

3.2 Preliminary concepts

In order to better introduce our model and strategy, we first introduce the basic definition and operation of the neutrosophic set, which is necessary to further understand our model.

Definition 1 neutrosophic set(NS): Let X be a space of objects. A generic elements in X is denoted by x. A neutrosophic set in X, denoted by A, is characterized by the truth-membership function $T_A(x)$, indeterminacy membership function $I_A(x)$ and falsity-membership function $F_A(x)$. $T_A(x), I_A(x), F_A(x)$ are standard or non-standard subsets of $[0^-, 1^+]$, that is, $T_A(x) : X \to [0^-, 1^+]$, $I_A(x) : X \to [0^-, 1^+]$, $F_A(x) : X \to [0^-, 1^+]$. There is no restriction on the sum of $T_A(x), I_A(x)$ and $F_A(x)$, therefore $0^- \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3^+$. Neutrosophic is built on a philosophical concept which makes it difficult to process during engineering applications or to apply to real applications.

Definition 2 single-valued neutrosophic set(SVNS): Let X be a space of objects with generic elements in X denoted by x. A is SVNS, which is a sub-class of NS and is defined as: $A = \{T_A(x), I_A(x), F_A(x)|x \in X\}$, where $T_A(x) : X \to [0,1]$, $I_A(x) : X \to [0,1]$ and $F_A(x) : X \to [0,1]$ with $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

For convenience, we can use $a = \{T, I, F\}$ to represent an element in the SVNS called the single-valued neutrosophic number (SVNN).

Definition 3 basic operational rules of SVNN: Let $a_1 = \{T_1, I_1, F_1\}$ and $a_2 = \{T_2, I_2, F_2\}$ be two SVNNs, then the operational rules are defined as follows:

(1)$\lambda a_1 = \left\langle 1-(1-T_1)^\lambda, (I_1)^\lambda, (F_1)^\lambda \right\rangle ; \lambda > 0$

(2)$a_1^\lambda = \left\langle (T_1)^\lambda, 1-(1-I_1)^\lambda, 1-(1-F_1)^\lambda \right\rangle ; \lambda > 0$

(3)$a_1 \oplus a_2 = \langle T_1 + T_2 - T_1 \cdot T_2, I_1 \cdot I_2, F_1 \cdot F_2 \rangle$

(4)$a_1 \otimes a_2 = \langle T_1 \cdot T_2, I_1 + I_2 - I_1 \cdot I_2, F_1 + F_2 - F_1 \cdot F_2 \rangle$

(5)The complement of a_1 is $a_1^c = \langle F_1, 1 - I_1, T_1 \rangle$

Definition 4 Euclidean distance of SVNN: Let $a_1 = \{T_1, I_1 \ , F_1\}$ and $a_2 = \{T_2, I_2, F_2\}$ be two SVNNs, then the Euclidean distance between a_1 and a_2 is defined as follows:

$$d(a_1, a_2) = \sqrt{\frac{|T_1 - T_2|^2 + |I_1 - I_2|^2 + |F_1 - F_2|^2}{3}} \tag{1}$$

Definition 5 weighted average operator of SVNS: Let $A_i = \langle T_i, I_i, F_i \rangle \, (i = 1, 2, \cdots, n)$ be a collection of SVNSs. The SVNSs weighted average operator (SVNSWA) is defined as follows:

$$\begin{aligned} & SVNSWA_\omega(A_1, A_2, \cdots, A_n) \\ & = \omega_1 \cdot A_1 \oplus \omega_2 \cdot A_2 \oplus \cdots \oplus \omega_n \cdot A_n = \sum_{i=1}^{n} \omega_i A_i \end{aligned} \tag{2}$$

where $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$ is weight vector of A_i and $\sum_{i=1}^{n} \omega_i = 1$.

Theorem 1 Let $A_i = \langle T_i, I_i, F_i \rangle \, (i = 1, 2, \cdots, n)$ be a collection of SVNSs. Then, their aggregated result using the SVNSWA operator is also a SVNS, and

$$\begin{aligned} & SVNSWA_\omega(A_1, A_2, \cdots, A_n) \\ & = \omega_1 \cdot A_1 \oplus \omega_2 \cdot A_2 \oplus \cdots \oplus \omega_n \cdot A_n \\ & = \left\langle 1 - \prod_{i=1}^{n} (1 - T_i)^{\omega_i}, \prod_{i=1}^{n} (I_i)^{\omega_i}, \prod_{i=1}^{n} (F_i)^{\omega_i} \right\rangle \end{aligned} \tag{3}$$

where $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$ is the weight vector of A_i and $\sum_{i=1}^{n} \omega_i = 1$.

3.3 Overall framework

Suppose there are m candidate POIs $l_1, l_2, \cdots, l_{m-1}, \, l_m$. We need to extract the geographic location information, topical information, comment information, and social relationships of the candidate POIs from the rich information of the LBSN. Our neutrosophic set based POI recommended framework is shown in Figure 1.

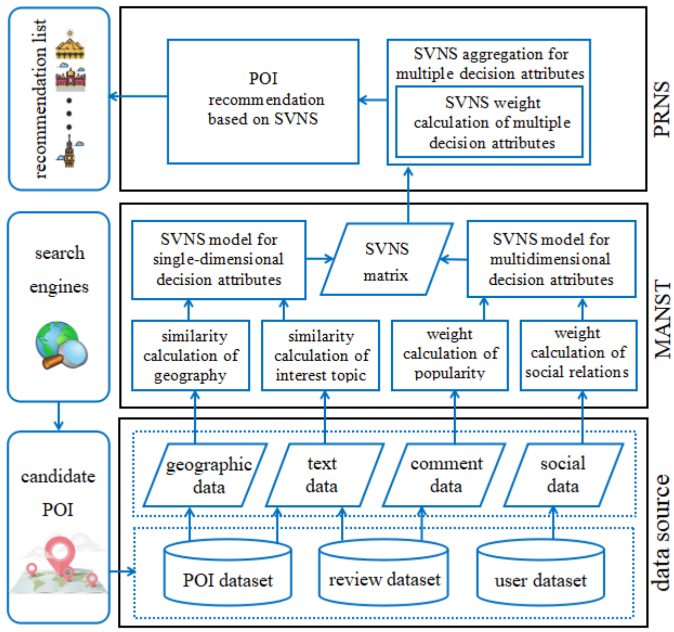

Figure 1 POI recommendation framework based on neutrosophic sets.

It consists of two parts, a multi-attribute neutrosophic set transformation model (MANST) and a POI recommendation based on neutrosophic sets (PRNS).For contextual information with different data structures, the MANST model uses the method based on similarity calculation or the method based on sentiment analysis to transform the diversity contextual data into neutrosophic sets, which can better measure the user's preference of a single attribute. The PRNS measures the importance of each contextual attribute and effectively integrates the attributes to find the POI that best meets the user's requirements. Based on the neutrosophic sets matrix obtained by MANST, the model calculates the weight of each attribute and aggregates the neutrosophic sets of multiple decision attributes for each POI, and then sorts them according to the neutrosophic numbers corresponding to each POI. Finally, the user will obtain a POI recommendation list of the form $l_{r1} \succ l_{r2} \succ \cdots \succ l_{rm}$. The POI with the highest ranking in the list best fits the user's preference and is more likely to be used by the user than a POI with a lower ranking.

4 Multiattribute SVNS transformation model

To build a POI multi-attribute SVNS transformation model, different methods should be adopted for single-dimensional and multi-dimensional context attribute data. The single-dimensional attribute is an independent, deterministic, non-multivariate relationship attribute. Unlike single-dimensional attributes, multi-dimensional attribute data often originates from a multi-relationship network of multiple users. For single-dimensional attributes, the SVNS transformation model based on the similarity calculation is established; for multi-dimensional attributes, the SVNS transformation model based on sentiment analysis is established.

4.1 Single-dimensional attribute SVNS transformation model based on similarity

We deal with two kinds of single-dimensional attributes: the geographical location and interest topic. We calculate the similarity between the candidate POI and visited POI in these two single-dimensional attributes.

(1)The geographic location. A frequently visited location is more matched with the user's geographic preferences [2]. Therefore, the geographic similarity of the candidate POI can be determined according to the geographical association relationship between the POIs that the user has accessed and the POIs that the user has not accessed. We use the triangular kernel function to calculate the geographic similarity between POIs. Compared to the traditional similarity calculation methods, it can better simulate the distance distribution between POIs and can filter out the less relevant POIs. The similarity $KE_b\left(j,g\right)$, between any two POIs, l_j and l_g, is calculated as follows:

$$KE_b\left(j,g\right)=\left(1-\frac{d\left(j,g\right)}{b}\right)I_{\{d(j,g)\leq b\}} \tag{4}$$

where $d\left(j,g\right)$ is the distance between POI l_j and l_g calculated by the haversine formula using the latitude and longitude information of the POI, b is the bandwidth parameter of the kernel function, and I is the indication function. When the distance between the POIs exceeds b, $KE_b\left(j,g\right)$ is 0; when the distance between POIs is less than b, the closer the distance between POIs is, the greater the value of $KE_b\left(j,g\right)$ is.

(2)The interest topics. The interest topics that users like are not unique, and the topics contained in a POI are also not unique. Users may be interested in a part of POI's topic, and not interested in another part. There are some part is in a fuzzy state. Therefore, we can calculate the similarity between the interest topics of the user likes and the interest topics contained in the candidate POI. We use latent dirichtlet allocation(LDA) topic model to extract the topic distribution. First, all the comments and introductory texts about the same POI are gathered into a POI document, d_{l_j}, and all text comments of the same user are also aggregated into a user document, d_{u_i}. Thus, a large collection of documents is obtained, each document corresponding to a POI or a user. After obtaining the topic distribution of each document, to determine the similarity between the interest topics that the user likes and the interest topics contained in the candidate POI, it is possible to compare the similarity of the topic distribution of the user documents and the POI documents.

Data cleaning is performed before d_{l_j} and d_{u_i} are processed using the topic model. Then the processed document content is input into the topic model. The topic distribution is obtained after using the Gibbs sampling algorithm for estimation. The topic distribution of user u_i is $O_{u_i}=\left\{t_i^1,t_i^2,\cdots,t_i^n\right\}$, and the topic distribution of POI l_j is $O_{l_j}=\left\{t_j^1,t_j^2,\cdots,t_j^n\right\}$. Each topic distribution value represents the percentage of the topic in all the document topics. For each document, the sum of the n topic distribution values is equal to 1.

Then, the topic distribution difference set $D_{ij} = \{d_{ij}^1, d_{ij}^2, \cdots, d_{ij}^n\}$, where $d_{ij}^k = |t_i^k - t_j^k|, k = 1, 2, \cdots, n$. Normalize D_{ij} as follows:

$$r_{ij}^k = 1 - \frac{d_{ij}^k}{max\left(d_{ij}^k\right)} \tag{5}$$

For the set $E_{ij} = \left\{r_{ij}^1, r_{ij}^2, \cdots, r_{ij}^k, \cdots, r_{ij}^n\right\}$, the kth element r_{ij}^k represents the similarity between the user and the kth topic of the POI. So far, the single-dimensional attribute similarity has been obtained. After that, the similarity set, uncertain set and difference set can be obtained according to the similarity degree. The purpose is to match the preference part, uncertainty part and non-preference part of the single-dimensional attribute with the three concepts of the truth membership, indeterminacy membership, and falsity membership of the SVNS and to obtain the SVNS of the single-dimensional attribute. To this end, the widely used golden section is adopted for the two thresholds, that is, when the values of similarity are located at [0, 0.382], (0.382, 0.618) and [0.618, 1], the degree of similarity between POI l_j and l_g on a certain attribute is lower, indeterminate, and higher.

For the candidate POI, l_j, and the POI, $l_g \in L$ (L is the POI set visited by the user) that the user has visited, the similarity set is $S_j^+ = \{s\,(j, g)\,|s\,(j, g) \geq 0.618\}$, correspondingly, the single-dimensional attribute similarity of l_j and l_g is

$$T_j = \frac{1}{|L|} \cdot |S_j^+| \tag{6}$$

The uncertain set is $S_j^0 = \{s\,(j, g)\,|0.382 < (j, g) < 0.618\}$, and the uncertainty degree is

$$I_j = \frac{1}{|L|} \cdot |S_j^0| \tag{7}$$

The difference set is $S_j^- = \{s\,(j, g)\,|\,(j, g) \leq 0.382\}$, and the difference degree is

$$F_j = \frac{1}{|L|} \cdot |S_j^-| \tag{8}$$

The above three values of the similarity degree, uncertainty degree and difference degree are respectively correspond to the truth-membership, indeterminacy-membership, and falsity-membership of the SVNS. Through the above formula, a user's geographic location, SVNS $A_{j1} = \langle T_{j1}, I_{j1}\ , F_{j1}\rangle$, and the interest topic, SVNS $A_{j2} = \langle T_{j2}, I_{j2}, F_{j2}\rangle$, on POI l_j are obtained.

4.2 Multi-dimensional attribute SVNS transformation model based on sentiment analysis

We deal with two kinds of multi-dimensional attributes: popularity and social relationships. The emotional information reflected in the multi-relationship network is conducive to the preference analysis of the multidimensional attributes. In terms of popularity, the popularity of a POI depends on the public reputation for this

POI, which can be reflected by user evaluations. For social relationships, considering that the positive and negative comments of friends have distinct influences on users, it is necessary to analyze the friends' comments on the POI. There two types of multi-dimensional attributes require an analysis of the user's comment data.

The user's comments often contain the user's preferences for POIs. First, the degree of positive, negative and uncertain emotional tendencies in the comments are identified, which can correspond to the truth membership, indeterminacy membership, and falsity membership of SVNS, and the SVNN corresponding to each comment can be obtained. Usually, the comments are short, and the emotions are strong and distinct, which is suitable for analysis using lexicon-based sentiment analysis techniques. First, the emotional words (including adjectives, nouns, adverbs, etc.) are extracted through text processing. The emotional tendency of the comment is calculated according to the relationship between the words and the emotional polarity and intensity of the emotional words. The final analysis depends largely on the validity of the sentiment lexicon. We use the VADER method [30] which is based on the lexicon and grammar rules for sentiment analysis, which can effectively identify the sentiment tendency of sentences. Different from other proposed sentiment lexicons, VADER's dictionary also considers the emotions of commonly used emojis and abbreviations. Compared with other widely used dictionaries, VADER's dictionary perform best in the field of social media and have good universality [30].

By identifying the positive, neutral or negative emotional propensity of the POI in comment C_j^h, the basic vector $S_j^h = \left(\alpha_j^h, \beta_j^h, \gamma_j^h\right)$, which represents the sentiment orientation of the sentence, can be obtained, where $\alpha_j^h, \beta_j^h, \gamma_j^h$ represent the positive, neutral, and negative emotionally oriented indicator variables, respectively. Then, the SVNNs corresponding to each comment $A_j^h = \left\langle T_j^h, I_j^h, F_j^h \right\rangle$, where $T_j^h = \alpha_j^h, I_j^h = \beta_j^h, F_j^h = \gamma_j^h$.

After obtaining the SVNN corresponding to each comment, different weights are assigned to each SVNS according to different characteristics of the multi-dimensional attributes. Therefore, the core problem of the transformation of the multi-dimensional attribute is to calculate the weight of each type of SVNS. For example, for popularity, the SVNS must calculate the weight according to the difference in the publication time of the comment; for the social relationship, the SVNS must calculate the weight by the difference in the familiarity and the behavior similarity between the user and his/her friend.

(1)Popularity weight calculation. Since the release time of a comment will have an impact on its reference value, each comment is given a weight, ω_j^h, depending on the comment release time. TT_j^h indicates the importance of comment C_j^h, can be calculated by the following formula:

$$TT_j^h = e^{\left(R_j^h - R_j\right)/\left(R_c - R_j\right)}, h = 1, 2, \cdots, q_j \tag{9}$$

where R_j^h indicates the time when comment C_j^h is issued, R_j indicates the time when POI l_j appears, and R_c indicates the current time. The weight of each comment, ω_j^h, can be calculated by the following formula:

$$\omega_j^h = \frac{TT_j^h}{\sum_{h=1}^{q_j} TT_j^h} \tag{10}$$

(2)Social relationship weight calculation. Usually the degree of social influence between users can be determined by whether they are friends or not. The check-in behavior is probably not similar among user and his/her friends. Sometimes, it even differ greatly. So it should give different weight to the evaluations from different friends.

When constructing the weights, on one hand, the behavior similarity among user and his/her friend sim_i^f must be considered. On the other hand, the credibility of a nodding acquaintance's suggestion is obviously different from that of a close friend's suggestion, so the familiarity among user and his/her friend fam_i^f should also be considered. The influence factor, SI_i^f, of the friend u_f on user u_i is composed of the similarity and familiarity, and is expressed as follows:

$$SI_i^f = sim_i^f \cdot fam_i^f, f = 1, 2, \cdots, p_j \tag{11}$$

where sim_i^f has a variety of measurement methods, such as the cosine, Jaccard and Pearson similarity measures, in which the cosine similarity is relatively accurate and convenient to calculate. Thus, we choose this method to calculate the user similarity, $sim_i^f = \frac{\sum_{l_g \in L} t_{ig} t_{fg}}{\sqrt{\sum_{l_g \in L} t_{ig}^2}\sqrt{\sum_{l_g \in L} t_{fg}^2}}$, where t_{ig} indicates the access status of the user u_i in POI l_g. The familiarity between friends is $fam_i^f = \frac{|Fi \cap F_f|}{|Fi \cup F_f|}$; this is the calculation between the user sets, so the Jaccard similarity is chosen to calculate the familiarity of friends. The more mutual friends there are between users, the closer the relationship between them is. The weight of user friends' comments, ω_i^f, can be calculated by the following formula:

$$\omega_i^f = \frac{SI_i^f}{\sum_{f=1}^{p_j} SI_i^f} \tag{12}$$

Finally, the SVNSWA operator in Eq. (2) is used to obtain the SVNS corresponding to the multi-dimensional attribute of the candidate POI, that is, the popularity SVNS of user u_i about POI l_j can be obtained:

$A_{j3} = SVNSWA_\omega\left(A_j^1, A_j^2, \cdots, A_j^{q_j}\right) = \sum_{h=1}^{q_j} \omega_j^h A_j^h = \langle T_{j3}, I_{j3}, F_{j3}\rangle$.

Social relationships SVNS is

$A_{j4} = SVNSWA_\omega\left(A_j^1, A_j^2, \cdots, A_j^{p_j}\right) = \sum_{h=1}^{p_j} \omega_j^h A_j^h = \langle T_{j4}, I_{j4}, F_{j4}\rangle$.

After transforming the data of various attributes into the SVNS, the SVNS matrix $Y = (A_{jz})_{m\times 4}$ of each attribute of the candidate POI is obtained, that is

$$Y = \begin{pmatrix} A_{11} & \cdots & A_{14} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{m4} \end{pmatrix} = \begin{pmatrix} \langle T_{11}, I_{11}, F_{11}\rangle & \cdots & \langle T_{14}, I_{14}, F_{14}\rangle \\ \vdots & \ddots & \vdots \\ \langle T_{m1}, I_{m1}, F_{m1}\rangle & \cdots & \langle T_{m4}, I_{m4}, F_{m4}\rangle \end{pmatrix}$$

where m is the number of candidate POIs and 4 is the number of attributes.

5 Context-aware recommendation based on the SVNS

In this section, we describe how to process the SVNS matrix to sort and select the candidate POIs.

5.1 Weight Calculation of the SVNS for multiple attributes

Now the four contextual attributes have an unified expression in SVNN. We should measure the user's preference in these four attribute, that is to say, we should determine the contextual attribute weight. Here we use a maximizing deviation method in which we use SVNS matrix information and assign the optimal weight of each attributes objectively.

Each attribute reflects a certain feature of the candidate POI, and each SVNS is a quantitative representation of the degree to which a certain attribute of the candidate POI conforms to the user preference. If an attribute has no difference for all the candidate POIs, then this attribute will have no effect on sorting the POIs. Such an attribute can have a weight of 0; otherwise, if this attribute makes the attribute values of all the candidate POIs have large differences, such attributes will play a more important role in the ordering of the POIs and should be given a larger weight.

$D(\omega)$ represents the total weighted deviation between all the candidate POIs under the four types of attributes, expressed as follows:

$$\begin{aligned} D(\omega) &= \sum_{z=1}^{4} \omega_z D_z = \sum_{z=1}^{4} \omega_z \sum_{j=1}^{m} D_{jz} = \sum_{z=1}^{4} \omega_z \sum_{j=1}^{m} \sum_{s=1}^{m} d(A_{jz}, A_{sz}) \\ &= \sum_{z=1}^{4} \sum_{j=1}^{m} \sum_{s=1}^{m} \omega_z \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}} \end{aligned} \tag{13}$$

where the weight vector of the attribute is $\omega = (\omega_1, \omega_2, \cdots, \omega_z)$. The Euclidean distance, $d(A_{jz}, A_{sz})$, between two SVNNs, A_{jz} and A_{sz}, can be calculated by Eq.(1). D_{jz} represents the deviation of the candidate POI l_j, and all the other alternative POIs for the attribute c_z. D_z indicates the total deviation between all the candidate POIs for the attribute c_z.

$D(\omega)$ represents the weighted total deviation between all the candidate POIs under all the attributes. According to the above analysis, the selected weight vector, ω, should maximize the total deviation between all the POIs under all the attributes. To this end, we construct a nonlinear programming model, so that calculating the weight vector ω, is equivalent to solving the following optimization model:

$$\begin{aligned} &maxD(\omega) = \sum_{z=1}^{4} \sum_{j=1}^{m} \sum_{s=1}^{m} \omega_z \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}} \\ &s.t. \begin{cases} \omega \geq 0, (1 \leq z \leq 4) \\ \sum_{z=1}^{4} \omega^2 = 1 \end{cases} \end{aligned} \tag{14}$$

By constructing lagrangian function, the optimal solution of the objective function is obtained by taking partial derivatives.

$$\omega_z^* = \frac{\sum_{j=1}^{m} \sum_{s=1}^{m} \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}}}{\sqrt{\sum_{z=1}^{4} \left(\sum_{j=1}^{m} \sum_{s=1}^{m} \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}} \right)^2}} \tag{15}$$

Then normalize the optimal solution ω_z^*

$$\omega_z = \frac{\sum_{j=1}^{m} \sum_{s=1}^{m} \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}}}{\sum_{z=1}^{4} \sum_{j=1}^{m} \sum_{s=1}^{m} \sqrt{\frac{|T_{jz}-T_{sz}|^2 + |I_{jz}-I_{sz}|^2 + |F_{jz}-F_{sz}|^2}{3}}} \tag{16}$$

where ω_z is the optimal weight vector of the attribute. According to Eq.(16), the weight of each attribute is the ratio of the deviation between the POI under this attribute and the total deviation between the POI under all the attributes. Therefore, if the dispersion between POIs under a certain attribute is larger, indicating that the candidate POI has a large difference in this attribute, the greater the influence of the attribute is on the user's choice of POI, and the greater its weight is. The weight obtained from Eq.(16) can objectively and truly reflect the contribution of each POI attribute to the user's selection of POI.

5.2 SVNS Aggregation of Multiple Attributes

Using the SVNSWA aggregation operator in Eq.(2), the SVNS of each attribute of the candidate POI l_j is integrated, and the SVNN of each candidate POI is obtained as follows:

$$A_j = SVNSWA_{\omega}\left(A_{j1}, A_{j2}, \cdots, A_{jm}\right) = \sum_{z=1}^{4} \omega_z A_{jz} \tag{17}$$

After obtaining the SVNN corresponding to each candidate POI, the SVNN comparison algorithm [31] is used for comparison. Finally, the POI sorting list, $l_{r1} \succ l_{r2} \succ \cdots \succ l_{rm}$, is recommended to the user. The highest ranked service in this list best meets the needs of the users and is more likely to be adopted by the users than those with lower rankings. The context-aware recommendation algorithm based on SVNS is shown in algorithm 1.

Algorithm 1 context-aware recommendation algorithm based on NS (CPRNS)

Require:

Candidate POI: $\{l_1, l_2, \cdots, l_j, l_{m-1}, l_m\}$, POI visited by recommended user u_i: $\{P_1, P_2, \cdots, P_g, P_{v-1}, P_v\}$;

Ensure:

POI recommendation list;

for $j = 1$ to m **do**
    for $g = 1$ to v **do**
        calculate $KE_b(j, g)$ using Eq. (4) ;
    end for
    calculate r_{ij}^k using Eq. (5);
    calculate T_{j1},T_{j2} using Eq. (6);
    calculate I_{j1},I_{j2} using Eq. (7);
    calculate F_{j1},F_{j2} using Eq. (8);
    obtain A_{j1},A_{j2};
    for $h = 1$ to q_j **do**
        calculate ω_j^h using Eq. (10);
        calculate S_j^h using vader;
    end for
    use Eq. (2) to aggregate the SVNN corresponding to each comment of POI l_j to get A_{j3};
    if user u_i has friends visited POI l_j **then**
        use Eq. (2) to aggregate SVNN corresponding to friends' comments to get A_{j4};
    end if
end for
obtain the candidate POI neutrosophic set matrix $Y = \left(A_{jz}\right)_{m \times 4}$;
calculate multi-attribute weight vector ω using Eq. (16) ;
for $j = 1$ to m **do**
    use Eq. (2) to aggregate SVNN of each attribute of POI l_j to get A_j;
end for

24: Sort candidate POIs using SVNN comparison algorithm;
25: **return** POI recommendation list

CPRNS is mainly composed of two parts. Algorithm 1 summarizes these two parts. The work completed in the first part (steps 1-18) is to transform various contextual information into neutrosophic sets. For one-dimensional attributes such as geographical location and interest topic, the neutrosophic set transformation method based on similarity calculation is adopted; for multi-dimensional attributes such as popularity and social relationship, the neutrosophic set transformation method based on sentiment analysis is adopted. The work completed in the second part (steps 19-25) is to obtain the POI ranking recommendation result by using the neutrosophic sets matrix corresponding to the candidate POI obtained in the previous part. In this part, the maximum deviation method is used to calculate the weight of each attribute, and the comparison algorithm of SVNN is used to compare the candidate POI. Finally, the algorithm obtains the POI recommendation list.

The time complexity of the algorithm is $O(m * v + m* \ h)$, m is the number of candidate POIs, v is the number of POIs visited by users, and h is the number of comments on candidate POI. The time complexity of the first part of the algorithm is $O\left(m * v + m * h\right)$, and the time complexity of the second part is $O\left(m\right)$, so the time complexity of the entire algorithm is $O\left(m * v + m * h\right)$.

6 Experiment

6.1 Experimental settings

(1)Dataset. To prove the validity of our method by experiments, we use the dataset from Yelp [32]. Yelp is one of the most popular LBSNs. Users can not only use Yelp to check in but also query the details of the POI. The Yelp dataset used in this paper consists of three parts: the POI dataset, the review dataset and the user dataset, which are taken from three JSON files in the Yelp dataset, and the social relationships are included in the user dataset. Table 1 shows the statistics of the experimental dataset. To ensure the validity of the experimental results, we filtered the users with fewer than 10 check-ins and fewer than 10 social relationships in the Yelp original dataset and POIs with fewer than 20 visits.

(2)Evaluation Criteria. In this paper, the commonly used ranking quality indicator Normalized Discounted Cumulative Gain (NDCG) is used as the evaluation indicator.

$$NDCG@N = \frac{DCG@N}{IDCG@N} \tag{18}$$

Where N is the recommended list length, and $DCG@N = \sum_{j=1}^{N} \frac{2^{rel_j}-1}{\log_2(r_j+1)}$. $IDCG@N$ is the $DCG@N$ value when the recommended POIs are ideally ranked, and rel_j is the graded relevance ranked at the position r_j defined in different recommendation scenarios. In the POI recommendation, according to ratings, it can be considered that $rel_j \in \{1, 2, 3, 4, 5\}$. NDCG is a number between 0 and 1. The larger the value, the better the sorting effect.

Accuracy is the proportion of the number of POIs that have been checked in by the user to N among the top N recommended POIs. The accuracy of recommendation results is defined as follows:

$$precision@N = \frac{\left|P\left(u_i\right) \bigcap R\left(u_i\right)\right|}{N} \tag{19}$$

Table 1 Statistics for the experiment datasets.

Statistic	Value
Number of POIs	188,593
Number of users	1,518,169
Number of check-ins	5,996,996
Average number of check-ins per POI	31.79
Average number of visited POIs per user	8.05

Where, $P(u_i)$ is the recommendation set generated for user u_i according to the training set, and $R(u_i)$ is the POI set that user u_i checked in the test set. Recall rate represents the ratio of the number of POIs that users have checked in among the first N recommended POIs to the number of POIs that users have checked in in the test set. The recall rate of recommended results is defined as follows:

$$recall@N = \frac{|P(u_i) \bigcap R(u_i)|}{R(u_i)} \tag{20}$$

(3)Comparison approaches. We compare our method with the following methods:

UserCF [33]:This method recommends the POIs visited by other users who are similar to user u_i, and calculates the user similarity using the cosine similarity formula. It predicts the score of user u_i according to the score of the other users similar to user u_i on the candidate POI, l_g, and sorts POIs according to the score.

ItemCF [34]:This method recommends the POI that is similar to a POI that user u_i has visited, and calculates the POI similarity using the cosine similarity. It predicts the score of user u_i for the candidate POI, l_g, according to the score of the other POIs that are similar to the candidate POI, l_g, and sorts the POIs according to the score.

PMF [35]: Model-based probability matrix decomposition: This method assumes that both user u_i and POI l_g follow the Gaussian distribution and learns the user preference by matrix decomposition, and then predicts the unknown values in the matrix.

GeoSoCa [20]: a context-aware method using the product rule to combine multiple attributes.

6.2 Baseline approaches

In order to verify the effectiveness of the weighting scheme for context attribute aggregation in this paper, we have established five baseline approaches to further verify the impact of the geographic location, interest topics, popularity and social relationships respectively on the recommendation results. These five methods are simplified versions of our proposed model: CPRNS-WG (without geographic location), CPRNS-WI (without interest topics), CPRNS-WP (without popularity), CPRNS-WS (without social relationships) and CPRNS-WPW(without personalized weighting). CPRNS-WG does not consider the geographic location information. CPRNS-WI does not consider interest topic information. CPRNS-WP does not consider the popularity information. CPRNS-WS does not consider the social relationship information. CPRNS-WPW uses the framework of the CPRNS but does not assign personalized weights to the four attributes. Specifically, it assigns the same weight to all the attributes.

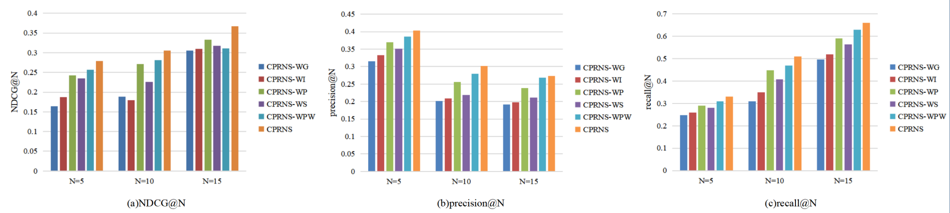

Figure 2 Baseline approaches comparison.

7 Results and Discussion

First, the baseline method is used to verify the effectiveness of the weighting scheme in the context attribute aggregation. Then, the CPRNS method is analyzed by case study and comparative experiment.

7.1 Validation of weighted scheme

Figure 2 illustrates how the three evaluation indicators of the CPRNS and baseline approaches vary with the length of the recommendation list. In Figure 2, the three evaluation indicators of the CPRNS are better than those of the other methods. It can be seen from the fact that the three evaluation indicators are better than the aggregation of the three attributes when the four attributes are aggregated, that the aggregation of the four attributes is crucial to the POI recommendation and is conducive to improving the recommendation accuracy. The reason for this conclusion is that the users are affected by many kinds of situational information in real life, and their preferences cannot be modeled unilaterally. Therefore, the POI recommendations should make full use of the various situational POI information. The impact of each attribute on the improvement of the recommendation results is different.

In Figure 2, the performance of the CPRNS is better than that of the CPRNS-WPW. The CPRNS assigns personalized weights to each attribute of different users, which shows the effectiveness of the weight calculation.

7.2 Case study

To illustrate the proposed method more clearly, we provide an example. User with the id YgavGxfAdjhkkbwlAY_9ZQ in the user dataset are randomly selected to recommend a POI. We consider a candidate list, $l_1, l_2, \cdots, l_8$ with m=8, and we need to optimize the order of the POI list based on the contextual information. To facilitate the evaluation of the experimental results, l_1, l_2, l_3 are set as the POIs that the user has visited.

According to the transformation model proposed in Section 5, the geographical location data, content text data, comment data and social relationship data can be processed into SVNS separately, and the results are shown in Table 2. The weights of the four attributes can be calculated by Eq.(16). Considering the sparsity of social data, some candidate POIs do not have social information, so we calculate their deviations and weights separately as shown in Table 3 and Table 4. The aggregation value of the candidate POI is obtained by using the aggregation operator, as shown

Table 2 The SVNS of each attribute in the case study.

POI	geographic location			interest topic			popularity			social relationship		
	T	I	F	T	I	F	T	I	F	T	I	F
l_1	0.54	0.25	0.21	0.77	0.03	0.20	0.20	0.76	0.04	0.24	0.76	0.00
l_2	0.71	0.25	0.04	0.70	0.03	0.27	0.25	0.71	0.03	-	-	-
l_3	0.58	0.25	0.17	0.67	0.07	0.27	0.17	0.76	0.07	-	-	-
l_4	0.54	0.29	0.17	0.53	0.10	0.37	0.20	0.73	0.05	0.19	0.80	0.01
l_5	0.12	0.38	0.50	0.70	0.13	0.17	0.23	0.70	0.07	0.21	0.74	0.05
l_6	0.62	0.17	0.21	0.67	0.00	0.21	0.19	0.75	0.06	0.26	0.71	0.03
l_7	0.04	0.29	0.67	0.77	0.00	0.23	0.20	0.75	0.05	-	-	-
l_8	0.58	0.21	0.21	0.53	0.07	0.40	0.24	0.73	0.03	-	-	-

Table 3 Weight of four attributes in the case study.

	geographic location	interest topic	Popularity	social relationship
deviation	2.3125	1.4363	0.2918	0.5388
weight	0.5050	0.3136	0.0637	0.1177

in Table 5. The comparison algorithm of SVNN[31] can be used to compare the size of aggregated values. Finally, the ranking list of the services is obtained: $l_2 \succ l_1 \succ l_6 \succ l_3 \succ l_8 \succ l_4 \succ l_7 \succ l_5$.

l_2 is the best candidate POI and will be recommended to users first. The NDCG of this recommended result can be calculated by Eq.(18). The result is $NDCG@8 = 0.85$. More importantly, the top two POIs in our list are consistent with the user preferences. CPRNS can help users find the candidate POI that best conforms to their preferences in all aspects. POI l_2 is the best candidate because it shows a higher truth membership and lower indeterminacy membership and falsity membership in each attribute.

The maximizing deviation method proposed in this paper can effectively reflect the differences between candidate POIs. The impact of the same attribute in different recommendation scenarios is different. The result of the weight calculation depends on the distribution of the attribute. If the difference of candidate POIs on a certain attribute is small, then the influence of the attribute on the recommendation result is small, and the weight of the attribute is small.

7.3 Comparison of the methods

Figure 3 illustrates the change in the three evaluation indicators for the CPRNS and methods without considering any attributes when the length of the recommended list is different.

In Figure3, the three evaluation indicators of CPRNS are better than those of other methods. The performance of UserCF and ItemCF are modest because in these two methods, the POI is recommended only according to the opinions of other users, rather than considering the users' personalized preferences. PMF performs well in traditional recommendation problems, but poorly in POI recommendations, because the data in POI recommendations is more sparse than that in traditional recommendation problems. The above method does not effectively deal with the large amount of implicit feedback check-in information in POI recommendations.

Table 4 Weight of three attributes in the case study.

	geographic location	interest topic	popularity
deviation	11.7512	5.4478	1.5468
weight	0.6269	0.2906	0.0825

Table 5 The aggregation SVNS of the candidate POI in the case study.

POI	aggregation SVNS
l_1	<0.6832, 0.1473, 0.0680>
l_2	<0.5933, 0.1573, 0.0000>
l_3	<0.4872, 0.2486, 0.1438>
l_4	<0.3853, 0.3052, 0.2399>
l_5	<0.5874, 0.0000, 0.1838>
l_6	<0.5858, 0.1893, 0.1807>
l_7	<0.3757, 0.0000, 0.3964>
l_8	<0.5443, 0.1691, 0.2157>

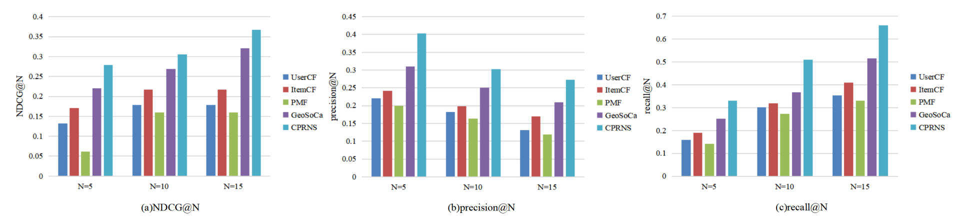

Figure 3 Other POI recommended technologies comparison.

The recommendation effect of GeoSoCa ranks second. Although GeoSoCa also takes into account contextual information, it only takes the product of the three scores as the final recommendation score, and does not consider the different influence of various contextual information on user selection.

The CPRNS models users' preferences based on four attributes and aggregates them with the personalized weights using the SVNSWA. This method always achieves the best recommendation quality on three evaluation indicators. These results validate the superiority of aggregating multiple attributes.

8 Conclusion

In view of the fuzzy and uncertain user preference reflected in the check-in data, this paper transforms the POI recommendation into multi-attribute decision-making problem from the perspective of user decision-making, and proposes a context-aware POI recommendation method based on the neutrosophic set. The four attributes of geographical location, interest topics, popularity and social relationships are effectively combined, and various attributes that affect the selection of POI are converted into the same representation based on neutrosophic set, providing us with an efficient model to study the POI recommendation problem. A single-dimensional attribute SVNS transformation model in geographic location and interest topic is constructed based on similarity, and a multi-dimensional attribute SVNS transformation model in popularity and social relationship is constructed based on sentiment analysis, so as to provide an effective quantitative modeling method for each attribute preference for users. The truth-membership, indeterminacy-membership and falsity-membership of each POI attribute can be clearly obtained by the neutrosophic set of each attribute, which improves the interpretability of the recommendation results and enables us to study and analyze candidates POI from the user decision-making perspective.

In addition, using the integrated operator of neutrosophic set to comprehensively calculate multiple attribute neutrosophic sets, the objective weight calculation method of each attribute is given, and the final recommendation list is generated by comprehensive consideration. The method can be effectively extended, not only can be applied to the synthesis of the above four attributes, but also can be extended to the integration of various attributes. Experimental results on real data sets show that our method has better recommendation accuracy. As part of our future work, we will further refine our solution to further improve the performance of POI recommendations.

Abbreviations
POI: point of interest; NS: neutrosophic set; MEC: Mobile edge computing; LBSN: location-based social network; MCDM: multi-criteria decision making; SVNS: single-valued neutrosophic set; SVNN: single-valued neutrosophic number; SVNSWA: SVNSs weighted average; MANST: multi-attribute neutrosophic set transformation; PRNS: POI recommendation based on neutrosophic sets; LDA: latent dirichtlet allocation; CPRNS: context-aware recommendation algorithm based on NS; NDCG: Normalized Discounted Cumulative Gain; CPRNS-WG: CPRNS without geographic location; CPRNS-WI: CPRNS without interest topics; CPRNS-WP: CPRNS without popularity; CPRNS-WS: CPRNS without social relationships; CPRNS-WPW: CPRNS without personalized weighting.

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Availability of data and materials
The datasets analysed during the current study are available in the Yelp repository, https://www.yelp.com/dataset

Authors' contributions
Meiguang Zheng, Yi Li, Yu Hu, Jie Li have written this paper and done the research which supports it. Meiguang Zheng, Yi Li, Zhengfang He and Liu Yang has collaborated in the conception, research and design of the paper. All authors have read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

Authors' information
Meiguang Zheng received her B.S. and Ph.D. degrees in computer science and technology from Central South University, Changsha, China, in 2005 and 2011 respectively. She is currently an associate professor at the school of Computer Science and Engineering, Central South University. Her research interests include Edge Computing, Cloud Computing, Service Computing and Federated Learning. She is currently leading some research projects supported by National Natural Science Foundation of China.
Yi Li received her M.S. degree in software engineering from Central South University, Changsha, China, in 2020. She is a researcher in China UnionPay Merchant Services Co., Ltd. Her research interests include Service Computing.
Zhengfang He received his M.S. degree in computer science and technology from Central South University, Changsha, China, in 2006. He is a researcher in Zhejiang Uniview Technologies Co., Ltd. His research interests include Computer Vision and Pattern Recognition.
Yu Hu received his bachelor's degrees in software engineering from Hebei Normal University, Shijiazhuang, China, in 2020. He is currently pursuing a graduate student in software engineering at the school of Computer Science and Engineering, Central South University. His research interests include Edge Computing and Data Caching.
Jie Li received his bachelor's degree in computer science and technology from Henan University of Technology, Zhengzhou, China, in 2019. He is currently pursuing graduate student in software engineering at the school of Computer Science and Engineering, Central South University. His research interests include Edge Computing and Mobile Computing.
Liu Yang received her M.S. and Ph.D. degrees in Computer Science from Central South University, Changsha, China, in 2005 and 2011 respectively. She is currently an associate professor at the school of Computer Science and Engineering, Central South University. Her research interests include semantic information service and knowledge graph representation learning. She is currently leading several research projects supported by National Natural Science Foundation of China.

Author details
[1]School of Computer science and Engineering, Central South University, ChangSha 410083, China. [2]China UnionPay Merchant Services Co., Ltd, WuHan 430070, China. [3]Zhejiang Uniview Technologies Co., Ltd, HangZhou 310051, China.

References
1. Si, Y., Zhang, F., Liu, W.: An adaptive point-of-interest recommendation method for location-based social networks based on user activity and spatial features. Knowledge-Based Systems **163**, 267–282 (2019). doi:10.1016/j.knosys.2018.08.031

2. Ye, M., Yin, P., Lee, W.C., Lee, D.L.: Exploiting geographical influence for collaborative point-of-interest recommendation, 325–334 (2011)
3. Zhu, J.H., Ming, Q.: Poi recommendation by incorporating trust-distrust relationship in lbsn. Journal on Communications **39**(7), 157–165 (2018)
4. Liu, S., Wang, L.: A self-adaptive point-of-interest recommendation algorithm based on a multi-order markov model. Future Generation Computer Systems **89**, 506–514 (2018)
5. Liu, B., Fu, Y., Yao, Z., Hui, X.: Learning geographical preferences for point-of-interest recommendation. In: Acm Sigkdd International Conference on Knowledge Discovery and Data Mining, pp. 1043–1051 (2013)
6. Xing, S., Liu, F., Wang, Q., Zhao, X., Li, T.: Content-aware point-of-interest recommendation based on convolutional neural network. Applied Intelligence **49**(3), 858–871 (2019)
7. Smarandache, F.: A unifying field in logics: Neutrosophic logic. Multiple-Valued Logic **8**(3), 489–503 (2002)
8. Ma, Y.X., Wang, J.Q., Wang, J., Wu, X.H.: An interval neutrosophic linguistic multi-criteria group decision-making method and its application in selecting medical treatment options. Neural Computing and Applications **28**(9), 1–21 (2017)
9. Zhang, H.Y., Pu, J., Wang, J.Q., Chen, X.H.: A novel decision support model for satisfactory restaurants utilizing social information: A case study of tripadvisor.com. Tourism Management **59**, 281–297 (2017)
10. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge & Data Engineering **17**(6), 734–749 (2005)
11. Gao, R., Li, J., Li, X., Song, C., Zhou, Y.: A personalized point-of-interest recommendation model via fusion of geo-social information. Neurocomputing **273**, 159–170 (2018)
12. Kuang, L., Tu, S., Zhang, Y., Yang, X.: Providing privacy preserving in next poi recommendation for mobile edge computing. In: Journal of Cloud Computing, vol. 9, pp. 1–11 (2020)
13. Han, J., Yamana, H.: Geographic diversification of recommended pois in frequently visited areas. In: ACM Transactions on Information Systems, vol. 38, pp. 1–39 (2019)
14. Cheng, C., Yang, H., King, I., Lyu, M.: Fused matrix factorization with geographical and social influence in location-based social networks. Proceedings of the National Conference on Artificial Intelligence, 17–23 (2012)
15. Capdevila, J., Arias, M., Arratia, A.: Geosrs : A hybrid social recommender system for geolocated data. Information Systems **57**, 111–128 (2016)
16. Ren, X.Y., Song, M.N., Song, J.D.: Point-of-interest recommendation based on the user check-in behavior. Chinese Journal of Computers **40**(1)
17. Liu, Y., Seah, H.S.: Points of interest recommendation from gps trajectories. International Journal of Geographical Information Systems **29**(6), 953–979 (2015)
18. Yin, H., Cui, B., Zhou, X., Wang, W., Zi, H., Sadiq, S.: Joint modeling of user check-in behaviors for real-time point-of-interest recommendation. In: Acm International on Conference on Information and Knowledge Management, vol. 35, pp. 1631–1640 (2015)
19. Davtalab, M., Alesheikh, A.A.: A poi recommendation approach integrating social spatio-temporal information into probabilistic matrix factorization. Knowledge and Information Systems **63**(1), 65–85 (2021)
20. Zhang, J.: Geosoca : Exploiting geographical,social and categorical correlations for point-of-interest recommendations categories and subject descriptors. ACM Special Interest Group on Information Retrieval, 443–452 (2015)
21. Liu, B., Xiong, H., Papadimitriou, S., Fu, Y., Yao, Z.: A general geographical probabilistic factor model for point of interest recommendation. IEEE Transactions on Knowledge & Data Engineering **27**(5), 1167–1179 (2015)
22. Guo, Y., Sengur, A., Ye, J.: A novel image thresholding algorithm based on neutrosophic similarity score. Measurement **58**, 175–186 (2014)
23. Bharti, P., Mittal, D.: An ultrasound image enhancement method using neutrosophic similarity score. Ultrasonic Imaging **42**(6), 271–283 (2020)
24. Guo, Y., Sengur, A.: Ncm: Neutrosophic c-means clustering algorithm. Pattern Recognition **48**(8), 2710–2724 (2015)
25. Chai, J.S., Selvachandran, G., Smarandache, F., Gerogiannis, V.C., Son, L.H., Bui, Q.-T., Vo, B.: New similarity measures for single-valued neutrosophic sets with applications in pattern recognition and medical diagnosis problems. Complex and Intelligent Systems **7**(2), 703–723 (2021)
26. Ye, J., Fu, J.: Multi-period medical diagnosis method using a single valued neutrosophic similarity measure based on tangent function. Computer Methods and Programs in Biomedicine **123**, 142–149 (2016)
27. Hua, M., Hu, Z., Li, K., Zhang, H.: Toward trustworthy cloud service selection: A time-aware approach using interval neutrosophic set. Journal of Parallel and Distributed Computing **96**(C), 75–94 (2016)
28. Bettini, C., Brdiczka, O., Henricksen, K., Indulska, J., Nicklas, D., Ranganathan, A., Riboni, D.: A survey of context modelling and reasoning techniques. Pervasive & Mobile Computing **6**(2), 161–180 (2010)
29. Liu, S.D., Meng, X.W.: Recommender systems in location-based social networks. Chinese Journal of Computers **38**(2), 322–336 (2015)
30. Hutto, C.J., Gilbert, E.: Vader: A parsimonious rule-based model for sentiment analysis of social media text. (2015)
31. Peng, J.-j., Wang, J.-q., Wang, J., Zhang, H.-y., Chen, X.-h.: Simplified neutrosophic sets and their applications in multi-criteria group decision-making problems. International Journal of Systems Science **47**(10), 2342–2358 (2016)
32. https://www.yelp.com/dataset_challenge
33. S. Breese, J., Heckerman, D., Kadie, C.: Empirical analysis of predictive algorithms for collaborative filtering. In: Proceedings of the 14th Annual Conference on Uncertainty in Artificial Intelligence., pp. 43–52 (1998)
34. Sarwar, B., Karypis, G., Konstan, J., Riedl, J.: Item-based collaborative filtering recommendation algorithms. Proceedings of ACM World Wide Web Conference **1**, 285–295 (2001)
35. Salakhutdinov, R., Mnih, A.: Probabilistic matrix factorization. Advances in Neural Information Processing Systems **20**(2), 1257–1264 (2087)

Figures

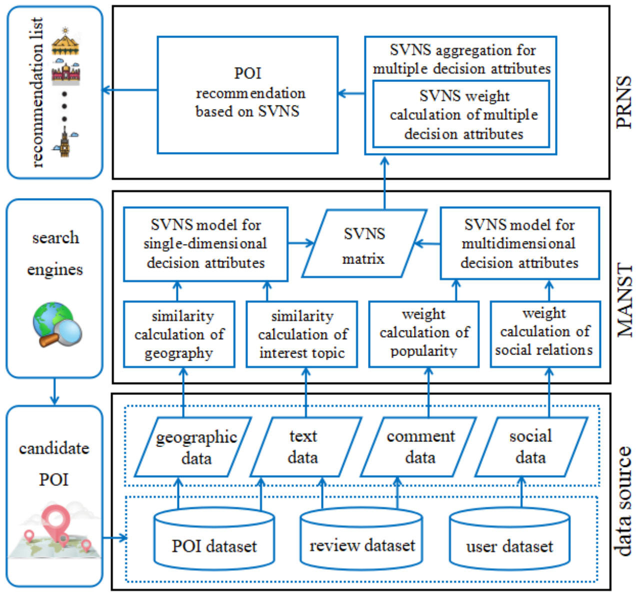

Figure 1 POI recommendation framework based on neutrosophic sets.

The framework consists of two parts: the multi-attribute neutrosophic sets transformation model (MANST) and the POI recommendation based on neutrosophic sets (PRNS). The function of the MANST model is to convert context data into neutrosophic sets through similarity calculation or sentiment analysis-based methods. The function of the PRNS model is to calculate the importance of each context attribute and effectively integrate these attributes to find the POI that best meets the needs of users.

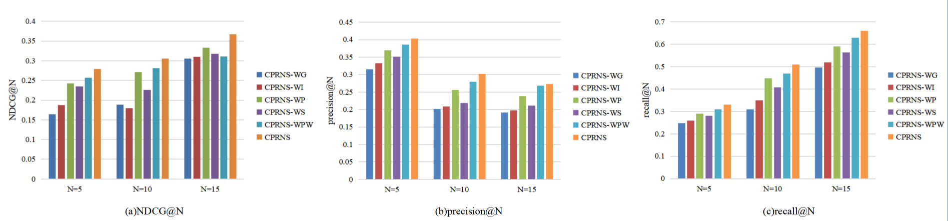

Figure 2 Baseline approaches comparison.

Figure 2 illustrates the experimental results of CPRNS and the baseline method on the three evaluation indicators. In this figure, the three indicators of the CPRNS method are better than the five baseline methods. From the introduction of the comparison method and the experimental results, it can be seen that the difference in the number of attributes and the aggregation of attributes are important for the recommendation of POI.

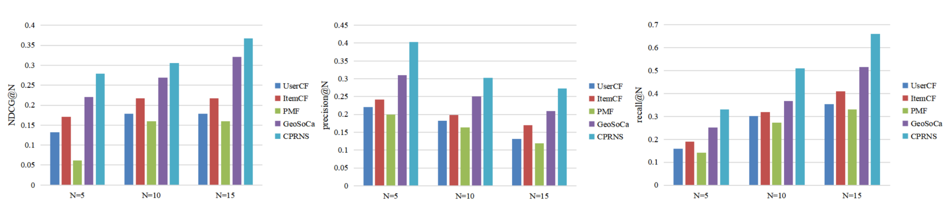

Figure 3 Other POI recommended technologies comparison.

Figure 3 illustrates the experimental results of CPRNS and other POI recommended methods on the three evaluation indicators. The UserCF and ItemCF methods are recommended based on the opinions of other users, without considering the user's preferences, so the experimental results are general. Due to the sparseness of data in POI recommendation, PMF method performs poorly in POI recommendation. The recommendation effect of the GeoSoCa method is good, but the different effects of various contextual information on users are not considered, so the recommendation effect is inferior to CPRNS.

Figure

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Figure 1 POI recommendation framework based on neutrosophic sets.

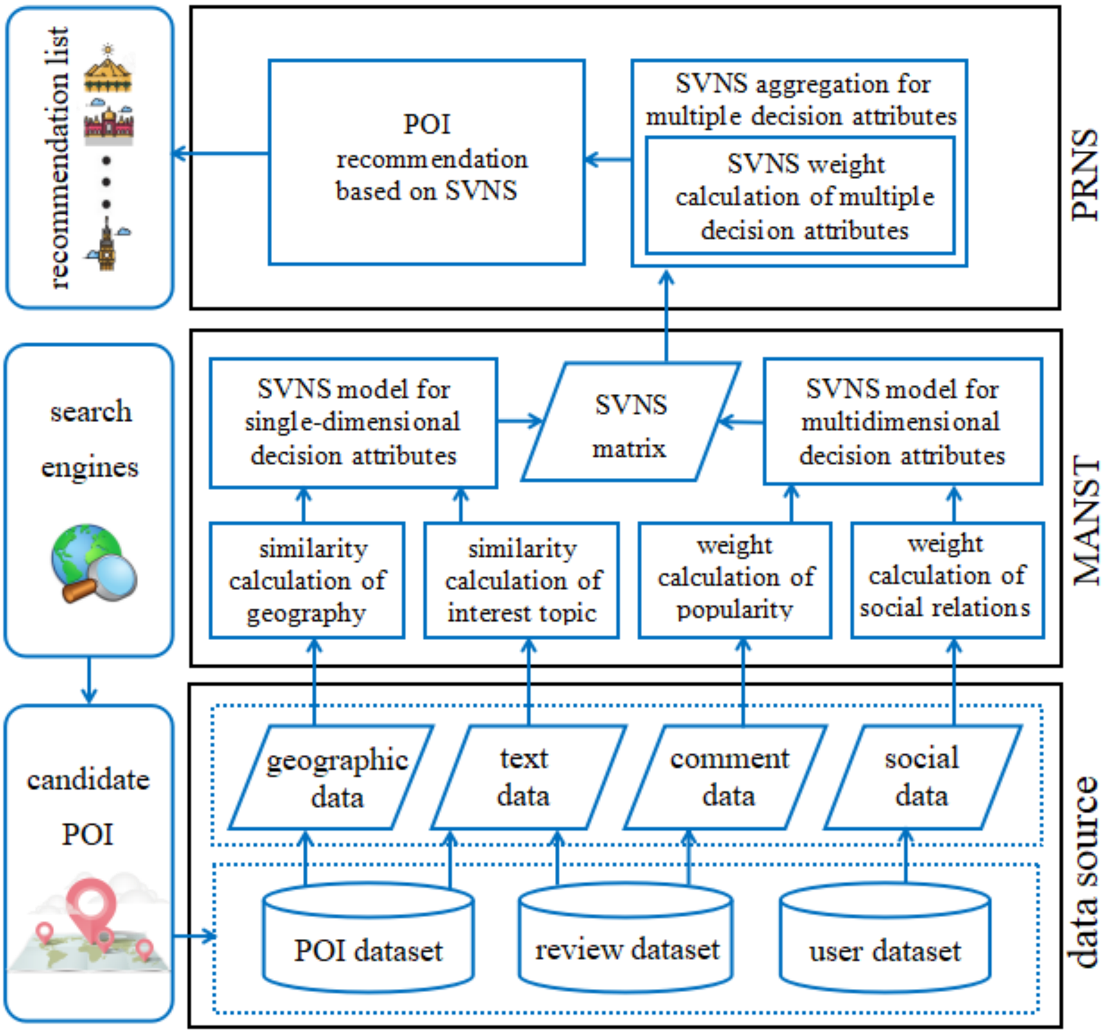


Figure 2 Baseline approaches comparison.

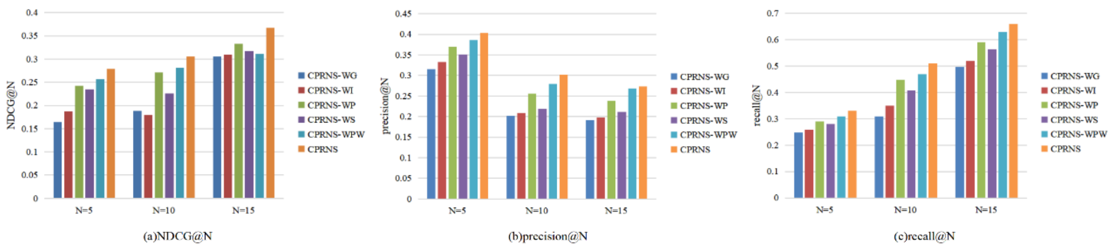
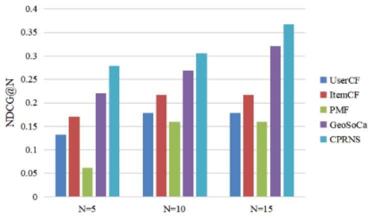
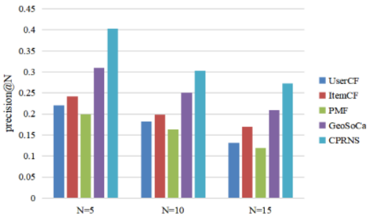


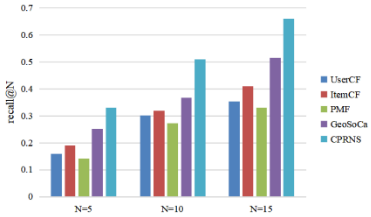
Figure 3 Other POI recommended technologies comparison.



(a)NDCG@N



(b)precision@N



(c)recall@N