Affective Impression: Sentiment-awareness POI Suggestion via Embedding in Heterogeneous LBSNs

Xi Xiong, Shaojie Qiao, Yuanyuan Li, Fei Xiong, Ling He, Nan Han

Abstract—Location-based social networks (LBSNs) add geographical information into traditional social networks and link people's virtual and physical lives. As an important application of LBSNs, point-of-interest (POI) suggestion has become an important method to help users explore interesting and attractive locations in LBSNs. The main problems of POI suggestion include data sparsity and cold start, which have been paid much attention by existing techniques. There are two major challenges which can greatly influence the performance of suggestion accuracy. One is the fuzzy boundary between sentiments, i.e., the fine distinction between sentiments makes it difficult to classify words and texts after word-sentiment mapping operation. The other challenge is the unreliability of data quality represented by similarity metrics, which relies on data integrity and path reachability of a heterogeneous network. To cope with the above two challenges, we present a novel framework called **C**ommunity-based Sentiment **E**xtraction and **Net**work **E**mbedding for POI **R**ecommendation (CENTER) for suggesting impressive POIs to a specific user in an effective fashion. The CENTER framework contains two essential techniques: (1) a latent probabilistic generative model called **C**ommunity-based **S**entiment **E**xtraction (CSE), which can accurately capture the sentiments from review content in LBSNs by taking into consideration the characteristics of social communities. The parameters of the CSE model can be inferred effectively by the Gibbs sampling method. The primary sentiments are obtained based on the distribution of sentiments; (2) a network embedding model called **S**entiment-aware **N**ework **E**mbedding for POI **R**ecommendation (SNER) is employed to learn the representation of the factors including POIs, users and textual sentiments in a low-dimensional embedding space. The joint training is utilized to alternatively sample all sets of edges in a heterogeneous information network. Extensive experiments were conducted on two large-scale real datasets, in order to evaluate the performance of the proposed CENTER framework. The results demonstrate that CENTER is superior to the state-of-the-art baseline methods in the effectiveness and efficiency of POI suggestion.

Index Terms—Network embedding, affective computing, location-based social networks, POI suggestion, heterogeneous networks, probabilistic graphical model.

1 Introduction

LOCATION-based social networks (LBSNs) [1] such as Foursquare[1] and Yelp[2] have become popular services to attract a huge volume of users sharing their life experiences in the physical world by mobile devices, such as check-in at points-of-interest (POI) [2], making friends, or reviewing on POIs. Users can request favorite POIs by location suggestion methods, which learn users' preferences from their behavioral history and have played a critical role in LBSN services. The services of POI suggestion not only contribute to users' navigation of new interesting places [3], but also facilitate companies to accurately push advertisements to target customers.

Different from traditional digital recommendation systems delivering virtual information, e.g., news, goods or music, POI suggestion in LBSNs typically involve users' relationship such as communities [4] and POIs' physical features such as locations. POI suggestion may suffer from several challenging problems, for example, data sparsity [2] and the cold start problem [5]. Cold start is a critical problem in the domain of recommendation, where users have not visited any POI, or have visited only a few POIs which provide insufficient information for POI suggestion. These two problems have been greatly alleviated by the existing

1. https://www.foursquare.com
2. https://www.yelp.com

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methods [6], [7]. To the best of our knowledge, there are two major challenges that affect the performance of suggestion accuracy:

1) Fuzzy boundary between sentiments. Users often post reviews about visited places. Some studies in [6], [8], [9] have exploited the sentiments from historical reviews and found that the decision-making of visiting a place in regard of a user is greatly affected by the attitudes of previous users. Sentiments is conventionally extracted from the textual content [10] based on the word-sentiment mapping dictionary [11]. However, it is still a difficult task to describe the subtle difference between sentiments in words and classify texts [12], which is a major obstacle to extract valuable information from textual content. We will give an illustrative example to present this problem.

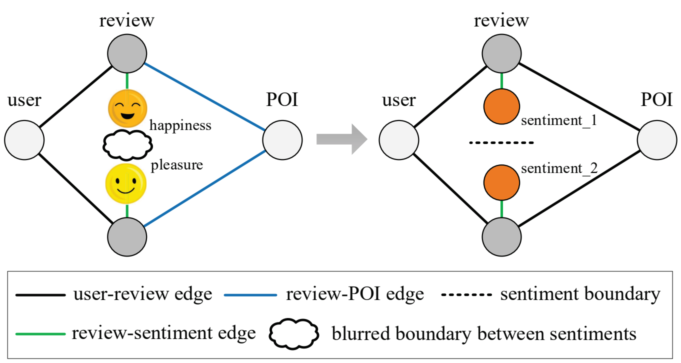


Fig. 1. Example showing the fuzzy boundary between sentiments and the clear boundary between clustered sentiments without exact meaning.

Example 1. As shown in the left part of Fig. 1, the sentiments are classified into different kinds such as happiness and pleasure. In general, each review contains more than one kind of sentiment, which is retrieved by the word-sentiment mapping dictionary. It is difficult to distinguish the fuzzy boundary between the fine-grained sentiments. Given eight types of sentiments including angry, disgusted/disgusting, sad, bored/boring, awed/awing, amused/amusing, content and excited/exciting based on the WordNet [13], the sentiment distribution like: excited (7), amused (5), content (8) can be figured out from several reviews such as “waitress served with smile and patience” and “The steak tasted pleasant” for a restaurant. Each sentiment is assigned a value between 1 and 10. The model returns the probable sentiments with the largest values.

In this work, sentiments are clustered into multiple categories without semantic meanings, each of which is regarded as an element to learn the low-dimensional vectors of users and POIs, of which the degrees of correlation can be used for POI suggestion.

2) Ineffectiveness of relation retrieval from heterogeneous data. LBSNs are formed by different categories of elements such as users, POIs and reviews, which can be regarded as different categories of vertices and connected by different types of relations. The degree of correlation between two elements with the same type [14] is usually represented by a similarity metric, which conveys meaningful semantics. Some studies in [15], [16] show that the similarity may not be reliable to be directly used in recommender systems if the data are sparse or with noise, that is, it is a difficult task to transform the complicated elements or factors to useful knowledge for POI suggestion. The approaches proposed in these literatures combine multiple factors for POI suggestion, but some important information such as latent sentiments in textual content is not appropriately exploited due to the lack of a similarity metric based on the heterogeneous relations.

This work is motivated by the solutions for these two problems existing in achieving the goal of accurate POI suggestion, that is, effectively extracting and exploiting historical information from multiple categories of heterogeneous network data with affective features which provide *affective impression* [17] to users.

A heterogeneous network [18], [19], [20], comprised of different categories of vertices and edges, has been viewed as a useful modeling tool to incorporate the complicated factors in LBSNs, such as social relationship, locations and textual sentiments. Regard of its flexibility in modeling the complexity of data, heterogeneous networks have been adopted in recommendation systems to represent the structures and relationships of auxiliary data [21]. One advantage of the proposed model is that: we take into consideration these two challenges in a unified way by analyzing the joint effect of multiple factors in a heterogeneous network.

In order to solve the problem of fuzzy boundary between sentiments and improve the effectiveness of POI suggestion, a latent probabilistic generative model, which is a statistical method based on Bayesian networks, is employed to accurately capture users’ sentiments by analyzing the reviews as well as important information in LBSNs including the effect of social communities. Another advantage of our proposed model is that review words can be classified into multiple categories of sentiments without exact semantic meaning, which retains valuable sentimental information in textual content.

It is a challenging task to propose an approach to effectively extract and represent valuable information in LBSNs because of data heterogeneity. Rather than representing vertices based on their similarities in the previous works, we provide a new method of learning the representation of heterogeneous networks by summarizing significant structural and dynamical features. Inspired by [22], we represent vertices in networks by low-dimensional vectors (called embedding vectors), which incorporates latent information instead of explicit links between vertices. Different from the similarity metrics, the learned embedding vectors are represented in a more compact fashion which is easy to be used and integrated. Moreover, the network embedding method is insensitive to sparse and noisy data. Learning a unique embedding representation for a vertex in a heterogeneous network by maximizing its co-occurrence probability with adjacent vertices and other factors can help greatly improve the efficiency of suggestion [14]. However, conventional network embedding methods represent vertices by such factors as users’ profiles, POIs’ profiles and locations. Latent sentiment in textual content such as reviews illustrate more information than other factors. In this work, we used a generative statistical model that allows a series of words extracted from review texts to be explained by unobserved sentiments, instead of directly classifying sentiments based on lexicons. When a user provides a few reviews for POIs, the proposed approach can still suggest new POIs, which can be inferred from his/her historical records.

By taking into account the aforementioned aspects, we propose a novel suggestion framework called CENTER which can accurately capture the sentiments from review content in LBSNs by considering social communities and learn the representation of POIs, users and textual sentiments in a low-dimensional embedding space. Fig. 2 shows the basic idea of the proposed model. The rates that users provide for multiple POIs are shown by different shades of colors in the left table. A large proportion of blank elements in the table indicate that the problem of unreliable data quality is serious. A POI has the attributes of geographical correlation, users' profiles and latent sentiments in textual content which are extracted by the probabilistic graph model and the embedding representation for a POI is shown by a small matrix (denoted by a 2×6 matrix in Fig. 2).

In this paper, we make the following contributions:

- We investigate the joint effect of social relationships, Geographical proximity and textual sentiment to handle the problems of fuzzy sentimental boundary and unreliable data quality in location suggestion in heterogeneous networks.
- We present a novel framework called **C**ommunity-based Sentiment **E**xtraction and **Net**work **E**mbedding for POI **R**ecommendation (CENTER) for suggesting impressive POIs to users, which contains two essential techniques: (i) a latent probabilistic generative model named **C**ommunity-based **S**entiment **E**xtraction (CSE), which can accurately capture the sentiments from review content in LBSNs by considering social communities. The parameters of the CSE model can be inferred effectively by the Gibbs sampling method. The primary sentiments are obtained from the distribution of sentiment; (ii) a network embedding model called **S**entiment-aware **N**ework **E**mbedding for POI **R**ecommendation (SNER) is employed to learn the representation of POIs, users and textual sentiments in a low-dimensional embedding space.
- Extensive experiments on two large-scale real datasets were conducted to evaluate the performance of the proposed CENTER framework. The results demonstrate CENTER is superior to the state-of-the-art baseline methods in the effectiveness and efficiency of POI suggestion.

The remainder of this paper is structured as follows: Section 2 discusses the related works. Section 3 introduces some significant definitions and present the problem. Section 4 illustrates the application framework of POI suggestion. Section 5 details the proposed CSE model which is used to extract sentiments. Section 6 introduces a network embedding method considering multiple kinds of sentiments. The experimental results are demonstrated in Section 7. Lastly, the full study is concluded in Section 8.

2 Related Works

In order to give effective suggestions of POIs in LBSNs, the recent works mainly focus on integrating important subjective and objective factors including the effect of textual content, social relationships between individuals and characteristics of geo-social networks.

Effect of social relationships. Social analysis attracts more attention with the growing of social networks. Social communities are groups of users with close ties and share similar interests. Yang et al. [15] incorporates two kinds of sparse information, i.e., the rating scores and the social trust relationships among a group of users. Users are transformed into a low-dimensional dimension by the matrix factorization approach according to the trust networks, which helps understand the influence of users' opinions. Wang et al. [16] studied the influence of discriminating strong and weak connections in social relationship suggestion, in which overlapped neighborhood is used to estimate the strength of connection. The Bayesian personalized ranking model is involved to integrate the difference of strong and weak connections. Crestani et al. [23] proposed two approaches beyond the concepts of social reverse height and social height, which take into account the top-ranking situation of the relevant and irrelevant items w.r.t. users' social relationships. The method focuses on the top-k users instead of all users in the suggestion list in real-world scenarios.

Geographical influence. Chen et al. [24] proposed a divide-and-conquer method to predict users' subsequent preferences based on POI types by ranking only a confined set of POIs and smoothing the missing information in LBSNs. Wang et al. [25] introduced an additive generative model, which integrates individual and crowd's interests within a specific geographical region, by leveraging the co-occurrence patterns of POIs as well as the textual information of POIs. Qiao et al. [26] proposes a hybrid location suggestion algorithm by taking into account users' familiarity and preference similarity, along with relationships.

Sentimental effect in textual content. Yin et al. [7] integrated the textual information of the given POIs with local preferences and personal interests of users, to handle the data sparsity problem for out-of-town suggestion (the distance between user location and target area is larger than a threshold). Ren et al. [27] presented a context-aware probabilistic matrix factorization approach for POI suggestion, which exploits multiple factors, i.e., textual content, geographical locations, social relationship, categorical correlation and POIs' popularity. Meng et al. [8] presented a principled and mathematical approach to exploit both positive and negative emotion on reviews, and proposed a novel framework to exploit emotion on reviews for recommendation systems from global as well as local perspectives.

Suggestion via network embedding. Network embedding is a new method which has been extended to many research domains such as the extraction of structural features as well as POI suggestion [28]. Xie et al. [2] introduced a common graph embedding model, which integrates the four factors including the sequentially

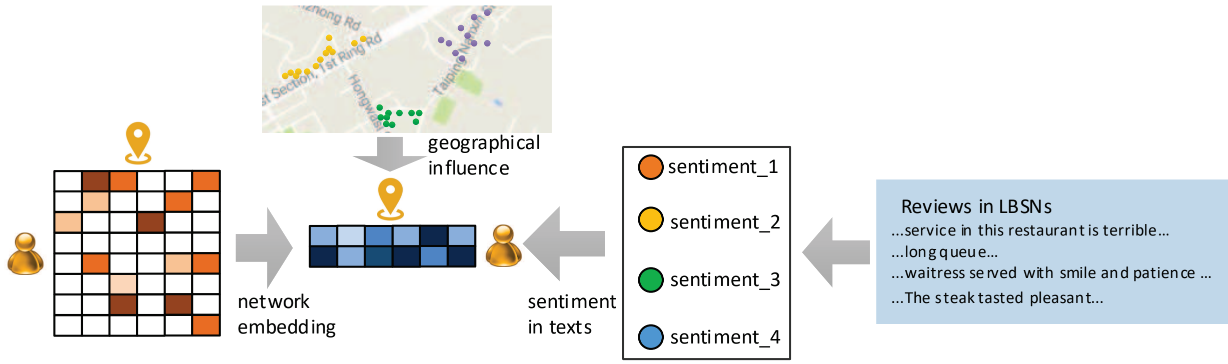


Fig. 2. Overview of the proposed POI suggestion approach.

visits, geographical effect, temporal effect and textual content, by transforming the original network into a low-dimensional graph with four sub-components. Then, they proposed a new sequential method to dynamically calculate users' recent preferences by embedding his or her checked-in POIs. Okura et al. [29] proposed an embedding-based method for news suggestion, which starts with distributed representations of articles based on a variant of a denoising autoencoder, then generates user representations by a recurrent neural network (RNN). Xie et al. [30] developed a network embedding model which tracks the sequential patterns of users' preferences efficiently by converting POIs into a low dimension. Unlike the Markov chain-based suggestion methods, this model can avoid the time-consuming computation on the POI-POI transition matrix by utilizing the dynamics of users' check-in behaviors and embedding them into the vectors of POIs. Shi et al. [14] proposed a suggestion method in heterogeneous networks by embedding multiple factors, which incorporates a random walk approach to produce informative sequential vertices for network embedding. The encoded vertices are converted by several fusion functions, and then integrated into a new matrix factorization model, which are combined to fulfill the task of rating prediction.

By analyzing the above approaches, latent sentiments extracted from textual content of reviews are not appropriately exploited for the purpose of POI suggestion. The methods proposed in [8], [27] even have an inaccurate classification of sentiments which will degrade the suggestion performance. These disadvantages motivate us to propose a novel model to improve the suggestion accuracy and efficiency by taking into consideration two essential issues: extracting sentiments as an intermediate variable without exact meanings, and embedding multiple factors including the extracted sentiments into POI suggestion.

3 Problem Statement

In this section, we first present important notations and definitions, and then formalize the POI suggestion problems. To facilitate understanding, Table 1 describe the important notations used in this paper.

TABLE 1
Notations and their meanings.

SYMBOL	DESCRIPTION
$\mathcal{U}, \mathcal{V}, \mathcal{Z}$	sets of users, POIs and sentiments
U, C, K	numbers of users, communities and sentiments
$\mathcal{M}_c$	a set of reviews w.r.t. community c
$\vec{v}, \vec{u}, \vec{z}$	embeddings of POI v, user u and sentiment z
$\mathcal{G}$	a heterogeneous network
$\mathcal{V}, \mathcal{E}$	a set of vetices, a set of edges
G_{vv}, G_{vu} G_{vz}	the POI-POI subgraph, the POI-user subgraph and the POI-sentiment subgraph
$\mathcal{D}$	a set of review records
u, z, c	a given user, a sentiment, a community
φ	the parameter of the multinomial distribution on the latent variable β w.r.t. a sentiment z
ϑ	the parameter of the multinomial distribution over the latent variable γ within $\mathcal{U}$
θ	the parameter of the multinomial distribution over the latent variable α
α, β, γ	the hyper-parameters of the Dirichlet distributions corresponding to θ, φ and ϑ, respectively

Definition 1 (POI). A POI is a uniquely identified place (e.g., a cafe or a cinema), which has two attributes in the proposed model, i.e, identifier v and geographical location l_v represented by longitude and latitude coordinates.

Definition 2 (Social community). Social communities are groups of users with dense connections, while the connections between groups are sparse [31]. A LBSN can be partitioned into lots of communities according to users' relationship.

Definition 3 (Textual content of a POI). In order to share their feelings or opinions with friends in a community, users post reviews to POIs. We view reviews as textual content of a POI and integrate textual content from user's reviews to suggest locations.

Definition 4 (Sentiment). Latent sentiments underlie in the textual content of POIs. Each word in a textual review belongs to one kind of sentiment and a review also belongs to a sentiment.

This study focuses on providing effective and efficient POI suggestion services. Here, we formalize the problem of location suggestion as follows.

Problem statement. Given a LBSN database, containing a collection of users $\mathcal{U}$, POIs $\mathcal{V}$ and relevant reviews, we intend to extract the latent sentiments $z_k \in \mathcal{Z}$ from users' reviews by considering the social communities $\mathcal{C}$ w.r.t. $\mathcal{U}$. Based on the POI-POI proximity of $\mathcal{V}$, user u's visiting history and the extracted sentiments $\mathcal{Z}$, we learn the representation of user $u_i \in \mathcal{U}$, POI $v_j \in \mathcal{V}$ and sentiment $z_k \in \mathcal{Z}$ in a low-dimensional space, that is, these items are converted into embedding vectors $\vec{u}_i$, $\vec{v}_j$ and $\vec{z}_k$. Finally, we provide suggestions with k POIs which the user u is probably interested in.

4 Working Mechanism

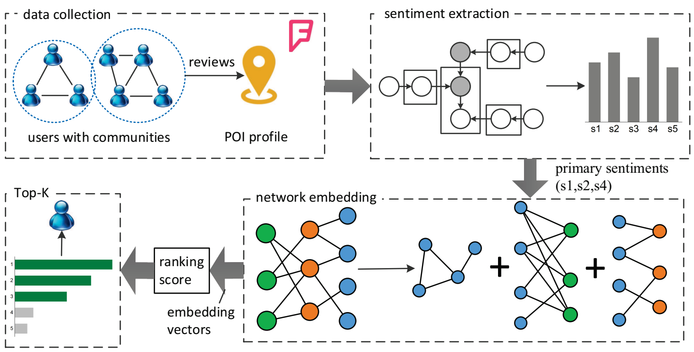


Fig. 3. Working mechanism of the CENTER model.

Basically, the CENTER approach involves four essential steps, as shown in Fig. 3.

1) Data are collected from popular LBSN portals, including: a) users' information, i.e., users' profiles and relationships among users; b) POIs' information, i.e., POI profiles and textual content of reviews w.r.t. POIs.

2) Compute the distribution of sentiments and obtain primary sentiments of a POI by the CSE model.

3) Learn the embeddings representation of POIs, users and sentiments by the SNER model, respectively .

4) Calculate POIs' ranking scores and find top-k locations for a user.

5 Community-based Sentiment Extraction Model

5.1 Generative Process of Textual Contents

Before creating a network embedding model, it is essential to infer the distributions of sentiments from community-based network data. In order to accomplish this task, we propose a probabilistic generative model called CSE (Community-based Sentiment Extraction), which models users' textual content by taking into account the influence of social communities. Fig. 4 shows the probabilistic generative process of CSE. The input of the CSE model is the review data of a POI and the output is the distribution of sentiments for this POI.

Different from the traditional method of text classification based on NLP, this method is a word

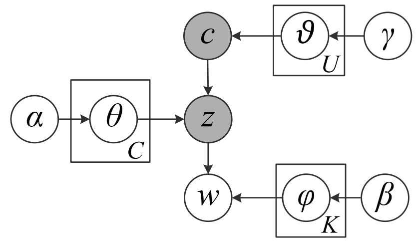


Fig. 4. Description of the community-based sentiment extraction model.

clustering model based on the theory of statistical learning without a lexicon. It is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. A sentiment is neither semantically nor epistemologically strongly defined. It is identified on the basis of automatic detection of the likelihood of word co-occurrence.

Algorithm 1 illustrates the probabilistic generative process of a word. When user u decides to generate a word, he first chooses a community c from all communities that he belongs to. Then a distribution of sentiment w.r.t. c is generated. In regard of a given sentiment z, the set of words $\mathcal{W}_c$ are generated from the distribution φ.

Algorithm 1: Generative process in CSE model

1 **foreach** *user* $u \in \mathcal{U}$ **do**
2 Sample $\vartheta \sim Dirichlet(\cdot|\gamma)$;
3 **foreach** *community* $c \in \mathcal{C}$ **do**
4 Sample $\theta \sim Dirichlet(\cdot|\alpha)$;
5 **end**
6 **end**
7 **foreach** *sentiment* $z \in \mathcal{Z}$ **do**
8 Sample $\varphi \sim Dirichlet(\cdot|\beta)$;
9 **end**
10 **foreach** *user* $u \in \mathcal{U}$ **do**
11 **foreach** *review* $(u, c, \mathcal{W}_c) \in \mathcal{M}_c$ **do**
12 Sample a community $c \sim Multi(\vartheta)$;
13 Sample a sentiment $z \sim Multi(\theta)$;
14 **foreach** *word index* $w \in \mathcal{W}_c$ **do**
15 Sample word $w \sim Multi(\varphi)$;
16 **end**
17 **end**
18 **end**

In Algorithm 1, when user u generates a word, we first sample the distribution parameters ϑ, θ, φ corresponding to the hyper-parameters in Table 1 by the random sampling method (lines 1-9). Then, we sample each variable according to its distribution (lines 10-18).

5.2 Parameter Inference

Based on the above generative process, the joint probability of the observed variables (c, z, w) and hidden variables (ϑ, θ, φ) are represented by the following equation.

$$
\begin{aligned}
&p(\vartheta, \theta, \varphi, c, z, w|\alpha, \beta, \gamma, \mathcal{U}) \\
&= \prod_{u \in \mathcal{U}} p(c|\vartheta, u)p(\vartheta|\gamma)p(z|\theta, c)p(\theta|\alpha)p(w|\varphi, z)p(\varphi|\beta)
\end{aligned} \tag{1}
$$

In Equation 1, $p(c|\vartheta, u)p(\vartheta|\gamma)$ represents the generative process $\gamma \rightarrow \vartheta \xrightarrow{u} c$, and $p(z|\theta, c)p(\theta|\alpha)$ represents the generative process $\alpha \rightarrow \theta \xrightarrow{c} z$, and $p(w|\varphi, z)p(\varphi|\beta)$ represents the generative process $\beta \rightarrow \varphi \xrightarrow{z} w$.

Given the hyper-parameters α, β, γ and the observed values c, z, w, we aim to infer the latent distribution parameters ϑ, θ and φ. Because it is a very difficult task to accurately calculating the posteriors of these parameters, the Markov Chain Monte Carlo (MCMC) method is adopted in this work to retrieve samples, as given in [32]. The MCMC method enables the process to converge to a target stationary distribution by constructing a Markov chain, then samples are drawn from this Markov chain. It is worthwhile to note that each sampled variable can be assigned a value in each state of the chain.

As a commonly-used MCMC algorithm, the Gibbs sampling can iteratively draw the values of latent variables from a Markov chain, in which their stationary distributions agree with the posteriors. The posterior distribution of Gibbs sampling is stationary. The samples are can therefore be used to estimate the distribution.

For each review $(u, c, \mathcal{W}_c)$, we first sample community c based on the following posterior probability:

$$p(c|c_\neg, z, u) \propto \frac{n_{u,c}^\neg + \gamma}{\sum_{u'}(n_{u',c}^\neg + \gamma)} \cdot \frac{n_{z,c}^\neg + \alpha}{\sum_{z'}(n_{z',c}^\neg + \alpha)} \quad (2)$$

where $c_\neg$ represents all communities excluding the current one; $n_{u,c}$ is the number of occurrence that community c is sampled w.r.t. user u; $n_{z,c}$ is the number of occurrence that sentiment z is sampled from community c; and the number $n^\neg$ denotes the number of items, e.g., communities and sentiments, excluding the current item.

Then, based on the newly sampled variables c, we sample the sentiment z w.r.t. community c according to the following posterior probability:

$$\begin{aligned} p(z|z_\neg, c, \mathcal{W}_c) \propto & \frac{n_{c,z}^\neg + \alpha}{\sum_{c'}(n_{c',z}^\neg + \alpha)} \\ & \cdot \prod_{w \in \mathcal{W}_c} \frac{n_{w,z}^\neg + \beta}{\sum_{w'}(n_{w',z}^\neg + \beta)} \end{aligned} \quad (3)$$

where $z_\neg$ represents all sentiments except the current one; $n_{c,z}$ is the number of occurrence that sentiment z is sampled from community c; and $n_{w,z}$ is the number of word w generated from sentiment z.

The hyper-parameters are specified to: α=$50/K$, β=0.01, γ=$50/C$ by empirical studies, following the study in [33]. Then we randomly initialize the index of sentiment z assigned to each word. During each iteration, the indices for communities and sentiments are updated by Equation 2 and Equation 3, respectively. The iteration is repeated until convergence. Due to the MCMC method, no matter what the initial values are, the model will converge to the same state. Lastly, the posterior samples are available to estimate the distribution of the parameter θ by exploiting the numbers of c and z which are assigned to the reviews.

5.3 Computational Complexity of the CSE Model

Suppose that the CSE model executes for I iterations, in each of which, all reviews are scanned. Given the notations introduced in Table 1, for each review, $\mathcal{O}(C+K)$ operations are required to sample latent communities and latent sentiments. If $\mathcal{M}_u$ denotes a series of reviews w.r.t. a user, the entire computational complexity can be represented by $\mathcal{O}(I \times (C+K)\sum_u |\mathcal{M}_u|)$. For our datasets (see 7.1.1), the value of C and K is less than 100 and the complexity is simplified to $\mathcal{O}(I \times \sum_u |\mathcal{M}_u|)$.

6 Network Embedding

The primary sentiments with the largest probabilities w.r.t. a POI can be extracted through the distribution of sentiments which is figured out by the CSE model. In this section, by taking the full consideration of the geographical relationship of POIs, POI-user relationship and POI-sentiment relationship, we present a **S**entiment-aware **N**etwork **E**mbedding model for POI **R**ecommendation (SNER model). As illustrated in Fig. 5, the embeddings are learned by the graph-based method. Since different factors are connected by POIs, the heterogeneous networks can be partitioned into a homogeneous subgraph and several bipartite subgraphs.

6.1 Formalization of Objective Functions

The similarity or relevance between POIs leads to the co-occurrence of some significant information. The key idea behind the network embedding in SNER is that POIs with similar inherent characteristics such as textual sentiments, user profiles and geographical locations co-occur closely in a low-dimensional embedding space.

Inspired by the LINE model [34], a novel network embedding model, which is applicable to large-scale homogeneous networks and learn the embeddings of vertices in the same category, we extend the model to learn embeddings of vertices with different categories in a heterogeneous network.

In order to capture the effect of textual sentiments, the effect of user's behaviors and the geographical influence, a heterogeneous network is divided into a homogeneous subgraph (as shown in Fig. 5(b)) and several bipartite subgraphs (as shown in Fig. 5(c) and Fig. 5(d)), which are composed of one or two types of vertices in each subgraph, e.g., in Fig. 5(c), the vertices are comprised of POIs and users. We illustrates our proposed SNER model in Fig. 5 and define the subgraphs of POI-POI, POI-user and POI-sentiment as follows.

Definition 5 (POI-POI subgraph). The POI-POI subgraph is denoted by $G_{vv} = (\mathcal{V} \bigcup \mathcal{V}, \mathcal{E}_{vv})$, which represents the geographical proximity, i.e., the local pairwise proximity between two POIs. Fig. 6 illustrates the generative process of POI-POI proximity. POIs are classified into several categories, such as restaurants and bars, which are shown in different colors. The process involves two steps: (1) all POIs are partitioned into some communities by geographical clustering methods such as the DBSCAN algorithm [35]. Then POIs with the same categories in a community become proximity. Each pair of POIs are connected by an edge (v_1, v_2), whose weight $w_{v_1 v_2}$ represents the proximity between v_1 and v_2 and is computed by the following equation:

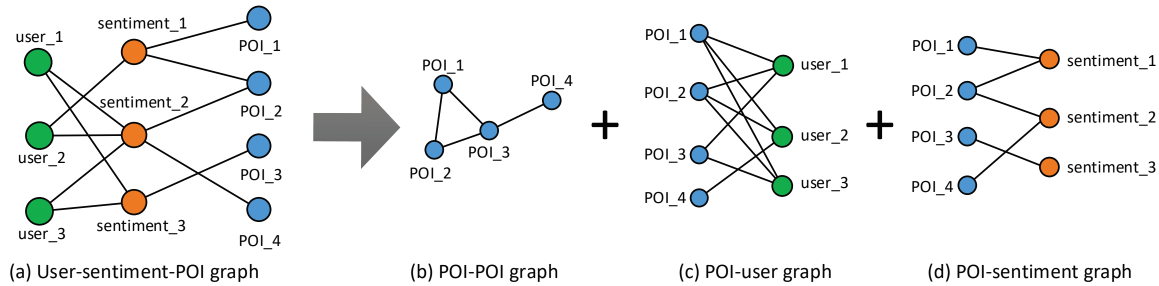


Fig. 5. Illustration of encoding geographical locations, review history and review sentiments into a low-dimensional vector by the graph-based method.

$$w(v_1, v_2) = \frac{1}{1 + e^{d(v_1, v_2)}} \tag{4}$$

where $d(v_1, v_2)$ is the geographical distance between v_1 and v_2. Two adjacent POIs with a small distance implies a large proximity value between 0 to 1. In general, a user prefers to select a region with more POIs which have the same category.

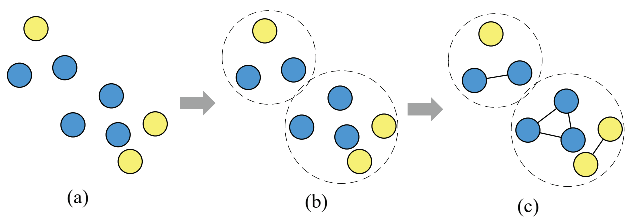


Fig. 6. Phases of generating the POI-POI proximity.

Definition 6 (POI-user subgraph). POI-user subgraph, denoted by $G_{vu} = (\mathcal{V} \bigcup \mathcal{U}, \mathcal{E}_{vu})$, is a bipartite subgraph where $\mathcal{V}$ and $\mathcal{U}$ represent a set of POIs and users, respectively. $\mathcal{E}_{vu}$ denotes a set of edges between POIs and users. If POI v_j is visited by user u_i, there will be an edge e_{ij} between them, otherwise none. The weight w_{ij} is set to the number of u_i's check-ins or reviews at v_j.

Definition 7 (POI-sentiment subgraph). POI-sentiment subgraph, denoted by $G_{vz} = (\mathcal{V} \bigcup \mathcal{Z}, \mathcal{E}_{vz})$, is a bipartite subgraph where $\mathcal{V}$ and $\mathcal{Z}$ represent a set of POIs and sentiments, respectively. $\mathcal{E}_{vz}$ denotes a set of edges between POIs and sentiments. If a POI v_j contains reviews with sentiment z_i, there will be an edge e_{ij} between them, otherwise none. The weight w_{ij} is set to the number of reviews with sentiment z_i w.r.t. v_j.

Assuming d denotes the number of dimensions, our goal of network embedding is to embed the aforementioned three subgraphs into a low-dimensional space $\mathbb{R}_d$. Then, we can describe POIs, users and sentiments by the vectors of $\vec{v}$, $\vec{u}$ and $\vec{z}$ as follows.

1) Given the homogeneous subgraph G_{vv}, we define the joint probability of POIs v_i and v_j by the following equation:

$$p(v_j, v_i) = \frac{1}{1 + \exp(-\vec{v}_j^T \cdot \vec{v}_i)} \tag{5}$$

where $\vec{v}_i$ is the embedding vector of POI v_i in $\mathcal{V}$. Equation 5 defines a distribution $p(\cdot, \cdot)$ over the space $V \times V$, whose empirical probability is defined as $\hat{p}(v_i, v_j)$=$w_{ij}/\mathcal{W}$, where $\mathcal{W}$=$\sum_{(i,j)\in\mathcal{E}} w_{ij}$. We define the following objective function to learn the embedding vectors, i.e., $\vec{v}_j$ and $\vec{v}_i$, which are used to represent v_j and v_i, respectively:

$$O_{vv} = d(\hat{p}(v_j, v_i), p(v_j, v_i)) \tag{6}$$

where $d(\cdot, \cdot)$ represents the KL-divergence between two distributions. In order to preserve the proximity of two POIs, we have to minimize the objective function in Equation 6, which can be transformed to the following equation by ignoring some constants that does not affect the result:

$$O_{vv} = -\sum_{e_{ij}\in\mathcal{E}_{vv}} w_{v_i v_j} \log p(v_j, v_i) \tag{7}$$

By learning $\{\vec{v}_i\}_{i=1...|\mathcal{V}|}$ which minimizes this objective, we can represent each POI v_i by a vector $\vec{v}_i \in \mathbb{R}_d$.

2) Given the bipartite subgraph G_{vu}, we define the conditional probability of POI v_j ($v_j \in \mathcal{V}$) visited by user u_i ($u_i \in \mathcal{U}$) as follows:

$$p(v_j|u_i) = \frac{\exp(\vec{v}_j^T \cdot \vec{u}_i)}{\sum_{v_k\in\mathcal{V}} \exp(\vec{v}_k^T \cdot \vec{u}_i)} \tag{8}$$

where $\vec{u}_i$ represents the embedding vector of user u_i, and $\vec{v}_j$ represents the embedding vector of POI v_j. Equation 8 defines a conditional distribution $p(\cdot|u_i)$ over all the POIs in the set $\mathcal{V}$, whose empirical probability is defined as $\hat{p}(v_j|u_i) = w_{ij}/deg_i$, where $deg_i = \sum_{v_k\in\delta(u_i)} w_{ik}$ and $\delta(u_i)$ is the adjacent vertices of u_i. The conditional distribution $p(\cdot|u_i)$ is set approximate to its empirical distribution $\hat{p}(\cdot|u_i)$ to obtain the weight w_{ij} on edge e_{ij}. Then, We define the following objective function to learn the embedding vectors, i.e., $\vec{v}_j$ and $\vec{u}_i$, which are used to represent v_j and u_i, respectively:

$$O_{vu} = \sum_{e_{ij}\in\mathcal{E}_{vu}} \lambda_i d(\hat{p}(v_j|u_i), p(v_j|u_i)) \tag{9}$$

where λ_i represents the importance of POI v_i in the POI-user subgraph, which can be represented and replaced by the degree $deg_i = \sum_{v_k\in\delta(u_i)} w_{ik}$. The objective function Equation 9 can be transformed to the following equation by ignoring some constants that does not affect the result:

$$O_{vu} = -\sum_{e_{ij}\in\mathcal{E}_{vu}} w_{u_i v_j} \log p(v_j|u_i) \tag{10}$$

By learning $\{\vec{v}_j\}_{j=1...|\mathcal{V}|}$ and $\{\vec{u}_i\}_{i=1...|\mathcal{U}|}$ which minimizes this objective, we can represent each POI v_j and u_i by vectors $\vec{v}_i, \vec{u}_i \in \mathbb{R}_d$, respectively.

3) Similarly, we compute the objective w.r.t. the bipartite subgraph G_{vz} by the following equation,

$$O_{vz} = -\sum_{e_{ij}\in\mathcal{E}_{vz}} w_{z_i v_j} \log p(v_j|z_i) \tag{11}$$

By learning $\{\vec{v}_j\}_{j=1...|\mathcal{V}|}$ and $\{\vec{z}_i\}_{i=1...|\mathcal{Z}|}$ which minimizes this objective, we can represent each POI v_j and z_i by vectors $\vec{v}_i, \vec{z}_i \in \mathbb{R}_d$, respectively.

6.2 Optimization of Objective Functions

Optimizing the objective functions 7, 10 and 11 is time-consuming, which requires the traversal of the overall sets of vertices when computing the three probabilities, i.e., $p(v_j, v_i)$, $p(v_j|u_i)$ and $p(v_j|z_i)$. we utilize the negative sampling method proposed in [36] to solve this problem, which samples a set of negative edges, i.e., outlying edges in accordance with the noise distribution for edges in these subgraphs. Specifically, the objective function for each edge (i, j) w.r.t. Equation 7, 10 and 11 is transformed as follows:

$$\log p(v_i, v_j) = \log \sigma(\vec{v}_i^T \cdot \vec{v}_j) + \sum_{n=1}^{R} E[\log \sigma(-\vec{v}_n^T \cdot \vec{v}_i)] \tag{12}$$

$$\log p(v_j|u_i) = \log \sigma(\vec{v}_j^T \cdot \vec{u}_i) + \sum_{n=1}^{R} E[\log \sigma(-\vec{v}_n^T \cdot \vec{u}_i)] \tag{13}$$

$$\log p(v_j|z_i) = \log \sigma(\vec{v}_j^T \cdot \vec{z}_i) + \sum_{n=1}^{R} E[\log \sigma(-\vec{v}_n^T \cdot \vec{z}_i)] \tag{14}$$

where $\sigma(x)$=1/(1 + $exp(x)$) is referred to the sigmoid function, R represents the number of negative edges. According to the empirical values given in [36], we specify R=5 and $v_n \sim P_n(v) \propto d_v^{3/4}$, where $P_n(v)$ represents the noise distribution of vertex v and d_v represents the degree of vertex v, and $E[]$ denotes the expectation value based on $P_n(v)$.

6.3 Joint Embedding Learning

In our proposed SNER model, three subgraphs are involved: POI-POI, POI-user, POI-sentiment. We aim to minimize all these objectives for learning the embeddings corresponding to these three subgraphs.

$$O = O_{vv} + O_{vu} + O_{vz} \tag{15}$$

In each step, the asynchronous stochastic gradient algorithm (ASGD) samples a small set of edges and then updates the parameters. Given a sampled edge (i, j), the gradient w.r.t. the embedding vector $\vec{u}_i$ is computed by the following equation:

$$\frac{\partial O_{vu}}{\partial \vec{u}_i} = w_{u_i v_j} \cdot \frac{\partial \log p(v_j|u_i)}{\partial \vec{u}_i} \tag{16}$$

For the objective functions 7 and 11, we also use the negative sampling approach by only replacing $\vec{u}_i$ of Equation 16 with $\vec{v}_i$ and $\vec{z}_i$ and then obtain the following equations, respectively:

$$\frac{\partial O_{vv}}{\partial \vec{v}_i} = w_{v_i v_j} \cdot \frac{\partial \log p(v_i, v_j)}{\partial \vec{v}_i} \tag{17}$$

$$\frac{\partial O_{vz}}{\partial \vec{z}_i} = w_{z_i v_j} \cdot \frac{\partial \log p(v_j|z_i)}{\partial \vec{z}_i} \tag{18}$$

The embedding vectors are updated by the following equations:

$$\vec{v}_i = \vec{v}_i - \eta \frac{\partial O}{\partial \vec{v}_i} = \vec{v}_i - \eta \frac{\partial O_{vv}}{\partial \vec{v}_i} \tag{19}$$

$$\vec{u}_i = \vec{u}_i - \eta \frac{\partial O}{\partial \vec{u}_i} = \vec{u}_i - \eta \frac{\partial O_{vu}}{\partial \vec{u}_i} \tag{20}$$

$$\vec{z}_i = \vec{z}_i - \eta \frac{\partial O}{\partial \vec{z}_i} = \vec{z}_i - \eta \frac{\partial O_{vz}}{\partial \vec{z}_i} \tag{21}$$

where η is a learning factor.

In the heterogeneous graph of POI-user-sentiment, the weights of the edges between different categories of vertices are not comparable to each other. We use a reasonable method called joint training to sample on the three sets of edges sequentially, which is introduced in detail in Algorithm 2.

Algorithm 2: Joint training

Input: A POI-POI grahp G_{vv}, a POI-user grahp G_{vu}, a POI-sentiment grahp G_{vz}, a learning factor η, the number of negative samples R
Output: A POI embedding vector $\vec{v}$, a user embedding vector $\vec{u}$, a sentiment embedding vector $\vec{z}$

while *not convergence* **do**
  Sample an edge from $\mathcal{E}_{vv}$ and extract R negative edges;
  Update POI embeddings acc. to Eq.19 ;
  Sample an edge from $\mathcal{E}_{vu}$ and extract R negative edges;
  Update POI embeddings and user embeddings acc. to Eq.19 and Eq.20 ;
  Sample an edge from $\mathcal{E}_{vz}$ and extract R negative edges;
  Update POI embeddings and sentiment embeddings acc. to Eq.19 and Eq.21 ;
end
return $\vec{v}, \vec{u}, \vec{z}$;

According to Algorithm 2, we sample one positive edge and R negative edges from each set of edges by the negative sampling method, then update the corresponding embedding vector, respectively.

6.4 Location Suggestion via the CENTER Model

Beneficial from these learned embeddings of users' profiles, POIs' profiles and sentiments, we can compute the users' probabilities of visiting a POI. For each unvisited POI v by u, we calculate v's ranking score as follows:

$$s(\vec{u}_i, \vec{v}_j) = \vec{u}_i^T \cdot \vec{v}_j + \sum_{k\in h_1(u_i)} \vec{v}_k^T \cdot \vec{v}_j + \sum_{k\in h_2(u_i)} \vec{z}_k^T \cdot \vec{v}_j \tag{22}$$

where $\vec{u}_i$, $\vec{v}_j$ and $\vec{z}_j$ are the embedding vectors of u_i, v_j and z_j, respectively. $h_1(u_i)$ is the set of sentiments conveyed by user u_i, and $h_2(u_i)$ is the list of u_i's visited POIs. All the embedding vectors can automatically capture the joint effect of users' profiles, POIs' profiles and sentiments via the subgraphs in Fig. 5. The first item in Equation 22 represents the similarity between user $\vec{u}_i$ and POI $\vec{v}_j$. The second item represents the similarity between POI $\vec{v}_j$ and other u_i's visited POIs. The last item represents the similarity between POI $\vec{v}_j$ and other sentiments conveyed by u_i from his review comments. Lastly, we need to find the top-k locations and recommend them to a target user.

6.5 Computational Complexity of the SNER Model

The computational complexity of optimization with negative sampling is $\mathcal{O}(t_0 \times (1 + R))$, where R represents the number of negative samples and t_0 is the time spent on one time of sampling. Generally, the number of steps for optimization is proportional to the number of edges in the network which can be represented by $|\mathcal{E}|$. Therefore, the entire computational complexity of optimization is $O(t_0 \times R \times |\mathcal{E}|)$, where t_0, R are constants. The proposed edge sampling method is very efficient since it is linear to the number of edges $|\mathcal{E}|$ and is irrelevant with the number of vertices $|\mathcal{V}|$. Therefore, the total time complexity of the CENTER model containing the two phases is $\mathcal{O}(I \times \sum_u |\mathcal{M}_u| + |\mathcal{E}|)$.

7 EXPERIMENTS

In this section, a series experiments are conducted to evaluate the performance of our proposed CENTER framework on real datasets. We will introduce the datasets, baseline approaches and the parameter settings for experiments, then demonstrate its effectiveness and efficiency by comparing it with the state-of-the-art suggestion methods.

7.1 Experimental Settings

7.1.1 Datasets

In order to show the performance of the proposed CENTER framework, the following two datasets are used in the experiments:

Foursquare dataset. Foursquare is a popular LBSN and can offer many location-based services, e.g., POI check-ins and posting online reviews for POIs. The dataset was collected from 75,140 users living in the areas of San Francisco, California in USA, and contains users' profiles, review content as well as POIs' profiles such as a location by its latitude and longitude.

Yelp Challenge dataset[3]**.** The dataset contains 1,326,101 users and 174,567 POIs from ten cities in four countries. In order to focus on POIs in a specific city, we only utilize the data in Las Vegas of USA. There are about 26,809 POIs and 1,605,396 reviews. Each review contains textual content and the meta information such as the time and locations of posting reviews. The city with a user's most visited POIs is regarded as his living city, which is not specified in this dataset. Through statistics, we find that there are about 337,084 users in the Las Vegas.

These datasets contain sensitive and privacy information such as comment words and locations. We use some privacy protection methods to preprocess these data: (1) only identity numbers are used instead of real POIs' names and users' names, and (2) the longitudes and latitudes of POIs are changed into relative coordinates.

7.1.2 Baseline Approaches

We compare our proposed CENTER approach with the following state-of-the-art POI suggestion techniques, all of which are proposed in the last five years and combine multiple types of factors for the purpose of POI suggestion.

TrustMF [15] incorporates two kinds of sparse information, i.e., the rating scores and the social trust relationship among the same group of users. Users are transformed into a low-dimensional vectors by the matrix factorization approach according to trust networks, which facilitates the understanding of users' influence on their opinions.

LSARS [6] is a latent probabilistic generative model which emulates users' check-in activities for both home-town and out-of-town scenarios by considering user interest drift and crowd sentiment, which can learn individual interests relevant to locations and sentiments from the profiles of POIs and reviews of users. However, the geographical influence is not considered when generating the review words in LSARS.

GME-S [30] is a network embedding model which can infer the sequential patterns of users' preferences efficiently by converting POIs into low-dimensional vectors. Different from the Markov chain-based suggestion methods, this model can avoid the computational cost of the POI-POI transition matrix by utilizing the dynamics of users' check-in behaviors and embedding them into the vectors of POIs.

HERec [14] is a suggestion method in heterogeneous networks by embedding multiple factors, which incorporates a random walk phrase to produce informative sequential vertices for network embedding. The encoded vertices are converted by several fusion functions, and then be integrated into a new matrix factorization model, which are combined to accomplish the task of rating prediction.

GE [2] is a common graph embedding model, which integrates the four factors including the sequentially visits, geographical effect, temporal cyclic effect and textual content in a unified fashion, by encoding the original network into a low-dimensional space with four subgraphs. Then, they proposed a new sequential method to dynamically calculate users' preferences by embedding his/her checked-in POIs.

The difference of the above POI suggestion methods are shown in Table 2, where the first line refers to several factors including geographical influence (denoted by Geo.), temporal effect (denoted by Temp.), users' preferences (denoted by Pref.), social relationship (denoted by Soc.), users' behaviors (denoted by Beh.), textual content (denoted by Tex.) as well as network embedding (denoted by Emb.).

In order to evaluate the effect of each factor in the CENTER framework, we designed four variant models

3. https://www.yelp.com/dataset/challenge

TABLE 2
Features of different suggestion methods

	Geo.	Temp.	Pref.	Soc.	Beh.	Tex.	Emb.
TrustMF			•	•	•		
LSARS			•		•	•	
GME-S		•	•	•	•		•
HERec			•	•			•
GE	•	•	•	•	•	•	•
CENTER	•		•	•	•	•	•

based on CENTER that omits the effects of social relationship, geographical relationship, users' reviewing behavior and textual sentiments, respectively as shown below.

CENTER-community is the first simplified version that omits the influence of community structure, i.e., the distribution of sentiment is the same within all social communities.

CENTER-geo is the second simplified version that neglects the influence of locations, which implies a POI connects to all POIs with the same category in the network.

CENTER-user is the third simplified version that eliminates the effect of users' reviewing behavior, i.e., the POI-user subgraph $\mathcal{G}_{vu}$ is removed.

CENTER-sentiment is the fourth simplified version that omits the sentimental effect of reviews, i.e., the POI-sentiment subgraph $\mathcal{G}_{vz}$ is removed.

7.1.3 Evaluation Metrics

As suggested by the previous studies [37], we utilize four widely-used metrics, i.e., precision and recall, F1 score and hit rate, to measure the effectiveness of distinct POI suggestion approaches. In the task of POI suggestion, precision measures the proportion of ground truth POIs in the suggested POIs, and recall measures the ratio of ground truth POIs to the actually visited POIs. F1 score is the harmonic mean of precision and recall. Given a collection of suggestion records, we partition each dataset into ten portions and use the 10-fold cross validation method to evaluate. Thus, the average precision and recall over all users can be adopt for the purpose of exact evaluation. Supposing $\mathcal{V}_u$ and $\mathcal{R}_u$ represent the visited POIs and suggested POIs w.r.t. user u. The metrics of precision, recall and F1 score are defined as follows,

$$Precision = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}}\frac{|\mathcal{V}_u \cap \mathcal{R}_u|}{|\mathcal{R}_u|} \tag{23}$$

$$Recall = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}}\frac{|\mathcal{V}_u \cap \mathcal{R}_u|}{|\mathcal{V}_u|} \tag{24}$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{25}$$

The hit rate is a measurement representing the fraction of hits [38], where one hit means that the suggestion list w.r.t. a specific user involves at least one POI that the user has visited. The hit rate is defined as:

$$Hitrate = \frac{|hit|}{|D_{test}|} \tag{26}$$

where $|hit|$ and $|D_{test}|$ represent the number of hits in the testing set and the number of all the testing cases, respectively. For a single testing case, hit is defined to 1 if the ground truth POI v appears in the top-k results, or 0 if not.

7.2 Effectiveness Analysis of Location Suggestion

The comparison between CENTER and the baseline methods with well-tuned parameters is presented in this section. Fig. 7 and Fig. 8 demonstrate the performance of POI suggestion with different k values in the Foursquare and the Yelp datasets, respectively. In experiments, the hit rate becomes relatively stable when k is larger than 15. Therefore, k is specified to {1,5,10,15,20}, because a larger value of k is not very important for location suggestion and is always not considered in the top-k suggestion [6].

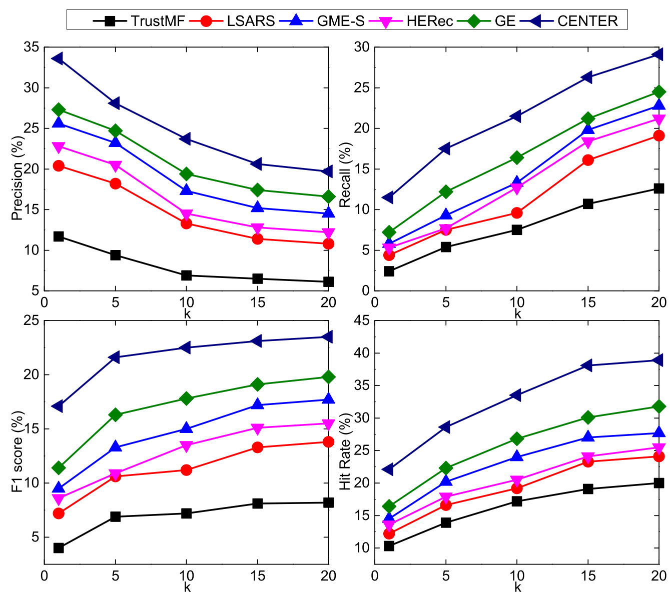


Fig. 7. Performance comparison on the Foursquare dataset.

As shown in Fig. 7 and Fig. 8, by compared with other baseline methods, the relative improvement on effective performance achieved by CENTER ranges from 2.2% to 21.9%. The reason for this is four-fold as shown below:

1) Learning the embeddings of POIs in a low-dimensional space can overcome the problem of data sparsity. The embedding is capable of significantly improving the performance of POI suggestion. In addition, we find that the methods with network embedding including GME-S, HERec, GE and CENTER outperform those without network embedding such as TrustMF and LSARS.

2) CENTER incorporates different categories of heterogeneous information, especially the latent sentiments in textual content, which shows that information in textual content are very useful for learning POI embedding as well as suggesting impressive POIs. It is worth to notice that although the GE model incorporates more factors such as the temporal effect, but it still has a worse performance than our CENTER method. This can be explained by the reason that GE only extracts the relationship between words and

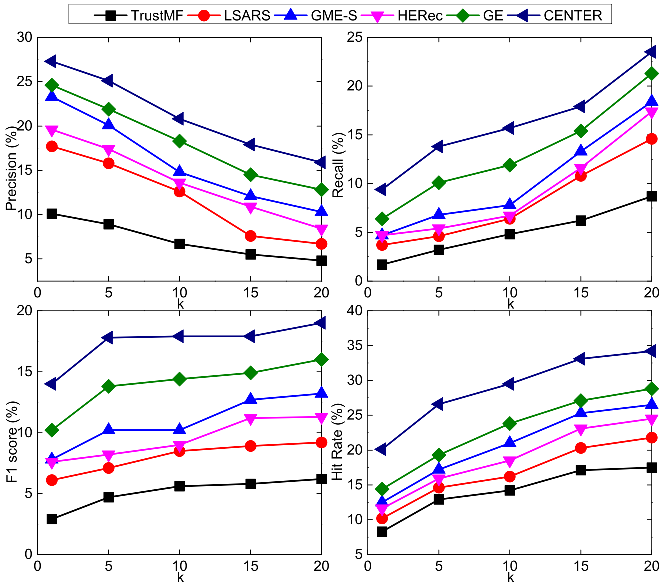


Fig. 8. Performance comparison on the Yelp dataset.

POIs, however, it cannot analyze the sentiments in textual content.

3) All methods show better performance in the Foursquare dataset than the Yelp dataset. This is because reviews in the Yelp dataset are more sparse than that in the Foursquare dataset, which also proves that the textual content is very important for suggestion.

4) The growth of k leads to the invariant of $\mathcal{V}_u$ and the increasing of $\mathcal{R}_u$. As shown in Equation 23 and 24, the precision is declined and the recall is growing accordingly.

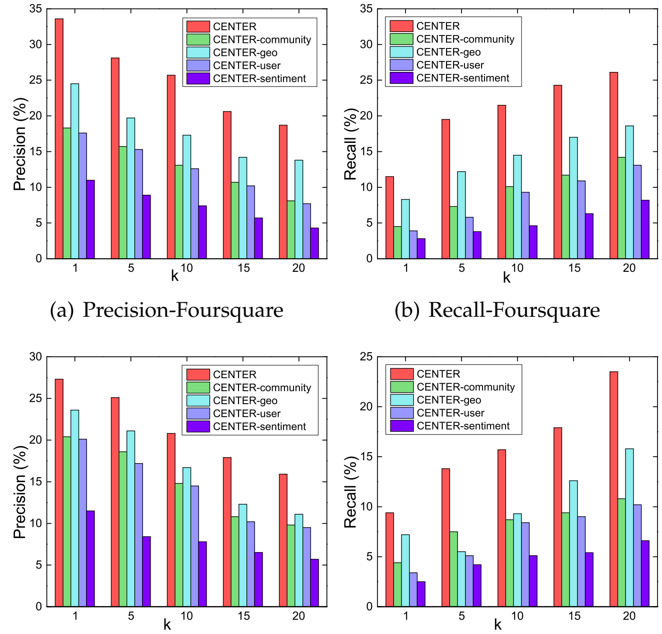
7.3 Impact of Different Factors

In order to explore the benefits of incorporating social relationship, geographical influence, users' profiles and textual sentiments into the CENTER model, respectively, we compare CENTER with the four variations, i.e., CENTER-community, CENTER-geo, CENTER-user, CENTER-sentiment, which are introduced in Section 7.1.2. The comparison results are given in Fig. 9.

As depicted in Fig. 9, the gap between CENTER and any its variants could present the benefit brought by each factor. CENTER outperforms its four variant versions with the gap ranging from 3.2% to 22.6% on the Foursquare dataset and ranging from 3.8% to 15.8% on the Yelp dataset, respectively. Each factor makes a different contribution to the improvement of the effectiveness of suggestion. According to the significance of these four factors, it is interesting to find that they a re ranked as sentiment>user profile>community>geographical effect. We can conclude that textual sentiment is more significant for POI suggestion than other factors.

7.4 Sensitivity Analysis of Parameters

It is critical to tuning parameters in order to acquire desired performance. we analyze the sensitivity of parameters in CENTER on these two datasets in this section.



(a) Precision-Foursquare (b) Recall-Foursquare (c) Precision-Yelp (d) Recall-Yelp

Fig. 9. Impact of different factors on the two datasets.

TABLE 3
Hit rates under different numbers of communities and embedding dimensions

(a) The Foursquare dataset.

	d=20	d=40	d=80	d=120	d=160	d=200
C=20	0.266	0.288	0.307	0.315	0.315	0.316
C=30	0.273	0.294	0.318	0.336	0.338	0.338
C=40	0.279	0.306	0.329	0.345	0.347	0.347
C=50	0.283	0.317	0.335	0.363	0.366	0.366
C=60	0.284	0.317	0.336	0.365	0.366	0.367
C=70	0.284	0.317	0.336	0.365	0.367	0.367

(b) The Yelp dataset.

	d=20	d=40	d=80	d=120	d=160	d=200
C=20	0.237	0.253	0.269	0.277	0.291	0.291
C=30	0.254	0.275	0.292	0.314	0.325	0.325
C=40	0.270	0.291	0.314	0.331	0.343	0.343
C=50	0.271	0.292	0.314	0.331	0.343	0.345
C=60	0.271	0.292	0.314	0.331	0.344	0.345

Based on the aforementioned discussion, the hyper-parameters α, β and γ are specified as α=50/K, β=0.01 and γ=50/C based on empirical studies. However, the performance of CENTER is greatly sensitive to the number of embedding dimensions and the number of communities w.r.t. a specific user. Table 3 shows the hit rate of the CENTER method with different number of embedding dimensions and communities on these two datasets when k=20.

From the two datasets, we observe the similar results that the hit rate of CENTER is sensitive to the number of embedding dimensions d and the number of individual's communities C, which shows a tendency that the hit rate increases with the d and C holistically, and then does not change greatly when these two parameters are large enough since it is converged.

To acquire an acceptable trade off between effectiveness and efficiency in model training, we set d=120 and C=50 on the Foursquare dataset, and d=160 and C=40 on the Yelp dataset. It is worthwhile to note that the performance of our CENTER reported in other experiments has the similar parameter setting.

7.5 Efficiency Comparison of Location Suggestion

In this section, we analyze the computational complexity of CENTER and compare the cost of training time with the baseline methods by experiments. CENTER consists of two major phases: sentiment extraction and network embedding, whose complexity has been analyzed in Section 5.3 and Section 6.5. Based on the above discussion, we further evaluate the efficiency of our proposed model by comparing it with the baseline methods. In order to observe the results of different networks with similar numbers of users, we extract another dataset containing 76,370 users from the Yelp dataset. All the experiments are conducted in the environment with Java (JDK 1.7), Windows 10, and run on a PC with a CPU of Core i7 (7500U) and 8GB RAM. The comparison results of the average training time of these approaches are given in Fig. 10.

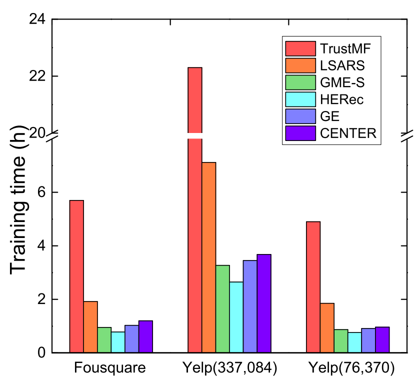


Fig. 10. Comparison of training time by different algorithms.

As shown in Fig. 10, most models have comparative training time except the TrustMF method. This is because the computational complexity of the TrustMF method are $\mathcal{O}(n^3)$, and other approaches have a complexity of $\mathcal{O}(n^2)$. Furthermore, the original Yelp dataset with 337,084 users also contains more links and reviews than the other two datasets, which greatly increases the training time. In addition, we find that LSARS, GE and CENTER need more time for training than GME-S and HERec because they contain a time-consuming step, i.e., textual analysis.

8 Conclusion

POI suggestion in LBSNs has become a significant approach to help users explore interesting and attractive POIs. To the best of our knowledge, we are the first to investigate the joint effect of social relationship, Geographical proximity and textual sentiment to address the challenges of fuzzy sentimental boundary and unreliable data quality in a unified fashion. We present a novel framework called CENTER for suggesting impressive POIs to a specific user, which contains two essential techniques: (i) a latent probabilistic generative model called CSE which can accurately capture review contents from LBSNs by considering social communities. The parameters of the CSE model can be inferred effectively by the Gibbs sampling method. The primary sentiments are obtained from the distribution of sentiment; (ii) a network embedding model called SNER is employed to learn the representation of POIs, users and textual sentiments in a low-dimensional embedding space. In addition, the joint training is utilized to alternatively sample all sets of edges. Extensive experiments on two large-scale real datasets evaluate the performance of the proposed CENTER framework. The results demonstrate CENTER outperforms the state-of-the-art baseline methods in the effectiveness and efficiency of POI suggestion. In summary, we believe the proposed CENTER framework can work well in real-world scenarios to provide personalized location-based services.

The proposed approach provides an alternative solution for the cold-start problem. For the cold-start user, which implies that a new user joins into the system for the first time, the suggestion results are computed by analyzing the review content and the visiting history from other users. Furthermore, for the cold-start POI, which denotes that a new POI appears, the suggestion results can be figured out by utilizing the data of similar POIs within an area. However, this model has some disadvantages, for example, it does not consider the sequential effect in order to reduce the computational complexity, and never support the incremental calculation of newly coming data, which are the future research directions.

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