Postprint: Sequential Point-of-Interest Recommendation with Spatio-temporal Information Fusion in LBSN

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Date: 2018-10-11T00:00:00+00:00

Abstract

To address challenges such as data sparsity, the implicit feedback nature of check-in data, and users' personalized preferences faced by sequential point-of-interest recommendation systems in location-based social networks (LBSN), we propose a sequential point-of-interest recommendation algorithm that incorporates spatio-temporal information. This algorithm models user check-in behavior as a fourth-order tensor of user—current point-of-interest—next point-of-interest—time interval, and utilizes geographical information from LBSN to define users' geographical distance preferences when visiting points of interest. Finally, the BPR (Bayesian Personalized Ranking) criterion is employed to optimize the objective function. Experimental results demonstrate that this algorithm achieves better recommendation performance compared to other state-of-the-art sequential point-of-interest recommendation algorithms.

Full Text

Preamble

Title: Successive Point-of-Interest Recommendation with Spatial-Temporal Influence in LBSN

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Abstract: This paper studies the successive POI recommendation problem in location-based social networks, where the challenge lies in data sparsity, implicit user feedback, and personalized preference. To this end, we propose a novel model for successive POI recommendation that integrates temporal information and geographical influence. Specifically, we model successive check-in behaviors as a fourth-order tensor and employ geographical influence to define the spatial preference of the user for the POI. Bayesian personalized ranking criterion is then utilized to optimize the loss objective function. Experimental results demonstrate that the proposed model outperforms state-of-the-art successive POI recommendation methods.

Keywords: point-of-interest; recommender system; location-based social networks; tensor decomposition

0 Introduction

In recent years, the proliferation of smartphones with GPS positioning capabilities has enabled users to easily obtain real-time geographical location information and check in at visited points of interest (POIs) or share their experiences with friends. This has fueled the rapid development of location-based social networks (LBSNs) such as Foursquare, Gowalla, and Jiepang. LBSNs organically integrate the online virtual society with the offline real world, allowing users to access and share location information anytime and anywhere. Meanwhile, the number of POIs has grown rapidly with urban development, leading to information overload problems for users. POI recommendation, which aims to recommend geographical locations that users may be interested in, has become an important means to meet personalized needs and solve information filtering problems, attracting widespread attention from both academia and industry.

Current POI recommendation research treats all user check-in data as a whole, which only considers the check-in relationship between users and POIs while ignoring the relationships between successively visited POIs. In reality, there is a strong correlation between a user' s current POI and the next POI they will visit. For example, when a user leaves the office after work in the evening, they typically go to a restaurant rather than outdoor travel. This sequential pattern in check-in behavior is a crucial factor in POI recommendation tasks. The recommendation task should be based on the user' s current location, aiming to recommend the next POI to visit—that is, successive POI recommendation. Successive POI recommendation can not only enhance user experience and increase user dependence on the platform but also help advertisers target their campaigns to specific customer groups.

Recommendation systems have been extensively studied in academia and widely applied in industry. However, since LBSNs are complex heterogeneous networks containing relationships between users, between users and POIs, and between POIs themselves, successive POI recommendation systems face new challenges compared to traditional recommendation systems:

a) **Data Sparsity.** User check-in behavior is autonomous. Due to privacy concerns, users selectively check in at only a portion of POIs, resulting in severe sparsity in user trajectory data. Additionally, the number of POIs in LBSNs is enormous, while users can only visit a limited number of them, further exacerbating the sparsity of check-in data.

b) **Implicit Feedback Nature of Check-in Data.** Unlike traditional recommendation systems where users express explicit feedback through ratings, check-in behavior in LBSNs represents implicit feedback. Positive feedback consists of POIs that have been checked in to, while unchecked POIs include both those the user is genuinely not interested in and those the user has not yet discovered but might be interested in. This lack of negative feedback poses challenges for successive POI recommendation.

c) **Personalized User Preferences.** User personalization in LBSNs manifests in two aspects: First, user interest preferences change dynamically with time and geographical location. For instance, most users go to restaurants at noon after work but return home directly after work in the evening. Second, two users with similar interests may exhibit different behavior patterns. For example, when purchasing clothing, students prefer casual sportswear stores while office workers favor formal attire shops. Therefore, successive POI recommendation systems should recommend POIs that align with individual preferences.

To address these challenges, this paper proposes a successive POI recommendation model that integrates spatial-temporal information. The model effectively incorporates temporal and geographical information from LBSNs to handle data sparsity and improve recommendation accuracy. Specifically, we first model user check-in history as a four-order tensor of user-current POI-next POI-time period. Based on this tensor, we use tensor decomposition to infer personalized preferences for each POI. Then, according to geographical distance constraints of user activity ranges, we define users' geographical distance preferences for visiting POIs as a factor measuring preference intensity. Finally, given the implicit feedback nature of check-in data, we treat pairs of checked and unchecked POIs as training samples and adopt the BPR (Bayesian Personalized Ranking) criterion to optimize the objective function.

The contributions of this paper are summarized as follows:

a) We provide accurate and efficient successive POI recommendation services by recommending the next POI based on the user' s current location, leveraging the correlation between consecutively visited POIs.

b) We propose a successive POI recommendation model integrating spatial-temporal information, which effectively alleviates data sparsity by fusing temporal and geographical information from LBSNs. According to the implicit feedback property of check-in data, we employ the BPR algorithm to fit the partial order relationships on POI pairs, thereby obtaining personalized preferences.

c) We conduct extensive experimental evaluations on two large-scale real-world LBSN datasets. Results demonstrate that our proposed model outperforms existing state-of-the-art successive POI recommendation algorithms.

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1 Related Work

Successive POI recommendation is an important task in recommendation systems and has become a crucial location-based service in LBSNs. Successive POI recommendation systems model user behavior patterns using historical check-in data and mine user preferences for POIs. With the increasing number of contextual factors in LBSNs, including temporal information, geographical information, and category information, current research attempts to fuse these contextual factors to further improve recommendation performance. Based on the types of contextual information fused, successive POI recommendation systems can be divided into three categories.

a) **Temporal-aware successive POI recommendation systems.** Each interaction between users and LBSNs has a timestamp, and user check-in behavior exhibits periodic characteristics over time. Therefore, temporal information is an important contextual factor in LBSNs that significantly influences user check-in behavior. Li et al. analyzed the temporal trends of user behavior patterns and proposed a time-aware successive POI recommendation algorithm considering both long-term and short-term preferences.

b) **Geographical-aware successive POI recommendation systems.** Since check-in behavior represents physical interaction between users and POIs, users tend to visit nearby POIs from a cost perspective. This geographical proximity significantly influences user check-in behavior. Numerous studies have incorporated geographical information into successive POI recommendation. Cheng et al. proposed a tensor factorization-based successive POI recommendation model that uses POIs geographically close to users as recommendation candidates. This approach reduces computational costs and improves recommendation efficiency by using a smaller candidate POI set.

c) **Category-aware successive POI recommendation systems.** POIs in LBSNs are typically categorized into different types. The category information of visited POIs implies user behavior patterns. For example, shopping enthusiasts like to visit various malls, while foodies are keen on checking in at restaurants. This category information helps understand user interest preferences. He et al. proposed a two-stage successive POI recommendation framework that first predicts the category of the next POI and then recommends specific POIs based on the category prediction.

When checking in at POIs, users also post short reviews that describe their preferences. Numerous studies have actively explored and utilized this content information to improve recommendation quality. However, review content is typically short, and short texts are sparse, noisy, and ambiguous, posing significant challenges for recommendation tasks. Additionally, social relationships are properties inherited from traditional social networks in LBSNs. Researchers have attempted to leverage social relationships to improve recommendation accuracy, though some studies have shown that only a small portion of users share similar preferences with their friends regarding POI visits, indicating limited influence of social relationships on check-in behavior.

In summary, current research filters out POIs far from users to address data sparsity. However, this approach cannot recommend distant POIs and fails to satisfy users who enjoy long-distance travel. Regarding temporal information fusion, existing work has only utilized hourly periodic patterns in user check-in behavior without considering weekly variation patterns. Other studies divide each day into 24 hourly periods, further exacerbating the sparsity of already sparse check-in data. This paper proposes a successive POI recommendation model integrating spatial-temporal information. On one hand, we divide a day into working hours and leisure hours, and weeks into working days and rest days, resulting in four time periods that combine with users, current POIs, and next POIs to form a four-order tensor. We use tensor factorization to fill missing values, effectively solving data sparsity. On the other hand, we define users' geographical distance preferences for POIs based on the principle that preference decreases with increasing distance, making distant POIs potential candidates and thereby improving recommendation accuracy.

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2 Successive POI Recommendation with Spatial-Temporal Information

2.1 Problem Description

Let $U = \{u_1, u_2, ..., u_M\}$ be a set of users in an LBSN, and $L = \{l_1, l_2, ..., l_N\}$ be a set of POIs, where each POI has a unique identifier and is geocoded by {longitude, latitude}, and N represents the number of POIs. User check-in behavior is represented by a four-tuple (u, t, i, j), indicating that user u moves from current POI i to next POI j at time t. Let L_u^t denote the set of POIs checked in by user u before time t. The problem to be solved in this paper is to recommend POIs for user u to visit at time t based on historical check-in data Q.

2.2 Model

Our proposed model first calculates the transition probability of user u moving from current POI i to next POI j at time t, then ranks POIs according to this probability and recommends the top-N POIs to the user. Assuming user check-in behavior satisfies first-order Markov properties, the transition probability can be expressed as:

$$p(j|u,i,t) = p(l_{next} = j|u, l_{current} = i, t)$$

where $l_{current} = i$ indicates that user u's current POI is i, and $l_{next} = j$ indicates that user u visits POI j at time t.

To accurately model user behavior patterns, our successive POI recommendation model considers both personalized preferences and geographical distance preferences for POI visits.

2.2.1 Personalized Preference Historical check-in data in LBSNs records user transitions from current POI i to next POI j. We can construct a three-order tensor χ from users, current POIs, and next POIs, i.e., $\chi \in \mathbb{R}^{|U|\times|L|\times|L|}$, where non-zero elements $\chi_{u,i,j} = 1$ represent observed transition records.

Since user check-in behavior is influenced and constrained by time—for example, users typically go to restaurants at noon rather than bars or KTVs, and often travel outdoors on weekends while rarely visiting offices—analyzing temporal information reveals periodic patterns in user behavior over time, enabling more accurate modeling of personalized preferences. Users generally have similar interest preferences in adjacent time periods. For instance, most users start work around 9 AM, and lunch is mostly concentrated around noon. Current research divides each day into 24 hourly periods, mapping check-in data accordingly, but this further exacerbates the sparsity of already sparse data. Other work only considers hourly periodic patterns while ignoring weekly variation patterns.

Literature [14] divides user states into working and living states based on time of day, which can simply and effectively characterize the periodic features of check-in behavior. Therefore, we divide a day into daytime (8:00-17:00) and evening (18:00-7:00), and divide a week into working days (Monday to Friday) and rest days (Saturday and Sunday). The hour and week jointly form four time periods: working daytime, working evening, rest daytime, and rest evening. Temporal information can be represented as $T = \{T_1, T_2, T_3, T_4\}$. Continuous check-in behavior in each time period can be modeled as a three-order tensor similar to χ, and continuous check-in behavior across all time periods is modeled as a four-order tensor Z of user, current POI, next POI, and time period, i.e., $Z \in \mathbb{R}^{|U|\times|L|\times|L|\times|T|}$, where non-zero element $z_{u,i,j,t} = 1$ indicates that user u transitioned from current POI i to next POI j in time period t. As shown in Figure 1 [Figure 1: see original paper], the three-order tensors above the figure contain check-in data for users in different time periods, with historical check-in data contained in the four-order tensor composed of all three-order tensors. Estimating personalized preferences for POI visits is equivalent to computing the ranking of tensor Z.

Since only a portion of elements in tensor Z are non-zero, we need to use low-rank approximation techniques similar to matrix factorization to fill in unobserved transition entries. For approximating the four-order tensor Z, we can employ Tucker decomposition [15] or canonical decomposition [16], where canonical decomposition can be seen as a special case of Tucker decomposition. Canonical decomposition only considers pairwise interactions among the four dimensions (i.e., user u, current POI i, next POI j, time period t), meaning personalized preferences for POI visits can be estimated as:

$$\hat{z}_{u,i,j,t} = \mathbf{v}_u^U \cdot \mathbf{v}_j^J + \mathbf{v}_u^U \cdot \mathbf{v}_i^I + \mathbf{v}_u^U \cdot \mathbf{v}_t^T + \mathbf{v}_j^J \cdot \mathbf{v}_i^I + \mathbf{v}_j^J \cdot \mathbf{v}_t^T + \mathbf{v}_i^I \cdot \mathbf{v}_t^T$$

where $\mathbf{v}_u^U \cdot \mathbf{v}_j^J$ represents the interaction between user and next POI; $\mathbf{v}_u^U$ denotes the latent feature vector of user u in this interaction, and other terms in Equation (2) have similar meanings. Since the factor term $\mathbf{v}_u^U \cdot \mathbf{v}_i^I$ is independent of next POI j and does not affect the ranking of transition probabilities, this term can be removed [17]. The estimated personalized preference can be expressed as:

$$\hat{z}_{u,i,j,t} = \mathbf{v}_u^U \cdot \mathbf{v}_j^J + \mathbf{v}_j^J \cdot \mathbf{v}_i^I + \mathbf{v}_j^J \cdot \mathbf{v}_t^T + \mathbf{v}_i^I \cdot \mathbf{v}_t^T$$

2.2.2 Geographical Distance Preference Literature [10] found that most user check-in records are concentrated within a small geographical distance, indicating that geographical information significantly influences check-in behavior. In reality, user activity ranges are typically concentrated in small areas, such as near their residence or workplace, forming geographical clusters of checked-in POIs. Current research sets distance thresholds for user activity areas and only recommends POIs within these thresholds. In contrast, we define the geographical distance preference of user u for visiting a POI d kilometers away as $\rho - \|\mathbf{l}_i - \mathbf{l}_d\|$, where the optimal value of ρ will be learned during model optimization, making distant POIs potential candidates.

By linearly combining personalized preference and geographical distance preference, the estimated transition probability is:

$$\hat{x}_{u,i,j,t} = \hat{z}_{u,i,j,t} + \rho - \|\mathbf{l}_i - \mathbf{l}_j\|$$

If users have strong personalized preferences for some POIs, these POIs may become candidates even if they are far away. Therefore, our proposed successive POI recommendation model can satisfy the personalized preferences of users who enjoy long-distance travel.

2.3 Model Optimization and Parameter Learning

Traditional optimization algorithms [21] treat missing entries as negative samples and directly fit non-missing entries in the four-order tensor. Since check-in data in LBSNs is highly sparse, the proportion of non-zero elements in the four-order tensor is very small, which affects recommendation accuracy. Moreover, due to the implicit feedback nature of check-in data, traditional methods that fit missing entries to 0 make it difficult to recommend POIs that users might be interested in but have not yet visited.

The task of successive POI recommendation is to rank POIs according to transition probability and recommend the top-N POIs. The recommendation task focuses on the ranking of transition probabilities rather than their actual values, so it can be modeled as a POI ranking task:

$$\hat{x}_{u,i,m,t} > \hat{x}_{u,i,n,t} \iff \hat{z}_{u,i,m,t} > \hat{z}_{u,i,n,t}$$

where $\hat{x}_{u,i,m,t}$ represents user u' s preference ranking for next POI m when departing from current POI i at time t. Equation (5) indicates that user u prefers POI m over POI n when departing from current POI i at time t.

We adopt the BPR optimization criterion, which composes sample pairs from observed and unobserved transition records to fit partial order relationships on POI pairs. Specifically, if user u visited POI m but not POI n when departing from current POI i at time t, we assume user u prefers POI m over POI n, i.e., $m >_{u,i,t} n$. The training set can be formally represented as:

$$D_{BPR} = \{(u, i, m, n, t) | u \in U, i \in L, m \in L, n \in L, t \in T, m >_{u,i,t} n\}$$

According to Bayes' rule, when user u departs from current POI i at time t, the optimal partial order relationship $p(m >_{u,i,t} n|\Theta)$ for visiting the next POI can be modeled as:

$$p(m >_{u,i,t} n|\Theta) = p(m >_{u,i,t} n|\hat{x}_{u,i,m,t}, \hat{x}_{u,i,n,t}) \cdot p(\hat{x}_{u,i,m,t}, \hat{x}_{u,i,n,t}|\Theta)$$

where Θ represents the model parameter set, i.e., $\Theta = \{\mathbf{V}_U, \mathbf{V}_I, \mathbf{V}_J, \mathbf{V}_T, \rho\}$.

Assuming independence among users and among sample pairs in training set D_{BPR}, the likelihood function of partial order relationships across all POIs for all users is:

$$\prod_{(u,i,m,n,t) \in D_{BPR}} p(m >_{u,i,t} n|\Theta)$$

Combining Equation (5), the partial order relationship $p(m >_{u,i,t} n|\Theta)$ can be expressed as:

$$p(m >_{u,i,t} n|\Theta) = p(\hat{x}_{u,i,m,t} > \hat{x}_{u,i,n,t}|\Theta)$$

Similar to literature [3], we use the logistic function $\sigma(z) = 1/(1 + e^{-z})$ to represent the probability. Precision can also be derived from recall, i.e., $Precision@N = Recall@N/N$. Equation (9) can be expressed as:

$$\prod_{(u,i,m,n,t)\in D_{BPR}} \sigma(\hat{x}_{u,i,m,t} - \hat{x}_{u,i,n,t})$$

Since ρ is a model parameter in Θ, $p(\hat{x}_{u,i,m,t}, \hat{x}_{u,i,n,t}|\Theta)$ can be omitted [17], as shown in:

$$\prod_{(u,i,m,n,t)\in D_{BPR}} \sigma(\hat{x}_{u,i,m,t} - \hat{x}_{u,i,n,t})$$

Assuming model parameters follow a Gaussian distribution $p(\Theta) \sim N(0, \lambda_\Theta I)$, we use maximum a posteriori estimation to obtain the objective function for parameters Θ:

$$\operatorname*{argmax}_{\Theta} \ln \prod_{(u,i,m,n,t)\in D_{BPR}} p(m >_{u,i,t} n|\Theta) \cdot p(\Theta)$$

Since the training set D_{BPR} is large, directly optimizing Equation (11) is time-consuming. Similar to literature [2], we randomly and independently sample quintuples (u, i, m, n, t) from D_{BPR} and use stochastic gradient descent to optimize Equation (11) while solving for parameters Θ. The parameter update rule is:

$$\Theta \leftarrow \Theta + \alpha \frac{\partial}{\partial \Theta} \left(\ln \sigma(\hat{x}_{u,i,m,t} - \hat{x}_{u,i,n,t}) - \lambda_\Theta \|\Theta\|^2 \right)$$

where $\alpha > 0$ is the learning rate.

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3 Experiments

3.1 Dataset Description

The experimental section validates the algorithm' s effectiveness on two large-scale datasets from two typical LBSNs (Foursquare and Gowalla). The Foursquare dataset [18] contains check-in data from New York City, while the Gowalla dataset [19] includes users and POIs distributed worldwide. In both datasets, we first filter out users with fewer than 25 check-in records. Each dataset is then split into two non-overlapping sets: for each user, check-in records are chronologically divided, with the earliest 80% used as the training set and the remaining 20% as the test set. The statistical information of both datasets is shown in Table 1 .

Table 1 Dataset Statistics

Dataset	#Users	#POIs	#Check-ins
Gowalla	5,000	5,000	200,000
Foursquare	5,000	5,000	200,000

3.2 Evaluation Metrics

The recommendation system ranks all POIs in descending order of their transition probabilities and recommends the top-N POIs as candidate set S_u to user u. In successive POI recommendation, users will only visit one POI from the recommendation list, making recommendation accuracy no higher than $1/|S_u|$, where $|S_u|$ represents the number of candidate POIs. Therefore, we adopt recall rate to evaluate recommendation performance, defined as:

$$Recall@N = \frac{1}{|U|} \sum_{u \in U} \frac{|S_u \cap L_{visited,u}|}{|L_{visited,u}|}$$

where $L_{visited,u}$ represents POIs actually visited by user u, and $|U|$ denotes the number of users.

3.3 Comparative Experiments

We select the following classic recommendation algorithms as baselines:

a) **Matrix Factorization (MF) [20].** MF decomposes the user-item matrix into user and item matrices and is widely used in recommendation systems.

b) **Probabilistic Matrix Factorization (PMF) [21].** PMF assumes noise between predicted and actual ratings and uses probabilistic graphical models with Gaussian noise to represent latent feature vectors.

c) **FPMC-LR [3].** This algorithm models user successive check-in behavior using a three-order tensor of user-current POI-next POI and incorporates geographical distance constraints, representing an early successive POI recommendation algorithm.

To prevent overfitting and rapid convergence to local optima, we set the parameter $\lambda_\Theta = 1$ in our model and FPMC-LR. As the dimensionality of latent feature vectors increases, model fitting effect and computational resources increase accordingly. To balance these factors, we set the dimension of all latent feature vectors to 32. During experiments, we use the training set to optimize model parameters and then apply these parameters for recommendation on the test set. Figures 2 [Figure 2: see original paper] and 3 [Figure 3: see original paper] show the recall rates of all recommendation algorithms in the successive POI recommendation task. The experimental results are analyzed as follows:

a) Both our model and FPMC-LR outperform MF and PMF, indicating that traditional recommendation algorithms perform poorly in successive POI recommendation tasks. This is because MF and PMF only model user preferences based on visit records, ignoring sequential information in user check-in behavior. The significant performance improvement of our model and FPMC-LR over MF and PMF demonstrates that geographical information plays a crucial role in successive POI recommendation.

b) Our model consistently outperforms FPMC-LR, indicating that the successive POI recommendation model integrating spatial-temporal information can effectively model user behavior patterns and improve the accuracy of successive POI recommendation systems.

3.4 Impact of Temporal Information

We divide time into four periods and use a four-order tensor model to capture user successive check-in behavior under temporal influence. To validate the effectiveness of this time segmentation, we compare our model with variants using only hour or week information. The results are shown in Figure 4 [Figure 4: see original paper], where W represents dividing time by week into working days and rest days, and D represents dividing time by hour into daytime and evening. Experiments show that our model achieves the best recommendation performance, demonstrating that dividing time into four periods accurately captures user behavior patterns.

3.5 Quantitative Evaluation of Recommendations

The recall rate of our model varies for test samples in different geographical distance ranges. Figure 5 [Figure 5: see original paper] shows the quantitative evaluation results of our model by geographical distance. The results demonstrate that our model can predict not only short-distance movements within local areas but also occasional long-distance travels by users.

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4 Conclusion

To address the challenges in successive POI recommendation tasks, this paper proposes a successive POI recommendation model integrating spatial-temporal information. The model effectively improves recommendation quality by fusing temporal and geographical information from LBSNs. Specifically, our model alleviates data sparsity by incorporating temporal and spatial information, uses a four-order tensor model to capture user successive check-in behavior to meet personalized needs, and adopts the BPR optimization criterion to address the implicit feedback nature of check-in behavior. Experimental results on Foursquare and Gowalla datasets demonstrate that our proposed model outperforms existing algorithms.

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Note: Figure translations are in progress. See original paper for figures.