Joint Modeling of Users' Interests and Mobility Patterns for Point-of-Interest Recommendation

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ABSTRACT

Point-of-Interest (POI) recommendation has become an important means to help people discover interesting places, especially when users travel out of town. However, extreme sparsity of user-POI matrix creates a severe challenge. To cope with this challenge, we propose a unified probabilistic generative model, *Topic-Region Model (TRM)*, to simultaneously discover the semantic, temporal and spatial patterns of users' check-in activities, and to model their joint effect on users' decision-making for POIs. We conduct extensive experiments to evaluate the performance of our TRM on two real large-scale datasets, and the experimental results clearly demonstrate that TRM outperforms the state-of-art methods.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information Filtering

Keywords

Recommender system; Location-based service; Probabilistic generative model; Joint Modeling

1. INTRODUCTION

The rapid development of Web 2.0, location acquisition and wireless communication technologies have fostered a number of location-based social networks (LBSNs), such as Foursquare and Facebook Places. In these LBSNs, users can post their physical locations or geo-tagged information in the form of "check-in", and share their visiting experiences for points of interest (POI). In LBSNs, it is crucial to utilize user check-in data to make personalized POI recommendation, which helps users know new POIs and explore new places and facilitates advertisers to launch mobile advertisements.

One of the most important problems for POI recommendation is how to deal with a severe challenge stemming from extreme sparsity of user-POI interaction matrix. There are millions of POIs in LBSNs, but a user can only visit a limited number of them. Moreover, the observation of travel locality exacerbates this problem. The observation of travel locality [5] made on LBSNs shows that the check-in records generated by users in their non-home cities only take up 0.47% of the ones generated in their home cities [11].

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This observation aggravates the data sparsity problem with POI recommendation for out-of-town users [3, 17].

The most popular approach in recommender systems is *collaborative filtering* [1]. There exists a considerable body of research [5, 13, 6, 3, 4] which deposits people's check-in history into user-POI matrix. Based on the matrix, a collaborative filtering-based method is then employed to infer the user's preference regarding each unvisited POI. The core idea of collaborative filtering is that similar users provide clues for making recommendation. Due to travel locality, most of these similar users are more likely to live in the same region with the target user. As a recommendation is made by considering POIs visited by the similar users, most of the recommended POIs would be located in the target user's home town. So, these CF-based methods cannot be directly applied to the POI recommendation for out-of-town users [3, 17].

To deal with the issue of data sparsity, especially for the out-of-town recommendation scenario, we propose a unified probabilistic generative model, namely Topic-Region Model (TRM), to simultaneously discover the semantic, temporal and spatial patterns of users' check-in activities, and model their joint effect on users' check-in behaviors. (1) Semantic Patterns. A recent analysis of the Whrrl dataset shows that the check-in activities of users exhibit a strong semantic regularity [12], e.g., the entropy of semantic categories in individual user's visited POIs is very small. (2) Temporal Patterns. As observed in [18, 4], users' activity contents exhibit strong temporal cyclic patterns in terms of hour of the day. For example, a user is more likely to go to a restaurant rather than a bar at lunch time. (3) Spatial Patterns. Many recent studies show that people tend to explore POIs near the ones that they have visited before [14]. So, POIs visited by users often form spatial clusters [6].

Note that while there are some recent studies [17, 18, 4, 6] that exploit one of the above patterns to improve POI recommendation, they lack an integrated analysis of their joint effect to deal with the issue of data sparsity, especially in the out-of-town scenario.

The remainder of the paper is organized as follows. Section 2 details TRM model. We deploy TRM to POI recommendation in Section 3. We report the experimental results in Section 4. Section 5 concludes the paper.

2. JOINT MODELING OF USER CHECK-IN ACTIVITIES

In this section, we first formulate the problem definition, and then present our proposed TRM.

2.1 Problem Formulation

Definition 1. **(POI)** A POI is defined as a uniquely identified specific site. In our model, a POI has three attributes: identifier,

Variable	Interpretation
$\boldsymbol{\vartheta_u}$	the spatial patterns of user u, expressed by a multinomial distribution over a set of regions
$\boldsymbol{\theta_u}$	the interests of user u, expressed by a multinomial distribution over a set of topics
$\boldsymbol{\phi_z}$	a multinomial distribution over words specific to topic z
$\boldsymbol{\psi_z}$	a multinomial distribution over time slots specific to topic z
$\boldsymbol{\varphi_{z,r}}$	a multinomial distribution over POI IDs specific to topic-region (z, r)
$\boldsymbol{\mu_r}$	the mean location of region r
$\boldsymbol{\Sigma_r}$	the location covariance of region r
$\gamma, \alpha, \beta, \eta, \tau$	Dirichlet priors to multinomial distributions $\boldsymbol{\vartheta_u}$, $\boldsymbol{\theta_u}$, $\boldsymbol{\phi_z}$, $\boldsymbol{\psi_z}$ and $\boldsymbol{\varphi_{z,r}}$, respectively

Table 1: Notations of parameters

location and contents. We use v to represent a POI identifier and l_v to denote its corresponding location attribute in terms of longitude and latitude coordinates. Besides, we use the notation W_v to denote the set of words describing POI v, such as tags and categories.

Definition 2. **(User Home Location)** We define a user's home location as the place where she lives, denoted as l_u. For a user whose home location is not explicitly given, we adopt the method developed by [11] which discretizes the world into 25 by $25km$ cells and defines the home location as the average position of check-ins in the cell with most of his/her check-ins.

Definition 3. **(Check-in Activity)** A check-in activity is represented by a five tuple $(u,\ v,\ l_v,\ W_v,\ t)$ that means user u visits POI v at time t.

Definition 4. **(User Profile)** For each user u, we create a user profile D_u, which is a set of check-in activities associated with user u. The dataset D used in our model consists of user profiles, i.e., $D = \{D_u : u \in U\}$ where U is the set of users.

Definition 5. **(Topic)** Given a collection of words W, a topic z is defined as a multinomial distribution over W, i.e., $\boldsymbol{\phi_z} = \{\phi_{z,w} : w \in W\}$ where each component $\phi_{z,w}$ denotes the probability of topic z generating word w.

PROBLEM 1. ***(POI Recommendation)*** *Given a target user u with her current location l and time t (that is, the query is $q = (u,\ t,\ l)$), our goal is to recommend a list of POIs that u would be interested in. Given a distance threshold d, the problem becomes an* ***out-of-town recommendation*** *if the distance between her current location and her home location (that is, $|l - l_u|$) is greater than d. Otherwise, the problem is a* ***home-town recommendation****.*

Following related studies [3, 10], we set $d = 100km$.

2.2 Model Description

For ease of presentation, we first list the notations used in TRM in Table 1. Figure 1 shows the graphical representation of TR-M where users' check-in records are modeled as observed random variables. As a POI has both semantic and geographical attributes, we introduce two latent random variables, topic z and region r, which are responsible for generating them, respectively. Based on the two latent factors, TRM aims to model users' interests and spatial patterns as well as their joint effect on users' visiting behaviors.

User Interest Modeling. Inspired by the early work about user interest modeling [9, 17], TRM adopts latent topics to characterize users' interests to overcome the data sparsity. Specifically, we infer individual user's interest distribution over a set of topics according to the contents (e.g., tags and categories) of his/her checked-in POIs, denoted as $\boldsymbol{\theta_u}$. Thus, a user is associated with a topic distribution, from which topics of check-in activities are sampled.

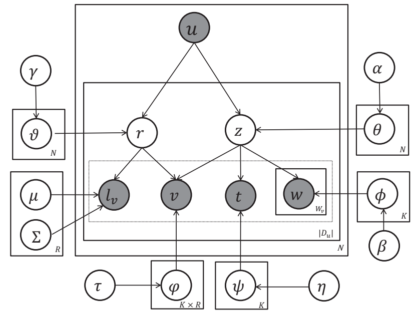


Figure 1: The Graphical Representation of TRM

Unfortunately, based on recent analysis of LBSNs data [12], about 30% of all POIs lack any meaningful content information. To address this problem, we exploit the association between the contents of checked-in POIs and the check-in time through latent topic z, since the check-in time provides important clues about the semantic content of POIs. Technically, each topic z in our TRM is not only associated with a word distribution $\boldsymbol{\phi_z}$, but also with a distribution over time $\boldsymbol{\psi_z}$. Thus, the introduction of check-in time is helpful to infer the topics of POIs whose contents are not available. To integrate the check-in time information to the topic discovery process, we employ the widely adopted discretization method in [4, 18] to split a day into hourly-based slots.

User Spatial Pattern Modeling. The spatial clustering phenomenon indicates that users are most likely to visit a number of POIs and these POIs are usually limited to some geographical regions [14]. In this component, the geographical space is divided into R regions. We apply a multinomial distribution $\boldsymbol{\vartheta_u}$ over regions to model u's spatial patterns. Following the literatures [8, 7], we assume a Gaussian distribution for each region r, and the location for POI v is characterized by $l_v \sim \mathcal{N}(\boldsymbol{\mu_r}, \boldsymbol{\Sigma_r})$, as follows:

$$P(l_v|\boldsymbol{\mu_r}, \boldsymbol{\Sigma_r}) = \frac{1}{2\pi\sqrt{|\boldsymbol{\Sigma_r}|}} \exp\left(\frac{-(l_v - \boldsymbol{\mu_r})^T \boldsymbol{\Sigma}_r^{-1}(l_v - \boldsymbol{\mu_r})}{2}\right) \quad (1)$$

where $\boldsymbol{\mu_r}$ and $\boldsymbol{\Sigma_r}$ denote the mean vector and covariance matrix.

Modeling The Joint Effect. As a POI has both semantic and geographical attributes, the propensity of a user u for a POI v is determined by the joint effect of u's personal interests and spatial mobility patterns. To model this joint effect, we introduce a joint latent factor topic-region which is responsible for generating the IDs of visited POIs, i.e., a topic-region (z, r) is associated with a distribution over POI IDs (that is $\boldsymbol{\varphi_{z,r}}$). As a matter of fact, a topic-region represents a geographical area in which POIs have same or similar semantics (e.g., categories or functions).

2.3 Model Inference

Exact inference for TRM model is difficult due to the intractable normalizing constant of the posterior distribution, we therefore exploit collapsed Gibbs sampling for approximate inference, following the studies [17, 16, 15]. As for the hyperparameters α, β, γ, η and τ, for simplicity, we take fixed values, i.e., $\alpha = 50/K$, $\gamma = 50/R$ and $\beta = \eta = \tau = 0.01$. At each iteration of our Gibbs sampler, for each user check-in record, we sample both the corresponding topic indicator z and the region indicator r. Below, we present the sampling formulas.

Sample topic indicator z according to:

$$\begin{aligned} P(z|\boldsymbol{z}_{\neg u,v}, \boldsymbol{r}, \boldsymbol{v}, \boldsymbol{l_v}, \boldsymbol{W_v}, \boldsymbol{t}, u, \cdot) \propto \frac{n_{u,z}^{\neg u,v} + \alpha}{\sum_{z'}(n_{u,z'}^{\neg u,v} + \alpha)} \times \\ \frac{n_{z,t}^{\neg u,v} + \eta}{\sum_{t'}(n_{z,t'}^{\neg u,v} + \eta)} \frac{n_{z,r,v}^{\neg u,v} + \tau}{\sum_{v'}(n_{z,r,v'}^{\neg u,v} + \tau)} \prod_{w \in W_v} \frac{n_{z,w}^{\neg u,v} + \beta}{\sum_{w'}(n_{z,w'}^{\neg u,v} + \beta)} \end{aligned} \quad (2)$$

where $\boldsymbol{z}_{\neg u,v}$ represents topic assignments for all check-in records except the current one, $n_{u,z}$ is the number of times that latent topic z has been sampled from the interest distribution of user u, $n_{z,w}$ is the number of times that word w is generated from topic z, and $n_{z,t}$ is the number of times that time slot t is generated from topic z; $n_{z,r,v}$ is the number of times that POI v is generated by topic-region (z, r); the number $n^{\neg u,v}$ with superscript $\neg u, v$ denotes a quantity excluding the current instance.

Sample region indicator r according to:

$$\begin{aligned}&P(r|\boldsymbol{r}_{\neg u,v}, \boldsymbol{z}, \boldsymbol{v}, \boldsymbol{l_v}, \boldsymbol{W_v}, \boldsymbol{t}, u, \cdot)\\ \propto &\frac{n_{u,r}^{\neg u,v} + \gamma}{\sum_{r'}(n_{u,r'}^{\neg u,v} + \gamma)} \frac{n_{z,r,v}^{\neg u,v} + \tau}{\sum_{v'}(n_{z,r,v'}^{\neg u,v} + \tau)} P(l_v|\boldsymbol{\mu_r}, \boldsymbol{\Sigma_r})\end{aligned} \tag{3}$$

where $n_{u,r}$ is the number of times that region r has been sampled from the spatial distribution of user u.

After each iteration, we employ the method of moments to update the Gaussian distribution parameters (i.e., $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$):

$$\boldsymbol{\mu_r} = E(r) = \frac{1}{|S_r|} \sum_{v \in S_r} l_v \tag{4}$$

$$\boldsymbol{\Sigma_r} = D(r) = \frac{1}{|S_r| - 1} \sum_{v \in S_r} (l_v - \boldsymbol{\mu_r})(l_v - \boldsymbol{\mu_r})^T \tag{5}$$

where S_r denotes the set of POIs associated with latent region r.

3. POI RECOMMENDATION USING TRM

Once we have learnt the model parameter set $\hat{\boldsymbol{\Psi}} = \{\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\vartheta}}, \hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\varphi}}, \hat{\boldsymbol{\psi}}, \hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}}\}$, given a target user u with the current time t and location l, i.e., $q = (u, t, l)$, we compute a probability of user u checking-in each unvisited POI v as in Equation 6, and then select top-k POIs with highest probabilities for the target user.

$$P(v|u, t, l, \hat{\boldsymbol{\Psi}}) = \frac{P(v, t|u, l, \hat{\boldsymbol{\Psi}})}{\sum_{v'} P(v', t|u, l, \hat{\boldsymbol{\Psi}})} \propto P(v, t|u, l, \hat{\boldsymbol{\Psi}}) \tag{6}$$

where $P(v, t|u, l, \hat{\boldsymbol{\Psi}})$ is calculated as follows:

$$P(v, t|u, l, \hat{\boldsymbol{\Psi}}) = \sum_r P(r|l, \hat{\boldsymbol{\Psi}}) P(v, t|u, r, \hat{\boldsymbol{\Psi}}) \tag{7}$$

where $P(r|l, \hat{\boldsymbol{\Psi}})$ denotes the probability of user u choosing region r given his current location l, and it is computed as in Equation 8 according to Bayes rule, in which the prior probability of latent region r can be estimated using Equation 9.

$$P(r|l, \hat{\boldsymbol{\Psi}}) = \frac{P(r)P(l|r, \hat{\boldsymbol{\Psi}})}{\sum_{r'} P(r')P(l|r', \hat{\boldsymbol{\Psi}})} \propto P(r)P(l|r, \hat{\boldsymbol{\Psi}}) \tag{8}$$

$$P(r) = \sum_u P(r|u)P(u) = \sum_u \frac{N_u + \kappa}{\sum_{u'}(N_{u'} + \kappa)} \hat{\vartheta}_{u',r} \tag{9}$$

where N_u denotes the number of check-ins generated by user u. In order to avoid overfitting, we introduce the Dirichlet prior parameter κ to play the role of pseudocount. The second part of Equation 7, $P(v, t|u, r, \hat{\boldsymbol{\Psi}})$, is computed as follows.

$$P(v, t|u, r, \hat{\boldsymbol{\Psi}}) = \sum_z P(z|u, \hat{\boldsymbol{\Psi}}) P(t|z, \hat{\boldsymbol{\Psi}}) P(v|z, r, \hat{\boldsymbol{\Psi}}) \tag{10}$$

Based on Equations (7-10), the original Equation 6 can be reformulated as follows.

$$\begin{aligned}&P(v|u, t, l, \hat{\boldsymbol{\Psi}})\\ &\propto \sum_r \left[P(r)P(l|r, \hat{\boldsymbol{\Psi}}) \sum_z P(z|u, \hat{\boldsymbol{\Psi}})P(t|z, \hat{\boldsymbol{\Psi}})P(v|z, r, \hat{\boldsymbol{\Psi}})\right]\\ &= \sum_r \left[P(r)P(l|\hat{\boldsymbol{\mu}}_{\boldsymbol{r}}, \hat{\boldsymbol{\Sigma}}_{\boldsymbol{r}}) \sum_z \hat{\theta}_{u,z} \hat{\psi}_{z,t} \hat{\varphi}_{z,r,v}\right]\end{aligned} \tag{11}$$

4. EXPERIMENTS

In this section, we first describe the settings of experiments and then demonstrate the experimental results.

4.1 Experimental Settings

4.1.1 Datasets

Foursquare. This dataset contains the check-in history of 4,163 users who live in the California, USA. For each user, it contains her social networks, check-in POI IDs, location of each check-in POI in terms of latitude and longitude, check-in time and the contents of each check-in POI. The total number of check-in records is 483,813, and the total number of social relationship is 32,512.

Twitter. This dataset is based on the publicly available twitter dataset [2]. But the original dataset does not contain the category and tag information about each POI. So, we crawled the content information associated with each POI from Foursquare with the help of its publicly available API [1]. The enhanced dataset contains 114,058 users and 1434,668 check-ins.

4.1.2 Comparative Approaches

TACF. TACF is the state-of-the-art time-aware POI recommendation method [18], which is a collaborative filtering model considering *temporal effect*.

GeoMF. GeoMF is a weighted matrix factorization model that exploits the *spatial patterns* of users' check-in activities [6].

LCA-LDA. LCA-LDA is a location-content-aware recommender model which is developed to support POI recommendation for users traveling in new cities [17].

UPS-CF. UPS-CF, proposed in [3], is a collaborative recommendation framework which incorporates social influence to support out-of-town recommendation.

4.1.3 Evaluation methods

For each user, we divide the user's activity records into a training set and a test set. For the scenario of home-town recommendation, we randomly select 30% of the activity records occurring at the user's home town as test set, and use the remaining activity records as the training set. Similarly, for the scenario of out-of-town recommendation, we randomly select 30% of the activity records generated by the user when he/she travels out of town as the test set.

To evaluate the recommendation methods, we adopt the evaluation methodology and measurement Accuracy@k proposed in [17, 16]. Specifically, for each activity record $(u,\ v,\ l_v,\ W_v, t)$ in the test set, we define hit@k as either the value 1, if the ground truth POI v appears in the top-k results, or the value 0, if otherwise. The overall Accuracy@k is defined by averaging over all test cases:

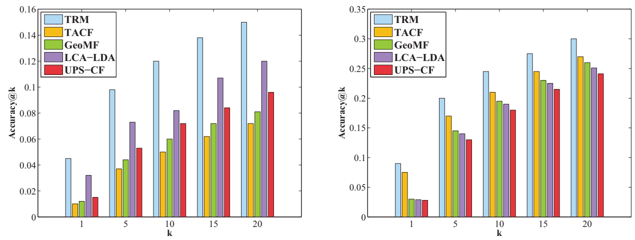
$$Accuracy@k = \frac{\#hit@k}{\#tests}$$

where $\#hit@k$ denotes the number of hits in the test set, and $\#tests$ is the number of all test cases.

4.2 Experimental Results

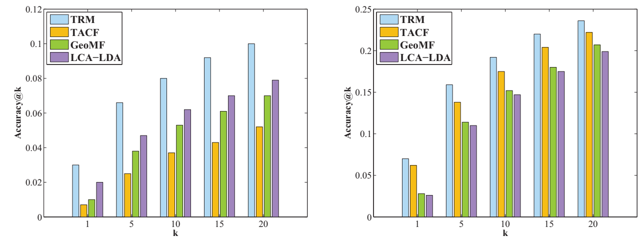
Figure 2(a) presents the recommendation accuracy in the scenario of out-of-town recommendation where the accuracy of TRM is about 0.122 when $k = 10$, and 0.151 when $k = 20$ (i.e., the model has a probability of 12.2% of placing an appealing POI in the top-10 and 15.1% of placing it in the top-20). Clearly, TRM outperforms other competitor models significantly, and the advantages of TRM are very obvious in this scenario. Several observations are

[1]https://developer.foursquare.com/



(a) Out-of-town Recommendation (b) Home-town Recommendation

Figure 2: Top-k Performance on Foursquare Dataset



(a) Out-of-town Recommendation (b) Home-town Recommendation

Figure 3: Top-k Performance on Twitter Dataset

made from the results: 1) TACF, UPS-CF and GeoMF drop behind TRM and LCA-LDA, showing the advantages of exploiting the semantic patterns of users' check-in activities. This is because users have very few check-in activity records in out-of-town regions, and these CF-based or matrix factorization-based methods suffer from the severe data sparsity, while the contents of user activities can serve as the medium to transfer users' interests inferred at home town to out-of-town regions. 2) TRM achieves much higher recommendation accuracy than LCA-LDA, showing the benefits of considering both temporal and geographical patterns.

In Figure 2(b), we report the performance of all recommendation models for the home-town scenario. From the figure, we can see that the recommendation accuracies of all methods are higher in Figure 2(b) than that in Figure 2(a). Besides, both LCA-LDA and GeoMF outperform TACF in Figure 2(a) while TACF slightly exceeds both of them in Figure 2(b) due to its incorporation of temporal patterns, showing that time-aware collaborative filtering method better suits the setting where the user-POI matrix is not sparse, and the model-based methods, especially the ones which integrate semantic patterns of users' activities are more capable of overcoming the difficulty of data sparsity in the out-of-town scenario. By the comparison between LCA-LDA and GeoMF in Figure 2(a) and 2(b), we observe that exploiting semantic patterns is more beneficial in out-town recommendation scenario while exploiting spatial patterns is more important in the home-town recommendation. Another observation is that the performance gap between our TRM and other competitor methods is not as big as in Figure 2(a), showing that the performance difference among recommendation methods become less obvious when the issue of data sparsity is not serious. The comparisons between Figure 2(a) and 2(b) also reveal that the two scenarios are intrinsically different, and should be separately evaluated.

Figure 3 reports the performance of the recommendation models on the Twitter dataset. We do not compare our model with UPS-CF since this dataset does not contain user social network information. From the figure, we can see that the trend of comparison result is similar to that presented in Figure 2, and the main difference is that all recommendation methods achieve lower accuracy. This may be because each user in the Foursquare dataset has more check-in records on average than users in the Twitter dataset.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed a unified probabilistic generative model TRM to model users' check-in activities in LBSNs, which simultaneously exploits the semantic, temporal and geographical patterns and also models their joint effect on users' visiting behaviors. We conducted extensive experiments to evaluate the performance of TRM on two real datasets, and the results showed TRM effectively overcomes the data sparsity and significantly improves recommendation accuracy, especially when users travel out of town.

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