Spatial-Temporal Topic Model for Cold-Start Event Recommendation

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ABSTRACT Event recommendation has attracted an increasing attention with the popularity of event-based social networks (EBSNs). The previous studies mainly focus on exploiting various contextual information to alleviate the cold-start problem in event recommendation. However, the interactions between different contextual factors, such as time, location and content, have not been modeled jointly. In this paper, we investigate the relationships among time, location and organizer in EBSNs, and propose a Spatial-Temporal Topic Model (STTM) for cold-start event recommendation. STTM can capture user’s interests on content and geographical space changing over time, and users have different event and venue topic distributions at different times in STTM. We perform an experimental evaluation on the real-world EBSNs dataset. The experimental results show the significant improvements of our method over other comparison methods, especially when dataset is more sparse.

INDEX TERMS Event recommendation, cold-start problem, topic model, spatio-temporal information.

I. INTRODUCTION

The newly emerged event-based social networks (EBSNs), such as Meetup¹ and Douban Event,² have attracted attention from both industry and academy. Compared with the traditional social networks (e.g., Facebook and LinkedIn) that connect people via their online interactions, EBSNs preserve both online and offline relations among users. For instance, Meetup allows users to join online groups that are created based on different topics and each group can create offline events (e.g., party, concert and conference) so that users can communicate with each other face-to-face in the real world. Each event is associated with a host group that creates the event, a time when it starts, a venue where the event is held and some textual content to describe it.

Event recommendation aiming to help users find the events they are likely to attend is an essential task in EBSNs, because the large number of events are distributed from EBSNs every day. One significant difference between recommendation for events and that for other domains (e.g., movie [1] and point-of-interest (POI) [2], [3]) is that the events have very short life cycle, i.e., the time interval between the start time and end time of events is usually several hours or a couple of days, while users can watch a movie or visit a POI at any time. Since all the events to be recommended have not start yet and receive few responses from users, event recommendation faces a serious cold-start problem [4], where new events with few responses are required to be recommended and the traditional collaborative filtering methods [5], [6] are ineffective to overcome this problem.

To alleviate the cold-start problem in event recommendation, the existing studies [7]–[10] mainly focus on incorporating various contextual information (e.g., host group, location, time and content of event) into their models. Some studies [7], [8], [10] jointly consider location, content and time information through collective matrix factorization, but the spatial influence is ignored. We argue that the spatial information plays a crucial role in user’s decision making of event attendance according to the First Law of Geography [11], i.e., everything is related to everything else, but near things are more related than distant things. Moreover, the spatial influence to the user’s decision making should change over time. Macedo et al. [9] exploit temporal, spatial, content and social information, but these factors are considered independently. The interactions among these factors can not be captured. The existing studies [8]–[10] shows that social,
content, space and time are most informative factors for cold-start event recommendation. However, the interactions among different contextual information have not been considered in a joint model, and the contextual information has not been well explored to cope with cold-start problem in event recommendation.

In light of this, we propose a Spatial-Temporal Topic Model (STTM) to capture interactions among content, venue, spatial and temporal factors to improve the performance of cold-start event recommendation, addressing the weaknesses of existing methods. STTM has two connected components: group-aware interest component inferring user’s content preferences based on the group that creates event and venue-aware mobility component modeling user’s venue preferences and geographical mobility. The two components are connected with start time of events based on the intuition that user’s content and venue preferences change over time. Note that some spatial-temporal topic models are proposed in previous works [21], [22]. There are significant differences between our model and previous spatial-temporal topic models. First of all, time is generated by latent topics in our model instead of generating other latent topics in STT [21], USTTM and MSTTM [22]. Secondly, event topics represented by the probability distribution over organizers of events are introduced in our model to capture user’s content preferences instead of traditional topics represented by the probability distribution over words describing locations in the previous models. Finally, the main contributions of this paper are summarized as:

- We propose Spatial-Temporal Topic Model (STTM) to capture the interactions among content, venue, spatial and temporal influences on user’s decision making of event attendance. A cold-start event recommendation method based on STTM is proposed.
- We learn latent content and venue topics from user attendance records with context information to capture user’s content and venue preferences changing over time, respectively.
- We conduct extensive experiments on real-world EBSNs dataset to evaluate the performance of our cold-start event recommendation method based on STTM. The experimental results demonstrate that our model outperforms the state-of-the-art methods.

The rest of this paper is organized as follows. Section II introduces the related work, and we define our problem in Section III. Section IV presents the proposed generation process, training algorithm and event recommendation method of STTM. Experimental results are presented in Section V. We conclude our work and describe the future work in Section VI.

**II. RELATED WORK**

**Event recommendation** has attracted increasing attention recently. Some studies [12], [13] utilize collaborative filtering [14] technique for event recommendation, but they ignore the cold-start problem, where all events to be recommended receive a few or no responses from users. Several recent researches [8]–[10] exploit multiple contextual information to alleviate the cold-start problem of event recommendation. Macedo et al. [9] model different contextual influences (e.g., social, spatial, temporal and content information) individually and combine these models through learning-to-rank technique [15]. Zhang et al. [10] utilize collective Bayesian Poisson factorization to jointly model multiple contextual influences. Jhamb et al. [8] model group influence from both user and event perspectives. Du et al. [16] use collaborative filtering method to model different contextual information to predict event attendance in EBSNs. Most previous studies [12], [13] ignore or underestimate the temporal influence on the performance of event recommendation. Macedo et al. [9] analyze the relations between time and event attendance in EBSNs and find that the different users have different time distribution on attending events. However, their experimental results show that the improvement contributed by temporal influence is very limited. Zhang et al. [10] argue that time is useless for event recommendation task, but the temporal influence in these studies is considered individually. Actually, the temporal influence is related to spatial and content information. In this paper, we propose a model to capture the relationships among spatial, temporal and content influence.

**Topic model** is originally proposed to discover latent semantic structure from text corpus, e.g., PLSA [17] and LDA [18]. Except for text analysis, topic models have been widely applied to various domains, such as recommender systems [20], [22]–[24]. Kurashima et al. [20] propose a topic model to jointly estimate both user’s preferences and activity area for location recommendation. Time and space factors are also incorporated in some previous topic models [21]–[23]. Hu et al. [21] propose STT model to capture the spatio-temporal influence of user check-ins for location recommendation. Yin et al. [23] jointly model user’s preferences and activity regions based on user check-in data for point-of-interest recommendation. Liu et al. [22] assume that time is a factor influencing other factors and propose two spatio-temporal topic models, i.e., USTTM and MSTTM from microscopic and macroscopic perspectives, respectively, to model and analyze check-in data. However, the previous spatial-temporal topic models are designed for LBSNs, such as Gowalla and Foursquare. In LBSNs, time plays an important role in user decision making. For example, a user visits park at 10 am and goes to restaurant at 8 pm. However, we argue that time is a factor influenced by other factors in EBSNs data, due to the significant differences between LBSNs and EBSNs. In EBSNs, user attends an event based on the content and geographical factors rather than the start time of the event. For instance, a user attends a concert not because the concert starts at 8 pm but because she/he is fun of the artist in the concert. Some previous research works [1,2] have shown that time has fewer influence than other factors, i.e., content and geographical information, in event recommendation. Therefore, time should be a factor that...
is influenced by other factors instead of influencing other factors in our topic model for event recommendation.

The main differences between the proposed method and existing spatial-temporal topic models (e.g., MSTTM, USTTM and STT) are summarized as follows. First of all, we assume that time is a factor that should be generated by other factors in EBSNs data, instead of influencing and generating other factors in check-in data, which is the key idea of USTTM and MSTTM. Secondly, based on the correlation between content and organizer and in our model, the events created by the same organizer have more similar content than the events held by different organizers, we introduce time events into our model to capture content influence by generating organizers of events, instead of the topics represented by the distribution over locations and words in USTTM and MSTTM. Thirdly, following the previous study in event recommendation [9], we split week into (equally) 7 days and each day is split into hourly based slots, instead of using continuous time.

Compared to STT, time is generated based on event topic and venue topic in our model, while time is used to generate latent topics in STT. Secondly, the user check-in location is generated by topic, region and check-in time in STT, while the check-in time is only generated by venue topic in our model. This is because the event topic in our model is used to capture user’s content preference on event instead of capturing location preference. Thirdly, STT only considers time and location influence and ignores content factor.

III. PRELIMINARIES

Event-based social network (EBSN) is defined as a heterogeneous graph \( G = (V, E) \), where \( V \) consists of five types of nodes \( \{U, E, V, O, T\} \) and \( E = \{< U, E >, < E, V >, < E, O >, < U, O >, < E, T >\} \) contains five types of relations between two nodes belong to different types. \( U \) and \( E \) denote the set of users and events, respectively. \( < U, E > \) denotes relations between two nodes and events (e.g., a user attends an event). Each event \( e \in E \) is created by an organizer (i.e., group) \( \alpha_e \in O \), held at a venue \( v_e \in V \), and starts at time \( t_e \in T \). Thus, \( < E, V > \), \( < E, O > \), and \( < E, T > \) denote hold relations between events and venues, organization relations between events and venue, and start time relations between events and time, respectively. \( < U, O > \) represents the membership relations between users and groups.

In an EBSN, a user may provide positive response to an event with a RSVP \(^3\) as "yes" or negative response to an event with a RSVP as "no". Because there are very few negative responses in the real-world EBSNs dataset, we only consider users’ positive responses. If user \( u \) gives positive response to an event \( e \), which has organizer \( \alpha_e \), venue \( v_e \), and start time \( t_e \), we have an event attendance record \( (u, e, \alpha_e, v_e, t_e) \).

\(^3\)RSVP stands for a French phrase “répondez s’il vous plaît”, meaning “please reply”.

IV. THE PROPOSED SPATIOTEMPORAL TOPIC MODEL

In this section, we propose our STTM for event recommendation. First, we introduce the general idea and model structure of STTM. Second, we present the details of STTM generative process. Third, we describe how to estimate the parameters and make event recommendation using STTM. At last, an event recommendation method based on STTM is introduced. For the ease of presentation, we first list the notations in Table 1 and show the graphical representation of STTM in Fig. 1.

A. MODEL STRUCTURE

In EBSNs, users decide to attend an event by considering content, location and start time of the event. The user’s preferences on content of event plays an crucial role in the decision making process. For example, a user who like rock music is more likely to attend a rock concert than a classical concert. The content of event is usually obtained by title and textual description of event. But exploring user preferences based on these content information may complicate our model. Fortunately, the existing research shows that there is significant correlation between content and organizer of event [24], i.e., the events created by same organizer are more similar than the events created by different organizer. Following this conclusion, we can model user preferences based on groups which create events rather than the textual information describing events. We model the preferences of user \( u \) on event as a multinomial distribution \( \theta_u \) over event

Given a set of event attendance records for the out of date events \( E_{old} \), a target user \( u \in U \) and the set of new events \( E_{new} \) that have not received response from users, cold-start event recommendation aims to generate a top-\( k \) list of new events that user \( u \) is likely to attend in the future. The recommended events are ranked according to the probability of user \( u \) attends each new event \( e \in E_{new} \). The core task of cold-start event recommendation is building a model to predict the probability of an event is attended by a user.
topics. Each event topic \( z \) is a multinomial distribution \( \eta_z \) over groups.

The users’ event attendance behaviors not only depend on the users’ preferences to the topic of event, but also are influenced by the venue where an event is held. For instance, the user who likes the classic music played in theater is less likely to attend a party with electronic music in nightspot. Therefore, we use latent venue topic \( r \) to describe the users’ preferences to venues. Similarly, we model the preferences of user \( u \) on venue as a multinomial distribution \( \varphi_u \) over venues and each venue topic \( r \) is represented as a multinomial distribution \( \rho_r \) over venues. Moreover, spatial influence also plays an important role in user decision making. Different users have different mobile patterns, that is region preferences and influences the location of events attended by users. The latent region is also represented as a venue topic, which generates the coordinates of venues by a Gaussian distribution \( \mathcal{N}(v|\mu_r, \Sigma_r) \). In other words, a latent venue topic \( r \) is represented as a multinomial distribution over venues and a Gaussian distribution over coordinates of venues simultaneously. The user preferences on venues and regions are described as a multinomial distribution over venue topics. It is well known that user preferences will change over time. Users may attend the events with different content at different time. For example, a user attends technique lectures during the day on Saturday and participates in networking events on Sunday night. Moreover, user preferences on venues and regions are also influenced by time. For instance, users will be more likely to attend the events near their work place during daytime, and attend the events held near their home during the night. Based on this intuition, event topic \( z \) and venue topic \( r \) are responsible for jointly generating start time \( t_e \) of the event attended by user. Thus, given an event topic \( z \) and venue topic \( r \), the start time \( t_e \) is generated from a hybrid model where the distribution is the product of two probabilities: \( \lambda_z \times \delta_r \) over time slots, where a week is split into 7 days and each day is split into hourly-based slots following [9]. We do not differentiate between week day and weekend, because it will lead to more loss of temporal information through discretization. For example, splitting a week into week day and weekend with two time slots regards each week days as same time and cannot differentiate between Saturday and Sunday. For the same reason, we also do not differentiate between day and evening.

### B. GENERATIVE PROCESS

The generative process of STTM is described in Algorithm 1. Given a user \( u \), when she attends an event \( e \), she first selects an event topic \( z \) and a venue topic \( r \) based on her event preferences \( \theta_e \) and venue preferences \( \varphi_u \) respectively. With the chosen event topic \( z \) and venue topic \( r \), the group \( \delta_e \) is generated by distribution \( \eta_z \), start time \( t_e \) is generated by the product of the two probabilities: \( P(t_e|z, \lambda_z) \times P(t_e|r, \delta_r) \). venue indicator \( v_e \) is generated by distribution \( \rho_r \), and venue coordinates is generated by spatial distribution \( \mathcal{N}(v_e|\mu_r, \Sigma_r) \). Note that our model does not generate the event \( e \) explicitly, because an event can be jointly identified by its group, venue and start time, i.e., \((\delta_e, v_e, t_e)\). Moreover, the events to be recommended are cold-start and modeling the generative process of the old events used for training is useless to predict the willingness of a user attending the new events.

### C. PARAMETER ESTIMATION

The input of this model are the number of event topics \( K \), the number of venue topics \( R \), and the event attendance records \((u, e, \delta_e, v_e, t_e)\), while the output of this model are the event topic distribution per user \( \theta_u \), venue topic distribution per user \( \varphi_u \), group distribution per event topic \( \eta_z \), venue distribution per venue topic \( \rho_r \), start time distribution per event topic and venue topic, mean \( \mu_r \) and covariance \( \Sigma_r \) of Gaussian distribution per venue topic.

To learn the parameters of STTM that maximize the marginal log-likelihood of the dataset and the marginalization

| Symbol | Interpretation |
|--------|----------------|
| \( K \) | The number of event topics |
| \( R \) | The number of venue topics |
| \( z \) | Index of event topic |
| \( r \) | Index of venue topic |
| \( \theta_u \) | Multinomial distribution over event topics specific to user \( u \) |
| \( \varphi_u \) | Multinomial distribution over venue topics specific to user \( u \) |
| \( \eta_z \) | Multinomial distribution over groups specific to event topic \( z \) |
| \( \rho_r \) | Multinomial distribution over venues specific to venue topic \( r \) |
| \( \lambda_z \) | Multinomial distribution over time specific to event topic \( z \) |
| \( \delta_r \) | Multinomial distribution over time specific to venue topic \( r \) |
| \( \mu \) | Mean location of venue topic \( r \) |
| \( \Sigma \) | Location covariance of event topic \( z \) |
| \( \alpha, \gamma \) | Dirichlet priors to \( \theta_u, \varphi_u \), respectively |
| \( \tau, \beta, \epsilon, \pi \) | Dirichlet priors to \( \eta_z, \rho_r, \lambda_z \) and \( \delta_r \), respectively |

### Algorithm 1: Probabilistic Generative Process in STTM

```plaintext
for each user \( u \) do
    Draw \( \theta_u \sim \text{Dirichlet}(\alpha) \)
    Draw \( \varphi_u \sim \text{Dirichlet}(\gamma) \)
end

for each event topic \( z \) do
    Draw \( \eta_z \sim \text{Dirichlet}(\tau) \)
    Draw \( \lambda_z \sim \text{Dirichlet}(\epsilon) \)
end

for each venue topic \( r \) do
    Draw \( \rho_r \sim \text{Dirichlet}(\beta) \)
    Draw \( \delta_r \sim \text{Dirichlet}(\pi) \)
end

for each event attendance \((u, e, \delta_e, v_e, t_e)\) do
    Draw event topic index \( z \sim \text{Multi}(\theta_u) \)
    Draw venue topic index \( r \sim \text{Multi}(\varphi_u) \)
    Draw group \( \delta_e \sim \text{Multi}(\eta_z) \)
    Draw venue \( v_e \sim \text{Multi}(\rho_r) \times \mathcal{N}(v_e|\mu_r, \Sigma_r) \)
    Draw start time \( t_e \sim \text{Multi}(\lambda_z) \times \text{Multi}(\delta_r) \)
end
```
is performed with respect to the event topic $z$ and venue topic $r$. We apply Gibbs EM algorithm [25], which is a mixture between Gibbs sampling and EM, to maximize the complete data likelihood in Equation 1, because the marginal log-likelihood of the dataset is difficult to maximize directly. In the E-step, we use collapsed Gibbs sampling [26] to sample latent event topics and venue topics by fixing $\mu$ and $\Sigma$, which can not be learned in E-step. The samples of event topics and venue topics can be used to estimate the parameters $\{\theta, \varphi, \eta, \lambda, \rho, \delta\}$. In the M-step, we learn model parameters $\mu$ and $\Sigma$ using maximum likelihood estimation by fixing other parameters. We iterate the two steps until convergence.

$$
P(e, v, e_0, v_0, z, r, \theta, \phi, \eta, \rho, \lambda, \delta; \alpha, \beta, \gamma, \epsilon, \tau, \pi, \mu, \Sigma) = P(z|\theta)P(\theta|\alpha)P(r|\varphi)P(\varphi|\gamma)P(\eta|\pi)P(\alpha|\epsilon)$$

$$= P(v_e|\rho)P(\rho|\mu)P(z_1|\lambda)P(t|\delta)P(\lambda|\pi)P(v_e|\mu, \Sigma)$$

Specifically, we iteratively draw event topics and venue topics for all event attendance records in the E-step. For $i$-th event attendance record of user $u$, event topic $r$ is firstly drawn from conditional distribution as follows:

$$P(z_i = z|z_{-i}, r, o, v, t, \Psi) \propto \frac{n_{u, z_i}^{z, i} + \alpha}{\sum_K (n_{u, z_i}^{z, i} + \alpha)} \frac{n_{z,o}^{z, i} + \tau}{\sum_o (n_{z,o}^{z, i} + \tau)} \frac{n_{r,t}^{z, i} + \epsilon}{\sum_t (n_{r,t}^{z, i} + \epsilon)}$$

(2)

where $K$ denotes the number of event topics; $n_{u,z}$ denotes the number of times that event topic $z$ has been assigned to user $u$, $n_{z,o}$ is the number of times that group $o$ is generated from topic $z$, and $n_{r,t}$ is the number of times that start time $t$ is generated from topic $z$. The number $n^z$ denotes a quantity excluding the current instance; $\Psi = \{\alpha, \beta, \tau, \gamma, \epsilon, \pi\}$ is the set of hyperparameters.

After event topic is sampled, we sample venue topic $r$ for the same event attendance record according to following posterior probability:

$$P(r_i = r|z_{-i}, o, v, t, \Psi) \propto \frac{n_{u,r}^{z, i} + \gamma}{\sum_{r'}^R (n_{u,r'}^{z, i} + \gamma)} \frac{n_{r,v}^{z, i} + \beta}{\sum_{v'}^V (n_{r,v'}^{z, i} + \beta)} \frac{n_{r,t}^{z, i} + \tau}{\sum_{t'}^T (n_{r,t'}^{z, i} + \tau)}$$

(3)

where $R$ denotes the number venue topics; $n_{u,r}$ denotes the number of times the venue topic $r$ is sampled for user $u$; $n_{r,v}$ denotes the number of times of venue $v$ is generated from venue topic $r$; $n_{r,t}$ denotes the number of times of start time $t$ is generated from venue topic $r$. In M-step, we optimize parameters $\mu$ and $\Sigma$ that maximize the log likelihood of the model by fixing all venue topic assignments obtained in E-step. The maximum likelihood estimation (MLE) can be computed in the closed form as follows:

$$\mu_r = \frac{1}{|S_r|} \sum_{v \in S_r} l_v$$

(4)

### Algorithm 2 Parameters Estimation of STTM

**Input:** user event attendance records $D$, number of iteration $I$, Priors $\alpha, \beta, \gamma, \pi, \epsilon$

**Output:** estimated parameters $\hat{\theta}, \hat{\varphi}, \hat{\eta}, \hat{\lambda}, \hat{\rho}, \hat{\delta}$ and $\hat{\Sigma}$

Initialize the clustering of venue by K-Means method. Update $\mu$ and $\Sigma$ according to Equations 4 and 5, respectively for each $D_u \in D$ do

for each event attendance record $(u, e, v, t, o) \in D_u$ do

Assign event topic and venue topic randomly

end

for iteration $= 1$ to $I$ do

for each $D_u \in D$ do

for each record $(u, e, v, t, o) \in D_u$ do

Update event topic assignment using Equation 2

Update venue topic assignment using Equation 3

end

end

Update $\mu$ and $\Sigma$ according to Equations 4 and 5, respectively

Estimate model parameters $\hat{\mu}$ and $\hat{\Sigma}$ according to Equations 6 to 8, respectively

return all model parameters

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

(5)

where $l_v$ is the geographical coordinate of venue $v$, $S_r$ denotes the collection of venues assigned with venue topic $r$.

After a sufficient number of iterations, the model parameters $\theta, \varphi, \rho, \eta, \lambda, \rho, \delta$ can be estimated based on approximated posteriors. The detailed parameters estimation framework is shown in Algorithm 2.

$$\theta_{u,z} = \frac{n_{u,z} + \alpha}{\sum_{z'}^K (n_{u,z'} + \alpha)}$$

$$\varphi_{u,r} = \frac{n_{u,r} + \gamma}{\sum_{r'}^R (n_{u,r'} + \gamma)}$$

$$\eta_{z,o} = \frac{n_{z,o} + \tau}{\sum_{o'}^O (n_{z,o'} + \tau)}$$

$$\rho_{r,v} = \frac{n_{r,v} + \beta}{\sum_{v'}^V (n_{r,v'} + \beta)}$$

$$\lambda_{z,t} = \frac{n_{z,t} + \epsilon}{\sum_{t'}^T (n_{z,t'} + \epsilon)}$$

$$\delta_{r,t} = \frac{n_{r,t} + \pi}{\sum_{t'}^T (n_{r,t'} + \pi)}$$

(6-8)

We analyze the time complexity of our model training algorithm. Suppose the process needs $I$ iterations to reach convergence. In each iteration, it requires to go through all user attendance records. For each user attendance records, it first requires $O(K)$ operations to compute the posterior distribution for sampling latent event topic, and then needs $O(R)$ operations to compute the posterior distribution for sampling latent venue topic. Moreover, it requires constant cost to update $\mu$ and $\Sigma$ in the M-step. The time complexity of initialization of model parameters is ignored. Thus, the whole time complexity is $O(I(K + R)D)$, where $|D|$ denotes the number of event attendance records for training model.
TABLE 2. The statistics of our datasets.

| Dataset | Chicago | Phoenix |
|---------|---------|---------|
| No. of Users | 1976 | 1048 |
| No. of Events | 23882 | 13702 |
| No. of RSVPs | 54798 | 30089 |
| No. of Groups | 722 | 369 |
| No. of Venues | 1813 | 922 |
| Density | $1.2 \times 10^{-3}$ | $2.1 \times 10^{-3}$ |

D. EVENT RECOMMENDATION USING STTM

Once we have estimated the model parameters $\Omega = \{\theta, \varphi, \eta, \rho, \lambda, \delta, \mu, \Sigma\}$, we can compute the probability of a new event $e$ will be attended by a given user $u_q$ as follows.

$$p(e, o_e, v_e, t_e | u_q, \Omega) = \sum_z \prod_r \sum_{t}\tilde{q}_{u_q, r, o_e, v_e, \delta, t_e} N(v_e | \mu_r, \Sigma_r) \quad (9)$$

The time complexity of our event recommendation method using STTM is $O(K + R)$ for each user-event pair. Because $K$ and $R$ are relatively small numbers, our method is efficient for online event recommendation.

V. EXPERIMENTS

In this section, we first introduce the experimental settings. Then, we report and discuss the experimental results.

A. EXPERIMENTAL SETTINGS

1) DATASETS

To evaluate the effectiveness of our proposed model, we use two real-world datasets crawled from Meetup, which contains the event attendance records within Chicago and Phoenix, respectively. For each user in datasets, we get their RSVPs and for each event we obtain the start time, the group that creates the event, and the venue of the event. For each dataset, we only consider the events held between 2013 and 2014. To reduce the noise data, we remove the users who have less than 10 RSVPs within the two years for each dataset. The average number of events for target users in Chicago and Phoenix are 10.72 and 10.06, respectively. The statistics of the two datasets are shown in Table 2.

2) COMPARISON METHODS

We compare our model with the following state-of-the-art event recommendation methods. Table 3 lists the characteristics of these methods.

- **MCLRE** [9] is a context-aware event recommendation method that models four contextual factors (i.e., social, content, spatial and temporal) respectively and adopts learning-to-rank technique to combine four models to generate final event recommendations.

- **GLFM** [8] models user preferences from a dual perspective of group influence based on matrix factorization [8]. GLFM can incorporate temporal, spatial, venue and popularity influences into the model. However, the popularity of an event that will be recommended is unknown in our cold-start event recommendation scenario. Therefore, we will not consider popularity influence in our implementation. Moreover, incorporating popularity influence into GLFM does not achieve better performance all the time [8].

- **CBPF** [10] exploits Bayesian Poisson factorization as basic unit to model user response, venue and organizer influence, respectively. Then, the collective matrix factorization is used to incorporate multiple basic units into a united model and variational inference is adopted to learn model parameters. CBPF does not consider geographical influence.

- **CPMF** [27] proposes collective pairwise matrix factorization to model user preferences on events, groups and locations. However, the spatial-temporal influence has not been considered in CPMF.

- **GEM** [7] is a graph-based embedding model to collectively map all the observed relations among users, events, locations, time and text content in a shared low-dimension space. GEM is proposed for joint event-partner recommendation task, but also can be applied to event recommendation scenario described in this paper.

- **STTM** [21] models spatio-temporal patterns of users’ check-in behaviors, which are generated by a combination of region, topic and time.

- **USTTM** [22] assumes time is factor that influences other factors and discovers microscopic spatio-temporal patterns of user check-ins by sampling a time interval from the continuous check-in time.

- **MSTTM** [22] extends USTTM to discover macroscopic patterns by employing words of tweets that are shared between cities.

To evaluate the influence of different factors considered in STTM, we implement 6 variant versions of STTM. STTM-V1 is the first variant version that does not consider venue-dependent time influence, i.e., venue topic $r$ does not generate start time $t$. STTM-V2 is the second variant version where event-dependent time influence is not considered, i.e., event topic $z$ does not generate start time $t$. STTM-V3 does not consider time influence and the start time $t$ is removed from STTM. STTM-V4, STTM-V5 and STTM-V6 does not consider group influence, venue influence and geographical influence, respectively.

All baselines are evaluated under the optimal settings. We set the value of hyperparameters in STTM as follows. $\alpha = 50/K, \gamma = 50/R, \beta = \tau = \epsilon = \pi = 0.01$.

3) EVALUATION METHOD

In order to simulate the realistic cold-start event recommendation scenario in our evaluation, we first sort the events by chronological order in terms of their start time. Then the attendance records related to early 80% events are selected as training set and remaining records are test set. Because the events in test set start later than the events in training set, the test events and training events are disjoint. Thus we can make sure that the candidate events to be recommended are new events that have not attended by any users. To evaluate the effectiveness of the proposed model for event
### TABLE 3. Features of different methods.

| Dataset | Geographical Influence | Venue Influence | Temporal Influence | Textual Content Effect | Group Influence | Social influence |
|---------|------------------------|-----------------|-------------------|------------------------|-----------------|-----------------|
| STTM    | ✓                      | ✗               | ✗                 | ✗                      | ✗               | ✗               |
| MCLRE   | ✗                      | ✓               | ✗                 | ✗                      | ✗               | ✗               |
| GLFM    | ✗                      | ✗               | ✓                 | ✗                      | ✗               | ✗               |
| CPMF    | ✗                      | ✗               | ✗                 | ✓                      | ✗               | ✗               |
| CBPF    | ✗                      | ✗               | ✗                 | ✗                      | ✗               | ✓               |
| GEM     | ✗                      | ✗               | ✗                 | ✗                      | ✗               | ✗               |
| STT     | ✗                      | ✗               | ✗                 | ✗                      | ✗               | ✗               |
| USTTM   | ✗                      | ✗               | ✗                 | ✗                      | ✗               | ✗               |
| MSTTM   | ✗                      | ✗               | ✗                 | ✗                      | ✗               | ✗               |

### FIGURE 2. Recall@k and Precision@k for Chicago and Phoenix.

Recommendation, we adopt Precision and Recall at position k of the recommendation list (i.e., Precision@k and Recall@k defined in Equation 10 and 11, respectively), both of which are widely applied to measure the accuracy of event recommendation [8], [10].

\[
\text{Precision@}_k = \frac{|R_k \cap D_{test}|}{k} \tag{10}
\]

\[
\text{Recall@}_k = \frac{|R_k \cap D_{test}|}{|D_{test}|} \tag{11}
\]

#### B. RECOMMENDATION EFFECTIVENESS

In this subsection, we report the comparison results between our proposed models and other state-of-the-art methods with well-tuned parameters. Figure 2 shows the Precision and Recall on the Chicago and Phoenix dataset. We only show the performance where k is set to 5, 10, 15, 20, as greater value of k is usually ignored for a typical top-k recommendation task.

We observe that our proposed STTM outperforms other competitor methods significantly in terms of both Precision and Recall metrics on two datasets. More quantitatively, the improvements on Chicago dataset, in terms of Recall@10, are 33.33, 34.15, 77.42, 109.52, 388.89, 633.34, 7233.34 and 21900 percent compared with CPMF, MCLRE, GLFM, CBPF, GEM, MTTM, UTTM and STT, respectively. STTM achieves higher recommendation accuracy than other competitor methods showing the benefit of joint modeling group, venue, temporal and spatial influence. Among baselines, CPMF and MCLRE outperforms other comparison methods.
This may be because CPMF and MCLRE consider triangular interactions among users, events and groups, while GLFM and CBPF have not explicitly model the interactions between users and events. GLFM outperforms CBPF, because GLFM utilizes both dual perspective group influence and incorporate venue and temporal factors into the model. GLFM and CBPF map groups and venue influences in the same latent space of event. However, this assumption may not be true, because users’ interests on event itself may be independent to their preferences on the venue of event. For example, a user frequently attending movie salons does not care the characters of venues, GEM achieves related low recommendation accuracy, because the group influence is not considered in GEM. MTTM, UTTM and STT are designed for location recommendation and ignore organizer information which plays an important role in recommendation for EBSNs. Therefore, they achieve related low recommendation accuracy. Since MTTM incorporates content information that has not been considered in UTTM and STT, MTTM outperforms UTTM and STT significantly. The last observation is that all methods perform better on Phoenix dataset than on Chicago dataset. The possible reason is that the sparsity of Phoenix dataset is lower than that of Chicago dataset. Moreover, our proposed STTM provides more improvements compared with other baseline methods on Chicago dataset than the improvements on Phoenix dataset. For instance, the improvement of STTM, baseline methods on Chicago dataset than the improvements STTM provides more improvements compared with other lower than that of Chicago dataset. Moreover, our proposed perform better on Phoenix dataset than on Chicago dataset. This illustrates that STTM achieves higher performance on the more sparse dataset.

C. INFLUENCE OF DIFFERENT FACTORS

In this subsection, we carry out an experimental study showing the benefits of each factor in STTM. Specifically, we compare STTM with its 6 variant versions, and the comparison results are shown in Figs 3.

From the results, we first observe that STTM consistently outperforms all other variant versions on two datasets. The performance gap between STTM and STTM-V1 validates the benefit of capturing interactions between time and location influence. The improvement of STTM compared with STTM-V2 shows the contribution of modeling the interactions between time and group influence. The performance gap between STTM and STTM-V3 shows the benefit of joint generating time from event topic and venue topic. Moreover, we find that the contribution of each factor to improve recommendation accuracy is different. STTM-V4 and STTM-V5 achieves worst performance on both datasets indicating that ignoring group and venue influence leads to bad performance. STTM-V6 achieves higher performance than other variant versions, showing that the geographical influence provides less contribution than other factors.

D. IMPACT OF HYPERPARAMETERS

In this subsection, we evaluate how the hyperparameters in STTM impact on the recommendation performance. We try different values of the hyperparameters of prior distributions, i.e., \{\alpha, \gamma, \beta, \epsilon, \tau\}, and find that the performance of STTM is not sensitive to these hyperparameters. Therefore, we fix the value of them and evaluate the impact of \(K\) and \(R\), which have significant impacts on recommendation performance. We report the Precision@10 and Recall@10 values when \(K\) and \(R\) change from 50 to 100 on the Phoenix dataset in Table 4 and 5, respectively. We observe that the recommendation accuracy of STTM first increases with the number of event topics and it does not change significantly when \(K\) is larger than 80. Similarly, the performance of STTM increases with the number of venue topics, and then it does not change much when \(R\) is larger than 80. The larger \(K\) and \(R\) indicate more complexity of model, which has more power to describe complex data. When the number of topics is less, model can not fit data well and leads to low performance. When the number of topics is larger than a threshold, model has enough power to describe data and the performance will do not increase with more topics in the model.

E. RECOMMENDATION EFFICIENCY

In this subsection, we first analyze the time complexity of STTM and comparison methods. The time complexity of our model is \(O((K + R)|D|)\), as mentioned in Section IV-C. The time complexity of variational inference of CBPF is \(O(|A_{u,v,e}| + |A_{u,v}| + |A_{e,v,w}|)KI\), where \(|A_{u,v,e}|\), \(|A_{u,v}|\) and \(|A_{e,v,w}|\) represent the number of nonzero elements in user-event matrix, user-friend matrix and event-word matrix, respectively. The time complexity of training GLFM is \(O(|G_u| |D|KI)\), where \(|G_u|\) denotes the average number of groups joined by each user. The time complexity of training multi-relational model of MCLRE is \(O(|D| + |A_{u,v,e}| + |A_{u,v}|)KI\) and the time complexity analysis of

### Table 4. Precision@10 for Phoenix.

| K  | 50   | 60   | 70   | 80   | 90   | 100  |
|----|------|------|------|------|------|------|
| R  |      |      |      |      |      |      |
| 50 | 0.233| 0.251| 0.264| 0.265| 0.281| 0.291|
| 60 | 0.245| 0.263| 0.269| 0.281| 0.285| 0.287|
| 70 | 0.259| 0.275| 0.283| 0.276| 0.284| 0.29 |
| 80 | 0.266| 0.267| 0.287| 0.287| 0.297| 0.296|
| 90 | 0.263| 0.271| 0.278| 0.289| 0.292| 0.298|
| 100| 0.267| 0.287| 0.292| 0.293| 0.295| 0.299|

### Table 5. Recall@10 for Phoenix.

| K  | 50   | 60   | 70   | 80   | 90   | 100  |
|----|------|------|------|------|------|------|
| R  |      |      |      |      |      |      |
| 50 | 0.233| 0.252| 0.267| 0.264| 0.279| 0.289|
| 60 | 0.242| 0.261| 0.268| 0.277| 0.283| 0.285|
| 70 | 0.258| 0.274| 0.28 | 0.279| 0.282| 0.288|
| 80 | 0.265| 0.268| 0.286| 0.285| 0.294| 0.294|
| 90 | 0.261| 0.272| 0.276| 0.287| 0.293| 0.294|
| 100| 0.266| 0.286| 0.291| 0.29 | 0.294| 0.296|
contextual features extraction in MCLRE is ignored, where \(|A_{o,e}| \text{ and } |A_{u,o}|\) denote the number of nonzero elements in organizer-event matrix and user-organizer matrix, respectively. CPMF requires \(O((|D| + |A_{u,o}| + |A_{u,v}|)KI)\) operations to training model, where \(|A_{u,v}|\) is the number of nonzero elements in user-venue matrix. The time complexity of training GEM is \(O(KI)\), which is lower than other methods. However, different models require different number of iterations until convergence.

To compare the practical recommendation efficiency of different methods, we first investigate how many iterations are required by our model to achieve convergence via measuring the perplexity, a widely-used metric for evaluating the performance of topic models [18], [28]. The lower perplexity on test set indicates the better generalization performance. Fig. 4 shows the relationship between test perplexity of the model and the number of iterations. We observe that our model achieves convergence after about 200 iterations, i.e., the difference between perplexities of two iterations is smaller than 0.1. Each iteration costs 75.34 ms.

We also compare our method with baselines in terms of training time. All algorithms are implemented in Java and run on a Windows 7 with 8G RAM. The experimental results show that CPMF and GLFM are two most efficiency methods, which cost 3.76 and 9.94 seconds respectively. Our method takes 25.31 seconds and outperforms MCLRE (99.87s), CBPF (281.66s) and GEM (4405.53s). GEM cost most time because more than 1 million iterations are required for GEM to achieve convergence, while CPMF and GLFM needs 10,000 iterations. MCLRE performs less efficient than CPMF and GLFM, because more contextual factors, i.e., temporal, geographical and content influence, are considered.

FIGURE 3. The influence of different factors on Chicago and Phoenix datasets.

FIGURE 4. Perplexity vs iterations.
in MCLRE and learning-to-rank technique is used to combine multiple contextual features.

Fig. 5 shows the memory consumption during the model training on Chicago dataset. We observe that GLFM consumes least memories (28.65 MB). Our model and CPMF require slightly more memories i.e., 30.92 MB and 31.77 MB, respectively. CBPF significantly consumes more memories than GLFM and CPMF, because CBPF exploits variational Bayesian inference which incorporates several additional auxiliary latent variables instead of stochastic gradient descent used in GLFM and CPMF. MCLRE and GEM require much more memories than other baselines. They consume 129.27 MB and 148.03 MB, respectively. The possible reason is that MCLRE creates not only positive samples but also negative samples, which require many memories, for training a ranking model using a list-wise learning-to-rank technique [13]. GEM is a graph-based embedding model where five graphs are preserved. Therefore, GEM occupies more memories than other baselines.

VI. CONCLUSION

To capture interactions among different contextual influence in event recommendation, we proposed a probability generative model, i.e., spatial-temporal topic model, jointly learning users’ event preferences and venue preferences which are represented by multinomial distribution over latent event topics and venue topics. Event topics capture the interactions between content and temporal influences, while venue topics model the interactions among venue, geographical and temporal influences. We conducted extensive experiments on real-world dataset crawled from Meetup to evaluate the recommendation performance of our model. The results showed that our model achieves higher recommendation accuracy than other comparison methods with comparable recommendation efficiency.

Incorporating social and textual content information into the model is left for future work. Moreover, as this paper focuses on improving recommendation accuracy, future research may investigate the methods providing higher recommendation diversity and serendipity.

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