EventRec: Personalized Event Recommendations for Smart Event-based Social Networks

Tunde J. Ogundele Chi-Yin Chow Jia-Dong Zhang
Department of Computer Science, City University of Hong Kong, Hong Kong
Email: jogundele3-c@my.cityu.edu.hk, chiychow@cityu.edu.hk, jiadongzh@gmail.com

***Abstract*—In recent years, there has been a tremendous increase in the popularity of event-based social networks which allow social and physical interactions among their members. One major challenge for their members is the difficulty of searching events that meet their preferences from a large number of upcoming events. To tackle this challenge, we propose a personalized event recommendation framework called EventRec that exploits the geographical, social and temporal influences of events on users to generate personalized event recommendations. In EventRec, we model the influence of two-dimensional geographical location of an event using the Kernel Density Estimation method along with the popularity of the event location. Furthermore, the social influence in EventRec does not rely only on the relevance of a group to a user, but it also considers the relevance of the group to her friends. The geographical and social influences are integrated with the temporal influence that considers the preferences of the user and her friends on the days of the week and time of events. Our performance evaluation is conducted using two large Meetup.com data sets, and experimental results show that the quality of recommendations of EventRec outperforms the state-of-the-art event recommendation techniques.**

I. Introduction

In an event-based social network (EBSN), its users can join various groups and group organizers can create physical events (e.g., party, boat trip, and hiking) for their members, as depicted in Fig. 1. Having come into the spotlight in recent years, EBSNs are gaining increased recognition and popularity. For an instance, Meetup.com has over 29.88 million members, 268,737 groups, and a monthly average of 585,041 events across 180 countries and allows individuals, groups, or a community with common interests to get together in a certain location and at a particular time [1]. Due to the large number of events, it is time-consuming for users to search for events that best match their interests.

Recommender systems filter overwhelming information and provide relevant recommendations for users. Event recommendations are different from traditional recommendations like movie, music, product or point-of-interest (POI) recommendations. For example, in traditional recommendations, items being considered for recommendation have usually been rated or consumed by other users, which makes it much easier to identify users' interests or preferences. However, in EBSNs, events cannot be rated until they start, and more importantly, they usually last for a short time period (e.g., one hour). Due to these two distinct properties, an event-based recommender system always has to deal with the cold-start problem for events.

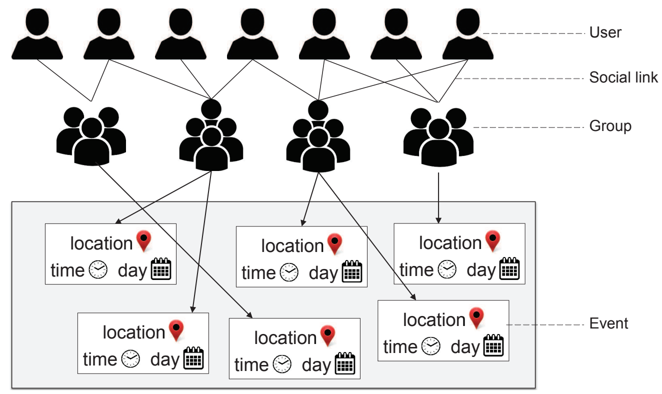
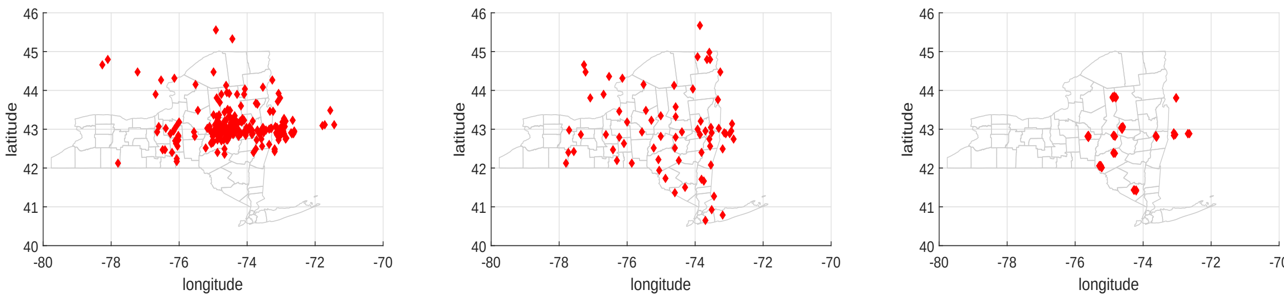


Fig. 1. An event-based social network

Real-world motivating examples. To develop a personalized event recommender system, the geographical, temporal, and social preferences of users are required to be exploited [2], [3], [4]. To show how these influences affect users' behaviors in EBSNs, the spatial and temporal analysis is conducted on Meetup.com data sets. Three users are selected in New York meetup.com data set. Figs 2 and 3 depict that the geographical and temporal influences on the attendance behaviour of these users are unique, respectively. Fig. 2 illustrates that User 1 visited 95 locations for 387 events with most of locations are within a certain region; User 2 attended 217 events at 54 locations; and User 3 participated in 306 events at only 11 locations. User 1 is interested in events located in the certain region, User 2 does not care about location much, and User 3 has strong preference on a few locations. In addition, temporal influence plays a significant role in shaping the behaviour of users in relation to event attendance. Fig. 3 depicts that User 1 is more interested in events held during weekends, while User 2 has no special preference on the days of the week and User 3 shows preferences on events on Friday and Saturday.

In the personalized event recommendations problem, the major objectives are to (1) estimate the preferences (i.e., relevance scores) of a member for upcoming events and (2) recommend the top-k events with the highest relevance scores to the member. In order to achieve these objectives, most of the existing event recommendation methods (e.g., [2],



(a) User 1 (b) User 2 (c) User 3

Fig. 2. The locations of events attended by the three users in the meetup.com New York data set

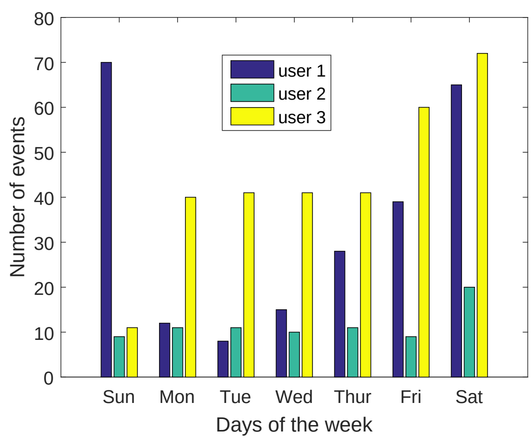


Fig. 3. Temporal pattern of three users in New York, USA

[3], [4], [5], [6], [7], [8]) learn the behaviour of a member from her attendance history by developing geographical, social and/or temporal models to compute the relevance score between the member and the upcoming event. In this paper, our main goal is to enhance the quality of event recommendations in EBSNs by proposing a unified model called EventRec that leverages on users spatial, social and temporal preferences.

The framework of EventRec includes models for geographical, social and temporal influences. **Geographical influence modeling.** We estimate a users personalized visited location distribution over the two-dimensional (i.e., longitude-latitude coordinates) geographical locations that a user has visited to attend different events [9]. These personalized visited location distributions estimate the user's preference for events locations. The model further considers the popularity of event locations for the user and her friends. **Social influence modeling.** The social influence of a user on an event is modeled by the relevance of the group to the user and other members in the group. **Temporal influence modeling.** Given the time of an event, we estimate its temporal influence for a user by aggregating the user's preferences of the days of the week and time and the popularity of the event time for the user and other group members.

The main contributions of this paper are summarized as follows:

- To estimate the geographical influence of events, a non-parametric Kernel Density Estimation (KDE) method [10] is employed to model the personalized two-dimensional locations distribution of a user and integrate it with the popularity of event locations. Our method gives more accurate prediction than existing methods based on K-mean clustering [3] or one-dimensional distance [2], [5]. (Section IV-A)
- We consider the relevance of the group to a user and other group members to model the social influence. Our method is different from the existing ones which only depend on the user's preference [6] or her friends' preferences [5]. (Section IV-B)
- We further consider the temporal influence of events by employing Jensen-Shanon divergence technique [11] to model users' preferences on the days of the week and time and the event time popularity based on historical participation records. (Section IV-C)
- The geographical and social influences are fused with the temporal influence to provide personalized event recommendations. (Section IV-D)
- To evaluate the performance of EventRec, extensive experiments are conducted on two large Meetup.com data sets in New York and San Francisco, USA. Experimental results show that EventRec gives better performance than the state-of-the-art event recommendation techniques and the geographical, social and temporal influences are important factors to event recommendations. (Sections V and VI)

The rest of this paper is organized as follows. Section II highlights related work. The system model of EventRec is defined in Section III. Section IV describes the modeling of geographical, temporal, and social influences for EventRec. Performance evaluation and experimental results are explained in Sections V and VI, respectively. Finally, we conclude this paper in Section VII.

II. Related Work

In this section, we highlight related work to EventRec which is grouped into two categories, namely, conventional and event recommender systems.

A. Conventional Recommender Systems

Recommender systems build models for users' historical ratings on items (or venues), predict ratings on new items for users, and recommend the top-k items with the highest predicted rating to users. In general, such models are developed based on the geographical, social and temporal influences of items for users.

Geographical influences. As geographical proximity usually affects the visiting behavior of users, geographical or location information has been utilized extensively for recommendations. Geographical influence is derived by using the collaborative filtering technique to estimate the user's preference on a location [5], [12], [13]. To estimate a user's preference on venues in location-based social networks, tips in forms of likes and dislikes are considered as ratings of users to checked-in venues and sentiment analysis techniques were employed to process tips [14]. With the assumption that the probability of a user visiting a location is a function of its distance, all location check-in history records are transformed into geographical distance distributions that is used to estimate the probability of the user visiting a new location [15]. In addition, the KDE method was used to model the geographical check-in distribution of locations for each user over the latitude and longitude coordinates [9], [16].

Social influences. The social links among users have been considered to improve the quality of recommendations and alleviate the data sparsity and cold-start problems. Friends visit more common locations than other people, and thus friend-based collaborative filtering is used to recommend new locations for a user based on her friends' visited locations [9], [17], [18], [19], [20], [21].

Temporal influences. Time plays a major role in people's preferences and activities, and temporal influence has been widely studied [7], [22], [23], [24], [25], [26]. Every user-generated venue checked-in time is split into eight equal-interval periods in a day to model the time influence as part of the inputs to a probabilistic tensor factorization algorithm [27]. Similarly, time is split into hours of a day and stored it as an additional dimension to a user-venue matrix, i.e., a user-time-venue cube [15], in which a cell is set to one for a visited the venue at a particular time; otherwise, the cell is set to zero; the cube is then fed into a collaborative filtering algorithm. Modeling time drifting patterns in user behavior (i.e., the popularity of an item and the baseline ratings of a user change over time) was considered to improve recommendation accuracy [28].

B. Event Recommender Systems in EBSNs

In this section, we distinguish EventRec from existing event recommendation techniques proposed for EBSNs.

Geographical influences. The geographical influence of an event can be modeled by the distance of the target event on the Gaussian distribution of the previously attended events through the KDE method [5]. With the assumption of knowing users' current locations, the geographical location influence could be based on the distance between the target user and other users that have attended events together [4]. Gauss formula was employed to compute the similarity between the distance of an event location and the attendance history to model [2]. K-means and Gaussian distributions were used to compute the probability of the location of an event in a region based on the users historical attended event locations to predict a user's regional preference on an event location[3]. In EventRec, the geographical influence of events on a user is modeled by using the KDE method over two-dimensional latitude and longitude coordinates and the popularity of event locations in ESBNs.

Social influences. In EBSNs, social links are in the form of groups, i.e., a member has a social link with each of other members in a group. Thus, the simplest social influence of events on users is either based on the group membership [4], [29] or friendships without considering any group membership [6], [30]. Social influences can also be modeled based on both friendships and group membership [31], or attendance records in a group [5]. The methods considering friendships and attendance records usually result into low-quality event recommendations due to the cold-start user problem (i.e., new members in a group have not had any strong relationship with other group member or attendance record yet). In EventRec, we model the social influence of events in a group based on the relevance of the group to the user and its members.

Temporal influences. The event time is an important factor in EBSNs because it has a great impact whether a user attends an event. Gauss formula was employed to model temporal influences based on the hour of the day and the day of the week of events [2]. The event time can also been split into 24×7 matrix and cosine function is employed to compute the temporal influence [5]. In EventRec, the temporal influence considers both the hour of the day and the day of the week of events, each of which is modeled through the Jensen-Shanon (JS) divergence technique that computes the similarity between the time of an event and the time of an past event attended by a user and the popularity of the event time.

III. System Model

In this section, we first define the key terms in EBSNs, and then define our problem. Table I shows the summary of key notations used in this paper.

Definition 1: Event. An event $e \in E$ is defined as a tuple of $e = (e.t, e.d, e.l)$ where $e.t$, $e.d$, and $e.l$ indicate the time, day of the week, and location of e, respectively, and $U(e)$ is a set of users who committed to join e.

Definition 2: Group. A group $g \in G$ has its members $U(g)$ and events $E(g)$.

Definition 3: Social Link. Given two users $u_i, u_j \in U$, $u_i \neq u_j$, a social link (or friendship) is established between u_i and u_j (i.e., $link(u_i, u_j) = 1$), if both u_i and u_j are in a common

TABLE I
NOTATIONS AND THEIR MEANING

Symbols	Meaning
E	Set of events $E = \{e_1, e_2, \ldots, e_{\|E\|}\}$
U	Set of users $U = \{u_1, u_2, \ldots, u_{\|U\|}\}$
G	Set of groups $G = \{g_1, g_2, \ldots, g_{\|G\|}\}$
$E(g)$, $U(g)$	Sets of events and users of group g
$G(u)$	Set of groups joined by user u
L	Set of past event locations
$L(u)$	Set of post event locations visited by u
$link(u_i, u_j)$	if u_i and u_j are in a common group (i.e., have a social link), $link(u_i, u_j) = 1$; otherwise, $link(u_i, u_j) = 0$
$M_L(\|U\|, \|L\|)$	Visit matrix: $m_l(u, l)$ is the frequency of user u visiting location l to attend events
$M_P(\|U\|, \|G\|)$	Group participation matrix: $m_p(u, g)$ is the number of g's events attended by user u
$M_D(\|U\|, \|D\|)$	Event day matrix: $m_d(u, d)$ is the number of events that were held on $d \in D$ (i.e., $D = \{Sun, Mon, Tue, \ldots, Sat\}$) and attended by user u
$M_T(\|U\|, \|T\|)$	Event hour matrix: $m_t(u, t)$ is the number of events that were held within hour period $t \in T$ (i.e., $T = \{0, 1, \ldots, 23\}$ as a day is split into 24 hour periods) and attended by user u

group (i.e., $u_i, u_j \in g$ and $g \in G$); otherwise, $link(u_i, u_j) = 0$, i.e., u_i and u_j do not have any common group.

EventRec is designed for an EBSN, in which there are a set of users $U = \{u_1, u_2, \ldots, u_{|U|}\}$, a set of groups $G = \{g_1, g_2, \ldots, g_{|G|}\}$, and a set of Events $E = \{e_1, e_2, \ldots, e_{|E|}\}$, where $|U|$, $|G|$, and $|E|$ are the total number of users, groups, and events, respectively. Each user u_i can join multiple groups $G(u_i)$ (i.e., $u_i \in U$ and $G(u_i) \subseteq G$) as their members, each group g_j can create events $E(g_j)$ (i.e., $g_j \in G$ and $E(g_j) \subseteq E$) for its members $U(g_j)$ (i.e., $U(g_j) \subseteq U$) to attend.

Problem definition. Given user u in group g, EventRec determines the geographical, social, and temporal influences of events in $E(g)$ based on u's preferences, in terms of a relevance score for each of these events, and then recommends top-k events with the highest relevance scores to u.

IV. Modeling of Influences in EventRec

In this section, we describe the models for the geographical, social, and temporal influences (Sections IV-A to IV-C), and then integrate these influences to provide event recommendations for users (Section IV-D).

A. Geographical Influence Modeling

The geographical influence model consists of two parts: the first part uses the KDE method to model the personalized two-dimensional location distribution of a user and the second one considers the location popularity.

Personalized two-dimensional location model. As we consider an event's location as a pair of latitude and longitude (lat, lon), the KDE function for $L(u)$ of user u is defined as:

$$\hat{f}(l) = \frac{1}{N\sigma^2} \sum_{l_i \in L(u)} m_l(u, l_i) \cdot K\left(\frac{l - l_i}{\sigma}\right), \qquad (1)$$

where $l_i = (lat_i, lon_i)^T$ is a two-dimensional location vector, σ is the bandwidth, N is the number of locations in the samples, and $K(.)$ is the Gaussian kernel function [10] that is given as:

$$K(x) = \frac{1}{2\pi} e^{-\frac{1}{2}x^T x}. \qquad (2)$$

The bandwidth for the Gaussian kernel is defined as:

$$\sigma = N^{-\frac{1}{6}} \sqrt{\frac{\hat{\sigma}^T \hat{\sigma}}{2}}, \qquad (3)$$

where $\hat{\sigma}$ is the sample standard deviation. Hence, the probability of user u attending an event at location l can be computed as follows:

$$p(l|L(u)) = \frac{1}{2\pi N\sigma^2} \sum_{l_i \in L(u)} e^{-\frac{1}{2\sigma^2}(l - l_i)^T (l - l_i)}. \qquad (4)$$

Location popularity. Another factor that affects a user's decision on whether attending an event is people's opinions about its location, namely, location popularity; and thus, our geographical influence model also takes location popularity into account. We determine the popularity of a location based on the frequency of a target user and the members in a corresponding group; and thus, the location popularity of location l in group g for target user u is computed by:

$$\hat{p}(l, u, g) = [p(l, u) + p(l, g)]/2, \qquad (5)$$

where $p(l, u) = \frac{m_l(u,l)}{\max_{l_j \in L}\{m_l(u,l_j)\}}$ and $p(l, g) = \frac{\sum_{u'_i \in U(g)} m_l(u'_i, l)}{\max_{l'_j \in L}\left\{\sum_{u'_i \in U(g)} m_l(u'_i, l'_j)\right\}}$. The denominator of $p(l, u)$ is the maximum visiting frequency of a location visited by u and the denominator of $p(l, g)$ is the maximum visiting frequency of a location visited by the members in g. Finally, given event e in group g for user u, the geographical influence score combining the personalized two-dimensional location model and location popularity is computed by:

$$GI(e, u, g) = [p(e.l|L(u)) + \hat{\rho}(e.l, u, g)]/2. \qquad (6)$$

B. Social Influence Modeling

In EBSNs, each user belongs to at least one group and can participate in events published by their corresponding groups. It makes sense that when a user belongs to more than one group, she usually has some preferred groups, namely, the group relevance of a user. In addition, a user treats other members in the same group as friends, as they share some common interests; and thus, our social influence model also considers the social relevance of a group to the user.

Group relevance to a user. Let $G(u)$ be a set of groups that user u belongs for event participation. The group relevance of u is given as:

$$\hat{r}(u, g) = \frac{m_p(u, g)}{\max_{g_i \in G(u)} \{m_p(u, g_i)\}}, \qquad (7)$$

where $m_p(u, g)$ is the number of g's events participated by u.

Social group relevance. The social group relevance is determined by the similarity of the group relevance of user u's friends in group g (Definition 3), as follows:

$$s(u,g) = \frac{\sum_{u'_i \in U(g) \wedge u'_i \neq u} sim(u,u'_i) \cdot m_p(u'_i,g)}{\sum_{u'_i \in U(g) \wedge u'_i \neq u} sim(u,u'_i)}, \quad (8)$$

where $sim(u_i,u_j) = \frac{\sum_{g_k \in G(u_i)} m_p(u_i,g_k) \cdot m_p(u_j,g_k)}{\sqrt{\sum_{g_k \in G(u_i)} m_p(u_i,g_k)^2} \cdot \sqrt{\sum_{g_k \in G(u_i)} m_p(u_j,g_k)^2}}$ calculates the similarity between users u_i and u_j. Then, $s(u,g)$ is normalized as:

$$\hat{s}(u,g) = \frac{s(u,g)}{\max_{g_i \in G(u)} \{s(u,g_i)\}}. \quad (9)$$

Finally, the social influence of g on u is determined as:

$$SI(u,g) = [\hat{r}(u,g) + \hat{s}(u,g)]/2. \quad (10)$$

C. Temporal Influence Modeling

To model the temporal influence in EventRec, we employ the Jensen-Shanon (JS) divergence technique [2], [11] to measure the similarity between the time of an event and the time of the past events participated by a user. The temporal influence consists of a user's preference on the days of the week with day popularity and her preference on the time of the day with time popularity.

The-days-of-the-week model. Let $D(u) = \{d_1, d_2, \cdots, d_{|D(u)|}\}$ be the day information of past events attended by user u, where $d_i \in \{1,2,3,4,5,6,7\}$ that denotes $\{\text{Sun}, \text{Mon}, \ldots, \text{Sat}\}$, respectively. Frequency distribution $m_d(u,\cdot)$ is then normalized as probability distribution γ. The-days-of-the-week model is given as:

$$\hat{T}_d(e,u,g) = [T_d^d(e,u,g) + T_d^p(e,g)]/2. \quad (11)$$

$T_d^d(e,u,g)$ indicates the relevance of event e to user u in terms of the days of the week that is calculated as:

$$T_d^d(e,u,g) = \frac{\sum_{d_i \in D_u} TSim(\gamma,\gamma') \cdot t_d(e.d,d_i)}{|D_u| \cdot TSim(\gamma,\gamma')}, \quad (12)$$

where $t_d(e.d,d_i)$ returns 1 for $e.d = d_i$ or 0 for $e.d \neq d_i$, γ' is a vector with non-zero value at index $e.d$ (e.g., if $e.d = 4$ (i.e. Wednesday), $\gamma' = [0,0,0,1,0,0,0]$), and the similarity score $TSim(\gamma,\gamma')$ is determined by:

$$TSim(\gamma,\gamma') = 1 - JS(\gamma,\gamma'). \quad (13)$$

The JS divergence computation is given by:

$$JS(\gamma,\gamma') = \frac{1}{2}\left[D_{KL}(\gamma,\lambda) + D_{KL}(\gamma',\lambda)\right], \quad (14)$$

where $\lambda = \frac{\gamma+\gamma'}{2}$ and $D_{KL}(p,q)$ is the standard function (called Kullback Leiber divergence) [11] that measures the divergence between distributions p and q as: $D_{KL}(p,q) = \sum_{i=1}^{n} p_i \log \frac{p_i}{q_i}$.

The day popularity in group g for event e is derived by:

$$T_d^p(e,g) = \frac{\sum_{u_i \in U(g)} m_d(u_i,e.d)}{\max_{d_j \in \{1,2,\ldots,7\}} \left\{\sum_{u_i \in U(g)} m_d(u_i,d_j)\right\}}. \quad (15)$$

The-time-of-the-day model. Due to the space limitation, we only state the differences in the the-time-of-the-day model as in the-days-of-the-week model: (1) Let $T(u) = \{h_1, h_2, \cdots, h_{|T(u)|}\}$ be the time information of past events attended by user u, where $h_i \in \{0,1,\ldots,23\}$ (i.e., the time is split into 24 hour periods), (2) $e.t$ is hour h_i of event e, (3) frequency distribution $m_t(u,\cdot)$ is normalized as probability distribution γ, and (4) γ' is a vector with a non-zero value at index $e.t$ and 23 zeros in other indexes. Our the-time-of-the-day model is determined as:

$$\hat{T}_t(e,u,g) = [T_t^t(e,u,g) + T_t^p(e,g)]/2. \quad (16)$$

Finally, the temporal influence of event e organized in group g for user u is computed by:

$$TI(e,u,g) = [\hat{T}_d(e,u,g) + \hat{T}_t(e,u,g)]/2. \quad (17)$$

D. Event Recommendations

In EventRec, we combine the geographical, social and temporal influences into unified preference score $s(e,u,g)$ for user on event e using the product rule:

$$s_p(e,u,g) = GI(e,u,g) \cdot SI(u,g) \cdot TI(e,u,g) \quad (18)$$

or the sum rule:

$$s_s(e,u,g) = [GI(e,u,g) + SI(u,g) + TI(e,u,g)]/3. \quad (19)$$

V. Experiment Settings

In this section, we describe the data sets, baseline techniques, and performance metrics.

Data sets. To evaluate the performance of EventRec, we use the Meetup.com [1] APIs to crawl data in New York (NY) and San Francisco (SF), USA from January 1, 2010 to March 30, 2016. Table II gives a statistical summary of the key fields of the data sets. Each of these data sets is divided into two halves of training and testing sets, with the testing set being the most recent events sets.

TABLE II
THE STATISTICAL SUMMARY OF THE DATA SETS

	Members	Events	Groups	Venue	RSVP
SF	324,485	169,120	11,367	18,126	1,665,591
NY	910,938	432,938	13,906	35,623	3,614,720

Evaluated event recommendation techniques. The state-of-the-art techniques considered as baselines to our proposed EventRec include:

- SRE exploits social influences of users in the EBSN (i.e., friends) for events recommendations [30].
- CFM exploits collaborative filtering technique and dynamics on temporal influence for users [28].
- CAER employs factors such as content, time, social group and geographical location to rank and recommend personalized events [5].
- PAAT uses singular value decomposition with a multi-factor neighborhood to predict events attendance for members by exploiting time, distance and content [2].

Performance metrics. To evaluate the quality of event recommendations, the standard metrics are used to measure precision and recall [9], [32]. Precision is the ratio of the number of events that a user attended to the total number of recommended top-k events, i.e.,

$$\text{Precision} = \frac{\text{No. of the attended top-}k\text{ events}}{\text{No. of the top-}k\text{ events}},$$

and recall is the ratio of the number of recommended top-k events that user u attended to the total number of events attended by u, i.e.,

$$\text{Recall} = \frac{\text{No. of the top-}k\text{ events attended by }u}{\text{No. of events attended by }u}.$$

Furthermore, precision and recall are examined for regular users with top-k values ranging from 2 to 50 and cold-start users top-k values from 1 to 10 due to the small total number of events attended by them.

VI. Experimental Results

To evaluate the performance of our EventRec, we compare the quality of its recommendations with the four baselines in Sections VI-A and VI-B. The importance of the geographical, social, and temporal influences of EventRec is evaluated in Section VI-C and the evaluation of the two fusion techniques (i.e., product and sum rules) is presented in Section VI-D.

A. Comparison of Event Recommendation Techniques

Fig. 4 depicts the quality of event recommendations in the NY and SF data sets. EventRec shows the best performance in both the precision and recall for all values of k.

SRE. Since SRE only exploits the social influence, it gives the worst performance.

CFM. CFM considers the collaborative social and temporal influences, so it performs better than SRE. However, its performance is worse than CAER, PAAT and EventRec due to the fact that CFM ignores the important geographical influence.

CAER. CAER [5] gives better recommendation quality than SRE and CFM. The main reason is that CAER considers the geographical influence by modeling the distance between the pair of home and event locations and aggregates it with social and temporal influences. However, its performs worse than our EventRec.

PAAT. PAAT [2] aggregates the relevance of content, geographical, social and temporal influences for event recommendations. It employs distance similarity for estimating the geographical influence of events. Although it gives better performance than other baselines, its recommendation quality is worse than EventRec.

EventRec. Our EventRec achieves the best performance in both precision and recall. The main reason is that EventRec has more sophisticated geographical, social, and temporal influence models: (1) EventRec models the geographical influence by exploiting the personalized two-dimensional geographical locations and location popularity. (2) EventRec models the social influence by considering the relevance of a group to a user and her friends. (3) For the temporal influence, EventRec further considers day and time popularity.

B. Comparison of Event Recommendation Techniques for Cold-Start Users

To evaluate the performance of our EventRec for cold-start users, we select users with limited attendance history from the data sets to constitute the cold-start users (Fig. 5). Due to the small number of events attended by the cold-start users, the values of k are set from 1 to 10 for the NY and SF data sets. As in Fig. 4, EventRec gives the best performance in both precision and recall. EventRec not only provides more accurate geographical influence by considering the personalized two-dimensional geographical locations through KDE, but it also exploits social preferences for geographical influence (i.e., location popularity) and temporal influence (i.e., the day and time popularity).

C. Contribution of the Geographical, Social and Temporal Influences in EventRec

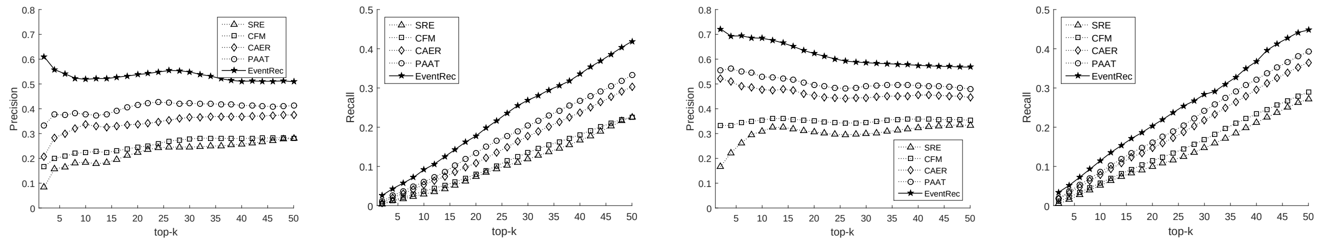
We study the contribution of the three geographical, social and temporal influences of EventRec based on Equations 6, 10, 17, respectively, for regular users (Fig. 6) and cold-start users (Fig. 7). In the experimental results, we observe that (1) each influence plays a significant role in EventRec for event recommendations, (2) the geographical influence is more important than the other two influences, and (3) the social influence is more important than the temporal influence. The results provide insights for us to further improve the recommendation quality of EventRec by learning personalized weights on different influences. For example, a higher weight is assigned to the geographical influence than the social and temporal influences for some users.

D. Comparison of the Fusion Methods

In the previous experiments, the product rule (Equation 18) is used to fuse the geographical, social and temporal influences for EventRec to generate event recommendations. Here, we compare the sum rule (Equation 19) with the product rule in this experiment. As depicted in Figs. 8 and 9, the product rule performs better than the sum rule for both regular and cold-start users. We argue that the geographical, social and temporal influences are intrinsically different from each other; and thus, it is inappropriate to apply the sum rule to add three different things together. Instead, it is better to use the product rule to treat each influence as a weight to adjust the preference score.

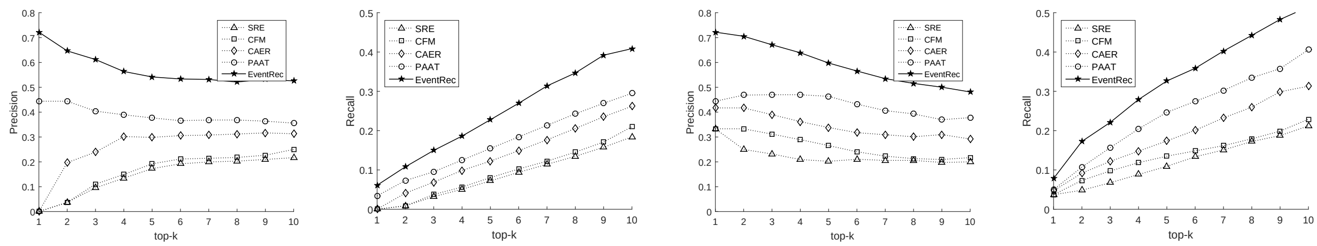
VII. Conclusion

In this paper, we have proposed an event recommendation framework called EventRec that exploits the geographical, social and temporal influences of events to provide event recommendations for users in event-based social networks. EventRec utilizes the two-dimensional geographical locations of events and location popularity to estimate the geographical influence of events to a user. In EventRec, the social influence model considers the relevance of a group to a user and her



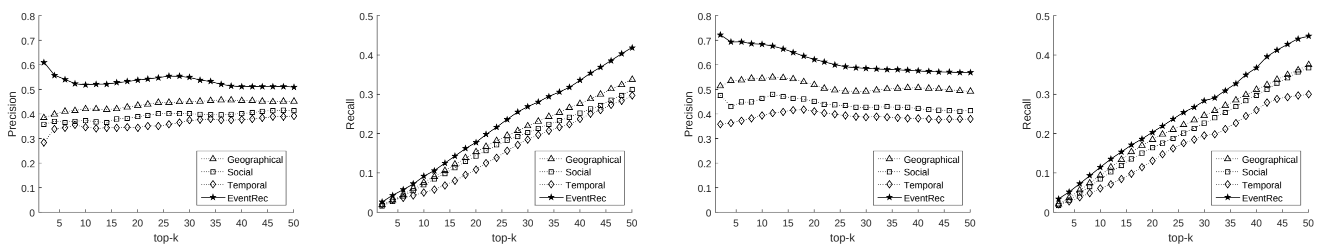
(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 4. Performance of event recommendation methods



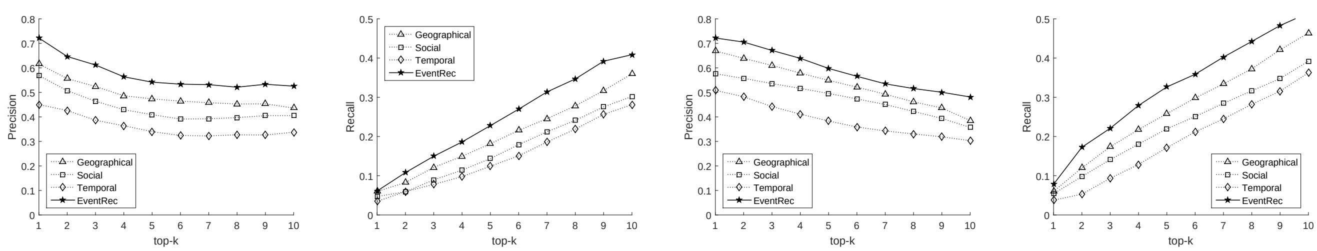
(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 5. Performance of event recommendation methods for cold-start users



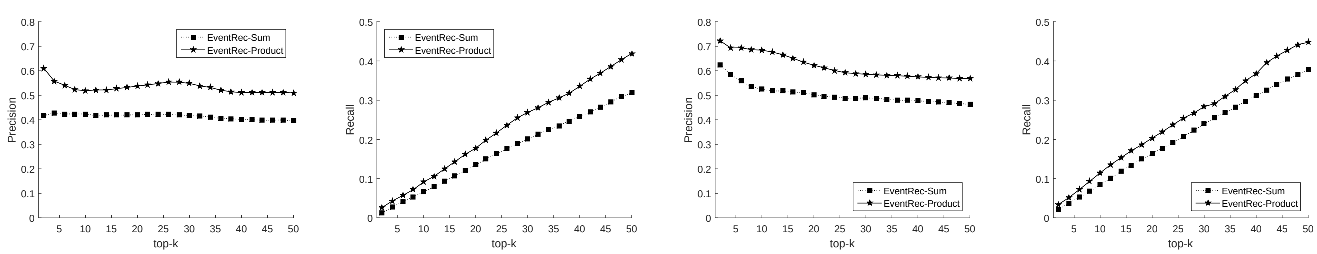
(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 6. Performance of the geographical, social, and temporal influences of EventRec



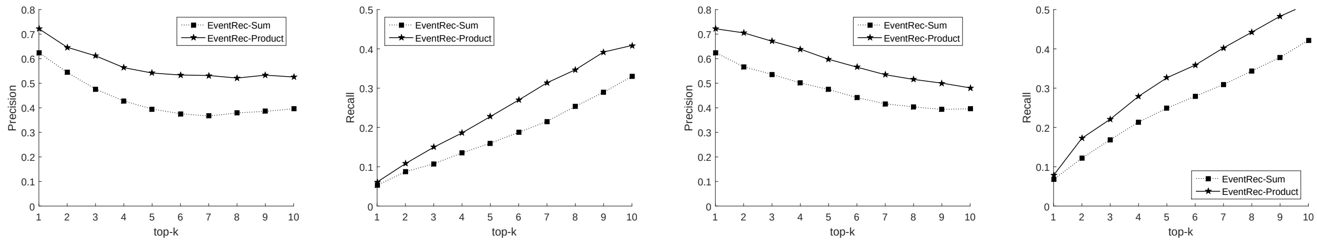
(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 7. Performance of the geographical, social, and temporal influences of EventRec for cold-start users



(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 8. Comparison of two integration methods based on the overall performance



(a) New York (Precision) (b) New York (Recall) (c) San Francisco (Precision) (d) San Francisco (Recall)

Fig. 9. Comparison of two integration methods based on the performance of cold-start users

friends, while we determine the temporal influence of an event based on the similarity of the days of the week and the time of the event and that of the past events attended by a user and the day and time popularity. The performance of EventRec is evaluated using two large-scale real data sets in New York and San Francisco crawled from Meetup.com. Experimental results show that EventRec performs better than the state-of-the-art event recommendation techniques in terms of both precision and recall for both regular and cold-start users. In addition, the product rule is a better method to combine the geographical, social and temporal influences together. We have two research directions to further improve the recommendation quality of EventRec, we will investigate (1) how to find out personalized weights for different influences, and (2) how to discover more social interaction patterns among users in a group.

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