Event Recommendation in Impromptu Event-based Social Networks

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Abstract

In recent years, event-based Social Network (EBSN), which incorporates online and offline social interactions, has experienced rapid growth and attracted a lot of research. In this paper, we propose Impromptu Event-Based Social Network (IEBSN) as an EBSN variant, where users setup impromptu events, get involved in event-related topics, and participate in nearby events. Impromptu events are not supposed to be well-planned and well-organized; creation and participation of events are more casual. Online interactions in IEBSN are not dependent on group relationship but event-based topic recommendation, so the user's privacy such as interest and preference is preserved from each other. A two-level event recommendation approach is presented. Firstly, it applies the topic model to retrieve topics from the content descriptions of event, and then uses user-topic matrix to conduct topic recommendation. Secondly, it composes user preference, event context, organizer influence, and user's dynamic responses to event recommendation.

Keywords: Event-based Social Network, Recommendation, Privacy

1 Introduction

Event-based social networks, such as Meetup, have experienced rapid growth and attracted more and more scholars to study. Liu et al.[6] first identify event-based social network (EBSN) as a co-existence of both online and offline social interactions. The release and participation of events is usually pre-planned and well-organized. However, there are many opportunities in daily life that people setup impromptu events[1]. For example, someone may want to play basketball with others at present.

The conventional EBSN applications are inevitable heavy for such casually social cases and impromptu nature of the events due to laborious maintenance of groups and organization of events. First, in many cases, the "accepted" or "rejected" event invitation in the group put users at risk of privacy because it will disclose users' preference and intention in the air. According to the statistics of Dong et al.[2], only 16% users chose to hide their group membership in Meetup for privacy consideration. Second, event participations are dependent on spatiotemporal context, which requires users' consideration in selection of subset of group.

To address this problem, we propose Impromptu Event-Based Social Network (IEBSN) as an EBSN variant, where users can setup an impromptu event with a short text of content description, get involved in the online event-related topics based on preference and user similarity, and participate in the events based on spatiotemporal context and organizer influence.

There are two prominent advantages of IEBSN. On one hand, it mitigates privacy risk by eliminating group relationship. As we know, group membership will disclose user's interest, preference, and even the temporal and spatial pattern of event participation. Once they are compromised by an adversary in

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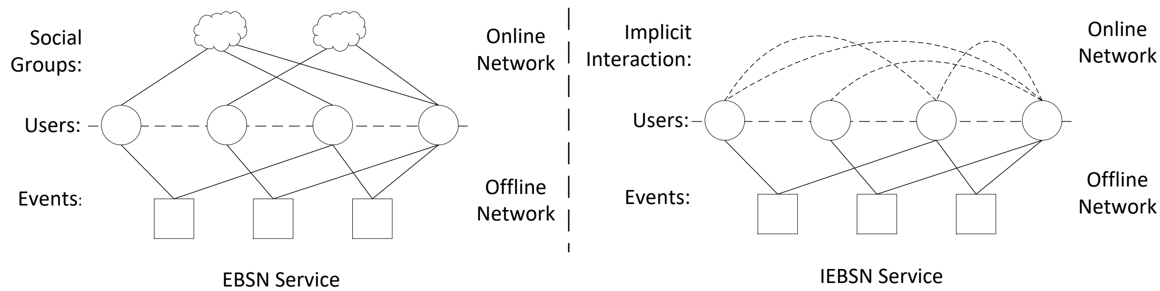

Figure 1: EBSN Model vs. IEBSN Model

the same group, it may arise a physical attack to the victim. Online interactions in IEBSN are not based on explicit group relationships but event-related topic recommendation. Only IEBSN service providers can collect data of users' participation of topic. It is hard for users to trace any other's online interactions, or link them to offline interactions.

On the other hand, it enhances the efficiency of event recommendation. EBSN event recommendation mainly faces challenges of data sparseness and cold start[3]. The user and event matrix is very sparse because users can only attend a limited number of events due to limitation of time and location[11]. We present a two-level event recommendation approach. The first level is event-related topic recommendation. The easier involvements of topics will get the user-topic matrix denser. Once the user gets involved in a topic, his interest is determined just as he joins in a group. It means that IEBSN will be reconstructed to be homogeneous to EBSN. The second level is topic-related event recommendation, where the context and organizer influence are considered. Furthermore, due to the freshness nature of impromptu events, the temporal score will be reduced significantly as time goes by, and users' response will also taken effect in event recommendation rapidly as well. The proposed event recommendation scheme will not only guarantee recommendation efficiency, but also make it easier for users to select proper events to participate in.

The remainder of this paper is organized as follows. In Section 2, we describe the differences between IEBSN and EBSN properties, and formally define IEBSN. In Section 3, the two-level event recommendation scheme is introduced. Finally, we conclude the paper in Section 4.

2 Impromptu event-related Social Network

In this section, an IEBSN definition is given firstly and then the properties of EBSNs and IEBSNs are compared.

2.1 Definition of Impromptu Event-Based Social Network

As an EBSN variant, a novel impromptu event-based social network is proposed to incorporate online and offline social interactions together by allowing users to publish and participate in events in a casual social way. The difference between EBSN and IEBSN model is illustrated as Figure 1.

Online social interactions. In order to mitigate privacy risks in IEBSN, online social interactions are not based on explicit group relationships but preference of topics. The topic-based online social interactions hide user interests from each other, thus to prevent adversaries to trace any target user's interactions and further make any physical attack offline. Besides, it allow users to go back and forward among topics in a more casual way, and inferring the pattern of user interests is more personalized. It means that the online social relationships are temporal on the short time period of an impromptu event.

Offline social interactions. IEBSN offline social interactions is the same as EBSN. In a social event, people physically get together at a specific time and location, and do something together. The social events in IEBSNs represent the offline interactions among event participants.

Based on the definition of EBSN, we define the IEBSN as follows.

Definition Formally, we define an IEBSN as a heterogeneous network $G = \langle U, A^{on}, A^{off} \rangle$, where U represents the set of users (vertices) with $|U| = n$, A^{on} stands for the set of topic-based online social interactions (arcs), and A^{off} denotes the set of offline social interactions (arcs). The topic-based online social interactions form an online social network $G^{on} = \langle U, A^{on} \rangle$, and the social event-based offline interactions compose an offline social network $G^{off} = \langle U, A^{off} \rangle$. □

2.2 Properties of IEBSN

Two problems mentioned in section 1 are also the biggest differences between IEBSN and EBSN. Liu et al.[6] analyze the unique properties of EBSNs. IEBSN also has these properties, but performs differently. Compared with EBSN, the properties of IEBSN are listed as follows.

- Freshness of impromptu events. Impromptu events generally has a short time period, the creation time may be before or after the start time within a few minutes. It requires the recommendation scheme reducing the temporal score remarkably as time goes by and updating results effectively with users' dynamic responses.

- Lightweight setup of event. It is relatively easier for users to create an impromptu events in such a casual way that just describe the content of event in a short text. The start time of event is automatically set to the present, and the end time is decided by the recommendation approach. The location of event is also automatically set to where the organizer is. Furthermore, the social features concerned in the contexts will infer much more intentions such as target participants.

- Privacy-preserving online interaction. It is relatively easier for users to create impromptu events in a casual way, and feel free to get involved in topics. Only IEBSN service providers can collect users' topic involvements; it is hard for any individual user to trace others' online interactions or link them to offline interactions.

3 Event Recommendation in IEBSN

In this section, we propose a two-level event recommendation scheme. The first level is topic recommendation, where topics are retrieved from content descriptions of events and then recommended to users. The second level is topic-related event recommendation, where the context and organizer influence are considered.

3.1 Topic Recommendation

There is no group in IEBSNs and topics play the role of groups. Considering that the content description of an impromptu event is usually a short text, we apply BTM model[10] to learn topics. Given a set of events $E = \{e_1, e_2, \cdots, e_n\}$, the topic model generates a topic set $T = \{t_1, t_2, \cdots, t_K\}$ for the corresponding set of content descriptions $D = \{d_1, d_2, \cdots, d_n\}$, where the number of topics is set to a specific value such as $K = 25$. We also obtain the event-topic map $H : E \to T$.

Given a set of user u_i's involved topics in the past T_{u_i}, and a set of topics which are retrieved from the events in a time period w to be recommended, i.e., $T_w = \{H(e_j) | e_j \in E\}$, we adopt Word2vec[9]

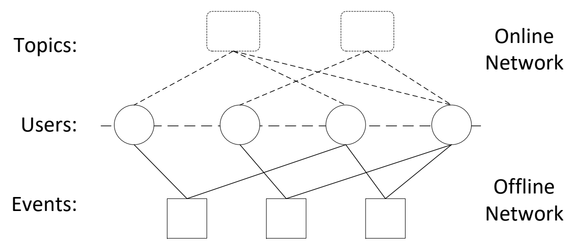

Figure 2: Reconstruction of IEBSN Model

for ranking. As topic recommendation succeeds, we can reconstruct IEBSN as an EBSN variant, as illustrated in Figure 2.

3.2 Topic-Related Event Recommendation

Once the topic of interest is selected, we will recommend topic-related events to the user. Formally, given a set of users U and a set of events E, let the user's topic preference be Z, temporal preference be T, spatial preferences be G, and organizer preference be O. Given a target user $u \in U$, a set of events E_u that the user u has participated in the past, the contextual signals $z \in Z$, $t \in T$, $g \in G$, and organizer influence signals $o \in O$, the top-n recommendation is computed as follows.

$$top\text{-}n(u,E) = \underset{e \in E \setminus E_u}{\arg\overset{n}{\max}} f(u,e,z,t,g,o) \tag{3.1}$$

We use context model and organizer influence model together as user preference to generate the relevance score of the event $e \in E \setminus E_u$ to the user $u \in U$.

3.2.1 Context Model

1) Temporal.

$$f_{time\_decay} = e^{-\alpha(t_{current} - t)} \tag{3.2}$$

$$f_{time\_sim} = cos(\frac{\sum_{e' \in E_u} \vec{e}}{|E_u|}, \vec{e}) \tag{3.3}$$

f_{time_decay} is a time decay function[4], where $\alpha \geq 0$ is a non-negative decay constants, $t_{current}$ is the current time, and t is the candidate event's start time. According to [7], we represent each event is a N-dimensional vector $\vec{e}$ in the space of N (such as $N = 24$) time slices of a day, with a vector component set to 1 whenever the event starts at the particular time. Function f_{time_sim} is to calculate the similarity between the user's historical event participation in temporal and the candidate event's publish time.

2) Spatial.

Formally, given the user $u \in U$, we firstly obtain the distance metric between the user and the candidate event as f_{loc_dist} indicates, where $dist(l, l_u)$ is the distance between candidate new event's lat-long coordinate l and user current lat-long coordinate l_u.

$$f_{loc\_dist} = \frac{1}{1 + dist(l, l_u)} \tag{3.4}$$

$$f_{loc\_sim} = \frac{1}{|L_u|} \sum_{l' \in L_u} K_{\mathbf{H}}(l - l') \tag{3.5}$$

f_{loc_sim} is a function to calculate the relevance of a new event for a user based on the aggregated likelihood of this event being located in any of the regions the user attended events in the past[7]. L_u is the set of user participated events' lat-long coordinate. $K_{\mathbf{H}}(\cdot)$ is the bivariate Gausian kernel, and $\mathbf{H}$ is a 2×2 symmetric and positive definite matrix.

3.2.2 Organizer Influence Model.

We use Popularity-aware Probabilistic Matrix Factorization (PPMF)[5] to predict the organizer influences on users. Given an organizer $o_j \in U$ and a user $u_i \in U$, let $c_{i,j}$ be the organizer influence of the organizer o_j to the user u_i, which is computed as follows.

$$f_{organizer\_influence} = \frac{c_{i,j} - \min\limits_{e_{o_k} \in E^{new}} (c_{i,k})}{\max\limits_{e_{o_k} \in E^{new}} (c_{i,k}) - \min\limits_{e_{o_k} \in E^{new}} (c_{i,k})} \tag{3.6}$$

where $c_{i,j} = P_{o_j} \cdot G_i^{\top} H_j$, G_i, H_j denote the user and organizer latent feature vectors respectively, and P_{o_j} is the popularity of organizer o_j.

Finally, to obtain top-n events, as illustrated in Equation (3.1), is an optimization problem. Given the results of $f_{time\_decay}, f_{time\_sim}, f_{loc\_dist}, f_{loc\_sim}$ and $f_{organizer\_influence}$, we combine these features linearly to calculate $f_{preference}$ as the degree of target user's preference for candidate events as follows.

$$f_{preference} = \omega_{td} f_{time\_decay} + \omega_{ts} f_{time\_sim} + \omega_{ld} f_{loc\_dist} + \omega_{ls} f_{loc\_sim} + \omega_{oi} f_{organizer\_influence} \tag{3.7}$$

The parameters $\omega_{td}, \omega_{ts}, \omega_{ld}, \omega_{ls}, \omega_{oi}$ are weights ranging from 0 to 1, which can be learned by Coordinate Ascent[8], a listwise learning to rank approach.

4 Conclusion

In this paper, we propose a novel Impromptu Event-Based Social Networks (IEBSN) model as an EBSN variant. It makes users to create and participate in events more conveniently and fast. The IEBSN features motivate consideration on privacy protection and event recommendation efficiency issues. On one hand, online interactions are not dependent on group membership, which is defined in EBSN, but based on event-related topic. Only IEBSN providers can collect users' topic involvements and infer user interests and preferences, which are hard to be traced by any other user. On the other hand, a two-level event recommendation method is proposed to address efficiency problem. In the first level, we use a topic model to retrieve the topic from the content description of events, and then recommend topics to users for online interactions. In the second level, we use context model and organizer influence model to recommend topic-related events to users for offline interactions. In the future works, we will make experiments on open dataset, give more detailed design and analysis, and present an IEBSN service.

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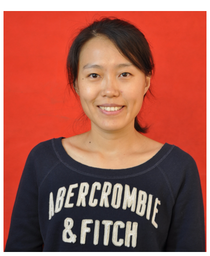
Author Biography



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