

# Recommender system in Event Based Social Networks

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# 1 Event-Based Social Network (EBSN)

An EBSN does not only contain online social interactions as in other conventional social networks, but also includes valuable offline social interactions captured in offline activities. Communities in EBSNs are more cohesive than those in other type of social networks. In the context of information flow, an interesting problem is event recommendation. [2]

## 1.1 Most popular EBSNs

With the proliferation of EBSNs such as Meetup.com, Douban (e.g., *beijing.douban.com*), and Facebook Events (*events.fb.com*), organizing and joining social events have become much easier than ever before. These platforms do not provide the same type of service. In particular, Douban and Facebook Events just offer a way to navigate events, filtering them based on different information such as location, time preference, and category. Both platforms are not entirely focused on event announcements, this can be considered more as an additional feature provided by the website. Although this utility has been developed with many powerful characteristics, events are usually buried in tons of other information, so the users rarely notice them. With the potential from the number of users, an application focusing only on events can solve this problem effectively. Meetup, on the other hand, is entirely focused on events recommendation, hence it can be considered as the EBSN for excellence. In Meetup, the user must join some groups, and actions on this site are all about events, from participating to an existing one to creating and promoting a new event. Meetup aims to create enduring like-minded communities and keep sustainable relationships through real-life activities called meetups. The results of [3] show that the social context (derived from group membership) is the most important factor in making decisions on this site. Different from that, Facebook is designed mainly for sharing information. Although the users can be congregated by public fan pages or groups, they might be total strangers in real-life. [4]

## 1.2 What services an EBSN offer

In Section 1.1, a list of the most popular EBSNs was presented. All the analyzed platforms offer some kind of events recommendation, such as content based, location based and time based. However, as one can notice, both Douban and Facebook Events do not address the problem of creating groups out of people meeting at events and the online platform does not aim to create connections between people in real-life. The recommendation of events, even if based on your online friends, does not take into account existing social circles. Moreover, even though the recommender was considering cluster of people based on common fan pages or groups, in most cases these factors do not correspond to real-life situations and do not mirror real social circles. Moreover, there is not a feature such as group of friends membership on Facebook.

Meetup does something more. The core concept of the platform is groups. Each group has a different profile, topic of interest, size and set of policies. These groups propose different events related to one or a few categories. Users can join events of different groups based on their interests. The Meetup recommender system, even if not explicitly said anywhere, it surely has one more feature added to the model, which is a group based one. Meetup groups are run by organizers. Organizers set up groups, organize events, and develop event content. They also pay a fee to run the group, under the expectation of sharing the cost with members that attend events. [6]

## 1.3 The problem with the existing platforms

All these networks are lacking something. This something is to give the possibility to the user to build a real-life group of friends or to strengthen an existing one, as shown in Figure 1. While Douban and Facebook Events stimulate communications on their online platforms, taking into consideration just virtual friends and groups, without building a real-life environment in which the user can build and evolve his social interactions, Meetup is trying to do so. However, Meetup is doing it in a way that is alienating and does not reflect the real-life structure of groups of friends. The following example will make this concept more clear. Opening the Meetup website (*meetup.com/find*) or the mobile application, the first three suggested groups in Lausanne area are

|   | Content+location+time based | Group based | Socially aware |
|---|-----------------------------|-------------|----------------|
|  | ✓                           | ✗           | ✗              |
|  | ✓                           | ✗           | ✗              |
|  | ✓                           | ✓           | ✗              |
|  | ✓                           | ✓           | ✓              |

Figure 1: From the top: Douban, Facebook, Meetup and our EBSN offered services and recommendations.

"SwissAI Machine Learning Meetup" with 1,687 members, "Lausanne BlaBla Language Exchange" with 1,139 members, and "Lausanne Culture Meetup" with 335 members. These groups are category specific and with a high number of participants. Although the user might find one or multiple friends joining events suggested by these groups, the activities carried out with these people will be limited to the category of the group. In addition, even if the user found the same person in multiple events belonging to different groups, which is highly unlikely, it would not mean that this particular user has created a real social circle with which he or she can improve his or her social life. To conclude, there is not such a platform that helps users find a new social circle with multiple interests or boost an existing group of friends by suggesting activities that belong to different topic of interest.

## 2 Context-aware recommendation in EBSN

The sheer volume of events available in EBSN often undermines the users' ability to choose the event that best fit their interests. Recommender systems (RS) appear as a natural solution for this problem. Differently from classic recommendation scenarios, the event recommendation problem is intrinsically cold-start. Indeed, events published in EBSNs are typically short-lived and, by

definition, are always in the future, having little or no trace of historical attendance. To overcome this problem, several contextual signals from the EBSN are exploited: répondez s'il vous plaît (RSVP), group membership, geographical location, time preference. A scheme of this idea is represented in Figure 2. The assumption is that these signals have a positive influence on the users' decision about attending an event.

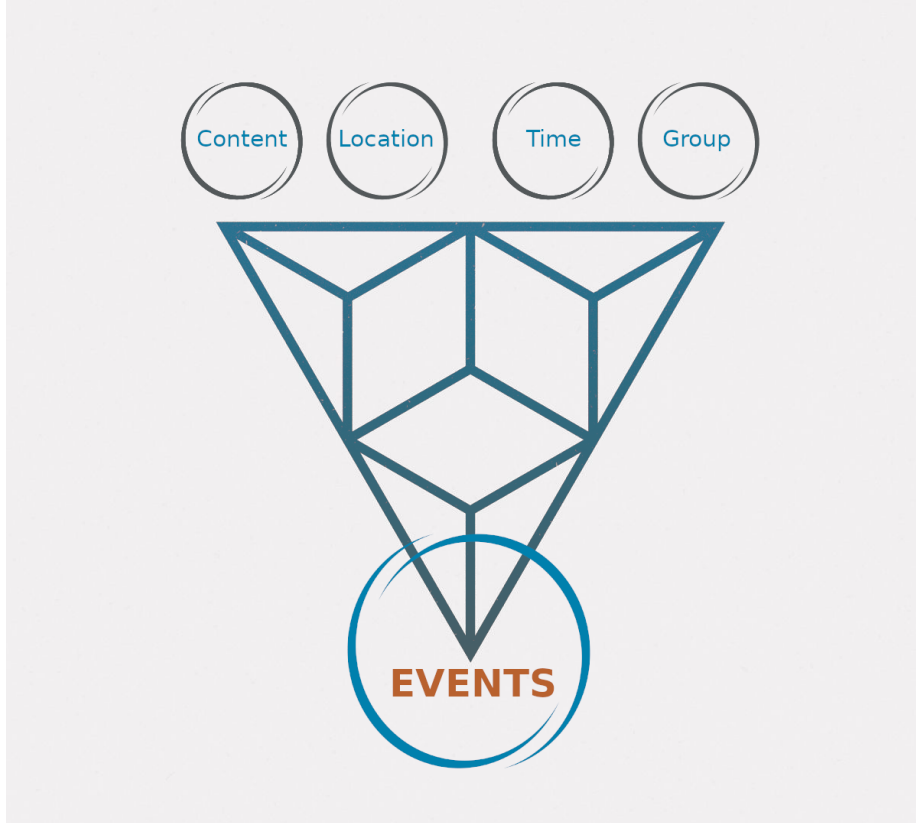


Figure 2: Context-aware recommendation system.

### 3 Problem setup

The event recommendation problem can be stated as follow: given a target user and a set of contextual signals, which of the available events are more likely to be attended (i.e. RSVP'ed "yes") by this user? This scenario is simulated by splitting the available RSVP data into two partitions, before and after timestamp  $\theta$ . The (user, events) pairs occurring before  $\theta$  form the training partition,

while those that occur after  $\theta$  form the test set. The task is to find a scoring function of the form:

$$\hat{s} : U \times E \times T \times G \times C \times D \rightarrow \mathbb{R} \quad (1)$$

where  $U$  is the set of users,  $E$  is the set of events,  $T$  are the users' temporal preferences,  $G$  is the set of groups,  $C$  is the set of textual content of events and  $D$  are the users' geographic distance preferences. Thus, for a given user  $u \in U$  and the contextual signals  $t \in T$ ,  $g \in G$ ,  $c \in C$ ,  $d \in D$ , the top- $n$  recommendations can be computed by:

$$\text{top-}n(u, t, g, c, d) := \arg \max_{e \in E \setminus E_u}^n \hat{s}(u, e, t, g, c, d) \quad (2)$$

where  $n$  denotes the number of events to be recommended and  $E_u$  is the set of events that user  $u$  has attended in the past. In top- $n$  recommendation settings, such as this, the goal is to minimize a ranking loss function of the form:

$$l : P(E) \times \mathbb{R}^E \rightarrow \mathbb{R} \quad (3)$$

which quantifies the misfit between the recommended list (generated by  $\hat{s} \in \mathbb{R}^E$ ) and the actual list (a subset of  $P(E)$ ) on the test users whose actual events are unknown during training.

## 4 Contextual models

### 4.1 Content-aware

Content-based filtering appears as a promising approach. In particular, besides its usual capacity of retrieving events with similar descriptions, it also captures recurrent events since these tend to have similar or nearly identical content. Each user is represented as a TF-IDF vector of the words extracted from the past events the user attended. Moreover, each event is weighted by its time distance to the recommendation instant by means of a time value of money

decay function [5]. Formally, the profile of user  $u \in U$  is defined as:

$$\vec{u} := \sum_{e \in E_u} \frac{1}{(1 + \alpha)^{\tau(e)}} \times \vec{e} \quad (4)$$

where  $\vec{e}$  is the TF-IDF representation of event  $e$ ,  $\alpha$  is a time decay factor and  $\tau(\alpha)$  return the number of days from the RSVP to  $e$  until the moment of recommendation. Finally, the candidate events are ranked based on their cosine similarity with respect to the target user:

$$\hat{s}_C(u, e) = \cos(\vec{u}, \vec{e}) \quad (5)$$

## 4.2 Social-aware

In some EBSNs, such as Meetup, users may join groups and interact with other users both online and face-to-face. In our case, groups will be created automatically based on the real-life connections of the user. An other approach would be to use a density based clustering algorithm to cluster users in groups based on their past attendance to events. In any case, the best way to find groups can only be corroborated by doing experiments and trying out different techniques. After group membership of each user has been found, two different models can be implemented to recommend events: group frequency and multi-relational model.

*Group frequency model:* The intuition of this method is that the likelihood of the target user  $u \in U$  attending event  $e \in E$  depends on the number of events this user attended with the users that are part of the group that  $e$  belongs to. In other words, the more events a user attends in a group, the higher the probability that this user will continue to attend events with the members of this group. Formally, assuming that  $g_e$  represents the group associated with the candidate event  $e$ , the relevance score of this event for the target user  $u \in U$  is:

$$\hat{s}_{S_1}(u, e) := \frac{|E_{u, g_e}|}{|E_u|} \quad (6)$$

where  $E_u$  denotes the set of all events that user  $u \in U$  attended and  $E_{u, g_e}$  denotes the set of events attended by  $u$  that were created by group  $g_e \in G$ .



*Multi-relational model:* With this method, which is more complex than the previous one, one might discover that users affiliated to the same or similar groups are prone to attend the same events created by these groups. The user-group relation is especially important because it enables the recommendation of cold-start events (with zero RSVP). This method is based on the Multi-Relational Factorization with Bayesian Personalized Ranking (MRBPR) [1]. the idea is to reconstruct the target relation  $R_{UE} \subseteq U \times E$  by considering a joint factorization approach that includes the auxiliary relations  $R_{UG} \subseteq U \times G$  and  $R_{GE} \subseteq G \times E$ . The parameters of the model  $\Theta = \{U, E, G\}$  are the latent matrices associated with each considered entity. The objective function is then expressed as follows:

$$\arg \min_{\Theta} \alpha L(R_{UE}, \mathbf{U} \mathbf{E}^T) \quad (7)$$

$$+ \beta L(R_{UG}, \mathbf{U} \mathbf{G}^T) \quad (8)$$

$$+ \gamma L(R_{GE}, \mathbf{G} \mathbf{E}^T) \quad (9)$$

$$+ \lambda_U \|\mathbf{U}\|^2 + \lambda_E \|\mathbf{E}\|^2 + \lambda_G \|\mathbf{G}\|^2 \quad (10)$$

where  $L$  is a loss function measuring the reconstruction error of the relation under construction,  $\alpha$ ,  $\beta$ ,  $\gamma$  are weights for the losses and  $\lambda_U$ ,  $\lambda_G$ ,  $\lambda_E$  are regularization parameters. Once the model is learned, the relevance score of an event  $e \in E$  for the target user  $u \in U$  is:

$$\hat{s}_{S_2}(u, e) = \sum_{f=1}^k \vec{u}_f \vec{e}_f \quad (11)$$

where  $\vec{u}$  and  $\vec{e}$  are the latent vectors of user  $u$  and event  $e$ , respectively.

### 4.3 Location-aware

The mobility pattern of users within a city may vary from user to user. The idea is to use a kernel-based density estimation approach to model the mobility patterns of individual users as distributions of geographic distances between the attended events. The relevance of a new event for a user is based on the likelihood of this event being located in any of the regions the user attended

events in the past. Formally, let  $L_u$  be the sample of latitude-longitude (lat-long) coordinates of the events the target user has attended in the past:

$$L_u := \bigcup_{e \in E_u} l_e \quad (12)$$

where  $l_e$  is the lat-long coordinate of event  $e \in E$ . A kernel density function  $\hat{f}$  is defined over  $L_u$  as follows:

$$\hat{f}(l) := \frac{1}{|L_u|} \sum_{l' \in L_u} K_{\mathbf{H}}(l - l') \quad (13)$$

where  $l$  is a lat-long coordinate,  $K_{\mathbf{H}}(\cdot)$  is the bivariate Gaussian kernel,

$$K_{\mathbf{H}}(\mathbf{x}) := \frac{1}{\sqrt{2\pi|\mathbf{H}|}} \epsilon^{-\frac{\mathbf{x}\mathbf{x}^T}{2\sqrt{\mathbf{H}}}} \quad (14)$$

The geographical preferences of a given user are then represented by the sum of all Gaussian distributions centered at  $l_e$ , for all  $e \in E_u$ :

$$\hat{s}_D(u, e) := \hat{f}(l_e) \quad (15)$$

#### 4.4 Time-aware

Another important factor is when the event occurs. This information is captured by assuming that users that attended events in the past at certain days of the week and at certain hours of the day will likely attend events with a similar temporal profile in the future. Formally, each event  $e$  is represented as a  $24 \times 7$ -dimensional vector  $\vec{e}$  in the space of all possible days of the week and hours of the day, with an entry set to 1 whenever the event happened at that particular day and hour. Each user is represented as:

$$\vec{u} := \frac{1}{|E_u|} \sum_{e \in E_u} \vec{e} \quad (16)$$

The temporal score for user  $u$  and event  $e$  can now be expressed as the cosine between their vector representation:

$$\hat{s}_T(u, e) := \cos(\vec{u}, \vec{e}) \quad (17)$$

## 5 Rank events with contextual features

The aforementioned recommenders are used as features for learning to rank events. In particular, let  $D := \{(\mathbf{x}_1, \mathbf{y}_1), \dots, (\mathbf{x}_n, \mathbf{y}_n)\}$  be the training set where  $\mathbf{x}_i := \{s_1(u, e), \dots, s_m(u, e), |U_e|\}$  is a feature vector containing the normalized scores generated for a given pair of user  $u \in U$  and event  $e \in E$  by each of the  $m$  context-aware recommenders, plus the number of RSVPs  $|U_e|$  the event  $e$  has received in the past. Also let  $y_i = \{0, 1\}$  denote whether user  $u$  attended event  $e$  (1) or not (0). The goal is to learn a function  $h(\mathbf{x})$  such that for any pair of training instances  $(\mathbf{x}_i, y_i)$  and  $(\mathbf{x}_j, y_j)$  the following implication holds:

$$h(\mathbf{x}_i) > h(\mathbf{x}_j) \leftrightarrow y_i > y_j \quad (18)$$

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