Exploiting the Dynamic Mutual Influence for Predicting Social Event Participation

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Abstract—It is commonly seen that social events are organized through online social network services (SNSs), and thus there are vested interests in studying event-oriented social gathering through SNSs. The focus of existing studies has been put on the analysis of event profiles or individual participation records. While there is significant dynamic mutual influence among target users through their social connections, the impact of *dynamic mutual influence* on the people's social gathering remains unknown. To that end, in this paper, we develop a discriminant framework, which allows to integrate the dynamic mutual dependence of potential event participants into the discrimination process. Specifically, we formulate the group-oriented event participation problem as a two-stage variant discriminant framework to capture the users' profiles as well as their latent social connections. The validation on real-world data sets show that our method can effectively predict the event participation with a significant margin compared with several state-of-the-art baselines. This validates the hypothesis that dynamic mutual influence could play an important role in the decision-making process of social event participation. Moreover, we propose the network pruning method to further improve the efficiency of our technical framework. Finally, we provide a case study to illustrate the application of our framework for event plan design task.

Index Terms—Dynamic social influence, social event, social network, user behavior

1 Introduction

The newly emerged *event-driven* social network services target at providing the opportunities for online people to gather together in offline events, which has become popular and attractive for millions of users all around the world. For instance, at Meetup.com, more than 10,000 events are organized every day, and RSVPs may even exceed 100 times per minute. This new business model imposes new challenges on social event analysis with considering *social effects*, and raises the difficulties for the event organizers to draw the event plan and predict the attendance.

Indeed, the "word-of-mouth" effects can strongly affect the social event participation. For instance, prior study has revealed that 10-30 percent of human movement could be explained by social factors, even more evident on long-ranged travels [3] which indicate casual social gathering rather than periodical commutes. Since face-to-face communication is inevitable for offline social gatherings, people usually tend to stay with the familiars, which leads to more cohesive communities for event-driven social networks than the ordinary ones [20]. Definitely, these results will help to better understand the features of social events. However, statistical analysis may only result in rough estimation of global trend, but may not lead to accurate personalized profiling and prediction, and then fail to support the event-oriented applications. Thus, comprehensive modeling on social effects is still required for the social event analysis.

For the past several years, some researches have considered the social effects as features or constraints in their studies, which can effectively improve the prediction results. For instance, [22] treated the static social connections as constraint in PMF, and [37] further proposed the two-way constraints between social connection and production adoption. These researches are intuitive with following the basic idea of [12], i.e., users tend to befriend those who hold similar preference, and friends tend to act similarly due to similar preference. This phenomenon might be reasonable as long-term interactions gradually affect preference. However, in event-oriented social network, cyber strangers are connected only via short-term social events, and these connections evolve frequently, thus influence might not be persistent enough. Moreover, it is common to see a user who has multifaceted interests, and connections which only reflect partially common interests should not conduct comprehensive constraints. For instance, a *programmer* may like *board games*, but his connections with colleagues do not necessarily mean they also like board games. In summary, simply treating social factors as *static* features or constraints could be too rough to estimate the decision-making process.

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Fig. 1. An illustration of dynamic influence within event participation.

More importantly, when we *reproduce* the organization process of a social event, we realize that social effects should be considered as *dynamic*, i.e., when making decisions within a group, people may listen to and can be influenced by some friends, and they will further influence the others. Usually, if two friends hold the same idea, their tendency will be mutually strengthened; on the contrary, opposite ideas lead to weaken confidence. Let's recall the above example of *programmer*, if he and his colleagues receive the invitation of a *board game* party at the same time, his colleagues may accept the invitation due to his instigation, even if they are not interested in board games. Actually, this example is not occasional especially for the users without strong preference, since they tend to simply follow the advices from their friends when hesitating. Correspondingly, if this programmer suddenly change his mind because of some accidental situations, his colleagues may probably take their words back, which results in the so-called *chain reaction* based on **D**ynamic **S**ocial **I**nfluence (*DSI*). In this case, the social mechanism could be different from traditional "cascade" where decisions are irreversible. As shown in Fig. 1, potential participants share their ideas in the social network, where mutual influence is digested to form new decisions and further spread. The iterative process will repeat until the final decision is stably achieved.

To describe the mutual influence in group decision-making, some works like [19] attempt to model the process in the perspective of game theory, where personal impact, social relations and game equilibrium are integrated together to provide a unified decision. However, in these researches, social effects here are simplified as game-playing or delegate-voting to achieve an identical conclusion, and personalized analysis could not be provided. To be specific, the effects of social interactions on individuals, as well as corresponding feedbacks are totally ignored. Thus, user behavior modeling based on dynamic mutual influence has not been fully exploited in the above studies.

To that end, in this paper, we aim at exploiting the dynamic mutual influence for decision-making process of social event participation. To be specific, we propose a novel two-stage discriminant framework, which allows integrating the dynamic mutual dependence of potential participants into the learning process. Based on the framework, we can model the group-oriented decision-making process to capture users' preferences as well as their latent social connections. To the best of our knowledge, we are among the first ones to investigate the impact of dynamic mutual influence on social event participation. Comprehensive validations on real-world data set indicate our framework can effectively improve the event participation prediction compared with several state-of-the-art baselines. Along this line, we further propose the network pruning method to improve the efficiency of our framework, and then application of event plan design task with different objectives has been discussed. These results validate the hypothesis that mutual social influence indeed plays an important role in the decision making process of potential event participants.

Overview. The rest of this paper is organized as follows. Section 2 further illustrates the motivation of this study with related statistics. In Section 3, we define the problem and formulate our discriminant framework, then technical details are explained in Section 4. In Section 5, we validate the general framework and reveal some interesting findings with case studies. After that, we have Section 6 to propose the pruning for improving efficiency, and Section 7 to discuss the event design application. Section 8 presents the related works. Finally, in Section 9, we conclude the paper.

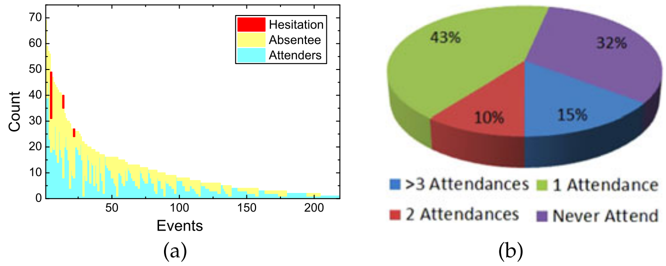

Fig. 2. User distribution on attendance. (a) User rates for different amount of attendances. (b) Distribution of responses for each event.

2 Investigation on Social Effects: Are Participations Affected by "Social"?

In this section, we will deeply discuss our motivation. Though prior arts have studied social effects on single event, questions still remain. First, persistent effects on event series have not been studied before. Second, homophily and influence are not distinguished. To answer these questions, some related statistical analysis will be introduced.

2.1 Data Set Description

Our study was conducted on a real-world data set collected from Meetup.com, one of the most popular online social websites that facilitates offline group meetings around the world. Specifically, we extracted event logs and user profiles via the official APIs of Meetup, which totally consists of 422 user groups, 9,605 social events and 24,107 related users. The distribution of event participation is shown in Fig. 2a, including 200 events randomly picked as samples.

Further, Meetup highlights group structure but ignores point-to-point connection, i.e., users have to join the groups to receive event invitations, which results in the event series organized by the same group. At the same time, the social effect could be reflected by group discussions or private contacts,

TABLE 1
Comparison for Social Factors in Event Series

	Average for All Events		First Attendance	
	Density	Ave. Weight	Degree	Ave. Weight
Active	0.7849	0.2343	0.1249	0.0109
Overall	0.4694	0.1305	0.0498	0.0062
P-Value	< 0.001	< 0.001	0.001	0.004

which could not be extracted by API. Thus, we constructed the weighted connections based on co-attendance of pairwise users, which is widely used in prior arts like [20] and [17]. What should be noted is that *social network here is only used in Pre-study*. In our DSI framework, we will reveal the latent social connections via modeling and parameter estimation.

Finally, to describe the attributes of social events, we extracted 2,856 key words (or terms) with unique ID (defined by Meetup) in the group descriptions and user profiles, and then learned the topics via LDA model [2]. After that, all the descriptions and user profiles are presented as vectors.

2.2 Social Effects on User Engagement

First, we will discuss the long-term social effects in event series, to discover whether the tight connection will kept users active in the group for a longer time. Since active users are usually more valuable for groups, we would like to reveal the social-related clues for improving their loyalty. Specifically, according to the statistics which is shown in Fig. 2b, only 14.74 percent users attended more than 3 events, who attended 11.08 events in average, much more than 3.24 for overall users. Thus, in the Pre-study, we treat those who have attended at least 3 events as *"active"*.

To reveal the clues, two sets of statistics were conducted. First, we counted the degrees and ave. link weights of users at their first attendance, to explore whether their initial status may influence their long-term activity. Second, we measured the density of small communities formed by active ones, to check whether they are indeed denser than the ordinary ones. The results are shown in Table 1, in which *P-Value* presents the T-test result (assuming that metrics of active users are higher than ordinary ones). Unsurprisingly, differences on all the measures are significant, which indicates that social effects indeed encourage users to be active.

Also, we realize that the initial connections might be extremely sparse. However, after the first attendance, the social factors will soon be enhanced by tight connection within active users. As shown in Fig. 3, when users attend more events, both the degree and weight grow rapidly. Interestingly, the degree turns stable soon, then decreases slowly, while the weight still keeps increasing. Clearly, some friends leave, but retained connection become stronger due to more co-occurrences. In summary, long-term active users hold denser communities than ordinary ones, which definitely means more significant social effects.

2.3 Preference in Social Event Participation

Second, we turn to study the homophily, i.e., to discover whether preference without social influence mainly determine the final decisions. As preferences are presented in vectors, *Cosine similarity* is introduced to estimate tendency. Particularly, two pairs are compared: attenders versus

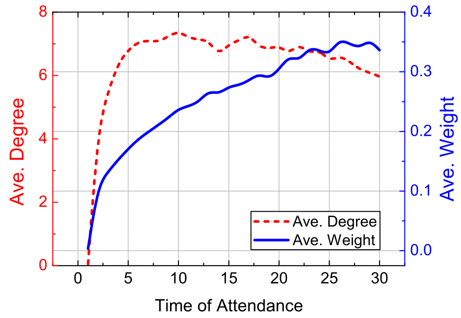

Fig. 3. Average degree and weight for different times of occurrence.

absentees of single events, and active users versus overall users for all the events. The results are shown in Table 2 with corresponding T-test result (assuming the former one is higher than the latter). Interestingly, though the attenders hold clear interest than the absentees, we found that the active users do not express explicit preference than ordinary ones.

Considering that most people quit after attending only one or two events, we can guess that for inactive users, they may be attracted by the topics at first; however, they quit soon since they could hardly befriend with others in the group. At the same time, for active users, though sometimes they don't like the events, they attend due to invitation from their friends. This phenomenon validates our motivation that preference might not be the main reason of participation in the long-term observation. Instead, the social factors may indeed affect the decision-making process of event participation, which might not be reflected by similar preferences, but direct effect on decisions.

3 Predicting Social Event Participation: Formulation, Discrimination, and Framework

As our motivation has been intuitively validated, in this section, we first formally define the problem and introduce some preliminaries. Then, our novel discriminant approach with social-influence-based threshold will be formulated. And finally, we demonstrate our two-stage framework for social event participation prediction.

3.1 Problem Statement

In this paper, we focus on the decision-making analysis of individual participation. Traditionally, social factors will be neglected, or at most treated as *static* constraint or feature, thus users could be analyzed individually. On the contrary, as we consider the *dynamic* social effects within users, it is necessary to put individuals into a group with network structure. Therefore, here we use the definition *target user group* to represent the group of users to be predicted. Formally, the predicting task can be defined as follows.

TABLE 2
Comparison for User Preference to Events

Single Event		All Events	
Attender	0.108	Active Users	0.106
Absentee	0.094	Overall Users	0.105
P-Value	0.016	P-Value	0.334

TABLE 3
Mathematical Notations

SYMBOL	DESCRIPTION
$\mathbf{U} = \{u_i\}$	the set of users
$\mathbf{E} = \{e_k\}$	the set of events
$\mathbf{p_i}$	preference vector for u_i
$\mathbf{a_k}$	attributes vector for e_k
w_{ij}	social connection strength from u_i to u_j
$f_{i,k}$	intention for u_i to attend e_k
$h_{i,k}$	threshold for u_i to attend e_k
$s_{i,k}$	attendance for u_i to e_k

Problem Statement. *Given the target user group* $\mathbf{U}$ *with weighted connections, the problem is to predict the participation* $s_{i,k}$ *of target event* e_k *for each user* $u_i \in \mathbf{U}$, *here* $s_{i,k} = 1$ *indicates the attendance, while* $s_{i,k} = 0$ *means the absence.*

To describe user profiles, we first exploit a vector $\mathbf{p}_i$ to present the preferences of user u_i, in which each element denotes the preference level on a specific aspect/topic. Correspondingly, we also have a vector $\mathbf{a}_k$ for each event e_k to indicate the attributes, which has the same dimensions with $\mathbf{p}_i$. Indeed, the similarities between $\mathbf{p}_i$ and $\mathbf{a}_k$ may roughly indicate the probability of u_i attending e_k without considering the social factors. What should be noted is that, here $\mathbf{a}_k$ and $\mathbf{p}_i$ are normalized vectors.

For the weighted connections within target user group $\mathbf{U}$, we use $W = \{w_{ij}\}$ to indicate the set of directional connection strengths (weights) to be revealed during the modeling, and w_{ij} corresponds to the social influence strength from u_i to u_j. The mathematical notations used throughout this paper are summarized in Table 3.

3.2 Discrimination with Social-Based Threshold

When we treat the event participation as a discriminant problem, intuitively, we have similarity function $f(u_i, e_k)$ and a threshold $h(u_i, e_k)$ for user u_i and event e_k, the individual participation $s_{i,k} = 1$, iff. $f(u_i, e_k) \geq h(u_i, e_k)$ and $s_{i,k} = 0$, iff. $f(u_i, e_k) < h(u_i, e_k)$.

To formulate the social effects in decision-making process, we have two choices, i.e., merging the social factors with $f(u_i, e_k)$ or $h(u_i, e_k)$. Traditionally, prior works integrate the social effects into $f(u_i, e_k)$ following the assumption that the social connections leads similar preferences, thus usually the social factors are formulated as constraint or features. At the same time, the thresholds $h()$ are usually set uniformly to keep the balance between precision and recall. However, as discussed above, we realize that social constraints on preference might not be appropriate and comprehensive enough under social event situation, further, social influence may directly affect the decision making.

Therefore, here we choose to merge the social effects with calculation of threshold $h(u_i, e_k)$. Specifically, we assume that $h(u_i, e_k)$ depends on the participation of friends. In our approach, the dependence is reflected by the variance of threshold $h(u_i, e_k)$. To formulate the dependence, we adapt the classic Independent Cascade (IC) model [8] for simulating the dynamic mutual influence within users. What should be noted is that IC model here could be replaced by other social influence model if needed, we choose IC here since it is widely used as one of the basic social influence modeling, and its effectiveness has been well proved. Particularly, if we denote $f(u_i, e_k)$ as $f_{i,k}$ and $h(u_i, e_k)$ as $h_{i,k}$, the threshold can be formulated as follows:

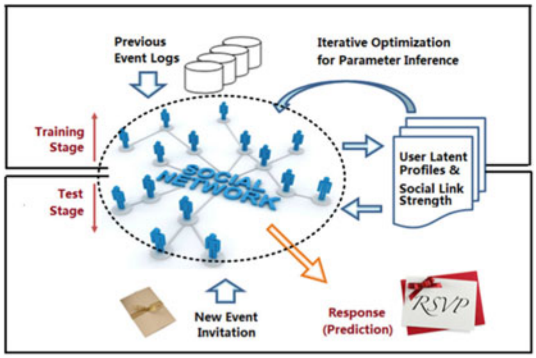

Fig. 4. Overview of our framework for event participation prediction.

$$h(u_i, e_k) = h_{i,0} \cdot \prod_{j \in N_i} [1 - \mathcal{I}(f_{j,k} - h_{j,k}) \cdot w_{ji}], \qquad (1)$$

where $\mathcal{I}(x)$ is a discriminant function to indicate friend's option, and $h_{i,0} \in [0, 1]$ denotes the parameter for personal participating activity, i.e., active users will hold lower $h_{i,0}$. Also, N_i means friends of u_i in the target group $\mathbf{U}$, and w_{ji} indicates the strength of social influence from u_j to u_i. Interestingly, higher w_{ji} may not only indicate the strong connection from u_j to u_i, but also indicate that u_i could be easily influenced, especially when all the w_{li} for $u_l \in N_i$ are relatively high. Furthermore, $w_{ij} < 0$ is eligible to present the *negative influence* that u_i and u_j usually hold opposite opinions. Finally, w_{ij} is normalized as $\Sigma_j |w_{ij}| = 1$.

For the discriminant function $\mathcal{I}(x)$, although we could intuitively define it as a *sign function* with binary values (i.e., $\mathcal{I}(x) = 0$ when $x < 0$, otherwise $\mathcal{I}(x) = 1$), some defects may exist. First, the impact will jump from 0 to 1 sharply, which might not be reasonable. Second, the sign function is difficult to be optimized. Thus, we introduce the *Sigmoid function* to approximate the sign function as follows:

$$\mathcal{I}(x) = \frac{1}{1 + e^{-\alpha x}}, \qquad (2)$$

where α presents the parameter to regulate the slope. Definitely, since Sigmoid function is smooth and derivable on the $\mathbb{R}$ set, the optimization task will be much easier to solve.

For the preference function $f(u_i, e_k)$, which depends on the characteristics of data set, the details will be introduced in general validation in Section 5. With the above formulation, we can integrate the user profiles and mutual influence into the unified discriminant framework. Indeed, this framework can reflect the intuition that users usually make their own decision for event participation, then they are influenced by friends to change their mind, this process repeats until they finally achieve the stable equilibrium.

3.3 Two-Stages Framework

Based on the definitions above, now we can formally present our two-stages framework for event participation prediction. Fig. 4 demonstrates the overview of framework.

Training Stage. Given a target user group $\mathbf{U} = \{u_i\}$ and a set of historical events $\mathbf{E} = \{e_k\}$, in which corresponding attendance record $\mathbf{S} = \{s^0_{i,k}\}$ for each pair of u_i and e_k are pre-known. Also, we have the event attributes $\mathbf{a}_k$ for each e_k. In this stage, we aim at inferring the latent profile $\mathbf{p}_i$ and activity measure $h_{i,0}$ for each u_i, as well as learning the connection strength $\{w_{ij}\}$ for pairwise users.

Test Stage. After obtaining the users' profiles $\langle \mathbf{p}_i, h_{i,0}\rangle$ and mutual affection strength $\{w_{ij}\}$ in the training stage, in the test stage, given a certain event e_k with attributes $\mathbf{a}_k$ and the corresponding target user group $\mathbf{U}_k = \{u_i\}$, we aim at predicting event participation $s_{i,k}$ for each $u_i \in \mathbf{U}_k$.

What should be noted is that, to ease the modeling, we assume the social connection strength always keep stable. To achieve the "*time-varying*" social effects for real-time update, we could introduce the "*time window*" to learn the temporal strength, which will be discussed in Section 5.4.3.

4 Technical Details for Predicting Social Event Participation

In this section, we will introduce the technical solutions for both training and test stage of our framework.

4.1 Iterative Optimization for Training Stage

Indeed, the task in training stage can be regarded as a supervised learning problem, which targets at minimizing the cost of discrimination errors on training data. Therefore, we can formulate the objective function, i.e., the cost function, for training stage as follows:

$$\arg\min_{\mathbf{p},h_0,w} \sum_{u_i\in U}\sum_{e_k\in E}[s^0_{i,k} - \mathcal{I}(f_{i,k} - h_{i,k})]^2, \tag{3}$$

where $s^0_{i,k}$ presents the ground truth of attendances. Intuitively, discrimination errors lead to higher cost, and minimizing the cost function may result in the optimized inference of users' profiles and social strength.

However, since the calculation of $h_{i,k}$ of users depends on the $f_{j,k}$ and $h_{j,k}$ of their friends, to optimize the mutual dependence is extremely difficult. To address this challenge, we propose a step-by-step iterative approach. To be specific, we treat the dynamic social influence as an iterative generation process, where the decision made in current round will only affect friends' thresholds in next round, which is reasonable in real world decision-making. The iterative formulation of our objective function is defined as follows:

$$F^t(U,E) = \sum_{u_i\in U}\sum_{e_k\in E}[s^0_{i,k} - \mathcal{I}(f^t_{i,k} - h^t_{i,k})]^2, \tag{4}$$

where we have

$$h^t_{i,k} = h^t_{i,0} \cdot \prod_{j\in N_i}[1 - \mathcal{I}(f^{t-1}_{j,k} - h^{t-1}_{j,k}) \cdot w^t_{ji}]. \tag{5}$$

Along this line, $\mathcal{I}(f^{t-1}_{j,k} - h^{t-1}_{j,k})$ will be treated as a constant in round t, thus the optimization task for parameters will be eased. After each round, all parameters will be updated and the mutual influence will be digested to achieve the new discrimination results. During this process, some decisions, i.e., $s_{i,k}$ may change due to variant social influence. This process will repeat until the cost is stable, which means no more decision changes. Details of training stage are summarized in Algorithm 1.

Algorithm 1. Iterative Solution for Training Stage.

Input: target user group $\mathbf{U} = \{u_i\}$, event set $\mathbf{E} = \{e_k\}$ and attendance records $\{s^0_{i,k}\}$;
Store: event attributes $\mathbf{a}_k$ for each $e_k \in \mathbf{E}$;
Output: users' profile $\langle \mathbf{p}_i, h_{i,0}\rangle$ and social strength w_{ij}

Iteration = *True*;
while (Iteration)
  Iteration = *False*;
  for $u_i \in \mathbf{U}$, $e_k \in \mathbf{E}$
    update $\langle \mathbf{p}_i, h_{i,0}\rangle$ and $\{w_{ij}\}$ until convergency;
    update $f_{i,k}$, $h_{i,k}$ based on Equation (1);
    update $s_{i,k}$ as $\mathcal{I}(f_{i,k} - h_{i,k})$;
    if $s_{i,k}$ changed **then** Iteration = *True*;
    end if
  end for
end while
return $\{\langle \mathbf{p}_i, h_{i,0}\rangle\}$, $\{w_{ij}\}$;

Finally, we turn to analyze the convergence of training stage. Intuitively, we could consider the update scheme for $\mathbf{p}_i$, $h_{i,0}$ and $w_{i,j}$ as block coordinate descent with respect to i, j. In this case, the convergence of Algorithm 1 could be guaranteed. Specifically, following the definition of $\mathcal{I}$ in Equation (2), the gradient of optimization task in Equation (4) is continuous with respect to $\mathbf{p}_i$, $h_{i,0}$ and $w_{i,j}$ for all $u_i, u_j \in U$. Since $\mathbf{p}_i$, h_0 and $w_{i,j}$ are bounded (as $\mathbf{p}_i$ and $w_{i,j}$ are normalized, and h_0 ranges between [0,1]) for all u_i, $u_j \in U$, we must have that the gradient of $F(U,E)$ with respect to i, namely $\nabla F(u_i, E)$, is continuous and bounded. Besides, following Theorem 9.7 in [34] we have that $\nabla F(u_i, E)$ is Lipschitz continuous. Then, following Theorem 2 in [33], we could now guarantee the global convergence of Algorithm 1.

4.2 Prediction for Test Stage

Since all the parameters, i.e., user profiles and social connections are inferred in the training stage, in the test stage, we aim at predicting the participation for the target user group to a certain event. Here we even don't need an objective function, but directly achieve the prediction with iteration.

Algorithm 2. Iterative Solution for Test Stage

Input: target user $\mathbf{U}$ and event e_k with attributes $\mathbf{a}_k$;
Store: users' profiles $\langle \mathbf{p}_i, h_{i,0}\rangle$ and connection weights w_{ij};
Output: $s_{i,k}$ for each $u_i \in \mathbf{U}$

for $u_i \in \mathbf{U}$
  calculate $f_{i,k}$ for each u_i;
end for
Iteration = *True*;
while (Iteration)
  Iteration = *False*;
  for $u_i \in \mathbf{U}$
    update $h_{i,k}$ based on Equation (1);
    update $s_{i,k}$ as $\mathcal{I}(f_{i,k} - h_{i,k})$;
    if $s_{i,k}$ changed **then** Iteration = *True*;
    end if
  end for
end while
return $\mathbf{S} = \{s_{i,k}\}$;

To be specific, we first calculate raw intention for each user. Then, in each step, threshold will be updated based on

Equation (1), and attendance will be re-predicted afterwards. This process will repeat until the prediction results are stable. What should be noted is that as negative influence may exist. Thus, even those who already select to attend may also change their mind due to negative influence from opposite members, which increase the steps to iterate. Details of test stage are summarized in Algorithm 2.

5 General Evaluation on DSI Framework

To validate our hypothesis that dynamic mutual influence may affect the decision making of social event participation, in this section, we conduct series of validations on a real-world data set. Also, some empirical case studies and discussions will be presented.

5.1 Evaluation Setup

In this section, we summarize the data set pre-processing and selected baseline algorithms for the evaluations.

5.1.1 Data Set Pre-Processing

As introduced in Section 2, we conducted our validations on the real-world data set collected from Meetup. To describe the users' profiles as well as the events' attributes, 30 topics, similar with 34 categories defined by Meetup, were learned by leveraging the classic LDA model, while more textual modeling techniques will be discussed later in Section 5.4.1.

For the preference function $f(u_i, e_k)$ mentioned in Section 3.2, as description could be easily normalized and presented in vectors, we could intuitively select the *Cosine similarity*. However, some cost factors, e.g., distance, time spending or financial cost may also affect the decision. Since these factors could hardly be normalized, we further multiplied the Cosine similarity with *Gaussian probability* for each cost factor, where means are learned during the training stage, and variances are set based on statistics. To be specific, $f(u_i, e_k)$ will be estimated as follows,

$$f(u_i, e_k) = cosine(\mathbf{a_k^T}, \mathbf{p_i^T}) \cdot \prod_c \mathcal{N}(p_i^c | a_k^c, \sigma_c^2), \tag{6}$$

where $\mathbf{a_k^T}$ and $\mathbf{p_i^T}$ present the vector corresponds to topics, and $\{c\}$ presents the cost factors. σ_c presents the variance which is determined by statistics of samples. Some more similarity metrics will be discussed in Section 5.4.2.

Besides, since we introduce the IC model to describe the dynamic influence within potential attenders, we treated the event organizers as *"seed users"* to start the influence process, which is combined with event description as input.

5.1.2 Evaluation Baselines

As we integrate the mutual social influence into the event participation prediction analysis, we chose three state-of-the-art baselines which correspond to both the traditional recommendation methods and social influence simulation for more comprehensive comparison.

- *Cost-aware PMF (GcPMF)* [5]. Probabilistic matrix factorization (PMF) is one of the basic tools for recommender system. To be specific, we select the GcPMF [5] as baseline, in which the cost factors mentioned above are also integrated.

TABLE 4
The Overall Performance of Each Approach

	DSI	SoRec	GcPMF	PSS
Precision (%)	**75.88**	60.23	47.47	46.15
Improvement (%)	-	+25.98	+59.85	+64.42
Variance	**0.022**	0.102	0.134	0.059
P-Value	-	0.000	0.000	0.000
Recall (%)	**75.34**	75.21	21.73	41.82
Improvement (%)	-	+0.17	+246.71	+80.16
Variance	**0.030**	0.112	0.234	0.180
P-Value	-	0.063	0.000	0.000

- *Social-based PMF (SoRec)* [22]: Following the intuition that social network will affect personal behaviors, the SoRec model enhanced PMF framework with *static social constraint*. As no explicit social network could be achieved in Meetup, we constructed the connection based on the rules in Pre-study.
- *Preference-sensitive Social Spread (PSS)* [39]: To analyze the event participation in the pure perspective of social influence, we also introduce the preference-sensitive social spread method as baseline, which follows the basic assumption that the social spread is determined by common preferences. Note that since social spread is actually a series of random events, thus, we repeat experiments for 500 times for each prediction to reduce the uncertainty.

5.2 Evaluation Results

Due to the group-based scheme of Meetup, we treated *group* as the unit of our experiments. To be specific, for one group, we conducted a set of experiments, and the average results for 422 groups are presented as the finals.

For the evaluation metric, as a typical discrimination problem, we selected the common used *Precision* and *Recall* rates. Also, for two PMF-based baselines, we chose the best threshold based on the P-R curves. Finally, the default α for *Sigmoid function* is set as 10, while the sensitiveness of α will be discussed later in Section 5.2.2.

5.2.1 Comparison of Overall Performance

First of all, we validate the prediction performance of our DSI framework comparing with different baselines. Considering that effectiveness of social-based algorithm heavily rely on the completeness of social network structure, and the data set is severely sparse as only less than 20 percent users attended at least 3 events in a group. Thus, we assign 90 percent events as training samples to ensure the quality of training, while the rest 10 percent are test samples. The robustness of DSI framework will be discussed later in Section 5.2.3.

The evaluation results of overall precision performance are shown in Table 4. Specifically, Our DSI approach achieves the performance above 70 percent and outperforms the baselines with significant margin, which indicates that the dynamic social influence indeed affects the event participation. Furthermore, the results are stable as variance for DSI among all the 422 groups is quite small, which proves the robustness of our DSI framework to a certain degree.

At the same time, based on the comparison between GcPMF and SoRec, though they are all PMF based

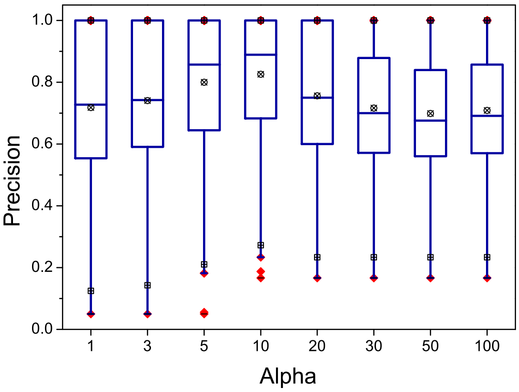

Fig. 5. Verification on robustness with different α.

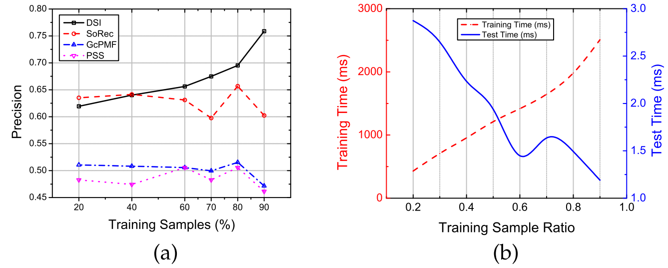

Fig. 6. Statistics for sample allocation with different ratio: (a) Performance in average. (b) Execution times in average.

algorithm, and GcPMF even integrates the cost factor. However, as significant improvement occurs with considering social constraint to assimilate users' latent preference with their friends, the effects of social factors has been further proven (even though SoRec only considers *static social factors* as constraints, that might be the reason why it failed to outperform our DSI framework).

Finally, we find that the PSS baseline achieves the worst performance. Though PSS describes the event organization process as social spread, which apprently has considered the social effects. However, essentially these spreads are still determined by the pairwise common preference. Clearly, these preference-sensitive social connections are proven as insufficient to support the decisions. Besides, the cold-start problem, which leads to sparse social network and interaction records, may further hurt the performance.

5.2.2 Parameter Sensitiveness

Then, we evaluate the sensitiveness of parameters. Since almost all the parameters are trained via modeling, only the slope parameter α in *Sigmoid function* is required for discussion. The result is shown in Fig. 5, where black node with cross inside indicates the average value (of *precision* for each group), while red nodes denote the maximal/minimal values. Also, the blue box indicate the range 25 to 75 percent among all the values, vertical lines extend the range as 10 to 90 percent, while the horizontal line inside means the median value. The output of *recall* is omitted due to similar trend.

Specifically, we utilize the Sigmoid function to approximate the sign function jumping from 0 to 1, thus a higher α might be better for approximation. However, smooth variation is still needed especially for those who don't hold clear opinion, thus their hesitation shall not lead to dramatic change in social influence. That may explain why performance achieves the peak when α is around 10, but not monotonously increasing.

5.2.3 Sample Allocation Sensitiveness

Also, we discuss about the sensitiveness of the training sample proportion, which is summarized in Fig. 6. To be specific, both effectiveness and efficiency are measured to provide comprehensive analysis.

According to the results shown in Fig. 6a, we unsurprisingly find that our performance degenerates with less training samples, which indicates that our framework is sensitive social network structure. Besides, the high ratio of freshmen leads to the severe "cold-start" problem, which impacts the result severely. However, it still works better than almost all the baselines. On the contrary, SoRec keeps relatively stable during the change, since it requires only some social-related statistics, but not the whole network.

At the same time, we summarize the execution time for different proportion of training samples in Fig. 6b. Indeed, we find for each group, which contains more than 20 events in average, it costs only a few milliseconds to predict potential attenders for all the events.

Based on the discussion above, we realize that *"time-varying"* social factors could also be available. Basically, in our DSI framework, we assume that the social influences always keep stable to ease the modeling. Indeed, connections or strength should be temporally updated to fit the real-time situation. Moreover, with controlling the frequency of update, we could achieve the balance between prediction accuracy and update frequency. Considering that our DSI framework could still perform well with limited training samples, as shown above, the effectiveness of "time-varying" social factors could be ensured. We will discuss the "time-varying" factors in detail in Section 5.4.3.

5.2.4 Performance on Different Application Scenario

Finally, we turn to validate whether our DSI framework could be utilized on other social-related application scenario as a supplementary experiment. Due to the "*word-of-mouth*" effect, users' decision could be affected by their friends. To verify whether our DSI framework could still perform well on different social-related applications, we conducted experiments on the Douban data set, which was discussed in [40] and collected from Douban, one of the most famous social media platform in China. In Douban, if one user posted a rating on a movie/book/etc., all his/her friends will be notified. Thus, we treat the behavior "*rating* on a movie" as an "*event*", and if two users rate the same movie, they will be treated as "*attending* the same event". Along this line, DSI framework could be transferred to model the social-oriented rating process.

To form a "*group*" for validation, we pick up the most influential node in the data set, who has 16,344 friends in total. In this case, the influential node could be regarded as a "*organizer*". Then, we select the Top 100 movies with most viewers among the organizer and his/her follower. Unfortunately, due to the various interests of users, even the most popular movie attracted less than 100 viewers. Thus, the data size of Douban data set is quite similar with Meetup data set discussed in general validation. For the rating, as Douban design a rating system between 1-5 stars, we treat

TABLE 5
Examples for Case Study

Group	A	B	C	D
Precision	96.15%	94.64%	48.20%	47.01%
Members	129	160	1088	273
Ave. Freshmen	20%	50%	35%	35%
Negative Edges	$<1\%$	$<1\%$	7%	4%

ratings above 3 as "*attenders*", i.e., $s_{i,k} = 1$ in DSI framework. Correspondingly, ratings below 3 are treated as "*absentee*", while ratings equal 3 means "*hesitation*". Similar with the general validation, we treat 90 percent of samples as training data, and then test the rest 10 percent samples.

According to the results, we find that our DSI framework performs well with *precision* as **79.72** percent in average, while *recall* achieves **85.25** percent. Moveover, in average each "event" costs **1.22** seconds for training, and **3.2** milliseconds for evaluating each event. It looks interesting as even there is no "dynamic influence", i.e., each user will rate an item only once without changing his/her rating, the social effect still benefits the predictions. Correspondingly, the most powerful baseline, i.e., the SoRec achieves *precision* as **70.84** percent and *recall* as **89.78** percent. As mentioned in Introduction, usually users may hold multifaceted interests, thus simple constraints on all the interests might not be proper, which may degrade the performance with worse prediction.

5.3 Case Study

To better understand the performance, i.e., how the dynamic social influence affects the prediction, we randomly select four groups as examples to illustrate some interesting discoveries. Details about these four groups are listed in Table 5, in which the precision is also listed for clear comparison. In particular, two crucial issues should be focused: 1) who are influencers and who are influenced; 2) how the mutual social influence functions.

5.3.1 Participants of Social Influence

For the first issue, two types of potential attenders should be carefully observed, namely the event organizers (also "seed users" in social influence), and the new comers who are fresh to the group and causing the "cold-start" problem. We focus on these two types since the organizers are who mainly exert their influence, which determines the organization process of social event. On the contrary, the freshman who are most probably to be influenced, could be difficult to predict due to deficient profiles. Thus, situations of these two types may significantly impact the performance.

In the perspective of *organizers*, for the former two groups, namely A and B, we realize that at least 5 members have been organizers in each group, and for every event, usually there are at least 2 hosts, even up to 5. On the contrary, for the latter two groups who suffer relatively poor precision, we found that they have stable hosts, i.e., only one or two users act as hosts for all the events. As organizers are usually authoritative in the group, for Group C and D, though they are huge groups with hundreds of members, the limited "authority" nodes result in the limited social influence, and definitely interfere the prediction. In summary, a sufficient number of authoritative hosts could better aggregate the majority, and then support the prediction.

Meanwhile, in the perspective of *freshmen*, we find that almost all the groups suffer severe "cold-start" problem, i.e., former members quitting and new ones coming. Usually, higher ratio of freshmen causes problems in prediction. Interestingly, we find that though the ratio of freshmen for Group B reaches more than 50 percent, it still gained more than 94 percent precision. With deep looking into the data, we realized that for the events organized by Group B, nearly half of the attenders are active users, while the rest are all strongly connected to them. There is even a freshman who acts as the organizer directly, which is rarely found in other groups. This phenomenon implies that the strong social influence may help to overcome the "cold-start" problem, which also supports our hypothesis of social effects.

5.3.2 Affection of Negative Social Influence

For the second issue, we discuss about the function of mutual influence. Since the discussion above mainly describe the normal influence within organizers and participants, in this part, we will focus on the special type of social influence, i.e., those negative influences which indicate that the two users are usually conflicting. For the four groups here, we find that the former two groups with better performance contain almost 100 percent positive edges, while the Group C suffers 7 percent negative edges, and nearly 4 percent for D, which definitely increases the level of uncertainty.

This result might indicate that strongly connected community with common goal will lead to better prediction, while an intricate group, in which members are mutually conflicting, will be in confusion. It might also explain the high ratio of freshman and low level of activity, e.g., though Group C contains more than 1,000 members, most of members attend only 1-2 events. Moreover, for each event, there are only around 10 attenders, while the rest usually refuse to attend. It seems that for the groups, a smaller size leads to more intensive connection and more sufficient interaction, which is in accordance with the idea in [38].

5.4 Related Discussions

In this section, we will discuss some related issues of the general validations.

5.4.1 Discussion on Textual Pre-Processing

To provide a more comprehensive validation of our DSI framework, besides the classic LDA model, we attempt to evaluate its effectiveness on more textual pre-processing techniques. In this case, Labeled LDA [28] and Word2vec [24] are selected for comparison.

Specifically, for Labeled LDA, we treat the keywords of each user as one document, and the categories of events which he/she has attended as corresponding labels. Totally, we have 34 labels, corresponding to 34 categories defined by Meetup. Also, for Word2vec, we set the number of dimension as 30, and the size for BOW as 1, 3 and 5 separately.

The results are shown in Table 6, where the number after "W2V" indicates the size of BOW. According to the results, we realize that advanced techniques tend to perform better than LDA. For the comparison between LDA and Labeled

TABLE 6
Performance on Different NLP Techniques

	LDA	LLDA	W2V (1)	W2V (3)	W2V (5)
Precision	75.88	78.19	78.65	85.61	84.31
Recall	75.34	76.55	77.86	84.23	82.45

LDA, the reason may be that classic LDA may fail to summarize some cold topics, which degrades the performance. At the same time, the best size of BOW for Word2Vec is around 3, but not 1, which means that even intuitively independent keywords are still semantically connected.

5.4.2 Discussion on Similarity Metrics

Then, we discuss performance on different similarity metrics. Intuitively, *cosine metric* is usually selected to measure the similarity between two vectors. To further evaluate the effectiveness, two more commonly used metrics, namely the *euclidean distance* and *Gaussian probability* are selected.

The comparison is shown in Table 7, where the number after Gaussian indicates the variance. Particularly, 0.33 is selected since it is near 1/30 (number of vector dimension). Clearly, since euclidean distance could be similar with cosine (if the vector is normalized via 2-norm), their performance are quite near. On the contrary, we select Gaussian to keep consistent with the cost factor measuring, but the performance seem worse, which may be due to the difficulty to choose proper mean variance, and the unified variance might be inappropriate.

5.4.3 Discussion on Time-Varying Factors

As mentioned above, connections should be temporally updated to fit the real-time situation, which result in the "*time-varying*" factors. Specifically, we could introduce the concept of "*time window*", i.e., we train the latent social factors using samples only within a short period. For example, historical records in Monday are used to predict behaviors in Tuesday, and then records in Tuesday are for Wednesday. Along this line, a small time window could be used to approximate the real-time update.

To validate the effectiveness of "time-varying" factors, we divided our data set into 5 folds, and then trained the model with previous fold to test the next fold, e.g., training on first 20 percent of samples, and then evaluate on the next 20 percent, and so on. In general validations, we attempted to train the model based on 20 percent of training data, and then tested on the rest 80 percent, which achieved the precision as **61.94** percent. However, in "time-varying" validation, we achieved the precision as **67.47**$\pm$**2.95** percent. Clearly, "time-varying" factors improve the performance as fixed connections might be outdated. Similarly, on the validation with 3 folds, we achieved the precision as **68.79**$\pm$**4.21** percent, better than the general result as **63.32** percent,

TABLE 7
Performance on Different Metrics

	Cosine	Euc.	Gau. (0.05)	Gau. (0.033)
Precision	75.88	75.91	75.28	75.39
Recall	75.34	75.28	71.78	71.53

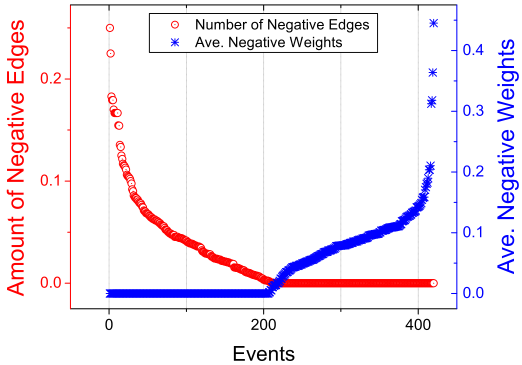

Fig. 7. Amount and average weights of negative edges for each group.

though not stable enough. In summary, "time-varying" factors truly help to improve the performance.

5.4.4 Discussion on Computational Cost

Afterwards, we discuss about the computational cost. Though social influence simulation is integrated, we still believe that it could apply to large-scale network. For the test stage, on the one hand, if there is no negative edges in the latent social network, we realize that the computational complexity is the same with *Linear Threshold* model [8], which could be fast enough for large-scale computation. On the other hand, even considering the negative edges, as shown in Fig. 7, usually we have less than 10 percent negative edges and relatively lower weights (lower than 0.1), thus they will not interfere a lot. Besides, for the training stage, which could be conducted offline and updated infrequently, the overall computational cost will be limited. Later in Section 6, we will conduct the network pruning to further improve the efficiency.

6 Evaluation on Efficiency Improvement with Network Pruning

Though in general the computational cost of our proposed DSI framework is limited, as discussed in Section 5.2.3. However, considering that there exist some huge communities with even thousands of users, the efficiency should be further improved. Thus, similar with [45], we introduce the *network pruning* method to control the computational cost.

6.1 Pruning Metrics

Intuitively, we assume that the influential users, i.e., those who may significantly affect others' decisions, will definitely rank in the top list following some social-based metrics. Correspondingly, if we filter the users based on several pre-set metrics, the time cost may be reduced, while the crucial users with significant influence will be kept. For the rest attenders, i.e., the freshmen or inactive users who are discussed in Pre-study in Section 2.2, since their interactions might be quite limited, their effects could be neglected without severely impair the performance.

Along this line, we conducted pruning validation on filtered data set with considering 90 to 50 percent users' influence, and the performance is shown in Fig. 8. Specifically, four metrics are discussed according to different aspects:

- *PageRank* [25]: The classic algorithm to measure the importance of nodes given the network structure,

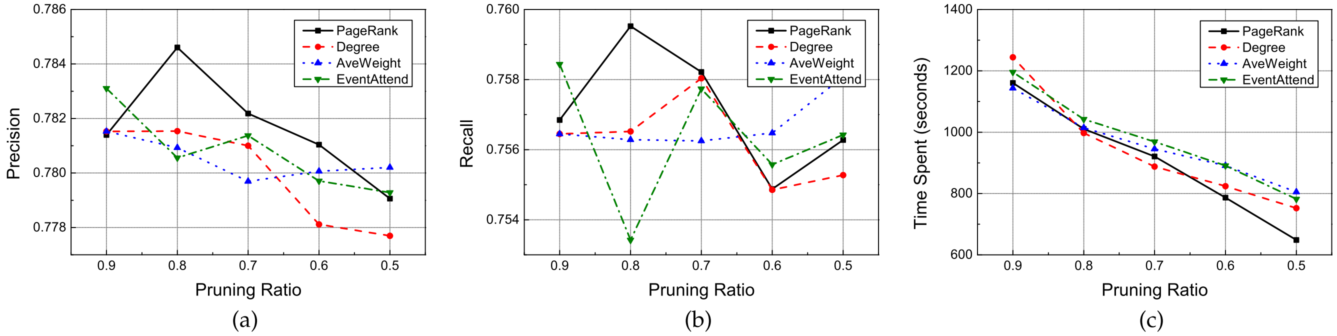

Fig. 8. The performance of network pruning for all the four metrics in three perspective: (a) Precision. (b) Recall. (c) Time.

which follows the assumption that the significance will spread via the connections.

- *Degree*: The heuristic algorithm to measure the centrality of nodes, which follows the assumption that the more connections lead to the stronger influence.
- *Average Weight* (abbr. *AveWeight*): The heuristic algorithm to measure the overall strength of connections, which follows the assumption that the stronger connections lead to the stronger influence.
- *Counts of Event Attended* (abbr. *EventAttend*): The heuristic algorithm to measure the enthusiasm, which follows the assumption that the more attendances indicate active users with stronger influence.

6.2 Validation and Discussion

The overall performance is shown in Fig. 8, including precision, recall and time cost under different settings. To be specific, the X-axis indicates the percentage of users who are remained, i.e., only 90 -50 percent of users could affect others' decisions, while for the rest users, they could only accept social influence, but will not influence the others.

What should be noted is that, the spent time here is indeed the total time cost for all the 422 groups including both training and test stage, with 90 percent training samples. For each group, it may take around 3 seconds without filtering, and around 1.5 seconds with 50 percent of users are filtered. Generally, the spent time is linearly decreasing, while the performance keeps relatively stable, which further prove the effectiveness and efficiency of our DSI framework.

According to the results, we realize that the *Degree* method always performs the worst, which may indicate that more connections may not lead to stronger impact, especially when majority of users are freshmen or inactive users. On the contrary, the *AveWeight* usually performs the best, as it focuses on the quality rather than only the quantity of connections, which definitely results in higher impact on decision-making process. Furthermore, performance of *PageRank* looks unstable. As *PageRank* measures the global influence in social network, performance is improved at the beginning since inactive users are removed. However, after that, some close friends with strong influence are deleted due to their limited global influence, which definitely degrades the performance.

Finally, some other rules could be discovered. First, some metrics lead to an increasing in 50 percent filtering. As freshmen or inactive users who may disturb the results are removed, the effects of social influence are even highlighted. Second, the ranking of time cost, which indicates how many connections are removed, is not the same with the performance ranking. This rule teaches us again that the quality, but not the quantity of link deletion decides the performance.

6.3 Case Study: How to Select Metric

As the overall performance under different metrics have been shown, in this section, we will continue our discussion with several case studies, to further reveal how to choose proper metric when facing to different situations.

Specifically, 9 groups are picked up for a comprehensive comparison, which are summarized in Table 8. In this table, 5 important statistical indexes are listed, including *amount of members*, *average attenders of each event*, *amount of connections*, *density of social graph*, and the *average strength of connections*. Besides, Table 8 also lists the precisions with all the four metrics, when the filtering ratio is *50 percent* with 90 percent samples for training. Since the trend of recall value is similar with the precision, here we omit the recall performance.

According to the summarization, we have revealed some detailed rules. First, for the *PageRank* metric, we can see it performs the best in the Group 1/2, but fail as the worst in

TABLE 8
Examples of Case Study for Network Pruning Performance

ID	Members	Ave. Attenders	Connections	Density	Ave. Weight	*EventAttend*	*PageRank*	*Degree*	*AveWeight*
Group 1	47	16	1,308	0.605	0.166	0.636	**0.727**	0.636	0.636
Group 2	141	22.43	13,790	0.699	0.158	0.683	**0.756**	0.609	0.683
Group 3	114	13.83	2,506	0.194	0.146	**0.750**	0.591	**0.750**	**0.750**
Group 4	289	10.3	7,828	0.09	0.152	**0.771**	0.723	**0.771**	0.762
Group 5	75	13.71	2,730	0.491	0.205	0.804	0.804	0.745	**0.823**
Group 6	90	11	1,323	0.165	0.191	0.653	0.735	0.653	**0.755**
Group 7	39	10.2	501	0.338	0.153	0.692	**0.846**	0.808	0.654
Group 8	52	7.5	166	0.063	0.098	0.667	0.667	**0.778**	0.667
Group 9	19	10.5	72	0.211	0.263	**1.000**	0.571	0.571	0.571

Group 3/4. Interestingly, Group 1 (short as G1) and G2 share the common grounds as they all have relatively higher *density*. Correspondingly, density of G3 and G4 are quite low. As mentioned above, the "*spread ability*" of PageRank in turn impair its performance. Correspondingly, in graph with higher density, members are directly mutual connected instead of indirectly linked via organizers. Thus, effects of direct influence will be more significant, which may lead to better performance of *PageRank*.

Second, the comparison between G5/6 and G7/8 has explained when *Degree* performs better than *AveWeight*. Obviously, higher weights are required to pick up those with stronger social influence, especially when there exist a huge number of connections, like in G5 and G6. In this situation, *AveWeight* could be better. On the contrary, when there are only limited connections with weak strength, *Degree* might be a better choice, at least it may indicate active users or "hub" to transfer information in the network.

Besides, it is interesting to find the *EventAttend* performs much better than all the other metrics in G9. With deep looking into this group, we realize that it is actually a small group which holds periodical gathering, and there exist only one stable organizer in this group. Thus, counts of attendance could measure the familiarity with other members, namely influence strength in this group. In summary, for the periodical gathering of small groups, the longer experience indicates higher position, i.e., stronger influence.

In summary, pruning metrics should be selected based on structure characteristics of given group. For instance, for small group with periodical gathering, "*EventAttend*" may be the best choice. On the contrary, if there is a large group with limited connections and weak strength, it will be better to choose "*Degree*" to reveal the hubs, who usually transfer information and affect others. Meanwhile, "*AveWeight*" fits the stronger connections, as influential nodes could be correctly revealed. Finally, dense graph, which indicates frequent connections, could be better analyzed by "*PageRank*", since close friends will be equally treated and wont be removed due to limited global influence.

7 Event Plan Design Applications

Based on our DSI framework, finally, we start to discuss about how to design a new event plan, i.e., to determine the event description according to different targets. Specifically, since we do not have direct ground truth to measure the performance, some indirect experiments and case studies were conducted to support our discussions.

7.1 Event Design with Targets

In the technical part of this paper, we design the objective function to reveal latent user profiles and social connections with given event description. Correspondingly, given the target user group, according to the different targets of event organizers, we could also design the objective function required to estimate the proper event topics, and then generate the event descriptions. For instance, if we hope to maximize the attendance expectation of certain user u, we could formulate the objective function as follow:

$$\arg\max_{\mathbf{a_e}} \; f_{u,e} - h_{u,e}, \tag{7}$$

Similarly, if we hope to attract as many attenders as possible, we could formulate as follow:

$$\arg\max_{\mathbf{a_e}} \sum_{u_i \in U_e} sign(f_{i,e} - h_{i,e}), \tag{8}$$

Some complicated objectives could be even designed. For instance, we could maximize the expectation or satisfaction of attenders, at the same time, control the number of attenders. To discuss the effectiveness of our solution, in this section, we will conduct several quantitative analysis on the target to *attract the most attenders*, i.e., the Equation (8) above. Since sign function is difficult to solve, similar with Section 3.2, we ease the objective function as follow:

$$\arg\max_{\mathbf{a_e}} \sum_{u_i \in U_e} \mathcal{I}(f_{i,e} - h_{i,e}), \tag{9}$$

To optimize this objective function, we also propose an iterative approach to approximate the final dynamic equilibrium, which is defined as follow:

$$T^t(U,e) = \sum_{u_i \in U_e} \mathcal{I}(f^t_{i,e} - h^t_{i,e}). \tag{10}$$

Along this line, the description vector $\mathbf{a}_e$ for the event e will be estimated. Since iteration process is quite similar with training stage of DSI, we omit the pseudo-code here.

7.2 Validation for Designed Event Attraction

As mentioned above, we do not have direct ground truth to measure the attraction. However, we intuitively assume that for one target group, the most popular events should share some common features. Thus, for indirect validation of event design, we compare the designed event plan with the existing events, and then select the most similar 5 events for approximation. For comparison, we select the Social Spread with preference, which treats the event design task as a social spread maximization problem on the target group. At the same time, in the perspective of group decision-making, we also select the simple voting strategy, or weighted voting based on different metrics. Specifically, four metrics mentioned in *network pruning* in Section 6.2, namely *PageRank*, *Degree*, *Ave.Weight* and *EventAttend*, are chosen to measure the weight of each voter.

Generally, we assume that if the designed event could be attractive for the target group, those similar events should also be popular, which means increasing attendance rate. Along this line, we measure the attendance rate, and corresponding improvement compared with the average. The results are summarized in Table 9. According to the results, we realize that our DSI framework designed the most attractive event, event improve the attendance rate. On the contrary, the Social Spread method still performs worse, which proves that preference-sensitive social influence might not be the adequate clue for event attendance. Besides, the voting-based heuristic methods achieve similar performance, which teaches us that delegate-voting on one-sided condition could not be reliable enough, so that boosting techniques are required.

7.3 Validation for Event Attendance Prediction

Finally, though we prove that the designed events are "similar" with highly-attractive events, it is still required to

TABLE 9
The Comparison of Most Similar Events for Attendance

	Improved	Average Margin
DSI	**13**	**+1.36%**
Social Spread	6	−4.35%
Voting	10	−0.44%
Voting + PageRank	10	−0.57%
Voting + Degree	10	−0.17%
Voting + Weight	9	−0.79%
Voting + Attendance	11	−0.64%

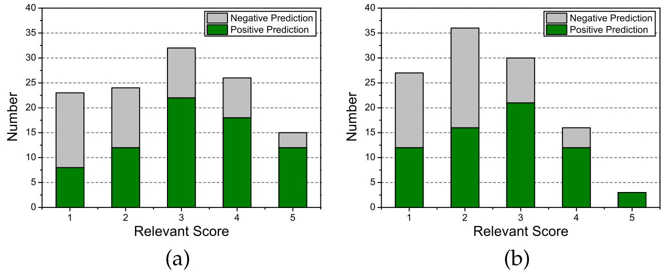

Fig. 9. Manually-labeling relevant score distribution for two cases.

measure the prediction effectiveness. Again, since we do not have exact records for validation, we conduct user study to evaluate the result. To be specific, we transfer the event attribute vector to the key words (terms) via utilizing the topic model. Then, given users' profiles and historic event attendance records, each target users are labeled by multiple volunteers with a score 1-5, in which 5 means highest positive intentions and 1 means the lowest. Two largest groups are selected for the user study, which are summarized in Fig. 9, where green parts denote those are predicted to attend (positive). Clearly, we can find that the positive predictions usually obtain higher relevant scores by experts, which ensures the effectiveness of our framework.

Unfortunately, there are still some users with high relevant scores are distinguished as absence. When we check these samples, we find most of them fill too many key words in their biology, e.g., 20 or even more words, which mislead the volunteers to believe that they hold diversified preference. However, their event records could hardly reflect the diversified preference. That might be parts of the reasons why high relevance leads to negative prediction.

8 Related Work

Generally, two types of social event analysis have been intensively studied in recent years, namely social event recommendation, and decision-making analysis. Specifically, some researchers focused on the conformity between users' profiles and event attributes. For example, [9] proposed a hybrid approach that is enriched with social influential features and user diversity model on decision making, [17] studied the offline ephemeral social networks to infer the latent preferences and social relations for ranking the recommended social events, and [15] proposed a combined CF model with considering multifaceted features of events. Furthermore, there are some related works focused on other practical problems. For example, [23] built the connections between events at different times by borrowing the feedback from past events to deal with the deficiency of explicit feedback, and [26] attempted to solve the cold-start problem of mobility via discovering the rule of popular events among the residents of an certain area. Finally, some researches did not directly focus on recommendation social events, but on the event-driven social groups. For example, [44] considered the geographical features, social features, and implicit patterns simultaneously in an unified model to achieve the recommendation of event-based groups, and [16] studied the event team formation with covering the required topic labels, as well as keep balance between social influence and communication cost. Besides, some studies target at planning social events and participants, e.g., [14] attempted to assign set of events for a group of users to attend via greedy-based algorithm, and [30] help user to plan the event participation dealing with spatio-temporal conflicts based on utility-aware solution.

Another related topic of this paper is the group-based recommendation, i.e., to recommend events to a social group but not individuals. Usually, previous works addressed this task mainly through the following two different directions. The first is to select a representative from the group, and then the representative will draw the overall conclusion. For example, [19] proposed a personal impact topic (PIT) model to enhance the group preference profile by considering the personal preferences and personal impacts of group members. Another direction is to achieve the agreement within group based on a certain consensus function. For example, [4] discussed about a group consensus function that captures the social, expertise, and interest dissimilarity among multiple group members. Indeed, some other factors might also be considered during the agreement process, e.g., [27] analyzed that how the personality of cooperation and trust could influence the group recommendation results, [1] discussed the monotonicity and efficiency for group recommendation, and [46] extract how the social opinions of majority, in terms of emotions, evolve when facing to external news.

In addition, although some works do not directly focus on the event participation problem, they still concentrate on some related topics. For instance, to simulate the social influence process in the data-driven perspective, [6] utilized the historical propagation traces to estimate the expected influence spread, and [21] discussed the spread behavior with considering temporal patterns. Along this line, [10] studied the potential information flow and proposed a new influence channel based approach for influence spread prediction, while [11] and [29] utilize this technique to estimate the location influence in LBSN. At the same time, [18] discussed about the individual influence to reveal the source of social attraction, and [36] further discussed the influence in the context-aware perspective. Some other studies maybe beneficial for modeling the influence spread process, e.g., [32] discussed the diversity of social influence, and [7] designed a general framework to distinguish those who spread the information but not activated. Also, [20] concerned about the comparison of social structure between online and offline social network, and [35] studied the spatial and temporal characteristics of event participation to reveal the group evolution for event organization. Some other works target at forming the proper group for social event maximal participation, such as [31] and [13]. Finally, some related work study the offline user behaviors in the perspective of *ephemeral social networks* (ESN), like [43] recommended offline geo-friends based on pattern-based heterogeneous information network analysis, and [42] discussed about the "social learning" mechanism between taxi drivers via ephemeral social networks.

9 Conclusion

In this paper, we investigated how to exploit the dynamic mutual influence for enhancing the prediction of social event participation. A unique characteristic of our method is that the social influence is integrated into the threshold calculation for the discriminant function, which reflects the dynamic mutual dependence within friends for event participation. Specifically, we designed a variant two-stage discriminant framework to capture both users' preferences and their latent social connections. General validations on the real-world offline event logs showed that our method could effectively predict the participation with a significant margin compared with several state-of-the-art baselines. Furthermore, validations on efficiency improvement with network pruning, as well as event design applications have been conducted. These results prove the importance of dynamic mutual influence which not only affects the user preferences, but also directly affects the decision-making process of event participation.

In the future, we would like to exploit more applications of the proposed method and develop the techniques to combine more types of social constraints into the learning framework. Furthermore, we will attempt to adapt our DSI framework by integrating more comprehensive characteristics and data sources.

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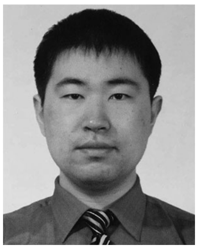

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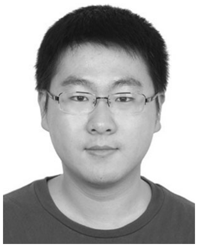

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