Exploring the Choice Under Conflict for Social Event Participation

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Abstract. Recent years have witnessed the booming of *event driven SNS*, which allow cyber strangers to get connected in physical world. This new business model imposes challenges for event organizers to draw event plan and predict attendance. Intuitively, these services rely on the accurate estimation of users' preferences. However, due to various motivation of historical participation(i.e. attendance may not definitely indicate interests), traditional recommender techniques may fail to reveal the reliable user profiles. At the same time, motivated by the phenomenon that user may face to *conflict of invitation* (i.e. multiple invitations received simultaneously, in which only a few could be accepted), we realize that these choices may reflect real preference. Along this line, in this paper, we develop a novel conflict-choice-based model to reconstruct the decision-making process of users when facing to conflict. To be specific, in the perspective of *utility* in choice model, we formulate users' tendency with integrating content, social and cost-based factors, thus topical interests as well as latent social interactions could be both captured. Furthermore, we transfer the choice of conflict-choice triples into the pairwise ranking task, and a learning-to-rank based optimization scheme is introduced to solve the problem. Comprehensive experiments on real-world data set show that our framework could outperform the state-of-the-art baselines with significant margin, which validates the hypothesis that conflict and choice could better explain user's real preference.

Keywords: Choice model · Conflict-Choice triples · Social event · Social network

1 Introduction

Nowadays, it is commonly seen that an offline social event is organized through online social network services (SNS), in this way cyber and physical world could be connected as online strangers will now communicate face-to-face in real world. Thanks to the highly interactive experience, this new business model has become popular and attractive for millions of users all around the world, e.g., more than 9,000 groups organize new event in local communities every day at Meetup.com[1].

[1] http://www.meetup.com/.

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This phenomenon raises new challenges for group leaders or event organizers to draw the event plan and predict the attendance, and intuitively, these analyses rely on the accurate estimation of users' preferences. Though a large amount of efforts have been made on summarizing users' historic participation, which follows the basic assumption that attendance may indicate preference. However, they may fail to describe the various motivations of users, e.g., people may attend some events only for killing leisure time, but it doesn't necessarily mean they indeed enjoy these events. Thus, new approach considering more comprehensive factors for user profiling is urgently required.

When analyzing historical event participation records, we realize that users may face to the situation of *invitation conflicts*, i.e., sometimes people may receive multiple invitation simultaneously, however, owing to the limitation, they could only select parts of them, while the rest should be rejected. Intuitively, these final decisions among conflicting invitations may better reflect users' real preference, e.g., from Meetup.com we found a programmer chose to attend a single party just on the same day with periodic iOS developing discussion, which indicates that he may be more inclined to attend such social activities. Indeed, the above example might not be occasional, and similar phenomenon could also be found in many other fields, like the alternative list in online shopping platform [10], or rating one another as "hot or not" in Facemash.com [16]. Motivated by this phenomenon, if we could precisely extract and analyze these **Conflict-Choice Triples**, i.e., pairwise conflicting choices (invitations) to be selected for one user, we could better understand users' real preference, and then effectively support related application, e.g., prediction or recommendation task.

Along this line, in this paper, we develop a novel conflict-choice-based model to reconstruct the decision-making process of users when facing pairwise invitations. To be specific, following the basic idea of choice model [18], we formulate users' tendency in the perspective of *utility* [20] with integrating users' preferences of event topics, social interaction and cost factors, thus comprehensive impacts have been captured. Furthermore, we transfer the choice of conflict-choice triples into the pairwise ranking task, thus a learning-to-rank based optimization scheme is introduced to learn users' preference. To the best of our knowledge, we are the first to discuss conflicting choice phenomenon in social event participation analysis and introduce the perspective of choice modeling for user profiling.

We conduct comprehensive experiments on real-world data set. The results show that our framework could outperform the state-of-the-art baselines with significant margin. Furthermore, to ensure the robustness and computational efficiency of our framework, we conduct parameter sensitiveness experiments and design an algorithm for optimizing model training time, which outcomes validate the hypothesis that conflicting choice could better explain user's real preference, and also confirm the application potential of our framework on social event participation analysis.

2 Conflict-Choices Model Formulation and Framework

In this section, we will introduce our novel conflict-choice-based model to reconstruct the decision-making process. According to our assumption, final decisions on conflicting choice triples could indicate users' real preference. Along this line, we first formally define the conflicting choice problem with related preliminaries, then, the conflict-choices model will be proposed with detailed technical solution. Finally, the two-stage framework will be illustrated.

2.1 Problem Statement

In this paper, we focus on the choice under conflicting invitation, which may indicate users' real preference. Specifically, we define and extract *Conflict-Choice Triples (CCT)* as follows:

Definition 1 (Conflict-Choice Triples (CCT)). *We define two events with corresponding user as a CCT if only when the following two conditions are satisfied simultaneously: (1) two invitation have been received within $\mathcal{T}$ days, and (2) two social events will be held within $\mathcal{T}$ days, where $\mathcal{T}$ is the periodic threshold to filter the triples. Finally, all the CCTs for a target user $\mathbf{u}$ is defined as $\mathbf{R_u}$.*

Intuitively, users' real preference could be reflected by the contrast between every event-pair from $\mathbf{R_u}$. To measure the contrast, we introduce the perspective of **Choice Utility** from *choice model*, then the problem of event participation can be defined as follows:

Definition 2 (Problem Statement). *Given a target user $\mathbf{u}$ and the set of $\mathbf{u}$'s conflict-choice triples $\mathbf{R_u} = \{r_i\}$, in which we use choice utility P_{u,e_k} to measure $\mathbf{u}$'s preference for each event $e_k \in r_i$. The problem of events participation prediction is to learn $\mathbf{u}$'s real preference by the contrast between pairwise events' choice utility from $\mathbf{R_u}$, and then utilize the real preference to analyse $\mathbf{u}$'s future participation decisions.*

In this paper, the choice utility P_{u,e_k} consists of *content-based utility* C_{u,e_k}, *social-based utility* S_{u,e_k} and *cost-based utility* D_{u,e_k}, the technical details of which will be introduced in Sect. 3.1. To define the notation of social connections, we construct social networks in which w_{uv} indicates the social influence strength from user u to user v. What should be noted is that the social influence strength w_{uv} will be trained in modeling. To describe topics distribution for each user, we exploit a vector $\mathbf{t}_u$ that will be learnt in training stage to indicate the preferences of user u, in which each dimension denotes the preference level on a specific aspect. Correspondingly, we have a vector $\mathbf{a}_k$ for each event e_k to indicate the attributes distribution, in which each dimension reflects the attribute on a specific aspect corresponding to $\mathbf{t}_u$. The mathematical notations used throughout this paper are summarized in Table 1.

Table 1. Mathematical Notations.

Symbol	Description
$\mathbf{u}$	the target user
$\mathcal{T}$	the periodic threshold
$\mathbf{E} = \{e_k\}$	the set of events
$\mathbf{R_u} = \{r_i\}$	the set of u's conflict-choice triple
$\mathbf{N_u}$	the set of u's total neighbors in the network
$\mathbf{N_{u,k}}$	the set of u's neighbors in e_k
$\mathbf{t_u}$	the profile vector for u
$\mathbf{a_k}$	the attributes vector for e_k
w_{uv}	social connection strength from user u to user v
C_{u,e_k}	u's content-based utility for e_k
S_{u,e_k}	u's social-based utility for e_k
D_{u,e_k}	u's cost-based utility for e_k
P_{u,e_k}	u's choice utility for e_k

2.2 Loss Function for Conflicting Choices

Now we turn to formulate the events participation prediction task. As mentioned above, the contrast between pairwise events' choice utility could reveal the actual preference of users, thus, we could intuitively treat this decision-making process as a pairwise ranking problem, i.e., rank the utility of two events in each conflicting event-pair. More specifically, we assume that users choosing one event of the conflicting event-pair is due to the pairwise ranking of *choice utility*, i.e., $P_{u,e_y} > P_{u,e_n}$. With the assumption above, we realize that correcting the partial ordering relation of *choice utility* in conflicting event-pairs will lead to optimal ranking results. Thus, the task of learning *choice utility* will be summarized as a pairwise ranking problem as follows:

Ranking Objective. By correcting the partial ordering relation of *choice utility* in conflicting event-pairs, we will get the appropriate *choice utility* P_{u,e_k}. To deal with this task, we formulate the loss function of pairwise ranking problem as follows:

$$\min_{w,\mathbf{t_u}} F(w, \mathbf{t_u}) = \sum_{r_i \in R_u} \sum_{e_y, e_n \in r_i} h(P_{u,e_n} - P_{u,e_y}), \tag{1}$$

where $h(x)$ is a loss function to assign a non-negative penalty according to the difference of choice utility $P_{u,e_n} - P_{u,e_y}$. Usually, we have the penalty $h(x) = 0$ when $P_{u,e_n} \leq P_{u,e_y}$. While for $P_{u,e_n} > P_{u,e_y}$, we have $h(x) > 0$ as loss. To ease the computation, here we utilize the squared loss function as follow:

$$h(x) = \max\{x, \varepsilon\}^2, \tag{2}$$

where ε presents the margin allowed for choice utility loss. To ensure accuracy of the results we set $\varepsilon = 0$, so $h(x)$ could also be rewrote as:

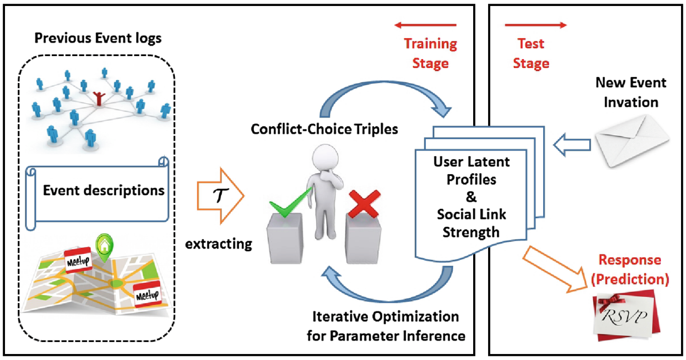

Fig. 1. Overview of our framework for event participation prediction.

$$\sum_{e_y, e_n \in r_i} h(P_{u,e_n} - P_{u,e_y}) = \sum_{e_y, e_n : P_{u,e_n} > P_{u,e_y}} (P_{u,e_n} - P_{u,e_y})^2. \tag{3}$$

With this formulation, we could optimize the loss function to estimate social connection strength w_{uv} and users' profile vector $\mathbf{t_u}$. Simultaneously, such training stage would highlight the difference between the two events, which may be the real preference contributing to the final choice.

2.3 Two-Stage Framework

Based on the above preliminaries, now we can formally present the overview of the two-stage framework for event participation prediction. Specifically, Fig. 1 demonstrates the overview of our framework.

Training Stage. Given a target user $\mathbf{u}$ and his/her historical events $\mathbf{E_{train}} = \{e_k\}$, in which participation record (attendance/absence) sorted by time for each e_k are pre-known, so we could extract the set of u's conflict-choice triple, namely $\mathbf{R_u}$. Also, we have the event attributes $\mathbf{a}_k$ for each e_k and the connection between $\mathbf{u}$ and his/her neighbors, while the strength $\{w_{uv}\}$ are unknown. In this stage, we aim at inferring the choice utility P_{u,e_k} for each e_k of u, as well as learning the connections strength $\{w_{uv}\}$ and users' profile vector $\mathbf{t_u}$.

Test Stage. After obtaining the social connections strength $\{w_{uv}\}$ and users' profile vector $\mathbf{t_u}$ in the training stage, in the test stage, given a target user and a set of event $\mathbf{E_{test}}$ with attributes $\mathbf{a}_k$ and the corresponding social network neighbors, we aim at predicting event participation for all e_k in $\mathbf{E_{test}}$.

3 Technical Details for Prediction of Event Participation

In this section, we introduce the technical details for event participation prediction, including the detailed technical solutions for choice utility and optimization task of our framework.

3.1 Choice Utility

Here, we first introduce how to simulate a user's choice utility to an event. Intuitively, the user's choice utility should be the combination of *content-based utility* (C_{u,e_k}), *social-based utility* (S_{u,e_k}) and *cost-based utility* (D_{u,e_k}), so we choose to multiply them to formulate the user's choice utility in decision-making process. To be specific, the choice utility of $\mathbf{u}$ to e_k will be estimated as follows:

$$P_{u,e_k} = C_{u,e_k} \cdot S_{u,e_k} \cdot D_{u,e_k}. \tag{4}$$

What should be noted is that we have not set weight for each factor, but in fact the weight for each factor would redistribute spontaneously during the parameters learning in the training stage of our framework.

Content-Based Utility. Intuitively, event's description is usually an important factor of users to attend an event or not. To measure users' tendency to the events' topic, we borrow the classic *Cosine similarity* between user profile vector and event description vector to indicate the content-based utility, as users' biography and events' descriptions could be easily normalized and presented in vectors. To be specific, content-based utility will be estimated as follows:

$$C_{u,e_k} = cosine(\mathbf{t_u}, \mathbf{a_k}) = \frac{\mathbf{t_u} \bullet \mathbf{a_k}}{\|\mathbf{t_u}\|\|\mathbf{a_k}\|}, \tag{5}$$

where $\mathbf{t_u}$ is the profile vector for u that will be learnt in training stage and $\mathbf{a_k}$ is the attributes vector for e_k learnt by LDA model in our framework.

Social-Based Utility. Second, the "word-of-mouth" effect is verified that could strongly affect the decision-making process of social event participation, and at least 10 %–30 % of human movement could be explained by social factors [5,22,23]. So it is reasonable to investigate the social impact on social event participation, and further, the effects during conflicting choice process. To formulate the encouragement, we borrow and adapt the classic Independent Cascade (IC) model [8] for simulating the interactional influence within users, which is widely used and its effectiveness has been well proved. To be specific, *social-based utility* will be estimated as follows:

$$S_{u,e_k} = 1 - \prod_{v \in N_{u,k}} (1 - w_{vu}), \tag{6}$$

where $\mathbf{N_{u,k}}$ is the set of neighbors of $\mathbf{u}$ who attend e_k.

Cost-Based Utility. Finally, the experimental results in [11,21] inspire us to study the influence of *cost-based utility* on an individual user's event participation prediction. We apply a general nonparametric technique, known as the kernel density estimation [17] (KDE), which is widely used to estimate a probability density function of an unknown variable based on a known sample. In our case, X_u is the known sample and y is denoted as the unknown variable. The probability density function of variable y using sample X_u is given by:

$$D_{u,e_k} = \frac{1}{|X_u|\sigma} \sum_{x \in X_u} K(\frac{y-x}{\sigma}), \tag{7}$$

where $|X_u|$ is the number of sample points in X_u, σ is a smoothing parameter called bandwidth and $K(\cdot)$ is the kernel function. To ease the modeling, we apply the normal kernel, which has been widely used in related studies.

3.2 Optimization Task

As all the formulations established, finally we could discuss about the optimization task of loss function Eq. 1. To be specific, we first approach the social connection strength w by deriving the gradient of $F(\cdot)$ with respect to w_{uv} and approach the users' profile vector $\mathbf{t_u}$ by deriving the gradient of $F(\cdot)$ with respect to t_u^m, and then use a gradient based optimization method to find proper w and $\mathbf{t_u}$ that minimize $F(\cdot)$. Specially, as defining $\gamma_{e_n e_y} = P_{u,e_n} - P_{u,e_y}$, then we have the derivative as follow:

$$\frac{\partial F(w, \mathbf{t_u})}{\partial w_{vu}} = \sum_{e_y, e_n : P_{u,e_n} > P_{u,e_y}} \frac{\partial h(\gamma_{e_n e_y})}{\partial \gamma_{e_n e_y}} (\frac{\partial P_{u,e_n}}{\partial w_{vu}} - \frac{\partial P_{u,e_y}}{\partial w_{vu}}), \tag{8}$$

$$\frac{\partial F(w, \mathbf{t_u})}{\partial t_u^m} = \sum_{e_y, e_n : P_{u,e_n} > P_{u,e_y}} \frac{\partial h(\gamma_{e_n e_y})}{\partial \gamma_{e_n e_y}} (\frac{\partial P_{u,e_n}}{\partial t_u^m} - \frac{\partial P_{u,e_y}}{\partial t_u^m}), \tag{9}$$

where t_u^m is the mth dimension of $\mathbf{t_u}$ and $h'(\gamma_{e_n e_y})$ could be easily achieved as derivation of square function:

$$\frac{\partial h(\gamma_{e_n e_y})}{\partial \gamma_{e_n e_y}} = 2 \cdot (P_{u,e_n} - P_{u,e_y}). \tag{10}$$

For the social connection strength w and users' profile vector $\mathbf{t_u}$, we have:

$$\frac{\partial P_{u,e_k}}{\partial w_{vu}} = C_{u,e_k} \cdot \prod_{x \in N_{u,k}, x \neq v} (1 - w_{xu}) \cdot D_{u,e_k}, \tag{11}$$

$$\frac{\partial P_{u,e_k}}{\partial t_u^m} = \frac{a_k^m \cdot \|\mathbf{t_u}\|^2 - t_u^m \cdot \mathbf{t_u} \bullet \mathbf{a_k}}{\|\mathbf{t_u}\|^3 \|\mathbf{a_k}\|} \cdot S_{u,e_k} \cdot D_{u,e_k}, \tag{12}$$

where after each iterative round $\mathbf{t_u}$ will be normalized. To deal with the optimization task, the gradient descent methods could be exploited.

4 Experiments and Discussions

To verify our hypothesis that the choice utility affects the decision making process of potential event participants, in this section, we conduct experiments on a real-world data set to measure the event participation predicting performance with conflict-choice model. Furthermore, some representative case studies and discussion will be presented.

4.1 Experimental Setup

Data Set Pre-processing. Our experiments were conducted on the real-world data set crawled via official APIs of Meetup.com. Specially, we crawled event logs totally includes 625 groups, 50,719 social events and 99,854 related users. For details, event descriptions (e.g., location and time), participation records (attendance/absence) and user profiles are extracted.

To describe the events' attributes, we exploited the key words in the group descriptions and user profiles. 2,856 key words (or terms) with unique ID (defined by Meetup) were collected in the dictionary in total, and Latent Dirichlet Allocation (LDA) model [2] was introduced to learn the topics. Specifically, we select 20 latent topics, as Meetup system defines 34 categories of events, and majority of events focus on around 20 types which is reflected by the data set. Finally, all descriptions are presented as a 20-dimensional attribute vectors.

In offline social event scenario, we intuitively assume the distance between user's home and event location as a geographical cost factor. What should be noted is that *cost-based utility* has the potential of integrating more cost factors, e.g., weather and road condition information, by introducing multivariate kernel density estimator.

Evaluation Baselines. For more comprehensive comparisons, several state-of-the-art baselines based on different assumption are selected as follows.

(1) **Discrete Choice Model (DCM)** [20]. Discrete Choice Model (DCM) is used to predict choices between multiple discrete alternatives in economics. We utilize the DCM method as baseline, which integrates the same content and cost factors, while we utilize the number of co-occurrence members as social feature.
(2) **RankNet (RKN)** [3]. RankNet is a widely used pairwise learning-to-rank (LTR) algorithm using neural network to model underlying ranking function, which utilizes gradient descent methods for learning ranking probabilistic cost functions. As our conflict-choice model is intrinsically a pairwise ranking problem, we use RankNet as a baseline, in which we use same features with **DCM**.
(3) **LambdaMART (LAM)** [4]. LambdaMART is the boosted tree version of LambdaRank, which defines the gradient of the loss function in order to solve the problem that sorting loss function could hardly be optimized. We select it as baseline since it is among the best learning-to-rank (LTR) algorithms, in which we use same features with **DCM**.
(4) **Information Spreading** [8]. As we try to reveal latent social interactions to describe users' real preference in conflicting choices, to better validate this assumption, we conduct social-spread-based model to study whether attendance is indeed the result of "word-of-mouth" effect. Since Meetup.com ignores point-to-point connection, we construct the social connections following the common used heuristic method like in [11] that edges could be added if two people have attended the same event, and two widely studied heuristic methods are selected to set the connection strength w_{uv} as

Table 2. Overall performance of each approach.

	CCT	DCM	RKN	LAM	ISO	ISN
MAP	**0.8513**	0.7683	0.8069	0.8299	0.6980	0.6699
Improvement(%)	-	10.788	5.5003	2.5826	21.968	27.066
P-Value	-	0.0000	0.0091	0.0387	0.0000	0.0000
F1 score	**0.8016**	0.7530	0.6885	0.7050	0.6249	0.5996
Improvement(%)	-	6.4542	17.873	15.130	29.859	35.283
P-Value	-	0.0000	0.0000	0.0000	0.0000	0.0000

(1) the co-occurrence frequency (**ISO**), and (2) the Jaccard Index of common neighbors **(ISN)**. Then, classic Independent Cascade (IC) model [8] will be conducted to simulate the spread process. To ensure the stable results, we repeat experiments for 500 times for each test.

4.2 Experiment Results

Due to the group-based scheme of Meetup, we treat *user-group pair* as the unit of our experiments. To be specific, for one target user in a target group, we will conduct a set of experiments, and the average results are presented as the finals.

Since we face to the severe sparse data that only less than 20 % users attended at least 5 events in a group, we assign 80 % events within one group as training samples to ensure the quality of training, while the rest 20 % are test samples. The samples are processed in time order to keep the rule of social group evolution.

As mentioned in test stage, to predict the participation, we indeed have two tasks, i.e., ranking the attendance probability with respect to their choice utility and then binary classifying to distinguish attendance/absence of participation. For each task, related metrics will be selected to measure the performance. For the ranking task, similar with the state-of-the-art learn to rank problems, **MAP** [19] is selected. For the binary classification task, typically, we select the common used **F1 score** for validation, which is a measure that combines precision and recall, namely the harmonic mean of precision and recall.

Comparison of Overall Performance. First of all, we show the overall prediction performance of our approach comparing with different baselines and the results are shown in Table 2. According to the results, we can find that our approach outperforms the other baselines with dramatic margin in **MAP** and **F1 score**, even 35 % better in some experiments. The performance highly supports our assumption that with introducing the conflicting choice utility, we could better estimate the event participation.

As expected, DCM methods performs better for binary classification, while RKN and LAM methods performs better in ranking task, which is determined by the algorithm internal mechanism. At the same time, it seems that the overall results of the DCM, RKN and LAM methods are worse than CCT. These baseline methods just make use of some statistics metrics, i.e., $|\mathbf{N_{u,k}}|$ and distance, but ignore the latent social interactions as well as probability density function of cost factors. Further, users' profile vector $\mathbf{t_u}$ are learned by LDA for these three baseline methods, which might not be enough because most people would not record all their interests in the home page. However we could train $\mathbf{t_u}$ in our CCT framework, which might be another reason.

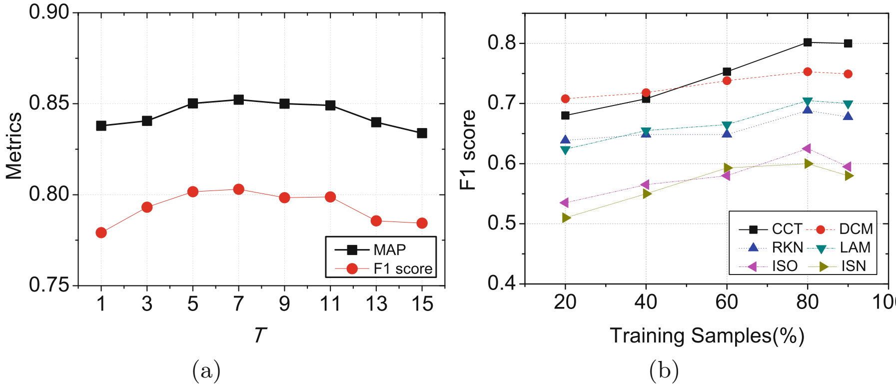

Fig. 2. Parameter Sensitiveness. (a) Prediction performance with different $\mathcal{T}$ (b) Prediction F1 score with different partition of training samples.

Finally, we surprisingly find that the baseline with information spreading methods, i.e., ISO and ISN, achieves the worst performance. Indeed, though preference factors are integrated between pairwise users, the information spreading methods still follows the essentially different assumption with the other three algorithms. Specifically, information spreading methods assumes the participation is mainly affected by the friends or opinion leaders' spread but not their own preference, which might not be reasonable enough. Information spreading methods ignoring *content-based utility* might be another reason. Also, the cold-start problem, which leads to insufficient pairwise interactions and sparse social network, may further impair the performance.

Evaluation on Parameter Sensitiveness. As the performance has been validated, in this subsection, we conduct the experiments for evaluating the parameter sensitiveness of our approach. In this task, there are two parameters concerned in our approach, i.e., the *periodic threshold* $\mathcal{T}$, as well as the sample allocation ratio.

For the *periodic threshold* $\mathcal{T}$, as mentioned in Sect. 2.1, we utilize $\mathcal{T}$ to describe the conflicting choice situation, thus a lower $\mathcal{T}$ might be better for approximation, because users face to sharper conflicting events. However, as Fig. 2(a) shows that performance achieves the peak when $\mathcal{T}$ is around 7 to 10 days, but not the lower the better. The reason of this phenomenon not only might be lower $\mathcal{T}$ restricts the number of conflict choice triples that covers user actual utility, but also might be the persistence of users' preference, namely users would not change their preference significantly in a short time. So even when they do not face to very sharp conflict-choice events, they also prefer to attend the events with high choice utility but reject the events with low choice utility. And this phenomenon might further indicate that most active users attend events not more than once a week.

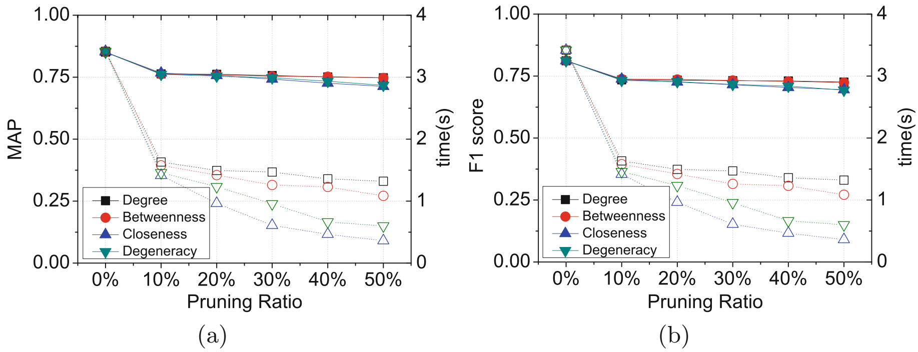

Fig. 3. Performance of Network Pruning. (a) MAP (b) F1 score.

Then, we discuss about whether the partition of training samples will influence the results, which is summarized in Fig. 2(b). We find that our framework performance improves rapidly when the partition of training samples increases, which indicates that our model is sensitive to the number of training triples. The reasons might be that we aim at predicting the events participation using social connections strength, thus it is required that most important connections strength have been trained. The methods that depend on connections strength, i.e., ISO and ISN, are sensitive to the train samples ratio for the same reason, too. On the contrary, the DCM, RKN and LAM methods keep in stable level during the train samples ratio change, since they just make use of some social statistics metrics.

Network Pruning to Optimize Training Time. As mentioned in Sect. 3.2, we use gradient descent methods to deal with the optimization task in model training stage. Specifically, we approach the social connection strength w_{uv} by first deriving the gradient of $F(\cdot)$ with respect to w_{uv}, and then use a gradient based optimization method to find proper w that minimize $F(\cdot)$, which is a time-consuming process, because the loss function iterates rounds to convergence and traverses all the connections in every round.

It is common to see that a user would not recognize all the members of every event she/he has ever attended, and the inactive neighbors of social network,

Table 3. Examples for Case Study

Precision	Sample A		Sample B		Sample C		Sample D	
	100 %		100 %		100 %		55 %	
Participation	Attend	Absent	Attend	Absent	Attend	Absent	Attend	Absent
Topic Sim	0.388	0.193	0.351	0.407	0.702	0.766	0.791	0.818
Members	16.50	17.50	7.750	2.750	11.57	11.67	51.25	45.22
Distance	5.376	5.381	11.06	10.98	1.889	5.112	18.56	11.42

such as freshers or social inactive members, are usually useless in the prediction process. So we design an algorithm for optimizing model training time by deleting the inactive neighbors of the social network. More specifically, we choose some appropriate metrics to ranking nodes in the social network, and then prune the marginal nodes. In network analysis, metrics of centrality identify the most influential persons in a social network, so we use some centrality metrics to simplify the social network by pruning nodes performing worse centrality. Here we select the widely used centrality metrics such as Degree, Betweenness, Closeness and Degeneracy centrality [1,7,14,15].

Finally, we discuss about whether the network pruning algorithm will significantly decrease the train time and how it influences the participation prediction, which is summarized in Fig. 3, in which solid symbols with solid line mean prediction performance, while hollow symbols with imaginary line mean training time. To be fair, the train time of network simplification algorithm is the sum of sorting nodes time and model training time. From the figure, we can clearly find that social network pruning could successfully improve the efficiency, while at the same time maintain relatively acceptable accuracy. And prediction performance does not degenerate when further simplify the network, the reason is that usually the actual important friends of a user are not much. Besides, we find that Closeness centrality preforms most significantly in improving efficiency.

4.3 Case Study

To better understand the performance, i.e., how the conflicting choice could reveal users' real preference, we randomly select four users as examples. Correspondingly, related social metrics of their attendance/absentee are listed. Details are shown in Table 3. Two key issues should be studied here: (1) whether conflict-choice-based model keeps working well for users with different types of utility, and (2) how the social-based utility could be summarized.

For the first issue, three types of potential participators should be carefully observed, namely the users who pay more attention to the three kinds of factors respectively. For the former three users, namely user A, B and C, we realize that user A pay more attention to content-based factors because this user prefer to attend events with higher topic similarity, and user B is a sociable user who chooses to attend events which more people attend, while user C is more likely to attend the nearby events. Besides, we find that these three typical users' participation prediction precision are 100 %, which is an intuitional evidence that our conflict-choice model is widely available.

On the contrary, for Sample D who suffers poor precision, we find that the group usually host large-scale events. With deep looking into the data, we realized that this group suffer "cold-start" problem, i.e., former members quitting and new ones coming, so social connection strength learned in training stage could not be used in participation prediction process. This phenomenon implies that stable group with strongly connections will lead to better prediction, which also supports our hypothesis of social effects.

Secondly, we discuss about the type of social-based influence. In our analysis, we set the reciprocal of attenders' amount as threshold, i.e., if connection strength passes the threshold, we treat the neighbor as "*close friend*". We find two typically types of social-based influence, i.e., authority influence and group influence. Authority influence is the phenomenon that the target user is mostly influenced by one active member, such as event organizer. Group influence is the phenomenon that the target user is influenced by a group of people, e.g., we find a user and his 9 friends form to small community in the group, members in this community prefer to attend events with each other.

Finally, we discuss the derivative application of case studying. By illustrating the representative users above, we could find some typical patterns of all the users and events organizers can attract the right attendants and predict the attendance according to it. For instance, for users in a small community of the group, if a certain proportion members in the community accept the RSVP, we recognize that the rest of members in the community prefer to attend the event. By introducing such rules above, we could decrease predicting process time and revise the prediction results.

5 Related Work

In this section, we briefly introduce the related works of our study. In general, the related works can be mainly grouped into two categories.

The first category related to this paper is the social event recommendation, which is different with the traditional items recommendation. Specifically, some researchers focused on the conformity between users' profiles and event attributes. For example, [9] proposed a hybrid event recommender that is enriched with linked open data and content information. Furthermore, a method for recommendation by collaborative ranking of future events based on users' preferences for past events is describe in [13]. And some works focus on recommendation to a group of members, [12] proposed a personal impact topic model to enhance the group preference profile by considering the personal preferences and personal impacts of group members. Finally, there are some related works focused on other practical problems. For example, a smartphone application developed by [6] recommend events according to the users Facebook profiles.

The second category is about conflicting choice utility. In this paper, we deeply analyze events participation prediction with considering conflict choice and choice utility. Indeed, plenty efforts have been made on understanding choice model which usually predict choices between two or more discrete alternatives [18] and have been widely examined in many fields, e.g., in economics peoples choose which product to buy in online shopping platform [10]. The other topic closely related to this category is choice utility, which is a representation of preference over a set of alternatives [20]. Choice utility also usually be introduced to model the situation that users face to competitive choice, e.g., authors explored the conflicting choosing process of user behavior when facing with recommendations by adopting utility theory in [24]. However, although the works mentioned above can reappear the process of people choosing and making decision, they still may suffer some defects due to they ignore the mutual influences among people.

6 Conclusion

In this paper, we investigate how people make decisions when facing to conflicting invitations, which may reflect users' real preference. Following this assumption, we propose a novel conflict-choice-based model for better reconstructing users' decision. To be specific, we formulate users' tendency with integrating content-based utility, social-based utility and cost-based utility in the perspective of choice utility, and then transfer the choice of conflict-choice triples into the pairwise ranking task to learn the model, thus the optimization goal is formulated and solved as a ranking-based loss function. At the same time, the latent social interactions within potential attenders and their topical interests will also be revealed. Comprehensive experiments on real-world data set show that our framework could outperform the state-of-the-art baselines with significant margin, which validates the hypothesis that conflict and choice could better explain user's real preference.

Though significant performance has been achieved, as the social parameters learned might be rough to reveal latent interactions, in the future, we will target at designing more complicated scheme to describe the social-based utility, especially to extend the point-to-point interaction to the superimposed effect of multiple attenders or even little community. Also, we would like to exploit more applications of the proposed method instead of only social event participation analysis, which may further validates the applicable potential of our novel framework.

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