Understanding Event Organization at Scale in Event-Based Social Networks

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Understanding real-world event participation behavior has been a subject of active research and can offer valuable insights for event-related recommendation and advertisement. The emergence of event-based social networks (EBSNs), which attracts online users to host/attend offline events, has enabled exciting new research in this domain. However, most existing works focus on understanding or predicting individual users' event participation behavior or recommending events to individual users. Few studies have addressed the problem of event popularity from the event organizer's point of view.

In this work, we study the latent factors for determining event popularity using large-scale datasets collected from the popular Meetup.com EBSN in five major cities around the world. We analyze and model four contextual factors: spatial factor using location convenience, quality, popularity density, and competitiveness; group factor using group member entropy and loyalty; temporal factor using temporal preference and weekly event patterns; and semantic factor using readability, sentiment, part of speech, and text novelty. In addition, we have developed a group-based social influence propagation network to model group-specific influences on events. By combining the COntextual features and Social Influence NEtwork, our integrated prediction framework COSINE can capture the diverse influential factors of event participation and can be used by event organizers to predict/improve the popularity of their events. Detailed evaluations demonstrate that our COSINE framework achieves high accuracy for event popularity prediction in all five cities with diverse cultures and user event behaviors.

CCS Concepts: • **Human-centered computing → Collaborative and social computing systems and tools**;

Additional Key Words and Phrases: Group event organization, social influence, user behavior modeling

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1 INTRODUCTION

With the proliferation of event-based social networks (EBSNs) such as Meetup.com, Plancast.com, Douban Location (e.g., beijing.douban.com), and Facebook Events (events.fb.com), organizing and joining social events have become much easier than ever before. Figure 1 illustrates the key elements in the popular Meetup EBSN. *Users* can join different Meetup *groups*, which belong to different group categories and usually have specific themes such as hiking, writing, or health. Each group can organize various types of real-world *events* and encourage its group members to attend.

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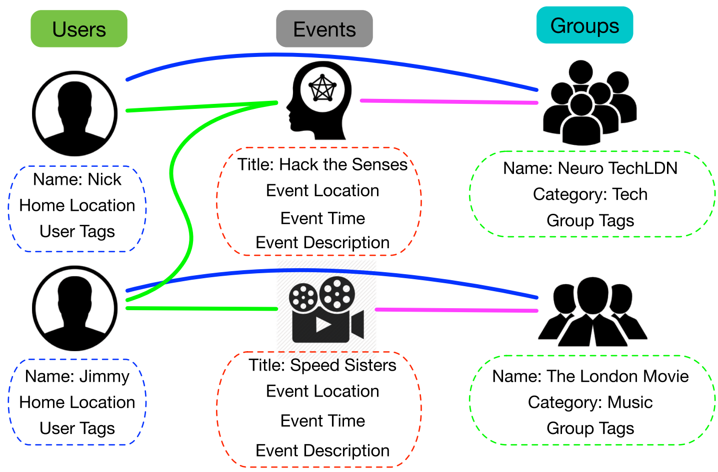

Fig. 1. An illustration of the key elements in the Meetup.com event-based social network (EBSN): *users* can join different *groups* and participate in *events* organized by different groups.

For most social groups, how to organize an event and attract more participants continues to be the major challenge. There are many things to consider: What venue to choose so it would be convenient for most members? What time works better given people's historical time preferences/constraints? How should one write the event title and description? How to keep regular attendees yet attract new users? Given the diversity and dynamics of social groups, it is expected that a one-size-fits-all solution may not work well. Instead, specific group/user/event characteristics need to be carefully studied to predict and possibly improve the popularity or success of an event.

Previous research has studied users' mobility or event participation behaviors in order to make personalized predictions or recommendations [9, 14, 43]. For example, the work by Du et al. discovered a set of factors that will influence individuals' attendance of activities, but the events they considered were organized by individuals, not groups [9]. Although those works shed some light on event organization, they focused on personalized prediction or recommendation by discovering individual users' preference profiles. To the best of our knowledge, no prior work has addressed the problem of identifying and combining the latent factors of group-organized event popularity to predict or improve the success of events organized by diverse social groups.

In this work, using 2 years of Meetup data collected in five major cities, we aim to capture the key factors that may impact the popularity of specific events organized by diverse social groups. The key insights and contributions of our work are summarized as follows.

Spatial and temporal analysis of event popularity. Event location and event time are two critical decision points for event organizers, which can significantly impact event popularity. Our study reveals that users prefer events that are close to their home locations, and the home-event distance follows a power-law distribution. Furthermore, different types of events may be held in different parts of a city. Figure 2 shows the distribution of event locations for three group categories in New York City. As can be seen, "Career/Business" events (shown in green) mostly occur in Downtown Manhattan, which is close to many finance and business companies; "Fine Arts/Culture" events (shown in orange) spread out further to museums, concert halls, and Broadway theaters; and "Outdoor/Adventure" events (shown in blue) are mostly held in the suburbs, far away from crowded downtown areas. We propose location measures regarding convenience, quality, popularity density, and competitiveness for the spatial model. We also capture users' temporal preferences and weekly event attendance patterns for the temporal model.

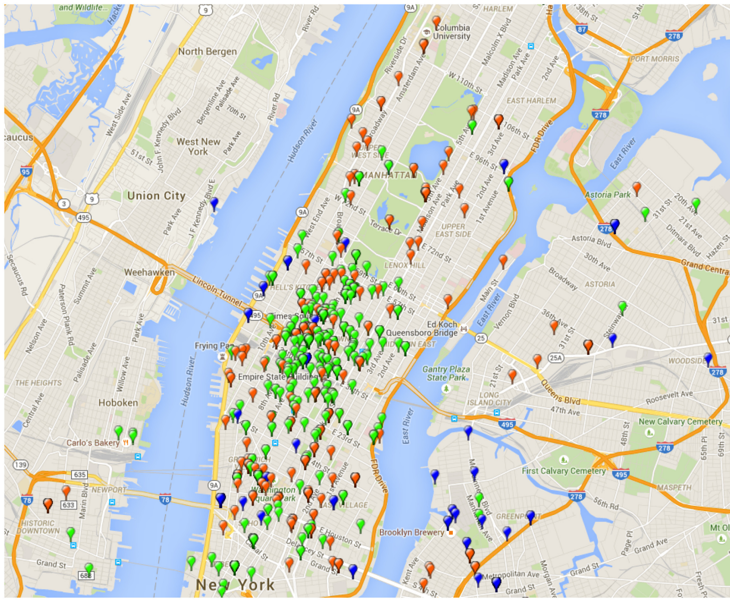

Fig. 2. Event location distribution of three group categories in New York City: "Career/Business"(green), "Fine Arts/Culture"(orange), and "Outdoor/Adventure" (blue).

Social and semantic analysis of event popularity. In EBSNs, users' personal interests are motivated by a complex set of factors. For instance, a working mother may be interested in finance, parenting, health, and fashion/beauty. The interest diversity of a group's members to some degree reflects the group's ability to retain current members and attract new users. We propose to model a group's social feature using its group members' *entropy* and *loyalty*. It is interesting to identify that Meetup groups with high entropy and high loyalty are more likely to be popular, but too-high loyalty has a negative impact on attracting potential users. Besides, the semantic quality of event content plays an important role, especially for irregular events. It is thus valuable for group organizers to spend time polishing event title and event description.

Group-based social influence for event popularity. In EBSNs, users' event attendance decisions can be affected by others who have already RSVPed to an event, and such social influence between users can vary depending on which group organizes the event. Events with similar contextual features but that are organized by different groups may still vary in terms of event popularity. Building on top of previous research on social influence maximization, we design a new group-based social propagation network, which uses historical event attendance logs to model group-specific social influence on people's event participation.

Event popularity prediction and influence analysis in real-world events. By identifying and modeling the contextual factors along with group-based social influence on event participation, we propose an integrated framework COSINE to predict the popularity of group-organized events. Evaluations using large-scale Meetup data in five different cities demonstrate high accuracy of our method. We also compare the predictive power of the individual factors for different types of groups, which offer valuable insights for event organizers.

2 RELATED WORK

In this section, we discuss works that are most relevant to ours, which can be divided into the following three categories.

Location-based social networks (LBSNs) and EBSNs have attracted increasingly more attention by researchers in recent years [6, 9, 20, 42, 43, 46, 47]. The works by Du et al. and Yu et al. proposed frameworks to predict individuals' event attendance and recommend event invitees [9, 43]. Ying et al. proposed a random-walk-based framework for user check-in recommendations [42]. Using geotemporal online check-in data collected from Foursquare, Huang et al. designed an unsupervised approach for local people classification [20]. All of the earlier works focused on exploring features that would affect individual users' daily lives. They either did not have group information in their datasets or did not address the problem from event organizers' point of view. Compared with these works, we focus on helping group-based event organizers understand the latent factors of event popularity and offer detailed models to interpret the individual influences of these latent factors.

Social influence analysis is another related research problem that has been widely studied in recent years. Goyal et al. proposed an influence maximization method based on historical user action logs [16, 17]. Lara et al. proposed a method to recommend groups for individual users by incorporating social relationship interactions [36]. However, none of these papers considered the difference of personal social influence among groups. A user who is influential in one group may not have the same effects in other groups. To address this concern, we design a new social propagation network to distinguish organizer social influence in different groups, which provides better influence prediction results.

Predicting the popularity of social network content is another related problem that has been widely studied. Himabindu et al. studied the number of up-votes for Reddit.com images to understand the interplay among titles, content, and communities [28]. Tan et al. and Yuan et al. focused on how to attract more retweets in Twitter [40, 44]. Phil et al. studied how social media intersects with political and civic engagement using Twitter data [4]. Gabor et al. used YouTube videos' historical popularity such as view counts and comments to predict their future success [39]. Song et al. analyzed donor behavior to help nonprofit projects obtain more funding support [38]. All these works focused on the popularity of online content, which does not contain offline contexts and interactions. As such, their techniques considered mainly semantic features and social features, but not contextual features. Compared with previous works, our research problem is different since attending offline events requires more personal effort than clicking a button or typing some words. There is more complex interplay among multiple factors in users' event participation and event organization.

Our work is also generally related to group behavior analysis, which is an active research topic in the community. Hsieh et al. explored a series of predictors of volunteer socializers in Reddit, an online social news-sharing community [19]. The works by Katharina et al. and Zou et al. analyzed group voting behaviors in Doodle polls [37, 48]. Zhang et al. studied group event scheduling via a newly designed OutWithFriendz mobile application [45]. This line of research is orthogonal to our work of event participation prediction, and insights gained from these works can be leveraged by our framework for further improvement.

3 DATA COLLECTION AND PROBLEM FORMULATION

In this section, we first introduce the datasets we have collected from Meetup, then present the problem formulation.

3.1 Meetup Data Collection

Meetup.com was founded in 2002 and has quickly developed into one of the most popular EBSNs all over the world. It offers great opportunities for people to organize online groups and offline events

Table 1. Statistics of Meetup Datasets

City	#Groups	#Users	#Events	#RSVPs
New York	2,802	248,211	270,321	1,613,634
Los Angeles	2,199	151,006	261,429	1,143,292
London	1,534	155,883	117,862	945,669
Toronto	1,214	98,495	130,136	721,395
Sydney	706	55,768	55,295	353,149

Table 2. Meetup Group Categories

paranormal	parents/family	outdoors/adventure
photography	movies/film	literature/writing
tech	pets/animals	education/learning
singles	health/wellbeing	cars/motorcycles
dancing	career/business	environment
fitness	religion/beliefs	language/ethnic
games	food/drink	movements/politics
LGBT	hobbies/crafts	fine arts/culture
support	fashion/beauty	alternative lifestyle
music	socializing	sports/recreation
women	sci-fi/fantasy	new age/spirituality

based on specific interests. Through Meetup's streaming API,[1] we are able to collect comprehensive Meetup data from five cities: New York (NYC), Los Angeles (LAX), London (LON), Toronto (TOR), and Sydney (SYD) for the period of July 2013 to June 2015. We choose these five cities because (1) they all have large-scale active groups and users and (2) they are located in four different countries and on three different continents, representing diverse cultures and group/event/user characteristics. During preprocessing, we remove inactive groups that have fewer than 15 offline events during the 2-year period. Table 1 summarizes the key statistics of the five datasets.

3.2 Problem Formulation

Our Meetup data contains three types of information:

• **Group data:** Each Meetup group has its creation time, list of group members, and list of events organized by the group. Each group belongs to a group category predefined by Meetup. There are 33 Meetup group categories in total, which are shown in Table 2.

• **Event data:** Each event contains a title, description, venue location, RSVPs by users, and event start time.

• **User data:** Each Meetup user has a home location (longitude and latitude), the user's interest tags, the groups the user belongs to, and events RSVPed by the user.

Table 3 summarizes the key notations we use throughout the article for each given city. Given a new event e with its organizer, venue location, start time, title, description, and the group it belongs to, our goal is to predict how many users would attend the event (i.e., event popularity). Please note here, instead of predicting the absolute popularity of all events, we predict the relative popularity of events in the group category $c \in C$ that they belong to. The reason is that

[1] https://www.meetup.com/meetup_api/.

Table 3. Key Data Notations in a Given City

Symbol	Meaning
U	the set of users
G	the set of groups
E	the set of events
C	the set of group categories
E_g	the set of events organized by group g
U_g	the set of active users in group g
U_e	the set of active users in event e
l_e	the location of event e
C_e	the group category of event e
C_g	the group category of group g
l_u	the home location of user u
N_e	the number of participants in event e
P_e	normalized event popularity
avg_c	the average event size in group category c

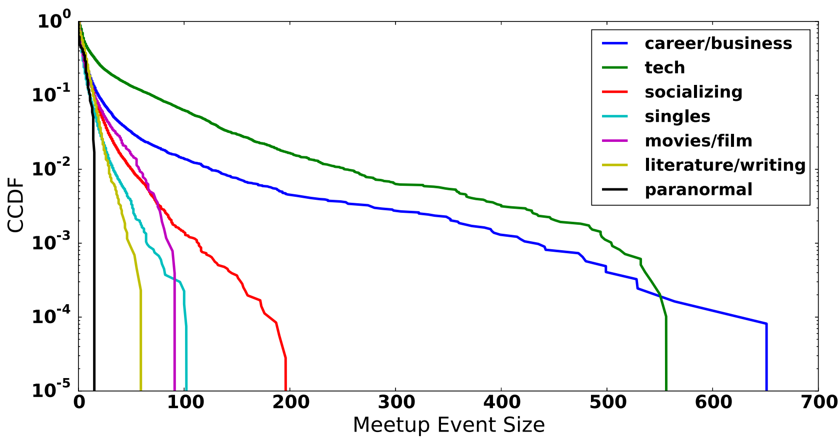

Fig. 3. The complementary cumulative distribution of event size by group category in New York.

Meetup event sizes vary significantly across different group categories. Having 50 participants may be considered a big success for one event, yet not good for another event. Figure 3 shows the complementary cumulative distribution (CCDF) of event size of selected group categories in New York. As can be seen in the figure, "Tech" and "Career/Business" groups tend to have large offline events with hundreds of participants. This is due to the fact that groups in these two categories would organize professional and formal seminars or talks for their members, which attract a large number of attendees. In comparison, "Literature/Writing" events have much smaller sizes, and all "Paranormal" events have fewer than 15 participants.

Based on the analysis above, we normalize event size by group category. Let N_e be the number of attendees of an event e and avg_c be the average number of event attendees in group category c that e belongs to. In this way, we predict the relative event popularity:

$$P_e = \frac{N_e}{avg_c}. \tag{1}$$

In other words, we estimate the level of popularity of each event relative to other events in the same group category. By normalizing event size and calculating relative event popularity, we aim to treat all events equally, regardless of whether they focus on a popular topic or not.

Please note that maximizing event popularity may not be the goal of every Meetup group. For certain events, the group organizers may prefer to keep the group size small. This topic is beyond the scope of this article. Our evaluation results do shed some light on this problem, and we plan to investigate it further as our future work.

4 CONTEXTUAL FEATURES

In this section, we describe in detail our modeling analysis in order to understand and model the latent factors that can impact event popularity. Specifically, consider a group organizer who is planning a new event; we could potentially leverage the following information: spatial, group, temporal, and semantic features.

4.1 Spatial Features

Choosing the right venue for an event is of particular importance in event organization. Intuitively, the event venue should be convenient for interested users (i.e., group members), yet not competing with too many other group events with similar themes nearby. To model these influences, we refer to earlier works that studied how to choose the location for retail stores [13, 23, 25, 27]. Inspired by the methodologies implemented in these articles, we propose the measures of location quality, convenience, density, and competitiveness for each offline event.

4.1.1 Location Quality. Jensen's location quality has been widely used in analyzing static retail stores' spatial interactions among different place categories [13, 23, 25]. It considers the colocation frequency of venues in different place categories. For instance, clothes stores are often located near cosmetics stores, and second-hand goods may be close to household shops. It implies that different place categories can have relative attractiveness value with each other. We extend this method to our EBSN setting. We hypothesize that group categories will have a similar attractiveness pattern between each other. For example, people who are interested in the "Women" theme may also be willing to attend "Fashion/Beauty" or "Patents/Family" events. To model this attractiveness property, we extend Jensen's inter coefficient to compute the relative number of events in other group categories that are near a given event. The value will be normalized compared with the scenario of placing all event locations uniformly random in the whole city area. Specifically, we first define the neighborhood event set:

$$N(e_1, r) = |\{e_2 \in E : dist(e_1, e_2) < r\}| \tag{2}$$

$$N_c(e_1, r) = |\{e_2 \in E : dist(e_1, e_2) < r \cap e_2 \in c\}|, \tag{3}$$

where $e_1 \in E$, $c \in C$, and r is the neighborhood radius. $dist(e_1, e_2)$ denotes the geographic distance between event e_1 and event e_2. We choose radius r to be 100 meters as [23] did, which yields the best results in our final prediction performance. Similar to Jensen's location quality measurements [23], in order to quantify the dependency between two different group categories, we assume that an event of category A at one location should not modify the average density of events of category B in the neighborhood area. Based on this intuition, we define the attractiveness value between two group categories as

$$Attr(C_a, C_b) = \frac{N - N_{C_a}}{N_{C_a} N_{C_b}} \sum_{e \in C_a} \frac{N_{C_a}(e, r)}{N(e, r) - N_{C_b}(e, r)}, \tag{4}$$

Table 4. Top 4 Most (and Least) Attractive Group Categories for Categories "Women," "Movies/Films," and "Sports/Recreation" Based on Jensen's Attractiveness Value (New York Dataset)

Women		**Movies/Film**		**Sports/Recreation**	
Support	4.49	Literature/Write	7.84	Photography	2.93
Fashion/Beauty	3.04	Sci-Fi/Fantasy	2.62	Music	1.66
Parents/Family	2.65	Tech	2.12	Food/Drink	1.62
Environment	2.48	Food/Drink	2.01	Paranormal	1.60
LGBT	0.53	Support	0.44	Career	0.48
Games	0.43	Paranormal	0.42	New Age	0.39
Sports/Rec	0.38	Cars/Motor	0.39	Support	0.28
Cars/Motor	0.27	Fitness	0.36	Fashion/Beauty	0.16

where C_a, C_b are two group categories, N is the total number of events, and N_{C_a} and N_{C_b} are the total number of events in category C_a and C_b. Here $Attr(C_a, C_b)$ represents the level at which category C_a attracts category C_b. Please note that $Attr(C_a, C_b) \neq Attr(C_b, C_a)$. According to our definition, the qualitative assessment is: If $Attr(C_a, C_b)$ is greater than 1, events in C_a have a positive attraction to events in C_b. Conversely, it represents a negative attractive tendency.

In Table 4, we selected three group categories and their top four and bottom four attractive categories computed by Jensen's attractiveness value using the New York dataset. The results seem reasonable. Offline events in category "Women" are often located around events in "Support" and "Fashion/Beauty." Intuitively, categories with low attractiveness would have relatively few common users, which is also reflected in Table 4. For example, events in category "Sports/Recreation" are seldom organized near "Fashion/Beauty," "Support," and "New Age" events.

After calculating the attractiveness value between categories, the overall location quality for hosting event e can be modeled by the attractiveness value of the groups around the location. We formally define location quality as

$$\hat{S1}_{spatial}(e) = \sum_{c \in \{C - C_e\}} \log(Attr(c, C_e)) \times (N_c(e, r) - \overline{N_c(e, r)}), \tag{5}$$

where C_e is the category of event e, and $\overline{N_c(e, r)}$ denotes the average number of events in category c that are within distance r from the events in category C_e.

4.1.2 Location Convenience. Figure 4 plots the probability of event participation given different user home-event distances for New York and London. Due to the space limit, we only show two cities. But all five cities have similar patterns. As shown in the figure, for home-event distances that are within 15 miles, which cover more than 85% of all home-event pairs in all cities, there is a clear linear relationship in the log-log plot, indicating a power-law distribution. In other words, most users attend nearby events and are less likely to participate in events that are far away.[2] Based on this analysis, we model an event's overall convenience score by aggregating the convenience scores of individual group members:

$$\hat{S2}_{spatial}(e) = \sum_{u \in U_g} Location\_Convenience(u, e). \tag{6}$$

[2]There are still some users who attended far-away events in our dataset, which we plan to investigate in our future work.

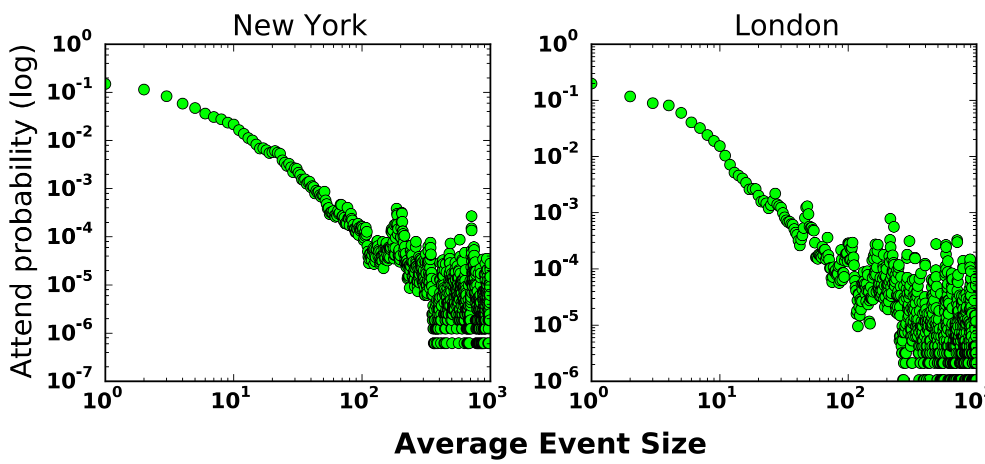

Fig. 4. Distribution of home-event distance versus probability of event participation.

Assuming that users' event attendance location convenience and users' home-event distance follows a power-law distribution, $Location\_Convenience(u, e)$ is defined as

$$Location\_Convenience(u, e) = k \times d(u, e)^b, \tag{7}$$

where $d(u, e)$ is the distance between user u's home location and event e's location, and k and b are coefficients that can be learned via the linear regression model.

4.1.3 Location Population Density. Generally, population density refers to the number of people living near a target location. Previous research suggests that the higher the population density, the larger the average store should be [22]. Intuitively, a denser place means more potential users to attend events. Formally we define population density as

$$\hat{S}3_{spatial}(e) = |\{u \in U : dist(u, e) < R\}|. \tag{8}$$

Here $dist(u, e)$ denotes the geographic distance between user u's home location and event e's location. The choice of parameter R will be discussed in the Evaluation section.

4.1.4 Location Competitiveness. Locations with higher population density may also imply more intensive competition. Hideo et al. discovered that when the number of retail stores in the same area increases, retailers have to devote more effort to price-cutting strategies [27]. Similarly, it is frequently observed that many groups with similar topics choose to meet in the same area, and as such events compete with each other to attract a shared pool of users. Based on this observation, we define location competitiveness in EBSN event organization based on the number of users (in group category C_e) whose home locations are within distance R from a given event e:

$$\hat{S}4_{spatial}(e) = -\frac{N_{C_e}(e, R)}{N(e, R)}. \tag{9}$$

4.2 Group Features

Some recent research works have studied urban social membership diversity in location-based social networks [7, 18, 33]. It has been observed that the diversity of check-ins in places to some extent reflects their popularity. These prior observations inspired us to study whether Meetup groups also bring together diverse users via offline events and how this diversity feature would

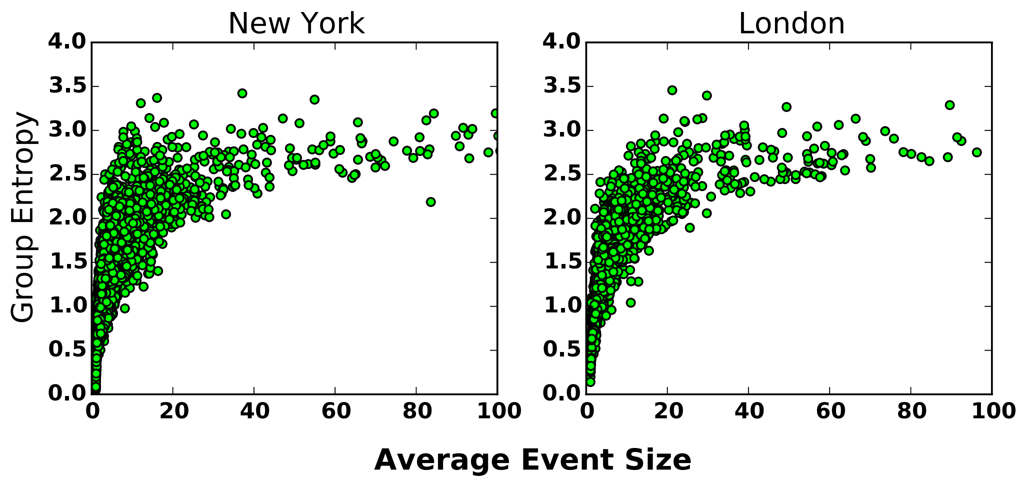

Fig. 5. Group member entropy versus group's average event size.

in return affect events' popularity. We propose two different measures to capture group diversity: entropy and loyalty, which are defined following [18] and [33].

4.2.1 Group Member Entropy. We employ entropy to measure the diversity of attendance made by the group members. We estimate a group's member entropy value as the Shannon entropy of its check-ins:

$$\hat{S1}_{group}(e) = -\sum_{u \in U_g} p_u \log p_u, \tag{10}$$

where p_u is the probability that a check-in is made by user u:

$$p_u = \frac{\sum_{e \in E_g} |u \in e|}{\sum_{e \in E_g} |U_e|}. \tag{11}$$

This measure is used similarly to the entropy measurement of check-ins in locations [8].

Figure 5 shows the relationship between a group's average event size and group entropy. We can see that group entropy increases when the average event size increases. It indicates that groups with diverse event participants are more likely to have larger event sizes. Intuitively, groups with higher diversity are more likely to attract new users, so it is easier for them to grow and develop.

4.2.2 Group Member Loyalty. Another metric for the diversity of a group is whether the group's members have concentrated interest on the group topic, i.e., to what extent the users are focused on attending events within the same category. As mentioned in Table 2, we have 33 group categories in our Meetup datasets. For each user u in group g, we compute the frequency of attended events in the same category as the user's loyalty:

$$loyalty(u, g) = \frac{\sum_{e \in E_u} |\{C_e = C_g\}|}{|E_u|}. \tag{12}$$

Then the group loyalty is measured as the average user loyalty of all active group members:

$$\hat{S2}_{group}(e) = \frac{\sum_{u \in U_g} loyalty(u, g)}{|U_g|}. \tag{13}$$

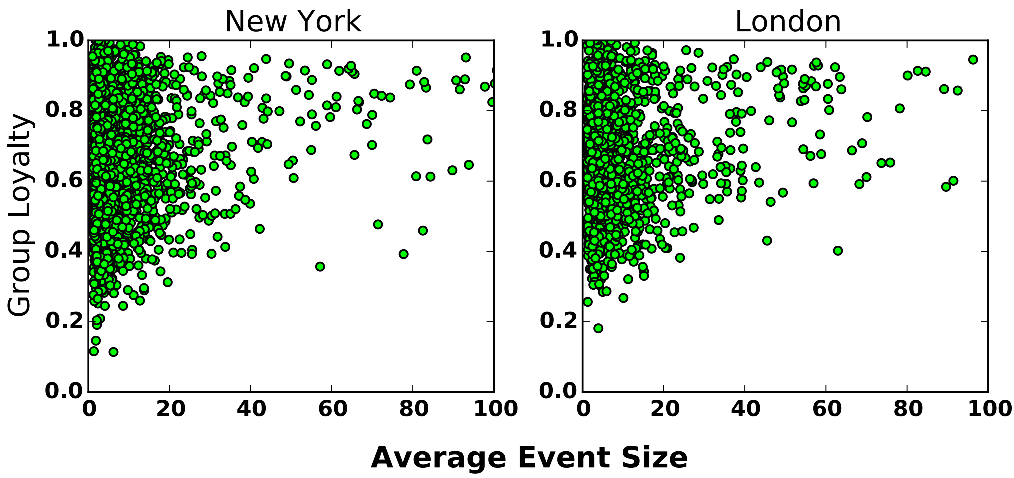

Fig. 6. Group member loyalty versus group's average event size.

Figure 6 compares the group's average event size versus group loyalty. Generally, groups with larger event sizes are more likely to have high member loyalty. However, groups with small event sizes can have very high or very low loyalty values. Intuitively, the lower loyalty of group members results in smaller event sizes (fewer people attending); higher loyalty of group members helps maintain larger event sizes, but very high loyalty can negatively impact event popularity because the members have very concentrated interest and may hamper the joining of new (and more diverse) users.

4.3 Temporal Features

Event start time is another critical factor that may impact event popularity.[3] For instance, some users may prefer to attend events after work, while others only have free time during weekends.

4.3.1 Temporal Preference. Liu et al. observed that social events in EBSNs exhibit regular temporal patterns [31]. As shown in Figure 7, most weekday events started in the evening, from 6:00 p.m. to 9:00 p.m. It is reasonable since users would only be free after school or work on weekdays. In contrast, on weekends, events are distributed more uniformly. We noticed that many outdoor activities in Meetup are held in the morning or afternoon on weekends.

To model how well the event start time matches group members' temporal preferences, we represent each event's start time as a 24×7 dimensional vector $\vec{e_t}$. For instance, if an event starts at 18:00 p.m. on Tuesday, then its $24 \times 2 + 18 = 66th$ element in the vector would be 1, and the remaining elements would be 0. Then we compute the temporal preference of each user $u \in U$ based on his or her historical event attendance with time decay as follows:

$$\vec{u_t} = \frac{1}{|E_u|} \sum_{e \in E_u} \frac{1}{(1+\eta)^{\theta(e)}} \vec{e_t}, \tag{14}$$

where E_u denotes the set of historical events that user u has participated in, η is the time decay parameter, and $\theta(e)$ denotes the number of past days. The use of the time decay function is needed because users' temporal preferences may change during the 2-year period of our datasets, and more recent data would better reflect users' temporal behavior.

[3]Event end time is not available at Meetup.

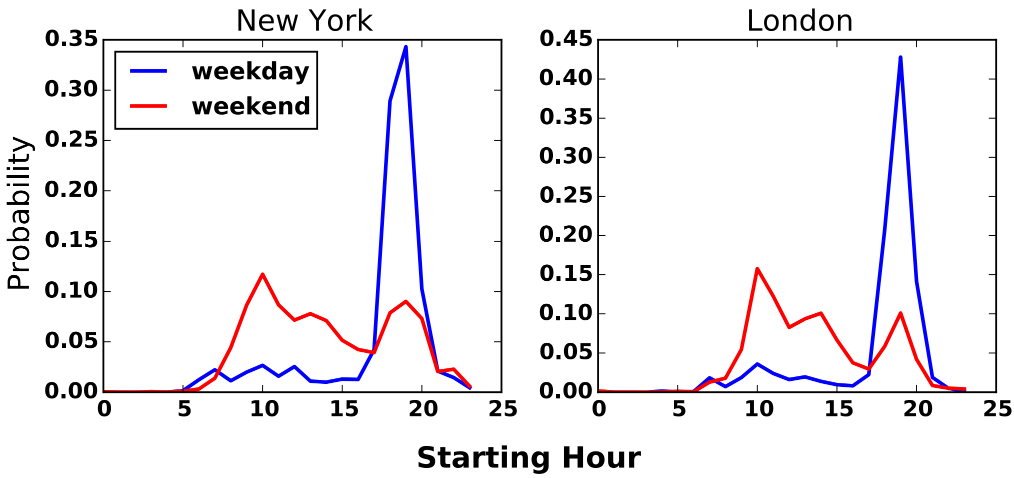

Fig. 7. Event start time by hour distribution, weekday versus weekend.

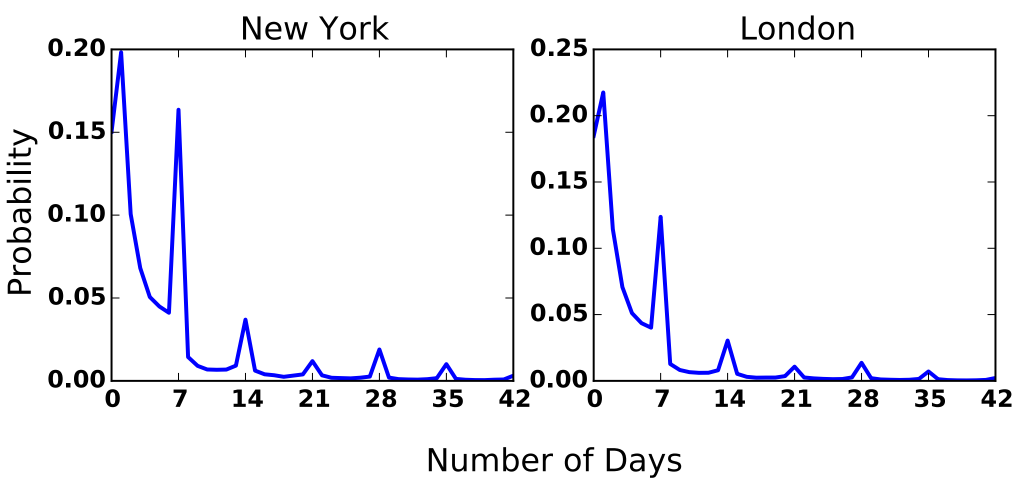

Fig. 8. Distribution of duration between two consecutive events organized by the same group.

Then we measure the overall satisfaction of event time by adding up the Jaccard similarity between event starting time $\vec{e_t}$ and all active group members' temporal preference $\vec{u_t}$:

$$\hat{S1}_{temporal}(e) = \sum_{u \in E_u} Jaccard(\vec{e_t}, \vec{u_t}) \tag{15}$$

$$Jaccard(\vec{e_t}, \vec{u_t}) = \frac{\sum_i \min(e_{t\,i}, u_{t\,i})}{\sum_i \max(e_{t\,i}, u_{t\,i})}, \tag{16}$$

where $e_{t\,i}$ refers to the ith element in vector e_t and $u_{t\,i}$ refers to the ith element in vector u_t.

4.3.2 Weekly Pattern of Events. Since each group can organize many events, we further analyze the number of days between consecutive events hosted by the same group, which is shown in Figure 8. It is clear that there is a peak every 7 days, implying that many groups hold events with a regular weekly pattern such as every week, every other week, or every month. Inspired by the analysis, we hypothesize that the number of days since the last event should be an important factor

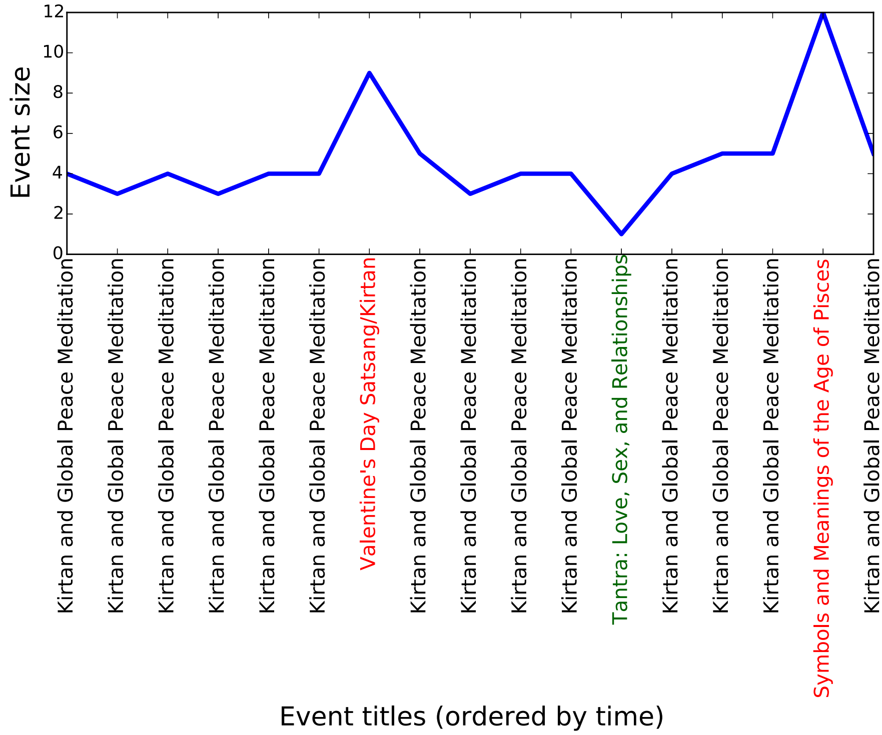

Fig. 9. Events organized by the Meetup group "Kirtan and Global Peace Meditation" in New York, ordered by time. For each event, we show its event title and actual event size.

to capture:

$$\hat{S2}_{temporal}(e) = e_{day} - e_{day}^{-1}, \tag{17}$$

where $e_{day} - e_{day}^{-1}$ denotes the number of days since the last event.

4.4 Semantic Features

Another step in modeling event popularity is to consider potential semantic factors. How vital is semantic information (event title and event description) for attracting more participants? Figure 9 shows a motivating example. Among the 17 events organized by the Meetup group "Kirtan and Global Peace Meditation," many events had the same event title as the group name, which were regular events of the group and had stable event size. The group also organized some special events with different event titles such as "Valentine's Day Satsang/Kitsan" and "Tandra: Love, Sex, and Relationships." The event size varied significantly for these special events. It is reasonable to believe that the semantic information can play a role, especially for nonregular events. To address this challenge, we leverage prior research on factors associated with content popularity on online social media platforms. The features considered in earlier studies are summarized in Table 5. This review broadly shows that commonly used semantic features in modeling content popularity include readability, semantic, part-of-speech tagging, and text novelty. More details of each semantic feature are described below:

Readability. Intuitively, to attract new participants, the description of an event should be easy to read and understand. To represent this feature, we measure the readability of event content (event title + event description). Readability score is calculated by Flesch-Kincaid grade level [26]

Table 5. Summary of Related Work That Identified Features That Play Significant Roles in Content Popularity in Online Social Media

Research Project	Factors Addressed
Lakkaraju et al. [28]	part-of-speech tags, sentiment, text novelty
Jou et al. [24]	sentiment and part-of-speech tags
Calefato et al. [5]	sentiment
Berger et al. [2]	sentiment
Tan and Lee [40]	part-of-speech tags
Gimpel et al. [15]	part-of-speech tags

and Flesch reading ease [11]. Larger values indicate better readability and can potentially attract more event participants.

Sentiment Analysis. An important field in natural language processing, sentiment analysis aims to automatically classify text by valence [34] and find authors' views on specific entities [10]. Previous works validated that sentiment serves as an important predictor of online item popularity. Himabindu et al. found that "positive" sentiment contributes to a title's popularity in certain topic communities [28]. Berger et al. discovered that positive or negative words increase social media propagation [2]. To capture the sentiment of event content, we implemented Vader [21], a widely used lexicon and rule-based sentiment analysis tool. For each event content, it assigns a negative, neutral, or positive score based on its sentiment expression.

Part-of-Speech Features. In our problem setting, certain types of events may favor highly descriptive, adjective-laden titles, while others may prefer simpler titles that consist of a few nouns and verbs. Previous works have shown the effectiveness of using POS features for social media information [15, 24]. To identify the type of each word in a Meetup event title, we performed automatic part-of-speech labeling using NLTK [3]. For every word in the event title, we map it to a part-of-speech (POS) tag. A binary feature is assigned to measure the presence of each POS tag. The features we used include adjective, apposition, adverb, conjunction, determiner, noun, numeral, particle, pronoun, verb, and punctuation marks.

Text Novelty. Text novelty detection has been used to measure a tweet's novelty given a previous set of tweets [35, 41]. Given our motivating example, using an original event title can be a double-edged sword. Appropriate novelty may inspire users' curiosity, while unsuitable novelty may reduce their interests. We use Jaccard similarity to identify the novelty of event titles by comparing with previous event titles. Explicitly, we define event title novelty as the aggregate similarity of the title and prior titles used by this group:

$$\hat{S1}_{semantic}(e) = \sum_{e' \in \{E_g - e\}} Jaccard(e_{title}, e'_{title}), \tag{18}$$

where e_{title} is the title of event e. The Jaccard similarity between two event titles is defined as

$$Jaccard(e_{title}, e'_{title}) = \frac{e_{title} \cap e'_{title}}{e_{title} \cup e'_{title}}.$$

Jaccard similarity between two titles measures the proportion of common words to the number of unique words in both titles.

5 GROUP-BASED SOCIAL INFLUENCE

Besides the contextual features of an event, the social influences of people who have RSVPed already can also affect other users' decisions to attend the event (thus event popularity). While there have been extensive prior works on social influence maximization, they focused on individual users, and all user actions are equally weighted [16, 17, 29]. The scenarios of groups and events organized by different groups have not been investigated by prior research. However, in EBSNs such as Meetup, the social influence of one user on another user can differ significantly from one group to another (e.g., a technology group vs. a movies group). To utilize such group-specific information in EBSNs, we propose a new social propagation network to model people's social influences on event popularity that are specific to the event's group organizers.

For each event e, consider a directed and weighted social graph, with each vertex representing a Meetup user, and there exists an edge from user v to user u if v RSVPed for event e before u did. The intuition is that user v's RSVP for event e may have affected user u's decision to attend the same event. Furthermore, the influence would wane as time goes by, so the longer the time duration between v's RSVP and u's RSVP, the smaller the influence of v on u. Let $N(u, e)$ be the set of users who RSVPed to e before u did; for each user $v \in N(u, e)$, we define v's direct influence credit on u as follows:

$$\begin{aligned} w_{v,u}(e) = \sum_{e'} \frac{infl(u)}{|N(u, e')|} [&\delta(G(e) = G(e')) \cdot \lambda_g \cdot decay_{v,u}(e') \\ &+ \delta(G(e) \neq G(e')) \cdot \lambda'_g \cdot decay_{v,u}(e')], \end{aligned} \tag{19}$$

where e' denotes any event in which v RSVPed before u. $infl(u)$ represents the fraction of activities that u attended under the influence of at least one other user [16]. This value is normalized by the number of potential influencers $|N(u, e')|$ such that the sum of all influence credits assigned to u in event e' is at most 1. And $decay_{v,u}(e')$ represents the influence decays over time in an exponential tendency as

$$decay_{v,u}(e') = exp\left(-\frac{t(u, e') - t(v, e')}{\tau_{v,u}}\right), \tag{20}$$

where $t(u, e')$ is the time that user u RSVPed for event e'. $\tau_{v,u}$ is the average time taken to propagate from user v to user u. The influence decay tendency is weighted differently by λ_g and λ'_g, depending on whether v and u coattended an event that was organized by the same group as e or not. In other words, we differentiate between the influence credits based on the actual group that organized an event, and the social influence obtained via an event organized by the same group would carry more weight.

Using the social propagation graph, we can compute the total influence of user v on user u for event e:

$$\Omega_{v,u}(e) = \sum_{z \in N(u,e)} \Omega_{v,z}(e) w_{z,u}(e). \tag{21}$$

And the total influence that event host h has on all group members can be computed as

$$\hat{Social}_{Influence}(e) = \sum_{u \in \{U_g - h\}} \Omega_{h,u}(e). \tag{22}$$

6 EVALUATIONS

In this section, we evaluate the effectiveness of our proposed framework for predicting event popularity. Furthermore, we analyze the individual contributions of the contextual features (spatial, group, temporal, and semantic) and group-based social influence. The datasets we use for evaluation have been described in Section 3, which contain 2-year Meetup data in five major cities.

We first describe the evaluation methodology, then present the detailed evaluation results and analysis.

6.1 Methodology and Metrics

As described in the problem formulation, our goal is to predict the normalized popularity value P_e for each event as the overall popularity level in its group category. Given the Meetup dataset collected in each of the five cities, we split the dataset into three parts. In every city, we use the first 80% offline events of each group as the training dataset, 10% are used for validation and parameter tuning, and the remaining 10% are used for testing. In our COSINE framework, to integrate all context features that we have constructed, we fit them into a Classification and Regression Tree (CART) model [32]. Then we fit the residual popularity defined below to our social influence model:

$$y_e = P_e - \hat{P}_e. \tag{23}$$

The parameters in Equation (19) are optimized by minimizing the least squares function $||y_e - \hat{y_e}||_2^2$ using the BFGS algorithm [30], which is an iterative method for solving unconstrained nonlinear optimization problems.

We use the coefficient of determination (R^2) as the primary evaluation metric, which is a statistical measure widely used in regression evaluation. It is defined as

$$R^2(P, \hat{P}) = 1 - \frac{\sum_e (P_e - \hat{P}_e)^2}{\sum_e (P_e - \overline{P})^2}, \tag{24}$$

where $\overline{P}$ is the mean of P. A higher value represents better performance. For the testing procedure, the final results we report are computed by $R^2(P_e, \hat{P}_e + \hat{y_e})$. We also compute two other widely used metrics, root-mean-square error (RMSE) and mean-absolute error (MAE), to evaluate the prediction performance.

We compare our COSINE framework with the following approaches:

- **NM** is a naive mean-based method that predicts future event popularity $\hat{P}_e$ as the average of historical event popularity of the same group.
- **LR** integrates all the contextual features into a linear regression model.
- **NN** integrates all the contextual features into a neural network regression model (multilayer perceptron regressor).
- **GB** integrates all the contextual features into a gradient boosting regression model.
- **SVR [1]** integrates all the contextual features into a support vector regression.
- **SVD-MFN [9]** is a state-of-the-art context-aware event attendance prediction algorithm for individual users, and we use its predictions for individual users to compute the overall popularity of each event.
- **Inf only** uses only our group-based social influence to predict P_e.
- **Cont only** uses only our contextual features to predict P_e directly.
- **Cont + Inf (-)** uses both contextual features and group-based social influence without considering group difference (i.e., $\lambda_g = \lambda'_g$).

6.2 Overall Prediction Performance

Figure 10 summarizes the event popularity prediction performance of different approaches using the R^2, *RMSE*, and *MAE* metrics in all five cities. As can be seen, the baseline approach NM is ineffective and only has an average R^2 of 0.177 across five cities. SVD-MFN did not achieve good results either, which indicates that individual-based event participation prediction does not

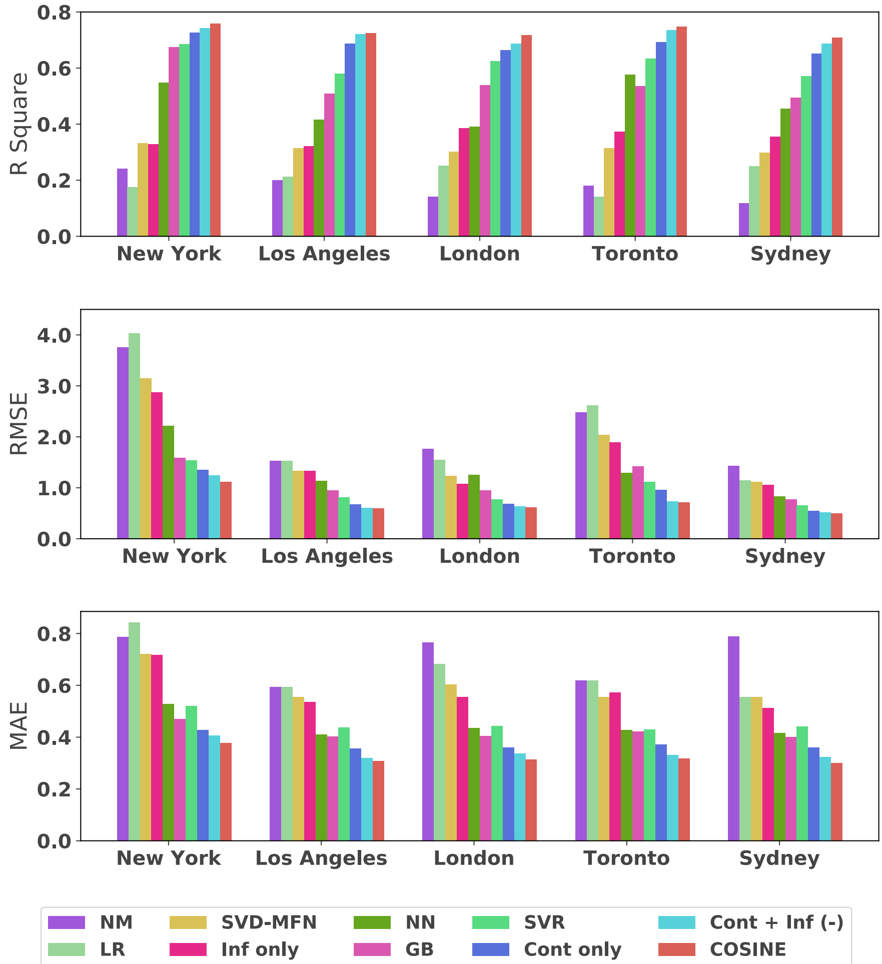

Fig. 10. Overall performance comparison of different models for event popularity prediction.

work well for event popularity prediction. One possible reason is that event participation is highly skewed, and most users do not participate in a given event. In contrast, our combined framework can provide much better prediction results. Our COSINE framework performs best in all five cities, achieving 0.758 for New York, 0.725 for Los Angeles, 0.717 for London, 0.748 for Toronto, and 0.709 for Sydney. It improves the prediction performance by 130% over the baseline approach and consistently outperforms other widely used regression models such as linear regression, multilayer perceptron regression, gradient boosting regression, and support vector regression. In addition, the improvement from Cont Only to Cont + Inf (-) and to COSINE demonstrates the effectiveness of our contextual features, the social influence feature, and the importance of differentiating social influences for different groups. Moreover, our prediction performance is consistent when using the other two metrics *RMSE* and *MAE*.

As discussed in the spatial and temporal features subsections, there are two parameters in our context model: radius R and time decay η. They are determined by a grid search on our validation set. The specific parameters values for New York, Los Angeles, London, Toronto, and Sydney are the following: radius R is set to 1 mile and the time decay parameter η is set to 0.01 for all five cities.

Table 6. Prediction Performance of Regular versus Irregular Events

	NYC	LAX	LON	TOR	SYD
Regular	**0.806**	**0.777**	**0.783**	**0.766**	**0.743**
Irregular	0.682	0.666	0.669	0.672	0.651

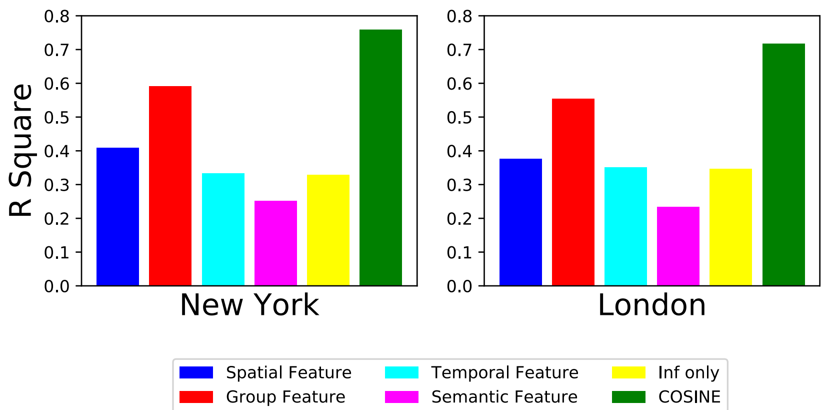

Fig. 11. Prediction performance of individual features and their combination.

6.3 Regular versus Irregular Events

As discussed in Section 4.3, many Meetup groups' events have a regular (weekly) pattern. Here, we compare the prediction performance of the COSINE framework for regular and irregular events. We extract regular events from our datasets using two principles: (1) the number of consecutive days since the last event by the same group is 7 or 14, and (2) it has the same start time as the last event or differs by at most 1 hour. The remaining events are regarded as irregular events. The ratio of regular events and irregular events is around 1:5. For each city, we compute the R^2 score for the regular and irregular events, respectively. The results are shown in Table 6. As expected, our COSINE framework achieves better prediction performance for regular events with an average R^2 score of 0.775. Nevertheless, the 0.668 average R^2 score we achieved for irregular events is still reasonably good.

6.4 Performance of Individual Factors

As described earlier, our context prediction model fuses together four types of factors: spatial, group, temporal, and semantic factors. To understand the individual contribution of each factor and their importance for different use cases, we conduct experiments using each individual feature only and compare their performance with our proposed influence model and the combined COSINE framework.

Figure 11 shows the results for New York and London. We can see that all four individual models contribute to the prediction performance and are substantially better than the naive mean baseline. In particular, our social model, which considers group member entropy and group member loyalty, performs significantly better than other individual models. Using the group model alone achieves an average R^2 score of 0.573 across the two cities. Our spatial model is the second-best-performing individual model. The semantic model did not perform as well as the other individual models. It is partially because semantic quality is more important for irregular events but not for regular events. To summarize, group membership, organizer social influence, event venue, and

Table 7. Performance for Different Group Categories in New York and London: Best Four Performing Categories and Worst Four Performing Categories

New York		London	
LGBT	0.834	Career/Business	0.774
Career/Business	0.821	Fine Arts/Culture	0.761
Tech	0.793	Sports/Recreation	0.760
Fitness	0.784	Tech	0.732
Health/Wellbeing	0.465	Parents/Family	0.397
Singles	0.439	Community	0.381
Outdoors	0.392	Paranormal	0.223
Fashion/Beauty	0.293	Alternative Lifestyle	0.199

event start time are crucial factors in event organization, and event content is also important for irregular events. And by integrating all these factors, our COSINE framework achieves much better prediction performance.

6.5 Performance versus Group Categories

Table 7 shows the R^2 scores for different group categories in the New York and London dataset, including the top four (best-performing) categories and bottom four (worst-performing) categories. We observe that "Career/Business" and "Tech" categories achieve the highest performance in both cities. Intuitively, this can be explained by the fact that regular events are easier to predict than irregular ones. Upon further investigation, we find that many Meetup groups in these two categories hold weekly study sessions, startup training forum, art association, and so forth. Their memberships and event sizes are relatively more stable than others. Events related to outdoor activities are more difficult to predict, as other factors may come into play for outdoor event participation, such as weather, event duration, and users' physical condition.

6.6 Performance for Groups with Different Characteristics

Besides group categories, groups can also differ in terms of creation time and activeness of organizing events. For instance, some Meetup groups have been around for many years, while others may be fairly new. And some groups are much more active than others and organize more events. We expect that the different models may perform differently for groups with different characteristics. To evaluate such impacts, we use the New York dataset and split groups along two orthogonal dimensions: (1) groups are classified as "old" (or "new") if their creation time is earlier (or later) than the median group creation time, and (2) groups are classified as "high activity" (or "low activity") if their number of events is above (or below) the median number of group organized events. This process splits the groups in the New York dataset into four subsets, and we present the prediction results for each subset respectively in Figure 12. Generally, our method performs better for "old, high-activity" groups since older groups tend to be more stable and high-activity groups have more historical event information for our model to leverage. In contrast, "new, low-activity" groups are much harder to predict. When examining the performance of the individual models, it is worth noticing that the social model plays a more important role in "old" groups, since they have more stable memberships. In addition, the temporal model performs much better for "high activity" groups than for "low activity" groups. Finally, for "new, low-activity" groups, the relative contribution of the semantic model is more significant.

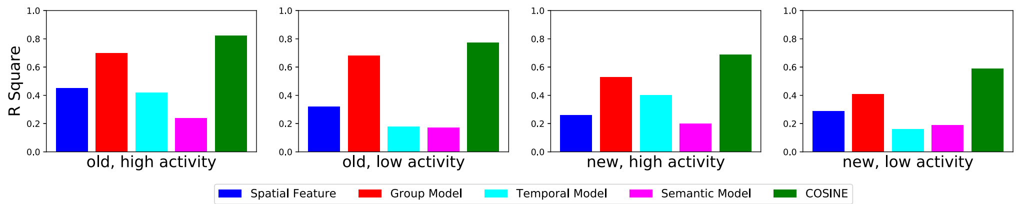

Fig. 12. Prediction performance comparison in groups with different characteristics using the New York dataset.

Table 8. Classification Accuracy for Category-Specific Events Using Different Semantic Patterns: StopWords Frequency or Part-of-Speech Tags

	NYC	LAX	LON	TOR	SYD
StopWords	0.840	0.822	0.865	0.861	0.834
Part-of-Speech	0.651	0.656	0.671	0.671	0.718

6.7 Event Content Writing Style

We now move on to study another interesting question: would organizers of different group categories write their event content differently? Given that the event titles would target users in certain categories, there should be some linguistic similarity within each category. To capture such semantic patterns in event content, we ignore category-specific words such as "jazz" in "music" related groups. For each event, we collect two kinds of features: (1) the frequency of stopwords used [12] (**StopWords**) and (2) part-of-speech tagging as mentioned in the semantic modeling subsection (**Part-of-Speech**). Based on the features above, we build a binary classifier to understand whether individual events use different writing patterns. For each city, we randomly select a group category and assign the positive label to all its events. We randomly select an equal number of events in other categories and assign the negative label to these events. We then construct an SVM classifier to predict the positive or negative labels. The classification accuracies are shown in Table 8. Both methods performed better than a random guess (0.5 accuracy), and the stopwords frequency achieves above 0.8 accuracy in identifying events of the same category. It implies some consistency of writing style within the same category and different writing styles across categories.

7 CONCLUDING DISCUSSION

In this work, we conducted the first study that addresses the problem of predicting event popularity in event-based social networks. We collected a large dataset that contains Meetup events in five cities located on three continents. We identified four types of features (spatial, group, temporal, and semantic) that play important roles in affecting group event popularity in the real world. We also designed a group-based social influence model to estimate the social influence between host and group members. Our combined COSINE framework achieved high prediction accuracy in all five cities. We further analyzed the contributions of individual models and the impact of different event organization scenarios.

Limitations and Future Work. One key limitation of this work is the representativeness of our dataset. Although our study uses a dataset that spans five cities across the globe, all of them are metropolitan cities. The users collected in our dataset may not be representative of people living in nonmetro areas or of those who are using other online event organization services.

Another limitation of this work lies in our metric to measure event popularity. Maximizing event popularity may not be the goal of every Meetup group. For certain events, the group organizers may prefer to keep the group at a small but stable size. Our evaluation results do shed some light on this problem as our prediction model performed well for some event categories, such as "Career/Business" and "Tech," but not as well in certain categories such as "Fashion/Beauty" and "Alternative Lifestyle."

As our future work, to improve our prediction framework's performance, we plan to investigate external factors that may be important for specific types of groups, such as weather for outdoor activities. Cross-group interaction (competition and coordination) may also be leveraged by the prediction framework. We will investigate the problem of group event popularity further by looking into specific categories where our model does not achieve satisfactory performance. Lastly, we also plan to expand our study to other cities and other EBSNs to see if our experimental results are representative of different scenarios.

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