Joint Event-Partner Recommendation in Event-based Social Networks

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Outlines

• Background
• Problem Formulation and Challenges
• Our Solution
  – A novel heterogeneous network embedding model
  – Efficient Online Recommendation
• Experiments
• Summary
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Event-based Social Networks

- People can create events of any kind and share them with others.

Bring people together with Facebook Events

Tools & tips to set up a great event, reach your audience, sell tickets and measure performance.
Event-based Social Networks

What do you love?

Do more of it with Meetup

Sign Up

Popular Meetups nearby

Friday, March 30, 10:00 AM
Petit Déjeuner Français du Vendredi
Hosted by Marian and 1 other
From Le Petit Déjeuner et Fran...

Friday, March 30, 7:15 PM
Greater Gotham Full Moon
#350 Sylvan Moon
Hosted by Rachelle
From NYC Hash House Harriers

Saturday, March 31, 11:00 AM
Rule of Law Expedited Walkout- Be ready! Blockad...
Hosted by Steve and 1 other
From #Resist: New York
Women's Cocktail Hour

Hosted by Natalie R.
From Brisbane Artificial Intelligence

Details

This meetup is intended to give women a space to discuss the latest tech and AI news and to connect with other women in the network. We acknowledge that women in technology are a minority and this is a small step to boost the number of women engaged in the tech network!
Event-based Heterogeneous Network
Event Recommendation

• Which events best match the user’s preferences?

• **Definition of Event Recommendation**
  - Given a target user $u$, we aim to predict top-n events the user is most likely to attend.
Limitations of Event Recommendation

• People as the social animals, more often than not, prefer to find partners before attending social events

• If a system only recommends an event alone, the user is most likely to refuse the recommendation if she cannot think of a partner to attend it with

• A serious social issue: most of young people have hundreds of friends on Facebook but in reality they often stay alone as they have nobody to hang out with
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Joint Event-Partner Recommendation

• A new recommendation paradigm – joint event-partner recommendation, to help users simultaneously find their interested events and suitable partners.

Hey, Tony. Guess you like liquid light shows.

Would you like to attend a liquid light show held at 120 Broadway, Suite 3650, New York together with Tim?

He also likes it and may be a suitable partner.

Tim
Problem Formulation

- Given an event-based social network, for each user $u$, we aim to recommend top-$n$ **event-partner pairs** $(u', x)$
  - $u$ and the recommended partner $u'$ would like to attend the recommended event $x$ together.
Challenge I: Cold Start

- Event Recommendation is intrinsically cold start.

Events to recommend are always in the future.
Challenge II: Complex Decision Process

• A successful event-partner recommendation depends on
  – whether the querying user will adopt the recommended event and partner
  – whether the recommended partner will accept the invitation from the querying user

• Reciprocity makes the decision process more complex
  – A successful recommendation is agreed between the user and the partner on the recommended event

• How to model this complex decision process?
Challenge III: Huge Prediction Space

- Assuming there are $N$ users and $M$ future events in the system, the number of possible event-partner combinations is $O(N \times M)$.

- Given a user, if we compute a matching score for each event-partner combination and then select top-$n$ ones with highest scores as recommendations, it would be infeasible due to the huge online computation cost.
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Heterogeneous network embedding

• We propose a generic heterogeneous network embedding model (GEM) for event-based social networks
  - To learn the representation of users and events in the same low-dimension latent space
• Due to the heterogeneity and diversity of relations in EBSNs, we decompose an EBSN into multiple bipartite graphs.
Overcoming Cold Start Issue

• Learning the representation of an cold start event from its associated content (e.g., textual description and title) and context information (e.g., time and location).

• Overcoming the cold-start issue via the event-word, event-location and event-time bipartite graphs
Event-Content

• Which type of events do users go to?

HIIT Workout
Hosted by Pam K and Ben M.
From The Rise: FREE Outdoor Fitness in NYC.

Details
This one workout will keep you amped up all week long. Seriously, give it a try and you will be hooked!

The exercises may change from week to week, but it is always a Tabata-style interval workout: 20 seconds of high intensity work followed by 10 seconds of rest. Then repeat! Exercises include sprints, burpees, squats, situps, box jumps, step ups, pushups, dips, and other “no-frills” exercises.

Content may help to capture similar and recurrent events.
Event-Time

- Which time do users go to events?

Temporal Distribution of Each User’s Activities over hours and days
Event-Location

- Where do users go to events?

Spatial Distribution of Each User’s Activities
Decomposing the complex decision process

- Efficiently modelling the complex decision process
  - We decompose the high order interactions among users, events and partners into three pair-wise interaction relationships
  - \((\text{user}, \text{event}, \text{partner}) \rightarrow (\text{user}, \text{event}) + (\text{partner}, \text{event}) + (\text{user, partner})\), captured by user-event and user-user graphs, respectively

![Diagram showing relationships between user, event, and partner preferences](image)
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Model Optimization by Negative Sampling

• Our aim is to embed the above five graphs (User-User, User-Event, Event-Location, Event-Time, Event-Content) into a shared low dimensional space \( \mathbb{R}^K \), and get the vector representations of users, events, locations, time slots and words, i.e., \( \vec{u}, \vec{x}, \vec{l}, \vec{t} \) and \( \vec{w} \).

• All the graphs share the vector representations of events and users.

```
1 iter ← 0;
2 while iter ≤ N do
3     Draw a bipartite graph \( G_{AB} \) from the five input graphs with the probability proportional to its number of edges;
4     Draw a positive edge \( e_{ij} \in \mathcal{E}_{AB} \);
5     Draw \( 2M \) negative edges for \( e_{ij} \) using fast adaptive negative sampling algorithm;
6     Update the associated nodes’ vectors using SGD;
7     iter=iter+1;
8 end
```
Bipartite Graph Embedding

• How to draw negative edges or examples?
• Constructing negative edges from one side is problematic and insufficient in the heterogeneous bipartite graphs and would lead to the slow convergence and low modelling accuracy
  – In the User-Event graph, if we only sample noise nodes from the event side to generate negative edges, the learned event vector could not discriminate between its positive users and negative users.

• Bidirectional Negative Sampling Strategy

\[
O_{AB} = - \sum_{(v_i, v_j) \in E_{AB}} w_{ij} \left( \log p(e_{ij} = 1) \right) + \sum_{k=1}^{M} \sum_{v_k \sim P_n(v)} \log(1 - p(e_{ik} = 1)) + \sum_{k=1}^{M} \sum_{v_k \sim P_n(v)} \log(1 - p(e_{kj} = 1)).
\]

Adaptive Sampler for Adversarial Negative Edges: unobserved edges with a high probability \( p(e_{ik} = 1) \) should be sampled as negative example for model optimization.
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Naïve method

• Based on the learned vector representations of users and events, given a target user $u$ and a candidate event-partner pair $(u', x)$, their matching score is computed as follows:

$$f(u, u', x) = \frac{1}{1 + \exp \left( - (u^T x + u'^T x + \bar{u}^T \bar{u} + \beta) \right)}$$

• Naïve method for top-$n$ recommendation
  – First compute a score for each event-partner pair $(u', x)$
  – Then select top-$n$ pairs with largest scores as recommendations
  – The time complexity is $O(|V_U| \cdot |V_X| \cdot K)$
Fast Online Recommendation

• All existing efficient online recommendation techniques (e.g., TA, AP, CBB, ALSH) are designed for finding the maximum (or top-n) dot-product for a given user vector over a set of item vectors.

• Our scoring function $f(u, u', x)$ cannot be expressed as a dot product between $\vec{u}$ and $(\vec{u}', \vec{x})$.

• We propose a novel space transformation method to map each event-partner pair to one point in a new space.

$$f(u, u', x) = \vec{p} \cdot \vec{q}$$

$$\vec{q} = (\vec{u}, \vec{u}, 1)$$

$$\vec{u}' = (\vec{x}, \vec{u}', \vec{x}) = \vec{p}$$
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### Basic statistics of Douban Event datasets

<table>
<thead>
<tr>
<th></th>
<th>Beijing</th>
<th>Shanghai</th>
</tr>
</thead>
<tbody>
<tr>
<td># of users</td>
<td>64,113</td>
<td>36,440</td>
</tr>
<tr>
<td># of events</td>
<td>12,955</td>
<td>6,753</td>
</tr>
<tr>
<td># of venues</td>
<td>3,212</td>
<td>1,990</td>
</tr>
<tr>
<td># of historical attendances</td>
<td>1,114,097</td>
<td>482,138</td>
</tr>
<tr>
<td># of friendship links</td>
<td>865,298</td>
<td>298,105</td>
</tr>
</tbody>
</table>
Comparison Methods – Cold Start Recommendation

- **PCMF**: a probabilistic collective matrix factorization model (AAAI’14)
  - can only model the binary relations
  - use uniform distribution to generate negative samples
- **CBPF**: a collective Bayesian Poisson factorization model for cold-start event recommendation (KDD’15)
- **PER**: modelling an EBSN as a heterogeneous information network (WSDM’14)
  - Extract meta-path based latent features from the EBSN to represent the similarity between users and events along different types of meta paths
- **PTE**: proposed for large-scale heterogeneous information network embedding (KDD’15)
  - Using Traditional Negative Sampling method for model optimization
- **GEM-P**: our model that adopts the popularity-biased negative sampling
- **GEM-A**: our model with our proposed adversarial negative sampling
Experimental Results

Cold-start Event Recommendation

(a) Beijing

(b) Shanghai
Experimental Results

Joint Event-Partner Recommendation (Scenario I)

(a) Beijing

(b) Shanghai
Experimental Results

Joint Event-Partner Recommendation (Scenario II)

(a) Beijing

(b) Shanghai
## Online Recommendation Efficiency

<table>
<thead>
<tr>
<th>Methods</th>
<th>Online Recommendation Time Cost(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=5</td>
</tr>
<tr>
<td>GEM-TA</td>
<td>2.21</td>
</tr>
<tr>
<td>GEM-BF</td>
<td>45.34</td>
</tr>
</tbody>
</table>
Summary

• Novel Problem - a novel recommendation paradigm: joint event-partner recommendation

• Comprehensive Model – a bipartite graph-based heterogeneous network embedding model to learn vector representations of cold-start events from their content and contextual information.
  – A novel bidirectional negative sampling method and a novel adaptive noise sampler to generate adversarial negative samples for model optimization

• Efficient Online Recommendation Techniques- a new space transformation method to project each event-partner pair to one point in a new space.
  – off-the-shelf online recommendation techniques can be directly used.
Thank you!