COM: A Generative Model for Group Recommendation

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Introduction

❖ People often participate in activities together with others
  ▪ having picnics with friends
  ▪ watching movies with spouses

❖ A great number of group event records are available, as users are willing to share their group activities on social networks

❖ Group recommendation: recommending a list of items for a group of users
  ▪ Facilitate groups making decisions
  ▪ Help web services improve user engagement

❖ It is a challenging task
  ▪ Conventional recommender systems are designed for individuals
  ▪ Difficult to make a trade-off among different members’ preferences
  ▪ Many groups are ad hoc
Related Work

- Previous solutions can be divided into two categories
  - Memory-based
  - Model-based

- Two popular memory-based approaches
  - Average (AVG):
    - Calculate recommendation score for each member
    - Average recommendation scores of group members
    - Users’ satisfactions are diverse (not fair to some users)
  - Least Misery (LM):
    - Calculate recommendation score for each member
    - Take the smallest recommendation score of group members
    - Score of an item is determined by the user who dislikes it most
Related Work

Two popular model-based approaches

- Social Influence-based Group (SIG) \textit{Ye et al. SIGIR’12}
  - When making a selection, the user either listens to her friend’s opinion, or follows her own preference
  - In a group, every pair of users influence each other
  - The pairwise influence may not be true, especially in large groups

- Personal Impact Topic Model (PIT) \textit{Liu et al. CIKM’12}
  - Different users have different impact scores
  - Users with larger impact scores will always select items for all groups based on their own preferences
  - Users’ impacts in groups should be topic-dependent
Consensus Model

- A group event $g$ consists of a set of users $u_g$ and an item $i_g$.
- Intuitions for the generative process of a group:
  - Each group is relevant to several topics with different matching degrees
    - e.g., a picnic group is more relevant to hiking and dining topics than to the body-building topic
  - The topics of the group attract users to join the group
A group event $g$ consists of a set of users $u_g$ and an item $i_g$.

Intuitions for the generative process of a group:
- Each group member selects an item either based on the topic, or her personal considerations of content factors.
  - e.g., when selecting a venue for picnic, a user may consider either the matching degree of a venue to the topic “hiking”, or some content factors, e.g., the travel distance to a venue.
Consensus Model

- A group event $g$ consists of a set of users $u_g$ and an item $i_g$
- Intuitions for the generative process of a group:
  - Different users make different trade-offs between the two factors
    - Toss a coin $c$ from user-specific Bernoulli distribution $\lambda_u$
    - Head: topic, tail: personal considerations of content factors
    - e.g., if a user does not mind traveling, then the topic “hiking” has a more significant influence to her selection. Thus, her toss result is more likely to be “head”
Consensus Model

- A group event $g$ consists of a set of users $u_g$ and an item $i_g$

Intuitions for the generative process of a group:

- A user may behave differently when selecting as a group member and as an individual. In a group, a user tends to match her preference to the topics of the group:
  - If head, select item based on the group topic attracted her
  - e.g., a movie fan will select a hill instead of a cinema for the picnic group

\[
\begin{align*}
\lambda_u & \backslash \lambda_g \\
|G| & \backslash |G| \\
\theta & \backslash \theta \\
z & \backslash z \\
u & \backslash u \\
i & \backslash i \\
\text{head} & \backslash \text{head} \\
\text{tail} & \backslash \text{tail}
\end{align*}
\]
Consensus Model

- For each topic $z_k$, $k = 1, \ldots, K$
  - Draw multinomial user distribution $\Phi^{zu}_k \sim Dir(\beta)$
  - Draw multinomial item distribution $\Phi^{zi}_k \sim Dir(\eta)$
- For each user $u_v$, $v = 1, \ldots, |U|$
  - Draw multinomial item distribution $\Phi^{ui}_v \sim Dir(\rho)$
  - Draw Bernoulli distribution $\lambda_v \sim Beta(\gamma)$
- For each group $g$
  - Draw topic distribution $\theta_g \sim Dir(\alpha)$
  - For each group member
    - Draw topic $z \sim Mult(\theta_g)$
    - Draw user $u \sim Mult(\Phi^{zu}_z)$
    - Toss a coin $c \sim Bernoulli(\lambda_u)$
      - If $c = 0$
        » Draw item $i \sim Mult(\Phi^{ui}_u)$
      - Else
        » Draw item $i \sim Mult(\Phi^{zi}_z)$

We employ Gibbs sampling to estimate the parameters
First, we use Gibbs sampling to estimate the topic distribution $\theta_t$ of the target group members $u_t$.

Then, based on the generative process, we rank candidate items $i$ as follows:

$$P(i|u_t, \theta_t) = \prod_{u \in u_t} \sum_{z \in Z} \theta_{t,z} \cdot \phi_{ZU}^{ZU} (\lambda_u \cdot \phi_{ZI}^{ZI} + (1 - \lambda_u) \cdot \phi_{UI}^{UI})$$

The influences of users in groups are topic-dependent.

- User $u$ is influential in group $g_t$ if she is an expert in topic $z$ (larger $\phi_{ZU}^{ZU}$ value) and the group is relevant to topic $z$ (larger $\theta_{t,z}$ value).
The probability that a user $u$ selects an item $i$ (based on personal considerations) is $\varphi_{u,i}^{UI}$.

We can revise its prior $\rho_{u,i}$ to incorporate content information:

- As a result, $P(i|u)$ is changed.

Venue recommendation:
- Users tend to visit their nearby venues.
- We assign larger value to $\rho_{u,i}$ if venue $i$ is close to the venues previously visited by user $u$.

Movie recommendation:
- Users are likely to watch movies casted by their favorite stars.
- We assign larger value to $\rho_{u,i}$ if movie $i$ is stared by user $u'$ favorite actors/actresses.
Experimental Setup

Two recommendation tasks on four datasets

- **Venue recommendation**: recommend venues for groups
  - Jiepang: group check-in records of a location-based social network
  - Plancast: event records of an event-based social network
- **Movie recommendation**: recommend movies for groups
  - MovieLens-Simi: groups with large similarities between members
  - MovieLens-Rand: randomly formed groups

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Plancast</th>
<th>Jiepang</th>
<th>MovieLens Simi</th>
<th>MovieLens Rand</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Users</td>
<td>41,705</td>
<td>28,88</td>
<td>891</td>
<td>3689</td>
</tr>
<tr>
<td>#Groups</td>
<td>13,885</td>
<td>23.621</td>
<td>3,000</td>
<td>3,000</td>
</tr>
<tr>
<td>#Items</td>
<td>8,016</td>
<td>9,746</td>
<td>441</td>
<td>1,518</td>
</tr>
<tr>
<td>#members</td>
<td>23.30</td>
<td>4.68</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>#group item</td>
<td>1.00</td>
<td>1.01</td>
<td>14.97</td>
<td>3.73</td>
</tr>
</tbody>
</table>
Experimental Setup

- For each dataset, we randomly mark off 20% of group records as the test set

- Evaluation metrics
  - **Recall@N**: how well a method can retrieve the true items among top-$N$ recommendations
  - **nDCG**: how well a method can rank the true items higher in the list
  - For both metrics, larger value indicates better performance

- Methods to be evaluated
  - **User-based CF**: CF-AVG, CF-LM, CF-RD (RD: relevance and disagreement, Yahia et al. PVLDB ’09)
  - **Model-based**: SIG (Ye et al. SIGIR ’12), PIT(Liu et al. CIKM ’12)
  - **Proposed models**: COMP (P: plain, without content information), COM (full model with content information)
Experimental Results

- We fix #topics $K$ at 250, and evaluate $\text{Recall}@N$ ($N = 5, 10, 20$)

- **CF-based approaches and SIG perform bad**
  - No interactions between members are considered by CF
  - No tags and few social relations are available for SIG

- **PIT performs better**
  - Users' influences are exploited

- **COMP and COM achieve superior accuracy**
  - COMP outperforms baselines by more than 20% w.r.t. $\text{Recall}@5$
  - COM further improve $\text{Recall}@5$ by more than 15%
  - Behavior changes in a group, topic-dependent influences and content information are considered
Experimental Results

- Evaluate Recall@5 and nDCG under different #topics $K$ (50 ~ 400)

- For both Recall@5 and nDCG, COMP outperforms baselines by more than 20%, and COM outperforms COMP by more than 15%
Experimental Results

- **Recall@5 and nDCG** for groups of different sizes on Plancast
  - COMP and COM outperform baselines for groups of different sizes

- **Topic Analysis**
  - Representative Movies for COM Topics

<table>
<thead>
<tr>
<th>Topic</th>
<th>Movies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comedy</td>
<td>Big (1988), Romancing the Stone (1984), Four Weddings and a Funeral (1994)</td>
</tr>
<tr>
<td>Action</td>
<td>Raiders of the Lost Ark (1981)</td>
</tr>
<tr>
<td>Animation</td>
<td>Toy Story 2 (1999), Mulan (1998), Peter Pan (1953)</td>
</tr>
</tbody>
</table>

Venue distribution of Topics on Plancast
Conclusion

- Most recommender systems are designed for individuals. How to make accurate recommendations for groups is still an open problem.
- We propose a probabilistic model COM (COnsensus Model) to simulate the generative process of group events.
- COM considers users behavior changes in groups, topic-dependent influences and content information, which can make group recommendations.
- Experimental results on four real-world datasets show that our proposed method can outperform state-of-the-art baselines significantly.
Q & A?

Thank You!

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Datasets

- **Plancast**
  - An event-based social network, on which a user can join different events
  - Each event involves a group of members and is held at a venue
  - We aim to recommend venue for the group of members.

- **Jiepang**
  - An location-based social network, on which a user can share physical locations by check-ins
  - Each check-in involves a user, time and a venue
  - We extract implicit group check-ins
    - Assumption: if a set of friends visit the same venue at the same time (within 0.5 hour), they are members of a group.
  - We aim to recommend venue for the group of friends.