Temporal Recommendation on Graphs via Long- and Short-term Preference Fusion

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Problem & Challenges

- Temporal dynamics is crucial in recommender system.
  - [Koren KDD09], [Liu IUI10], etc
- Temporal recommendation focuses more on **local** recommendation models for each user
- When modeling individual, one’s behavior is usually determined by long-term interests and short-term interests
- Challenges
  - How to represent and balance users’ long-term and short-term preferences?
Motivation for Session-based Temporal Graph (STG)

- input data <user, item, time>
- User-Item Matrix usually can be represented as a bipartite graph
- When incorporating time factors, we introduced a new type of node – “session node”
  - Session: dividing the time slices into bins and binding the bins with corresponding users
- Time dimension is a local effect of user, treat time as a universal dimension shared by all users is not very effective, e.g. tri-partite graph or tensor

User-Item Matrix

<table>
<thead>
<tr>
<th></th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
</tr>
</thead>
<tbody>
<tr>
<td>U1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>U2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Bipartite graph

Add time factors as session node
Injected Preference Fusion (IPF on STG)

- An algorithm based on STG, which balancing the impact of long-term and short-term preferences when making recommendation

- Basic Idea:
  - Injected Preferences into both user node ($\beta$) and session node ($1 - \beta$)
  - Then in propagation process, the preferences were propagated to an unknown item node
  - Finally, the nodes which get most preferences will be recommended to current user
Injected Preference Fusion on STG

Making recommendation for U1 at time T1:

Session Temporal Graph (STG)

STG edge weight definition:

\[ w(v, v') = \begin{cases} 
1 & v \in U \cup S, v' \in I \\
\eta_u & v \in I, v' \in U \\
\eta_s & v \in I, v' \in S 
\end{cases} \]

\[ \eta = \eta_u / \eta_s \]

\( \eta = \infty \): two items only connected via user nodes;

\( \eta = 0 \): two items only connected via session nodes;

Paths from user node:

- user -> item -> user -> item
- user -> item -> session -> item

Paths from session node:

session -> item -> user -> item
session -> item -> session -> item
Experiments

- Data sets
  - CiteULike

<table>
<thead>
<tr>
<th></th>
<th>User</th>
<th>Item</th>
<th>User-item pair</th>
<th>sparsity</th>
</tr>
</thead>
<tbody>
<tr>
<td>User</td>
<td>4,607</td>
<td>16,054</td>
<td>109,346</td>
<td>99.85%</td>
</tr>
</tbody>
</table>

- Delicious

<table>
<thead>
<tr>
<th></th>
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<th>Item</th>
<th>User-item pair</th>
<th>sparsity</th>
</tr>
</thead>
<tbody>
<tr>
<td>User</td>
<td>8,861</td>
<td>3,257</td>
<td>59,694</td>
<td>99.79%</td>
</tr>
</tbody>
</table>

- Evaluation Metric

  Hit Ratio: Put the latest item of each user into test set, then generate a list of N (N=10) items for everyone at time t. If the test item appears in the recommendation list, we call it a hit.

- Compared Algorithms

  - Temporal User KNN
  - Temporal Item KNN
  - Temporal Personalized Random Walk
β’s impact – Balance the Injected Preferences on User and Session node

- Optimal results were get when β belongs to [0.1, 0.6];
- Proves the impacts of both long-term and short-term preferences in making good recommendation
η’s impact -- Control the ratio of preferences (from an item node) flow to user node against to session node

\[ \eta = \frac{\eta_u}{\eta_s} \]

- Proves the effectiveness of balancing long-term and short-term preferences in propagation process
- Since X-axis is the logarithm value, it means the optimal hit ratio can be get for a wide range of η

CiteULike

- \( \eta = 0 \), item-item connected only by session
- \( \eta = \infty \), item-item connected only by user

Delicious

- \( \eta = 0 \), item-item connected only by session
- \( \eta = \infty \), item-item connected only by user
Session size’s impact on Hit Ratio of IPF

- The result is not very sensitive to the size of time window
  - On CiteULike, the optimal time window is about one week
  - On Delicious, the optimal time window is about one day
- Users’ interests on research topics (CiteULike) drift more slowly than interests on browsing web pages (Delicious), proves with our real life experience.
Overall Accuracy Comparison

- User Temporal Item KNN as baseline,
  - On CiteULike, MS-IPF improves TItemKNN up to 15.02%;
  - On Delicious, MS-IPF improves TItemKNN up to 34.45%
Conclusion

- Propose a Session-based Temporal Graph (STG) to incorporate temporal information on the graph.
- Based on STG, we propose Injected Preference Fusion (IPF) to balance the impact of users’ long-term and short-term preferences.
- Compare with other approaches on two real datasets, which confirm that STG’s effectiveness for incorporating temporal data, and IPF is effective to balance users’ long-term and short-term preferences.