Who You Would Like to Share With? A Study of Share Recommendation in Social E-commerce

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Introduction

- **Recommender systems** help users discover items of interest from a large resource collection.

- Recommender systems are everywhere, e.g., Amazon, Quora, Douban.

- Recommender systems play a pivotal role in various online services.
Introduction

- Real-world recommender system consists diverse nodes/edges, known as heterogeneous graph.
- Nodes: user, item, shop
- Edges: user-buy-item, user-social-user, user-share-friend
Introduction

- **Share recommendation**, which aims to predict whether a user will share an item with his friend \( P(\text{Friend}|\text{User}, \text{Item}) \).

*Binary Interaction*

\[ Pr(\text{Item}|\text{User}) \]

\[ Pr(\text{User}|\text{User}) \]

*Ternary Interaction*

\[ Pr(\text{Friend}|\text{User}, \text{Item}) \]
Introduction

- **Challenges in share recommendation**
  - Rich Heterogeneous Information
    - Handle the complex interaction information and utilize the diverse feature information simultaneously
  - Complex ternary interaction
    - The suitability of a share action, which evaluates the matching degree of \( \langle u, i, v \rangle \)
  - Asymmetric Share Action
    - \( P(u_3|u_2, i_3)(\checkmark) \) \( P(u_2|u_3, i_3)(\times) \)
Model

- Handle rich information.
- Improve ternary suitability.
- Depict asymmetry.
Model

- Feature Embedding
  - Dynamic/inductive embedding
  - Reduce parameter complexity

\[
x_u = \sigma \left( W_U \cdot \left( \left\| \frac{f^U}{e_{u_k}} \right\|_{k=1} + b_U \right) \right)
\]
Model

- Tripartite Heterogeneous Graph Neural Networks
  - Unify structural and attribute information
  - Diverse interaction $\rightarrow$ multiple representations
  - Real-time prediction

\[
\begin{align*}
\Phi^U_1, \Phi^U_2, \ldots, \Phi^U_{k_1} &= HeteGNN^U (u; \Phi^U_1, \Phi^U_2, \ldots, \Phi^U_{k_1}). \\
\Phi^U_u &= \sigma(W^U \Phi^u \cdot (x_u || x_u^\mathcal{N}^U_u) + b^U), \\
\mathcal{N}^U_u &= \text{MeanPooling}(\{x_n | \forall n \in \mathcal{N}^U_u \}).
\end{align*}
\]
Model

- Dual Co-Attention Mechanism
- Interaction-aware attention weights
- Discover diverse share motivations

\[
\Phi^U_{u,i} = \text{CoAtt}_{U,I}(x^U_{u,i}, \cdots, x^U_{k_1}, x^I_i)
\]

\[
\alpha^m_{u,i} = q^T_{U,I} \cdot \sigma(W^U,I \cdot (x^U_m || x^I_i) + b^U,I),
\]

\[
\phi^U_{u,i} = \frac{\exp(\alpha^m_{u,i})}{\sum_{m=1}^{k_1} \exp(\alpha^m_{u,i})},
\]

\[
h_u = \sum_{m=1}^{k_1} \phi^U_{u,i} \cdot x^U_{u,i}
\]
Model

- Transitive Triplet Representation
  - Asymmetry of share action
  - Item translating
    \[ r_{u,i,v} = |z_u + z_i - z_v| \]

- Loss Function
  \[ \hat{y}_{u,i,v} = \sigma(W \cdot r_{u,i,v} + b) \]
  \[ L = \sum_{u,i,v \in Y^+ \cup Y^-} (y_{u,i,v} \log \hat{y}_{u,i,v} + (1 - y_{u,i,v}) \log (1 - \hat{y}_{u,i,v})) \]
Experiment

- **Comparison Methods**
  - **Baselines**
    - LR/DNN/XGBoost
    - GraphSAGE (NIPS17)
    - IntentGC/IntentGC+ (KDD19)
    - MEIRec/MEIRec+ (KDD19)
  - **Variants**
    - HGSRec \[\]
    - HGSRec \[\]

- **Dataset**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>3-days</th>
<th>4-days</th>
<th>5-days</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\langle u, i, v \rangle) in Training</td>
<td>3,324,367</td>
<td>4,443,996</td>
<td>5,611,531</td>
</tr>
<tr>
<td>(\langle u, i, v \rangle) in Validation</td>
<td>1,401,395</td>
<td>1,401,395</td>
<td>1,401,395</td>
</tr>
<tr>
<td>#User in Training</td>
<td>1,064,426</td>
<td>1,315,126</td>
<td>1,546,017</td>
</tr>
<tr>
<td>#Item in Training</td>
<td>537,048</td>
<td>679,784</td>
<td>818,290</td>
</tr>
<tr>
<td>#User in Validation</td>
<td>539,959</td>
<td>539,959</td>
<td>539,959</td>
</tr>
<tr>
<td>#Item in Validation</td>
<td>247,907</td>
<td>247,907</td>
<td>247,907</td>
</tr>
<tr>
<td>#Instances of U-s-U</td>
<td>13,419,250</td>
<td>16,622,210</td>
<td>19,596,190</td>
</tr>
<tr>
<td>#Instances of U-v-I-v-U</td>
<td>26,838,500</td>
<td>33,244,420</td>
<td>39,192,380</td>
</tr>
<tr>
<td>#Instances of U-b-I-b-U</td>
<td>5,367,700</td>
<td>6,648,884</td>
<td>7,838,476</td>
</tr>
<tr>
<td>#Instances of U-b-I</td>
<td>26,852,400</td>
<td>33,989,200</td>
<td>40,914,500</td>
</tr>
</tbody>
</table>
## Experiment

### Offline Results

<table>
<thead>
<tr>
<th>Methods</th>
<th>3-days</th>
<th>4-days</th>
<th>5-days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>40%  60%  80%  100%</td>
<td>40%  60%  80%  100%</td>
<td>40%  60%  80%  100%</td>
</tr>
<tr>
<td>LR</td>
<td>0.6756 0.6762 0.6726 0.6769</td>
<td>0.6758 0.6765 0.6768 0.6772</td>
<td>0.6762 0.6767 0.6772 0.6774</td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.7204 0.7214 0.7213 0.7218</td>
<td>0.7208 0.7211 0.7215 0.7249</td>
<td>0.7272 0.7254 0.7178 0.7214</td>
</tr>
<tr>
<td>DNN</td>
<td>0.7130 0.7120 0.7167 0.7203</td>
<td>0.7104 0.7133 0.7148 0.7180</td>
<td>0.7096 0.7112 0.7146 0.7151</td>
</tr>
<tr>
<td>GraphSAGE</td>
<td>0.7055 0.7097 0.7086 0.7089</td>
<td>0.6982 0.6969 0.7046 0.7103</td>
<td>0.6911 0.6966 0.7125 0.7106</td>
</tr>
<tr>
<td>IntentGC</td>
<td>0.6223 0.6178 0.6220 0.6225</td>
<td>0.6187 0.6230 0.6311 0.6317</td>
<td>0.6260 0.6291 0.6311 0.6315</td>
</tr>
<tr>
<td>IntentGC+</td>
<td>0.7315 0.7337 0.7392 0.7434</td>
<td>0.7387 0.7399 0.7422 0.7451</td>
<td>0.7414 0.7422 0.7453 0.7479</td>
</tr>
<tr>
<td>MEIRRec</td>
<td>0.6494 0.6510 0.6530 0.6553</td>
<td>0.6545 0.6555 0.6566 0.6572</td>
<td>0.6519 0.6558 0.6620 0.6563</td>
</tr>
<tr>
<td>MEIRRec+</td>
<td>0.7682* 0.7740* 0.7706* 0.7820*</td>
<td>0.7607* 0.7725* 0.7687* 0.7636*</td>
<td>0.7658* 0.7720* 0.7662* 0.7766*</td>
</tr>
<tr>
<td>HGSRec_{att}</td>
<td>0.8663 0.8695 0.8716 0.8726</td>
<td>0.8700 0.8727 0.8731 0.8751</td>
<td>0.8711 0.8723 0.8734 0.8759</td>
</tr>
<tr>
<td>HGSRec_{tra}</td>
<td>0.7817 0.7910 0.7950 0.7995</td>
<td>0.7640 0.7912 0.7709 0.7963</td>
<td>0.7822 0.7889 0.7883 0.8137</td>
</tr>
<tr>
<td>HGSRec</td>
<td><strong>0.8684</strong> 0.8720 0.8736 0.8745</td>
<td><strong>0.8705</strong> 0.8739 0.8743 0.8769</td>
<td><strong>0.8727</strong> 0.8753 0.8772 0.8792</td>
</tr>
<tr>
<td>Improvements</td>
<td>13.0%  12.7%  13.4%  11.7%</td>
<td>13.1%  12.4%  13.7%  14.8%</td>
<td>14.0%  13.2%  14.5%  13.2%</td>
</tr>
</tbody>
</table>
Experiment

(a) Attention distributions of meta-paths and corresponding averaged attention values

(b) Performance of meta-paths and corresponding averaged attention values
Experiment

Online Results

![Graph showing online results with two lines representing XGBoost and HGSRec](image-url)
Conclusion

- Discover interesting problems from the real-world scenario.
- A simple yet effective model is welcome in the industry.
THANKS

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