Meta-learning on Heterogeneous Information Networks for Cold-start Recommendation

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Outline

▸ Motivation
▸ MetaHIN
▸ Experiments
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Cold-start Recommendation

Recommender System
- collaborative filtering
- content-based filtering
- …

What about a new user or a new item?

Cold-start Problem
- New users or new items
- The interaction data is very sparse
Existing Methods

Existing alleviations

- Data level
  - Content-based
  - HIN-based

- Model level
  - Meta-learning
Our Idea

Address the cold-start problem at both data and model levels?

Exploit the power of both meta-learning at the model level and HINs at the data level

NON-TRIVIAL!
Challenges

C1: How to model HINs in the meta-learning setting?

- Existing methods model HINs under traditional supervised or unsupervised learning settings

C2: How to model the general knowledge across tasks?

- Previous work: Only adapt to new tasks (e.g., new users) from a globally shared prior
- Our work: There exist multifaceted semantics brought by HINs
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Overall Framework of MetaHIN

C1: Task construction augmented with semantic contexts

C2: Semantic and task-wise adaptations
Semantic-enhanced Task Constructor

Support set of $u$

$$S_u = (S_u^R, S_u^P)$$

- rated items
- semantically related items
- meta-path reachable items

$$S_u^P = (S_u^{p_1}, S_u^{p_2}, \ldots, S_u^{p_n})$$

$$S_u = \bigcup_{i \in S_u^R} C_{u,i}^p$$

$$C_{u,i}^p = \{j : j \in \text{items reachable along } p \text{ starting from } u-i\}$$
Co-adaptation Meta-learner

**Base Model** $f_\theta = (g_\phi, h_\omega)$ parameterized by $\theta = \{\phi, \omega\}$

- $\mathbf{x}_u = g_\phi(u, \mathbf{C}_u) = \sigma(\text{MEAN}([\mathbf{W}e_j + \mathbf{b} : j \in \mathbf{C}_u]))$

- $\hat{r}_{ui} = h_\omega(\mathbf{x}_u, \mathbf{e}_i) = \text{MLP}(\mathbf{x}_u \oplus \mathbf{e}_i)$
Co-adaptation Meta-learner

\[ \theta = \{\phi, \omega\} \]

Adaptation on support set

Optimization on query set

\[ \theta^{P_1}_{u_2} = \{\phi^{P_1}_{u_2}, \omega^{P_1}_{u_2}\} \]

Semantic-wise adaptation w.r.t. loss on support set

\[ \phi^{P_1}_{u_2} \leftarrow \phi \]

Task-wise adaptation w.r.t. loss on support set

\[ \omega^{P_1}_{u_2} \leftarrow \omega \]

Backpropagation on query set in meta-training

Semantic-wise adaptation

\[ \phi^p_u = \phi - \alpha \frac{\partial L_{T_u}^{p}(\omega, x^p_u, S^R_u)}{\partial \phi} \]

Task-wise adaptation

\[ \omega^p_u = \omega^p - \beta \frac{\partial L_{T_u}^{p}(\omega^p, x^{p(S)}_u, S^R_u)}{\partial \omega^p} \]
Optimization

- Objective function to optimize global prior $\theta = \{\phi, \omega\}$

$$\min_{\theta} \sum_{T_u \in T_{tr}} \mathcal{L}_{T_u}(\omega_u, x_u, Q_u^R)$$

where

$$\mathcal{L}_{T_u}(\omega_u, x_u, Q_u^R) = \sum_{i \in Q_u^R} (r_{ui} - \hat{r}_{ui})^2$$

- Rating prediction model adapted to $u$
- User preferences (embeddings) adapted to $u$
- Ground truth
- Predicted rating
Experiments

- How does MetaHIN perform compared to state-of-the-art approaches?
- How does MetaHIN benefit from the multifaceted semantic contexts and co-adaptation meta-learner?
- How is MetaHIN impacted by its hyper-parameters?
Setup

- **Datasets**
  - Dbook: #node: 42,070, #edge: 839,465
  - MovieLens: #node: 20,137, #edge: 1,019,817
  - Yelp: #node: 86,874, #edge: 1,429,218

- **3+1 scenarios**
  - Three cold-start scenarios:
    - (UC) User Cold-start, i.e., recommendation of existing items for **new users**;
    - (IC) Item Cold-start, i.e., recommendation of **new items** for existing users;
    - (UIC) User-Item Cold-start, i.e., recommendation of **new items for new users**
  - One traditional scenario
    - recommendation of existing items for existing users
### Performance Comparison (RQ1)

Table 2: Experimental results in four recommendation scenarios and on three datasets. A smaller MAE or RMSE value, and a larger nDCG@5 value indicate a better performance. The best method is bolded, and second best is underlined.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Model</th>
<th>DBook</th>
<th>MovieLens</th>
<th>Yelp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE ↓ RMSE ↓ nDCG@5 ↑</td>
<td>MAE ↓ RMSE ↓ nDCG@5 ↑</td>
<td>MAE ↓ RMSE ↓ nDCG@5 ↑</td>
<td></td>
</tr>
<tr>
<td>Existing items for new users</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(User Cold-start or UC)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dbook</td>
<td>3.05 ± 5.26%</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>MovieLens</td>
<td>2.89 ± 5.55%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yelp</td>
<td>2.22 ± 5.19%</td>
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</tr>
</tbody>
</table>

- **Dbook**: 3.05-5.26%
- **MovieLens**: 2.89-5.55%
- **Dbook**: 2.22-5.19%
Performance Comparison (RQ1)

- **improvement**
  - non-cold-start < UC ~ IC < UIC

- **support set**
  - the larger the set, the better the performance;
  - MetaHIN is robust to set size.

**Figure 3**: Performance improvement of MetaHIN.

**Figure 4**: Impact of the size of support sets in UIC scenario.
Model Analysis (RQ2)

- **MetaHIN-BM**
  base model without meta-learning

- **MetaHIN-FT**
  fine-tune the base model

- **MetaHIN-TA**
  only task-wise adaptation

- **MetaHIN-ID**
  independently adopts task-wise adaptation
Parameter Analysis (RQ3)

- **Number of Co-adaptations**
  
  $s$ and $t$ are the number of semantic- and task-wise adaption step

- **Embedding Dimensions**

  $d$ is the dimensions of user embeddings
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Conclusions

- **MetaHIN** alleviates the cold-start problem at both data and model levels.
- A **semantic-enhanced task constructor** to explore rich semantics on HINs in the meta-learning setting.
- A **co-adaptation meta-learner** with semantic- and task-wise adaptions to cope with different semantic facets within each task.
- Extensive experiments on three datasets.
Thank you!

Q&A

More materials in
http://shichuan.org
http://www.yfang.site
https://yuanfulu.github.io