Learning **Intents** behind Interactions with **Knowledge Graph** for Recommendation

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Ubiquitous Personalized Recommendation

- Serves as a fundamental tool
- Supports for various applications.
  - E-commerce, social network, content-sharing, fashion …
Problem Formulation
Recommendation

- **Input:**
  - Historical user-item interactions (e.g., click, view, purchase)

- **Output:**
  - Given an item, how likely a user would interact with it
Problem Formulation
Knowledge Graph-based Recommendation

- **Additional Input:**
  - **Knowledge Graph (KG)**
    - Background knowledge of items (e.g., item attributes, facts)
    - Rich semantics & relations & connections

- **Core 1:** Behavioral Similarity of Users
- **Core 2:** Content Relatedness of Items
**KG-based Recommender Evolving**

**Graph Neural Network (GNN)-based**
- Core: information propagation & aggregation → higher-order connections
  
  - CKE [2016]
  - CFGK [2018]

**Policy-based**
- Core: learning path-finding policy → higher-order connections
  
  - KGPolicy [2020]
  - PGPR [2019]

**(Meta) Path-based**
- Core: path extraction over a sequence of triplets → higher-order connections
  
  - KPRN [2019]
  - RippleNet [2018]

**Embedding-based**
- Core: knowledge graph embedding over triplets → first-order connections
  
  - KGAT [2019]
  - KGNN-LS [2019]
Limitations of GNN-based Efforts On User Intents

None considers user-item relations at a finer-grained level of intents:

- They only model one single relation between users & items, however, a user generally has **multiple intents** to adopt items.

**Basic idea:** Similar users have similar preferences on items.

**However:** Obscure intents would **confound** the modeling of users’ behavioral similarity.

**Our idea:** Conditioning on similar intents, similar users have similar preferences on items.

- “director” & “star” → watch $i_1$ & $i_5$
- “star” & “partner” → watch $i_2$
Limitations of GNN-based Efforts On Relational Paths

Information aggregation schemes are mostly node-based:

- They only collect information from neighboring nodes, without differentiating which paths it comes from.

**Node-based**

- 1-hop: \{i_1, i_2\}
- 2-hop: \{v_1, v_2, v_3\}
- 3-hop: \{v_3\}

**Path-based**

- Relation dependencies \((p_1, r_2, r_3)\) between \(v_1\) & \(v_3\)

**Basic idea:** Node-based aggregation mixes information of neighborhoods.

**However:** It fails to preserve the relation dependencies & sequencies carried by paths → Relational paths

**Our idea:** Treating relational paths as an information channel to conduct information propagation.
Step 1. **Representation Learning of Intents**

- **Motivation**: Semantics of user intents can be expressed by KG relations.
- **Idea**: assign each intent with a distribution over KG relations → **Use attention strategy to create intent embedding**

- **Intent Representation**
  
  \[ e_p = \sum_{r \in \mathcal{R}} \alpha(r, p) e_r \]

- **Intent embedding shared by all users**
  
  \[ e_p = \sum_{r \in \mathcal{R}} \alpha(r, p) e_r, \]

- **Attentive combination over KG relation embeddings**

- **Independence Modeling**

- **Commonality of all users**

- **User Intent Modeling**

- **Quantify importance of relation** \( v_3 \) **to intent** \( p \)
Our Solution

User Intent Modeling (2)

Step 2. Independence Modeling of Intents

- **Motivation**: Different intents should contain **different & unique** information.
- **Idea**: encourage the representations of intents to differ from each others → Add independence regularization to intent embeddings

**Intent Representation**

$$e_p = \sum_{r \in R} \alpha(r, p) e_r$$

**Mutual Information**

$$L_{IND} = \sum_{p \in \mathcal{P}} -\log \frac{\exp (s(e_p, e_p)/\tau)}{\sum_{p' \in \mathcal{P}} \exp (s(e_p, e_p')/\tau)}$$

Minimize the information amount between any two different intents.

**Distance Correlation**

$$L_{IND} = \sum_{p, p' \in \mathcal{P}, p \neq p'} dCor(e_p, e_{p'})$$

Minimize the associations of any two different intents.
Our Solution
Relational Path-aware Aggregation (1)

Step 1. Aggregation over Intent Graph (IG)

- **Motivation**: IG contains rich collaborative information of users.
- **Idea**: users with similar intents would exhibit similar preference towards items → Intent-aware aggregation for user-intent-item triplet \((u, p, i)\)

\[
e_{u}^{(1)} = \frac{1}{|N_u|} \sum_{(p,i) \in N_u} \beta(u, p) e_p \odot e_{i}^{(l-1)}
\]

\[
e_{i}^{(l)} = \frac{1}{|N_i|} \sum_{(r,v) \in N_i} e_r \odot e_{v}^{(l-1)}
\]

\[
e_{u}^{(1)} = \frac{1}{|N_u|} \sum_{(p,i) \in N_u} \beta(u, p) e_p \odot e_{i}^{(0)},
\]

\[
\beta(u, p) = \frac{\exp(e_{p}^T e_{u}^{(0)})}{\sum_{p' \in \mathcal{P}} \exp(e_{p'}^T e_{u}^{(0)})}
\]

Generate user-specific intent representations
Our Solution

Relational Path-aware Aggregation (2)

Step 2. Aggregation over Knowledge Graph

- **Motivation**: KG reflects content relatedness among items.
- **Idea**: each KG entity has different semantics in different relational contexts → Relation-aware aggregation for item-relation-entity triplet \((i, r, v)\)

\[
e^{(l)}_{i} = \frac{1}{|N_u|} \sum_{(p, i) \in N_u} \beta(u, p) e_p \odot e^{(l-1)}_i
\]

\[
e^{(l)}_{e} = \frac{1}{|N_i|} \sum_{(r, v) \in N_i} e_r \odot e^{(l-1)}_v
\]

Element-wise product between relation \(r\) & connected entity \(v\).

\[
e^{(1)}_i = \frac{1}{|N_i|} \sum_{(r, v) \in N_i} e_r \odot e^{(0)}_v
\]
Our Solution
Overall Framework

Knowledge Graph-based Intent Network (KGIN)

Representation of item, which memorizes the relational signals carried by the relational paths

$$e_i^{(l)} = \sum_{s \in \mathcal{N}_i^l} \frac{e_{r_1}}{|\mathcal{N}_{s_1}|} \odot \frac{e_{r_2}}{|\mathcal{N}_{s_2}|} \odot \cdots \odot \frac{e_{r_l}}{|\mathcal{N}_{s_l}|} \odot e_s^{(0)}$$

- reflects the interactions among relations
- preserves the holistic semantics of paths

$$s = i \xrightarrow{r_1} s_1 \xrightarrow{r_2} \cdots s_{l-1} \xrightarrow{r_l} s_l$$

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### Experiment Settings

#### Datasets
- Amazon-Book, Last-FM, Alibaba-iFashion

#### Evaluation Metrics
- recall@K, ndcg@K

#### Baselines

<table>
<thead>
<tr>
<th>Data</th>
<th>User Intents</th>
<th>Independence of Intents</th>
<th>Information Aggregation</th>
<th>Higher-order Connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF</td>
<td>ID</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CKE</td>
<td>IG</td>
<td>-</td>
<td>-</td>
<td>First-order</td>
</tr>
<tr>
<td>KGAT</td>
<td>IG + KG</td>
<td>-</td>
<td>Node-based</td>
<td>Higher-order</td>
</tr>
<tr>
<td>KGNN-LS</td>
<td>KG</td>
<td>-</td>
<td>Node-based</td>
<td>Higher-order</td>
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<tr>
<td>CKAN</td>
<td>IG + KG</td>
<td>-</td>
<td>Node-based</td>
<td>Higher-order</td>
</tr>
<tr>
<td>R-GCN</td>
<td>IG + KG</td>
<td>-</td>
<td>Node-based</td>
<td>Higher-order</td>
</tr>
<tr>
<td>KGIN</td>
<td>IG + KG</td>
<td>Intent</td>
<td>Mutual Information / Distance Correlation</td>
<td>Higher-order</td>
</tr>
</tbody>
</table>
Experiment
Overall Performance Comparison

<table>
<thead>
<tr>
<th></th>
<th>Amazon-Book recall</th>
<th>Amazon-Book ndcg</th>
<th>Last-FM recall</th>
<th>Last-FM ndcg</th>
<th>Alibaba-iFashion recall</th>
<th>Alibaba-iFashion ndcg</th>
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</thead>
<tbody>
<tr>
<td>MF</td>
<td>0.1300</td>
<td>0.0678</td>
<td>0.0724</td>
<td>0.0617</td>
<td>0.1095</td>
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<td>CKE</td>
<td>0.1342</td>
<td>0.0698</td>
<td>0.0732</td>
<td>0.0630</td>
<td>0.1103</td>
<td>0.0676</td>
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<tr>
<td>KGAT</td>
<td>0.1487</td>
<td>0.0799</td>
<td>0.0873</td>
<td>0.0744</td>
<td>0.1030</td>
<td>0.0627</td>
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<td>KGNN-LS</td>
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<td>0.0560</td>
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<td>0.1039</td>
<td>0.0557</td>
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<tr>
<td>CKAN</td>
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<td>0.0698</td>
<td>0.0812</td>
<td>0.0660</td>
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<tr>
<td>R-GCN</td>
<td>0.1220</td>
<td>0.0646</td>
<td>0.0743</td>
<td>0.0631</td>
<td>0.0860</td>
<td>0.0515</td>
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<tr>
<td><strong>KGIN-3</strong></td>
<td><strong>0.1687</strong>*</td>
<td><strong>0.0915</strong>*</td>
<td><strong>0.0978</strong>*</td>
<td><strong>0.0848</strong>*</td>
<td><strong>0.1147</strong>*</td>
<td><strong>0.0716</strong>*</td>
</tr>
<tr>
<td>%Imp.</td>
<td>13.44%</td>
<td>14.51%</td>
<td>11.13%</td>
<td>13.97%</td>
<td>3.98%</td>
<td>5.91%</td>
</tr>
</tbody>
</table>

- KGIN consistently yields the **best** performance on all three datasets.

- This verifies the importance of:
  - Capturing collaborative signal in **intent-aware interaction graphs**;
  - Preserving **holistic semantics of paths**;

- KGIN can better encode collaborative signals & item knowledge into user and item representations.
• Increasing the **depth of DGCF** substantially enhances the recommendation.

<table>
<thead>
<tr>
<th></th>
<th>Amazon-Book</th>
<th></th>
<th>Last-FM</th>
<th></th>
<th>Alibaba-iFashion</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>recall</td>
<td>ndcg</td>
<td>recall</td>
<td>ndcg</td>
<td>recall</td>
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<tr>
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<td>0.0707</td>
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<tr>
<td>KGIN-2</td>
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<td>0.0892</td>
<td>0.0920</td>
<td>0.0791</td>
<td>0.1162</td>
</tr>
<tr>
<td>KGIN-3</td>
<td>0.1687</td>
<td>0.0915</td>
<td>0.0978</td>
<td>0.0848</td>
<td>0.1147</td>
</tr>
</tbody>
</table>

• Increasing the **intent number** from 1 to 8 significantly enhances the performance.
• KGIN first induces intents — **the commonality of all users** — with various combinations of KG relations.

• KGIN creates **instance-wise explanations** for each interaction the personalization of a single user.
Take-home messages

• We approach better relational modeling from two dimensions:
  • uncovering user-item relationships at the granularity of intents, which are coupled with KG relations to exhibit the explainable semantics;
  • relational path-aware aggregation, which integrates relational information from multi-hop paths to refine the representations.

Future Work

• Incorporating causal concepts to determine whether the intents are the causation of user behaviors.
THANK YOU!

Learning Intents behind Interactions with Knowledge Graph for Recommendation, WWW’2021

https://github.com/huangtinglin/Knowledge_Graph_based_Intent_Network