Learning Intents behind Interactions with Knowledge Graph for Recommendation

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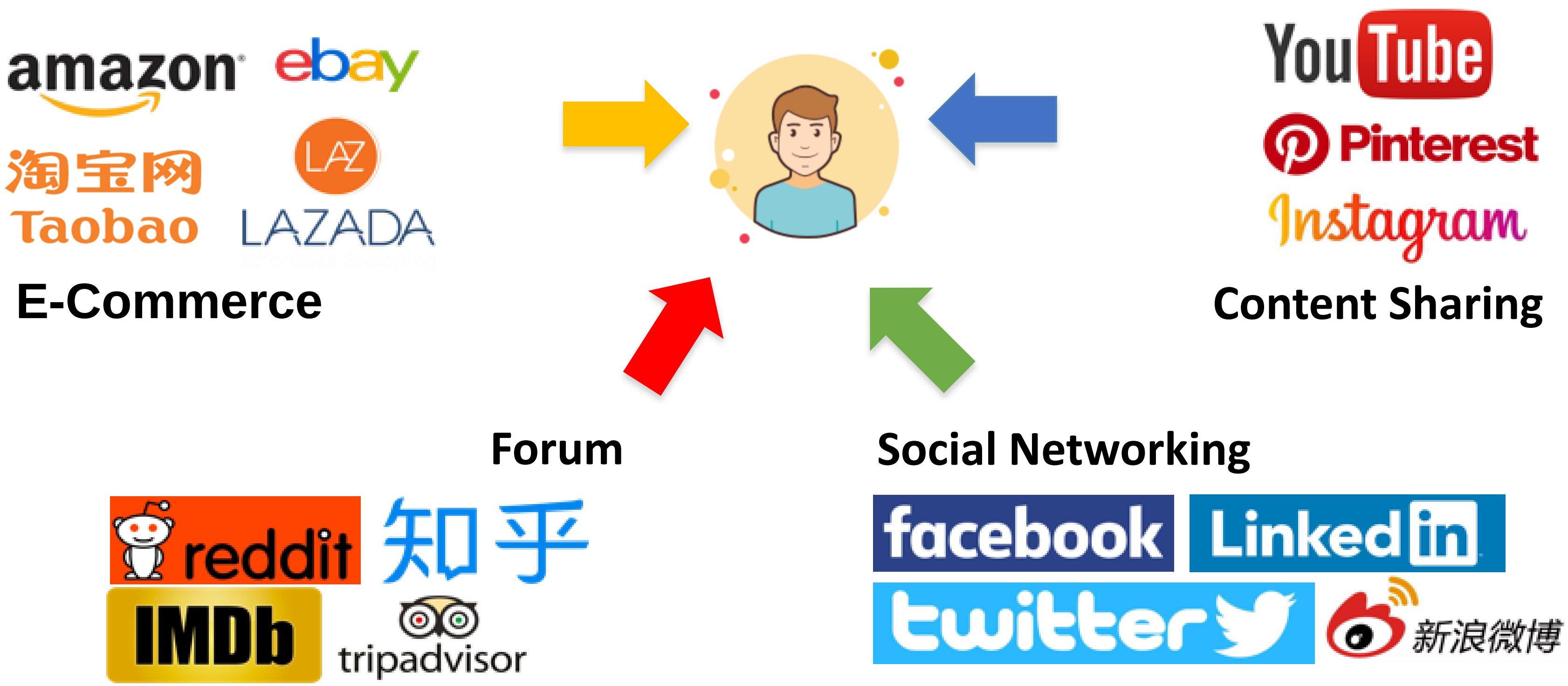
Ubiquitous Personalized Recommendation

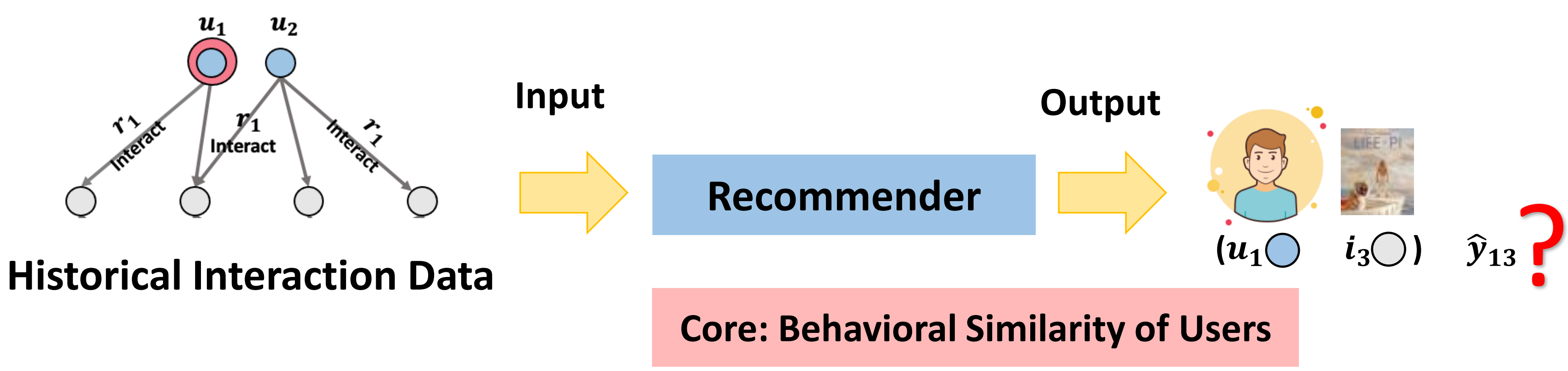
- Serves as a fundamental tool
- Supports for various applications.
  - E-commerce, social network, content-sharing, fashion …



Problem Formulation

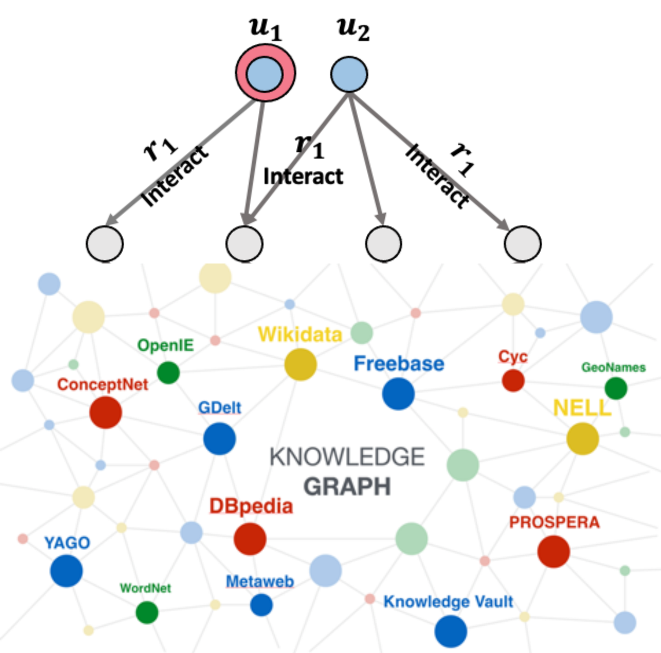
Recommendation

- **Input:**
  - Historical user-item interactions (e.g., click, view, purchase)
- **Output**:
  - Given an item, how likely a user would interact with it

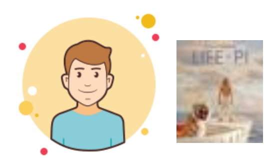


Knowledge Graph-based Recommendation

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



Input → **Recommender** → **Output**



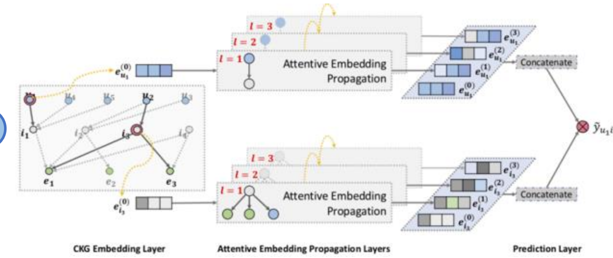
(u_1, i_3) $\hat{y}_{13}$?

Core 1: Behavioral Similarity of Users
Core 2: Content Relatedness of Items

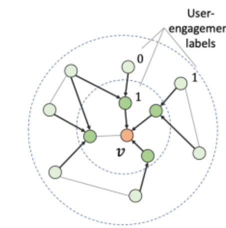
KG-based Recommender Evolving

Graph Neural Network (GNN)-based

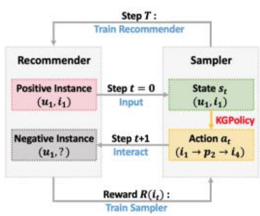
- Core: information propagation & aggregation → higher-order connections



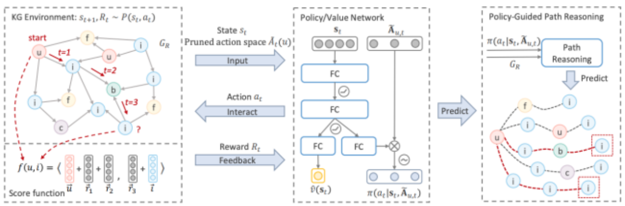
KGAT [2019]



KGNN-LS [2019]



KGPolicy [2020]



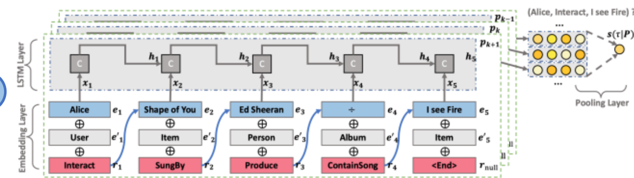
PGPR [2019]

Policy-based

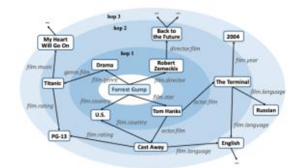
- Core: learning path-finding policy → higher-order connections

(Meta) Path-based

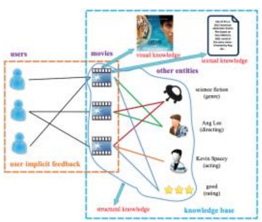
- Core: path extraction over a sequence of triplets → higher-order connections



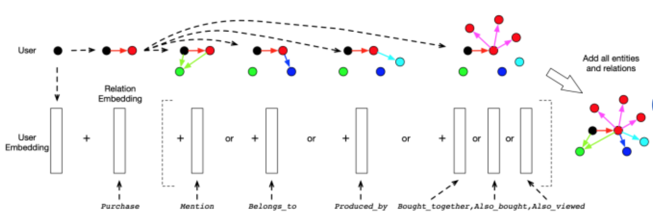
KPRN [2019]



RippleNet [2018]



CKE [2016]



CFKG [2018]

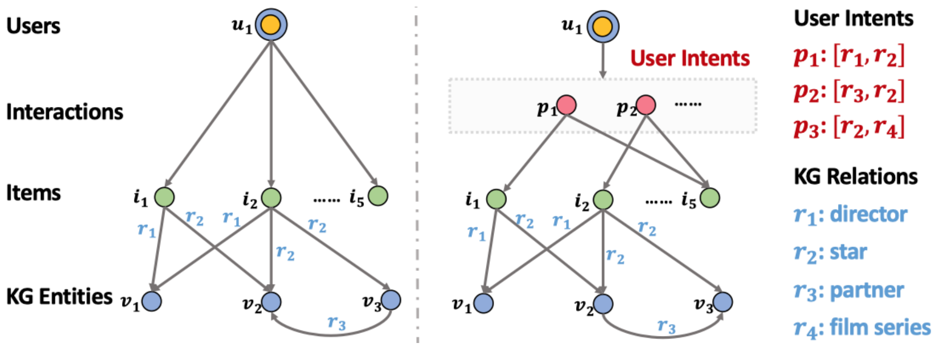
Embedding-based

- Core: knowledge graph embedding over triplets → first-order connections

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



- "director" & "star" → watch i_1 & i_5
- "star" & "partner" → watch i_2

Basic idea: Similar users have similar preferences on items.

⇩

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

⇩

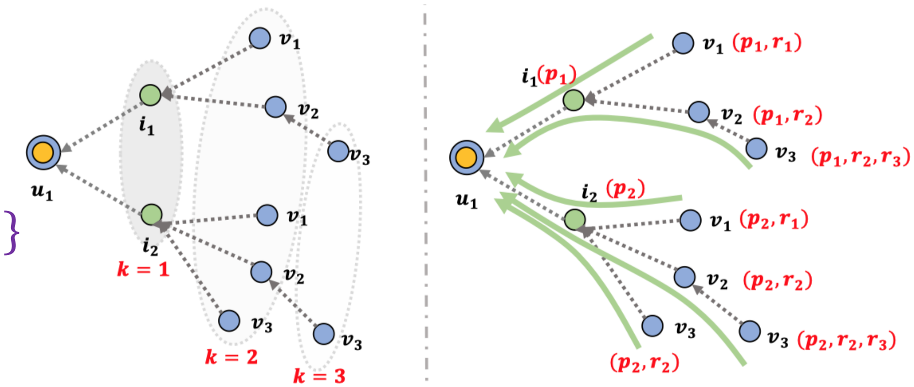
Our idea: Conditioning on similar intents, similar users have similar preferences on items.

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: $\{v_3\}$



Node-based Neighborhood Aggregation

Relational Path Neighborhood Aggregation

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

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

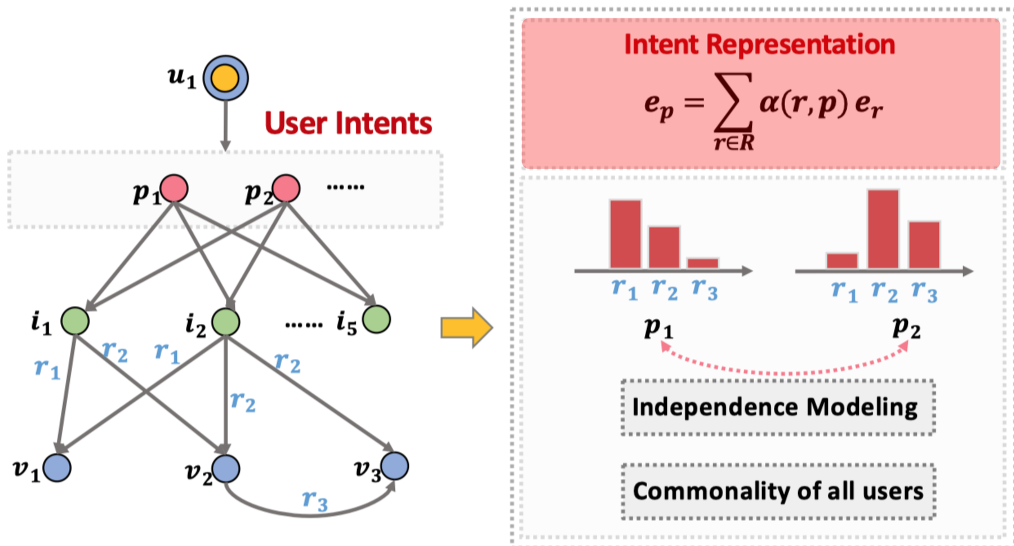
However: It fails to preserve the **relation dependencies & sequencies** carried by paths → **Relational paths**

Our idea: Treating relational paths as **an information channel** to conduct information propagation.

User Intent Modeling (1)

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**



User Intent Modeling

Intent embedding shared by all users

$$\mathbf{e}_p = \sum_{r \in \mathcal{R}} \alpha(r,p)\mathbf{e}_r,$$

Attentive combination over KG relation embeddings

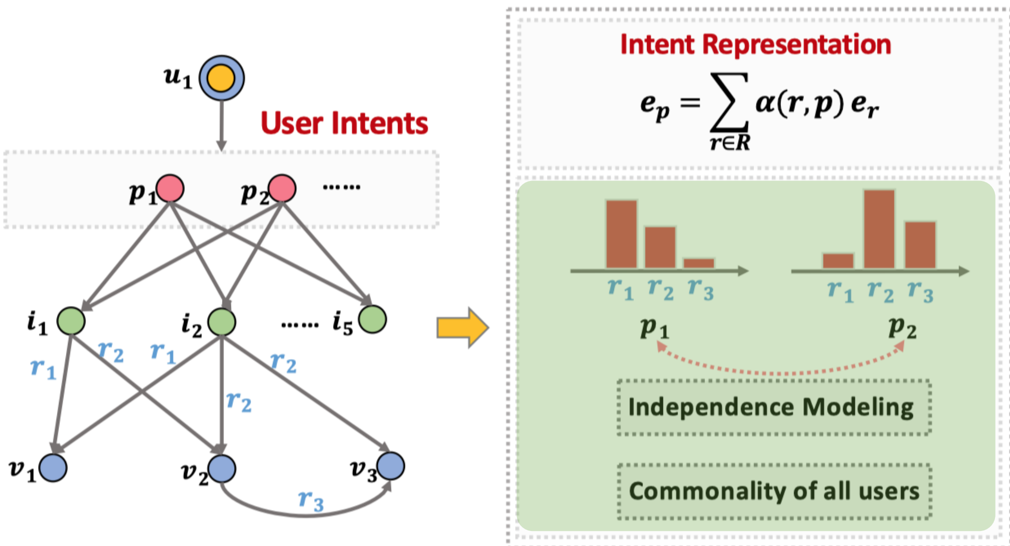
$$\alpha(r,p) = \frac{\exp(w_{rp})}{\sum_{r' \in \mathcal{R}} \exp(w_{r'p})},$$

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**



User Intent Modeling

- **Mutual Information**

$$\mathcal{L}_{\text{IND}} = \sum_{p \in \mathcal{P}} -\log \frac{\exp\left(s(\mathbf{e}_p, \mathbf{e}_p)/\tau\right)}{\sum_{p' \in \mathcal{P}} \exp\left(s(\mathbf{e}_p, \mathbf{e}_{p'})/\tau\right)},$$

Minimize the information amount between any two different intents.

- **Distance Correlation**

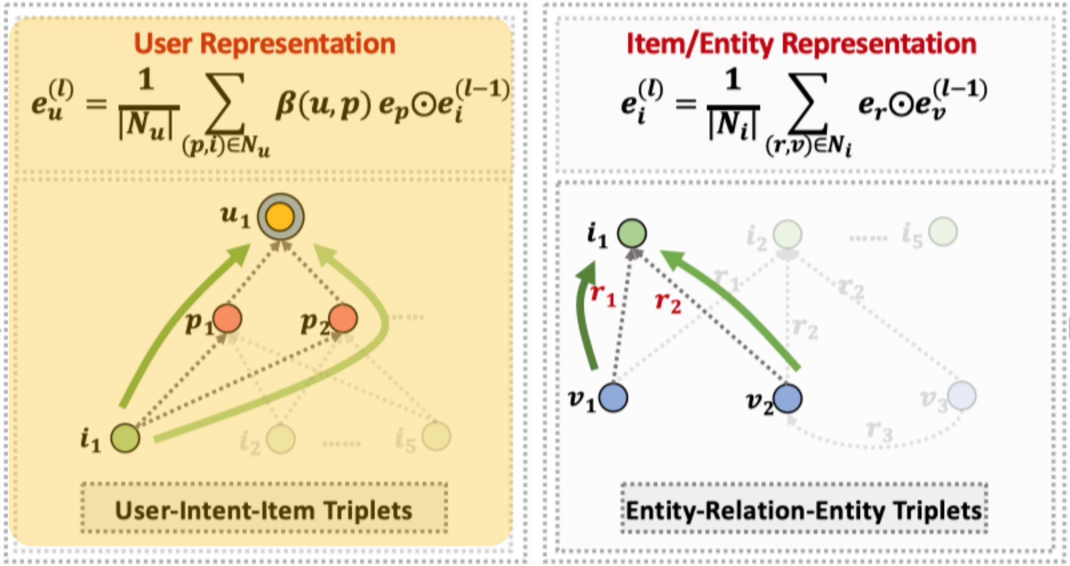
$$\mathcal{L}_{\text{IND}} = \sum_{p,p' \in \mathcal{P},\ p \neq p'} dCor(\mathbf{e}_p, \mathbf{e}_{p'}),$$

Minimize the associations of any two different intents.

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)



Element-wise product between intent p & historical item i.

$$\mathbf{e}_u^{(1)} = \frac{1}{|\mathcal{N}_u|} \sum_{(p,i)\in\mathcal{N}_u} \beta(u,p)\mathbf{e}_p \odot \mathbf{e}_i^{(0)},$$

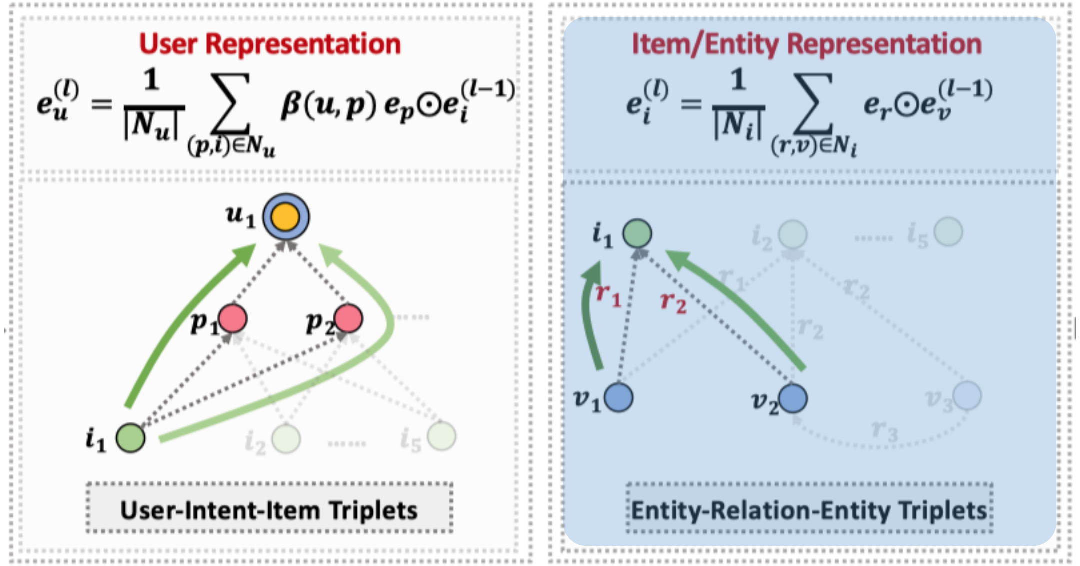
$$\beta(u,p) = \frac{\exp(\mathbf{e}_p^\top \mathbf{e}_u^{(0)})}{\sum_{p'\in\mathcal{P}} \exp(\mathbf{e}_{p'}^\top \mathbf{e}_u^{(0)})}$$

Generate user-specific intent representations

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)



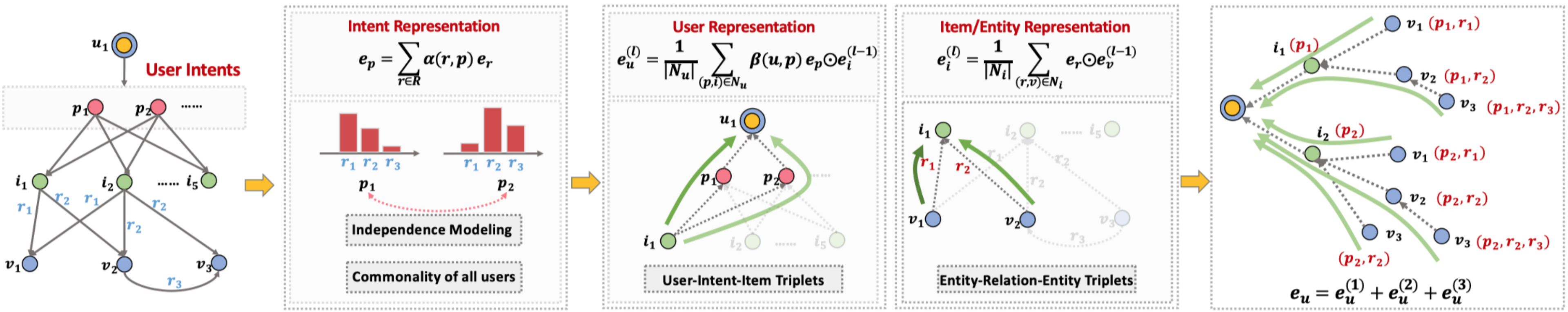
Element-wise product between relation r & connected entity v.

$$\mathbf{e}_i^{(1)} = \frac{1}{|\mathcal{N}_i|} \sum_{(r,v)\in\mathcal{N}_i} \mathbf{e}_r \odot \mathbf{e}_v^{(0)},$$

Our Solution

Overall Framework

Knowledge Graph-based Intent Network (KGIN)



User Intent Modeling — Aggregation Layer over Intent Graph (IG) — Aggregation Layer over Knowledge Graph (KG) — Final User (or Item) Representation

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

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

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

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

Experiment
Settings

Datasets

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

Evaluation Metrics

- recall@K, ndcg@K

Baselines

	Data	User Intents	Independence of Intents	Information Aggregation	Higher-order Connectivity
MF	ID	-	-	-	-
CKE	IG	-	-	-	First-order
KGAT	IG + KG	-	-	Node-based	Higher-order
KGNN-LS	KG	-	-	Node-based	Higher-order
CKAN	IG + KG	-	-	Node-based	Higher-order
R-GCN	IG + KG	-	-	Node-based	Higher-order
KGIN	**IG + KG**	**Intent**	**Mutual Information / Distance Correlation**	**Relational Path-based**	**Higher-order**

Experiment
Overall Performance Comparison

	Amazon-Book		Last-FM		Alibaba-iFashion	
	recall	ndcg	recall	ndcg	recall	ndcg
MF	0.1300	0.0678	0.0724	0.0617	0.1095	0.0670
CKE	0.1342	0.0698	0.0732	0.0630	<u>0.1103</u>	<u>0.0676</u>
KGAT	<u>0.1487</u>	<u>0.0799</u>	0.0873	<u>0.0744</u>	0.1030	0.0627
KGNN-LS	0.1362	0.0560	<u>0.0880</u>	0.0642	0.1039	0.0557
CKAN	0.1442	0.0698	0.0812	0.0660	0.0970	0.0509
R-GCN	0.1220	0.0646	0.0743	0.0631	0.0860	0.0515
KGIN-3	**0.1687***	**0.0915***	**0.0978***	**0.0848***	**0.1147***	**0.0716***
%Imp.	13.44%	14.51%	11.13%	13.97%	3.98%	5.91%

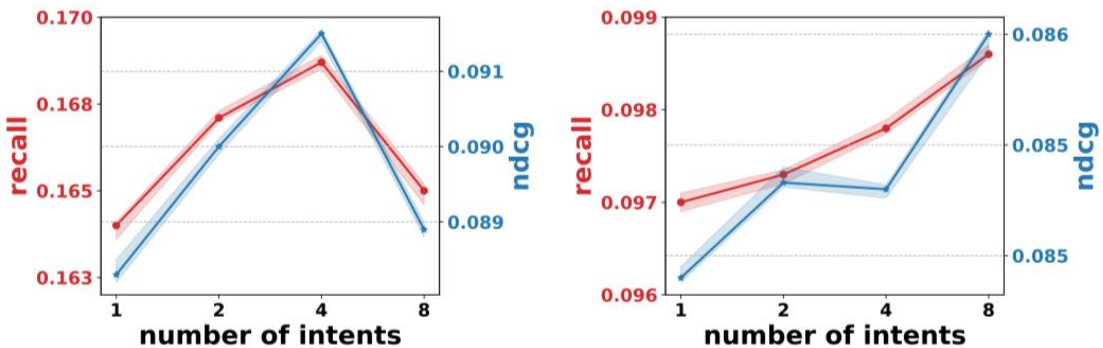
- KGIN consistently yields the **best** performance on all three datasets.
- This verifies the importance of:
  - Capturing collaborative signal in **intent-aware interaction graphs**;
  - Preserving **holistic semantics of paths**;
- KGIN can better encode collaborative signals & item knowledge into user and item representations.

Experiment
Study of KGIN

- Increasing the **depth of DGCF** substantially enhances the recommendation.

	Amazon-Book		Last-FM		Alibaba-iFashion	
	recall	ndcg	recall	ndcg	recall	ndcg
KGIN-1	0.1455	0.0766	0.0831	0.0707	0.1045	0.0638
KGIN-2	0.1652	0.0892	0.0920	0.0791	0.1162	0.0723
KGIN-3	0.1687	0.0915	0.0978	0.0848	0.1147	0.0716

- Increasing the **intent number** from 1 to 8 significantly enhances the performance.



(a) Amazon-Book (b) Last-FM

Experiment

Explainability of KGIN

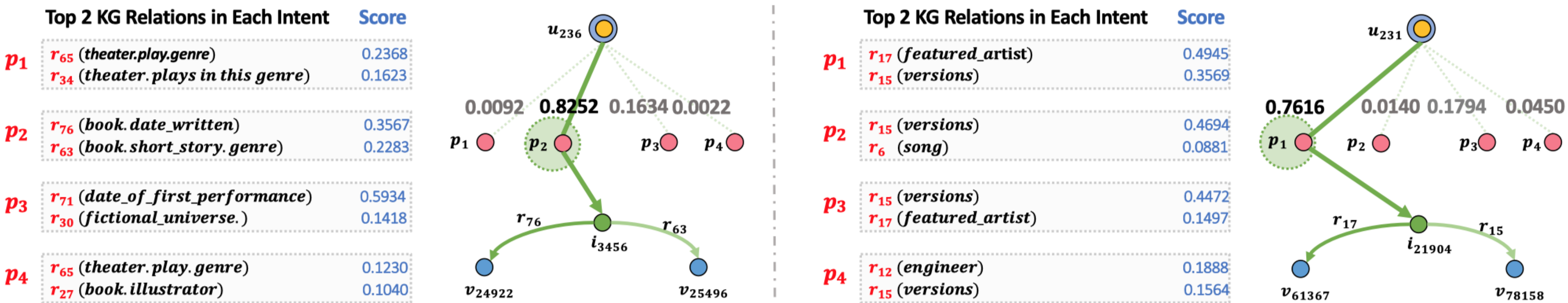


Figure 5: Explanations of user intents and real cases in Amazon-Book (left) and Last-FM (right). Best viewed in color.

- 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.

Conclusion & Future Work

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

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