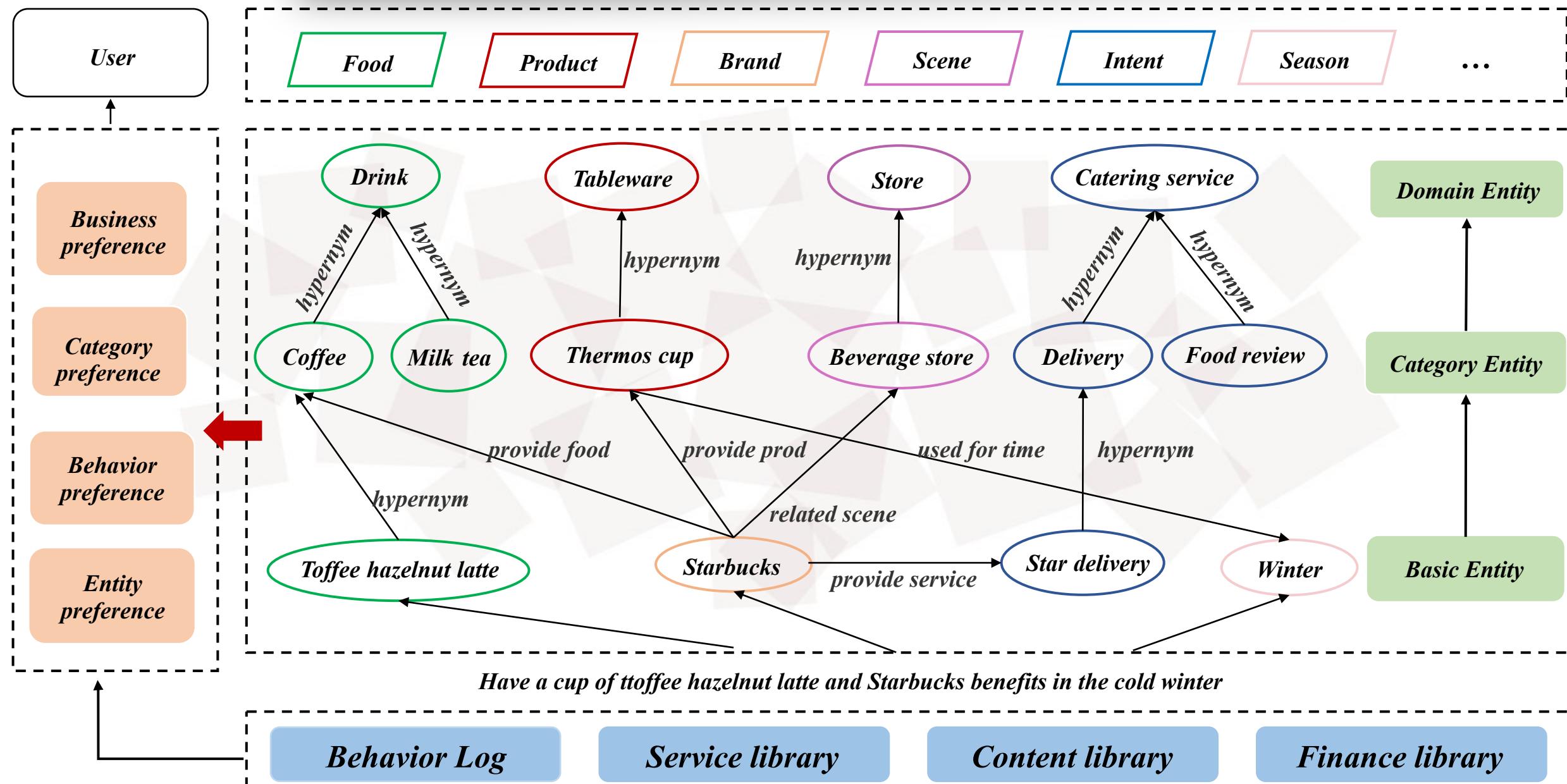


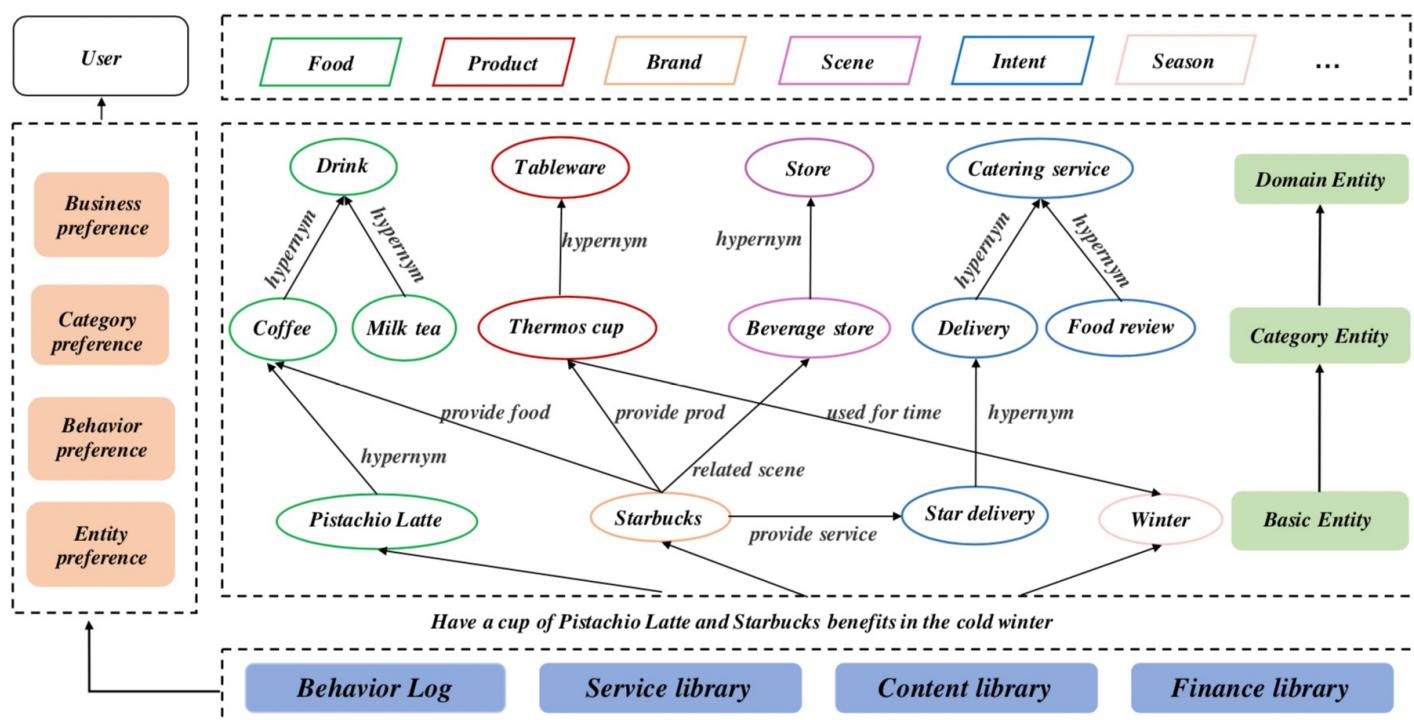


Commonsense Knowledge Graph towards Super APP and Its Applications in Alipay

Xiaoling Zhang*, Binbin Hu*, Jun Chu, Zhiqiang Zhang, Gangnan Zhang,
Jun Zhou, Wenliang Zhong
Ant Group, Hangzhou, China







Entity Extraction

Fields with strong expertise

Crawlers and external public data

Knowledge-related intent

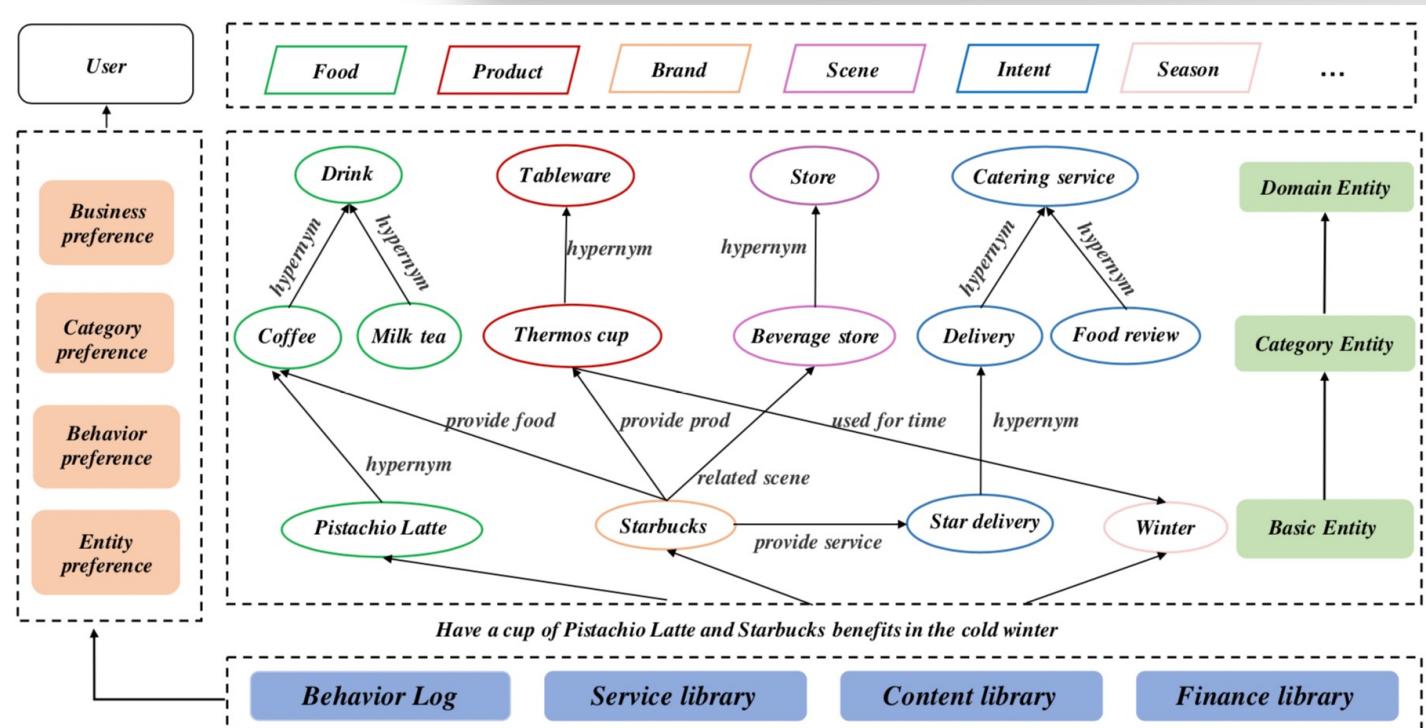
Directly introduced

Existing structural knowledge

Knowledge system with domain experts

knowledge from user behaviors and services

Entity extraction with sequence labeling



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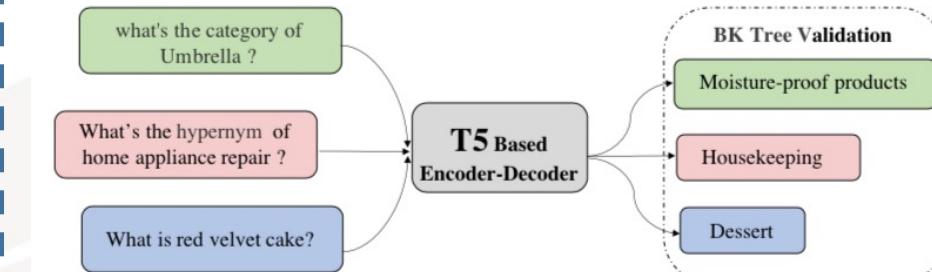
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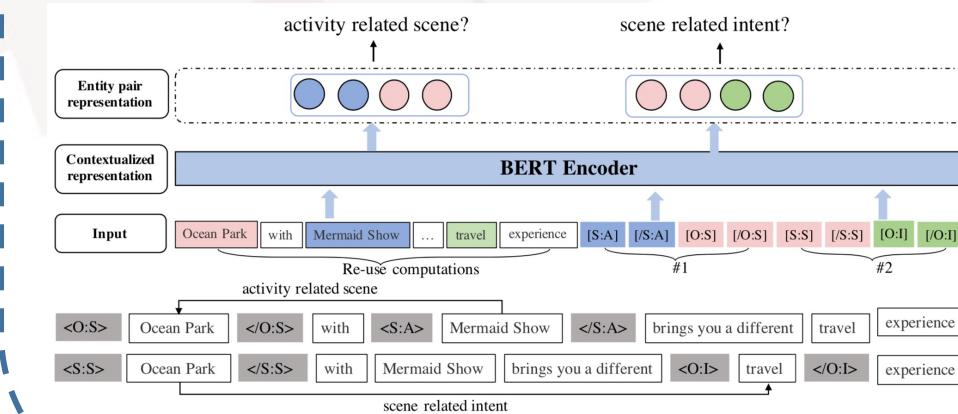
Entity extraction with sequence labeling

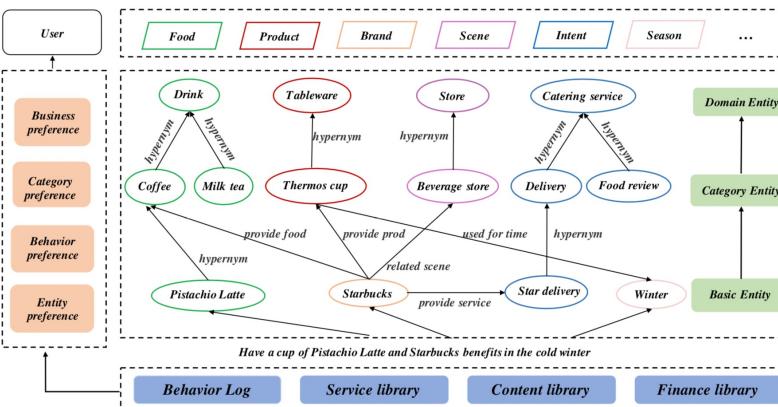
Relation Construction

a) Hierarchical Relation



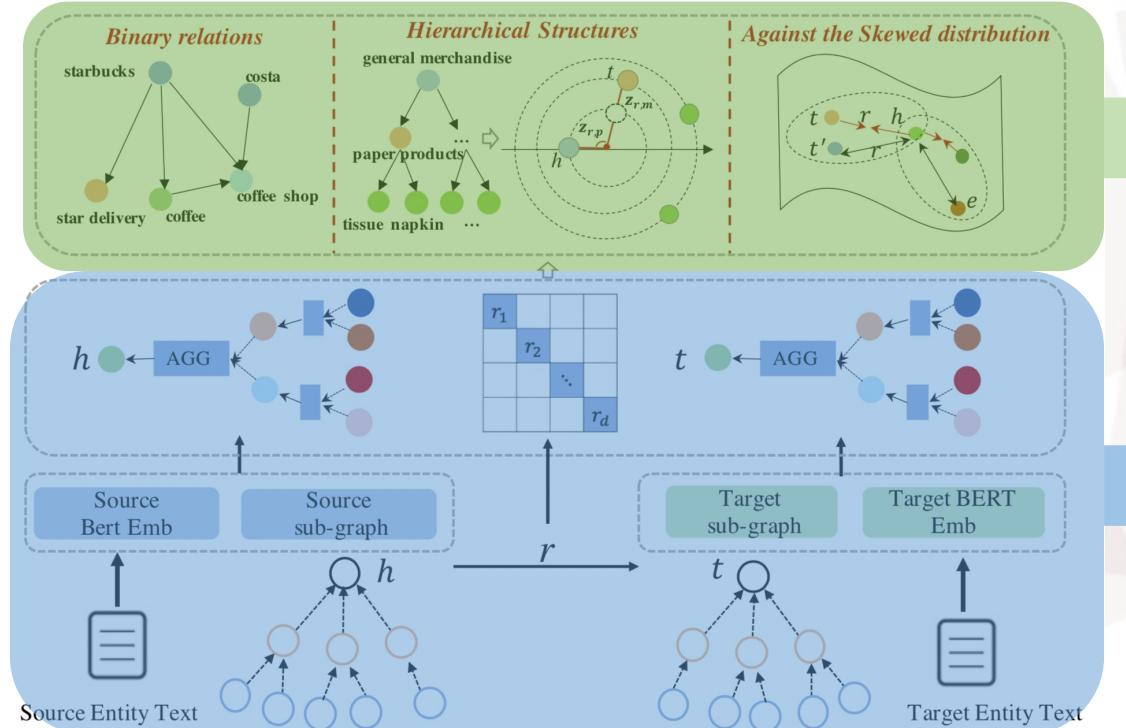
a) Spatio-temporal Relation





Challenges

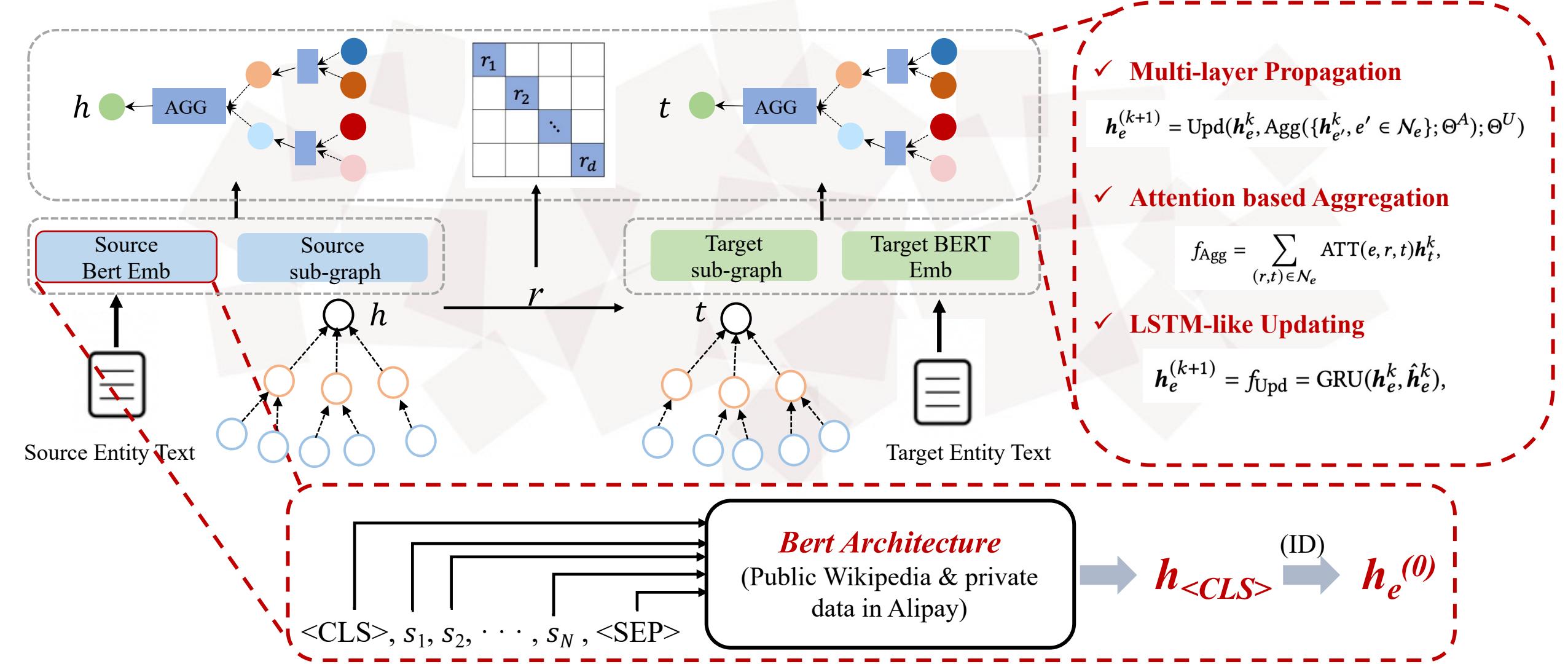
- **Textual and structural information complement each other in KGE**
Both structural match and semantic match matters
(*<Chinese_gold,brand_provide_service,Jewelry>*)
- **SupKG exhibit the skewed data distribution**
More than 80% of entities with less than 5 degrees;
KGE methods are easily misled towards remaining high-degree entities
- **Hierarchical structures are ubiquitous in SupKG**
(*Pistachio_Latte → Coffee → Drink*)



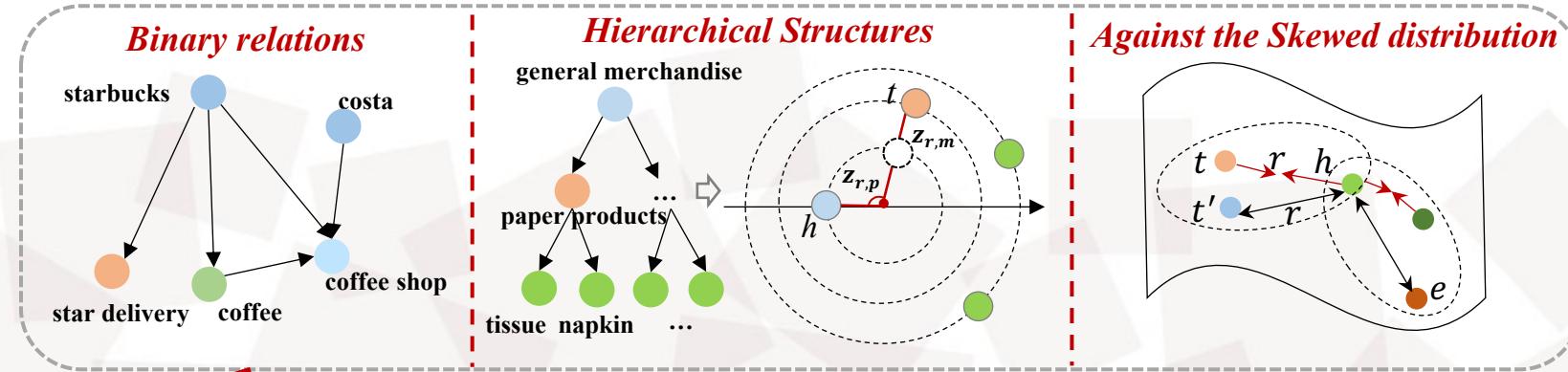
Fine-grained Relation Pattern Preservation
in SupKG with a Multi-task Component

Bridging Language Representations with
Knowledge Structure in SupKG

Bridging Language Representations with Knowledge Structure in SupKG



Fine-grained Relation Pattern Preservation in SupKG with a Multi-task Component



✓ DistMult based interaction

$$\mathbf{m}_{h,r,t} = \mathbf{z}_h^{\mathcal{D}T} \mathbf{M}_r \odot \mathbf{z}_t^{\mathcal{D}},$$

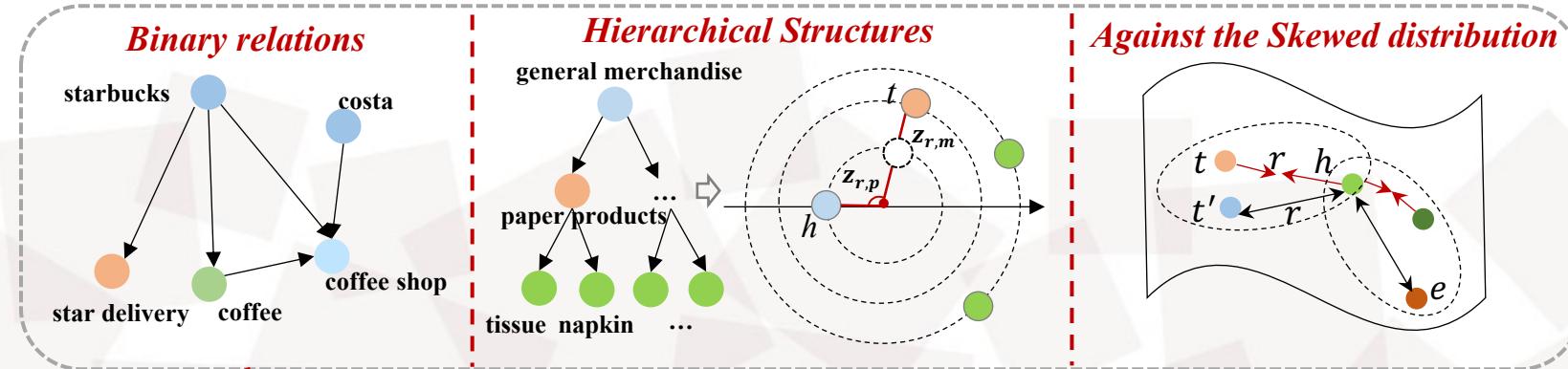
✓ MLP based scoring

$$s_{h,r,t}^{\mathcal{D}} = f^K(\mathbf{W}_K \cdots f^1(\mathbf{W}_1 \mathbf{m}_{h,r,t} + \mathbf{b}_1) + \mathbf{b}_L),$$

✓ CR loss with negatives

$$\mathcal{L}^{\mathcal{D}} = - \sum_{<h,r,t> \sim \mathcal{G}, <h',r,t'> \sim \mathcal{G}'} \log(s_{h,r,t}^{\mathcal{D}}) + \log(1 - s_{h',r,t'}^{\mathcal{D}})$$

Fine-grained Relation Pattern Preservation in SupKG with a Multi-task Component



✓ DistMult based interaction

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✓ Mapping as modulus and phase

$$\mathbf{h}_e^{(L)} \longrightarrow [\mathbf{z}_{e,m}^{\mathcal{H}}; \mathbf{z}_{e,p}^{\mathcal{H}}]$$

✓ Distance in the polar coordinate system

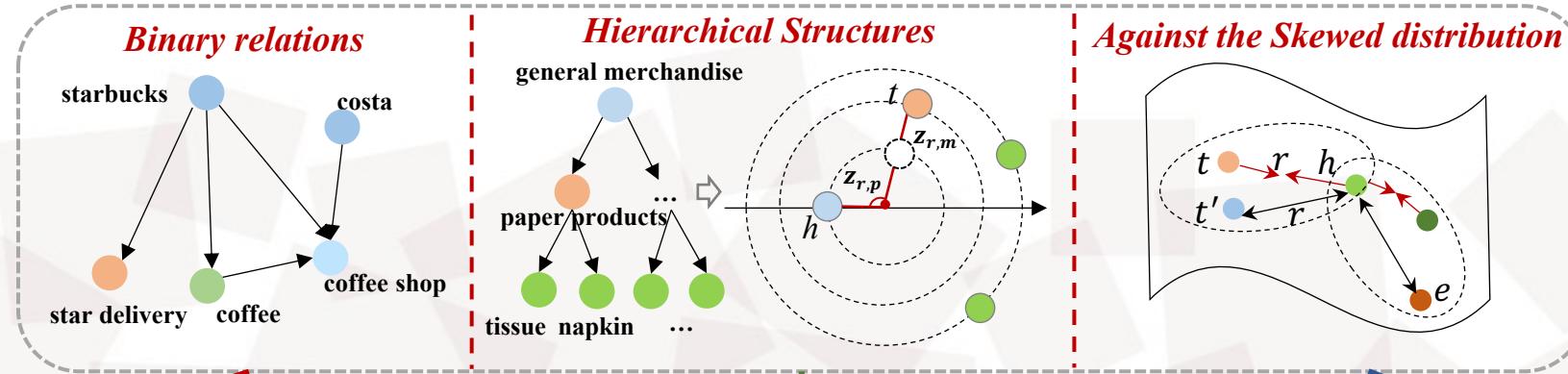
$$s_{h,r,t}^{\mathcal{H}} = \|\mathbf{z}_{h,m}^{\mathcal{H}} \odot \mathbf{z}_{r,m}^{\mathcal{H}} - \mathbf{z}_{t,m}^{\mathcal{H}}\|_2 + \lambda \|\sin(\mathbf{z}_{h,p}^{\mathcal{H}} + \mathbf{z}_{r,p}^{\mathcal{H}} - \mathbf{z}_{t,p}^{\mathcal{H}})\|_1$$

✓ Margin based loss

$$\mathcal{L}^{\mathcal{H}} = - \sum_{\langle h, r, t \rangle \sim \mathcal{G}, \langle h', r, t' \rangle \sim \mathcal{G}'} \log(\sigma(\gamma - s_{h,r,t}^{\mathcal{H}}) + \log(\sigma(s_{h',r,t'}^{\mathcal{H}} - \gamma)).$$



Fine-grained Relation Pattern Preservation in SupKG with a Multi-task Component



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✓ Entity-level contrast

$$\mathcal{L}_e^C = - \sum_{\langle h, t \rangle \sim \mathcal{G}} \left(\log \frac{\exp(s(\mathbf{z}_h^{(1)}, \mathbf{z}_h^{(2)})/\tau)}{\sum_{e \in \mathcal{E}} \exp(s(\mathbf{z}_h^{(1)}, \mathbf{z}_e^{(2)})/\tau)} + \log \frac{\exp(s(\mathbf{z}_t^{(1)}, \mathbf{z}_t^{(2)})/\tau)}{\sum_{e \in \mathcal{E}} \exp(s(\mathbf{z}_t^{(1)}, \mathbf{z}_e^{(2)})/\tau)} \right),$$

✓ Margin based loss

$$\mathcal{L}_t^C = - \sum_{\langle h, r, t \rangle \sim \mathcal{G}} \log \frac{\exp(\phi(h, r, t)/\tau)}{\sum_{\langle h, r, t' \rangle \in \mathcal{N}} \exp(\phi(h, r, t')/\tau)},$$

✓ Heterogeneous and unstructured data source

	AliCoCo	AliCoCo2	SupKG
# Entity	57, 125	163, 460	17, 343, 492
# Relation type	2	91	88
# Relation instance	131, 968	813, 315	103, 526, 390

SupKG has to deal with a lot of vanilla text of rather multiplex and heterogeneous behaviors, covering city service, traveling, entertainment, health care, and so on

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(SupKG aims at answering “which service is needed at what time and where”)

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✓ Distinct emphasis from e-commerce for relation extraction

(SupKG aims at answering “which service is needed at what time and where”)

✓ More powerful representation capability

Incorporating language representations in the information propagation process is a more reasonable way for complementing textual and structural information.

CL empowers the representation

	Hit@5	Hit@10	Hit@15	Hit@20	MRR
AliCoCo2	0.2298	0.2844	0.3009	0.3128	0.1693
OURS	0.2514	0.2958	0.3179	0.3403	0.1984

Table 7: Performance comparison with Alicoco2 on triplets $< h, r, t >$ with semantic distance $\cos(h, t) \geq \delta$. Here h, t are semantic embedding from BERT for head and tail entities, respectively.

More optimization-friendly in learning hierarchy

	Hit@5	Hit@10	Hit@15	Hit@20	MRR
Ours-HyL	0.3339	0.4406	0.4900	0.5246	0.2487
OUS	0.3557	0.4446	0.4954	0.5310	0.2571

Table 8: Hyperbolic loss (i.e., “Ours-HyL”) versus polar coordinate system (i.e., “OUS”) in the proposed framework.

➤ Overall performance

Methods	Hit@K				MRR
	K = 5	K = 10	K = 15	K = 20	
TransE [4]	0.2346	0.3145	0.3652	0.4019	0.1555
TransR [19]	0.1751	0.2247	0.2622	0.2916	0.1410
TransD [17]	0.2483	0.3068	0.3407	0.3638	0.1834
TransH [29]	0.2488	0.3071	0.3419	0.3667	0.1828
ConvE [10]	0.1658	0.2229	0.2718	0.3133	0.1234
RESCAL [22]	0.2825	0.3238	0.3487	0.3681	0.2206
BLP [9]	0.2299	0.3115	0.3613	0.3981	0.1515
HAKE [33]	0.2169	0.2541	0.2732	0.2871	0.1669
RGCN [24]	0.0675	0.0962	0.1189	0.1414	0.0526
KGNN [15]	0.1477	0.2187	0.2699	0.3128	0.1053
AliCoCo2 [20]	0.3402	0.4395	0.4705	0.4926	0.2433
OURS	0.3557	0.4446	0.4954	0.5310	0.2571

Table 3: Quantitative comparison of different methods.

➤ Ablation study

TI	GS	HL	CL	Hit@K				MRR
				K = 5	K = 10	K = 15	K = 20	
✓		✓	✓	0.2605	0.3032	0.3319	0.3548	0.2095
✓	✓	✓	✓	0.2576	0.3076	0.3408	0.3664	0.2014
✓	✓			0.2102	0.2897	0.3417	0.3822	0.1485
✓	✓	✓		0.3341	0.4236	0.4786	0.5186	0.2462
✓	✓		✓	0.2359	0.3254	0.3826	0.4251	0.1651
✓	✓	✓	✓	0.3557	0.4446	0.4954	0.5310	0.2571

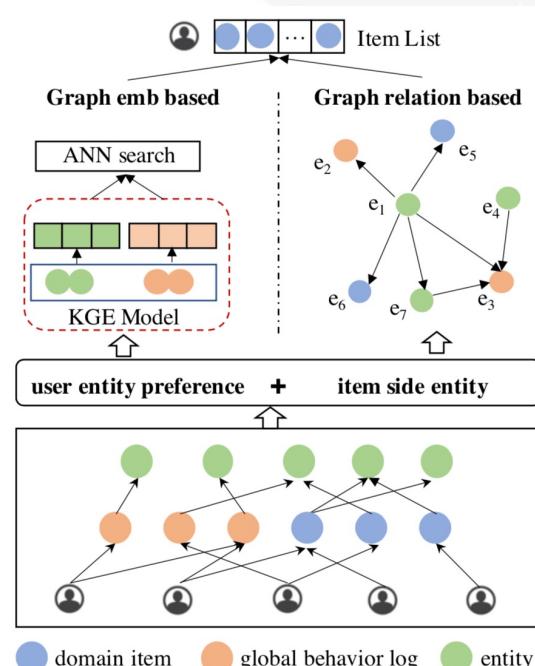
Table 4: Ablation studies of our proposal. “TI” means textual information; “GS” means graph structure; “HL” means hierarchy aware learning module; “CL” means contrastive learning module.

- ✓ Our complete representation framework **consistently and significantly surpasses** all the baselines across all metrics in the industrial knowledge graph
- ✓ In the ablation study, we could observe an apparent performance decrease once the corresponding component is removed, indicating **all signals considered play critical roles in high-quality learning**

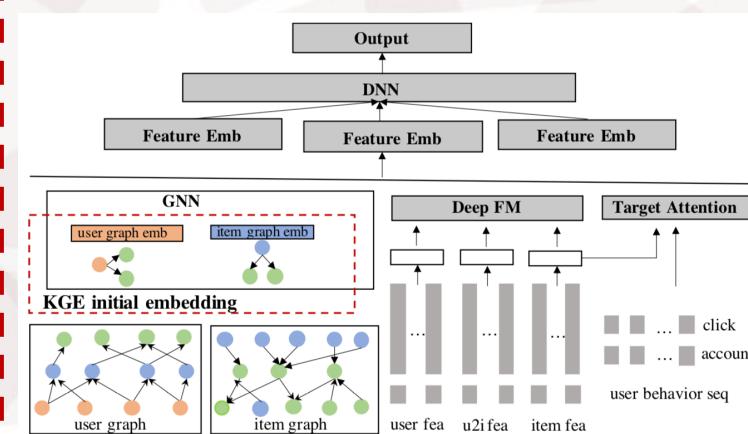
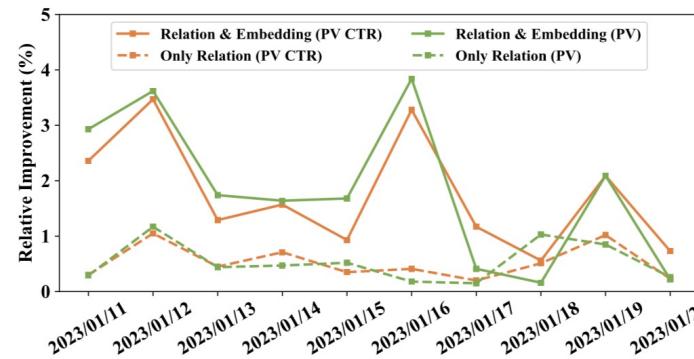
10 Application

Source entity	Relation	Target entities retrieved
Musical instrument shop (乐器行)	scene_related_prod	Ukulele (乌克里里), Folk drum (民族鼓), Violin (小提琴), old records (老唱片) Percussion instrument (敲打乐器)
CBA	activity_need_prod	Basketball shoes (篮球鞋), Basketball (篮球), Sneaker (球鞋), Jersey (球衣)
Anti-inflammatory (消炎药)	prod_in_scene	Drugstore (药店), Fair-price drugstore (平价药店), TCM pharmacy (中药坊), Children's hospital (儿童医院), Community hospital (社区医院)
Bartending (调酒)	intent_related_food	Cocktail (鸡尾酒), Blueberry wine(蓝莓酒),Plum wine(青梅酒), Foreign wine(洋酒)
Family trip (亲子游)	intent_related_scene	Parent-child park(亲子乐园), Adventure park (探险乐园), wild animal park(野生动物园)

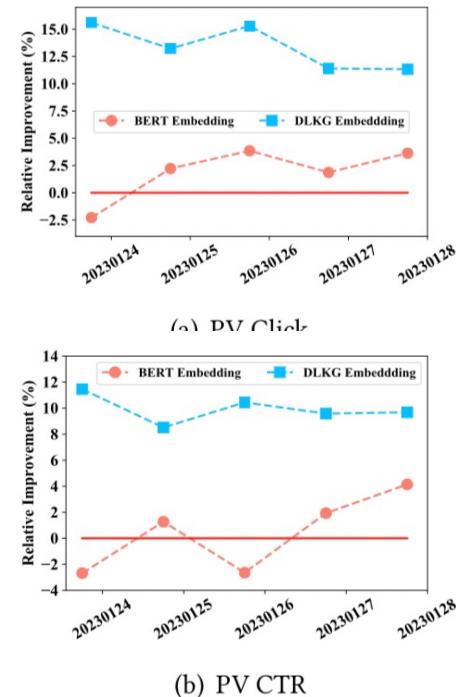
Supplementing 5 million potential knowledge through semantic and structural matching



Integrating global behaviors with SupKG for matching



Enhancing item and user representation in graph-based ranking



- ✓ We propose **SupKG**, a commonsense knowledge graph toward Super APP to help comprehensively characterize user behaviors across different business scenarios in a more fine-grained manner.
- ✓ We devise a novel representation learning framework, enabling various applications to draw support from effective representations of entities and relations from SupKG.
- ✓ We perform a series of offline/online to demonstrate that i) the proposed representation learning framework could substantially help supplement potential knowledge for SupKG; ii) the learned embedding and SupKG could well warm up various downstream by provide high-quality SupKG knowledge.



Thanks ! More details will be published in our paper

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