# Commonsense Knowledge Graph towards Super APP and Its Applications in Alipay

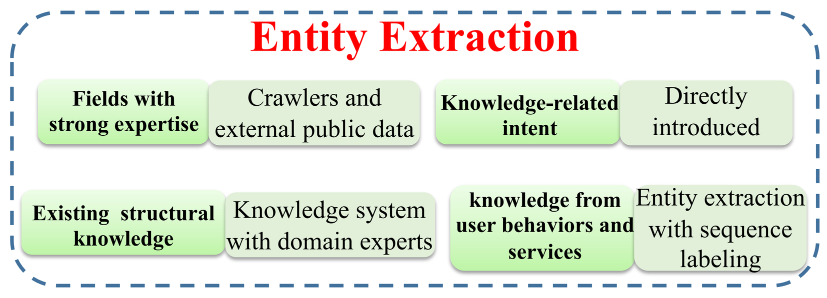
Xiaoling Zang*, Binbin Hu*, Jun Chu, Zhiqiang Zhang,
Gangnan Zhang, Jun Zhou, Wenliang Zhong
Ant Group

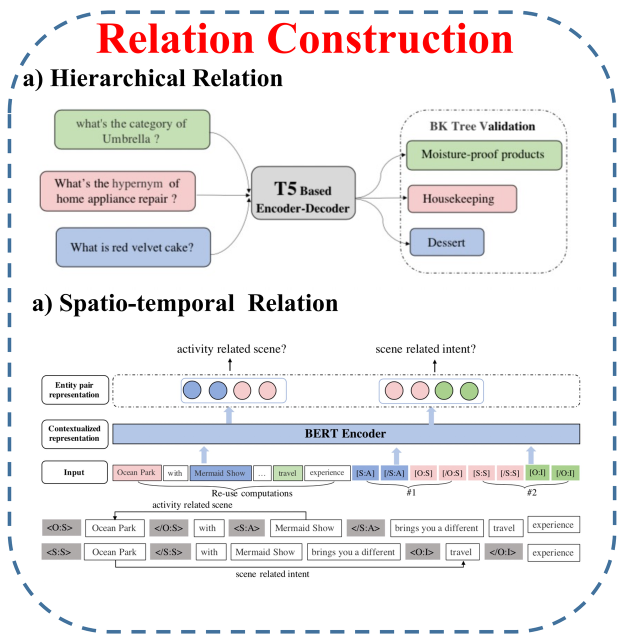
## Background & SupKG


**Super App**
- Open ecology
- Numerous scenarios
- Heterogeneous data

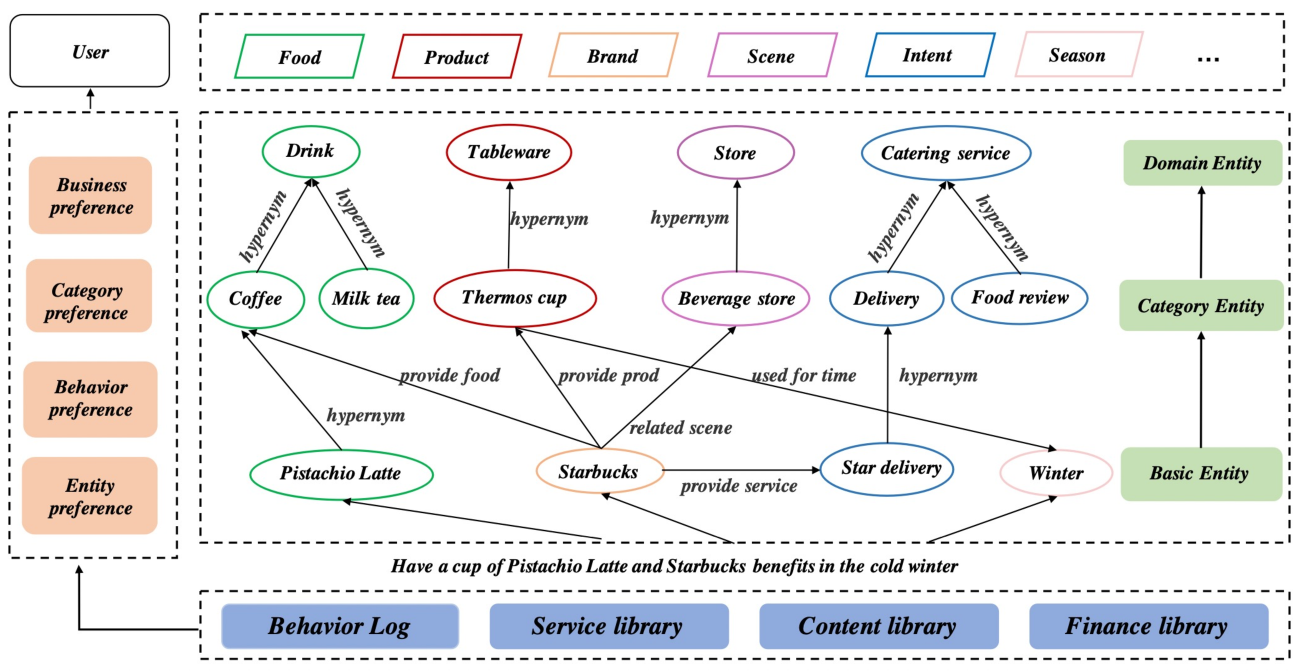
**Challenges**
- Huge gap between scenarios
- Difficulty for effective information transfer and information

**Solution** A "Bridge": SupKG



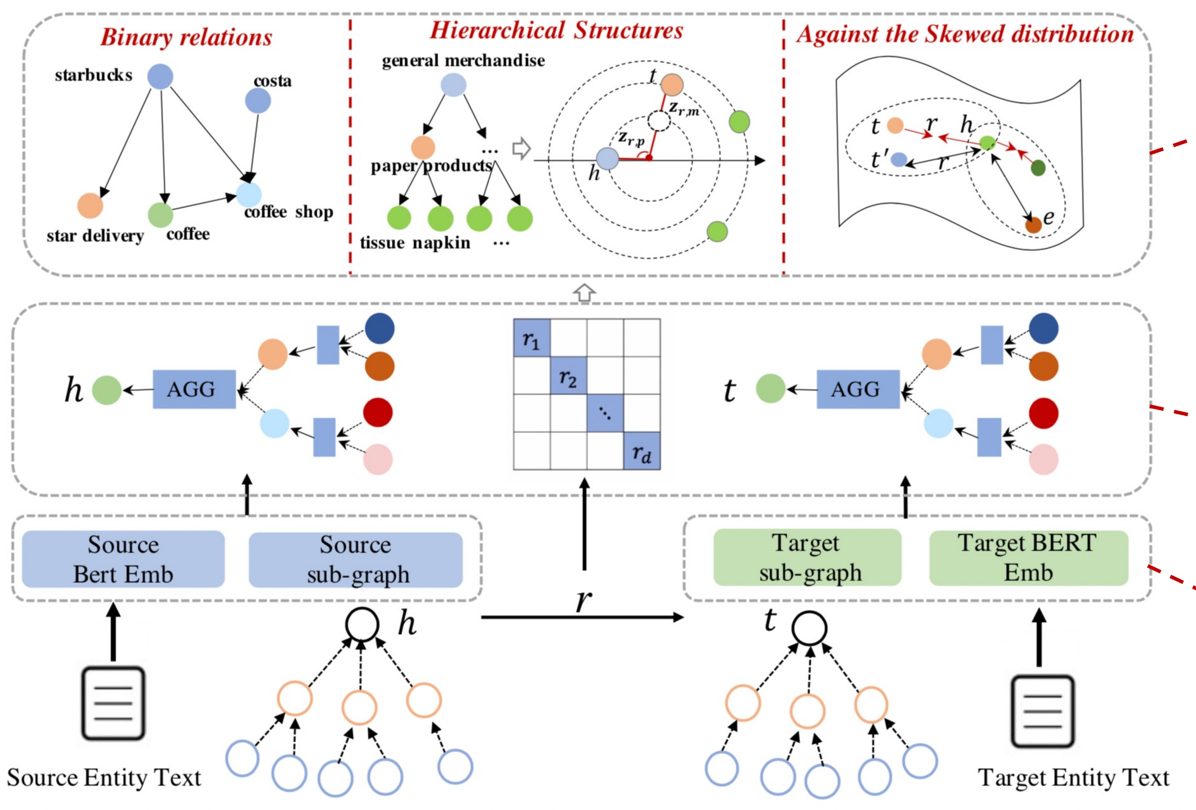

### Commonsense Knowledge Graph towards Super APP (SupKG)

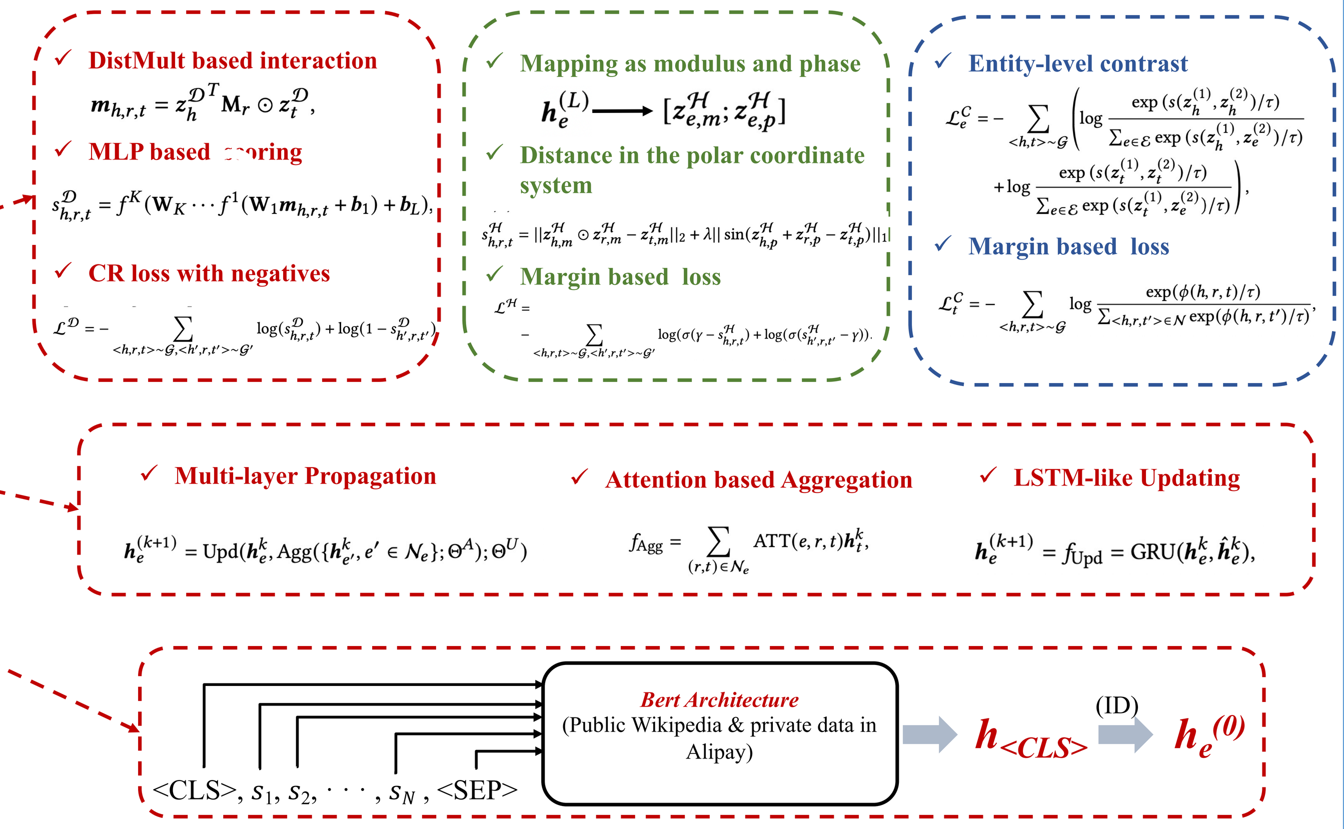



## Representation Learning of SupKG

### 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
  $(Pistachio\_Latte \rightarrow Coffee \rightarrow Drink)$




## Experiments & Applications

### Compared to AliCoCos

✓ **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**

✓ **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.**

### Over performance comparison

| Methods | Hit@K K = 5 | K = 10 | K = 15 | K = 20 | MRR |
|---|---|---|---|---|---|
| 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.**

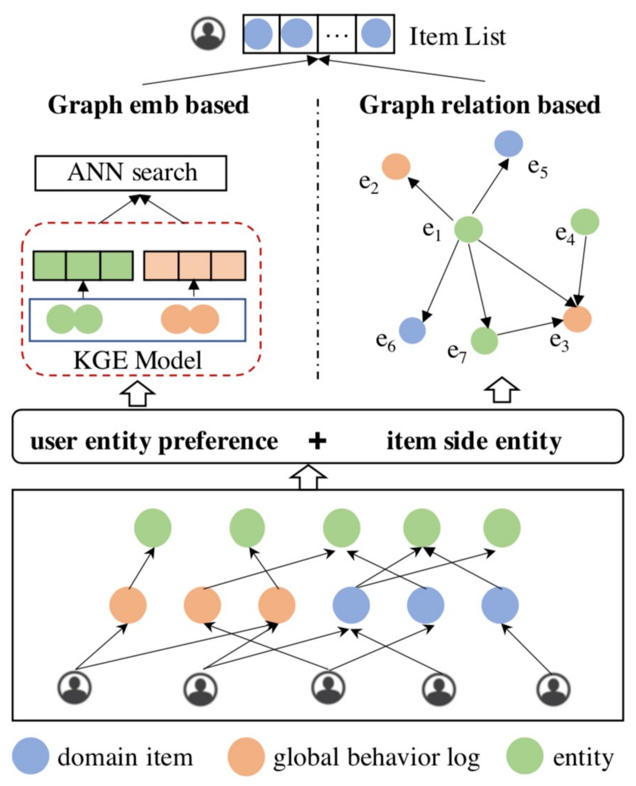
### Ablation study

| TI | GS | HL | CL | Hit@K K = 5 | K = 10 | K = 15 | K = 20 | MRR |
|---|---|---|---|---|---|---|---|---|
| ✓ | | ✓ | ✓ | 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** |

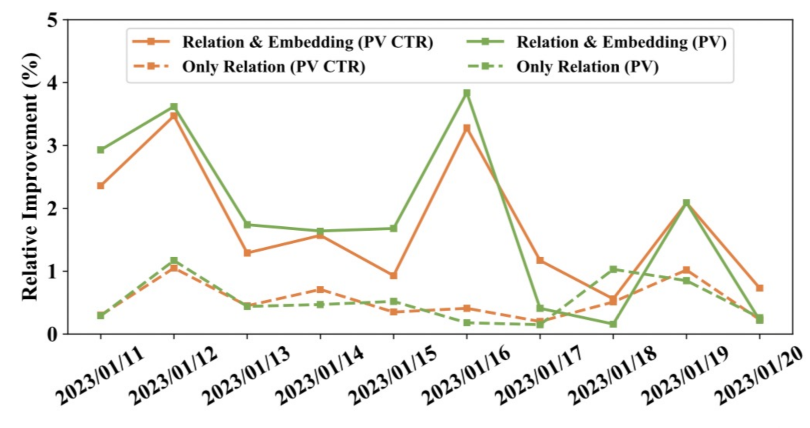
**Table 4: Ablation studies of our proposal. "TI" means textual information; "GS" means graph structure; "HL" means hierarchy aware learning module; "CL" means contrastive learning module.**

### Supplementing potential knowledge

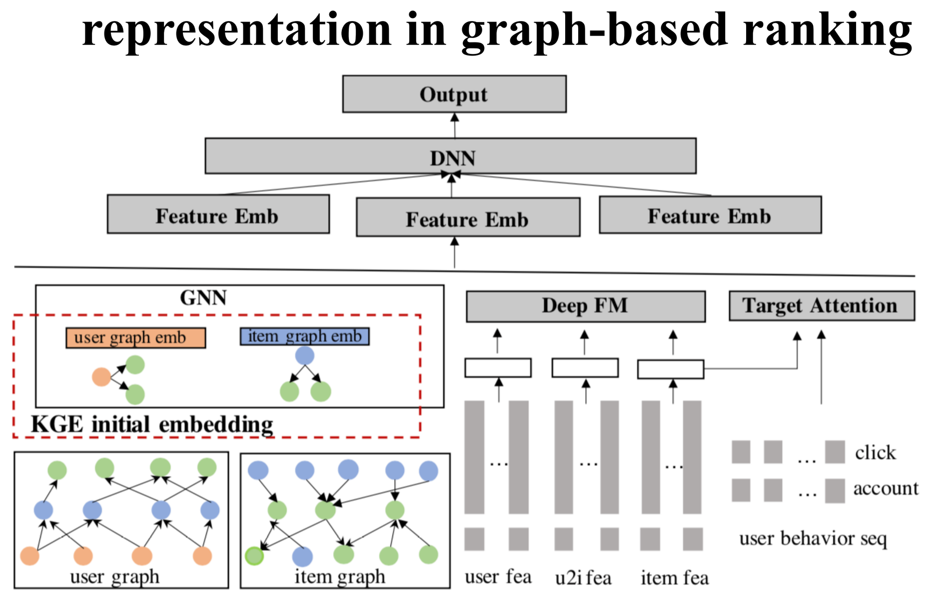
| Source entity | Relation | Target entities retrieved |
|---|---|---|
| Musical instrument shop (乐器行 ) | scene_related_prod | Ukulele (乌克里里), Folk drum (民族鼓), Violin (小提琴), old records (老唱片) Percussion instrument (敲打乐器) |
| CBA | activity_need_prod | Basketball shoes (篮球鞋), Basketball (篮球), Sneaker (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) |

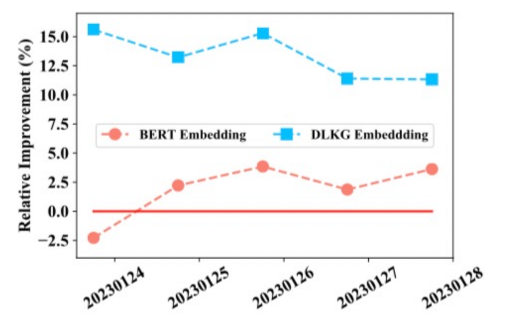



### Integrating global behaviors With SupKG for matching

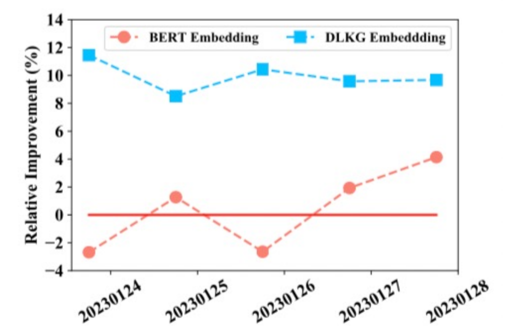



### Enhancing item and user representation in graph-based ranking




(a) PV Click




(b) PV CTR

## Conclusions

- 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.
- 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.