ATBRG: Adaptive Target-Behavior Relational Graph Network for Effective Recommendation

SIGIR 2020

Alibaba & Ant Financial Services

Current Method

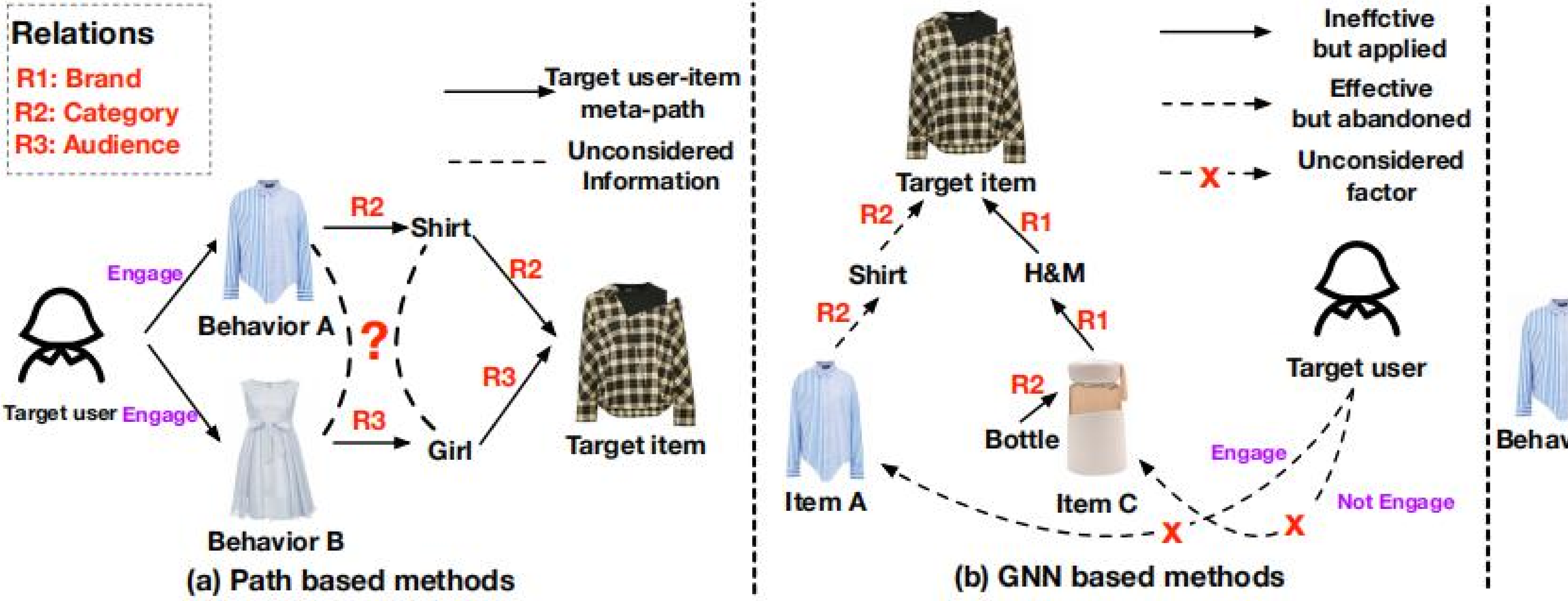
- explore independent meta-paths for user-item pairs over KG

(fails to capture info fully)

- employ GNN on whole KG to produce representations for users and items separately

(GNN enriches repre. U and I separately by neighbors, ignores mutual effect during propagation)

Core problem



Main Work

- Propose a new framework,

Adaptive **T**arget-**B**ehavior **R**elational **G**raph network

to **capture structural relations** of target user-item pairs over KG
to associate the given target item with user behaviors over KG

Main Work

- Graph connect and graph prune techniques

to construct adaptive target-behavior relational graph

- Improvement of 5.1% on CTR of Taobao App

ATBRG

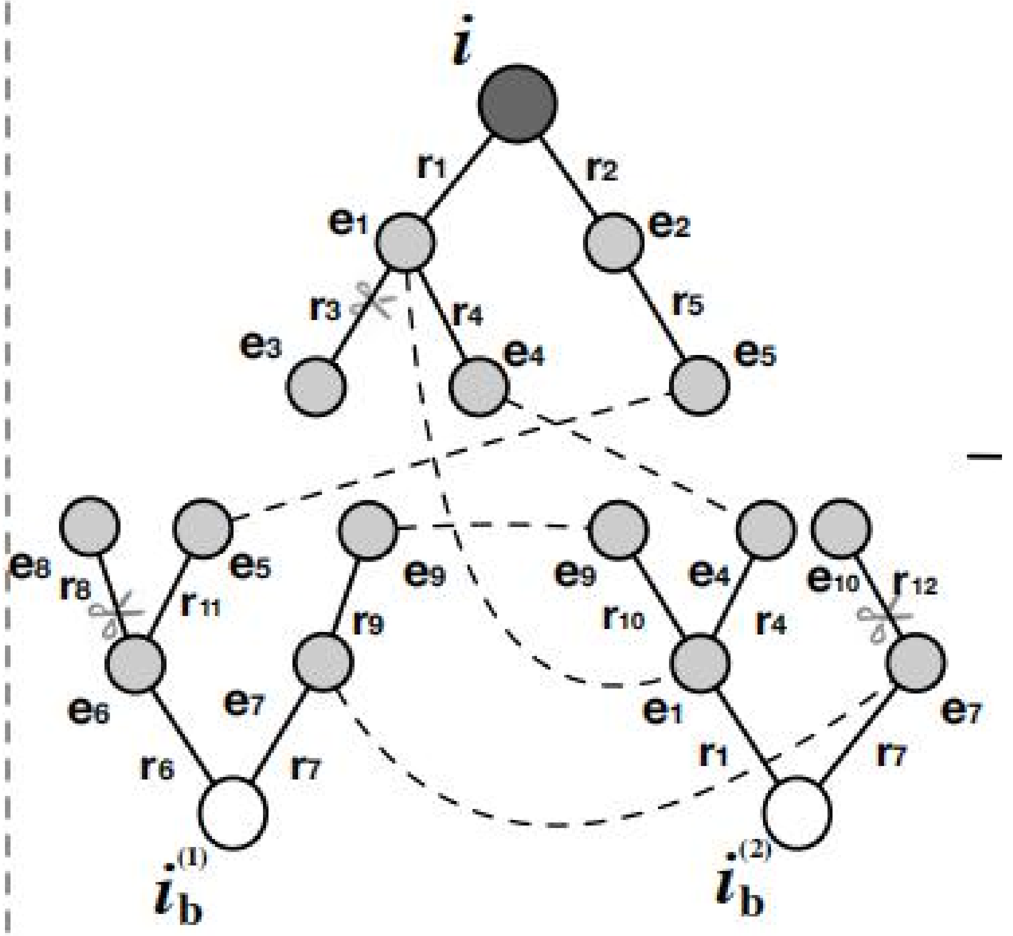
1. Graph construction part
2. Model part

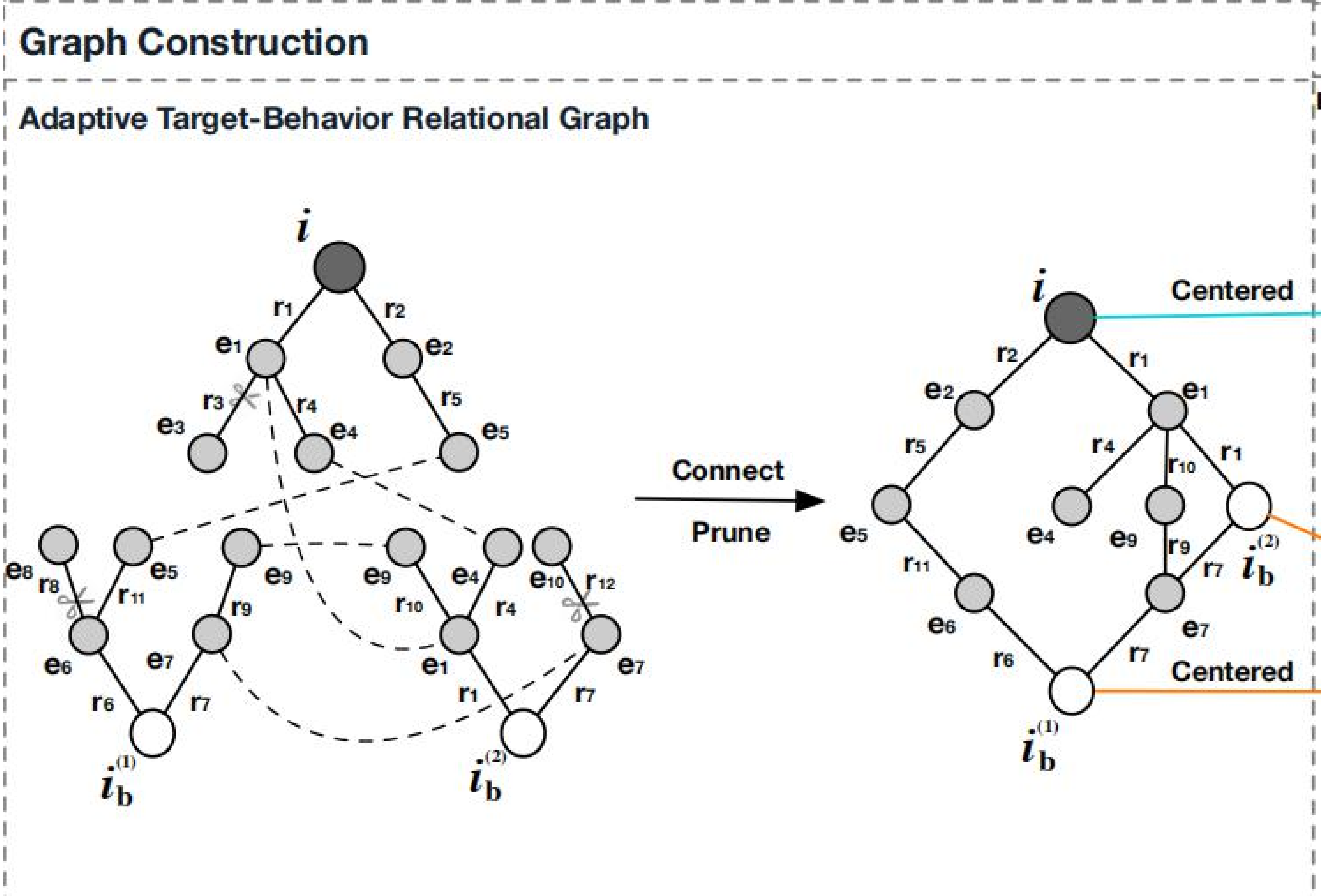
Graph construction

Algorithm 1 Graph construction

Input: Target item i; User behavior $\mathcal{B}_{ui}$; Knowledge graph $\mathcal{G}$;
Output: $\mathcal{G}_{ui}$: Adaptive target-behavior relational graph for $\langle u, i \rangle$;

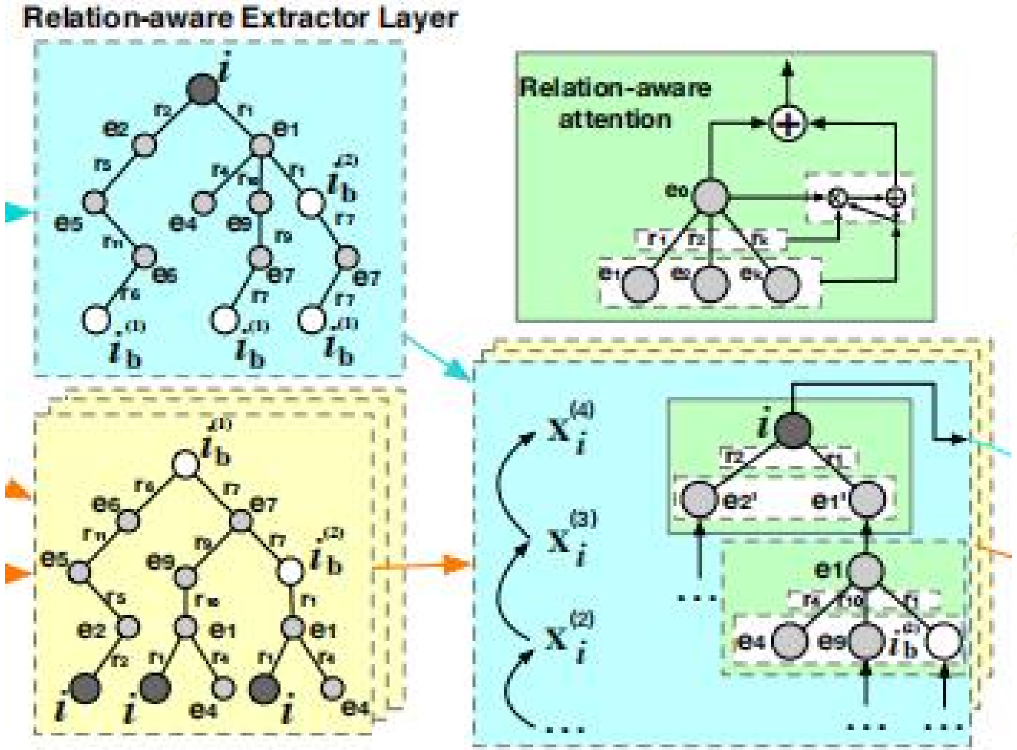
for item $v \in [i, \mathcal{B}_{ui}]$ **do**:
  for entity $e \in \phi(v)$ **do**:
    Construct path $p = (e, r_k, e_k, ..., e_1, r_1, v)$;
    $\mathcal{G}_{ui}[entity] \leftarrow \mathcal{G}_{ui}[entity] \cup p$; ▷ Graph connect.
  end for
end for
for entity $e \in \mathcal{G}_{ui}$ **do**:
  New item hash set s;
  for path $p \in \mathcal{G}_{ui}[e]$ **do**:
    Collect item v on the path;
    $s \leftarrow s \cup v$;
  end for
  if $s.size = 1$ **then**:
    Prune e in $\mathcal{G}_{ui}$; ▷ Graph prune.
  end if
end for




Graph Construction
Adaptive Target-Behavior Relational Graph
i
r1
r2
e1
e2
r3
r4
r5
e3
e4
e5
e8
e5
e9
e9
e4
e10
r8
r11
r9
r10
r4
r12
e6
e7
e1
e7
r6
r7
r1
r7
$i_b^{(1)}$
$i_b^{(2)}$
Connect
Prune
Centered
Centered

Model Part

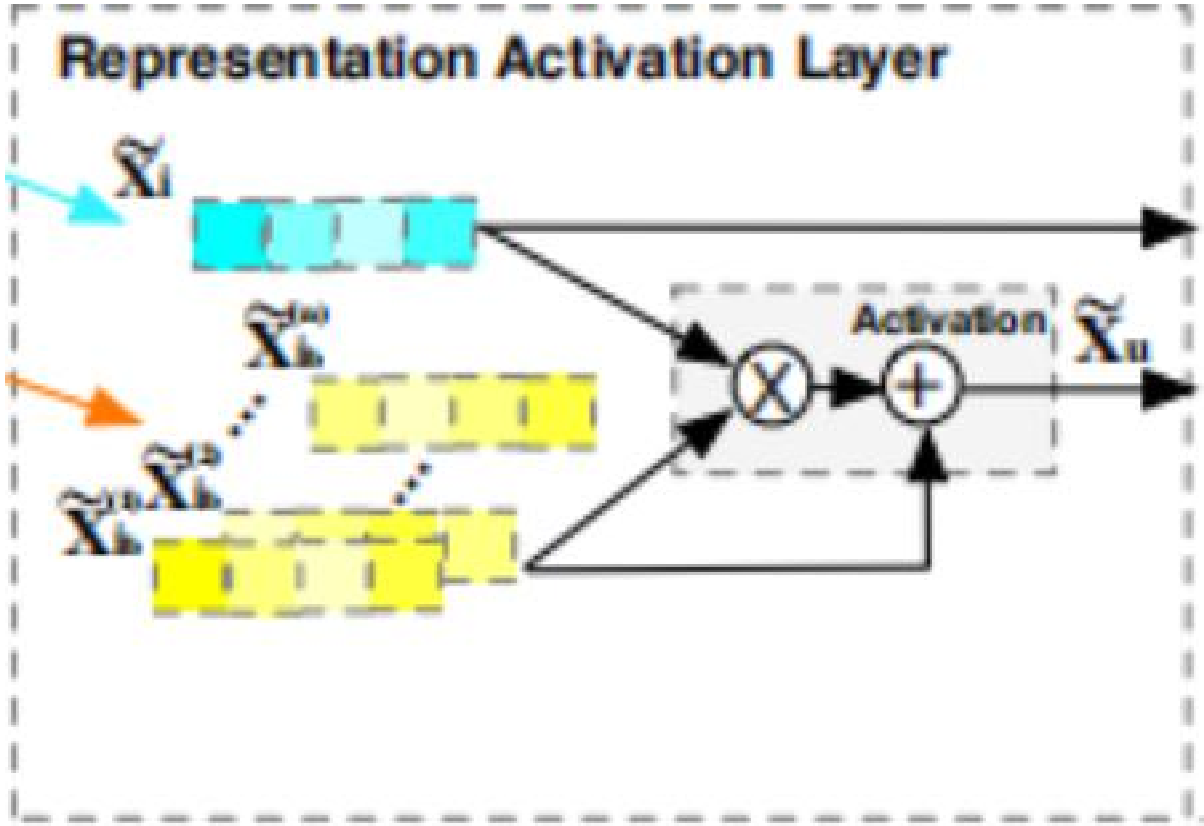
- 1. Embedding layer
- 2. Relation-aware Extractor layer



$$\alpha^{(l)}(h,r,t) = \frac{\exp(\mathbf{x}_r \mathbf{W}_\alpha f(\mathbf{x}_h^{(l)} \oplus \mathbf{x}_t^{(l)}))}{\sum_{(r',t')\in \mathcal{N}_h^{(l)}} \exp(\mathbf{x}_{r'} \mathbf{W}_\alpha f(\mathbf{x}_h^{(l)} \oplus \mathbf{x}_{t'}^{(l)}))},$$

$$\mathbf{x}_h^{(l+1)} = \mathbf{x}_h^{(l)} \oplus \sum_{(r,t)\in \mathcal{N}_h^{(l)}} \alpha^{(l)}(h,r,t)\mathbf{x}_t^{(l)}.$$

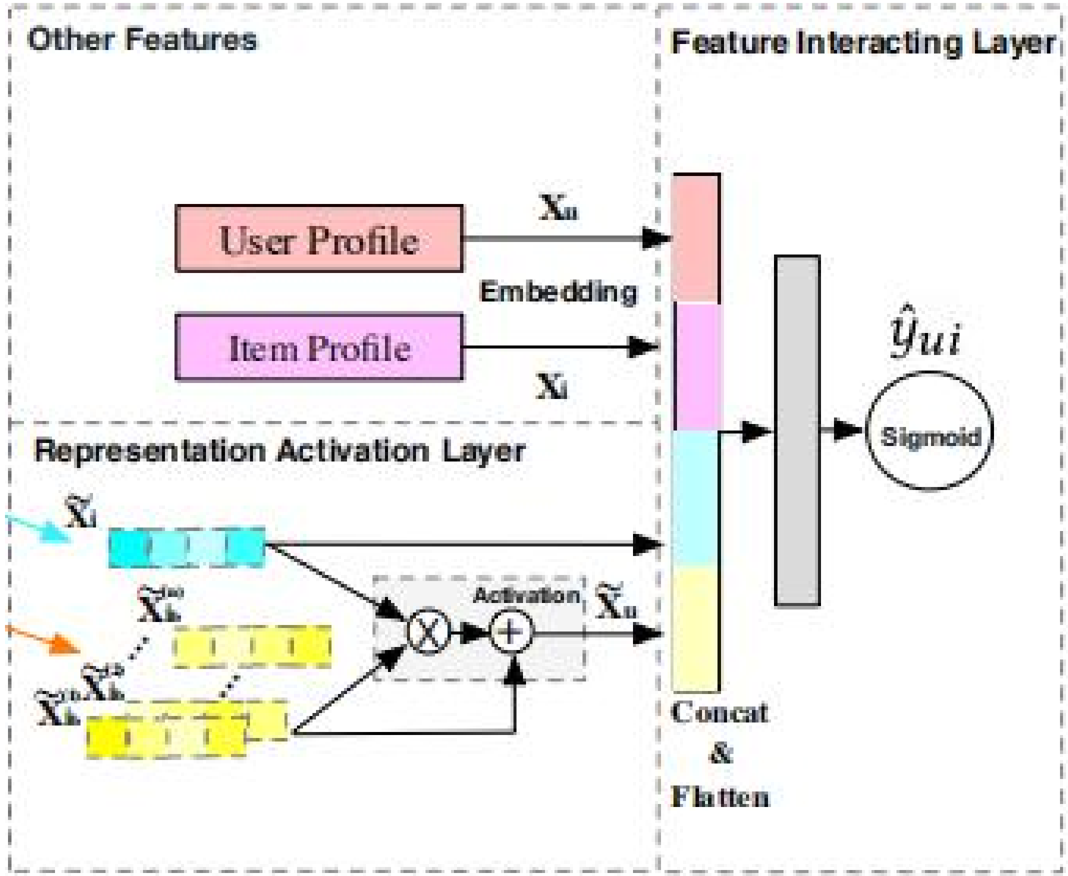
- 3. Representation Activation Layer



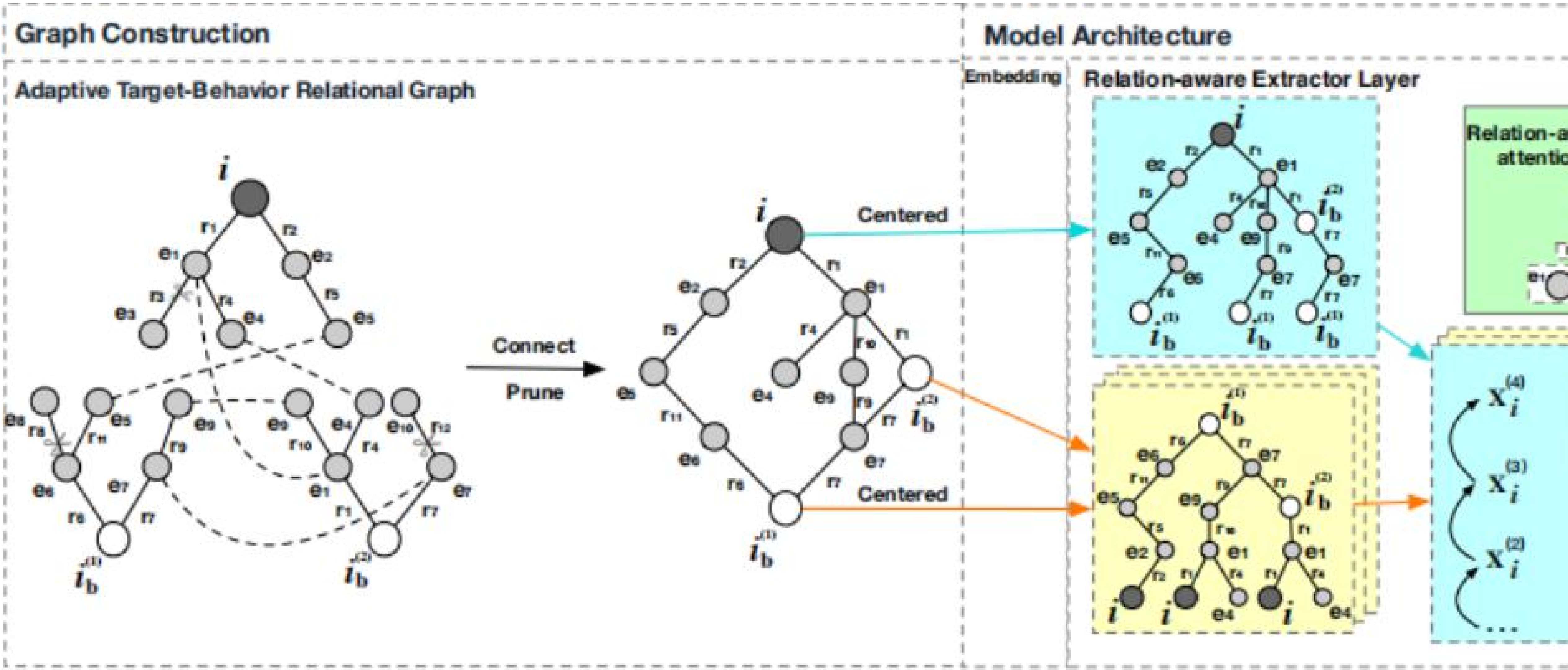
$$\beta(u, i, i_b) = \frac{\exp(\widetilde{\mathbf{x}}_{i_b} \mathbf{W}_\beta \widetilde{\mathbf{x}}_i))}{\sum_{i'_b \in \mathcal{B}_{ui}} \exp(\widetilde{\mathbf{x}}_{i'_b} \mathbf{W}_\beta \widetilde{\mathbf{x}}_i)},$$

$$\widetilde{\mathbf{x}}_u = \sum_{i'_b \in \mathcal{B}_{ui}} \beta(u, i, i_b) \widetilde{\mathbf{x}}_{i'_b},$$

• 4. Feature Interaction Layer



$$\hat{y}_{ui} = \sigma(f(f(f(\mathbf{x}_u \oplus \mathbf{x}_i \oplus \widetilde{\mathbf{x}}_u \oplus \widetilde{\mathbf{x}_i})))),$$


Graph Construction
Adaptive Target-Behavior Relational Graph
Connect
Prune
Centered
Centered
Model Architecture
Embedding
Relation-aware Extractor Layer

Experiments

- Dataset：
- Taobao
- YELP

Model	Taobao		Yelp†	
	AUC	RI	AUC	RI
YoubtubeNet	0.6017	+2.72%	0.7109	+26.00%
DeepFM	0.6037	+2.38%	0.7334	+22.14%
DIN	0.6058	+2.03%	0.7520	+19.12%
DIEN	0.6061	+1.97%	0.7581	+18.16%
DSIN	0.6073	+1.77%	0.7774	+15.23%
RippleNet	0.5975	+3.44%	0.7324	+22.31%
KGAT	0.6062	+1.96%	0.7876	+13.73%
KPRN	0.6096	+1.39%	0.8260	+8.45%
ATBRG	**0.6181***	-	**0.8958***	-