Unify Local and Global Information for Top-N Recommendation

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Reported by Ke Gan

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Introduction

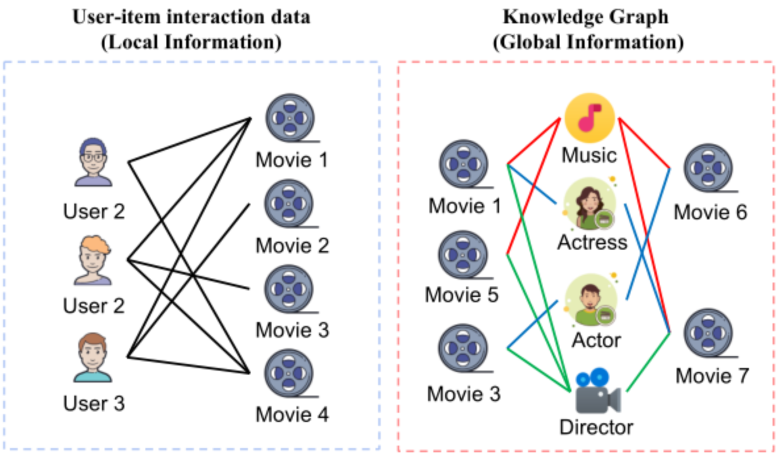


Figure 1: Illustration of local Information and global information. Local information is the user-item interaction data, which is a bipartite graph with users and items and interactions. Global information is a heterogeneous knowledge graph with multiple types of relationships and entities.

structural information in the graph

collaborative signals in user-item interaction data

Approach

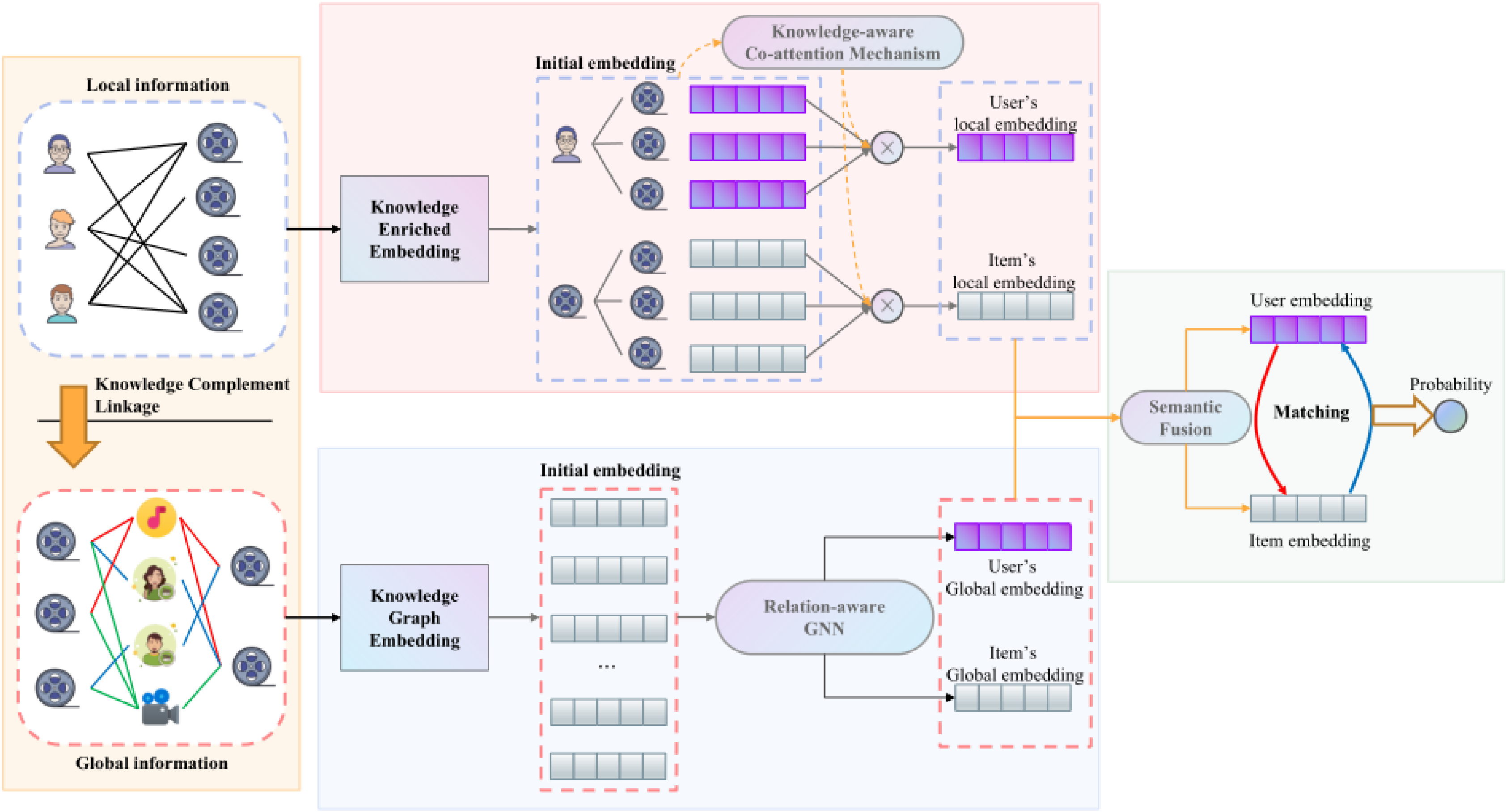


Figure 2: Illustration of the knowledge-aware duet model KADM, which compromises four components: i) Knowledge Complement Linkage (orange background, left), which maps items to external entities to capture rich semantic information in KG. ii) Local Model (red background, middle), which learns local representations of users and items from the local information. iii) Global Model (blue background, middle), which learns global representations of users and items based on the global information. iv) Prediction (green background, right), which alleviates the semantic gap between the local and global information by a gated network and calculates the final predicted probability.

Approach

Knowledge Complement Linkage

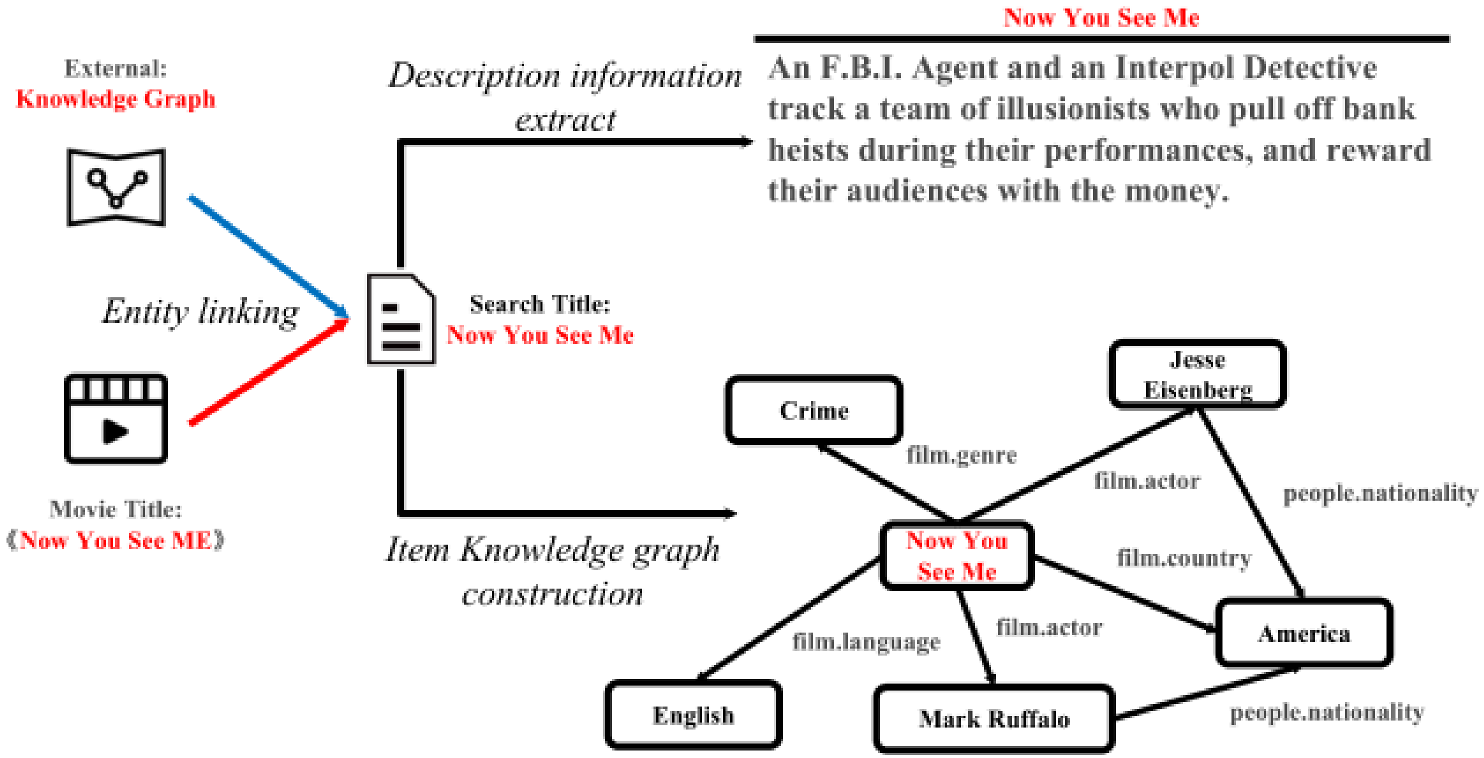


Figure 3: The process of knowledge complement linkage for each item, including entity linking, disambiguating entities, extracting items' description information and construct items' knowledge graph from external KGs.

Approach

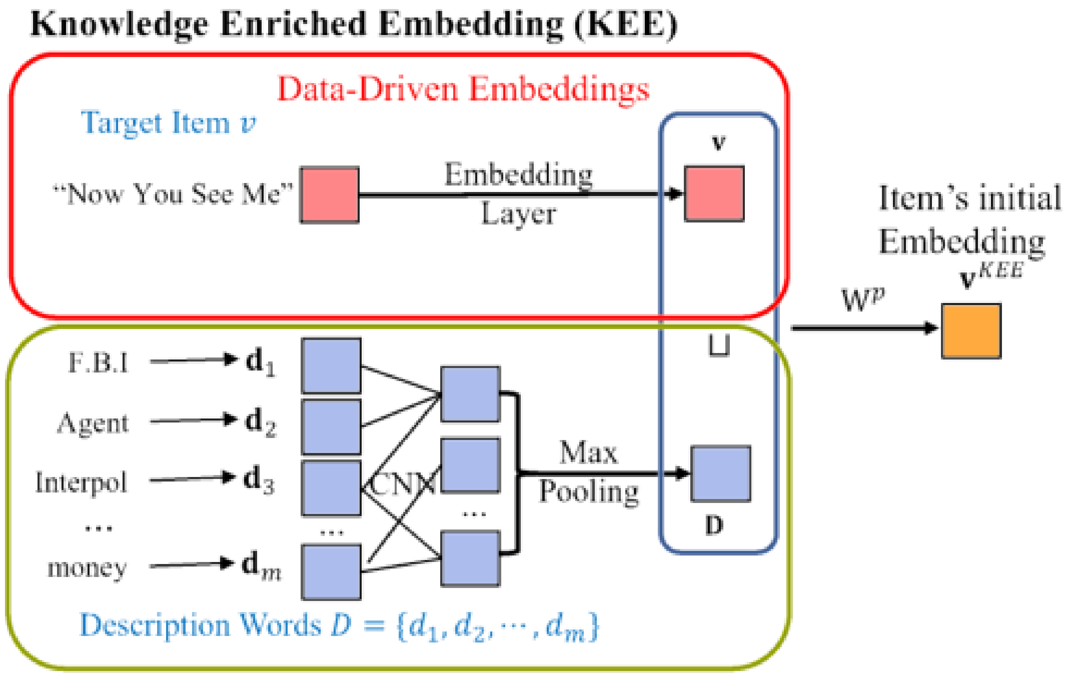
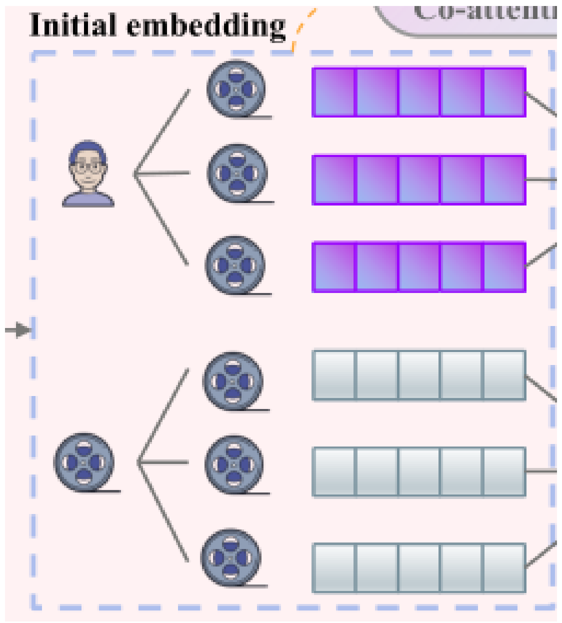


Figure 4: Illustration of Knowledge Enriched representation (KEE), which generates the enriched representation of items with their textual descriptions.

Encoding user and item.

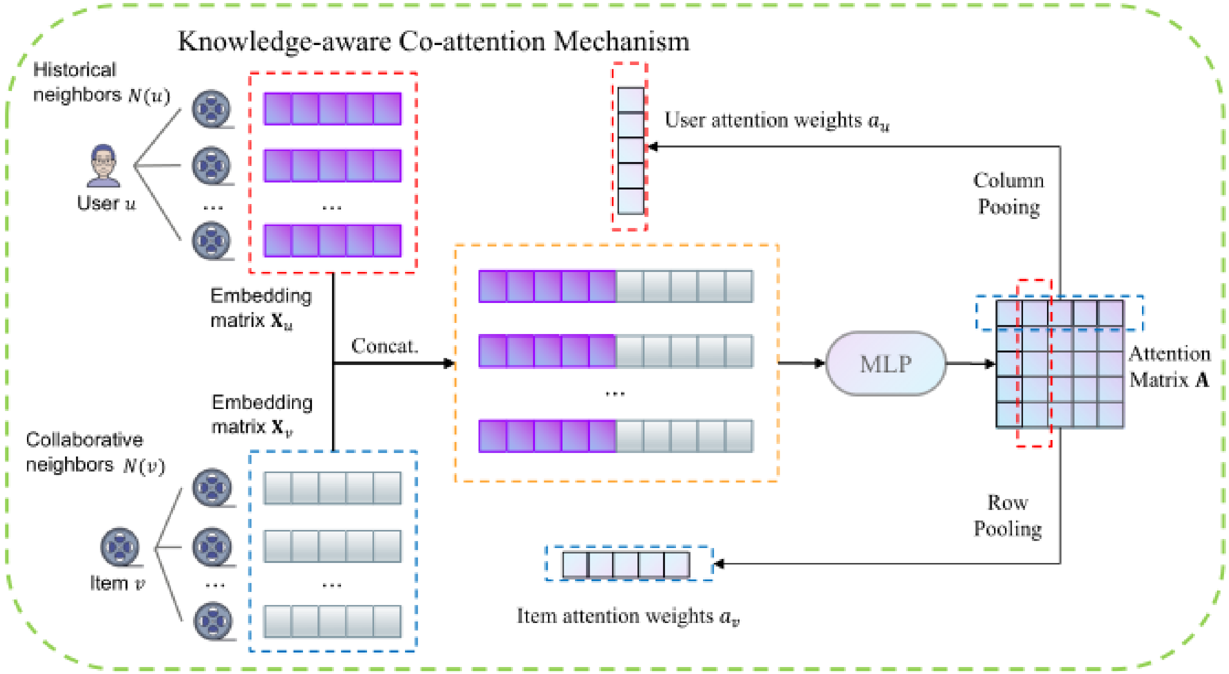


$$\mathbf{U} \in \mathbb{R}^{K\times 1}$$

$$\mathbf{V} \in \mathbb{R}^{K\times 1}$$

$$\mathbf{X_u} \in \mathbb{R}^{K\times d} \text{ and } \mathbf{X_v} \in \mathbb{R}^{K\times d},$$

Approach



$$\mathrm{A}_{ij} = \mathrm{Attention}(\mathrm{X}_u^i, \mathrm{X}_v^j), \quad (1)$$

$$\mathbf{A} \in \mathbb{R}^{K \times K}$$

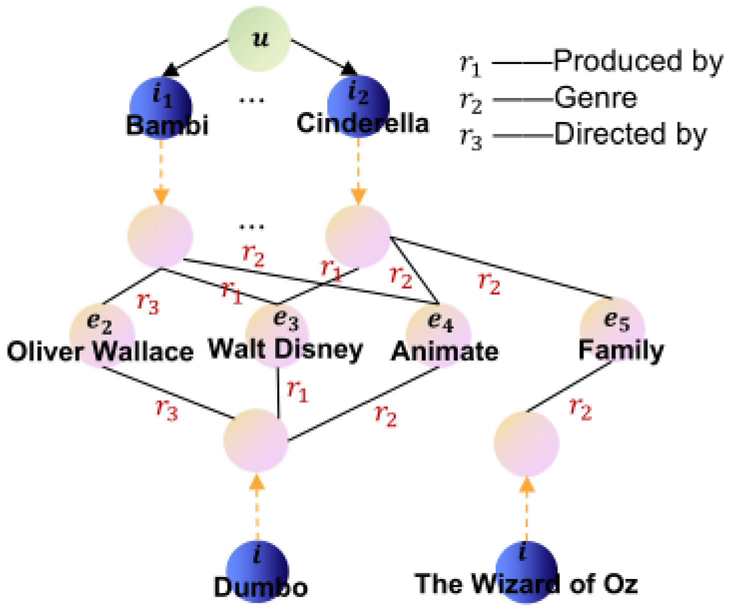
$$\begin{aligned} \boldsymbol{a}_u &= \textbf{Mean-Pooling}(\{A_{i\cdot}\}_{i=1}^{K}), \\ \boldsymbol{a}_v &= \textbf{Mean-Pooling}(\{A_{\cdot j}\}_{j=1}^{K}), \end{aligned} \quad (2)$$

$$\boldsymbol{a}^u \in \mathbb{R}^{K \times 1} \text{ and } \boldsymbol{a}^v \in \mathbb{R}^{1 \times K}$$

$$\begin{aligned} \mathrm{u}^{\mathrm{Local}} &= \boldsymbol{a}_u'^{\mathrm{T}} \mathrm{X}_u, \ \boldsymbol{a}_u' = \sigma(\boldsymbol{a}_u), \\ \mathrm{v}^{\mathrm{Local}} &= \boldsymbol{a}_v' \mathrm{X}_v, \ \boldsymbol{a}_v' = \sigma(\boldsymbol{a}_v), \end{aligned} \quad (3)$$

Approach

Enclosing subgraph extraction



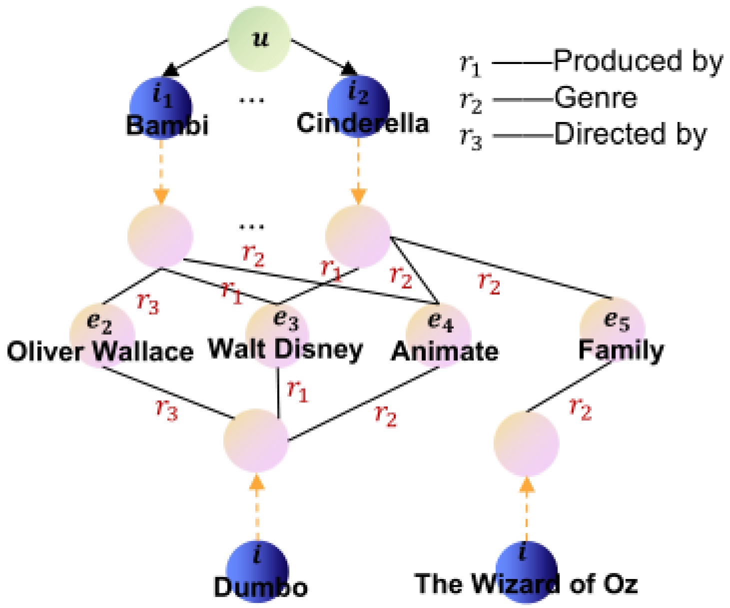
represent user u with its interacted items set N(u)

construct the entity set E(u) for user u and target entity e for item v

For each $e_i \in E(u)$, we compute the enclosing subgraph for e_i and e by taking the intersection of $N_k(e_i)$ and $N_k(e)$

Approach

Neural encoding of subgraph



$$\mathbf{e}_h^r + \mathbf{e}_r \approx \mathbf{e}_t^r$$

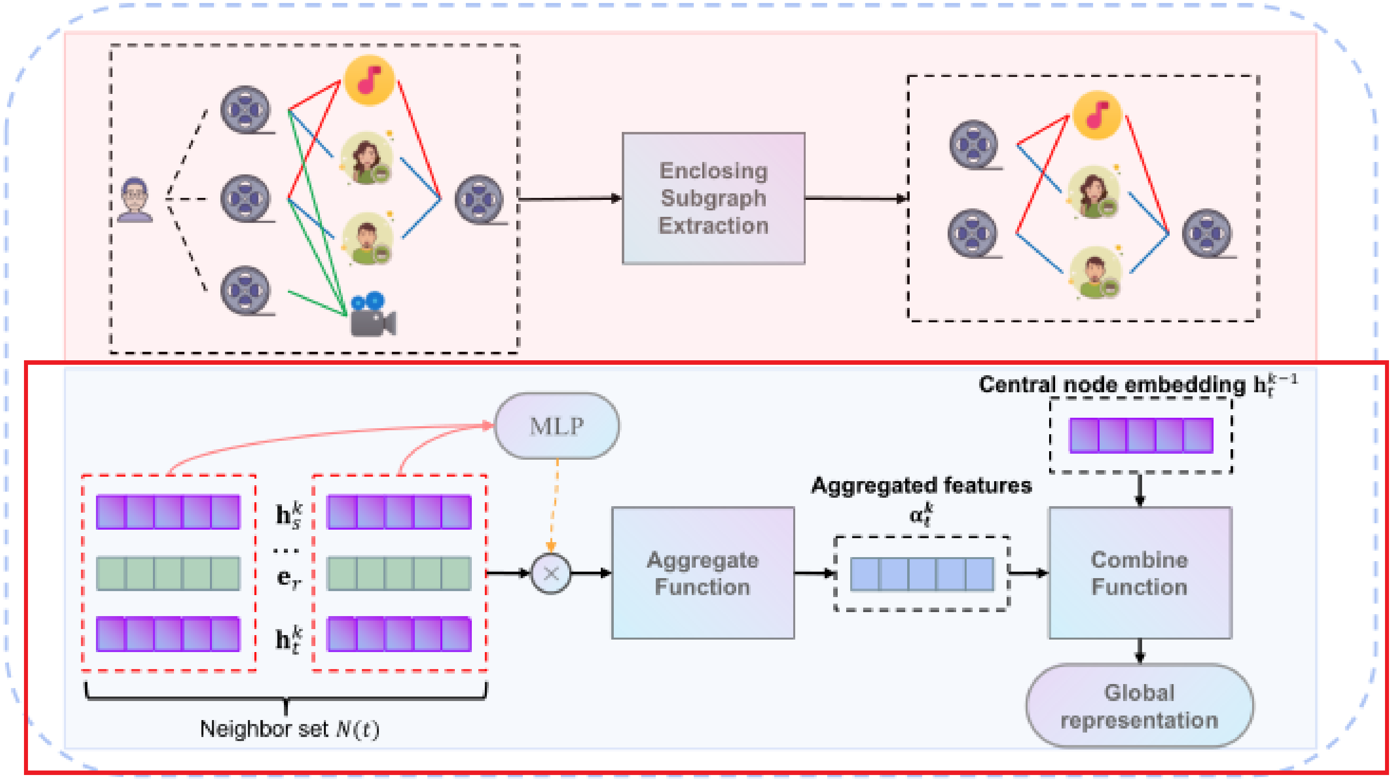
$$\mathbf{e}_h^r = \mathbf{e}_h \mathbf{M}_r \text{ and } \mathbf{e}_t^r = \mathbf{e}_t \mathbf{M}_r$$

$$g_r(h,t) = ||\mathbf{e}_h^r + \mathbf{e}_r - \mathbf{e}_t^r||_2^2. \quad (4)$$

$$\mathcal{L}_{KG} = \sum_{(h,h',r,t,t') \in \Gamma} \max(0, g_r(h,t) + \gamma - g_r(h',t')), \quad (5)$$

Approach

Relation-aware GNN for Representation Learning.



$$\mathbf{a}_i^k = \text{AGGREGATE}^k(\mathbf{h}_s^{k-1} : s \in \mathcal{N}(t), \mathbf{h}_t^{k-1}),$$
$$\mathbf{h}_t^k = \text{COMBINE}^k(\mathbf{h}_t^{k-1}, \mathbf{a}_t^k),$$

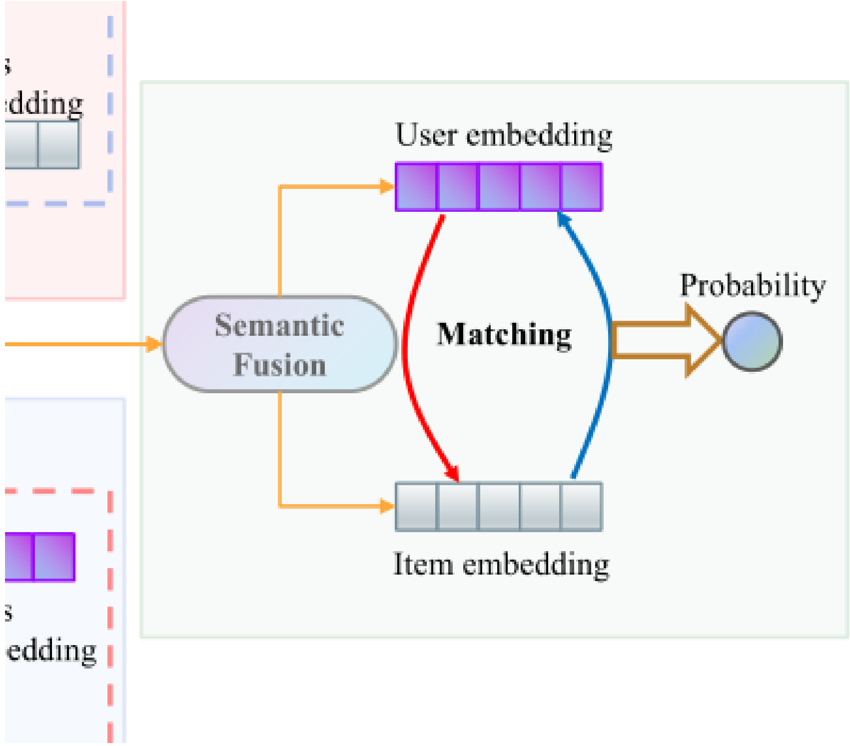
$$\mathbf{a}_t^{k+1} = \sum_{r=1}^{\mathcal{R}} \sum_{s \in \mathcal{N}_r(t)} \omega_{rst}^{k+1} \mathbf{W}_r^{k+1} \mathbf{h}_s^k, \tag{6}$$

$$\mathbf{c} = \text{ReLU}(\mathbf{W}_1[\mathbf{h}_s^k \oplus \mathbf{h}_t^k \oplus \mathbf{e}_r] + \mathbf{b}_1),$$
$$\omega_{rst}^{k+1} = \sigma(\mathbf{W}_2\mathbf{c} + \mathbf{b}_2), \tag{7}$$

$$\mathbf{h}_t^{k+1} = \text{LeakyReLU}(\mathbf{W}_3\mathbf{h}_t^k + \mathbf{a}_t^{k+1}). \tag{8}$$

$$\mathbf{v}^{\text{Global}} = \mathbf{h}_v^L,$$
$$\mathbf{u}^{\text{Global}} = \frac{1}{|\mathcal{N}(u)|} \sum_{v_i \in \mathcal{N}(u)} \mathbf{h}_{v_i}^L, \tag{9}$$

Approach



$$
\begin{aligned}
\mathbf{u}^{\text{Final}} &= \alpha \cdot \mathbf{u}^{\text{Global}} + (1-\alpha) \cdot \mathbf{u}^{\text{Local}}, \\
\alpha &= \sigma(\mathbf{W}_{\text{gate}}[\mathbf{u}^{\text{Global}} \sqcup \mathbf{u}^{\text{Local}}]),
\end{aligned} \tag{10}
$$

$$
Pr(u, v) = nn(\mathbf{u}^{\text{Final}}, \mathbf{v}^{\text{Final}}), \tag{11}
$$

$$
Loss = -\sum_{(u,v_i,v_j)\in O} -\ln \sigma(Pr(u, v_i) - Pr(u, v_j)) + \lambda ||\Theta||_2^2, \tag{12}
$$

Experiment

Table 1: Basic statistics of the datasets.

		MovieLens-1M	Last.FM
User-Item Feedback	#Users	6,040	1,851
	#Items	3,389	2,315
	#Interactions	997,024	59,781
Knowledge Graph	#Entities	392,966	10,367
	#Relations	49	63
	#Triplets	2,112,838	245,043

Table 2: Comparative results of MovieLens-1M and Last.FM. For Recall, NDCG, the larger value is better.

Model	Last.FM		MovieLens-1M	
	recall	ndcg	recall	ndcg
FM	0.568	0.448	0.534	0.610
NFM	0.535	0.412	0.590	0.620
CKE	0.553	0.483	0.635	0.670
CFKG	0.577	0.484	0.621	0.672
KGAT	0.657	0.550	0.652	0.701
MVIN	0.672	0.583	0.658	0.713
CKAN	0.686	0.590	0.673	0.721
KADM	**0.736**	**0.625**	**0.694**	**0.752**

Experiment

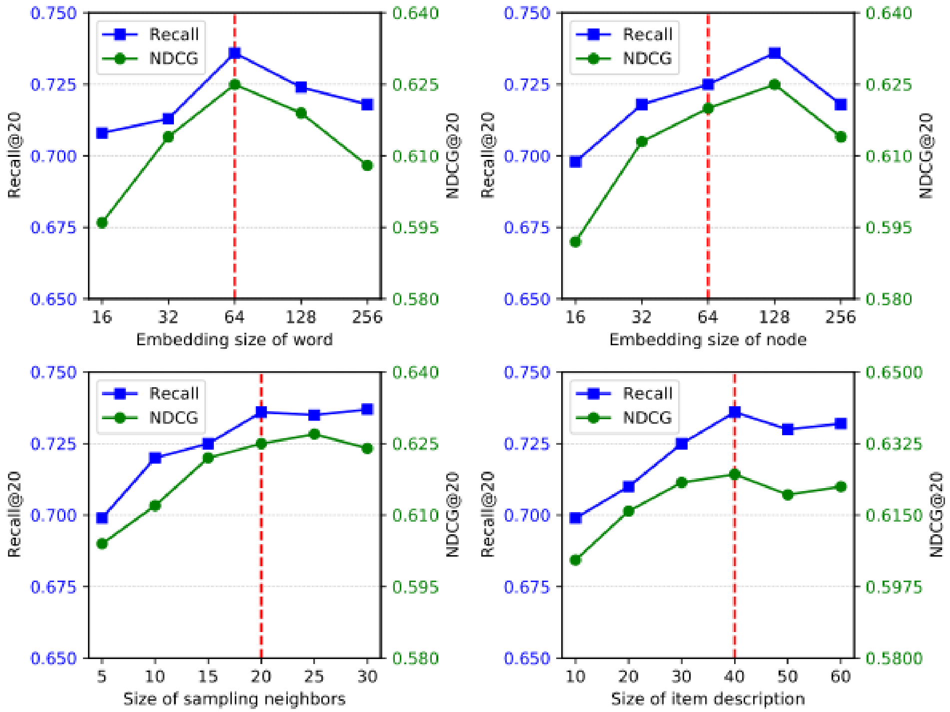


Figure 7: Evaluation of KADM on Last.FM w.r.t different hyper-parameters.

Table 3: Effect of different network configurations.

Model	Last.FM		MovieLens-1M	
	recall	ndcg	recall	ndcg
KADM-co	0.704	0.613	0.669	0.719
KADM-rel	0.695	0.607	0.662	0.714
KADM-local	0.674	0.572	0.654	0.708
KADM-global	0.689	0.603	0.663	0.716
KADM	0.736	0.625	0.694	0.752

Experiment

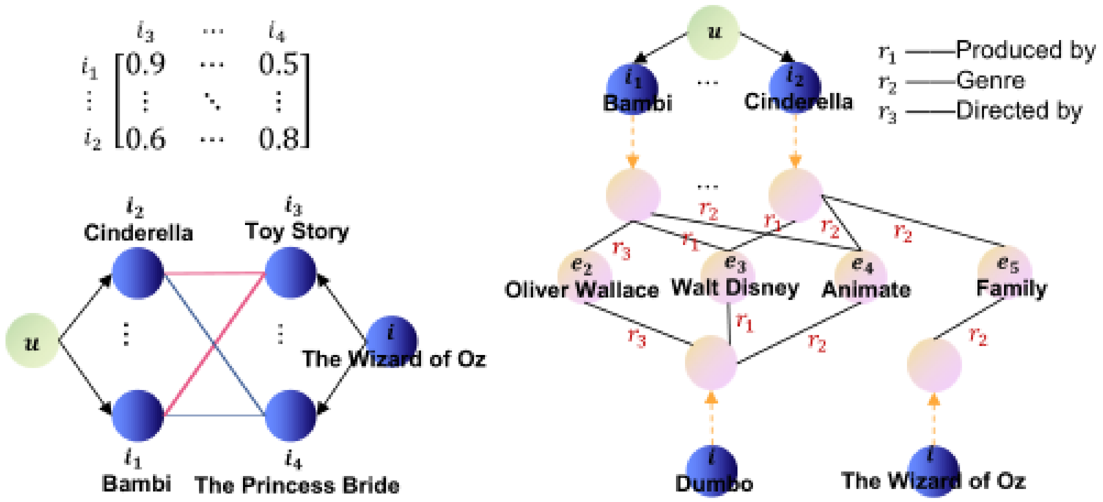


Figure 8: A real example from MovieLens-1M, including local information (left) and global information (right).

Thank you!