Heterogeneous Graph Neural Network: Models and Applications

叶泽凯

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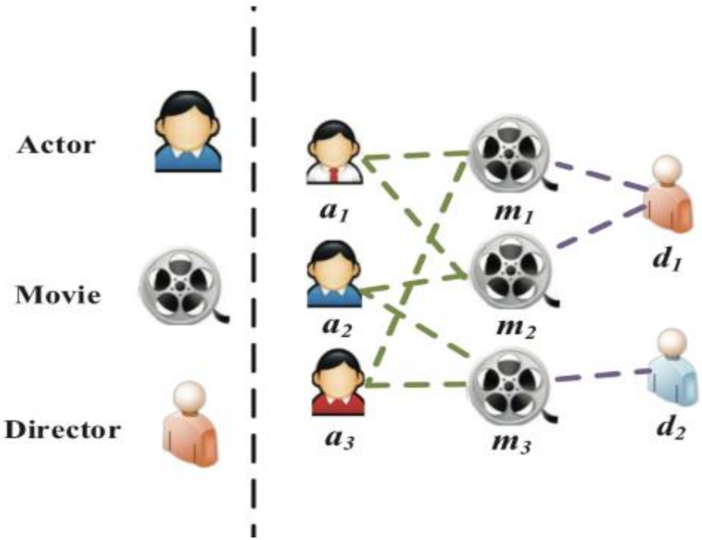
Introduction



Existing graph neural networks focus on homogeneous graph:

- Cannot handle multiple types of nodes and edges.
- Cannot capture rich semantic information.

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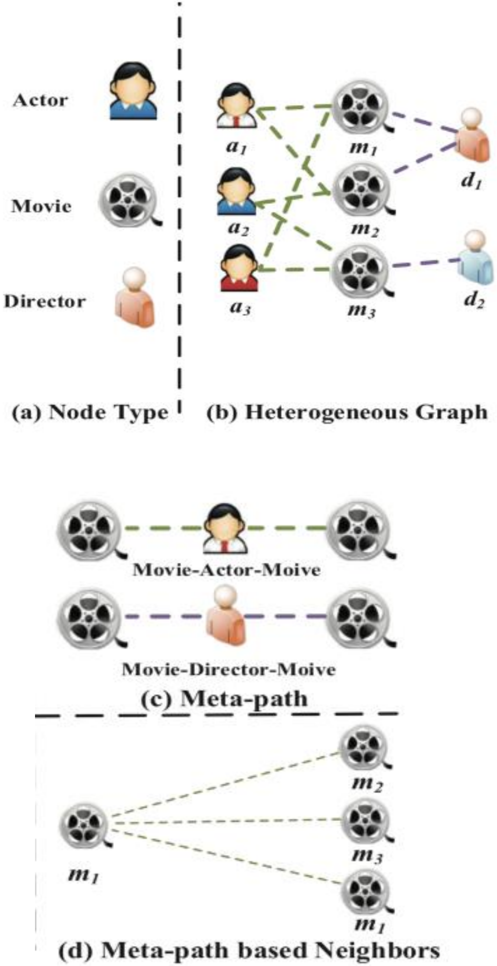

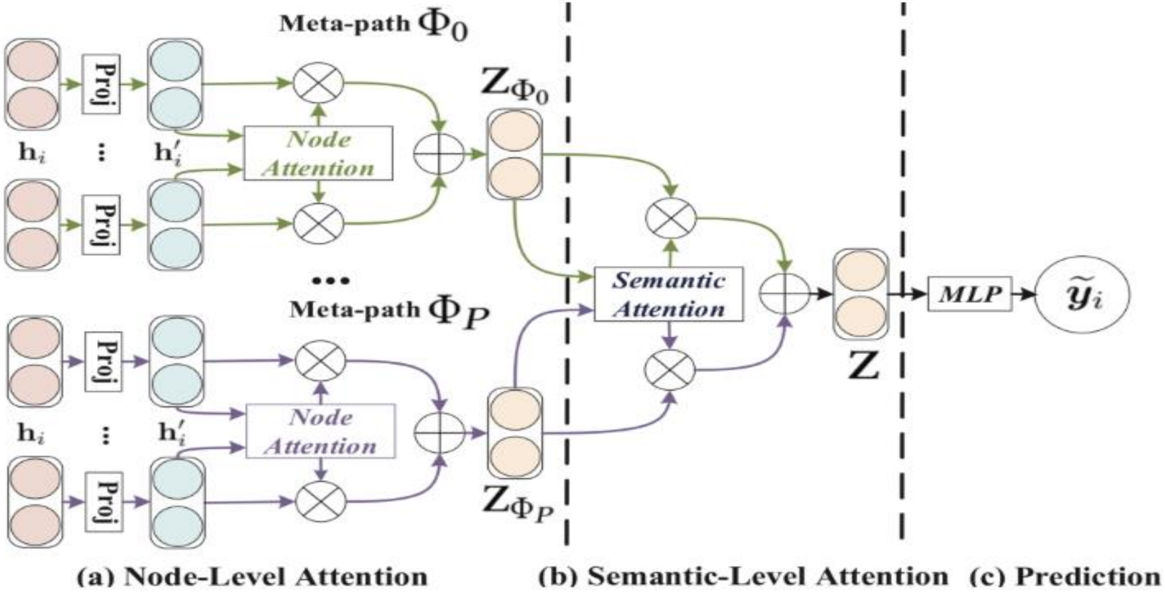

Graph Structure

Importance of Different Meta-paths

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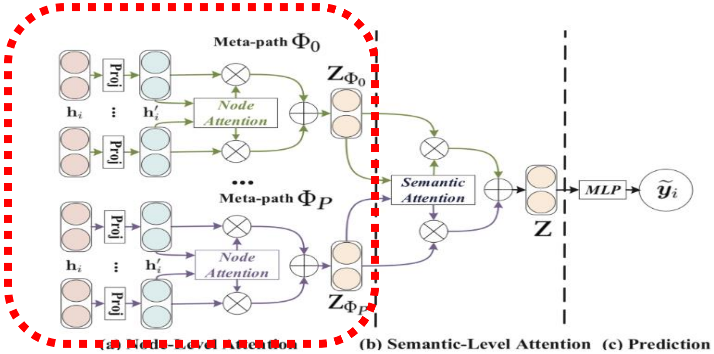
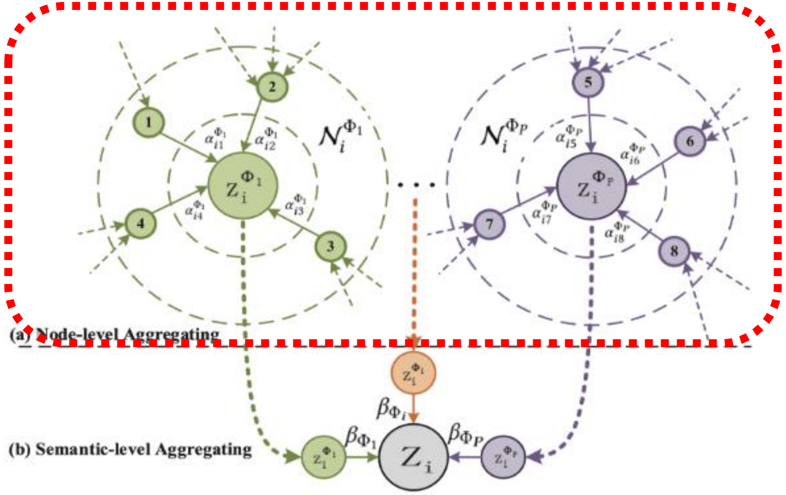
Heterogeneous Graph Attention Network
WWW,2019



Heterogeneous Graph Attention Network



type-specific transformation

$$\mathbf{h}'_i = \mathbf{M}_{\phi_i} \cdot \mathbf{h}_i,$$

Importance of Neighbors

$$e_{ij}^{\Phi} = att_{node}(\mathbf{h}'_i, \mathbf{h}'_j; \Phi).$$

$$\alpha_{ij}^{\Phi} = softmax_j(e_{ij}^{\Phi}) = \frac{\exp\left(\sigma(\mathbf{a}_{\Phi}^{\mathrm{T}} \cdot [\mathbf{h}'_i \| \mathbf{h}'_j])\right)}{\sum_{k \in \mathcal{N}_i^{\Phi}} \exp\left(\sigma(\mathbf{a}_{\Phi}^{\mathrm{T}} \cdot [\mathbf{h}'_i \| \mathbf{h}'_k])\right)},$$

Node-Level Aggregating

$$\mathbf{z}_i^{\Phi} = \sigma\left(\sum_{j \in \mathcal{N}_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot \mathbf{h}'_j\right).$$

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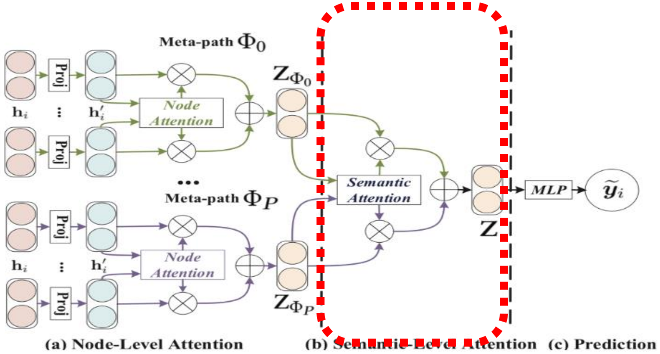

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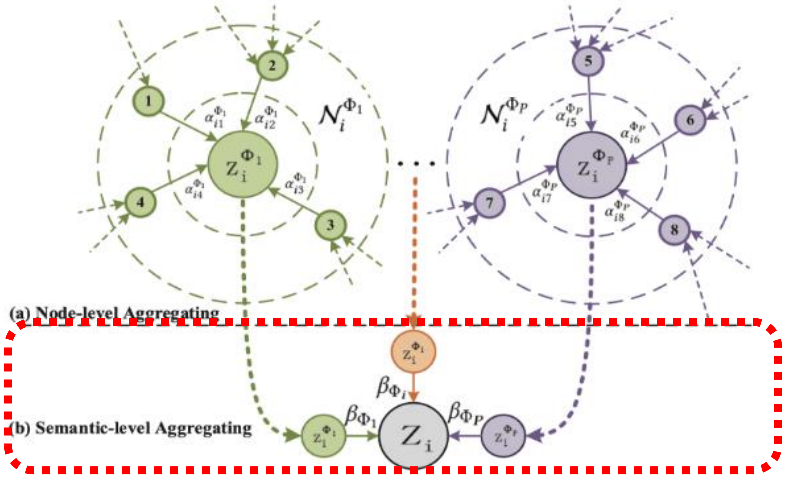

Semantic-Level Attention

$$(\beta_{\Phi_0}, \beta_{\Phi_1}, \ldots, \beta_{\Phi_P}) = att_{sem}(\mathbf{Z}_{\Phi_0}, \mathbf{Z}_{\Phi_1}, \ldots, \mathbf{Z}_{\Phi_P}).$$

Importance of Meta-path

$$w_{\Phi_i} = \frac{1}{|\mathcal{V}|} \sum_{i \in \mathcal{V}} \mathbf{q}^{\mathrm{T}} \cdot \tanh(\mathbf{W} \cdot \mathbf{z}_i^{\Phi} + \mathbf{b}),$$

$$\beta_{\Phi_i} = \frac{\exp(w_{\Phi_i})}{\sum_{i=1}^{P} \exp(w_{\Phi_i})},$$

Semantic-Level Aggregating

$$\mathbf{Z} = \sum_{i=1}^{P} \beta_{\Phi_i} \cdot \mathbf{Z}_{\Phi_i}.$$

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Baselines

- Deepwalk
- Esim
- Metapath2vec
- GCN
- GAT
- HAN_{nd}
- HAN_{sem}
- HAN

Table 2: Statistics of the datasets.

Dataset	Relations(A-B)	Number of A	Number of B	Number of A-B	Feature	Training	Validation	Test	Meta-paths
DBLP	Paper-Author	14328	4057	19645	334	800	400	2857	*APA*
	Paper-Conf	14328	20	14328					*APCPA*
	Paper-Term	14327	8789	88420					*APTPA*
IMDB	Movie-Actor	4780	5841	14340	1232	300	300	2687	*MAM*
	Movie-Director	4780	2269	4780					*MDM*
ACM	Paper-Author	3025	5835	9744	1830	600	300	2125	*PAP*
	Paper-Subject	3025	56	3025					*PSP*

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Table 3: Qantitative results (%) on the node classification task.

Datasets	Metrics	Training	DeepWalk	ESim	metapath2vec	HERec	GCN	GAT	HAN_{nd}	HAN_{sem}	HAN
ACM	Macro-F1	20%	77.25	77.32	65.09	66.17	86.81	86.23	88.15	89.04	**89.40**
		40%	80.47	80.12	69.93	70.89	87.68	87.04	88.41	89.41	**89.79**
		60%	82.55	82.44	71.47	72.38	88.10	87.56	87.91	**90.00**	89.51
		80%	84.17	83.00	73.81	73.92	88.29	87.33	88.48	90.17	**90.63**
	Micro-F1	20%	76.92	76.89	65.00	66.03	86.77	86.01	87.99	88.85	**89.22**
		40%	79.99	79.70	69.75	70.73	87.64	86.79	88.31	89.27	**89.64**
		60%	82.11	82.02	71.29	72.24	88.12	87.40	87.68	**89.85**	89.33
		80%	83.88	82.89	73.69	73.84	88.35	87.11	88.26	89.95	**90.54**
DBLP	Macro-F1	20%	77.43	91.64	90.16	91.68	90.79	90.97	91.17	92.03	**92.24**
		40%	81.02	92.04	90.82	92.16	91.48	91.20	91.46	92.08	**92.40**
		60%	83.67	92.44	91.32	92.80	91.89	90.80	91.78	92.38	**92.80**
		80%	84.81	92.53	91.89	92.34	92.38	91.73	91.80	92.53	**93.08**
	Micro-F1	20%	79.37	92.73	91.53	92.69	91.71	91.96	92.05	92.99	**93.11**
		40%	82.73	93.07	92.03	93.18	92.31	92.16	92.38	93.00	**93.30**
		60%	85.27	93.39	92.48	93.70	92.62	91.84	92.69	93.31	**93.70**
		80%	86.26	93.44	92.80	93.27	93.09	92.55	92.69	93.29	**93.99**
IMDB	Macro-F1	20%	40.72	32.10	41.16	41.65	45.73	49.44	49.78	**50.87**	50.00
		40%	45.19	31.94	44.22	43.86	48.01	50.64	52.11	50.85	**52.71**
		60%	48.13	31.68	45.11	46.27	49.15	51.90	51.73	52.09	**54.24**
		80%	50.35	32.06	45.15	47.64	51.81	52.99	52.66	51.60	**54.38**
	Micro-F1	20%	46.38	35.28	45.65	45.81	49.78	55.28	54.17	55.01	**55.73**
		40%	49.99	35.47	48.24	47.59	51.71	55.91	56.39	55.15	**57.97**
		60%	52.21	35.64	49.09	49.88	52.29	56.44	56.09	56.66	**58.32**
		80%	54.33	35.59	48.81	50.99	54.61	56.97	56.38	56.49	**58.51**

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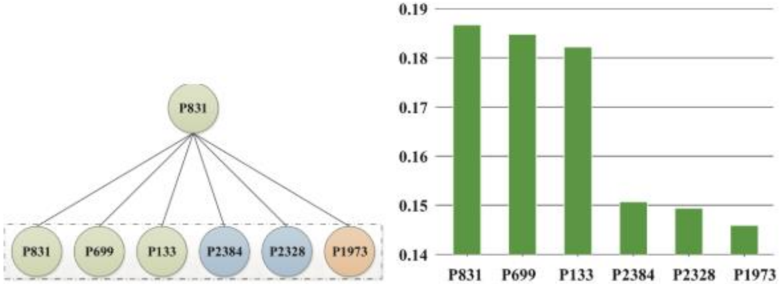
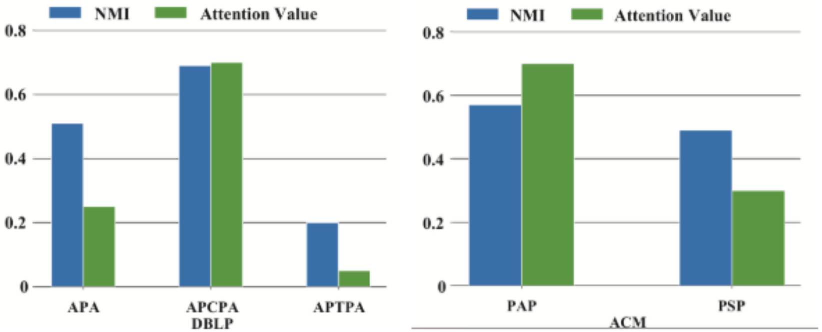


(a) Meta-path based neighbors of P831 (b) Attention values of P831's neighbors

Figure 4: Meta-path based neighbors of node P831 and corresponding attention values (Different colors mean different classes, e.g., *green* means Data Mining, *blue* means Database, *orange* means Wireless Communication).



(a) NMI values on DBLP (b) NMI values on ACM

Figure 5: Performance of single meta-path and corresponding attention value.

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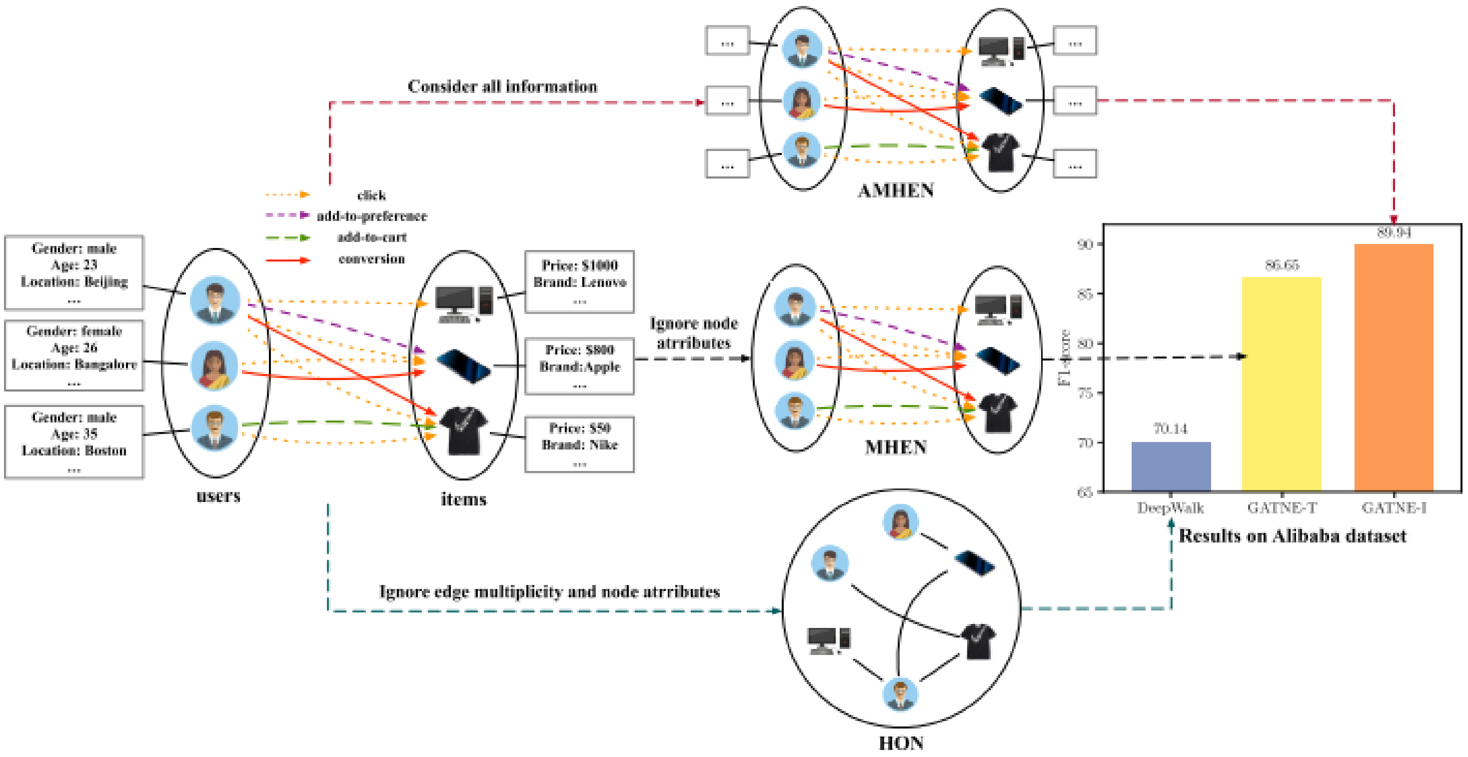

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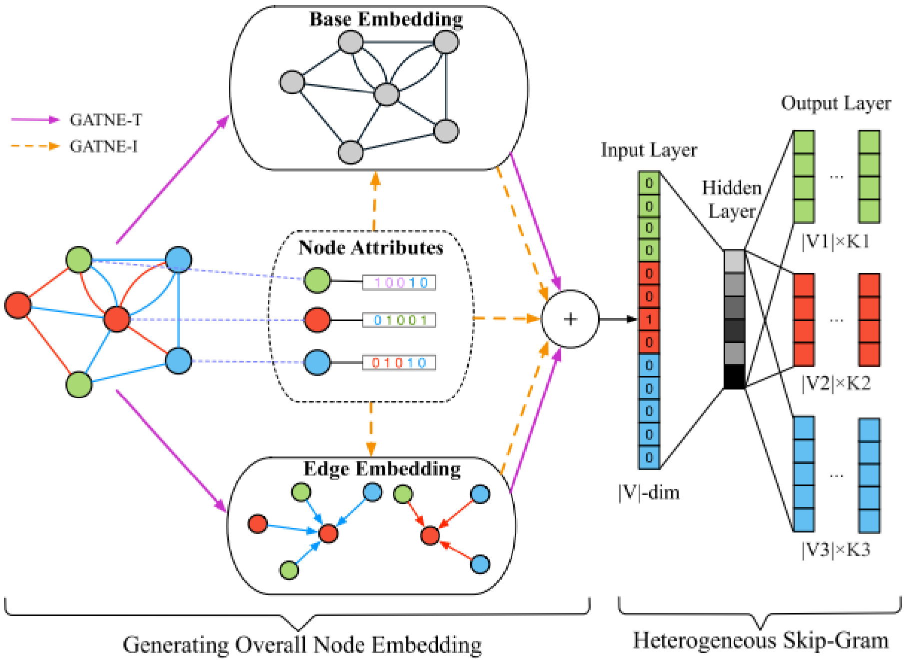
Representation Learning for Attributed Multiplex Heterogeneous Network
KDD,2019



GATNE-T

$$\mathbf{u}_{i,r}^{(k)} = aggregator(\{\mathbf{u}_{j,r}^{(k-1)}, \forall v_j \in \mathcal{N}_{i,r}\}),$$

$$\mathbf{U}_i = (\mathbf{u}_{i,1}, \mathbf{u}_{i,2}, \ldots, \mathbf{u}_{i,m}).$$

$$\mathbf{a}_{i,r} = \mathrm{softmax}(\mathbf{w}_r^T \tanh(\mathbf{W}_r \mathbf{U}_i))^T,$$

$$\mathbf{v}_{i,r} = \mathbf{b}_i + \alpha_r \mathbf{M}_r^T \mathbf{U}_i \mathbf{a}_{i,r},$$

GATNE-I

$$\mathbf{v}_{i,r} = \mathbf{h}_z(\mathbf{x}_i) + \alpha_r \mathbf{M}_r^T \mathbf{U}_i \mathbf{a}_{i,r} + \beta_r \mathbf{D}_z^T \mathbf{x}_i,$$

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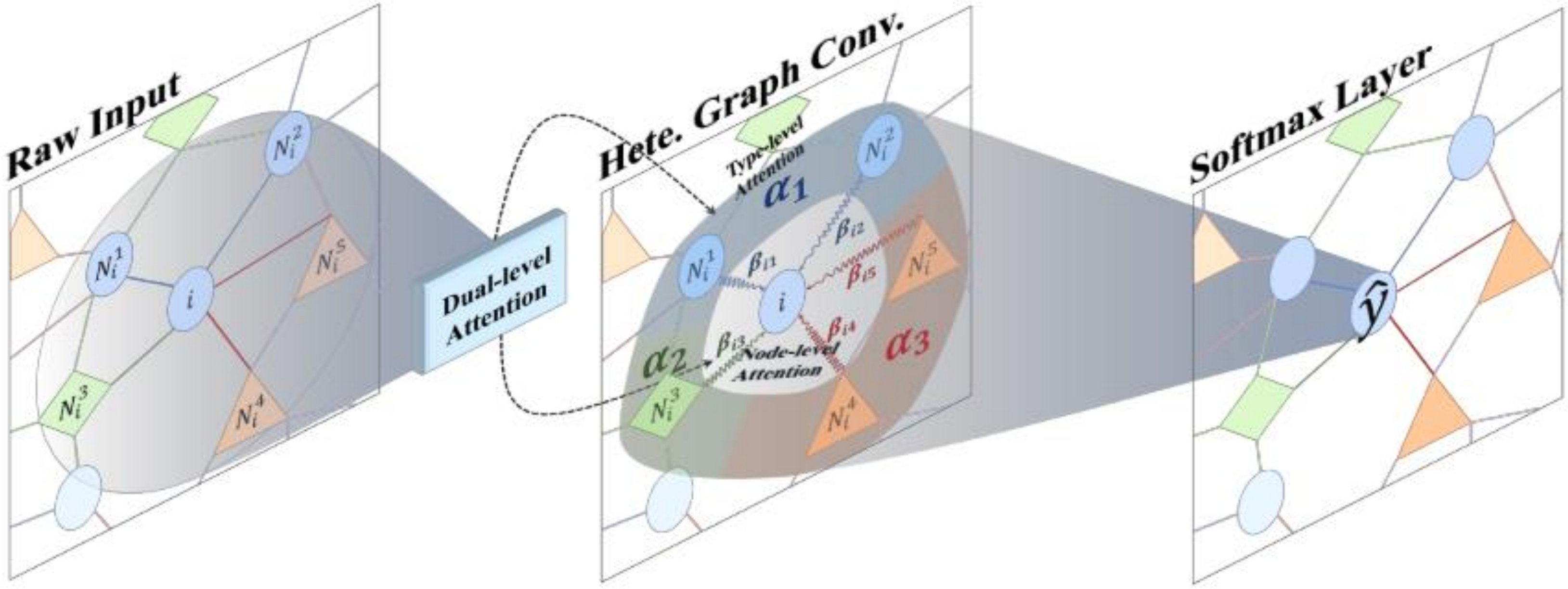
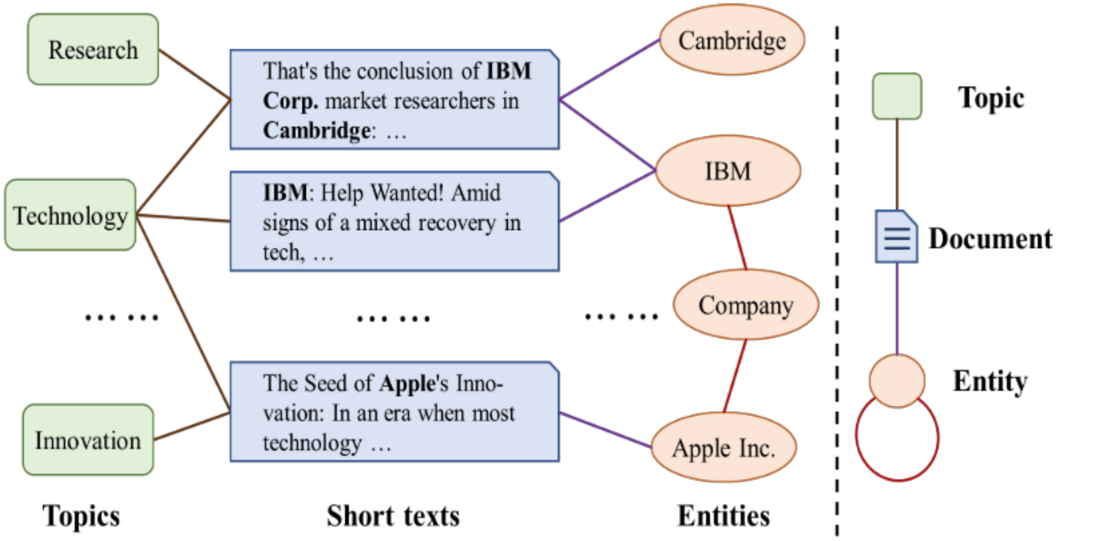


Heterogeneous Graph **Dual-level Attention** **Semi-supervised Training**

Linmei Hu, Tianchi Yang, Chuan Shi, Houye Ji, Xiaoli Li
Heterogeneous Graph Attention Networks for Semi-supervised ShortText Classification.
EMNLP/IJCNLP (1),2019



(a) HIN for short texts (b) HIN schema

- **Nodes**

  Text: Document in the corpus.

  Topic: Mined by LDA.

  Entity: Recognized by Tagme.

- **Edges**

  Text-topic: The text is assigned to the Top P topics.

  Text-Entity: The text contains the entity.

  Entity-Entity: The similarity score between two entities

Linmei Hu, Tianchi Yang, Chuan Shi, Houye Ji, Xiaoli Li
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Type-level Attention

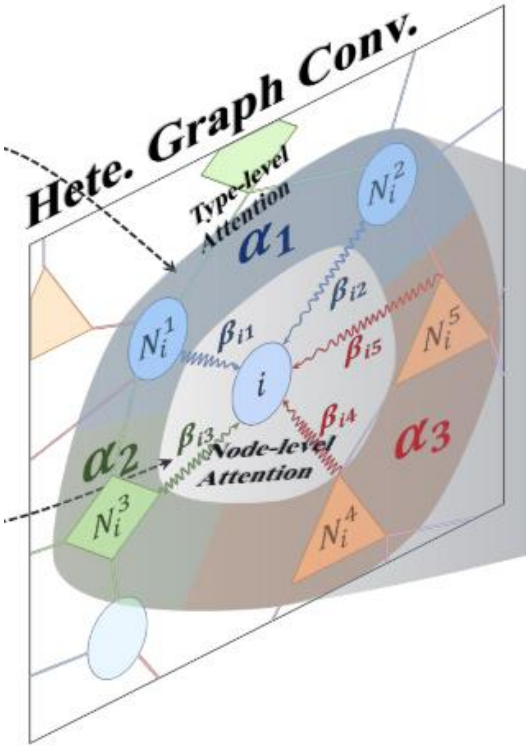
$$a_{\tau} = \sigma(\mu_{\tau}^{T} \cdot [h_v || h_{\tau}]), \qquad \alpha_{\tau} = \frac{\exp(a_{\tau})}{\sum_{\tau' \in \mathcal{T}} \exp(a_{\tau'})}.$$

Node-level Attention

$$b_{vv'} = \sigma(\nu^{T} \cdot \alpha_{\tau'}[h_v || h_{v'}]), \quad \beta_{vv'} = \frac{\exp(b_{vv'})}{\sum_{i \in \mathcal{N}_v} \exp(b_{vi})}.$$

Dual-level Attention Based Hete. Graph Conv.

$$H^{(l+1)} = \sigma(\sum_{\tau \in \mathcal{T}} \mathcal{B}_{\tau} \cdot H_{\tau}^{(l)} \cdot W_{\tau}^{(l)}).$$



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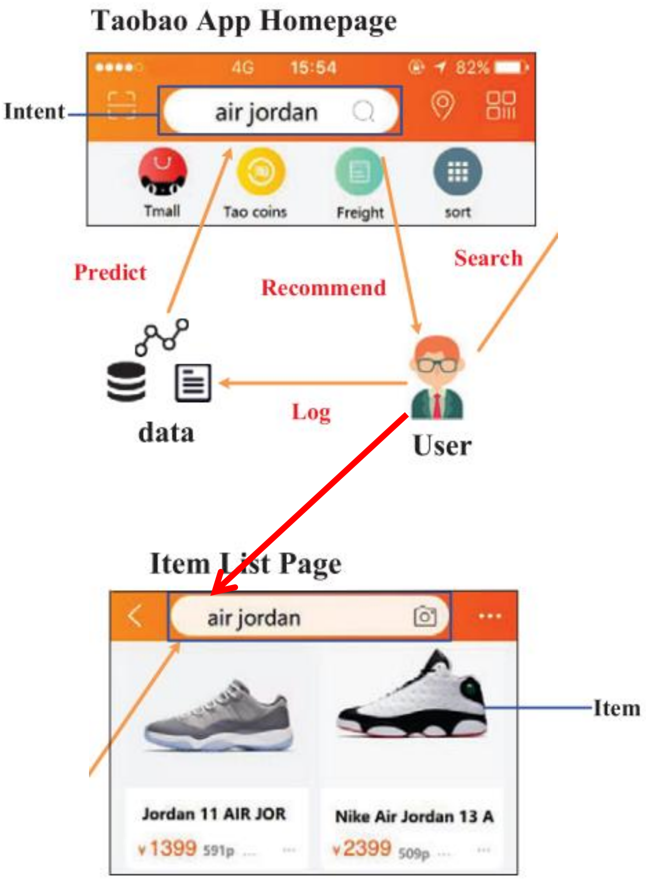

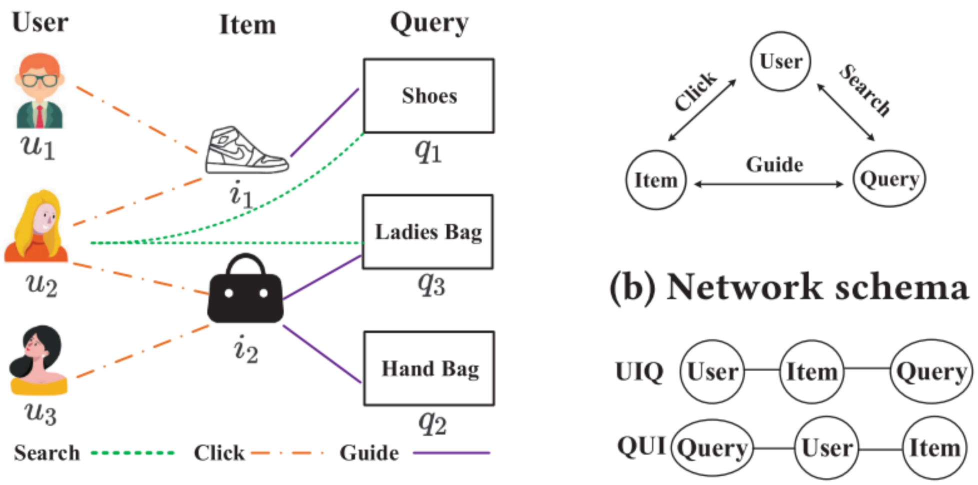

(a) Toy example

(b) Network schema

(c) Metapaths

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KDD,2019

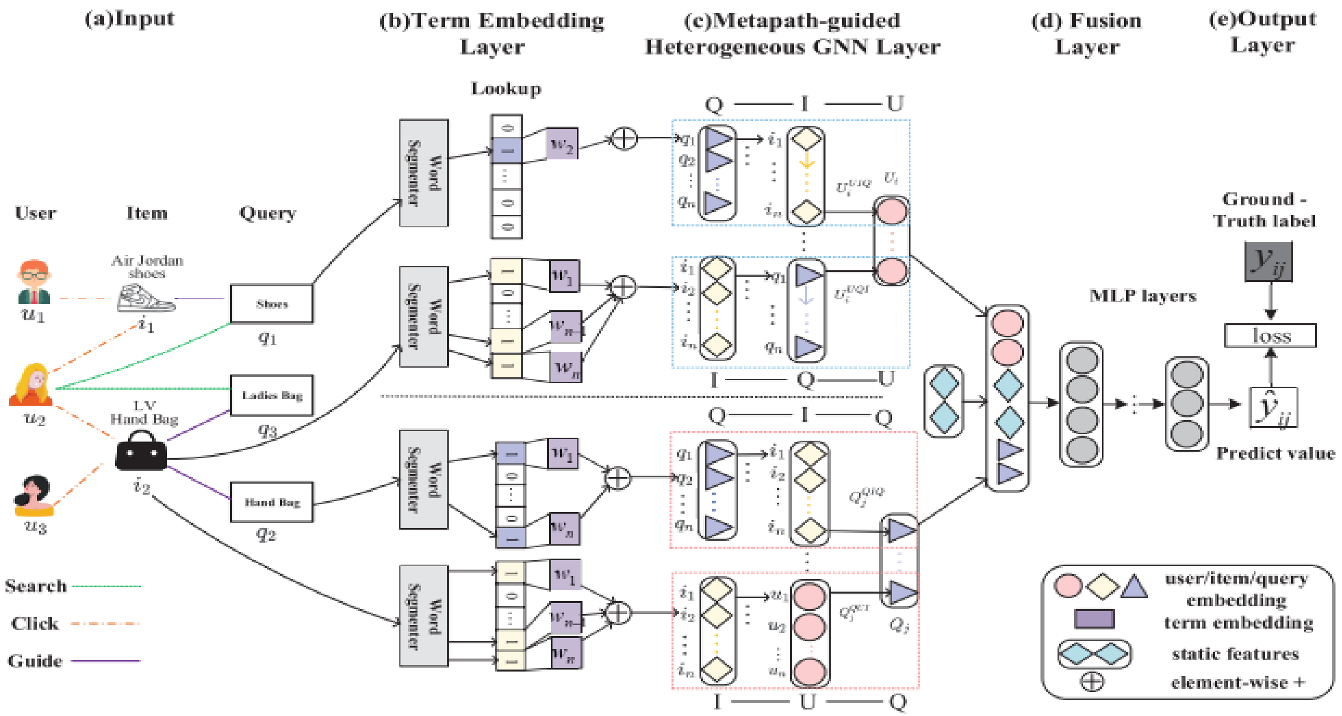

Figure 3: The framework of MEIRec.

Handle large and Dynamic data **Capture rich semantics** **Task-specific loss**

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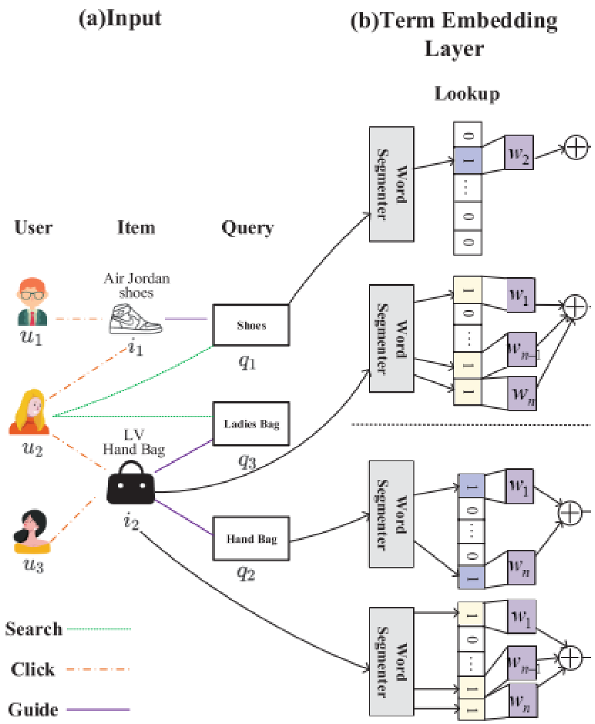

Parameter share

Queries and items are constituted by the same term embedding

$$
\begin{array}{rccccc}
 & \{w_1, & w_2, & \cdots, & w_{n-1}, & w_n\} \\
q_2 = & (1, & 0, & \cdots, & 0, & 1) \\
i_2 = & (1, & 0, & \cdots, & 1, & 1).
\end{array}
$$

Reduce parameter space complexity

Traditional latent factor model:

MEIRec:

New objects

The embedding of new objects (item, query) can be computed by trained term embedding in the testing phase

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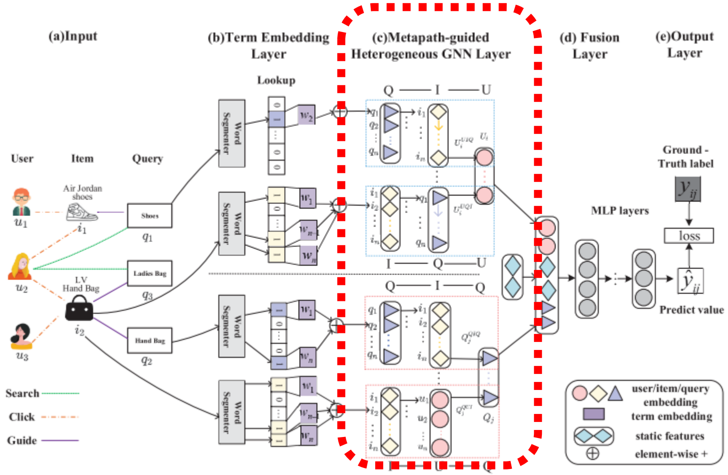

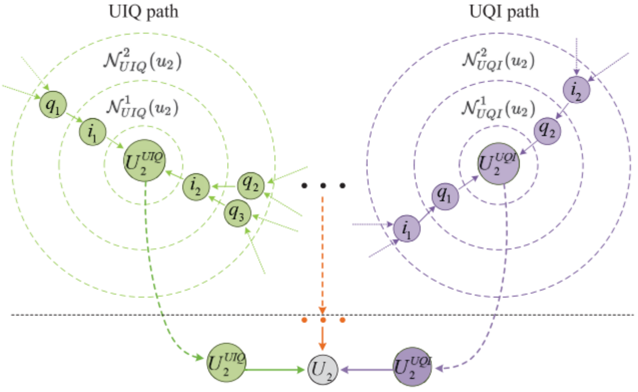

Initial embedding

$$E_{q_2} = g(e_{w_1}, e_{w_n}), E_{i_2} = g(e_{w_1}, e_{w_{n-1}}, e_{w_n}),$$

Neighbor aggregation

$$I_j^{\mathrm{UIQ}} = g(E_{q_1}, E_{q_2}, \cdots),$$

$$U_i^{\mathrm{UIQ}} = g(I_1^{\mathrm{UIQ}}, I_2^{\mathrm{UIQ}}, \cdots),$$

Meta-path Aggregating

$$U_i = g(U_i^{\rho_1}, U_i^{\rho_2}, \cdots, U_i^{\rho_k}),$$

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Spammers normally take the following two adversarial tricks to circumvent the anti-spam system:

- **Camouflage:** Using different expressions with similar meaning.
- **Deforming the comments:** Spammers replace some key-words in the comments with rarely used Chinese characters or typos deliberately.

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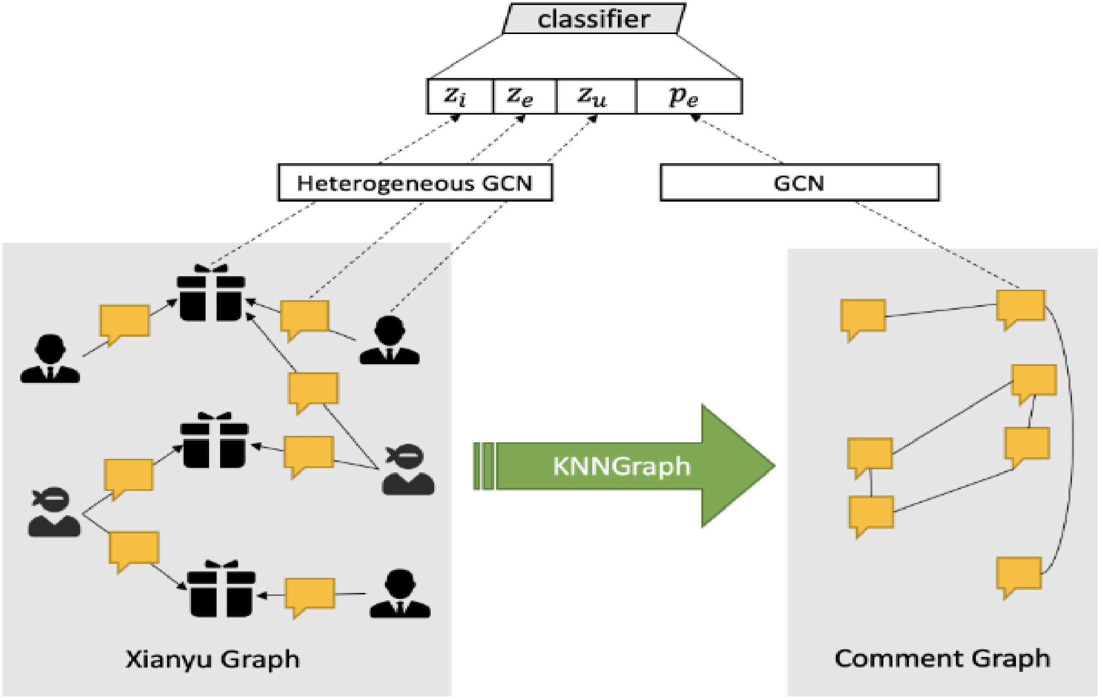
Spam Review Detection with Graph Convolutional Networks
CIKM,2019

Heterogeneous graph

- Item-comment-user
- Metapaths
- 2-hop neighborhood aggregation



Homogeneous graph

- comment-comment
- Made by KNNGraph
- Smoothing process

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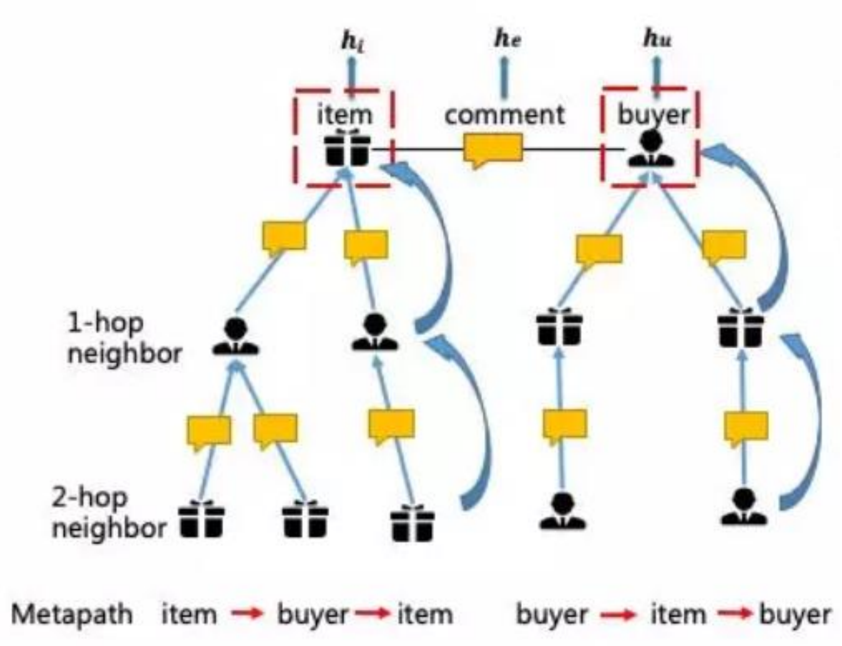

$$h_e^l = \sigma\left(W_E^l \cdot AGG_E^l(h_e^{l-1}, h_{U(e)}^{l-1}, h_{I(e)}^{l-1})\right)$$

$$AGG_E^l\left(h_e^{l-1}, h_{U(e)}^{l-1}, h_{I(e)}^{l-1}\right) = concat\left(h_e^{l-1}, h_{U(e)}^{l-1}, h_{I(e)}^{l-1}\right)$$

$$h_{N(u)}^l = \sigma\left(W_U^l \cdot AGG_U^l(\mathcal{H}_{IE}^{l-1})\right)$$

$$h_{N(i)}^l = \sigma\left(W_I^l \cdot AGG_I^l(\mathcal{H}_{UE}^{l-1})\right)$$

$$h_u^l = concat\left(V_U^l \cdot h_u^{l-1}, h_{N(u)}^l\right)$$

$$h_i^l = concat\left(V_I^l \cdot h_i^{l-1}, h_{N(i)}^l\right)$$

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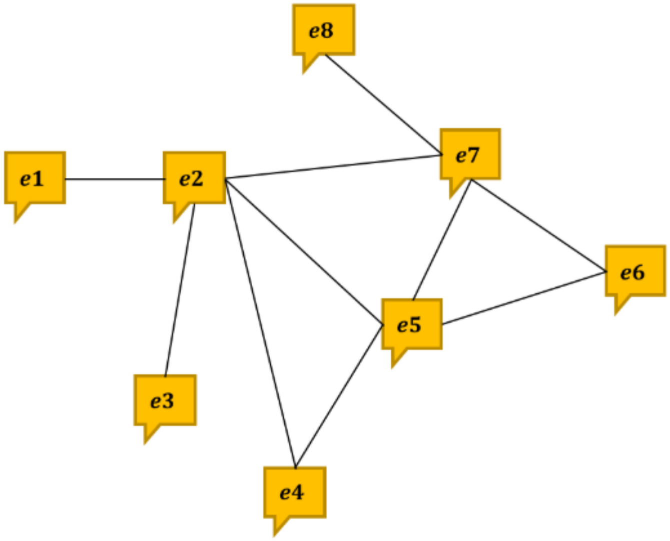

the Comment Graph is constructed as follows:

• Remove all the duplicated comments.
• Generate comments embeddings by the method described in.
• Obtain the similar comment pairs by employing the approx- imate KNN Graph algorithm.
• Remove comment pairs posted by same user or posted un- der same item, since the local context has been taken into consideration on Xianyu Graph.

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Thanks