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Dynamic Group Link Prediction in Continuous-Time Interaction Network

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Introduction

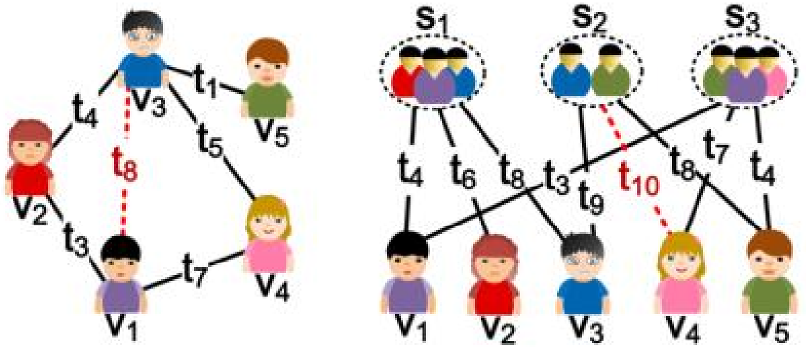


Figure 1: Difference between continuous-time link prediction and continuous-time group link prediction. (1) As shown in left part, in continuous-time link prediction, we predict the probability of an edge existing between individual v_1 and v_3 at future time t_8. (2) As shown in right part, in continuous-time group link prediction, we infer the possibility of generating a link between individual v_4 and group s_2 at future time t_{10}.

First, previous methods rarely discuss future links between individuals and groups, but tend to mine missing ones. The assumption that all members are connected to the group at the same time makes the fine-grained raw temporal information missing.

Second, individuals are assumed to be isolated from each other, which neglects the neighborhood information that laterally depicts dynamic link preferences.

Third, equal treatment of all group members leads to ignoring the diversity of members’ importance in groups.

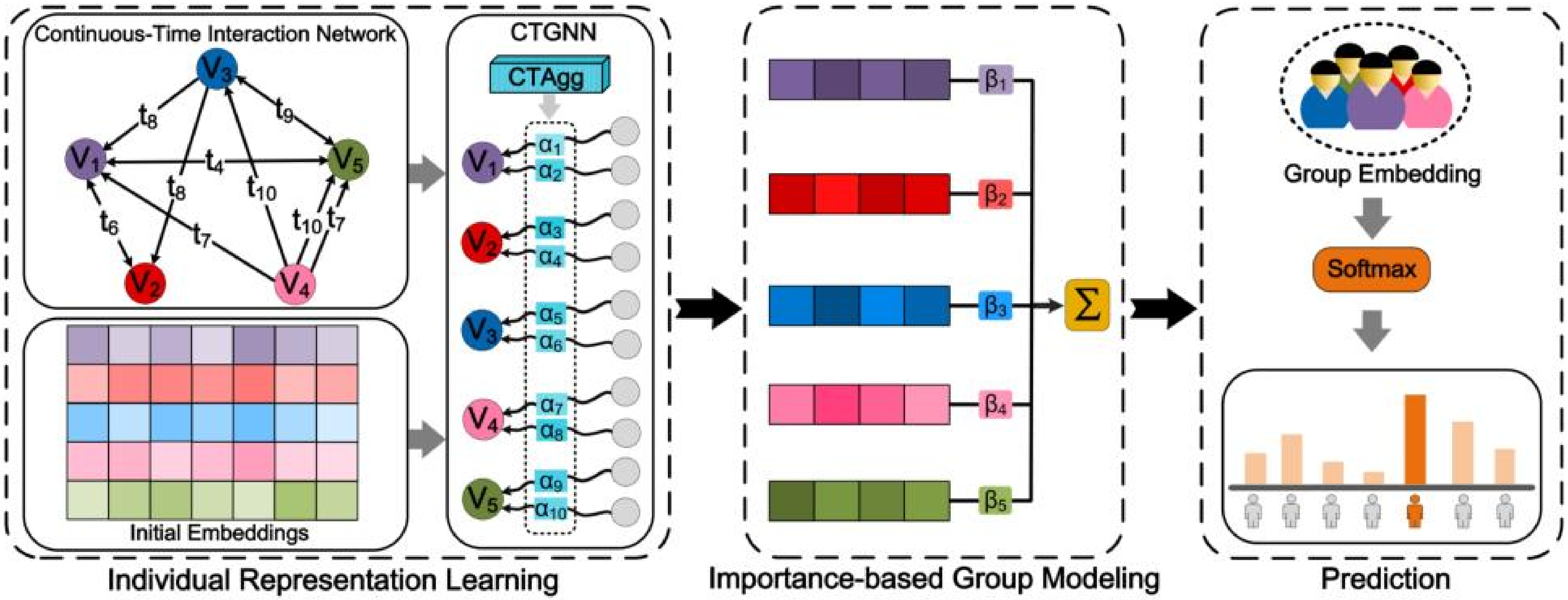


Figure 3: The overall framework of CTGLP. CTGLP is composed of three main components: individual representation learning, importance-based group modeling and prediction.

Method

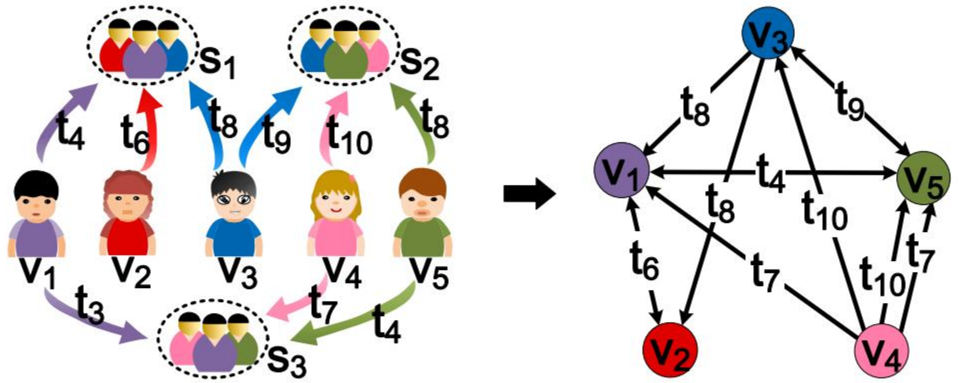


Figure 2: A toy example of the construction of a continuous-time interaction network.

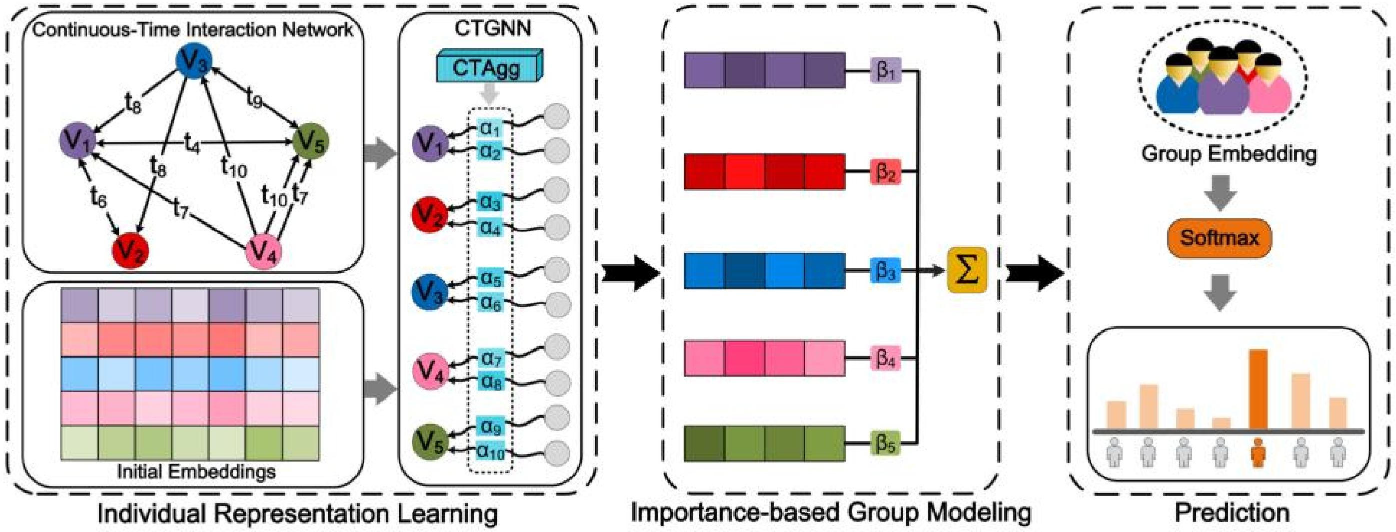
$G = (V, E^T, T) \qquad e^t_{ij} \in E^T \qquad t \in T$

$S = \{s_1, s_2, \ldots, s_M\} \qquad s_i = \{v^{t_1}_{i,1}, v^{t_2}_{i,2}, \ldots, v^{t_k}_{i,k}\} \subseteq V$

$$v^{t'}_{i,k+1} = \mathcal{F}(v^{t_1}_{i,1},\ v^{t_2}_{i,2},\ \ldots, v^{t_k}_{i,k}), \qquad (1)$$

$v^{t'}_{i,k+1} \in V \backslash s_i \qquad t' > t$

Method



$$\Gamma_{\mathcal{T}}(u) = \{(v,t) \mid e = (u,v,t) \in E^T \cap t < \mathcal{T}\}. \quad (2)$$

$$Samp = \begin{cases} \Gamma_{\mathcal{T}}(u), & |\Gamma_{\mathcal{T}}(u)| \le \theta; \\ r_\theta(\Gamma_{\mathcal{T}}(u)), & |\Gamma_{\mathcal{T}}(u)| > \theta, \end{cases} \quad (3)$$

$$\hat{\mathcal{N}}^l_{\mathcal{T}}(u) = Samp_l\left(\Gamma^l_{\mathcal{T}_l}(\dots Samp_1(\Gamma^1_{\mathcal{T}_1}(u)))\right), \quad (4)$$

$$\mathcal{T}_{i+1} < \mathcal{T}_i \text{ for } 1 \le i < l, \text{ and } \mathcal{T}_1 = \mathcal{T}.$$

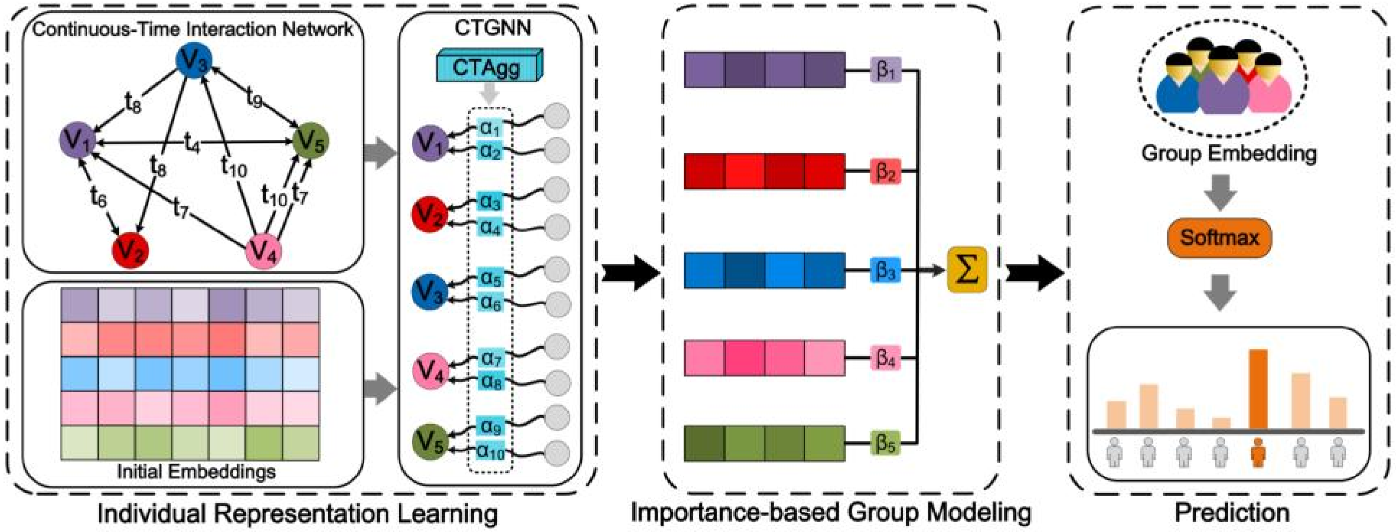
$$\vec{\mathbf{n}}_u^{(l)} = \mathrm{AGG}^{(l)}(\{\alpha_{uv}^t \cdot \vec{\mathbf{h}}_v^{(l-1)},\ v \in \hat{\mathcal{N}}_t^l(u)\}), \quad (5)$$

$$\vec{\mathbf{h}}_u^{(l)} = \sigma(\mathbf{W}^{(l)} \cdot \mathrm{COM}(\vec{\mathbf{h}}_u^{(l-1)},\ \vec{\mathbf{n}}_u^{(l)}) + \mathbf{w}^{(l)}), \quad (6)$$

$$\alpha_{uv}^t = \frac{\exp(t_{uv} - t)}{\sum_{v \in \hat{\mathcal{N}}_t^l(u) \cup u} \exp(t_{uv} - t)}, \quad (7)$$

$$\begin{aligned} \vec{\mathbf{e}}_u^{(1)} &= \sigma(\mathbf{U}^{(1)} \cdot \vec{\mathbf{h}}_u + \mathbf{u}^{(1)}), \\ \vec{\mathbf{e}}_u^{(2)} &= \sigma(\mathbf{U}^{(2)} \cdot \vec{\mathbf{e}}_u^{(1)} + \mathbf{u}^{(2)}), \\ &\cdots \\ \vec{\mathbf{z}}_u &= \sigma(\mathbf{U}^{(j)} \cdot \vec{\mathbf{e}}_u^{(j-1)} + \mathbf{u}^{(j)}), \end{aligned} \quad (8)$$

Method



$$\beta_{ik} = \frac{\frac{1}{\log(T-t_k)}}{\sum_{j=1}^{K}\frac{1}{\log(T-t_j)}}, \quad (9)$$

$$\vec{\mathbf{p}}_i = \sum_{j=1}^{K}\beta_{ij}\cdot\vec{\mathbf{z}}_{i,j}, \quad (10)$$

$$\vec{\mathbf{m}}_i = \mathbf{C}_2\cdot\sigma(\mathbf{C}_1\cdot\vec{\mathbf{p}}_i+\mathbf{c}), \quad (11)$$

$$\begin{aligned}\vec{\mathbf{q}}_i^{(1)} &= \sigma(\mathbf{G}^{(1)}\cdot\vec{\mathbf{m}}_i+\mathbf{g}^{(1)}),\\ &\cdots\\ \vec{\mathbf{q}}_i^{(k)} &= \sigma(\mathbf{G}^{(k)}\cdot\vec{\mathbf{q}}_i^{(k-1)}+\mathbf{g}^{(k)}),\end{aligned} \quad (12)$$

$$\mathbf{P}_i = \mathrm{Softmax}(\mathbf{Q}\cdot\vec{\mathbf{q}}_i^{(k)}+\mathbf{q}) \quad (13)$$

$$\mathcal{L} = \frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{N}y_{ij}\log(P_{ij}) \quad (14)$$

Experiments

Datasets	Nodes	Edges	Groups	Unseen*
ML100K	755	59 118	590	42
CiaoDVD	8 714	165 598	4 040	1 195
ML25M	16 065	1 048 836	18 882	1 578
$\text{ML100K}_{\text{w/o}}$	650	22 683	510	0
$\text{CiaoDVD}_{\text{w/o}}$	5 766	85 562	3 341	0
$\text{ML25M}_{\text{w/o}}$	9 998	491 704	16 494	0

* The value indicates the number of nodes that are not presented during training.

Table 1: Statistics of two versions of the three datasets. Note that the subscript w/o denotes the dataset without unseen nodes.

Experiments

	Method	HR@K(%) K=10	HR@K(%) K=20	NDCG@K(%) K=10	NDCG@K(%) K=20	MRR@K(%) K=10	MRR@K(%) K=20
ML100K	LSTM	15.9	22.7	8.7	10.4	6.6	7.0
	CVAE	28.8±1.5	39.0±1.7	16.1±1.4	18.6±1.4	12.3±2.2	13.0±2.3
	CVAEH	23.7±1.9	32.2±1.0	12.3±1.1	14.5±0.8	8.9±1.3	9.5±1.3
	MLP	14.4±1.1	26.1±1.2	6.3±1.4	9.3±1.2	4.1±1.2	4.7±1.4
	GSAGE	27.1±0.7	35.6±0.4	16.2±0.4	18.3±0.4	12.9±0.6	13.5±0.5
	CTGLP	**30.5±0.9**	**42.4±0.5**	**21.5±0.9**	**24.4±0.8**	**18.6±0.7**	**19.4±0.7**
CiaoDVD	LSTM	10.6	14.7	6.0	7.0	4.5	4.8
	CVAE	**21.6±0.7**	27.1±0.8	**11.9±0.5**	13.4±0.3	**9.0±0.4**	**9.4±0.3**
	CVAEH	16.1±0.8	23.5±1.9	10.0±1.1	11.9±1.3	8.2±1.1	8.7±1.2
	MLP	15.2±1.5	20.5±2.6	7.2±0.6	8.6±0.8	4.8±0.5	5.2±0.4
	GSAGE	17.6±0.8	24.8±0.8	8.8±0.7	10.6±0.5	6.1±0.5	6.5±0.6
	CTGLP	20.8±0.6	**28.7±0.7**	11.7±0.4	**13.7±0.2**	8.8±0.7	**9.4±0.8**
ML25M	LSTM	20.5	25.3	13.9	15.1	11.9	12.2
	CVAE	22.6±2.1	26.9±2.1	16.6±1.6	17.7±1.7	14.7±1.5	15.0±1.5
	CVAEH	19.4±0.8	23.4±0.6	14.3±1.1	15.3±0.8	12.7±1.0	12.9±0.8
	MLP	19.6±1.4	23.4±3.1	14.4±1.5	15.4±2.0	12.8±1.6	13.1±1.8
	GSAGE	27.1±0.4	31.9±0.6	17.1±0.3	18.3±0.4	14.0±0.2	14.3±0.3
	CTGLP	**30.0±0.7**	**35.8±0.8**	**19.6±0.4**	**21.0±0.5**	**16.3±0.6**	**16.7±0.6**

Table 2: Performance of various methods on datasets *with* unseen nodes. Items with the highest values are marked in **bold**.

	Method	HR@K(%) K=10	HR@K(%) K=20	NDCG@K(%) K=10	NDCG@K(%) K=20	MRR@K(%) K=10	MRR@K(%) K=20
$ML100K_{w/o}$	AA	8.8	18.7	4.3	6.8	3.1	3.8
	CN	7.7	18.7	3.5	6.3	2.2	3.0
	DW	0.0	2.0	0.0	0.5	0.0	0.1
	n2v	0.0	4.0	0.0	1.0	0.0	0.3
	HTNE	0.0	8.0	0.0	2.0	0.0	0.5
	LSTM	4.7	7.0	2.0	2.6	1.2	1.3
	CVAE	**30.0±1.6**	**38.0±1.1**	17.7±1.1	19.6±1.1	13.8±1.3	14.3±1.3
	CVAEH	24.0±3.0	28.0±2.3	12.2±1.9	13.1±1.8	8.4±1.9	8.7±1.9
	CTGLP	28.0±1.0	34.0±0.6	**22.1±0.9**	**23.5±1.0**	**20.3±0.8**	**20.7±0.8**
$CiaoDVD_{w/o}$	AA	20.4	28.7	12.6	14.8	10.3	10.9
	CN	19.3	30.1	12.1	14.8	9.9	10.6
	DW	0.9	1.9	0.3	0.6	0.2	0.3
	n2v	0.5	1.0	0.2	0.4	0.1	0.2
	HTNE	0.5	2.0	0.2	0.5	0.1	0.2
	LSTM	13.0	16.6	8.2	9.1	6.7	7.0
	CVAE	22.1±1.7	26.8±1.0	12.6±1.1	13.8±0.9	9.7±0.9	10.0±0.9
	CVAEH	22.5±0.9	27.7±1.0	13.1±0.7	14.4±0.6	10.2±0.6	10.5±0.6
	CTGLP	**25.5±0.9**	**30.7±1.0**	**17.0±0.5**	**18.3±0.4**	**14.3±0.9**	**14.7±1.0**
$ML25M_{w/o}$	AA	42.5	45.1	31.8	32.4	28.5	**28.7**
	CN	42.7	45	**31.9**	**32.5**	**28.6**	**28.7**
	DW	2.1	5.4	0.7	1.5	0.3	0.5
	n2v	1.3	3.5	0.5	1.0	0.2	0.4
	HTNE	1.3	3.1	0.5	0.9	0.2	0.3
	LSTM	27.3	32.6	19.8	21.1	17.5	17.8
	CVAE	27.8±0.5	34.2±0.6	19.3±0.4	20.9±0.7	16.6±0.7	17.1±0.5
	CVAEH	27.2±0.4	32.1±0.7	19.3±0.5	20.6±0.4	16.9±0.4	17.2±0.4
	CTGLP	**45.8±1.1**	**54.4±0.9**	28.3±0.8	30.5±1.0	22.9±1.1	23.5±1.3

Table 3: Performance of various methods on datasets *without* unseen nodes. Items with the highest values are marked in **bold**.

Experiments

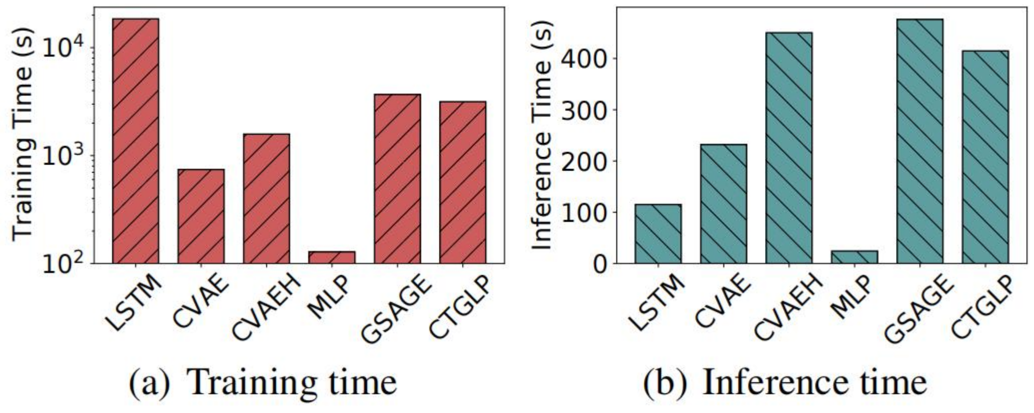


Figure 4: Comparison of training time and inference time of six methods on ML25M.

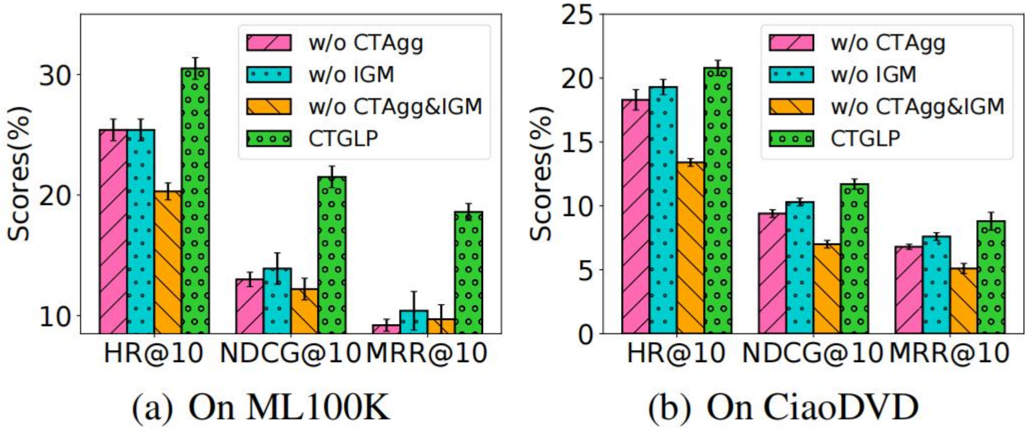


Figure 5: Impact of various components on performance under ML100K and CiaoDVD. IGM denotes the importance-based group modeling.

Experiments

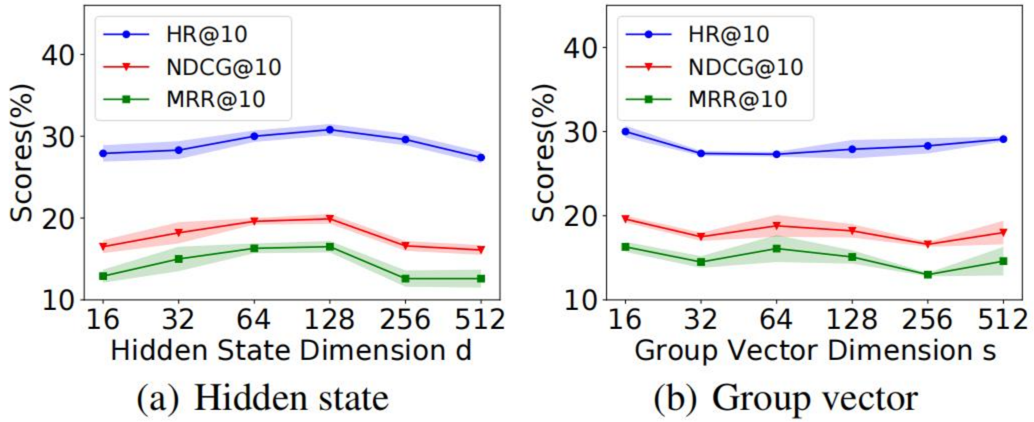


Figure 6: Impact of embedding dimension on method performance under ML25M.

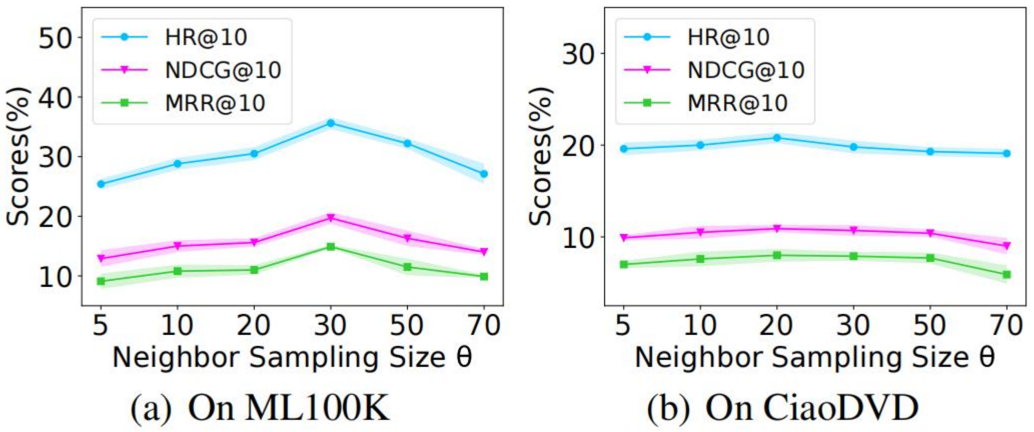


Figure 7: Impact of embedding dimension on method performance on datasets ML100K and CiaoDVD.

Thank you!