Chongqing University of Technology

Enhancing Multi-Scale Diffusion Prediction via Sequential Hypergraphs and Adversarial Learning

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https://github.com/CZ-TAO12/DisenIDP

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Reported by Yuyang Lai

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Introduction

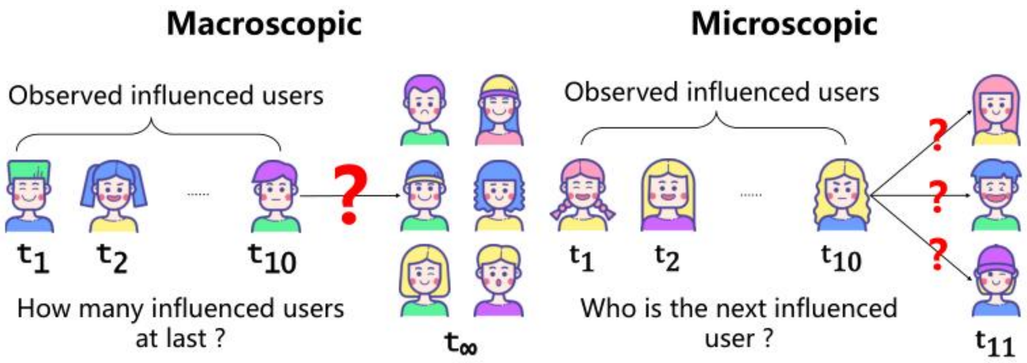


Figure 1: Illustrations depicting macroscopic cascade size prediction (left) and microscopic next influenced user prediction (right).

Firstly, information dissemination involves complex interactions not only within a given cascade but also between different cascades.

Secondly, ensuring the purity of public features in the presence of potential contamination by private features poses a significant challenge.

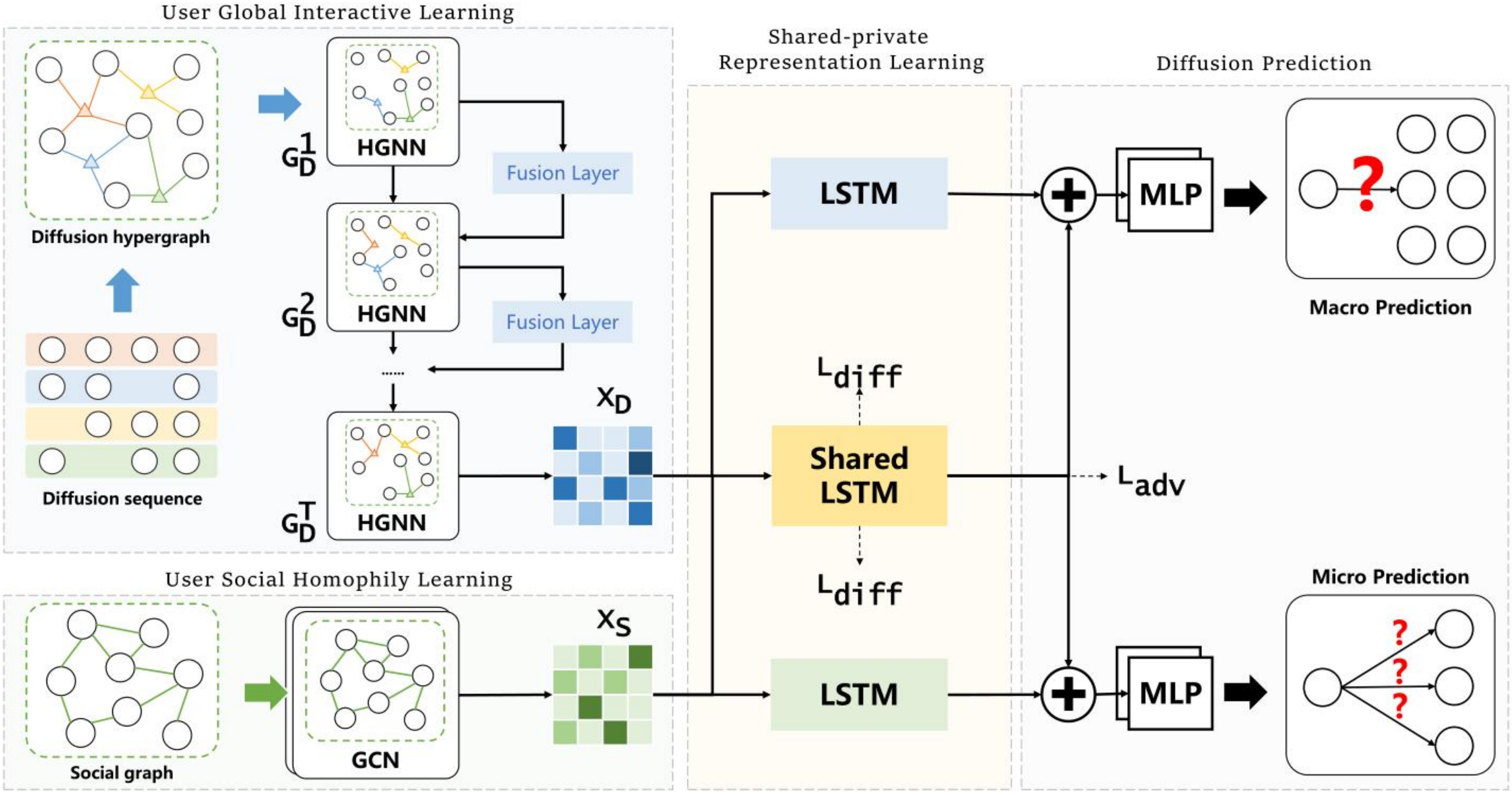


Figure 2: The architectural overview of our model.

Method

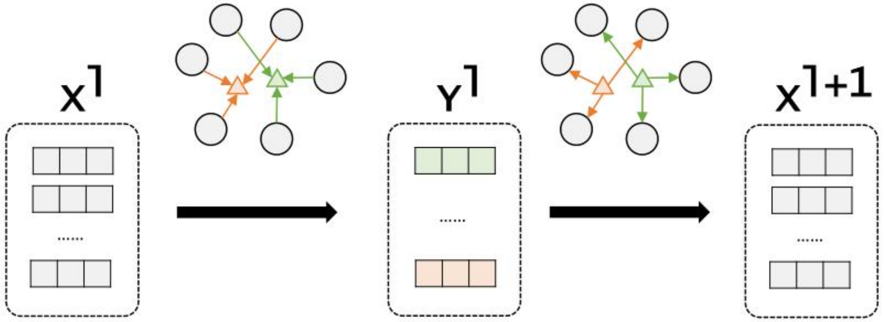
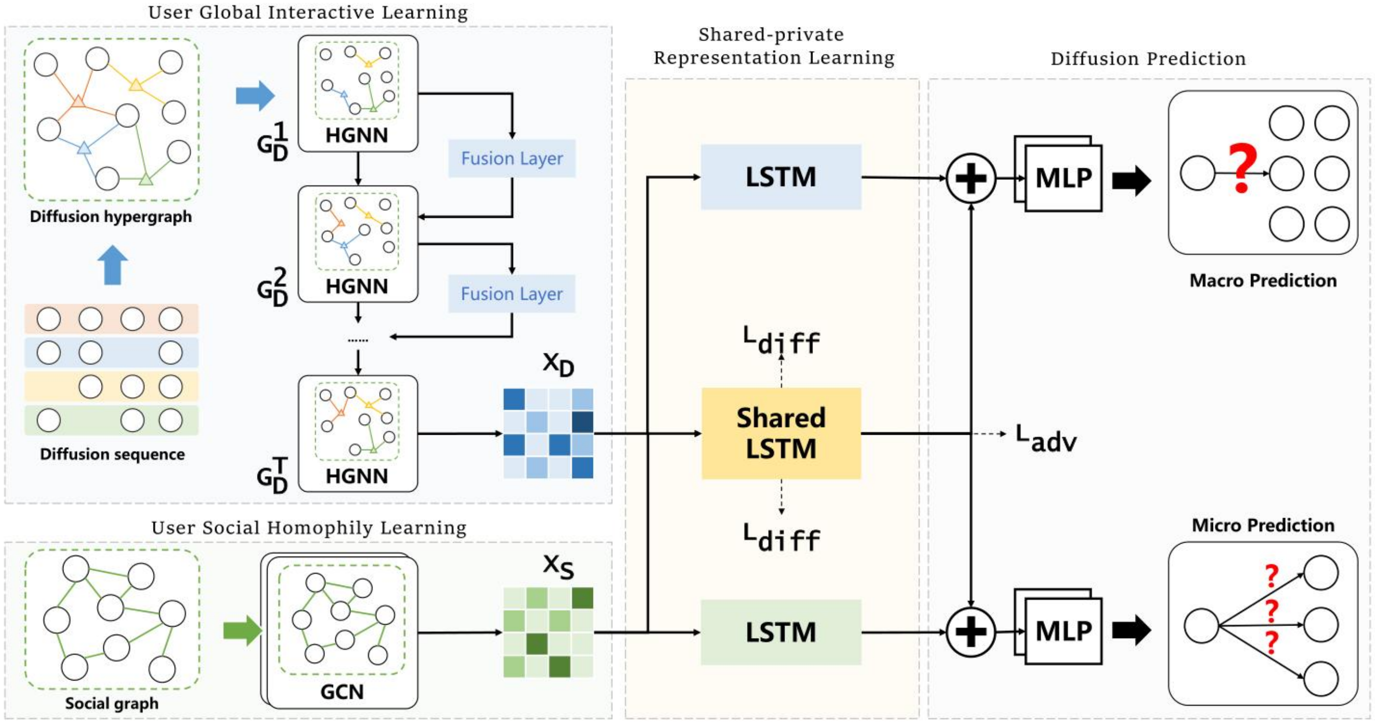


Figure 3: The two stages of hypergraph convolution.



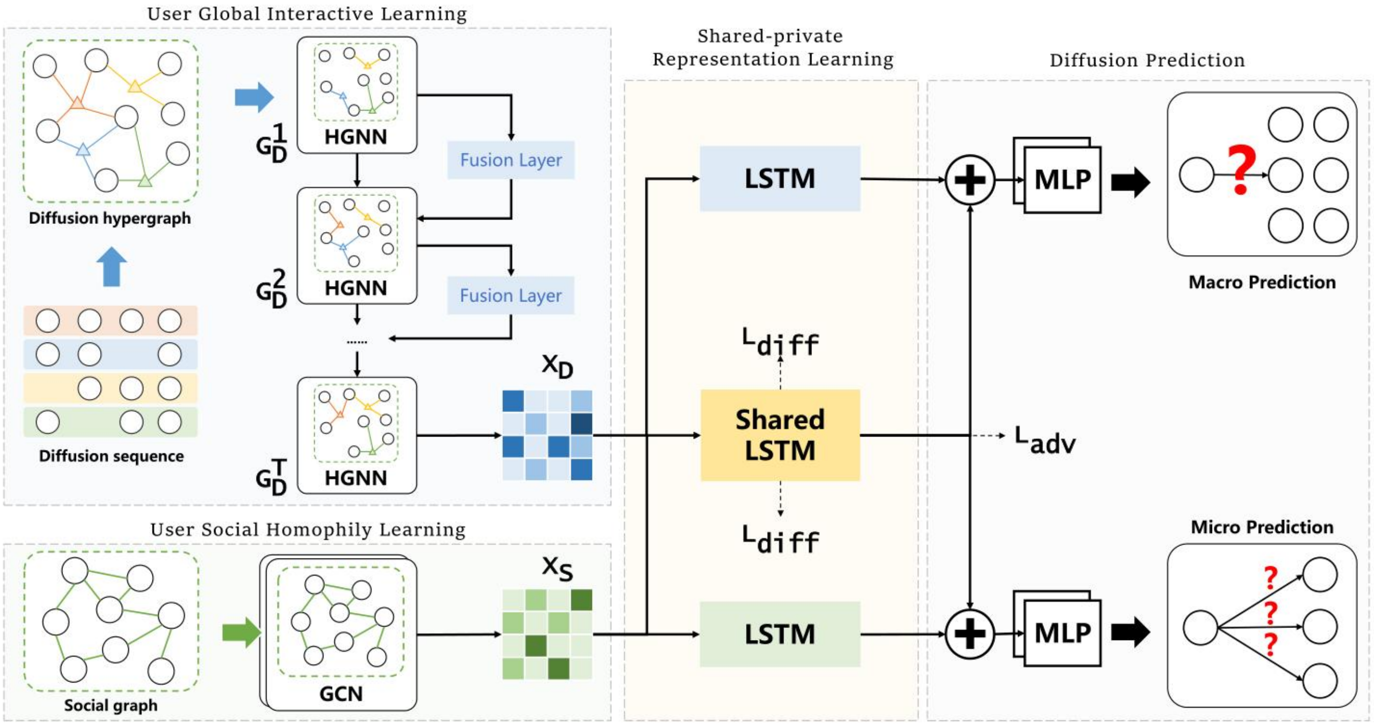
$$y_{j,t}^{l} = \sigma\left(w_{e_j^t} \cdot \sum_{u_i^t \in \mathcal{N}_v(e_j^t)} \frac{x_{i,t}^{l}}{|\mathcal{N}_v(e_j^t)|} \right), \tag{1}$$

$$x_{i,t}^{l+1} = \sigma\left(\Theta^l \cdot \sum_{e_j^t \in \mathcal{N}_e(u_i^t)} \frac{y_{j,t}^{l}}{|\mathcal{N}_e(u_i^t)|} \right), \tag{2}$$

$$x_{i,t+1}^{0} = \alpha x_{i,t}^{L} + (1-\alpha) x_{i,t}^{0}$$
$$\alpha = \frac{\exp(\mathbf{W}_{F_2}^{T}\sigma(\mathbf{W}_{F_1} x_{i,t}^{L}))}{\exp(\mathbf{W}_{F_2}^{T}\sigma(\mathbf{W}_{F_1} x_{i,t}^{L})) + \exp(\mathbf{W}_{F_2}^{T}\sigma(\mathbf{W}_{F_1} x_{i,t}^{0}))}, \tag{3}$$

$$\mathbf{X}_S^{l+1} = \sigma(\tilde{\mathbf{D}}_S^{-\frac{1}{2}} \tilde{\mathbf{A}}_S \tilde{\mathbf{D}}_S^{-\frac{1}{2}} \mathbf{X}_S^{l} \mathbf{W}_S), \tag{4}$$

Method



$$h_t = \mathbf{LSTM}(h_{t-1}, x_t, \theta_p), \qquad (5)$$

$$\begin{aligned} h_t^{cas} &= \mathbf{LSTM}(h_{t-1}^{cas}, x_t^d, \theta_{cas}) \\ h_t^{user} &= \mathbf{LSTM}(h_{t-1}^{user}, x_t^s, \theta_{user}), \end{aligned} \qquad (6)$$

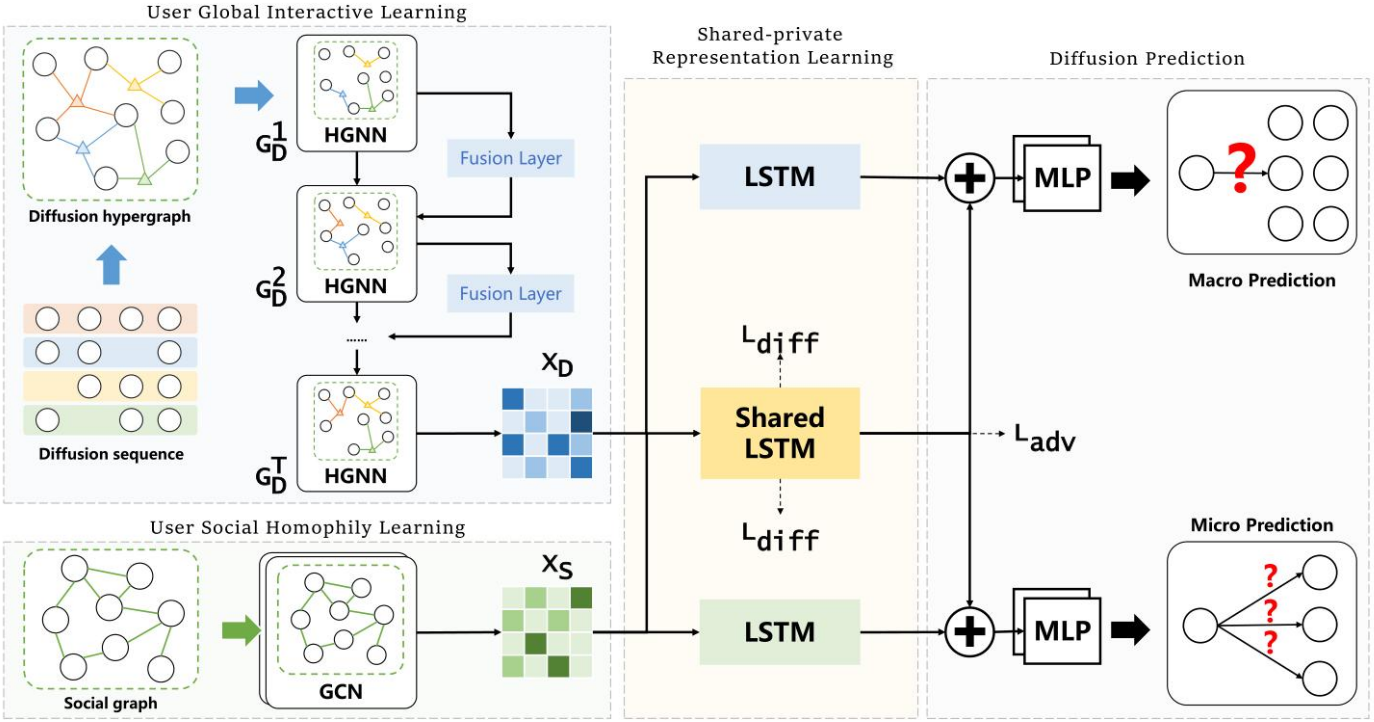
$$\begin{aligned} f_t &= \sigma(x_{t-1}^D W_f + x_{t-1}^S U_f + h_{t-1} V_f + b_f), \\ i_t &= \sigma(x_{t-1}^D W_i + x_{t-1}^S U_i + h_{t-1} V_i + b_i), \\ o_t &= \sigma(x_{t-1}^D W_o + x_{t-1}^S U_o + h_{t-1} V_o + b_o), \\ \tilde{c}_t &= \tanh(x_{t-1}^D W_c + x_{t-1}^S U_c + h_{t-1} V_c + b_c), \\ c_t &= \tilde{c}_t \cdot i_t + c_{t-1} \cdot f_t, \qquad h_t = o_t \cdot \tanh c_t, \end{aligned} \qquad (7)$$

$$D(h, \theta_D) = softmax(b + Uh), \qquad (8)$$

$$L_{adv} = \min_{\theta_{share}} \max_{\theta_D} \sum_{k=1}^{2} \sum_{n=1}^{N} (\log D(h_n^k) + \log(1 - D(h_n^{share}))), \qquad (9)$$

$$L_{diff} = \left\| {H^{share}}^T H^{cas} \right\|_F^2 + \left\| {H^{share}}^T H^{user} \right\|_F^2, \qquad (10)$$

Method



$$S_m = \mathrm{MLP}(\mathrm{concat}(h^{cas}, h^{share})), \tag{11}$$

$$L_{macro} = \frac{1}{M}\sum_{m=1}^{M}(S_m - \hat{S}_m)^2, \tag{12}$$

$$p_i = \mathrm{softmax}(\mathrm{MLP}(\mathrm{concat}(h^{user}, h^{share}))). \tag{13}$$

$$L_{micro} = -\sum_{j=2}^{|d_m|}\sum_{i=1}^{|U|}\hat{p}_{ji}\log(p_{ji}), \tag{14}$$

$$L = \lambda L_{macro} + (1-\lambda)L_{micro} + L_{adv} + \gamma L_{diff}, \tag{15}$$

Experiments

Dataset	Christ	Android	Douban	Meme
# Users	2,897	9,958	12,232	4,709
# Links	35,624	48,573	39,658	209,194
# Cascades	589	679	3,475	12,661
Avg. Length	22.9	33.3	21.76	16.24

Table 1: Statistics of datasets. Christ is short for the dataset Christianity, and Meme is short for the dataset Memetracker.

Model	Christ	Android	Douban	Meme
DeepCas	1.446	2.122	2.122	2.231
DeepHawkes	1.111	1.971	1.725	1.143
CasCN	1.046	0.981	1.476	0.967
CasFlow	0.765	1.041	0.465	0.535
TCSE-net	2.391	2.882	1.033	2.285
FOREST	1.726	0.556	0.825	0.621
DMT-LIC	1.692	0.201	0.741	0.701
MINDS	**0.572**	**0.151**	**0.404**	**0.506**

Table 4: Experimental results on four datasets in terms of *MSLE*, where lower scores indicate better performance. Christ is short for the dataset Christianity, and Meme is short for the dataset Memetracker.

Experiments

Models	Christianity			Android			Douban			Memetracker		
	@10	**@50**	**@100**	**@10**	**@50**	**@100**	**@10**	**@50**	**@100**	**@10**	**@50**	**@100**
TopoLSTM	0.1559	0.3653	0.4777	0.0460	0.1318	0.2103	0.0306	0.0143	0.0184	0.1908	0.3687	0.4683
NDM	0.0464	0.1145	0.1461	0.0170	0.0423	0.0555	0.0388	0.0506	0.0528	0.0931	0.1228	0.1279
SNIDSA	0.0660	0.2098	0.3502	0.0271	0.0829	0.1299	0.0702	0.1807	0.2324	0.1395	0.2945	0.3977
Inf-VAE	0.0767	0.2569	0.3853	0.0318	0.0938	0.1452	0.1364	0.2361	0.3059	0.1165	0.3096	0.4200
DyHGCN	0.2380	0.4689	0.5923	0.0748	0.1746	0.2596	0.1438	0.2648	0.3329	0.2522	0.4603	0.5710
TAN-DURD	0.1908	0.4406	0.5697	0.0281	0.1024	0.1658	0.0841	0.1604	0.2175	0.2139	0.4247	0.5383
FOREST	0.2746	0.4665	0.5603	0.0866	0.1739	0.2314	0.1106	0.1986	0.2559	0.2648	0.4502	0.5499
DMT-LIC	0.2768	0.4442	0.5669	0.0932	0.1639	0.2315	0.1465	0.2506	0.3054	0.2746	0.4619	0.5656
MINDS	**0.3214**	**0.4978**	**0.6250**	**0.1096**	**0.1989**	**0.2766**	**0.1956**	**0.3087**	**0.3641**	**0.2819**	**0.4760**	**0.5790**

Table 2: Results on four datasets (*Hits@k* scores for k = 10, 50 and 100), where higher scores indicate better performance.

Models	Christianity			Android			Douban			Memetracker		
	@10	**@50**	**@100**	**@10**	**@50**	**@100**	**@10**	**@50**	**@100**	**@10**	**@50**	**@100**
TopoLSTM	0.0523	0.0619	0.0635	0.0166	0.0202	0.0213	0.0354	0.0824	0.0884	0.0870	0.0955	0.0969
NDM	0.0144	0.0177	0.0182	0.0059	0.0070	0.0072	0.0141	0.0824	0.0884	0.0463	0.0480	0.0481
SNIDSA	0.0246	0.0306	0.0326	0.0100	0.0122	0.0129	0.0371	0.0419	0.0148	0.0605	0.0674	0.0689
Inf-VAE	0.0172	0.0254	0.0272	0.0076	0.0103	0.0110	0.0543	0.0588	0.0598	0.0425	0.0509	0.0525
DyHGCN	0.1062	0.1167	0.1184	0.0392	0.0434	0.0446	0.0801	0.0856	0.0865	0.1410	0.1502	0.1518
TAN-DURD	0.0752	0.1167	0.1184	0.0099	0.0130	0.0139	0.0359	0.0401	0.0409	0.0991	0.1086	0.1102
FOREST	0.1569	0.1658	0.1672	0.0628	0.0667	0.0675	0.0655	0.0694	0.0702	0.1429	0.1514	0.1528
DMT-LIC	0.1649	0.1728	0.1746	0.0622	0.0652	0.0662	0.0812	0.0856	0.0897	0.1496	0.1581	0.1595
MINDS	**0.1955**	**0.2037**	**0.2054**	**0.0677**	**0.0716**	**0.0727**	**0.1142**	**0.1199**	**0.1213**	**0.1535**	**0.1623**	**0.1638**

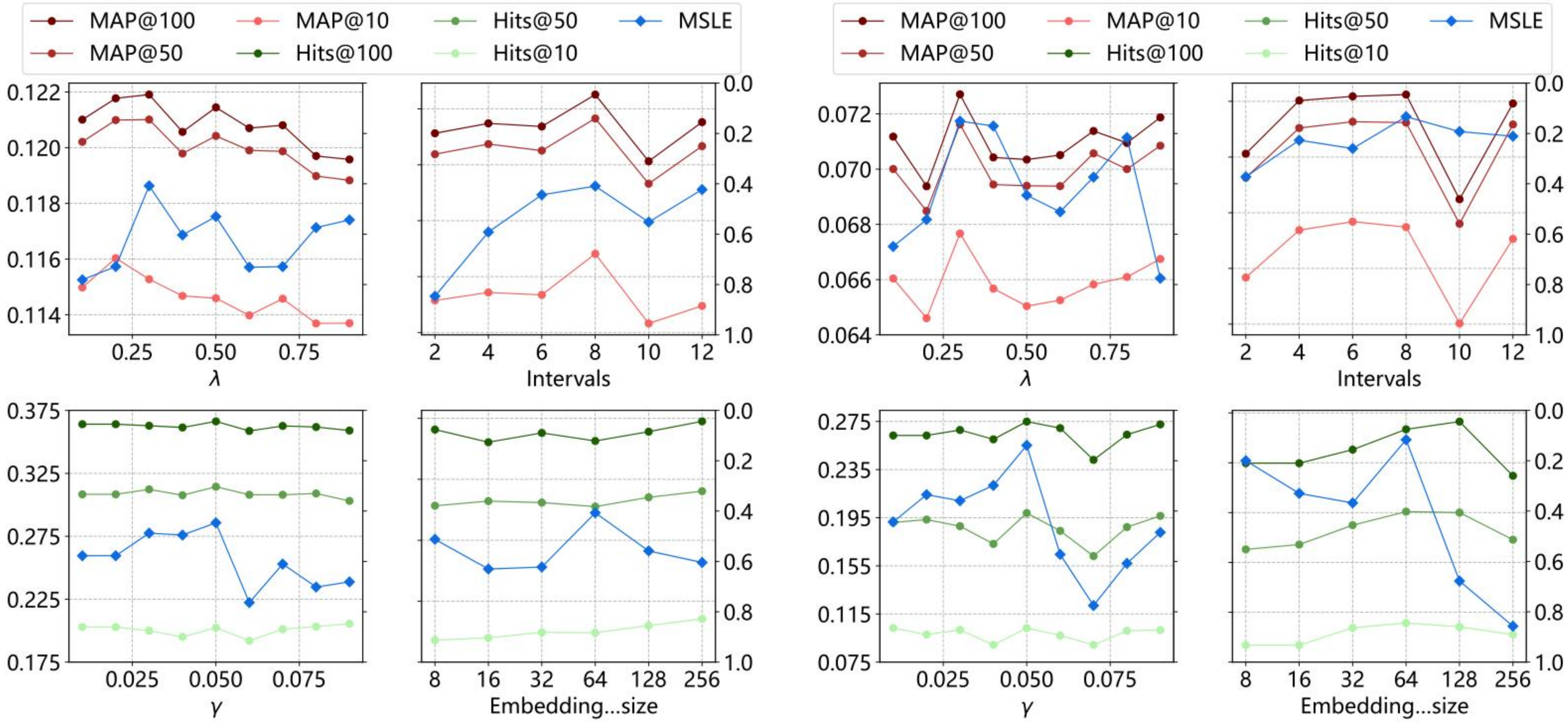
Table 3: Results on four datasets (*MAP@k* scores for k = 10, 50 and 100), where higher scores indicate better performance.

Experiments

Models	Christianity			Douban		
	Hits@100	MAP@100	MSLE	Hits@100	MAP@100	MSLE
w/o AdvDiff	0.5893	0.1958	0.971	0.3682	0.1170	0.642
w/o Diff	0.6004	0.1949	1.222	0.3688	0.1173	0.712
w/o Adv	0.5915	0.1926	0.861	0.3572	0.1193	0.742
w/o HGNN	0.5871	0.2013	1.074	0.3692	0.1178	0.581
w/o Macro	0.5580	0.1874	9.255	0.3665	0.1191	4.669
w/o Micro	0.5871	0.1937	0.865	0.3591	0.1174	0.711
MINDS	**0.6250**	**0.2054**	**0.572**	**0.3736**	**0.1213**	**0.549**

Table 5: Ablation study on Christianity and Douban datasets. We design six variants to demonstrate the rationale behind our model: *w/o AdvDiff* removes L_{adv} and L_{diff}. *w/o Diff* removes L_{diff}. *w/o Adv* removes L_{adv}. *w/o HGNN* replaces sequential hypergraphs with sequential digraphs and HGNN with GAT. *w/o Macro* removes L_{macro}. *w/o Micro* removes L_{micro}.

Experiments



(a) Douban (b) Android

$$L = \lambda L_{macro} + (1-\lambda)L_{micro} + L_{adv} + \gamma L_{diff}, \quad (15)$$

Thank you!