Exploiting Explicit and Implicit Item relationships for Session-based Recommendation

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Code&data： https://github.com/ZihaoLi97/WSDM23-DGNNs--for-Session-based-Recommendation

Reported by Changjiang Hu

Introduction

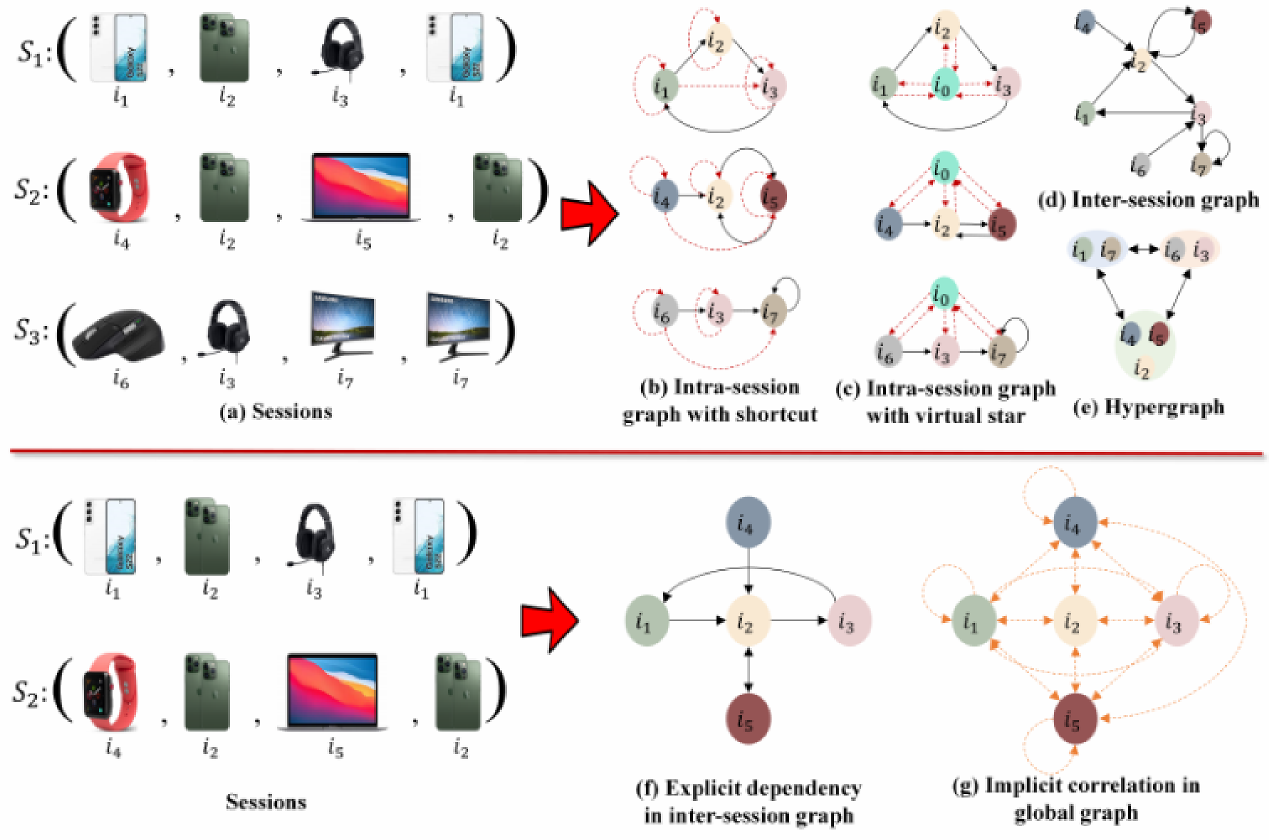


Figure 1: The upper half shows different graph structures for modeling item relationships in an example of three sessions.

Existing graph-based methods either neglect implicit correlations among items or consider explicit and implicit relationships altogether in the same graphs.

In this paper, the author capture the prior knowledge encapsulated in explicit dependencies and learned implicit correlations among items simultaneously in a flexible and more interpretable manner for effective recommendations.

Method

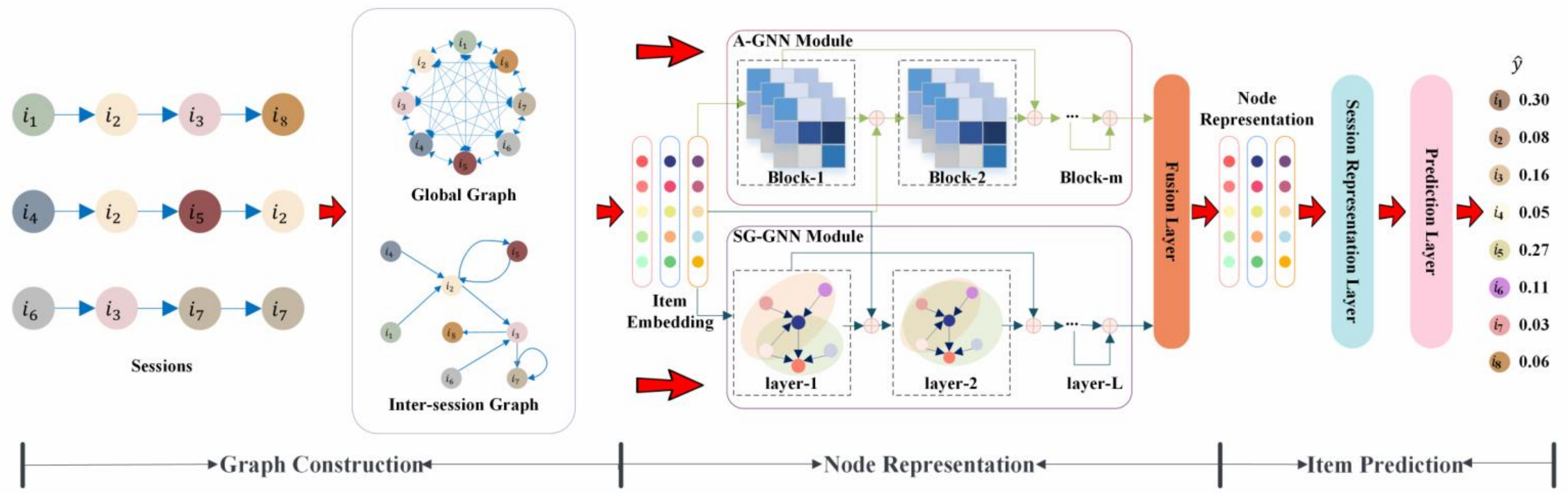
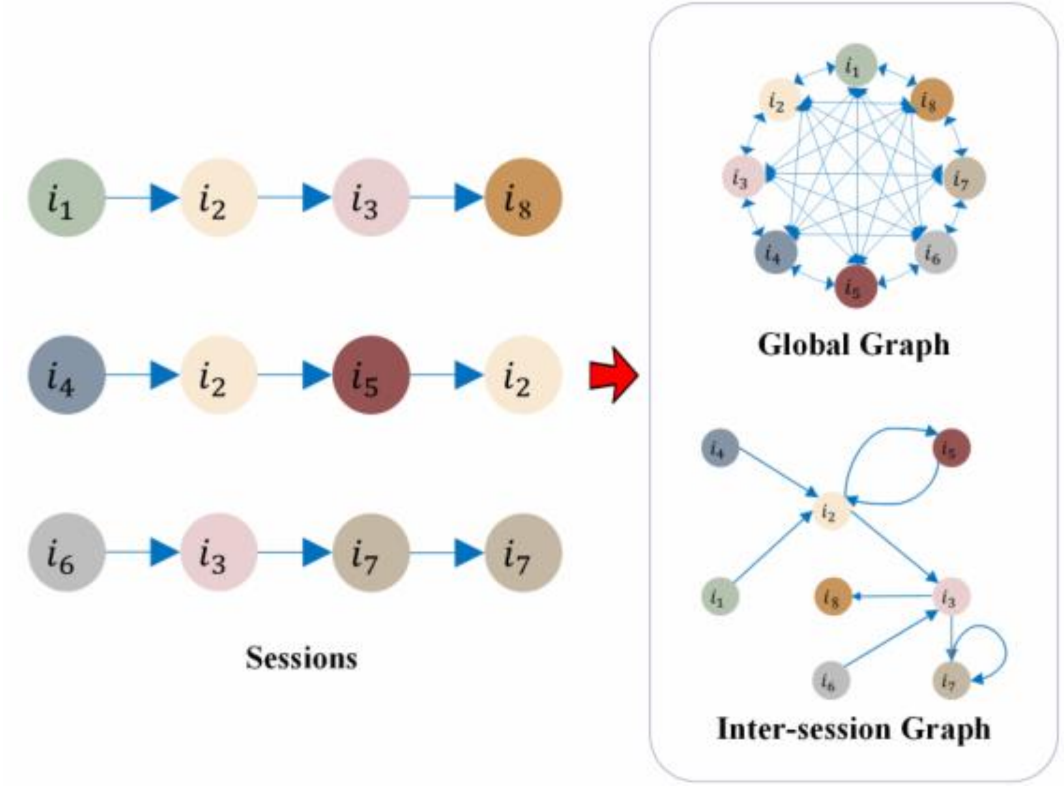


Figure 2: Architecture of DGNN.

Method



PRELIMINARIES:

user set: $\mathcal{I} = \{i_1, i_2, i_3, \ldots i_N\}$

a session: $s = [i_1, i_2, i_3, \ldots, i_o]$

Graph for explicit dependencies:

$$\mathcal{G}^s = (\mathcal{V}, \mathcal{E})$$

Graph for implicit correlations:

$$\mathcal{G}^g = (\mathcal{V}, \mathcal{E})$$

Method

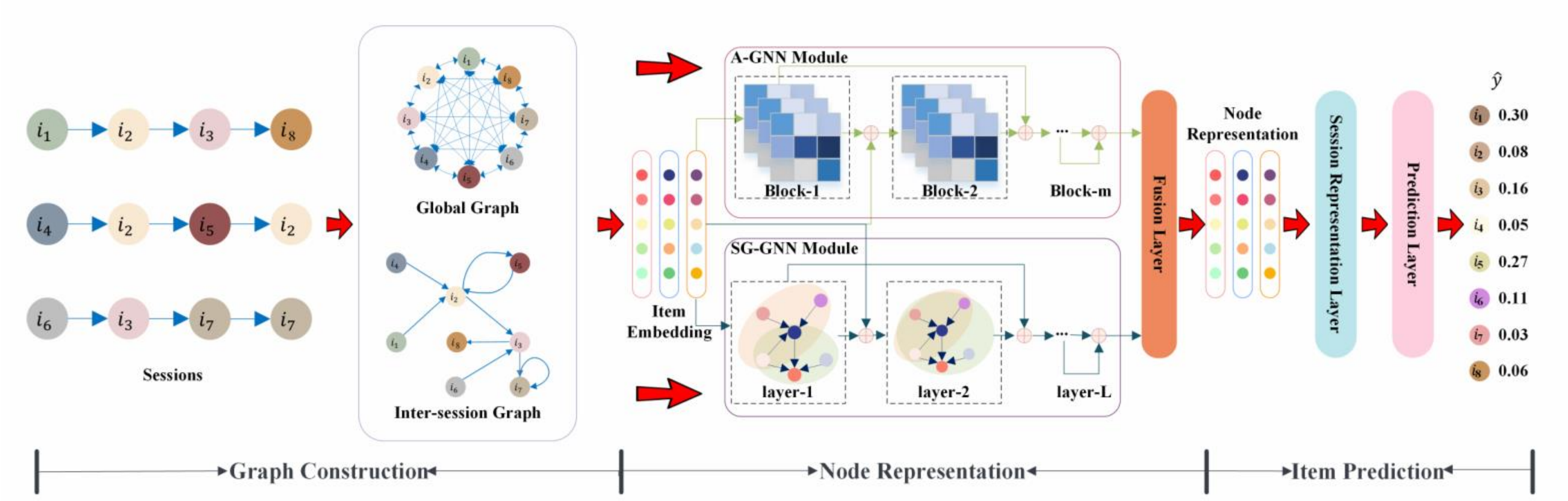
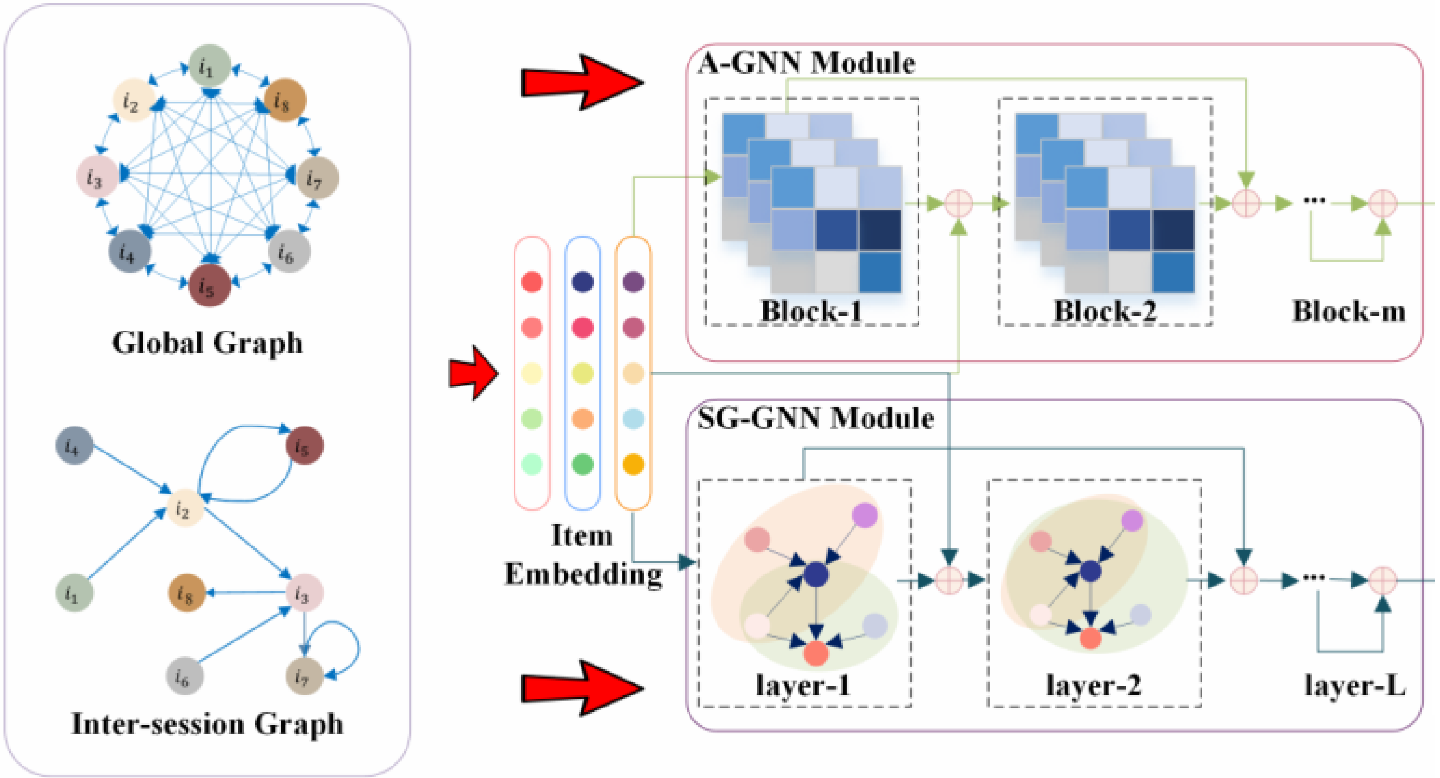


Figure 2: Architecture of DGNN.

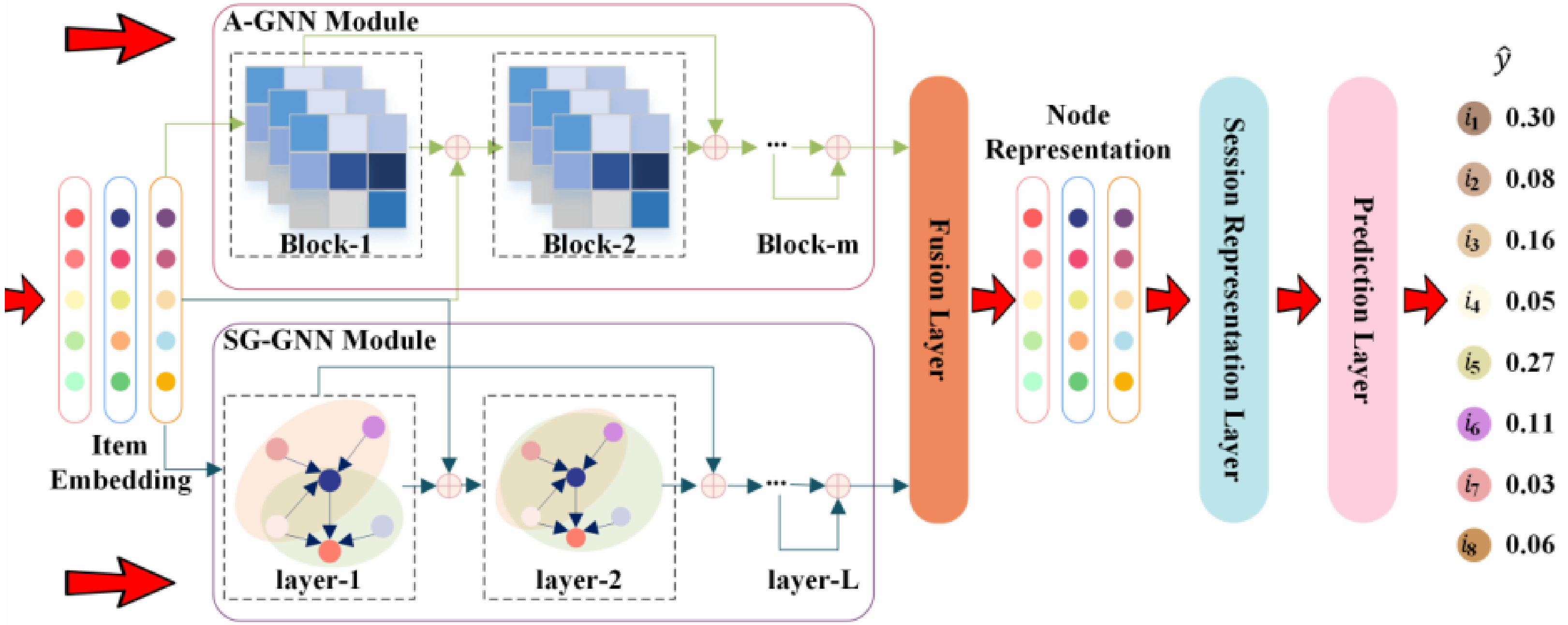
$$
\begin{aligned}
\mathbf{X}^{(m)}_{\text{A-GNN}} &= \text{A-GNN}(\mathbf{X} + \mathbf{X}^{(1)}_{\text{A-GNN}} + \ldots + \mathbf{X}^{(m-1)}_{\text{A-GNN}}, \mathbf{A}^{g}) \\
\mathbf{X}^{(l)}_{\text{SG-GNN}} &= \text{SG-GNN}(\mathbf{X}^{(l-1)}_{\text{SG-GNN}}, \tilde{\mathbf{A}}^{s}) \\
\tilde{\mathbf{X}} &= \text{F}(\mathbf{X}^{(m)}_{\text{A-GNN}}, \mathbf{X}^{(l)}_{\text{SG-GNN}}) \\
\mathbf{s} &= \text{SR}(\tilde{\mathbf{X}}) \\
\hat{\mathbf{y}} &= \text{P}(\mathbf{s}, \mathbf{X})
\end{aligned}
\tag{1}
$$



A-GNN Module:

$$
\begin{aligned}
&\mathbf{Q}_i = \mathbf{X}\mathbf{W}_i^{Q}, \quad \mathbf{K}_i = \mathbf{X}\mathbf{W}_i^{K}, \quad \mathbf{V}_i = \mathbf{X}\mathbf{W}_i^{V} \\
&\mathbf{A}_i^{g} = \mathrm{Dropout}(\tanh(\mathbf{Q}_i\mathbf{K}_i^{T})) \\
&\mathbf{X}_{\text{A-GNN}_i} = \mathbf{A}_i^{g}\mathbf{V}_i \\
&\mathbf{X}_{\text{A-GNN}} = \mathrm{Dropout}(\mathrm{ReLU}([\mathbf{X}_{\text{A-GNN}_0}||\ldots||\mathbf{X}_{\text{A-GNN}_k}])\mathbf{W}^{M})
\end{aligned}
\tag{2}
$$

$$
\mathbf{X}_{\text{A-GNN}}^{(m)} = \text{A-GNN}(\mathbf{X} + \mathbf{X}_{\text{A-GNN}}^{(1)} + \ldots + \mathbf{X}_{\text{A-GNN}}^{(m-1)}, \mathbf{A}^{g}) \tag{3}
$$



Session Representation Layer：

$$\alpha_i = \mathbf{q}^T \sigma(\mathbf{W}_1 \tilde{\mathbf{x}}_m + \mathbf{W}_2 \tilde{\mathbf{x}}_i + \mathbf{c})$$

$$\mathbf{s}_g = \sum_{i=1}^{m} \alpha_i \tilde{\mathbf{x}}_i \quad (7)$$

$$\mathbf{s} = [\mathbf{s}_l || \mathbf{s}_g] \mathbf{W}_3 \quad (8) \qquad \mathbf{s}_l = \tilde{\mathbf{x}}_m$$

$$\hat{\mathbf{z}} = \mathbf{s}^T \mathbf{X} \quad (9)$$

$$\hat{\mathbf{y}} = \mathrm{softmax}(\hat{\mathbf{z}}) \quad (10)$$

$$\mathcal{L}(\hat{\mathbf{y}}) = -\sum_{i=1}^{n} \mathrm{y}_i log(\hat{\mathrm{y}}_i) + (1 - \mathrm{y}_i) log(1 - \hat{\mathrm{y}}_i) \quad (11)$$

SG-GNN Module and Fusion Layer ：

$$\mathbf{J} = \mathbf{X}\mathbf{W}_J, \quad \mathbf{P} = \mathbf{X}\mathbf{W}_P, \quad \mathbf{Z} = \mathbf{X}\mathbf{W}_Z$$
$$\mathbf{R} = \tilde{\mathbf{A}}^s \mathbf{J} \mathbf{W}_R, \quad \mathbf{U} = \tilde{\mathbf{A}}^s \mathbf{J} \mathbf{W}_U \quad (4)$$
$$\mathbf{X}_{\text{SG-GNN}} = \mathbf{P} + \mathrm{ReLU}(\mathbf{R} + \mathbf{Z}) \odot \mathbf{U}$$

$$\mathbf{X}_{\text{SG-GNN}}^{(l)} = \text{SG-GNN}(\mathbf{X}_{\text{SG-GNN}}^{(l-1)}, \tilde{\mathbf{A}}^s) \quad (5)$$

$$\tilde{\mathbf{X}} = [\mathbf{X}_{\text{A-GNN}}^{(M)} || \mathbf{X}_{\text{SC-GNN}}^{(L)}] \mathbf{W}_F \quad (6)$$

Experiments

Table 1: Statistics of datasets

	Diginetica	Yoochoose1/64	Yoochoose1/4	Gowalla	Last.FM
#clicks	981,620	557,248	8,326,407	1,122,788	3,835,706
#train sessions	716,835	369,859	5,917,745	675,561	2,837,644
#test sessions	60,194	55,898	55,898	155,332	672,519
#items	42,596	16,766	29,618	29,510	38,615
#length ≤ 5	537,546	289,490	4,234,915	627,100	1,136,909
#length >5	239,483	136,267	1,738,734	203,793	2,373,254
Average length	4.80	6.16	5.71	4.32	9.16

Experiments

Table 2: Experimental results (%) on the four datasets. The best results are highlighted in boldface, and the second-best results are underlined. * denotes a significant improvement of DGNN over the best baseline results (t-test P<.05).

Model	Diginetica		Yoochoose 1/64		Yoochoose 1/4		Gowalla		Last.FM	
	HR@20	MRR@20	HR@20	MRR@20	HR@20	MRR@20	HR@20	MRR@20	HR@20	MRR@20
POP	0.89	0.28	6.71	1.65	1.37	0.31	1.46	0.38	5.26	1.26
Item-KNN	37.75	11.57	51.60	21.81	52.31	21.70	38.60	16.66	14.90	4.04
FPMC	26.53	6.66	45.62	15.01	51.86	17.50	29.91	11.45	12.86	3.78
GRU4Rec	29.45	8.22	60.64	22.89	59.53	22.60	41.98	18.37	17.90	5.39
NARM	49.70	16.00	68.32	28.63	69.73	29.23	50.07	23.92	21.83	7.59
SR-GNN	50.73	17.78	70.57	30.94	71.36	31.89	50.32	24.25	22.33	8.23
SGNN-HN	55.67	19.45	72.13	32.60	73.52	32.63	55.28	27.58	25.07	9.40
LESSR	51.71	18.15	70.59	31.46	72.67	33.12	51.34	25.49	23.37	9.01
MSGIFSR	<u>57.11</u>	<u>20.05</u>	<u>73.13</u>	<u>33.50</u>	<u>74.01</u>	<u>33.74</u>	<u>56.64</u>	<u>29.02</u>	<u>27.63</u>	<u>10.86</u>
GC-SAN	51.70	17.61	70.66	30.04	71.83	30.93	50.68	24.67	22.64	8.42
GCE-GNN	54.02	19.04	70.91	30.63	71.40	31.49	53.96	24.53	24.39	8.63
DGNN	**67.65***	**27.89***	**75.85***	**34.09***	**76.90***	**36.02***	**58.51***	**30.40***	**47.17***	**23.38***
Improv.	18.46%	49.10%	3.72%	1.76%	3.90%	6.76%	3.30%	4.76%	70.72%	115.29%

Experiments

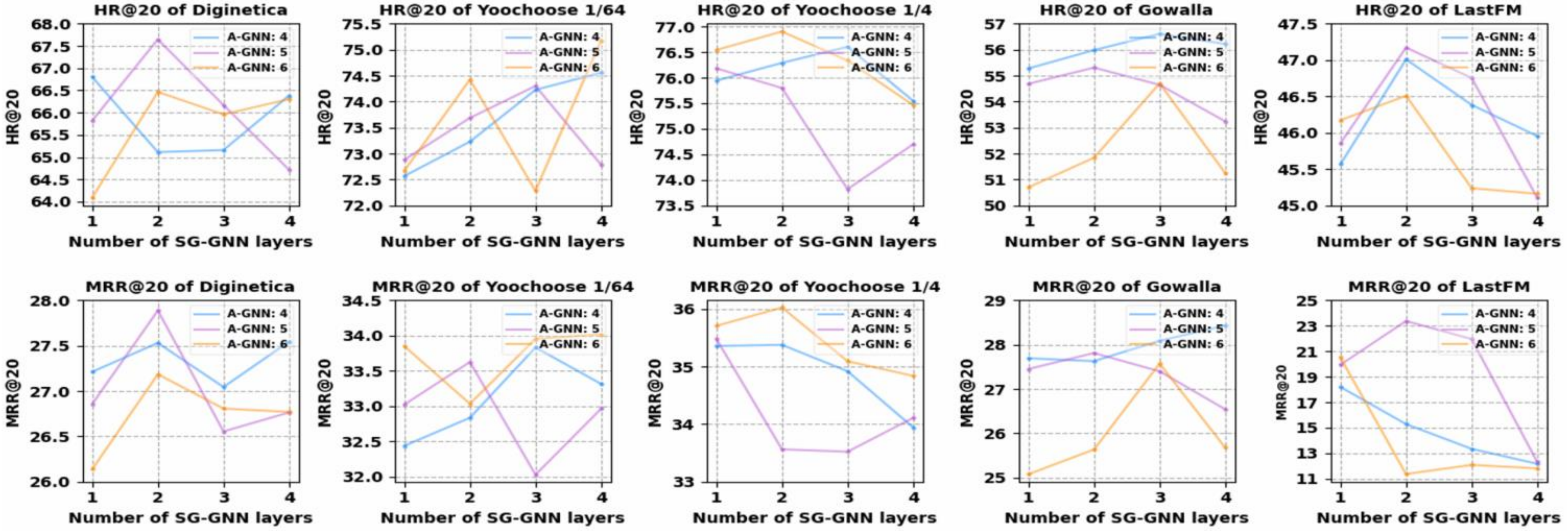


Figure 3: Parameter sensitivity of the number of A-GNN blocks and IP-GNN layers.

Experiments

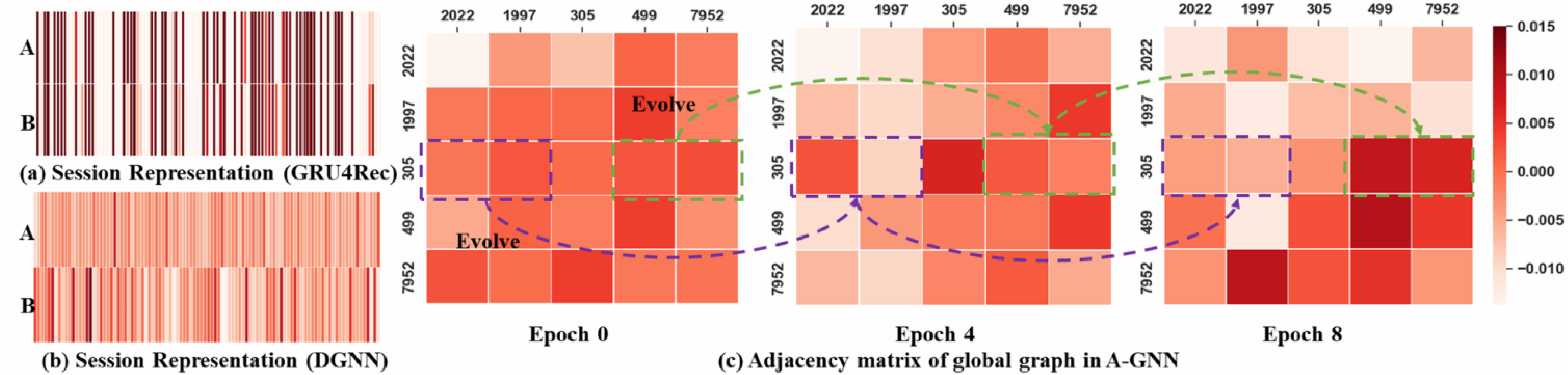


Figure 4: (a) and (b) are the representations of session A:{7951, 7952, 4999, 7952, 305} and session B:{4999, 7951, 7952, 305, 7952} generated by GRU4Rec and DGNN. (c) visualizes the adjacency matrices in A-GNN at epochs 0, 4, and 8, respectively.

Experiments

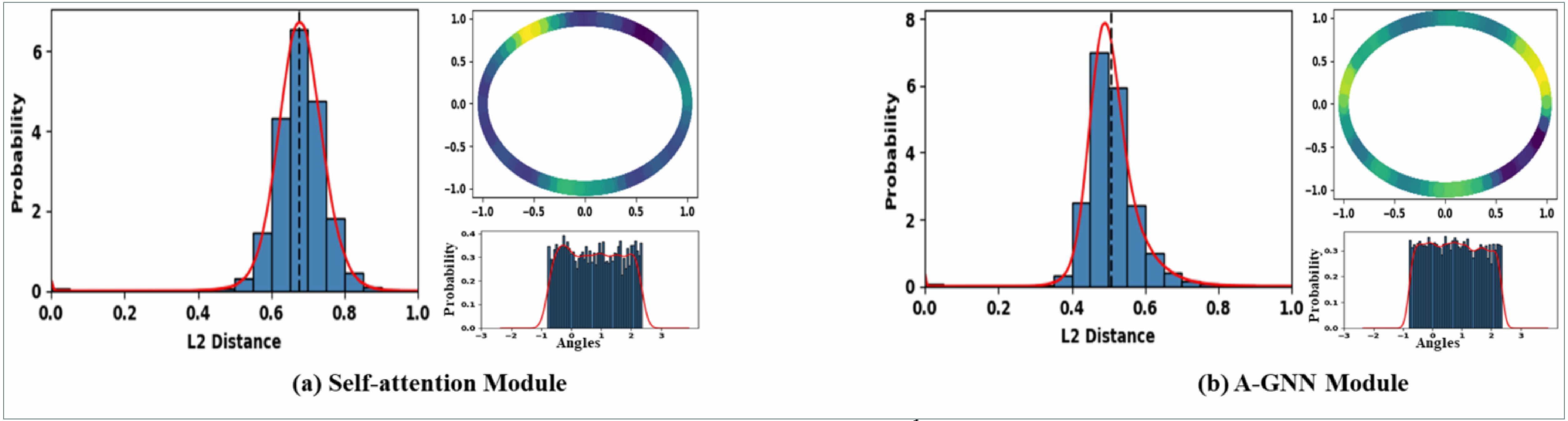


Figure 5: Item representations of (a) self-attention and (b) A-GNN on $\mathcal{S}^1$ (two-dimensional space). Alignment analysis: the histograms show the distributions of l_2 distance between the representations of item pairs, where the black dotted lines indicate the mean distances. Uniformity analysis: the other plots in subfigures show the distributions of item representations with Gaussian kernel density estimation (KDE) in $\mathbb{R}^2$ (top-right) and with von Mises-Fisher (vMF) KDE on angles (bottom-right), i.e., $\arctan2(y, x)$ for each point $(x, y) \in \mathcal{S}^1$. The darker the color, the denser the distribution in the top-right plots. Item representations generated by A-GNN are more aligned (lower l_2 distances) and uniform (evenly distributed).

Table 3: Results (%) of ablation experiments.

Datasets		MLP-SR	w/o A-GNN	w/o SG-GNN	w/o $\sum$	w Self-Att	w GGNN	DGNN
Diginetica	HR@20	58.60	53.26	49.67	50.54	50.83	64.22	**67.65**
	MRR@20	20.77	17.71	16.50	17.44	16.54	25.14	**27.89**
Yoo 1/64	HR@20	70.07	71.28	68.10	73.23	70.68	69.25	**75.85**
	MRR@20	30.53	30.87	28.68	32.21	30.84	28.90	**34.09**
Yoo 1/4	HR@20	70.23	74.97	69.88	69.45	75.24	76.64	**76.90**
	MRR@20	31.02	33.41	30.32	30.78	33.38	35.99	**36.02**
Gowalla	HR@20	51.73	52.62	49.47	55.31	50.70	**59.27**	58.51
	MRR@20	25.12	25.63	23.75	26.59	24.37	28.85	**30.40**
LastFM	HR@20	21.98	23.89	21.06	23.39	23.21	38.12	**47.17**
	MRR@20	8.13	9.09	7.74	9.02	8.91	17.47	**23.38**

Table 4: Time and Space Complexity. We set the size of learnable parameter matrices to the dimension of the item embedding d, and the size of graphs to $N \times N$ for SG-GNN and GGNN.

Module	Number of Parameters	FLOPs
GGNN	$d \times (11d + 8)$	$2d \times (2N + 11d)$
SG-GNN	$d \times 5d$	$2d \times (2N + 5d)$