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Int-GNN: a User Intention Aware Graph Neural Network for Session-Based Recommendation

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https://github.com/xuguangning1218/IntGNN_ICASSP2023

Agenda

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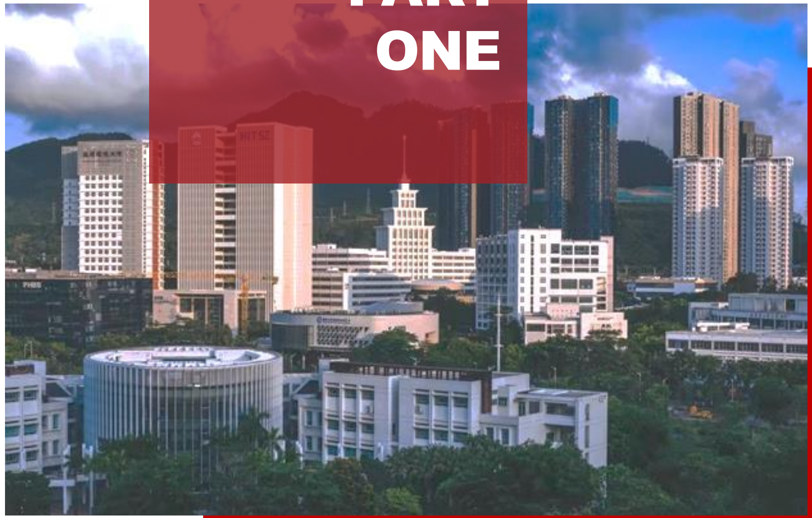
PART ONE



Introduction of SBR

Introduction of Session Based Recommendation

Session-Based Recommendation (SBR) is a type of recommendation system that provides personalized recommendations to users based on their current session behavior (mostly users do not login).

The aim of this task is designed to capture short-term user preferences and interests, which may be difficult to capture using traditional collaborative filtering approaches that rely on long-term user-item interactions.

The SBR is particularly useful in e-commerce and content recommendation scenarios (music, movie, short video, etc.) where users often have specific short-term needs and preferences.

Formal Formulation of the SBR prediction

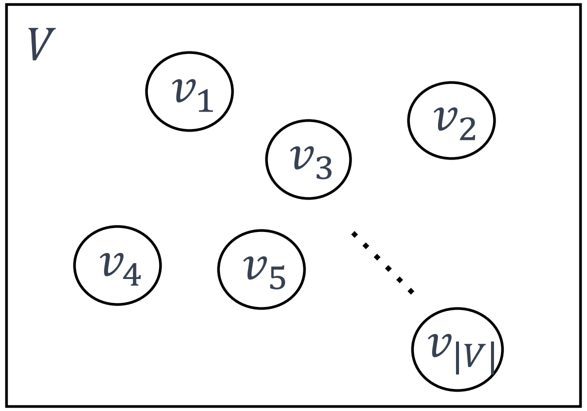
Let a set $V = \{v_1, v_2, \dots, v_{|V|}\}$ denote **items** involved in all sessions and a vector $\boldsymbol{S} = [v_1, v_2, \dots, v_n]$ denotes an anonymous **session** with n interactions, where $v_i \in V$ means the i-th interaction item.

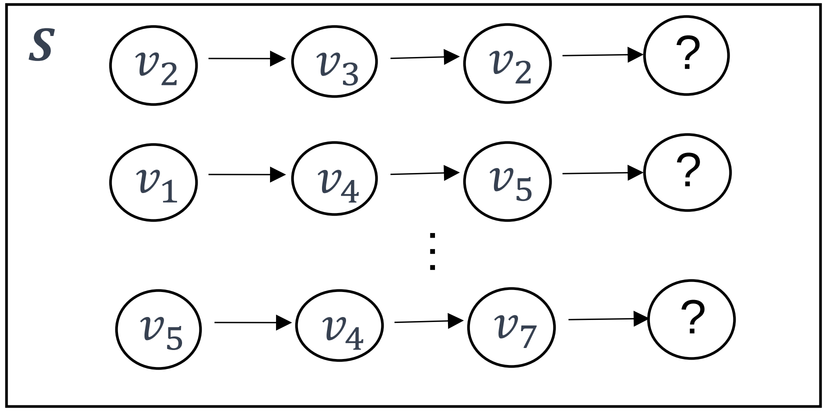
The target of the SBR is to estimate a probability $\hat{y}_i$ of the potential interaction item, where $\hat{y}_i$ is the i-th value of a probability vector $\hat{\boldsymbol{y}} = [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_{|V|}]$.

The objective function is presented as follows:

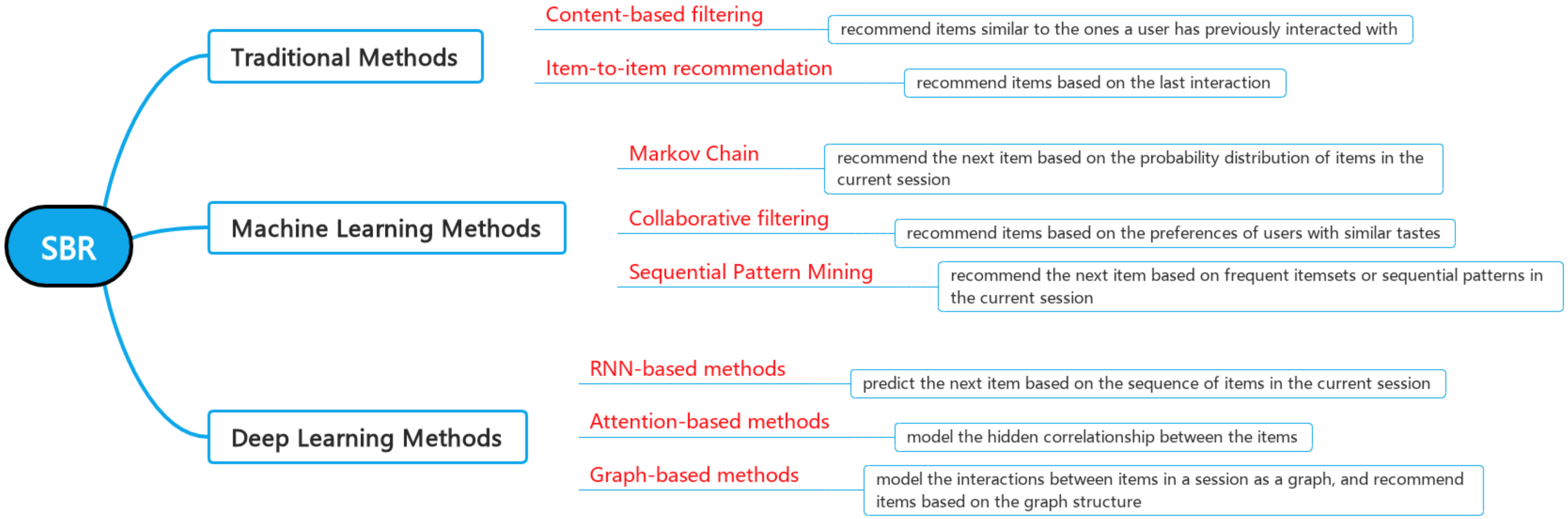
$$\hat{y}_i(\theta^*) = \max_{\theta} P\{v_{n+1} | v_1, v_2, \dots, v_n, \theta\}$$

where θ denotes learnable parameters.





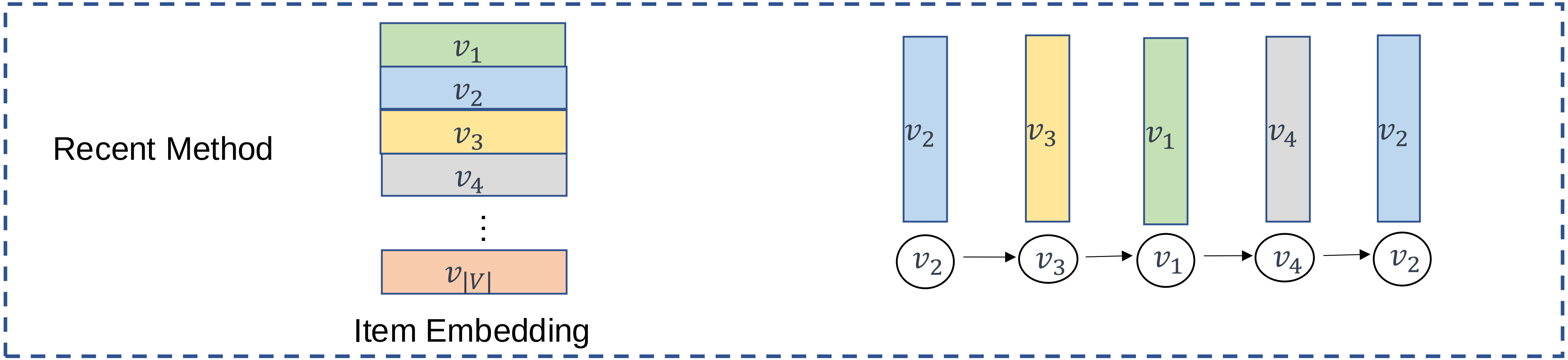
The Research Methods of SBR

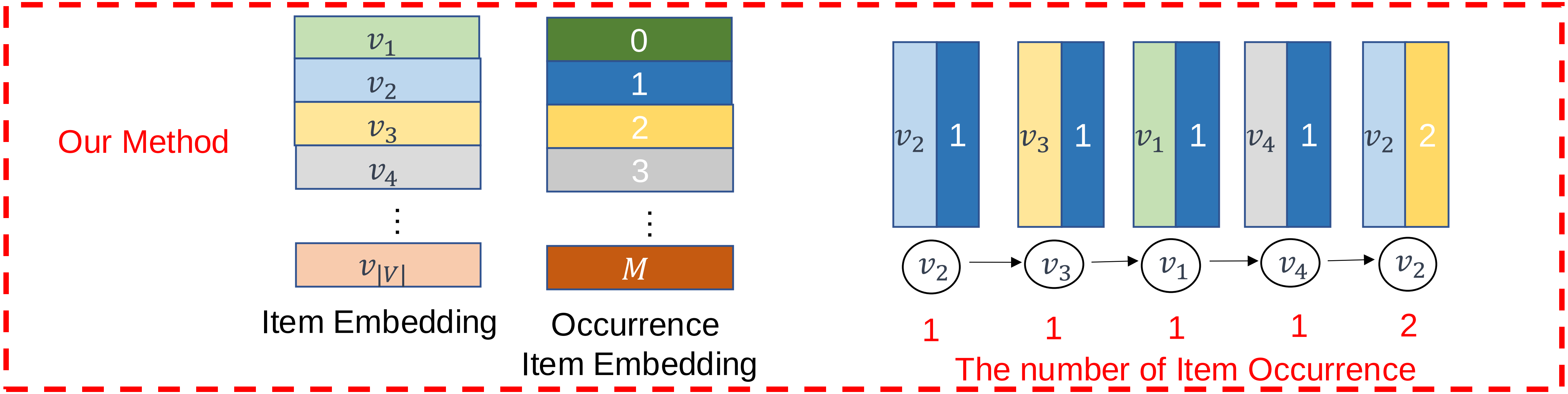


In this work, we focus on the Graph-based methods on deep learning domain.

Motivation of this work #1

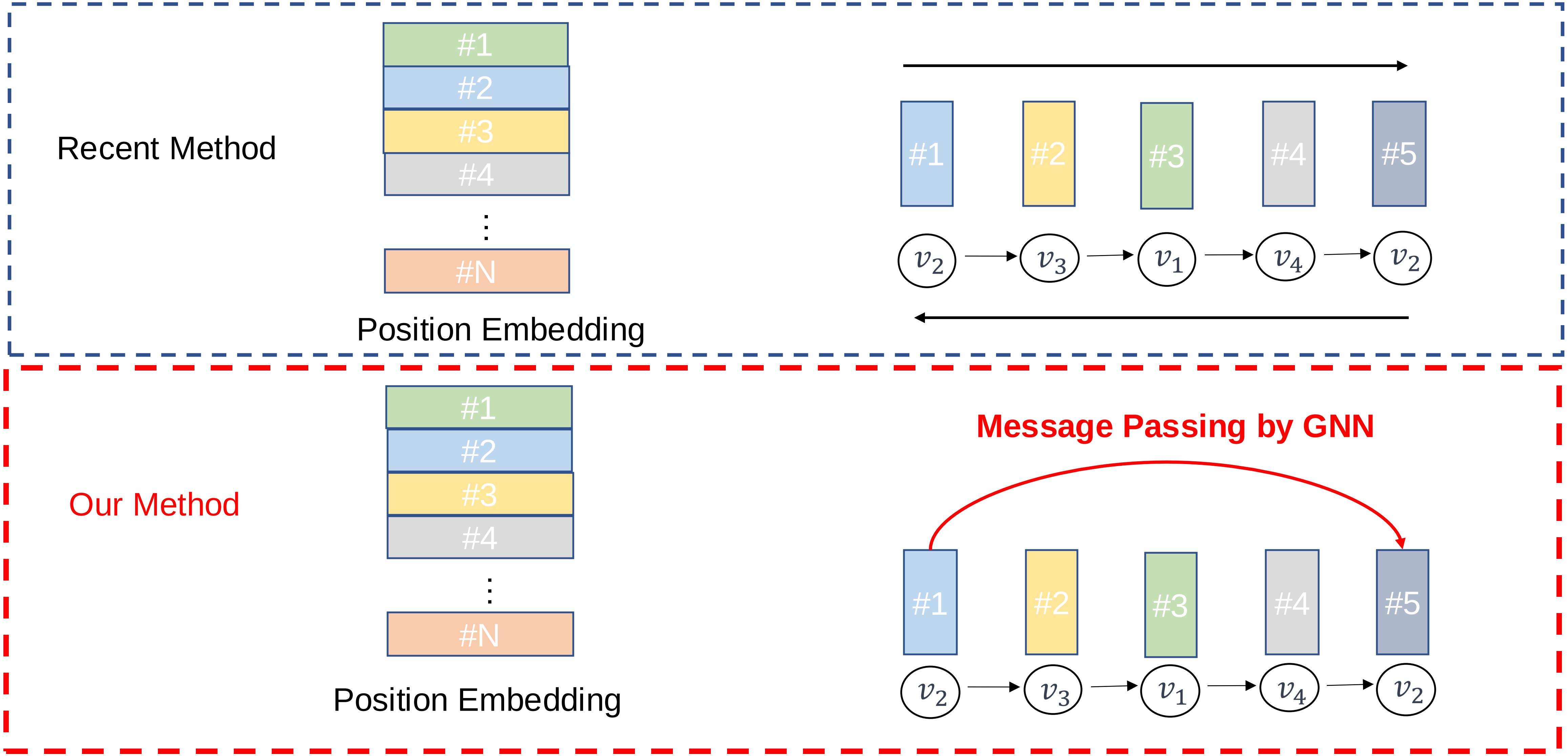
1. Most of the works tempt to capture user intention based on the items' characteristics. In our work, we proposed to capture user intention by using the number of item occurrence.





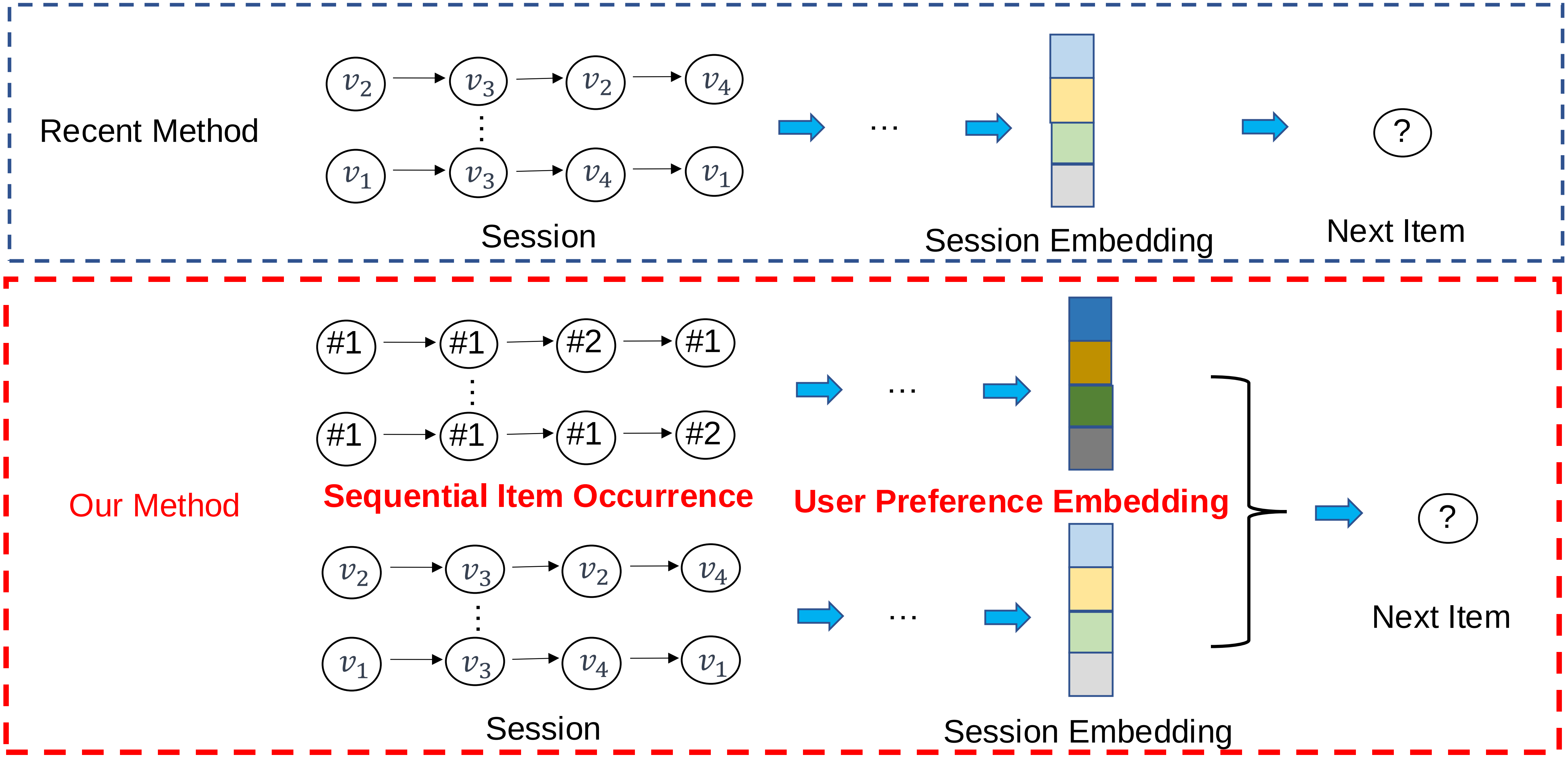
Motivation of this work #2

1. The long-range correlation is usually overlooked or captured by simple (reverse) position embedding. In our work, we proposed to capture long-range correlation by integrating a graph constrain on position embedding.



Motivation of this work #3

1. Design Multi-Score Generator to extract the user preference which is shown by the number of item occurrence.



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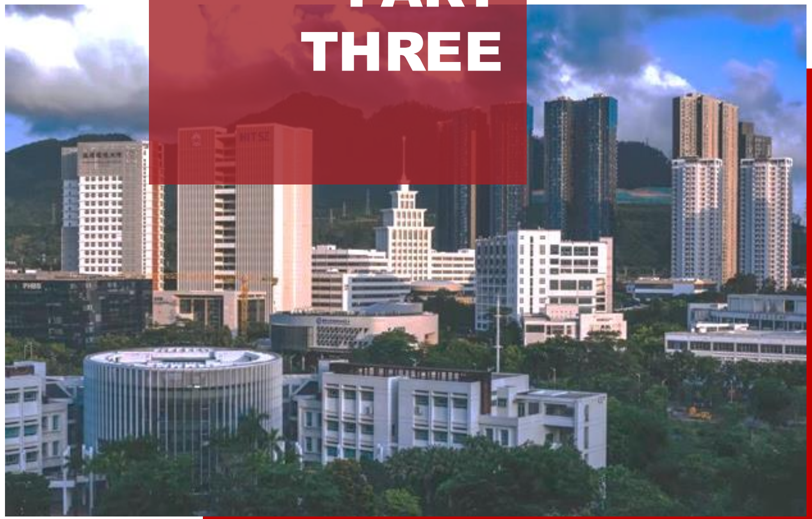
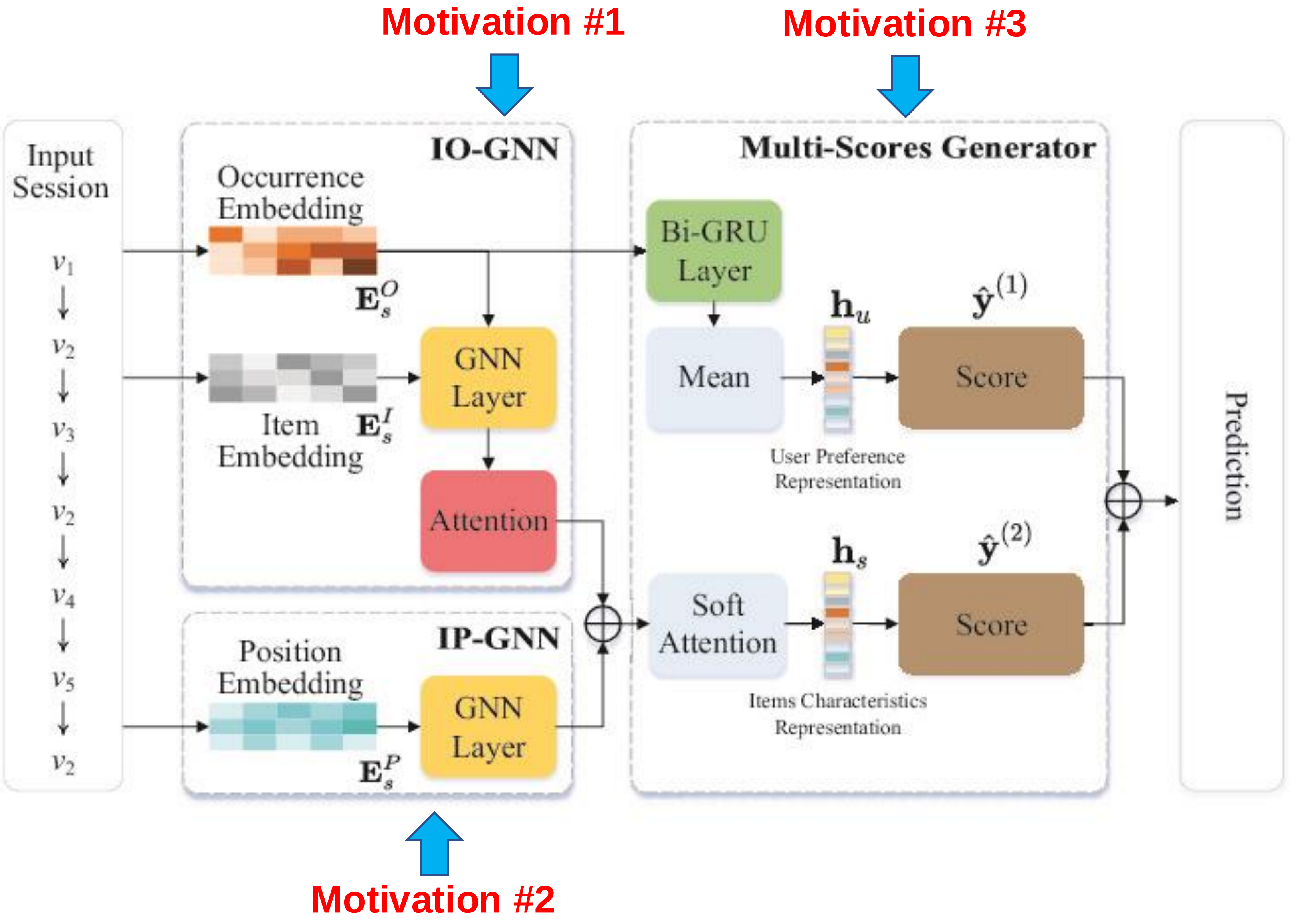
PART THREE



Methodology

The Overview of Int-GNN



The detailed implement of IO-GNN

Global Item Occurrence Embedding: $E^O = [e_0^O, e_1^O, \dots, e_M^O]$

The Readout Function: $E_S^O(v_2) = e_2^O$

$$\overset{\boldsymbol{e_2^O}}{v_2} \rightarrow \overset{e_1^O}{v_3} \rightarrow \overset{e_1^O}{v_1} \rightarrow \overset{e_1^O}{v_4} \rightarrow \overset{\boldsymbol{e_2^O}}{v_2} \quad \Rightarrow \quad \boldsymbol{E_S^O}$$

Global Item Embedding & the readout: $E^I = [e_1^O, e_2^O, \dots, e_{|V|}^O]$ $\Rightarrow$ $\boldsymbol{E_S^I}$

Message Passing of IO-GNN:

$$Z_S^{in} = A_S^{in}(E_S^I W_1 + E_S^O)$$

$$Z_S^{out} = A_S^{out}(E_S^I W_2 + E_S^O)$$

$$Z_S' = Z_S^{in} + Z_S^{out}$$

Sequential Item Occurrence Embedding:

$$\overset{\boldsymbol{e_1^O}}{v_2} \rightarrow \overset{e_1^O}{v_3} \rightarrow \overset{e_1^O}{v_1} \rightarrow \overset{e_1^O}{v_4} \rightarrow \overset{\boldsymbol{e_2^O}}{v_2} \quad \Rightarrow \quad \boldsymbol{E_S^{SI}}$$

Sequential Item Occurrence Attention: $\alpha_i = \dfrac{\sigma(Z_{S,i}' W + b) E_S^{SI}(v_i)}{\left\| E_S^{SI}(v_i) \right\|_2}$

Result of the IO-GNN: $Z_{S,i} = \alpha_i Z_S'$

The detailed implement of IP-GNN

Position Embedding & readout: $E^P = [e_1^P, e_2^P, \dots, e_N^P]$ ➡ $\boldsymbol{E_S^P}$

Graph for Position: $A_{i,j} = \begin{cases} 1, v_i = v_j \\ 0, v_i \neq v_j \end{cases}$ where i, j are the position in the session

Result of the IP-GNN: $Z_P = A_P E_S^P \mathrm{W} + \mathrm{B}$

The Multi-Scores Generator

User Preference Embedding: $E_u^O = [E_S^O(v_1), E_S^O(v_2), \dots, E_S^O(v_{|V|})]$

User Preference Representation: $\mathrm{h}_u = Mean(FC(BiGRU(E_S^{SI})))$

First Score: $y_1 = \tilde{E}_{\mathrm{u}}^O \tilde{h}_{\mathrm{u}}^T$

Item Characteristics Representation: $\mathrm{h}_s = \frac{\sum_{i=1}^{n} q^T \sigma\left(\left(Z_{s,i} + Z_{P,i}\right)W + b\right)}{\|q\|_2} E_{S,i}^I$

Second Score: $y_2 = \mu \tilde{E}^I \tilde{h}_S^T$

Result of the Multi-Scores Generator: $y = SoftMax(y_1 + y_2)$

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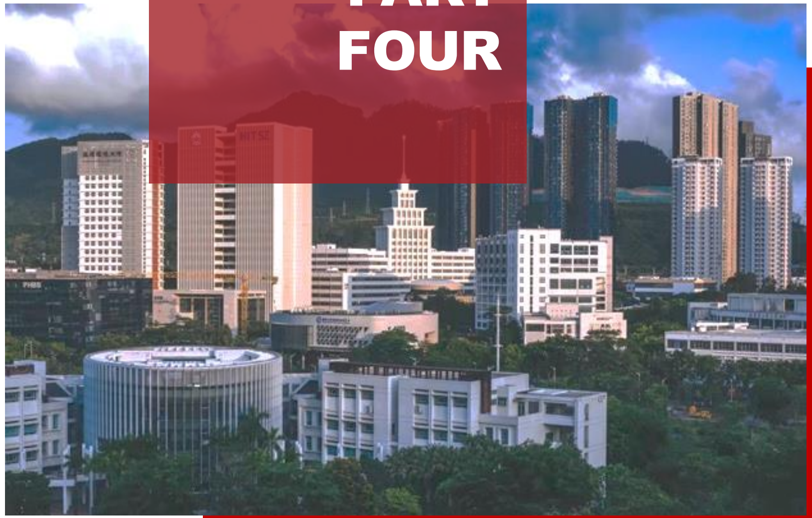
PART FOUR



Experiment Result & Analysis

Dataset Description

Dataset	# train	# test	# items	avg length
Diginetica	719,470	60,858	43,097	5.12
Tmall	351,268	25,898	40,728	6.69
RetailRocket	433,643	15,132	36,968	5.43

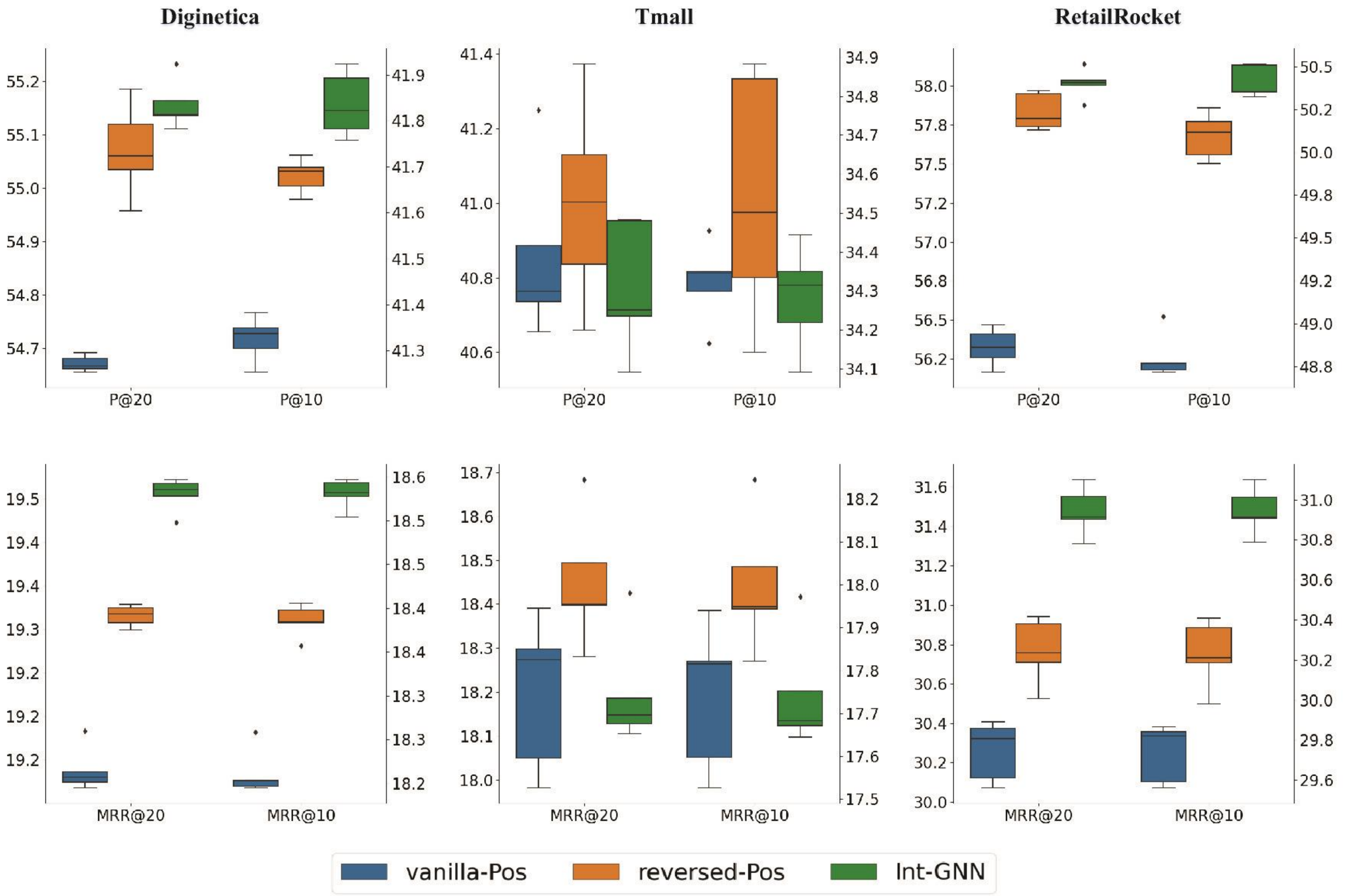
Main Comparison

Method	Diginetica				Tmall				RetailRocket			
Metrics	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10
POP	1.18	0.28	0.76	0.26	2.00	0.90	1.67	0.88	1.12	0.30	0.61	0.27
GRU4Rec	29.45	8.33	17.93	7.33	10.93	5.89	9.47	5.78	44.01	23.67	38.35	23.27
NARM	49.70	16.17	35.44	15.13	23.30	10.70	19.17	10.42	50.22	24.59	42.07	24.88
STAMP	45.64	14.32	33.98	14.26	26.47	13.36	22.63	13.12	50.96	25.17	42.95	24.61
SR-GNN	50.73	17.59	36.86	15.52	27.57	13.72	23.41	13.45	50.32	26.57	43.21	26.07
NISER	53.39	18.72	40.20	17.82	33.79	16.67	28.46	16.38	54.90	29.89	47.69	29.38
LESSR	51.71	18.15	36.16	15.64	27.88	12.08	22.68	11.68	53.05	28.01	45.76	27.51
GCE-GNN	54.22	19.04	41.16	18.15	33.42	15.42	28.01	15.08	50.60	25.39	43.53	24.89
DSAN	53.76	18.99	40.29	18.05	36.45	18.17	30.91	**17.76**	56.54	30.74	49.05	30.21
DHCN	53.18	18.44	39.87	17.53	31.42	15.05	26.22	14.60	53.66	27.30	46.15	26.85
COTREC	54.18	19.07	**41.88**	18.16	36.35	18.04	30.62	17.65	56.17	29.97	48.61	29.46
Int-GNN	**55.16±0.04**	**19.46±0.02**	41.84±0.06	**18.53±0.02**	**40.77±0.16**	**18.20±0.12**	**34.28±0.12**	17.74±0.12	**58.02±0.08**	**31.48±0.11**	**50.41±0.08**	**30.94±0.11**
improve	1.7%	1.9%	-0.1%	2.0%	11.86%	0.27%	10.91%	-0.09%	2.61%	2.39%	2.77%	2.42%

Ablation study

Method	Diginetica				Tmall				RetailRocket			
Metrics	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10
Int-GNN	55.16±0.04	**19.46±0.02**	**41.84±0.06**	**18.53±0.02**	40.77±0.16	18.20±0.12	34.28±0.12	17.74±0.12	**58.02±0.08**	31.48±0.11	**50.41±0.08**	30.94±0.11
w/o-IO-GNN	54.94±0.05	19.32±0.03	41.60±0.03	18.39±0.03	40.33±0.12	19.08±0.09	34.07±0.18	18.64±0.09	57.88±0.09	**31.57±0.10**	50.30±0.10	**31.05±0.10**
w/o-IP-GNN	52.23±0.08	18.07±0.03	39.07±0.14	17.15±0.04	**40.87±0.13**	18.36±0.17	**34.43±0.27**	17.91±0.18	54.04±0.17	28.67±0.10	46.79±0.15	28.16±0.09
w/o-MScore	**55.19±0.07**	19.26±0.02	41.78±0.05	18.33±0.02	39.54±0.22	18.24±0.11	32.98±0.15	17.78±0.11	57.68±0.09	31.08±0.02	49.93±0.15	30.54±0.03
w/o-IO-IP	52.00±0.05	18.27±0.02	39.00±0.05	17.37±0.02	40.28±0.11	19.01±0.05	34.18±0.09	18.59±0.06	53.51±0.09	28.78±0.08	46.46±0.08	28.29±0.07
w/o-IO-MScore	54.92±0.05	19.17±0.02	41.61±0.06	18.25±0.02	39.38±0.04	18.91±0.06	33.22±0.11	18.48±0.06	57.27±0.10	30.86±0.10	49.56±0.10	30.33±0.10
w/o-IP-MScore	52.34±0.07	18.03±0.03	39.02±0.05	17.10±0.04	39.63±0.11	18.31±0.10	33.10±0.11	17.86±0.10	53.52±0.11	28.01±0.06	46.11±0.11	27.49±0.07
vanilla-GNN	52.11±0.06	18.21±0.01	38.95±0.05	17.29±0.01	39.18±0.22	**19.36±0.05**	33.14±0.11	**18.94±0.05**	53.19±0.13	28.33±0.07	45.87±0.05	27.81±0.07

The analysis of IP-GNN



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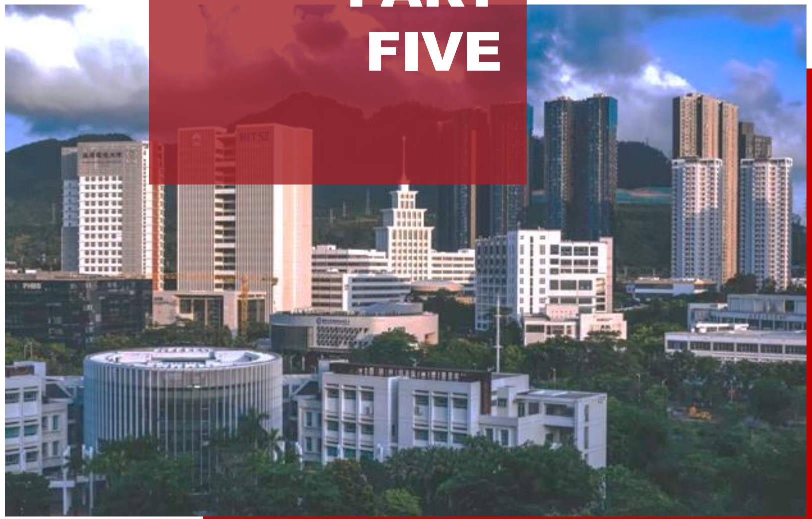
PART FIVE



Conclusion & Future Work

Conclusion & Future Work

In this paper, we proposed utilizing the number of item occurrences to give insight into user intention capturing. Upon this concept, we model user intention by the Int-GNN model, which includes the IO-GNN, the IP-GNN, and the Multi-Scores Generator by considering user intention in the number of item occurrences, user intention in item re-interaction intervals, and user preference, respectively. Extensive experiments show the superiority of the Int-GNN.

For future work, we plan to explore the pattern of the item occurrence in heterogenous dataset to find the user intention.

Thank you for Listening