The 23rd AAAI Conference on Artificial Intelligence (AAAI-19)

Session-based Recommendation with Graph Neural Networks

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Outline

1. Preamble
2. The Proposed Method
3. Experiments and Analysis
4. Conclusions

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Preamble

Session-based Recommendation with Graph Neural Networks

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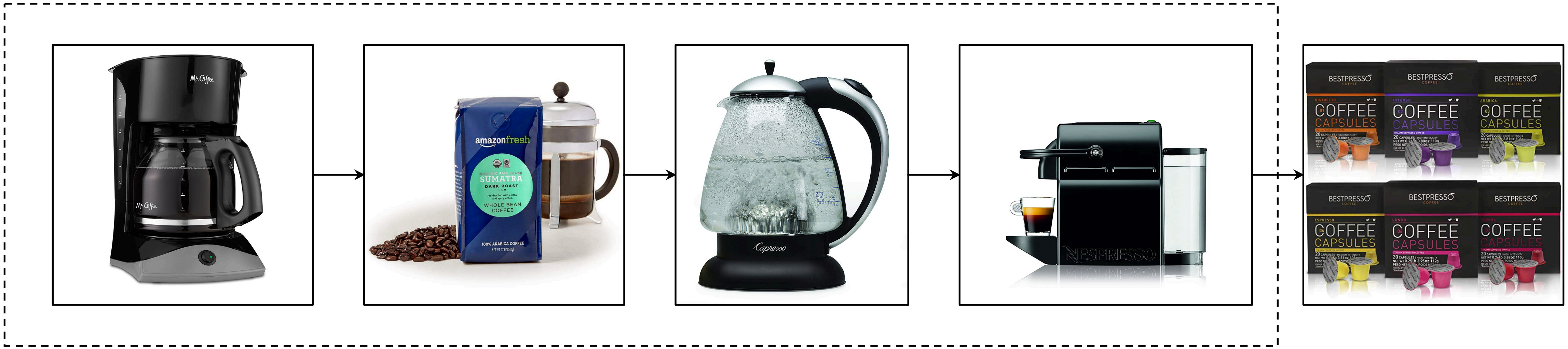
Session-based Recommendation

- Recommendation systems help users find relevant items that meet their interests.
- Previous recommendation systems rely on long-term user profiles to make recommendations.
  - However, in real-world applications, long-term profiles may not exist.
  - Only user behavior during an ongoing session is available.

Session-based Recommendation (cont.)



Previously visited items

Item to be recommended

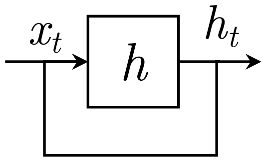
- No information about the actual user.
- Only **timestamp** and (possibly limited) clicked **items** available.

Recurrent Neural Networks (RNNs)

- Recently, many proposals based on RNNs have been developed for session-based recommendation.

- Hidden state
  - Next hidden state depends on the input and the current hidden state

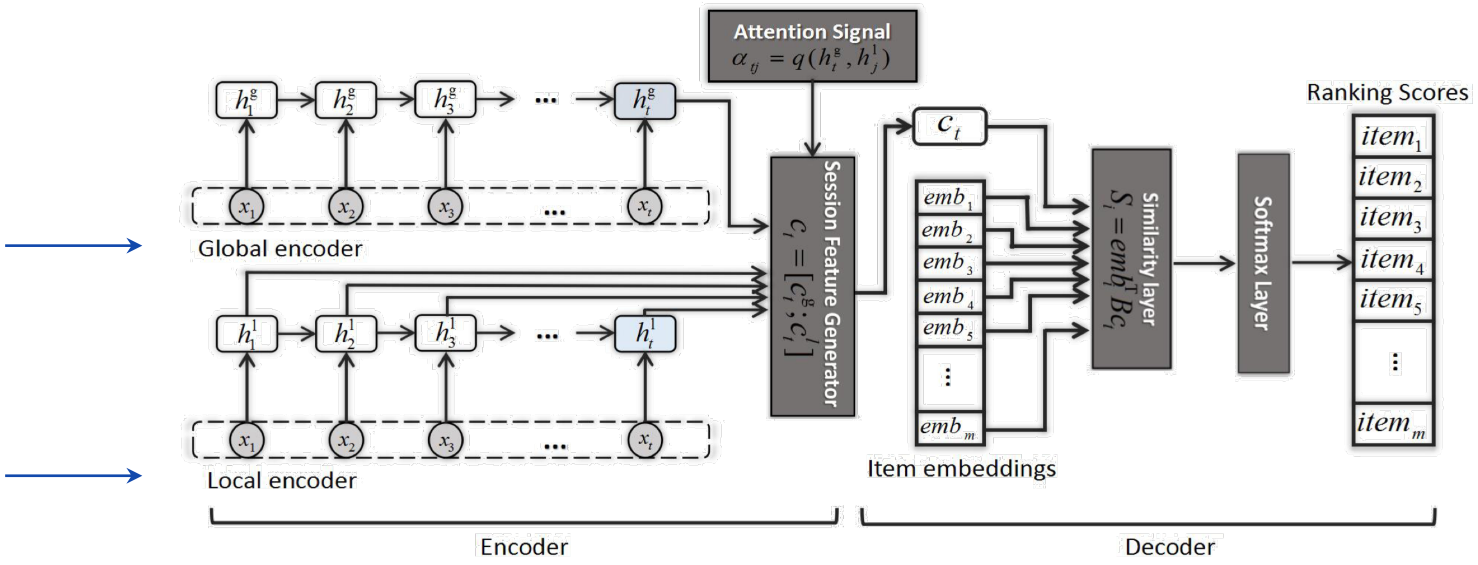
$$h_t = \tanh(Wx_t + Uh_{t-1})$$



- RNNs can be of arbitrary (infinite) depths
- Optimizing via back-propagation through time (BPTT)

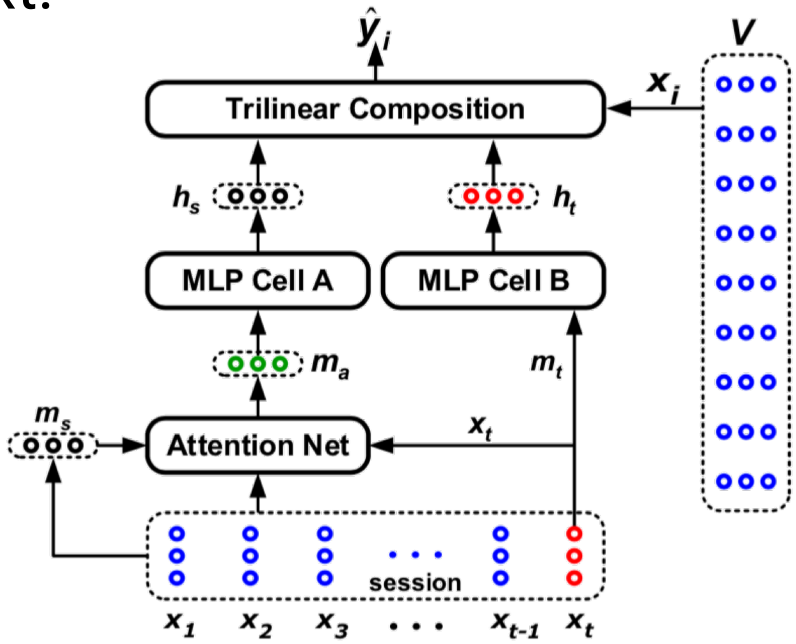
Recent Progress

- NARM: Neural Attentive Recommendation Machine [Li et al. 2017a]
  - For the global recommender, the user behavior in one session is inadequate and estimating user representations may not be sufficient.



Recent Progress (cont.)

- STAMP: Short-Term Attention/Memory Priority Model [Liu et al. 2018]
  - An attentive model for next-click prediction
  - Only models single-way transitions between consecutive items and neglects the context.

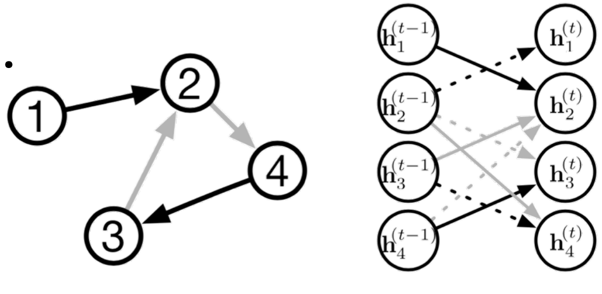


Motivations

- How to effectively capture the item transitions in session sequences?
- To facilitate recommendation, how to obtain accurate item embeddings and session embeddings?

Graph-based Neural Networks

- Graph Neural Networks (GNNs) [Scarselli et al. 2009]
    - Propagation: computes representation for each node.
    - Output mapping: maps from node representations and corresponding labels to an output.
    - Model training via Almeida-Pineda algorithm
- Gated Graph Neural Networks (GGNNs) [Li et al. 2016]
    - Uses gated recurrent units.
    - Unrolls the recurrence for **a fixed number of steps**.
    - Computes gradients through Backpropagation through time.



(a) (b)

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The Proposed Method

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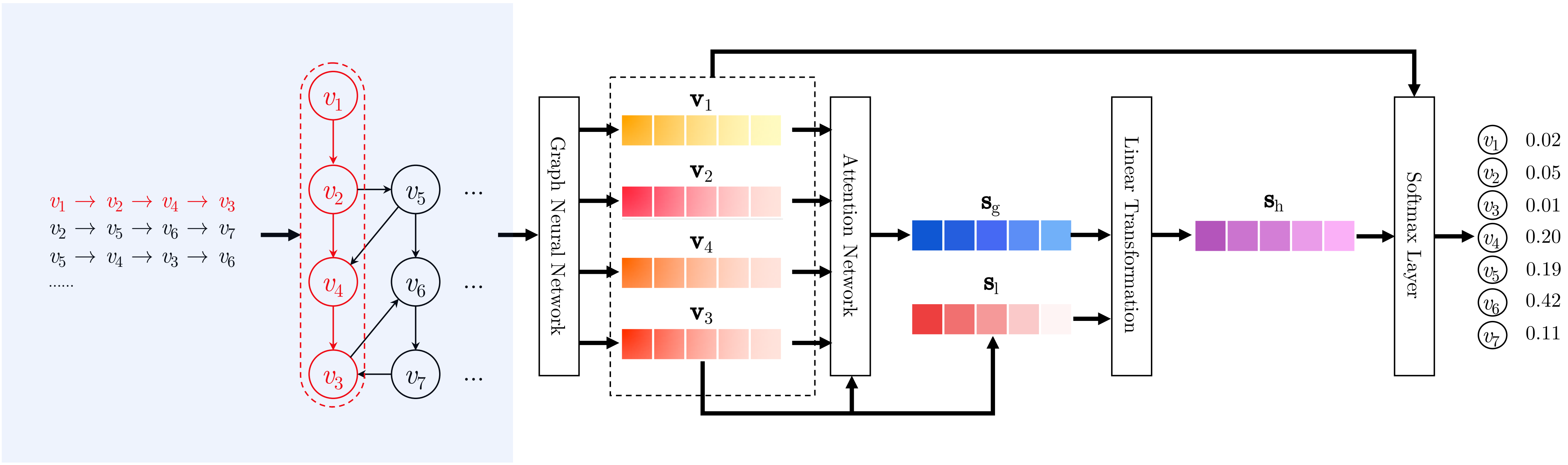
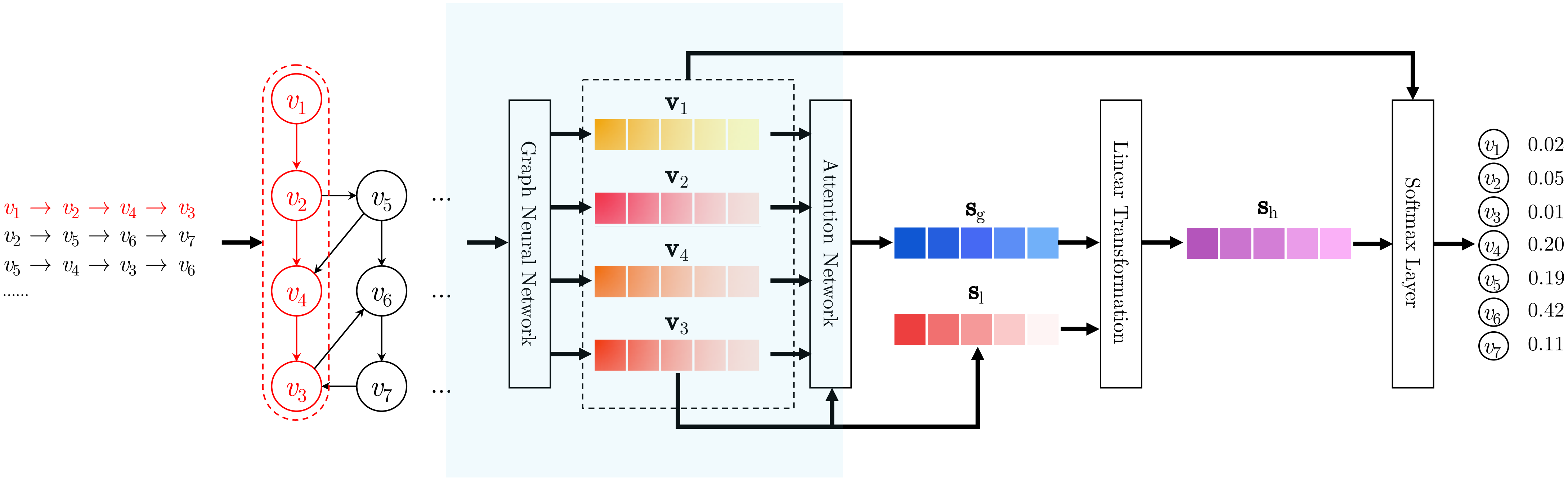
An Overview of Our Approach



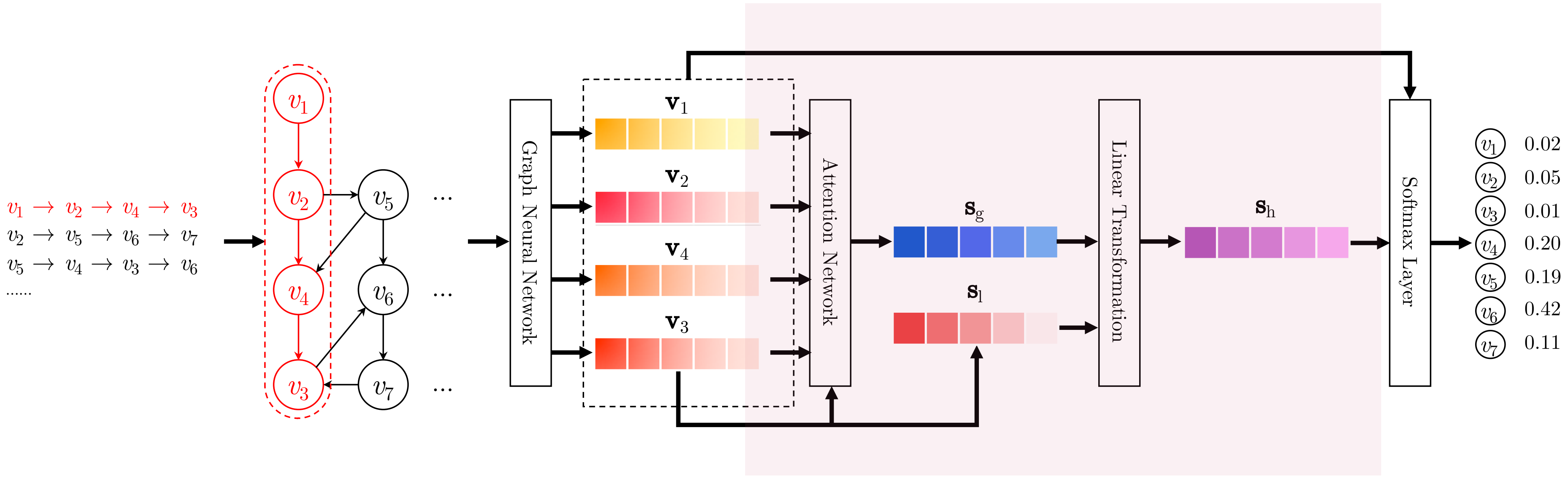
(a) **Session graph modeling**

An Overview of Our Approach



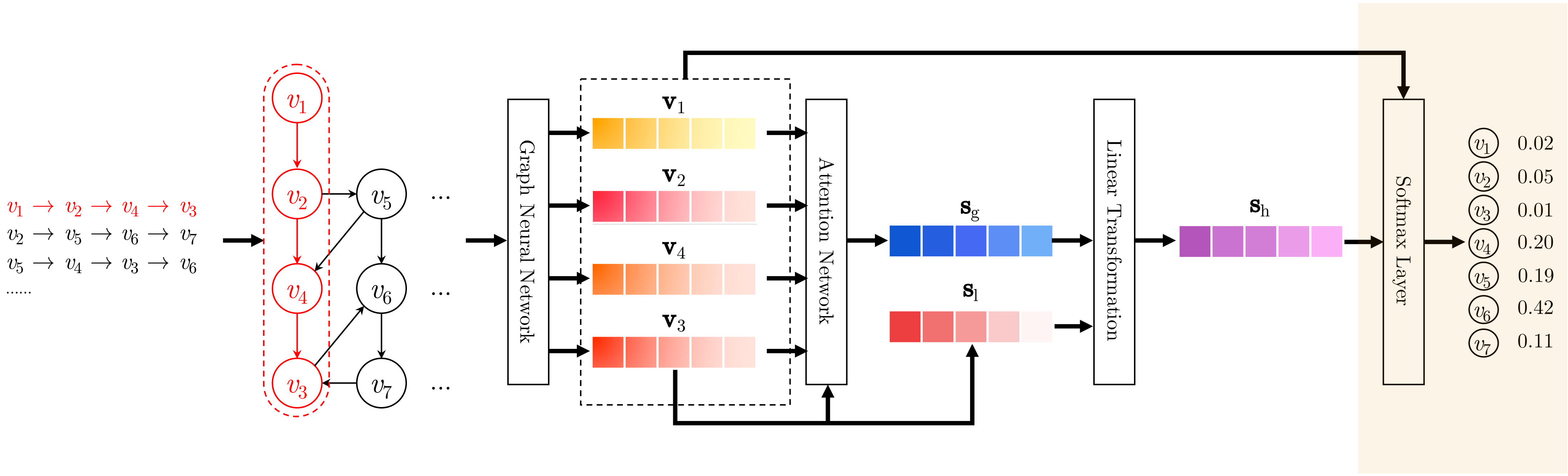
(b) **Node representation learning**

An Overview of Our Approach



(c) **Session representation generating**

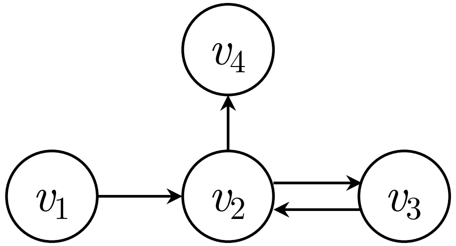
An Overview of Our Approach



(d) **Making recommendation**

Constructing Session Graphs

- Each session sequence s is modeled as a directed graph $\mathcal{G}_s = (\mathcal{V}_s, \mathcal{E}_s)$.
- Edge weight normalization: the occurrence of the edge divided by the outdegree of that edge's start node



$$s = [v_1, v_2, v_3, v_2, v_4]$$

normalization $\longrightarrow$

	1	2	3	4
1	0	1	0	0
2	0	0	1/2	1/2
3	0	1	0	0
4	0	0	0	0

Learning Item Embeddings on Graphs

- We adopt GGNNs for learning unified representations for all nodes in session graphs.

- Propagation rules:

connection matrix

$$\mathbf{a}_{s,i}^{t} = \mathbf{A}_{s,i:} \left[\mathbf{v}_1^{t-1}, \ldots, \mathbf{v}_n^{t-1}\right]^{\top} \mathbf{H} + \mathbf{b},$$

$$\mathbf{z}_{s,i}^{t} = \sigma\left(\mathbf{W}_z \mathbf{a}_{s,i}^{t} + \mathbf{U}_z \mathbf{v}_i^{t-1}\right),$$ Reset gate

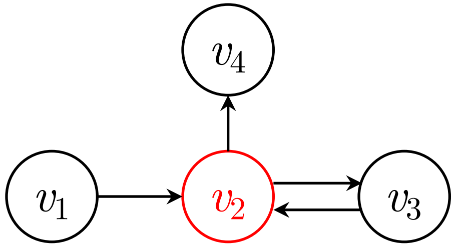
$$\mathbf{r}_{s,i}^{t} = \sigma\left(\mathbf{W}_r \mathbf{a}_{s,i}^{t} + \mathbf{U}_r \mathbf{v}_i^{t-1}\right),$$ Update gate

$$\widetilde{\mathbf{v}_i^{t}} = \tanh\left(\mathbf{W}_o \mathbf{a}_{s,i}^{t} + \mathbf{U}_o \left(\mathbf{r}_{s,i}^{t} \odot \mathbf{v}_i^{t-1}\right)\right),$$ Candidate

$$\mathbf{v}_i^{t} = \left(1 - \mathbf{z}_{s,i}^{t}\right) \odot \mathbf{v}_i^{t-1} + \mathbf{z}_{s,i}^{t} \odot \widetilde{\mathbf{v}_i^{t}}.$$ Final representation

The Connection Matrix

- The connection matrix $\mathbf{A}_s \in \mathbb{R}^{n \times 2n}$ determines how nodes within the graph communicate with each other, which is defined as a concatenation of two adjacency matrices $\mathbf{A}_s^{(\mathrm{out})}$ and $\mathbf{A}_s^{(\mathrm{in})}$.
- $\mathbf{A}_{s,i:} \in \mathbb{R}^{1 \times 2n}$ are the two columns of blocks in $\mathbf{A}_s$ corresponding to node $v_{s,i}$.



$\mathbf{A}_{s,i:} \in \mathbb{R}^{1 \times 2n}$

	Outgoing edges				Incoming edges			
	1	2	3	4	1	2	3	4
1	0	1	0	0	0	0	0	0
2	0	0	1/2	1/2	1/2	0	1/2	0
3	0	1	0	0	0	1	0	0
4	0	0	0	0	0	1	0	0

Generating Session Embeddings

- A session is represented directly by node embedding involved in that session.
- **Local embedding**

$$\mathbf{s}_{\mathrm{l}} = \mathbf{v}_n$$

- **Global embedding**

$$\alpha_i = \mathbf{q}^\top \sigma(\mathbf{W}_1 \mathbf{v}_n + \mathbf{W}_2 \mathbf{v}_i + \mathbf{c}),$$

$$\mathbf{s}_{\mathrm{g}} = \sum_{i=1}^{n} \alpha_i \mathbf{v}_i$$

- **Hybrid embedding**

$$\mathbf{s}_{\mathrm{h}} = \mathbf{W}_3 \left[\mathbf{s}_l; \mathbf{s}_g\right]$$

Making Recommendation

- Compute the score for each candidate item by dot product session embeddings with item embeddings:

$$\hat{\mathbf{y}} = \mathrm{softmax}\left(\mathbf{s}_{\mathrm{h}}^{\top} \mathbf{v}_i\right)$$

- The cross-entropy loss function:

$$\mathcal{L}(\hat{\mathbf{y}}) = -\sum_{i=1}^{m} \mathbf{y}_i \log\left(\hat{\mathbf{y}}_i\right) + \left(1 - \mathbf{y}_i\right) \log\left(1 - \hat{\mathbf{y}}_i\right)$$

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Experiments and Analysis

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Experiment Setup

- Datasets
  - **Yoochoose 1/64** and **Yoochoose 1/4** from RecSys Challenge 2014
  - **Diginetica** from CIKM Cup 2016
- Baselines
  - **POP** and **S-POP**
  - **Item-KNN** [Sarwar et al. 2001]
  - **BPR-MF** [Rendle et al. 2009]
  - **FPMC** [Rendle et al. 2010]
  - **GRU4REC** [Hidasi et al. 2016]
  - **NARM** [Li et al. 2017a]
  - **STAMP** [Liu et al. 2018]

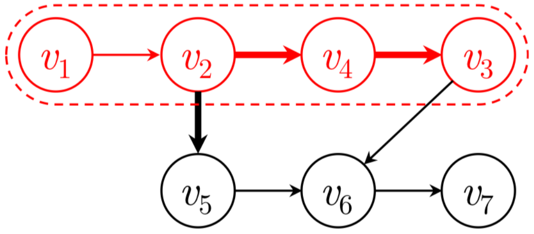
Comparison with Baselines

Method	Yoochoose 1/64		Yoochoose 1/4		Diginetica	
	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20
POP	6.71	1.65	1.33	0.30	0.89	0.20
S-POP	30.44	18.35	27.08	17.75	21.06	13.68
Item-KNN	51.60	21.81	52.31	21.70	35.75	11.57
BPR-MF	31.31	12.08	3.40	1.57	5.24	1.98
FPMC	45.62	15.01	–	–	26.53	6.95
GRU4REC	60.64	22.89	59.53	22.60	29.45	8.33
NARM	68.32	28.63	69.73	29.23	49.70	16.17
STAMP	68.74	29.67	70.44	30.00	45.64	14.32
SR-GNN	**70.57**	**30.94**	**71.36**	**31.89**	**50.73**	**17.59**

Variants of Connection Schemes

- Since user behavior in sessions is limited, we propose two connection schemes to augment relationships between items in each session graph:
  - (a) **SR-GNN-NGC** aggregates all session sequences together and model them as a directed global item graph.

$s_1 = [v_1, v_2, v_4, v_3]$
$s_2 = [v_2, v_4, v_6, v_7]$
$s_3 = [v_2, v_5, v_3, v_6]$
……

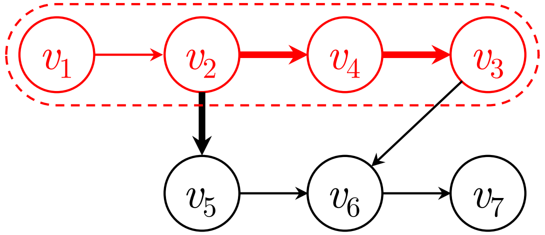


	$\mathbf{A}_g^{(out)}$							$\mathbf{A}_g^{(in)}$						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	1/2	1/2	0	0	1	0	0	0	0	0	0
3	0	0	0	0	0	1	0	0	0	0	1	0	0	0
4	0	0	1	0	0	0	0	0	1	0	0	0	0	0
5	0	0	0	0	0	1	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	1	0	0	1/2	0	1/2	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Variants of Connection Schemes (cont.)

- Since user behavior in sessions is limited, we propose two connection schemes to augment relationships between items in each session graph:
  - (b) **SR-GNN-FC** models all high-order relationships between items within one session as direct connections explicitly.

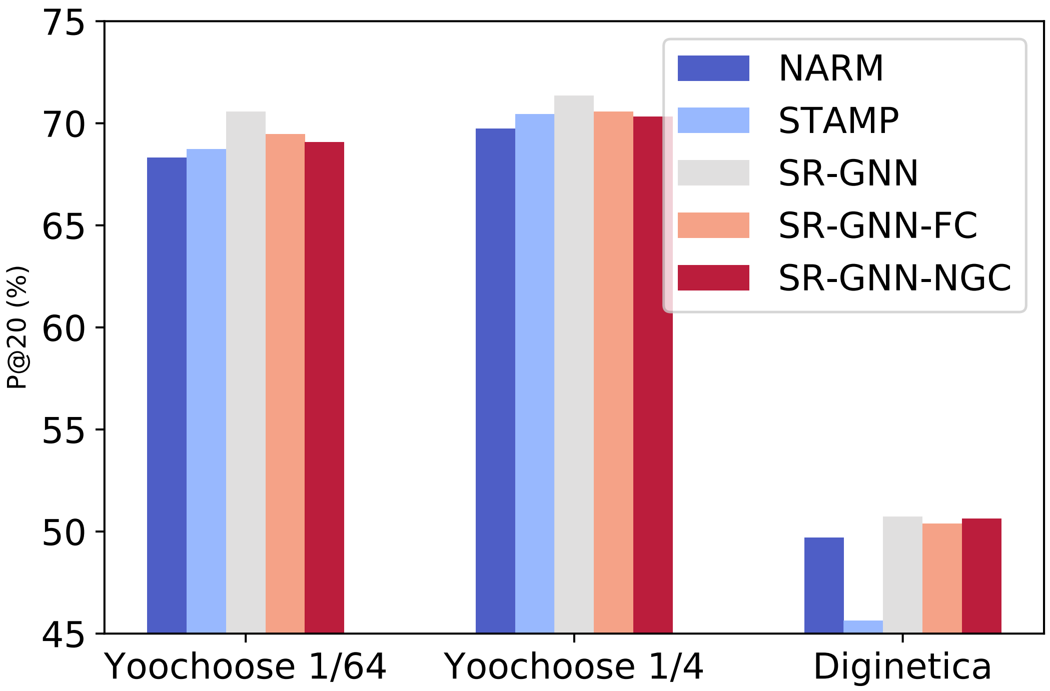
$$s_1 = [v_1,\ v_2,\ v_4,\ v_3]$$
$$s_2 = [v_2,\ v_4,\ v_6,\ v_7]$$
$$s_3 = [v_2,\ v_5,\ v_3,\ v_6]$$
$$\ldots\ldots$$



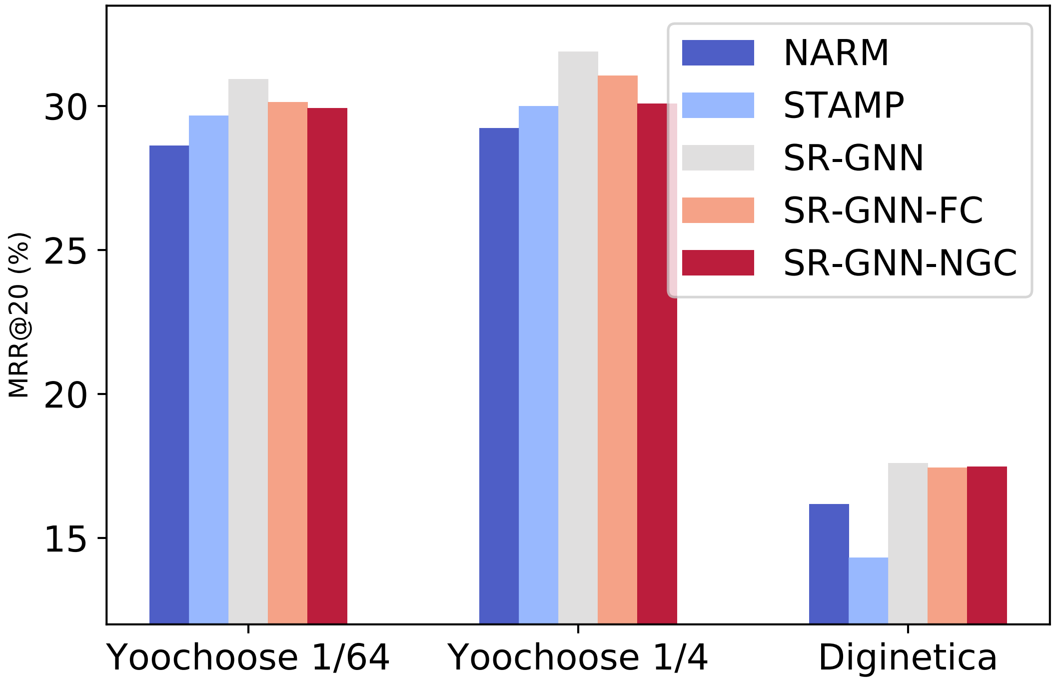
	$\mathbf{A}_g^{(out)}$				$\mathbf{A}_g^{(in)}$				$\mathbf{A}_g^{(FC)}$			
	1	2	3	4	1	2	3	4	1	2	3	4
1	0	1	0	0	0	0	0	0	1	0	1	1
2	0	0	0	1	1	0	0	0	1	1	1	0
3	0	0	0	0	0	0	0	1	1	1	1	1
4	0	0	1	0	0	1	0	0	1	1	0	1

Comparison with Connection Schemes

Precision@20



MRR@20

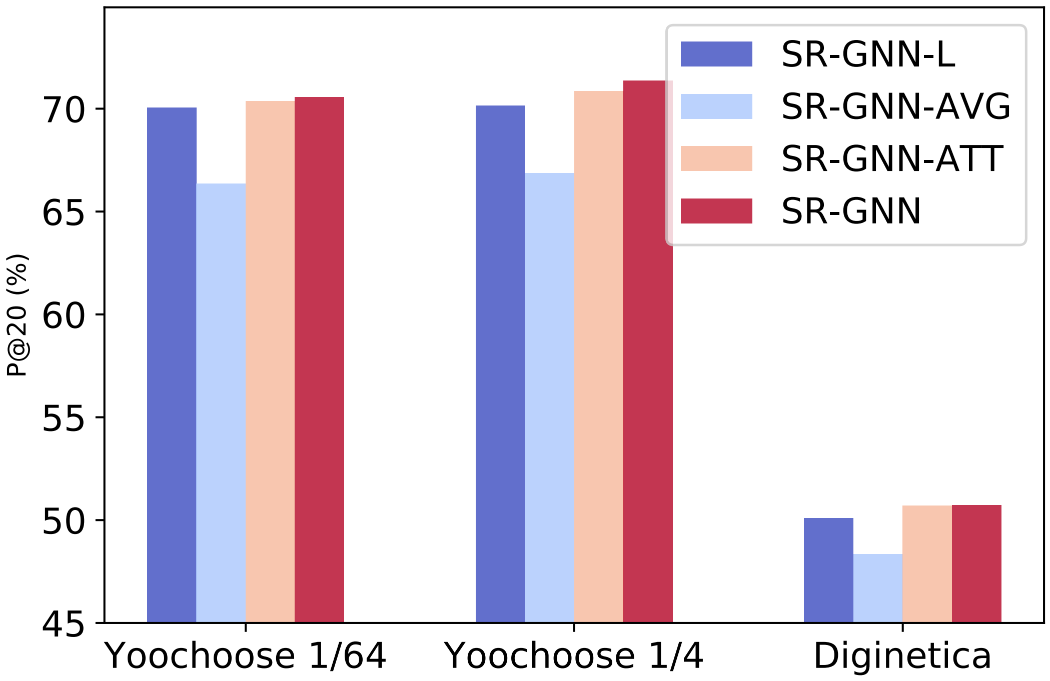


Variants of Session Representations

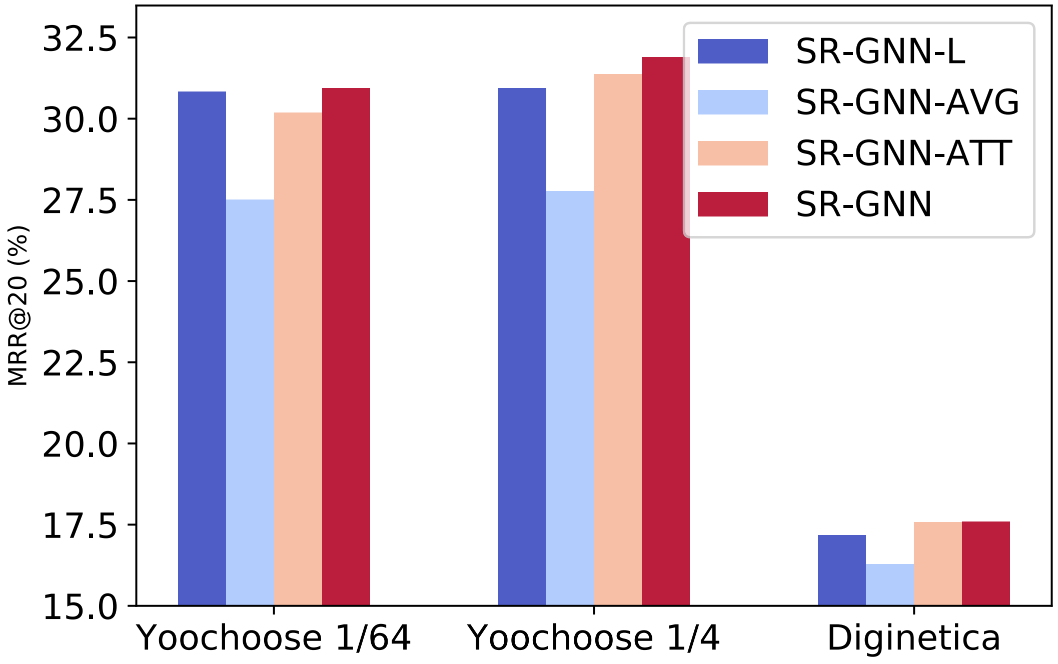
- Ablation study on session representations:
  - (a) **SR-GNN-L**: local embedding only
  - (b) **SR-GNN-AVG**: global embedding with average pooling
  - (c) **SR-GNN-ATT**: global embedding with attention networks

Comparison of Session Representations

Precision@20



MRR@20



Comparison of Sequence Lengths

- **Short** group: session lengths ≤ 5
- **Long** group: session lengths > 5

- Yoochoose 1/64
  - Short (70.1%)
  - Long (29.9%)
- Diginetica
  - Short (76.4%)
  - Long (23.6%)

Comparison of Sequence Lengths (cont.)

Method	Yoochoose 1/64		Diginetica	
	Short	Long	Short	Long
NARM	**71.44**	60.79	**51.22**	45.75
STAMP	70.69	64.73	47.26	40.39
SR-GNN-L	70.11	69.73	49.04	50.97
SR-GNN-ATT	70.31	70.64	50.35	51.05
SR-GNN	70.47	**70.70**	50.49	**51.27**

Precision@20

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Concluding Remarks

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Wrapping Up

1. Session-based recommendation is indispensable where users' preference and historical records are hard to obtain.
2. We present a novel architecture for session-based recommendation that incorporates graph models into representing session sequences.
3. The proposed method not only considers the complex structure and transitions between items of session sequences, but also develops a strategy to combine long-term preferences and current interests of sessions to better predict users' next actions.
4. Comprehensive experiments confirm that the proposed algorithm can consistently outperform other state-of-art methods.

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Paper

Code

Thank You

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