

# Session-based Recommendation with Graph Neural Networks

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## Technical Highlights

We propose a novel method, Session-based Recommendation with Graph Neural Networks (SR-GNN), consisting of:

1. Modeling session graphs
2. Learning node representations
3. Generating session representations
4. Making recommendation

Extensive experiments conducted on real datasets show that SR-GNN evidently outperforms SOTA methods consistently.

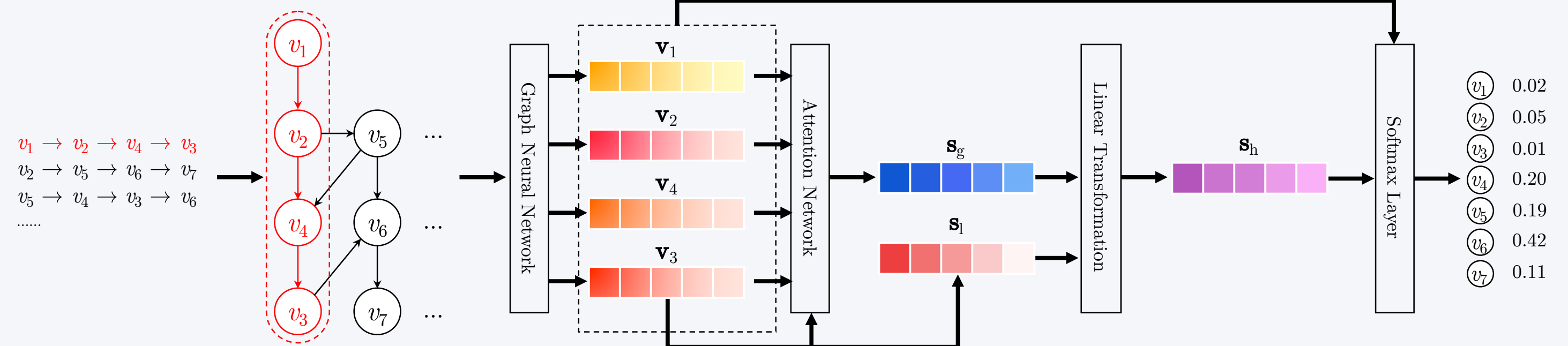


Figure 1. The workflow of SR-GNN.

## Introduction

### Background

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

### Motivations

- Most RNN-based methods only model single-way transitions between consecutive items and neglect the context. How to effectively capture those item transitions in session sequences?
- To facilitate recommendation, how to obtain accurate item embeddings and session embeddings?

### Our Model

- Model session sequences as graph-structured data.
- Based on session graphs, use Gated Graph Neural Networks (GGNNs) [?] to capture complex transitions of items and generate item embeddings.
- Represent each session as the composition of the global preference and the current interest of that session using an attention network.

## SR-GNN (1/2)

### Step 1. Constructing Session Graphs

Each session sequence  $s$  is modeled as a directed graph  $\mathcal{G}_s = (\mathcal{V}_s, \mathcal{E}_s)$ .

### Step 2. Learning Item Embeddings on Graphs

Adopting GGNNs for learning unified representations for all nodes in session graphs:

$$\mathbf{a}_{s,i}^t = \mathbf{A}_{s,i} [\mathbf{v}_1^{t-1}, \dots, \mathbf{v}_n^{t-1}]^\top \mathbf{H} + \mathbf{b}, \quad (1)$$

$$\mathbf{z}_{s,i}^t = \sigma(\mathbf{W}_z \mathbf{a}_{s,i}^t + \mathbf{U}_z \mathbf{v}_i^{t-1}), \quad (2)$$

$$\mathbf{r}_{s,i}^t = \sigma(\mathbf{W}_r \mathbf{a}_{s,i}^t + \mathbf{U}_r \mathbf{v}_i^{t-1}), \quad (3)$$

$$\tilde{\mathbf{v}}_i^t = \tanh(\mathbf{W}_o \mathbf{a}_{s,i}^t + \mathbf{U}_o (\mathbf{r}_{s,i}^t \odot \mathbf{v}_i^{t-1})), \quad (4)$$

$$\mathbf{v}_i^t = (1 - \mathbf{z}_{s,i}^t) \odot \mathbf{v}_i^{t-1} + \mathbf{z}_{s,i}^t \odot \tilde{\mathbf{v}}_i^t, \quad (5)$$

Connection matrix  $\mathbf{A}_s$  represents weighted connections of outgoing and incoming edges in the graph. An example is provided below:

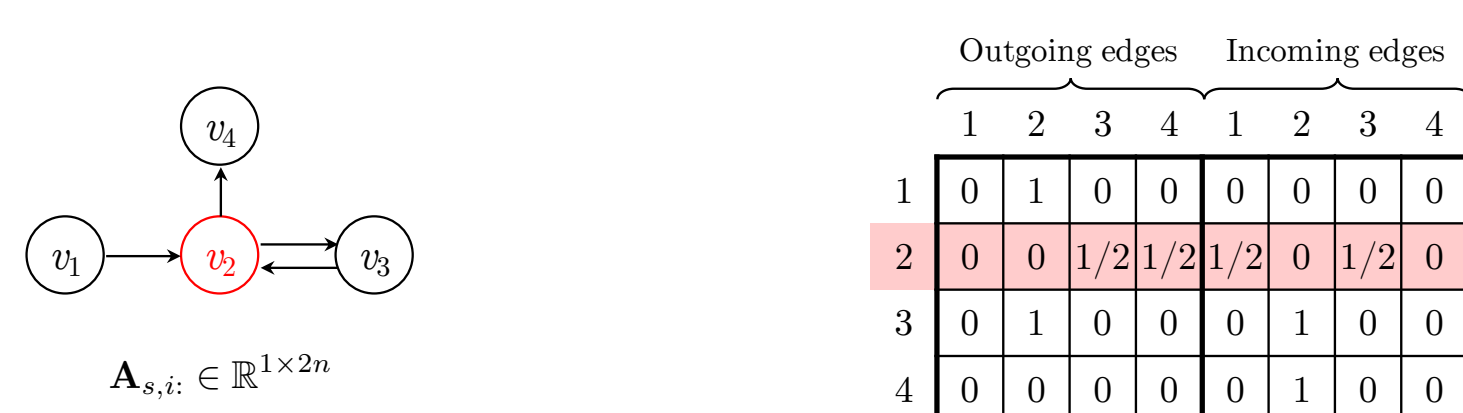


Figure 2. An example of the connection matrix.

## SR-GNN (2/2)

### Step 3. Generating Session Embeddings

Represent a session by node embedding involved in that session.

Local embedding emphasizes the impact of the last click:

$$\mathbf{s}_l = \mathbf{v}_n \quad (6)$$

Global embedding is obtained via a soft-attention net:

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

$$\mathbf{s}_g = \sum_{i=1}^n \alpha_i \mathbf{v}_i \quad (7)$$

Hybrid embedding combines two embedding vectors:

$$\mathbf{s}_h = \mathbf{W}_3 [\mathbf{s}_l; \mathbf{s}_g] \quad (8)$$

### Step 4. Making Recommendation

Compute the recommending score by dot product session embedding with item embedding:

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{s}_h^\top \mathbf{v}) \quad (9)$$

## Experiments and Analysis (1/2)

### I. 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	<b>70.57</b>	<b>30.94</b>	<b>71.36</b>	<b>31.89</b>	<b>50.73</b>	<b>17.59</b>

Table 1. The performance with other baselines over three datasets

### II. Comparison with Connection Scheme Variants

Two connection schemes to augment relationships between items in each session graph:

- SR-GNN-NGC replaces the connection matrix with edge weights extracted from the global graph.
- SR-GNN-FC appends another connection matrix, which represents all higher-order relationships using boolean weights.

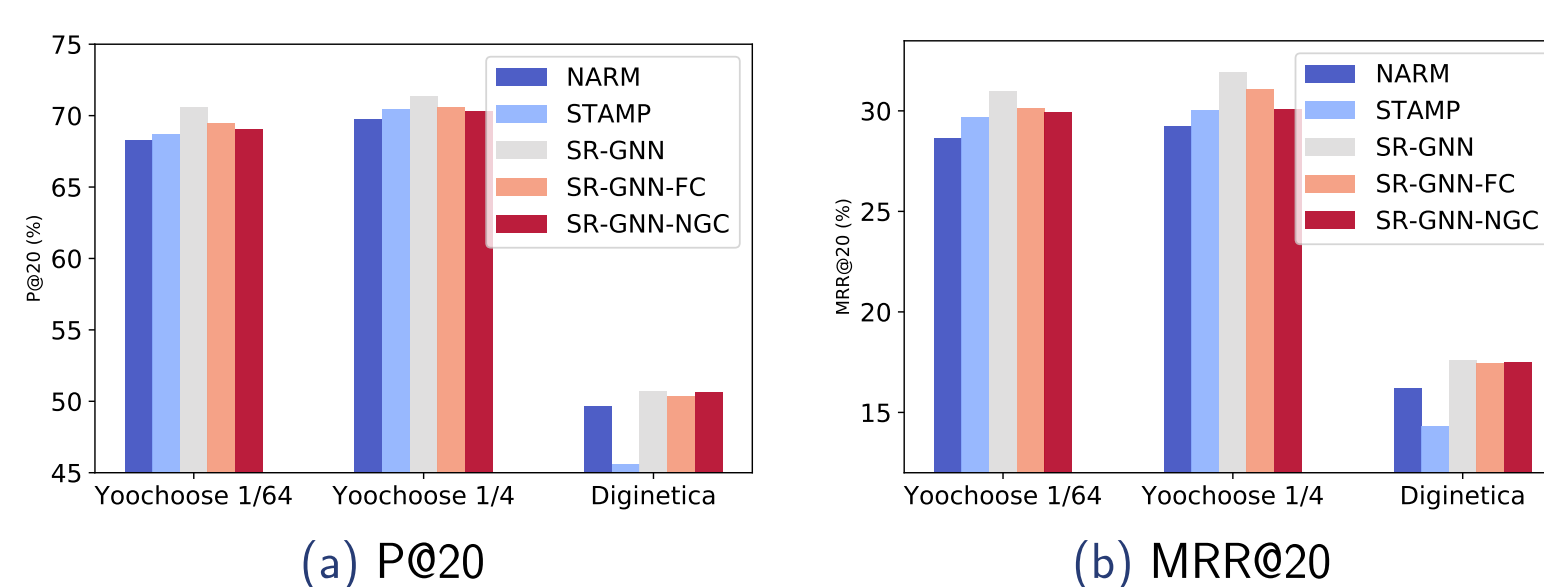


Figure 3. The performance of different connection schemes

## Experiments and Analysis (2/2)

### III. Analysis on Session Sequence Lengths

Method	Yoochoose 1/64		Diginetica	
	Short	Long	Short	Long
NARM	<b>71.44</b>	60.79	<b>51.22</b>	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	<b>70.70</b>	50.49	<b>51.27</b>

Table 2. The performance of different methods with different session lengths evaluated in terms of P@20

## Concluding Remarks

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. SR-GNN 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.

## Contact Us



Poster

Paper

Code

## Bibliographies

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