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Target Attentive Graph Neural Networks for Session-based Recommendation

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Outline

1. Preamble
2. The Proposed Method
3. Experiments
4. Concluding Remarks

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Session-based Recommendation

Previously visited items

Item to be recommended

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

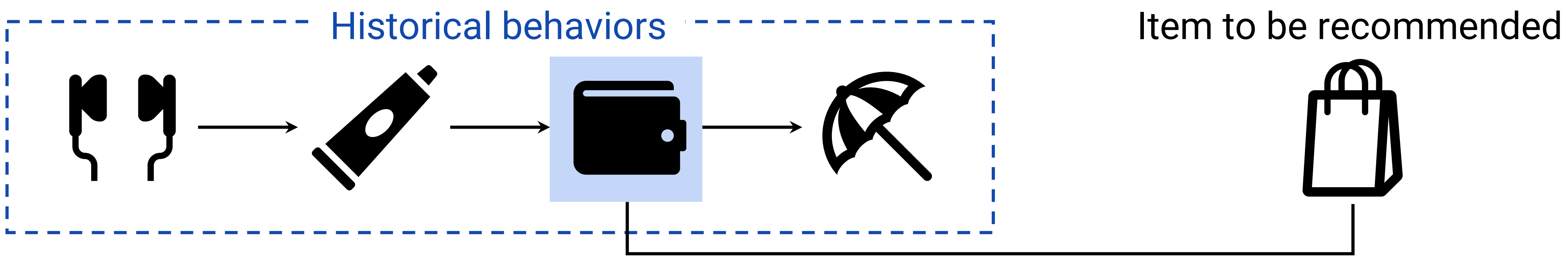
Graph-based Recommender Models

- Limitation of previous sequential methods:
  - Sequence-based methods only model sequential transitions between consecutive items, with complex transitions neglected.
  - Suppose a session is $s = v_1 \rightarrow v_2 \rightarrow v_1 \rightarrow v_3$. It is hard to capture such a to-and-fro relationship between item v_1 and items (v_2, v_3).
- SR-GNN [Wu et al. 2019] proposes to model sessions as **graphs**.
  - Discover the complex transitional patterns underneath sessions through session graphs.
  - This natural means of encoding rich temporal patterns within sessions produces more accurate representations for items.

[Wu et al. 2019] S. Wu, Y. Tang, Y. Zhu, L. Wang, X. Xie, and T. Tan, Session-based Recommendation with Graph Neural Networks, in *AAAI*, 2019, pp. 346–353.

Representing Diverse User Interests

- Representing one session using one fixed embedding vector cannot express users' **diverse** interests, considering abundant candidate items and user behaviors.
- The interests of a user with rich behaviors can be **specifically activated** given a target item [Zhou et al. 2018].



[Zhou et al. 2018] G. Zhou, X. Zhu, C. Song, Y. Fan, H. Zhu, X. Ma, Y. Yan, J. Jin, H. Li, and K. Gai, Deep Interest Network for Click-Through Rate Prediction, in *KDD*, 2018, pp. 1059—1068.

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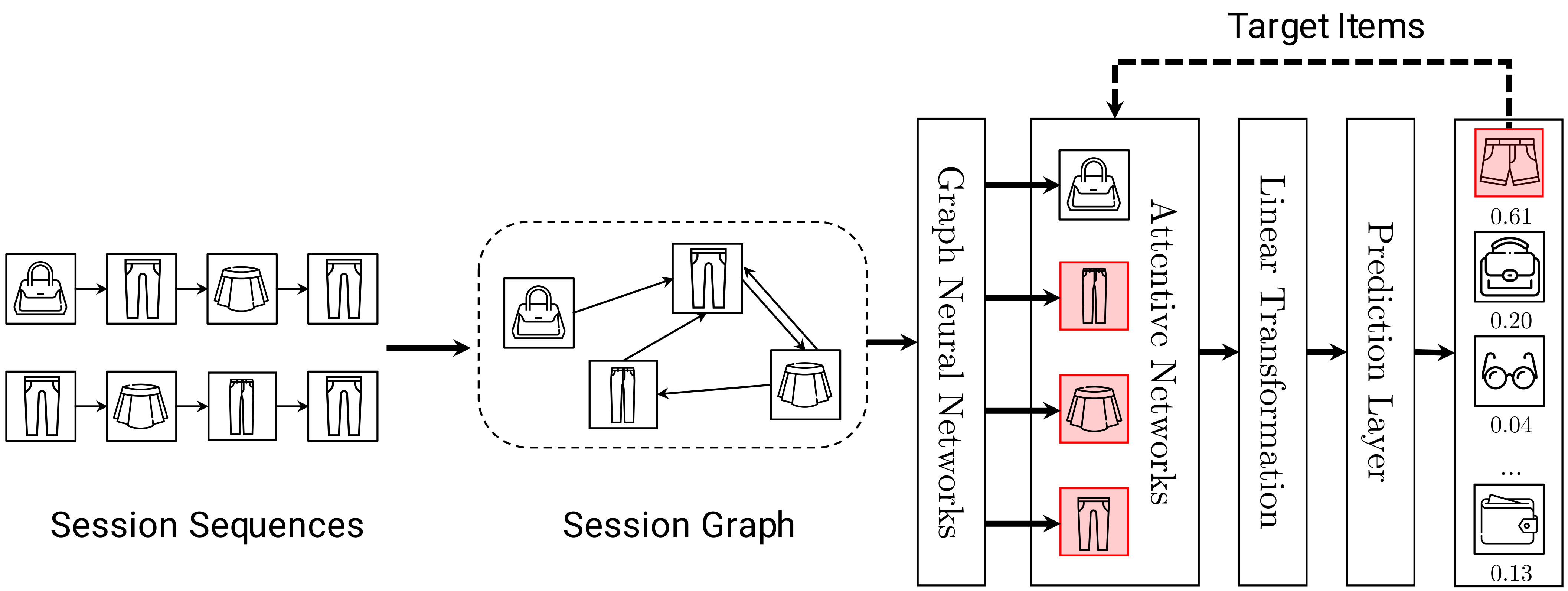
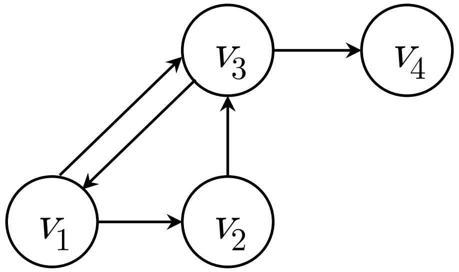
Model: Target Attentive GNN



Graph Modeling

- Each session sequence is modeled as a directed graph.
  - Edge weight normalization: the occurrence of the edge divided by the outdegree of that edge's start node.
  - Treat incoming and outgoing edges separately to reflect bidirectional relationships.



Session graph $\mathcal{G}_s$

	Outgoing edges				Incoming edges			
	1	2	3	4	1	2	3	4
1	0	1/2	1/2	0	0	0	1	0
2	0	0	1	0	1	0	0	0
3	1/2	0	0	1/2	1/2	1/2	0	0
4	0	0	0	0	0	0	1	0
	$\boldsymbol{A}_s^{(\text{in})}$				$\boldsymbol{A}_s^{(\text{out})}$			

Adjacency matrix $\boldsymbol{A}_s$

Learning Item Embeddings

- We use Gated GNNs [Li et al. 2016] to learn item representations for all nodes in session graphs.
  - The GGNN model aggregates features from neighboring nodes and adopts memory units to better preserve useful information.

$$
\begin{aligned}
\boldsymbol{a}_{s,i}^{(t)} &= \boldsymbol{A}_{s,i:}\left[\boldsymbol{v}_1^{(t-1)},\ldots,\boldsymbol{v}_{s_n}^{(t-1)}\right]^\top \boldsymbol{H}+\boldsymbol{b},\\
\boldsymbol{z}_{s,i}^{(t)} &= \sigma\left(\boldsymbol{W}_z\boldsymbol{a}_{s,i}^{(t)}+\boldsymbol{U}_z\boldsymbol{v}_i^{(t-1)}\right),\\
\boldsymbol{r}_{s,i}^{(t)} &= \sigma\left(\boldsymbol{W}_r\boldsymbol{a}_{s,i}^{(t)}+\boldsymbol{U}_r\boldsymbol{v}_i^{(t-1)}\right),\\
\widetilde{\boldsymbol{v}_i^{(t)}} &= \tanh\left(\boldsymbol{W}_o\boldsymbol{a}_{s,i}^{(t)}+\boldsymbol{U}_o\left(\boldsymbol{r}_{s,i}^{(t)}\odot\boldsymbol{v}_i^{(t-1)}\right)\right),\\
\boldsymbol{v}_i^{(t)} &= \left(1-\boldsymbol{z}_{s,i}^{(t)}\right)\odot\boldsymbol{v}_i^{(t-1)}+\boldsymbol{z}_{s,i}^{(t)}\odot\widetilde{\boldsymbol{v}_i^{(t)}},
\end{aligned}
$$

Constructing Target-Aware Embeddings

- We introduce a novel target attention mechanism to calculate soft attention scores over all items with respect to each target item to **adaptively** capture relevant historical behaviors.
- The obtained target embedding for representing users' interests varies with different target items.

$$\beta_{i,t} = \operatorname{softmax}(e_{i,t}) = \frac{\exp\left(\boldsymbol{v}_t^\top \boldsymbol{W} \boldsymbol{v}_i\right)}{\sum_{j=1}^{m} \exp\left(\boldsymbol{v}_t^\top \boldsymbol{W} \boldsymbol{v}_j\right)}$$

$$\boldsymbol{s}_{\text{target}}^{t} = \sum_{i=1}^{s_n} \beta_{i,t} \boldsymbol{v}_i$$

Generating Session Embeddings

- We represent a session by node embeddings involved in that session, along with the user's target embedding.
  - **Local embedding** (short-term preference)

$$\boldsymbol{s}_{\text{local}} = \boldsymbol{v}_{s_n}$$

  - **Global embedding** (long-term preference)

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

$$\boldsymbol{s}_{\text{global}} = \sum_{i=1}^{s_n} \alpha_i \boldsymbol{v}_i.$$

  - **Final representation**

$$\boldsymbol{s}_t = \boldsymbol{W}_3 [\boldsymbol{s}^t_{\text{target}}; \boldsymbol{s}_{\text{local}}; \boldsymbol{s}_{\text{global}}]$$

Making Recommendation

- We compute the recommendation score for each item by taking inner-product of item embeddings and session embeddings.

$$\hat{z}_t = \boldsymbol{s}_t^\top \boldsymbol{v}_t,$$
$$\hat{\boldsymbol{y}} = \mathrm{softmax}\left(\hat{\boldsymbol{z}}\right).$$

- For training the model, we define the loss function as the cross-entropy of the prediction and the ground truth.

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

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Experiment Setup

- Dataset statistics

Statistics	Yoochoose 1/64	Diginetica
# Clicks	557,248	982,961
# Training sessions	369,859	719,470
# Test sessions	55,898	60,858
# Unique items	17,377	43,097
Average length	6.16	5.12

Experiment Setup (cont.)

- Baselines
  - Frequency-based POP and S-POP
  - Similarity-based Item-KNN [Sarwar et al. 2001]
  - Bayesian personalized ranking (BPR-MF) [Rendle et al. 2009]
  - Factorizing personalized Markov chain model (FPMC) [Rendle et al. 2010]
  - RNN-based GRU4REC [Hidasi et al. 2016]
  - Neural attentive recommender model (NARM) [Li et al. 2017]
  - Short-term attention/memory priority model (STAMP) [Liu et al. 2018]
  - Graph-based SR-GNN [Wu et al. 2019]

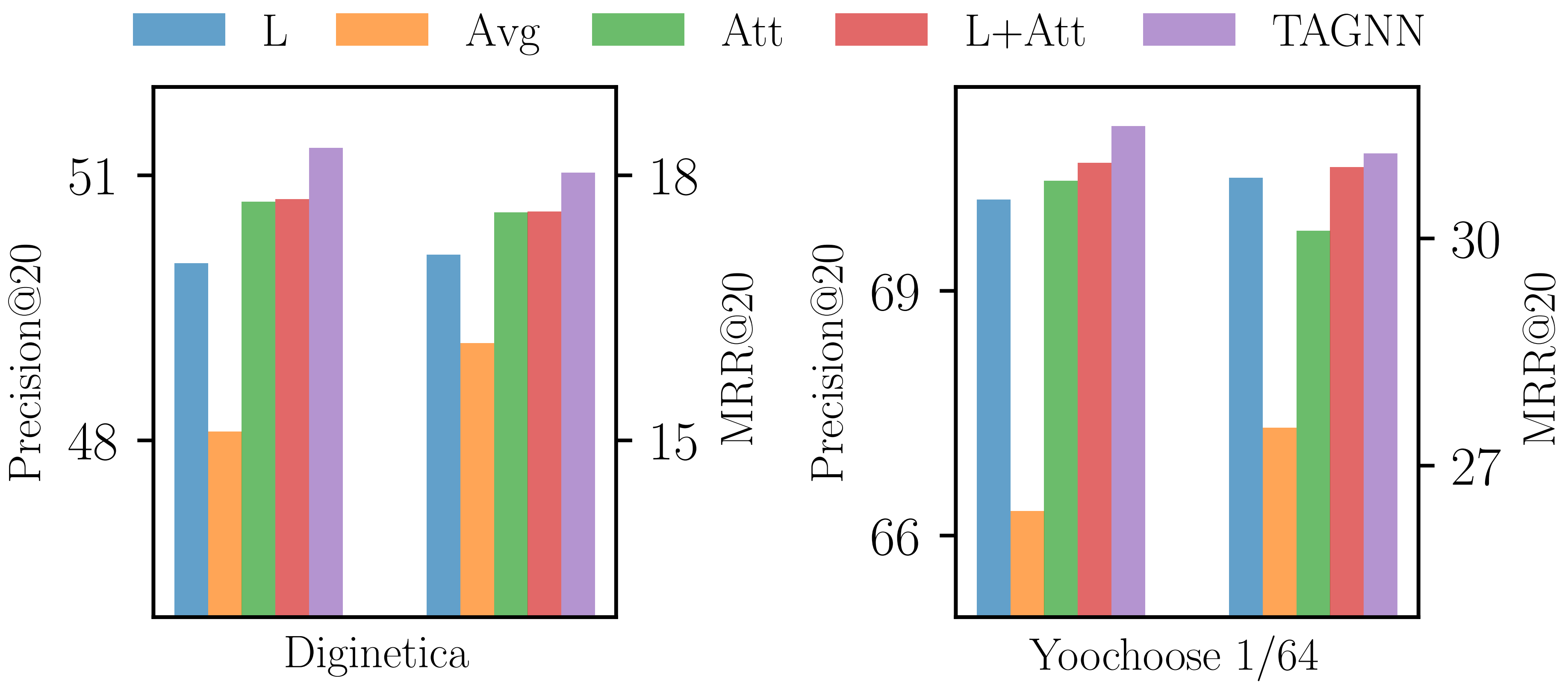
Comparison with Baselines

Method	Diginetica		Yoochoose 1/64	
	Recall@20	MRR@20	Recall@20	MRR@20
POP	0.89	0.20	6.71	1.65
S-POP	21.06	13.68	30.44	18.35
Item-KNN	35.75	11.57	51.60	21.81
BPR-MF	5.24	1.98	31.31	12.08
FPMC	26.53	6.95	45.62	15.01
GRU4REC	29.45	8.33	60.64	22.89
NARM	49.70	16.17	68.32	28.63
STAMP	45.64	14.32	68.74	29.67
SR-GNN	50.73	17.59	70.57	30.94
TAGNN	**51.31**	**18.03**	**71.02**	**31.12**

Ablation Studies

- Model variants to analyze how different representations for user preference affect performance:
  - (a) local embedding only (TAGNN-L)
  - (b) global embedding using average pooling only (TAGNN-Avg)
  - (c) attentive global embedding (TAGNN-Att)
  - (d) local embedding plus attentive global embedding (TAGNN-L+Att)

Ablation Studies (cont.)



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Wrapping Up

1. Session-based recommendation is indispensable where users' preference and historical records are hard to obtain.
2. We have developed a novel target attentive graph neural network model for session-based recommendation.
3. By incorporating graph modeling and a target-aware attention module, the proposed TAGNN jointly considers user interests given a certain target item as well as complex item transitions in sessions.
4. Extensive experiments on real-world benchmark datasets demonstrate the effectiveness of our model.

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THANKS
Code
Paper
Slides