SDM: Sequential Deep Matching Model for Online Large-scale Recommender System

Fuyu Lv Taiwei Jin Changlong Yu Fei Sun
Quan Lin Keping Yang Wilfred Ng

Alibaba Group 阿里巴巴集团

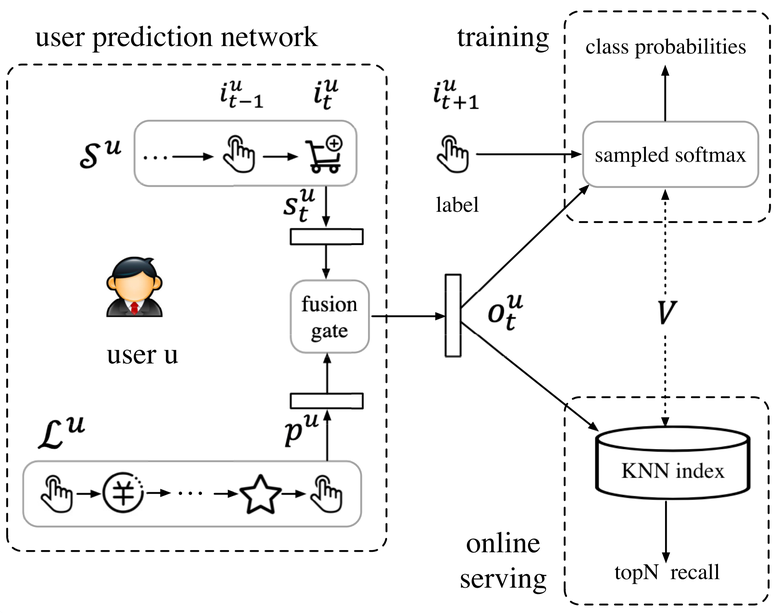
The Hong Kong University of Science and Technology

Motivation

- To capture dynamic evolution of users' interests, we introduce deep sequential recommendation model in matching stage of recommender system at Taobao.
- For the purpose of representing difference levels of interest, we model user behavior sequences by combing short-term sessions and long-term behaviors.
- We tackle two inherent problems in real- world applications: (1) users' multiple interest tendencies in one session. (2) effectively combing short-term and long-term preferences.

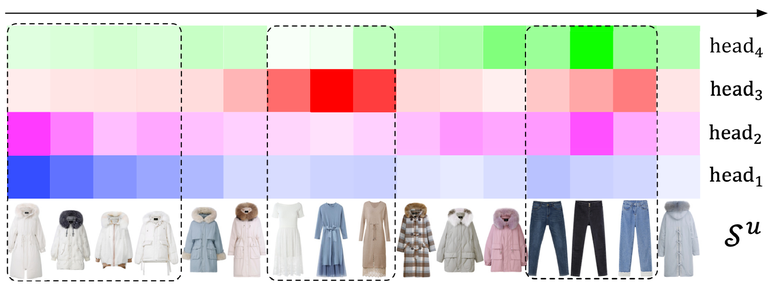
System Deployment

The item embedding vectors V are imported into a KNN search system. Meanwhile, the user prediction network is deployed on a high-performance real-time inference system of machine learning.

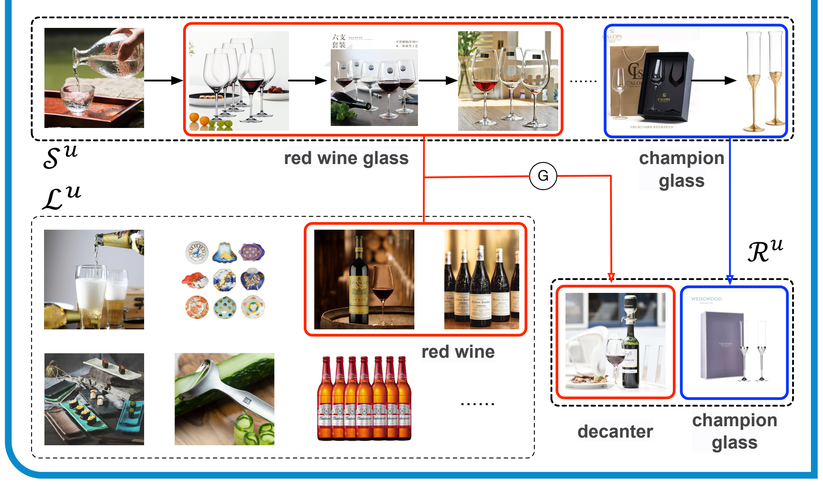


Case Study

Visualization of attention weights from head_1 to head_4 in multi-head attention over a short-term session $\mathcal{S}^u$ sampled from offline test dataset of Taobao.



A short-term session $\mathcal{S}^u$ and long-term behaviors $\mathcal{L}^u$ from a sampled user on our online system.



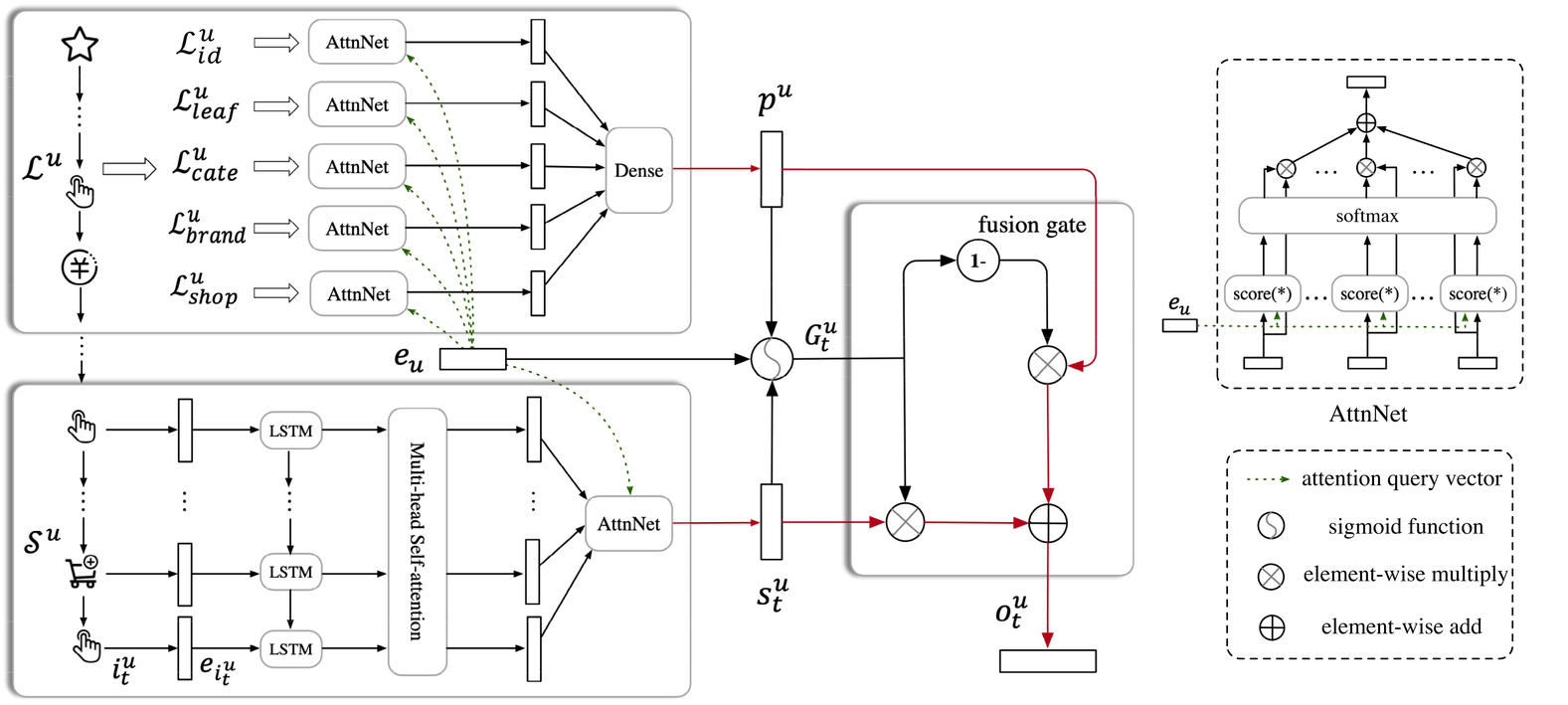
Sample Source Code

We are recommendation team of Alibaba Group.

Welcome to join us!

(a) Github (b) Wechat

Model Design



- **Sequence Generation:** We get each latest session of user u, namely $\mathcal{S}^u$, by sorting the interacted items in the ascending order of time. The long-term behaviors of u that happened before $\mathcal{S}^u$ in past 7 days are denoted by $\mathcal{L}^u$.
- **Embedding:** We describe items and users from different side information.
- **Recurrent Layer:** To capture and characterize the global temporal dependency in the short-term sequence data, we apply LSTM network as the recurrent cell.
- **Attention Mechanism:** Multi-head attention is applied to solve the issue of multiple interests by representing preferences from different views.
- **Long-term Behaviors Fusion:** We elaborately design a gated neural network that takes user profile, short-term and long-term representations as inputs.

Data Sets and Evaluations

Statistics of Offline and Online Datasets

Dataset	Data Type	Data Split	#[a]Users	#Items	#Records	#Sessions	S.len[b]	L.size[c]	Time Interval
JD	offline	train	802,479	154,568	9,653,777	2,666,189	3.3	20	15/Mar/2018 - 8/Apr/2018
		test	10,366	74,564	498,492	15,069	8.6	20	9/Apr/2018 - 15/Apr/2018
Taobao	offline	train	498,633	2,053,798	45,157,298	7,011,385	6.1	20	15/Dec/2018 - 21/Dec/2018
		test	13,237	588,306	1,170,401	13,237	9.2	20	22/Dec/2018
	online	train	3.3×10^8	1×10^8	2.1×10^{10}	2.7×10^9	7.1	50	Dec/2018
		test	3.3×10^8	1×10^8	/	/	8.1	50	Dec/2018

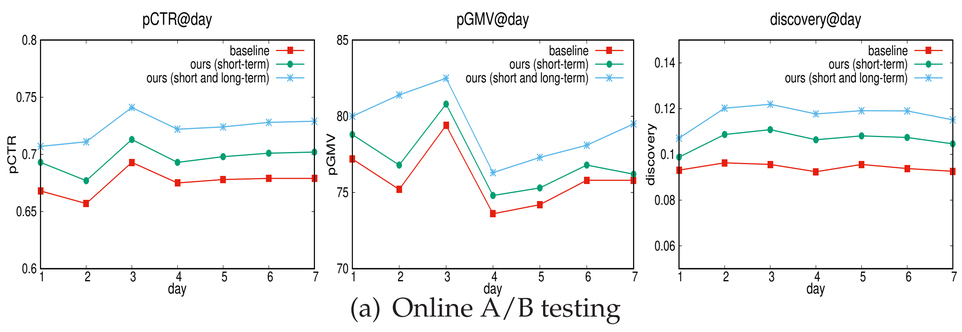
[a] # means the number of. [b] S.len is the average length of short-term behaviors. [c] L.size is the maximum size of each subset in long-term behaviors.

Evaluation Metrics

- For offline testing, we use **HitRate@K**, **Precision@K**, **Recall@K** and **F1@K**.
- For online testing, we consider the most important online metrics: **pCTR**, **pGMV** and **discovery**.

Experiments

Models	Taobao				JD			
	HitRate@100	Recall@100	Precision@100	F1@100	HitRate@20	Recall@20	Precision@20	F1@20
Item-based CF	60.27%	3.24%	2.00%	2.43%	67.50%	9.08%	9.41%	8.99%
DNN	60.88%	2.85%	1.83%	2.18%	68.43%	8.93%	9.65%	8.98%
GRU4REC	65.60%	3.66%	2.30%	2.77%	69.44%	9.33%	9.83%	9.29%
NARM	66.97%	3.57%	2.25%	2.70%	70.33%	9.07%	9.58%	9.04%
SHAN	67.30%	3.71%	2.33%	2.80%	70.54%	9.42%	10.02%	9.41%
BINN	67.55%	3.49%	2.20%	2.64%	72.19%	9.38%	9.93%	9.36%
SDMMA	68.24%	3.68%	2.32%	2.79%	70.41%	9.21%	9.72%	9.18%
PSDMMA	69.43%	3.75%	2.37%	2.84%	71.21%	9.21%	9.78%	9.20%
PSDMMAL	70.72%	**3.86%**	2.44%	**2.93%**	73.25%	9.47%	10.13%	9.48%
PSDMMAL-N	**73.13%**	3.83%	**2.45%**	2.92%	**74.33%**	**9.68%**	**10.42%**	**9.72%**
PSDMMAL-NoS	65.41%	3.38%	2.14%	2.56%	70.07%	9.05%	9.60%	9.03%



(a) Online A/B testing

#heads	HitRate@K	Recall@K	Precision@K	F1@k
1	70.00%	3.82%	2.40%	2.88%
2	70.64%	3.83%	2.41%	2.89%
4	**70.72%**	**3.86%**	**2.44%**	**2.93%**
8	70.21%	3.77%	2.37%	2.85%

fusion	HitRate@K	Recall@K	Precision@K	F1@K
multiply	67.09%	3.42%	2.16%	2.59%
concat	69.74%	3.70%	2.34%	2.80%
add	70.24%	3.75%	2.37%	2.84%
gated	**70.72%**	**3.86%**	**2.44%**	**2.93%**

(b) Effectiveness of multi-head and gate