Behavior Sequence Transformer for E-commerce Recommendation in Alibaba

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Introduction

Despite the success of Embedding&MLP framework on CTR, it is inherently far from satisfying since it ignores one type of very important signals in practice, i.e., the sequential signal underlying the users' behavior sequences, i.e., users' clicked items in order. In reality, the order matters for predicting the future clicks of users. For example, a user tends to click a case for a cellphone after he or she bought an iphone at Taobao, or tries to find a suitable shoes after buying a pair of trousers. In this sense, it is problematic without considering this factor when deploying a prediction model in the rank stage at Taobao.

To address the aforementioned problems, we try to incorporate sequential signal of users' behavior sequences into RS at Taobao. We apply the self-attention mechanism to learn a better representation for each item in a user's behavior sequence by considering the sequential information in embedding stage, and then feed them into MLPs to predict users' responses to candidate items. The key advantage of the Transformer is that it can better capture the dependency among words in sentences by the self-attention mechanism, and intuitively speaking, the "dependency" among items in users' behavior sequences can also be extracted by the Transformer. Therefore, we propose the user **B**ehavior **S**equence **T**ransformer (**BST**) for e-commerce recommendation at Taobao.

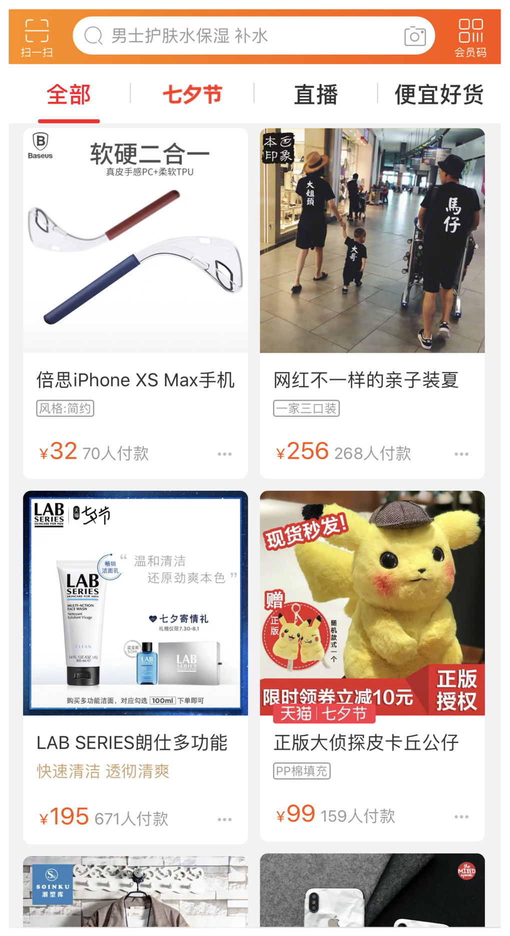

Figure 1:Taobao recommender system.

Architecture

The model architecture of the proposed BST is show in Figure 2. BST takes as input the user's behavior sequence, including the target item, and "Other Features". It firstly embeds these input features as low-dimensional vectors. To better capture the relations among the items in the behavior sequence, the transformer layer is used to learn deeper representation for each item in the sequence. Then by concatenating the embeddings of Other Features and the output of the transformer layer, the three-layer MLPs are used to learn the interactions of the hidden features, and sigmoid function is used to generate the final output. Note that the "Positional Features" are incorporated into "Sequence Item Features".

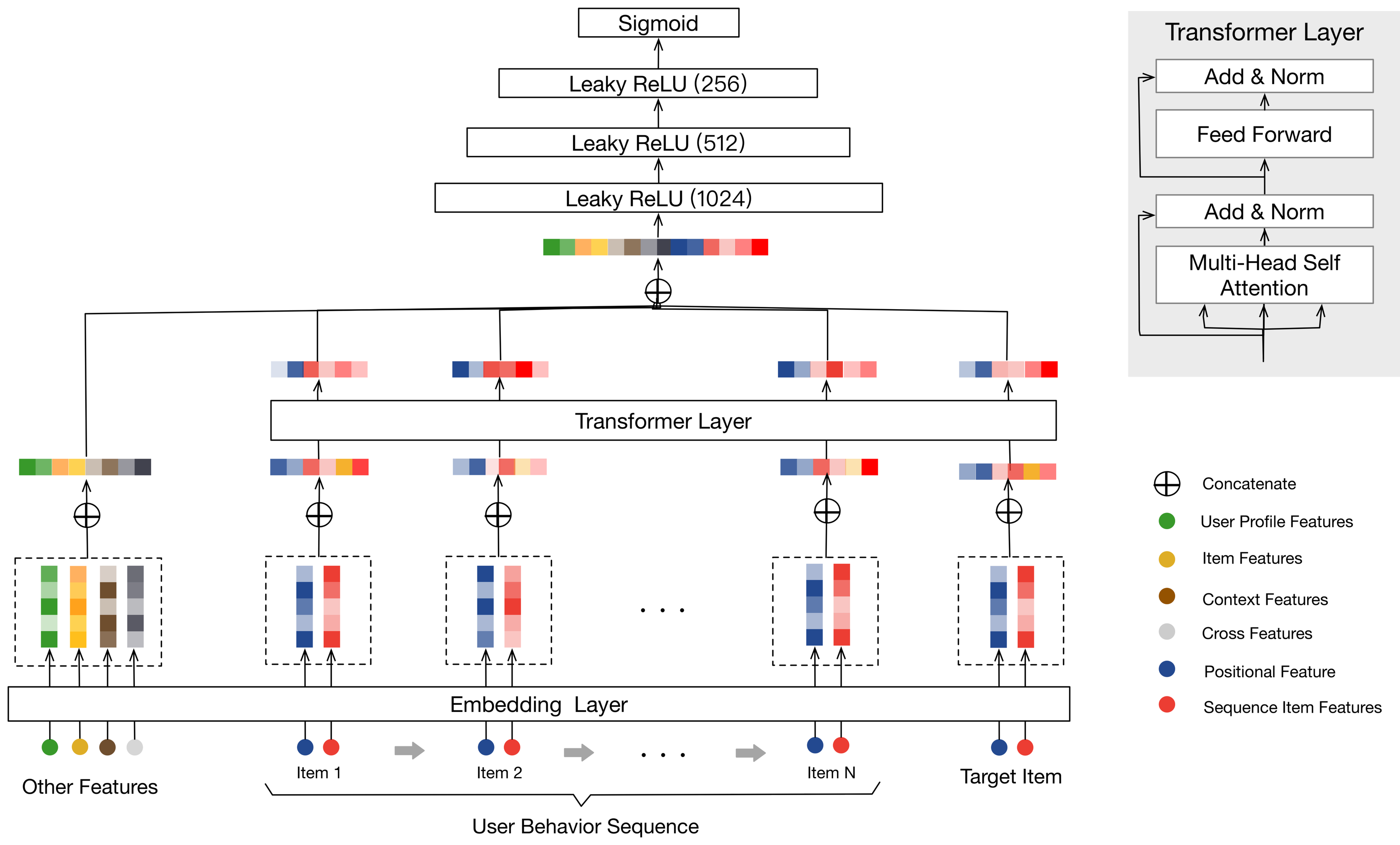

Figure 2:Architecture of BST.

The key components of BST is Transformer layer, which learns a deeper representation for each item by capturing the relations with other items in the behavior sequences. The Transformer is consist of self-attention layer, point-wise feed-forward networks and stacking the self-attention blocks. Besides, LayerNorm is add for avoid overfitting and learn meaningful features hierarchically.

Table 1:The "Other Features" shown in left side of Figure 2. We use much more features in practice, and show a number of effective ones for simplicity.

User	Item	Context	Cross	Sequence item
gender	category_id	match_type	age * item_id	item_id
age	shop_id	display position	os * item_id	category_id
city	tag	page No.	gender * category_id	position bias
...	...	...	...	...

For Sequence item, we use two types of features to represent, "Sequence Item Features"(in red) and "Positional Features" (in dark blue), where "Sequence Item Features" include *item_id* and *category_id*, and "Positional Features" is time difference between the recommending time and the timestamp when user click item.

Experiment

Dataset

Experiment dataset is constructed from the log of Taobao App. We construct an offline dataset based on users' behaviors in eight days. We use the first seven days as training data, and the last day as test data. The statistics of the dataset is shown in Table 2. The dataset is extremely large and sparse.

Table 2:Statistics of the constructed Taobao dataset.

Dataset	#Users	#Items	#Samples
Taobao	298,349,235	12,166,060	47,556,271,927

Results Analysis

The results are shown in Table 3, from which, we can see the superiority of BST comparing to baselines. In specific, the AUC of offline experiment is improved from 0.7734 (WDL), 0.7846(WDL(+Seq)) and 0.7866 (DIN) to 0.7894 (BST). In online experiments, we show that BST clearly outperforms the WDL by 7.57% increase in CTR metric, outperforms other methods.

Table 3:Offline AUCs and online CTR gains of different methods. Online CTR gain is relative to the control group.

Methods	Offline AUC	Online CTR Gain	Average RT(ms)
WDL	0.7734	-	13
WDL(+Seq)	0.7846	+3.03%	14
DIN	0.7866	+4.55%	16
BST($b=1$)	**0.7894**	**+7.57%**	20
BST($b=2$)	0.7885	-	-
BST($b=3$)	0.7823	-	-

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