

# Non-invasive Self-attention for Side Information Fusion in Sequential Recommendation

Chang Liu<sup>1</sup>, Xiaoguang Li<sup>2\*</sup>, Guohao Cai<sup>2</sup>, Zhenhua Dong<sup>2</sup>, Hong Zhu<sup>2</sup>, Lifeng Shang<sup>2</sup>

<sup>1</sup> The University of Hong Kong, <sup>2</sup> Huawei Noah's Ark Lab

lcon7@connect.hku.hk, {lixiaoguang11, caiguohao1, dongzhenhua, zhuhong8, shang.lifeng}@huawei.com

## Abstract

Sequential recommender systems aim to model users' evolving interests from their historical behaviors, and hence make customized time-relevant recommendations. Compared with traditional models, deep learning approaches such as CNN and RNN have achieved remarkable advancements in recommendation tasks. Recently, the BERT framework also emerges as a promising method, benefited from its self-attention mechanism in processing sequential data. However, one limitation of the original BERT framework is that it only considers one input source of the natural language tokens. It is still an open question to leverage various types of information under the BERT framework. Nonetheless, it is intuitively appealing to utilize other side information, such as item category or tag, for more comprehensive depictions and better recommendations. In our pilot experiments, we found naive approaches, which directly fuse types of side information into the item embeddings, usually bring very little or even negative effects. Therefore, in this paper, we propose the **NON**-inVasive self-Attention mechanism (NOVA) to leverage side information effectively under the BERT framework. NOVA makes use of side information to generate better attention distribution, rather than directly altering the item embeddings, which may cause information overwhelming. We validate the NOVA-BERT model on both public and commercial datasets, and our method can stably outperform the state-of-the-art models with negligible computational overheads.

## 1 Introduction

Recommender systems aim to model users' profiles for personalized recommendations. They are challenging to design yet business valuable. The sequential recommendation task is to predict the next item a user would be interested in, given his historical behaviors (Fang et al. 2019). Compared with user-level or similarity-based static methods, sequential recommender systems also model the users' varying interests, hence are considered more appealing for real applications.

Recently, there is a trend to apply neural network approaches for sequential recommendation tasks, such as RNN and CNN frameworks (Fang et al. 2019). The neural networks are now widely applied and generally perform

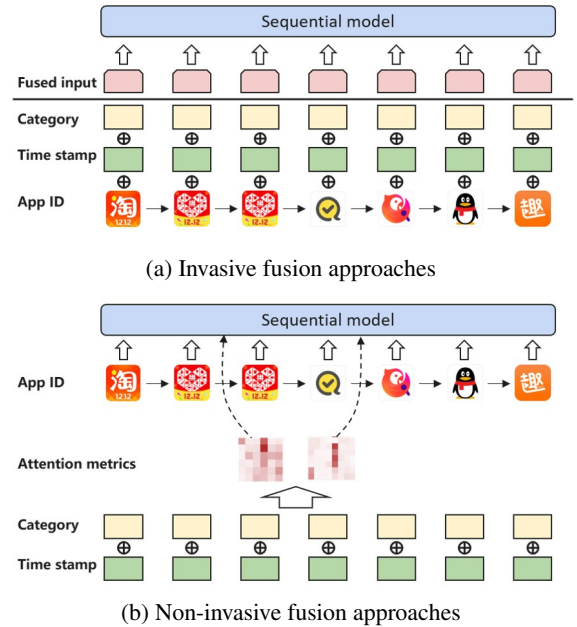


Figure 1: An illustration of invasive and non-invasive methods. The invasive methods fuse all kinds of information irreversibly, and then feed them into sequential models. For the non-invasive method, the side information only participants in the attention matrix calculation, while item information is kept in an independent vector space.

stronger than traditional models such as (Davidson et al. 2010), (Linden, Smith, and York 2003), (Rendle et al. 2012), (Koren, Bell, and Volinsky 2009), (Rendle, Freudenthaler, and Schmidt-Thieme 2010) and (He and McAuley 2016).

As stated in (Fang et al. 2019), within the family of artificial neural networks, the transformer-based models (Vaswani et al. 2017) are considered more advanced in handling sequential data, for their self-attention mechanism. Studies like (Sun et al. 2019; Chen et al. 2019b,a) that apply transformers for sequential recommendation tasks have proved their superiority over other frameworks such as CNN and RNN (Hidasi et al. 2015). The BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al. 2018) is a leading transformer model with bidirectional self-

\*Equal contribution

attention design. With the BERT model, (Sun et al. 2019) achieves the SOTA accuracy, obviously higher than the unidirectional transformer methods (Radford et al. 2018; Kang and McAuley 2018).

Although the BERT framework has achieved SOTA performances for many tasks, it has not been systematically studied for utilizing different types of side information. Intuitively, in addition to item IDs, it is attractive to leverage the side information, such as ratings and item descriptions, for more comprehensive depictions hence higher prediction accuracy. However, the BERT framework is originally designed to take only one type of inputs (i.e., word IDs), limiting the use of side information. Through pilot experiments, we found that existing methods usually utilize side information invasively (Figure 1), but with scarce effects. Theoretically, side information should be beneficial by providing more data. Nonetheless, it is challenging to design models that can efficiently make use of the extra information.

Hence, in this research, we study how to utilize various side information efficiently under the successful BERT framework. We propose a novel Non-inVasive self-Attention mechanism (NOVA) that can consistently improve prediction accuracy with side information and achieve state-of-the-art performances in all our experiments. As shown in Figure 1, with NOVA, the side information acts as an auxiliary for the self-attention module to learn better attention distribution, instead of being fused into item representations, which might cause side effects such as information overwhelming. We verified the NOVA-BERT design on both laboratory datasets and a private dataset collected from a real application store. The results prove the superiority of the proposed method. Three of our main contributions are:

1. We present the NOVA-BERT framework, which can efficiently employ various side information for sequential recommendation tasks.
2. We also propose the non-invasive self-attention (NOVA) mechanism, a novel design that enables self-attention for compounded sequential data.
3. Detailed experiments and deployment are conducted to prove the NOVA-BERT’s effectiveness. We also include visualization analysis for better interpretability.

## 2 Related Works

The techniques for recommender systems have evolved for a long time. Recently, researchers tend to adopt neural networks in the recommender system domain for their powerful ability (Fang et al. 2019). Moreover, among the DNNs, the trend has also shifted from CNN to RNN, and then Transformers (Vaswani et al. 2017). One of the Transformer-based models, BERT (Devlin et al. 2018) is considered an advanced sequential neural network, for its bidirectional self-attention mechanism. (Sun et al. 2019) has proven the superiority of BERT by achieving the SOTA performances.

In the sequential recommendation domain, it is also a long-discussed topic to make full use of side information to improve accuracy. As shown in Table 1, under different frameworks such as CNN, RNN, Attention models, and

BERT, several previous works tried to leverage side information. Nonetheless, most of them use side information without too much investigation on how side information should be added. Almost all of them use a simple kind of practices we call ‘invasive’ fusion.

**Invasive approaches** Most previous works, like (Hidasi et al. 2016), directly fuse side information into the item representations, as shown in Figure 1(a). They usually use fusing operations (e.g., summation, concatenation, gated sum) to merge extra information with the item ID information, and then feed the mixture to the neural network. We call this kind of direct merging practices ‘invasive approaches’ because they alter the original representations.

As shown in Table 1, previous CNN and RNN works have tried to leverage side information by directly fusing the side information into item embeddings with operations such as concatenation and addition. Some other works like GRU (Lei, Ji, and Li 2019) and (Hidasi et al. 2016) proposed a more complex mechanism of feature fusion gate and other training tricks, trying to make feature selection a learnable process. However, according to their experiment results, simple approaches cannot effectively leverage the rich side information under various scenarios. Although (Hidasi et al. 2016) improves prediction accuracy by deploying a parallel subnet for each type of side information, the model becomes cumbersome and inflexible.

Another research, (Bogina and Kuflik 2017), does not alter the item embeddings directly, but includes dwell time with RNN models by the trick called item boosting. The general idea is to let the loss function be aware of dwell time. The longer a user looks at an item, the more interested he/she is. However, this trick heavily depends on heuristics and is limited to behavior-related side information. On the other side, some item-related side information (e.g., price) describes items’ intrinsic features, which are not like dwell time and cannot be easily utilized by this approach.

## 3 Methodology

In this section, we introduce the research domain and our methodology in detail. In Sec. 3.1 to 3.3, we specify the research problem and explain side information, BERT, and self-attention. Then, we present our Non-invasive Self-attention and different fusion operations in Sec. 3.4. Finally, the NOVA-BERT model is illustrated in Sec. 3.5. We denote **NO**n-inVasive self-Attention by **NOVA** in short.

### 3.1 Problem Statement

Given a user’s historical interactions with the system, the sequential recommendation task asks the next item will be interacted with, or the next action will be made. Let  $u$  denotes a user, his/her historical interactions can be represented as a chronological sequence:

$$\mathbb{S}_u = [v_u^{(1)}, v_u^{(2)}, \dots, v_u^{(n)}]$$

where the term  $v_u^{(j)}$  represents the  $j$ th interaction (also known as behavior) the user has made (e.g., download an APP). When there is only one type of actions and no side

	Addition(weighted)	Concatenation	Gating	Loss fusion
CNN		CASER(Tang and Wang 2018)		
RNN	p-RNN(Hidasi et al. 2016)	MCI(Twardowski 2016), Zhang.(Zhang et al. 2014)	TISSA(Lei, Ji, and Li 2019)	IDT(Bogina and Kuflik 2017)
Attention-based	SASRec(Kang and McAuley 2018)	CSAN(Huang et al. 2018), ATrank(Zhou et al. 2018)	TISSA(Lei, Ji, and Li 2019)	
Hybrid		M3C & M3R (Tang et al. 2019)		
BERT	BERT4Rec(Sun et al. 2019)	Chen.(Chen et al. 2019a)		

Table 1: Previous studies involving side information fusion. The first column represents different backbones, and the first row represents different fusion methods.

information, each interaction can be represented by simply an item ID:

$$v_u^{(j)} = ID^{(k)}$$

where  $ID^{(k)} \in \mathbb{I}$ , denoting the  $k$ th item's ID.

$$\mathbb{I} = \{ID^{(1)}, ID^{(2)}, \dots, ID^{(m)}\}$$

is the vocabulary of all items to be considered in the system.  $m$  is the vocabulary size, indicating the total number of items in the problem domain.

Given the history of a user  $\mathbb{S}_u$ , the system predicts the next item that the user will interact with most likely:

$$I_{pred} = ID^{(\hat{k})}$$

$$\hat{k} = \arg\max_k P(v_u^{(n+1)} = ID^{(k)} | \mathbb{S}_u)$$

### 3.2 Side Information

Side information can be anything that provides extra useful information for recommendations, which can be categorized into two types, item-related or behavior-related.

Item-related side information is intrinsic and describes the item itself, besides item IDs (e.g., price, date of production, producer). Behavior-related side information is bounded with an interaction initiated by a user, such as type of action (e.g., purchase, rate), time of execution, or the user feedback scores. The order of each interaction (i.e., position IDs in original BERT) can also be taken as a kind of behavior-related side information.

If side information is involved, an interaction becomes:

$$v_u^{(j)} = (I^{(k)}, b_{u,j}^{(1)}, \dots, b_{u,j}^{(q)})$$

$$I^{(k)} = (ID^{(k)}, f_k^{(1)}, \dots, f_k^{(p)})$$

where  $b_{u,j}^{(\cdot)}$  denotes a behavior-related side information of the  $j$ th interaction made by user  $u$ .  $I^{(\cdot)}$  represents an item, containing an ID and several pieces of item-related side information  $f_k^{(\cdot)}$ . Item-related side information is static and stores intrinsic features of each particular item. Hence the vocabulary can be rewritten as:

$$\mathbb{I} = \{I^{(1)}, I^{(2)}, \dots, I^{(m)}\}$$

The goal is still to predict the next item's ID:

$$I_{pred} = ID^{(\hat{k})}$$

$$\hat{k} = \arg\max_k P(v_u^{(n+1)} = (I^{(k)}, b_1, b_2, \dots, b_q) | \mathbb{S}_u)$$

where  $b_1, b_2, \dots, b_q$  are the latent behavior-related side information, if behavior-related side information is considered. Noted that the model should still be able to predict the next item regardless of the behavior-related side information being assumptive or ignored.

### 3.3 BERT and Invasive Self-attention

BERT4Rec (Sun et al. 2019) is the first to utilize the BERT framework for sequential recommendation tasks, achieving SOTA performances. As shown in Figure 2, under the BERT framework, items are represented as vectors, which are called embeddings. During training, some items are randomly masked, and the BERT model will try to recover their vector representations and hence the item IDs, using the multi-head self-attention mechanism (Vaswani et al. 2017):

$$SA(Q, K, V) = \sigma\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where  $\sigma$  is the softmax function,  $d_k$  is a scale factor,  $Q$ ,  $K$  and  $V$  are derived components for query, key and value. The BERT follows an encoder-decoder design, to generate a contextual representation for each item in the input sequence. BERT employs an embedding layer to store  $m$  vectors, each corresponding to an item in the vocabulary.

To leverage side information, conventional methods like (Sun et al. 2019; Chen et al. 2019a) use separate embedding layers to encode side information into vectors, and then fuse them into the ID embeddings with a fusion function  $\mathcal{F}$ . This invasive kind of approach injects side information into the original embeddings, and generate a mixed representation:

$$E_{u,j} = \mathcal{F}(\mathcal{E}_{id}(ID),$$

$$\mathcal{E}_{f1}(f^{(1)}), \dots, \mathcal{E}_{fp}(f^{(p)}),$$

$$\mathcal{E}_{b1}(b_{u,j}^{(1)}), \dots, \mathcal{E}_{bq}(b_{u,j}^{(q)}))$$

where  $E_{u,j}$  is the integrated embedding for the  $j$ th interaction of user  $u$ ,  $\mathcal{E}$  is the embedding layer that encodes objects into vectors. The sequence of the integrated embeddings is fed into the model as the input of user history.

The BERT framework will update the representations layer by layer with self-attention mechanism:

$$R_{i+1} = \text{BERT\_Layer}(R_i)$$

$$R_1 = (E_{u,1}, E_{u,2}, \dots, E_{u,n})$$

In original BERT (Devlin et al. 2018) and Transformer (Vaswani et al. 2017), the self-attention operation is a positional invariant function. Therefore, a position embedding is added to each item embedding to encode the position information explicitly. Position embeddings can also be viewed as a type of behavior-related side information (i.e., the order of an interaction). From this perspective, the original BERT also take positional information as the only side information, using addition as the fusion function  $\mathcal{F}$ .

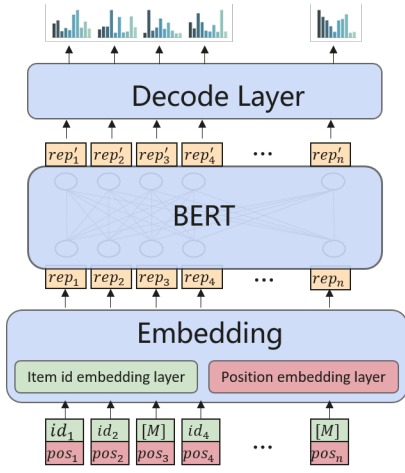


Figure 2: BERT4Rec. Item IDs and positions are encoded into vectors respectively, and then added together as integrated item representations. During training, item IDs are randomly masked (shown as  $[M]$ ) for the model to recover.

### 3.4 Non-invasive Self-attention (NOVA)

If we consider the BERT framework end-to-end, it is an auto-encoder with stacked self-attention layers. The identical embedding map is used in both encoding item IDs and decoding the restored vector representations. Therefore, we argue that the invasive methods have the drawback of compound embedding space, because item IDs are irreversibly fused with other side information. Mixing the information from IDs and other side information might make it unnecessarily difficult for the model to decode the item IDs.

Accordingly, we proposed a novel method called non-invasive self-attention (NOVA), to maintain the consistency of embedding space, while exploiting side information to model the sequences more efficiently. The idea is to modify the self-attention mechanism and carefully control the information source of the self-attention components, namely query  $Q$ , key  $K$ , and value  $V$  (Vaswani et al. 2017). More than the integrated embedding  $E$  defined in Section 3.3, the NOVA also keeps a branch for pure ID embeddings:

$$E_{u,j}^{(ID)} = \mathcal{E}_{id}(ID)$$

Hence, for NOVA, the user history now consists of two sets of representations, the pure ID embeddings and the integrated embeddings:

$$R_u^{(ID)} = (E_{u,1}^{(ID)}, E_{u,2}^{(ID)}, \dots, E_{u,n}^{(ID)})$$

$$R_u = (E_{u,1}, E_{u,2}, \dots, E_{u,n})$$

NOVA calculate  $Q$  and  $K$  from the integrated embeddings  $R$ , and  $V$  from the item ID embeddings  $E^{(ID)}$ . In practice we process the whole sequence in tensor form (i.e.,  $R$  and  $R^{(ID)} \in \mathbb{R}^{B \times L \times h}$ , where  $B$  is the batch size,  $L$  is the sequence length and  $h$  is the size of embedding vectors). NOVA can be formalized as:

$$\text{NOVA}(R, R^{(ID)}) = \sigma\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

with  $Q, K, V$  calculated by linear transform:

$$Q = RW_Q, K = RW_K, V = R^{(ID)}W_V$$

The comparison between NOVA and invasive ways for side information fusing is illustrated in Figure 3. Layer by layer, the representations along the NOVA layers are kept within a consistent vector space formed purely by the context of item IDs,  $E^{(ID)}$ .

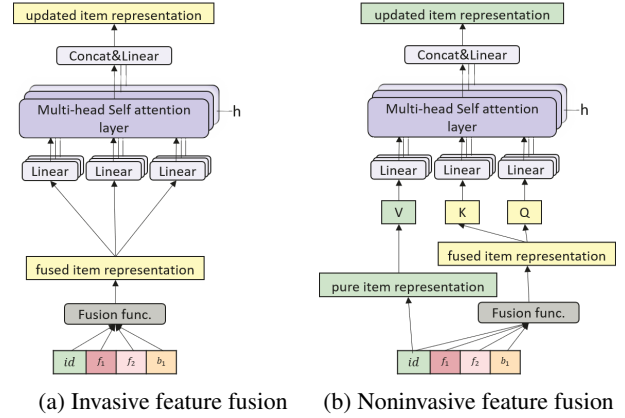


Figure 3: Comparison between invasive and non-invasive ways of self-attention for feature fusion. Both fuse item-related and behavior-related side information with a fusion function, but NOVA only fuse them in the Query & Key.

### 3.5 Fusion Operations

NOVA leverages side information differently from invasive methods, treating it as an auxiliary and fusing side information into Keys and Queries with the fusion function  $\mathcal{F}$ . In this research, we also study different kinds of fusion functions and their performances.

As mentioned above, position information is also a kind of behavior-related side information, and the original BERT utilizes it with the straightforward operation of addition:

$$\mathcal{F}_{\text{add}}(f_1, \dots, f_m) = \sum_{i=1}^m f_i$$

Moreover, we define the ‘concat’ fusor to concatenate all side information, followed by a fully connected layer to uniform the dimension:

$$\mathcal{F}_{\text{concat}}(f_1, \dots, f_m) = \mathbf{FC}(f_1 \odot \dots \odot f_m)$$

Inspired by (Lei, Ji, and Li 2019), we also design a gating fusor with trainable coefficients derived from the context:

$$\mathcal{F}_{\text{gating}}(f_1, \dots, f_m) = \sum_{i=1}^m G^{(i)} f_i$$

$$G = \sigma(FW^F)$$

where  $F$  is the matrix form of all the features  $[f_1, \dots, f_m] \in \mathbb{R}^{m \times h}$  and  $W^F$  is a trainable parameter of  $\mathbb{R}^{h \times 1}$ ,  $h$  is the dimension of feature vectors to be fused,  $f_i \in \mathbb{R}^h$

### 3.6 NOVA-BERT

As illustrated in Figure 4, we implement our NOVA-BERT model under the BERT framework with the proposed NOVA operation. Each NOVA layer takes two inputs, the supplementary side information and the sequences of item representations, then outputs updated representations of the same shape, which will be fed to the next layer. For the input of the first layer, the item representations are pure item ID embeddings. Since we only use side information as auxiliary to learn better attention distributions, the side information does not propagate along with NOVA layers. The identical set of side information is explicitly provided for each NOVA layer.

The NOVA-BERT follows the architecture of the original BERT in (Devlin et al. 2018), except replacing the self-attention layers by NOVA layers. Hence, the extra parameters and computation overheads are negligible, mainly introduced by the lightweight fusion function.

We believe that with NOVA-BERT, the hidden representations are kept in the same embedding space, which will make the decoding process a homogeneous vector search and benefit the prediction. Results in the next section also empirically verify the effectiveness of NOVA-BERT.

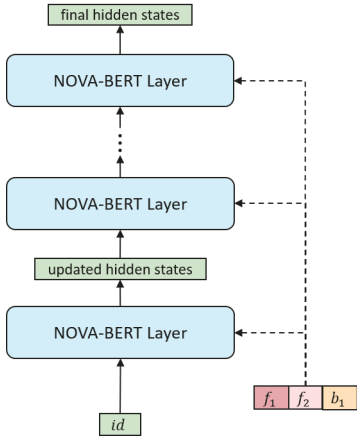


Figure 4: NOVA-BERT. Each NOVA layer takes two inputs, item representations and side information.

## 4 Experiments

In this section, we evaluate the NOVA-BERT framework on both public and private datasets, aiming to discuss NOVA-BERT more in the following aspects:

- 1. Effectiveness.** Whether the NOVA-BERT approach outperforms conventional invasive feature fusion methods?
- 2. Thoroughness.** How do the components of NOVA-BERT contribute to the improvements (e.g., different types of side information, fusion function)?
- 3. Interpretability.** How does side information affect the attention distribution hence improve prediction accuracy?
- 4. Efficiency.** How does NOVA-BERT perform in terms of efficiency for future real-world deployments?

Dataset	#records	#users	Len	Side information available
ML-1m	988,129	6,040	165	year, genres, rating
ML-20m	19,723,277	138,493	142	year, genres, rating
APP	1,774,867	100,000	18	category, developer, size, tag

Table 2: Dataset statistics. ‘Len’ for mean sequence length.

### 4.1 Experiment Settings

**Datasets** We evaluated our methods on the public MovieLens datasets and a real-world dataset called APP. Please refer to Table 2 for detailed descriptions of the datasets.

We sort the rating/downloading records by chronological order, to construct each user’s interaction history. Following the practice of (Kang and McAuley 2018; Sun et al. 2019), we use the heading subsequence for each user’s record without the last two elements as the training set. The second last items in the sequences are used as the validation set for tuning hyper-parameters and finding the best checkpoint. The last elements from these sequences construct the test set. Short sequences having less than five elements are discarded to eliminate disturbances from the cold-start problem. The experiment aims to focus on side information fusion and hold a fair comparison with other methods.

**Hyper-parameter Settings** For all the models in this research, we train them with Adam optimizer using a learning rate of  $1e-4$  for 200 epochs, with a batch size of 128. We fix the random seeds to alleviate the variation caused by randomness. The learning rate is adjusted by a linear decay scheduler with a 5% linear warm-up.

We also apply grid-search to minimize the bias of our experiment results. The searching space contains three hyper-parameters,  $hidden\_size \in \{128, 256, 512\}$ ,  $num\_heads \in \{4, 8\}$  and  $num\_layers \in \{1, 2, 3, 4\}$ . In the end we use 4 heads and 3 layers, as well as 512 hidden size for MovieLens Datasets and 256 for the APP dataset.

### 4.2 Evaluation Metrics

Following (Kang and McAuley 2018), we employ two widely-adopted evaluation metrics: Hit Ratio(HR@k), and Normalized Discounted Cumulative Gain (NDCG@k), with  $k \in \{5, 10\}$ . Particularly, we rank the whole vocabulary, which means the model gives a prediction score on every item, indicating the degree of recommendation.

Some practices, such as (Sun et al. 2019) uses a smaller candidate set, for example, the ground truth plus 100 randomly sampled negative items with chance proportional to popularity. During pilot experiments, we found that the practice may result in severe bias. For example, the unpopular ground-truth item is obvious among other negative candidates, who are drawn because of their high popularity. The model tends to take advantage of the loose metric. Therefore, we rerun the baselines with the ranking-all metric.

### 4.3 Experiment Results

As stated before, (Sun et al. 2019) has proven the extraordinary performance of the BERT framework under a wide

Method	Fusion func	ML-1m				ML-20m				APP			
		HR@10	ND@10	HR@5	ND@5	HR@10	ND@10	HR@5	ND@5	HR@10	ND@10	HR@5	ND@5
BERT4Rec	Add (posID)	25.24	13.98	16.61	11.20	30.70	18.83	22.89	16.31	27.44	16.39	19.73	13.91
BERT + Invasive methods	Add	24.65	13.73	16.82	11.23	31.00	18.94	23.09	16.39	27.57	16.45	19.82	13.95
	Concat	24.92	14.00	16.57	11.30	31.21	19.21	23.38	16.68	27.38	16.11	19.38	13.53
	Gating	24.60	13.61	16.39	10.98	31.29	19.25	23.44	16.71	27.61	16.36	19.72	13.82
NOVA-BERT	Add	28.34	16.55	20.22	13.95	31.65	19.40	<b>23.59</b>	16.76	27.73	16.54	19.88	14.02
	Concat	27.70	16.18	19.82	13.64	<b>31.68</b>	<b>19.42</b>	<b>23.59</b>	<b>16.81</b>	<b>28.00</b>	16.65	20.02	14.08
	Gating	<b>28.65</b>	<b>16.80</b>	<b>20.45</b>	<b>14.16</b>	31.22	19.15	23.30	16.60	27.85	<b>16.68</b>	<b>20.08</b>	<b>14.17</b>

Table 3: Experiment results in %, ‘ND’ stands for the NDCG metric. We evaluate NOVA-BERT by comparing it with the SOTA model BERT4Rec (Sun et al. 2019) and its invasive modifications. The best results are boldfaced. For each dataset, we use all available side information. The baseline BERT4Rec, however, does not support other side information except position ID.

range of scenarios. Therefore, in this paper, we choose their SOTA method as the baseline and focus on leveraging side information under the BERT framework. We also examine the fusion functions of addition, concatenation, and gating.

In Table 3, the NOVA-BERT outperforms all other methods on the three datasets and all metrics. Compared with the Bert4Rec(Sun et al. 2019) exploiting only position IDs, the invasive approaches use several kinds of side information but have very limited or even adverse improvements. On the contrary, the NOVA-BERT can effectively leverage the side information and stably outperform all other methods.

However, the improvements brought by NOVA are on different scales for the datasets. In our experiments, for larger and denser datasets, the scale of improvement decreases. For the ML-1m task, NOVA with gating fuser outperforms the baseline by 13.51% in HR@10, while all invasive methods perform worse than the baseline. However, in ML-20M and APP tasks, the relative improvements brought by noninvasive approaches decrease to 3.19% and 1.48%, respectively. We hypothesize that with a more affluent corpus, the models are possible to learn good enough item embeddings even from the item context itself, leaving a smaller space for side information to make supplements.

Furthermore, the results also demonstrate the robustness of NOVA-BERT. No matter what fusion function is employed, the NOVA-BERT can consistently outperform the baselines. The best fusion function may depend on the dataset. In general, the gating method has a strong performance, possibly benefited from its trainable gating mechanism. The results also suggest that for real-world deployments, the type of fusion function can be a hyper-parameter and should be tuned according to the dataset’s intrinsic properties, to reach the best online performance.

#### 4.4 Contributions of Different Side Information

In Section 3.2, we categorized side information as item-related and behavior-related. We also investigate the contributions of the two types of side information under the **ML-1m** task. By definition, publishing year and category are item-related, while rating score is behavior-related.

Table 4 shows the results of different types of side information. The original BERT framework considers no side information except the position ID, denoted as *None* in the first row. When complete side information is given, the NOVA-

BERT presents the most significant improvement. Meanwhile, in separate, the item-related and behavior-related side information bring nonobvious benefits to the accuracy. Since item-related side information (year and genre) is intrinsic features of the movies, it might be latently derived from the massive data sequences, hence resulting in the similar accuracy. On the other hand, if behavior-related side information is also combined, the improvement is noticeable greater than the sum of improvements brought by either of them. This observation suggests that the impacts brought by different types of side information are not independent. Moreover, the NOVA-BERT benefits more from synthesis side information and has a strong ability to utilize the rich data without being troubled by information overwhelming.

In the case of **ML-1m**, comprehensive side information can boost the accuracy most under NOVA-BERT. However, it is reasonable to believe that the contributions of different types of side information also depends on the data quality. For that reason, we also consider side information selection as a dataset dependent factor.

Side-info	HR@10	NDCG@10	HR@5	NDCG@5
None	0.2809	0.1636	0.2015	0.1383
Item	0.2743	0.1609	0.1927	0.1346
Behavior	0.2815	0.1655	0.2005	0.1393
All	0.2865	0.1680	0.2045	0.1416

Table 4: Ablation study on side information type. NOVA-BERT with gating fuser is tested on the ML-1m dataset. Side information of each row: I) no extra side information (posID only), II) item-related (year+genre), III) behavior-related (rating), IV) all available side information.

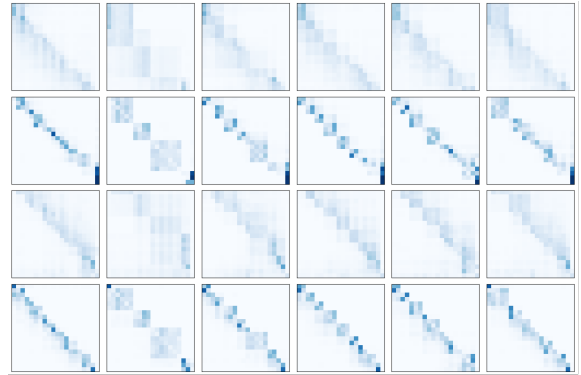
#### 4.5 Visualization of Attention Distribution

To provide more discussions on NOVA-BERT’s interpretability, we visualize the attention distribution of the bottom NOVA layer. In Figure 5, we present the comparison of attention scores of 6 randomly chosen samples (columns), each row represents a head from the multi-head self-attention. Every pixel denotes the attention intensity from the row item to the column item. All the attention scores in a row sum to 1. In Figure 5(a), the attention scores from the original BERT4Rec model is visualized. In Figure





(a) BERT4Rec. Position ID is the only side information supported.



(b) NOVA-BERT. All available side information employed.

Figure 5: Influence of side information on attention distribution. The graphs show attention matrices of different attention heads (4 rows) from random samples (6 columns). Each matrix denotes the item-to-item attention. The darker the color, the higher the score. Compared with the original BERT4Rec, the NOVA-BERT presents an articulate pattern of attention distribution.

5(b), we show the attention scores of the NOVA-BERT. The model is fed with all available kinds of side information.

As shown in the graph, the attention scores from the NOVA-BERT show a stronger pattern in terms of locality, concentrating approximately along the diagonal. On the other side, it is not observed in the graph for the baseline model. The contrast is prevailing, according to our observation over the whole dataset. We noticed that side information leads the model to form more explicit attention in early layers. The observation demonstrates that the NOVA-BERT, which takes side information as an auxiliary for calculating attention matrix, can learn targeted attention distribution and hence improve the accuracy.

Additionally, we also conduct case studies to understand more about the attention distribution of NOVA, with more detailed analysis. Please refer to the Appendix for details.

**More explanations on NOVA’s attention matrix** Because of the sophisticated high dimension embedding space and the intricate network architecture, it is hard to fully comprehend how and why an item attended the other. However, from the visualization results, we found that with side information provided, there is a trend for the NOVA-BERT to learn a more structured pattern of attention scores.

Due to the limited interpretability of deep neural networks, we cannot assert that NOVA-BERT’s attention pattern is absolutely better. Nonetheless, we found the observed patterns similar to those in the study (Kovaleva et al. 2019), which presents a correlation between this kind of attention distributivity and better performances in natural language processing tasks. Additionally, NOVA-BERT also shows the correlation in sequential recommendation tasks, suggesting that attention is indeed smartly distributed.

## 5 Deployment and Cost of NOVA-BERT

NOVA-BERT consistently surpasses the current deployed methods in real-world scenarios, according to our online tests. In Table 5, the efficiency results of NOVA-BERT and part of the baseline models are listed. We evaluate the mod-

els in terms of FLOPs and sizes, with ‘addition’ being the fusion function. As shown in the table, NOVA-BERT has almost no extra computational overheads and the same size as the invasive method. Moreover, since the NOVA-BERT is well supported by parallel computing and GPU acceleration, the inference time is also approximately the same as the original BERT. We also claim that since the parameters are mainly brought by extra embedding layers, for deployment we may use look-up table to replace the embedding layers and result in similar model size as the original BERT.

	#FLOPs ( $\times 10^9$ )	Size (MB)
Ori-BERT	0.4796	35.5
Invasive-add	0.4986	42.6
NOVA-BERT (add)	0.4988	42.6

Table 5: Complexity in computation and model size.

## 6 Conclusion and Future Work

In this work, we present the NOVA-BERT recommender system and the non-invasive self-attention mechanism (NOVA). Instead of fusing side information directly into the item representations, the proposed NOVA mechanism utilizes the side information as directional guidance and keeps the item representations undoped in their vector space. We evaluate the NOVA-BERT on both experimental datasets and industrial applications, achieving SOTA performances with negligible overheads in computation and model size.

Although the proposed method reaches the SOTA performance, there are still several intriguing directions for future studies. For example, fusing side information at every layer may not be the best approach, and stronger fusing functions are also expected. Additionally, we will continue studying and evolving our approach for higher online performances as well as deploy it in industrial products.

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