

Attention over Self-attention: Intention-aware Re-ranking with Dynamic Transformer Encoders for Recommendation

Zhuoyi Lin, Sheng Zang, Rundong Wang, Zhu Sun, Chi Xu, and Chee Keong Kwoh

Abstract—Re-ranking models refine the item recommendation list generated by the prior global ranking model with intra-item relationships. However, most existing re-ranking solutions refine recommendation list based on the implicit feedback with a shared re-ranking model, which regrettably ignore the intra-item relationships under diverse user intentions. In this paper, we propose a novel Intention-aware Re-ranking Model with Dynamic Transformer Encoder (RAISE), aiming to perform user-specific prediction for each target user based on her intentions. Specifically, we first propose to mine latent user intentions from text reviews with an intention discovering module (IDM). By differentiating the importance of review information with a co-attention network, the latent user intention can be explicitly modeled for each user-item pair. We then introduce a dynamic transformer encoder (DTE) to capture user-specific intra-item relationships among item candidates by seamlessly accommodating the learnt latent user intentions via IDM. As such, RAISE is able to perform user-specific prediction without increasing the depth (number of blocks) and width (number of heads) of the prediction model. Empirical study on four public datasets shows the superiority of our proposed RAISE, with up to 13.95%, 12.30%, and 13.03% relative improvements evaluated by Precision, MAP, and NDCG respectively.

Index Terms—Item re-ranking, User-specific prediction, User intention modeling, Dynamic transformer.

1 INTRODUCTION

IN the era of big data, recommender systems are widely adopted by the online platforms (e.g., Amazon and YouTube), so as to alleviate the problem of information overload [1], [2]. Accordingly, latent factor models, e.g., matrix factorization [3], [4], and deep learning models, e.g., NeuMF [5], have demonstrated their effectiveness to achieve personalized recommendations by learning user and item representations. Despite the great success, one fundamental assumption of the above solutions is that a global ranking model is designed to optimize the overall performance of item recommendations. This could lead to sub-optimal for individual users because it ignores the local item distributions for each user [6], [7].

To remedy the above issue, a shared re-ranking model is employed to refine the initial recommendation lists provided by the prior global ranking model for each user. Specifically, by taking into account the relationships among item candidates in a user’s initial recommendation list, the intra-item relationships for the target user can be explicitly modeled [6], [7], [8]. As such,

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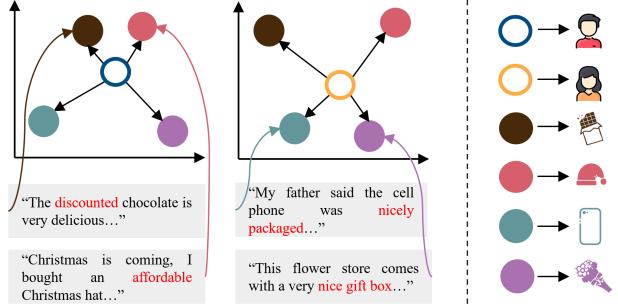


Fig. 1: An illustration of users’ complex intentions in the latent space. The left user can be price-sensitive and hence cheap items (i.e., chocolate and Christmas hat) are closer in the latent space, while the right user may prefer the nicely packaged items so that the representations of cell phone and bouquet are more similar.

re-ranking models are able to re-rank the item candidates and generate more personalized recommendation list for each target user. However, we argue that the existing manner of modeling intra-item patterns is insufficient, as such item relationships could vary a lot under different user intentions¹. Intuitively, users have multiple intentions to adopt certain items; meanwhile, different user intentions could drive different user behaviors and item relationships [9], [12]. Taking Fig. 1 as an example, the representations of two cheap items could be similar for a price-sensitive user,

1. Following Wang et al. [9], user intention is a high-level concept, which could be the reasons of a user to purchase a certain item (e.g., timing, price, user interest and shopping for others). Note that we focus on refining the item recommendation lists with learnt latent user intentions from text reviews rather than predicting the next item with instant intention for the target user (e.g., sequential recommendation models such as BERT4Rec [10] and IMfOU [11]).

while the representations of the two aforementioned items could be different for a user who often buys gifts for her friends, as she may be more concerned with whether items are well packaged. Besides, although the existing re-ranking models can capture the intra-item relationships among item candidates, they are shared by all users in a dataset, which may not be sufficiently ‘personalized’.

Consequently, we are seeking to investigate the re-ranking task through modeling user-specific intra-item relationships based on user intentions. However, this is not trivial because of two main challenges. (1) Basically, user intentions are diverse and complex, which may vary greatly when confronted with different items. How to accurately capture user intentions is of crucial importance to deliver a performance-enhanced re-ranking model. (2) To provide sufficient personalization, a shared re-ranking model is not feasible. However, it is impractical to assign each user a prediction model. Hence, a tailored solution need to be designed in order to achieve both effectiveness and efficiency.

To tackle these challenges, we propose a novel Intention-aware Re-ranking Model with Dynamic Transformer Encoder (RAISE). In particular, we first devise an *intention discovering module* (IDM) to mine latent user intentions from text reviews. As illustrated in Fig. 1, such auxiliary information contains users’ preferences and item properties, which could be useful for modeling user intentions and item relationships [13], [14]. Given a user-item pair, IDM applies a co-attention network to estimate review-to-review matching scores and differentiate users’ diverse intentions from text reviews. This enables intention-aware representations to be generated by weighting the text representations with learnt matching scores. We then design a *dynamic transformer encoder* (DTE) to perform user-specific predictions by seamlessly accommodating the learnt latent user intentions. Under the hood, the dynamic self-attention mechanism captures the user-specific intra-item relationships and provides the driving force: an individual attention network is applied over the self-attention layer, to contextualize the item representations based on the learnt user intentions. Our proposed DTE advances the classic transformer encoder by learning specialized transformations of input item sequences, which increases the representational capability with limited extra computational cost and keeps efficient inference. To summarize, this paper makes the following contributions.

- We emphasize the importance of modeling diverse user intentions for the re-ranking task, whereby an IDM is devised to help extract user intentions from text reviews.
- We design a DTE to explicitly capture the user-specific intra-item patterns based on the learnt user intentions via IDM. By applying an individual attention network over the self-attention layer, DTE enables our proposed RAISE to perform user-specific predictions in an efficient manner.
- We conduct extensive experiments and ablation studies on four public datasets to verify the effectiveness and interpretability of our proposed RAISE.

2 RELATED WORKS

This section first briefly reviews existing re-ranking studies. Since our proposed RAISE aims to perform user-specific prediction based on the input item sequences and user intentions, we then present existing review-aware recommendation methods and input-dependent recommendation models.

Re-ranking Models for Recommendation. They aim to capture the mutual relationships between items in the initial recommendation list for each user. For example, DLCM [6] uses gated recurrent unit (GRU) to sequentially encode the information of top candidates into document representations, and SetRank [15] uses multi-head self-attention mechanisms and an attention rank loss function to re-rank documents for the document retrieval task. In addition, Seq2Slate [16] exploits mutual influences between items with pointer networks, which treats the recommendation task as a sequence generation problem. Recently, a graph neural network (GNN) based re-ranking method IRGPR [8] has been proposed to fuse the information from multi-hop neighbors and item relationships. It essentially models the global user-item and item-item relationships rather than the local item-item relationships among the initial recommendation lists. The most related work to ours is PRM [7]. By employing transformer encoders to encode the input items, the mutual influences between item candidates can be captured to refine the initial recommendations. However, the transformer encoders are shared by all users in PRM, which ignores user intentions and could lead to sub-optimal performance.

To sum up, existing works follow the same paradigm of modeling the intra-item relationships to re-rank the initial recommendation and regrettably ignore diverse user intentions. By contrast, we focus on exploiting latent user intentions from text reviews to capture the intra-item relationships specifically for each user in an effective manner. This enables RAISE to provide user-specific prediction and achieve more personalized recommendation.

Review-aware Recommendation Methods. Our work benefits from review-aware recommendation models which aim to exploit richer semantic information from the text reviews. Early studies such as HFT and TopicMF [13], [14] demonstrate that better rating prediction accuracy can be achieved by modeling text reviews with topic models. Empowered by the powerful representational capabilities of deep neural networks, deep learning recommendation models such as DeepCoNN, TransNets, and MPCN [17], [18], [19] are proposed to predict missing ratings from text reviews with convolutional neural networks (CNN) [20] and attention networks [21]. As for ranking tasks, TAFA [22] provides recommendations by jointly learning representations from user reviews and implicit feedback. Recently, TIM [23] models users and items within the topic space which is learned from the review data. Another direction of this field is to provide explanations for item recommendations based on text reviews [24], [25], [26]. Different from the above works which mainly focus on tackle rating prediction tasks or ranking tasks with text reviews, we focus on distinguishing user intentions from reviews so as to construct user-specific re-ranking model.

Input-dependent Models. Recently, input-dependent models have shown effectiveness in various domains, such as language modeling [27], [28] and computer vision [29], [30]. In recommendation, IFM [31] and DIFM [32] are presented to re-weight the representations of features and weights for different input instances before performing feature interactions. Inspired by these studies, we design a dynamic transformer encoder which performs an individual attention network on the self-attention layer and enables modeling user-specific intra-item patterns unveiled by the user intentions. We demonstrate that the proposed dynamic transformer encoder is computationally efficient with superior performance in this study.

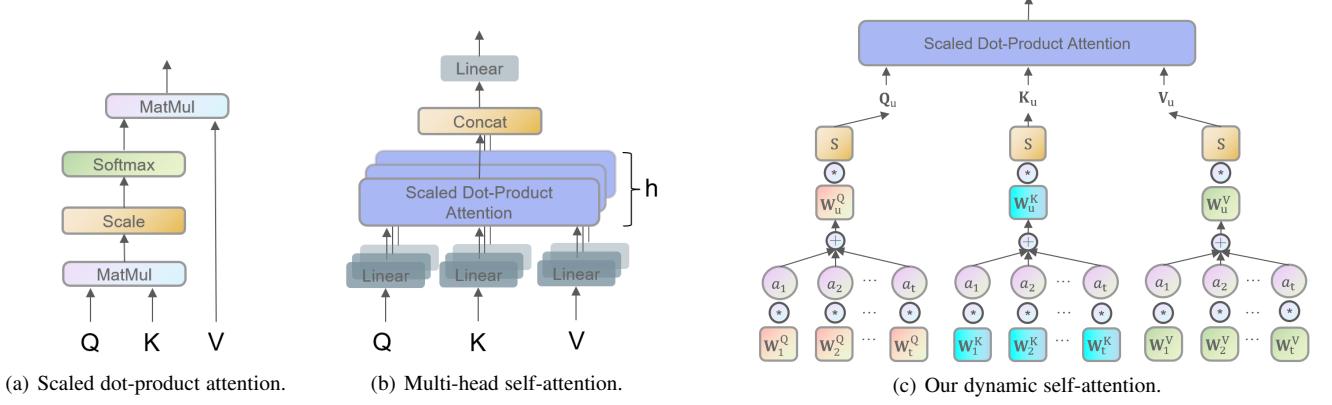


Fig. 2: Illustration of dynamic self-attention, which is the key design of dynamic transformer encoder.

TABLE 1: Main mathematical notations used in RAISE.

Notations	Definitions and Descriptions
$\mathbf{p}_u, \mathbf{q}_i$	Latent representations of user u and item i which are learnt by GMF from implicit feedback.
\mathcal{S}_u	Initial item recommendation list learnt by GMF for user u .
\hat{y}_{ui}	Predicted score for user u to item i
$\mathcal{R}_u, \mathcal{R}_i$	User u and item i 's review sequences.
c_{kj}	Matching score between user's k th review and item's j th review
$\mathbf{r}_i^{(u)}, \mathbf{r}_i^{(i)}$	Intention-aware review representations for u - i pair.
\mathbf{o}_i	Position embedding of item i .
\mathbf{s}_i	Item i 's final representation which is the input of the dynamic transformer encoders.
$\mathbf{Q}_u, \mathbf{K}_u, \mathbf{V}_u$	User-specific query, key, and value representations.
$\mathbf{W}_u^Q, \mathbf{W}_u^K, \mathbf{W}_u^V$	User-specific transform matrices.
\mathbf{a}_t	Shared attention weights in the dynamic transformer encoder.

3 PRELIMINARIES

Notations and Problem Formulation. Given a set of users $\mathcal{U} = \{u_1, u_2, \dots\}$, and a set of items $\mathcal{I} = \{i_1, i_2, \dots\}$, we adopt GMF [5] as the prior global ranking model, which predicts the missing interaction score (\hat{y}_{ui}) between the target user u and target item i with their learnt representations denoted as \mathbf{p}_u and \mathbf{q}_i , respectively. In this way, an initial recommendation list $\mathcal{S}_u = [i_1, i_2, \dots, i_n]$ can be generated by ranking the estimated interaction scores for user u . Given \mathcal{S}_u , \mathbf{p}_u and $\{\mathbf{q}_i | i \in \mathcal{S}_u\}$ learnt from GMF, the goal of our study is essentially how to effectively capture the intra-item relationships under different user intentions from text reviews and efficiently perform user-specific refinement for \mathcal{S}_u . Hence, we further introduce two review sequences $\mathcal{R}_u = \{r_1^{(u)}, r_2^{(u)}, \dots, r_{l_u}^{(u)}\}$ and $\mathcal{R}_i = \{r_1^{(i)}, r_2^{(i)}, \dots, r_{l_i}^{(i)}\}$ for user u and item i , which contains the reviews written by user u and reviews received by item i , respectively. Note that l_u and l_i are the maximum number of reviews of u and i . As such, each user-item pair in the training set can be denoted as a 6-tuple $(u, i, \mathbf{p}_u, \mathbf{q}_i, \mathcal{R}_u, \mathcal{R}_i)$, and RAISE is trained to re-rank the item candidates in \mathcal{S}_u for user u .

Self-attention Mechanism. Our work benefits from the self-attention mechanism due to its effectiveness to capture the intra-item patterns among item candidates [21]. As shown in Fig. 2(a). After linearly projecting the input sequence \mathbf{S} to obtain queries (\mathbf{Q}) and keys (\mathbf{K}) of dimension d_k , and values (\mathbf{V}) of dimension

d_v , the attention function produces outputs of dimension d , which is defined as follows:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (1)$$

where $\mathbf{Q} = \mathbf{S}\mathbf{W}^Q$, $\mathbf{K} = \mathbf{S}\mathbf{W}^K$, and $\mathbf{V} = \mathbf{S}\mathbf{W}^V$

where \mathbf{W}^Q , \mathbf{W}^K , and \mathbf{W}^V are transform matrices.

In addition, the self-attention mechanism can be multi-headed by employing a number of heads h [21], [28]. As shown in Figure 2(b), each head learns separate attention weights from different representation subspaces:

$$\text{Multi-head}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)\mathbf{W}^O \quad (2)$$

where $\text{head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V)$

where $\mathbf{W}^O \in \mathbb{R}^{hd_v \times d}$, $\mathbf{W}_i^Q \in \mathbb{R}^{d \times d_k}$, $\mathbf{W}_i^K \in \mathbb{R}^{d \times d_k}$, $\mathbf{W}_i^V \in \mathbb{R}^{d \times d_v}$ are transform matrices used in the multi-head self-attention. Normally, d_k and d_v are set to d/h . The extra computational cost of multi-head self-attention is limited compared with that of normal self-attention function with full dimensionality (see Eq.1). We will provide a more detailed discussion in Model Complexity and Scalability.

4 THE PROPOSED METHOD

In this section, we first briefly introduce the architecture of our proposed re-ranking method RAISE, then we present each component of RAISE in detail.

4.1 Overall of RAISE

The overall architecture of RAISE is presented in Fig. 3(a), which consists of *intention discovering module* (IDM), *dynamic transformer encoders* (DTE), and *prediction layer*. Given an initial list \mathcal{S}_u and learnt representations \mathbf{p} and \mathbf{q} from GMF, the goal of RAISE is to refine \mathcal{S}_u by modeling the local intra-item relationships based on user intentions. To this end, IDM first discovers user intentions from text review with a co-attention module. The learnt intention-aware representations from text review are then fed into the DTE to help capture user-specific item relationships. Accordingly, a new predicted score for each item candidate in \mathcal{S}_u is generated via the prediction layer. Finally, a re-ranked item list can be achieved by ranking the predicted scores.

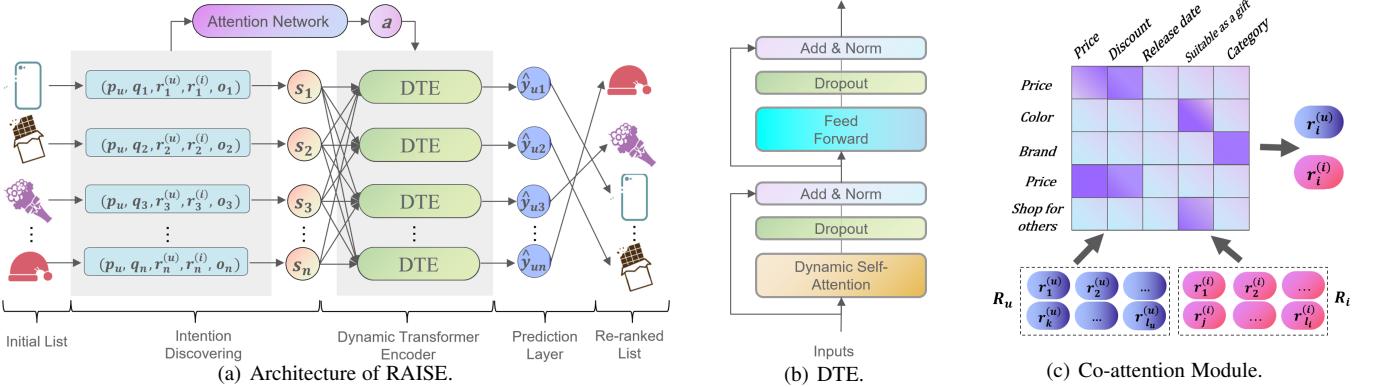


Fig. 3: Overall framework of RAISE.

4.2 Intention Discovering Module (IDM)

4.2.1 Intention-aware Review Representation

Learning informative user intentions is of crucial importance for RAISE to perform more personalized re-ranking. Intuitively, text reviews written by users are usually semantic and encode users' diverse intentions, which could lead to better modeling of user behavior when confronted with an item [17], [19].

We hence employ a co-attention module to generate two intention-aware representations for each user-item pair with regard to the diverse intentions behind their reviews, as illustrated in Fig. 3(c). Specifically, given two input review sequences \mathcal{R}_u and \mathcal{R}_i , we first obtain the representation of each single text review by simply adding its constituent word representations. As such, two embedding sequences $\mathcal{R}_u^e = \{\mathbf{r}_1^{(u)}, \mathbf{r}_2^{(u)}, \dots, \mathbf{r}_{l_u}^{(u)}\}$ and $\mathcal{R}_i^e = \{\mathbf{r}_1^{(i)}, \mathbf{r}_2^{(i)}, \dots, \mathbf{r}_{l_i}^{(i)}\}$ can be achieved. To distinguish the importance of reviews according to the intentions behind them, we then compute the review-level matching scores between every user-item review pair with a co-attention network, given by,

$$c_{kj} = f(\mathbf{r}_k^{(u)})^T \mathbf{M} f(\mathbf{r}_j^{(i)}) \quad (3)$$

where the matching matrix $\mathbf{C} = [c_{kj}]$ indicates how well the intentions behind a user review and an item review matches each other; $\mathbf{M} \in \mathbb{R}^{d \times d}$ is a trainable transform matrix; $\mathbf{r}_k^{(u)}, \mathbf{r}_j^{(i)} \in \mathbb{R}^d$ denote the representations of the k -th review of user u and the j -th review of item i , respectively. Meanwhile, we employ two MLPs to encode the review representation denoted as $f(\cdot)$ in Eq. 3. Since each row (column) of \mathbf{C} indicates how much the main intention of a user (item) review matches those of all item (user) reviews, the refined representations of a text review regarding users and items can be weighted by the strength of its main intention,

$$\begin{aligned} \mathbf{r}_k^{(u)'} &= \frac{1}{|\mathcal{R}_i^e|} \sum_j c_{kj} * \mathbf{r}_k^{(u)}; \\ \mathbf{r}_j^{(i)'} &= \frac{1}{|\mathcal{R}_u^e|} \sum_k c_{kj} * \mathbf{r}_j^{(i)}. \end{aligned} \quad (4)$$

Then we add up all the reviews of user u and item i respectively in order to obtain the intention-aware representations $\mathbf{r}_i^{(u)}$ and $\mathbf{r}_i^{(i)}$. Despite the simplicity, it is an effective way to encode the quantity of each intention behind a review sequence into the final intention-aware representations,

$$\mathbf{r}_i^{(u)} = \sum_k \mathbf{r}_k^{(u)'}, \quad \mathbf{r}_i^{(i)} = \sum_j \mathbf{r}_j^{(i)'}. \quad (5)$$

Note that for each user-item pair, their intention-aware representations are unique and will be different w.r.t. other users or items. In other words, the intention-aware representations are contextually learnt according to the input review sequences. This enables RAISE to capture intra-item patterns based on the matched user intentions between the review sequences of the target user u and those of item candidates in \mathcal{S}_u , leading to more personalized recommendations.

4.2.2 Intention-aware Sequential Representation

Before introducing the DTE, a meaningful input sequential representation \mathbf{S} should be generated in advance, to encode sequential item candidates in the initial list \mathcal{S}_u . We notice that most of the existing re-ranking models capture intra-item relationships from the implicit feedback data [7], [16], [33]. However, implicit feedback only indicate if a user has interacted with an item, thus it could be hard to learn effective item representations from implicit feedback alone. Besides, the learnt item representations from implicit feedback are shared by all users, which is unreasonable as item representations may vary greatly under different user intentions. Hence, we propose to represent item candidates with both the implicit feedback data and text review data. To this end, the user-specific item representations \mathbf{s}_i can be achieved with latent representations learnt by GMF and intention-aware representations obtained in the IDM:

$$\begin{aligned} \mathbf{s}_i &= \mathbf{W}^S [\text{Concat}(\mathbf{s}_i^{(im)}, \mathbf{s}_i^{(re)})] + \mathbf{o}_i \\ \mathbf{s}_i^{(im)} &= f(\text{Concat}(\mathbf{p}_u, \mathbf{q}_i)) \\ \mathbf{s}_i^{(re)} &= f(\text{Concat}(\mathbf{r}_i^{(u)}, \mathbf{r}_i^{(i)})) \end{aligned} \quad (6)$$

where \mathbf{W}^S is a projection matrix; $\mathbf{s}_i^{(im)}$ and $\mathbf{s}_i^{(re)}$ denote item representations learnt from the implicit feedback data via GMF and text review information via IDM, respectively; inspired by PRM [7], we also encode the initial positions of item candidates in \mathcal{S}_u denoted as \mathbf{o}_i . At last, the representation of \mathcal{S}_u can be obtained by concatenating the representation (\mathbf{s}_i) of each item in \mathcal{S}_u ,

$$\mathbf{S} = \text{Concat}(\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_n)^T \quad (7)$$

which is then fed into DTE for further refinement.

4.3 Dynamic Transformer Encoder (DTE)

4.3.1 User-specific Transformer Encoders

A fundamental assumption of the transformer architecture is that the transform matrices used in the self-attention layer are shared

by all input samples. However, user intentions could be diverse and complex in recommendation scenarios, thus the prediction model should be different for each user to achieve maximal personalization. Having realized the vital role of user-specific recommendation engines, we hence propose the DTE as described in Fig. 3(b). By performing attention network over the self-attention layer in the transformer encoder, the capacity of the transformer encoder is improved without increasing its depth (blocks of transformer encoders) or width (number of heads). An illustration of how we obtain user-specific queries (\mathbf{Q}_u), user-specific keys (\mathbf{K}_u), and user-specific values (\mathbf{V}_u) is presented in Fig. 2(c). Specifically, given the input embedding \mathbf{S} obtained from the IDM, the output of dynamic self-attention $\hat{\mathbf{S}}$ can be described as follows:

$$\hat{\mathbf{S}} = \text{Attention}(\mathbf{Q}_u, \mathbf{K}_u, \mathbf{V}_u) = \text{Softmax}\left(\frac{\mathbf{Q}_u \mathbf{K}_u^T}{\sqrt{d_k}}\right) \mathbf{V}_u \quad (8)$$

where $\mathbf{Q}_u = \mathbf{S} \mathbf{W}_u^Q$, $\mathbf{K}_u = \mathbf{S} \mathbf{W}_u^K$, and $\mathbf{V}_u = \mathbf{S} \mathbf{W}_u^V$

where $\mathbf{S} \in \mathbb{R}^{n \times d}$ and $\hat{\mathbf{S}} \in \mathbb{R}^{n \times d}$ are the input and output of DTE respectively; \mathbf{W}_u^Q , \mathbf{W}_u^K , and \mathbf{W}_u^V are learned user-specific transform matrices. By comparing Eq. 8 with Eq. 1, it showcases an important merit of our dynamic self-attention module. By assembling the transform matrices before scaled dot-product, it achieves stronger representation power while keeping computational efficiency. We will analyze the efficiency of DTE in Model Complexity and Scalability. In what follows, we present how to learn the three user-specific transform matrices \mathbf{W}_u^Q , \mathbf{W}_u^K , and \mathbf{W}_u^V .

4.3.2 Attention over Self-attention

Inspired by recent efforts [28], [34] which improve multi-head transformer architecture with mixture of experts and attention mechanisms, in this paper, we propose to learn three specialized transform matrices for each user by attentively aggregating multiple transform matrices before the scaled dot-product process:

$$\begin{aligned} \mathbf{W}_u^Q &= a_1 \mathbf{W}_1^Q + a_2 \mathbf{W}_2^Q + \cdots + a_t \mathbf{W}_t^Q \\ \mathbf{W}_u^K &= a_1 \mathbf{W}_1^K + a_2 \mathbf{W}_2^K + \cdots + a_t \mathbf{W}_t^K \\ \mathbf{W}_u^V &= a_1 \mathbf{W}_1^V + a_2 \mathbf{W}_2^V + \cdots + a_t \mathbf{W}_t^V \end{aligned} \quad (9)$$

where a_t is the shared attention weight across the three types of transform matrices, and t is the number of transform matrices for each \mathbf{Q}_u , \mathbf{K}_u , and \mathbf{V}_u .

In order to learn a meaningful attention weight $\mathbf{a} = [a_1, a_2, \dots, a_t]$ for each user, we employ an attention network over the self-attention layer in the DTE:

$$\begin{aligned} \mathbf{a} &= \text{Softmax}(\mathbf{W}^A \mathbf{e} + \mathbf{b}^A) \\ \mathbf{e} &= \text{ReLU}[\mathbf{W}^E (\bar{\mathbf{p}}_{\mathcal{S}_u} \odot \bar{\mathbf{q}}_{\mathcal{S}_u}) + \mathbf{b}^E] \end{aligned} \quad (10)$$

where \mathbf{W}^A , \mathbf{W}^E are learnable projection matrices; and \mathbf{b}^A , \mathbf{b}^E are bias vectors. In order to encode all information in the initial list \mathcal{S}_u and learn effective attention weights for each user, we obtain $\bar{\mathbf{p}}_{\mathcal{S}_u}$ and $\bar{\mathbf{q}}_{\mathcal{S}_u}$ by accumulating all latent representations (\mathbf{p}_u and \mathbf{q}_i) learnt via GMF and intention-aware representations ($\mathbf{r}_i^{(u)}$ and $\mathbf{r}_i^{(i)}$) learnt via IDM,

$$\begin{aligned} \bar{\mathbf{p}}_{\mathcal{S}_u} &= \frac{1}{n} \sum_{i \in \mathcal{S}_u} (\mathbf{p}_u + \mathbf{r}_i^{(u)}); \\ \bar{\mathbf{q}}_{\mathcal{S}_u} &= \frac{1}{n} \sum_{i \in \mathcal{S}_u} (\mathbf{q}_i + \mathbf{r}_i^{(i)}) \end{aligned} \quad (11)$$

Algorithm 1: The RAISE Algorithm

Input: \mathcal{S}_u , \mathbf{p}_u , $\{\mathbf{q}_i | i \in \mathcal{S}_u\}$, \mathcal{R}_u^e , $\{\mathcal{R}_i^e | i \in \mathcal{S}_u\}$ and predicted score \tilde{y}_{ui} from GMF.

Output: Model parameters Θ .

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1 for each user  $u \in \mathcal{U}$  do
2   for each item candidate  $i \in \mathcal{S}_u$  do
3     Obtain  $\mathbf{r}_i^{(u)}$  and  $\mathbf{r}_u^{(i)}$  with Eqs. (3-5);
4     Compute  $\mathbf{S}$  for the initial list  $\mathcal{S}_u$  with Eqs. (6-7);
5     Compute  $\hat{y}_{ui}$  with Eq. 12;
6     Calculate  $\mathcal{L}$  based on Eq. 13;
7     Update  $\Theta$  to minimize  $\mathcal{L}$ , using  $\nabla_\theta \mathcal{L}$  ;

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where n is the length of \mathcal{S}_u . By estimating \mathbf{a} with information from both implicit feedback data and text review data, the specialized transform matrices can be obtained by Eq. 9, thus leading to user-specific predictions.

4.4 Prediction Layer

In this layer, a new ranking score \hat{y}_{ui} is estimated for each item candidate in the initial list \mathcal{S}_u . This enables us to generate a final re-ranked list for the target user u by sorting the item candidates according to their new scores from highest.

$$\hat{y}_{ui} = \text{Softmax}(\mathbf{F}^{(b)} \mathbf{W}^P + \mathbf{b}^P), i \in \mathcal{S}_u \quad (12)$$

where $\mathbf{F}^{(b)}$ is the output of b blocks of the DTE. Meanwhile, \mathbf{W}^P and \mathbf{b}^P are transform matrix and bias vector for the prediction layer. We employ a negative log likelihood loss to train our RAISE, as suggested by [7],

$$\mathcal{L} = - \sum_{u \in \mathcal{U}_{tr}} \sum_{i \in \mathcal{S}_u} y_{ui} \log \hat{y}_{ui} \quad (13)$$

where \mathcal{U}_{tr} refers to the set of users in the training set.

4.5 Model Complexity and Scalability

The self-attention mechanism is adopted to compute the mutual relationships among item candidates in \mathcal{S}_u , whose computational complexity is $\mathcal{O}(n^2d)$. To capture the mutual relationships from different sub-spaces, multi-head self-attention mechanism is usually applied, and its computational complexity is $\mathcal{O}(n^2d + nd^2)$, i.e., the extra computational cost is nd^2 . In this study, we propose DTE to aggregate transform matrices with attention weights learnt from an attention network based on user intentions. The key insight is that within reasonable cost of model size, DTE provides user-specific predictions and improves representation capability in an efficient way (low extra computational cost). Specifically, the extra computational cost of DTE is $\mathcal{O}(td^2)$ compared with the self-attention mechanism. As such, DTE is more computationally efficient than multi-head self-attention on the premise that $t < n$, which usually holds (the optimal t is no larger than 4, while n is 50 in this study). Note that DTE takes only one scaled dot-product operation. This means that one can increase the capacity of the prediction model by increasing t with only a small increase in inference cost because each additional parameter requires only 1 additional multiply-add.

As noted in Table 2, our proposed dynamic transformer encoder advances the classic multi-head transformer encoder in following aspects. (1) Compared to multi-head transformer encoder,

TABLE 2: Per-layer complexity, extra computational cost compared with self-attention (SA) layer, and indication of input-dependent support for different layer types, where n is the sequence length; d is the representation dimension; and t is the number of experts.

Layer type	Complexity (per layer)	Extra Cost	Input-dependent
SA	$\mathcal{O}(n^2d)$	N.A	×
Multi-head SA	$\mathcal{O}(n^2d + nd^2)$	nd^2	×
Dynamic SA	$\mathcal{O}(n^2d)$	td^2	✓

TABLE 3: Data statistics.

Dataset	#User	#Item	#Review/#Rating	Density
Sports and Outdoors	35,598	18,357	296,337	0.05%
Health and Personal Care	38,609	18,534	346,355	0.05%
Clothing, Shoes and Jewelry	39,387	23,033	278,677	0.03%
Video Games	24,303	10,672	231,780	0.09%

DTE provides a more efficient solution to boost the representational capability without increasing the depth (number of DTE blocks b) and width (number of heads h). (2) By parameterizing the transform matrices in a dynamic self-attention layer as a linear combination of t experts, DTE is able to perform user-specific (input-dependent) prediction in an efficient manner. Besides, our RAISE can be built upon any latent factor or deep learning based recommendation models. Such scalability enables RAISE to refine recommendation lists generated by existing ranking models in an efficient manner. Hence, one can achieve more personalized and explainable recommendation without modifying their current recommendation engines.

5 EXPERIMENTS

In this section, we conduct extensive experiments to answer the following research questions².

- **RQ1:** Is RAISE able to perform competitively to baseline re-ranking solutions?
- **RQ2:** How does the proposed IDM and DTE affect the performance of RAISE?
- **RQ3:** Is RAISE able to generate meaningful explanations for item recommendation?
- **RQ4:** How do the key hyper-parameters affect the performance of RAISE?

5.1 Experimental Setup

Datasets. We conduct experiments on four public datasets from Amazon³ as listed in Table 3, including ‘Sports and Outdoors’, ‘Health and Personal Care’, ‘Clothing, Shoes and Jewelry’ and ‘Video Games’. The selected datasets are widely used in recommendation studies and come from different domains. After obtaining the initial recommendation lists generated by GMF, we randomly select 80% users to construct the training set, use 10% users as the validation set, and leave the remaining 10% as the testing set for each dataset [6], [7]. In addition, we follow previous works [5], [7] to convert explicit rating data to binary implicit feedback. In particular, the label is 1 if the target user has rated the target item; otherwise 0.

Comparing Methods. We compare with the following state-of-the-art counterparts.

2. Our source code will be released upon acceptance.

3. jmcauley.ucsd.edu/data/amazon/

- **GMF** [5] generalizes the matrix factorization model in a non-linear manner, which is a widely adopted baseline for recommendation tasks. Note that GMF is the prior global ranking model of all re-ranking baselines in this paper.
- **DLCM** [6] is a classic re-ranking model, which encodes item candidates in the initial list sequentially with GRU.
- **PRM** [7] feeds the generated “personalized vectors” into the transformer network to refine initial item lists.
- **SetRank** [15] re-ranks items with the multi-head self-attention mechanism and an attentive loss function.

Note that the source code of Seq2Slate [16] is not released and our re-implemented version performs unsatisfactorily. Meanwhile, we also find that the performance of IRGPR [8]⁴ is poor in our experimental setting, although we have carefully tuned its parameters. Therefore, we omit the comparison with Seq2Slate and IRGPR in this paper.

Training Details. For a fair comparison, we set $d = 32$ and $n = 50$ for all re-ranking methods. We follow the configuration presented in [5], [6], [7], [15], and all the baselines are trained until convergence. For our proposed RAISE, we tune the number of hidden layers from 1 to 4 for MLP structures. The maximum number of reviews l_u and l_i are set to 20. We use the pre-trained BERT [35] to obtain the representations of each word appeared in text reviews. The learning rate is selected from $\{1e - 1, 1e - 2, 1e - 3, 1e - 4\}$; batch size is chosen from $\{256, 512, 1024\}$ and dropout rate varies in the range of $[0.1, 0.5]$ stepped by 0.1. Moreover, the number of transform matrices t and the number of DTE blocks b are searched from $\{1, 2, 4, 8, 10\}$, and $\{1, 2, 3, 5, 8, 10\}$. Our model is implemented with Pytorch⁵, optimized with Adam [36], and trained on one Nvidia TITAN Xp GPU with 12 GB memory associated with Intel Exon CPU E5-2630 v4@2.20GHz.

Evaluation Metrics. We adopt the same evaluation metrics with PRM [7] to evaluate the performance of all methods: Precision (Pre@ k) and Mean Average Precision (MAP@ k), where k is the length of the recommendation list. *Precision* evaluates the fraction of correct recommendations in recommendation lists for all users, and *MAP* computes the mean average precision of all ranked lists cut off by k . In addition, we also evaluated the recommendation performance by normalized discounted cumulative gain (NDCG@ k) which takes the position of correct recommendations into account [4], [5]. Note that higher metric values indicate a better recommendation performance.

5.2 Experimental Results

5.2.1 Performance Comparison (RQ1)

Table 4 presents the overall performance of the proposed RAISE and comparing methods on four Amazon datasets. As a whole, all re-ranking methods are able to refine the initial recommendation list generated by the global ranking model GMF. This verifies the effectiveness of modeling intra-item patterns for re-ranking tasks. Moreover, we can observe that RAISE performs better than the other three state-of-the-art re-ranking models: DLCM, SetRank and PRM. In particular, RAISE achieves up to 13.95% relative improvement w.r.t. Pre@5, 12.30% relative improvement w.r.t. MAP@1, and 13.03% relative improvement w.r.t. NDCG@5 on ‘Health and Personal Care’ dataset, compared to the second best

4. <https://github.com/wwliu555/IRGPR>

5. pytorch.org/

TABLE 4: The performance comparison on all datasets (%). ‘Improvement’ indicates how much RAISE has improved over the second best method which is underlined. We use ‘*’ to denote statistically significant improvements (paired t-test with p -value < 0.05). We run all methods for 5 times and report their average value in this table.

Datasets	Models	Pre@1	Pre@5	Pre@10	MAP@1	MAP@5	MAP@10	NDCG@1	NDCG@5	NDCG@10
Sports and Outdoors	GMF	32.14	34.76	26.73	32.14	46.76	48.66	32.16	42.26	51.56
	DLCM	55.12	41.14	29.48	55.12	63.56	60.08	51.25	52.77	59.99
	SetRank	54.64	40.24	29.45	54.64	62.15	58.97	54.45	51.16	57.94
	PRM	79.44	54.83	35.39	79.44	81.53	76.98	79.33	70.46	74.36
	RAISE	85.45*	60.63*	37.77*	85.45*	86.96*	83.48*	85.45*	77.84*	80.30*
	Improvement	7.57%	10.58%	6.73%	7.57%	6.66%	8.44%	7.71%	10.47%	7.99%
Health and Personal Care	GMF	30.65	33.52	26.07	30.65	44.66	46.56	30.39	40.72	49.65
	DLCM	49.23	37.73	27.52	49.23	57.70	55.41	49.19	48.48	56.17
	SetRank	50.09	37.96	28.00	50.09	59.14	56.67	49.95	48.66	55.87
	PRM	73.96	52.17	34.56	73.96	78.04	74.15	74.00	67.61	72.01
	RAISE	83.08*	59.48*	36.73*	83.08*	85.53*	82.21*	83.08*	76.42*	78.99*
	Improvement	12.33%	13.95%	6.28%	12.33%	9.60%	10.87%	12.27%	13.03%	9.69%
Clothing, Shoes and Jewelry	GMF	42.83	46.52	33.24	42.83	59.69	62.42	42.91	57.96	67.19
	DLCM	68.06	50.79	34.65	68.06	73.40	71.10	67.72	67.02	74.32
	SetRank	69.60	50.69	34.46	69.60	73.09	70.61	69.27	66.39	73.36
	PRM	92.06	65.94	40.35	92.06	92.15	89.08	92.08	86.69	89.00
	RAISE	95.30*	70.39*	41.66*	95.30*	95.32*	93.25*	95.30*	91.33*	92.38*
	Improvement	3.52%	6.75%	3.25%	3.52%	3.44%	4.68%	3.50%	5.35%	3.41%
Video Games	GMF	40.80	43.66	34.23	40.80	57.23	57.86	40.61	50.39	58.63
	DLCM	58.82	47.09	35.33	58.82	66.77	64.00	58.76	56.68	63.86
	SetRank	58.93	46.23	34.86	58.93	67.21	64.11	58.96	55.67	62.22
	PRM	74.65	55.76	39.03	74.65	79.58	75.14	74.65	68.07	72.15
	RAISE	81.35*	59.43*	40.68*	81.35*	83.99*	79.33*	81.35*	73.16*	76.30*
	Improvement	8.98%	6.58%	4.23%	8.98%	5.54%	5.58%	8.98%	7.48%	5.75%

TABLE 5: The effects of key components of RAISE (%).

Dataset	Model	Pre		MAP		NDCG	
		@5	@10	@5	@10	@5	@10
Sports and Outdoors	RAISE	60.63	37.77	86.96	83.48	77.84	80.30
	RAISE _{w/o IDM}	59.70	37.44	86.88	82.76	76.85	79.40
	RAISE _{w/o DTE}	59.18	37.22	86.14	82.03	76.23	78.94
	RAISE _{w/o Both}	58.50	36.78	86.00	81.83	75.55	78.28
Health and Personal Care	RAISE	59.48	36.73	85.53	82.21	76.42	78.99
	RAISE _{w/o IDM}	58.34	36.12	84.08	81.02	75.06	77.92
	RAISE _{w/o DTE}	58.54	36.57	84.78	81.24	75.38	78.26
	RAISE _{w/o Both}	53.10	34.38	79.93	76.03	68.95	73.14
Clothing, Shoes and Jewelry	RAISE	70.39	41.66	95.32	93.25	91.33	92.38
	RAISE _{w/o IDM}	69.10	40.86	94.81	92.59	90.19	91.53
	RAISE _{w/o DTE}	70.12	41.56	95.26	93.12	91.07	92.37
	RAISE _{w/o Both}	67.68	40.58	93.36	91.06	88.50	90.51
Video Games	RAISE	59.43	40.68	83.99	79.33	73.16	76.30
	RAISE _{w/o IDM}	57.43	39.65	82.06	77.51	70.66	74.08
	RAISE _{w/o DTE}	58.77	40.39	83.52	78.79	72.42	75.49
	RAISE _{w/o Both}	56.39	39.39	81.14	76.24	69.43	73.30

re-ranking algorithm. We also observe that RAISE gains slightly less improvement on the ‘Clothing, Shoes and Jewelry’ dataset. A possible explanation could be the difficulty of model training due to the extremely sparse data, especially for RAISE which refines recommendations with review information, as we can see the review density of this dataset is lower than 0.05% as shown in Table 3.

5.2.2 Effects of IDM and DTE (RQ2)

To investigate the effectiveness of two key components of RAISE, we compare RAISE with its three variants listed as follows: (1) RAISE_{w/o IDM}: removing the intention-aware representations learnt via IDM in Eq. 6; (2) RAISE_{w/o DTE}: replacing DTEs with normal transformer encoders as shown in Eq. 1; (3) RAISE_{w/o Both}: removing both IDM and DTEs from RAISE simultaneously. The results are reported in Table 5.

By analyzing the performance comparison, we have the following observations. (1) Being equipped with IDM, our proposed RAISE is able to effectively learn useful patterns from review information and further enrich the representations of users and items. (2) By employing an attention network over the self-attention layer, the proposed DTE performs better than the normal transformer encoder under our setting, showing its stronger representational capability without increasing the depth or width. (3) The combination of IDM and DTE brings the largest improvements, which showcases that RAISE is able to generate more personalized recommendations by seamlessly accommodating the learnt latent user intentions extracted from the text reviews.

5.2.3 Interpretability of RAISE (RQ3)

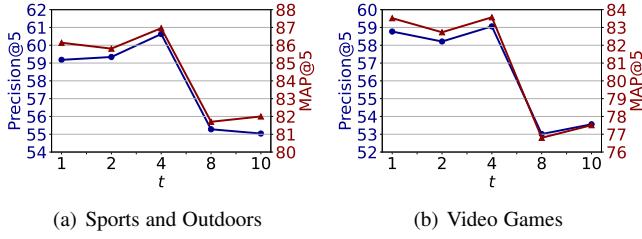
We now discuss another important property of our proposed RAISE: the interpretability. To this end, we randomly pick eight user-item review pairs with high matching scores among the testing set of the four datasets and highlight the similar intention(s) between user and item reviews in Fig. 4. Taking Fig. 4(a) as an example, user 719 wrote about “I feel so well equipped when I have this multi-tool with me”, and then the co-attention mechanism assigns higher matching score to the item review that mentioned “This one has all the tools I was looking for”. We find that, even there are very few words that occur in common between two reviews, the selected review pairs are identified to be consistent with regard to some high-level concepts. This indicates it is a practical way to find meaningful item reviews for the target user. By distinguishing the importance of reviews between two input sequences \mathcal{R}_u and \mathcal{R}_i , RAISE is capable of boosting the interpretability of recommendation engines.

5.2.4 Hyper-parameter Sensitivity Analysis (RQ4)

We finally examine how the number of transform matrices (t), the length of the initial recommendation list (n) and the number of DTE blocks (b) affect the performance of RAISE. The results are depicted in Figs. (5-7), and similar trends can be observed with $k = \{10, 20\}$ as well as the rest two datasets.

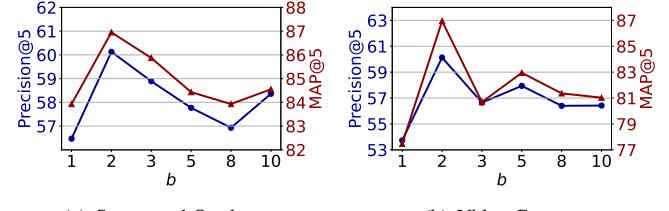
Review from (u_{719}, i_{3328})	Review from (u_{31}, i_{491})	Review from (u_{14005}, i_{6442})	Review from (u_2, i_{12})
" I feel so well equipped when I have this multi-tool with me ..."	"I use the Pro Health line of products and this toothpaste is high quality also ..."	" ... the quality of workmanship and how comfortable and well they fit ..."	"Great game! I love the storyline and graphics, as well as the fighting style..."
"... This one has all the tools I was looking for - sturdy pliers, scissors, sharp plain edge blade, file, saw, and the all-important awl ..."	"This package includes an Oral-B Professional Deep Sweep rechargeable electric toothbrush..."	" ... These sandals are very comfortable ... the arch support in these sandals is excellent ..."	"... Overall, the game is kind of repetitious, fighting the same bad guys..."
(a) Sports and Outdoors	(b) Health and Personal Care	(c) Clothing, Shoes and Jewelry	(d) Video Games
Review from (u_{182}, i_{1146})	Review from (u_{78}, i_{788})	Review from (u_{97}, i_{471})	Review from (u_{320}, i_{3829})
"Probably the best feature of this Club Champ product is the ball return..."	"I have sore and tight shoulders from work so end up going to a lot of massages to release the knots ..."	"He likes things basic and this is exactly that. A basic passport and money holder for travel..."	"This is the best music ... I have played all the Guitar Hero games as well as some other rythm games ..."
"...The ball return is nice feature especially for impatient kids..."	"...This product does seem to make a difference in my knee and back pain ..."	"...Took this on a trip outside of the US and the item was lightweight, discreet and very handy..."	"When it comes to music games... one of the most electrifying music franchise games of all time ..."
(e) Sports and Outdoors	(f) Health and Personal Care	(g) Clothing, Shoes and Jewelry	(h) Video Games

Fig. 4: Selected user-item review pairs with high matching scores from the four datasets.



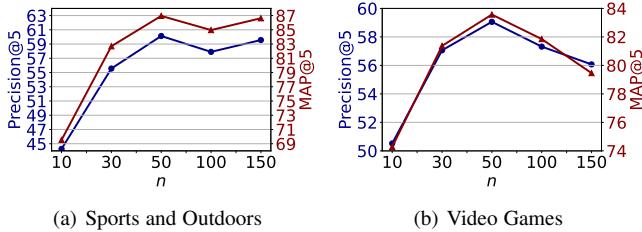
(a) Sports and Outdoors

(b) Video Games



(a) Sports and Outdoors

(b) Video Games



(a) Sports and Outdoors

(b) Video Games

Fig. 5: Impact of t at Pre@5% and MAP@5%.

From Fig. 5, we can see that a small number of transform matrices ($t \leq 4$) is sufficient to distinguish the main intentions of users. This indicates our DTE does not actually add much space complexity and verifies our assumption that user behavior is driven by multiple intentions with different contributions. From Fig. 6, we notice that the performance of RAISE initially improves with the increase of n ($n \leq 50$), and the performance begins to decrease after a certain point ($n > 50$) on both datasets. Intuitively, a longer initial list contains more item candidates and richer intra-item patterns, which is beneficial to re-ranking models. However, since RAISE is empowered by the transformer architecture, it may not be a good choice to blindly increase the length of initial list, as the transformer architecture is quadratic to n (see Model Complexity and Scalability). Besides, a long initial list could be hard for the transformer architecture to model effective mutual relationships. Furthermore, the results on the number of DTE blocks are plotted in Fig. 7, indicating that only one or two DTE blocks are usually

sufficient for RAISE to achieve its optimal performance.

6 CONCLUSION AND FUTURE WORKS

In this paper, we propose a novel re-ranking method RAISE to refine the recommendation list. Equipped with the intention discover module (IDM) and dynamic transformer encoder (DTE), our proposed RAISE performs user-specific re-ranking by exploiting user intentions with the help of text reviews. By constructing RAISE upon prior global ranking models, one can easily achieve personalization, efficiency, and interpretability without modifying their current recommendation engines. Empirical study verifies the additional gains brought by the devised IDM and DTE. In future work, we will investigate how to mine user intentions from other auxiliary information such as social networks and knowledge graphs for further performance-enhanced re-ranking approaches.

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REFERENCES

- [1] Z. Sun, Q. Guo, J. Yang, H. Fang, G. Guo, J. Zhang, and R. Burke, "Research commentary on recommendations with side information: A survey and research directions," *Electronic Commerce Research and Applications*, vol. 37, p. 100879, 2019.
- [2] Z. Lin, L. Feng, R. Yin, C. Xu, and C. K. Kwok, "Glimg: Global and local item graphs for top-n recommender systems," *Information Sciences*, vol. 580, pp. 1–14, 2021.
- [3] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, 2009.
- [4] Z. Lin, L. Feng, Y. Zhang, R. Yin, C. K. Kwok, and C. Xu, "Comet: Convolutional dimension interaction for collaborative filtering," *arXiv preprint arXiv:2007.14129*, 2020.
- [5] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua, "Neural collaborative filtering," in *Proceedings of the 26th International Conference on World Wide Web*, 2017, pp. 173–182.
- [6] Q. Ai, K. Bi, J. Guo, and W. B. Croft, "Learning a deep listwise context model for ranking refinement," in *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, 2018, pp. 135–144.
- [7] C. Pei, Y. Zhang, Y. Zhang, F. Sun, X. Lin, H. Sun, J. Wu, P. Jiang, J. Ge, W. Ou *et al.*, "Personalized re-ranking for recommendation," in *Proceedings of the 13th ACM Conference on Recommender Systems*, 2019, pp. 3–11.
- [8] W. Liu, Q. Liu, R. Tang, J. Chen, X. He, and P. A. Heng, "Personalized re-ranking with item relationships for e-commerce," in *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, 2020, pp. 925–934.
- [9] X. Wang, H. Jin, A. Zhang, X. He, T. Xu, and T.-S. Chua, "Disentangled graph collaborative filtering," in *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2020, pp. 1001–1010.
- [10] F. Sun, J. Liu, J. Wu, C. Pei, X. Lin, W. Ou, and P. Jiang, "Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer," in *Proceedings of the 28th ACM international conference on information and knowledge management*, 2019, pp. 1441–1450.
- [11] X. Guo, C. Shi, and C. Liu, "Intention modeling from ordered and unordered facets for sequential recommendation," in *Proceedings of the 29th International Conference on World Wide Web*, 2020, p. 1127–1137.
- [12] T. Chen, H. Yin, H. Chen, R. Yan, Q. V. H. Nguyen, and X. Li, "Air: Attentional intention-aware recommender systems," in *35th International Conference on Data Engineering*, 2019, pp. 304–315.
- [13] J. McAuley and J. Leskovec, "Hidden factors and hidden topics: understanding rating dimensions with review text," in *Proceedings of the 7th ACM Conference on Recommender Systems*, 2013, pp. 165–172.
- [14] Y. Bao, H. Fang, and J. Zhang, "Topicmf: Simultaneously exploiting ratings and reviews for recommendation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2014, pp. 2–8.
- [15] L. Pang, J. Xu, Q. Ai, Y. Lan, X. Cheng, and J. Wen, "Setrank: Learning a permutation-invariant ranking model for information retrieval," in *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2020, pp. 499–508.
- [16] I. Bello, S. Kulkarni, S. Jain, C. Boutilier, E. Chi, E. Eban, X. Luo, A. Mackey, and O. Meshi, "Seq2slate: Re-ranking and slate optimization with rnns," *arXiv preprint arXiv:1810.02019*, 2018.
- [17] L. Zheng, V. Noroozi, and P. S. Yu, "Joint deep modeling of users and items using reviews for recommendation," in *Proceedings of the 10th ACM International Conference on Web Search and Data Mining*, 2017, pp. 425–434.
- [18] R. Catherine and W. Cohen, "Transnets: Learning to transform for recommendation," in *Proceedings of the 11th ACM conference on recommender systems*, 2017, pp. 288–296.
- [19] Y. Tay, A. T. Luu, and S. C. Hui, "Multi-pointer co-attention networks for recommendation," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2018, pp. 2309–2318.
- [20] Y. Kim, "Convolutional neural networks for sentence classification," in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*. Doha, Qatar: Association for Computational Linguistics, Oct. 2014, pp. 1746–1751. [Online]. Available: <https://www.aclweb.org/anthology/D14-1181>
- [21] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Advances in Neural Information Processing Systems*, 2017, pp. 5998–6008.
- [22] J. P. Zhou, Z. Cheng, F. Pérez, and M. Volkovs, "Tafa: two-headed attention fused autoencoder for context-aware recommendations," in *14th ACM Conference on Recommender Systems*, 2020, pp. 338–347.
- [23] F. J. Peña, D. O'Reilly-Morgan, E. Z. Tragos, N. Hurley, E. Duriakova, B. Smyth, and A. Lawlor, "Combining rating and review data by initializing latent factor models with topic models for top-n recommendation," in *14th ACM Conference on Recommender Systems*, 2020, pp. 438–443.
- [24] Y. Zhang, X. Chen *et al.*, "Explainable recommendation: A survey and new perspectives," *Foundations and Trends® in Information Retrieval*, pp. 1–101, 2020.
- [25] P. Sun, L. Wu, K. Zhang, Y. Fu, R. Hong, and M. Wang, "Dual learning for explainable recommendation: Towards unifying user preference prediction and review generation," in *Proceedings of The Web Conference 2020*. New York, NY, USA: Association for Computing Machinery, 2020, p. 837–847. [Online]. Available: <https://doi.org/10.1145/3366423.3380164>
- [26] T.-H. Le and H. W. Lauw, "Synthesizing aspect-driven recommendation explanations from reviews," *IJCAI*, 2021.
- [27] F. Wu, A. Fan, A. Baevski, Y. N. Dauphin, and M. Auli, "Pay less attention with lightweight and dynamic convolutions," in *Proceedings of the 7th International Conference on Learning Representations*, 2019, pp. 1–14.
- [28] H. Peng, R. Schwartz, D. Li, and N. A. Smith, "A mixture of $h - 1$ heads is better than h heads," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 2020, pp. 6566–6577.
- [29] B. Yang, G. Bender, Q. V. Le, and J. Ngiam, "Condeconv: Conditionally parameterized convolutions for efficient inference," in *Advances in Neural Information Processing Systems*, 2019, pp. 1307–1318.
- [30] Y. Chen, X. Dai, M. Liu, D. Chen, L. Yuan, and Z. Liu, "Dynamic convolution: Attention over convolution kernels," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 11030–11039.
- [31] Y. Yu, Z. Wang, and B. Yuan, "An input-aware factorization machine for sparse prediction," in *Proceedings of the 28th International Joint Conferences on Artificial Intelligence*, 2019, pp. 1466–1472.
- [32] W. Lu, Y. Yu, Y. Chang, Z. Wang, C. Li, and B. Yuan, "A dual input-aware factorization machine for ctr prediction," in *Proceedings of the 29th International Joint Conference on Artificial Intelligence*, 2020, pp. 3139–3145.
- [33] T. Zhuang, W. Ou, and Z. Wang, "Globally optimized mutual influence aware ranking in e-commerce search," in *Proceedings of the 27th International Joint Conference on Artificial Intelligence*, 2018, pp. 3725–3731.
- [34] S. Iida, R. Kimura, H. Cui, P.-H. Hung, T. Utsuro, and M. Nagata, "Attention over heads: A multi-hop attention for neural machine translation," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, 2019, pp. 217–222.
- [35] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.
- [36] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proceedings of the 3rd International Conference on Learning Representations*, 2015, pp. 1–15.



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