

# MODELING FIELD-LEVEL FACTOR INTERACTIONS FOR FASHION RECOMMENDATION

Yujuan Ding<sup>1</sup>, P.Y. Mok<sup>1</sup>, Xun Yang<sup>2</sup>, Yanghong Zhou<sup>1</sup>

<sup>1</sup>The Hong Kong Polytechnic University, <sup>2</sup>University of Science and Technology of China

## ABSTRACT

Personalized fashion recommendation aims to explore patterns from historical interactions between users and fashion items and thereby predict the future ones. It is challenging due to the sparsity of the interaction data and the diversity of user preference in fashion. To tackle the challenge, this paper investigates multiple factor fields in fashion domain, such as *colour*, *style*, *brand*, and tries to specify the implicit user-item interaction into field level. Specifically, an attentional factor field interaction graph (AFFIG) approach is proposed which models both the user-factor interactions and cross-field factors interactions for predicting the recommendation probability at specific field. In addition, an attention mechanism is equipped to aggregate the cross-field factor interactions for each field. Extensive experiments have been conducted on three E-Commerce fashion datasets and the results demonstrate the effectiveness of the proposed method for fashion recommendation. The influence of various factor fields on recommendation in fashion domain is also discussed through experiments.

**Index Terms**— Fashion recommendation, Factor interaction modeling, attribute incorporation

## 1. INTRODUCTION

Fashion industry drives a significant part of global economy, which has been undergoing large-scale digital transformation and creating a growing demand for supportive technologies, including recommendation [1–6]. Personalized fashion recommendation aims to recommend suitable fashion items to users based on their fashion preference, which has received increasing research attention over the past years [7–11] for its industrial and academic significance.

The key to successful personalized recommendation is effectively capturing the personal preference of users, i.e., the interaction patterns of users with items in their historical behaviours (implicit feedback). However, user’s shopping behaviours in fashion domain are usually complex and diverse, making it difficult to capture such patterns directly from the implicit feedback. Moreover, since new fashion items are emerging fast, the data sparsity is always a challenge in personalized fashion recommendation. In fact, the decision-making in fashion is dependent on multiple domain-



**Fig. 1.** Modelling the factor interaction across fields (attributes) and field-level interaction with users for personalized fashion recommendation

specific aspects of products [12]. For example, a previous study [12] found that shoppers who are highly fashion and brand conscious are more inclined to buy stylish clothes. This inspires us to investigate detailed factors that might influence the use’s choices instead of focusing on the implicit user-item interactions only. In this way, we can incorporate more content information and also explore the latent field-specific user preference, which are promising to alleviate the data sparsity problem.

To this end, considering the characteristics of fashion domain, we take fashion attributes as different factor fields which can affect the interaction between users and items by taking different factors. For example, *colour* is one important factor field in fashion domain, an item in different colours (with different factors in the field of *colour*) would be differently attractive to consumers. Other influential factor fields in fashion domain include *style*, *brand*, *price* and etc [13, 14]. To determine whether an item should get recommended in certain field, we need to evaluate the attractiveness of the specific factor in this field, and also the user’s interest in this factor. Since the factor of each field is not at play independently, the attractiveness of is certainly influenced by other factor fields. For example, as shown in Fig. 1, when evaluating the *colour* of the item, the influence from [*printing*: *strawberry*] and other factors should be considered. Moreover, the interaction between the *user*: *Anna* and the *colour*: *pink* should also be considered to achieve personalized recommendation.

In this paper, we propose a novel Attentional Factor Field Interaction Graph (AFFIG) model. It models the user-factor interactions to explore the latent field-level user preference. Besides, it builds the factor field graph (FFG) to model the

influence between factors across the fields and obtain the factor representation that incorporates the context of the item. An attention mechanism is devised for the FFG to aggregate all cross-field influences with adjustive ratios. The results of two parts, the modelling of user-factor interaction and contextual representation of the factor, are then combined together to predict the recommendation score for the specific field. In the end, the holistic prediction scores can be obtained by aggregating all fields, which are further employed in calculating the pairwise loss and train the model. Extensive experiments on three E-Commerce datasets demonstrate the effectiveness of the proposed AFFIG. Furthermore, we empirically investigate the importance of various factor fields to the recommendation results in fashion domain.

## 2. RELATED WORK

Collaborative Filtering (CF)-based methods are mostly applied in personalized fashion recommendation, which try to capture user-item interaction patterns from the implicit user feedback [15–17]. Based on general CF-based recommendation models, previous works focused on the incorporation of visual information of fashion items [8–10, 18], for example, introducing either global or regional visual features into the CF-based recommendation frameworks. Despite of the progresses, none of them dig deep to model the detailed user preference from various fashion aspects. Factorization Machine (FM) and its variants [19–21] are also applicable for personalized fashion recommendation, which leverage the feature-level interactions to predict the final recommendation probability given the user feature list and item feature list. Such a modeling certainly takes advantage of more information, and can also alleviate the sparsity problem of the user-item interaction by modeling the feature-level interactions. However, they are not able to model the user and item interaction in specific fields, therefore fail to capture the field-level user preference. In recent years, graph neural network (GNN) [22] has been applied in personal recommendation and boost the CF-based models by leveraging high-order connectives [23]. However, existing works are limited in taking more advantage of collaborative signals between user and items while fail to take advantage of other side information.

## 3. PROBLEM FORMULATION

The goal of this work is to model the field-level user preference and contextual factor attractiveness to predict the recommendation probability in specific factor field, such as *colour* and *style*, and further obtain holistic prediction score for a given item and user. For easy understanding, the specific task in this work is defined in this section.

We have the user set  $\mathcal{U} = \{u_t\}_{t=1}^{N_u}$ , item set  $\mathcal{I} = \{i_t\}_{t=1}^{N_i}$  and the factor field set  $\mathcal{F} = \{f_t\}_{t=1}^{N_f}$ , in which  $N_u$ ,  $N_i$  and  $N_f$  denote the number of users, items and fields respectively. For

easy illustration, we use  $u$  to denote a user,  $i$  or  $j$  to denote an item, and  $f$  or  $g$  to denote a field, which means  $u \in \mathcal{U}$ ,  $i, j \in \mathcal{I}$  and  $f, g \in \mathcal{F}$ . The interaction set between users and items are defined as  $\mathcal{R} = \{(u, i)\}$ , which describes the historical shopping behaviors of users.

For each factor field  $f$ , there is a factor set  $\mathcal{A}^f$ , which contains all factors belonging to this field. Each item  $i$  is associated with a factor list  $\mathbf{a}_i = [a_i^f \text{ for } f \in \mathcal{F}]$ , and each factor in the list belongs to one factor field  $a_i^f \in \mathcal{A}^f$ . Note that in our setting, there is only one factor for each field, and the item ID is treated as a special item field. The user is represented by ID only. The the problem is formulated as follows:

- **Input:** The user sets  $\mathcal{U}$ , the item factor sets  $\{\mathbf{a}_i\}_{i \in \mathcal{I}}$ , and the user-item interactions  $\mathcal{R}$ .
- **Output:** A predictive model which outputs not only the holistic interaction score  $y_{ui}$  for a given user-item pair  $(u, i)$ , but also specific interaction scores  $\{y_{ui}^f\}$  in multiple influential factor fields of fashion products.

## 4. APPROACH

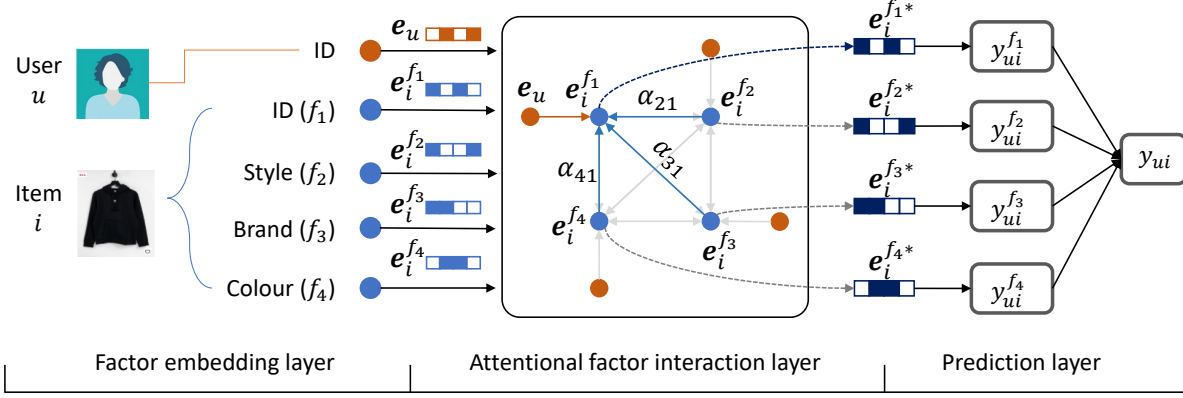
In this section, we introduce the Attentional Factor Field Interaction Graph (AFFIG) model. As illustrated in Fig. 2, the proposed model embraces three main parts: (1) a factor embedding layer for initializing factor embeddings, (2) attentional factor-level interaction layer to model detailed interaction patterns and (3) prediction layer for producing factor-level and holistic interaction scores.

### 4.1. Factor Embedding Layer

As mentioned in section 3, each user is represented by ID and each item is represented by a set of factors and each factor corresponds to one factor field (item ID is also treated as a factor). Following the strategies of mainstream recommendation models [20, 21, 24], we use low-dimensional dense embedding to model each factor. Specifically, we have the embedding table for users  $\mathbf{E}_U$  and embedding tables for items  $\{\mathbf{E}_I^f\}_{f \in \mathcal{F}}$ , in which  $\mathbf{E}_I^f$  is specifically for the field  $f$ . Based on the embedding tables, we can have the representation for a given user  $u$ , which is  $\mathbf{e}_u \in \mathbf{E}_U$ . Given an item  $i$  with factors  $\mathbf{a}_i = [a_i^f \text{ for } f \in \mathcal{F}]$ , the representation is composed with the embedding of different factor fields, which is  $\mathbf{E}_i = [\mathbf{e}_i^f \text{ for } f \in \mathcal{F}]$  and  $\mathbf{e}_i^f \in \mathbf{E}_I^f$ .

### 4.2. Attentional Factor-level Interaction Layer

Our factor-level interaction includes two parts, 1) the interaction between user and item factors and 2) the interaction between item factors across fields. The user-factor interaction captures the factor-level user preference and the cross-field factor interaction captures the detailed popularity of the item with certain attribute combinations. Given the embedding  $\mathbf{e}_u$  for user  $u$  and the factor-level embeddings  $\mathbf{E}_i$  for item  $i$ , the



**Fig. 2.** Framework of the proposed FFIG, which includes three parts: Factor embedding layer, Attentional factor interaction layer and Prediction layer. The framework takes four fields of item factors as an example.

interaction between user  $u$  and the factor of field  $f$  of  $i$  is calculated as:

$$\mathbf{e}_{ui}^f = \mathbf{e}_u \odot \mathbf{e}_i^f. \quad (1)$$

The interaction between factors across fields for the item is modeled in a similar way as follows:

$$\mathbf{e}_i^{fg} = \mathbf{e}_i^f \odot \mathbf{e}_i^g. \quad (2)$$

We aggregate the interaction between all cross-field factors for each factor with a attention mechanism to adaptively model the cross-field influences between factors. Specifically, for field  $f$ , the attention coefficients for different fields are calculated as follows:

$$\mathbf{e}_i^{fg} = \mathbf{W}[\mathbf{e}_i^f || \mathbf{e}_i^g], \quad (3)$$

$$\alpha_i^{fg} = \text{softmax}(\mathbf{e}_i^{fg}) = \frac{\exp(\mathbf{e}_i^{fg})}{\sum_{k \in \mathcal{F}} \exp(\mathbf{e}_i^{fk})}, \quad (4)$$

where  $\mathbf{W}$  is a projection matrix. Note that self-interaction is included. The aggregation of factor interactions across fields for field  $f$  can therefore be obtained by:

$$\mathbf{e}_i^f = \sum_{g \in \mathcal{F}} \alpha_i^{fg} \mathbf{e}_i^g. \quad (5)$$

In the end, we combine the two interaction parts together and obtain the final representation for the field  $f$  for the follow-up prediction of interaction probability of this field as:

$$\mathbf{e}_{ui}^{f*} = \mathbf{e}_i^f + \mathbf{e}_{ui}^f. \quad (6)$$

### 4.3. Fashion Preference Prediction

**Field-specific preference:** Given the final representation of each factor field after interacted with the user and cross-field factors, we can now predict the field-specific user fashion

preferences. For field  $f$ , the recommendation probability is predicted as:

$$y_{ui}^f = h^f(\mathbf{e}_{ui}^{f*}), \quad (7)$$

where  $h^f$  is the predictor specifically for field  $f$ . It is implemented by a linear projection layer in our method.

**Holistic preference:** After obtaining the factor field-specific recommendation predictions, the holistic recommendation score can be further obtained by combining field-level predictions. In our implementation, we simply sum up and obtain the final probability score:

$$y_{ui} = \sum_{f \in \mathcal{F}} y_{ui}^f. \quad (8)$$

### 4.4. Model Training

Following previous works [18,25], the pairwise Bayesian personalized ranking (BPR) loss is adopted in our approach to optimize the model parameters under the assumption that the observed interaction should have higher predictive score than unobserved interactions. The entire model is optimized by minimizing the following objective:

$$\min_{(u,i,j) \in \mathcal{O}} \sum -\ln s(y_{ui} - y_{uj}) + \eta \|\Theta\|, \quad (9)$$

where  $\mathcal{O} = \{(u, i, j) | (u, i) \in \mathcal{R}^+, (u, j) \in \mathcal{R}^-\}$  denotes the pairwise training triples.  $\mathcal{R}^+$  and  $\mathcal{R}^-$  denote observed and unobserved interaction sets, respectively.  $\Theta$  denotes all the trainable parameters and  $s(\cdot)$  is the Sigmoid function.  $L_2$  regularization is applied to avoid over-fitting.

## 5. EXPERIMENT

### 5.1. Dataset

We prepare three datasets, i.e., Amazon-Women, Amazon-Men and iFashion to evaluate the effectiveness of the proposed method, which are based on the Amazon Review

**Table 1.** Statistic of datasets

Dataset	#Interaction	#User	#Item
Amazon-Women	292,906	57,515	166,545
Amazon-Men	61,111	13,911	39,864
iFashion	193,972	10,000	149,772

**Table 2.** Factor fields for each dataset and the number of factors for each field. cate- $n$  denotes  $n$ -th levels of category. A-W and A-M denote Amazon-Women and Amazon-Men datasets respectively.

Fields	colour	style	brand	price	cate-1	cate-2
A-W	30	11	1656	9	7	51
A-M	30	11	377	9	4	24
iFashion	colour	upper length	shoe closure	neck-line	sleeve length	closure type
	59	5	5	11	10	14
	pattern	lower length	occasion	toe shape	heel type	pants fit
	11	6	4	4	5	3
	toe type	dress shape	shoes dec	sleeve style	sweater style	coat style
	4	7	5	10	5	2
	cate-1	cate-2	sub-3	style		
	4	11	59	11		

(Clothing, Shoes and Jewelry section) [26] and the iFashion datasets [7] respectively. Since the Amazon and iFashion datasets cover different information, we have different settings for the two groups of datasets from the investigated factor fields to data preprocessing. Specifically, we dropped users with very few interactions to ensure the quality of data for the two Amazon datasets. Since the iFashion dataset is very large-scale, we randomly sampled 10,000 users from the original dataset and build a subset dataset using the sampled users and all their interacted items as well as the interaction records.

For **Amazon-Women** and **Amazon-Men**, we investigated six factor fields that important in fashion domain, including, *Colour*, *Style*, *Brand*, *Price* and two levels of *Category*. All factor information of the items is extracted from the textual descriptions and product images provided in the original datasets. More specifically, brand and price information are directly extracted from the meta-data. For category information, we applied hierarchical keywords matching strategy to extract two levels of categories for each fashion product from product description, and also manually checked to prevent mis-match as possible. Moreover, we applied the colour analysis tool colourThief to extract the colour information and the commercial fashion image tagging tool ViSenze to extract the style information. Both colour and style are extracted based on item images.

For **iFashion** dataset, we extract all field factors based on the image of each item by applying a commercial tool ViSenze. In total there are 22 fields included in our experiments, including *three levels of categories*, *style*, and other fashion related attributes (Refer to Table 2 for the whole list). In our dataset, each user has a sequence of interaction with items in chronological order. We use the early interactions for training and late ones for testing for each user. The splitting ratio is about 9:1 for each user. The statistics of three datasets after preprocessing are shown in Table 1.

## 5.2. Experimental Settings

**Baselines:** Five competitive recommendation models which are closely related to our method are selected as the baselines. All compared methods are introduced as follows:

- **MF** [25] is the Matrix Factorization model using BPR loss.
- **FM** [19] is a factorization machine method that takes all user and item information as features of an input interaction and can predict the score of the input by modeling second-order feature interactions.
- **NFM** [21] implements the FM with neural network.
- **AFM** [20] is an FM method with the attention mechanism.
- **LightGCN** [23] is one of the state-of-the-art CF-based methods that models high-order CF signal incorporation with GNN and has achieved preferable performance in many personalized recommendation tasks.
- **FFIG** is our method using average pooling in factor interaction aggregation (using  $\mathbf{e}_i^f = \frac{1}{N_f} \sum_{g \in \mathcal{F}} \mathbf{e}_i^g$  in Eq. 5).
- **AFFIG** is our method applying attention mechanism in interaction aggregation (applying Eq. 5).

In summary, MF and LightGCN use only the user-item interaction records while other methods, i.e., FM, NFM, AFM and our (A)FFIG methods leverage factor information.

**Implementation details:** We implemented all compared methods by PyTorch. The embedding size for user and item factors is set to 64 for all methods. In the training process, we set the batch size to 512, learning rate to 0.02 and weight decay to  $1e-6$  for all methods. Dropout rate is set to 0.2 for MF and LightGCN, 0.8 for FM and NFM, and 0.5 for other methods to achieve best performance for every method.

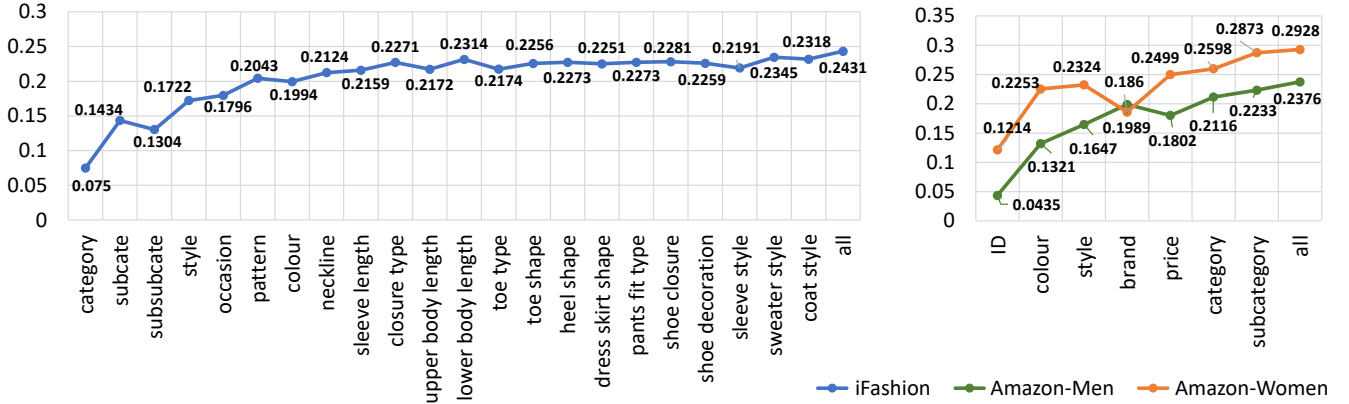
**Evaluation:** We randomly sample 99 negative items for each user [27, 28] in the test set and combine all positive and negative samples to build the candidate item pools. The test set is fixed and same for all experiments. We evaluate the recommendation performance with three common top- $k$  ranking metrics: Precision@10, Recall@10 and NDCG@10.

## 5.3. Experimental Results

**Recommendation performance:** In Table 3, we show the overall recommendation performance of the proposed method and all the baselines on three datasets. From the results we

**Table 3.** Overall Performance Comparison

	Amazon-Women			Amazon-Men			iFashion		
	Precision	Recall	NDCG	Precision	Recall	NDCG	Precision	Recall	NDCG
MF	0.0315	0.3019	0.2166	0.0180	0.1772	0.1153	0.0404	0.1650	0.1326
FM	0.0367	0.3516	0.2241	0.0300	0.2953	0.1779	0.0457	0.1878	0.1331
NFM	0.0292	0.2788	0.1546	0.0300	0.2948	0.1804	0.0333	0.1356	0.0904
AFM	0.0414	0.3961	0.2541	0.0328	0.3229	0.1975	0.0698	0.3024	0.1941
LightGCN	0.0382	0.3658	0.2552	0.0268	0.2638	0.1765	0.0447	0.1823	0.1439
FFIG	0.0459	0.4364	0.2723	0.0402	0.3944	0.2310	<b>0.0916</b>	<b>0.4029</b>	<b>0.2523</b>
AFFIG	<b>0.0501</b>	<b>0.4756</b>	<b>0.2928</b>	<b>0.0407</b>	<b>0.3995</b>	<b>0.2376</b>	0.0877	0.3920	0.2431




**Fig. 3.** NDCG@10 results of the AFFIG model without incorporating one factor field on three datasets. Each result in the figure corresponds to one variant of AFFIG without one field. Lower performance means greater impact of the corresponding field on the recommendation performance.

can see that 1) our FFIG method outperforms all baselines on all three datasets in terms of all three evaluation metrics; 2) in general, all factor included methods, i.e., FM, NFM, AFM and our FFIG and AFFIG show better performance than MF which only models user-item interactions. However, even though LightGCN models user-item interaction solely, it achieves much better performance since it incorporates more high-order CF signals; 3) NFM shows particularly disappointing performance on Amazon-Women and iFashion datasets since it is very easy to over-fit through our experimental observation; 4) by applying attention mechanism in aggregating across-field factor interactions, the AFFIG method outperforms FFIG on two Amazon datasets, while such a design does not work for the iFashion dataset.

**Investigation of factor fields:** The focus of our method is the incorporation of rich and domain-specific factors belonging to multiple fields for fashion items and field-level decomposition of the user-item interaction probability. In this part, we investigate how different factor fields can affect the overall recommendation performance. Specifically, on each dataset, we evaluate the proposed AFFIG method excluding one field at each experiment. The performance of all AFFIG variants without any one field is shown in Fig. 3 for three datasets re-

spectively.

From the left part of Fig. 3, we can observe the influence of the content factor fields to the overall recommendation results for iFashion dataset. As we can see, several important fields such as different level of *categories*, *style*, *occasion* and *colour* have greater impact on the final results than other. In terms of the Amazon datasets, showing in the right part of Fig. 3, the impact of different factor fields show consistency on two datasets except for *brand*. Overall, ID is the most important field and excluding it greatly degrades the recommendation performance for both Women and Men cases. In addition, *colour* and *style* show significant influence on the recommendation performance while the *categories* information seems less important for Amazon datasets than for iFashion dataset. It needs to mention that the Amazon datasets are purchase records with large time span while the iFashion dataset is composed with click records in a short session. When people randomly browse items, they are quite likely to choose one category of items constantly, therefore we can guess that the user's interactions with items in iFashion dataset have clear patterns related to category, which makes the category information particular important to this dataset. However, such a pattern can be much weaker in the Amazon case since people

	Id	0.0202		Id	0.9752
	Category	0.0039		Category	0.7966
	Subcategory	0.0149		Subcategory	0.9313
	Subsubcategory	0.0019		Subsubcategory	0.4205
	Style	0.3556		Style	0.7394
	Colour	0.6417		Colour	0.2296
	Occasion	0.0233		Dress shape	0.9468
	Overall	0.1516		Sleeve style	0.7627
Historical choices User:376b4ac8			Overall 0.7253		

**Fig. 4.** Example showing AFFIG predicts recommendation scores for items from different factor-fields, and aggregates all to make recommendation.

usually do not stick to **BUY** only one category of items.

**Case Study:** We illustrate an example of the iFashion dataset in Fig. 4. For a given user 376b4ac8 and two candidate items 7c145052 and b1ffd519, our AFFIG model is able to predict the recommendation scores for two items from different factor fields, and then aggregate them together to obtain the final score. For example, for the positive item, our model predicts it to have high scores for its subcategory, dress shape, and lower scores for its colour, which is quite reasonable based on the user’s historical picks. In comparison, the negative item is predicted to have low possibility in terms of all factor fields.

## 6. CONCLUSION

This paper worked on the personalized fashion recommendation problem, aiming to decompose the user-item interaction into factor field-level to alleviate the data sparsity problem and therefore improve the recommendation results. The AFFIG method was proposed that predicts the field-level recommendation probability by modeling the interactions between user and the specific factor as well as those between factors across fields. Experimental results on three benchmark fashion datasets prove the effectiveness of AFFIG. Empirical studies also discuss the impact of different factor fields in fashion domain on recommendation performance.

In future work, we shall focus on the several directions to improve our method. First, more high-order interactions at field level can be explored to consider more cross-field influence between factors as well as the factor combinations. Second, our model can be extended to cold-start recommendation problems and recommendation for other domains by investigating different factor fields for the sake of more accurate and inspiring recommendation results.

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