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Wenhao Guo
college of management and economic, wh_guo@tju.edu.cn

Jin Tian
College of Management and Economics, Tianjin University, jtian@tju.edu.cn

Minqiang Li
College of Management and Economics, Tianjin UniversityCollege of Management and Economics, Tianjin UniversityCollege of Management and Economics, Tianjin University, mqli_tju@163.com

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Short Paper

Wenhao Guo
College of Management and Economics, Tianjin university
Tianjin, China
wh_guo@tju.edu.cn

Jin Tian
College of Management and Economics, Tianjin university
Tianjin, China
jtian@tju.edu.cn

Minqiang Li
College of Management and Economics, Tianjin university
Tianjin, China
mqli@tju.edu.cn

Abstract

Nowadays, sequential recommender systems are widely used in E-commerce fields to capture consumers' dynamic preferences in short terms. Existing transformer-based recommendation models mainly consider consumer preference for the products and some related features, such as price. However, besides such objective features, some subjective features, such as consumers' preference for product quality, also affect consumers' purchase decisions. In this paper, we design a Sequential Recommender system based on Objective and Subjective features (SROS). We construct subjective features by using natural language processing to analyze online consumer reviews. Then we design a feature-level multi-head self-attention to explore the interactions between objective features and subjective features and capture consumers' dynamic preferences for them among different purchases. Experimental results on real-world datasets demonstrate the effectiveness of the proposed model.

Keywords: Sequential recommendation, natural language processing, multi-head self-attention, deep learning, E-commerce

Introduction

Most E-commerce platforms with explosive growth have employed recommender systems to increase their sales (Fang et al., 2019). Recommender systems model consumer's preferences for different products and predict consumer's next purchase. They help consumers to find preferred products among thousands of products provided by the platforms. Recently, deep learning-based sequential recommender systems have been introduced to capture consumer's short term preferences by using the transformer with the self-attention mechanism (Wang et al., 2021). Compared with the traditional recommender systems such as matrix factorization-based recommendation (Polat & Du, 2005; Xue et al., 2017) and context-based recommendation (Adomavicius & Tuzhilin, 2011) which explore consumer's static preference, the sequential recommender systems mine consumer's dynamic preference from consumer's historical purchase sequence.

The conventional sequential recommender systems only use consumer IDs and product IDs to construct consumer purchase behavior and predict consumer's next purchase (Hidasi et al., 2015; Kang & McAuley, 2018; Sun et al., 2019). Consumers also have different preferences for product features such as price, brand

and size (Wang & Hazen, 2016; Wells et al., 2011). These preferences affect consumers' purchase decisions. Some sequential recommender systems have taken these features into consider to make more accurate recommendations (Kang & McAuley, 2018; Zhou et al., 2020).

The features of products include objective features and subjective features (Kashyap et al., 2022; Luo et al., 2008). Generally, the objective features are the quantitative features that can be easily observed and measured, often determined by the retailers and manufactures (Luo et al., 2008). Examples of objective features include price and category of a product. The subjective features are the qualitative features that are not so easy to be observed and measured, often perceived by all the consumers (Luo et al., 2008). In our research, we define the subjective features as price utility, which describes the affordability of a product's price, and quality utility, which describes the durability of the product. Unlike existing works, we aggregate all consumers' subjective perceptions to derive the subjective features of the products and reduce the potential bias caused by individual consumer's preference on the features. Both the objective and subjective features contribute to consumer's preference and purchase (Dzyabura & Jagabathula, 2018). On the one hand, existing transformer-based sequential recommender systems mainly consider the objective features in consumer's purchase history. However, the purchase of products with different subjective features also reflects consumer's preference. We can capture more accurate preference by involving the subjective features in transformer-based sequential recommender systems. On the other hand, there are already some studies that analyze consumer reviews to involve consumer's subjective perception to the product in recommendation models (Duan et al., 2022; Xia et al., 2021). However, these studies typically extract each consumer's subjective perception based on each review they give for a product. These approaches overlook consumers' preferences for subjective features that are not explicitly expressed in their reviews. Besides, the objective and subjective features also have cross effect on consumer's choices. For example, a consumer might accept high price because the product is with high quality utility and high price utility. Existing studies of transformer-based sequential recommender systems and review-aware recommender systems simply embed all the features and learn them commonly. They don't pay much attention on the interaction of the preferences to different types of features and the difference between consumer's preference to the product and to the features of the product.

In this paper, we aim to mine product's subjective features from online consumer reviews and consider consumer's preference for objective and subjective features and their interactions in sequential recommender systems. We propose a Sequential Recommender system based on Objective and Subjective features (SROS). Firstly, we construct subjective features by using natural language processing to analyze online consumer reviews. Unlike the most review-aware recommendation models, our approach summarizes all consumers' subjective perceptions of the product to calculate its overall subjective feature. Through this method, we can learn about consumer preferences for product features based on their choices, even when they have not expressed their opinions in a review. We design a feature-level multi-head self-attention-based preference interaction layer to explore the interactions between objective features and subjective features and explore consumer's dynamic preference to them among different purchases. Then we combine the products, features and interactions among features in consumer's purchase history and use product-level multi-head self-attention to learn consumer's preferences for the product and its objective and subjective features. Finally, we predict consumer's next purchase of product with different features. Experimental results demonstrate that the proposed model achieves better performance than the compared recommendation models.

Literature Review

Our research is related to the research on objective and subjective features of product. According to the existing study, product has objective and subjective features (Luo et al., 2008). Besides, consumers have a separate utility for these subjective and objective features (Adhikari, 2015). These utilities have different effect on different consumer's purchase (Dalmoro et al., 2019). Our work pay attention on how the price, price utility and quality utility affect each consumer's preference interactively.

Our research is also related to context-aware recommendations, sequential recommendations and review-aware recommendations. Context-aware recommendations not only considered the purchase but also considered the context of the purchase such as price, time, and location (Wei et al., 2014). Deep-learning has been applied to capture consumer's preferences towards the features in the context-aware recommendations recently (Juan et al., 2016; Xiao et al., 2017). However, these context-aware recommendations haven't paid attention on the dynamic preferences towards different features. Sequential recommendations are introduced to capture consumer's dynamic preference (Hidasi et al., 2015). The traditional transformer-based sequential recommendations only considered the product in purchase sequence (Sun et al., 2019). Nowadays, some studies begin to involve the product features into sequential recommendation (Hidasi et al., 2016; Kang & McAuley, 2018). However, they mainly focused on consumer's preference for the objective features and ignored the subjective features. Many review-aware methods mine consumers' opinions on different aspects of a product and involve them in recommendation systems based on matrix factorization or deep learning techniques (Duan et al., 2022; Kamehkhosh & Jannach, 2017). These works highly rely on the comprehensiveness of aspects included in reviews, that is, if the consumer express not enough preference or biased preference for the aspects or doesn't give the reviews at all, it will be hard for these methods to mine consumer's preference for the features. Besides, the existing works also ignored the interaction between objective and subjective features and their cross effect on consumer behavior.

SROS method

Problem Formulation

The problem we deal with is the product recommendation for consumers. We let $c_i \in \boldsymbol{C}$ where c_i is the consumer with index i, $\boldsymbol{C}$ is the consumers set, $p_j \in \boldsymbol{P}$ where p_j is the product with index j, $\boldsymbol{P}$ is the products set. For each product p_j, we assume that the objective features set is $\left\{f\_o_j^1, f\_o_j^2, \ldots\right\}$, the subjective features set is $\left\{f\_s_j^1, f\_s_j^2, \ldots\right\}$. The purchase sequence of consumer c_i is $\boldsymbol{s}_i = \left\{p_i^1, p_i^2, p_i^3 \ldots p_i^t\right\}$. Our aim is to predict consumer's next purchase p_i^{t+1} in time $(t+1)$.

Objective and Subjective Features Constructing

The objective features such as price are typically discretized into several levels because consumers usually have general feelings to these features (Zhang et al., 2022). In this work, we also discretize the objective features into different levels. In our datasets, the price is only objective feature that can be discretized. The objective price feature of product p_j, $f\_o_j^{\text{pr}}$ is set as

$$f\_o_j^{\text{pr}} = \begin{cases} low & \text{if } z_j < z^1 \\ medium & \text{if } z_j \geq z^1 \text{ and } z_j < z^2 \\ high & \text{if } z_j \geq z^2 \end{cases} \tag{1}$$

where $f\_o_j^{\text{pr}}$ is divided into 3 levels. z_j is the price of product. z^1 is the first tertile of all products' prices. z^2 is the second tertile of all products' prices.

We mine product's subjective features from online consumer reviews. At first, we learn all consumer's reviews by the Word2Vec method (Mikolov et al., 2013). The Word2Vec model learns the representations of words in reviews. Then we construct the related utility dictionary and sentiment dictionary. We consider the price utility and quality/use utility mainly. So "price" and "quality/use" are set as the seed words. We use Word2Vec to find the words familiar to the seed words and delete the unrelated words artificially to construct the price utility dictionary and quality/use utility dictionary. We construct the sentiment polarity dictionary based on the SentiWordNet dictionary (Baccianella et al., 2010). The SentiWordNet dictionary is widely used to extract consumer's sentiment polarity from consumer reviews (Da'u et al., 2020; Luo et al., 2021). We also extend the sentiment polarity dictionary by adding selected sentiment words that are familiar to the seed words. The added sentiment words are derivative words such as "pricey", "priceless", and "inexpensive" which have been mentioned in consumer reviews but not included in the original sentiment polarity dictionary.

We use utility dictionary and sentiment polarity dictionary to calculate the subjective score from each consumer to each product. We select the sentences that including the words in utility dictionary from online consumer review. Then we employ the nltk method and the sentiment polarity dictionary to get the subjective score. We summarize the subjective price score of product p_j as

$$x_j = \frac{\sum_{c_i \in \chi_j} x_{ij}}{|\chi_j|} \tag{2}$$

where x_j is the subjective price score of product p_j, χ_j is the set of consumers that have purchased product p_j. x_{ij} is the subjective price score from consumer c_i to product p_j. The subjective quality score is calculated in the same way.

We consider the situation that consumers usually cannot read all reviews to obtain a comprehensive understanding of the subjective feature and they also obtain a fuzzy understanding similar with the objective features. So we also discretize the subjective features into different levels as objective features. The subjective price utility feature of product p_j, $f\_s_j^{\mathrm{prU}}$ is set as

$$f\_s_j^{\mathrm{prU}} = \begin{cases} low & \text{if } x_j < x^1 \\ medium & \text{if } x_j \geq x^1 \text{ and } x_j < x^2 \\ high & \text{if } x_j \geq x^2 \end{cases} \tag{3}$$

where $f\_s_j^{\mathrm{prU}}$ is also divided into 3 levels. x^1 is the first tertile of all products' subjective price scores. x^2 is the second tertile of all products' subjective price scores. The quality utility $f\_s_j^{\mathrm{quU}}$ is calculated in the same way.

Embedding Module

We construct the SROS method referring to the SASRec method (Kang & McAuley, 2018) as shown in Figure 1. The SROS methods mainly include three modules: embedding module, preference interacting module and learning and predicting module.

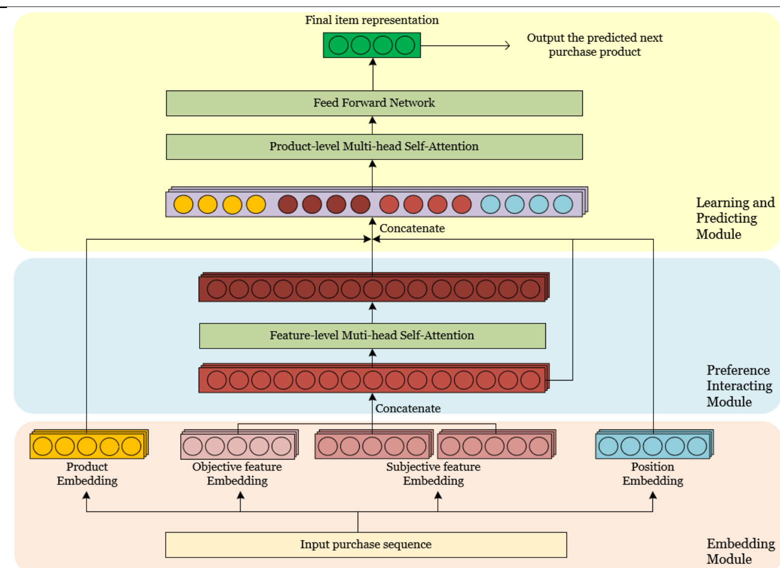

Figure 1. Overview of the proposed SROS method

At first, we embed the products, the objective features, the subjective features, and the position of each product in the purchase sequence.

$$\boldsymbol{e}_i^k = embedding\left(p_i^k\right) \tag{4}$$

$$\boldsymbol{e\_o}_i^k = embedding\left(f\_o_k^{\mathrm{pr}}\right) \tag{5}$$

$$\boldsymbol{e\_sp}_i^k = embedding\left(f\_s_k^{\mathrm{prU}}\right) \tag{6}$$

$$\boldsymbol{e\_sq}_i^k = embedding\left(f\_s_k^{\mathrm{quU}}\right) \tag{7}$$

$$\boldsymbol{e\_pos}_i^k = embedding\left(pos_i^k\right) \tag{8}$$

where $\boldsymbol{e}_i^k$, $\boldsymbol{e\_o}_i^k$, $\boldsymbol{e\_sp}_i^k$, $\boldsymbol{e\_sq}_i^k$, and $\boldsymbol{e\_pos}_i^k$ are the embedding of the product p_i^k, the objective features, the subjective features, and the position of product p_i^k in consumer c_i 's purchase sequence. The embedding is calculated for the convenience of deep learning in next modules.

Preference Interacting Module

In the preference interacting module, we design a feature-level multi-head self-attention to process the subjective and objective features of products in each consumer's purchase sequence. Our aim is to explore the interaction of consumer's preference to these features. Firstly, we concatenate the embedding of subjective and objective features of products as

$$\boldsymbol{f}_i^k = concat\left(\boldsymbol{e\_o}_i^k, \boldsymbol{e\_sp}_i^k, \boldsymbol{e\_sq}_i^k\right) \tag{9}$$

where $\boldsymbol{f}_i^k$ is the combination of the product p_i^k 's features purchased by consumer c_i . It represents consumer c_i 's preference for the features. The multi-head self-attention is widely used to highlight the interaction of the different parts of input (Vaswani et al., 2017). So, we apply it in the Preference Interacting Module to capture the interaction of the objective and subjective features among consumer's purchase history. We stack $\boldsymbol{f}_i^k$ into $\boldsymbol{F}_i$ by the dimension of purchase sequence of consumer c_i . Then we set the query, key and value in each head referring to the classical multi-head self-attention as

$$\boldsymbol{Q}_i^b = \boldsymbol{W}_Q^b \boldsymbol{F}_i \tag{10}$$

$$\boldsymbol{K}_i^b = \boldsymbol{W}_K^b \boldsymbol{F}_i \tag{11}$$

$$\boldsymbol{V}_i^b = \boldsymbol{W}_V^b \boldsymbol{F}_i \tag{12}$$

where $\boldsymbol{Q}_i^b$, $\boldsymbol{K}_i^b$, and $\boldsymbol{V}_i^b$ are the query, key and value in the b head, $\boldsymbol{W}_Q^b$, $\boldsymbol{W}_K^b$, and $\boldsymbol{W}_V^b$ are learnable matrixes. Then we calculate the output of this head as

$$\boldsymbol{h}_i^b = \sigma\left(\frac{\left(\boldsymbol{Q}_i^b\right)^{\mathrm{T}} \boldsymbol{K}_i^b}{\sqrt{\dfrac{d}{n\_heads}}}\right)\boldsymbol{V}_i^b \tag{13}$$

where $\boldsymbol{h}_i^b$ is the output of this head, $\sigma(\bullet)$ is the SoftMax function. d is the size of input embedding. n_heads is the number of heads. Then we concatenate the output in each head and get the final output as

$$\boldsymbol{h}_i^{\mathrm{inf}} = concate\left(\boldsymbol{h}_i^1, \boldsymbol{h}_i^2 \ldots \boldsymbol{h}_i^{n\_heads}\right) \tag{14}$$

where $\boldsymbol{h}_i^{\mathrm{inf}}$ is interacted feature embedding. It is the output of all the heads. In this module, consumer's choices for different features are included in $\boldsymbol{F}_i$ and then reflected in $\boldsymbol{Q}_i^b$, $\boldsymbol{K}_i^b$, and $\boldsymbol{V}_i^b$. We calculate the $\sigma\left(\frac{\left(\boldsymbol{Q}_i^b\right)^{\mathrm{T}} \boldsymbol{K}_i^b}{\sqrt{\frac{d}{n\_heads}}}\right)$ as self-attention weight score in b head. The self-attention weight score represents the interaction between consumer's choices affected by the features. We multiply the self-attention weight score and $\boldsymbol{V}_i^b$ to represent the embedding of the objective and subjective features. Different from the original embedding, $\boldsymbol{h}_i^{\mathrm{inf}}$ represents not only the features but also the interaction of consumer's preference to the objective and subjective features among consumer's purchase history. Different heads capture interactions from different representation subspaces at different positions. We also use the item masked mechanism in the preference interacting module to avoid the leaking of future purchase.

Learning and Predicting Module

After calculating the interacted feature embedding in the preference interacting module, we concatenate the item embedding, interacted feature embedding, original feature embedding and position embedding as

$$\boldsymbol{h}_i = concate\left(\boldsymbol{h}_i^{\mathrm{pro}}, \boldsymbol{h}_i^{\mathrm{inf}}, \boldsymbol{h}_i^{\mathrm{orf}}, \boldsymbol{h}_i^{\mathrm{pos}}\right) \tag{15}$$

where $\boldsymbol{h}_i$ is the embedding used for next steps. $\boldsymbol{h}_i^{\mathrm{pro}}, \boldsymbol{h}_i^{\mathrm{inf}}, \boldsymbol{h}_i^{\mathrm{orf}}, \boldsymbol{h}_i^{\mathrm{pos}}$ are the item embedding, interacted feature embedding, original feature embedding and position embedding in consumer i 's purchase history. We concatenate the four parts of embeddings to represent the comprehensive information of product, the features and the interactive features. So, we explore consumer's preference by using the comprehensive information. Then we stack $\boldsymbol{h}_i$ into $\boldsymbol{H}$ by all consumers and put $\boldsymbol{H}$ into multi-head self-attention and point-wise feed-forward networks as

$$\boldsymbol{S} = Attention\left(\boldsymbol{W}_Q^{'}\boldsymbol{H}, \boldsymbol{W}_K^{'}\boldsymbol{H}, \boldsymbol{W}_V^{'}\boldsymbol{H}\right) \tag{16}$$

$$\boldsymbol{M} = Relu\left(\boldsymbol{S}\boldsymbol{W}^{(1)} + \boldsymbol{b}^{(1)}\right)\boldsymbol{W}^{(2)} + \boldsymbol{b}^{(2)} \tag{17}$$

where $\boldsymbol{S}$ is the results of multi-head self-attention and $\boldsymbol{M}$ is the results of point-wise feed-forward networks. $\boldsymbol{W}_Q^{'}$, $\boldsymbol{W}_K^{'}$, $\boldsymbol{W}_V^{'}$, $\boldsymbol{W}^{(1)}$, and $\boldsymbol{W}^{(2)}$ are learnable matrixes. $\boldsymbol{b}^{(1)}$ and $\boldsymbol{b}^{(2)}$ are learnable bias terms. The $Attention(\bullet)$ is similar with multi-head self-attention in Preference Interacting Module. However, it is product-level which explores the interaction among the comprehensive information of product. The product-level multi-head self-attention models not only consumer's preference for the objective and subjective features of the product but also consumer's preference for the product itself. $Relu(\bullet)$ is the Relu function. After e layers of multi-head self-attention and point-wise feed-forward networks, we predict the purchase in $(t+1)$ by using the representation of consumer c_i in time t, $\boldsymbol{M}_{it}^e$ as

$$y_{ik}^{t+1} = \boldsymbol{M}_{it}^e \boldsymbol{e}_i^k \tag{18}$$

where y_{ik}^{t+1} is the relevance of product p_i^k purchased by consumer c_i in time $(t+1)$. We rank the relevance for all products for consumer to recommend the next product p_i^{t+1}.

Experiments

Datasets and Evaluation Metrics

We conduct our experiments on three public datasets from Amazon.com (Ni et al., 2019). They are musical instrument dataset, office product dataset and appliances dataset. The musical instrument and office product datasets include price as an objective feature and price utility and quality utility as subjective features. In the appliances dataset, the objective features consist not only price but also category and brand, while the subjective features consist of price utility and quality utility. Regarding the objective features category and brand, we do not discretize them but just embed them. Each purchase record includes consumer ID, product ID, consumer review to the product, and purchase time. We use Precision, Recall, MRR and NDCG as evaluation metrics. Precision and Recall are accuracy-aware metrics. MRR and NDCG are ranking-aware metrics.

Compared Models

We compare our SROS method with a series of recommendation models. We incorporate (1) the context-aware deep-learning models which take the features in each purchase into consider, such as AFM (Xiao et al., 2017) and FFM (Juan et al., 2016), (2) the sequential recommendation models which only consider the consumer and products in the purchase history, such as SASRec (Kang & McAuley, 2018), (3) the sequential recommendation models which directly embed the features of products, such as GRU4RecF (Hidasi et al., 2016) and SASRecF (Kang & McAuley, 2018; Zhao et al., 2021).

Results

We testify the recommendation performance of the proposed SROS model. All data is divided into 70% of data for learning and the remaining 30% for testing. The experiments of each algorithm are running for 10 times for T-test. We use Top-10 recommendation. The results are shown in Table 1.

Datasets	Method	PRE@10	REC@10	MRR@10	NDCG@10
Musical Instruments	AFM	0.0098***	0.0554***	0.0243***	0.0270***
	FFM	0.0088***	0.0508***	0.0416***	0.0371***
	SASRec	0.0096***	0.0957***	0.0668***	0.0737***
	GRU4RecF	0.0103**	0.1030**	0.0715**	0.0789**
	SASRecF	0.0097**	0.0961**	0.0664**	0.0739**
	SROS	0.0110	0.1105	0.0780	0.0855
Office Products	AFM	0.0054***	0.0345***	0.0146***	0.0171***
	FFM	0.0065***	0.0406***	0.0255***	0.0250***
	SASRec	0.0145*	0.1452**	0.1128***	0.1205***
	GRU4RecF	0.0143**	0.1431***	0.1143**	0.1211***
	SASRecF	0.0129***	0.1290***	0.0972***	0.1048***
	SROS	0.0148	0.1481	0.1181	0.1252
Appliances	AFM	0.0085***	0.0829***	0.0401***	0.0498***
	FFM	0.0086***	0.0823***	0.0561***	0.0619***
	SASRec	0.0151***	0.1505***	0.1161***	0.1242***
	GRU4RecF	0.0170***	0.1695***	0.1332***	0.1418***
	SASRecF	0.0179***	0.1790***	0.1438***	0.1522***
	SROS	0.0189	0.1885	0.1505	0.1595

Table 1. The performance of SROS and compared models

*p<0.1, **p<0.05, ***p<0.01

The results in Table 1. show that the SROS method outperforms all the compared algorithms on the three datasets and all metrics. Our SROS method brings improvement of 2.01% to 9.09% compared with the second-best methods. SROS outperforms much better than context-aware deep-learning models. It shows that the proposed method can capture consumer's dynamic preference for the features in the purchase history. SROS outperforms better than the sequential recommendation model without feature embedding, which shows that our consideration of objective and subjective features in recommendation is effective. SROS also outperforms the sequential recommendations which only consider the objective features. It shows that our consideration of the interaction of objective and subjective features is necessary. The objective and subjective features have cross effect on consumer preference.

Conclusion

In this paper, we present the SROS recommender system to consider the objective and subjective features of products. We firstly construct objective and subjective features of products by using natural language processing on online consumer reviews. Then we design a feature-level multi-head self-attention in SROS to explore the interaction between consumer's preference for objective and subjective features. We combine the information of product, product features and interactions of product features to capture more exact consumer preference. We will try to explore more different features and analyze their different effects on consumer behavior to extend our work. Moreover, we propose the SROS model solely based on consumer review data. In the future, we will try to incorporate more types of multimodal data (e.g., consumer clickstream data and consumer's feedback on recommended products from the platform) to mine more accurate subjective features and provide better recommendations to consumers.

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