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Personalized product search based on user transaction history and hypergraph learning

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Abstract

As the e-commerce shopping websites like Amazon become more and more popular, amounts of products spring up on the internet and bring great difficulties to product search. However, the conventional text-based search is confined to retrieving products relevant to query and personalized product search is still a challenging problem in e-commerce. Consequently, in this paper, we propose a personalized product search approach, which combines personalized multimedia recommendation into searching. First, we construct a hypergraph based on products' descriptions and user's transaction history. Then the similarity between products and the user is calculated based on two kind of textural feature extraction methods. After that, iterative procedure is introduced to obtain the final relevance score of each product to the user. Experimental results on our collected Amazon dataset show the effectiveness of the proposed approach. The MAP@5 of our method can reach 0.48 and the MAP@10 can reach 0.44. We propose a new re-ranking method for personalized product search, in which we utilize user's transaction history to choose products which is closer to the user's preference into the higher positions. Experimental results on our collected dataset show that our method is much better than the comparison methods.

Keywords Personalized product search · Hypergraph · Transaction history

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1 INTRODUCTION

With the development of e-commerce shopping websites, amounts of products spring up everywhere on the Internet and this phenomenon has brought great challenges to information filtering. Information overload has become very crucial to the success of e-commerce [9]. Meanwhile, e-shopping has become an important part of our lives today. When searching through shopping sites, users want to seek products which not only are relevant to their search queries, but also can satisfy their personal interests. The quality of product search not only relates to users' degree of satisfaction but also affects the interests of the e-commerce companies.

The booming of e-commerce in recent years has led to the generation of large amounts of transaction history data including plenty of products [20]. Particularly, each product can be defined by its specification which is essentially a set of attributes. Through this kind of unique data source we can mine business related knowledge and understand user preference. For example, many interesting questions can be potentially answered by mining transaction history: which kind of material or style does the user prefers? Automatic acquisition of such knowledge not only enables improvement of user's satisfaction, but also creates many opportunities of other applications such as market research, business intelligence, and targeted advertising.

Nowadays, product search is mainly based on textual query [5, 10, 17, 21, 27, 34]. Users can search the item they desired through inputting a few words such as dress and they will get a list of products. They will waste plenty of time to select satisfactory products. Consequently, it is necessary to re-rank those products which are closer to user's preference into higher positions to save users' time and enhance degree of satisfaction.

Typical search engines on e-commerce sites allow users to change the order in which the search results are presented with the predefined sort criteria. Common sort orders include "by sales rank", "by average customer rating", and often "by price" [11]. Although these re-ranking methods take users' opinions into consideration, they still have some shortcomings. First, because of seldom considering users' preferences, such as color, style and material, these methods would return some products not satisfying their interests. Second, for long tail products satisfying users' preferences but having low volume of sales or high price, they are seldom recommended to users. Recently, how to exploring user preferences from various related information to fulfill personalized recommendation and search is a hot research topic [14, 15, 28, 30, 41, 42], for example, exploring users social circles [28], rating behaviours [41], sequential location information [14, 15, 30] and so on. Consequently, we propose a new personalized product search method by integrating the users' preferences.

Overall, the most important task for us is to establish relationship between users and products, and among products, based on the textual descriptions of products and transaction history of users. Hypergraph is good at describing relationship among heterogeneous objects and it has been widely used in recommendation system [25] and image retrieval [7, 17, 18, 21, 38].

In this paper, we propose a hypergraph learning-based approach to accomplish personalized product search based on user's transaction history. Figure 1 illustrates the schedule of our framework. In our system, every user is represented by the textual descriptions of products obtained from the transaction history and each product is represented by its textual descriptions.

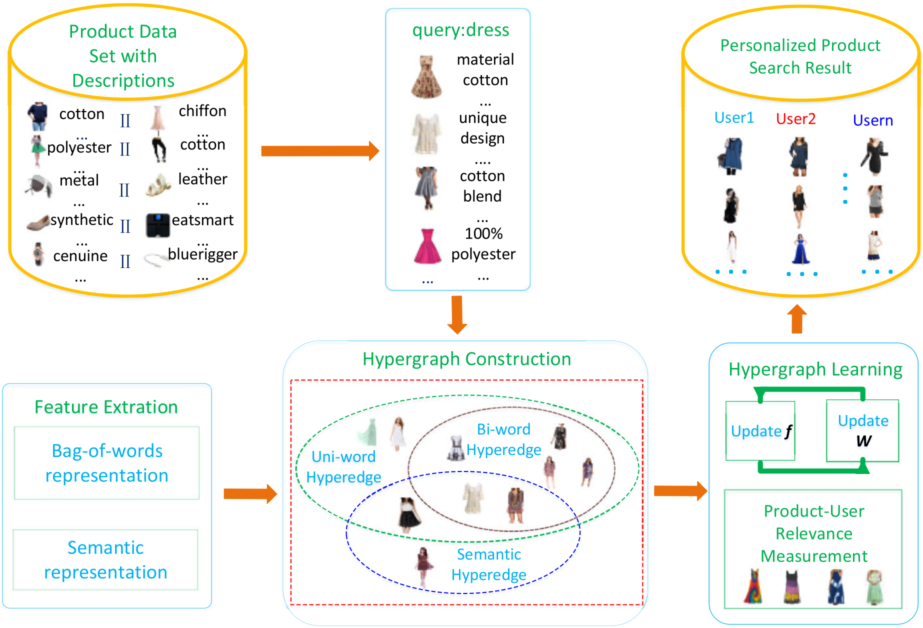

Fig. 1 The framework of proposed method, product-user relevance score y represents initial relevance score vector y. Take product set whose category items contains "dress" as an example

We construct a hypergraph for a user's textual query, in which the vertices denote the products and hyperedges are subsets of these products. Our constructed hypergraph contains three kind of hyperedges. The first two kind are generated by the words and the last one by the semantic methods. All hyperedges are based on the textual descriptions of products in user's transaction history relevant to the query. In the learning process, we identify the final product-user relevance scores by an iteratively updating approach.

The major contributions of this paper are as flows:

(1) We realize a personalized product search approach based on user's transaction history. This method simultaneously uses hypergraph learning to give users personalized product search results.
(2) We develop a kind of new hypergraph for personalized product search. Our constructed hypergraph contains three types of hyperedge, i.e. the uni-word, the bi-word and the semantic hyperedge. All kind of hyperedges are based on the textual descriptions of products in the user's transaction history relevant to the query.
(3) We propose utilizing two kind of textual feature methods to extract users' and products' textual feature, which are TF-IDF and LDA. Through TF-IDF we can get the co-occurrence characteristic of words and through LDA we can get the semantic characteristics of textual descriptions.

The remainder of this paper is organized as follows. In section 2, we review the related work of the image retrieval and hypergraph learning. The system overview is illustrated in section 3. Section 4 elaborates feature extraction. Hypergraph construction, product-user relevance score and hypergraph learning process are elaborated in section 5. Experiments are shown in section 6, and discussions are stated in Section 7. Finally, conclusion and future work are given in section 8.

2 Related work

In this section, we briefly introduce the related work on image retrieval and hypergraph learning.

2.1 Image retrieval

As the images grow complex and diverse on the internet, retrieval of the right images becomes a difficult challenge. Various typle of query can be utilized, such as search by images [22, 32, 39], free hand-drawn sketches [16, 31, 35, 36, 40], and text [5, 10, 17, 21, 27, 34,]. More and more researches are done on text-based image retrieval. Shi et al. [32] explores spatial and channel contribution to focus more on region of interest and make the global image representation vector more representative. Wang et al. [35] introduces a convolutional neural network (CNN) semantic re-ranking system to enhance the performance of sketch-based image retrieval and the system can leverage category information brought by CNNs to support effective similarity measurement between the images. Liu et al. [17] propose a tag ranking scheme, aiming to automatically rank the tags associated with a give image according to their relevance to the image content. Duan et al. [5] propose a reranking framework for large-scale TBIR, where pseudo-relevant images retrieved by tag matching are partitioned into clusters using visual and textual features. Qian et al. [27] propose an image retagging approach aiming at a wide range coverage of semantics. The top-ranked tags are not only highly relevant to the image but also have significant semantic compensations with each other. Hamano et al. [10] present a method enabling accurate tag refinement by effectively leveraging multilingual sources of tags and considering the hierarchical structure of tags.

Most image retrieval systems use words associated with the image in order to retrieve it, which is similar with personalized product search based on user transaction history. Generally, the personalization and adaptation of search results is typically achieved by deriving short- and long-term user profiles or by modeling the context of a search action from query, click-through, and other types of data [2, 14, 15, 28, 30, 41, 42]. To the best of our knowledge, there are two kind of personalized search: search on a personal collections and search on a general corpus with personalized result lists [1]. The typical representation of the first case is Email search [13]. What we concern in this paper is the latter. Qian et al. [28] fuse three social factors, personal interest, interpersonal interest similarity, and interpersonal influence, into a unified personalized recommendation model based on probabilistic matrix factorization for personalized recommendation. Jiang et al. [15] proposes an author topic model-based collaborative filtering (ATCF) method combining user preference topics to facilitate comprehensive points of interest (POIs) recommendations for social users. In this paper, we mainly concern about that each user has its own unique transaction history and they will get personalized result list in product search. As far as I know, few personalized methods have been proposed in product search based on user's transaction history. With the blending of multiple models, Wu et al. [37] build a stacking ensemble model to integrate the output of individual models and produce a more accurate prediction result. Ai et al. [1] propose one hierarchical embedding model as the first latent space model that jointly learns distributed representations for queries, produces, and users with a deep neural network. Gray et al. [8] develop an alternative algorithm to quantitatively classify clothing, brands, or fashion customers as exhibiting a combination of styles. Different from two papers mentioned above, we focus on a query less scenario where only category and descriptions are provided and consequently query relevance isn't concerned. Futhermore, we develop a hypergraph based on products' descriptions and user's transaction history, and experiments show that our method is effective in personalized product search.

2.2 Hypergraph-based applications

Graph learning has been proven to be an effective method to improve the performance of unsupervised and semi-supervised data modeling by uncovering the underlying structures of vertices [44]. However, one edge in graph can only associates with two vertices, which means one edge can only capture the relationship of two vertices [33]. Fortunately, hypergraph does not suffer from the drawbacks of graph and can model higher order relationship among three or more vertices containing grouping information [43].

Hypergraph learning has been proven to be an effective method to improve the performance of image retrieval [7, 18, 34, 38], image classification [19, 43], and object recognition [6]. Recently, hypergraph has also been widely adopted in personalized multimedia recommendation tasks [4, 25], for their effectiveness in higher-order relationship modeling.

Gao et al. [7] propose a hypergraph-based approach to simultaneously utilize visual information and tags for images to obtain retrieval results which is more relevant to the query in image retrieval. Liu et al. [18] implement a unified hypergraph in which images and other social contents are all denoted as vertices and their various relationships are denoted as hyperedges that connect these vertices to fast find the similar images to a given query. Yu et al. [38] construct a hypergraph by adapting CDH and MSD as basic image descriptors to rank images and get similar images. Wang et al. [34] propose a global and local visual features fusion approach to learn the relevance of images by hypergraph approach. Zhou et al. [43] generalize a powerful methodology of spectral clustering to hypergraphs, and further develop algorithms for hypergraph embedding and transductive classification on the basis of the spectral hypergraph clustering approach. Liu et al. [19] propose a novel elastic net hypergraph (ENHG) for two learning tasks, namely spectral clustering and semi-supervised classification. Gao et al. [6] propose a hypergraph analysis approach to address the problem of how to precisely estimate the distance between two objects represented by multiple views in view-based 3-D object retrieval and recognition. Pliakos et al. [25] propose a multi-reference image recommendation system based on a unified hypergraph, through which relevant images from a large pool are recommended to a reference user or a reference geo-location. Bu et al. [4] integrate multi-source media information and propose to model high-order relations in social media information by hypergraph instead of traditional graph. In this paper, we develop a kind of new hypergraph with three types of hyperedge, i.e. the uni-word, the bi-word and the semantic hyperedge.

3 System overview

In this section, we show the main procedures of our proposed method. As shown in Fig. 1, we take query "*dress*" as an example to illustrate the main procedures of our approach. We first select the products whose category contains "*dress*" as the product dataset to be sorted and products relevant to "*dress*" from user's transaction history to represent the user. Then, for each selected product and the user, we extract their bag-of-words representation and semantic representation from their textual descriptions. Third, a hypergraph with three kind of hyperedges is constructed based on the feature of the user. Next, we obtain the product-user relevance vector, by user's and product's textual feature. Finally, based on the hypergraph incident matrix and initial relevance vector, we obtain the product-user relevance scores by hypergraph learning. We sort the products by descending order according to the final product-user relevance vector.

4 Feature extraction

In this section, we employ the textual feature to represent each product and each user.

We denote the product dataset which is relevant to query q by $\chi = \{x_1, x_2, \ldots, x_n\}$, where x_i means the i-th product and n represents the number of products. Thus, for query q and user u, we only need to conduct personalized product search on χ.

Meanwhile, we select products which are relevant to query q from user's transaction history and choose the textual descriptions of these products to represent user u. We remove stop words and words which appear just for once from the descriptions of every product in χ and the descriptions representing user u. After preprocessing, we can get corpus c. For the query q, the total number of words left in corpus c is denoted by n_T. Here, let n_u be the total number of words left under query q representing user u.

4.1 Bag-of-words representation

Term frequency-inverse document frequency (TF-IDF) is a numerical statistic, quantifying the importance of a term in a document, belonging to a corpus [26]. In this paper, we use TF-IDF as a base textural feature representation.

First, we train a TF-IDF model for corpus c. Then we can get TF-IDF vector w_{pT} of every product p in χ and TF-IDF vector w_{uT} of user u. The dimensions of w_{pT} and w_{uT} are both n_T.

4.2 Semantic representation

Latent Dirichlet Allocation (LDA) [3] is a kind of feature extraction method for document and it can also keep the semantic feature of the document. LDA is widely applied in text feature representation and dimension reduction. We adopt LDA to obtain the semantic information of document.

We train an LDA model for corpus c and set the number of topic number in our LDA model to be n_L. After that, we can get LDA vector w_{pL} of every product p in χ and LDA vector w_{uL} of user u. The dimension of w_{pL} and w_{uL} is n_L.

Through LDA vector w_{uL} which can represent the probability of each topic, we can know topics user u is interested in and the number of them can be n_{uL}.

5 Hypergraph learning based product search

In this section, we will introduce the hyperedge construction, present the product-user relevance measurement and introduce hypergraph learning process.

Let $G = (V, E, W)$ denote the hypergraph under the query q by user u, where V is the vertex set, E is the hyperedge set and W is the weights of the hyperedges. We regard each product in χ as a vertex in V. In this paper we generate three kind of hyperedges, namely the uni-word hyperedge, the bi-word hyperedge and the semantic hyperedge.

The hyperedge construction part in Fig. 1 shows one example of our hypergraph. From the example we can see that products share common features will be associated with each other. In Fig. 1, we show the hyperedge construction for an example "dress".

5.1 Uni-word Hyperedge construction

To realize personalization and build relationship among products, we utilize words representing user u to generate the uni-word hyperedge. The uni-word hyperedge means that products in χ containing the same words are connected together. Thus, for the n_u words, we get the corresponding n_u hyperedge.

5.2 Bi-word Hyperedge construction

In fact, just utilizing single word clue is not reliable enough to represent the relationship among products in χ and we utilize the multiple words simultaneously to enhance the relationship among products. Consequently, we construct bi-word hyperedge to effectively express relationship of these products.

We construct the second type of hyperedge based on pairwise combination of words representing user u. To control the size of hypergraph, we rank all words through their TF-IDF values in w_{uT} and select α percent of words representing user u as words to be combined. The number of words we select is αn_u. Then we choose one word from words selected and one word from the n_u words to form the second kind of hyperedge. Through this way, we can get the bi-word hyperedge whose number can be $(\alpha n_u - 1) \times n_u/2$.

5.3 Semantic Hyperedge construction

We design the semantic hyperedge by utilizing the semantic information of products' descriptions. The semantic hyperedge means that the products whose probability in this topic are bigger than zero will be connected together. Concerning that the topic number user u is interested in is n_{uL}, we can get the semantic hyperedge whose number is n_{uL}.

Concerning the three kind of hyperedges, there are $n_u + (\alpha n_u - 1) \times n_u/2 + n_{uL}$ hyperedges. So, the total edge number is $|E| = n_u + (\alpha n_u - 1) \times n_u/2 + n_{uL}$.

By the three kind of hyperedges we associate products sharing common features with each other.

5.4 Product-user relevance measurement

In this part, we will introduce how we calculate product-user relevance score. We select the distance between products and user as initial relevance vector y.

Let $y(p, u)$ denote the relevance score of a product p to user u. In this paper, $y(p, u)$ is measured by a linear combination of scores of the BoW represenation $y_T(p, u)$ and the semantic representation $y_L(p, u)$ as follows:

$$y(p,u) = \beta \times y_T(p,u) + (1-\beta) \times y_L(p,u) \tag{1}$$

where $\beta \in [0, 1]$ is the weight of the distance between $y_T(p, u)$ and $y_L(p, u)$. $\beta = 1$ means that we only consider the concurrence information of words, while $\beta = 0$ means that we only consider the semantic information.

In this paper, $y_T(p, u)$ is measured by the cosine similarity [24] based on w_{pT} and w_{uT} as follows:

$$y_T(p,u) = \cos\left(w_{pT}, w_{uT}\right) = \frac{< w_{pL}, w_{uL} >}{\left(w_{pT}\right)\left(w_{uT}\right)} \tag{2}$$

where <, > is the inner product of two vectors and $\|\cdot\|$ represents the vector norm. Similarly, $y_L(p, u)$ is determined as follows:

$$y_L(p,u) = \cos\left(w_{pL}, w_{uL}\right) = \frac{< w_{pL}, w_{uL} >}{\left(w_{pL}\right)\left(w_{uL}\right)} \tag{3}$$

5.5 Hypergraph learning based product-user relevance refinement

After getting hypergraph $G = (V, E, W)$ based on query q by user u, the optimization function $Q(f)$ of the hypergraph can be formulated as follows:

$$Q(f) = \mathrm{argmin}_{f,W}\{\Omega(f) + \lambda R(f) + \mu\Psi(W)\} \tag{4}$$

where λ, μ are the regularization parameters, and f is the final relevance score vector between product and user. Meanwhile, f needs to be learned and it will be used to sort the products in the χ by descending order.

The normalized cost term $\Omega(f)$ in Eq. (4) is defined as

$$\Omega(f) = f^T L f \tag{5}$$

where L is known as Zhou's normalized Laplacian of hypergraph [25]. The loss item $R(f)$ is defined as

$$R(f) = (f-y)^2 = \sum_{v\in V}(f(v)-y(v))^2 \tag{6}$$

where y is the initial relevance vector we obtained by Eq. (1).

Take $W = \{w_1, w_2, \ldots, w_{|E|}\}$ as the weight vector of the hyperedges, and then we utilize l2-norm on the weights of hyperedges as follows:

$$\Psi(W) = \sum_{i=1}^{|E|} w_i^2 \tag{7}$$

In this paper, we set the initial weight of hyperedges W as $1/|E|$.

We get the final relevance scores f by hypergraph learning as shown in Eq. (4) by iteration algorithm [7, 17]. Finally, we sort the products according to learned f in descending order to get the final personalized product search result.

6 Experiments

In order to demonstrate the effectiveness of our hypergraph learning based personalized product search method, we collected 15,000 users' transaction histories from Amazon, which include all kind of products users have bought. There are about fifteen transaction records for each user on average. Every transaction record includes product's category, title and descriptions etc. We systematically make comparisons the following three approaches:

a) Cosine Similarity: we use the TF-IDF value of every product p and user u as their feature vector. We adopt cosine similarity measure to calculate the distance, which can be used to re-rank those product items according user's transaction history.

b) Personalized PageRank: Personalized PageRank (PPR) has been applied to the task of recommendation to provide personalized searching results for users [12]. By incorporating both the product-product relevance and user-product relevance, PPR produces valuable personalized recommendations for users. In this paper, we apply cosine similarity measure to calculate the relevance.

c) Extended Query Likelihood with User Models (UQL): The query likelihood model (QL) is a language modeling approach and is extended to consider the effect of users in personalized product search [1]. In this paper, we use it as follows. Given a user u, the probability that a user u is generated from a product p is calculated as follows:

$$P_{QL}(u|p) = \sum_{w \in u} tf_{w,u} log \frac{tf_{w,p} + \mu P(w|c)}{|p| + \mu} \tag{8}$$

where $tf_{w,u}$ means the frequency of word w in u and $P(w|c)$ means the frequency of word w in corpus c divided by the total num of words in corpus c.

After comparing our method with cosine similarity, we can prove the effectiveness of hypergraph. PPR and UQL are classical method for personalized search. To make fair comparisons for three methods, we use the parameters as commonly used. In this paper, we set damping factor in PPR as 0.75 [12] and μ in Eq. (8) as 2000 [1].

6.1 Dataset

In our experimental setups, we select one subset of the products under the category of dress, which has more than 1700 products, to simulate user search scene under query *dress*. This is because the similarity among dresses is easier to identify and users has more transaction history under category *dress*. Every product has one picture and roughly three descriptions. To realize personalization, we select those who bought at least three products in the same category, and finally we select the top 30 users for testing. This is because the personalized search result of 30 users can show the effectiveness of our methods. We set the products under the category of dress in user's transaction as user's profile. The object of our experiments is to find products that are similar with the products that users have bought. If product in the personalized search result is similar with the products that user has bought, we consider it hit. Figure 2 gives us four examples.

6.2 Performance evaluation

6.2.1 Criteria of performance evaluation

We measure the relevance performance of the personalized search results in terms of Mean Average Precision (MAP), which are widely used in the recent recommendation literature [23]. MAP@n denotes the mean values of AP@n for all queries and $AP@n$ can be expressed as follows:

Fig. 2 four cases in red box when the left product that user has bought is similar with the right one in the reranking result

$$AP@n = \frac{1}{n}\sum_i^n\left(\sum_j^i \frac{rel_j}{i}\right) \tag{9}$$

where rel_i indicates the relevant level of product x_i to the user u, which is defined

$$rel_i = \begin{cases} 1, & if\ x_i\ is\ relevant\ to\ u \\ 0, & if\ x_i\ is\ irrelevant\ to\ u \end{cases} \tag{10}$$

6.2.2 Performance analysis

Let MAP@n denotes the mean values of AP@n for all the 30 users. MAP@n with depth = 5 and 10 are easier to calculate than depth = 20 and these two can prove the effectiveness of our method. The results of them are shown in Table 1. From the result of MAP@5 and MAP@10 we can clearly see that our method achieves better performance than all the three competing methods. From Table 1, when the depth is 5, the MAP of our method can reach 0.48, while Cosine Similarity, PPR, and UQL are 0.42, 0.37 and 0.40 respectively. We can get the same conclusion when the depth is 10.

Figures 3 and 4 show the top 10 results for two different users about query "*dress*" for all the four methods respectively. The relevant results are marked by red frames. From Fig. 3 we can see that for user 1 there are just two irrelevant products in the top10 results and both are low-ranking. From Fig. 4 we can see that for user 2 there are just three irrelevant products in the top10 results.

Table 1 The performances of different measures on dress datasets

	Cosine Similarity	PPR	UQL	ours
MAP@5	0.42	0.37	0.40	0.48
MAP@10	0.41	0.34	0.36	0.44

Fig. 3 Top 10 retrieval result for query "*dress*" for user 1, red box indicates the relevant products

Fig. 4 Top 10 retrieval result for query "*dress*" for user 2, red box indicates the relevant products

7 Discussion

In this section, we completely discuss the impact of different parameters involved in our proposed method. We will discuss the parameter α which means the proportion of words used in the bi-word hyperedge construction, the effect of different kind of hypergraph, the parameter β in Eq. (1), the topic number in LDA model and the stability of our method under different λ and different LDA model.

7.1 Discussion about the parameter α

In this subsection, we validate the proposed parameter α, which means the proportion of words we select to form bi-word hyperedge in section V. Figure 5 shows the MAP@5 and MAP@10 of our method under different α. We get this result without considering the semantic hypergraph and the distance $y_L(p, u)$ which means $\beta = 1$ in Eq. (1). From the result we can find our method get a better result when $\alpha = 0.8$ and $\alpha = 1.0$. However, bigger α means more second kind of hyperedge and more computation load. Finally, we choose $\alpha = 0.2$ and $\lambda = 0.5$, which can obtain better result and reduce computation respectively.

7.2 Discussion about different kind of hypergraph

In this section, we validate the different kind of hypergraphs. Let uni-word (UW) denote our method with only the first kind of hyperedge respectively. We can get the means of bi-word (BW), semantic (S), uni-word+bi-word (UW + BW), uni-word+semantic (UW + S), bi-word+semantic (BW + S) and uni-word+bi-word+semantic (UW + BW + S) in the same way. From Fig. 6 we can see that we will get the worst result when only using the semantic hyperedge and get the best result when using the three kind of hyperedges. Meanwhile, we will obtain the second best result when using the uni-word hyperedge and semantic hyperedge. The performances of different kind of hypergraphs in Fig. 6 prove that it is effective to combine the three kinds of hypergraphs.

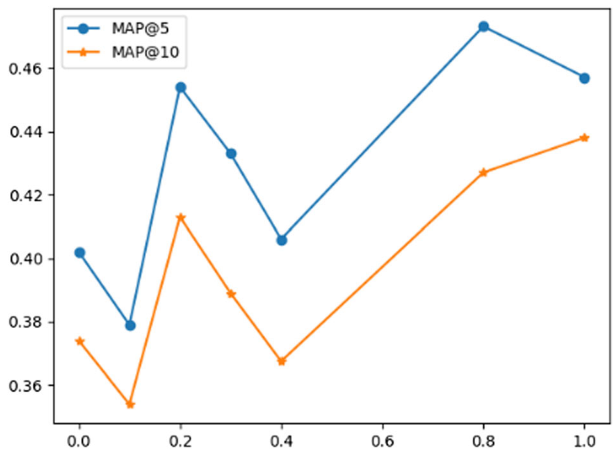

Fig. 5 Performance under $\alpha = \{0.0,0.1,0.2,0.3,0.4,0.8, 1.0\}$ without considering the third kind of hypergraph and the distance between the semantic representation

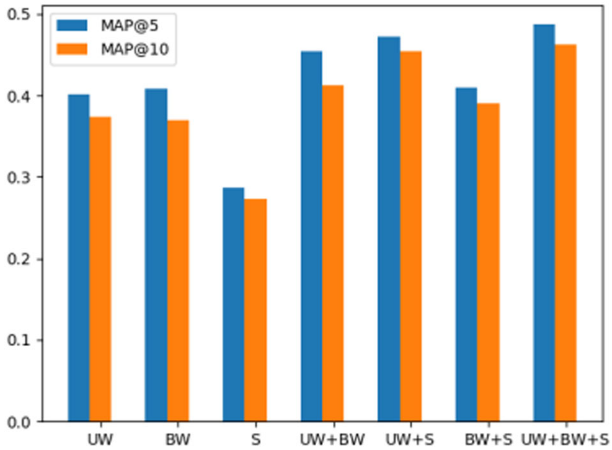

Fig. 6 Performance under different kind of hyperedges

7.3 Discussion about the parameter β

In this subsection, we discuss the parameter β in Eq. (1). We can clearly know that the parameter β determines weight of the distance between $y_T(p, u)$ and $y_L(p, u)$. We tuned β from 0.0 to 0.5 when the topic number is equal to 100 and finally found we get the best result when $\beta = 0.1$. From the conclusion we can get that when $y_L(p, u)$ makes up very small percentage of the product-user relevance score, we will get the best result (Fig. 7).

7.4 Discussion about the topic number n_L

In this subsection, we discuss the impact of parameter n_L, which determines the topic number in our topic model LDA. Figure 8 shows the MAP@5 and MAP@10 of our method under different n_L. We can clearly see that the worst performance of our method is better than the

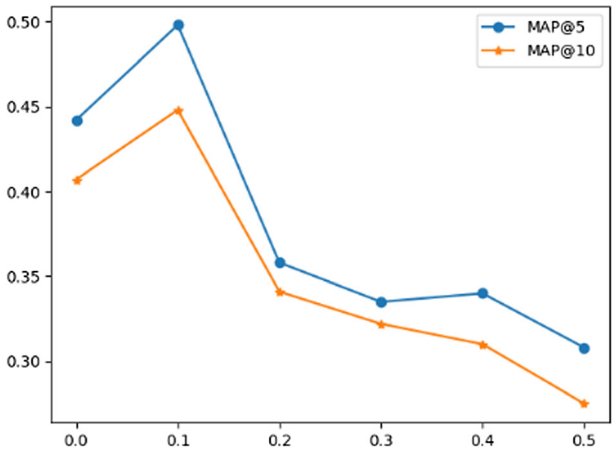

Fig. 7 Performance under $\beta = \{0.0, 0.1, 0.2, 0.3, 0.4, 0.5\}$ when the topic number is equal to 100

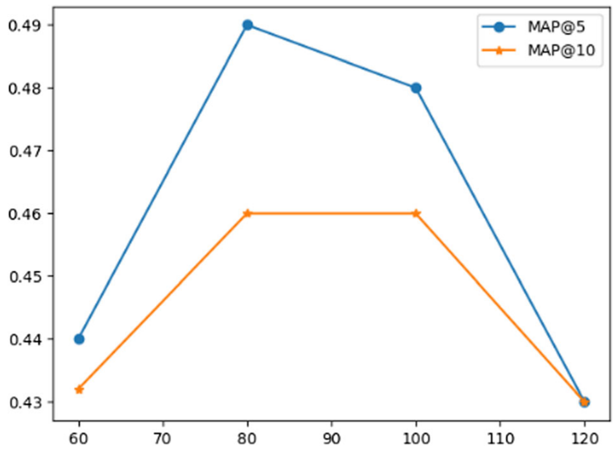

Fig. 8 Performance under $n_L = \{60,80,100,120\}$

three kind of comparing method. We will get the best result when $n_L = 80$ and its MAP@5 is equal to 0.49.

7.5 Discussion about stability of model under different λ

In this subsection, we will discuss the parameter λ in Eq. (4). We get result as Fig. 9 when the topic number is equal to 100. From the result we can see that the worst result when MAP@10 is equal to 0.44 is better than the three kind of comparing method. Therefore, our proposed method not only outperforms the comparing methods but exhibit relatively smooth change under different λ.

7.6 Discussion about stability of model under different topic model

As far as we know, LDA model is one generation model and it will generate different model every time. To prove the stability of our method, we test our method under different LDA

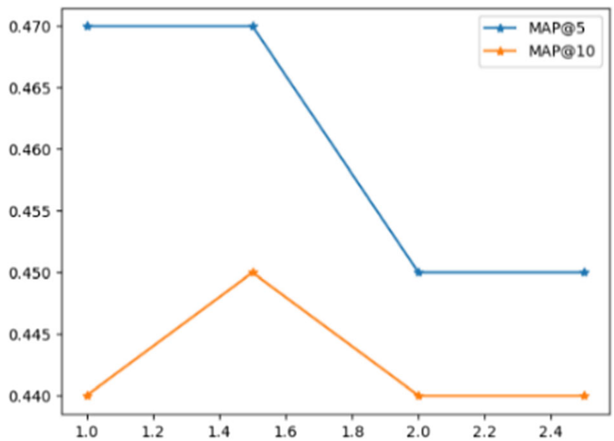

Fig. 9 Performance under different λ when the topic number is equal to 100

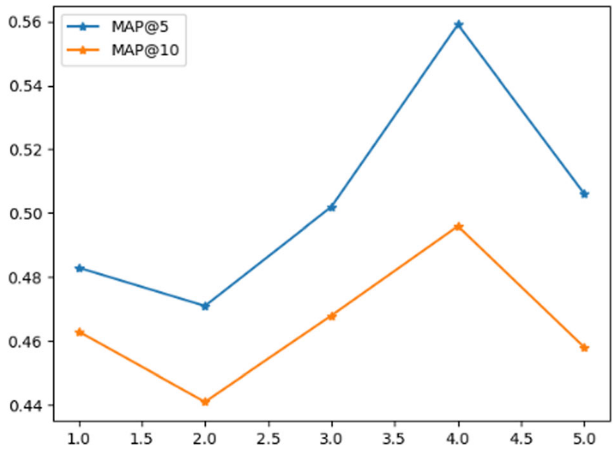

Fig. 10 Performance under different LDA model when the topic number is equal to 100 and λ is equal to 1

model for five times. We get result as Fig. 10 when the topic number is equal to 100 and λ in Eq. (3) is equal to 1. From the result we can see that the worst result is better than the three kind of comparing method. Therefore, our proposed method not only outperforms the comparing methods but exhibit relatively smooth change under different LDA model.

8 Conclusion and future work

In this paper, we propose a new re-ranking method for personalized product search, in which we utilize user's transaction history to choose products which is closer to the user's preference into the higher positions. Experimental results on our collected dataset show that our method is much better than the comparative methods. However, we only consider the descriptions of the products and ignore the visual information. In our future work, we will utilize products' visual feature to get a more robust result.

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Compliance with ethical standards

Conflict of interest Authors declare that we have no conflict of interest.

Studies with human or animal participants This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Ai Q, Zhang Y, Bi K, Chen X (2017) Learning a hierarchical embedding model for personalized product search[C]. ACM SIGIR, pp 645–654

2. Bennett PN, Kelly D, White RW, Zhang Y (2015) Overview of the special issue on contextual search and recommendation[J]. ACM Trans Inf Syst
3. Blei DM, Ng AY, Jordan MI (2003) Latent dirichlet allocation[J]. J Mach Learn Res:993–1022
4. Bu J, Tan S, Chen C, Wang C, Wu H, Zhang L, He X (2010) Music recommendation by unified hypergraph: combining social media information and music content[C]. ACM International conference on Multimedia:391–400
5. Duan L, Li W, Tsang IW (2011) Improving web image search by bag-based reranking[J]. IEEE Trans Image Process 20(11):3280–3290
6. Gao Y, Wang M, Tao D, Ji R, Dai Q (2012) 3-d object retrieval and recognition with hypergraph analysis[J]. IEEE Trans Image Process 21(9):4290–4303
7. Gao Y, Wang M, Zha Z-J, Shen J (2013) Visual-textual joint relevance learning for tag-based social image search[J]. IEEE Trans Image Process 22(1):163–176
8. Gray C, Beattie M, Belay H, Hill S, Lerch N (2015) Personalized online search for fashion products[C]. IEEE Systems and Information Engineering Design Symposium:91–96
9. Gupta M, Kumar P, Mishra R (2017) Interest diffusion in heterogeneous information network for personalized item ranking[C]. ACM CIKM:2087–2090
10. Hamano S, Ogawa T, Haseyama M (2018) Tag refinement based on multilingual tag hierarchies extracted from image folksonomy[C]. IEEE International Conference on Image Processing:1327–1331
11. Jannach D, Ludewig M (2017) Investigating personalized search in E-commerce[C]. FLAIRS:645–650
12. Jeh G, Widom J (2003) Scaling personalized web search[C]. WWW, pp 271–279
13. Jiang D, Pai J, Li H (2013) Mining search and browse logs for web search: a survey[J]. ACM Trans Intell Syst Technol 4(4):1–37
14. Jiang S, Qian X, Fu Y, Mei T (2016) Personalized travel sequence recommendation on multi-source big social media[J]. IEEE Transactions on Big Data 1(2):43–56
15. Jiang S, Qian X, Shen J, Fu Y, Mei T (2018) Author topic model-based collaborative filtering for personalized POI recommendations[J]. IEEE Transactions on Multimedia 17(6):907–918
16. Khan MA, Jalal AS (2019) A fuzzy rule based multimodal framework for face sketch-to-photo retrieval[J]. Expert Syst Appl 134:138–152
17. Liu D, Hua XS, Yang L (2009) Tag ranking[C]. WWW, pp:351–360
18. Liu Y, Shao J, Xiao J, Wu F, Zhuang Y (2013) Hypergraph spectral hashing for image retrieval with heterogeneous social contexts[J]. Neurocomputing.
19. Liu Q, Sun Y, Wang C, Liu T, Tao D (2017) Elastic net hypergraph learning for image clustering and semi-supervised classification[J]. IEEE Trans Image Process 26(1):452–463
20. Long B, Bian J, Dong A, Chang Y (2012) Enhancing product search by best-selling prediction in e-commerce[C]. ACM CIKM, pp:2479–2482
21. Lu D, Liu X, Qian X (2016) Tag based image search by social re-ranking[J]. IEEE Transactions on Multimedia 18(8):1628–1639
22. Lu X, Zheng X, Li X (2017) Latent semantic minimal hashing for image retrieval[J]. IEEE Trans Image Process 26(1):355–368
23. Manotumruksa J, Macdonald C, Ounis I (2017) Personalized ranking framework with multiple sampling criteria for venue recommendation[C]. ACM CIKM
24. Pazzani M, Billsus D (1997) Learning and revising user profiles: the identification of interesting web sites[J]. Mach Learn 27:313–331
25. Pliakos K, Kotropoulos C (2014) Personalized and geo-referenced image recommendation using unified hypergraph learning and group sparsity optimization[C]. ISCCSP:306–309
26. Pliakos K, Kotropoulos C (2014) Social image search exploiting joint visual-textual information within a fuzzy hypergraph framework[C]. IEEE 16th International Workshop on Multimedia Signal Processing
27. Qian X, Hua XS, Tang YY (2014) Social image tagging with diverse semantics[J]. IEEE Transactions on Cybernetics 44(12):2493–2508
28. Qian X, Feng H, Zhao G, Mei T (2014) Personalized recommendation combining user interest and social circle[J]. IEEE Trans Knowl Data Eng 26(7):1487–1502
29. Qian X, Lu D, Wang Y, Zhu L, Tang Y, Wang M (2017) Image re-ranking based on topic diversity[J]. IEEE Trans Image Process 26(8):3734–3747
30. Qian X, Lu X, Han J, Du B (2017) On combining social media and spatial technology for personalized recommendation[C]. Proc IEEE 105(10):1937–1952
31. Qian X, Tan X, Zhang Y, Hong R, Wang M (2018) Enhancing sketch-based image retrieval by re-ranking and relevance feedback[J]. IEEE Trans Image Process 25(1):195–208
32. Shi X, Qian X (2019) Exploring spatial and channel contribution for object based image retrieval[J]. Knowl-Based Syst

33. Wang L, Zhao Z, Su F (2014) Tag-based social image search with Hyperedges correlation[C]. Visual Communication & Image Processing Conference:330–333
34. Wang Y, Zhu L, Qian X (2018) Joint hypergraph learning for tag-based image retrieval[J]. IEEE Trans Image Process 27(9):4437–4451
35. Wang L, Qian X, Zhang Y, Shen J, Cao C (2020) Enhancing sketch-based image retrieval by CNN semantic re-ranking[J]. IEEE Transactions on Cybernetics
36. Wang L, Qian X, Zhang X, Hou X (2020) Sketch-based image retrieval with multi-clustering re-ranking[J]. IEEE Transactions on Circuits and Systems for Video Technology
37. Wu C, Yan M, Si L (2017) Ensemble methods for personalized e-commerce search challenge at CIKM cup 2016[C]. ACM CIKM.
38. Yu S, Niu D, Zhao X, Liu M (2017) Color image retrieval based on the hypergraph and the fusion of two descriptors[C]. CISP-BMEI.
39. Zhai H, Lai S, Jin H, Qian X, Mei T (2020) Deep transfer hashing for image retrieval[J]. IEEE Transactions on Circuits and Systems for Video Technology
40. Zhang Y, Qian X, Tan X, Han J, Tang Y (2016) Sketch-based image retrieval by salient contour reinforcement[J]. IEEE Transactions on Multimedia 18(8):1604–1615
41. Zhao G, Lei X, Qian X, Mei T (2019) Exploring users'internal influence from reviews for social recommendation[J]. IEEE Transactions on Multimedia 21(3):771–781
42. Zhao G, Liu Z, Chao Y, Qian X (2020) CAPER: context-aware personalized emoji recommendation[J]. IEEE Trans Knowl Data Eng
43. Zhou D, Huang J, Schölkopf B (2006) Learning with hypergraphs: clustering, classification, and embedding[C]. NIPS.
44. Zhu L, Shen J, Jin H, Zheng R, Xie L (2015) Content-based visual landmark search via multimodal hypergraph learning[J]. IEEE Transactions on Cybernetics 45(12):2756–2769

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