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# Mining user-contributed photos for personalized product recommendation ☆

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ABSTRACT

With the advent and popularity of social media, users are willing to share their experiences by photos, reviews, blogs, and so on. The social media contents shared by these users reveal potential shopping needs. Product recommender is not limited to just e-commerce sites, it can also be expanded to social media sites. In this paper, we propose a novel hierarchical user interest mining (*Huim*) approach for personalized products recommendation. The input of our approach consists of user-contributed photos and user generated content (UGC), which include user-annotated photo tags and the comments from others in a social site. The proposed approach consists of four steps. First, we make full use of the visual information and UGC of its photos to mine user's interest. Second, we represent user interest by a topic distribution vector, and apply our proposed *Huim* to enhance interest-related topics. Third, we also represent each product by a topic distribution vector. Then, we measure the relevance of user and product in the topic space and determine the rank of each product for the user. We conduct a series of experiments on Flickr users and the products from Bing Shopping. Experimental results show the effectiveness of the proposed approach.



## 1. Introduction

With the rapid development of e-commerce, products recommender system has been exploited to suggest attractive and useful products' information to facilitate user's decision-making process. The intelligent of products recommendation can help users to deal with information overload and provide them personalized services [39]. Product recommendation is popular in e-commerce sites. Some e-commerce sites such as Amazon and Bingshopping recommend products to users based on previous buys as well as what others have been bought when they bought the same product. They keep tracks of users spending and analyze their interests by collaborative filtering [3]. However, in collaborative filtering based products recommendation approaches, only the relevance of users is considered. Thus, they are not personalized to user's interest.

With the booming of social networks, more and more people are will to share their personal affairs, new things and their favorite photos with their friends. For example, Facebook has about one billion users. Flickr is photo sharing website, it also have a very large amount of users. The total number of photos shared by users in Flickr had reached 6 billion by August 2011. There are about 3 million photos uploaded by users each day. The user contributed photos and user generated content can reveal the user's interests very well [44–46,50,51]. Thus the social media websites are the ideal platforms to facilitate the personalized products recommendation.

To improve user experience by making ads relevant to the webpage content, Broder et al. proposed a system for contextual ad matching based on a combination of semantic and syntactic features [40]. They used the semantic phrase to classify the webpage and the ads into taxonomy, and then ranked ads by the proximity of the ads and webpage categories. Although they classified both ads and page content within a large taxonomy, they ignored that some ads are relevant to several topics. For instance, the tag *canon* is relevant to digital camera and also relevant to the bags of camera. Thus, it is better to represent user interests by topic distribution vector rather than taxonomy.

Taking above mentions into consideration, we propose a novel hierarchical user interest mining (*Huim*) method to explore user's potential shopping needs based on user-contributed photos in her/his social media sites. We recommend personalized products according to the mined user interests. There are three main problems needed to be solved: (1) the gap between appearances of user-contributed photos and their textual descriptions (i.e. UGC). For example, when a user uploaded some images of her new iphone, she may label images by the words "*the amazing*

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*apple*". In this circumstance, the tag of *apple* has two meanings: fruit and electronic product. So we need to mine more content related information from both the visual information and the UGC of user contributed photos. (2) The noise and ambiguous tags in UGC have negative effect to mine user's interests. The textual descriptions contain informal expressions with noise tags (such as the preposition and other non-topic tags) and some ambiguous tags which generated by users. Thus, to recommend personalized products, we need to suppress the noise and ambiguous tags, and to enhanced user interest topics for the user contributed photos. (3) How to measure the relevance of user and product. If a user shared some photos of basketball game, then it is reasonable to suggest some products about basketball like knee pad, and it is also acceptable to recommend basketball video games of 360 Xbox. Among the above three problems measuring the relevance is the core problem in product recommendation.

To fulfill personalized product recommendation, we propose a hierarchical topic vector representation approach to represent user interest and product. Our approach is carried out as follows: (1) tag enrichment for the user contributed photos, (2) introduce a public topic space and map user interest and product descriptions to it and get their topic distribution vectors, (3) enhance user interested topics by a hierarchical approach is proposed to suppress noise and ambiguous textual descriptions, (4) measure the relevance of user and product in the hierarchical public topic space and rank the products for the user.

The main contributions of this paper are summarized as follows: (1) propose a personalized product recommendation system which mining users' interests from their contributed photos; (2) propose an effective user and product relevant measurement approach by introducing a hierarchical public topic space; (3) propose an effective hierarchical user interest representation approach which is robust to suppress noise and ambiguous textual description and enhance user interested topics.

Compared to our preliminary version [50], several improvements are made: (1) the detailed steps of the proposed hierarchical user interest mining approach are provided; (2) we extend the approach from brand recommendation to more general product recommendation, and (3) more experimental results and discussions are provided.

The remainder of this paper is organized as follows. In Section 2, we present the related works on products recommendation, user interest mining and multimedia advertising. In Section 3, our personalized products recommendation based on hierachical user interest mining approach is introduced in detail. Experiments and discussions are given in Section 4 and conclusions are drawn in Section 5.

## 2. Related work

In this section, we briefly review the related works on products recommendation, user interest mining from social media, and multimedia advertising.

### 2.1. Products recommendation

Products recommendation has been emphasized with the advent of E-commerce [4,7,12]. The previous works [28–31] has been mainly focused on collaborative filtering based recommender system since it was first implemented by Goldberg et al. [27]. Ricci et al. designed a hybrid collaborative/content based recommendation approach [28]. This approach has the advantage to overcome the shortcomings of content- and collaborative-filtering based recommendation approaches. And then, various clustering and data mining technologies were proposed in product and services recommendation [49–51]. Qian et al. propose a user preferred vocabulary mining approach to recommend user preferred vocabularies for the user newly shared photos [51]. Wesley et al. developed a mining association rules procedure from a datasets to support on-line products recommendation [32]. They proposed clustering module and extracting module to mine user's hidden habits from the datasets. The clustering module is based on a self-organized map neural-network to carry out data grouping. The extracting module uses rough set theory to determine rules for the clusters and their relationships. They used analytic hierarchy process to determine the related weights of customer and lifetime value, based on which products are recommended to group of customers using an associated rule mining approach. Liu and Shih suggested a novel recommendation methodology that combined group decision-making and data mining to address the lifetime value of a customer to a firm [33]. Cao and Li proposed fuzzy-based system to retrieve optimal products based on the customer's interactions with their system [34]. Zheng et al. explore location information for personalized travel recommendation and friends recommendation [25,26].

### 2.2. User interest mining

The success and popularity of social media sites have generated many interesting and challenging problems to the research community. Mining users' interests from their contributed information have attracted much attention [20,35–38,49–51]. User interest mining approaches can be classified into one of the following two categories: text based, and visual content and text combined approaches. In text-based approach, Li et al. discovered social interest only by user-generated tags [35]. Their research results on a large scale real-world traces shown that user generated tags are highly consistent with the web content. User interests were represented by the patterns of several high co-occurrence and frequently appeared tags. Feng and Qian represent user interest by the nature category constrained topic vector distribution. Services/products/items and user interests can be represented by the topic vector distribution [49,50]. Banerjee et al. used text mining technology to extract users' interests from their micro-blogs [36]. They classified keywords into two types: content-indicative and usage-indicative. Then they discovered the usage statistics of the co-occurrence of two types of keywords to represent users' interests. Choudhury et al. [37] and Wang et al. [20] took both the visual content of user shared images and the context of social media into consideration to mine user interest.

Usually, user generated textual descriptions including tags are noisy. So, many tag enhancement/filtering approaches are proposed to improve tag quality [44–48]. For example, Tang et al. propose a sparse based semi-supervised learning approach to infer semantic concepts from social community user-contributed photos and noisy tags [44–46]. Qian et al. proposed an effective tag filtering approach by using the similar compatible principle [47]. Li et al. propose a latent community classification and multi-kernel learning based image annotation approach to solve the tag ambiguous problem [48].

### 2.3. Multimedia advertising

Products recommendation has a slightly different from advertising. It is a special case of advertising. Advertising pays little attention on advertiser and bid. However, the core problems of them are the same: the relevance of ads or products and user. According to the formats of advertising, there are four types of approaches: text-based advertising [6,10,41,42], image based advertising [5,13,14,19,20,22], game based advertising [11], and video based advertising [2,9,15–18,23].

The text based advertising approaches have successful applications, many online systems are developed and embedded into searching engines, such as AdSense [41], BritePic [42], and PageSensing [10]. Google's AdSense analyzed the webpage's content, and then provided some relevant text ads or some image ads [41]. The the recommended ads were spotted in the right column of image. This is often not effectively in get user's attention. BritePic embedded ads in the corner of the image [42]. The position is fixed for all images. They only considered textual relevant between the surrounding text of image and the description of ads. They ignored the visual similarity between image content and ads. Zhou and Liu proposed a page frame segmentation approach for inserting ads into the margin of electronic books [6].

In video-based advertising, VideoSense automatically analyzed video content to get relevant ads, and detected the insertion point for ads by the feature of video frame switch and the attractive of video content [15,16]. AdImage was an effective video advertising approach associated relevant ads to viewed videos by specific image objects [23]. It also took advertisers' bids and unspent budgets into consideration to maximize advertising revenues. In order to make video a more substantial, ads were embedded in the specific region of a frame [9,23]. This kind of video advertising approaches have successful applications in sports video. Because smooth region of sports video has low appreciative generally, so inserting ads in these areas caused less invaded. For example, inserting ads in the smooth area of the top of the goalmouth in soccer video has been viewed as has little turbulence to the video content but also draw users' attention [9].

Image-based advertising was more intuitive than text ads and more concise than video ads. ImageSense relied on the image description information (e.g. surrounding text), the expansion of the text information (e.g. extended text), and the concept of higher level text to reduce the semantic gap between user's image and textual description [13,14]. GameSense was a web-based and a game-related advertising system [11], which built based on the framework of ImageSense. The suggested ads were changed with the processing of web game.

Among the image-based advertising, Wang et al. not only took image visual content into consideration, but also suggested ads based on user interest modeling [19,20]. They represent user interest by a topic distribution vector based on hierarchical topic space like Evans et al. [1]. They represent user interest by topic vector and measuring the relevance of user and products using the cosine of the two vectors. However, one of the main disadvantages is that user interest representation approach is sensitive to noise tags and ambiguous tags. Another disadvantage is that their user interest vector is a long sequences and very sparse. Moreover, they only map the user information and product description to the leaf node in the hierarchical topic space. The category information of hierarchical topic space has less contribution for making the topic vector discriminative in representing various user interests. Based on the above concerns, we proposed a novel hierarchical user interest mining method is proposed to recommend more personalized products for the users.

## 3. Approach

### 3.1. Overview

This section details our proposed solutions on personalized products recommendation based on user-contributed photos from social media sites. The input of our approach is user shared photos of the same webpage and their corresponding textual descriptions. The system is shown in Fig. 1. Our approach consists of three parts: (1) hierarchical user interest representation. We map user's information (UGC and enriched tags of the photos) to a hierarchical public topic space. And we represent user interest by a high-dimensional topic vector, which is a point of the public topic space as shown in Fig. 1. (2) Products representation. Products are mapped to the same public topic space to get their topic distribution vectors. Each product also corresponds to a point in Fig. 1. The public topic space acts as a bridge between user and products. (3) Product ranking. In the public topic space, both user's interest

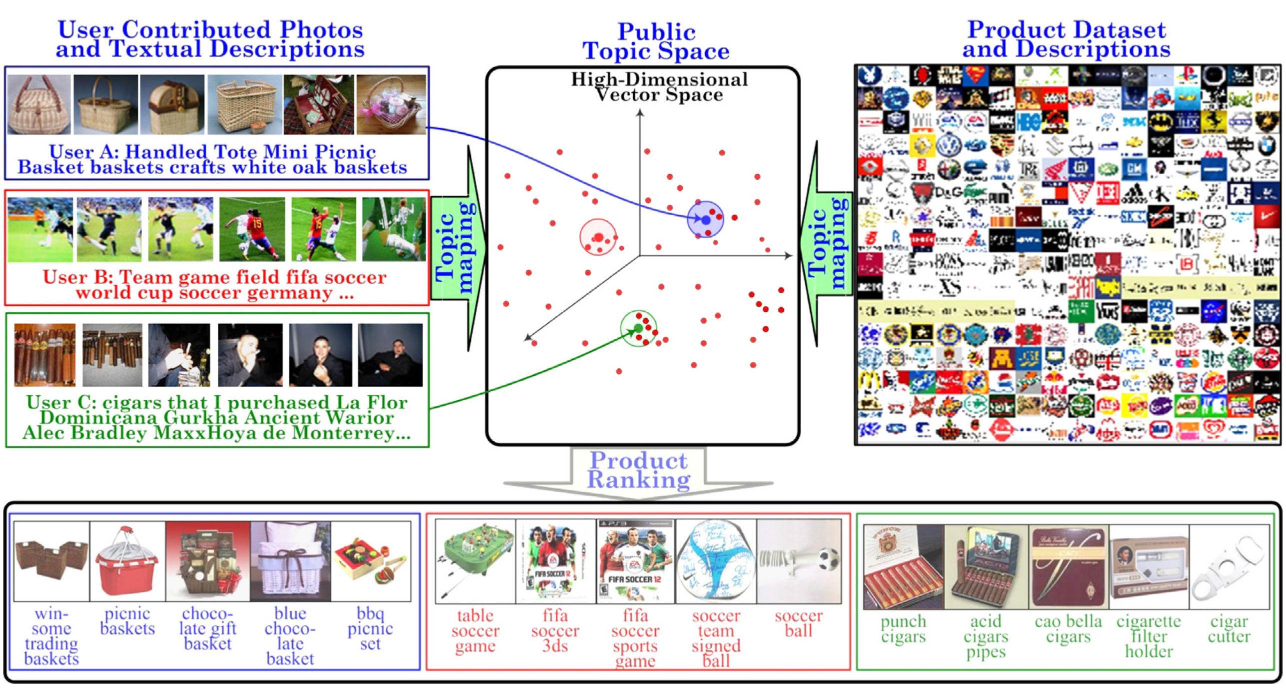


**Fig. 1.** Our system overview. Given user-contributed photos and UGC in a webpage, user's interest and product are represented by a high-dimensional space. And ads products are shown as small red points in the public topic space. The products of the nearest five points to the user topic vector are given at bottom. The points in the each of the three circles represent the products in the top 5 of the user A–C, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- Antiques and Collectibles (3,542)
- Autos@ (440)
- Beauty Products@ (1,333)
- Books@ (2,844)
- Children (1,265)
- Clothing (5,322)
- Computers@ (18)
- Consumer Electronics (3,371)
- Crafts (7,268)
- Death Care (78)
- Education@ (1,228)
- Entertainment (2,868)
- Ethnic and Regional (1,084)
- Flowers (856)
- Food (5,237)
- Furniture@ (1,357)
- General Merchandise (904)
- Gifts (1,403)
- Health (5,627)
- Holidays (422)
- Home and Garden (8,707)
- Jewelry (2,342)
- Major Retailers@ (61)
- Music (1,955)
- Niche (742)
- Office Products (543)
- Outdoor Recreation@ (1,764)
- Pets (2,203)
- Photography (597)
- Publications (3,358)
- Recreation (4,887)
- Religious@ (4)
- Sports (5,596)
- Tobacco (336)
- Tools (543)
- Toys and Games (1,564)
- Travel (174)
- Vehicles (4,245)
- Visual Arts (4,293)
- Weddings (263)
- Wholesale@ (164)

**Fig. 2.** Part of ODP Categories. There are 41 subcategories belonging to shopping category. We only use part of ODP categories relevant to shopping to build the public topic space. The digit behind each subcategory, such as (3542) behind the subcategory Antiques and Collectibles, is the number of websites relevant to it.

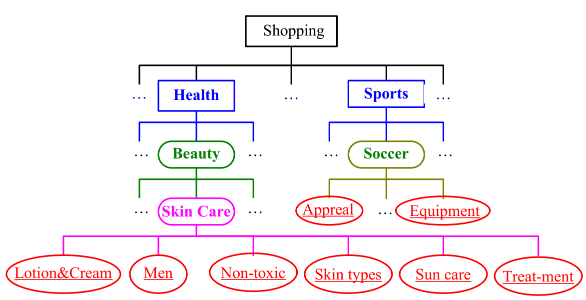


**Fig. 3.** Sketch of ODP tree structure of category Shopping.

and a product are represented by a high dimensional topic vector. Thus the relevance of user and product can be measured by the correlation of their topic vectors. In this paper we use the cosine of them to measure their relevance and then we determine the ranks of the products as shown in the bottom of Fig. 1. The points in the each of the three circles represent the products in the top 5 for the user A–C, respectively. And therefore, we first introduce the public topic space, and then detail the three main steps in turn.

### 3.2. Public topic space

We mine user interest and product topic with help of the public topic space, a uniform space, which need to have the following two characteristics: (1) contain most of user interest categories and products categories, and (2) have uniform category to include user interest and products with relevant topics. Here, we build two public topic spaces, namely the ODP (open directory project) space and brand topic space, by ontology of ODP and brand products datasets [13].

#### 3.2.1. ODP topic space

ODP (http://www.dmoz.org) is a manually edited ontology directory by a great amount of specialist editors, which contains almost five million URLs classified into nearly 80,000 categories as shown in Fig. 2. Each category can be seen as a node in the tree, which we call ODP tree. There are seven layers and *3772* leaf nodes of the tree. There are 34 nodes at the first layer. These 34 nodes in the first layer build their own sub-trees of ODP tree, and different sub-tree has different depth. Each node of ODP tree is corresponding to a topic, and the topics at lower layers are the detailed classification of topics of upper layers. The ODP hierarchical structure had been adopted in ads recommendation [8,20,24]. In ODP, each category includes so many theme-relevant websites, where the documents of them can bridge the gap between user and products. The product recommendation based on the structure of ODP is similar to collaborative filtering based approaches [3]. The goal is to recommend personalized product for a user. So we confine the recommendations in the category *Shopping*. The corresponding hierarchical structure of topic tree is shown in Fig. 3, respectively. From the hierarchical structure of public topic tree, we find that different sub-tree has different layer number. We denote the maximum layer number of a sub-category as its depth. Thus the depth of *Shopping* is seven and the depth of a leaf node is zero. We give two subcategories of shopping, e.g. *Health* and *Sports*, to show the structure of ODP tree. The depth of the sub-tree of the *Sports* is two, and that of *Health* is three, with its leaf nodes: Lotion and Cream, Men, Non-toxic, Skin types, Sun care and Treatment etc.

#### 3.2.2. Brand topic space

Different from ODP tree based topic space, brand tree based topic space contains more brand information. It is helpful for recommend products with user favorite brands. From ODP tree we cannot mine user's brand preference because ODP's webs content have less relevance to brand. So, we build brand tree from volumes of brands' descriptions including brand category, brand name, products' description of the brand, and some keywords of the products' description [13]. Table 1 shows the brand descriptions of three brands Nike, Nestlé, and Apple.

Brand tree has two layers as shown in Fig. 4. The first layer is products category layer, and the second is brand layer. There are *20* category in the first layer which covers all brand categories. They are: (1) Arts and Entertainment, (2) Automobile, (3) Clothes

**Table 1**
Examples of brand descriptions.

| | Nike | Nestlé | Apple |
|---|---|---|---|
| Brand category | Sports | Food and dining | Computers, electronics |
| Brand name | Nike | Nestlé | Apple |
| Product's description | Nike is a major American supplier of athletic shoes, apparel and sports equipment | Nestlé is a multinational packaged food company founded and headquartered in Vevey, Switzerland. It resulted from a merger in 1905 between the Anglo-Swiss Milk Company for milk products established by the Page Brothers in Cham, Switzerland, in 1866 and the Farine Lactée Henri Nestlé Company set up in 1867 by Henri Nestlé to provide an infant food product | Apple Inc is an American multinational corporation with a focus on designing and manufacturing consumer electronics and closely related software products. Established in Cupertino, California on April 1, 1976, Apple develops, sells, and supports a series of personal computers, portable media players, mobile phones, computer software, and computer hardware and hardware accessories |
| Product's keywords | Athletic shoes, sport | Nestlé Baby food, dairy products, breakfast cereals, confectionery, bottled water Henri Nestlé, Peter Brabeck-Letmathe Vevey, Switzerland. | Apple, Mac, Mac OS X, Mac OS X Server, iPod, QuickTime, iLife, iWork, Safari, Apple Remote Desktop, Xsan, Final Cut Studio, Aperture, Logic Studio, Cinema Display, AirPort, Apple Mighty Mouse, Xserve, iPhone, Apple TV, Steve Jobs, Steve Wozniak |

and Fashion and Beauty product, (4) Community and Government, (5) Computers and Electronics, (6) Education, (7) Food and Dining, (8) Health and Medicine, (9) Home and Family, (10) Hotel, (11) Industry and Energy, (12) Legal and Financial, (13) Media and Communications, (14) Miscellaneous, (15) Office Products, (16) Other, (17) Pets, (18) Sports, (19) Tools and Hardware, (20) Travel and Transportation.

Different category in the first layer has different brand nodes in the second layer. Totally there are *7284* brand nodes in the second layer. For example, the Sports category has brand nodes of ADIDAS, NIKE, and YONEX etc. as shown in Fig. 4.

From the tree structure, we can see that the first layer is the coarsest classification. The deep the tree, the more detailed the classification of the category. Thus, in the tree, all the leaf nodes can be viewed as the *local* descriptions for the theme (user or product) and the parent nodes have the *global* description for the theme. So, our user interest and product representation approach making full use of the hierarchical structure, and the global and local descriptions to improve user interest and product representation.

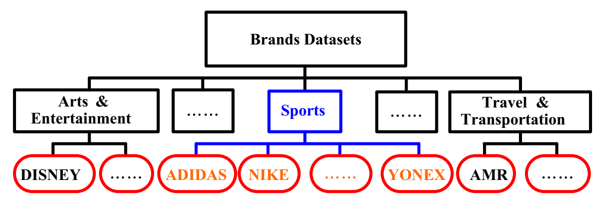


**Fig. 4.** Sketch of brand tree based topic space.

### 3.3. Hierarchical user interest mining

We detect user interest from user-contributed photos and UGC in a webpage. We suppose that the photos in a webpage have the same topic. The proposed user interest mining approach is different with direct mapping based approach by Wang et al. [20] (denoted Argo). Argo only maps tag list to leaf nodes of hierarchical topic tree to get user interest topic distribution. This kind of user interest mining approach is sensitive to the noise tags and ambiguous tags. To reduce their influence to the user interesting mining performances, we take both leaf nodes and their ancestor nodes into consideration, and make full use of the hierarchical structure of public topic space to enhance user interested topics.

Our hierarchical user interest mining approach consists of the following three steps: (1) we construct a final tag list for the user-contributed photos in a webpage with UGC by enriching relevant tags for the photos using their visual information by image annotation [21]. Let $T=\{t_1, t_2, \ldots, t_M\}$ denotes the final tag list which consists of $M$ unique tags. They consist of tags generated by the user and newly enriched tags. (2) We build hierarchical leaf node indexing for the ODP and brand tree, (3) we map each tag of $T$ to the nodes of public topic spaces such as ODP tree and brand tree to get user interested topic distributions. Before going to the details of the proposed approach, we give the symbols and their descriptions utilized in this paper in Table 2.

#### 3.3.1. Leaf nodes indexing

To enable real-time usage of hierarchical user interest mining, we build indexing of leaf nodes to their ancestors based on the structure of public topic tree. We build the indexing of the leaf nodes to the ancestor nodes according to the parent-child relationship of the hierarchical structure. The leaf nodes are classified in different categories at different layer. Let $n_i$ denote the $i$th ($i=1,\ldots,N$) leaf node in the public topic space.

The index of leaf node $n_i$ at different layer can be represented by a vector $[c_i^1, \ldots, c_i^L]$, where $c_i^l$ denotes the category information that leaf node $n_i$ belonging to at the $l$th layer. For the ODP tree, there are 3772 leaf nodes and the total layer number is seven as shown in Fig. 3, i.e. $(N,L)=(3772,7)$. The first layer has 34 nodes. During the leaf node indexing, if the depth $d$ of a leaf node $n_i$ is less than the total layer number $L$, then we assign $c_i^l = c_i^d$, $l \in \{d+1, \ldots, L\}$.

For the Brand topic tree space, there are 7284 leaf nodes and the total layer number is two as shown in Fig. 4, i.e. $(N,L)=(7284,2)$. It is simple than ODP tree based topic space but includes more brand information to mine user's brand preference.

#### 3.3.2. Topic mapping

We first map user photos' tag list (UGC and enriched tags) to leaf nodes of the public topic space to get user interest topic distribution. We use TF-IDF (term frequency and inverse document frequency) of each tag appeared in each leaf node to measure their similarity. And then user interest is disclosed by a tag can be represented by a topic distribution vector.

**Table 2**
Symbols and their descriptions utilized in this paper.

| Symbol | Description | Symbol | Description |
|---|---|---|---|
| $n_i$ | The $i$th ($i=1,\ldots,N$) leaf node in the public topic space | $c_i^l$ | The category information that leaf node $n_i$ belonging to at the $l$th layer |
| $g_t$ | The topic distribution vector of tag $t$ | $G_{M\times N}$ | Topic distribution matrix of the $M$ tags |
| $tfidf_t\,(j)$ | The relevance of tag $t$ to the $j$th leaf node | $F(x,y)$ | Frequencies that tag $y$ appears in document $x$ |
| $d_j$ | The topic's description documents of the $j$th leaf node | $N$ | Dimension of $g_t$ |
| $D(x,y)$ | Denotes that whether tag $y$ appears in document $x$ or not | $\mathbf{e}_t^H$ | The topic distribution vector of tag $t$ at layer $H$ |
| $\boldsymbol{\omega}_t^H$ | The weight vector for the tag $t$ at the first $H$ layers | $e_t^H(j)$ | The $j$th element of vector $\mathbf{e}_t^H$ for the tag $t$ |
| $L\omega_t^h(j)$ | The local $l$ weights of tag $t$ to the category node $c_j^h$ at the $h$th layer | $G\omega_t^h(j)$ | The global weights of tag $t$ to the category node $c_j^h$ at the $h$th layer |
| $c(j)$ | The category index that the leaf node $j$ belonging to at the $h$-layer | $LC_t^h(x)$ | The local weight of tag $t$ to the category $x$ |
| $d_p^x$ | The topic's description documents of the $p$th node of the category $x$ at the $h$th layer | $N_x^h$ | The leaf node number of the category $x$ of $h$th layer |
| $GC_t^h(x)$ | The global weights of a tag $t$ to the category $x$ | $V^H$ | The enhanced topic vector at hierarchical depth $H$ |
| $C_x^h$ | The total category number of at the $h$th layer | $v1$ and $v2$ | The topic distribution vectors of user interest and product descriptions |

We map all the $T$ tags in final tag list to topics of leaf nodes of public topic space. Let $G_{M\times N}$ to denote topic distribution matrix of the $M$ tags, which is expressed as follows:

$$G=[\mathbf{g}_{t_1};\mathbf{g}_{t_2};\ldots;\mathbf{g}_{t_M}] \tag{1}$$

where $\mathbf{g}_t$ is the topic distribution vector of tag $t$. The dimension of $\mathbf{g}_t$ is $N$.

$$\mathbf{g}_t(j)=tfidf_t(j), j\in\{1,\ldots,N\} \tag{2}$$

where $tfidf_t\,(j)$ is the relevance of tag $t$ to the $j$th leaf node. It is calculated as follows:

$$\begin{cases} tfidf_t(j)=F(d_j,t)\times\log\frac{N}{\sum_{j=1}^{N}D(d_j,t)} \\ s.t.\sum_{j=1}^{N}tfidf_t(j)=1, 0\le tfidf_t(j)\le 1 \end{cases} \tag{3}$$

where $F(x,y)$ is frequencies that tag $y$ appears in document $x$, $d_j$ is the topic's description documents of the $j$th leaf node. $D(x,y)$ denotes that whether tag $y$ appears in document $x$ or not. $D(x,y)=1$ means that tag $y$ appears in document $x$. $D(x,y)=0$ means that tag $y$ does not appear in document $x$. From Eq. (3), we have the higher the $tfidf_t\,(j)$, the more relevant of the $i$th tag to $j$th leaf node.

In Argo [20], the final topic distribution of a tag list $T$ is represented by the average distribution vector of the tags as follows:

$$A=1_{1\times M}\times G_{M\times N} \tag{4}$$

where all elements of $\mathbf{1}_{1\times M}$ equal one. However, Agro ignored the importance of reducing the noise tags and ambiguous tags in the final list $T$, which has negative influence to mine user interest accurately. So, we propose a hierarchical user interest mining approach to reduce the influence of noise and ambiguous tags and enhance user interest topics in topic mapping process.

### 3.3.3. *Enhanced topic mapping*

Based on the final tag list of $T$, the topic distribution matrix $G$ is obtained. With the indexing of leaf nodes to their ancestor nodes, we analyze each tag's importance from its local and global distributions to enhance user interested topic. This consists of the following two steps: (1) we count the tag's frequencies that the leaf nodes belonging to the categories at different layer. We determine the tag's importance to a category by its inverse tag frequency. (2) We get the enhanced topic distribution by fusing the topic distribution, and global and local weights at different layers. The enhanced topic distribution matrix by fusing the global and local weights of the first $H$ layers (denoted hierarchical depth $H$) is as follows:

$$E^H=[\mathbf{e}_{t_1}^H;\mathbf{e}_{t_2}^H;\ldots;\mathbf{e}_{t_M}^H], H\in\{1,\ldots,L\} \tag{5}$$

where $\mathbf{e}_t^H$ is the topic distribution vector of tag $t$ at layer $H$, it is expressed as follows:

$$\mathbf{e}_t^H=\boldsymbol{\omega}_t^H\otimes\mathbf{g}_t^H \tag{6}$$

where the operator $\otimes$ means the direct product of two vector with the same dimension, $\boldsymbol{\omega}_t^H$ is the weight vector for the tag $t$ at the first $H$ layers. In this paper $\mathbf{g}_t$ is the topic distribution vector of tag $t$ as shown in Eq. (2). $e_t^H(j)$ is the $j$th element of vector $\mathbf{e}_t^H$ for the tag $t$, it is expressed as follows:

$$e_t^H(j)=\omega_t^H(j)\times g_t(j) \tag{7}$$

where the weight matrix $\boldsymbol{\omega}_t^H$ is obtained by taking both local and global weights of tag $t$ of the first $H$ layers into consideration.

$$\omega_t^H(j)=\sum_{h=1}^{H}(L\omega_t^h(j)+G\omega_t^h(j)) \tag{8}$$

where $L\omega_t^h(j)$ and $G\omega_t^h(j)$ are the local and global weights of tag $t$ to the category node $c_j^h$ at the $h$th layer.$L\omega_t^h(j)$ is expressed as follows:

$$L\omega_t^h(j)=LC_t^h(c(j)) \tag{9}$$

where the $c(j)$ is the category index that the leaf node $j$ belonging to at the $h$-layer, the local weight of tag $t$ to the category $x$ $LC_t^h(x)$ is determined as follows:

$$\begin{cases} LC_t^h(x)=N_x^h/\sum_{p=1}^{N_x^h}D(d_p^x,t) \\ s.t.\sum_x LC_t^h(x)=1, 0\le LC_t^h(x)\le 1 \end{cases} \tag{10}$$

where $d_p^x$ is the topic's description documents of the $p$th node of the category $x$ at the $h$th layer. $N_x^h$ is the leaf node number of the category $x$ of $h$th layer. The term $\sum_{p=1}^{N_x^h}D(d_p^x,t)$ is the frequency that $t$ appears in the document of the category $x$ at the $h$th layer. Thus, the higher $LC_t^h(x)$, the more important of the tag to the category $x$.

On the other hand, we analyze tag's global importance to enhance user interested topics. First, we count the tag's frequency at all of the categories in each layer. If the tag appears in the document of the next layer child nodes of the category, we determine that the tag appears in the category. Second, we represent the tag's global weight $G\omega_t^h(j)$ in Eq. (8) by the inverse tag frequency at all of the categories in a layer as follows:

$$G\omega_t^h(j)=GC_t^h(c(j)) \tag{11}$$

where $GC_t^h(x)$ is the global weights of a tag $t$ to the category $x$. It is determined as follows:

$$GC_t^h(x)=C_x^h/\sum_{p=1}^{C_x^h}D(d_p^h,t) \tag{12}$$

where the sum $\sum_{p=1}^{C_x^h}D(d_p^h,t)$ is the frequency that $t$ appears in all the categories of the $h$th layer. $C_x^h$ is the total category number of at the $h$th layer. Thus, the higher the $GC_t^h(x)$, the more important the tag to the categories of the $h$th layer.

Finally, the enhanced topic vector $V^H$ at hierarchical depth $H$ is obtained as by using the average topic vector of the tags in the final tag list $T$ as follows:

$$V^H = 1_{1\times M} \times G^H_{M\times N} \tag{13}$$

For user information and each of the products we represent them in the hierarchical topic space. For building products topic vectors, we use each subcategory's keywords as textual description of products belonging to this subcategory as the final tag list. Based on the public topic space, the topic distribution vectors of product and user, we can measure their relevance.

### 3.4. Relevance measurement for user and products

By the proposed hierarchical topic space mapping based approach, both user interests and product descriptions are represented by topic vectors. The measurement of relevance of a user and a product is converted to measure the similarity of two vectors. In this paper, we use the cosine similarity of two vectors to measure the similarity of two vectors as follows:

$$S = \cos(v1, v2) \tag{14}$$

where $v1$ and $v2$ are the topic distribution vectors of user interest and product descriptions. According to the relevant score of a user to product we can recommend personalized products for the user.

Last, we randomly choose 10 products from top 5 subcategories as top 10 recommended products (two products from each subcategory) because products of same subcategory only have difference in colors and sizes etc. If we rank all of the products, the targeted products probably in one subcategory, which will result in poor user experience.

## 4. Experiments and discussions

To show the effectiveness of the proposed personalized product recommendation approach using *Huim*, we compare it with Argo [20]. Experiments are conducted on real Flickr users and products of Bingshopping [43].

### 4.1. Datasets

We have crawl products from Bingshopping to test the performances of the proposed personalized products recommendation approach. There are about 30 million products with 5071 subcategories. We use each subcategory's keywords as texts description of products belonging to this subcategory. Given a product's textual descriptions, we get the corresponding tag list after tag enrichment. And then we get ads product's topic distributions by hierarchical topic representation.

We use 125 Flickr users' photo sets to test our personalized products recommender system. Our product recommendation is based on the user-contributed photos and the user generated content in a webpage of Flickr based on the assumption that photos of the same page has the same topic.

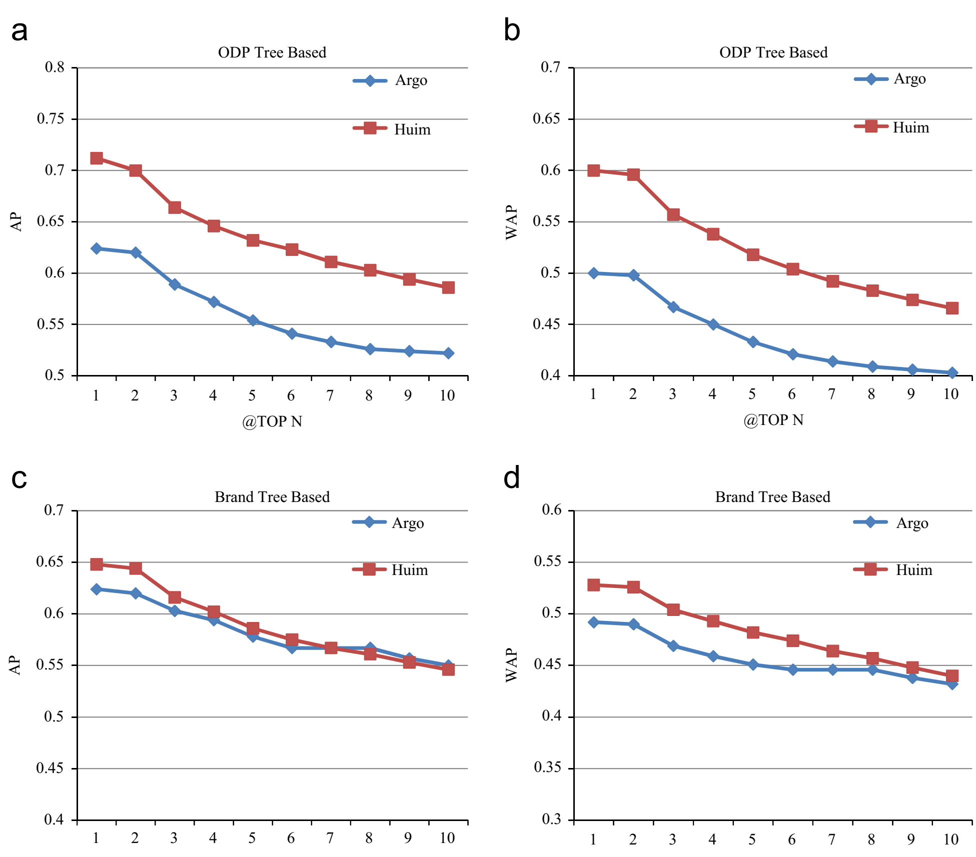


**Fig. 5.** Performance comparisons between Argo and *Huim* based on ODP tree and brand tree. The AP and WAP of top 10 recommended products are shown in (a)–(d), respectively.

### 4.2. Performances evaluation approach

We invite eight volunteers to evaluate the top 10 targeted products for each of the Flickr user as irrelevant, relevant or perfect like Argo [20]. Before evaluating, they have to learn users' interest by browsing their shared photos and the textual descriptions. "irrelevant" means the recommended product is a false-alarm. "relevant" means the recommended product is somewhat relevant, and "perfect" means strong relevance. And then, AP (average precision) and WAP (weighted average precision) are used for performance evaluations which are defined as follows:

$$AP=(p+r)/(p+r+i) \tag{15}$$

$$WAP=(p+0.5r)/(p+r+i) \tag{16}$$

where $p$, $r$, $i$ denote the number of "perfect", "relevant", and "irrelevant" products/brands, respectively.

### 4.3. Performance comparison between Argo and Huim

We introduce two public topic space ODP tree based and brand tree based topic space. We conduct series of experiments to compare our hierarchical user interest mining (*Huim*) method with Argo [20] based on the two public topic spaces. The performances of Argo and *Huim* based on ODP tree and brand tree are compared and shown in Fig. 5, respectively

In Fig. 5(a) and (b) the AP and WAP of Argo and *Huim* based on ODP tree space are shown. From Fig. 5(a) and (b), we can see that both AP and WAP values decline with the increase of top ranked products, with the rank is in the range of [1,10]. The average AP and WAP values of *Huim* based on ODP tree are above those of Argo about 7.66% and 8.27%, respectively. While in Fig. 5(c) and (d) the AP and WAP of Argo and *Huim* based on brand tree space are shown. The average AP and WAP values of the top five ranked results of *Huim* based on brand tree are above those of Argo about 1.54% and 3.44%, respectively. This is caused by the fact that the brand tree topic space only has two layers. The performances improvement of *Huim* over Argo is not as large as that based on the ODP tree topic space, where the maximum layer number of ODP is seven. However, from the experimental results, it is clear that introducing the hierarchical topic space based representation approach is effective for representing user's interest and product descriptions.

The computational costs of Argo and Huim are very close. For the case that we only using the textual descriptions of user's photo set (not carrying out image tag enrichment), the corresponding

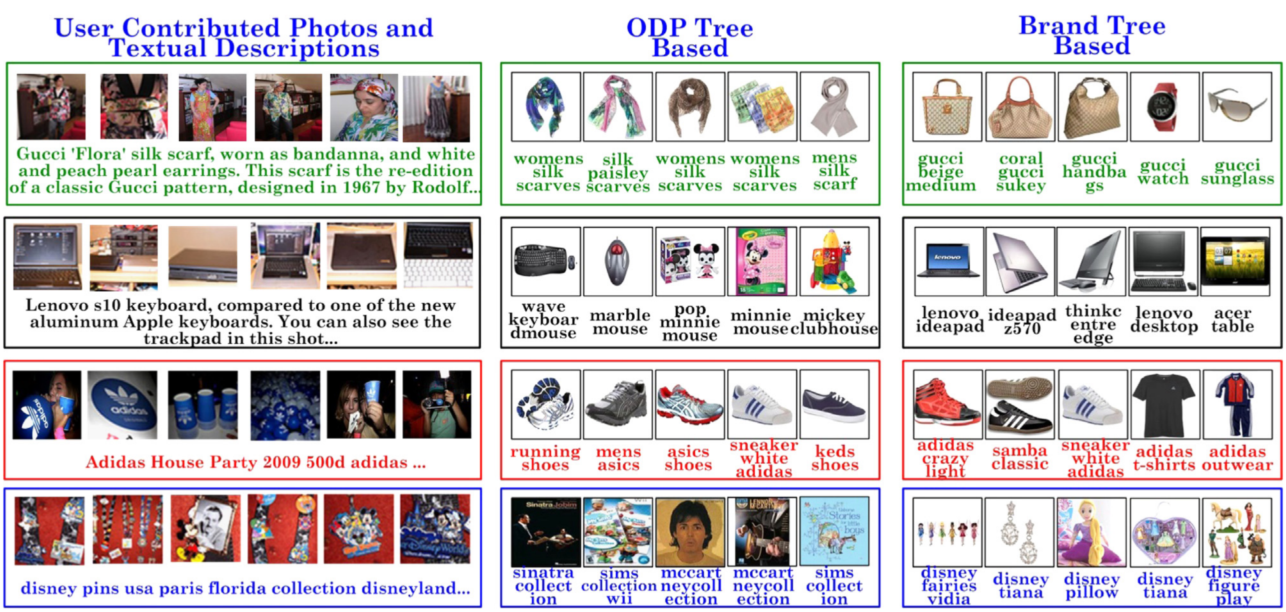


**Fig. 6.** Some cases comparison when users labeled brand name in their uploaded photos like *Gucci*, *Lenovo*, *Adidas*, and *disney*.

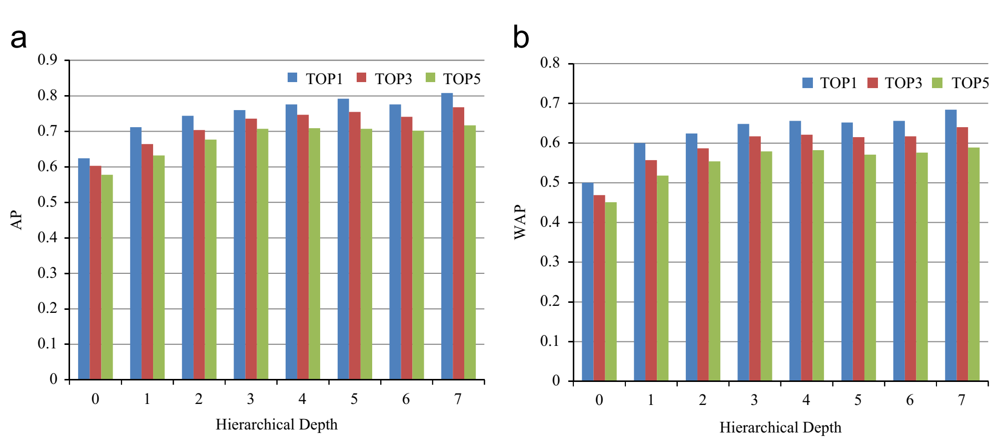


**Fig. 7.** Product recommendation performances *Huim* at different hierarchical depth in the range [0,7] for the ODP space based approach. (a) the AP and (b) WAP of the performance of TOP1, TOP3 and TOP5 recommended products.

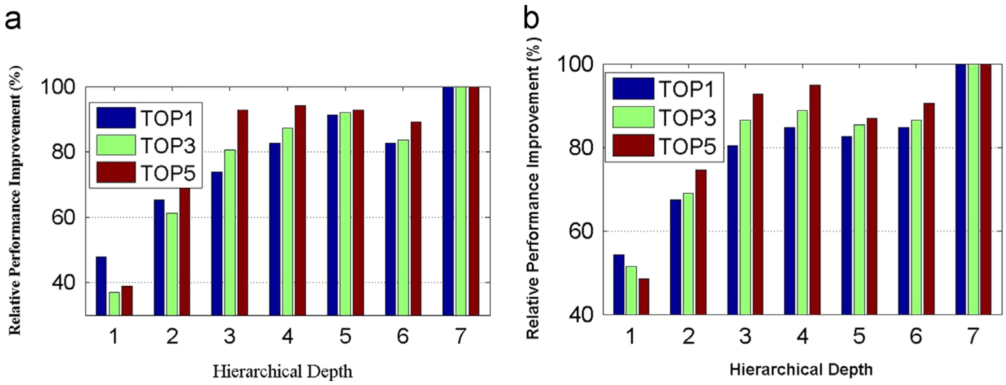


**Fig. 8.** The relative performance improvement at different hierarchical depth. (a) AP (b) WAP.

computational costs of Argo and ours are 8.91 ms (micro-seconds) and 9.28 ms, respectively, in C# environment of windows 7 platform with 16 G ram and CPU E5-2620.

### 4.4. Comparison for ODP and brand

As shown in Fig. 5, although the performance of *Huim* based on ODP tree is superior to brand tree. It is worth noting that the recommended products of brand tree based are more personalized than ODP tree based when users labeled brand name in some photos. Four users with favorite brands and the corresponding top 5 products by ODP tree based and brand tee based are shown in Fig. 6. For example, when user labels *Adidas* in the third user, the ODP tree based method recommends usual shoes while brand tree based method recommends kinds of *Adidas* shoes. That is because brand tree based topic space has more brand related tags than ODP tree based topic space, which could reflect user's brand preference better. Correspondingly, the recommended results are more related to the user favorite brands.

### 4.5. Impact of hierarchical depth

In this section, we discuss the impact of hierarchical depth to the product recommendation performance. As mentioned above, there are seven layers of ODP tree based topic space and two layers of brand tree based topic space. And therefore, we conduct series of experiments to test the performance of ODP tree based *Huim* under different hierarchical layer.

The products recommendation performances of Huim for the TOP1, TOP3 and TOP5 under different hierarchical depths in the range [0,7] are shown in Fig. 7, respectively. The performances of *Huim* under hierarchical depth "0" mean only the leaf nodes are utilized in user/product topic vector representation. This case (i.e.Huim under $H=0$) is identical to Argo. We find that both AP and WAP values of the TOP 1, TOP 3 and TOP 5 increase with the increase of hierarchical depth. Because the larger the hierarchical depth, more ancestors of leaf nodes is used to restrain the noise and ambiguous tags. Even though some noise textual descriptions cannot be suppressed at a specified layer, they are likely to be filtered by other layers in the hierarchical topic space. Thus the performances of fusing more layers are with better results. We get the maximum AP and WAP values for the TOP1 recommended products of ODP when the seven layers are fused. From the result of this experiment, we can see that *Huim* method can adaptively get the optimal performance by enhancing user interest layer by layer based on hierarchical topic space.

From Fig. 7 we find that the first, second and the third layers have large contributions for improving the recommendation performances. The related performances of different hierarchical

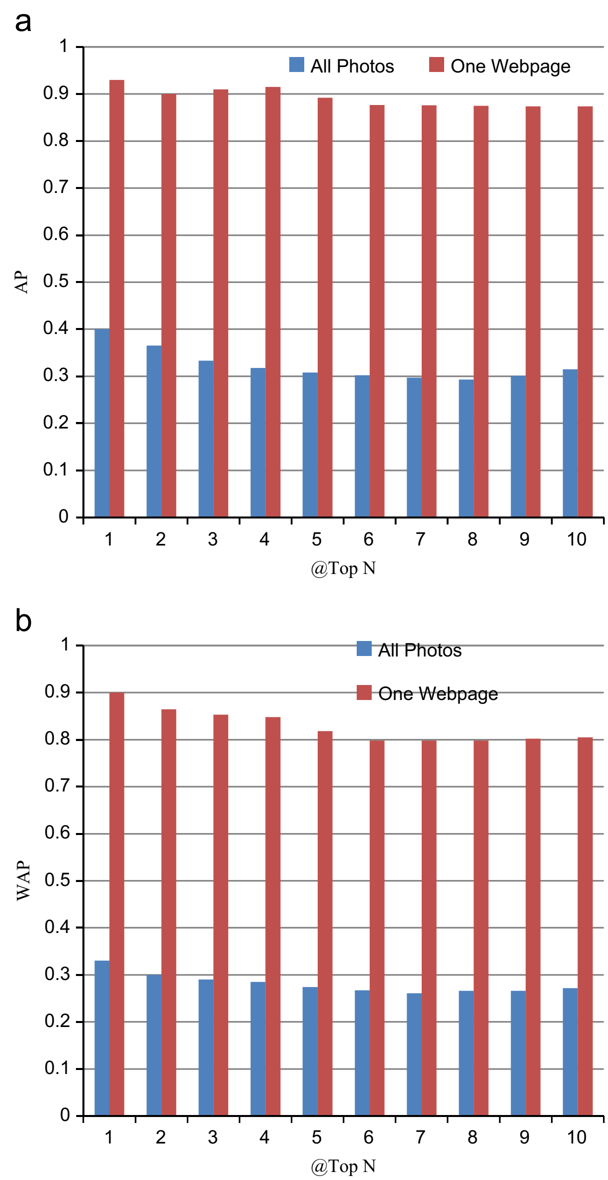


**Fig. 9.** Performances of top 10 results of ODP tree based *Huim* using all photos and photos in a webpage.(a) AP, and (b) WAP of ranked product index in the range [1,10].

depth to the final performances of AP and WAP are given in Fig. 8 (a) and (b), respectively. From this figure, we find that even using only the first layer categorization information about 50% improvement can be made. Generally speaking when all the hierarchical


**Fig. 10.** Some examples of ODP tree based *Huim* under hierarchical depth seven. The left column shows part of user contributed photos and UGC in a webpage. The middle column shows the process of *Huim*. The red labels mean user interested topics which are enhanced by *Huim*. And the green labels mean the noise topics of the topic distribution which are restrained. The right column shows the top 5 recommended products by Argo and *Huim*. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

layers are utilized in user and product description representation better performances are achieved.

### 4.6. Impact of different inputs

User-contributed photos and their descriptions in different webpages may have too many topics, which make the user interests not salient. In our approach, we set photos of user's in one webpage as input for personalized product recommendation. This is based on the assumption that the photos of same page have same topic. To verify the rationality of our hypothesis, we use randomly selected 15 users to test the impact of using different kinds of inputs to personalized products recommendation performances. Totally, there are $15 \times 316$ webpages for the 15 users and each webpage containing 18 photos and the corresponding textual descriptions.

The performances are shown in Fig. 9, where "All Photos" means all of user's photos and textual descriptions are utilized to mine his or her interest, and "One Webpage" means only the information in a webpage is utilized. Then we get the AP and WAP of top ten recommendations by enhancing user interest topic with all the seven layers. From Fig. 9, we can see that both AP and WAP of "One Webpage" are superior to "All Photos" at about 60%. This comparison also shows that the photos in a webpage are highly related to a specified topic, which is helpful for recommending personalized products.

### 4.7. Examples of ODP tree based Huim

Fig. 10 shows some examples of the processing of ODP Tree based *Huim* under hierarchical depth seven. As shown in Fig. 10, the left part is user's one webpage's photos and UGC. The process of *Huim* is shown in the middle. The tags in red are highly relevant to user interest and the tags in green are irrelevant. For example, in the first user, we find that her-contributed photos are related to her favorite desserts *cake*, *chocolate*, and *cookbooks* etc. The proposed Huim can enhance the user interested topics and suppress other irrelevant topics, such as *hockey* and *classical opera* effectively. Compared to Argo, the top five recommended products are well personalized. For the second user, the user interested topic is focused on *iphone*, so the recommendation results of Huim are mainly related to the electronic devices, which are far better than those recommended by Argo.

While for the third user, she shared some photos about her new born baby, and she may be interested in baby products. Using our approach the user interested related tags *baby*, *gifts and baby* and *children* mean user interested topics are enhanced while the green labels like *electronics* and *model* are restrained effectively. Thus, the recommended top five products in the right are personalized.

## 5. Conclusion

In this paper, a personalized product recommendation approach is proposed by mining user interest from user-contributed photos in social media sites. User's interests can be well disclosed from their shared photos in a webpage. The topic space can be utilized to measure the bridge the gaps in measuring the relevance of a user and products. The hierarchical structures of topic spaces are valuable for enhancing user's interested topics and suppress noise and ambiguous textual descriptions. The deep the hierarchical depth fused in enhancing user interest or products descriptions, the better recommendations. ODP and brand based topic public trees are utilized in personal product recommendation. When user has favorite brands, then our approach can recommend brand preferred products for the user. At present, our research only mine user interest from user's shared photos and labeled texts without consideration the location information and the influences of their friends in their social communities. In our future works, we will take these information into account to recommend more personalized products.

## References

[1] A.Evans, M.Fernandez, et al., Adaptive multimedia access: from user needs semantic personalization, in: IEEE International Symposium on Circuits and Systems, May 2006, pp. 2097–2100.
[2] C.-H. Chang, K.-Y. Hsieh, M.-C. Chung, J.-L. Wu, ViSA: virtual spotlighted advertising, ACM Multimedia (2008) 837–840. (Oct.).
[3] F Fouss, A Pirotte, J.M. Renders, M. Saerens, Random-walk computation of similar-ities between nodes of a graph, with application to collaborative recommendation, IEEE Trans. Knowl. Data Eng. (2007) 355–369.
[4] H.H.Dai, L.Z.Zhao, Z.Q.Nie, J.-R.Wen, L.Wang, Y.Li, Detecting online commercial intention, ACM International WWW Conference, 829–837, May. 2006.
[5] H.Y Liu, S.Q Jiang, Q.M Huang, C.S Xu, A generic virtual content insertion system based on visual attention analysis, ACM Multimedia (2008) 379–388. (Oct.).
[6] H.N.Zhou, Z.Y.Liu, Page frame segmentation for contextural advertising in print on demand books, in: CVPR Workshops, Aug. 2009, pp. 17–22.
[7] J.Hu, H.-J.Zeng, H.Li, C.Niu, Z.Chen, Demographic prediction based on user's browsing behavior, ACM International WWW Conference, 151–160, May. 2007.
[8] J. Trajkova, S. Gauch, Improving ontology-based user profiles, RIAO (2004) 380–389.
[9] K.W Wan, X Yan, X.G Yu, C.S Xu, Robust goal-mouth detection for virtual content insertion, ACM Multimedia (2003) 468–469. (Nov.).
[10] L.S.Li, T.Mei, X.Niu, C.-W.Ngo, PageSense: style-wise web page advertising, ACM International WWW Conference, 1273–1276, Apr. 2010.
[11] L.S Li, T Mei, X.-S Hua, GameSense: game-like in-image advertising, Multimedia Tools Appl. (2009) 145–166. (Oct.).
[12] P. Chatterjee, D.L. Hoffman, T.P. Novak, Modeling the clickstream: implications for web-based advertising efforts, Marketing Sci. 22 (4) (2003) 520–541.
[13] T. Mei, X.-S. Hua, S. Li, Contextual in-image advertising, ACM Multimedia (Oct. 2008) 439–448.
[14] T. Mei, X.-S. Hua, Contextual internet multimedia advertising, IEEE Spec. Issues Internet Vision 98 (8) (2010) 1416–1433. (Aug.).
[15] T. Mei, X.-S. Hua, S.P. Li, VideoSense: a contextual in-video advertising system, IEEE Circuits Syst. Soc. 19 (12) (2009) 1866–1879. (Dec.).
[16] T. Mei, X.-S. Hua, L.J. Yang, S.P. Li, VideoSense: towards effective online video advertising, ACM Multimedia (2007) 1075–1084. (Sep.).
[17] T. Mei, J. Guo, X.-S. Hua, AdOn: toward contextual overlay in-video advertising, ACM Multimedia (2010) 335–344.
[18] W.-S. Liao, K.-T. Chen, W.H. Hsu, AdImage: video advertising by image matching and Ad scheduling optimization, ACM SIGIR (2008) 767–768. (Jul.).
[19] X.-J. Wang, M. Yu, L. Zhang, W.-Y. Ma, Advertising based on users' photos, ICME 2009 (2009) 1640–1643. (Jun.).
[20] X.-J. Wang, M. Yu, L. Zhang, R. Cai, W.-Y. Ma, Argo: intelligent advertising by mining a user's interest from his photo collections, ACM Data Min. Audience Intell. Advertising (2009) 18–26. (Jun.).
[21] X.-J. Wang, L. Zhang, X.-R. Li, W.-Y. Ma, Annotating images by mining image search results, pattern analysis and machine intelligence, IEEE Trans. Pattern Anal. Mach. Intell. (2008) 1919–1932.
[22] X.-S.Hua, T.Mei, S.P.Li, When multimedia advertising meets the New Internet Era, in: International Workshop on Multimedia Signal Processing, 2008, pp. 1–5.
[23] Y.Q Li, K.W. Wan, X. Yan, C.S. Xu, Real time advertisement insertion in baseball video based on advertisement effect, ACM Multimedia (2005) 343–346. (Nov.).
[24] Y.F Chen, G.-R Xue, Y Yu, Advertising keyword suggestion based on concept hierarchy, ACM WSWDM (2008) 251–260. (Feb.).
[25] Y. Zheng, L. Zhang, Z. Ma, X. Xie, W.-Y. Ma, Recommending friends and locations based onindividual location history, ACM Trans. Web (2011). (Feb.).
[26] Y. Zheng, X. Xie, Learning travel recommendations from user-generated GPS traces, ACM Trans. Intell. Syst. Technol. (2011). (Jan.).
[27] D. Goldberg, D. Nichols, B.M. Oki, D. Terry, Using collaborative filtering to weave an information tapestry, ACM Spec. Issues Inf. Filtering (1992) 61–70. (Dec.).
[28] F. Ricci, A. Venturini, D. Cavada, N. Mirzadeh, et al., Product recommendation with interactive query management and twofold similarity, Lect. Notes Comput. Sci. 2689 (2003).
[29] J.S. Breese, D. Heckerman, C. Kadie, Empirical analysis of predictive algorithms for collaborative filtering, Proc. Uncertainty Artif. Intell. (1998) 43–52.
[30] B. Sarwar, G. Karypis, J. Konstan, J. Riedl, Analysis of recommendation algorithms for e-commerce, Proc. Electron. Commer. (2000) 158–167.
[31] C.N. Ziegler, S.M. McNee, J.A. Konstan, G. Lausen, Improving recommendation lists through topic diversification, Proceedings on WWW, 22–32, 2005.
[32] S.W. Changchien, T.C. Lu, Mining association rules procedure to support on-line recommendation by customers and products fragmentation, Expert Syst. Appl. (2001) 325–335. (May.).
[33] D.R. Liu, Y.Y. Shih, Integrating AHP and data mining for product recommendation based on customer lifetime value, Inf. Manage. (2005) 387–400. (Mar.).

[34] Y.K. Cao, Y.F. Li, An intelligent fuzzy-based recommendation system for consumer electronic products, Expert Syst. Appl. (2007) 230–240. (Jul.).
[35] X.Li, L.Guo, Y.H.Zhao, Tag-based social interest discovery, Proceedings on WWW, 675–684, 2008.
[36] N. Banerjee, D. Chakraborty, K. Dasgupta, et al., User interests in social media sites: an exploration with micro-blogs, Proc. Inf. Knowl. Manage. (2009) 1823–1826.
[37] M.D. Choudhury, H. Sundaram, Y.R. Lin, et al., Connecting content to community in social media via image content, user tags and user communication, in: IEEE International Conference on Multimedia and Expo, Jul. 2009, pp. 1238–1241.
[38] S. Asur, B.A. Huberman, Predicting the future with social media, Comput. Soc. (2010).
[39] G. Adomavicius, A. Tuzhilin, Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions, IEEE Trans. Knowl. Data Eng. (2005) 734–749. (Jun.).
[40] A. Broder, M. Fontoura, V. Josifovski, L. Riedel, A semantic approach to contextual advertising, ACM SIGIR (2007) 559–566.
[41] AdSense: ⟨http://www.google.com/adsense/⟩.
[42] BritePic:⟨http://www.britepic.com/⟩.
[43] BingShopping: ⟨http://cn.bing.com/shopping⟩.
[44] J. Tang, R. Hong, S. Yan, T. Chua, G. Qi, R. Jain, Image annotation by k nn-sparse graph-based label propagation over noisily tagged web images, ACM Trans. Intell. Syst. Technol. (TIST) 2 (2011) 14.
[45] J. Tang, S. Yan, R. Hong, G. Qi, T. Chua, Inferring semantic concepts from community-contributed images and noisy tags, in: Proceedings of the MM, 2009, 223–232.
[46] J. Tang, Z. Zha, D. Tao, T. Chua, Semantic-gap-oriented active learning for multilabel image annotation, IEEE Trans. Image Process. 21 (2012) 2354–2360.
[47] X. Qian, X. Hua, X. Hou, Tag filtering based on similar compatible principle, in: Proceedings of the International Conference on Image Processing, 2012,2349–2352.
[48] Q. Li, Y. Gu, X. Qian, LCMKL: latent-community and multi-kernel learning based image annotation, ACM CIKM (2013).
[49] H. Feng, X. Qian, Recommendation via user's personality and social contextual, ACM CIKM (2013).
[50] H. Feng, X. Qian, Recommend social network users favorite brands, PCM (2013).
[51] X. Qian, X. Liu, C. Zheng, Y. Du, X. Hou, Tagging photos using users' vocabularies, Neurocomputing 111 (2013) 144–153.

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