Personalized Multimedia Information Retrieval based on User Profile Mining

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***Abstract*—This paper focuses on how to retrieve personalized multimedia information based on user interest which can be mined from user profile. After analyzing the related works, a general structure of the personalized multimedia information retrieval system is given, which combines online module and offline module. Firstly, we collect a large-sale of photos from multimedia information sharing websites. Then, we record the information of the users who upload the multimedia information. For a given user, we save his history data which could describe the multimedia data. Secondly, the relationship between contents of multimedia data and semantic information is analyzed and then the user interest model is constructed by a modified LDA model which can integrate all the influencing factors in the task of multimedia information retrieval. Thirdly, the query distributions of all the topics can be estimated by the proposed modified LDA model. Thirdly, based on the above offline computing process, the online personalized multimedia information ranking algorithm is given which utilize the user interest model and the query word. Fourthly, multimedia information retrieval results are obtained using the proposed personalized multimedia information ranking algorithm. Finally, performance evaluation is conducted by a series of experiments to test the performance of the proposed algorithm compared with other methods on different datasets.**

***Index Terms*—Multimedia Information Retrieval, User Interest Model, Topic Model**

I. Introduction

As is illustrated in Wikipedia, information retrieval refers to the activity of obtaining information resources relevant to an information need from a collection of information resources. Searches can be based on metadata or on full-text indexing. Automated information retrieval systems can be utilized to reduce what has been called "information overload". Many universities and public libraries use IR systems to provide access to books, journals and other documents. Web search engines are the most visible IR applications. Particularly, we have witnessed a substantial progress in the acquisition and storage of digital media such as images, video and audio. With the rapid increase of digital multimedia collections, effective and efficient retrieval techniques have become increasingly important [1] [2].

In recent years, the rapid increase of video archives and video sharing resources on the internet has lead to the explosive growing of multimedia data. It makes effective and efficient techniques for browsing and retrieving these data highly desired and activates tremendous research interests on multimedia information retrieval. Generally, queries for multimedia retrieval can be divided into two categories: text-based and example-based (also called query-by-example). In the first category, the query information is described in text, whereas the query is an example in the second category, such as an image or a video clip. In this work, we focus on example-based multimedia information retrieval [3-6].

Particularly, most existing researches about multimedia information retrieval do not consider the users' interest, and without considering users' preference in the information retrieval process may drop the retrieving performance. The searching results of a non-personalized image retrieval engine is illustrated in Fig. 1.

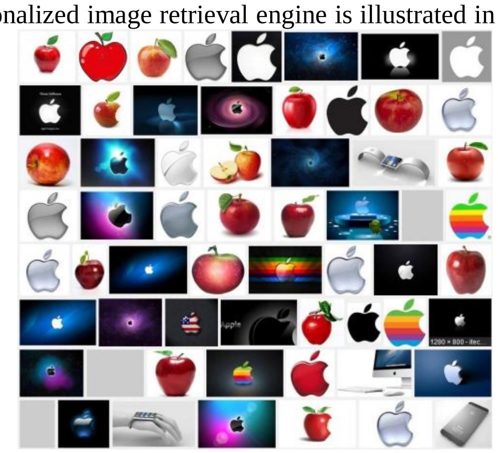

Figure 1. Examples of the image searching results by the query word "apple"

Personalizing the search process based on the searcher's personal attributes and preferences while evaluating a query, is a great challenge that has been

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extensively studied in the information retrieval community but still remains a stimulating task. It is of great interest since user queries are in general very short and provide an incomplete specication of individual users' information needs. This can be implemented through tracking and aggregating users' interaction with the system. In general, such aggregation includes users' previous queries, click-through analysis, and even eye-tracking during the search session. Users' interactions are structured into a user profile that can be utilized during search. A user profile is usually employed in two main scenarios, either through personalized query expansion, i.e., adding new terms to the query and re-weighting the original query terms based on the user profile, or through re-ranking and filtering the search results while incorporating users' interests accordingly [7].

The main innovations of this paper lie in the following aspects:

(1) We propose a novel framework for personalized multimedia information retrieval which is made up of online process and offline process.

(2) The modified LDA model for personalized multimedia information retrieval is design to integrate all influencing factors in the information retrieval process.

(3) For a given target user, the proposed algorithm can effectively utilize the information of the users with similar interests and related topics to calculate the ranking list of multimedia information according to the query term.

The rest of the paper is organized as the following sections. Section 2 introduces the related works. Section 3 illustrates the proposed scheme for personalized multimedia information retrieval. In section 4, a series of experiments are designed and implemented to make performance evaluation. Finally, we conclude the whole paper in section 5.

II. RELATED WORKS

In this section, we will survey on the research works which are related to this paper in two aspects. Firstly, the related works about personalized multimedia information retrieval are introduced as follows.

Choi et al. proposed methods to provide personalized mobile information retrieval system using near field communication smartphone, which will be then used for smartphone users. Besides, this study aims to verify its efficiency through a comparative analysis of existing studies [8].

Pereira et al proposed a new model for aggregating multiple criteria evaluations for relevance assessment. In this paper, an information retrieval context is considered, where relevance is modeled as a multidimensional property of documents. The usefulness and effectiveness of such a model are demonstrated by means of a case study on personalized information retrieval with multi-criteria relevance [9].

Yoo et al. present a hybrid query processing method for the effective retrieval of personalized information on the Semantic Web. The hybrid query processing method utilizes both the query rewriting method and the reasoning method. Particularly, this paper distinguishes knowledge that is frequently changed from knowledge that is not. The query rewriting method is used for frequently changed knowledge; otherwise the reasoning approach is used. The query rewriting method refers to individual requirements to extend user queries instead of conducting inference [10].

Oussalah et al. advocated a fuzzy based approach for information retrieval where a new model is put forward. Also, its feasibility and performance are demonstrated through a testing with a large-scale University database and whose results are compared to a standard commercial Boolean model [11].

Mylonas et al. concentrated on the combination of contextualization and personalization methods to improve the performance of personalized information retrieval. The key aspects in this paper lies in the following aspects. (1) the explicit distinction between historic user context and live user context, (2) the use of ontology-driven representations of the domain of discourse, as a common, enriched representational ground for content meaning, user interests, and contextual conditions, enabling the definition of effective means to relate the three of them, and (3) the introduction of fuzzy representations as an instrument to properly handle the uncertainty and imprecision involved in the automatic interpretation of meanings, user attention, and user wishes [12].

As user interest model plays an important role in personalized multimedia information retrieval to narrow the semantic gap. In the following parts, we introduce the works which utilizing the user interest model to implement personalized multimedia information retrieval as follows.

Zhang et al. developed a novel user interest model according to short-term and long-term interests. Short-term interests are represented by collecting visual and semantic features. Visual features are collected by MARS relevance feedback. Semantic features are constructed by building a mapping from image low-level visual features to high-level semantic features on the basis of SVM. On the other hand, long-term interests are inferred by inference engine from the collected short-term interests [13].

In paper [14], Kramar et al. proposed a method which can infer additional keywords for a search query by leveraging a social network context and a method to build this network from the stream of user's activity on the Web. The approach was evaluated on real users using a personalized proxy server platform. The query expansion method was integrated into Google search engine and where possible, the original query was expanded and additional search results were retrieved and displayed.

Xiong et al. investigated topic cluster features and user interests of an actual BBS forum, analyzing user posting and replying behavior. According to the growing process of BBS, the authors suggest a network model in which each agent only replies to the posts that belong to its specific topics of interest. A post that is replied to will be immediately assigned the highest priority on the post list [15].

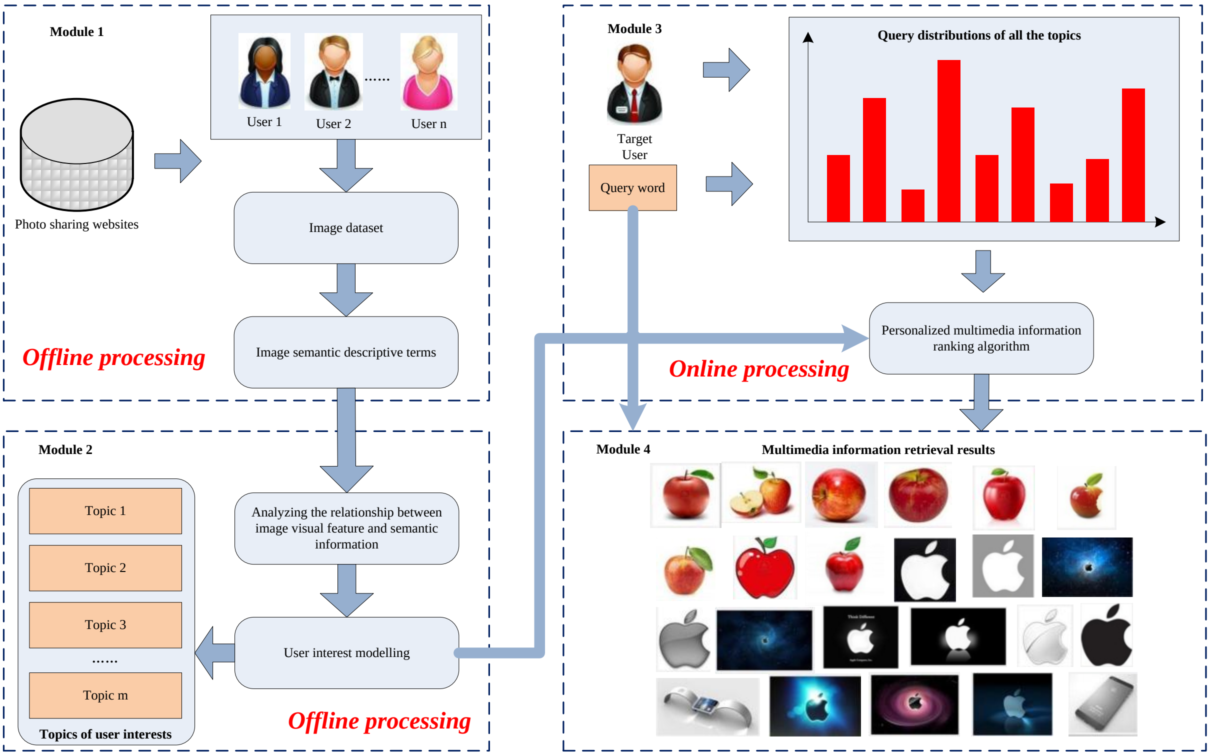


Figure 2. Structure of the personalized multimedia information retrieval system

Ni et al. proposed a generative model, the Topic-based User Interest model, to capture the user interest in the User-Interactive Question Answering systems. Particularly, the proposed method aims to model the user interest in the UIQA systems with latent topic method, and extract interests for users by mining the questions they asked, the categories they participated in and relevant answer providers. The authors applied the TUI model to the application of question recommendation, which automatically recommends to certain user appropriate questions he might be interested in [16].

Zhang et al. present a novel personalized image retrieval approach based on user interest model. User interest model is developed based on short-term and long-term interests. Short-term interests are represented by collecting visual and semantic features. Visual features are collected by MARS relevance feedback. Semantic features are constructed by building a mapping from image low-level visual features to high-level semantic features on the basis of SVM. Long-term interests are inferred by inference engine from the collected short-term interests [17].

Chi et al. investigated a user attention model based on visual rhythm analysis for automatic determination of ROI in a video. The visual rhythm, which is an abstraction of a video, is a thumbnail version of a video by a 2-D image that captures the temporal information of a video sequence. Four sampling lines, including diagonal, anti-diagonal, vertical, and horizontal lines, are employed to obtain four visual rhythm maps in order to analyze the location of the ROI from video data [18].

Godoy present a document clustering algorithm, named WebDCC, which carried out incremental, unsupervised concept learning over Web documents in order to acquire user profiles. Unlike most user profiling approaches, the propsoed algorithm offered comprehensible clustering solutions that can be easily interpreted and explored by both users and other agents. By extracting semantics from Web pages, this algorithm also produced intermediate results that can be finally integrated in a machine-understandable format such as an ontology [19].

Chi et al. present an effective model by using improved growing cell structures to model users' interest. The GCS is a kind of self-organizing map neural network with changeable network structure. By virtue of the clustering and structure adaptation capability of GCS, the proposed model maps the problem of learning and keeping track of user interests into a clustering and cluster-maintaining problem. Each cluster found by GCS represents an interest category of a user and the cluster maintaining, including cluster addition and deletion, corresponds to the addition of user's new interests and the removal of user's old interests [20].

III. The Proposed Scheme

A. Structure of the Personalized Multimedia Information Retrieval System.

At first, we will illustrate the Structure of the personalized multimedia information retrieval system which is implemented by both offline processing mode and online processing mode (shown in Fig. 2). Furthermore, the proposed system is made up of four module.

In module 1, we collect a large-sale of photos from photo sharing websites, such as Flickr. At the same time, we record the information of the users who upload the photos. For a given user, we save the user tagging data which could describe the visual contents of the image. Based on the results provided by module 1, in module 2, the relationship between image visual feature and semantic information is analyzed and then the user interest model is constructed by estimating the distribution of user interest topics. Based on the above offline processing module, the query distributions of all the topics can be obtained. Afterward, the online personalized multimedia information ranking algorithm can be designed by integrating user interest model, the query word and the target user. Finally, in module 4, multimedia information retrieval results are obtained using the proposed personalized multimedia information ranking algorithm.

B. Modeling User Interest based on User Profile Mining

In this section, we propose a topic-based user interest model to represent the user interests in the personalized multimedia information retrieval system. As LDA is a powerful probabilistic generative topic model, and it has many advantages in the fields of intelligent computing, in this paper, we design a modified LDA model to represent user interest. Before describing the modified LDA model, the standard LDA model should be introduced in advance. LDA model belongs to a kind of probabilistic generative model, and the graphical representation of LDA model is shown in Fig. 3

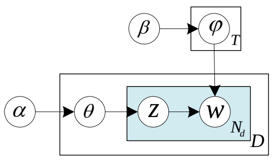


Figure 3. Illustration of LDA model

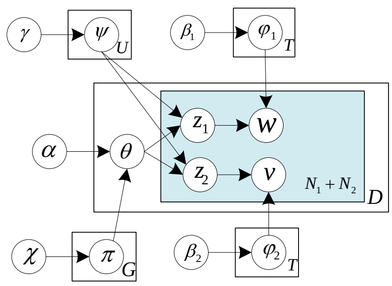


Figure 4. The modified LDA model for Personalized multimedia information retrieval

In Fig. 3, the parameter α and β denote the Dirichlet distribution θ and φ respectively. Particularly, θ refers to the topic proportions. The generative process for each element d in the Corpus D, and this process can be formally described as follows.

(1) Choose $\theta \sim Dir(\alpha)$

(2) For each w in element d do the following steps

1) Choose a topic $z_n \sim Mult(\theta)$

2) Choose a word w_n from $p(w_n | z_n, \beta)$ which is a multinomial probability conditioned on the topic z_n

To make the LDA model suitable to the application of the personalized multimedia information retrieval, we propose a modified LDA model to integrate all the influencing factors in this application. Particularly, the modified LDA model is given in Fig. 4.

In this modified LDA model, the Symbol *G*, *U*, *D* and *T* represent the number of user groups, users, data element of multimedia information, and topics respectively. Particularly, the Symbol N_1 and N_2 denote the number of visual words and user-supplied tags in the dataset. In this modified LDA model, each user group g is related to a multinomial distribution π, and each user is related to a multinomial distribution θ over different topics. At the same time, the parameter φ_1 and φ_2 mean the multinomial distribution over visual words and user-supplied tags. Next, the Gibbs sampling method for the proposed modified LDA model is illustrated as follow.

To joint probability distribution for different entities based on the hyperparameters γ, χ, β_1 and β_2 should be determined in advance(shown in Eq.1).

$$
\begin{aligned}
& p(d,z,u,c,\psi,\pi,\varphi_1,\varphi_2 | \alpha,\chi,\gamma,\beta_1,\beta_2) \\
&= p(d | \varphi_1,\varphi_2,z) \cdot p(\varphi_1,\varphi_2 | \beta_1,\beta_2) \cdot p(z | u,\pi) \\
&\cdot p(\pi | \alpha) \cdot p(u | c,\psi) \cdot p(\psi | \gamma) \cdot p(c)
\end{aligned} \tag{1}
$$

Afterwards, the desired distribution is the posterior given the element *d* as follows.

$$
\begin{aligned}
& p(z,u,c,\psi,\pi,\varphi_1,\varphi_2 | \alpha,\chi,\gamma,\beta_1,\beta_2) \\
&= \frac{p(d,z,u,c,\psi,\pi,\varphi_1,\varphi_2 | \alpha,\chi,\gamma,\beta_1,\beta_2)}{\sum_G \sum_U \sum_T p(d,z,u,c,\psi,\pi,\varphi_1,\varphi_2 | \alpha,\chi,\gamma,\beta_1,\beta_2)}
\end{aligned} \tag{2}
$$

C. Personalized Multimedia Information Ranking Method

After modeling the user interest, personalized multimedia information retrieval can be implemented by the personalized multimedia information ranking method as follows.

For a given target user, $R(u)$ represents the ranked list of the users which have similar interests to user u, and $T(u)$ means the ranking topic list for the user u. Particularly, the above two lists can be represented as follows.

$$R(u) = \{r_1(u), r_2(u), \cdots, r_m(u)\} \tag{3}$$

$$T(u) = \{t_1(u), t_2(u), \cdots, t_n(u)\} \tag{4}$$

Integrating the above lists $R(u)$ and $T(u)$, the information of target user profile is defined as follows.

$$UP(u) = \{R(u), T(u)\} \tag{5}$$

Afterwards, the personalized multimedia information retrieval results can be obtained by calculating the ranking score in the following equation.

$$Score(q,d\,|UP(u)) = \mu \cdot Score(q,d) + (1-\mu) \cdot [\rho \cdot \sum_{v\in R(u)} w(u,v)\cdot w(v,d)] + (1-\rho)\cdot \sum_{t\in T(u)} w(v,t)\cdot w(t,d)] \quad (6)$$

where $Score(q,e|UP(u))$ refers to the personalized ranking score of the multimedia data d for the query term q for the target user u. $Score(q,d)$ denotes the ranking score without considering personalized information. Furthermore, $w(u,v)$ and $w(v,d)$ denote the relationship strength of the target user u and the term t. On the other hand, $w(u,t)$ and $w(t,d)$ represent the relationship weight between v and t for the multimedia data d.

To make the proposed algorithm more flexible, we set several parameters to control the influence degree of personalization as the following aspects.

(1) The value of $R(u)$ is determined by the characteristics of the given photo sharing website.

(2) The parameter μ is designed to control the weight of the personalized degree in the process of personalized information retrieval.

(3) The parameter ρ represent the influence degree between persons and the terms for personalization.

Particularly, how to select suitable parameters is given in section 4.

IV. Experiments

In this section, a series of experiments are conducted to make performance evaluation. First of all, two important parameters ρ and μ of the personalized multimedia information ranking algorithm should be determined, because choosing the value of the above two parameters accurately can effectively promote the accuracy of the multimedia information retrieval system. We design a experiment utilizing the MAP as the metric by adjusting the value of ρ and μ. Particularly,

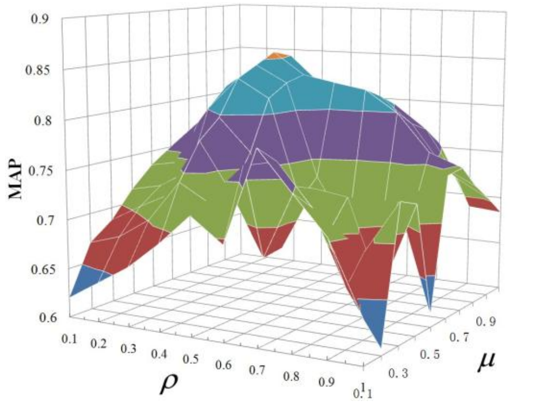


Figure 5. MAP under different values of parameter ρ and μ

Evaluating the results multimedia information retrieval can utilize the MAP (mean average precision) as the metric which is defined based on AP(average precision). Furthermore, AP can be defined as the sum of accuracy which is calculated by calculating the ration of correct elements in all the results which are returned by the information retrieval systems. Afterwards, MAP can be defined as the average value of the AP which is gained by the retrieval system's inquiring for many times. Therefore, MAP can effectively evaluate the performance of the information retrieval system.

As is shown in Fig. 5, the value of MAP reaches its maximum when parameter ρ and μ are equal to 0.4 and 0.6 respectively. Afterwards, the results of users interest modeling is shown in Table.1.

TABLE I. Overview of User Interests Used in This Experiment

Topic number	Categories of user interest	Terms of specific interest
Topic 1	Travel	Nature, Vacation, Landscape, Holoday
Topic 2	Sports	Football, Swimming, Tennis, Basketball
Topic 3	IT	Computer, Network, Programming, Software
Topic 4	Reading	Book, Novel, Literature, Poem
Topic 5	Movie	FILM, Actress, Theatre, Actor,TV
Topic 6	Music	Jazz, Pop, Guitar, Live, Band, Rock
Topic 7	Diet	Food, Cooking, Cola, Fresh, Fruit, Vegetables
Topic 8	Photography	Portrait, Face, Color, Light, Canon, Nikon, Camera
Topic 9	Philately	Stamp, Collecting, Postage, Postoffice, Mail
Topic 10	Astronomy	Star, Moon, Telescope, Space, Planet, Sky

Based on the user model proposed in Table.1, we will test the performance of personalized image retrieval process in three datasets, and compared with other three methods, which are 1) LPIS [22], 2) JustClick [23], 3)IPMIBR [24].

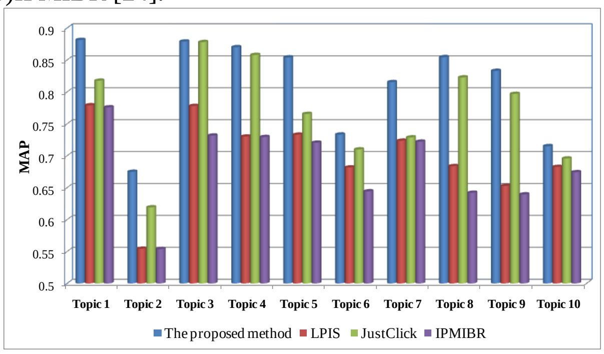


Figure 6. Performance evaluation under the MAP metric for different methods based on NUS-WIDE dataset.

Firstly, we perform the experiments on a large-scale web image dataset which is named NUS-WIDE [21]. This dataset includes 269648 images with 5018 unique tags collected from Flickr. We crawled the images' owner information and obtained owner user ID of 247 849 images. Particularly, the collected images belong to 50 120 unique users. The experiment using NUS-WIDE dataset is shown in Fig. 6.

Secondly, the Corel5K and Corel10K Datasets are utilized in the following experiments. There are 10000 images which contain 100 categories in the Corel series dataset, of which each category contains 100 images of size 192×128 in JPEG format. All images come from Corel Gallery Magic 20, 0000 (within 8 CDs).The first 5000 images is used to construct the Corel5K Dataset, and all the 10000 images is used to made the Corel10K dataset. Afterwards, the experiments utilizing Corel5k and Corel10K NUS-WIDE dataset are shown in Fig. 7. and Fig. 8 respectively.

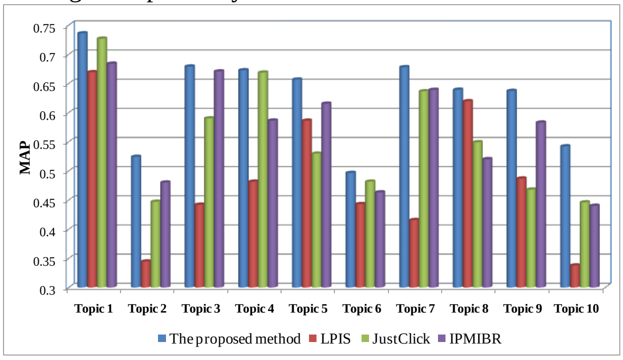


Figure 7. Performance evaluation under the MAP metric for different methods based on Corel5K dataset.

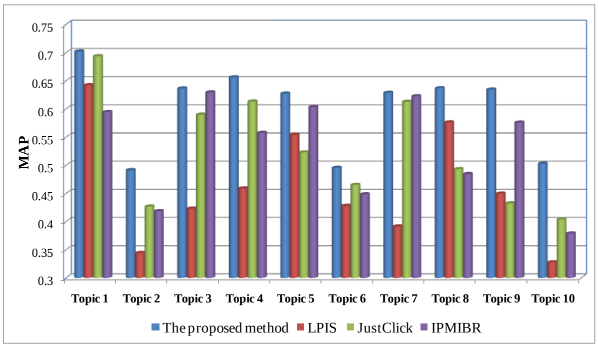


Figure 8. Performance evaluation under the MAP metric for different methods based on Corel10K dataset.

Next, we will test the influence of the topic numbers to the system performance in the above three dataset, and the experimental results is shown in Fig. 9.

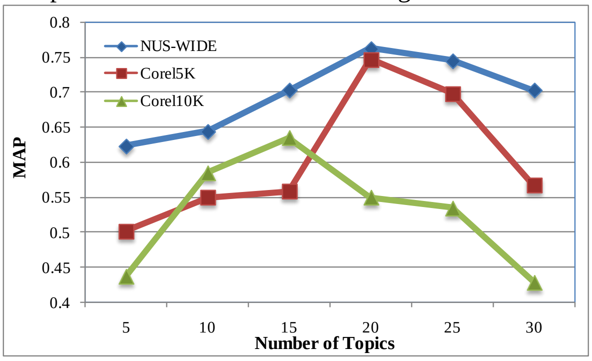


Figure 9. Performance evaluation for different dataset with the number of topics varying.

As is shown in Fig. 10, we give two image searching example for two different persons with different interest to illustrate the experimental results more directly.

From all above experimental results, we can see that the proposed scheme can work effectively, the reasons lie in that 1) The proposed framework for personalized multimedia information retrieval which is made up of online process and offline process can work effectively. Therefore, the time cost of this algorithm is satisfied by user. 2) The modified LDA model for personalized multimedia information retrieval can effectively integrate all influencing factors in the information retrieval process. 3) The proposed algorithm can effectively provide personalized information retrieving to target users, because it can utilize the information of the users with similar interests and related topics to calculate the ranking list of multimedia information according to the query word.

V. CONCLUSIONS

In this paper, we propose a novel personalized multimedia information retrieval algorithm by mining the user profile. We collect a large-sale of photos from multimedia information sharing websites as the multimedia data. Afterwards, the information of the users who upload the multimedia information is recorded. For the target user, his history data which could describe the multimedia data is saved as well. Next, the relationship between contents of multimedia data and semantic information is analyzed and then the user interest model is constructed by a modified LDA model. Based on the above steps, the multimedia information retrieval results can be gained through the proposed personalized multimedia information ranking algorithm.

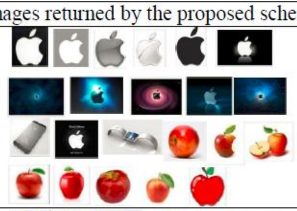
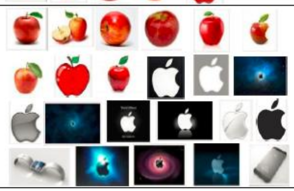
User interest	Images returned by the proposed scheme
IT	
Diet	

Figure 10. Examples of personalized multimedia information retrieval results for two users with different interests

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