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Retrieval and Re-Ranking of Images with Better Optimization Using Hyper Graph

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ABSTRACT

The process of image search includes searching of images based on user given keywords. Most of the image retrieval techniques are based on text based image retrievals. But it has certain problems like images are time duplicated, low precision, and irrelevant. This paper represents the multiple scenario may occur due to sparse and noisy textual query. Because of this user cannot be always sure of perfect images being obtained in available time. To moderate image search user clicks are introduced into the search query so that the relevance between given query and result obtained should be maximized. User clicks are integrated to textual features to make refinement of textual query. The major bottleneck is likely mismatch between the image content and the given text. Image search re-ranking attempts to resolve this bottleneck by relying on both the text information and visual information during the image search process. This paper represents the trends in image search reranking and optimization with hyper graph.
Keywords: Hyper Graph, VCLTR, Natural Language Processing, Data Mining, Information Retrieval, Discounted Cumulative Gain, Fast Alternating Linearization Method

I. INTRODUCTION

In the of image search user cannot be always sure of perfect images being obtained in available time. It is difficult for users to accurately describe the visual content of target images only using keywords and hence text based image search suffers from the ambiguity of query keywords. For example, using apple as a query keyword, the retrieved images belong to different categories, such as apple laptop, apple logo, apple fruit. To capture users' search intention, additional information has to be used in order to solve the ambiguity. Most of the existing techniques make use of textual information to retrieve image, which creates the inconvenience. The probable mismatch between the content of an image and the text from a web page is a major problem. The extracted text does not always precisely describe the characteristics of the image content, as required by the query. The existing ranking model cannot integrate visual features, which are efficient in refining the click-based search results. The major challenge is the correlation of similarities of visual features and images' semantic meaning, which are needed to interpret users' intention to search. Recently, it has been proposed to match images in a semantic space that used attributes or reference classes closely related to the semantic meanings of images as basis. The Machine Learning Approach can be applied to image re-ranking problem. The machine learning has wide applications in Information Retrieval (IR), Data mining (DM), and Natural Language Processing (NLP). In Machine Learning training data consists of lists of items with some partial order specified between items in each list. This order is typically induced by giving a numerical or ordinal score or a binary judgment (e.g. "relevant" or "not relevant") for each item. The ranking model will be produce by considering conditional probability distribution value that takes 1 for relevant and 0 for irrelevant query document pair. This paper represents visual and click features based learning to rank (VCLTR). The proposed system can handle the problems of textual features, i.e. the semantic gaps in describing the relevance between images and query, and can also overcome the drawbacks of visual re-ranking, i.e. the noise spread and the inability to relegate irrelevant images that have initially been ranked in a high position. Using the click features creates a robust and accurate ranking model, and adopting the visual features will further enhance the model's performance.

1. Literature Review

Machine-learned ranking has extensive uses in retrieving documents, searching definitions, answering questions, and summarizing documents [1].Traditionally, the ranking model is manually created without training [2].This model describes a conditional probability distribution. To take document retrieval as an example, the probability model can be constructed using the frequency of words shown in the query and the document. The training stage is therefore unnecessary.

To measure the performance of a search engine, the discounted cumulative gain (DCG) has been widely adopted to evaluate relevance in the context of search engines [3]. The objective function of a regression model, obtained through point wise operations [4] was one of the solutions to rank as either a regression or classification problem. However, these methods neglect the preference relationship that exists among the documents.

The pair wise approach [5][6] minimizes above problem and successfully used in document retrieval. This approach collects document pairs from the ranking lists, and assigns a label to each pair that describes the relative relevance of the two documents. It then trains a classification model with the labeled data and adopts it for ranking.

2. Proposed Work

The proposed system is used to develop image search and ranking model for search engine by integrating user click features and visual features of the image. The objectives of proposed system are:

- To Define Image dataset for the system.
- To train dataset for given query and form a pair (Xq, Rq) Xq denotes query vector, Rq denotes relevance vector.
- To build multiple Hyper graph from visual features of image based on click features corresponding to clicked image.
- To obtain Model Parameter w by applying Fast Alternating Optimization.
- To optimize smooth term and non-smooth term of objective function by setting the partial derivative to zero and using cutting plane algorithm respectively.

System Architecture

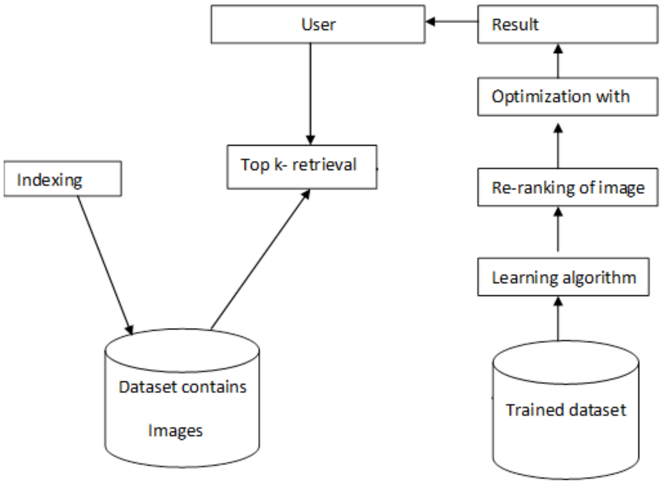

Figure 1. System architecture of Retrieval and Re-ranking of Images with better optimization using hyper graph"

The system architecture for image search and re-ranking includes same architecture as information retrieval system. For Image search user gives the textual query describing image, the search engine process the query and retrieves relevant web links that contains required result. The Indexer plays important role in the retrieval system as it provides indexing for retrieved links based on their popularity and arranged in descending order. After that only top-k results are shown to user.

This traditional image search will not perform well because textual information cannot describe accurate semantics of query. To achieve good image retrieval results machine learning approach is used. This learning model first performs training on dataset and forms a pair of result that gives query vector and relevance vector. The learning algorithm learns image features and click feature provided by user clicks. By integrating the visual features and click features, objective function is modified and hyper graph regularize and linear model are, respectively considered for two features. The combination of user clicks and image features produce more relevant results. The optimization of obtained result will be carried out by fast alternating linearization method (FALM).This method can alternately minimize two different approximations of the original objective function by keeping one function unchanged and linearizing the other. In this paper, we propose a hypergraph based transductive algorithm to the field of image retrieval. Based on the similarity matrix computed from various feature descriptors, we take each image as a 'centroid' vertex and form a hyper edge by a centroid and its k-nearest neighbors. To further exploit the correlation information among images, we propose a novel hyper graph model called the probabilistic hypergraph, which presents not only whether a vertex belongs to a hyper edge.

II. METHODS AND MATERIAL

Module 1: Indexer:

In this approach, for image search user gives the textual query describing image, the search engine process the query and retrieves relevant web links that contains required result. The Indexer plays important role in the retrieval system as it provides indexing for retrieved links based on their popularity and arranged in descending order. The aim in the indexing step is to provide the users with a set of high-level entry points into the dataset.

This index also determines whether a word exists within a particular document, since it stores no information regarding the frequency and position of the word. Such an index determines which documents match a query but does not rank matched documents. In some designs the index includes additional information such as the frequency of each word in each document or the positions of a word in each document. Position information enables the search to identify word proximity to support searching for phrases; frequency can be used to help in ranking the relevance of documents to the query. Such topics are the central research focus of information retrieval.

Module 2: Top-k results:

In this approach, an image retrieval process begins when a user enters a query into the system. Queries are formal statements of information needs, for example search strings in web search engines. In image retrieval a query does not uniquely identify a single image in the collection. Instead, several images may match the query, perhaps with different degrees of relevancy. User queries are matched against the database information. Depending on the application the data objects may be, for example, text documents, images, audio, mind maps or videos.

Often the documents themselves are not kept or stored directly in the Information Retrieval (IR) system, but are instead represented in the system by document surrogates or metadata. Most Information Retrieval systems compute a numeric score on how well each image in the database matches the query, and rank the images according to this value. The top ranking images are then shown to the user.

Module 3: Training on dataset using machine learning approach

In this approach, learning model first performs training on dataset and forms a pair of result that gives query vector and relevance vector. The training data consists of queries and documents. Each query is associated with a number of documents. The relevance of the documents with respect to the query is also given. The relevance information can be represented in several ways. Here, we take the most widely used approach and assume that the relevance of a document with respect to a query is represented by a label, while the labels denote several grades (levels).

In the training phase, a set of queries Q= {q1, q2,…, qn} where n denotes the number of queries, is given. There is a set of documents di = { $d_1^i, d_2^i, \ldots\ldots, d_{m(qi)}^i$ } associated with each of the queries qi. Then there is a list of labels yi = $\{y_1^i, y_2^i, \ldots\ldots, y_{m(qi)}^i\}$ provided together with the documents di where m (qi) is the number of documents given for the query qi. y_j^i denotes label of the jth document d_j^i of the ith query qi. A feature vector $x_j^i \in X$ is specified for each query-document pair (qi , d_j^i) i=1,2,….,n ; j=1,2,…, m(qi), Finally, we can define training dataset as a set

$$\text{Strain}=\{(qi, di, yi)\}_{i=1}^{n}$$

Module 4: Ranking and optimization using Image features and Click features

This approach learns the image features and click feature provided by user clicks. By integrating the visual features and click features, objective function is modified and hyper graph regularizer and linear model are, respectively considered for two features. The combination of user clicks and image features produce more relevant results. The optimization of obtained result will be carried out by fast alternating linearization method (FALM). This method can alternately minimize two different approximations of the original objective function by keeping one function unchanged and linearizing the other.

Table 1. Descriptions of Data Sets

Dataset	Keyword	Image	Search engine
I	135	70.000	Bing Image search
II	168	82000	Bing Image search

III. RESULTS AND DISCUSSION

A. Dataset

This dataset consists of about 70,000 images for representative queries collected from the query log of Bing. We choose this dataset to evaluate our approach for the following reasons: (1) it is a real-world web image dataset; (2) it contains the click feature and visual feature of the image (3) it is publicly available. There are roughly 200 images for each query.

As summarized in Table 1, we create three data sets to evaluate the performance of our approach in different scenarios. In data set I, 120; 000 testing images for re-ranking were collected from the Bing Image Searchwith 120 query keywords. Data set II uses the same testing images as in data set I. However, its training images of reference classes were collected from the Google Image Search. Testing the performance of re-ranking and the training images of reference classes can be collected at different time (since the update of reference classes may be delayed).

IV. CONCLUSION

The paper represents a machine learning framework for image retrieval, in which hypergraph is used to represent the relevance relationship among the vertices (images). This approach learns the image features and click feature provided by user clicks. The combination of user clicks and image features produce more relevant results. The optimization of obtained result will be carried out by fast alternating linearization method (FALM for better accurate result. The effectiveness of the proposed method is demonstrated by extensive experimentation on three general purpose image databases

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