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Research Article

Image Tag Ranking for Efficient Matching and Retrieval

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ABSTRACT

Image annotation has become important research area as plethora of images are available over Internet and social media. Working with those images or retrieving those images is very essential for many applications in the real world. In this context, it is important to have semantic annotations to images for better search performance. The annotations or tags are associated with images in order take advantage of them while searching for images. Many existing studies focused on the image annotations as multi-label classification problem. The issue with this approach is that it needs more number of training images. In order to overcome this problem, in this paper, we proposed a framework that can reduce number of training images required. We built an approach that exploits the strength of tag ranking in the context of image retrieval. The tags associated with the images are identified as relevant and then ranked in descending order in order to ensure that highly satisfied images come in the image search. We built a prototype application to demonstrate the proof of concept. The empirical results revealed that the proposed system is working fine with image retrieval and tag ranking.

Keywords: Image annotation, tag ranking, image retrieval.

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ABSTRACT

Image annotation has become important research area as plethora of images are available over Internet and social media. Working with those images or retrieving those images is very essential for many applications in the real world. In this context, it is important to have semantic annotations to images for better search performance. The annotations or tags are associated with images in order take advantage of them while searching for images. Many existing studies focused on the image annotations as multi-label classification problem. The issue with this approach is that it needs more number of training images. In order to overcome this problem, in this paper, we proposed a framework that can reduce number of training images required. We built an approach that exploits the strength of tag ranking in the context of image retrieval. The tags associated with the images are identified as relevant and then ranked in descending order in order to ensure that highly satisfied images come in the image search. We built a prototype application to demonstrate the proof of concept. The empirical results revealed that the proposed system is working fine with image retrieval and tag ranking.

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1. INTRODUCTION

With the invention of digital cameras and cameras associated with mobile phones paved way for the large number of images accumulated in World Wide Web (WWW) and other databases associated with enterprises. These images are important for many applications. In fact many applications are associated with these images in terms of storing and retrieval of images. Image search is one of the important activities. In order to serve image search Content Based Image Retrieval (CBIR) [1] technique came into existence. The mechanism of CBIR helps the applications to give an image as input and get all related images. This is also known as query by example (QBE). The procedure is illustrated in Figure 1.

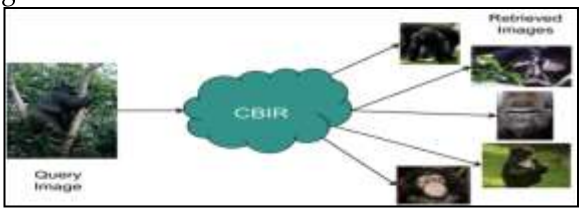

Figure 1: General Approach Used in CBIR

As shown in Figure 1, CBIR procedure is illustrated. An image is given as input. Such image is known as query image. Then the CBIR system performs search operation in order to have relevant images. The retried images are also shown in the picture which is one way or other relevant to query image. This phenomenon is known as CBIR.

Later on Tag Based Image Retrieval (TBIR) came into existence. With respect to TBIR, it helps in accurately retrieving images. The TBIR mechanism helps every image to have manually assigned tags. These tags can be used in the search operation in order to have satisfactory results. A user can perform textual query and the TBIR can find out relevant images. TBIR is more effective when compared with CBIR with respect to fining relevant images [3]. However, it takes lot of time to assign tags to images manually. To overcome this problem many studies came into existence. They focused on the image annotation as multi-label classification problem [12] there multiple training images are needed. To overcome this problem, in this paper we proposed a framework that manages with less number of training images.

Besides it makes use of image tag ranking process which improves search result satisfaction. The remainder of the paper is structured as follows. Section II provides review of literature. Section III presents the proposed system in detail. Section IV presents implementation details. Section V shows experimental results while section VI concludes the paper.

2. RELATED WORK

This section reviews relevant literature pertaining to automatic annotations to images besides tag ranking. Detailed surveys are found in [1] and [2] on this area. The aim of automatic image annotation is to identify keywords or tags that can reflect visual features of an image. Thus semantic gap between low-level features and high-level semantic content is filled. The automatic image annotation schemes are classified into three categories. First category is known as generative models that make use of joint distribution between visual features and tags. Second category is known as discriminative model that considers image annotation as a classification problem. Third category is known as search based mechanism. There are some mixture models too. Gaussian mixture model [3] finds the dependency between visual features and keywords.

Kernel density estimation approach is followed in [4] and [5] where estimation of conditional probability and distribution of visual features are exploited. Probabilistic Latent Semantic Analysis (pLSA) [6] is used for image annotation. In the same fashion Latent Dirichlet Annotation [7], [8] and Hierarchical Dirichlet Processes [9] are other approaches followed. Discriminative models explored in [10] and [11] make use of multi-class classification for image annotation. In [12] Multi-resolution hidden Markov Model (MHMM) is used to find the relationship between visual content and tags. In [13] an algorithm is used for achieving the same. It is known as Structured Max-Margin (SMM) algorithm. As explored in [14], it becomes an issue when number of tags is more. Multi-label learning is another issue to be handled. Keyword correlation approach is followed in [15], [16] and [17] to overcome this problem. In [18] search based approach is followed where visually similar images are more likely to share keys is the main assumption used. In [19] a divide and conquer approach is followed in order to identify salient features from text and use them for image retrieval. In this paper, we proposed an approach that makes use of training and testing phase with limited number of training images to achieve tag ranking based solution.

3. PROPOSED SYSTEM

We proposed a framework that has two phases. They are known as training phase and testing phase. In the training phase, the visual features of given training images are extracted. Then the tags relevant to such image are found. Afterwards the tags are classified into relevant and irrelevant tags.

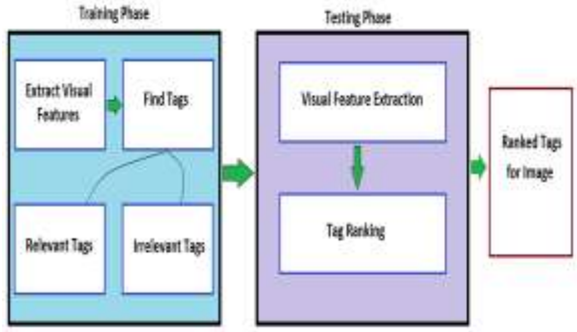

Figure 2: Proposed Framework

In the testing phase the most relevant tags are taken as input and an image is taken as input. The image visual features are extracted and then the tags are ranked in descending order. These ranked tags can help in image search and image retrieval applications in the real world. With the virtual of semantic nature of tag ranking it can work sometimes better than CBIR system.

4. EXPERIMENTAL RESULTS

This section provides experimental results. The experiments are made with a prototype application that demonstrates tag ranking using the proposed approach. The results are presented in the form of statistics in tabular format and visualization in the form of graphs for better intuitive understanding.

Iterations	Value of Objective Function
1	600
2	500
3	400
4	300
5	200
6	150
7	150
8	150
9	150
10	150
11	150
12	150
13	150

Table 1: Iterations vs. Objective Function for Image Dataset

As shown in Table 1, it is evident that the objective function is decreased when iterations are increased. The initial objective function is 600 and it is set to 150 in the last iteration.

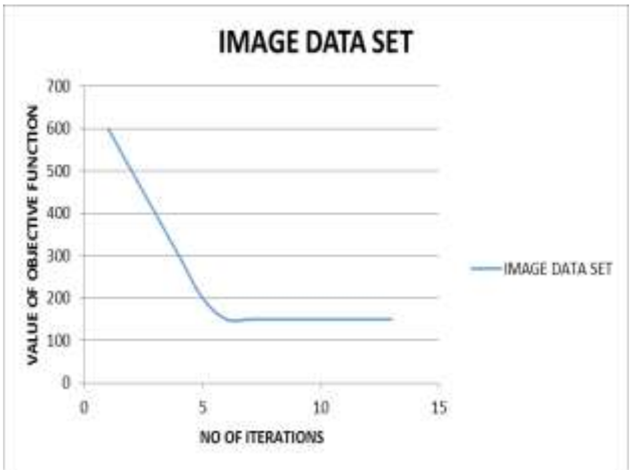

Figure 3: Number of Iterations vs. Value of Objective Function

As shown in Figure 3, it is evident that number of iterations is 15 represented in horizontal axis and the value of objective function is taken 0 to 700 in vertical axis. The results revealed that the initial objective function is 600 and that is gradually decreased as number of iterations is increased.

Top K	C+F	R+F	C+T	R+T
1	27	21	18	15
2	30.5	22	19	15.5
3	30.9	21.9	19.1	16
4	34	24	20	17

Table 2: Results of Top-K Analysis

As shown in Table 2, it is evident that Top-k results are presented. C+F indicates classification loss with Frobeneous form. R+F indicates Frobenius norm for regularization. C+T represents classification loss while R+T indicate the proposed approach for tag ranking. The results revealed that top-k annotated tags are taken in horizontal axis and average precision is taken in vertical axis. The average precision differs from different top-k values.

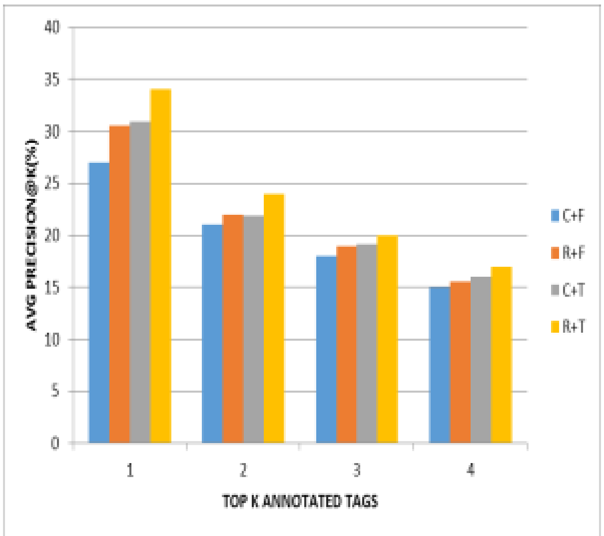

Figure 4: Top K Annotations vs. Average Precision for Different Approaches

As shown in Figure 4, it is evident that the average precision is decreasing when number of top-k annotation tags increase. The results reveal the trends in average precision for different approaches against top k value used for annotation tags.

Avg Precision	k=10	k=7	k=4	k=1
1	21	25	30	43
2	24	26	32	45
3	24.5	26.5	34	46
4	20	24	29	40
5	16	16.5	20	29

Table 3: Average Precision Against k value

As shown in Table 3, average precision is increased from 1 to 5 gradually. When k value is 10, it showed 21 to 16. There is reduction of value gradually. The average recall shows two trends here. The first trend is that when k value is decreased, the average recall value increased. The second trend is that when average precision is increased, the average recall is decreased.

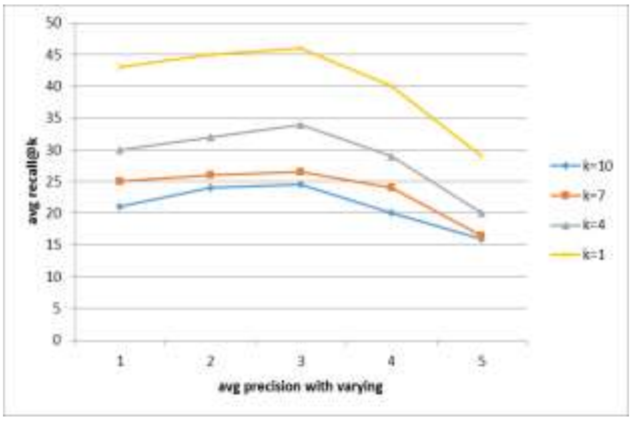

Figure 5: Average Precision vs. Average Recall for Different K Values

As shown in Figure 5, average precision is increased from 1 to 5 gradually. When k value is 10, it showed 21 to 16. There is reduction of value gradually. The average recall shows two trends here. The first trend is that when k value is decreased, the average recall value increased. The second trend is that when average precision is increased, the average recall is decreased.

5. CONCLUSIONS AND FUTURE WORK

In this paper we studied the problem of automatic image annotation and tag ranking. Images in the real world can be annotated and ranked. The annotation process is nothing but associating some tags to an image for efficient image search and retrieval. The CBIR systems are able to produce relevant images by using low level image features. However, the high level image semantics and low-level image features may not match. To overcome this problem, in this paper we proposed a framework for tag based image retrieval. Towards this end we used two phases known as training phase and testing phase. In the training phase, the images are used to extract visual features and most relevant tags are associated with them. In the testing phase, this knowhow is used to have ranked tags associated with every input image. Thus the proposed system achieves more satisfactory results in the queries as it can exploit semantic features pertaining to image tags. We built a prototype application to demonstrate the proof of concept. The empirical results revealed that the proposed system is working fine with image retrieval and tag ranking. This research can be extended further to combine both CBIR and TBIR features in order to have synergic effect in achieving accurate results.

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