Scientific Journal Impact Factor (SJIF): 4.364
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

TAG BASED IMAGE RANKING

Tejal Gavate[1], Rasika Khairnar[2], Viraj Rathod[3] and Ruchira Muley[4]
[1,2,3,4] *Student, Dept. Of Computer Engineering, KKWIEER college, Maharashtra, India.*

Abstract- The extent in the number of images has seen a prominent rise in the past decade. Image annotation with its research traits has gained much importance in the research field. At times image annotation is considered as multi label classification problem. On the contrary the main demerit is the requirement of a large number of training images with clean and complete semantics. This shortcoming is served by a combined approach of tag ranking and matrix recovery. The problem of making a binary decision for every tag is avoided in this approach and instead we rank the tags in descending order of their relevance. In addition, the proposed system also collects the aggregated data collected from the proposed models for different tags into a matrix and casts it into a matrix recovery problem. The matrix trace norm is assigned explicit control for controlling the model complexity, for establishing a reliable prediction model.

Key words- automatic image annotation , tag ranking , matrix recovery

I. INTRODUCTION

In today's era people have started to take advantages of the services available all of over the globe. The Internet has become world's largest library, largest ever encyclopaedia. With that the digitization started at a much faster pace. Digital photos were now no scarce; the reason for the largely amounted digital pictures was in fact digital cameras and phones. The usual process for retrieving pictures had become more and more important, more than ever. It was an important research topic. Initially, Content Based Image retrieval (CBIR) addressed this challenge by trying to match visual content with the query image. Although the CBIR technique had its own limitations, some images had low visual semantics to match with the query image. Further the Tag Based Image Retrieval (TBIR) came into scenario, what TBIR did was it assigned the images keywords/tags, manually. The user could now search for the desired image through typing in keywords; after the keywords match the manually assigned tag images were retrieved. Manually assigning could no longer survive in the high paced world so, algorithms for automatic image annotation were developed. It was seen as a multi-label classification problem, wherein binary classification model for being the simplest. The problem for this was, for annotation of images a large number of training images. In this system, the work is focused on tag ranking as well with the tag assigning. Instead of assigning binary decision for each tag, the tag ranking technique assigns priority to each tag in a descending order.

A typical tag ranking has the following sections:
Section 2. Reviews the related work on automatic image annotation and tag ranking.
Section 3. It introduces the formulation details of the proposed framework and describe an efficient algorithm for computing the optimal solution.
Section 4. Data sets are reported and analyzed in this section.
Section 5. Finally it concludes this work.
Section 6: References and related papers

II. IMPLEMENTATION

This section gives details of various techniques used in this framework. Which are?

2.1 Automatic image Annotation: Automatic image annotation aims to find a subset of keywords/ tags that describes the visual content of an image. It plays an important role in bridging the semantic gap between low-level features and high-level semantic content of images. Most automatic image annotation algorithms can be classified into three categories generative models that model the joint distribution between tags and visual features, discriminative models that view image annotation as a classification problem, and search based approaches. Below, we will briefly review approaches in each category. Both mixture models and topic models, two wellknown approaches in generative model, have been successfully applied to automatic image annotation. In a Gaussian mixture model is used to model the dependence between keywords and visual features. In kernel density estimation is applied to model the distribution of visual features and to estimate the conditional probability of keyword assignments given the visual features. Topic models annotate images as samples from a specific mixture of topics, which each topic is a joint distribution between image features and annotation keywords. Various topic models have been developed for image annotation, including probabilistic latent semantic analysis (pLSA), latent Dirichlet allocation and hierarchical Dirichlet processes. Since a large number of training examples are needed for estimating the joint probability distribution over both features and keywords, the generative models are unable to handle the challenge of large tag space with limited number of training images Discriminative models, views image annotation as a multi-class classification problem, and learn one binary classification model for either one or multiple tags. A 2D multi resolution hidden Markov model (MHMM) is proposed to model the relationship between tags and visual content .A structured max-margin algorithm is developed in to exploit the dependence among tags. One problem with discriminative approaches for image annotation is imbalanced data distribution because each binary classifier is designed to distinguish image of one class from images of the other classes. It becomes more severe when tags is large .Another limitation of these approaches is that they are unable to capture the correlation among classes, which is known to be important in multi-label learning.

2.2 Tag ranking: Tag ranking aims to learn a ranking function that puts relevant tags in front of the irrelevant ones. In the simplest form, it learns a scoring function that assigns larger values to the relevant tags than to those irrelevant ones. In, the authors develop a classification framework for tag ranking that computes tag scores for a test image based on the neighbor voting. It was extended in to the case where each image is represented by multiple sets of visual features. Liu et al. Utilizes the Kernel Density Estimation (KDE) to calculate relevance scores for different tags, and performs a random walk to further improve the performance of tag ranking by exploring the correlation between tags. Similarly, Tang et al. Proposed a two-stage graph-based relevance propagation approach. In, a two-view tag weighting method is proposed to effectively exploit both the correlation among tags and the dependence between visual features and tags. In, a max-margin riffled independence model is developed for tag ranking. As mentioned in the introduction section, most of the existing algorithms for tag ranking tend to perform poorly when the tag space is large and the number of training images is limited.

2.3 Low-rank: In mathematics, low-rank approximation is a minimization problem, in which the cost function measures the fit between a given matrix (the data) and an approximating matrix (the optimization variable), subject to a constraint that the approximating matrix has reduced rank. The problem is used for mathematical modeling and data compression. The rank constraint is related to a constraint on the complexity of a model that fits the data. In applications, often there are other constraints on the approximating matrix apart from the rank constraint, e.g., non-negativity and Henkel. We study the rank, trace-norm and max-norm as complexity measures of matrices, focusing on the problem of fitting a matrix with matrices having low complexity. We present generalization error bounds for predicting unobserved entries that are based on these measures. We also consider the possible relations between these measures. We show gaps between them, and bounds on the extent of such gaps.

2.4 Matrix recovery: A common modelling assumption in many engineering applications is that the underlying data lies (approximately) on a low-dimensional linear subspace. This property has been widely exploited by classical Principal Component Analysis (PCA) to achieve dimensionality reduction. However, real-life data is often corrupted with large errors or can even be incomplete. Although classical PCA is effective against the presence of small Gaussian noise in the data, it is highly sensitive to even sparse errors of very high magnitude. We propose powerful tools that exactly and efficiently correct large errors in such structured data. The basic idea is to formulate the problem as a matrix rank minimization problem and solve it efficiently by nuclear-norm minimization. Our algorithms achieve state-of-the-art performance in low-rank matrix recovery with theoretical guarantees. Please browse the links to the left for more information. The introduction section provides a brief overview of the low-rank matrix recovery problem and introduces state-of-the-art algorithms to solve. Please refer to our papers in the references section for complete technical details, and to the sample code section for MATLAB packages. The applications section showcases engineering problems where our techniques have been used to achieve state-of-the-art performance.

2.5 Trace norm: Trace-norm and max-norm as complexity measures of matrices, focusing on the problem of fitting a matrix with matrices having low complexity. We present generalization error bounds for predicting unobserved entries that are based on these measures. We also consider the possible relations between these measures.

III. SYSTEM ARCHITECTURE

This paper presents the methodology for Tag based image ranking. The approach of relevant and irrelevant tags is use to prioritize the tags according to user relevancy. Here, relevant tags are those who actually present in the image and irrelevant are those which are not actually present in the image but they come in the category of this image. For example: in below fig. image belongs to the category nature, the image contains cloud, lake , mountain, etc. but it does not contain desert, airplane which can be in the image related to nature.
The actual working has two parts training and testing.

3.1 Training : In training part few data set are used in which for each image both relevant and irrelevant tags are assigned. After that relevat tags are arrange as per priority. There are two cases for priority:
1.Tag Rank: In this priority is given to number of occurrence of same tag. Highest priority to the tag which has maximum number of occurrence in same image
2.Tag Position: In this priority is calculated by measuring portion of image capture by that tag. Highest priority to the tag which covers maximum area.

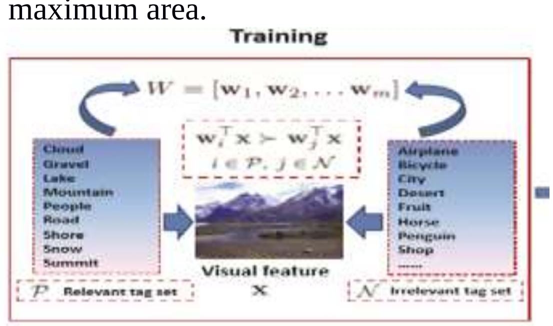

Fig 3.1 Training phase

3.2 Testing: In this when new image need to be added then train images are used to find out the tags for new image. Matrix recovery approach is used to analyse the whole image. At the last rank of this images are prioritized as explain in training phase.

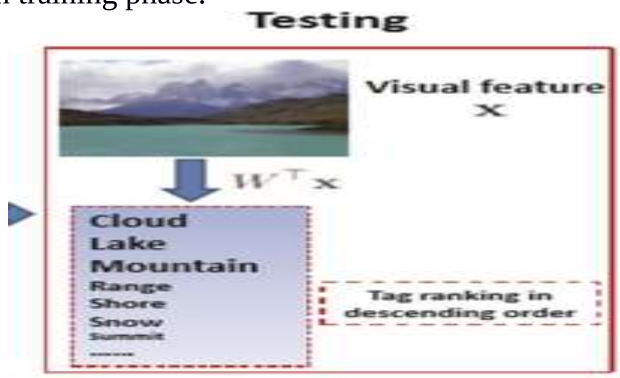

Fig 3.2 Testing phase

Algorithm:

Finding Relevance Score Algorithm:

1. Initialize the variables St , Si, w , n, i.
2. Calculate St ∗ Si.

Where St : Textual result list of retrieved images from TBIR system;

Where Si : Visual result list of retrieved images from CBIR system;

3. Store the product St ∗ Si into wi; i.e. wi = Si ∗ St
4. Calculate the OWA operator(it Transforms finite number of input into a single output)

   Orness(w) = 1

   n−1 åni =1 (n-i)wi
5. For calculation of new relevance for fused list

   newRel = mainRel + (SupRel / PosRel + 1)
6. Finally selection is performed from the list to merge those retrieved images with high relevance score.

IV. CONCLUSION

In this work, we have proposed a novel tag ranking scheme for tag based image ranking. The proposed scheme casts the tag ranking problem into a matrix recovery problem and introduces trace norm regularization to control the model complexity. Extensive work on image annotation and tag ranking have significantly outperformed several state-of-the-art methods for image annotation especially when the number of training images is limited and when many of the assigned image tags are missing. In the future, we plan to apply the proposed framework to the image annotation problem when image tags are acquired by crowdsourcing that tend to be noisy and incomplete .

REFERENCES

[1] Learning to Rank Image Tags with Limited Training Examples Songhe Feng, Zheyun Feng, and Rong Jin
[2] L. Wu, R. Jin, and A. Jain, "Tag completion for image retrieval," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 35, no. 3, pp. 716–727, 2013.
[3] Makadia, V. Pavlovic, and S. Kumar, "Baselines for image annotation," International Journal of Computer Vision, vol. 90, no. 1, pp. 88–105, 2010.
[4] G. Carneiro, A.Chan, P. Moreno, and N. Vasconcelos, "Supervised learning of semantic classes for image annotation and retrieval," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 394–410, 2007.
[5] C. Yang, M. M. Dong, and F. Fotouhi, "Region-based image annotation through multiple-instance learning," in ACM Int Conf. on Multimedia, 2005.

