

# Advanced Learning Technique to Rank Image Tags With Training Patterns

Sandhya.C.K, Dr.Nagabushan

P.G. Student, Department of CSE,SJMIT, Chitradurga, Karnataka, India

Professor and PG coordinator, Department of CSE, SJMIT, Chitradurga, Karnataka, India

**ABSTRACT;** With an expanding number of pictures that are accessible in web-based social networking, picture comment has risen as an imperative research theme because of its application in picture coordinating and recovery. Most reviews cast picture comment into a multilabel characterization issue. The fundamental inadequacy of this approach is that it requires an extensive number of preparing pictures with perfect and finish explanations so as to take in a dependable model for label expectation. We address this restriction by building up a novel approach that consolidates the quality of label positioning with the energy of grid recuperation. Rather than making a parallel choice for each tag, the approach positions labels in the sliding request of their importance to the given picture, essentially improving the issue. Furthermore, the proposed strategy totals the expectation models for various labels into a grid, and throws label positioning into a lattice recuperation issue. It acquaints the framework follow standard with unequivocally control the model multifaceted nature, so that a solid forecast model can be scholarly for label positioning notwithstanding when the label space is huge and the quantity of preparing pictures is restricted. Probes numerous outstanding picture informational indexes exhibit the adequacy of the proposed structure for label positioning contrasted and the cutting edge approaches for picture comment and label positioning

**KEYWORDS:** Automatic image annotation, tag ranking, matrix recovery, low-rank, trace norm.

## I. INTRODUCTION

THE popularity of digital cameras and mobile phone cameras leads to an explosive growth of digital images that are available over the internet. How to accurately retrieve images from enormous collections of digital photos

has become an important research topic. Content-based image retrieval (CBIR) addresses this challenge by identifying the matched images based on their visual similarity to a Digital Object Identifier 10.1109/TIP.2015.2395816 query image [1]. However due to the semantic gap between the low-level visual features used to represent images and the high-level semantic tags used to describe image content, limited performance is achieved by CBIR techniques [1], [2]. To address the limitation of CBIR, many algorithms have been developed for tag based image retrieval (TBIR) that represents images by manually assigned keywords/tags. It allows a user to present his/her information needs by textual information and find the relevant images based on the match between the textual query and the assigned image tags. Recent studies have shown that TBIR is usually more effective than CBIR in identifying the relevant images [3].

Since it is time-consuming to manually label images, various algorithms have been developed for automatic image annotation [4][11]. Many studies view image annotation as a multi-label classification problem [12][17], where in the simplest case, a binary classification model is built for each tag. The main shortcoming of this approach is that in order to train a reliable model for tag prediction, it requires a large number of training images with clean and complete annotations. In this work, we focus on the tag ranking approach for automatic image annotation [18][25]. Instead of having to decide, for each tag, if it should be assigned to a given image, the tag ranking approach ranks tags in the descending order of their relevance to the given image. By avoiding making binary decision for each tag, the tag ranking approach significantly simplifies the problem, leading to a better performance than the traditional classification

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 12, July 2017

based approaches for image annotation [25]. In addition, studies have shown that tag ranking approaches are more robust to noisy and missing tags than the classification approaches

## II. RELATED WORK

In this section we review the related work on automatic image annotation and tag ranking. Given the rich literature on both subjects, we only discuss the studies closely related to this work, and refer the readers to [30] and [31] for the detailed surveys of these topics.

### A. 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 (i) generative models that model the joint distribution between tags and visual features, (ii) discriminative models that view image annotation as a classification problem, and (iii) search based approaches. Below, we will briefly review approaches in each category.

### B. 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 [18], 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 [46] to the case where each image is represented by multiple sets of visual features. Liu et al. [19] 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. [47] proposed a two-stage graph-based relevance propagation approach. In [21], 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 [26], 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.

## III. EXPERIMENTAL RESULTS

In this section, we first describe the experimental setup, including image datasets, feature extraction, and evaluation measures. We then present three sets of experiments to verify the effectiveness of the proposed tag ranking approach, where the first experiment evaluates the performance of image annotation with limited training examples, the second experiment evaluates the performance of image annotation using training images with missing tags, and the last experiment examines the performance of the proposed algorithm for tag ranking. We finally evaluate the sensitivity of the proposed algorithm to parameter  $\lambda$ .

### A. Image Datasets

To evaluate the proposed algorithm for image tagging, we conduct extensive experiments on five benchmark datasets for image annotation/tagging, including Corel5K, ESPGame, IAPRTC-12, Pascal VOC2007 and SUNAttribute. The first three image datasets are used to evaluate the performance of automatic image annotation, and the last two image datasets are used to evaluate tag ranking since a relevance score is provide for every assigned tag. Table I summarizes the statistics of the image datasets used in the study.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 12, July 2017

## B. Evaluation Measures

Firstly, to evaluate the performance of automatic image annotation, we adopt the Average Precision (  $AP@K$  ) and Average Recall (  $AR@K$  ) as the evaluation metrics, which are defined as [3]:

$$AP@K = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{N_c(i)}{K} \quad (11)$$

$$AR@K = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{N_c(i)}{N_g(i)} \quad (12)$$

where  $K$  is the number of truncated tags,  $n_t$  is the number of test images,  $N_c(i)$  is the number of correctly annotated tags for the  $i$ th test image,  $N_g(i)$  is the number of tags assigned to the  $i$ th image. Both average precision and recall compares the automatically annotated image tags to the manually assigned ones.

In addition, we use the Normalized Discounted Cumulative Gains at top  $K$  (  $NDCG@K$  ) to measure the performance of different tag ranking approaches. It reflects how well a computed ranking agrees with the ideal (ground truth) ranking, with the emphasis on the accuracy of the top ranked items. It is defined as [26]:

$$NDCG@K = \frac{1}{Z} \sum_{i=1}^K \frac{2^{rel(i)} - 1}{\log(1 + i)} \quad (13)$$

where  $K$  is called truncation level,  $Z$  is the normalization constant to make sure the optimal ranking get the NDCG score of 1, and  $rel(i)$  is the relevance score for the  $i$ -th ranked tag. Finally, for the proposed method, we set  $\lambda = 1$  for all experiments except for the last one where we evaluate the impact of parameter  $\lambda$ .

## C. Experimental (I): Automatic Image Annotation With Limited Number of Training Images

In the first experiment, we evaluate the annotation performance of the proposed image tagging method with limited training images. To this end, we randomly sample only 10% of images for training and use the remaining 90% for testing. Each experiment is repeated 10 times, each with a different splitting of training and testing data. We report the result based on the average over the trials. The following state-of-the-art approaches for image annotation are used as the baseline approaches in the evaluation:

- *Joint Equal Contribution Method (JEC)* [4]: It finds appropriate annotation words for a test image based on a  $k$  nearest neighbor classifier that used a combined distance measure derived from multiple sets of visual features.
- *Tag Propagation Method (TagProp)* [7]: It propagates the tag information from the labeled images to the unlabeled ones via a weighted nearest neighbor graph, where RBF kernel function is used for computing weights between images.
- *Multi-Class SVM Method (SVM)* [58]: It simply implements One-versus-All (OvA) SVM classifier for each tag, and ranks the tags based on the output probability values.

*Fast Image Tagging Method (FastTag)* [59]: It explores multi-view learning technique for multi-label learning. In particular, it defines two classifiers, one for each view of the data, and introduces a co-regularizer in the objective function to enforce that the predictions based on different views are consistent for most training examples.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

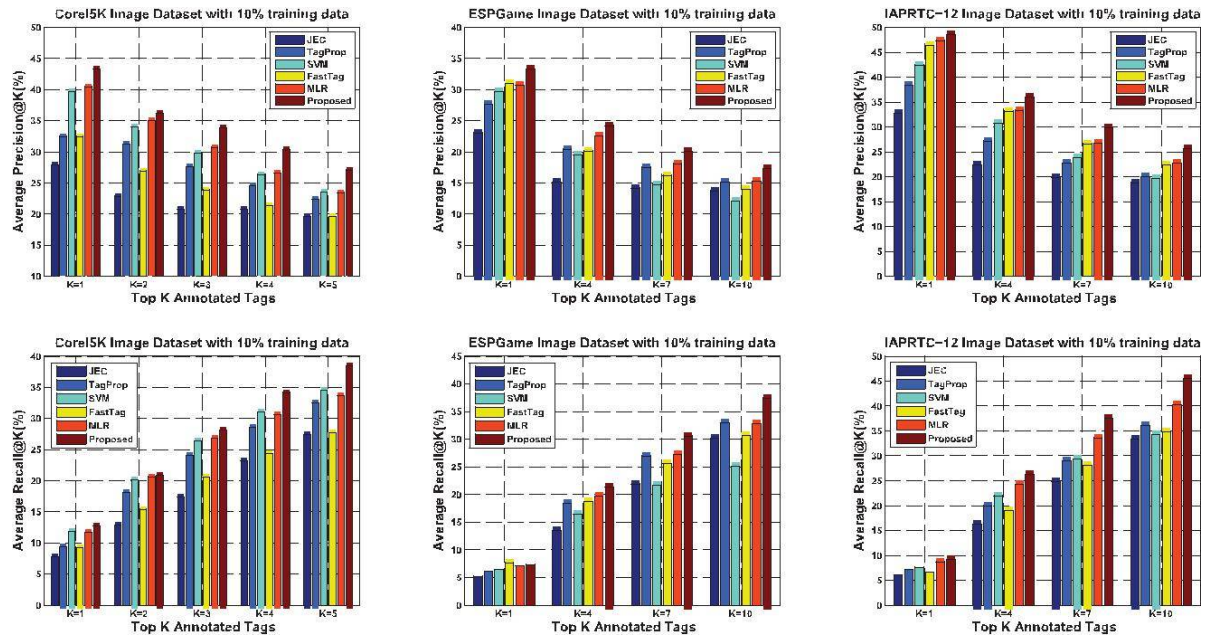


Fig. 3. Average precision and recall for automatic Image annotation on Corel5K, ESPGame and IAPRTC-12 datasets.

## D. Experiment (II): Automatic Image Annotation With Incomplete Image Tags

In this experiment, we examine the performance of the proposed method when training image are partially annotated. To this end, similar to [24], we randomly select only 20%, 40%, and 60% of the assigned tags for training images. This setting allows us to test the sensitivity of the proposed method to the missing tags. Since the maximum number of annotated tags for the Corel5K dataset is 5, we only conduct the experiments on ESPGame and IAPRTC-12 datasets, where the maximum number of assigned tags are 15 and 23, respectively.

## IV. CONCLUSION

In this work, we have proposed a novel tag ranking scheme for automatic image annotation. The proposed scheme casts the tag ranking problem into a matrix recovery problem and introduces trace norm regularization to control the model complexity. Extensive experiments on image annotation and tag ranking have demonstrated that the proposed method significantly outperforms 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] R. Datta, D. Joshi, J. Li, and J. Z. Wang, "Image retrieval: Ideas, influences, and trends of the new age," *ACM Comput. Surv.*, vol. 40, no. 2, 2008, Art. ID 5.
- [2] J. Wu, H. Shen, Y. Li, Z.-B. Xiao, M.-Y. Lu, and C.-L. Wang, "Learning a hybrid similarity measure for image retrieval," *Pattern Recognit.*, vol. 46, no. 11, pp. 2927–2939, 2013.
- [3] L. Wu, R. Jin, and A. K. Jain, "Tag completion for image retrieval," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 3, pp. 716–727, Mar. 2013.
- [4] A. Makadia, V. Pavlovic, and S. Kumar, "Baselines for image annotation," *Int. J. Comput. Vis.*, vol. 90, no. 1, pp. 88–105, 2010.
- [5] J. Tang, R. Hong, S. Yan, T.-S. Chua, G.-J. Qi, and R. Jain, "Image annotation by kNN-sparse graph-based label propagation over noisily tagged web images," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 2, pp. 1–16, 2011.



ISSN(Online) : 2319-8753  
ISSN (Print) : 2347-6710

## International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 12, July 2017

- [6] M. Guillaumin, T. Mensink, J. Verbeek, and C. Schmid, "TagProp: Discriminative metric learning in nearest neighbor models for image auto-annotation," in *Proc. IEEE 12th Int. Conf. Comput. Vis.*, Sep./Oct. 2009, pp. 309–316.
- [7] S. Zhang, J. Huang, Y. Huang, Y. Yu, H. Li, and D. N. Metaxas, "Automatic image annotation using group sparsity," in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.*, Jun. 2010, pp. 3312–3319.