Survey on Multi-label Dictionary Learning for Automatic Image Annotation

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Abstract-*Annotation of image automatically is a novel research area now days. The process of automatic image annotation is utilized for subset of word selected group of word to image or select the keyword given by person to the image. Techniques designed previously of weakly supervised multi-label image annotation depend on the representation of unsupervised feature. The parts of unsupervised element representation are not straightforwardly associated with particular marks. In specific conditions, there is a major difference in training data as well as the testing information; say the label consolidation of the testing information and training information is not generally reliable. At the point when the features as well as labels are retrieved from the training pictures, at the beginning develop the label matrix to investigate the label group. Next, pursue the dictionary learning system to take in the discriminative word reference representation. At that point compute the importance in the visual words as well as their relating labels. Next, extract the labels of visual words by making utilization of a multi-task learning system. At last, by making use of C4.5 algorithm for calculating the score for annotation of the image and propagation of label is retrieved. This survey presents a study of different methods performed by different researchers on the Multi-label Dictionary Learning for Image Annotation.*

Keywords-Image annotation, input feature space, label consistency regularization, label correlation, multi-label dictionary learning, output label space, partial-identical label embedding.

I. INTRODUCTION

In multi-label learning, more than one class can be assigned to an instance. With the increase in the number of data sets where each image has multiple labels, there have been a vast amount of studies that focus on developing strong classification methods for image categorization. Many researchers employ decomposition methods, particularly one-vs-all framework, with SVM, naïve bayes, C4.5 etc. as a base classifier. In this setting, a separate classifier is trained for each image label, leading to an independent prediction for each label on a query image. Although decomposition based methods are frequently used to solve multi-label classification, they do have some limitations. To overcome the limitations of decomposition techniques, there have been many direct multi-label learning methods proposed in the literature that do not decompose or transform the multi-label learning problem into a set of binary classification tasks. In this dissertation, we are particularly interested in multi-label ranking, in which the learning task is formulated as a bipartiteranking problem. Multi-label ranking is an example of a direct multi-label learning approach that can exploit label correlations. Also, by avoiding a binary decision, multi-label ranking is usually more robust than the classification approaches, particularly when the number of classes is very large.

Ranking has been successfully used in other application domains such as document classification and recommender systems. For example, it makes more sense in recommender systems to provide the user an ordered list of items that she/he might be interested in. Also, since the preference ratings given by the users are not universal (i.e., the rating “7” is not same for every user) ranking results would be easier to obtain compared to predicting the exact ratings. Similarly, ranking labels might be useful for image categorization systems. Consider an image search system where the search is based on image labels. Being able to rank image labels can be useful for refining the search. For example, if a user is interested in finding “cafe shop” images from the internet to decide where to go, then a system that only focuses on the label “cafe shop” would not help in refining the search. If the user is looking for images of pet-friendly cafe shops where more people read books than use computers, then ranking labels would be useful. Such a system would aim to retrieve images where the labels cafe shops, books, cats, dogs, have higher scores than the label computer. This does not mean that the image should not contain any computers, but the emphasis on the other labels is set to be higher.

This survey presents the study of various systems developed by various researchers for analyzing data from online social web sites.

In this study Section II gives the Literature review for Social Media Data for Student Learning.

II. LITERATURE REVIEW

In paper [1], authors developedimage annotation system known as MLDL. It can charge multi-label dictionary learning inside feature space as well as partial-identicallabel consolidated in output label space, concurrently. For learning feature's discriminativerepresentation in the feature space of input MLDC uses the label consistency regularization term. Also made use of MLDL on three datasets for annotation of images.

In paper [2], authors have developed new label embedding dictionary representation technique SLED, to provide the answer of the issue of image annotation in a loss supervised setting. The main addition is explicitly fusing the label information into dictionary representation as well as investigates the semantic correlations in co-occurrence labels. Furthermore, in view of the semantic dictionary representation as well as the exclusive group of label, designed model can take care of the issue of inconsistent label consolidation in training as well as testing information.

In paper [3], authors have implemented hierarchical multi-label learning system having dual fuzzy hypergraph regularization. Also found the intrinsic relations between feature space as well as label space.

In paper [4], authors have proposed a multi-label extension for dictionary depending classification technique, which has a transformation of the classification threshold as well as an addition of a graph-based regularization which supports the sparse codesdiscriminative nature by holding fast to the intrinsic geometrical structure of the information complex, as caught by the diagram Laplacian, the subsequent sparse codes have better discriminating power as well as can fundamentally improve performance of the classification.

In paper [5] authors developed a new joint multi-label multi instance learning system for image classification. Proposed MLMIL system can model the relation in semantic labels as well as regions, and also the correlations from the labels in an integrated manner. MLMIL is flexible to get different dependencies in regions, like the spatial configuration of the region labels.

In paper [6] authors have framework, correlated label propagation, for multi-label learning which explicitly solve the issue of label dependence. Dissimilar with the present systems to multi-label learning which either treat class label independently or only take into count the pair wise correlations, designed algorithm uses label correlations of any order.

In paper [7] authors have developed a multi-label sparse coding system for feature extraction as well as classification in the context of automatic image annotation. At start, every image is encoded in a super vector, generated by universal Gaussian Mixture Models on image patches which are order less. After that, a label sparse coding depended subspace learning algorithm is used to effectively harness multi-label data for dimensionality reduction. At last, the sparse coding technique for multi-label information is developed for propagating the multi-labels of the training images to the query image with the sparse 1 reconstruction coefficients.

As shown in table 1, literature review of various papers has been listed, giving possibility of research gap.

III. PROPOSED SYSTEM

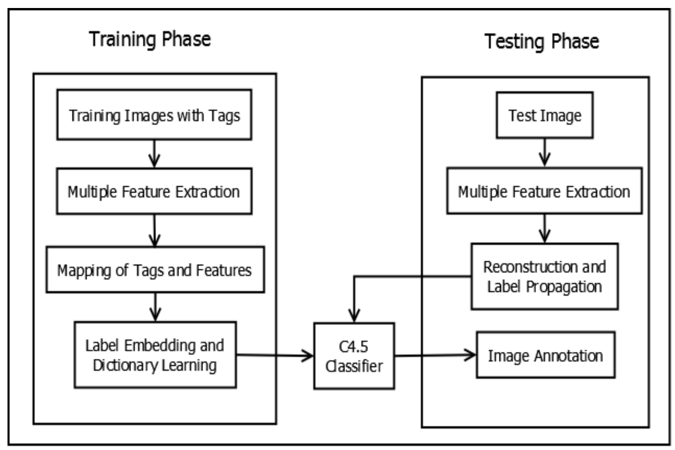

Figure: System Architecture

Figure 1 shows the proposed system architecture. The system will work in several steps, Training Images with Labels and Multiple Feature Extraction, Mapping of Labels & Features, Label Embedding and Dictionary Learning, Image Testing, Image Annotation.

Table 1. Survey Table

Sr no.	Title	Publication/ year	Techniques	Advantages	Research gap
1.	Multi-Label Dictionary Learning for Image Annotation	IEEE June 2016	MLDL	obtain desirable annotation effects	Efficiency can be increased
2.	SLED: Semantic Label Embedding Dictionary Representation for Multilabel Image Annotation	IEEE Sept. 2015	SLED	solve the problem of inconsistent label combinations between training and testing data	incomplete labeled training data
3.	Multi-Label Learning With Fuzzy Hypergraph Regularization for Protein Subcellular Location Prediction	IEEE Dec. 2014	Dual fuzzy hypergraph regularization.	outperforms the two state-of-the-art multi-location protein subcellular location prediction methods in terms of the four measures	expected to improve the prediction performance
4.	Graph-constrained supervised dictionary learning for multi-label classification	IEEE, 2016	multi-label xtension to dictionary based classification methods	enhance classification performance	---
5.	Joint multi-label multi-instance learning for image classification	IEEE, 2008	MLMIL	high classification performance	---

IV.CONCLUSION

This paper analyses various techniques used for multi-label dictionary learning for image annotation. Also given the advantages and drawbacks present in the different studies performed by various researchers. To deal with drawbacks in present systems we presented an idea of the new system.

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