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Joint Multilabel Classification with Community-Aware Label Graph Learning

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ABSTRACT: As an important and challenging problem in machine learning and computer vision, multilabel classification is typically implemented in a max-margin multilabel learning framework, where the inter-label separability is characterized by the sample-specific classification margins between labels. However, the conventional multilabel classification approaches are usually incapable of effectively exploring the intrinsic inter-label correlations as well as jointly modeling the interactions between inter-label correlations and multilabel classification. To address this issue, we propose a multilabel classification framework based on a joint learning approach called label graph learning (LGL) driven weighted Support Vector Machine (SVM). In principle, the joint learning approach explicitly models the inter-label correlations by LGL, which is jointly optimized with multilabel classification in a unified learning scheme. As a result, the learned label correlation graph well fits the multilabel classification task while effectively reflecting the underlying topological structures among labels. Moreover, the inter-label interactions are also influenced by label-specific sample communities (each community for the samples sharing a common label). Namely, if two labels have similar label-specific sample communities, they are likely to be correlated. Based on this observation, LGL is further regularized by the label Hyper graph Laplacian. Experimental results have demonstrated the effectiveness of our approach over several benchmark data sets.

I. INTRODUCTION

Image annotation has been an active research topic in the recent years due to its potentially large impact on both image understanding and web/database image search. Image retrieval plays an important role in information retrieval due to the overwhelming image and video data brought by modern technologies. One of notorious bottleneck in the image retrieval is how to associate an image or video with some semantic keywords to describe its semantic content [2, 3]. This poses a challenging computer vision topic, image annotation, which has attracted broad attentions in the recent years. However, manual image annotation is an expensive and labour intensive procedure and hence there has been great interest in coming up with automatic ways to retrieve images based on content.Recent years have witnessed the extensive applications of multilabel classification in machine learning, data mining, and computer vision. The main goal of multilabel classification is to effectively and automatically annotate a sample with a set of relevant binary labels. In general, multilabel classification is posed as a problemof max-margin multilabel learning, which learns label-specific scoring functions encouraging the inter-label separability [4]. However, the existing literature in this area is typically weak in capturing the intrinsic inter-label correlations with no capability of jointing modeling the interactions between inter-label correlations and multilabel classification. In this system, We mainly focus on how to perform adaptive inter label correlation learning within a multilabel classification framework. In current research on multi-label classification (MLC), it seems to be a communities that optimal predictive performance can only be achieved by methods that explicitly account for possible dependencies between class labels. Indeed, there is an increasing number of papers providing evidence for this conjecture, mostly by virtue of empirical studies [7,8]. Often, a new approach to exploiting label dependence is proposed, and the corresponding method is shown to outperform others in terms of different loss functions.With the ever-growing amount of digital image data in multimedia databases, there is a great need for algorithms that can provide effective semantic indexing. Categorizing digital images using keywords, however, is the quintessential example of a challenging classification problem. Several aspects contribute to the difficulty of the image categorization problem, including the large variability in appearance, illumination and pose of different objects. Moreover, in the multi-label setting the interaction between objects also needs to be modeled. The aim of this paper is to elaborate on the issue of label, We propose a joint learning scheme for simultaneously modeling label graph learning and multilabel classification. The proposed learning scheme explicitly models the inter-label

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correlations by label graph learning, which is jointly optimized with multilabel classification. As a result, the learned label correlation graph is capable of well fitting the multilabel classification task while effectively reflecting the underlying topological structures among labels.

II. LITERATURE SURVEY

[1] J. Read, B. Pfahringer, G. Holmes, and E. Frank, "Classifier chains for multi-label classification," J. Mach. Learn., vol. 85, no. 3, pp. 333–359, Dec. 2011.

This paper shows that binary relevance-based methods have much to offer, and that high predictive performance can be obtained without impeding scalability to large datasets. We exemplify this with a novel classifier chains method that can model label correlations while maintaining acceptable computational complexity. We extend this approach further in an ensemble framework.

[2] G. Tsoumakas, I. Katakis, and L. Vlahavas, "Random k-labelsets for multilabel classification," IEEE Trans. Knowl. Data Eng., vol. 23, no. 7, pp. 1079–1089, Jul. 2011.

In these paper, the number of classes may become very large and at the same time many classes are associated with very few training examples. To deal with these problems, this paper proposes breaking the initial set of labels into a number of small random subsets, called label sets Andemploying LP to train a corresponding classifier. The labelsets can be either disjoint or overlapping depending on which of two strategies is used to construct them

[3] W. Bi and J. T. Kwok, "Multilabel classification with label correlations and missing labels," in Proc. Assoc. Adv. Artif. Intell., 2014, pp. 1680–1686.

In this paper we propose to incorporate structured semantic correlations to solve themissing label problem of multi-label learning. Specifically, we project images tothe semantic space with an effective semantic descriptor. A semantic graph is thenconstructed on these images to capture the structured correlations between them.We utilize the semantic graph Laplacian as a smooth term in the multi-label learning formulation to incorporate the structured semantic correlations.

[4]M.-L. Zhang and K. Zhang, "Multi-label learning by exploiting label dependency," in Proc. ACM SIGKDD Conf., 2010, pp. 999–1008.

In this paper, we propose to use a Bayesian network structure to efficiently encode the conditional dependencies of the labels as well as the feature set, with the feature set as the common parent of all labels. Tomake it practical, we give an approximate yet efficient procedure to find such a network structure. With the help of this network, multi-label learning is decomposed into a series single-label classification problems, where a classifier is constructed for each label by incorporating its parental labels as additional features.

[5] S.-J. Huang and Z.-H.Zhou, "Multi-label learning by exploiting label correlations locally,"in Proc. Assoc. Adv. Artif.Intell., 2012, pp. 949–955.

In this paper, we propose the ML-LOC approach which allows label correlations to be exploited locally. To encode the local influence of label correlations, we derive a LOC code to enhance the feature representation of each instance. The global discrimination fitting and local correlation sensitivity are incorporated into a unified framework, and an alternating solution is developed for the optimization.

III. PROPOSED WORK

The search procedure of our proposed system consists of the following phases:

1. The user speaks a natural sentence to describe the intended images.
2. The speech is recognized and further decomposed into keyword(s) which can be represented by exemplary images. Using speech recognition to transfer the audio input to text.
3. Decomposing the text into keywords by entity extraction by selecting preferred exemplar(s) and composes a schematic collage as a composite image.

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4. The composite image is then used as a visual query to search for similar images.
5. Uploading the query, including picture from the user and GPS information generated by the client, and show detailed result both as text contents and markers on the Google Map.
6. Then using the image retrieval modules we can retrieve the images from server using CCV. We can also retrieve images with the location using GPS.
7. The Result can be displayed with further information like GPS locations and image descriptions. We present a community-aware regularize to capture the context-dependent inter-label interaction information. The proposed regularize is based on the group sparsity driven hyper graph Laplacian which encodes community-aware smoothness information on the learned label graph

IV. CONCLUSION

We have proposed a joint learning scheme for simultaneously modeling label graph learning and multilabel classification. The proposed learning scheme explicitly models the inter-label correlations by label graph learning, which is jointly optimized with multilabel classification. As a result, the learned label correlation graph is capable of well fitting the multilabel classification task while effectively reflecting the underlying topological structures among labels. In addition, we have presented a community-aware regularizer to capture the context-dependent inter-label interaction information. The proposed regularizer is based on the group sparsity driven hyper graph Laplacian, which effectively encodes the community-aware smoothness information on the learned label graph. Experimental results have demonstrated the effectiveness of our approach over several benchmark datasets.

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