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A Review on Label Graph Learning For Joint Multilabel Classification

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Abstract- Recently, image categorization has been an active research topic due to the urgent need to retrieve and browse digital images via semantic keywords. 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 proposed an efficient visual aided image search application on mobile phone combined with local spot and scene search. Mobile visual search became an active filed areas in pass few year. It involves methods from several research areas. Due to the complexity of visual information compared with text or voice signals we develop a joint multilabel classification by using text, image and voice input.

Index Terms- Multilabel Classification; Image Annotation; CCV; Label Graph Learning .

1. 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 problem of 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 interlabel 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 system 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 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.

The rest of the paper has been organized as: section 2 indicates motivation, section 3 highlights the related work along with their downsides, section 4 discusses the proposed system modules, section 5 gives the development algorithm of the system. Section 6 shows the mathematical model of the system, section 7 displayed development envirnment, section 8 shows result followed by conclusion and references.

2. MOTIVATION

Multilabel classification is a popular application in machine learning. Conventional approaches decompose the learning problem into a series of independent binary classification problems regardless of the label coincidence. Several other approaches achieve the label prediction with a pairwise design. RankSVM is a typical approach to maximizing the margin of a label pair. Existing another pairwise approach SVMmAP to discriminatively solve the learning-to-rank problem in which the structural SVM framework utilized associated with the mean average precision (mAP)loss function. However, all these approaches and their extensions are not capable of effectively exploiting the label-level relevance as a significant structure information. So there is a need to develop a system which mainly mainly focus on how to perform adaptive interlabel correlation learning within a multilabel classification framework in order to design a efficient visual aided image search application on mobile phone combined with local spot and scene search.

3. RELATED WORK

Literature survey is the most important step in software development process. In the literature, many approaches seek to utilize the inter-label interaction for multilabel classification. However, these approaches often take an indirect strategy for implicitly characterizing the relationships among labels, and thus introduce a set of auxiliary prior parameters, resulting in the inflexibility of multilabel classification in practice. Following these efforts, a number of approaches choose to directly construct the label correlation matrix using the additional prior data before the learning process of multilabel classification. Clearly, such approaches consider the tasks of label correlation learning and multilabel classification separately, and therefore ignore the intrinsic relationships (mutually reinforced or correlated) between these two tasks. As a result, the learned classification models are incapable of effectively encoding the intrinsic discriminative information on interlabel separability and correlation [2]. To alleviate this issue, we propose a joint learning scheme that simultaneously conducts label correlation learning and multilabel classification. In the learning scheme, the inter-label correlations are explicitly modeled by label graph learning, which aims to adaptively discover the underlying topological structures among labels from the data.

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In general, multilabel classification is posed as a problem of max-margin multilabel learning, which learns label-specific scoring functions encouraging the inter-label separability. However, the existing literature in this area is typically weak in capturing intrinsic inter-label correlations with no capability of jointing modeling the interactions between inter-label correlations and multilabel classification.

User interaction is an effective way to handle the semantic gap problem in image annotation. To minimize user effort in the interactions, many active learning methods were proposed. These methods treat the semantic concepts individually or correlatively. However, they still neglect the key motivation of user feedback: to tackle the semantic gap. The size of the semantic gap of each concept is an important factor that affects the performance of user feedback. User should pay more efforts to the concepts with large semantic gaps, and vice versa. In this paper, we propose a semantic-gap-oriented active learning method, which incorporates the semantic gap measure into the information-minimization-based sample selection strategy. A novel multi-label correlated Green's function approach is proposed to annotate images over a graph. The correlations among labels are integrated into the objective function which improves the performance significantly. In this also propose a new adaptive decision boundary method for multi-label assignment to deal with the difficulty of label assignment in most of the existing rank-based multi-label classification algorithms [10]. Instead of setting the threshold heuristically or by experience, our method principally compute it upon the prior knowledge in the training data. It perform methods on three commonly used image annotation testing data sets. Experimental results show significant improvements on classification performance over four other state-of-the-art methods. As a general semi supervised learning framework, other local feature based image annotation methods could be easily incorporated into our framework to improve the performance.

Most active learning approaches select informative or representative unlabeled instances to query their labels for classification. Although several active learning algorithms have been proposed to combine the two criteria for query selection uses ad hoc in finding unlabeled instances that are both informative and representative [12]. The supervised machine learning techniques is applied to multilabel image classification problems. Supervised learning, within the available data repository, only part of the data are labeled and utilized for training performances heavily rely on the quality of training images. The supervised learning techniques having hinders to large scale problems. High-order label correlation driven active learning is motivated by the virtue of leveraging label correlations to improve multi-label classification high-order label correlation driven active learning approach that uses the iterative learning algorithm to choose the informative example-label pairs from which it learns so as to learn an accurate classifier with less annotation efforts.

4. MODULE

1. Text-Based search module
2. Voice to search module
3. Image to Search module

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.
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.

5. ALGORITHM

The CCV is a whole-image query algorithm. A coherent region of colors in an image is a region of color which is larger than some threshold. This module retrieves images which have similar distributions of coherent colors.
An image which is a sub-image of a database image may be used as the query but the parent from which it was derived is unlikely to be found. A histogram of 64 bins (4x4x4) is generated for both coherent and incoherent colors and these are matched separately. As for Histogram RGB, 64 bins has been chosen as a trade-off between accuracy and speed. The total size of the feature vector for a CCV is therefore 64x2 integer numbers (512 bytes per feature).

Coherence and incoherence are arbitrarily defined as greater and less than 5 per. of the total image area, respectively. This means if a pixel is part of a region which is less than 5 per. of the total image area it is added to the incoherent histogram within the CCV. If it is greater than 5 per of the total image area it is added to the coherent histogram within the CCV.

6. MATHEMATICAL MODEL

A. User Module:
Set (P) = {p0, p1, p2, p3, p4, p5, p6, p7}

P0=User Registration.
P1=User Login.
P2=Pass Text Input.
P3=Pass Image Input.
P4=Pass Voice Input.
P5=Choose Semantic Image.
P6=Visual Query Formulation.
P7=Multilabel Image Search.

B. Text Query:
Set (C) = {p0, p1, p3, p4, p6, f0, f1, f2}
f0= Text Data Input.
f1=Entity Extraction.
f2=Keyword Extraction.

C. Voice Query:
Set (T) = {d0, d1, d2, f1, p1, p2, p3, p5, p6}
d0= Speech Recognization.
d1= Key Entity Extraction.
d2=Image search.

D. Query Image:
Set (L) = {e0, e1, e2, f1, p0, p1, p4, p7}
e0= Input Image Selection
e1= Feature Extraction Of Images.
e2=Color and Texture Feature Extraction.

Union and Intersection of project:
Set (P) = {p0, p1, p2, p3, p4, p5, p6, p7, p8}
Set (C) = {p0, p1, p3, p4, p6, f0, f1, f2}
Set (T) = {p1, p2, p3, p5, p6, f1, d0, d1, d2}
Set (L) = {p0, p1, p4, p7, f1, d1, e0, e1, e2}

7. DEVELOPMENT ENVIRONMENT

The proposed system requires Eclipse that is an open source software development environment. Eclipse consists of an Extensible plugin system and an IDE. The Android project has been developed in the Helios version of Eclipse, as it has plugins that are mainly used for Android.

7. 1 Android SDK
Integrated Development Environment (IDE) is used in Android development in order to make it more straight forward and quick. It has been recommended for the developers because of its simplicity in working. Android is basically a multitasking platform. To give an example, the application has one application for navigation, another application for games, and another messaging. These applications can work simultaneously because of this multitasking ability of the Android platform.

7.2 ADT Plugin
ADT (Android Development Tools) is a plugin developed by Google. Its main purpose is for developing Android mobile applications in Eclipse. It makes it easy and convenient for all the Android developers working in Eclipse environment to quickly create Android projects and debug the programs whenever needed.
Text editor should not be used in the development of large applications having a large amount of code as the text editor cannot highlight wrong spellings.

7.3 Android Emulator
Android emulator is a virtual mobile device which is included in every Android SDK which runs on the users computer. Android emulators are used to test Android applications, so there is no need of any physical device.
Android emulator supports Android Virtual Device (AVD) configuration, which in itself is an emulator containing specific Smartphone Operating System. Using AVD, one can easily test his applications.
Any application running on an emulator can use the services provided by the Android platform like play audio, store or retrieve data etc. But with these features comes a few limitations. Neither does it support Bluetooth, nor does it support SMS/MMS communication.

8. SCREENSHOTS

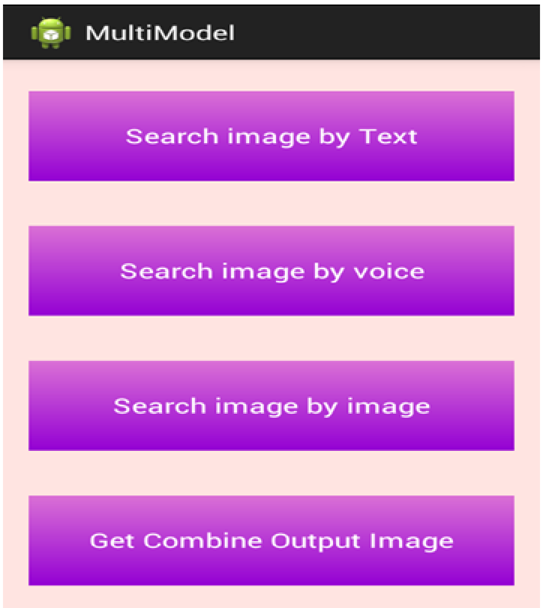

Fig. 1. Home Page

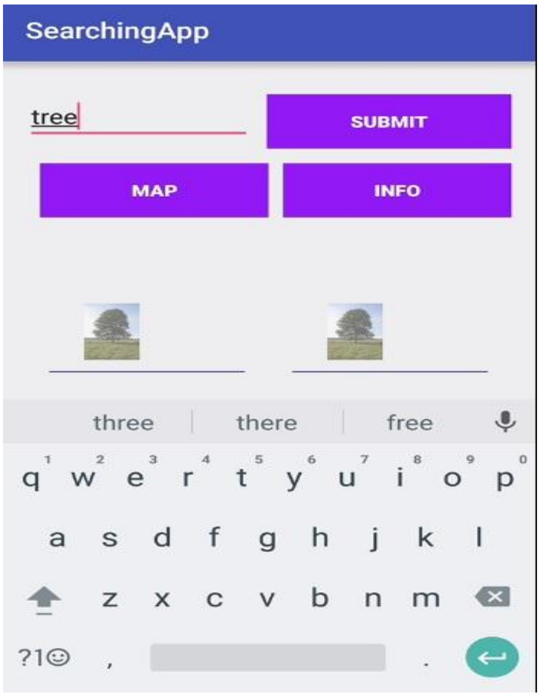

Fig. 2. Text Search

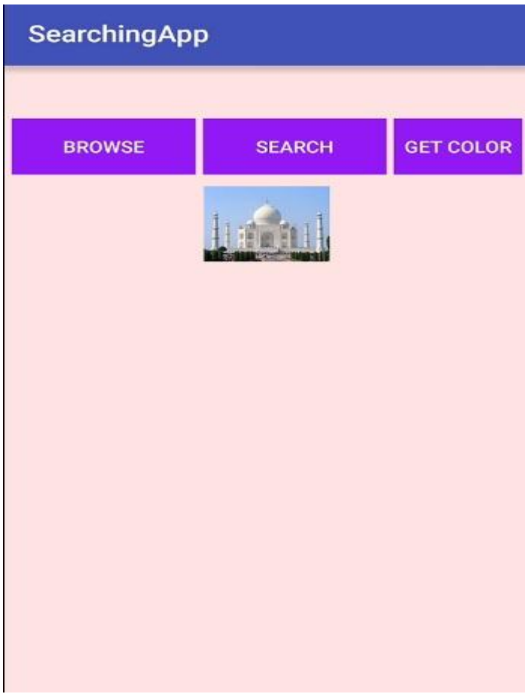

Fig. 3. Combine Search

9. 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 hypergraph 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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REFERENCES

[1] X. Kong, M. K. Ng, and Z.-H. Zhou, "Transductive multilabel learning via label set propagation," IEEE Trans. Knowl. Data Eng., vol. 25, no. 3, pp. 704–719, Mar. 2013.

[2] 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.

[3] M.-L. Zhang and Z.-H. Zhou, "Multilabel neural networks with applications to functional genomics and text categorization," IEEE Trans. Knowl. Data Eng., vol. 18, no. 10, pp. 1338–1351, Oct. 2006.

[4] 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.
[5] J. Deng et al., "Large-scale object classification using label relation graphs," in Proc. Eur. Conf. Comput. Vis., 2014, pp. 48–64.
[6] W. Bi and J. T. Kwok, "Multilabel classification with label correlations and missing labels," in Proc. Assoc. Adv. Artif. Intell., 2014, pp. 1680–1686.
[7] M.-L. Zhang and K. Zhang, "Multi-label learning by exploiting label dependency," in Proc. ACM SIGKDD Conf., 2010, pp. 999–1008.
[8] K. Balasubramanian and G. Lebanon, "The landmark selection method for multiple output prediction," in Proc. Int. Conf. Mach. Learn., 2012, pp. 983–990.
[9] 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.
[10] W. Bi and J. Kwok, "Efficient multi-label classification with many labels," in Proc. Int. Conf. Mach. Learn., 2013, pp. 405–413.
[11] J. Xiao, J. Hays, K. A. Ehinger, A. Oliva, and A. Torralba. SUN database: Large-scale scene recognition from abbey to zoo. In CVPR, 2010.
[12] C. Yang, M. Dong, and J. Hua, "Region-based image annotation using asymmetrical support vector machine-based multiple-instance learning", In CVPR, 2006.
[13] Z.-j. Zha, X.-s. Hua, T. Mei, J. Wang, and G.-j. Q. Zengfu, "Joint multi-label multi-instance learning for image classification", In CVPR, 2008.