Learning Subclass Representations for Visually-varied Image Classification

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ABSTRACT
In this paper, we present a subclass-representation approach that predicts the probability of a social image belonging to one particular class. We explore the co-occurrence of user-contributed tags to find subclasses with a strong connection to the top level class. We then project each image on to the resulting subclass space to generate a subclass representation for the image. The novelty of the approach is that subclass representations make use of not only the content of the photos themselves, but also information on the co-occurrence of their tags, which determines membership in both subclasses and top-level classes. The novelty is also that the images are classified into smaller classes, which have a chance of being more visually stable and easier to model. These subclasses are used as a latent space and images are represented in this space by their probability of relatedness to all of the subclasses. In contrast to approaches directly modeling each top-level class based on the image content, the proposed method can exploit more information for visually diverse classes. The approach is evaluated on a set of 2 million photos with 10 classes, released by the Multimedia 2013 Yahoo! Large-scale Flickr-tag Image Classification Grand Challenge. Experiments show that the proposed system delivers sound performance for visually diverse classes compared with methods that directly model top classes.

Categories and Subject Descriptors
H.3 [Information Storage and Retrieval]: Content

Keywords
Large scale image classification, Subclass representation

1. INTRODUCTION
This paper describes the approach that we developed to address the Yahoo! Large-scale Flickr-tag Image Classification Grand Challenge. This challenge is formulated:

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an extremely large range of visual representations. However, the subclasses of it, such as “flower”, “bird”, “forest”, are much more homogeneous in terms of the visual information. For this reason, we first discover the subclasses, which are tags frequently and exclusively co-occurring with the top-level class labels, for representing each image. Then, we train a binary classifier for each selected subclass. For a given image, the confidence scores of all subclass classifiers are concatenated to produce a high level representation. Thus, the representation is developed to learn models of the top-level classes. This is illustrated by Fig. 2. The final results are predicted by the ranking model based on the the learned subclass representation.

The contribution of this paper lies in the following aspects:

- This method uses a co-occurrence based method to discover subclasses. Compared with semantic ontology based subclass generation methods [2] or using predefined concepts as subclasses [9], the proposed subclass representation is expected to be more discriminative in terms of predicting the target classes.

- The proposed method uses confidence score instead of binary decision of the subclass classifiers as the high level features. This strategy can develop useful representations even if the performance of subclass classifier is not reliable.

The remainder of the paper is organized as follows: in Section 2, we present the details of the proposed method. The experimental framework and results are presented in Section 3 and Section 4. Then, in Section 5 we discuss previous research contributions that are related to our approach proposed in this paper. Finally, Section 6 summarizes our contributions and discusses future work.

2. LEARNING SUBCLASS REPRESENTATION

2.1 Mining Subclasses

As discussed above, subclasses of one class (the target class) are expected to be strongly connected with the target class and, moreover, relatively more stably reflected in visual features than the target class. To define such subclasses, we exploited the tags annotating the images. We first generate a co-occurrence matrix between photos’ tags and their top-level classes, and measure each tag’s connection to one class by its distinctive score, defined as:

$$S_{ij} = \frac{C_{ij}}{\sum_j C_{ij}}$$

where $C_{ij}$ is the number of co-occurrence of the $i$-th tag and the $j$-th top level class. Note that in the setting of Yahoo! Challenge, the predefined top-level classes are also chosen from the user-contributed tags.

The selected subclasses for class-$j$ can be then defined as the tags that have their distinctive scores above a pre-defined threshold, as shown below:

$$T_{selj} = \{t_i | S_{ij} > \text{Thr}_\text{distin}, t_i \in T\}$$

where $t_i$ denotes the $i$-th tag, and $T$ denotes the set of all tags. Note that some tags may be only assigned to a very small number of images in one class. For those tags, the limited number of training images prevents them from being effective subclasses. Taking this into account, we further rank all selected tags, $t_i$, in $T_{selj}$ by the number of photos in class-$j$ that are tagged with $t_i$.

2.2 Subclass Representation

To generate a subclass-based representation for an image, we first use the images tagged with the subclasses to train models, i.e., Support Vector Machines (SVMs), for classifying subclasses, and then, use the confidence scores for predicting each subclass as the new representation for the image. In this sense, as illustrated in Fig. 2, the image features can be treated as the first level representation for an image, while the confidence scores of subclasses are the high level representation. Based on the subclass representations, we further learn the model that characterize the connection between these representations and the top-level class.

3. EXPERIMENTAL FRAMEWORK

3.1 Dataset

To verify the performance of the proposed approach, we carry out our experiments on a dataset of photos released by the Multimedia 2013 Yahoo! Large-scale Flickr-tag Image Classification Grand Challenge. The dataset contains 2 million Flickr photos with 10 classes, i.e., 150K training and 50K test images per class. The class labels are amongst the top tags annotated by the Flickr users. Since the release does not includes the tags associated with the photos, we re-crawled the photos’ tags using the photo ID provided in the metadata.

To develop our system, the training dataset is randomly divided into three parts with the ratio 4:3:1. The first is for training models for predicting subclasses based on image features, the second is for training models for target classes based on confidence scores from the learned subclass models, and the last is for validation and parameter selection. The test data from the grand challenge is used to evaluate the proposed system.

3.2 Multi-class Classification

To model the connection between image feature and subclass, and the connection between subclass representation and top class, we choose an SVM-based approach. For the purpose of classification for multiple classes, we apply one-against-one training strategy, which is reported to have bet-
ter training time efficiency and prediction accuracy compared with other multi-class support vector machines, e.g., one-against-all [8]. To generate probability estimation from the SVM model, we apply the algorithm proposed in [10] and modified its original implementation in LibSVM [1] to make it suitable for distributed computing on a Hadoop-based distributed server.

3.3 Baselines
We compare our subclass-representation-based approach, denoted in the following as $\text{SVM}_{\text{SubClassProb}}$, to two other approaches that closely relate to our approach, as listed below.

- $\text{SVM}_{\text{VisFeat}}$: Directly model target the 10 top-level classes based on image features.
- $\text{SVM}_{\text{ClassProb}}$: Project image features on to top-level 10-classes space.

4. RESULTS

4.1 Learning Subclass Models
To learn the subclasses using the co-occurrence matrix between photos’ tags and their classes, the $\text{Thr}_{\text{distin}}$ in Eq. (2) is set to 0.6, and then we manually select the subclasses in the top 10 tags of each class, which results in a total of 54 subclasses. As some classes may contain few distinctive tags compared with other classes, they may have few subclasses, i.e., class “travel” only contain 1 subclass. In contrast, some classes may contain more distinctive tags, i.e., 14 subclasses for class “nature”. To train these subclass models for projecting images on to the subclass space, we use a maximum 10k images per subclass as training data. Note that some subclasses may contain less than 10k images. The performance on the validation set, Average Precision (AP) for these subclasses models are illustrated in Fig. 3.

4.2 Classification Results
Fig. 4 illustrates the performance in terms of mean average precision (MAP), across all 10 top-level classes, for the proposed approach and the baselines with respect to different training data scales. As can be seen, for classes “food”, “people”, “sky”, “nature”, $\text{SVM}_{\text{SubClassProb}}$ gains more improvements compared to other classes. This is due to the fact that, for these classes, they own more subclasses compare to other classes, i.e., there are more distinctive tags in these classes. Also, some classes, “sky”, “people”, contains visually highly consistent subclasses, as illustrated in Fig. 3 which give a strong support for top classes. This is especially obvious for class “sky”, in which there is a subclass that has a very strong visual consistency, providing a good support for the top class. Interestingly, for the class “food”, which owns many subclasses, and each of them has a relative low AP, however, this class still has reliable performance. We conjecture that these subclass classifiers are providing useful discriminative information in form of probabilities that they yield with respect to non-relevant subclasses.

5. RELATED WORK
Our work is closely related to method used for predicting tags with high intra-class variation, in particular, sub-category based methods or methods based on learning high level representations are often explored. We discuss these methods here in turn.

Generating sub-categories has been considered as an effective method to deal with classification problems where intra-class variation is high. The ImageNet [2] organizes image dataset with labels corresponding to a semantic hierarchy. This method is able to build comprehensive ontology for large scale dataset. However, for a particular dataset, the sub-categories generated by data driven strategies are expected to be more discriminative. [11] exploits co-watch information to learn latent sub-tags for video tag prediction. [7] proposes to discover the image hierarchy by using both visual and tag information. Our method generates category-specific subclasses by exploring image/tag co-occurrence, and trains classifiers for each subclass-tag. These subclasses based models are expected to be discrimi-
Learning higher level representation is adopted when the low-level image features are not discriminative enough for the purpose of classification [6, 5]. For the supervised representation learning methods, a predefined set of models are trained based on image features. The output of these models is considered as the high level representations for predicting image categories. Recently, deep neural networks have been used on unsupervised learning image representations with large scale image dataset [6, 5]. This representation has achieved promising results on different classification and tagging tasks [4]. Our methods used the output of trained subclass classifiers as the high level features. This structure can easily extend to deeper levels by finding discriminative tags for the subclasses.

6. CONCLUSION

We have presented a subclass-representation approach to the task of retrieving/ranking large scale social images to one particular class solely based on visual content. The main contribution of the approach is that by projecting the image feature representation on to a subclass space generated by exploiting the co-occurrence information of user-contributed tags, it makes use not only of the content of the photos themselves, but also of information concerning the co-occurrence of the photo’s tags with tags corresponding to top-level classes.

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