International Journal of Modern Trends in Engineering and Research
www.ijmter.com
e-ISSN No.:2349-9745, Date: 2-4 July, 2015

OBJECT CATEGORIZATION USING CLASSEMES AND METACLASS BY LINEAR SVM

Mrs.Rubala N[1], Prof. V. S. Bhatlavande [2], Prof. M. S. Biradar [3]
[1]*Department of E&TC, Siddhant College of Engineering, nrubala@gmail.com*
[2]*Department of E&TC, Siddhant College of Engineering,vallsyb@gmail.com*
[3]*Department of E&TC, Siddhant College of Engineering, msbiradar2002@rediffmail.com*

Abstract - This paper describes new descriptor for images which allows the construction of efficient and compact classifiers with good accuracy on object category recognition. The descriptors are the classifier that produces the features of each image. The descriptor is the output of a large number of weakly trained object category classifiers on the image. Unlike other attributes and hand defined classes, our features are learned automatically. We first train the classifier using dataset. Then by learning basis classes which gives us features information we are getting good accuracy. All methods are thoroughly evaluated on object classification datasets using a multitude of feature descriptors. The advantage of this descriptor is that it allows object-category queries to be made against image databases using efficient classifiers (efficient at test time). This paper also describes meta-classes which partitions the classes into subsets. In training phase we use support vector machine (SVM) classifier. The advantage of classemes using classifier is that training and testing can be done efficiently. We provide insight of when combination methods can be expected to work and how the benefit of complementary features can be exploited most efficiently.

Keywords- Classemes, SVM classifier, Object classification, Object Recognition, Metaclass

I. INTRODUCTION

Over the last decade the accuracy of object categorization systems has dramatically improved. All proposed systems have focused on a scenario of recognition involves a fixed set of categories, known before the creation of the database; the second, is that there are no constraints on the learning and testing time of the object classifiers. However, these categorization systems do not scale well to recognition in large image collections due to their large computational costs and high storage requirements. In this paper we consider the problem of designing a system that enables accurate real-time recognition of arbitrary categories in gigantic image collections, where the classes are not defined in advance. Object categorization is training a classifier to recognize categories of objects, using only the images retrieved automatically with an Internet search engine. Ideally, automatic image collection would allow classifiers to be trained with nothing but the category names as input. As demonstrated in recent literature on object categorization [1], these nonlinearities are critical to achieve good categorization accuracy with low-level features. The advantage of our approach is that our classification model, nonlinear in the low level features, remains linear in our descriptor and thus it enables efficient training and testing. Probabilistic method of SVM introduced by Luis Gonzalez[2], Support Vector Machines (SVMs) are learning machines which implement the structural risk minimization inductive principle to obtain good generalization on a limited number of learning patterns. The other method is the use of attributes [3],[4],[5] which are fully-supervised classifiers trained to recognize certain properties in the image such as "has beak", "near water", While attributes [14] have been used as features for recognition. The description consists of arbitrary semantic attributes, like shape, color or even geographic information.

II. PROPOSED METHOD

2.1 Classemes

The gigantic image collection is stored in memory for efficient testing which can be compacted by binary codes. This means that a new category can be presented as a set of training images, and a classifier learned from these new images can be run efficiently against the large database. In this approach, the basis classes are defined directly as the real-world object categories of the labeled training set. Our work has focused on methods to retain high recognition accuracy even with linear classifiers. It is divided into three categories. The first category involves the mapping of higher dimensional feature spaces which approximates kernel distances [6][7], To learn about thousands of objects from millions of images, we need a model with a large learning capacity. The second category involves use of huge number of features In order to be able to keep large data sets in memory with such representations; the vectors must be stored in compressed form and then decompressed on the fly "one at a time" during training and testing.

Table 1. Highly weighted Classemes

New Category	Highly Weighted Classemes				
Cowboy-hat	Helmet	Sports track	Cake pan	Collectible	Muffin pan
Duck	Bomber plane	Body of water	Swimmer	Walking	Straight
Elk	Figure skater	Bull male herd animal	Cattle	Gravesite	Dead body
Frisbee	Water craft surface	SCSI cable	Alarm Clock	Hindu	Serving tray
Trilobite-101	Convex thing	Mined area	CD player	Roasting pan	Western hemisphere person
Wheel barrow	Taking care of something	Baggage porter	Canopy closure open	Rowing shell	Container pressure barrier

The Third category includes measuring the likelihood that an image belongs to a particular Flicker group using a trained classifier [8][9]. Our approach is based on Classemes which was first introduced in [9] and uses large image collection, simple classifiers such as linear SVMs can approach state-of-the art accuracy, satisfying the requirements listed above. However, the reason this descriptor will work is slightly more subtle we represent image x in C dimensional vector P(x) hence Pc evaluate on x:

$$P(X) = \frac{\{P1(X)}{PC(X)\}}$$

The classifiers h1...C (the basis classifiers) are learned during an offline stage from a large labeled data set of images. The database DS represents our general visual knowledge-base.

2.2 Classemes Learning

Each row of the table may be viewed as expressing the category as a weighted sum of building blocks; however the true building blocks are not the classemes labels that we can see, but their underlying dumb components, which we cannot. Classifier based representation provides us with two fundamental advantages: 1) Compactness. Only C entries are needed to describe each image. By limiting C to relatively small values (say, a few thousands), we can store even large image collections in memory (rather than on the hard-drive) for more efficient recognition. 2) High accuracy with linear models for each category, a set of training images are selected by issuing a query of an image. A typical situation might be that a new object category, or set of categories, is defined by a set of training images. The output images are realistic which gives similarity of trained image. The training images are converted to classemes vectors, and then any classifier can be trained taking the classemes vectors as input. We first train our basis classifier on low level representation by texture, shape and visual clues of color distribution and spatial transformation of the image.[3].The basis classifier must be evaluvate as faster[10]. Finite dimensional feature maps for additive kernels.

2.3 Metaclass

To use classemes classification, several strategies were implemented: multiclass SVMs, neural networks, decision forests and a nearest-neighbor classifier. Classemes is very simple to implement and scalable to the size of the training database but it is sub-optimal in several aspects. Metaclass should produce similar outputs on images of the same object category and to capture properties of the image.

H_3 :{Van ,Car} Vs {Reptiles, Mammals}
H_2 :{Reptiles} Vs { Mammals}
H_1 :{Van} Vs { Car}

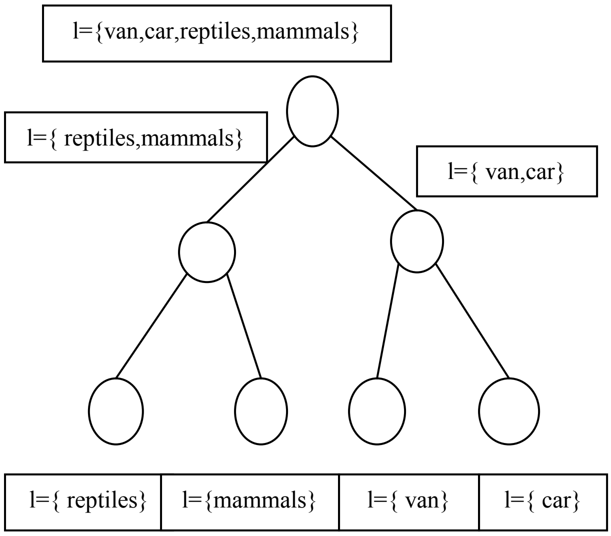


Figure 1. Metaclass label tree and Learning classifier for each metaclass

Our method is based on the algorithm of label tree in which number of classes are large We adopt the label embedded tree[11][13]training procedure from this prior work, but use it to learn meta-classes, i.e, set of classes that can be easily recognized from others. We provide below a review of the label tree algorithm, contextualized for our objective. Let X_l be the set of distinct class labels in the training set X. The label tree is generated in a top-down fashion starting from the root of the tree. Each node has associated a set of object class labels. Let us now consider a node with label set .We need to describe its subset. The two subset define a partition of the label set of the main set. If we denote mm and mn the label set of two subsets, then we need $m_m U\ m_n = m$ and $m_m n\ m_n = \phi$.Ideally, we want to choose the partition$\{m_m,\ m_n\}$ so that a binary classifier $h(m_m,m_n)(X)$. Trained to distinguish these two metaclass makes as few mistakes as possible. Unfortunately we do to know the accuracy of the classifier before training it. Instead, we can use the confusion matrix of one-vs-the-rest classifiers learned for the individual object classes to determine a good partition of intuitively, The final meta-class descriptor is defined as the concatenation of all meta-class classifiers learned in the creation of the tree. In our experiment, SVM is used for comparison.SVM is used for training. It is effective for learning with small sampling in high-dimensional spaces. The objective in SVM [15] is to find a decision plane that maximizes the interclass margin. that are useful for categorization. Datasets available for prediction tasks are growing over time, resulting in increasing scale in all their measurable dimensions.[12].

III. EXPERIMENTS AND RESULT

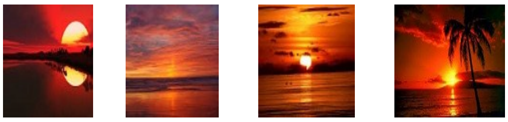
3.1 Dataset

1. Caltech 256[17]: Database for object categorization containing approximately 30k images which is sub portioned into several categories. These datasets progressively increases in current categorization algorithm. These datasets represent lighting conditions, poses backgrounds, image sizes. Overall the processing is simple without the need of cropping or other processing. In Caltech-256, each category has 80 images. Images from each category are downloaded from Google, pic search. Duplicates will be removed by detecting pixel similarity between images. We select N train and N test images from each class to train and test the classifier. Performance of each class C which are correctly classified as belonging to class C. The cumulative performance is calculated by counting the total number of correctly classified test images N test within each of N class classes.

3.2 Image Search

While a few scene types ("beach," "mountain") can be well described by the statistics of low-level features, models for more complex and subtle categories ("nursery," "laundromat") should capture the appearance and spatial configuration of key scene elements – without being told what these elements might be or where they might be located. Another example is weakly supervised object localization, where we are given a set of images containing instances from the same category ("horse," "bus") and told to build a model for that category without knowing exactly where these instances are. Scene recognition approaches based on low-level appearance information work poorly on categories that are characterized not by global perceptual characteristics, but by the identities and composition of constituent objects. we train a binary LSVM classifier for each class using images from all the other classes as negative data. At test time, we label the test image with the class getting the highest response.

Query image



Output images

Figure 2. Experimental results of scene recognition

Table 2. Object categorization Results Comparisons on database

Database	Accuracy
Caltech	**54.2**
MIT	**48.8**

IV. CONCLUSION

In this paper we have presented image descriptors, which measure the closeness of visual concepts called basis classes. The images are trained and tested efficiently during offline. These descriptors are useful for high level object recognition. By using the noisy training data from web image search in a novel way: to train "category-like" classifiers, the descriptor is essentially given access to knowledge about what humans consider "similar" when they search for images on the web. We have emphasized throughout the paper that this is not the main motivation for their use, and we do so again here. It may be that one might view the classemes as a form of highly nonlinear random projection, and it is interesting future work to see if something close to random splits will yield equivalent performance. We tested our classifier using benchmark: caltech256, Scene recognition. The database also contains number of images.

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