HIERARCHICAL OBJECT CLASSIFICATION USING IMAGENET DOMAIN ONTOLOGIES

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Abstract: We present a binary tree based object classification method in this paper. The binary tree builds a group of classes using ImageNet domain ontologies. A binary decision function is introduced in the root node of the decision tree using the positive samples of the first group for training. The decision function continues dividing the groups in sub-sequent groups when approaching the leaf nodes and provides positive and negative samples for multi-class problems. We have tested our method on the PASCAL Visual Object Classes Challenge 2006 (VOC2006) dataset and have achieved comparable accuracy for group classification. The results show that the proposed method is a powerful class binarization technique for hierarchical objects group classification.

1 INTRODUCTION

The recent approaches in object classification systems shows that Support Vector Machines provides better recognition rates as compare to the other existing approaches. We introduce an object classification method using hierarchical object class structure using ImageNet domain ontologies. We have introduced a conceptual ontology based phenomena to group object class hierarchies. For example mammal was introduced as a group having two member groups carnivore and ungulate hoofed mammal. These two groups have some association to the mammal group based on their characteristics. The root nodes of each subgroup are defined as classes have common relationship to the subgroup. This is new way out for training group level classifier using the group labels instead of training directly root nodes. The prediction score generated by the group level classifier is used to choose the sub-group training samples. A base-level classifier is trained using the minimum positive samples identified by the group/sub-group level classifier prediction scores. We have tested our approach on a publicly available well known dataset provided for VOC challenge in 2006. The results we provide shows that the group classifier performs significantly better than the individual classifiers.

This paper is organized as following. The next section describes the related work including the description and how we differ as compared to other approaches. Section 3 will provide our approach and how we build a decision function providing the experiments and our results. The last section provides error analysis and continues with future work.

1.1 Related Work

Madzarov et al. (G. et al., 2009) has introduced a novel architecture using binary decision tree for solving multiclass problem. They have introduced a clustering based method to training binary decision functions using SVM. They claims that their method perform faster than single class one-against-one and for multi-class one-against-all available methods and provides better recognition rates. A popular approach is introduced by Marcin et al. (Marszałek and Schmid, 2007) using lexical semantic networks for the object recognition task. They introduce the concept of visual appearance based learning by defining the inter-class relationship using semantic hierarchy of discriminative classifiers. A higher level layered object categorization architecture has been proposed by Lei et al. (Cheng, 2009) for object categorization using hierarchical category information. The object categories are built with bottom-up and top-down approaches using cognitive rules using inter-category relationship at higher level concepts.
Mailot et al. (Maillot et al., 2004) carried out a

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similar work using machine learning and knowledge representation techniques using visual concept ontology. They introduced visual concept ontological concepts(spatial, color and texture concepts and relations) as an intermediate relations using machine learning and knowledge domain. We have used the domain ontological concept defined in the work of Jia Deng et al. (Deng et al., 2009). They combined the image datasets using WordNet hierarchy utilizing subtrees and synsets of millions of images. We carried our working using ImageNet domain ontologies to generalize the task due to its strong logical grouping.

2 OBJECT CLASS HIERARCHIES

The hierarchical classification structure contains the group having all the sub-sequent nodes. The Root node is trained with all training examples and thereafter test with the test data. Individual classifiers are trained on training data selected by the group classifier. The process continues until we reach from a group to class level classifier training. The idea is to use the reduced training examples based on the prediction score of the group level classifier. The global workflow of the system is presented in Fig. 1.

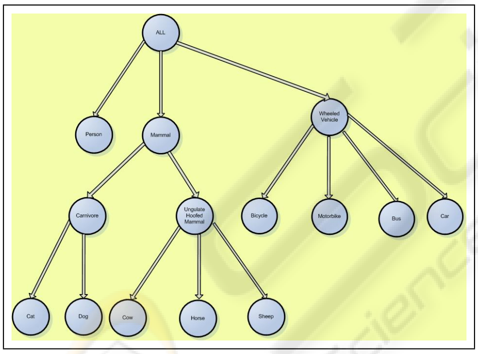

Figure 1: Pipeline for hierarchical object classification system using ImageNet Domain ontologies.

We followed a rather simple but powerful approach to built the histograms using a scale-invariant feature transform (SIFT) (Lowe, 2004). We built a histogram for each image descriptor and concatenate them for each image. We have chosen SIFT features because of their invariance to image scale and rotation as well as robust for illumination, noise, viewpoint and partial occlusions as well as highly distinctive.

3 THE ALGORITHM

We have chosen N number of groups for a given set of training examples. These training examples belongs to a fixed number of classes $C = c_1, ..., c_N$. We have trained a binary classifier to assign these training examples to the corresponding correct groups and classes. The basic algorithm is based on the following steps:-

- Step 1: Training Examples $X := (x_1, \ldots, x_N)$ where $X \subseteq \mathbb{R}^N$
- Step 2: Classes $C := (c_1, \ldots, c_K)$ where $C \subseteq \mathbb{R}^K$ and $K \leq N$
- Step 3: For all given x_i
- Step 4: Group Labels $N := (n_1, \ldots, n_T)$ where $N \subseteq \mathbb{R}^T$ and $T < K$
- Step 5: Sub Group Labels $S_N := (s_{n_1}, \ldots, s_{n_r})$ where $S_N \subseteq N$
- Step 6: x_N are assigned to its relevant c_K
- Step 7: Return x_i, C_i where C_i is the corresponding class of x_i

4 EXPERIMENTS AND RESULTS

In this section we evaluate the hierarchical object classification method. This section covers the evaluation scheme, SVM parameter selection and dataset details. We provide an empirical evaluation of the provided method.

4.1 Evaluation Scheme

We have trained the SVM on the "train" VOC 2006 dataset. We train SVM classifier for each group and use to the prediction score to choose the positive samples for each sub-sequent group. We have chosen full training data to train the root classifier, although the individual classifiers are trained on training data selected by the group classifier. We carried out our experiments using SVMlight with the default parameters, although the choice of the C-parameter selection depends on the average precision on the "val" dataset. We did not choose the weight factor because we found that the "train" set was normalized and have equal weight to the positive and negative samples.

4.2 Results

The results we provide show a consistent improvement at each group level. Depending on the prediction score of each group the choice of positive samples for each sub-sequent group is quite sensitive task. The results are quite promising and provide sufficient motivation to explore and optimize the sub-sequent tree nodes by improving the decision function. The recognition rate is provided in the Table 1.

Table 1: VOC2006 results - The group scores are obtained on VAL dataset while the rest are on test dataset.

Groups	Wheeled Vehicle	Carnivore	Hoofed Mammal
	83.28	70.24	69.65
Classes	Bicycle—53.17	Cow—15.97	Cat—34.61
	Bus— 43.07	Horse—11.95	Dog—30.77
	Car— 61.06	Sheep—26.36	
	Motorbike—25.16		

5 CONCLUSIONS

We have analyzed and found that the proposed algorithm provide a comparable accuracy for classification when used to classify a particular group. The initial idea worked quite well but thereafter need to be refined to identify the cause of failure when moving to the sub-group and then to the base classifier. Especially for those classes where we already have very few training samples in the whole dataset; if not identified correctly at root-node fails completely when reaching down to the base classifier. The available object classification datasets for Pascal VOC challenges contain very few positive examples for some classes and are not balanced. Although training SVM or boosting algorithm with very few training examples is an active area of research for machine learning community (Hu et al., 2007), (Mutch and Lowe, 2008) and (Janez Brank and Mladenic, 2003). A comparative study could be carried out using existing learning techniques like boosting to training the hierarchical classification tree and to compare them with SVM approach.

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