Joint Learning for Multi-class Object Detection

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Abstract: In practice, multiple objects in images are located by consecutively applying one detector for each class and taking the best confident score. In this work, we propose to show the advantage of grouping similar object classes into a hierarchical structure. While this approach has found interest in image classification, it is not analyzed for the object detection task. Each node in the hierarchy represents one decision line. All the decision lines are learned jointly using a novel problem formulation.

Based on experiments using PASCAL VOC 2007 dataset, we show that our approach improves detection performance compared to a baseline approach.

1 INTRODUCTION

Recent years have seen a steady progress in the domain of object detection in still images. Focus has been on developing robust features (e.g. (Dalal and Triggs, 2005a)), capturing object variation (e.g. (Felzenszwalb et al., 2010)) or incoorporating contextual information (*e.g.* (Desai et al., 2011; Choi et al., 2012)) to just name a few.

In this paper, we focus on showing that combining classes into a hierarchical structure further improves object detection performance. In image classification, tree-like hierarchies have gained in popularity (*e.g.* (Bengio et al., 2010; Griffin and Perona, 2008)) as they allow to improve performance and detection time compared to a classical one-versus-all (OvA) technique. Improved performance using binary trees have been shown also in text categorization in *e.g.* (Tsochantaridis et al., 2004). At this point, it is essential to distinguish between the object detection and the categorization (classification) task. In the former case, the goal is to correctly *localize* k possible object classes in an image. In the latter case, the task is to *distinguish* between k given categories. The main difference lies in the classes that the classifier needs to distinguish : In object detection, one is further confronted with the background label which is usually not modelled given us $k+1$ classes. This background class needs special attention and how to successfully manage this issue is one of the contributions of the underlying paper.

One difficulty in object detection is the ability to generalize well from the training data. Most state-of-the-art approaches assume a flat separation between the object categories and concentrate on improving the performance of a generic detector. However, from childhood on, humans tend to organize different classes into a set of clusters (Joshua B. Tenenbaum1, 2011) giving them the ability to generalize from only few seen (training) samples. This kind of representation assumes that nearby object classes share common properties. The importance of sharing between different classes was among others also point out in (Torralba et al., 2004; Salakhutdinov et al., 2011; Ott and Everingham, 2011). Traditional techniques such as OvA SVM detectors are unable to capture common properties between classes.

We propose to group automatically similar classes into a tree structure. The k leaf nodes of the tree represent the individual classes. The background class is not modelled. The predecessors of the leaf nodes are called *super-classes* as they group several classes together. Each vertex in the tree represents a linear classifier. There are two intuitions why our tree improves performance. First, similar classes share common features increasing the discriminative power of

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super-classes. Second, the increased number of linear classifiers allows to be non-linear during detection. This is due to the approximation of the non-linear decision line between classes by a piece-wise linear classification function.

We call the linear SVMs for each vertex a filter. There are as many filters as nodes in the tree. Every filter is represented by a weight vector. These weight vectors are learned in a novel joint framework. During detection, we extract features in the image on different scales. Every location is then scored by all the filters in the tree. The scores of individual paths are added together producing k final scores. These scores are ranked and the highest score determines the foreground class. In case of a background region, the score is negative. This allows us to implicitely classify background regions without modelling it in the tree. Our algorithm combines ranking and classification constraints. We rank between the k classes and are able to between foreground and background label. This is very different from the classification task where all the possible classes are directly modelled and one needs to rank among the known classes.

In summary, we make the following contributions: (i) We show that hierarchical learning improves object detection performance. (ii) We combine ranking and classification constraints into one *hybrid* learning framework. All the weight vectors in the tree are learned jointly. (iii) Our approach is independent of the underlying feature descriptor and many descriptors can be exploited (*e.g.* (Dalal and Triggs, 2005b; Felzenszwalb et al., 2010; Zhang et al., 2011)).

In Sec. 2 we give an overview of the previous works. In Sec. 3, we describe our detector and show in Sec, 4 how it is trained, We show the evaluations in Sec, 5 and conclude in Sec. 6.

2 RELATED WORK

Multi-class detection is a challenging task and an important subject of research. We show an approach that is generic in the choice of features. This is an important constraint on our formulation as feature descriptors change over time. Traditional techniques such as OvO (Kressel, 1999) or DAGSVM (Platt et al., 2000) cannot be exploited as they are only able to distinguish between k known categories thus not handling background.

Tree structures are widely used in image classification not handling a negative class. Here, we further have to discriminate background regions. To our best knowledge, Salakhutdinov *et al*. (Salakhutdinov et al., 2011) were the first to present a tree structure for object detection where the weight vectors are learned iteratively one after another. We jointly optimize over the tree. Their objective was to show that equilibrating the number of samples between classes helps to improve object detection. We show that grouping classes based on their feature similarity improves performance.

In the domain of object detection, the idea of feature sharing using boosting was proposed by Torralba *et al*. (Torralba et al., 2007). The decisions among the classes are shared using combined weak classifiers. Opelt *et al*. (Opelt et al., 2008) enhanced the previous system by further incorporating geometric part information.

Others take a more global approach by sharing parts instead of features. Razavi *et al*. (Razavi et al., 2011) apply a voting scheme where different parts shared among classes use multi-class hough transform to determine the object label. A similar technique (Ott and Everingham, 2011) applies a modified version of the DPM (Felzenszwalb et al., 2010) where common parts are found and grouped together. Other approaches include sharing part locations and deformations across the classes such as in (Fidler and Leonardis, 2007; Fidler et al., 2010; Zhu et al., 2010).

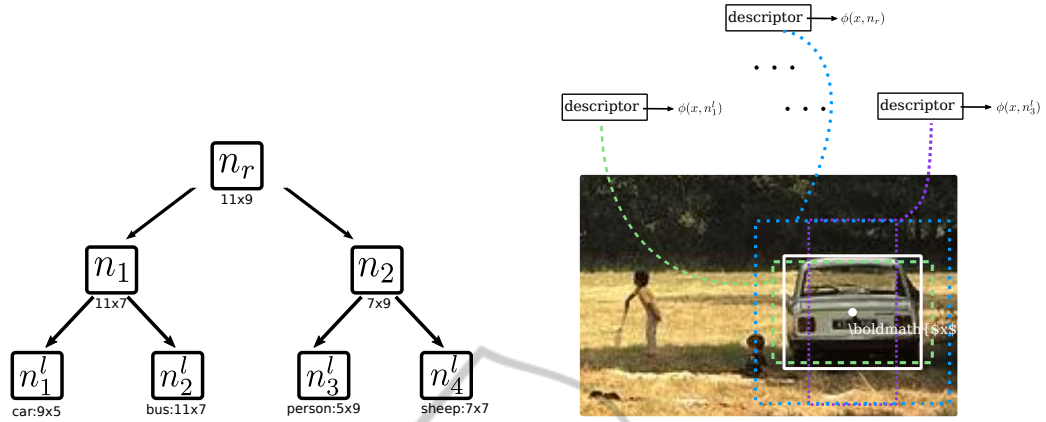
These approaches in object detection lack to use a generic feature descriptor as they are a multi-class extension of their single-class formulation.

As mentioned earlier, hierarchical classification using SVM has been a subject of research in classification. (Griffin and Perona, 2008) exploit binary trees where each node in the tree is learned in a top-down manner. Structured SVM was used in (Tsochantaridis et al., 2004; Cai and Hofmann, 2004) to learn the filters of a tree jointly. Zhou *et al*. (Xiao et al., 2011) enforce orthogonality between parent and child in a tree. Dekel *et al*. (Dekel et al., 2004) speed up the training process by updating the vectors in the tree using an online approach. In (Gao and Koller, 2011; Marszalek and Schmid, 2008) the strict separation between categories is relaxed and each class can be further split into sub-classes.

Again, these approaches are not suited for multi-class object detection with a dominant background label. We show an elegant algorithmic approach to overcome the previously mentioned limitations.

3 SYSTEM OVERVIEW

In this section, we introduce our notation of the hierarchical classification module. We present our multi-class detection procedure and describe how our model attributes a score to different locations in an image.



(a) (b)

Figure 1: (a) We annotate the root filter by n_r and the leaf filters by n_y^l where y is its position from the left and corresponds to a class. We also show the filter dimensions. The sizes for the leaf nodes are learned in as in (Felzenszwalb et al.,). The parents' nodes choose between the maximum height and width among their children's dimensions. The attribute vector and the final score for the 'car' class is also depicted for an example. In (b), the example from (a) is used to show how the nodes extract features around a center position x. The white bounding box indicates the ground truth annotation.

Let $|T|$ be an arbitrary tree with k leaf nodes. Each path to a leaf node models a class. $n_i.i \in \{1,\ldots,|T|\}$ designates any node in the tree and $|T|$ is the total number of leaf nodes. Further, n_r and $n_i^l, i \in \{1,\ldots,k\}$ shall represent the root node and the i-th leaf node as annotated in Fig. 1. $\text{anc}(n_i)$ is the set of the ancestors of node n_i including itself and $\text{desc}(n_i)$ the set of the descendants excluding n_i. Each path to node n_i is determined by its attribute vector $\Lambda_i = (\lambda_1,\ldots,\lambda_j,\ldots,\lambda_{|T|}) \in \mathbb{R}^{|T|}$ with

$$\lambda_j = \begin{cases} 1 & ,\text{if } n_j \in \text{anc}(n_i) \\ 0 & ,\text{otherwise} \end{cases} \quad (1)$$

In other words, the entries λ_j in the attribute vector are 1 for nodes lying on the path up to the node n_i and 0 otherwise (see Fig. 1). In addition, let x be a position in an image. The feature vector $\phi_i(x)$ the features for node n_i at the location x. As can be seen in Fig. 1, every node extracts features around a region centered by x. We refer to the concatenated vector of all the feature vectors from top-to-bottom and left-to-right by $\Phi(x)$. The class labels $y_i \in \mathcal{Y} \equiv \{y_1,\ldots,y_k,y_{bg}\} \equiv \mathcal{Y}^+ \cup \{y_{bg}\}$ are positive for the target classes and negative $y_{bg} = -1$ for the background regions.

Every node represents a parameter vector w_i determined during training. They are filters attributing a partial score $w_i^T \cdot \phi_i(x)$ to a location x. Finally, let $w = \{w_r, w_2, \ldots, w_{|T|}\}$ be the stacked vector of all $w(n_i)$.

3.1 Our Object Detection Model

Given an input image, our objective is to locate objects belonging to the k target classes. We assign to ever possible location in the image a label $y_i \in \mathcal{Y}^+$ if the object is an target object or $y_i = y_{bg}$ if the region is background.

Our object detection process follows the following pipeline as shown in Fig. 2. The input image is scaled with different scaling factors to allow detecting objects of various sizes. Next, features are extracted for every scale. The grouping of all these features across all levels is called a feature pyramid. We do not limit our choice to a specific feature descriptor. Here, we report our experiments on a variant of the histogram of orientated gradients (HOG) (Dalal and Triggs, 2005b) as proposed in (Felzenszwalb et al., 2010) for its popularity and simplicity. Our hierarchical classifier attributes a score and label to every location in the feature pyramid. For a positive region, there maybe several positive responding positions around that region. We merge all the overlapping responses using a non-maxima suppression step (see Sec. 3.2). The result is a set of possible instances of the target objects.

Our detection module unifies classification and ranking tasks. The objects in the feature pyramid are ranked among the k target class. The class label is determined by the highest scoring class. The object is classified as background if the highest score is negative.

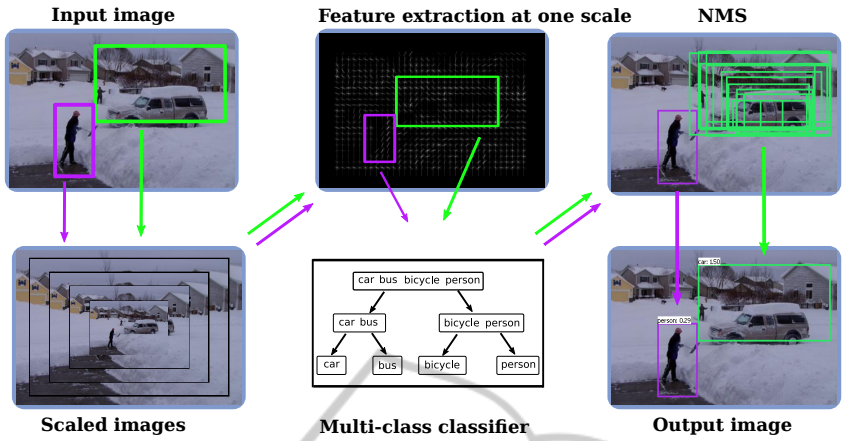


Figure 2: We use a sliding window approach to detect objects of different categories in still images. Our hierarchical detector ranks and classifies between object categories and background.

3.2 Inference

For a given location x in the feature pyramid, we calculate a score score(x) which is the best score produced by all the single classes:

$$\text{score}(x) = \max_{y \in \{1,\ldots,k\}} \text{score}_y(x) \quad (2)$$

The object label $\hat{y}$ is determined by :

$$\hat{y} = \begin{cases} -1 & \text{, if score}(x) \leq 0 \\ arg\max\ \text{score}(x) & \text{, otherwise} \end{cases} \quad (3)$$

Next, let $\Phi_i(x)$ define the concatenated feature vectors of all the features $\phi_i(x)$ extracted by each node lying on the path to node n_i. The features extracted by nodes not being an ancestor of n_i are zeroed. More formally:

$$\Phi_i(x) = \Lambda_i \otimes \Phi(x) = \begin{pmatrix} \lambda_1 \cdot \phi_r(x) \\ \lambda_2 \cdot \phi_1(x) \\ \cdots \\ \lambda_{|T|} \cdot \phi_k^l(x) \end{pmatrix} \quad (4)$$

This kind of representation allows to define classes by local to global parameters as individual classes are grouped together into global super-classes. Then, the scoring function of a class y is given by:

$$\text{score}_y(x) = w^T \cdot \Phi_y^l(x) \quad (5)$$

The Eq. 5 is used in Eq. 3 and Eq. 2 to determine the final class score and label of a position x in the feature pyramid.

3.3 Non-maxima Suppression

We assume that object instances of the same class cannot share the same location in an image. We suppress multiple instances using our non-maxima suppression scheme (NMS). We treat every class separately. For a given class, we sort all the scores in decreasing order and reject the remaining detections having a sufficient overlap (*e.g.* 0.5%) with the higher scoring detections. Thus, we assure that same instances do not share the same positions. Different object categories can share nearby locations *e.g.* a person and bicycle.

4 LEARNING THE HIERARCHICAL TREE MODEL

In this section, we describe our learning algorithm which automatically learns the tree structure, the dimensions of the filters and the weight vectors of each node in the tree in a joint hybrid framework.

4.1 Learning the Hierarchy

The tree T is built in an automatic way. The goal is to hierarchically group similar classes. We say two classes are similar if they are likely to be confused. Grouping classes together allows to better generalize to future unseen examples as the super-classes are trained using all the samples of its descendant classes. For example a 'bicycle' and a 'motorbike' share many features and training a super-class node {'bicycle','motorbike'} increases their discriminative power.

We build a class similarity matrix $\mathcal{S} : k \times k$ where each element s_{ij} measures the similarity between class i and j. To this end, a detector is trained for each class. The k detectors classify the objects of all the other classes. The similarity s_{ij} is the median value given by classifying examples of class i with the

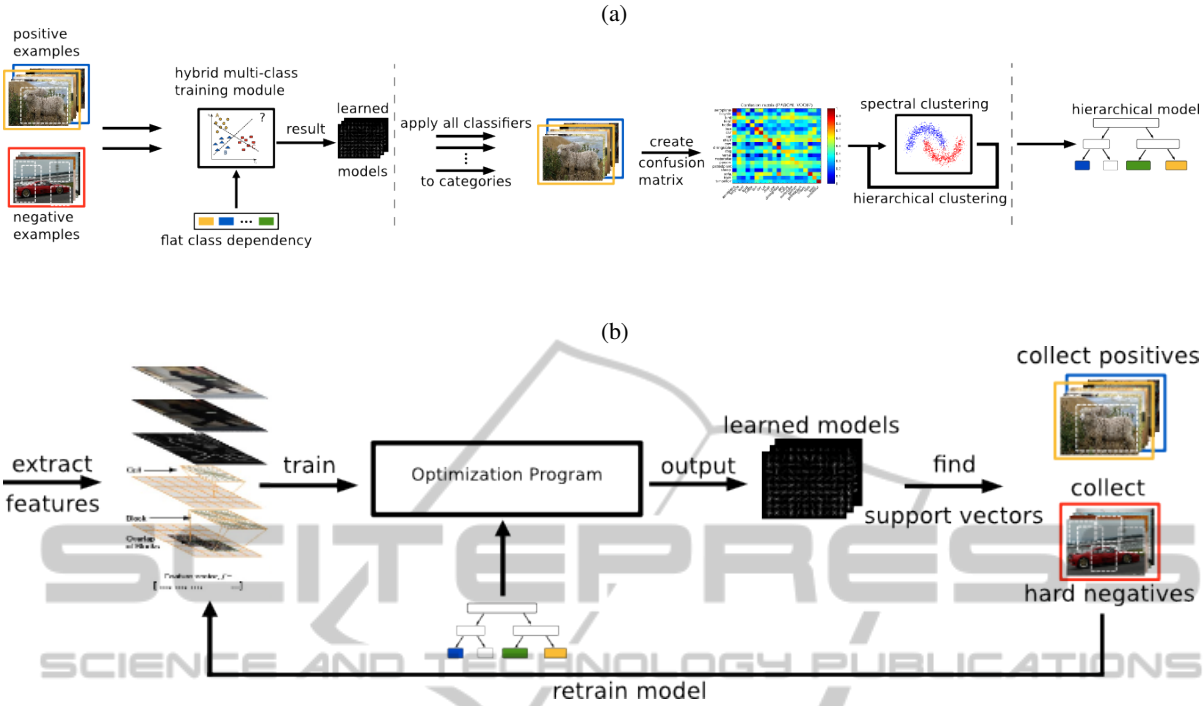


Figure 3: Illustating the different steps during the training process. (a) shows the creation of the hierarchy. The hybrid multi-class training module is shown in (b). Given some training data, it extracts the features, trains the filters of the tree and if necessary applies boostrapping to collect support vectors.

detection model of class j. To obtain a symmetrical matrix, we average with its transposed:

$$\mathcal{S} \leftarrow \frac{1}{2}(S+S^T) \tag{6}$$

Spectral clustering (Luxburg, 2007) is a clustering technique which uses the spectrum of a similarity matrix to partition the data. The objective is to build (two) groups having a high intra-class but low inter-class similarity. We apply spectral clustering hierarchically to $\mathcal{S}$. At each iteration, the data is split into two groups until the leaf nodes are reached. We enforce balanced binary trees in the k-means step of the spectral clustering algorithm. The result is the structure of our tree T. The tree building process is depicted in Fig. 3.

4.2 Problem Formulation

As described in Sec. 3, our hierarchical framework ranks and classifies object regions. We use support vector machines (SVM) to learn the weight vectors, of each node in the tree. Traditional SVM solvers as (Joachims, 1999; Chang and Lin, 2011) minimize a max margin problem subject to classification constraints. Other solvers such as RankSVM (Joachims, 2002) or PRSVM (Chapelle and Keerthi, 2010) train on ranking constraints where the goal is to rank the correct class label higher than all the other classes.

We suggest a novel optimization problem consisting of a mixture of classification *and* ranking constraints. Given n^+ positive and n^- negative samples, the problem is formulated as following:

$$\min_{w,\xi_i(j)\geq 0} \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{n^+}(\xi_i + \sum_{j=1}^{n^+}\xi_{ij}) + \sum_{i,j}^{n^-\times n^+}\xi_{ij}\right) \tag{7a}$$

$$s.t.\ \ \forall y_i \in \mathcal{Y}^+, \forall y_j \in \mathcal{Y}^+ : w^T \cdot \delta\Phi_i(y_j) \geq 1-\xi_{ij} \tag{7b}$$

$$: w^T \cdot \Phi^l_{y_i}(x_i) \geq 1-\xi_i \tag{7c}$$

$$\forall y_i \in \{y_{bg}\}, \forall y_j \in \mathcal{Y}^+ : -w^T \cdot \Phi^l_{y_j}(x_i) \geq 1-\xi_{ij}, \tag{7d}$$

where $\delta\Phi_i(y) = \Phi^l_{y_i}(x_i) - \Phi^l_y(x_i)$ and w a concatenation of the filter weights in the tree T. The objective function 7a minimizes two kinds of errors:

1. $\sum_{i=1}^{n^+}\xi_i + \sum_{i,j}^{n^-n^+}\xi_{ij}$ is the error of classifying target regions as negative or classifying a background sample as one of the k classes.

Algorithm 1: Learn weight vectors of each node in T.

1: Input: Tree T
2: Samples: $\{(x_1,y_1),\ldots,(x_n,y_n)\} \in \mathcal{X}\times\mathcal{Y}$
3: Output: $w = \{w_r,\ldots,w_{|T|}\}$
4: $\mathcal{W} = \emptyset$
5: **repeat**
6: **for all** $i = 1\ldots n$ **do**
7: $\bar{y}_i = \arg\max_{y\in\mathcal{Y}^+} 1 + w^T\cdot\Phi^l_y(x_i)$
8: **end for**
9: $\mathcal{W} \leftarrow \frac{1}{n}\{\sum_{i=1}^{n^+}(w^T\cdot\Phi_{y_i}(x_i) - \max(w^T\cdot\Phi_{\bar{y}_i}(x_i),0) - \sum_{i=1}^{n^-} w^T\cdot\Phi^l_{\bar{y}_i}(x_i)\} \geq 1-\xi$
10: $\mathcal{W} \rightarrow \text{SVM}^{light}$
11: **until** stopping criteria is reached

2. $\sum_{j=1}^{n^+}\xi_{ij}$ is the error of classifying an object of class y_i as y_j.

7d and 7c represent the $(n^+ + n^-)$ classification constraints where as 7b are the $(n^+ \times n^-)$ ranking constraints. This makes a total of $(n^+ \times n^- + n^+ + n^-)$ constraints which need to be optimized (Sec. 4.3).

4.3 Cutting-plane Optimization

The optimization problem in Eq. 7 is a convex optimization problem. We apply the cutting plane algorithm (Joachims et al., 2009) to considerable speed-up detection time. First, the n-slack formulation in Eq. 7 is rewritten as a 1-slack formulation, All the constraints share the same slack variable ξ thus giving us the following learning task:

$$\min_{w,\xi\geq 0}\ \frac{1}{2}\|w\|^2 + C\xi \tag{8a}$$

$$s.t.\ \forall(\bar{y}_1,\cdots,\bar{y}_n)\in\mathcal{Y}^{+n}:$$
$$\frac{1}{n}\{\sum_{i=1}^{n^+}(w^T\cdot\delta\Phi_i(\bar{y}) + w^T\cdot\Phi^l_{y_i}(x_i)) - \sum_{i=1}^{n^-} w^T\cdot\Phi^l_{\bar{y}}(x_i)\} \geq 1-\xi. \tag{8b}$$

At the first sight, the formulation suffers from the huge amount of constraints $\mathcal{Y}^n$ namely one constraint for each possible combination of labels $(\bar{y}_1,\cdots,\bar{y}_n)\in\mathcal{Y}^n$. The cutting plane algorithm only uses a small subset of all possible constraints by iteratively building a working set $\mathcal{W}$ of constraints. At each iteration, one constraint at a time is added to $\mathcal{W}$. The cutting plane optimization is summarized in Algorithm 1.

The algorithm starts with an empty working set and a starting weight vector w. In line 7, the most discriminative class label is calculated for each training sample. The label $\bar{y}_i$ is the class which confuses most with the ground truth class. Line 9 adds the new constraint into the working set. This constraint is the sum of individual constraints producing only one single new constraint per iteration. We use SVM^{light} (Joachims, 1999) to solve the constraints in the working set.

4.4 Implementation Details

We changed the publicly available SVMStruct package (Joachims et al., 2009) to include our definition of the joint feature vector and the combined constraints. The object descriptors are histogram of orientated gradients (Felzenszwalb et al., 2010).

During training, we first learn the hierarchy. Using the tree, we train a model based on all positive samples and randomly collected negatives. This model is iteratively used to collect high scoring negative samples called hard negatives. This bootstrapping procedure strongly improves object detection systems.

The nodes are characterized by a pair (v_i, dim_i). v_i is a vector specifying the location of the filter relative to the root position. dim_i designates the dimensions of node n_i. These dimensions for every class are built in a bottom-to-up fashion. First the dimensions of the leaf filters are determined as in (Felzenszwalb et al.,). The aspect ratio is chosen to be the most common mode in the annotated bounding boxes. The size is picked up not to be larger than 80% of the data. Given the width and height of each node, the dimensions of the remaining nodes are the maximum width W_i respectively height H_i over its children dimensions (refer to Fig. 1 for an example):

$$W_i = \max_{n_j\in\text{desc}(n_i)} W_j \qquad H_i = \max_{n_j\in\text{desc}(n_i)} H_j \tag{9}$$

5 EXPERIMENTAL RESULTS

The following section shows the evaluations of our approach on the PASCAL VOC'07 (Everingham et al.,) dataset and protocol. The dataset has a total of 20 classes represented by 12608 annotated objects. It is equally divided into a training and validation set. We study and illustrate (1) the importance of hierarchy to increase multi-class object detection performance which is the main contribution of this work and (2) the ability to generalize fast when using our tree. We use simple HOG features to show our contribution. As such, our results are relative to the performance of HOG and should not be compared to

state-of-the-art object detectors. More powerful features could have been used. We opted for HOG for its popularity and widespread usage.

Detection Models. Our method is tested on five designed detection algorithms which allow to validate the different aspects of our method : (1) One-vs-All (OvA) treats every class separately. It trains an SVM for each class. The final decision functions are transformed into a probabilistic output using (Platt et al., 2000). (2) The second model called 'ours_flat' learns all the weight vectors jointly using the hybrid learning algorithm but no hierarchical structure. The last model 'ours_tree' trains a complete hierarchical model using the combination of ranking and classification constraints.

Detection Performance. The goal is to show how the hierarchical structure optimized using the hybrid training algorithm improves detection performance. We evaluate on 5 different settings by varying the number of classes $k = \{2,4,6,8,10\}$ and show that the improvement is true independent of k. The 10 selected classes are: {'bus', 'bicycle', 'motorbike', 'car', 'aeroplane', 'person', 'cow', 'horse', 'dog', 'cat'}. Among the classes are certain ones where we would expect a strong degree of feature sharing (*e.g.*'car' and 'bus') and other categories with less common properties (*e.g.*'person' and 'aeroplane').

Table 1 illustrates the detection performance of the detection models for the different settings (k) in terms of the mean average precision (mAP) used in PASCAL VOC'07 evaluation protocol. The tree structure for $k = 10$ classes with the corresponding similarity matrix used to deduce the tree is depicted in Fig. 5. 'ours_flat' achieves slightly better results compared to OvA. A joint learning of all filters and mixing classification and ranking constraints achieve at least as good results as OvA. Using our complete algorithm 'ours_tree' which uses a tree yields the best results. This is due to an increase of the number of linear filters used for the final classification and the feature sharing between neighboring nodes.

The individual scores for $k = 10$ are depicted in table 2. 8 out of 10 classes improve in performance compared to OvA using our joint learning framework. Only 2 classes {'bus','dog'} degrade in performance. The classes 'car' (+3.1) and bicycle (+5.9) have the best increase in performance.

Fast Generalizing Ability. We learn a model representing the classes {'bicycle','motorbike'} using OvA and our hierarchical detector. We investigate how quickly the average precision (AP) of class 'motorbike' achieves its maximum score when we vary the number of its training examples. The intuition behind this setup is to understand how the knowledge of class 'bicycle' helps to quickly learn the similar class 'motorbike'. This comes close to transfer learning techniques (*e.g.* (Aytar and Zisserman, 2011; Lim et al., 2011)) aiming at learning a new class with as few examples as possible. Here, the class 'bicycle' using all of its examples helps the class 'motorbike' having fewer examples but highly similar features and examples.

Table 1: Mean average precision (mAP) of the 4 detection models. Our hierarchical approach always improves over OvA.

k	2	4	6	8	10
OvA	24.1	23.4	20.6	18.3	15.2
ours_flat	24.4	23.9	20.7	18.8	15.5
ours_tree	**25.5**	**25.7**	**23.6**	**20.6**	**16.4**

In Fig. 4, we illustrate the relative average precision of class 'bicycle' using these two techniques in function of the relative percentage of examples used. We normalize all the AP to the AP when full examples are available for both classes. We note that for OvA, having very few training examples only 40% of the final score is reached. However, using the hierarchical classifier, even with very few training examples, nearly the full AP is attained. Our approach is able to generalize fast when a small amount of samples are available. This is due to the fact that these two classes have may features and examples in common.

6 CONCLUSIONS

We presented a novel hierarchical multi-class detection system. Our approach is not limited to the choice of the object descriptors. We combined ranking and classification constraints giving a new optimization problem. Foreground objects are *ranked* among each other while being able to *classify* foreground/background regions. We learn the model in a joint framework where we first learn the hierarchy between objects and the train all the weight vectors jointly.

The experimental results clearly showed an increase of detection performance for different settings in the number of classes. This is due to the increased number of discriminative weight vectors learned. Moreover, similar classes share features and examples which help to generalize faster. This was further illustrated in our experiments where having few samples for one class still allowed to achieve the score when the full training set is available.

In the future, we would like to enhance our hierar-

Table 2: Mean average precision for each class after learning $k = 10$ classes.

class	aero	bike	bus	car	cat	cow	dog	horse	mbike	person
#samples	306	353	229	1250	376	259	510	362	339	4690
OvA	17.6	20.3	**24.0**	29.2	2.3	8.4	3.1	14.4	15.3	17.5
ours_flat	17.9	24.6	21.8	26.2	**6.0**	8.2	**4.5**	12.1	**15.6**	18.1
ours_tree	**20.3**	**26.2**	21.5	**32.3**	2.3	**11.4**	1.2	**15.4**	15.5	**18.2**

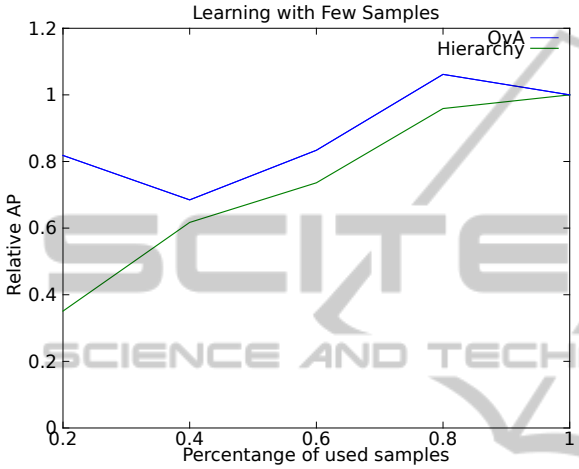
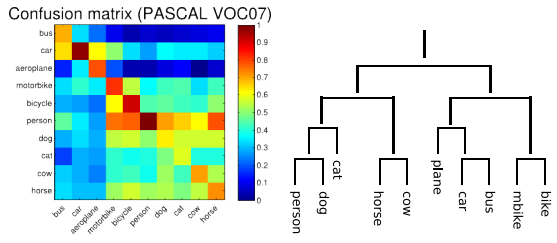


Figure 4: The generalization ability of our approach. We train a model for two classes {'motorbike','bicycle'} with OvA and with our algorithm. We vary the number of examples and analyze the influence on the AP compared to the AP when all the examples are available. OvA slowly increases in performance as the number of examples increases. Our approach achieves much faster its final AP score. We noted a slightly better AP when using 80% of the dataset. We believe that using all the samples introduces more noise in the training process shifting the separating decision line.



(a) (b)

Figure 5: (a) The similarity matrix $\mathcal{S}$ obtained for $k = 10$ classes when building the taxonomy. (b) The resulting tree structure derived by the similarity matrix $\mathcal{S}$.

chy with the deformable part model of (Felzenszwalb et al.,). This new hierarchical deformable part model allows us to automatically find parts between object classes and understand its role to improve object detection performance.

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