LSDA: Large Scale Detection Through Adaptation

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Abstract

A major challenge in scaling object detection is the difficulty of obtaining labeled images for large numbers of categories. Recently, deep convolutional neural networks (CNN) have emerged as clear winners on object classification benchmarks, in part due to training with 1.2M+ labeled classification images. Unfortunately, only a small fraction of those labels are available for the detection task. It is much cheaper and easier to collect large quantities of image-level labels from search engines than it is to collect detection data and label it with precise bounding boxes. In this paper, we propose a Deep Detection Adaptation (DDA) algorithm which learns the difference between the two tasks and transfers this knowledge to classifiers for categories without bounding box annotated data, turning them into detectors. Our method has the potential to enable detection for the tens of thousands of categories that lack bounding box annotations, yet have plenty of classification data. Evaluation on the ImageNet LSVRC-2013 detection challenge demonstrates the efficacy of our approach. This algorithm enables us to produce a >7.5K detector corresponding to available classification data from all leaf nodes in the ImageNet tree. Models and software are available at lsda.berkeleyvision.org.

1 Introduction

Both classification and detection are key visual recognition challenges, though historically very different architectures have been deployed for each. Recently, the RCNN model [1] showed how to adapt an ImageNet classifier into a detector, but required bounding box data for all categories. We ask, is there something generic in the transformation from classification to detection that can be learned on a subset of categories and then transferred to other classifiers?

One of the fundamental challenges in training object detection systems is the need to collect a large amount of images with bounding box annotations. The introduction of detection challenge datasets, such as PASCAL VOC [2], have propelled progress by providing the research community a dataset with enough fully annotated images to train competitive models although only for 20 classes. Even the more recent ImageNet detection challenge dataset [3] has extended the set of annotated images, it only contains data for 200 categories. As we look forward towards the goal of scaling our systems to human level category detection, it becomes impractical to collect a large quantity of bounding box labels for tens or hundreds of thousands of categories.

In contrast, image level annotation is comparatively easy to acquire. The prevalence of image tags allows search engines to quickly produce a set of images that have some correspondence to any particular category. ImageNet [3], for example, has made use of these search results in combination
Figure 1: The core idea is that we can learn detectors (weights) from labeled classification data (left), for a wide range of classes. For some of these classes (top) we also have detection labels (right), and can learn detectors. But what to do about the classes with classification data but no detection data (bottom)? Can we learn something from the paired relationships for the classes for which we have both classifiers and detectors, and transfer that to the classifier at the bottom to make it into a detector?

with manual outlier detection to produce a large classification dataset comprised of over 20,000 categories. While this data can be effectively used to train object classifier models, it lacks the supervised annotations needed to train state of the art detectors.

In this work, we propose Deep Detector Adaptation (DDA), an algorithm that learns to transform an image classifier into an object detector. To accomplish this goal, we use supervised convolutional neural networks (CNN), which have recently been shown to perform well both for image classification [4] and object detection [1]. We cast the task as a domain adaptation problem, considering the data used to train classifiers (images with category labels) as our source domain, and the data used to train detectors (images with bounding boxes and category labels) as our target domain. We then seek to find a general transformation from the source domain to the target domain, that can be applied to any object classifier to adapt it into an object detector. (See Figure 1)

Girshick et al. (RCNN) [1] demonstrated that adaptation, in the form of fine-tuning, is very important for transferring deep features from classification to detection and partially inspired our approach. However, the RCNN algorithm uses classification data only to pre-train a deep network and, in fact, still requires a large number of bounding boxes to train each detection category.

Our DDA algorithm uses image classification data to train strong classifiers and requires detection bounding box labeled data for only a small subset of the final detection categories and much less time. It uses the classes labeled with both classification and detection labels to learn a transformation of the classification network into a detection network. It then applies this transformation to adapt classifiers for categories without any bounding box annotated data into detectors.

Our experiments on the ImageNet detection task show significant improvement (+50% mAP) over a baseline of just using raw classifier weights on object proposal regions. One can adapt any ImageNet-trained classifier into a detector using our approach, whether or not there are corresponding detection labels for that class.

2 Related Work

Recently, Multiple Instance Learning (MIL) has been used for training detectors using weak labels, i.e. images with category labels but not bounding box labels. The MIL paradigm estimates latent labels of examples in positive training bags, where each positive bag is known to contain at least one positive example. Ali et al [5] constructs positive bags from all object proposal regions in a weakly labeled image that is known to contain the object, and uses a version of MIL to learn an object detector. A similar method [6] learns detectors from PASCAL VOC images without bounding box labels. MIL-based methods are a promising approach that is complimentary to ours. They have not yet been evaluated on the large-scale ImageNet detection challenge to allow for direct comparison.
Deep convolutional neural networks (CNN) have emerged as state of the art on popular object classification benchmarks (ILSVRC, MNIST) [4]. In fact, “deep features” extracted from CNNs trained on the object classification task are also state of the art on other tasks, e.g., subcategory classification, scene classification, domain adaptation [7] and even image matching [8]. Unlike the previously dominant features (SIFT, HOG), deep CNN features can be learned for each specific task, but only if sufficient labeled training data are available. RCNN [1] showed that fine-tuning deep features on a large amount of bounding box labeled data significantly improves detection performance.

Domain adaptation methods aim to reduce dataset bias caused by a difference in the statistical distributions between training and test domains. In this paper, we treat the transformation of classifiers into detectors as a domain adaptation task. Many approaches have been proposed for classifier adaptation; e.g., feature space transformations [9], model adaptation approaches [10, 11] and joint feature and model adaptation [12, 13]. However, even the joint learning models are not able to modify the feature extraction process and so are limited to shallow adaptation techniques.

Several supervised domain adaptation models have been proposed for object detection. Given a detector trained on a source domain, they adjust its parameters on labeled target domain data. These include variants for linear support vector machines [14-16], as well as adaptive latent SVMs [17] and adaptive exemplar SVM [18]. A related recent method of [19] proposes a fast adaptation technique based on Linear Discriminant Analysis. These methods require labeled detection data for all object categories, both in the source and target domains, which is absent in our scenario. To our knowledge, ours is the first method to adapt to held-out categories that have no detection data.

3 Deep Detector Adaptation (DDA)

Suppose we have classification training data (image with category label) for \(i = 1, ..., K\) categories, and detection training data (image with bounding box and category label) for a subset of \(m\) categories. In practice, we could have \(m < K\) (as is the case in ImageNet). We are interested in performing detection for all \(K\) categories. We refer to the categories with only classification data as set \(A = \{m : K\}\), and categories with both classification and detection data as set \(B = \{1 : m\}\).

We propose a Deep Detection Adaptation (DDA) algorithm for adapting classifiers to detectors, outlined in Figure 2. It first learns a standard classification network of Krizhevsky et al. [4] on all \(K\) categories (Fig.2(a)), and then adapts this network on the labeled detection data set \(B\) (Fig.2(b)) using a similar approach to Girschick et al. [1]. It then transfers the adapted parameters to the unlabeled categories in set \(A\) (Fig.2(c)). We discuss these steps in detail below.

3.1 Training the Classification Network

We first use all available images in sets \(A\) and \(B\) to train a network that can classify images among the \(K\) categories. We adopt the convolutional neural net architecture of Krizhevsky et al. [4], which achieved state-of-the-art performance on the ImageNet ILSVRC2012 classification challenge. However, this network requires a large amount of data and time to train its approximately 60 million parameters. To train our network with \(K\) categories, we start from pre-training the CNN trained on the ILSVRC2012 classification dataset, which contains 1.2 million classification-labeled images of 1000 categories. Pre-training on this dataset has been shown to be a very effective technique [7, 20, 1], both in terms of performance and in terms of limiting the amount of in-domain labeled data needed to successfully tune the network.

To fine-tune the pre-trained network we remove the 1000-way classification output layer while keeping all other parameters (layers 1-7), and then add a new \(K\)-way classification layer, a multinomial logistic regression, to recognize our particular \(K\) categories. This can be done very efficiently (5 hours) versus training the whole network from scratch (5 days). The resulting network is shown in Fig.2(a). For clarity of presentation we show the final output layer separated into two sections: \(f_{CA}\) and \(f_{CB}\), to indicate which parameters correspond to the sets \(A\) and \(B\).

3.2 Adapting the Classification Network for Detection

We next transform our classification network into a detection network using the available detection data from set \(B\). Inspired by the success of the recent Regions with CNN features (RCNN) [1]
algorithm, we begin by collecting positive and background bounding boxes for each category using the selective search algorithm [21], and use each region as input to the CNN, after padding and warping it to the CNN’s input size. Note that the RCNN algorithm requires bounding box annotated data for all categories and so cannot directly be applied to our scenario to train all $K$ detectors.

Instead, we learn a generic, category-invariant transformation on the labeled set B, that can then be applied to a pre-trained classification network for set A to turn it into a detection network, without any extra training.

There are two key aspects of this adaptation: adding a background class to reject patches that do not belong to any object category, and adapting the network parameters to the new task. The former is necessary to transform a multi-class problem into a multi-label problem, where each object is competing with the background in addition to all the other classes. The latter is necessary both to adapt the hidden layers to capture the additional background class, and to adapt the network to the new detection domain where objects are often small, occluded and have other statistics that differ from the classification domain.

We first add a background class to the output layer (shown in red). We then use the available detection dataset B to fine-tune the hidden layers 1-7 and the output layer containing $fc_B$ plus the background class. We will later transfer the resulting adapted hidden layers 1-7 to categories in set A. Since there is no detection data for categories in A, the output layer weights $fc_A$ corresponding to those categories cannot be updated via fine-tuning.

Fine-tuning consists, in our case, of forward propagating each image patch through the network and using the known label to compute the final loss (as in [1]). The weights are then updated by back propagating the gradient errors through the network. For the background class we gather negatives
by sampling selective search windows that have low overlap (less that 0.5) with any of ground truth bounding box annotated data.

We then adapt the output layer $f_{c_A}$ of categories for which no detection data is available, see Fig. 2(c). (Note that $f_{c_B}$ has already been adapted by fine-tuning in the previous stage).

The simplest approach is to directly add the unchanged $f_{c_A}$ layer, plus the learned background layer, on top of the adapted layers 1-7 from the adapted detection network. This would result in a network that is adapted for detection and produces scores for all categories in $A$. Since we will directly use the last layer of the network as our detector, we are able to perform this adaptation. In contrast, RCNN [1] uses an SVM trained on activations from layer 7 as its final detection model and therefore could not transfer information to the held out categories in this way.

In addition, since the inputs coming from layer 7 to $f_{c_A}$ have changed as a result of the adaptation, we compute a correction term which further adapts the $f_{c_A}$ weights in a fashion similar to how the $f_{c_B}$ weights have changed. Let us define the weights of the output layer of the original classification network as $W^c$, and the weights of the output layer of the adapted detection network as $W^d$, where the weights in $f_{c_B}$ have changed, $W^d_B \neq W^c_B$. We consider computing a bias vector that corresponds to the average offset of the detection from classification weights,

$$\Delta W_{avg} = \frac{1}{|B|} \sum_{i \in B} W_i^d - W_i^c. \quad (1)$$

Then the adapted detection weights for categories $j \in A$ would be: $W_j^d = W_j^c + \Delta W_{avg}$. While this approach is very general, it will not learn adaptations that are specific to particular types of categories. For example, the difference between classification and detection of birds may be very unlike the difference between classification and detection of people. For this reason, we consider a more flexible version of the above adaptation approach where we consider the average offset parameter of the $k$ nearest neighbors within set $B$. Here we define nearest neighbors as those categories with the nearest (minimal Euclidean distance) $\ell_2$-normalized fc7 parameters in the classification network. This corresponds to the classification model being most similar and hence, we assume, the detection model should be most similar. We denote the $k^{th}$ nearest neighbor in set $B$ of category $j \in A$ as $N_B(j, k)$,

$$\forall j \in A : W_j^d = W_j^c + \frac{1}{k} \sum_k \left[ W_{N_B(j,k)}^d - W_{N_B(j,k)}^c \right]. \quad (2)$$

### 3.3 Detection with Adapted Models

With our fully adapted network we are able to detect all $K$ categories in test images. Given a test image, we run selective search [21] to extract regions of interest. As before, we then pad and warp each region to be the right size for input into our network. We then forward propagate the region through our adapted network to produce a $K + 1$ dimensional score vector – for the $K$ desired categories and a background class. Finally, for each category $i$, we compute a discriminative score $W_i^d x - W_i^c x$, where $b$ is the background class and $x$ is the input. This score can be then thresholded to obtain a yes/no decision.

In contrast to the RCNN [1] model which trains SVMs on the extracted features from layer 7 and bounding box regression on the extracted features from layer 5, we directly use the final score vector to produce the prediction scores without any retraining. This choice results in a small performance loss, but offers the flexibility of being able to directly combine the classification portion of the network that has no detection labeled data, and reduces the training time from 3 days to roughly 5.5 hours.

### 4 Experiments

To demonstrate the effectiveness of our approach we present quantitative results on the ILSVRC2013 detection dataset. The dataset offers a 200-category detection challenge. The training set has $\sim$400K annotated images and on average 1.534 object classes per image. The validation set has 20K annotated images with $\sim$50K annotated objects. We simulate having access to classification labels for
all 200 categories and having detection annotations for only the first 100 categories (alphabetically sorted).

4.1 Experiment Setup & Implementation Details

We start by separating our data into classification and detection sets for training and a validation set for testing. Since the ILSVRC2013 training set has on average fewer objects per image than the validation set, we use this data as our classification data. Note: for classification data we only have access to a single image-level annotation that gives a category label. In effect, since the training set may contain multiple objects, this single full-image label is a weak annotation, even compared to other classification training data sets. Next, we use the same split on the ILSVRC2013 validation in half as [1] did, producing two sets: val1 and val2. To construct our detection training set, we take the images with bounding box labels from val1 for only the first 100 categories. Since the validation set is relatively small, we augment our detection set with 1000 bounding box annotated images per category from the ILSVRC2013 training set (following the protocol of [1]). Finally we use the second half of the ILSVRC2013 validation set (val2) for our evaluation.

We implement our CNN architectures and execute all fine-tuning using the open source software package, Caffe [22], and plan to make our model definitions along with all hyperparameters publicly available upon acceptance of this paper.

4.2 Quantitative Analysis on Held-out Categories

We evaluate the importance of each piece of our algorithm through an ablation study. In Table 1, we explore different adaptation combinations. The first row shows the result of directly using all classification parameters within the detection pipeline, and serves as a baseline performance. The last row shows the performance achievable by our detection network if it had access to detection data for all 200 categories, and serves as a performance upper bound. All rows in between show performance of DDA using different hidden layer and output layer adaptations. We find that the best performance comes from learning the background category layer and adapting all convolutional and fully connected layers, taking mAP on the held-out categories from 10.31% up to 15.85%. Additionally, using output layer adaptation ($k = 5$) further improves performance, bringing mAP to 15.97% on the held-out categories.

| Detection Adaptation Layers | Output Layer Adaptation | mAP Trained 100 Categories | mAP Held-out 100 Categories | mAP All 200 Categories |
|-----------------------------|------------------------|-----------------------------|-----------------------------|------------------------|
| No Adapt (Classification Network) | -                      | 12.63                       | 10.31                       | 11.90                  |
| fcbgrend                        | -                      | 14.93                       | 12.22                       | 13.60                  |
| fcbgrnd,fc6                    | -                      | 24.72                       | 13.72                       | 19.20                  |
| fcbgrnd,fc7                    | -                      | 23.41                       | 14.57                       | 19.00                  |
| fcbgrnd,fcB                    | -                      | 18.04                       | 11.74                       | 14.90                  |
| fcbgrnd,fc6,fc7                | -                      | 25.78                       | 14.20                       | 20.00                  |
| fcbgrnd,fc6,fc7,fcB            | -                      | 26.33                       | 14.42                       | 20.40                  |
| fcbgrnd,layers1-7,fcB          | -                      | 27.81                       | 15.85                       | 21.83                  |
| fcbgrnd,layers1-7,fcB          | Avg NN (k=5)            | **28.12**                   | **15.97**                   | 22.05                  |
| fcbgrnd,layers1-7,fcB          | Avg NN (k=100)         | 27.91                       | 15.96                       | 21.94                  |
| Oracle: Full Detection Network | -                      | 29.72                       | 26.25                       | 28.00                  |

Table 1: Ablation study for the pieces of DNN. We consider removing different pieces of our algorithm to determine which pieces are essential. We consider training with the first 100 (alphabetically) categories of the ILSVRC2013 detection validation set (on val1) and report mean average precision (mAP) over the 100 trained on and 100 held out categories (on val2). We find the best improvement is from fine-tuning all convolutional fully connected layers and using output layer adaptation.

To achieve RCNN performance requires additionally learning SVMs on the activations of layer 7 and bounding box regression on the activations of layer 5. Each of these steps adds between 1-2mAP at high computation cost and using the SVMs removes the adaptation capacity of the system.
In Figure 3, we report results for our full system performance. In Figure 3(a) we show the performance of our system relative to other state-of-the-art detection systems, all of which use the full 200 categories of detection data during training. Despite our dramatic disadvantage, our adaptation system ranks 4th overall on the ILSVRC2013 detection challenge. In Figure 3(b), we show the relative performance of our method compared to the full detection network which is trained using detection data from all 200 categories. Despite having half the training data and no detection data for half the categories, our algorithm is able to learn to transform the classification network and brings performance from only being 40% as effective as the full detection network up to >78% as effective overall and >60% as effective on the held-out categories.

4.3 Error Analysis on Held Out Categories

We next present an analysis of the types of errors that our system (DDA) makes on the held out object categories. First, in Figure 5, we consider three types of false positive errors: Loc (local-
Figure 5: Comparison of error type breakdown on the categories which have no training bounding boxes available (held-out categories). We show that after adapting the network using our algorithm (DDA), the percentage of false positive errors due to localization and background confusion is reduced (b) as compared to directly using the classification network in a detection framework (a).

In Figure 6 we show examples of the top scoring Oth error types for DDA on the held-out categories. This means the detector localizes an incorrect object type. For example, the lemon detector localized and mislabeled an orange (far right corner).

4.4 Large Scale Detection

To showcase the capabilities of our technique we produced a 7604 category detector. The first categories correspond to the 200 categories from the ILSVRC2013 challenge dataset which have bounding box labeled data available. The other 7404 categories correspond to the leaf nodes in the ImageNet database and are trained using the available full image labeled classification data. We trained a full detection network using the 200 fully annotated categories and trained the other 7404 last layer nodes using only the classification data. Since we lack bounding box annotated data for

3We modified the analysis software made available by Hoeim et al. [23] to work on ILSVRC-2013 detection
Figure 7: Example top detections from our 7604 category detector. Detections from the 200 categories that have bounding box training data available are shown in blue. Detections from the remaining 7404 categories for which only classification training data is available are shown in red.

the majority of the categories we show example top detections in Figure 7. The results are filtered using non-max suppression across categories to only show the highest scoring categories.

5 Conclusion

We have presented an algorithm that is capable of transforming a classifier into a detector. We use CNN models to train both a classification and a detection network. Our multi-stage algorithm uses corresponding classification and detection data to learn the change from a classification network to a detection network, and applies that difference to future classifiers for which there is no available detection data.

We show quantitatively that without seeing any bounding box annotated data, we can increase performance of a classification network by 50% relative improvement using our adaptation algorithm. Given the significant improvement on the held out categories, our algorithm has the potential to enable detection of tens of thousands of categories. All that would be needed is to train a classification layer for the new categories and use our fine-tuned detection model along with our output layer adaptation techniques to update the classification parameters directly.

Our approach significantly reduces the overhead of producing a high quality detector. We hope that in doing so we will be able to minimize the gap between having strong large-scale classifiers and strong large-scale detectors.

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