Self-Taught Object Localization with Deep Networks
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Abstract

This paper introduces self-taught object localization, a novel approach that leverages deep convolutional networks trained for whole-image recognition to localize objects in images without additional human supervision, i.e., without using any ground-truth bounding boxes for training. The key idea is to analyze the change in the recognition scores when artificially masking out different regions of the image. The masking out of a region that includes the object typically causes a significant drop in recognition score. This idea is embedded into an agglomerative clustering technique that generates self-taught localization hypotheses. The proposed object localization scheme outperforms the state-of-the-art in both precision and recall for small number of subwindow proposals (e.g. producing a relative gain of 22% for top-1 hypothesis). Furthermore, our experiments show that the proposed automatically-generated annotations can be used to train object detectors yielding recognition results remarkably close to those obtained by training on manually-annotated bounding boxes.

1. Introduction

Object recognition, one of the fundamental open challenges of computer vision, can be defined in two subtly different forms: 1) whole-image classification [19], where the goal is to categorize a holistic representation of the image, and 2) detection [30], which instead aims at decomposing the image into a set of regions or subwindows individually tested for the presence of the target object. Object detection provides several benefits over holistic classification, including the ability to localize objects in the image, as well as robustness to irrelevant visual elements, such as uninformative background, clutter or the presence of other objects. However, while whole-image classifiers can be trained with image examples labeled merely with class information (e.g., “chair” or “pedestrian”), detectors require richer annotations consisting of manual selections specifying the region or the bounding box containing the target objects in each individual image example. Unfortunately, such detailed annotations are expensive and time-consuming to acquire. This effectively limits the applicability of detectors to scenarios involving only few categories (e.g., [14]). Furthermore, these manual selections are often rather subjective and noisy, and as such they do not provide optimal ground truth regions for training detectors.

Conversely, image class labels are much easier to obtain. This has enabled the creation of huge image categorization datasets, such as the ImageNet collection [1], which in turn have spurred dramatic advances in object class recognition [19, 27]. Furthermore, recent work has shown that models and features learned using class labels can be effectively leveraged to improve other tasks, such as detection [14], weakly-supervised localization [31], attribute classification [34] and depth prediction [7]. The transferring of knowledge from pretrained image categorization models to other domains has been so successful that it has become the de facto standard for several vision problems.

Our work belongs to this genre of methods as it performs object localization by leveraging a whole-image classifier trained on a large collection of class-labeled examples without object location information. We refer to our approach as self-taught object localization. The key idea is to analyze how the recognition score of the classifier varies as we artificially mask-out regions in the image. Intuitively, when the region containing the object is artificially occluded the whole-image classification score will drop sig-
significantly. Fig. 1 shows how the partial masking out of the input is propagated through the deep convolutional network and how this affects the recognition score. We embed this idea into a hierarchical clustering technique that merges regions according to their relative drop in classification score in addition to criteria of feature and size similarity, and spatial vicinity. This produces for each image a set of subwindows that are deemed likely to contain the object.

The proposed method combines bottom-up segmentation with top-down (discriminative) information given by the classifier. However, we demonstrate that it can also be used in scenarios where the object label of the image is not provided. In such cases we exploit the fact that the top-predicted classes of the whole-image classifier are very likely to contain the correct category (e.g., the convolutional network in [19] has a top-5 accuracy of 18%).

An important aspect of our approach is the choice of whole-image classifier used to perform self-taught localization. We exploit the power of deep networks since, although they perform holistic image recognition, they have been shown to be impressively accurate even in presence of clutter and multiple objects [19]. In addition, deep networks are particularly suited for our strategy because they operate directly on pixels, which we mask out, in contrast to other models (such as those based on bag of visual words) that discard the spatial information.

Our experiments on the ILSVRC2012 dataset [1] show a relative increment of more than 22% in terms of top-1 precision and recall with respect to the state of the art in object subwindow proposal. We also show that our self-taught localization model trained on the ILSVRC2012 classes is able to generalize effectively to new categories of the PASCAL 2007 dataset [10]. Finally, we demonstrate that the subwindows automatically-generated by our approach can be used as positive training examples to learn object detectors without any additional human supervision. Our detection results on 200 classes of ILSVRC2012 are close to those obtained with the same detection model trained on manually-annotated bounding boxes.

2. Related work

In the last few years, several successful attempts have been made to apply deep networks to object localization and detection problems [14, 27, 29, 9]. In [14], a convolutional network [19] is fine-tuned on ground truth bounding boxes and then applied to classify subwindows generated by the region proposal algorithm of Uijlings et al. [30]. In [27, 9, 29] the network is trained to perform regression on the vector-space of bounding boxes of an image in order to avoid the high computational cost of traditional sliding window approaches. These deep networks have shown promising results compared to standard detection schemes relying on hand-crafted features (e.g., [12, 30]). However, all of the aforementioned approaches require manually-annotated ground truth bounding boxes as training data. In contrast, our method automatically populates the images with bounding boxes likely to contain object, which can then be used for training detectors. We effectively replace the traditional manually-selected bounding boxes with regions automatically estimated from training images annotated only with class labels, which are easy to obtain even for a large number of training images. This framework enables scalable training of object detectors at a much reduced annotation cost. The idea of exploiting class label annotations to generate object locations was also explored in [24], however their work focused on the classification task, without providing any quantitative results on the localization task.

In the context of object localization, subwindow proposal methods [2, 8, 30, 4, 3, 18, 36, 25, 22, 26, 32, 16] aim at generating bounding boxes that yield high recall for a high number of candidates, i.e., they maximize the probability that each object in the image is covered by at least one subwindow. These methods perform well at testing time and successfully replace the classic, computationally expensive sliding window approach. Although they provide the great benefit of speeding up detection at test time, these subwindow proposals cannot be used in lieu of ground truth bounding boxes to train a detector because of their low precision caused by the presence of many false positives. In addition, many of these techniques (e.g., [2, 4, 18]) require ground truth bounding boxes during training, thus effectively increasing the amount of manual annotations needed to train a recognition system. Our algorithm can also be viewed as a subwindow proposal method but it provides precision superior to that of prior methods for low number of candidates. The precision of our approach is high enough that detectors trained on our automatically-generated bounding boxes perform nearly on par with detectors learned from ground-truth annotations.

Even though deep networks have shown impressive results, there is still little understanding of what are the critical factors contributing to their outstanding performance. Recently, much work has been devoted to better comprehend deep networks through visualizations of the learned (intermediate) representations [33, 28], semantic interpretation of individual units [20], by studying the emergence of detectors [35] or by fooling them with artificial images [23]. Liu and Wang [21] have also analyzed what a classifier has learned but for the specific case of bag of features and SVM [21]. Instead, we study the effects of selectively masking out the input of deep networks, which can provide new insights on what the network has learned and how this can be exploited for object localization.

The idea of masking out the input of deep networks has been previously explored in [33, 15, 6] with objectives different from ours. [33] investigates the correlation between
occlusion of image regions and classification score for the purpose of analyzing and visualizing the learned features. Although [33] did not provide quantitative results on the task of localization, in our experiments we have attempted to adapt their occlusion-box strategy to perform object localization but we found that this yields much poorer results compared to our approach besides being a lot more costly (for details see Section 4). The methods in [15, 6] mask out the background to learn foreground features. Our idea is complementary, since we want to exploit the foreground mask-out mechanism and not simply as a feature analysis tool but also as an effective procedure to perform object localization. Simonyan et al. [28] proposed an approach that computes a class-specific saliency map by identifying the pixels that are most useful to predict the classification score of a deep network. Instead, in our experiments we demonstrate that our approach provides state-of-the-art results even when used without class labels to compute sub-window proposals for objects of arbitrary classes.

3. Self-Taught object localization

The aim of Self-Taught Localization (in brief STL) is to generate bounding boxes that are very likely to contain objects. The proposed approach relies on the idea of masking out regions of an image provided as input to a deep network. The drop in recognition score caused by the masking out is embedded into an agglomerative clustering method which merges regions for object localization.

Input mask-out. Let us assume to have a deep network \( f : \mathbb{R}^N \mapsto \mathbb{R}^C \) that maps an image \( x \in \mathbb{R}^N \) of \( N \) pixels to a confidence vector \( y \in \mathbb{R}^C \) of \( C \) classes. The confidence vector is defined as \( y = [y_1, y_2, \ldots, y_C]^T \), where \( y_i \) corresponds to the classification score of the \( i \)-th class.

We propose to mask out the input image \( x \) by replacing the pixel values in a given rectangular region of the image \( b = [b_x, b_y, w, h] \in \mathbb{N}^4 \) with the 3-dimensional vector \( g \) (one dimension for each image channel), where \( b_x \) and \( b_y \) are the \( x \) and \( y \) coordinates and \( w \) and \( h \) are the width and height, respectively. The masking vector \( g \) is learned from a training set as the mean value of the individual image channels. We denote the function that masks out the image \( x \) given the region \( b \) using the vector \( g \) as \( h_g : \mathbb{R}^N \times \mathbb{N}^4 \mapsto \mathbb{R}^N \). Please note that the output of the function is again an image (see Fig. 1).

We then define the variation in classification score of the image \( x \) subject to the masking out of a bounding box \( b \) as the output value of function \( \delta_f : \mathbb{R}^N \times \mathbb{N}^4 \mapsto \mathbb{R}^C \) given by

\[
\delta_f(x, b) = \max(f(x) - f(h_g(x, b)), 0) \tag{1}
\]

where the \( \max \) and the difference operators are applied component-wise. This function compares the classification scores of the original image to those of the masked-out image. Intuitively, if the difference for the \( c \)-th class is large, the masked-out region is very discriminative for that class. Thus the region \( b \) is deemed likely to contain the object of class \( c \).

We use the function \( \delta_f \) to define two variants of drop in classification score, depending on the availability of class label information for the image. When the ground truth class label \( c \) of \( x \) is provided, we define the drop function \( d_{CL} : \mathbb{R}^N \times \mathbb{N}^4 \mapsto \mathbb{R} \) as

\[
d_{CL}(x, b) = \delta_f(x, b)^T I_c, \tag{2}
\]

where \( I_c \in \mathbb{N}^C \) is an indicator vector with 1 at the \( c \)-th position and zeros elsewhere. This drop function enables us to generate class-specific window proposals in order to populate a training set with bounding boxes likely to contain instances of class \( c \). We denote the method that uses \( d_{CL} \) as STLCL.

If the class information is not available, for example when testing a detector, we use the top-\( C_I \) classes predicted by the whole-image classifier \( f \) to define \( d_U : \mathbb{R}^N \times \mathbb{N}^4 \mapsto \mathbb{R} \) as

\[
d_U(x, b) = \delta_f(x, b)^T I_{top-C_I}, \tag{3}
\]

where \( I_{top-C_I} \in \mathbb{N}^C \) is an indicator vector with ones at the top-\( C_I \) predictions for the image \( x \) and zeros elsewhere. Since the function is not using the class label, the setup is unsupervised and as a consequence class-agnostic. In practice, we used the top-5 predictions of the deep network \( f \) applied to the whole image by leveraging the high recognition accuracy of [19] (the probability of getting the correct class in the top-5 is 18\%). The STL method that uses \( d_U \) is named STL-U.

As deep convolutional network \( f \) we adopt the model introduced in [19] which has been proven to be very effective for image classification. Since the network is applied to mean-centered data, replacing a region of the image with the learned mean RGB value is effectively equivalent to zeroing out that section of the network input as well as the corresponding units in the hidden convolutional layers (see Fig. 1). We want to point out that our masking-out approach is general and it can be applied to any other classifier that operates on raw pixels.

**Agglomerative clustering.** The initialization of the proposed agglomerative clustering consists of a set of \( K \) rectangular regions \( \{b_1, b_2, \ldots, b_K\} \) generated for an image \( x \) using the segmentation method proposed in [13]. Note that in practice we mask out the rectangular bounding boxes enclosing the segments rather than the segments themselves. We found experimentally that if we mask out the segments, the shape information of the segment is preserved and used
by the network to perform recognition, thus causing less substantial drops in classification.

The goal of the agglomerative clustering is to fuse regions (bottom-up) and generate windows that are likely to contain objects (top-down). We propose an iterative method that greedily compares the available regions, and at each iteration merges the two regions that maximize the similarity function discussed below. This procedure terminates when only one region (covering the whole image) is left. The set of generated subwindows are then sorted according to the drop in classification (Eq. 2 for STL_{CL} and Eq. 3 for STL_{U}). We also perform non-maximum suppression of the subwindows with overlap more than 50%.

We define the similarity between regions using four terms capturing the intuitions expressed below. Two bounding boxes are likely to contain parts of the same object if

1. they cause similar large drops in classification score:
   \[ s_{\text{drop}}(x, b_i, b_j) = 1 - \frac{|d_m(x, b_i) - d_m(x, b_j)|}{\max (1 - d_m(x, b_i), 1 - d_m(x, b_j))} \]

2. they are similar in appearance:
   \[ s_{\text{app}}(x, b_i, b_j) = z(\phi(x, b_i), \phi(x, b_j)) \]

3. they cover the image as much as possible, encouraging small windows to merge early:
   \[ s_{\text{size}}(x, b_i, b_j) = 1 - \frac{\text{size}(b_i) + \text{size}(b_j)}{\text{size}(x)} \]

4. they are spatially near each other:
   \[ s_{\text{fill}}(x, b_i, b_j) = 1 - \frac{\text{size}(b_i \cup b_j) - \text{size}(b_i) - \text{size}(b_j)}{\text{size}(x)} \]

where the index \( m \in \{ \text{CL}, \text{U} \} \) in the first term selects STL_{CL} or STL_{U} presented in the previous subsection, \( z(\cdot, \cdot) \) is the histogram intersection similarity between the network features extracted by \( \phi(\cdot, \cdot) \) (see Sec. 4 for details), \( b_i \cup b_j \) is the bounding box that contains \( b_i \) and \( b_j \). The overall similarity score \( s \) is defined as a convex combination of the terms above:

\[ s(b_i, b_j, x) = \sum_{l \in \mathcal{L}} \alpha_l s_l(b_i, b_j, x), \quad (4) \]

where \( \mathcal{L} = \{ \text{drop, app, size, fill} \} \) and the \( \alpha_l \) are set to be uniform weights in our experiments. We empirically found that removing \( s_{\text{drop}} \) from Eq. 4 will cause a drop of 8% and 10% in terms of precision and recall, respectively.

Figure 2 illustrates the intuition behind the similarity measure encoded by \( s_{\text{app}} \). This similarity is large if the two regions exhibit similar classification drops when occluded (corresponding to points on the diagonal of the \( xy \)-plane in the 3D plot) and it is especially large when the drop in score is substantial (points close to \((1,1)\) in the plot). The term \( s_{\text{app}} \) encourages aggregation of regions similar in appearance, while \( s_{\text{size}} \) and \( s_{\text{fill}} \) borrowed from [30] favor early merging of small regions and regions that are near each other, respectively.

There are many advantages of the proposed similarity with respect to [30]. First, it does not rely on the hand-engineered features used in [30], but instead it leverages the features learned by the deep network. Moreover, our similarity exploits the discriminant power of the deep convolutional network enabling our method to generate class-specific window proposals. Even when used in the class-agnostic regime of Eq. 3 it will tend to generate subwindows that are most informative for recognition (since their occlusion causes large classification drops). Thus, our approach can be viewed as a hybrid scheme combining bottom-up cues (size, appearance) with top-down information (object-class recognition), unlike [30] where the merging of regions is driven by a pure bottom-up procedure.

4. Experiments

In this section we present comparative results of our approach with state-of-the-art methods on the task of object subwindow proposal. We also show how the proposed method generalizes well to unseen datasets and classes. Finally, we show that STL_{CL} can be used to generate bounding box annotations for training object detectors.

Implementation details. In our experiments, we used the convolutional network software Caffe [17] with the model trained on ILSVRC-2012 provided by the authors. Inspired by [14], the descriptor (\( \phi \)) used in the term \( s_{\text{app}} \) of STL is the vector from the last fully-connected layer (before the soft-max) of the network.

Datasets. Our experiments were carried out on two challenging benchmarks: ILSVRC-2012-LOC [1] and PASCAL-VOC-2007 [10]. ILSVRC-2012-LOC is a large-scale benchmark for object localization containing 1000
categories. The training set contains 544,546 images with 619,207 annotated bounding boxes. The validation set contains 50,000 images for a total of 76,750 annotated bounding boxes. Furthermore, we use a reduced subset of 200 randomly selected classes from ILSVRC-2012-LOC (which we denote as ILSVRC-2012-LOC-200\(^1\)) as this allowed us to perform faster training and testing, thus enabling a more comprehensive study of the different variants of our method and previously proposed algorithms on the detection task. PASCAL-VOC-2007 contains 20 categories, for a total of 9,963 images divided into training, validation and testing splits. Each image contains multiple objects belonging to different categories at different positions and scales, for a total of 24,640 ground truth bounding boxes.

Object subwindow proposal. Given a test image, the goal is to generate the best set of bounding boxes that enclose the objects of interest with high probability. A true positive is a proposed bounding box whose intersection over union with the ground truth is at least 50\% [10]. The performance is then measured in terms of the mean of the average recall and precision per class [30] as done in the PASCAL benchmark [10].

\(^1\)We show in the supplementary material that the difference between the results of our method on ILSVRC-2012-LOC (1000 classes) and the ones on ILSVRC-2012-LOC-200 (200 classes) are negligible. This indicates that the accuracy on the set of 200 classes is representative of the performance on the larger set. To enable future comparisons with our results, we will make publicly available the list of 200 classes.

We then compared STL to recent state-of-the-art sub-window proposal methods: SELSEARCH [30] (fast version), BING [2] (MAXBGR version), EDGEBOXES [36] and MCG [3]. We note that these prior proposal methods do not make use of image class label when proposing subwindows. Thus, the supervised version of STL (STL\(_{CL}\)) is in a sense given an unfair advantage over them as it can generate class-specific proposals consistent with the ground-truth label. However, we will demonstrate that our unsupervised STL\(_{U}\) (which does not make use of class labels) provides results nearly equivalent to STL\(_{CL}\) and superior to prior class-agnostic proposal methods for low number of candidates, even when tested on unseen classes (i.e., classes that are not those recognized by \(f\)). We also include as baseline method the conventional sliding window strategy commonly used in detection: a set of rectangles of different sizes is slid over the image and at each position we compute the confidence score as the sum of the classification scores of the top-5 classes predicted by the deep network. The set of subwindows is generated by sliding a square box across the image, using 7 different scales. This produces a number of subwindows that is comparable to the one produced by our method, thus yielding a similar computational cost for detection. This comparison is important as it shows the performance obtained with a subwindow sampling strategy, as opposed to using a system that selects subwindows based on image content.
Figures 3(a,b) show the results in terms of recall and precision on ILSVRC-2012-LOC-200 (training set) and ILSVRC-2012-LOC (validation set - 1000 classes) respectively. Note that while ILSVRC-2012-LOC-200 (training) includes images that were used to train the deep network, ILSVRC-2012-LOC (validation) does not and thus it is useful to assess the ability of STL to work on new images not seen during the training of the whole-image classifier. Figure 3(a) shows that our method outperforms all the other methods for the first 100 proposed subwindows. We have a relative improvement in the top-1 recall of +22% over BING, that is the best method for the top-1 case. The sliding window approach performs very poorly (~46% in absolute value for top-1 bounding boxes) demonstrating the need for a method that generates bounding boxes of appropriate shape, size and position rather than based on a fixed grid and scale. Note that the performance difference between using the class label of the image (STLCL) and not using it (STLc) is small (+1.3% for STLCL). This indicates that our STL approach works equally well even when not given the class label information. Fig. 3(b) shows consistent performance on ILSVRC-2012-LOC (validation), i.e., on images not used for the training of the deep network, indicating that STL naturally generalizes to unseen examples.

We have also experimented with a simple baseline that slides occlusion boxes of different scale over a fixed grid of the image and uses the corresponding drops in classification score to localize the object. This is reminiscent of the approach described in [33], which was used for feature visualization but not for localization. However, we found that even when using a number of occlusion boxes much larger than that used by our method (which implies a higher computational cost, like standard sliding window), the localization results were much poorer, e.g., recall at rank 1 on the ILSVRC-2012-LOC validation dataset is 18% lower than that produced by our method.

Note that methods such as SELSEARCH, BING, EDGEBOXES and MCG were designed to obtain high recall when using a large number of proposals, which is a desirable property at testing time. However it yields precision not sufficiently high to train a detector. In contrast, STL is by far the best method in term of both precision and recall for a small number of proposals.

In the supplementary material we provide further evidence that supports the quality of the proposed method with visualization of the mask-out effect on the convolutional feature maps and in terms of drop in classification and visualization of the automatically-generated top-1 bounding box. We show examples where our method succeeds and where it fails, such as in the case of images containing multiple objects or with context correlating with the object.

Generalization to new datasets and novel classes. We show the ability of the proposed method to generalize to unseen datasets and classes, using the PASCAL-VOC-2007 benchmark [10]. The images of this set have very different statistics than the ones in ILSVRC-2012-LOC, as each image can contain multiple objects belonging to different categories. Moreover, we point out that, unlike BING and EDGEBOXES, the images from this dataset were not used to train or fine-tune the classification network used by STL. Nevertheless, as shown in Fig. 3(c), our method is able to generalize to this new scenario. This result shows that STLU performs well on arbitrary classes, as the categories of PASCAL-VOC-2007 do not exactly correspond to classes present in ILSVRC-2012-LOC.

Generating annotations for training detectors. We show that the bounding boxes generated by STLCL (Sec. 3) can be exploited as annotations when training object detectors, thus eliminating the need for ground truth annotations. First, we compare STLCL to the state-of-the-art methods of Wang et al. [31] and Cinbis et al. [5], which have been used to generate class-specific annotations on PASCAL-VOC-2007 trainval set. In order to test on this dataset, we adapted STLCL (trained on ILSVRC-2012-LOC classes) by remapping PASCAL-VOC-2007 categories into ILSVRC-2012-LOC classes. We used the PASCAL-to-ImageNet class correspondences available at http://image-net.org/challenges/LSVRC/2012/analysis/. In case of one-to-many correspondence our method used the class with the highest prediction score of the network. Table 1 shows the results in terms of annotation accuracy as computed in [31, 5]. STLCL provides the best average annotation accuracy and significantly outperforms the other methods on 10 classes.

As a second experiment, we trained 200 detectors (one

<table>
<thead>
<tr>
<th>Classes</th>
<th>[5]</th>
<th>[31]</th>
<th>STLCL</th>
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<tr>
<td>aeroplane</td>
<td>56.6</td>
<td>80.1</td>
<td>79.0</td>
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<tr>
<td>bicycle</td>
<td>58.3</td>
<td>63.9</td>
<td>55.6</td>
</tr>
<tr>
<td>bird</td>
<td>28.4</td>
<td>51.5</td>
<td>48.8</td>
</tr>
<tr>
<td>boat</td>
<td>20.7</td>
<td>14.9</td>
<td>47.0</td>
</tr>
<tr>
<td>bottle</td>
<td>6.8</td>
<td>21.0</td>
<td>17.2</td>
</tr>
<tr>
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<td>54.9</td>
<td>55.7</td>
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<tr>
<td>car</td>
<td>69.1</td>
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Table 1. Annotation accuracy on PASCAL-VOC-2007 (trainval).
Table 2. The first row reports which method is used to generate the bounding boxes of the positive set, and those of the negative and test set. The second row contains the mean Average Precision (%) calculated as the mean across all 200 classes for ILSVRC-2012-LOC-200.

<table>
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</tr>
<tr>
<td>mAP (all classes)</td>
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<td>18.31</td>
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<tr>
<td>mAP (all classes)</td>
<td>20.43</td>
<td>18.31</td>
<td>18.31</td>
</tr>
</tbody>
</table>

Table 3. Each column contains the best classes (blue) and the worst classes (red) for the object-detectors trained using the annotation method listed at the top. All methods were trained on ILSVRC-2012-LOC-200. Average Precision (%) is listed for each class.

![Table](data:image/table.png)

for each class in ILSVRC-2012-LOC-200), using for each a training set of 50 positive images and 4,975 negative images (obtained by sampling 25 examples from each negative class). The test set is composed by 10,000 images of the ILSVRC-2012-LOC-200 validation set. As detection model, we use the RCNN detector of [14], with the difference that we train it with the smaller negative mining procedure described in [30]. However, while [30, 14] exploited manually-annotated bounding boxes as positive examples, in our training procedure we replace the ground truth regions with the top-K bounding boxes produced by the class-specific STLCL on training images of class c, i.e., we use the class label information for localization of the positive regions.

The negative set is set using the bounding boxes that overlap less than 30% with any STLCL subwindows from the positive images, and one randomly-chosen bounding box from each negative image. At each iteration, a linear SVM [11] is trained by automatically choosing the hyperparameter with a 5-fold cross-validation that maximizes the average precision. The negative set is augmented for the next training iteration by adding for each negative image the bounding box with the highest positive score. At testing time, each detector is tested on the generated subwindows of a given image, the detection scores are sorted and then pruned via non-maximum suppression: we remove a subwindow if it overlaps for more than 70% with a subwindow that has higher score.

We experimented with different combinations of proposal methods for the positive and the negative bounding boxes. For each combination, at test time on each input image we used the same proposal method that was applied to generate the negative boxes during training. For all combinations we use the top-3 candidates as positive bounding boxes to obtain a good recall/precision trade-off based on the results of Figure 3.

Table 2 shows the results in terms of mean average precision (mAP) across all the 200 classes for each method computed according to the PASCAL VOC criterion [10]. The first row reports the method used to generate the positive training boxes, the second row indicated the method for the negative and test boxes. Our approach is STLCL+STL_U (sixth column of Table 2), and it involves using our proposal method based on class labels (since when training a detector they are always available) to generate the positive boxes and our unsupervised approach to produce the negative boxes as well as the proposals on the test images. We compare this approach to BING, EDGE BOXES, MCG and SELSEARCH, where each of these methods was used to generate both the positive boxes as well as the negative and testing boxes of the detector (second to fifth columns of Table 2). We also compared our method to the fully-supervised approach based on manually-annotated positive boxes as proposed in [30] (named GROUND TRUTH+SELSEARCH in Table 2). From these results we notice that STLCL+STL_U outperforms all the other automatic annotation methods, yielding a relative improvement of 42% over the worse method (BING) and 7% over the best competitor (SELSEARCH). This suggests that STLCL generates reliable bounding boxes for the positive set.

An interesting observation that can be drawn from Figure 3(a) is that while STLCL produces the highest precision for a small number of subwindows (and therefore it is the preferred method to generate the positive boxes),
Figure 4 shows the average precision (AP) on the individual 200 classes obtained with the fully-supervised approach **GROUNDTRUTH+SELFSEARCH** (x-axis) and our method **STL-CL+SELSEARCH** (y-axis). Each point represents the AP of these two methods on one particular class.

Instead other methods yield higher recall for large numbers of proposals. This suggests that using, for example, **SELSEARCH** for the negative and test images can be advantageous. Based on this observation, we performed an experiment where we tested "the best of the two worlds", i.e., using **STL-CL** to generate the positive set and **SELSEARCH** for the negative and test set (Table 3, fourth column). We also tested combination of other proposal methods for positive subwindows with **SELSEARCH** for negative/test subwindows and reported the results on Table 3 (second and third column). Table 3 (second row) shows that **STL-CL+SELSEARCH** outperforms all the other combinations. Moreover, **STL-CL+SELSEARCH** shows a relative drop in performance of only 19.6% with respect to the fully supervised method (last column). This is a remarkable result given that our method uses only class labels.

We also tested **STL-CL+SELSEARCH** using the top-1 bounding box obtaining a mAP of 20.93%, which reduces to 17.6% the relative gap with respect to the fully-supervised method.

Table 3 shows also the best-10 and worst-5 classes for each method along with the respective APs. It is interesting to notice that 8 out of the 10 best categories are shared between the detectors trained on the ground truth annotations (last column) and our STL-CL (forth column) as opposed to 5 out of 10 of our competitors.

In Fig. 4 we report the AP on each individual class for the proposed method **STL-CL+SELSEARCH** (y-axis) and the fully-supervised approach **GROUNDTRUTH+SELSEARCH** (x-axis). Quite surprisingly, for 41 classes (all points above the diagonal) the proposed method achieves accuracy better than that obtained when using ground truth annotations.

**Analysis of computational costs.** Let $K$ be the number of segments produced by the method of [13]. During initialization, the similarity of Eq. 4 is evaluated for all segment pairs, for a total of $O(K^2)$ times. However, note that only $K$ evaluations of the convolutional network using Caffe are needed, one for each masked-out segment (Eq. 1).

At the first iteration of the clustering procedure, two of the segments are merged, and there will be $K-1$ remaining segments. Only the similarities involving the newly created segment are updated, which amount to $O(K)$ similarity evaluations, but these can be obtained with a single network evaluation of the image with only the newly merged segment masked-out. In every subsequent iteration, the total number of segments will decrease by one. Thus, in total only $2 \cdot K$ network evaluations are performed over the entire procedure, including those done at initialization.

In practice, the $2 \cdot K$ network evaluations of an image take about 210 seconds on CPU or 26 seconds on GPU for typical values of $K$ used in our experiments. We stress that our code is written in Python and no effort in optimizing it has been made. MCG, **EDGEBOXES**, **SELSEARCH** and **BING** are highly optimized and they take 25, 0.25, 10 and 0.2 seconds per image, respectively.

The runtime of STL can be optimized by merging only adjacent segments during agglomerative clustering. Moreover, note that most of the computation is done during the initialization of the clustering algorithm (when $K$ mask-out operations are performed). At the same time, these segments are very small (compared to the size of the image) and therefore most of the ConvNet features with limited receptive field do not change. Exploiting this observation, a big advantage can be derived by reusing computations. We leave the optimization of the STL code as future work.

**5. Conclusions**

This work presents self-taught localization, which leverages the discriminant power of convolutional networks trained on image class labels to automatically determine the subwindows that are most likely to contain the objects of interest. We tested STL on the task of object window proposal and showed that it consistently outperforms the state of the art for small number of candidates. We demonstrated that detectors trained on localization hypotheses automatically generated by STL achieve performance nearly comparable to those produced when training on manual bounding boxes. In future work we will investigate the possibility of fine-tuning the network as a localizer on the subwindows generated by STL and how to use them in a multiple instance learning framework in order to have more robust object detectors. The code of our method will be available soon.

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References


Additional Material

Introduction

In this supplementary material we provide further evidence that supports the quality of the proposed method. These additional experiments were produced using the same version of the algorithm explained in our paper and include:

- Quantitative analysis showing that ILSVRC-2012-LOC-200 is a representative subset of ILSVRC-2012-LOC;
- Visualization of the mask-out effect in terms of convolutional feature maps and drop in classification (Figures 2, 3 and 4);
- Visualization of top-1 bounding boxes generated by STLCL (our method) and SELSEARCH (Table 1).

Note: this document is best viewed in color.

ILSVRC-2012-LOC-200 Represents ILSVRC-2012-LOC

First of all, we show in Fig. 1 that the difference between the results of our method on ILSVRC-2012-LOC (1000 classes) and the ones on ILSVRC-2012-LOC-200 (200 classes) are negligible. This indicates that the accuracy on the set of 200 classes is representative of the performance on the larger set. For this reason, in all our experiments of detection (Sec. 3 of the main paper) we used the smaller ILSVRC-2012-LOC-200 datasets, as this allowed us to perform faster training and testing, thus enabling a more comprehensive study of the different variants of our method and previously proposed algorithms. We will make available the list of 200 classes used in our experiments along with the code of the proposed method.

Visualizing the Mask-out Effect

Mask-out effect. We show some qualitative examples of the effect of the mask-out operation on images in Figure 2, 3 and 4. Each row reports network input (i.e., the image) and feature maps from each of the 5 convolutional layers of the network (shown as a grid of $F \times F$ feature maps). The first row in each set shows the original images, while the second row shows the effects on the the masked-out image.

We also report the value of the drop in classification (Eq. 1 in the paper) caused by the mask-out operation.

In Fig. 2, we can see some cases where the proposed method succeeds, i.e., where masking out the object region causes a significant drop in classification score. It is interesting to visually note how the mask-out operation propagates through the intermediate convolutional layers of the net until reaching the classification output (as evidenced by the drop). The mask-out operation essentially corresponds to zeroing out the feature map values corresponding to pixels in the masked-out region (e.g. rectangular dark blue box in norm1 feature maps). Fig. 3 shows slightly more complex examples where the drop is not as pronounced as in Fig. 2 but it is still reasonably high.

Fig. 4 shows some hard examples where our localization method is prone to fail because the drop in recognition is not high. In Fig. 4(a), masking out one of the two dogs causes a small drop since there is still one dog that can be recognized by the network. Moreover, a small drop may happen also when the convolutional network uses contextual information (for example the color distribution of the background) that has learned as correlating to some specific category during training, e.g., the eagle and the background landscape in Fig. 4(b). Finally, the basketball example in Fig. 4(c) shows that the network is still able to classify the object (the ball) even when the object of interest is masked out. This is due to the frequent co-occurrence in the training set of basket-
ball and basketball player. The network therefore learned the co-occurrence of the two different objects but not the characteristic of the basketball itself. Fortunately, because STL relies on three other terms it can propose good subwindows also in cases where the mask-out term fails.

**Top-1 bounding box.** We show in Table 1 the top-scoring bounding box on a few sample images of the dataset ILSVRC-2012-LOC-200, using different bounding box proposal methods. In the case of our method (STL$_{CL}$), we show the top bounding box selected according to Eq. 1 in the paper. As already highlighted by the quantitative results, the subwindows produced by STL$_{CL}$ are more accurate than those produced by SELSEARCH. It is also interesting to notice in the last row of the table that multiple similar instances of the same object are often grouped together because STL$_{CL}$ yields the maximum drop in classification when all of them are masked out.
Figure 2. Successful examples where masking out the object yields large drops in classification score. Each row reports network input (i.e., the image) and the feature maps from each of the 5 convolutional layers of the network (shown as a grid of $F \times F$ feature maps). The first row in each set shows the original image, the second row the masked-out image.

(a) Drop = 1.000

(b) Drop = 0.915
Figure 3. More complex examples. Because of the presence of some context, the drop in classification score caused by masking out the object (while preserving the context) is not as large as in the previous Figure.
Figure 4. Cases where the masking out of the object fails to significantly drop the classification score due to multiple objects (a) or the presence of context useful to recognize the object, such as in (b) and (c).
Table 1. Top-scoring bounding boxes generated by $\text{STL}_{\text{CL}}$ and $\text{SELSEARCH}$ for a few sample images from the dataset ILSVRC-2012-LOC-200.