Diverse Sampling for Self-Supervised Learning of Semantic Segmentation

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Abstract

We propose an approach for learning category-level semantic segmentation purely from image-level classification tags indicating presence of categories. It exploits localization cues that emerge from training classification-tasked convolutional networks, to drive a “self-supervision” process that automatically labels a sparse, diverse training set of points likely to belong to classes of interest. Our approach has almost no hyperparameters, is modular, and allows for very fast training of segmentation in less than 3 minutes. It obtains competitive results on the VOC 2012 segmentation benchmark. More, significantly the modularity and fast training of our framework allows new classes to efficiently added for inference.

1. Introduction

The problem of semantic segmentation (category-level labeling of pixels) has attracted significant attention. Most recent progress can be attributed to advances in deep learning and to availability of large, manually labeled data sets. However, the cost and complexity of annotating segmentation are significantly higher than that for classification; consequently, we have orders of magnitude more images and categories in classification data sets such as ImageNet [24] or Places2 [32], than in segmentation data sets, such as VOC [8] or MS-COCO [15].

Given this gap, and the objective difficulty in rapidly closing it, many researchers have considered weakly supervised segmentation, where the goal is still pixel-level labeling at test time, but only spatially coarser annotations are available at training time. Common examples of such annotations include partial annotations, in which only a subset of pixels is labeled; bounding boxes, where a square with an associated label is drawn around objects of interest; and image tags, where labels provide no spatial information and simply indicate whether or not a particular class is present somewhere in the image. We focus on this last, arguably weakest, level of per-image supervision.

There is mounting evidence that this task, while difficult, is not hopeless. Units sensitive to object localization have been shown to emerge as part of the representations learned by convolutional neural networks (CNNs) trained for image classification [31]. Furthermore, some localization methods demonstrate the utility of features learned by classification CNNs by using them to achieve competitive results [18, 31].

Our method is inspired by recent work [23] demonstrating that reasonable segmentation accuracy could be achieved with very few point-wise labels provided by human annotators. In this paper we propose an automatic version of this idea, replacing human annotators with an automatic labeling procedure. Our approach starts by learning noisy localization networks separately for each foreground class, trained solely with image-level classification tags, and using a novel multiple instance learning loss (global softmax, Section 3) adapted for the segmentation task. By combining the localization evidence provided by these networks with a novel diversity sampling procedure, we obtain sparse, informative, and accurate set of labeled pixels. We can use these samples to rapidly train a fully-convolutional multi-class pixel-wise label predictor operating on hyper-column/zoomout representation of image features [9, 17] in less than 3 minutes.

In contrast to much previous work, our approach is simple and modular. It almost entirely lacks hyper-parameters like thresholds and weighting coefficients. It also allows for easy addition of new foreground classes or incorporation of more image examples for some classes, without the need to retrain the entire system. We also avoid complex integration with externally trained components, other than the basic ImageNet-trained neural network we use to extract pixel features. Consequently while competitive models take hours to train, our framework takes less than 3 minutes. Despite this simplicity we obtain results on VOC 2012 data set that improve upon most of previous work on image-level weak supervision of segmentation.

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2. Background

Semantic segmentation has seen major progress in recent years, at least as measured by benchmark performance, nearly doubling the accuracy from 2012 [3, 4] to today’s leading methods [16, 5, 30]. Much of this progress can be attributed to (re)introduction of convolutional neural networks. The availability of training data with manually annotated segmentation masks, in particular VOC[8] and recently MS-COCO [15], has been instrumental in these developments, however recent work has shown that training on weaker annotations, such as partial labeling [23], object bounding boxes [19, 7, 10] or other cues such as object sizes [20], can produce results very close to those using strongly-supervised training. However, closing this gap with strongly-supervised methods trained exclusively on image-level tags, which is the regime we consider in this paper, remains more challenging.

Our work was in part inspired by the experiments in [23] showing that very sparse point-wise supervision allows training reasonable CNN-based segmentation models. Our approach aims to replace manual annotation with “self-supervision” obtained automatically from image-level tags. Similarly to other recent work, we obtain self-supervision by leveraging the recently established observation: CNNs trained for image classification tasks appear to contain internal representations tuned to object localization [2, 31, 18, 6]. These representations have been Combined with a pooling strategy to obtain self-supervision, which can be used to train a segmentation model, often with a variant of the Expectation-Maximization algorithm [19, 28] or with multiple instance learning (MIL) [21, 22, 11, 13].

Some recent methods combine image-level supervision with additional components, such as object proposals [22], saliency [26] or objectness measures [23]. Most of these components require localization annotations, such as bounding boxes and/or segmentation masks, which introduces a dependency on additional, often expensive annotations beyond image-level tags. In contrast, our approach is simple and modular, and does not require any external systems, other than the initial CNN [25] pretrained on the ImageNet classification task [24], making the entire pipeline independent of any requirements beyond image-level annotations.

The most established benchmark for this task remains the VOC 2012 data set, with the standard performance measure being intersection over union averaged over 21 classes (mIoU), which can be reported on val or on test set. The latter arguably more rigorous since the labels are withheld and evaluation frequency limited. In Section 4 we show that despite its simplicity and efficiency, our approach outperforms most competing methods on this benchmark.

Finally, there is a body of work related to exploring and exploiting diversity in learning and vision. Most relevant to our work is the DivMBest algorithm [1, 29] which somewhat resembles our procedure for greedy diverse sampling of points described in Section 3.2. The form of the diversity-infused objective and the context are quite different, however: DivMBest is used to sample assignments in a structured prediction settings for a single input example, whereas we aim to sample examples (image points); in applications of DivMBest the diverse samples are typically fed to a post-processing stage like reranking whereas in our case, the diverse sample is directly used as a training set for a segmentation algorithm.

3. Automatic pointwise self-supervision for segmentation

The basis of our self-supervision method is the localization maps obtained for each of the foreground classes. These maps are sampled for each class, and the resulting sparse set of point-wise labels on the training images is used to train the final segmentation network. We describe these steps in detail below.

3MS-COCO is larger in categories and images, but at the moment does not allow for a proper category-level semantic segmentation evaluation, due to its focus on instance-level detection.
3.1. Learning localization with image-level tags

We start by extracting an image feature map using a pre-trained fully convolutional network. Then for each foreground class \( c \), we construct a per-location localization network on top of these features, which outputs two scores per location \( i \): \( S(c, i) \) for foreground, and \( \bar{S}(c, i) \) for background (which in this case means anything other than the foreground class at hand).

An obvious next step now is to convert these scores into image-level foreground probability, using some sort of pooling scheme; this can then be used to compute image-level classification log-loss and backpropagate it to the localization network. We consider two such schemes.

The per-pixel softmax model We can convert the scores into per-location posterior probabilities using the standard (over-parameterized) softmax model, and apply max pooling over the resulting probability map:

\[
p(c) = \frac{\max_i \exp S(c, i)}{\sum_i \exp S(c, i) + \exp \bar{S}(c, i)},
\]

(1)

This can be interpreted as requiring that for images containing foreground, the network assign at least one location high probability while for images without the foreground, all locations must have low probability. The background scores \( \bar{S} \) do not have a direct meaning other than to normalize the probabilities.

The global softmax model An alternative is to apply max-pooling separately for the two score maps, and convert the maxima to the image-level probability:

\[
p(c) = \frac{\max_i \exp S(c, i)}{\sum_i \exp S(c, i) + \max_i \exp \bar{S}(c, i)}.
\]

(2)

This model no longer is equivalent to the per-location softmax, and in fact does not provide per-location probability map. It specifically encourages the background scores to be high for images without the foreground. It also routes the gradient of the loss via two locations in each image, instead of one with (1), and therefore may facilitate faster training.

It is worth noting that this approach does not include an explicit “background localization” model. Background is defined separately for each foreground class as its complement, and jointly as the complement of all foreground classes. Adding another foreground class would require only training one new localization model for that class; the definition of segmentation background would then automatically be updated, and reflected in the sampling process described below.

3.2. Sampling strategies for self-supervision

We now consider the goal of translating class-specific score maps to supervisory signal for semantic segmentation. Our general framework for this will be to select a sparse set of locations from the training images, for which we will assign class labels. The segmentation predictor is then trained by learning to map the image features for these locations to the assigned class labels.

Let \( S(i, c) \) be the score at spatial index \( i \) for a class \( c \) produced by our image-level classification model. One approach would be to densely label \( y_i = \text{argmax}_c S(i, c) \). Background requires a separate treatment: it is not a “real” class, rather it’s defined by not being one of the foreground classes. Hence, we do not have a separate model for it, and instead can assign background labels to pixels in which no foreground class attains a sufficient score: \( y_i = \bar{y} \) if \( \max_c S(i, c) < \tau \). This simplistic strategy has two problems: (1) some classes may have systematically lower scores than others, and (2) it is unclear how to optimally set the value of \( \tau \).

However, our hypothesis is that while the scoremaps provide only coarse localization, and an inconsistent level of confidence across images and classes, the maximum activations of a class scoremap when that class is present appear to reliably correspond with pixels containing the correct class. (We verified this qualitatively, on a few classes and a number of training images). So, an alternative approach is to label as \( c \) the \( k \) locations corresponding with highest scores for class \( c \). However the size of objects varies widely across images, and it isn’t clear what \( k \) should be. If \( k \) is too high, the labels will be very noisy. If \( k \) is too low, most of the pixels will be tightly clustered portions of each class, e.g., wheels of cars, or faces of people; training on such examples is much less effective because many of the samples will highly correlated.

The method we propose here alleviates these problems by relying on diversity sampling. Let \( z_i \) be the image feature vector at spatial index \( i \), normalized to unit norm, and let \( F \) be the set of foreground classes present in the image. For each class \( c \in F \) we define the \( k \)th sampled location \( x_k^c \) from that image by induction:

\[
x_1^c = \text{argmax}_i S(i, c), \quad x_k^c = \text{argmax}_i \left\{ S(i, c) \left[ 1 - \max_{k' < k} \left| z_i \cdot z_{x_{k'}^c} \right| \right] \right\}
\]

(3)

(4)

where \( \cdot \) denotes the dot product. In other words, we aim to select points with the highest scores for class \( c \), but penalize them for similarity to previously selected points for that class. This encourages selection of a set of examples that jointly provides more information (due to diversity), and is likely to be accurate (due to high scores).

The definition of similarity as dot product in feature space, rather than as spatial proximity, is important. If features at two points are similar, they will appear as similar to the eventual pixel classifier (since it operates on those features), regardless of how close they are in the image; labeling only one of them is sufficient. On the other hand,
two points nearby may have very different feature representations and thus it is beneficial to label both to give the pixel classifier more information.

This approach also naturally leads to a threshold-free method for selecting background points. We let the $k^{th}$ sample, $x_{k,bg}$ for be defined as:

$$x_{k,bg} = \arg\min_i \max_{c \in F,k} \| z_i \cdot z_{c,x_k} \|, \max_{k' < k} \| z_i \cdot z_{c,x_k} \|$$

where $k'$ ranges over indices of selected points for each foreground class, and $k''$ ranges over points selected so far for the background. This simply searches at each step for the image location most dissimilar to any foreground points – thus maximizing the chance of correctly identifying background points, and to any other background points selected – thus maximizing diversity. Our diversity sampling strategy is illustrated in Figures 1, 3.

### 3.3. Training semantic segmentation using self-supervision

Once the self-supervision labels are obtained, we are ready to train the segmentation as a per-pixel fully convolutional multi-class (including background) classifier network, with receptive field of 1×1. This can be done by using the standard convnet training machinery, with zero-masking applied to the loss in locations where no labels are available; whether to fine-tune the underlying network that extracts the visual features per location is a choice.

| $k$  | 1   | 5   | 10  | 20  | 50  |
|------|-----|-----|-----|-----|-----|
| mIoU | 35.1 | 37.2 | 39.3 | 40.6 | 40.4 |

Table 3: mIoU on VOC 2012 val as a function of $k$ points in diverse sampling, with global softmax model

### 4. Experiments

In order to compare our method to other work on segmentation, we conduct all of our experiments on the VOC 2012 data set. For training images (10,582 images in the train-aug set) we discard all annotations except for image-level labels indicating which of the 20 foreground classes is present in each image. We evaluate various versions of our method, as well as its components individually, on the val set, and finally use the models chosen based on tese experiments to obtain results on the test set from the VOC evaluation server. All experiments were done in Torch7, using Adam [12] update rule when training networks.

#### 4.1. Experimental setup

**Pixel features** As the base CNN we use the VGG-16 network trained on ImageNet and publicly available from the authors of [25], from which we remove all layers above pool5. This network is run in the fully convolutional mode on input images resized to 256×336 pixels. Then each of the 13 feature maps (outputs of all convolutional layers, with pooling applied when available) is resized to 1/4 of the input resolution, and concatenated along feature dimensions. This produces a tensor in which each location on the coarse 64×84 grid has a 4,224-dimensional feature vector. This closely follows the hypercolumn extraction protocol in [9] (but using all layers) and [17], but without superpixel pooling.

When computing dot products in diversity sampling (3),(5) we normalize zoomout feature vectors to unit norm in two stages: each feature dimension is normalized to be zero-mean, unit variance over the entire training set, then each feature vector is scaled to be unit Euclidean norm.

**Localization models** For each class, the fully convolutional localization network consists of a 1×1 convolutional layer with 1024 units, followed by ReLU and the 1×1 convolutional layer with 2 units, which outputs the score maps $S$ for the foreground and ̅$S$ for background. At training time, for the global softmax model (2) this is further followed by global max pooling layer and the softmax layer, while for the per-pixel softmax (1) the order of softmax and max pooling is reversed.

For each class, we train the network on all positive examples for that class (images that contain it) and a randomly sampled equal number of negative examples, with batch size of 1 image, learning rate $1e^{-4}$ which after 2 epochs is decreased to $1e^{-5}$ for one additional epoch and momentum 0.9.

We experimented with adding higher layer features (fc7 from VGG-16) to the input to localization networks, but found that it makes localization worse: it is too easy for the network to determine presence of objects from these complex, translation invariant features. We do however bring these features back when training the final segmentation model, described next.

**Segmentation model** To provide image-level priors, which have been reported to improve segmentation results in both fully supervised [17] and weakly supervised [22] settings, we augment the zoomout feature map with the global features (layer fc7 of VGG-16, pooled over the entire image and replicated for all locations). The combined feature map (8320 features per location) is fed to a 1×1 conv. layer with 512 units, followed by ReLU, and the 21-channel prediction layer, followed by the softmax loss layer. We train this network on the selected set of points pooled over all training images, using batch size 100 (note: this means 100 sample points, not 100 images!), fixed learning rate $1e^{-6}$, and momentum 0.9, for two epochs. With these
settings, typical time to train the final segmentation model is less than 3 minutes on a single Titan X GPU.

4.2. Evaluation of model components

We start by evaluating components of our approach on the val set.

Localization model  As shown in Table 1, the global softmax model (2) obtains significantly better results than the per-pixel softmax (1). Therefore we choose it for all the subsequent experiments.

Self-supervision by localization maps  We could attempt using the score maps obtained by localization network directly as the predicted segmentation maps. Specifically, we considered assigning each pixel to the highest scoring class (after normalizing the scores so that for each class on average images with the foreground present have the highest score of 1), or to the background if the highest foreground score is below threshold. This results in poor segmentation accuracy: the highest val mIoU after sweeping the threshold values was 25.66, for threshold of 0.2.

We also made an attempt to use these score-based segmentation maps as the source of self-supervision directly, without sampling. That is, we can train the segmentation network in the usual fully-supervised way, giving it the score map-based dense segmentation labels as if it were ground truth. The results were very poor; in large fraction of the pixels the localization models uncertain, and while our sampling focuses on high-score points, dense self-supervision is forced to make a decision in those uncertain points as well, leading to a very noisy labeling.

### Table 1: Comparison of localization models on VOC 2012 val

| Model       | mIoU |
|-------------|------|
| Pixel softmax | 38.0 |
| Global softmax | 40.6 |

### Table 2: Comparison of point sampling strategies for self-supervision

| Sampling       | mIoU |
|----------------|------|
| Dense          | 15.0 |
| Spatial        | 33.4 |
| Top $k = 20$   | 30.7 |
| Diverse, $k = 20$ | 40.6 |

### Table 4: Comparison of competitive segmentation methods, supervised with image-level tags. For reference, top of the table includes representative numbers methods trained with stronger supervision regimes on VOC 2012 data, or on additional data.

| Method                  | VOC 2012 val | VOC 2012 test | comments                                                                 |
|-------------------------|--------------|---------------|--------------------------------------------------------------------------|
| DeepLab-CRF [5]         | 68.7         | 71.6          | fully supervised                                                          |
| FCRN [27]               | 74.8         | 77.3          | fully supervised                                                          |
| BoxSup [7]              | 62.0         | 64.6          | bounding box-supervised                                                   |
| Bbox-Seg [19]           | 60.6         | 62.2          | bounding box-supervised                                                   |
| 1 point [23]            | 35.1         |               | manual annotation, 1 pt/class                                             |
| 1 point + Obj [23]      | 42.7         | 51.2          | + objectness prior                                                        |
| STC [26]                | 49.8         |               | externally trained saliency model and 40K extra images                   |
| MIL-sppx [22]           | 36.6         | 35.8          | superpixel smoothing                                                      |
| CCCN [20]               | 35.3         | 35.6          |                                                                         |
| EM-Adapt [19]           | 38.2         | 39.6          |                                                                         |
| Ours                    | 40.6         | 41.2          | no post-processing                                                        |
| Ours                    | 45.2         | 46            | CRF post-processing, less than 3 minutes training time                   |
| SEC [13]                | 50.7         | 51.5          | 7-8 hours training time                                                  |

Figure 2: Example segmentations on extra classes from MS-COCO dataset added to the segmentation model trained on VOC dataset.
**Effect of sampling strategy**  For our diverse sampling method, we need to set the value of \( k \). Table 3 shows the effect this value has on \( \text{val} \) accuracy. The optimal \( k \) among those tested is 20, but the behavior is stable across a large range of values.

We also compared alternative sampling strategies, namely selecting the top \( k \) scoring points for each class, or using diversity but in spatial domain instead of in feature domain. Table 2 shows that the diversity sampling using feature similarity is indeed superior to those. Figure 3 shows a few qualitative examples of diverse sampling outputs. Notably, sampling for background is usually quite accurate, even though it is oblivious to the actual class scores and is entirely driven by diversity w.r.t. to the foreground and within background.

### 4.3. Final segmentation results

Based on the preliminary experiments on \( \text{val} \) above, we could identify the optimal setting for our approach: global softmax localization model, with diverse sampling, \( k = 20 \). We report the results of this method in Table 4. We also report the results of applying fully-connected CRF [14] with author’s default parameters on top of our predictions.

The top portion of the table contains representative results for stronger supervision scenarios, for reference; these are not directly comparable to our results. Among the methods trained on the same data and in the same regime as ours, our results are the highest. It is interesting that we obtain similar results to those with *manual* annotation of a single point per class per image [23] (better than their results without objectness prior), although our point selection is fully automatic.

We are aware of additional results from concurrent work appearing on arXiv. The STC [26], reporting test mIoU of 51.2; it is trained on 40,000 additional images, collected in a carefully designed procedure to make them easy to learn from. STC also uses an externally trained saliency mechanism, which requires mask annotations to train.

The only other method trained solely on VOC data which has higher accuracy is SEC [13], achieving 51.5 mIoU on test. However, their approach is considerably more complex than ours, employing hyperparameters that determine various thresholds, and the time to train the final segmentation system with SEC is almost two orders of magnitude higher than ours (7-8 hours vs. 3 minutes for us). SEC also uses significantly larger field of view for the underlying segmentation network than in our experiments (378 vs. 224 for us), and results reported in [13] suggest that this may be very important. We plan to investigate whether increasing field of view of the segmentation network improves our results as well.

Not only does our method obtain competitive results, but due to its very fast training of segmentation model, it is practical to add new classes on the fly, unlike other approaches.

We show some qualitative results obtained by our model on \( \text{val} \) images in Figure 4.

### Adding new object classes on the fly

One of the key characteristics of our model is modularity. Consider that we want to add new classes like Giraffe and Elephant which are not part of VOC dataset. We train localization model for new classes with only image level tags from MS-COCO dataset for Giraffe and Elephant. Since we have trained the localization model for each class separately, there is no need to re-train the other classes localization models. The segmentation training data for new classes is the sparse set of diverse points extracted from localization model output. Sparsity significantly speedup the segmentation training and diversity leads to high quality segmentation output. It takes less than 3 minutes to re-train the segmentation model with additional classes without hurting its accuracy on Pascal segmentation benchmark. Hence it is practical to add new classes on the fly. Qualitative examples of segmentation results for the new classes are shown in Figure 2.

### 5. Conclusions

We have proposed an approach to learning category-level semantic segmentation when the only annotation available is tags indicating the presence (or absence) of each foreground class in each image. Our approach is based on a form of self-supervision, in which a sparse, visually diverse set of points in training images is labeled based on class-specific localization maps, predicted from the image tags.

Among the appealing properties of our method are its simplicity, near absence of hyperparameters (and insensitivity to the only hyperparameter, the self-supervision sample size), modularity (easy to update the model with new classes and/or examples), lack of reliance on complex external components requiring strong supervision, and last but not least, competitive empirical performance and speed.

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Figure 3: Examples of diverse sampling outputs. For each foreground class, we show the localization score map from global softmax model, and the selected 20 points. For background, the map shows the max over dot products with any selected foreground points.
Figure 4: Examples of segmentations learned through our self-supervision approach. From left: input image, ground truth, thresholded localization score maps, segmentation learned with diverse $k = 20$ sampling, CRF post-processing.
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