CONDITIONAL NETWORKS FOR FEW-SHOT SEMANTIC SEGMENTATION

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ABSTRACT

Few-shot learning methods aim for good performance in the low-data regime. Structured output tasks such as segmentation present difficulties for few-shot learning because of their high dimensionality and the statistical dependencies among outputs. To tackle this problem, we propose the co-FCN, a conditional network learned by end-to-end optimization to perform fast, accurate few-shot segmentation. The network conditions on an annotated support set of images via feature fusion to perform inference on an unannotated query image. Once learned, our conditioning approach requires no further optimization for new data. Additional annotated inputs are used to update the output via a single inference step, making the model suitable for interactive use. Our conditional network significantly improves few-shot accuracy over the prior state-of-the-art.

1 INTRODUCTION

Convolutional networks are driving progress in the visual recognition of what and where, enabled partly by large labeled datasets that are expensive and time consuming to collect. Few-shot learning holds the promise of data efficiency; in the extreme case, one-shot learning requires only a single annotation of a new concept. Some current methods rely on meta-learning, or learning to learn, in order to quickly adapt to new domains or tasks. While these methods are promising, the focus has been on classification, and little has been done for structured output tasks. Current methods largely cannot be applied out-of-the-box to the structured output setting due to the high dimensionality of the output space, as well as the statistical dependencies among outputs that result from the spatial correlation of pixels in the input.

Semantic segmentation is a challenging core task for visual recognition. Networks optimized end-to-end have achieved state-of-the-art performance, but rely on large pixel-wise labeled datasets that are particularly onerous to collect, rendering any relief in the annotation burden practically significant. We therefore address the problem of few-shot semantic segmentation, as first proposed by Shaban et al. (2017). In our co-FCN network, we augment the FCN (Shelhamer et al., 2016) architecture with a conditioning branch to incorporate the few-shot annotations. No gradients flow at test time; given a new few-shot task, solving it is a single forward pass in the network. During training, we simulate few-shot tasks by sampling them from a densely labeled semantic segmentation dataset.

Our work is related to one-shot and interactive approaches to segmentation. Shaban et al. (2017) are the first to address few-shot semantic segmentation. Our method significantly improves on the accuracy of their results. Caelles et al. (2017) show the effectiveness of fine-tuning for video object segmentation, but requiring optimization for every input at test time is too costly in computation and annotation. Xu et al. (2016) meta-learn state-of-the-art interactive object segmentation, but are restricted to propagating annotations within a single image, and cannot propagate across images. Our contributions cover conditioning features vs. parameters, and evaluating stronger segmentation and meta-learning baselines.

2 CONDITIONAL ARCHITECTURE AND FEW-SHOT OPTIMIZATION

Few-shot segmentation aims to learn to segment new concepts, given only a few annotated examples of those concepts. A k-shot task consists of the labeled *support set* of k image-annotation pairs, and the unlabeled *query*.

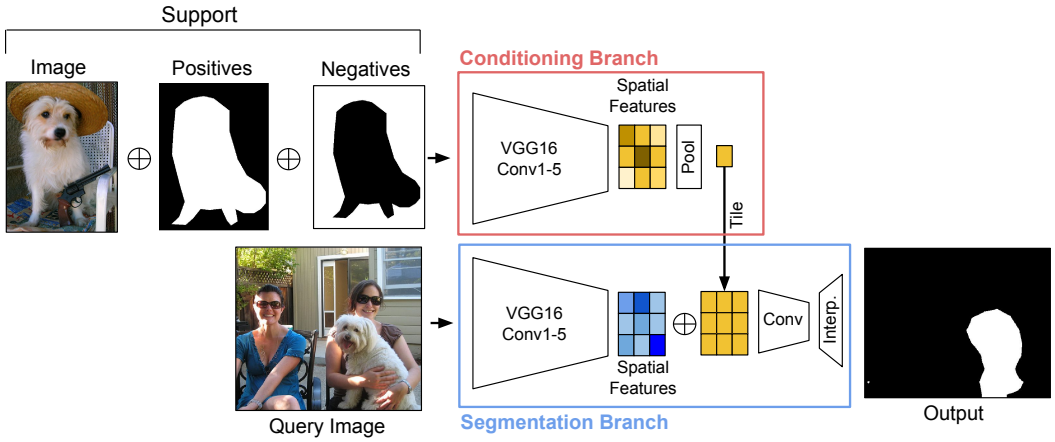

Figure 1: co-FCN performs few-shot segmentation in a single forward pass of the network. The conditioning branch (top) takes the support as input to guide inference via fusing features (as illustrated here) or predicting parameters. The segmentation branch (bottom) densely segments the query given the conditioning. For training (not pictured), few-shot tasks are synthesized from a densely labeled dataset. The loss compares the predicted segmentation of the query image with the target, which is defined jointly by the support and the ground truth semantic segmentation of the query. The two branches are learned jointly and end-to-end.

We adapt the fully convolutional network (FCN) approach for image-to-image tasks (Shelhamer et al., 2016) to the few-shot setting. In practice, FCNs deliver accurate and coherent pixelwise predictions, but they require too many parameters for fine-tuning to succeed as a few-shot learning method. Instead, we align the few-shot training and testing paradigms to produce a model that requires no optimization at test time.

The co-FCN is shown in schematic form in Figure 1. The segmentation branch, given conditional features or parameters, is a standard FCN that segments the query. The conditioning branch takes the support set as input and produces a spatially globally pooled prediction that informs the segmentation of the query. This prediction may consist of features which are then fused with query features, and further processed to produce the output. Alternatively, the conditioning branch may predict the parameters of the linear classification layer at the end of the query branch. We explore both choices in our experiments. Both branches are fully convolutional to decompose the problem and prevent overfitting.

For training, we synthesize few-shot segmentation tasks from a densely annotated semantic segmentation dataset. First, we sample a concept (e.g., "dog"), then sample a support set of images that contain the concept. The annotations are ground truth semantic segmentation labels binarized to encode only the sampled concept. The cross-entropy loss is computed between the prediction for the query and its binarized label. The network is directly optimized for the few-shot task; conditioning and segmentation branches are jointly optimized end-to-end. We fine-tune from ILSVRC (2010-2012) pre-training to improve stability and data efficiency. To handle k-shot learning from a support set of size k, we simply average the conditional features computed independently for each member of the support. This averaged feature is then fused with the query branch to produce the k-shot prediction.

3 Few-Shot Segmentation Results

We show results on the PASCAL VOC dataset (Everingham et al.) and its further annotations from SBDD (Hariharan et al., 2011) as is standard for semantic segmentation. See Table 1 for intersection-over-union scores. We follow the few-shot protocol of Shaban et al. (2017) by defining four splits of held-out classes, and constructing our training set from all images containing non-held-out classes. We remap any occurrences of held-out class annotations to background during training. For evaluation, we sample $1,000$ support-query tuples that contain the held-out classes. To better gauge

the effect of conditioning, we score methods on all of the data ('Overall'), and pairs in which the query image contains the reference class and other classes ('Multi'). All of our experiments measure generalization accuracy on the held-out classes.

	Overall		Multi-Class	
Method	1-Shot	5-Shot	1-Shot	5-Shot
FG-BG	52.4	-	43.6	-
Fine-tuning	55.1	55.6	44.9	45.4
Shaban et al. (2017)[1]	55.2	-	46.3	-
co-FCN (param.)	56.0	-	46.9	-
co-FCN (feat.)	**60.1**	**60.8**	**50.9**	**50.9**
Oracle	80.8	-	76.4	-

[1]Result for our re-implementation of the method - Shaban et al. (2017) reports 40.8 for 1-shot, which we believe could be the result of computing the binary mean IU metric differently.

Table 1: Few-shot segmentation evaluation on PASCAL VOC with the standard intersection-over-union (IU) metric. We follow the experimental protocol of Shaban et al. (2017) and report the mean IU achieved by each method averaged across four class-wise splits ('Overall'). We also report the mean IU achieved on query images containing multiple classes ('Multi-Class'). Our co-FCN results are shaded: feature fusion is state-of-the-art. Parameter prediction generally performs worse, whether fully convolutional or global. Note that FG-BG is a strong baseline. Oracle is trained for semantic segmentation on all classes in the dataset and scored on the same binary masks.

Baselines We compare to fine-tuning, current few-shot methods for general use, the prior work on few-shot segmentation, and foreground-background segmentation.

- Fine-tuning: As it is the standard approach to transfer learning, we try regular optimization by fine-tuning. We follow Caelles et al. (2017) by fine-tuning a pre-trained foreground-background segmentor on the support set.
- MAML Finn et al. (2017): In preliminary experiments fine-tuning from MAML did not give any improvement over fine-tuning from ILSVRC pre-training.
- Global Parameter Prediction: Shaban et al. (2017) meta-learn a conditional parameter predictor to regress the score layer parameters of a segmentor. Their predictor is global instead of local and fully convolutional. They make use of higher dimensional parameters, and so rely on weight hashing to reduce overfitting. We report results from our re-implementation of their method.
- Foreground-Background: To check that co-FCN makes use of the support, we compare against a foreground-background segmentor that is independent of the support. We train for binary segmentation on the union of training classes for each split.

4 Discussion

Fully convolutional conditioning is state-of-the-art for learning how to guide fast and accurate few-shot segmentation. In addition to being more accurate than fine-tuning, our conditional model is also much faster because it requires no optimization at test time. This makes the co-FCN suitable for interactive use, such as propagating labels to segment a personal photo collection. Our method could also be applied to automatically annotate unlabeled data. Further experiments are required to assess the ability of the model to transfer to unseen datasets.

Future work could investigate the generality of few-shot conditioning with respect to the type of segmentation task. For instance, video object segmentation requires instance-wise propagation of annotations instead of class-wise propagation as done here.

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