ADVERSARIAL LEARNING FOR SEMI-SUPERVISED SEMANTIC SEGMENTATION

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ABSTRACT

We propose a method for semi-supervised semantic segmentation using the adversarial network. While most existing discriminators are trained to classify the input images as real or fake on the image level, we apply a discriminator in a fully convolutional manner to differentiate between the predicted probability maps and the ground truth segmentation distribution with the joint consideration of the spatial resolution. We show that the proposed discriminator can be used to improve the performance on semantic segmentation by coupling the adversarial loss with the standard cross entropy loss on the segmentation network. In addition, the fully convolutional discriminator enables the semi-supervised learning through discovering the trustworthy regions in the prediction results of the unlabeled images, providing additional supervisory signals. Contrast to the existing methods that utilize weakly-labeled images, our method leverages unlabeled images without any annotation to enhance the segmentation model. The experimental results on both the PASCAL VOC 2012 dataset and the Cityscapes dataset demonstrate the effectiveness of our algorithm.

1 INTRODUCTION

Semantic segmentation is the task to assign a semantic label, e.g., person, dog, or road, to each pixel in the images. It is essential to a wide range of applications, such as autonomous driving and image editing. For decades, many methods have been proposed to tackle the task (Long et al., 2015; Zheng et al., 2015; Liu et al., 2015; Yu & Koltun, 2016; Lin et al., 2016; Yu & Koltun, 2016), and abundant standard evaluation datasets have been constructed (Everingham et al., 2010; Mottaghi et al., 2014; Cordts et al., 2016; Zhou et al., 2017), targeting different sets of scene/object categories as well as various real-world applications. However, the task remains challenging because of the object/scene appearance variations, occlusions, and the lack of context understanding. Recently, Convolutional Neural Network (CNN) based methods such as the fully convolutional neural network (FCN) (Long et al., 2015) have achieved significant improvement on the task of semantic segmentation, and most state-of-the-art methods are based on FCN with advanced modifications and additional modules.

Although CNN-based approaches have achieved astonishing performance, they require an enormous amount of training data. Different from image classification and object detection, semantic segmentation requires accurate per-pixel annotations for each training image, which can cost considerable expense and time. To ease the effort of acquiring high-quality data, semi- or weakly-supervised methods have been applied to the task of semantic segmentation. These methods often assume that there is limited or none per-pixel annotation available and exploit additional annotations on the image-level (Pinheiro & Collobert, 2015; Papandreou et al., 2015; Hong et al., 2015; Qi et al., 2016; Pathak et al., 2015a), box-level (Dai et al., 2015), or even point-level (Bearman et al., 2016).

In this paper, we propose to tackle the semi-supervised semantic segmentation with adversarial learning. The recent success of the Generative Adversarial Networks (GANs) (Goodfellow et al., 2014) enables many possibilities for unsupervised and semi-supervised learning. A typical GAN consists of two sub-networks, i.e., generator and discriminator, in which these two sub-networks play a min-max game in the training process. The generator takes a sample vector and outputs a sample of the target data distribution, e.g., human faces, while the discriminator aims to differentiate between the generated and target samples. Then the generator is trained to confuse the discriminator through back-propagation and therefore generates samples that are similar to the target distribution. In this paper, we apply a similar methodology and treat the segmentation network as the generator in a GAN

framework. Different from the typical generators that are trained to generate images given noise vectors, our segmentation network outputs the probability maps of the semantic labels given an input image. Under this setting, we wish to push the outputs of the segmentation network as close as the ground truth label maps spatially in a high-order structure, rather than only the point-wise supervision of the label maps.

To this end, we adopt an adversarial learning scheme and propose a fully convolutional discriminator that learns to differentiate between the ground truth label maps and the segmentation prediction probability maps. Combined with the standard point-wise supervision using cross-entropy loss, our method employ use an adversarial loss that encourages the segmentation network to produce prediction probability maps close to the ground truth label maps in a high-order structure. The idea is similar to the use of probabilistic graphical models such as Conditional Random Fields (CRFs) (Zheng et al., 2015; Chen et al., 2016; Lin et al., 2016), but without the extra post-processing module during the testing phase. By employing the adversarial learning, we further take advantage of the proposed fully convolutional discriminator under the semi-supervised setting.

One way to allow the discriminator to exploit unlabeled data is to train the segmentation network using the adversarial learning with the cross-entropy loss removed. However, this approach does not bring improvement according to our experiments because the adversarial loss will aggressively encourage the predictions to be close to the ground truth distribution and neglects the correctness of segmentation. Instead, we utilize the confidence maps generated by our discriminator network as the supervisory signal to guide the cross-entropy loss in a "self-taught" manner. The confidence maps indicate which regions of the prediction distribution are close to the ground truth label distribution so that the segmentation network can trust these predictions and can be trained via a masked cross-entropy loss. By adopting the proposed framework, we show that the segmentation accuracy can be further improved by adding images without any annotations in the domain of the labeled images.

The contributions of this work are as follows:

- We propose an adversarial learning framework for semantic segmentation and facilitate the semi-supervised setting by leveraging unlabeled images to aid the training of the segmentation network.
- We develop a fully-convolutional discriminator to provide spatial support instead of single confidence value for adversarial learning.
- With the trained discriminator, we present a semi-supervised algorithm to train the segmentation network via exploiting unlabeled images with the confidence maps generated by the discriminator as the supervisory signal.

2 Related Work

Fully supervised semantic segmentation. Recent state-of-the-art methods for semantic segmentation are based on the rapid development of CNN. As proposed by Long et al. (2015), one can transform a classification CNN, e.g. AlexNet (Krizhevsky et al., 2012), VGG (Simonyan & Zisserman, 2015), or ResNet (He et al., 2016), to a fully-convolutional network (FCN) that tackles the task of semantic segmentation. Many advanced methods are then proposed based on the FCN framework. To employ the long-range inference, Conditional Random Fields (CRFs) are widely used as the post-processing module of FCN (Chen et al., 2016; Zheng et al., 2015; Lin et al., 2016). Chen et al. (2016) apply the dense CRF to the output of FCN, while Zheng et al. (2015) use Recurrent Neural Network (RNN) to simulate the mean-field optimization for CRF with learnable parameters. Furthermore, Lin et al. (2016) directly train an extra network branch to learn the pair-wise potential term in the CRF.

Other than CRF, recent methods show that the context information can be exploited by introducing moderate modifications to the network structure. Yu & Koltun (2016) propose to use dilated convolution for encouraging the network to "see" more, i.e., enlarging the receptive field, and thereby more context information is perceived. In an aggressive way to consider global context, Zhao et al. (2017) add the spatial pyramid pooling layers to allow each spatial location to perceive the global features and achieve improvements on several datasets. However, these methods require a substantial amount of training data and are not guaranteed to converge well under the scenario of lacking supervised training data.

Weakly- and semi-supervised semantic segmentation. To reduce the heavy effort of labeling segmentation ground truth, many weakly-supervised approaches are proposed in recent years. In

the weakly-supervised setting, the segmentation network is not trained at the pixel level with fully annotated ground truth. Instead, the network is trained with various weak-supervisory signals that are more easily to obtain. Image-level labels are exploited as the supervisory signal in most methods. Pinheiro & Collobert (2015) and Pathak et al. (2015b) use Multiple Instance Learning (MIL) to generate latent segmentation label maps for supervised training. On the other hand, Papandreou et al. (2015) refer to the image-level labels to penalize the prediction of non-existent object classes, while similarly Qi et al. (2016) use object localization to refine the segmentation. Hong et al. (2015) refer to the labeled images to train a classification network as the feature extractor for deconvolution. In addition to image-level supervisions, the segmentation network can also be trained with bounding boxes (Dai et al., 2015; Khoreva et al., 2017), point supervision (Bearman et al., 2016), or web videos (Hong et al., 2017).

However, these weakly supervised approaches still fall behind the fully-supervised ones, especially because the detailed boundary information is difficult to infer from these weak-supervisory signals. Hence semi-supervised learning is also considered in some methods to enhance the prediction performance. In such a setting, partial fully-annotated data and optional weakly-labeled data are used for the segmentation network training. Hong et al. (2015) jointly train their network with image-level supervised images and few fully-annotated images in the encoder-decoder framework. Dai et al. (2015) and Papandreou et al. (2015) also expand their weakly-supervised approaches to the semi-supervised setting for utilizing extra strongly-annotated data.

Different from the aforementioned methods, our method can leverage unlabeled images in model training, hence greatly saving the cost of manual annotation. In fact, we treat the output of our fully convolutional discriminator as the supervisory signals, which compensate for the absence of image annotations and enable semi-supervised semantic segmentation. Our self-taught learning framework for segmentation is related to Pathak et al. (2015a) where the prediction maps of unlabeled images are used as ground truth. However, in Pathak et al. (2015a) the prediction maps are refined by several designed constraints before training, while we use the confidence map of the discriminator network as the selection criterion for self-taught learning.

Generative adversarial networks. After Goodfellow et al. (2014) propose the GAN framework and its theoretical foundation, the GAN draws recent attention with several improvements in implementation (Radford et al., 2016; Denton et al., 2015; Arjovsky et al., 2017; Mao et al., 2016; Berthelot et al., 2017). The methodology of adversarial training has been applied to a wide range of applications, including image genration (Radford et al., 2016), image completion (Li et al., 2017), super-resolution (Ledig et al., 2016), object detection (Wang et al., 2017), domain adaptation (Hoffman et al., 2016) and semantic segmentation (Luc et al., 2016; Souly et al., 2017).

The work closest in scope to ours is the one proposed by Luc et al. (2016), where the adversarial network is used to aid the training for semantic segmentation. However, it does not show substantial improvement over the baseline. On the other hand, Souly et al. (2017) propose to generate adversarial examples using GAN for semi-supervised semantic segmentation. Koziński et al. (2017) propose to use extra unlabeled data for adversarial learning. However, they train the discriminator to differentiate predictions between the training and validation sets, while in this work we train the fully convolutional discriminator with spatial support between predictions and ground truth label maps. It turns out that the output of our discriminator can serve as the supervisory signals to enable semi-supervised semantic segmentation.

3 Algorithm Overview

Figure 1 shows the overview of the proposed algorithm. Our system is composed of two networks: segmentation network and discriminator network. The segmentation one can be any network designed for semantic segmentation, e.g., FCN (Long et al., 2015), DeepLab (Chen et al., 2016), DilatedNet (Yu & Koltun, 2016). Given an input image with dimension $H \times W \times 3$, the segmentation network outputs the class probability maps of size $H \times W \times C$, where C is the number of semantic categories of the target dataset.

Our discriminator network is an FCN-based network, which takes class probability maps as the inputs, either from the segmentation network or ground truth label maps and then outputs spatial probability maps with a size of $H \times W \times 2$. The first channel of the output from the discriminator represents the probability of a sample generated from the segmentation network, while the second

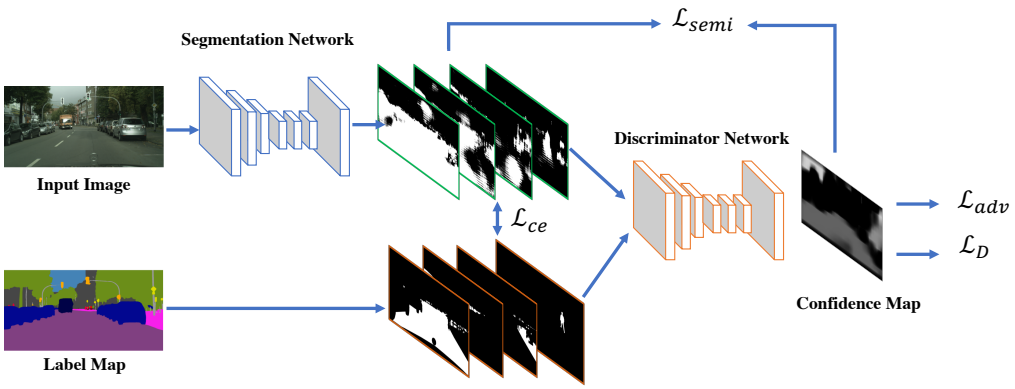

Figure 1: Overview of the proposed system for semi-supervised semantic segmentation. With a fully-convolution discriminator network trained using the loss $\mathcal{L}_D$, we optimize the segmentation netwrok using three loss functions during the training process: cross-entropy loss $\mathcal{L}_{ce}$, adversarial loss $\mathcal{L}_{adv}$, and semi-supervised loss $\mathcal{L}_{semi}$.

channel shows the probability map of a sample being the ground truth label. Contrast to the typical GAN discriminators which take fix-sized input images (64×64 in most cases) and output a single probability value, we transform our discriminator to a fully-convolutional network that can take the arbitrary size of inputs. Importantly, we find this transformation is essential to enable the proposed adversarial learning scheme.

During the training process, we use both labeled and unlabeled images under the semi-supervised setting. When using the labeled data, the segmentation network is supervised by both the standard cross-entropy loss with the ground truth label map and the adversarial loss with the discriminator network. Note that we only train the discriminator network with the labeled data.

For the unlabeled data, we train the segmentation network with the proposed semi-supervised method. After obtaining the initial segmentation prediction of the unlabeled image from the segmentation network, we obtain a confidence map by passing the segmentation prediction through the discriminator network. We then treat this confidence map as the supervisory signal using a "self-taught" scheme to train the segmentation network with a masked cross-entropy loss. The intuition is that this confidence map indicates the local quality of the predicted segmentation so that the segmentation network knows which regions to trust.

4 Semi-Supervised Training with Adversarial Network

In this section, we address the detailed learning scheme of the segmentation and discriminator networks, as well as the designed network architectures.

4.1 Training Scheme

Given an input image $\mathbf{X}_n$ with the dimension of $H \times W \times 3$, we denote the segmentation network as $S(\cdot)$ and the predicted probability map as $S(\mathbf{X}_n)$ with the dimension of $H \times W \times C$, where C is the category number. For our fully-convolutional discriminator, we denote it as $D(\cdot)$ that outputs a two-class confidence map $D(\mathbf{P}_n)$ with the size of $H \times W \times 2$, where $\mathbf{P}_n$ is the class probability map with the size of $H \times W \times C$, from either the ground truth label Y_n or the segmentation network as $S(\mathbf{X}_n)$.

Discriminator network training. To train the discriminator network, we minimize the spatial cross-entropy loss $\mathcal{L}_D$ with respect to two classes. The loss can be formally written as:

$$\mathcal{L}_D = -\sum_{h,w} (1 - y_n) \log(D(\mathbf{P}_n)^{(h,w,0)}) + y_n \log(D(\mathbf{P}_n)^{(h,w,1)}), \tag{1}$$

where $y_n = 0$ if the sample is drawn from the segmentation network, and $y_n = 1$ if the sample is from the ground truth label. Note that, the discriminator network takes a C-channel probability map

as input. In order to convert the ground truth label map Y_n with the size of $H \times W \times 1$ to C channels, we employ the simplest one-hot encoding scheme by constructing the probability maps P_n, where $P_n^{(h,w,c)} = 1$ if and only if $Y_n^{(h,w)} = c$.

One concern raised by (Luc et al., 2016) is that the discriminator network may easily distinguish whether the probability maps come from the ground truth by detecting the one-hot probability. However, we do not observe this phenomenon during the training phase. One reason is that we use a fully-convolutional scheme to predict spatial confidence, which increases the difficulty to learn the discriminator. In addition, we try the *Scale* scheme proposed in (Luc et al., 2016), where the ground truth probability channel is slightly diffused to other channels according to the distribution of segmentation network output. However, the results show no difference, and thus we do not adopt this scheme in the experiments.

Segmentation network training. We propose to train the segmentation network via minimizing a multi-task loss function:

$$\mathcal{L}_{seg} = L_{ce} + \lambda_{adv}\mathcal{L}_{adv} + \lambda_{semi}\mathcal{L}_{semi}, \tag{2}$$

where $\mathcal{L}_{ce}$ denotes the standard spatial multi-class cross entropy loss, $\mathcal{L}_{adv}$ denotes the adversarial loss, and $\mathcal{L}_{semi}$ denotes the semi-supervised loss. λ_{adv} and λ_{semi} are two constants for balancing the multi-task training.

We first consider the scenario using annotated data. Given an input image $\mathbf{X}_n$, ground truth $\mathbf{Y}_n$ and prediction results $\mathbf{P}_n = S(\mathbf{X}_n)$, we obtain the cross-entropy loss as:

$$\mathcal{L}_{ce} = -\sum_{h,w}\sum_{c\in C} Y_n^{(h,w,c)} \log(\mathbf{P}_n^{(h,w,c)}). \tag{3}$$

We adopt the adversarial learning through the adversarial loss $\mathcal{L}_{adv}$ given a fully-convolutional discriminator network $D(\cdot)$:

$$\mathcal{L}_{adv} = -\sum_{h,w} \log(D(\mathbf{P}_n)^{(h,w,1)}). \tag{4}$$

With this adversarial loss, we seek to train the segmentation network to fool the discriminator by maximizing the probability of the segmentation prediction being considered as the ground truth distribution (label 1).

Training with unlabeled data. Now we consider the adversarial training under the semi-supervised setting. For unlabeled data, it is obvious that we cannot apply $\mathcal{L}_{ce}$ since there is no ground truth annotation available. The adversarial loss $\mathcal{L}_{adv}$ is still applicable as it only requires the discriminator network. We observe that the gradients computed by $\mathcal{L}_{adv}$ are always toward the correct direction, i.e. the ground truth classes. However, we find that the performance deprecates when applying the adversarial loss on unlabeled data without $\mathcal{L}_{ce}$. This is reasonable because the discriminator is served as a regularization and might over-correct the prediction to fit the ground truth distribution.

Thus, we propose to utilize the trained discriminator with unlabeled data using a "self-taught" strategy. The main idea is that the trained discriminator can generate a confidence map, i.e. $D(\mathbf{P}_n)^{(h,w,1)}$, which infers some regions of the prediction results are close enough to the ground truth distribution. We then apply this confidence map on the prediction $\hat{Y}_n$ and generate a masked prediction as the self-taught ground truth. We denote the semi-supervised loss as:

$$\mathcal{L}_{semi} = -\sum_{h,w}\sum_{c\in C} \hat{Y}_n^{(h,w,c)} \log(\mathbf{P}_n^{(h,w,c)}) \cdot I(D(\mathbf{P}_n)^{(h,w,1)} > T_{semi}), \tag{5}$$

where T_{semi} is the threshold to control the sensitivity of the self-taught process. In practice, we find that this strategy works for a reasonable range of T_{semi} (0.3-0.6).

4.2 Network Architecture

Segmentation network. We adopt the DeepLab-v2 (Chen et al., 2016) framework with ResNet-101 (He et al., 2016) model pre-trained on the ImageNet dataset (Deng et al., 2009) as our segmentation baseline network. However, we do not employ the multi-scale fusion proposed in Chen

et al. (2016) due to memory concern. Following the practice of recent work on semantic segmentation (Chen et al., 2016; Yu & Koltun, 2016), we remove the last classification layer and modify the stride of the last two convolution layers from 2 to 1, making the resolution of the output feature maps effectively $1/8\times$ of the input image size. To enlarge the receptive fields, we apply the dilated convolution (Yu & Koltun, 2016) to the conv4 and conv5 layers with a stride of 2 and 4, respectively. After the last layer, we employ the Atrous Spatial Pyramid Pooling (ASPP) proposed in Chen et al. (2016) as the final classifier. Finally, we apply an 8x up-sampling layer on the final layer along with the softmax output to match the size of input image.

Discriminator network. For the discriminator network, we follow the structure used in Radford et al. (2016). It consists of the 5 convolution layers with kernel 4×4 with channel numbers {64, 128, 256, 512, 1} and stride of 2. Each convolution layer is followed by a Leaky-ReLU parameterized by 0.2 except the last layer. To transform the network to a fully-convolutional network, a 32x up-sampling layer is added on the last layer to rescale the output to the size of the input map. Note that we do not employ the batch-normalization layers. We find that the batch-normalization layer is highly unstable since the system can be only trained with a small batch size.

5 Experimental Results

Implementation details. We implement our network using the PyTorch framework. We train our system on a single TitanX GPU with 12 GB memory. Throughout the training, we use the Stochastic Gradient Descent (SGD) with the Nesterov acceleration as the optimizer, where the momentum to 0.9 and the weight decay to 1e-4.. The initial learning rate is set to 2.5e-4 and is decreased with polynomial decay with power 0.9 as mentioned in Chen et al. (2016).

For semi-supervised training, we randomly interleave the labeled data and unlabeled data iteratively and apply the training scheme described in section 4.1 accordingly. We update both the segmentation network and discriminator network jointly. In each iteration, only the batch containing the ground truth data are used for training the discriminator. When randomly sampling partial labeled and unlabeled data from the datasets, we average several experiment results with different random seeds to ensure the evaluation fairness.

Evaluation datasets and metric. In this work, we conduct the experiments on two representative semantic segmentation datasets: PASCAL VOC 2012 (Everingham et al., 2010) and Cityscapes (Cordts et al., 2016). While the PASCAL VOC dataset contains the common objects in photos captured in daily activities, the Cityscapes dataset mainly targets the urban scene understanding. On both datasets, we use the mean Intersection over Union (mean IU) as the evaluation metric.

The PASCAL VOC 2012 dataset is a commonly used evaluation dataset for semantic segmentation. It comprises 20 common objects with annotations on daily captured photos. We use the extra annotation set in SBD (Hariharan et al., 2011), resulting in 10,582 training images. We evaluate our models on the standard validation set with 1449 images. During training, we employ the random scaling and cropping with size 321×321. We train each model on the PASCAL VOC dataset for 20k iterations with batch size 10.

The Cityscapes dataset has 50 videos with driving scenes, and 2975, 500, 1525 images are extracted and annotated with 19 classes for training, validation, and testing, respectively. Each annotated frame is the 20th frame in a 30-frames snippet, where only these images with annotations are considered in the training process. We resize the input image to 512×1024 without any random cropping/scaling. We train each model on the Cityscapes dataset for 40k iterations with batch size 2.

Results on the PASCAL VOC 2012 dataset. Table 1 shows the evaluation results on the PASCAL VOC 2012 dataset. To validate the semi-supervising scheme, we randomly sample 1/8, 1/4, 1/2 images as labeled, and used the rest of training images as the unlabeled data for the proposed semi-supervised learning. We show the performance comparisons with FCN (Long et al., 2015), Dilation10 (Yu & Koltun, 2016), and DeepLab-v2 (Chen et al., 2016) to demonstrate that our baseline model is comparable with other state-of-the-art methods. Note that our baseline model is equivalent to the DeepLab-v2 model without multi-scale fusion. The adversarial loss brings consistent performance improvement ($1.6\% - 2.8\%$) over different amounts of training data. Incorporating the proposed semi-supervised learning brings overall $2.8\% - 3.4\%$ improvement. We notice that our proposed

Table 1: Results on the VOC 2012 *validation* set.

Methods	Data Amount 1/8	1/4	1/2	Full
FCN-8s (Long et al., 2015)	N/A	N/A	N/A	67.2
Dilation10 (Yu & Koltun, 2016)	N/A	N/A	N/A	73.9
DeepLab-v2 (Chen et al., 2016)	N/A	N/A	N/A	77.7
our baseline	66	68.3	69.8	73.6
baseline + $\mathcal{L}_{adv}$	67.6	71	72.6	74.9
baseline + $\mathcal{L}_{adv}$ + $\mathcal{L}_{semi}$	68.8	71.6	73.2	N/A

Table 2: Results on the Cityscapes *validation* set.

Methods	Data Amount 1/8	1/4	1/2	Full
FCN-8s (Long et al., 2015)	N/A	N/A	N/A	65.3
Dilation10 (Yu & Koltun, 2016)	N/A	N/A	N/A	67.1
DeepLab-v2 (Chen et al., 2016)	N/A	N/A	N/A	70.4
our baseline	52.4	58.3	62.6	66.4
baseline + $\mathcal{L}_{adv}$	53.8	59.1	63.7	67.7
baseline + $\mathcal{L}_{adv}$ + $\mathcal{L}_{semi}$	54.2	59.7	64.5	N/A

Table 3: Adversarial learning comparison with Luc et al. (2016) on VOC 2012 *validation* set.

	Baseline	Adversarial
Luc et al. (2016)	71.8	72.0
ours	73.6	74.9

Table 4: Semi-supervised learning comparisons on VOC 2012 *validation* set without using additional labels of SBD.

	Data Amount	Fully-supervised	Semi-supervised
Papandreou et al. (2015)	Full	62.5	64.6
Souly et al. (2017)	Full	59.5	64.1
ours	Full	66.3	68.4
Souly et al. (2017)	30%	38.9	42.2
ours	30%	57.4	60.6

semi-supervised method brings consistent 0.8% improvement on top of the adversarial learning though different amount of unlabeled data is used.

Figure 3 shows a visual comparison of the segmentation results generated by the proposed method. We observe that the segmentation boundary has significant improvement when compared the baseline model.

Results on the Cityscapes dataset. Table 2 shows the evaluation results on the Cityscapes dataset. By applying the adversarial loss $\mathcal{L}_{adv}$, the model achieves $0.8\% - 1.4\%$ gain over the baseline model under the semi-supervised setting. This shows that our adversarial training scheme can encourage the segmentation network to learn the structural information from the ground truth distribution. Combining the adversarial learning and proposed semi-supervised learning, the performance further improves with $0.4\% - 0.8\%$ mean IU gain.

Comparisons with state-of-the-art methods We show the adversarial learning comparison with Luc et al. (2016) in Table 3. There are some differences of the adversarial setup between Luc et al. (2016) and our method. First, we employ the standard DCGAN (Radford et al., 2016) discriminator network while Luc et al. (2016) design network structures for different datasets. Second, our discriminator network does not take the RGB image as additional input and directly work on prediction map. Finally, we use the one-hot encoding for the ground truth transform while Luc et al. (2016) propose *Scale* scheme to diffuse the ground truth probability map.

We show the semi-supervised learning comparisons in Table 4. To compare with Papandreou et al. (2015) and Souly et al. (2017), we train our model on the original PASCAL VOC 2012 train set (1464 images) without the additional SBD annotations (Hariharan et al., 2011), and use the rest of images as the unlabeled data. It is worth noting that in Papandreou et al. (2015) the image level labels are available for the rest images outside the train set, and in Souly et al. (2017) the additional unlabeled images are generated through their generator.

Hyper parameter analysis. Our proposed algorithm is parametrized by three hyper parameters: λ_{adv} and λ_{semi} are two parameters for balancing the multi-tasking learning in (2), and T_{semi} is used to control the sensitivity in the semi-supervised learning described in (5). We evaluate these hyper parameters using the PASCAL VOC dataset under the fully- and semi-supervised setting. We show the comparison results of different parameter settings in Table 5. We first evaluate the effect on λ_{adv} using fully-supervised setting. Note that we do not any unlabeled data, i.e. $\lambda_{semi} = 0$. The baseline model without adversarial learning ($\lambda_{adv} = 0$) achieves 73.6% mean IU. When $\lambda_{adv} = 0.01$, the model achieves 74.9% mean IU with 1.3% improvement. When $\lambda_{adv} = 0.05$, the performance deprecates to 73.0% mean IU, which indicates that the adversarial loss is too large.

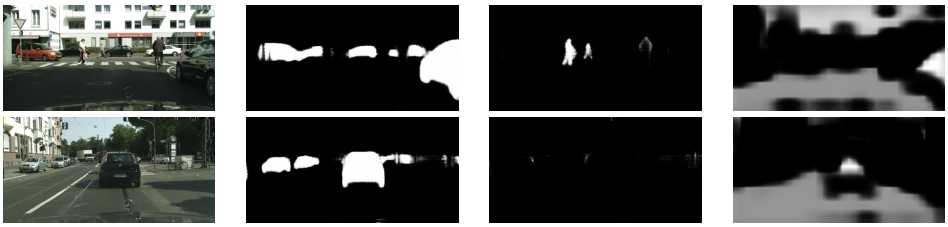

Figure 2: Visualization of the confidence maps. Given the probability maps generated by the segmentation network, the confidence maps is then obtained from the discriminator. In the confidence maps, the brighter regions indicate that they are close to the ground truth distribution.

Second, we show the comparisons of different values of λ_{semi} with 1/8 amount of data under the semi-supervised setting. We set $\lambda_{adv} = 0.1$ and $T_{semi} = 0.2$ for the comparisons. Overall, $\lambda_{semi} = 0.1$ achieves the best performance of 68.8% mean IU with 1.2% gain.

Lastly, we perform the experiments with different value of T_{semi}, where we set $\lambda_{adv} = 0.01$ and $\lambda_{semi} = 0.1$. High T_{semi} suggests that we only trust regions of high structural similarity with the ground truth distribution. We find that our proposed strategy performs well for a wide range of values of T_{semi} (0.1-0.3). The method performs best when $T_{semi} = 0.2$. When $T_{semi} = 0$, we trust all the pixel predictions in unlabeled images, resulting performance degradation. In Figure 2 we show the visualization of generated confidence maps given the predicted probability maps.

Ablation study. We present the ablation study of our proposed system in Table 6 on the PASCAL VOC dataset. First, we examine the impact of using fully convolutional discriminator (FCD). To construct a discriminator that is not fully-convolutional, we replace the last convolution layer of the discriminator with a fully-connected layer that outputs a single neuron as in typical GAN models(Radford et al., 2016; Goodfellow et al., 2014), while we perform bilinear resizing on the segmentation output map to 32x32. As a result, the performance becomes worse (-1.0% using full data and -0.9% with 1/8 data). This shows that the use of the fully-convolutional discriminator network is essential to the performance of the adversarial learning. Second, we apply the semi-supervised learning method without the adversarial loss. The results show that the adversarial training on the labeled data is important to our semi-supervised scheme. If the segmentation network does not seek to fool the discriminator, the confidence maps generated by the discriminator would be meaningless, providing weaker supervisory signals.

Table 5: Hyper parameter analysis.

Data Amount	λ_{adv}	λ_{semi}	T_{semi}	Mean IU
Full	0	0	N/A	73.6
Full	0.005	0	N/A	74.0
Full	0.01	0	N/A	74.9
Full	0.02	0	N/A	74.6
Full	0.04	0	N/A	74.1
Full	0.05	0	N/A	73.0
1/8	0.01	0	N/A	67.6
1/8	0.01	0.05	0.2	68.6
1/8	0.01	0.1	0.2	68.8
1/8	0.01	0.2	0.2	68.5
1/8	0.01	0.1	0	66.5
1/8	0.01	0.1	0.1	68.0
1/8	0.01	0.1	0.2	68.8
1/8	0.01	0.1	0.3	68.7
1/8	0.01	0.1	1.0	67.6

Table 6: Ablation study of the proposed method on the PASCAL VOC dataset.

$\mathcal{L}_{adv}$	$\mathcal{L}_{semi}$	FCD	Data Amount 1/8	Data Amount Full
			66.0	73.6
✓		✓	67.6	74.9
✓			66.6	74.0
	✓	✓	65.7	N/A
✓	✓	✓	68.8	N/A

6 Conclusions

In this work, we propose an adversarial learning scheme for semi-supervised semantic segmentation. We train a fully convolutional discriminator network to enhance the segmentation network with both

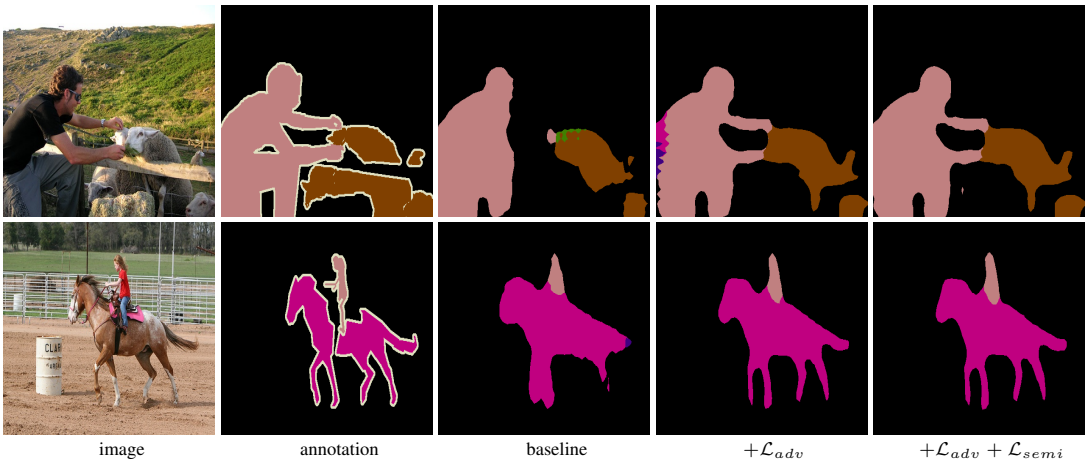

Figure 3: Comparisons on the PASCAL VOC 2012 dataset using 1/2 labeled data.

labeled and unlabeled data. With labeled data, the adversarial loss for the segmentation network is designed to learn higher order structural information without post-processing. For unlabeled data, the confidence maps generated by the discriminator network act as the self-taught signal for refining the segmentation network. Extensive experiments on the Cityscapes dataset and on the PASCAL VOC 2012 dataset are performed to validate the effectiveness of the proposed algorithm.

REFERENCES

Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein gan. *arXiv preprint arXiv:1701.07875*, 2017.

Amy Bearman, Olga Russakovsky, Vittorio Ferrari, and Li Fei-Fei. What's the point: Semantic segmentation with point supervision. In *ECCV*, 2016.

David Berthelot, Tom Schumm, and Luke Metz. Began: Boundary equilibrium generative adversarial networks. *arXiv preprint arXiv:1703.10717*, 2017.

Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. In *arXiv:1606.00915*, 2016.

Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *CVPR*, 2016.

Jifeng Dai, Kaiming He, and Jian Sun. Boxsup: Exploiting bounding boxes to supervise convolutional networks for semantic segmentation. In *ICCV*, 2015.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, 2009.

Emily L Denton, Soumith Chintala, Rob Fergus, et al. Deep generative image models using a laplacian pyramid of adversarial networks. In *NIPS*, 2015.

Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. In *IJCV*, 2010.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *NIPS*, 2014.

Bharath Hariharan, Pablo Arbeláez, Lubomir Bourdev, Subhransu Maji, and Jitendra Malik. Semantic contours from inverse detectors. In *ICCV*, 2011.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

Judy Hoffman, Dequan Wang, Fisher Yu, and Trevor Darrell. Fcns in the wild: Pixel-level adversarial and constraint-based adaptation. In *arXiv preprint arXiv:1612.02649*, 2016.

Seunghoon Hong, Hyeonwoo Noh, and Bohyung Han. Decoupled deep neural network for semi-supervised semantic segmentation. In *NIPS*, 2015.

Seunghoon Hong, Donghun Yeo, Suha Kwak, Honglak Lee, and Bohyung Han. Weakly supervised semantic segmentation using web-crawled videos. In *CVPR*, 2017.

A. Khoreva, R. Benenson, J. Hosang, M. Hein, and B. Schiele. Simple does it: Weakly supervised instance and semantic segmentation. In *CVPR*, 2017.

Mateusz Koziński, Loïc Simon, and Frédéric Jurie. An adversarial regularisation for semi-supervised training of structured output neural networks. In *arXiv preprint arXiv:1702.02382*, 2017.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012.

Christian Ledig, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, et al. Photo-realistic single image super-resolution using a generative adversarial network. In *arXiv preprint arXiv:1609.04802*, 2016.

Yijun Li, Sifei Liu, Jimei Yang, and Ming-Hsuan Yang. Generative face completion. In *CVPR*, 2017.

Guosheng Lin, Chunhua Shen, Anton van dan Hengel, and Ian Reid. Efficient piecewise training of deep structured models for semantic segmentation. In *CVPR*, 2016.

Ziwei Liu, Xiaoxiao Li, Ping Luo, Chen Change Loy, and Xiaoou Tang. Semantic Image Segmentation via Deep Parsing Network. In *ICCV*, 2015.

Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *CVPR*, 2015.

Pauline Luc, Camille Couprie, Soumith Chintala, and Jakob Verbeek. Semantic segmentation using adversarial networks. In *NIPS Workshop on Adversarial Training*, 2016.

Xudong Mao, Qing Li, Haoran Xie, Raymond YK Lau, and Zhen Wang. Multi-class generative adversarial networks with the l2 loss function. *arXiv preprint arXiv:1611.04076*, 2016.

Roozbeh Mottaghi, Xianjie Chen, Xiaobai Liu, Nam-Gyu Cho, Seong-Whan Lee, Sanja Fidler, Raquel Urtasun, and Alan Yuille. The Role of Context for Object Detection and Semantic Segmentation in the Wild. In *CVPR*, 2014.

George Papandreou, Liang-Chieh Chen, Kevin Murphy, and Alan L Yuille. Weakly-and semi-supervised learning of a dcnn for semantic image segmentation. In *ICCV*, 2015.

Deepak Pathak, Philipp Krahenbuhl, and Trevor Darrell. Constrained convolutional neural networks for weakly supervised segmentation. In *ICCV*, 2015a.

Deepak Pathak, Evan Shelhamer, Jonathan Long, and Trevor Darrell. Fully convolutional multi-class multiple instance learning. In *ICLR*, 2015b.

Pedro O Pinheiro and Ronan Collobert. Weakly supervised semantic segmentation with convolutional networks. In *CVPR*, 2015.

Xiaojuan Qi, Zhengzhe Liu, Jianping Shi, Hengshuang Zhao, and Jiaya Jia. Augmented feedback in semantic segmentation under image level supervision. In *ECCV*, 2016.

Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In *ICLR*, 2016.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In *ICLR*, 2015.

Nasim Souly, Concetto Spampinato, and Mubarak Shah. Semi and weakly supervised semantic segmentation using generative adversarial network. In *ICCV*, 2017.

Xiaolong Wang, Abhinav Shrivastava, and Abhinav Gupta. A-fast-rcnn: Hard positive generation via adversary for object detection. In *CVPR*, 2017.

Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. In *ICLR*, 2016.

Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In *CVPR*, 2017.

Shuai Zheng, Sadeep Jayasumana, Bernardino Romera-Paredes, Vibhav Vineet, Zhizhong Su, Dalong Du, Chang Huang, and Philip HS Torr. Conditional random fields as recurrent neural networks. In *ICCV*, 2015.

Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Semantic understanding of scenes through the ade20k dataset. In *CVPR*, 2017.