Semi-Supervised Semantic Segmentation via Dynamic Self-Training and Class-Balanced Curriculum

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Abstract. In this work, we propose a novel and concise approach for semi-supervised semantic segmentation. The major challenge of this task lies in how to exploit unlabeled data efficiently and thoroughly. Previous state-of-the-art methods utilize unlabeled data by GAN-based self-training or consistency regularization. However, these methods either suffer from noisy self-supervision and class-imbalance, resulting in a low unlabeled data utilization rate, or do not consider the apparent link between self-training and consistency regularization. Our method, Dynamic Self-Training and Class-Balanced Curriculum (DST-CBC), exploits inter-model disagreement by prediction confidence to construct a dynamic loss robust against pseudo label noise, enabling it to extend pseudo labeling to a class-balanced curriculum learning process. While we further show that our method implicitly includes consistency regularization. Thus, DST-CBC not only exploits unlabeled data efficiently, but also thoroughly utilizes all unlabeled data. Without using adversarial training or any kind of modification to the network architecture, DST-CBC outperforms existing methods on different datasets across all labeled ratios, bringing semi-supervised learning yet another step closer to match the performance of fully-supervised learning for semantic segmentation. Our code and data splits are available at: https://github.com/voldemortX/DST-CBC.

Keywords: semi-supervised semantic segmentation, self-training, curriculum learning

1 Introduction

Semantic segmentation has unprecedentedly improved as a typical dense prediction task that predicts semantic labels for every pixel, ever since the introduction of the fully convolutional networks [24]. Recent works [5, 19, 23, 35] further push the performance of semantic segmentation systems to a new height. However, the success of recent seman-

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Fig. 1. Illustration of dynamic self-training. (a) Predicted probabilities from the current model (orange) in training. (b) Predicted probabilities from the previous best-performing model (blue). (c) Generated pseudo label. We choose the confidence of the current model to derive the weight for dynamic loss. As low-confidence suggests the current model disagrees with the previous model that generated the pseudo labels, this indicates possible pseudo label error. While the confidence of the pseudo labeling model is not as informative and could amplify high-confidence errors.

Semi-supervised semantic segmentation methods builds upon the heavy cost of manual labeling. As we show in our experiments (See Table 3 Baseline), even carefully tuned, the performance of a semantic segmentation network still degrades rapidly with limited annotations. Moreover, Cordts et al. [7] have reported an 1.5h average annotation time on one high-resolution urban scene image, which renders it infeasible to produce a large well-labeled semantic segmentation dataset. One way to reduce labor-intensive manual annotations is to label only a small part of the dataset, then use semi-supervised learning techniques to utilize the remaining unlabeled data.

Originated from the idea of entropy minimization [11], a line of methods has been proposed to somehow generate pseudo supervision from the model itself in absence of manual supervision, i.e., self-training [18]. But the pseudo labels tend to be incorrect, often a pseudo label selection scheme is needed, e.g., confidence thresholding [37, 39]. Recent semi-supervised semantic segmentation methods [15, 26] use a complex GAN-based mechanism to select high-quality pseudo labels online, which integrates a discriminator to distinguish between real labels and fake labels. Thus, when a pseudo label is real enough, it is selected as supervision. Despite their efforts, the major drawback from self-training, pseudo label noise still remains. Proved by their observations that only $27\% \sim 36\%$ pixels can be pseudo labeled without leading to degraded performance [15], while the other unlabeled data are left unexploited.

There is another drawback from the process of selecting top-confident pseudo labels: easier (high-confidence) classes often dominate self-training due to the class-imbalance problem in semantic segmentation. This yet remains unmentioned in the
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In the semi-supervised semantic segmentation literature, only Zou et al. [39] have confronted this problem in another similar task that is also in need of exploiting unlabeled data for semantic segmentation. To tackle this problem, they propose an iterative pseudo labeling scheme where they pseudo label a larger fraction of unlabeled data at every self-training round, with the pseudo labels fairly distributed across different classes. However, even with class-balancing, they still can only pseudo label a relatively small fraction of the unlabeled data (30% ~ 50%) [39, 38].

In this paper, we mainly consider two drawbacks in self-training: pseudo label noise and class-imbalance. Our Dynamic Self-Training and Class-Balanced Curriculum (DST-CBC) 1) regards the current model’s confidence as a cue of disagreement between the current model and its previous self1, to further identify possible incorrect pseudo labels, providing a more robust dynamic self-training loss (see Fig. 1), complimentary to selecting top-confident pseudo labels offline; and 2) with this pseudo label noise tolerance provided by dynamic self-training, DST-CBC draws inspiration from [39] and formulates a class-balanced labeling curriculum, where more unlabeled data are gradually labeled in an easy-to-complex curriculum learning [1] fashion, pushing the unlabeled data utilization rate to 100%. Note that our method does not introduce any extra networks, the performance gains we report are solely from exploiting unlabeled data.

There also exists another line of methods that have achieved great performance in semi-supervised learning, which enforces prediction consistency after perturbation, especially with a teacher-student architecture [36]. Consistency regularization has been introduced to semantic segmentation only recently [10]. We show with theoretical insights in section 3.2, by generating pseudo labels for the original images offline and conducting self-training with data augmentation, DST-CBC implicitly enforces the consistency between the perturbed images and the original unperturbed images through pseudo supervision. The best-performing model from the previous self-training round, which generates pseudo labels for the current round, acts as the teacher.

Therefore, DST-CBC combines the advantage of both entropy minimization and consistency regularization, along with label noise robustness and class-balanced curriculum learning in one concise framework.

Our contributions are summarized as follows:

- We propose DST-CBC, a novel framework that exploits inter-model disagreement by prediction confidence to achieve robust self-training, and further facilitates the formulation of a class-balanced pseudo labeling curriculum to efficiently exploit all unlabeled data for semi-supervised semantic segmentation.
- We explain how offline self-training with data augmentation combines the merits of both entropy minimization and consistency regularization through theoretical insights and experiments.
- We demonstrate via extensive and realistic [28] experiments that DST-CBC outperforms previous state-of-the-art methods on both PASCAL VOC 2012 and Cityscapes across all labeled ratios.

1In self-training, we fine-tune from the pseudo labeling model, so terms previous self.
2 Related Works

2.1 Semi-supervised Learning and Semantic Segmentation

Semi-supervised learning [3] is a long-going topic in the machine learning industry. In recent years, it has attracted much attention in image classification [36, 28, 16, 2]. However, semantic segmentation is a much more complex dense prediction task. It is reported that semi-supervised learning methods derived for classification do not necessarily work well with semantic segmentation [10]. Nonetheless, all semi-supervised learning methods work by explicitly or implicitly injecting some form of prior knowledge in absence of ample manual annotations.

There are two major kinds of prior knowledge that have seen success in semi-supervised semantic segmentation. The first approach exploits consistency regularization, especially with a teacher-student architecture [36], it basically means similar inputs should yield similar outputs. This approach has been introduced to semi-supervised semantic segmentation by high-dimensional data augmentation [10]. The second approach is based on entropy minimization [11], it encourages the network to make confident decisions on unlabeled data, closely related to self-training [18]. In [15], an additional discriminator is added to select real enough predictions as pseudo labels. Concurrent to our work, Mittal et al. [26] build upon [15] and further combine the first approach by adding another multi-label mean teacher (MLMT) branch. However, methods that based on entropy minimization never properly consider the pseudo label noise. Through a robust self-training loss, our method explicitly exploits entropy minimization and implicitly exploits consistency regularization accordingly in one concise framework.

There are also other approaches that have utilized to address semi-supervised semantic segmentation or related tasks. Souly et al. [34] directly use a GAN with an additional fake class to exploit unlabeled data; Peng et al. [30] tackle semi-supervised CT or MRI scan segmentation by co-training an ensemble where individual models are enforced to agree on unlabeled data. Differently in dynamic self-training, we perceive disagreement between the current model predictions and the pseudo labels as a signal to down-weight the loss; also with MRI scans. MASSL [6] exploits the unlabeled data by an auxiliary reconstruction task, drawing inspiration from earlier work with the ladder networks [31], while Kervadec et al. [17] use self-training on a task curriculum with an auxiliary target-size prediction task. However, up until now, these methods have not demonstrated good results on complex semantic segmentation datasets, e.g. PASCAL VOC 2012, Cityscapes.

2.2 Unsupervised Domain Adaptation for Semantic Segmentation

Since the emergence of the GTAV [32] and SYNTHIA [33] datasets, attentions are drawn to adapt models learned in a well-labeled synthetic dataset to unlabeled real dataset, i.e. unsupervised domain adaptation (UDA). UDA has ample labeled data in one domain, e.g. synthetic, and unlabeled data in another domain, e.g. realistic. While semi-supervised learning has only limited labeled data, but in the same domain as the unlabeled data. These are different tasks, but they do share similarities by having partial labeled data.
We focus on the self-training based approaches in UDA for semantic segmentation. In [39], UDA is cast as an expectation-minimization problem by iterating between pseudo labeling the unlabeled data with class-balancing and attaining a new model with the new pseudo labels, Zou et al. [38] further add entropy regularization, they achieve comparable performance with other state-of-the-art UDA methods. Self-training is later used as an incremental part in complex UDA systems [20].

However, these methods do not have a robust self-training scheme like ours. With our dynamic self-training, we are able to extend the class-balanced pseudo labeling process in [39] to a complete labeling curriculum, labeling more data at every round until all are pseudo labeled.

2.3 Curriculum Learning

Curriculum learning proposes a learning process like humans, i.e. from easy to complex. It is observed to reach a better local optima in non-convex optimization problems [1].

There are two types of curriculum in semantic segmentation with unlabeled data. The first type composes a task curriculum where tasks easier than pixel-level segmentation is added. This idea has been introduced in UDA [37, 21], as well as semi-supervised segmentation of MRI scans [17], often with a network modified for multi-tasking. The second type gradually learns from easy to complex with the same task. In [39, 38], self-training is cast as an iterative process where more data are pseudo labeled at each iteration. Similarly, we integrate a class-balanced curriculum to learn from more confident (easier) pseudo labels first, and gradually utilize all pseudo labels.

3 Dynamic Self-training and Class-Balanced Curriculum

Dynamic Self-Training and Class-Balanced Curriculum (DST-CBC) is a framework composed of two complimentary components. An overview is illustrated in Fig. 2. Dynamic self-training processes labeled data and unlabeled data together (1:1 in a mini-batch) but differently. It applies standard cross-entropy loss on labeled data, while it exploits unlabeled data by training with pseudo labels and calculating a robust dynamic loss based on the current model’s confidence. Class-balanced curriculum breaks the self-training process into identical rounds, where pseudo labels within each round are generated offline by the best-performing model from the previous round.

The rest of this section is organized as follows: first, in section 3.1, we introduce the robust loss used in dynamic self-training; next, in section 3.2, we explain in detail how offline self-training works with data augmentation; last, we specify the class-balanced labeling curriculum in section 3.3.

3.1 Dynamic Self-Training

Dynamic self-training differs from vanilla self-training by dynamically weighting the losses for pseudo labeled data according to the current model’s confidence.

Self-training utilizes pseudo labels generated by a model, rather than human annotators. Therefore, the pseudo labels tend to be incorrect, similar to the scenario of learning with noisy labels [27].
In order to tolerate pseudo label noise while not completely discard part of the unlabeled data, we perfect the vanilla self-training process via a more robust loss $L_r$ that is dynamically weighted by different weights $\omega \in \mathbb{R}^{H \times W}$ at every pixel:

$$L_r = \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} \sum_{c=0}^{C-1} \omega^{(i,j)}(f_{\text{cur}}(x^{(i,j,c)})) y^{(i,j,c)},$$

(1)

$f_{\text{cur}}(\cdot)$ is the current model, $x \in \mathbb{R}^{H \times W \times C}$ is an unlabeled image, and $y \in \mathbb{R}^{H \times W \times C}$ is its corresponding one-hot pseudo label.

The dynamic weights $\omega$ is a pixel-wise weight map generated according to the current model’s confidence (see Fig. 1). More specifically, dynamic weight for spatial location $(i, j)$ is defined as:

$$\omega^{(i,j)} = \sum_{c=0}^{C-1} y^{(i,j,c)}(f_{\text{cur}}(x))^{(i,j,c)} \gamma.$$

(2)

Here a pixel ignored in pseudo labeling due to low-confidence is annotated by $y^{(i, j)} = 0$. $\gamma$ is a hyperparameter, larger $\gamma$ assigns relatively less weight at low-confidence pixels.

Note that this is different from other self-training methods [37, 21, 39, 38] that utilize the confidence from the original pseudo labeling process. Through the class-balanced pseudo labeling curriculum, we already utilize the that confidence by selecting top-confident pseudo labels. As the current model diverges from its previous self, dynamic self-training further utilizes the inter-model disagreement to identify incorrect pseudo labels on-the-fly. This is effective especially when the pseudo labeling ratio
is high, allowing the self-training process to salvage learnable information form noisy pseudo labels. Moreover, dynamic self-training can also detect high-confidence errors made by the pseudo labeling model, if the original confidence of the pseudo labeling model is used as dynamic weights, these errors will only be amplified, leading to degraded performance.

3.2 Offline Self-Training with Data Augmentation

First we clarify the definitions of online and offline self-training: in a semi-supervised learning setting, by different manners of pseudo labeling, self-training can be classified as **offline self-training**, where pseudo labels are generated offline by a specific model [39], e.g. the model learned with only labeled data, this is related to the expectation-minimization algorithm [8], where the pseudo labels can be seen as unobserved latent variables; or **online self-training**, where the pseudo labels are selected online, within training process by the model itself [15, 26, 21], this is more closely related to direct entropy minimization.

Now in the rest of this subsection, we explain in detail why entropy minimization and consistency regularization can be brought together by offline self-training with data augmentation.

Without loss of generality, let us define $x$ as an unlabeled image, and let $f(\cdot)$ denote a classification model which outputs a probability distribution over classes.

The idea of entropy minimization literally means to minimize the entropy $H$ on the probability distribution outputted by the model:

$$H = - \sum_{c=0}^{C-1} p_c \log(p_c),$$

(3)

where $C$ is the number of classes, and $p_c$ is the probability assigned to class $c$. It is clear that $H$ is minimized when any class has a probability of 1. In self-training, high confidence predictions are selected as hard pseudo labels, encouraging the most probable class to have a probability of 1, thus minimizes the entropy.

Quite differently, consistency-based methods often use the mean squared error (MSE) loss $L_{mse}$ to enforce outputs from two differently perturbed versions of the same unlabeled image to be similar:

$$L_{mse} = ||f(g_1(x)) - f(g_2(x))||_2^2.$$  

(4)

Here $g_1(\cdot)$ and $g_2(\cdot)$ represent different image transformations (or sometimes called noises). The better-performing teacher-student architecture [36] does not use the same network $f(\cdot)$ with these differently perturbed images, rather it integrates an exponential moving average of the student model’s weights as the teacher model. With a teacher-student architecture, eq. (4) becomes:

$$L_{mse} = ||t(g_1(x)) - s(g_2(x))||_2^2,$$

(5)

where $t(\cdot)$ and $s(\cdot)$ refers to the teacher model and the student model respectively. The teacher model can be viewed as a special form of online-ensemble of the student model.
Thus, from the viewpoint of knowledge distillation [14], the teacher is more suitable to supervise the student, while the student distills knowledge from it.

In DST-CBC, which is a form of offline self-training, the pseudo label \( l = \text{argmax} (f_{\text{off}}(x)) \) is generated by the best-performing model \( f_{\text{off}}(\cdot) \) from the previous self-training round. There are no perturbation or very small perturbation such as resizing to a fixed size. While in the current self-training round, complex data augmentation strategies \( g_n(\cdot) \) are used on \( x \). Therefore, output \( f(g_n(x)) \) from the current model \( f_{\text{cur}}(\cdot) \) is constrained to be similar to the prediction of the unperturbed image \( f_{\text{off}}(x) \). Only here we use a cross-entropy loss instead of MSE loss with \( l \) as the label. The best-performing model \( f_{\text{off}} \) acts as the teacher, while the current model in training acts as the student. And the teacher is suitable to supervise the student because it takes in images without noises. Therefore, through offline self-training with data augmentation, consistency regularization in a teacher-student style is implicitly combined with entropy minimization.

We point out that the difference between \( f_{\text{off}}(\cdot) \) and \( f_{\text{cur}}(\cdot) \) is usually more significant than in the teacher-student architecture, this could lead to even better performance [16].

### 3.3 Class-Balanced Curriculum

In this subsection we specify the details of our pseudo labeling process.

In the class-balanced curriculum, we use an offline pseudo labeling process similar to [39]. As analyzed in section 3.2, the pseudo labels can be better utilized if they are generated offline.

The generation of pseudo labels is naturally related to prediction confidence. Concretely, a pixel \( x \)'s pseudo label \( l \), given network \( f(\cdot) \) that predicts a probability distribution, is chosen by:

\[
l = \begin{cases} 
    \text{argmax}(f(x)), & \text{max}(f(x)) > T \\
    \text{IGNORE}, & \text{otherwise}.
\end{cases}
\]

Here \( T \) is a threshold in range \([0, 1)\). IGNORE denotes labels ignored in the pseudo labeling process because of low-confidence.

We rank the confidence of all the pixels classified to each class. Then select top-confident pseudo labels in every class with the same ratio \( \alpha \). Therefore, the pseudo labeling process is class-balanced, easier classes will not dominate the pseudo label selection based on prediction confidence.

We increase \( \alpha \) at each self-training round and fine-tune the best-performing model from the previous round. In DST-CBC, we specify 5 self-training rounds with \( \alpha = 20\%, 40\%, 60\%, 80\%, 100\% \), respectively. Pseudo labels for the first self-training round is generated by the model trained on the manually annotated part of the dataset alone by standard fully-supervised learning.
Algorithm 1: Pseudo labeling process

Input: Network \( f(\cdot) \) used to generate pseudo labels, all unlabeled images \( X \), labeling ratio \( \alpha \), number of classes \( C \).

Output: Pseudo labels \( Y \).

1. \( N = \text{length}(X) \);
2. \( R = \{r_0, r_1, \ldots, r_{C-1}\} \);
3. for \( i = 1 \) to \( N \) do
   4. \( p = f(X_i) \);
   5. \( ml = \text{argmax}(p) \);
   6. \( mp = \text{max}(p) \);
   7. for \( j = 0 \) to \( C - 1 \) do
      8. \( r_j = \text{concat}(r_j, mp[ml == j]) \);
   9. \( T = \{t_0, t_1, \ldots, t_{C-1}\} \);
10. for \( j = 0 \) to \( C - 1 \) do
    11. \( \text{sort}(r_j) \);
    12. \( t_j = r_j[\alpha \times \text{length}(r_j)] \);
13. for \( i = 1 \) to \( N \) do
14. \( p = f(X_i) \);
15. \( c = \text{argmax}(p) \);
16. \( mp = \text{max}(p) \);
17. \( Y_i[mp > t_c] = c \);
18. \( Y_i[mp \leq t_c] = \text{IGNORE} \);
19. return \( Y \);

The pseudo labeling process in each self-training round is summarized in Algorithm 1. Line 1-8 accumulate all the confidences. In practice, however, we observe only sampling 5% \( \sim \) 10% of pixels is enough to provide a good threshold estimation. Line 9-12 rank the confidences for each class. Line 13-18 assign the final pseudo labels for top \( \alpha \) confident pixels, while ignore the others.

4 Experiments

4.1 Datasets

We conduct our experiments on PASCAL VOC 2012 [9] and Cityscapes [7].

The PASCAL VOC 2012 dataset captures common objects with 21 classes, including the background class. In our experiments, 10582 images (plus the extra annotations from SBD [12]) are used for training, and 1449 images form the \textit{val} set, which is used for evaluations. We split the training set to different labeled ratios (1/106, 1/50, 1/20, 1/8, 1/4 and 1) from 3 different random shuffles. More specifically, at each random shuffle of the whole training set, we take the first 1/106, 1/50 etc. as labeled data. In this way we ensure a larger labeled ratio is strictly superior than corresponding smaller labeled ratios.
The Cityscapes dataset contains urban driving scenes from 50 cities. Images for semantic segmentation are annotated as 19 classes. 2975 images that have fine annotations are used for training, 500 images are used as the val set. Similar to [10, 26], we down-sample all the images by a factor of 2 to a spatial resolution of 513 × 1025. We also randomly split the training set to different labeled ratios (1/30, 1/8, 1/4, 1) like in PASCAL VOC 2012.

4.2 Implementation Details

In all our experiments, we use the same DeeplabV2 model as [10, 15, 26], which utilizes a ResNet-101 [13] backbone pre-trained on MSCOCO [22], equivalent to the original DeeplabV2 model without multi-scale fusion [4]. Note that we do not use the adversarial training in [15, 26], thus we have a lower oracle performance when training with all labels. While Hung et al. [15] report improvement from adversarial training alone, without exploiting the unlabeled data. However, their original oracle performance without adversarial training is 73.6% mean IoU on PASCAL VOC 2012, roughly the same as ours (73.5%).

We implement our method using the PyTorch [29] framework and mixed precision training [25], all experiments are conducted on a single RTX 2080Ti GPU. We train our models using a batch size of 8. In self-training, 8 images in one batch is consisted of 4 labeled images and 4 unlabeled images (although a customized ratio might bring better performance, we do not tune it in this work), and the concept of an epoch means traversing all unlabeled data one time.

In training, we use SGD with momentum 0.9 and the poly learning rate schedule [4]. Learning rate and weight decay are set to \(2 \times 10^{-3}\) and \(5 \times 10^{-4}\) at fully-supervised learning. Data augmentations include random resizing, random cropping and random flipping. On PASCAL VOC 2012, we train and pseudo label at a spatial resolution of 321 × 321 and train for \((30 \times \sqrt{\frac{1}{\text{labeled ratio}}})\) epochs in fully-supervised learning, 6 epochs in each self-training round; on Cityscapes, we train and pseudo label at 257×513 and double the number of training epochs.

If not specified, all reported numbers in our experiments are averaged from 3 runs on 3 different random data splits in term of mean intersection-over-union (mean IoU).

4.3 Results

Our dynamic self-training loss introduces a new hyperparameter \(\gamma\) (see eq. 2). Therefore, we first empirically fix the learning rate and weight decay values, and show the impact of using different \(\gamma\) in Table 1. \(\gamma = 0\) is equivalent to standard cross-entropy loss; a higher \(\gamma\) gives low-confident pseudo labels relatively less weight in dynamic training, thus is more robust to errors; a smaller \(\gamma\) (e.g. \(\gamma < 1\)) even degrades the performance. The best performance is achieved by \(\gamma = 9\).

We also find that the importance of learning rate and weight decay choice is often ignored in works concerning self-training. Thus, we fix \(\gamma = 9\) and experiment with a few different learning rates and weight decays in Table 2. The results demonstrate that
Table 1. Fixed learning rate of $2 \times 10^{-3}$ and weight decay of $1 \times 10^{-3}$, different $\gamma$ with PASCAL VOC 2012 1/20 random split 1

| $\gamma$ | mean IoU (%) |
|----------|--------------|
| 0        | 67.63        |
| 0.5      | 66.61        |
| 1        | 68.49        |
| 3        | 69.12        |
| 5        | 69.28        |
| 8        | 69.87        |
| 9        | **69.98**    |
| 10       | 69.72        |
| 12       | 69.29        |

Table 2. Effects of learning rate (lr) and weight decay (wd) with PASCAL VOC 2012 1/20 random split 1

| lr       | mean IoU (%) | wd       | mean IoU (%) |
|----------|--------------|----------|--------------|
| $4 \times 10^{-3}$ | 66.71        | $2 \times 10^{-3}$ | 68.28        |
| $2 \times 10^{-3}$ | **69.98**    | $1 \times 10^{-3}$ | 69.98        |
| $1 \times 10^{-3}$ | 69.50        | $5 \times 10^{-4}$ | **70.33**    |
| $5 \times 10^{-4}$ | 67.36        | $2.5 \times 10^{-4}$ | 69.89        |

(a) $\gamma = 9$, wd = $1 \times 10^{-3}$

(b) $\gamma = 9$, lr = $2 \times 10^{-3}$

the choice of learning rate and weight decay does matter in self-training (2% – 3% in mean IoU).

Other methods that use fine-tuning in self-training usually choose a smaller learning rate than in fully-supervised learning. While we find that a larger learning rate (same as in fully-supervised learning) yields better performance. This could be due to the larger inter-model divergence caused by a larger learning rate, making the dynamic weights more informative and consistency regularization stronger. The theories behind this insight are outside the scope of this paper.

Note that all our experiments in searching of the final method and hyperparameter configuration, including the ablation study, are all conducted with random split 1. We only run experiments once on the other 2 random splits to provide the averaged numbers. Because using an average across different random splits here will be equivalent to exploiting more data, although will probably lead to a better hyperparameter choice.

We further complete our experiments on PASCAL VOC 2012 using the best hyperparameter setting found earlier. Only empirically scale down $\gamma$ to 4 when we have more than 1000 labels on PASCAL VOC 2012, since the pseudo labels are supposed to have better quality. As shown in Table 3, DST-CBC outperforms previous state-of-the-art methods by a large margin with extremely limited labels (100 labels, 1/50, 1/20). Although DST-CBC seems to have inferior results measured by absolute mean IoU performance on some labeled ratios (1/8, 1/4), we argue that the overall goal of semi-supervised learning is to reach the performance of its fully-supervised counterpart (oracle) by exploiting unlabeled data. Thus, we also list the relative mean IoU performance below, where our method shows consistent superiority. We believe further hyperparameter search on each labeled ratio could lead to better performance, but we do not delve into that in this work.
Table 3. Mean IoU (%) results and comparisons with other methods on PASCAL VOC 2012 val set

| method                  | 1/106 (100 labels) | 1/50 | 1/20 | 1/8  | 1/4  | full (oracle) |
|-------------------------|--------------------|------|------|------|------|---------------|
| Baseline (DeeplabV2)    | 45.7 [44.8]        | 55.4 | 62.2 | 66.2 | 68.7 | 73.5          |
| CowMix [10]             | 52.1               | -    | -    | -    | 71.0 | 73.4          |
| [15]                    | 38.8†              | 57.2* | 64.7* | 69.5 | 72.1 | 74.9          |
| S4GAN + MLMT [26]       | -                  | 63.3 | 67.2 | 71.4 | -    | 75.6          |
| Ours (DST-CBC)          | 61.6 [59.2]        | 65.5 | 69.3 | 70.7 | 71.8 | 73.5          |

Relative Performance

| Baseline (DeeplabV2)    | 62.2% [61.0%]      | 75.4% | 84.6% | 90.1% | 93.5% | 100%          |
| CowMix [10]             | 71.0%              | -     | -     | -     | 96.7% | 100%          |
| [15]                    | 51.8%†             | 76.4%* | 86.4%* | 92.8% | 96.3% | 100%          |
| S4GAN + MLMT [26]       | -                  | 83.7% | 88.9% | 94.4% | -    | 100%          |
| Ours (DST-CBC)          | 83.8% [80.5%]      | 89.1% | 94.3% | 96.2% | 97.7% | 100%          |

* reported by [26], † reported by [10].

We then use the same hyperparameters on Cityscapes, only doubled the learning rate since we observe by training loss that the self-training process can not fully converge with learning rate \(2 \times 10^{-3}\). As demonstrated in Table 4, without additional hyperparameter tuning, DST-CBC still outperforms other methods in term of relative performance.

Since we solely exploit the unlabeled data without improving the fully-supervised baseline, we have a relatively lower fully-supervised oracle performance. However, as suggested in [28], we report carefully tuned baseline results on limited data, some results appear considerably higher than in other works.

We also experiment with very small validation sets to provide realistic evaluations on the most extreme labeled ratio (only 100 labeled images), because the validation set is 14 times larger than the training set (5 times larger on Cityscapes), the setting of semi-supervised learning is hardly realistic [28]. We refer to this small validation set as valtiny. valtiny has 20 images and 19 images on PASCAL VOC 2012 and Cityscapes respectively, i.e. roughly one image for each class. Therefore, the original val set is used as a test set. We report performance from models trained with valtiny to validate and select the best model at each self-training round, as well as at fully-supervised baseline training phase on Table 3 and Table 4 (results in []). Up to 2.4% mean IoU drop due to wrong model selection in self-training is observed. Note that even using the smallest possible validation set, our method still outperforms CowMix [10], which is the method that claims to have better performance with extremely limited data. To the best of our knowledge, we are the first to experiment with valtiny on semi-supervised semantic segmentation.
Table 4. Mean IoU (%) results and comparisons with other methods on Cityscapes val set

| method                           | 1/30 (100 labels) | 1/8  | 1/4  | full (oracle) |
|----------------------------------|-------------------|------|------|---------------|
| Baseline (DeeplabV2)             | 45.5 [45.4]       | 56.7 | 61.1 | 66.9          |
| CowMix [10]                      | 49.0              | 60.5 | 64.1 | 69.0          |
| [15]                             | -                 | 58.8 | 62.3 | 67.7          |
| S4GAN + MLMT [26]                | -                 | 59.3*| 61.9*| 65.8*         |
| Ours (DST-CBC)                   | 48.7 [48.2]       | 60.5 | 64.4 | 66.9          |

Relative Performance

| method                           | 68.0% [67.9%]     | 84.8% | 91.3% | 100%          |
|----------------------------------|-------------------|------|------|---------------|
| Baseline (DeeplabV2)             | 71.0%             | 87.7% | 92.9% | 100%          |
| CowMix [10]                      | -                 | 86.9% | 92.0% | 100%          |
| [15]                             | -                 | 90.1%*| 94.1%*| 100%*         |
| Ours (DST-CBC)                   | **72.8% [72.0%]** | 90.4%| 96.3% | 100%          |

* use the same baseline model but without COCO-pretraining.

4.4 Ablation Study

In this subsection, we first break DST-CBC apart and show the improvements brought by each part in Table 5a. We observe that by pseudo labeling all data and conduct vanilla offline self-training for 30 epochs (ST), there is already decent performance, almost on par or better than other methods. Adding dynamic weights on ST (DST) gives 2.55% increase in mean IoU. Further breaking the 30 epochs to 5 class-balanced curriculum rounds (DST-CBC), another 1.17% boost is observed. However, when the curriculum is not class-balanced (DST-C), dynamic weighting leads to degraded performance (−1.49%).

Then instead of calculating the dynamic weights on-the-fly (DST-CBC), we store the original confidence of the previous best-performing model that generated the pseudo labels, and use them to replace dynamic weights (OW). The performance degradation by using these weights is severe, because high-confidence mistakes from the pseudo labels are amplified. The performance is even worse than simple ST (66.38% vs. 66.61%). Therefore, the importance of exploiting the inter-model disagreement to infer incorrect pseudo labels is verified.

We also design experiments to confirm the insights from section 3.2, results shown in Table 5b. First we take the pseudo labeling process online (OST), but the performance deteriorates rapidly in training, a fixed confidence threshold of 0.9 has to be used to stabilize online self-training (OST-T). Only limited performance gain can be observed by online self-training (+1.62% compared to Baseline), which is equivalent to entropy minimization alone. Since online self-training is more sensitive to pseudo label noise and is already inferior because of that, we then try and quantify the effect of consistency regularization by turning data augmentation off for the pseudo labeled data to better illustrate the point (noted by -NA). The performance degradation from offline self-training is fairly significant (−0.96%). While almost not noticeable for online self-
Because even with data augmentation, the teacher-student style consistency regularization can not be enforced if the pseudo labels are generated online. Thus, the superiority brought by entropy minimization and consistency regularization in offline self-training with data augmentation is verified.

| method          | mean IoU (%) | method          | mean IoU (%) |
|-----------------|--------------|-----------------|--------------|
| Baseline (DeeplabV2) | 61.68        | ST              | 66.61        |
| ST              | 66.61        | ST-NA           | 65.65 (−0.96)|
| DST             | 69.16        | OST-T           | 63.30        |
| DST-C           | 67.67        | OST-T-NA        | 62.95 (−0.35)|
| DST-CBC         | 70.33        | OST             | 61.96        |
| OW              | 66.38        | OST-NA          | 61.98 (−0.02)|

(a) Different parts of DST-CBC  (b) Effect of consistency

5 Conclusions

In this paper, we have presented Dynamic Self-Training and Class-Balanced Curriculum (DST-CBC) for semi-supervised semantic segmentation. Two complimentary components have been proposed, Dynamic Self-Training and Class-Balanced Curriculum, where the former aims to achieve pseudo label noise robustness in self-training through weighting the per-pixel loss with prediction confidence, and the latter builds upon that robustness, provides a pseudo labeling curriculum to progressively label all unlabeled data. We evaluate the proposed method on both PASCAL VOC 2012 and Cityscapes with realistic considerations. The experiments clearly demonstrate the effectiveness of DST-CBC over other state-of-the-art methods, also prove our analysis of the link between entropy minimization and consistency regularization through offline self-training with data augmentation.

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Supplementary Materials for “Semi-Supervised Semantic Segmentation via Dynamic Self-Training and Class-Balanced Curriculum”

A.1 Detailed Results of DST-CBC

As demonstrated in Fig. 3, DST-CBC improves performance at every self-training round. Round 0 represents the fully-supervised baseline with only manually labeled data. We observe that at self-training round 2, where 40% unlabeled data are pseudo labeled, the performance of DST-CBC reaches the performance of vanilla offline self-training (66.58% vs. 66.61%), while the overall self-training epochs are far fewer at this point (2 × 6 = 12 vs. 30). However, DST-CBC has none or limited improvement in self-training round 5 on Cityscapes (see Fig. 4), that is not so surprising, since the Cityscapes dataset has no background class, the original ground truth labels only covered around 88% pixels. Thus, using the word all to describe pseudo label coverage in DST-CBC is hardly partial.

In Fig. 5, we resize the ground truth labels to match the spatial resolution of pseudo labels, and test for the pseudo labeling mean IoU (note that this evaluation scheme is a bit different from the standard scheme we use in other experiments where ground truth labels remain unchanged). The results show the final pseudo labeling accuracy from a class-balanced curriculum, i.e. round 5, is considerably higher than in vanilla offline self-training (∼6%).

![Fig. 3. Mean IoU (%) performance of DST-CBC on each self-training round with 1/20 random split 1, PASCAL VOC 2012. Red dotted line represents vanilla offline self-training performance.](image-url)
Fig. 4. Mean IoU (%) performance of DST-CBC on each self-training round with 1/8 random split 1, Cityscapes.

Fig. 5. Pseudo label mean IoU (%) of DST-CBC on each self-training round with 1/20 random split 1, PASCAL VOC 2012. Red dotted line represents the pseudo label mean IoU of vanilla offline self-training.
A.2 Data Augmentations

Table 6. Data augmentation schemes used sequentially in training.

|                  | PASCAL VOC 2012                  | Cityscapes               |
|------------------|---------------------------------|--------------------------|
| random resize    | $321 \times 321 \sim 505 \times 505$ | $257 \times 513 \sim 513 \times 1025$ |
| random crop      | $321 \times 321$                | $257 \times 513$         |
| random horizontal flip (probability) | 50%                             | 50%                      |