Semi-Supervised Semantic Segmentation via Gentle Teaching Assistant

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Abstract

Semi-Supervised Semantic Segmentation aims at training the segmentation model with limited labeled data and a large amount of unlabeled data. To effectively leverage the unlabeled data, pseudo labeling, along with the teacher-student framework, is widely adopted in semi-supervised semantic segmentation. Though proved to be effective, this paradigm suffers from incorrect pseudo labels which inevitably exist and are taken as auxiliary training data. To alleviate the negative impact of incorrect pseudo labels, we delve into the current Semi-Supervised Semantic Segmentation frameworks. We argue that the unlabeled data with pseudo labels can facilitate the learning of representative features in the feature extractor, but it is unreliable to supervise the mask predictor. Motivated by this consideration, we propose a novel framework, **Gentle Teaching Assistant (GTA-Seg)** to disentangle the effects of pseudo labels on feature extractor and mask predictor of the student model. Specifically, in addition to the original teacher-student framework, our method introduces a teaching assistant network which directly learns from pseudo labels generated by the teacher network. The gentle teaching assistant (GTA) is coined gentle since it only transfers the beneficial feature representation knowledge in the feature extractor to the student model in an Exponential Moving Average (EMA) manner, protecting the student model from the negative influences caused by unreliable pseudo labels in the mask predictor. The student model is also supervised by reliable labeled data to train an accurate mask predictor, further facilitating feature representation. Extensive experiment results on benchmark datasets validate that our method shows competitive performance against previous methods. We promise to release our code towards reproducibility.

1 Introduction

The rapid development in deep learning has brought significant advances to semantic segmentation [25, 4, 47] which is one of the most fundamental tasks in computer vision. Existing methods often heavily rely on numerous pixel-wise annotated data, which is labor-exhausting and expensive. Towards this burden, great interests have been aroused in Semi-Supervised Semantic Segmentation, which attempts to train a semantic segmentation model with limited labeled data and a large amount of unlabeled data.

The key challenge in semi-supervised learning is to effectively leverage the abundant unlabeled data. One widely adopted strategy is pseudo labeling [23]. As shown in Figure 1, the model assigns pseudo labels to unlabeled data based on the model predictions on-the-fly. These data with pseudo labels will be taken as auxiliary supervision during training to boost performance. To further facilitate semi-supervised learning, the teacher-student framework [37, 41, 38] is incorporated. The teacher model, which is the Exponential Moving Average (EMA) of the student model, is responsible for

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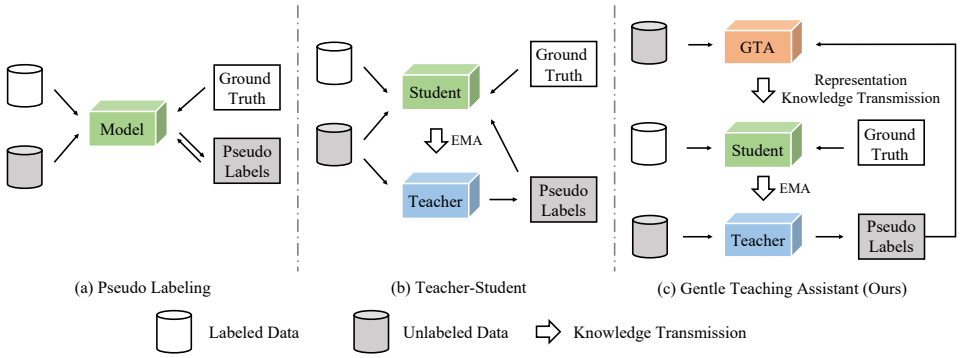

Figure 1: **Comparison with previous frameworks.** **(a)** The vanilla pseudo labeling framework. The model generates pseudo labels by itself and in turn, learns from them. **(b)** The pseudo labeling with the teacher-student framework. The teacher model is responsible for generating pseudo labels while the student model learns from the pseudo labels and the ground-truth labels simultaneously. Knowledge Transmission is conducted between the two models via Exponential Moving Average (EMA) of all parameters. **(c)** Our method attaches a gentle teaching assistant (GTA) module to the teacher-student framework. Different from the original one in (b), the gentle teaching assistant (GTA) learns from the pseudo labels while the student model only learns from ground-truth labels. We design the representation knowledge transmission between the GTA and student to mitigate the negative influence caused by unreliable pseudo labels.

generating smoothly updated pseudo labels. Via jointly supervised by limited data with ground-truth labels and abundant data with pseudo labels, the student model can learn more representative features, leading to significant performance gains.

Although shown to be effective, the pseudo labeling paradigm suffers from unreliable pseudo labels, leading to inaccurate mask predictions. Previous research work alleviates this problem by filtering out predictions that are lower than a threshold of classification scores [2, 34, 45]. However, this mechanism can not perfectly filter out wrong predictions, because some wrong predictions may have high classification scores, named over-confidence or mis-calibration [15] phenomenon. Moreover, a high threshold will heavily reduce the number of generated pseudo labels, limiting the effectiveness of semi-supervised learning.

Towards the aforementioned challenge, it is necessary to propose a new pseudo labeling paradigm that can learn representative features from unlabeled data as well as avoid negative influences caused by unreliable pseudo labels. Delving into the semantic segmentation framework, it is composed of a feature extractor and a mask predictor. Previous works ask the feature extractor and the mask predictor to learn from both ground-truth labels and pseudo labels simultaneously. As a result, the accuracy of the model is harmed by incorrect pseudo labels. To better leverage the unlabeled data with pseudo labels, a viable solution is to let the feature extractor learn feature representation from both ground-truth labels and pseudo labels, while the mask predictor only learns from ground-truth labels to predict accurate segmentation results.

Accordingly, we propose a novel framework, Semi-Supervised Semantic Segmentation via **Gentle Teaching Assitant (GTA-Seg)**, which attaches an additional gentle teaching assistant (GTA) module to the original teacher-student framework. Figure 1 compares our method with previous frameworks. In our method, the teacher model generates pseudo labels for unlabeled data and the gentle teaching assistant (GTA) learns from these unlabeled data. Only knowledge of the feature extractor in the gentle teacher assistant (GTA) is conveyed to the feature extractor of the student model via Exponential Moving Average (EMA). We coin this process as **representation knowledge transmission**. Meanwhile, the student model also learns from the reliable ground-truth labels to optimize both the feature extractor and mask predictor. The gentle teaching assistant (GTA) is called gentle since it not only transfers the beneficial feature representation knowledge to the student model, but also protects the student model from the negative influences caused by unreliable pseudo labels in the mask predictor. Furthermore, a re-weighting mechanism is further adopted for pseudo labels to suppress unreliable pixels.

Extensive experiments have validated that our method shows competitive performance on mainstream benchmarks, proving that it can make better utilization of unlabeled data. In addition, we can observe from the visualization results that our method boasts clearer contour and more accurate classification for objects, which indicates better segmentation performance.

2 Related Work

Semantic Segmentation Semantic Segmentation, aiming at predicting the label of each pixel in the image, is one of the most fundamental tasks in computer vision. In order to obtain the dense predictions, FCN [25] replaces the original fully-connected layer in the classification model with convolution layers. The famous encoder-decoder structure is borrowed to further refine the pixel-level outputs [29, 1]. Meanwhile, intensive efforts have been made to design network components that are suitable for semantic segmentation. Among them, dilated convolution [43] is proposed to enhance receptive fields, global and pyramid pooling [24, 4, 47] are shown to be effective in modeling context information, and various attention modules [46, 48, 12, 19, 36] are adopted to capture the pixel relations in images. These works mark milestones in this important computer vision task, but they pay rare attention to the data-scarce scenarios.

Semi-Supervised Learning Mainstream methods in Semi-Supervised Learning [50] (SSL) fall into two lines of work, self-training [14, 23] and consistency reguralization [22, 33, 28, 40, 37]. The core spirit of self-training is to utilize the model predictions to learn from unlabeled data. Pseudo Labeling [23], which converts model predictions on unlabeled data to one-hot labels, is a widely-used technique [2, 34, 45] in semi-supervised learning. Another variant of self-training, entropy minimization [32], is also proved to be effective both theoretically [39] and empirically [14]. Consistency Regularization [33, 40] forces the model to obtain consistent predictions when perturbations are imposed on the unlabeled data. Some recent works unveil that self-training and consistency regularization can cooperate harmoniously. MixMatch [2] is a pioneering holistic method and boasts remarkable performance. On the basis of MixMatch, Fixmatch [34] further simplify the learning process while FlexMatch [45] introduces a class-wise confidence threshold to boost model performance.

Semi-Supervised Semantic Segmentation Semi-Supervised Semantic Segmentation aims at pixel-level classification. Borrowing the spirit of Semi-Supervised Learning, self-training and consistency regularization gives birth to various methods. One line of work [51, 6, 18, 38] applies pseudo labeling in self-training to acquire auxiliary supervision, while methods based on consistency pursue stable outputs at both feature [21, 49] and prediction level [31]. Apart from them, Generative Adversarial Networks (GANs) [13] are often leveraged to provide additional supervision in relatively early methods [35, 27, 20]. Some recent works [44] unveil another interesting phenomenon that the most fundamental training paradigm, equipped with strong data augmentations, can serve as a simple yet effective baseline. In this paper, we shed light on semi-supervised semantic segmentation based on pseudo labeling and strives to alleviate the negative influence caused by noisy pseudo labels.

3 Method

3.1 Preliminaries

Semi-Supervised Semantic Segmentaion In Semi-Supervised Semantic Segmentation, we train a model with limited labeled data $D_l = \{x_i^l, y_i^l\}_{i=1}^{N^l}$ and a large amount of unlabeled data $D_u = \{x_i^u, y_i^u\}_{i=1}^{N^u}$, where N^u is often much larger than N^l. The semantic segmentation network is composed of the feature extractor f and the mask predictor g. The key challenge of Semi-Supervised Semantic Segmentation is to make good use of the numerous unlabeled data. And one common solution is pseudo labeling [23, 42].

Pseudo Labeling Pseudo Labeling is a widely adopted technique for semi-supervised segmentation, which assigns pseudo labels to unlabeled data according to model predictions on-the-fly. Assuming there are $\mathcal{K}$ categories, considering the jth pixel on the ith image, the model prediction p_{ij}^u and the corresponding confidence c_{ij}^u will be

$$p_{ij}^u = g(f(x_{ij}^u)),\ c_{ij}^u = \max_k p_{ij}^u,\ \text{with } k \in \mathcal{K}, \tag{1}$$

where larger c_{ij}^u indicates that the model is more certain on this pixel, which is consequently, more suitable for generating pseudo labels. Specifically, we often keep the pixels whose confidence value is greater than one threshold, and generate pseudo labels as

$$\hat{y}_{ij}^u = \begin{cases} \arg\max_k p_{ij}^u, & c_{ij}^u > \gamma_t \\ \text{ignore}, & \text{otherwise} \end{cases}, \tag{2}$$

where γ_t is the confidence threshold at the t iteration. We note that γ_t can be a constant or a varied value during training. The jth pixel on i^{th} image with a confidence value larger than γ_t will be assigned with pseudo label $\hat{y}_{ij}^u$. The unlabeled data that are assigned with pseudo labels will be taken as auxiliary training data, while the other unlabeled data will be ignored.

Teacher-Student Framework Teacher-Student [37, 38] framework is a currently widely applied paradigm in Semi-Supervised Segmentation. This framework consists of one teacher model and one student model. The teacher model is responsible for generating pseudo labels while the student model learns from both the ground-truth labels and pseudo labels. Therefore, the loss for the student model is

$$L = L_l + \mu L_u, L_u = \sum_i \sum_j L_{ce}(x_{ij}^u, \hat{y}_{ij}^u) \tag{3}$$

In Semi-Supervised Semantic Segmentation, L_l and L_u are the cross-entropy loss on labeled data and unlabeled data with pseudo labels, respectively [38], and μ is a loss weight to adjust the trade-off between them. The optimization of the student model can be formulated as

$$\theta^{student} := \theta^{student} - \lambda \frac{\partial L}{\partial \theta^{student}}, \tag{4}$$

where λ denotes the learning rate. In the Teacher-Student framework, after the parameters of the student model are updated, the parameters of the teacher model will be updated by the student parameters in an Exponential Moving Average (EMA) manner.

$$\theta^{teacher}(t) = \alpha\theta^{teacher}(t-1) + (1-\alpha)\theta^{student}(t), \tag{5}$$

where $\theta^{teacher}(t)$ and $\theta^{student}(t)$ denote the parameters of the teacher and student model at t-th iteration, respectively. α is a hyper-parameter in EMA, where $\alpha \in [0, 1]$.

3.2 Gentle Teaching Assistant

In this section, we will introduce our Gentle Teaching Assistant framework for semi-supervised semantic segmentation (GTA-Seg), as shown in Figure 2, which consists of the following three steps.

Step 1: Pseudo Label Generation and Re-weighting. Similar to previous work [38], the teacher model is responsible for generating pseudo labels. A confidence threshold is also adopted to filter out the pseudo labels with low confidence. For the kept pixels, instead of treating all of them equally, we propose a re-weighting mechanism according to the confidence of each pixel as follows,

$$w_{ij}^u = \frac{(c_{ij}^u + \tau) \cdot 1(c_{ij}^u > \gamma_t)}{\sum_i \sum_j (c_{ij}^u + \tau) \cdot 1(c_{ij}^u > \gamma_t)} \cdot \sum_i \sum_j 1(c_{ij}^u > \gamma_t). \tag{6}$$

In our re-weighting strategy, the pixel with higher confidence will be highlighted while the other will be suppressed. As a result, the negative influence caused by unreliable pseudo labels can be further alleviated. We adopt Laplace Smoothing [26] to avoid over penalization where τ is a predefined coefficient. With this re-weighting mechanism, the unsupervised loss on unlabeled data becomes

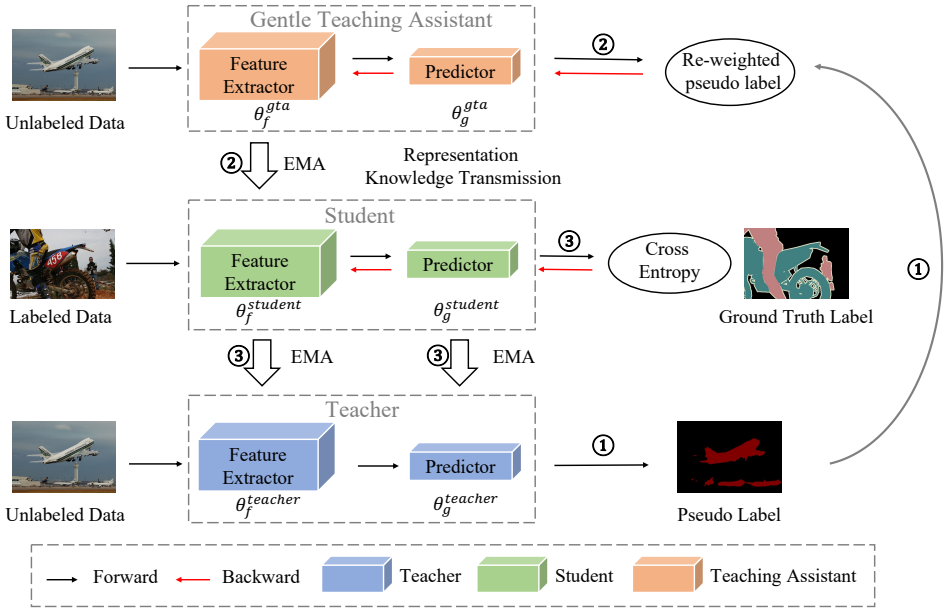

Figure 2: **Method Overview.** Our Gentle Teaching Assistant (GTA) framework can be divided into three steps. **Step 1**: The teacher model generates pseudo labels and then the gentle teaching assistant can learn from them. One re-weighting strategy is incorporated to assign importance weights to the generated pseudo labels. **Step 2**: The gentle teaching assistant model performs representation knowledge transmission, which only conveys the learned knowledge in the feature extractor to the student model via Exponential Moving Average (EMA). **Step 3**: After absorbing the knowledge from our gentle teaching assistant, the student model learns from ground-truth labels and optimizes all parameters. Finally, the parameters of the teacher model will also be updated according to the student model via EMA at the end of each training iteration.

$$L_u = \sum_i \sum_j w_{ij}^u L_{ce}(x_{ij}^u, \hat{y}_{ij}^u). \tag{7}$$

Step 2: Representation Knowledge Transmission via Gentle Teaching Assistant (GTA). Gentle Teaching Assistant (GTA) plays a crucial role in our framework. Previous works force the student model to learn from both labeled and unlabeled data simultaneously. Although the unlabeled data with pseudo labels can help the student model learn more representative features, we argue that it is dangerous to treat ground-truth labels and pseudo labels equally since the incorrect pseudo labels will mislead the mask prediction. Therefore, we want to disentangle the effects of pseudo labels on feature extractor and mask predictor of the student model. Concretely, our solution is to introduce one additional gentle teaching assistant, which learns from the unlabeled data and only transfers the beneficial feature representation knowledge to the student model, protecting the student model from the negative influences caused by unreliable pseudo labels.

After optimized on unlabeled data as in Eq. 8, the gentle teaching assistant model is required to convey the learned representation knowledge in feature extractor to the student model via Exponential Moving Average (EMA) as in Eq. 9,

$$\theta^{gta} := \theta^{gta} - \lambda \frac{\partial L_u}{\partial \theta^{gta}}. \tag{8}$$

$$\theta_f^{student}(t) = \alpha \theta_f^{student}(t-1) + (1-\alpha)\theta_f^{gta}(t), \tag{9}$$

where $\theta^{gta}(t)$ is the parameters of the gentle teaching assistant model at t-th iteration, $\theta^{student}(t)$ is the parameters of the student model at t-th iteration, and θ_f denotes the parameters of the feature

Algorithm 1: Gentle Teaching Assistant for Semi-Supervised Semantic Segmentation (GTA-Seg).

Input : Labeled data $D_l = \{x_i^l, y_i^l\}_{i=1}^{N^l}$, unlabeled data $D_u = \{x_i^u\}_{i=1}^{N^u}$
Output : Teacher Model

Initialization;
for *minibatch* $\{x^l, y^l\}, \{x^u\} \in \{D_l, D_u\}$ **do**
  Step 1:
    Teacher model generates pseudo labels on x_u by Eq. (2);
    Re-weight pseudo labels by Eq. (6) and compute unsupervised loss L_u by Eq. (7);
  Step 2:
    Update Gentle Teaching Assistant (GTA) by unlabeled data Eq. (8);
    Representation knowledge Transmission from GTA to student by Eq. (9);
  Step 3:
    Compute supervised loss by Eq. (10) ;
    Update student model by labeled data via Eq. (11) ;
    Update teacher model by Eq. (12) ;
end

extractor. Through our representation knowledge transmission, the unlabeled data is leveraged to facilitate feature representation of the student model, but it will not train the mask predictor.

Step 3: Optimize student model with ground truth labels and update teacher model. With the gentle teaching assistant module, the student model in our framework is only required to learn from the labeled data,

$$L_l = \sum_i \sum_j L_{ce}(x_{ij}^l, y_{ij}^l), \tag{10}$$

$$\theta^{student} := \theta^{student} - \lambda \frac{\partial L_l}{\partial \theta^{student}}. \tag{11}$$

Here, the whole model, including the feature extractor as well as the mask predictor, is updated according to the supervised loss computed by the ground-truth labels of labeled data.

Then the teacher model is updated by taking the EMA of the student model according to the traditional paradigm in the teacher-student framework.

$$\begin{aligned} \theta_f^{teacher}(t) &= \alpha \theta_f^{teacher}(t-1) + (1-\alpha)\theta_f^{student}(t), \\ \theta_g^{teacher}(t) &= \alpha \theta_g^{teacher}(t-1) + (1-\alpha)\theta_g^{student}(t). \end{aligned} \tag{12}$$

Finally, the teacher model, which absorbs the knowledge of both labeled and unlabeled data from the student model, will be taken as the final model for inference.

4 Experiment

4.1 Datasets

We evaluate our method on **1) PASCAL VOC 2012** [9]: a widely-used benchmark dataset for semantic segmentation, with 1464 images for training and 1449 images for validation. Some researches [6, 42] augment the training set by incorporating the 9118 coarsely annotated images in SBD [16] to the original training set, obtaining 10582 labeled training images, which is called the augmented training set. In our experiments, we consider both the original training set and the augmented training set, taking 92, 183, 366, 732, and 1464 images from the 1464 labeled images in the original training set, and 662, 1323 and 2645 images from the 10582 labeled training images in the augmented training set. **2) Cityscapes** [7], a urban scene dataset with 2975 images for training and 500 images for validation. We sample 100, 186, 372, 744 images from the 2975 labeled images in the training set. We take the split in [51] and report all the performances in a fair comparison.

Table 1: Results on PASCAL VOC 2012, original training set. We have 1464 labeled images in total and sample different proportions of them as labeled training samples. All the other images in the training set (including images in the augmented training set) are used as unlabeled data. We report the number of labeled samples / the total number of samples in the first row. The proportion of labeled data in the whole train set is reported in the second row (Label Ratio). We use ResNet-101 as the backbone and DeepLabv3+ as the decoder.

Method Label Ratio	92 / 10582 0.9%	183 / 10582 1.7%	366 / 10582 3.4%	732 / 10582 7.0%	1464 / 10582 13.9%
SupOnly	45.77	54.92	65.88	71.69	72.50
MT [37]	51.72	58.93	63.86	69.51	70.96
CutMix [11]	52.16	63.47	69.46	73.73	76.54
PseudoSeg [51]	57.60	65.50	69.14	72.41	73.23
PC2Seg [49]	57.00	66.28	69.78	73.05	74.15
GTA-Seg (Ours)	**70.02**	**73.16**	**75.57**	**78.37**	**80.47**

Table 2: Results on PASCAL VOC 2012, augmented training set. We have 10582 labeled images in total and sample different proportions of them as labeled training samples. All the other images in the training set are used as unlabeled data. The notations and network architecture are the same as in Table 1.

Method Label Ratio	662 / 10582 6.25%	1323 / 10582 12.5%	2645 / 10582 25.0%	5291 / 10582 50.0%
MT [37]	70.51	71.53	73.02	76.58
CutMix [11]	71.66	75.51	77.33	78.21
CCT [31]	71.86	73.68	76.51	77.40
GCT [20]	70.90	73.29	76.66	77.98
CPS [6]	74.48	76.44	77.68	78.64
AEL [18]	77.20	77.57	78.06	80.29
GTA-Seg (Ours)	**77.82**	**80.47**	**80.57**	**81.01**

Table 3: Results on Cityscapes dataset. We have 2975 labeled images in total and sample different proportions of them as labeled training samples. The notations and network architecture are the same as in Table 1. * means that we reimplement the method with ResNet-101 backbone for a fair comparison.

Method Ratio	100 / 2975 3.3%	186 / 2975 6.3%	372 / 2975 12.5%	744 / 2975 25.0%
DMT [10]	54.82	-	63.01	-
CutMix [11]	55.73	60.06	65.82	68.33
ClassMix [30]	-	59.98	61.41	63.58
Pseudo-Seg [51]	60.97	65.75	69.77	72.42
DCC* [21]	61.15	67.74	70.45	73.89
GTA-Seg (Ours)	**62.95**	**69.38**	**72.02**	**76.08**

4.2 Implementation Details

We take ResNet-101 [17] pre-trained on ImageNet [8] as the network backbone and DeepLabv3+ [5] as the decoder. The segmentation head maps the 512-dim features into pixel-wise class predictions.

We take SGD as the optimizer, with an initial learning rate of 0.001 and a weight decay of 0.0001 for PASCAL VOC. The learning rate of the decoder is 10 times of the network backbone. On Cityscapes, the initial learning rate is 0.01 and the weight decay is 0.0005. Poly scheduling is applied to the learning rate with $lr = lr_{init} \cdot (1 - \frac{t}{T})^{0.9}$, where lr_{init} is the initial learning rate, t is the current iteration and T is the total iteration. We take 4 GPUs to train the model on PASCAL VOC, and 8 GPUs on Cityscapes. Following previous works, input images are center cropped in PASCAL VOC during evaluation, while on Cityscapes, sliding window evaluation is adopted. The mean of Intersection over Union (mIoU) measured on the validation set serves as the evaluation metric.

4.3 Experimental Results

PASCAL VOC 2012 We first evaluate our method on the original training set of PASCAL VOC 2012. The results in Table 1 validate that our method surpasses previous methods by a large margin. Specifically, our method improves the supervised-only (SupOnly) model by 24.25, 18.24, 9.69, 6.68, 7.97 in mIoU when 0.9%, 1.7%, 3.4%, 7.0%, 13.9% of the data is labeled, respectively. When compared to the readily strong semi-supervised semantic segmentation method, our method still surpasses it by 13.02, 6.88, 5.79, 5.32, 6.32 respectively. We note that in the original training set, the ratio of labeled data is relatively low (0.9% to 13.9%). Therefore, the results verify that our method is effective in utilizing unlabeled data in semi-supervised semantic segmentation.

We further compare our method with previous methods on the augmented training set of PASCAL VOC 2012, where the annotations are relatively low in quality since some of labeled images come from SBD [16] dataset with coarse annotations. We can observe from Table 2, our method consistently outperforms the previous methods in a fair comparsion.

Table 4: Ablation Study on the components in our method, on the original training set of PASCAL VOC 2012, with 183 labeled samples.

Teacher-Student	Gentle Teaching Assistant	Re-weighted	mIoU
✗	✗	✗	54.92
✓	✗	✗	58.93
✓	✓	✗	72.10
✓	✓	✓	73.16

Table 5: Comparison of knowledge transmission mechanisms. The experiment settings follow Table 4.

Method	mIoU
SupOnly	54.92
Original EMA	64.07
Unbiased ST [3]	65.92
Ours	72.10

Table 6: Results of the three models on the original PASCAL VOC 2012. The experiment settings follow Table 4.

Method	mIoU
Gentle Teaching Assistant	70.10
Student Model	72.71
Teacher Model	73.16

Table 7: Ablation study on our re-weighting strategy for pseudo labeling on the original PASCAL VOC 2012. The experiment settings follow Table 4.

Confidence-based Re-weighting	Laplace Smoothing	mIoU
✗	✗	72.10
✓	✗	70.67
✓	✓	73.16

Cityscapes For Cityscapes, as shown in Table 3, our method still shows competitive performance among previous methods, improving the existing state-of-the-art method by 1.80, 1.64, 1.57, 2.19 in mIoU when 3.3%, 6.25%, 12.5%, 25.0% of the data is labeled.

4.4 Analyses

Component Analysis We analyze the effectiveness of different components in our method, *i.e.*, the original teacher-student framework, gentle teaching assistant and re-weighted pseudo labeling as in Table 4. According to the results in Table 4, the carefully designed gentle teaching assistant mechanism (the third row) helps our method outperform the previous methods, pushing the performance about 13.1 higher than the original teacher-student model (the second row). Further, the re-weighted pseudo labeling brings about 1.1 performance improvements. With all of these components, our method outperforms the teacher-student model by over 14.0 and SupOnly by over 18.0 in mIoU.

Gentle Teaching Assistant As mentioned in Table 4, our proposed gentle teaching assistant framework brings about remarkable performance gains. Inspired by this, we delve deeper into the gentle teaching assistant model in our framework. We first consider the representation knowledge transmission mechanism. In Table 5, we compare our mechanism with other methods such as the original EMA [37] that updates all of the parameters via EMA and Unbiased ST [3] that introduces an additional agent to convey representation knowledge. We can observe that all these mechanisms boost SupOnly remarkably, while our mechanism is superior to other methods.

We next pay attention to the three models in our framework, *i.e.* gentle teaching assistant model, student model, and teacher model. Table 6 reports the evaluation performance of them. All of them show relatively competitive performance. For the teacher assistant model, it is inferior to the student model. This is reasonable since it is only trained on pseudo labels, while the student model inherits the representation knowledge of unlabeled data from the gentle teaching assistant as well as trained on labeled data. In addition, the teacher model performs best, which agrees with previous works [37].

Re-weighted Pseudo Labeling In our method, we design the re-weighting strategy for pseudo labels as Eq. 6, which contains 1) confidence-based re-weighting, 2) Laplace Smoothing. Here we conduct further ablation study on our design. Table 7 shows that though effective in other tasks such as semi-supervised object detection [41], in our framework, adopting confidence-base re-weighting is harmful, dropping the performance from 72.10 to 70.67. On the contrary, our strategy, with the help of Laplace Smoothing [26] which alleviates over-penalization, pushes the readily strong performance to a higher level.

Visualization Besides quantitative results, we present the visualization results to further analyze our method. We note that the model is trained on as few as 183 labeled samples and about 10400

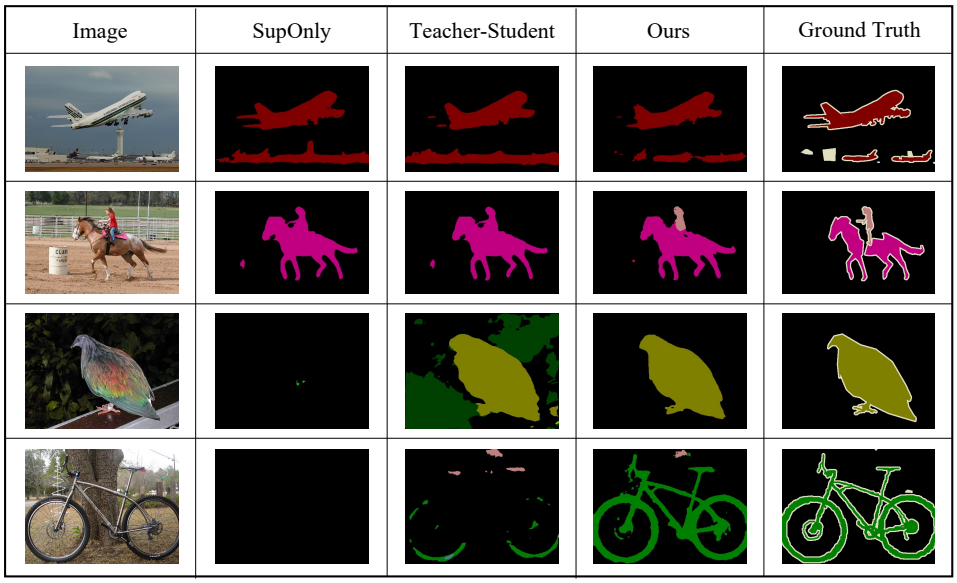

Figure 3: **Visualization Results** on PASCAL VOC 2012, with the original training set. We train the model with 183 labeled data, the other settings are the same as Table 1. From left to right, we show the raw images, results on SupOnly (the model trained merely on labeled data), Teacher-Student model, and our method, as well as the ground truth respectively.

unlabeled samples. As shown in Figure 3, facing such limited labeled data, training the model merely in the supervised manner (SupOnly) appears to be vulnerable. Under some circumstances, the model is even ignorant of the given images (the third and the fourth row). While methods that utilize unlabeled data (teacher-student model and our method), show stronger performance. Further, compared with the original teacher-student model, our method shows a stronger ability in determining a clear contour of objects (the first row) and recognizing the corresponding categories (the second row). Our method is also superior to previous methods in distinguishing objects from the background (the third and fourth row).

Limitations Comparing the performance of our method on the original (Table 1) and augmented (Table 2) training set of PASCAL VOC 2012, our method outperforms previous methods by a remarkable margin in the original set, while the superiority is relatively slight in the augmented set. We conjecture that this phenomenon can be attributed to the low-quality labeled data in the augmented set where some of the images come from the coarse annotations in SBD [16] dataset. This indicates one limitation of our method that it only attempts at making better use of the unlabeled data, but little attention has been paid to the labeled data. We consider it promising to conduct research on how to better leverage the labeled data in semi-supervised semantic segmentation, especially when the annotations are also noisy.

5 Conclusion

In this paper, we propose a novel framework, Gentle Teaching Assistant, for semi-supervised semantic segmentation (GTA-Seg). Concretely, we attach an additional teaching assistant module to disentangle the effects of pseudo labels on the feature extractor and the mask predictor. GTA learns representation knowledge from unlabeled data and conveys it to the student model via our carefully designed representation knowledge transmission. Through this framework, the model optimizes representation with unlabeled data, as well as prevents it from overfitting on limited labeled data. A confidence-based pseudo label re-weighting mechanism is applied to further boost the performance. Extensive experiment results prove the effectiveness of our method.

References

[1] Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(12):2481–2495, 2017.

[2] David Berthelot, Nicholas Carlini, Ian Goodfellow, Nicolas Papernot, Avital Oliver, and Colin A Raffel. Mixmatch: A holistic approach to semi-supervised learning. In *Advances in Neural Information Processing Systems*, volume 32, 2019.

[3] Baixu Chen, Junguang Jiang, Ximei Wang, Jianmin Wang, and Mingsheng Long. Debiased pseudo labeling in self-training. *arXiv preprint arXiv:2202.07136*, 2022.

[4] 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. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(4):834–848, 2017.

[5] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *European Conference on Computer Vision*, pages 801–818, 2018.

[6] Xiaokang Chen, Yuhui Yuan, Gang Zeng, and Jingdong Wang. Semi-supervised semantic segmentation with cross pseudo supervision. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 2613–2622, 2021.

[7] 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 *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3213–3223, 2016.

[8] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 248–255. Ieee, 2009.

[9] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(2):303–338, 2010.

[10] Zhengyang Feng, Qianyu Zhou, Qiqi Gu, Xin Tan, Guangliang Cheng, Xuequan Lu, Jianping Shi, and Lizhuang Ma. Dmt: Dynamic mutual training for semi-supervised learning. *Pattern Recognition*, page 108777, 2022.

[11] Geoff French, Samuli Laine, Timo Aila, Michal Mackiewicz, and Graham Finlayson. Semi-supervised semantic segmentation needs strong, varied perturbations. In *British Machine Vision Conference*, 2019.

[12] Jun Fu, Jing Liu, Haijie Tian, Yong Li, Yongjun Bao, Zhiwei Fang, and Hanqing Lu. Dual attention network for scene segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3146–3154, 2019.

[13] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27, 2014.

[14] Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. In *Advances in Neural Information Processing Systems*, volume 17, 2004.

[15] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International Conference on Machine Learning*, pages 1321–1330. PMLR, 2017.

[16] Bharath Hariharan, Pablo Arbeláez, Lubomir Bourdev, Subhransu Maji, and Jitendra Malik. Semantic contours from inverse detectors. In *IEEE International Conference on Computer Vision*, pages 991–998. IEEE, 2011.

[17] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 770–778, 2016.

[18] Hanzhe Hu, Fangyun Wei, Han Hu, Qiwei Ye, Jinshi Cui, and Liwei Wang. Semi-supervised semantic segmentation via adaptive equalization learning. In *Advances in Neural Information Processing Systems*, volume 34, 2021.

[19] Zilong Huang, Xinggang Wang, Lichao Huang, Chang Huang, Yunchao Wei, and Wenyu Liu. Ccnet: Criss-cross attention for semantic segmentation. In *IEEE International Conference on Computer Vision*, pages 603–612, 2019.

[20] Zhanghan Ke, Di Qiu, Kaican Li, Qiong Yan, and Rynson WH Lau. Guided collaborative training for pixel-wise semi-supervised learning. In *European Conference on Computer Vision*, pages 429–445. Springer, 2020.

[21] Xin Lai, Zhuotao Tian, Li Jiang, Shu Liu, Hengshuang Zhao, Liwei Wang, and Jiaya Jia. Semi-supervised semantic segmentation with directional context-aware consistency. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1205–1214, 2021.

[22] Samuli Laine and Timo Aila. Temporal ensembling for semi-supervised learning. In *International Conference on Learning Representations*, 2017.

[23] Dong-Hyun Lee et al. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In *International Conference on Machine Learning Workshop*, volume 3, page 896, 2013.

[24] Wei Liu, Andrew Rabinovich, and Alexander C Berg. Parsenet: Looking wider to see better. *arXiv preprint arXiv:1506.04579*, 2015.

[25] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3431–3440, 2015.

[26] Christopher Manning, Prabhakar Raghavan, and Hinrich Schütze. Introduction to information retrieval. *Natural Language Engineering*, 16(1):100–103, 2010.

[27] Robert Mendel, Luis Antonio de Souza, David Rauber, João Paulo Papa, and Christoph Palm. Semi-supervised segmentation based on error-correcting supervision. In *European Conference on Computer Vision*, pages 141–157. Springer, 2020.

[28] Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, volume 41, pages 1979–1993. IEEE, 2018.

[29] Hyeonwoo Noh, Seunghoon Hong, and Bohyung Han. Learning deconvolution network for semantic segmentation. In *IEEE International Conference on Computer Vision*, pages 1520–1528, 2015.

[30] Viktor Olsson, Wilhelm Tranheden, Juliano Pinto, and Lennart Svensson. Classmix: Segmentation-based data augmentation for semi-supervised learning. In *IEEE Winter Conference on Applications of Computer Vision*, pages 1369–1378, 2021.

[31] Yassine Ouali, Céline Hudelot, and Myriam Tami. Semi-supervised semantic segmentation with cross-consistency training. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 12674–12684, 2020.

[32] Alfréd Rényi. On measures of entropy and information. In *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*, volume 4, pages 547–562. University of California Press, 1961.

[33] Mehdi Sajjadi, Mehran Javanmardi, and Tolga Tasdizen. Regularization with stochastic transformations and perturbations for deep semi-supervised learning. In *Advances in Neural Information Processing Systems*, volume 29, 2016.

[34] Kihyuk Sohn, David Berthelot, Nicholas Carlini, Zizhao Zhang, Han Zhang, Colin A Raffel, Ekin Dogus Cubuk, Alexey Kurakin, and Chun-Liang Li. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. volume 33, pages 596–608, 2020.

[35] Nasim Souly, Concetto Spampinato, and Mubarak Shah. Semi supervised semantic segmentation using generative adversarial network. In *IEEE International Conference on Computer Vision*, pages 5688–5696, 2017.

[36] Ke Sun, Bin Xiao, Dong Liu, and Jingdong Wang. Deep high-resolution representation learning for human pose estimation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 5693–5703, 2019.

[37] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Advances in Neural Information Processing Systems*, volume 30, 2017.

[38] Yuchao Wang, Haochen Wang, Yujun Shen, Jingjing Fei, Wei Li, Guoqiang Jin, Liwei Wu, Rui Zhao, and Xinyi Le. Semi-supervised semantic segmentation using unreliable pseudo-labels. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2022.

[39] Colin Wei, Kendrick Shen, Yining Chen, and Tengyu Ma. Theoretical analysis of self-training with deep networks on unlabeled data. In *International Conference on Learning Representations*, 2021.

[40] Qizhe Xie, Zihang Dai, Eduard Hovy, Thang Luong, and Quoc Le. Unsupervised data augmentation for consistency training. In *Advances in Neural Information Processing Systems*, volume 33, pages 6256–6268, 2020.

[41] Mengde Xu, Zheng Zhang, Han Hu, Jianfeng Wang, Lijuan Wang, Fangyun Wei, Xiang Bai, and Zicheng Liu. End-to-end semi-supervised object detection with soft teacher. In *IEEE International Conference on Computer Vision*, pages 3060–3069, 2021.

[42] Lihe Yang, Wei Zhuo, Lei Qi, Yinghuan Shi, and Yang Gao. St++: Make self-training work better for semi-supervised semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2022.

[43] Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. In *International Conference on Learning Representations*, 2016.

[44] Jianlong Yuan, Yifan Liu, Chunhua Shen, Zhibin Wang, and Hao Li. A simple baseline for semi-supervised semantic segmentation with strong data augmentation. In *IEEE International Conference on Computer Vision*, pages 8229–8238, 2021.

[45] Bowen Zhang, Yidong Wang, Wenxin Hou, Hao Wu, Jindong Wang, Manabu Okumura, and Takahiro Shinozaki. Flexmatch: Boosting semi-supervised learning with curriculum pseudo labeling. volume 34, 2021.

[46] Hang Zhang, Kristin Dana, Jianping Shi, Zhongyue Zhang, Xiaogang Wang, Ambrish Tyagi, and Amit Agrawal. Context encoding for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 7151–7160, 2018.

[47] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 2881–2890, 2017.

[48] Hengshuang Zhao, Yi Zhang, Shu Liu, Jianping Shi, Chen Change Loy, Dahua Lin, and Jiaya Jia. Psanet: Point-wise spatial attention network for scene parsing. In *European Conference on Computer Vision*, pages 267–283, 2018.

[49] Yuanyi Zhong, Bodi Yuan, Hong Wu, Zhiqiang Yuan, Jian Peng, and Yu-Xiong Wang. Pixel contrastive-consistent semi-supervised semantic segmentation. In *IEEE International Conference on Computer Vision*, pages 7273–7282, 2021.

[50] Xiaojin Jerry Zhu. Semi-supervised learning literature survey. 2005.

[51] Yuliang Zou, Zizhao Zhang, Han Zhang, Chun-Liang Li, Xiao Bian, Jia-Bin Huang, and Tomas Pfister. Pseudoseg: Designing pseudo labels for semantic segmentation. 2021.

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section **??**.
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1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 4.4
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2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
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3. If you ran experiments...
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(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

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