# DECOUPLED FINETUNING FOR DOMAIN GENERALIZABLE SEMANTIC SEGMENTATION

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## ABSTRACT

Joint finetuning of a pretrained encoder and a randomly initialized decoder has been the de facto standard in semantic segmentation, but the vulnerability of this approach to domain shift has not been studied. We investigate the vulnerability issue of joint finetuning, and propose a novel finetuning framework called Decoupled FineTuning for domain generalization (DeFT) as a solution. DeFT operates in two stages. Its first stage warms up the decoder with the frozen, pretrained encoder so that the decoder learns task-relevant knowledge while the encoder preserves its generalizable features. In the second stage, it decouples finetuning of the encoder and decoder into two pathways, each of which concatenates a usual component (UC) and generalized component (GC); each of the encoder and decoder plays a different role between UC and GC in different pathways. UCs are updated by gradients of the loss on the source domain, while GCs are updated by exponential moving average biased toward their initialization to retain their generalization capability. By the two separate optimization pathways with opposite UC-GC configurations, DeFT reduces the number of learnable parameters virtually, and decreases the distance between learned parameters and their initialization, leading to improved generalization capability. DeFT significantly outperformed existing methods in various domain shift scenarios, and its performance could be further boosted by incorporating a simple distance regularization.

## 1 INTRODUCTION

The current de facto standard for learning semantic segmentation is to jointly finetune a pretrained encoder and a segmentation decoder on training data with segmentation labels (Long et al., 2015; Noh et al., 2015; Ronneberger et al., 2015; Chen et al., 2017; Zhao et al., 2017; Xie et al., 2021; Yu et al., 2022; Chen et al., 2023). This practice allows significant performance improvement, but it also often leads to models vulnerable to domain shift in testing caused by, for example, weather conditions and geolocations they do not experience in training (Ganin et al., 2016; Pan et al., 2018; Saito et al., 2018; Yue et al., 2019a; Choi et al., 2021). A straightforward solution to this issue is to collect a vast amount of training data from diverse domains. However, this does not guarantee that the collected data cover any potential test domains, and more importantly, pixel-wise class annotation for such data will be prohibitively expensive.

To resolve this issue, we study domain generalization for semantic segmentation, *i.e.*, learning a model on a single source domain so that it generalizes well to unseen, arbitrary target domains that may arise in testing (Yue et al., 2019b; Lee et al., 2022; Zhao et al., 2022; Chattopadhyay et al., 2023; Kim et al., 2023a). A large body of domain generalization research has focused on simulating diverse target domains by data or feature augmentation during training (Lee et al., 2022; Zhao et al., 2022; Chattopadhyay et al., 2023), or removing domain-specific information from features (Choi et al., 2021; Peng et al., 2022; Pan et al., 2018; 2019). Although these approaches have driven remarkable success, there is still large room for further improvement in that they do not take into account potential negative impact of the joint finetuning of encoder and decoder, the common practice in semantic segmentation, on domain generalization.

We argue that the joint finetuning of encoder and decoder can degrade the generalization capability of the entire model. First, the joint finetuning causes the pretrained encoder to overfit to the source domain and thus corrupts its generalization capability (Kumar et al., 2022; Saito et al., 2023). Also,

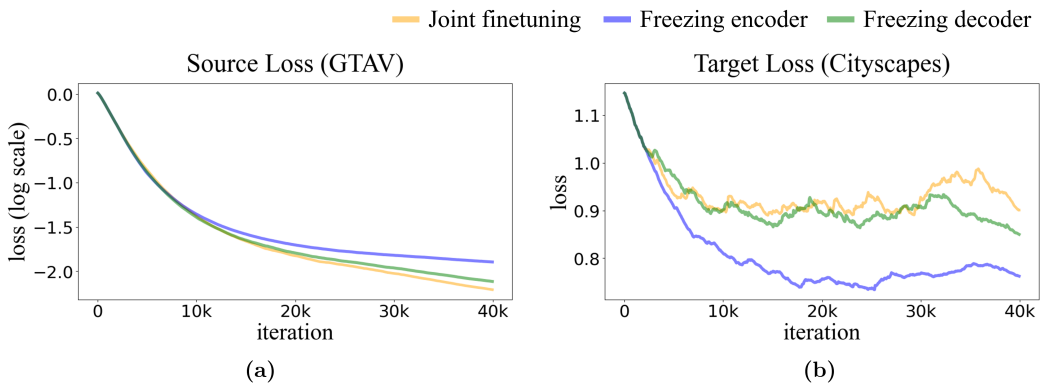


Figure 1: We empirically verify that the joint finetuning causes overfitting to the source domain and degrades the generalization capability by comparing (a) loss on the source domain–GTAV (Richter et al., 2016) and (b) that on an unseen target domain–Cityscapes (Cordts et al., 2016) during finetuning. On the other hand, freezing either the encoder or decoder before being overfitted mitigates the issue to some extent. This result suggests that preventing one of the encoder and decoder from being trained with the other overfitted to the source domain may improve the entire model's generalization. Of course, simply freezing one of the modules is far from the optimal solution due to the lack of task-relevant knowledge of the frozen module, as demonstrated in Table 1.

Table 1: Comparison between the proposed framework, DeFT, and freezing either an encoder or decoder; all the methods are trained on GTAV using ResNet-50 backbone. After the warm up stage, we selectively freeze either the encoder or decoder while continuing to update the other module. The results indicate that the model cannot learn sufficient task-relevant knowledge when one module is not updated at all, especially the encoder, which contains most of the parameters of the model.

| Method | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|
| Freezing Encoder | 41.88 | 36.85 | 44.59 | 41.11 |
| Freezing Decoder | 42.52 | 38.75 | 45.03 | 42.10 |
| DeFT | **50.06** | **43.17** | **50.51** | **47.91** |

the decoder relying on the encoder's output inevitably draws distorted decision boundaries, and in turn produces gradients that causes the encoder to be more overfitted. Figure 1 empirically verifies this argument.

Building on this insight, we propose a new, simple yet effective finetuning framework dubbed **De**coupled **F**ine**T**uning for domain generalization (DeFT); its overall pipeline is illustrated in Figure 2. DeFT comprises two stages. In the first stage, the decoder is warmed up with a pretrained encoder that remains frozen, following Kumar et al. (2022). By warming up on the source domain, the decoder learns the target task (*i.e.*, semantic segmentation in this paper) without distorting the generalizable knowledge of the pretrained encoder.

The main contribution of DeFT lies in its second stage, which finetunes both the encoder and decoder but in a decoupled manner. Motivated by the observation in Figure 1, we propose decoupling the finetuning of the two trainable modules in the model, which are the encoder and decoder. To this end, we employ two parallel encoder-decoder pathways for finetuning, each combining a usual component (UC) and a generalized component (GC). UC is updated using the standard error backpropagation based on the training loss from the source domain. On the other hand, GC is not updated using the gradients that might be overfitted to the source domain. As a result, GC maintains its generalization capability during the finetuning, guiding the coupled UC's updates using its generalizable knowledge. Note that each of the encoder and decoder plays a different role between UC and GC in different pathways.

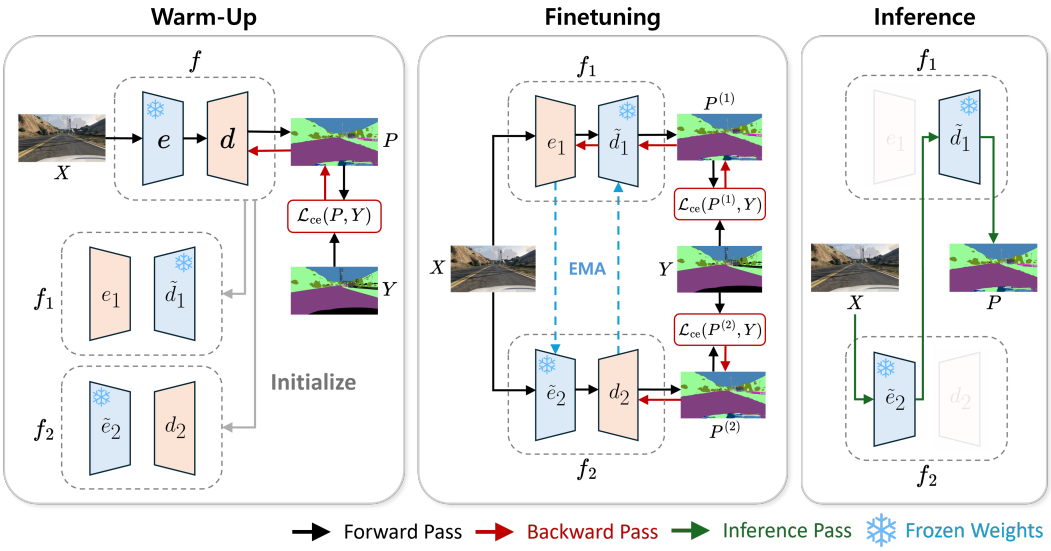


Figure 2: An overview of DeFT. The first step of DeFT is to warm up the decoder with the frozen, pretrained encoder. After warming up the decoder, we introduce two parallel encoder-decoder pathways to conduct the decoupled finetuning. In the pathways, the parameters of encoders and decoders are initialized with those from the warmed-up model. In the second step, DeFT finetunes both the encoder and decoder in a decoupled manner: the GCs ($\tilde{d}_1$ and $\tilde{e}_2$) are updated by the exponential moving average of their counterpart UCs ($d_2$ and $e_1$), while the UCs are updated by gradients of the loss. Our final model for inference is configured as the combination of the well-generalized GCs ($\tilde{d}_1$ and $\tilde{e}_2$), *i.e.*, $f_{\text{final}} = \tilde{d}_1 \circ \tilde{e}_2$.

A naïve strategy for managing GCs is not updating them at all, which however leads to a suboptimal solution due to the lack of task-relevant knowledge in GCs as demonstrated in Table 1. To allow GCs to learn task-relevant knowledge while preserving their generalization capability, we adopt a variant of exponential moving average (EMA) (Tarvainen & Valpola, 2017) that is biased towards the model's initial parameters, as an update scheme for GCs. This EMA method assigns higher weights to the early parameters during the finetuning, performing gradual temporal ensemble in the parameter space.

At the end of finetuning, DeFT produces two GC-UC pairs. Since GCs better preserve the rich and generalizable knowledge from pretraining and thus have better generalization capability than UC, we set our final model as the combination of two GCs, *i.e.*, EMA encoder and EMA decoder.

Our method was evaluated on five different datasets, Cityscapes (Cordts et al., 2016), BDD-100K (Yu et al., 2020), Mapillary Neuhold et al. (2017), GTAV (Richter et al., 2016) and SYNTHIA (Ros et al., 2016), and it demonstrated superior performance to previous work in every experiments. In summary, our contribution is three-fold:

- We empirically demonstrate that joint finetuning of the encoder and decoder degrades generalization performance, and simply decoupling them in the finetuning process can substantially improve the performance.
- We propose a novel training framework for domain generalizable semantic segmentation, dubbed as DeFT, which finetunes the encoder and decoder in a decoupled manner. We also provide detailed analysis of our method through extensive experiments.
- DeFT is evaluated on various domain shift scenarios using multiple semantic segmentation datasets, where it outperformed previous work by large margins in all evaluations.

# 2 RELATED WORK

## 2.1 DOMAIN GENERALIZABLE SEMANTIC SEGMENTATION

The objective of domain generalization is to develop models that generalize well to *unseen* domains (Muandet et al., 2013; Li et al., 2018b). Early methods (Li et al., 2017; 2018a; Pan et al., 2018; Nam et al., 2021; Zhou et al., 2021) primarily focused on classification tasks. Recently, significant progress has been made in semantic segmentation (Yue et al., 2019b; Lee et al., 2022; Zhao et al., 2022; Chattopadhyay et al., 2023; Kim et al., 2023a). Yue et al. (2019b) suggest learning features invariant to random style variations in the input. Methods like Lee et al. (2022); Zhao et al. (2022) simulate diverse style spaces by manipulating the channel-wise means and standard deviations of features. Additionally, Chattopadhyay et al. (2023) introduced a frequency-domain randomization technique, particularly for strong augmentation in high-frequency regions. Furthermore, Kim et al. (2023a) collected a variety of images with different styles from web repositories to enhance generalization performance.

However, the listed methods still adopt joint finetuning, despite its negative impact on generalization ability, which remains a common practice in existing frameworks. To address this generalization issue in previous work, we propose a novel decoupled finetuning strategy called DeFT, and present a dedicated training algorithm based on EMA.

## 2.2 WEIGHT AVERAGING FOR MODEL ENSEMBLING

Weight averaging has been explored as an effective method for leveraging the historical training trajectories of deep neural networks to improve generalization performance. Snapshot ensembling (SSE) (Huang et al., 2017) and fast geometric ensembling (FGE) (Garipov et al., 2018) were early attempts to utilize weight trajectories from historical training by employing cyclic learning rates to guide the learning process through multiple local minima, which are then saved as ensemble members. Building on FGE, stochastic weight averaging (SWA) (Izmailov et al., 2018) updates a pretrained model using a cyclical or high constant learning rate, gathers model parameters during training, and averages them to form a model ensemble. Extending from SWA, trainable weight averaging (TWA) (Li et al., 2023) introduced a technique that allows for weight averaging with adjustable coefficients. Additionally, model soups (Wortsman et al., 2022a) demonstrated that averaging the weights of multiple models finetuned with different hyperparameters can improve both accuracy and robustness.

We adopt a variant of EMA as temporal ensembling in the model parameter space for DeFT, allowing the model to learn task-relevant knowledge while minimizing overfitting to the source domain.

## 2.3 ROBUST FINETUNING FOR OUT-OF-DOMAIN GENERALIZATION

Robust finetuning using pretrained weights enhances out-of-domain (OOD) performance. Recent studies (Wen et al., 2021; Gouk et al., 2021) demonstrate that leveraging pretrained models can significantly booster robustness on OOD datasets. Moreover, the finetuning process plays a critical role in improving OOD generalization capability. Research (Nagarajan & Kolter, 2019; Lin & Zhang, 2019; Gouk et al., 2021; Li & Zhang, 2021) indicates that generalization performance is affected by the distance between the initial and finetuned models: as this distance increases, generalization tends to decline. WiSE-FT (Wortsman et al., 2022b) shows significant improvements in OOD generalization by linearly interpolating pretrained weights with finetuned ones during inference. LP-FT (Kumar et al., 2022) demonstrates that simultaneously finetuning both the final linear layer and the feature backbone can distort pretrained features, and proposes a two-stage training strategy: first, warming up the decoder while freezing the encoder, then finetuning the entire network. Lastly, Tian et al. (2023) introduces per-layer regularization, which automatically learns constraints for more accurate finetuning.

Our method adopts a two-step training strategy motivated by LP-FT, but it is clearly different from LP-FT: after warming up the decoder, we finetune encoder and decoder in a disjoint manner with the proposed DeFT framework, rather than jointly finetuning them as in LP-FT.

# 3 METHOD

We consider training a domain-generalizable segmentation model, $f = d \circ e$, with an encoder $e$ and decoder $d$ using labeled images from a single source domain, where the image height, width, and the number of semantic classes are denoted by $h$, $w$, and $c$, respectively. Our framework, dubbed DeFT, consists of two stages: warming up the decoder while freezing the pretrained encoder (Section 3.1), followed by decoupled finetuning of the encoder and decoder (Section 3.2).

## 3.1 WARMING UP THE DECODER WITH A PRETRAINED ENCODER

The first step of DeFT is to warm up the decoder on the source domain dataset using the pretrained encoder, which remains frozen. For an input image $X$ and its ground truth $Y$, let $P = f(X) = d(e(X))$ be the class probability map, where $P \in \mathbb{R}^{h \times w \times c}$. Let $\mathcal{L}_{\text{ce}}(P, Y)$ denote a standard pixel-wise cross-entropy loss, which is given by:

$$\mathcal{L}_{\text{ce}}(P, Y) = -\frac{1}{h \cdot w} \sum_{i=1}^{h \cdot w} Y_i^\top \cdot \log(P_i), \tag{1}$$

where $i$ is the pixel index and $Y_i$ is the one-hot vector of the ground truth for pixel $i$. Then, the weights of the randomly initialized decoder $d$ are updated using gradients of the cross-entropy loss $\mathcal{L}_{\text{ce}}(P, Y)$, while the pretrained encoder is frozen. This warming up stage enables the decoder to learn the target task without distorting the generalizable knowledge of the pretrained encoder.

## 3.2 DECOUPLED FINETUNING OF ENCODER AND DECODER

After warming up the decoder, the encoder and decoder are fine-tuned in a *decoupled manner*. During decoupled finetuning, they are assigned as one of two components, the generalized component (GC) and the usual component (UC), but are different from each other. Then UC is updated using gradients of the training loss from the source domain, while GC is updated by an exponential moving average (EMA) scheme to retain its generalization capability.

To decouple the encoder and decoder then finetune both, we define two distinct pathways, which can be represented as two segmentation models $f_1$ and $f_2$ that share the same architecture but have opposing configurations for UC and GC. Let $f_1 = \tilde{d}_1 \circ e_1$ and $f_2 = d_2 \circ \tilde{e}_2$ be the segmentation models, where $\tilde{d}_1$ and $\tilde{e}_2$ are the GCs, and $d_2$ and $e_1$ are the UCs. The weights of UCs, $d_2$ and $e_1$, are updated using the cross-entropy loss $\mathcal{L}_{\text{ce}}(P^{(1)}, Y)$ and $\mathcal{L}_{\text{ce}}(P^{(2)}, Y)$, where $P^{(1)} = f_1(X)$ and $P^{(2)} = f_2(X)$ are the predictions of $f_1$ and $f_2$, respectively. On the other hand, GC in one model is not updated by the cross-entropy loss but by the exponential moving average of UC in the other, with an update ratio $\beta$:

$$\tilde{\theta}_{d_1}^{t+1} = \beta \tilde{\theta}_{d_1}^{t} + (1-\beta)\theta_{d_2}^{t}, \quad \tilde{\theta}_{e_2}^{t+1} = \beta \tilde{\theta}_{e_2}^{t} + (1-\beta)\theta_{e_1}^{t}, \tag{2}$$

where $\tilde{\theta}_{d_1}^{t}$ and $\tilde{\theta}_{e_2}^{t}$ are the weights of $\tilde{d}_1$ and $\tilde{e}_2$ at the $t$-th iteration, respectively. Updates of UCs and GCs are conducted simultaneously during the second stage.

## 3.3 CONFIGURING OUR FINAL MODEL FOR INFERENCE

DeFT produces two encoders, $e_1$ and $\tilde{e}_2$, and two decoders, $\tilde{d}1$ and $d_2$. As the two GCs better preserve their initial states which are more generalizable and thus have superior generalization capability compared to the UCs, we set our final model as the combination of the two GCs from $f_1$ and $f_2$: $f_{\text{final}} = \tilde{d}_1 \circ \tilde{e}_2$. Since each GC from different pathways is updated based on its counterpart UC in Eq. (2), their feature distributions are implicitly aligned, properly adapting to each other.

## 3.4 EMPIRICAL JUSTIFICATION FOR DEFT

The decoupled finetuning improves the model's generalization capability by enabling the encoder and decoder to be trained independently, each benefiting from less-overfitted decision boundaries or features derived from their respective generalized counterparts. Moreover, it can tighten the

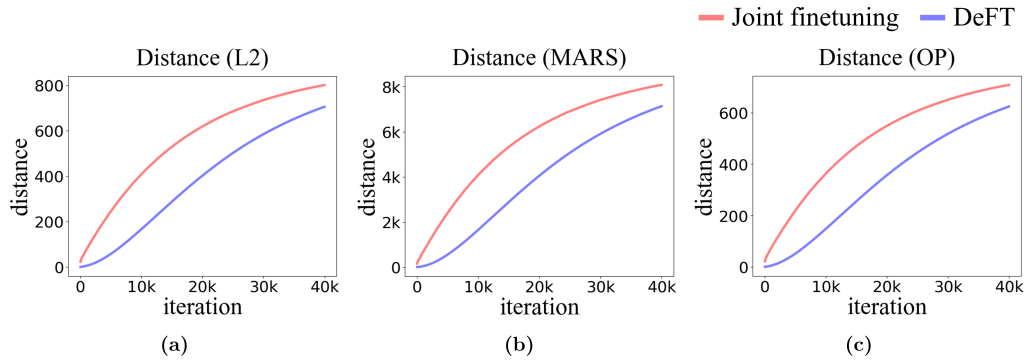


Figure 3: We empirically demonstrate that the model jointly finetuned tends to move further away from its initial parameters than the model finetuned with DeFT. We measure the distance between the current and initial parameters of each model using three metrics: (a) L2 norm (Nagarajan & Kolter, 2019), (b) MARS norm (Gouk et al., 2021), and (c) operator norm (Long & Sedghi, 2020). The final model $f_{\text{final}}$ is used to measure the distance for DeFT. The results show that the model finetuned with DeFT exhibits a shorter distance from its initial parameters than the jointly finetuned one, resulting in better generalization performance.

generalization bounds of the model, as it reduces both *the number of parameters* to be optimized at each pathway and *the distance from initial parameters*, *i.e.*, the distance between the learned parameters and their initial values.

DeFT divides a single optimization objective of joint finetuning, which handles all the parameters in the model simultaneously, into two separate optimization objectives: one for the encoder and one for the decoder. As a result, each of the networks $f_1$ and $f_2$ is trained on a separate objective with fewer parameters to optimize compared to the original model. This leads to a tighter generalization bound for each module than the joint finetuning (Du et al., 2018; Long & Sedghi, 2020).

We also empirically demonstrate that DeFT reduces the distance from initial parameters, which is one of the critical factors for the model's generalization bounds (Nagarajan & Kolter, 2019; Long & Sedghi, 2020; Gouk et al., 2021; Li & Zhang, 2021). Thanks to the EMA update scheme in DeFT, GCs are updated to maintain their initial states, partially retaining their initial weights. GCs, $\tilde{e}_2$ and $\tilde{d}_1$, which comprise our final model, exhibit a shorter distance from their initialization as shown in Figure 3, resulting in better domain generalization capability.

Moreover, we compare DeFT to other methods which explicitly regularize the distance from initial parameters: using low learning rates and adding a distance regularization into optimization objective. The results in Table 2 show that simply reducing the learning rate does not always lead to performance improvement, rather degrading its generalization performance due to the increased the risk of falling in local minima. For the distance regularization, we add a regularization term to the optimization objective to regularize the sum of the Euclidean distances from initial parameters. Let $L$ be the number of layers in the model, and, $W_i$ and $W_i^{(0)}$ be weights of the model and its initial parameters of the $l$-th layer. Then the revised training loss after warming up the decoder is given by:

$$\mathcal{L}_{\text{training}} = \mathcal{L}_{\text{ce}} + \alpha \cdot \sum_{i=1}^{L} \|W_i - W_i^{(0)}\|, \tag{3}$$

where $\|\cdot\|$ denotes the Frobenius norm for matrices and the Euclidean norm for vectors, respectively. The results reported in Table 3 demonstrate that DeFT outperforms joint finetuning, even the distance regularization is applied. The result also suggests that distance regularization can be applied orthogonally to DeFT.

Table 2: Analysis of the impact of learning rate. We investigate whether reducing the learning rate after the warm-up stage can lead to better generalization. All the methods are trained on GTAV using ResNet-50 backbone. The results demonstrate that a small learning rate increases the risk of falling in local minima, resulting in suboptimal performance.

| Method | Learning rate | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|---|
| Joint Finetuning | 1e-2 | 42.32 | 40.33 | 44.88 | 42.51 |
| | 3e-3 | 44.87 | 42.10 | 49.38 | 45.45 |
| | 1e-3 | 44.01 | 39.47 | 47.45 | 43.64 |
| | 1e-4 | 40.84 | 37.38 | 44.83 | 41.02 |
| DeFT | 1e-2 | **50.06** | **43.17** | **50.51** | **47.91** |

Table 3: Impact of distance-based regularization. All the methods are trained on GTAV using ResNet-50 backbone. DeFT outperforms joint finetuning in both settings. The result also suggests that the distance regularization is orthogonal to DeFT and further improve its performance.

| Method | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|
| Joint Finetuning | 42.32 | 40.33 | 44.88 | 42.51 |
| Joint Finetuning + Distance Regularization | 46.06 | 40.80 | 47.93 | 44.93 |
| DeFT | 50.06 | 43.17 | 50.51 | 47.91 |
| DeFT + Distance Regularization | **51.09** | **43.46** | **51.58** | **48.71** |

# 4 EXPERIMENTS

In this section, we first describe the experimental settings and implementation details, followed by a demonstration of the effectiveness of our DeFT framework through a series of extensive experiments, including various ablation studies.

## 4.1 EXPERIMENTAL SETUP

**Datasets.** We use three real-world datasets, Cityscapes (Cordts et al., 2016), BDD-100K (Yu et al., 2020), and Mapillary (Neuhold et al., 2017), and two synthetic datasets, GTAV (Richter et al., 2016) and SYNTHIA (Ros et al., 2016) for the experiment. **Cityscapes** is a real-world urban driving scene dataset, comprising 2,985 images for training and 500 for validation. **BDD-100K** is another real-world urban driving scene dataset, and we use the 1,000 validation images for evaluation. **Mapillary** consists of 25,000 images collected from various worldwide locations, and we use 2,000 validation images for evaluation. **GTAV** contains 24,966 images generated from the Grand Theft Auto V (GTAV) game engine, split into 12,403 images for training and 6,382 for validation. **SYNTHIA** is a photo-realistic synthetic urban scene dataset, consisting of 9,400 images. We use 6,382 validation images for evaluation.

**Network architecture.** We utilize DeepLab v3+ (Chen et al., 2018) as the segmentation model with ImageNet (Deng et al., 2009) pretrained ResNet-(50/101) (He et al., 2016) backbone networks. During training, we introduce two segmentation models that share the same architecture.

**Implementation details.** The model is trained with a batch size of 4 using the SGD optimizer with a momentum of 0.9. For the warm-up stage, the model is trained for 2K iterations for Cityscapes and 8K iterations for GTAV, with a learning rate of 1e-2 and a weight decay of 5e-3. During decoupled finetuning, the model is trained for 40K iterations with a learning rate of 1e-2 and a weight decay of 5e-4. We employ a polynomial learning rate decay schedule with a power of 0.9. For data augmentation, we adopt color jittering, Gaussian blurring, random horizontal flipping with a probability of 0.5, random scaling in the range [0.5, 2.0], and random cropping with a size of $768 \times 768$. The weight update ratio $\beta$ is set to 0.9999. We use the mean Intersection-over-Union (mIoU) as the evaluation metric. We exclude the auxiliary cross-entropy loss applied to the encoder, which is proposed in PSPNet (Zhao et al., 2017) and adopted in previous works (Pan et al., 2018; Lee et al., 2022;

Table 4: Quantitative result comparison in mIoU (%) using ResNet-50 and ResNet-101 backbones. The model is trained on GTAV and evaluated on Cityscapes (C), BDD100K (B), and Mapillary (M).

| Methods | ResNet-50 | | | | ResNet-101 | | | |
|---|---|---|---|---|---|---|---|---|
| | C | B | M | Avg. | C | B | M | Avg. |
| Baseline | 35.16 | 29.71 | 31.29 | 32.05 | 35.73 | 34.06 | 33.42 | 34.40 |
| IBN-Net (Pan et al., 2018) | 33.85 | 32.30 | 37.75 | 34.63 | 37.37 | 34.21 | 36.81 | 36.13 |
| DRPC (Yue et al., 2019a) | 37.42 | 32.14 | 34.12 | 34.56 | 42.53 | 38.72 | 38.05 | 39.77 |
| ISW (Choi et al., 2021) | 36.58 | 35.20 | 40.33 | 37.37 | 37.20 | 33.36 | 35.57 | 35.38 |
| WildNet (Lee et al., 2022) | 44.62 | 38.42 | 46.09 | 43.04 | 45.79 | 41.73 | 47.08 | 44.87 |
| SAN-SAW (Peng et al., 2022) | 39.75 | 37.34 | 41.86 | 39.65 | 45.33 | 41.18 | 40.77 | 42.43 |
| DIRL (Xu et al., 2022) | 41.04 | 39.15 | 41.60 | 40.60 | - | - | - | - |
| SHADE (Zhao et al., 2022) | 44.65 | 39.28 | 43.34 | 42.42 | 46.66 | 43.66 | 45.50 | 45.27 |
| PASTA (Chattopadhyay et al., 2023) | 44.12 | 40.19 | 47.11 | 43.81 | 45.33 | 42.32 | 48.60 | 45.42 |
| TLDR (Kim et al., 2023b) | 46.51 | 42.58 | 46.18 | 45.09 | 47.58 | 44.88 | 48.80 | 47.09 |
| BlindNet (Ahn et al., 2024) | 45.72 | 41.32 | 47.08 | 44.71 | - | - | - | - |
| DeFT (Ours) | **50.06** | **43.17** | **50.51** | **47.91** | **52.14** | **45.16** | **53.15** | **50.15** |

Table 5: Quantitative result comparison in mIoU (%) using ResNet-50 backbone. The model is trained on Cityscapes and evaluated on BDD-100K (B), SYNTHIA (S), and GTAV (G).

| Methods | B | S | G | Avg. |
|---|---|---|---|---|
| Baseline | 44.96 | 23.29 | 42.55 | 36.93 |
| IBN-Net (Pan et al., 2018) | 48.56 | 26.14 | 45.06 | 39.92 |
| DRPC (Yue et al., 2019a) | 49.86 | 26.58 | 45.62 | 40.69 |
| ISW (Choi et al., 2021) | 50.74 | 26.20 | 45.00 | 40.64 |
| WildNet (Lee et al., 2022) | 50.94 | 27.95 | 47.01 | 41.97 |
| SAN-SAW (Peng et al., 2022) | 52.95 | 28.32 | 47.28 | 42.85 |
| DIRL (Xu et al., 2022) | 51.80 | 26.50 | 46.52 | 41.61 |
| SHADE (Zhao et al., 2022) | 50.95 | 27.62 | 48.61 | 42.39 |
| BlindNet (Ahn et al., 2024) | 51.84 | 28.51 | 47.97 | 42.77 |
| DeFT (Ours) | **53.12** | **28.87** | **48.72** | **43.57** |

Zhao et al., 2022; Chattopadhyay et al., 2023; Ahn et al., 2024), as it degrades OOD generalization capability.

### 4.2 Comparison with the state-of-the-art

In this subsection, we conduct a series of experiments to evaluate the effectiveness of DeFT. DeFT is compared with existing domain generalization methods, including IBN-Net (Pan et al., 2018), DRPC (Yue et al., 2019a), ISW (Choi et al., 2021), WildNet Lee et al. (2022), SAN-SAW (Peng et al., 2022), DIRL Xu et al. (2022), SHADE Zhao et al. (2022), PASTA (Chattopadhyay et al., 2023), TLDR (Kim et al., 2023b), and BlindNet (Ahn et al., 2024), using five datasets: (C)ityscapes, (B)DD-100K, (M)apillary, (S)YNTHIA, and (G)TAV, and two different backbone networks: ResNet-50 and ResNet-101. To evaluate the generalization ability of our method on various unseen domains, we conduct experiments in two scenarios: 1) the model is trained on GTAV and evaluated on Cityscapes, BDD-100K, and Mapillary, or 2) the model is trained on Cityscapes and evaluated on BDD-100K, SYNTHIA, and GTAV. For the first case, the results in Table 4 show that our method outperforms all other methods by a large margin when trained on GTAV, using either ResNet-50 or ResNet-101 as a backbone. Similarly, the results in Table 5 demonstrate that our method also outperforms all other methods in the second case, where the model is trained on Cityscapes with ResNet-50 backbone.

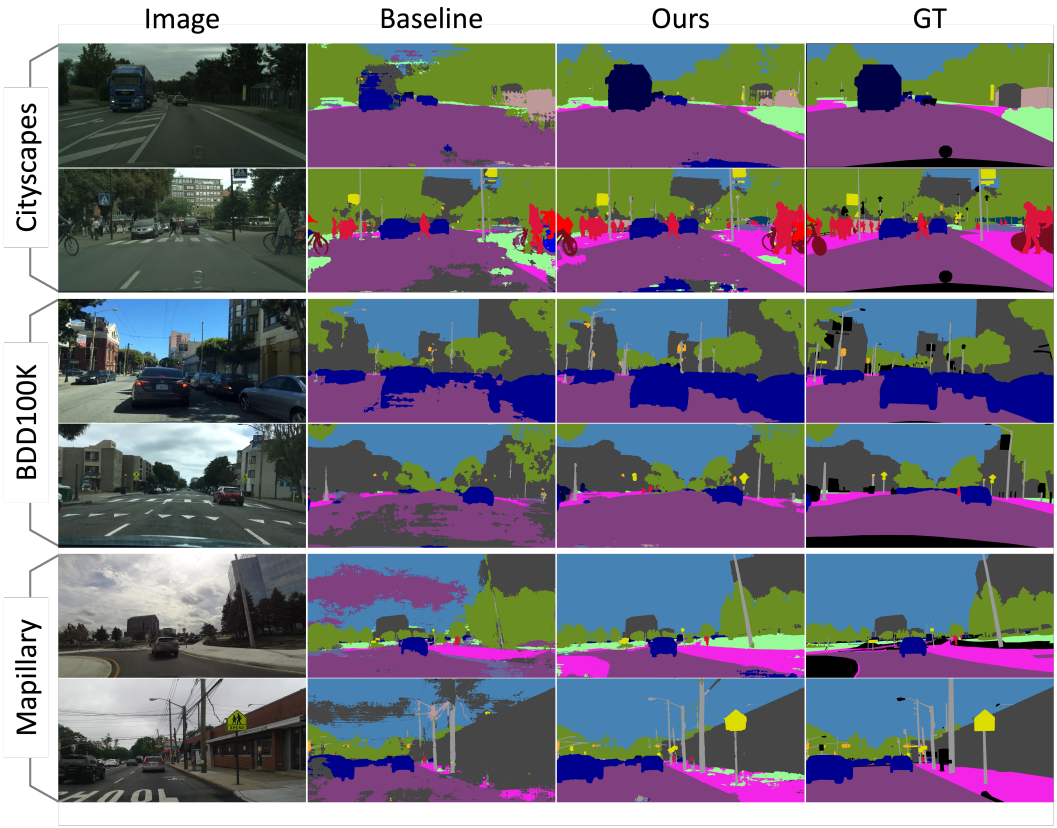


Figure 4: Qualitative results of DeFT and its baseline. The model is trained on the GTAV dataset using ResNet-50 and tested on the Cityscapes, BDD100K, and Mapillary datasets.

Table 6: Ablation study of the impact of individual component for training. Aux. and Aug. denote the auxiliary cross-entropy loss attached to the encoder and data augmentation, respectively. All the methods are trained on GTAV using ResNet-50 backbone. Warm-Up represent warming up the decoder while freezing the encoder before finetuning, and DeFT is the proposed decoupled finetuning.

| w/o Aux. | Aug. | Warm-Up | DeFT | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|---|---|---|
| | | | | 35.16 | 29.71 | 31.29 | 32.05 |
| ✓ | | | | 36.58 | 34.49 | 39.08 | 36.72 |
| ✓ | ✓ | | | 40.77 | 37.87 | 43.39 | 40.66 |
| ✓ | ✓ | ✓ | | 42.32 | 40.33 | 44.88 | 42.51 |
| ✓ | ✓ | ✓ | ✓ | **50.06** | **43.17** | **50.51** | **47.91** |

### 4.3 Ablation Studies

In this subsection, we study the individual contribution and effectiveness of each component within our method. For the all experiments, the model is trained on GTAV and evaluted on Cityscapes, BDD100K and Mapillary with ResNet-50 backbone.

**Ablation study of the impact of individual component for training.** To investigate the contribution of individual component during training, we investigate the impact of various training components and measure its performance. We consider four different components for the experiments : removing the auxiliary cross-entropy loss attached to the encoder (w/o Aux.), data augmentation (Aug.), decoder warming up (Warm-up) and our DeFT framework (DeFT). Note that w/o Aux., Aug. and Warm-up conduct joint finetuning, instead of decoupled finetuning. The results in Table 6

Table 7: Analysis on the impact of final model configuration.

| ID | $e_1$ (UC) | $\tilde{e}_2$ (GC) | $\tilde{d}_1$ (GC) | $d_2$ (UC) | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|---|---|---|---|
| I | ✓ | | | ✓ | 39.30 | 37.41 | 43.14 | 39.95 |
| II | ✓ | | ✓ | | 43.15 | 39.82 | 45.55 | 42.84 |
| III | | ✓ | | ✓ | 47.29 | 41.84 | 49.33 | 46.15 |
| IV | | ✓ | ✓ | | **50.06** | **43.17** | **50.51** | **47.91** |

Table 8: Ablation study of the impact of the update ratio $\beta$ in Eq. (2).

| EMA update ratio ($\beta$) | Cityscapes | BDD100K | Mapillary | Avg. |
|---|---|---|---|---|
| 0.99 | 44.37 | 40.79 | 46.81 | 43.99 |
| 0.999 | 46.19 | 42.14 | 48.81 | 45.71 |
| 0.9999 | **50.06** | **43.17** | **50.51** | **47.91** |

show that each component contributes to the performance, and applying all of them improves the most.

**Ablation study on final model configuration.** We set our final model as the combination of two GCs, *i.e.*, EMA encoder $\tilde{e}_2$ and EMA decoder $\tilde{d}_1$, as GCs preserve the rich and generalizable knowledge. To investigate this, we conduct additional ablation study on various combination of GCs and UCs. We measure the performance of each combination when the whole training ends, and the results are listed in Table 7. The experiments show that superior generalization capability of GC (Exp. II, III and IV) than UC (Exp. I), where using both of GCs outperforms all other settings by a large margin.

**Ablation study on the impact of the update ratio $\beta$.** We employ the exponential moving average as an update scheme for GC with the update ratio $\beta$ in Eq. (2). To investigate the impact of $\beta$, we conducted additional experiments by varying the values of $\beta$. The results in Table 8 demonstrate that assigning a higher weight to the model's initial parameters yields better generalization performance.

## 5 Conclusion

In this paper, we have demonstrated the detrimental effects of jointly finetuning the encoder and decoder in semantic segmentation models on domain generalization. Our empirical analysis revealed that this common practice leads to overfitting on the source domain, thereby degrading the model's generalization capability. To address this issue, we introduced DeFT, a novel and effective training framework that decouples the finetuning of the encoder and decoder. This decoupled finetuning prevents them from being trained based on their counterpart, which might be overfitted to the source domain, resulting in improved generalization capability. DeFT operates in two stages. In the first stage, we warm up the decoder while keeping the pretrained encoder frozen. In the second stage, we decouple the finetuning process by employing two parallel encoder-decoder pathways, each consisting of usual components (UCs) and generalized components (GCs). The UCs are updated through standard backpropagation on the source domain, while the GCs are updated using a biased exponential moving average of the UCs' parameters. This approach enables the GCs to learn task-relevant information while maintaining their generalization ability. Our extensive experiments on five diverse datasets demonstrate that DeFT consistently outperforms existing methods in domain generalizable semantic segmentation.

**Limitation and discussion.** Although our framework demonstrates impressive performance improvements, as shown through extensive experiments investigating its effect, there is still room for further theoretical analysis. Also, there might be better design choices for GC, although the EMA model shows its generalization capability. We believe developing a deeper theoretical understanding and exploring a better alternative configurations for the Generalized Component could be one of the promising future research directions.

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# A ALGORITHMS FOR EACH STAGE OF DEFT

In this sections, we present PyTorch-like pseudocodes for each stage of DeFT. Algorithm 1 describes the training procedure for decoder warm-up, and Algorithm 2 describes the training procedure for decoupled finetuning and the configuration of the final model for inference.

**Algorithm 1** Pseudocode for Decoder Warm-Up, PyTorch-like

```
# e: pretrained encoder e
# d: randomly initialized decoder d
# CE: standard pixel-wise cross entropy loss L_ce

freezing_weights(e)

for x, y in source_loader:      # load a minibatch x with n samples
    p = d(e(x))                 # prediction P = f(X) = d(e(X))
    L = CE(p, y)                # calculate loss

    L.backward()
    update(d)                   # only the decoder d is updated
```

**Algorithm 2** Pseudocode for Decoupled Finetuning and Inference, PyTorch-like

```
# e: warmed-up encoder e, the same as the pretrained encoder
# d: warmed-up decoder d
# CE: standard pixel-wise cross entropy loss L_ce
# beta: EMA update ratio β

e1 = copy(e)                    # UC encoder e_1
e2 = copy(e)                    # GC encoder ẽ_2

d1 = copy(d)                    # GC decoder d̃_1
d2 = copy(d)                    # UC decoder d_2

freezing_weights(e2)
freezing_weights(d1)

for x, y in source_loader:      # load a minibatch x with n samples
    p1 = d1(e1(x))              # prediction P^(1) from f_1 = d̃_1 ∘ e_1
    L1 = CE(p1, y)              # calculate loss

    p2 = d2(e2(x))              # prediction P^(2) from f_2 = d_2 ∘ ẽ_2
    L2 = CE(p2, y)              # calculate loss

    L1.backward()
    L2.backward()

    update(e1)                  # update UC encoder e_1
    update(d2)                  # update UC decoder d_2

    update_EMA(e2, e1, beta)    # update GC encoder ẽ_2
    update_EMA(d1, d2, beta)    # update GC decoder d̃_1

def update_EMA(gc, uc, beta):
    for param_gc, param_uc in zip(gc.parameters(), uc.parameters()):
        param_gc = beta * param_gc + (1 - beta) * param_uc

def inference(x):
    return d1(e2(x))            # final model f_final = d̃_2 ∘ ẽ_1
```

## B ADDITIONAL QUALITATIVE RESULTS

In this section, we provide additional qualitative results on Cityscapes (Cordts et al., 2016) in Figure 5, BDD100K (Yu et al., 2020) in Figure 6, and Mapillary (Neuhold et al., 2017) in Figure 7, respectively, which are not presented in the main sections due to the space limit. We use the model trained on the GTAV (Richter et al., 2016) using ResNet-50 (He et al., 2016) backbone. We also provide the color code of 19 classes in Figure 8.

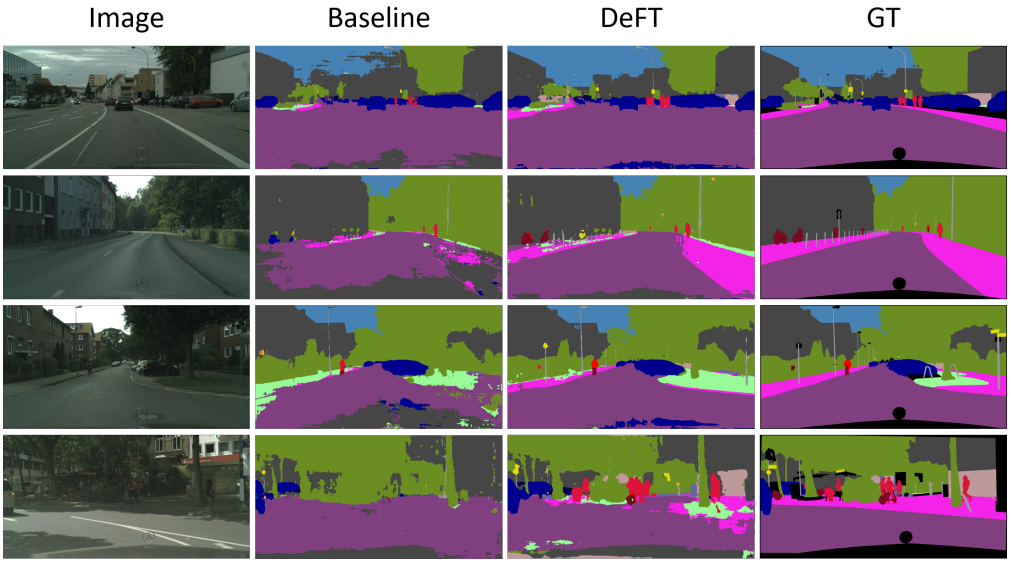


Figure 5: Qualitative results of DeFT and its baseline on Cityscapes dataset.

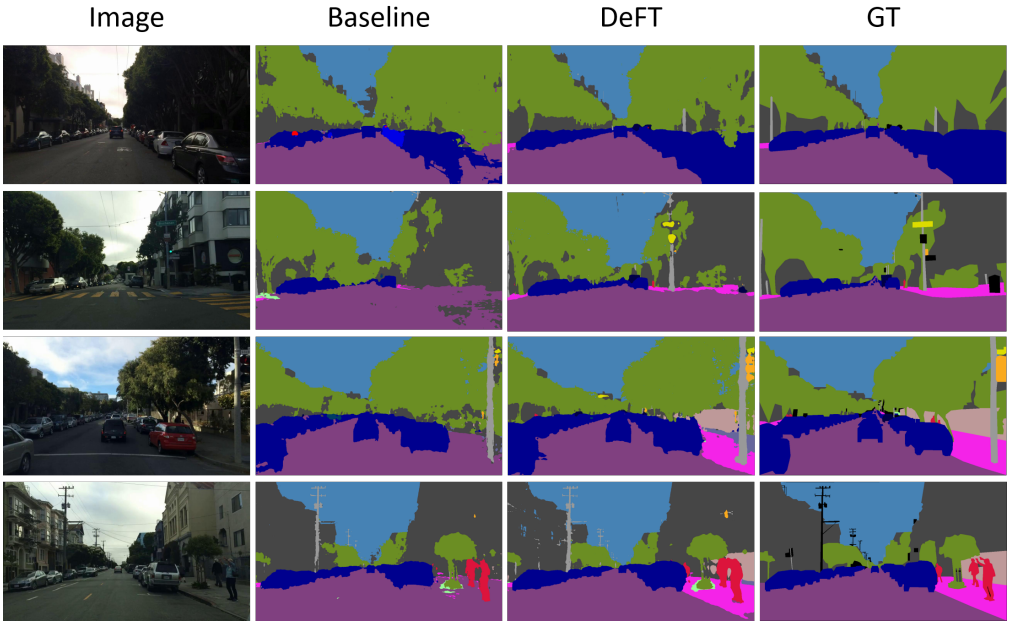


Figure 6: Qualitative results of DeFT and its baseline on BDD100K dataset.

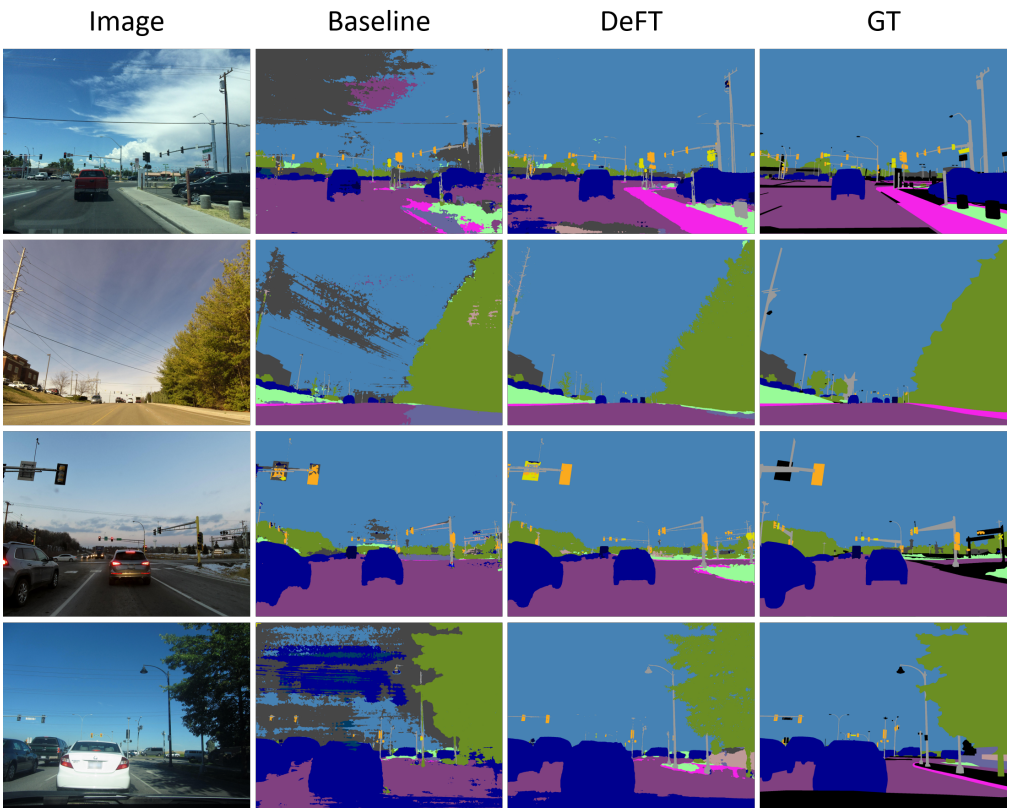


Figure 7: Qualitative results of DeFT and its baseline on Mapillary dataset.

Figure 8: The color code of 19 classes on the training and test datasets.

## C TARGET LOSS FLUCTUATION

We conduct an additional experiment on the target loss variation of DeFT during training. All the models are trained on GTAV (source domain) and evaluated on Cityscapes (target domain). We compare the target loss variation of DeFT with those of joint finetuning settings (Figure 1) in Figure 9.

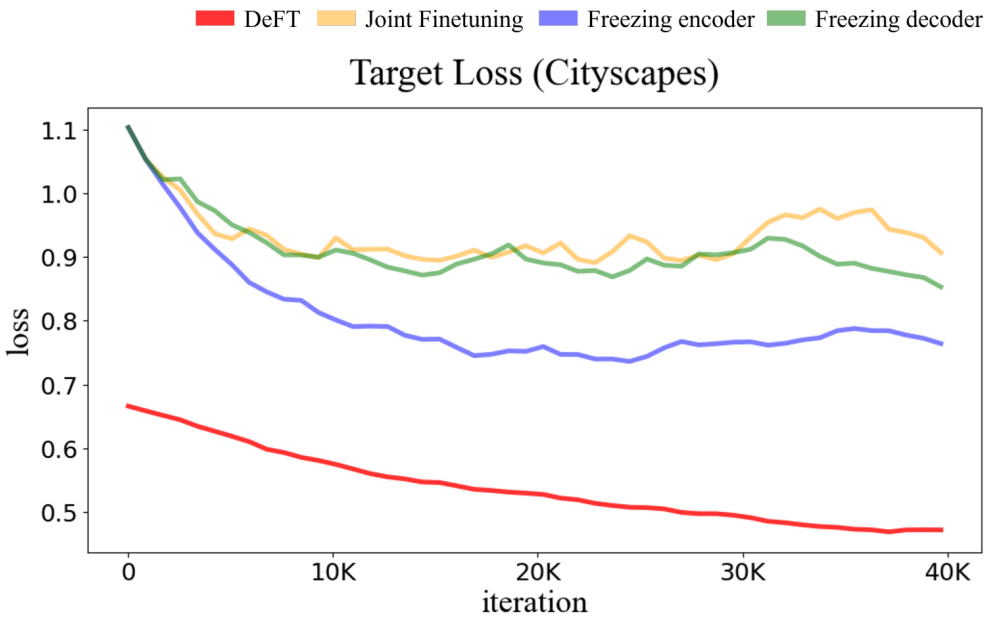


Figure 9: Target loss variation on Cityscapes dataset. We empirically verify that DeFT shows significantly lower target loss on Cityscapes dataset. Also, DeFT effectively mitigates target loss fluctuations during training, which means better generalization capability.