Rectifying Pseudo Label Learning via Uncertainty Estimation for Domain Adaptive Semantic Segmentation

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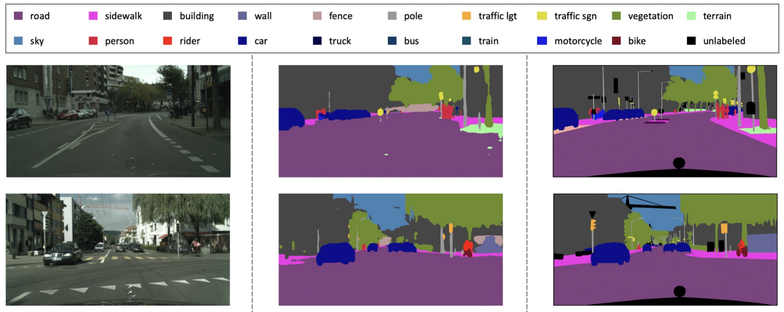
1. Motivation

- Pseudo Labels are **inaccurate**. However, most existing domain adaptation methods directly utilize noisy pseudo labels or manually set the confidence threshold for model learning.



(a) unlabeled target-domain inputs (b) generated pseudo labels (c) ground-truth labels

2. Contributions

- We are among the first attempts to exploit the uncertainty estimation and enable the automatic threshold to learn from noisy pseudo labels.
- Without introducing extra parameters or modules, we formulate the uncertainty as the prediction variance. Specifically, we introduce a new regularization term, variance regularization, which is compatible with the standard cross- entropy loss.
- The proposed method has achieved significant improvements over the conventional pseudo label learning, yielding competitive performance to existing methods.

3. Method

- Uncertainty can help.

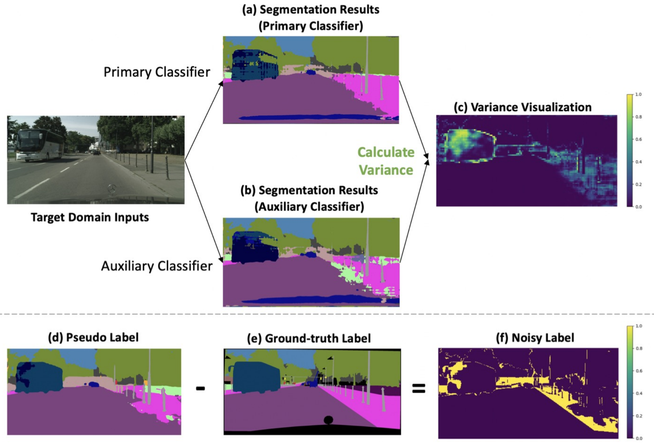


Illustration of the prediction variance between two classifiers, i.e., the primary classifier and the auxiliary classifier. The areas, where have ambiguous predictions, obtain large value of the prediction variance. Meanwhile, we could observe that the high-variance area has considerable over-laps with the noise in the pseudo label.

- Objective (Just put Uncertainty in training.)

We involve the uncertainty term during the training process. The second term prevents Variance to be too large.

Core : $L_{rect} = \mathbb{E}[\frac{1}{Var(p_t)} Bias(p_t) + Var(p_t)]$

Bias : $L_{ce} = \mathbb{E}[-\hat{p}_t^j \log F(x_t^j|\theta_t)]$.

Variance : $D_{kl} = \mathbb{E}[F(x_t^j|\theta_t) \log(\frac{F(x_t^j|\theta_t)}{F_{aux}(x_t^j|\theta_t)})]$.

Rectified : $L_{rect} = \mathbb{E}[exp\{-D_{kl}\} L_{ce} + D_{kl}]$

4. Experiments

- Quantitative Results

Table 5 Variance Regularization vs. Handcrafted Threshold

Methods	Threshold	mIoU
MRNet Zheng andYang (2020)	–	45.5
Pseudo Learning	> 0.99	45.5
Pseudo Learning	> 0.95	47.2
Pseudo Learning	> 0.90	48.4
Pseudo Learning	> 0.80	48.1
Pseudo Learning	> 0.70	48.2
Pseudo Learning	> 0.00	48.3
Ours	–	50.3

The proposed method is free from hand-crafted threshold. '> k' denotes that we only utilize the label confidence > k to train the model. We report the mIoU accuracy on GTA5 → Cityscapes

Fixed Threshold??

Adaptive Threshold.

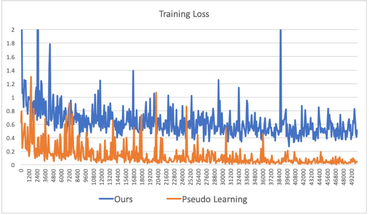
Methods	Right-prediction Certainty	Wrong-prediction Certainty	Uncertainty Gap
MC-dropout 0.5	0.9945	0.9733	0.0212
MC-dropout 0.7	0.9870	0.9396	0.0474
MC-dropout 0.9	0.9486	0.8118	0.1368
Ours	0.9767	0.8410	0.1357
Ours + dropout 0.5	0.9673	0.8065	**0.1608**

MC-Dropout Vs. Uncertainty

Distance Functions	mIoU
$\mathbb{E}[(F(x_t^j\|\theta_t) - F_{aux}(x_t^j\|\theta_t))^2]$	49.6
$\mathbb{E}[F_{aux}(x_t^j\|\theta_t) \log(\frac{F_{aux}(x_t^j\|\theta_t)}{F(x_t^j\|\theta_t)})]$	49.4
$\mathbb{E}[F(x_t^j\|\theta_t) \log(\frac{F(x_t^j\|\theta_t)}{F_{aux}(x_t^j\|\theta_t)})]$	50.3

Ablation study on distance functions.

The training loss of the proposed method and the pseudo label learning. →

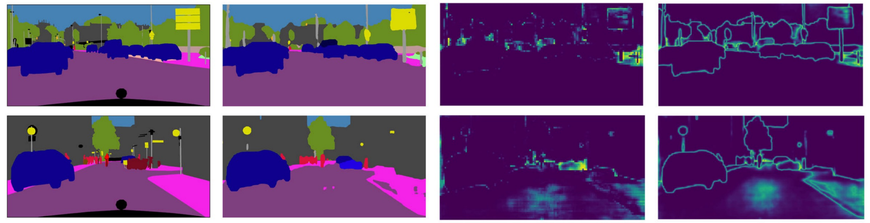


From **48.3%** to **50.3%** mIoU On GTA5 -> CityScapes

From **46.5%** to **47.9%** mIoU On SYNTHIA -> CityScapes

- Qualitative Results

Variance Vs. Confidence Score



Ground Truth Our Prediction Prediction Variance Prediction Confidence