Balanced Learning for Domain Adaptive Semantic Segmentation

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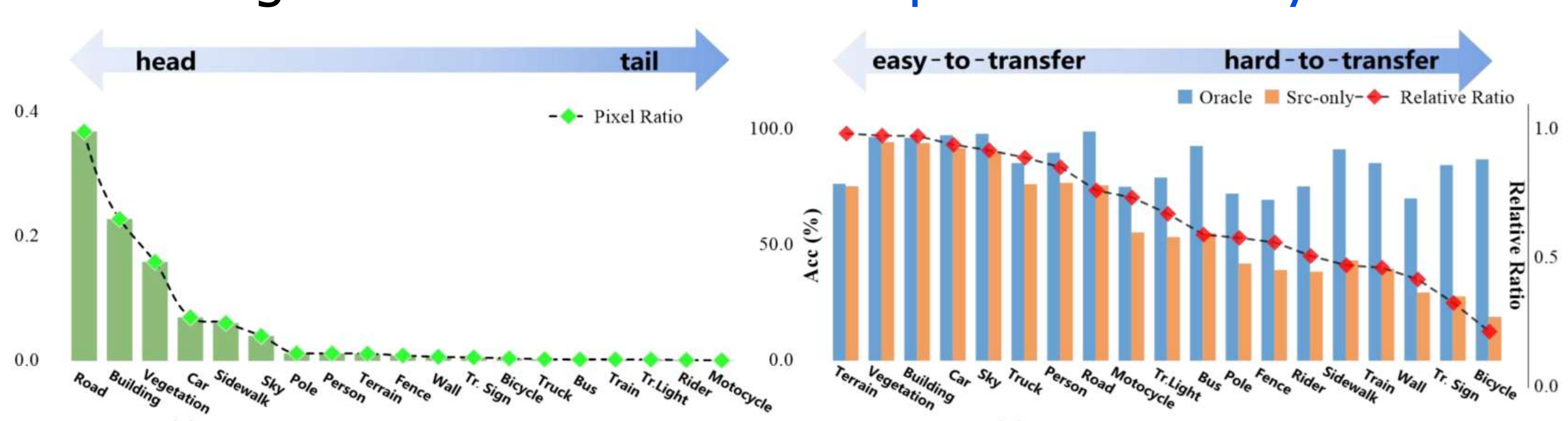
TLDR. Directly Assessing and alleviating class bias in UDA task without prior knowledge of distribution shift

Introduction

Goal. Domain adaptive semantic segmentation aims to mitigate the performance degradation of segmentation networks by transferring knowledge from labeled source domains to unlabeled target domains.

Distribution Shift. Class bias is complicated in UDA.

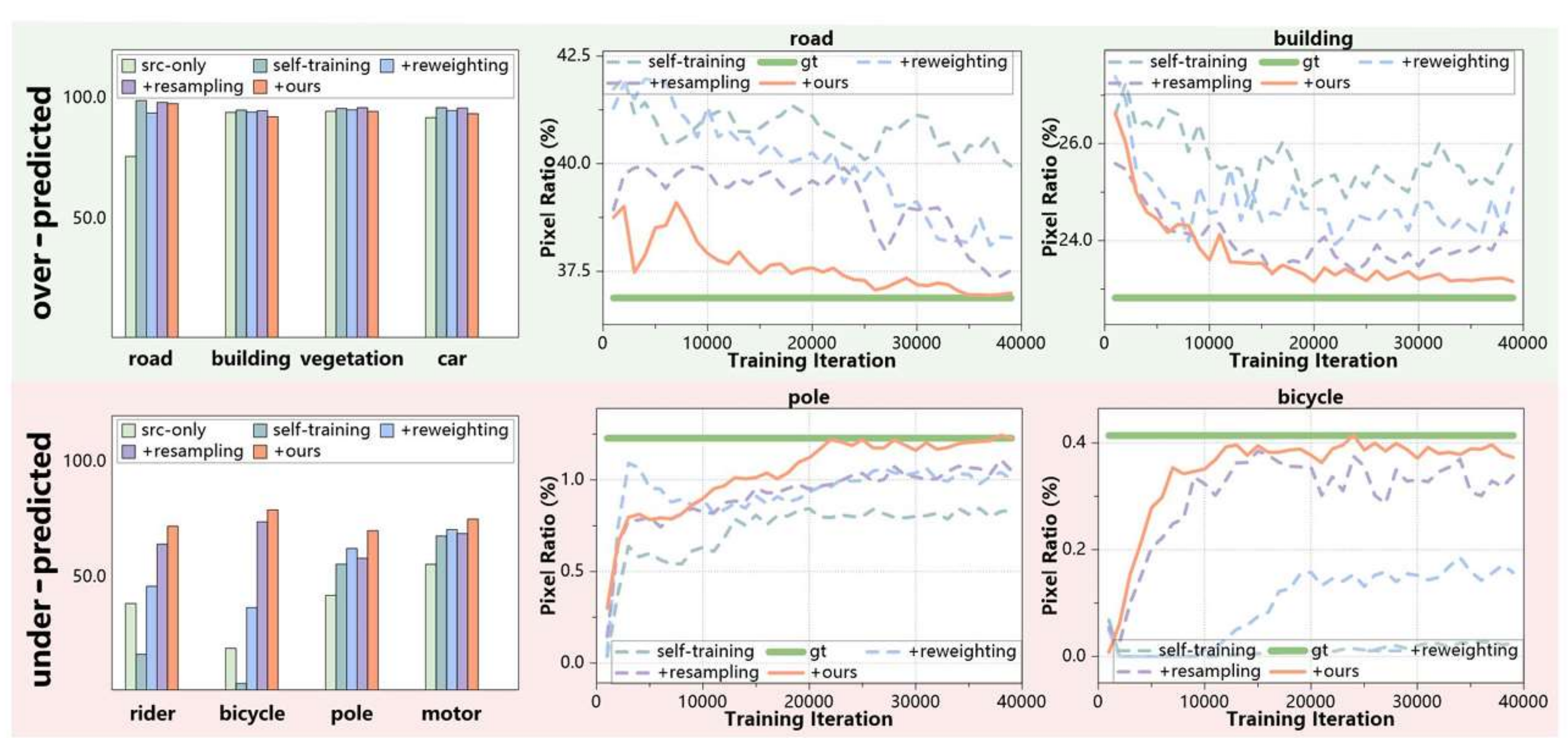
- Inherent class imbalance leads biased predictions towards head classes, studied as long-tail problem.
- Data and label distribution shifts lead to performance degradation that varies significantly across classes, resulting in different levels of adaptation difficulty.



(a) Pixels Distribution Discrepancy (b) Adaptation Discrepancy

Mainstream Paradigm. Existing strategies are still heuristic and rely on the assumption that training and test domains share identical data and label distributions.

- Loss re-weighting assigns different weights to classes, making the model pay more attention to tail classes.
- Sample re-sampling directly adjust the class sample distribution during training, proving more effective.

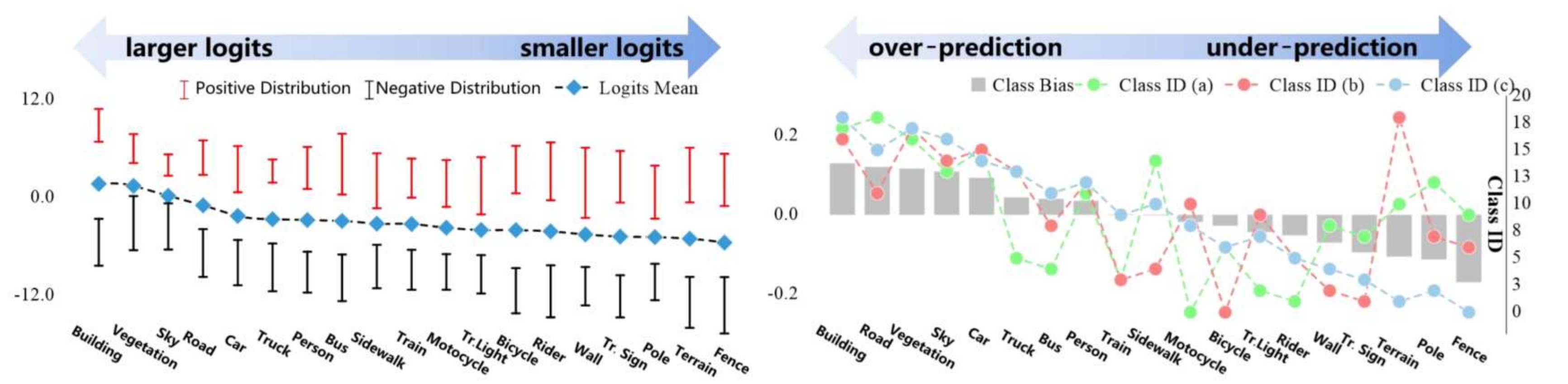


(a) Class-wise Accuracy (b) Pseudo-label Frequency

Motivation

Logits distributions. we propose to assess the degree of class bias by analyzing the distribution of logits predicted by the network.

- Definition 1. Element in logits set matrix, $\mathcal{M}_{cl}$:
$$\mathcal{M}_{cl} = \{f_\theta(x_{ij})[l] \mid y_{ij} = c\}.$$
- Definition 2. Bias of network towards class l, Bias(l):
$$\text{Bias}(l) = \frac{1}{C}\sum_{c\in[C]} \mathbb{P}\left(\arg\max_{c'\in[C]} f_\theta(x)\,[c'] = l \,\middle|\, y = c\right) - \frac{1}{C}.$$



(c) Logits Distribution Discrepancy (d) Class Bias Discrepancy

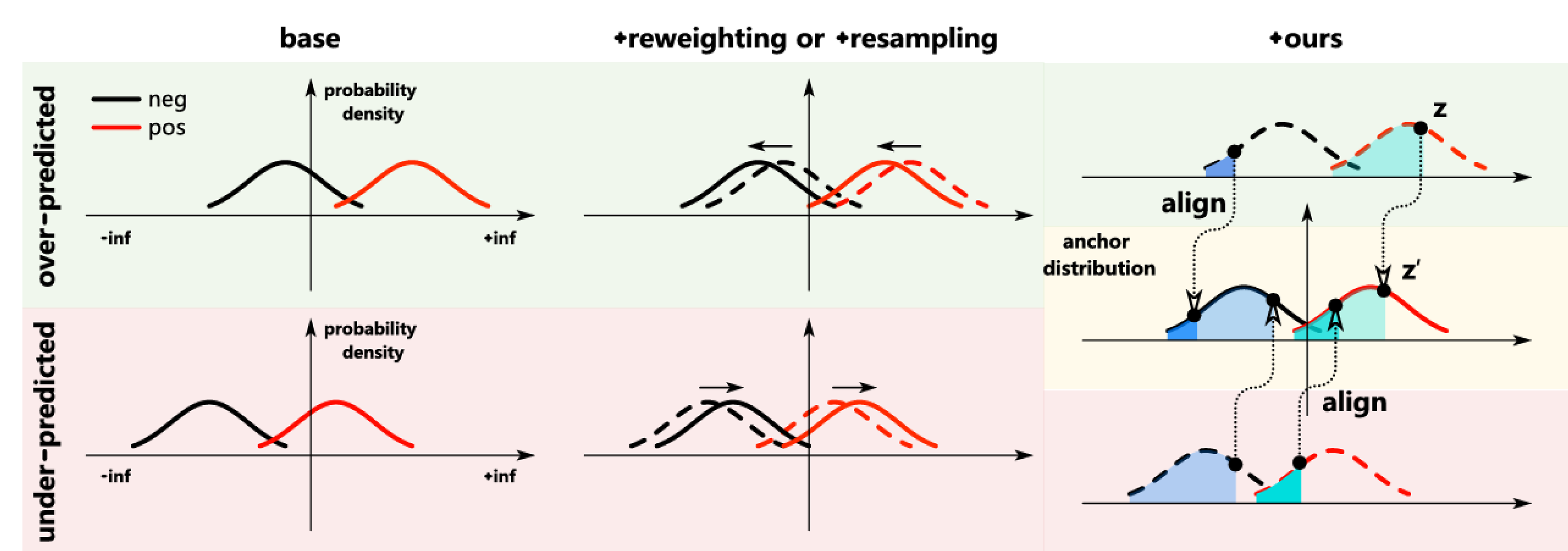
Theoretical insight: Aligned logits → unbiased predictions

Empirical analysis: Logit differences correlate with class bias.

Method

BLDA. Our post-hoc logits adjustment method aligns the logits distributions of all classes with anchor distributions to achieve balanced prediction.

$$z' = \begin{cases} F_p^{-1}(F_{cl}(z)), & \text{if } c = l \\ F_n^{-1}(F_{cl}(z)), & \text{if } c \neq l \end{cases}, \quad \Delta_{cl}(z) = z' - z$$



Online logits adjustment tailored for self-training in UDA:

$$\tilde{\ell}^{s}_{ce} = -\log \frac{\exp(f_\theta(x^S_{ij})[y^S_{ij}] - \tau\Delta^S_{y^S_{ij},y^S_{ij}}(f_\theta(x^S_{ij})[y^S_{ij}]))}{\sum_{c=1}^{C}\exp(f_\theta(x^S_{ij})[c] - \tau\Delta^S_{y^S_{ij},c}(f_\theta(x^S_{ij})[c]))},$$

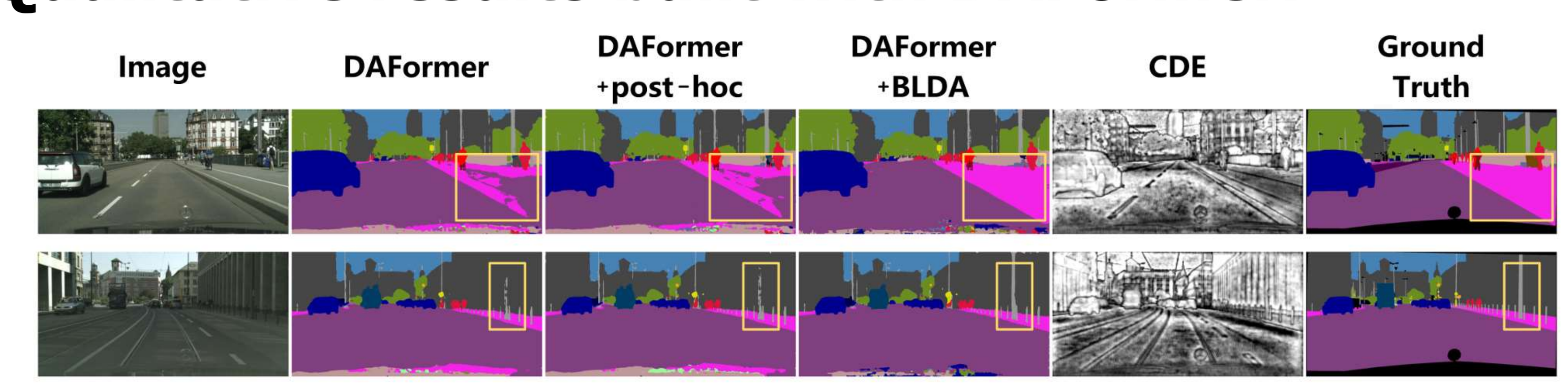
$$\tilde{\ell}^{u}_{ce} = -\log \frac{\exp(f_\theta(x^T_{ij})[\hat{y}^T_{ij}] - \tau\Delta^T_{\hat{y}^T_{ij},\hat{y}^T_{ij}}(f_\theta(x^T_{ij})[\hat{y}^T_{ij}]))}{\sum_{c=1}^{C}\exp(f_\theta(x^T_{ij})[c] - \tau\Delta^T_{\hat{y}^T_{ij},c}(f_\theta(x^T_{ij})[c]))}.$$

Experiments

Quantitative results on GTAv→ Cityscapes.

Method	Arch.	mIou (↑)	std (↓)	mAcc (↑)	std (↓)
DACS* (Tranheden et al., 2021)	C	52.1	27.1	65.8	26.5
+BLDA	C	**54.7**	**25.6**	**69.0**	**24.2**
DAFormer(C)* (Hoyer et al., 2022a)	C	56.2	24.0	69.3	23.8
+BLDA	C	**58.1**	**23.2**	**74.9**	**21.6**
DAFormer (Hoyer et al., 2022a)	T	68.3	16.8	77.8	14.2
+BLDA	T	**70.7**	**15.5**	**82.0**	**11.9**
CDAC* (Wang et al., 2023)	T	69.2	16.7	78.7	13.8
+BLDA	T	**71.0**	**15.4**	**82.5**	**11.5**
HRDA (Hoyer et al., 2022b)	T	73.8	15.4	82.2	13.2
+BLDA	T	**75.6**	**13.8**	**85.1**	**10.7**
MIC (Hoyer et al., 2023)	T	75.9	14.8	83.2	11.6
+BLDA	T	**77.1**	**13.5**	**86.3**	**9.8**

Qualitative results built with DAFormer.



Visualization Results of Logits Distribution.