Category-Adaptive for Semantic Segmentation Domain Adaptation

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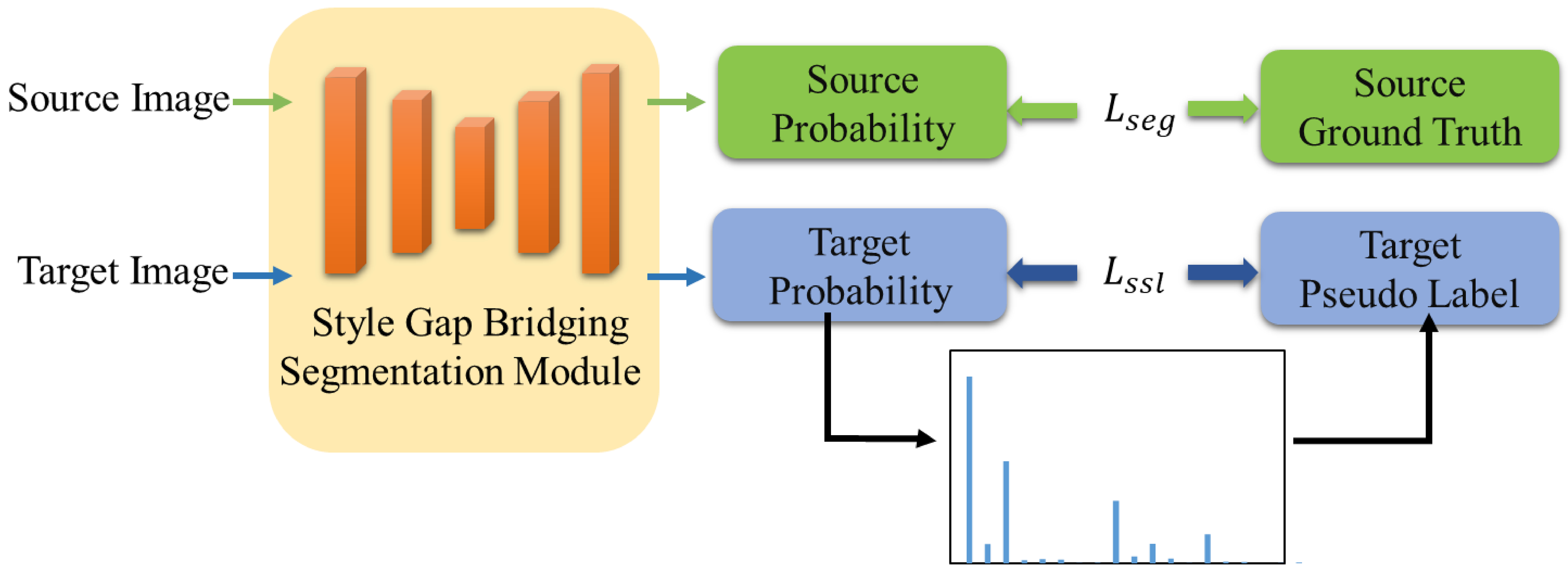
Cross-Domain Adaptation for Semantic Segmentation

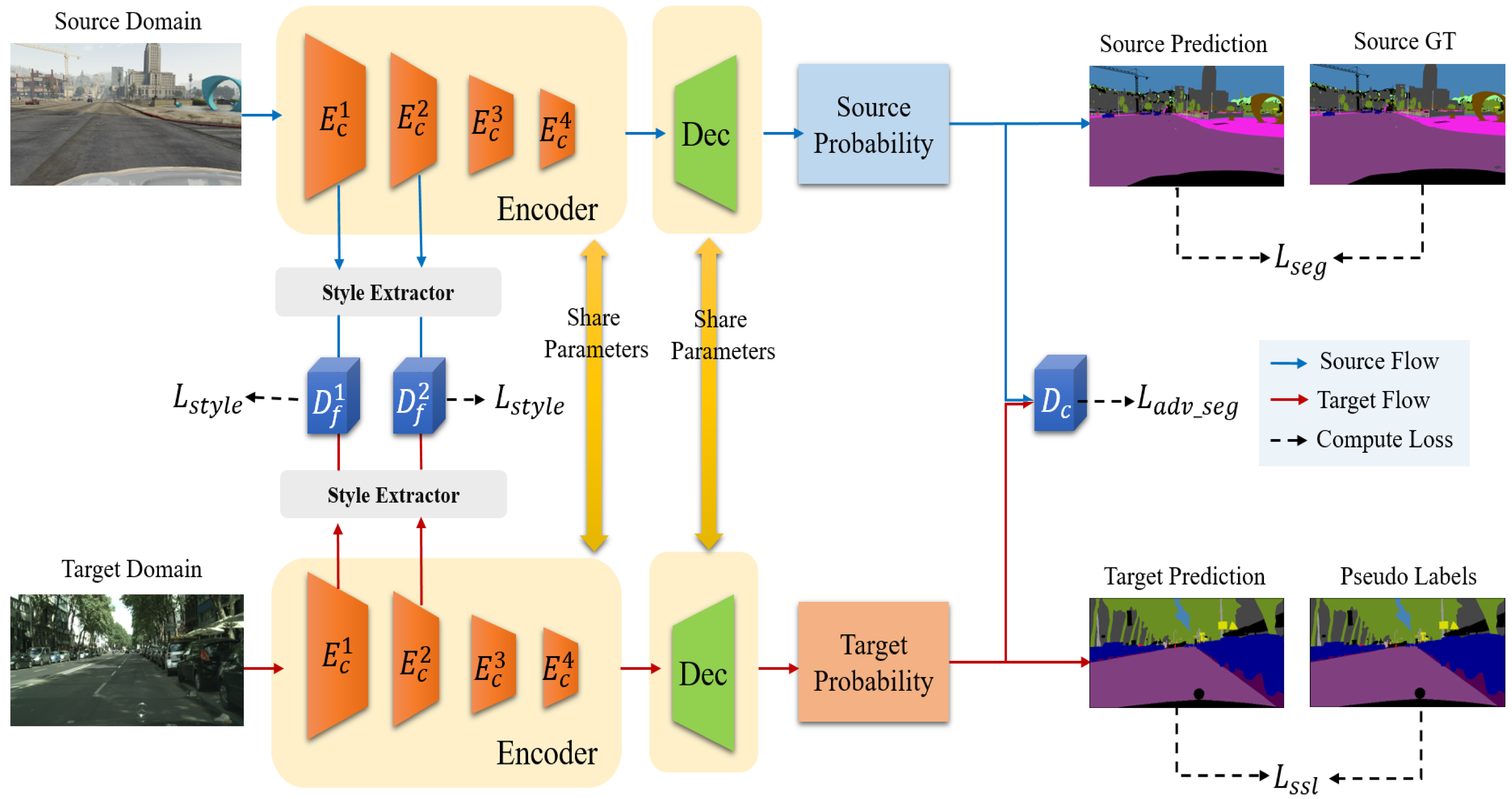


Category Adaptive Thresholds

Our contributions:

- Adversarial learning is introduced for the style gap bridging mechanism.
- A new category-adaptive threshold mechanism is proposed to choose pseudo labels for self-supervised learning.

Architecture of Proposed Method



Loss functions:

1. Segmentation Loss $\mathcal{L}_{seg}$
2. Domain Adaptation Loss $\mathcal{L}_{adv\_seg}$
3. Style loss $\mathcal{L}_{style}$
4. Self-supervised Loss $\mathcal{L}_{ssl}$

Pseudo Labeling Mechanism

1. Define the category centroid of class c:

$$f^c = \frac{1}{|\mathcal{P}^c|} \sum_{|\mathcal{X}_t|} \sum_{h=1}^{H_t} \sum_{w=1}^{W_t} \mathbb{1}_{[c=\arg\max_{c'} P_t^{hwc'}]} P_t^{hw}$$

2. Define pseudo labels m_t^{hwc} based on entropy comparison and given threshold $\triangle$:

$$m_t^{hwc} = \mathbb{1}_{[H(P_t^{hw})<H(f^c)-\Delta,\, c=\arg\max_{c'} P_t^{hwc'}]}$$

3. self-supervised learning based on pseudo labels:

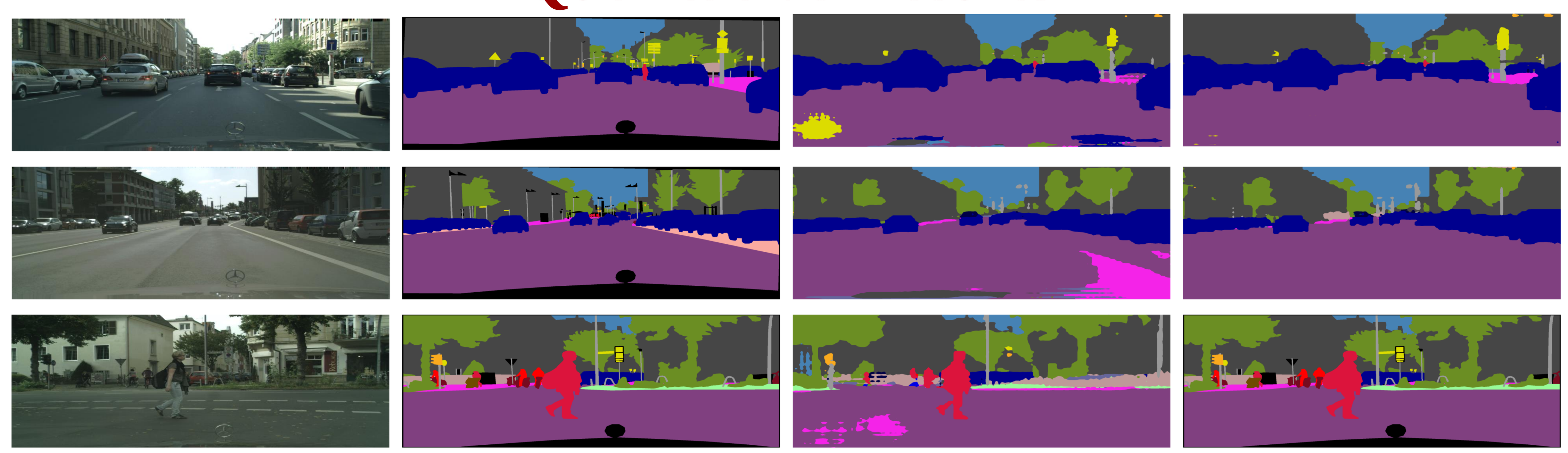
$$\mathcal{L}_{ssl} = -\frac{1}{H_t W_t} \sum_{h=1}^{H_t} \sum_{w=1}^{W_t} \sum_{c=1}^{C} m_t^{hwc} \hat{y}_t^{hwc} \log P_t^{hwc}$$

Quantitative Results

GTA5 $\rightarrow$ Cityscapes

Method	road	sidewalk	building	wall	fence	pole	t-light	t-sign	vegetation	terrain	sky	person	rider	car	truck	bus	train	motorbike	bicycle	mIoU
CBST[4]	89.6	**58.9**	78.5	33.0	22.3	**41.4**	**48.2**	39.2	83.6	24.3	65.4	49.3	20.2	83.3	39.0	48.6	**12.5**	20.3	35.3	47.0
Cycada [19]	86.7	35.6	80.1	19.8	17.5	38.0	39.9	**41.5**	82.7	27.9	73.6	**64.9**	19	65.0	12.0	28.6	4.5	31.1	42.0	42.7
ADVENT [6]	87.6	21.4	82.0	34.8	26.2	28.5	35.6	23.0	84.5	35.1	76.2	58.6	30.7	84.8	34.2	43.4	0.4	28.4	35.2	44.8
DCAN [20]	85.0	30.8	81.3	25.8	21.2	22.2	25.4	26.6	83.4	36.7	76.2	58.9	24.9	80.7	29.5	42.9	2.5	26.9	11.6	41.7
CLAN [21]	87.0	27.1	79.6	27.3	23.3	28.3	35.5	24.2	83.6	27.4	74.2	58.6	28.0	76.2	33.1	36.7	6.7	**31.9**	31.4	43.2
BDL [5]	91.0	44.7	84.2	34.6	**27.6**	30.2	36.0	36.0	**85.0**	**43.6**	83.0	58.6	31.6	83.3	35.3	49.7	3.3	28.8	35.6	48.5
Ours	**91.7**	51.1	**85.0**	**38.7**	26.7	32.1	38.1	34.6	84.3	38.6	**84.9**	60.7	**32.8**	**85.2**	**41.9**	**49.8**	2.8	28.5	**45.0**	**50.2**

Qualitative Results



(a) Image (b) GT (c) BDL (d) Ours

Style Gap Bridging Comparison

style gap bridging mechanism	style modeling	mIoU
MSE	Gram matrix	44.7
	mean & std	45.1
adversarial learning	mean (Ours)	45.5

Ablation Studies

GTA5 $\rightarrow$ Cityscapes

model	mIoU
original	44.6
original + adv	45.5
original + adv + SSL once	48.5
original + adv + SSL twice	50.2