

Towards Robust Pseudo-Label Learning in Semantic Segmentation: An Encoding Perspective

Wangkai Li¹, Rui Sun¹, Zhaoyang Li¹, Tianzhu Zhang^{1, 2}

¹University of Science and Technology of China, ²Deep Space Exploration Laboratory



中国科学技术大学

University of Science and Technology of China

DSEL
DEEP SPACE EXPLORATION LAB
深空探测实验室

NEURAL INFORMATION
PROCESSING SYSTEMS

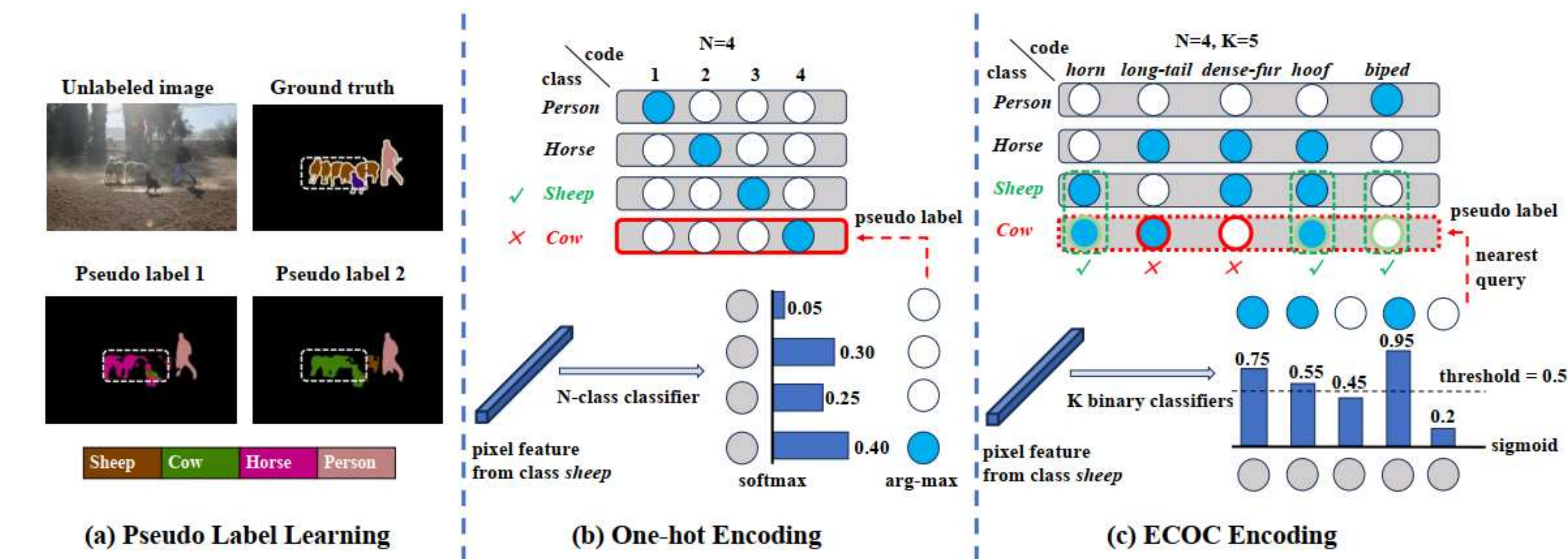
TLDR. Utilize ECOC encoding to **denoise pseudo-labels** for label-scarce semantic segmentation **at the bit level**

Introduction

Goal. Domain-adaptive / semi-supervised semantic segmentation aims to avoid laborious pixel-wise annotation using annotated and unlabeled data simultaneously.

Mainstream Paradigm. Self-training and consistency regularization generates pseudo labels for unlabeled data as supervision, summarized as pseudo-label learning.

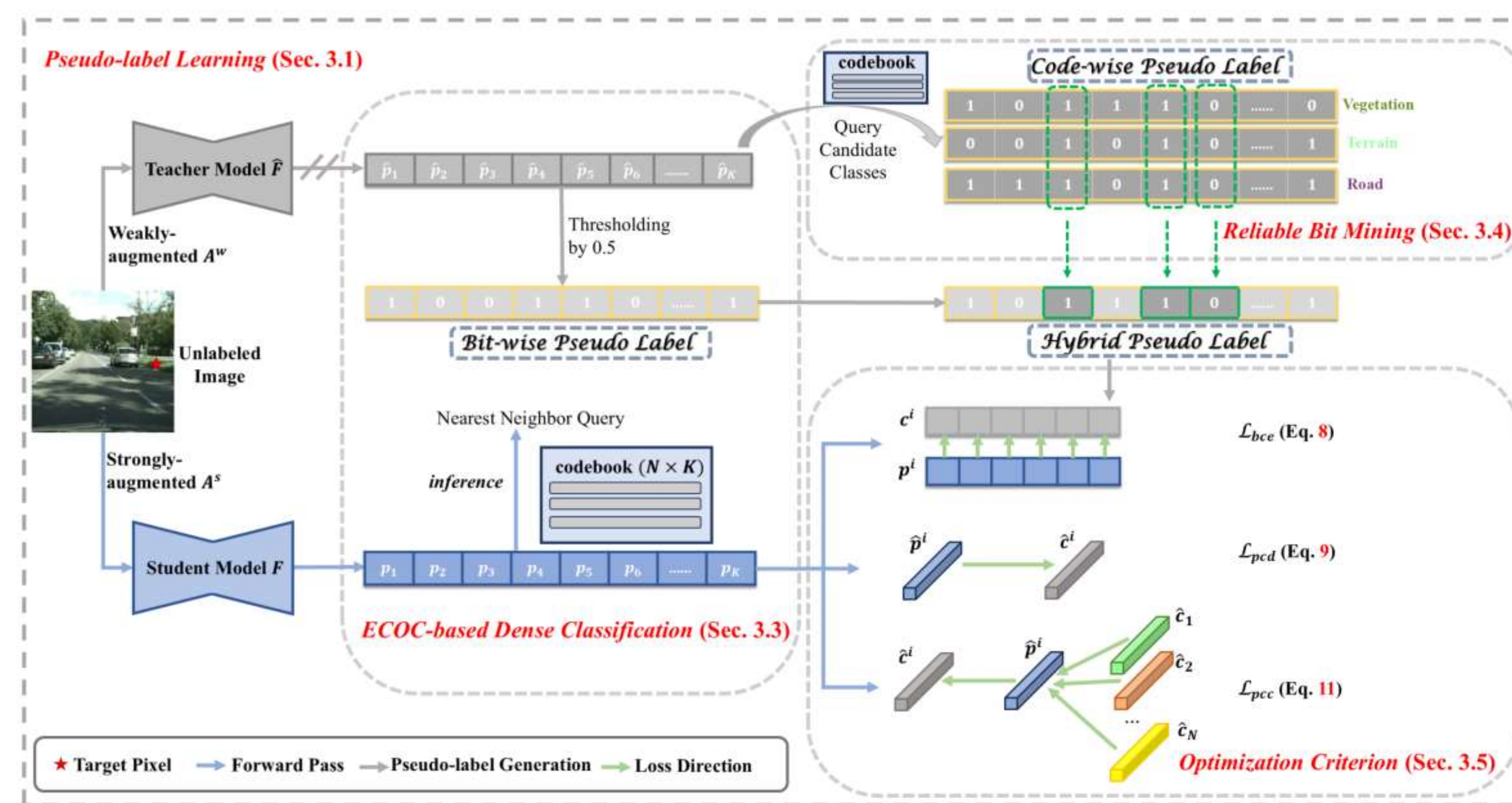
Problem. Pseudo-label learning under UDA/SSL improves segmentation but suffers from noisy pseudo-labels; one-hot encoding amplifies these errors during training.



Motivation.

- One-hot limitations: Enforces hard class assignments, ignores shared attributes among confusing classes.
- ECOC advantages: Enables bit error correction by large Hamming distances, stabilizes learning via shared bits.
- Theoretical guarantee:
 - In fully supervised settings, ECOC can serve as an effective equivalent to one-hot encoding.
 - In pseudo-label learning, ECOC exhibits greater robustness with a tighter classification error bound.

Method



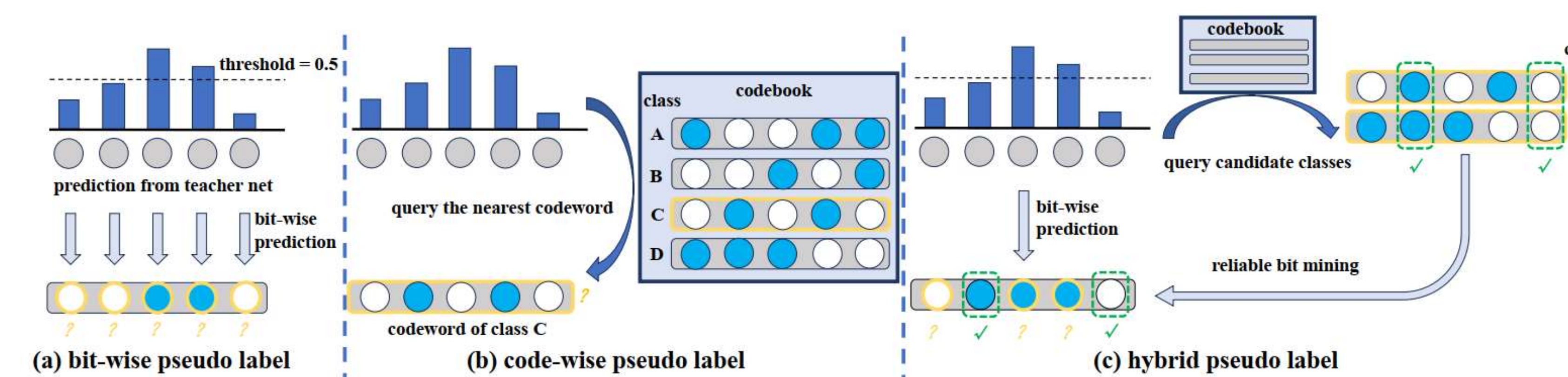
ECOC-based Dense Classification. Replace N -way softmax with K independent sigmoid heads (K bits).

$$d_{SH}(c_n, p^i) = \frac{1}{K} \sum_{k=1}^K \|p(k|z_i) - c_{nk}\|_1,$$

$$\hat{n}^i = \underset{n}{\operatorname{argmin}} \{d_{SH}(c_n, p^i)\}.$$

Reliable Bit Mining. Extract reliable bits from code-wise labels within candidates and fuse them with bit-wise labels, obtain more robust pseudo-labels in a hybrid way:

$$c_{hyb}^i = \mathcal{M}^i \odot c_{code}^i + (1 - \mathcal{M}^i) \odot c_{bit}^i.$$



Optimization Criterion. Typically binary cross-entropy:

$$\mathcal{L}_{bce}^i = -\frac{1}{K} \sum_{k=1}^K [c_{(k)}^i \log p(k|z_i) + (1 - c_{(k)}^i) \log(1 - p(k|z_i))]$$

- Pixel-code distance: $\mathcal{L}_{pcd}^i = 1 - \cos(\hat{p}^i, \hat{c}^i)$
- Pixel-code contrast:

$$\mathcal{L}_{pcc}^i = \log(1 + \sum_{\hat{c} \in \hat{C}^-} \exp(\langle \hat{p}^i, \hat{c} - c^i \rangle / \tau))$$

Experiments

Quantitative Results on GTAV → Cityscapes.

Method	Arch.	Road	Sidewalk	Building	Wall	Fence	Pole	Light	Sign	Veg	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motor	Bike	mIoU
GTAV → Cityscapes (Val.)																					
ProDA [100]	C	87.8	56.0	79.7	46.3	44.8	45.6	53.5	53.5	88.6	45.2	82.1	70.7	39.2	88.8	45.5	50.4	1.0	48.9	56.4	57.5
CPSL [45]	C	92.3	59.5	84.9	45.7	29.7	52.8	61.5	59.5	87.9	41.6	85.0	73.0	35.5	90.4	48.7	73.9	26.3	53.8	53.9	60.8
TransDA [11]	T	94.7	64.2	89.2	48.1	45.8	50.1	60.2	40.8	90.4	50.2	93.7	76.7	47.6	92.5	56.8	60.1	47.6	49.6	55.4	63.9
ADFormer [30]	T	96.7	75.1	88.8	57.5	45.9	45.6	55.4	59.8	90.2	45.6	92.1	70.8	43.0	91.0	78.9	79.3	68.7	52.7	65.0	69.2
CDAC [83]	T	97.1	78.7	91.8	59.6	57.1	59.1	66.1	72.2	91.8	53.1	94.5	79.4	51.6	94.6	84.9	87.8	78.7	64.9	67.6	75.3
DACS [79]	C	89.9	39.7	87.9	39.7	39.5	38.5	46.4	52.8	88.0	44.0	88.8	67.2	35.8	84.5	45.7	50.2	0.2	27.3	34.0	52.1
+ECOCseg	C	95.6	71.8	90.2	37.8	31.4	44.8	50.8	58.8	90.4	50.3	91.3	68.6	23.5	91.2	49.8	55.4	8.8	15.2	9.8	54.5
DAFormer [34]	T	95.7	70.2	89.4	53.5	48.1	49.6	55.8	59.4	89.9	47.9	92.5	72.2	44.7	92.3	74.5	78.2	65.1	55.9	61.8	68.3
+ECOCseg	T	96.7	75.6	89.4	54.0	51.4	55.1	59.4	61.9	90.1	46.6	90.0	71.5	42.4	92.8	79.7	85.4	79.1	60.0	58.2	70.5
MIC [35]	T	97.4	80.1	91.7	61.2	56.9	59.7	66.0	71.3	91.7	51.4	94.3	79.8	56.1	94.6	85.4	90.3	80.4	64.5	68.5	75.9
+ECOCseg	T	97.9	81.4	91.9	62.2	54.3	64.2	67.4	76.1	92.9	54.4	94.2	82.1	53.0	95.2	89.6	90.8	82.3	61.9	69.4	76.9

Visualization Results of Reliable Bits.

