D²ADA: Dynamic Density-aware Active Domain Adaptation for Semantic Segmentation

國立臺灣大學 National Taiwan University

Tsung-Han Wu[1], Yi-Syuan Liu[1], Shao-Ji Yuan[1], Hsin-Ying Lee[1], Tung-I Chen[1], Kuan-Chih Huang[1], Winston H. Hsu[1,2]

[1]National Taiwan University [2]Mobile Drive Technology

MobileDrive

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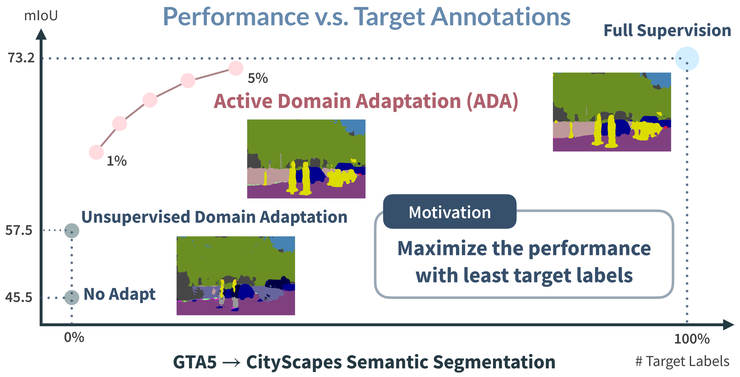
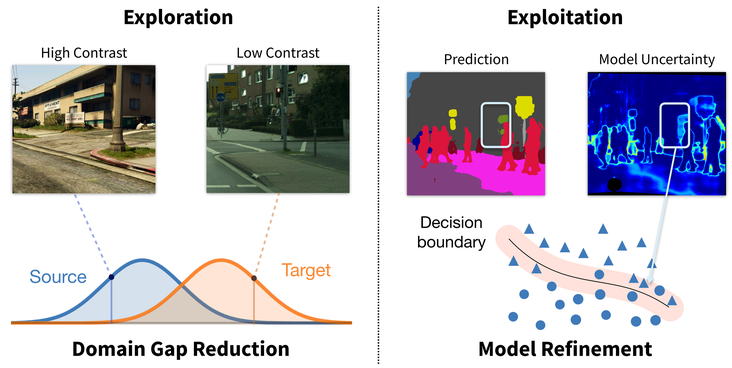
Domain Adaptation Tradeoff



Active Domain Adaptation

- **WHY**: Reduce manual annotation effort on target domain
- **HOW**: Iteratively select limited valuable data for labeling

Conventional Data Selection Strategies



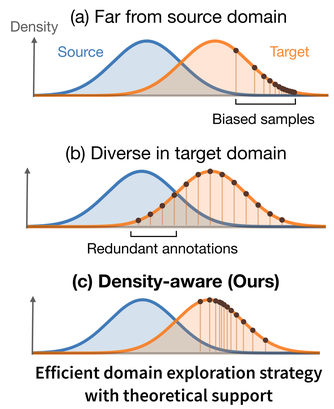
Our Contributions

- **Density-aware selection**: Pave a new way for the ADA problem
- **Dynamic scheduling policy**: Balance exploration and exploitation
- **Experimental Results**: Achieve SOTA performance on the two tasks

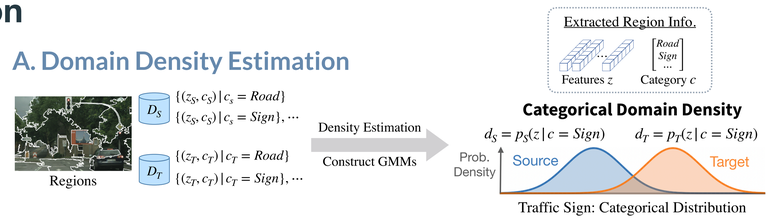
arXiv GitHub

Density-aware Selection

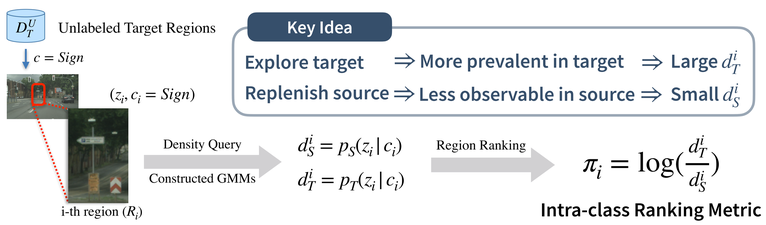
Method Illustrations



A. Domain Density Estimation



B. Density-ware Region Ranking



C. Theoretical Foundation

Generalization Bound of Domain Adaptation

$$\varepsilon_{test} \le \varepsilon_{train} + \frac{M}{\sqrt{2}}\sqrt{D_{KL}(p_T(c,z) \,||\, p_S(c,z))}$$

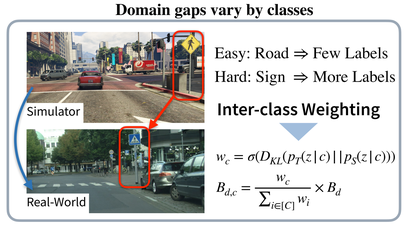
$$D_{KL}(p_T(c) \,||\, p_S(c)) + \mathbb{E}[D_{KL}(p_T(z|c) \,||\, p_S(z|c))]$$

$$\frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{p_T(z_i|c)}{p_S(z_i|c)}\right) = \frac{1}{N}\sum_{i=1}^{N}\pi_i \text{ (Our Metric)}$$

Select regions with large π ⇒ Make ε_{test} smaller

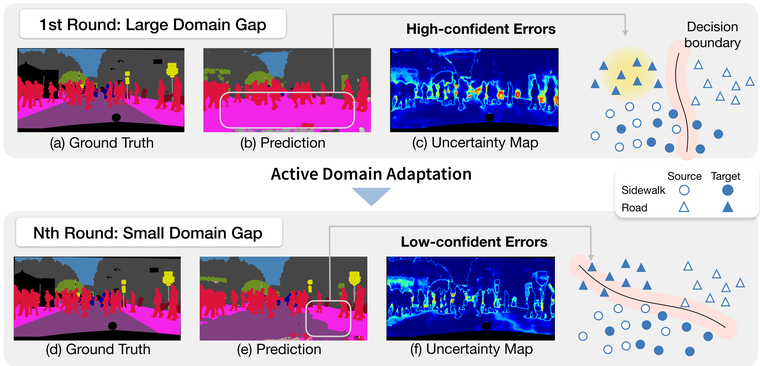
D. Class-Balanced Selection

Domain gaps vary by classes

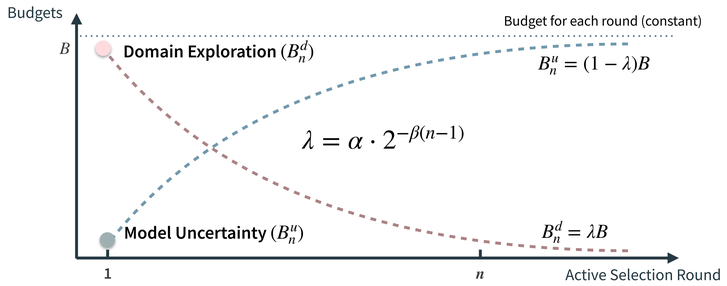


Dynamic Scheduling Policy

A. Exploration v.s. Exploitation

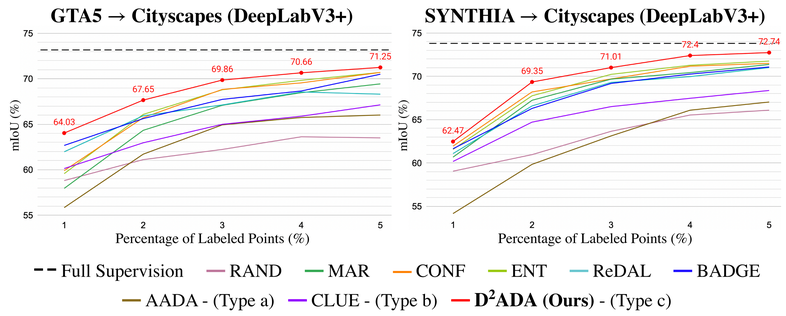


B. Labeling Budget Allocation



Experimental Results

A. Comparison with Active Learning Baselines



B. Comparison with Domain Adaptation Methods

Type	Method	Venue	(a) GTA5 mIoU	(b) SYN. mIoU	mIoU*
UDA	IAST	ECCV 2020	51.5	49.8	57.0
	ProDA	CVPR 2021	57.5	55.5	62.0
	BAPA-Net	ICCV 2021	57.4	53.3	61.2
WDA	WDA (Point)	ECCV 2020	56.4	57.2	63.7
ADA	LabOR (V2, 2.2%)	ICCV 2021	66.6	-	-
	MADA (V3+, 5%)	ICCV 2021	64.9	68.1	73.3
	RIPU (V3+, 5%)	CVPR 2022	71.2	71.4	76.7
	D²ADA (V2, 5%)	ECCV 2022	69.7	70.6	76.3
	D²ADA (V3+, 5%)	ECCV 2022	**71.3**	**72.7**	**77.7**
Full Target	DeepLabV2	-	71.3	72.5	77.5
	DeepLabV3+	-	73.2	73.8	78.4

5% Labels ⇓ 97% mIoU

ECCV TEL AVIV 2022