DUDA:
Dual Domain Adaption for Semantic Segmentation
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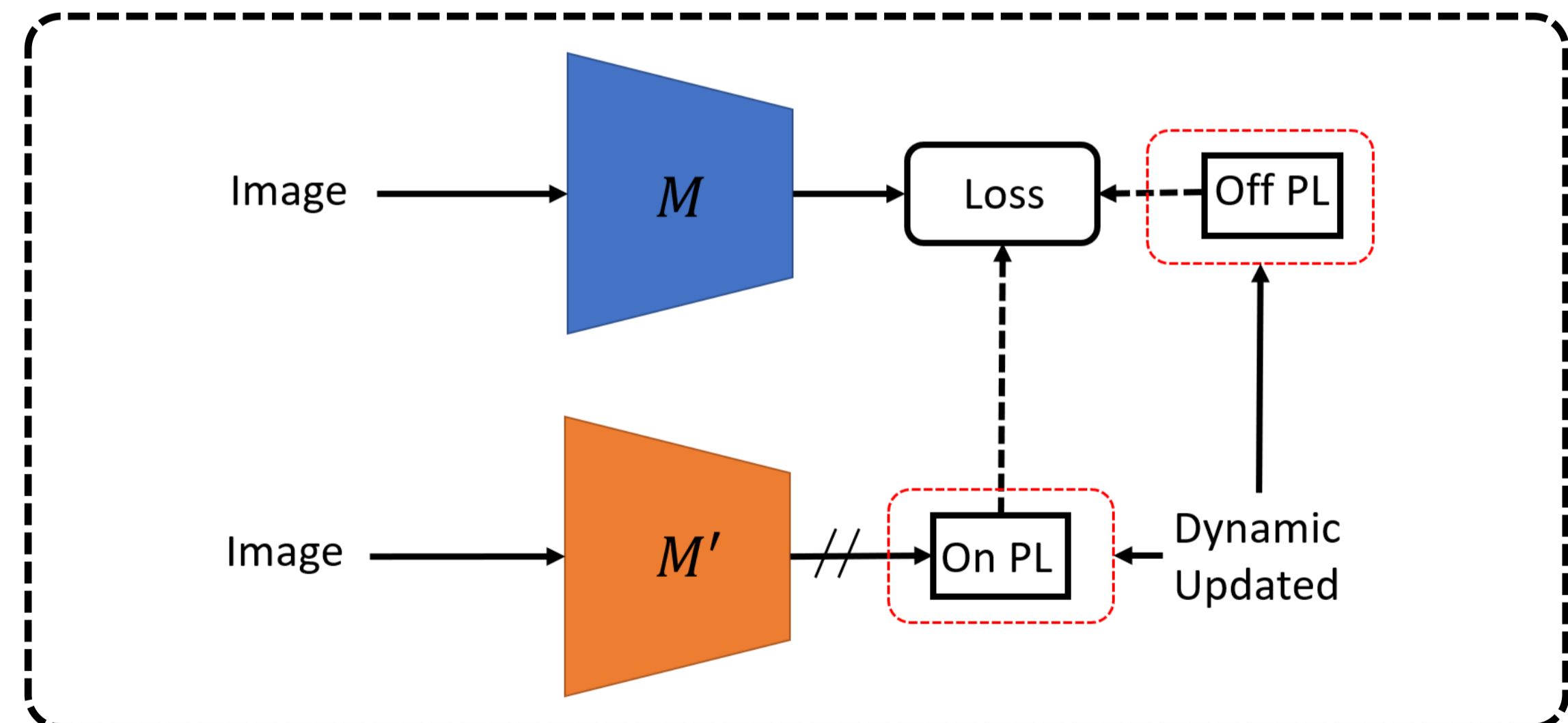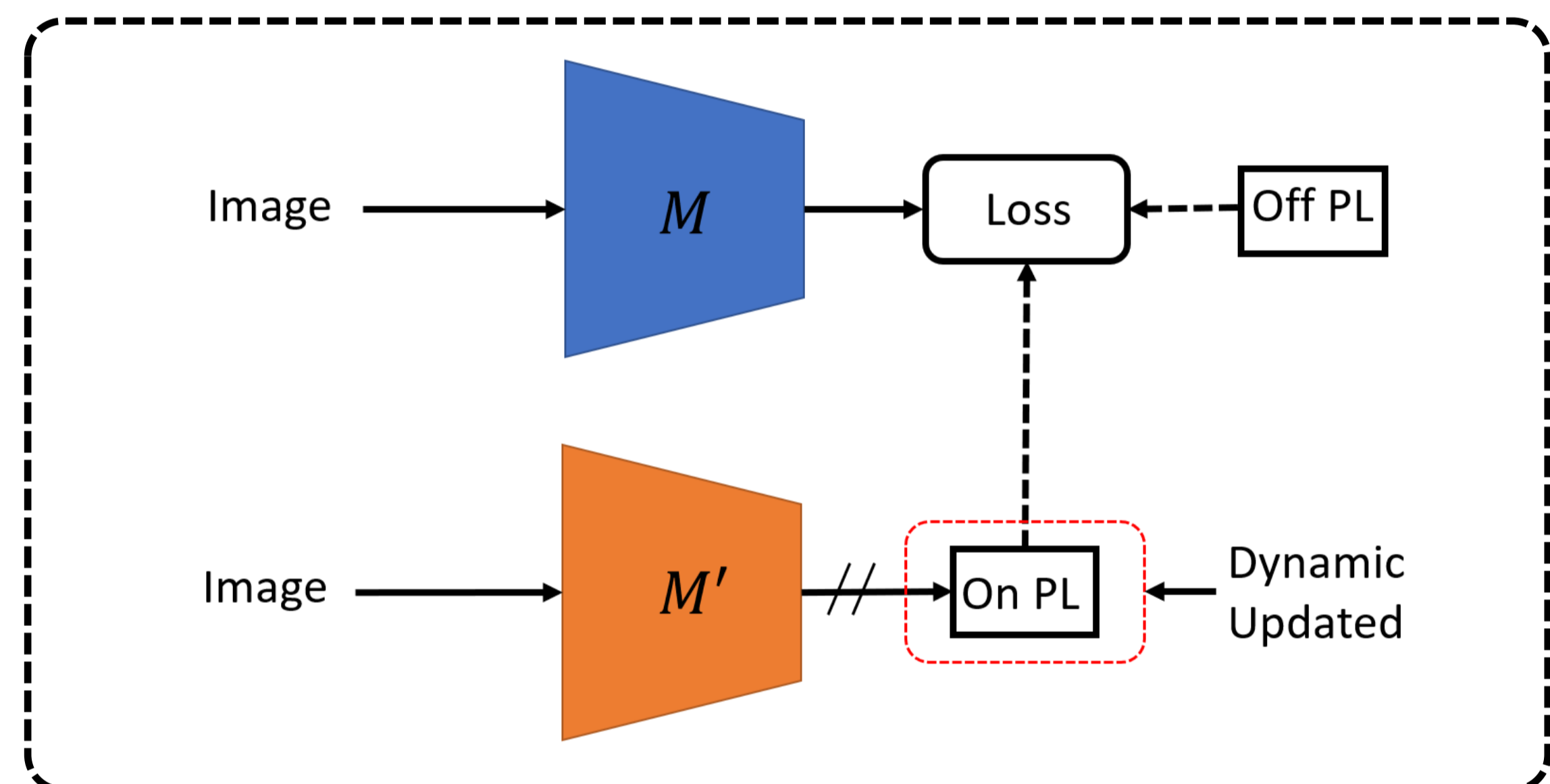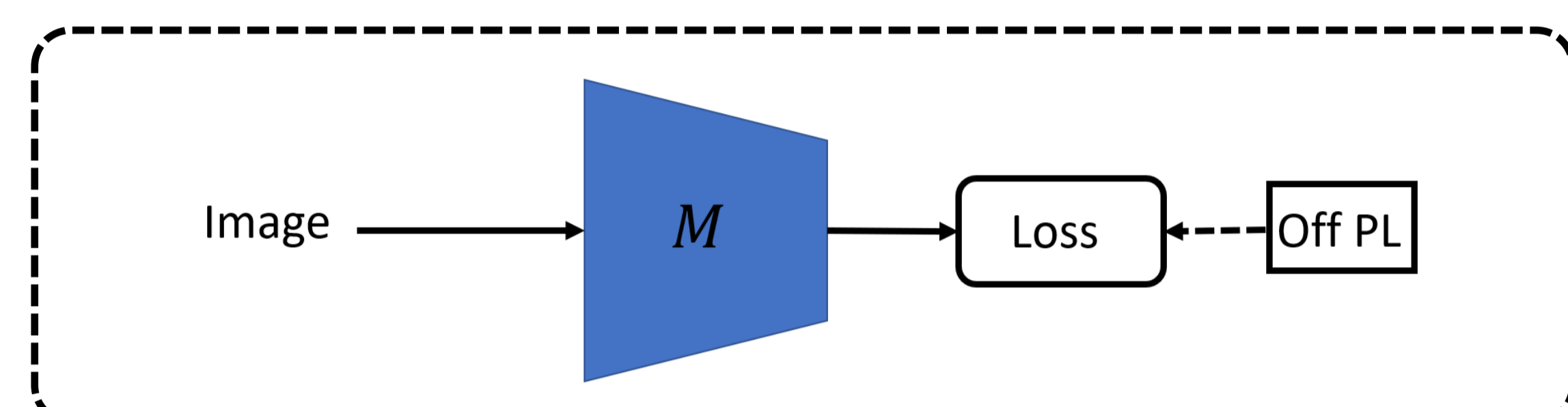### Zhejiang University

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Introduce

Current self-training method in semantic segmentation include static offline pseudo label and dynamic online pseudo label and the static offline pseudo label is updated by stage. We argue that the offline pseudo label also need updated during training and historical consistency information is employed here to update the offline pseudo label.

Our contributions can summary as follows:
- Online and offline dual update pseudo label update stage
- Online and offline dual regularization

Method and Analysis
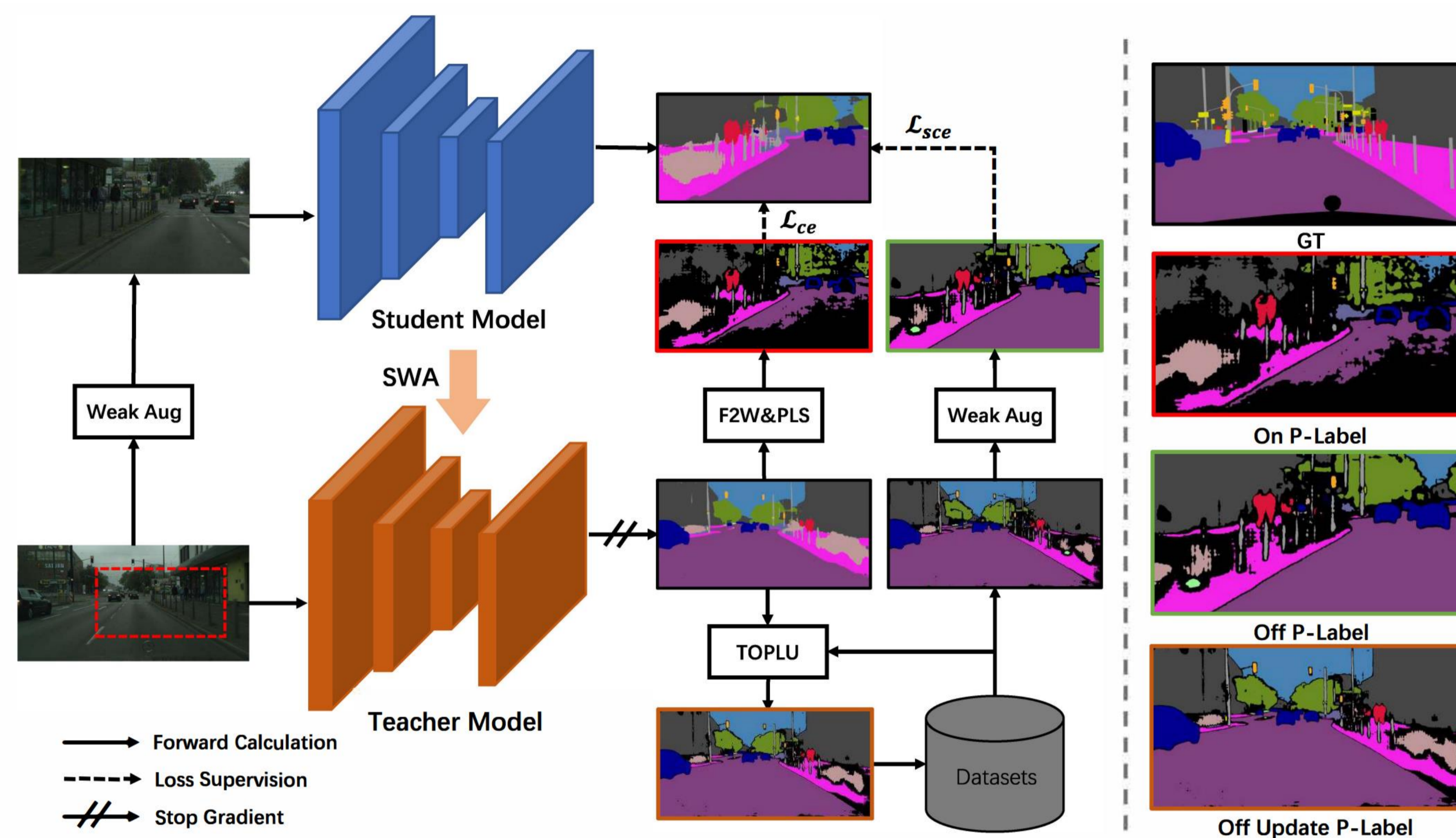
The whole **DUDA framework** include a gradient updated student model and a **SWA** updated teacher model. The teacher model provides the on-the-fly online pseudo label and update the offline pseudo label via **TOPLU** algorithm. TOPLU algorithm is designed that combines current predict result and previous saved result. The historical consistency information is utilized in TOPLU.
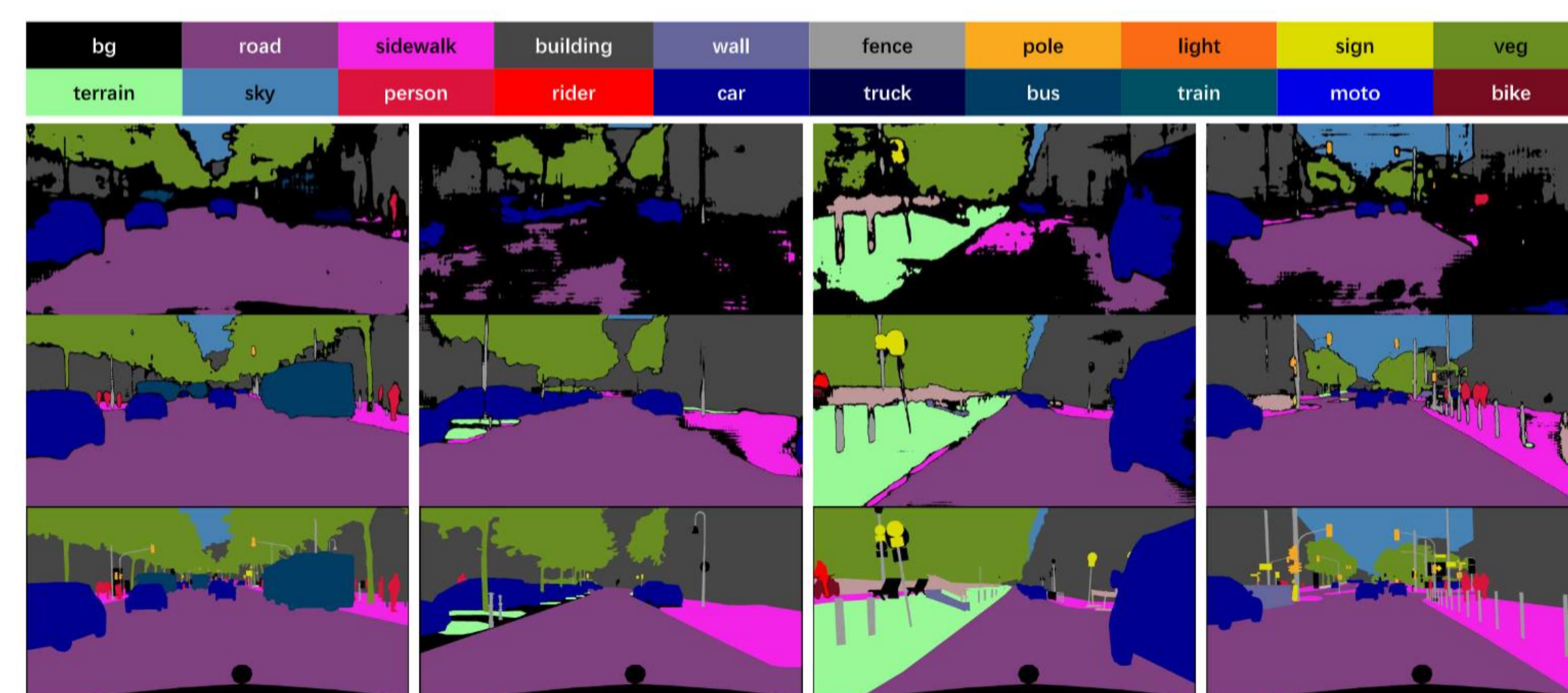
Three steps of TOPLU Algorithm
1. **High-confidence acceptance:** Batch level CBST is applied to select high confident pixel.
2. **Inconsistent discard:** Comparing with previous result and discard the inconsistent result.
3. **Consistent acceptance:** Comparing with previous result and acceptance the inconsistent result.

The image above shows the refinement result of the offline pseudo label in the DUDA. The image right image is the t-SNE visualize. The refined pseudo label bring better separated features.
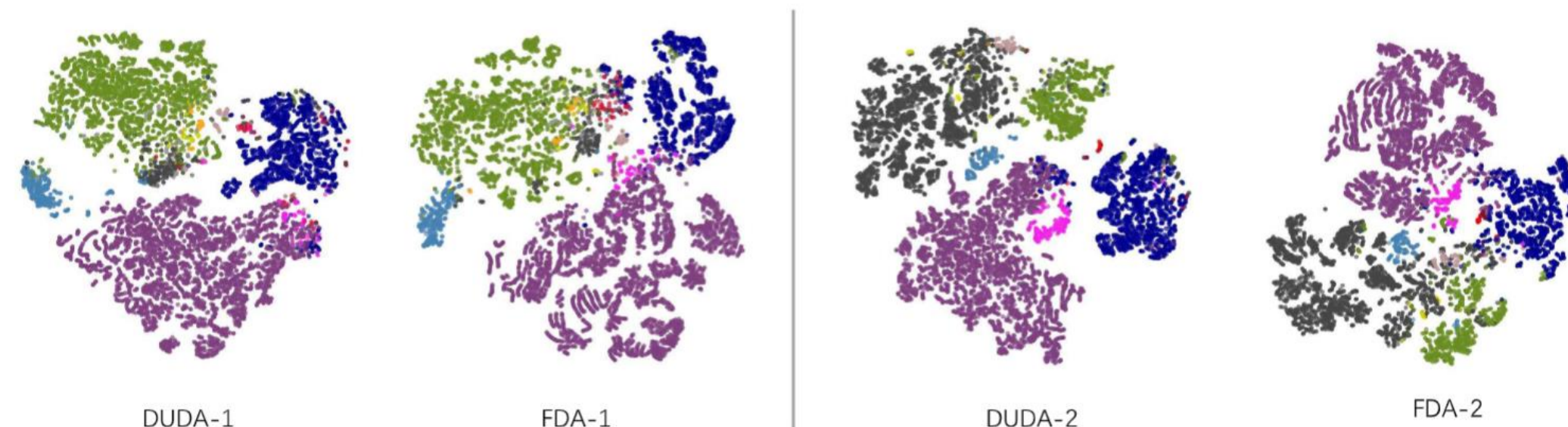
Experimental Results

Experiment on GTA5-to-Cityscapes Benchmark

method	road	sdwlk	bldng	wall	fence	pole	light	sign	veg	trm	sky	psn	rider	car	trunck	bus	train	moto	bike	mIoU
CBST [46]	91.8	53.5	80.5	32.7	21.0	34.0	28.9	20.4	83.9	34.2	80.9	53.1	24.0	82.7	30.3	35.9	16.0	25.9	42.8	45.9
IntraDA [22]	90.6	36.1	82.6	29.5	21.3	27.6	31.4	23.1	85.2	39.3	80.2	59.3	29.4	86.4	33.6	53.9	0.0	32.7	37.6	46.3
WSDA [23]	91.6	47.4	84.0	30.4	28.3	31.4	37.4	35.4	83.9	38.3	83.9	61.2	28.3	83.7	28.8	41.3	8.8	24.7	46.4	48.2
SUDA [39]	91.1	52.3	82.9	30.1	25.7	38.0	44.9	38.2	83.9	39.1	79.2	58.4	26.4	84.5	37.7	45.6	10.1	23.1	36.0	48.8
CaCo [11]	91.9	54.3	82.7	31.7	25.0	38.1	46.7	39.2	82.6	39.7	76.2	63.5	23.6	85.1	38.6	47.8	10.3	23.4	35.1	49.2
IAST [20]	94.1	58.8	85.4	39.7	29.2	25.1	43.1	34.2	84.8	34.6	88.7	62.7	30.3	87.6	42.3	50.3	**24.7**	35.2	40.2	52.2
FDA [36]	92.5	53.3	82.4	26.5	27.6	36.4	40.6	38.9	82.3	39.8	78.0	62.6	34.4	84.9	34.1	63.1	16.9	27.7	46.4	50.5
Seg-U [45]	90.4	31.2	85.1	36.9	25.6	37.5	**48.8**	**48.5**	85.3	34.8	81.1	64.4	36.8	86.3	34.9	52.2	1.7	29.0	44.6	50.3
TPLD [26]	94.2	60.5	82.8	36.6	16.6	39.3	29.0	25.5	85.6	44.9	84.4	60.6	27.4	84.1	37.0	47.0	31.2	36.1	50.3	51.2
ProDA [41]	91.5	52.4	82.9	**42.0**	35.7	40.0	44.4	43.3	87.0	43.8	79.5	66.5	31.4	86.7	41.1	52.5	0.0	45.5	53.8	53.7
MFA [40]	94.5	61.1	**87.6**	41.4	35.4	41.2	47.1	45.7	86.6	36.6	87.0	70.1	38.3	87.2	39.5	54.7	0.3	45.4	57.7	55.7
DUDA(ours)	**94.6**	**66.4**	87.0	41.5	**41.2**	**48.7**	41.6	45.7	**87.8**	**46.8**	**87.2**	**72.3**	**38.5**	**89.1**	38.9	**61.4**	0.0	**51.5**	**61.1**	**58.4**

Experiment on SYNTHIA-to-Cityscapes Benchmark

method	road	sdwk	bldng	light	sign	veg	sky	psn	rider	car	bus	moto	bike	mIoU
CBST [46]	68.0	29.9	76.3	22.8	29.5	77.6	78.3	60.6	28.3	81.6	23.5	18.8	39.8	48.9
IntraDA [22]	84.3	37.7	79.5	9.2	8.4	80.0	84.1	57.2	23.0	78.0	38.1	20.3	36.5	48.9
WSDA [23]	92.0	53.5	80.9	3.8	6.0	81.6	84.4	60.8	24.4	80.5	39.0	26.0	41.7	51.9
SUDA [39]	83.4	36.0	71.3	18.2	26.7	72.4	80.2	58.4	30.8	80.6	38.7	36.1	46.1	52.2
CaCo [11]	87.4	48.9	79.6	17.4	28.3	79.9	81.2	56.3	24.2	78.6	39.2	28.1	43.8	53.6
IAST [20]	81.9	41.5	83.3	30.9	28.8	83.4	85.0	65.5	30.8	86.5	38.2	33.1	52.7	57.0
FDA [36]	79.3	35.0	73.2	19.9	24.0	61.7	82.6	61.4	31.1	83.9	40.8	38.4	51.1	52.5
Seg-U [45]	87.6	41.9	83.1	31.3	19.9	81.6	80.6	63.0	21.8	86.2	40.7	23.6	53.1	54.9
TPLD [26]	80.9	44.3	82.2	20.5	30.1	77.2	80.9	60.6	25.5	84.8	41.1	24.7	43.7	53.5
ProDA [41]	**87.1**	44.0	83.2	**45.8**	**34.2**	**86.7**	81.3	68.4	22.1	87.7	50.0	31.4	38.6	58.5
MFA [40]	85.4	41.9	**84.1**	22.2	23.9	83.6	80.7	**71.5**	**35.8**	86.6	47.6	37.2	**62.5**	58.7
DUDA(ours)	84.4	**43.4**	80.3	29.3	28.9	75.6	**88.1**	69.3	33.8	**88.1**	**60.1**	**47.0**	57.8	**59.7**

Visualize of the Predict Result GTA5-to-Cityscapes Benchmark