Fuzzy Positive Learning for Semi-supervised Semantic Segmentation

Thu 22 Jun 7:30 a.m. - 9:00 a.m.
West Building Exhibit Halls ABC 296

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https://github.com/qpc1611094/FPL.

JUNE 18-22, 2023
CVPR
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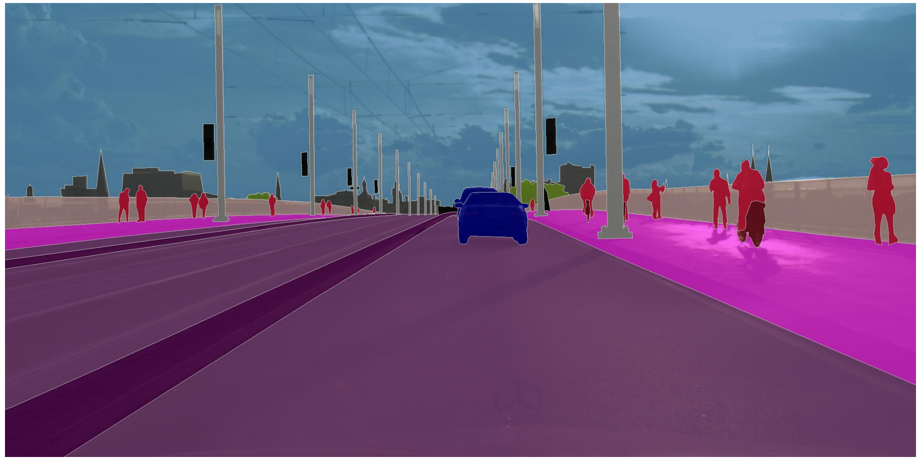
Background------Definition of Semi-supervised Segmentation

A limited labeled dataset with pixel-level annotations:



A huge unlabeled dataset without any annotation:

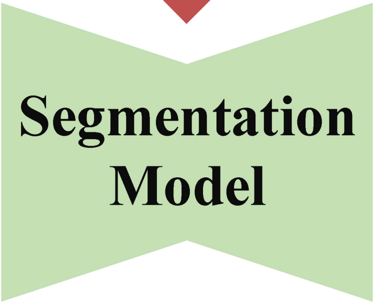
...

Motivation------Limitation of Pseudo Label-based Learning

Explore semantics from unlabeled data

Predict

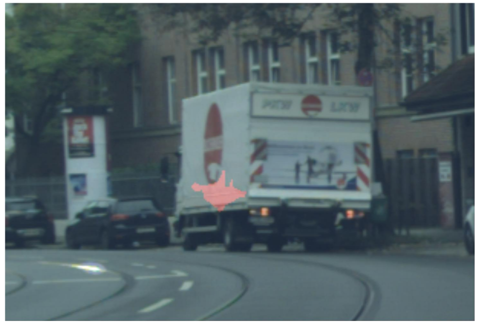
Train



Unreliable pseudo labels

Ground Truth

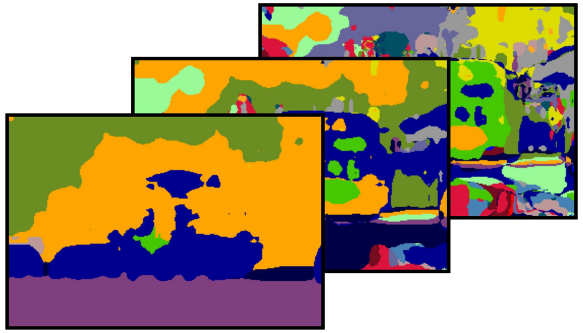
Pseudo label



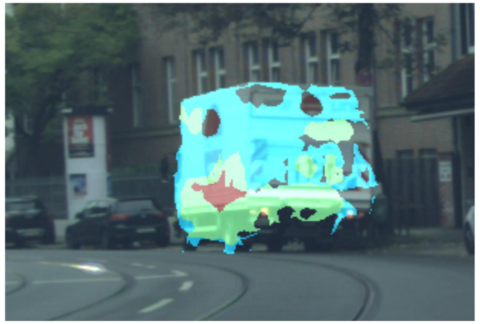
Inclusion of GT for Truck

Learn from multiple probably correct candidate labels.

Ground Truth

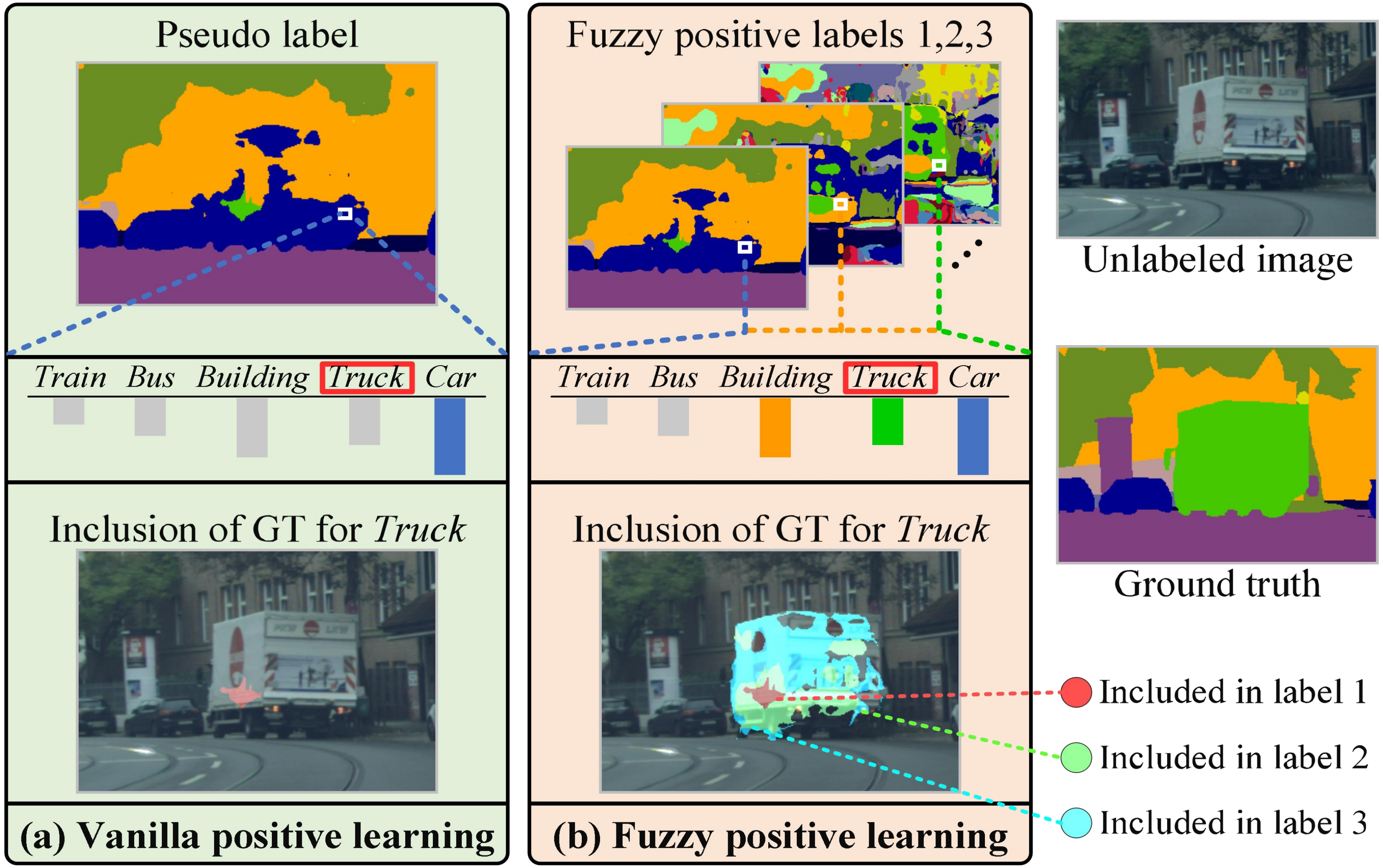


Candidate labels



Inclusion of GT for Truck

Motivation------Compare with vanilla methods



Two pending issues:

1. How to provide an adaptive number of labels for each pixel?
2. How to exploit the possible GT semantics from multiple fuzzy labels.

Method------Pipeline

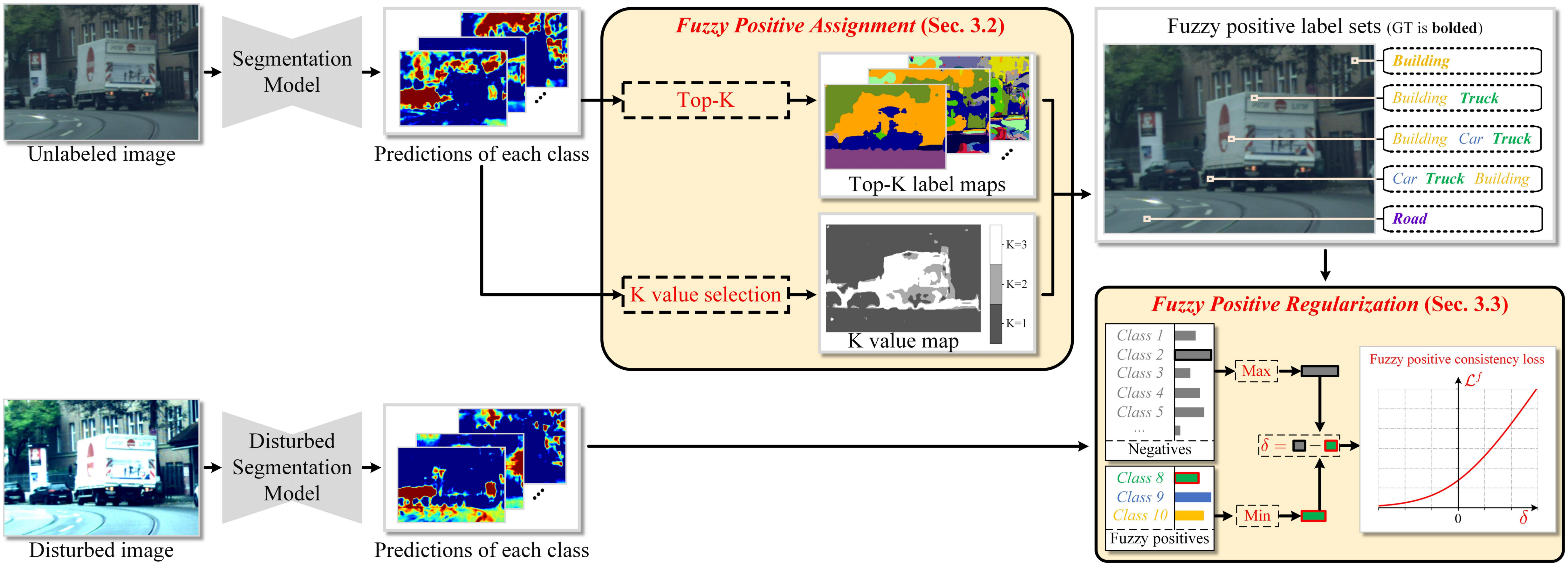


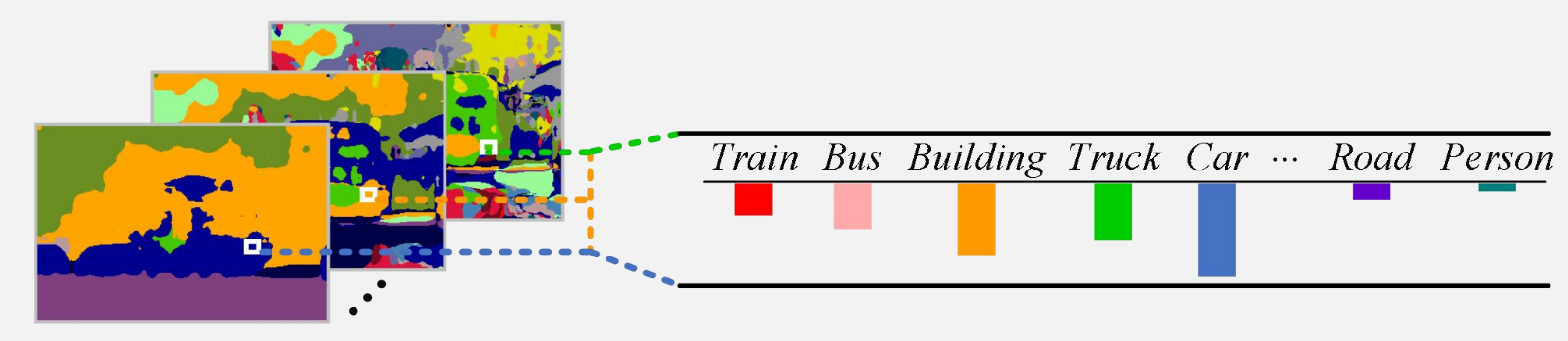
Figure 2. **Pipeline illustration of our FPL**, where FPA densely allocates multiple labels as a fuzzy positive label set for each pixel, while FPR enforces the discrimination of the fuzzy positive assigns with the rest negative labels to facilitate more reliable semantic generalization.

Realized in a plug-and-play manner

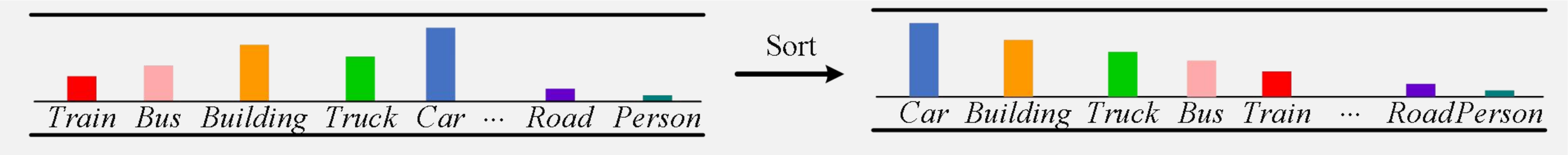
Method------Fuzzy Positive Assignment (FPA)

How to allocate K candidate labels?

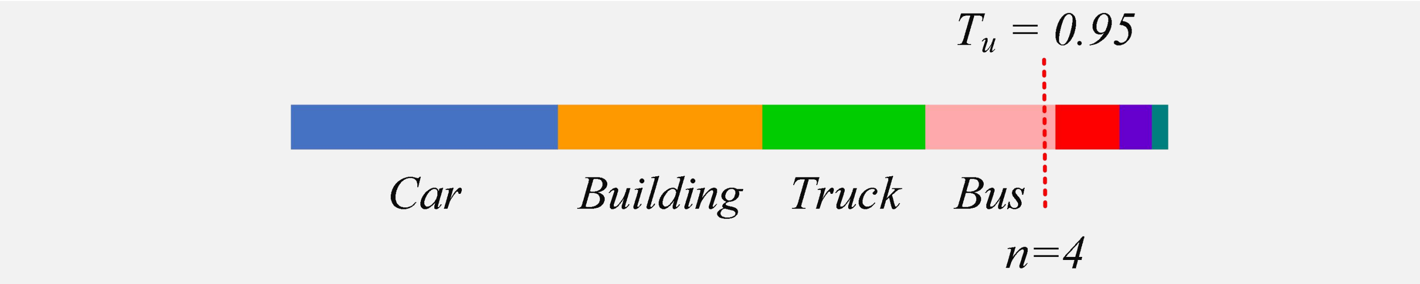
a. Set upper probability threshold T_u , get each pixel's prediction



b. Sort all probability values from large to small: $p_1, p_2, p_3, ..., p_C$



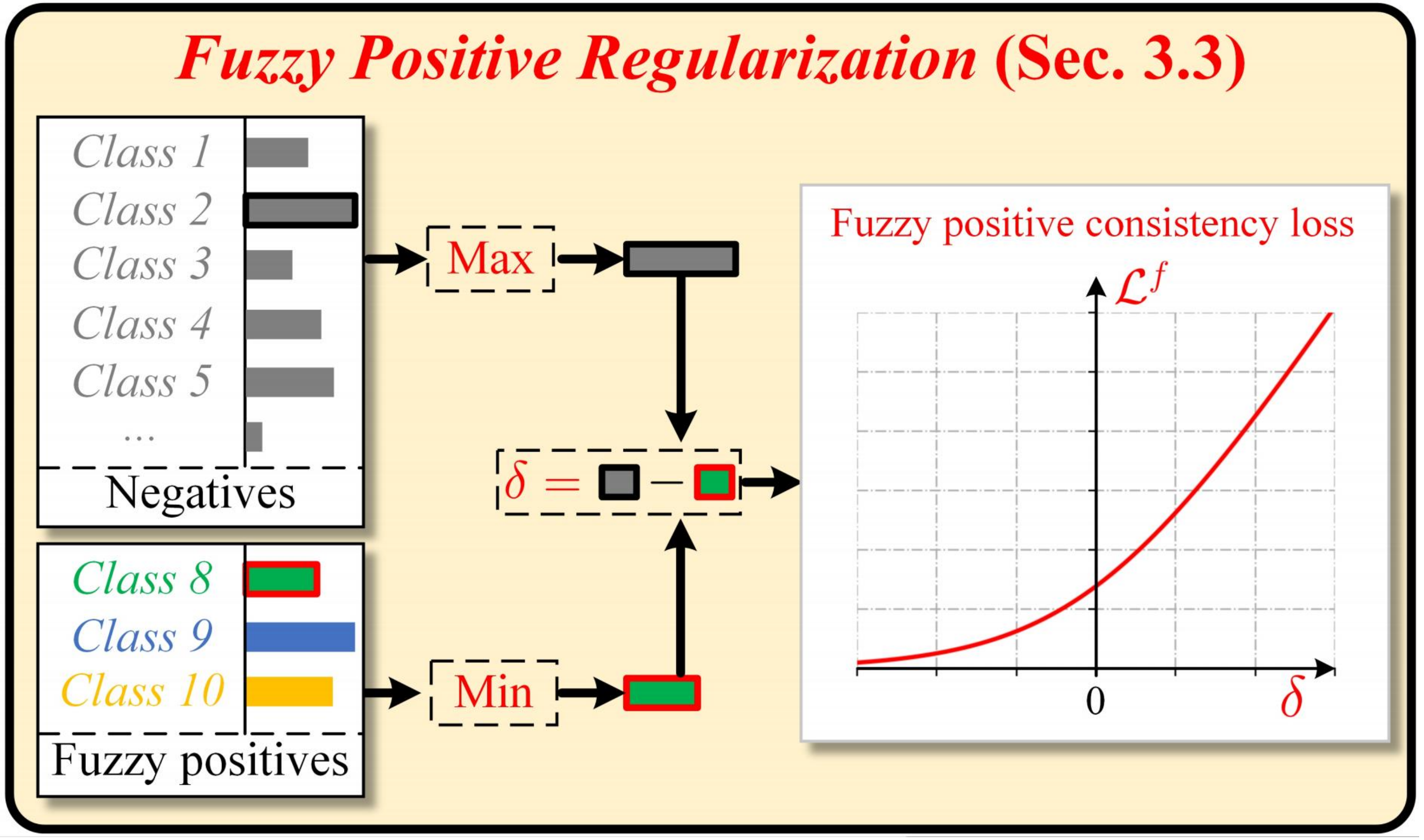
c. Record the first *n* value that satisfies the cumulative probability greater than T_u: $p_1+p_2+...+p_n>=T_u$



d. $K=max(n-1, 1) = 3$

Method------Fuzzy Positive Regularization (FPR)

How two learn the segmentation task with multiple labels?



$$\min_{i \in \mathbb{Y}_{us}} (z^i_{us}) > \max_{j \notin \mathbb{Y}_{us}} (z^j_{us}),$$

$$\mathcal{L}^f_{us} = ReLU(\max_{j \notin \mathbb{Y}_{us}} (z^j_{us}) - \min_{i \in \mathbb{Y}_{us}} (z^i_{us})).$$

$$\mathcal{L}^f_{us} = \log(1 + \sum_{i \in \mathbb{Y}_{us}} e^{-z^i_{us}} \times \sum_{j \notin \mathbb{Y}_{us}} e^{z^j_{us}}).$$

Note that the classical cross entropy loss is a special case of FPR when *K=1*.

Experiments------Quantitative experiment

Method	ResNet 50				ResNet 101			
	1/32 (93)	1/16 (186)	1/8 (372)	1/4 (744)	1/32 (93)	1/16 (186)	1/8 (372)	1/4 (744)
MT [40]	-	66.14	72.03	74.47	-	68.08	73.71	76.53
CCT [34]	-	66.35	72.46	75.68	-	69.64	74.48	76.35
GCT [17]	-	65.81	71.33	75.30	-	66.90	72.96	76.45
U²PL [43]	-	-	-	-	-	74.90	76.48	78.51
CPS w/o cutmix† [5]	54.40	68.68	73.06	75.75	59.70	71.22	74.98	77.45
FPL+CPS w/o cutmix	55.77(↑1.37)	69.71(↑1.03)	74.43(↑1.37)	76.76(↑1.01)	61.00(↑1.30)	72.05(↑0.83)	75.67(↑0.69)	77.57(↑0.12)
CPS w/ cutmix† [5]	71.33	74.05	76.92	77.77	72.51	74.72	77.62	78.93
FPL+CPS w/ cutmix	**72.39**(↑1.06)	**74.80**(↑0.75)	**77.32**(↑0.40)	**78.53**(↑0.76)	73.20(↑0.69)	75.74(↑1.02)	**78.47**(↑0.85)	**79.19**(↑0.26)
AEL† [14]	68.39	74.03	75.83	76.18	73.00	75.26	78.07	78.26
FPL+AEL	71.21(↑2.82)	74.54(↑0.51)	76.25(↑0.42)	76.88(↑0.70)	**75.01**(↑2.01)	**76.58**(↑1.32)	78.19(↑0.12)	78.46(↑0.20)

Table 1. **The mIoU on Cityscapes.** Results marked by † are reproduced in the same experimental environment as FPL.

Method	ResNet 50			ResNet 101		
	1/16 (662)	1/8 (1323)	1/4 (2646)	1/16 (662)	1/8 (1323)	1/4 (2646)
MT [40]	66.77	70.78	73.22	70.59	73.20	76.62
CCT [34]	65.22	70.87	73.43	67.94	73.00	76.17
CutMix-Seg [11]	68.90	70.70	72.46	72.56	72.69	74.25
GCT [17]	64.05	70.47	73.45	69.77	73.30	75.25
CAC [21]	70.10	72.40	74.00	72.40	74.60	76.30
CPS w/o cutmix† [5]	68.13	72.79	74.24	72.50	74.97	77.14
FPL+CPS w/o cutmix	68.67(↑0.54)	73.03(↑0.36)	74.80(↑0.56)	73.18(↑0.68)	75.74(↑0.77)	77.47(↑0.33)
CPS w/ cutmix† [5]	71.78	73.44	74.90	74.48	76.44	77.68
FPL+CPS w/ cutmix	**72.52**(↑0.74)	**73.74**(↑0.30)	75.35(↑0.45)	74.98(↑0.50)	**77.75**(↑1.31)	78.30(↑0.62)
AEL† [14]	69.93	73.17	75.50	74.20	76.58	77.98
FPL+AEL	71.01(↑1.08)	73.69(↑0.52)	**76.61**(↑1.11)	**74.98**(↑0.78)	76.73(↑0.15)	**78.35**(↑0.37)

Table 2. **The mIoU on VOC2012.** Results marked by † are reproduced in the same experimental environment as FPL.

Justification------Positive Gradient Score

An analysis using positive gradient score:

$$R_{us} = \frac{\partial \mathcal{L}_{us}}{\partial z_{us}^{gt}} \bigg/ \sum_{i \in Y_{us}} \frac{\partial \mathcal{L}_{us}}{\partial z_{us}^{i}},$$

We can split all pixels into 3 cases:

Case 1. The pseudo label is correct, that is, the GT is the top-1 predicted category.

$$R_{us}^{v} = \frac{p_{us}^{gt} - 1}{p_{us}^{pse} - 1} = 1, \quad R_{us}^{f} = \frac{e^{-z_{us}^{gt}}}{\sum_{i \in \mathbb{Y}_{us}} e^{-z_{us}^{i}}} \in [0,1],$$

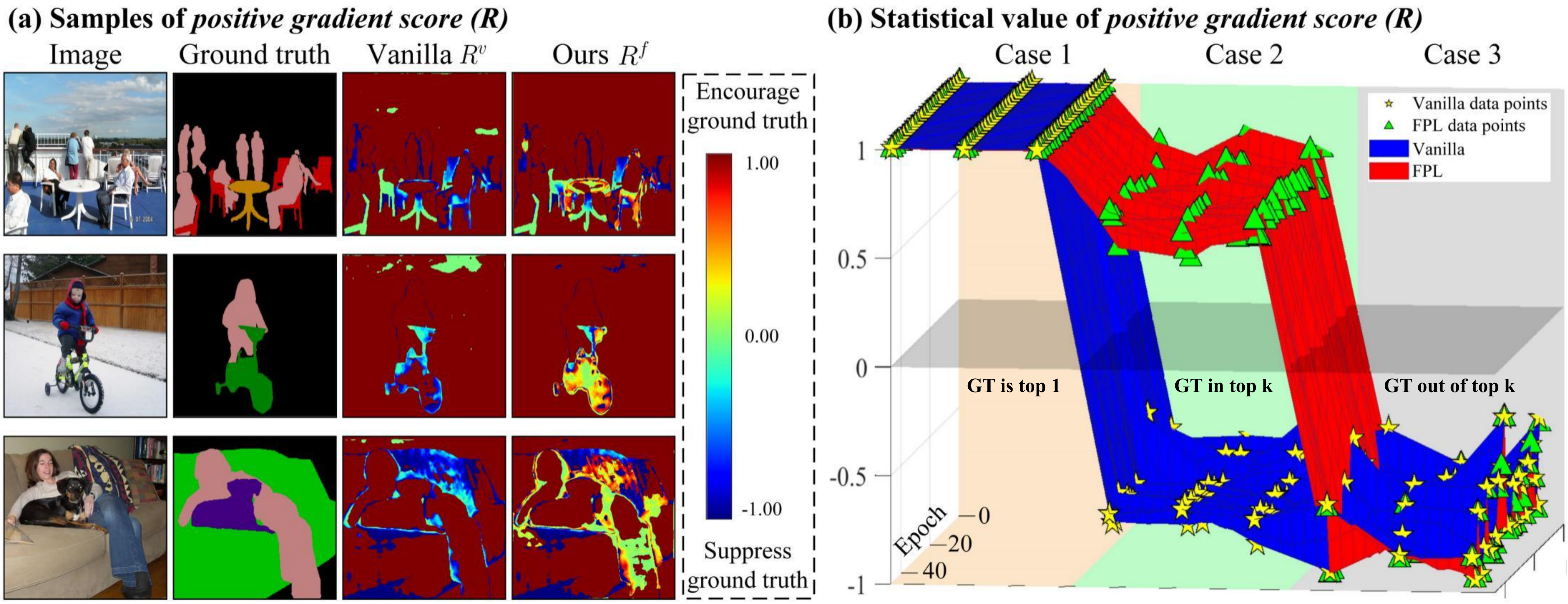
Case 2. The top-1 prediction is wrong, but the GT is in the categories with top-K probabilities.

$$R_{us}^{v} = \frac{p_{us}^{gt}}{p_{us}^{pse} - 1} \in [-1,0], \quad R_{us}^{f} = \frac{e^{-z_{us}^{gt}}}{\sum_{i \in \mathbb{Y}_{us}} e^{-z_{us}^{i}}} \in [0,1].$$

Case 3. The pseudo label is wrong, and the GT is also outside the fuzzy positive labels

$$R_{us}^{v} = \frac{p_{us}^{gt}}{p_{us}^{pse} - 1} \in [-1,0], \quad R_{us}^{f} = \frac{-e^{z_{us}^{gt}}}{\sum_{j \notin \mathbb{Y}_{us}} e^{z_{us}^{j}}} \in [-1,0]$$

Justification------Positive Gradient Score



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Thank You !

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