Adaptive Affinity Fields for Semantic Segmentation

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Code

Overview

CNN   Prediction

arg min

Ground Truth

Adaptive Affinity Field

3x3 Affinity Field

kxk Affinity Field

Categorical Adversarial Weighting

arg max

Adaptive Affinity Field Loss

Training Only
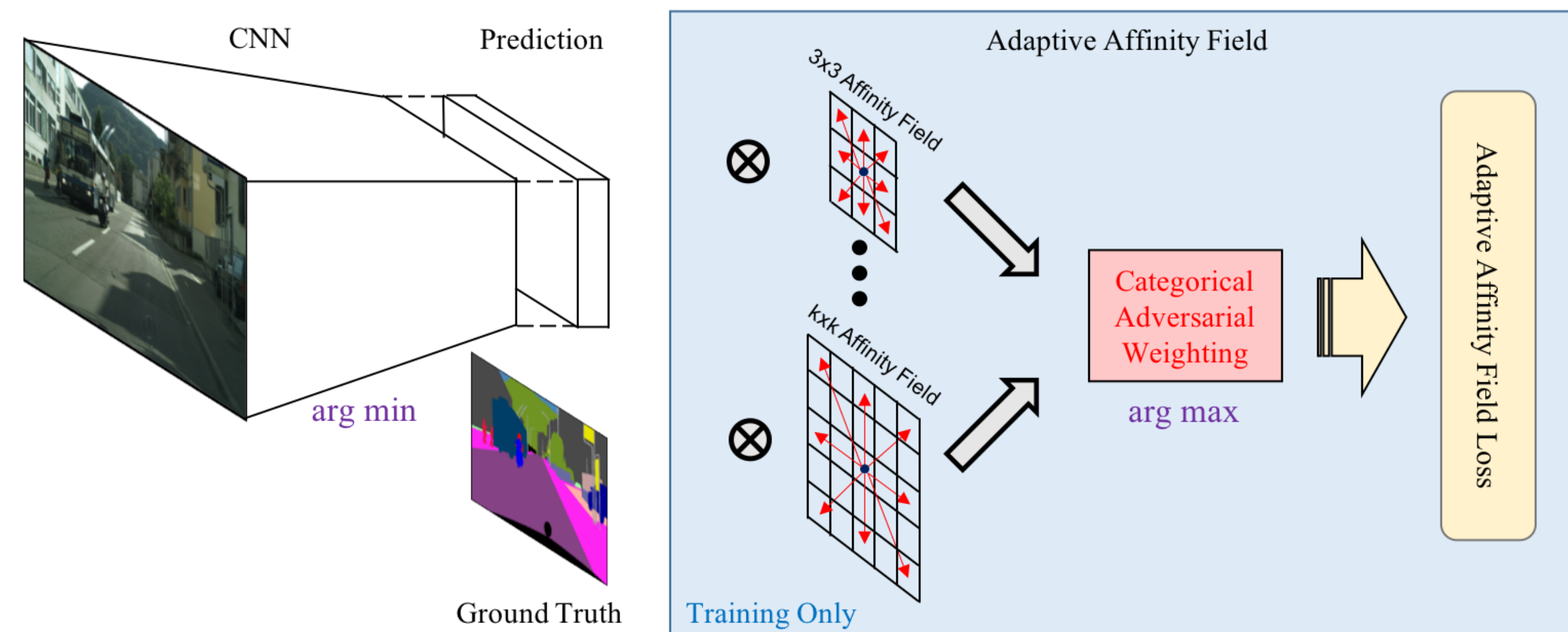
- Existing methods often use per-pixel supervision and ignore label correlations among pixels.

- Our method captures and matches semantic relations between pixels in the label space.

- **Effective representation**: Encode spatial structures in distributed, pixel-centric relations.

- **Efficient computation**: 2 hyper-parameters only, zero overhead during inference.

- **Accurate segmentation**: Get details right and generalize to visual appearance changes.

Method	Structure Guidance	Training	Run-time Inference	Performance
CRF [15]	input image	medium	yes	76.53
GAN [12]	ground-truth labels	hard	no	76.20
Our AAF	label affinity	easy	no	**79.24**

Table 1. Performance (% mIoU) is reported with PSPNet on Cityscapes validation set.

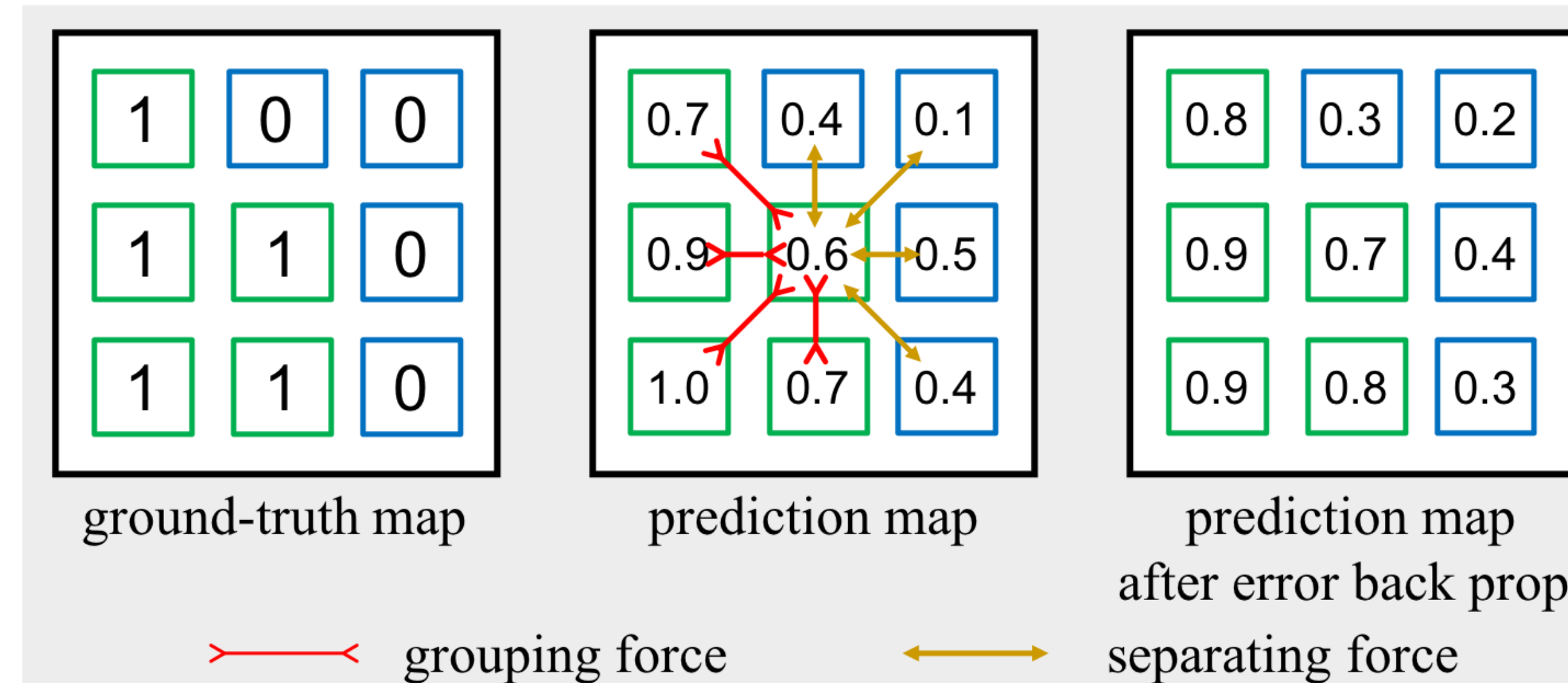- Pixel-wise labeling loss:

$$\mathcal{L}^i_{\text{unary}} = \mathcal{L}^i_{\text{cross-entropy}} = -\log \hat{y}_i(l).$$

- Region-wise labeling loss:

$$\mathcal{L}^i_{\text{unary}}(\hat{y}_i, y_i) + \lambda \mathcal{L}^i_{\text{region}}\big(\mathcal{N}(\hat{y}_i), \mathcal{N}(y_i)\big)$$

- CRF: label consistency btw visually similar pixels

- GAN: structure priors in label predictions

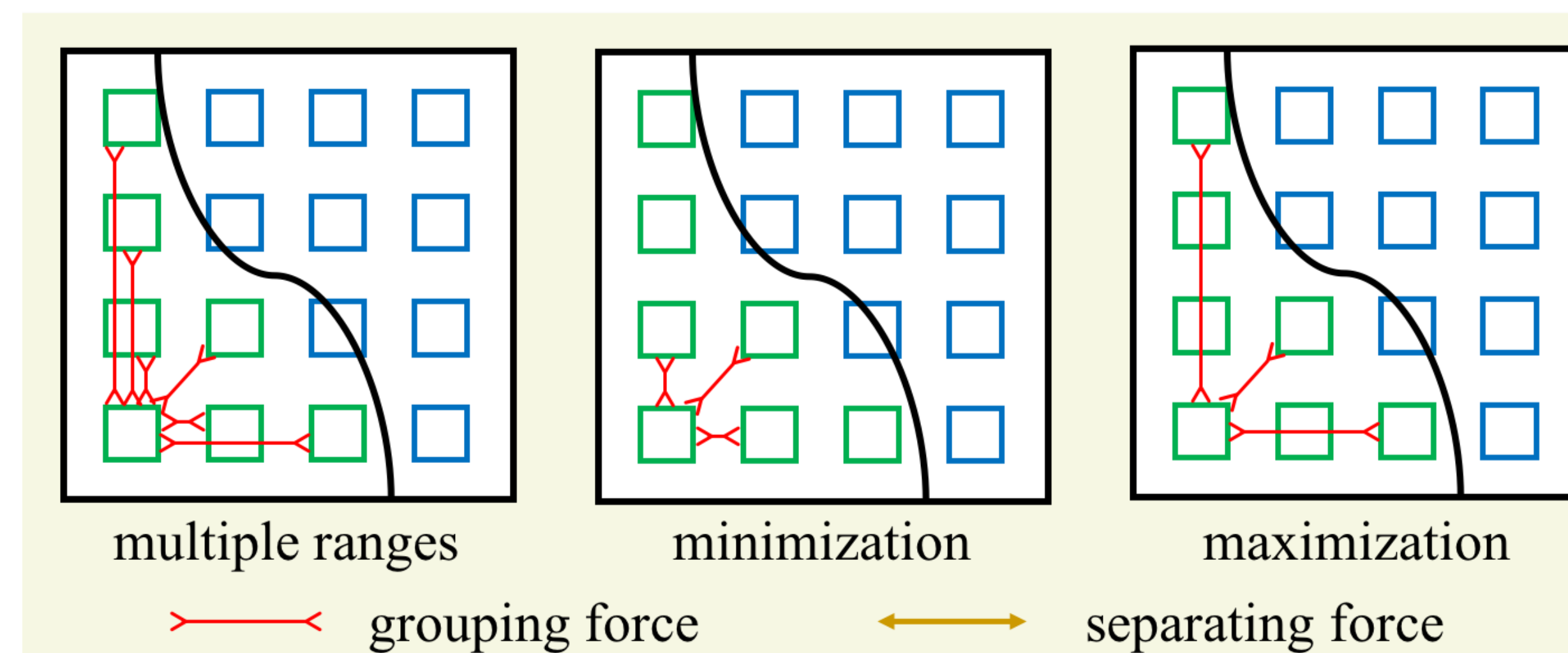- **Our AAF: pixel-centric label pattern similarity**

Our Model

1	0	0
1	1	0
1	1	0

ground-truth map

0.7	0.4	0.1
0.9	0.6	0.5
1.0	0.7	0.4

prediction map

0.8	0.3	0.2
0.9	0.7	0.4
0.9	0.8	0.3

prediction map after error back prop.

grouping force   separating force

- **Pixels of same / diff. gt labels desire same / diff predictions regardless of actual label values.**

- Our affinity field loss:

$$\mathcal{L}^{ic}_{\text{affinity}} = \begin{cases} \mathcal{L}^{i\bar{b}c}_{\text{affinity}} = D_{KL}(\hat{y}_j(c)\|\hat{y}_i(c)) & \text{if } y_i(c) = y_j(c) \\ \mathcal{L}^{ibc}_{\text{affinity}} = \max\{0, m - D_{KL}(\hat{y}_j(c)\|\hat{y}_i(c))\} & \text{otherwise} \end{cases}$$

- No message passing or iterative refinement.

multiple ranges   minimization   maximization

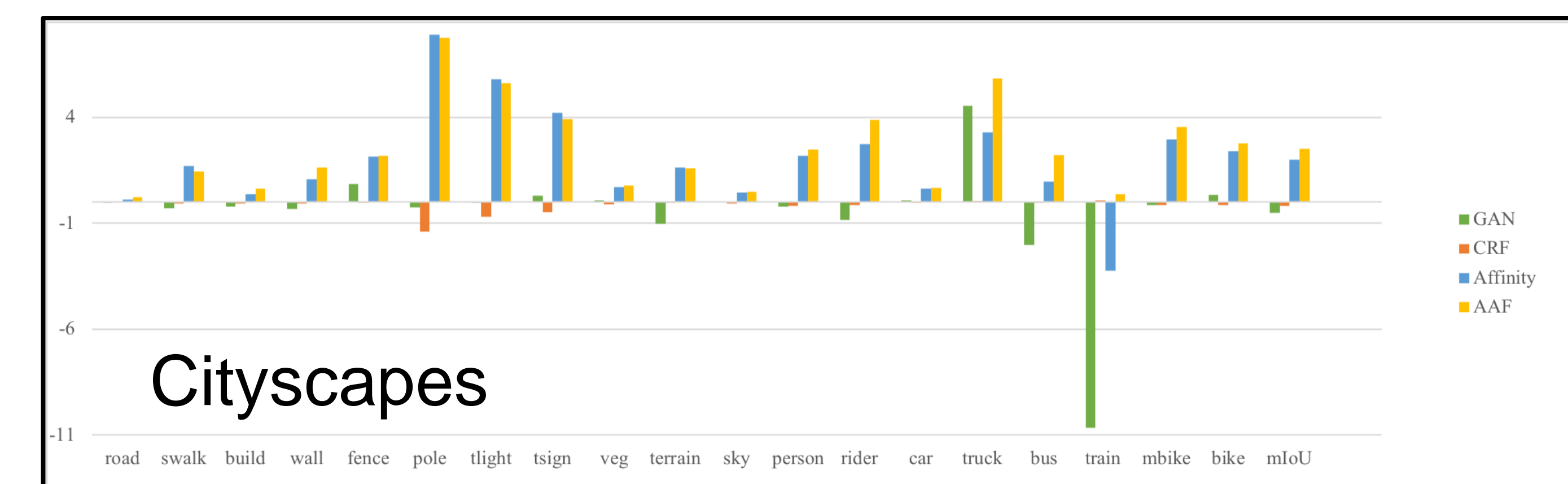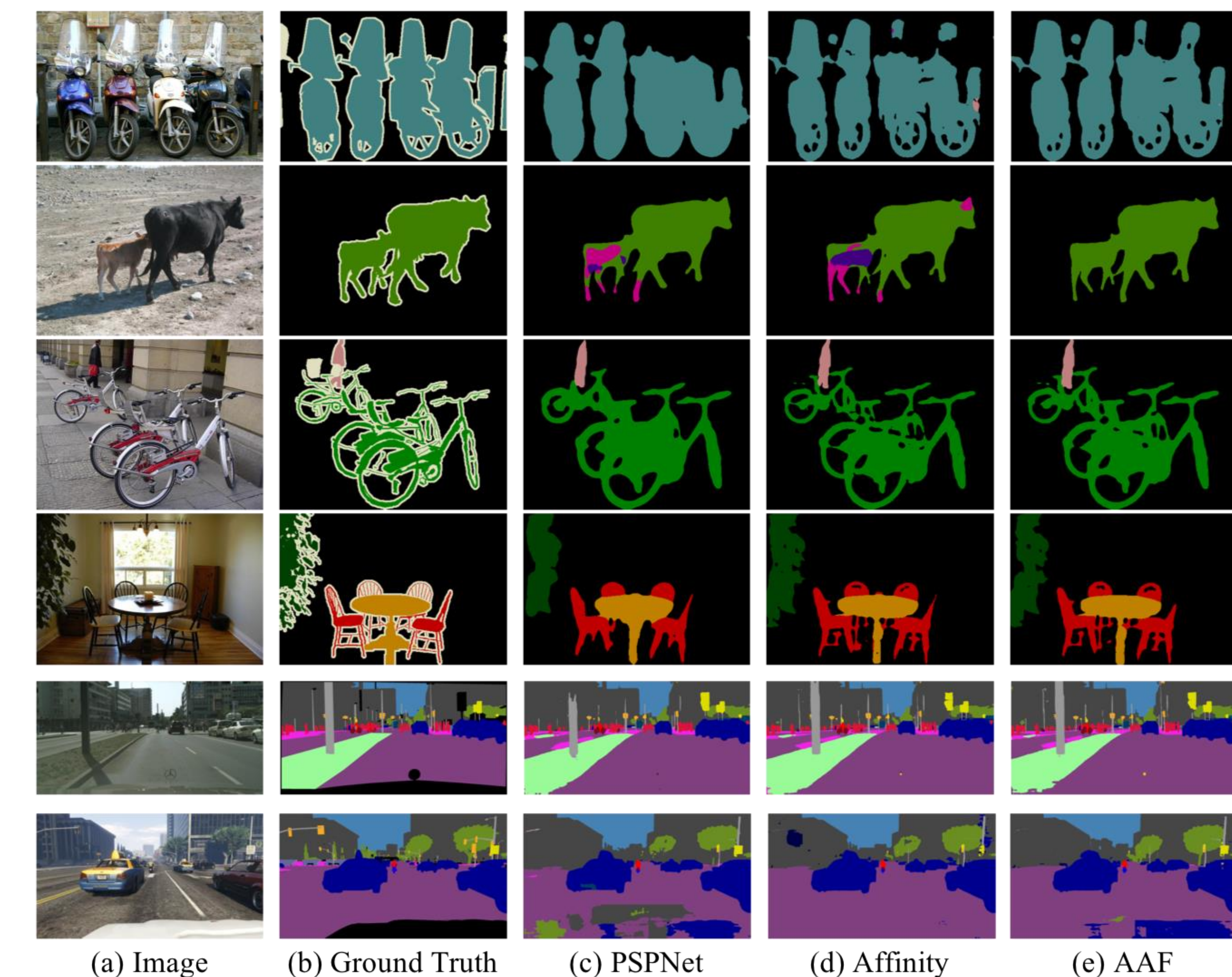grouping force   separating force

- Affinity fields in small / large neighborhoods encode near / long range structural relations.

- One size does not fit all classes; picking the one with minimal affinity loss results in trivial solutions.

- **Select the right size by pushing the affinity field matching to the hard negative cases.**

- **Our adversarial learning for adaptive kernel sizes:**

$$\mathcal{L}_{\text{multiscale}} = \sum_c \sum_k w_{ck} \mathcal{L}^{ck}_{\text{region}} \quad \text{s.t.} \quad \sum_k w_{ck} = 1$$

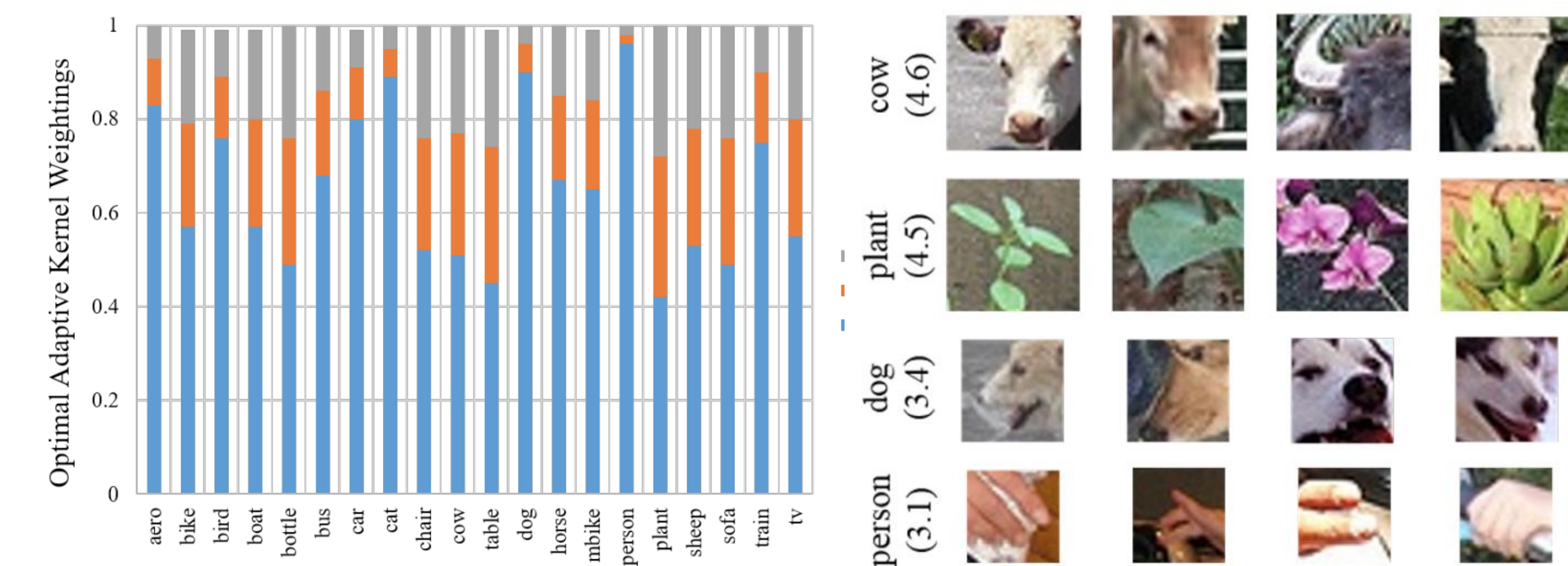$$S^* = \underset{S}{\arg\min} \max_w \mathcal{L}_{\text{unary}} + \mathcal{L}_{\text{multiscale}}$$

Our Results

(a) Image   (b) Ground Truth   (c) PSPNet   (d) Affinity   (e) AAF

Cityscapes

GAN / CRF / Affinity / AAF

road swalk build wall fence pole tlight tsign veg terrain sky person rider car truck bus train mbike bike mIoU

- More accurate segmentation on PASCAL VOC and Cityscapes

Method	road	swalk	build.	wall	fence	pole	tlight	tsign	veg.	terrain	sky	person	rider	car	truck	bus	train	mbike	bike	mIoU	pix. acc
PSPNet	61.79	**34.26**	37.30	**13.31**	18.52	26.51	31.64	17.51	55.00	8.57	**82.47**	42.73	**49.78**	**69.25**	**34.31**	**25.00**	33.14	6.86	35.06	35.06	68.78
Affinity	75.26	30.34	44.10	12.91	**20.19**	**29.78**	31.50	23.98	**64.25**	11.83	74.32	48.28	49.12	67.39	25.82	23.82	20.29	**41.48**	5.63	**36.86**	75.13
AAF	**83.07**	27.82	**51.16**	10.41	18.76	28.58	**31.74**	**24.98**	61.38	**12.25**	70.65	**50.53**	48.06	53.35	26.80	20.97	24.50	39.56	**9.37**	36.52	**78.28**

- Better generalization: Trained on Cityscapes, tested on GTA5

Optimal Adaptive Kernel Weightings

aero bike bird boat bottle bus car cat chair cow table dog horse mbike person plant sheep sofa train tv

cow (4.6)   plant (4.5)   dog (3.4)   person (3.1)

- Learned kernel sizes for different classes