SEAL: A Framework Towards Simultaneous Edge Alignment and Learning

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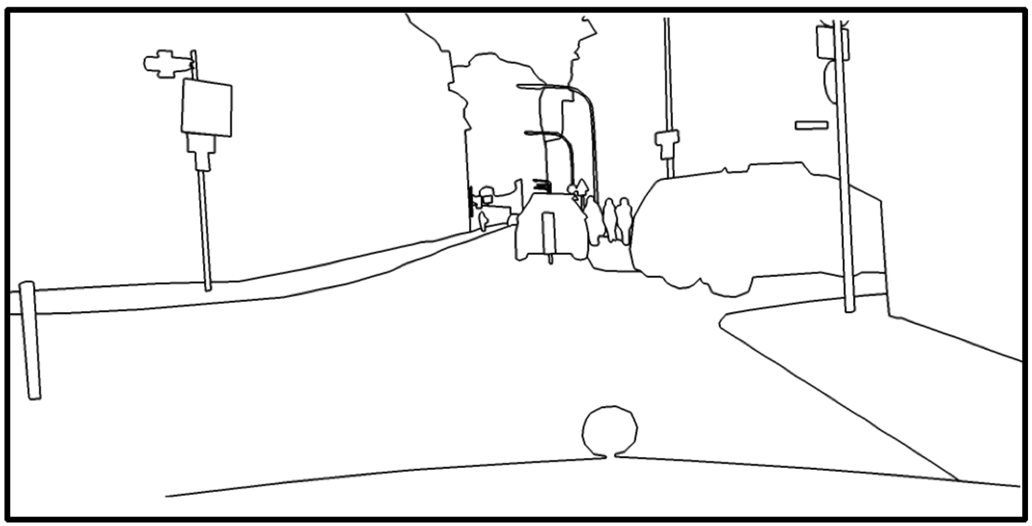
NVIDIA Research

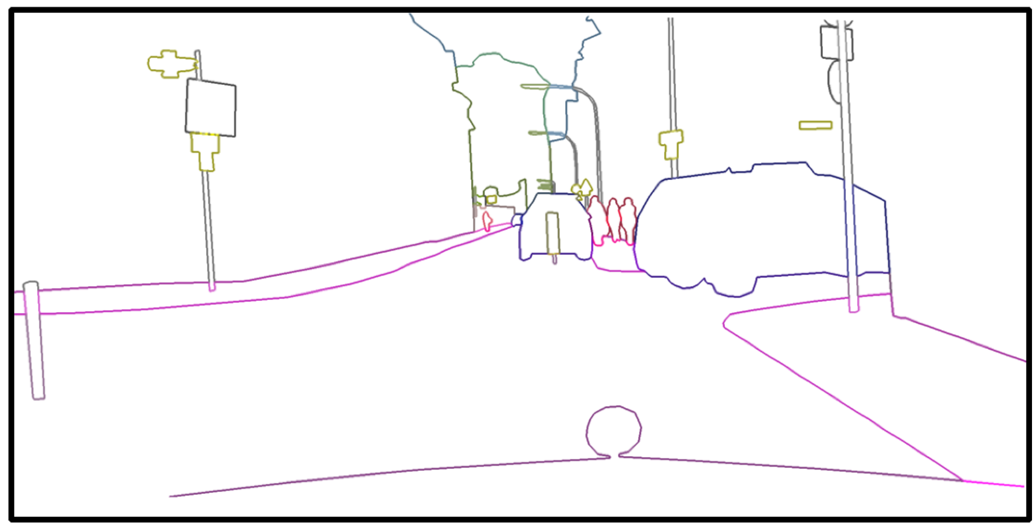
Edge Detection Problems

Original Image

Perceptual Edges

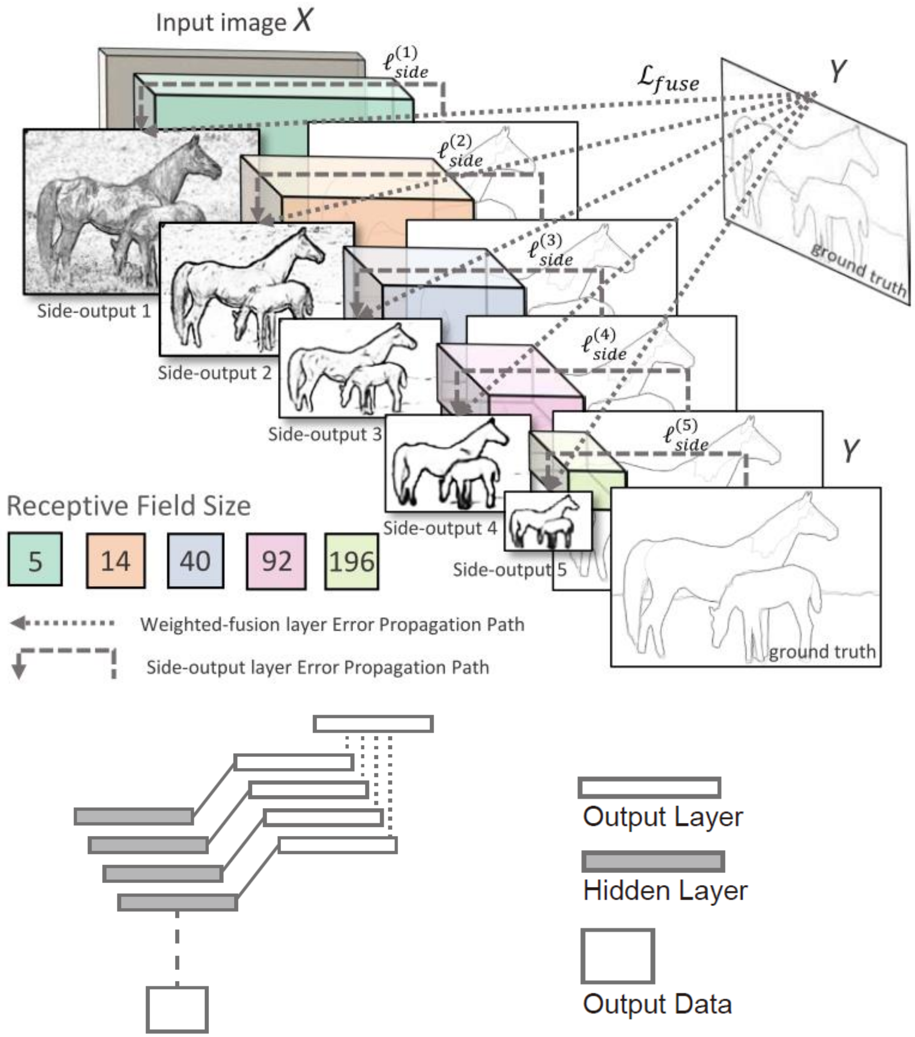


Semantic Edges

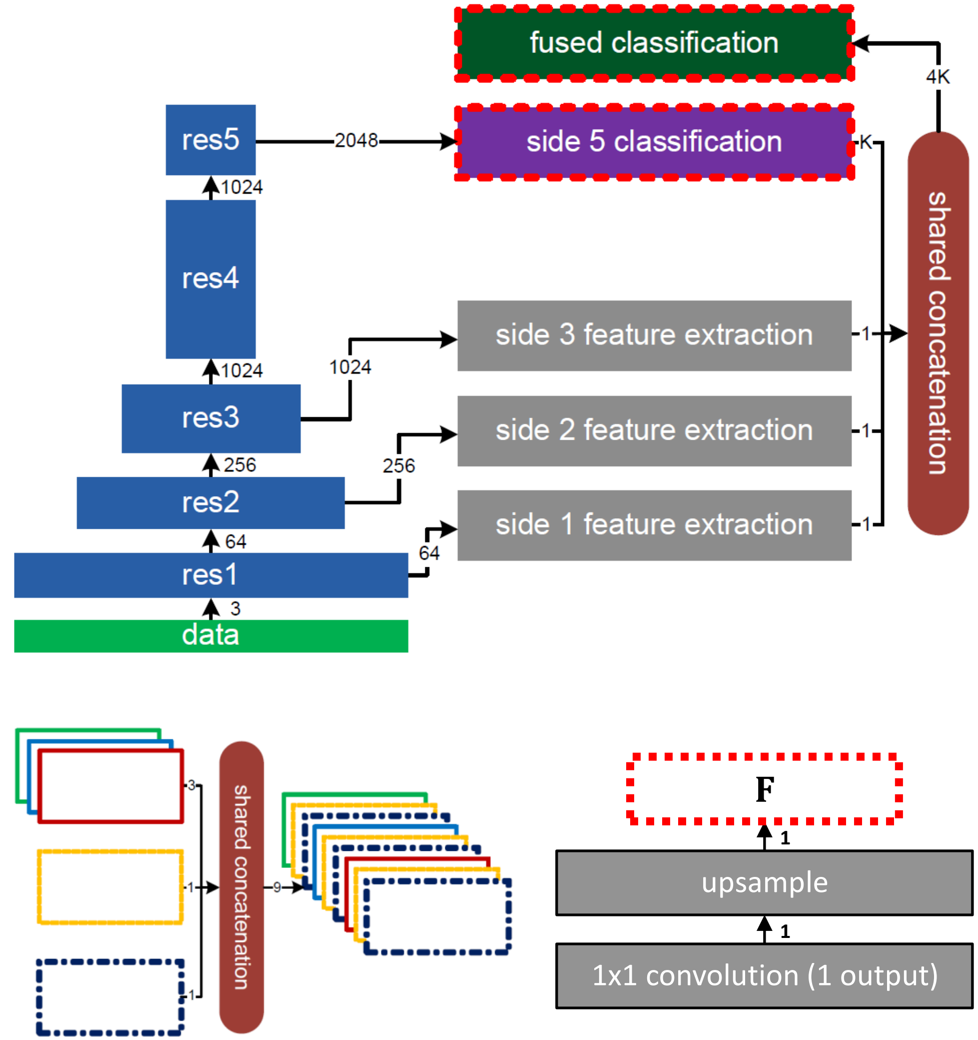


Category-Aware Semantic Edges

Edge Detection with Convolutional Networks

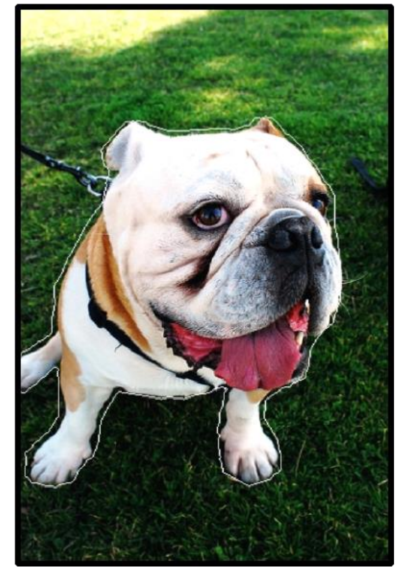


Saining Xie et al., **Holistically-Nested Edge Detection**, ICCV15



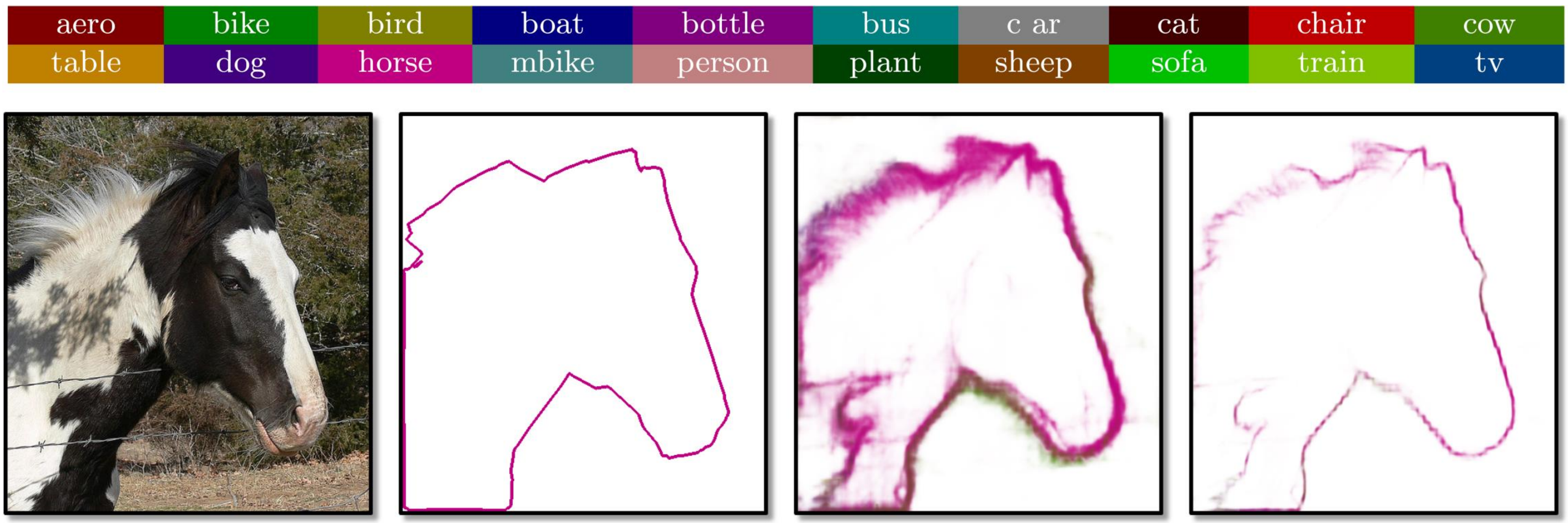
Zhiding Yu et al., **CASENet: Deep Category-Aware Semantic Edge Detection**, CVPR17

Challenge: Misalignment in Human Annotations

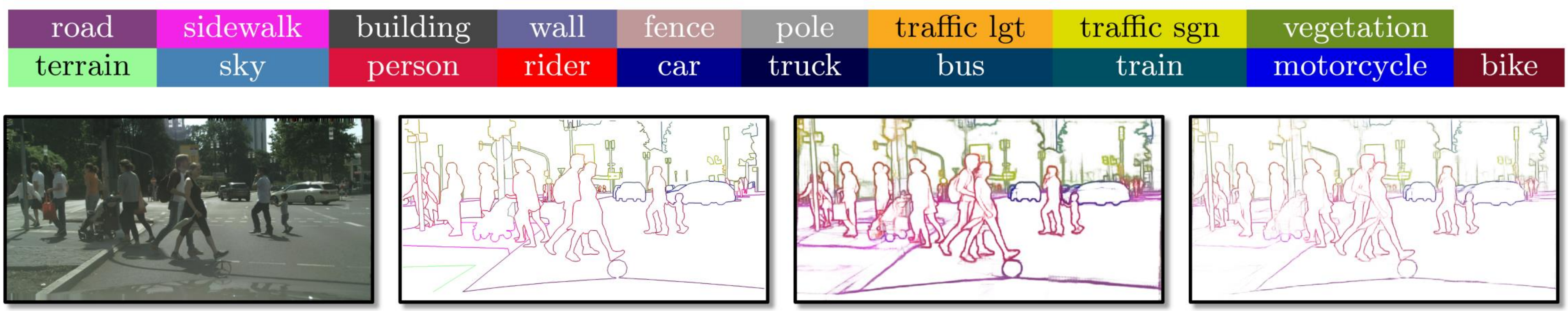


Motivation 1: Auto Alignment of Edge Labels

Motivation 2: Learn to Predict Crisp Edges

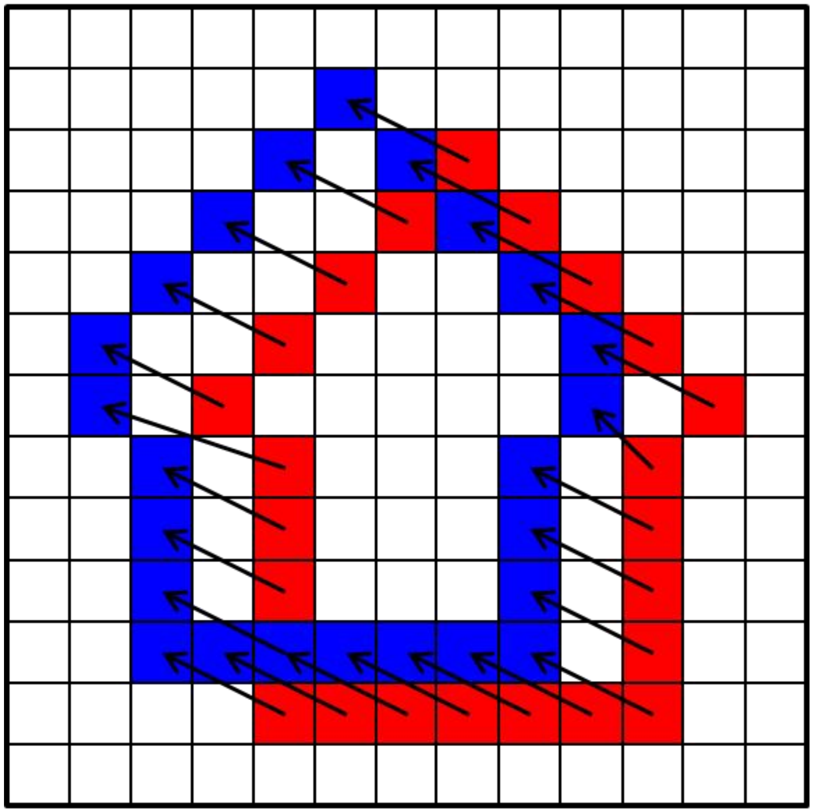


(a) Original image (b) Ground truth (c) CASENet (d) SEAL



(e) Original image (f) Ground truth (g) CASENet (h) SEAL

Simultaneous Edge Alignment and Learning



$\mathbf{p} = (x_p, y_p), \mathbf{q} = (x_q, y_q)$: Pixel index

$k \in \{1, ..., K\}$: Semantic class index

$\mathbf{y} = \{y_\mathbf{q}^k \in \{0, 1\}\}$: Human annotation

$\hat{\mathbf{y}} = \{\hat{y}_\mathbf{p}^k \in \{0, 1\}\}$: Aligned edge label

(red) $y_\mathbf{q}^k = 1$ (blue) $\hat{y}_\mathbf{p}^k = 1$ ↖ $m(\mathbf{q}) - \mathbf{q}$

Traditional edge learning:

$$\max_{\mathbf{W}} \mathcal{L}(\mathbf{W}) = P(\mathbf{y}|\mathbf{x}; \mathbf{W})$$

Simultaneous edge alignment & learning:

$$\max_{\hat{\mathbf{y}}, \mathbf{W}} \mathcal{L}(\hat{\mathbf{y}}, \mathbf{W}) = P(\mathbf{y}, \hat{\mathbf{y}}|\mathbf{x}; \mathbf{W}) = P(\mathbf{y}|\hat{\mathbf{y}})P(\hat{\mathbf{y}}|\mathbf{x}; \mathbf{W})$$

$$= \prod_k P(\mathbf{y}^k|\hat{\mathbf{y}}^k) P(\hat{\mathbf{y}}^k|\mathbf{x}; \mathbf{W})$$

Edge prior — Network likelihood

A Probabilistic Model

Likelihood under multilabel edge learning:

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{W}) = \prod_{k} \underbrace{P(\mathbf{y}^k|\hat{\mathbf{y}}^k)}_{\text{red}} \underbrace{P(\hat{\mathbf{y}}^k|\mathbf{x};\mathbf{W})}_{\text{blue}}$$

Edge prior model

$$P(\mathbf{y}^k|\hat{\mathbf{y}}^k) \propto \sup_{m\in\mathcal{M}(\mathbf{y}^k,\hat{\mathbf{y}}^k)} \prod_{(\mathbf{p},\mathbf{q})\in E_m} \exp\left(-\frac{\|\mathbf{p}-\mathbf{q}\|^2}{2\sigma^2}\right)$$

$$= \exp\left(-\inf_{m\in\mathcal{M}(\mathbf{y}^k,\hat{\mathbf{y}}^k)} \sum_{(\mathbf{p},\mathbf{q})\in E_m} \frac{\|\mathbf{p}-\mathbf{q}\|^2}{2\sigma^2}\right)$$

Network likelihood model

$$P(\hat{\mathbf{y}}^k|\mathbf{x};\mathbf{W}) = \prod_{\mathbf{p}} P(\hat{y}_{\mathbf{p}}{}^k|\mathbf{x};\mathbf{W})$$

$$= \prod_{\mathbf{p}} h_k(\mathbf{p}|\mathbf{x};\mathbf{W})^{\hat{y}_{\mathbf{p}}^k}(1-h_k(\mathbf{p}|\mathbf{x};\mathbf{W}))^{(1-\hat{y}_{\mathbf{p}}^k)}$$

Taking log of the likelihood, we have:

$$\log\mathcal{L}(\hat{\mathbf{y}}, \mathbf{W}) = \sum_k \Bigg\{ -\inf_{m\in\mathcal{M}(\mathbf{y}^k,\hat{\mathbf{y}}^k)} \sum_{(\mathbf{p},\mathbf{q})\in E_m} \frac{\|\mathbf{p}-\mathbf{q}\|^2}{2\sigma^2}$$

$$+ \sum_{\mathbf{p}} \Big[\hat{y}_{\mathbf{p}}^k \log\sigma_k(\mathbf{p}|\mathbf{x};\mathbf{W}) + (1-\hat{y}_{\mathbf{p}}^k)\log(1-\sigma_k(\mathbf{p}|\mathbf{x};\mathbf{W}))\Big]\Bigg\}$$

Step 1: Updating network parameters:

$$\min_{\mathbf{W}} -\log\mathcal{L}_N(\mathbf{W}) = \sum_k \sum_{\mathbf{p}} -\Big[\hat{y}_{\mathbf{p}}^k \log\sigma_k(\mathbf{p}|\mathbf{x};\mathbf{W})$$

$$+ (1-\hat{y}_{\mathbf{p}}^k)\log(1-\sigma_k(\mathbf{p}|\mathbf{x};\mathbf{W}))\Big]$$

Step 2: Updating estimated ground truth:

$$\min_{\hat{\mathbf{y}}^k} -\log\mathcal{L}_E(\hat{\mathbf{y}}^k) = \inf_{m\in\mathcal{M}(\mathbf{y}^k,\hat{\mathbf{y}}^k)} \sum_{(\mathbf{p},\mathbf{q})\in E_m} \frac{\|\mathbf{p}-\mathbf{q}\|^2}{2\sigma^2}$$

$$-\sum_{\mathbf{p}} \Big[\hat{y}_{\mathbf{p}}^k \log\sigma_k(\mathbf{p}) + (1-\hat{y}_{\mathbf{p}}^k)\log(1-\sigma_k(\mathbf{p}))\Big]$$

$$\text{s.t.} \quad |\hat{\mathbf{y}}^k| = |\mathbf{y}^k|$$

Reformulating as an assignment problem:

$$\min_{m\in\mathrm{M}} \sum_{(\mathbf{p},\mathbf{q})\in E_m} \underbrace{\frac{\|\mathbf{p}-\mathbf{q}\|^2}{2\sigma^2}}_{\text{Edge prior}} + \underbrace{\log(1-\sigma(\mathbf{p})) - \log\sigma(\mathbf{p})}_{\text{Network self-correction}}$$

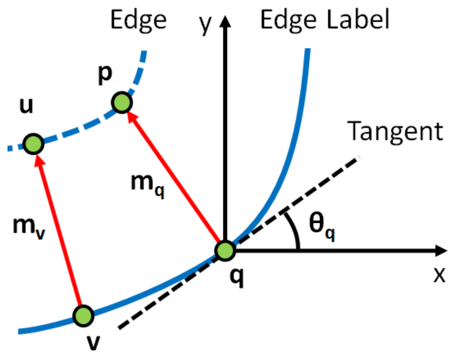
Edge prior **Network self-correction**

Theorem: The minimizer of the assignment problem is also a minimizer of the constrained optimization problem **Step 2**.

Incorporating Biased Kernel and Markov Prior

Issue with isotropic Gaussian kernels:

Without B.K. & M.P.



Graphical Illustration

Biased Gaussian kernel and neighbor smoothness:

$$P(\mathbf{y}|\hat{\mathbf{y}}) \propto \sup_{m \in \mathcal{M}(\mathbf{y},\hat{\mathbf{y}})} \prod_{(\mathbf{p},\mathbf{q}) \in E_m} \exp(-\mathbf{m_q}^\top \Sigma_\mathbf{q} \mathbf{m_q}) \prod_{\substack{(\mathbf{u},\mathbf{v}) \in E_m, \\ \mathbf{v} \in \mathcal{N}(\mathbf{q})}} \exp(-\lambda \|\mathbf{m_q} - \mathbf{m_v}\|^2)$$

$$\mathbf{m_q} = \mathbf{p} - \mathbf{q}, \text{ and } \mathbf{m_v} = \mathbf{u} - \mathbf{v}$$

$$\Sigma_\mathbf{q} = \begin{bmatrix} \frac{\cos(\theta_\mathbf{q})^2}{2\sigma_x^2} + \frac{\sin(\theta_\mathbf{q})^2}{2\sigma_y^2} & \frac{\sin(2\theta_\mathbf{q})}{4\sigma_y^2} - \frac{\sin(2\theta_\mathbf{q})}{4 * \sigma_x^2} \\ \frac{\sin(2\theta_\mathbf{q})}{4\sigma_y^2} - \frac{\sin(2\theta_\mathbf{q})}{4\sigma_x^2} & \frac{\sin(\theta_\mathbf{q})^2}{2\sigma_x^2} + \frac{\cos(\theta_\mathbf{q})^2}{2\sigma_y^2} \end{bmatrix}$$

Optimization as the following assignment problem:

$$\min_{m \in \mathbf{M}} \mathcal{C}(m) = \mathcal{C}_{Unary}(m) + \mathcal{C}_{Pair}(m)$$

$$= \sum_{(\mathbf{p},\mathbf{q}) \in E_m} \left[\mathbf{m_q}^\top \Sigma_\mathbf{q} \mathbf{m_q} + \log((1 - \sigma(\mathbf{p}))/\sigma(\mathbf{p})) \right]$$

$$+ \lambda \sum_{(\mathbf{p},\mathbf{q}) \in E_m} \sum_{\substack{(\mathbf{u},\mathbf{v}) \in E_m, \\ \mathbf{v} \in \mathcal{N}(\mathbf{q})}} \|\mathbf{m_q} - \mathbf{m_v}\|^2$$

Relaxation by decouple mappings in pairwise cost:

$$\mathcal{C}_{Pair}(m, m') = \sum_{(\mathbf{p},\mathbf{q}) \in E_m} \sum_{\substack{(\mathbf{u},\mathbf{v}) \in E_{m'}, \\ \mathbf{v} \in \mathcal{N}(\mathbf{q})}} \|\mathbf{m_q} - \mathbf{m_v}\|^2$$

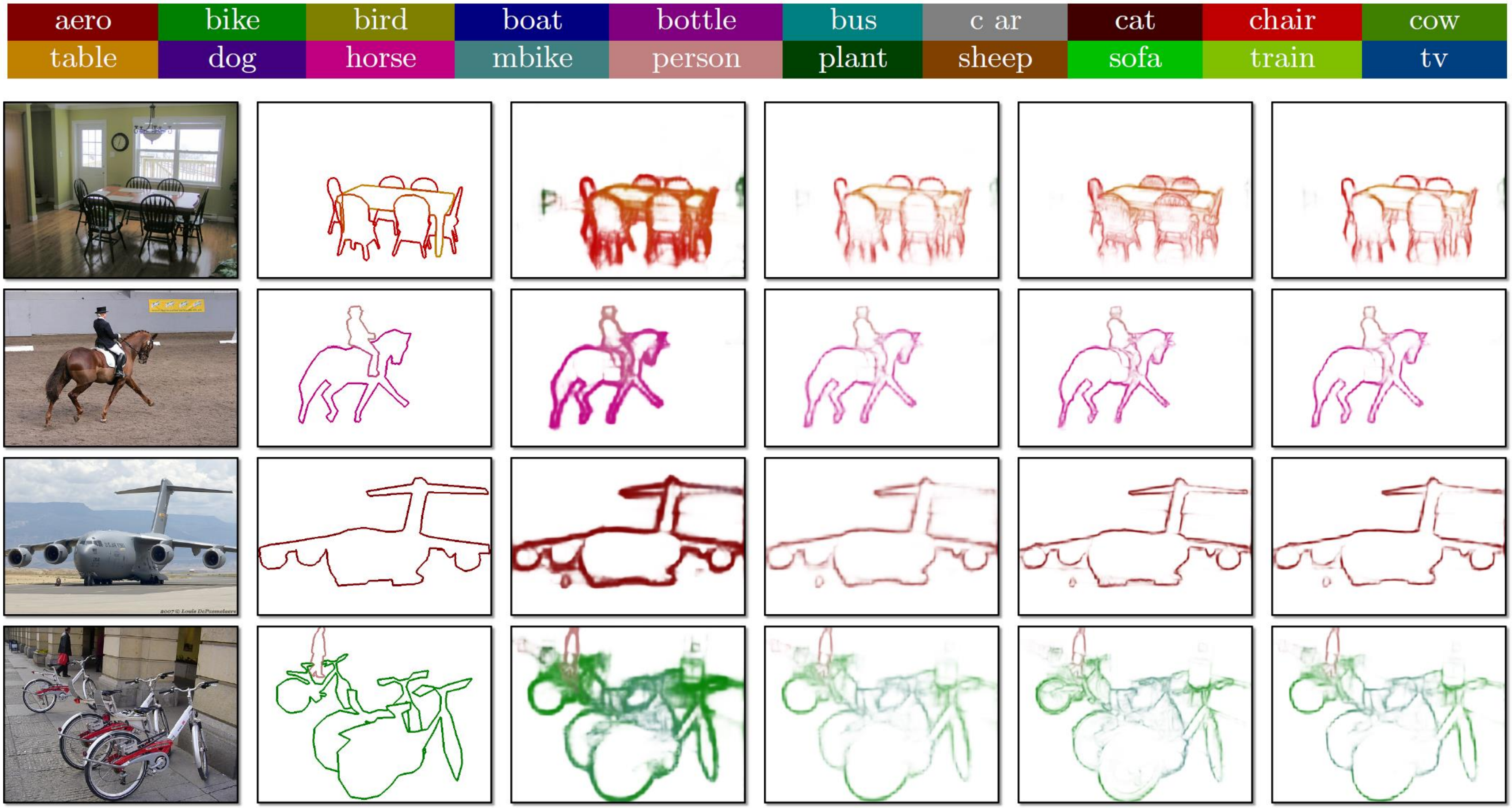
Take iterated conditional mode like optimization:

$$\text{Initialize: } m^{(1)} = \arg\min_{m \in \mathbf{M}} \mathcal{C}_{Unary}(m)$$

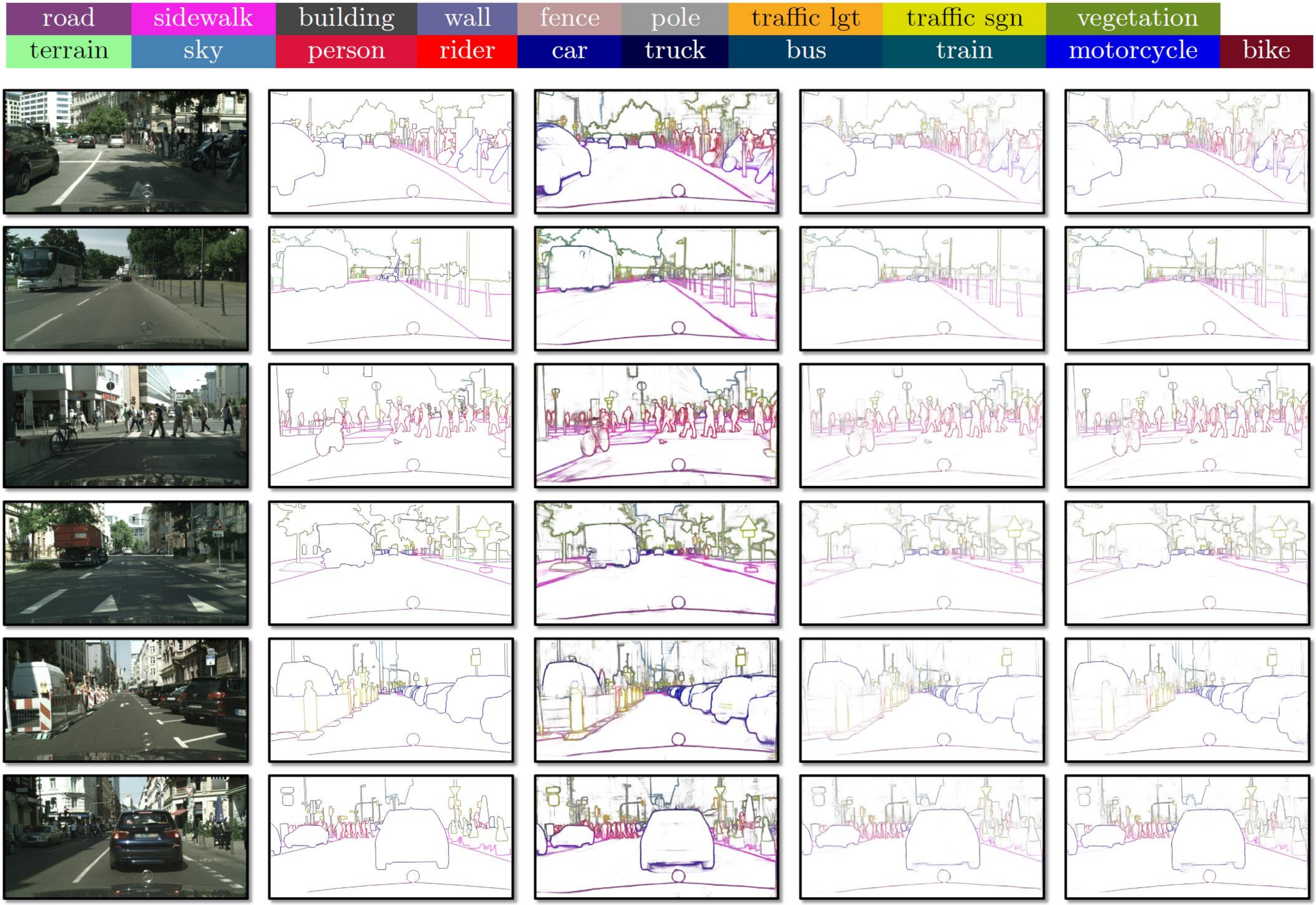
$$\text{Assign: } m^{(t+1)} = \arg\min_{m \in \mathbf{M}} \mathcal{C}_{Unary}(m) + \mathcal{C}_{Pair}(m, m^{(t)})$$

$$\text{Update: } \mathcal{C}_{Pair}(m, m^{(t)}) \rightarrow \mathcal{C}_{Pair}(m, m^{(t+1)})$$

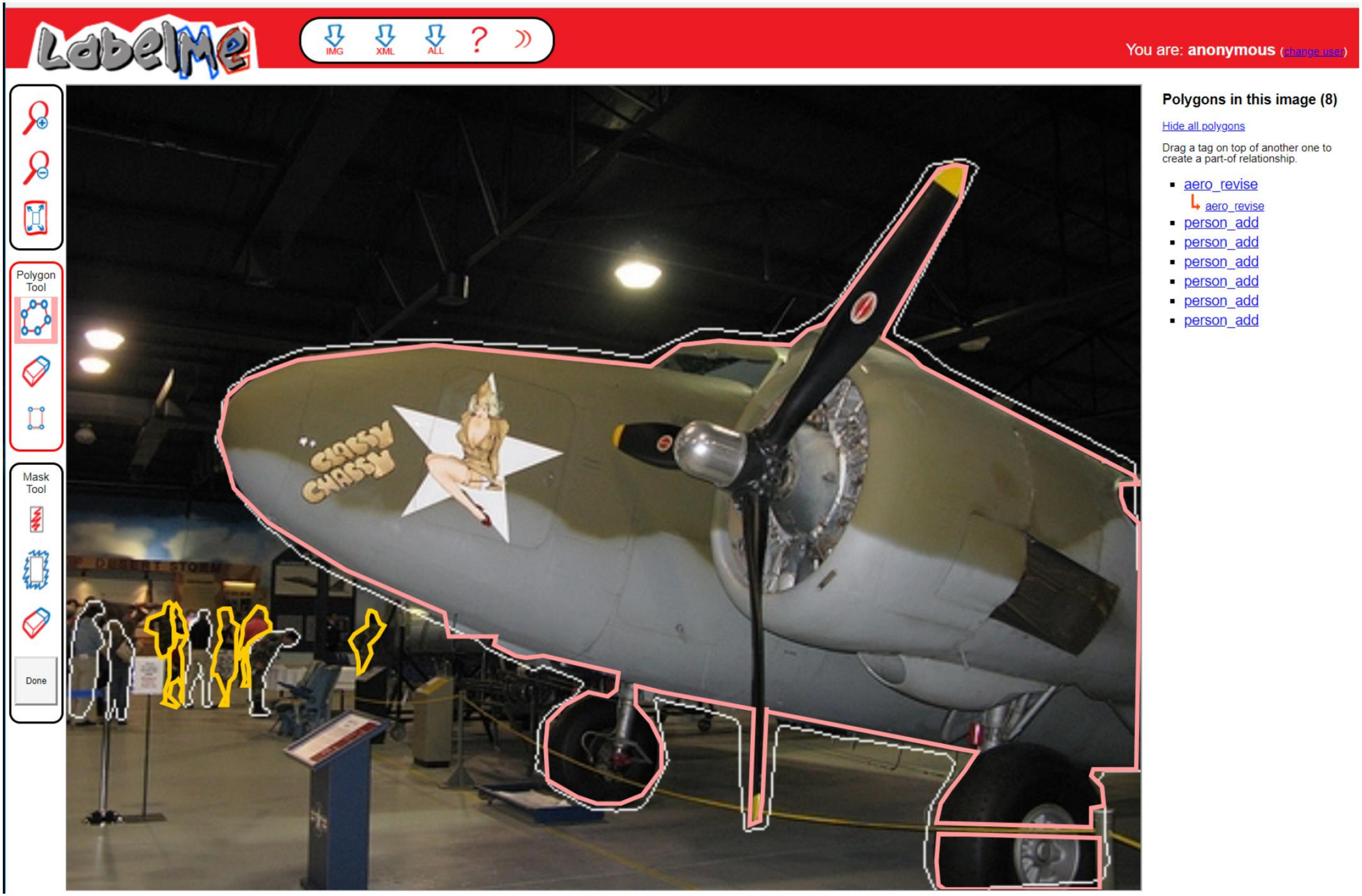
Experiment: Qualitative Results on SBD



Experiment: Qualitative Results on Cityscapes



SBD Test Set Re-Annotation



Experiment: Quantitative Results

MF scores on the SBD test set. Results are measured by %.

Metric	Method	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
MF (Thin)	CASENet	74.5	59.7	73.4	48.0	67.1	78.6	67.3	76.2	47.5	69.7	36.2	75.7	72.7	61.3	74.8	42.6	71.8	48.9	71.7	54.9	63.6
	CASENet-S	75.9	62.4	75.5	52.0	66.7	79.7	**71.0**	79.0	**50.1**	70.0	39.8	77.2	74.5	65.0	77.0	47.3	72.7	51.5	72.9	57.3	65.9
	CASENet-C	**78.4**	60.9	74.9	49.7	64.4	75.8	67.2	77.1	48.2	71.2	40.9	76.1	72.9	64.5	75.9	**51.4**	71.3	51.6	68.6	55.4	64.8
	SEAL	78.0	**65.8**	**76.6**	**52.4**	**68.6**	**80.0**	70.4	**79.4**	50.0	**72.8**	**41.4**	**78.1**	**75.0**	**65.5**	**78.5**	49.4	**73.3**	**52.2**	**73.9**	**58.1**	**67.0**
MF (Raw)	CASENet	65.8	51.5	65.0	43.1	57.5	68.1	58.2	66.0	45.4	59.8	32.9	64.2	65.8	52.6	65.7	40.9	65.0	42.9	61.4	47.8	56.0
	CASENet-S	68.9	55.8	70.9	47.4	62.0	71.5	64.7	71.2	48.0	64.8	37.3	69.1	68.9	58.2	70.2	44.3	68.7	46.1	65.8	52.5	60.3
	CASENet-C	**75.4**	57.7	73.0	48.7	62.1	72.2	64.4	74.3	46.8	68.8	38.8	73.4	71.4	**62.2**	72.1	**50.3**	69.8	48.4	66.1	53.0	62.4
	SEAL	75.3	**60.5**	**75.1**	**51.2**	**65.4**	**76.1**	**67.9**	**75.9**	**49.7**	**69.5**	**39.9**	**74.8**	**72.7**	62.1	**74.2**	48.4	**72.3**	**49.3**	**70.6**	**56.7**	**64.4**

MF scores on the re-annotated SBD test set. Results are measured by %.

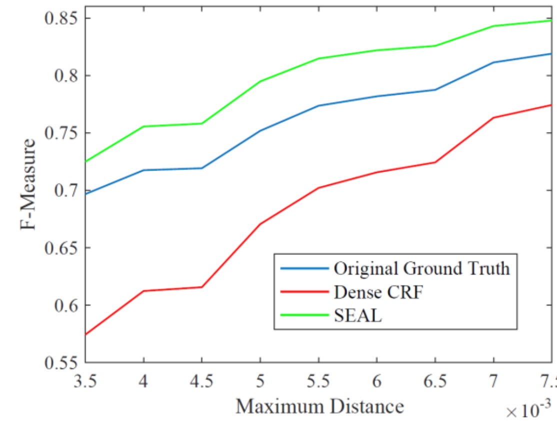
Metric	Method	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
MF (Thin)	CASENet	83.6	75.3	82.3	63.1	70.5	83.5	76.5	82.6	56.8	76.3	47.5	80.8	80.9	75.6	80.7	54.1	77.7	52.3	77.9	68.0	72.3
	CASENet-S	**84.5**	**76.5**	**83.7**	**65.3**	71.3	**83.9**	**78.3**	84.5	**58.8**	76.8	50.8	81.9	**82.3**	**77.2**	82.7	**55.9**	78.1	54.0	**79.5**	69.4	**73.8**
	CASENet-C	83.9	71.1	82.5	62.6	71.0	82.2	76.8	83.4	56.5	**76.9**	49.2	81.0	81.1	75.4	81.4	54.0	**78.5**	53.3	77.1	67.0	72.2
	SEAL	**84.5**	**76.5**	**83.7**	64.9	**71.7**	83.8	78.1	**85.0**	**58.8**	76.6	**50.9**	**82.4**	82.2	77.1	**83.0**	55.1	78.4	**54.4**	79.3	**69.6**	**73.8**
MF (Raw)	CASENet	71.8	60.2	72.6	49.5	59.3	73.3	65.2	70.8	51.9	64.9	41.2	67.9	72.5	64.1	71.2	44.0	71.7	45.7	65.4	55.8	62.0
	CASENet-S	75.8	65.0	78.4	56.2	64.7	76.4	71.8	75.2	55.2	68.7	45.8	72.8	77.0	68.1	76.5	47.1	75.5	49.0	70.2	60.6	66.5
	CASENet-C	80.4	67.1	79.9	57.9	65.9	77.6	72.6	79.2	53.5	72.7	45.5	76.7	79.4	71.2	78.3	**50.8**	77.6	50.7	71.6	61.6	68.5
	SEAL	**81.1**	**69.6**	**81.7**	**60.6**	**68.0**	**80.5**	**75.1**	**80.7**	**57.0**	**73.1**	**48.1**	**78.2**	**80.3**	**72.1**	**79.8**	50.0	**78.2**	**51.8**	**74.6**	**65.0**	**70.3**

MF scores on the Cityscapes validation set. Results are measured by %.

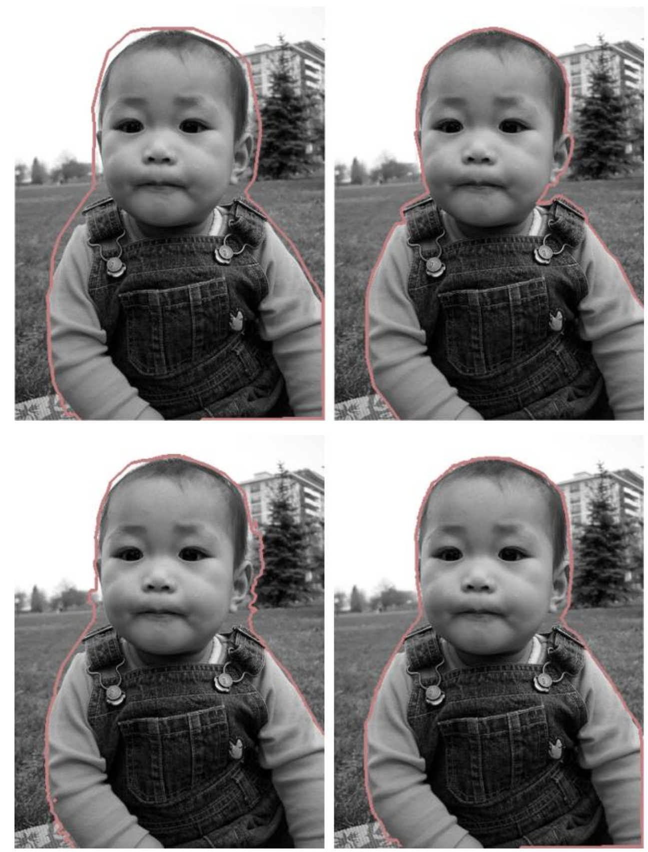
Metric	Method	road	sidewalk	building	wall	fence	pole	t-light	t-sign	veg	terrain	sky	person	rider	car	truck	bus	train	motor	bike	mean
MF (Thin)	CASENet	86.2	74.9	74.5	47.6	**46.5**	72.8	70.0	73.3	79.3	57.0	86.5	80.4	66.8	88.3	49.3	64.6	**47.8**	**55.8**	71.9	68.1
	CASENet-S	**87.6**	77.1	**75.9**	**48.7**	46.2	**75.5**	**71.4**	75.3	80.6	59.7	86.8	81.4	68.1	**89.2**	**50.7**	**68.0**	42.5	54.6	72.7	**69.1**
	SEAL	**87.6**	**77.5**	**75.9**	47.6	46.3	**75.5**	71.2	**75.4**	**80.9**	**60.1**	**87.4**	**81.5**	**68.9**	88.9	50.2	67.8	44.1	52.7	**73.0**	**69.1**
MF (Raw)	CASENet	66.8	64.6	66.8	39.4	40.6	71.7	64.2	65.1	71.1	50.2	80.3	73.1	58.6	77.0	42.0	53.2	39.1	46.1	62.2	59.6
	CASENet-S	79.2	70.8	70.4	42.5	42.4	73.9	66.7	68.2	74.6	54.6	82.5	75.7	61.5	82.7	46.0	59.7	39.1	47.0	64.8	63.3
	SEAL	**84.4**	**73.5**	**72.7**	**43.4**	**43.2**	**76.1**	**68.5**	**69.8**	**77.2**	**57.5**	**85.3**	**77.6**	**63.6**	**84.9**	**48.6**	**61.9**	**41.2**	**49.0**	**66.7**	**65.5**

Experiments: Boundary Alignment

Ablation study on SBD. Left to right: isotropic kernel, biased kernel, Biased kernel + MRF



Visualization of boundary alignment on the Cityscapes Dataset



Original GT, re-annotated GT, dense CRF, SEAL