

# Multi-Class Segmentation with Relative Location Prior

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# Introduction



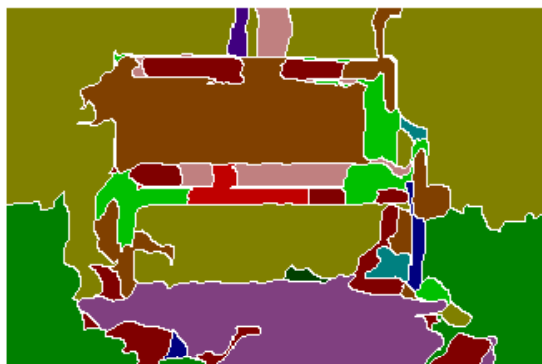
(a) Base image



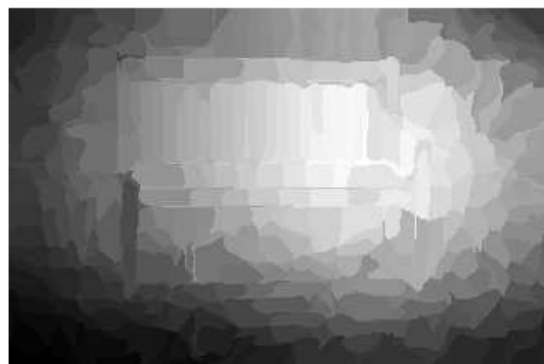
(b) Superpixel over-segmentation



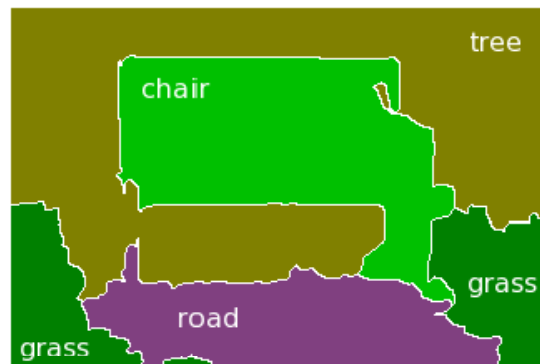
(c) Baseline CRF segmentation



(d) First-stage predictions



(e) Relative location feature (for *chair*)



(f) Second-stage segmentation

# Image segmentation

- Over-segmentation algorithm
- Get superpixels region
- $V(I) = \{S_1, S_2, \dots, S_n\}$  for image I

# Appearance Features

- Each superpixel, 83-dimension description incorporating region size, location, color, shape and texture features. Build it with the way of Barnard et al.
- Append the weight average of appearance over the neighbors for each superpixel to description vector

$$\frac{\sum_{S_j \in \mathcal{N}(S_i)} |S_j| \cdot \phi(S_j)}{\sum_{S_j \in \mathcal{N}(S_i)} |S_j|}$$

$$\mathcal{N}(S_i) = \{S_j \mid (S_i, S_j) \in \mathcal{E}(\mathcal{I})\}$$

is the set of super pixels which are neighbors of  $S_i$  in the images and  $|S_j|$  is the number of pixels in superpixel  $S_j$

# Appearance features

- Apply AdaBoost that have learned for each class  $c'$  to the vector of descriptors and normalize over all classes to get the probability

$$P^{\text{app}}(c_i = c' \mid S_i, \mathcal{I}) = \frac{\exp\{\sigma_{c'}\}}{\sum_c \exp\{\sigma_c\}}$$

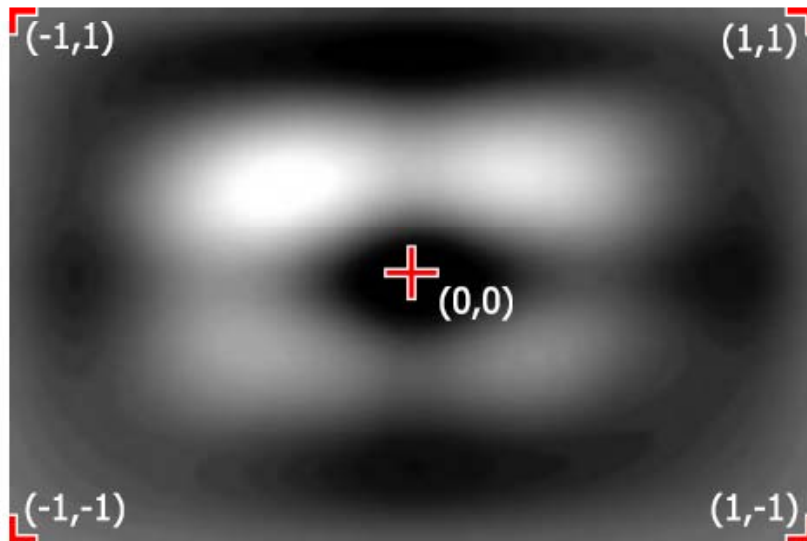
$\sigma_c$  output of the AdaBoost classifier for class  $c$

Then, define appearance features as:

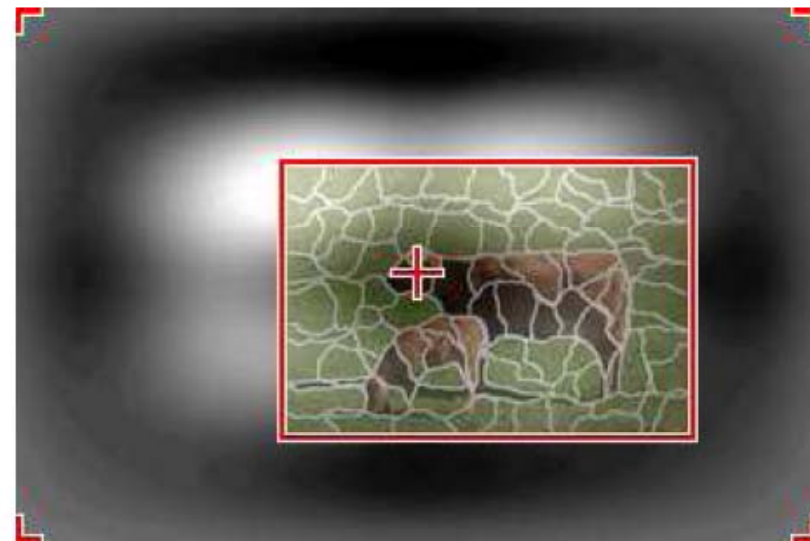
$$f^{\text{app}}(S_i, c_i, \mathcal{I}) = w_{c_i}^{\text{app}} \cdot \log P^{\text{app}}(c_i \mid S_i, \mathcal{I})$$

# Relative Location Probability Maps

- Map  $M_{c|c'}(u,v)$ : encode the probability that pixel  $p$  at offset  $(u,v)$  from  $p'$  (with labeled  $c'$ ) has label  $c$
- $M_{c|c'}(u,v)$  is normalized image coordinates  $(u,v) \in [-1,1] \times [-1,1]$



(a) Relative location prior (*grass to cow*)



(b) Computing relative location offsets

# Relative Location Features

```

Input :  $\mathcal{I}$            // test image
         $\mathcal{H}$            // learned models
         $\{M_{c|c'}\}$  // relative location maps
Output:  $\mathcal{L}$            // pixel labels for  $\mathcal{I}$ 

```

```

// Initial prediction: appearance features only
foreach superpixel  $S_i \in \mathcal{I}$  do
|  $\hat{c}_i \leftarrow \operatorname{argmax}_c P^{\text{app}}(c | S_i, \mathcal{I})$ 
end

```

```

// Compute relative location votes (Eq. 2,3)
foreach superpixel  $S_i \in \mathcal{I}$  do
|   foreach class  $c$  do
|   |    $v_c^{\text{other}}(S_i) = \sum_{j \neq i: \delta_j \neq \delta_i} \alpha_j \cdot M_{c|\delta_j}(\hat{x}_i - \hat{x}_j, \hat{y}_i - \hat{y}_j)$ 
|   |    $v_c^{\text{self}}(S_i) = \sum_{j \neq i: \delta_j = \delta_i} \alpha_j \cdot M_{c|\delta_j}(\hat{x}_i - \hat{x}_j, \hat{y}_i - \hat{y}_j)$ 
|   end
end

```

```

// Compute relative location feature (Eq. 4)
foreach superpixel  $S_i \in \mathcal{I}$  do
|   foreach class  $c_i$  do
|   |    $f^{\text{rloc}}(S_i, c_i, \mathcal{I}) = w_{c_i}^{\text{other}} \cdot \log v_{c_i}^{\text{other}}(S_i)$ 
|   |    $+ w_{c_i}^{\text{self}} \cdot \log v_{c_i}^{\text{self}}(S_i)$ 
|   end
end

```

```

// Final prediction with relative location:
// Logistic regression (Eq. 6) or CRF (Eq. 8)
 $\hat{c} \leftarrow \operatorname{argmax}_c P(c | \mathcal{I}; \mathbf{w})$ 
foreach superpixel  $S_i \in \mathcal{I}$  do
|   foreach pixel  $p \in S_i$  do
|   |    $\mathcal{L}[p] \leftarrow \hat{c}_i$ 
|   end
end

```

```
return  $\mathcal{L}$ 
```

1

2

3

4

5



# Complexity

Benefit from using superpixels is that complexity of their methods depends on the inherent complexity of image rather than resolution



# Complexity

## Sowerby database images

### **200 superpixels**

- computing the relative location : 0.2 s
- pre-partition into 200 superpixels: 5.3 s

### **400 superpixels**

- Compute relative location 0.2 s
- Running Inference 31 s

# Simple (Logistic Regression) model

- independently to each superpixel, they define feature function into  $f_{\text{reloc}}$ ,  $f_{\text{app}}$ , and bias term  $f^{\text{bias}}(c_i) = w_{c_i}^{\text{bias}}$

$$P(c_i | \mathcal{I}; w) \propto \exp \left\{ f^{\text{reloc}}(S_i, c_i, \mathcal{I}) + f^{\text{app}}(S_i, c_i, \mathcal{I}) + f^{\text{bias}}(c_i) \right\}$$

- The weight for logistic model:

$$w = \{w_{c_i}^{\text{other}}, w_{c_i}^{\text{self}}, w_{c_i}^{\text{app}}, w_{c_i}^{\text{bias}} \mid c_i = 1, \dots, K\}$$

# Conditional Random Field

- Pairwise affinity potential
- Such as: given two adjacent superpixels, a pairwise feature might assign a greater value for labeling of cow and grass than it would for cow and airplane, because cows are often next to grass and rarely next to airplane.
- In addition to , features define for logistic model, we define the pairwise feature between all adjacent pixels

$$f^{\text{pair}}(c_i, c_j, \mathcal{I}) = \frac{w_{c_i, c_j}^{\text{pair}}}{0.5(d_i(\mathcal{I}) + d_j(\mathcal{I}))}$$

Number of superpixels adjacent to  $S_i$

# Conditional Random Field

Then, the full CRF model is:

$$P(c | \mathcal{I}; \mathbf{w}) \propto \exp \left\{ \sum_{S_i \in \mathcal{V}(\mathcal{I})} \left( f^{\text{relloc}}(S_i, c_i, \mathcal{I}) + f^{\text{app}}(S_i, c_i, \mathcal{I}) + f^{\text{bias}}(c_i) \right) + \sum_{(S_i, S_j) \in \mathcal{E}(\mathcal{I})} f^{\text{pair}}(c_i, c_j, \mathcal{I}) \right\}$$

- The first summation is over individual superpixels
- The second summation is over pairs of adjacent superpixels

# Experiment Result

- MSRC Databases [ 21-class and 9-class objects]
- Corel and Sowerby Databases [7 classes objects]

# Experiment Result

- Random separate into balance between testing and training

## Training

- train the boosted appearance classifier
- constructing the image dependent relative location prior
- train parameter for logistic regression
- train parameter for CRF models

## Testing

- Use the rest to be considered
- Use train parameter to run in testing

# Experiment Result

- Each experiment will be tested
  1. Baseline logistic regression classifier
  2. Baseline CRF
  3. Logistic regression model augmented with their image-dependent relative location feature
  4. CRF model augmented with their relative location feature.

Note: to ensure robustness, 5 different train/test partitionings for large database and 10 different random prtitionings for small databases and report minimum and maximum and average performance.

Also: contrast to all state-of-the-art methods that normally do evaluated only a single-fold.



# MSRC Databases[21-class]

- 21-class: more comprehensive and complex
- Consisting 591 images of building, grass, tree, cow, sheep, sky, airplane, water, face, car, bicycle, flower, sign, bird, book, chair, road, cat, dog, body, boat.
- Ground truth: foreground label often overlapped with background object and have void class that doesn't fall into 21-class. They skip void class in both train and testing

# MSRC Databases[21-class]

Algorithm	21-class MSRC Accuracy				9-class MSRC Accuracy			
	Min.	Avg.	Max.	Std.	Min.	Avg.	Max.	Std.
Shotton <i>et al.</i> [24]		72.2%*		n/a		-		-
Yang <i>et al.</i> [31]		75.1%*		n/a		-		-
Schroff <i>et al.</i> [22]		-		-		75.2%*		n/a
Baseline Logistic	61.8%	63.6%	65.4%	1.67%	77.5%	78.9%	79.8%	1.05%
Baseline CRF	68.3%	70.1%	72.0%	1.81%	81.2%	83.0%	84.4%	1.28%
Logistic + Rel. Loc.	73.5%	75.7%	77.4%	1.74%	87.6%	88.1%	88.9%	0.67%
CRF + Rel. Loc.	74.0%	76.5%	78.1%	1.82%	87.8%	88.5%	89.5%	0.82%

\* For the other works, results are only reported on a single fold

# MSRC Databases[21-class]

	building	grass	tree	cow	sheep	sky	airplane	water	face	car	bicycle	flower	sign	bird	book	chair	road	cat	dog	body	boat
building	<b>72.3</b> (72.1)	0.8 (1.2)	3.2 (3.5)	1.1 (1.1)	0.6 (0.3)	2.4 (3.4)	0.5 (1.1)	3.2 (2.5)	1.8 (1.3)	2.6 (2.7)	0.4 (0.3)	- (-)	1.5 (1.4)	0.4 (0.1)	1.6 (2.4)	0.5 (0.2)	5.4 (5.4)	- (0.2)	<b>0.6</b> (0.3)	0.5 (0.3)	0.5 (0.1)
grass	0.1 (0.4)	<b>94.8</b> (94.3)	2.7 (3.4)	0.8 (0.7)	0.3 (0.3)	- (-)	0.4 (0.3)	0.1 (0.2)	- (-)	- (-)	0.1 (-)	- (-)	- (-)	0.1 (-)	- (-)	0.1 (-)	0.2 (0.2)	- (-)	- (-)	0.2 (0.1)	- (-)
tree	4.6 (6.7)	5.0 (6.6)	<b>81.3</b> (79.1)	0.1 (0.3)	- (0.1)	2.2 (2.3)	0.6 (0.5)	1.9 (1.0)	0.2 (0.1)	0.4 (1.2)	0.7 (0.8)	- (0.1)	0.5 (0.1)	0.6 (0.3)	- (-)	0.3 (0.2)	8.3 (0.3)	- (-)	0.4 (0.2)	0.2 (0.1)	0.1 (0.1)
cow	0.1 (5.6)	14.9 (14.1)	4.2 (3.3)	<b>66.3</b> (58.6)	1.8 (4.1)	0.2 (0.3)	- (0.2)	2.0 (3.3)	0.1 (1.2)	- (0.8)	- (0.1)	0.6 (1.6)	0.1 (0.4)	2.3 (1.0)	- (0.1)	0.5 (0.1)	0.1 (0.3)	1.1 (1.4)	5.2 (2.9)	0.4 (0.7)	- (-)
sheep	- (7.1)	12.1 (11.6)	0.2 (3.4)	2.6 (3.9)	<b>71.0</b> (57.9)	- (0.3)	- (0.1)	0.4 (3.1)	0.1 (0.3)	- (0.1)	- (0.1)	- (0.2)	- (-)	2.3 (1.2)	- (-)	0.3 (-)	8.3 (6.9)	- (0.8)	2.7 (2.8)	- (0.2)	- (-)
sky	2.2 (2.5)	- (-)	1.0 (0.6)	0.1 (-)	- (-)	<b>92.6</b> (91.2)	0.5 (0.4)	3.3 (4.4)	- (-)	0.1 (0.1)	- (-)	- (-)	0.2 (0.2)	- (0.1)	- (0.1)	- (-)	0.1 (0.4)	- (-)	- (-)	- (-)	- (-)
airplane	20.2 (30.6)	1.8 (2.7)	1.0 (4.1)	- (0.1)	- (-)	2.3 (1.7)	<b>73.6</b> (53.2)	0.3 (0.4)	- (-)	0.4 (5.6)	- (0.2)	- (-)	- (0.7)	- (-)	- (-)	- (0.1)	0.3 (0.4)	- (-)	- (-)	- (-)	- (0.3)
water	3.6 (5.5)	4.4 (5.3)	3.0 (4.6)	0.2 (0.2)	0.3 (0.3)	4.4 (4.8)	0.1 (0.1)	<b>69.6</b> (65.5)	- (-)	2.3 (2.0)	1.4 (0.7)	0.1 (-)	- (0.1)	0.2 (0.3)	- (0.2)	0.3 (-)	9.2 (9.2)	- (0.1)	0.2 (0.2)	0.3 (0.1)	0.4 (0.9)
face	4.2 (11.9)	0.3 (0.5)	1.5 (2.8)	0.9 (3.5)	- (0.1)	0.1 (0.1)	- (-)	0.1 (0.1)	<b>70.2</b> (66.2)	0.1 (0.5)	- (0.2)	1.1 (0.5)	- (0.1)	0.1 (-)	7.6 (1.4)	0.3 (0.1)	0.1 (0.3)	2.0 (1.8)	0.3 (1.2)	11.3 (8.7)	- (-)
car	12.5 (17.3)	- (0.1)	3.7 (4.5)	- (-)	- (-)	1.6 (2.4)	- (1.8)	5.9 (9.7)	- (0.2)	<b>68.9</b> (53.6)	- (0.8)	1.7 (2.3)	0.8 (0.9)	0.4 (0.1)	- (0.7)	- (-)	3.4 (3.6)	- (0.2)	- (-)	- (0.4)	1.1 (1.2)

Baseline CRF

their method

# MSRC databases[21-class]

car	12.5 (17.3)	- (0.1)	3.7 (4.5)	- (-)	- (-)	1.6 (2.4)	- (1.8)	5.9 (9.7)	- (0.2)	<b>68.9</b> (53.6)	- (0.8)	1.7 (2.3)	0.8 (0.9)	0.4 (0.1)	- (0.7)	- (-)	3.4 (3.6)	- (0.2)	- (-)	- (0.4)	1.1 (1.2)
bicycle	16.7 (26.8)	0.2 (0.5)	2.5 (8.8)	- (-)	- (-)	- (0.1)	- (0.2)	0.8 (0.8)	- (0.2)	0.8 (5.0)	<b>71.7</b> (50.3)	0.6 (0.3)	- (0.2)	- (-)	- (-)	1.2 (0.1)	5.2 (5.1)	- (0.1)	- (-)	0.3 (1.4)	- (0.1)
flower	0.1 (1.8)	2.9 (5.0)	5.6 (6.3)	3.8 (7.9)	1.2 (1.2)	0.6 (1.4)	- (0.1)	0.2 (1.1)	3.1 (3.3)	- (0.7)	1.7 (2.6)	<b>67.6</b> (54.4)	2.8 (2.4)	5.9 (1.5)	0.1 (3.0)	- (0.1)	- (0.3)	0.1 (0.2)	1.2 (0.2)	3.1 (6.3)	- (-)
sign	21.0 (26.8)	- (0.2)	1.3 (3.1)	- (0.5)	- (-)	1.1 (2.2)	- (0.7)	0.7 (1.0)	0.2 (0.6)	0.1 (4.1)	- (0.6)	1.6 (1.7)	<b>54.8</b> (44.6)	0.5 (0.2)	13.2 (9.9)	2.3 (0.1)	1.9 (1.9)	0.9 (0.3)	- (-)	0.5 (1.2)	- (0.4)
bird	5.5 (18.0)	9.3 (5.5)	14.5 (15.8)	3.1 (4.8)	7.2 (11.3)	5.8 (5.0)	0.6 (1.3)	7.8 (5.7)	- (0.6)	3.5 (5.9)	3.0 (0.2)	- (-)	1.1 (1.7)	<b>23.0</b> (11.5)	- (0.1)	3.8 (1.0)	8.3 (5.8)	0.1 (0.5)	1.1 (2.2)	0.4 (2.0)	1.8 (0.9)
book	3.1 (9.3)	0.1 (1.6)	0.2 (1.2)	0.1 (2.3)	- (0.2)	- (0.2)	- (0.9)	0.4 (0.8)	0.5 (0.8)	- (2.2)	- (0.3)	6.7 (4.8)	0.1 (1.4)	- (0.1)	<b>82.5</b> (67.4)	0.6 (0.9)	0.2 (1.4)	0.1 (0.3)	- (0.4)	3.2 (2.9)	2.1 (0.4)
chair	28.0 (39.2)	6.0 (7.5)	4.8 (8.5)	6.8 (8.1)	- (0.1)	0.1 (0.1)	0.1 (2.9)	0.3 (1.1)	- (0.6)	1.0 (2.1)	0.3 (1.4)	2.1 (2.0)	- (0.4)	1.6 (0.4)	2.0 (2.6)	<b>39.6</b> (16.5)	5.6 (4.2)	0.9 (0.4)	- (0.2)	0.2 (0.9)	0.6 (0.7)
road	5.1 (8.2)	0.6 (0.9)	0.3 (0.4)	- (0.1)	0.3 (0.1)	1.5 (1.7)	0.5 (0.2)	9.1 (9.9)	0.4 (0.3)	2.2 (1.7)	0.6 (0.3)	0.1 (-)	- (0.1)	0.1 (-)	- (0.1)	0.3 (0.2)	<b>77.0</b> (74.5)	0.6 (0.2)	0.5 (0.3)	1.0 (0.7)	- (-)
cat	2.7 (12.9)	- (0.1)	2.3 (3.1)	0.8 (8.3)	- (-)	- (0.4)	- (0.1)	3.1 (2.4)	0.7 (2.1)	0.4 (2.8)	0.2 (1.1)	9.9 (1.6)	- (-)	2.2 (1.7)	- (0.6)	- (-)	11.7 (9.5)	<b>60.4</b> (43.5)	5.2 (7.8)	0.3 (1.9)	- (0.1)
dog	2.9 (9.4)	2.3 (2.7)	4.8 (2.7)	3.7 (7.3)	1.5 (4.8)	2.9 (5.7)	- (0.1)	0.2 (2.5)	7.8 (8.1)	0.1 (0.2)	- (0.4)	- (-)	- (-)	2.6 (2.5)	- (0.2)	0.4 (0.2)	5.7 (7.6)	11.7 (7.9)	<b>49.6</b> (34.8)	4.0 (2.9)	- (-)
body	5.1 (9.7)	3.3 (3.1)	3.3 (1.8)	7.6 (9.6)	0.2 (1.3)	0.1 (0.4)	- (0.1)	2.1 (2.3)	8.1 (6.7)	0.5 (4.5)	0.9 (1.8)	8.6 (3.6)	0.6 (1.2)	0.4 (0.4)	1.8 (4.5)	3.4 (0.4)	2.8 (3.5)	0.1 (0.1)	1.6 (0.9)	<b>49.5</b> (43.9)	0.2 (0.3)
boat	22.4 (33.0)	0.2 (1.0)	0.7 (3.8)	- (0.1)	- (-)	1.2 (1.0)	- (1.2)	26.0 (8.8)	- (0.1)	30.1 (32.8)	1.0 (0.9)	- (-)	0.7 (0.5)	2.0 (1.4)	- (0.3)	- (0.2)	1.5 (1.0)	- (0.1)	- (-)	0.2 (1.5)	<b>14.0</b> (12.0)

# MSRC Databases[9-class]

- 9-class
- 120 images trained, 120 images tested

# MSRC Databases[21-class]

Algorithm	21-class MSRC Accuracy				9-class MSRC Accuracy			
	Min.	Avg.	Max.	Std.	Min.	Avg.	Max.	Std.
Shotton <i>et al.</i> [24]		72.2%*		n/a		-		-
Yang <i>et al.</i> [31]		75.1%*		n/a		-		-
Schroff <i>et al.</i> [22]		-		-		75.2%*		n/a
Baseline Logistic	61.8%	63.6%	65.4%	1.67%	77.5%	78.9%	79.8%	1.05%
Baseline CRF	68.3%	70.1%	72.0%	1.81%	81.2%	83.0%	84.4%	1.28%
Logistic + Rel. Loc.	73.5%	75.7%	77.4%	1.74%	87.6%	88.1%	88.9%	0.67%
CRF + Rel. Loc.	74.0%	76.5%	78.1%	1.82%	87.8%	88.5%	89.5%	0.82%

\* For the other works, results are only reported on a single fold

# Corel and Sowerly Databases

- 7-class
- Corel contain 100 images
- Sowerly contain 104 images
- Train both by 60 images, the rest are used for tested.
- 10 different random for train/test partitioning and report minimum, maximum and average for the test set.

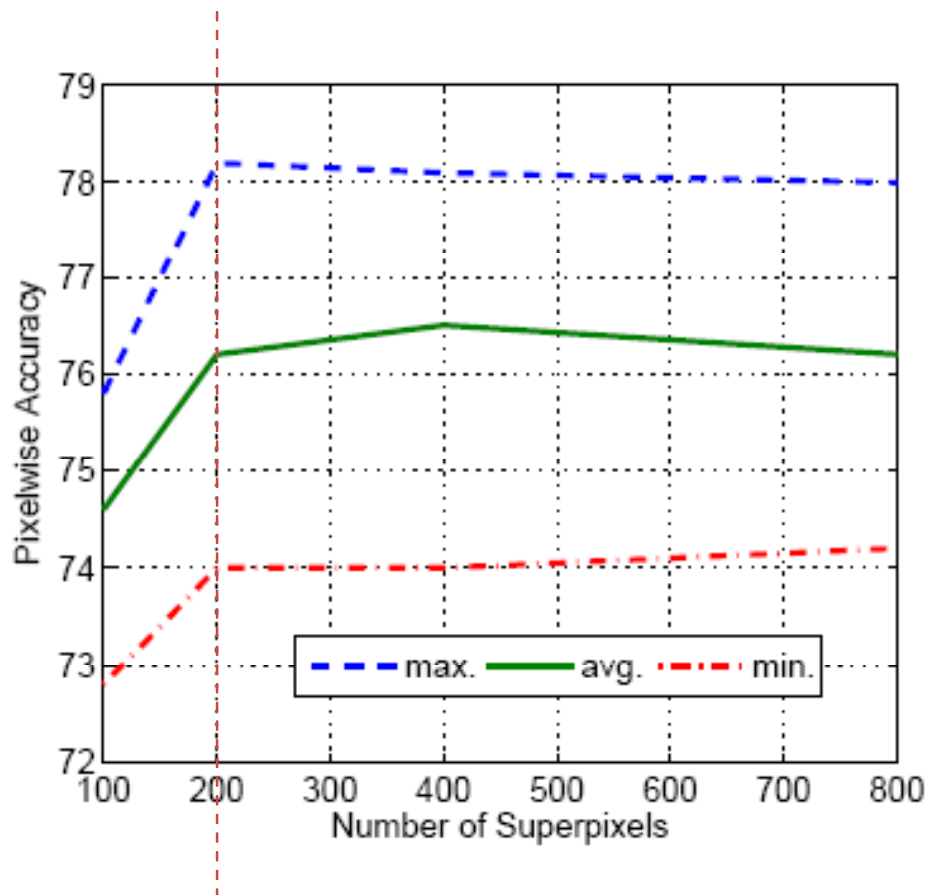
# Corel and Sowerly Databases

Algorithm	7-class Corel Accuracy				7-class Sowerby Accuracy			
	Min.	Avg.	Max.	Std.	Min.	Avg.	Max.	Std.
He <i>et al.</i> [9]		<b>80.0%*</b>		n/a		<b>89.5%*</b>		n/a
Kumar <i>et al.</i> [12]		-		-		89.3%*		n/a
Shotton <i>et al.</i> [24]		74.6%*		n/a		88.6%*		n/a
Yang <i>et al.</i> [31]		-		-		88.9%*		n/a
Baseline Logistic	68.2%	72.7%	76.8%	2.68%	84.7%	86.4%	88.0%	0.92%
Baseline CRF	69.6%	74.9%	78.5%	2.80%	84.9%	87.2%	88.6%	1.01%
Logistic + Rel. Loc.	70.7%	76.4%	81.6%	3.07%	84.9%	87.2%	88.5%	0.98%
CRF + Rel. Loc.	71.1%	77.3%	82.5%	3.15%	85.2%	87.5%	88.8%	0.98%

\* For the other works, results are only reported on a single fold

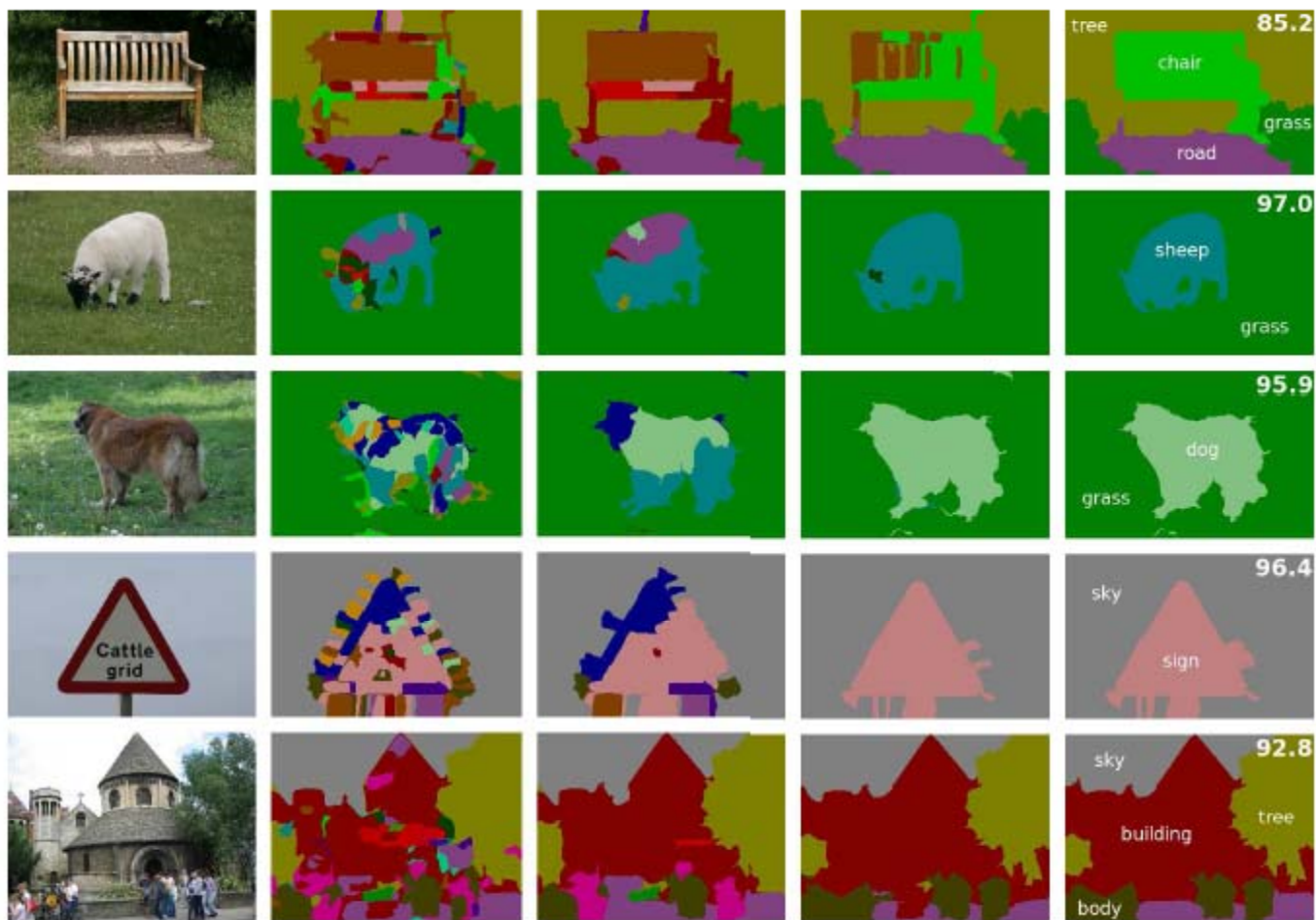


# Robustness to Over-segmentation

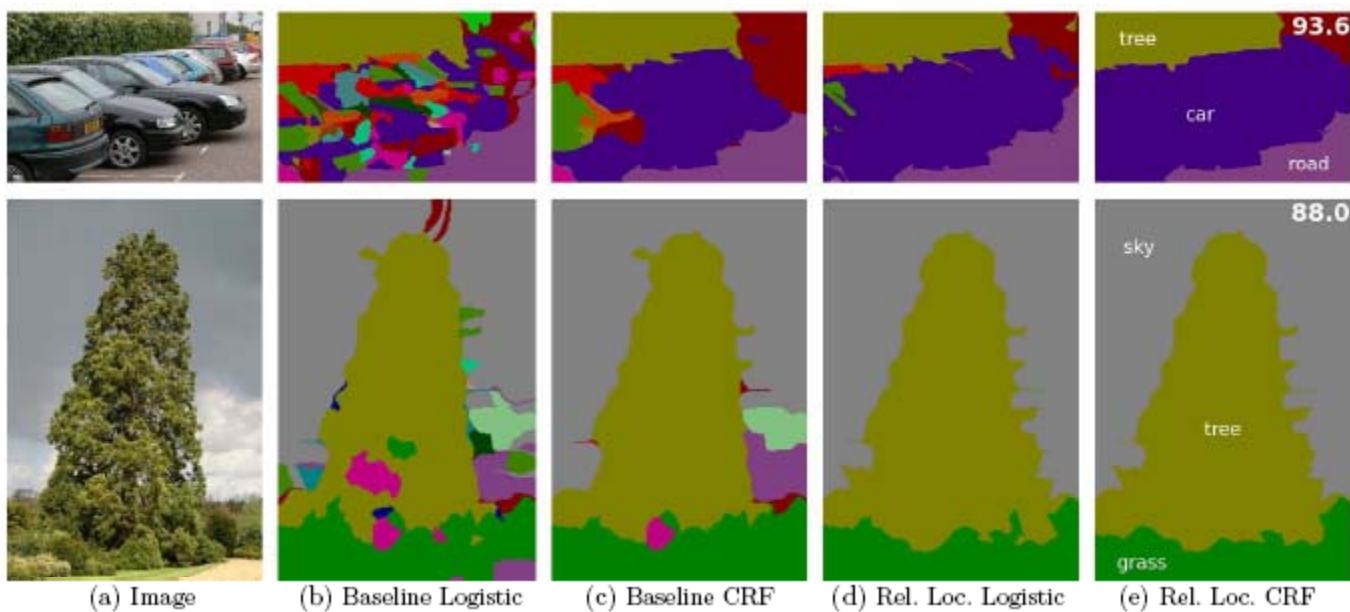


- Using different number of superpixels
- After approx 200 superpixels, the accuracy of algorithm insensitive to change in number of superpixels

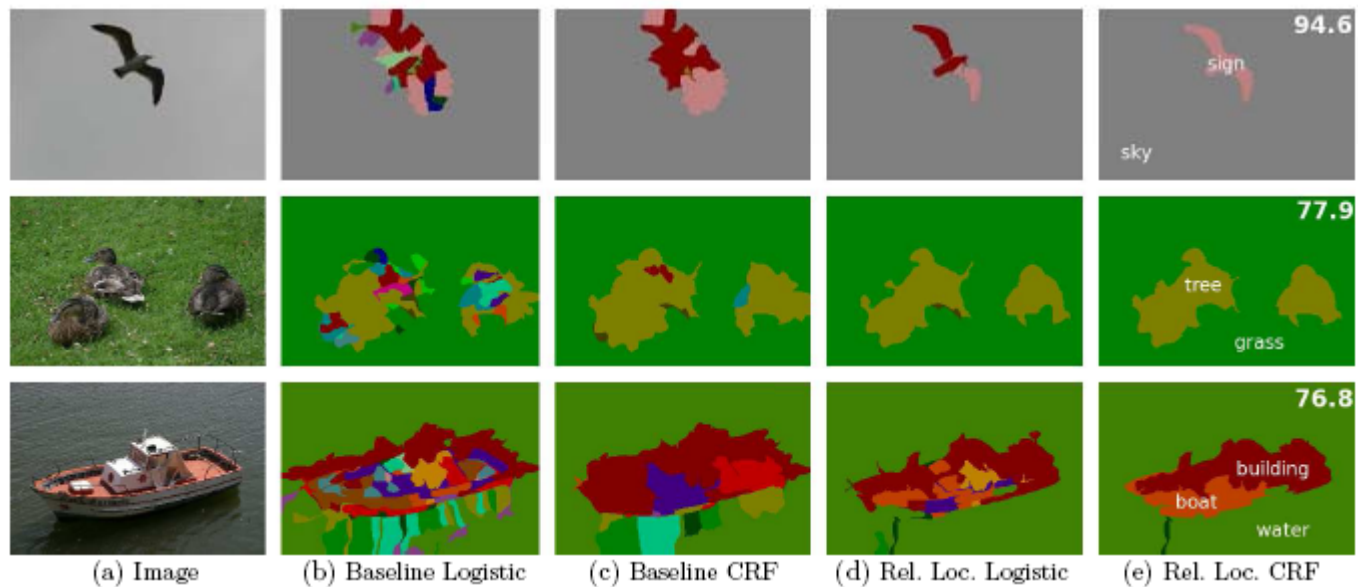
# Quality assessment



# Quality assessment



# Quality assessment



	building	grass	tree	cow	sheep	sky	airplane	water	face	car
bicycle	flower	sign	bird	book	chair	road	cat	dog	body	boat

# The End

- Thank you....