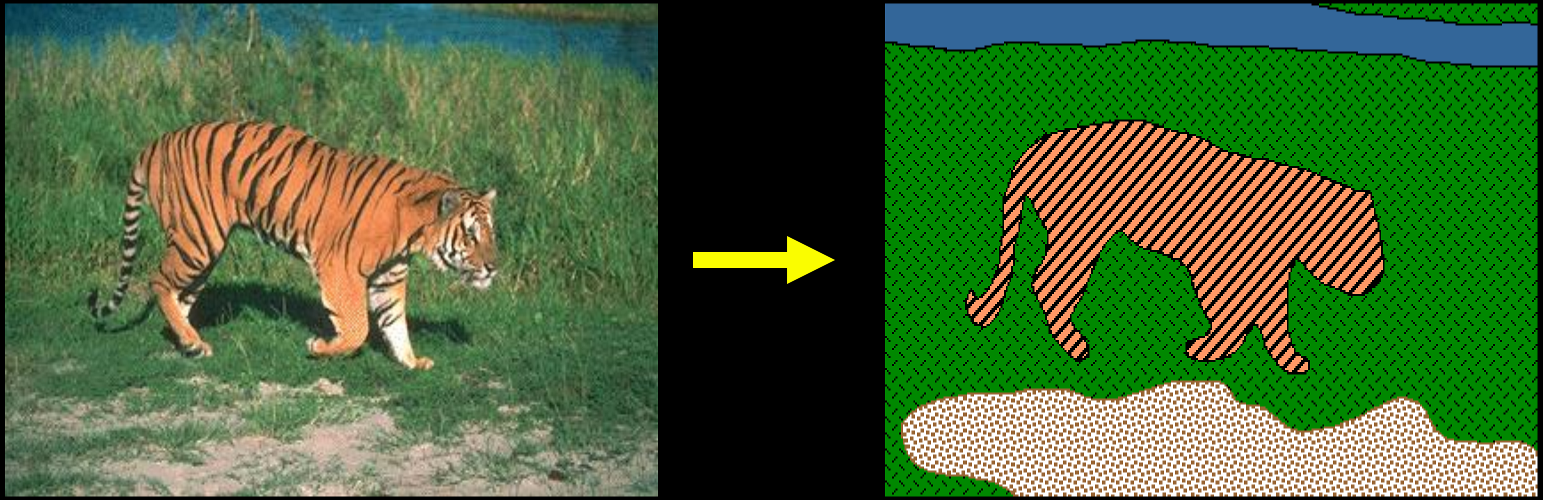
“Fovea Detector”

- https://www.shadertoy.com/view/4dsXzM

From Images to Objects



"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees." --Max Wertheimer, 1923

Recap

- Segmentation vs Boundary Detection vs semantic segmentation / scene parsing
- Why boundaries / Grouping?
- Recap: Canny Edge Detection
- The Berkeley Segmentation Data Set
- pB boundary detector ~2001
- Sketch Tokens 2013

Recap: modern boundary detection

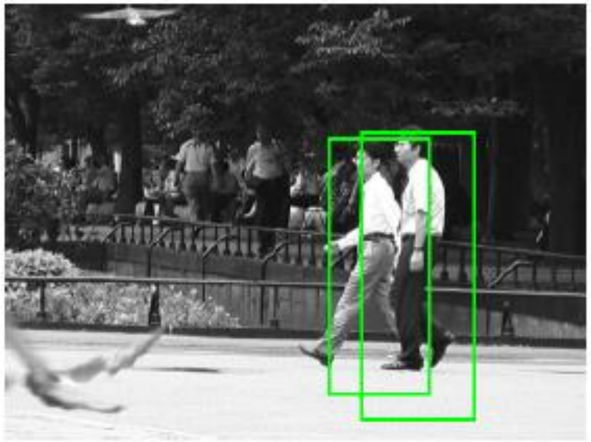
- Learn from humans where image boundaries are.
- Boundaries aren't super well defined.
  - Depth discontinuities
  - Semantic boundaries
  - Texture boundaries
  - Illumination boundaries

Today: Scene Parsing / Semantic Segmentation

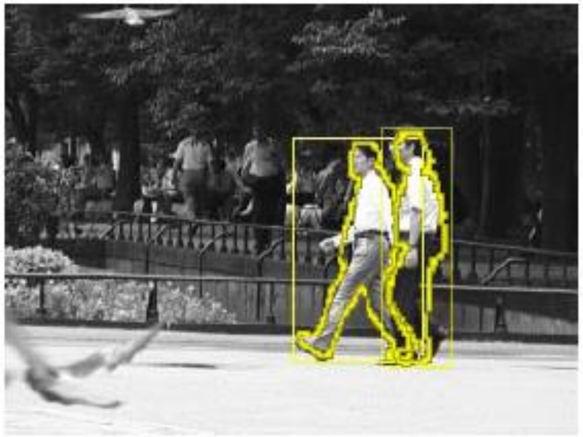
- Label every pixel of an image with a category label (usually with the help of contextual reasoning).
- Well known example: TextonBoost
- Detailed look at the “non parametric” approach of Tighe and Lazebnik

Object Recognition and Segmentation are Coupled

No Segmentation



Approximate Segmentation



Good Segmentation

Images from
[Leibe *et al.* 2005]

The Three Approaches

- Segment → Detect
- Detect → Segment
- Segment ←→ Detect

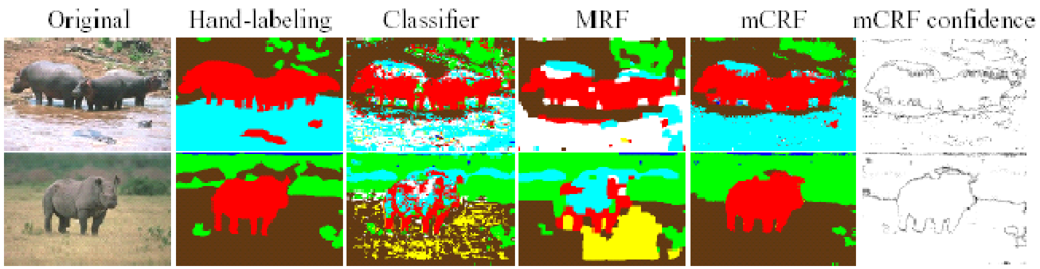
Segment first and ask questions later.

- Reduces possible locations for objects
- Allows use of shape information and makes long-range cues more effective
- But what if segmentation is wrong?

[Duygulu *et al* ECCV 2002]

Object recognition + data-driven smoothing

- Object recognition drives segmentation
- Segmentation gives little back

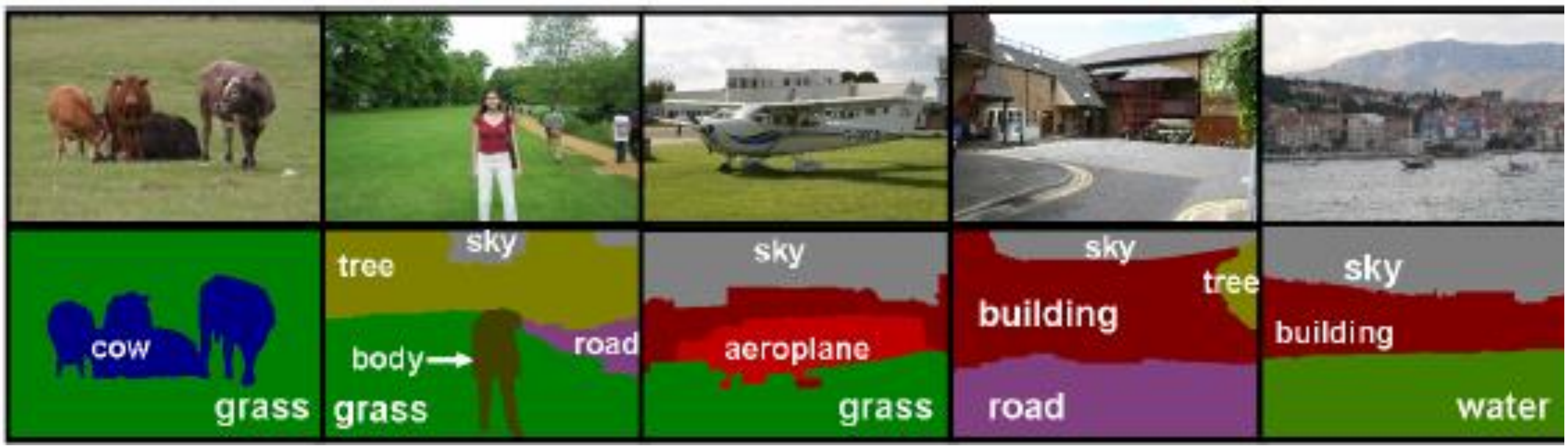


He *et al.* 2004

TextonBoost

TextonBoost: Joint Appearance, Shape and Context Modeling for Multi-Class Object Recognition and Segmentation

J. Shotton ; University of Cambridge
J. Jinn, C. Rother, A. Criminisi ; MSR Cambridge



Slides modified from Derek Hoiem

The Ideas in TextonBoost

- Textons from Universal Visual Dictionary paper [Winn Criminisi Minka ICCV 2005]
- Color models and GC from “Foreground Extraction using Graph Cuts” [Rother Kolmogorov Blake SG 2004]
- Boosting + Integral Image from Viola-Jones
- Joint Boosting from [Torralba Murphy Freeman CVPR 2004]

What’s good about this paper

- Provides recognition + segmentation for many classes (for the time it was published)

- Combines several good ideas

- Very thorough evaluation

TextonBoost Overview

$$\log P(\mathbf{c}|\mathbf{x},\boldsymbol{\theta}) = \sum_i \overbrace{\psi_i(c_i,\mathbf{x};\boldsymbol{\theta}_\psi)}^{\text{shape-texture}} + \overbrace{\pi(c_i,\mathbf{x}_i;\boldsymbol{\theta}_\pi)}^{\text{color}} + \overbrace{\lambda(c_i,i;\boldsymbol{\theta}_\lambda)}^{\text{location}}$$

$$+ \sum_{(i,j)\in\mathcal{E}} \overbrace{\phi(c_i,c_j,\mathbf{g}_{ij}(\mathbf{x});\boldsymbol{\theta}_\phi)}^{\text{edge}} - \log Z(\boldsymbol{\theta},\mathbf{x})$$

Shape-texture: localized textons

$$\psi_i(c_i,\mathbf{x};\boldsymbol{\theta}_\psi) = \log \widetilde{P}_i(c_i|\mathbf{x})$$

Color: mixture of Gaussians

$$P(x|c) = \sum_k P(k|c)\mathcal{N}(x\,|\,\bar{x}_k,\Sigma_k) \qquad \pi(c_i,x_i;\boldsymbol{\theta}_\pi) = \log\sum_k \boldsymbol{\theta}_\pi(c_i,k)P(k|x_i)$$

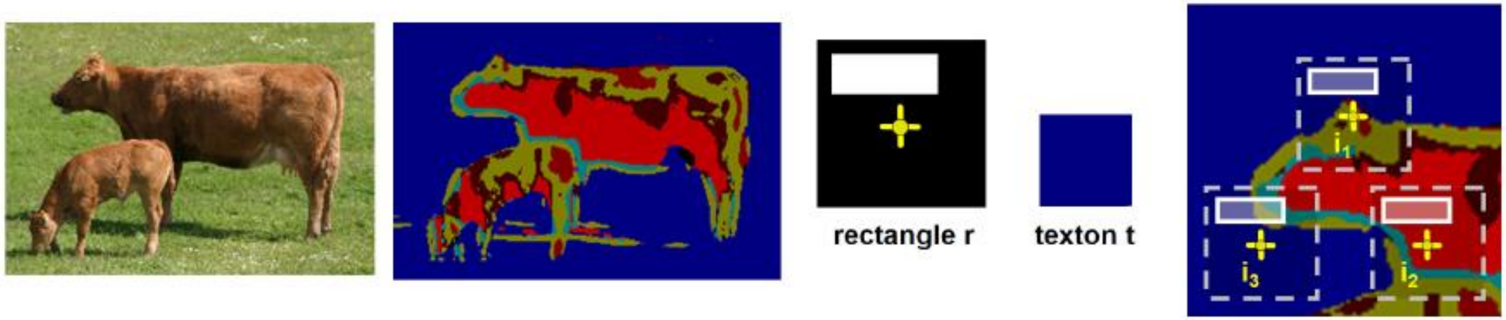
Location: normalized x-y coordinates

$$\lambda_i(c_i,i;\boldsymbol{\theta}_\lambda) = \log \boldsymbol{\theta}_\lambda(c_i,\hat{i})$$

Edges: contrast-sensitive Pott’s model

$$\phi(c_i,c_j,\mathbf{g}_{ij}(\mathbf{x});\boldsymbol{\theta}_\phi) = -\boldsymbol{\theta}_\phi^T\mathbf{g}_{ij}(\mathbf{x})\delta(c_i\neq c_j) \qquad \mathbf{g}_{ij} = [\exp(-\beta\|x_i-x_j\|^2),1]^T$$

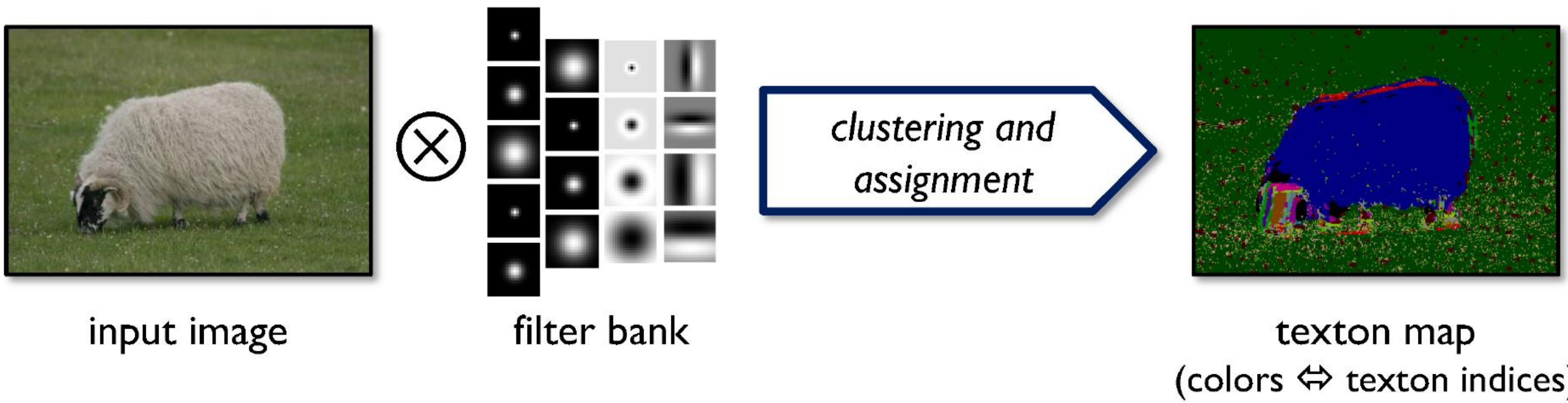
Texture-Shape



(a) Input image (b) Texton map (c) Feature pair = (r,t) (d) Superimposed rectangles

- 17 filters (oriented gaus/lap + dots)
- Cluster responses to form textons
- Count textons within white box (relative to position i)
- Feature = texton + rectangle

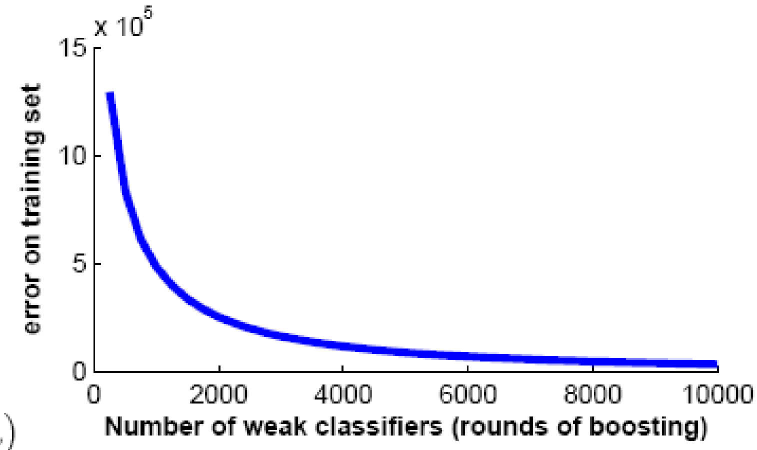
Texton Visualization



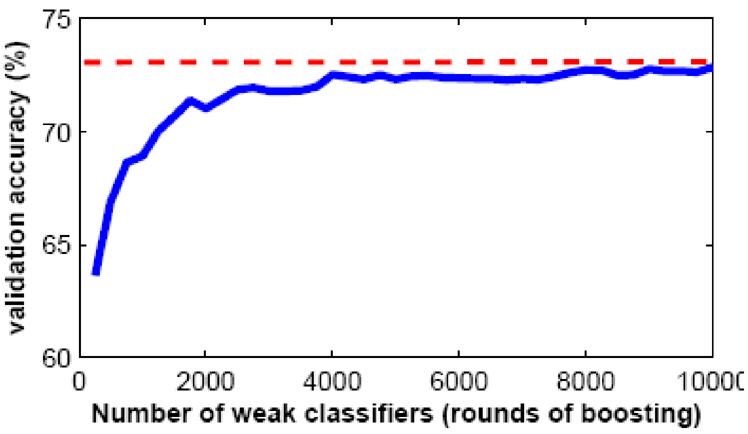
Results on Boosted Textons

- Boosted shape-textons in isolation
  - Training time: 42 hrs for 5000 rounds on 21-class training set of 276 images

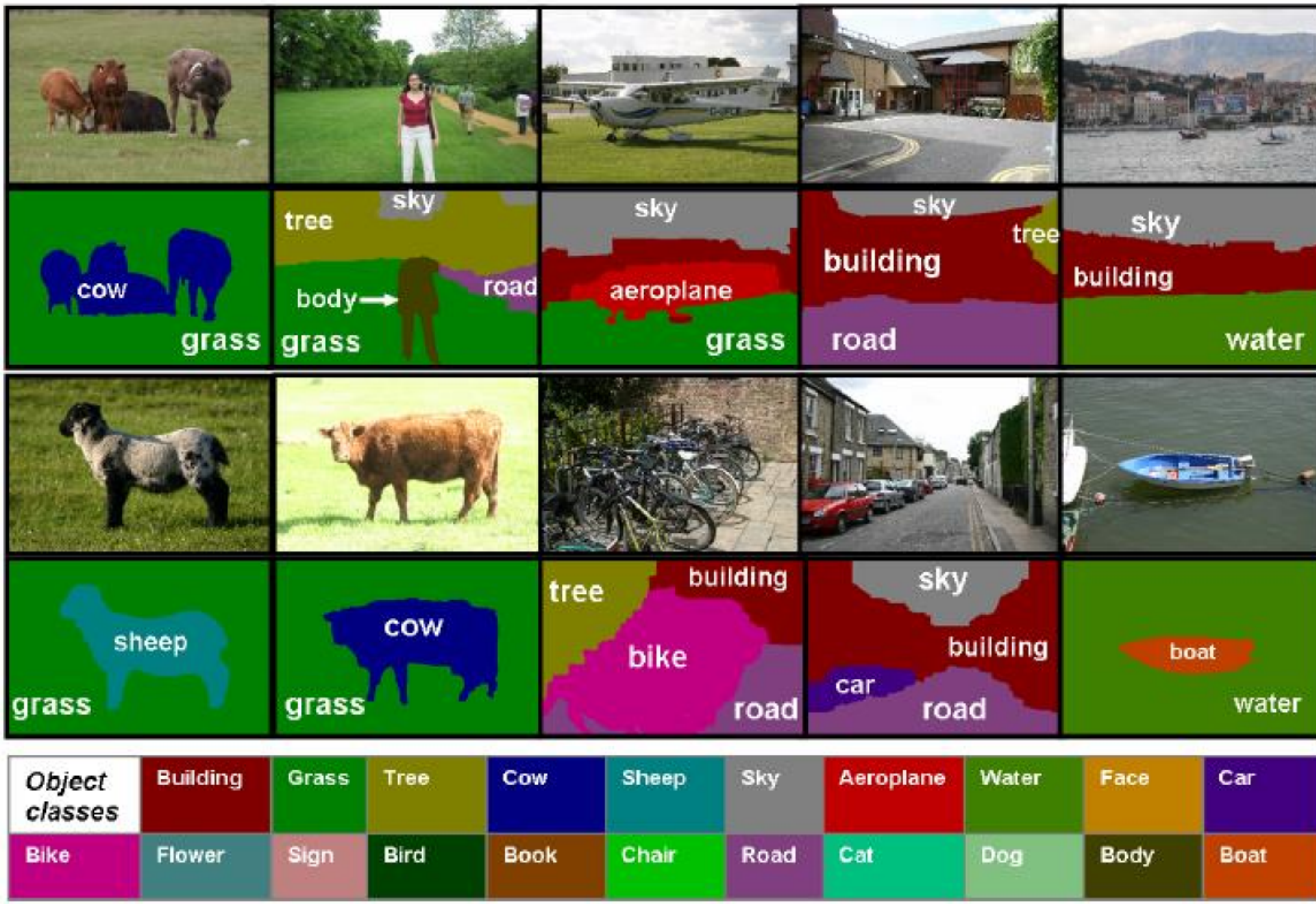
(a)



(b)



Qualitative (Good) Results



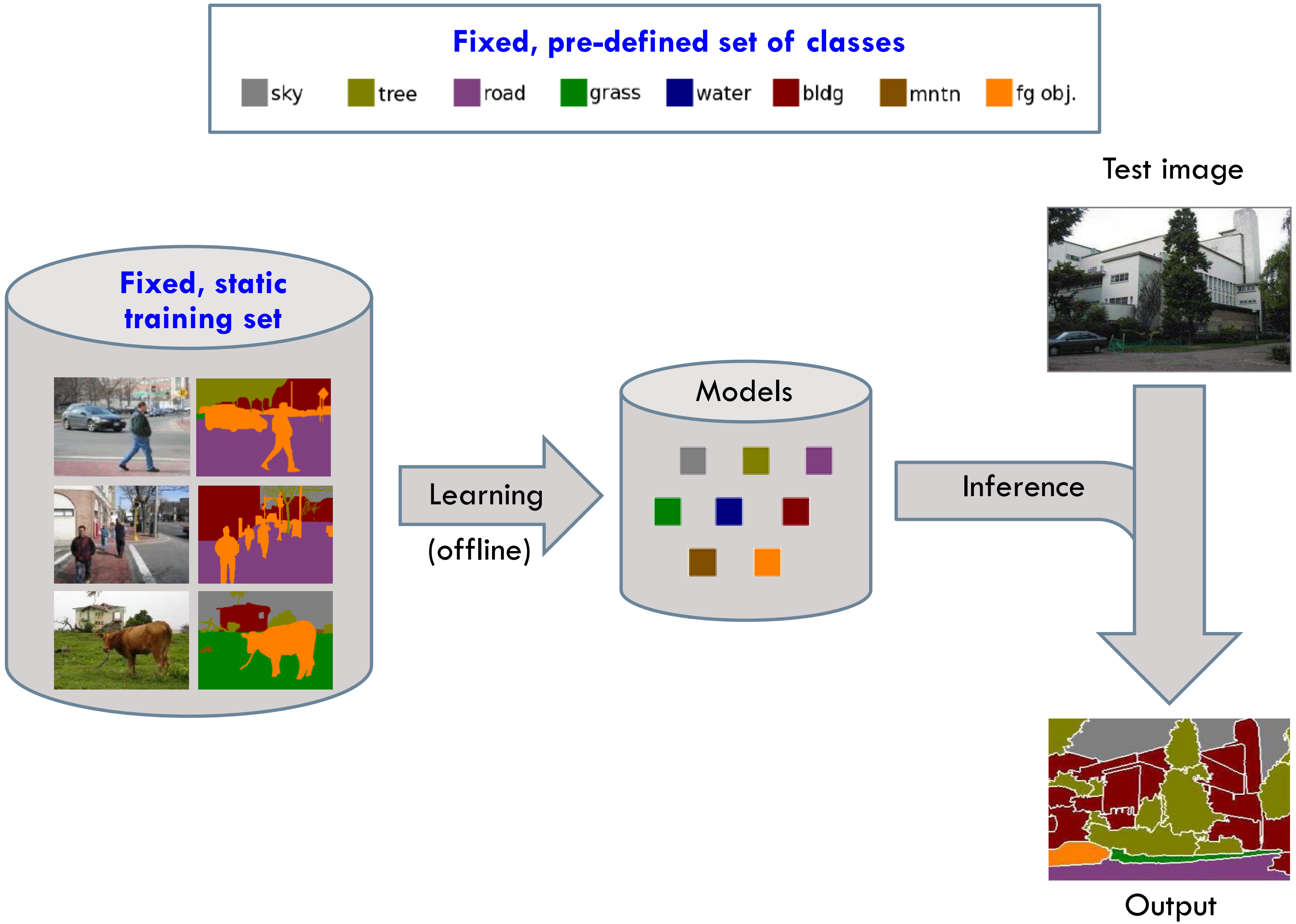
Qualitative (Bad) Results

- But notice good segmentation, even with bad labeling

Quantitative Results

True class \ Inferred class	building	grass	tree	cow	sheep	sky	aeroplane	water	face	car	bike	flower	sign	bird	book	chair	road	cat	dog	body	boat
building	**61.6**	4.7	9.7	0.3		2.5	0.6	1.3	2.0	2.6	2.1		0.6	0.2	4.8		6.3	0.4		0.5	
grass	0.3	**97.6**	0.5								0.1									1.3	
tree	1.2	4.4	**86.3**	0.5		2.9	1.4	1.9	0.8	0.1							0.1		0.2	0.1	
cow		30.9	0.7	**58.3**				0.9	0.4			0.4			4.2					4.1	
sheep	16.5	25.5	4.8	1.9	**50.4**									0.6			0.2				
sky	3.4	0.2	1.1			**82.6**		7.5									5.2				
aeroplane	21.5	7.2				3.0	**59.6**	8.5													
water	8.7	7.5	1.5	0.2		4.5		**52.9**		0.7	4.9			0.2	4.2		14.1	0.4			
face	4.1		1.1						**73.5**	7.1					8.4			0.4	0.2	5.2	
car	10.1		1.7							**62.5**	3.8		5.9	0.2			15.7				
bike	9.3		1.3							1.0	**74.5**		2.5			3.9	5.9		1.6		
flower		6.6	19.3	3.0								**62.8**			7.3		1.0				
sign	31.5	0.2	11.5	2.1		0.5		6.0		1.5		2.5	**35.1**		3.6	2.7	0.8	0.3		1.8	
bird	16.9	18.4	9.8	6.3	8.9	1.8		9.4						**19.4**			4.6	4.5			
book	2.6		0.6						0.4			2.0			**91.9**					2.4	
chair	20.6	24.8	9.6	18.2		0.2					3.7				1.9	**15.4**	4.5		1.1		
road	5.0	1.1	0.7					3.4	0.3	0.7	0.6		0.1	0.1	1.1		**86.0**			0.7	
cat	5.0		1.1	8.9				0.2		2.0					0.6		28.4	**53.6**	0.2		
dog	29.0	2.2	12.9	7.1				9.7							8.1		11.7		**19.2**		
body	4.6	2.8	2.0	2.1	1.3	0.2			6.0	1.1					9.9		1.7	4.0	2.1	**62.1**	
boat	25.1		11.5			3.8		30.6		2.0	8.6		6.4	5.1			0.3				**6.6**

Closed-universe recognition



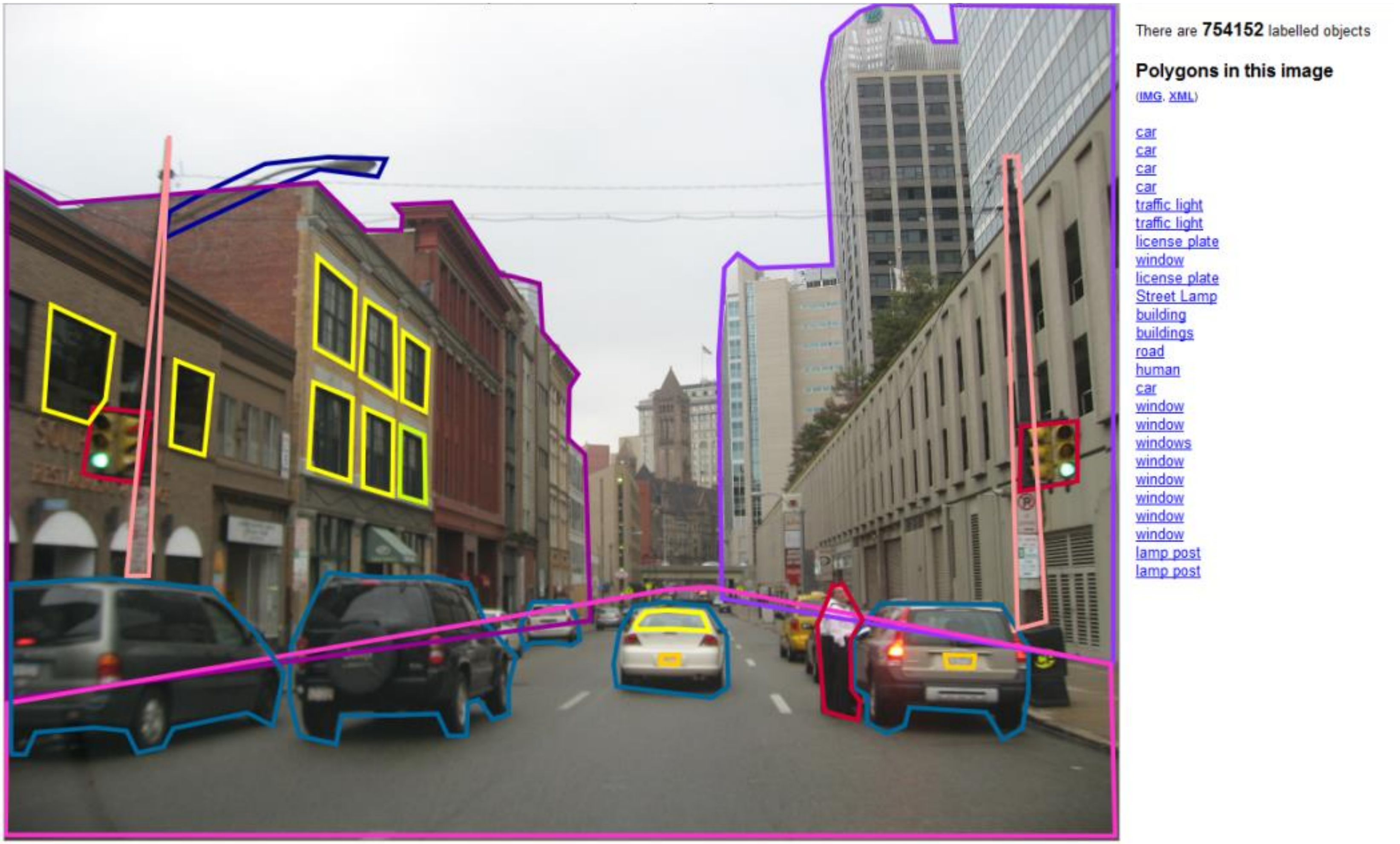
Closed-universe datasets

- Small amount of data
- Static datasets
- Limited variation
- Full annotation

Open-universe datasets

- Large amount of data
- Evolving datasets
- Wide variation
- Incomplete annotation

Open-universe recognition



Evolving training set

http://labelme.csail.mit.edu/

Open-universe recognition

Very large/open-ended set of classes

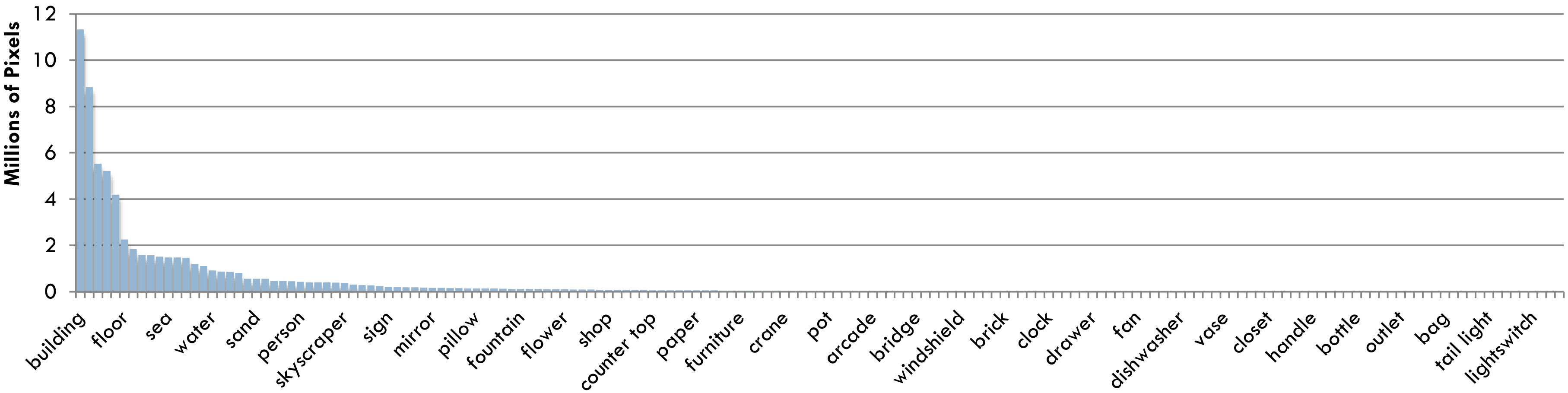
building mountain tree sky road sea car field window plant river grass rock sidewalk sand door desert bridge person balcony fence staircase awning sign crosswalk streetlight boat bus pole sun cow bird moon • • • wall plate table chair ground desk bookshelf utensil glass screen floor bed placem

Open-universe recognition

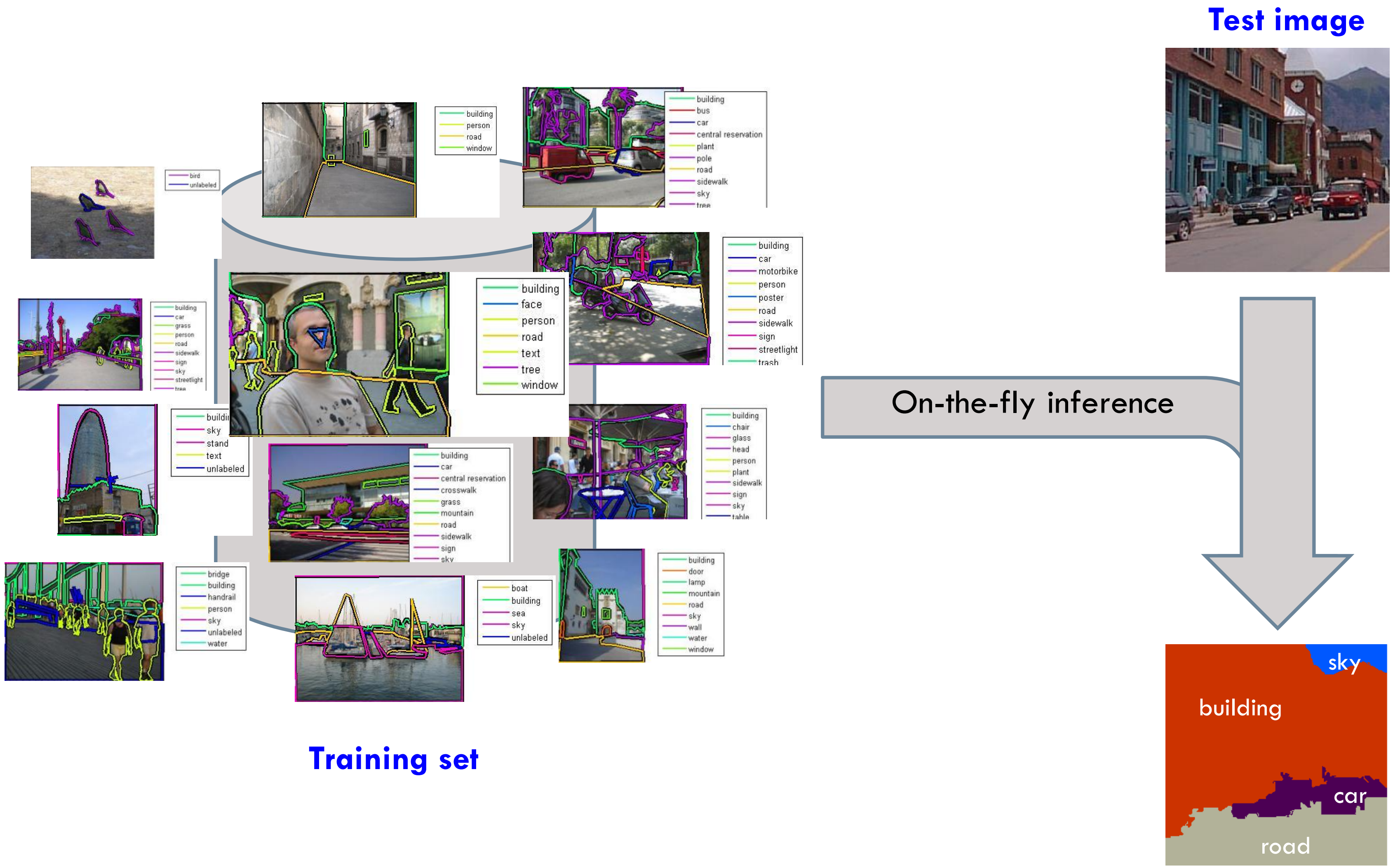
Very large/open-ended set of classes

building mountain tree sky road sea car field window plant river grass rock sidewalk sand door desert bridge person balcony fence staircase awning sign crosswalk streetlight boat bus pole sun cow bird moon • • • wall plate table chair ground desk bookshelf utensil glass screen floor bed placem

Unbalanced data distribution



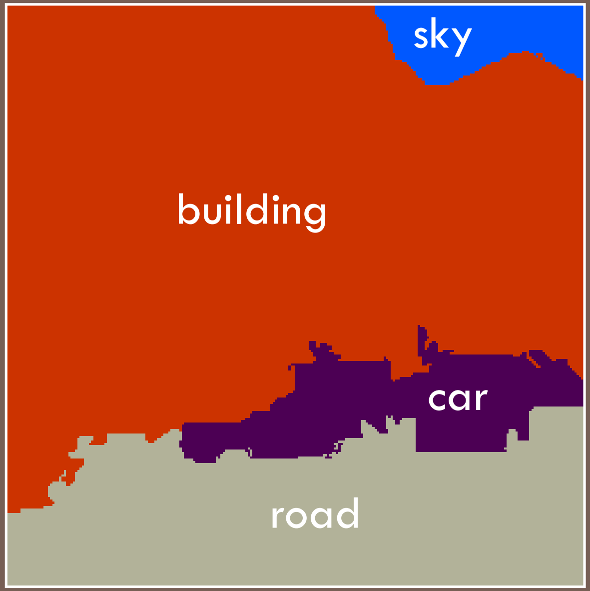
Potential solution: Lazy learning



LARGE-SCALE NONPARAMETRIC IMAGE PARSING

Joseph Tighe and Svetlana Lazebnik

ECCV 2010



Step 1: Scene-level matching

Color Histogram

Spatial Pyramid
(Lazebnik et al., 2006)

Gist
(Oliva & Torralba, 2001)

Step 2: Region-level matching

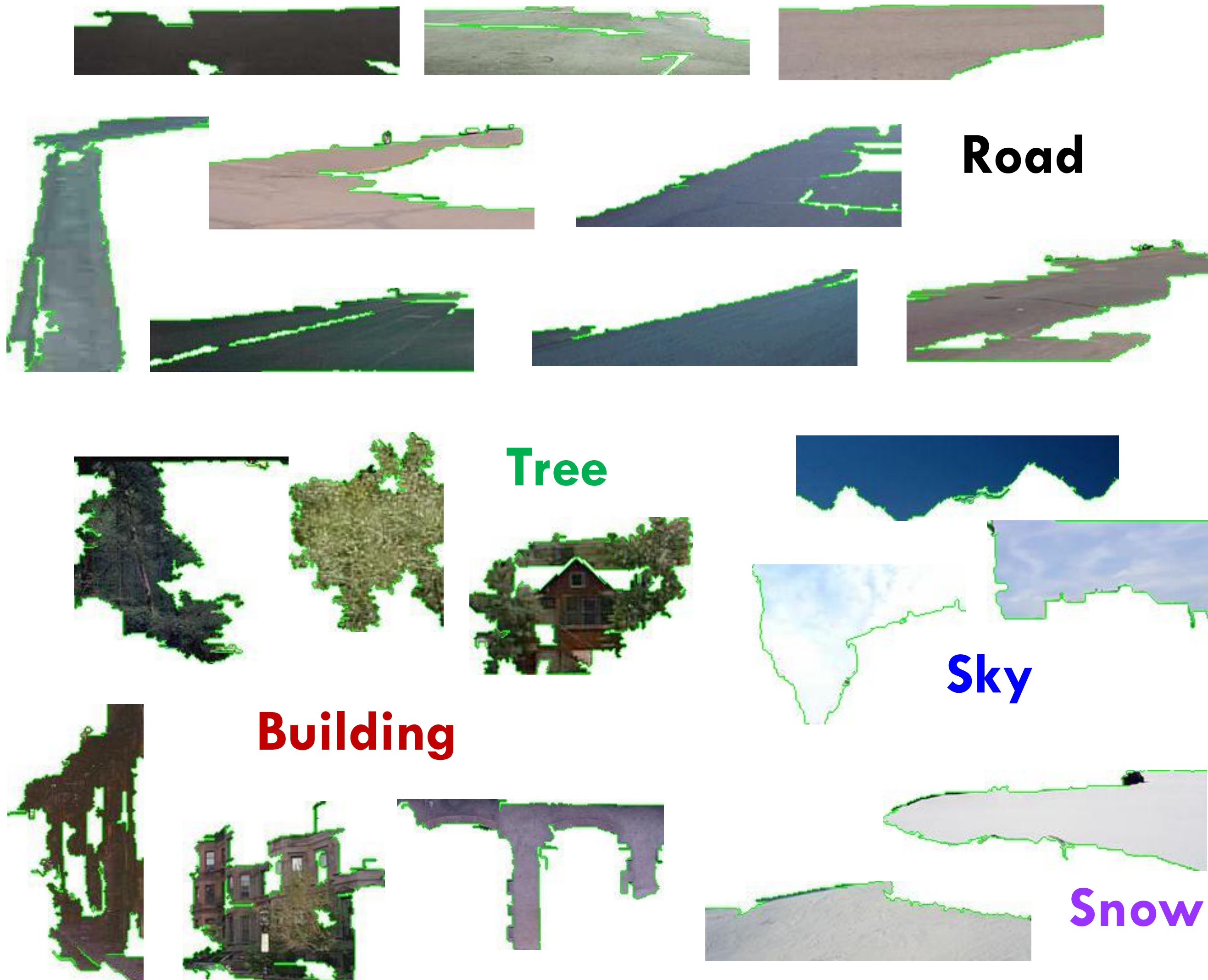
Superpixels
(Felzenszwalb & Huttenlocher, 2004)

Superpixel features

Shape	Mask of superpixel shape over its bounding box (8×8)	64
	Bounding box width/height relative to image width/height	2
	Superpixel area relative to the area of the image	1
Location	Mask of superpixel shape over the image	64
	Top height of bounding box relative to image height	1
Texture/SIFT	Texton histogram, dilated texton histogram	100×2
	SIFT histogram, dilated SIFT histogram	100×2
	Left/right/top/bottom boundary SIFT histogram	100×4
Color	RGB color mean and std. dev.	3×2
	Color histogram (RGB, 11 bins per channel), dilated hist.	33×2
Appearance	Color thumbnail (8×8)	192
	Masked color thumbnail	192
	Grayscale gist over superpixel bounding box	320

Step 2: Region-level matching

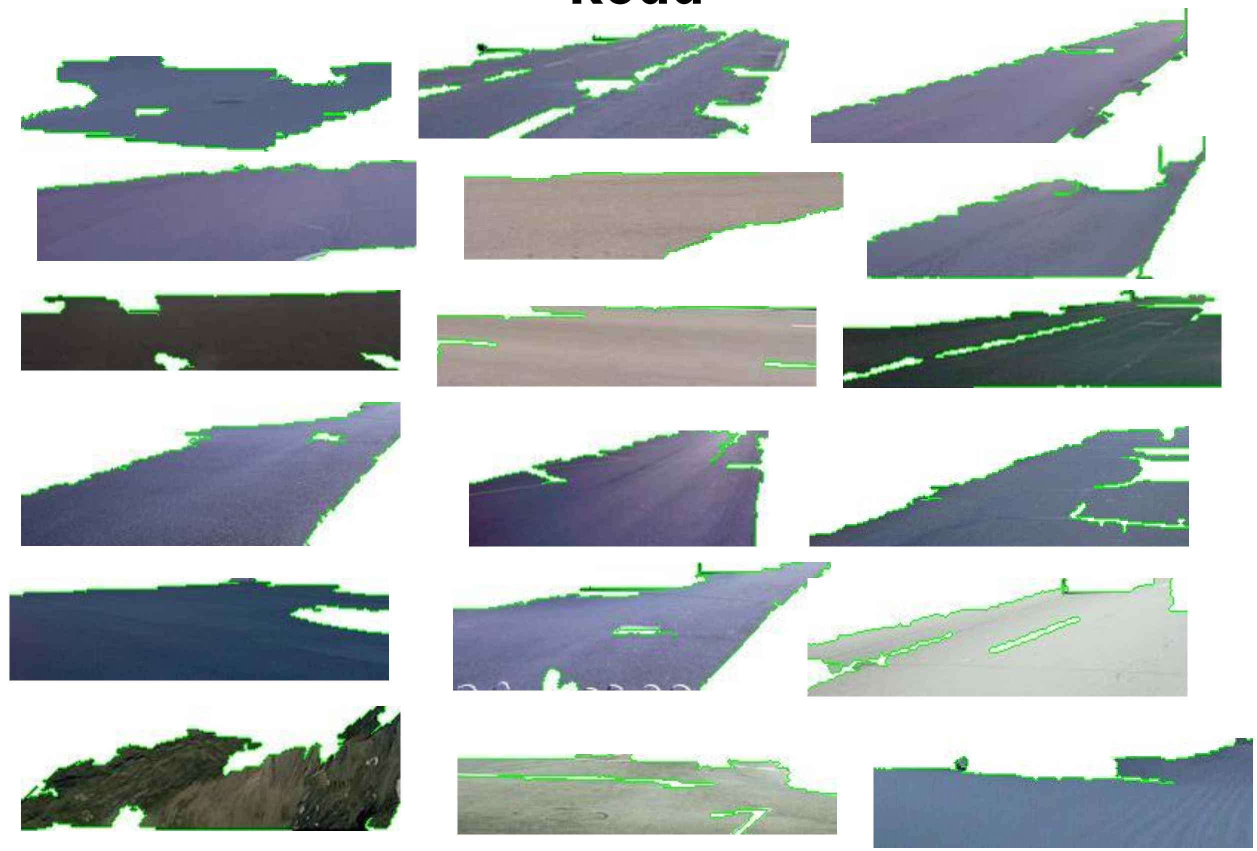
Pixel Area (size)

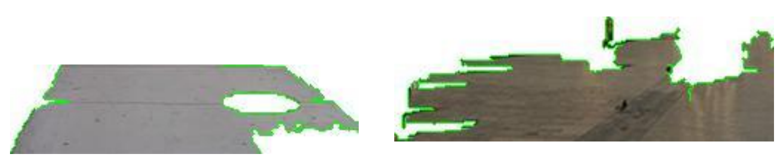


Step 2: Region-level matching

Absolute mask
(location)

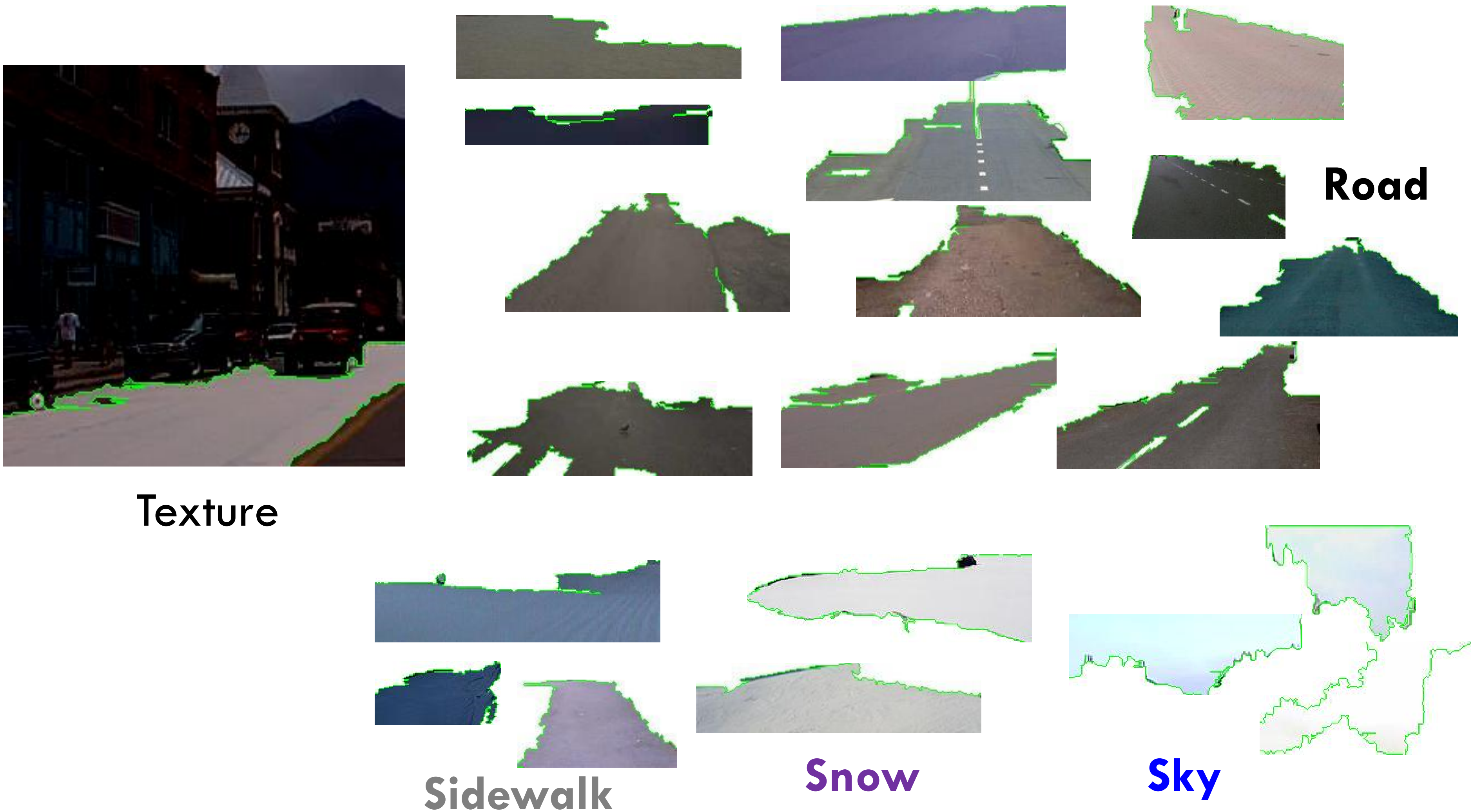
Road





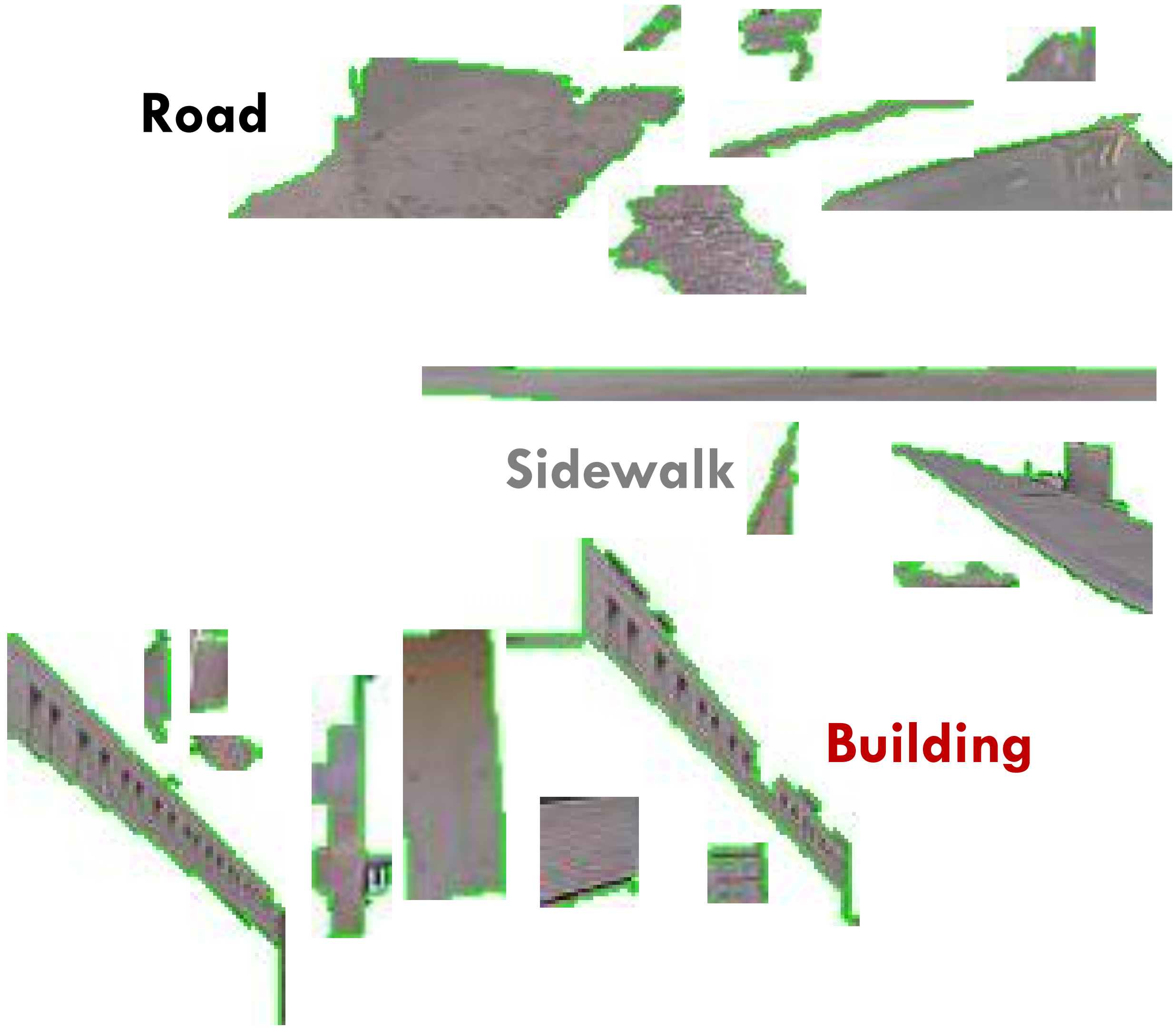
Sidewalk

Step 2: Region-level matching



Step 2: Region-level matching

Color histogram



Region-level likelihoods

- Nonparametric estimate of class-conditional densities for each class c and feature type *k*:

$$\hat{P}(f_k(r_i) \mid c) = \frac{\#(N(f_k(r_i)), c)}{\#(D, c)}$$

kth feature type of ith region

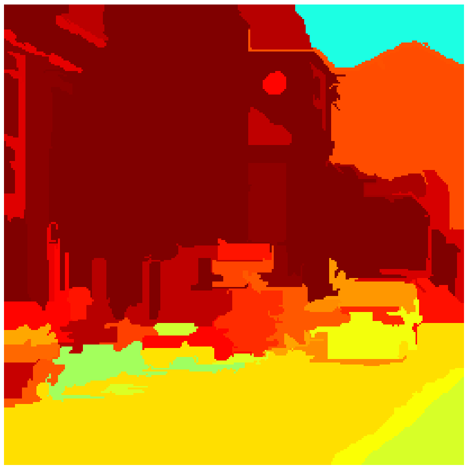
Features of class c within some radius of r_i

Total features of class c in the dataset

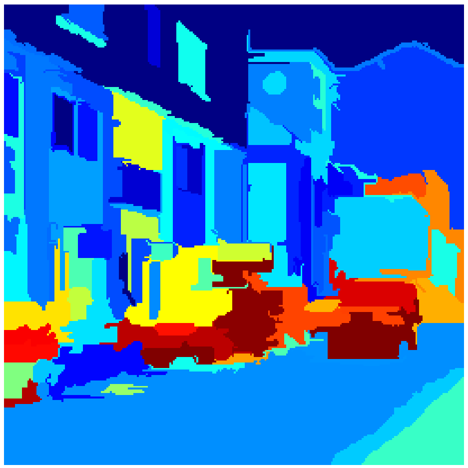
- Per-feature likelihoods combined via Naïve Bayes:

$$\hat{P}(r_i \mid c) = \prod_{\text{features } k} \hat{P}(f_k(r_i) \mid c)$$

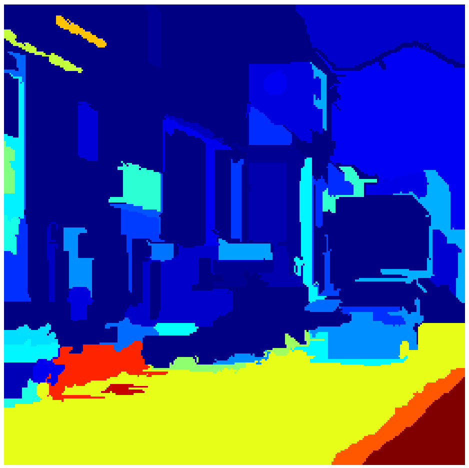
Region-level likelihoods



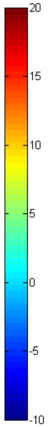
Building

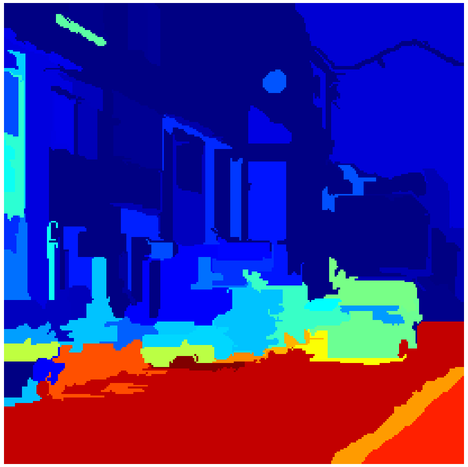


Car

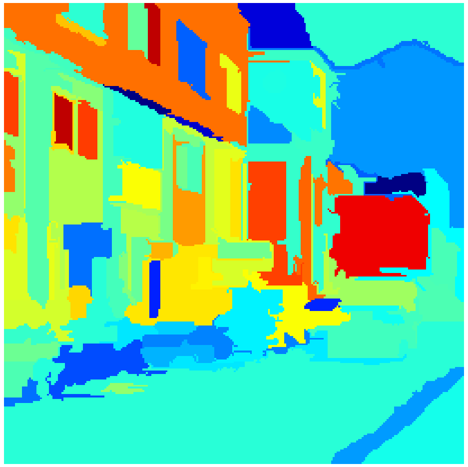


Crosswalk





Road



Window

Sky

Step 3: Global image labeling

- Compute a global image labeling by optimizing a Markov random field (MRF) energy function:

$$E(\mathbf{c}) = \sum_{i} -\log \underbrace{L(r_i, c_i)}_{\text{Likelihood score for region } r_i \text{ and label } c_i} + \lambda \sum_{i,j} \underbrace{\delta[c_i \neq c_j]}_{\text{Smoothing penalty}} \underbrace{\varphi(c_i, c_j)}_{\text{Co-occurrence penalty}}$$

Vector of region labels

Regions

Neighboring regions

Efficient approximate minimization using α-expansion (Boykov et al., 2002)

Step 3: Global image labeling

- Compute a global image labeling by optimizing a Markov random field (MRF) energy function:

$$\underset{\text{Vector of region labels}}{E(\mathbf{c})} = \sum_{\substack{i \\ \text{Regions}}} -\log \underbrace{L(r_i, c_i)}_{\text{Likelihood score for region } r_i \text{ and label } c_i} + \lambda \sum_{\substack{i,j \\ \text{Neighboring regions}}} \underbrace{\delta[c_i \neq c_j]}_{\text{Smoothing penalty}} \underbrace{\varphi(c_i, c_j)}_{\text{Co-occurrence penalty}}$$

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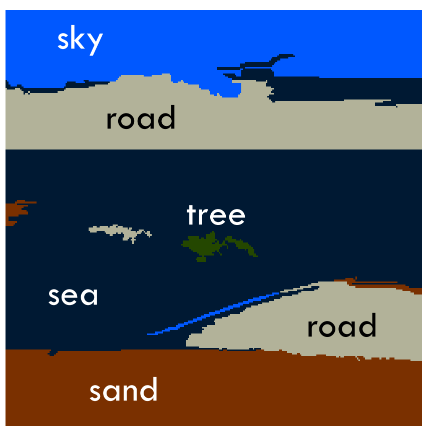
Vector of region labels

Regions

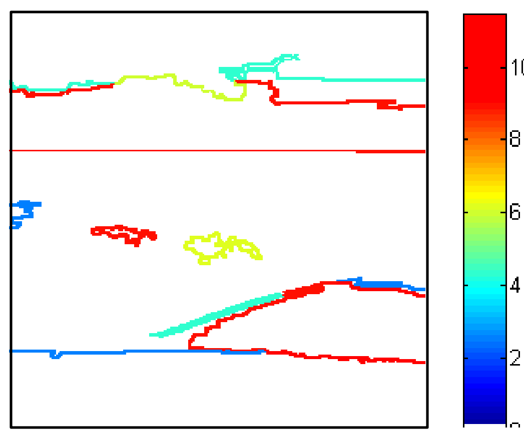
Neighboring regions

Original image

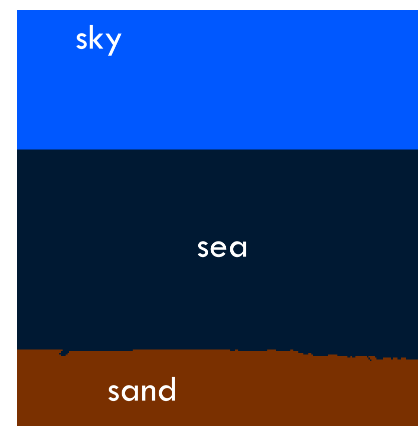
Maximum likelihood labeling



Edge penalties

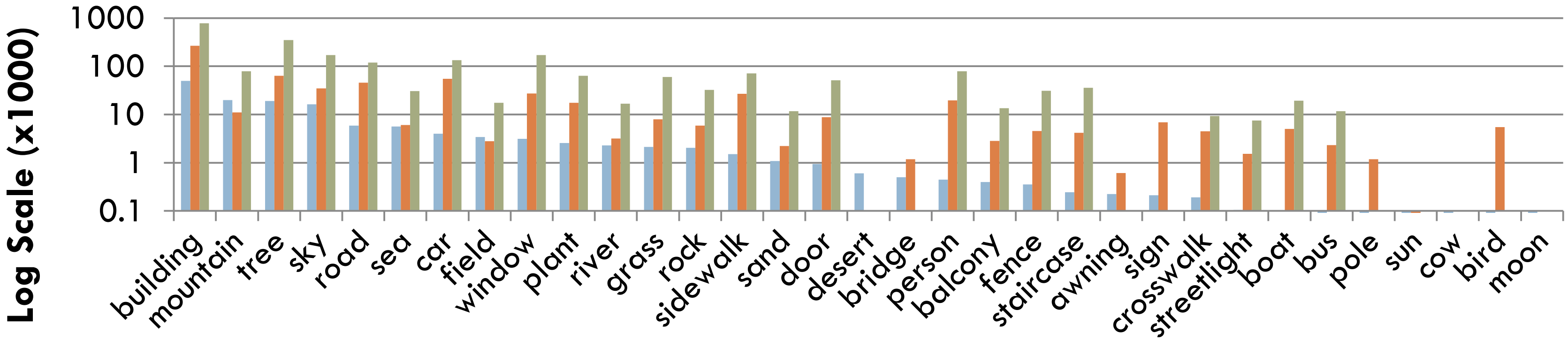


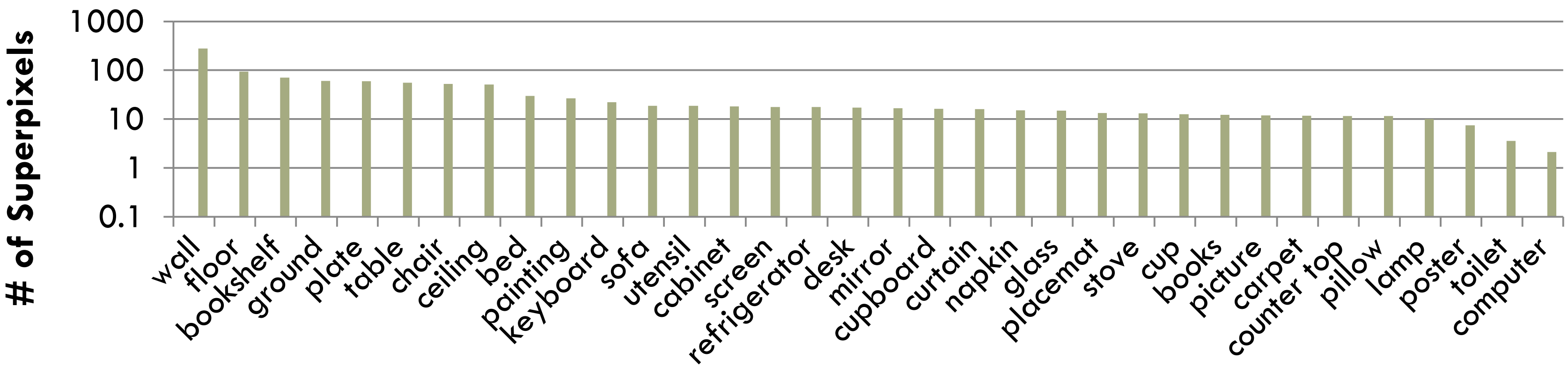
MRF labeling



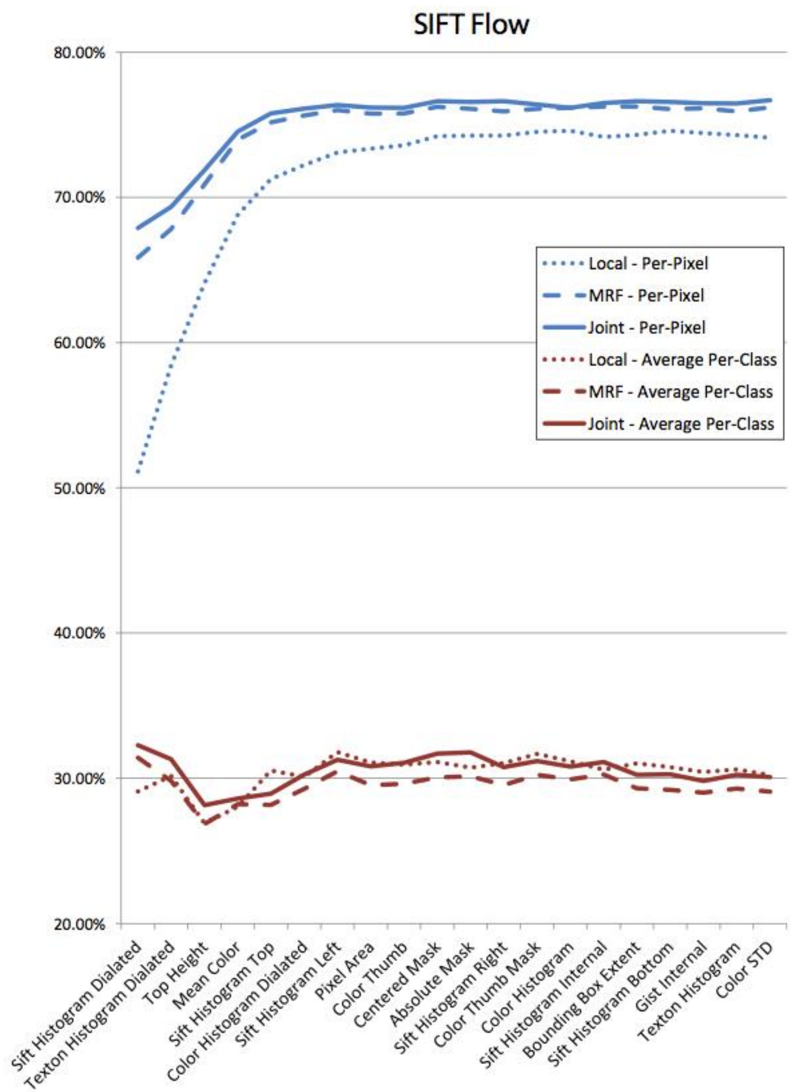
Datasets

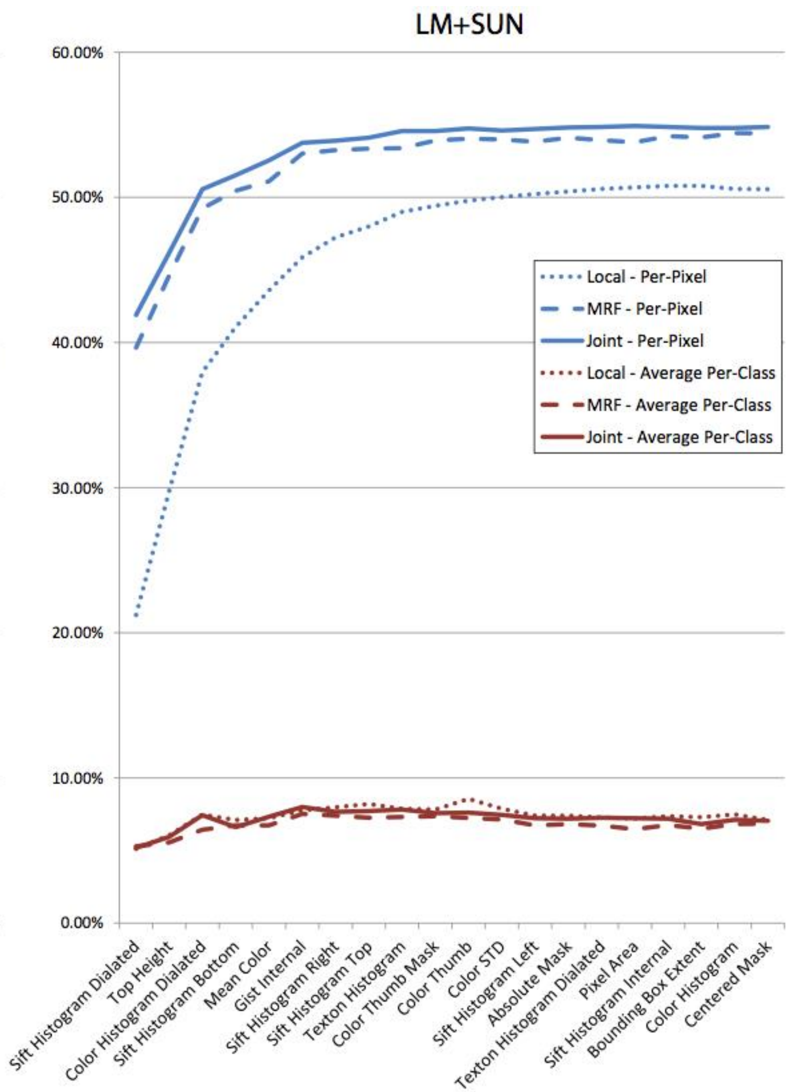
	Training images	Test images	Labels
SIFT Flow (Liu et al., 2009)	2,488	200	33
Barcelona	14,871	279	170
LabelMe+SUN	50,424	300	232



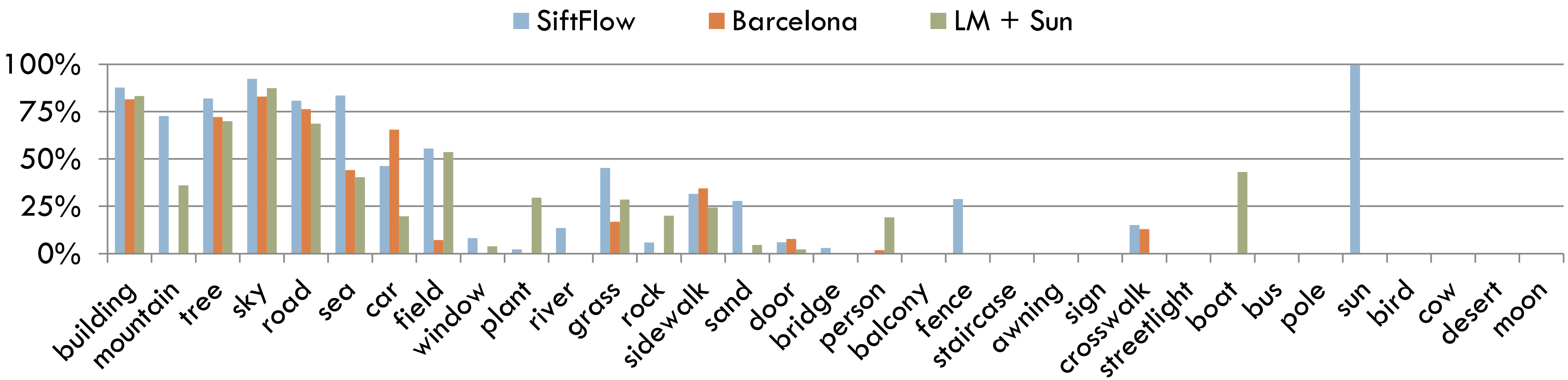


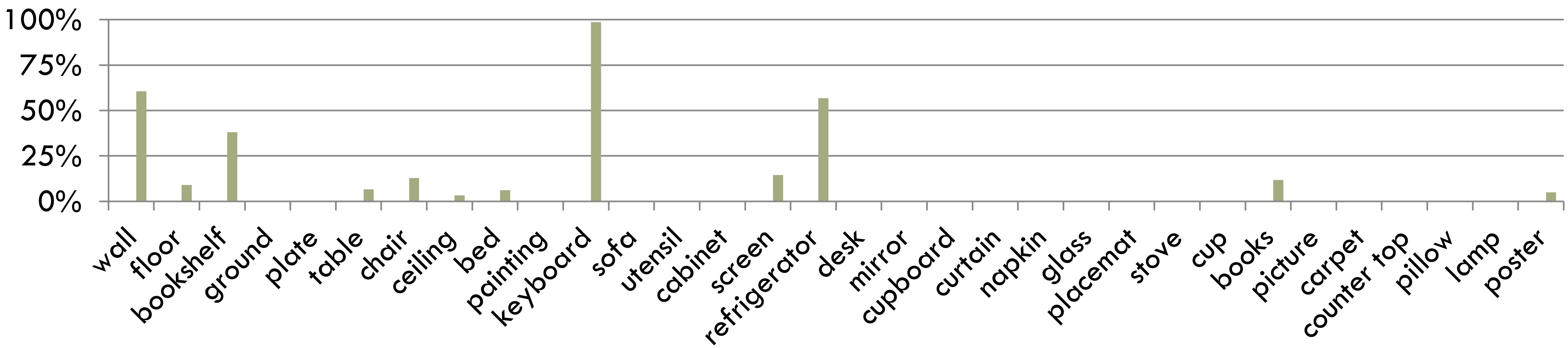
Overall performance



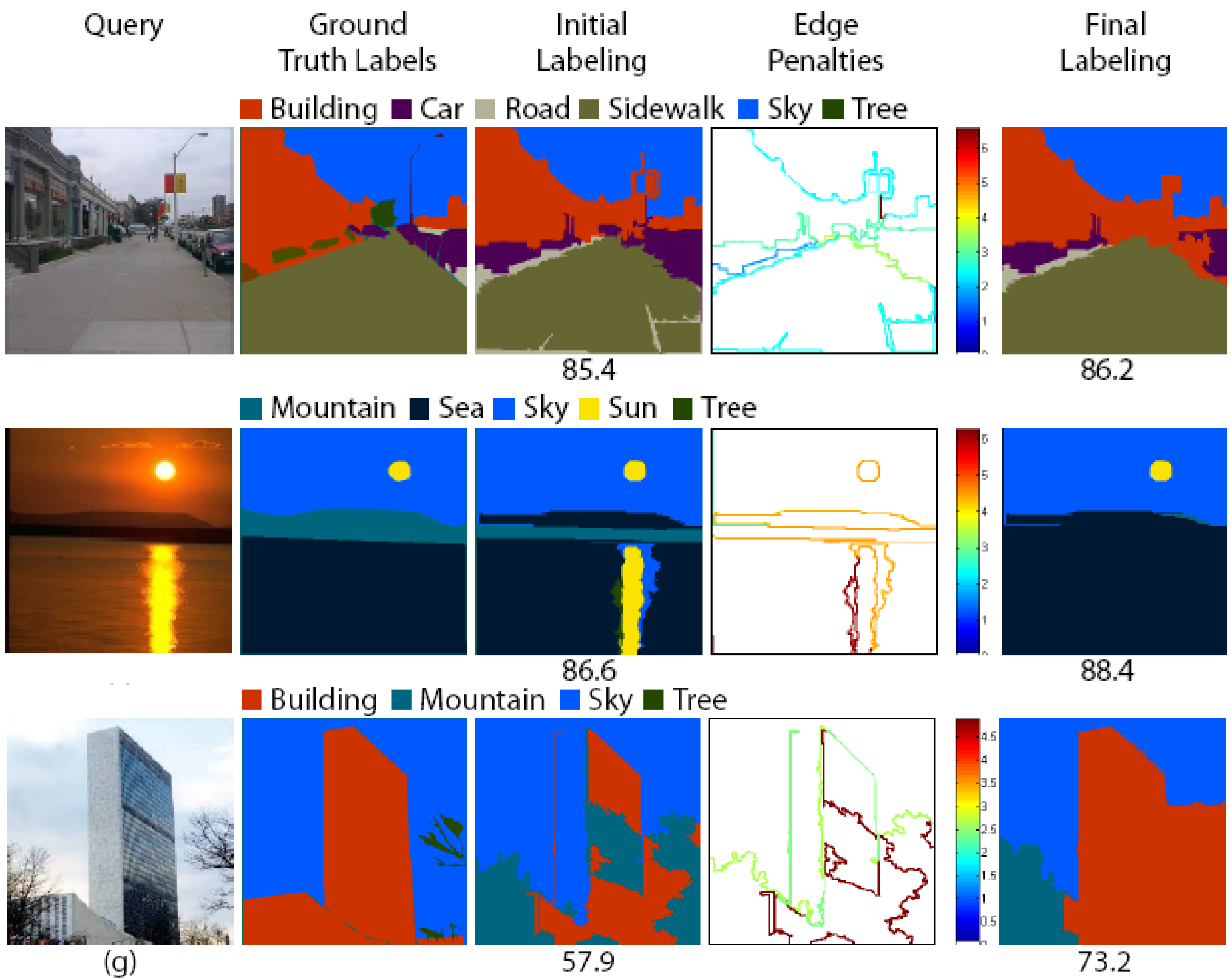


Per-class classification rates

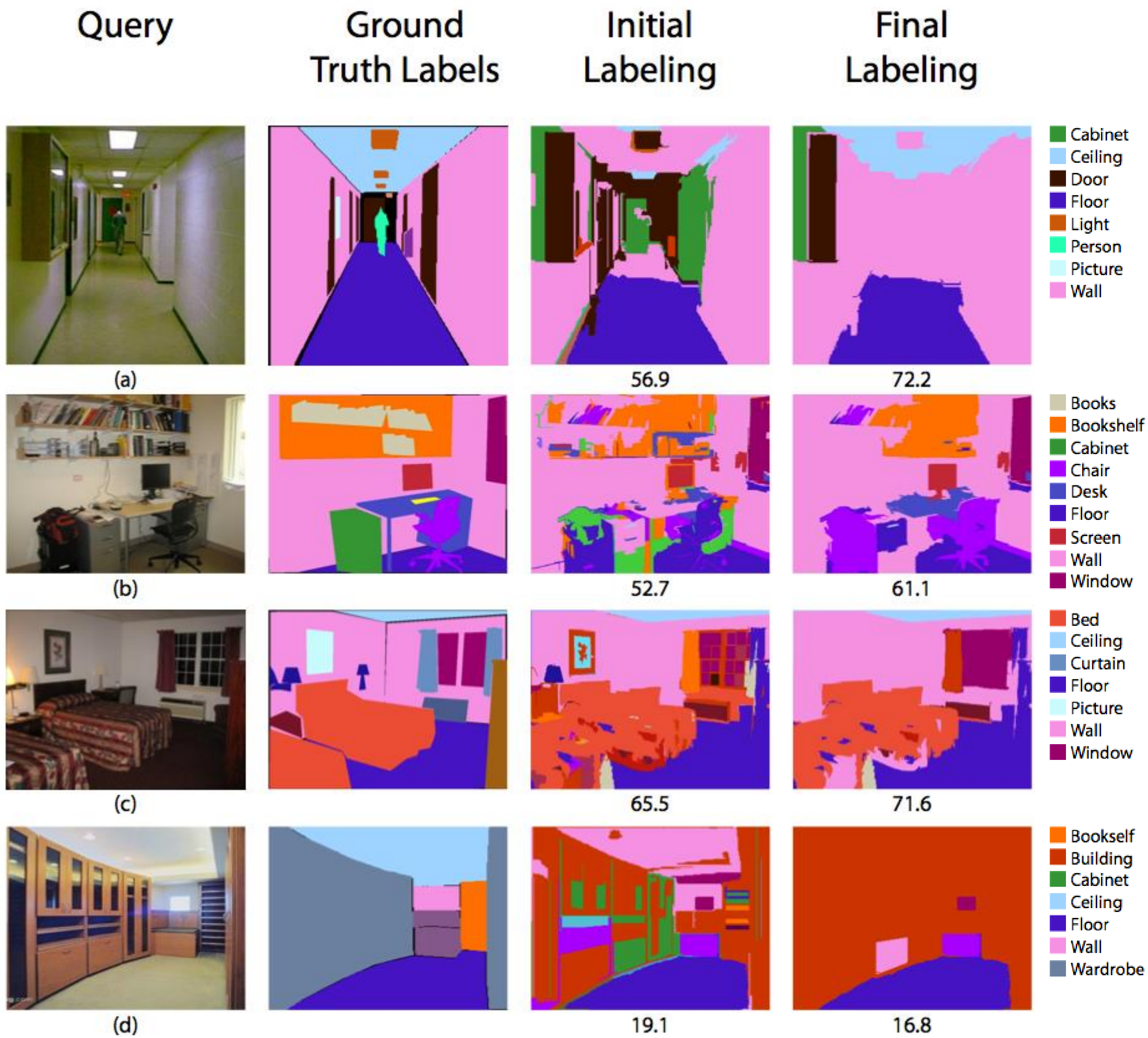




Results on SIFT Flow dataset



Results on LM+SUN dataset



Summary so far

- A lazy learning method for image parsing:
  - Global scene matching
  - Superpixel-level matching
  - MRF optimization
- Challenges
  - Indoor images are hard!
  - We do well on “stuff” but not on “things”

We get the “stuff” but not the “things”