# SuperParsing: Scalable Nonparametric Image Parsing with Superpixels

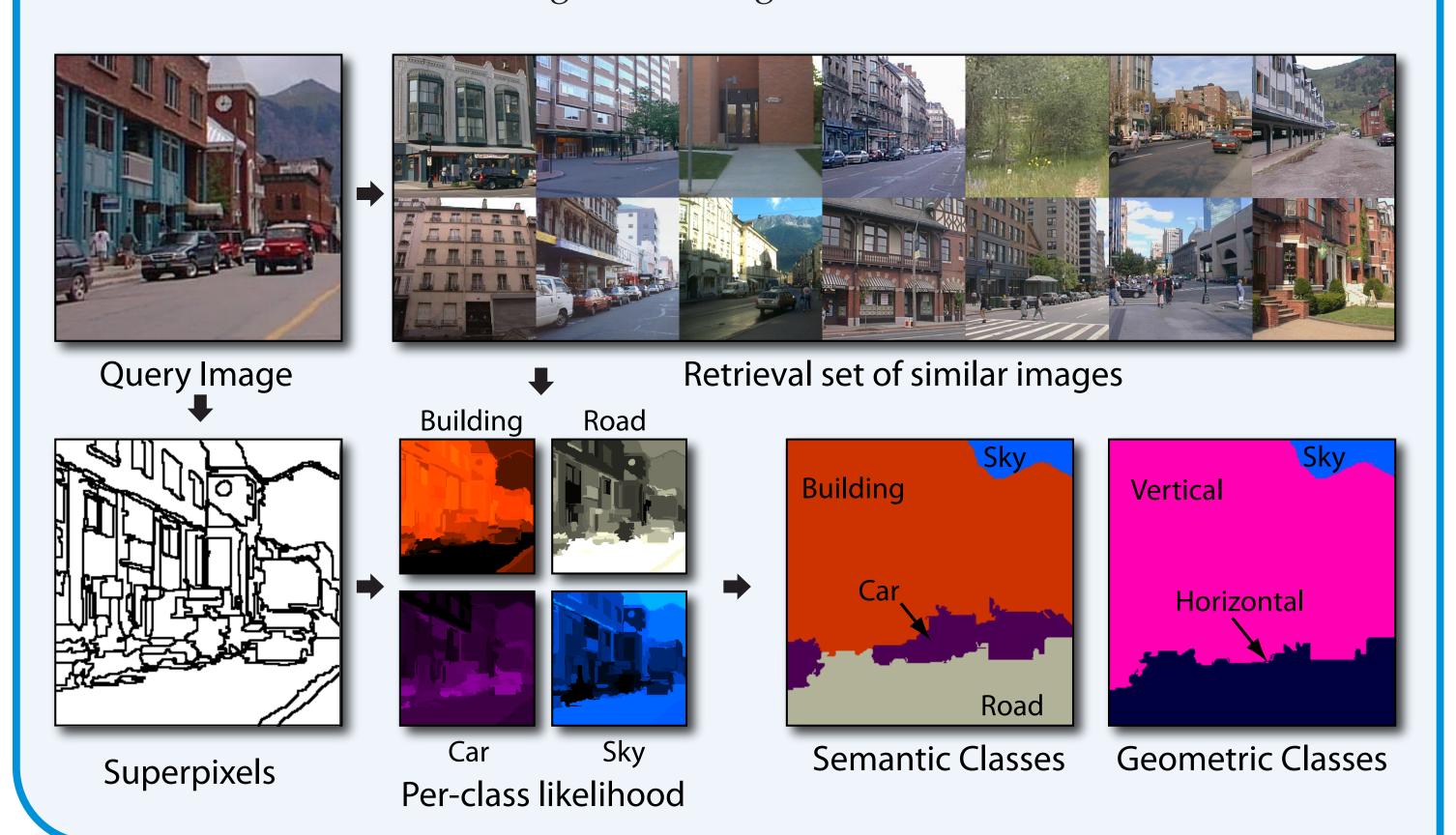
Joseph Tighe and Svetlana Lazebnik

Dept. of Computer Science, University of North Carolina at Chapel Hill

http://www.cs.unc.edu/SuperParsing

#### Overview

- "Open universe" system: no training required, easy to accommodate an evolving dataset as new classes or new training exemplars are added
- State of the art performance on the SIFT Flow dataset (Liu et al., CVPR 2009)
- New large-scale baseline for image parsing: per-pixel recognition results on a subset of LabelMe consisting of 15k images, 170 labels



# Image Parsing Method

Given a query (test) image:

- Find a retrieval set of 200 similar images by taking the minimum per-feature rank of four global image features.
- For each test superpixel  $s_i$  described by multiple local features  $\{f_i^k\}$ , compute a likelihood ratio score for each class c found in the retrieval set:

$$L(s_i, c) = \frac{P(s_i|c)}{P(s_i|\neg c)} = \prod_k \frac{P(f_i^k|c)}{P(f_i^k|\neg c)}.$$

The feature likelihood  $P(f_i^k|c)$  is given by a nonparametric density estimate:

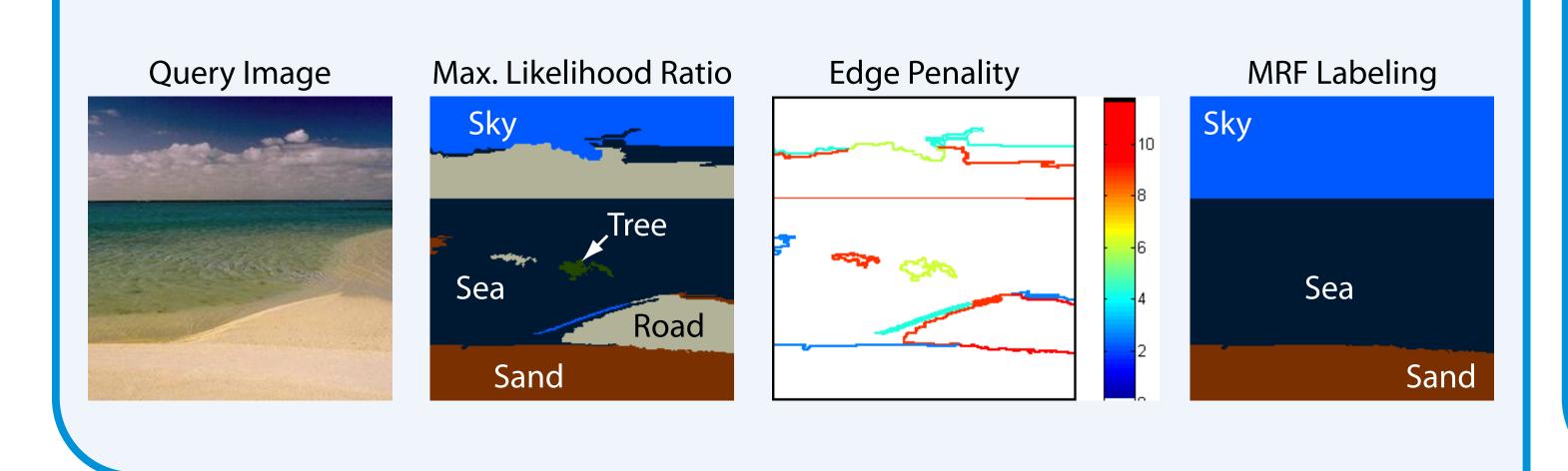
 $P(f_i^k \mid c) = \frac{\#(\text{retrieval set features of class } c \text{ within a fixed radius of } f_i^k)}{\#(\text{total features of class } c \text{ in the training set})}$ 

• Use MRF inference to solve for the label field  $\mathbf{c} = \{c_i\}$  over the entire test image:

$$J(\mathbf{c}) = \sum_{s_i \in SP} -w_i \log L(s_i, c_i) + \lambda \sum_{(s_i, s_j) \in A} E_{\text{edge}}(c_i, c_j),$$

where  $w_i$  is a weight based on the superpixel size, and edge penalty  $E_{\rm edge}$  is based on the co-occurrence of adjacent labels in the training set:

$$E_{\text{edge}}(c_i, c_j) = -\log[(P(c_i|c_j) + P(c_j|c_i))/2] \times \delta[c_i \neq c_j].$$

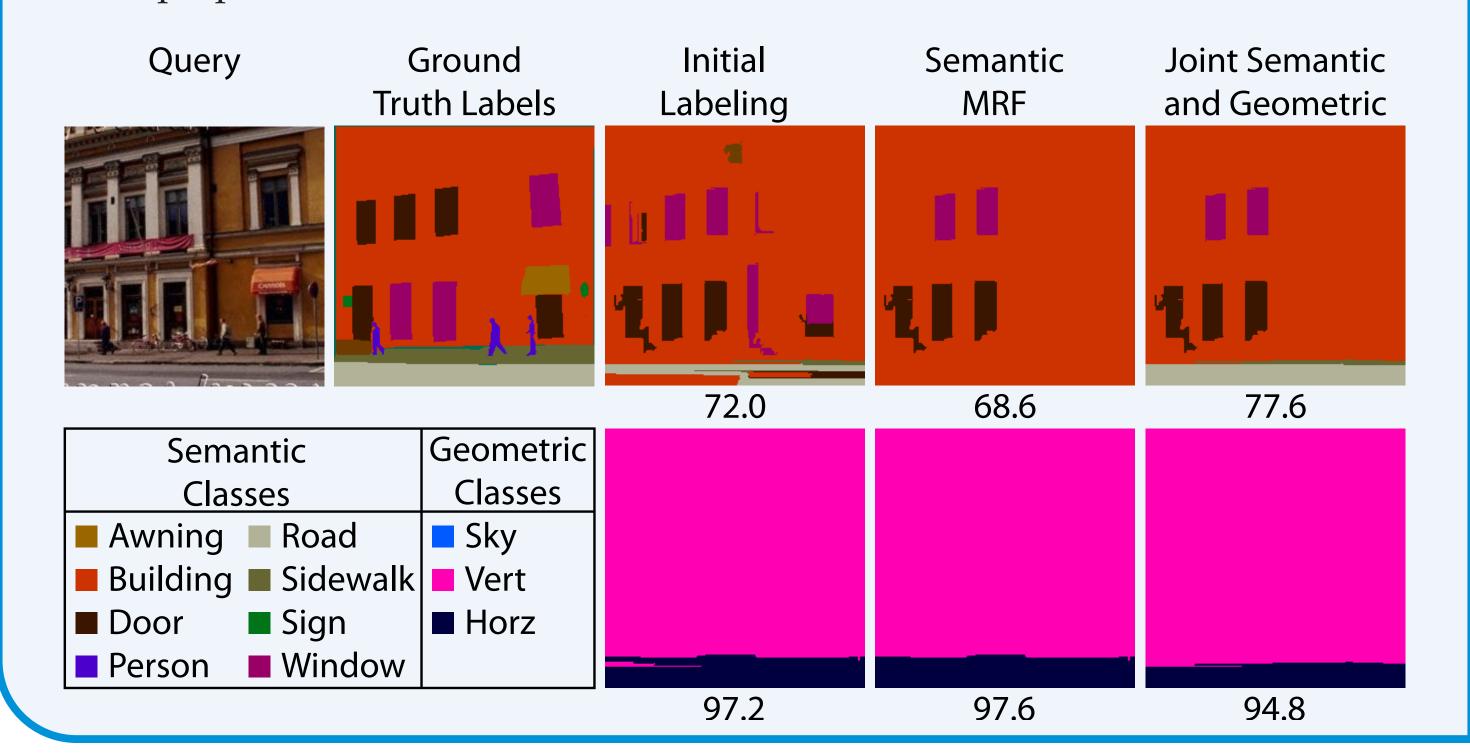


# Joint Semantic and Geometric Labeling

Simultaneously solve for a field of *semantic* labels (c) and *geometric* labels (g) over the image by optimizing

$$H(\mathbf{c}, \mathbf{g}) = J(\mathbf{c}) + J(\mathbf{g}) + \mu \sum_{s_i \in SP} \varphi(c_i, g_i),$$

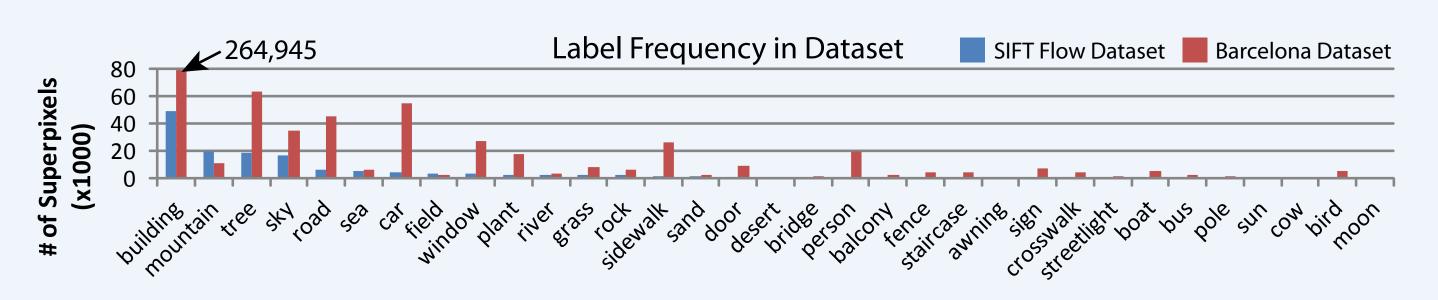
where  $\varphi(c_i, g_i)$  is a coherence term between the semantic and geometric label of the same superpixel.



# Results on Large-Scale Datasets

Liu et al. (CVPR 2009)

- SIFT Flow dataset (Liu et al., CVPR 2009): 2,488 training images, 200 test images, 33 labels
- Barcelona dataset (a new large-scale benchmark): 14,871 training images, 279 test images, 170 labels



Per-pixel classification rates (with average per-class rates in parentheses):

74.75

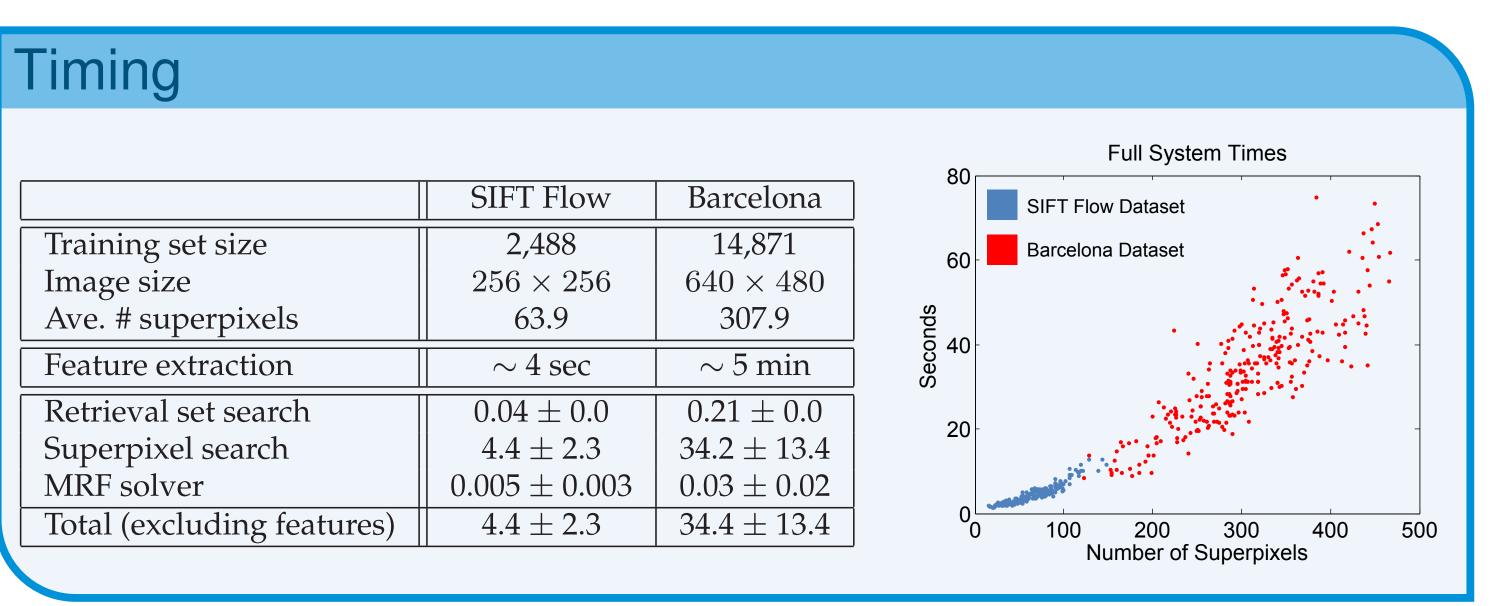
	Local labeling	73.2 (29.1)	89.8	62.5 (8.0)	89.9				
	MRF	76.3 (28.8)	89.9	66.6 (7.6)	90.2				
	Joint semantic/geometric	76.9 (29.4)	90.8	66.9 (7.6)	90.7				
Per-class Performance SIFT Flow Dataset Barcelona Dataset									
75%									
50% -		1 -							
25% - 0% -									
bilding tain the 3th out sea calking plant the plass to the mall sund out sent the ball the saint and the sign and the sign of the single sing									
$\phi_{s}$	<b>1</b> 0	510	* * *	, , , , , , , , , , , , , , , , , , ,					

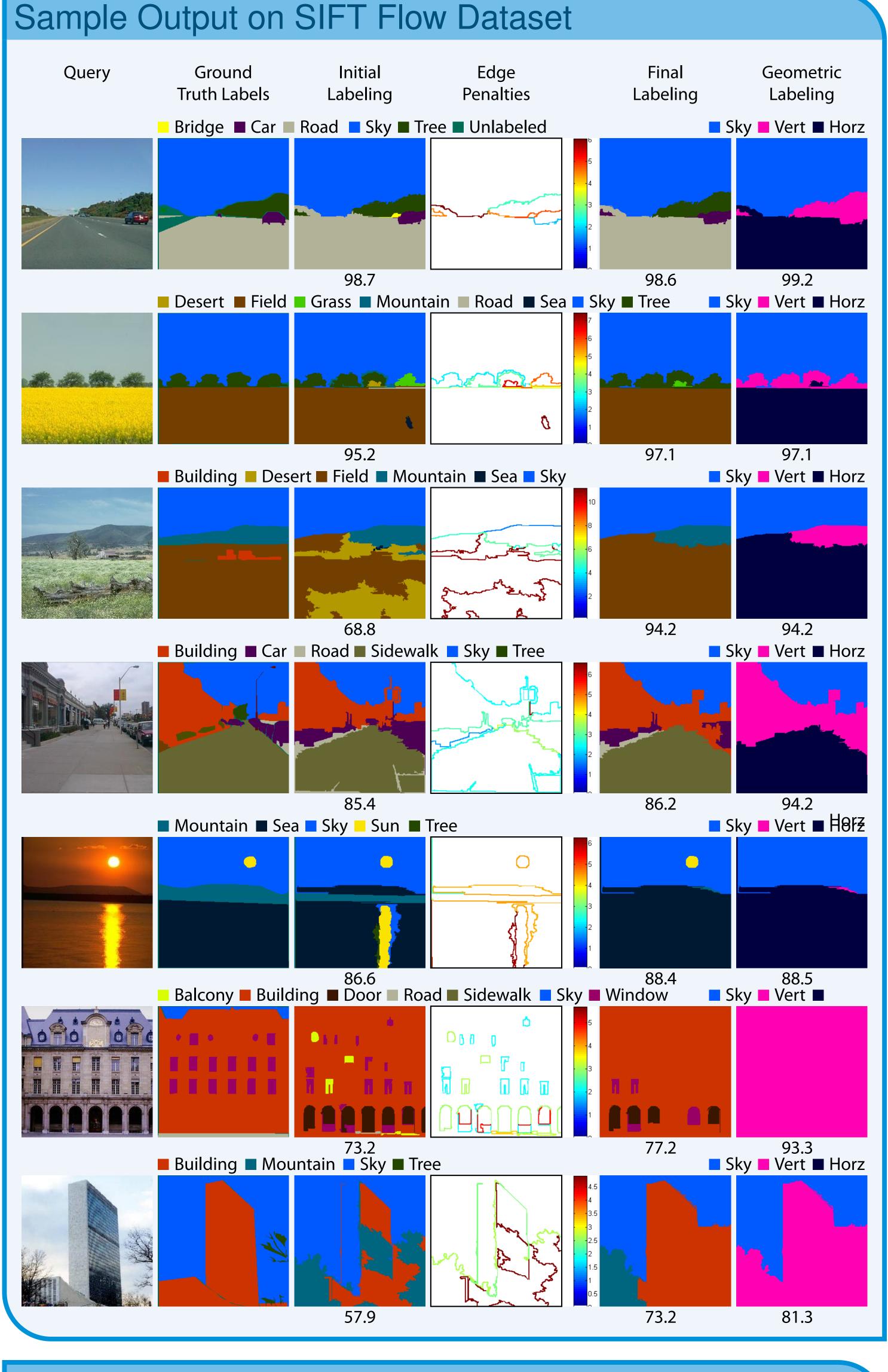
Geometric

Barcelona

Semantic Geometric

N/A





### Small Datasets

Results on two small-scale datasets using trained boosted decision tree classifiers (instead of retrieval set and superpixel search):

	Stanford Dataset		Geometric Context Dataset		
	715 images, 8 classes		300 images, 7 classes		
	Semantic	Geometric	Sub-classes	Main classes	
Gould et al. (ICCV 2009)	76.4	91.0	N/A	86.9	
Hoiem et al. (IJCV 2007)	N/A	N/A	61.5	88.1	
Local labeling	76.9	90.5	57.6	87.8	
MRF	77.5	90.6	61.0	88.2	
Joint semantic/geometric	77.5	90.6	61.0	88.1	

### Funding

This research was supported in part by NSF CAREER award IIS-0845629, Microsoft Research Faculty Fellowship, and Xerox.