

Finding Things: Image Parsing with Regions and Per-Exemplar Detectors



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Image parsing

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

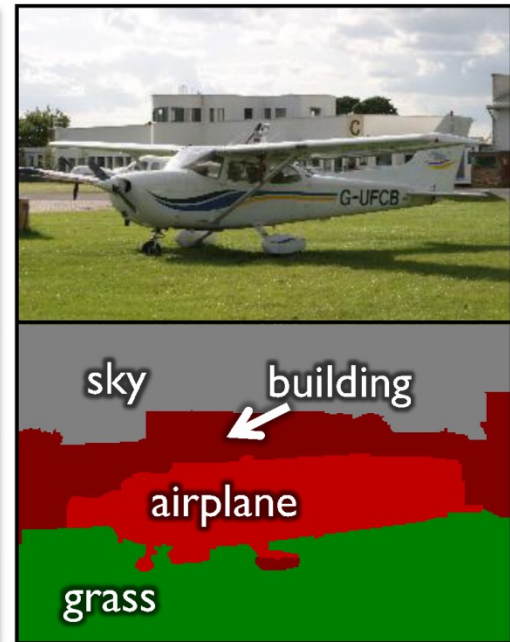
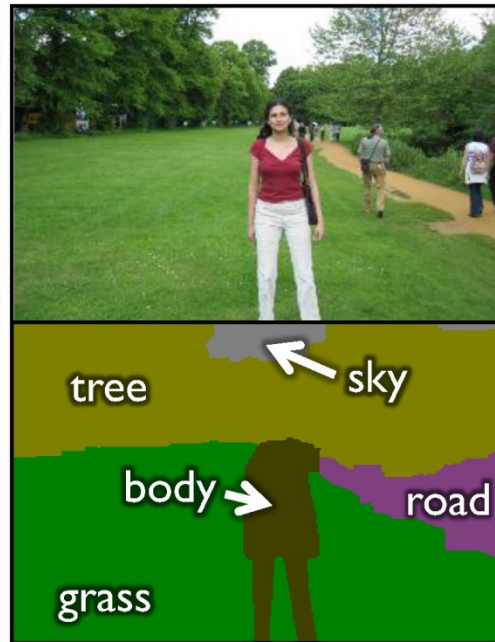
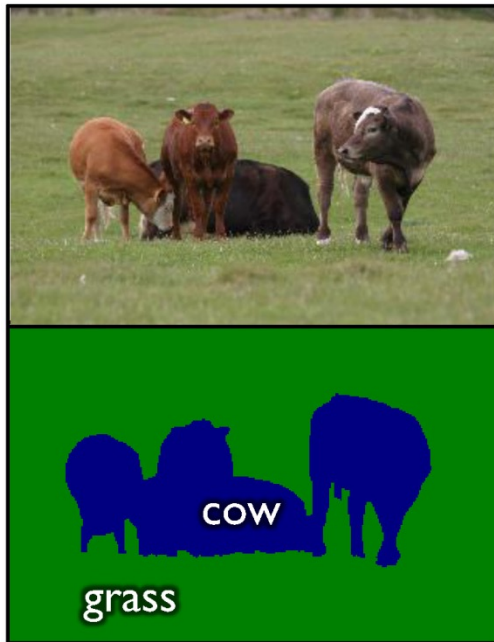
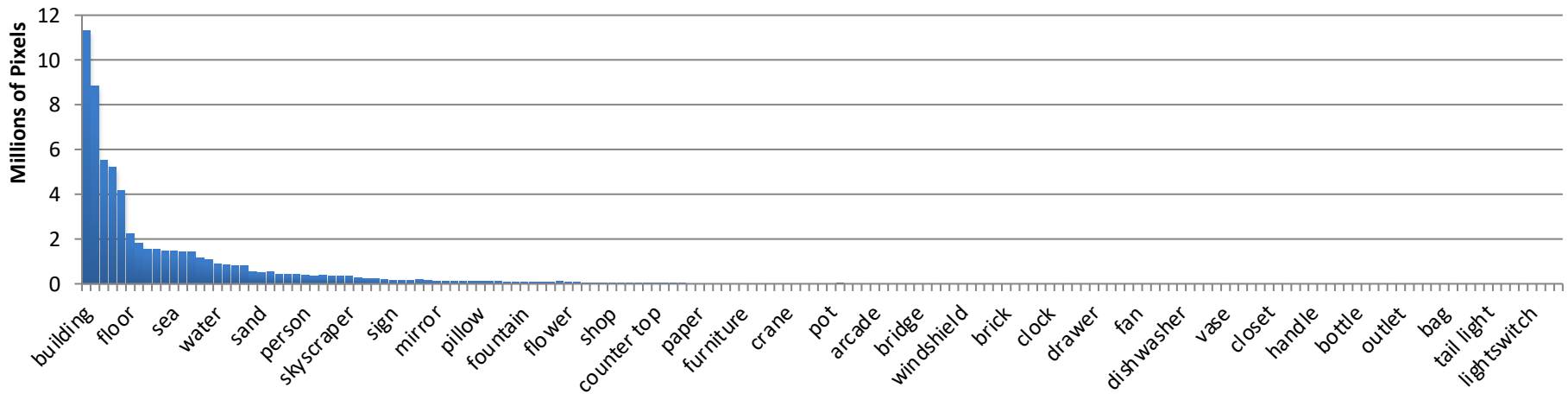


Figure from Shotton et al. (2009)

He et al. (2004), Hoiem et al. (2005), Shotton et al. (2006, 2008, 2009), Verbeek and Triggs (2007), Rabinovich et al. (2007), Galleguillos et al. (2008), Brostow et al. (2008), Gould et al. (2009), Sturges et al. (2009), Zhang et al. (2010), Ladicky et al. (2010), Liu et al. (2011), Floros et al. (2011), Farabet et al. (2012), Eigen and Fergus (2012), Myeong et al. (2012)

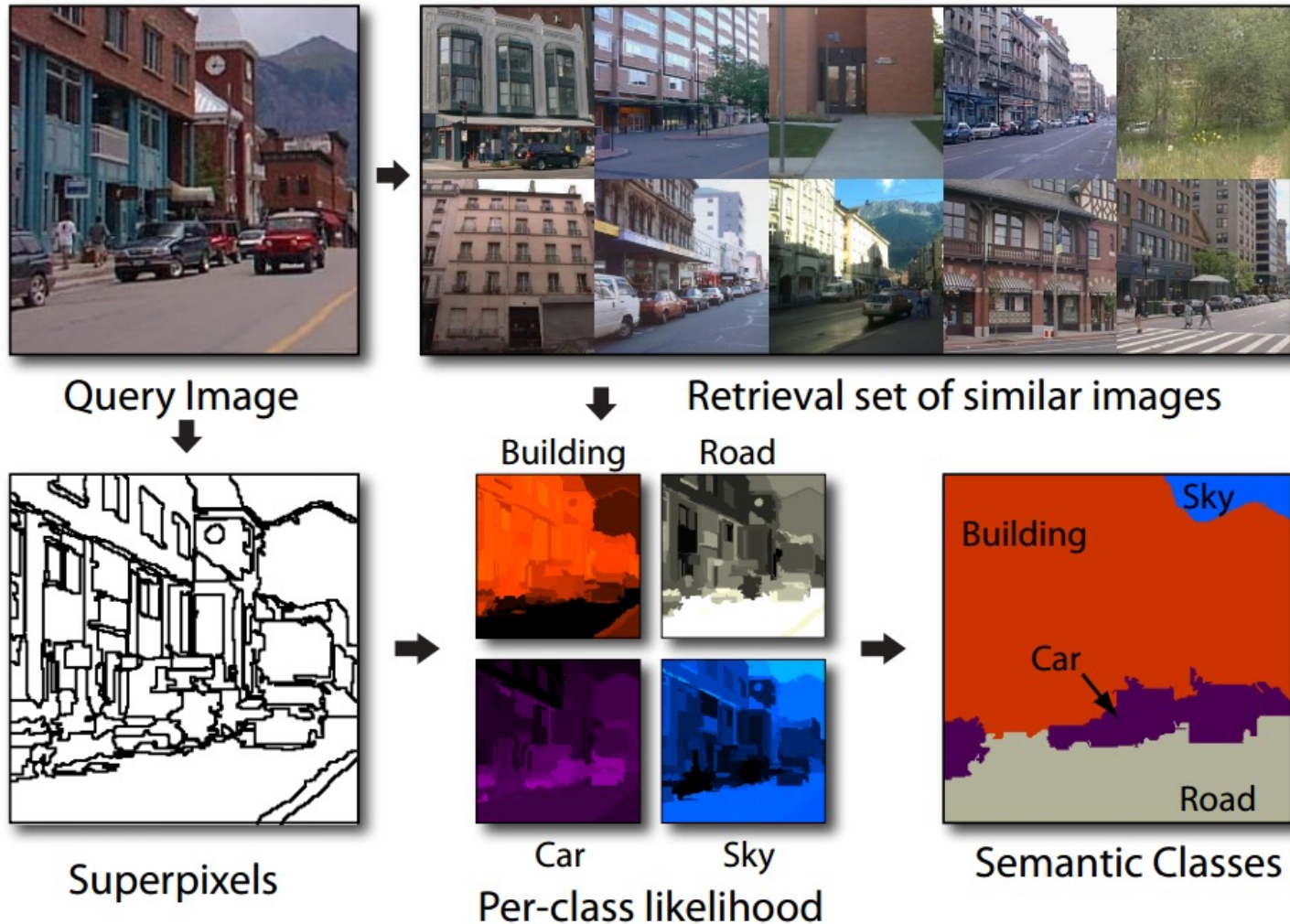
Towards broader coverage

Hundreds of classes and tens of thousands of images

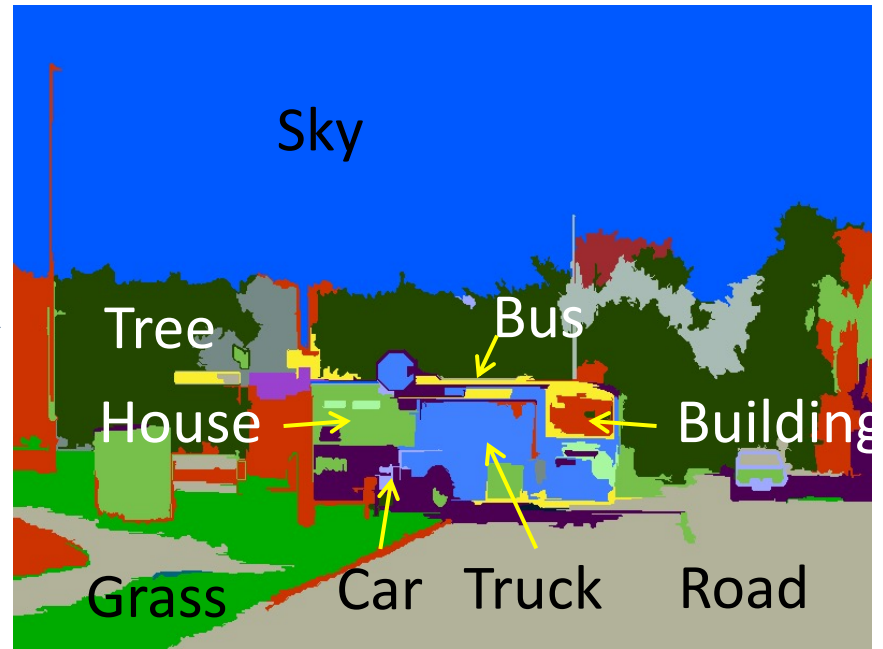


<http://labelme.csail.mit.edu/>

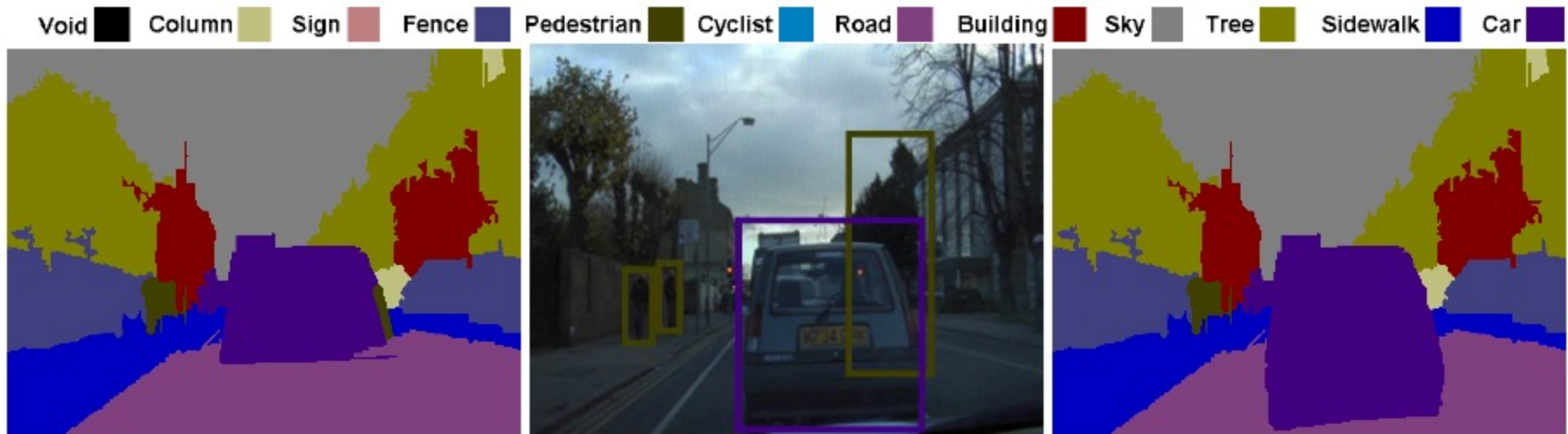
Our previous work region-based parsing



Finding Things



To get the things, use detectors



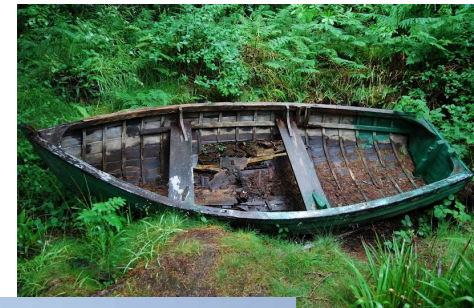
Result without
detections

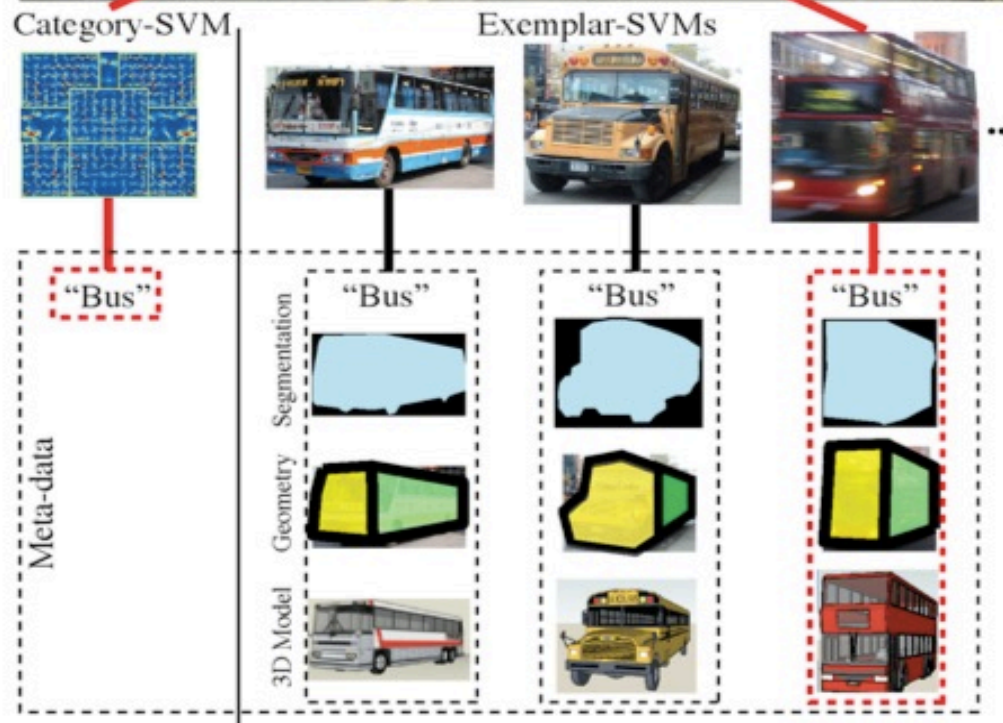
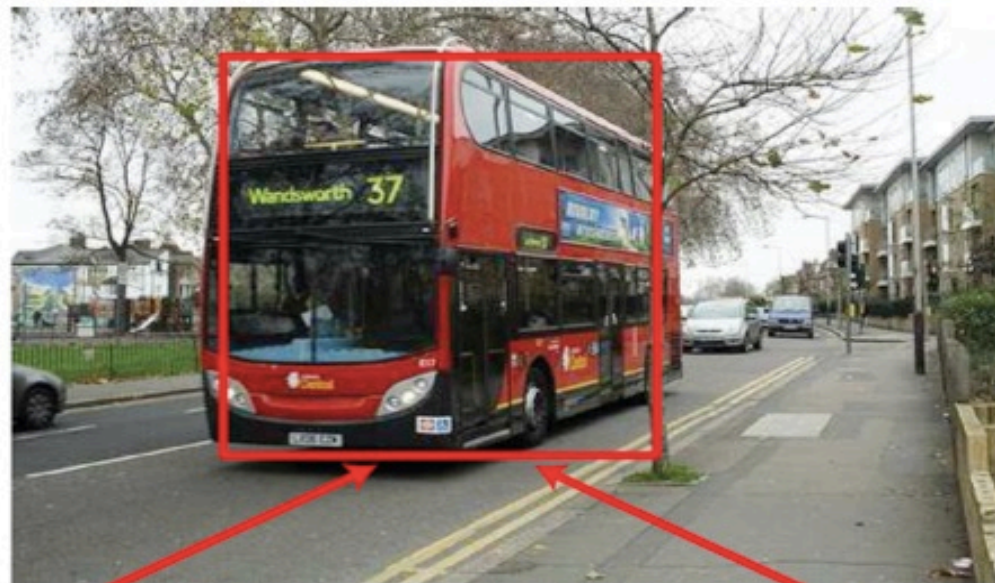
Set of detections

Final Result

Problems with standard sliding window detectors

- They return only bounding box hypotheses, and obtaining segmentation hypotheses from them is challenging
- They do not work well for classes with few training examples and large intra-class variation





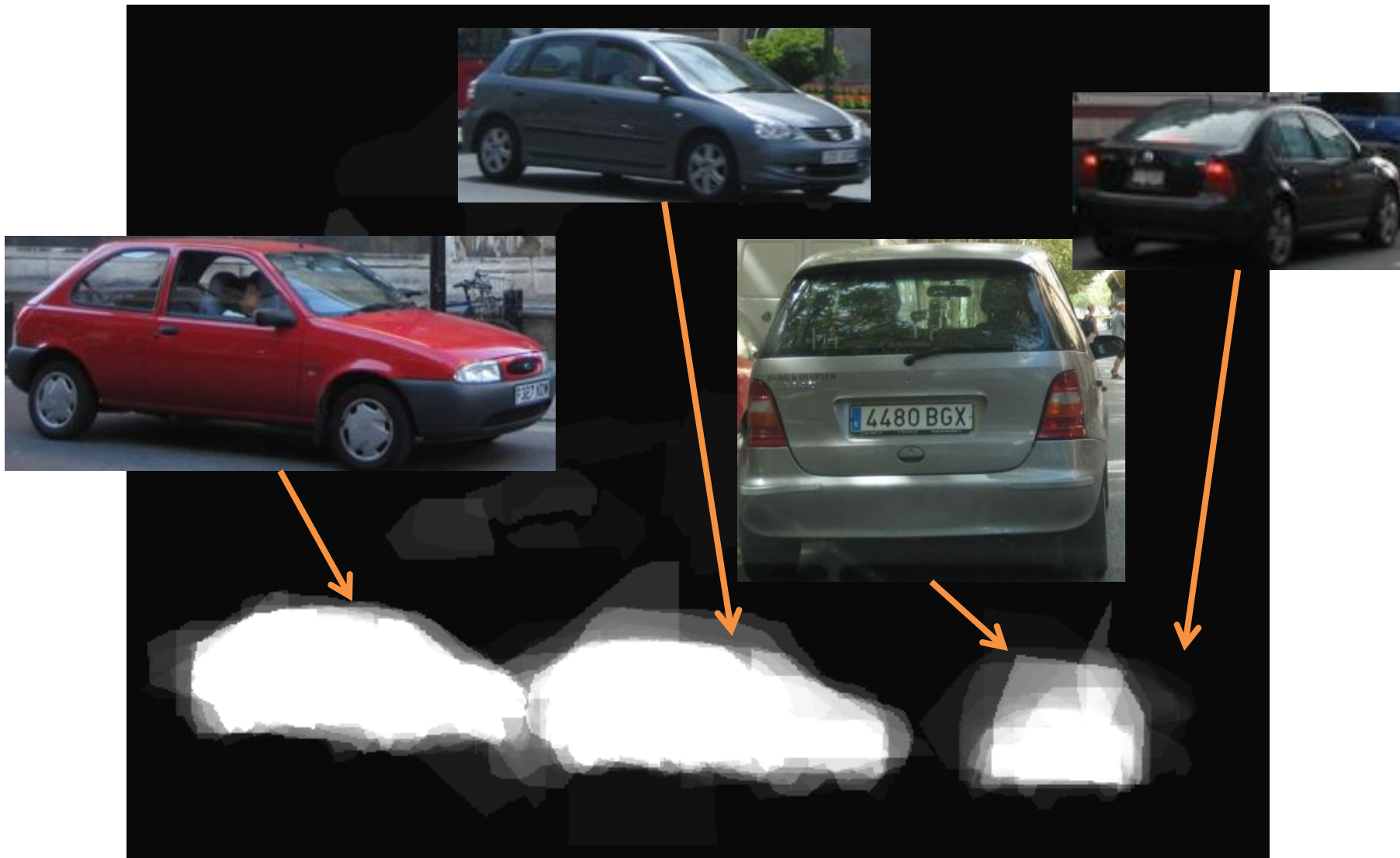
Tomasz Malisiewicz, Abhinav Gupta, Alexei A. Efros
 Ensemble of Exemplar-SVMs for Object Detection and Beyond. In ICCV 2011

Our approach



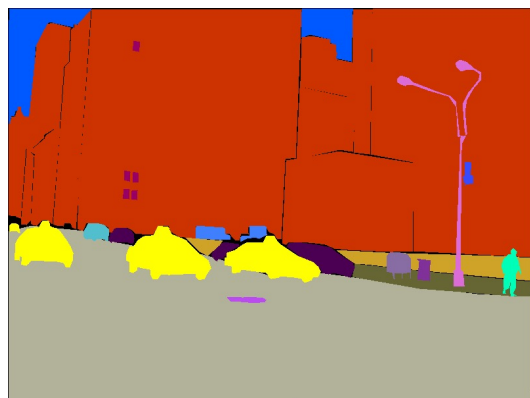
Test image

Detector-based data term





Query image



Ground truth

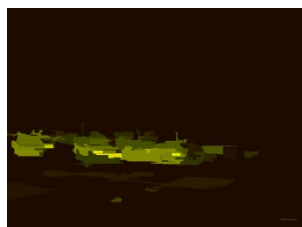
- | | |
|-------------|---------------|
| taxi | truck |
| car | person |
| building | mailbox |
| road | van |
| sky | window |
| fence | trash can |
| sidewalk | manhole |
| streetlight | traffic light |



Query image



Ground truth



taxi



car

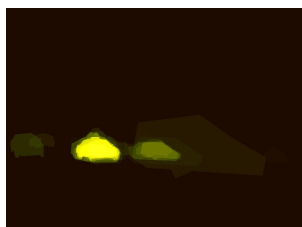


road



building

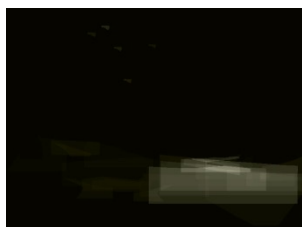
Region-based parsing result (67.2%)



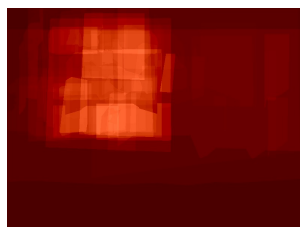
taxi



car



road



building

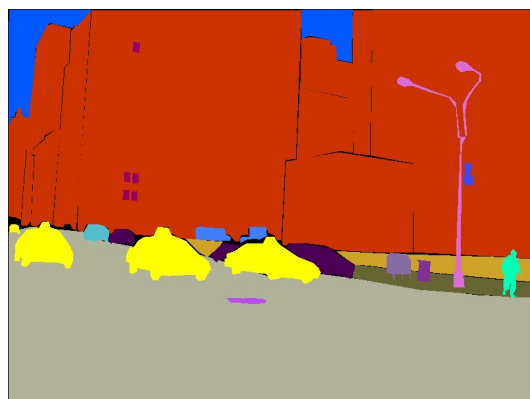


Detector-based parsing result (50.8%)

- | | |
|-------------|---------------|
| taxi | truck |
| car | person |
| building | mailbox |
| road | van |
| sky | window |
| fence | trash can |
| sidewalk | manhole |
| streetlight | traffic light |

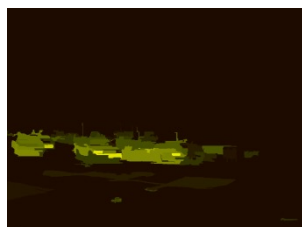


Query image



Ground truth

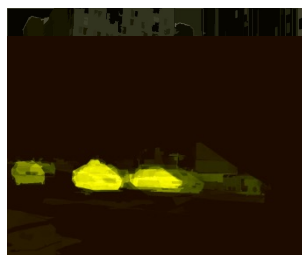
- | | |
|---|---|
| ■ taxi | ■ truck |
| ■ car | ■ person |
| ■ building | ■ mailbox |
| ■ road | ■ van |
| ■ sky | ■ window |
| ■ fence | ■ trash can |
| ■ sidewalk | ■ manhole |
| ■ streetlight | ■ traffic light |



taxi



car



taxi



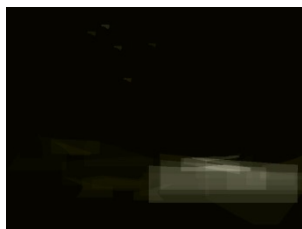
car



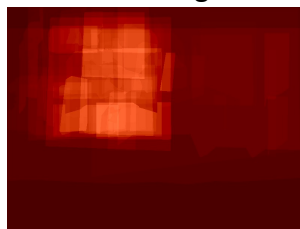
road



building



road

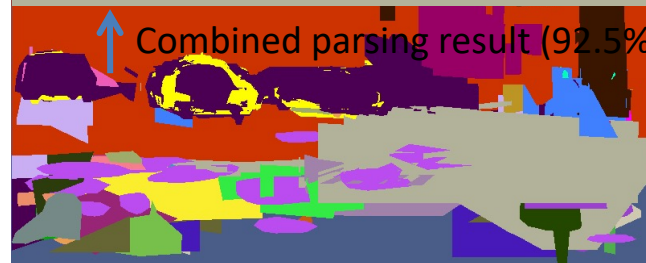


building

Region-based parsing result (67.2%)



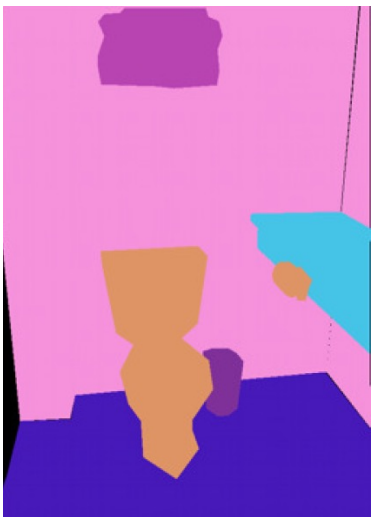
Combined parsing result (92.5%)



Detector-based parsing result (50.8%)



Query image



Ground truth

- | | |
|-------------|-----------|
| toilet | pot |
| plate | glass |
| wall | cup |
| counter top | tree |
| floor | painting |
| mirror | towel |
| person | trash can |



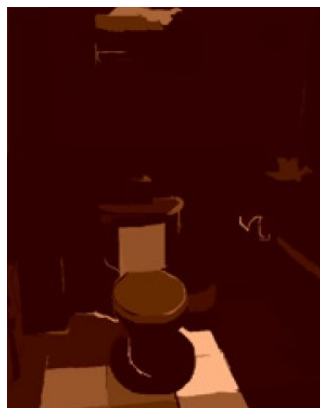
Query image



Ground truth

- | | |
|---|--|
| ■ toilet | ■ pot |
| ■ plate | ■ glass |
| ■ wall | ■ cup |
| ■ counter top | ■ tree |
| ■ floor | ■ painting |
| ■ mirror | ■ towel |
| ■ person | ■ trash can |

Region-based parsing
result (30.9%)



toilet



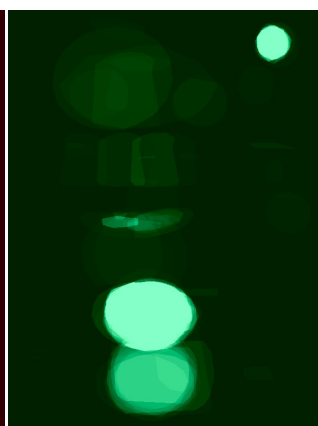
plate



wall



toilet



plate



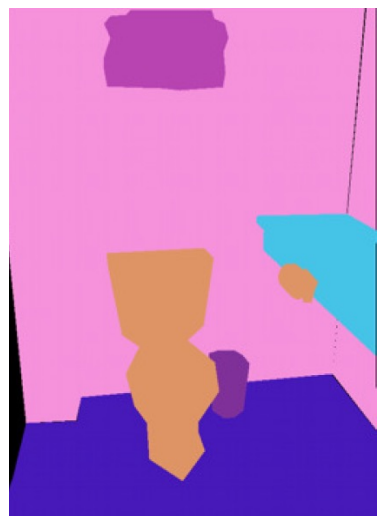
wall



Detector-based parsing
result (24.8%)



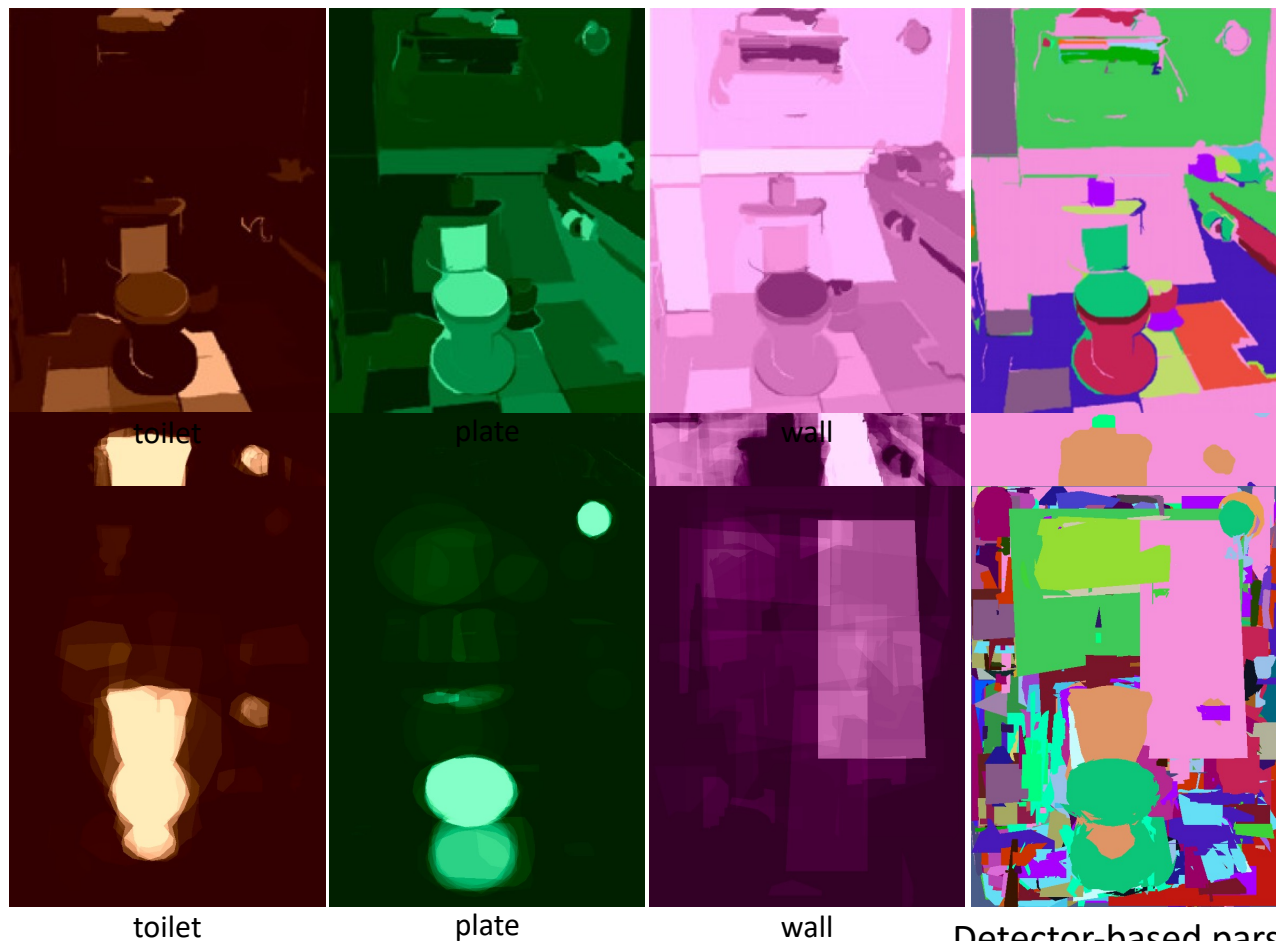
Query image



Ground truth

- | | |
|---|--|
| ■ toilet | ■ pot |
| ■ plate | ■ glass |
| ■ wall | ■ cup |
| ■ counter top | ■ tree |
| ■ floor | ■ painting |
| ■ mirror | ■ towel |
| ■ person | ■ trash can |

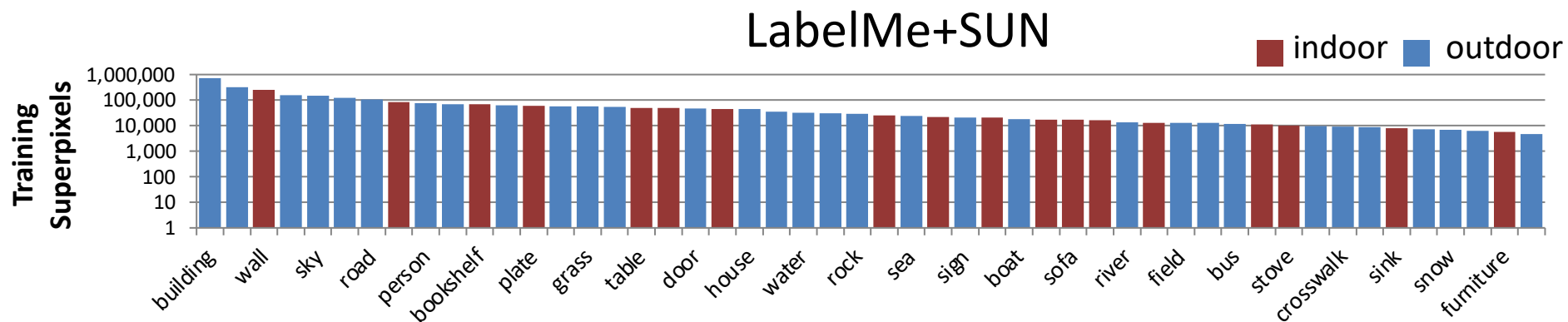
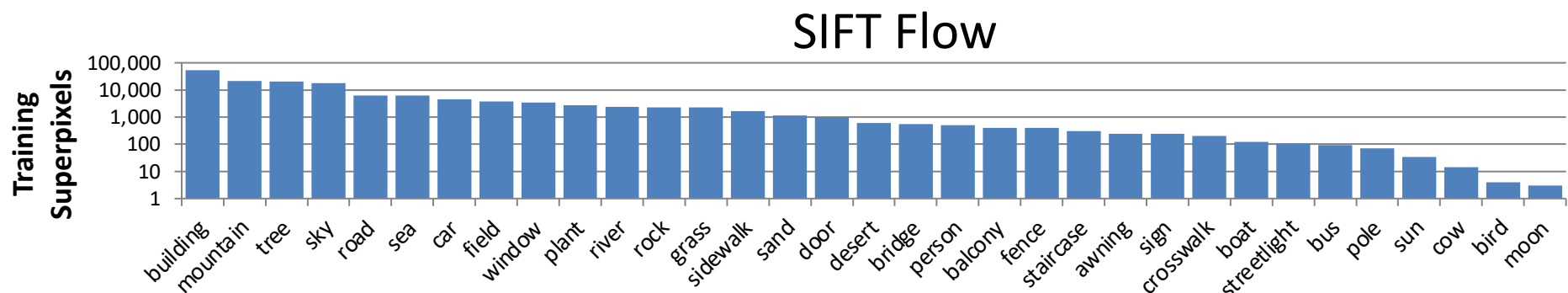
Region-based parsing
result (30.9%)



Detector-based parsing
result (24.8%)

Evaluation: Datasets

	Training Images	Test Images	Labels
SIFT Flow (Liu et al., 2009)	2,488	200	33
LabelMe+SUN	45,176	500	232

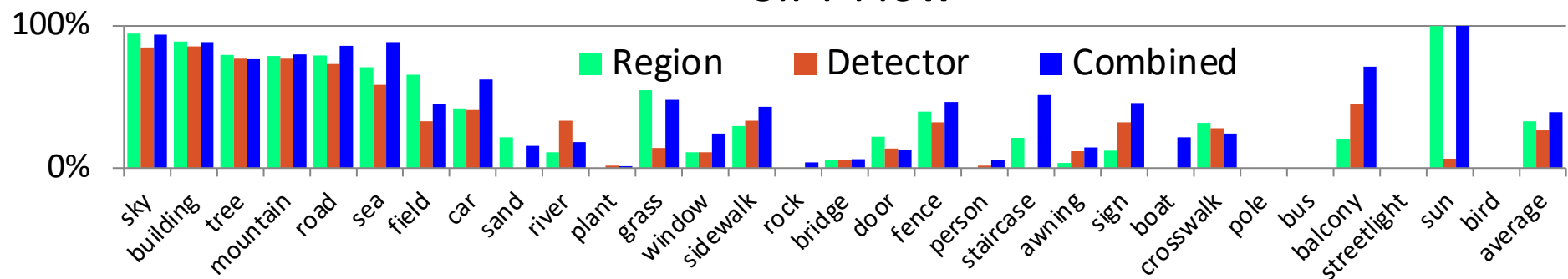


Quantitative evaluation

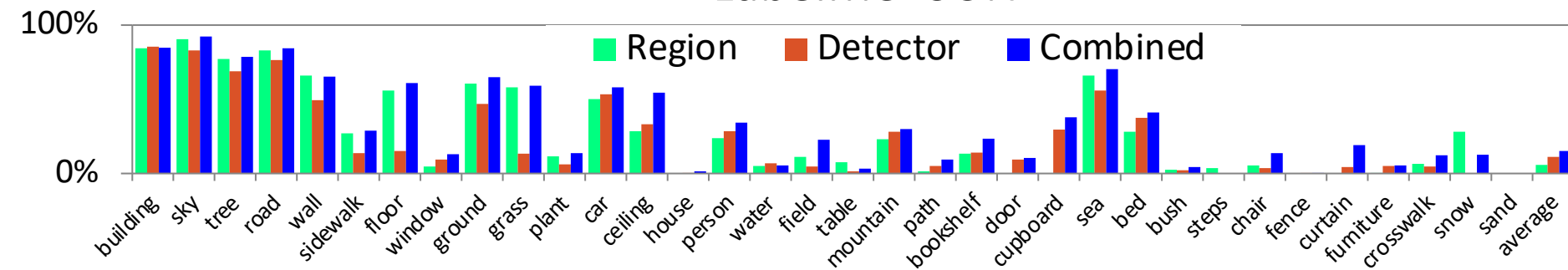
	Region-based	Detector-based	Region + Detector Combined
SIFT Flow (Liu et al., 2009)	77.7 (32.8)	71.1 (26.7)	78.6 (39.2)
LabelMe+SUN	58.3 (5.9)	52.5 (11.3)	61.4 (15.2)

Per-pixel rate (average per-class rate)

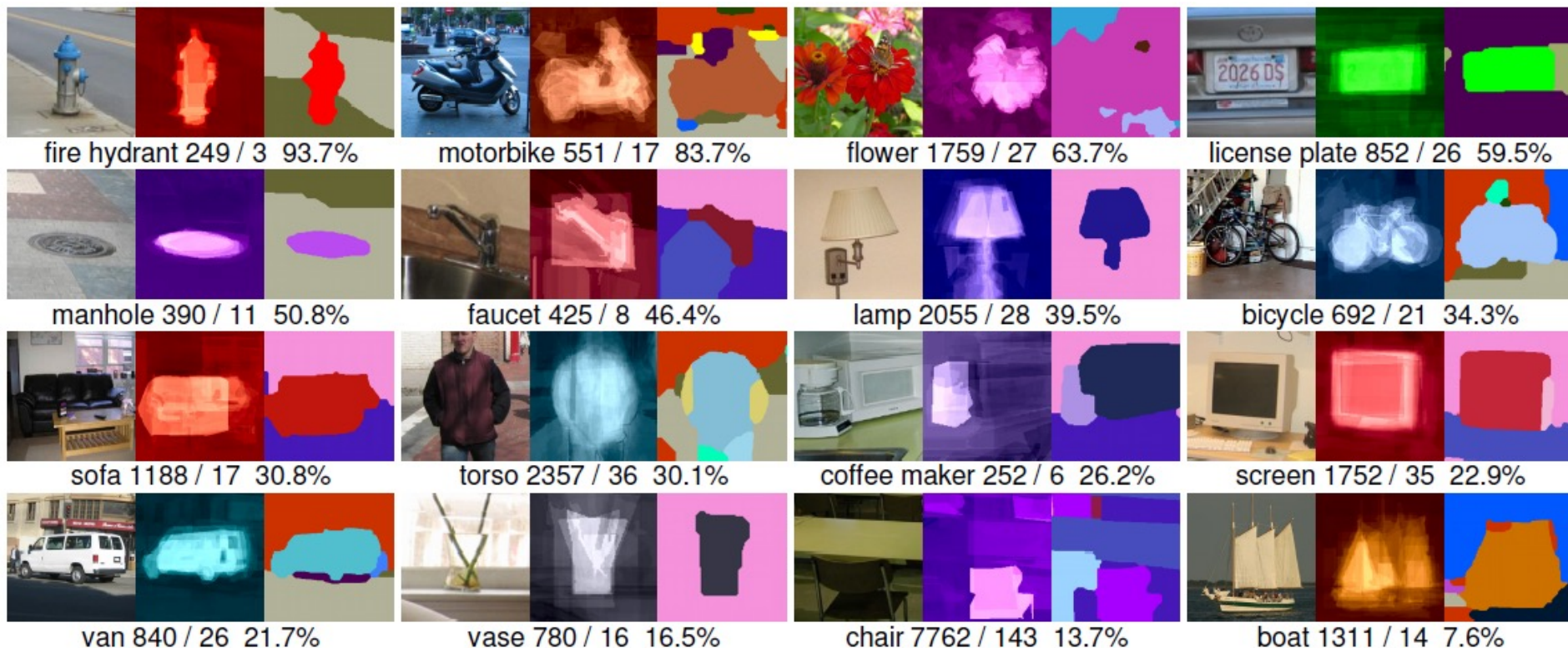
SIFT Flow



LabelMe+SUN



Toward Broad Coverage



Comparison to state of the art

SIFT Flow	Per-Pixel	Per-Class
Our approach	78.6	39.2
Tighe and Lazebnik (2013)	77.0	30.1
Liu et al. (2011)	76.7	N/A
Farabet et al. (2012)	78.5	29.6
Farabet et al. balanced (2012)	74.2	46.0
Eigen and Fergus (2012)	77.1	32.5
Myeong et al. (2012)	77.1	32.3

Comparison to state of the art

LabelMe+SUN	Per-Pixel	Per-Class
Our approach	61.4	15.2
Outdoor	65.5	15.3
Indoor	46.3	12.2
Tighe and Lazebnik (2013)	54.9	7.1
Outdoor	60.8	7.7
Indoor	32.1	4.8

Now what?

- Other researchers should push for bigger datasets, broader coverage
- For us – lots more work to do
 - Improve computational efficiency of exemplar SVM training: try whitened HOG approach of Hariharan et al. (ECCV 2012)
 - Leverage the object separation the per-exemplar detectors are already providing to separate the objects in our final parsing

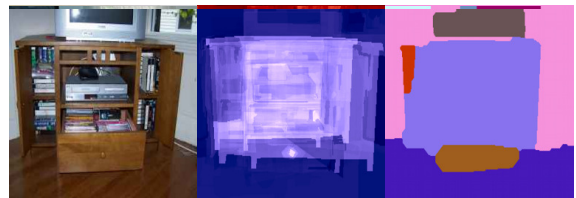
Code and data publicly available on our websites:
<http://www.cs.unc.edu/~jtighe/Papers/CVPR13/>



parking lot 1000/247/100.0000%



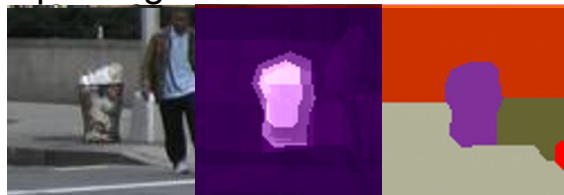
parking lot 1000/247/100.0000%



chess 1000/247/100.0000%



fish 1000/247/100.0000%



chess 1000/247/100.0000%



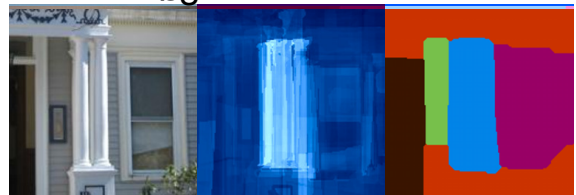
chess 1000/247/100.0000%



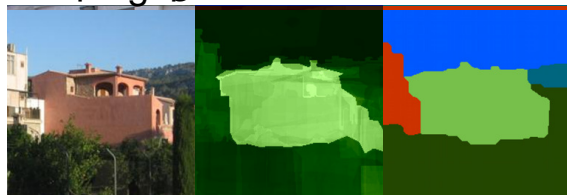
lip 1000/247/100.0000%



lip 1000/247/100.0000%



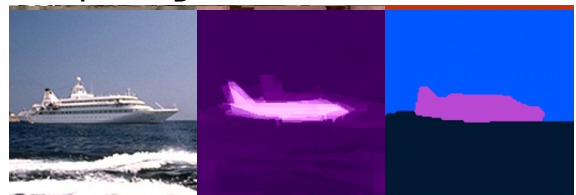
lip 1000/247/100.0000%



pet 1000/247/100.0000%



pet 1000/247/100.0000%



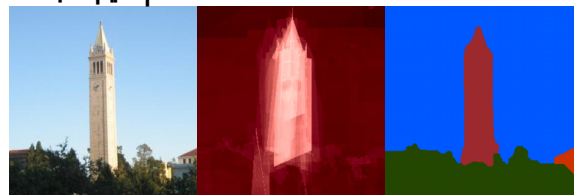
pet 1000/247/100.0000%



di 1000/247/100.0000%



di 1000/247/100.0000%



di 1000/247/100.0000%

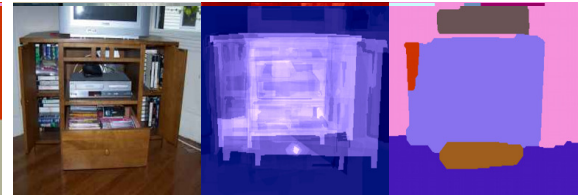
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parking lot 10000/247125.32%



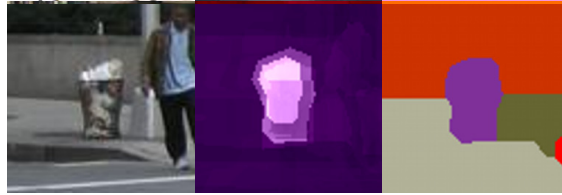
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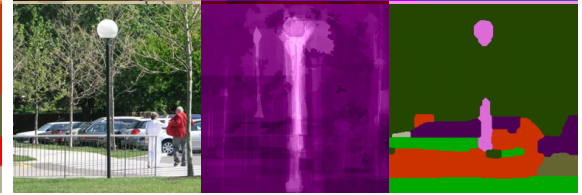
chess 10000/247125.32%



fish 10000/247125.32%



chess 10000/247125.32%



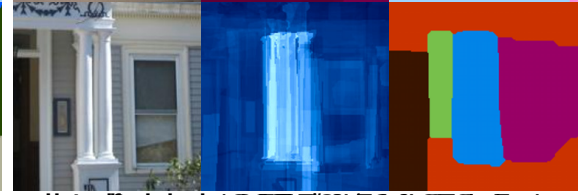
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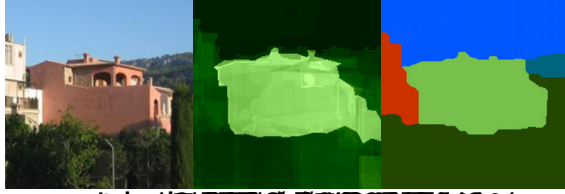
lip 10000/247125.32%



lip 10000/247125.32%



lip 10000/247125.32%



pet 10000/247125.32%



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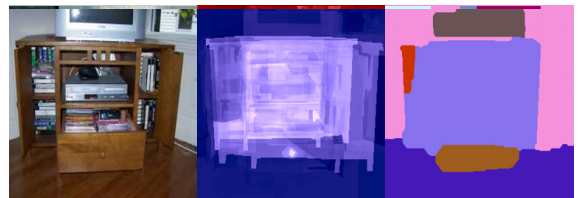
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parking lot 1000/1000 100.00%



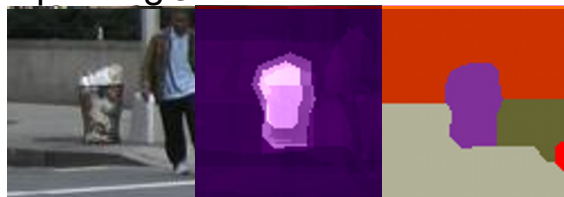
parking lot 1000/1000 100.00%



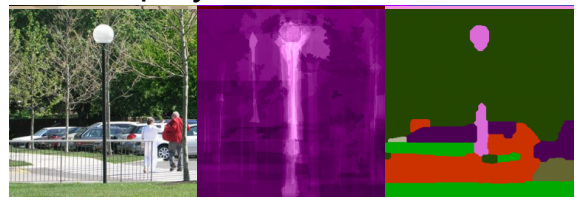
chess 1000/1000 100.00%



fish 1000/1000 100.00%



chess 1000/1000 100.00%



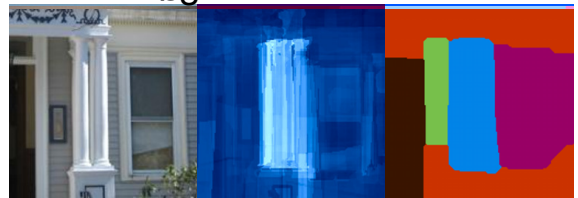
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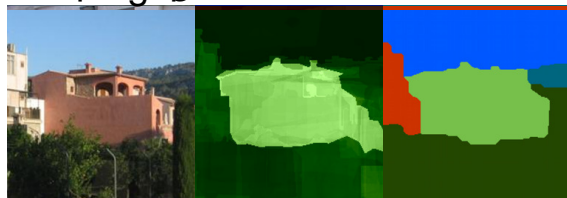
lip 1000/1000 100.00%



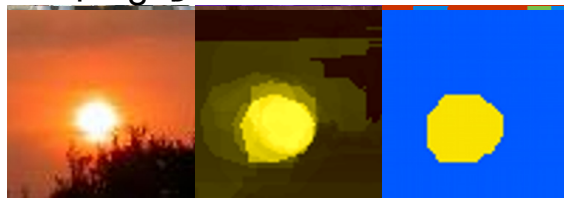
lip 1000/1000 100.00%



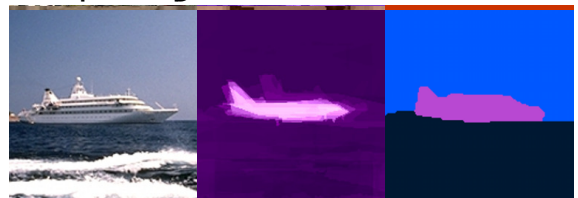
lip 1000/1000 100.00%



pepper 1000/1000 100.00%



pepper 1000/1000 100.00%



pepper 1000/1000 100.00%



chess 1000/1000 100.00%



chess 1000/1000 100.00%



chess 1000/1000 100.00%