

Learning Depth-Sensitive Conditional Random Fields for Semantic Segmentation of RGB-D Images

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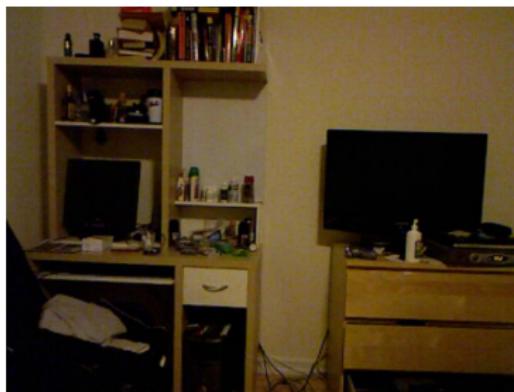


Bonn, Germany

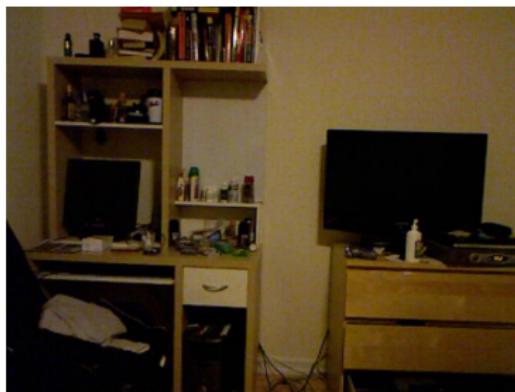
June 4, 2014

¹now at Amazon.com

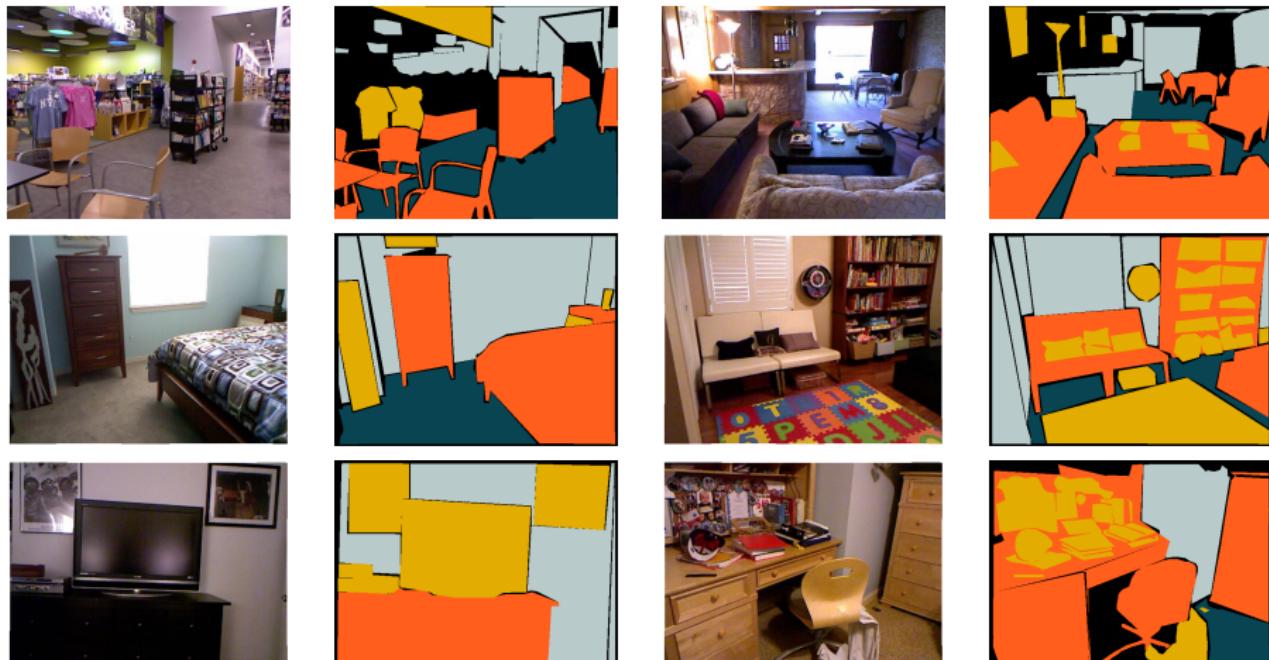
Semantic Segmentation of Structure Classes



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Dataset: NYUv2



Ground

Structure

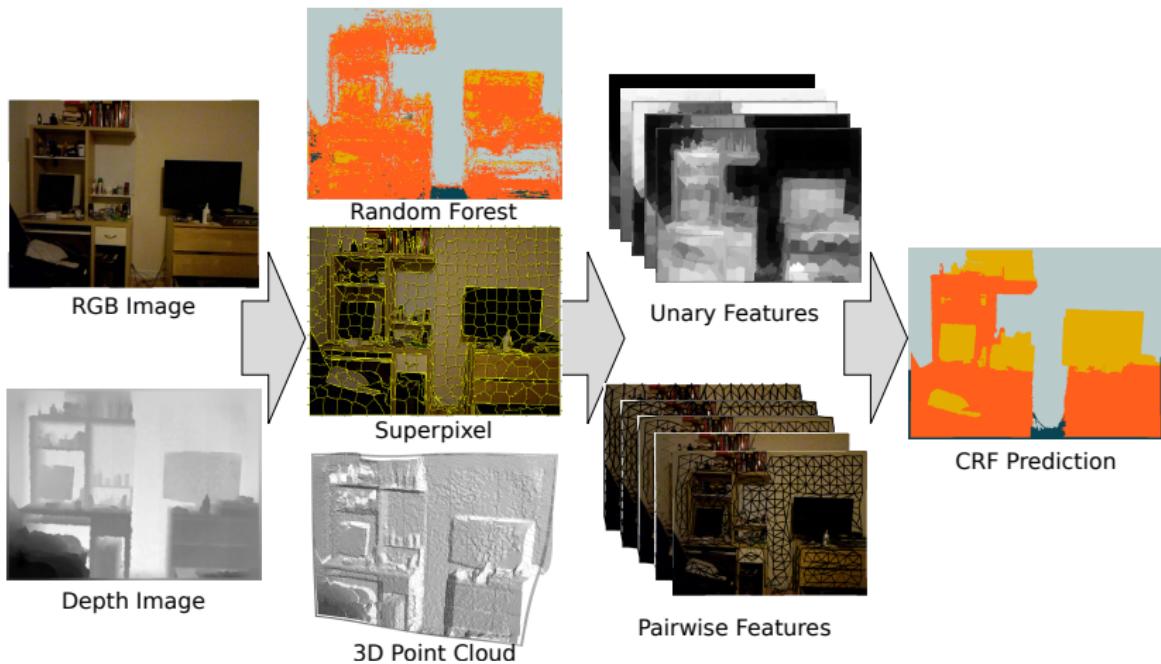
Furniture

Props

Void

795 training images, 654 test images.

Overview



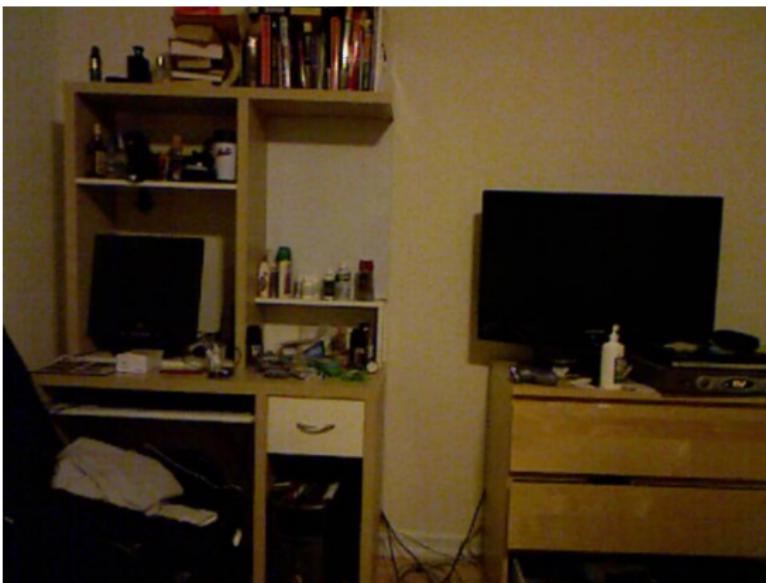
Outline

Structured prediction formulation

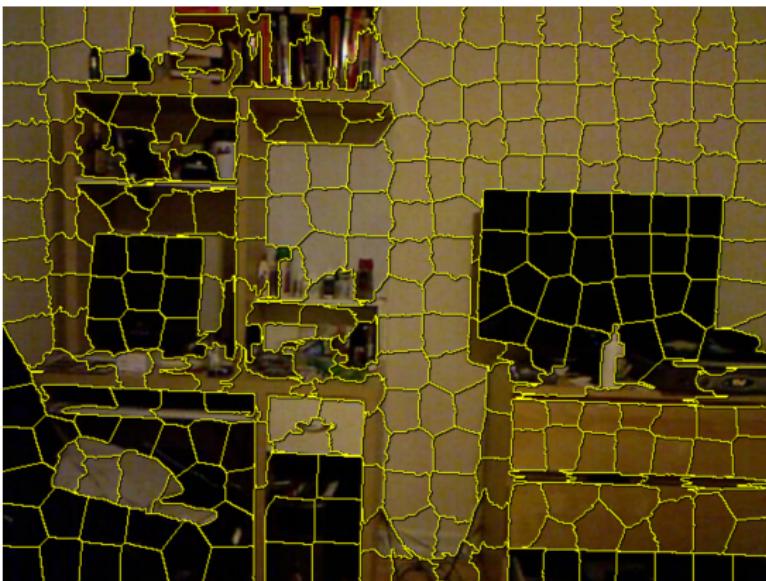
Unary and Pairwise Features

Experiments

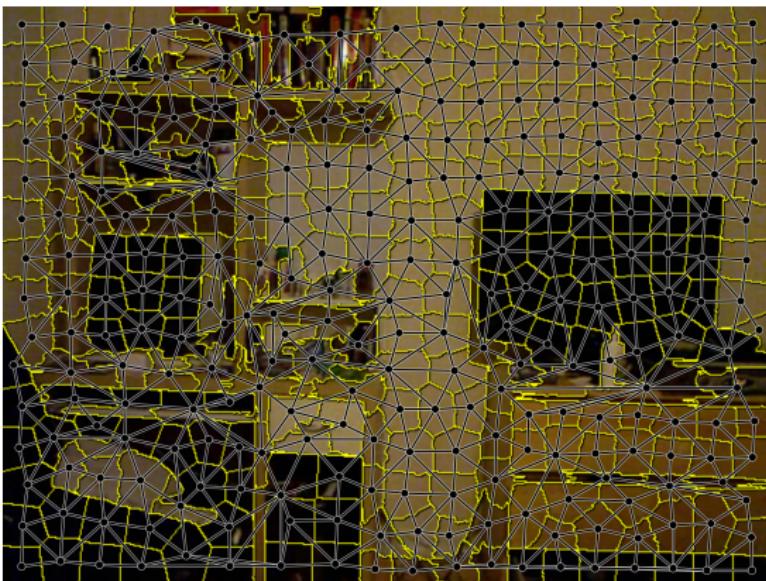
Semantic Segmentation as Structured Prediction



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Semantic Segmentation as Structured Prediction



Structured Prediction

Learn prediction function of the form

$$g(x, w) := \arg \max_{y \in \mathcal{Y}} w^T \psi(x, y)$$

Objective

$$\min_w \frac{1}{2} \|w\|^2 + C \sum_i \ell(x^i, y^i, w)$$

$$\ell(x^i, y^i, w) = [\max_{y \in \mathcal{Y}} \Delta(y^i, y) + w^T \psi(x^i, y) - w^T \psi(x^i, y^i)]_+.$$

Pairwise models

$$\mathbf{w}^T \psi(x, y) = \sum_{(i,j) \in E} w_{i,j} \psi_{i,j}(x, y_i, y_j) + \sum_i w_i \psi_i(x, y_i)$$

Pairwise models

$$\mathbf{w}^T \psi(x, y) = \sum_{(i,j) \in E} w_{i,j} \psi_{i,j}(x, y_i, y_j) + \sum_i w_i \psi_i(x, y_i)$$

$$\psi_i(x, y_i) = f(x_i) \otimes \mathbf{1}_{y_i}$$

$$\psi_i(x, y_i, y_j) = f(x_i, x_j) \otimes \mathbf{1}_{y_i} \otimes \mathbf{1}_{y_j}$$

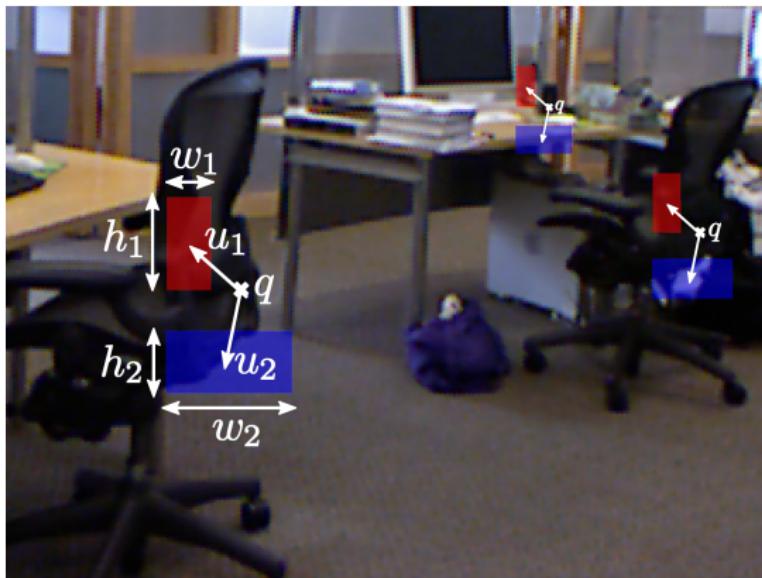
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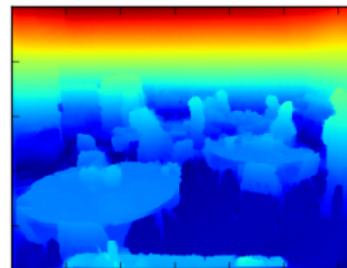
Random Forest Unary Potentials



GPU implementation from Stückler et al. [2014].
Number of trees: 3, max-depth: 18

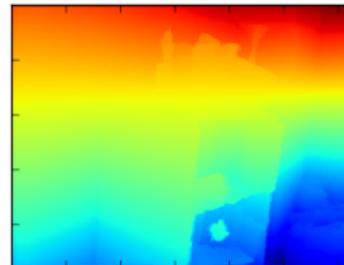
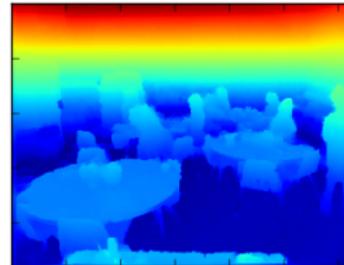
Absolute height potentials

$$f_{\text{height}}(x_i) = \mathbf{n}_{\text{flat}}^T \mathbf{n}_{x_i}$$



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$$f_{\text{height}}(x_i) = \mathbf{n}_{\text{flat}}^T \mathbf{n}_{x_i}$$



Color Contrast

$$f_{\text{color}}(x_i, x_j) = \exp(-\gamma \|c_i - c_j\|^2).$$



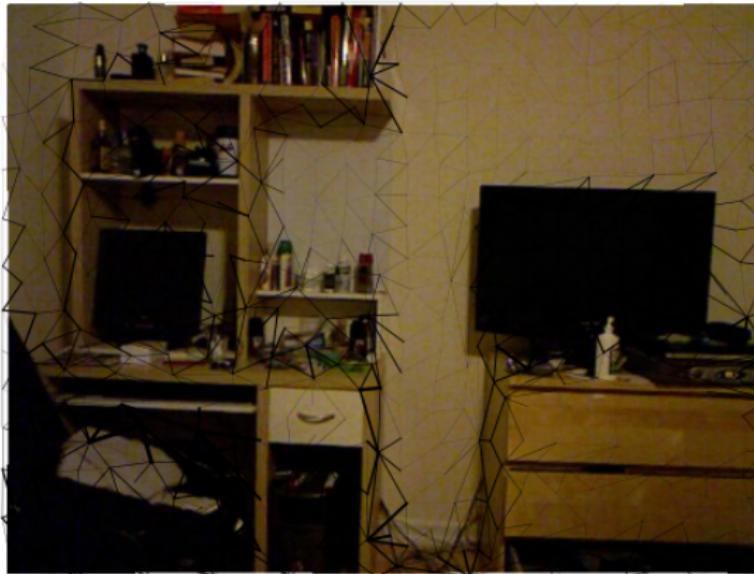
Edge direction

$$f_{\text{direction}}(x_i, x_j) = \triangleleft(\text{pos}_{x_i} - \text{pos}_{x_j}, [0, 1]^T)$$



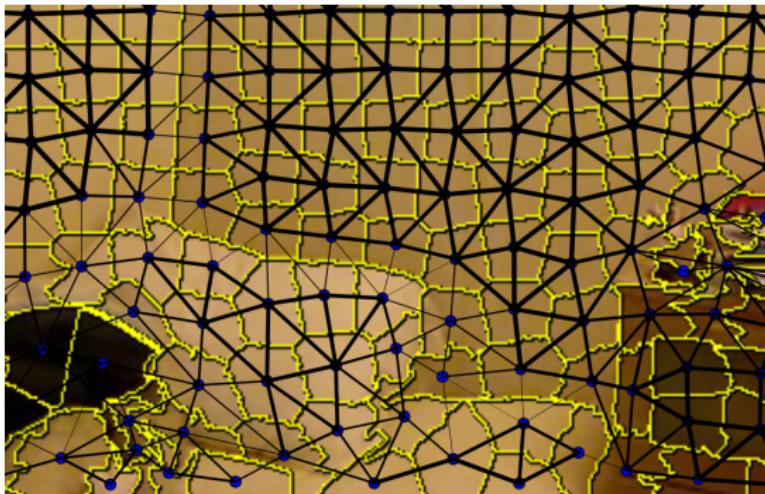
Depth Difference

$$f_{\text{depth}}(x_i, x_j) = (d_i - d_j)/Z$$



Pairwise Normal Orientation

$$f_{\text{normals}}(x_i, x_j) = 1 - \frac{1}{\pi} \cdot \langle \mathbf{n}_{x_i}, \mathbf{n}_{x_j} \rangle$$



Summary of Feature Functions

$$f(x_i) = f_{\text{RandomForest}}(x_i) \oplus f_{\text{height}}(x_i) \oplus 1$$

$$f(x_i, x_j) = f_{\text{color}}(x_i, x_j) \oplus f_{\text{direction}}(x_i, x_j) \oplus f_{\text{depth}}(x_i, x_j) \oplus f_{\text{normals}}(x_i, x_j) \oplus 1$$

Learning and Optimization

- ▶ 1-slack SSVM

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PyStruct Introduction Examples References Search

Examples

Plotting the objective and constraint caching in 1-slack SSVM
SVM objective values

Efficient exact learning of 1-slack SSVMs
Learning directed interactions on a 2d grid

SSVM as CRF
Learning interactions on a 2d grid

Iterative Image Segmentation on Pascal VOC
DCP Letter sequence recognition

Latent Dynamics CRF
Chameleon-Singer Multi-Class SVM

Latent SVM for soft vs. even digit classification
Multi-label classification
Latent Variable Hierarchical CRF
Comparing PyStruct and SVMlib

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<http://pystruct.github.io>

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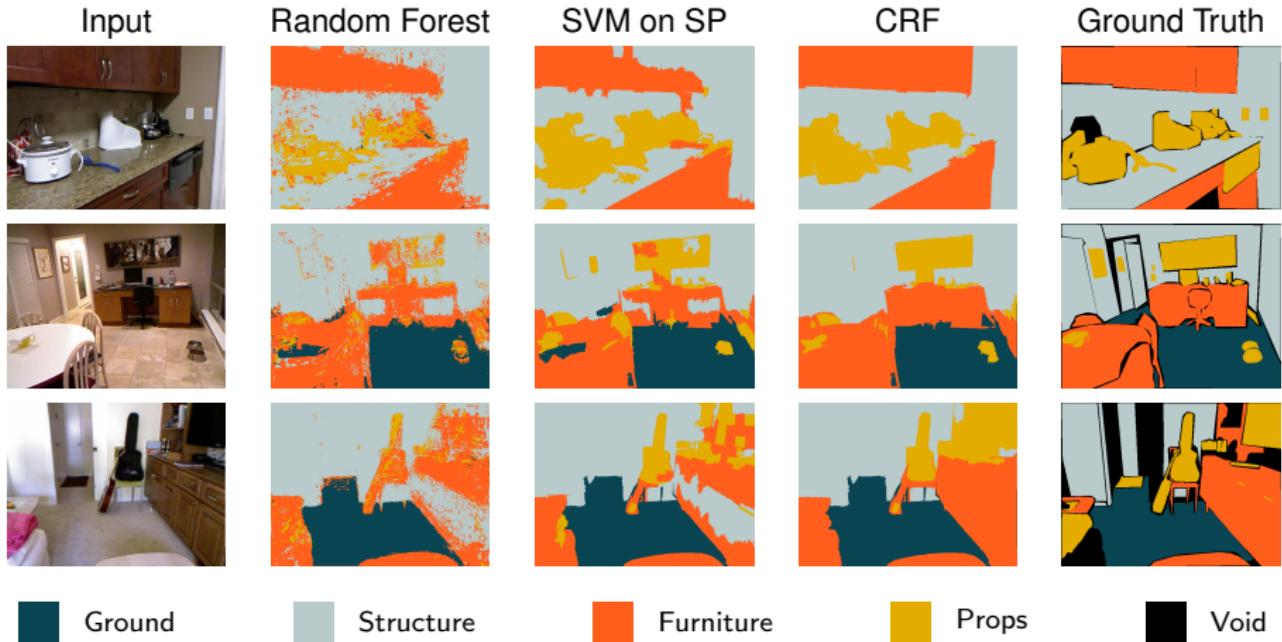
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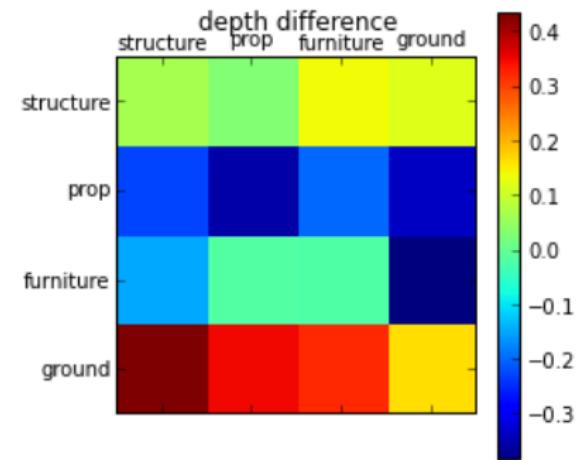
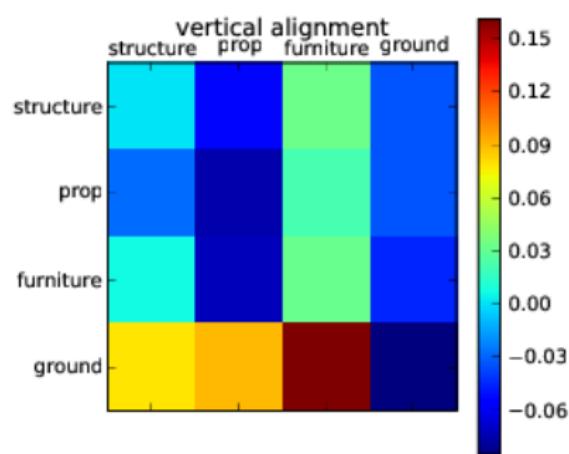
Results

	ground	structure	furniture	props	class avg	pixel avg
RF	90.8	81.6	67.9	19.9	65.0	68.3
RF + SP	92.5	83.3	73.8	13.9	65.7	70.1
RF + SP + SVM	94.4	79.1	64.2	44.0	70.4	70.3
RF + SP + CRF	94.9	78.9	71.1	42.7	71.9	72.3
Silberman et al. [2012]	68	59	70	42	59.6	58.6
Couprise et al. [2013]	87.3	86.1	45.3	35.5	63.5	64.5
Stückler et al. [2014] [†]	95.6	83.0	75.1	14.2	67.0	70.9

Qualitative Results



Learned Potentials



Take Home

- ▶ Can incorporate geometric relations into CRF.
- ▶ Learn all potentials.
- ▶ Exact learning of CRF possible.
- ▶ Code available: <http://github.com/amueller/segmentation>

Thank you for your attention.

Questions?