Structured Prediction for Semantic Segmentation

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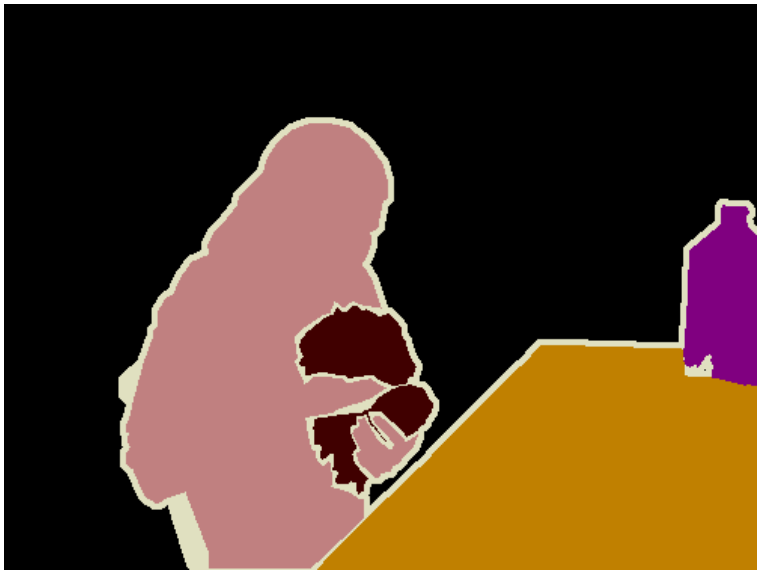
1. Structured Prediction for Semantic Segmentation
2. Learning Depth-Sensitive Conditional Random Fields
3. Learning Loopy CRFs Exactly
4. PyStruct

Semantic Segmentation

Semantic Segmentation



Multi-Label Classification

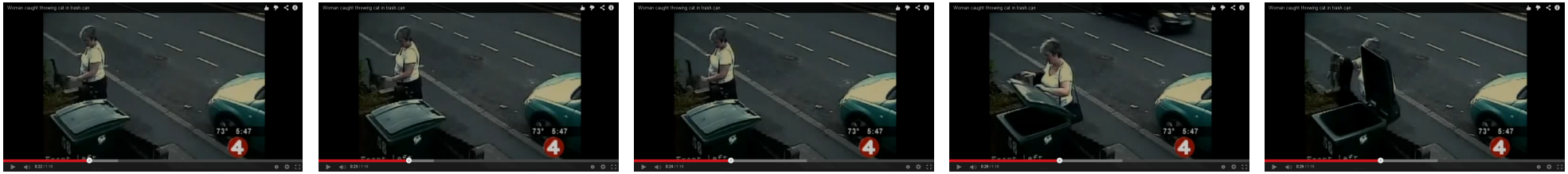
	Politics	Sports	Finance	Domestic	Religion
News Story1	1	0	0	1	1
News Story2	0	1	0	1	0
News Story3	0	0	1	0	0

Multi-Label Classification

	Politics	Sports	Finance	Domestic	Religion
News Story1	1	0	0	1	1
News Story2	0	1	0	1	0
News Story3	0	0	1	0	0

	Owns Car	Smokes	Married	Self-Employed	Has Kids
Customer1	1	0	1	0	1
Customer2	1	1	0	1	0
Customer3	0	1	1	0	0

Sequence Tagging



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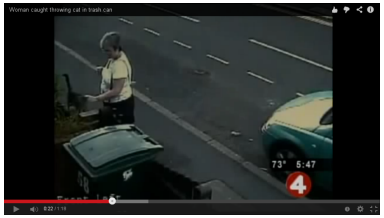

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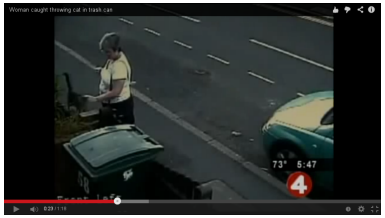

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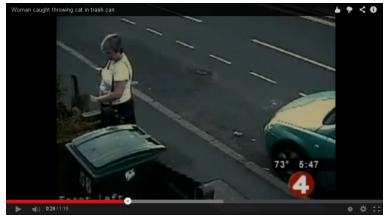

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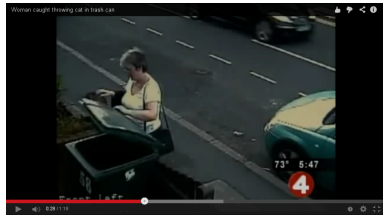
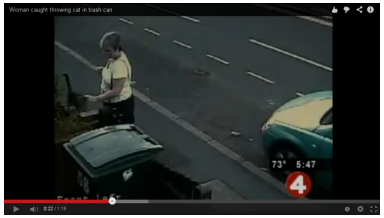


Open trash can.

Put cat in trash can.

Sequence Tagging



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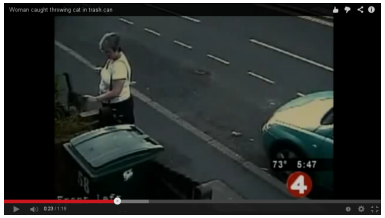

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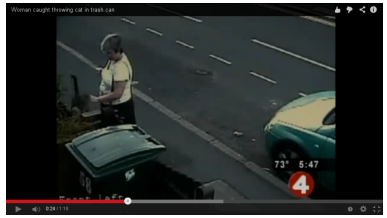

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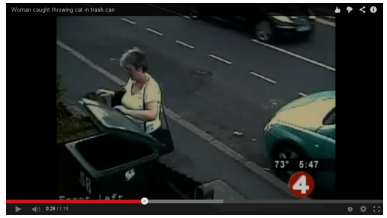

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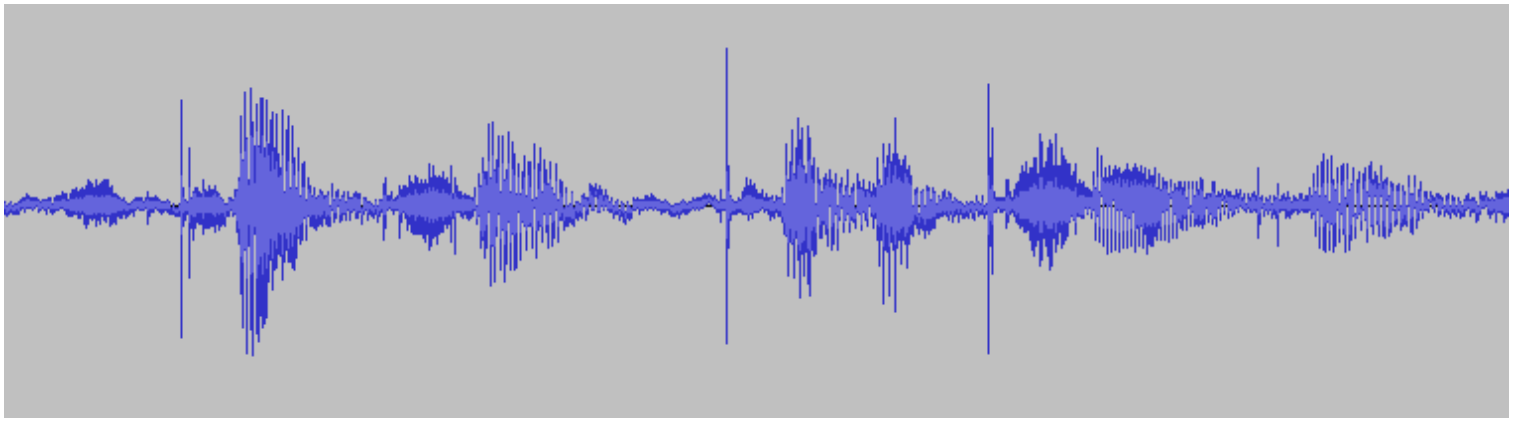

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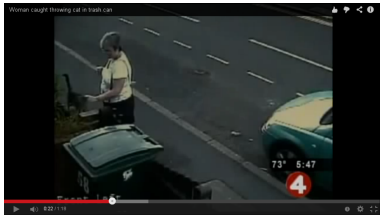

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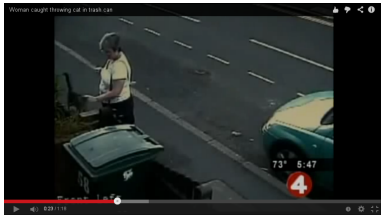

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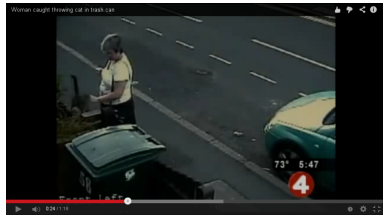

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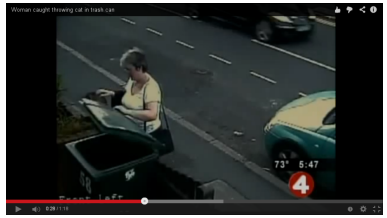

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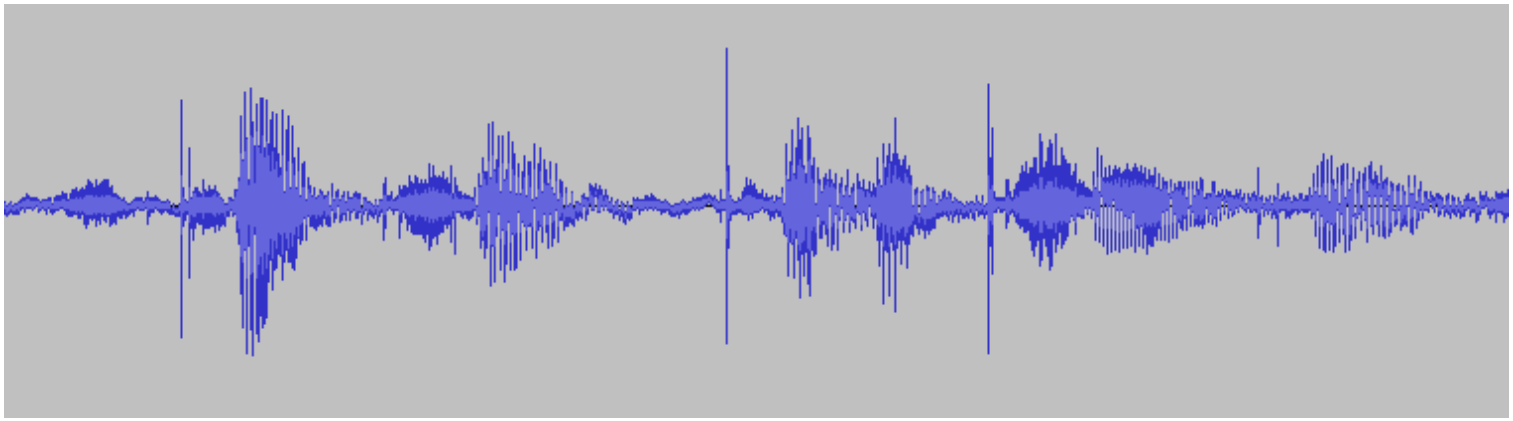
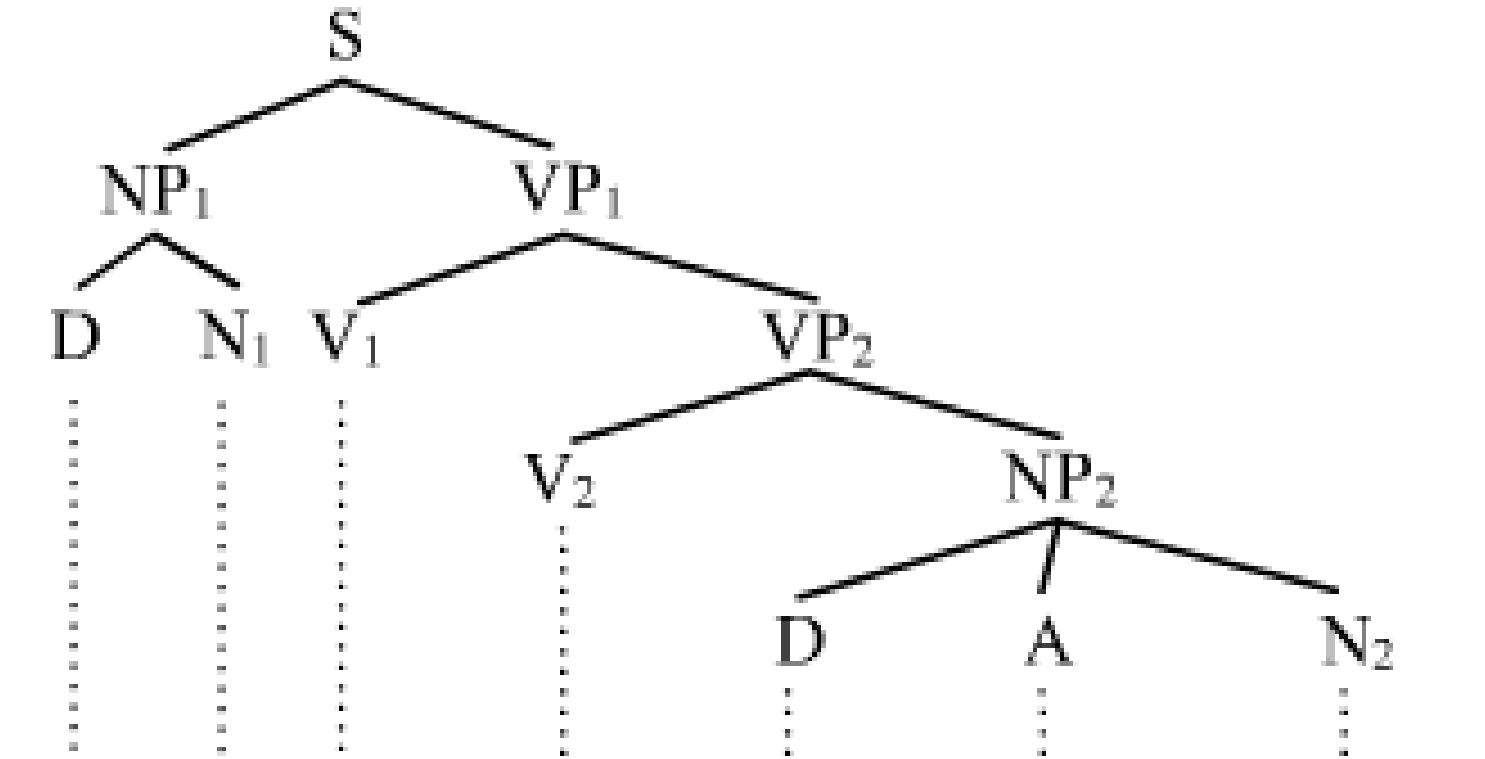


Struc-tured pre-dic-tion in Py-thon

Predicting Parse Trees



Constituency relation (PSG)

Structured Prediction for Semantic Segmentation

Semantic Segmentation as Structured Prediction

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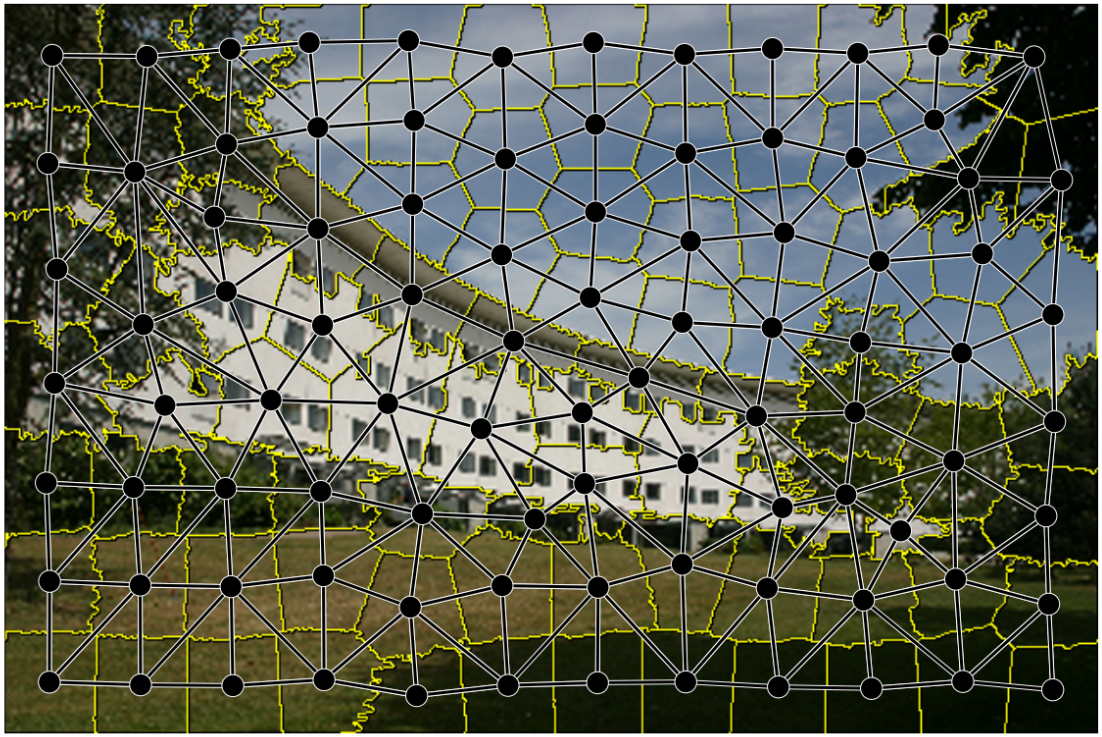

Predicting Structured Objects

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

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If you like:

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If you like:

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

Predicting discrete vectors

$$y = (y_1, y_2, \ldots, y_{n_i})$$

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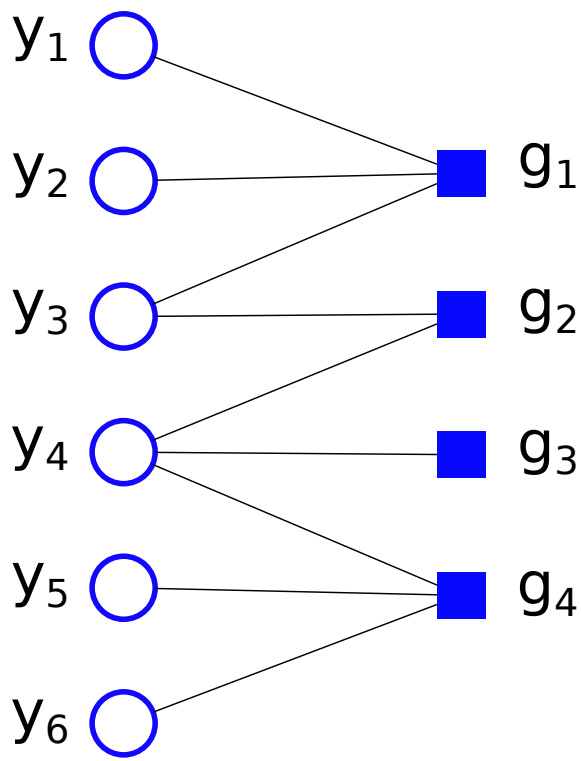
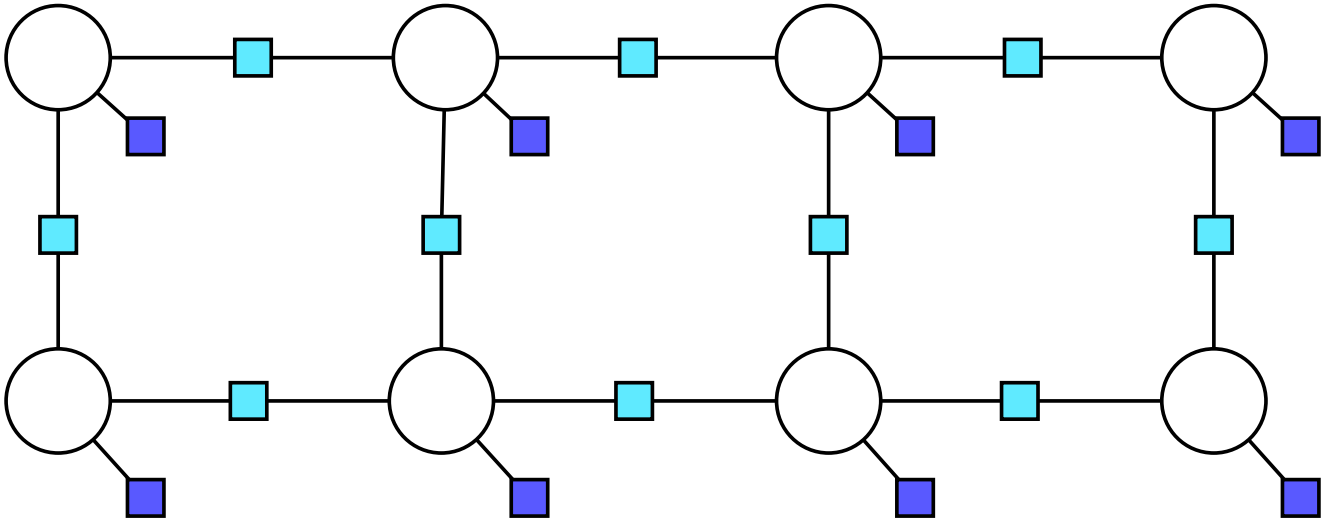
$$\begin{aligned} f(x, w) &= \underset{y \in \mathcal{Y}}{\arg\max}\, w^T \psi(x, y) \\ &= \underset{y_1, y_2, \ldots, y_{n_i}}{\arg\max}\, w^T \psi(x, y) \end{aligned}$$

Factor Graphs

$$g(x, y) = g_1(x, y_1, y_2, y_3) + g_2(x, y_3, y_4) + g_3(x, y_4) + g_4(x, y_4, y_5, y_6)$$

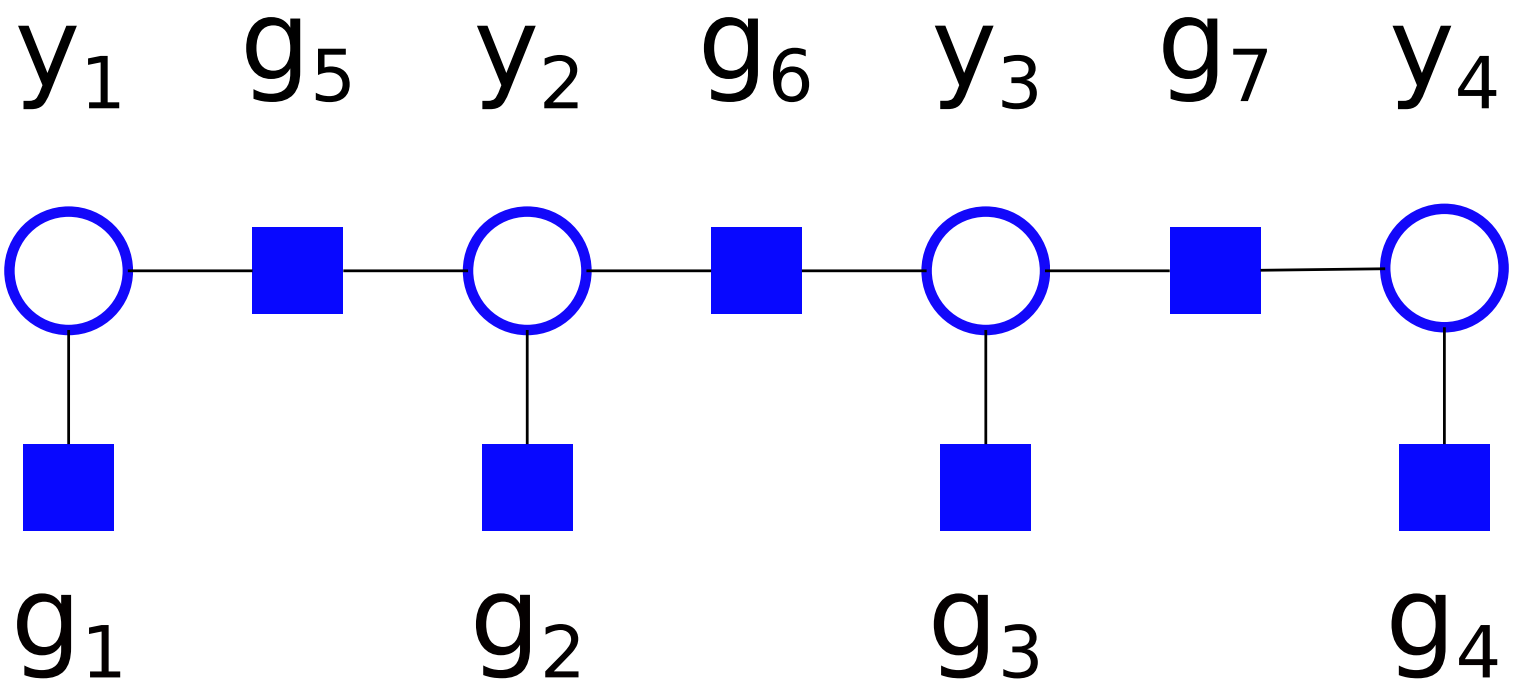


Pairwise Models



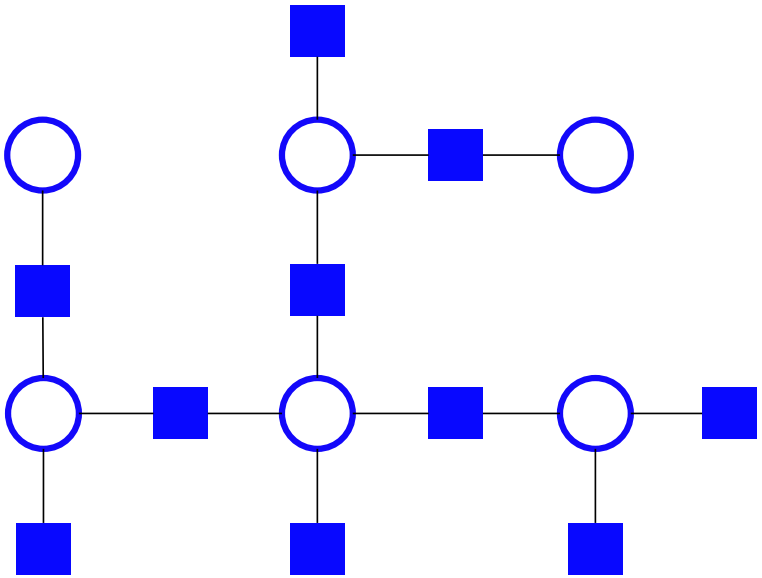
$$w^T \psi(x, y) = \sum_{(i,j) \in E} w_{i,j} \psi_{i,j}(x, y_i, y_j) + \sum_{i \in I} w_i \psi_i(x, y_i)$$

Factor Graph for HMM

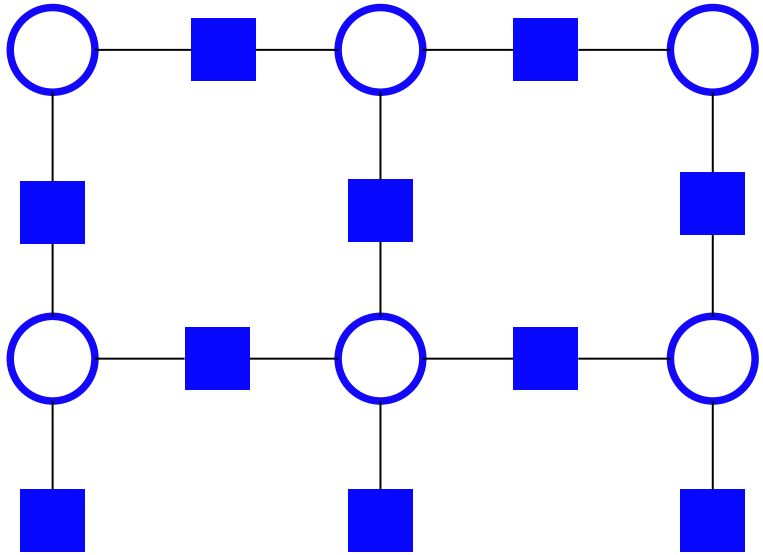


Inference

Easy



Tricky



Probabilistic Learning

$$p(y|x, w) = \frac{1}{Z} exp(w^T \psi(x, y))$$

$$Z = \sum_{y' \in \mathcal{Y}} exp(w^T \psi(x, y'))$$

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$$Z = \sum_{y' \in \mathcal{Y}} exp(w^T \psi(x, y'))$$

Objective

$$\max_w \sum_i \log(p(y^i|x^i, w))$$

$$= \max_w \sum_i w^T \psi(x^i, y^i) - \log(Z)$$

Structured Prediction

Learn prediction function of the form

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Learn prediction function of the form

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

Objective

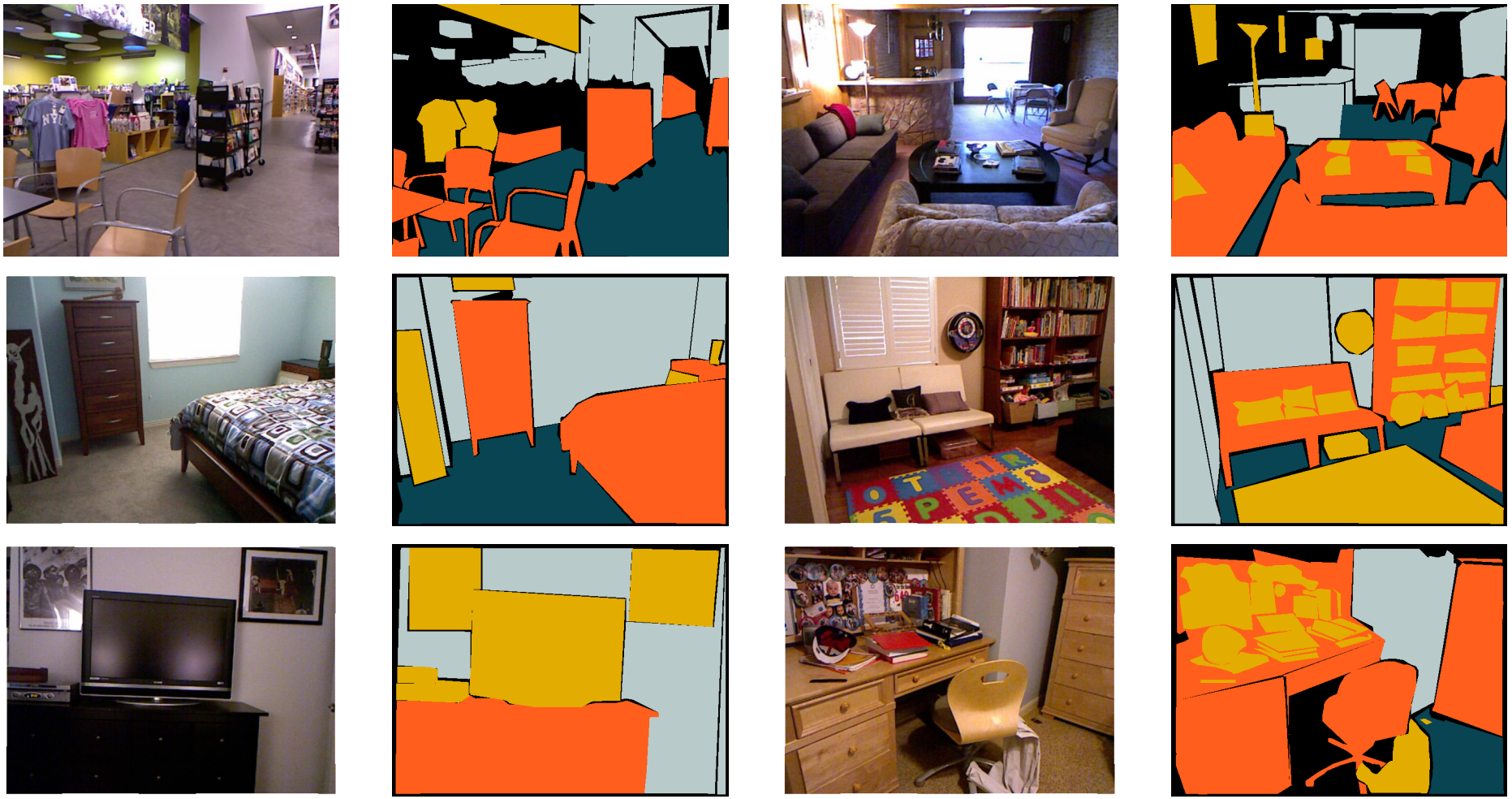
$$\min_w \frac{1}{2}\|w\|^2 + C \sum_i \ell(x^i, y^i, w)$$

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

(author?) [4]

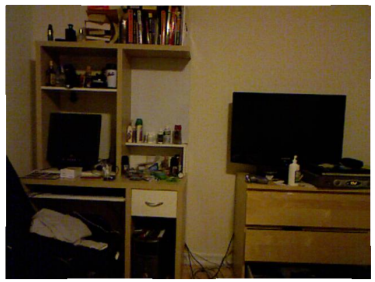
Learning Depth-Sensitive Conditional Random Fields

Dataset: NYUv2



795 training images, 654 test images.

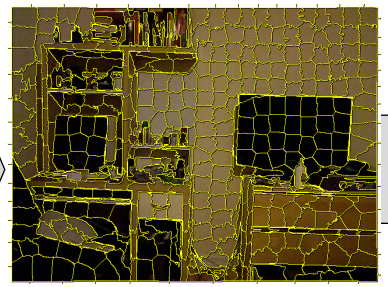
Overview



RGB Image

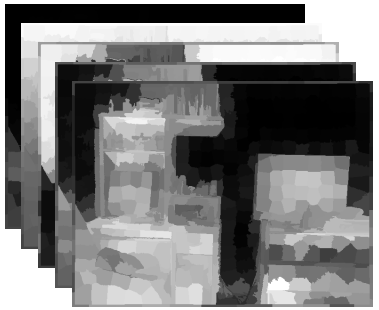
Depth Image

Random Forest



Superpixel

3D Point Cloud



Unary Features

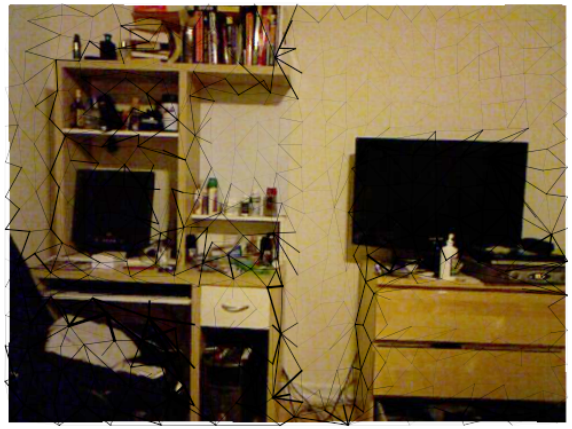
Pairwise Features

CRF Prediction

Pairwise Features

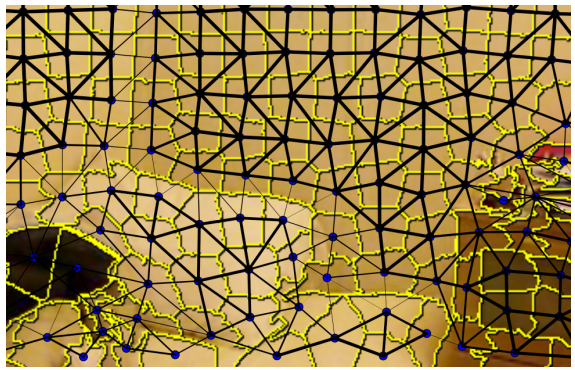
$$f_{\text{color}}(x_i, x_j) = \exp\left(-\gamma \|c_i - c_j\|^2\right)$$

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



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

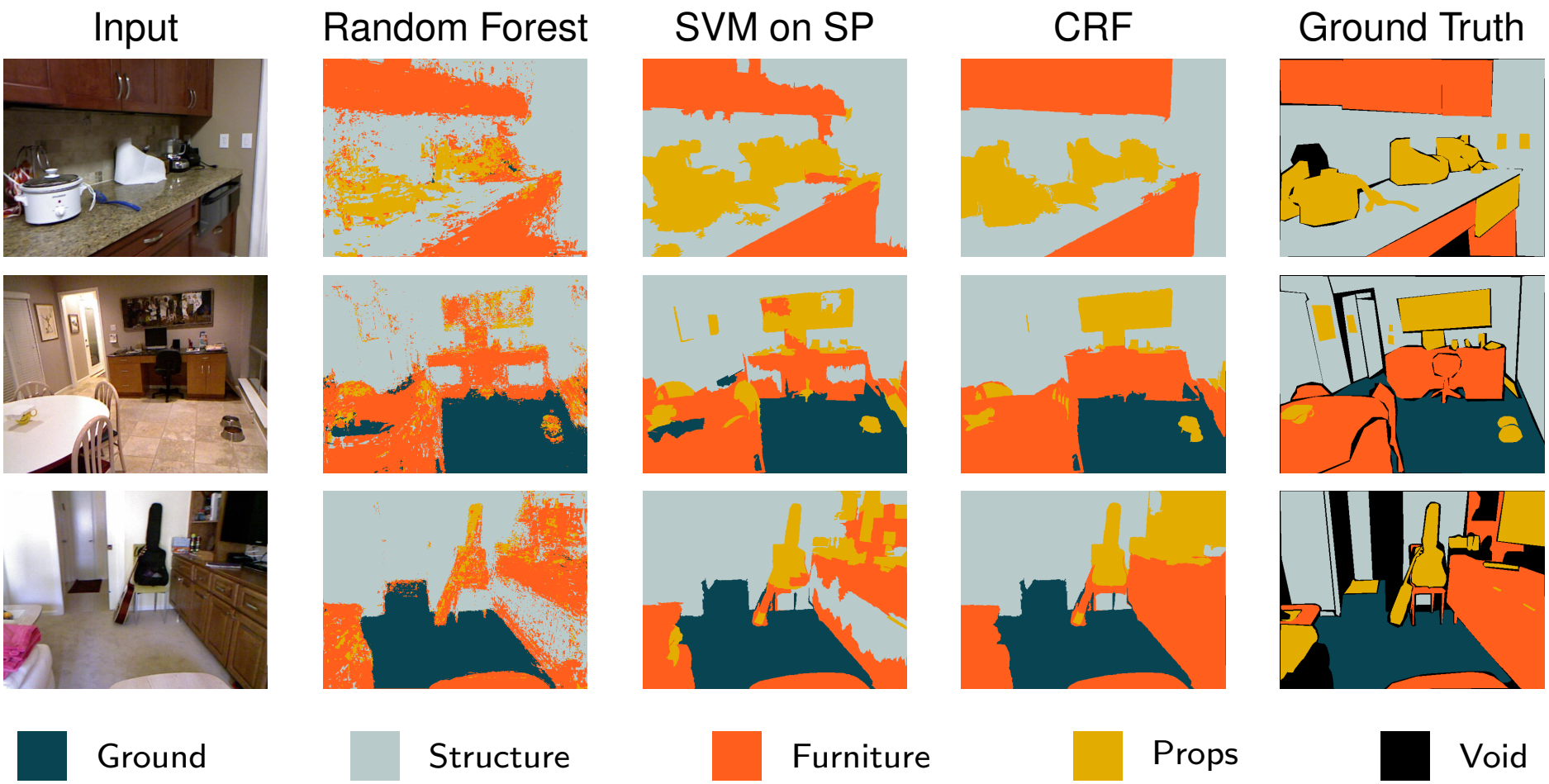
$$f_{\text{normals}}(x_i, x_j) = 1 - \frac{1}{\pi}\sphericalangle(\mathbf{n}_{x_i}, \mathbf{n}_{x_j})$$



Learning and Optimization

- 1-slack SSVM
- Inference using fusion moves and AD^3.
- Exact learning in loopy model [9].

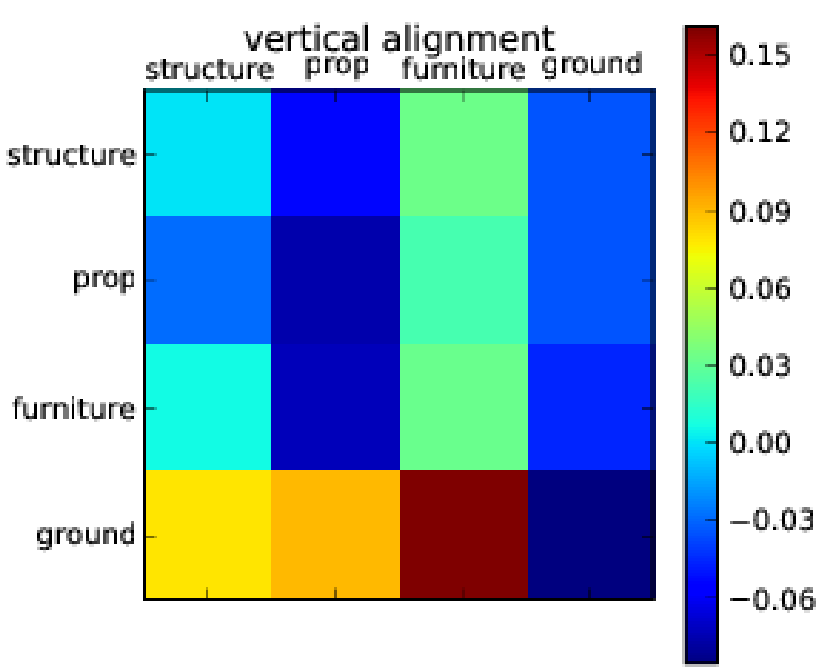
Qualitative Results

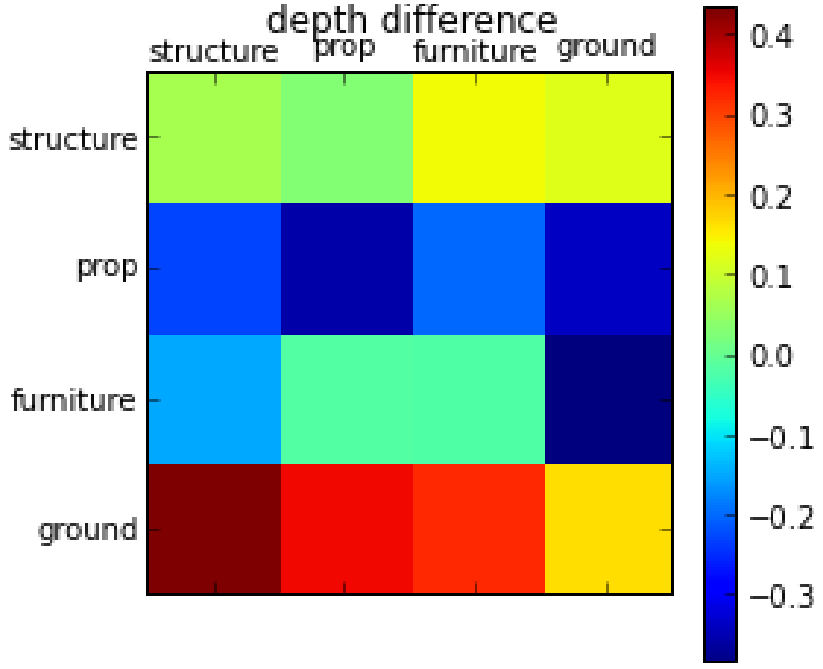


Results

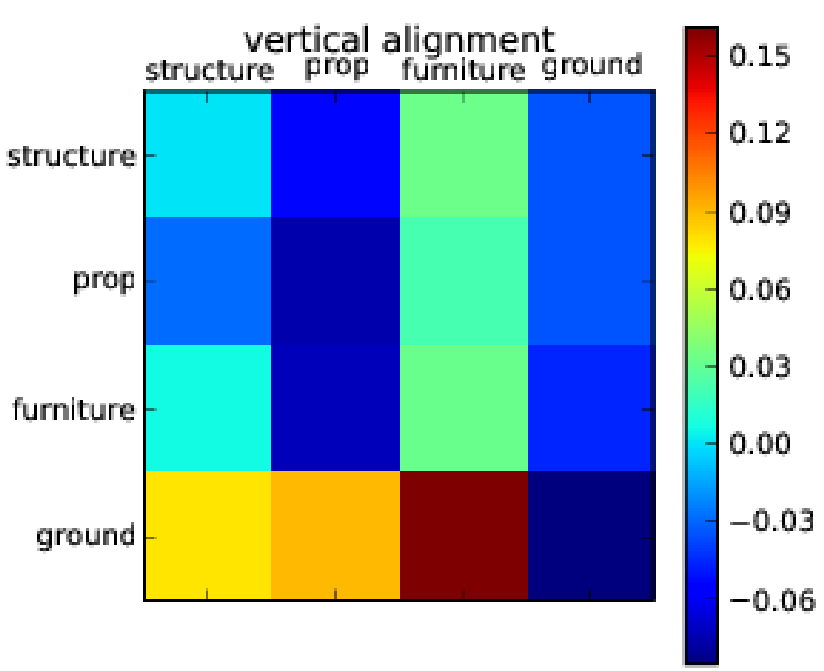
	ground	structure	furniture	props	class avg	pixel avg
RF	90.8	81.6	67.9	19.9	65.0	68.3
RF + SP	92.5	83.3	**73.8**	13.9	65.7	70.1
RF + SP + SVM	94.4	79.1	64.2	**44.0**	70.4	70.3
RF + SP + CRF	**94.9**	78.9	71.1	42.7	**71.9**	**72.3**
(author?) [10]	68	59	70	42	59.6	58.6
(author?) [1]	87.3	**86.1**	45.3	35.5	63.5	64.5
(author?) [11]†	**95.6**	83.0	**75.1**	14.2	67.0	70.9

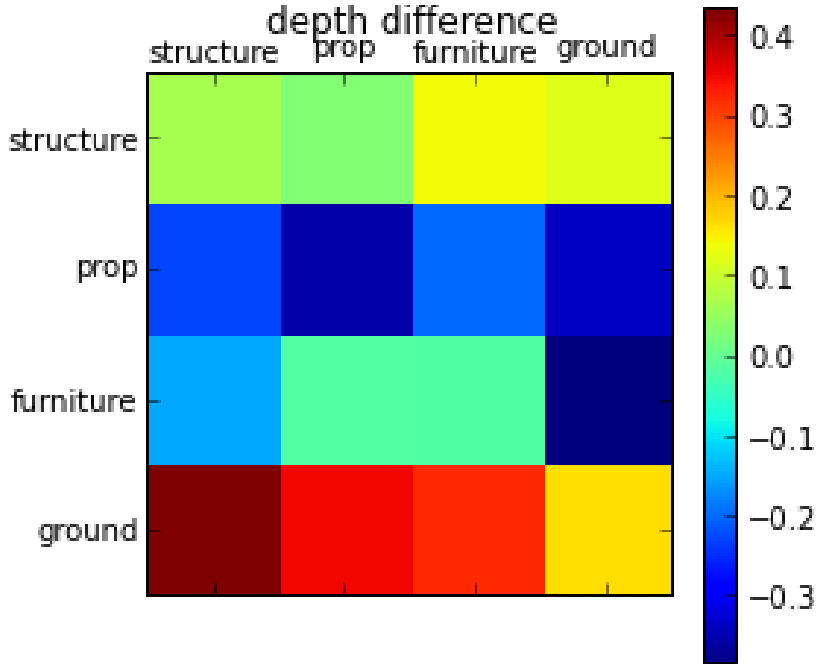
Learned Potentials





Learned Potentials





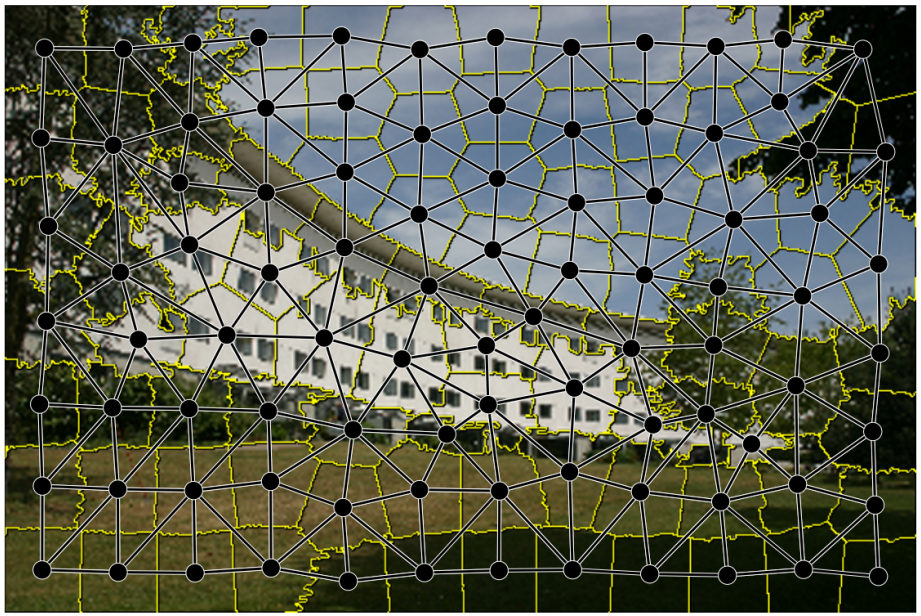
- Ground is at bottom.
- Walls are behind other objects.
- Ground is often in front of other objects.
- Furniture is in front of the walls.

Summary

- Can incorporate geometric relations into CRF.
- Learn all potentials.
- Exact learning of CRF possible.

Learning Loopy CRFs Exactly

How Intractable Are Loopy Models?



- In general, inference in loopy models is NP-hard.
- Learning relies on inference.
- How good can we get in practice?
- Focusing on 1-slack cutting plane algorithm.

Efficient Caching

$$\ell(x^i, y^i, w) = [\max_{y \in \mathcal{Y}} \Delta(y^i, y) + w^T \psi(x^i, y) - w^T \psi(x^i, y^i)]_+ \quad (1)$$

- Maximizing over y main bottleneck.

Efficient Caching

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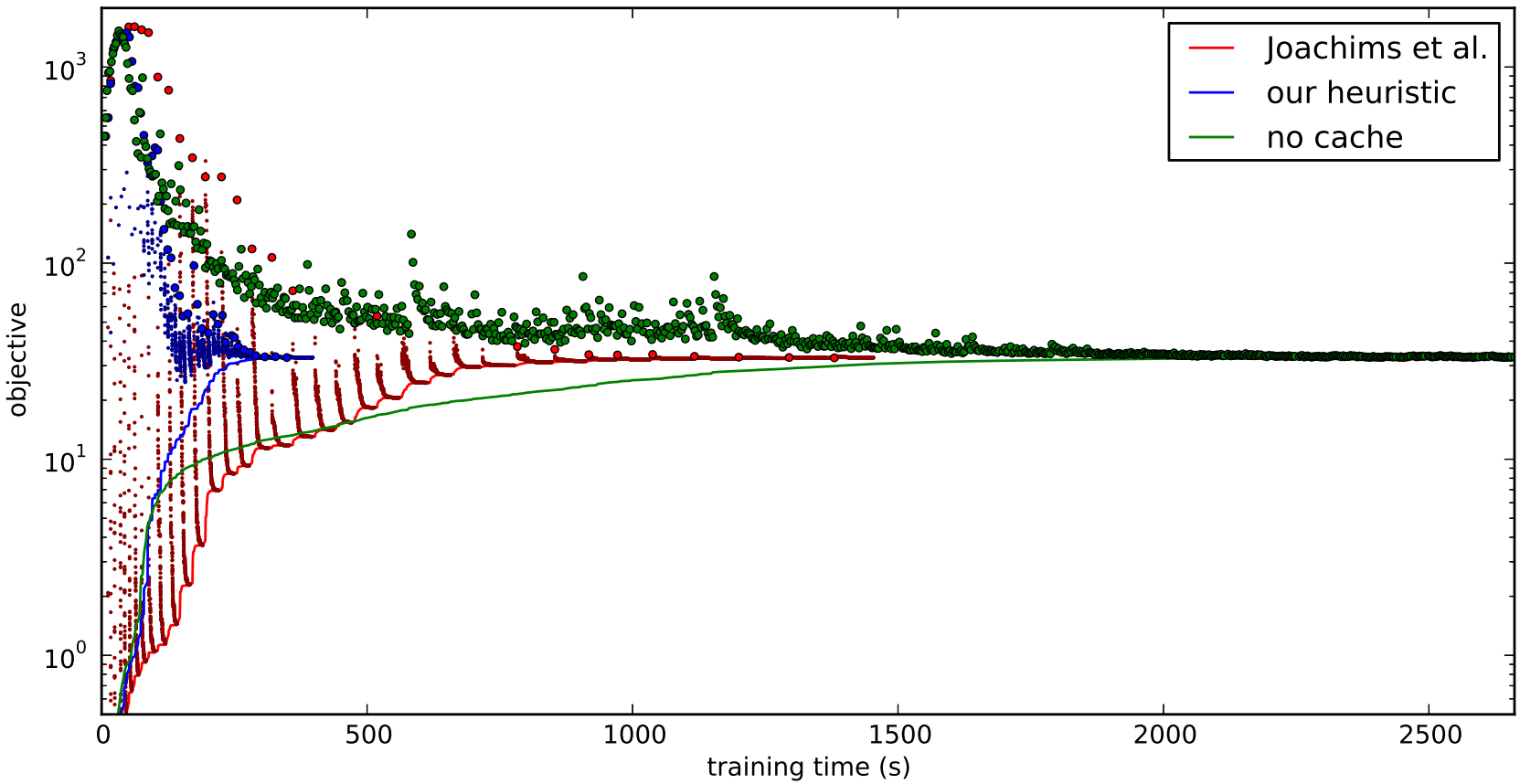
- Maximizing over y main bottleneck.
- Reusing (caching) of previous found maxima can speed up optimization.
- Natural trade-off between time spent on finding maximum (inference) and time spent on optimization.
- Novel heuristic

$$o^C - o^I < \frac{1}{2}(o^I - o_{\mathcal{W}})$$

where o^C is the cached primal, o^I primal using inference I and $o_{\mathcal{W}}$ the dual.

Caching Comparison



Combining Inference Algorithms

- Use fast inference in the beginning, use good inference at the end.

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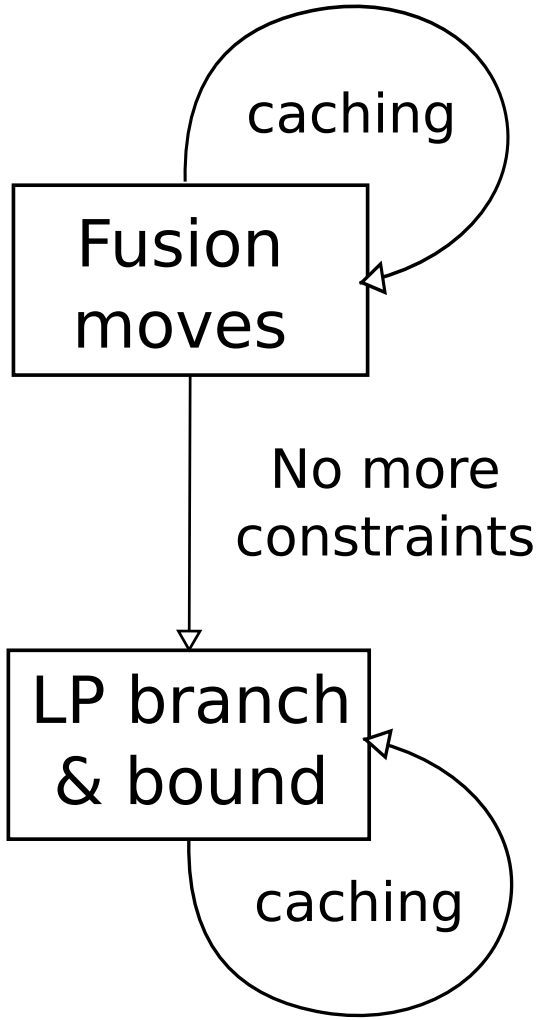
- Theoretically sound with cutting plane algorithm.

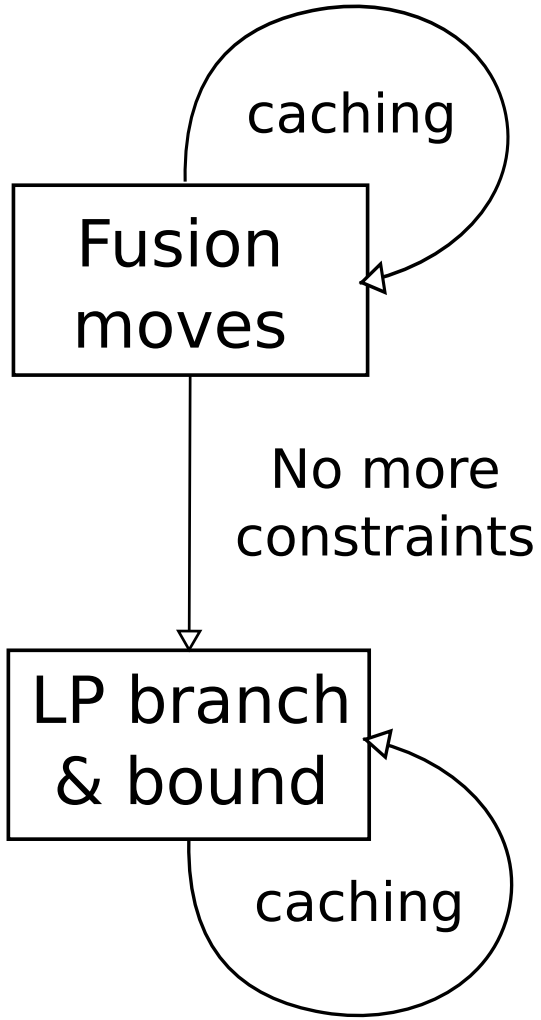
Combining Inference Algorithms

- Use fast inference in the beginning, use good inference at the end.
- Theoretically sound with cutting plane algorithm.
- Combine three procedures using efficient heuristic.

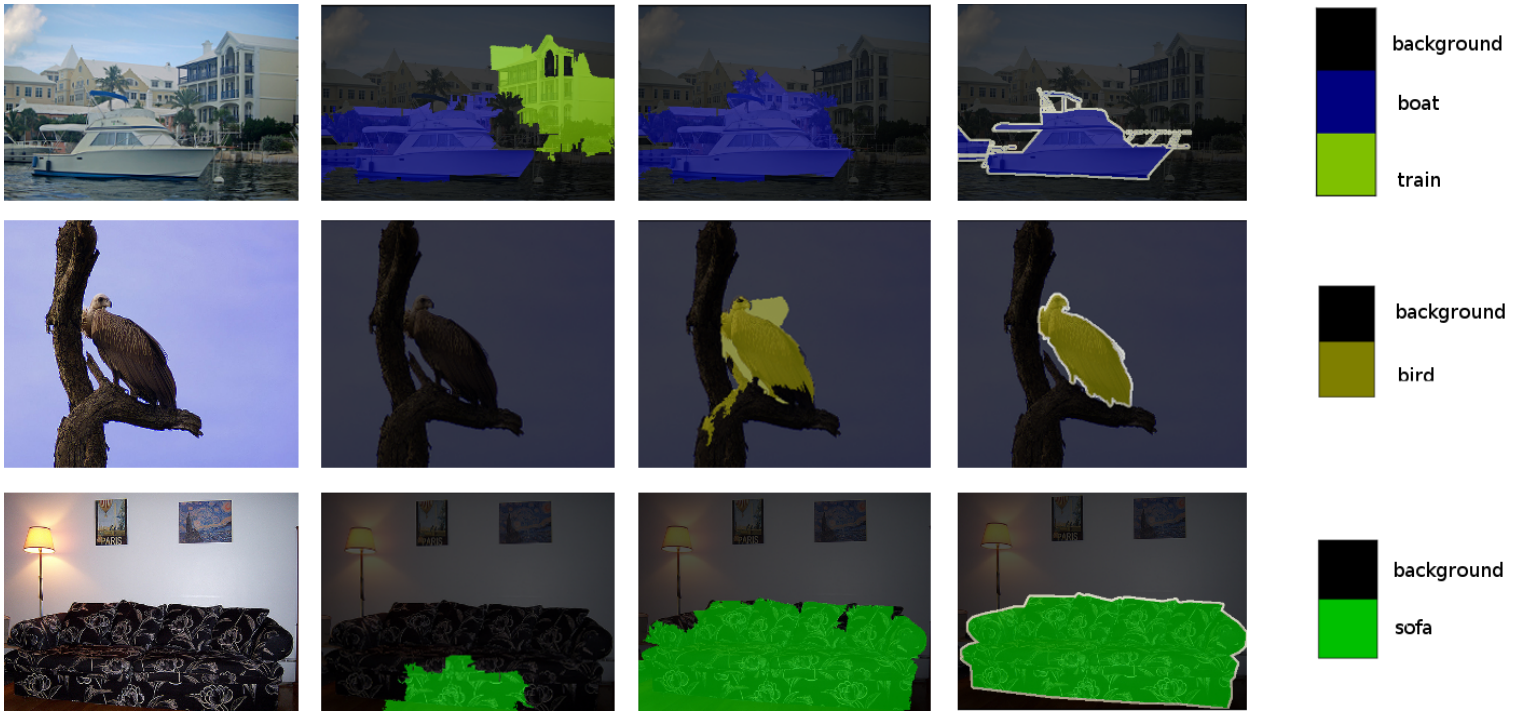


Combining Inference Algorithms

- Use fast inference in the beginning, use good inference at the end.
- Theoretically sound with cutting plane algorithm.
- Combine three procedures using efficient heuristic.
- Result: can learn exactly on two popular segmentation benchmarks!



Results on Pascal VOC2010 and MSRC-21



Pascal VOC 2010	Jaccard
Unary terms only	27.5
Pairwise model (move making)	30.2
Pairwise model (exact)	30.4
(author?) [2]	27.4
(author?) [5]	30.2
(author?) [6]	30.8

MSRC-21	Average	Global
Unary terms only	77.7	83.2
Pairwise model (move making)	79.6	84.6
Pairwise model (exact)	79.0	84.3
(author?) [7]	75.8	85.0
(author?) [3]	77	75
(author?) [8]	78.9	83.7

Summary

- We can learn some interesting loopy models exactly.
- Move-making was already very close.
- Exact learning is not necessarily slow (≈5 min).
- Makes learning more reproducible and simpler.

PyStruct

Simple structured prediction

Estimator = Learner + Model + Inference

Simple structured prediction

Estimator = Learner + Model + Inference

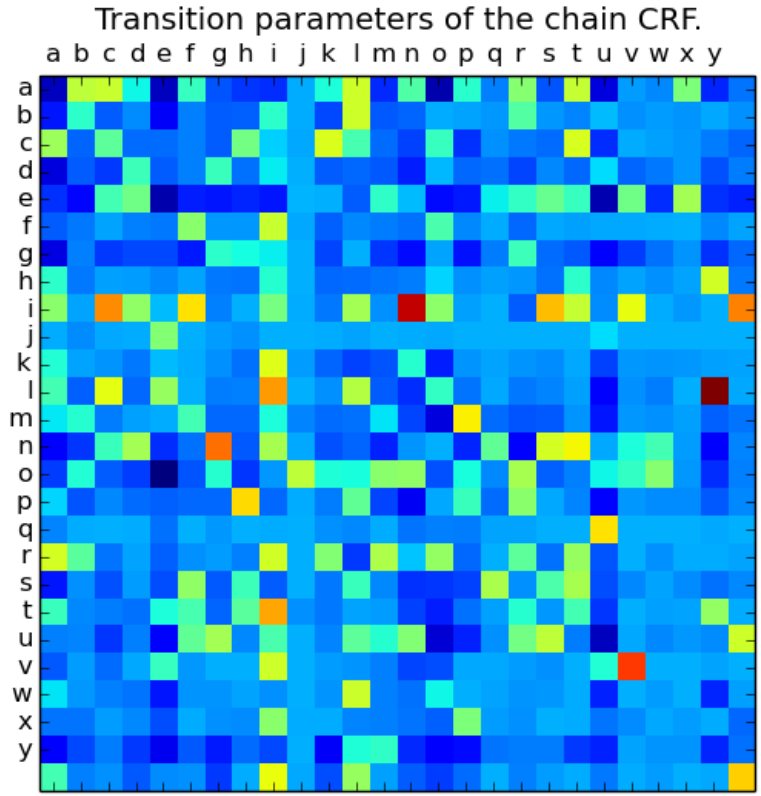
- Learner: SubgradientSSVM, StructuredPerceptron, OneSlackSSVM, LatentSSVM
- Model: BinaryClf, MultiLabelClf, ChainCRF, GraphCRF, EdgeFeatureGraphCRF
- Inference: Linear Programming, QPBO (PyQPBO), Dual Decomposition (AD3), Message Passing (OpenGM), Everything (OpenGM)

Example OCR

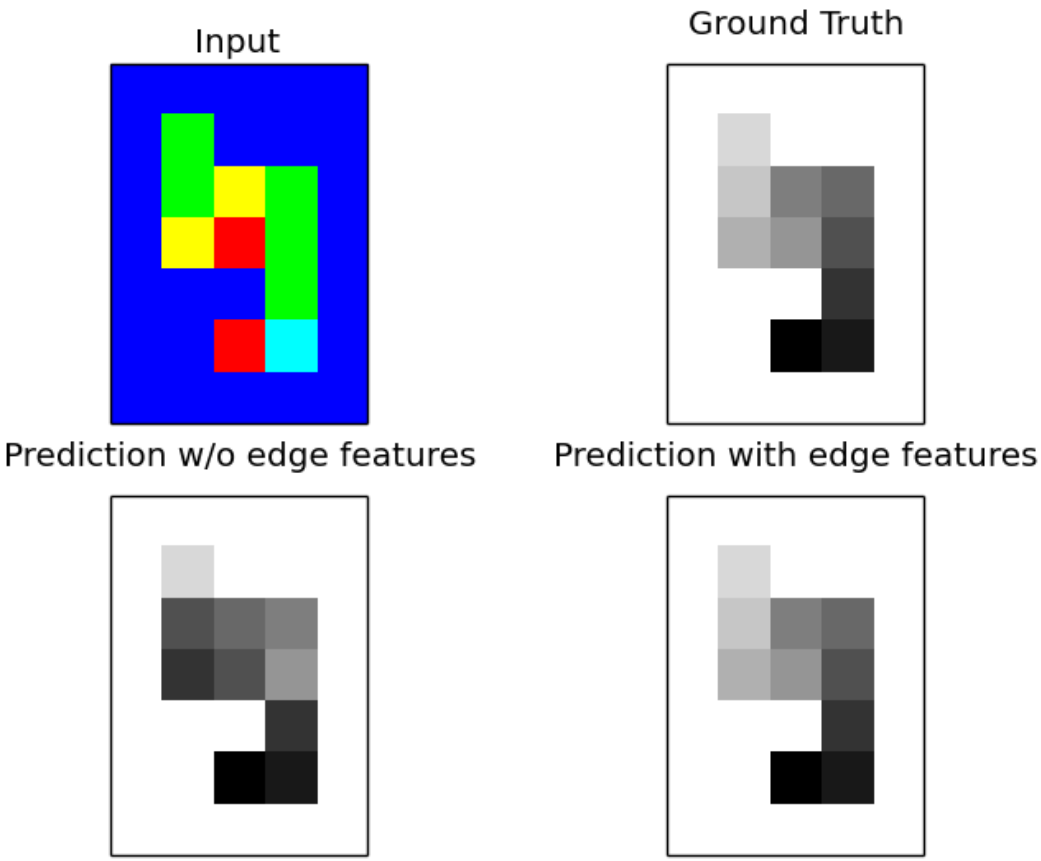
```
from pystruct.datasets import load_letters
from pystruct.models import ChainCRF
from pystruct.learners import OneSlackSSVM

abc = "abcdefghijklmnopqrstuvwxyz"

letters = load_letters()
X, y, folds = letters['data'], letters['labels'], letters['folds']
# we convert the lists to object arrays, as that makes slicing much more
# convenient
X, y = np.array(X), np.array(y)
X_train, X_test = X[folds == 1], X[folds != 1]
y_train, y_test = y[folds == 1], y[folds != 1]

# Train linear SVM
svm = LinearSVC(dual=False, C=.1)
# flatten input
svm.fit(np.vstack(X_train), np.hstack(y_train))

# Train linear chain CRF
model = ChainCRF()
ssvm = OneSlackSSVM(model=model, C=.1, inference_cache=50, tol=0.1, verbose=3)
ssvm.fit(X_train, y_train)
```

Example OCR


a f e t e r i a
a a f t a a f t m a r r i i a a
m b r a c e s
m m b b r r a a c c e e s s
p o i l f n g
p p a a i i c c i i m n d g
a f e t e r i a
a a f f o o d d o o l l z i n n

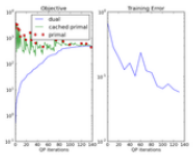

Transition parameters of the chain CRF.
a b c d e f g h i j k l m n o p q r s t u v w x y

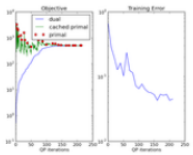
Example Snake

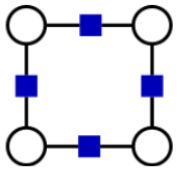


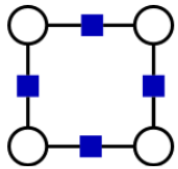
PyStruct | Introduction | Examples | References | Search

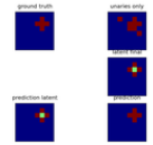
Examples

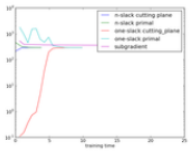

Plotting the objective and constraint caching in 1-slack SSVM

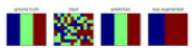

Efficient exact learning of 1-slack SSVMs

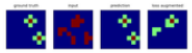

SVM as CRF


Semantic Image Segmentation on Pascal VOC

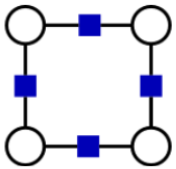

Latent Dynamics CRF


SVM objective values

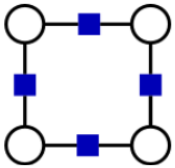

Learning directed interactions on a 2d grid


Learning interactions on a 2d grid

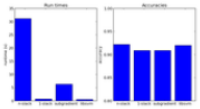

OCR Letter sequence recognition

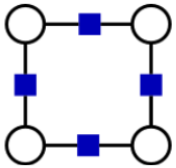

Crammer-Singer Multi-Class SVM


Latent SVM for odd vs. even digit classification


Mult-label classification


Latent Variable Hierarchical CRF


Binary SVM as SSVM


Comparing PyStruct and SVM-Struct

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http://pystruct.github.io

Summary of Contributions

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- Loss-based learning yields meaningful geometric relations in RGB-D data. State-of-the-art results on NYU V2 RGB-D dataset.

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- Loss-based learning yields meaningful geometric relations in RGB-D data. State-of-the-art results on NYU V2 RGB-D dataset.
- Show feasibility of exact learning for image segmentation, state-of-the-art results on MSRC-21, on par with comparable approaches on Pascal VOC 2010.

Summary of Contributions

- Loss-based learning yields meaningful geometric relations in RGB-D data. State-of-the-art results on NYU V2 RGB-D dataset.
- Show feasibility of exact learning for image segmentation, state-of-the-art results on MSRC-21, on par with comparable approaches on Pascal VOC 2010.
- Well tested, efficient software implementation for learning structured prediction. Already used by other researchers.

Future Directions

Future Directions

- More complex models for semantic segmentation.
- Integrate over time in NYU dataset.

Overview

- *PyStruct - Structured Prediction in Python*
  Andreas C. Müller and Sven Behnke. Journal of Machine Learning Research 2014.
- *Learning a Loopy Model for Semantic Segmentation Exactly*
  Andreas C. Müller and Sven Behnke. International Conference on Computer Vision Theory and Applications 2014.
- *Learning Depth-Sensitive Conditional Random Fields for Semantic Segmentation*
  Andreas C. Müller and Sven Behnke. International Conference on Robotics and Automation 2014.

Additional Slides Exact Learning

n-Slack Cutting Plane Training of Structural SVMs

Require: training samples $\{(x^1, y^1), \ldots, (x^k, y^k)\}$, regularization parameter C, stopping tolerance ϵ.

Ensure: parameters θ, slack $(\xi_1, \ldots, \xi_k)$

1: $\mathcal{W}_i \leftarrow \emptyset, \xi_i \leftarrow 0$ for $i = 1, \ldots, k$

2: **repeat**

3: **for** i=1, . . . , k **do**

4: $\hat{y} \leftarrow I(x^i, y^i, \theta) := \arg\max_{\hat{y} \in \mathcal{Y}} \delta(y^i, \hat{y}) - \theta^T [\Phi(x^i, y^i) - \Phi(x^i, \hat{y})]$

5: **if** $\delta(y^i, \hat{y}) - \theta^T [\Phi(x^i, y^i) - \Phi(x^i, \hat{y})] \geq \xi_i + \epsilon$ **then**

6: $\mathcal{W}_i \leftarrow \mathcal{W}_i \cup \{\hat{y}\}$

7:

$$(\theta, \xi_1, \ldots, \xi_k) \leftarrow \arg\min_{\theta, \xi_1, \ldots, \xi_k} \frac{\|\theta\|^2}{2} + C \sum_{i=1}^{k} \xi_i$$

s.t. for $i = 1, \ldots, k$ $\forall \hat{y} \in \mathcal{W}_i$:

$$\theta^T [\Phi(x^i, y^i) - \Phi(x^i, \hat{y}^i)] \geq \delta(y^i, \hat{y}^i) - \xi_i$$

8: **until** no $\mathcal{W}_i$ changes anymore.

1-Slack Cutting Plane Training of Structural SVMs

Require: training samples $\{(x^i, y^i), \ldots, (x^i, y^i)\}$, regularization parameter C, stopping tolerance ϵ.

Ensure: parameters θ, slack ξ

$\mathcal{W} \leftarrow \emptyset$

repeat

$$(\theta, \xi) \leftarrow \arg\min_{\theta,\xi} \frac{\|\theta\|}{2}^2 + C\xi$$

$$\text{s.t. } \forall \hat{\mathbf{y}} = (\hat{y}^1, \ldots, \hat{y}^k) \in \mathcal{W} :$$

$$\theta^T \sum_{i=1}^{k} [\Phi(x^i, y^i) - \Phi(x^i, \hat{y}^i)] \geq \sum_{i=1}^{k} \delta(y^i, \hat{y}^i) - \xi$$

for i=1, . . . , k **do**

$\hat{y}^i \leftarrow I(x^i, y^i, \theta) := \arg\max_{\hat{y} \in \mathcal{Y}} \sum_{i=1}^{k} \delta(y^i, \hat{y}) - \theta^T \sum_{i=1}^{k} [\Phi(x^i, y^i) - \Phi(x^i, \hat{y})]$

$\mathcal{W} \leftarrow \mathcal{W} \cup \{(\hat{y}^i, \ldots, \hat{y}^i)\}$

$\xi' \leftarrow \sum_{i=1}^{k} \delta(y^i, \hat{y}^i) - \theta^T \sum_{i=1}^{k} [\Phi(x^i, y^i) - \Phi(x^i, \hat{y}^i)]$

until $\xi' - \xi < \epsilon$

Block-Coordinate Frank-Wolfe Algorithm

Require: training samples $\{(x^i, y^i), \ldots, (x^i, y^i)\}$, regularization parameter C, stopping tolerance ϵ.

Ensure: parameters θ

$\theta_0, \theta_0^i, \bar{\theta}_0 \leftarrow \mathbf{0}, \quad \ell_0, \ell_0^i, t \leftarrow 0$

repeat

$t \leftarrow t + 1$

Pick i uniformly at random from $\{1, \ldots, k\}$.

Perform loss-augmented prediction on sample i:

$$\hat{y} \leftarrow I(x^i, y^i, \theta) := \arg\max_{\hat{y} \in \mathcal{Y}} \Delta(y^i, \hat{y}) - \theta^T [\Phi(x^i, y^i) - \Phi(x^i, \hat{y})]$$

Compute parameter and loss updates based on sample i:

$$\theta_s \leftarrow \frac{C}{n} \Phi(x, \hat{y})$$
$$\ell_s \leftarrow \frac{C}{n} \delta(y^i, \hat{y})$$

Compute optimum step size η:

$$\eta \leftarrow \frac{(\theta_t^i - \theta_s)^T \theta_t + C(\ell_s - \ell_k^i)}{\|\theta_t^i - \theta_s\|^2} \text{ and clip to } [0, 1]$$

Update per-sample parameters and loss estimate:

$$\theta_{t+1}^i \leftarrow (1 - \eta)\theta_{t+1}^i + \eta\theta_s$$
$$\ell_{t+1}^i \leftarrow (1 - \eta)\theta_{t+1}^i + \eta\ell_s$$

Update global parameters and loss estimate:

$$\theta_{t+1} \leftarrow \theta_{t+1} + \theta_t^i - \theta_{t+1}^i$$
$$\ell_{t+1} \leftarrow \ell_{t+1} + \ell_t^i - \ell_{t+1}^i$$

Compute the weighted running average:

$$\bar{\theta}_{t+1} = \frac{k}{k+2} \bar{\theta}_k + \frac{2}{k+2} \theta_{k+1}$$

until $(\theta - \theta_s)^T \theta - \ell + \ell_s \leq \epsilon$

where θ_s and ℓ_s are recomputed over the whole dataset.