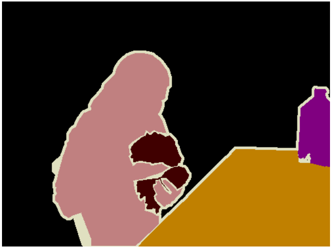
Structured Prediction and PyStruct

Andreas Müller

April 10, 2018

Semantic Segmentation

Semantic Segmentation



Learning Structured Prediction for Semantic Segmentation

Semantic Segmentation as Structured Prediction

Semantic Segmentation as Structured Prediction

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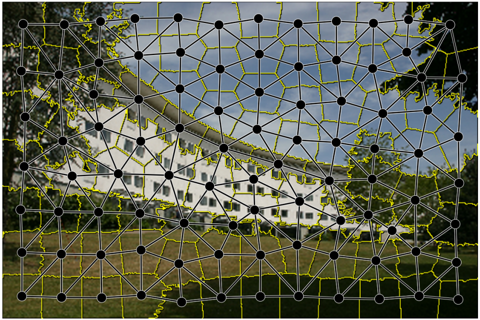
Semantic Segmentation as Structured Prediction



Structured Prediction

Learn prediction function of the form

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

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Objective

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

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

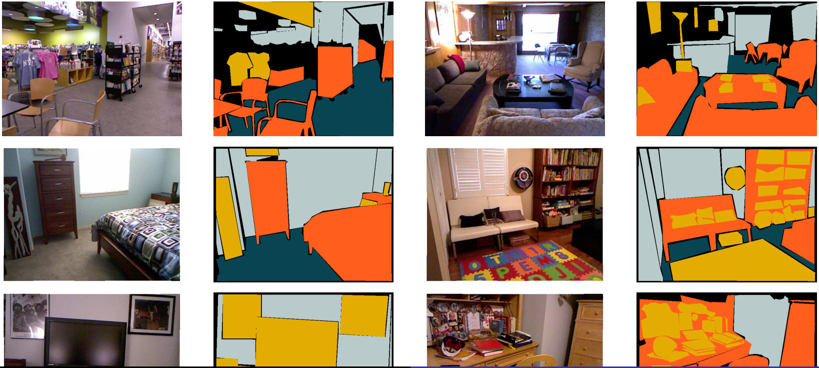
?

Pairwise Models

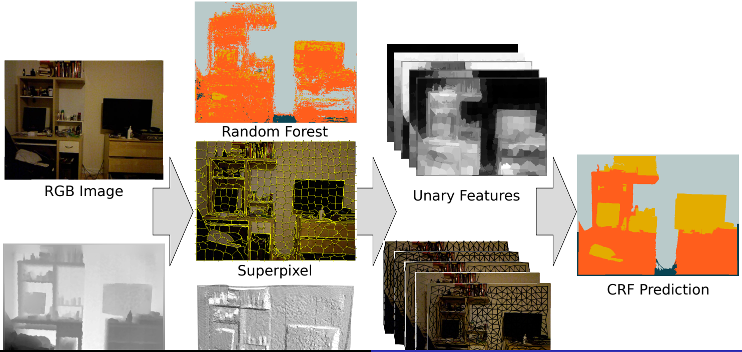
$$w^T \psi(x, y) = \sum_{(i,j) \in E} w_{i,j} \psi_{i,j}(x, y_i, y_j) + \sum_{i \in I} w_i \psi_i(x, y_i)$$

Learning Depth-Sensitive Conditional Random Fields

Dataset: NYUv2



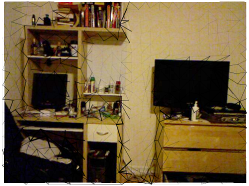
Overview


Random Forest
RGB Image
Superpixel
Unary Features
CRF Prediction

Pairwise Features

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

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



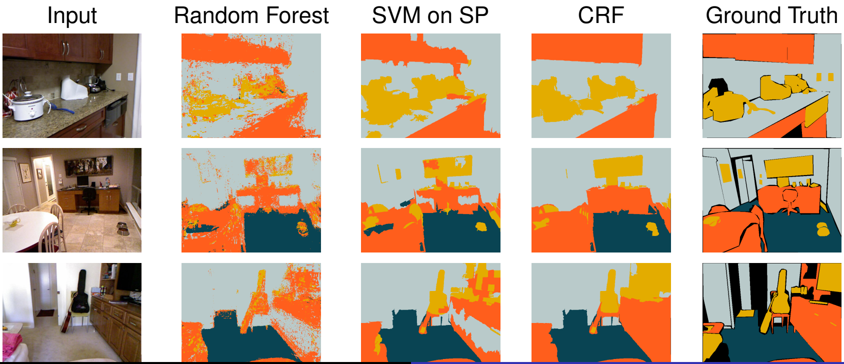
$$f_{\text{direction}}(x_i, x_j) = \sphericalangle(\text{pos}_{x_i} - \text{pos}_{x_j}, [0, 1]^T)$$

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

Learning and Optimization

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

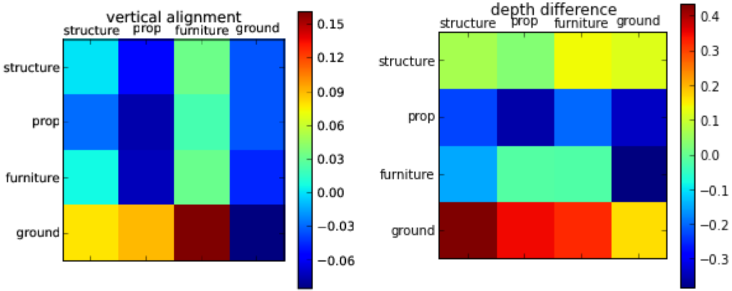
Qualitative Results



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**
?	68	59	70	42	59.6	58.6
?	87.3	**86.1**	45.3	35.5	63.5	64.5
?†	**95.6**	83.0	**75.1**	14.2	67.0	70.9

Learned Potentials



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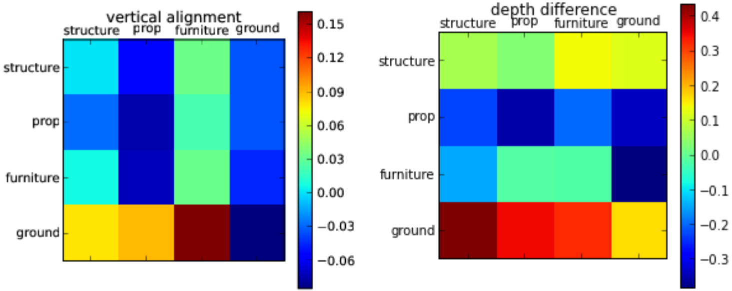


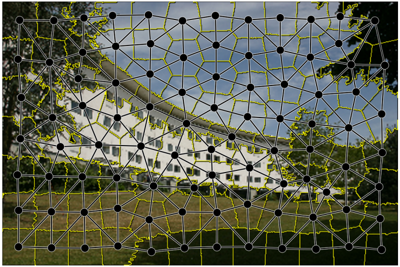
- Ground is at bottom

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

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

- Maximizing over y main bottleneck.

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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

Caching Comparison

Combining Inference Algorithms

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

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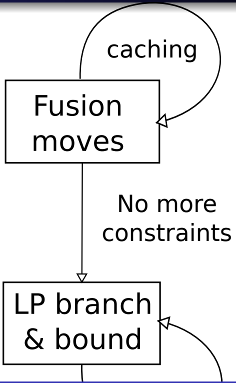
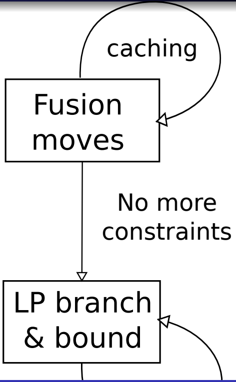
- Combine three procedures using efficient heuristic.

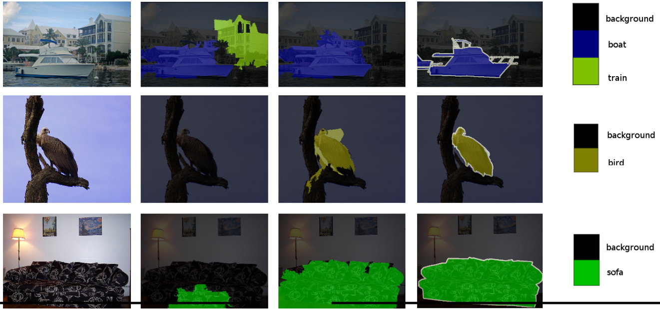


Combining Inference Algorithms

- 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

MSRC-21	Average	Global

Summary

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

Weakly Supervised Object Class Segmentation

Motivation

Motivation

Setup

Person

Car

Setup

Person

Car

Object Class Segmentation as MIL

Results

car1_img.png car1_gt.png car1_pos.png

person1_img.png person1_gt.png person1_pos.png

ITM Clustering

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Information Theoretic Approach

- $(x_i, y_i) \sim p(X, Y),\ X \in \mathbb{R}^d, Y \in \{1, \ldots, k\}$

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- $(x_i, y_i) \sim p(X, Y), \; X \in \mathbb{R}^d, Y \in \{1, \ldots, k\}$
- Maximize mutual information:

$$I(X, Y) = D_{\mathrm{KL}}\big(p(X, Y) \,\|\, p(X)p(Y)\big)$$

$$= H(X) - \sum_{y=1}^{k} p(Y = y) H(X \mid Y = y)$$

Optimization Problem

$$\hat{l}(\mathbf{x}, \mathbf{y}) = -d \sum_{y=0}^{k} p(y) \log(\bar{L}_y) - \sum_{y=0}^{k} p(y) \log p(y) + C$$

- Minimum spanning tree based entropy estimate of **?**

Optimization Problem

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- Maximize approximately by searching over subforests of Euclidean MST.

Qualitative Results

K-Means MeanNN Agglomerative ITM

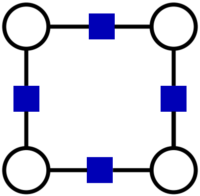
Summary

- Formulate clustering as maximizing mutual information of data and cluster indicators.
- Use non-parametric entropy estimate based on data MST.
- Efficient appoximate optimization using dynamic programming.
- Good empirical results, no parameters to tune.

PyStruct - Structured Prediction in Python

PyStruct - Simple Structured Prediction

- Implements common and state-of-the-art structural solvers (optimizing for w).



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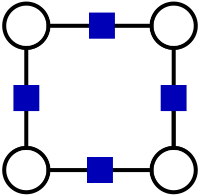

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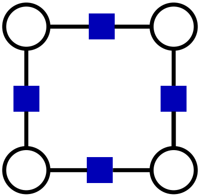

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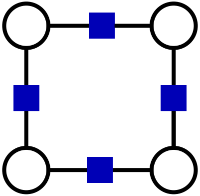
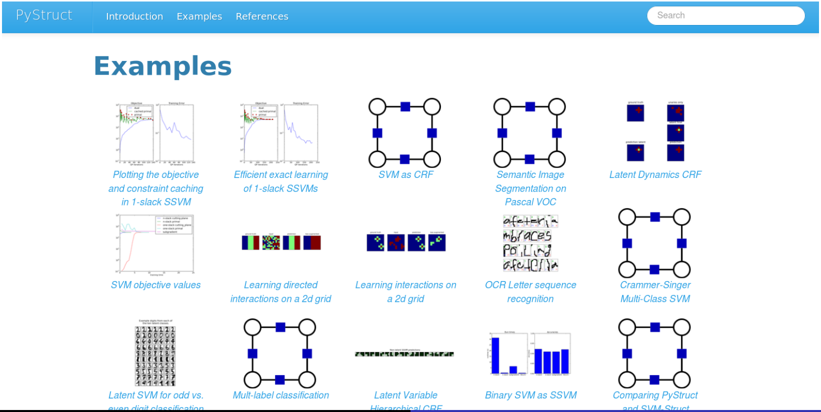
- Implements common and state-of-the-art structural solvers (optimizing for w).
- Implements powerful models for many use cases.
- Interface to popular inference libraries: LibDAI, OpenGM, QPBO, AD3.
- Well docmented, includes common




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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Future Directions

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- More complex models for semantic segmentation.
- Integrate over time in NYU dataset.
- ITM for superpixels.
- Large scale weakly supervised segmentation.

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.
- *Multi-Instance Methods for Partially Supervised Image Segmentation*
  Andreas C. Müller and Sven Behnke. IARP Workshop on Partially Supervised Learning 2011.
- *Information Theoretic Clustering using Minimum Spanning Trees*
  Andreas C. Müller, Sebastian Nowozin and Christoph H. Lampert. German Conference on Pattern Recognition 2012.

Additional Slides Exact Learning

n-Slack Cutting Plane Training of Structural SVMs

2 [1] training samples $\{(x^1, y^1), \dots, (x^k, y^k)\}$, regularization parameter C, stopping tolerance ϵ. parameters θ, slack $(\xi_1, \dots, \xi_k)$ $\mathcal{W}_i \leftarrow \emptyset, \xi_i \leftarrow 0$ for $i = 1, \dots, k$ i=1, …, k $\hat{y} \leftarrow I(x^i, y^i, \theta) := \underset{\hat{y} \in \mathcal{Y}}{\arg\max}\, \delta(y^i, \hat{y}) - \theta^T[\Phi(x^i, y^i) - \Phi(x^i, \hat{y})]$

$\delta(y^i, \hat{y}) - \theta^T[\Phi(x^i, y^i) - \Phi(x^i, \hat{y})] \geq \xi_i + \epsilon$ $\mathcal{W}_i \leftarrow \mathcal{W}_i \cup \{\hat{y}\}$

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

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

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

no $\mathcal{W}_i$ changes anymore.

1-Slack Cutting Plane Training of Structural SVMs

2 [1] training samples $\{(x^i, y^i), \dots, (x^i, y^i)\}$, regularization parameter C, stopping tolerance ϵ. parameters θ, slack ξ
$\mathcal{W} \leftarrow \emptyset$

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

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

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

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

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

Block-Coordinate Frank-Wolfe Algorithm

1.4 [1] training samples $\{(x^i, y^i), \dots, (x^i, y^i)\}$, regularization parameter C, stopping tolerance ϵ. parameters θ $\theta_0, \theta_0^i, \bar{\theta}_0 \leftarrow \mathbf{0}, \quad \ell_0, \ell_0^i, t \leftarrow 0$ $t \leftarrow t+1$ Pick i uniformly at random from $\{1, \dots, k\}$. 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: $\eta \leftarrow \frac{(\theta_t^i - \theta_s)^T \theta_t + C(\ell_s - \ell_k^i)}{\|\theta_t^i - \theta_s\|^2}$ 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: $\bar{\theta}_{t+1} = \frac{k}{k+2}\bar{\theta}_k + \frac{2}{k+2}\theta_{k+1}$ $(\theta - \theta_s)^T\theta - \ell + \ell_s \leq \epsilon$ where θ_s and ℓ_s are recomputed over the whole dataset.

Motivation

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

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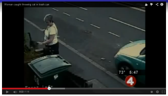
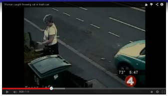
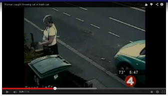
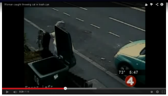
News Story1	1	0	0	1	1
News Story2	0	1	0	1	0
News Story3	0	0	1	0	0

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

Sequence Tagging

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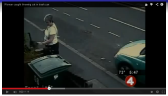
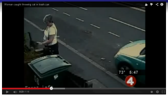


Stroke cat.



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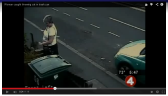
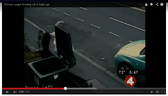


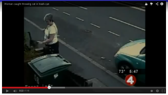
Stroke cat.

Open trash can.



Put cat in trash can.

Sequence Tagging



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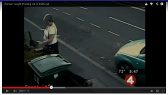

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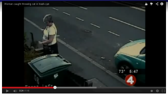

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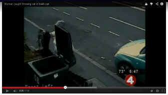
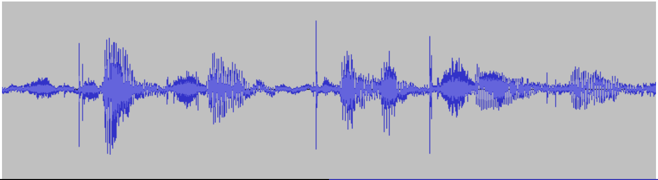
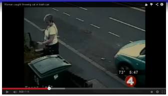


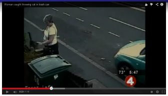
Put cat in trash can.



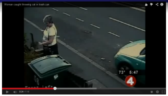
Sequence Tagging



Stroke cat.

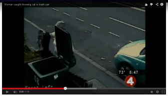


Stroke cat.

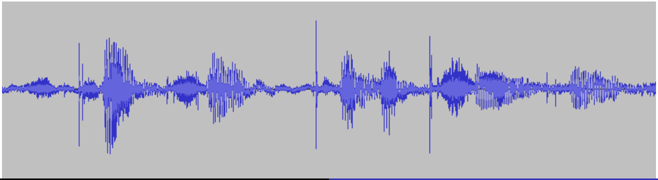


Stroke cat.

Open trash can.



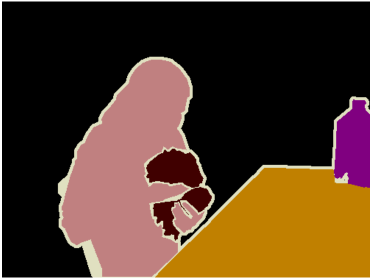
Put cat in trash can.



Predicting Parse Trees

Semantic Images Segmentation

Semantic Images Segmentation



Predicting Structured Objects

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

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

Inference and Factor Graphs

Predicting discrete vectors

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

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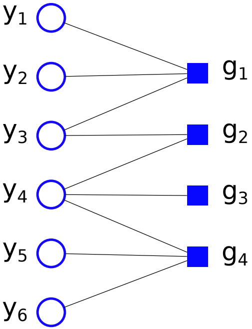
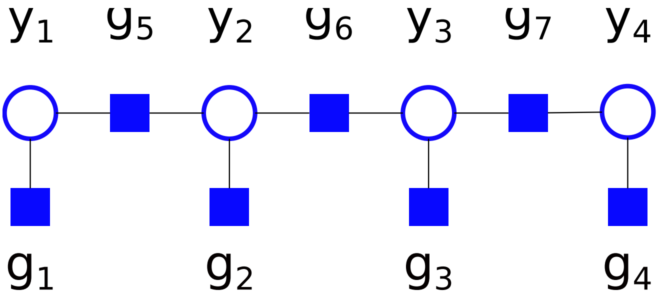
$$\begin{aligned} f(x, w) &= \arg\max_{y \in \mathcal{Y}} w^T \psi(x, y) \\ &= \arg\max_{y_1, y_2, \dots, y_{n_i}} w^T \psi(x, y) \end{aligned}$$

Factor Graphs

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

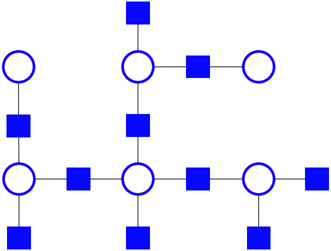


Factor Graph for HMM

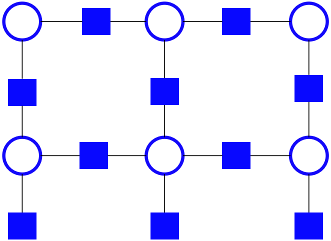


Inference

Easy



Tricky



Learning

Probabilistic Learning

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

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

Probabilistic Learning

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

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Objective

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

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

Max-Margin Learning

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

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

PyStruct

Simple structured prediction

Estimator = Learner + Model + Inference

Simple structured prediction

Estimator = Learner + Model + Inference

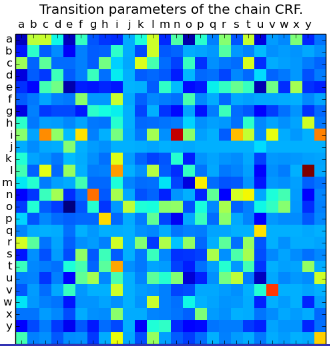
- Learner: SubgradientSSVM, StructuredPerceptron, OneSlackSSVM, LatentSSVM
- Model: BinaryClf, MultiLabelClf, ChainCRF, GraphCRF, EdgeFeatureGraphCRF
- Inference: Linear Programming, QPBO (PyQPBO), Dual Decomposition (AD3), Message Passing (OpenGM), Everything (OpenGM)

Example OCR

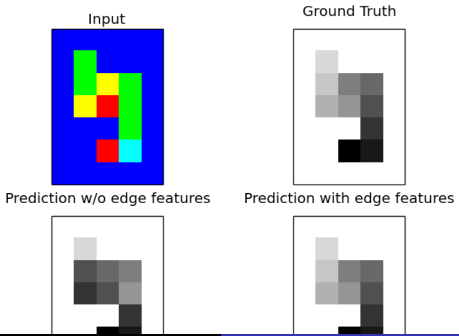
```
from pystruct.datasets import load_letters
from pystruct.models import ChainCRF
from pystruct.learners import OneSlackSSVM

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()
```

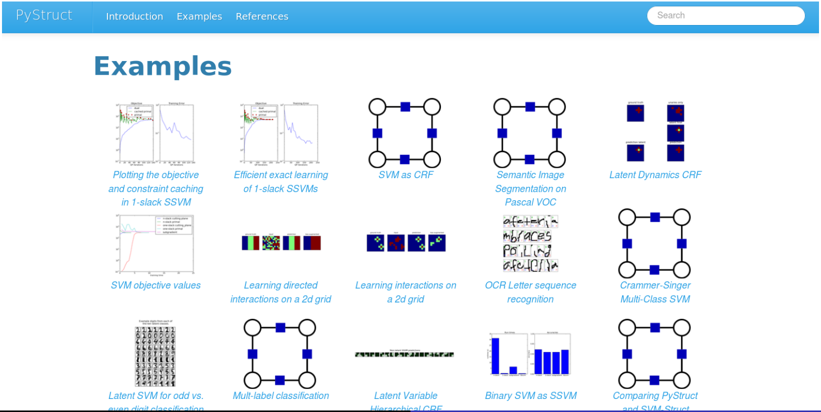
Example OCR


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 i 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
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.
Mult-label classification
Latent Variable
Binary SVM as SSVM
Comparing PyStruct