

# Structured Prediction and PyStruct

Andreas Müller

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# Motivation

# Multi-Label Classification

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|             | 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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# 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



# Sequence Tagging



Stroke cat.



Stroke cat.



Stroke cat.



Open trash can.



Put cat in trash can.

# Sequence Tagging



Stroke cat.



Stroke cat.



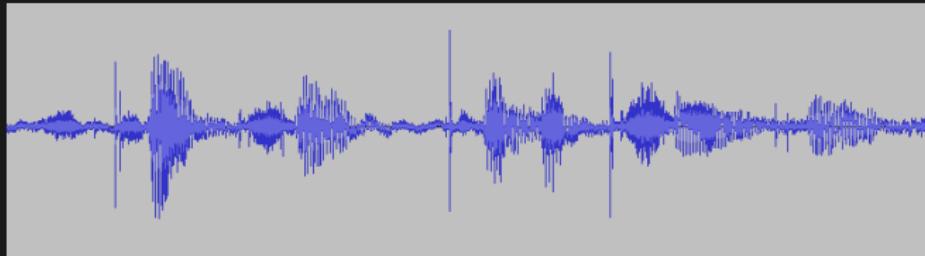
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# Sequence Tagging



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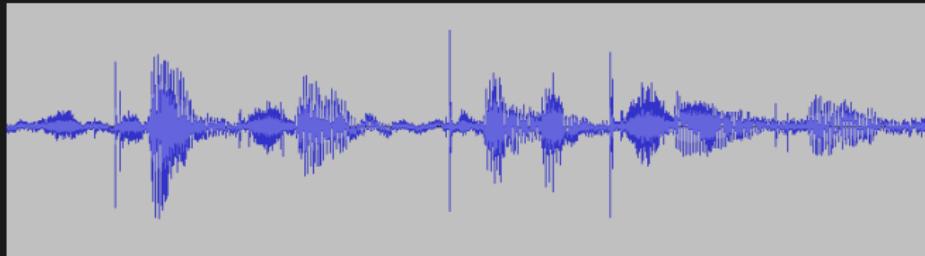
Stroke cat.



Open trash can.

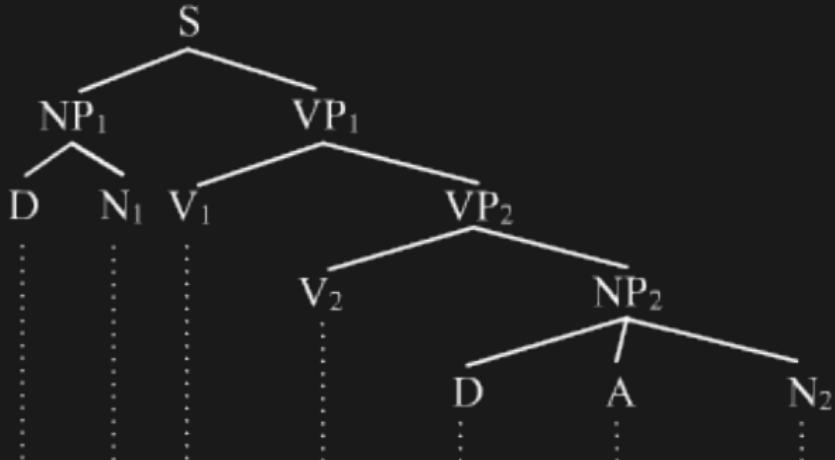


Put cat in trash can.



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

# Predicting Parse Trees



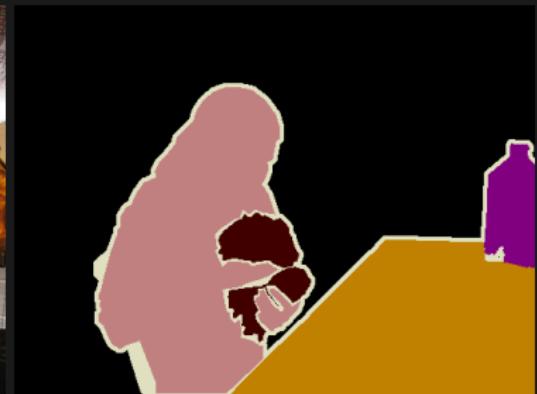
This tree is illustrating the constituency relation.

Constituency relation (PSG)

# Semantic Images Segmentation



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# Predicting Structured Objects

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

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$$\arg \max_{y \in \mathcal{Y}} p(y|x, w)$$

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

# Inference and Factor Graphs

# Predicting discrete vectors

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

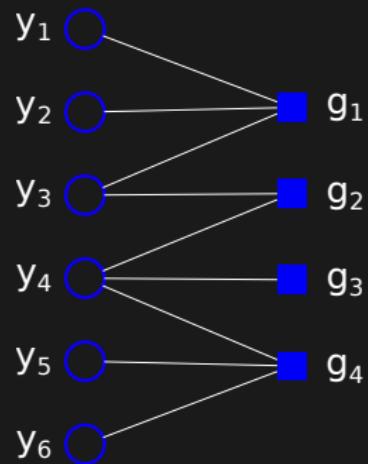
# Predicting discrete vectors

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

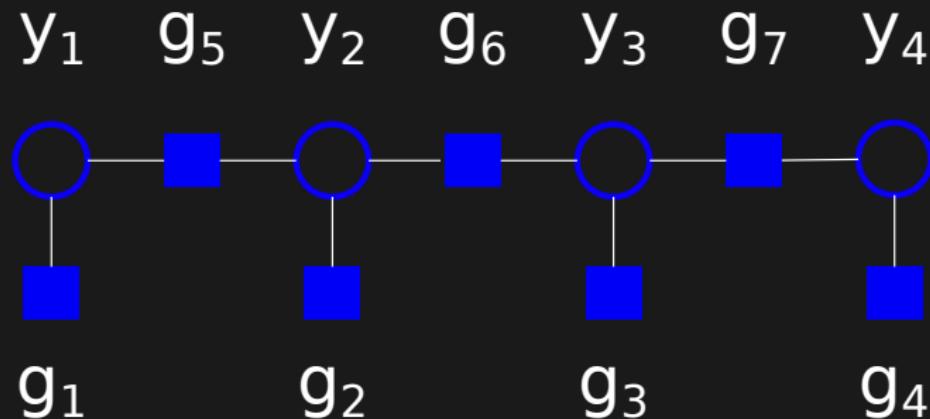
$$\begin{aligned} f(x, w) &= \arg \max_{y \in \mathcal{Y}} w^T \psi(x, y) \\ &= \arg \max_{y_1, y_2, \dots, y_{n_i}} w^T \psi(x, y) \end{aligned}$$

# Factor Graphs

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

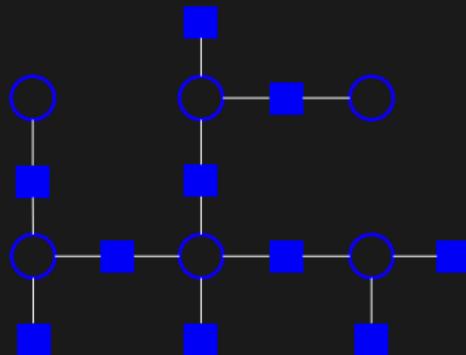


# Factor Graph for HMM

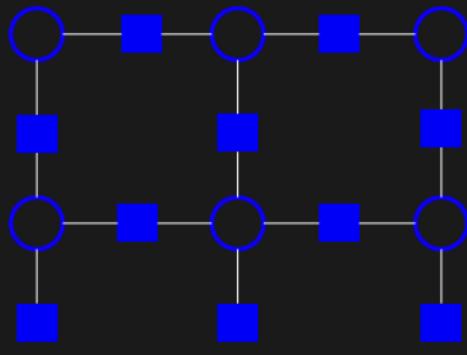


# Inference

Easy



Tricky



# Learning

# Probabilistic Learning

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

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

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Objective

$$\begin{aligned} & \max_w \sum_i \log(p(y^i|x^i, w)) \\ &= \max_w \sum_i w^T \psi(x^i, y^i) - \log(Z) \end{aligned}$$

# 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

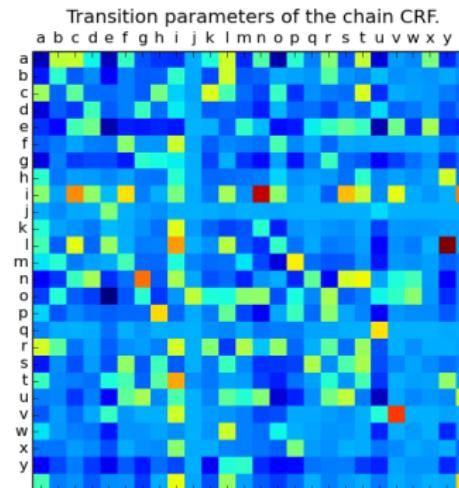
abc = "abcdefghijklmnopqrstuvwxyz"

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]

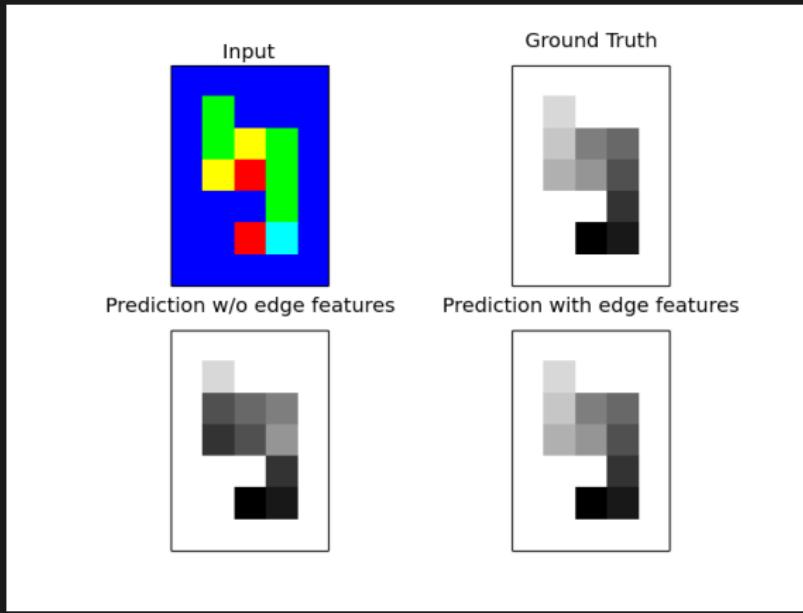
# Train linear SVM
svm = LinearSVC(dual=False, C=.1)
# flatten input
svm.fit(np.vstack(X_train), np.hstack(y_train))

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

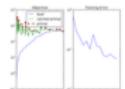
# Example OCR



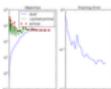
# Example Snake



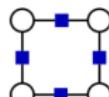
## Examples



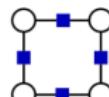
Plotting the objective and constraint caching in 1-slab SSVM



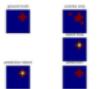
Efficient exact learning of 1-slab SSVMs



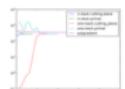
SVM as CRF



Semantic Image Segmentation on Pascal VOC



Latent Dynamics CRF



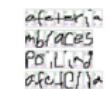
SVM objective values



Learning directed interactions on a 2d grid



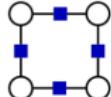
Learning interactions on a 2d grid



OCR Letter sequence recognition



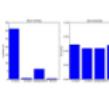
Latent SVM for odd vs. even digit classification



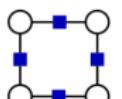
Mult-label classification



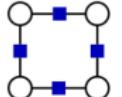
Latent Variable Hierarchical CRF



Binary SVM as SSVM



Crammer-Singer Multi-Class SVM



Comparing PyStruct and SVM-Struct