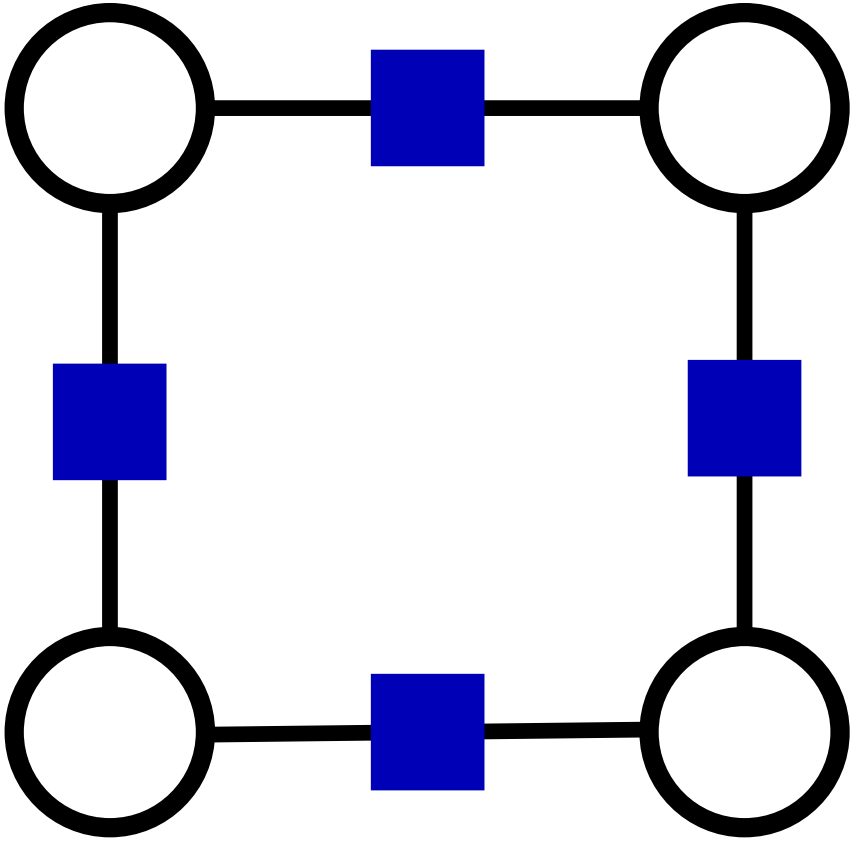
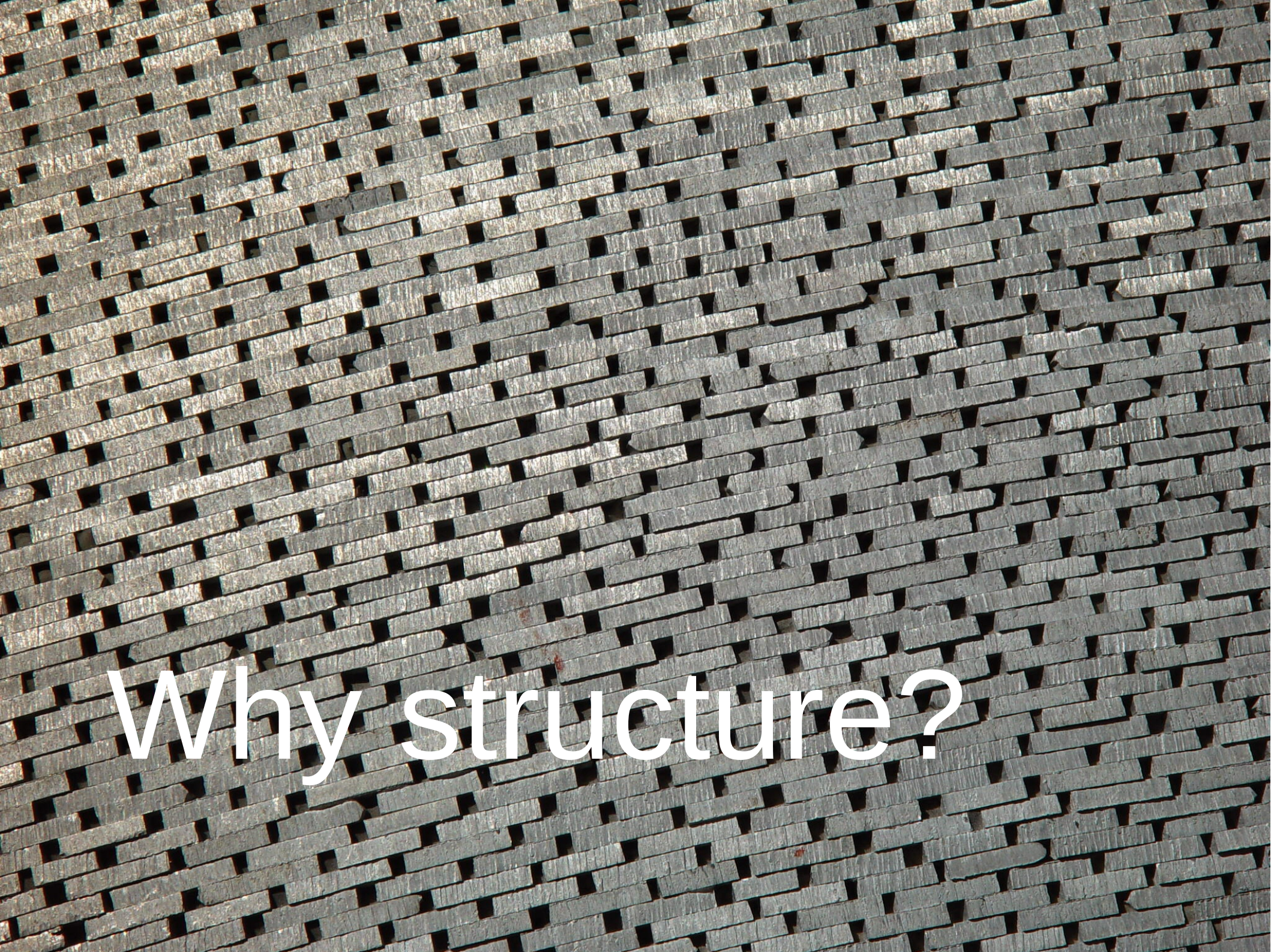


PyStruct
Structured Prediction in Python

Andreas Mueller (NYU Center for Data Science, scikit-learn)

Structured Prediction

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


Why structure?

Applications: 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

Applications: 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

Applications: Sequence Tagging

Applications: Sequence Tagging

Stroke cat.

Stroke cat.

Stroke cat.

Open trash can.

Put cat in trash can.

Applications: Image Segmentation


CAUTION: MATH

The Essence of Structured Prediction

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

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

If you like:

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

Pairwise Structured Models

$$\underset{y_1,y_2,\ldots,y_n}{\arg\max}\ w^T\psi(x,y)$$

$$= \underset{y_1,y_2,\ldots,y_n}{\arg\max} \sum_I w_i^T\psi(x,y_i) + \sum_{(i,j)\in E} w_{i,j}^T\psi(x,y_i,y_j)$$

Pairwise Structured Models

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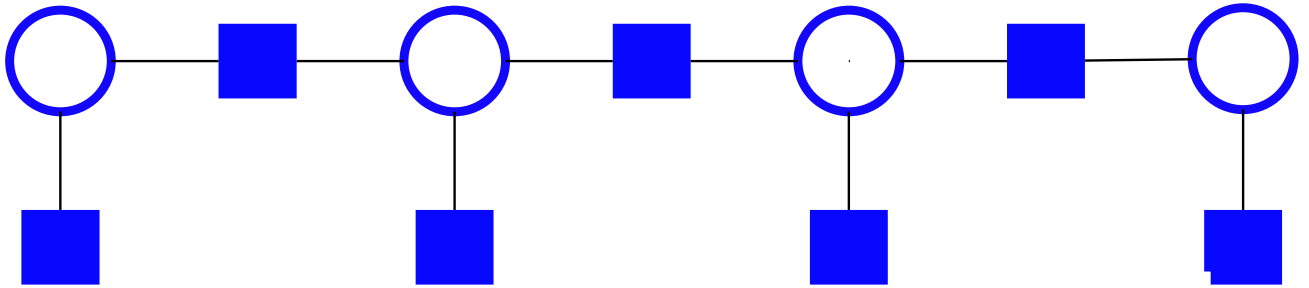

PyStruct Architecture

Estimator = Learner + Model + Inference

$$\underset{y_1,y_2,\ldots,y_n}{\arg\max}\ w^T\psi(x,y)$$

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```
model = ChainCRF(inference="max_product")
ssvm = OneSlackSSVM(model=model, C=.1, inference_cache=50,,
                    tol=0.1, verbose=3)
ssvm.fit(X_train, y_train)
```

Implemented Methods

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, everything (OpenGM)

Sequence Tagging example


```
model = ChainCRF(inference="max_product")
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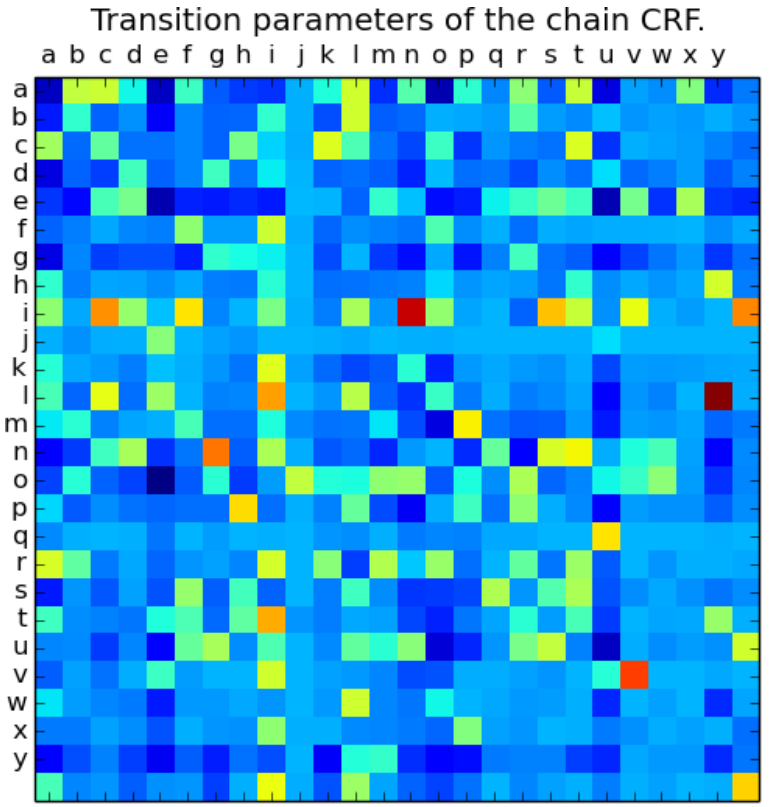
Sequence Tagging example

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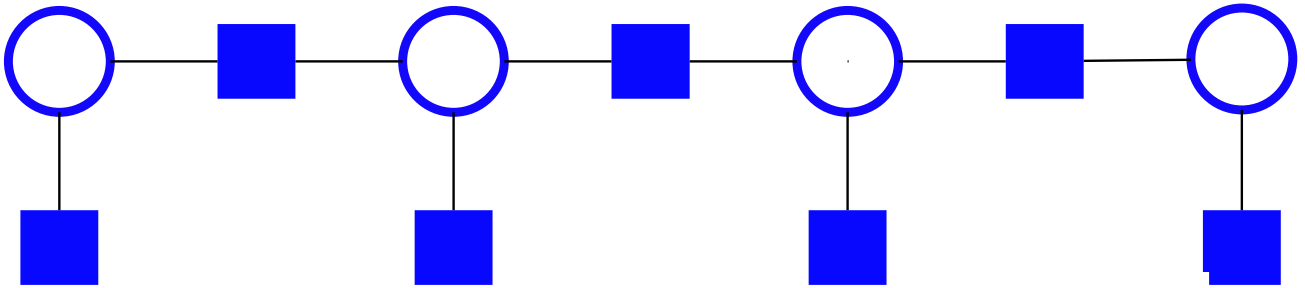
The Devil is in the Inference

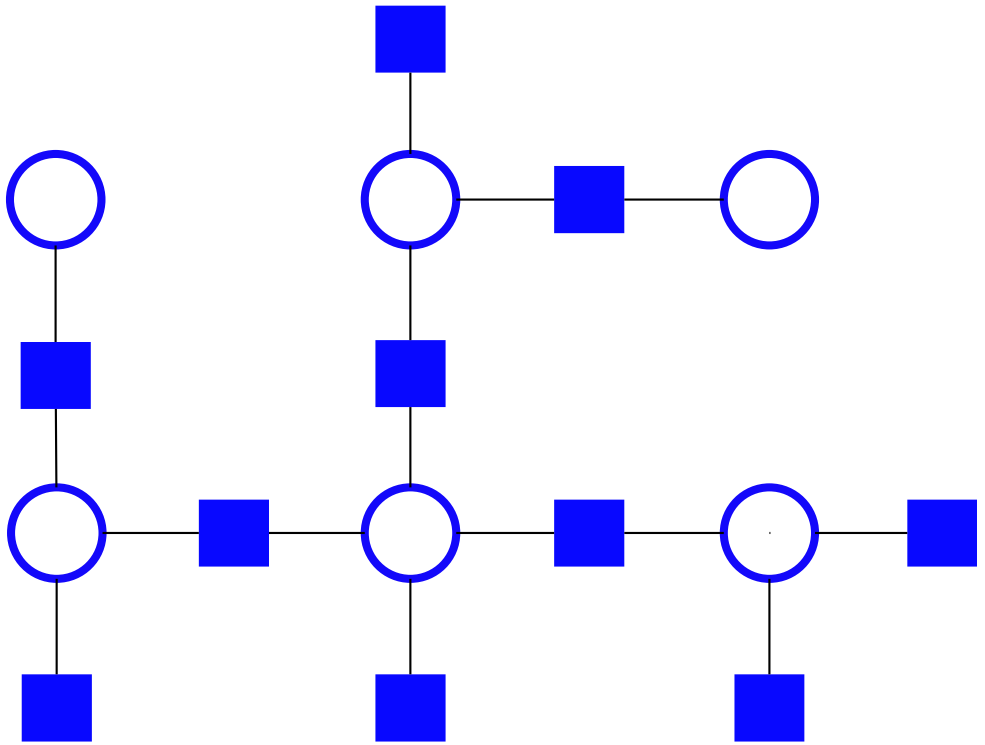
$$\underset{y_1,y_2,\ldots,y_n}{\arg\max}\ w^T\psi(x,y)$$



Easy: Dynamic Programming

The Devil is in the Inference

$$\underset{y_1,y_2,\ldots,y_n}{\arg\max}\; w^T \psi(x, y)$$



Easy: Dynamic Programming

The Devil is in the Inference

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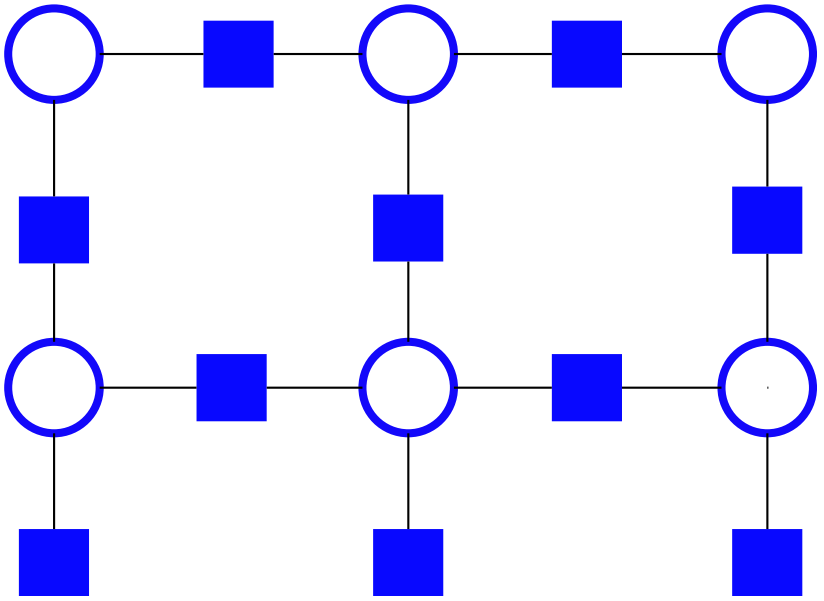
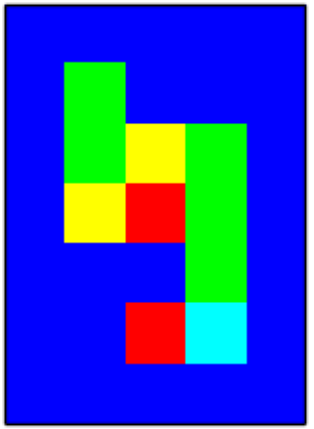


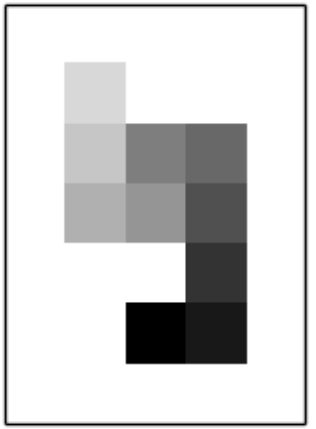
HARD!
AD3, QPBO, LP, Loopy BP, ….

Grid Graphs: Snakes

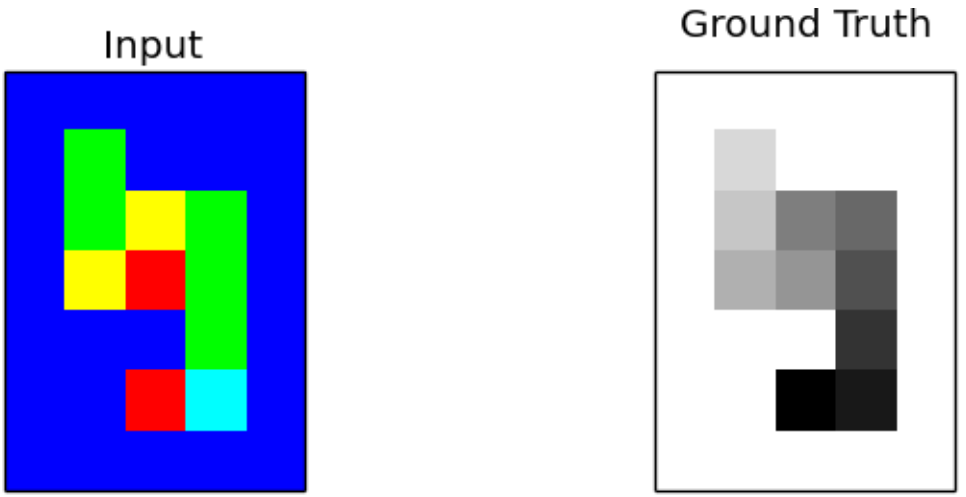
Input



Ground Truth



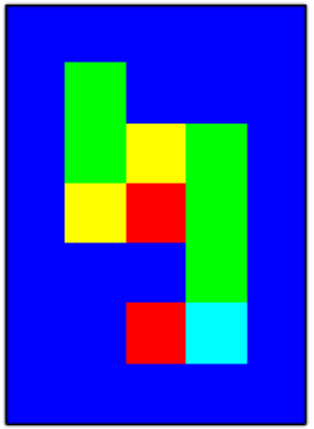
Grid Graphs: Snakes




```
crf = EdgeFeatureGraphCRF(inference_method='qpbo')
ssvm = OneSlackSSVM(crf, inference_cache=50, C=.1, tol=.1,
                    switch_to='ad3', n_jobs=1)
ssvm.fit(X_train_edge_features, Y_train_flat)
```

Grid Graphs: Snakes

Input



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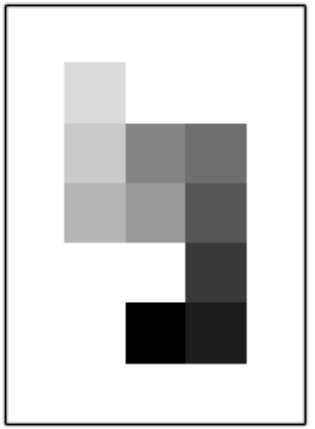
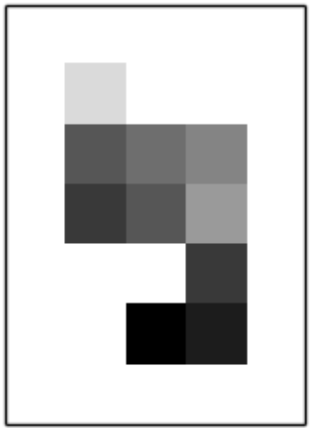
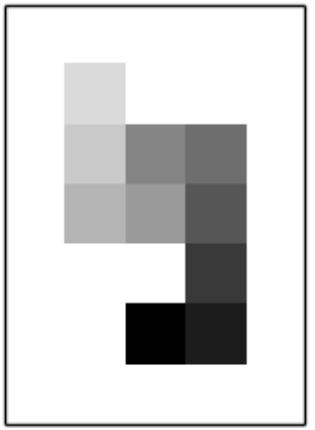


Prediction w/o edge features



Prediction with edge features



Classes of Inference Algorithms

Exact Algorithms
Max-Product (Chains, Trees) `'max-product'`

Exhaustive (usually too expensive)

Relaxed algorithms + branch & bound
`('ad3', {'branch_and_bound': True})`

Relaxed
Linear Programming (slooow) `'lp'`
Dual Decomposition `'ad3'`

Approximate / heuristics
Loopy message passing `'max-product'`
QPBO `'qpbo'`

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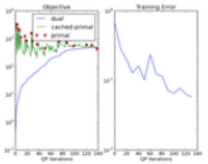
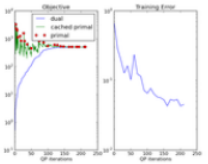
Approximate / heuristics
Loopy message passing `'max-product'`
QPBO `'qpbo'`

Install OpenGM for many more!

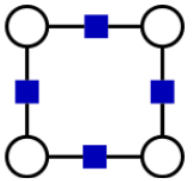
Examples



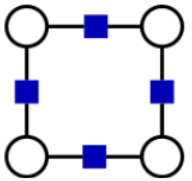
Plotting the objective and constraint caching in 1-slack SSVM



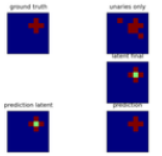
Efficient exact learning of 1-slack SSVMs



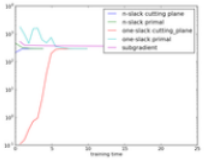
SVM as CRF



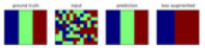
Semantic Image Segmentation on Pascal VOC



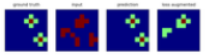
Latent Dynamics CRF



SVM objective values

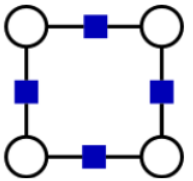


Learning directed interactions on a 2d grid



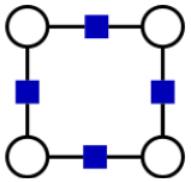
Learning interactions on a 2d grid

OCR Letter sequence recognition



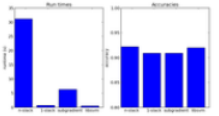
Crammer-Singer Multi-Class SVM

Latent SVM for odd vs. even digit classification

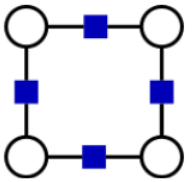


Mult-label classification

Latent Variable Hierarchical CRF



Binary SVM as SSVM



Comparing PyStruct and SVM-Struct

Back to top

Thank you for your attention.

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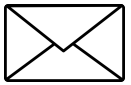
 @amueller

 t3kcit@gmail.com

 http://amueller.github.io