Shogun Workshop 2013

Structured Output Learning

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About me

- Involved with Shogun for about one and half years.
- Participated in two GSoC:
  - 2012 - Structured output learning (this talk!).
  - Ongoing this summer - Distance metric learning.

Outline

Introduction
- Structured Output Learning
- Examples

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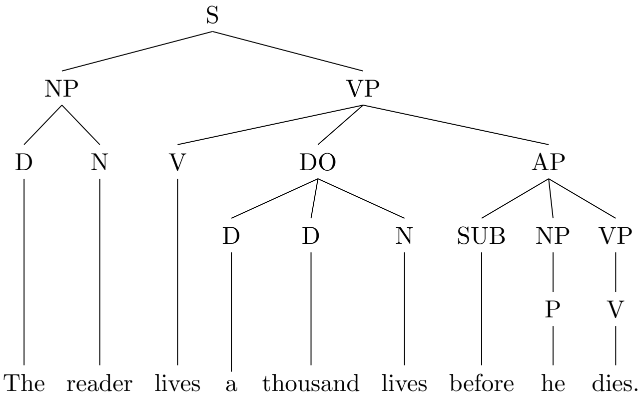
- To obtain this function f, we use *training* data $\{(x_i, y_i)\}_{i=1}^{n}$.

Structured Output Learning

- Non-structured output learning
  - The inputs in $\mathcal{X}$ can be any kind of objects.
  - The outputs in $\mathcal{Y}$ are singular, each label is represented by a single number.
- Structured output learning
  - The inputs in $\mathcal{X}$ can be any kind of objects.
  - The outputs in $\mathcal{Y}$ are complex, each label has multiple variables.

Natural Language Processing (NLP) – Parse trees

- $\mathcal{X}$ = sentences.
- $\mathcal{Y}$ = parse trees.



Computer Vision – Segmentation

- $\mathcal{X}$ = images.
- $\mathcal{Y}$ = segmented images.

Structured Prediction and Learning in Computer Vision (Nowozin and Lampert, 2011).

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    - Too many classes!
    - E.g.: $\mathcal{Y}$ = binary sequences of length 250 $\rightarrow 2^{250}$ distinct sequences.
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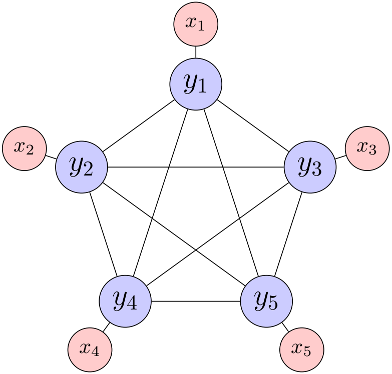
    - It becomes a geometrical problem, where SVM principles can be applied.

Joint feature map

- Observation-label interactions.
- Label-label interactions.



$$\psi(x, y) = \begin{bmatrix} \sum_i \psi_u(x_i, y_i) \\ \\ \sum_{i,j} \psi_p(y_i, y_j) \end{bmatrix}$$

SO-SVM prediction: inference or arg max

Given an observation $x \in \mathcal{X}$, the SO-SVM finds its corresponding label $y^* \in \mathcal{Y}$ maximizing a score:

$$y^* = \arg\max_{y \in \mathcal{Y}} \left(\mathbf{w}^T \psi(x, y) \right) .$$

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  - For $y \in \mathcal{Y}$ graphs, no general efficient algorithm (Koller and Friedman, 2009).
    - Use approximations.
    - Find a subset within $\mathcal{Y}$.

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- One that is completely different from the ground truth label.
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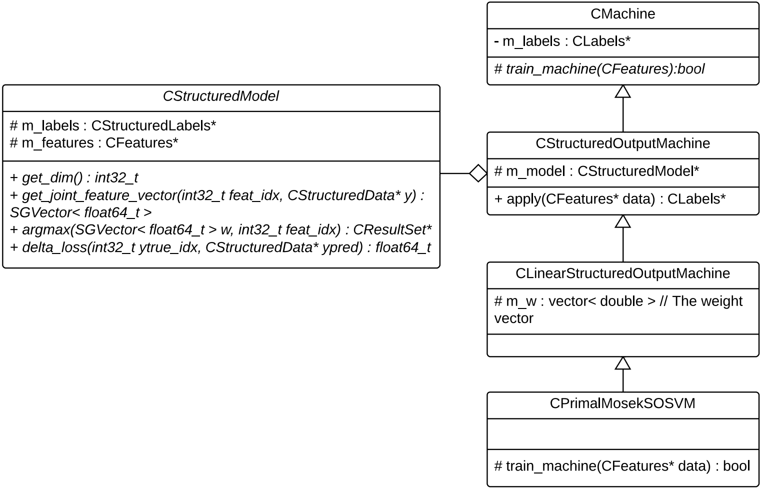
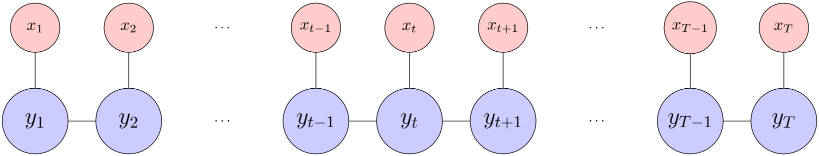
The traditional zero-one loss ranks both predictions in the same way.

- This is not a good idea.
- Use instead a loss that takes into account the structure of the labels. Typically, the Hamming loss is used.

Simplified class hierarchy



Label sequence learning



$$y^* = \arg\max_{y \in \mathcal{Y}} \left(\mathbf{w}^T \psi(x, y) \right) \rightarrow \text{Viterbi}$$

C++ example: training data setup

```
// Create binary label sequences
CSequenceLabels* labels =
    new CSequenceLabels(num_examples);
// Fill in the sequences, one could look like [0 0 1 1]

// Create matrix features
CMatrixFeatures<float>* features =
    new CMatrixFeatures<float>(num_examples);
// Fill in the features, one could look like
//     [0 1 2 1]
//     [1 2 0 2]
//     [2 1 0 0]
```

C++ example: training

```
CHMSVMModel* model =
    new CHMSVMModel(features, labels, SMT_TWO_STATE);
CPrimalMosekSOSVM* sosvm =
    new CPrimalMosekSOSVM(model, labels);
sosvm->train();

sosvm->get_w().display_vector("w");
sosvm->get_slacks().display_vector("slacks");

// Free memory
SG_UNREF(sosvm);
```

Python example

```
from shogun.Structure  import TwoStateModel, \
    PrimalMosekSOSVM
from shogun.Evaluation import StructuredAccuracy

model = TwoStateModel.simulate_data(num_examples, \
    example_length, num_features, num_noise_features)

sosvm = PrimalMosekSOSVM(model, model.get_labels())
sosvm.train()
predicted = sosvm.apply()

evaluator = StructuredAccuracy()
acc = evaluator.evaluate(predicted, labels)
print('Train accuracy = %.4f' % acc)
```

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Some possible extensions of the SO learning framework are twofold:

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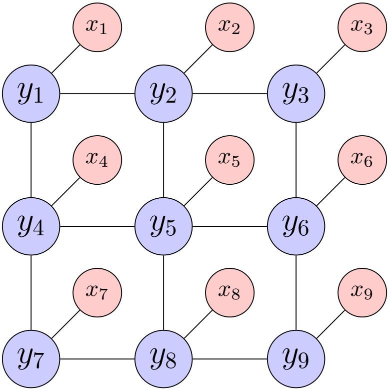
Some possible extensions of the SO learning framework are twofold:

- Parameter estimation or learning (aka training).
  - Solvers in the dual to leverage kernels, online solvers, other approaches different from margin maximization, etc.
- Structured models.
  - What if there is no structured model to represent the labels of my application at hand?
  - SWIG director classes may help.

New structured model: motivation

Graph labelling for image segmentation.



SWIG directors example: inheritance

```
from shogun.Structure import DirectorStructuredModel

class MyGridGraphModel(DirectorStructuredModel):

  def get_joint_feature_vector(self, feat_idx, y):

  def delta_loss(self, y1, y2):

  def argmax(self, w, feat_idx, training):
```

SWIG directors example: using the new model

```
from subgradient_sosvm import StochasticSubgradientSOSVM

model = MyGridGraphModel(train_features, train_labels)
sosvm = StochasticSubgradientSOSVM(model, train_labels)
sosvm.train()
predicted = sosvm.apply(test_features)

evaluator = StructuredAccuracy()
acc = evaluator.evaluate(predicted, test_labels)

print('Test accuracy = %.4f' % acc)
```

Thank you for coming!
Questions, doubts and suggestions are most welcome!!

References

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