Event Classification with Structured Output Learning

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Structured Output Learning

- Binary classification: $\{x_i, y_i\}_{i=1}^m$, $x_i \in \mathbb{R}^d, y_i \in \{-1, +1\}$.
  - well studied, logistic regression, SVM, etc.
- Multiclass classification: $y_i \in \{A, B, C\}$
  - single variate output, decomposable
- What if multiple interdependent output variables?
  - classifying independently: ignoring output structure
  - better solution: joint embedding $\phi(x_i, y_i)$ + linear classifiers
- Structured output learning (SOL) techniques:
  - conditional random fields, structured SVM, etc.

Structured Output Learning

- Structured SVM optimisation problem
  - joint embedding into $\mathbb{R}^d$ using $\phi(x_i, y_i)$
  - find projection $\mathbf{w}$ maximising the margin
  - ℓ_2 regularisation as in standard SVM

$$\min_{\mathbf{w}} \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{m}\xi_i \tag{1}$$

$$\text{s.t.} \quad \mathbf{w}^T\phi(x_i, y_i) - \mathbf{w}^T\phi(x_i, y) \geq \Delta(y_i, y) - \xi_i, \ \ \forall y \in \mathcal{Y}\backslash y_i, \forall i$$

$$\xi_i \geq 0 \ \ \forall i$$

Event Classification as SOL

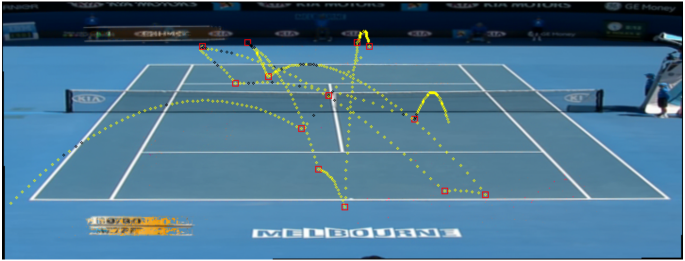

Figure: An example of ball tracking and ball event detection results.

Event Classification as SOL

- Joint embedding defined implicitly:

$$
\begin{aligned}
& < \phi(x_i, y_i), \phi(x_j, y_j) > \qquad (2) \\
= \; & \sum_{s=2}^{o_i} \sum_{t=2}^{o_j} [\![y_i^{s-1} = y_j^{t-1}]\!] [\![y_i^s = y_j^t]\!] + \eta \sum_{s=1}^{o_i} \sum_{t=1}^{o_j} [\![y_i^s = y_j^t]\!] K(x_i, x_j)
\end{aligned}
$$

- Find the optimal **w** by solving Eq. (1)
- Discriminative approach:
  - interested in $P(Y|X)$ rather than $P(X, Y)$
- Generative approach:
  - hidden Markov model (HMM), modelling $P(X, Y)$

Simulation with an Artificial Court Game

- Artificial court game with 4 types of events:
  - serve, bounce, hit, net
- Initial probabilities: 0.80, 0.10, 0.05, 0.05
- Transitional probabilities:

$$\begin{pmatrix} 0 & 0.80 & 0 & 0.20 & 0 \\ 0 & 0.20 & 0.60 & 0 & 0.20 \\ 0 & 0.65 & 0.15 & 0.15 & 0.05 \\ 0 & 0 & 0 & 0 & 1.00 \end{pmatrix}$$

Simulation with an Artificial Court Game

- Observation for 4 events:
  - exp. A: Gaussian densities; exp. B: uniform densities
  - 10 dimensional vectors, same covariance, different means
  - parameter γ controlling separation
- 1000 training sequences, 1000 test sequences
- Performance metrics: per token error and per label error
- Compare generative HMM and discriminative SOL
  - in HMM Gaussian observation density assumed: valid in exp. A while invalid in exp. B

Simulation with an Artificial Court Game

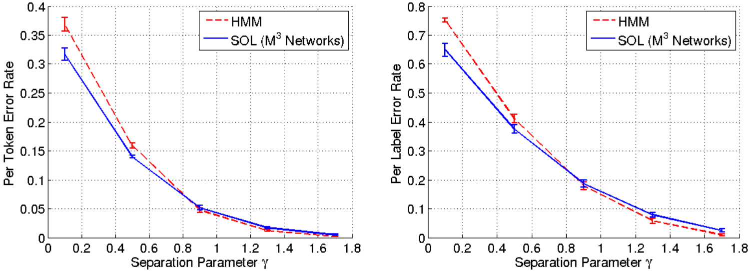

Figure: Left: token error. Right: label error. Normal observation density.

Simulation with an Artificial Court Game

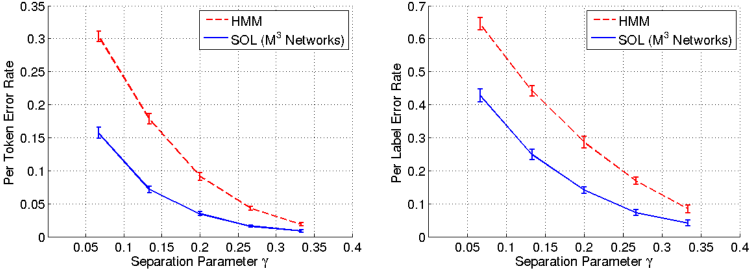

Figure: Left: token error. Right: label error. Uniform observation density.

Results with Real World Tennis Games

- Two real world tennis games
  - Australian Open 2003 women's singles, 71 play shots
  - Australian Open 2008 women's doubles, 163 play shots
- Ball tracking and key event detection fully automatic
- Observation features:
  - acceleration + velocity + position
  - acceleration + velocity
- Leave-one-out evaluation
- Compare generative HMM and discriminative SOL

Results with Real World Tennis Games

Table: Australian 2003 Singles

	Per token error rate		Per label error rate	
	HMM	SOL	HMM	SOL
Without ball positions	0.1529	0.1449	0.6761	0.6338
With ball positions	0.1210	0.1051	0.6338	0.5211

Table: Australian 2008 Doubles

	Per token error rate		Per label error rate	
	HMM	SOL	HMM	SOL
Without ball positions	0.2206	0.1832	0.8589	0.8098
With ball positions	0.1656	0.1531	0.8589	0.8160

Conclusions and Future Work

- Event classification is a structured problem
    - output structure: sequence
- Traditionally done with generative HMM
- SOL vs. HMM: fewer assumptions, better classification performance
- Overall performance still low
    - other modalities as observation: audio, player action
    - learning their importance in MKL setting