Learning Structural SVMs with Latent Variables

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Cornell University
Computer Science

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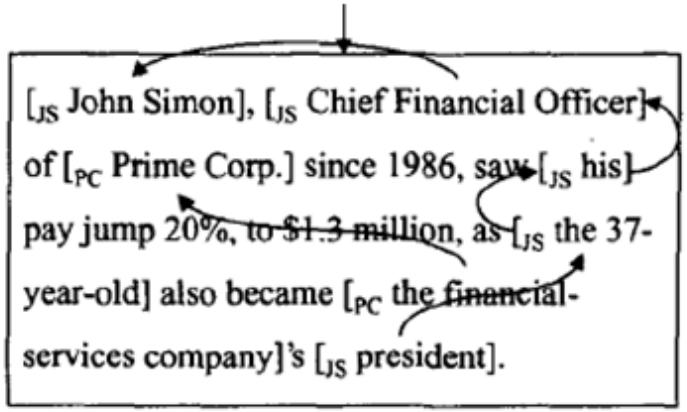
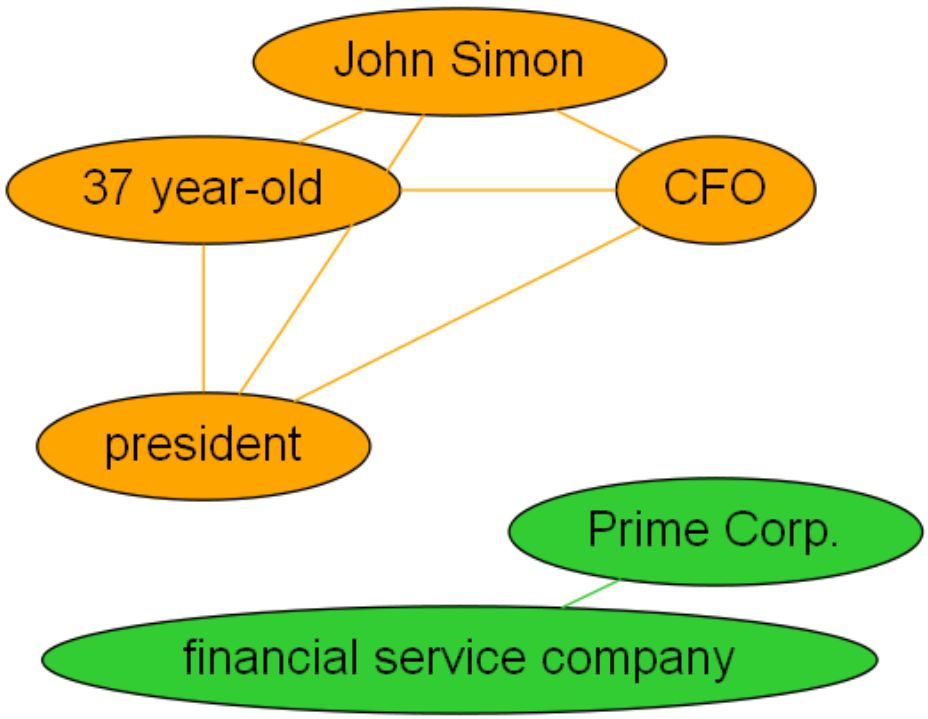
- This talk: Latent variables in *supervised prediction tasks*

An Example: Noun Phrase Coreference

[from Cardie & Wagstaff '99]





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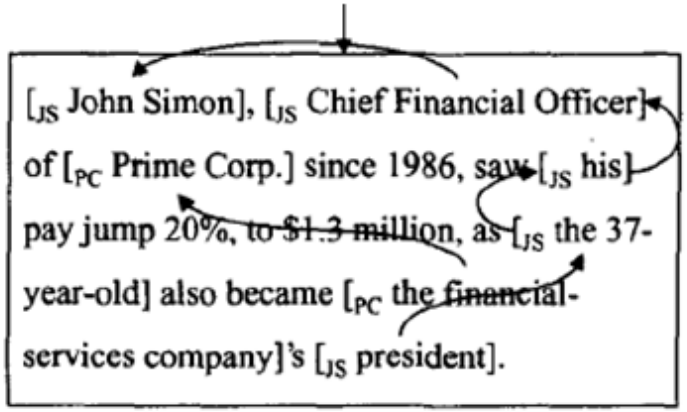

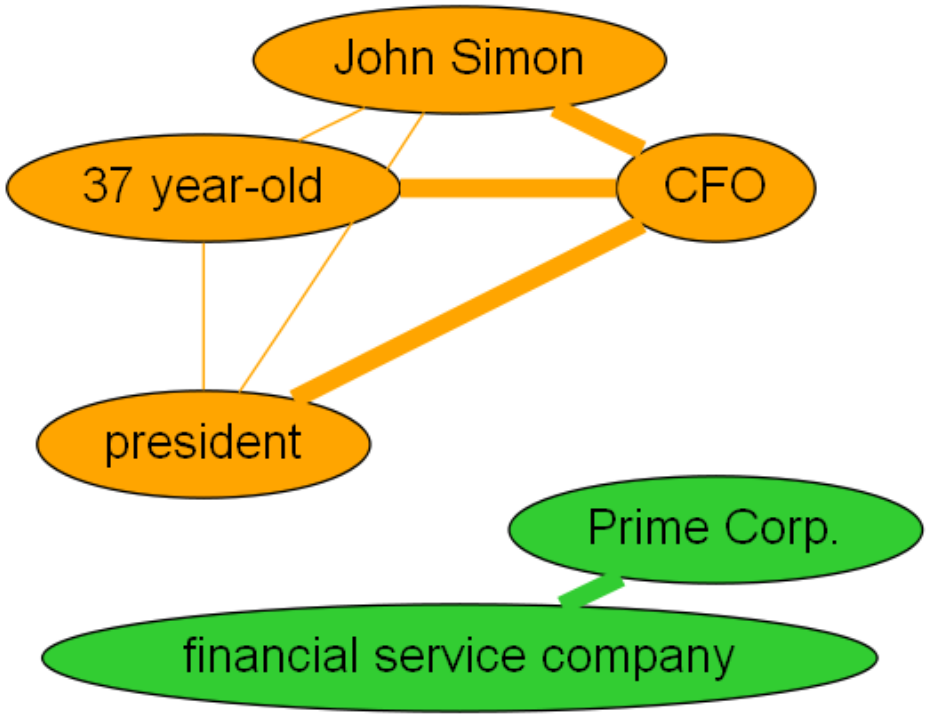

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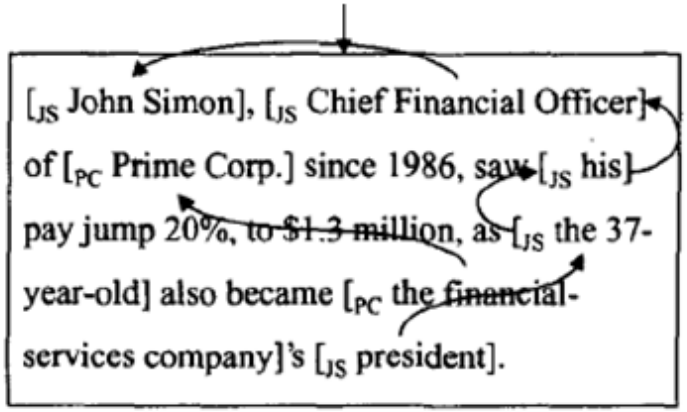

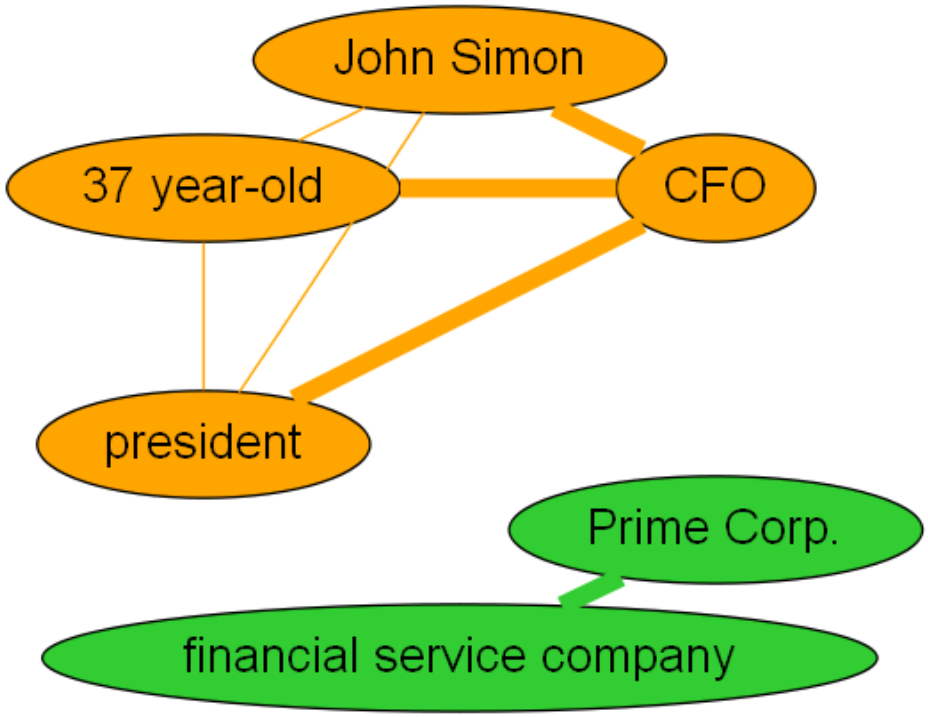

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- Other examples: Machine Translation

Latent Variables in Structured Output Learning

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  - Hidden Markov Models in speech recognition and bioinformatics

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  - Discriminative PCFG with latent annotations [Petrov & Klein '07]
- Large-Margin Models
  - Large-margin criterion for Hidden CRF in vision community [Felzenswalb et al. '08, Wang & Mohri '08]
  - Semi-supervised Structural SVM [Zien & Brefeld '07]

Structural SVMs

- Want to learn a linear prediction rule:

$$f_{\vec{w}}(x) = \text{argmax}_{y \in \mathcal{Y}} \, \vec{w} \cdot \Phi(x, y)$$

Structural SVM (Margin rescaling)

$$\min_{\vec{w}, \vec{\xi}} \frac{1}{2} \|\vec{w}\|^2 + C \sum_{i=1}^{n} \xi_i$$

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- Great prediction performance on many structured prediction problems

Introducing Latent Variables to Structural SVMs

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- Many interesting question to consider:
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  - Non-convex training objective?
  - Inference problems?

Latent Structural SVMs - Prediction Rules

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- Linear scoring rule; requires joint inference over y and h

Latent Structural SVMs - Formulation

Optimization Problem for Latent Structural SVM

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- ξ_i upper bounds the loss
- Reduces to standard structural SVM if latent variable not present

Latent Structural SVMs - Formulation

- In Structural SVM prediction loss is bounded by:

$$\Delta(y_i, f_{\vec{w}}(x_i)) \leq \underbrace{\max_{\hat{y} \in \mathcal{Y}} [\vec{w} \cdot \Phi(x_i, \hat{y}) + \Delta(y_i, \hat{y})]}_{convex} - \underbrace{\vec{w} \cdot \Phi(x_i, y_i)}_{linear} = \xi_i$$

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- In the case with latent variables:

$$\begin{aligned}&\Delta(y_i, f_{\vec{w}}(x_i))\\ \leq &\underbrace{\max_{(\hat{y},\hat{h})\in\mathcal{Y}\times\mathcal{H}} [\vec{w}\cdot\Phi(x_i,\hat{y},\hat{h}) + \Delta(y_i,\hat{y},\hat{h})]}_{convex} \underbrace{- \max_{h\in\mathcal{H}} \vec{w}\cdot\Phi(x_i,y_i,h)}_{concave} = \xi_i\end{aligned}$$

Latent Structural SVMs - Formulation

- Why have the restriction on loss function Δ?

$$\max_{(\hat{y},\hat{h})\in\mathcal{Y}\times\mathcal{H}} [\vec{w}\cdot\Phi(x_i,\hat{y},\hat{h}) + \Delta((y_i,h),(\hat{y},\hat{h}))] - \max_{h\in\mathcal{H}} \vec{w}\cdot\Phi(x_i,y_i,h)$$

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- Inclusion of h introduce dependencies between convex term and concave term
- Allows efficient solution algorithm while retaining modeling power

Non-Convex Objective - The CCCP Algorithm

- Concave-Convex Procedure[Yuille & Rangarajan '03]
- Employed in many recent machine learning work [Collobert et al. '06, Smola et al. '05, Chapelle et al. '08]

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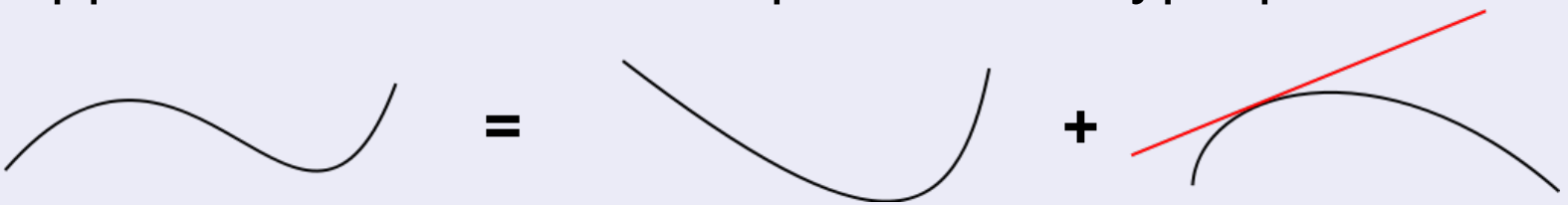

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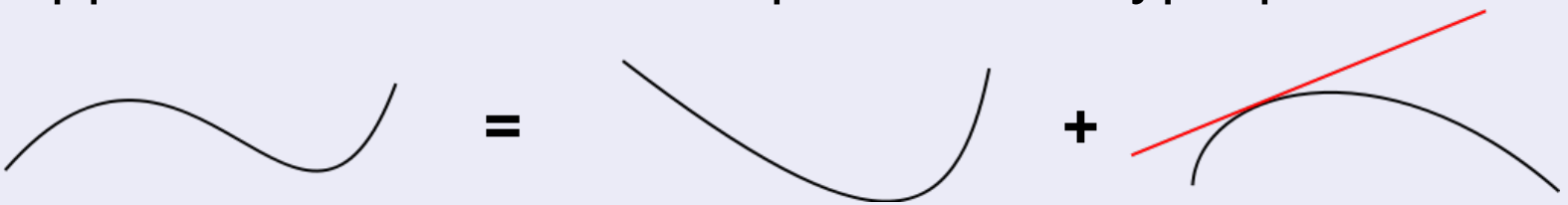
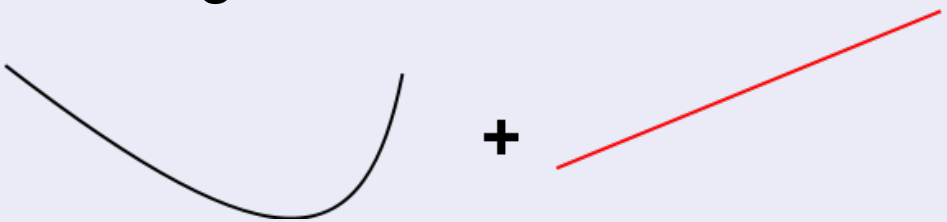


3. Minimize the resulting convex sum. Iterate until convergence



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- Our objective can be written as:

$$\min_{\vec{w}} \underbrace{\left[\frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{n} \max_{(\hat{y},\hat{h})\in\mathcal{Y}\times\mathcal{H}} [\vec{w}\cdot\Phi(x_i,\hat{y},\hat{h}) + \Delta(y_i,\hat{y},\hat{h})]\right]}_{convex}$$

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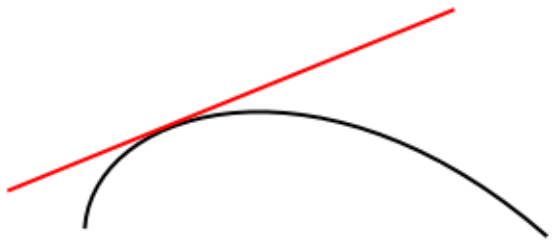
- Computing the upper bounding hyperplane is the same as completing the latent variables:

$$h_i^* = \text{argmax}_{h\in\mathcal{H}}\, \vec{w}\cdot\Phi(x_i,y_i,h)$$



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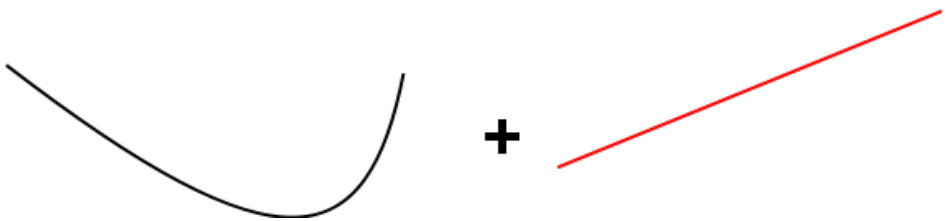
- Cutting plane algorithm to solve convex optimization problem



Summary of Latent Structural SVM

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- Restriction on the loss function Δ
- Three related inference problems:

Prediction:	$\text{argmax}_{(y,h)\in\mathcal{Y}\times\mathcal{H}}\ \vec{w}\cdot\Phi(x_i, y, h)$
Loss-augmented:	$\text{argmax}_{(\hat{y},\hat{h})\in\mathcal{Y}\times\mathcal{H}}[\vec{w}\cdot\Phi(x_i, \hat{y}, \hat{h}) + \Delta(y_i, \hat{y}, \hat{h})]$
Variable Completion:	$\text{argmax}_{h\in\mathcal{H}}\ \vec{w}\cdot\Phi(x_i, y_i, h)$

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Variable Completion:	$\text{argmax}_{h\in\mathcal{H}}\ \vec{w}\cdot\Phi(x_i, y_i, h)$

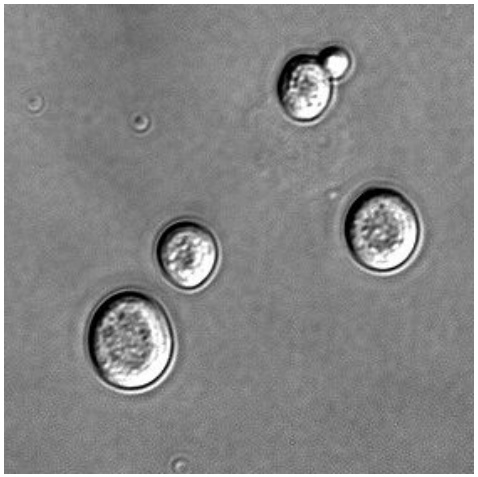
- No computation of partition functions required

Applications

- Discriminative motif finding
- Noun phrase coreference resolution

Discriminative Motif Finding

- Input x: DNA sequences containing ARS from S. cerevisiae and S. kluyveri



S. cerevisiae

```
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```

S. kluyveri

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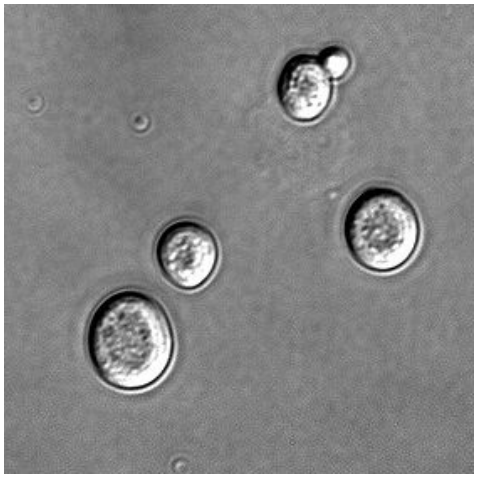

- Label y: Whether the sequence replicates in S. cerevisiae

S. cerevisiae

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S. kluyveri

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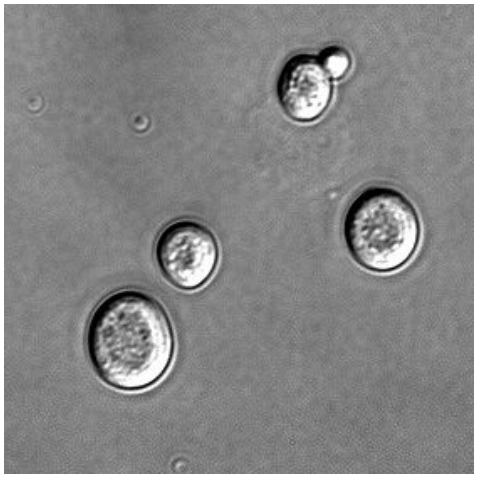

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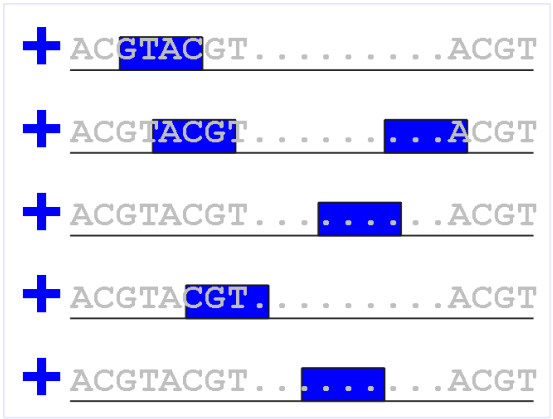
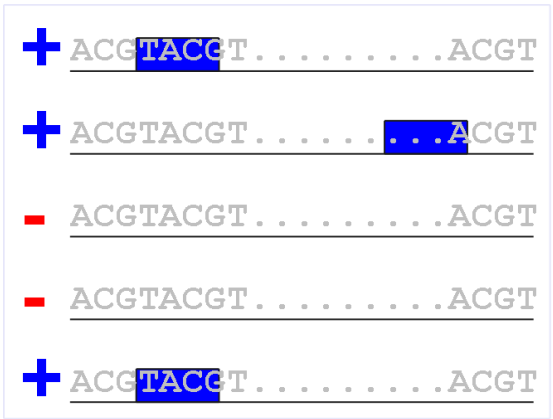


S. kluyveri



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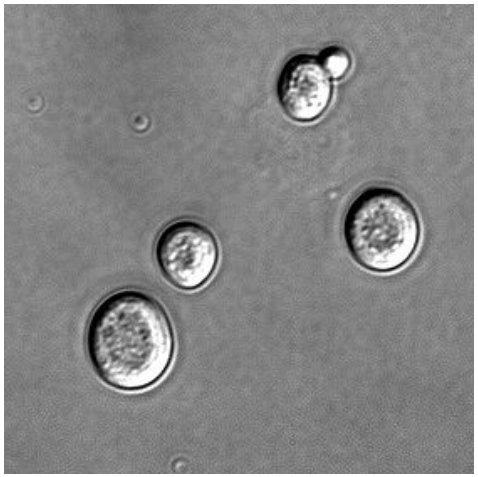

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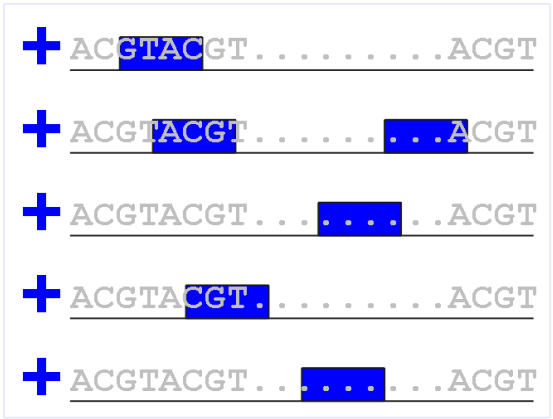
- Latent variable h: position of the motif
- Task: Find out the predictive motif

S. cerevisiae



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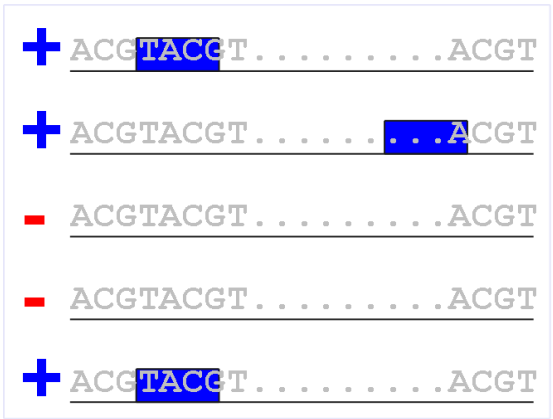

Discriminative Motif Finding - Formulation

- Feature vector Φ: Position-specific weight matrix plus parameters for Markov background model

$$\Phi(x, y, h) = \underbrace{\sum_{i=1}^{h} \phi_{BG}(x_i)}_{\text{background}} + \underbrace{\sum_{j=1}^{l} \phi_{PSM}^{(j)}(x_{h+j})}_{\text{motif}} + \underbrace{\sum_{i=h+l+1}^{n} \phi_{BG}(x_i)}_{\text{background}}$$

d Position weight matrix (PWM)

A	−1.93	0.79	0.79	−1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	−1.93	−1.93	0.79
C	0.45	−1.93	0.79	1.68	−1.93	−1.93	−1.93	0.45	−1.93	−1.93	−1.93	−1.93	0.00	0.79
G	0.00	0.45	−1.93	−1.93	−1.93	−1.93	−1.93	−1.93	0.66	−1.93	1.30	1.68	1.07	−1.93
T	0.15	0.66	−1.93	−1.93	1.07	0.66	0.79	0.00	0.00	0.79	−1.93	−1.93	−0.66	−1.93

[from Wasserman 2004]

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- Loss function Δ: Zero-one loss

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[from Wasserman 2004]

- Loss function Δ: Zero-one loss
- Inference: enumeration, as y is binary and h is linear in sequence length

Discriminative Motif Finding - Results

- Data - 197 yeast DNA sequences from S. cerevisiae and S. kluyveri.

Discriminative Motif Finding - Results

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- $\sim$6000 intergenic sequences for background estimation

Discriminative Motif Finding - Results

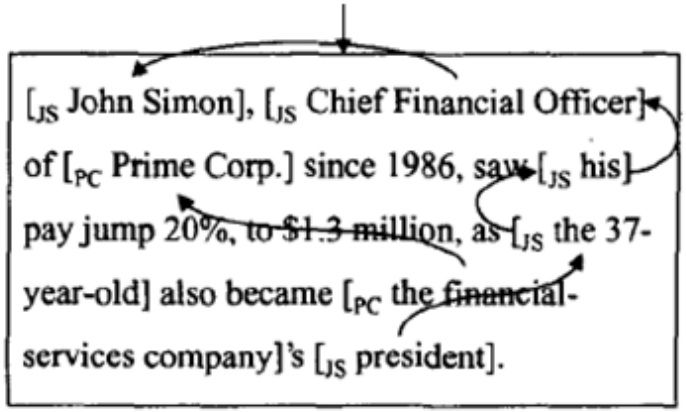
- Data - 197 yeast DNA sequences from S. cerevisiae and S. kluyveri.
- $\sim$6000 intergenic sequences for background estimation
- 10-fold CV, 10 random restarts for each parameter setting

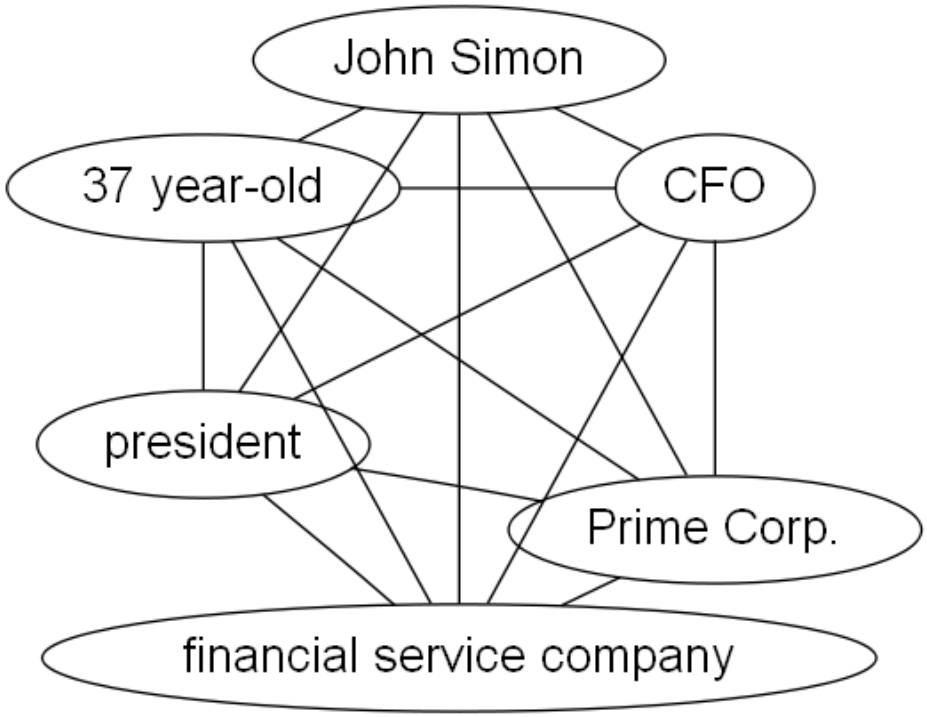
Algorithm	Error Rate
Gibbs Sampler (w=11)	37.9%
Gibbs Sampler (w=17)	35.06%
Latent Structural SVM (w=11)	11.09%
Latent Structural SVM (w=17)	12.00%

Noun Phrase Coreference

- Input x: Noun phrases with edge features

[from Cardie & Wagstaff '99]

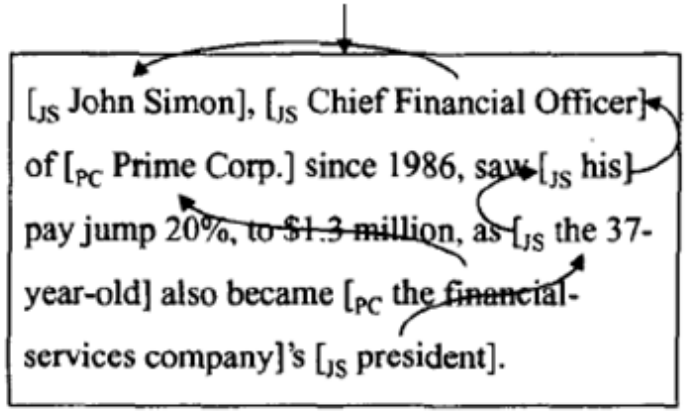


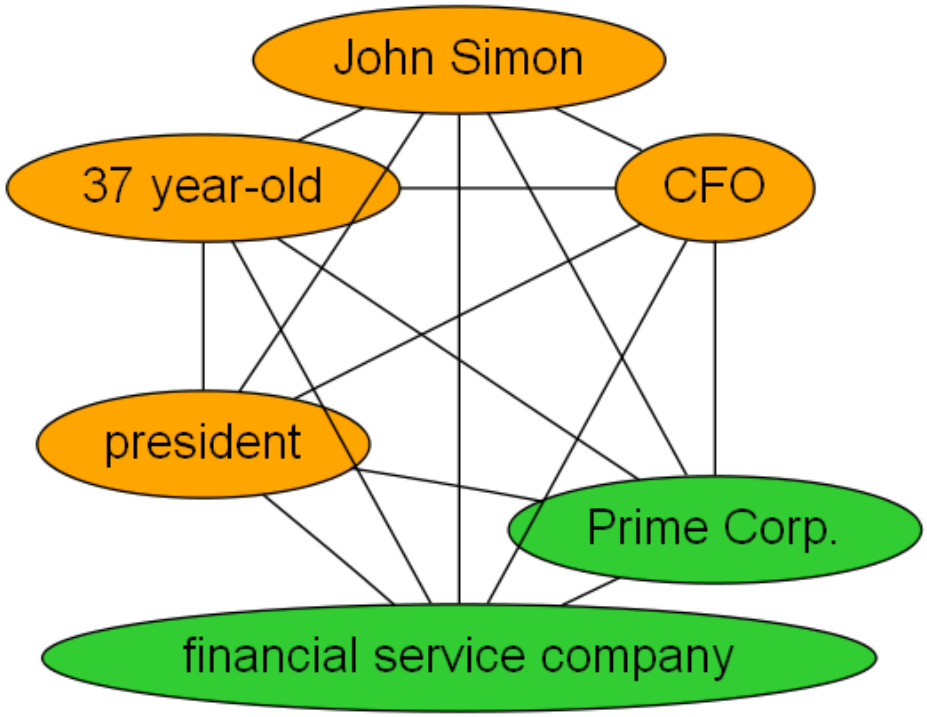


Noun Phrase Coreference

- Input x: Noun phrases with edge features
- Label y: Clusters of noun phrases

[from Cardie & Wagstaff '99]

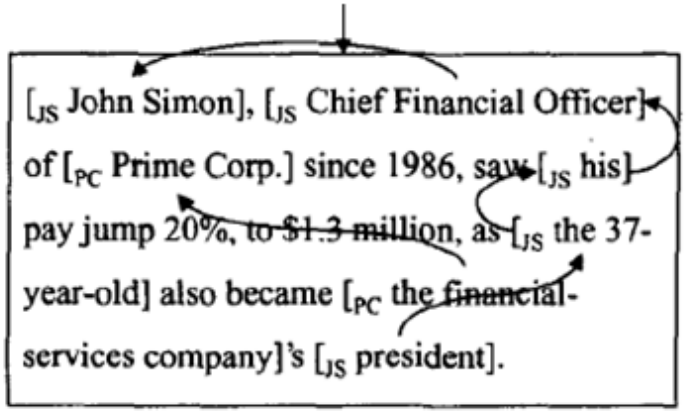


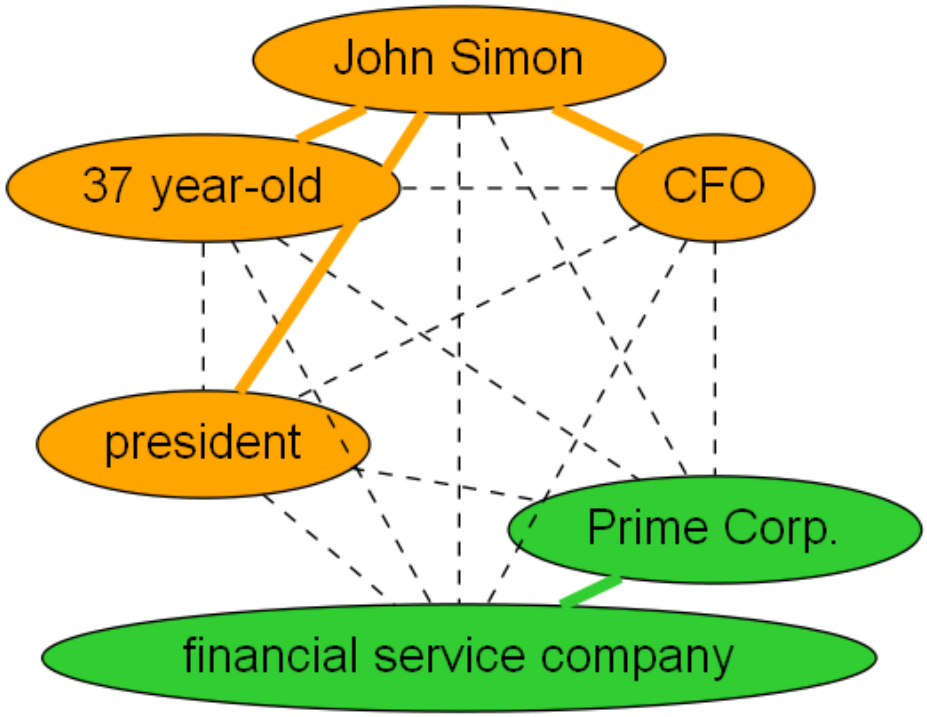


Noun Phrase Coreference

- Input x: Noun phrases with edge features
- Label y: Clusters of noun phrases
- Latent variable h: 'Strong' links as trees

[from Cardie & Wagstaff '99]

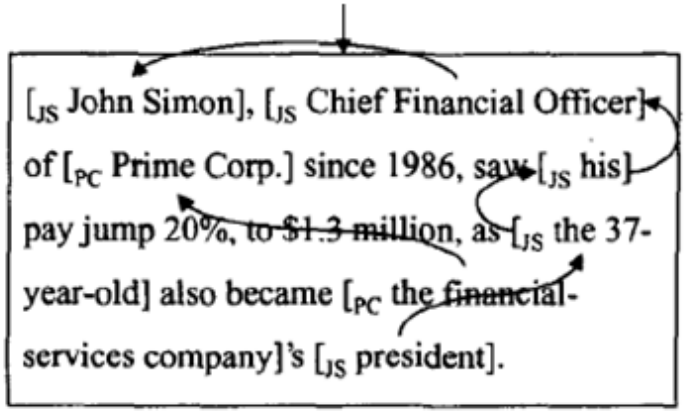


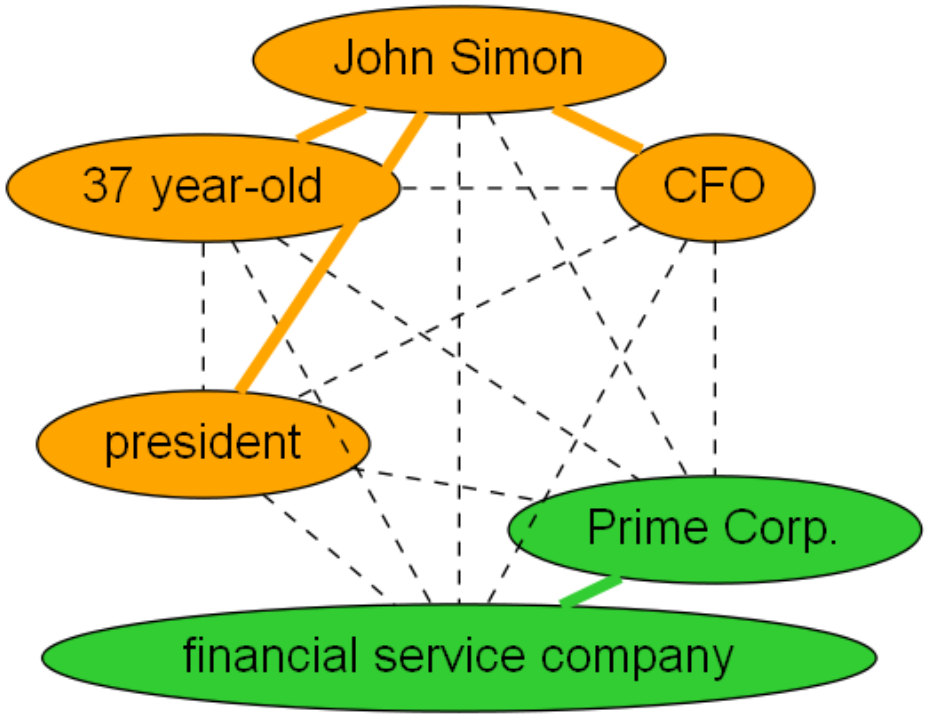


Noun Phrase Coreference

- Input x: Noun phrases with edge features
- Label y: Clusters of noun phrases
- Latent variable h: 'Strong' links as trees
- Task: Cluster the noun phrases using single-link agglomerative clustering

[from Cardie & Wagstaff '99]





Noun Phrase Coreference - Formulation

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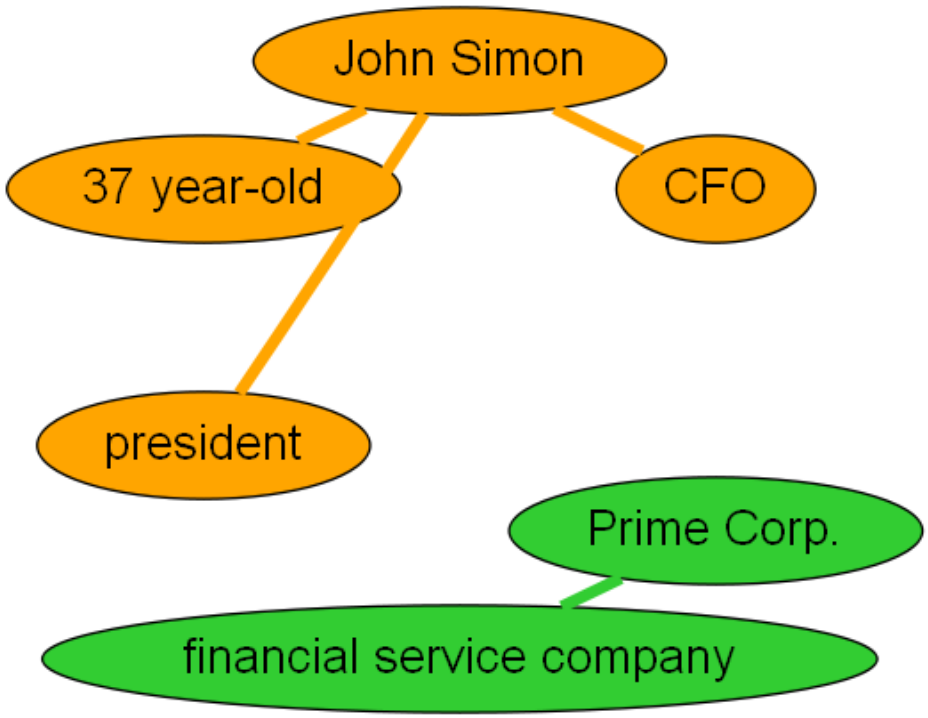
$$\Phi(x, y, h) = \sum_{(i,j) \in h} x_{ij}$$



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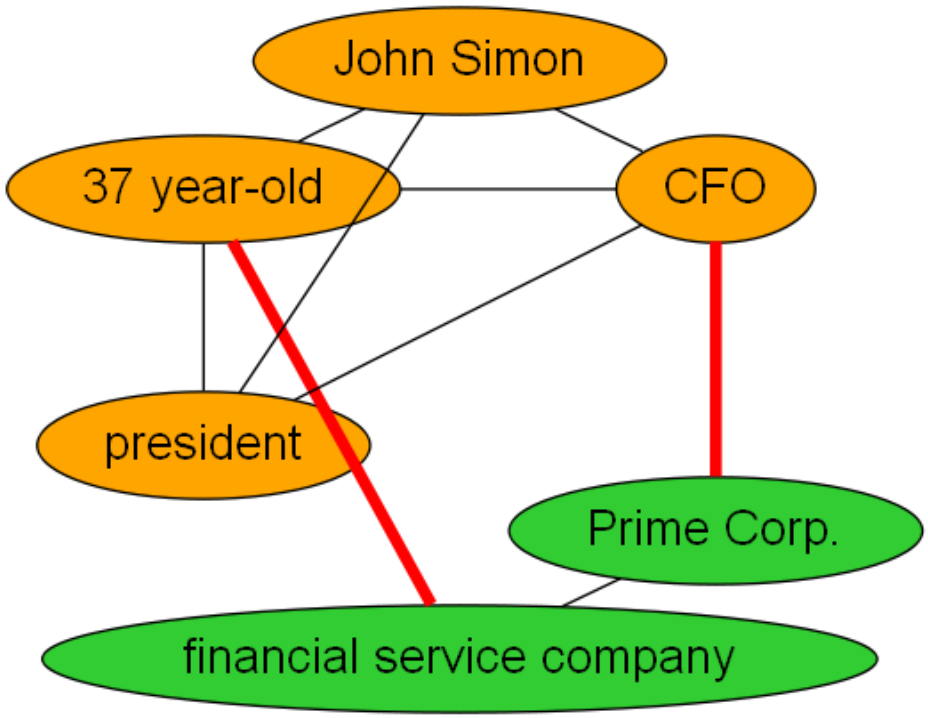
$$\Delta(y, \hat{y}, \hat{h}) = \underbrace{n(y)}_{\#nodes} - \underbrace{k(y)}_{\#components} + \sum_{(i,j) \in \hat{h}} \underbrace{\ell(y, (i,j))}_{+1/-1}$$



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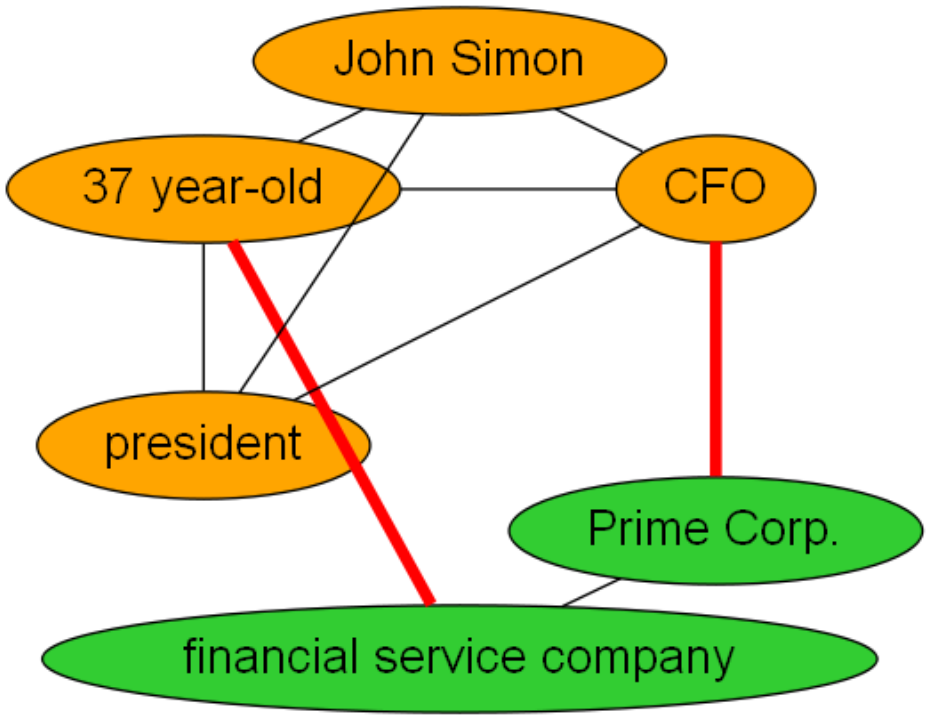
- Inference: Any Maximum Spanning Tree algorithm



Noun Phrase Coreference - Results

- Test on MUC 6 data, using the same features as in [Ng & Cardie '02]

Noun Phrase Coreference - Results

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Noun Phrase Coreference - Results

- Test on MUC 6 data, using the same features as in [Ng & Cardie '02]
- Initialize spanning trees by chronological order
- 10-fold CV results:

Algorithm	MITRE loss	Pair loss
$SVM^{cluster}$ [Finley & Joachims '05]	41.3	2.89
Latent SSVM	44.1	2.66
Latent SSVM (asymmetric loss)	35.6	4.11

Conclusions

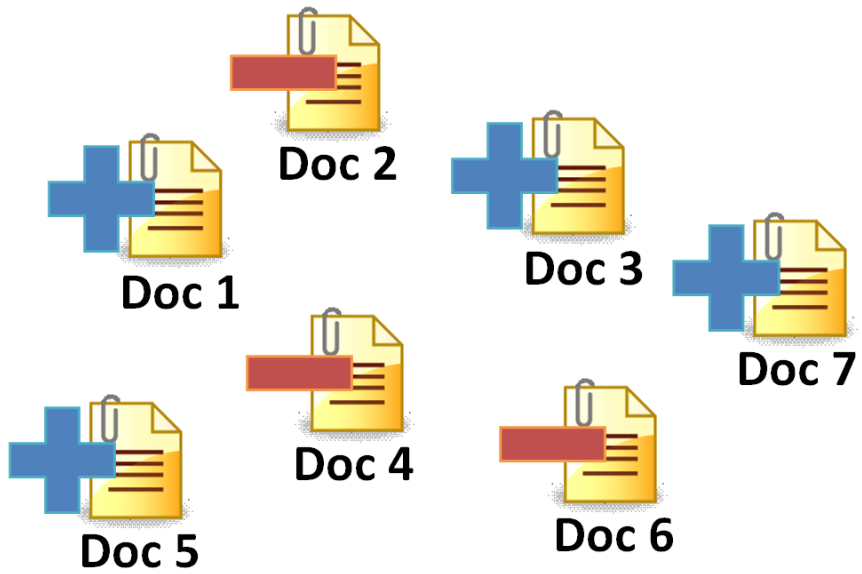
- A formulation of structural SVM that can handle latent variables
- Efficient solution algorithm for the formulation
- Demonstrated the use of the algorithm on three applications, with good prediction performance
- Modular design allows us to focus only on the design of feature vector, loss function, and inference procedures
- Link to software package:
  `http://www.cs.cornell.edu/~cnyu/latentssvm/`

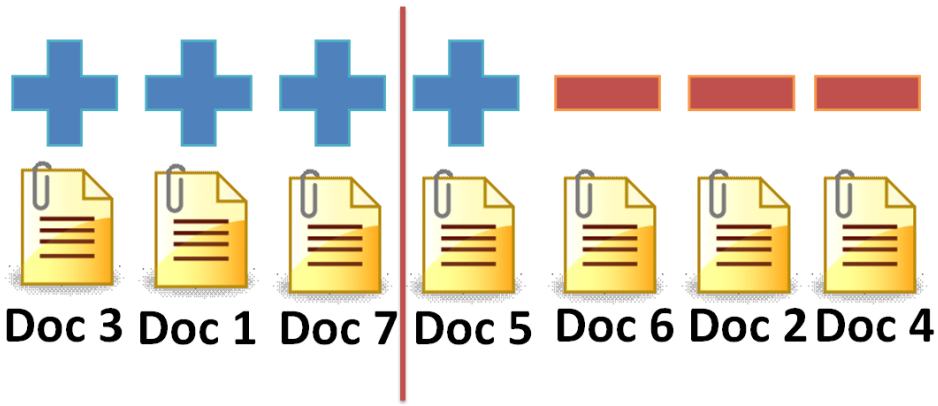
Thank you!

Optimizing Precision@k

- Input x: A query with an associated collection of documents
- Label y: Relevance judgments of each document
- Latent variable h: Top k relevant documents

Query q: ICML 2009





Optimizing Precision@k - Formulation

- Feature vector Φ: sum of features from top k documents

$$\Phi(x, y, h) = \sum_{j=1}^{k} x_{h_j}$$

- Loss function Δ: One minus precison@k

$$\Delta(y, \hat{y}, \hat{h}) = 1 - \frac{1}{k} \sum_{j=1}^{k} [y_{\hat{h}_j} == 1]$$

- Depends only on top k document selected by h
- Inference: Sorting

Optimizing Precision@k - Results

- OHSUMED dataset from LETOR 3.0 benchmark
- Initialize *h* with weight vector trained on classification accuracy
- 5-fold CV results: