

Probabilistic
Graphical
Models



Representation

Markov Networks

Conditional
Random
Fields

Motivation

- Observed variables X
- Target variables Y

$$X \rightarrow Y$$

$P(X, Y)$
joint

$P(Y|X)$
conditional

X

image
segmentation

pixel values
& processed feature.



Y
pixel labels

text processing

words in a
sentence

parts of speech

CRF Representation

$\phi_1(\mathbf{D}_1), \dots, \phi_k(\mathbf{D}_k)$ Gibbsoid

$$\tilde{P}(\bar{x}, \bar{y}) = \prod_{i=1}^k \phi_i(\bar{D}_i) \quad \text{unnormalized measure}$$

$$Z(\bar{x}) = \sum_{\bar{y}} \tilde{P}(\bar{x}, \bar{y}) \quad \text{different } Z(\bar{x}) \text{ for every assignment } \bar{x} \text{ to the obs. variables } \bar{x}$$

$$P(\bar{y} | \bar{x}) = \frac{1}{Z(\bar{x})} \tilde{P}(\bar{x}, \bar{y}) \quad \left(\sum_{\bar{y}} P(\bar{y} | \bar{x}) = 1 \text{ for all } \bar{x} \right)$$

CRFs and Logistic Model

$$\phi_i(X_i, Y) = \exp\{w_i \mathbf{1}\{X_i = 1, Y = 1\}\}$$

$$\phi_i(x_i, Y=1) = \exp\{w_i x_i\}$$

$$\phi_i(x_i, Y=0) = 1$$

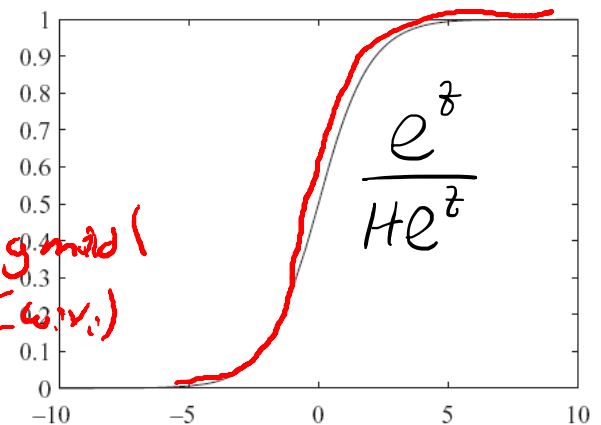
$$\tilde{p}(Y=1 | x_1, \dots, x_n) = \exp\left(\sum_i w_i x_i\right)$$

$$\tilde{p}(Y=0 | x_1, \dots, x_n) = 1$$

$$p(Y=1 | x_1, \dots, x_n) = \frac{\exp(\sum_i w_i x_i)}{1 + \exp(\sum_i w_i x_i)}$$

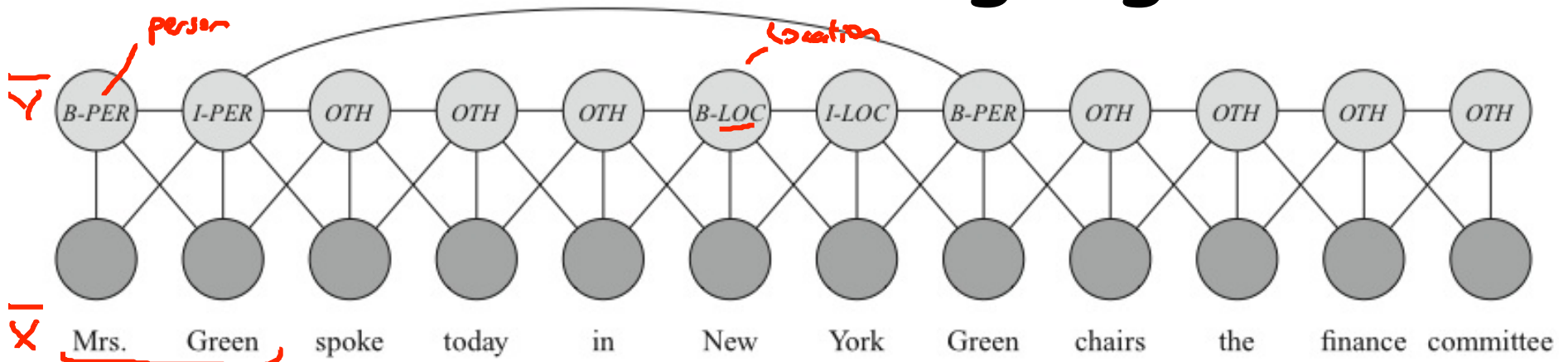
$$\frac{p(Y=1, x_1, \dots, x_n)}{p(x_1, \dots, x_n)}$$

$$= \text{sigmoid}(\sum_i w_i x_i)$$



Daphne Koller

CRFs for Language

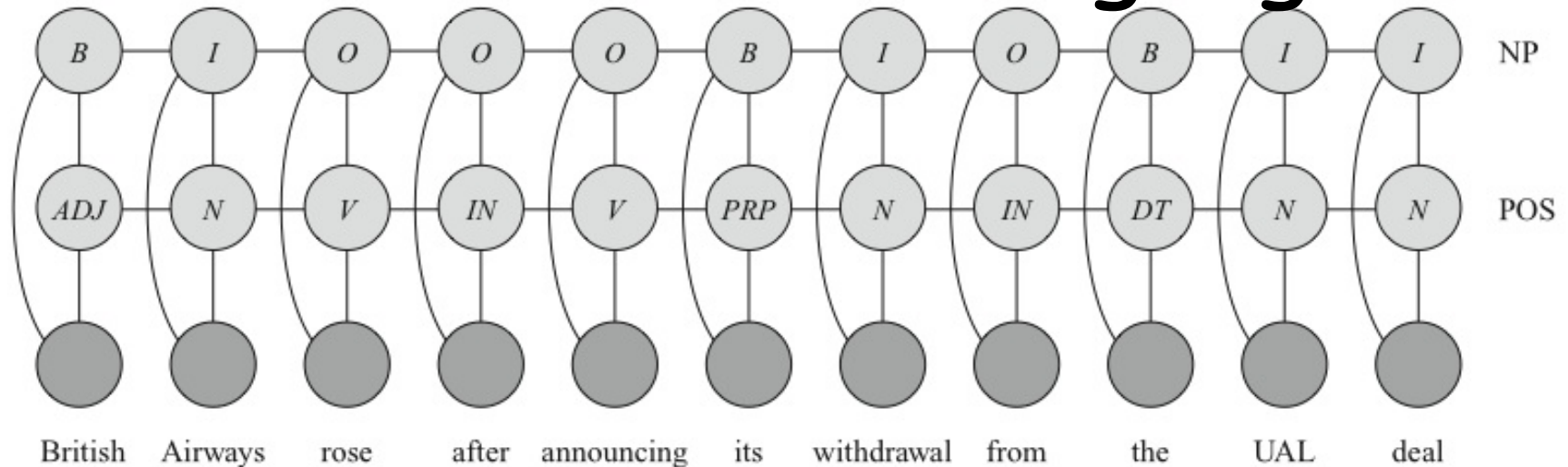


Features: word capitalized, word in atlas or name list, previous word is "Mrs", next word is "Times", ...

$$\tilde{P}(\bar{y}, \bar{y})$$

$$\Rightarrow P(\bar{y} | \bar{x})$$

More CRFs for Language



KEY

| | | | |
|------------|--------------------|------------|-------------------------------|
| <i>B</i> | Begin noun phrase | <i>V</i> | Verb |
| <i>I</i> | Within noun phrase | <i>IN</i> | Preposition |
| <i>O</i> | Not a noun phrase | <i>PRP</i> | Possessive pronoun |
| <i>N</i> | Noun | <i>DT</i> | Determiner (e.g., a, an, the) |
| <i>ADJ</i> | Adjective | | |

Summary

- A CRF is parameterized the same as a Gibbs distribution, but normalized differently
- Don't need to model distribution over variables we don't care about
- Allows models with highly expressive features, without worrying about wrong independencies