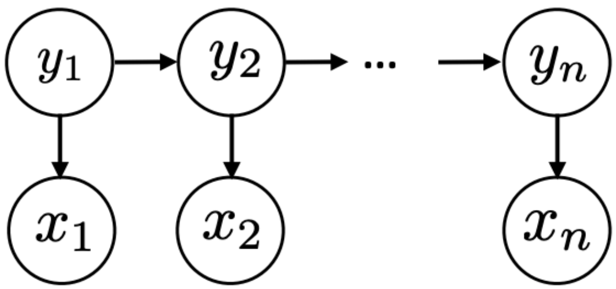
Named Entity Extraction

Recall: HMMs

- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$



$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} P(y_i | y_{i-1}) \prod_{i=1}^{n} P(x_i | y_i)$$

- Training: maximum likelihood estimation (with smoothing)
- Inference problem: $\text{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) = \text{argmax}_{\mathbf{y}} \frac{P(\mathbf{y}, \mathbf{x})}{\cancel{P(\mathbf{x})}}$
- Viterbi: $\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$

This Lecture

- CRFs: model (+features for NER), inference, learning
- Named entity recognition (NER)

Named Entity Recognition

Barack Obama will travel to Hangzhou today for the G20 meeting .

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PERSON LOC ORG

Named Entity Recognition

B-PER	I-PER	O	O	O	B-LOC	O	O	O	B-ORG	O	O
Barack	*Obama*	*will*	*travel*	*to*	*Hangzhou*	*today*	*for*	*the*	*G20*	*meeting*	.
PERSON					LOC				ORG		

- BIO tagset: begin, inside, outside

Named Entity Recognition

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- BIO tagset: begin, inside, outside
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?

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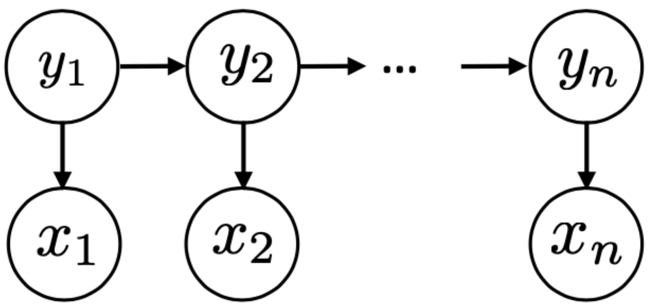
- BIO tagset: begin, inside, outside
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?
  - Lots of O's, so tags aren't as informative about context
  - Insufficient features/capacity with multinomials (especially for unks)

CRFs

Conditional Random Fields

- HMMs are expressible as Bayes nets (factor graphs)



- This reflects the following decomposition:

$$P(\mathbf{y}, \mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\ldots$$

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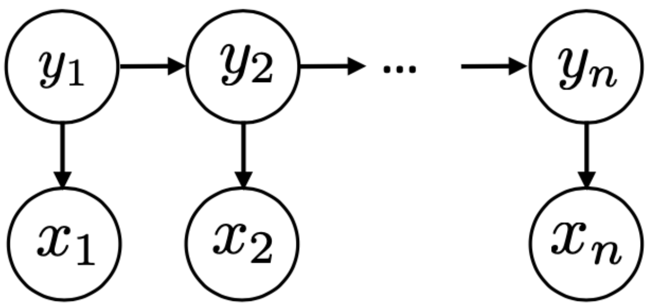

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- Locally normalized model: each factor is a probability distribution that normalizes

Conditional Random Fields

- HMMs: $P(\mathbf{y}, \mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\dots$
- CRFs: discriminative models with the following globally-normalized form:

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_k \exp(\phi_k(\mathbf{x}, \mathbf{y}))$$

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any real-valued scoring function of its arguments

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Sequential CRFs

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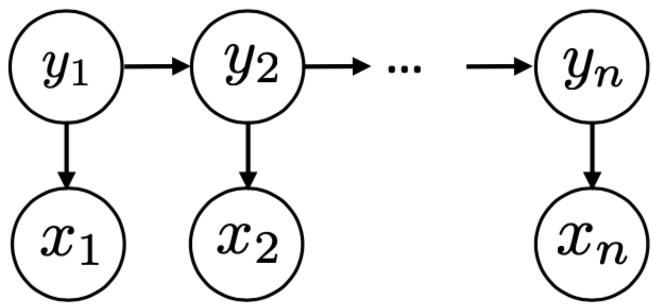
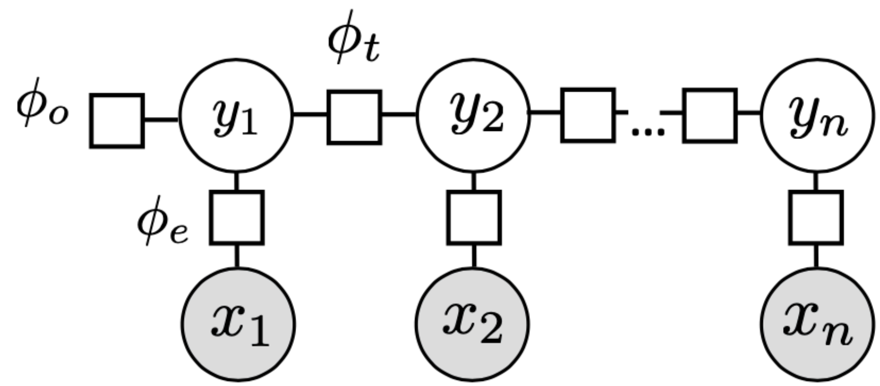


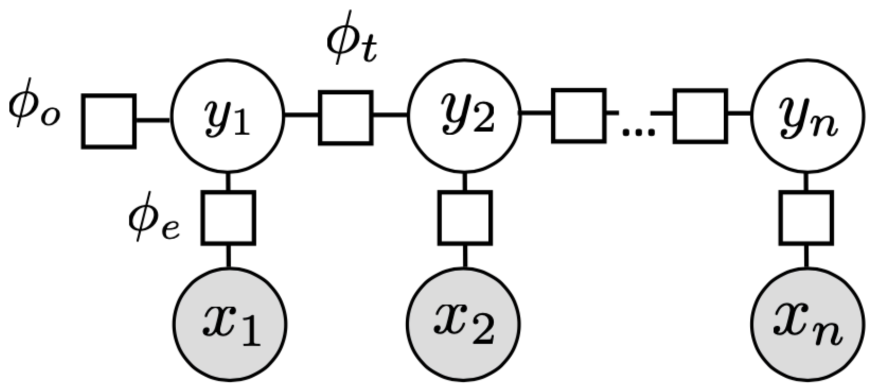


- CRFs:

$$P(\mathbf{y}|\mathbf{x}) \propto \prod_k \exp(\phi_k(\mathbf{x},\mathbf{y}))$$

$$P(\mathbf{y}|\mathbf{x}) \propto \exp(\phi_o(y_1)) \prod_{i=2}^{n} \exp(\phi_t(y_{i-1},y_i)) \prod_{i=1}^{n} \exp(\phi_e(x_i,y_i))$$

Sequential CRFs



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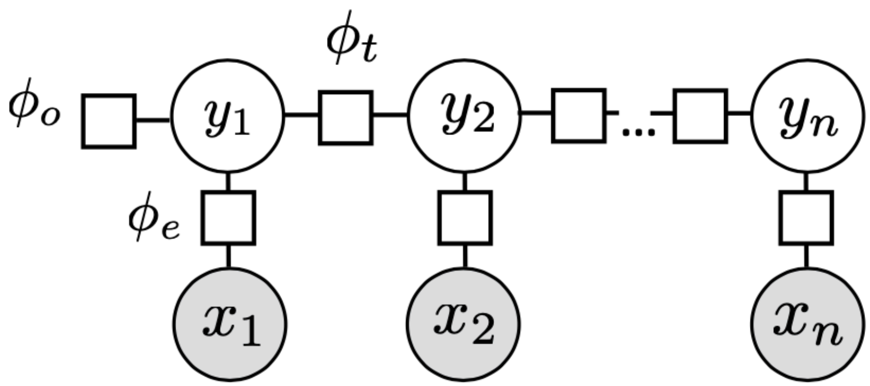
- We condition on **x**, so every factor can depend on all of **x** (including transitions, but we won't do this)

Sequential CRFs



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$$\prod_{i=1}^{n} \exp(\phi_e(y_i, i, \mathbf{x}))$$

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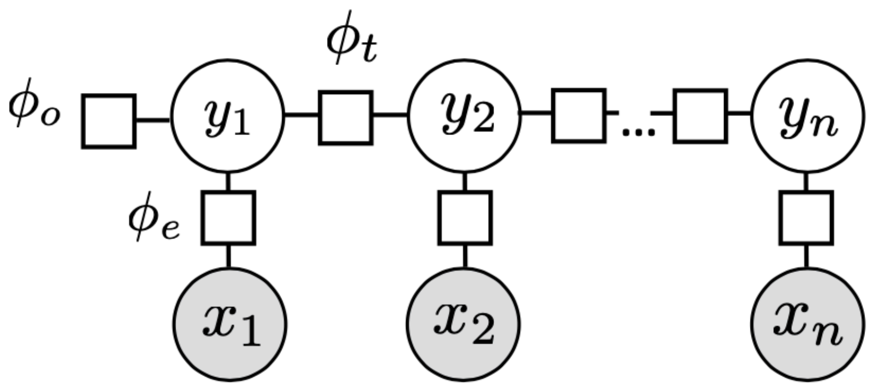

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token index — lets us look at current word

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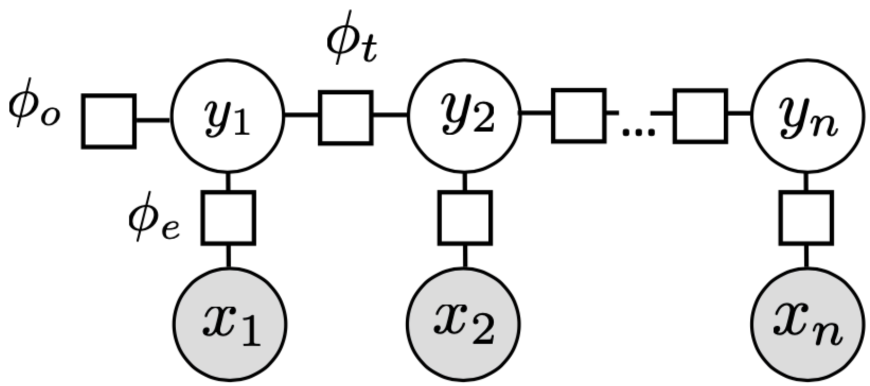
Sequential CRFs



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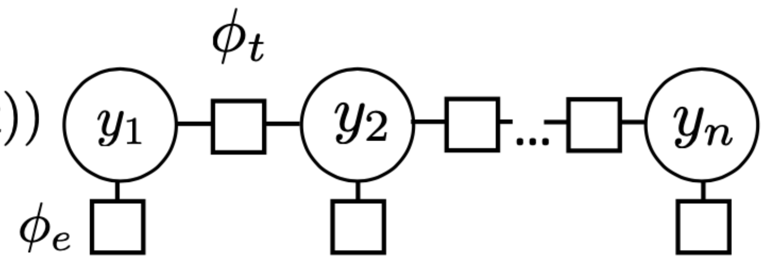
Feature Functions

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$$



- Phis can be almost anything! Here we use linear functions of sparse features

$$\phi_e(y_i, i, \mathbf{x}) = w^\top f_e(y_i, i, \mathbf{x}) \quad \phi_t(y_{i-1}, y_i) = w^\top f_t(y_{i-1}, y_i)$$

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Looks like our single weight vector multiclass logistic regression model

Basic Features for NER

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x}) \right]$$

O B-LOC

Barack Obama will travel to *Hangzhou* *today for the G20 meeting .*

Transitions: $f_t(y_{i-1}, y_i) = \mathrm{Ind}[y_{i-1} \ \& \ y_i]$ = Ind[O — B-LOC]

Emissions: $f_e(y_6, 6, \mathbf{x}) =$ Ind[B-LOC & Current word = *Hangzhou*]

Ind[B-LOC & Prev word = *to*]

Features for NER

$$\phi_e(y_i, i, \mathbf{x})$$

LOC
Leicestershire is a nice place to visit…

PER
Leonardo DiCaprio won an award…

LOC
I took a vacation to Boston

ORG
Apple released a new version…

LOC PER
Texas governor Greg Abbott said

ORG
According to the New York Times…

Features for NER

- Word features (can use in HMM)
  - Capitalization
  - Word shape
  - Prefixes/suffixes
  - Lexical indicators
- Context features (can't use in HMM!)
  - Words before/after
  - Tags before/after
- Word clusters
- Gazetteers

Leicestershire

Boston

Apple released a new version…

According to the New York Times…

CRFs Outline

- Model: $$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$$

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top\left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Inference: argmax P(**y**|**x**) from Viterbi

- Learning: run forward-backward to compute posterior probabilities; then

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=1}^{n} f_e(y_i^*, i, \mathbf{x}) - \sum_{i=1}^{n}\sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$