Lecture 5: Sequence Models II

Alan Ritter

(many slides from Greg Durrett, Dan Klein, Vivek Srikumar, Chris Manning, Yoav Artzi)

Recall: HMMs

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

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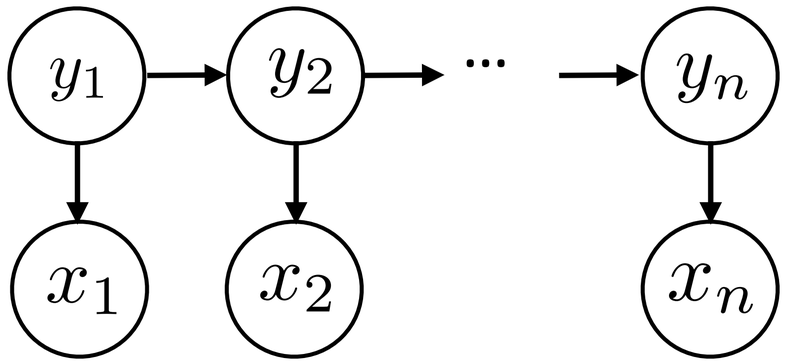

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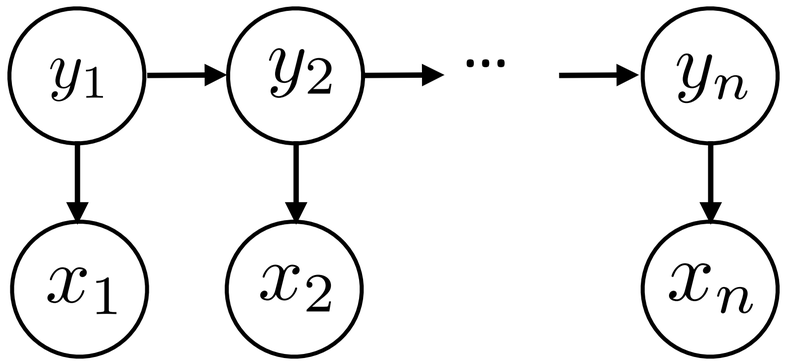

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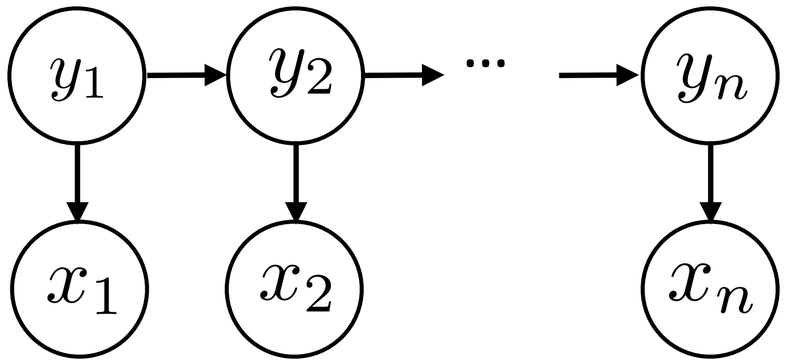

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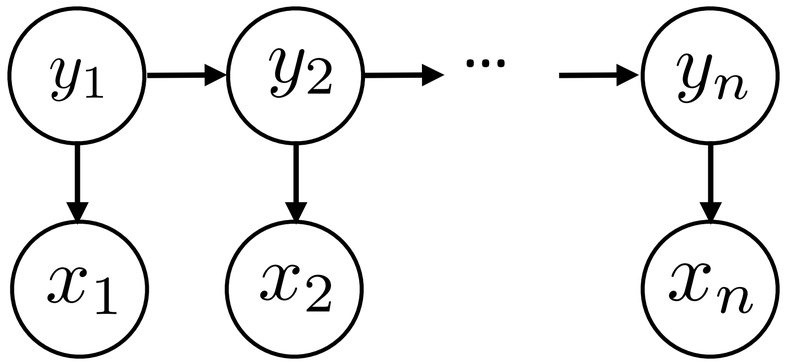

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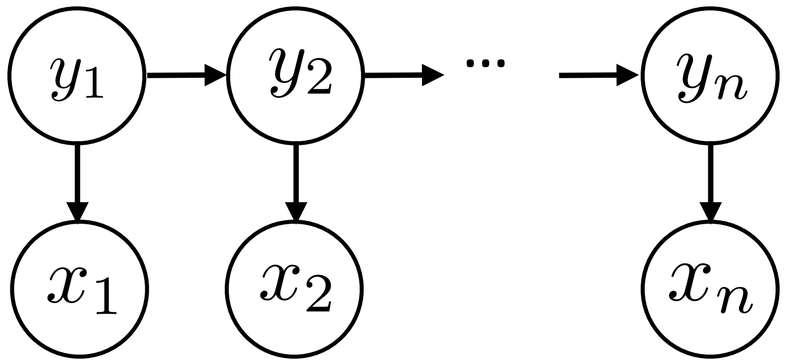

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- Viterbi: $\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$

This Lecture

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

Named Entity Recognition

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

Named Entity Recognition

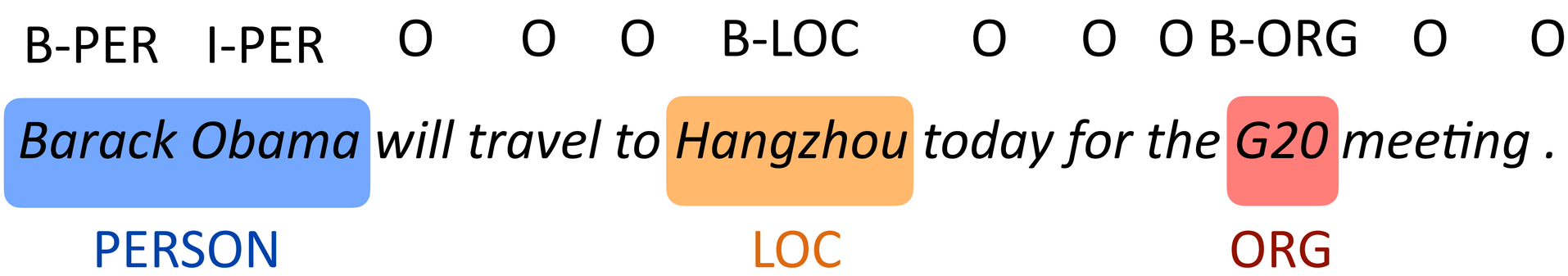
Barack Obama *will travel to* *Hangzhou* *today for the* *G20* *meeting .*

PERSON LOC ORG

Named Entity Recognition

- BIO tagset: begin, inside, outside

Named Entity Recognition



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- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?

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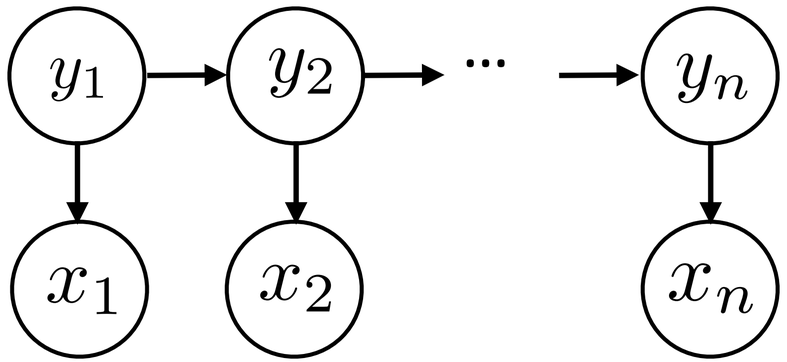
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?
  - Lots of O's, so tags aren't as informative about context
  - Insufficient features/capacity with multinomials (especially for unks)

CRFs

Conditional Random Fields

- HMMs are expressible as Bayes nets (factor graphs)



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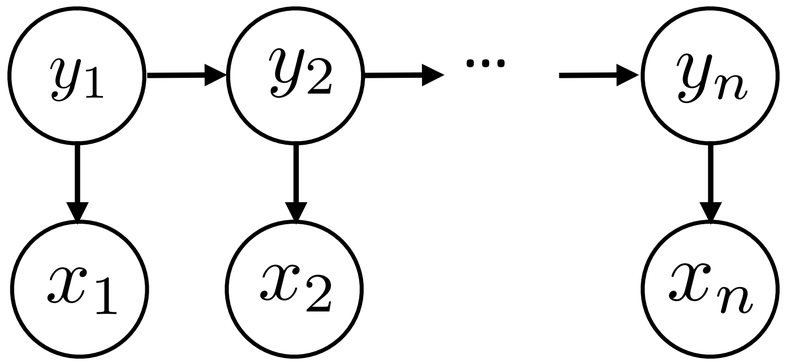

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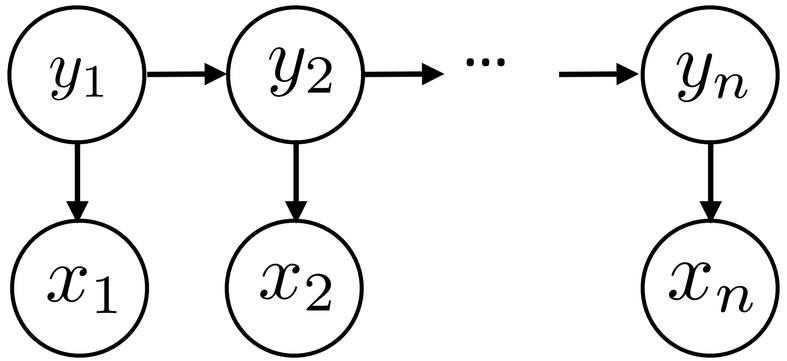

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- Locally normalized model: each factor is a probability distribution that normalizes

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- Naive Bayes : logistic regression :: HMMs : CRFs
  local vs. global normalization <-> generative vs. discriminative

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- Naive Bayes : logistic regression :: HMMs : CRFs
  local vs. global normalization <-> generative vs. discriminative
- Locally normalized discriminative models do exist (MEMMs)

Sequential CRFs

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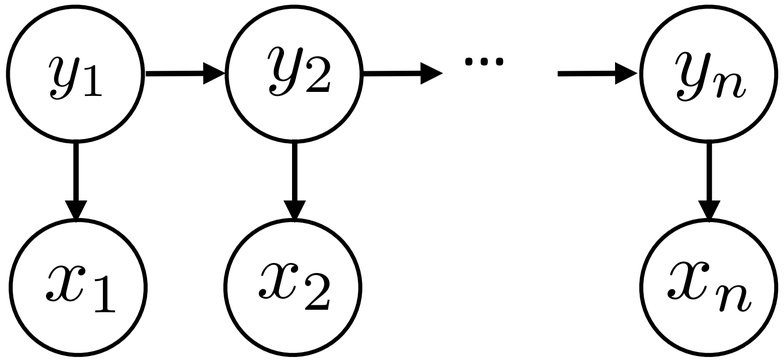

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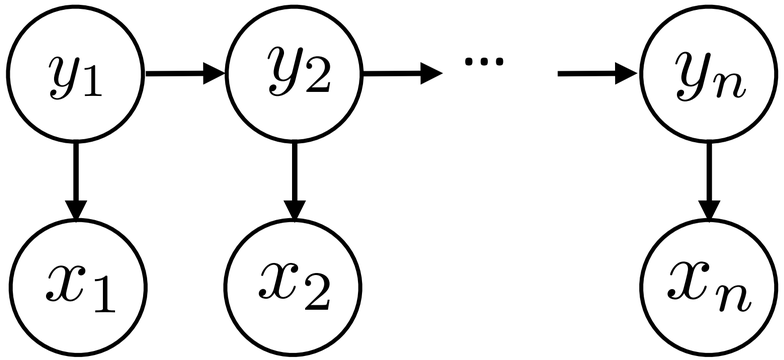

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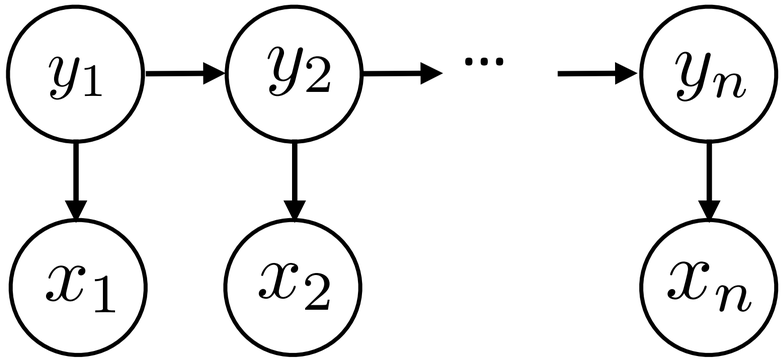

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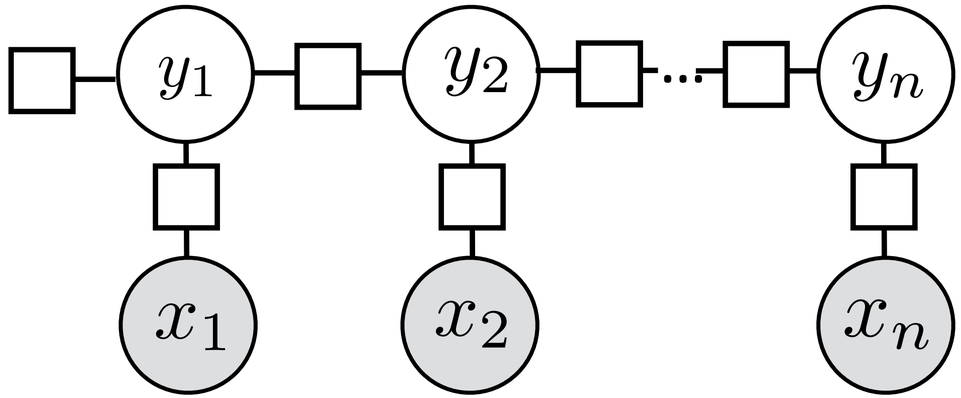

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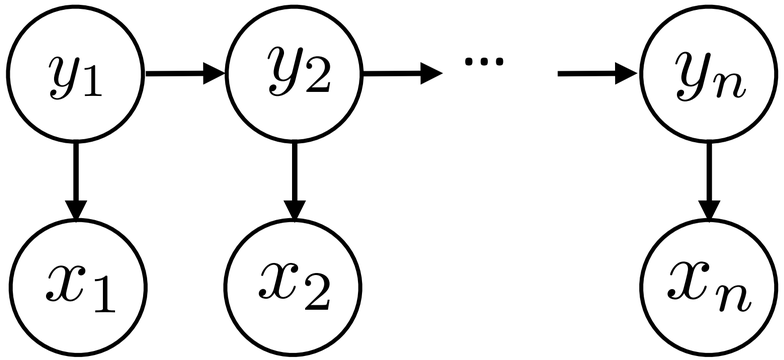

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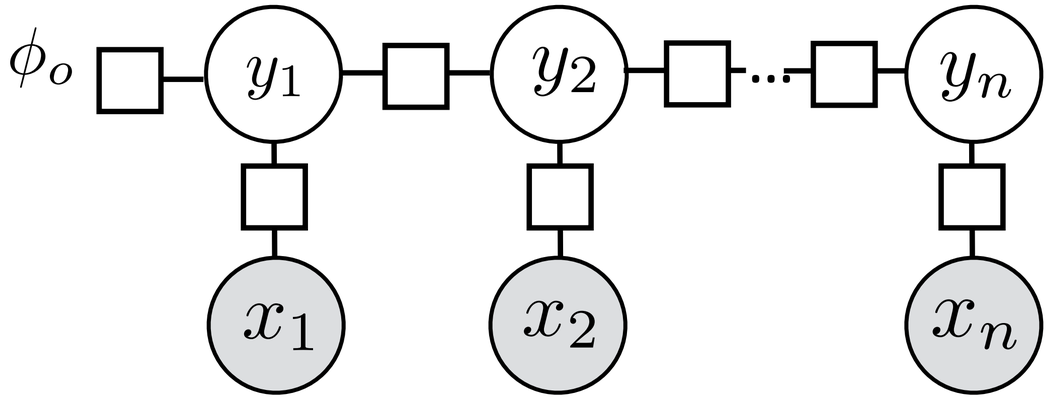

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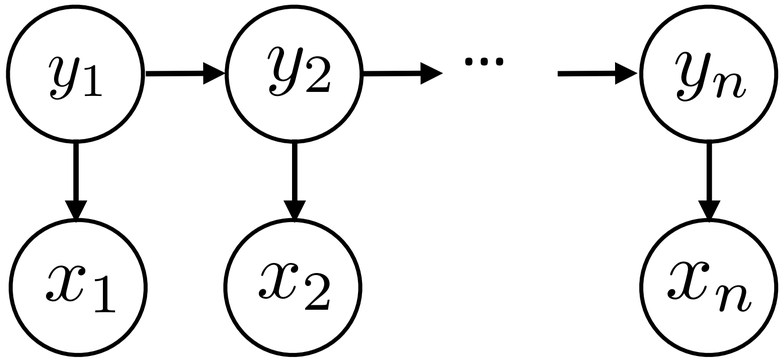

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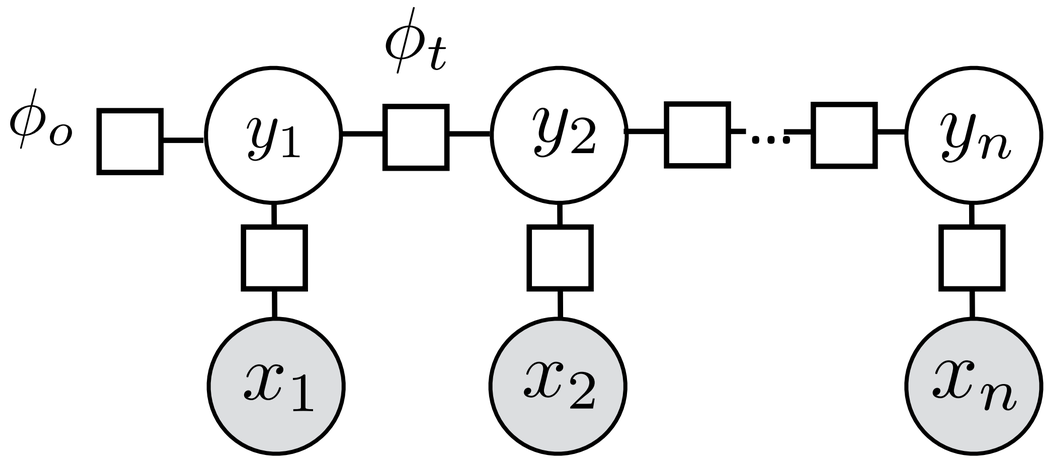

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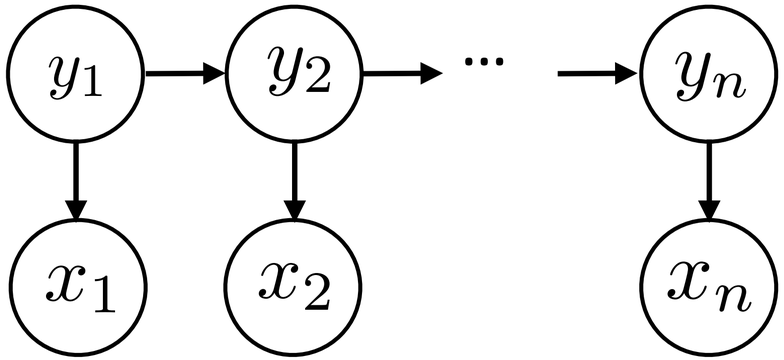

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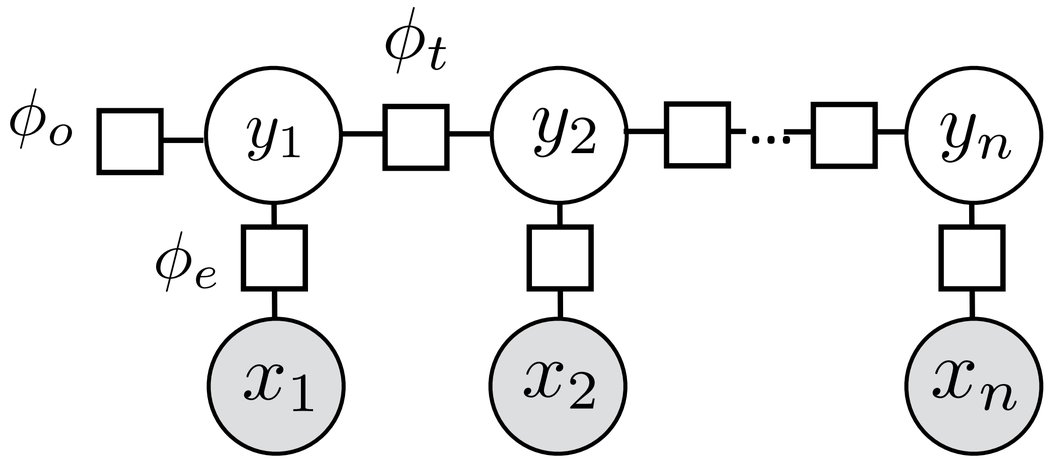

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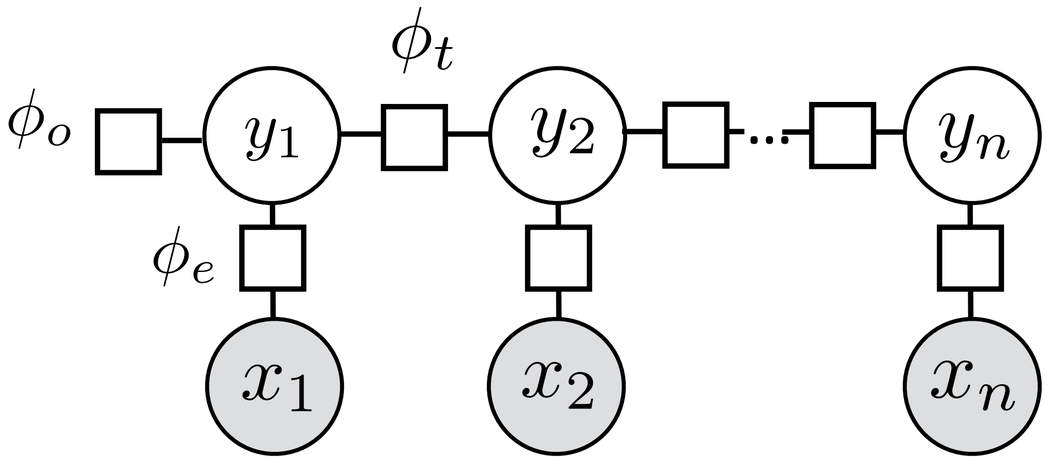

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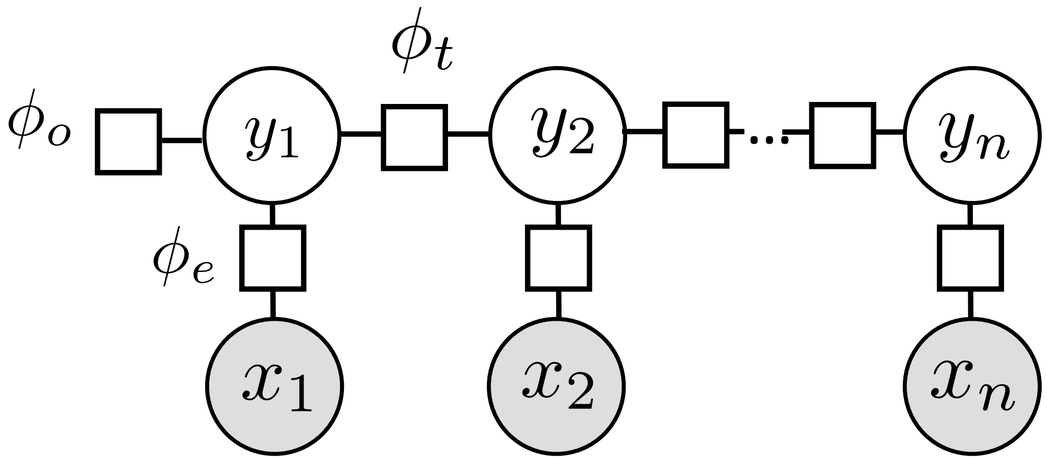

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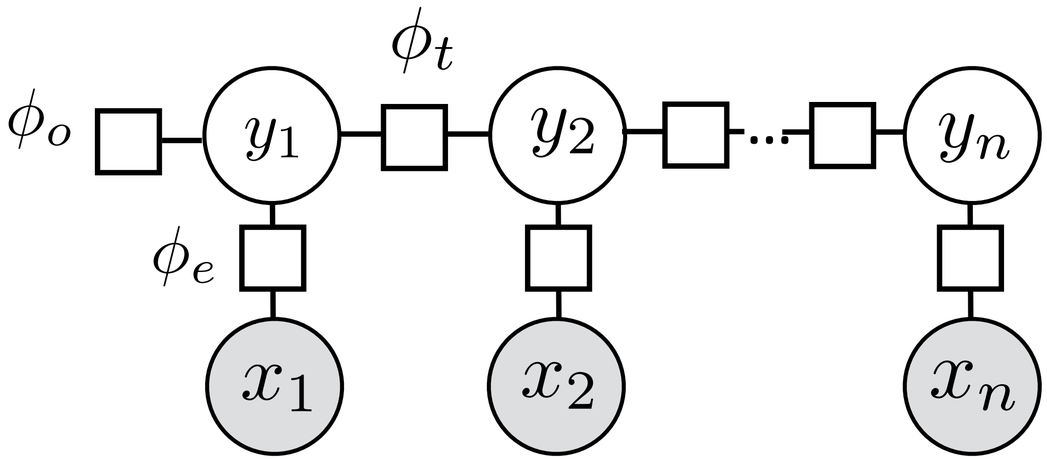
- We condition on **x**, so every factor can depend on all of **x** (including transitions, but we won't do this)

Sequential CRFs



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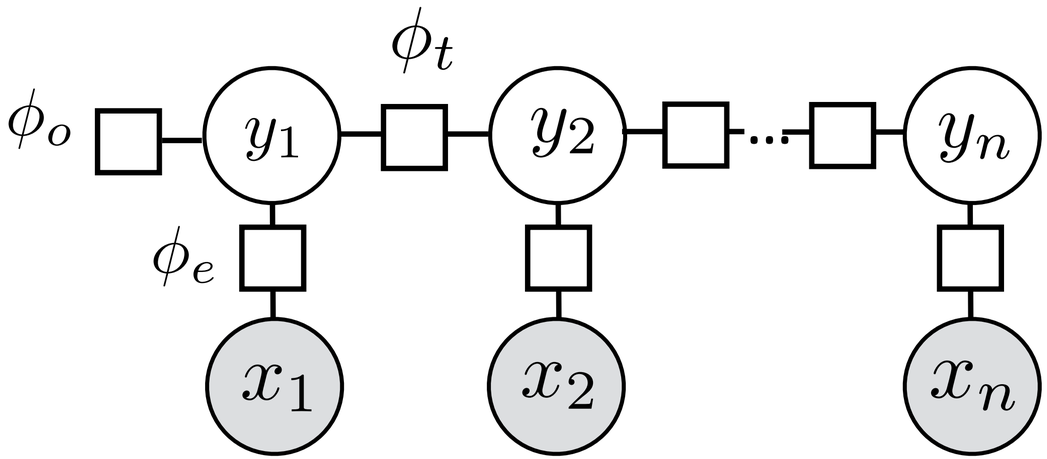

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token index — lets us look at current word

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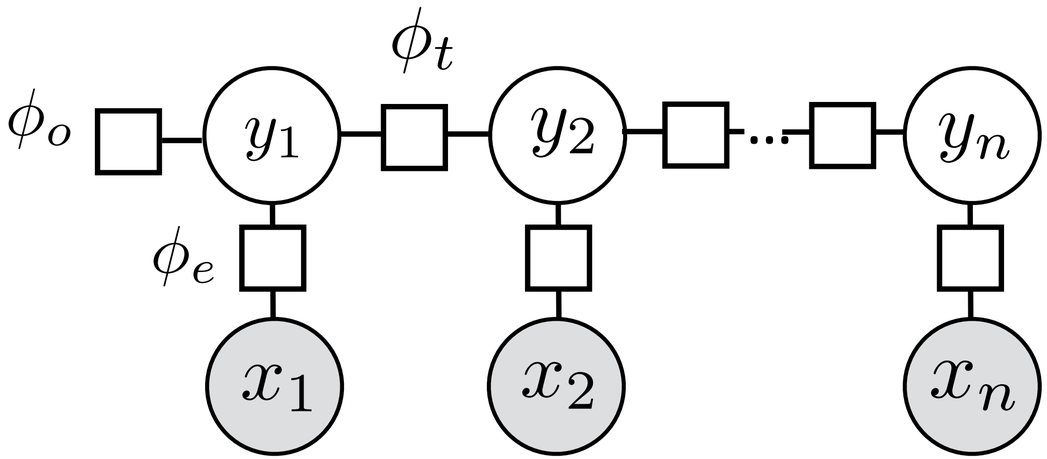

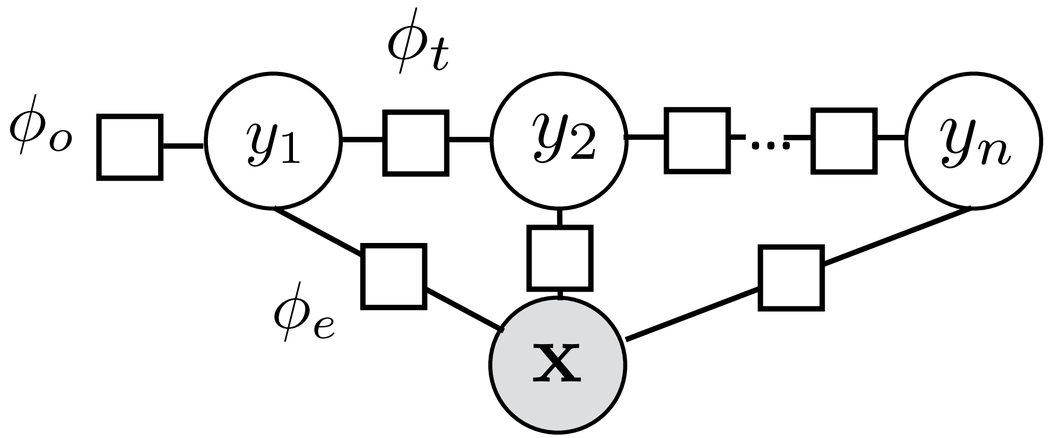

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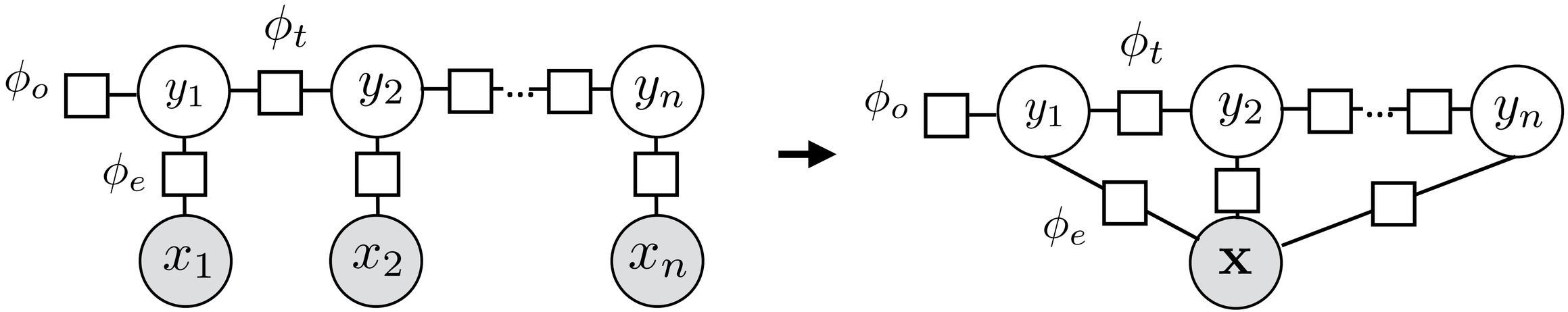

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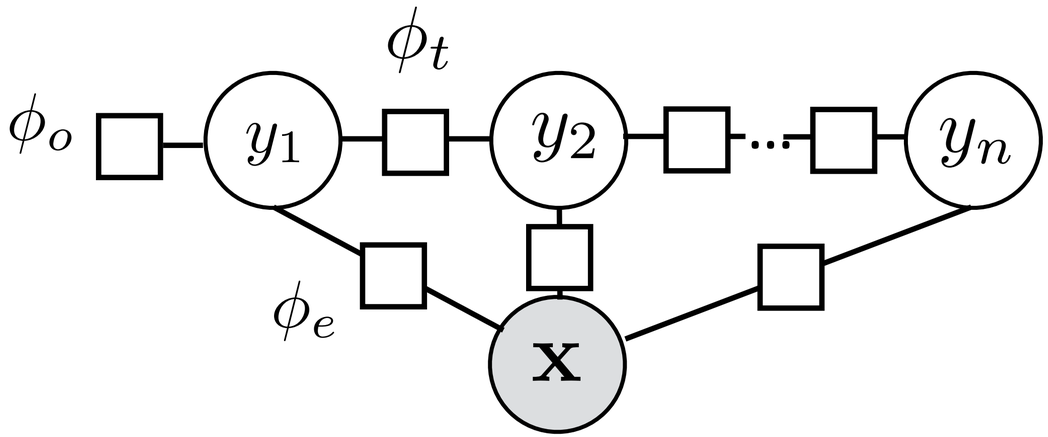
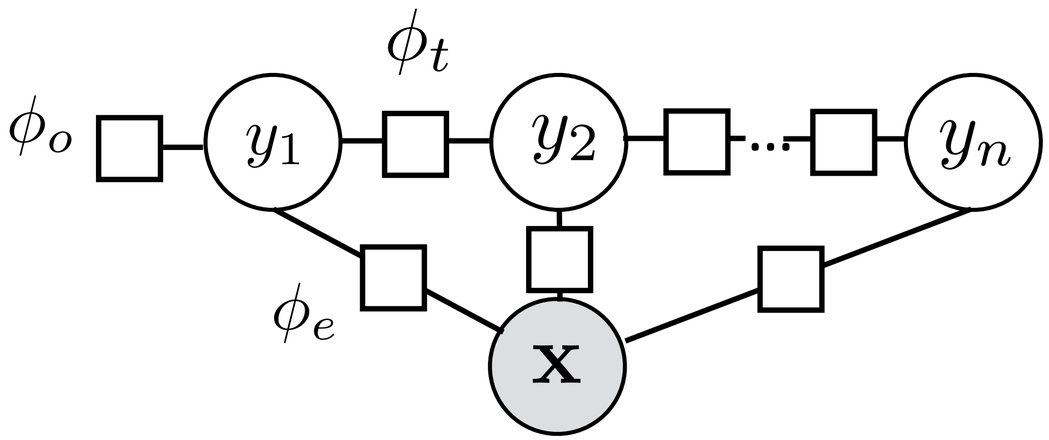
- We condition on **x**, so every factor can depend on all of **x** (including transitions, but we won't do this)
- **y** can't depend arbitrarily on **x** in a generative model

Sequential CRFs



Sequential CRFs



- Notation: omit **x** from the factor graph entirely (implicit)

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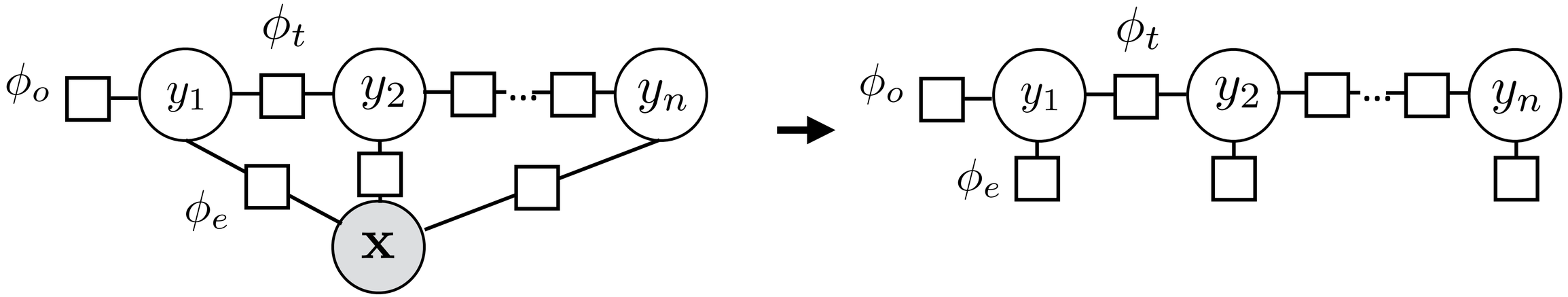

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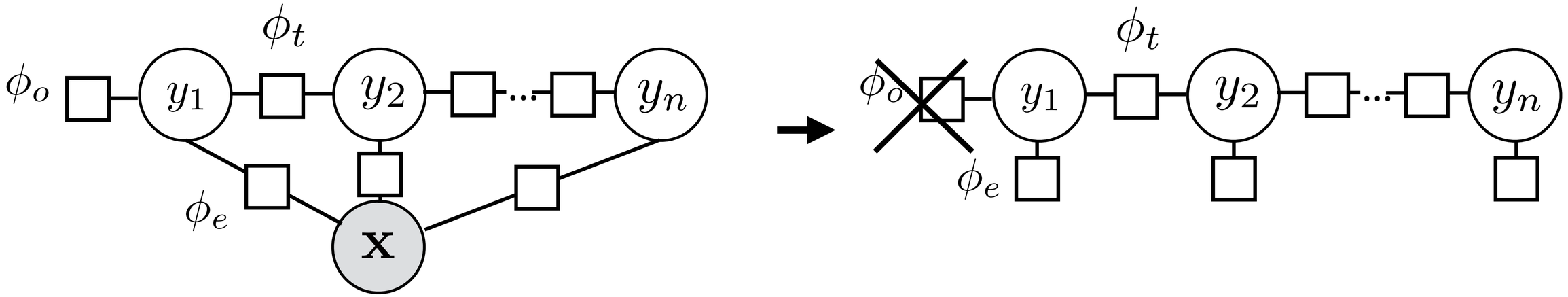

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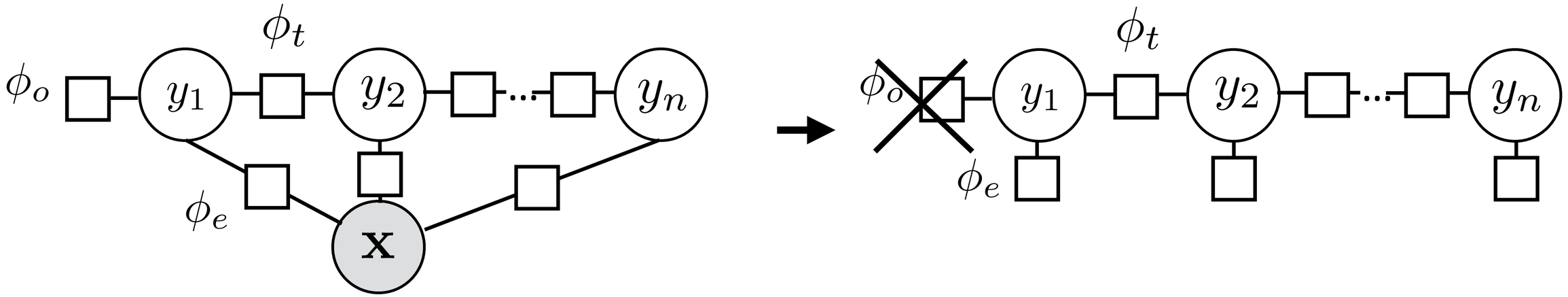

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Sequential CRFs:

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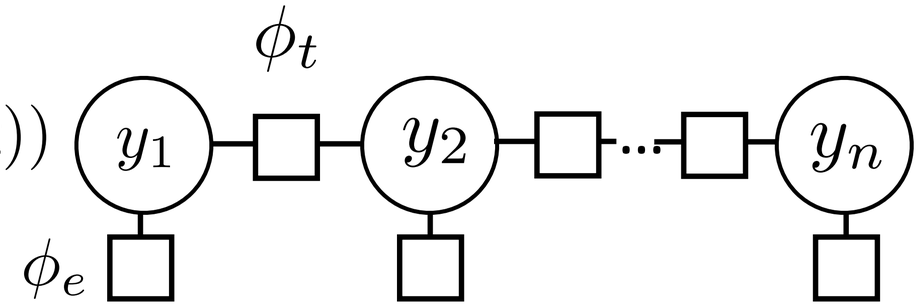

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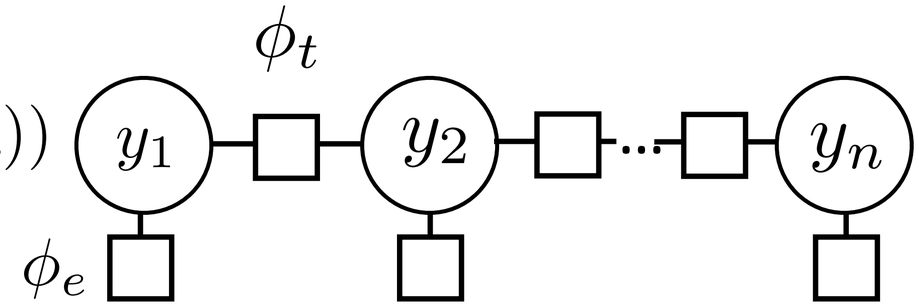

- Phis can be almost anything! Here we use linear functions of sparse features

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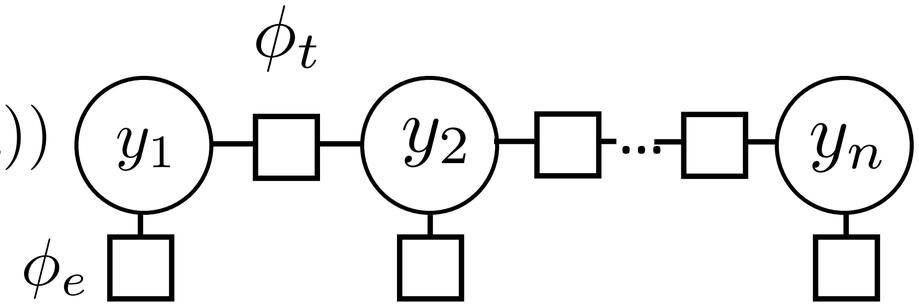

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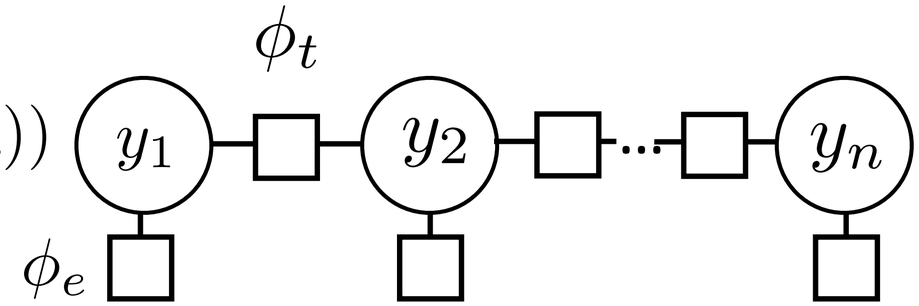

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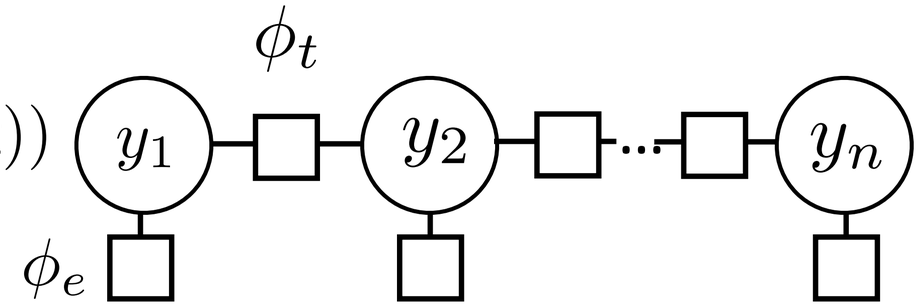

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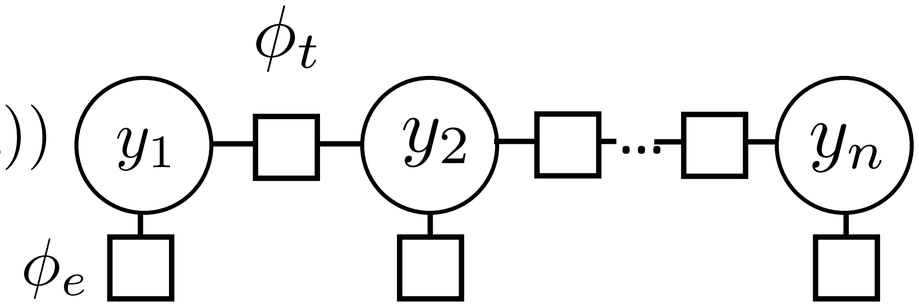

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- Looks like our single weight vector multiclass logistic regression model

Basic Features for NER

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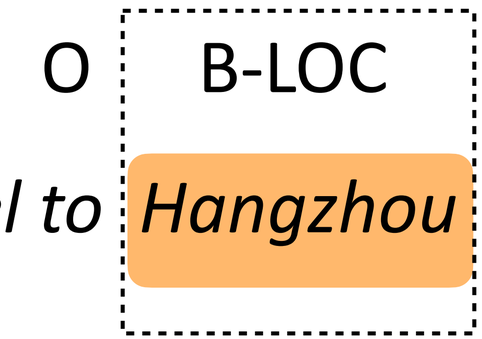

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O B-LOC

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

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

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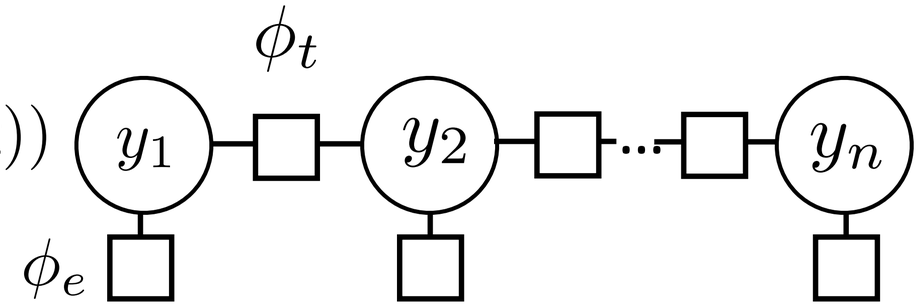
- Inference
- Learning

Computing (arg)maxes

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



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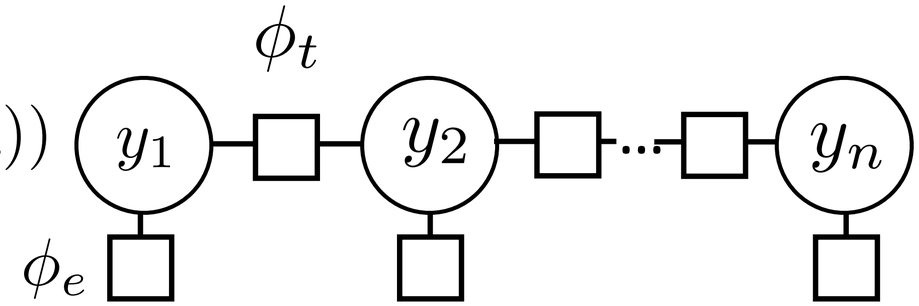

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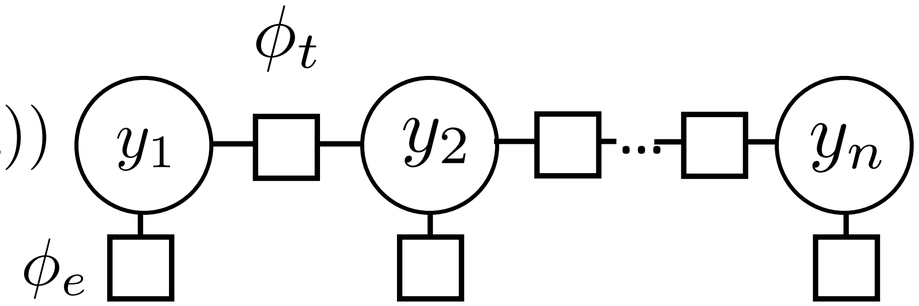

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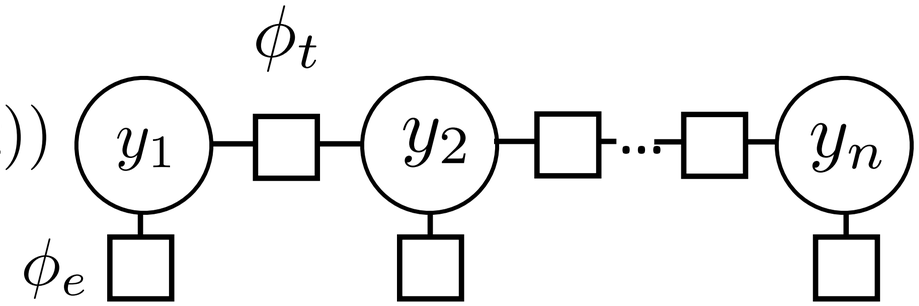

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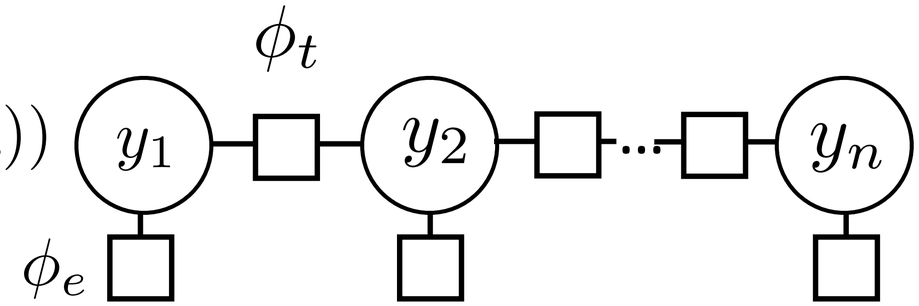

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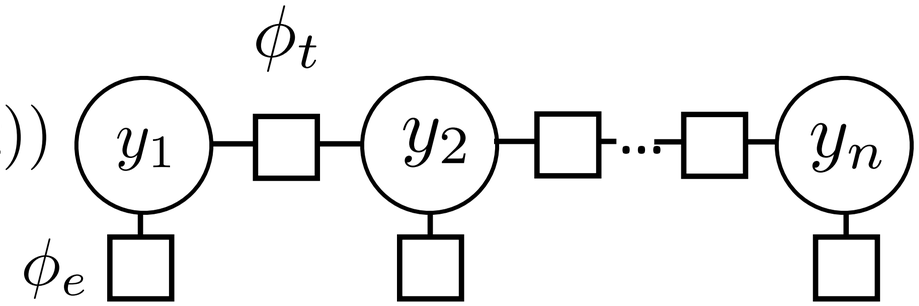

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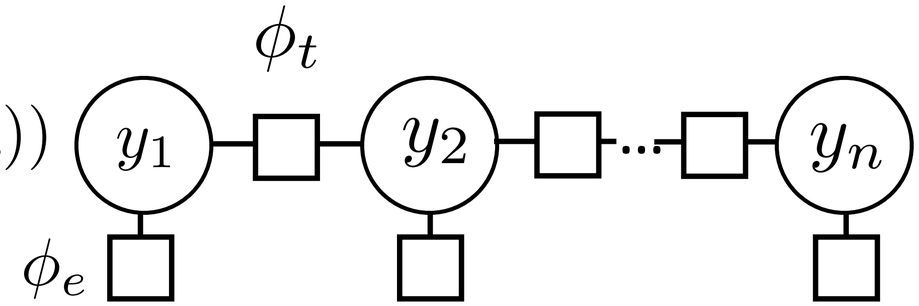

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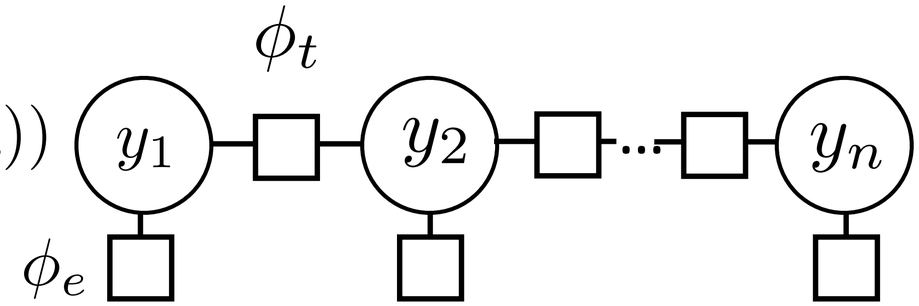

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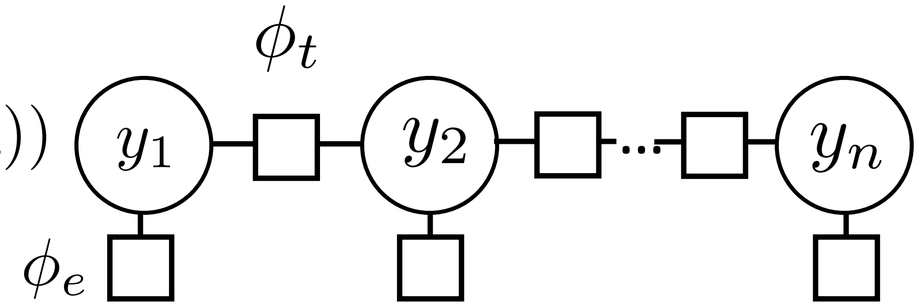

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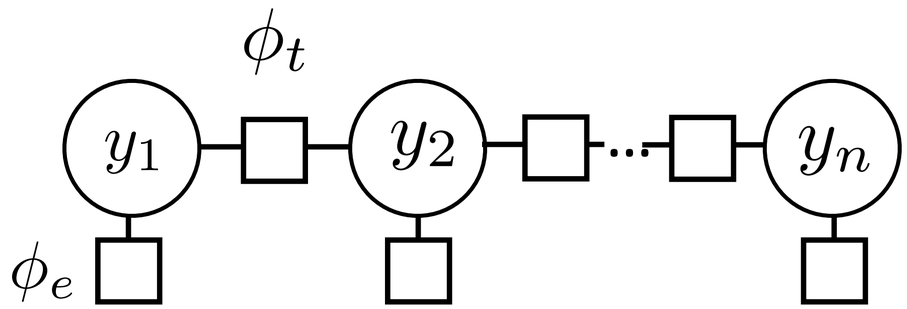
$$= \max_{y_2,\ldots,y_n} e^{\phi_t(y_{n-1},y_n)} e^{\phi_e(y_n,n,\mathbf{x})} \ldots e^{\phi_e(y_2,2,\mathbf{x})} \boxed{\max_{y_1} e^{\phi_t(y_1,y_2)} e^{\phi_e(y_1,1,\mathbf{x})}}$$

$$= \max_{y_3,\ldots,y_n} e^{\phi_t(y_{n-1},y_n)} e^{\phi_e(y_n,n,\mathbf{x})} \ldots \max_{y_2} e^{\phi_t(y_2,y_3)} e^{\phi_e(y_2,2,\mathbf{x})} \max_{y_1} e^{\phi_t(y_1,y_2)} \text{score}_1(y_1)$$

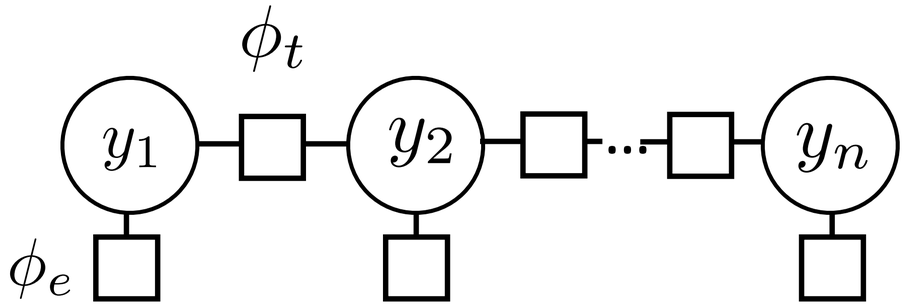
- $\exp(\phi_t(y_{i-1}, y_i))$ and $\exp(\phi_e(y_i, i, \mathbf{x}))$ play the role of the Ps now, same dynamic program

Inference in General CRFs



Inference in General CRFs

- Can do inference in any tree-structured CRF



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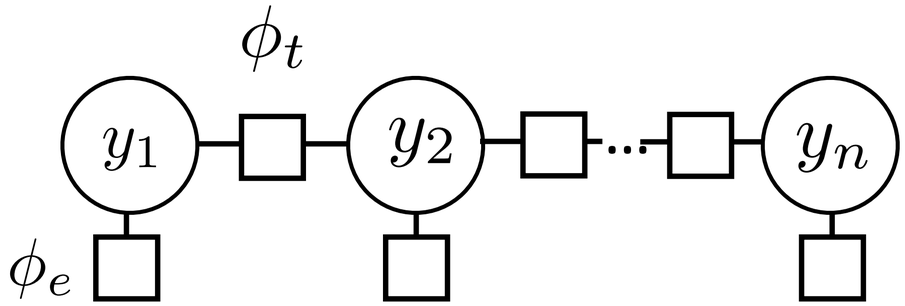

- Max-product algorithm: generalization of Viterbi to arbitrary tree-structured graphs (sum-product is generalization of forward-backward)

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

Training CRFs

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

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intractable! $-\mathbb{E}_{\mathbf{y}} \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x}) \right]$

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- Let's focus on emission feature expectation

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$$\mathbb{E}_{\mathbf{y}}\left[\sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right] = \sum_{\mathbf{y}\in\mathcal{Y}} P(\mathbf{y}|\mathbf{x})\left[\sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

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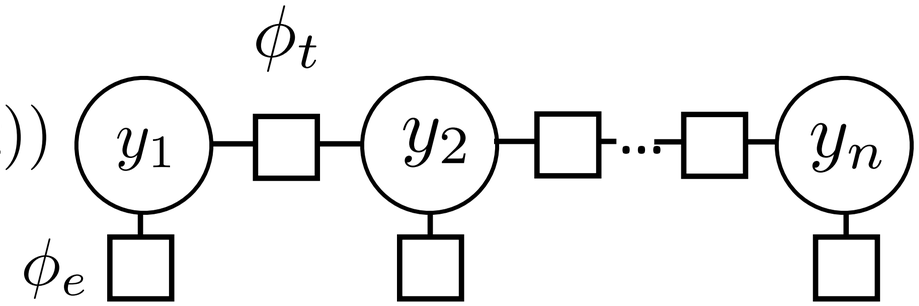
Computing Marginals

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



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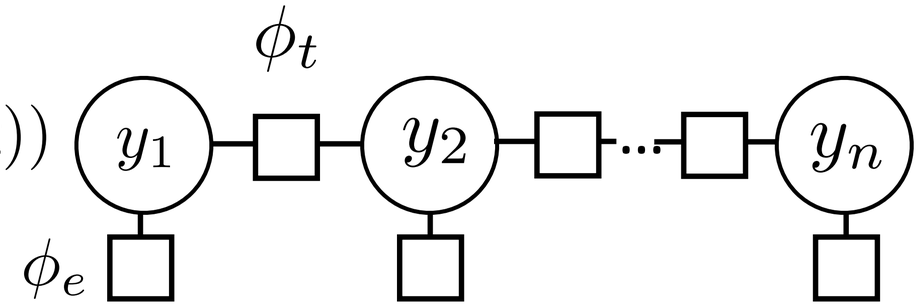

- Normalizing constant $Z = \sum_{\mathbf{y}} \prod_{i=2}^{n} \exp(\phi_t(y_{i-1}, y_i)) \prod_{i=1}^{n} \exp(\phi_e(y_i, i, \mathbf{x}))$

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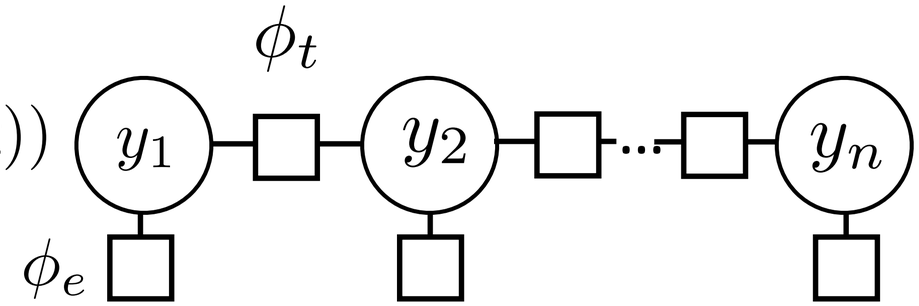

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- Analogous to P(**x**) for HMMs

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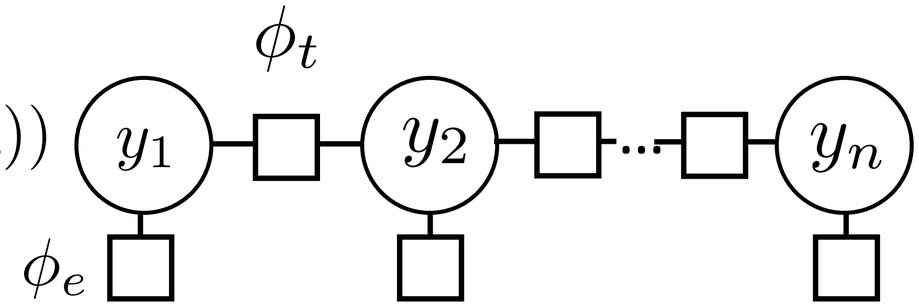

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$$P(y_i = s|\mathbf{x}) = \frac{\text{forward}_i(s)\text{backward}_i(s)}{\sum_{s'}\text{forward}_i(s')\text{backward}_i(s')}$$

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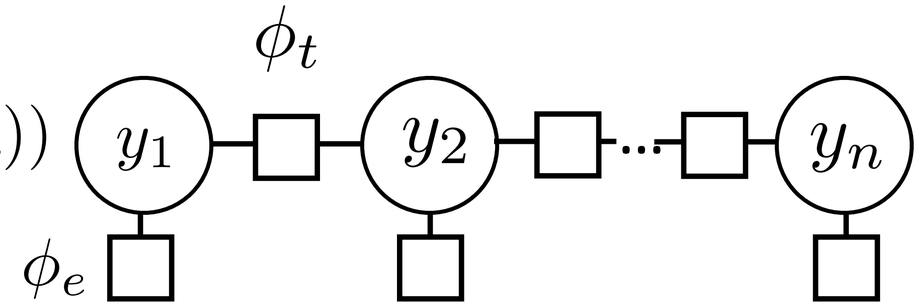

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Z for CRFs, P(**x**) for HMMs

Posteriors vs. Probabilities

$$P(y_i = s|\mathbf{x}) = \frac{\text{forward}_i(s)\text{backward}_i(s)}{\sum_{s'} \text{forward}_i(s')\text{backward}_i(s')}$$

- Posterior is *derived* from the parameters and the data (conditioned on **x**!)

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$$P(x_i|y_i), P(y_i|y_{i-1})$$

HMM

Model parameter (usually multinomial distribution)

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CRF		

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CRF	Undefined (model is by definition conditioned on **x**)	

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Training CRFs

- For emission features:

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

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gold features — expected features under model

- Transition features: need to compute $P(y_i = s_1, y_{i+1} = s_2|\mathbf{x})$ using forward-backward as well

CRFs Outline

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

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

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

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

Pseudocode

for each epoch

    for each example

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        extract features on each emission and transition (look up in cache)

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How to “Cheat” with Automatic Differentiation

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How to “Cheat” with Automatic Differentiation

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compute potentials phi based on features + weights

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accumulate gradient over all emissions and transitions

- Compute P(Y|X), using the forward algorithm to get Z(X)
- Use auto-diff through the computation graph of the dynamic program, to compute gradients.

Structured SVM / Structured Perceptron

Structured Perceptron

- Structured Perceptron Update:

$$\hat{y} = \operatorname{argmax}_{y \in \mathcal{Y}} w^\top f(x, y)$$

$$w = w + f(x, y^*) - f(x, \hat{y})$$

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Viterbi Algorithm

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Replaces Expectation With argmax

Structured SVM

Structured SVM

- CRF: $\log P(\mathbf{y}|\mathbf{x}) \propto \sum_{i=2}^{n} w^\top f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} w^\top f_e(x_i, y_i)$

Structured SVM

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- We can formulate an SVM using the same features

Structured SVM

- CRF: $\log P(\mathbf{y}|\mathbf{x}) \propto \sum_{i=2}^{n} w^\top f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} w^\top f_e(x_i, y_i)$
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- Same as normal Viterbi but boost wrong labels' scores by 1 (if using Hamming loss)
- Only need Viterbi, not forward-backward…hmm…

NER

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- CRF with lexical features can get around 85 F1 on this problem

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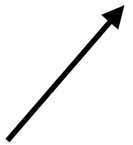

Tanjug

From Wikipedia, the free encyclopedia

Tanjug (/ˈtʌnjʊg/) (Serbian Cyrillic: Тањуг) is a Serbian state news agency based in Belgrade.[2]

Nonlocal Features

The delegation met the president at the airport, Tanjug said.

Finkel and Manning (2008), Ratinov and Roth (2009)

Nonlocal Features

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- More complex factor graph structures can let you capture this, or just decode sentences in order and use features on previous sentences

Finkel and Manning (2008), Ratinov and Roth (2009)

Semi-Markov Models

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

Sarawagi and Cohen (2004)

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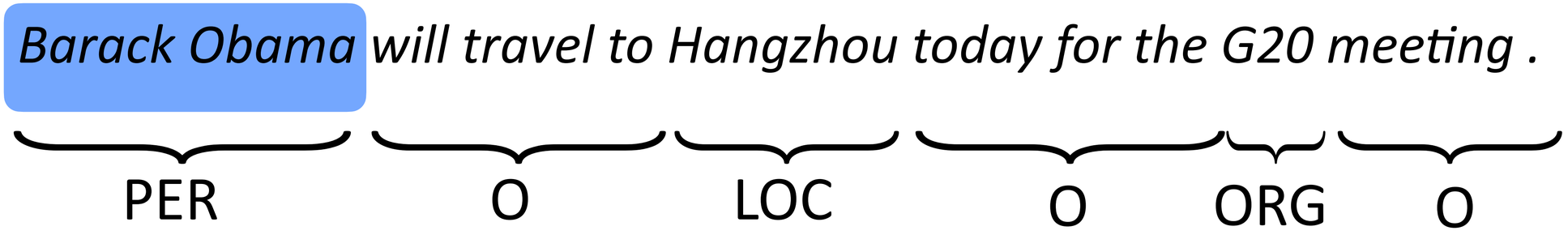

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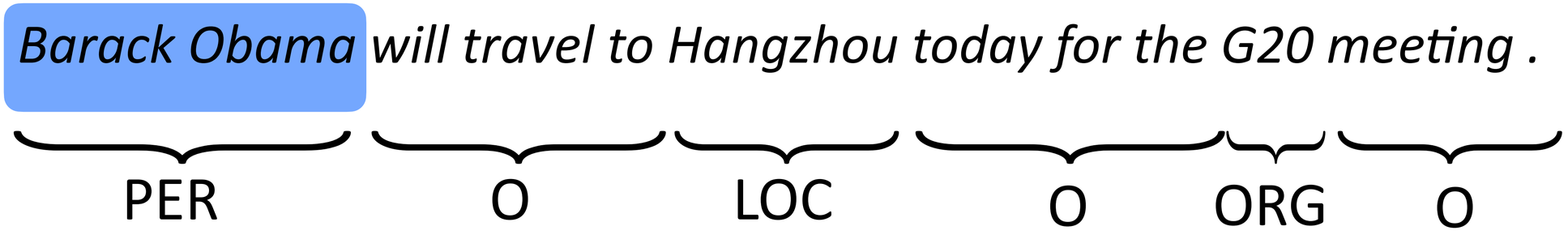

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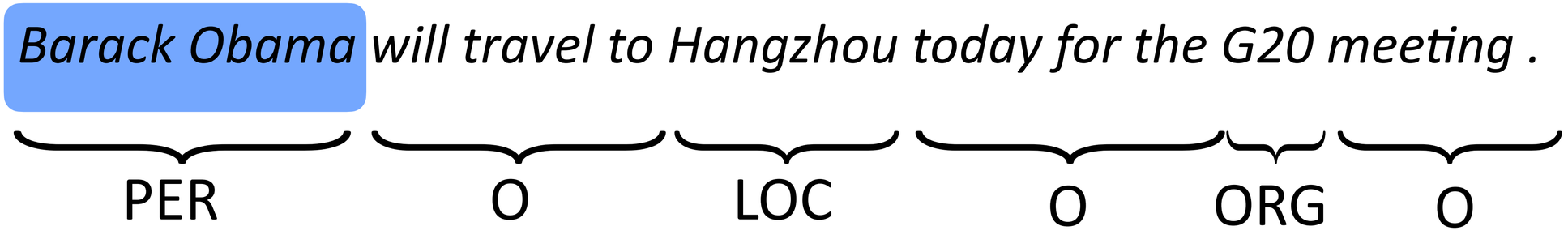

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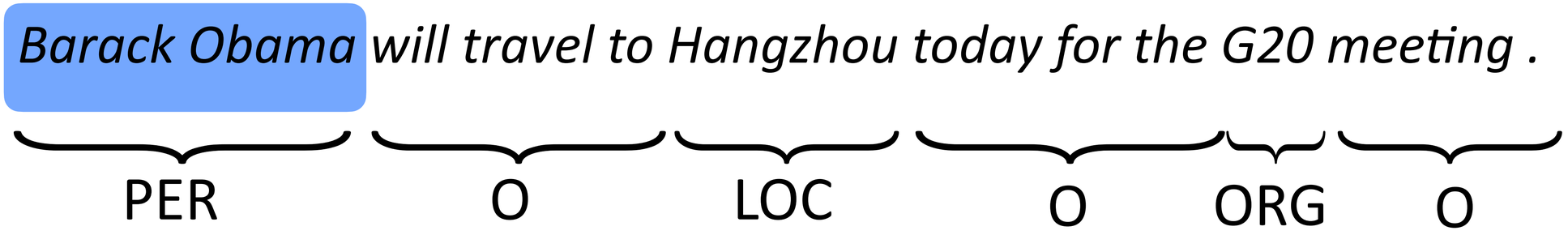

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- Cons: there's an extra factor of *n* in the dynamic programs

Sarawagi and Cohen (2004)

Evaluating NER

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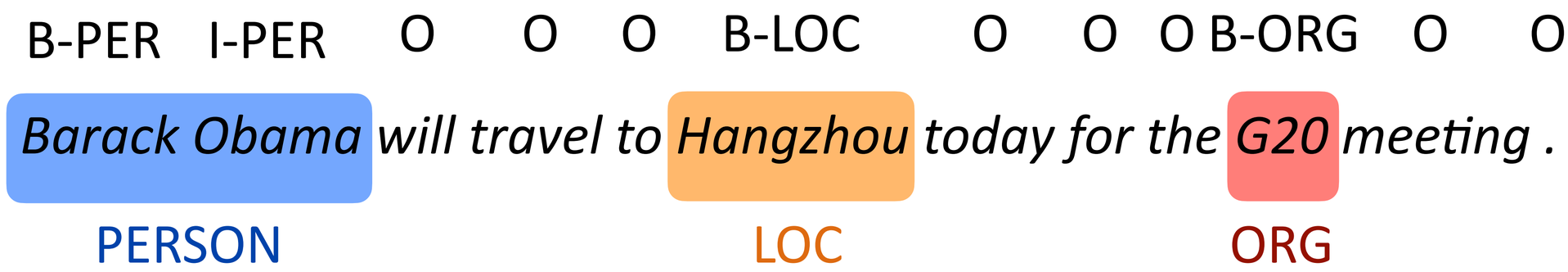

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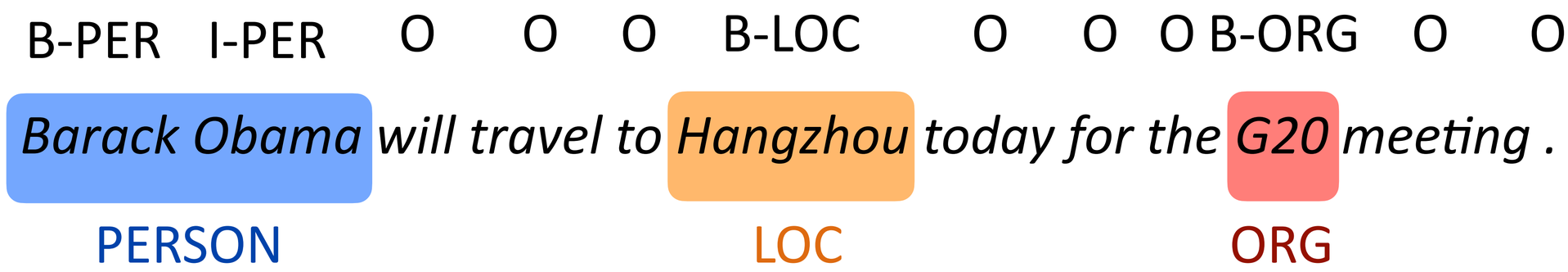

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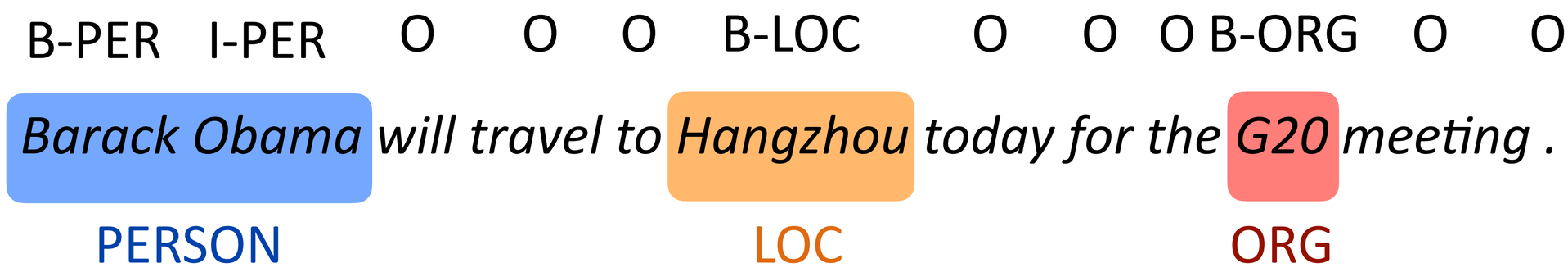

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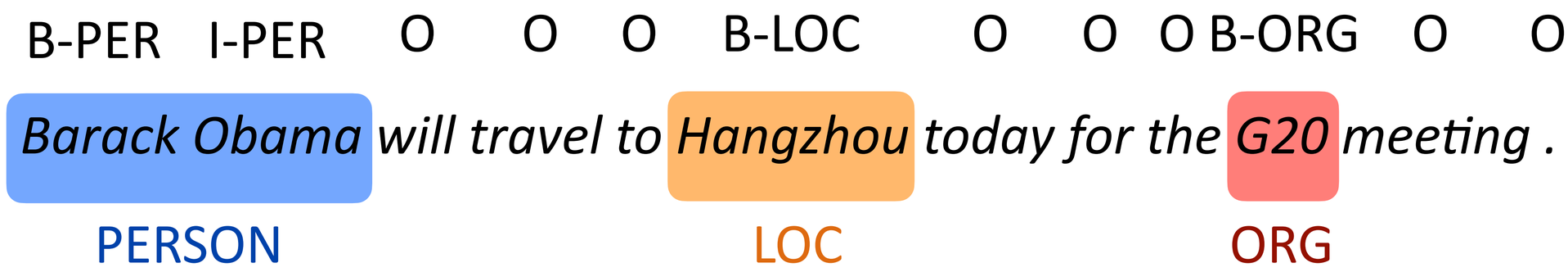

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  - F-measure: harmonic mean of these two

How well do NER systems do?

	System	Resources Used	F_1
+	LBJ-NER	Wikipedia, Nonlocal Features, Word-class Model	90.80
-	(Suzuki and Isozaki, 2008)	Semi-supervised on 1G-word unlabeled data	89.92
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Lample et al. (2016)

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BERT-Large
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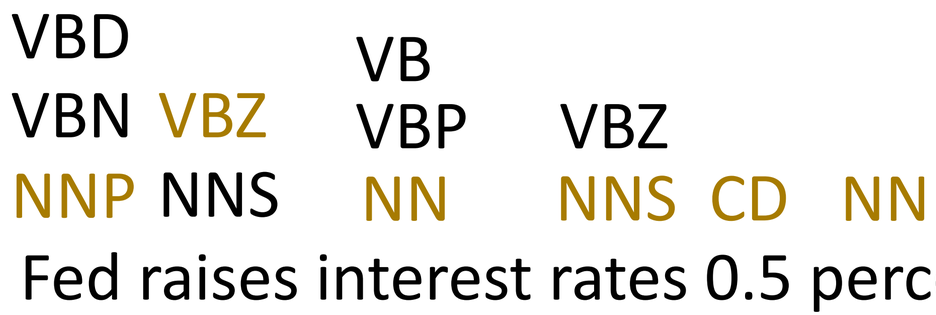
Beam Search

Viterbi Time Complexity

VBD		VB				
VBN	VBZ	VBP	VBZ			
NNP	NNS	NN	NNS	CD	NN	
Fed	raises	interest	rates	0.5	percent	

Viterbi Time Complexity



- n word sentence, s tags to consider — what is the time complexity?

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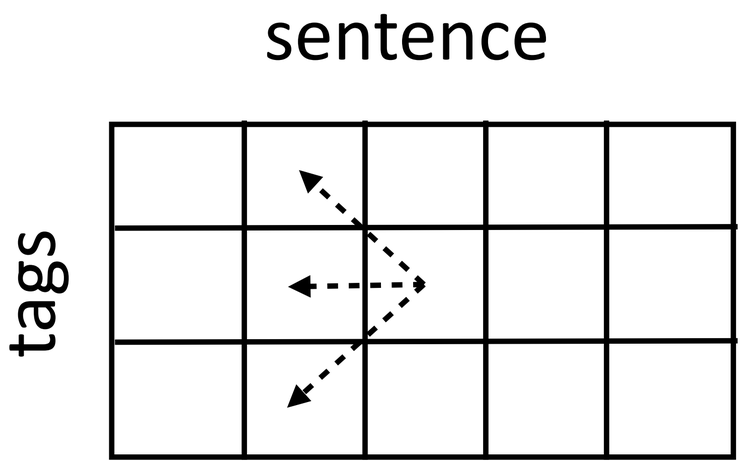

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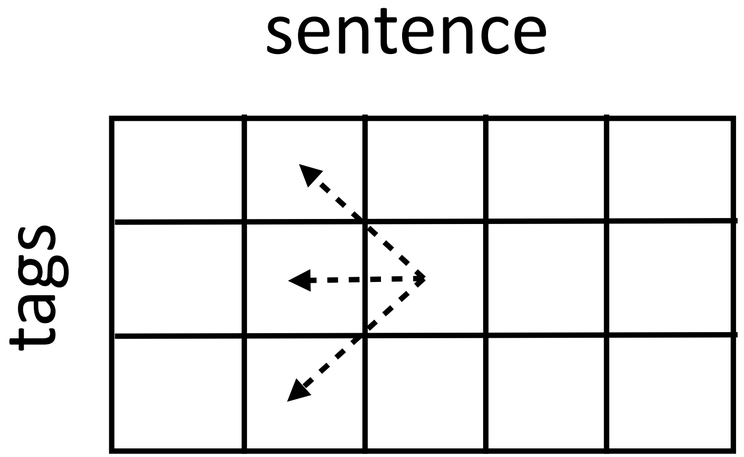

- $O(ns^2)$ — s is ~40 for POS, n is ~20

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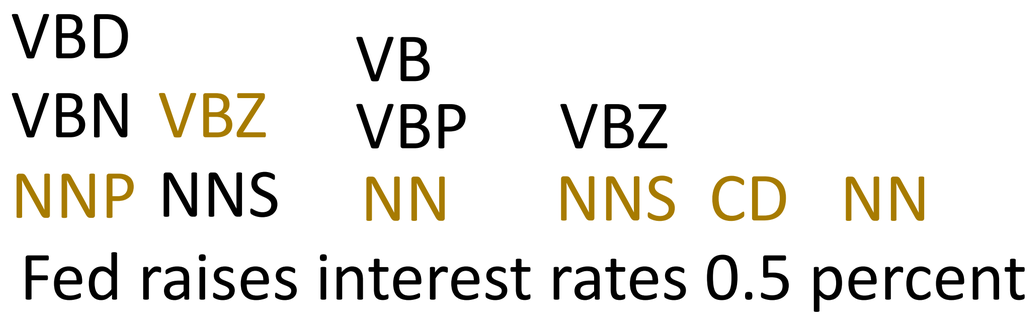

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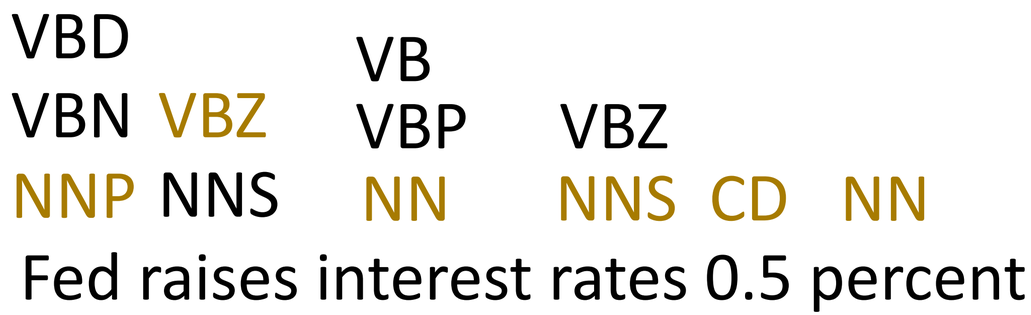

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- Can any of these be:
  - Determiners?
  - Prepositions?
  - Adjectives?
- Features quickly eliminate many outcomes from consideration — don't need to consider these going forward

Beam Search

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- Maintain a beam of *k* plausible states at the current timestep

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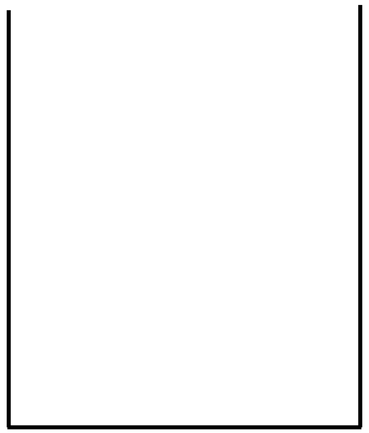

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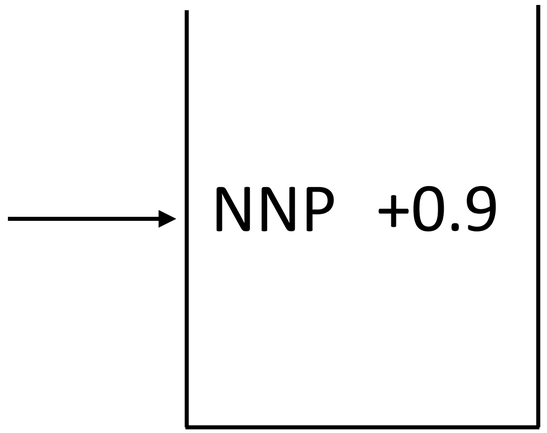

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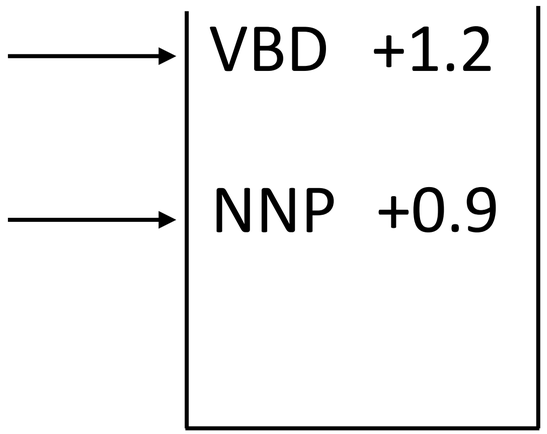

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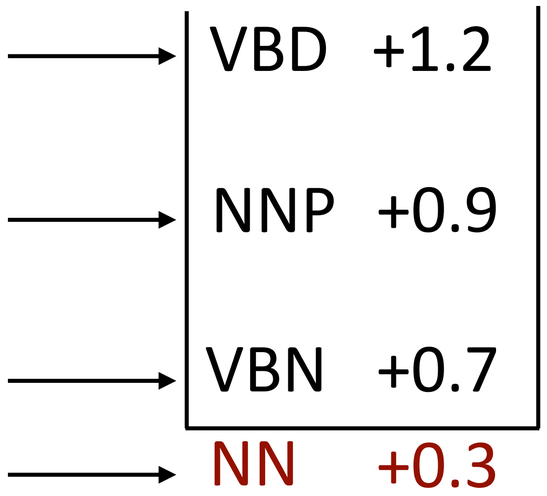

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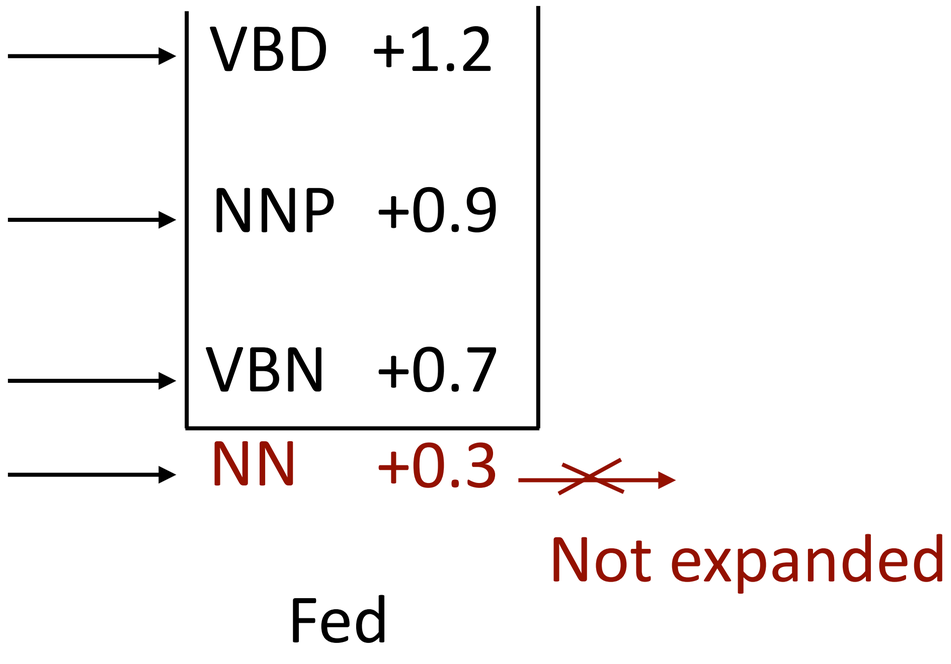

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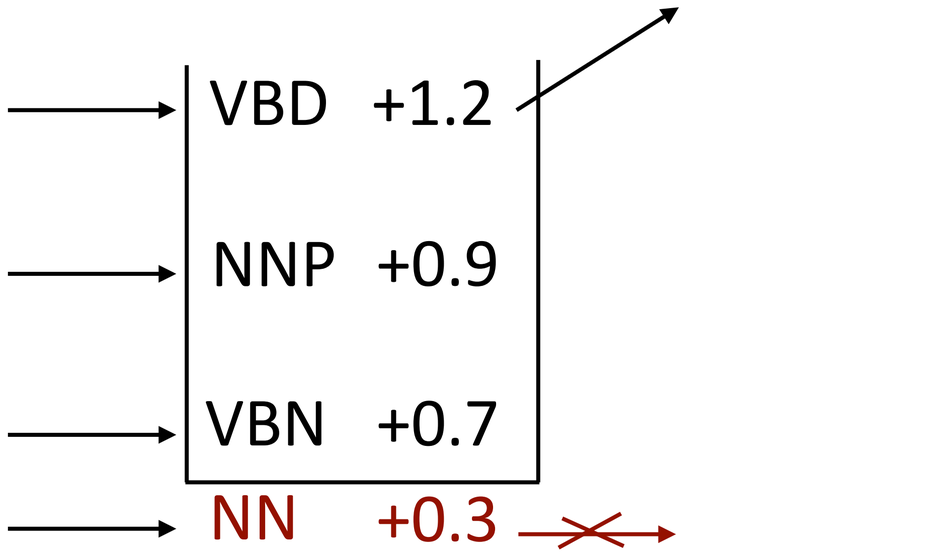

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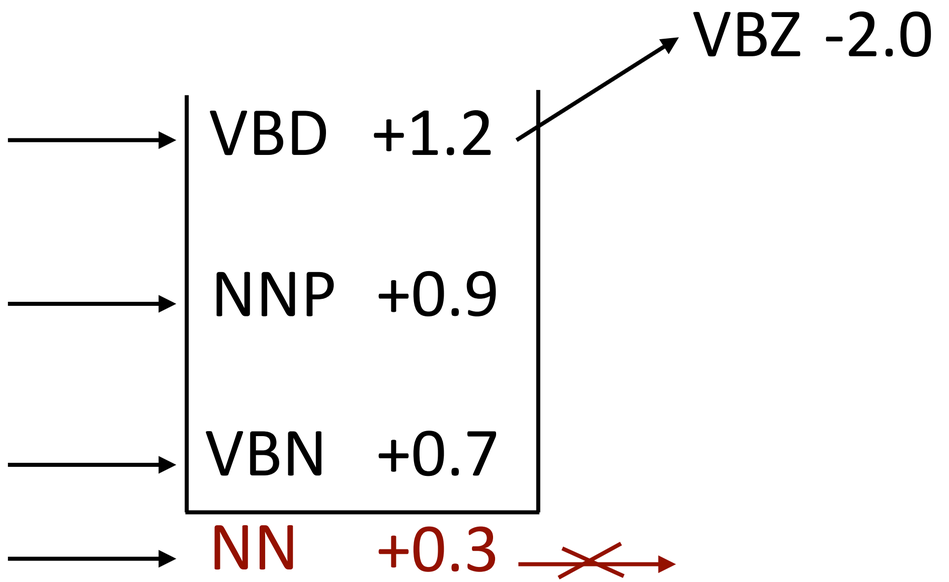

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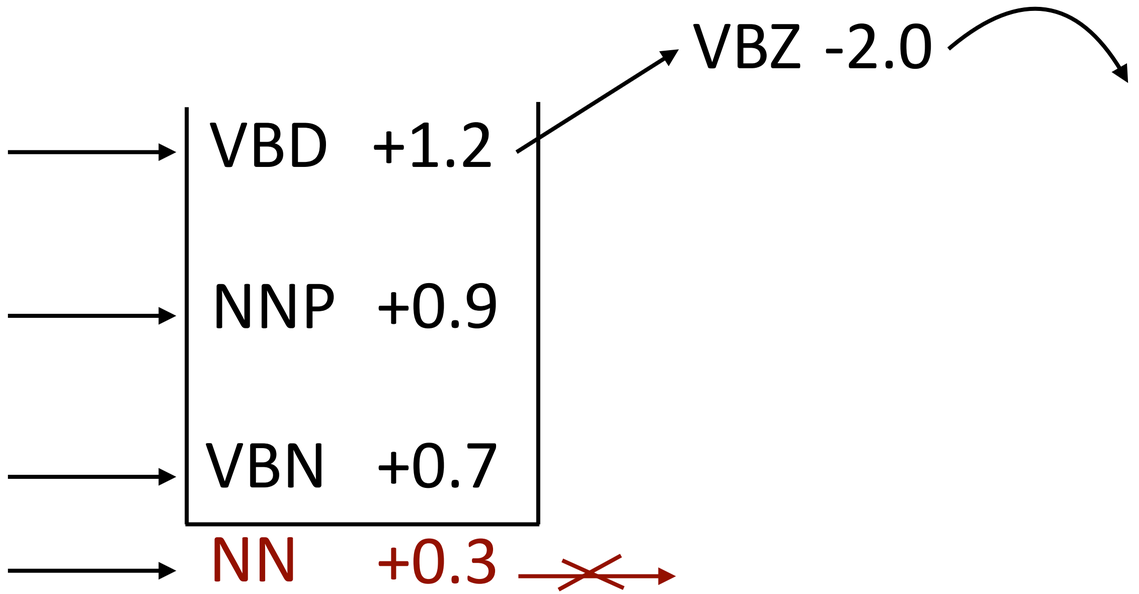

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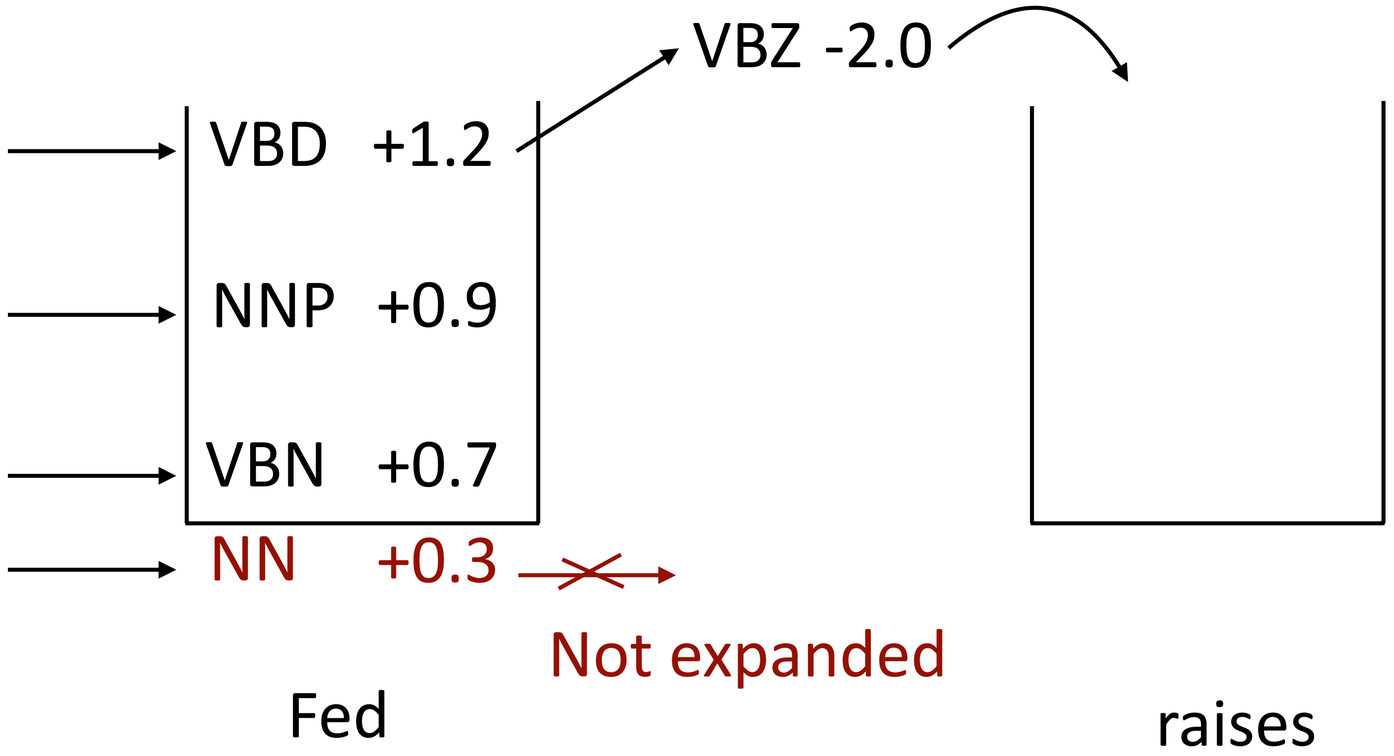

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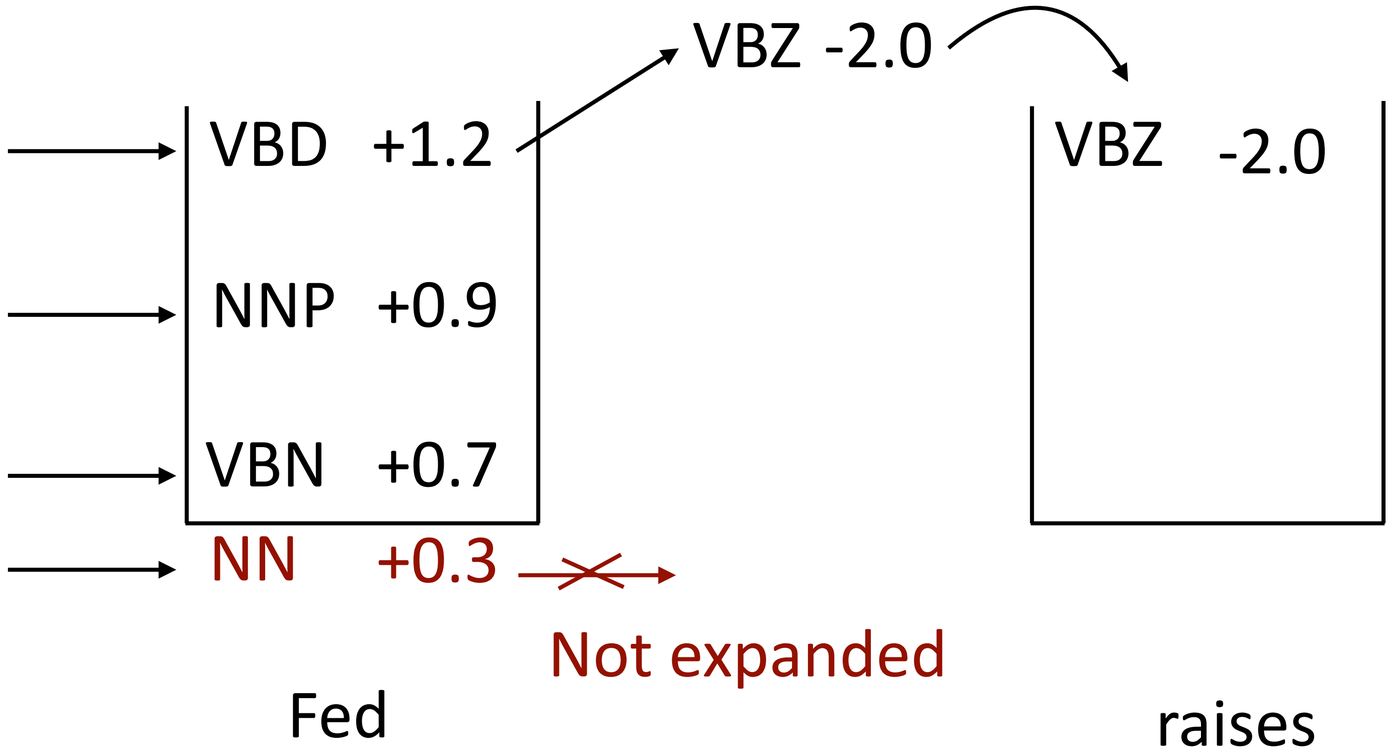

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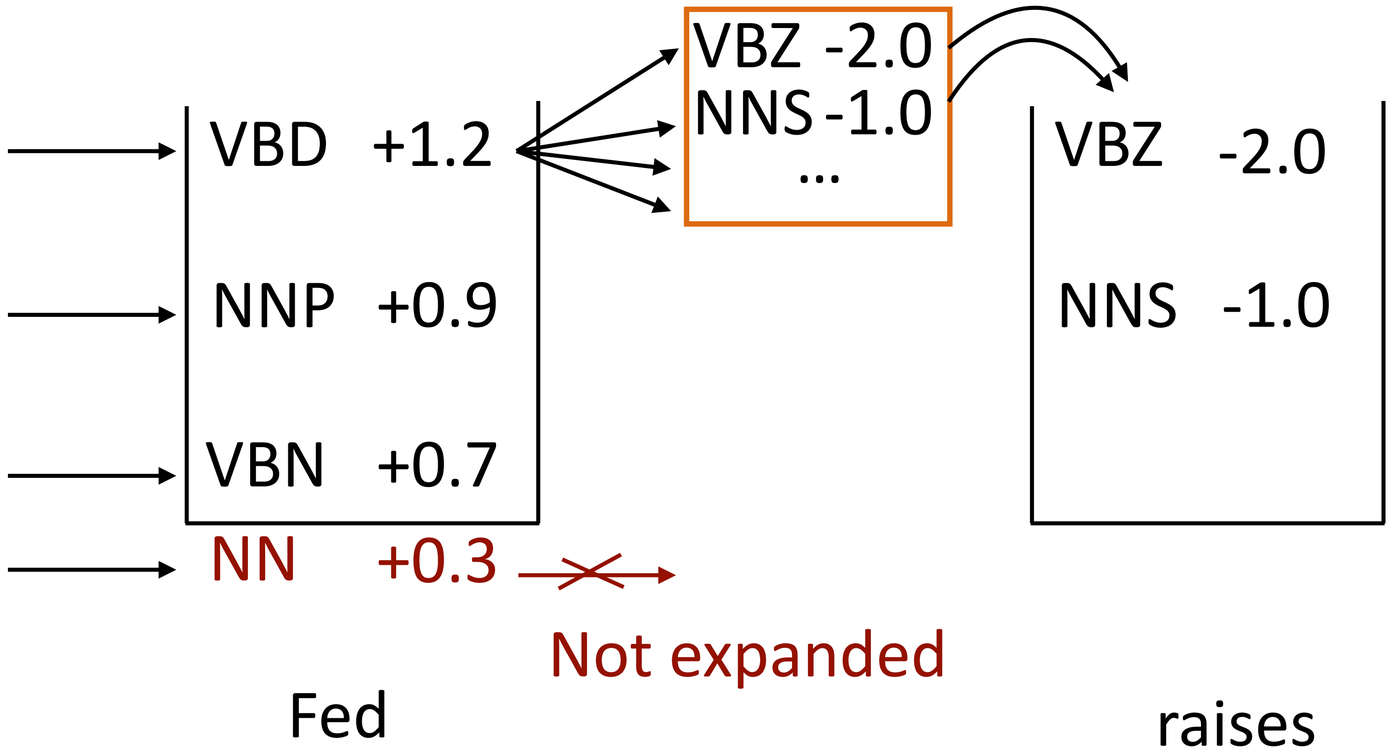

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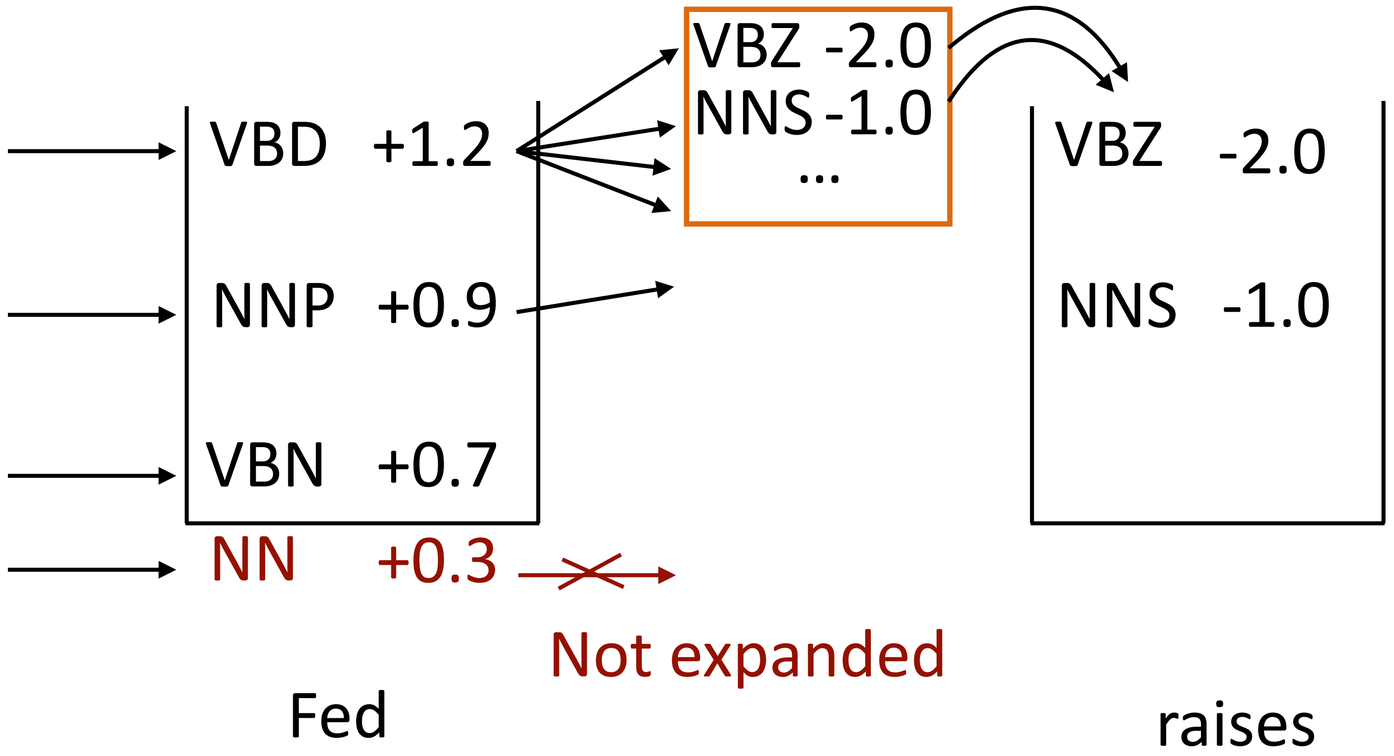

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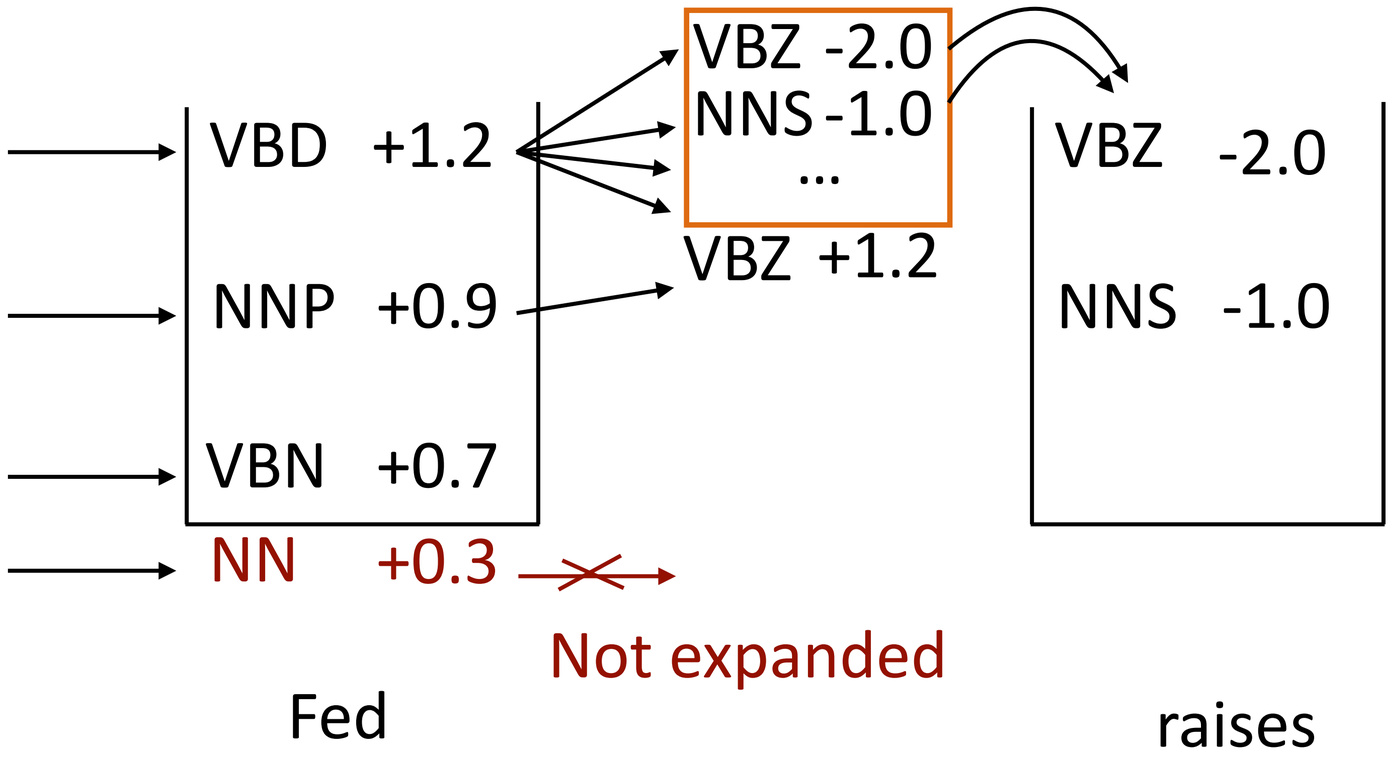

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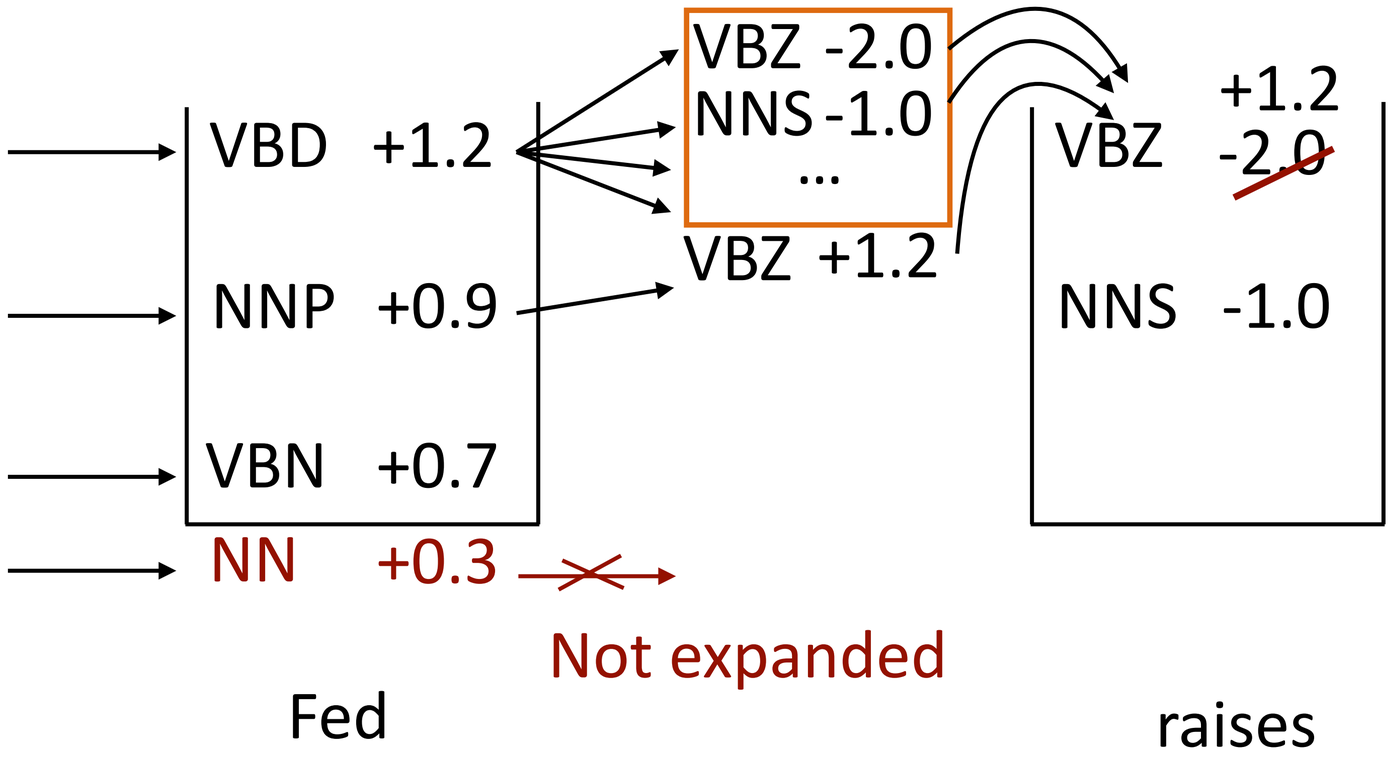

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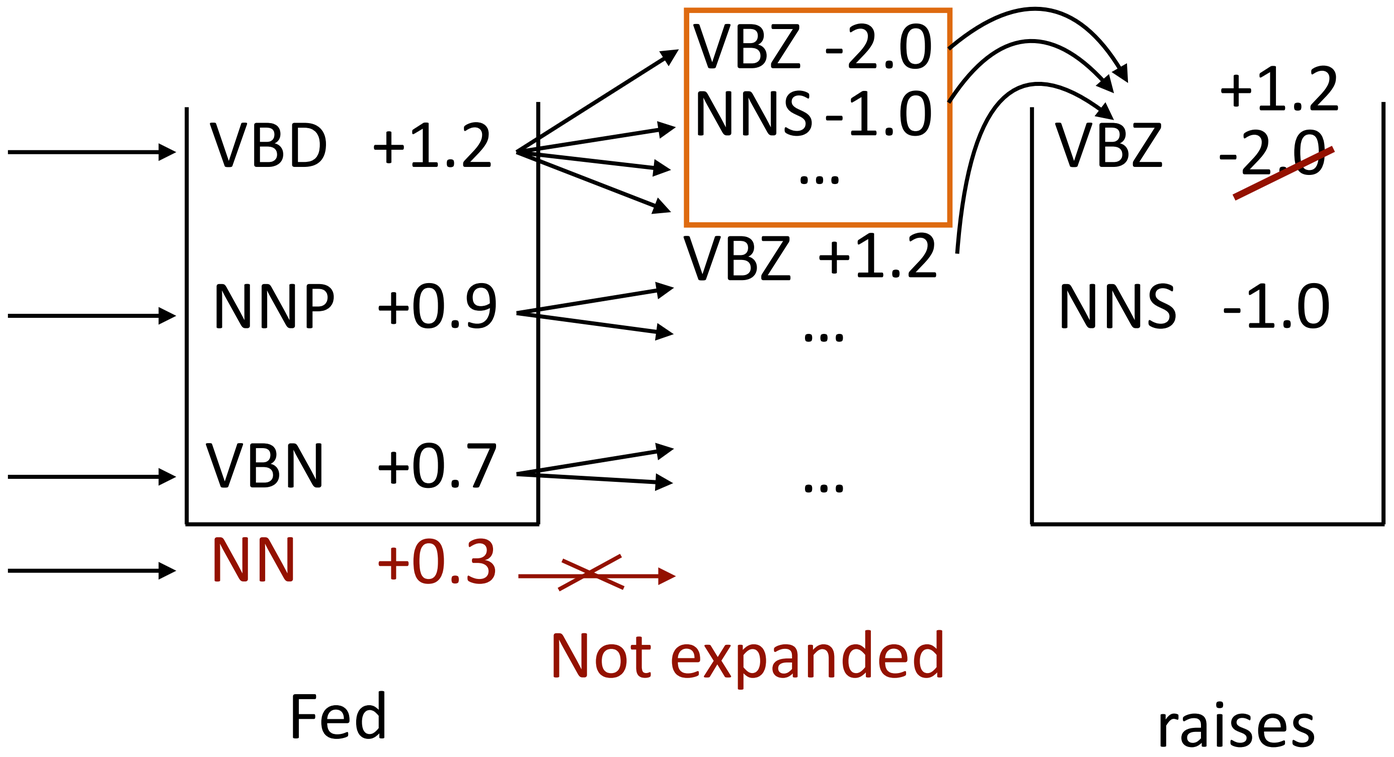

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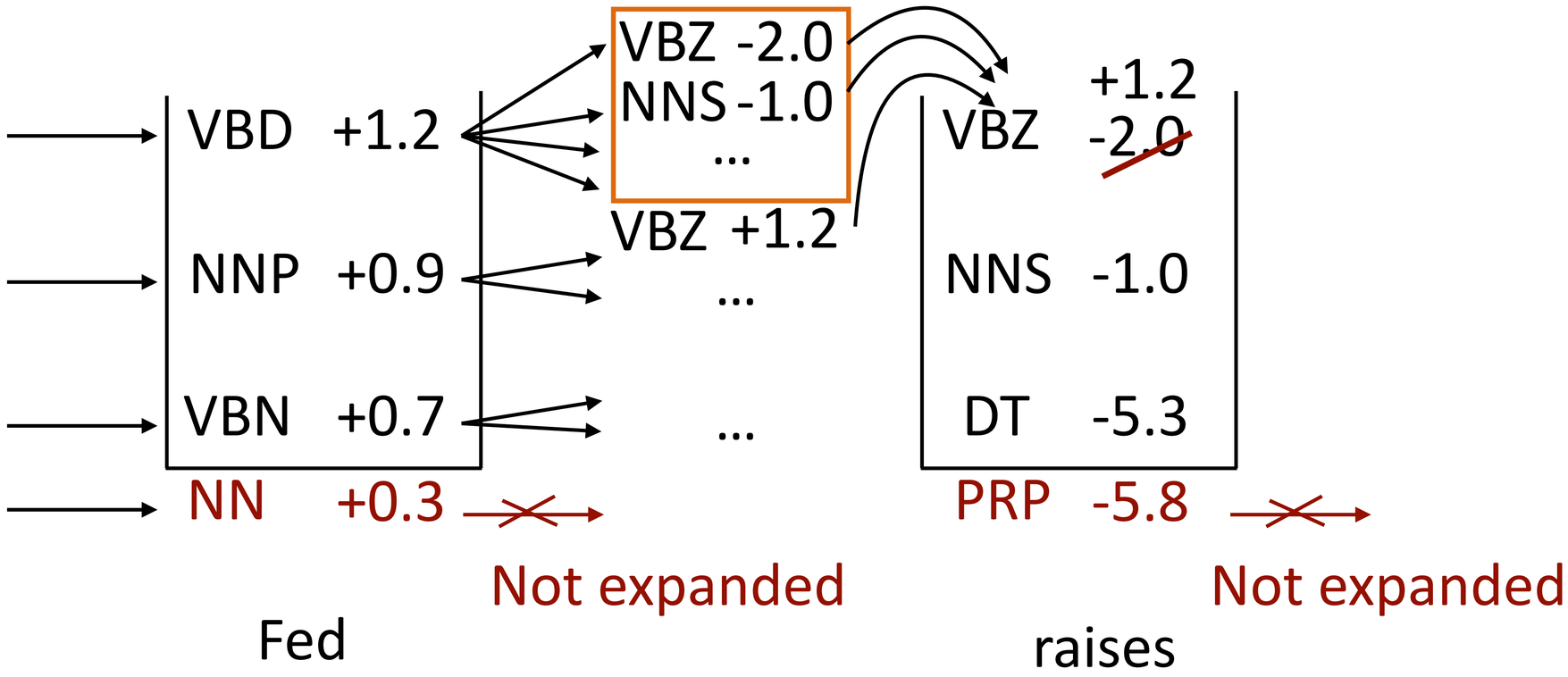

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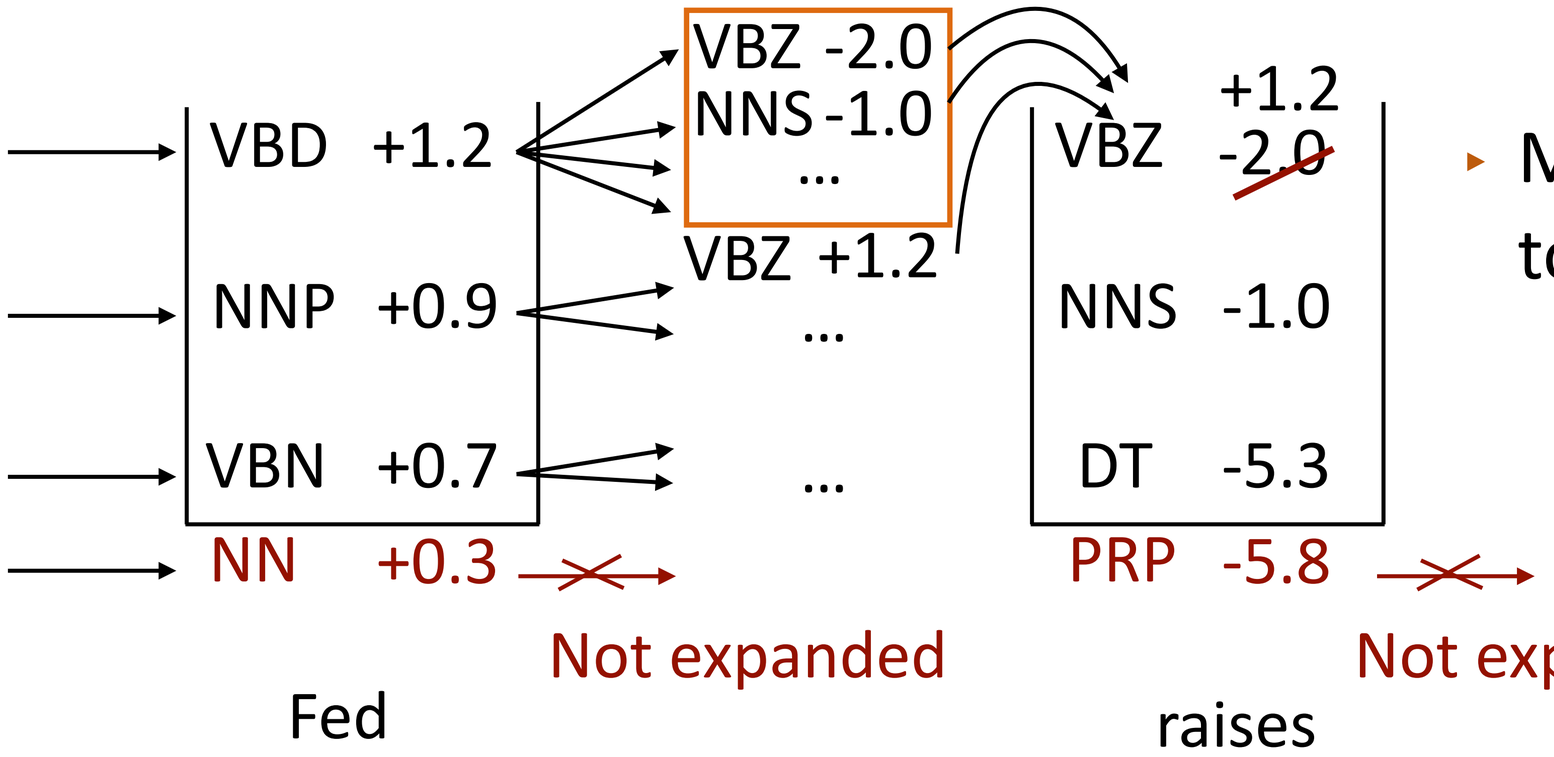

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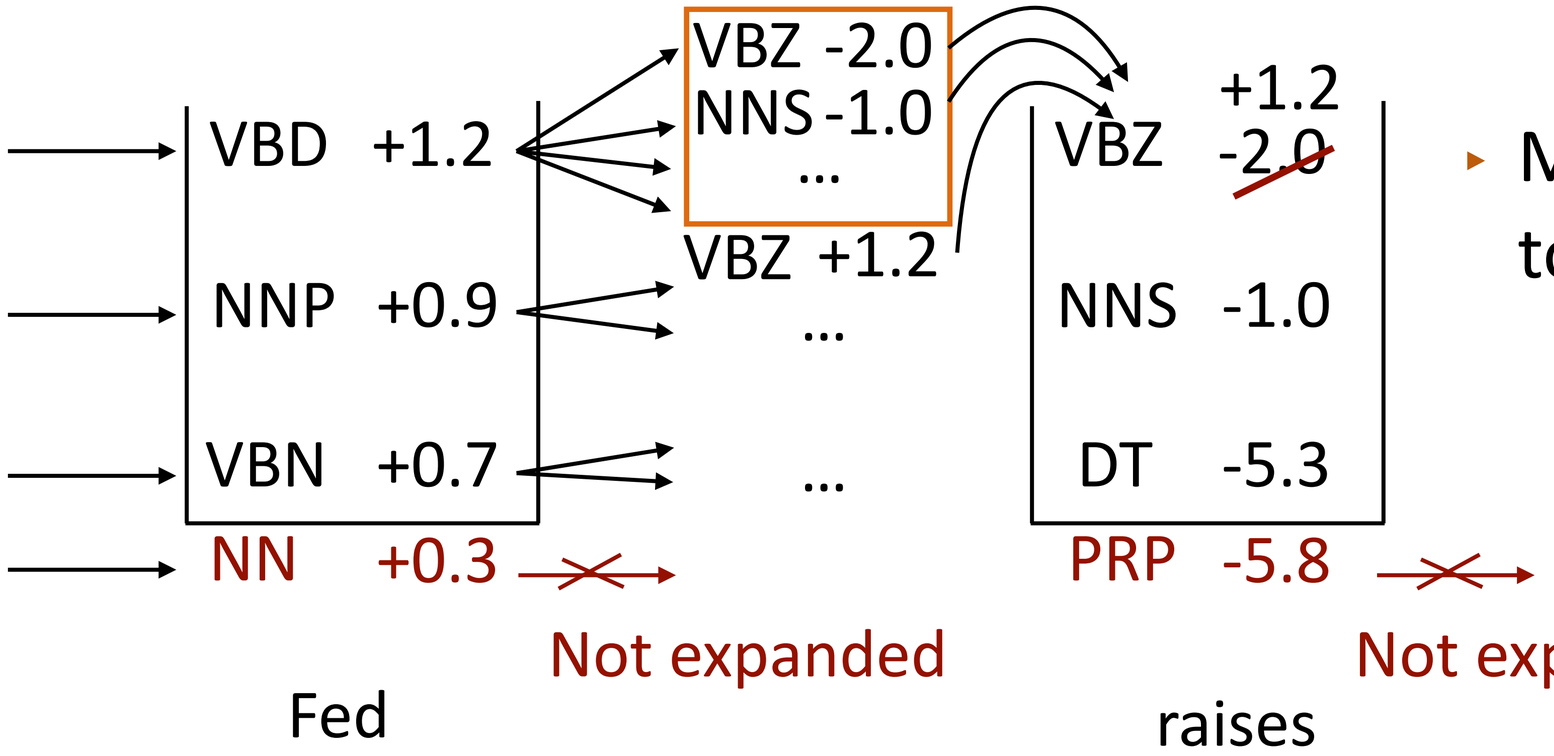

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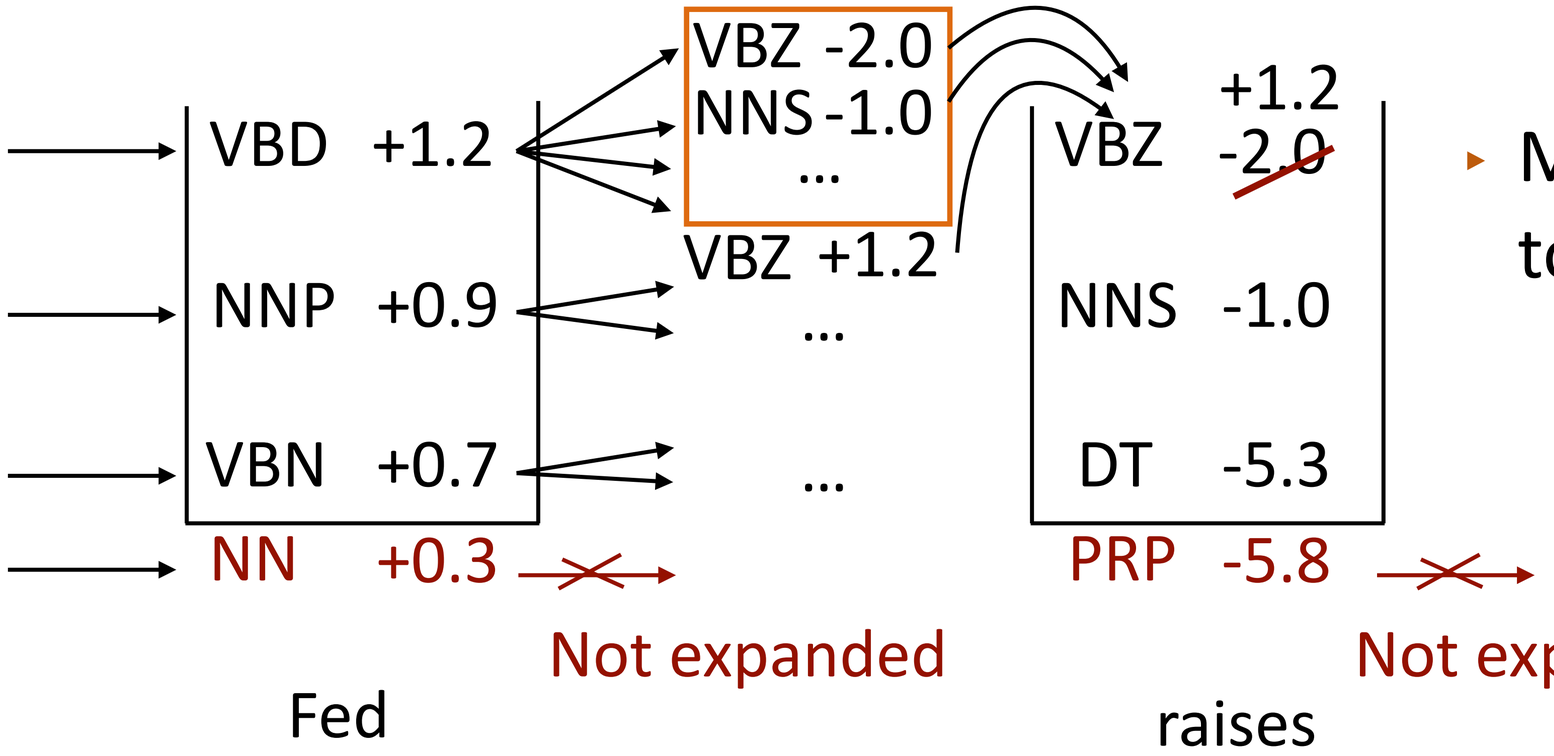

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- If beam search is much faster than computing full sums, can use structured perceptron instead of CRFs
- Very similar to structured SVM