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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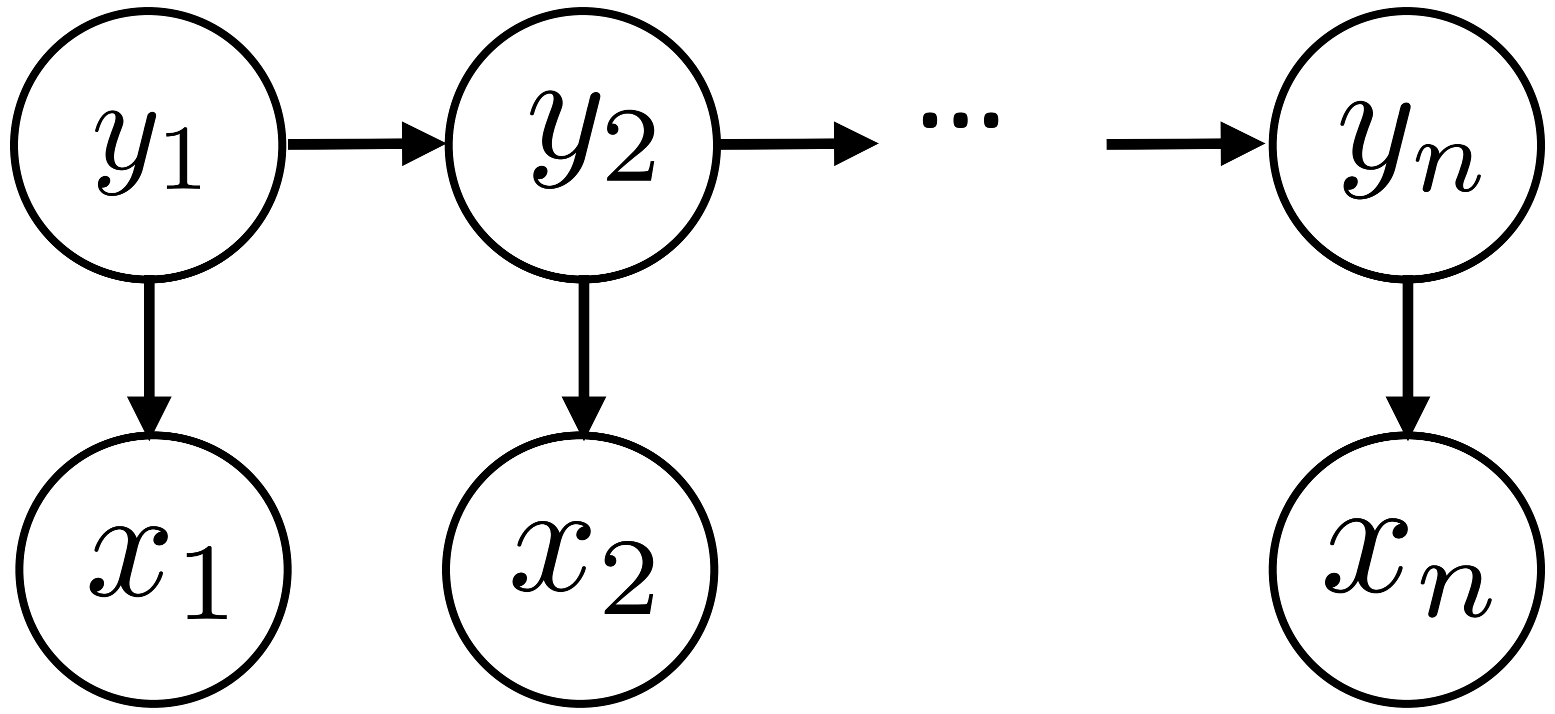

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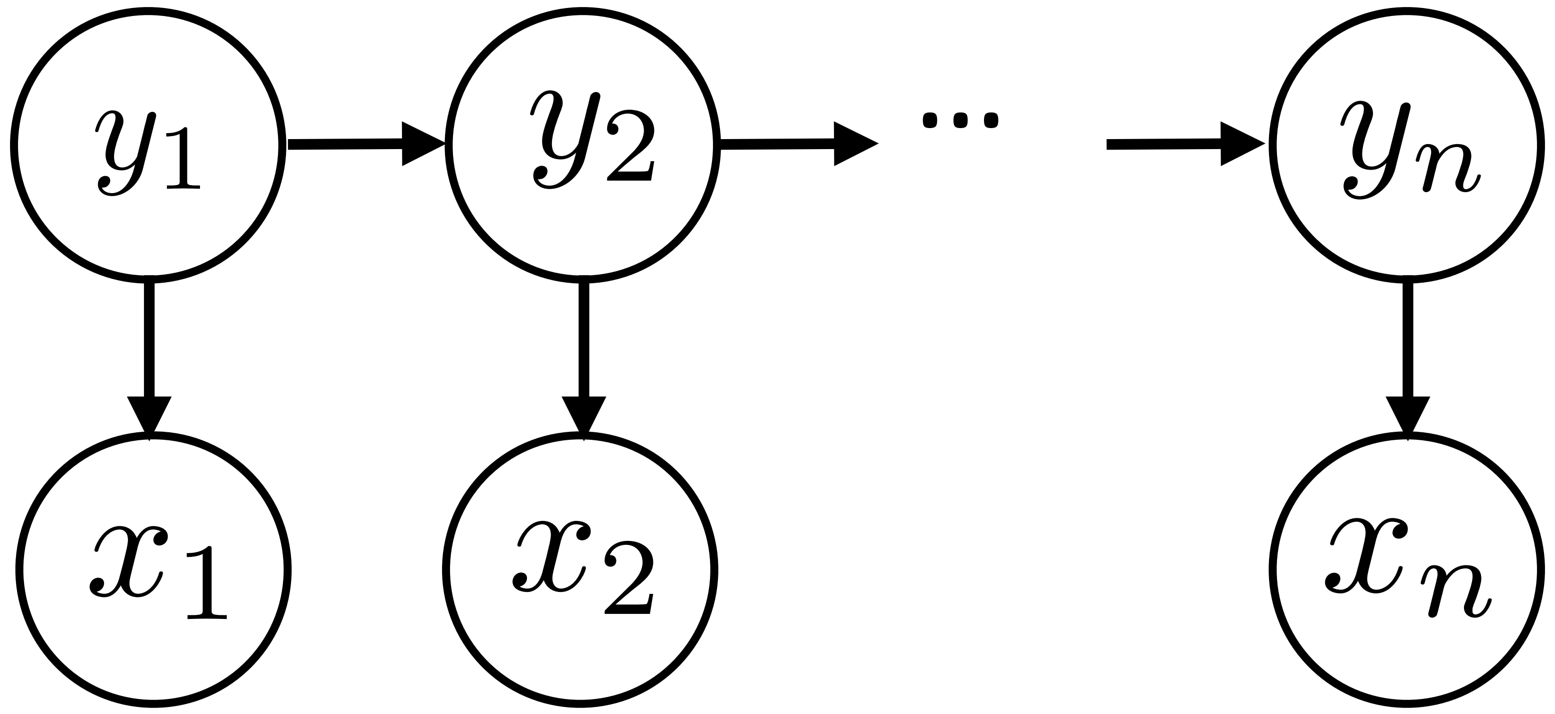

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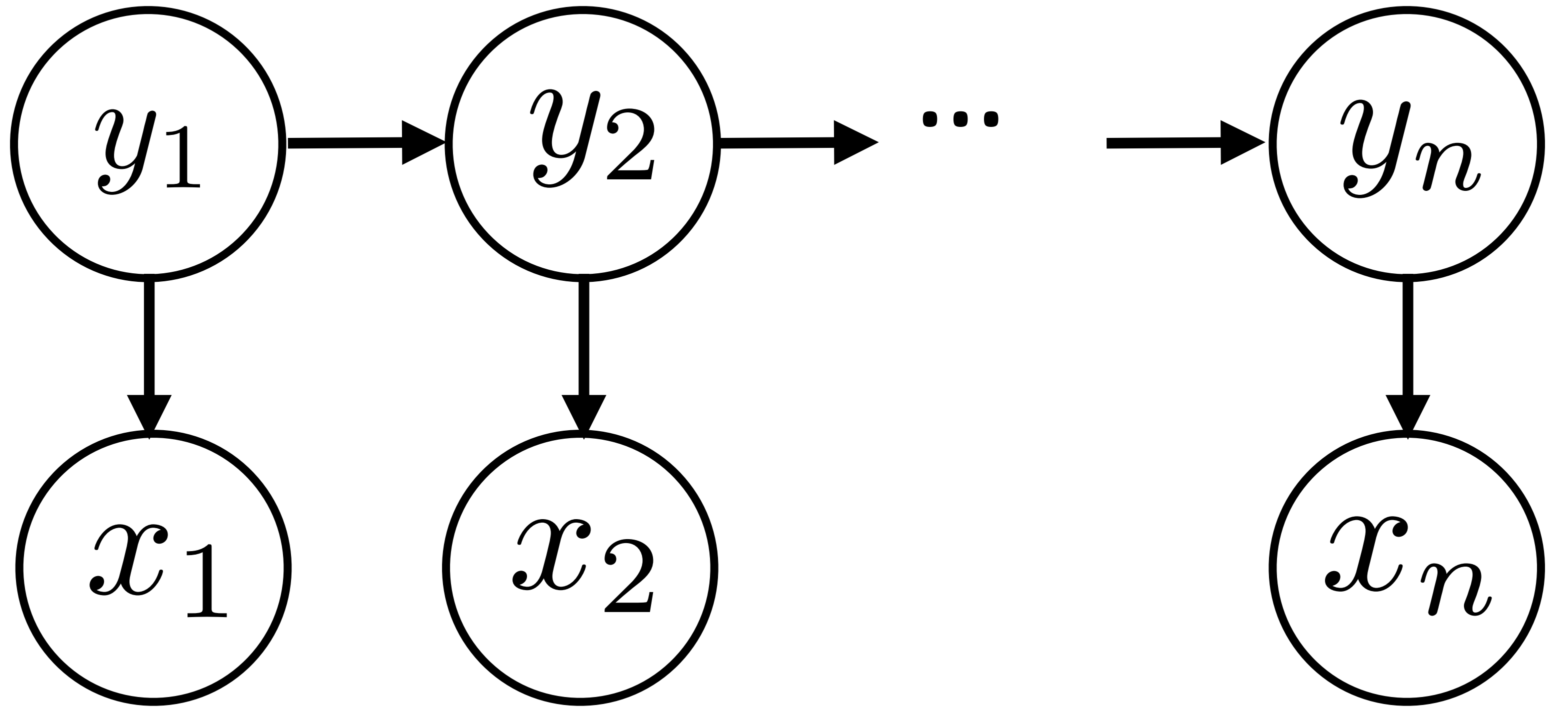

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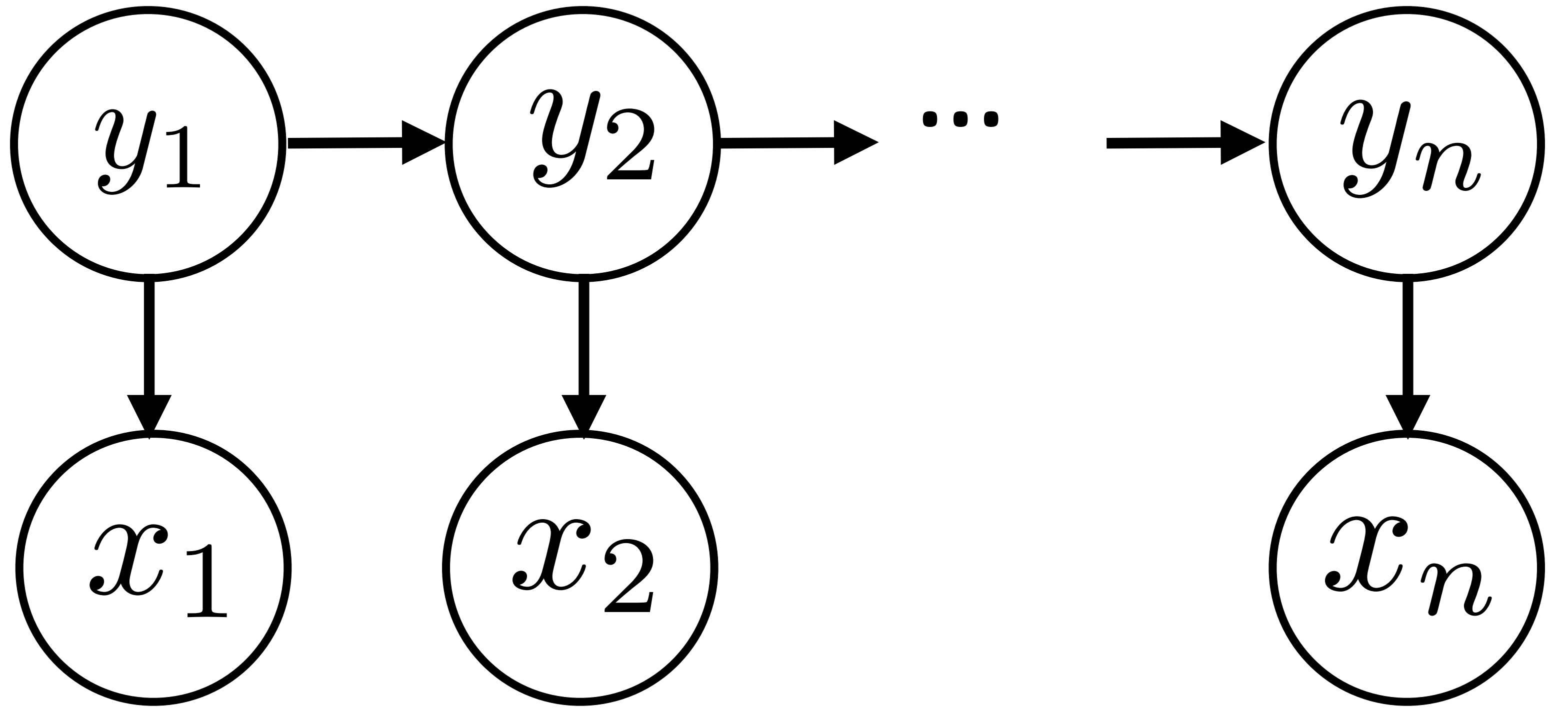

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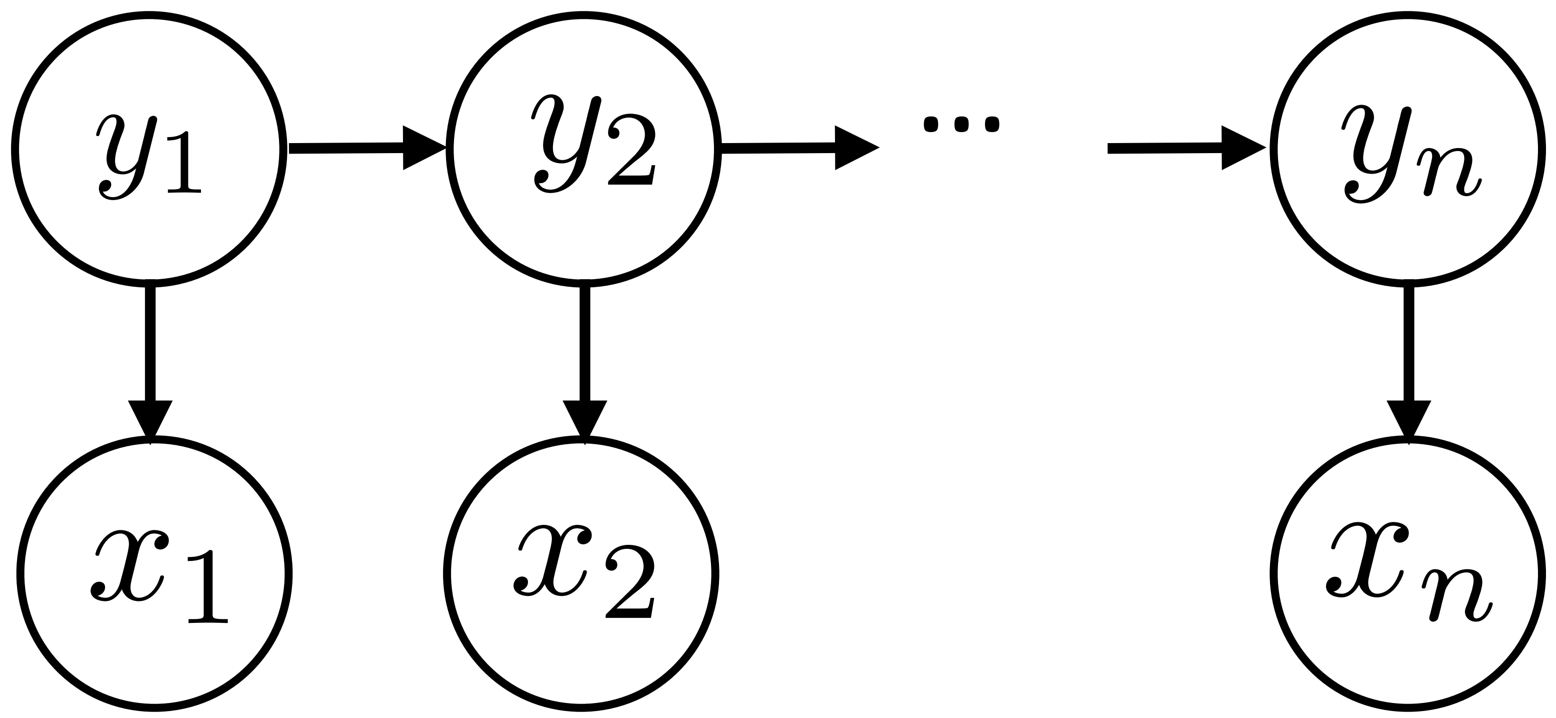

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- Viterbi: $\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$

This Lecture

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

Named Entity Recognition

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PERSON LOC ORG

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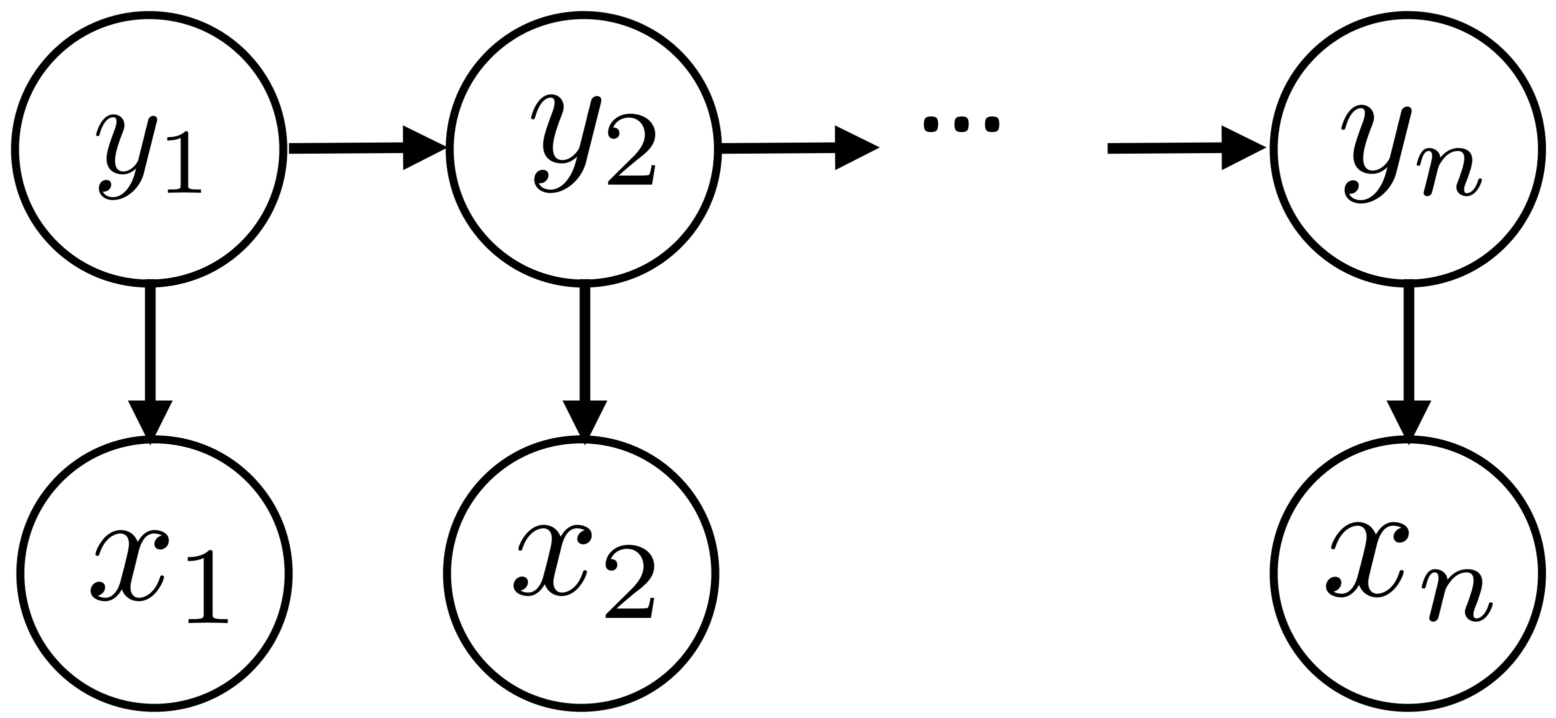
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?
  - Lots of O's, so tags aren't as informative about context
  - Insufficient features/capacity with multinomials (especially for unks)

CRFs

Conditional Random Fields

- HMMs are expressible as Bayes nets (factor graphs)



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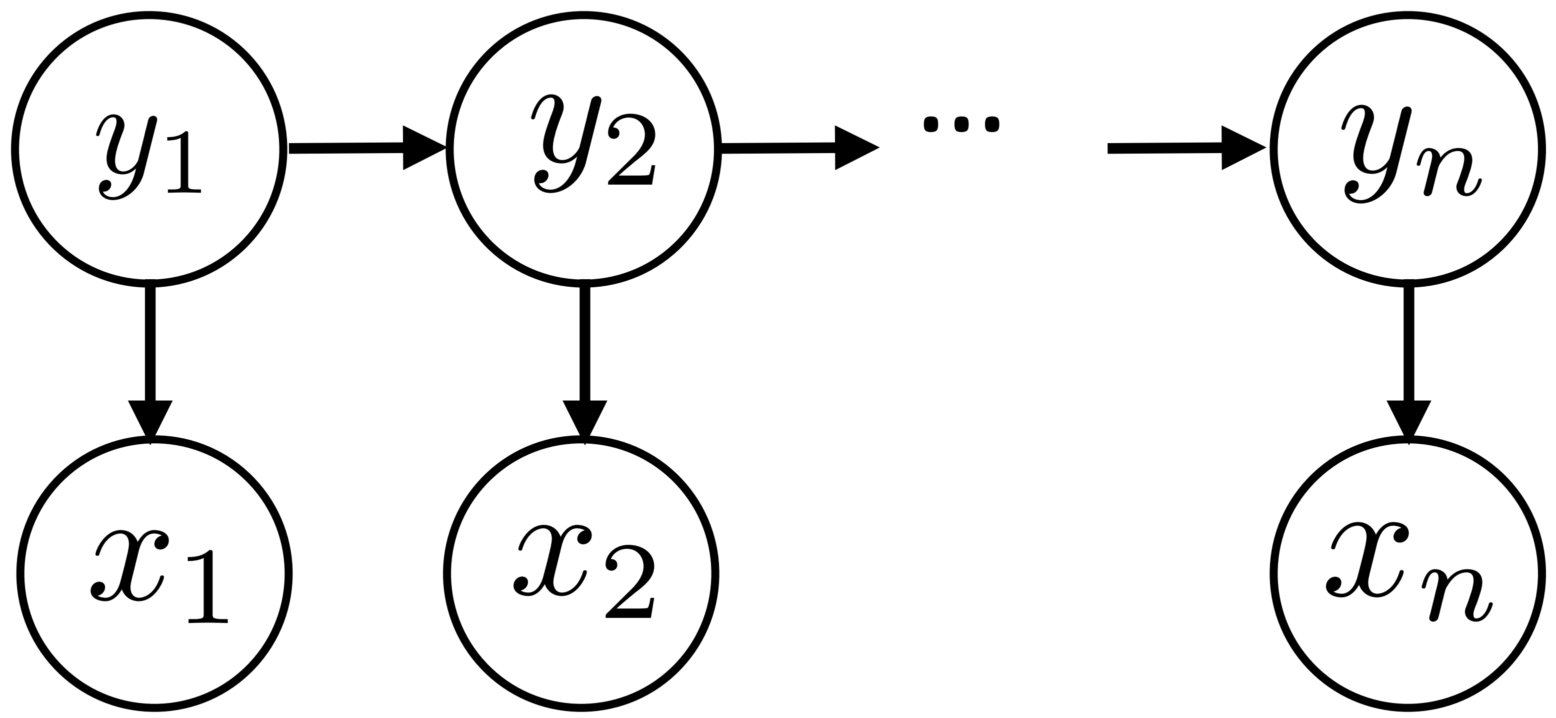

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$$P(\mathbf{y}, \mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\ldots$$

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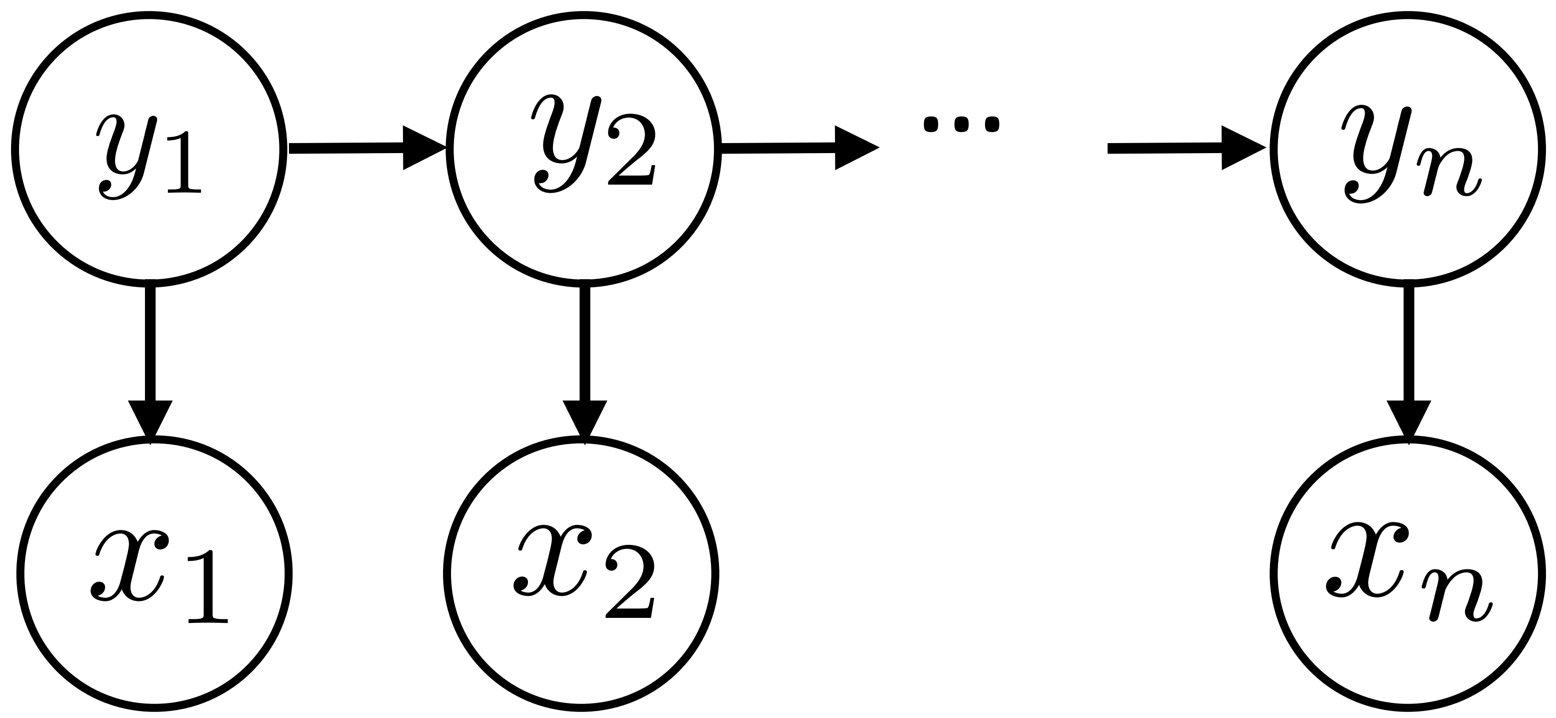

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- Locally normalized model: each factor is a probability distribution that normalizes

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  local vs. global normalization <-> generative vs. discriminative

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  local vs. global normalization <-> generative vs. discriminative

- Locally normalized discriminative models do exist (MEMMs)

Sequential CRFs

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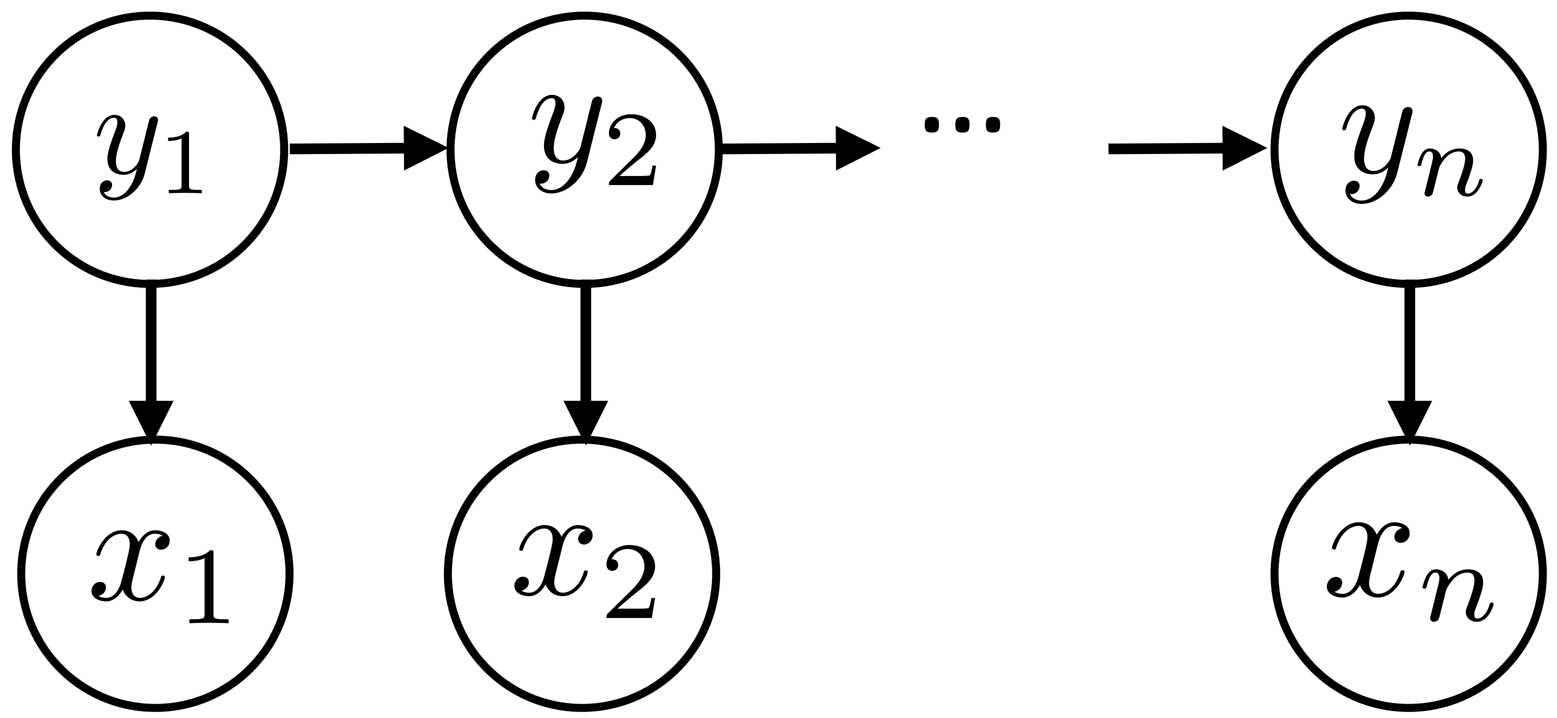

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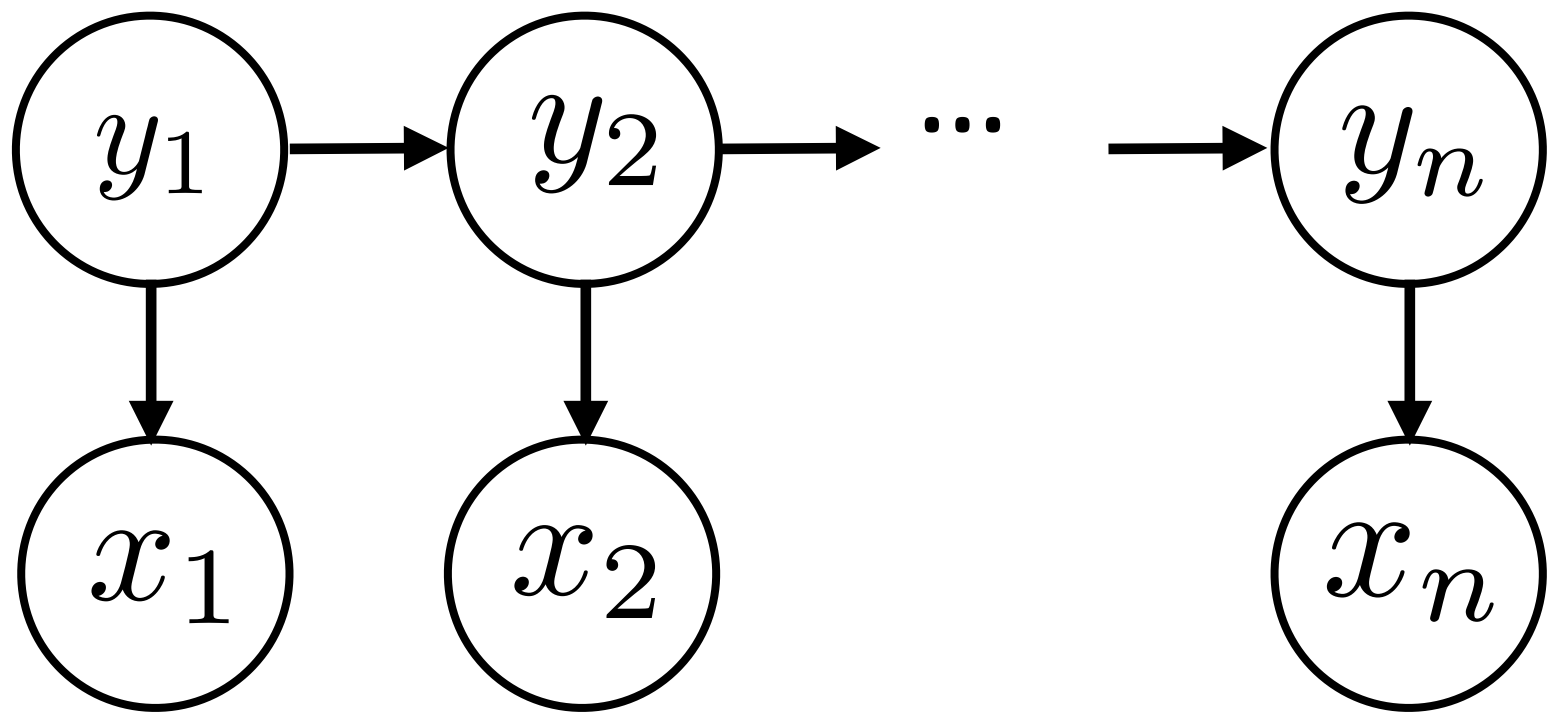

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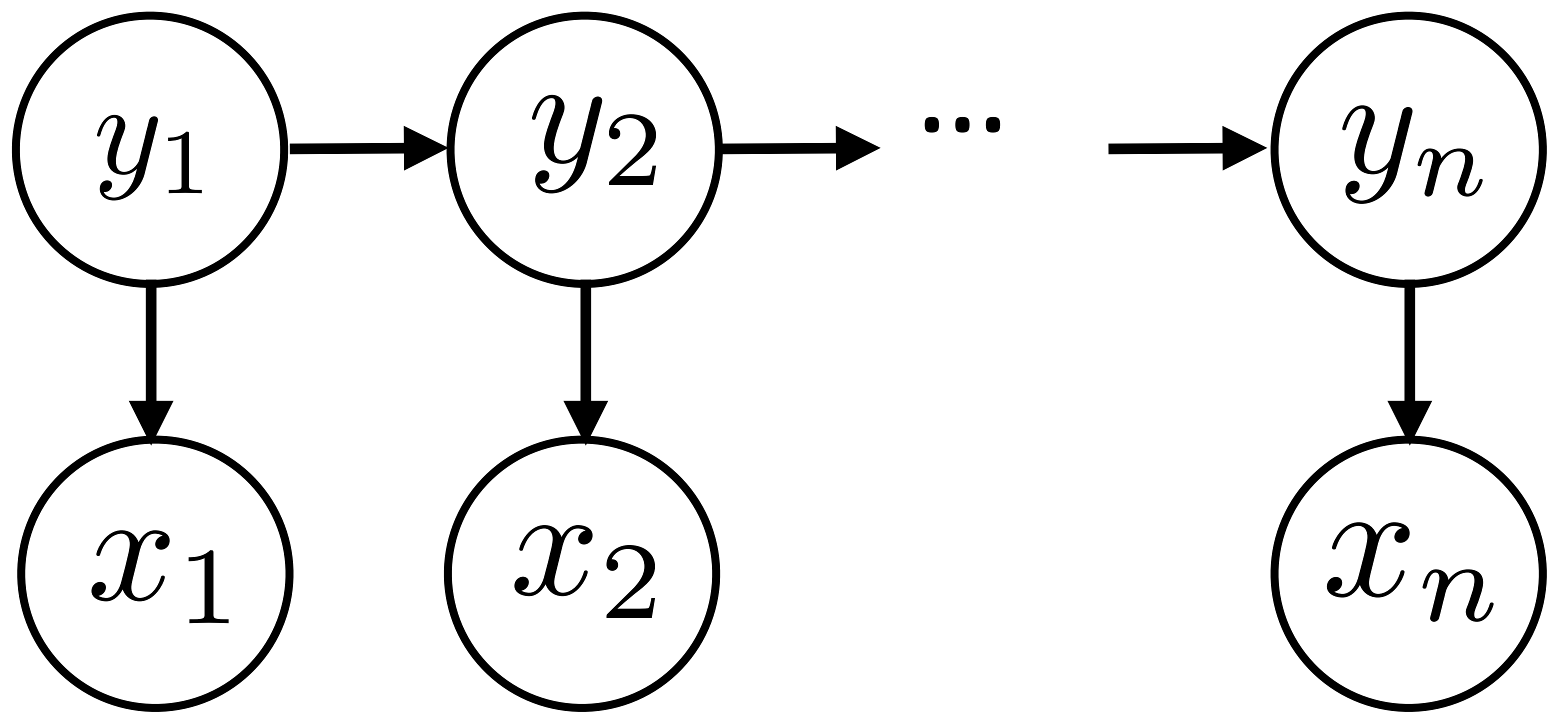

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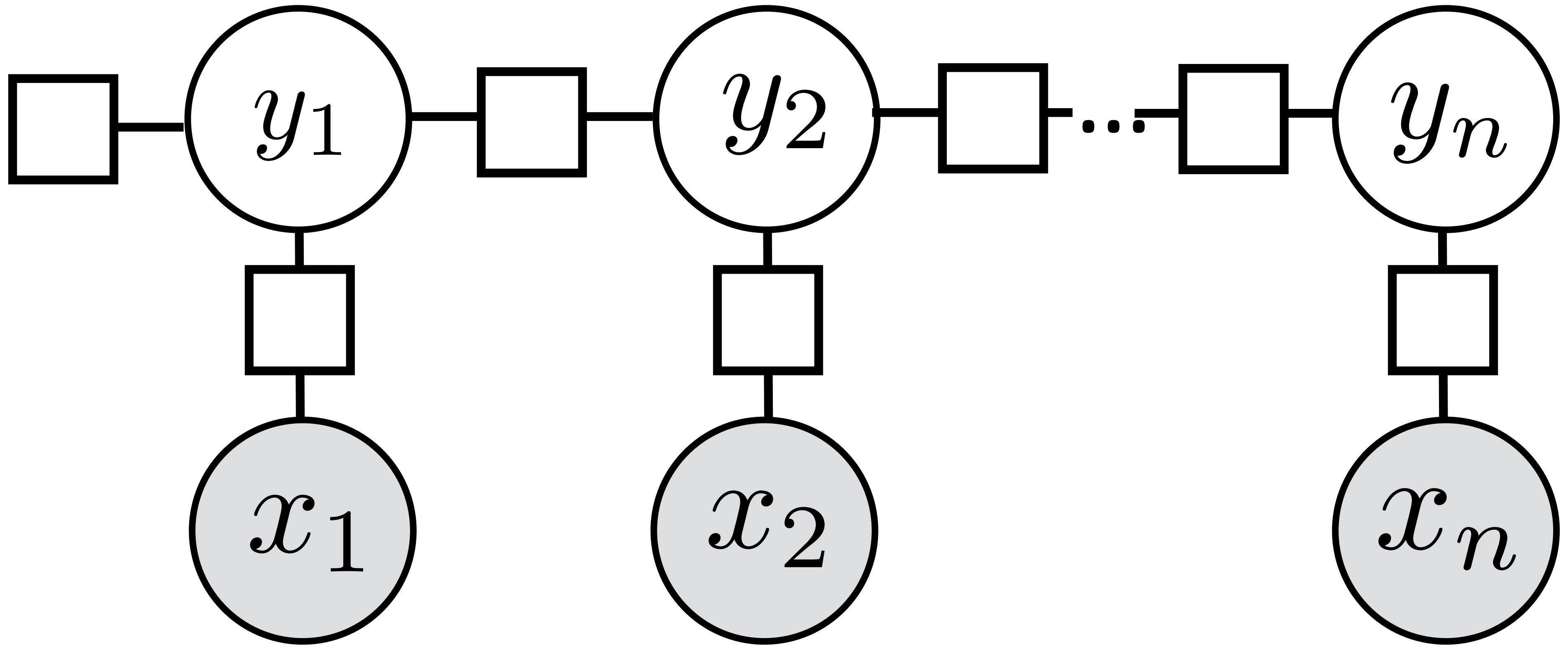

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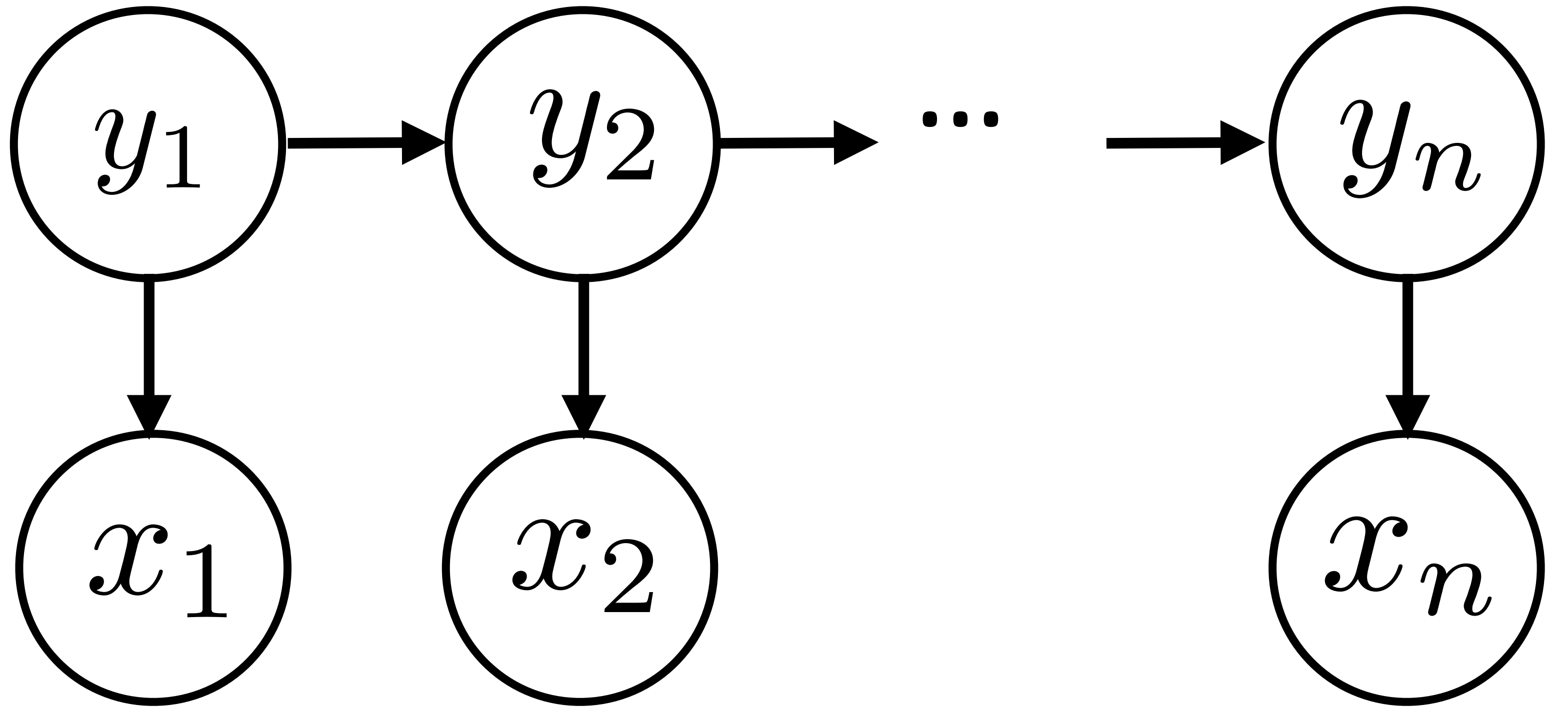

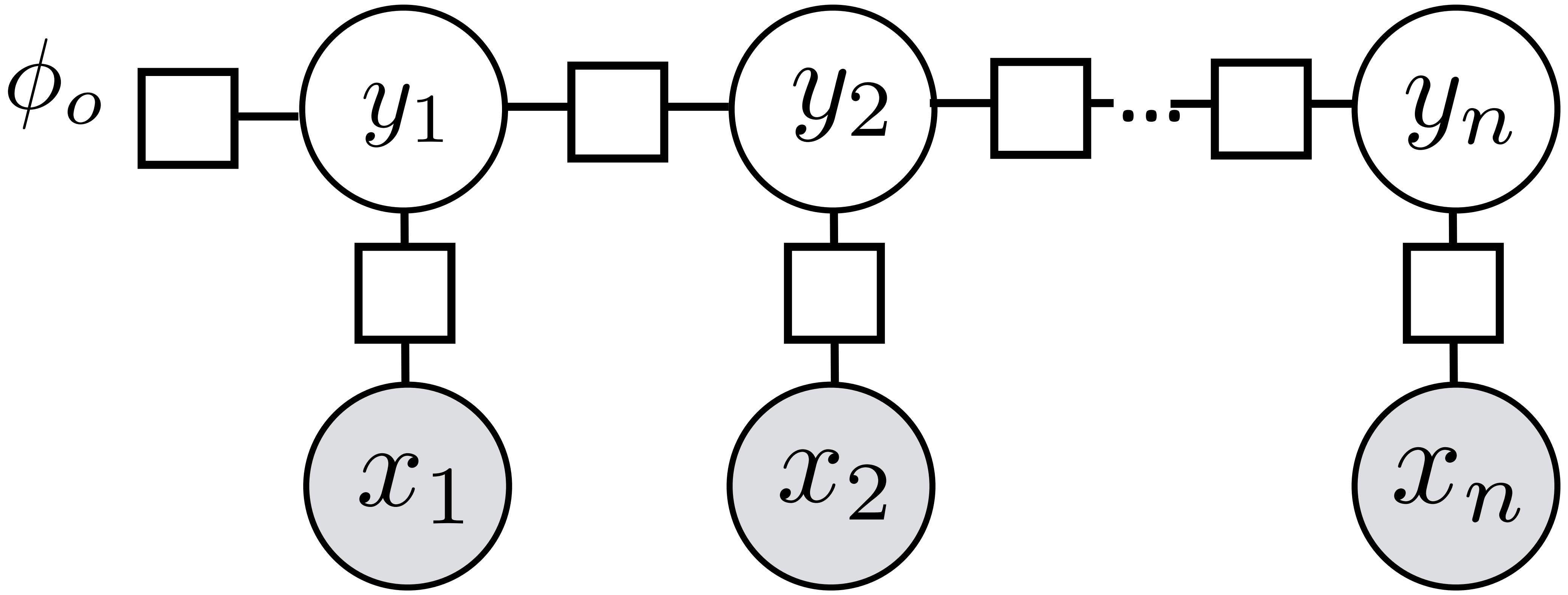

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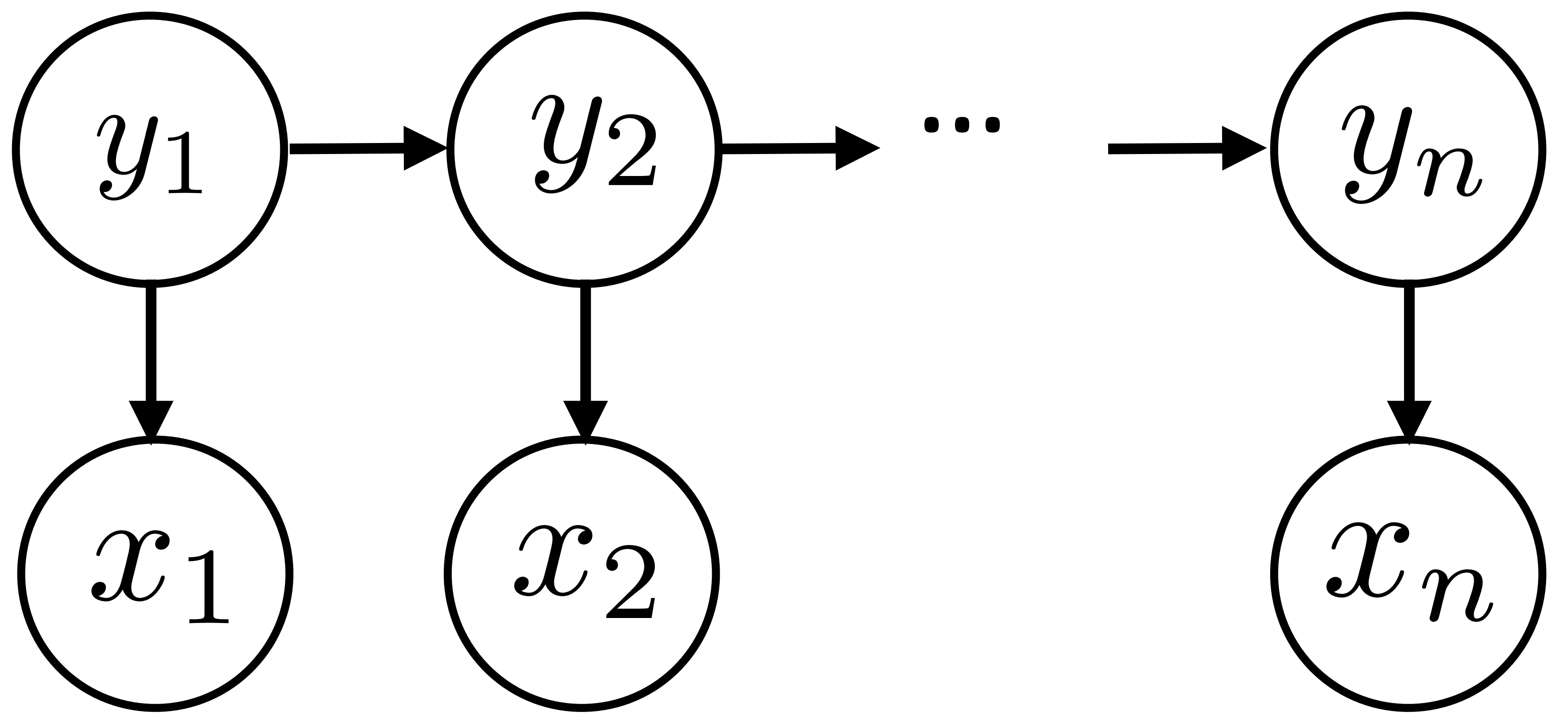

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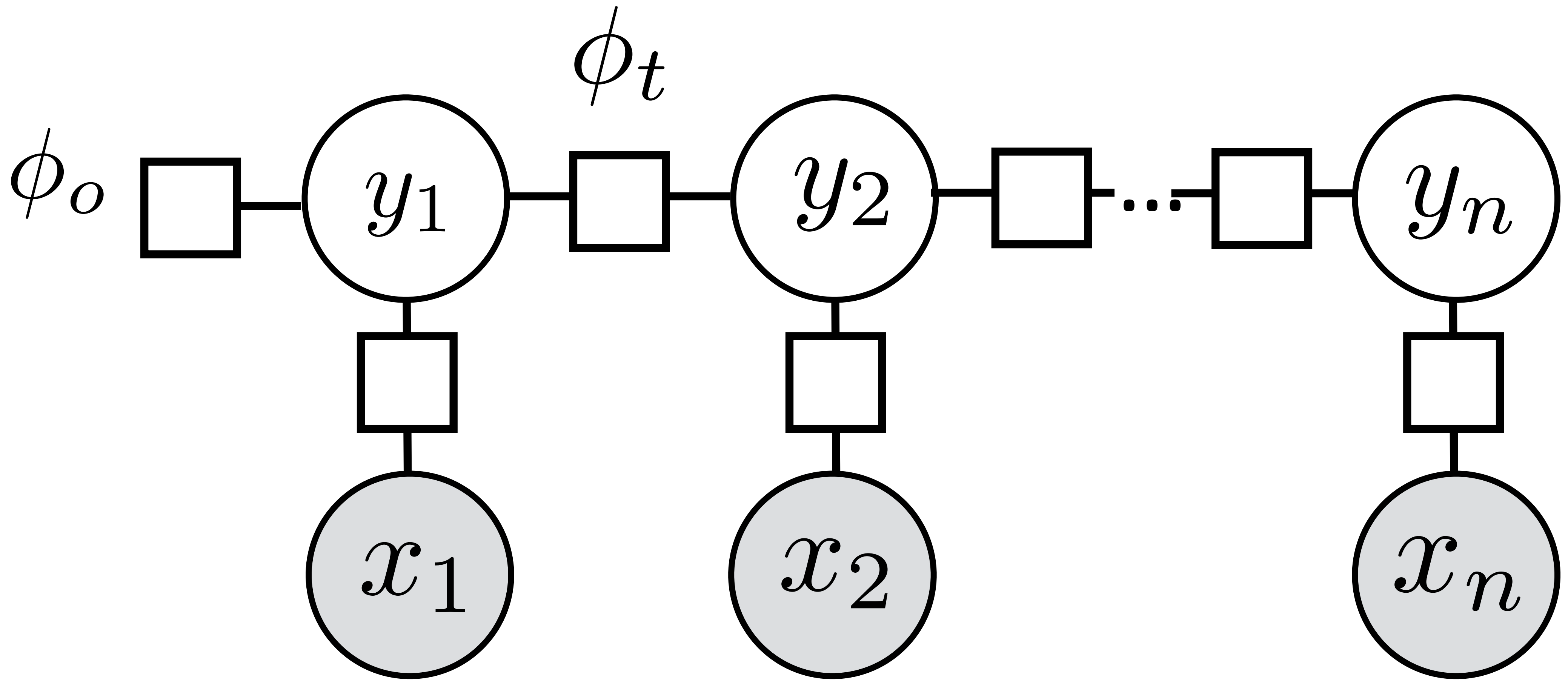

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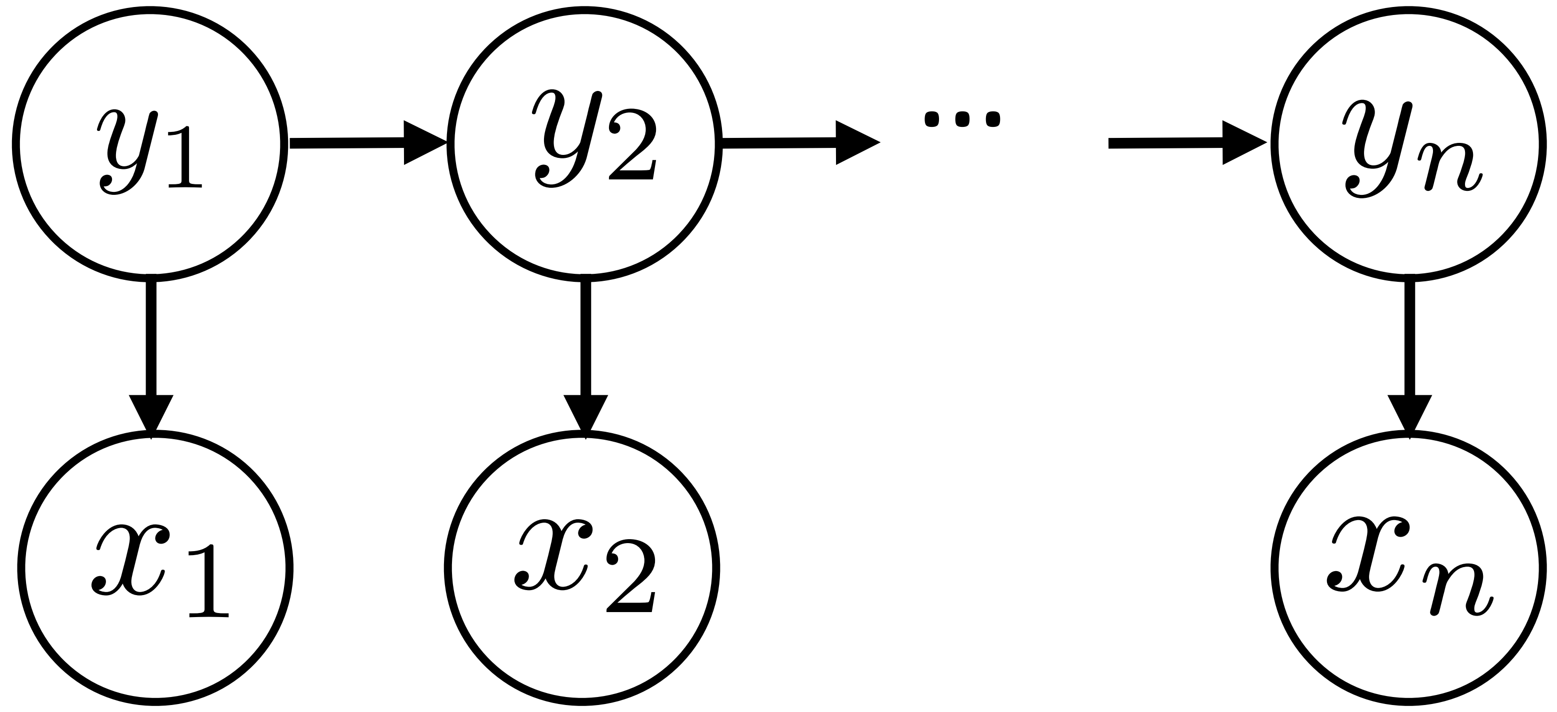

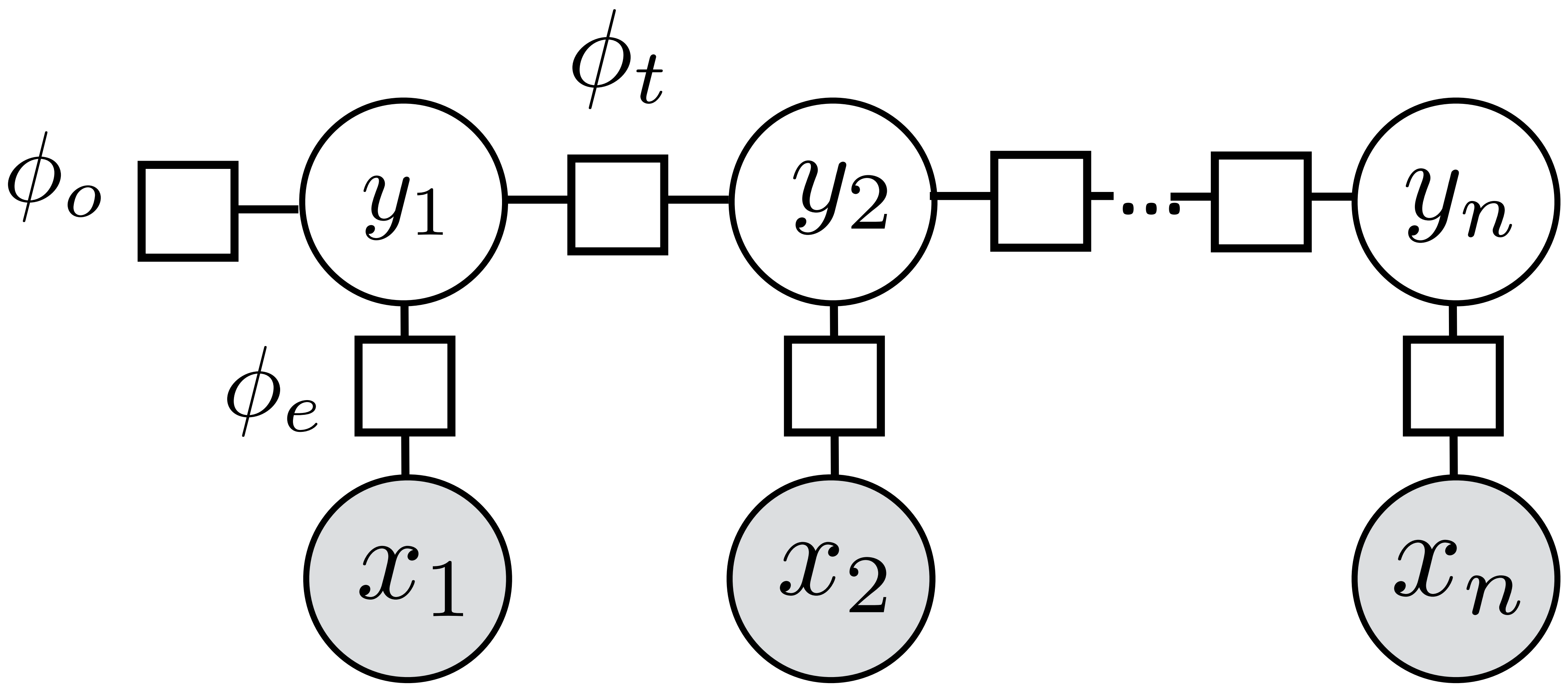

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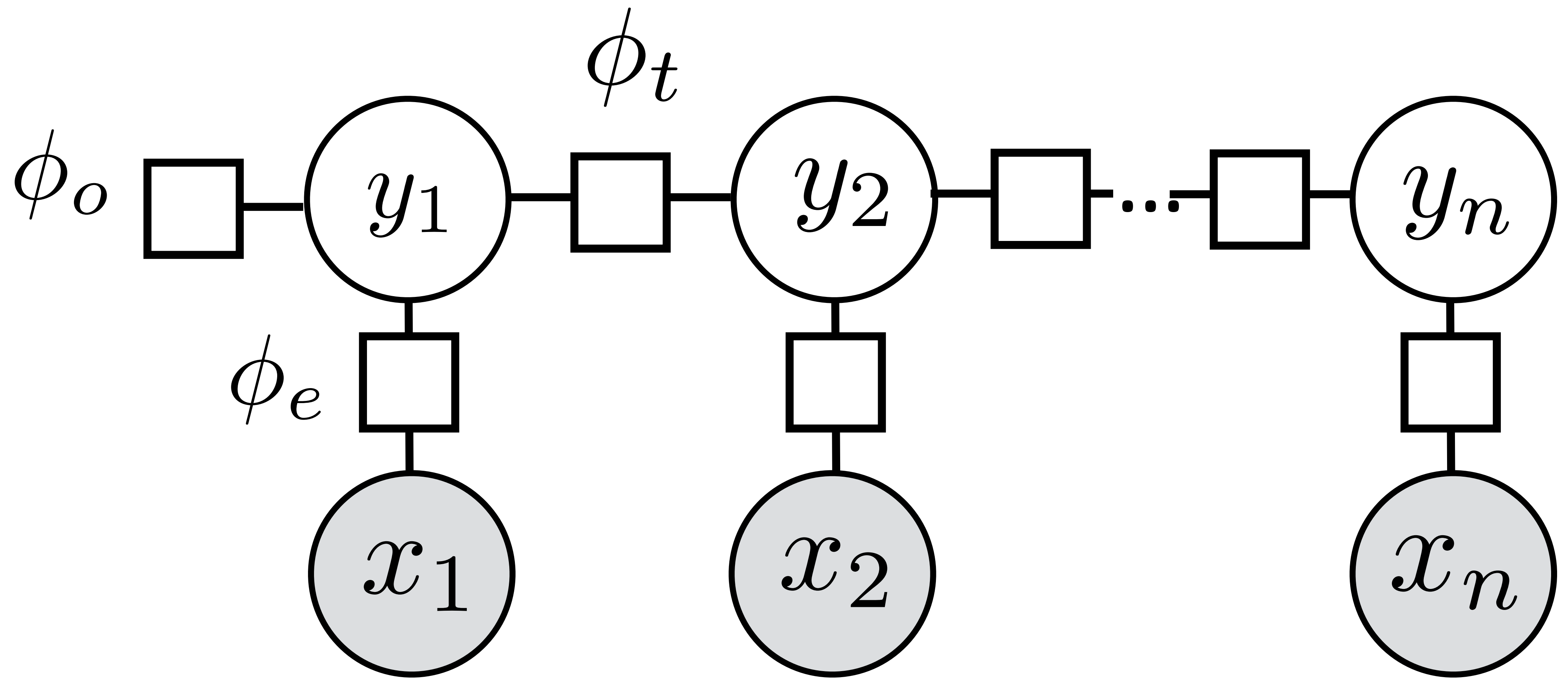

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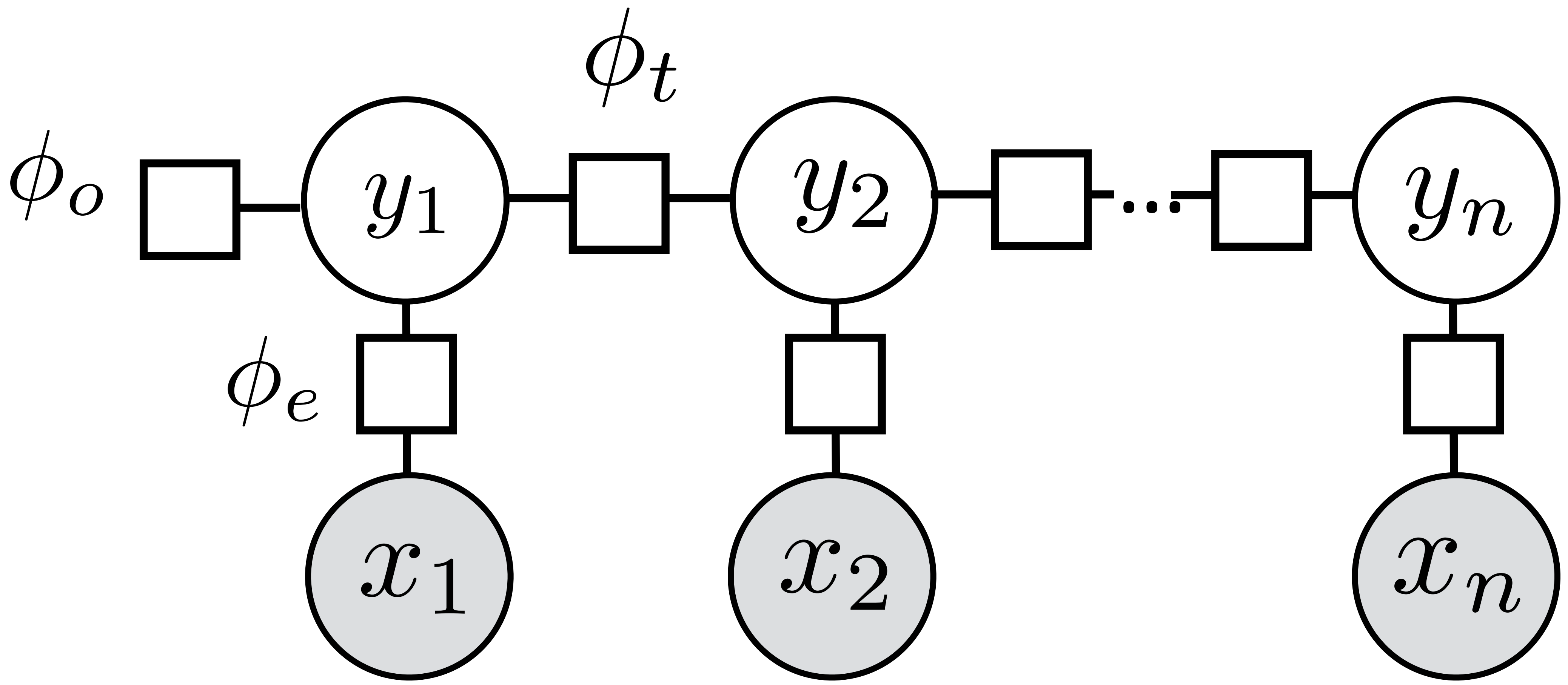

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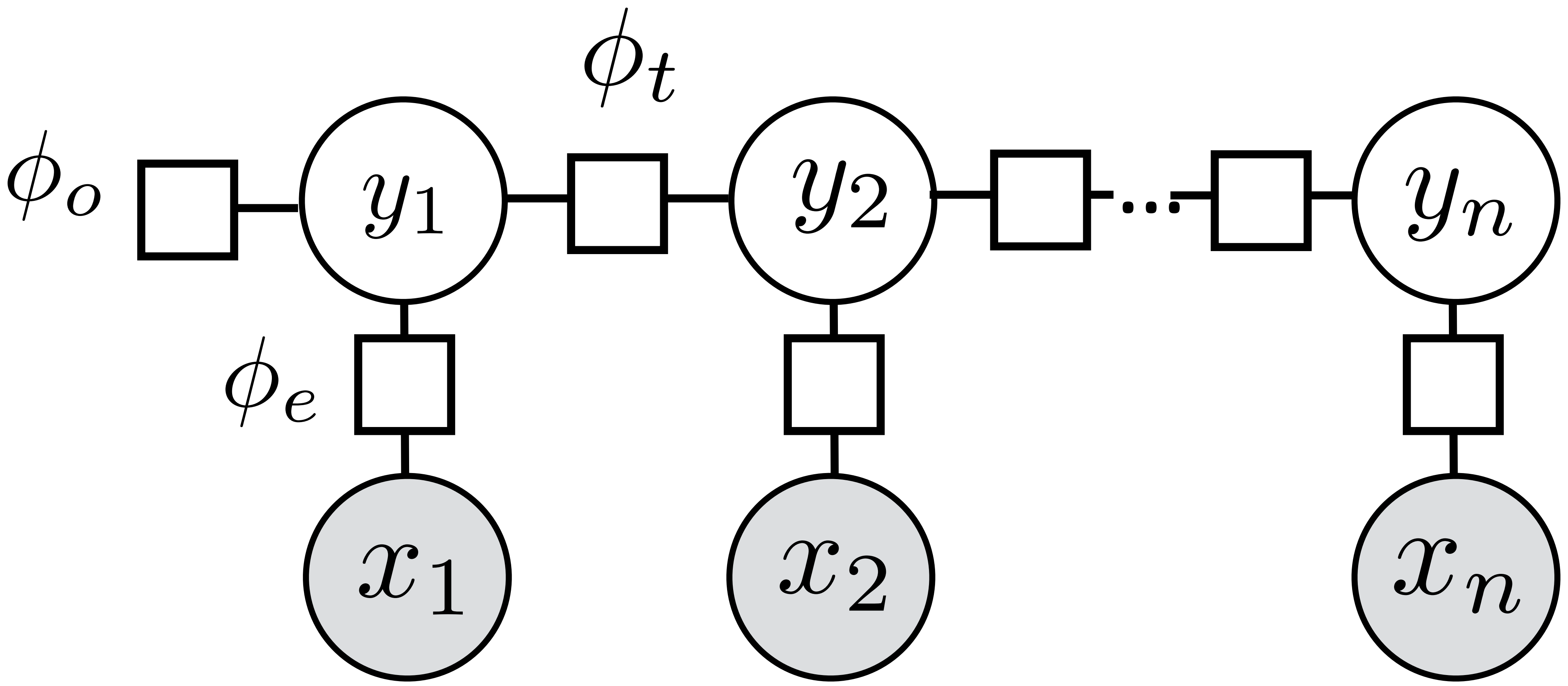

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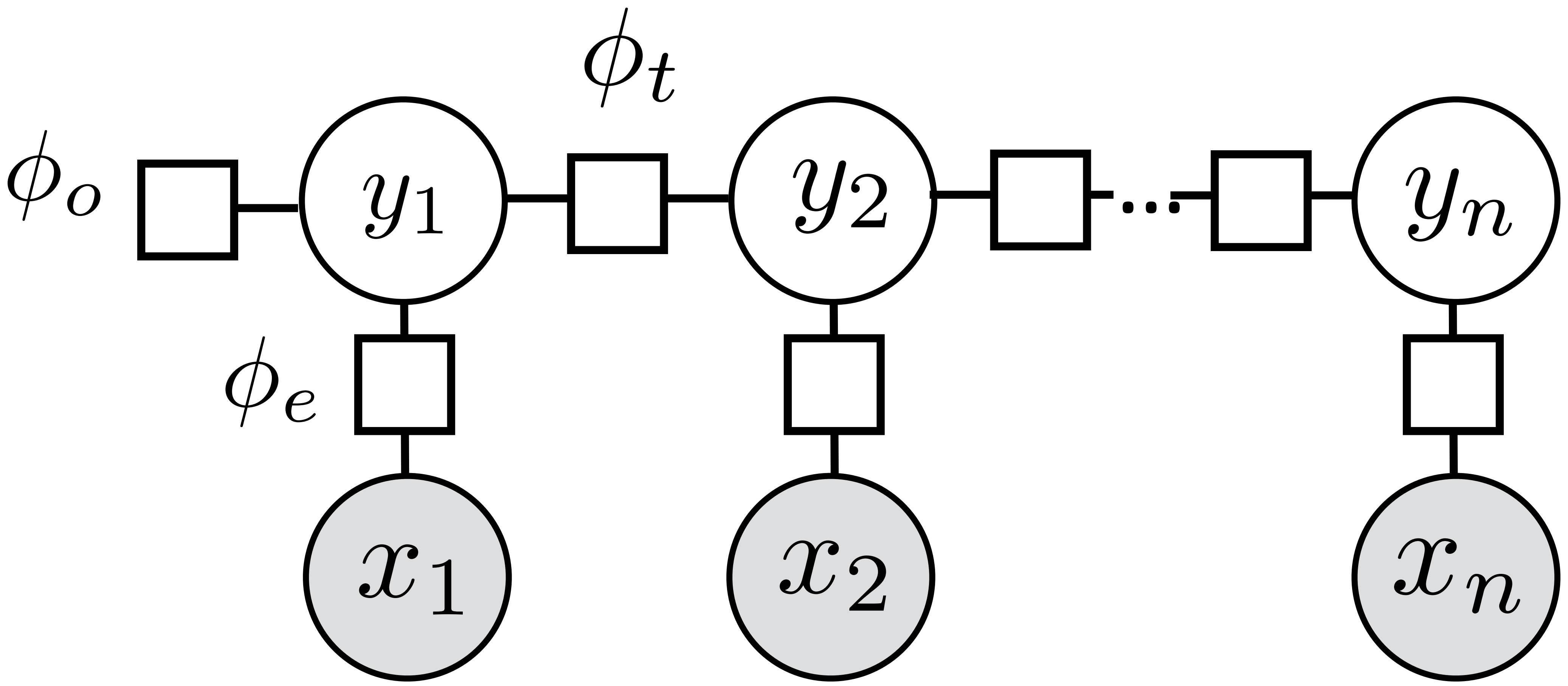

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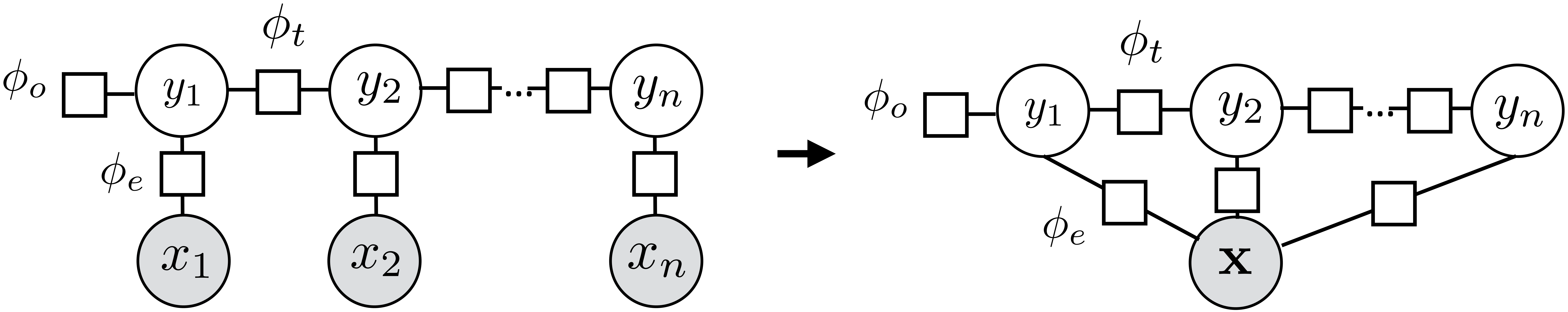

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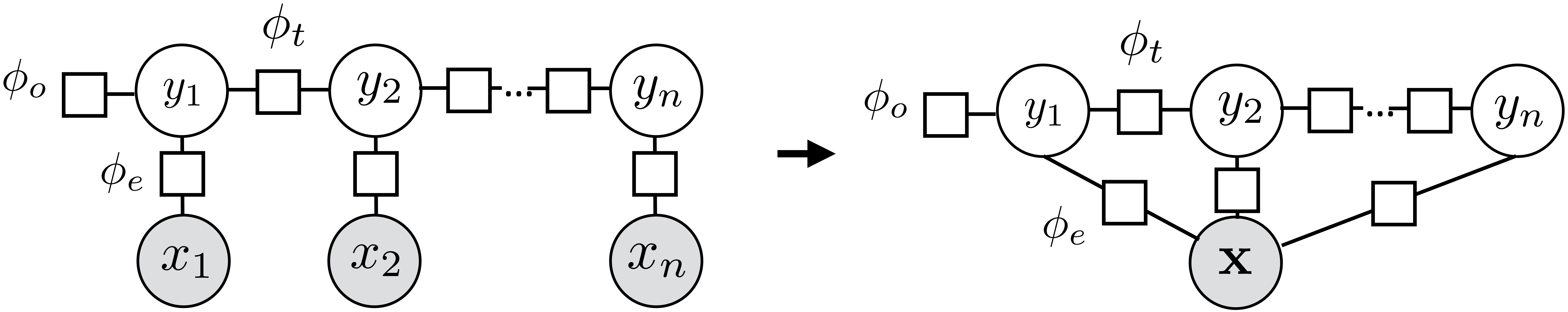

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- **y** can't depend arbitrarily on **x** in a generative model

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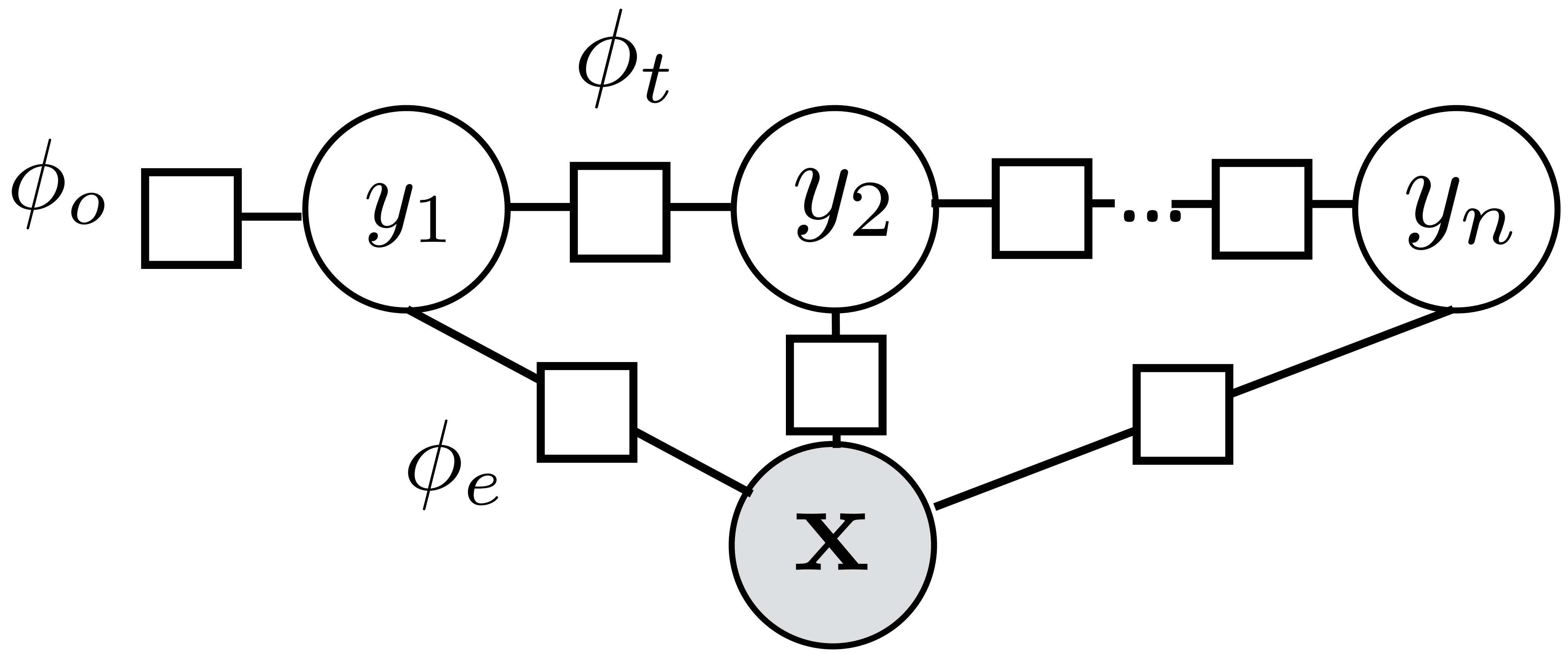

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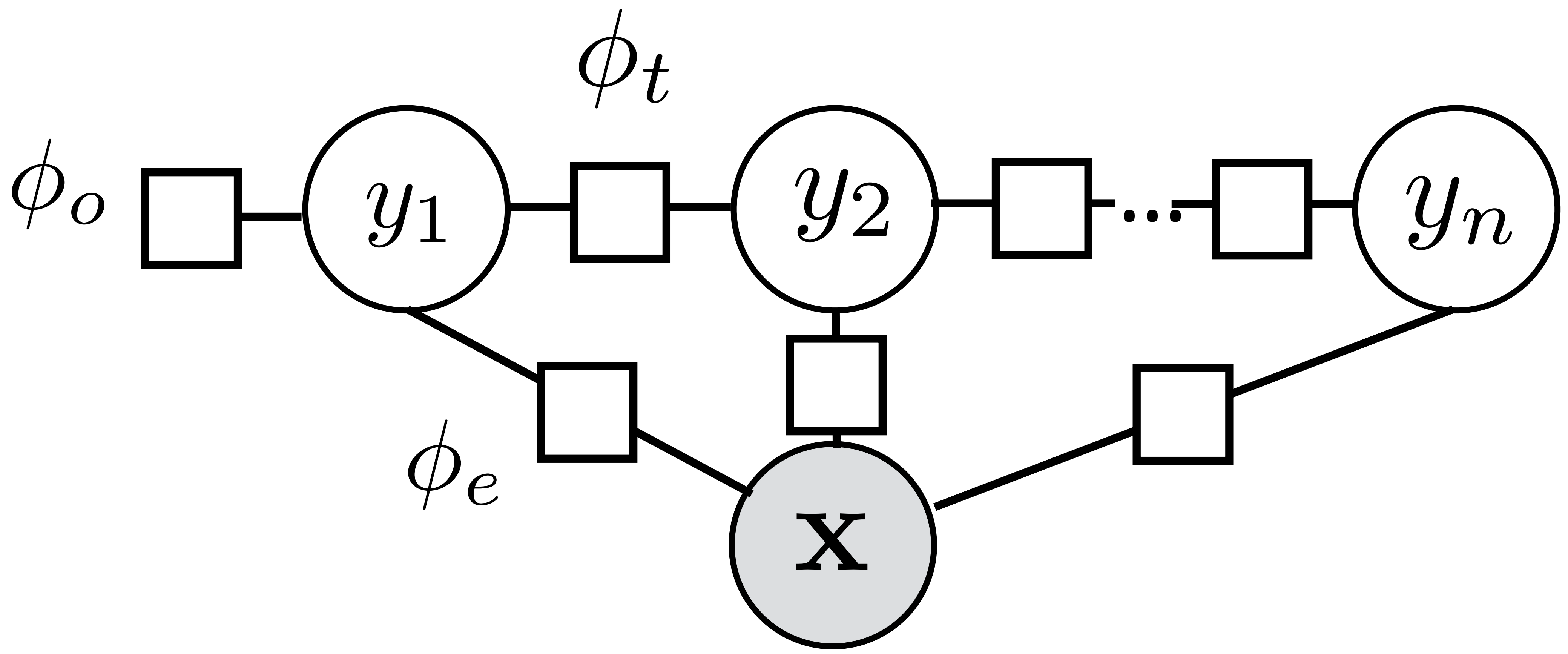

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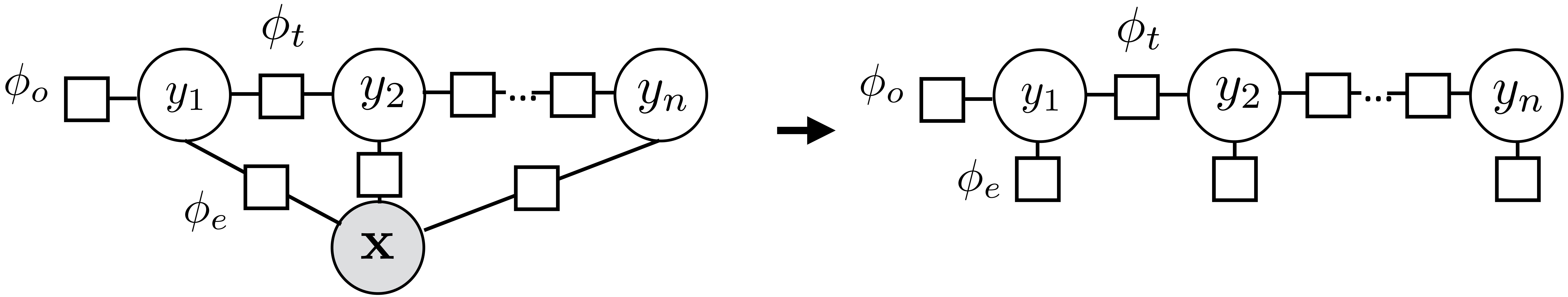

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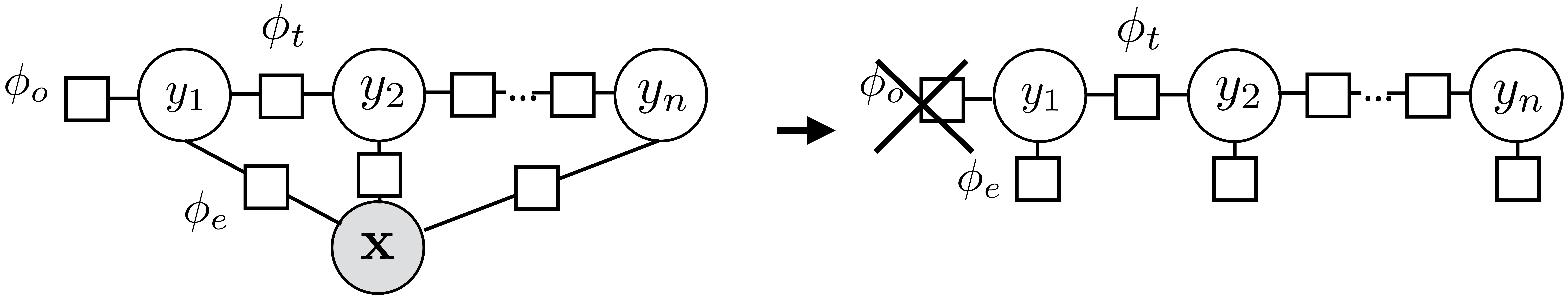

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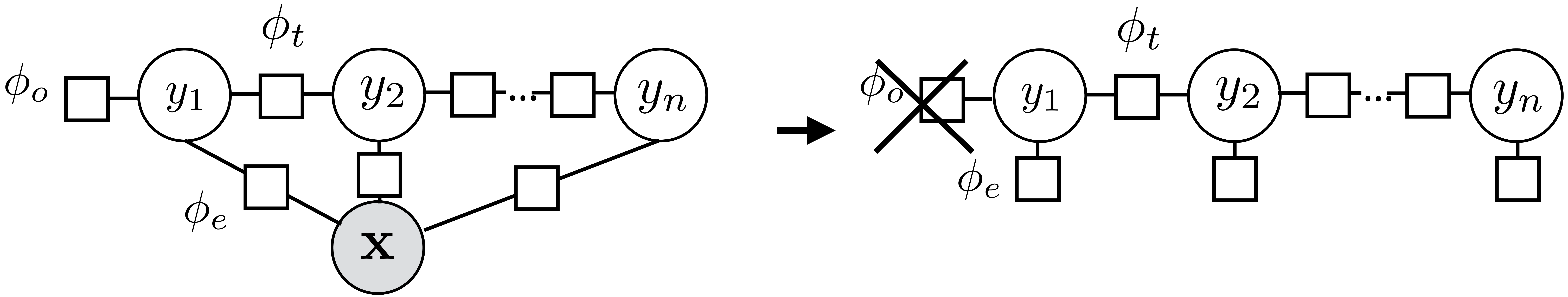

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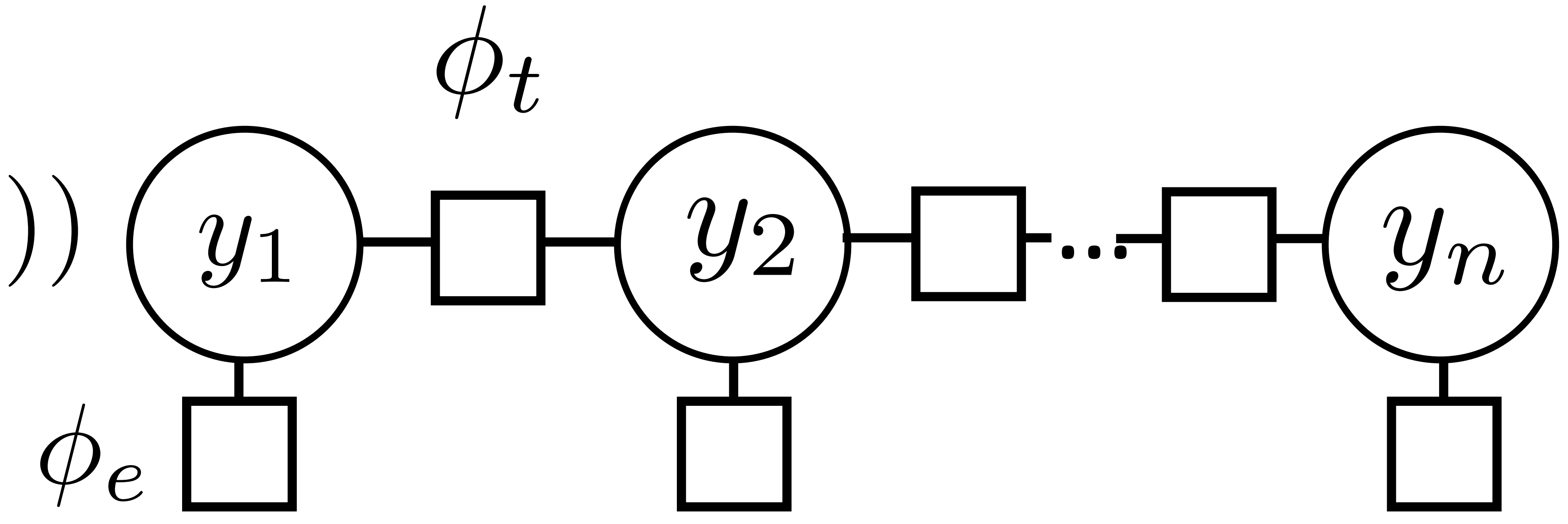

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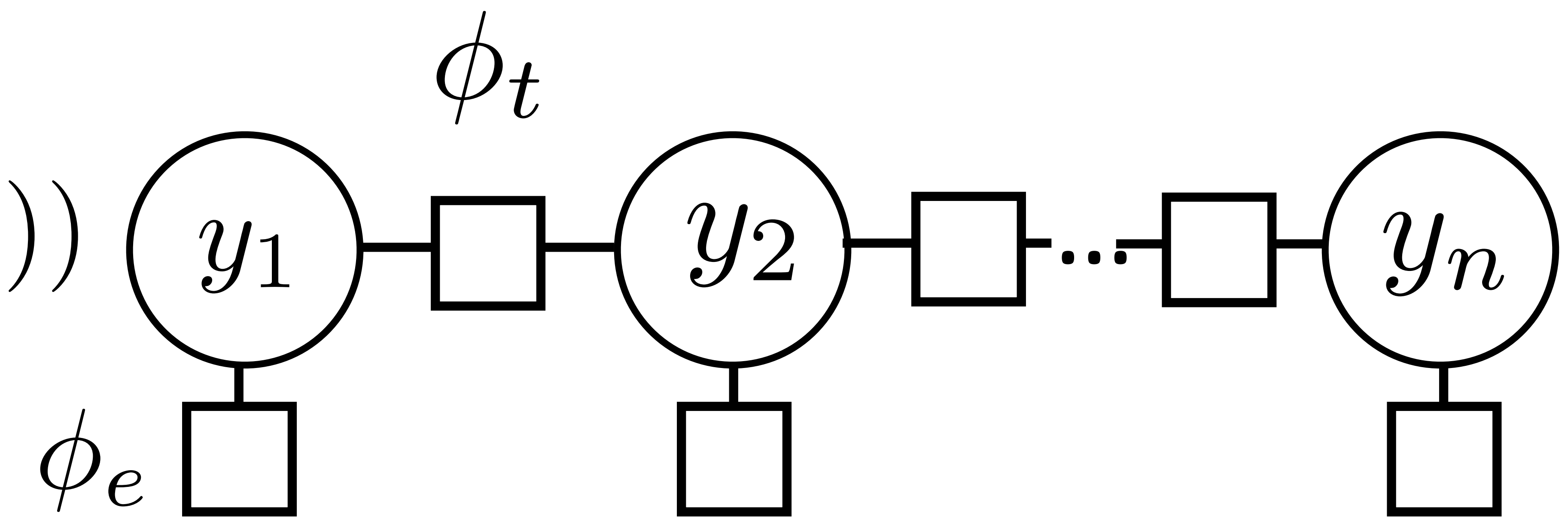

- Phis can be almost anything! Here we use linear functions of sparse features

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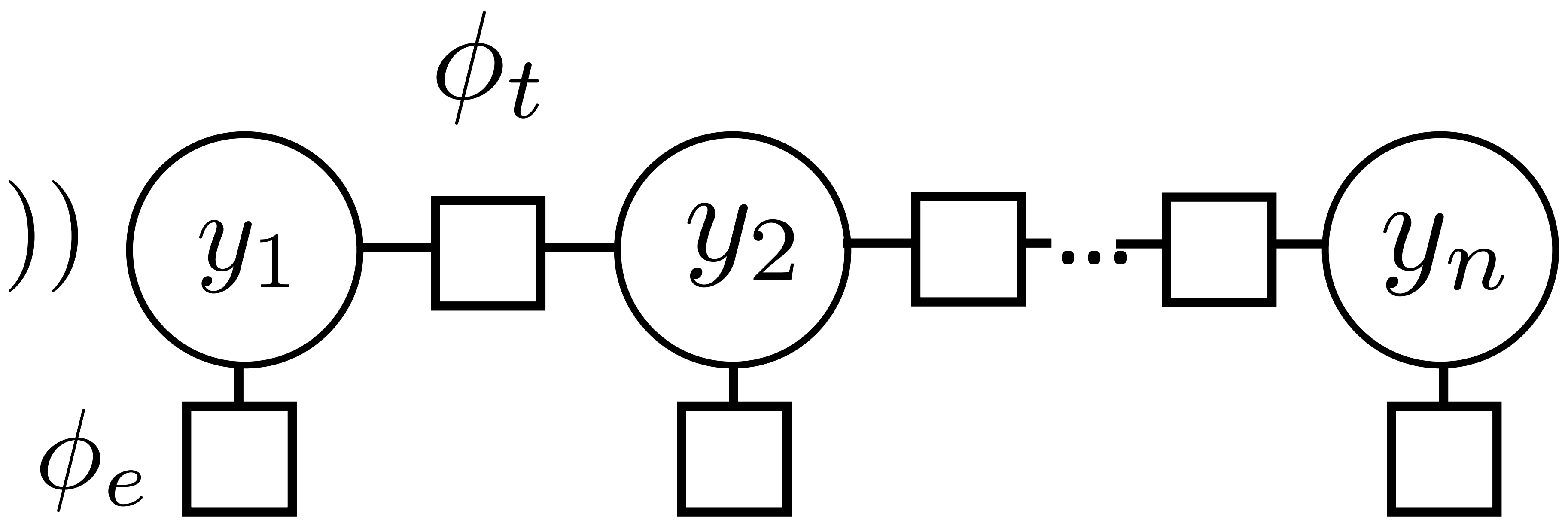

- Phis can be almost anything! Here we use linear functions of sparse features

$$\phi_e(y_i, i, \mathbf{x}) = w^\top f_e(y_i, i, \mathbf{x})$$

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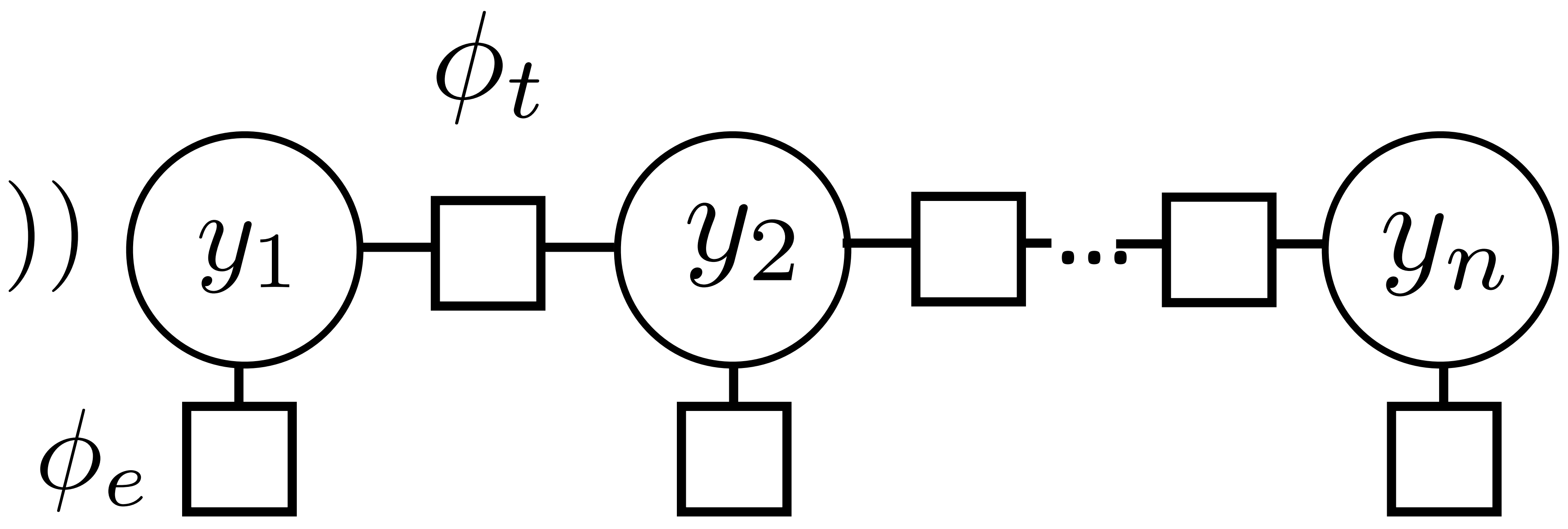

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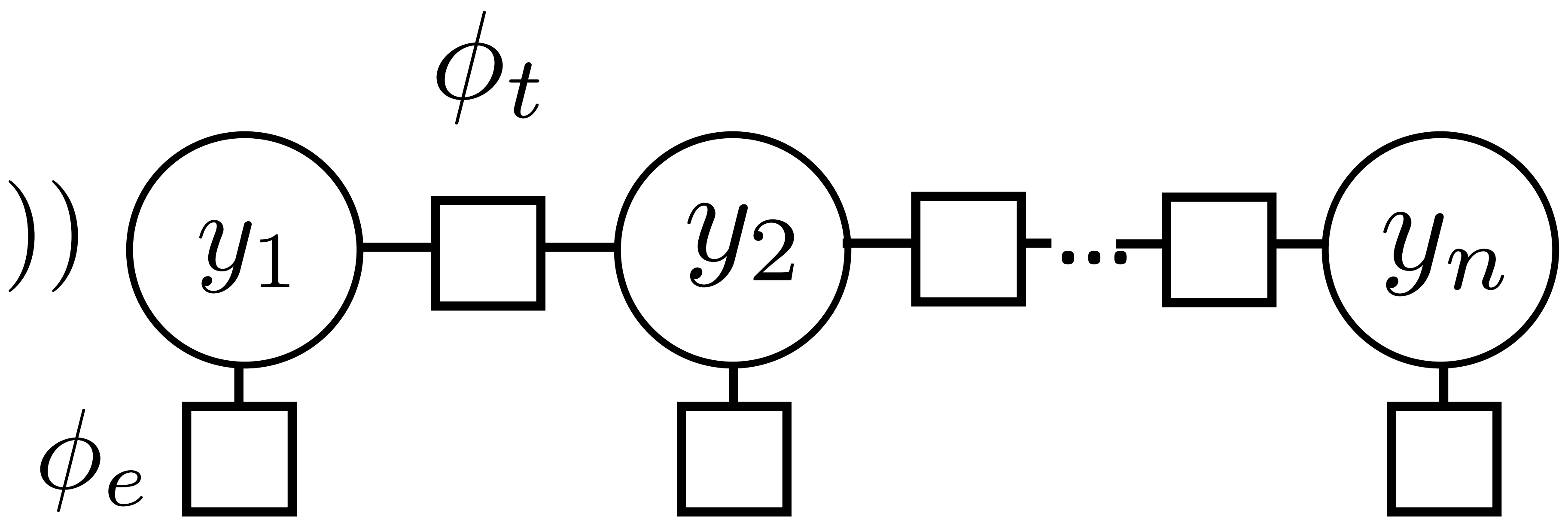

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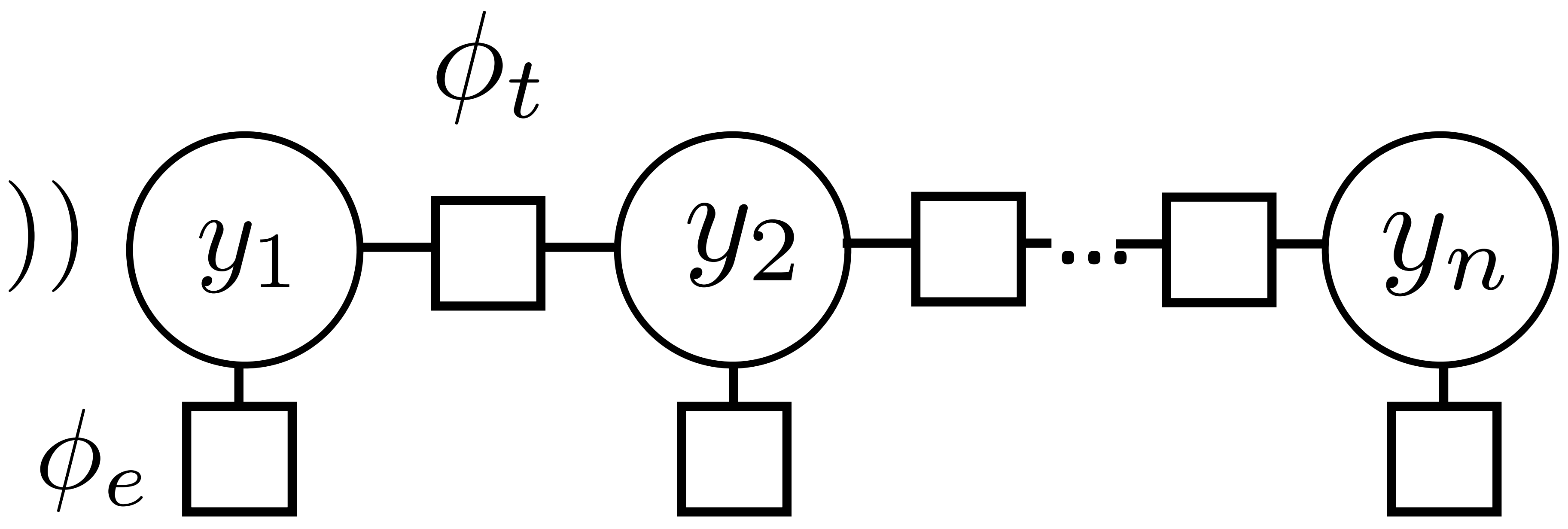

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- Looks like our single weight vector multiclass logistic regression model

Basic Features for NER

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

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

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O B-LOC

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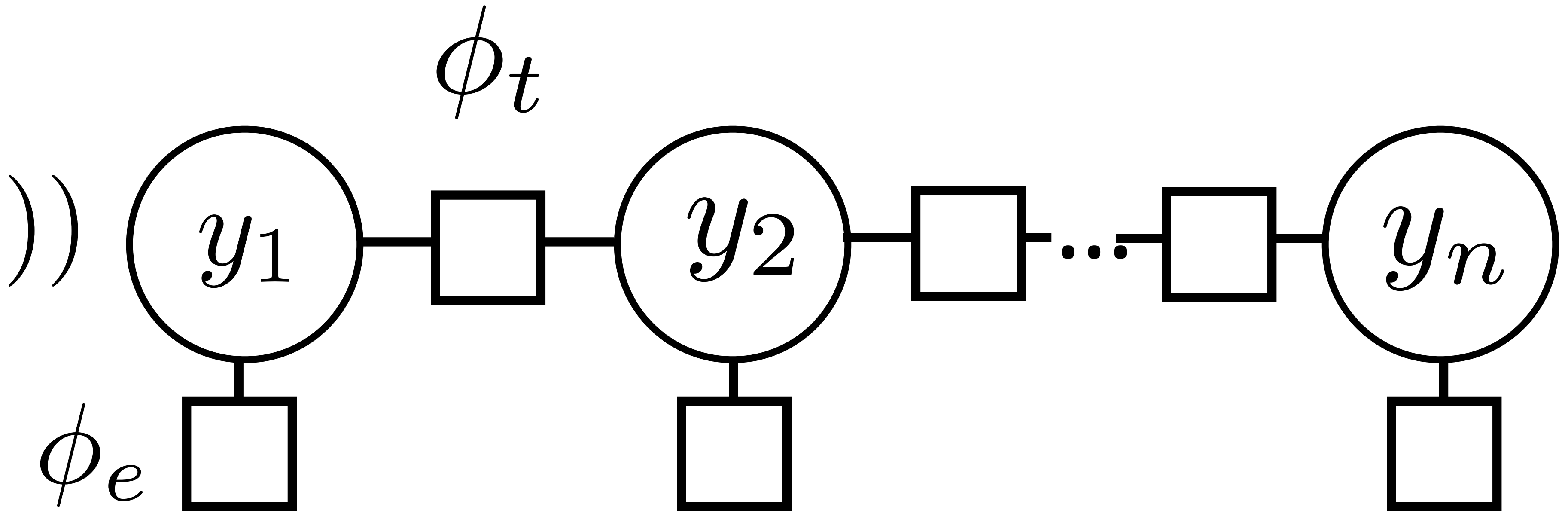
- Inference

- 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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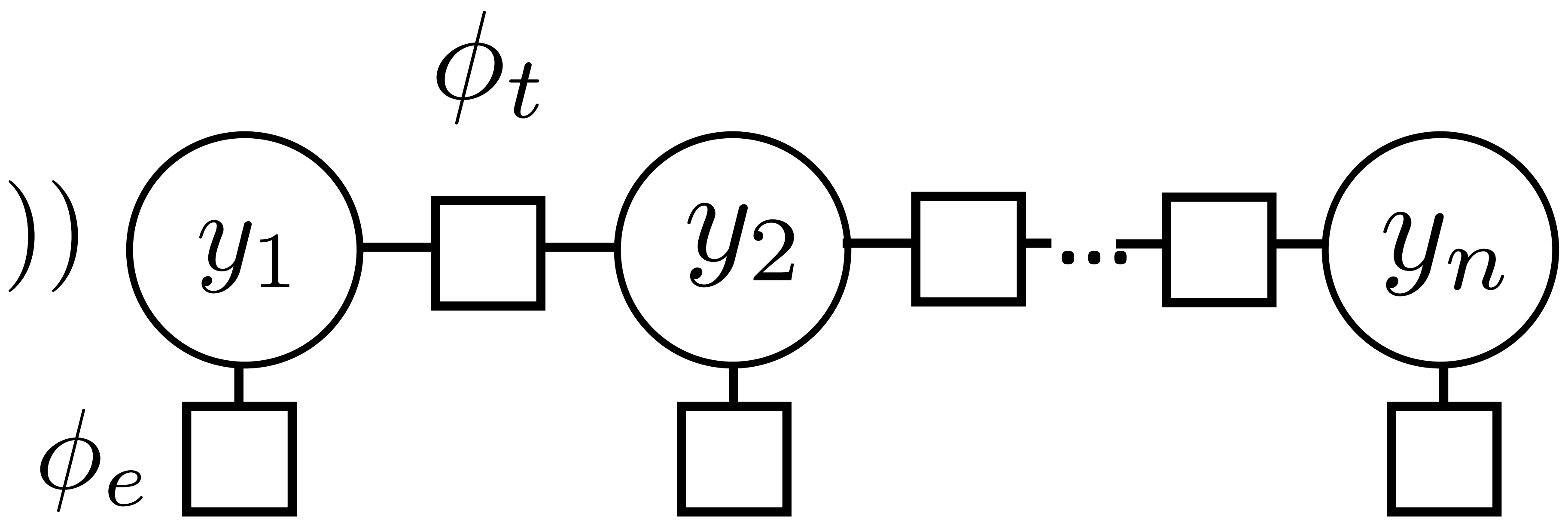

- $\text{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x})$: can use Viterbi exactly as in HMM case

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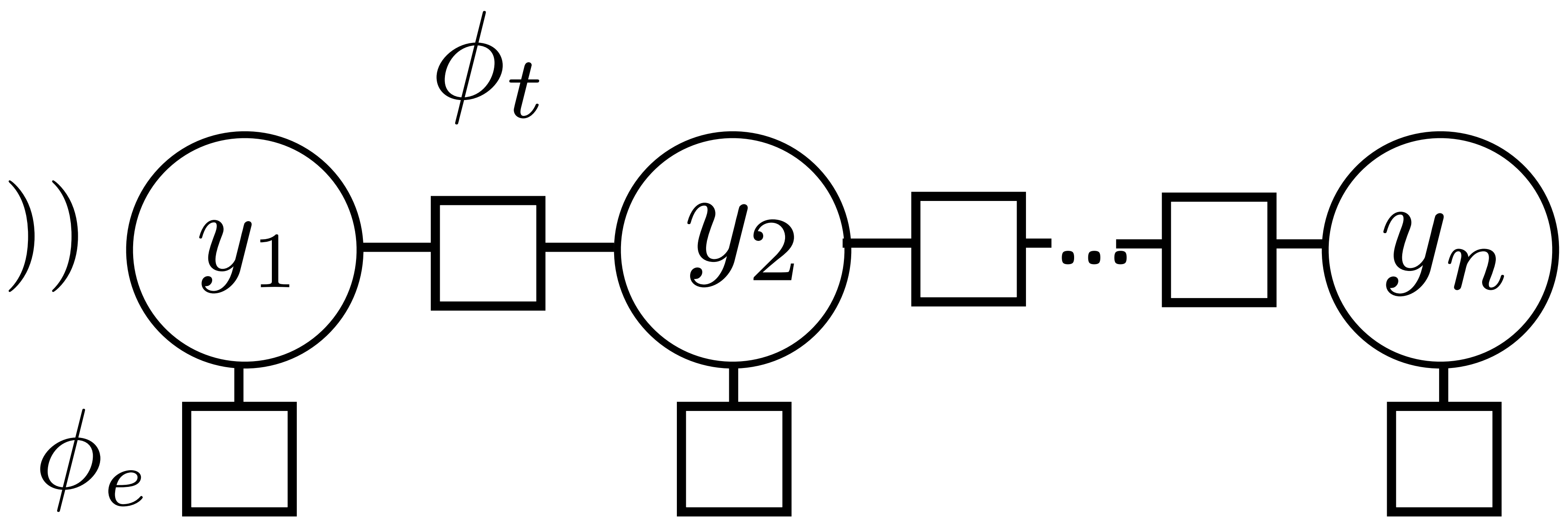

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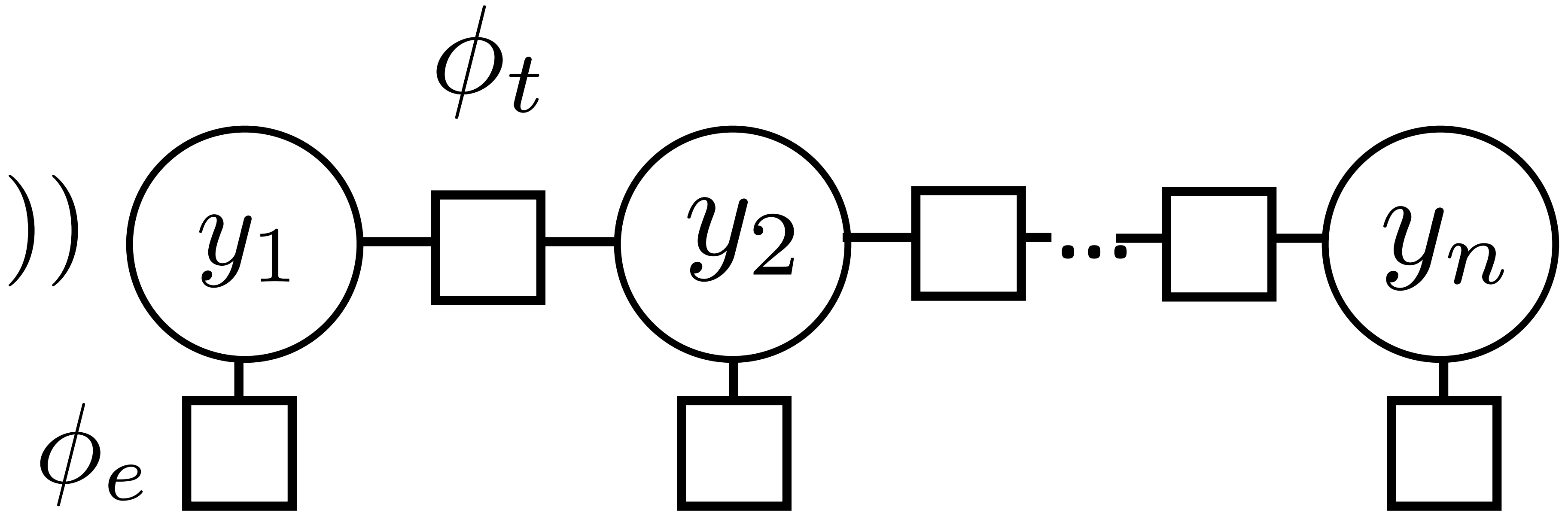

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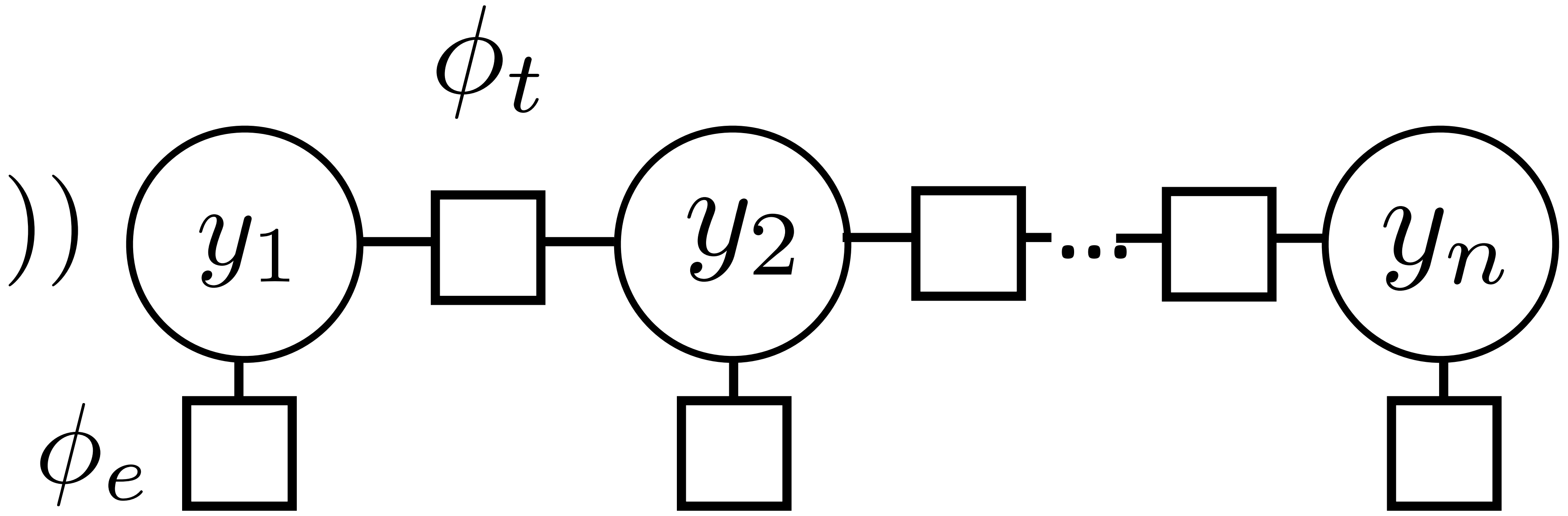

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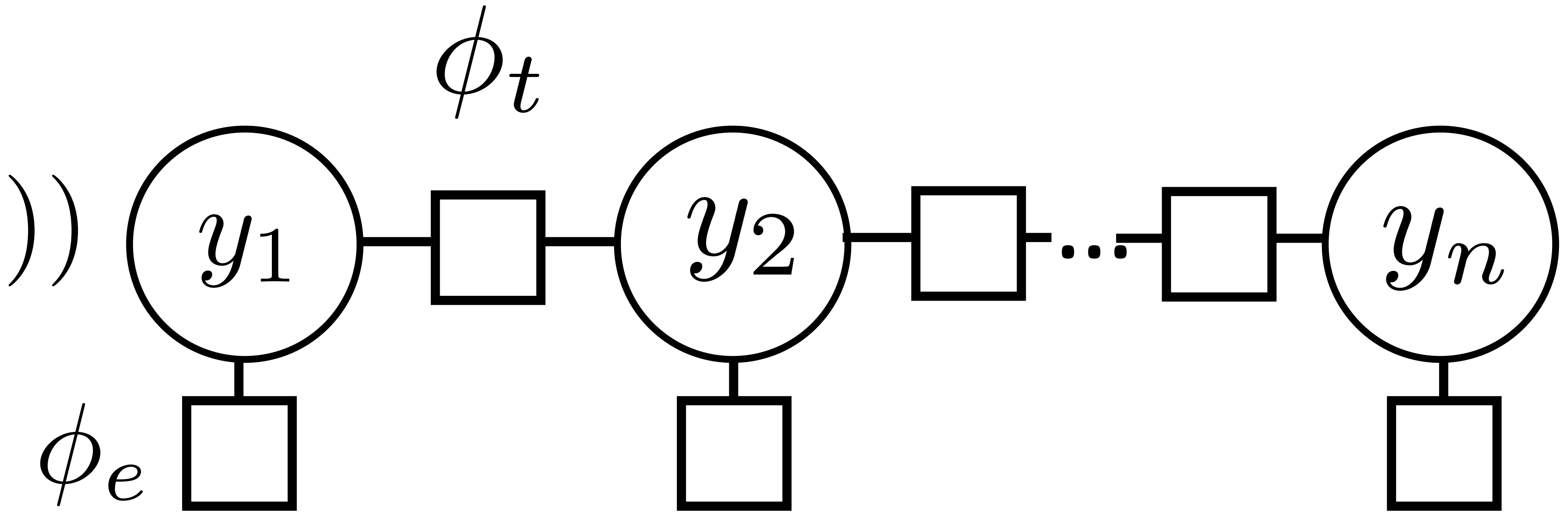

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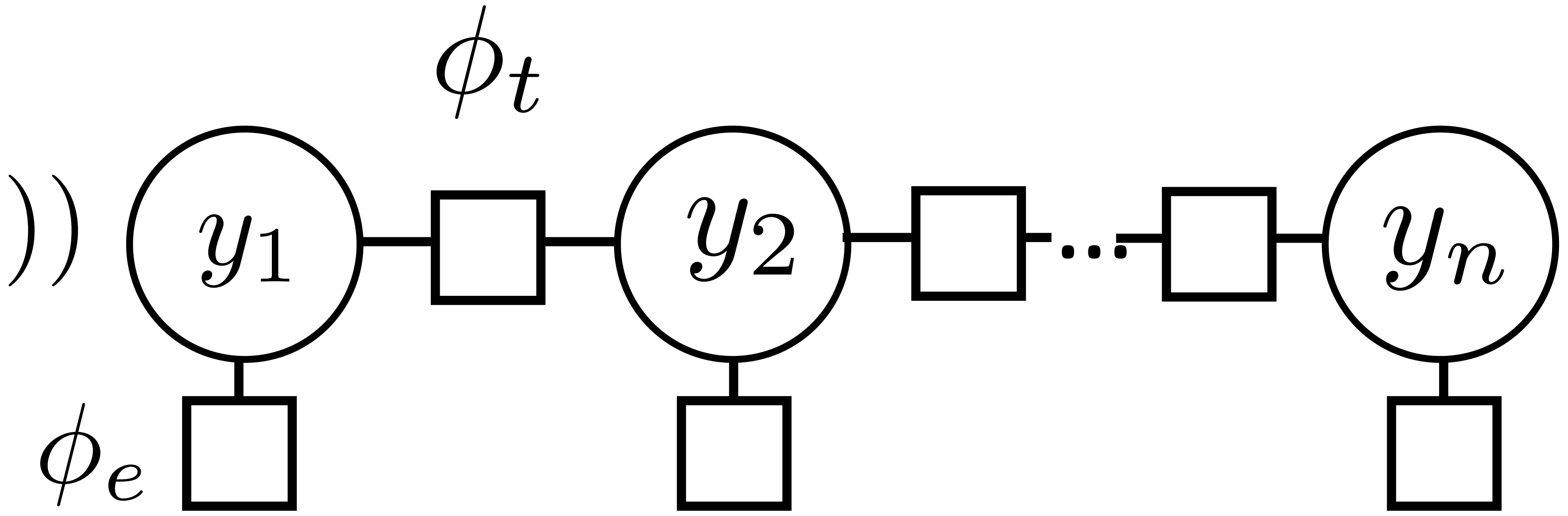

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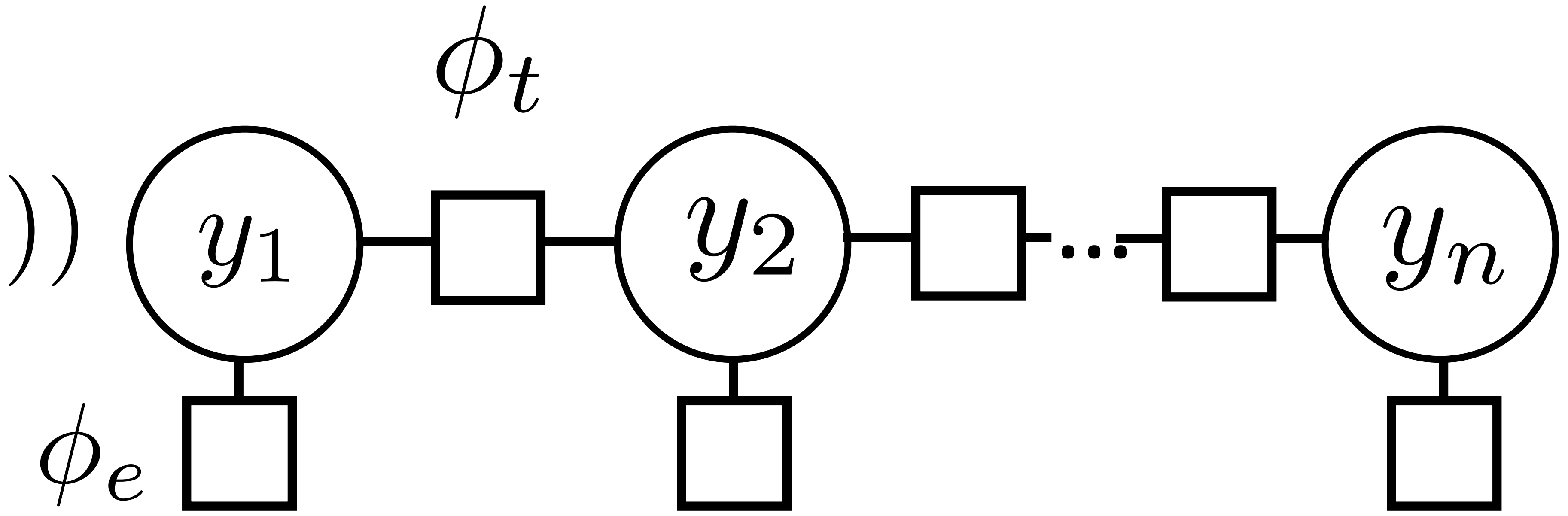

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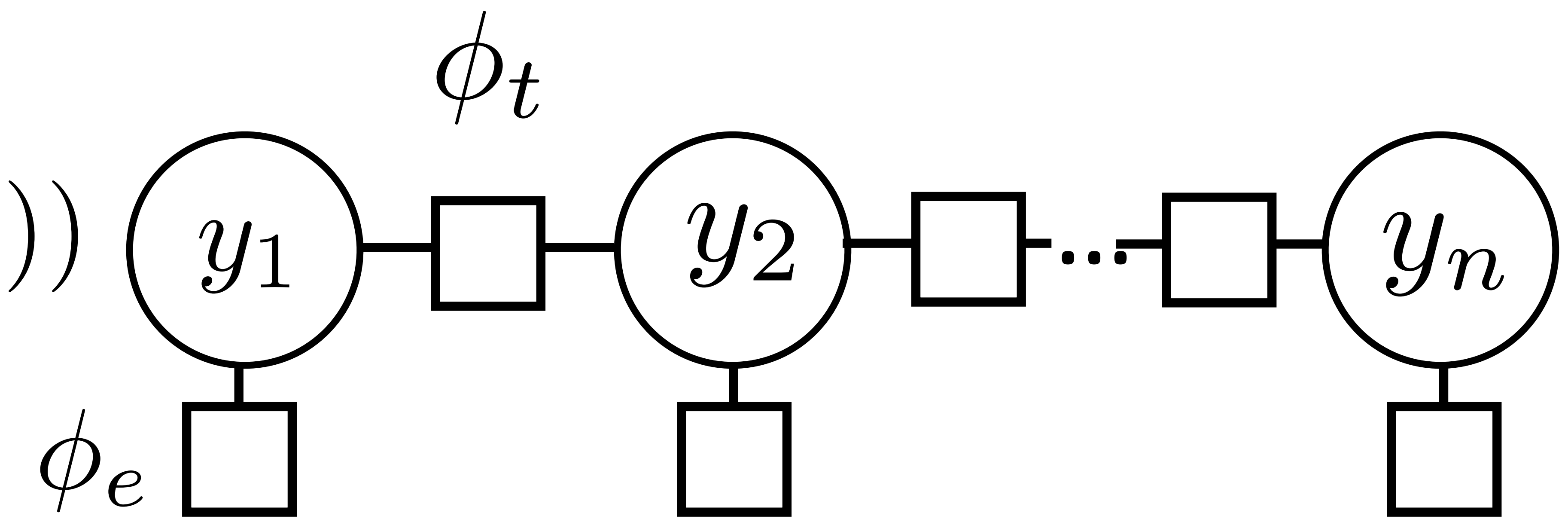

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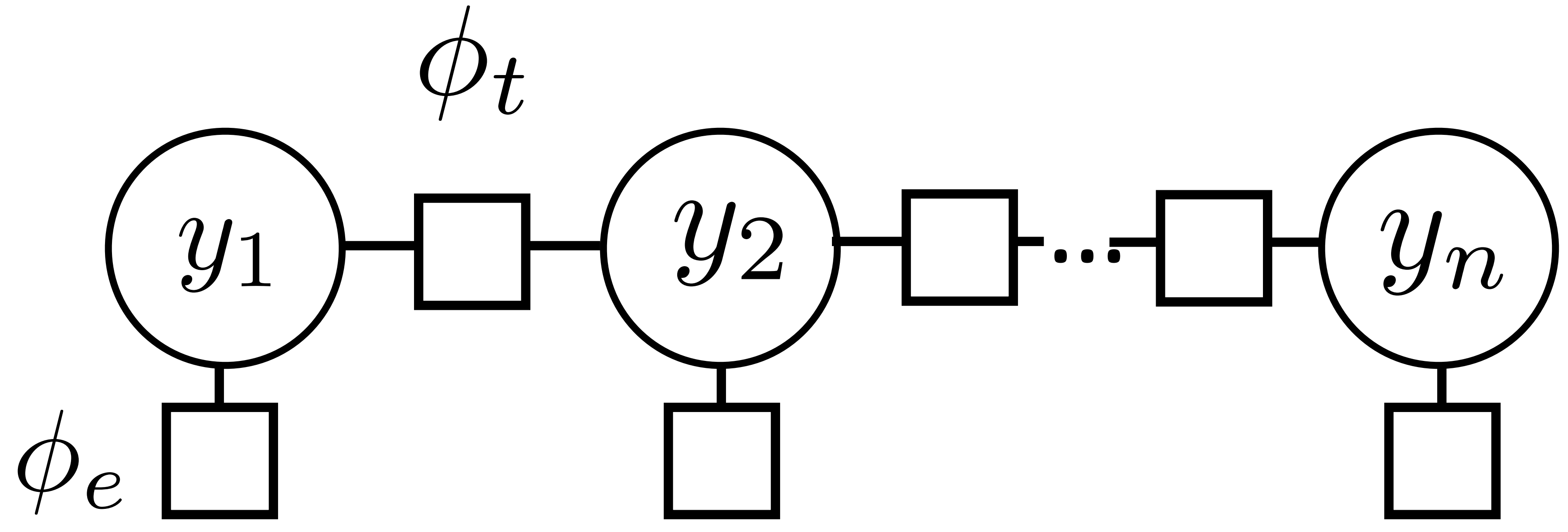
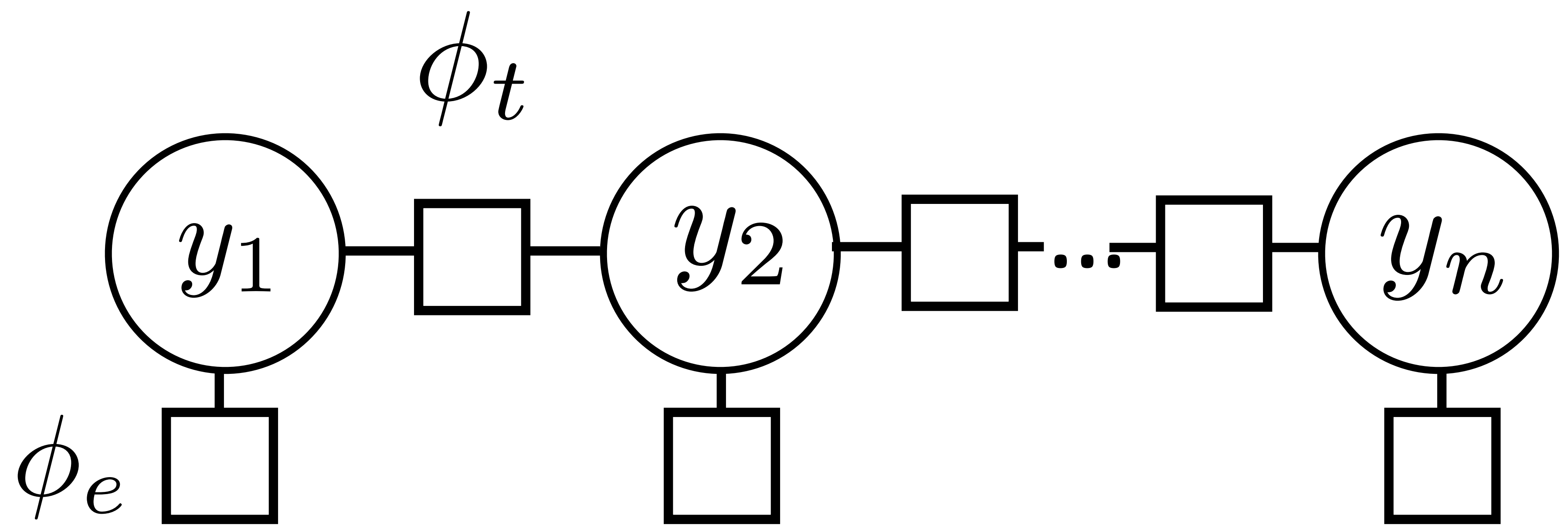
- $\exp(\phi_t(y_{i-1}, y_i))$ and $\exp(\phi_e(y_i, i, \mathbf{x}))$ play the role of the Ps now, same dynamic program

Inference in General CRFs



Inference in General CRFs

- Can do inference in any tree-structured CRF



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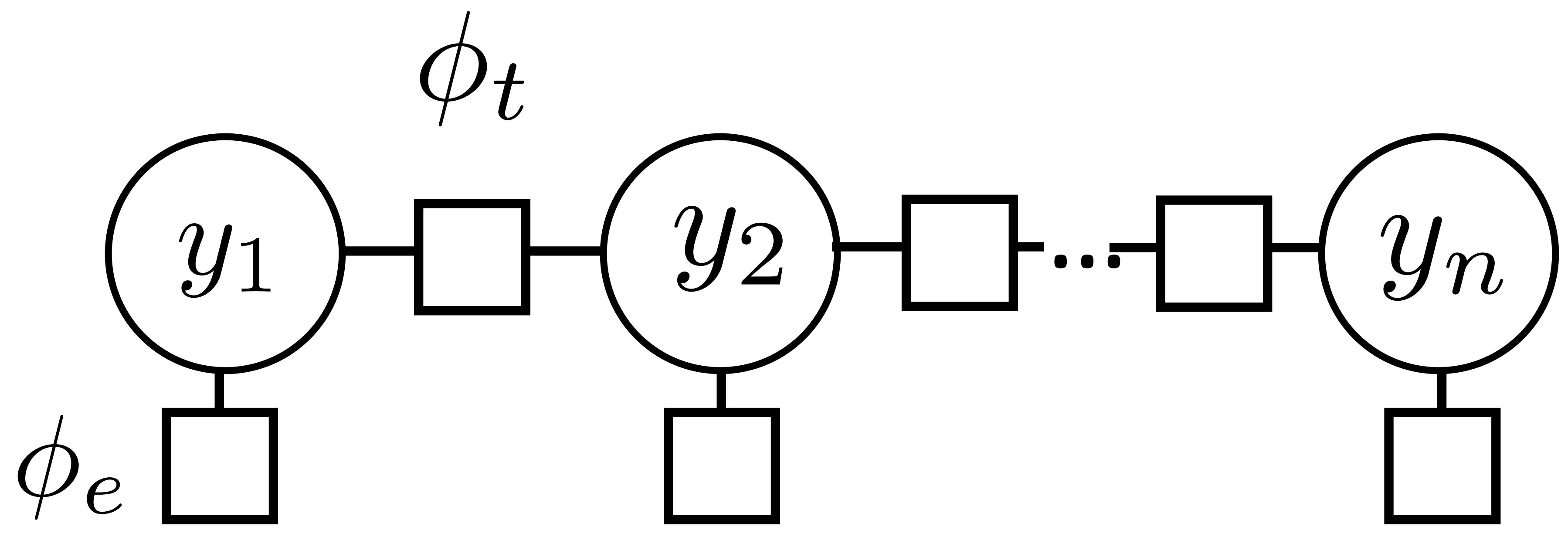

- Max-product algorithm: generalization of Viterbi to arbitrary tree-structured graphs (sum-product is generalization of forward-backward)

CRFs Outline

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

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- 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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- Logistic regression: $P(y|x) \propto \exp w^\top f(x, y)$

Training CRFs

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Training CRFs

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

intractable!

Training CRFs

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- Let’s focus on emission feature expectation

Training CRFs

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

- Let's focus on emission feature expectation

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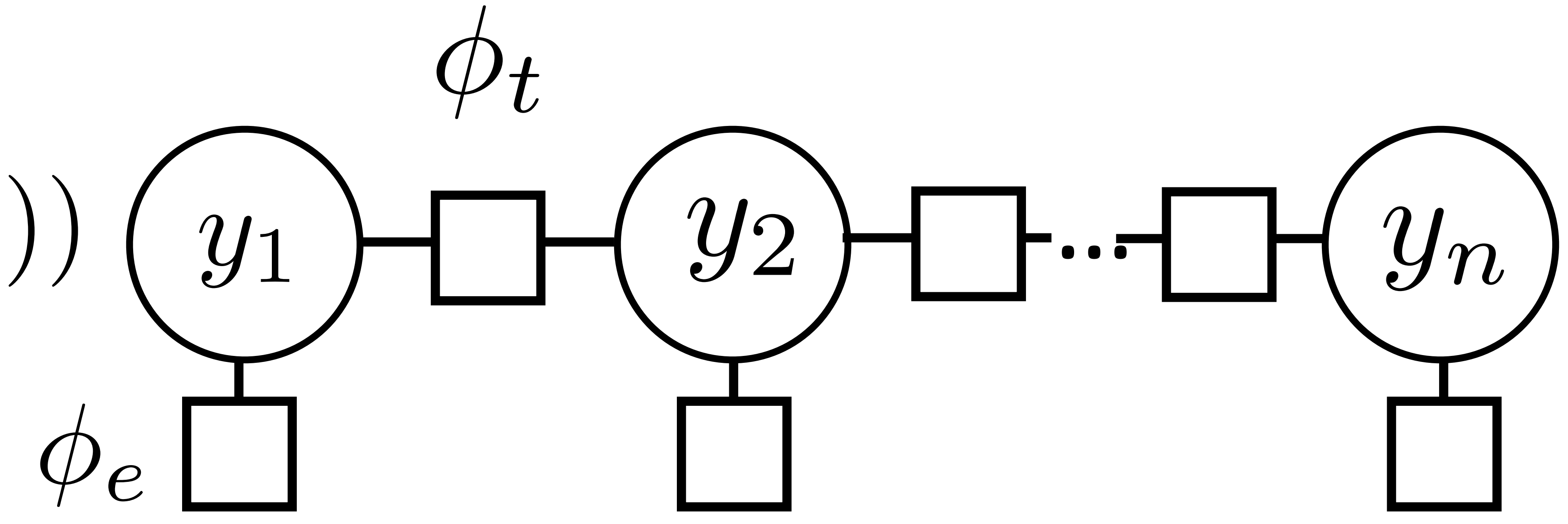
Computing Marginals

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



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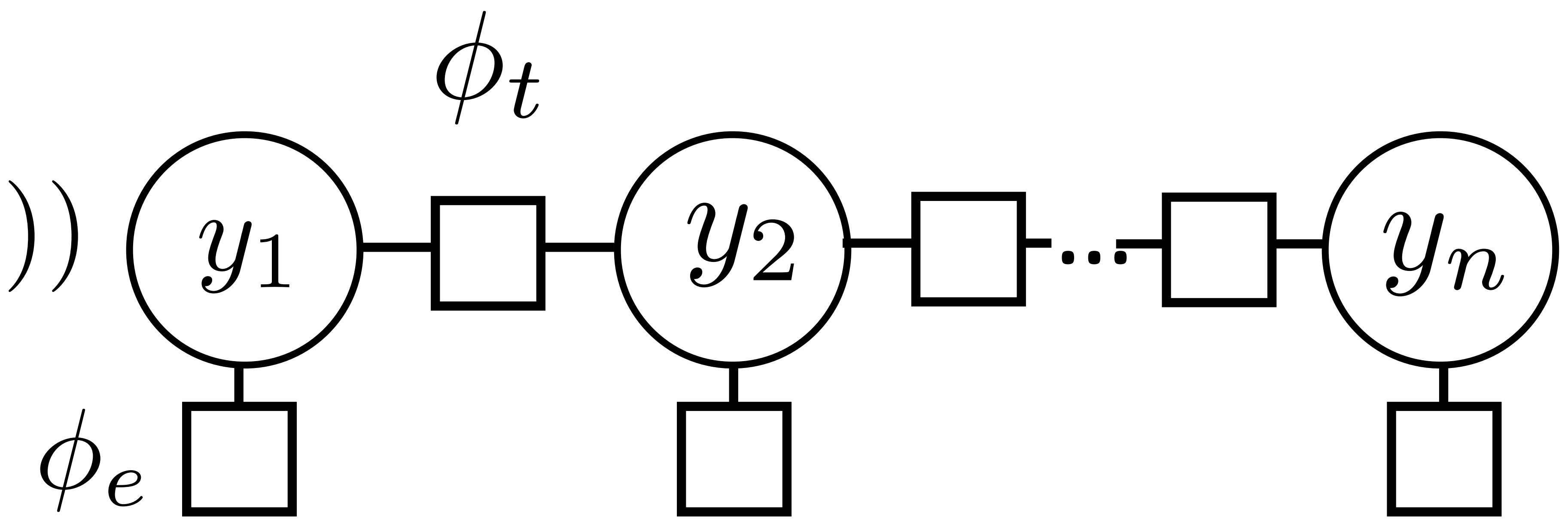

- Normalizing constant $Z = \sum_{\mathbf{y}}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$

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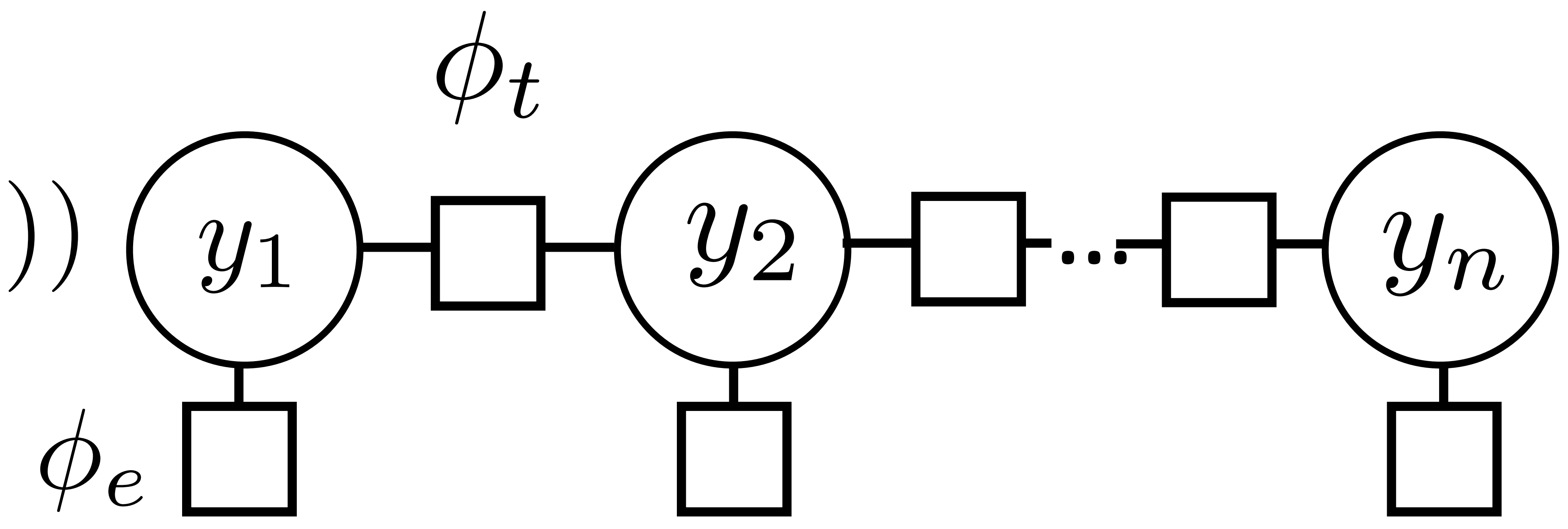

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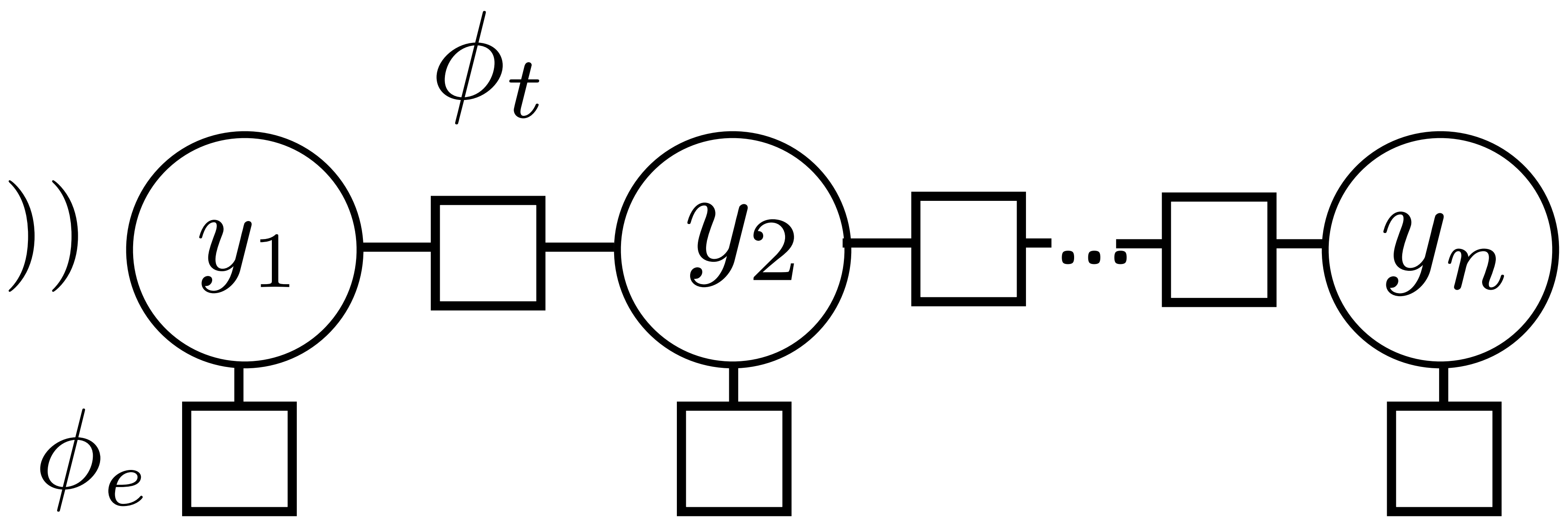

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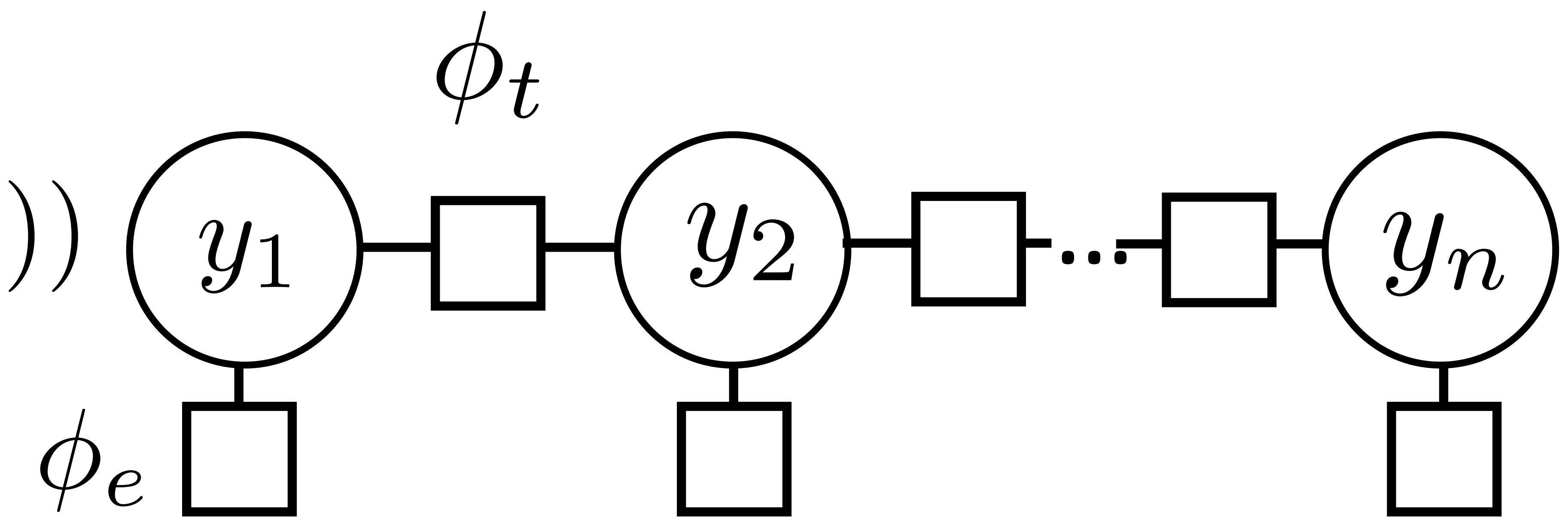

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Posteriors vs. Probabilities

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- For emission features:

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- 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

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Pseudocode

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for each epoch
    for each example
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How to “Cheat” with Automatic Differentiation

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- 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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Replaces Expectation
With argmax

Structured SVM

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- Exponentially large state space! Use Viterbi for loss-augmented decode
- 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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Tanjug

From Wikipedia, the free encyclopedia

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

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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PER O LOC O ORG O

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- ***y*** is a set of touching spans of the sentence
- Pros: features can look at whole span at once
- Cons: there's an extra factor of *n* in the dynamic programs

Sarawagi and Cohen (2004)

Evaluating NER

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		

Evaluating NER

B-PER	I-PER	O	O	O	B-LOC	O	O	O	B-ORG	O	O
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PERSON (*Barack Obama*), LOC (*Hangzhou*), ORG (*G20*)

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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
-	(Ando and Zhang, 2005)	Semi-supervised on 27M-word unlabeled data	89.31
-	(Kazama and Torisawa, 2007a)	Wikipedia	88.02
-	(Krishnan and Manning, 2006)	Non-local Features	87.24
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Devlin et al. (2019) **92.8**

Beam Search

Viterbi Time Complexity

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

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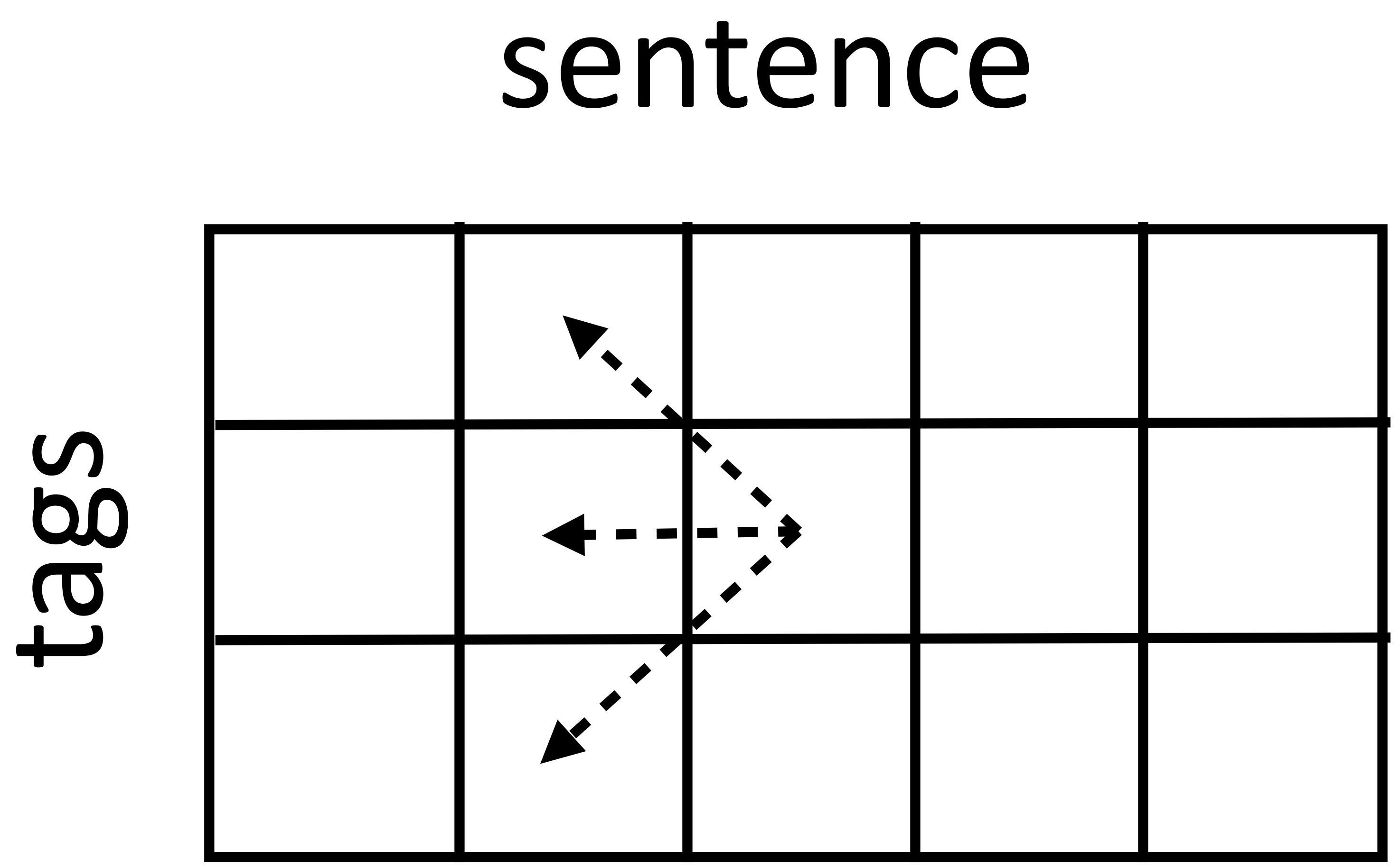

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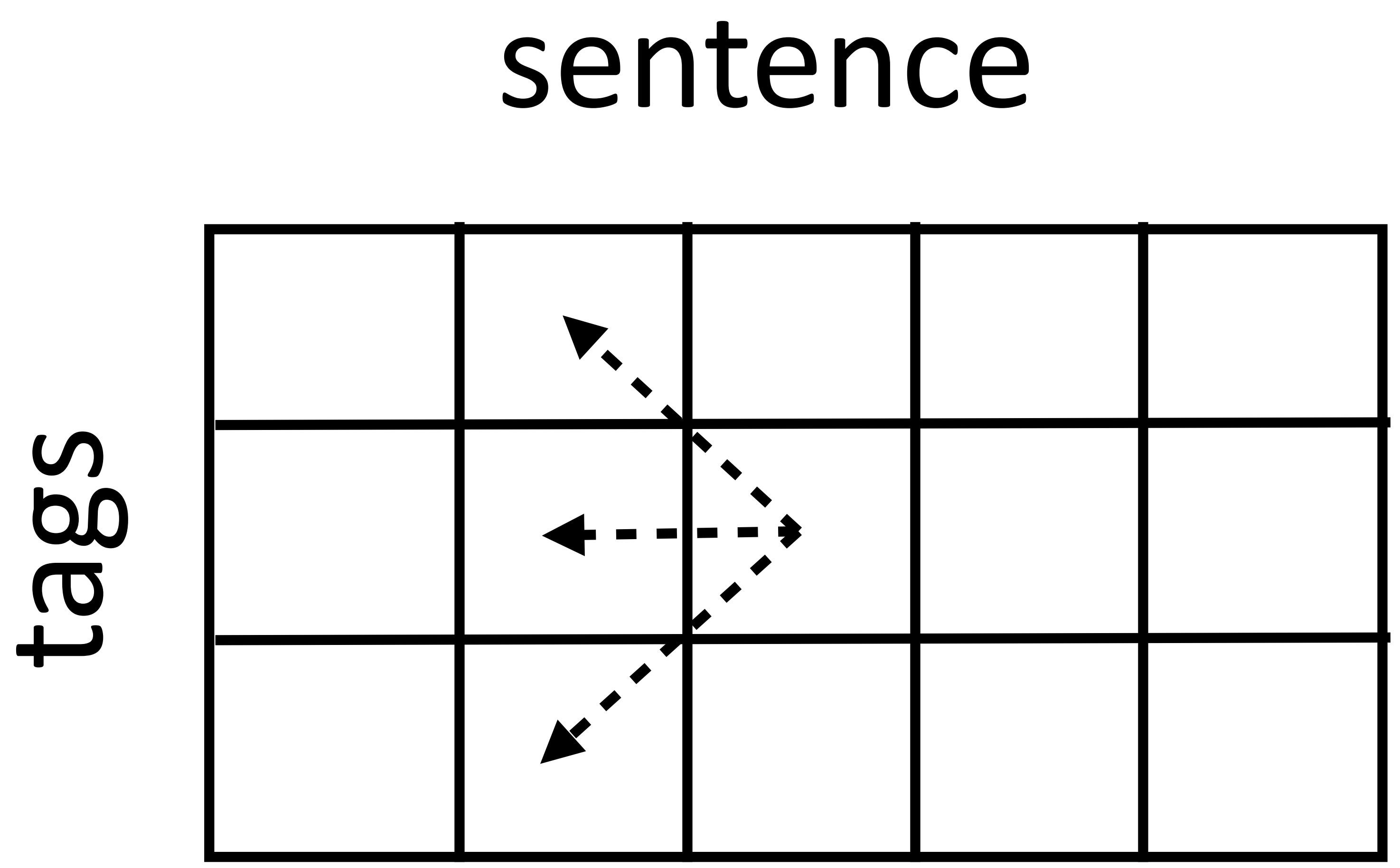

- $O(ns^2)$ — s is ~40 for POS, n is ~20

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

Beam Search

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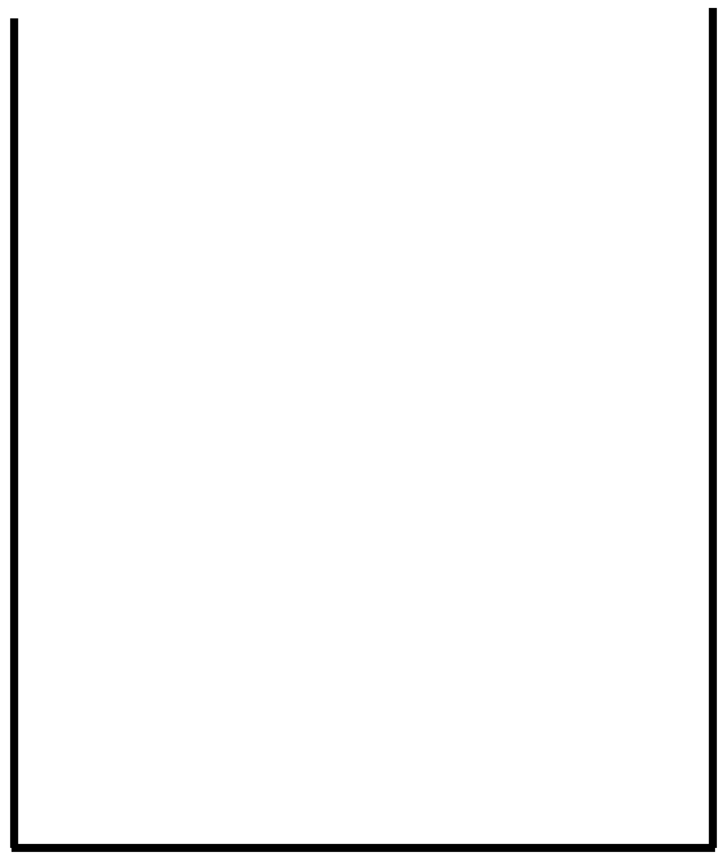

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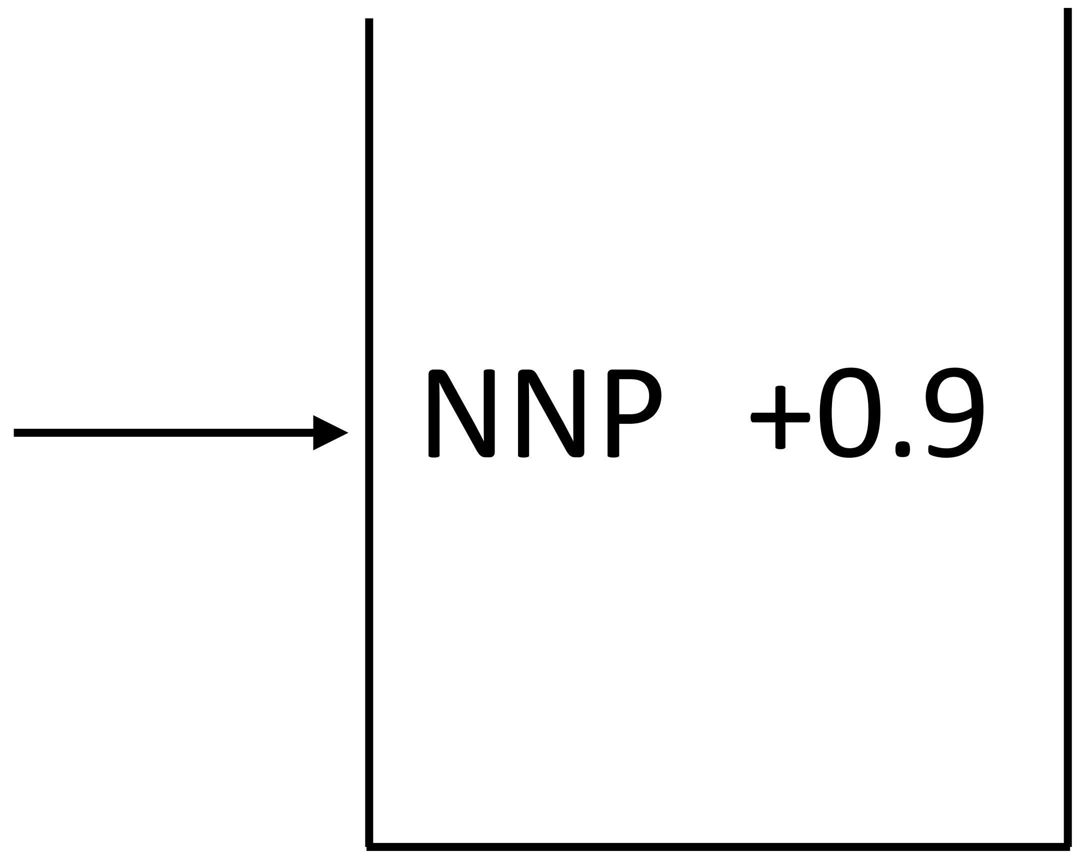

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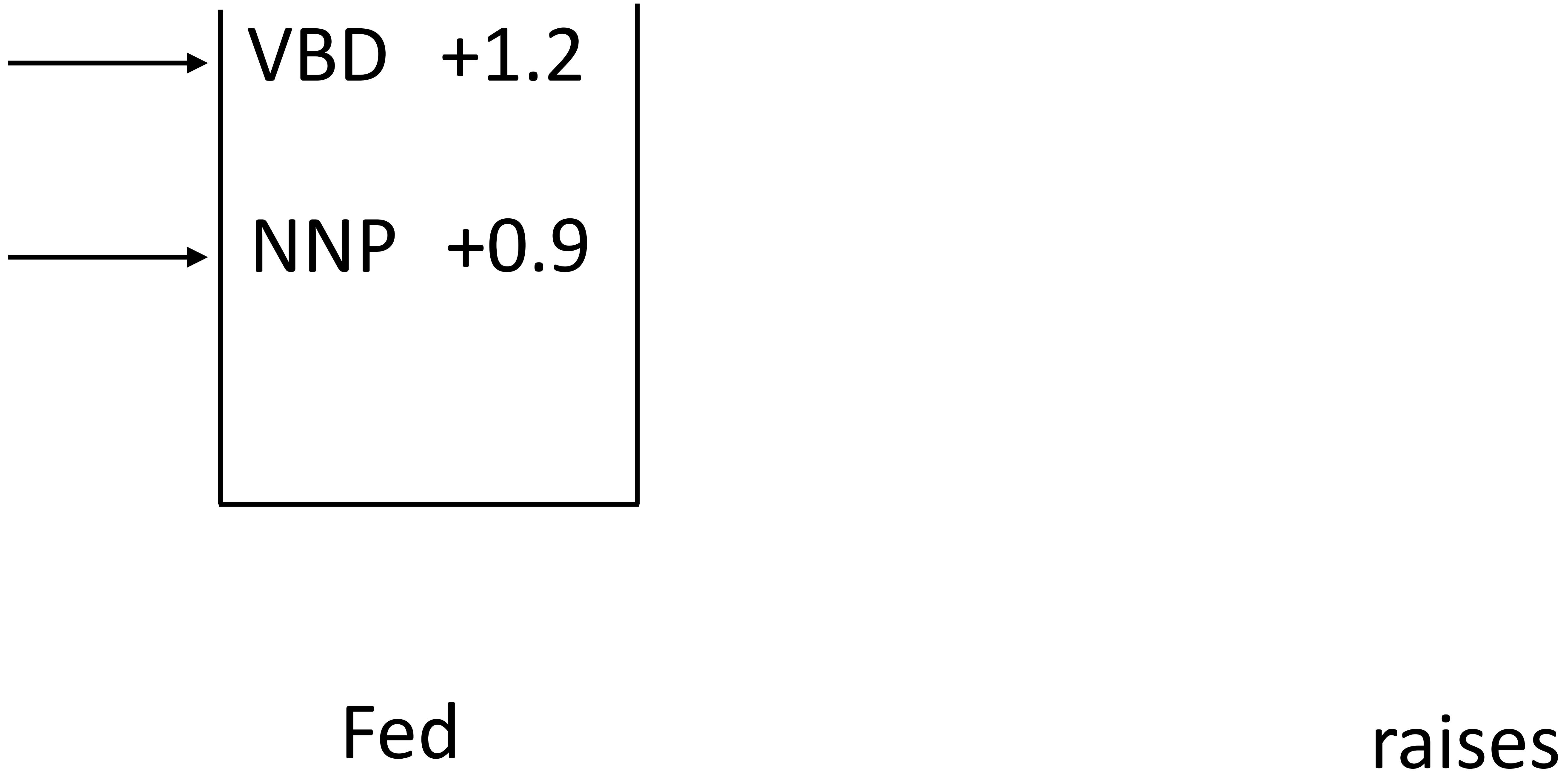

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VBD +1.2

NNP +0.9

VBN +0.7

NN +0.3

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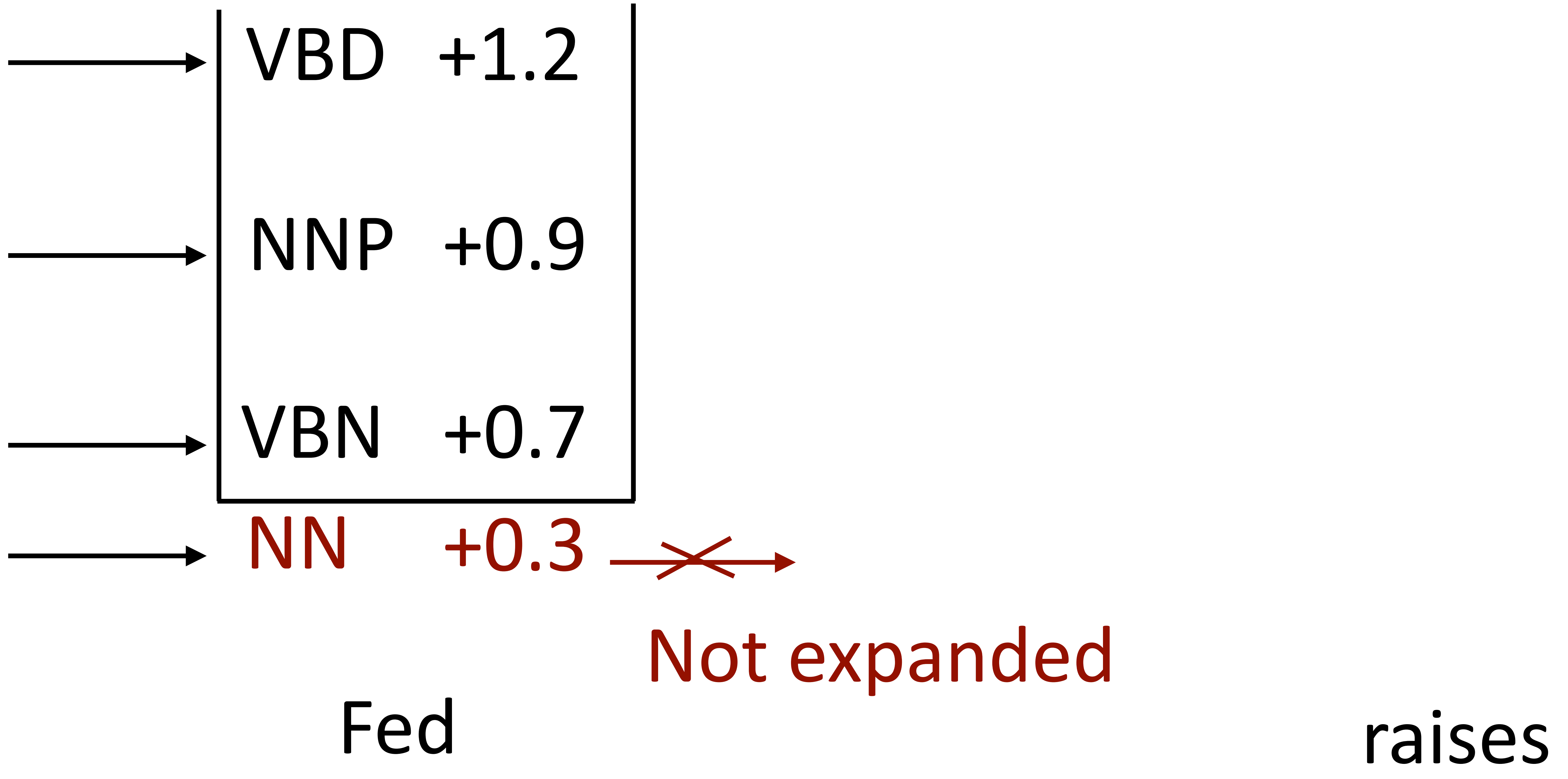

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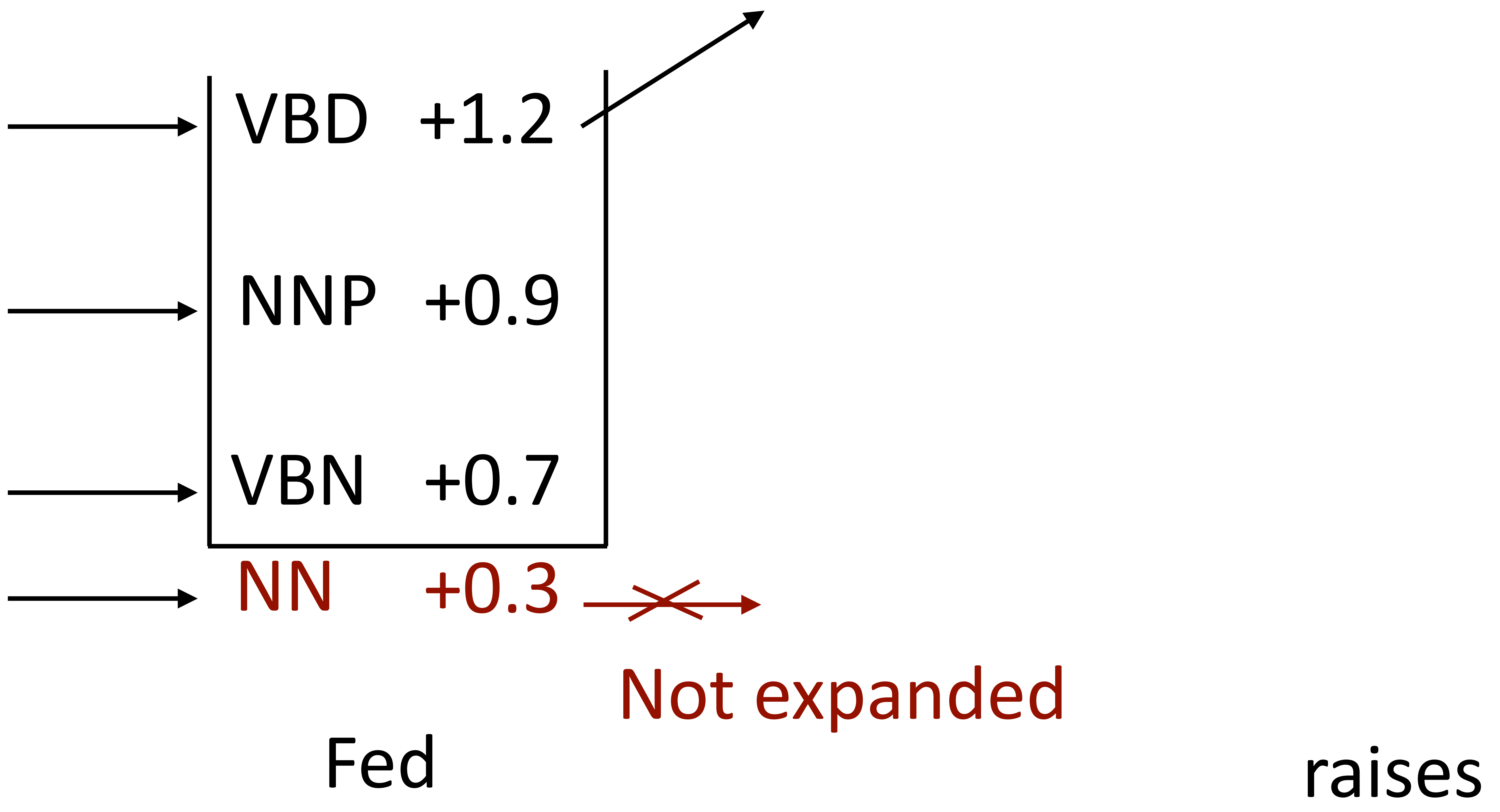

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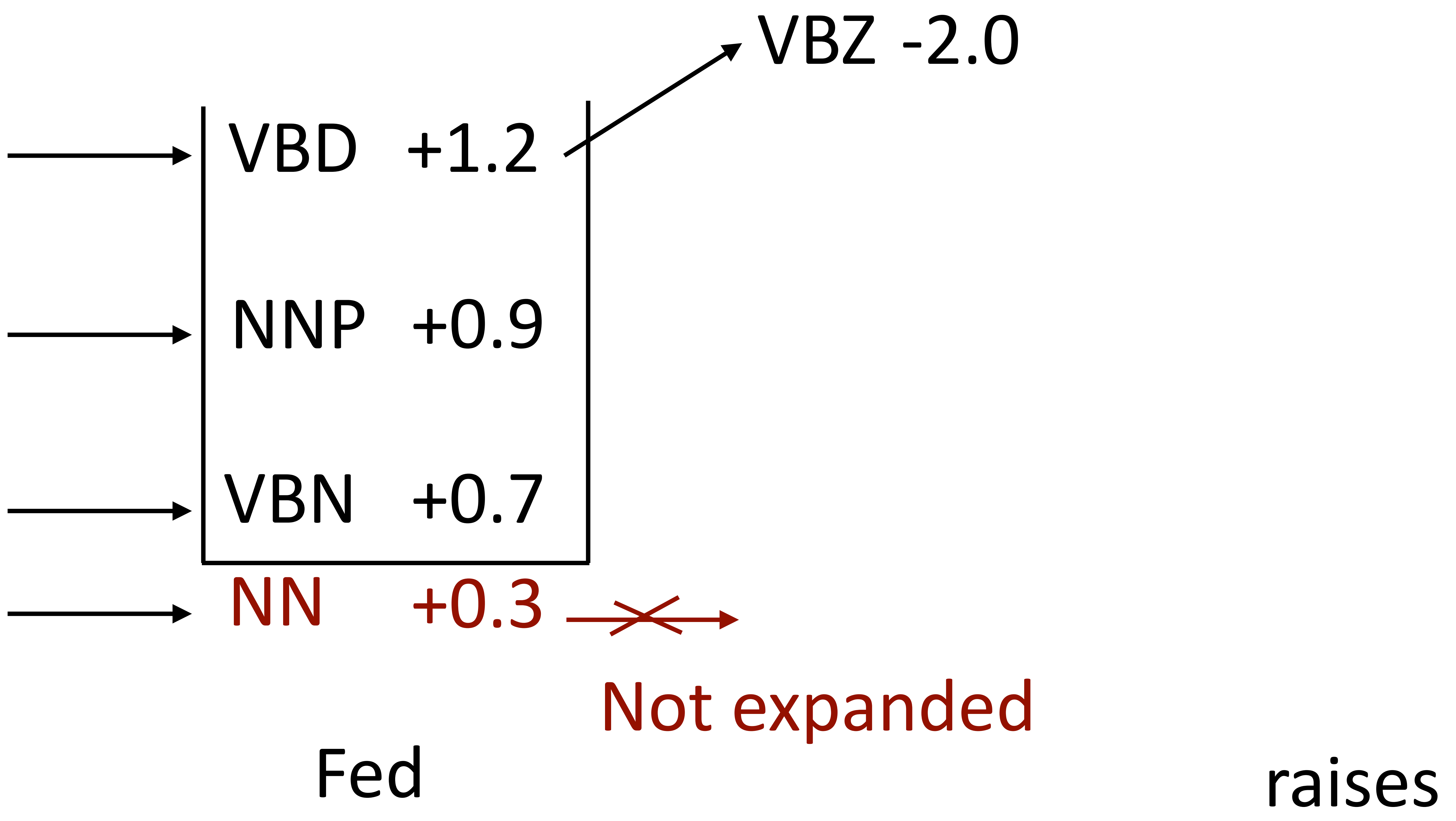

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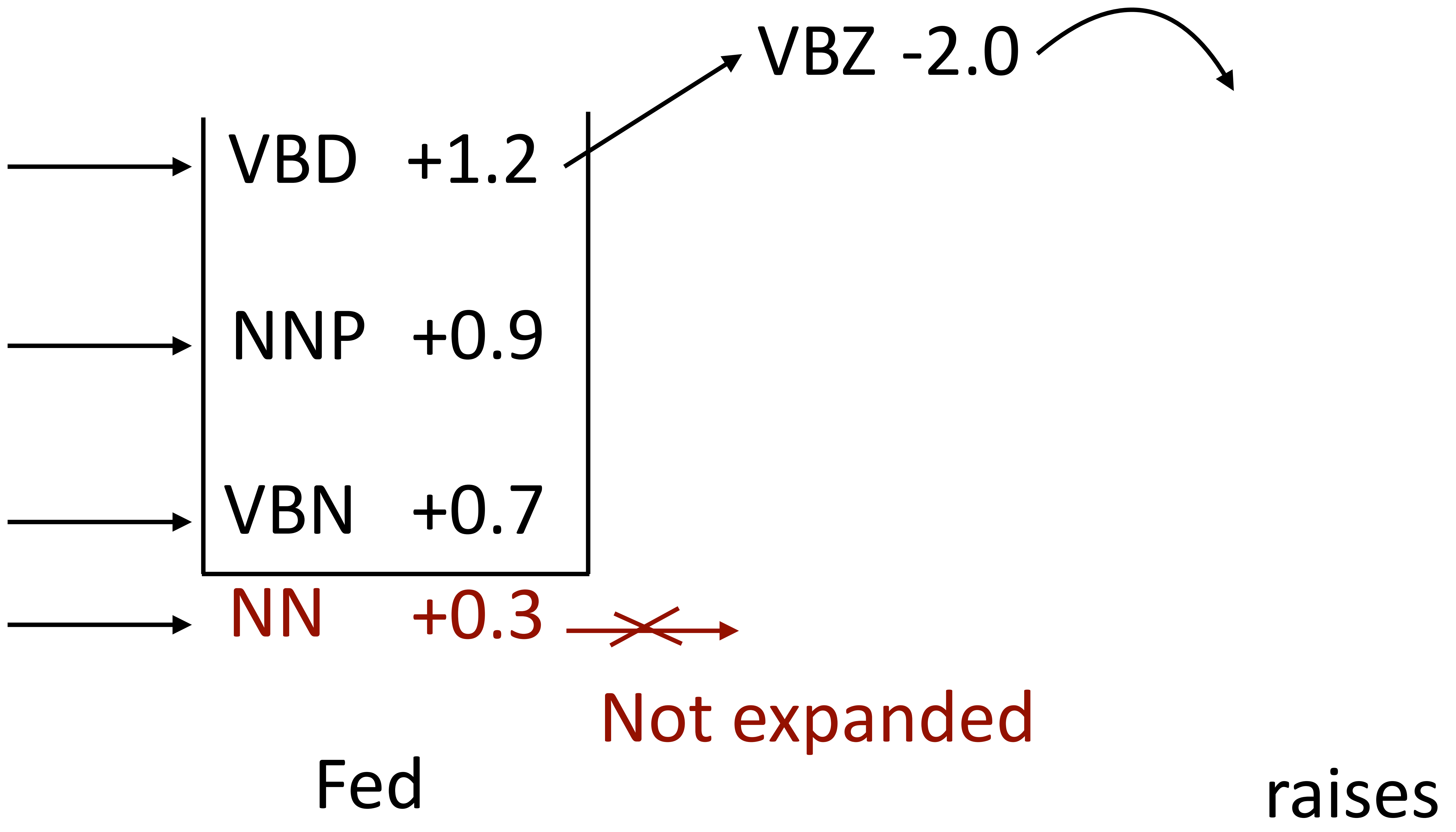

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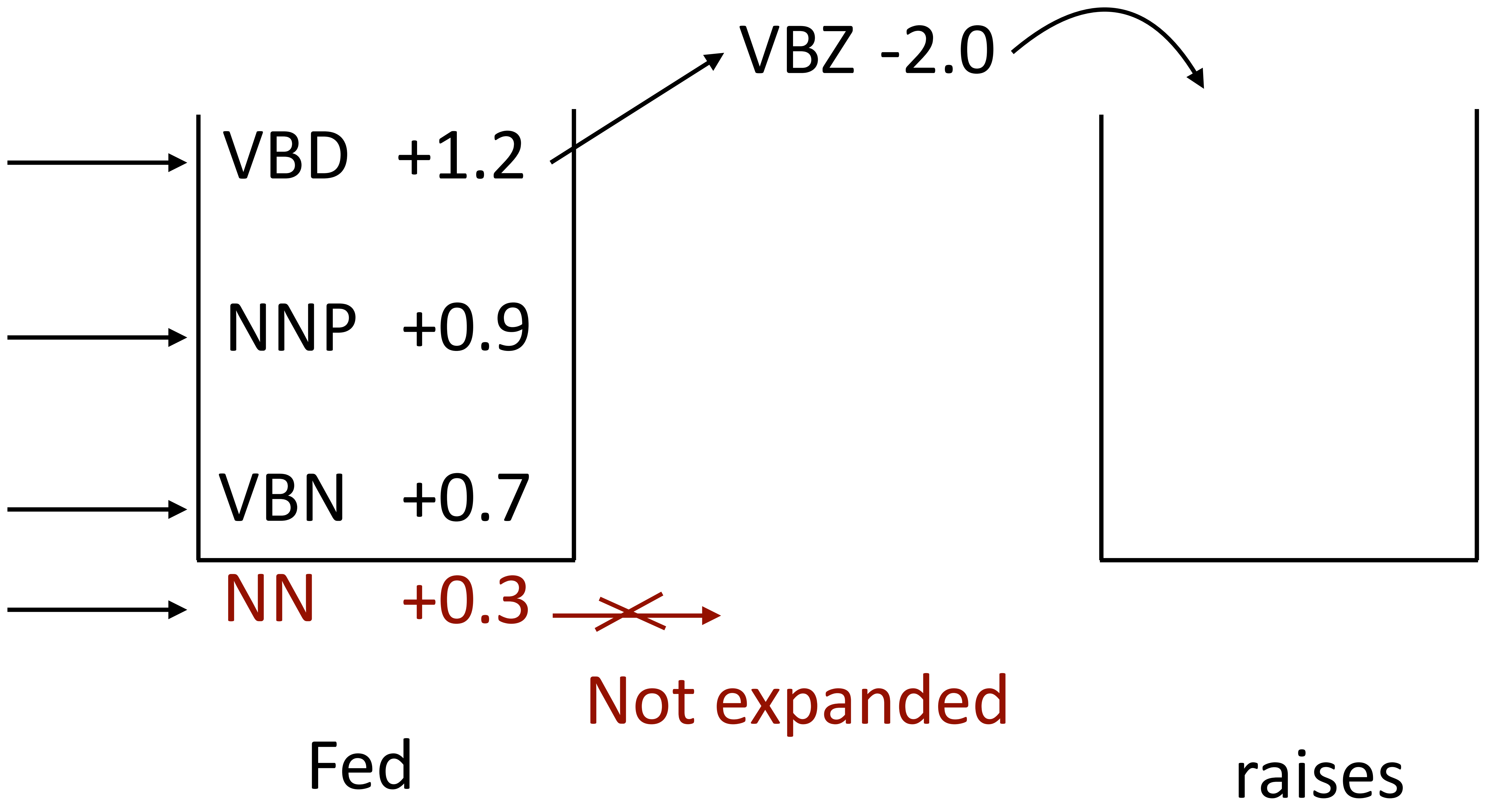

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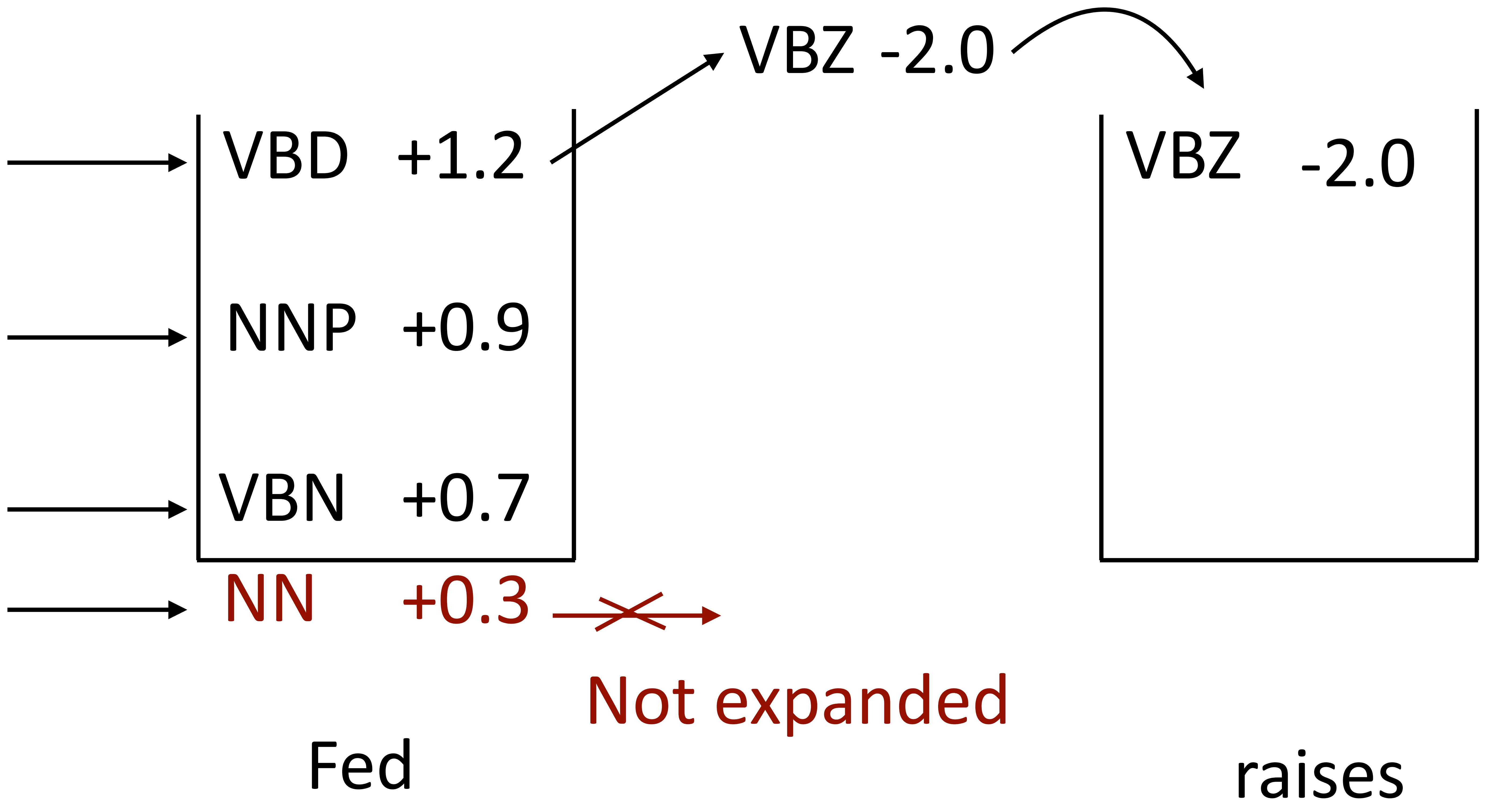

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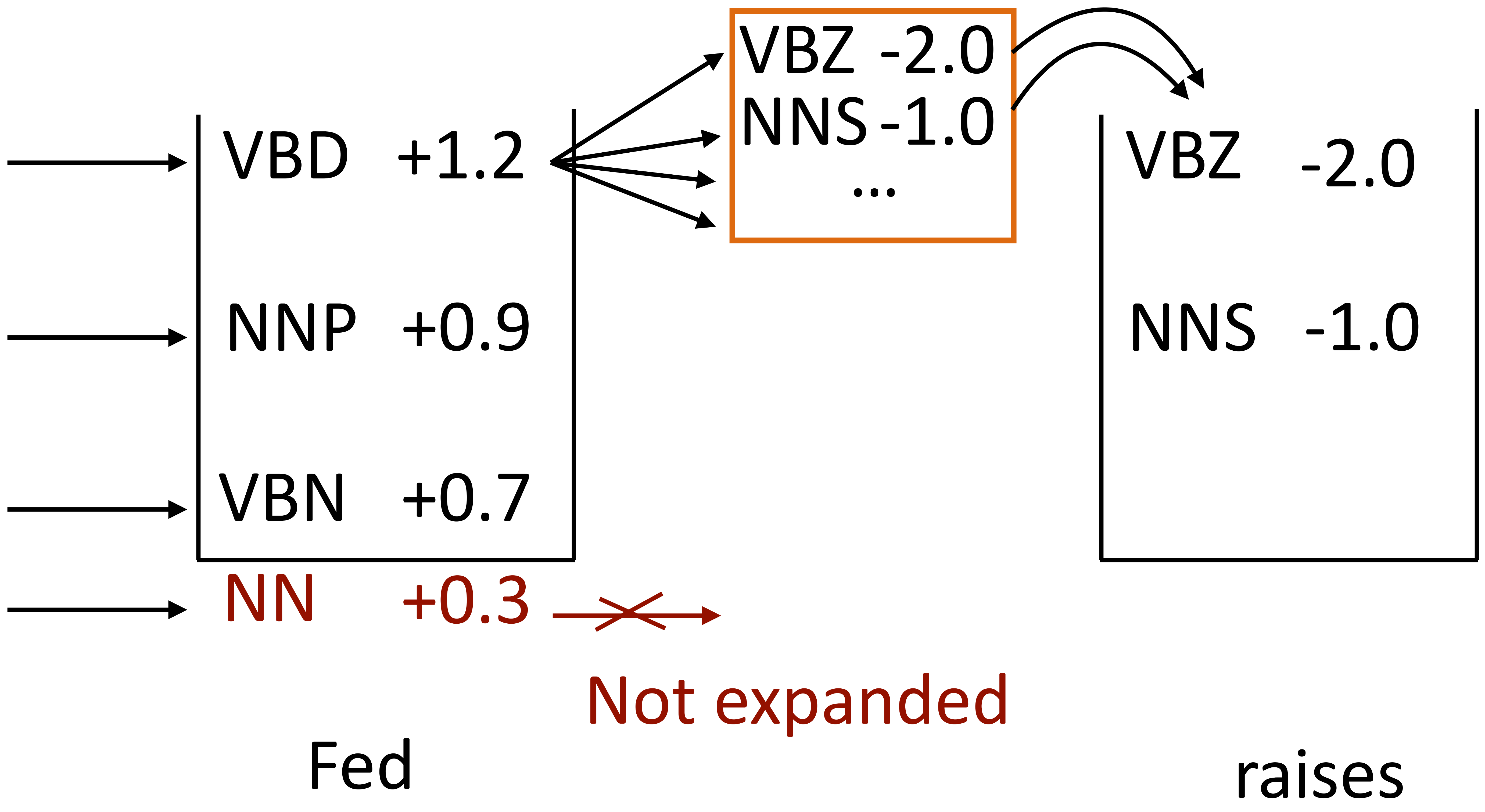

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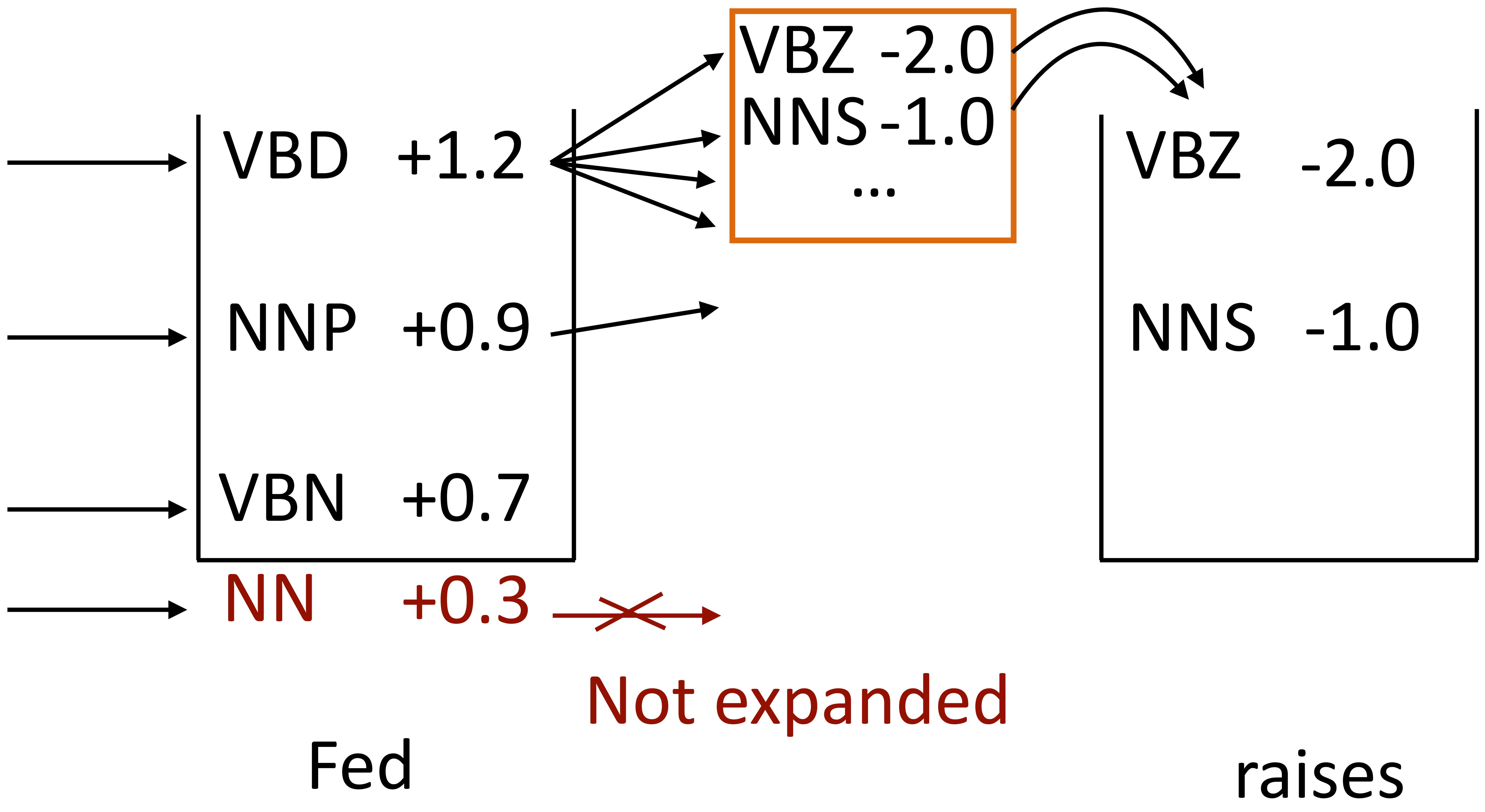

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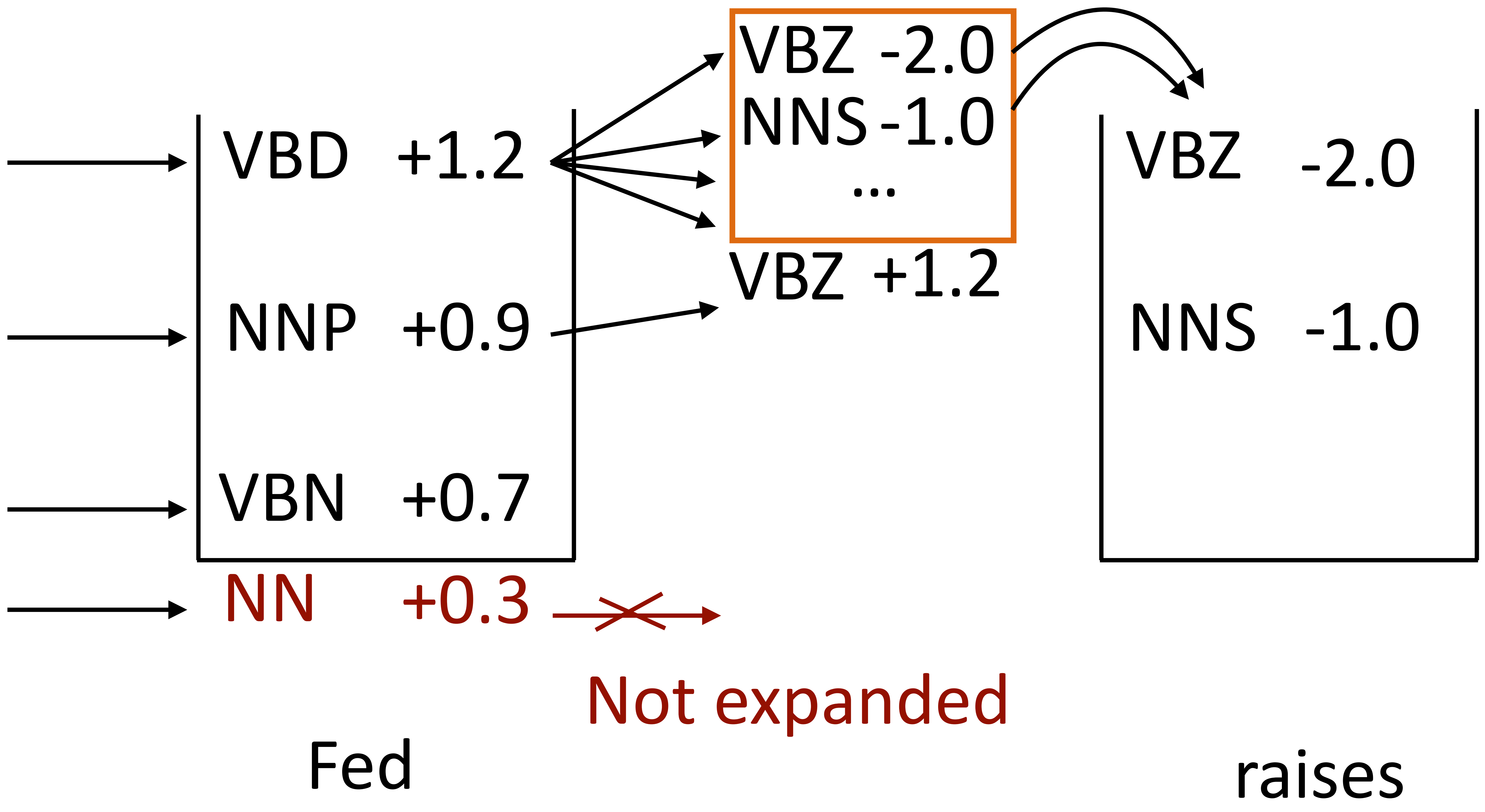

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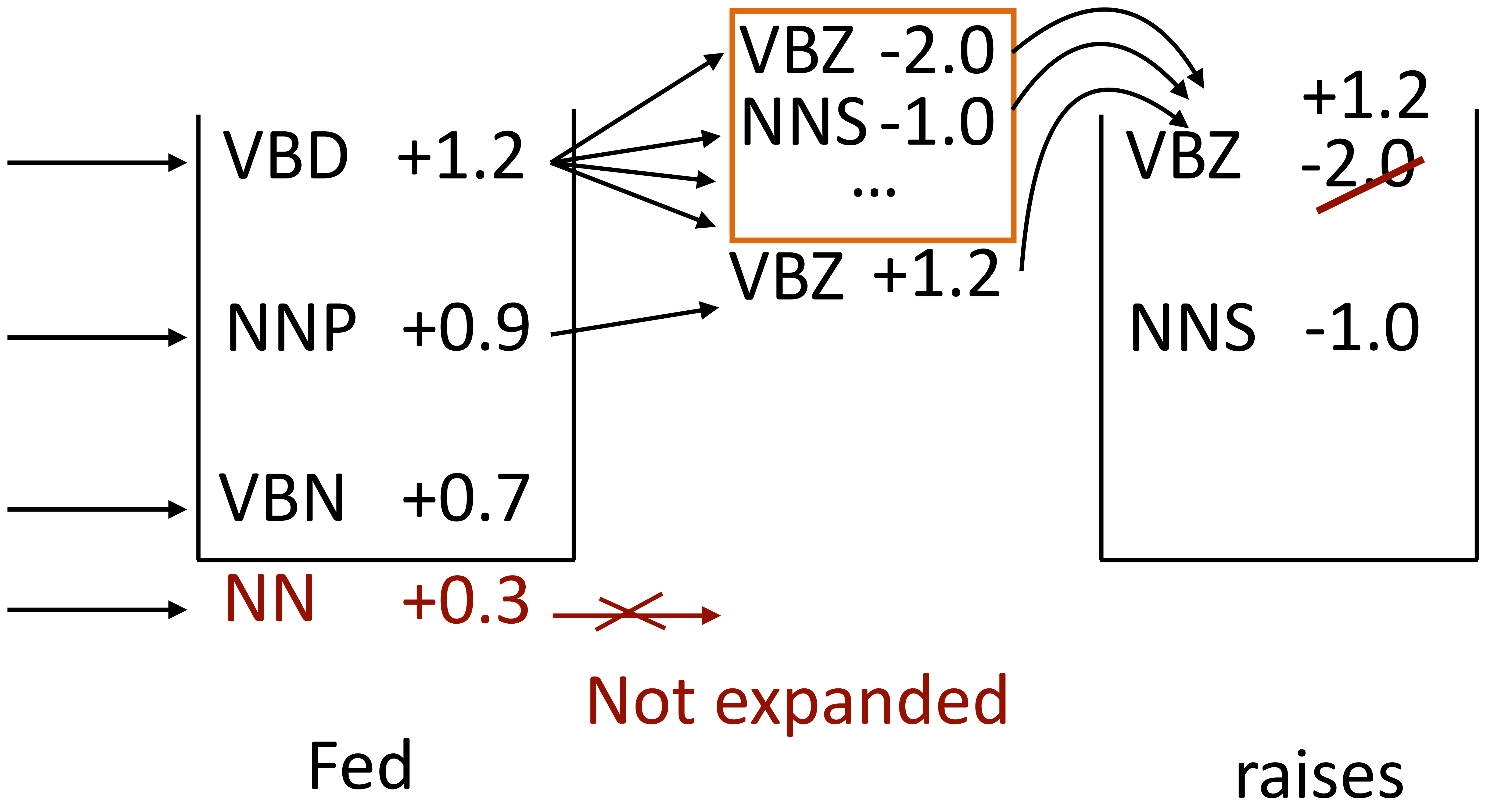

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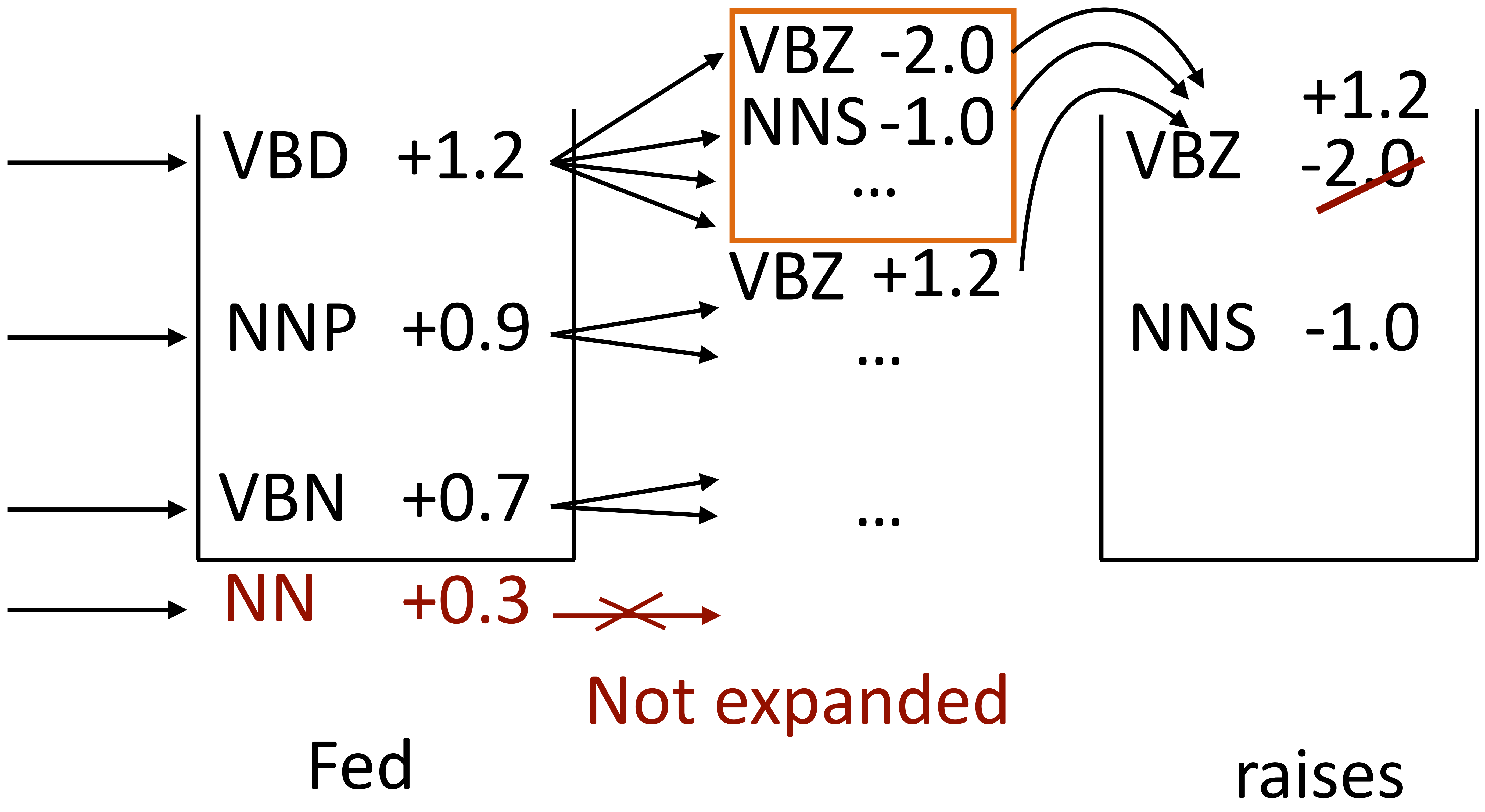

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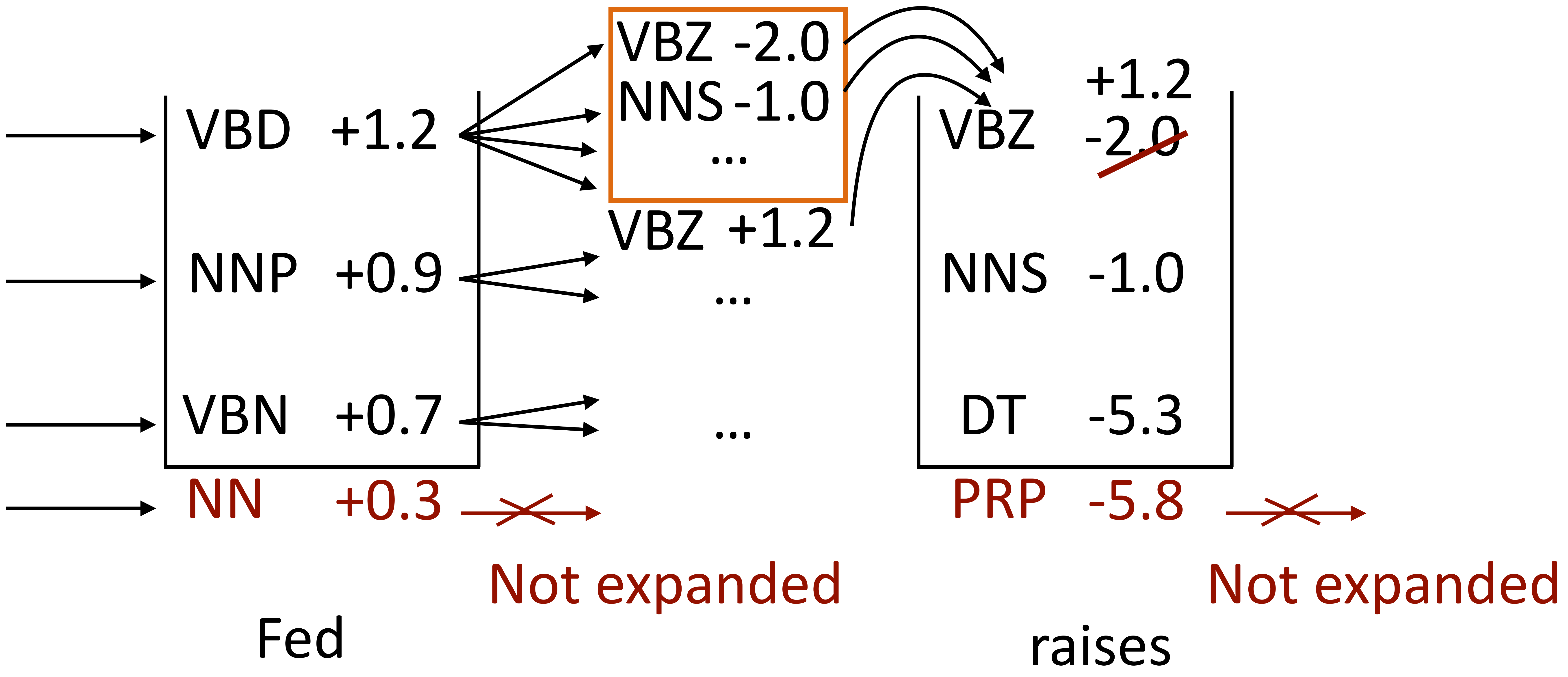

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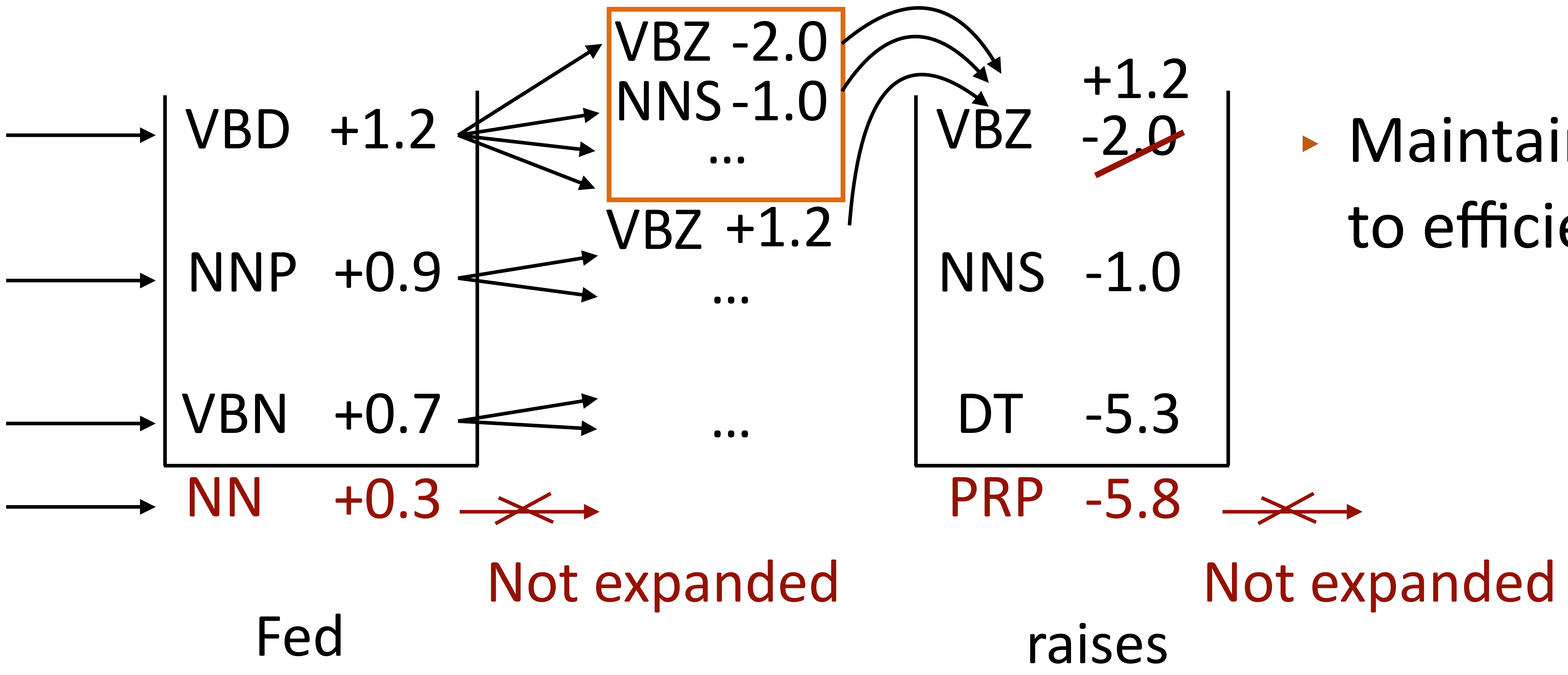

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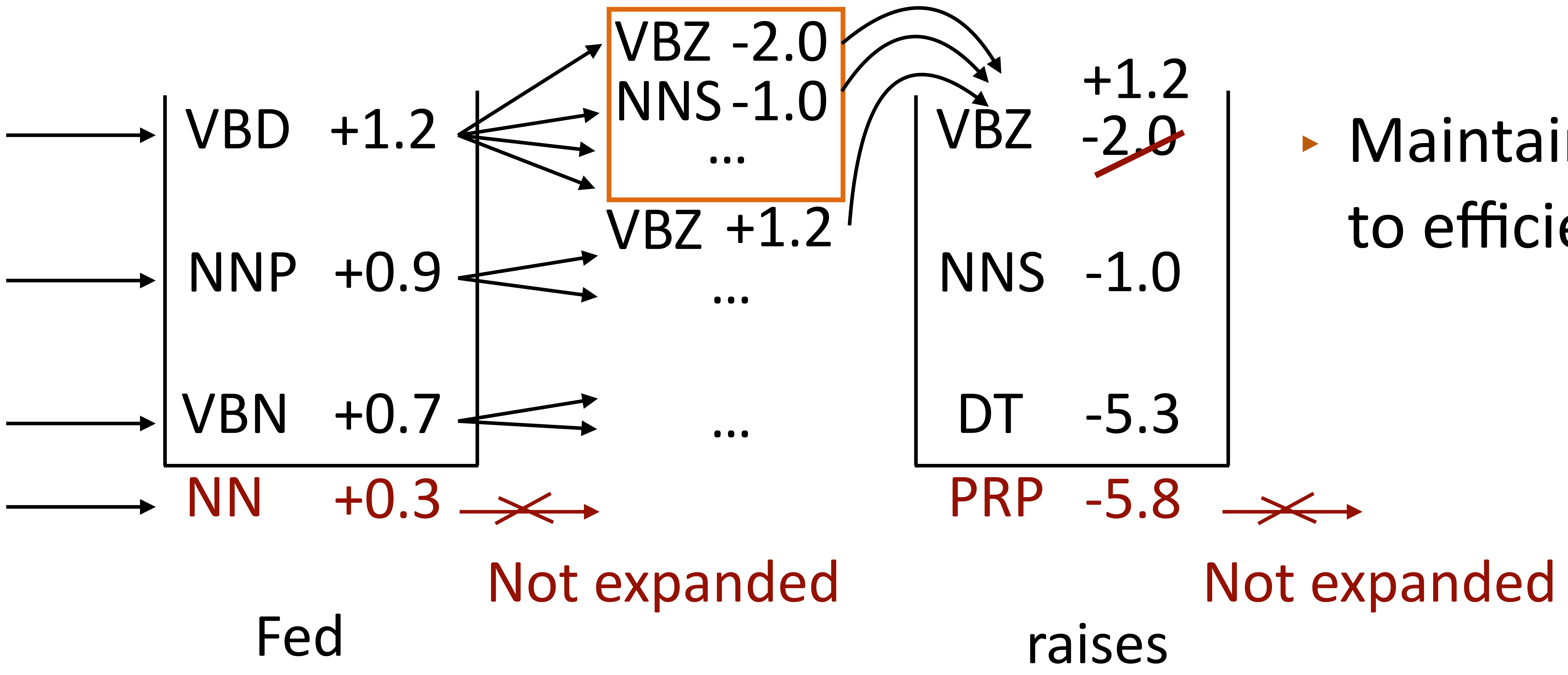

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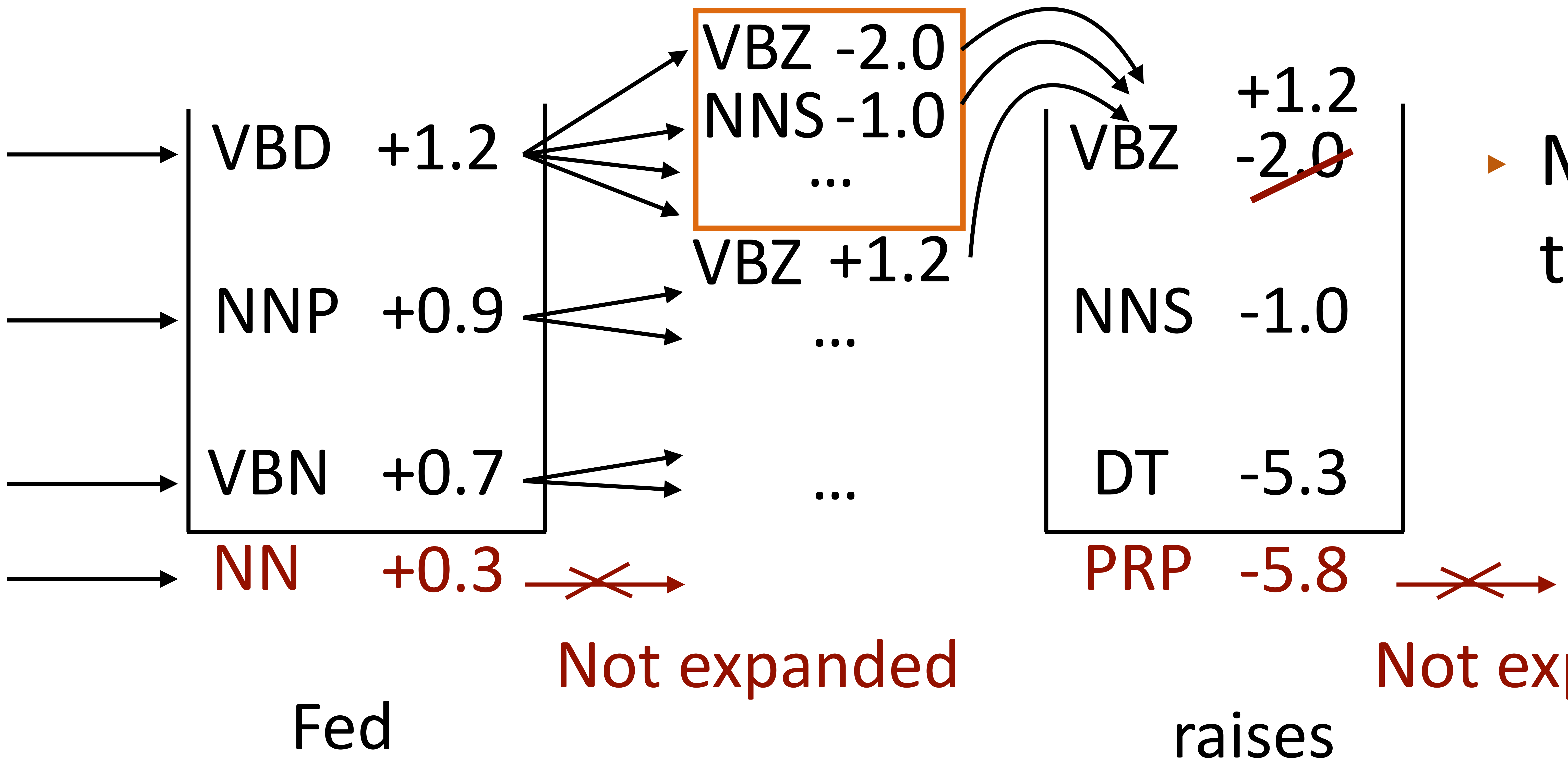

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- If beam search is much faster than computing full sums, can use structured perceptron SVM instead of CRFs
- Very similar to structured SVM