# Lecture 5: Sequence Models II

Alan Ritter

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

# Recall: HMMs

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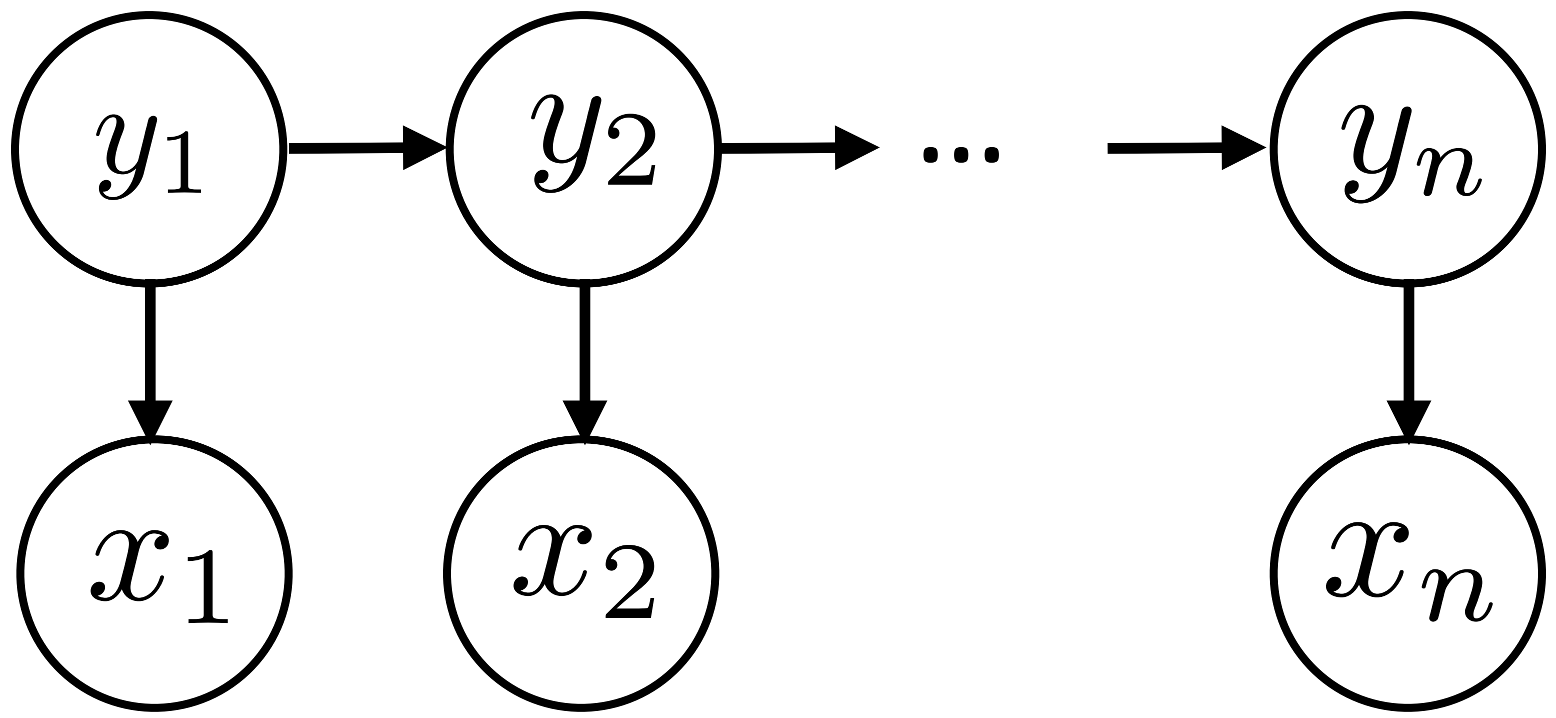

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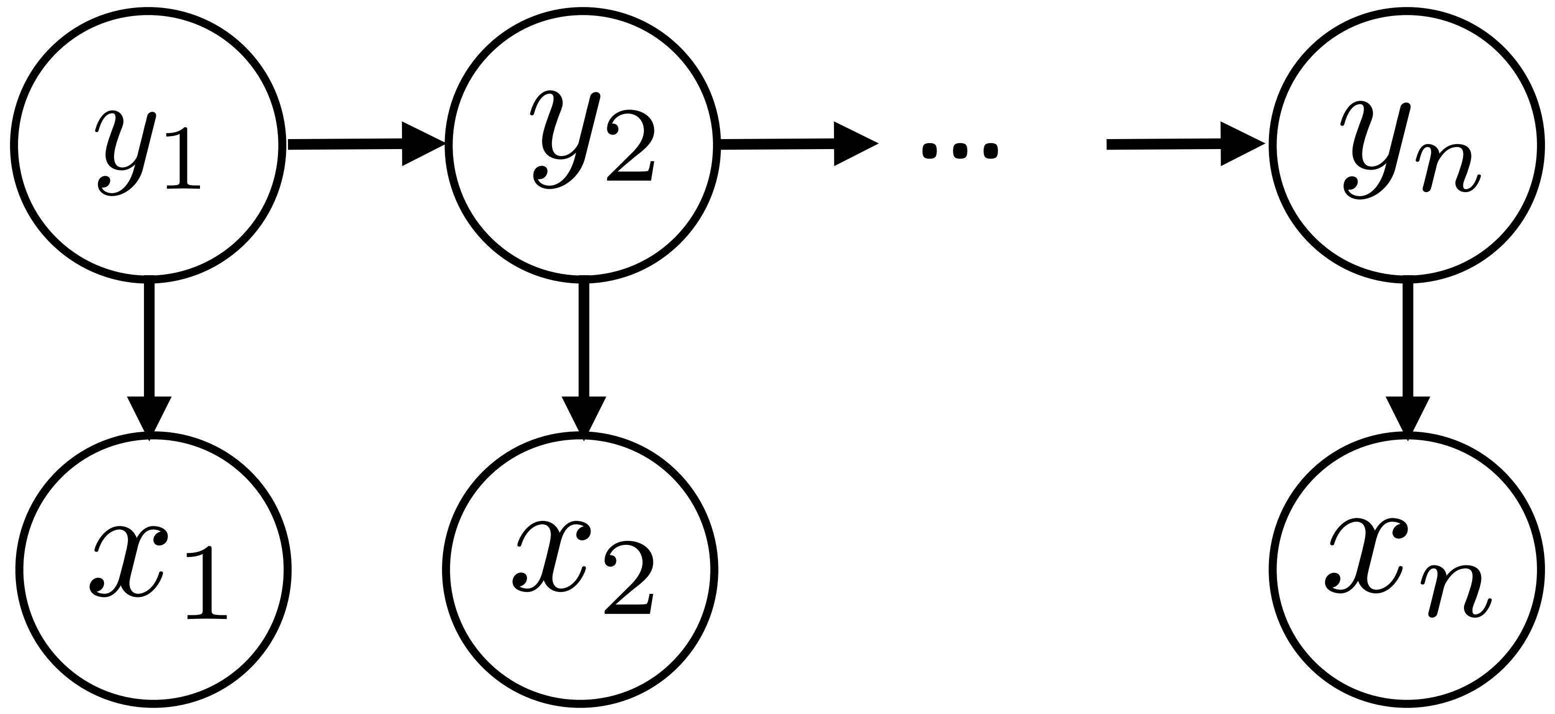

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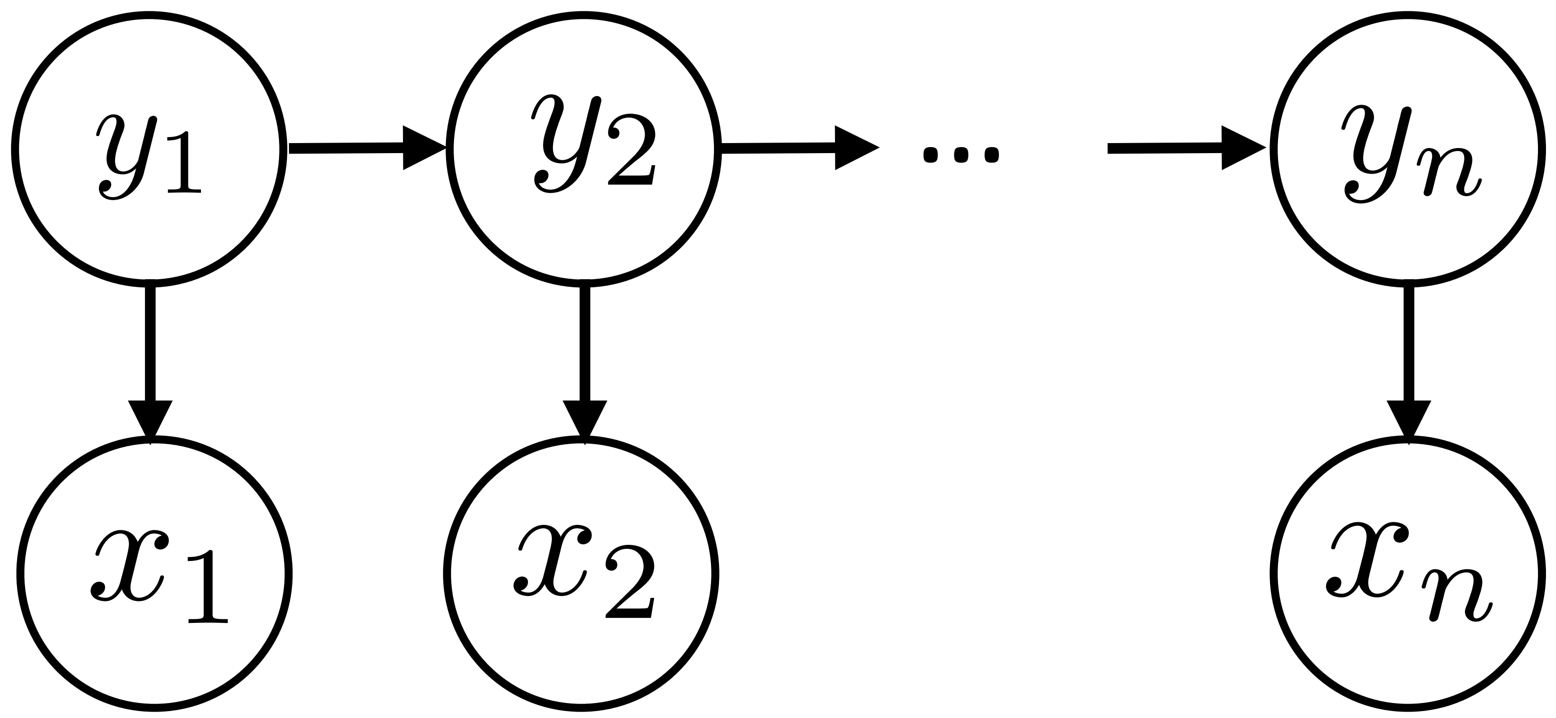


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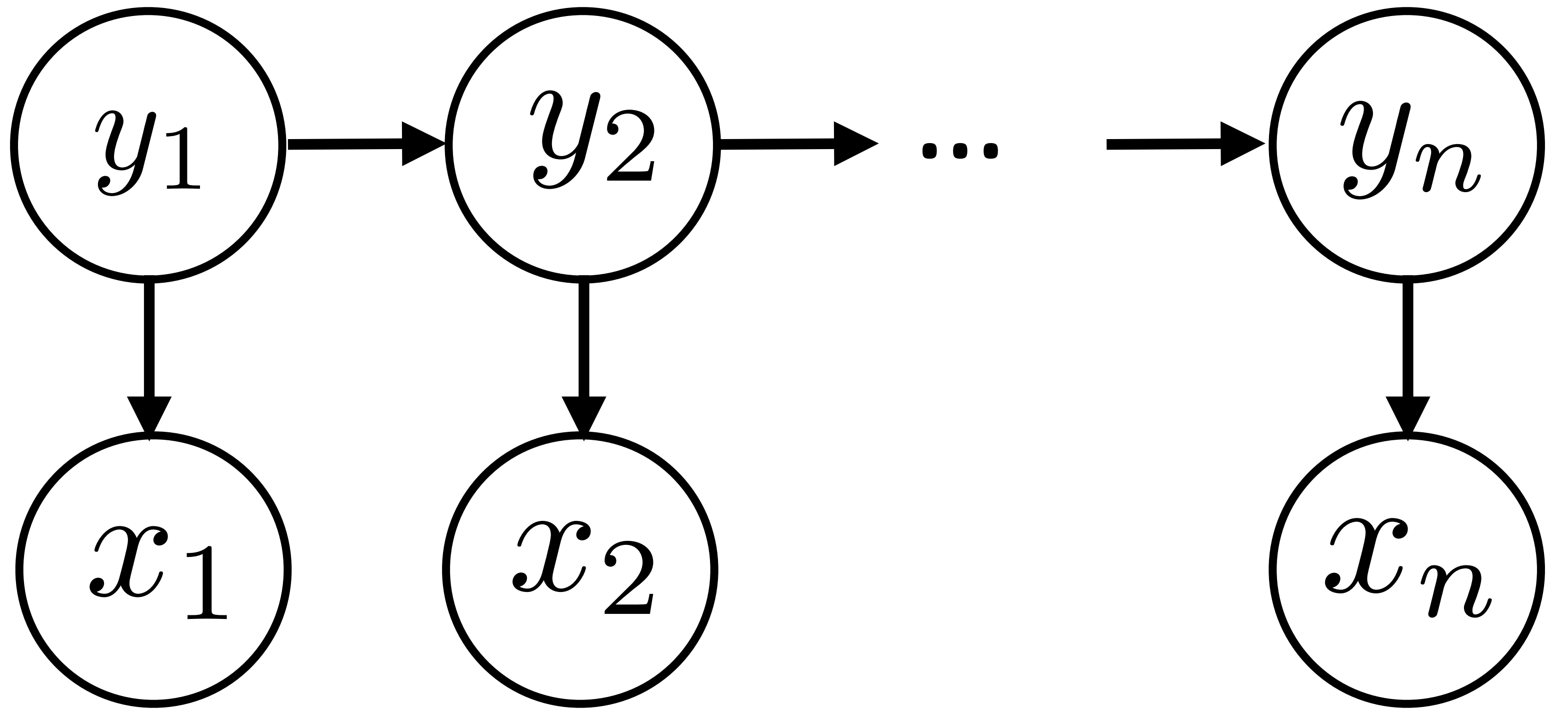


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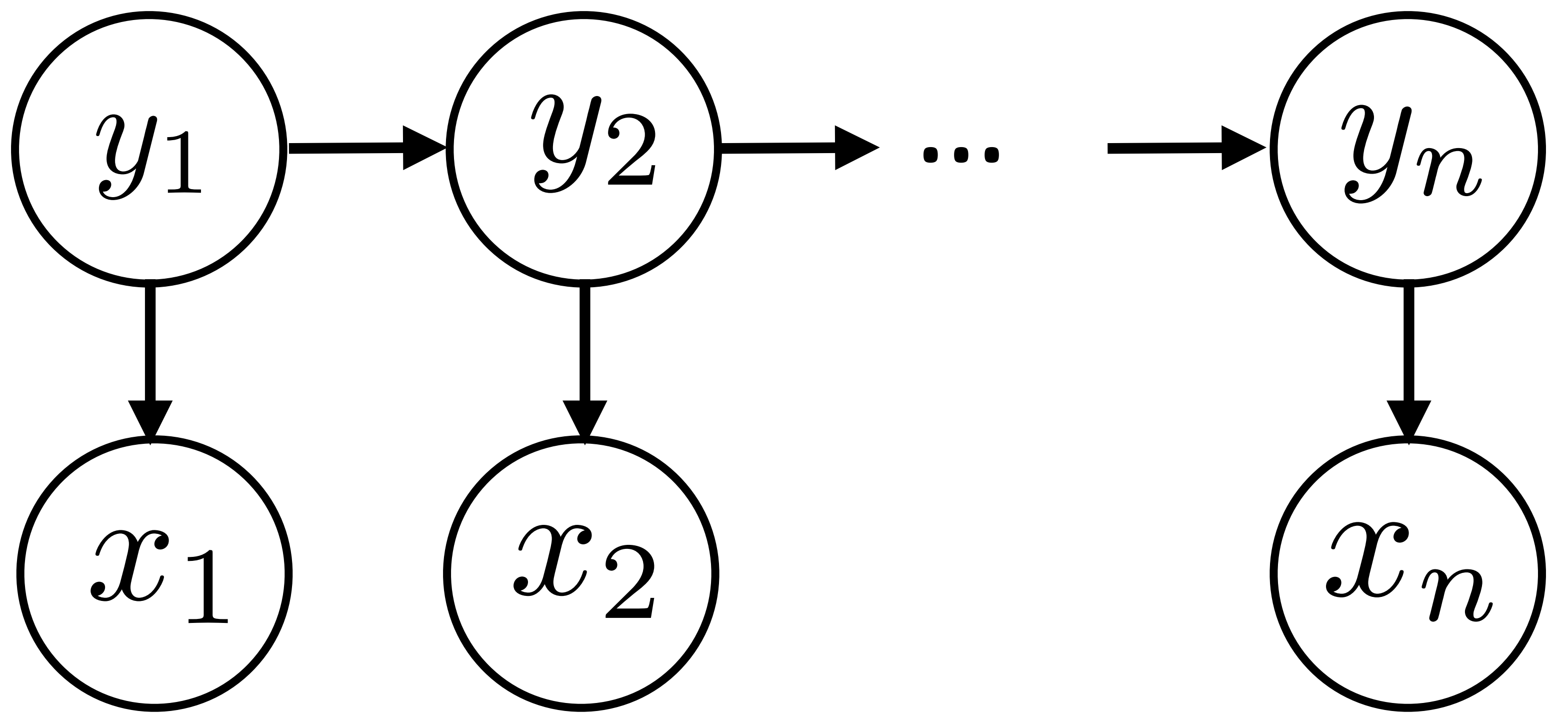

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- Viterbi: $\mathrm{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \mathrm{score}_{i-1}(y_{i-1})$

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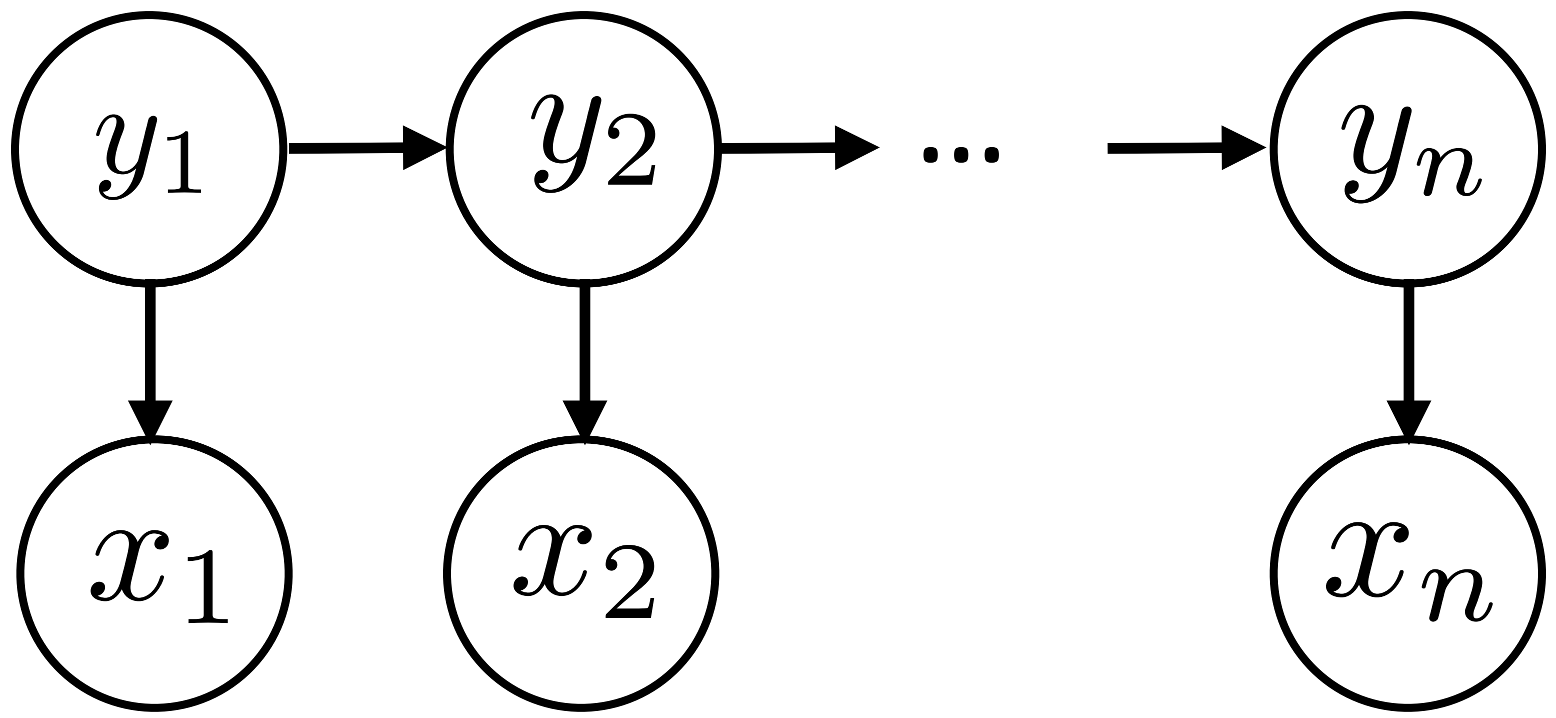
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?
  - Lots of O's, so tags aren't as informative about context
  - Insufficient features/capacity with multinomials (especially for unks)

# CRFs

# Conditional Random Fields

- HMMs are expressible as Bayes nets (factor graphs)



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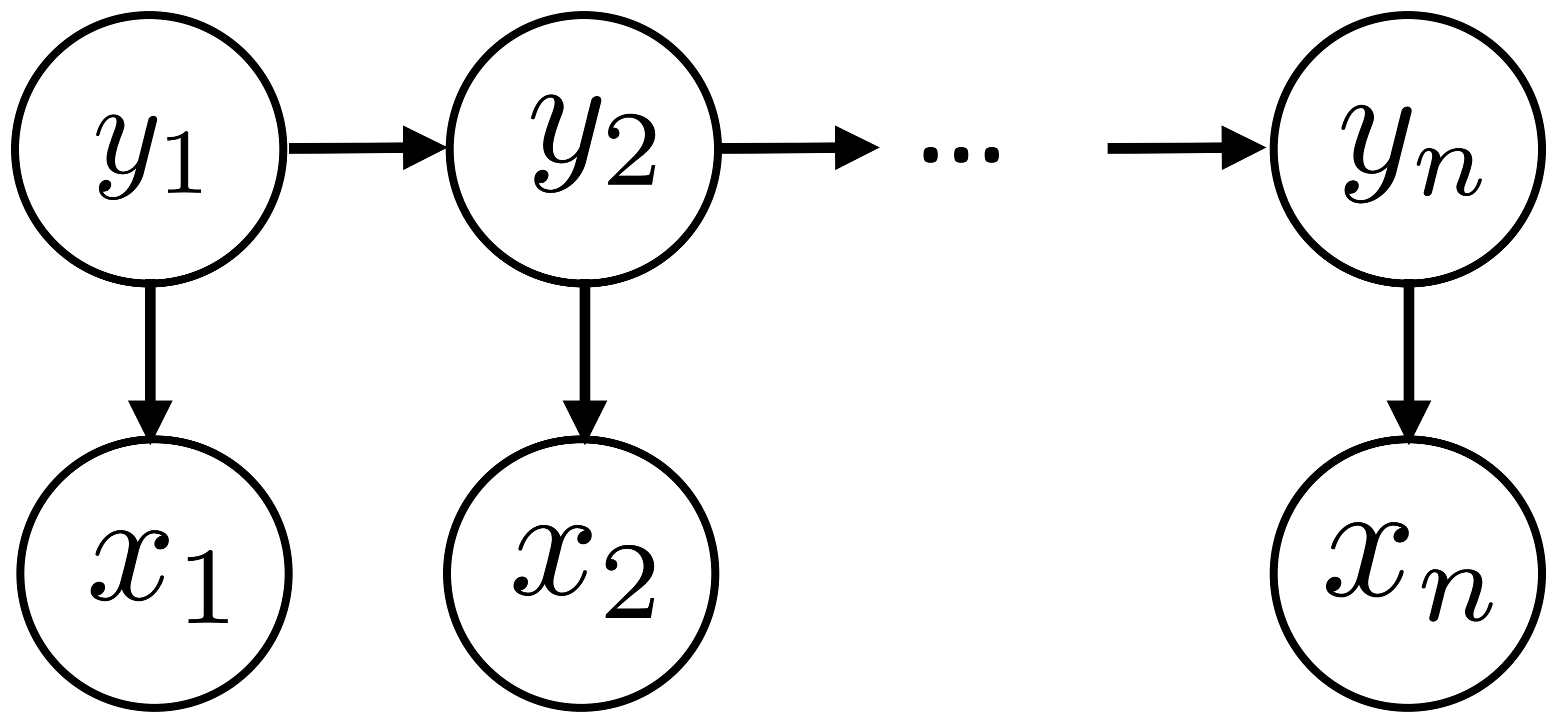


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$$P(\mathbf{y}, \mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\ldots$$

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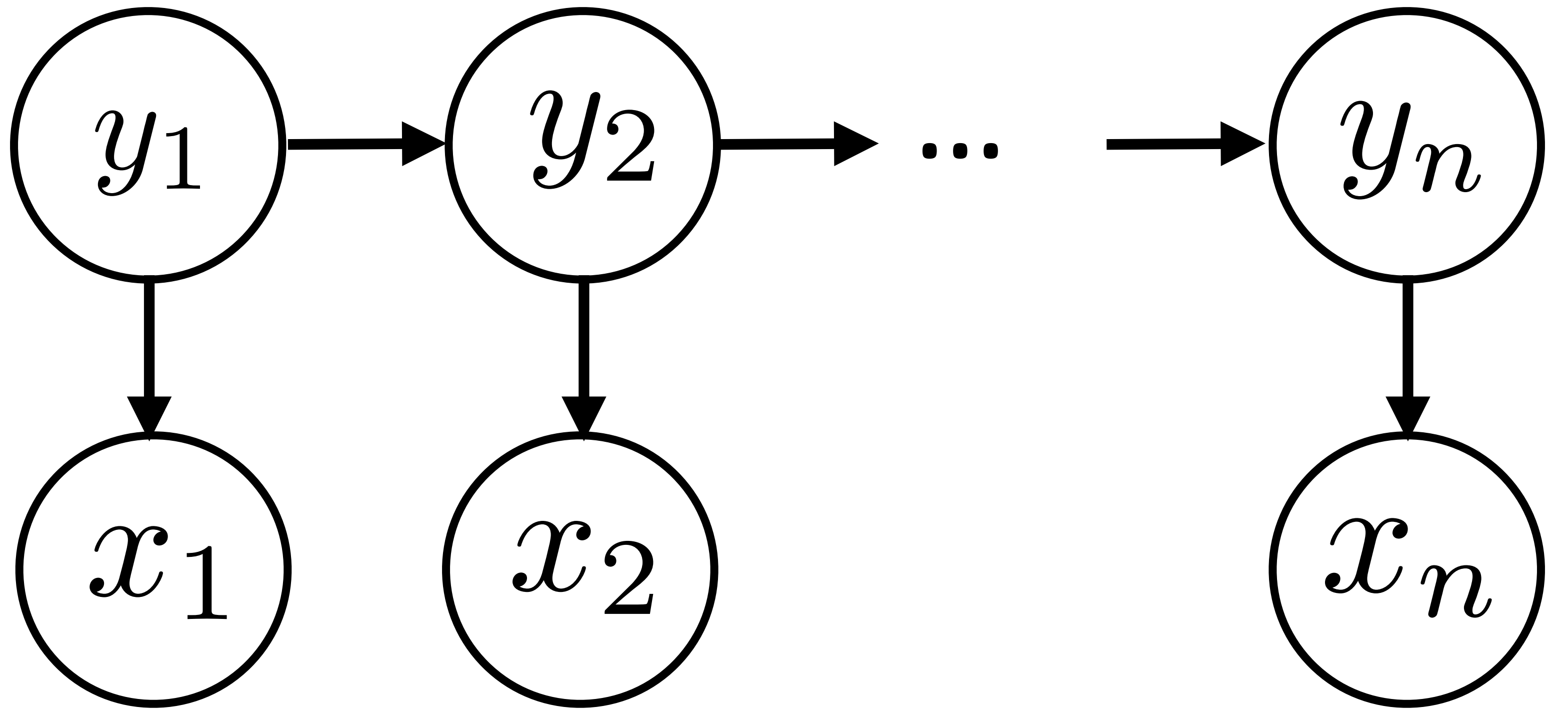


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- Locally normalized model: each factor is a probability distribution that normalizes

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- How do we max over ***y***? Intractable in general — can we fix this?

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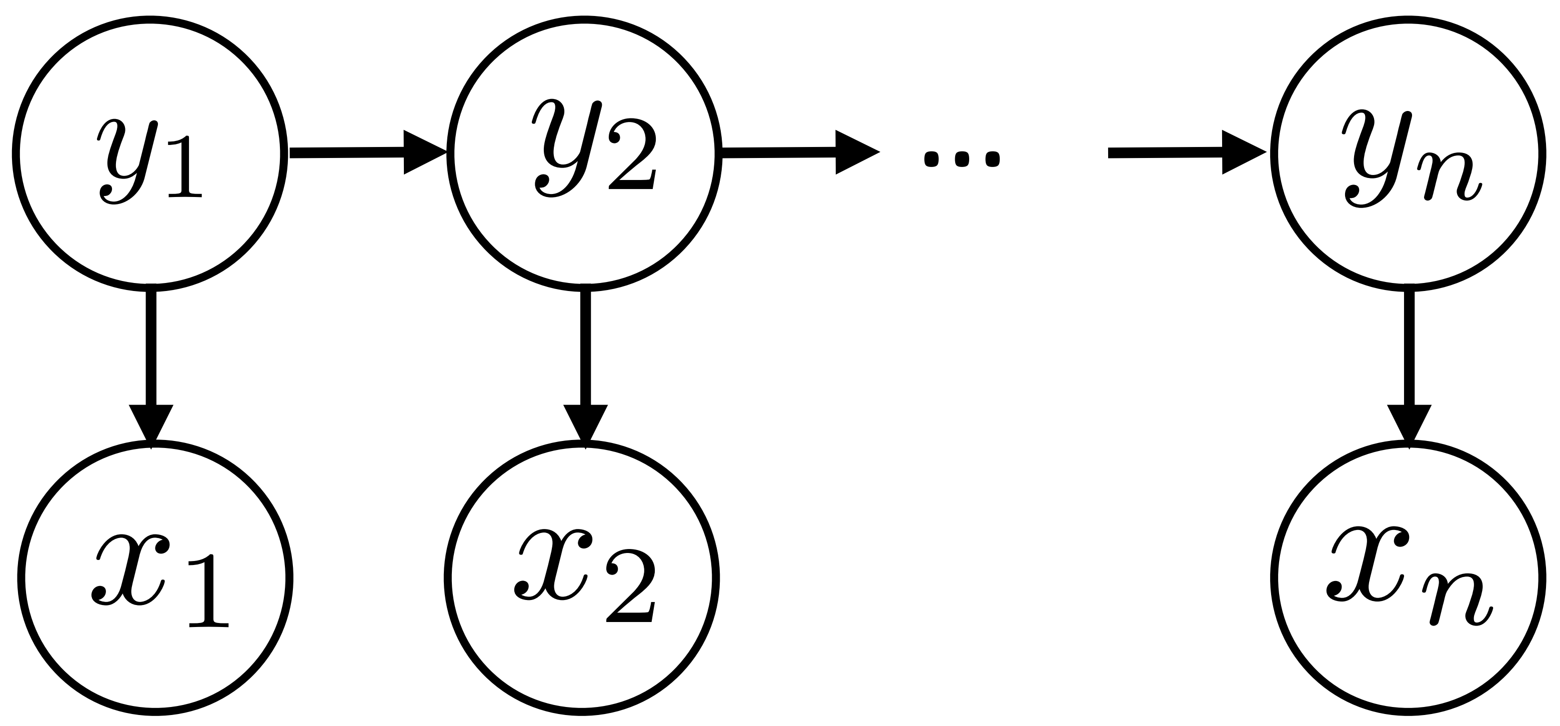

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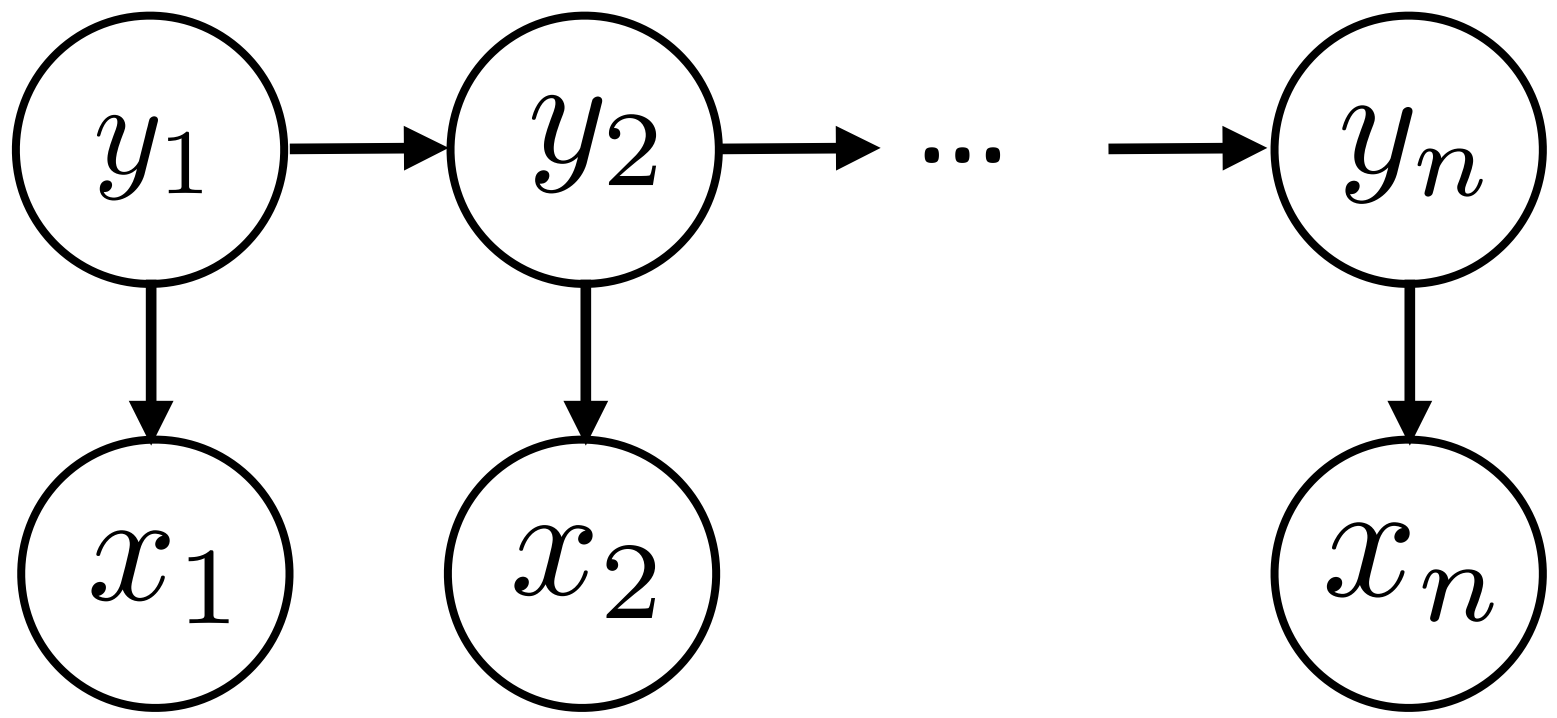


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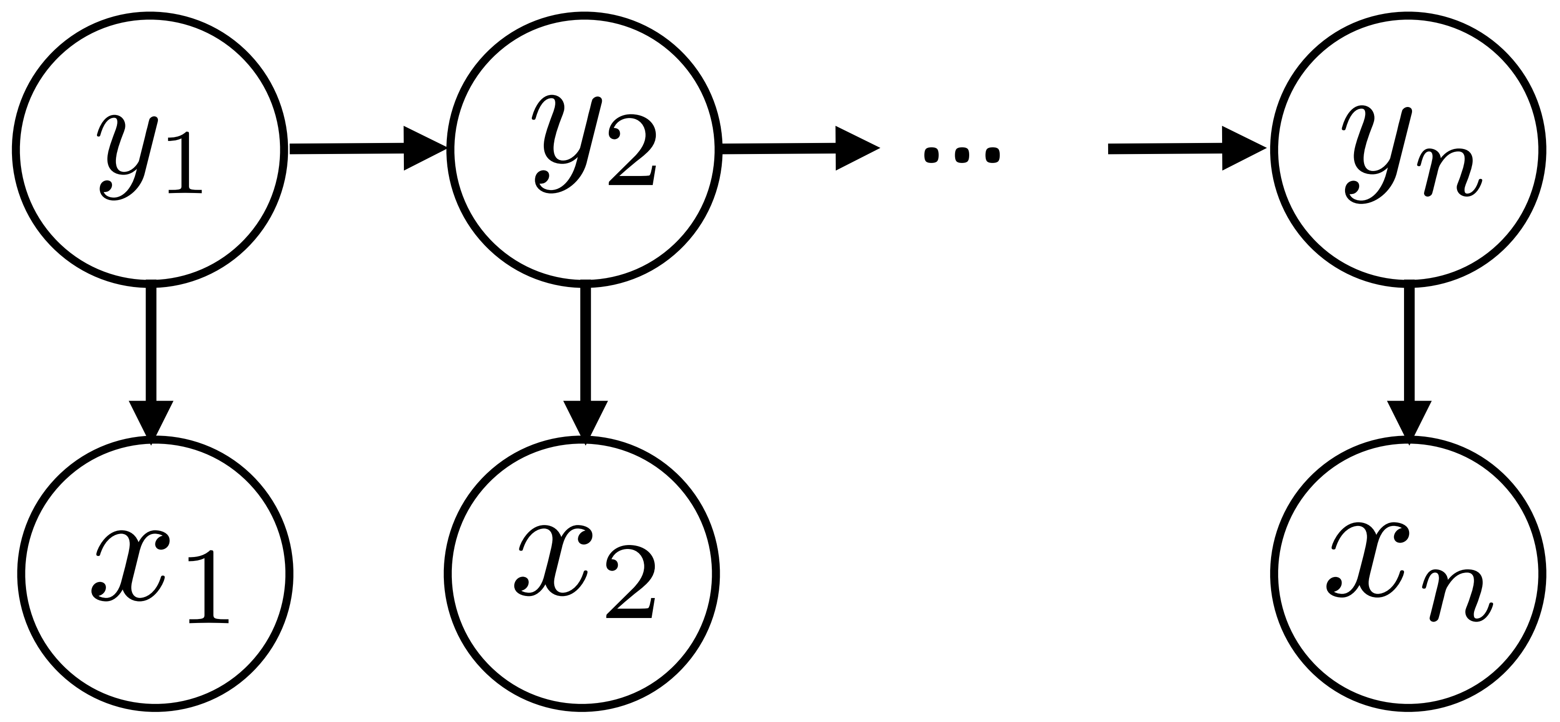


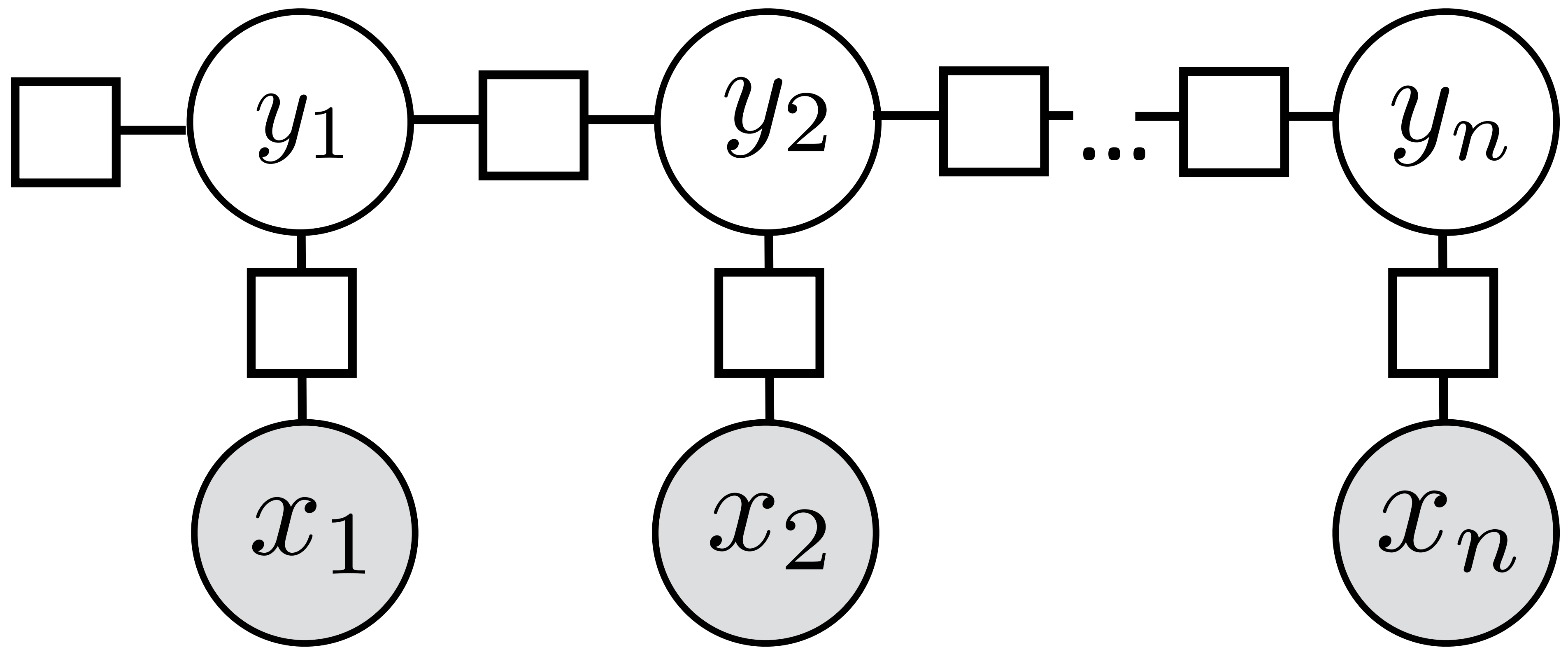


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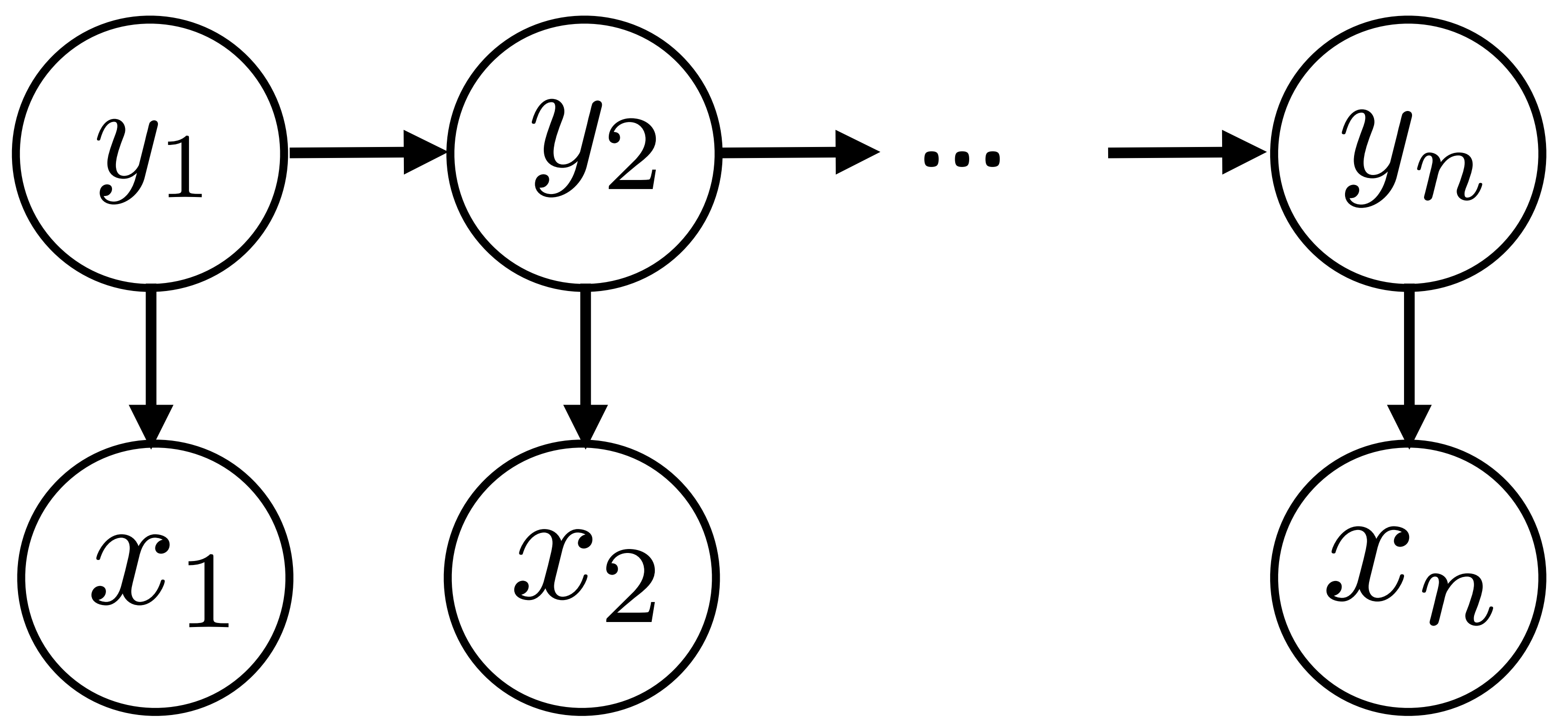


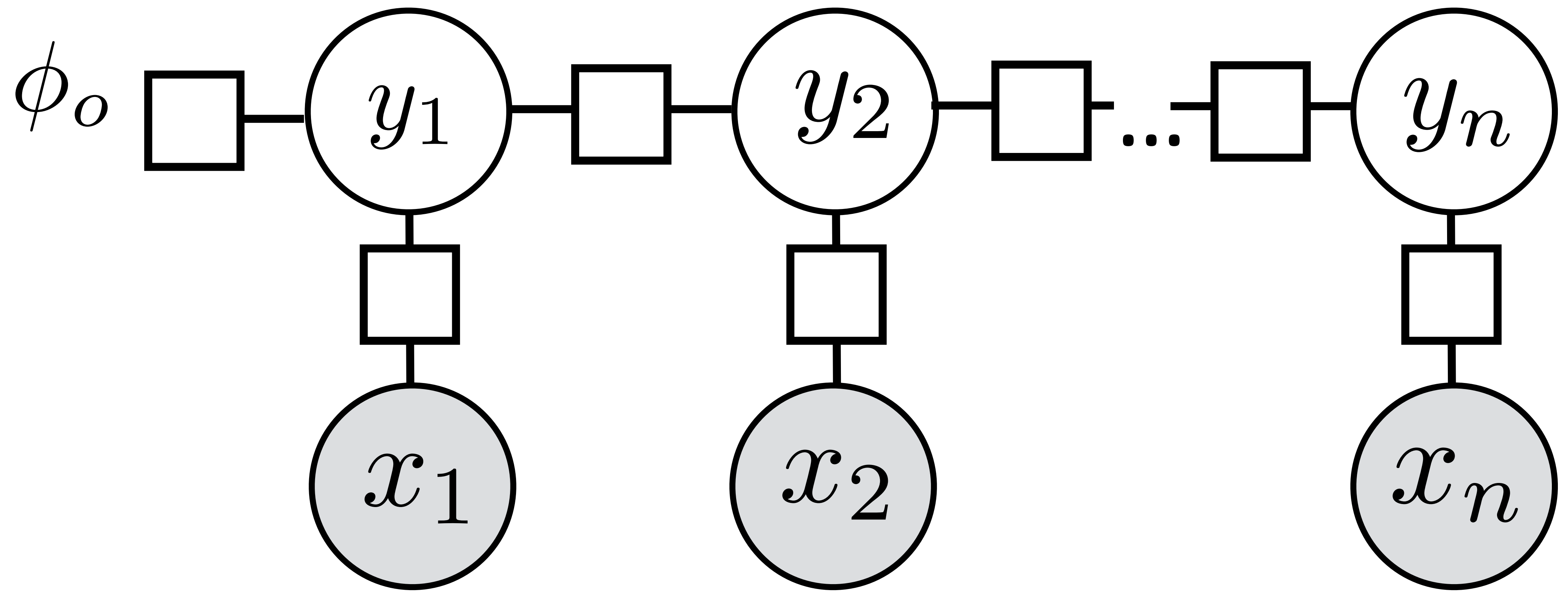


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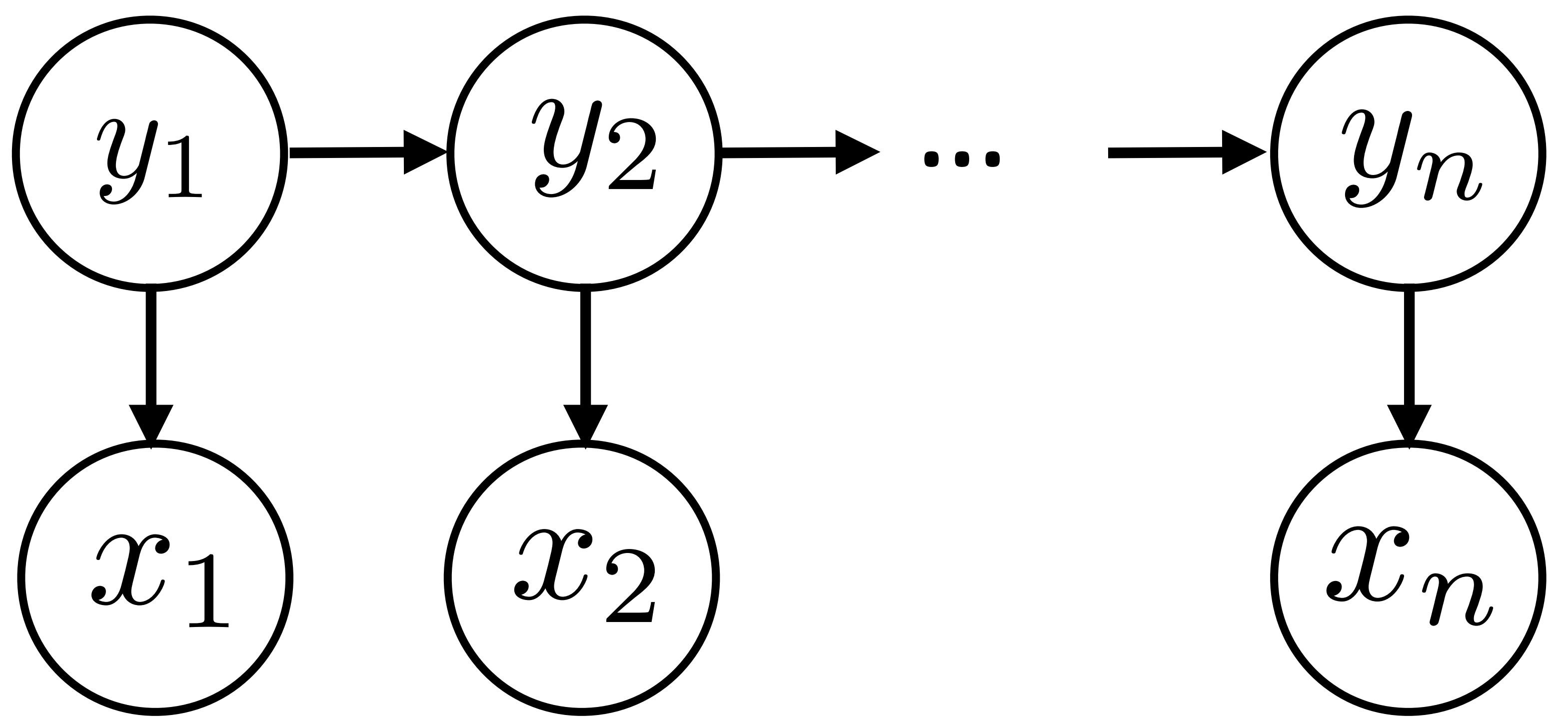


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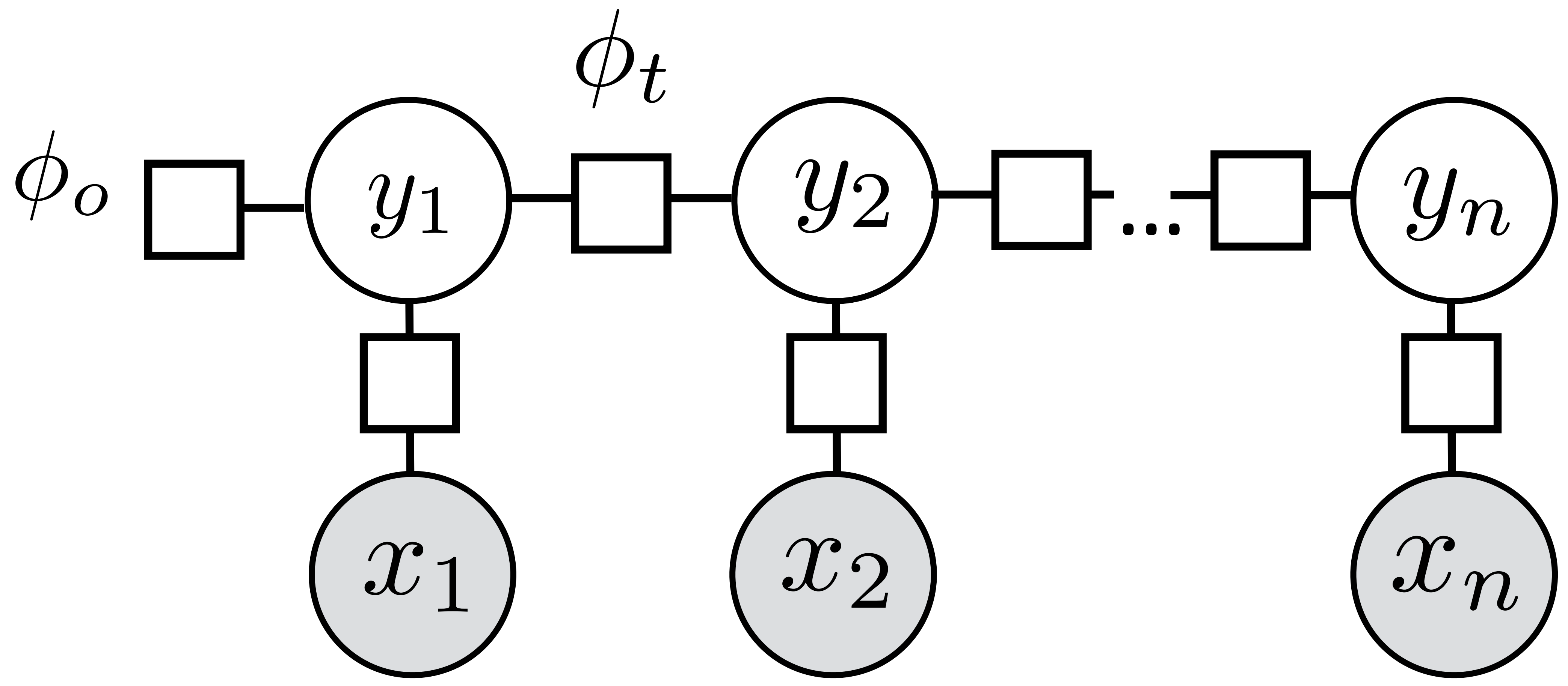


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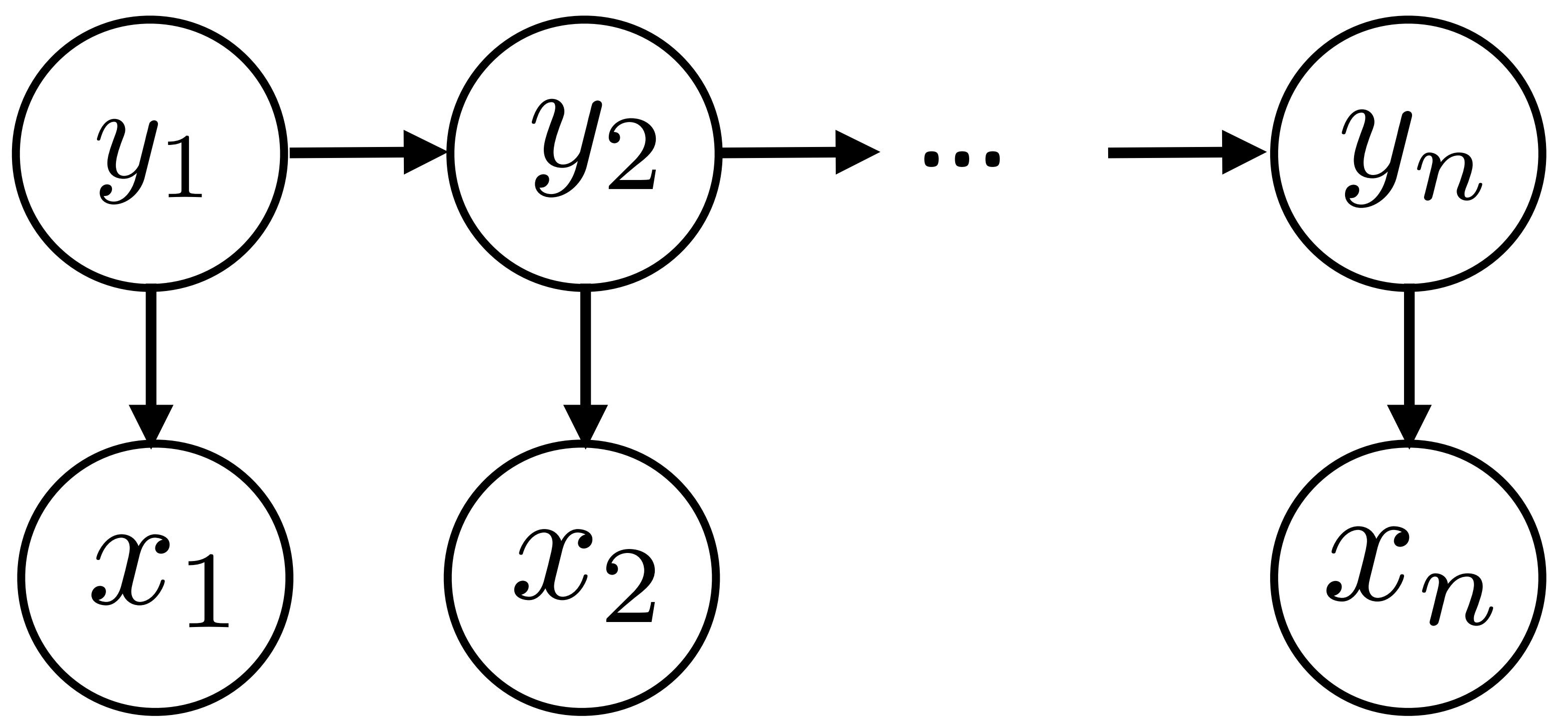

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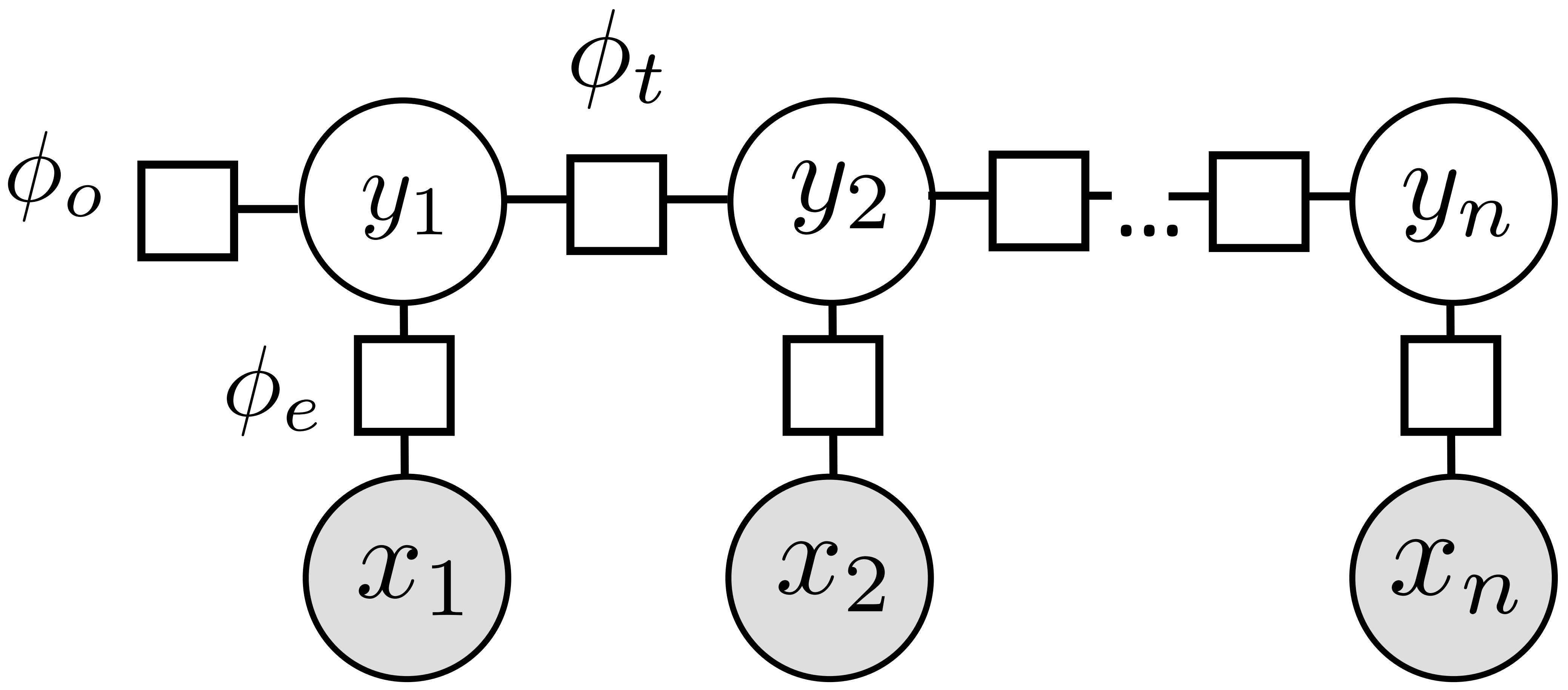

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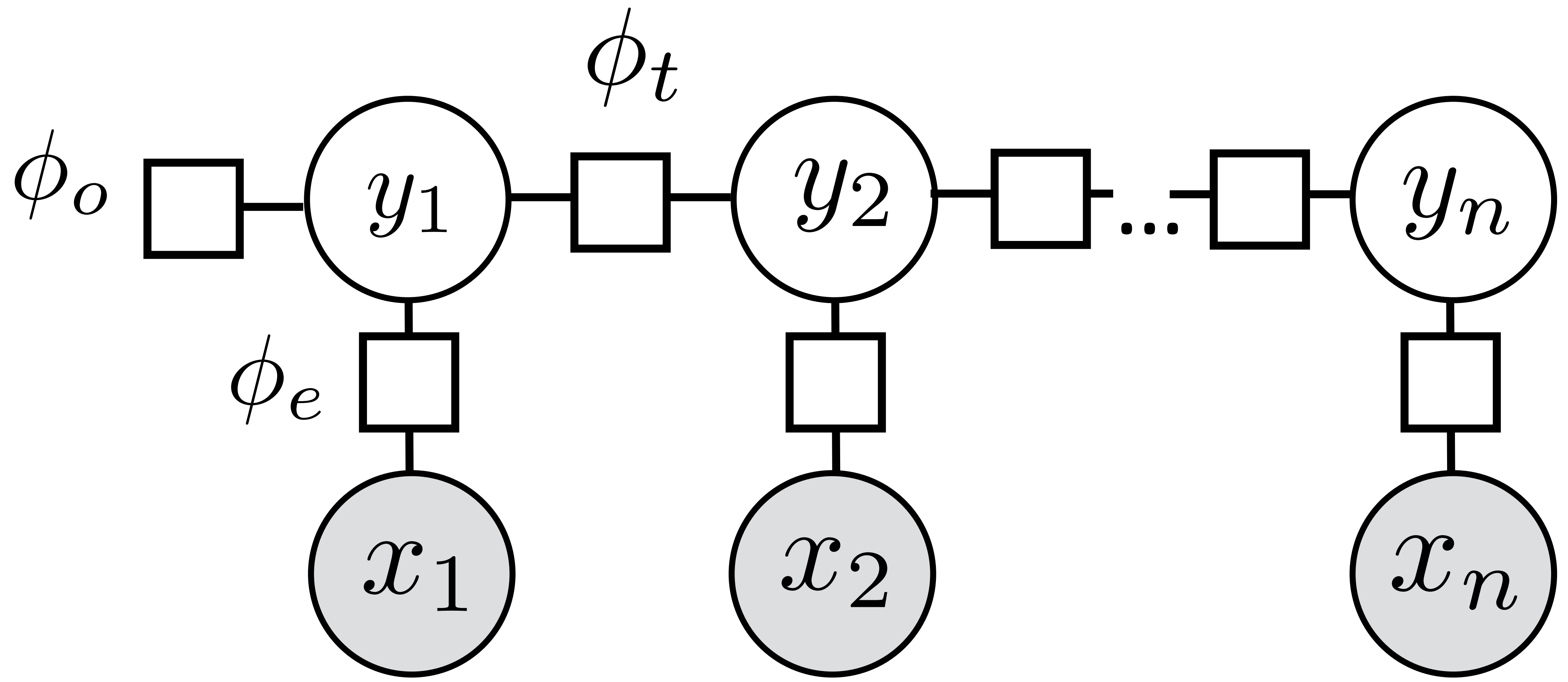


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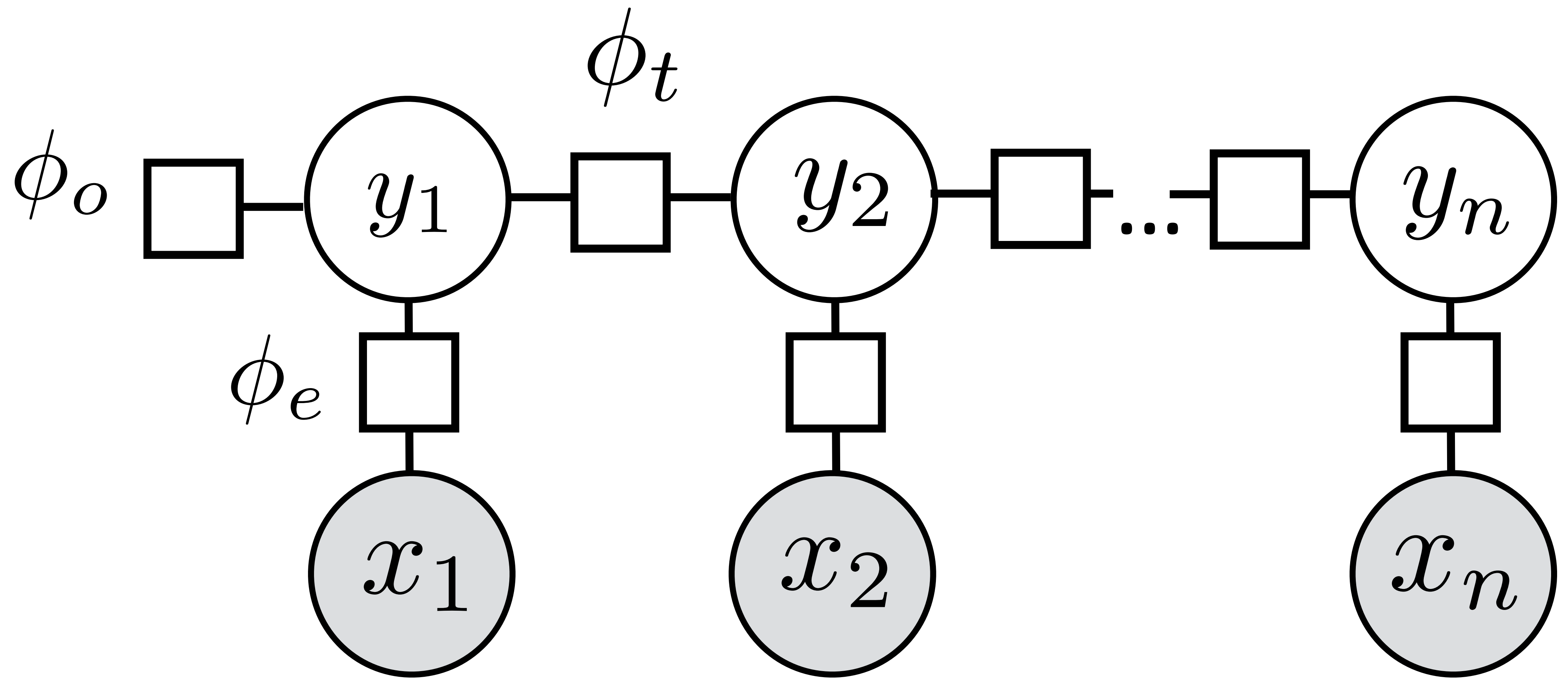


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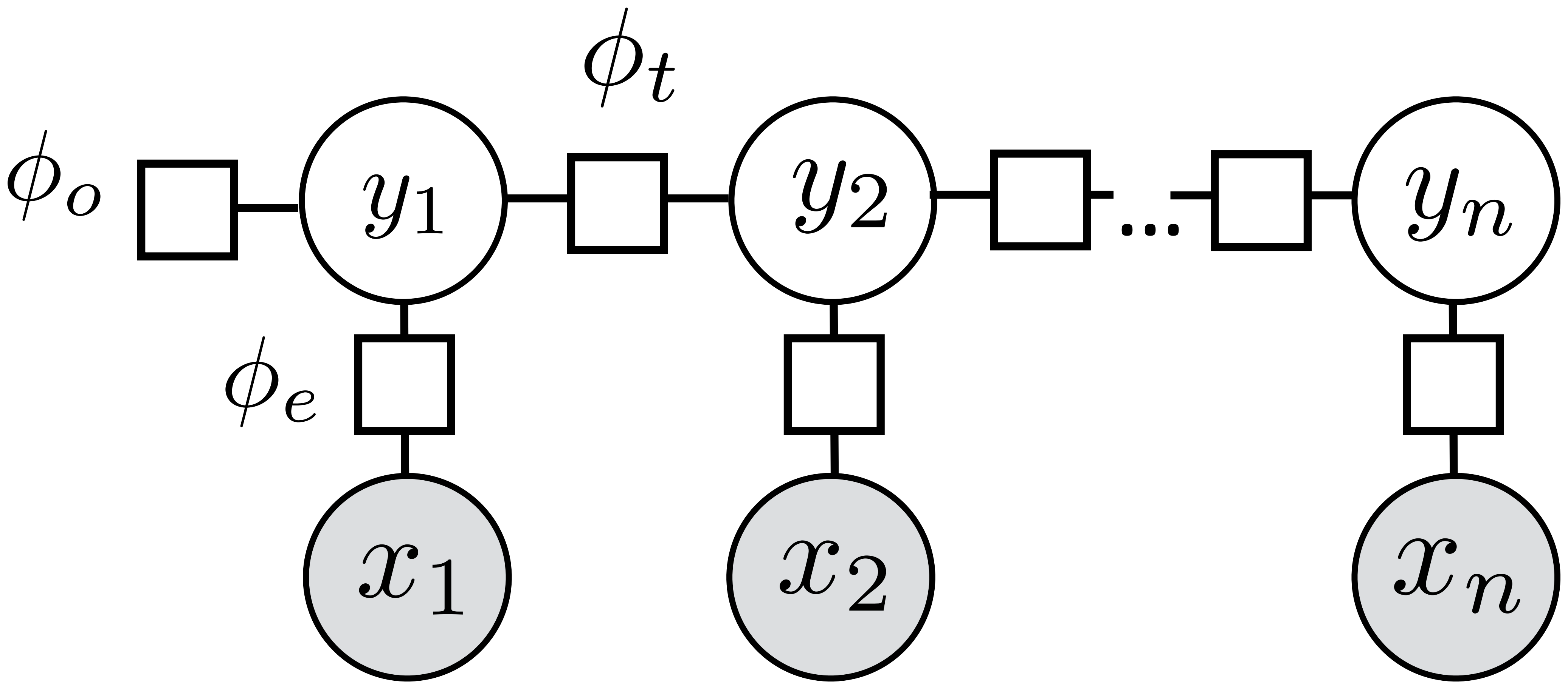


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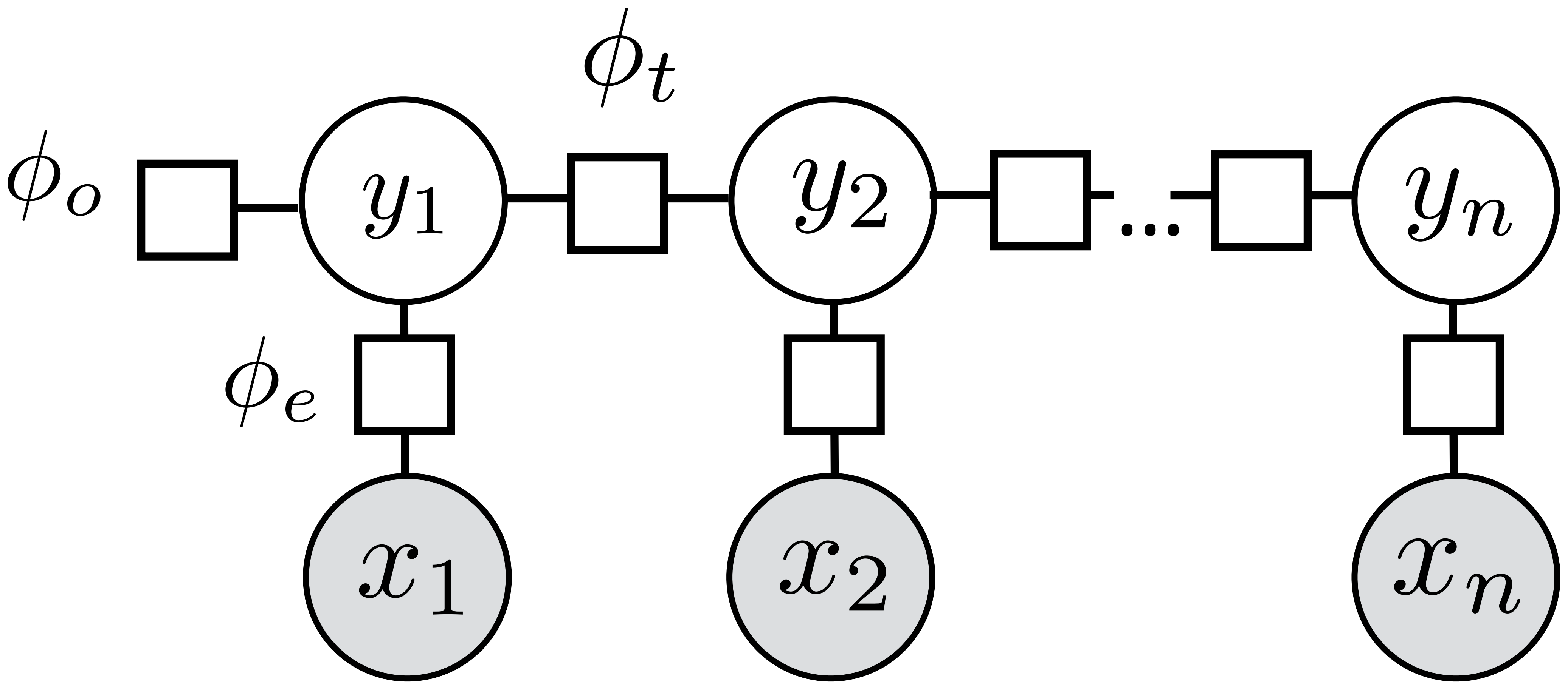


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token index — lets us look at current word

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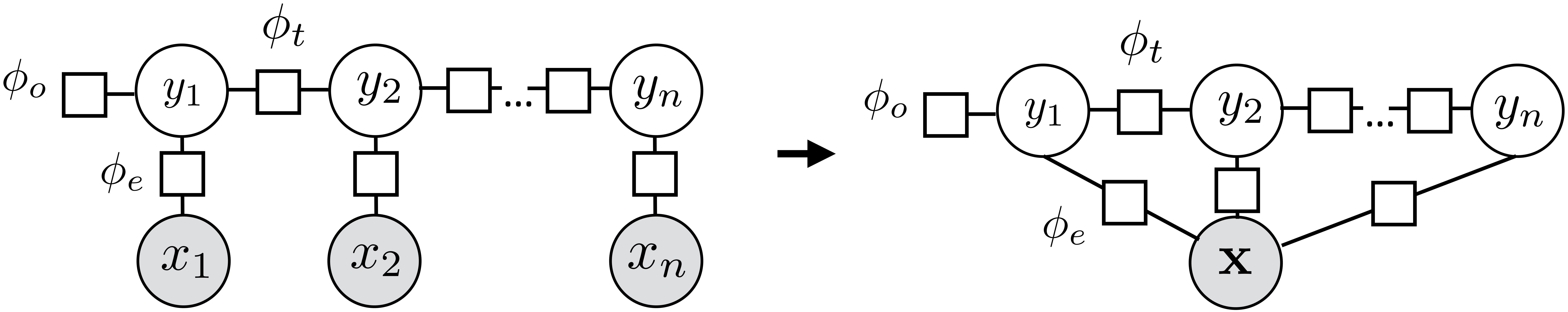


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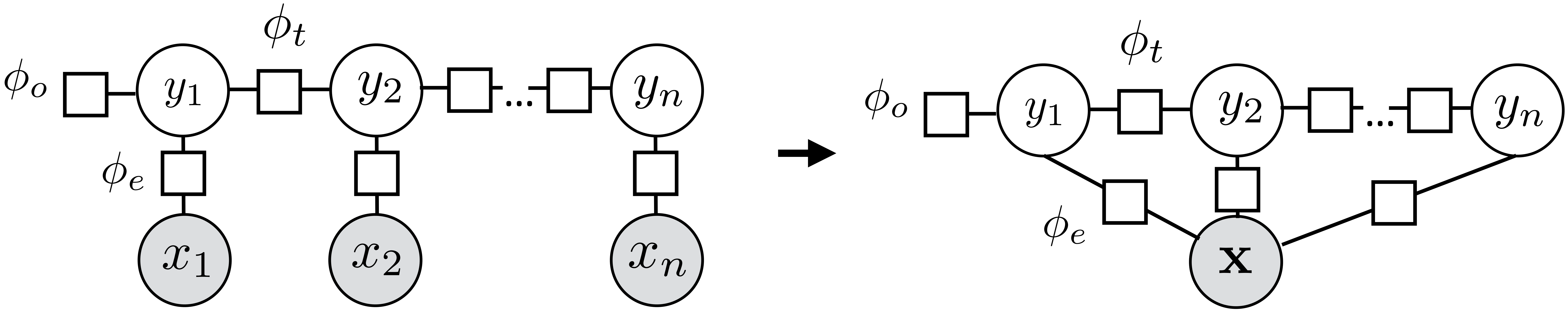


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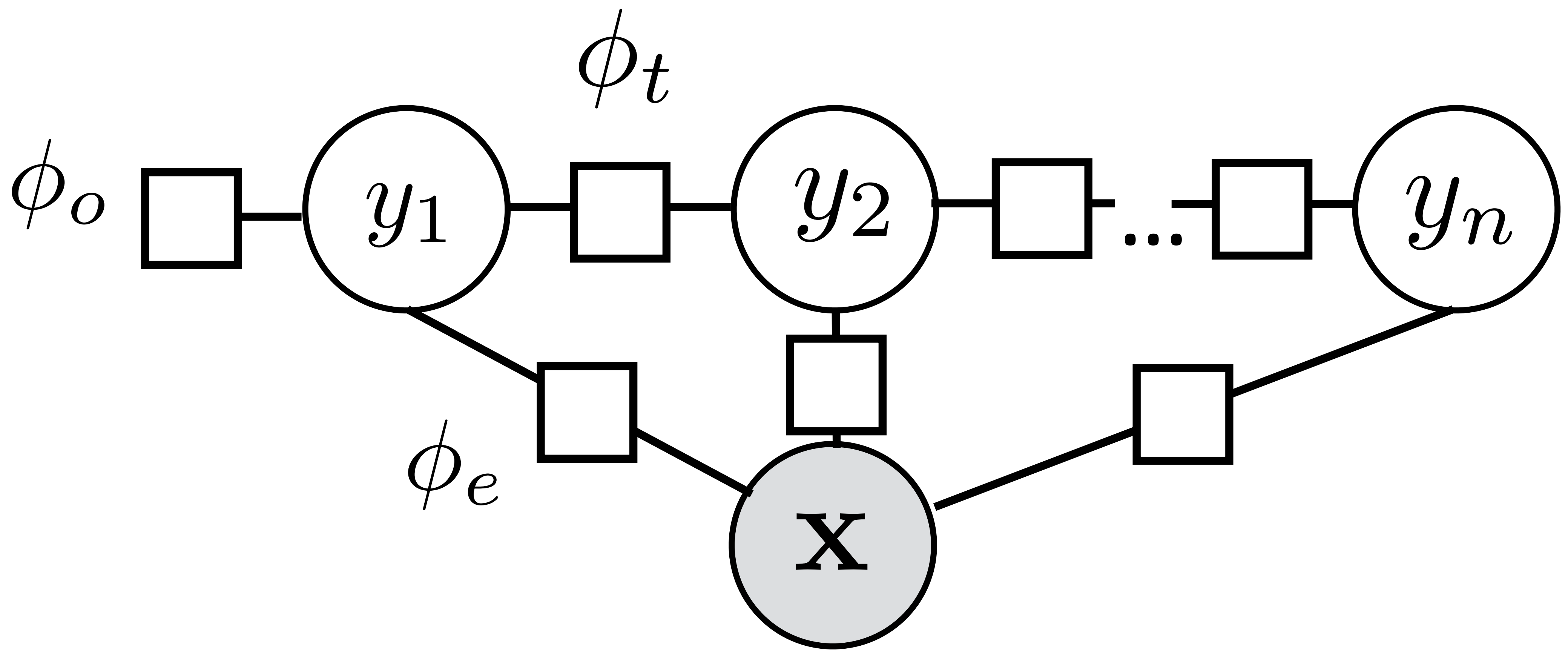
- **y** can't depend arbitrarily on **x** in a generative model

# Sequential CRFs



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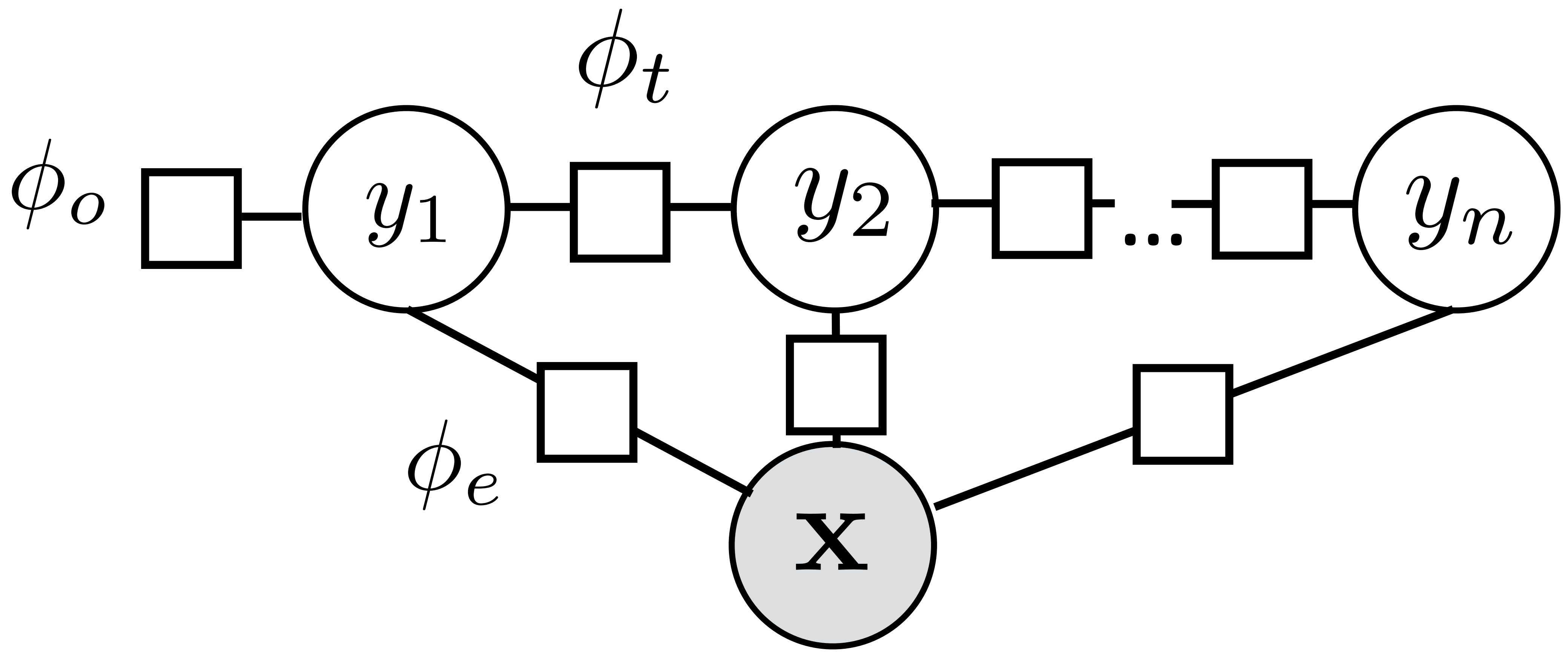


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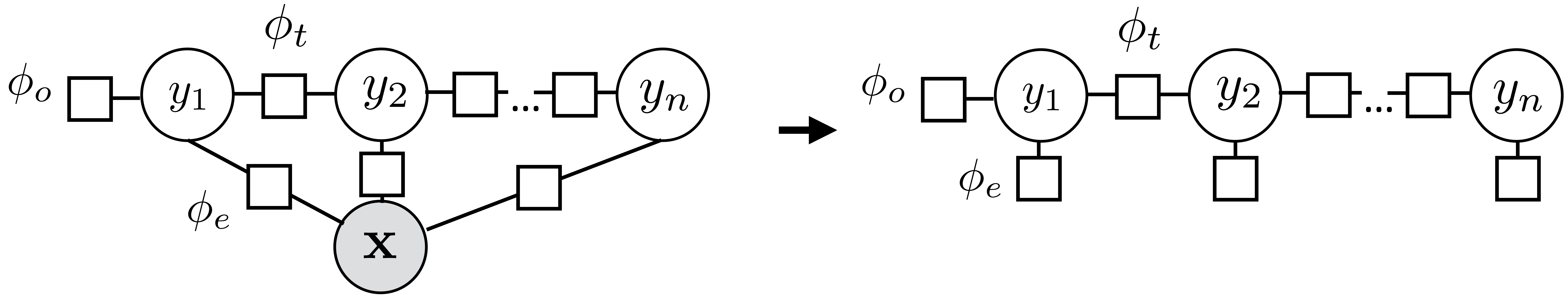


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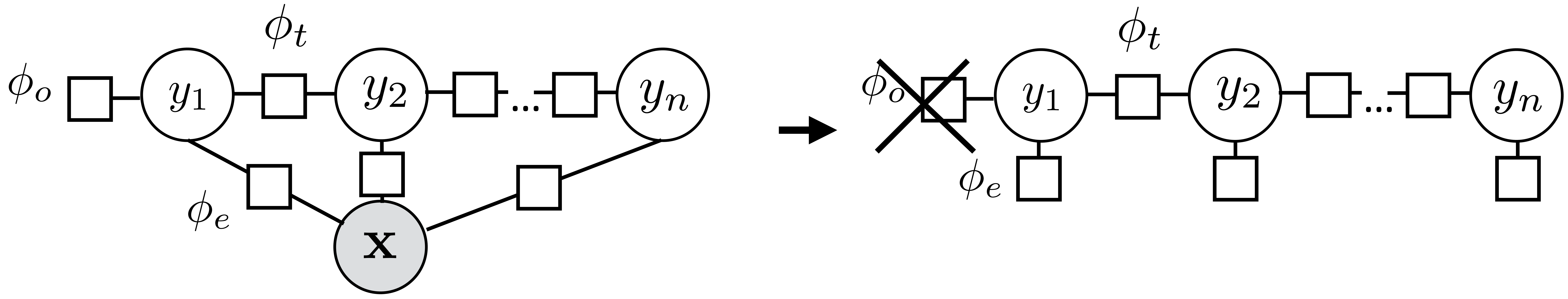


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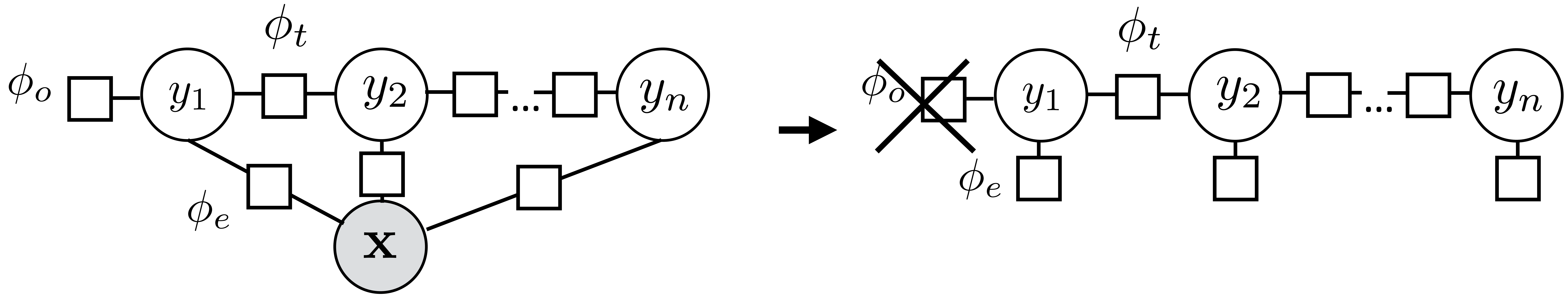


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Sequential CRFs:

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# Feature Functions

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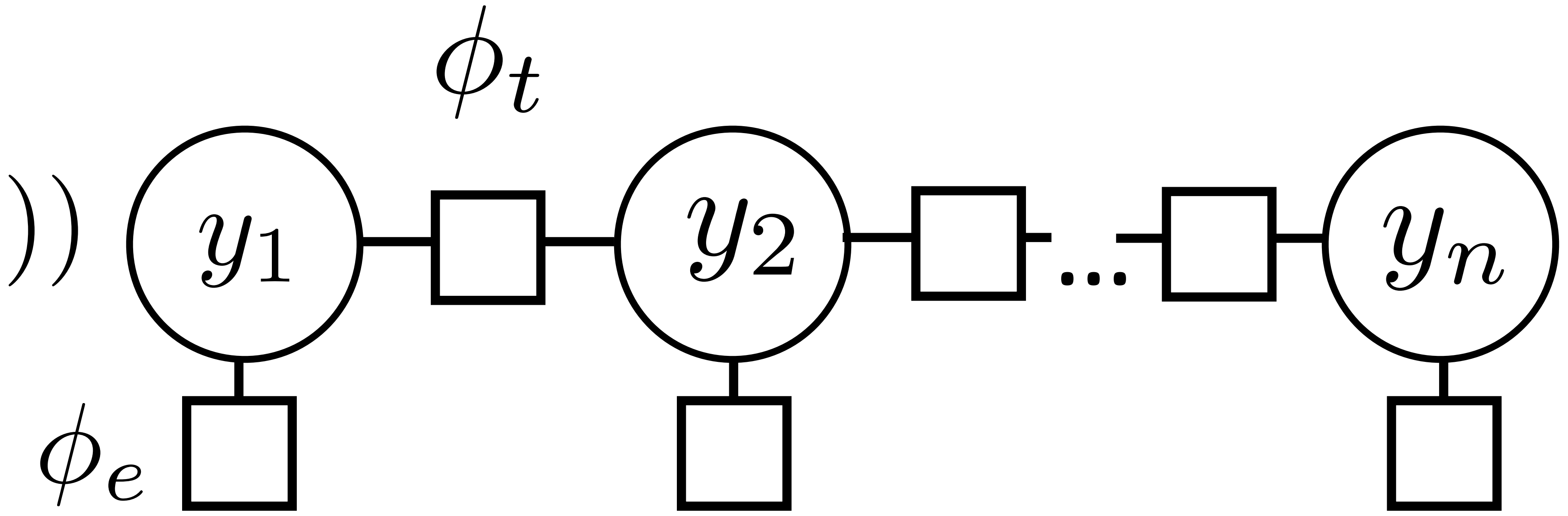

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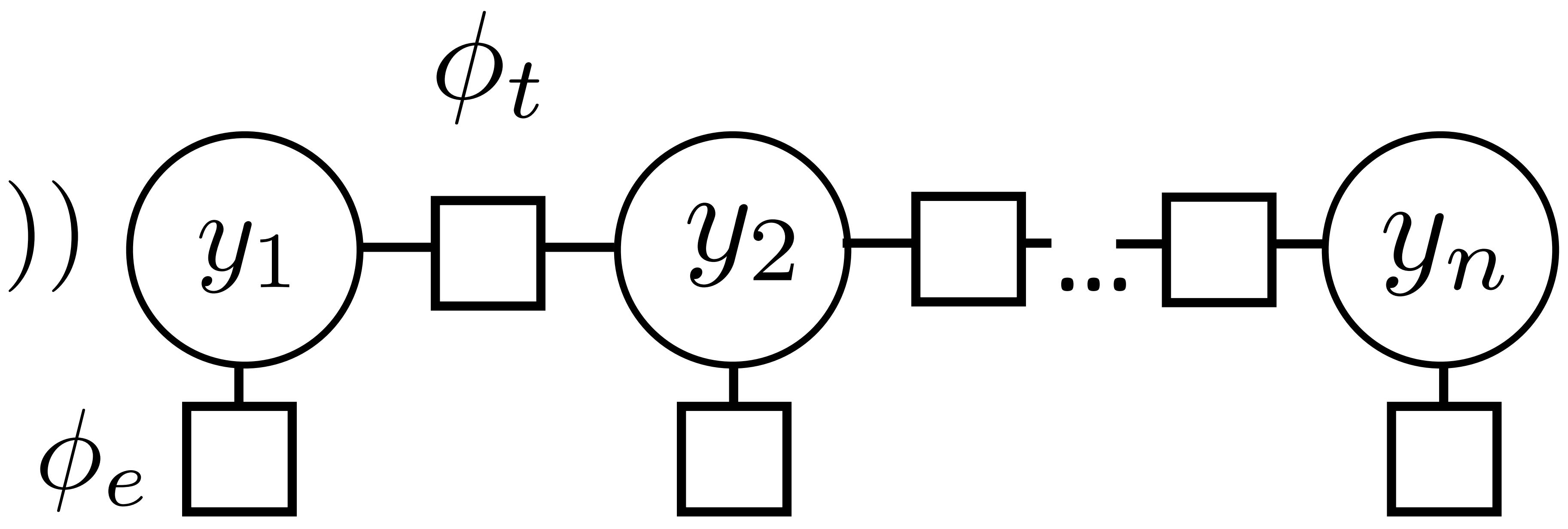


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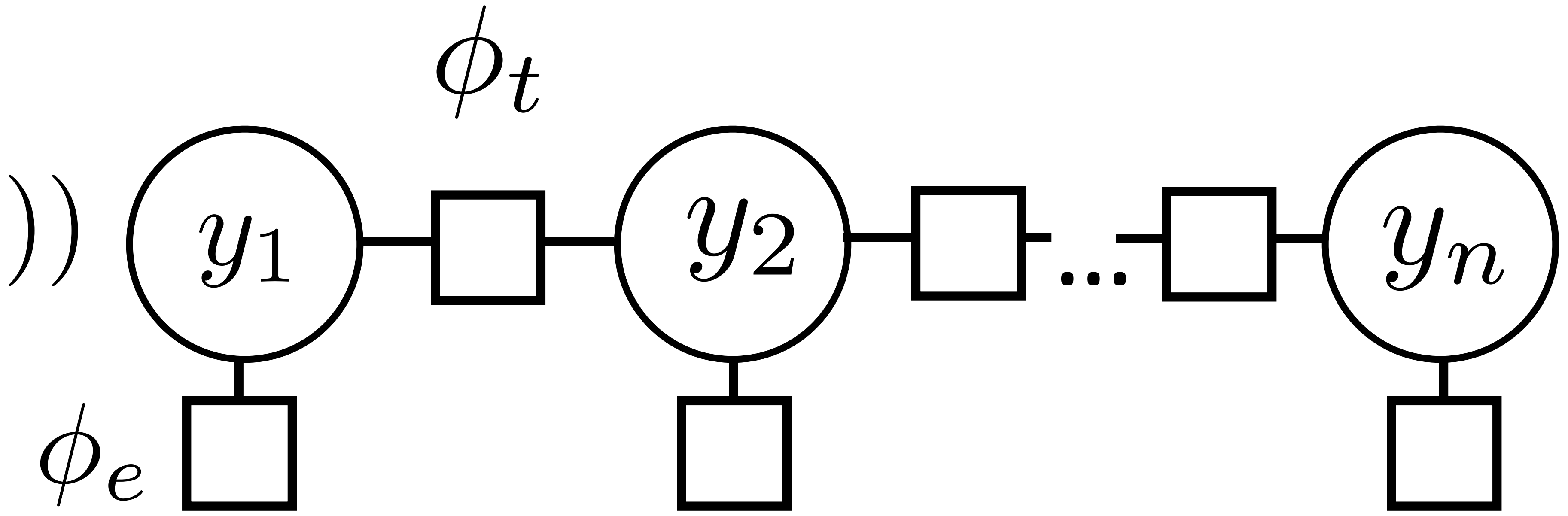


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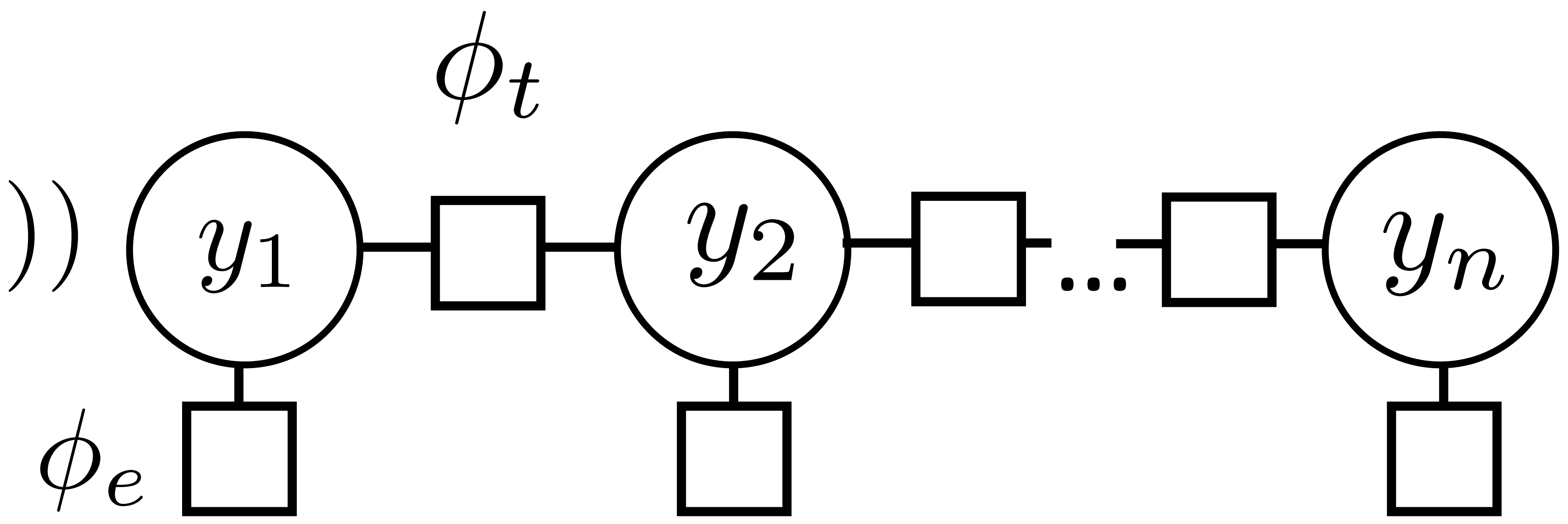


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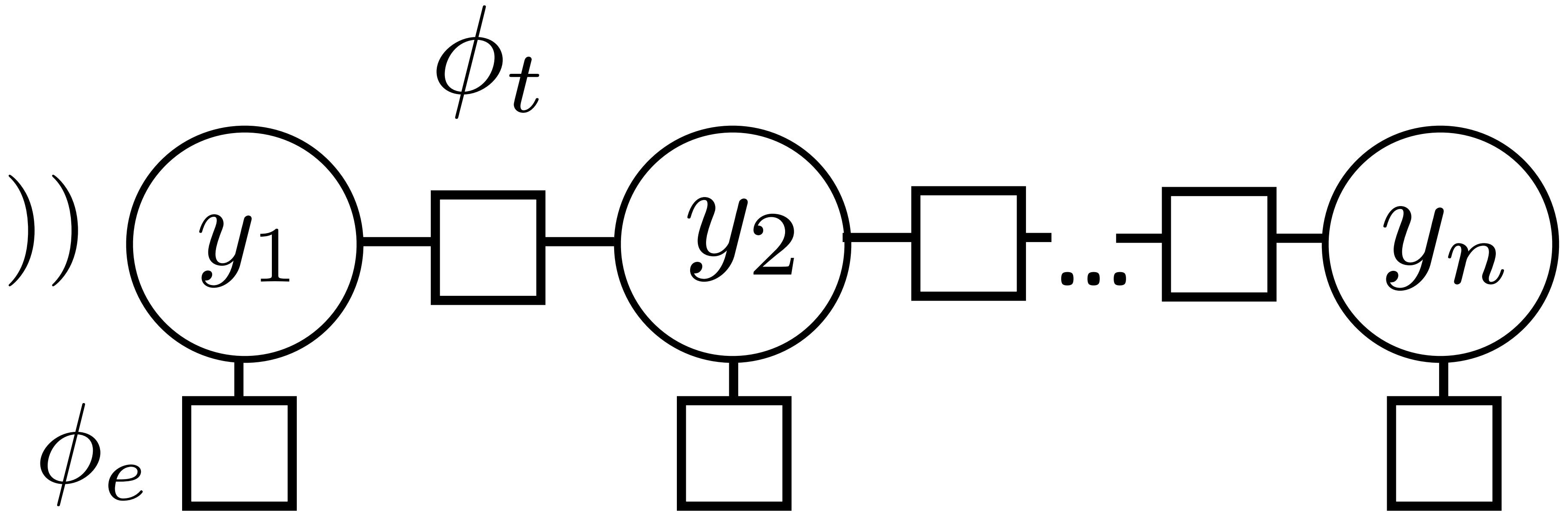


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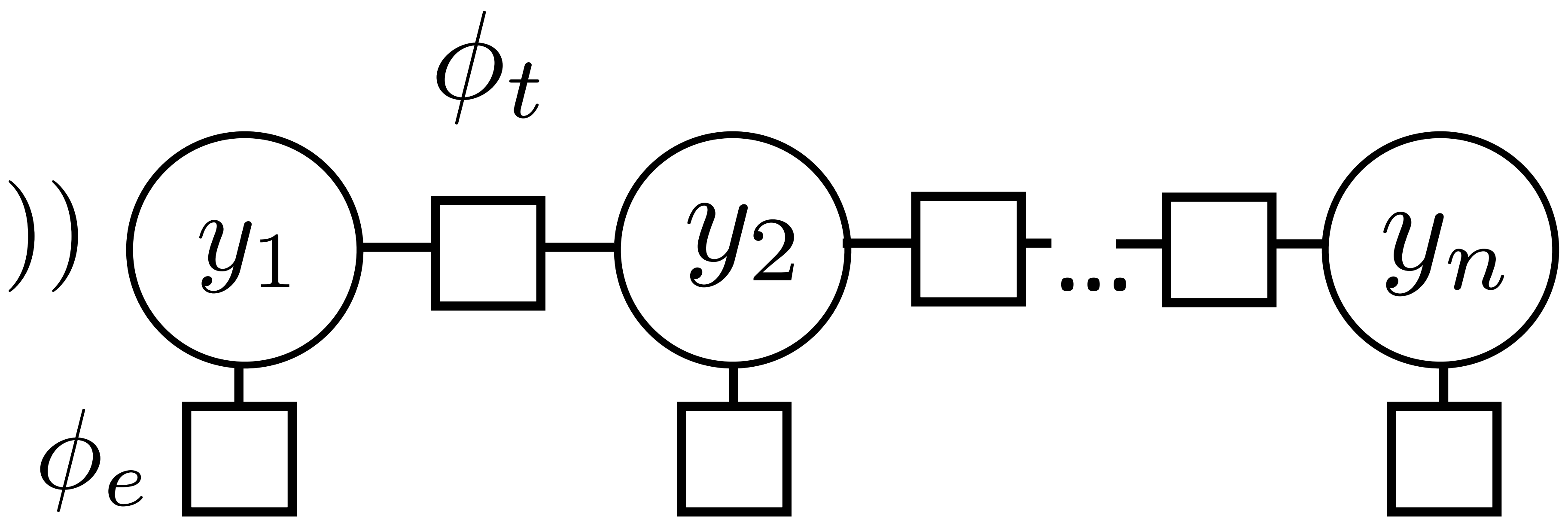


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- Looks like our single weight vector multiclass logistic regression model

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

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

# Features for NER

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

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…*

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# 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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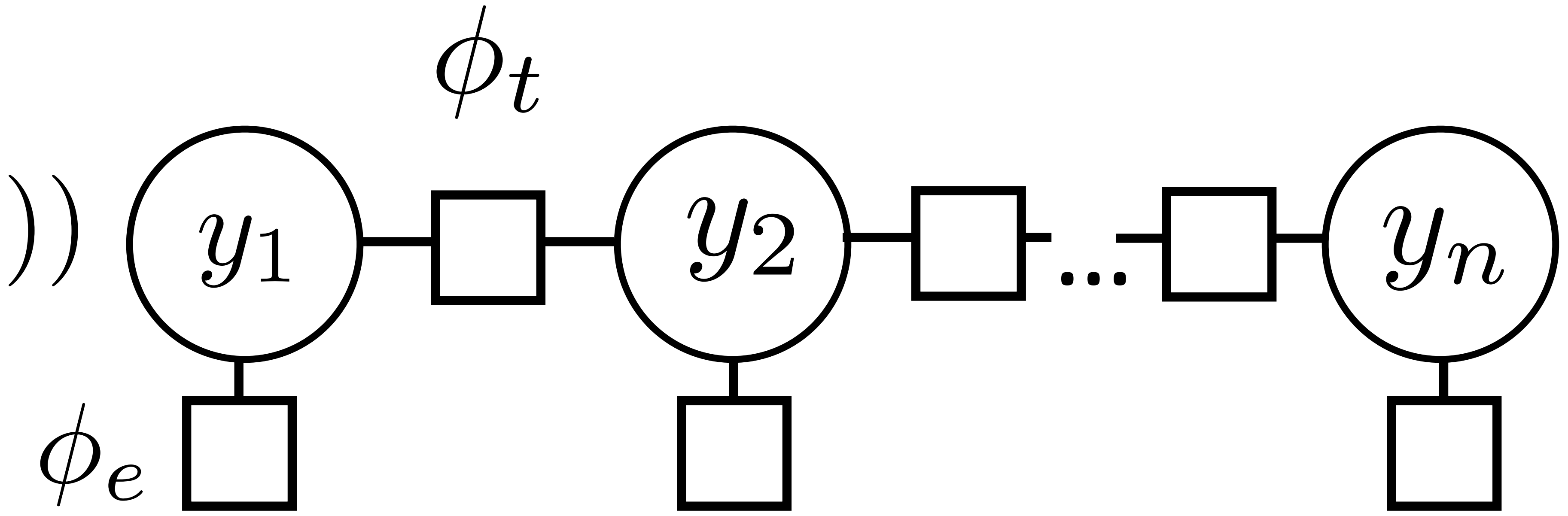
- Inference
- Learning

# 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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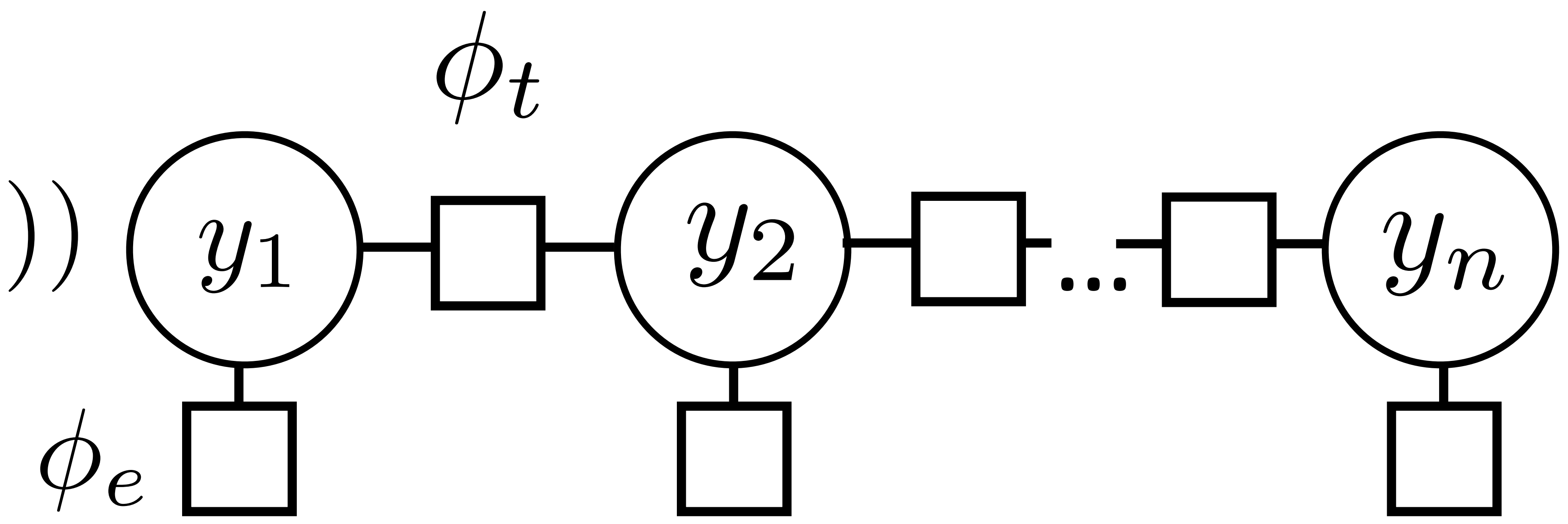


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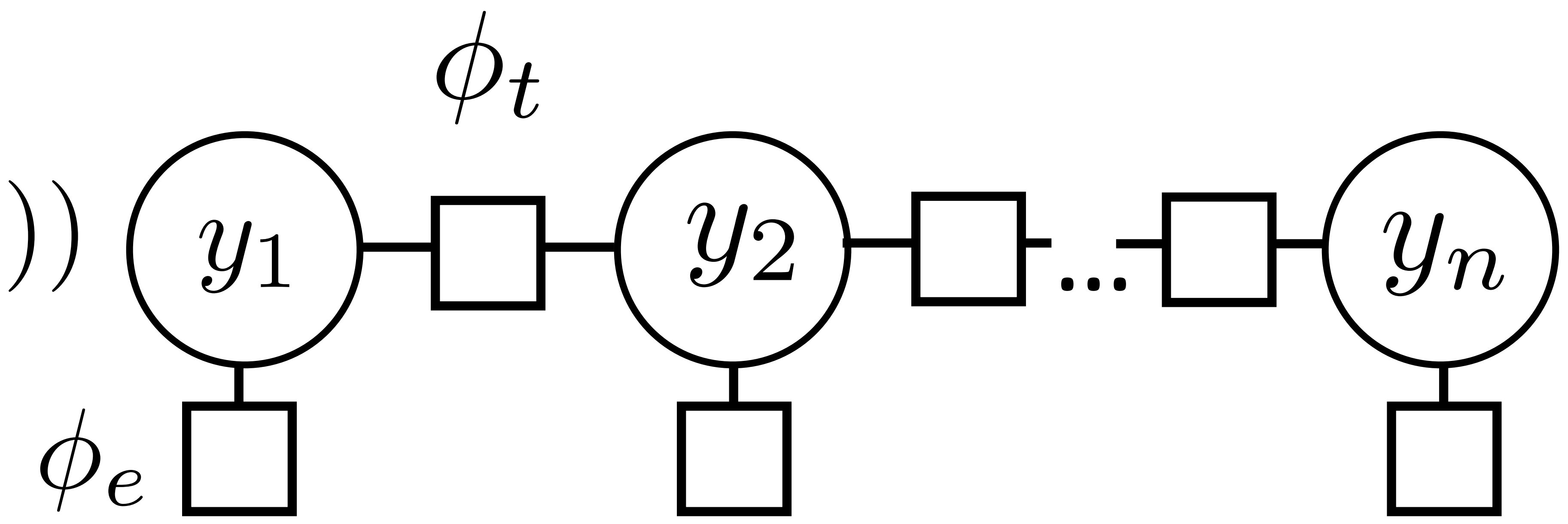


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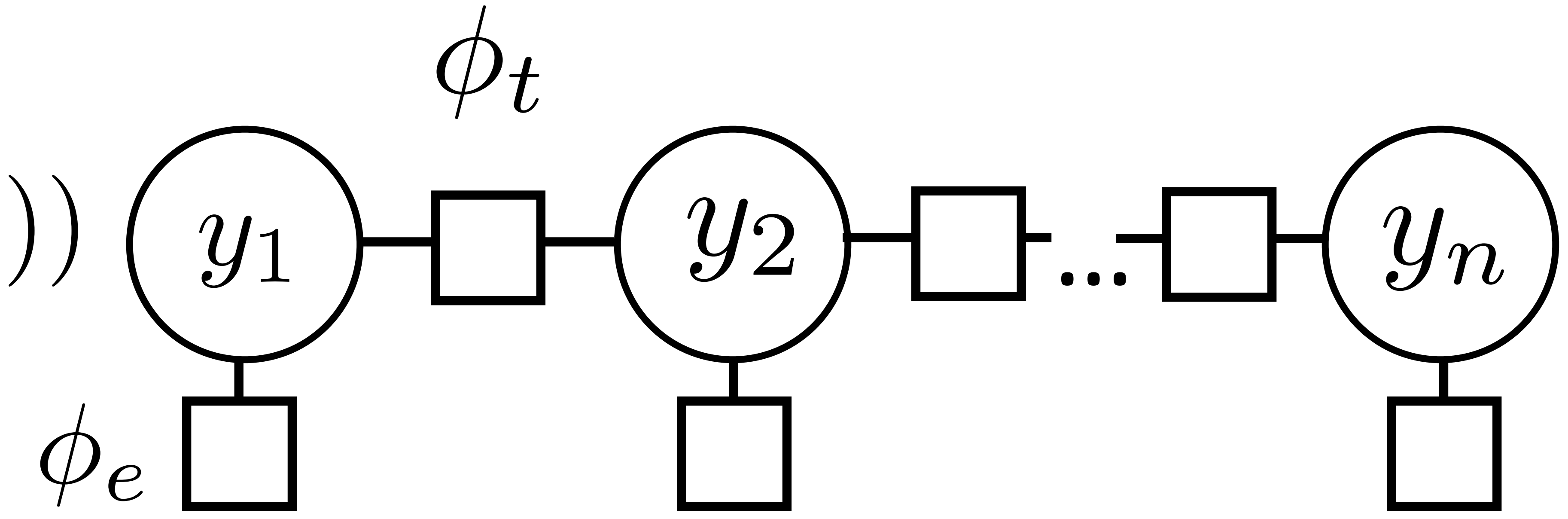


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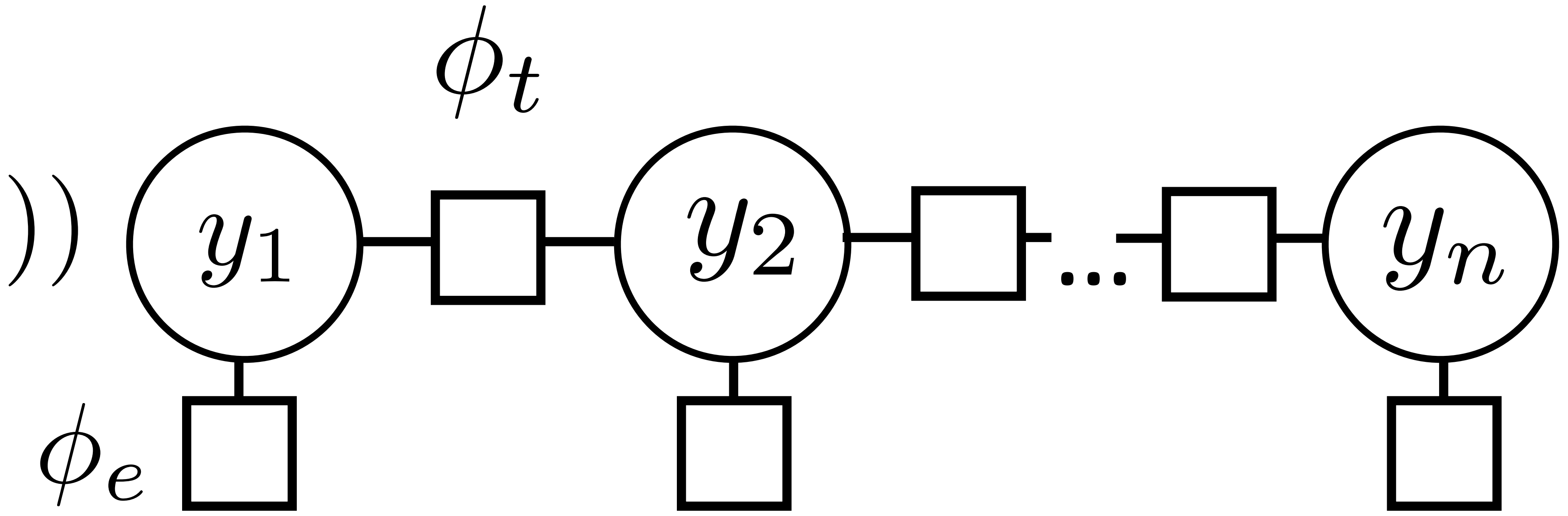


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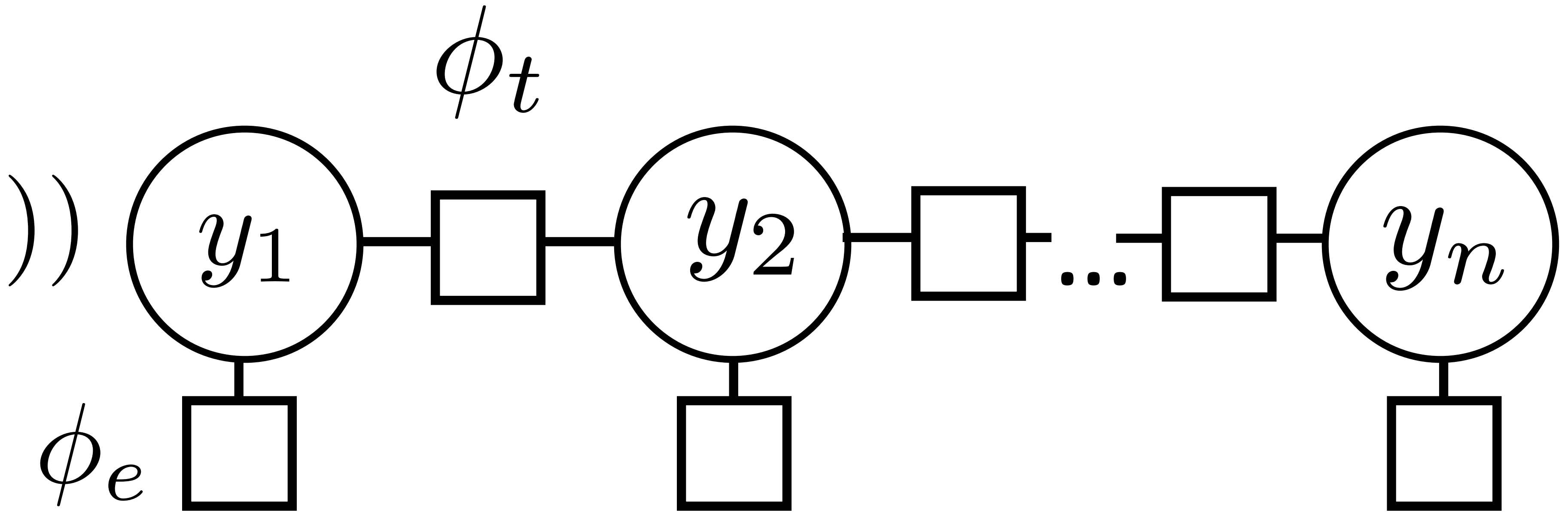


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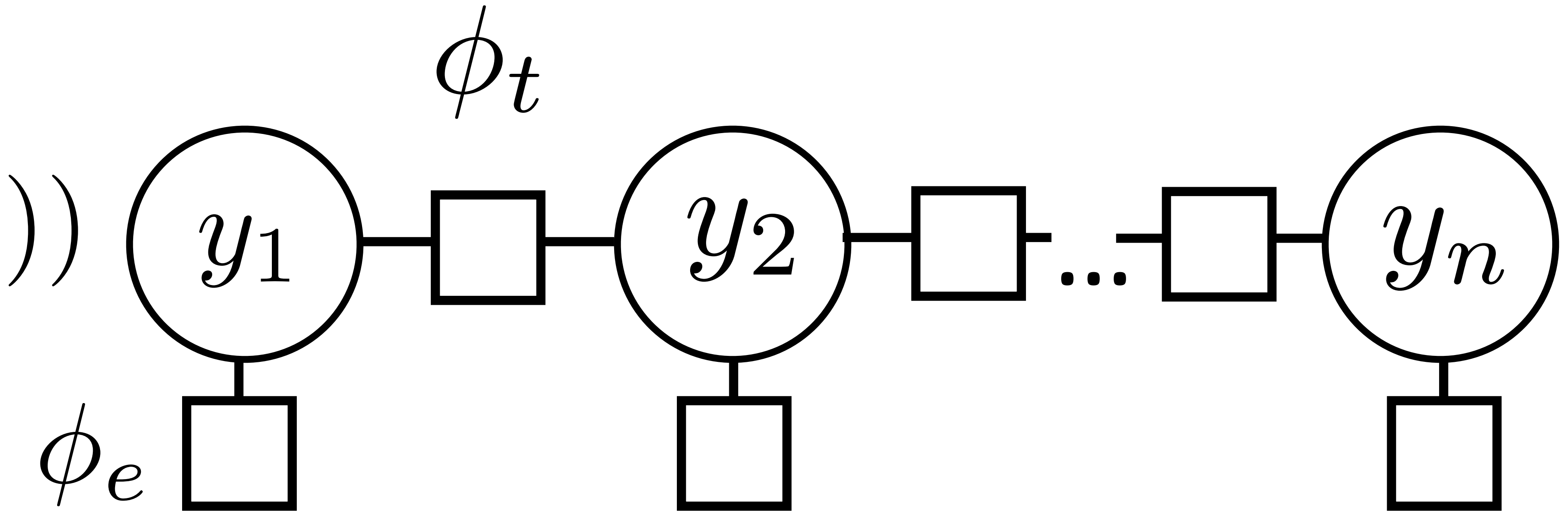


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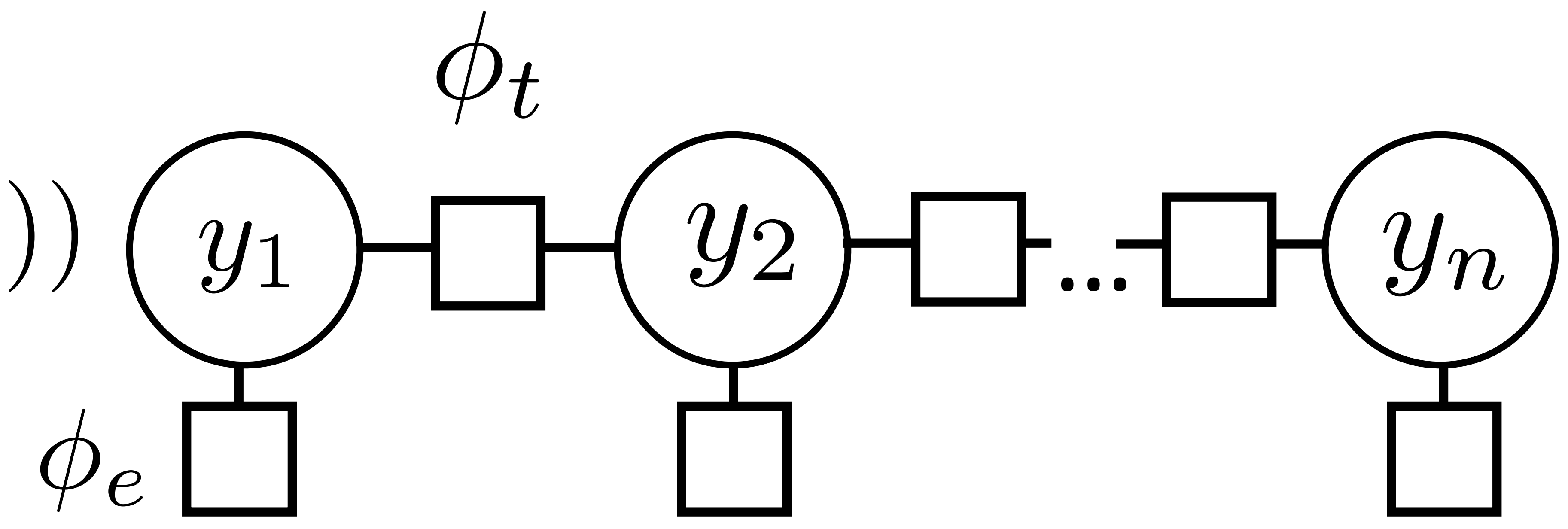


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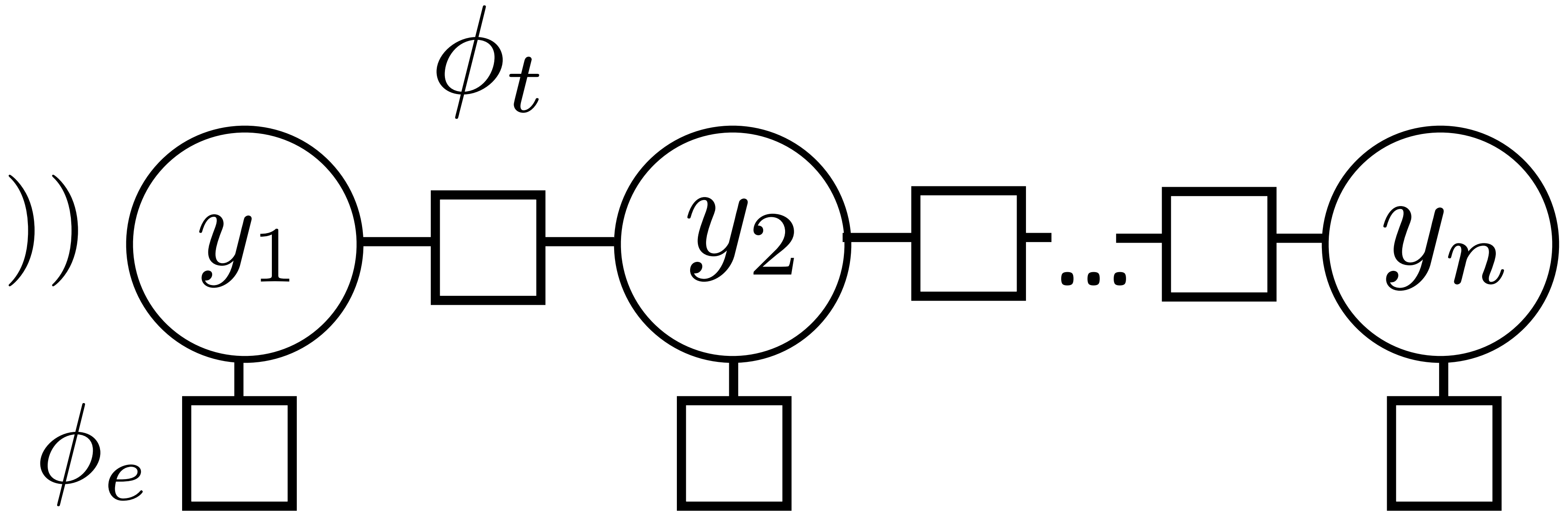


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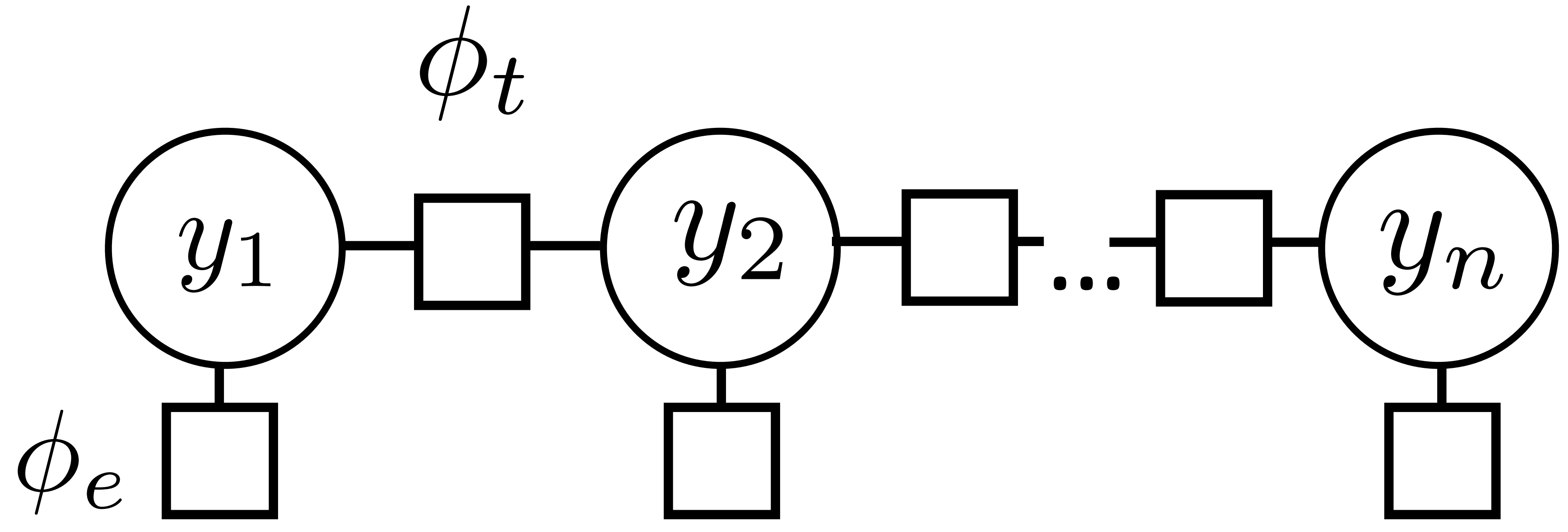
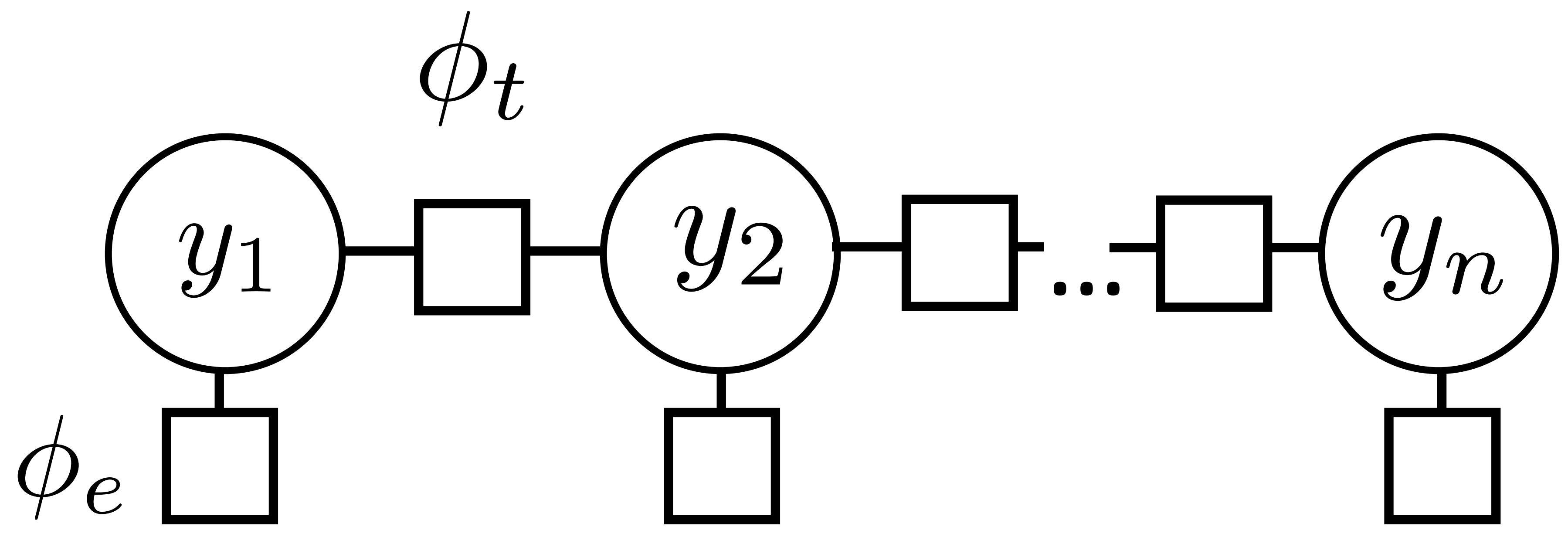
- $\exp(\phi_t(y_{i-1}, y_i))$ and $\exp(\phi_e(y_i, i, \mathbf{x}))$ play the role of the Ps now, same dynamic program

# Inference in General CRFs



# Inference in General CRFs

- Can do inference in any tree-structured CRF



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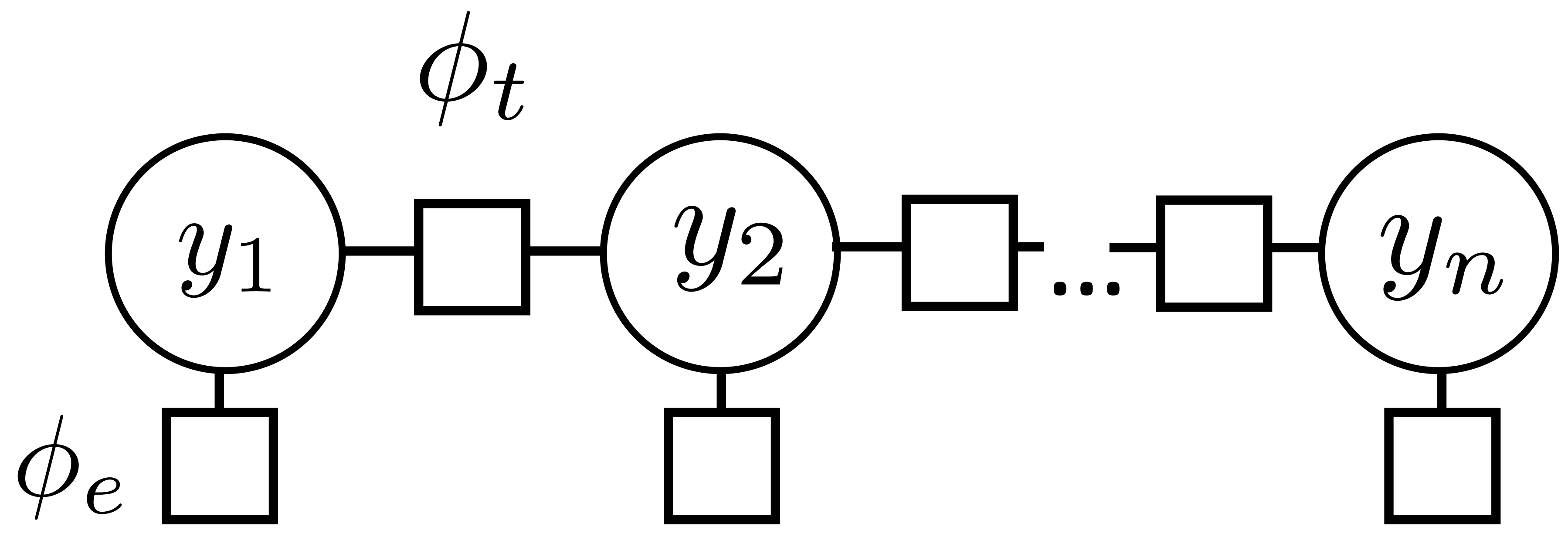


- Max-product algorithm: generalization of Viterbi to arbitrary tree-structured graphs (sum-product is generalization of forward-backward)

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

intractable!

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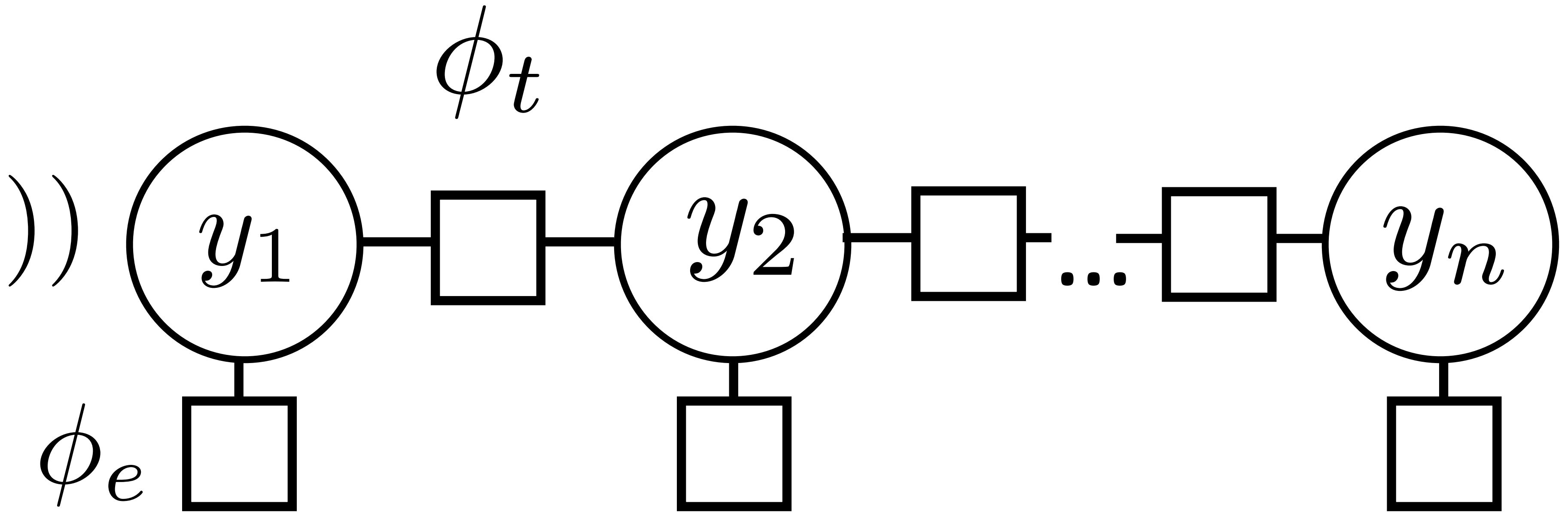
# Computing Marginals

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



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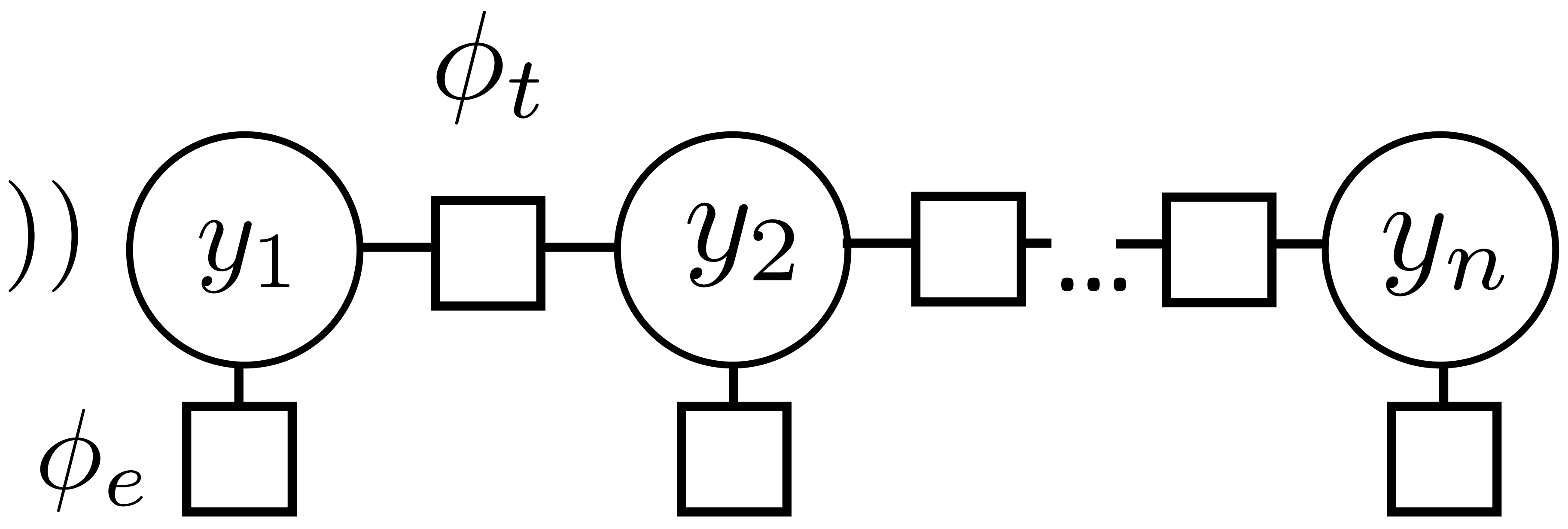


- Normalizing constant $Z = \sum_{\mathbf{y}}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$

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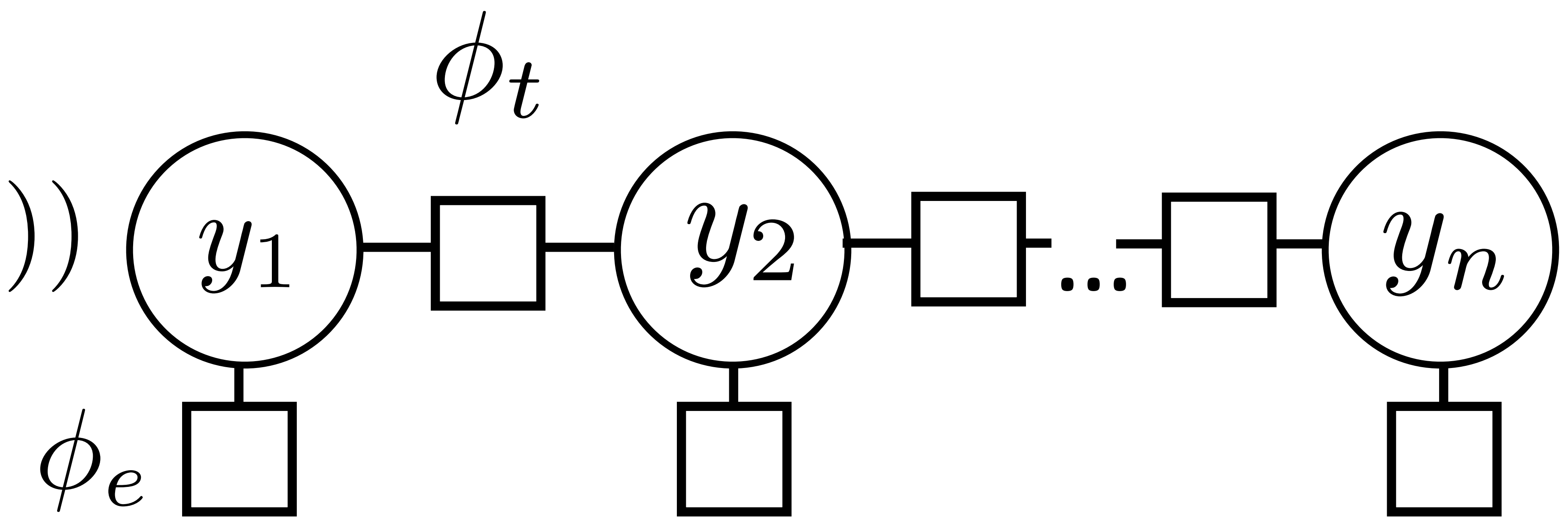


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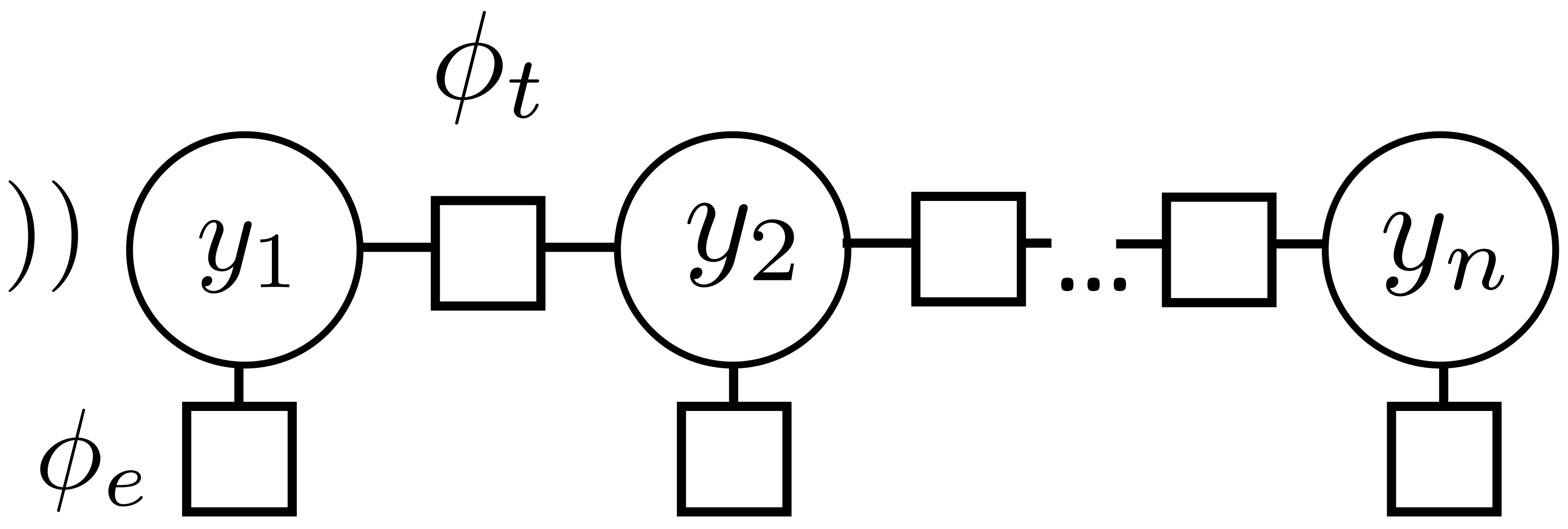


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- For both HMMs and CRFs:

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

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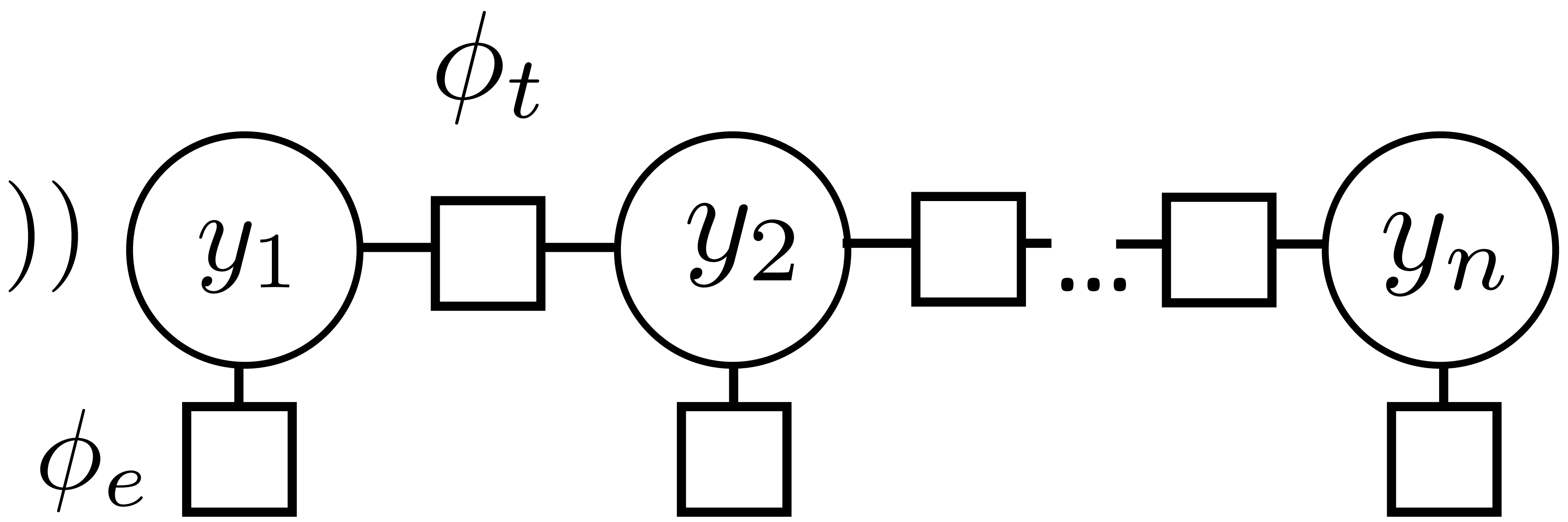


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# Posteriors vs. Probabilities

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

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

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

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

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

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

# Pseudocode

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for each epoch
    for each example
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        accumulate gradient over all emissions and transitions
```

# Structured Perceptron

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- Structured Perceptron Update:

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

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Replaces Expectation With argmax

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

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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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- 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 | | |

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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 |
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| - | (Kazama and Torisawa, 2007a) | Wikipedia | 88.02 |
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| - | (Kazama and Torisawa, 2007b) | Non-local Features | 87.17 |
| + | (Finkel et al., 2005) | Non-local Features | 86.86 |

Ratinov and Roth (2009)

Lample et al. (2016)

| | |
|---|---|
| LSTM-CRF (no char) | 90.20 |
| LSTM-CRF | **90.94** |
| S-LSTM (no char) | 87.96 |
| S-LSTM | 90.33 |

# 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 |
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BiLSTM-CRF + ELMo
Peters et al. (2018) **92.2**

# 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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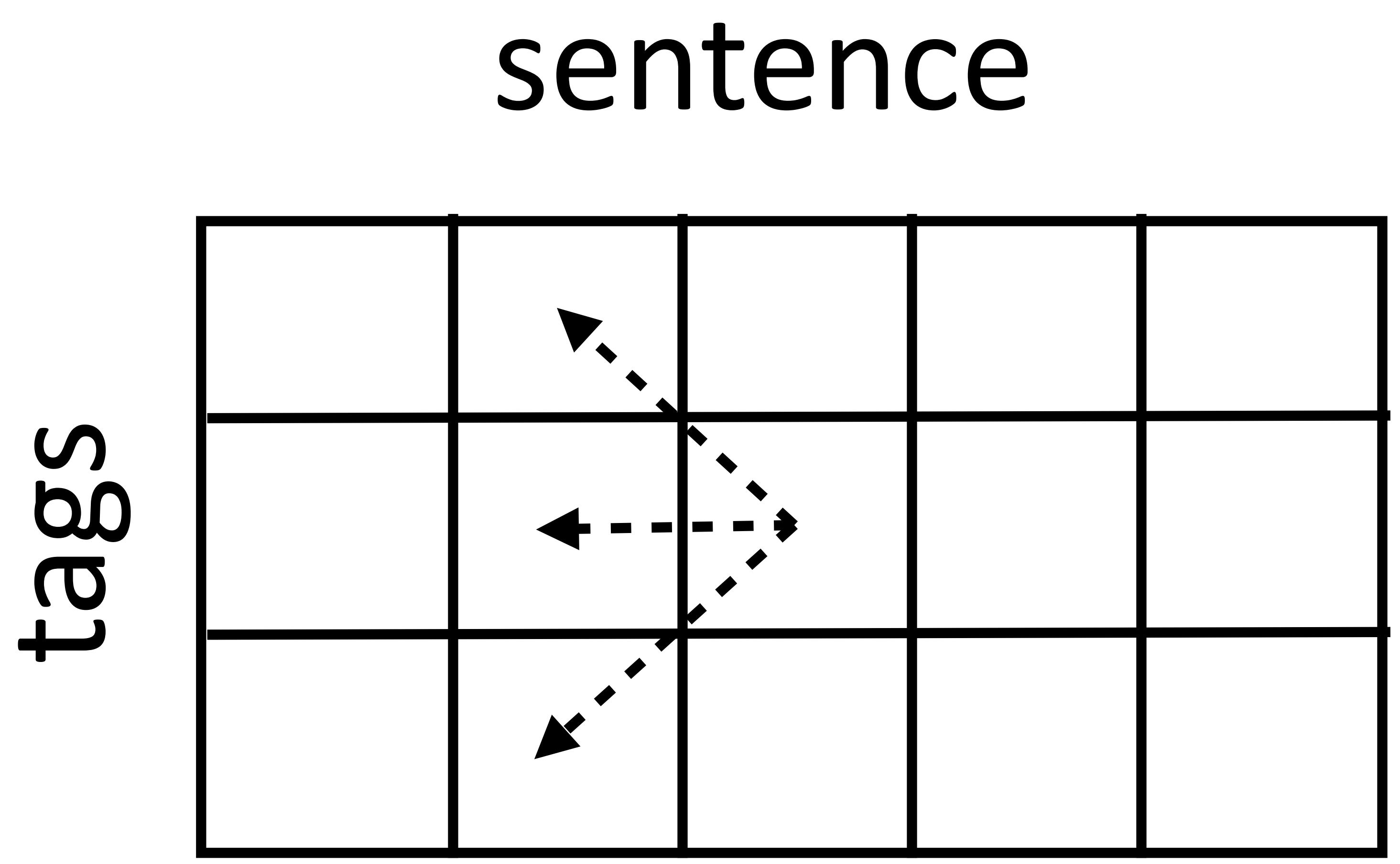

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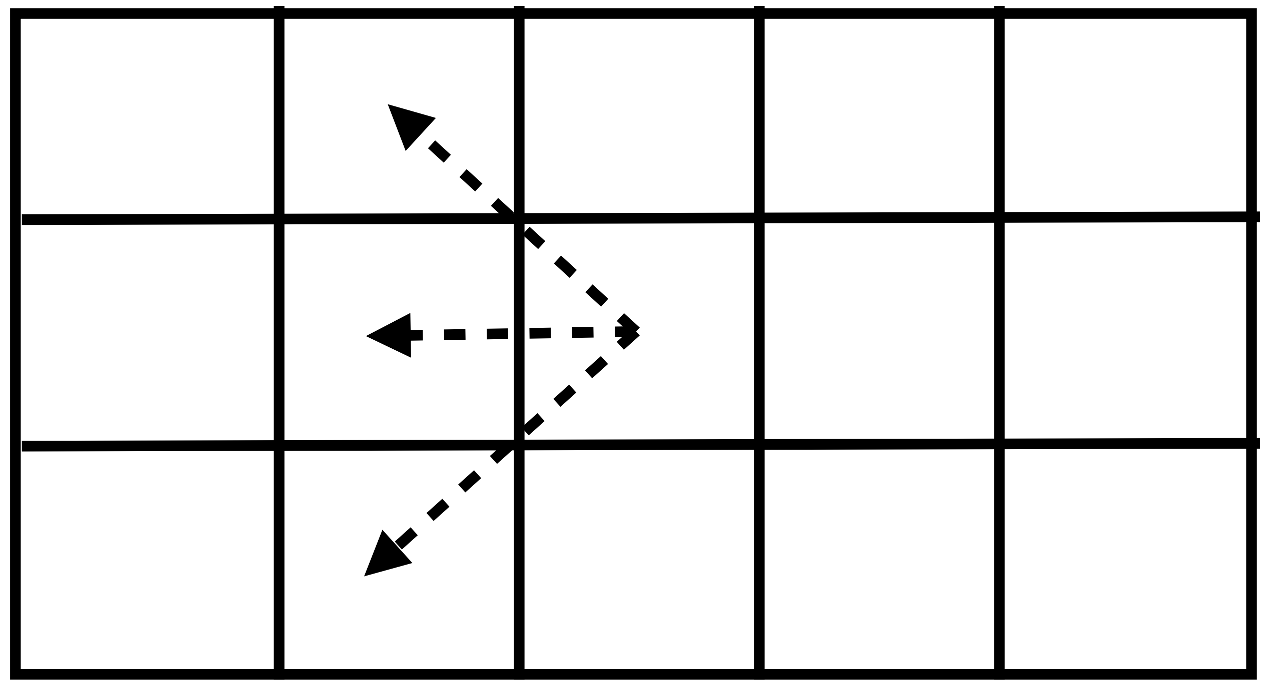
sentence

tags



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

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- Many tags are totally implausible
- 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

# Beam Search

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

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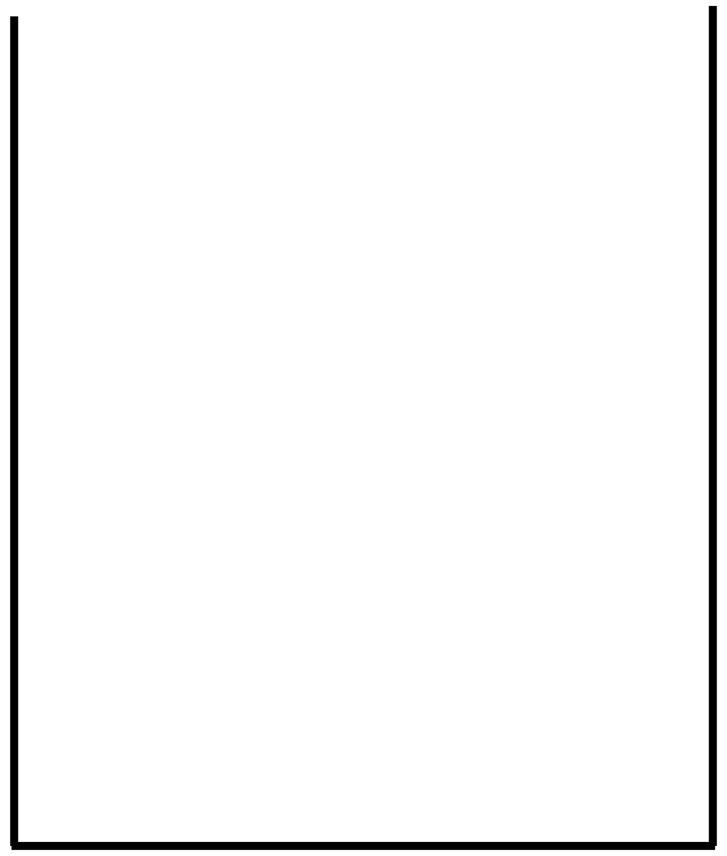

Fed

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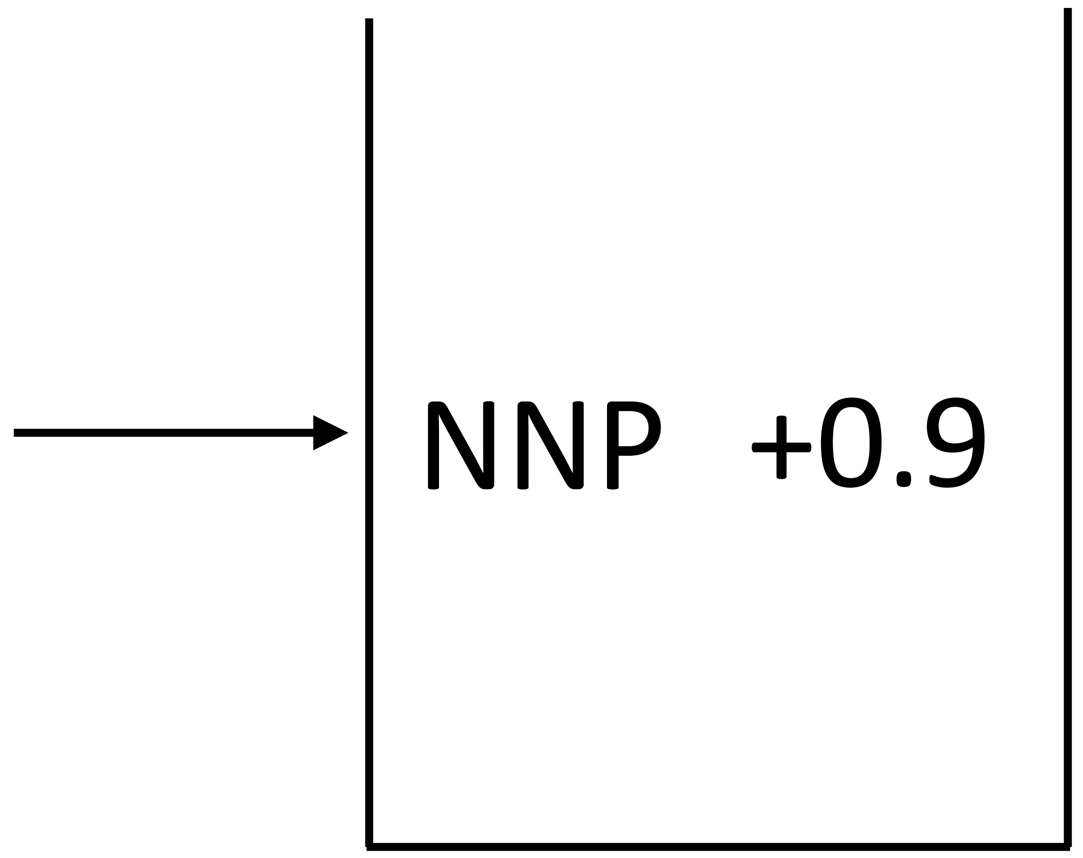


Fed raises

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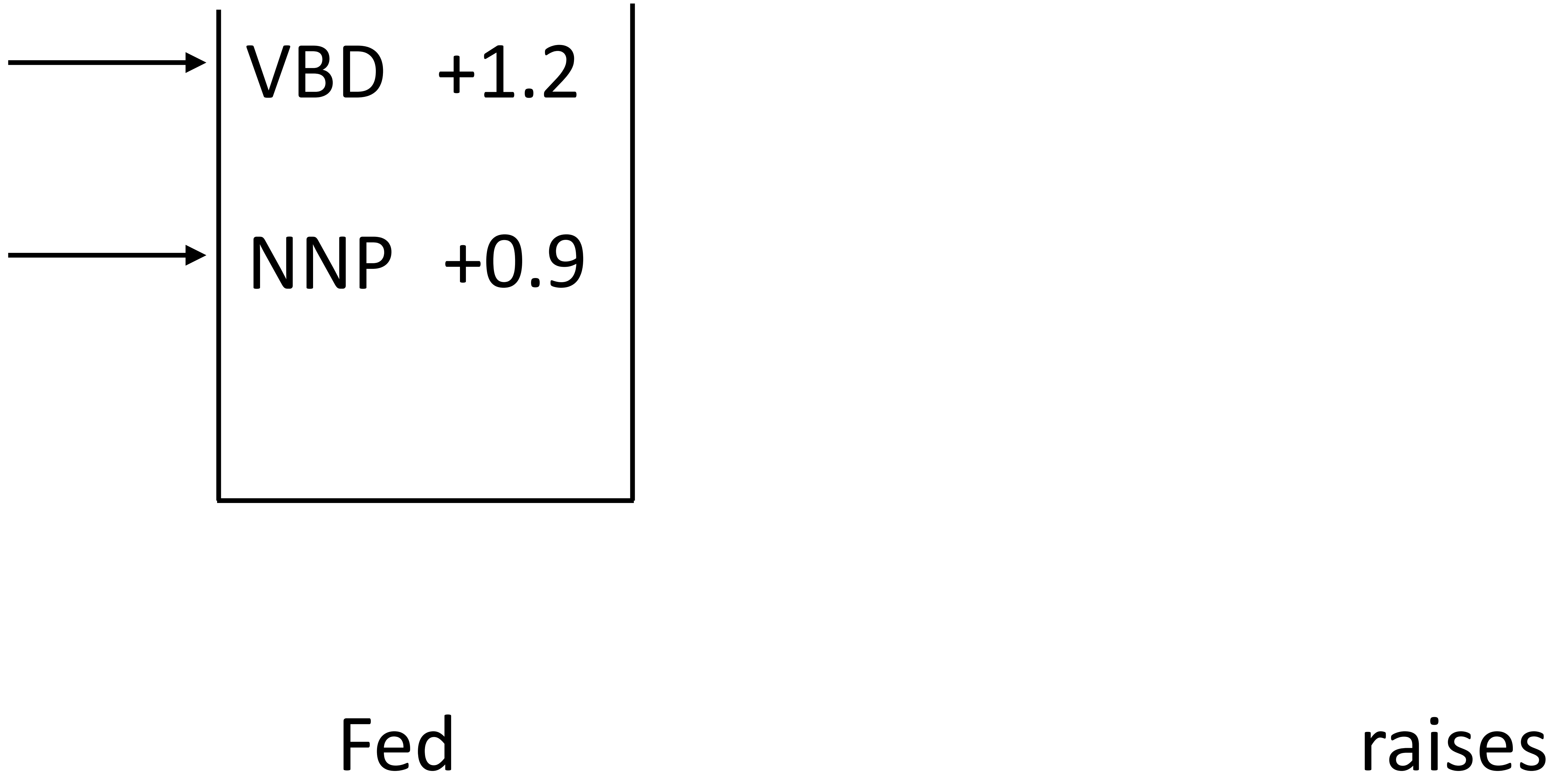

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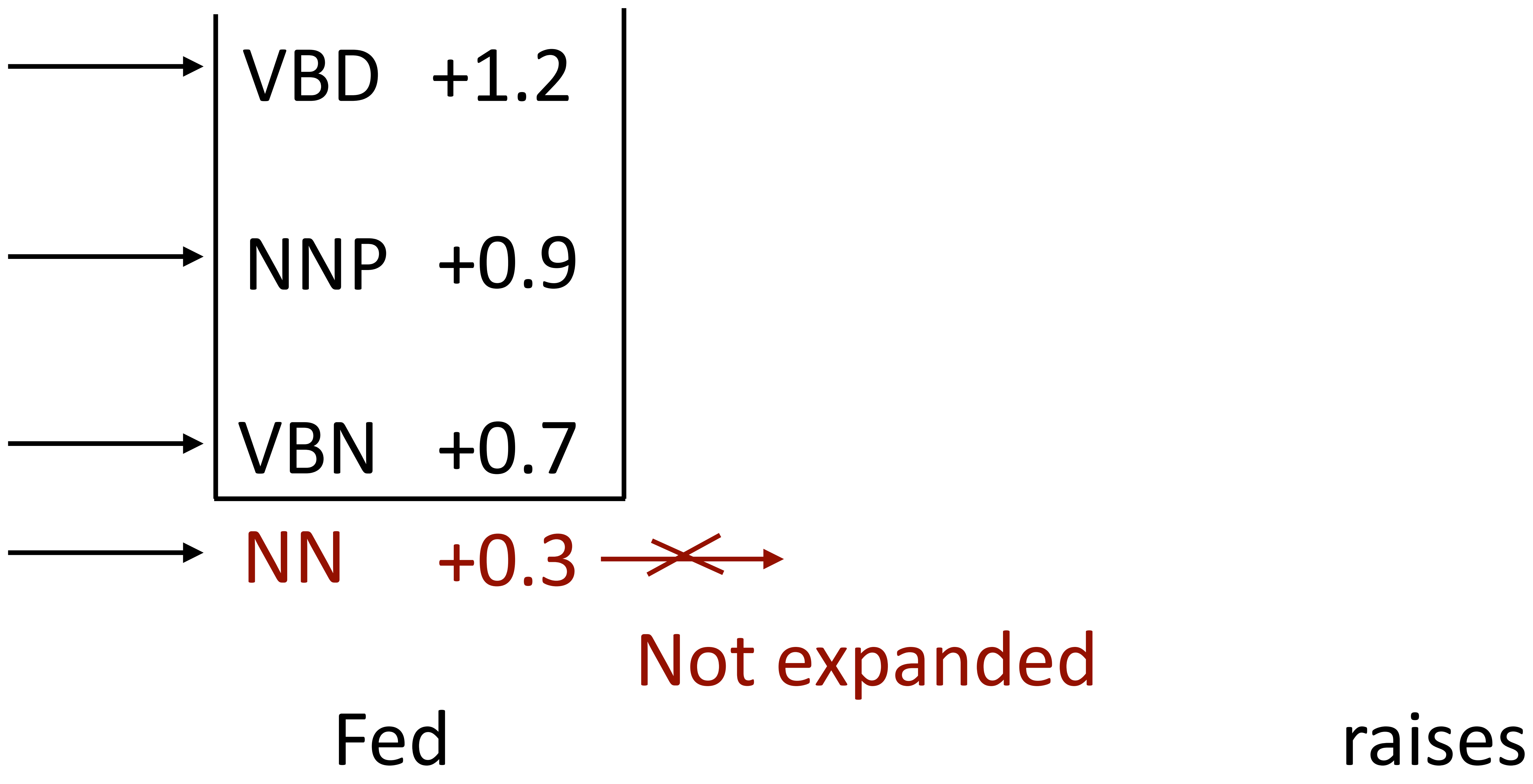

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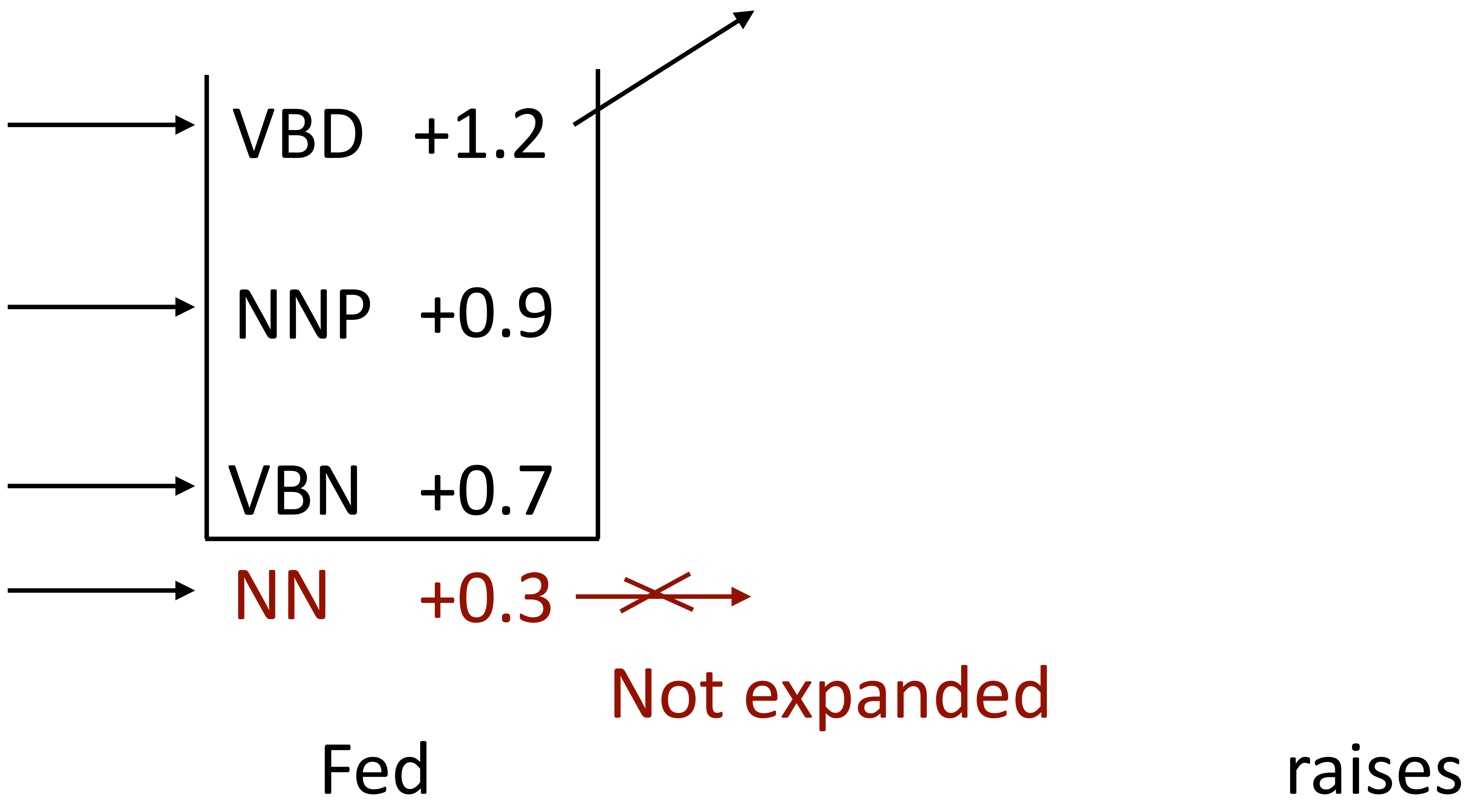

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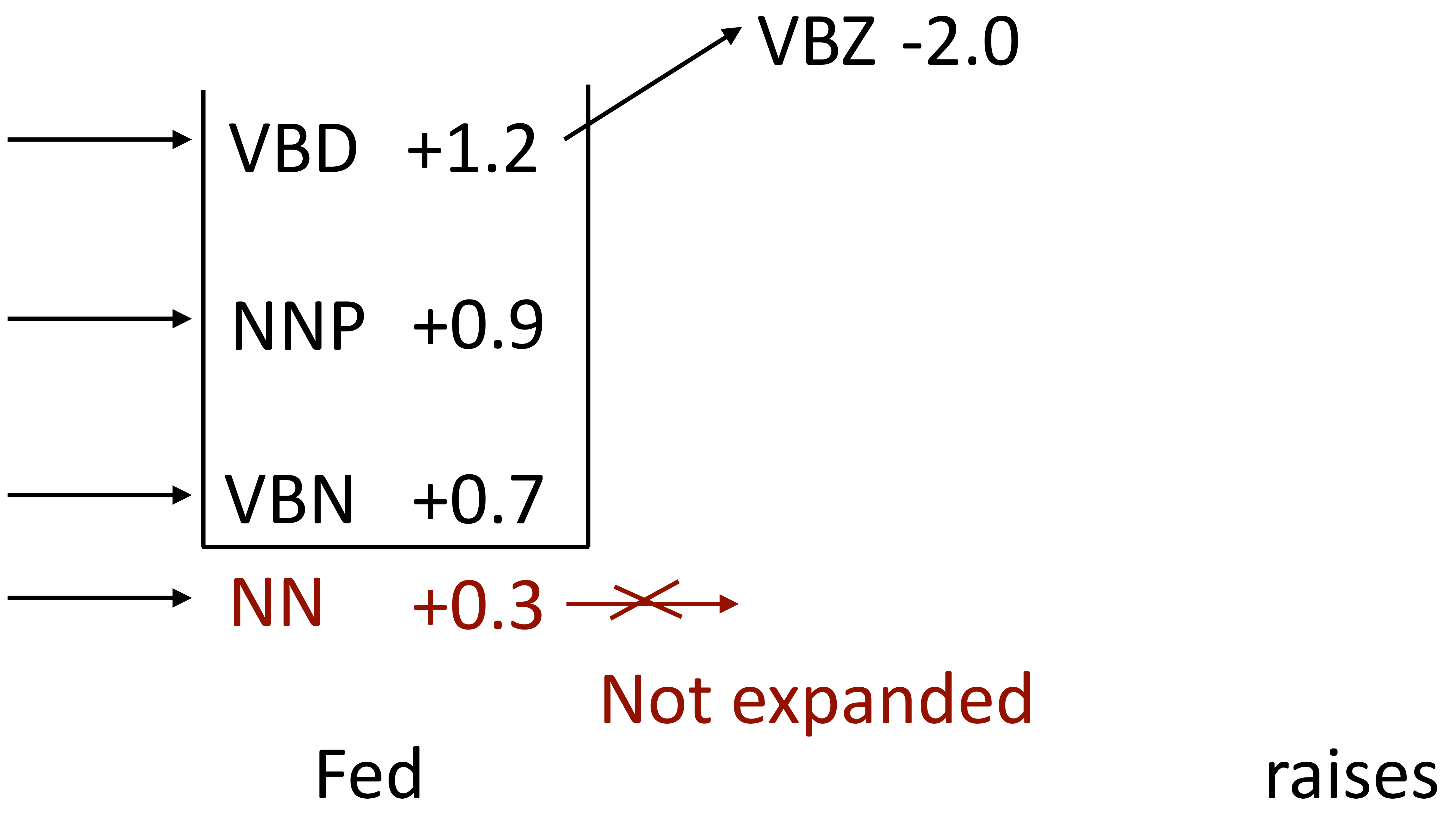

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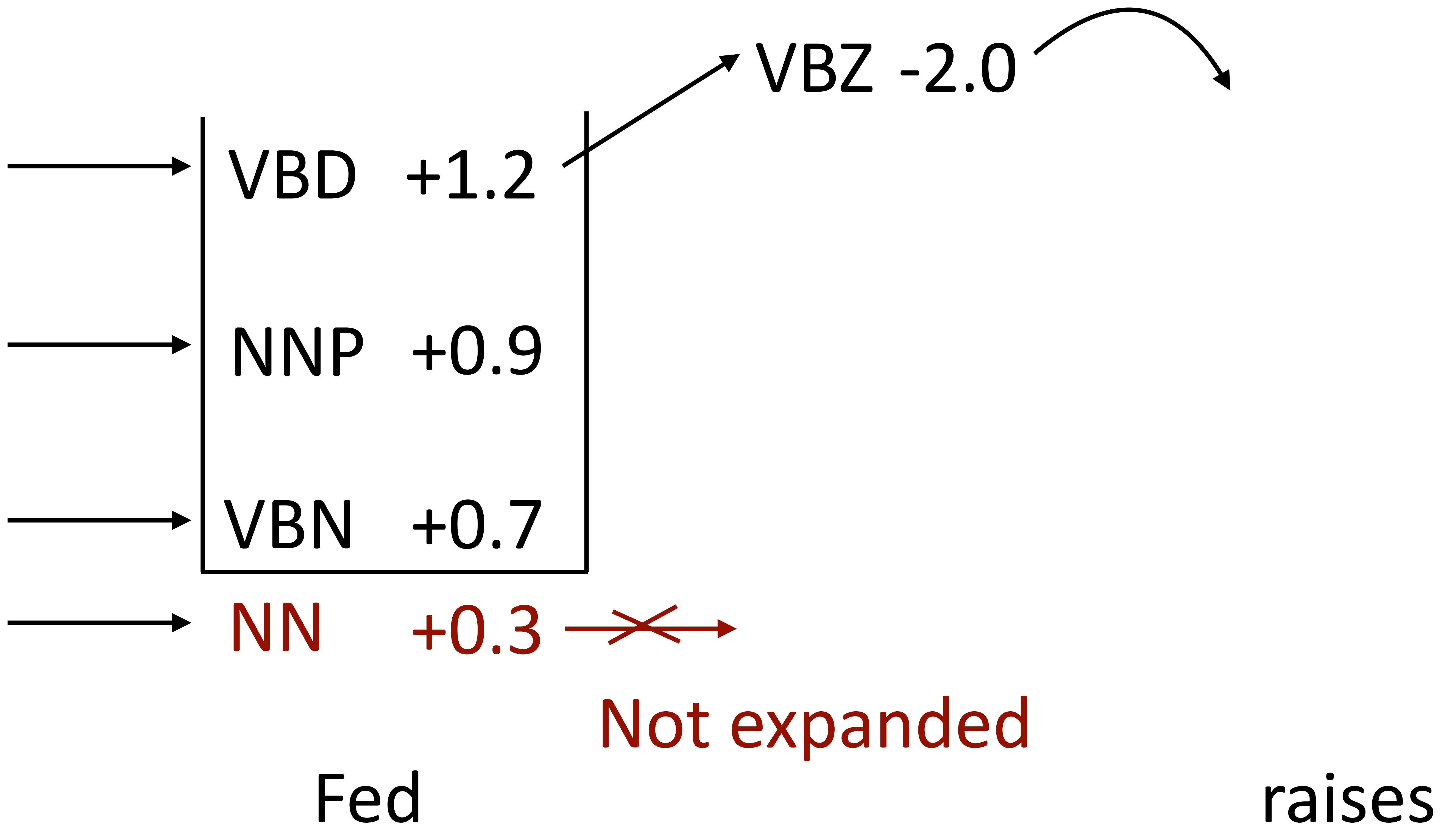

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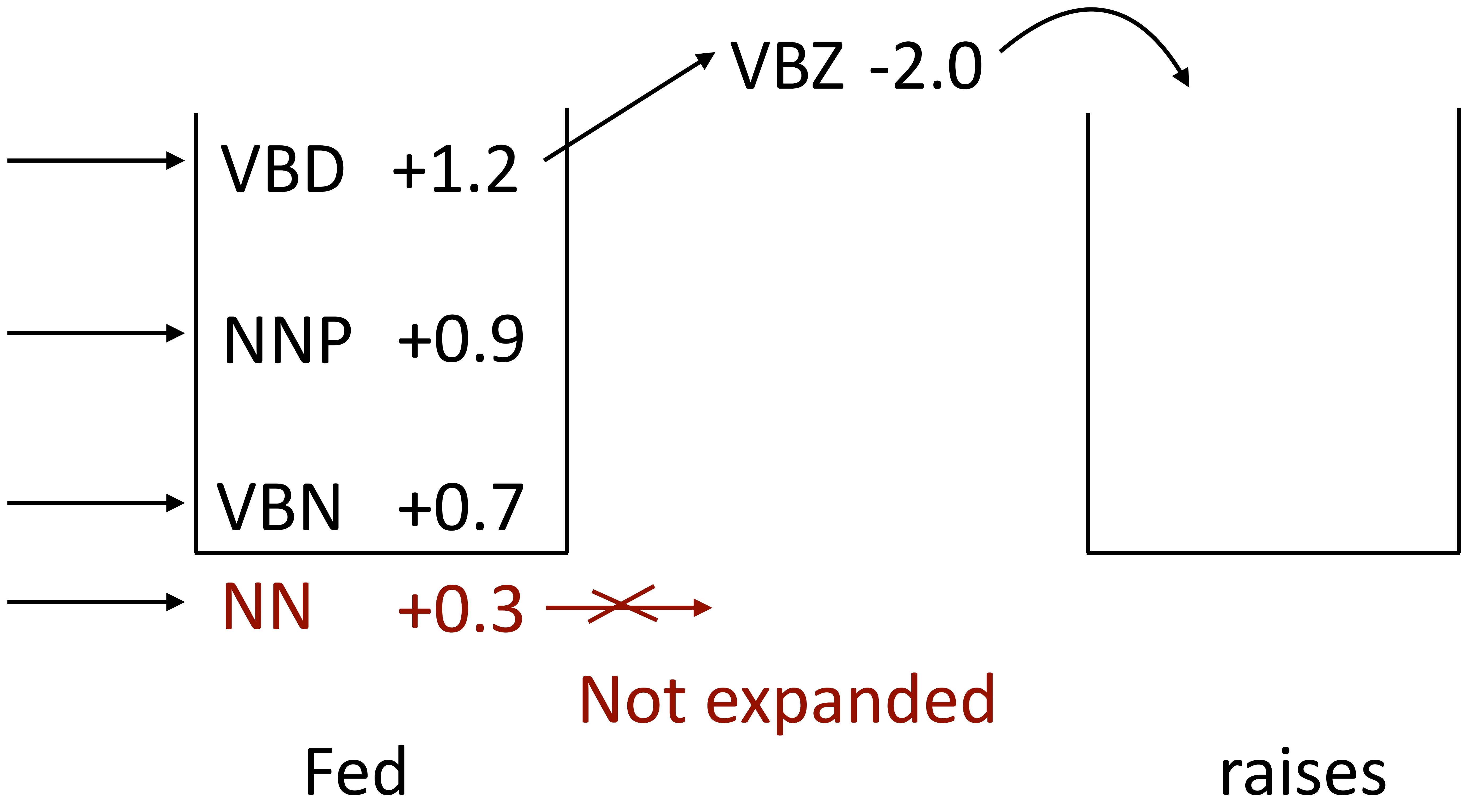

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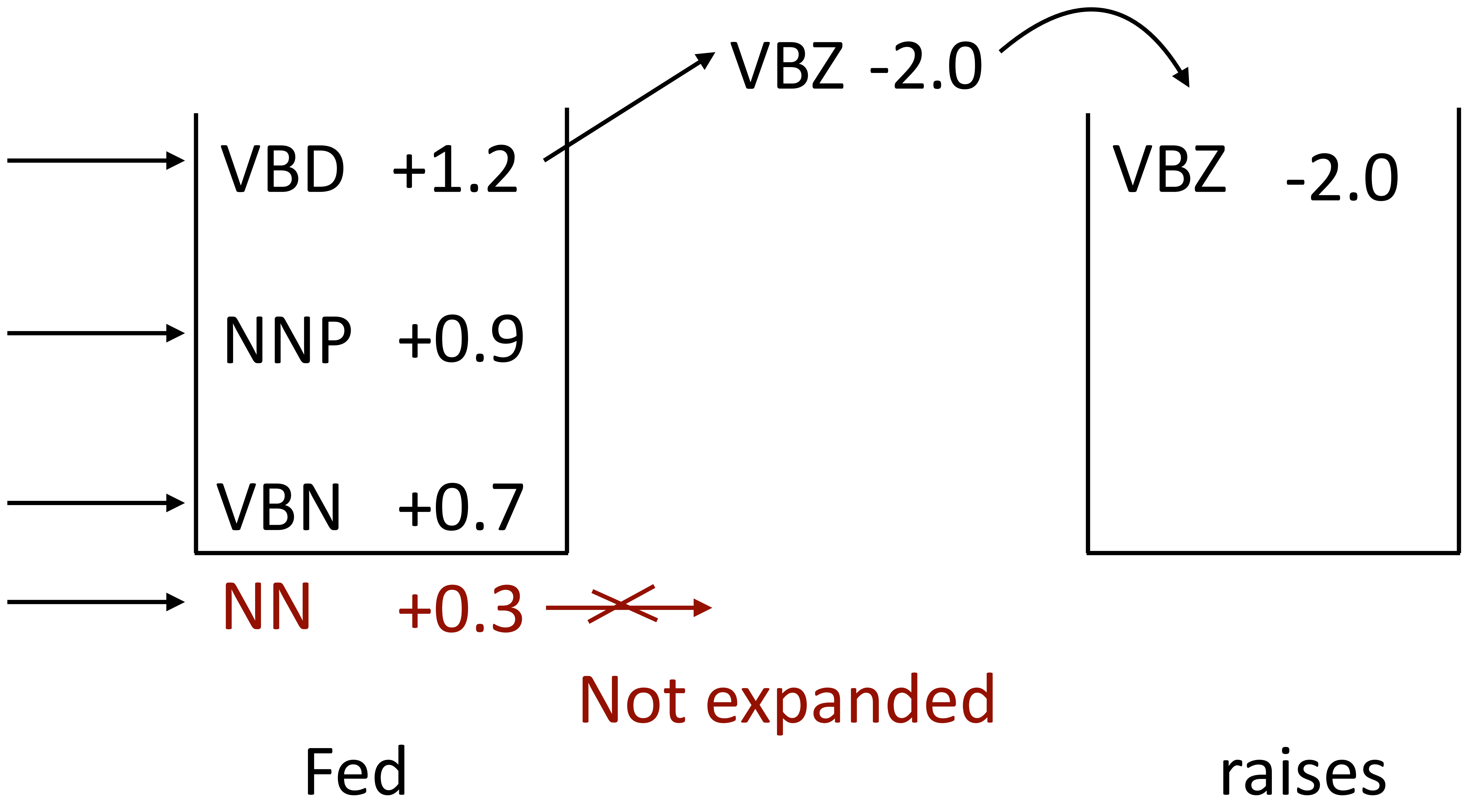

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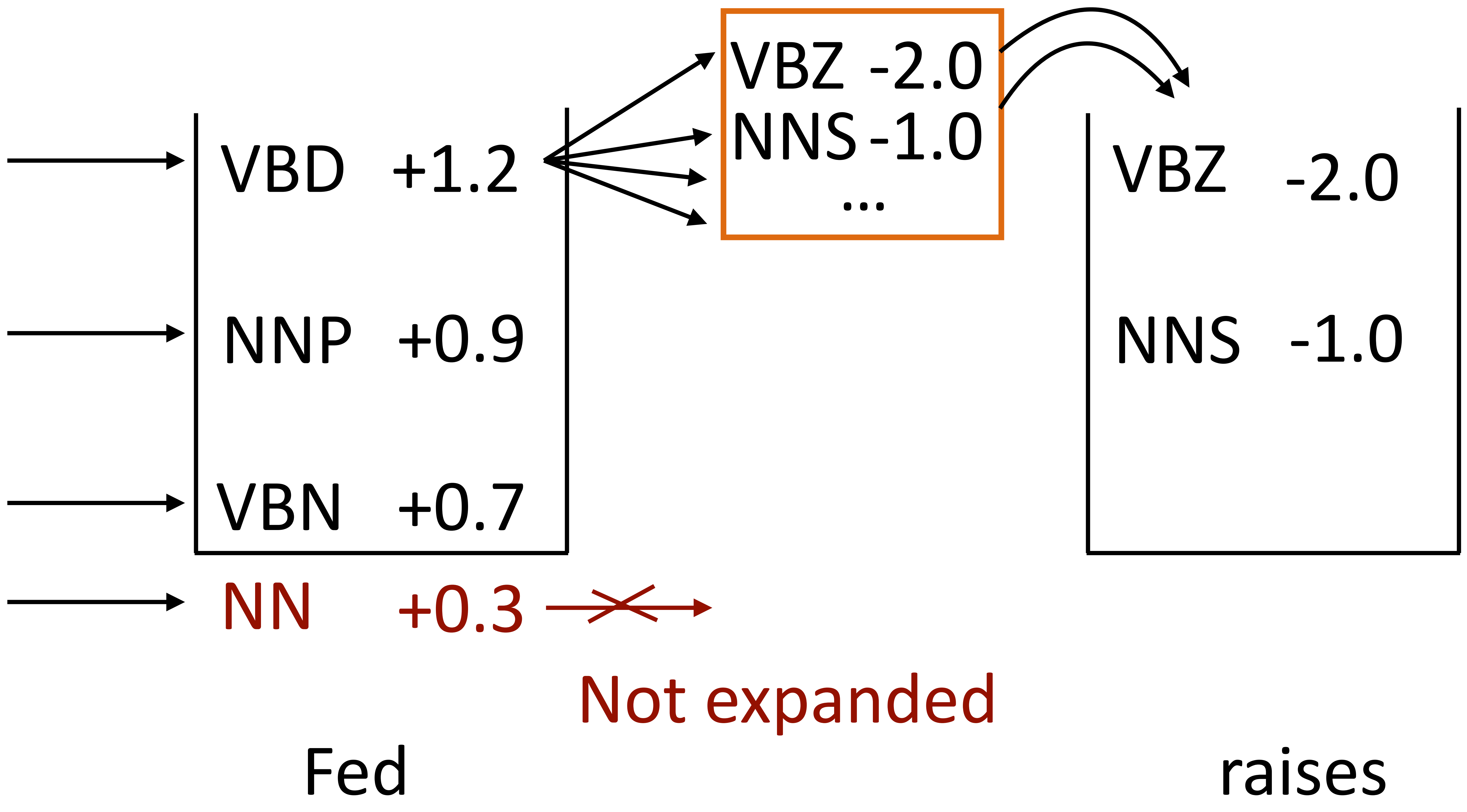

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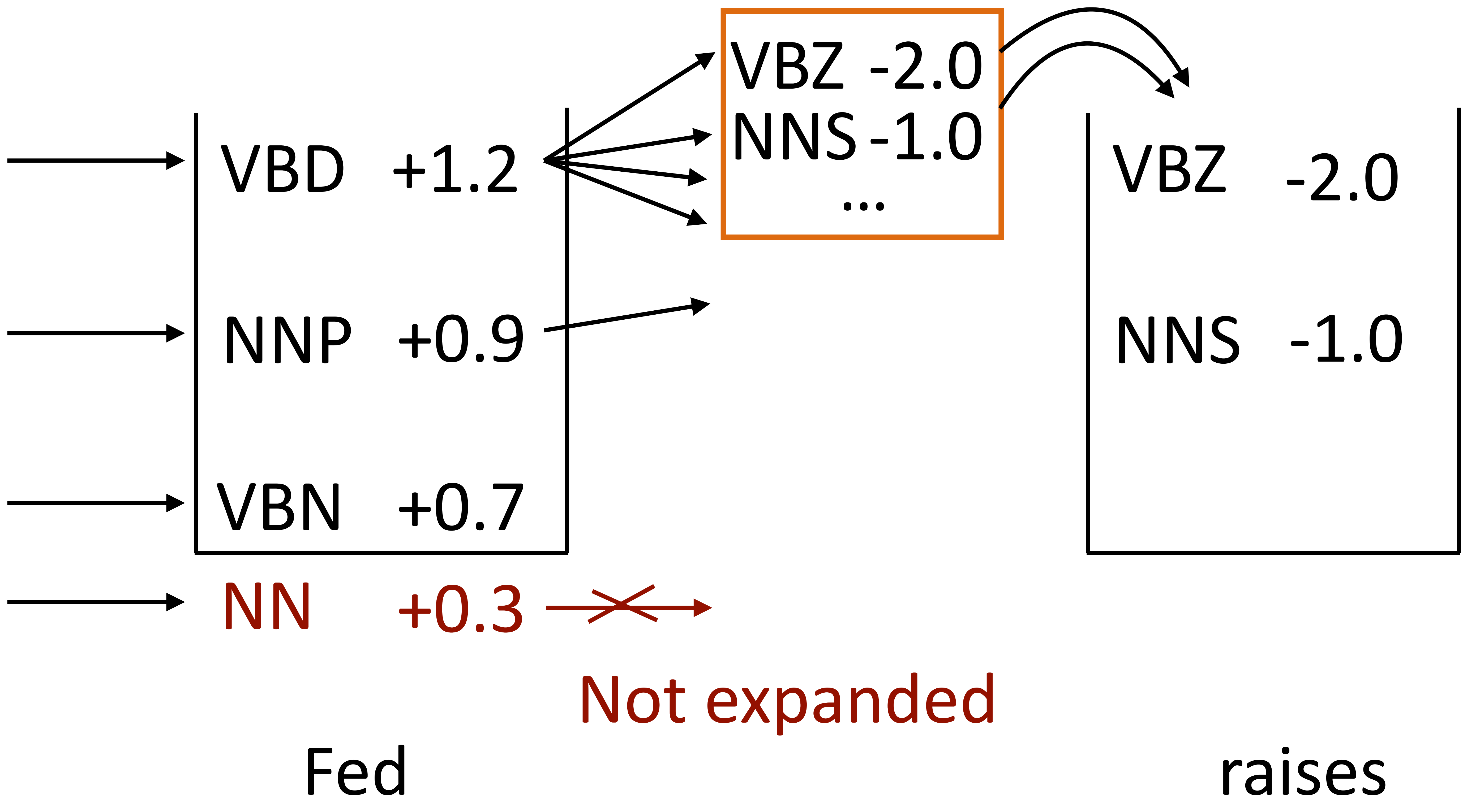

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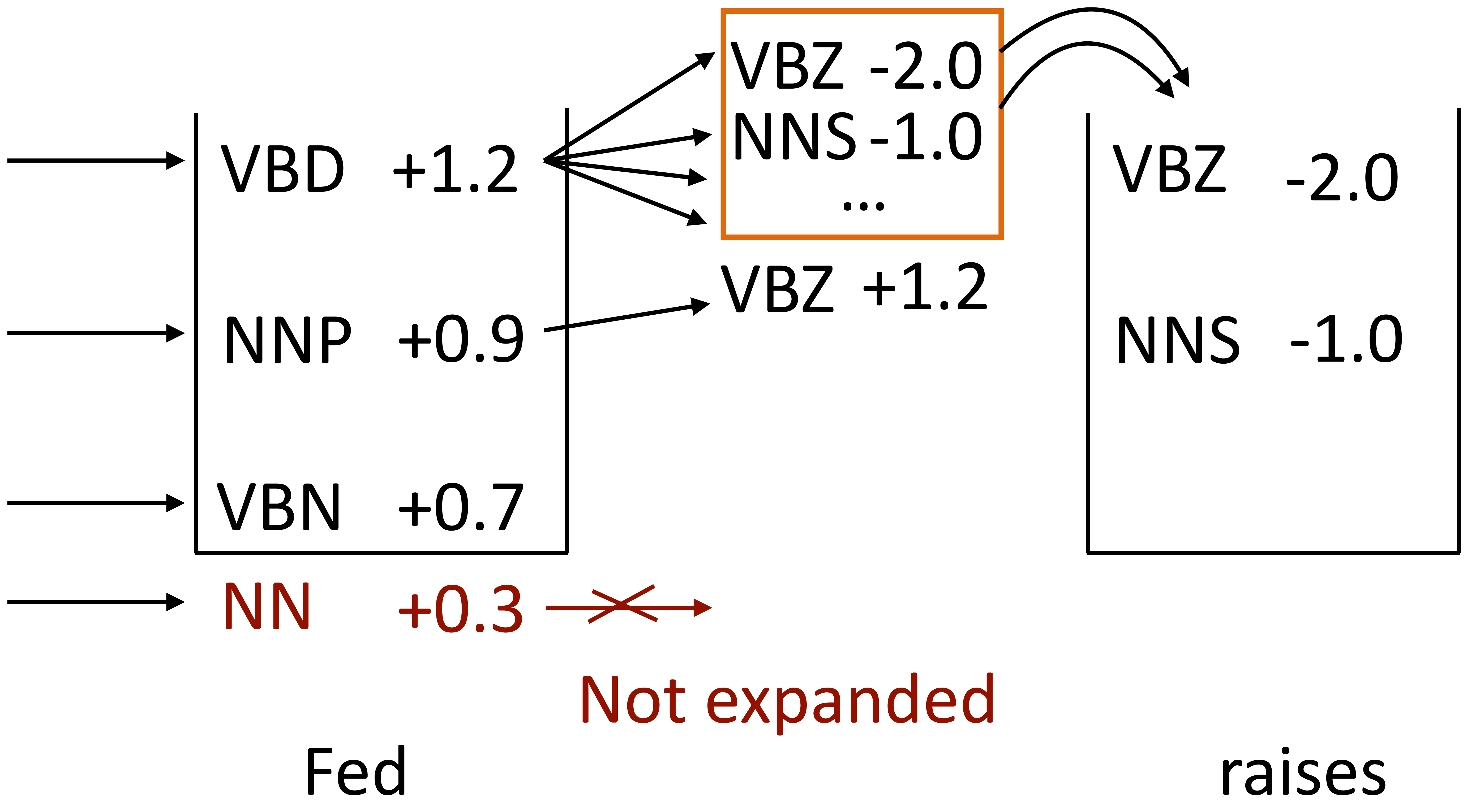

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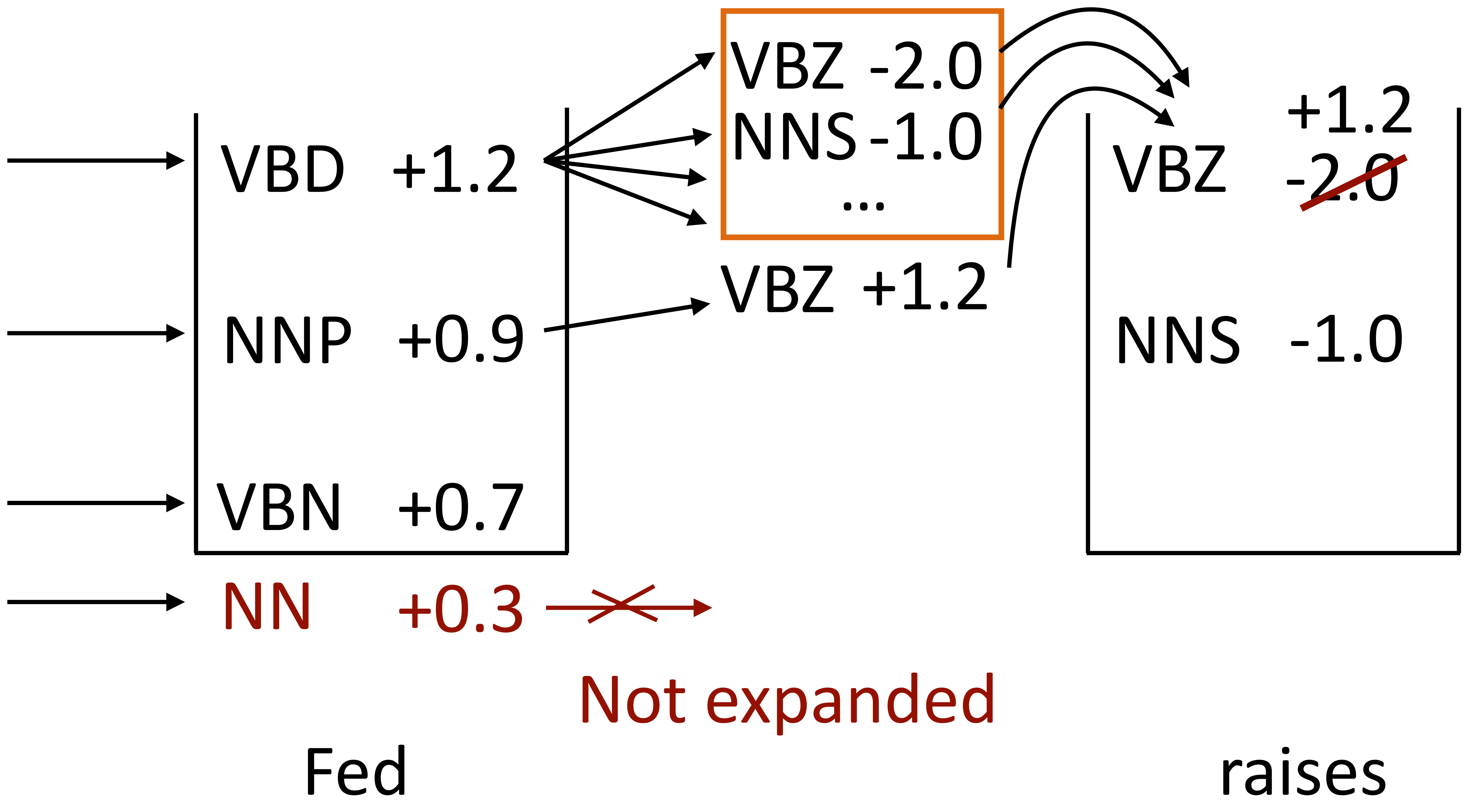

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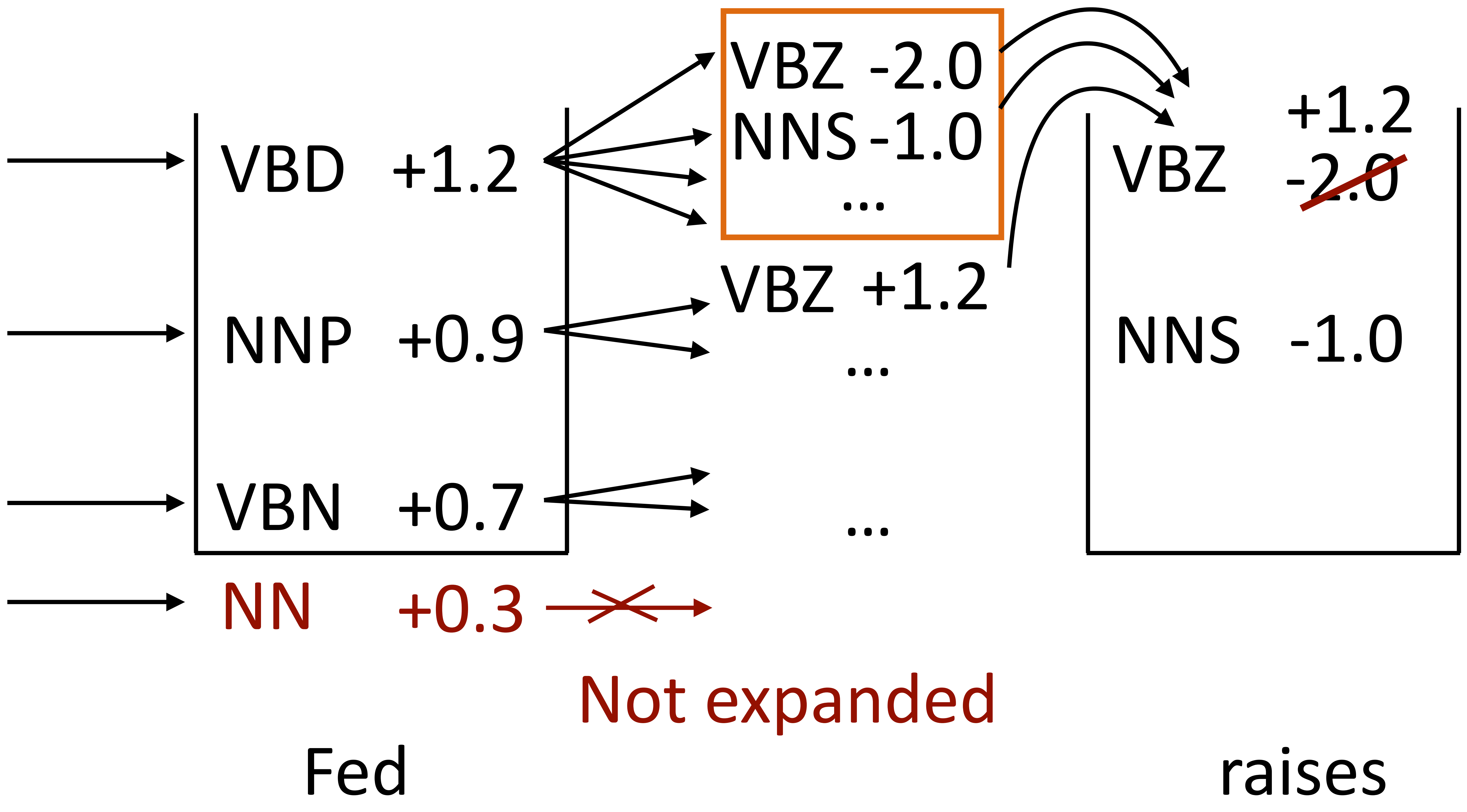

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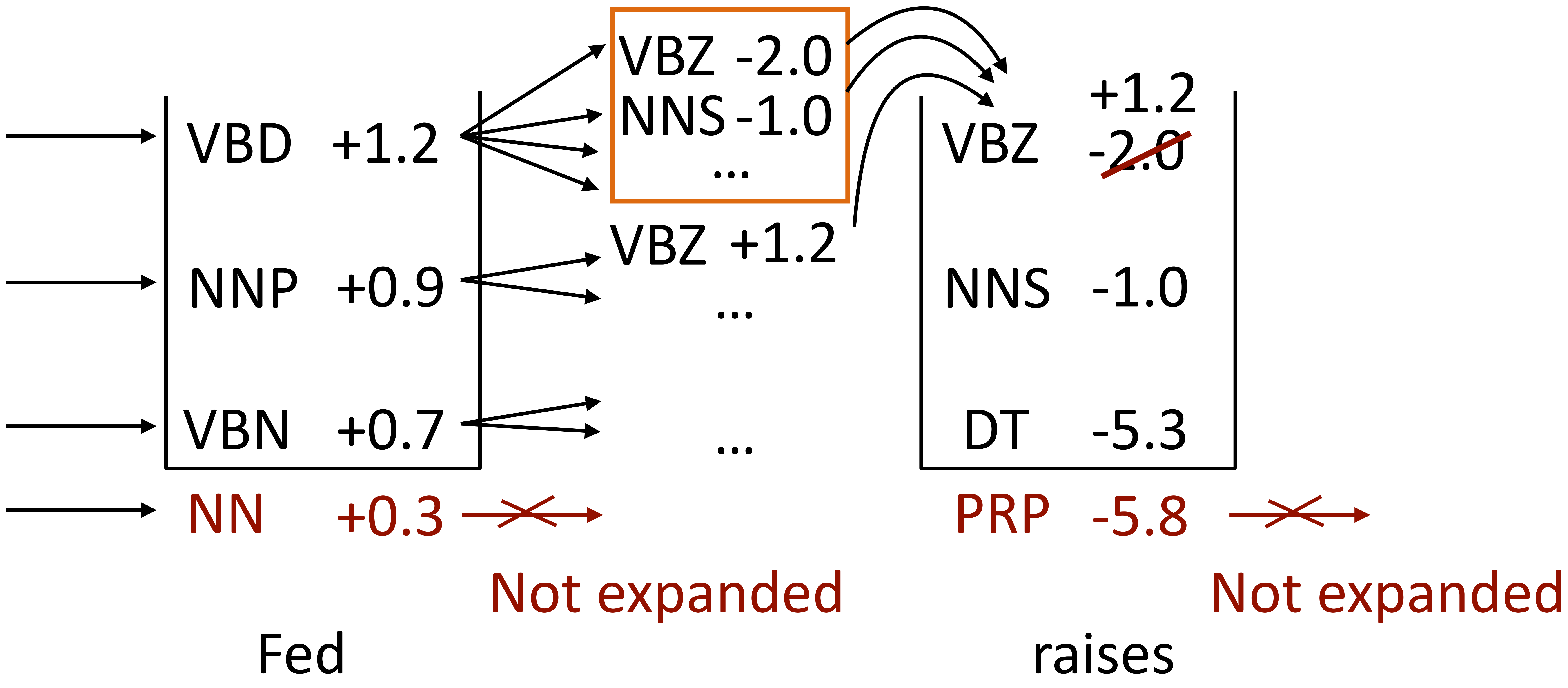

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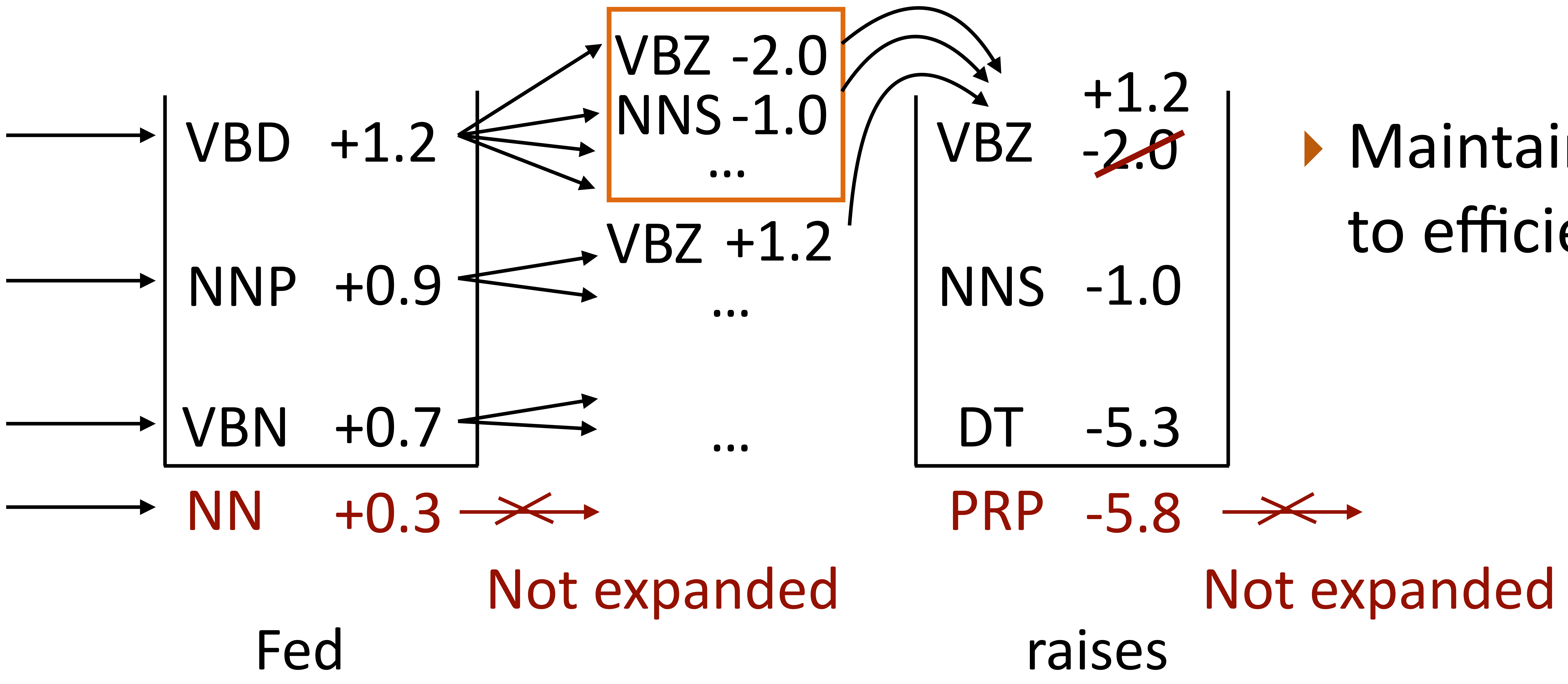


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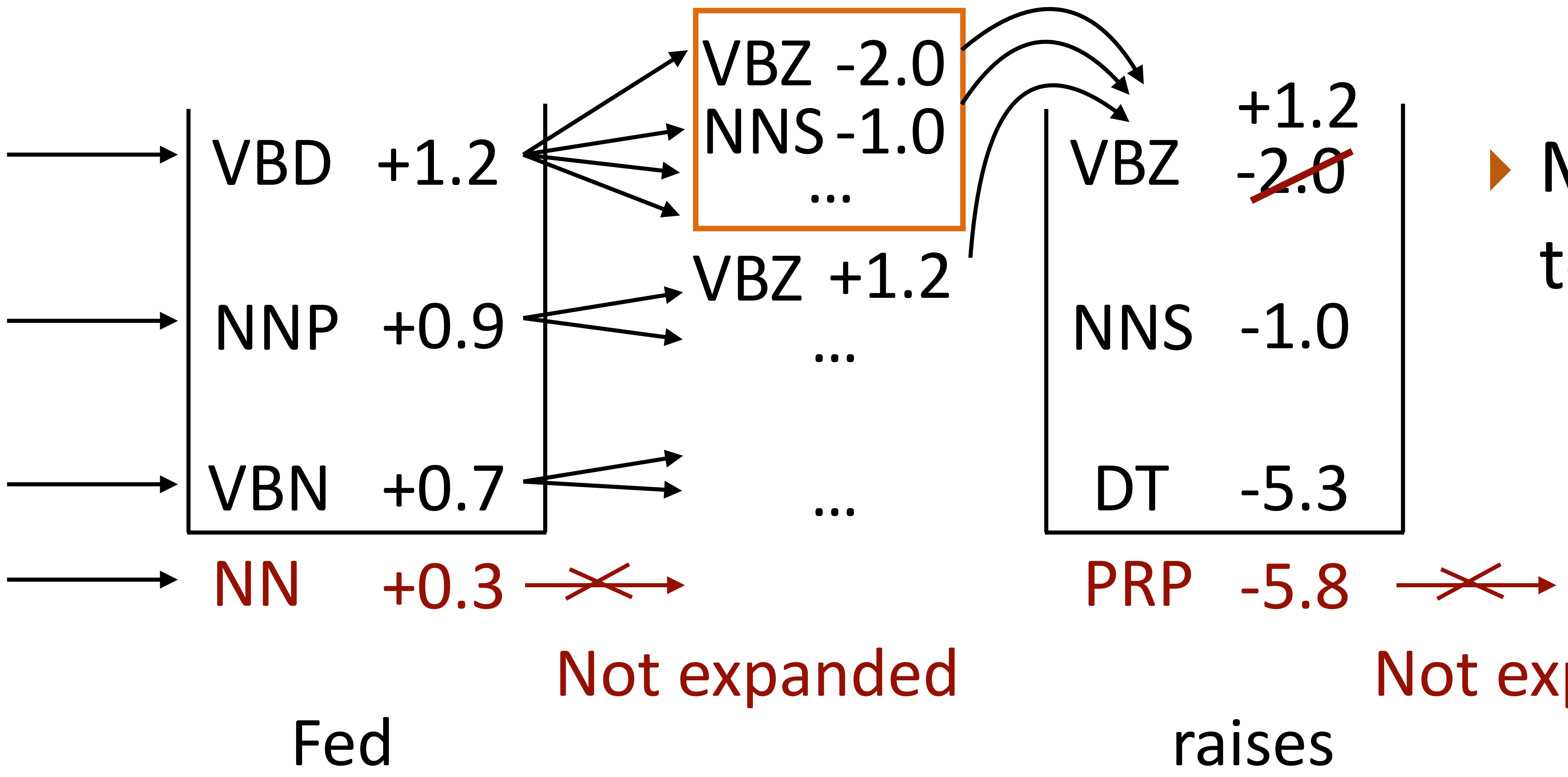


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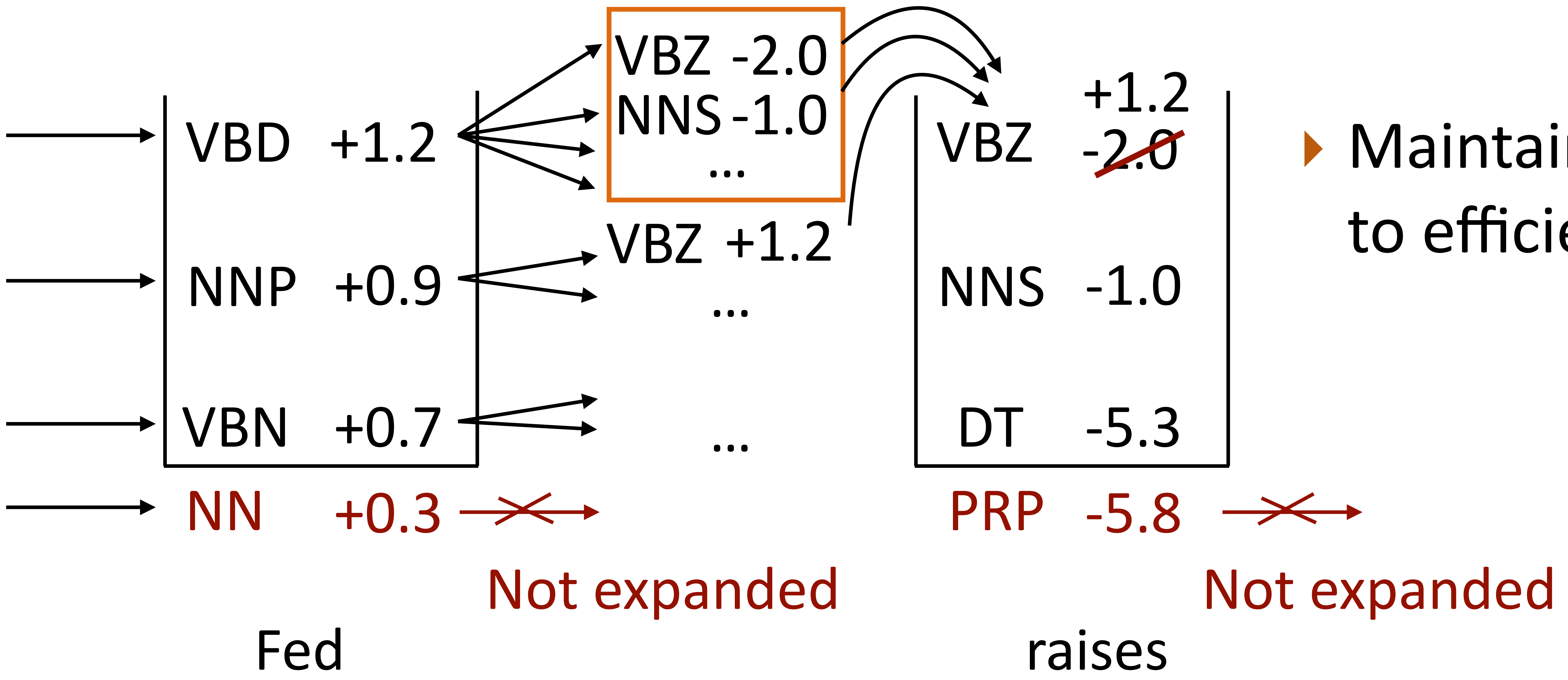


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- Beam size of k, time complexity O(nks log(ks))

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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