Review Slides

Introduction to Natural Language Processing
Computer Science 585—Fall 2009
University of Massachusetts Amherst

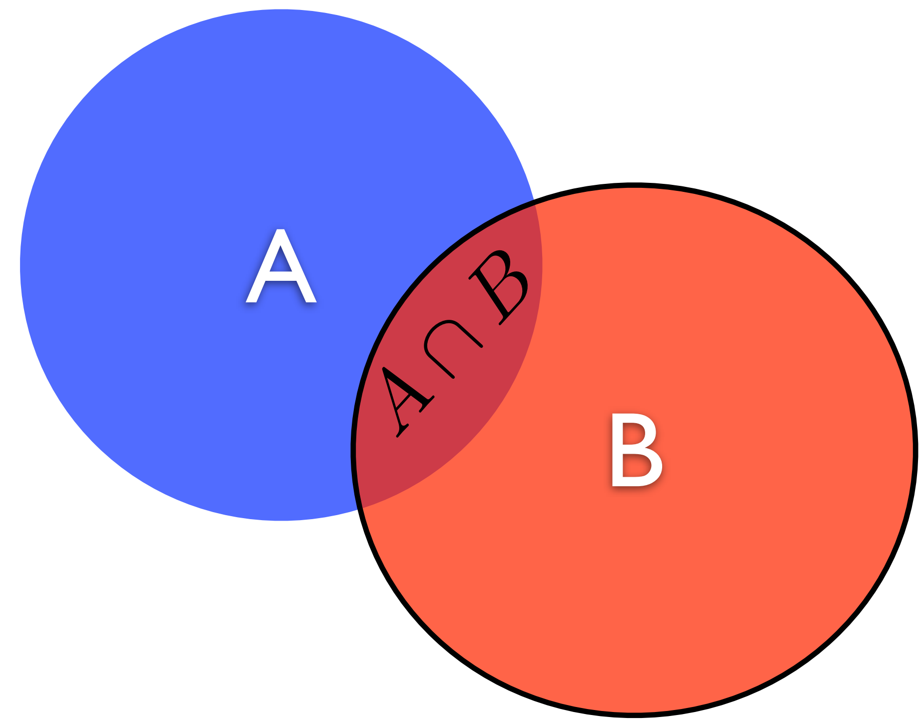
David Smith

Final Exam

- Wednesday, Dec. 16, 10:30, CS 142
- At least 2/3 from course's second half
- Focus on modeling techniques, such as:
  - Log-linear models
  - Sequence labeling, e.g. for information extraction
  - Formal semantics, simple λ-expressions
  - Word clustering
  - Simple machine translation algorithms: IBM Model-1, ITG

Conditional Probability

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$



$$P(A,B) = P(B)P(A \mid B) = P(A)P(B \mid A)$$

$$\begin{aligned} P(A_1, A_2, \ldots, A_n) &= P(A_1)P(A_2 \mid A_1)P(A_3 \mid A_1, A_2) \\ &\quad \cdots P(A_n \mid A_1, \ldots, A_{n-1}) \end{aligned}$$

Chain rule

Independence

$$
\begin{array}{rcl}
P(A, B) & = & P(A)P(B) \\
& \Leftrightarrow & \\
P(A \mid B) = P(A) & \wedge & P(B \mid A) = P(B)
\end{array}
$$

In coding terms, knowing *B* doesn't help in decoding *A*, and vice versa.

Another View of Markov Models

$$
\begin{aligned}
p(w_1, w_2, \ldots, w_n) \quad &= \quad p(w_1)p(w_2 \mid w_1)p(w_3 \mid w_1, w_2) \\
&\quad\quad p(w_4 \mid w_1, w_2, w_3) \cdots p(w_n \mid p_1, \ldots, p_{n-1})
\end{aligned}
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Markov independence assumption

$$p(w_i \mid w_1, \ldots w_{i-1}) \approx p(w_i \mid w_{i-1})$$

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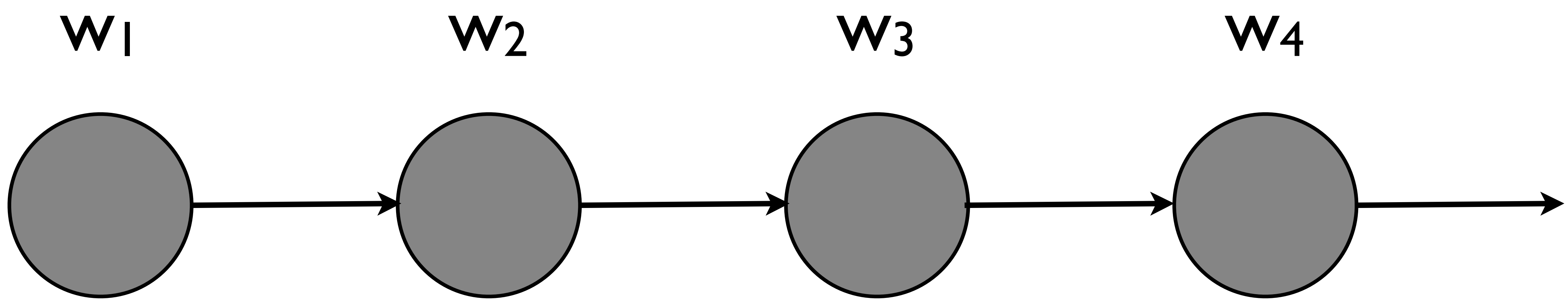

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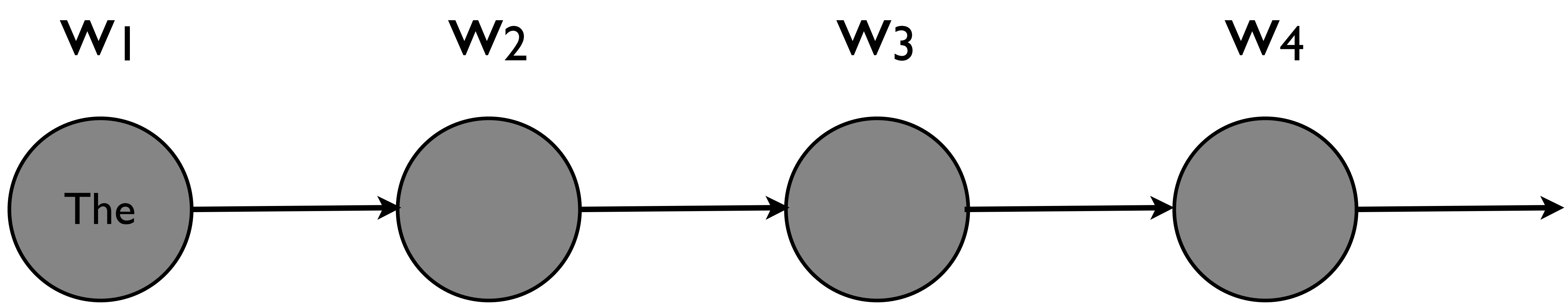

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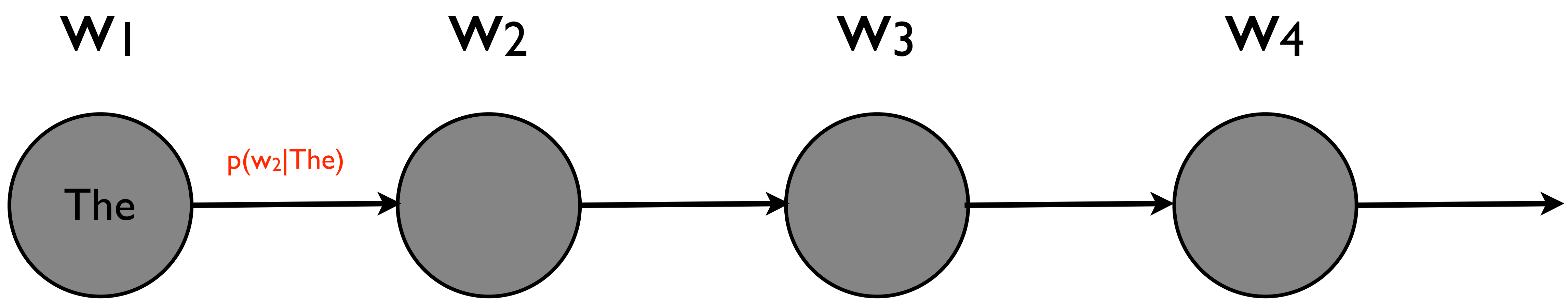

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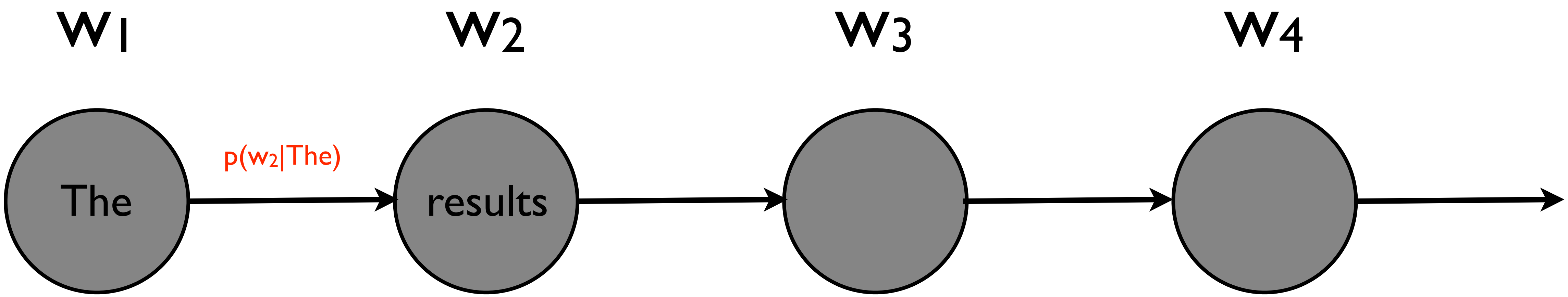

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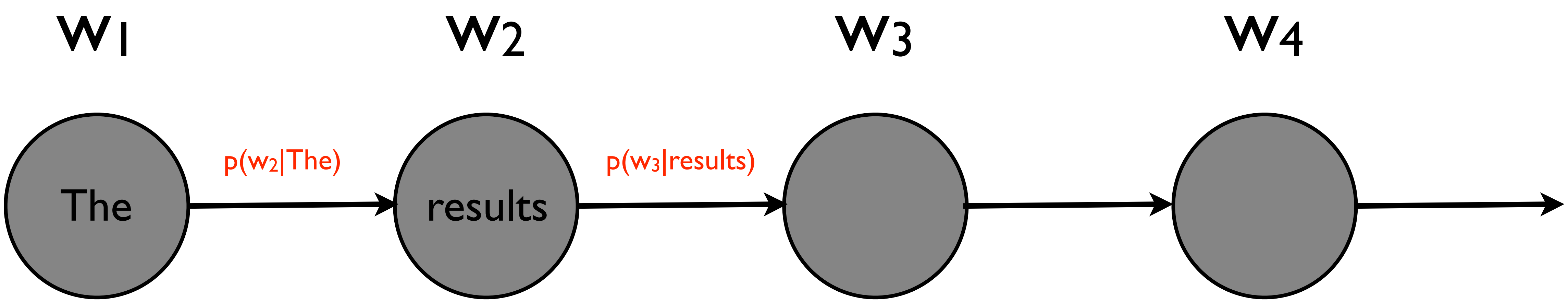

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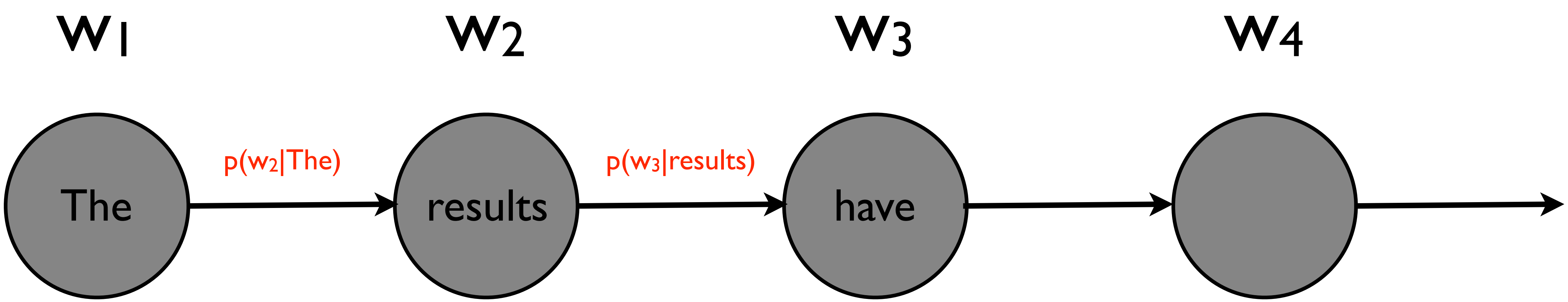

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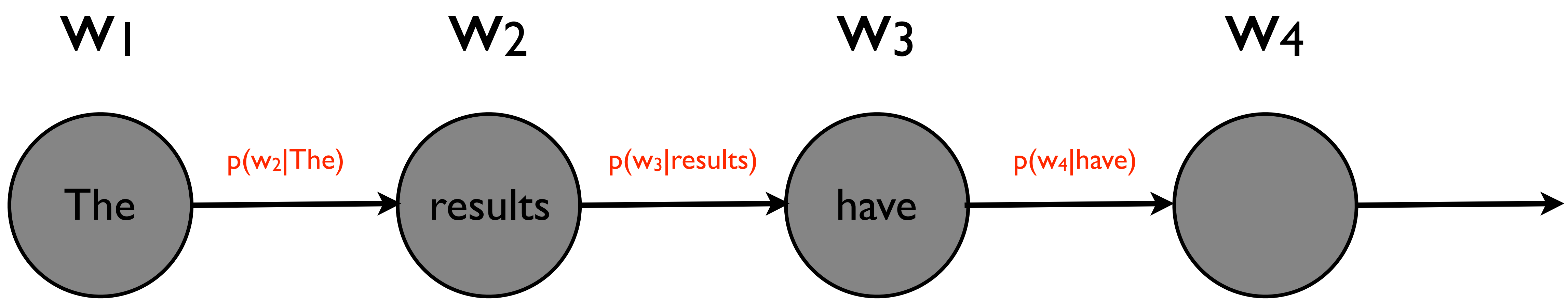

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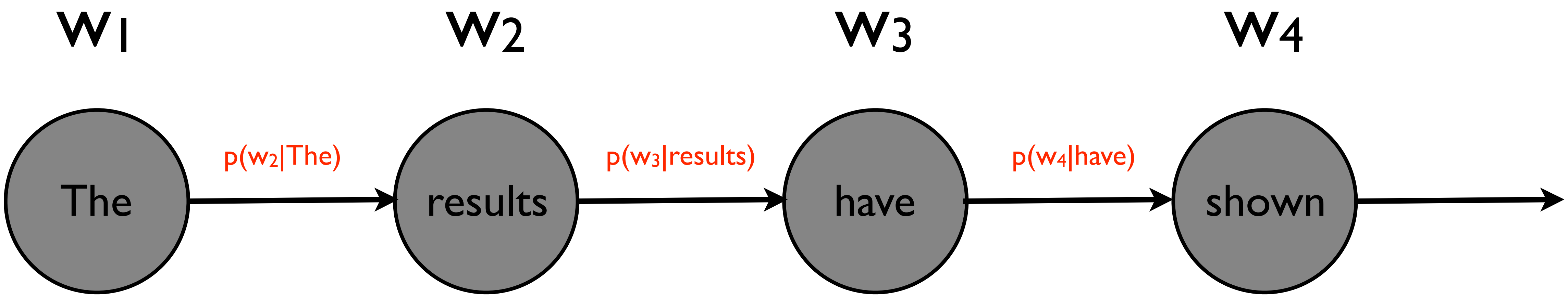

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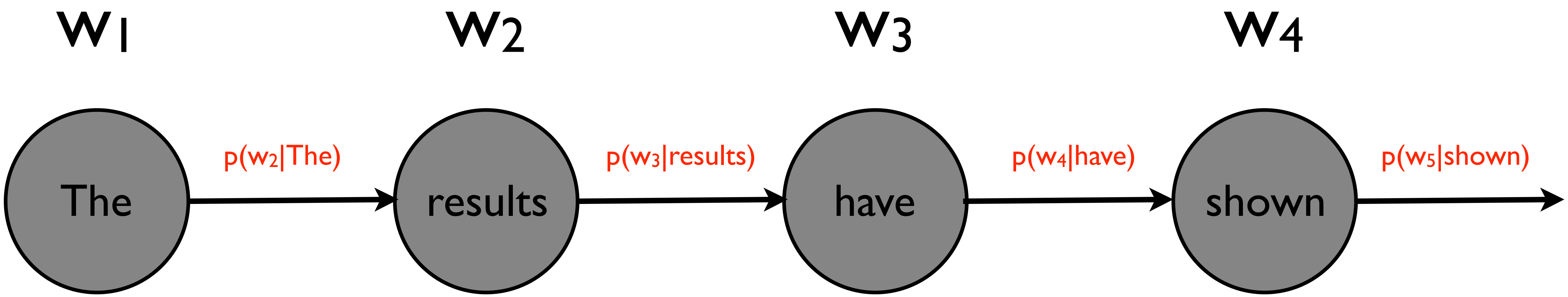
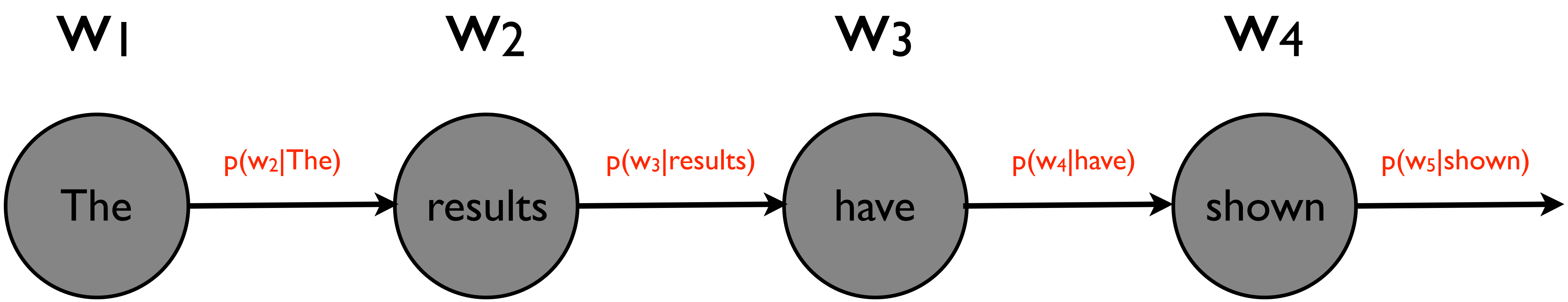


Yet Another View

Directed graphical models: *lack* of edge means conditional independence



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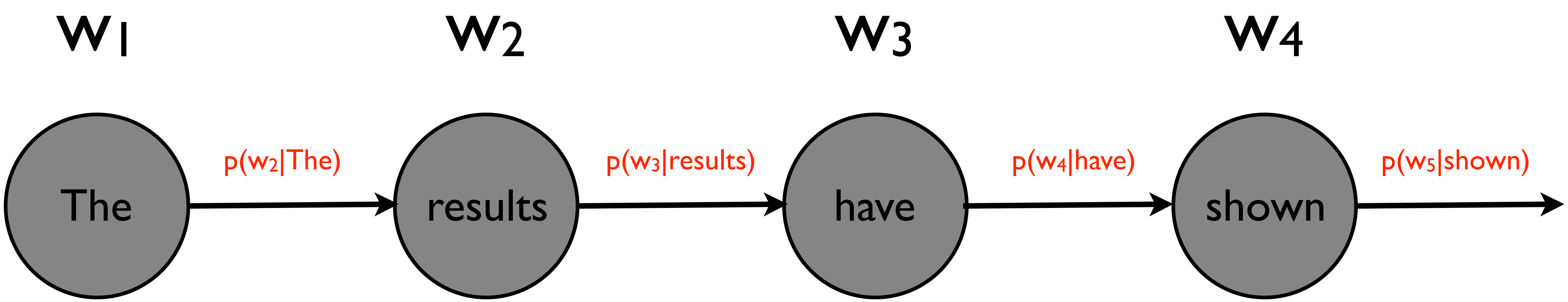

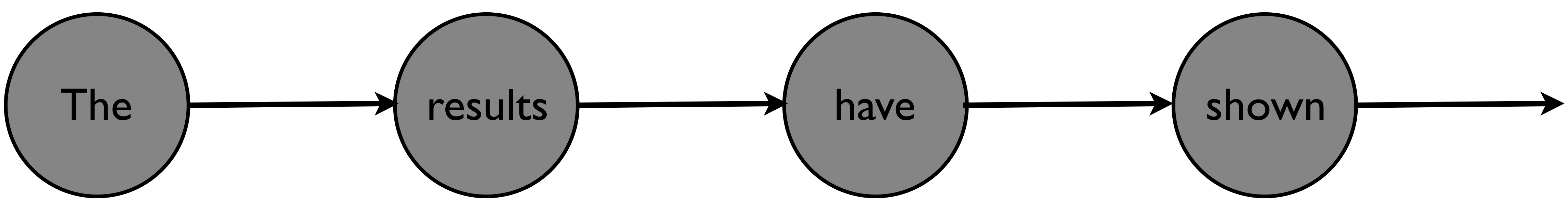

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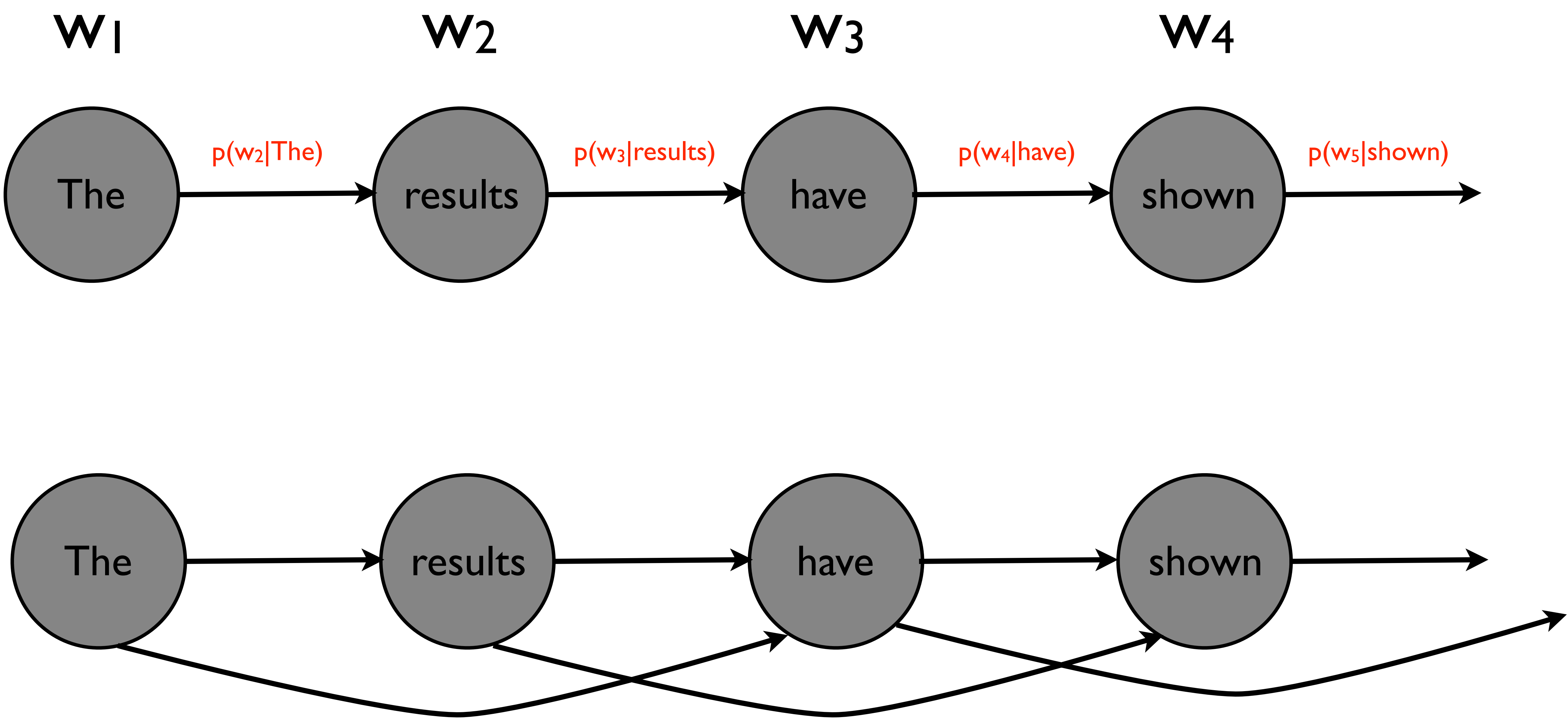

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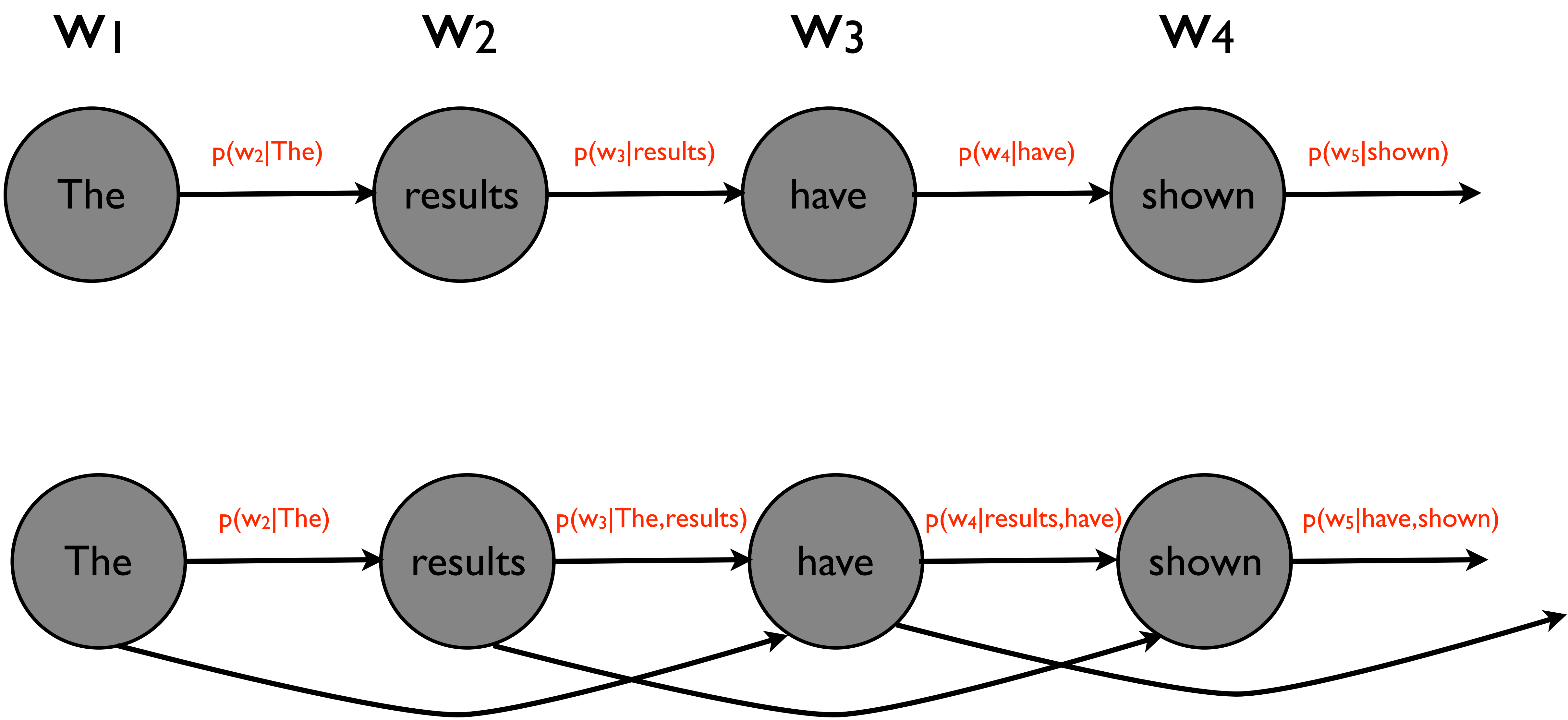
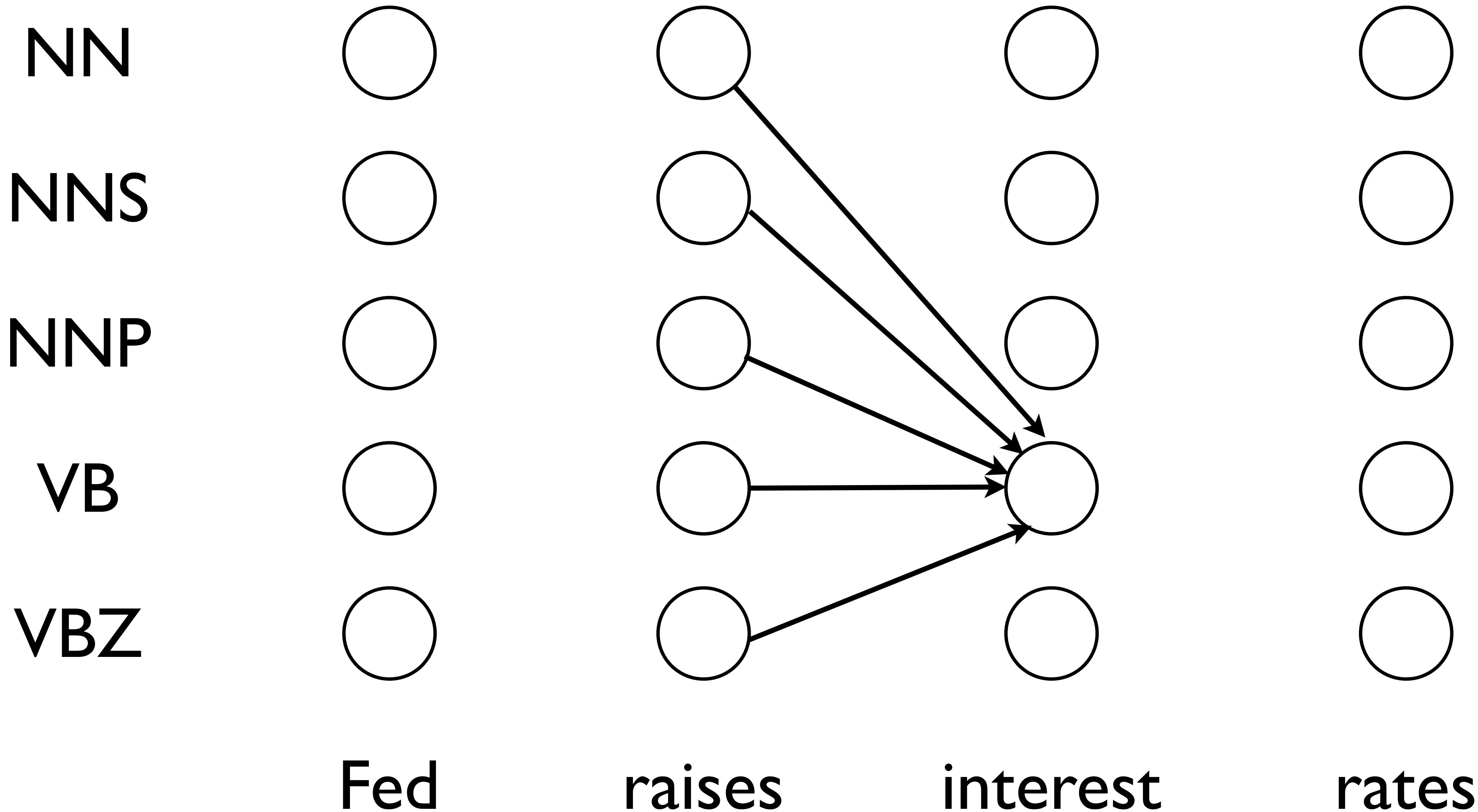


Forward Algorithm (LM)



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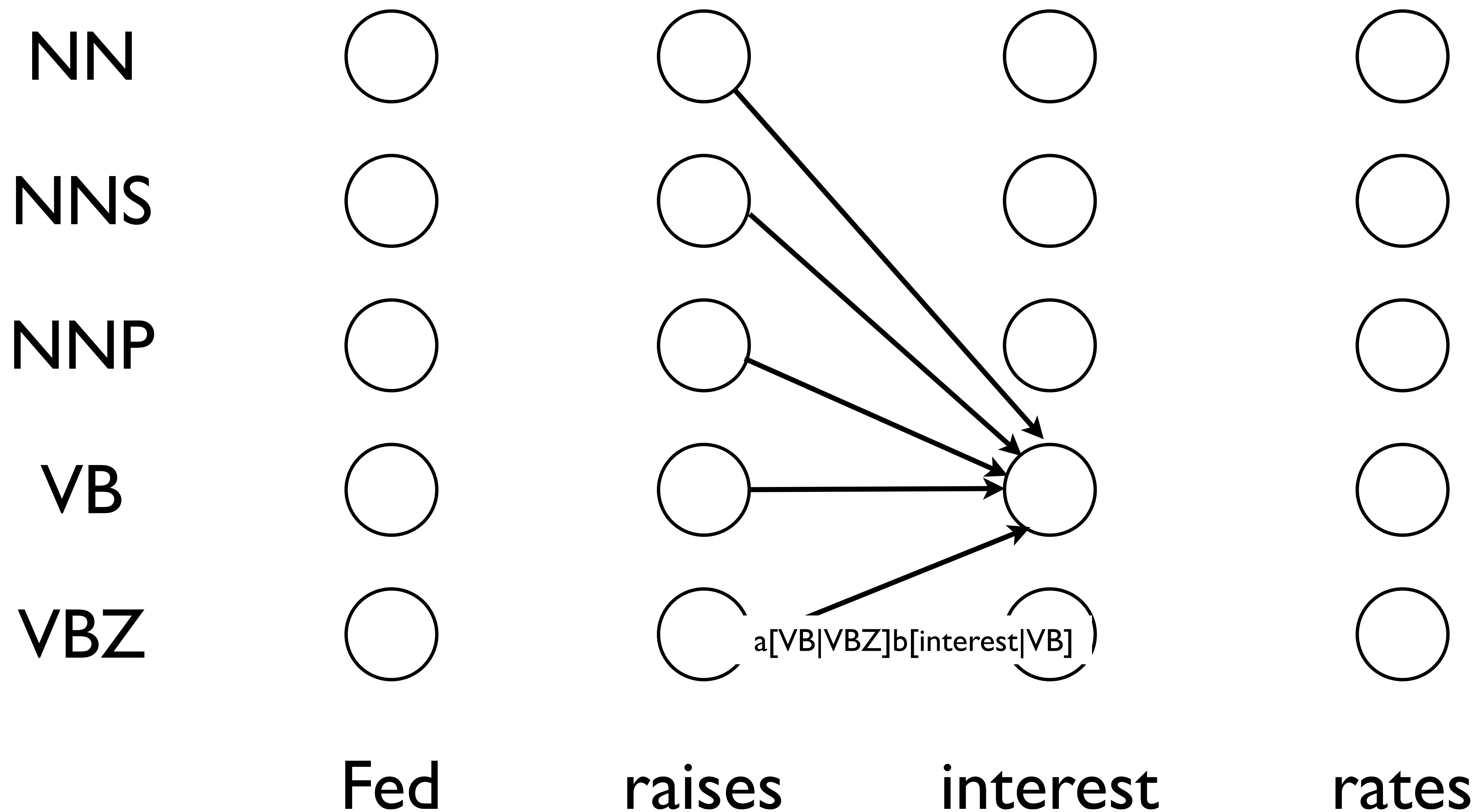

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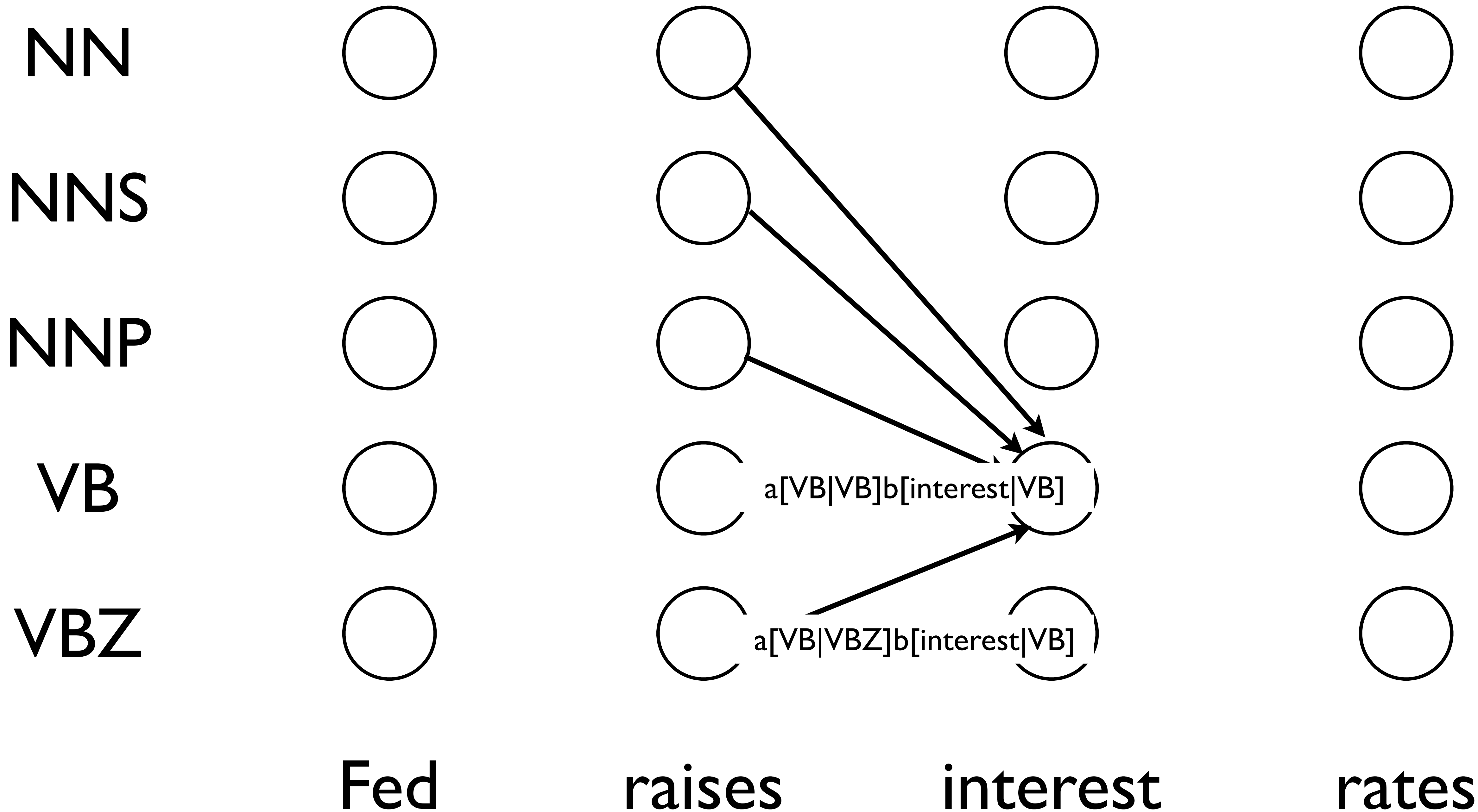

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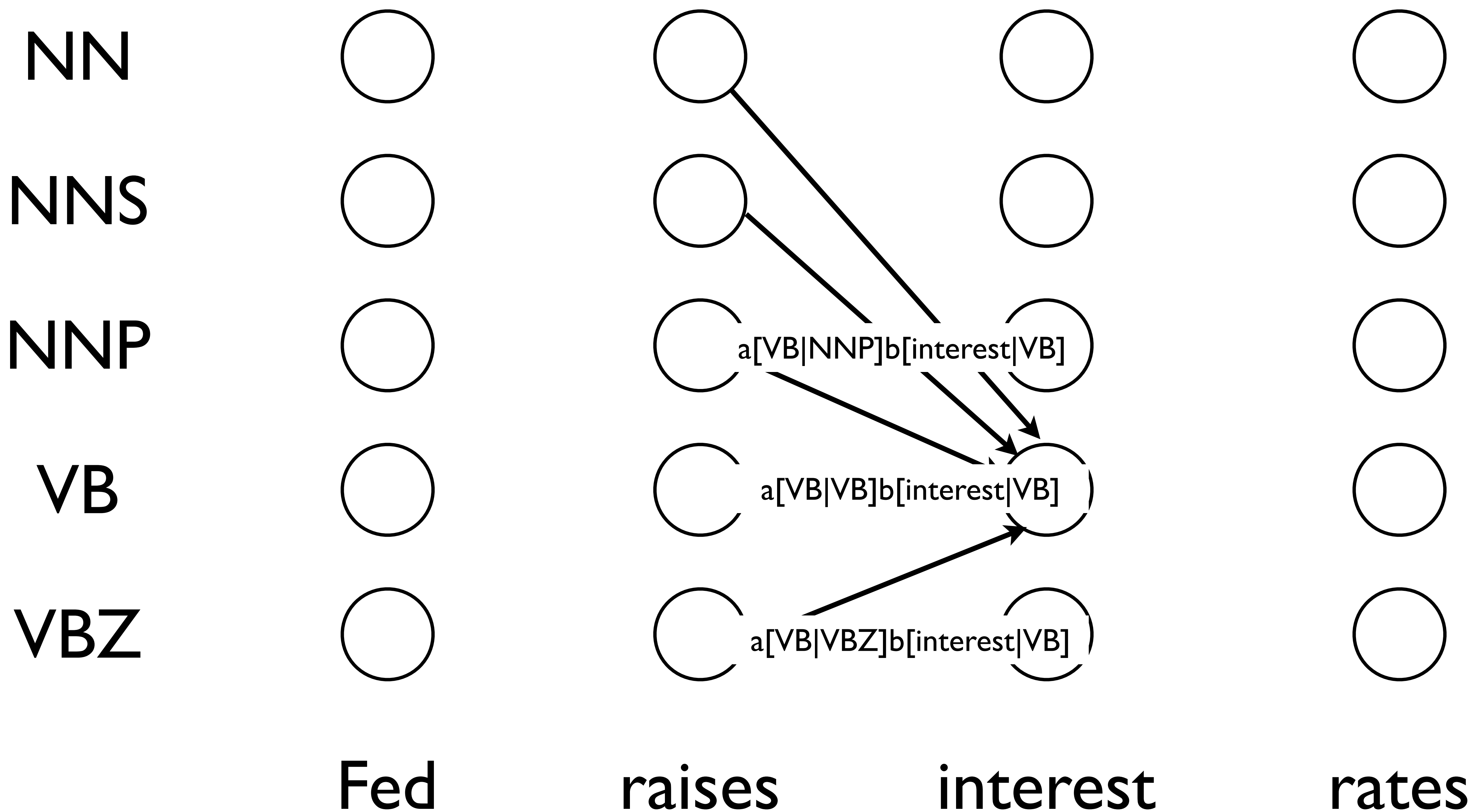

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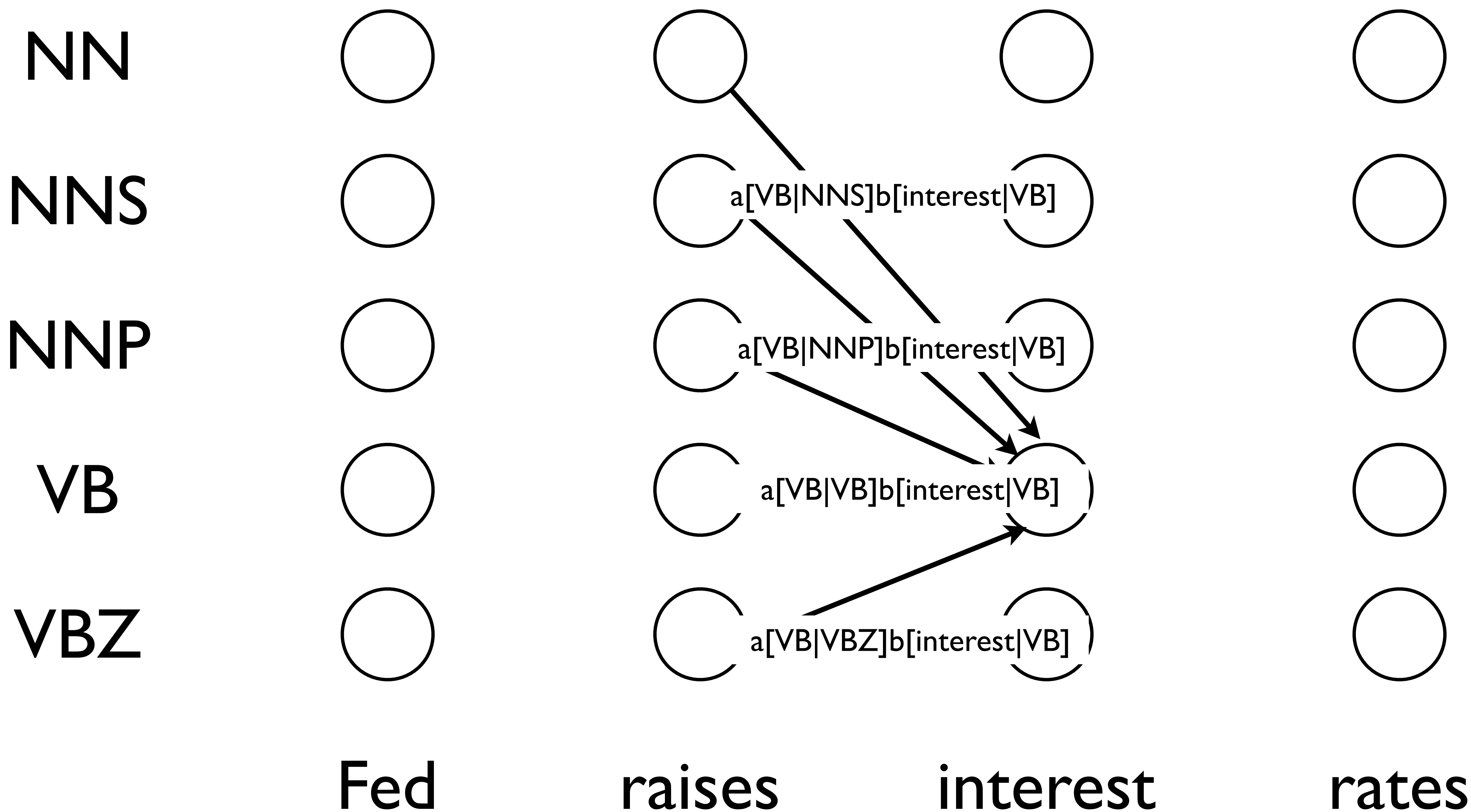

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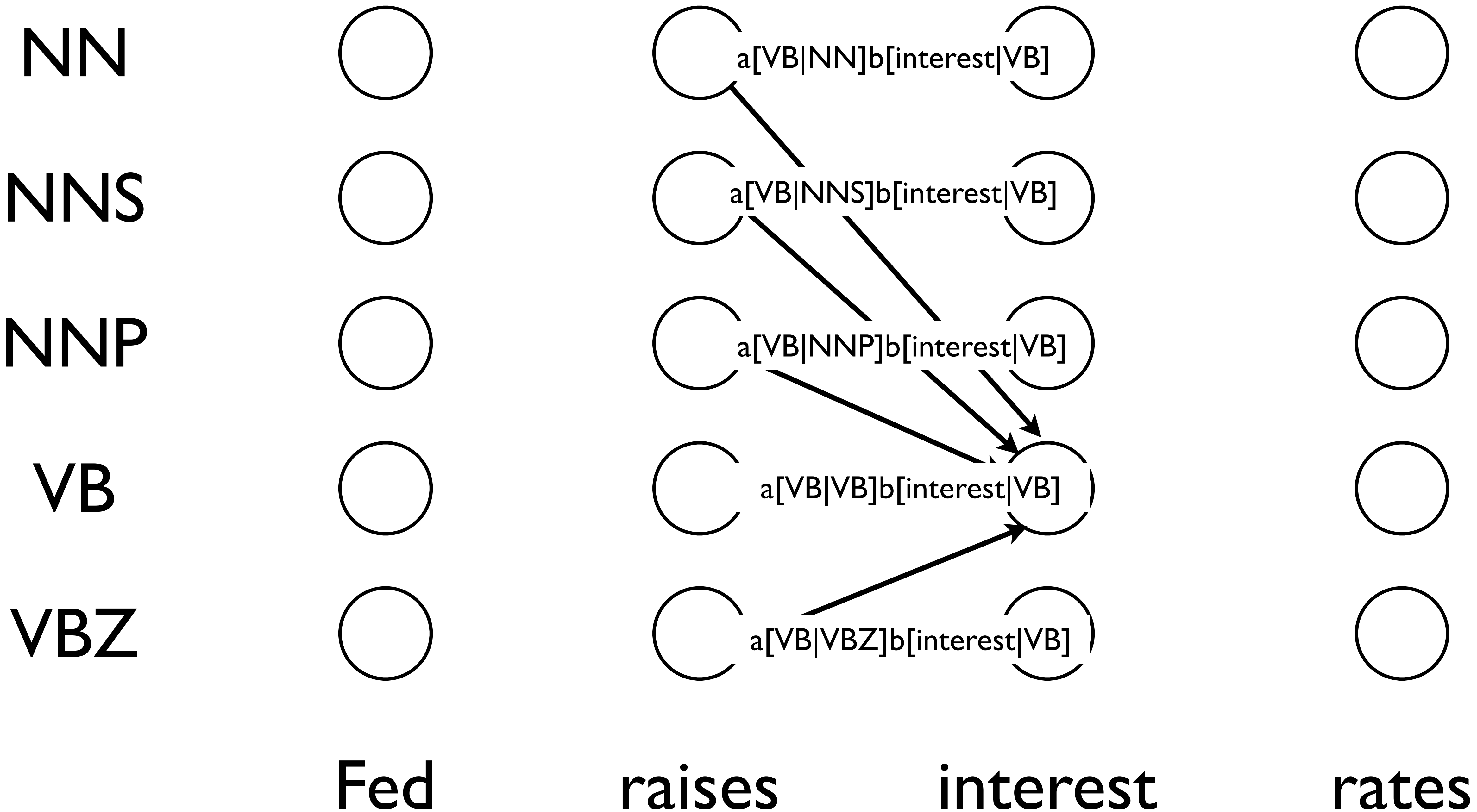

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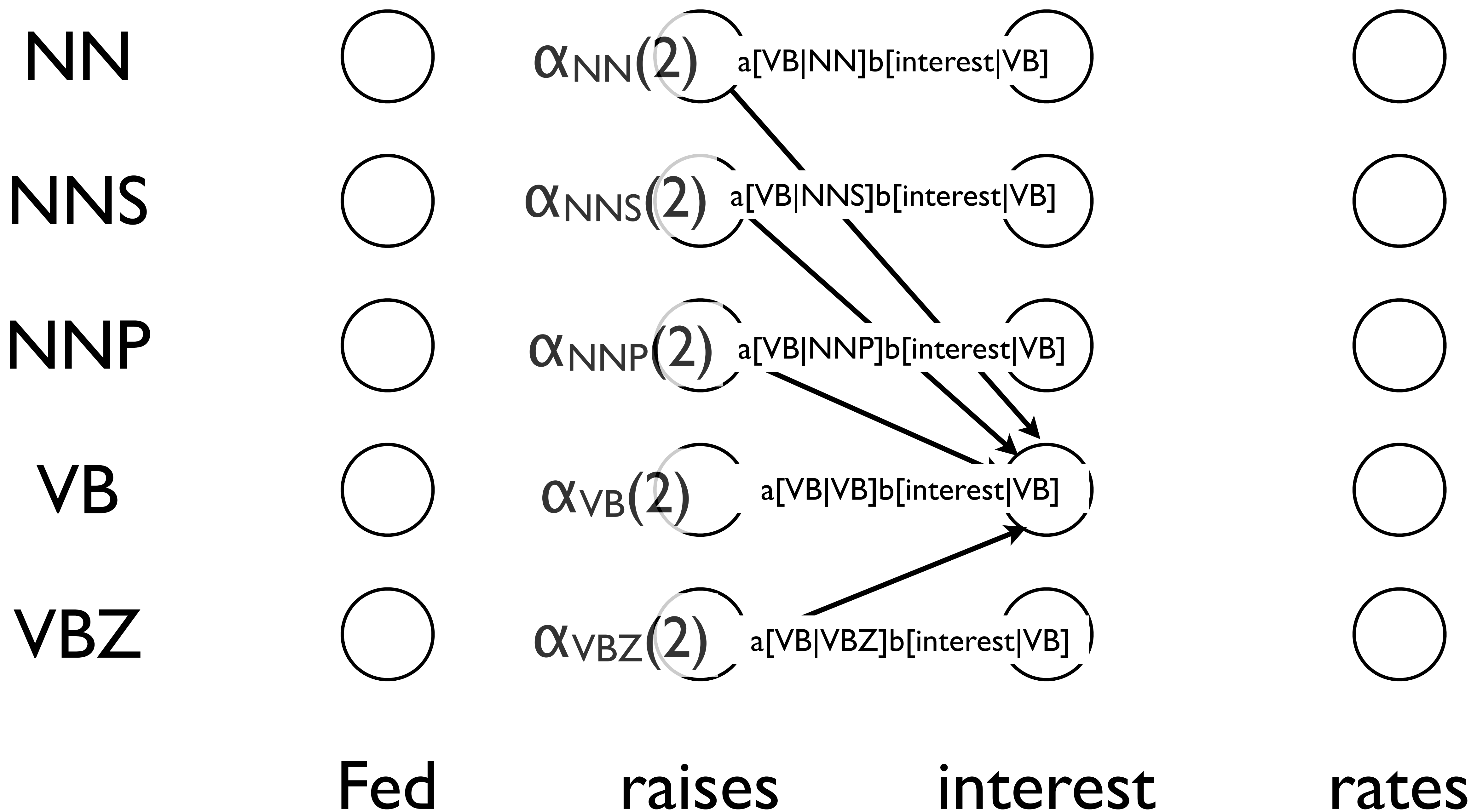

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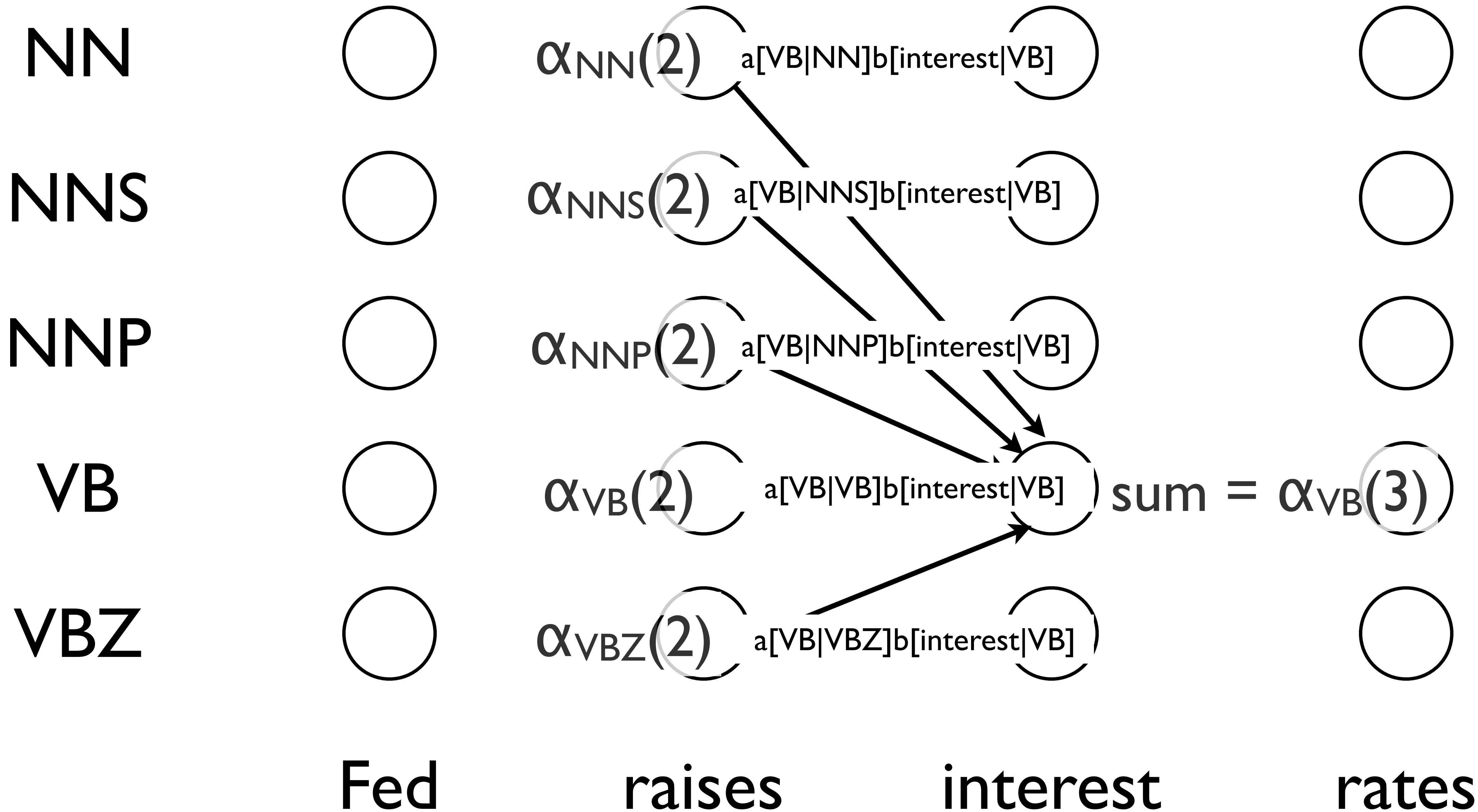

Setting up a Classifier

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- What we want:

  $p(☺ \mid w_1, w_2, ..., w_n) > p(☹ \mid w_1, w_2, ..., w_n)$?

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    - $p(w_1, w_2, ..., w_n \mid ☺)$

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Bayes' Theorem

By the definition of conditional probability:

$$P(A, B) = P(B)P(A \mid B) = P(A)P(B \mid A)$$

we can show:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

Seemingly trivial result from 1763; interesting consequences...

REV. T. BAYES

A “Bayesian” Classifier

$$p(R \mid w_1, w_2, \ldots, w_n) = \frac{p(R)p(w_1, w_2, \ldots, w_n \mid R)}{p(w_1, w_2, \ldots, w_n)}$$

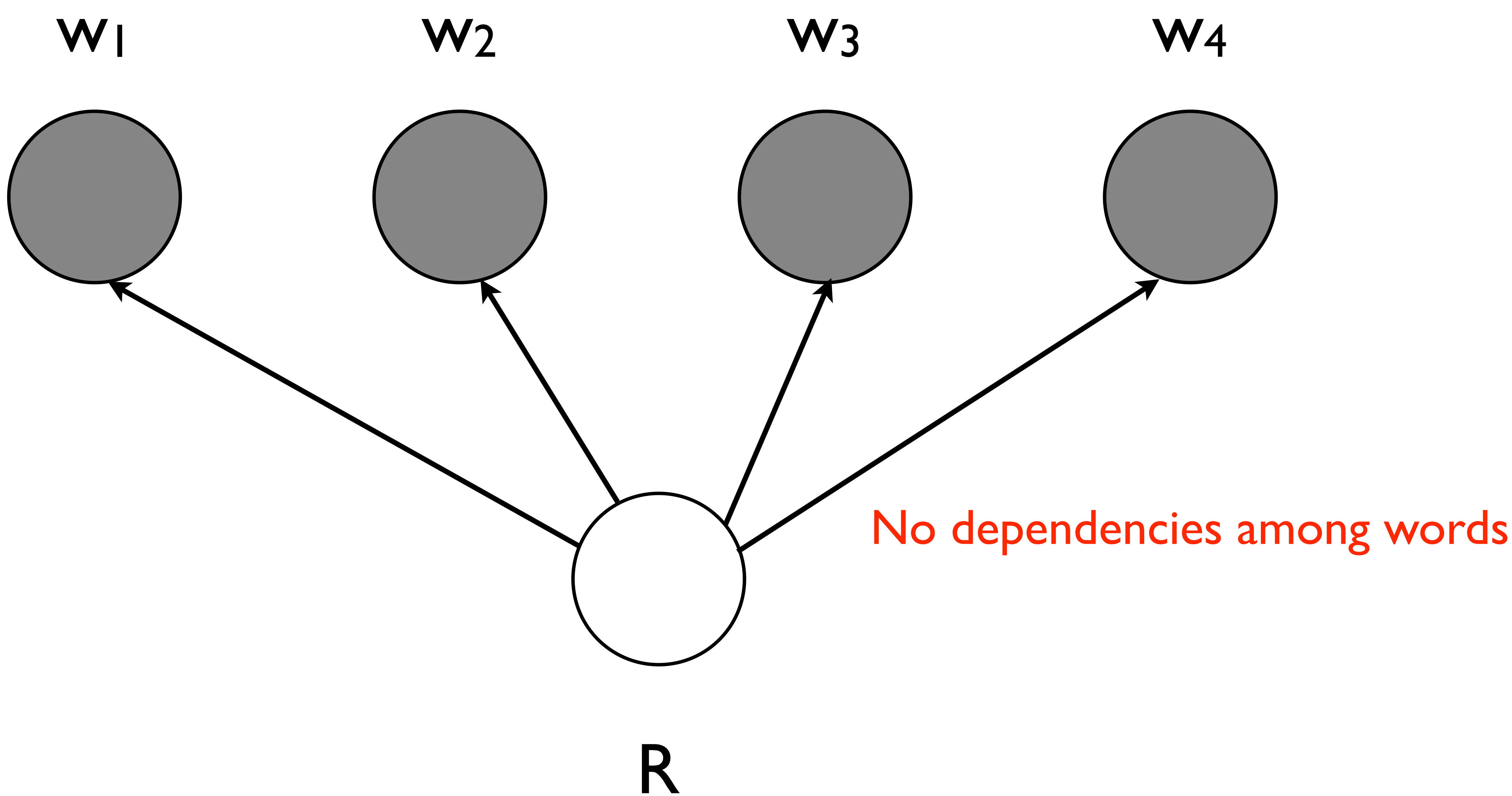
$$\max_{R \in \{\ddot\smile, \ddot\frown\}} p(R \mid w_1, w_2, \ldots, w_n) = \max_{R \in \{\ddot\smile, \ddot\frown\}} p(R)p(w_1, w_2, \ldots, w_n \mid R)$$

Posterior

Prior

Likelihood

Naive Bayes Classifier



NB on Movie Reviews

- Train models for positive, negative
- For each review, find higher posterior
- Which word probability ratios are highest?

```
>>> classifier.show_most_informative_features(5)

classifier.show_most_informative_features(5)
Most Informative Features
   contains(outstanding) = True              pos : neg    =     14.1 : 1.0
         contains(mulan) = True              pos : neg    =      8.3 : 1.0
        contains(seagal) = True              neg : pos    =      7.8 : 1.0
   contains(wonderfully) = True              pos : neg    =      6.6 : 1.0
         contains(damon) = True              pos : neg    =      6.1 : 1.0
```

What's Wrong With NB?

- What happens for word dependencies are strong?
- What happens when some words occur only once?
- What happens when the classifier sees a new word?

Generative vs. Conditional

- What is the most likely label for a given input?
- How likely is a given label for a given input?
- What is the most likely input value?
- How likely is a given input value?
- How likely is a given input value with a given label?
- What is the most likely label for an input that might have one of two values (but we don't know which)?

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Sequence Labeling

- Inputs: $x = (x_1, \ldots, x_n)$
- Labels: $y = (y_1, \ldots, y_n)$
- Typical goal: Given x, predict y

- Example sequence labeling tasks
  - Part-of-speech tagging
  - Named-entity-recognition (NER)
    - Label people, places, organizations

NER Example:

Red Sox and Their Fans Let Loose

Elise Amendola/Associated Press

Fans of the slugger David Ortiz in Boston's Copley Square.

By PETE THAMEL
Published: October 31, 2007

BOSTON, Oct. 30 — Jonathan Papelbon turned Boston's World Series victory parade into a full-scale dance party Tuesday as the Red Sox put an exclamation point on the 2007 season.

E-MAIL
PRINT
REPRINTS
SAVE

First Solution: Maximum Entropy Classifier

- Conditional model p(y|x).
  - Do not waste effort modeling p(x), since x is given at test time anyway.
  - Allows more complicated input features, since we do not need to model dependencies between them.
- Feature functions f(x,y):
  - $f_1(x,y)$ = { word is Boston & y=Location }
  - $f_2(x,y)$ = { first letter capitalized & y=Name }
  - $f_3(x,y)$ = { x is an HTML link & y=Location}

First Solution: MaxEnt Classifier

- How should we choose a classifier?

- Principle of maximum entropy
  - We want a classifier that:
    - Matches feature constraints from training data.
    - Predictions maximize entropy.

- There is a unique, exponential family distribution that meets these criteria.

First Solution: MaxEnt Classifier

- Problem with using a maximum entropy classifier for sequence labeling:
- It makes decisions at each position independently!

Second Solution: HMM

$$P(\mathbf{y},\mathbf{x}) = \prod_t P(y_t \mid y_{t-1}) P(x \mid y_t)$$

- Defines a generative process.
- Can be viewed as a weighted finite state machine.

Second Solution: HMM

- HMM problems: (ON BOARD)
  - Probability of an input sequence.
  - Most likely label sequence given an input sequence.
  - Learning with known label sequences.
  - Learning with unknown label sequences?

Second Solution: HMM

- How can represent we multiple features in an HMM?
  - Treat them as conditionally independent given the class label?
    - The example features we talked about are not independent.
  - Try to model a more complex generative process of the input features?
    - We may lose tractability (i.e. lose a dynamic programming for exact inference).

Second Solution: HMM

- Let's use a conditional model instead.

Third Solution: MEMM

- Use a series of maximum entropy classifiers that know the previous label.
- Define a Viterbi algorithm for inference.

$$P(\mathbf{y} \mid \mathbf{x}) = \prod_t P(y_t \mid y_{t-1}, \mathbf{x})$$

Third Solution: MEMM

- Combines the advantages of maximum entropy and HMM!
- But there is a problem…

Problem with MEMMs: Label Bias

- In some state space configurations, MEMMs essentially completely ignore the inputs.

- Example (ON BOARD).

- This is not a problem for HMMs, because the input sequence is generated by the model.

Fourth Solution: Conditional Random Field

- Conditionally-trained, undirected graphical model.
- For a standard linear-chain structure:

$$P(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z} \prod_t \Psi_t(y_t, y_{t-1}, \mathbf{x})$$

Bigram model: potentials consider pairs of labels

$$\Psi_t(y_t, y_{t-1}, \mathbf{x}) = \exp\left[\sum_k \lambda_k f_k(y_t, y_{t-1}, \mathbf{x})\right]$$

Dot-product of weights and features

$$Z = \sum_{\mathbf{y}'} \prod_t \Psi(y'_t, y'_{t-1}, \mathbf{x})$$

Normalize over all possible outputs using forward alg.

Fourth Solution: CRF

- Have the advantages of MEMMs, but avoid the label bias problem.

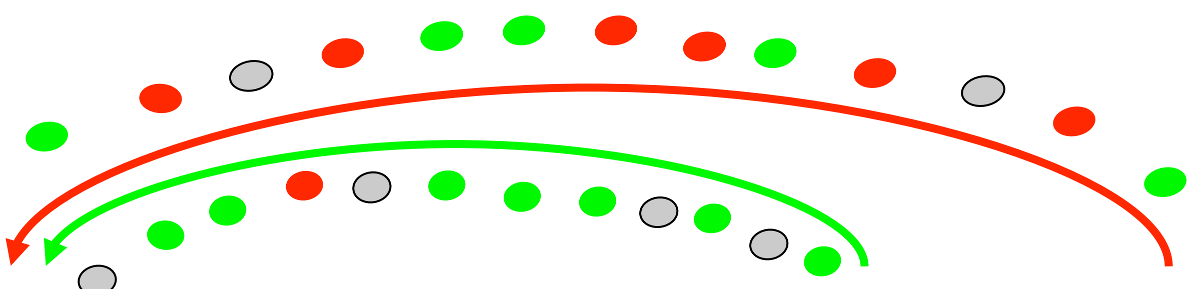
- CRFs are globally normalized, whereas MEMMs are locally normalized.

- Widely used and applied. CRFs give state-the-art results in many domains.

Example Applications

- CRFs have been applied to:
  - Part-of-speech tagging
  - Named-entity-recognition
  - Table extraction
  - Gene prediction
  - Chinese word segmentation
  - Extracting information from research papers.
  - Many more…

Edge-Factored Parsers (McDonald et al. 2005)



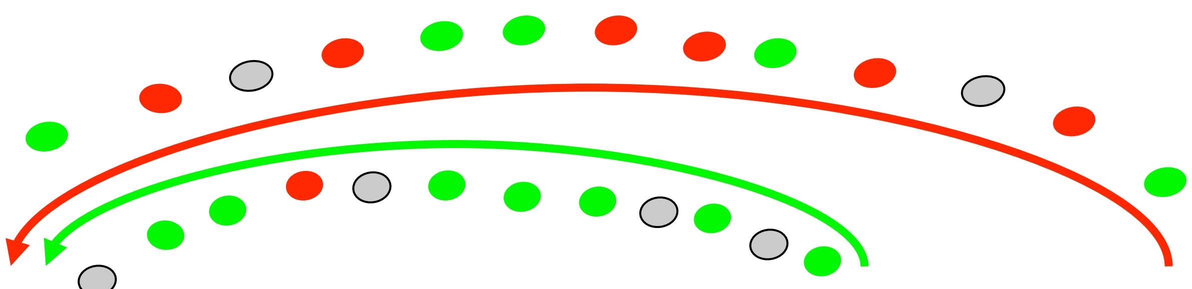
Byl	jasný	studený	dubnový	den	a	hodiny	odbíjely	třináctou
V	A	A	A	N	J	N	V	C
byl	jasn	stud	dubn	den	a	hodi	odbí	třin

"It was a bright cold day in April and the clocks were striking thirteen"

31

Edge-Factored Parsers (McDonald et al. 2005)

- Which edge is better?



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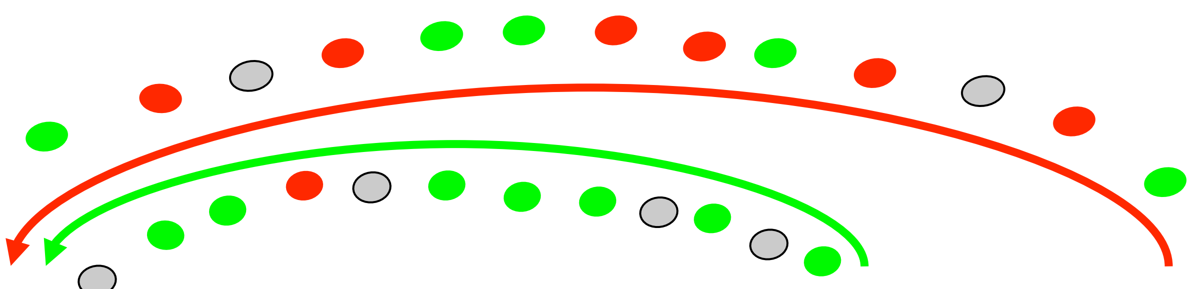
- Which edge is better?

our current weight vector



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Edge-Factored Parsers (McDonald et al. 2005)

- Which edge is better?
- Score of an edge e = θ · **features**(e)

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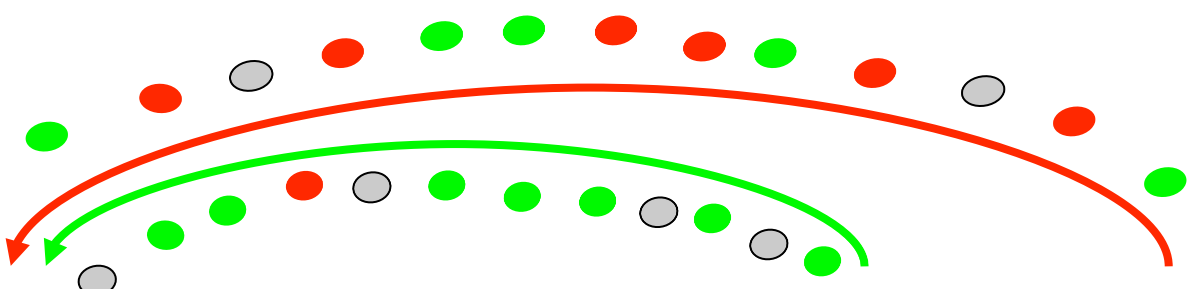

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Edge-Factored Parsers (McDonald et al. 2005)

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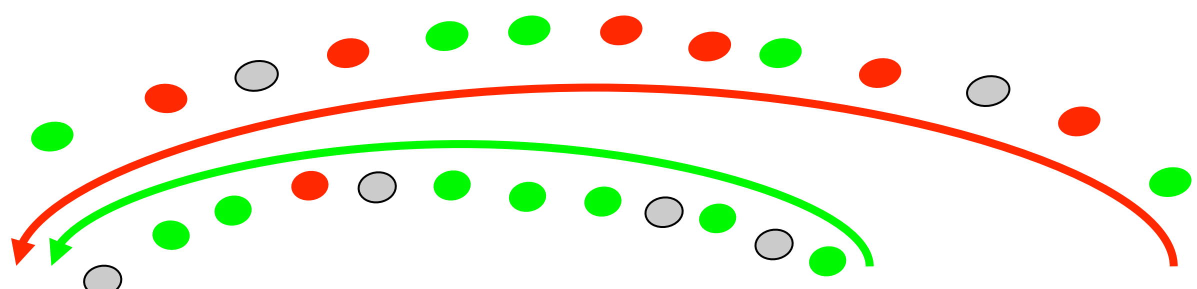
- Score of an edge e = θ · **features**(e)
- Standard algos ➔ valid parse with max <u>total</u> score

our current weight vector



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Recipe for Conditional Training of p(y | x)

1. Gather constraints/features from training data

$$\alpha_{iy} = \tilde{E}[f_{iy}] = \sum_{x_j, y_j \in D} f_{iy}(x_j, y_j)$$

2. Initialize all parameters to zero
3. Classify training data with current parameters; calculate expectations $E_\Theta[f_{iy}] = \sum_{x_j \in D} \sum_{y'} p_\Theta(y'|x_j) f_{iy}(x_j, y')$
4. Gradient is $\tilde{E}[f_{iy}] - E_\Theta[f_{iy}]$
5. Take a step in the direction of the gradient
6. Repeat from 3 until convergence

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EM!

Where have we seen expected counts before?

Gradient-Based Training

- $\lambda := \lambda + \text{rate} * \text{Gradient}(F)$
- After all training examples? (batch)
- After every example? (on-line)
- Use second derivative for faster learning?
- A big field: numerical optimization

Overfitting

- If we have too many features, we can choose weights to model the training data perfectly
- If we have a feature that only appears in spam training, not ham training, it will get weight ∞ to maximize p(spam | feature) at 1.
- These behaviors
  - Overfit the training data
  - Will probably do poorly on test data

Solutions to Overfitting

- Throw out rare features.
  - Require every feature to occur > 4 times, and > 0 times with ling, and > 0 times with spam.
- Only keep, e.g., 1000 features.
  - Add one at a time, always greedily picking the one that most improves performance on held-out data.
- Smooth the observed feature counts.
- Smooth the weights by using a prior.
  - max $p(\lambda|data)$ = max $p(\lambda, data) = p(\lambda)p(data|\lambda)$
  - decree $p(\lambda)$ to be high when most weights close to 0

Smoothing with Priors

- What if we had a prior expectation that parameter values wouldn't be very large?
- We could then balance evidence suggesting large (or infinite) parameters against our prior expectation.
- The evidence would never totally defeat the prior, and parameters would be smoothed (and kept finite)
- We can do this explicitly by changing the optimization objective to maximum posterior likelihood:

  $\log P(y, \lambda \mid x) = \log P(\lambda) + \log P(y \mid x, \lambda)$

  Posterior Prior Likelihood

(First Order) Logic
Some Preliminaries

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Three major kinds of objects

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    - "In the set of goldfish there exists one swallowed by Gilly"
- Here goldfish is a predicate on entities
  - This is the same semantic type as red
  - But note: `goldfish` is noun and `red` is adjective

Compositional Semantics

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- Add a “sem” feature to each context-free rule
  - S $\rightarrow$ NP loves NP
  - S[sem=loves(x,y)] $\rightarrow$ NP[sem=x] loves NP[sem=y]
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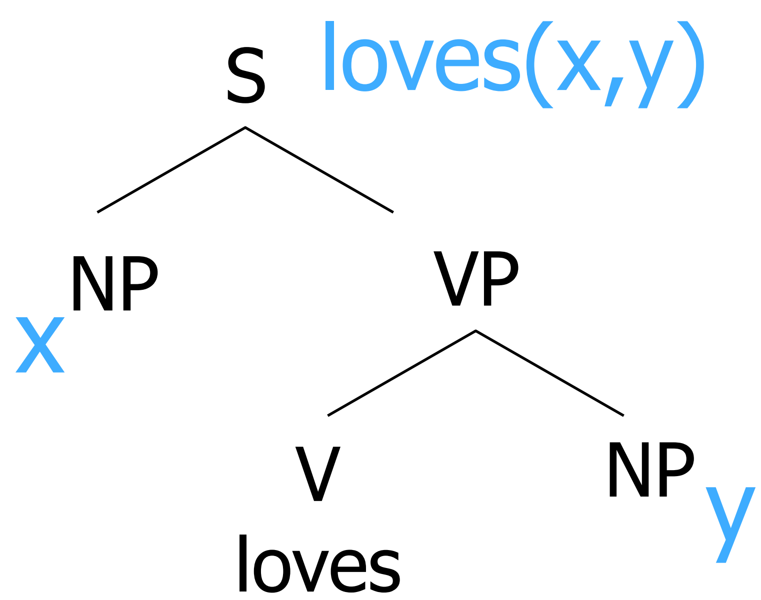

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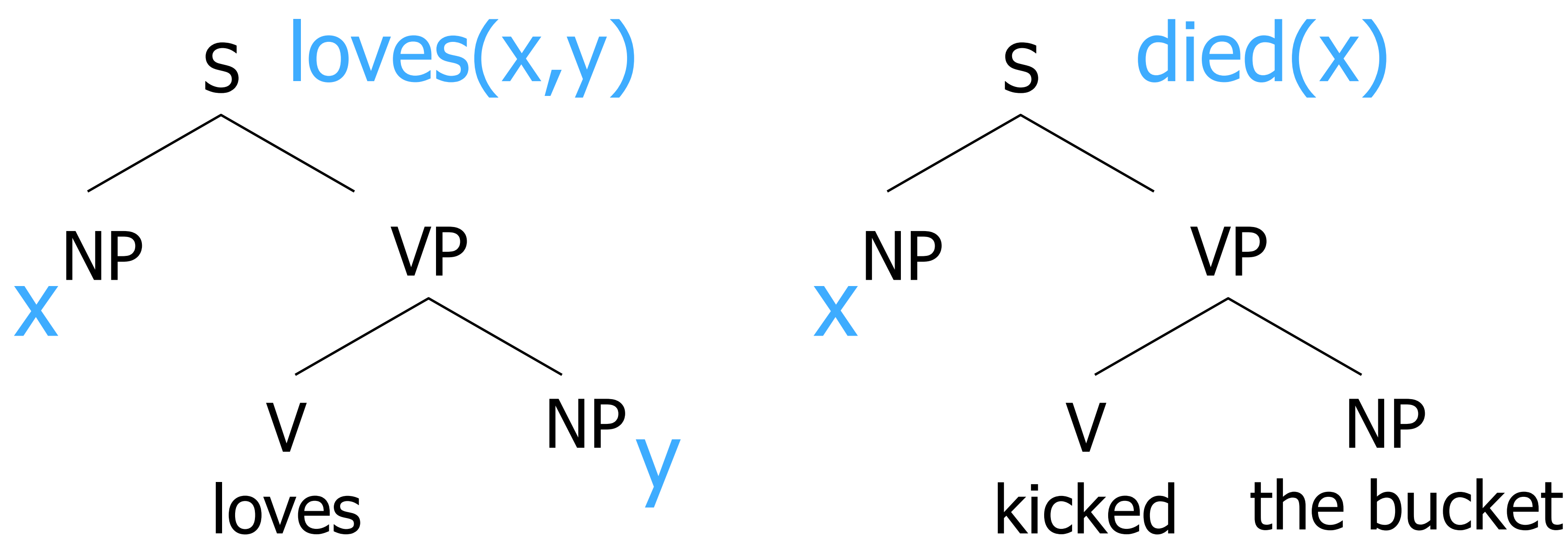

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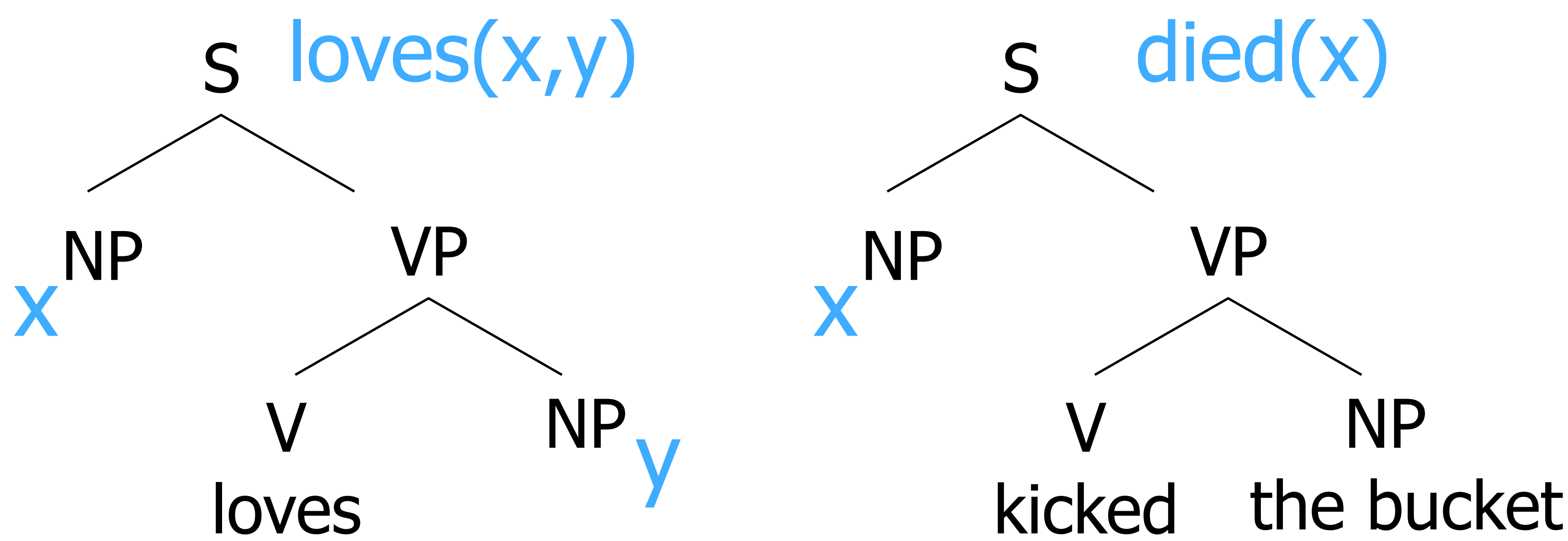


- Template filling: S[sem=showflights(x,y)] → I want a flight from NP[sem=x] to NP[sem=y]

"Non-constituents" in CCG – Right Node Raising

$$
\begin{array}{cccccc}
\textit{Google} & \textit{sells} & \textit{but} & \textit{Microsoft} & \textit{buys} & \textit{shares} \\
\hline
NP & (S\backslash NP)/NP & conj & NP & (S\backslash NP)/NP & NP \\
\xrightarrow{\quad >\mathbf{T}} & & & \xrightarrow{\quad >\mathbf{T}} & & \\
S/(S\backslash NP) & & & S/(S\backslash NP) & & \\
\multicolumn{2}{c}{\xrightarrow{\qquad\qquad >\mathbf{B}}} & & \multicolumn{2}{c}{\xrightarrow{\qquad\qquad >\mathbf{B}}} & \\
\multicolumn{2}{c}{S/NP} & & \multicolumn{2}{c}{S/NP} & \\
\multicolumn{5}{c}{\xrightarrow{\qquad\qquad\qquad\qquad <\Phi>}} & \\
\multicolumn{5}{c}{S/NP} & \\
\multicolumn{6}{c}{\xrightarrow{\qquad\qquad\qquad\qquad\qquad >}} \\
\multicolumn{6}{c}{S}
\end{array}
$$

CCG Semantics

- Categories encode argument sequences
- Parallel syntactic combinator operations and lambda calculus semantic operations

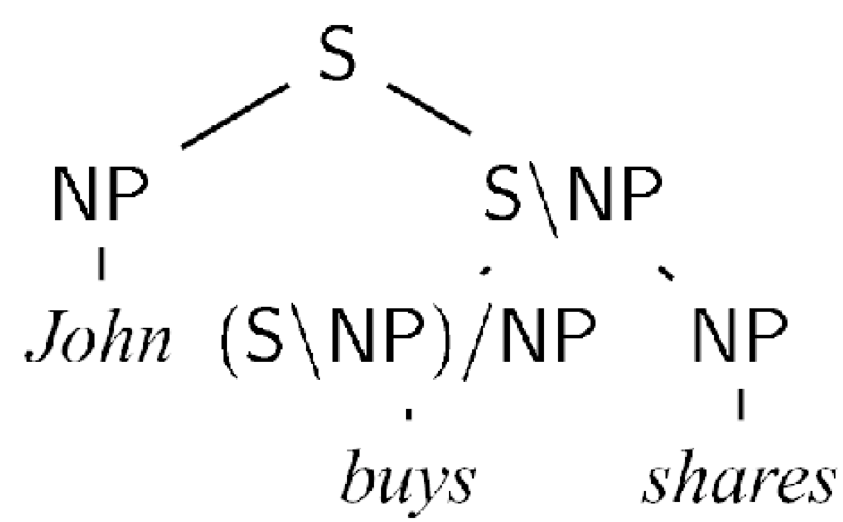
$John \vdash \mathsf{NP} : john'$

$shares \vdash \mathsf{NP} : shares'$

$buys \vdash (\mathsf{S}\backslash\mathsf{NP})/\mathsf{NP} : \lambda x.\lambda y.buys'xy$

$sleeps \vdash \mathsf{S}\backslash\mathsf{NP} : \lambda x.sleeps'x$

$well \vdash (\mathsf{S}\backslash\mathsf{NP})\backslash(\mathsf{S}\backslash\mathsf{NP}) : \lambda f.\lambda x.well'(fx)$



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- Represent each word **type** w by a point in k-dimensional space
  - e.g., k is size of vocabulary
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From corpus:

Arlen Specter **abandoned** the Republican **party**.
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The **party** **above** the art gallery was, **above** all, a laboratory for synthesizing **zygotes** and beer.

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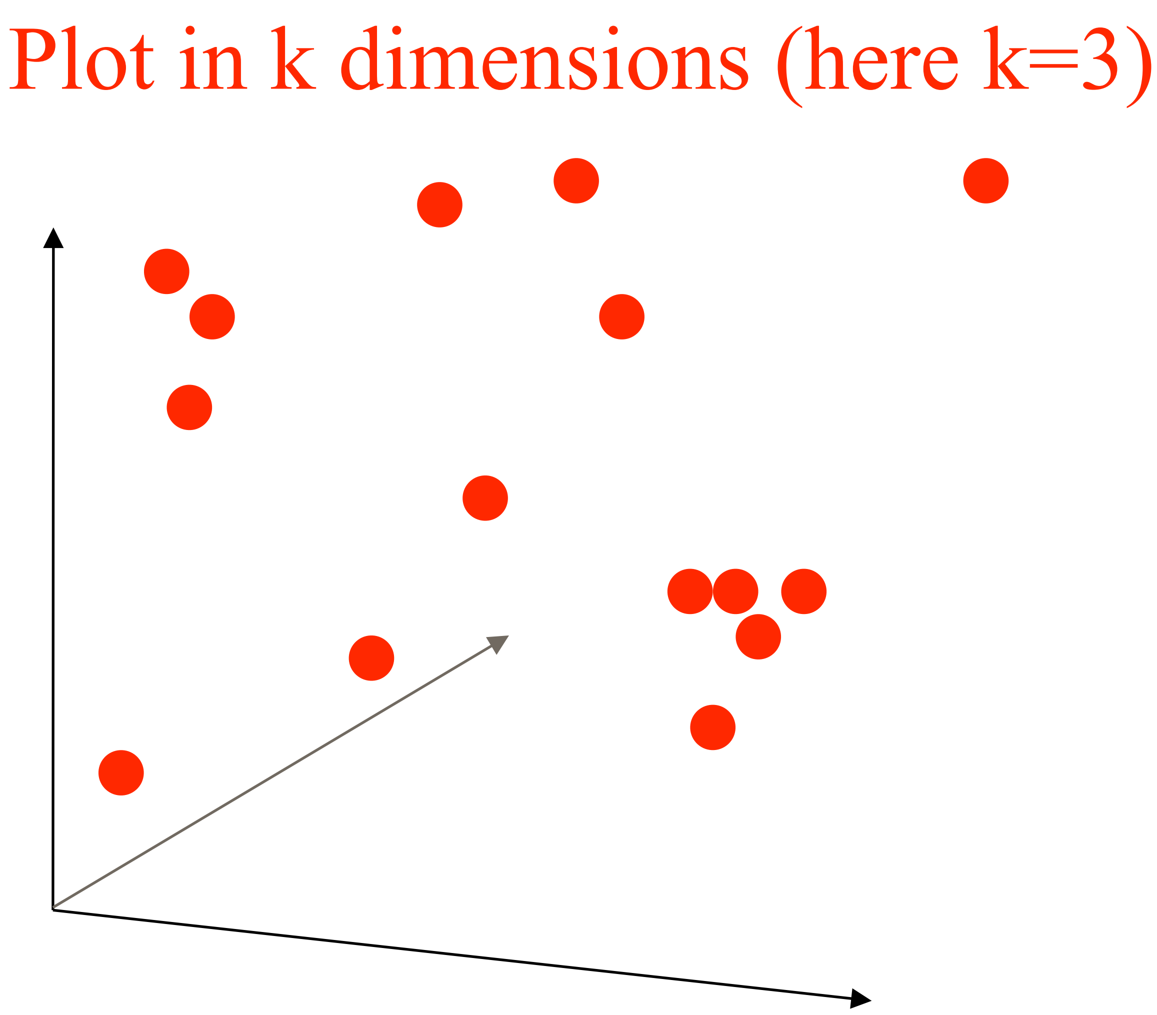
Learning Classes by Clustering

- Plot all word types in k-dimensional space
- Look for **clusters** of close-together types



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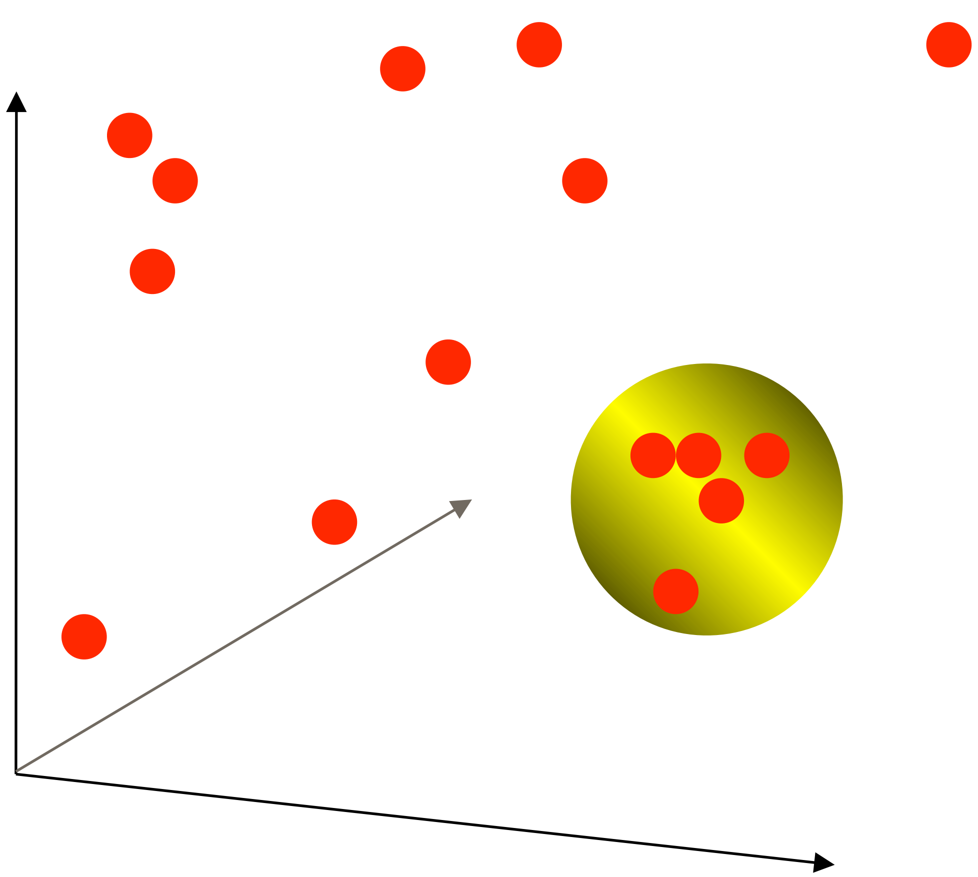

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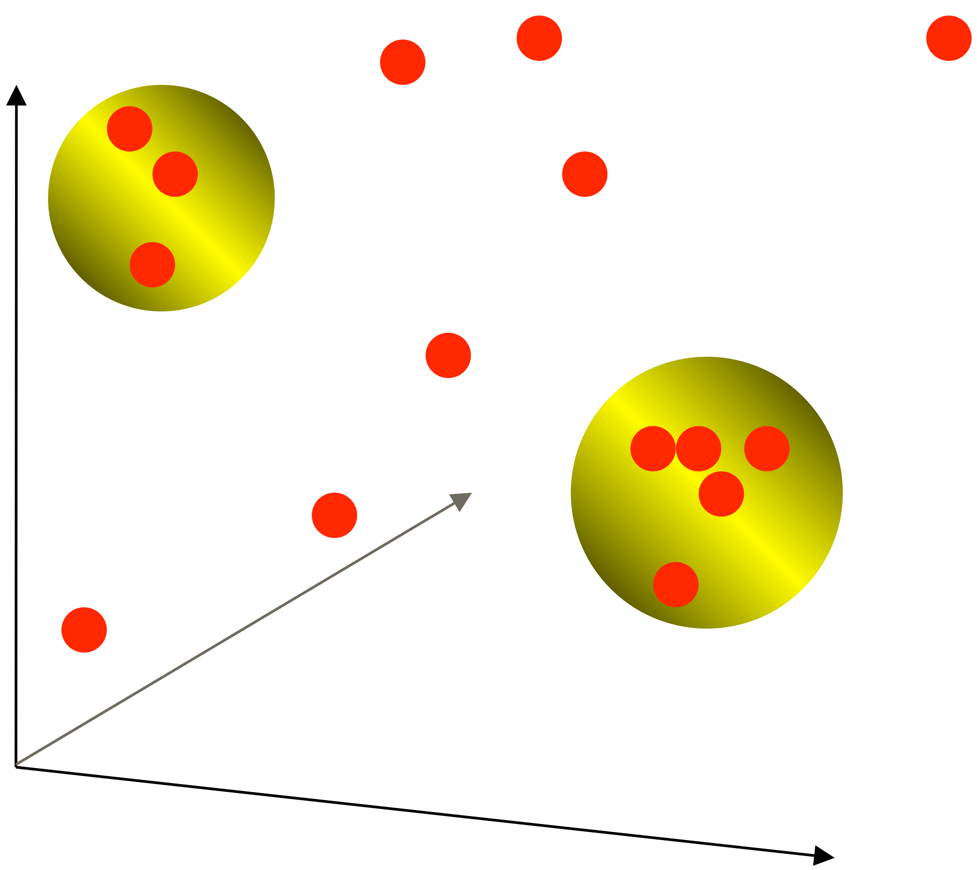

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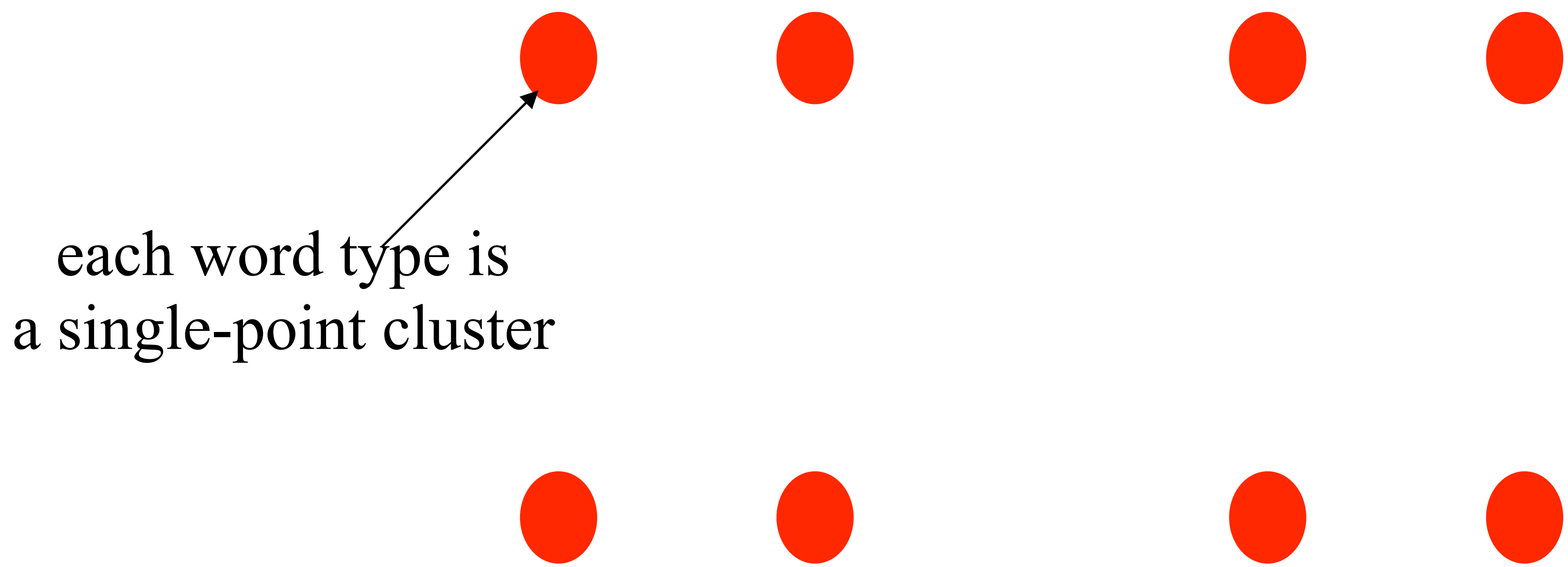

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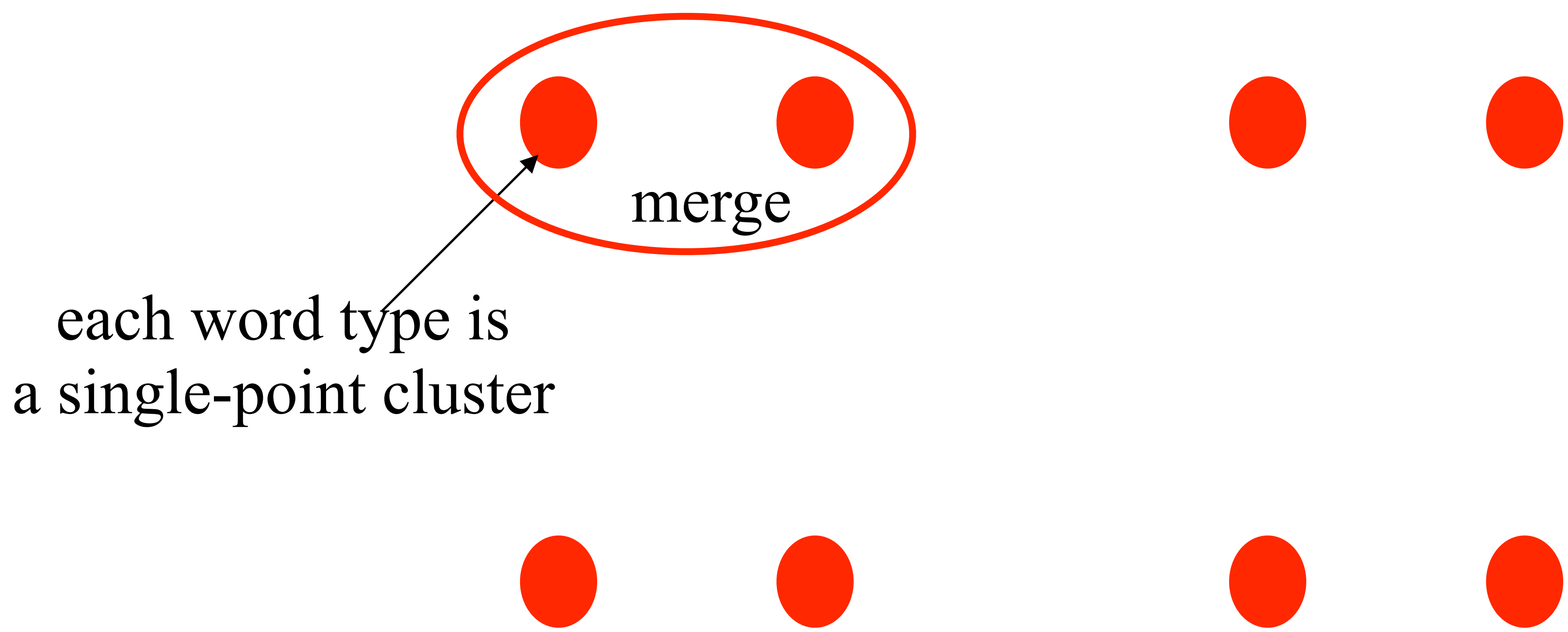

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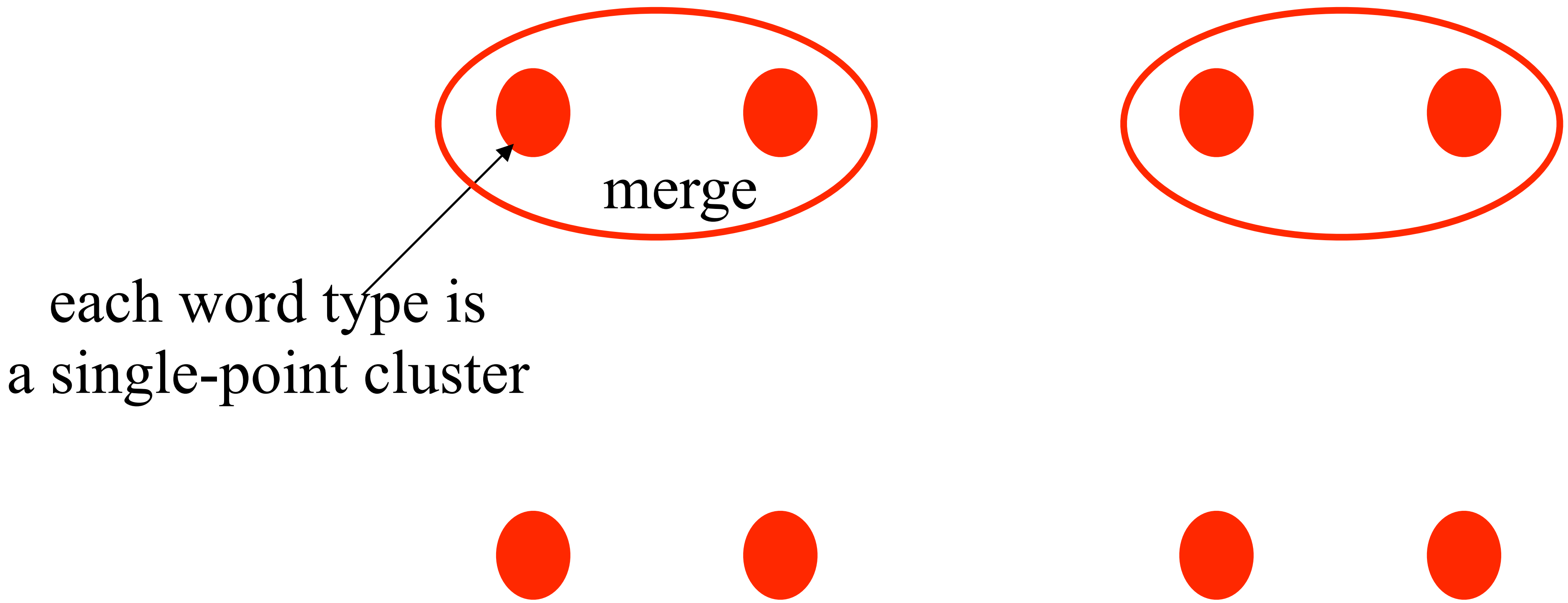

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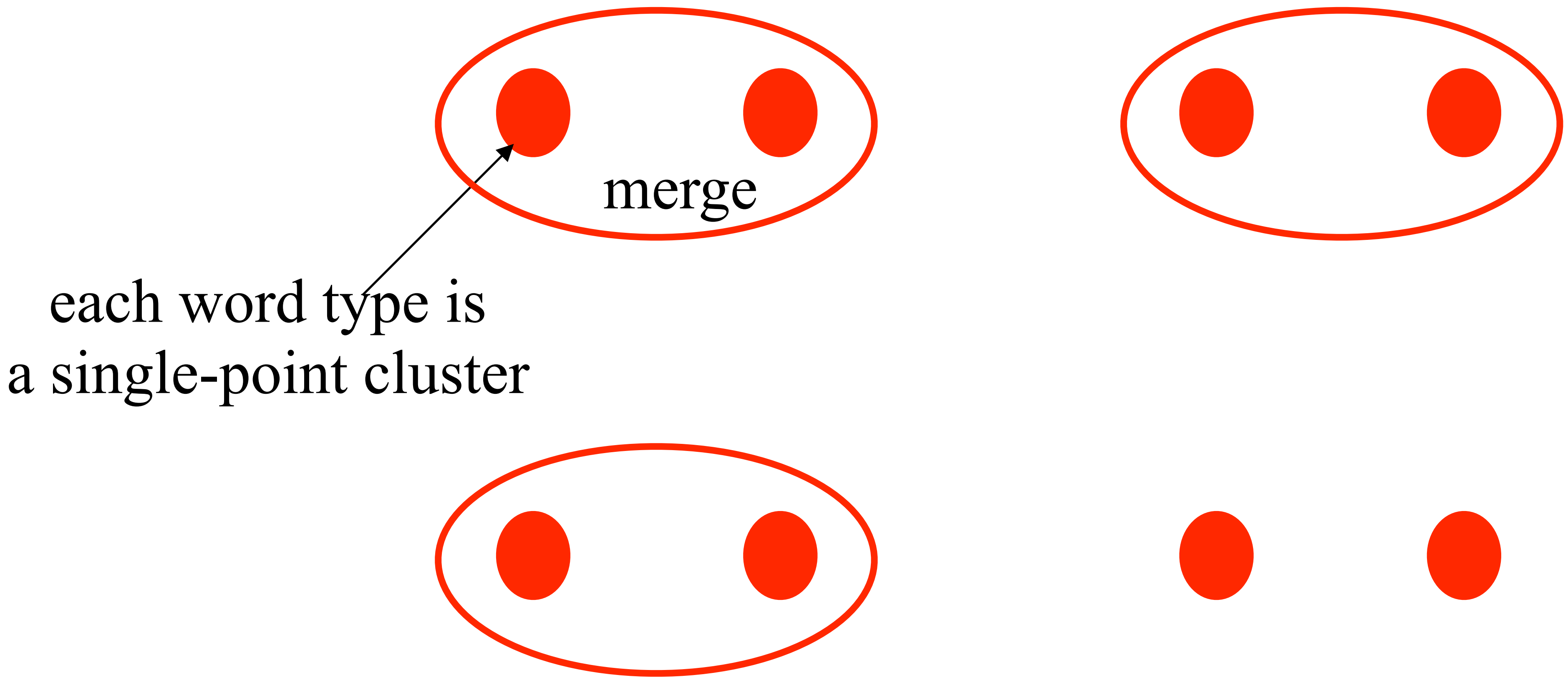

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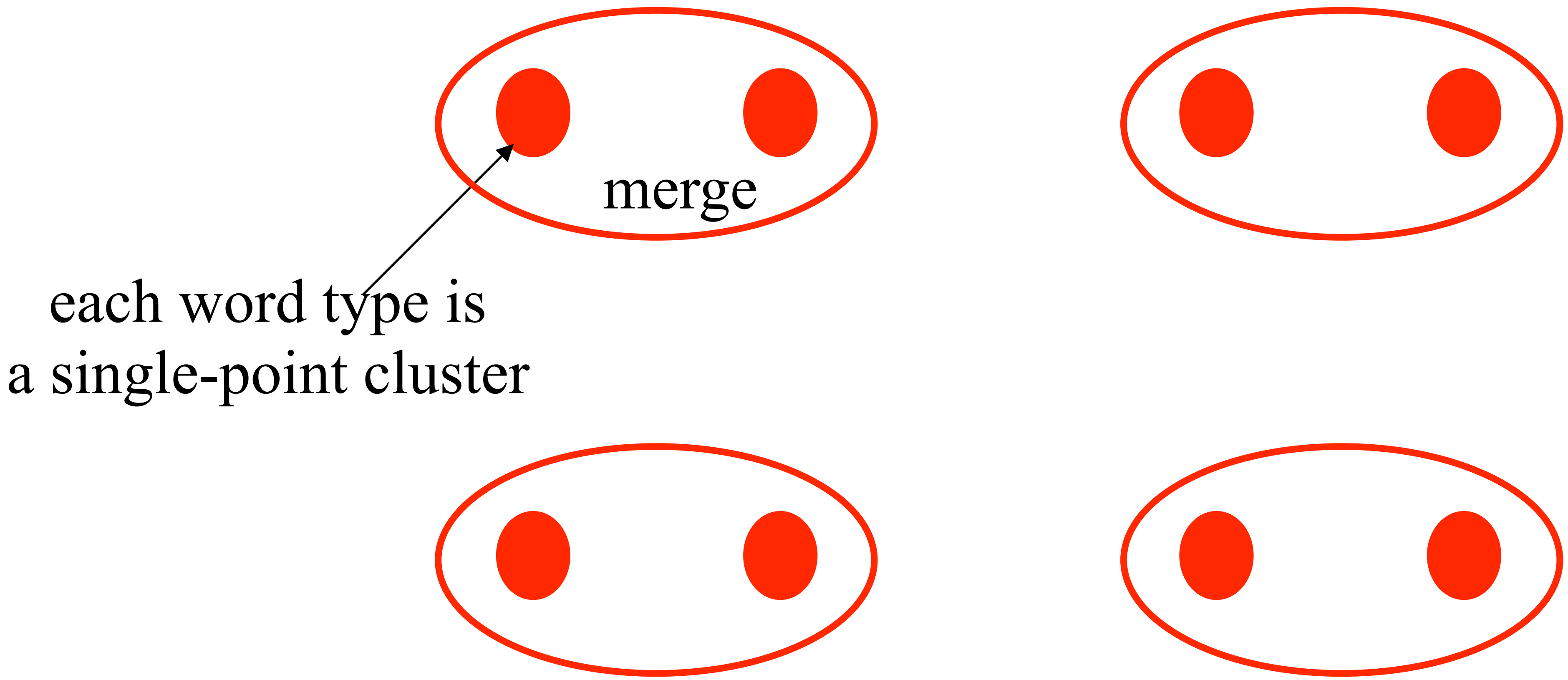

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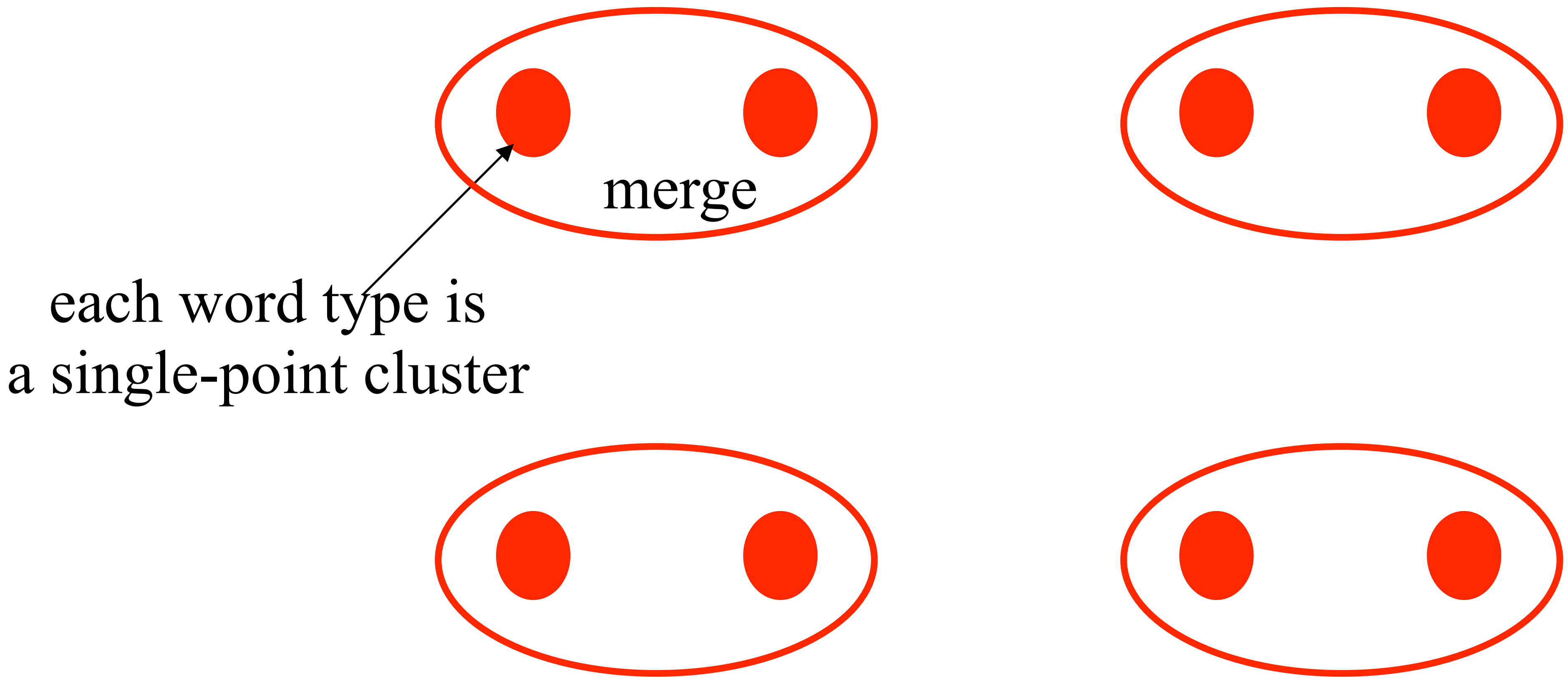

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Single-link: clusters are close if any of their points are

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example from Manning & Schütze

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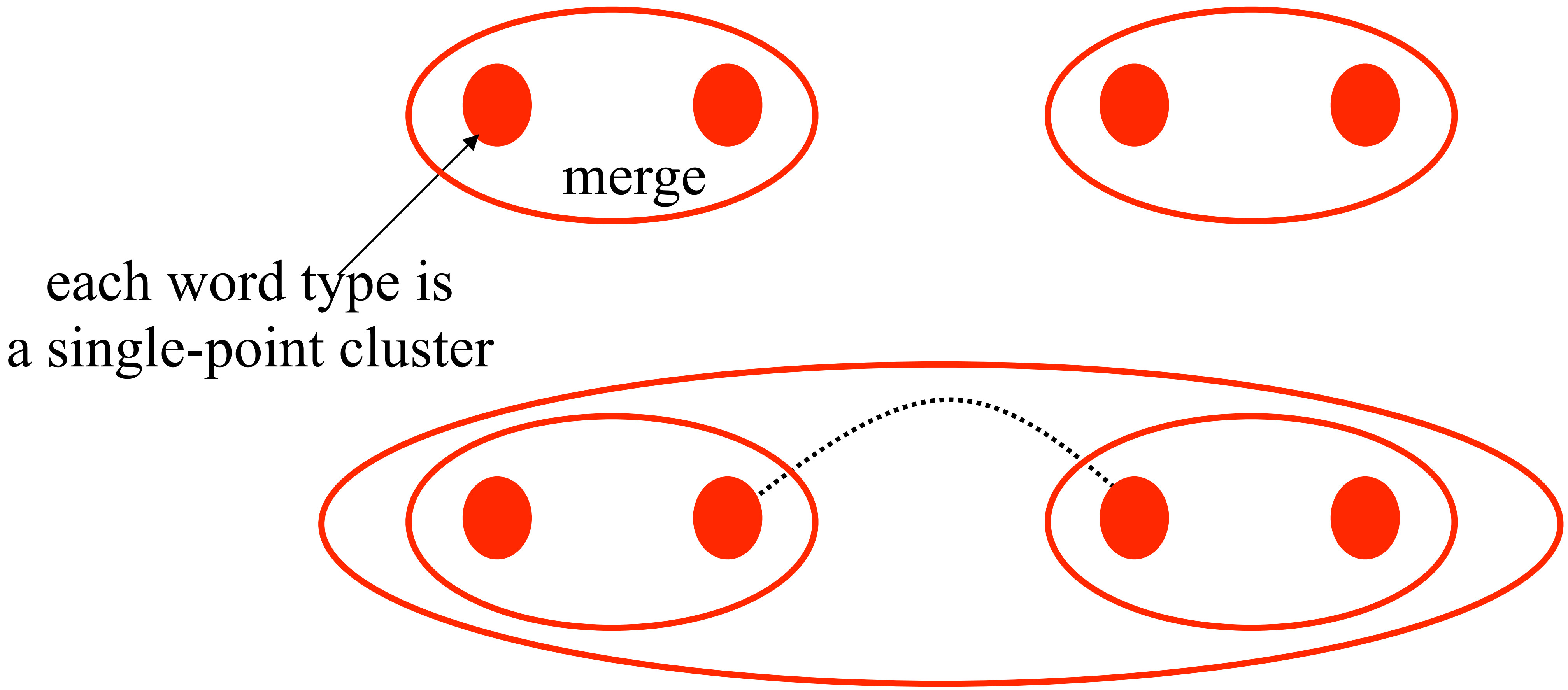

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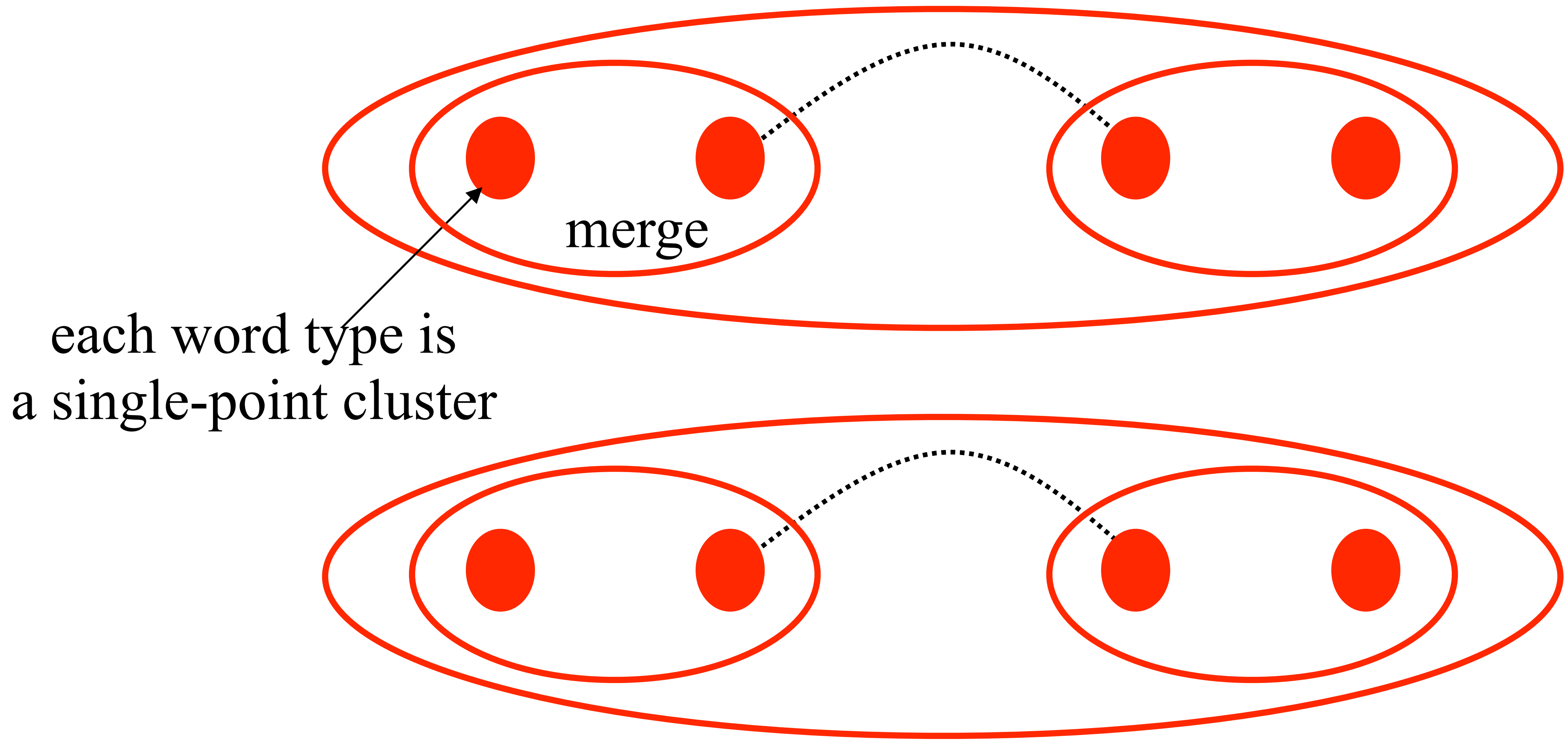

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- Some flexibility in defining dist(a,b)
  - Might not be Euclidean distance; e.g., use vector angle

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- Parameters: k points representing cluster centers
- Hidden structure: for each data point (word type), which center generated it?

Lexical translation

- How to translate a word → look up in dictionary

  Haus — *house, building, home, household, shell.*

- *Multiple translations*
  - some more frequent than others
  - for instance: *house*, and *building* most common
  - special cases: *Haus* of a *snail* is its *shell*

- Note: During all the lectures, we will translate from a foreign language into English

Collect statistics

- Look at a *parallel corpus* (German text along with English translation)

Translation of *Haus*	**Count**
house	8,000
building	1,600
home	200
household	150
shell	50

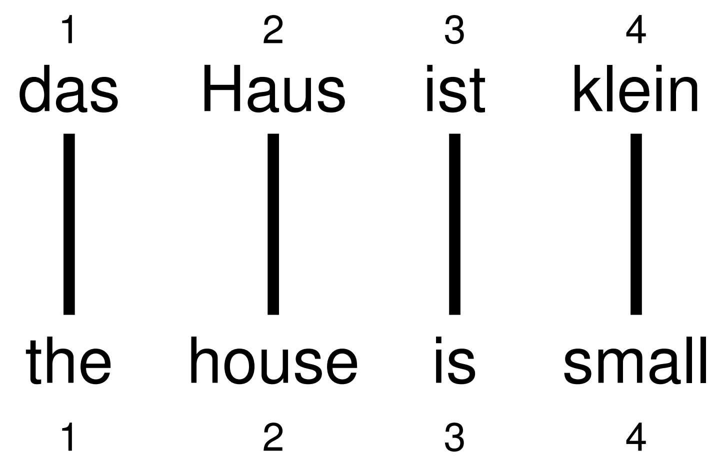
Estimate translation probabilities

- *Maximum likelihood estimation*

$$p_f(e) = \begin{cases} 0.8 & \text{if } e = \textit{house}, \\ 0.16 & \text{if } e = \textit{building}, \\ 0.02 & \text{if } e = \textit{home}, \\ 0.015 & \text{if } e = \textit{household}, \\ 0.005 & \text{if } e = \textit{shell}. \end{cases}$$

Alignment

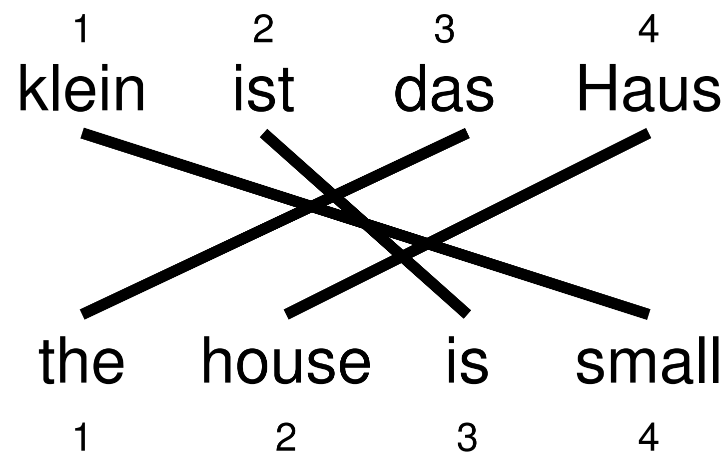
- In a parallel text (or when we translate), we **align** words in one language with the words in the other



- Word *positions* are numbered 1–4

Reordering

- Words may be **reordered** during translation



$$a : \{1 \rightarrow 3, 2 \rightarrow 4, 3 \rightarrow 2, 4 \rightarrow 1\}$$

IBM Model 1

- *Generative model*: break up translation process into smaller steps
  - **IBM Model 1** only uses *lexical translation*

- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \rightarrow i$

$$p(\mathbf{e}, a|\mathbf{f}) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

  - parameter ϵ is a *normalization constant*

Example

das	
e	$t(e\|f)$
the	0.7
that	0.15
which	0.075
who	0.05
this	0.025

Haus	
e	$t(e\|f)$
house	0.8
building	0.16
home	0.02
household	0.015
shell	0.005

ist	
e	$t(e\|f)$
is	0.8
's	0.16
exists	0.02
has	0.015
are	0.005

klein	
e	$t(e\|f)$
small	0.4
little	0.4
short	0.1
minor	0.06
petty	0.04

$$\begin{aligned} p(e,a|f) &= \frac{\epsilon}{4^3} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\ &= \frac{\epsilon}{4^3} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\ &= 0.0028\epsilon \end{aligned}$$

Learning lexical translation models

- We would like to *estimate* the lexical translation probabilities $t(e|f)$ from a parallel corpus

- ... but we do not have the alignments

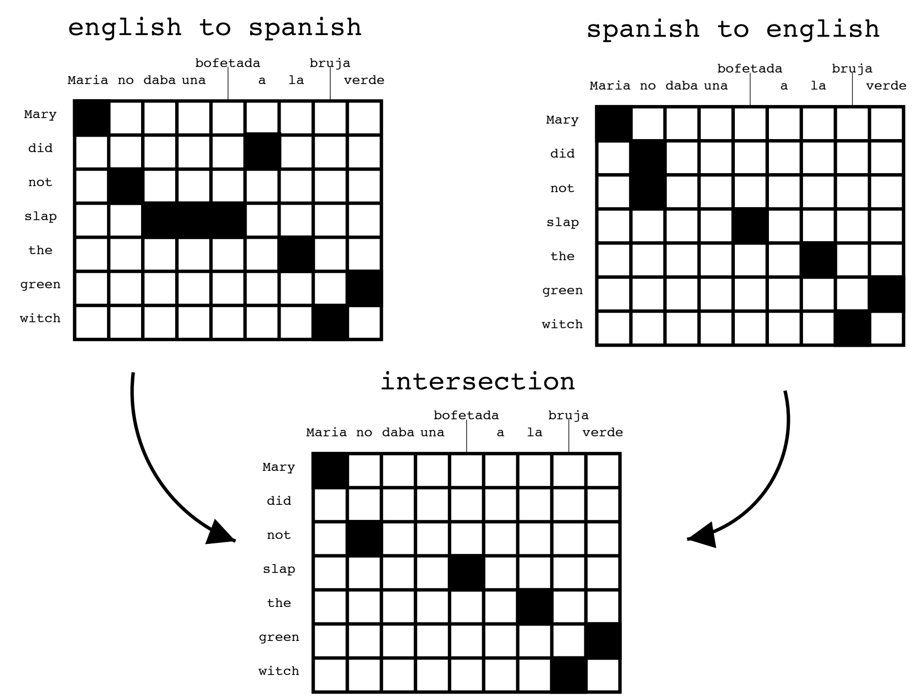
- **Chicken and egg problem**
  - if we had the *alignments*,
    $\rightarrow$ we could estimate the *parameters* of our generative model
  - if we had the *parameters*,
    $\rightarrow$ we could estimate the *alignments*

EM algorithm

- **Incomplete data**
  - if we had *complete data*, would could estimate *model*
  - if we had *model*, we could fill in the *gaps in the data*

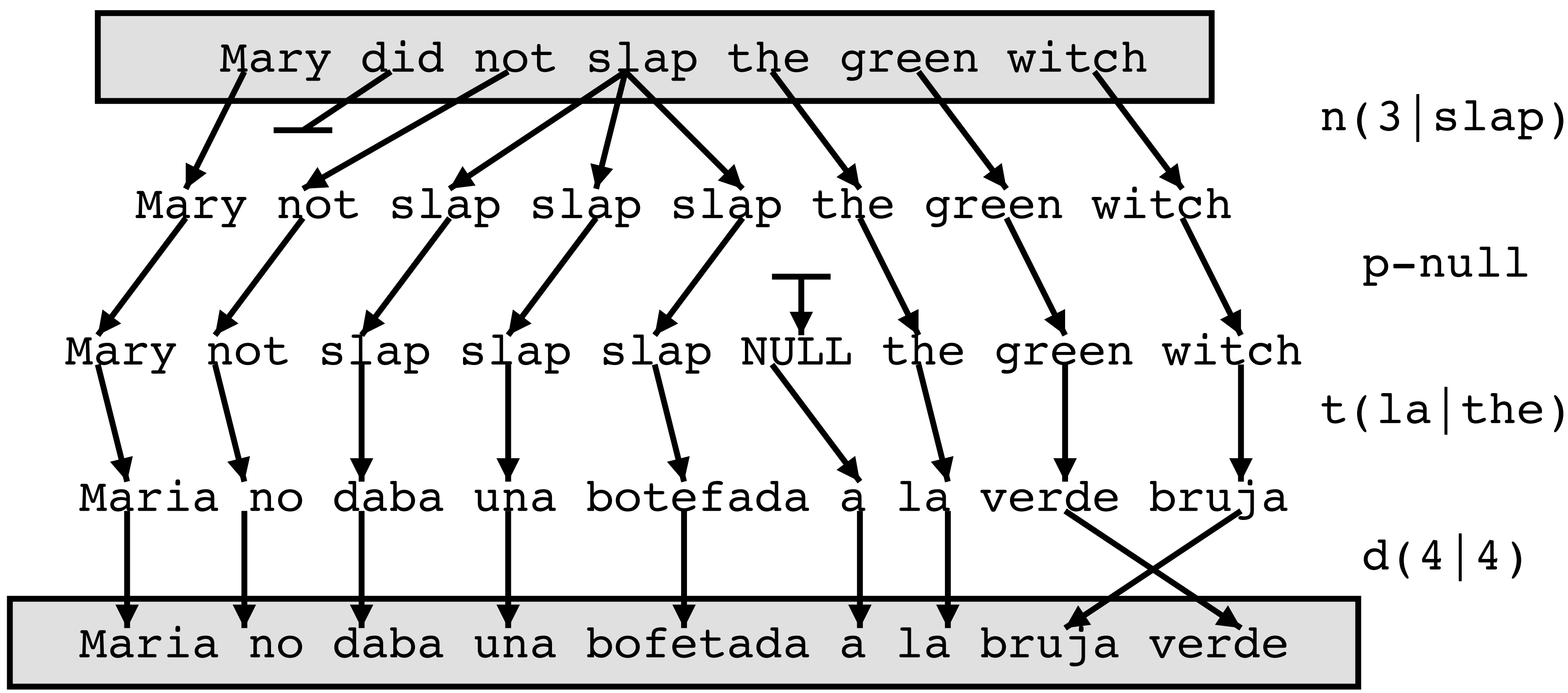
- **Expectation Maximization (EM)** in a nutshell
  - initialize model parameters (e.g. uniform)
  - assign probabilities to the missing data
  - estimate model parameters from completed data
  - iterate

Symmetrizing word alignments



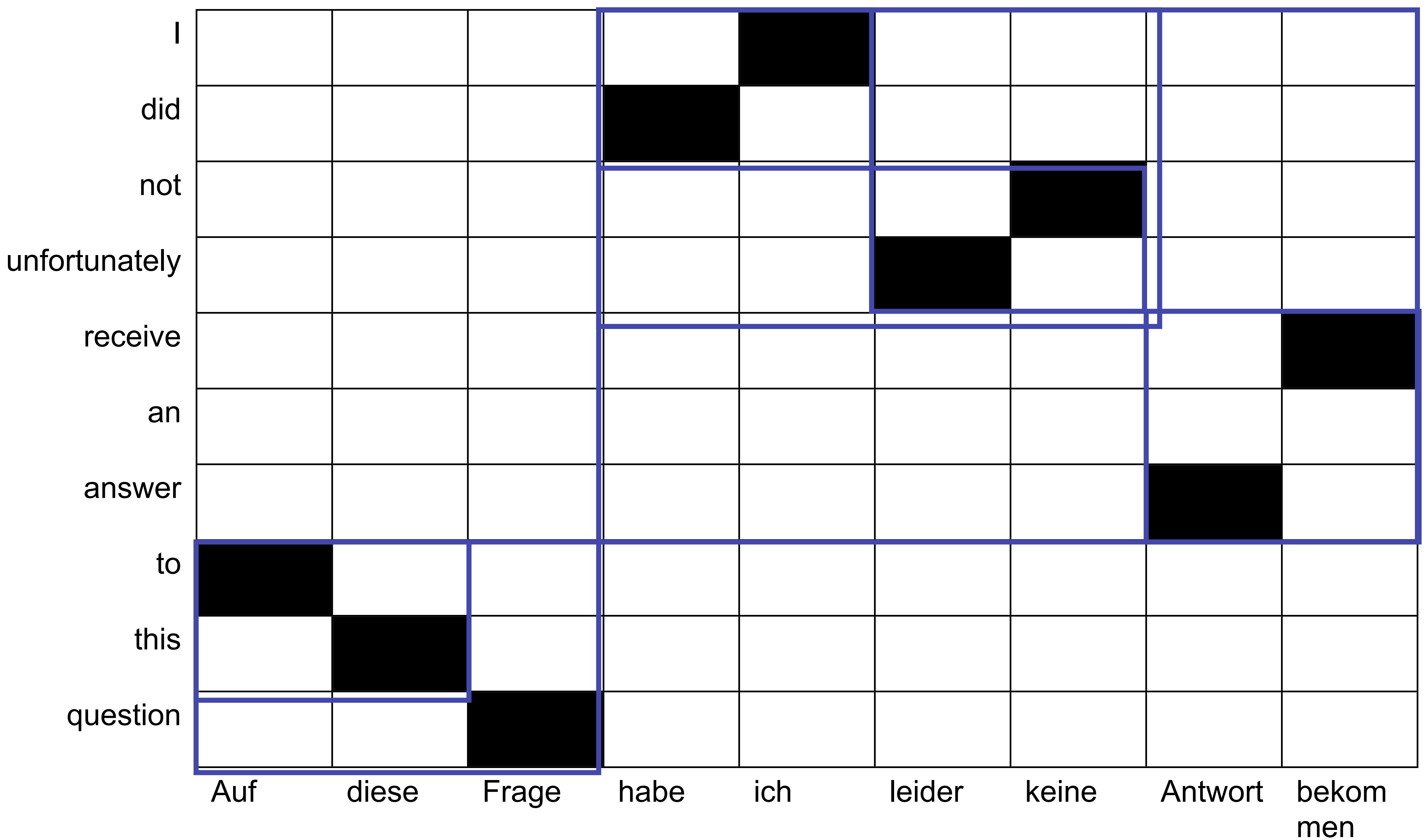
- *Intersection* of GIZA++ bidirectional alignments

IBM Model 4



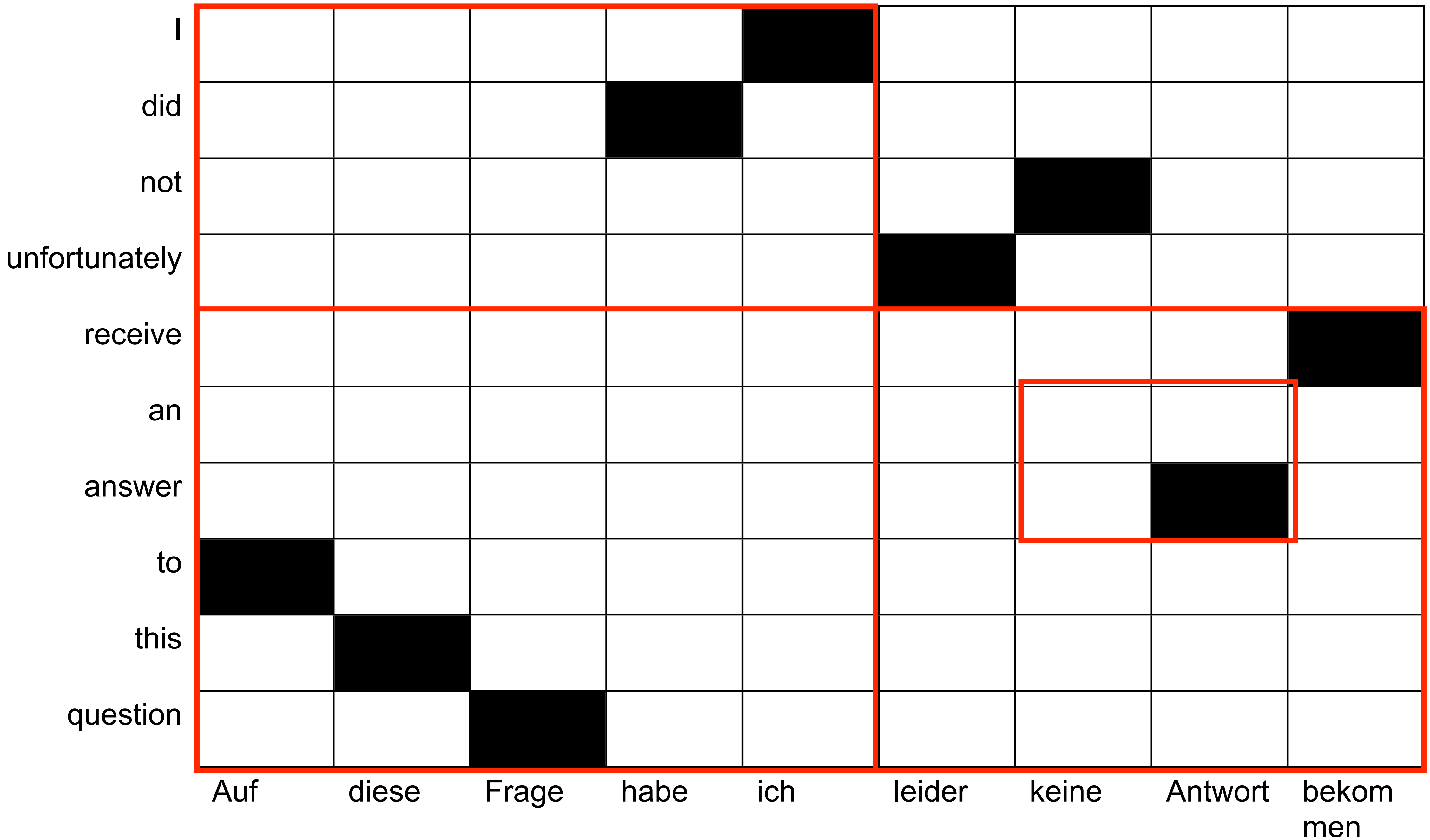
Mary did not slap the green witch
Mary not slap slap slap the green witch
Mary not slap slap slap NULL the green witch
Maria no daba una botefada a la verde bruja
Maria no daba una bofetada a la bruja verde
n(3|slap)
p-null
t(la|the)
d(4|4)

Phrase Models



Some good phrase pairs.

Phrase Models

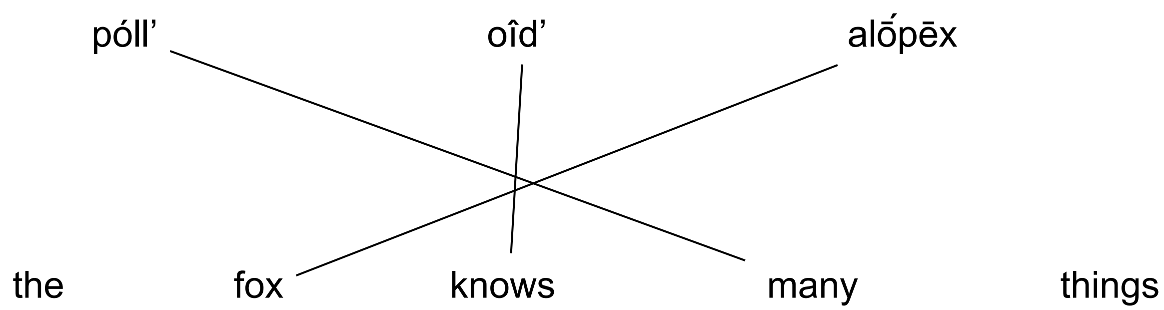


Some bad phrase pairs.

Synchronous Grammars

- Just like monolingual grammars except...
  - Each rule involves pairs (tuples) of nonterminals
  - Tuples of elementary trees for TAG, etc.
- First proposed for source-source translation in compilers
- Can be constituency, dependency, lexicalized, etc.
- Parsing speedups for monolingual grammar don't necessarily work
  - E.g., no split-head trick for lexicalized parsing
- Binarization less straightforward

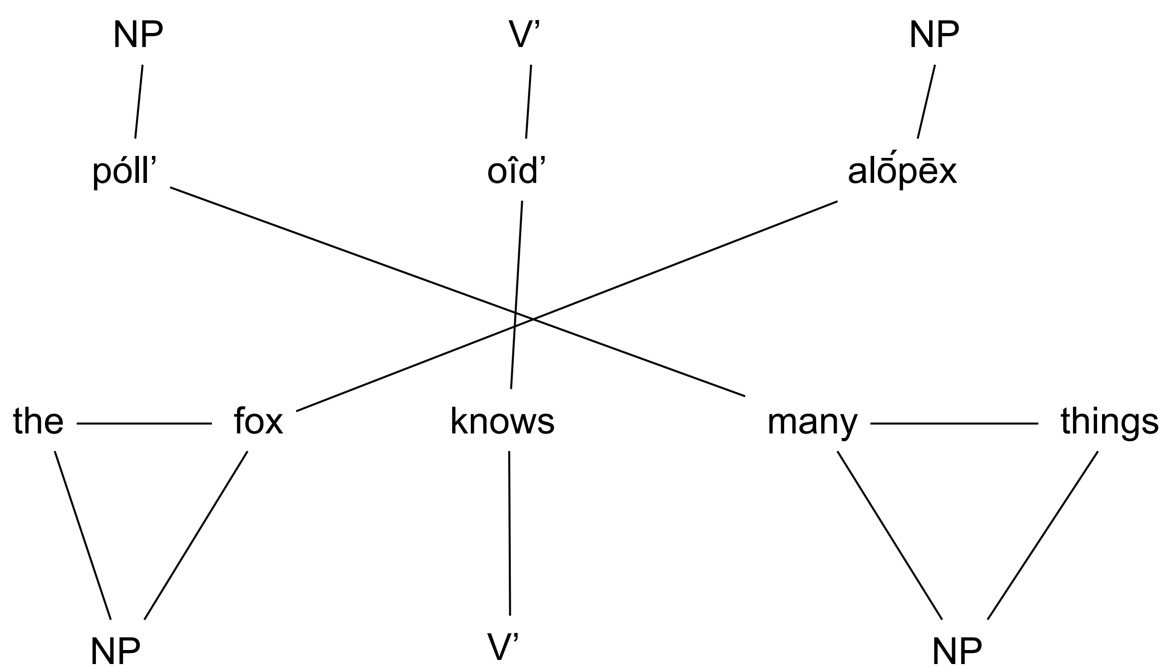
Bilingual Parsing



	póll’	oîd’	alṓpēx
the			
fox			NN/NN
knows		VB/VB	
many	JJ/JJ		
things			

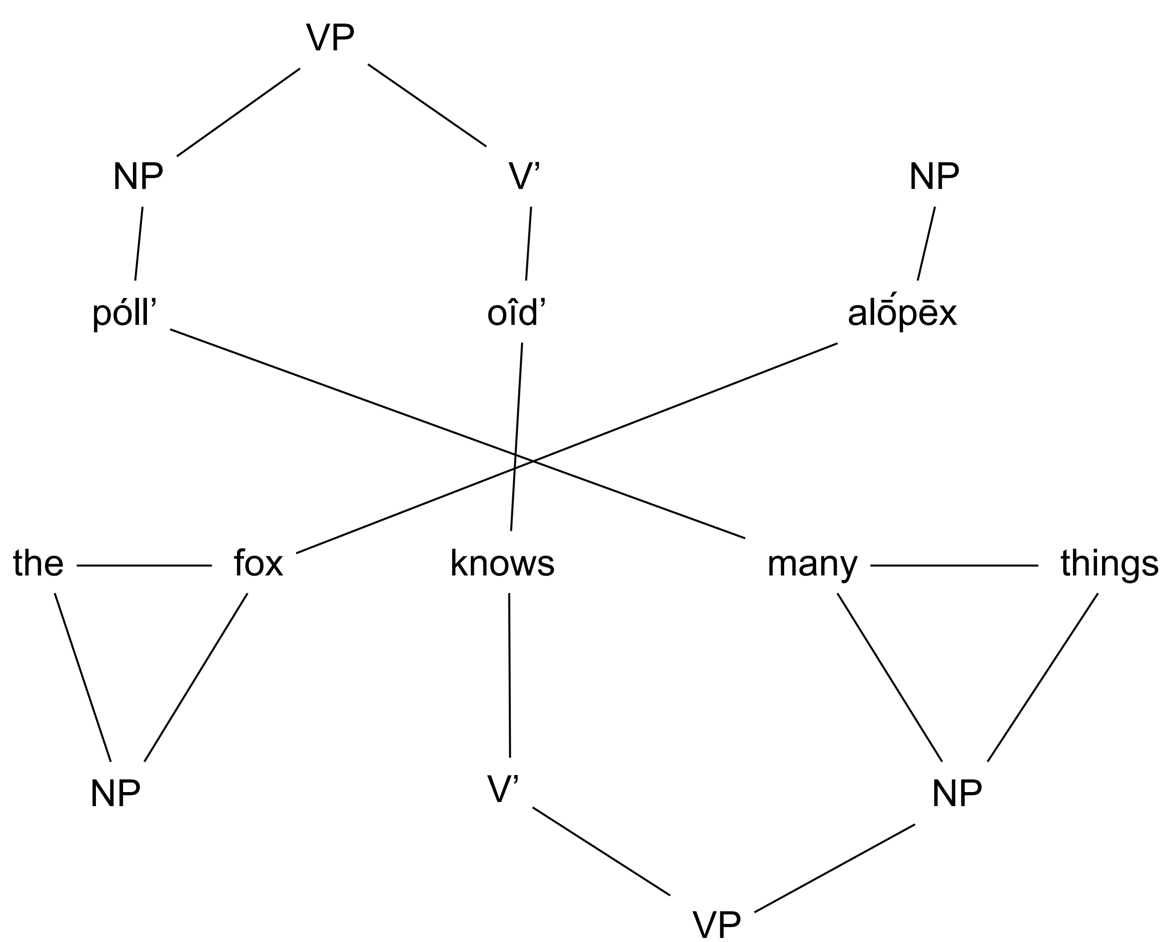
A variant of CKY chart parsing.

Bilingual Parsing



<table>
<tr><th></th><th>póll’</th><th>oîd’</th><th>alṓpēx</th></tr>
<tr><td>the</td><td></td><td></td><td rowspan="2">NP/NP</td></tr>
<tr><td>fox</td><td></td><td></td></tr>
<tr><td>knows</td><td></td><td>VP/VP</td><td></td></tr>
<tr><td>many</td><td rowspan="2">NP/NP</td><td></td><td></td></tr>
<tr><td>things</td><td></td><td></td></tr>
</table>

Bilingual Parsing



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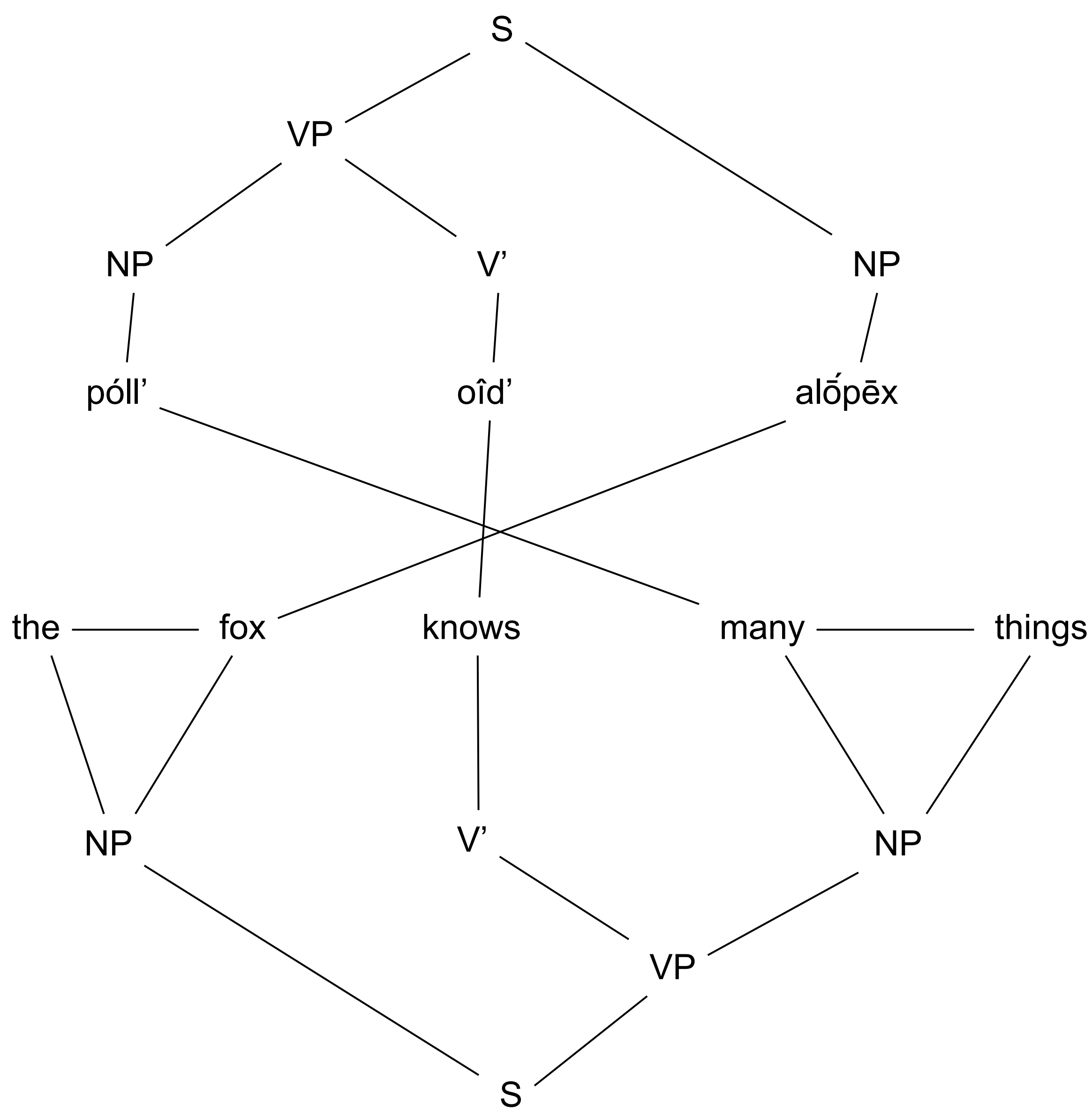
<tr><th></th><th>póll’</th><th>oîd’</th><th>alṓpēx</th></tr>
<tr><td>the</td><td></td><td></td><td rowspan="2">NP/NP</td></tr>
<tr><td>fox</td><td></td><td></td></tr>
<tr><td>knows</td><td colspan="2" rowspan="3">VP/VP</td><td></td></tr>
<tr><td>many</td><td></td></tr>
<tr><td>things</td><td></td></tr>
</table>

Bilingual Parsing



	póll’	oîd’	alṓpēx
the			
fox			
knows		S/S	
many			
things			