# Lecture 10: Machine Translation I

Alan Ritter

(many slides from Greg Durrett)

# This Lecture

- MT and evaluation
- Word alignment
- Language models
- Phrase-based decoders
- Syntax-based decoders (probably next time)

# MT Basics

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- Everyone has a friend => $\exists x \forall y$ `friend(x,y)` => Tous a un ami
  $\forall x \exists y$ `friend(x,y)`

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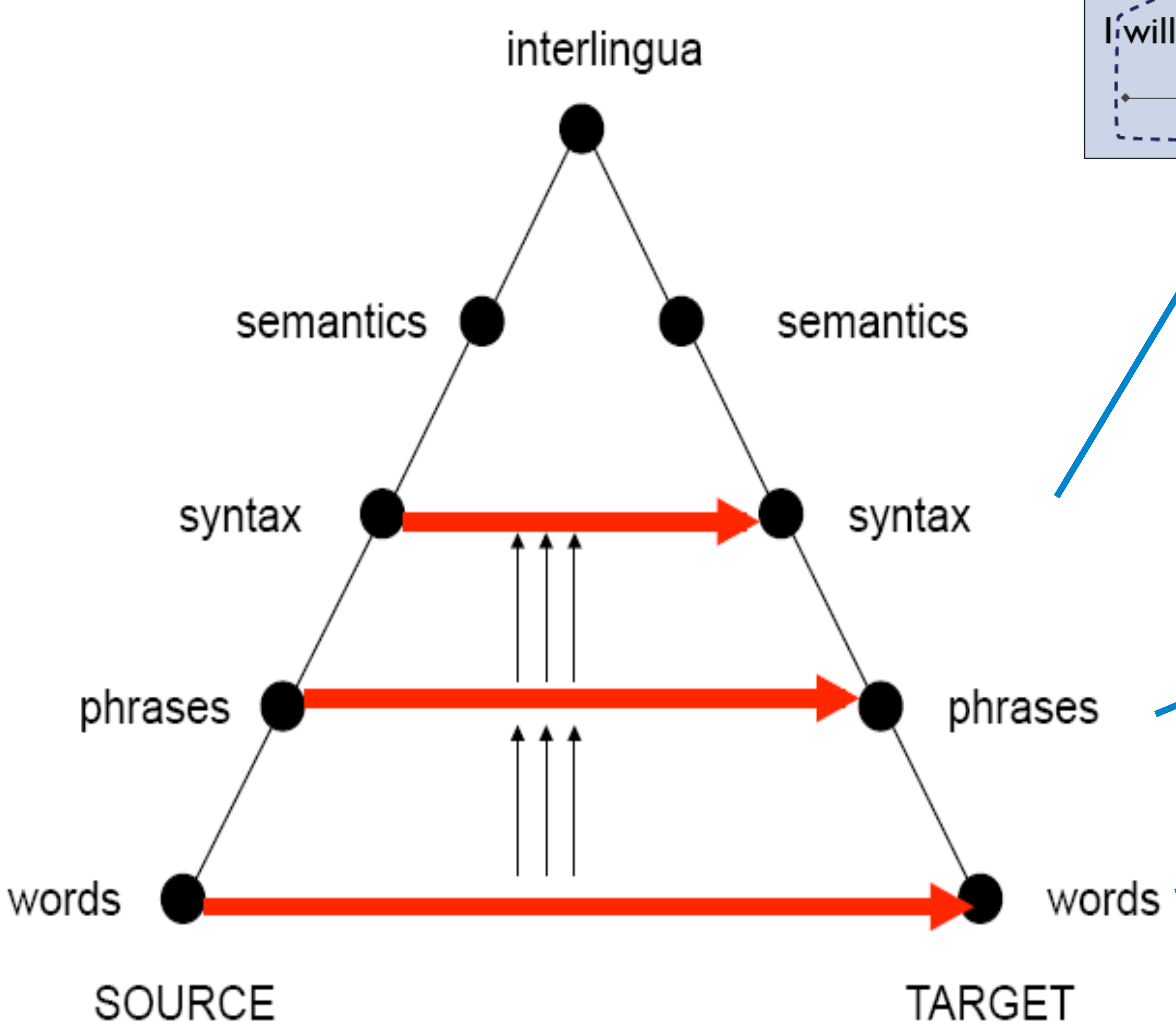
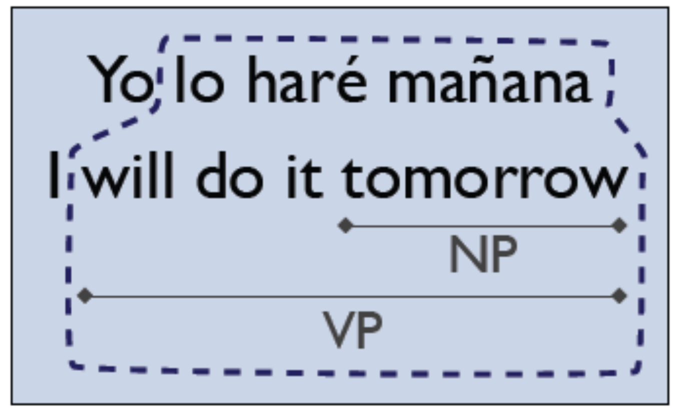
- I have a friend => $\exists x\ \mathtt{friend(x,self)}$ => J'ai un ami

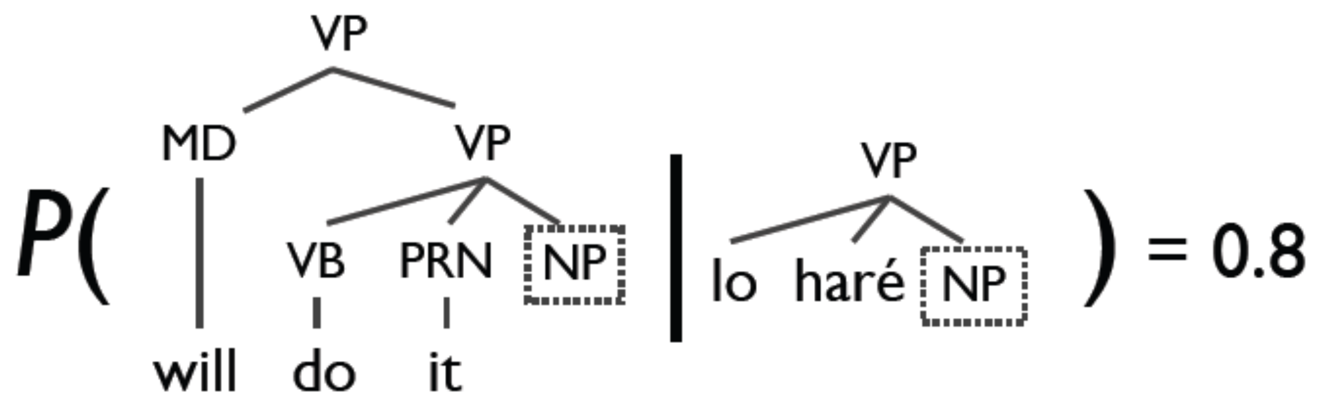
  J'ai une amie

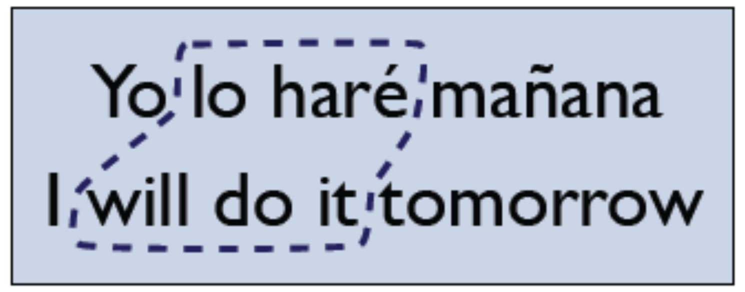
  - May need information you didn't think about in your representation
  - Hard for semantic representations to cover everything
- Everyone has a friend => $\exists x \forall y\ \mathtt{friend(x,y)}$ / $\forall x \exists y\ \mathtt{friend(x,y)}$ => Tous a un ami
  - Can often get away without doing all disambiguation — same ambiguities may exist in both languages

# Levels of Transfer: Vauquois Triangle

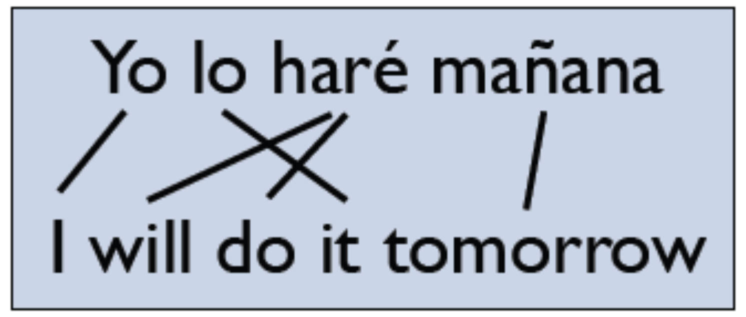



| *English* (E) | *P*( E \| lo haré ) |
|---|---|
| will do it | 0.8 |
| will do so | 0.2 |




| *English* (E) | *P*( E \| mañana ) |
|---|---|
| tomorrow | 0.7 |
| morning | 0.3 |

- Today: mostly phrase-based, some syntax

Slide credit: Dan Klein

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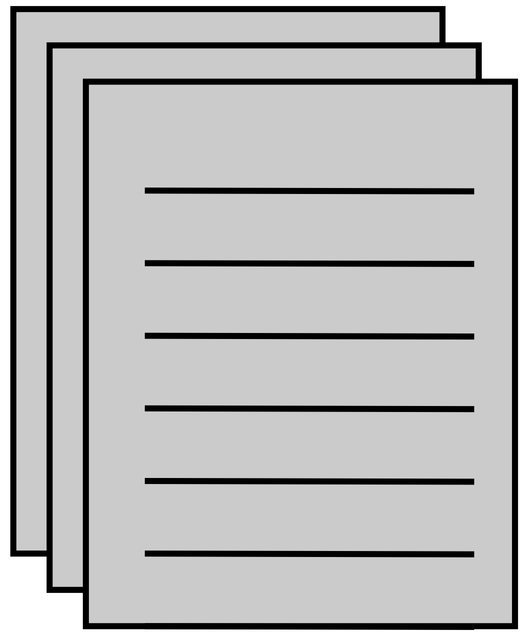
  - How to identify phrases? Word alignment over source-target bitext
  - How to stitch together? Language model over target language
  - Decoder takes phrases and a language model and searches over possible translations
- NOT like standard discriminative models (take a bunch of translation pairs, learn a ton of parameters in an end-to-end way)

# Phrase-Based MT

cat ||| chat ||| 0.9
the cat ||| le chat ||| 0.8
dog ||| chien ||| 0.8
house ||| maison ||| 0.6
my house ||| ma maison ||| 0.9
language ||| langue ||| 0.9
…

Phrase table P(f|e)



Language model P(e)

Unlabeled English data

$$P(e|f) \propto P(f|e)P(e)$$

Noisy channel model: combine scores from translation model + language model to translate foreign to English

"Translate faithfully but make fluent English"

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| | | 1-gram | 2-gram | 3-gram |
|---|---|---|---|---|
| hypothesis 1 | I am exhausted | 3/3 | 1/2 | 0/1 |
| hypothesis 2 | Tired is I | 1/3 | 0/2 | 0/1 |
| hypothesis 3 | I I I | 1/3 | 0/2 | 0/1 |
| reference 1 | I am tired | | | |
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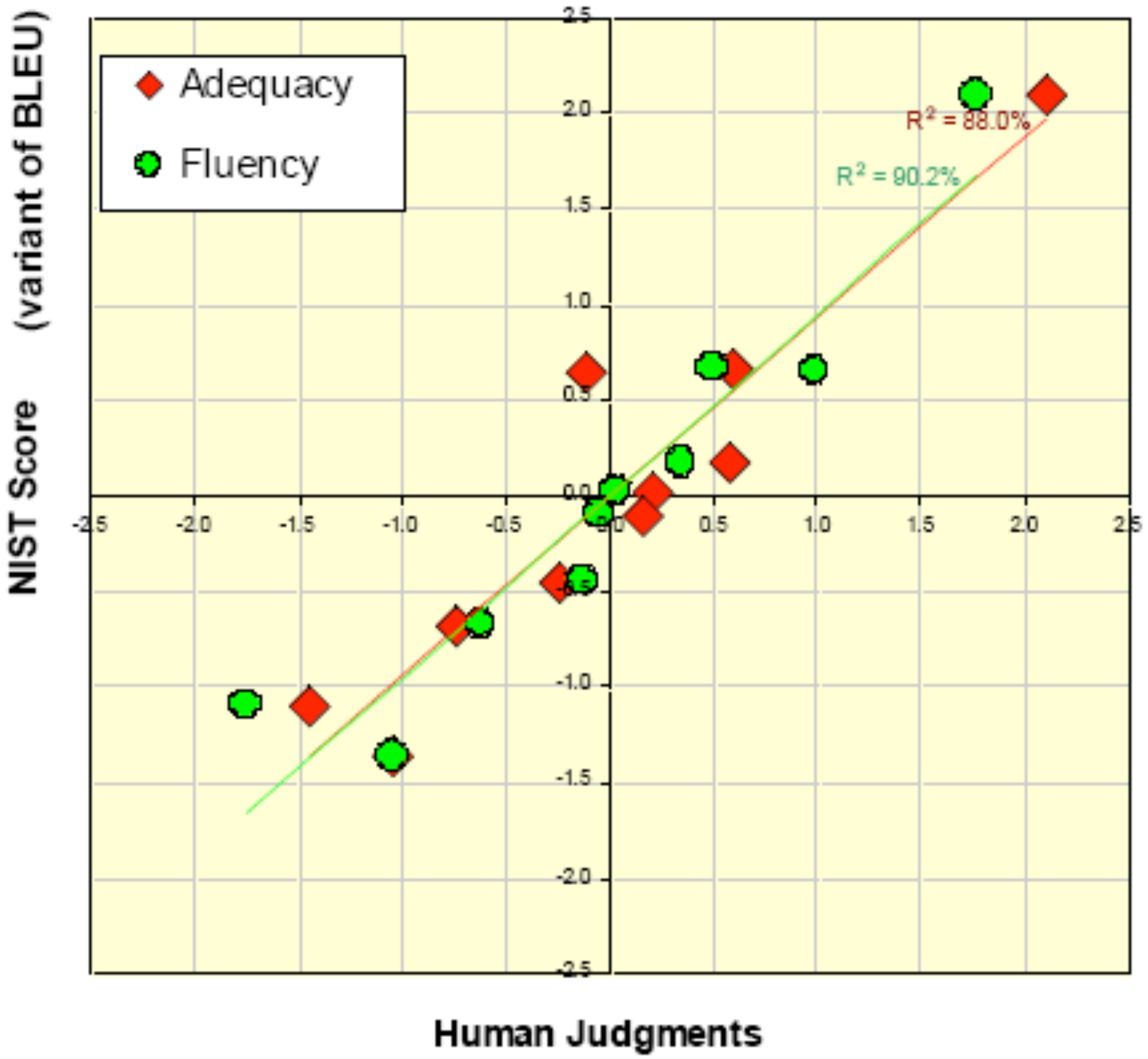
- Does this capture fluency and adequacy?

# BLEU Score

- Better methods with human-in-the-loop
- HTER: human-assisted translation error rate
- If you're building real MT systems, you do user studies. In academia, you mostly use BLEU




slide from G. Doddington (NIST)

# Word Alignment

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- Input: a bitext, pairs of translated sentences

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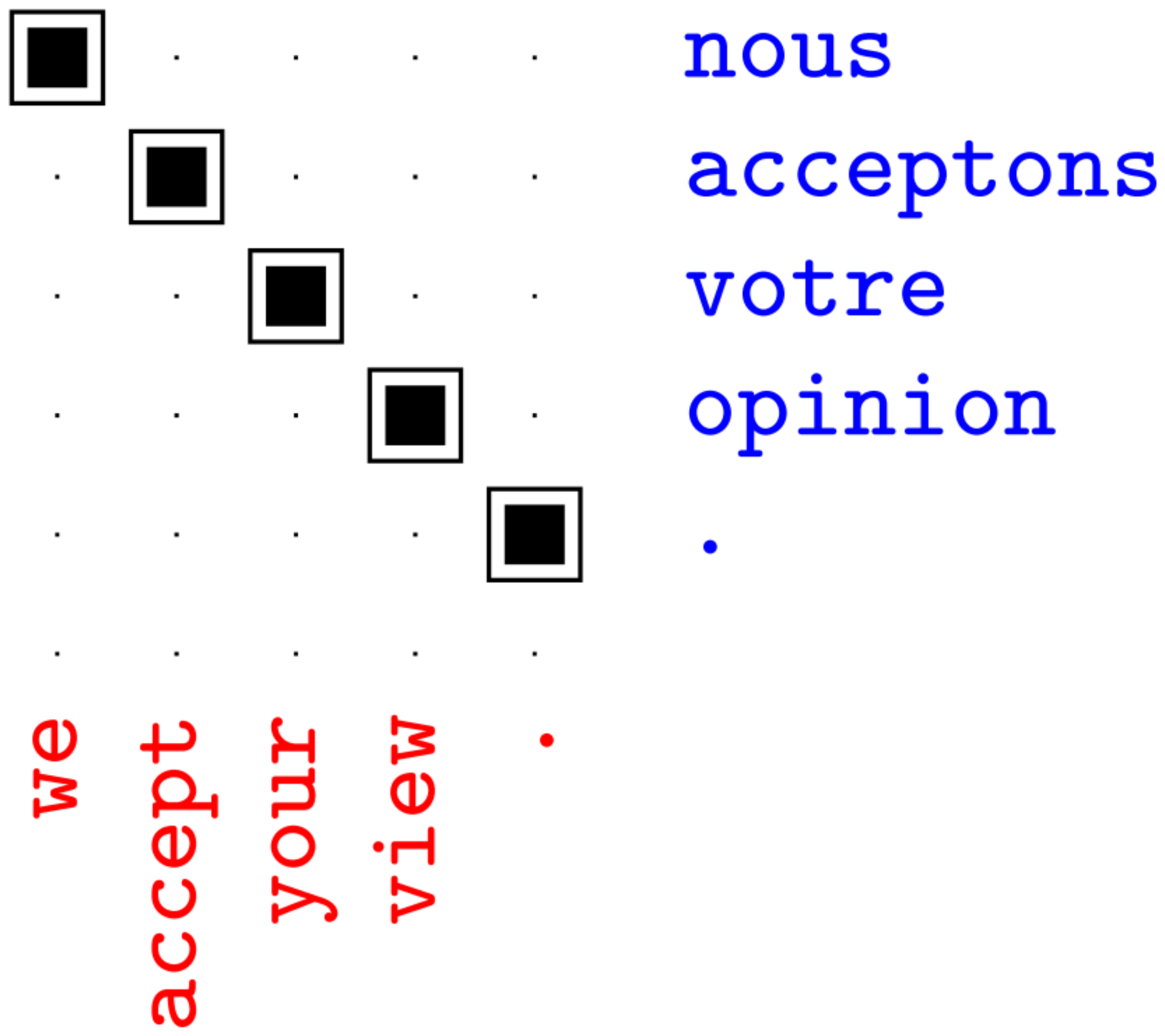

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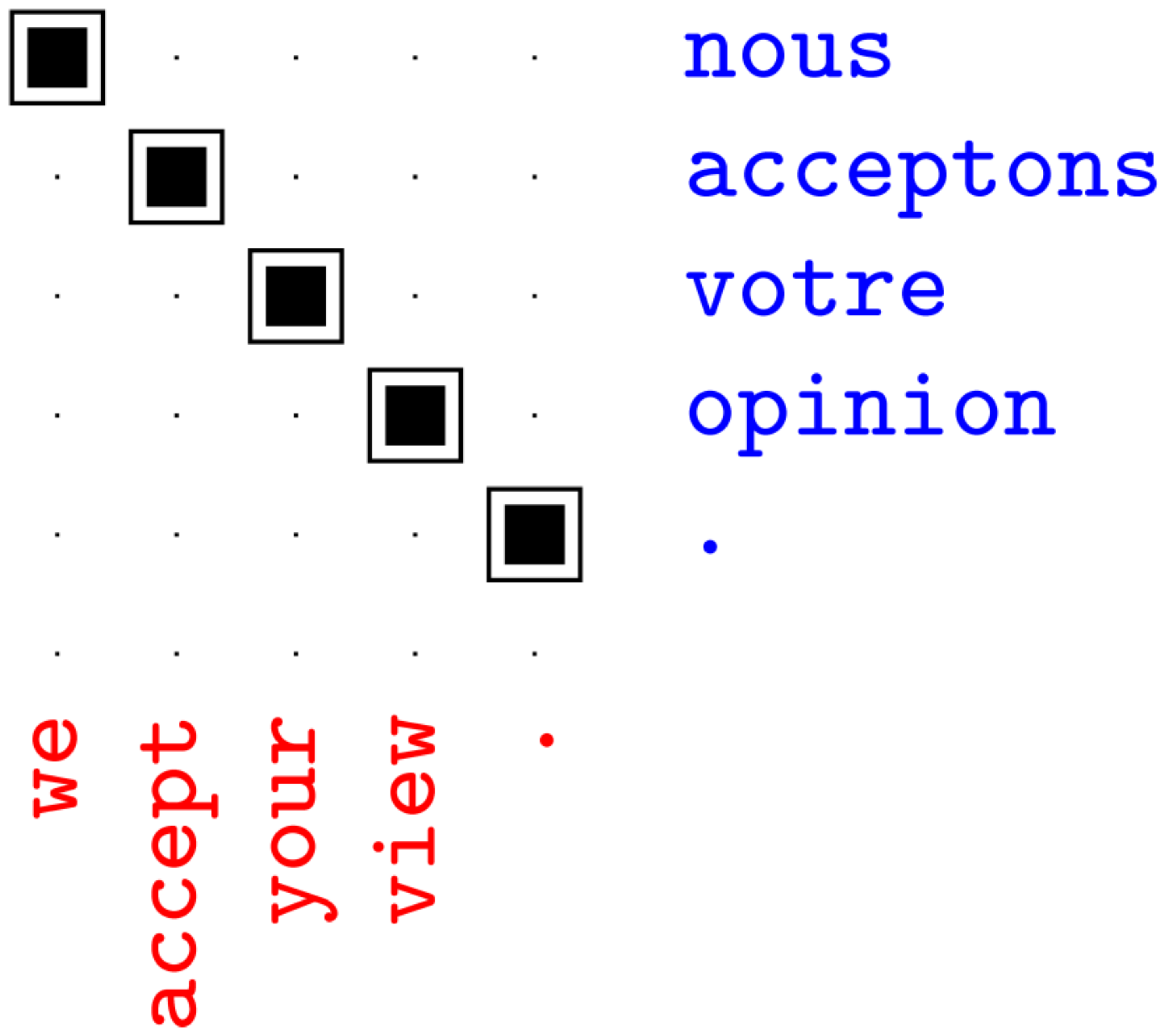

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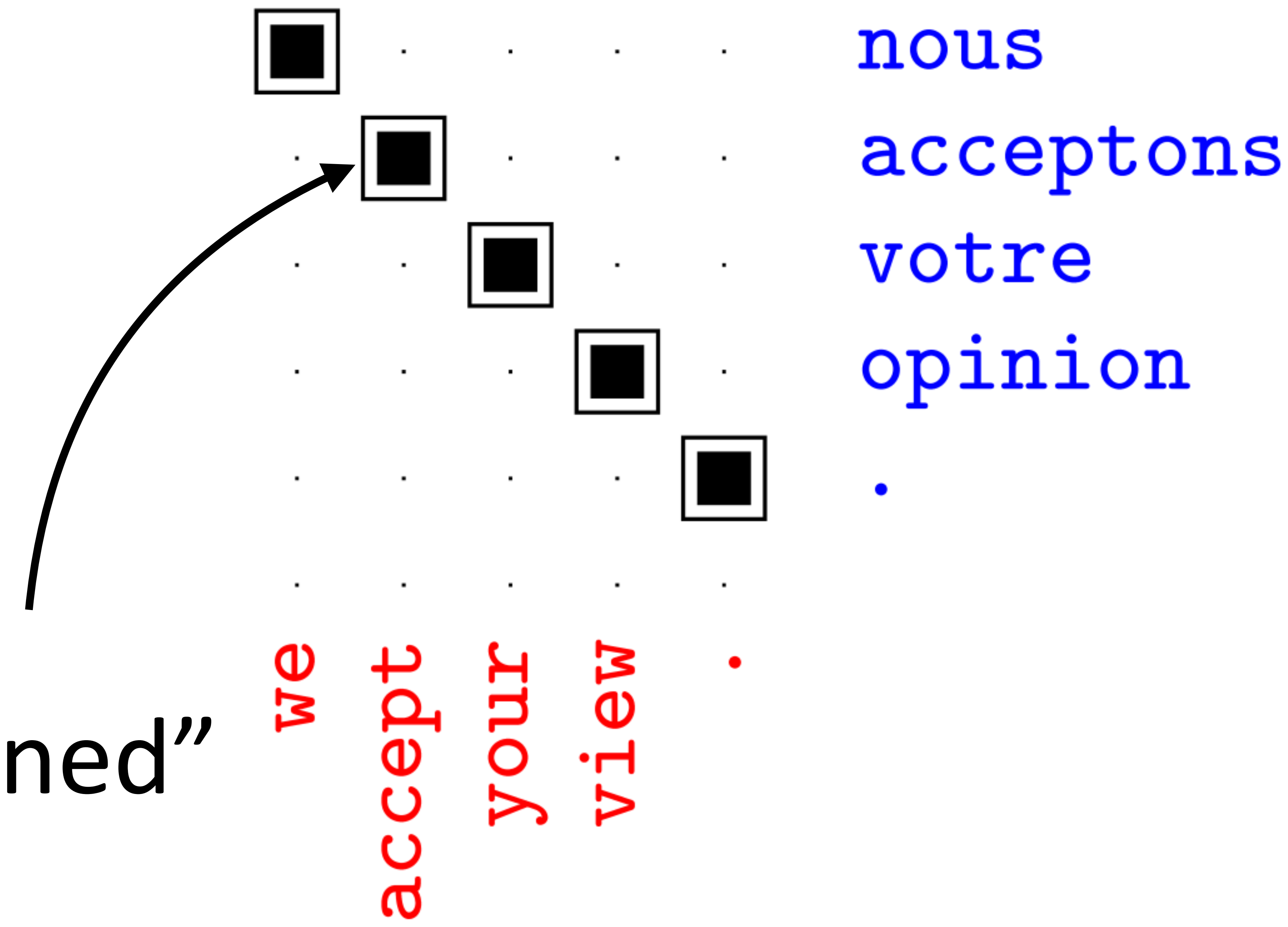


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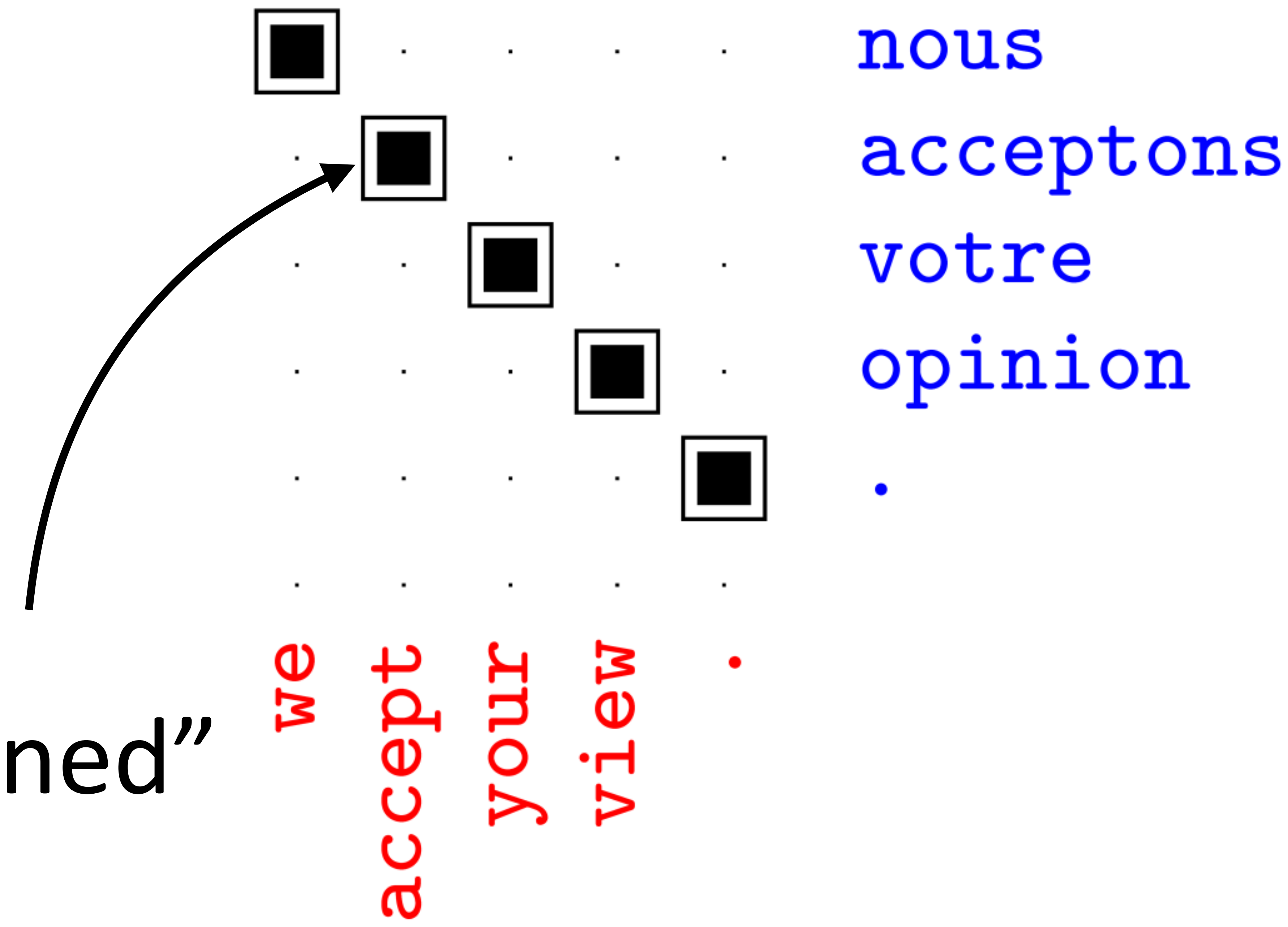
- Output: alignments between words in each sentence
  - We will see how to turn these into phrases

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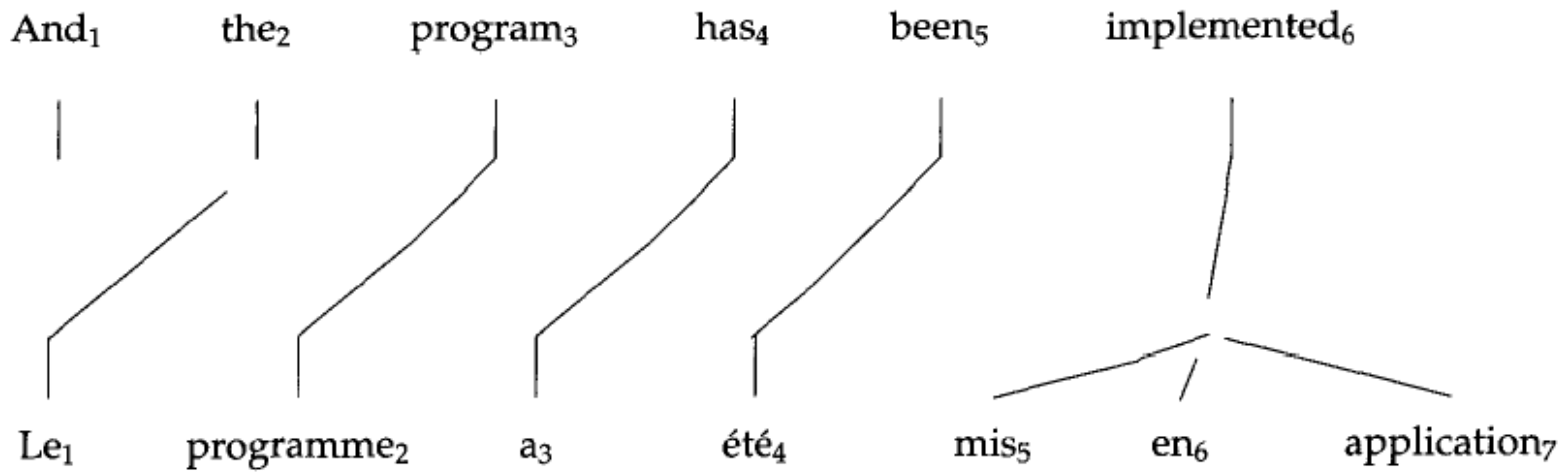
# 1-to-Many Alignments



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- Latent variable model: $P(\mathbf{f}|\mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}|\mathbf{a}, \mathbf{e})P(\mathbf{a})$

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- Correct alignments should lead to higher-likelihood generations, so by optimizing this objective we will learn correct alignments

# IBM Model 1

- Each French word is aligned to *at most* one English word

$$P(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \prod_{i=1}^{n} P(f_i | e_{a_i}) P(a_i)$$

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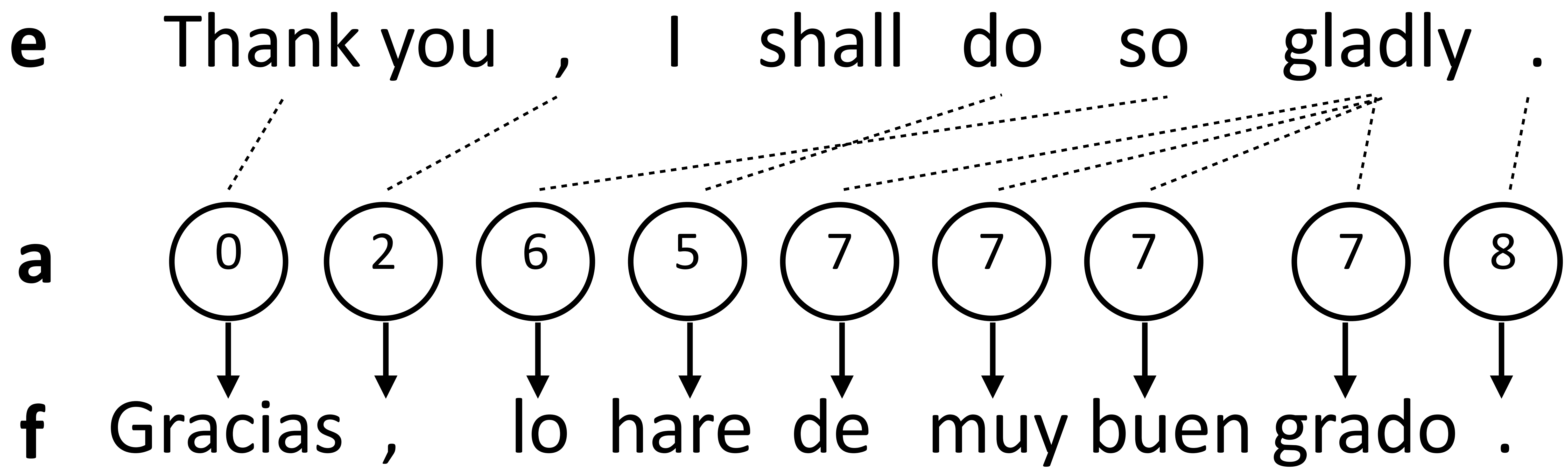


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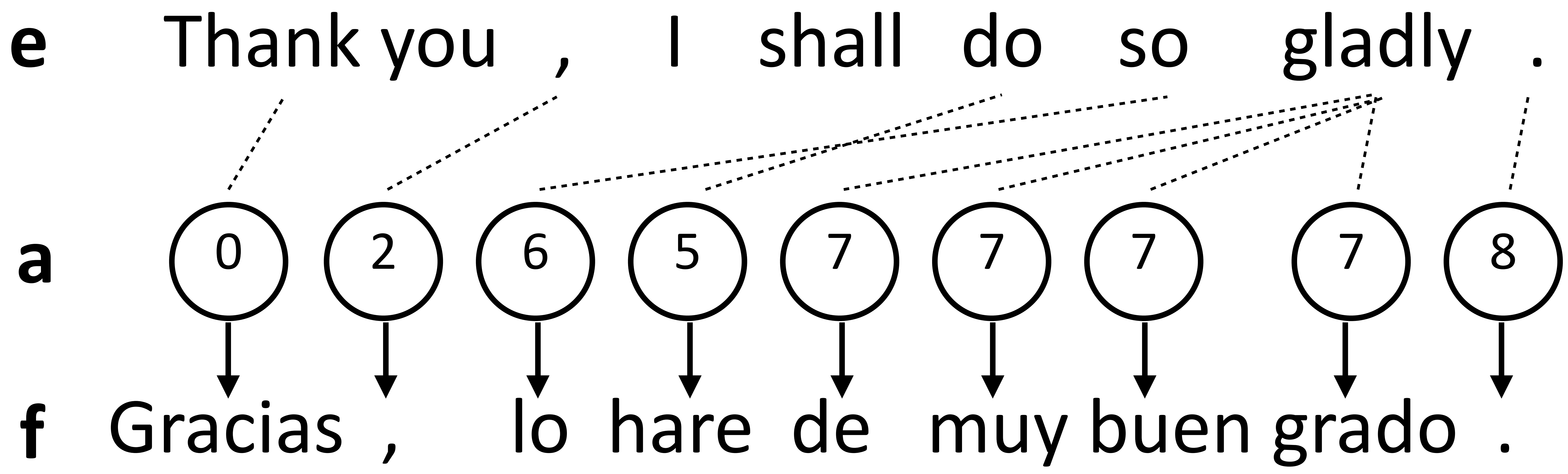


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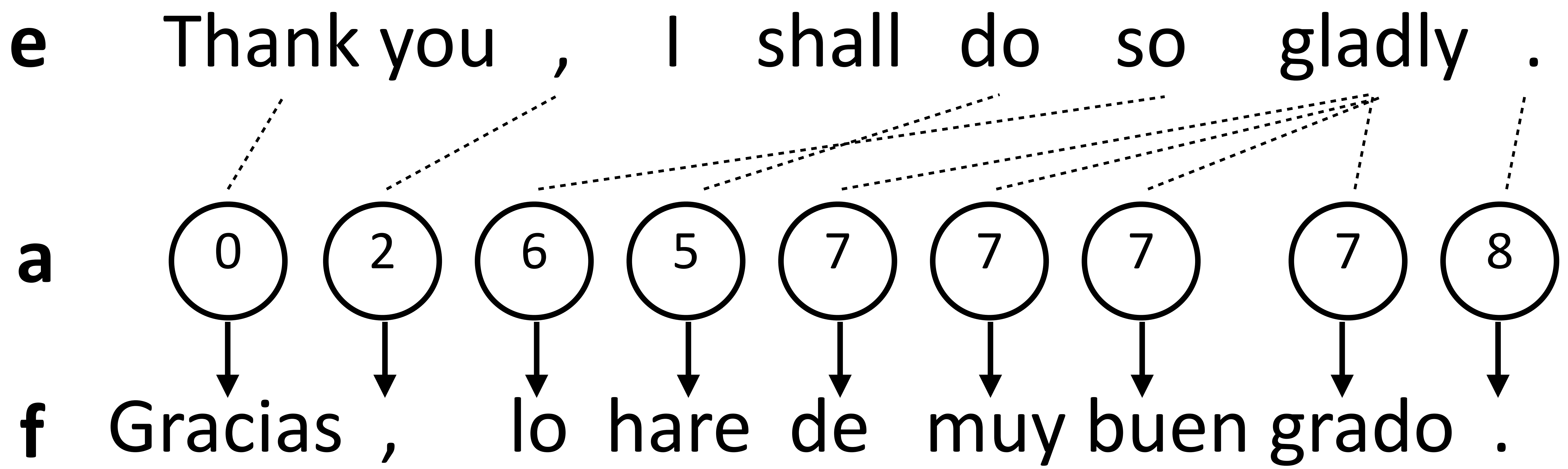


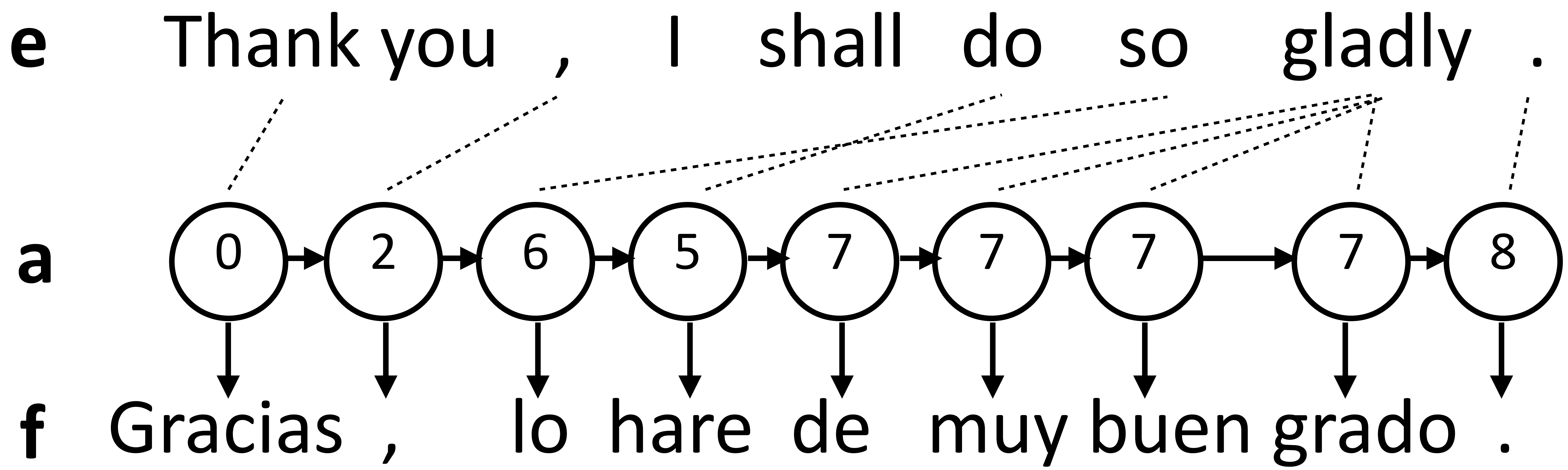

- Set P(a) uniformly (no prior over good alignments)
- $P(f_i|e_{a_i})$: word translation probability table

Brown et al. (1993)

# HMM for Alignment

- Sequential dependence between a's to capture monotonicity

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \prod_{i=1}^{n} P(f_i|e_{a_i})P(a_i|a_{i-1})$$

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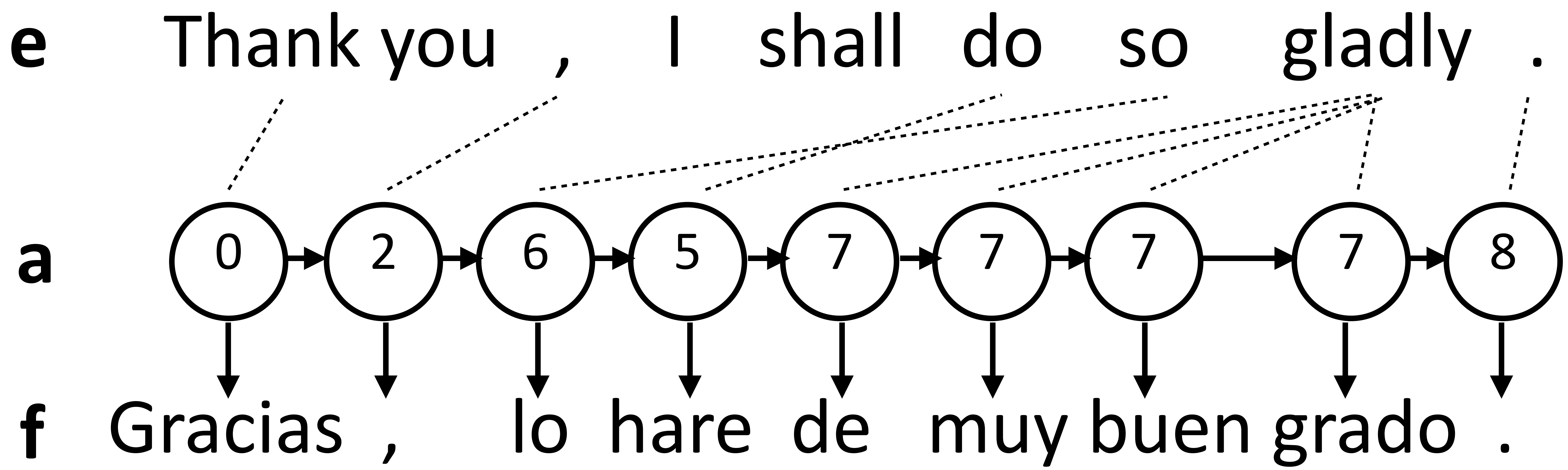
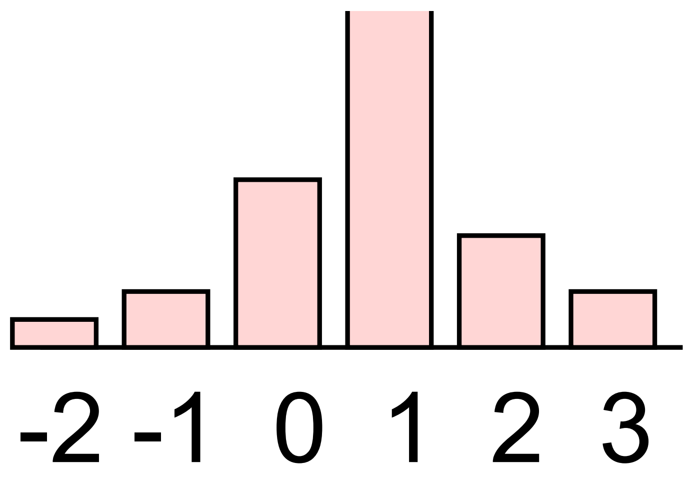



- Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$

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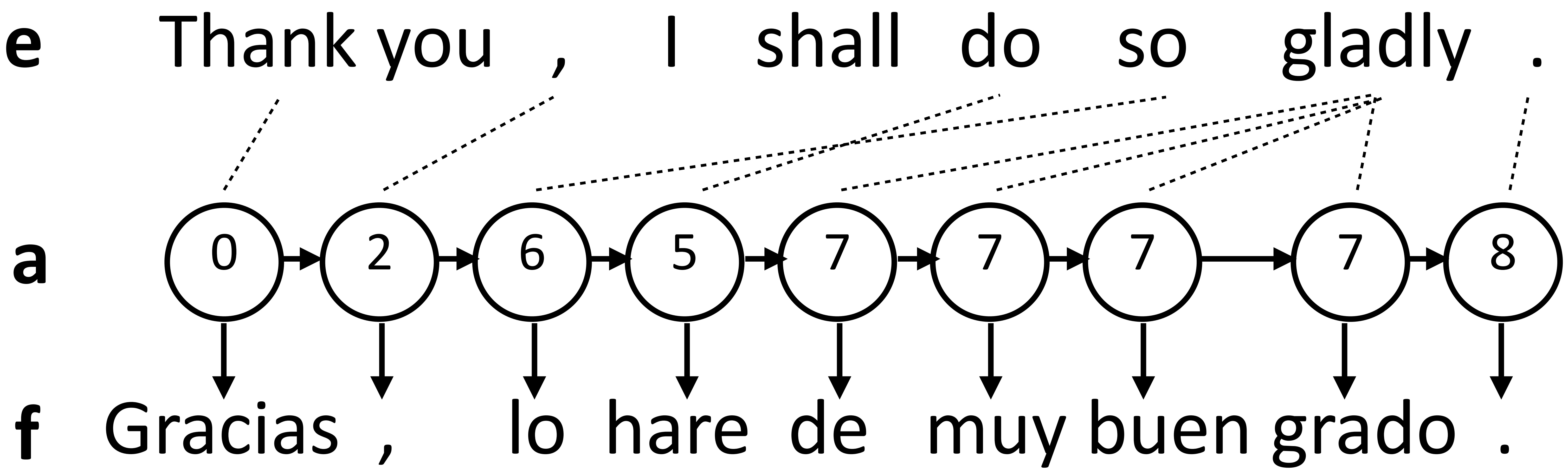


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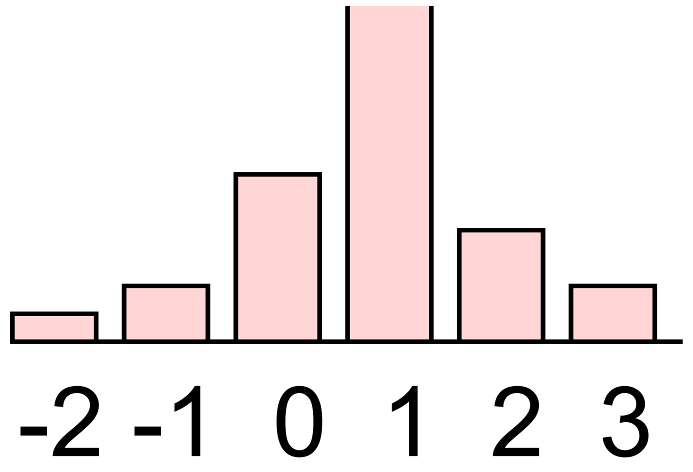
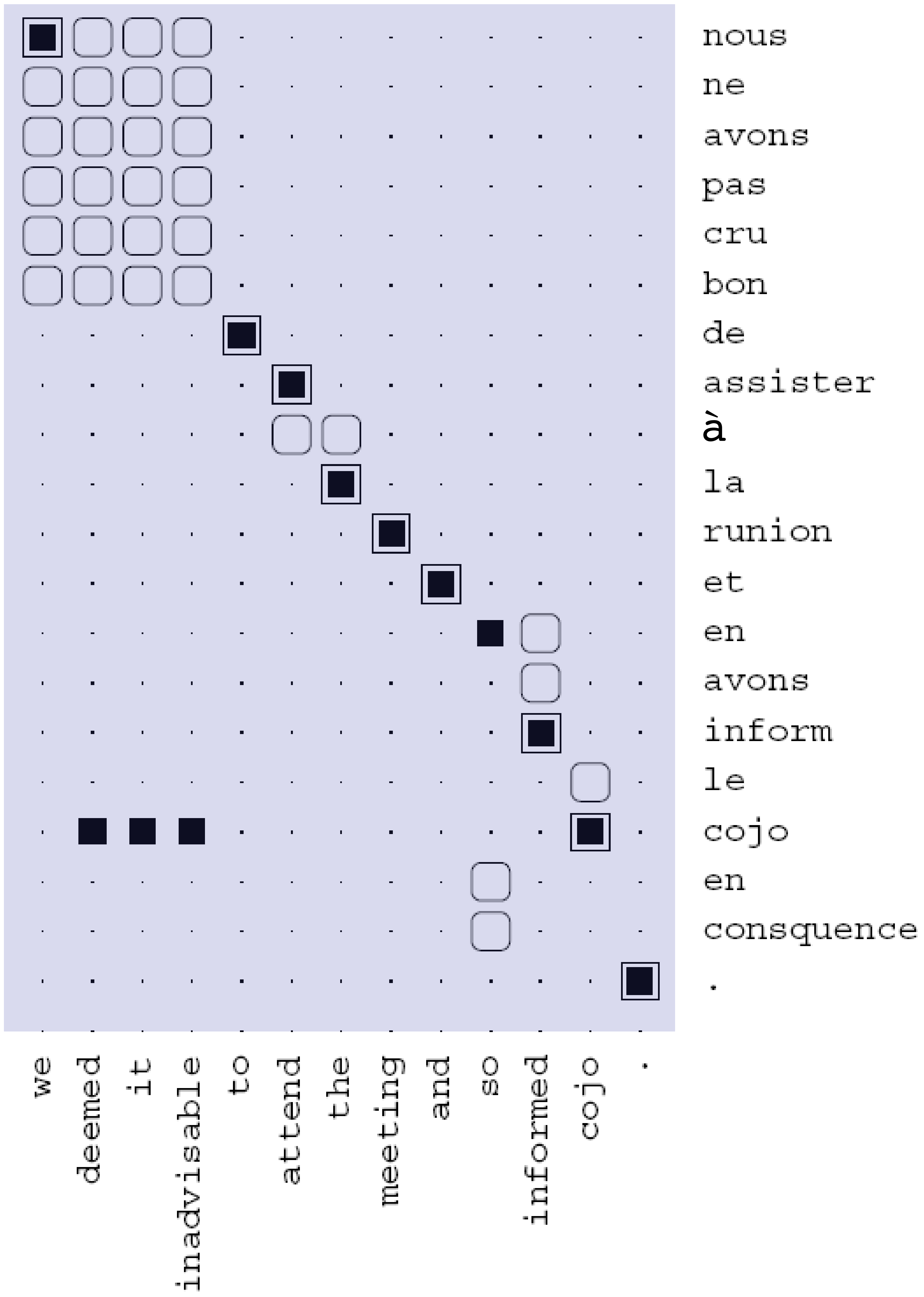



- $P(f_i|e_{a_i})$: same as before

Brown et al. (1993)

# HMM Model

- Which direction is this?



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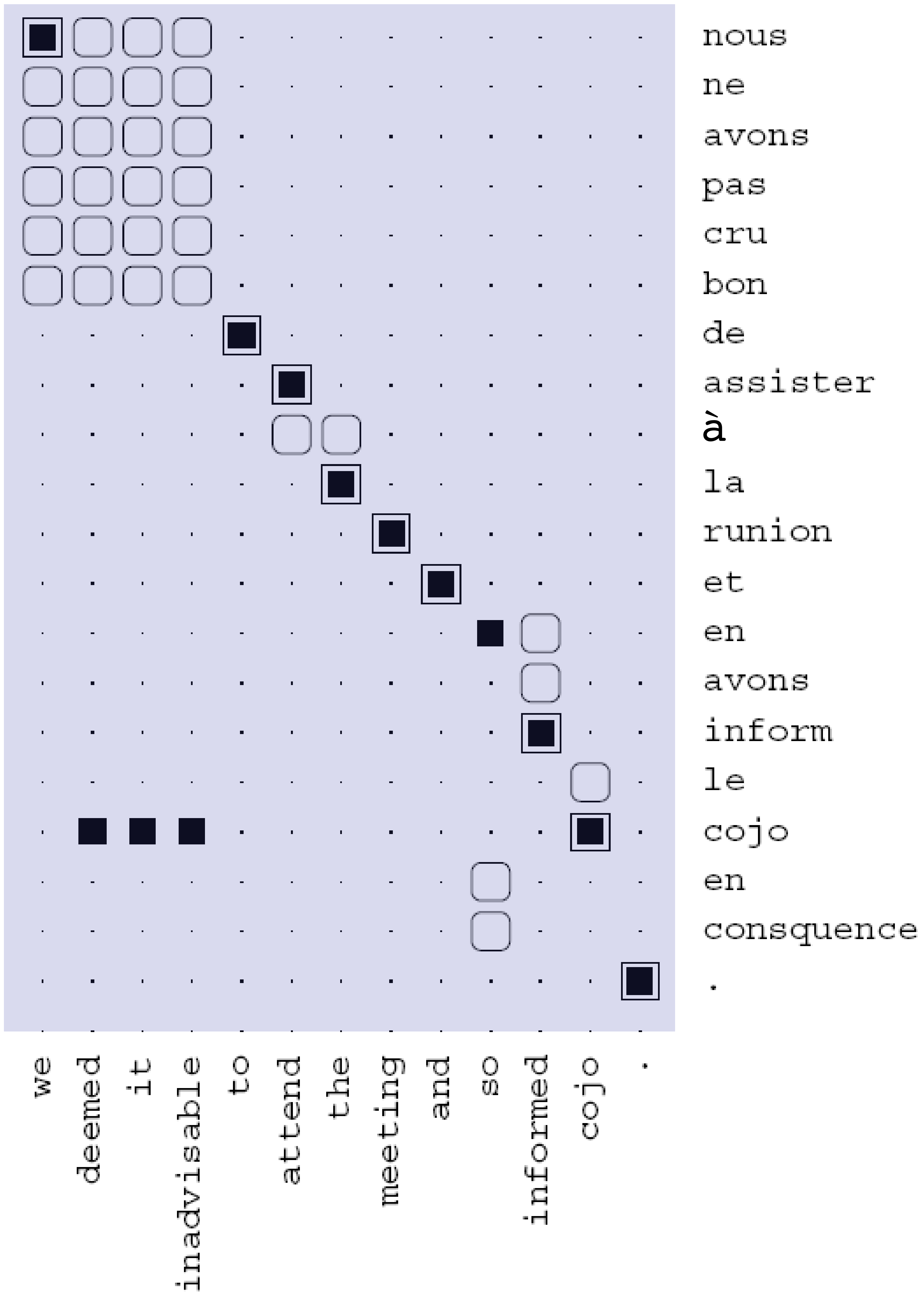
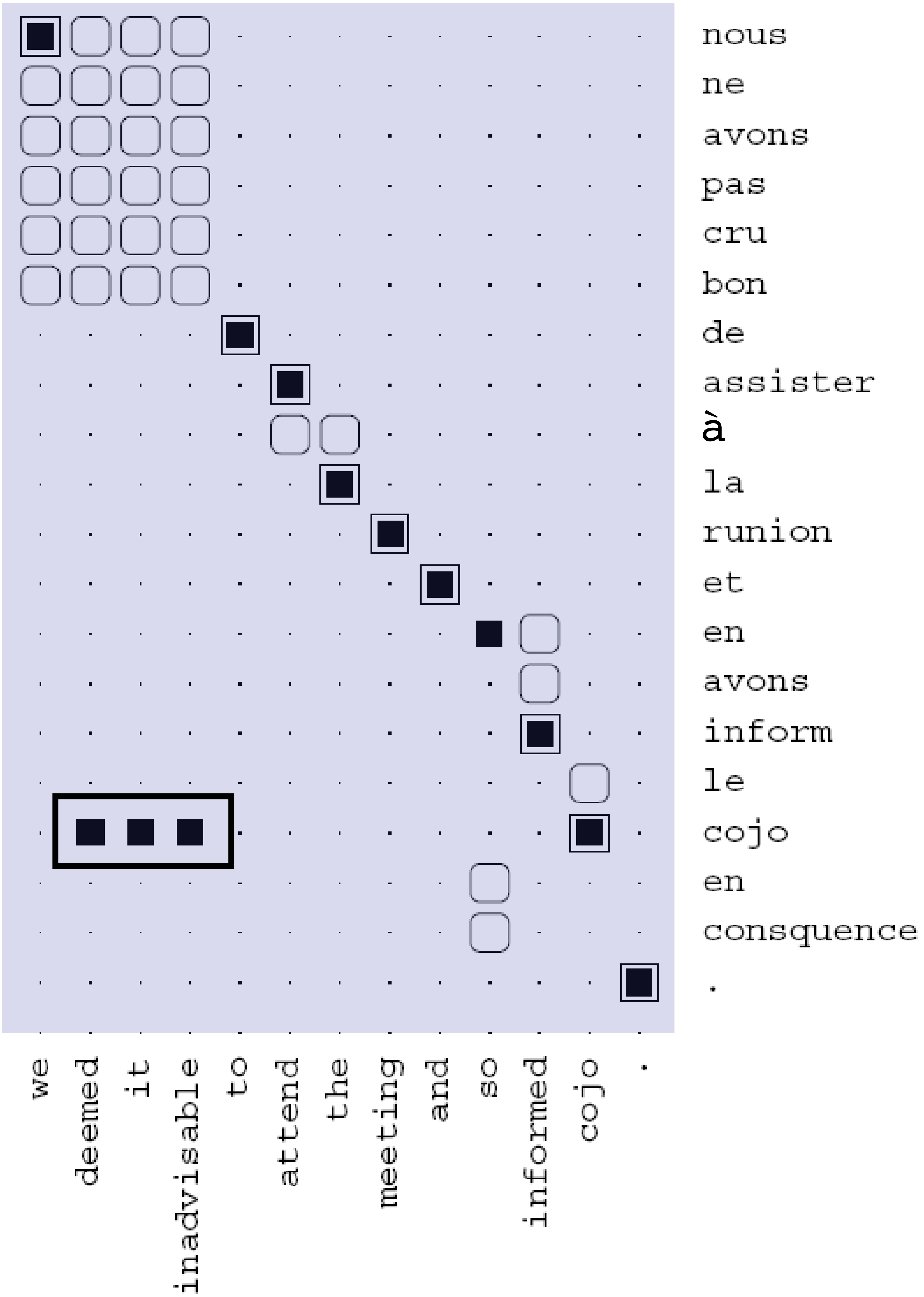


# HMM Model

- Which direction is this?
- Alignments are generally monotonic (along diagonal)
- Some mistakes, especially when you have rare words (*garbage collection*)



# Evaluating Word Alignment

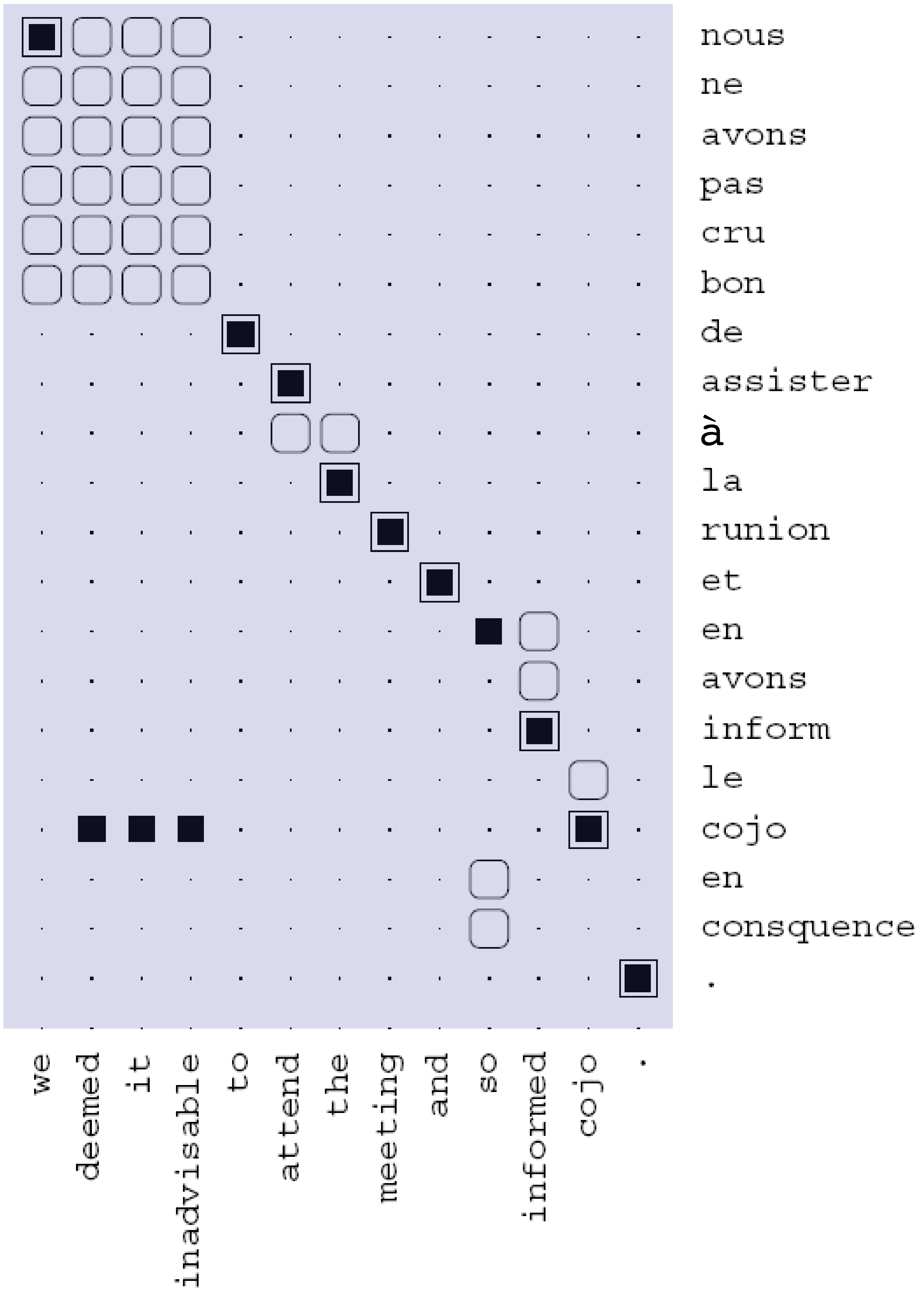
- “Alignment error rate”: use labeled alignments on small corpus

| Model | AER |
|---|---|
| Model 1 INT | 19.5 |
| HMM E→F | 11.4 |
| HMM F→E | 10.8 |
| HMM AND | 7.1 |
| HMM INT | 4.7 |
| GIZA M4 AND | 6.9 |

- Run Model 1 in both directions and intersect “intelligently”
- Run HMM model in both directions and intersect “intelligently”

# Phrase Extraction

- Find contiguous sets of aligned words in the two languages that don't have alignments to other words



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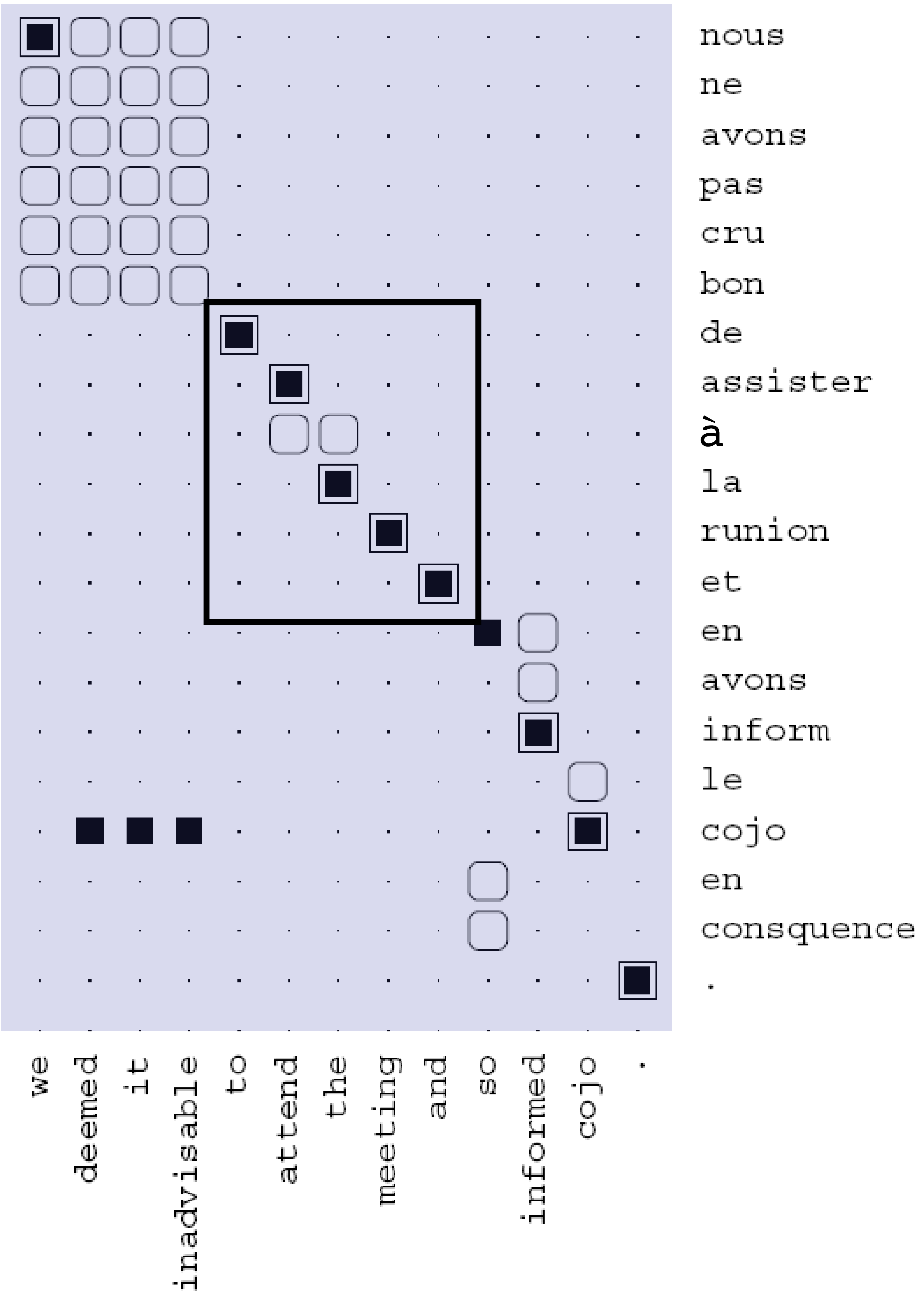

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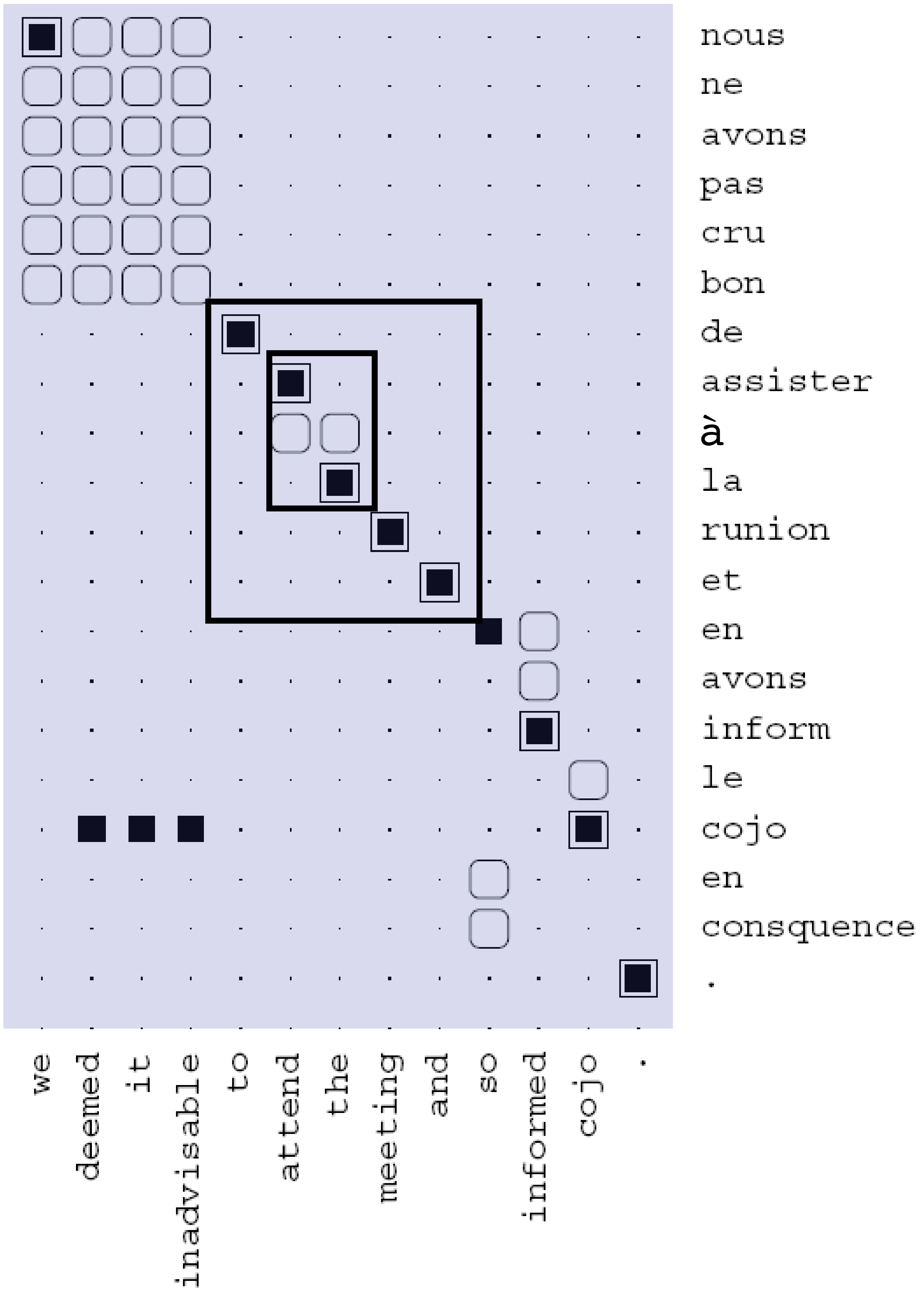

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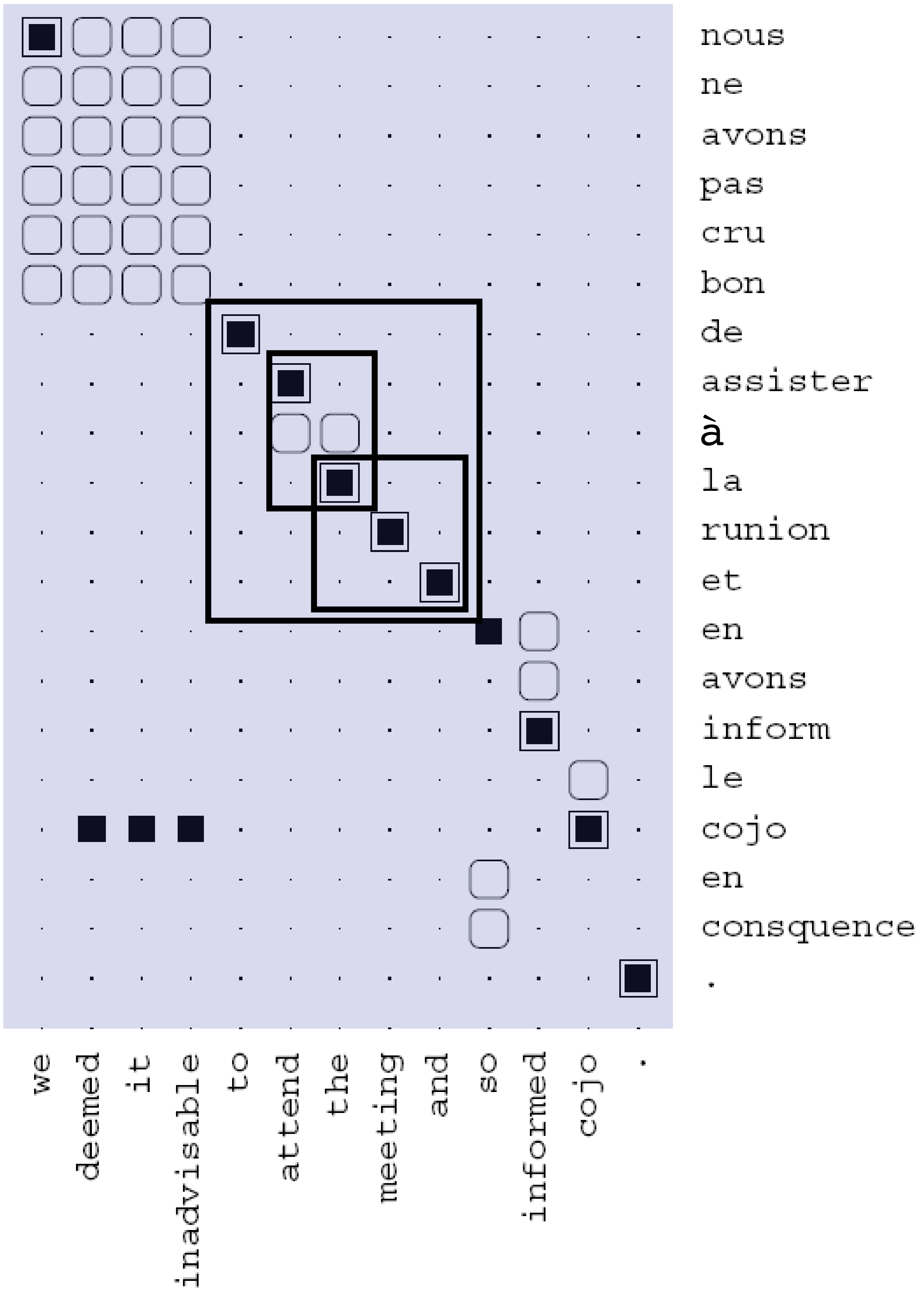

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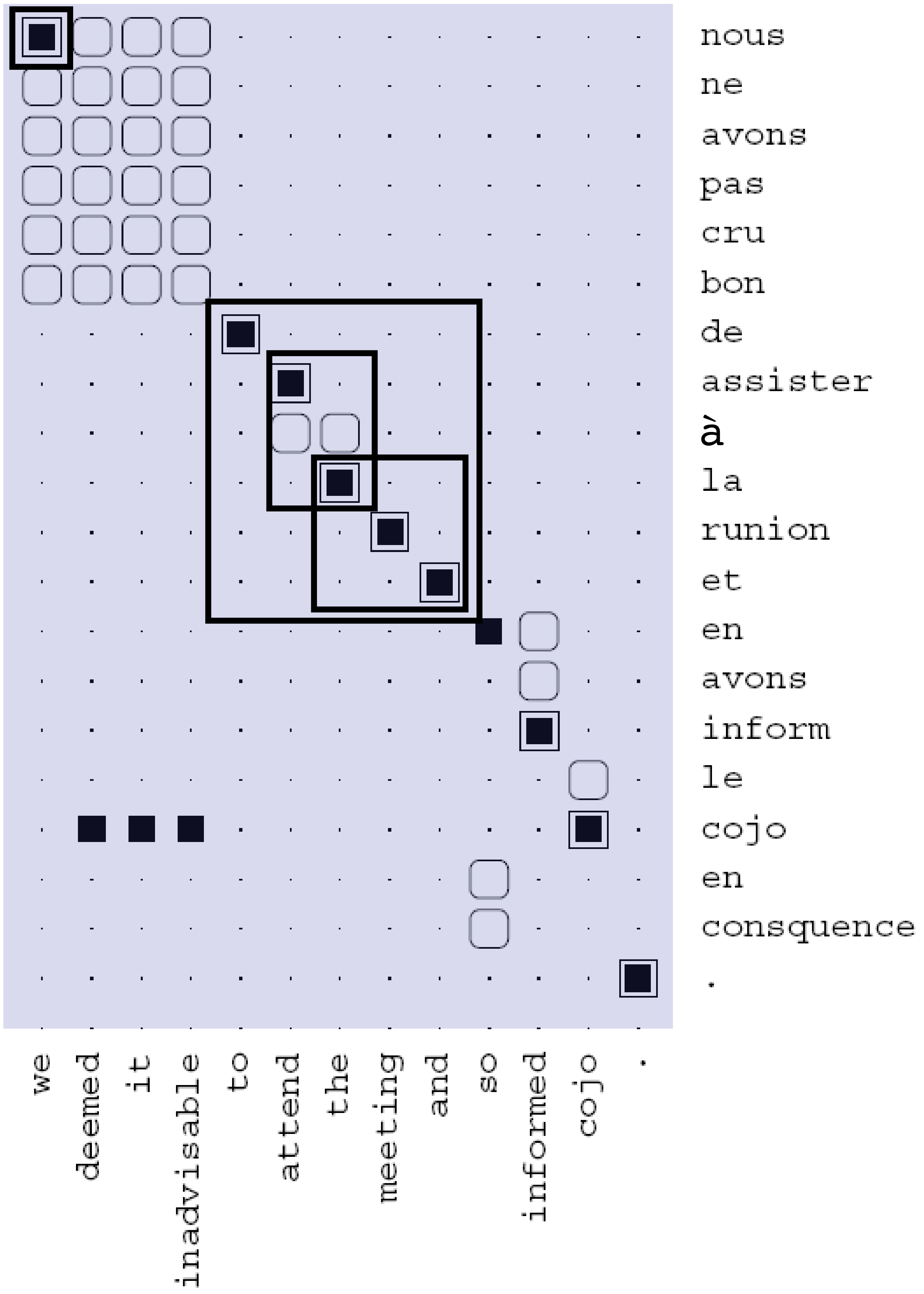

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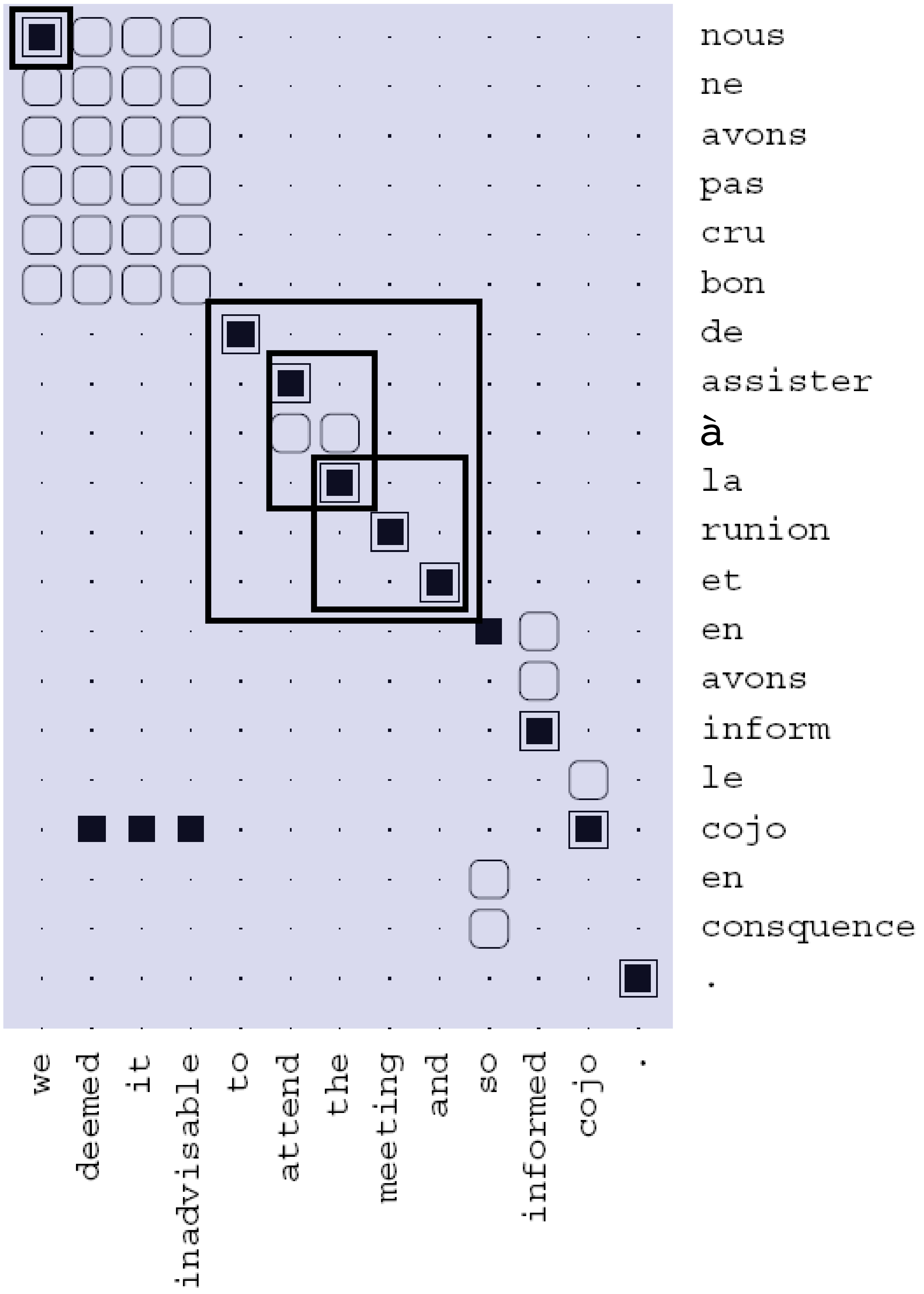

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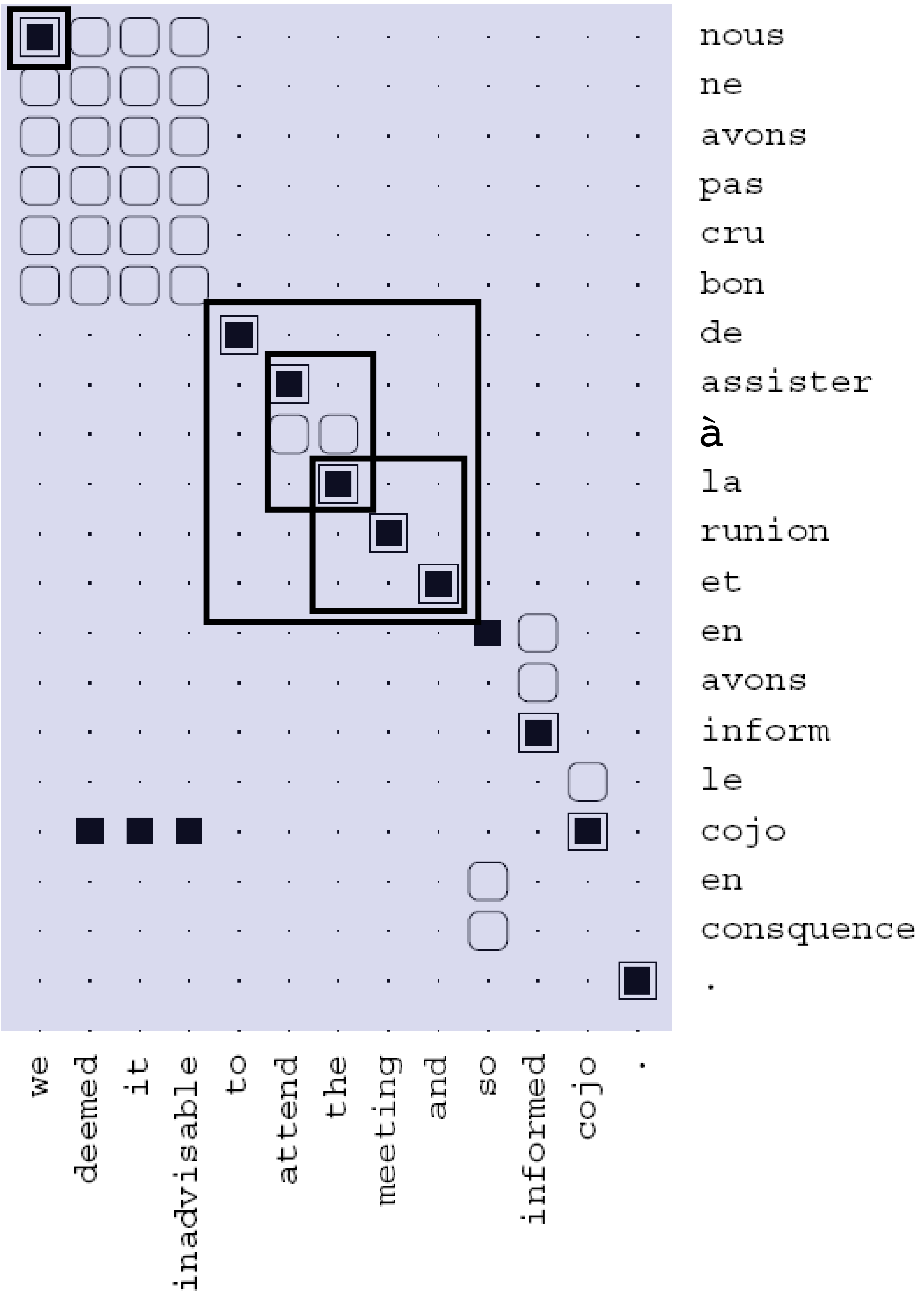
…

- Lots of phrases possible, count across all sentences and score by frequency

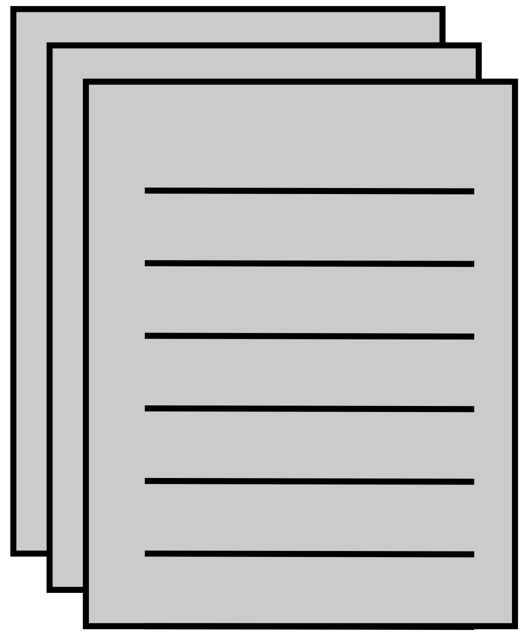


# Language Modeling

# Phrase-Based MT

cat ||| chat ||| 0.9
the cat ||| le chat ||| 0.8
dog ||| chien ||| 0.8
house ||| maison ||| 0.6
my house ||| ma maison ||| 0.9
language ||| langue ||| 0.9
…

Phrase table P(f|e)



Language model P(e)

Unlabeled English data

$$P(e|f) \propto P(f|e)P(e)$$

Noisy channel model: combine scores from translation model + language model to translate foreign to English

"Translate faithfully but make fluent English"

# N-gram Language Models

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Maximum likelihood estimate of this probability from a corpus

- Just relies on counts, even in 2008 could scale up to 1.3M word types, 4B n-grams (all 5-grams occurring >40 times on the Web)

# Smoothing N-gram Language Models

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- Kneser-Ney smoothing: this trick, plus low-order distributions modified to capture fertilities (how many distinct words appear in a context)

# Engineering N-gram Models

- For 5+-gram models, need to store between 100M and 10B context-word-count triples

(a) Context-Encoding

| $w$ | $c$ | $val$ |
|---|---|---|
| 1933 | 15176585 | 3 |
| 1933 | 15176587 | 2 |
| 1933 | 15176593 | 1 |
| 1933 | 15176613 | 8 |
| 1933 | 15179801 | 1 |
| 1935 | 15176585 | 298 |
| 1935 | 15176589 | 1 |

(b) Context Deltas

| $\Delta w$ | $\Delta c$ | $val$ |
|---|---|---|
| 1933 | 15176585 | 3 |
| +0 | +2 | 1 |
| +0 | +5 | 1 |
| +0 | +40 | 8 |
| +0 | +188 | 1 |
| +2 | 15176585 | 298 |
| +0 | +4 | 1 |

(c) Bits Required

| $\|\Delta w\|$ | $\|\Delta c\|$ | $\|val\|$ |
|---|---|---|
| 24 | 40 | 3 |
| 2 | 3 | 3 |
| 2 | 3 | 3 |
| 2 | 9 | 6 |
| 2 | 12 | 3 |
| 4 | 36 | 15 |
| 2 | 6 | 3 |

- Make it fit in memory by *delta encoding* scheme: store deltas instead of values and use variable-length encoding

Pauls and Klein (2011), Heafield (2011)

# Neural Language Models

- Early work: feedforward neural networks looking at context

Mnih and Hinton (2003)

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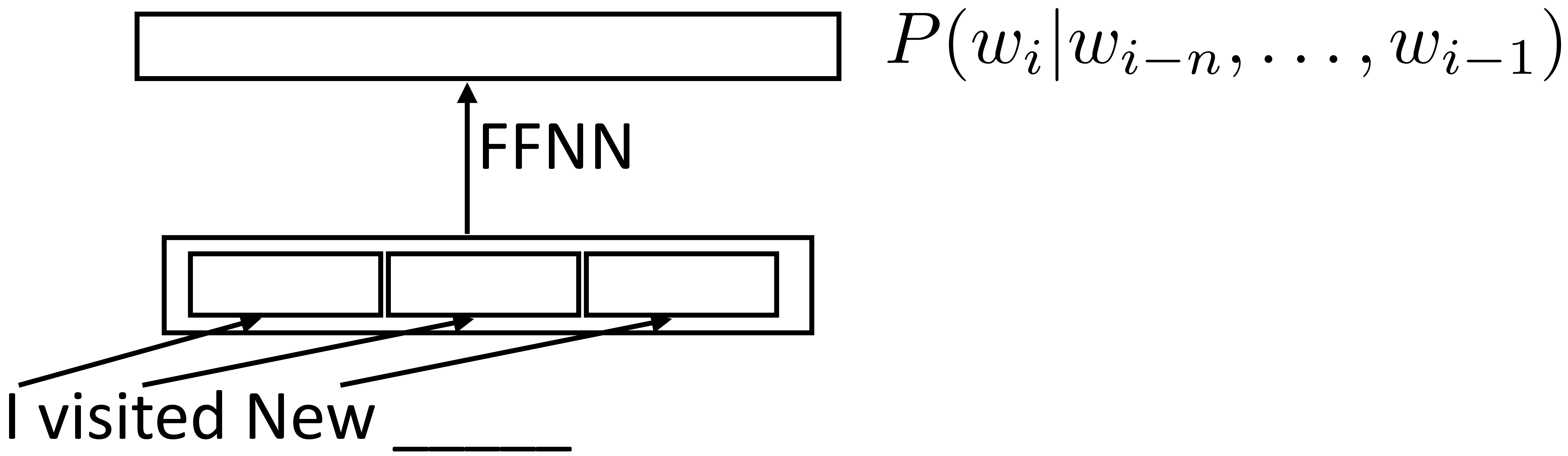


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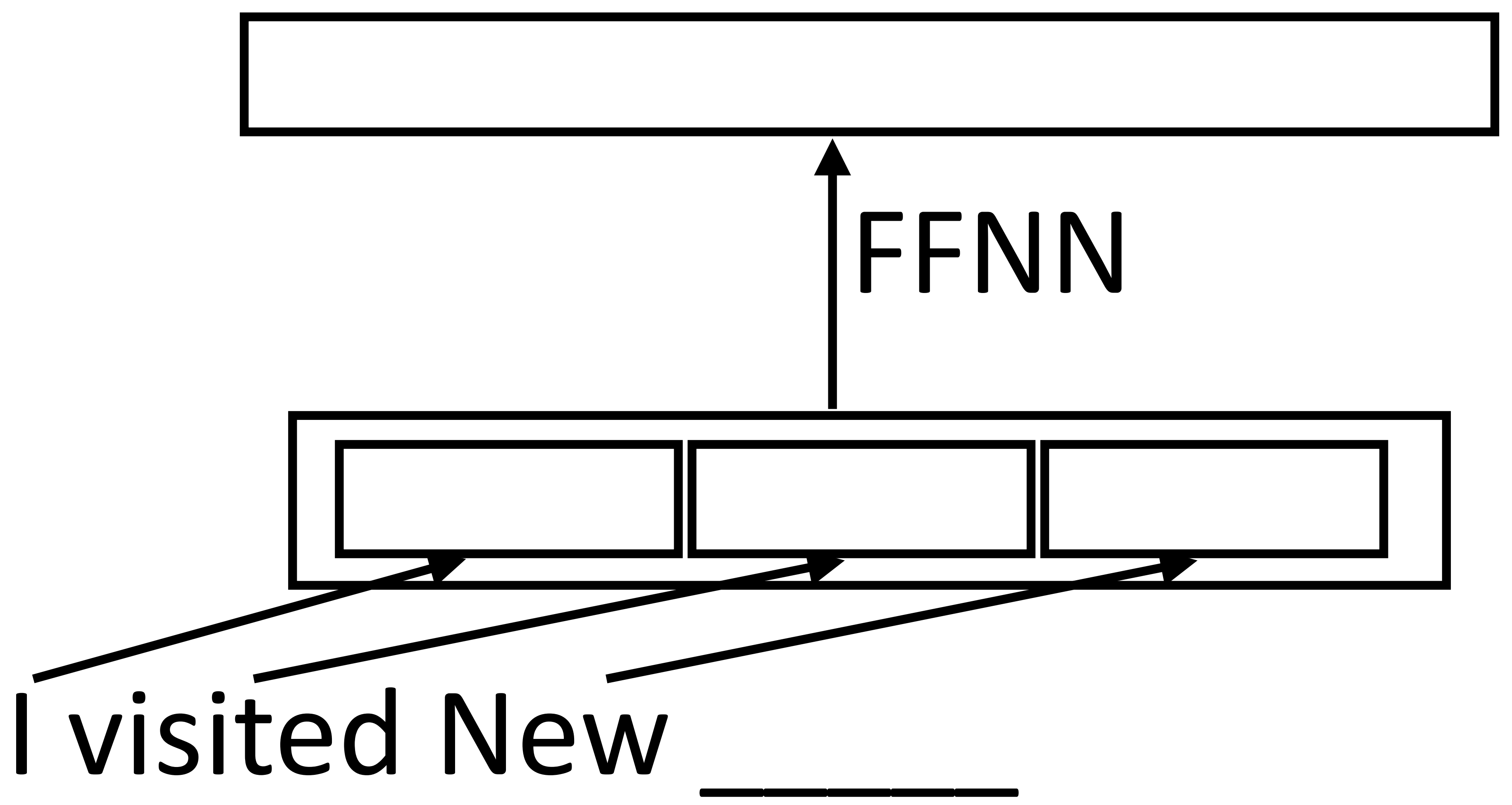
$$P(w_i|w_{i-n},\ldots,w_{i-1})$$




- Variable length context with RNNs:

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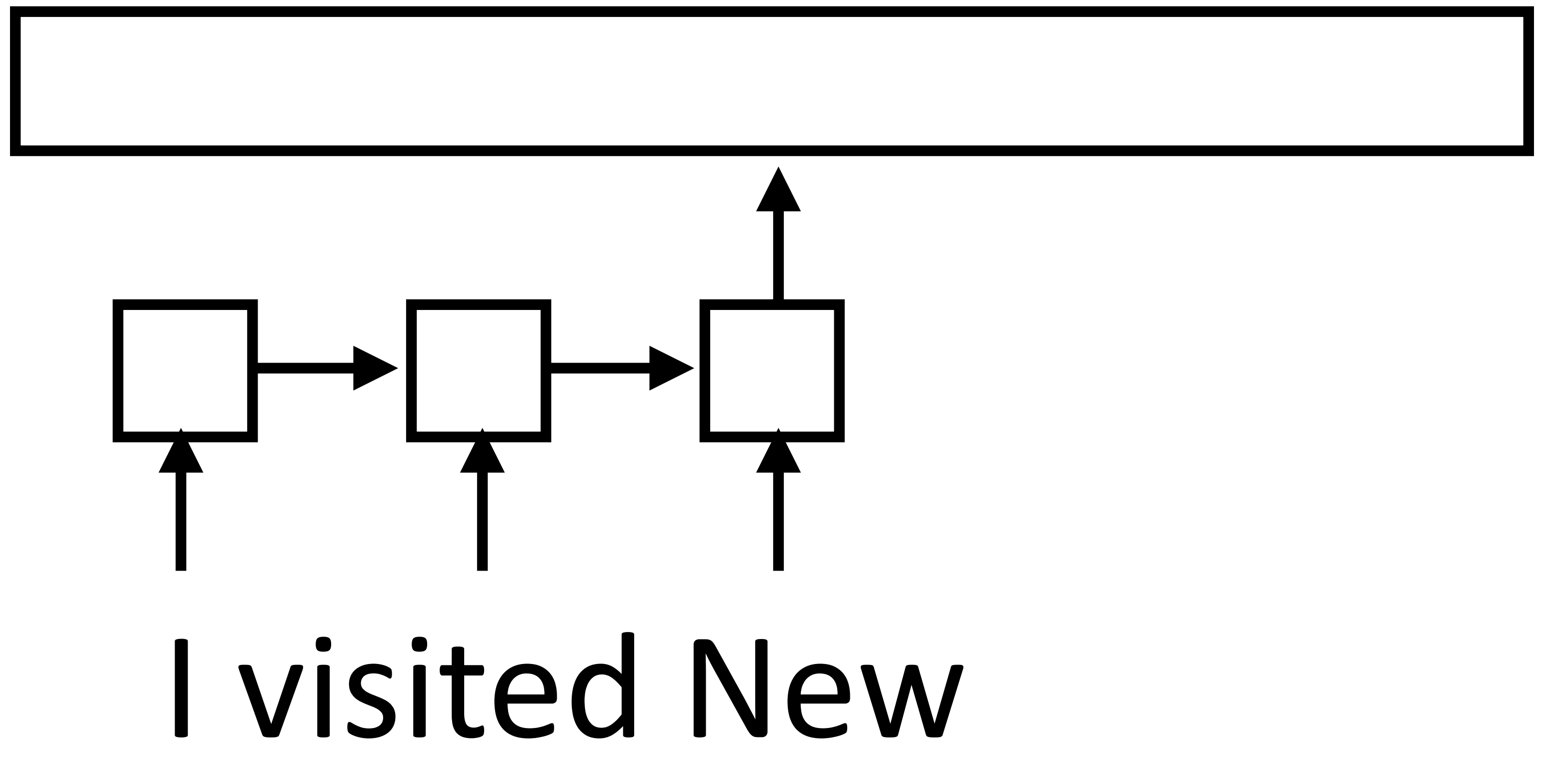


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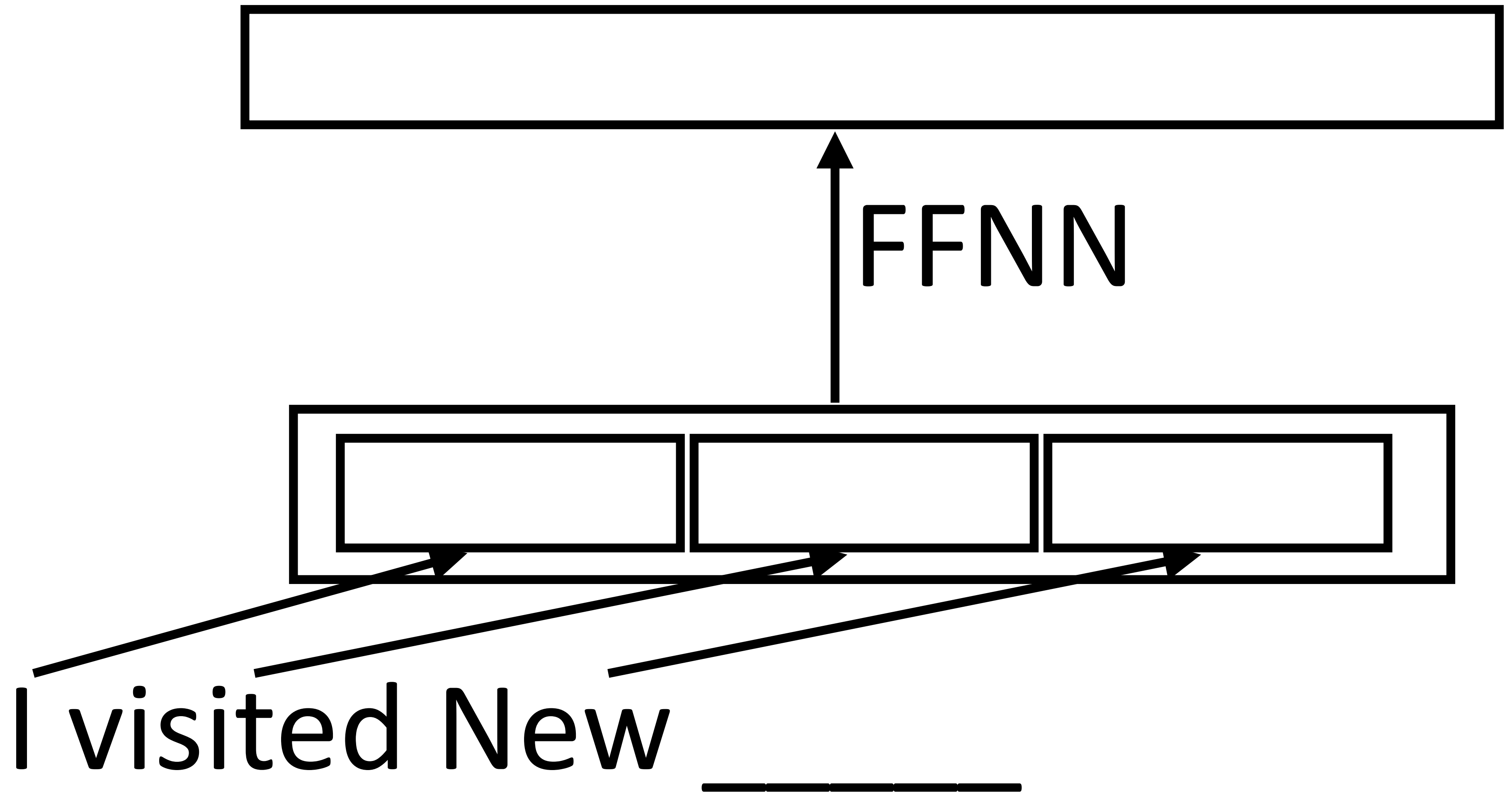


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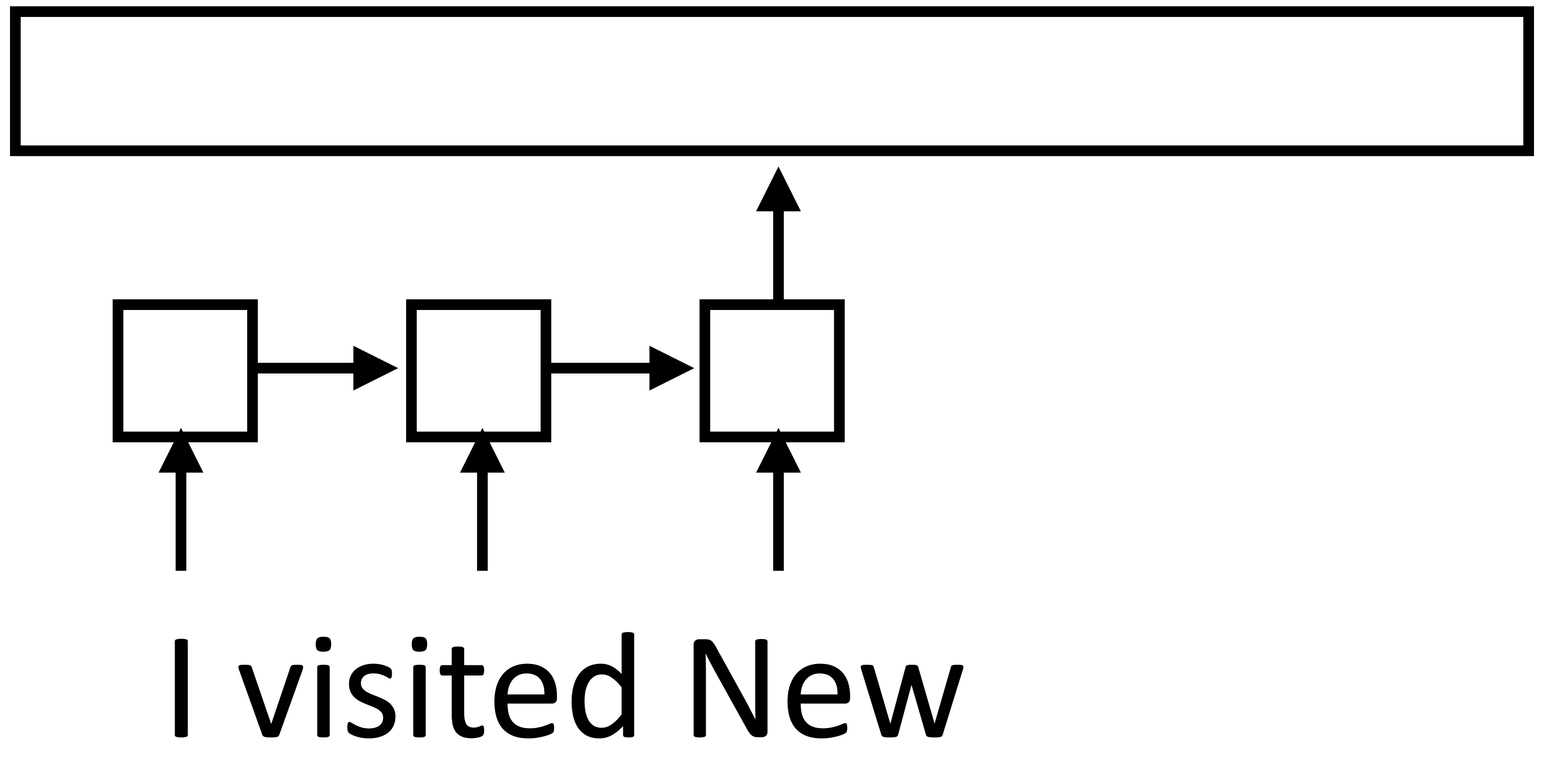


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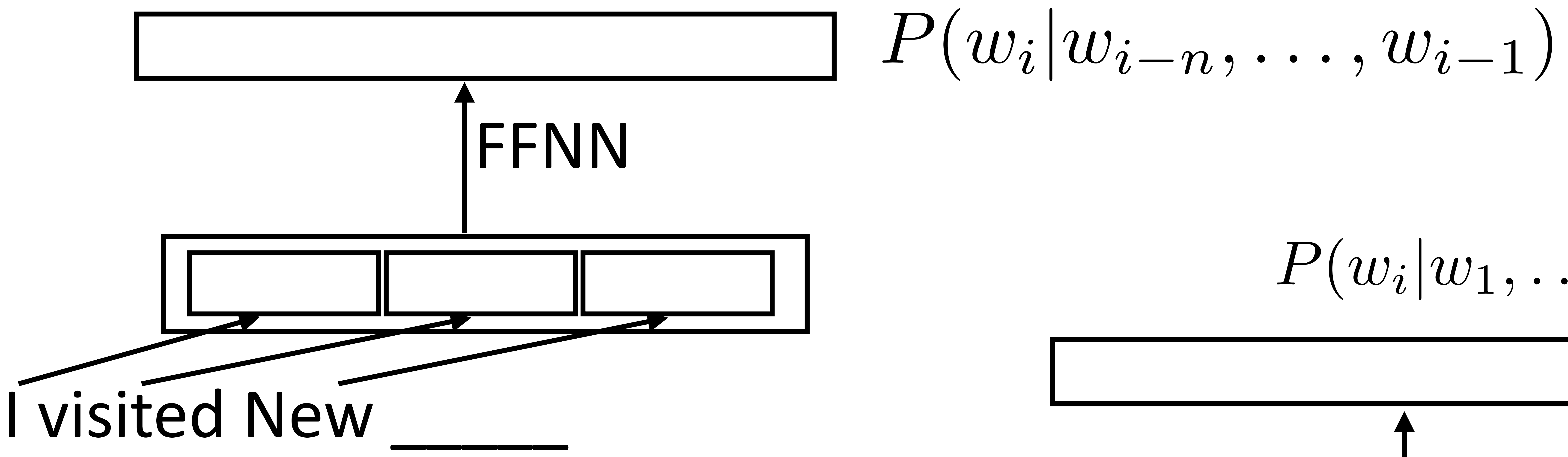


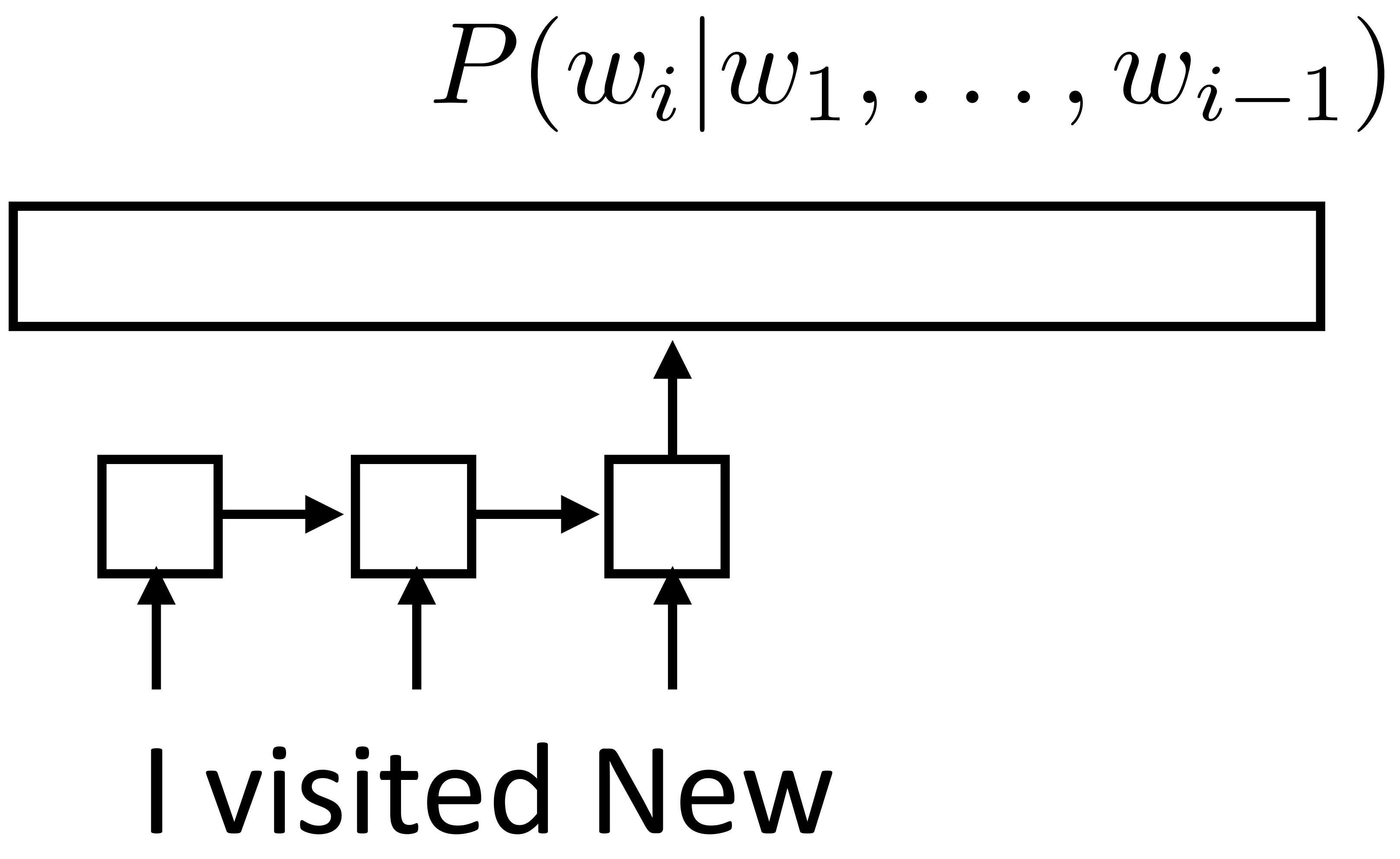


- Variable length context with RNNs:
  - Works like a decoder with no encoder
- Slow to train over lots of data!

Mnih and Hinton (2003)

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  - NLL = -2 -> on average, correct thing has prob 1/4 -> PPL = 4. PPL is sort of like branching factor

# Results

Merity et al. (2017), Melis et al. (2017)

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- Kneser-Ney 5-gram model with cache: PPL = 125.7
- LSTM: PPL ~ 60-80 (depending on how much you optimize it)
- Melis et al.: many neural LM improvements from 2014-2017 are subsumed by just using the right regularization (right dropout settings). So LSTMs are pretty good

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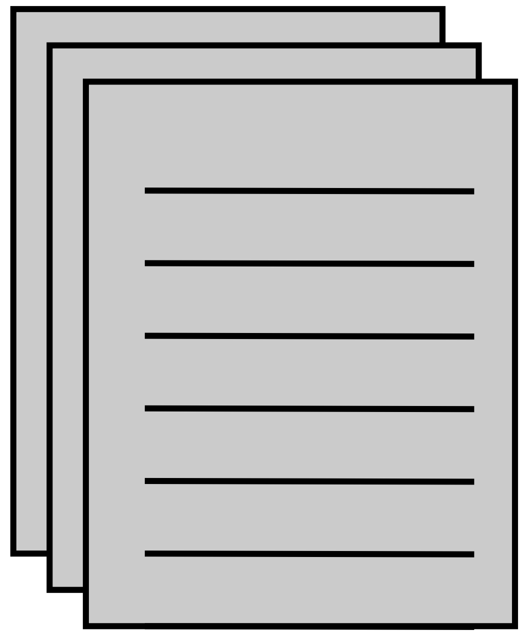

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# Decoding

# Phrase-Based Decoding

- Inputs:
  - Language model that scores $P(e_i|e_1, \ldots, e_{i-1}) \approx P(e_i|e_{i-n-1}, \ldots, e_{i-1})$
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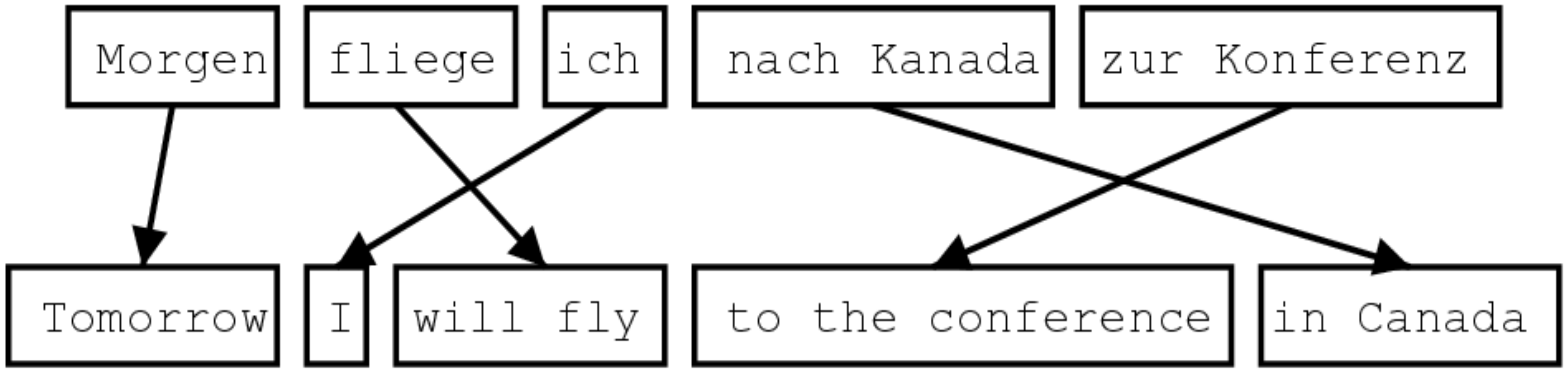


# Phrase lattices are big!

| 这 | 7人 | 中包括 | 来自 | 法国 | 和 | 俄罗斯 | 的 | 宇航 | 员 | . |
|---|---|---|---|---|---|---|---|---|---|---|
| **the** | 7 people | including | by some | | **and** | the russian | **the** | the astronauts | | , |
| it | 7 people included | | by france | | and the | the russian | | international astronautical | of rapporteur . | |
| this | 7 out | including the | **from** | the french | and the russian | | the fifth | | . | |
| these | 7 among | including from | | the french and | | of the russian | of | space | members | . |
| that | 7 persons | including from the | | of france | and to | russian | of the | aerospace | members . | |
| | 7 include | | from the | of france and | | russian | | **astronauts** | | . the |
| | 7 numbers include | | **from france** | | and russian | | of astronauts who | | | . " |
| | 7 populations include | | those from france | | and russian | | | astronauts . | | |
| | 7 deportees included | | come from | **france** | **and russia** | | in | astronautical | personnel | ; |
| | 7 philtrum | including those from | | **france and** | | **russia** | a space | | **member** | |
| | | including representatives from | | france and the | | **russia** | | astronaut | | |
| | | include | came from | **france and russia** | | | by cosmonauts | | | |
| | | include representatives from | | french | **and russia** | | | cosmonauts | | |
| | | include | came from france | | and russia 's | | | cosmonauts . | | |
| | | **includes** | coming from | french and | | russia 's | | cosmonaut | | |
| | | | | french and russian | | | 's | astronavigation | member . | |
| | | | | french | **and russia** | | **astronauts** | | | |
| | | | | | and russia 's | | | | special rapporteur | |
| | | | | | , and | **russia** | | | rapporteur | |
| | | | | | , and russia | | | | rapporteur . | |
| | | | | | , and russia | | | | | |
| | | | | | or | russia 's | | | | |

Slide credit: Dan Klein

# Phrase-Based Decoding

- Input
- Translations

lo haré | rápidamente | .

I'll do it | quickly | .

quickly | I'll do it | .

*The decoder…*

*tries different segmentations,*

*translates phrase by phrase,*

*and considers reorderings.*

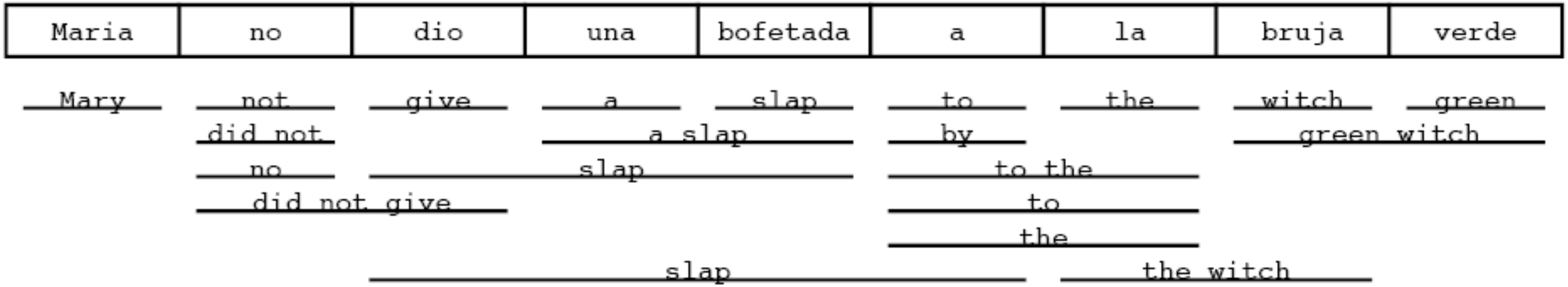
$$\arg\max_{\mathbf{e}} \left[P(\mathbf{f}|\mathbf{e}) \cdot P(\mathbf{e})\right]$$

- Decoding objective (for 3-gram LM)

$$\arg\max_{\mathbf{e}} \left[ \prod_{\langle \bar{e}, \bar{f} \rangle} P(\bar{f}|\bar{e}) \cdot \prod_{i=1}^{|\mathbf{e}|} P(e_i|e_{i-1}, e_{i-2}) \right]$$

Slide credit: Dan Klein

# Monotonic Translation

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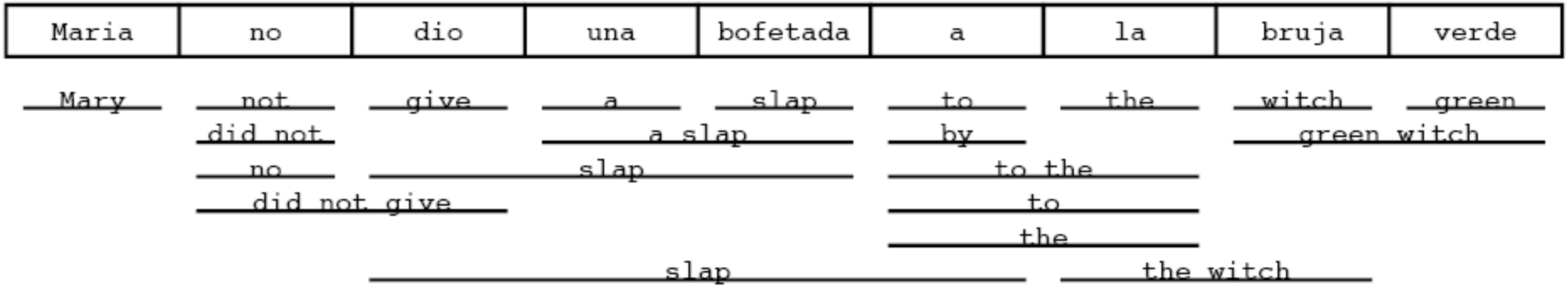


- If we translate with beam search, what state do we need to keep in the beam?

$$\arg\max_{\mathbf{e}} \left[ \prod_{\langle \bar{e}, \bar{f} \rangle} P(\bar{f} | \bar{e}) \cdot \prod_{i=1}^{|\mathbf{e}|} P(e_i | e_{i-1}, e_{i-2}) \right]$$

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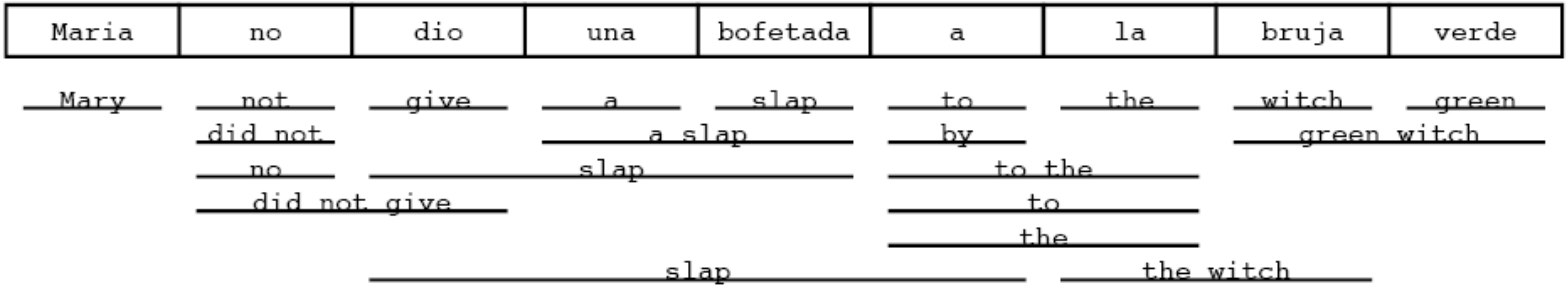


- If we translate with beam search, what state do we need to keep in the beam?
  - What have we translated so far?

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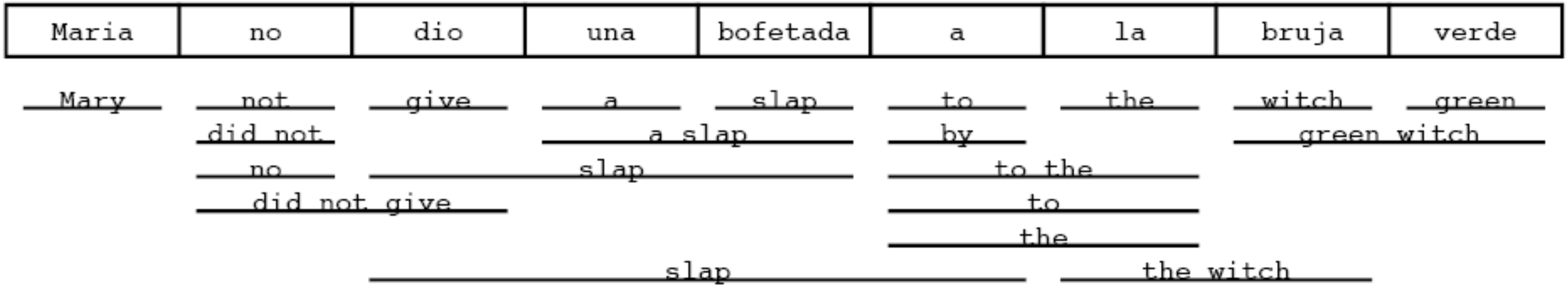


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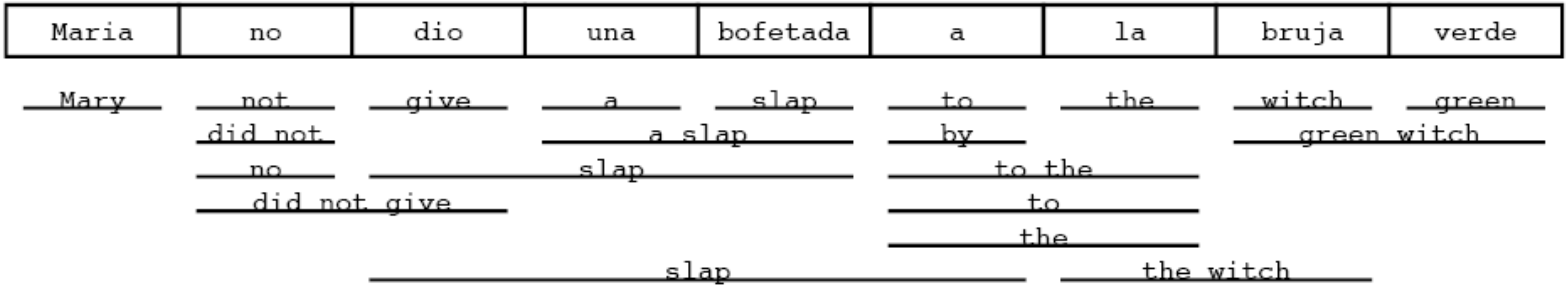


- If we translate with beam search, what state do we need to keep in the beam?
  - What have we translated so far?
  - What words have we produced so far?
  - When using a 3-gram LM, only need to remember the last 2 words!

$$\arg\max_{\mathbf{e}} \left[ \prod_{\langle \bar{e}, \bar{f} \rangle} P(\bar{f}|\bar{e}) \cdot \prod_{i=1}^{|\mathbf{e}|} P(e_i|e_{i-1}, e_{i-2}) \right]$$

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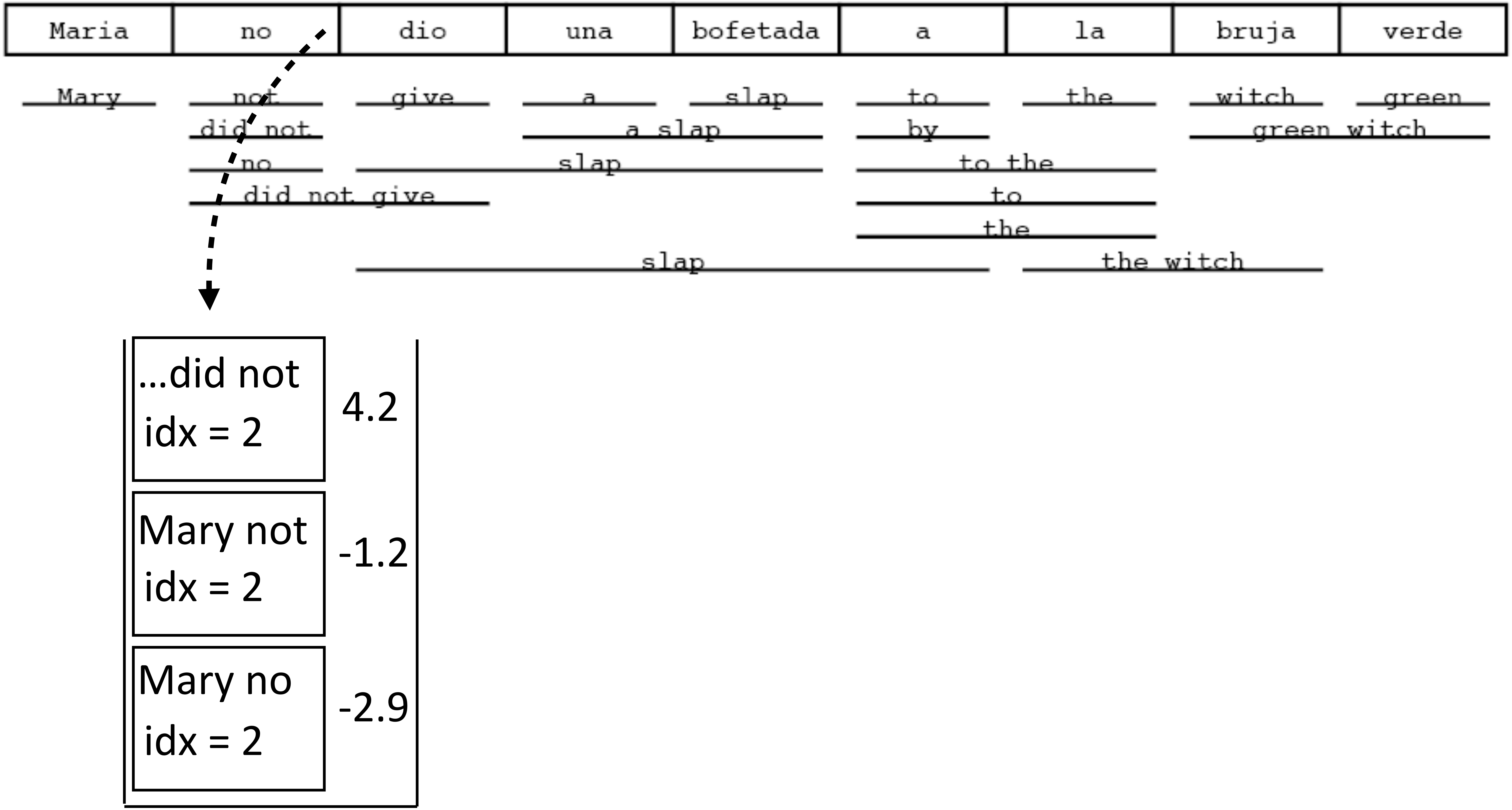

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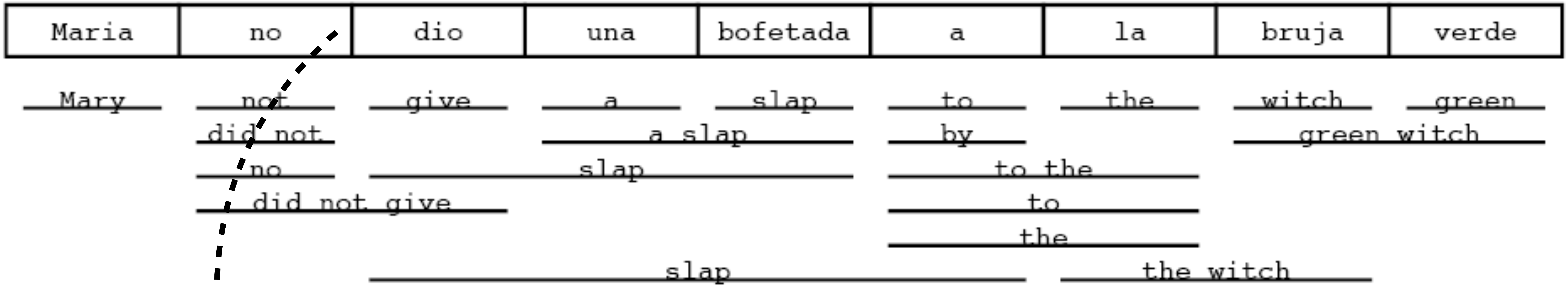


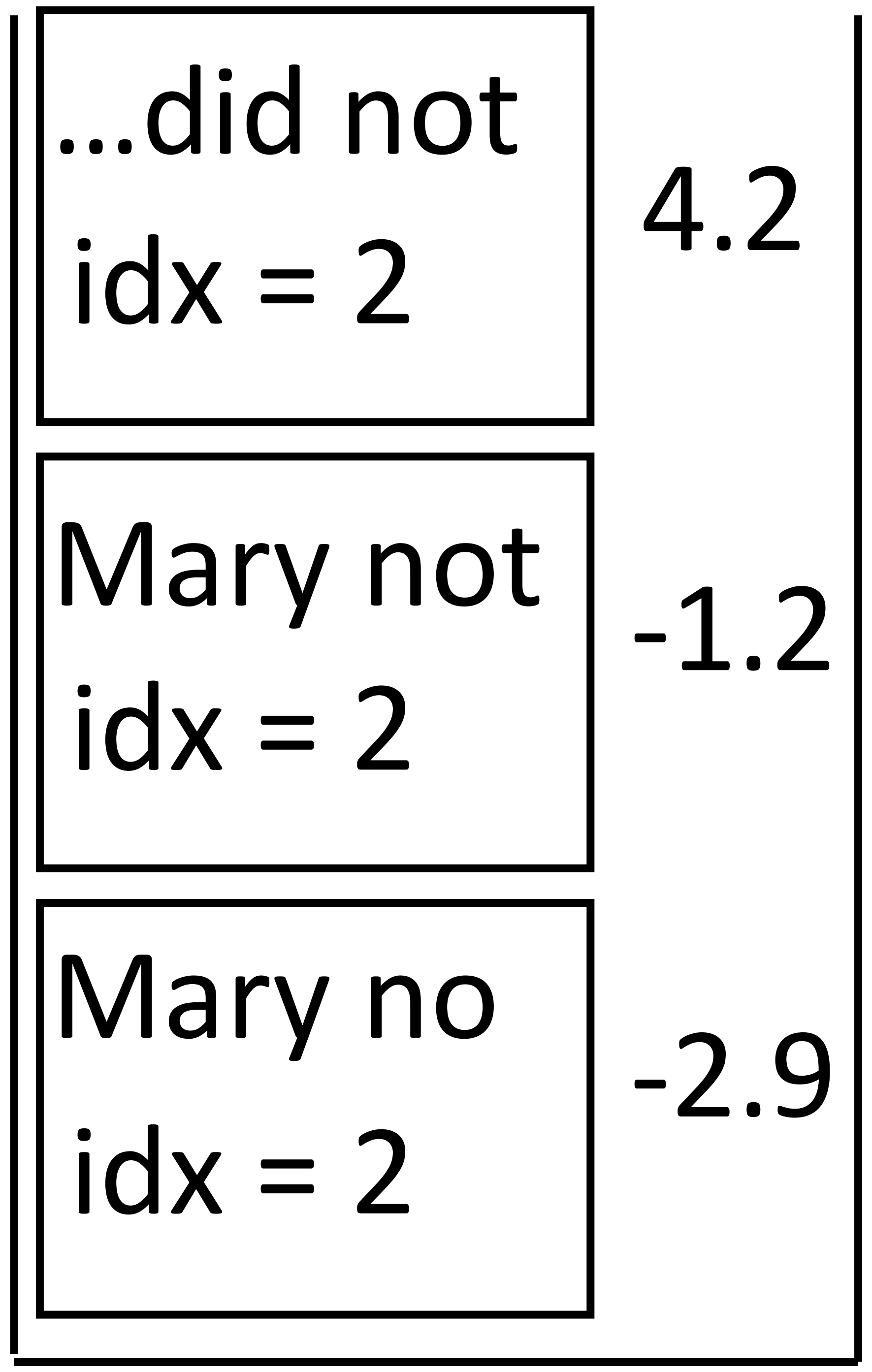


$$\text{score} = \log\,[\underbrace{P(\text{Mary})\,P(\text{not} \mid \text{Mary})}_{\text{LM}}\ \underbrace{P(\text{Mary} \mid \text{Maria})\,P(\text{not} \mid \text{no})}_{\text{TM}}]$$

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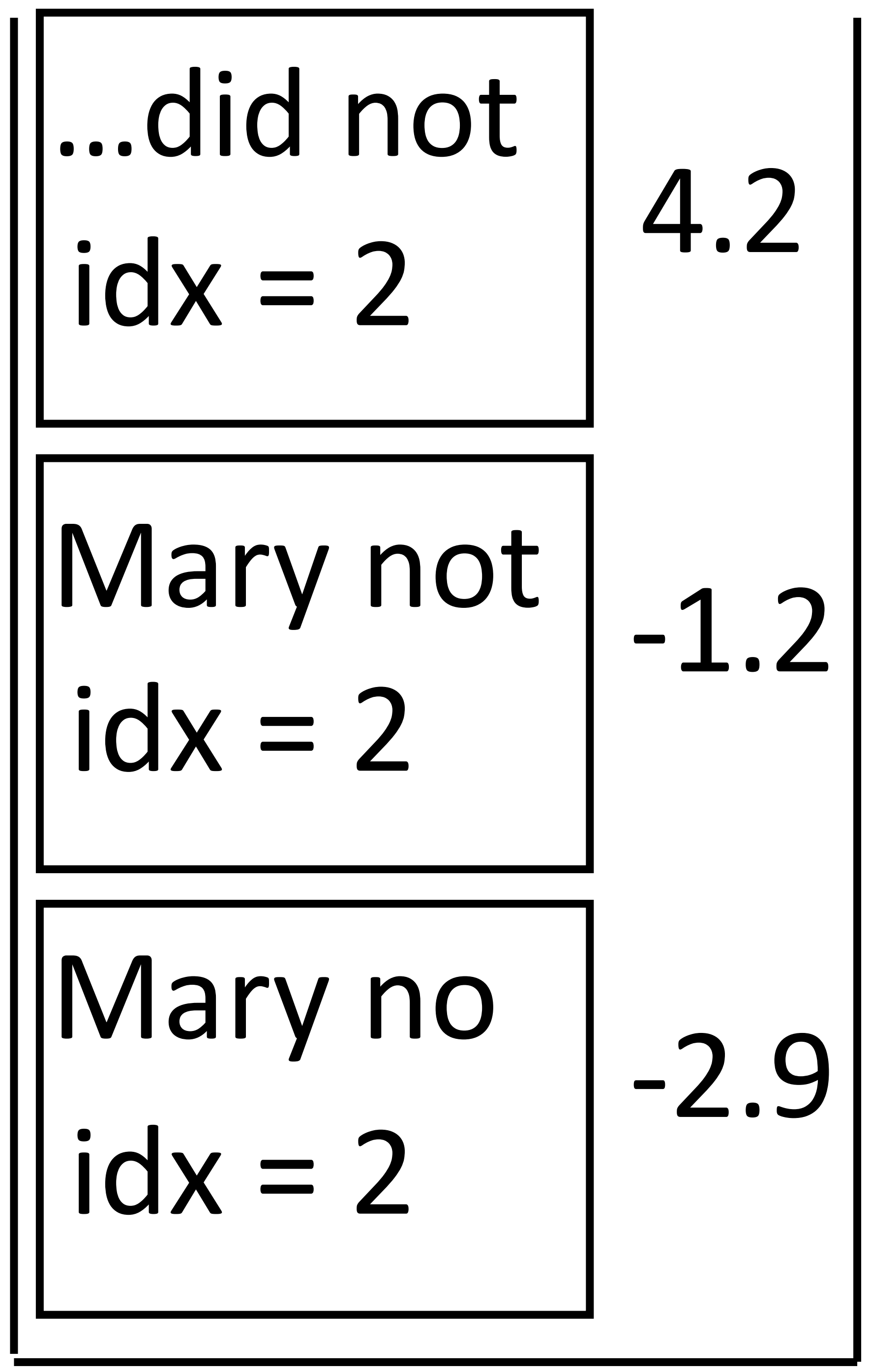


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In reality: score = $\alpha \log P(\text{LM}) + \beta \log P(\text{TM})$

…and TM is broken down into several features

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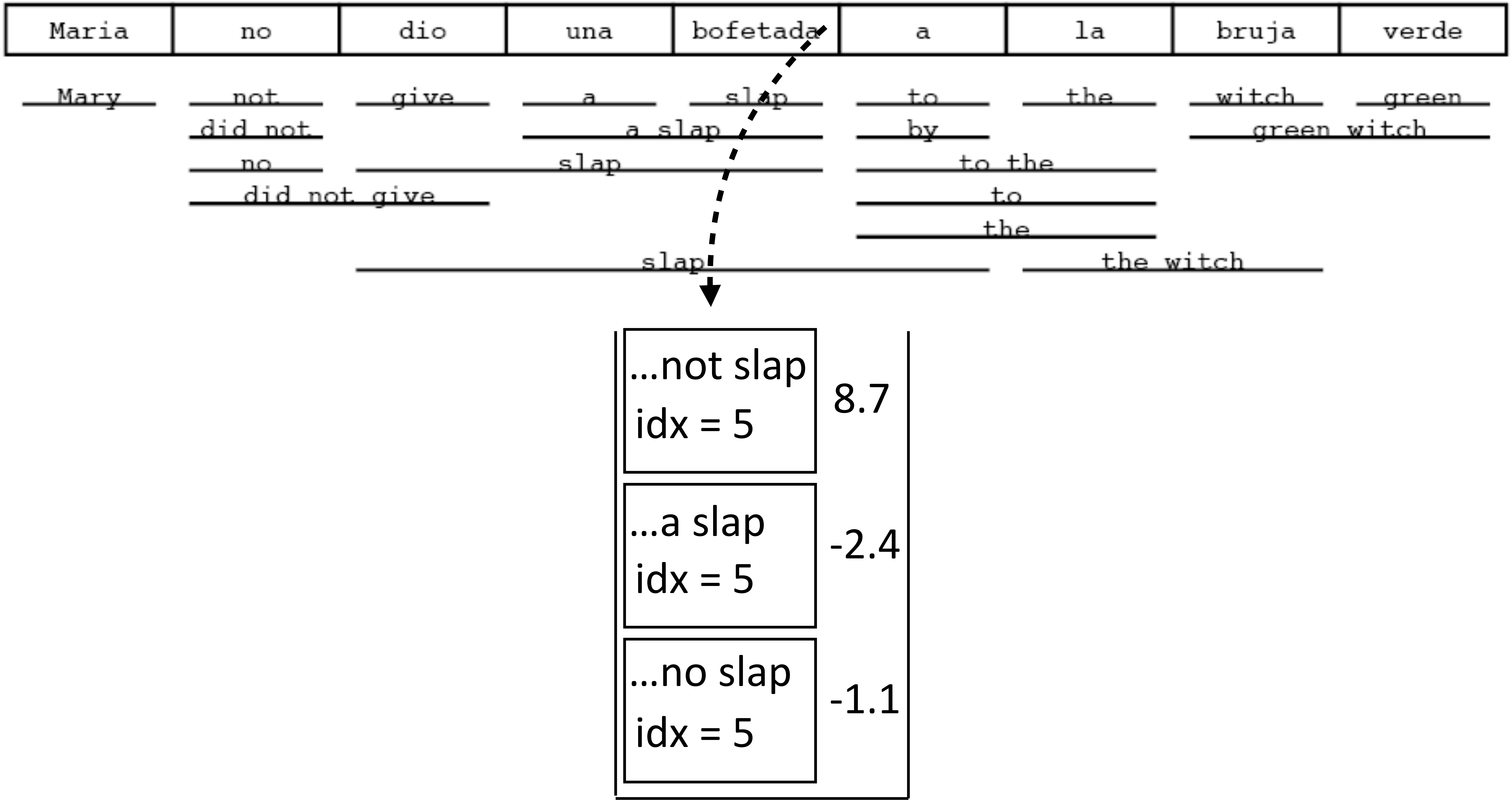

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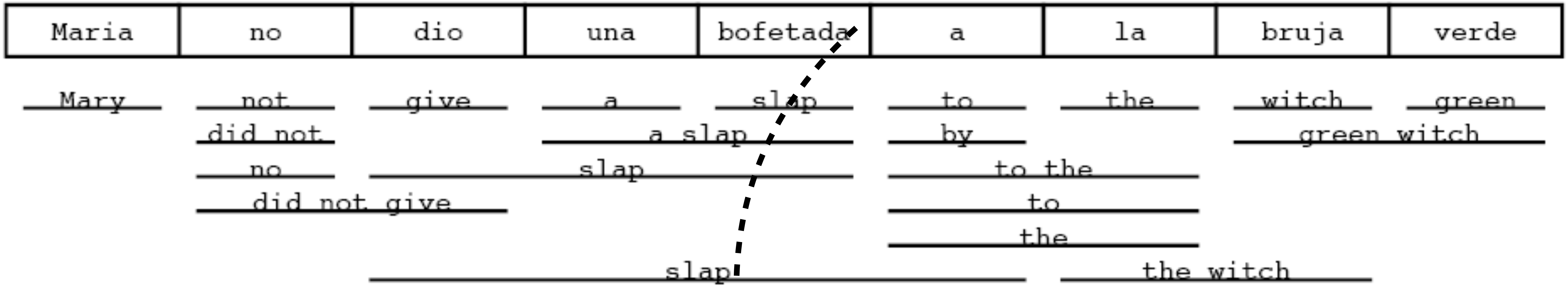


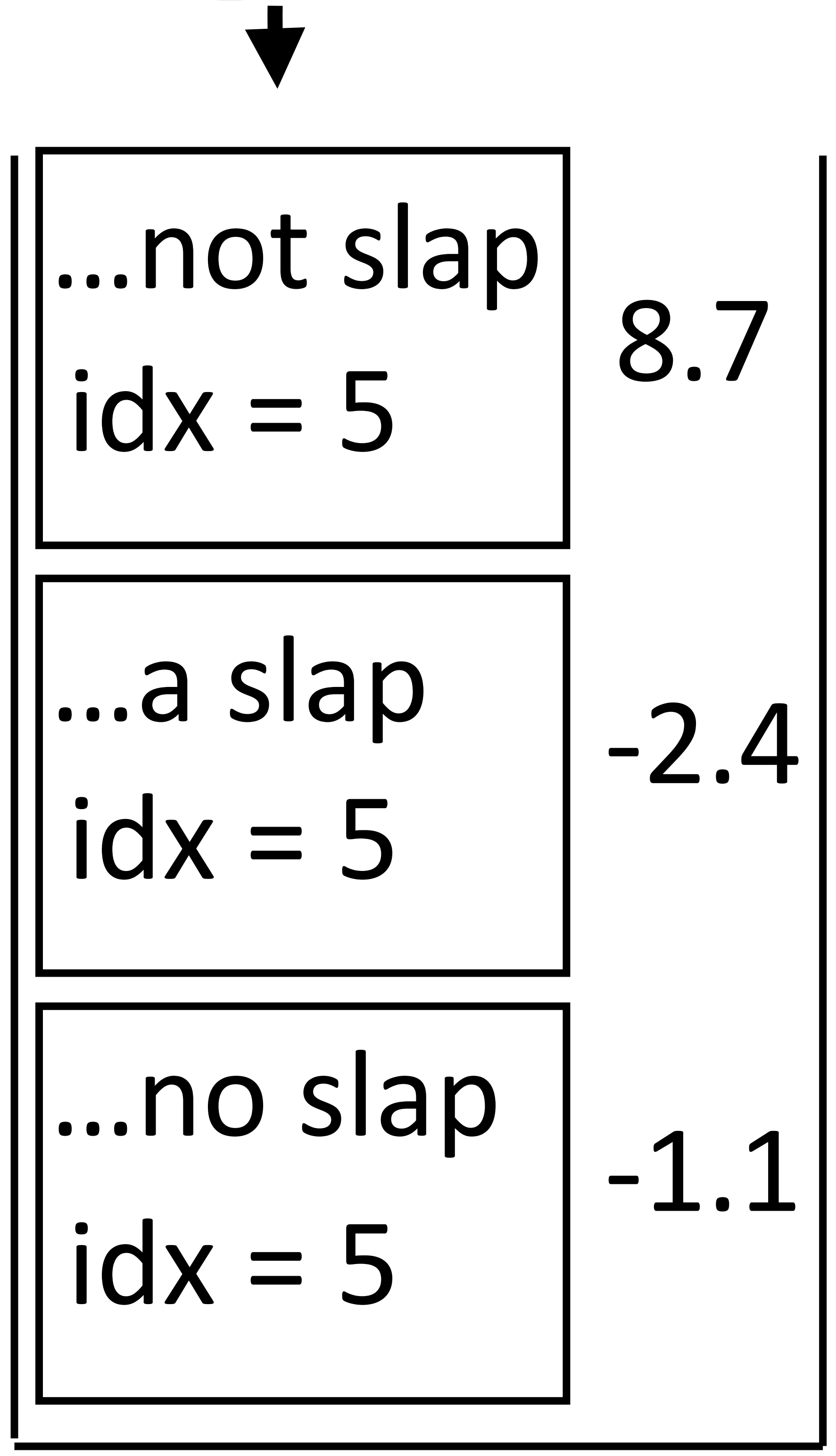


- Several paths can get us to this state, max over them (like Viterbi)

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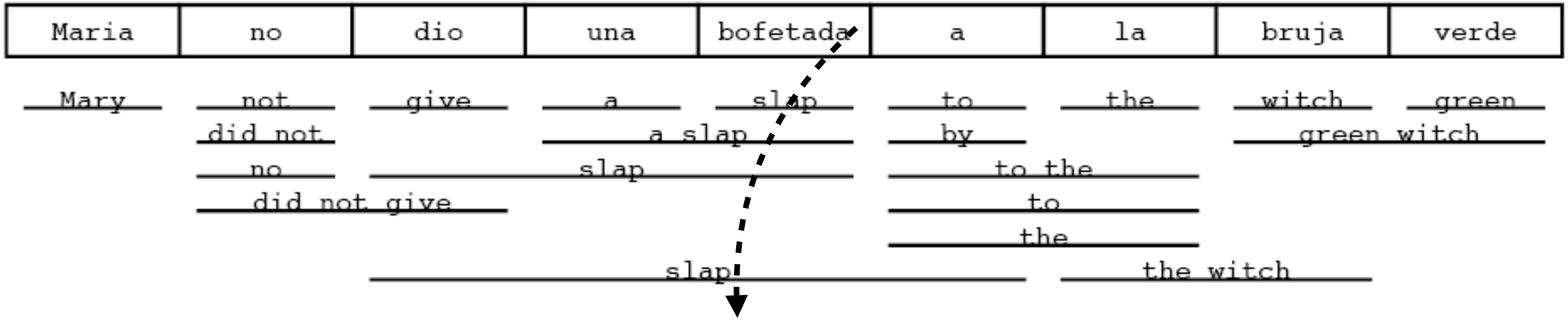


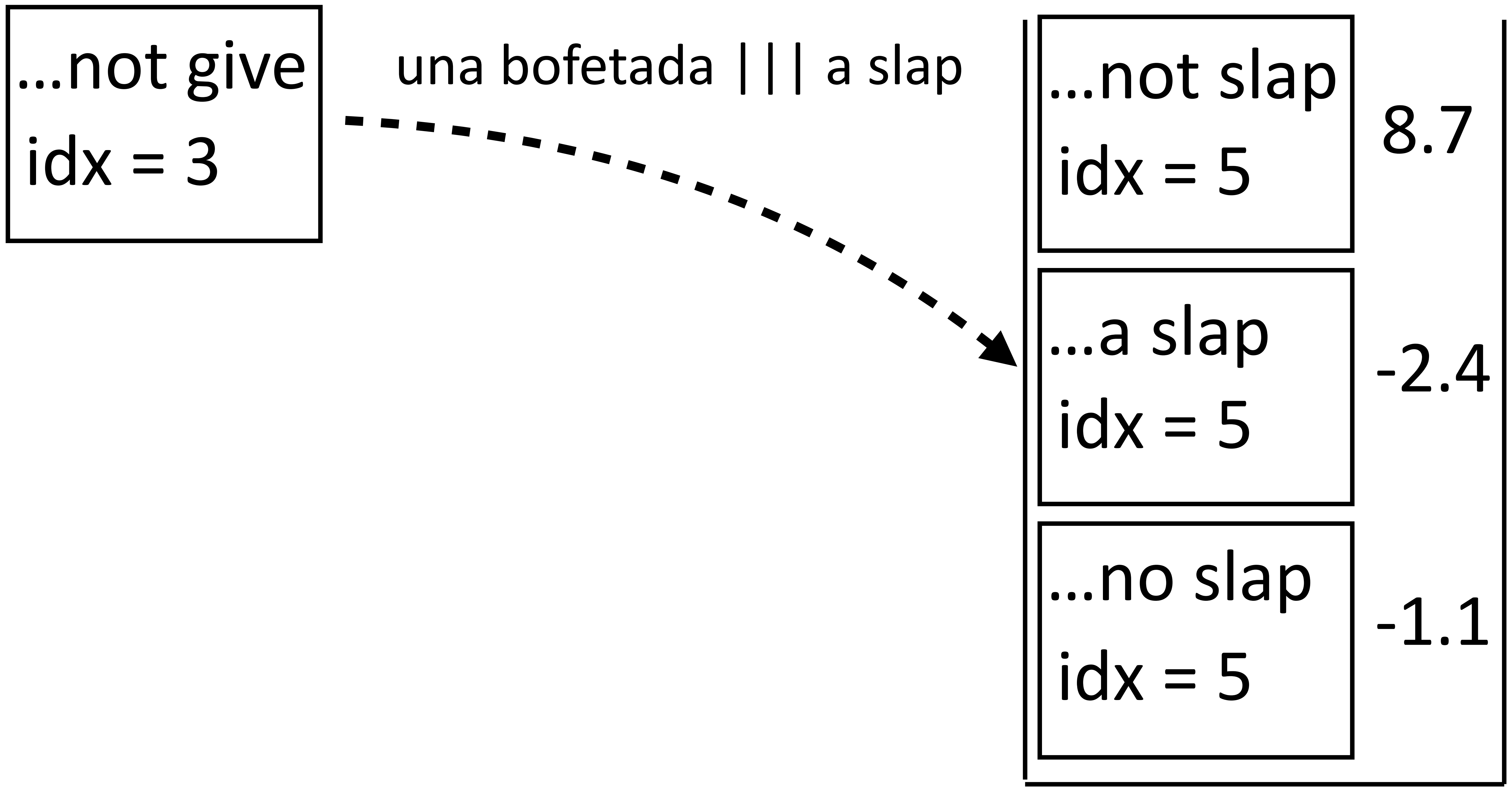


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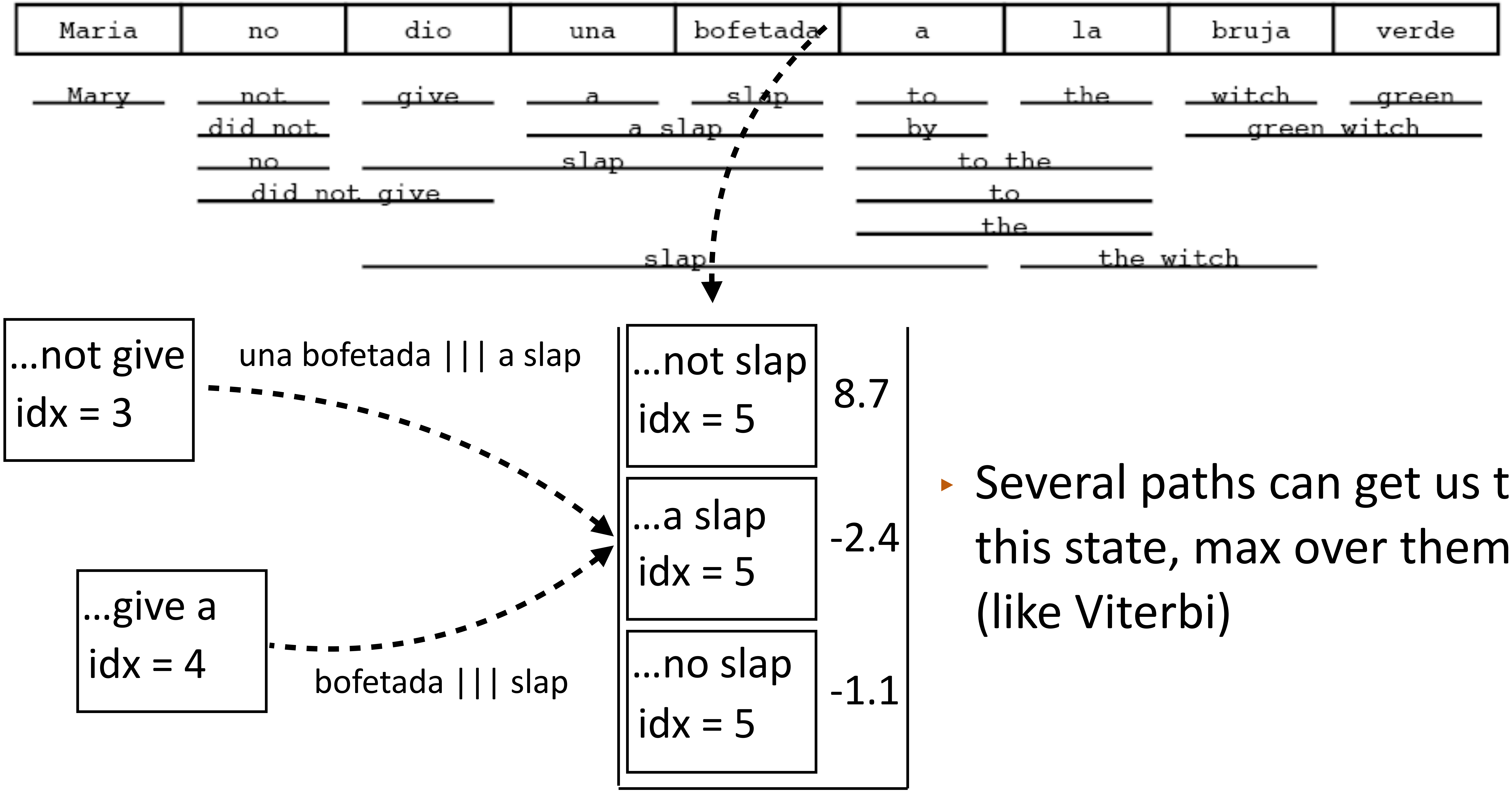


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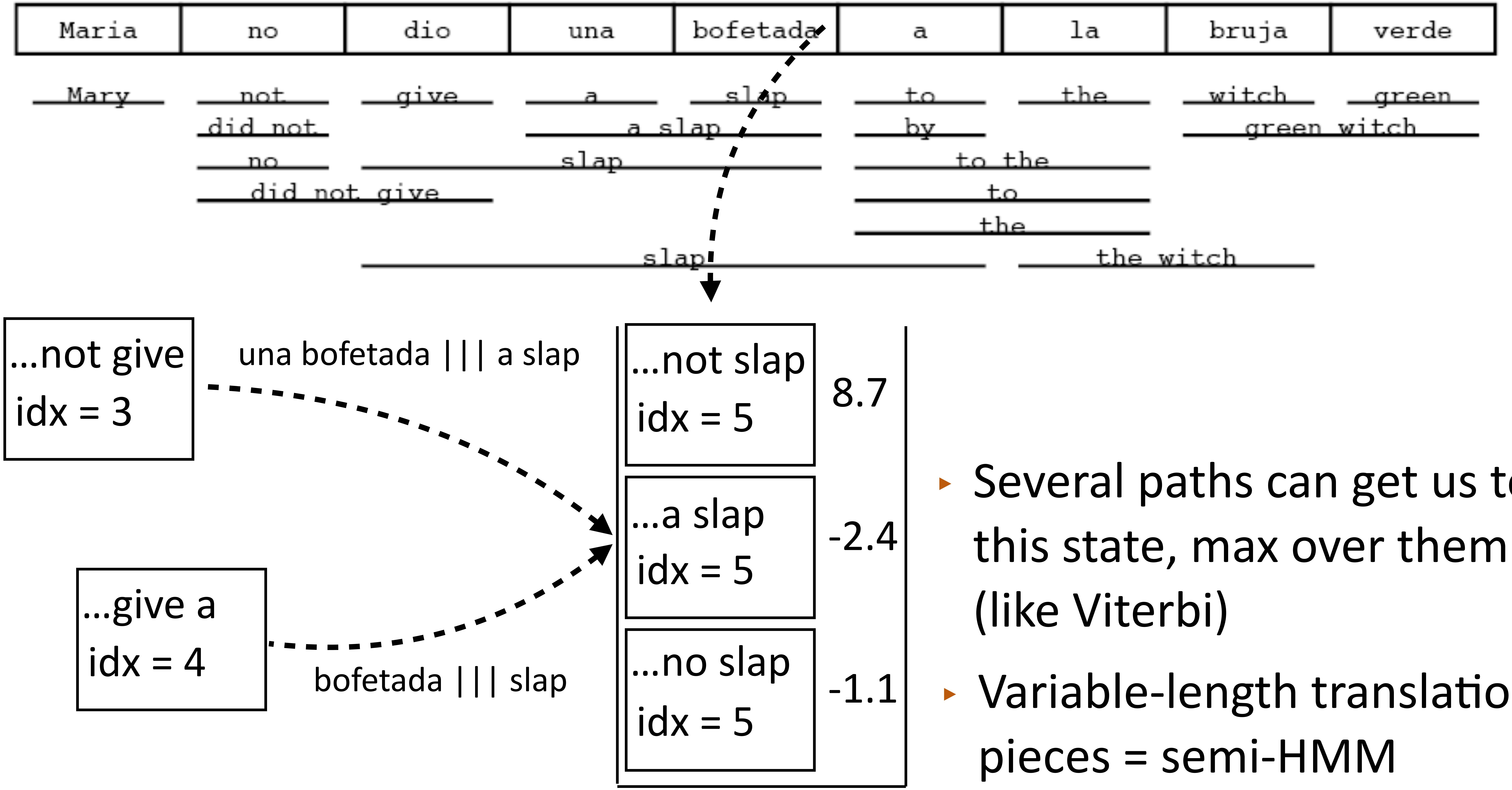
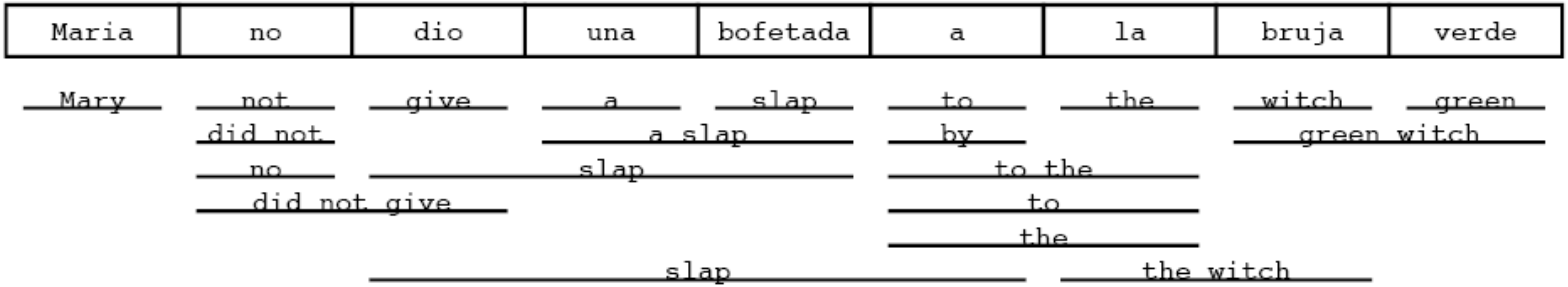



- Several paths can get us to this state, max over them (like Viterbi)
- Variable-length translation pieces = semi-HMM

# Non-Monotonic Translation

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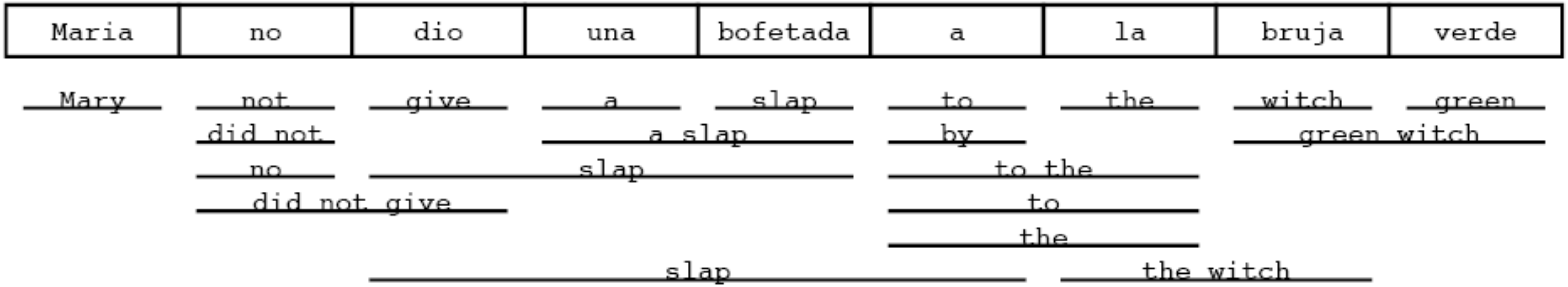


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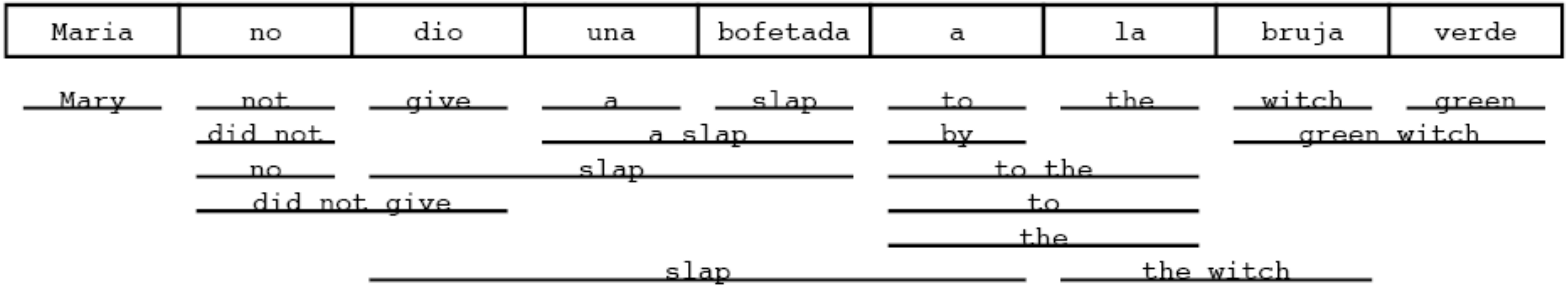


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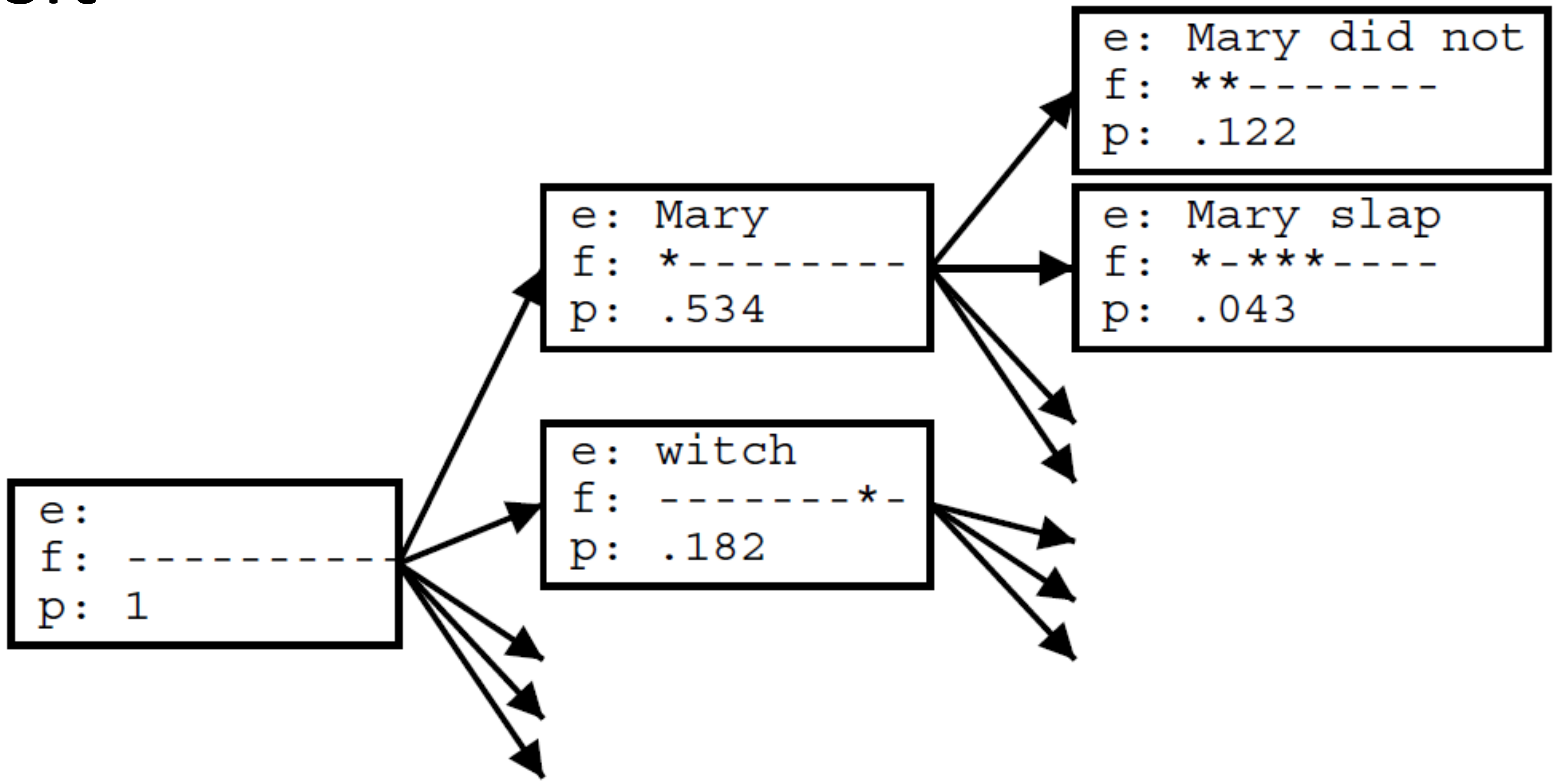

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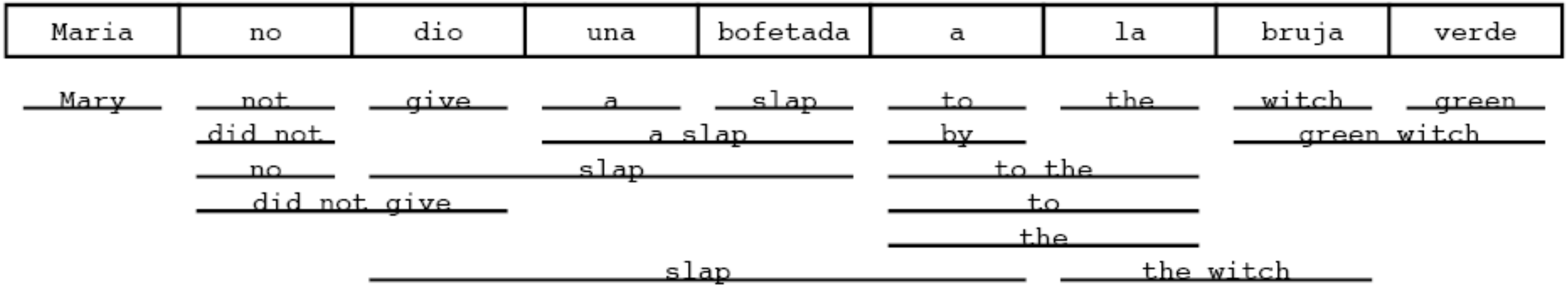


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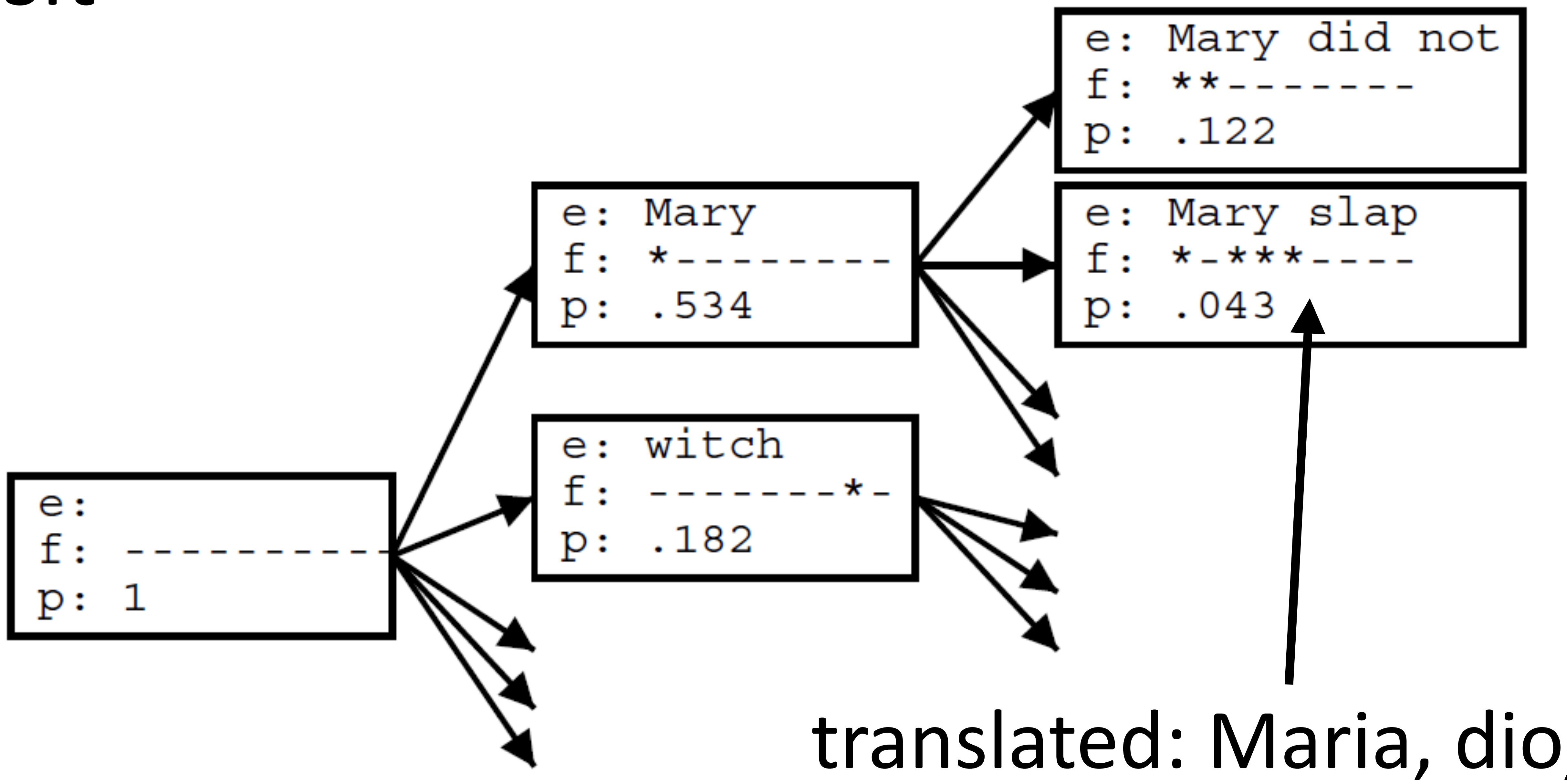


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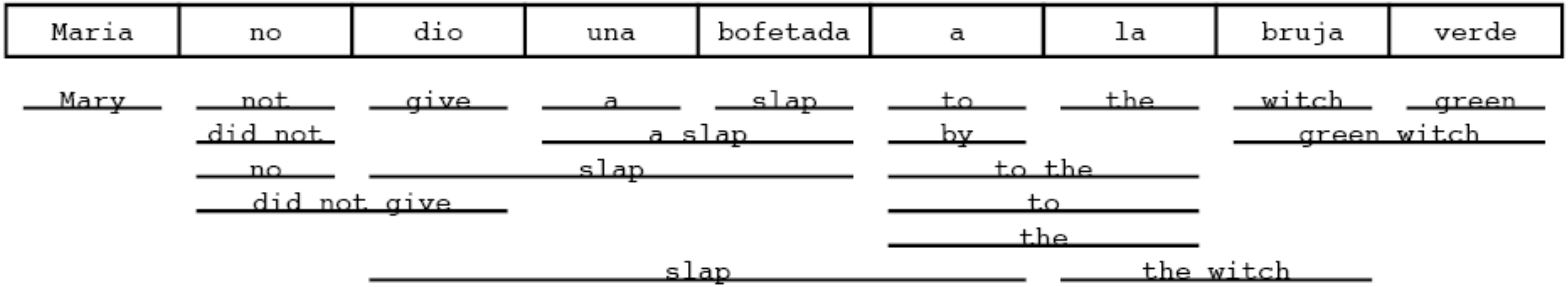


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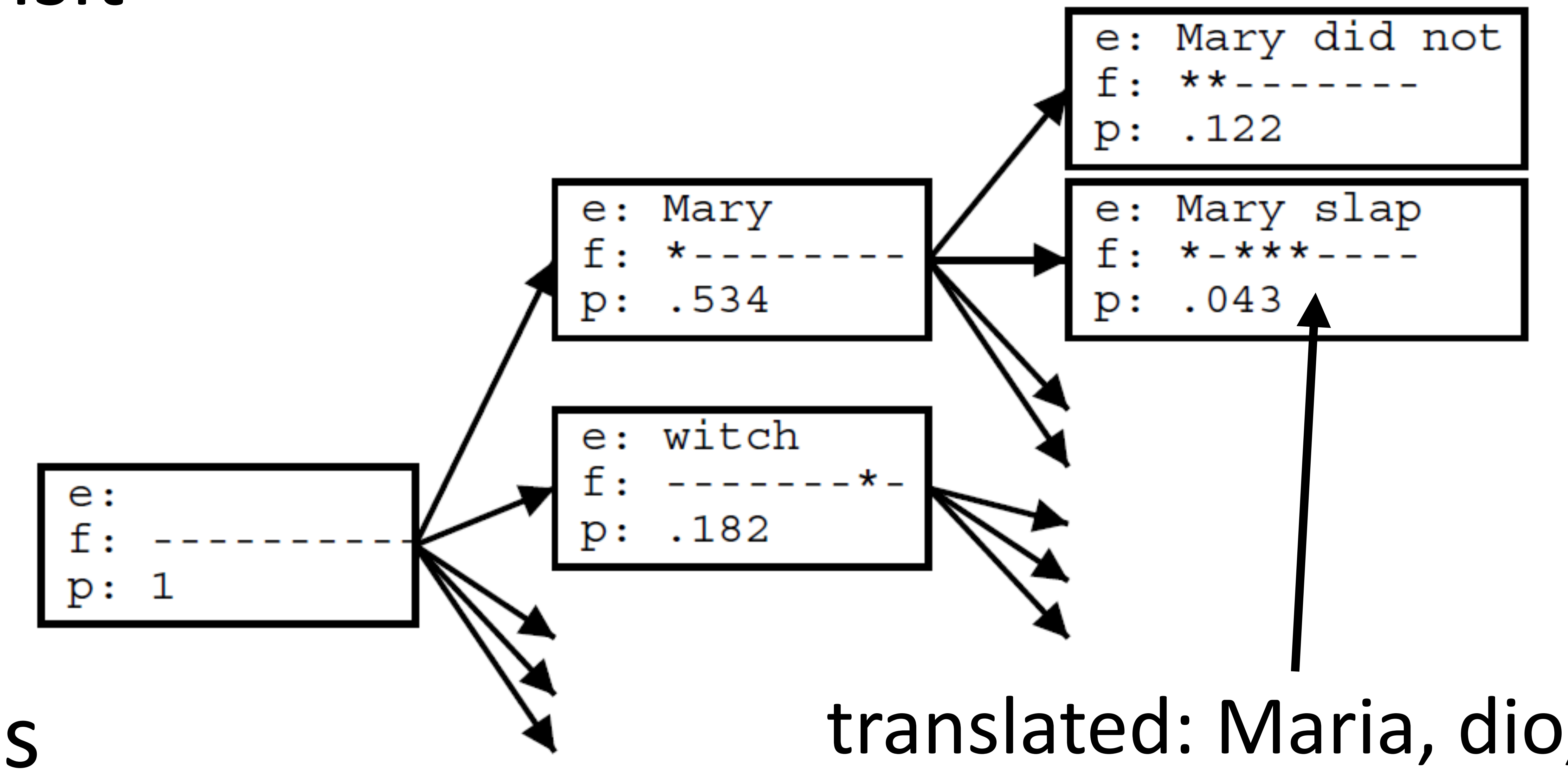
- State needs to describe which words have been translated and which haven't
- Big enough phrases already capture lots of reorderings, so this isn't as important as you think

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score = $\alpha$ log P(LM) + $\beta$ log P(TM)

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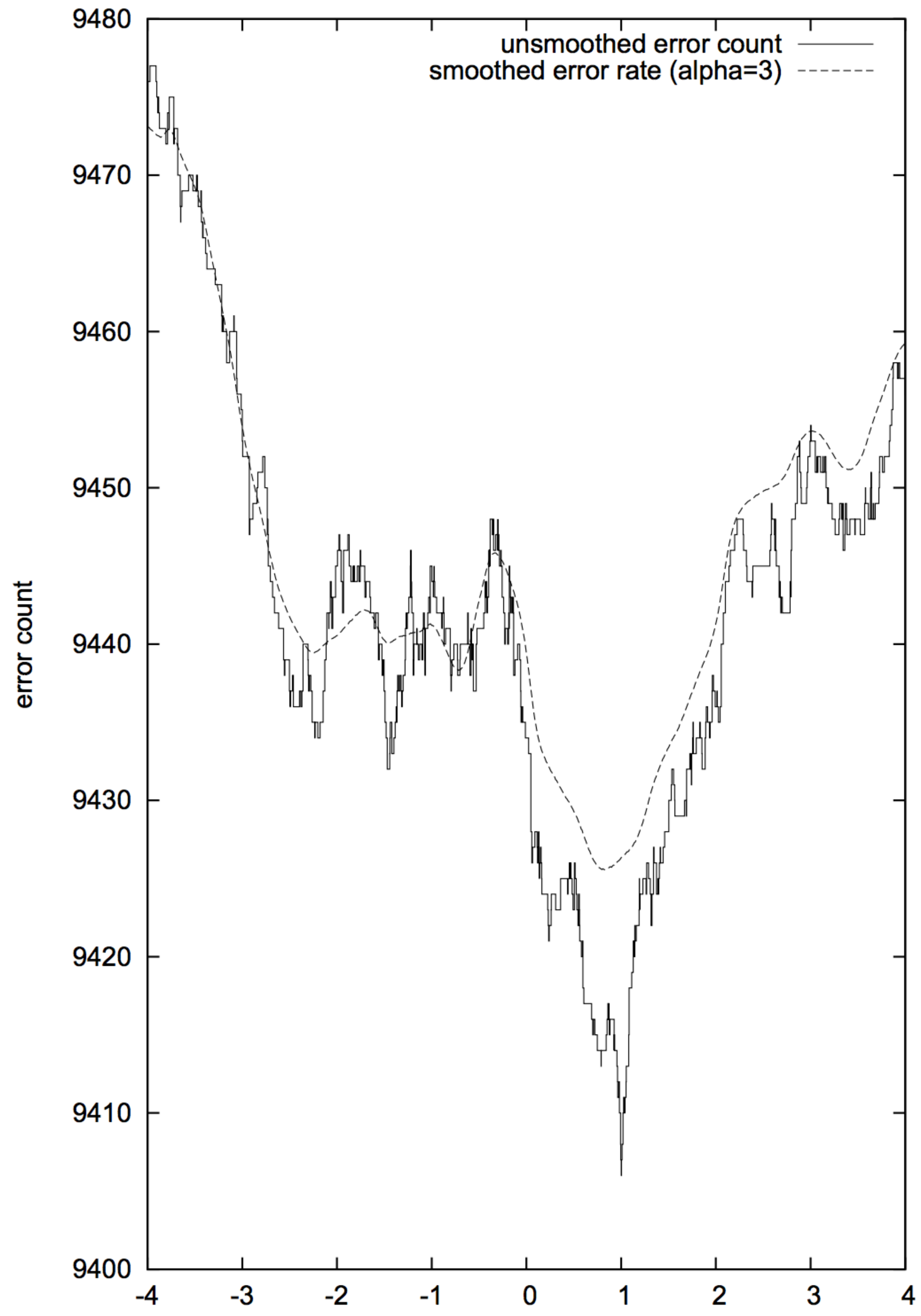

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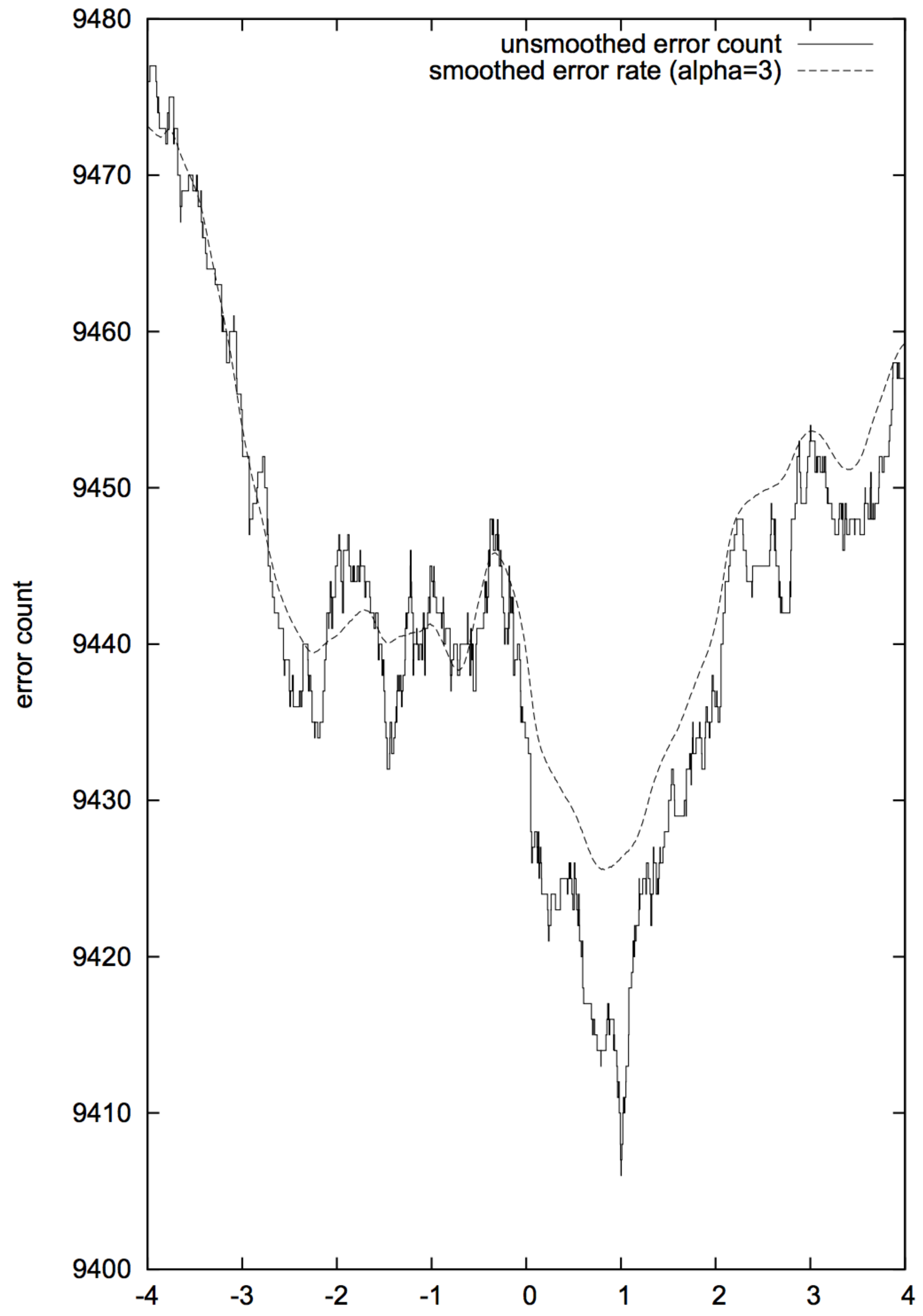
…and TM is broken down into several feature

- Usually 5-20 feature weights to set, want to optimize for BLEU score which is not differentiable
- MERT (Och 2003): decode to get 1000-best translations for each sentence in a small training set (<1000 sentences), do line search on parameters to directly optimize for BLEU



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- Next time: results on these and comparisons to neural methods

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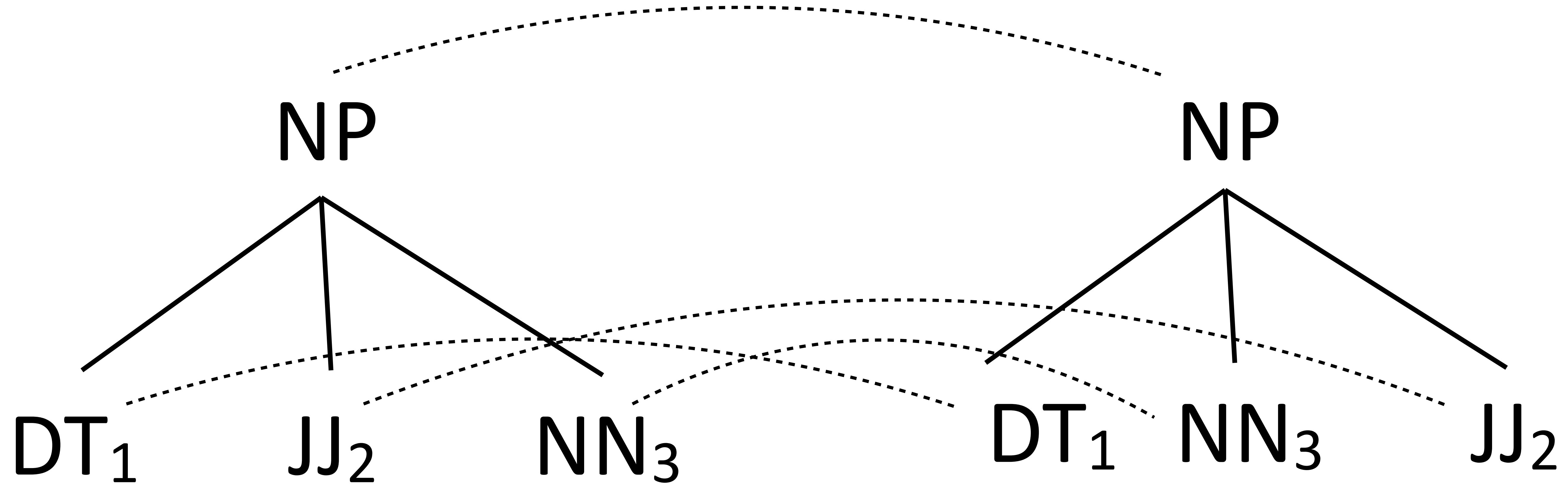

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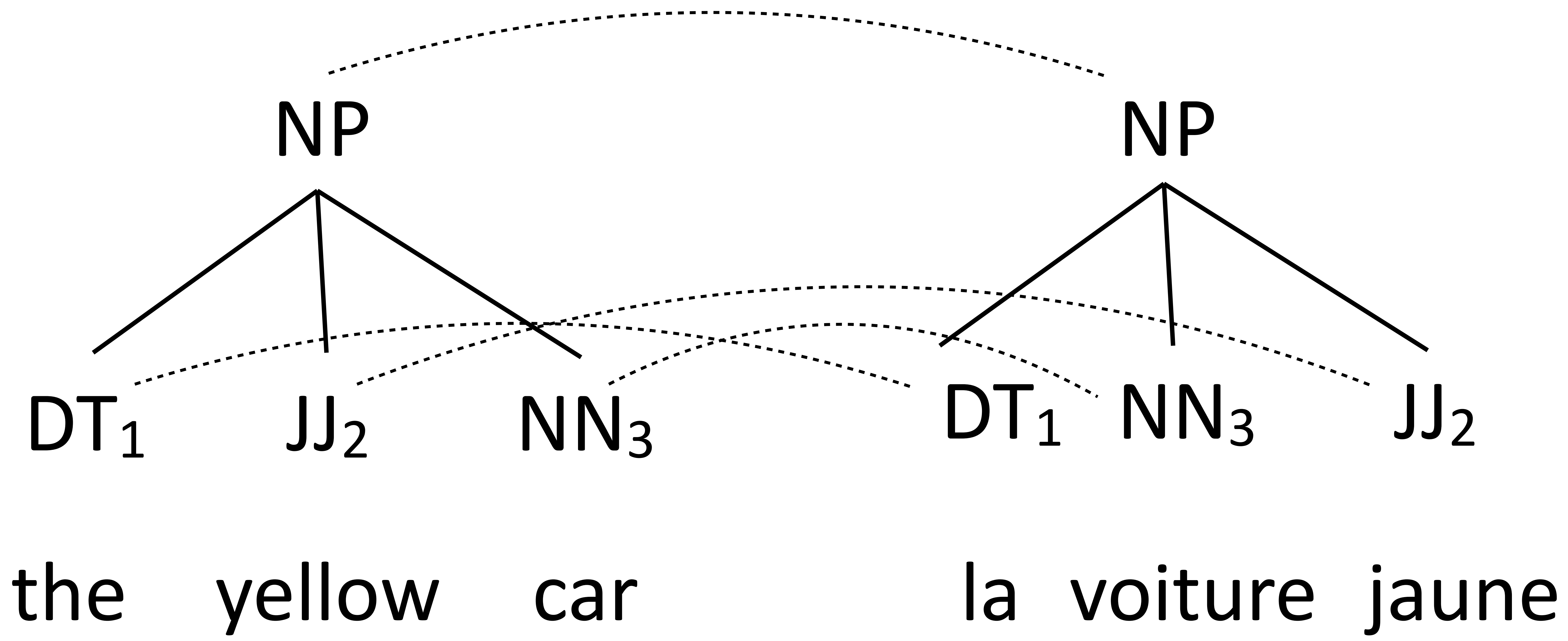

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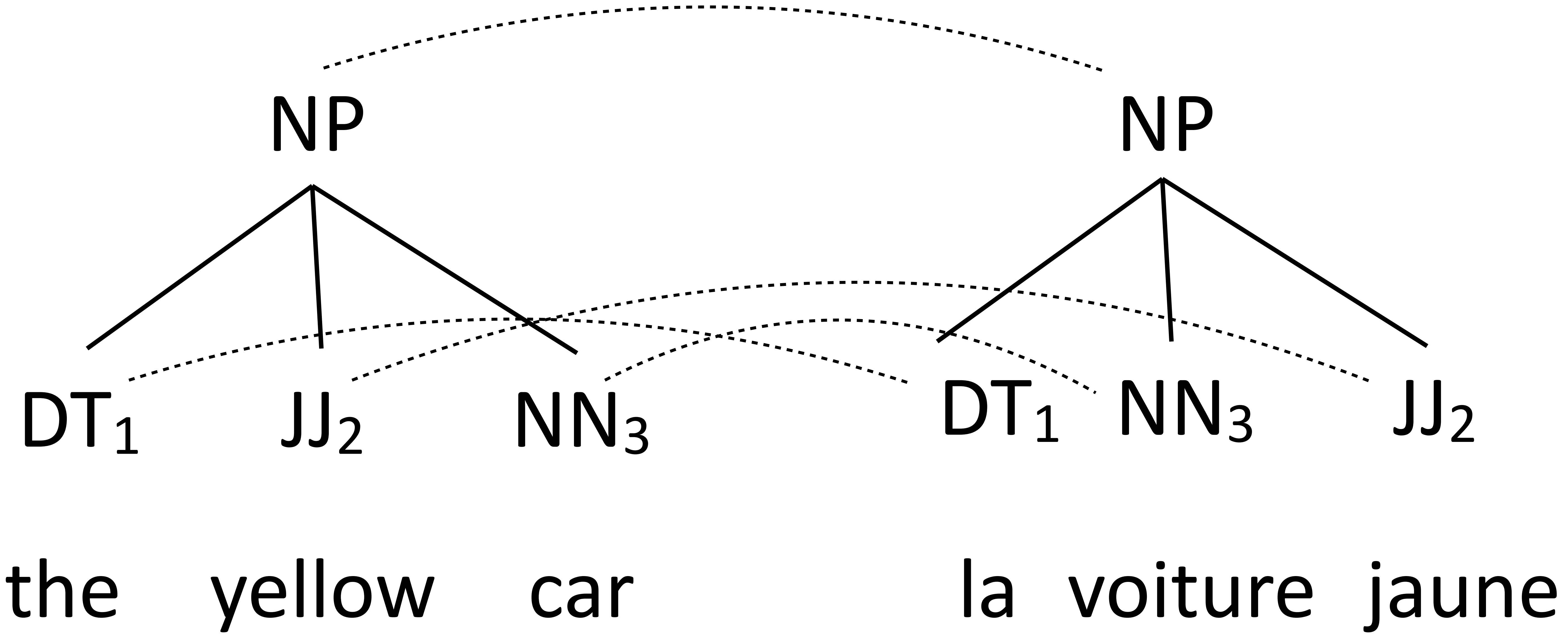


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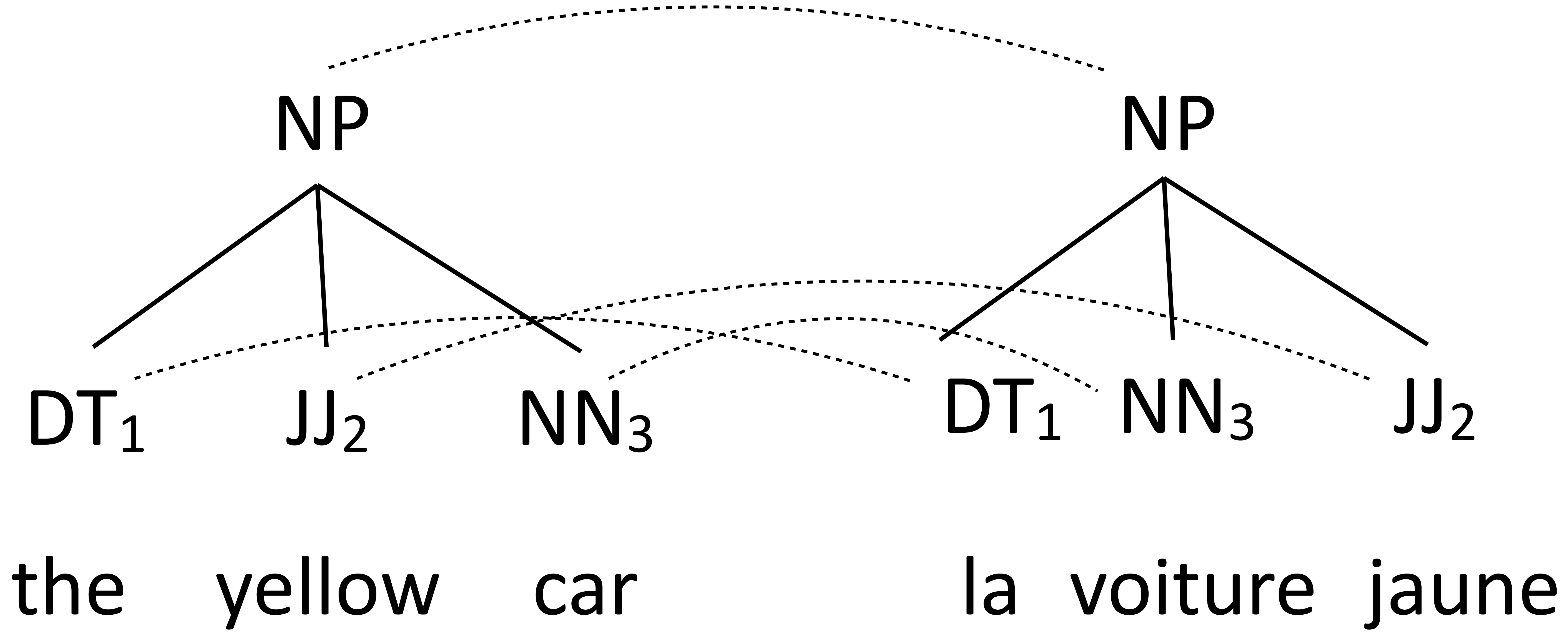


- Translation = parse the input with "half" of the grammar, read off the other half
- Assumes parallel syntax up to reordering

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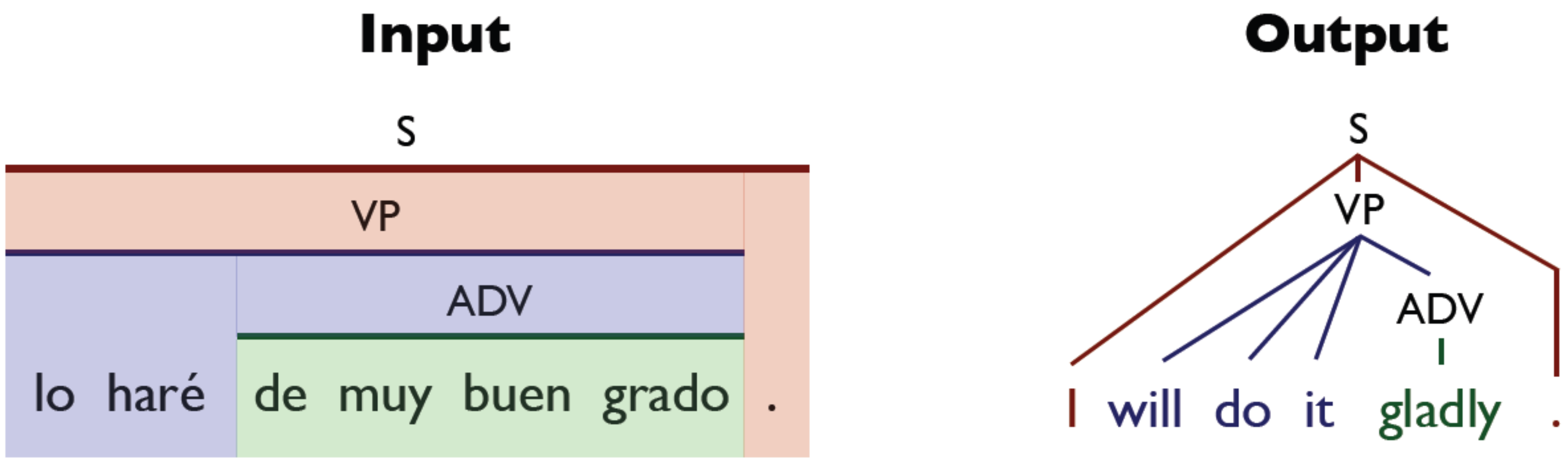


- Use lexicalized rules, look like "syntactic phrases"
- Leads to HUGE grammars, parsing is slow

**Grammar**

S → ⟨ VP . ; I VP . ⟩ **OR** S → ⟨ VP . ; you VP . ⟩

VP → ⟨ lo haré ADV ; will do it ADV ⟩

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

ADV → ⟨ de muy buen grado ; gladly ⟩

Slide credit: Dan Klein

# Takeaways

- Phrase-based systems consist of 3 pieces: aligner, language model, decoder
  - HMMs work well for alignment
  - N-gram language models are scalable and historically worked well
  - Decoder requires searching through a complex state space
- Lots of system variants incorporating syntax
- Next time: neural MT