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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People's Daily, August 30, 2017

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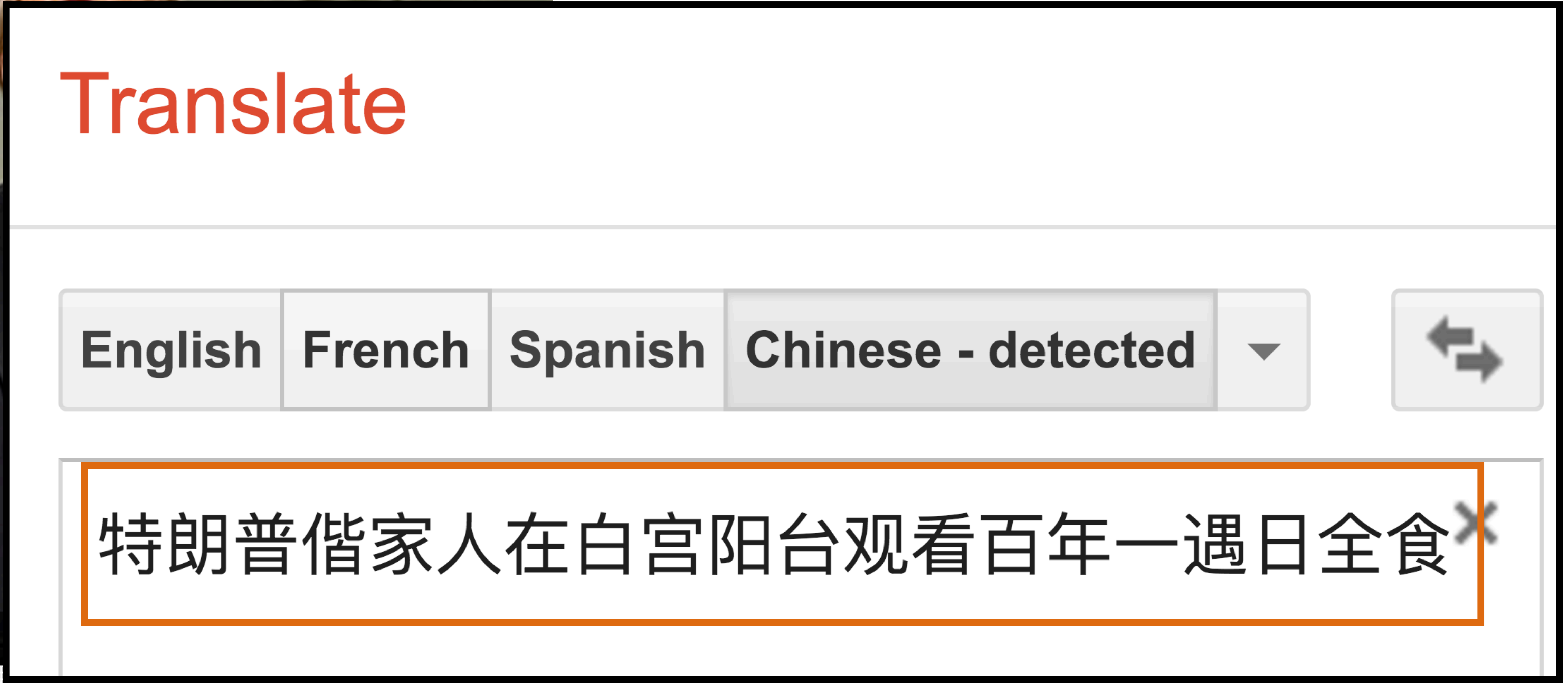

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Trump Pope family watch a hundred years a year in the White House balcony

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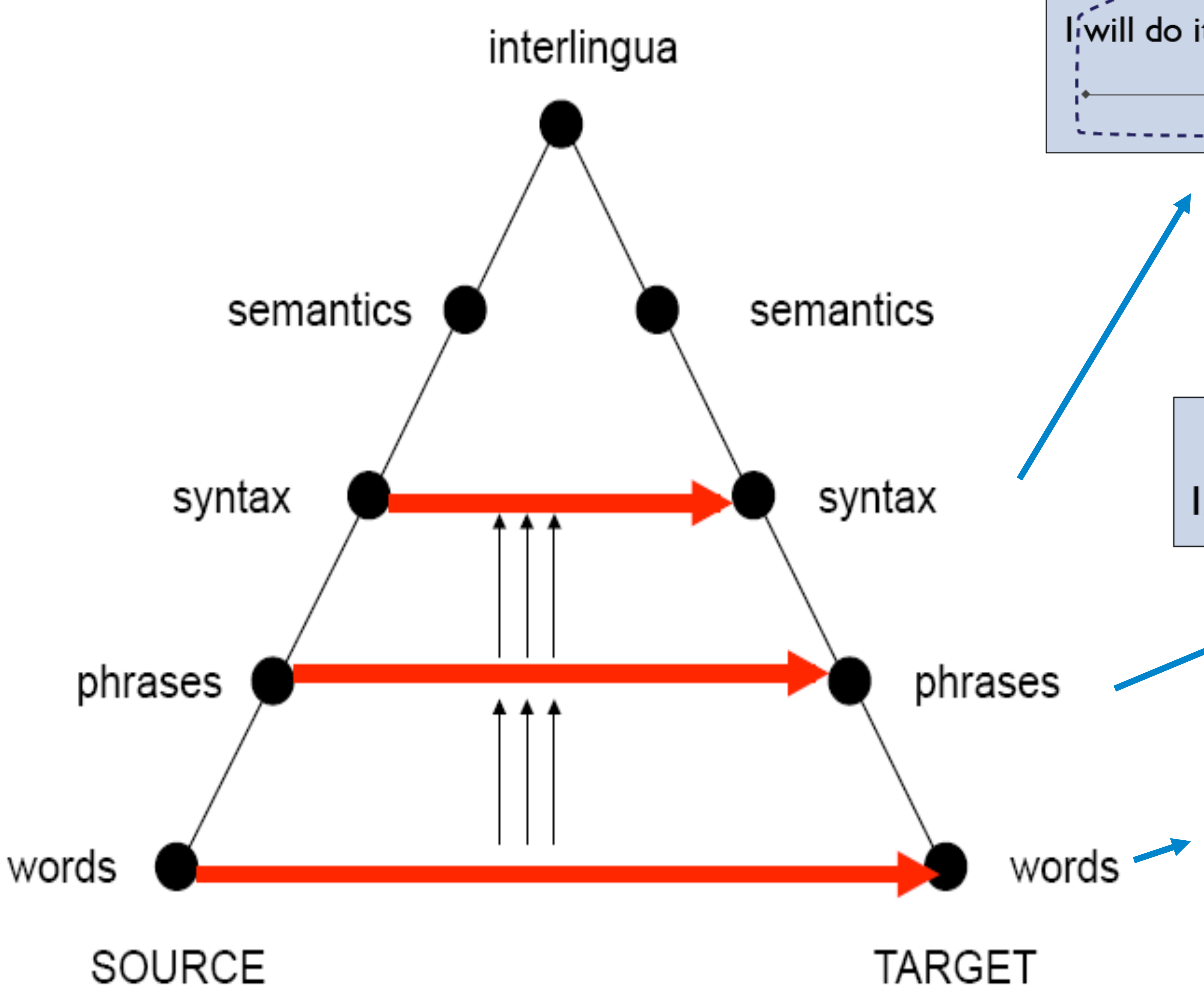
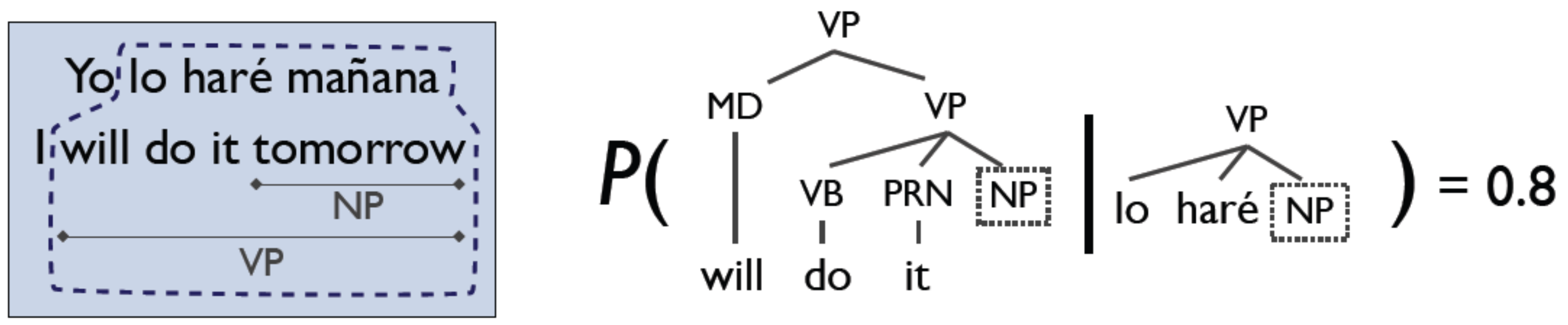
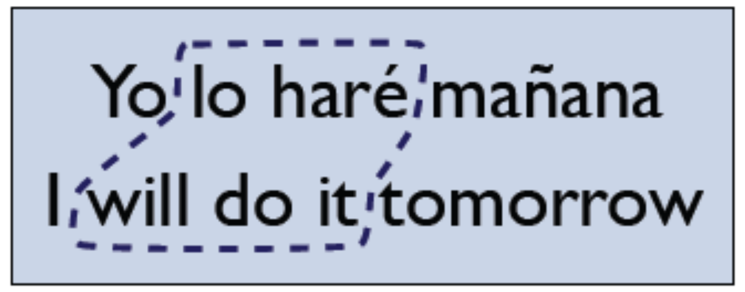
- Everyone has a friend => `∃x∀y friend(x,y)` / `∀x∃y friend(x,y)` => Tous a un ami

  - Can often get away without doing all disambiguation — same ambiguities may exist in both languages

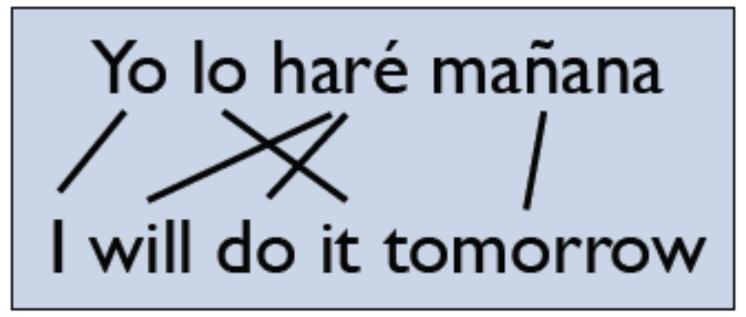
Levels of Transfer: Vauquois Triangle







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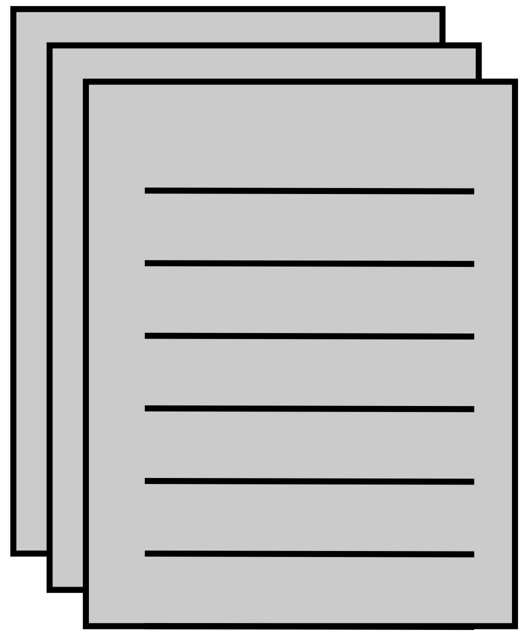
  - How to stitch together? Language model over target language
  - Decoder takes phrases and a language model and searches over possible translations
- NOT like standard discriminative models (take a bunch of translation pairs, learn a ton of parameters in an end-to-end way)

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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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

reference 2 — I am ready to sleep now and so exhausted

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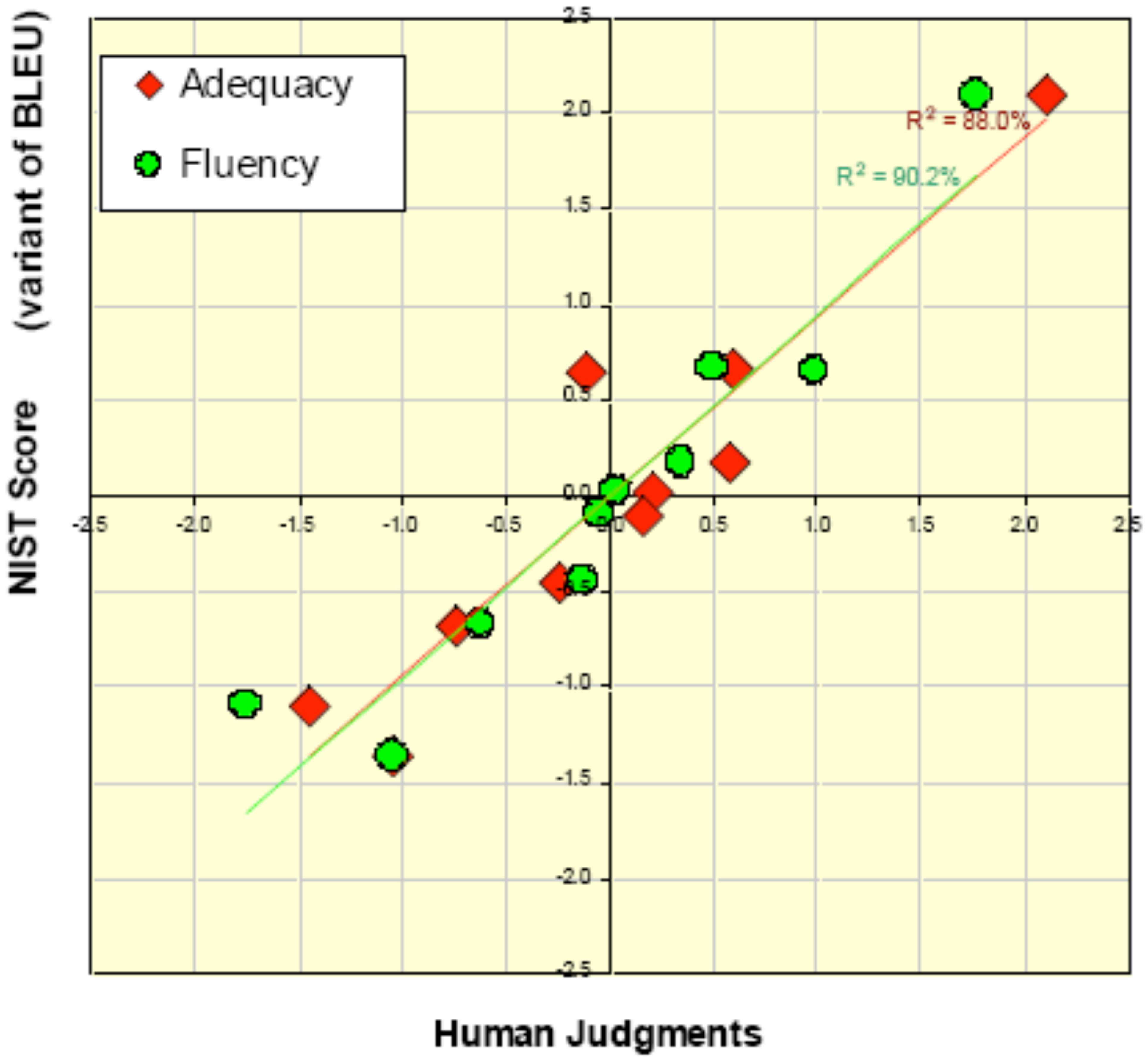
- Does this capture fluency and adequacy?

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

  nous acceptons votre opinion . ||| we accept your view

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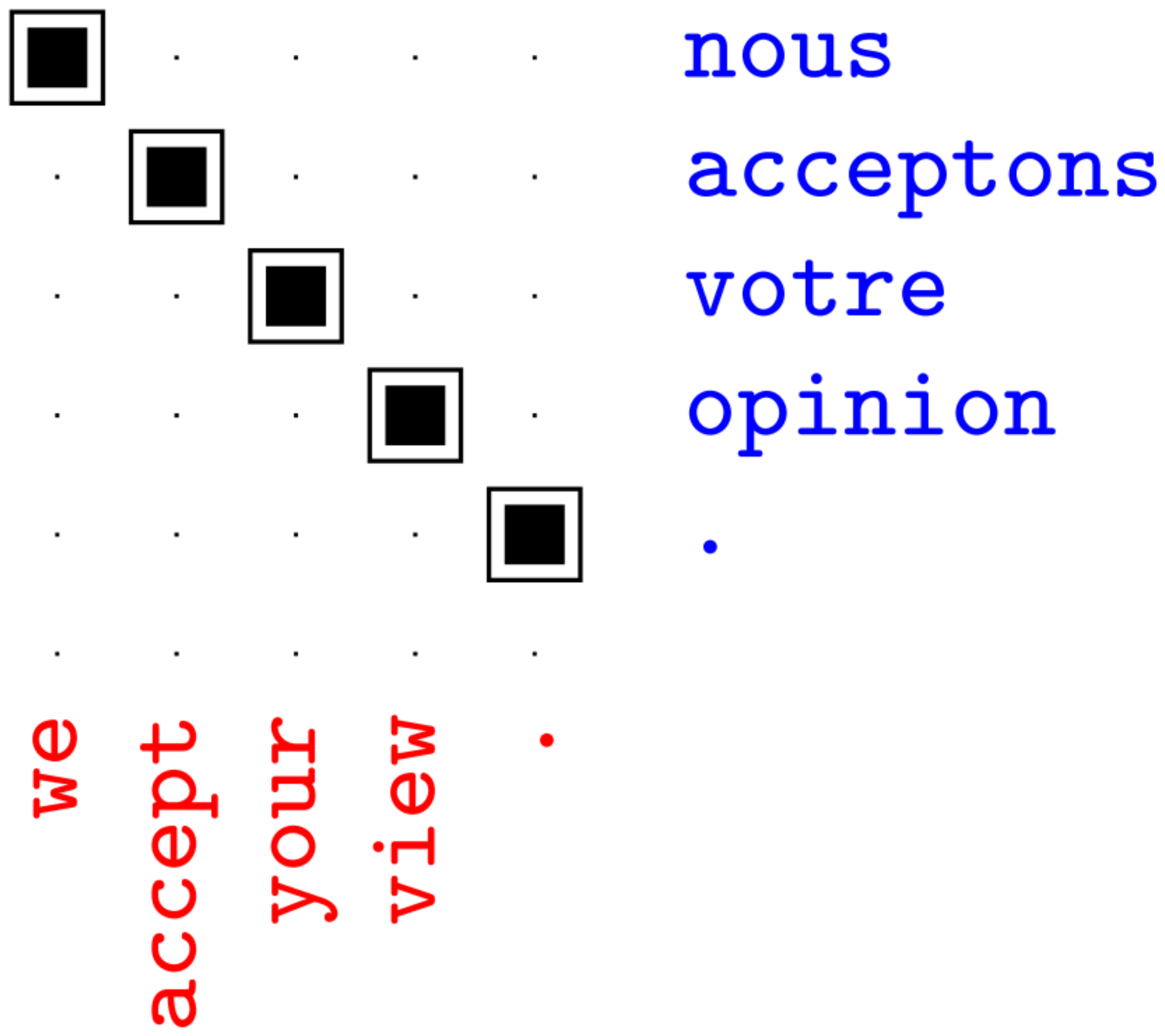

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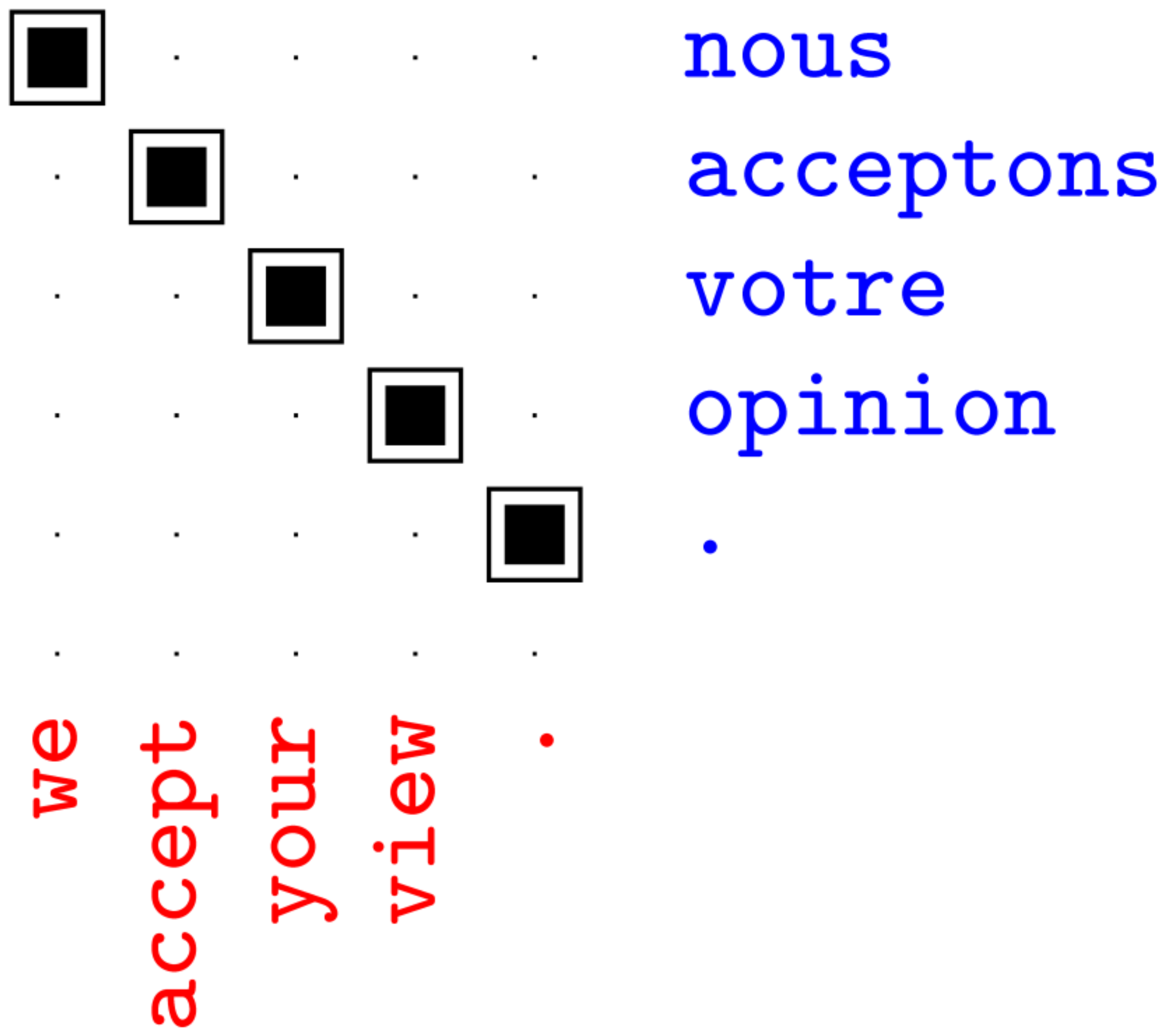

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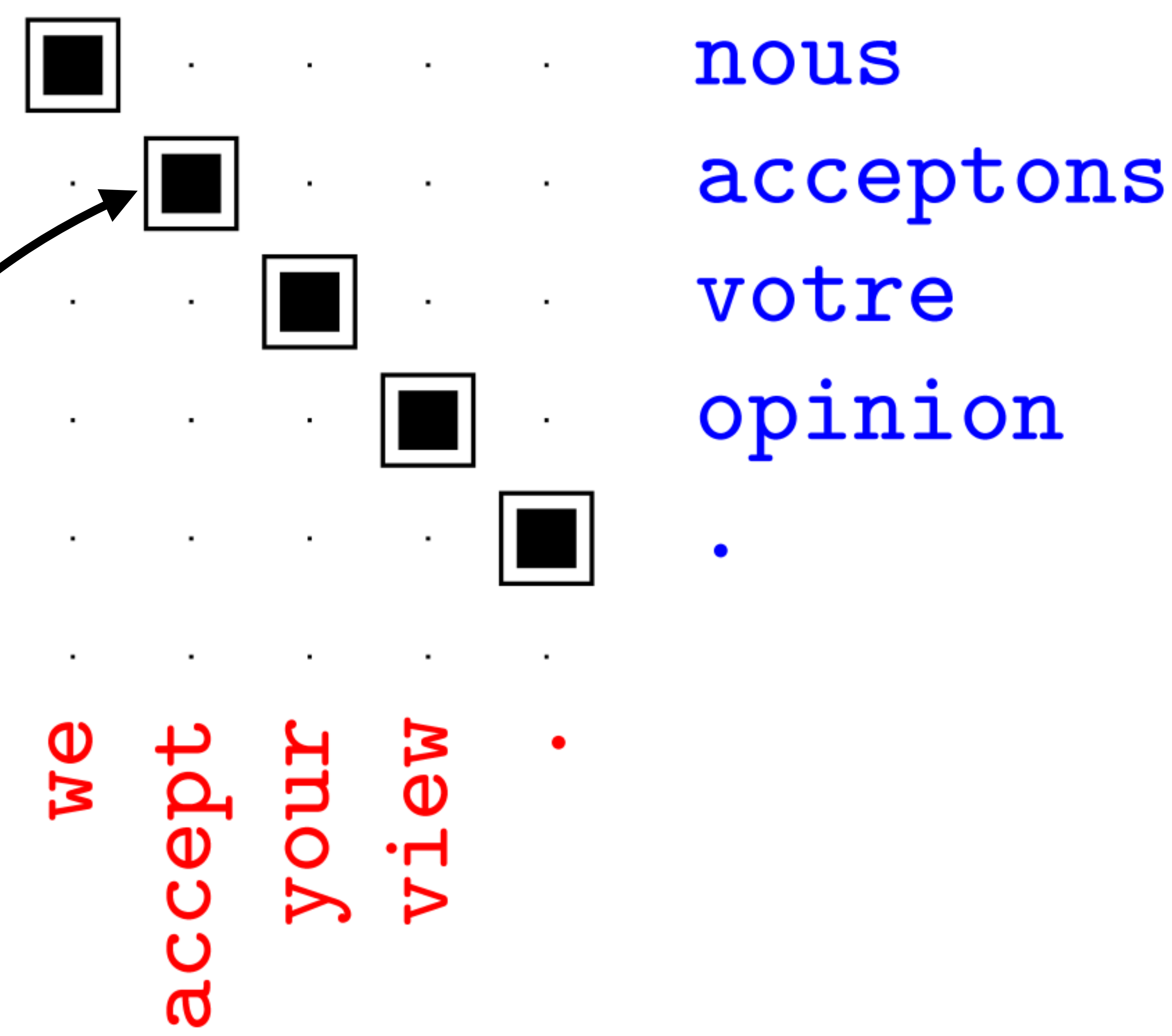

"accept and acceptons are aligned"

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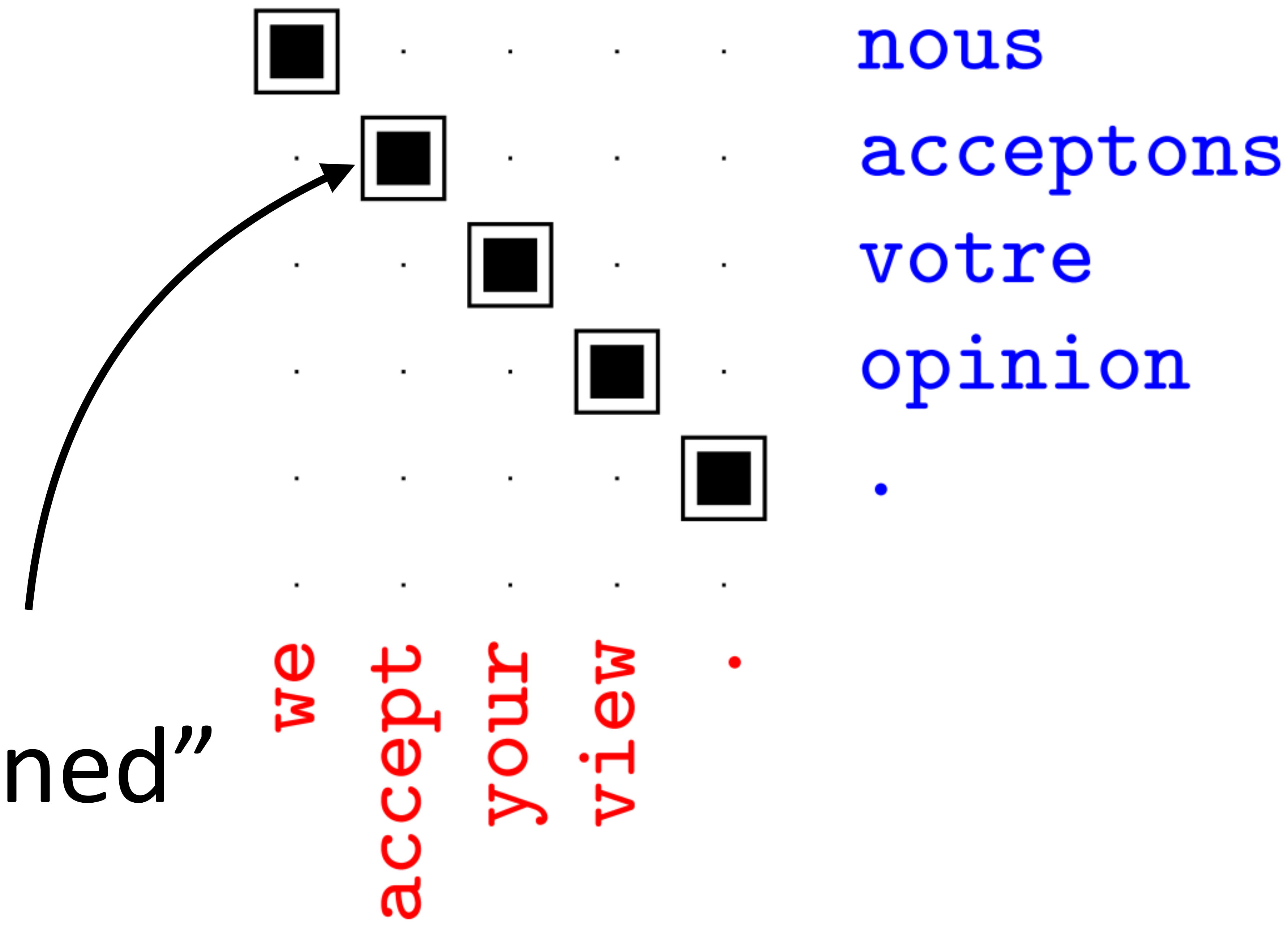
- Output: alignments between words in each sentence
  - We will see how to turn these into phrases



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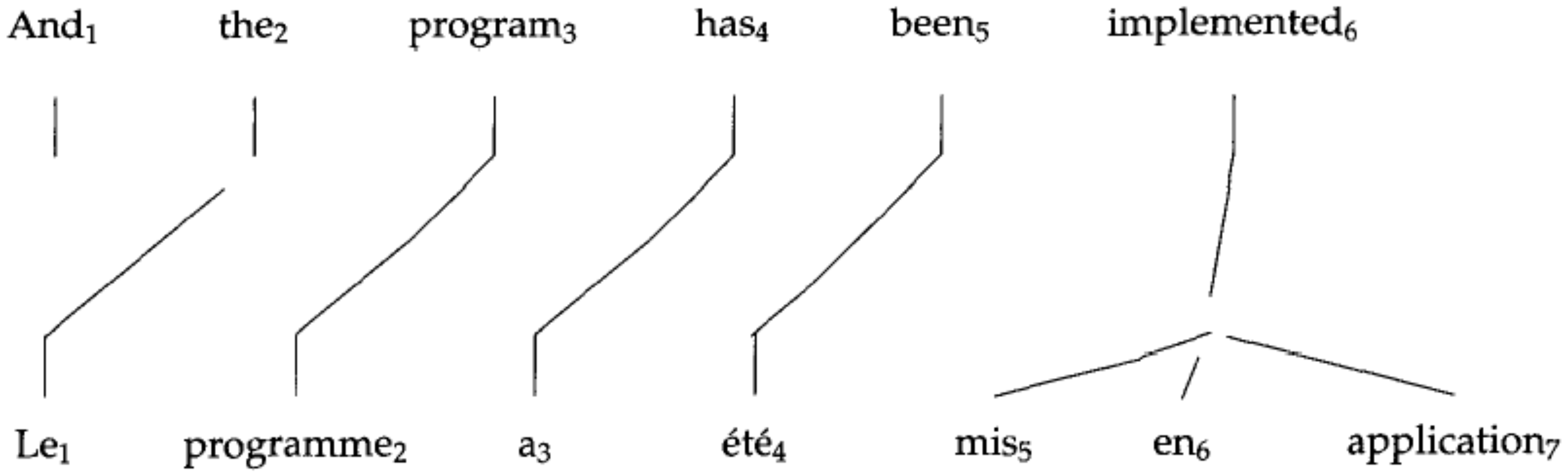
1-to-Many Alignments



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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

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

Brown et al. (1993)

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e Thank you , I shall do so gladly .

Brown et al. (1993)

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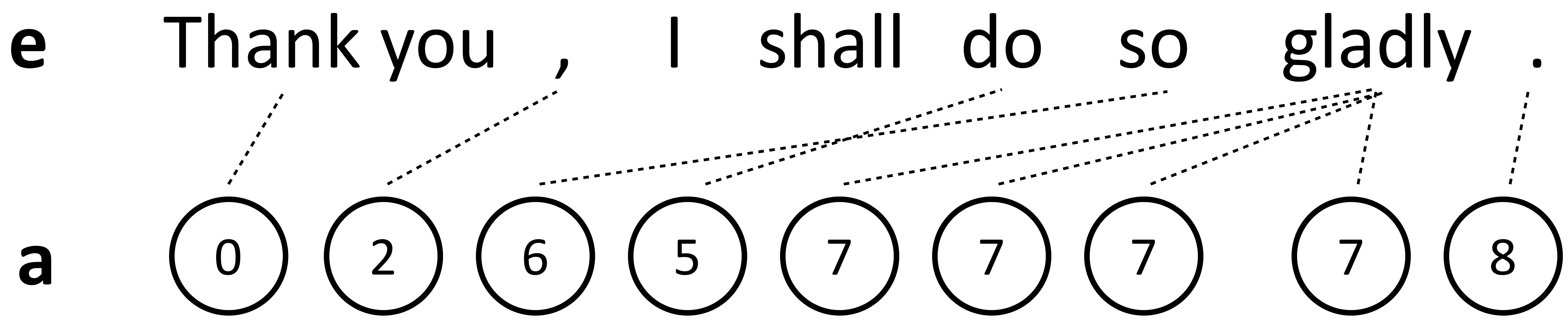

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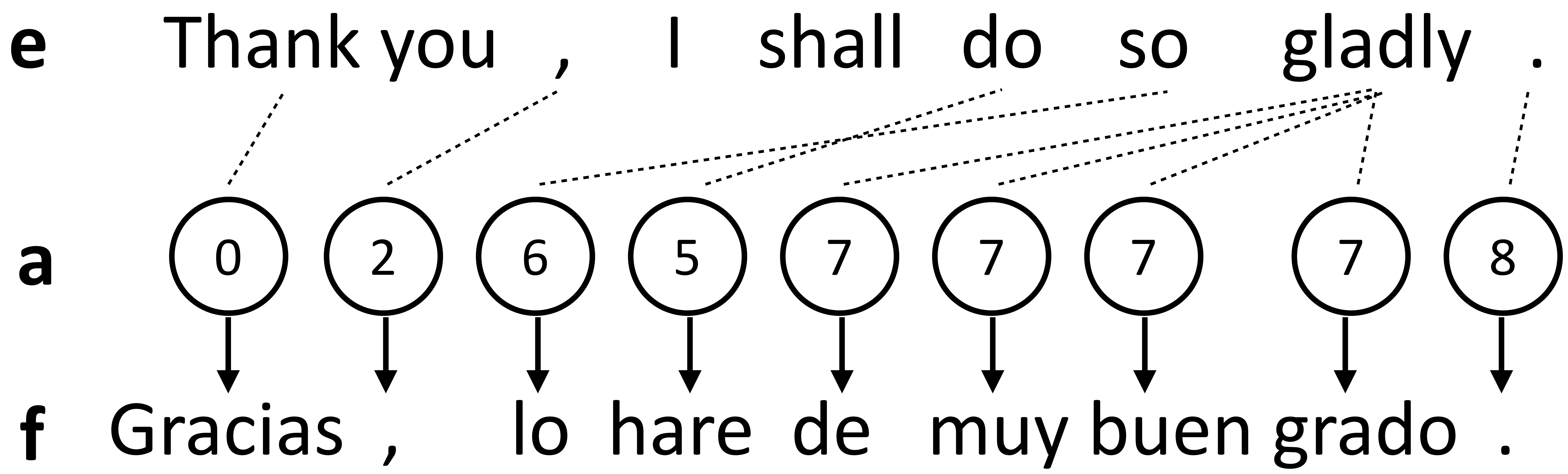

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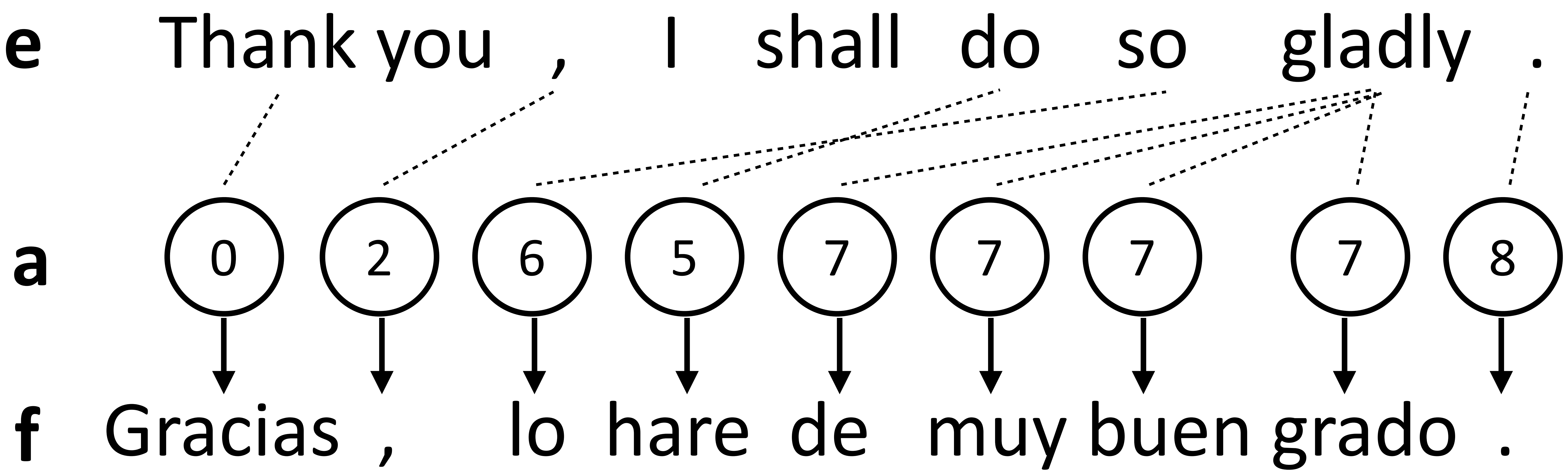

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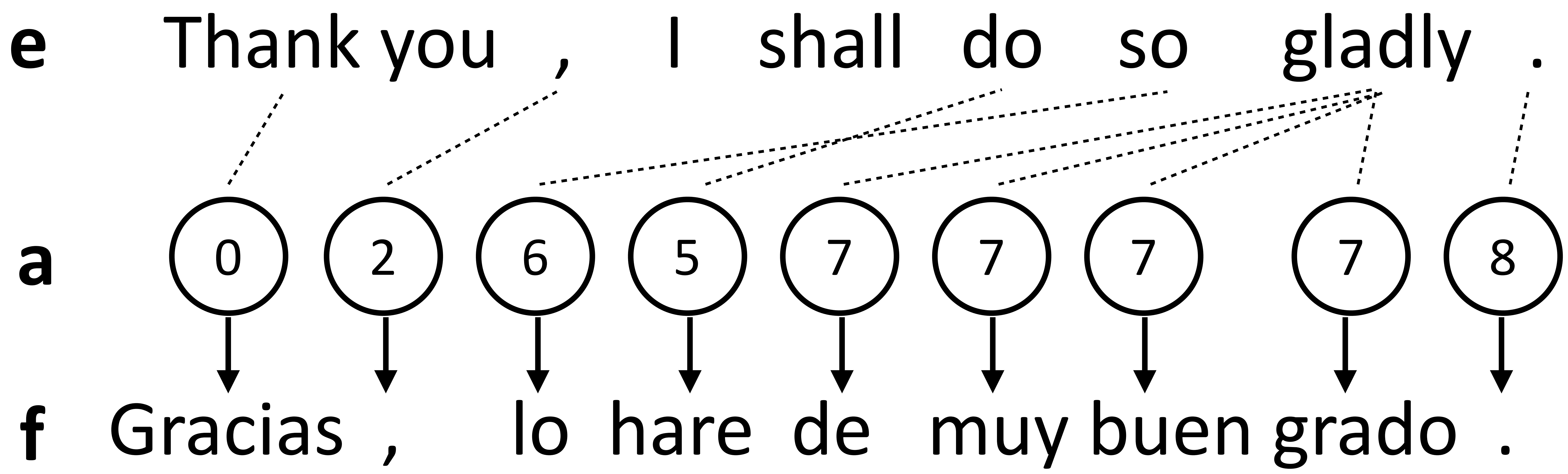

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- $P(f_i|e_{a_i})$: word translation probability table

Brown et al. (1993)

HMM for Alignment

- Sequential dependence between a's to capture monotonicity

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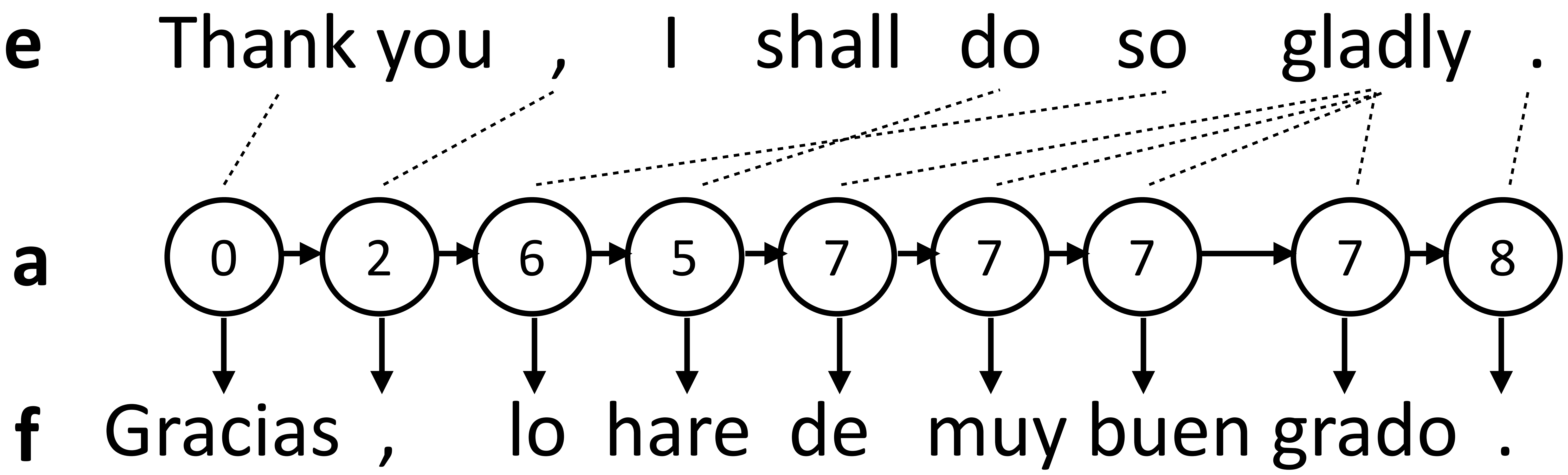

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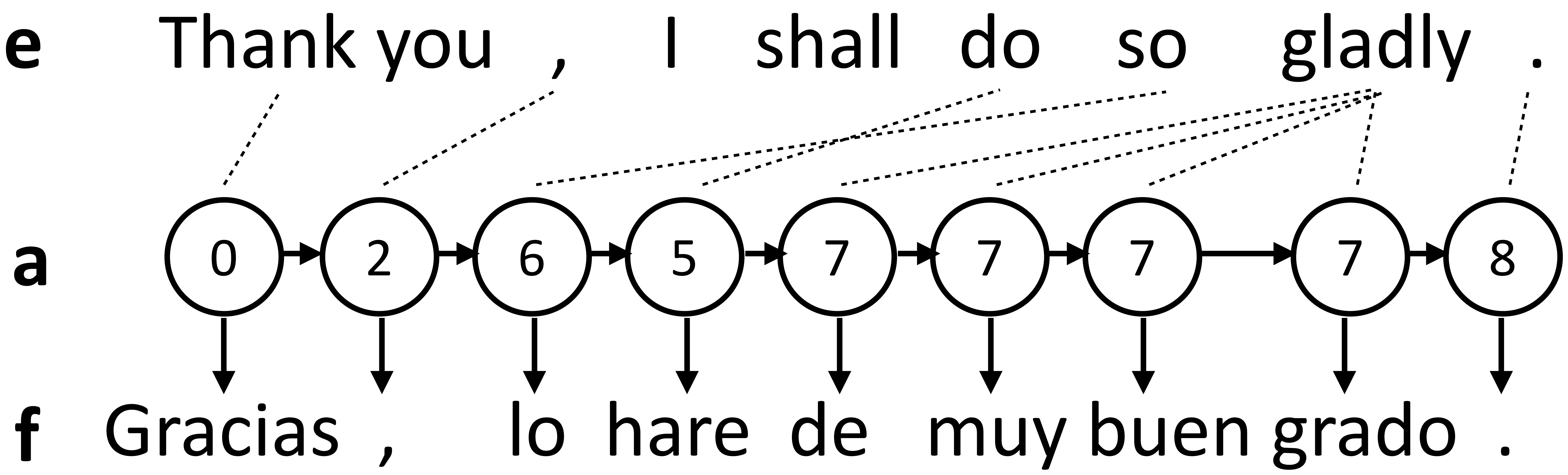
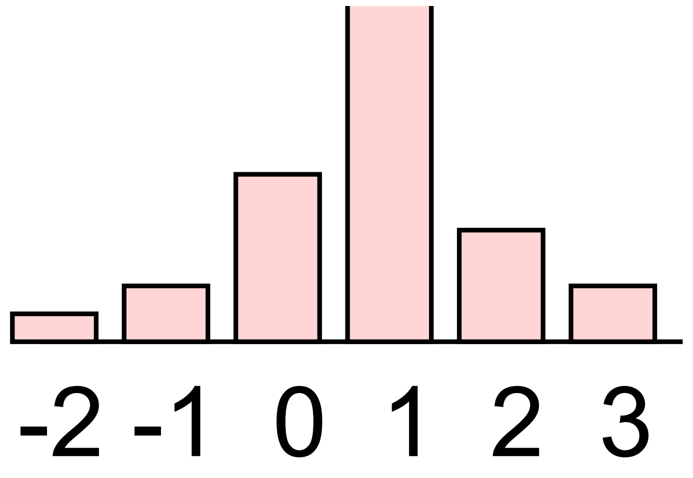


- Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$



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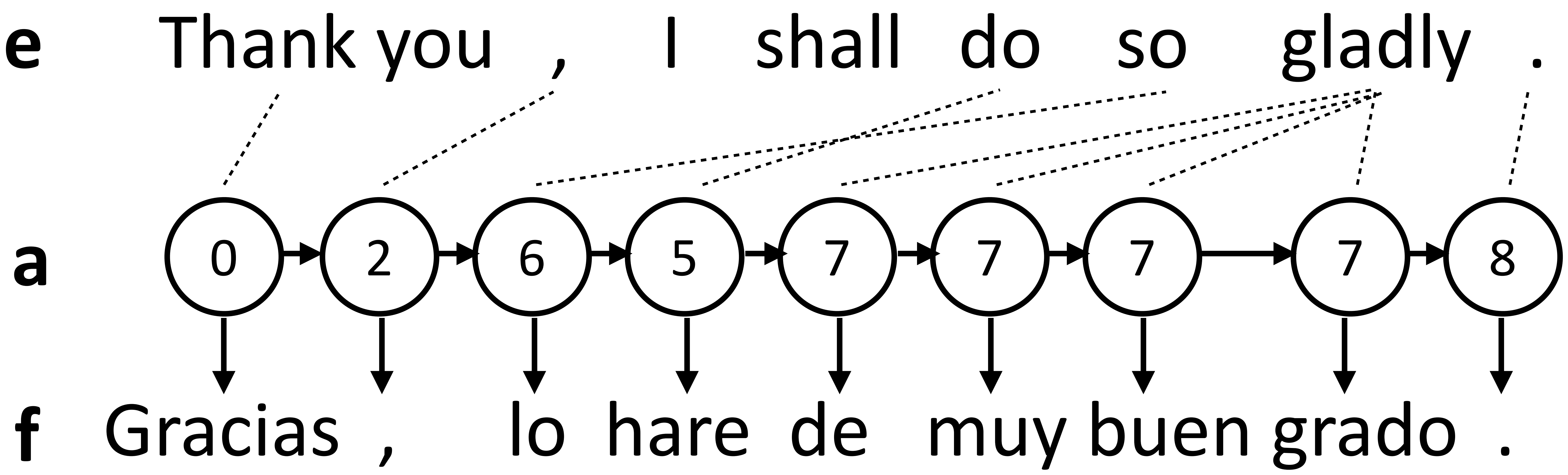

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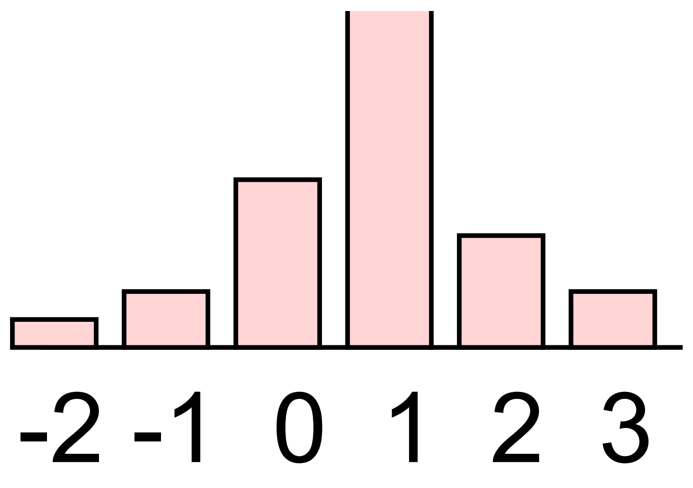
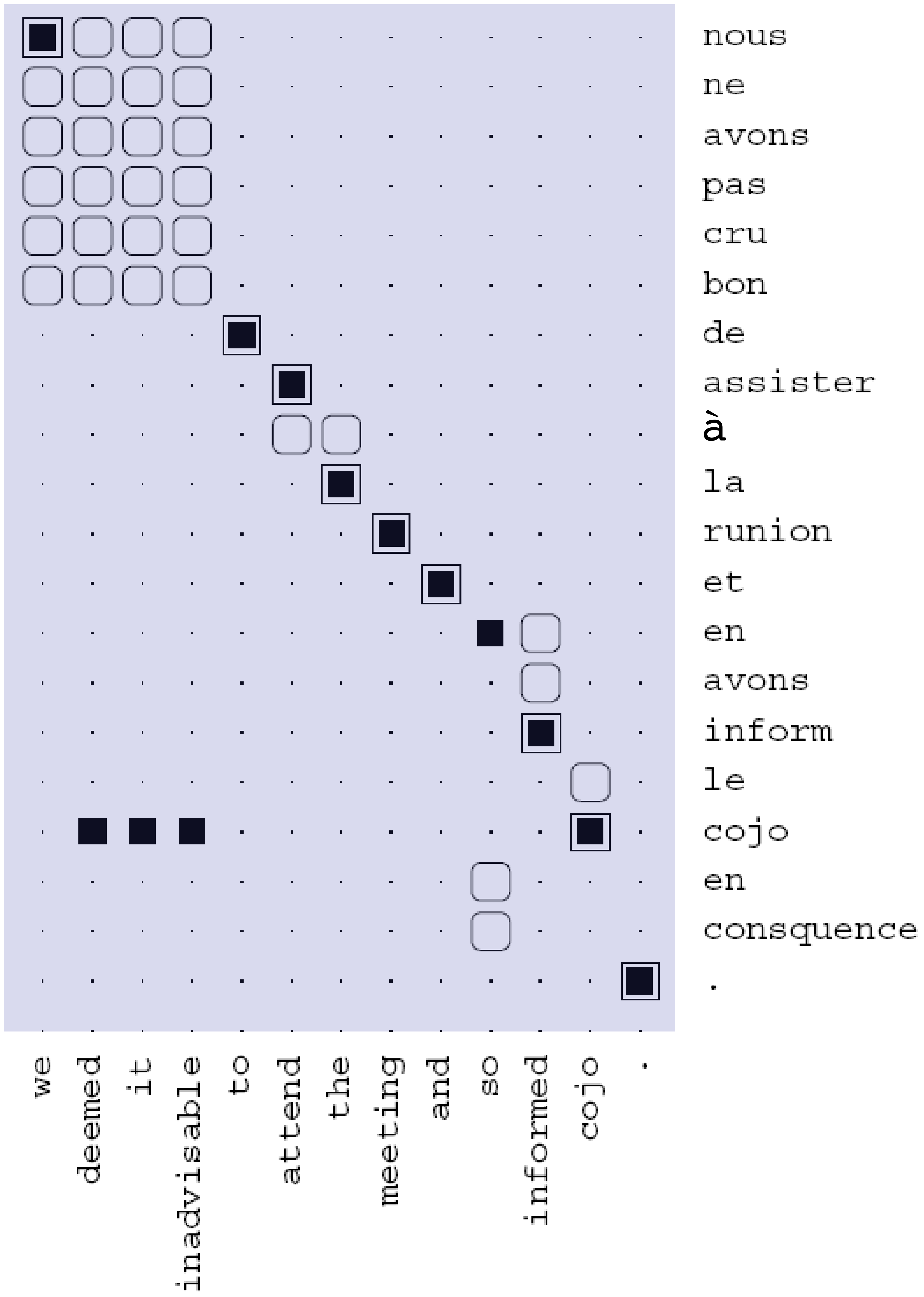


- $P(f_i | e_{a_i})$: same as before

Brown et al. (1993)

HMM Model

- Which direction is this?



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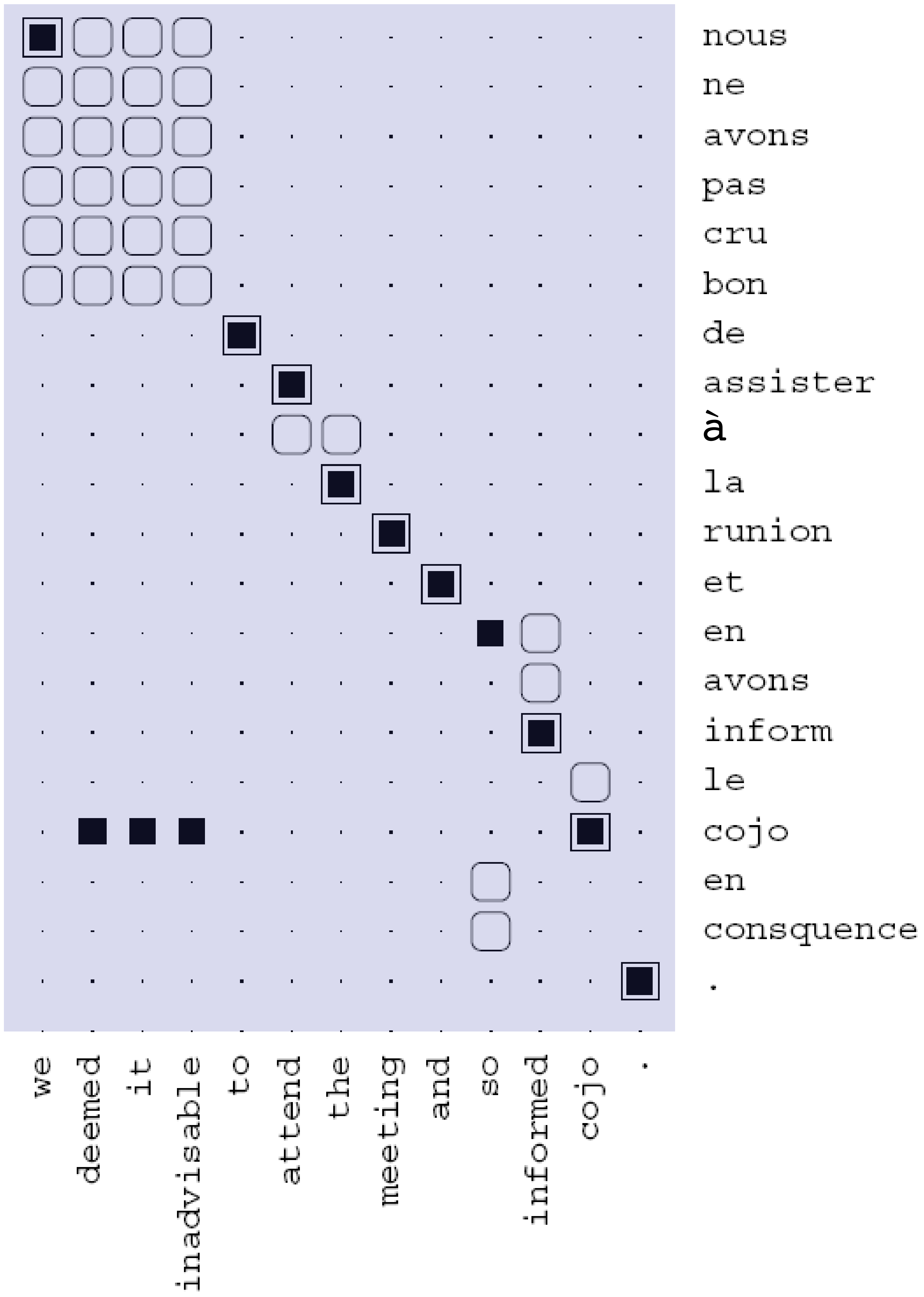
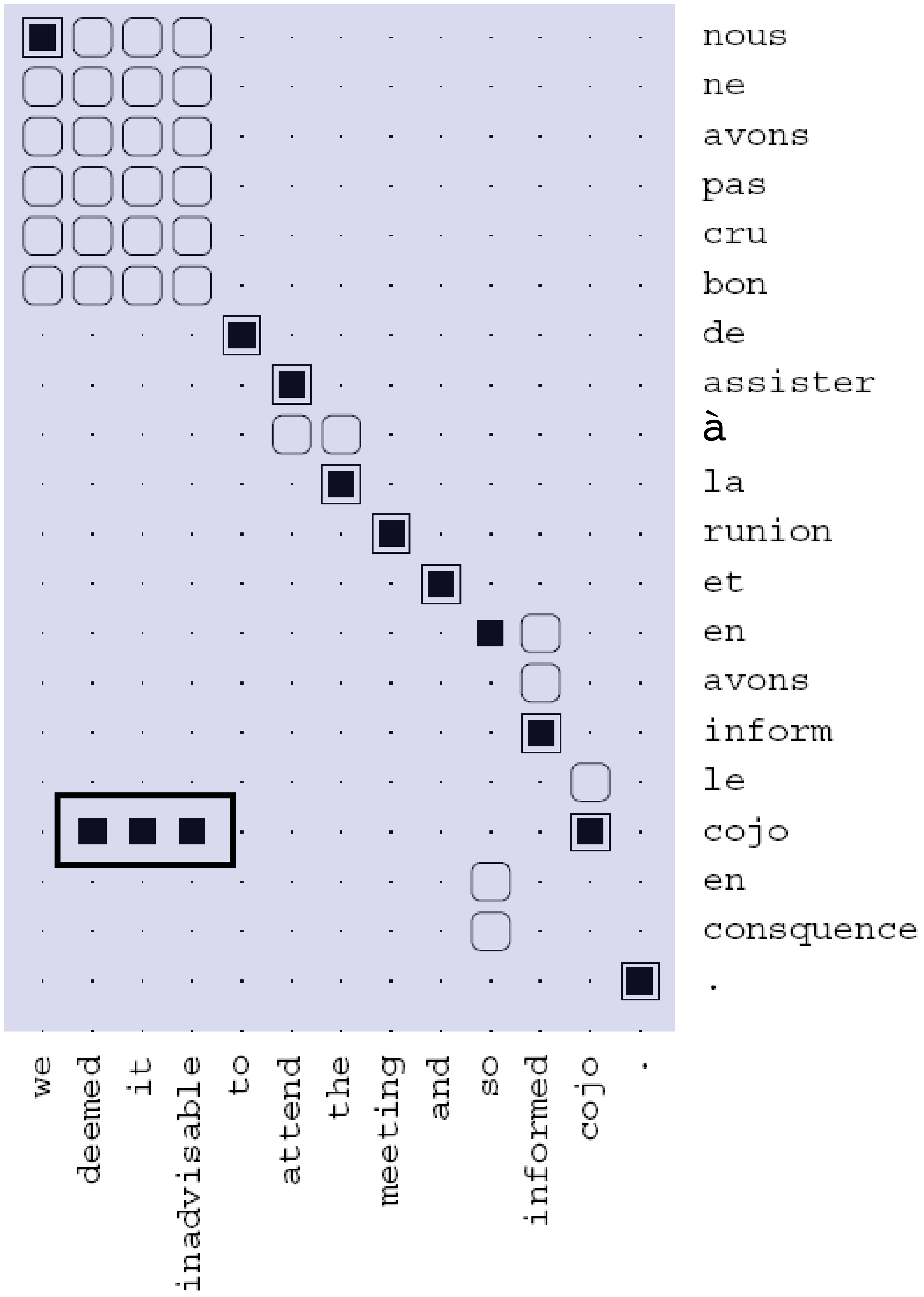


HMM Model

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



Evaluating Word Alignment

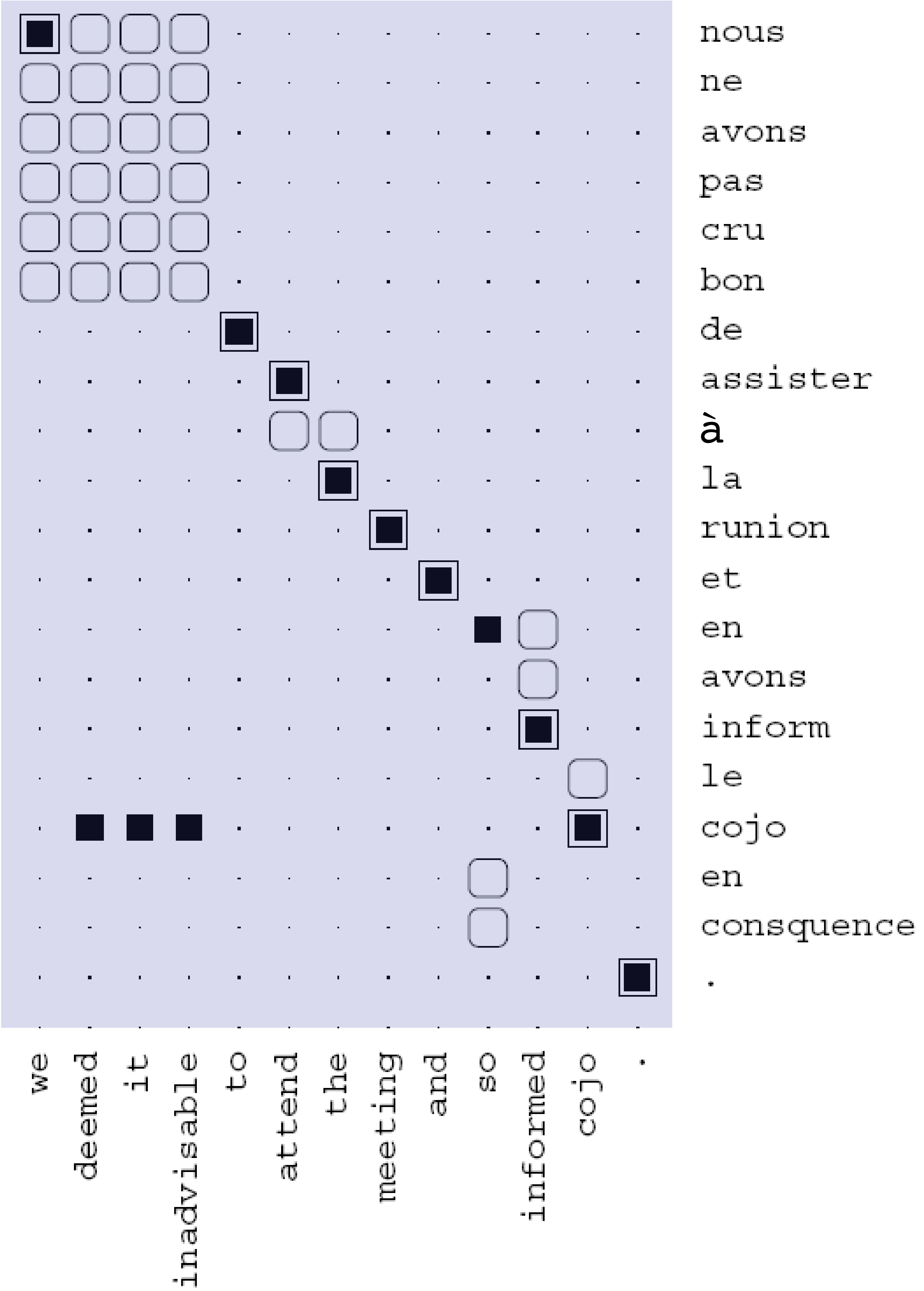
- "Alignment error rate": use labeled alignments on small corpus

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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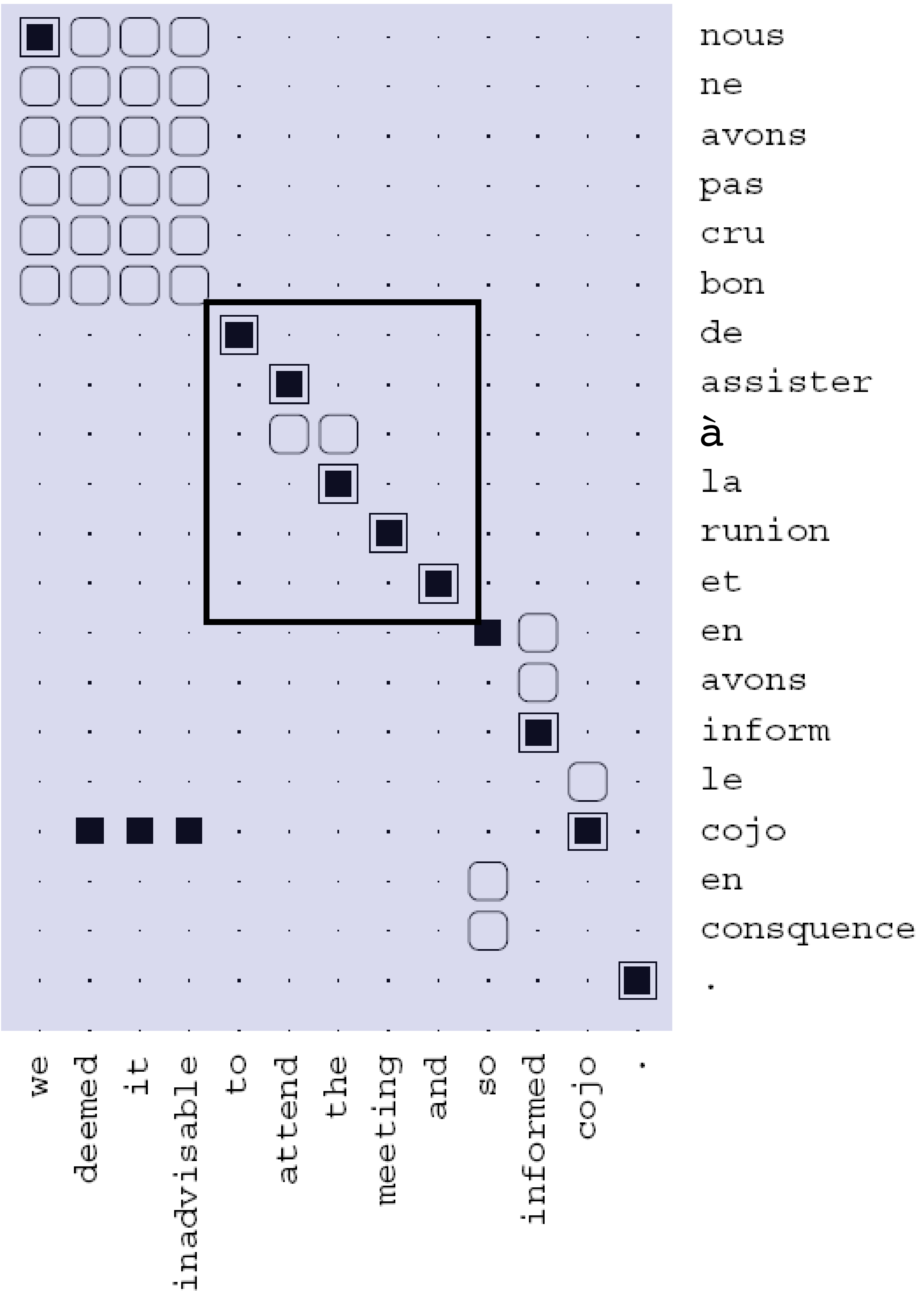

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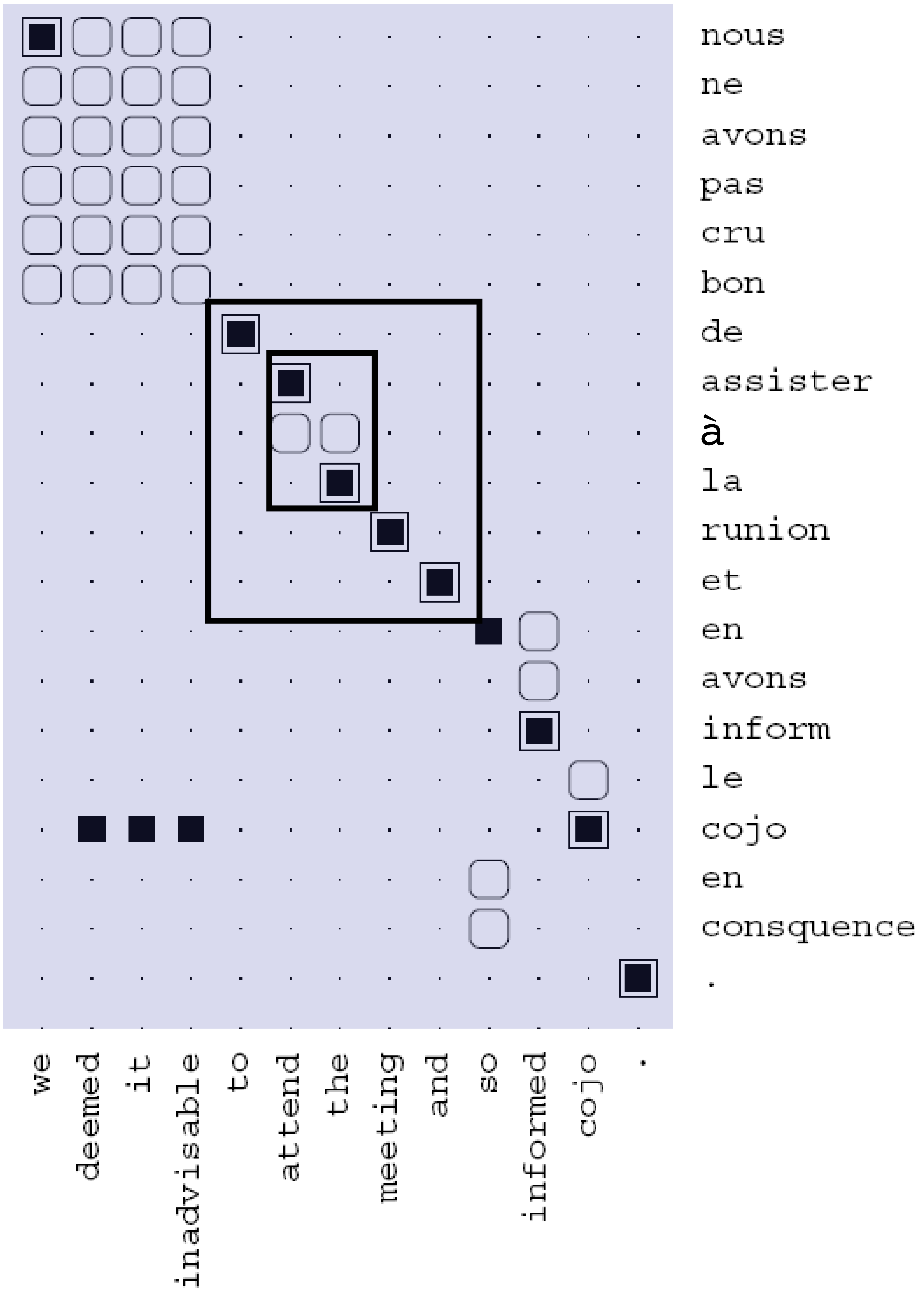

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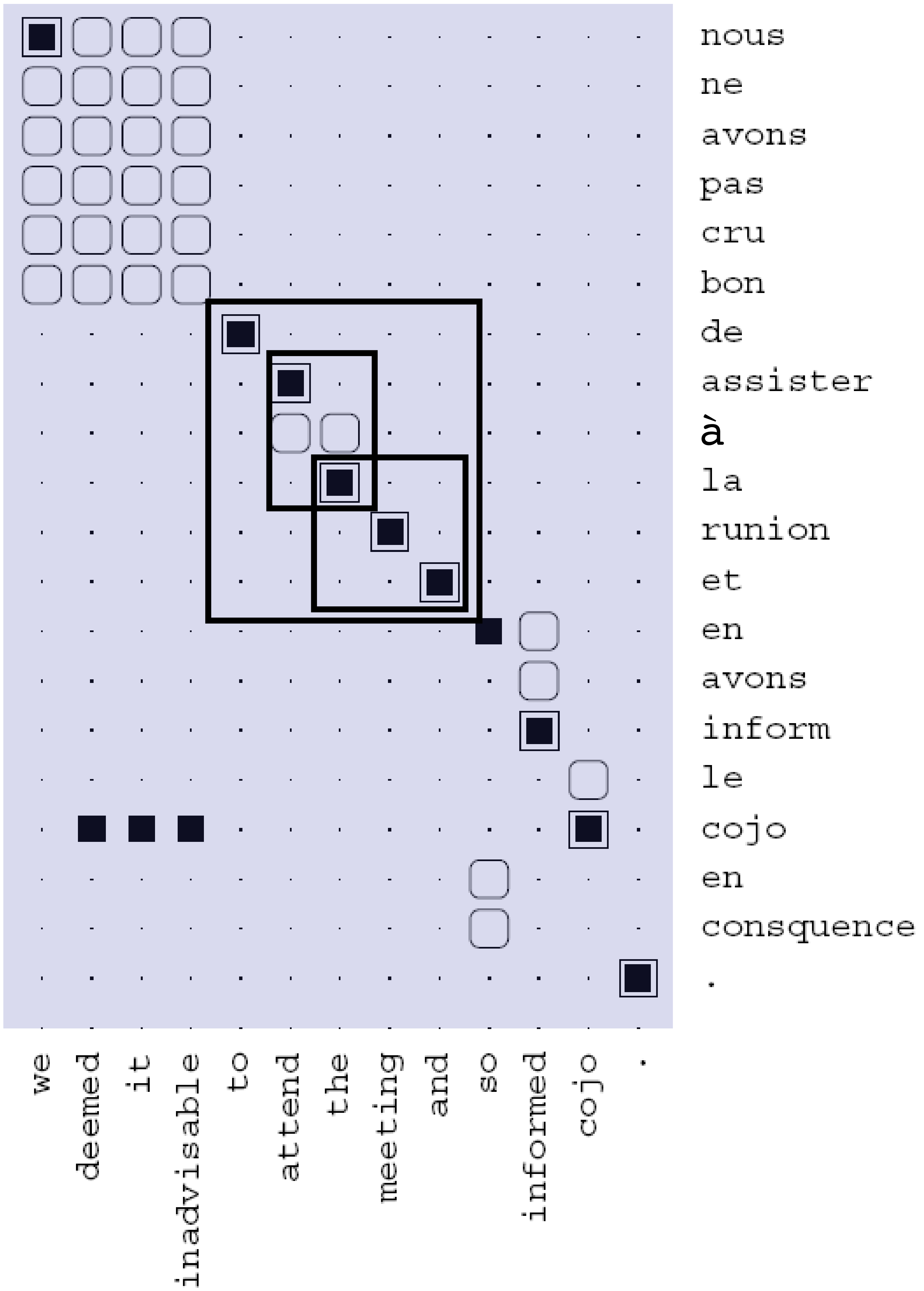

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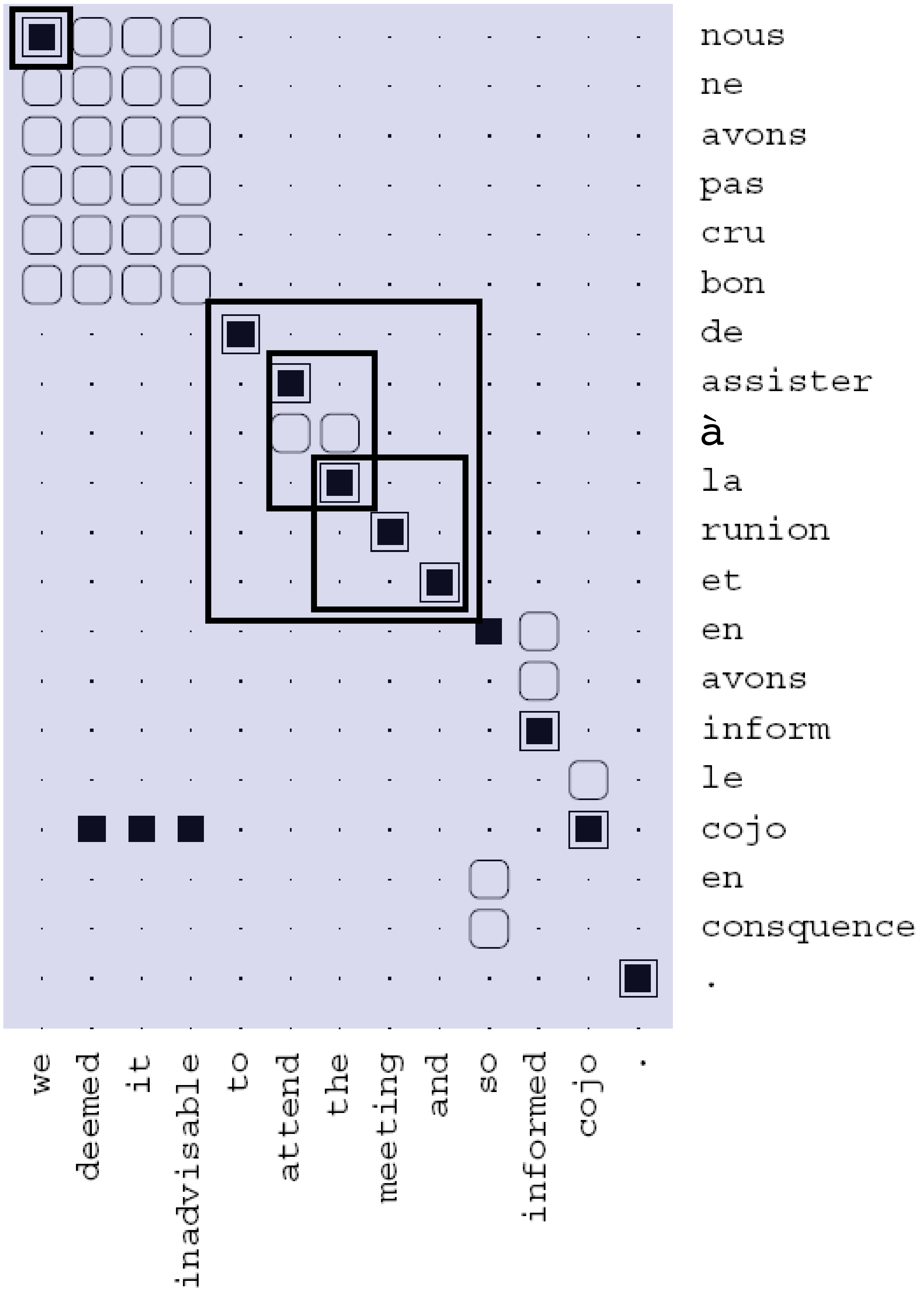

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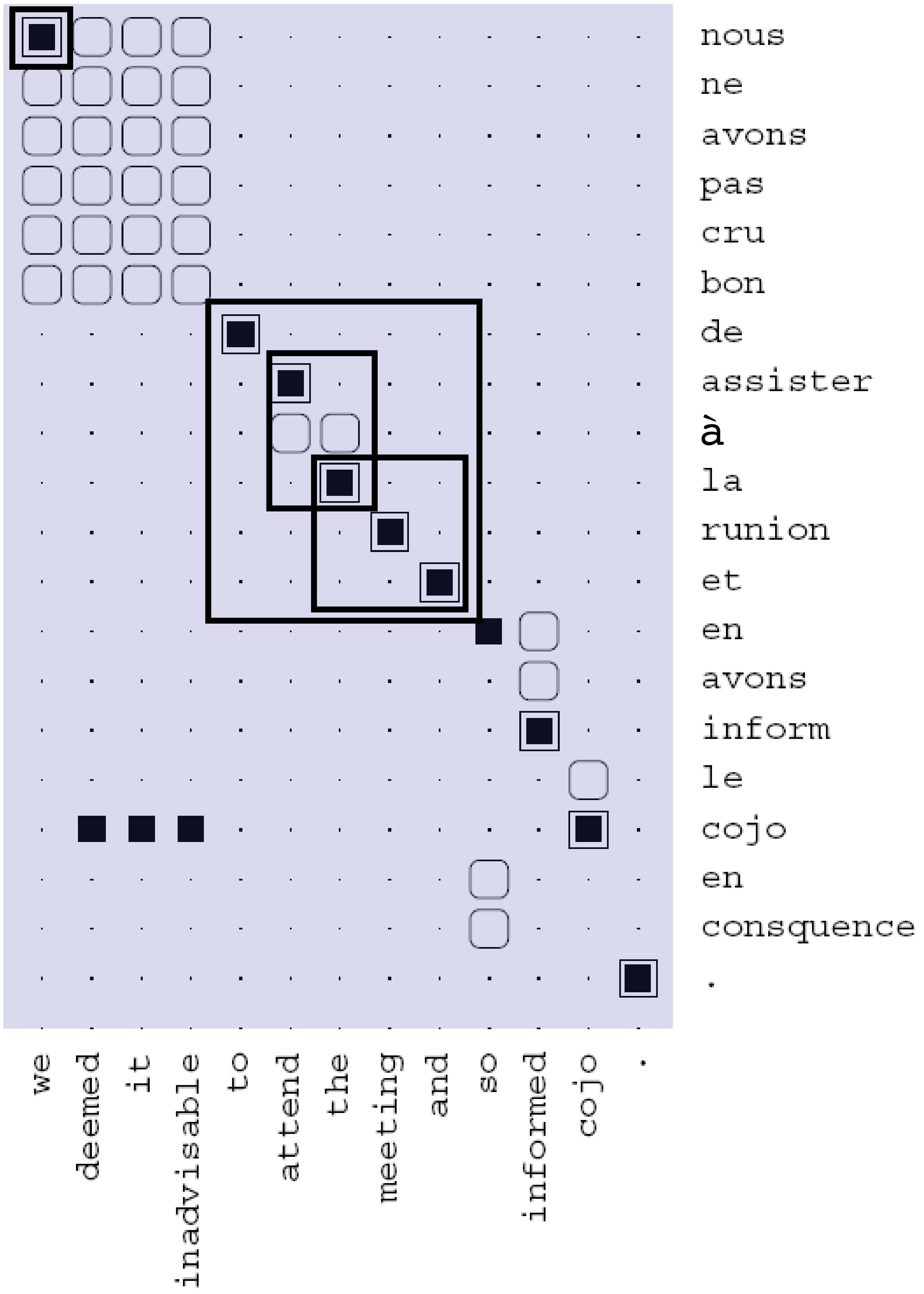

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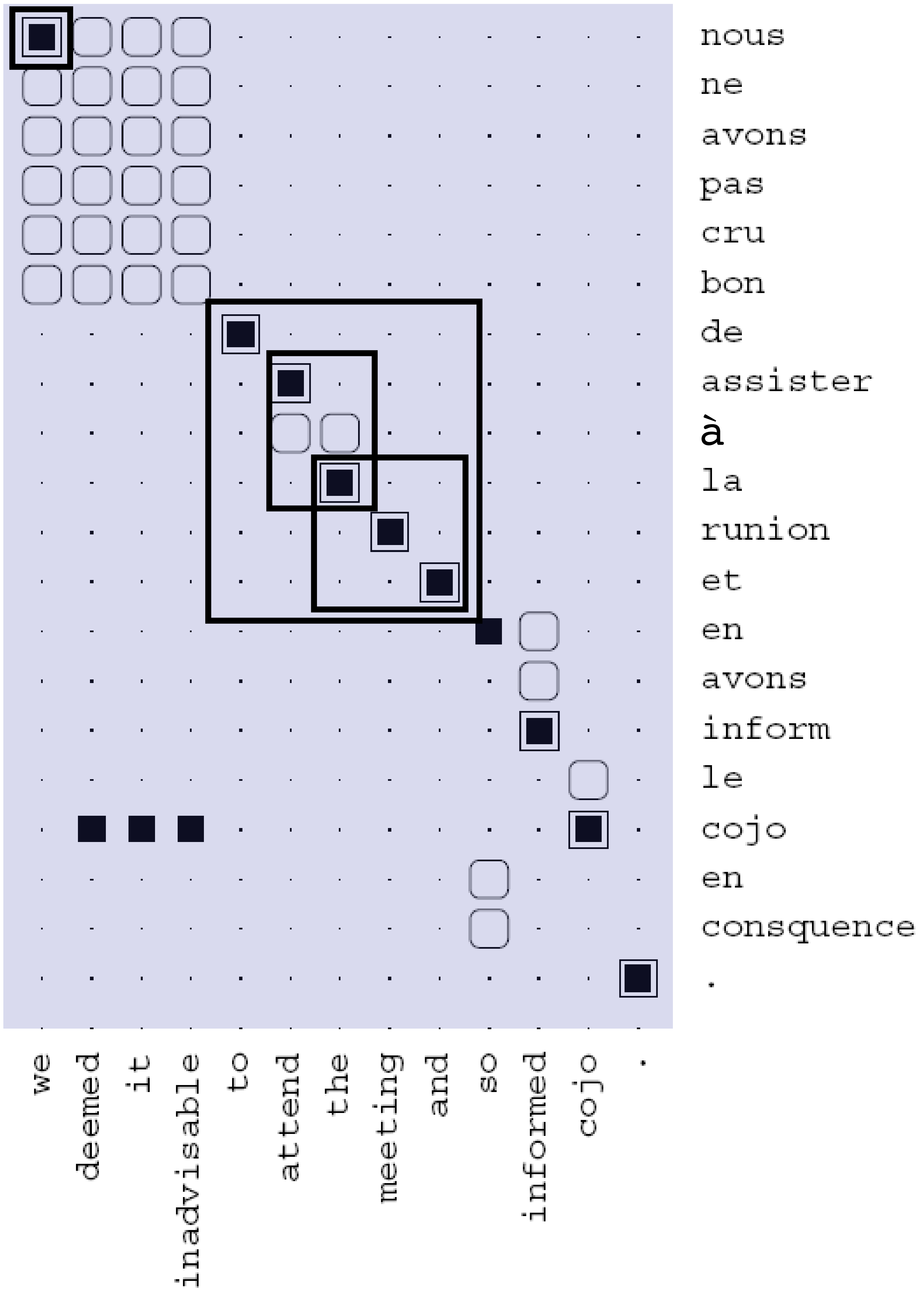
- Lots of phrases possible, count across all sentences and score by frequency

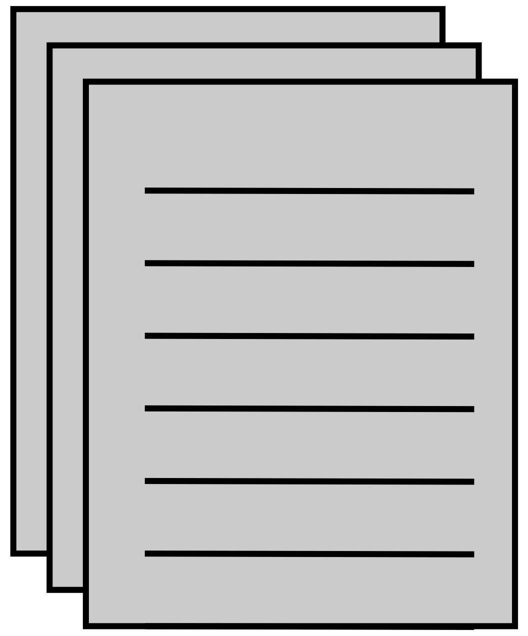


Language Modeling

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"

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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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$$P(x|\text{visited San}) = \frac{\text{count}(\text{visited San}, x) - k}{\text{count}(\text{visited San})} + \lambda\frac{\text{count}(\text{San}, x)}{\text{count}(\text{San})}$$

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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

Δw	Δc	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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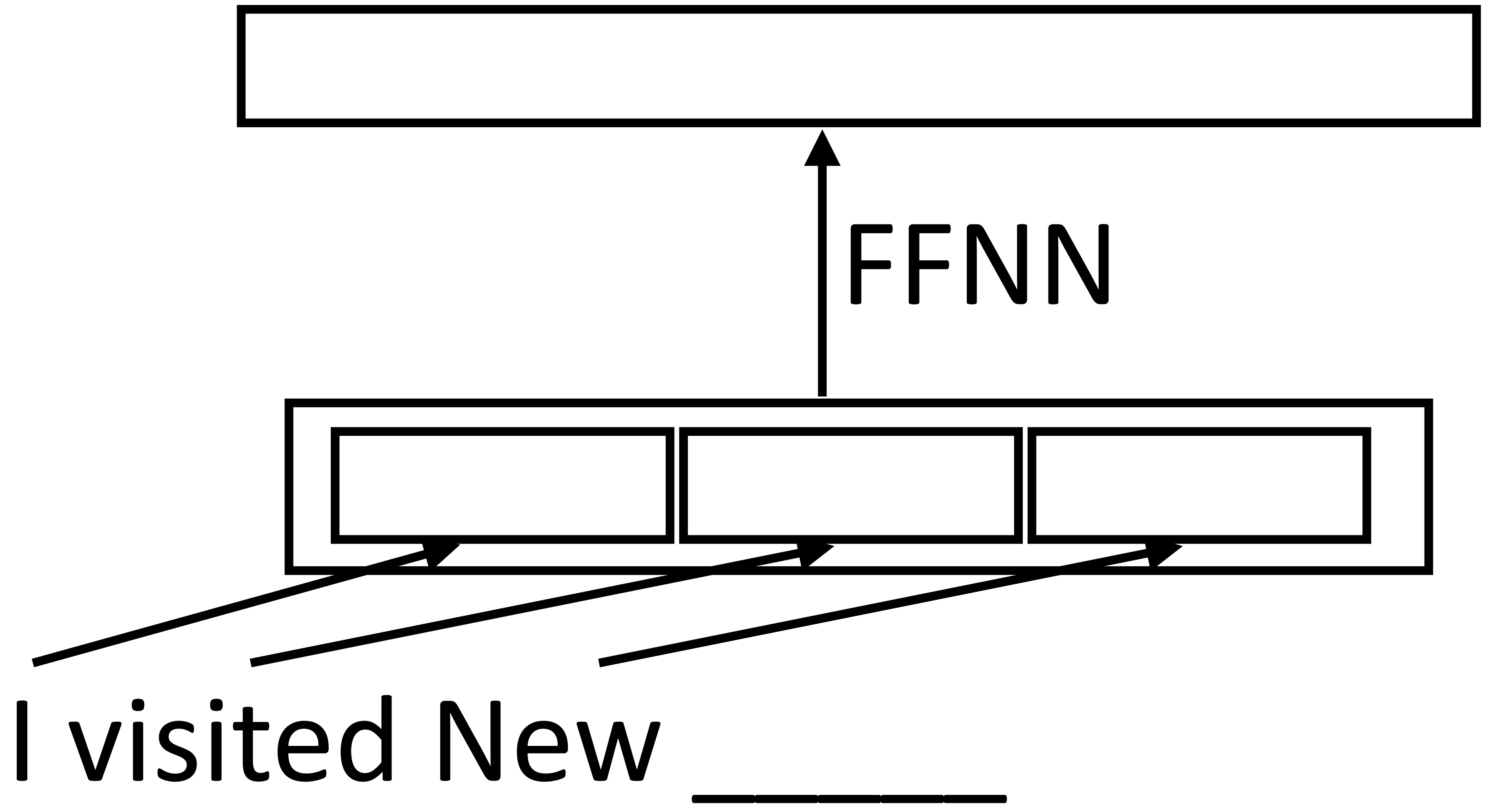

$P(w_i | w_{i-n}, \ldots, w_{i-1})$

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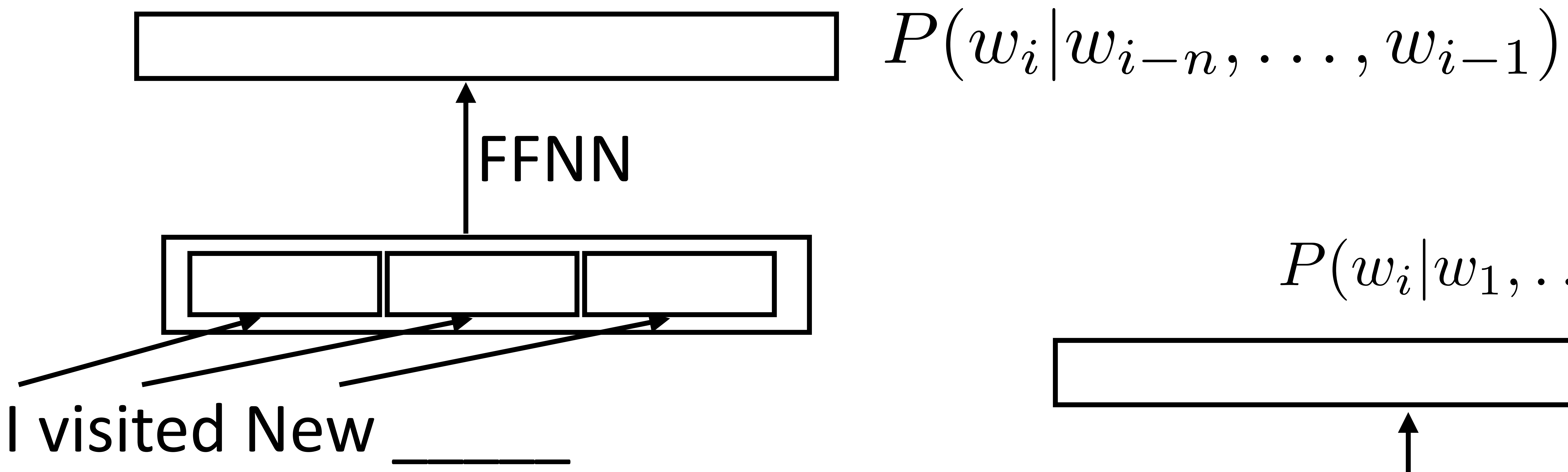
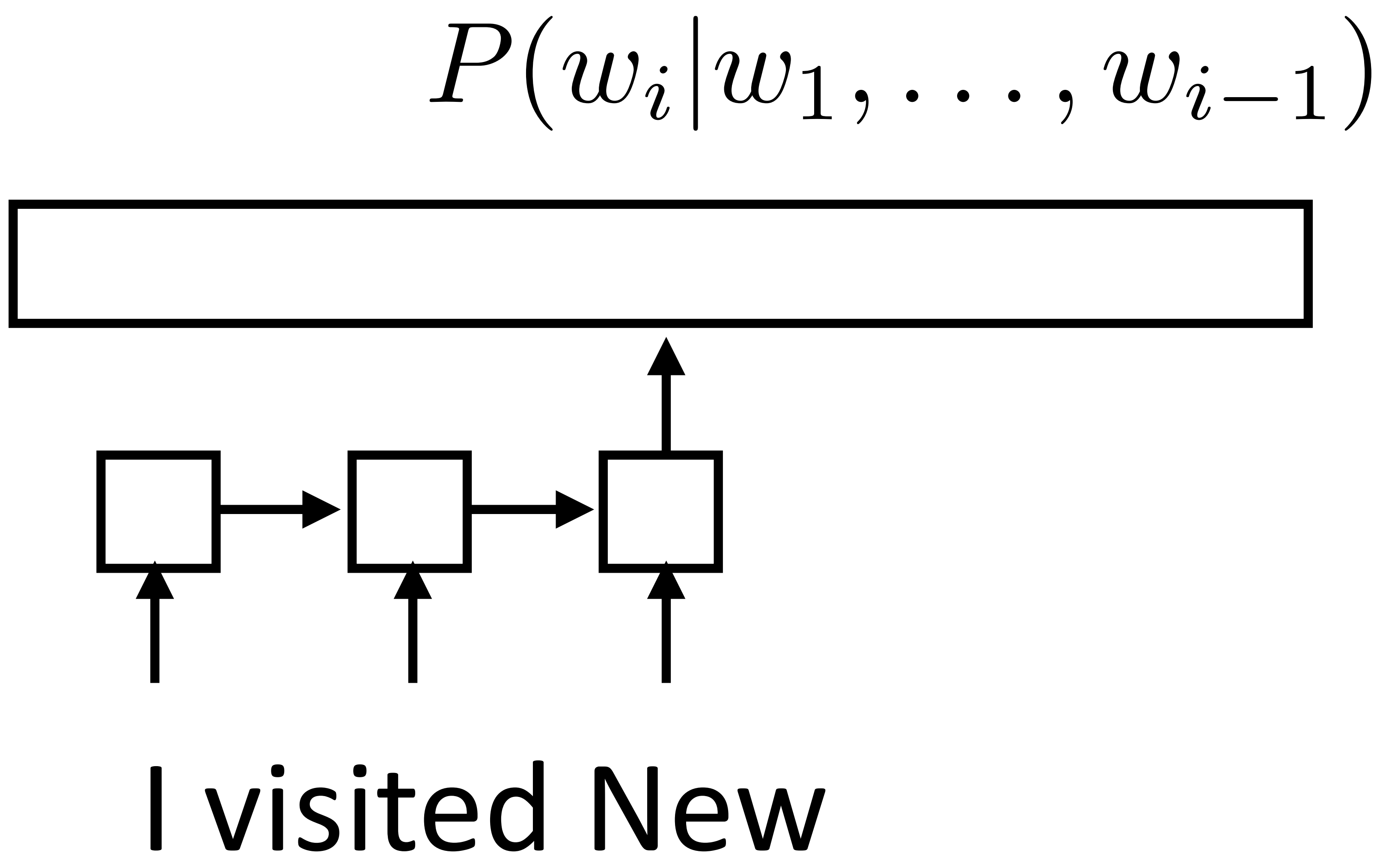


- Variable length context with RNNs:



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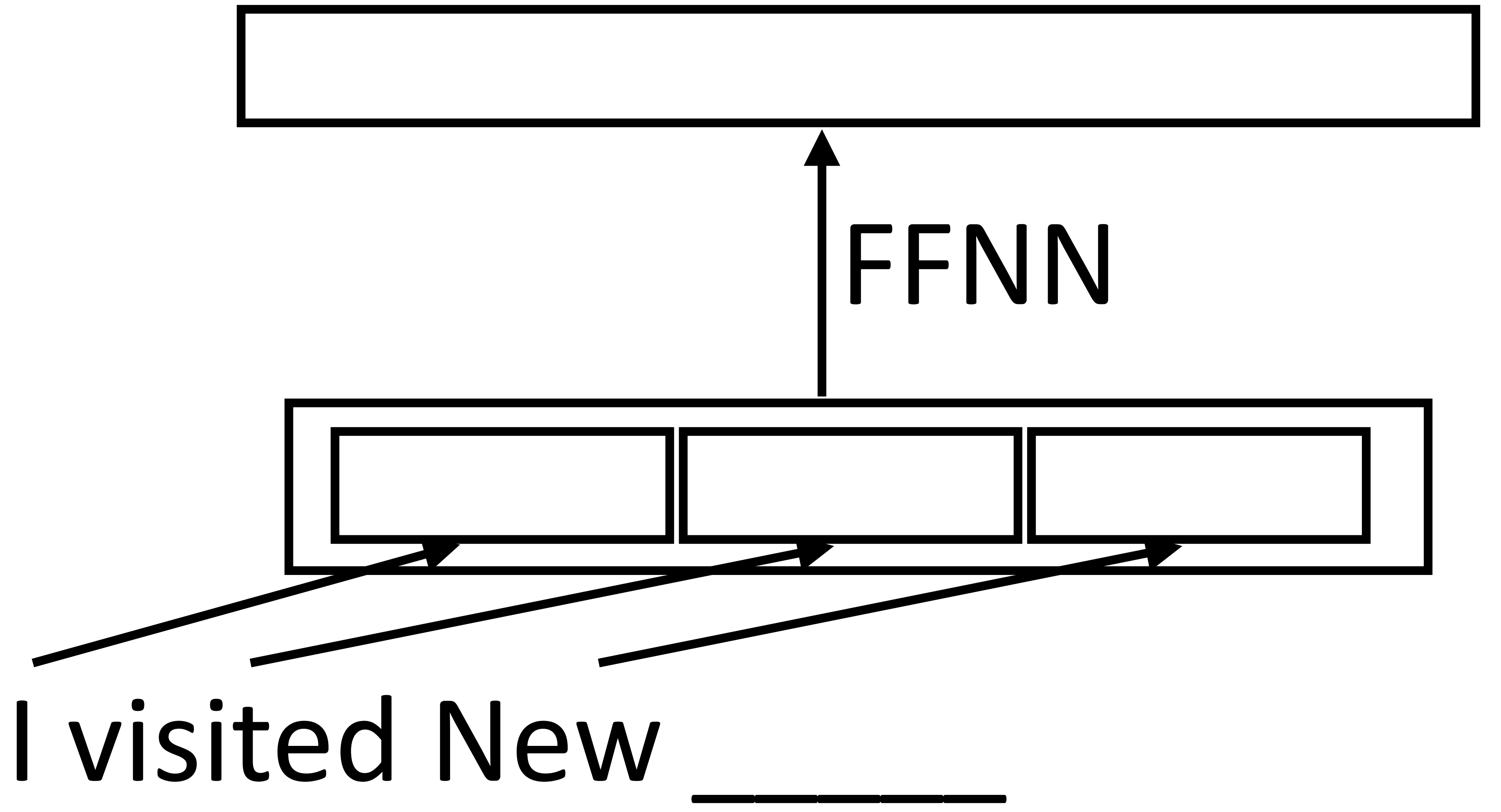

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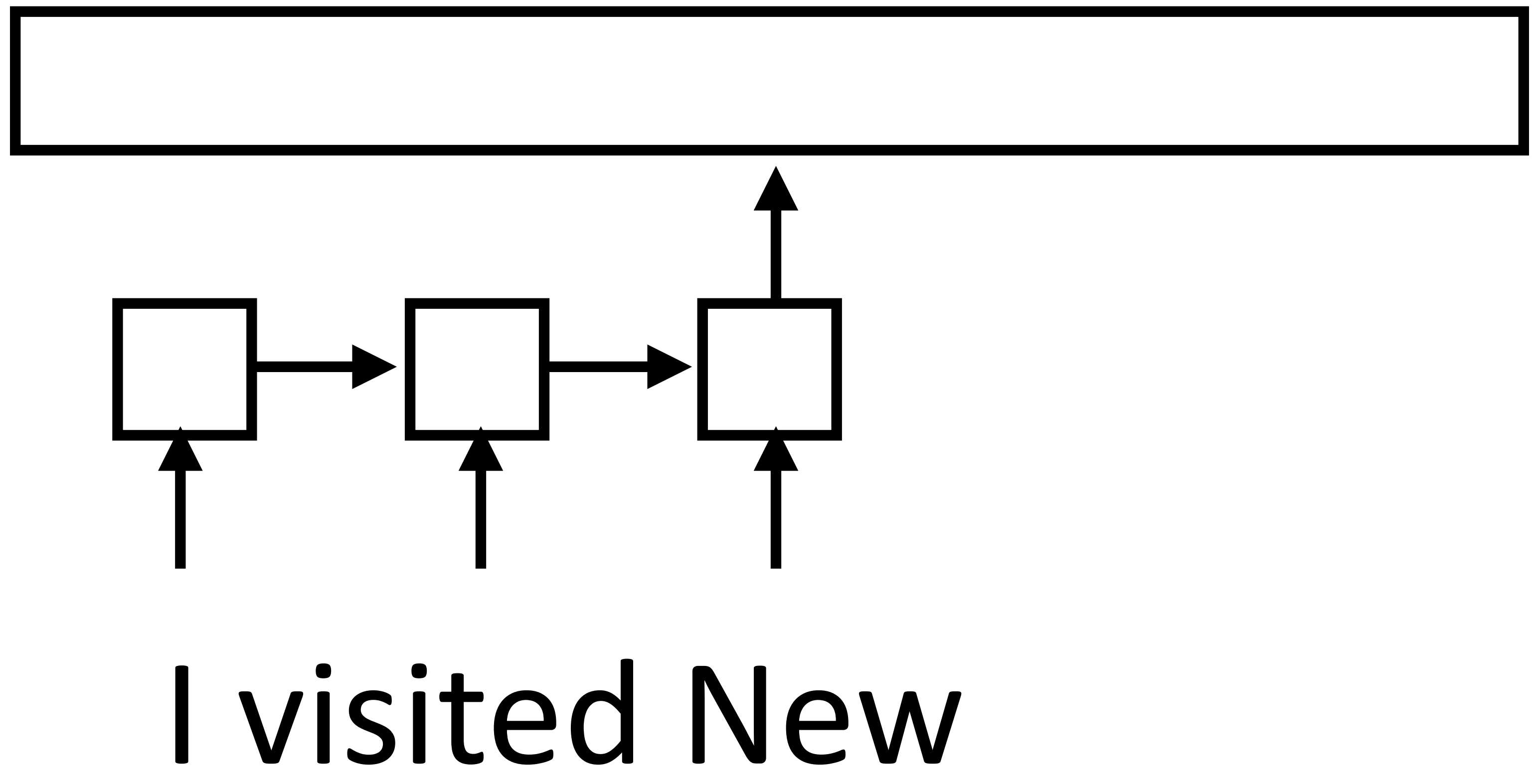

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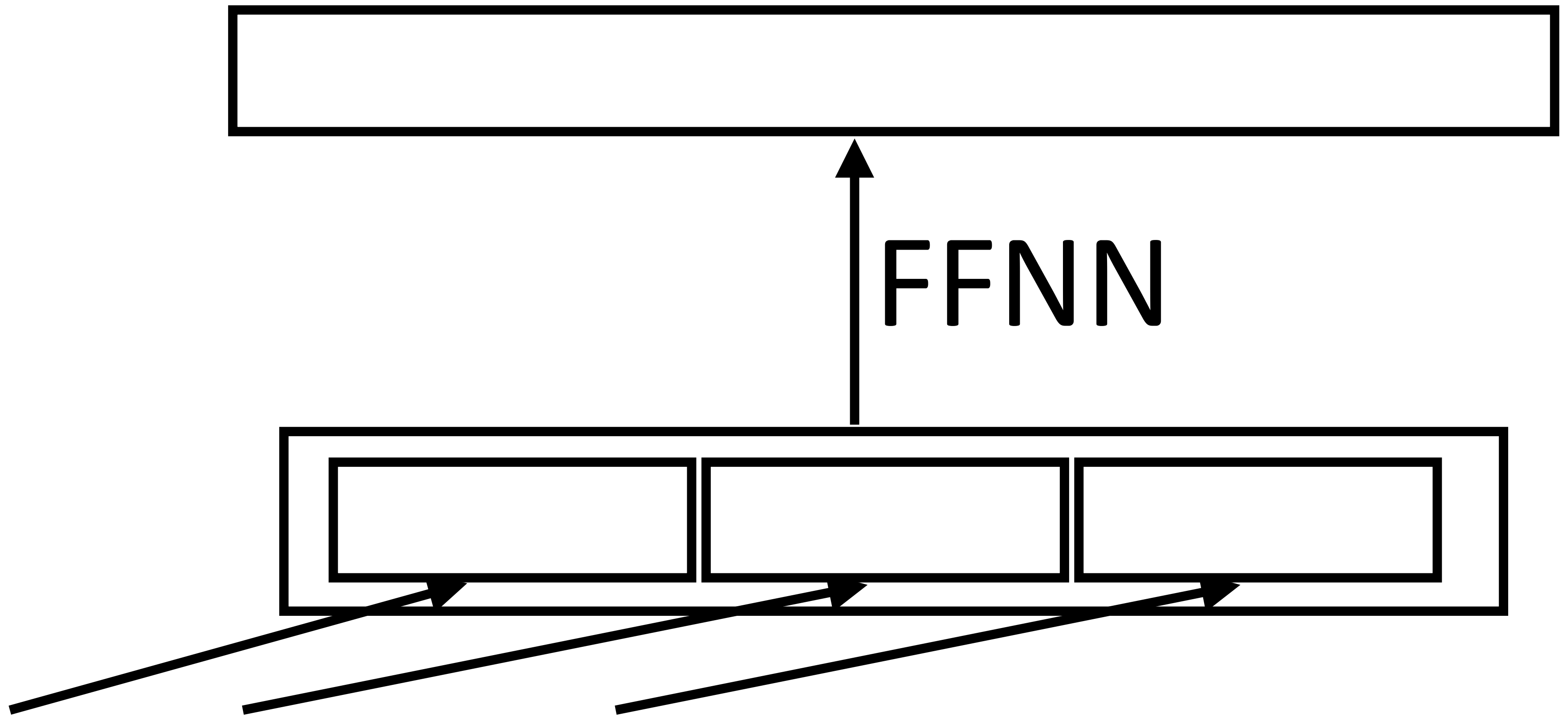

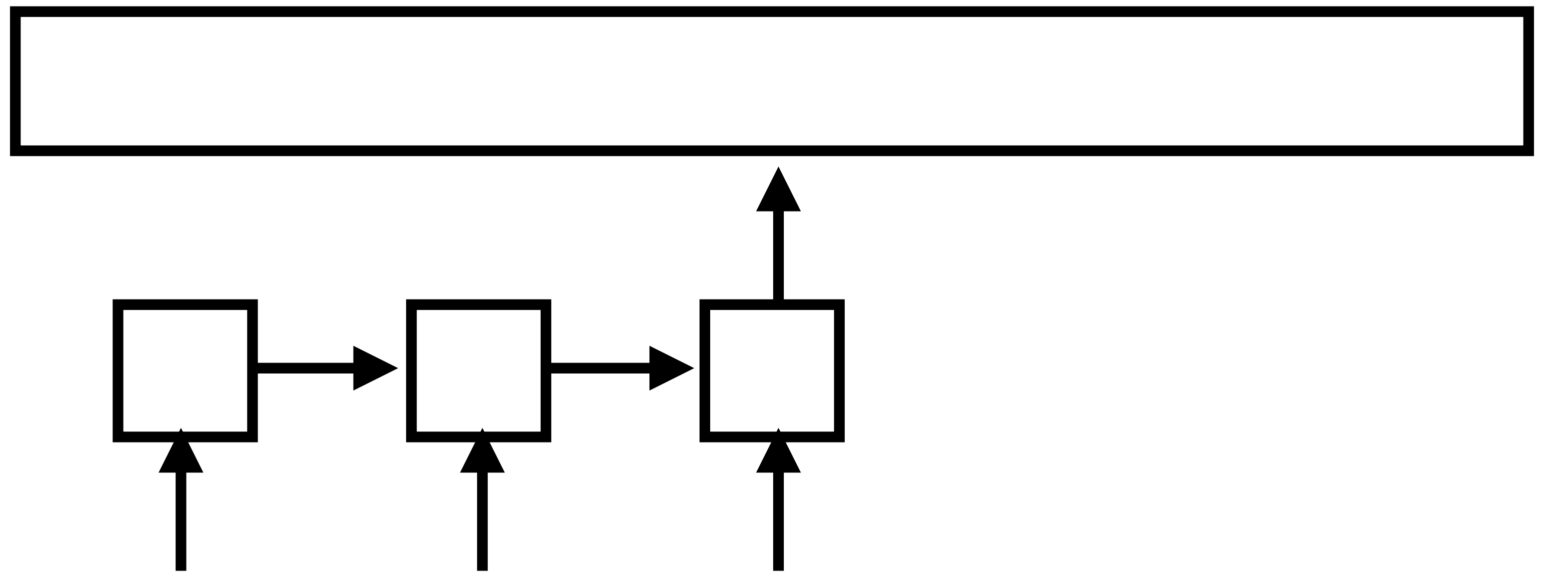

- Variable length context with RNNs:
  - Works like a decoder with no encoder
- Slow to train over lots of data!

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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

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

Decoding

Phrase-Based Decoding

- Inputs:
  - Language model that scores $P(e_i|e_1,\ldots,e_{i-1}) \approx P(e_i|e_{i-n-1},\ldots,e_{i-1})$
  - Phrase table: set of phrase pairs (**e**, **f**) with probabilities P(**f**|**e**)

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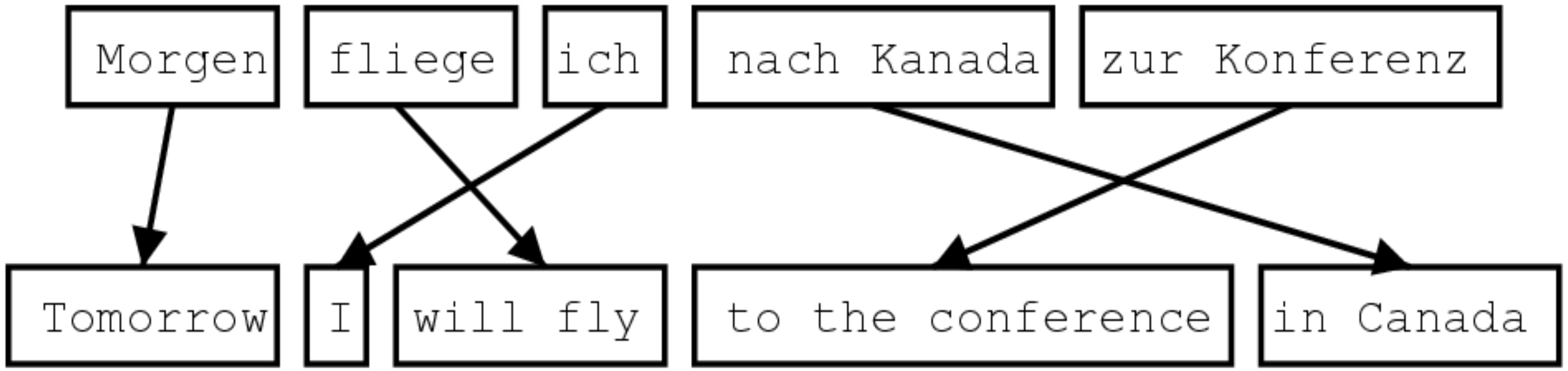

Phrase lattices are big!

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

lo haré | rápidamente | .

- Translations

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)

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

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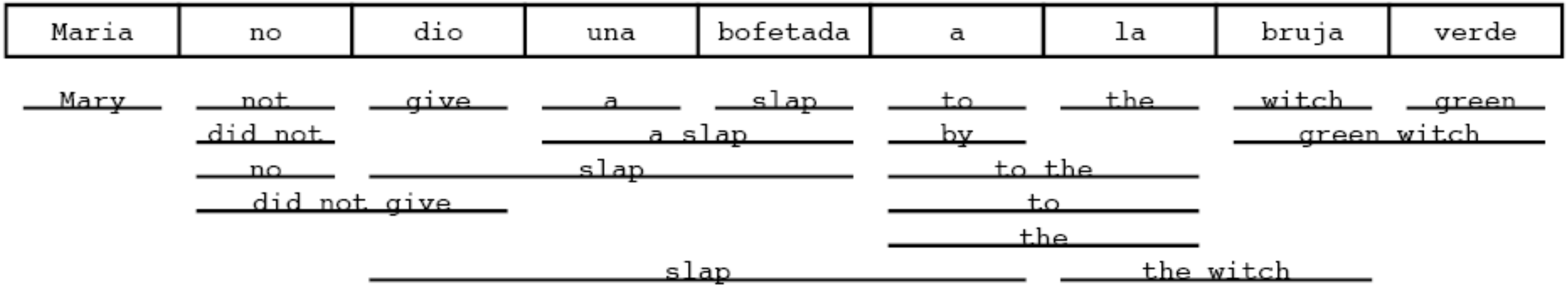
Monotonic Translation



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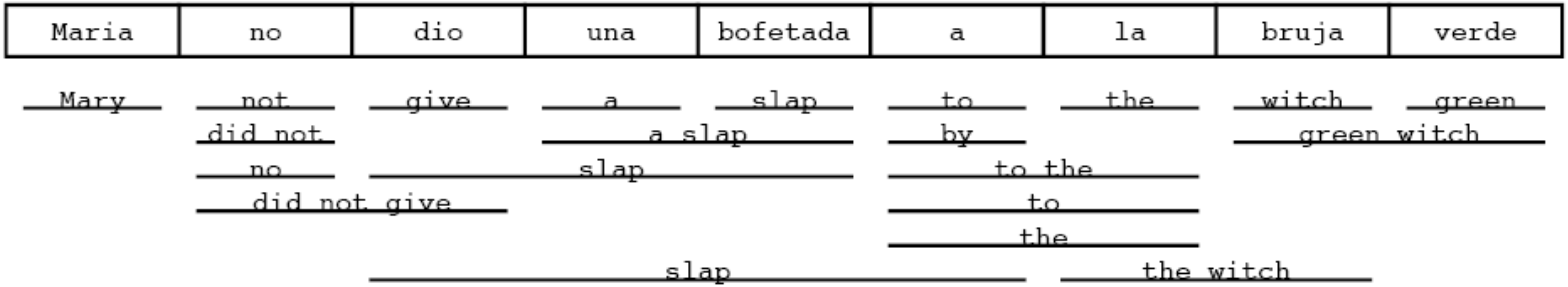

- If we translate with beam search, what state do we need to keep in the beam?

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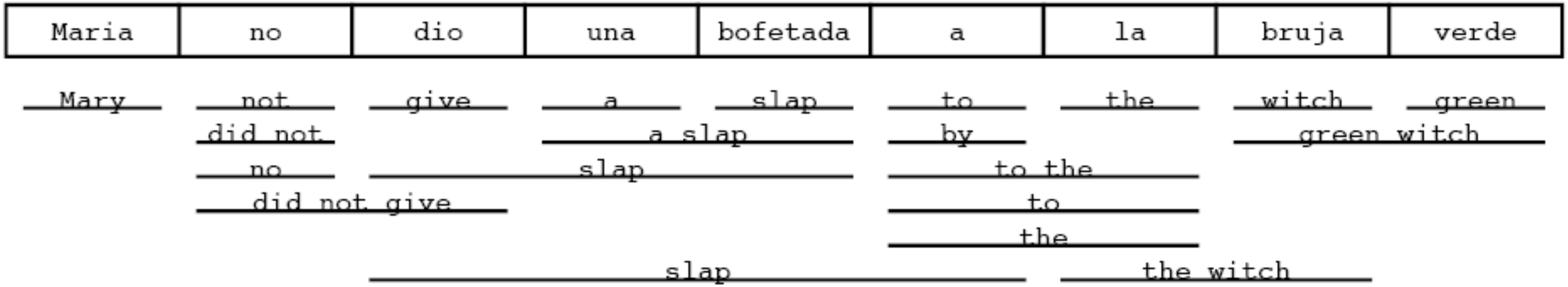

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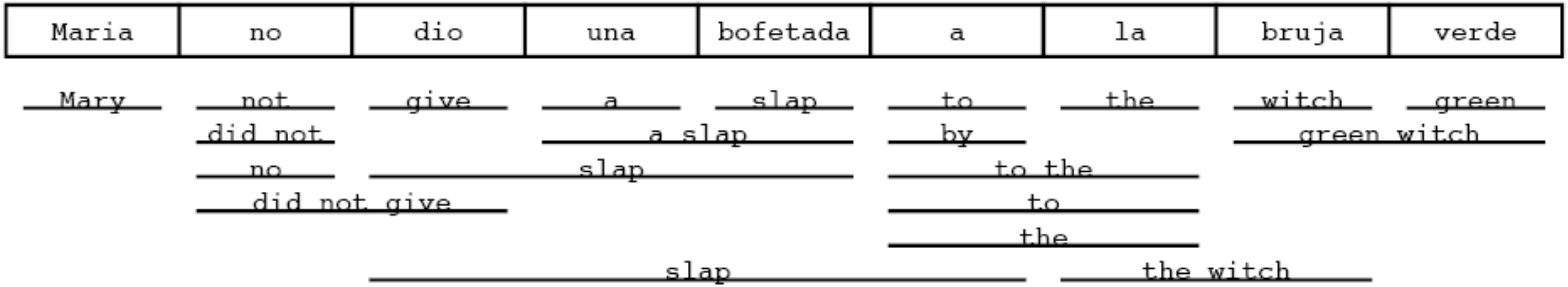

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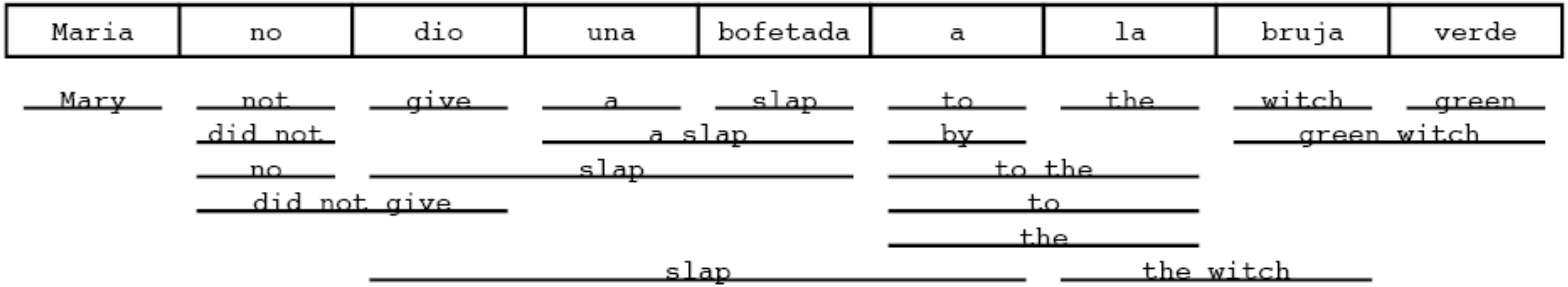

- If we translate with beam search, what state do we need to keep in the beam?
  - What have we translated so far?
  - What words have we produced so far?
  - When using a 3-gram LM, only need to remember the last 2 words!

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

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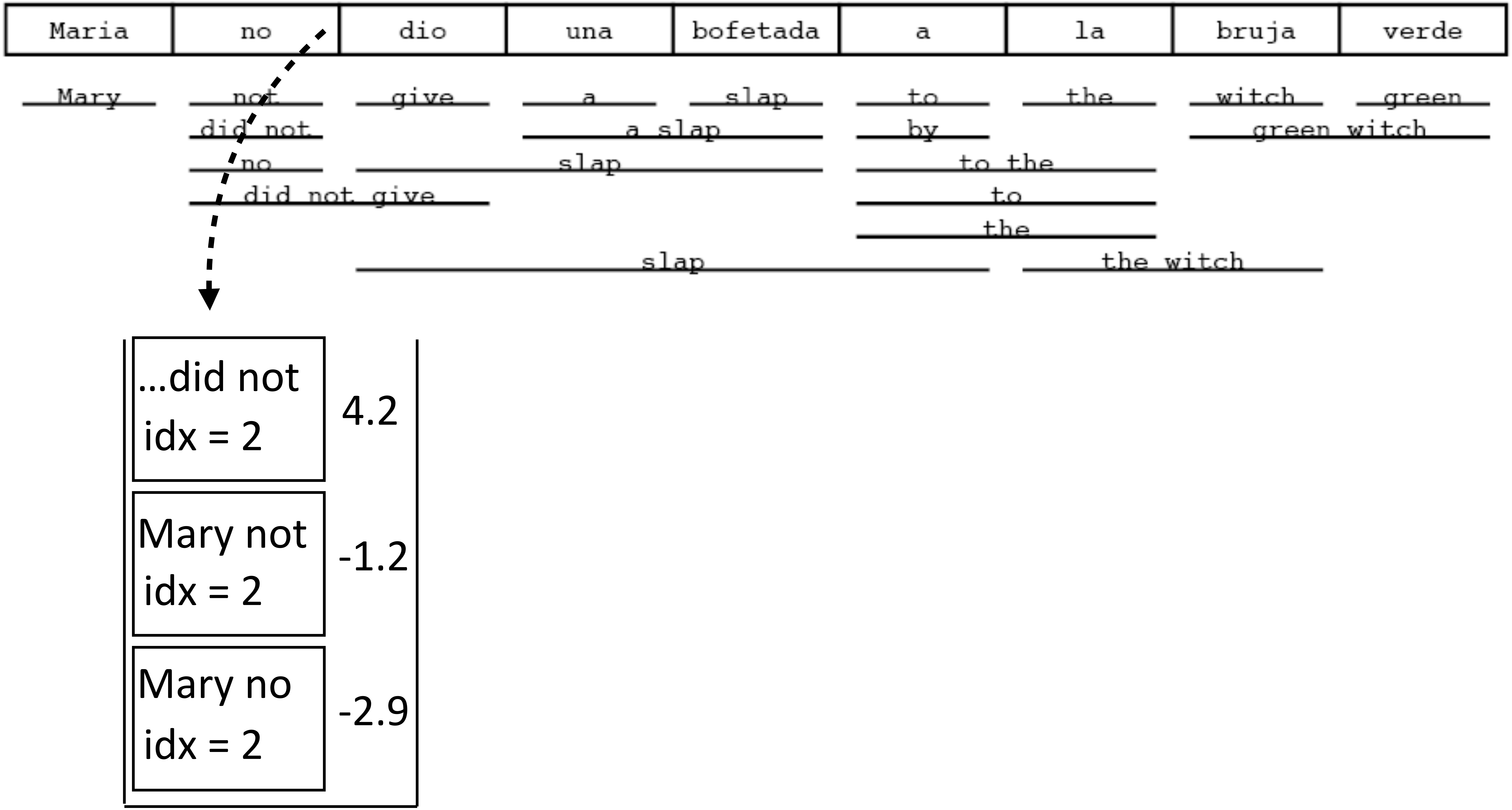

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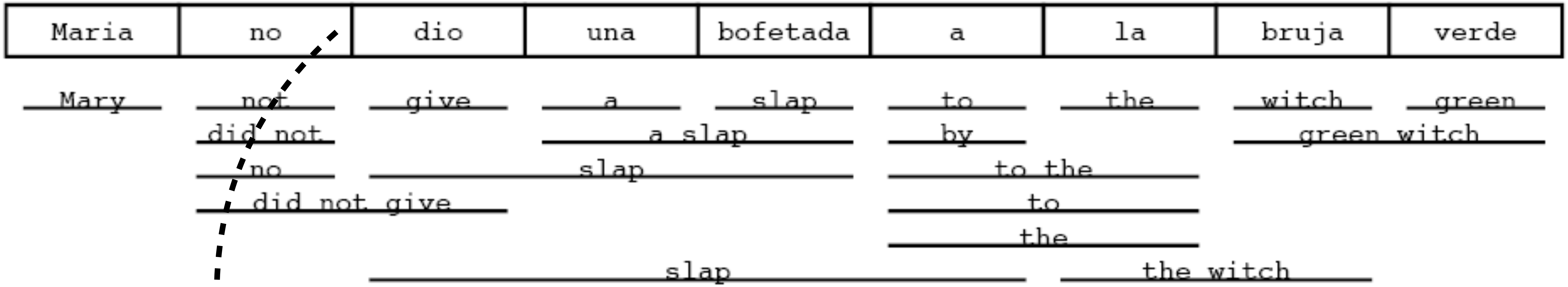

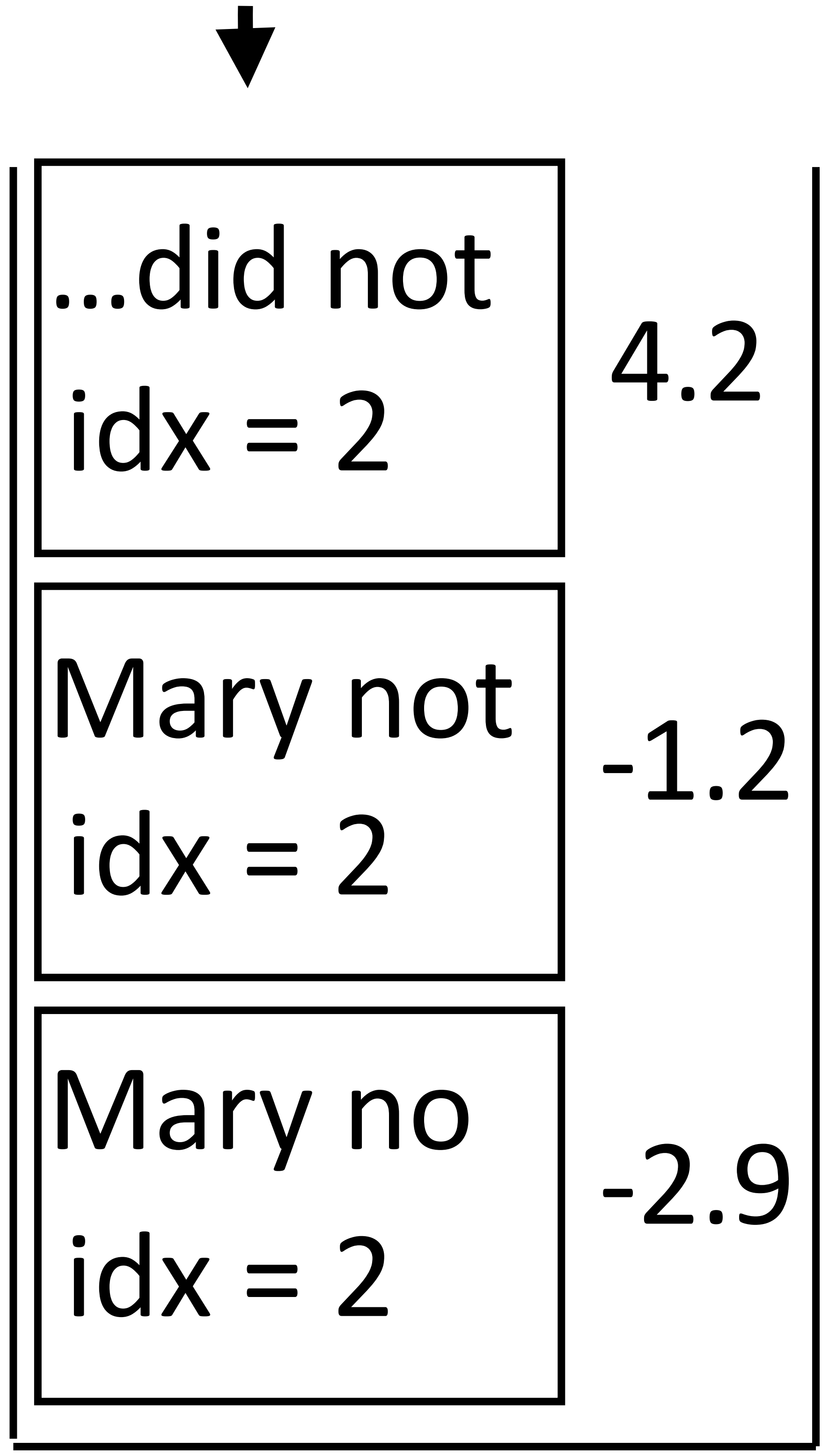

$$\text{score} = \log\,[\underbrace{P(\text{Mary})\,P(\text{not} \mid \text{Mary})}_{\text{LM}}\;\underbrace{P(\text{Mary} \mid \text{Maria})\,P(\text{not} \mid \text{no})}_{\text{TM}}]$$

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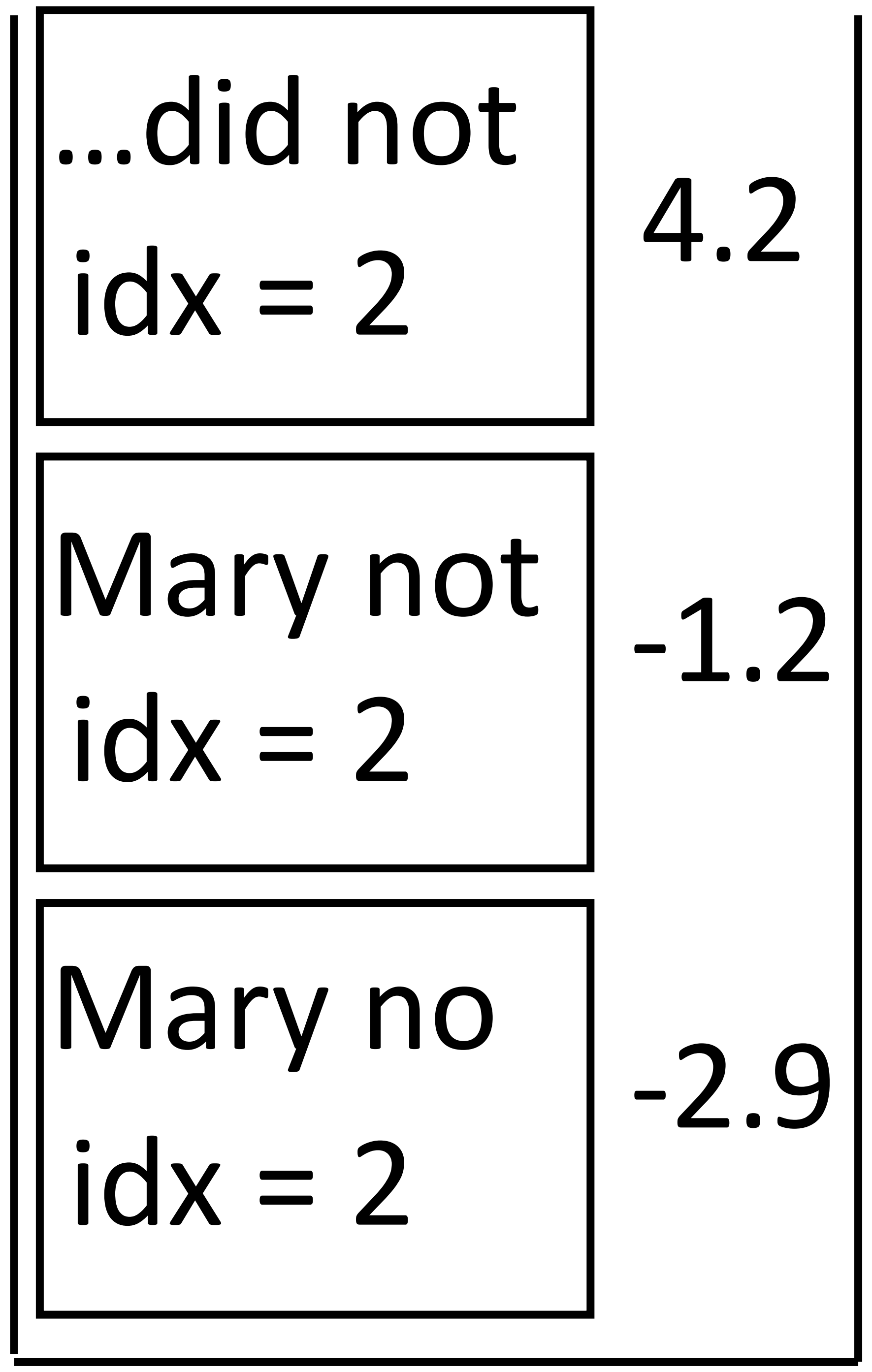

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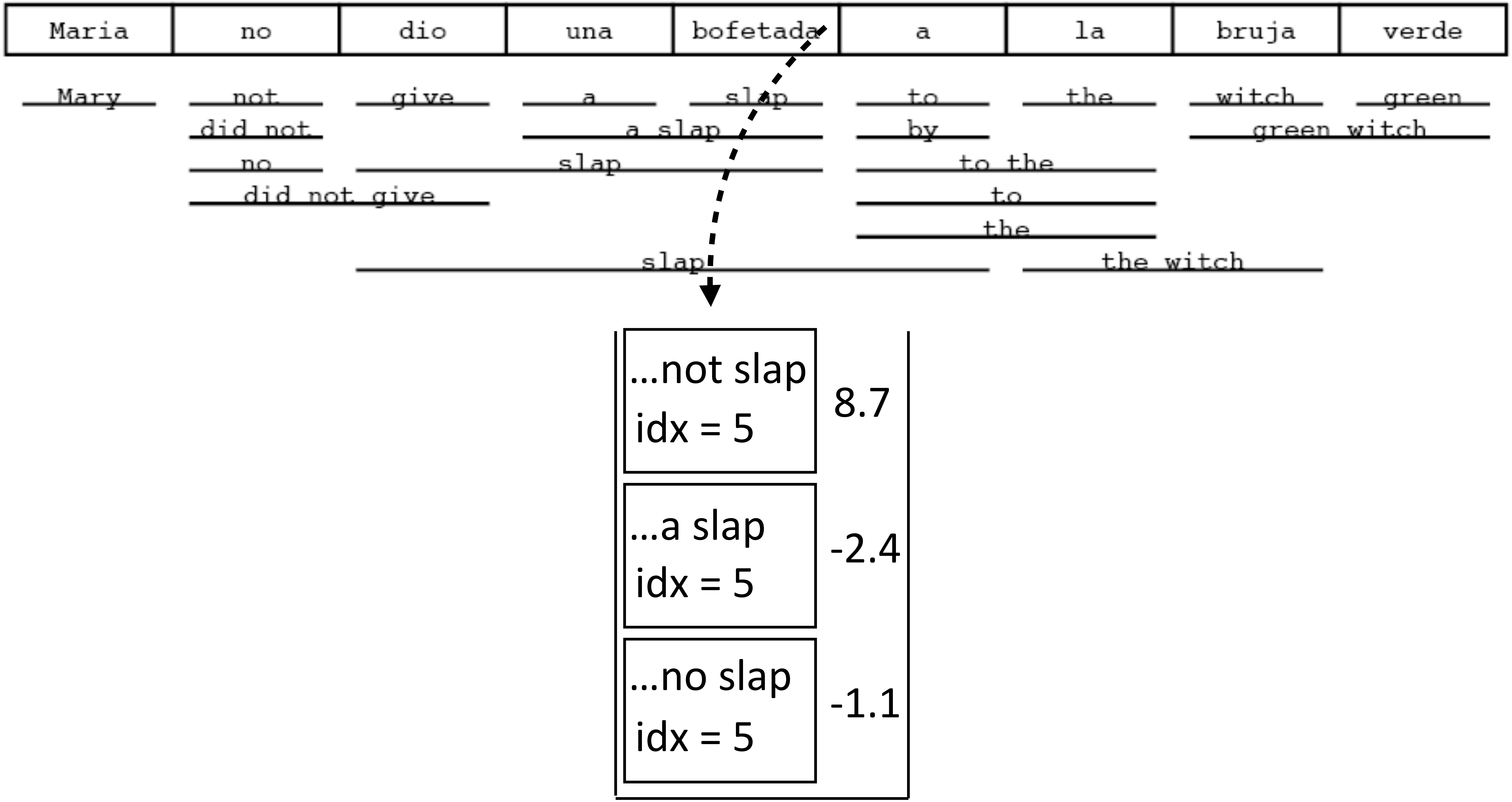
In reality: score = $\alpha \log P(LM) + \beta \log P(TM)$

...and TM is broken down into several features

Monotonic Translation



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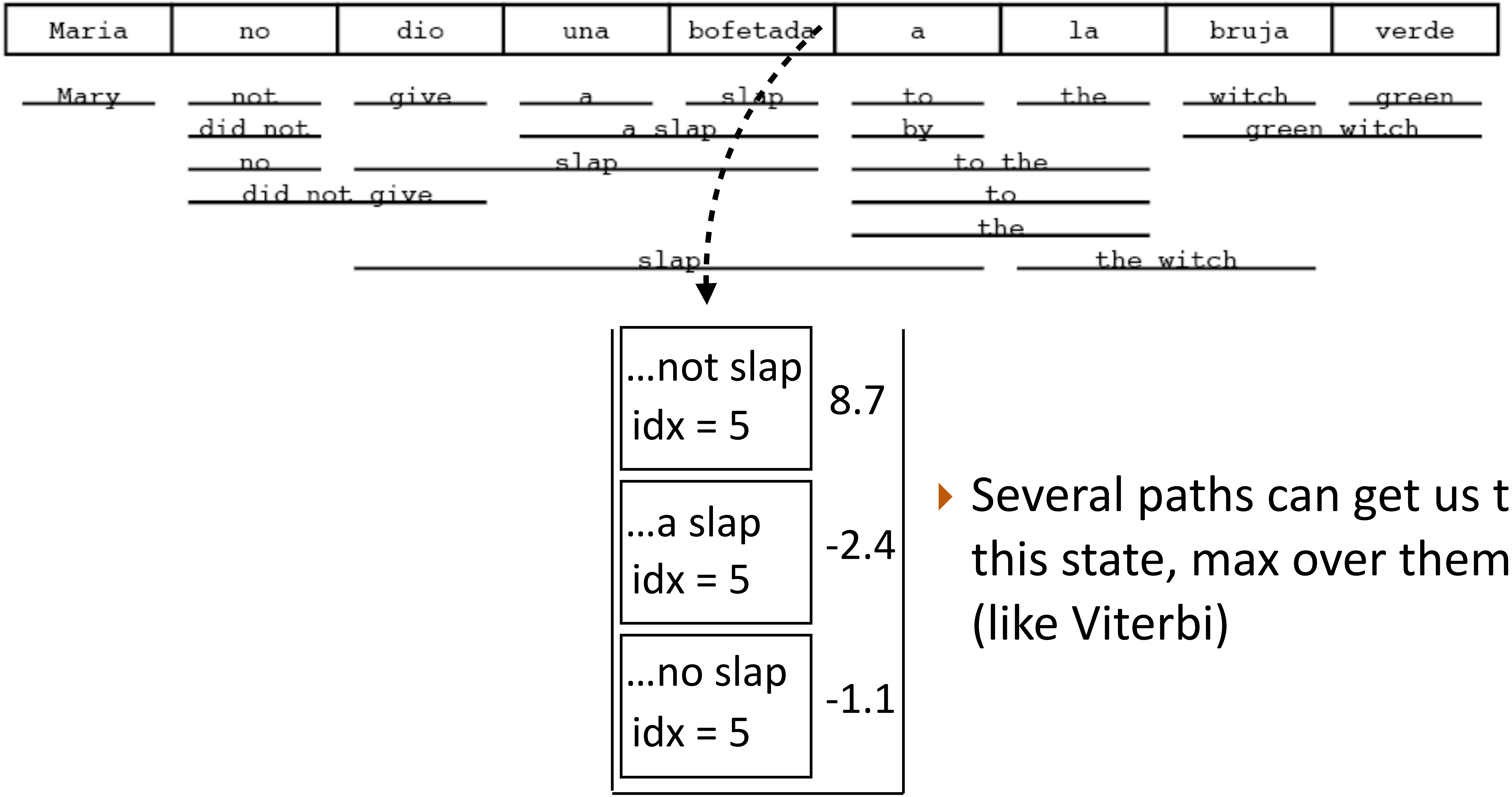

- Several paths can get us to this state, max over them (like Viterbi)

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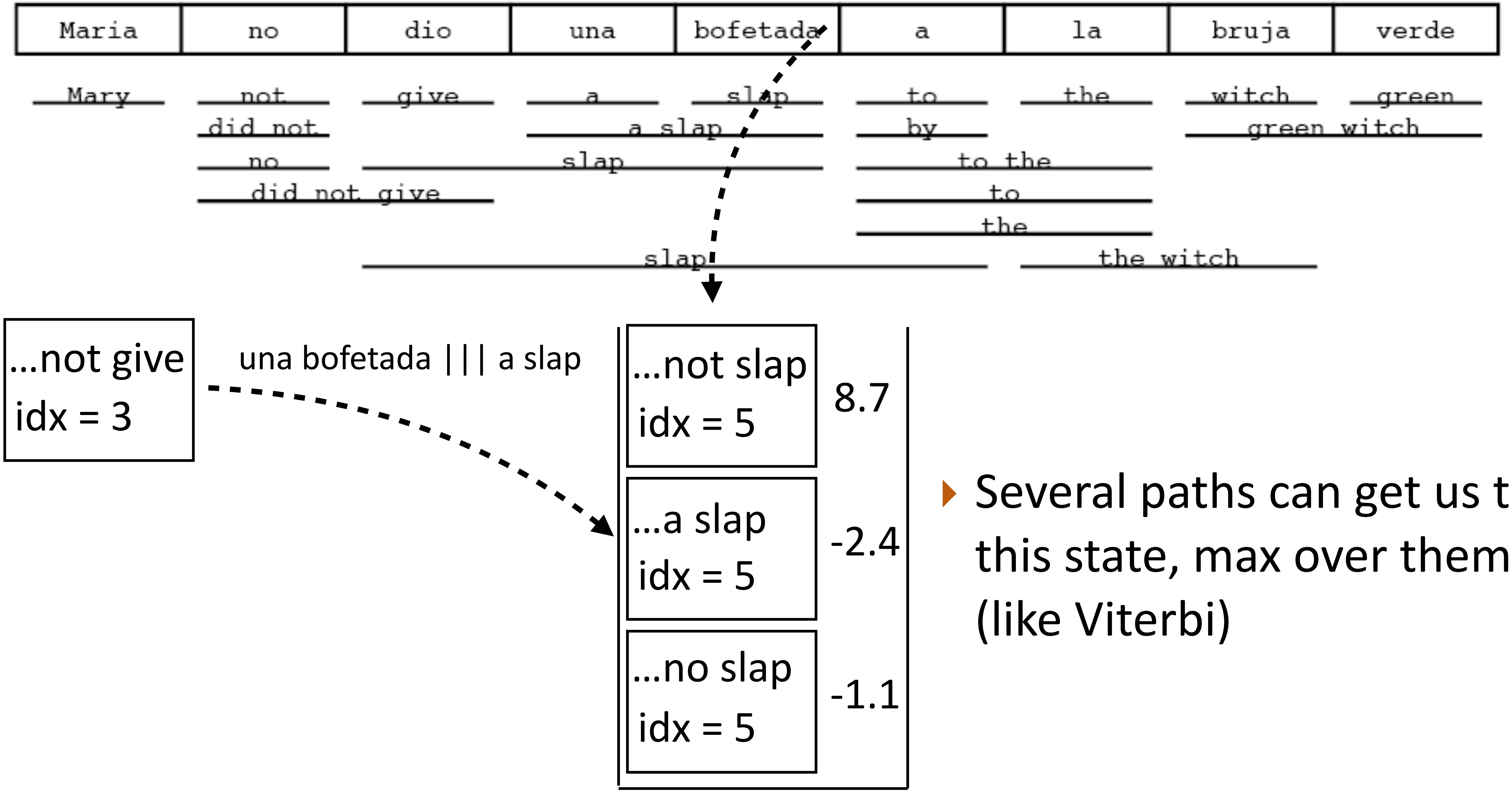

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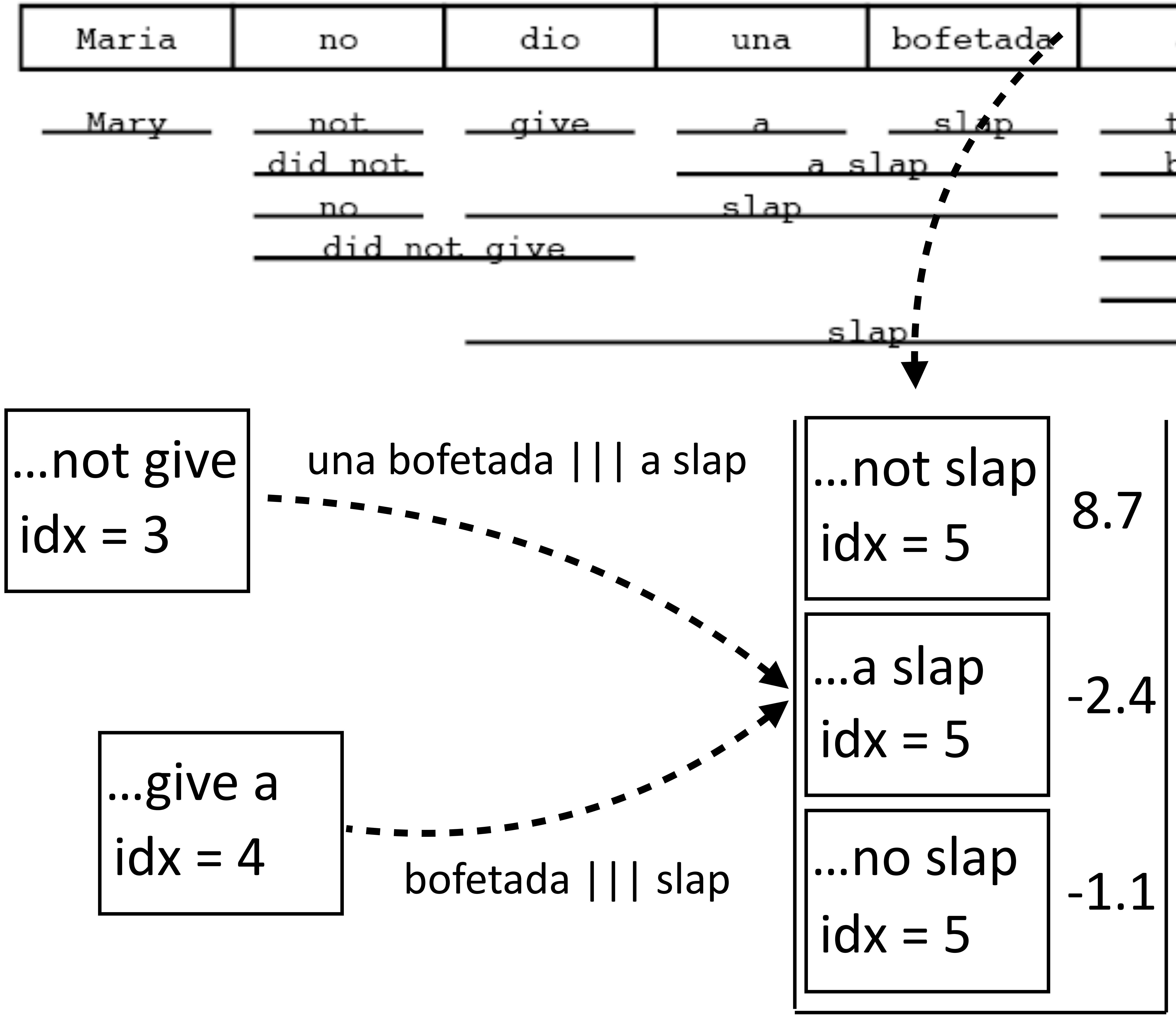

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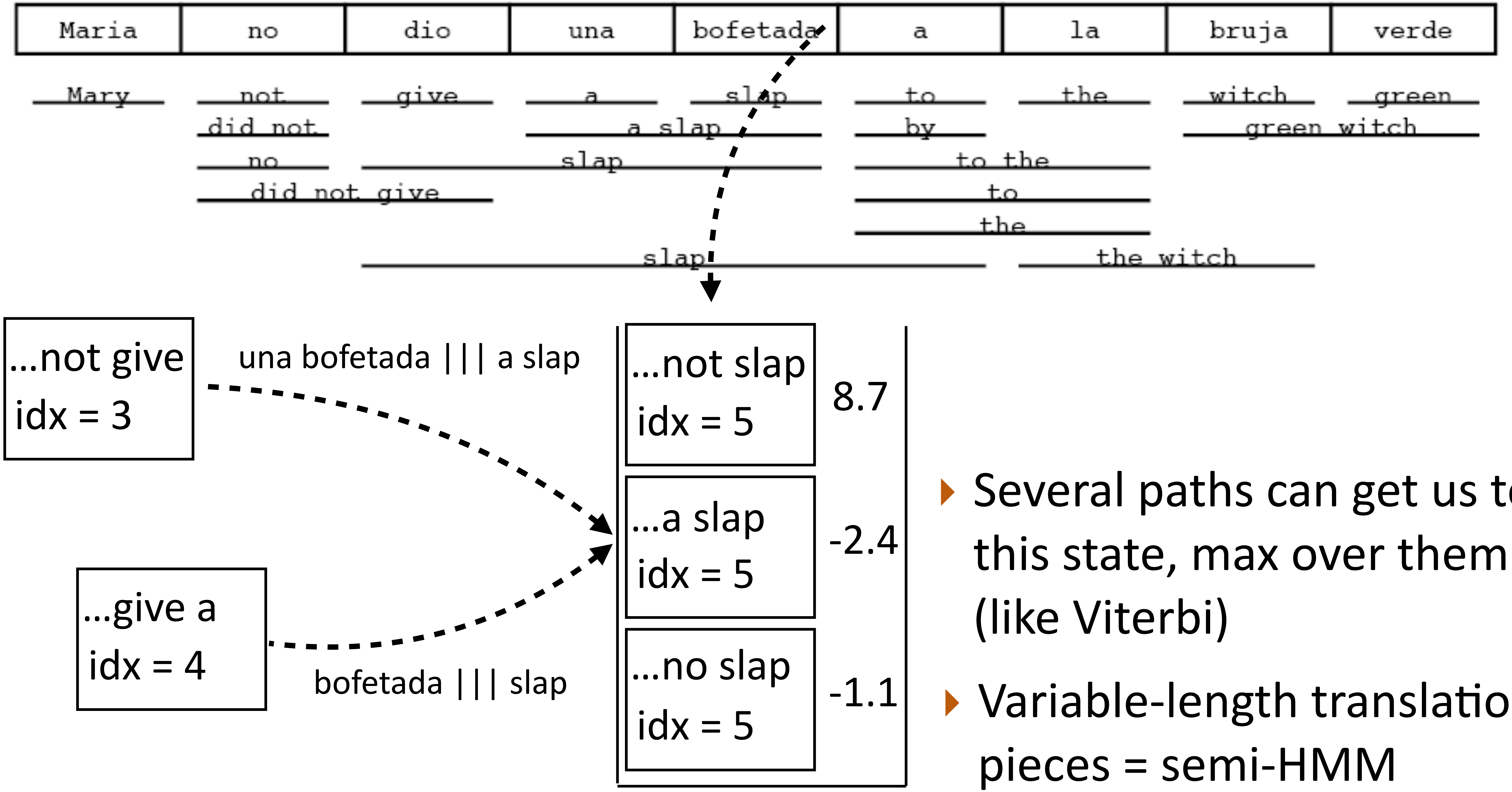

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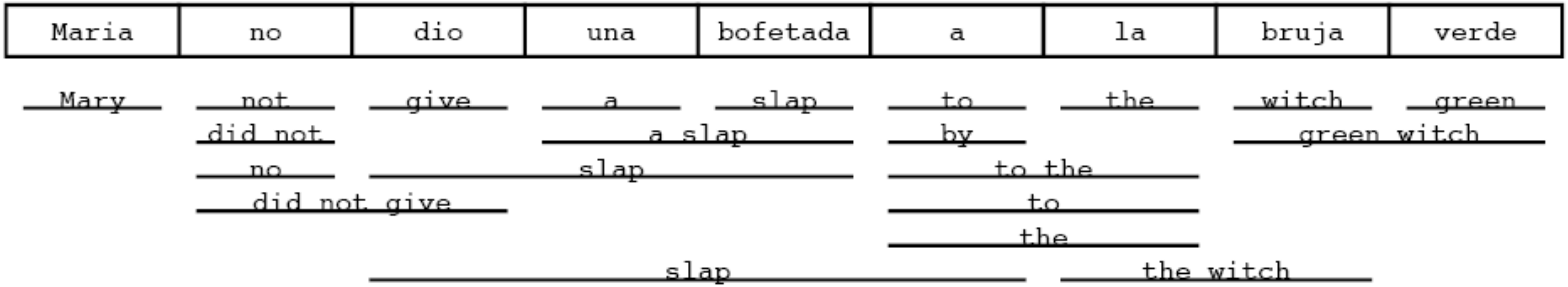
- Variable-length translation pieces = semi-HMM

Non-Monotonic Translation



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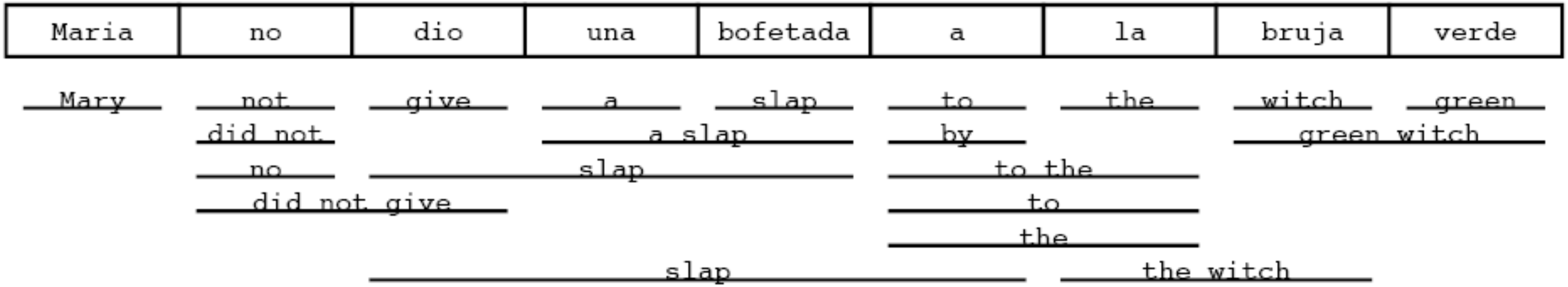

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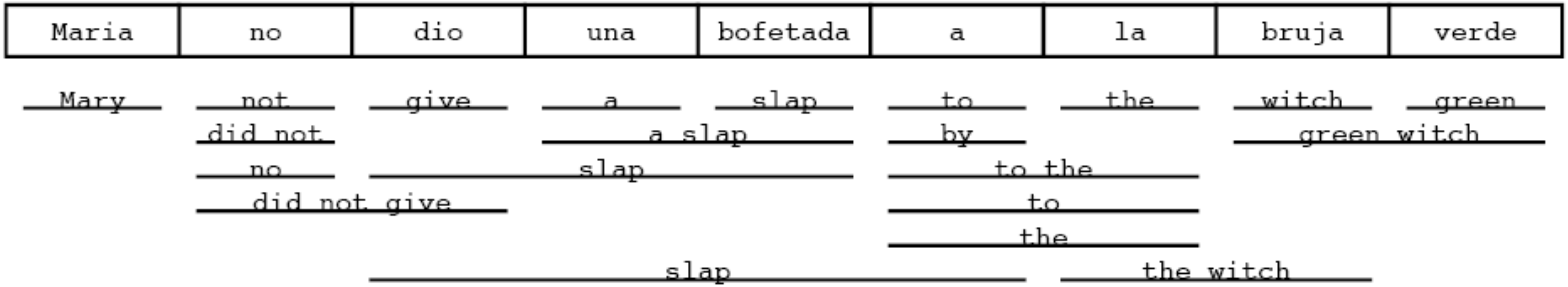

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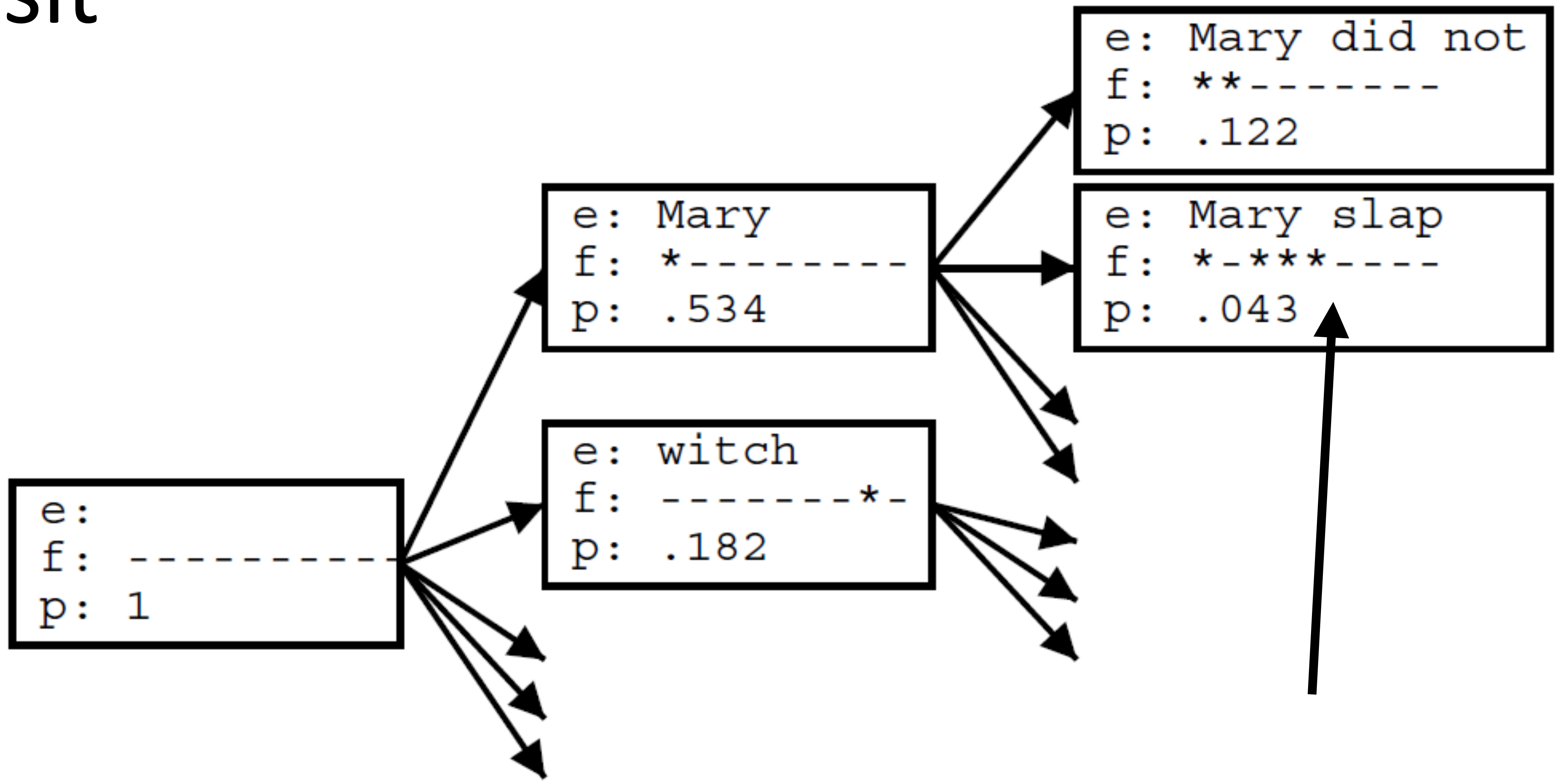

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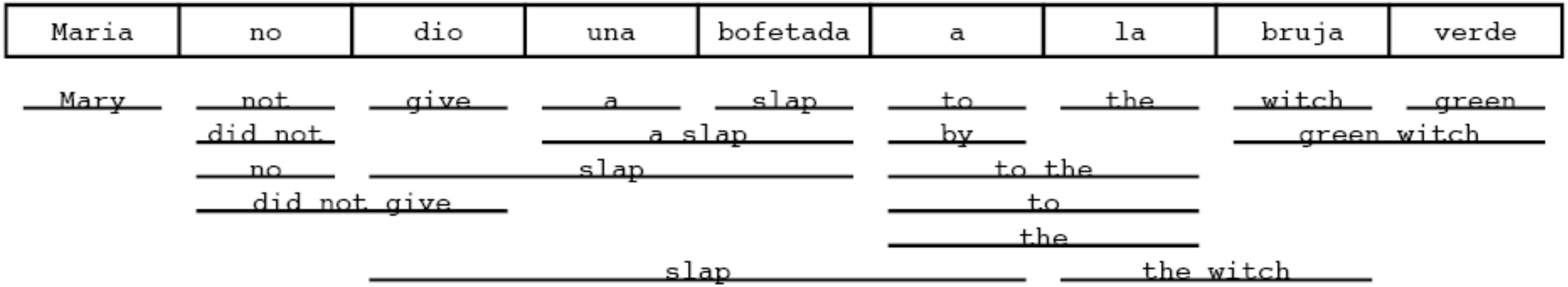

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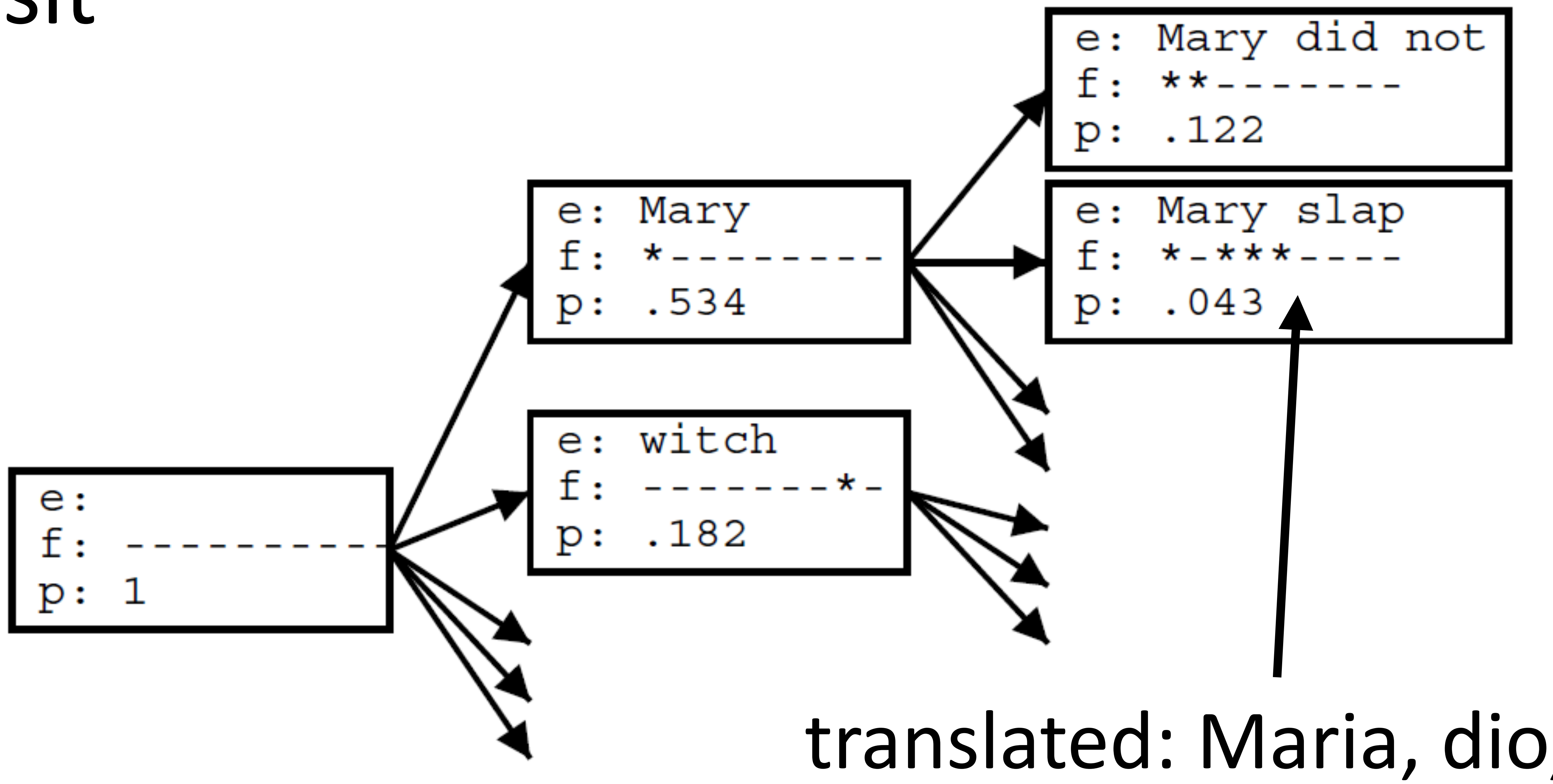
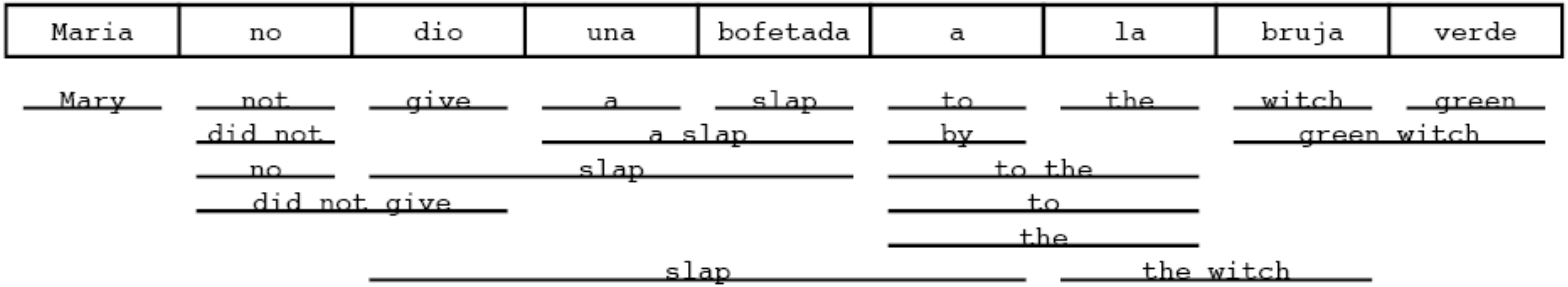
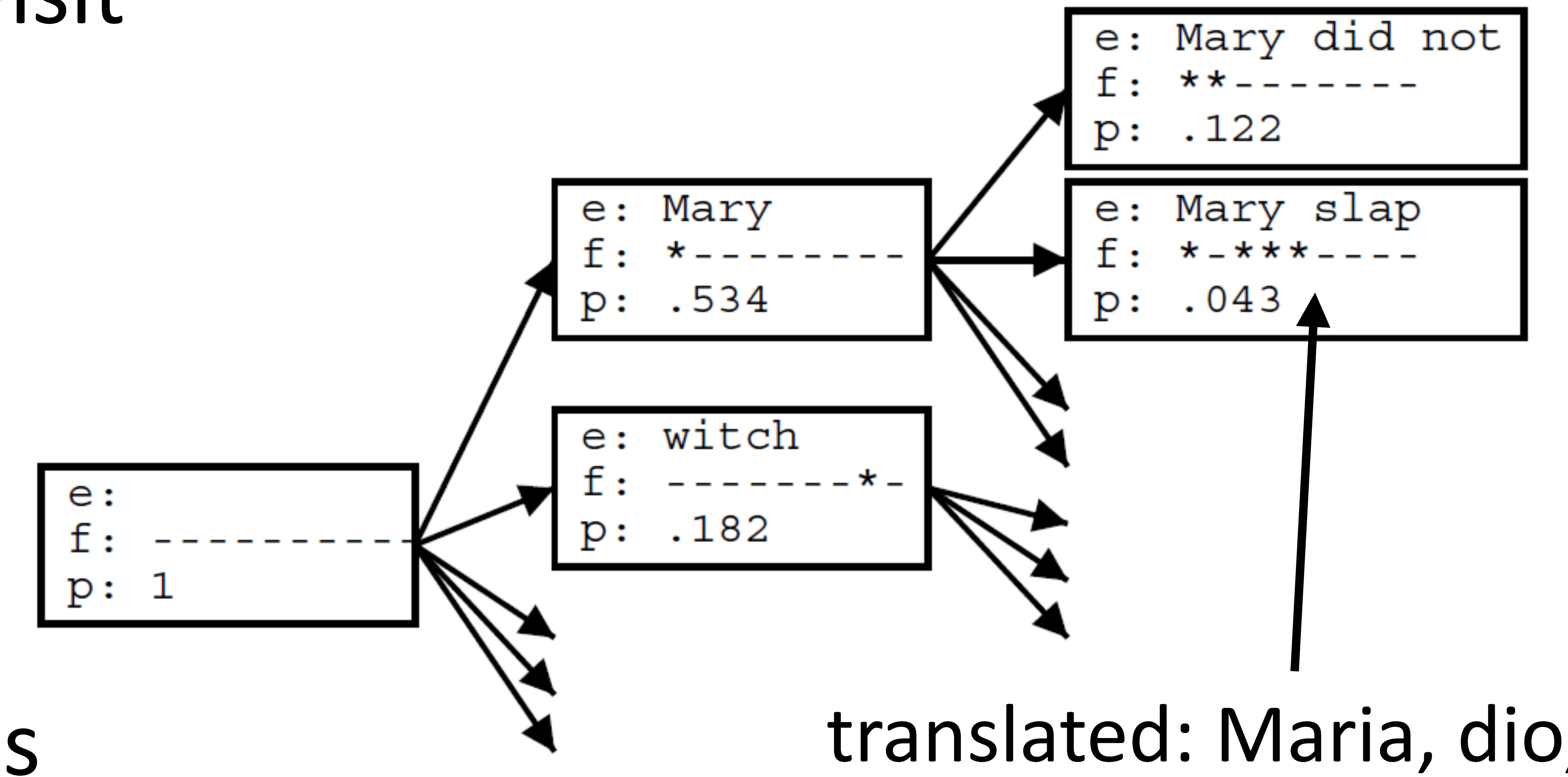


translated: Maria, dio, una, bofetada

Non-Monotonic Translation



- Non-monotonic translation: can visit source sentence "out of order"
- 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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Training Decoders

score = α log P(LM) + β log P(TM)

…and TM is broken down into several features

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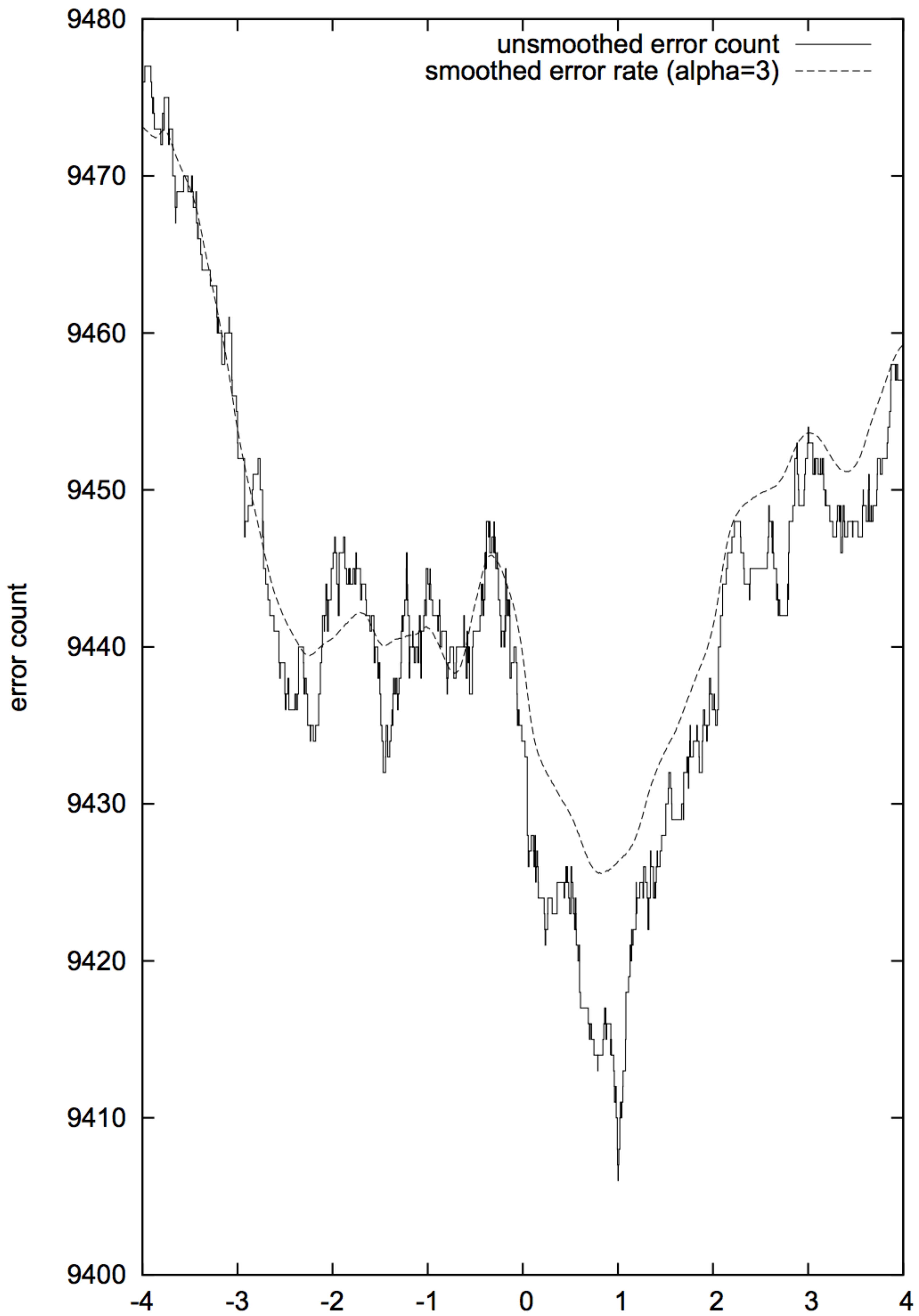

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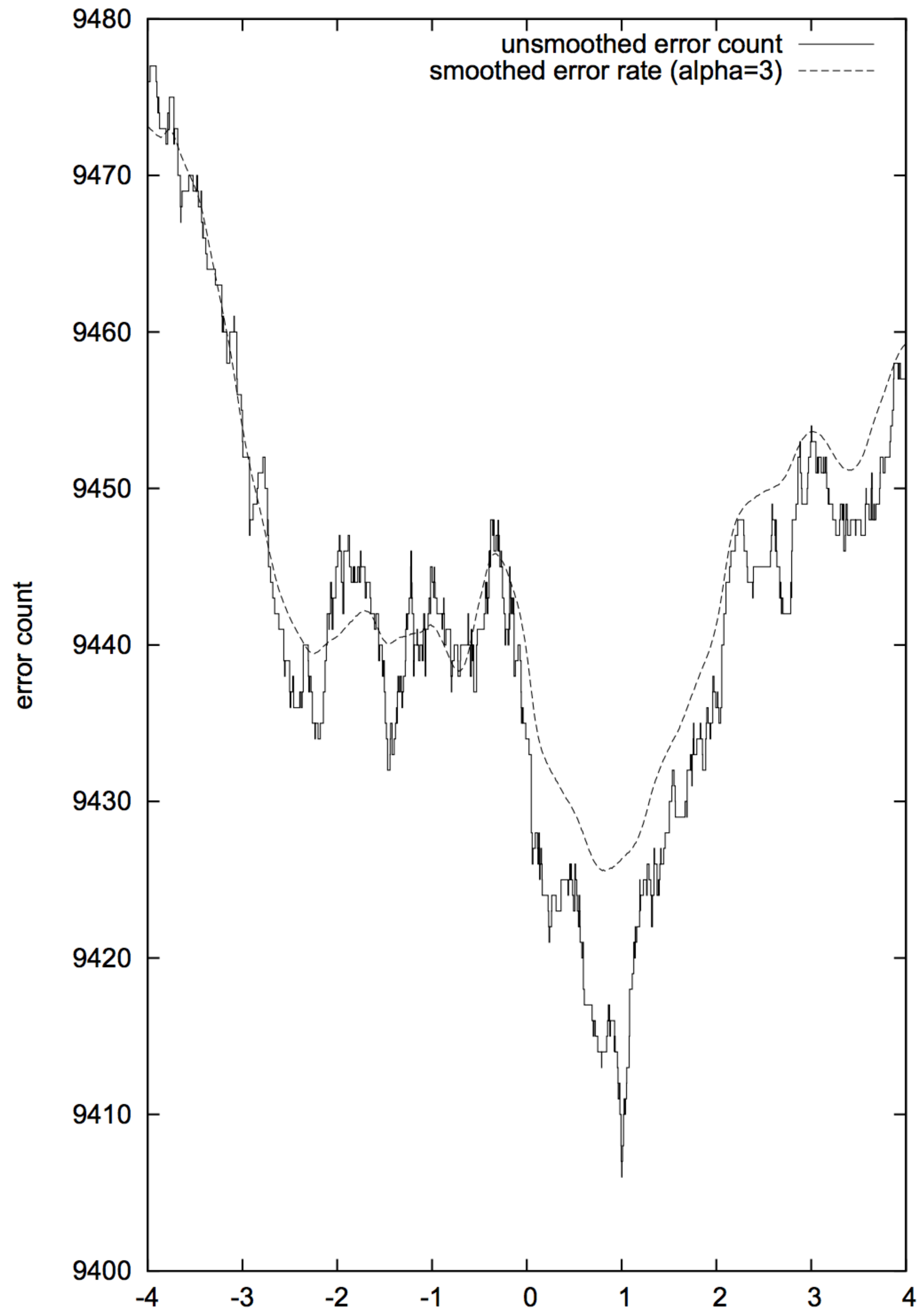
…and TM is broken down into several feature

- 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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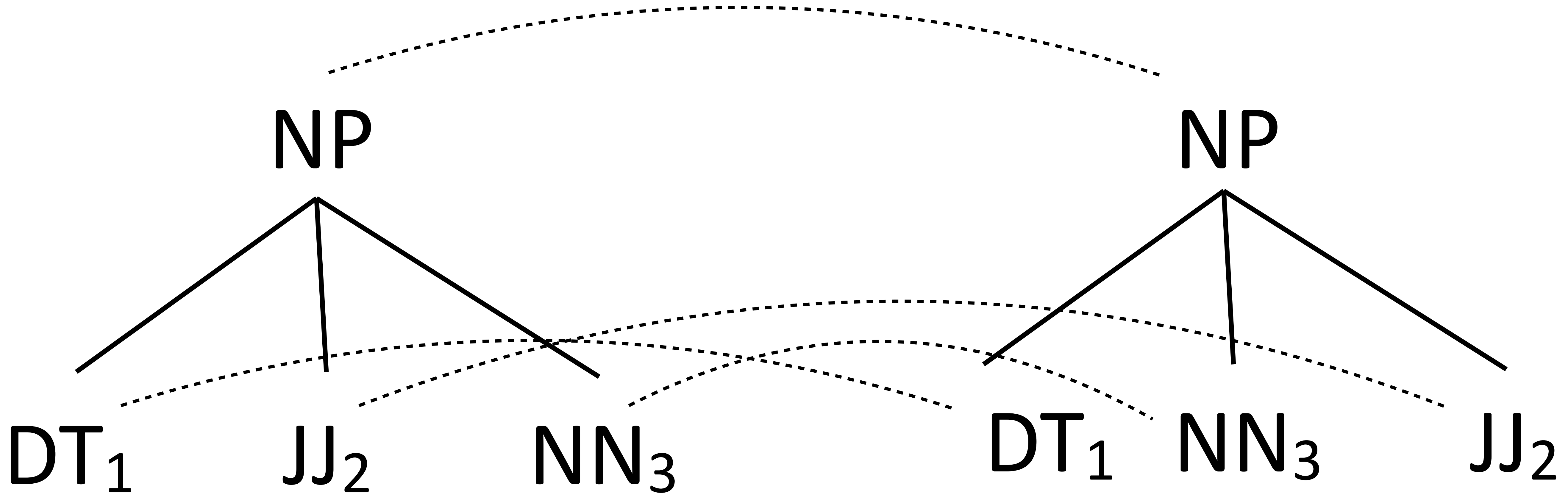

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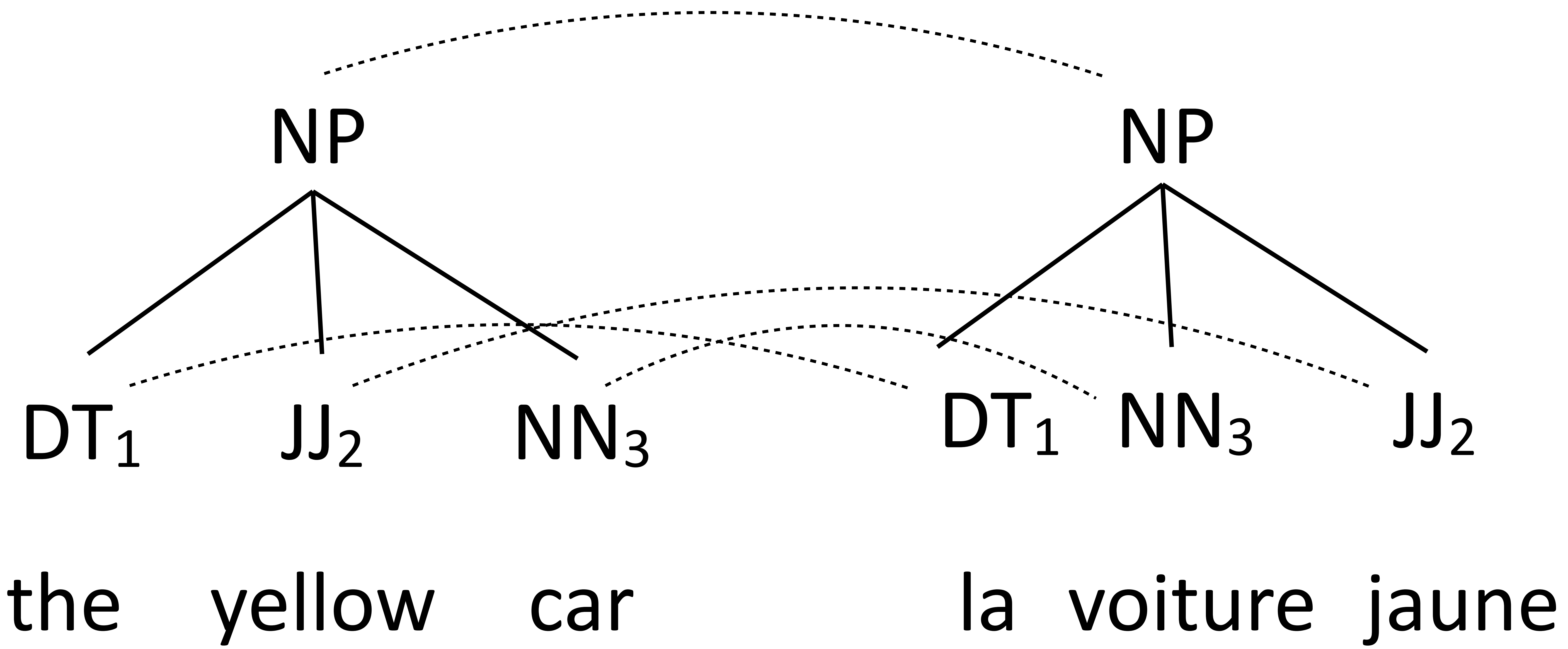

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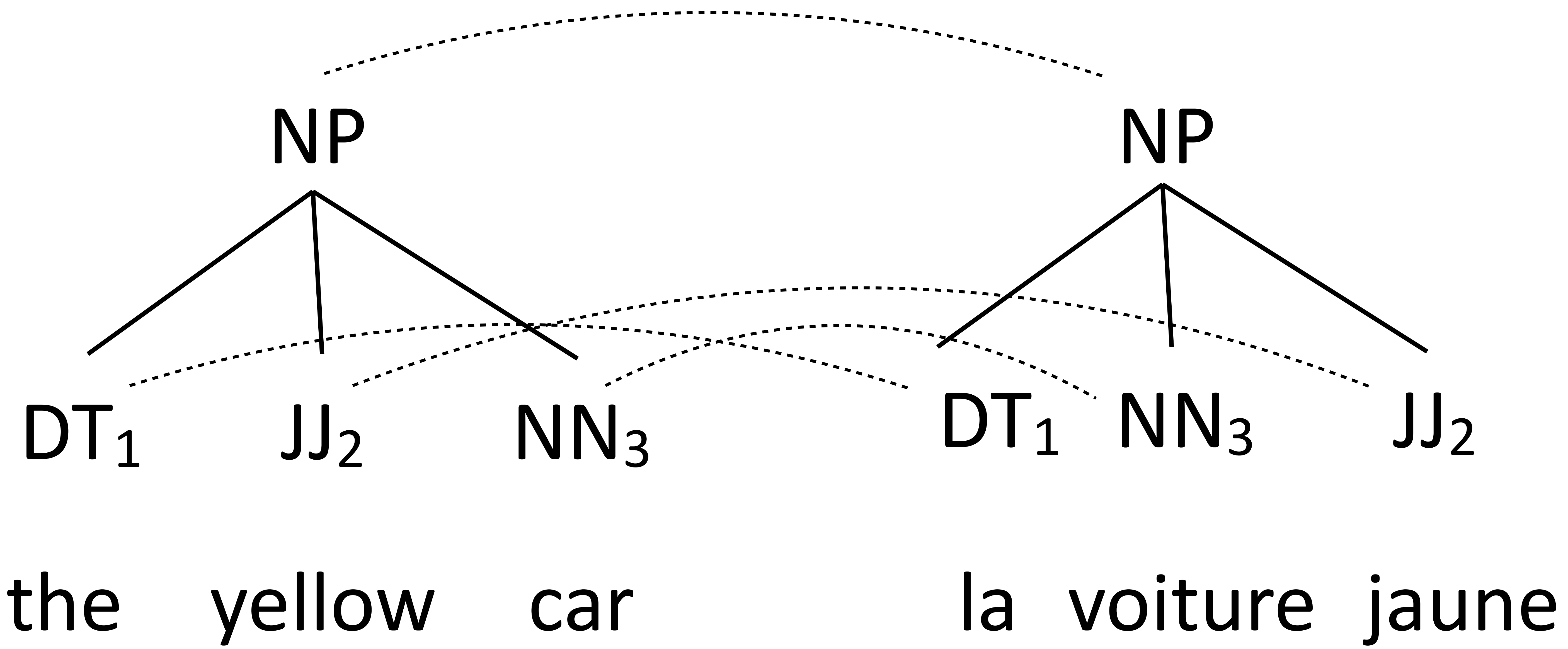

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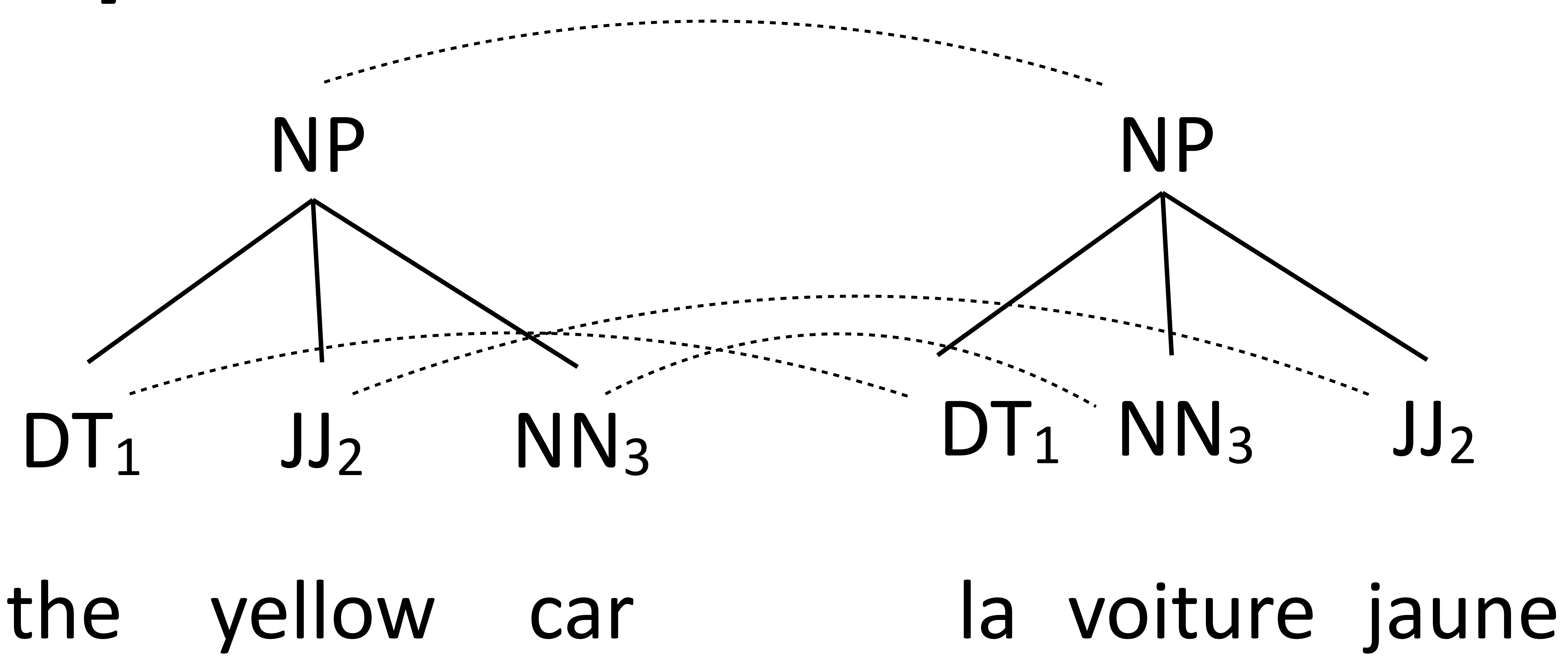

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- Assumes parallel syntax up to reordering

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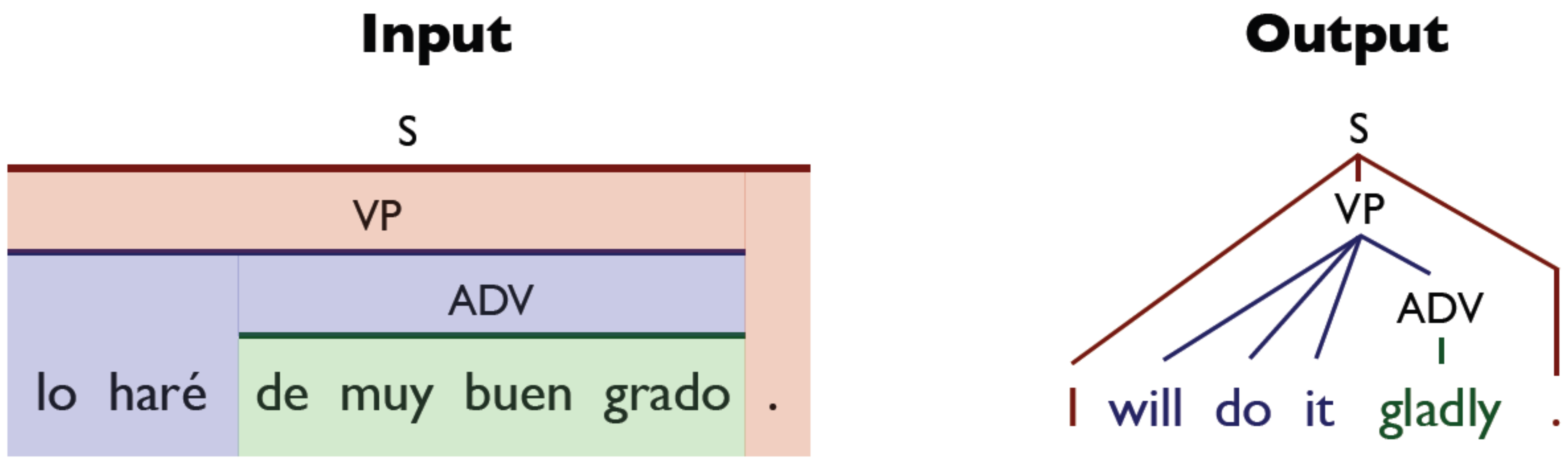

- Use lexicalized rules, look like “syntactic phrases”
- Leads to HUGE grammars, parsing is slow

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