

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

MT Basics



< 2/8

特朗普偕家人在白宫阳台观看百年一遇日全食

>

People's Daily, August 30, 2017

MT Basics



A photograph of a woman with blonde hair, wearing a black sleeveless dress and 3D glasses, looking upwards. She is standing next to a man in a dark suit. The background is a light-colored wall.

Translate

English French Spanish Chinese - detected ▾

特朗普偕家人在白宫阳台观看百年一遇日全食

2/8 特朗普偕家人在白宫阳台观看百年一遇日全食

People's Daily, August 30, 2017

MT Basics



A photograph of Melania Trump wearing 3D glasses, looking up at a solar eclipse. She is wearing a black sleeveless dress. A man in a suit is partially visible behind her.

Translate

English French Spanish Chinese - detected ▾

特朗普偕家人在白宫阳台观看百年一遇日全食

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

MT Basics



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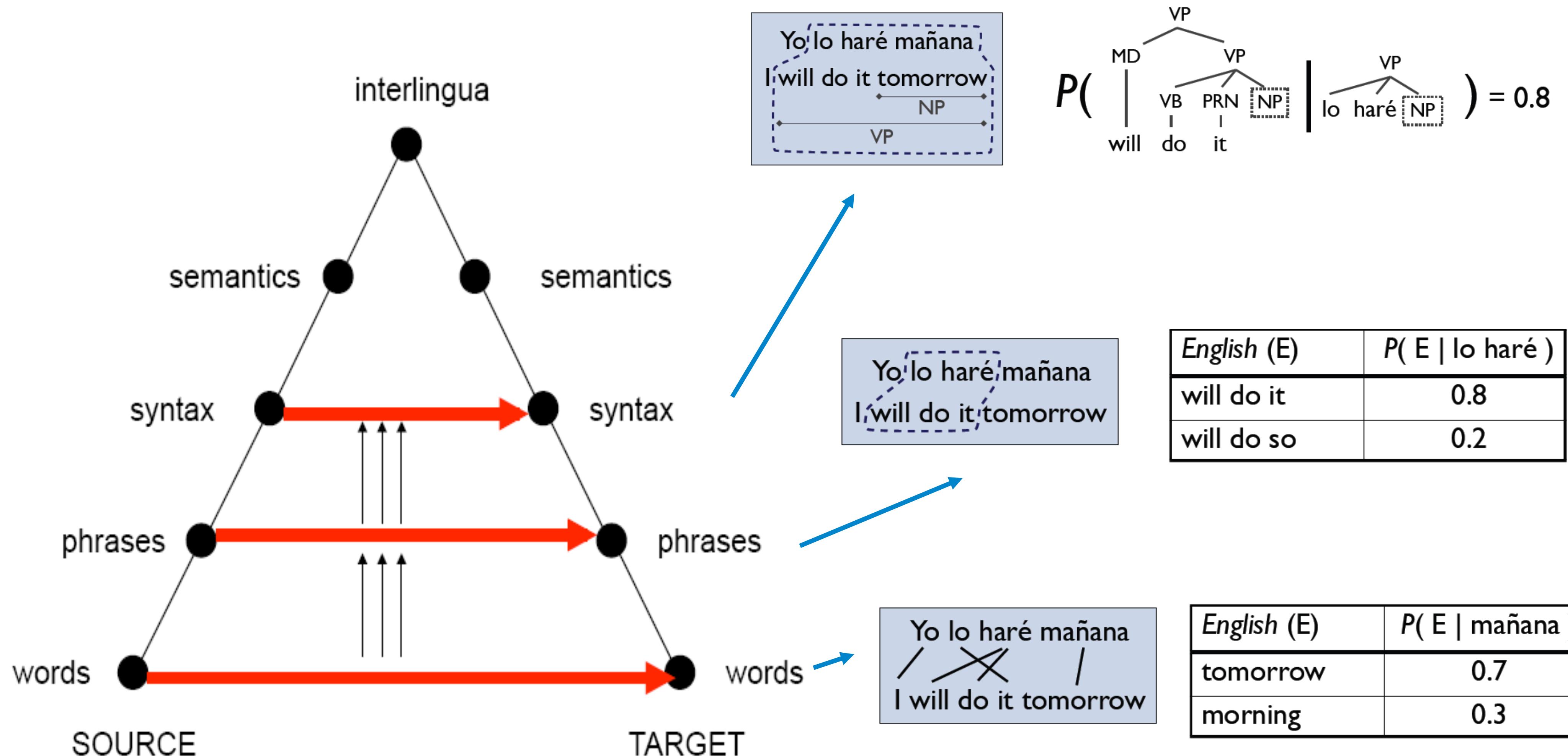
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 $\forall x \exists y \text{ friend}(x, y)$
 - ▶ Can often get away without doing all disambiguation — same ambiguities may exist in both languages

Levels of Transfer: Vauquois Triangle



- Today: mostly phrase-based, some syntax

Slide credit: Dan Klein

Phrase-Based MT

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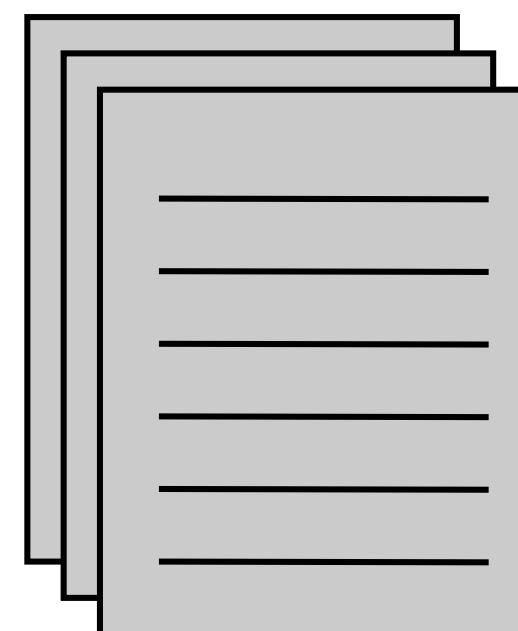
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 - ▶ Decoder takes phrases and a language model and searches over possible translations
- ▶ NOT like standard discriminative models (take a bunch of translation pairs, learn a ton of parameters in an end-to-end way)

Phrase-Based MT

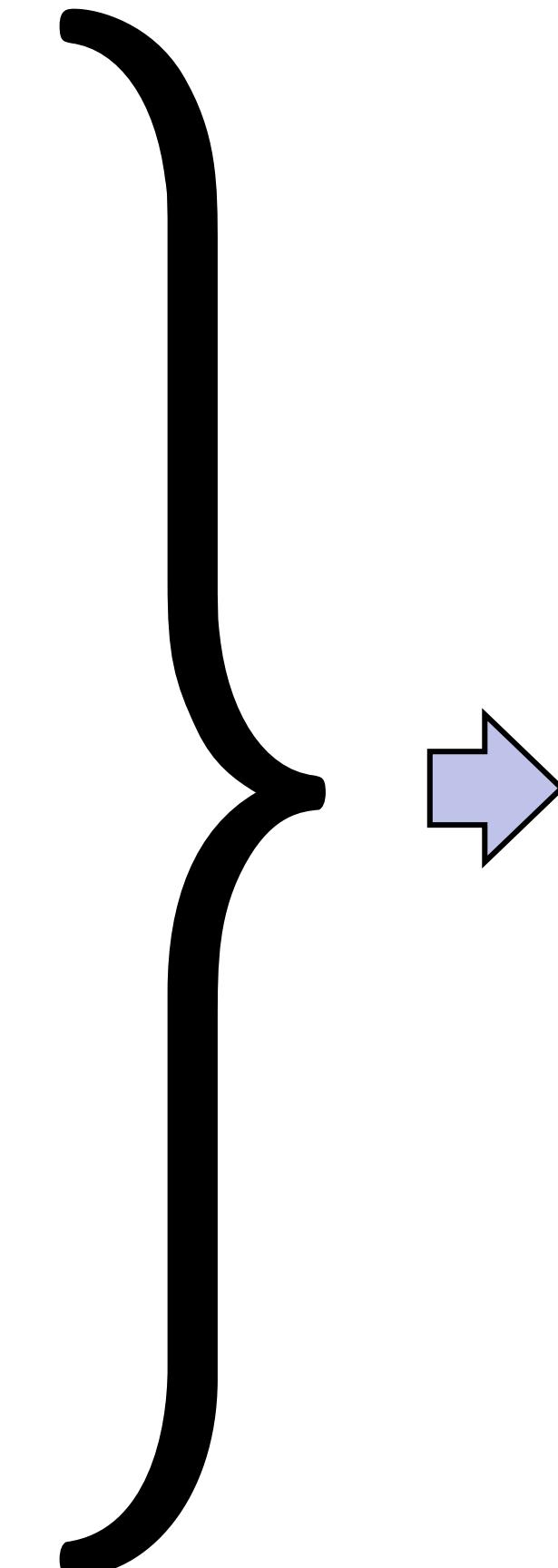
```
cat ||| chat ||| 0.9  
the cat ||| le chat ||| 0.8  
dog ||| chien ||| 0.8  
house ||| maison ||| 0.6  
my house ||| ma maison ||| 0.9  
language ||| langue ||| 0.9  
...
```

Phrase table $P(f|e)$



Unlabeled English data

Language model $P(e)$



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

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 ==		
	hypothesis 2	Tired is I -		
	hypothesis 3	I I I -		
	reference 1	I am tired ==		
	reference 2	I am ready to sleep now and so exhausted ==		

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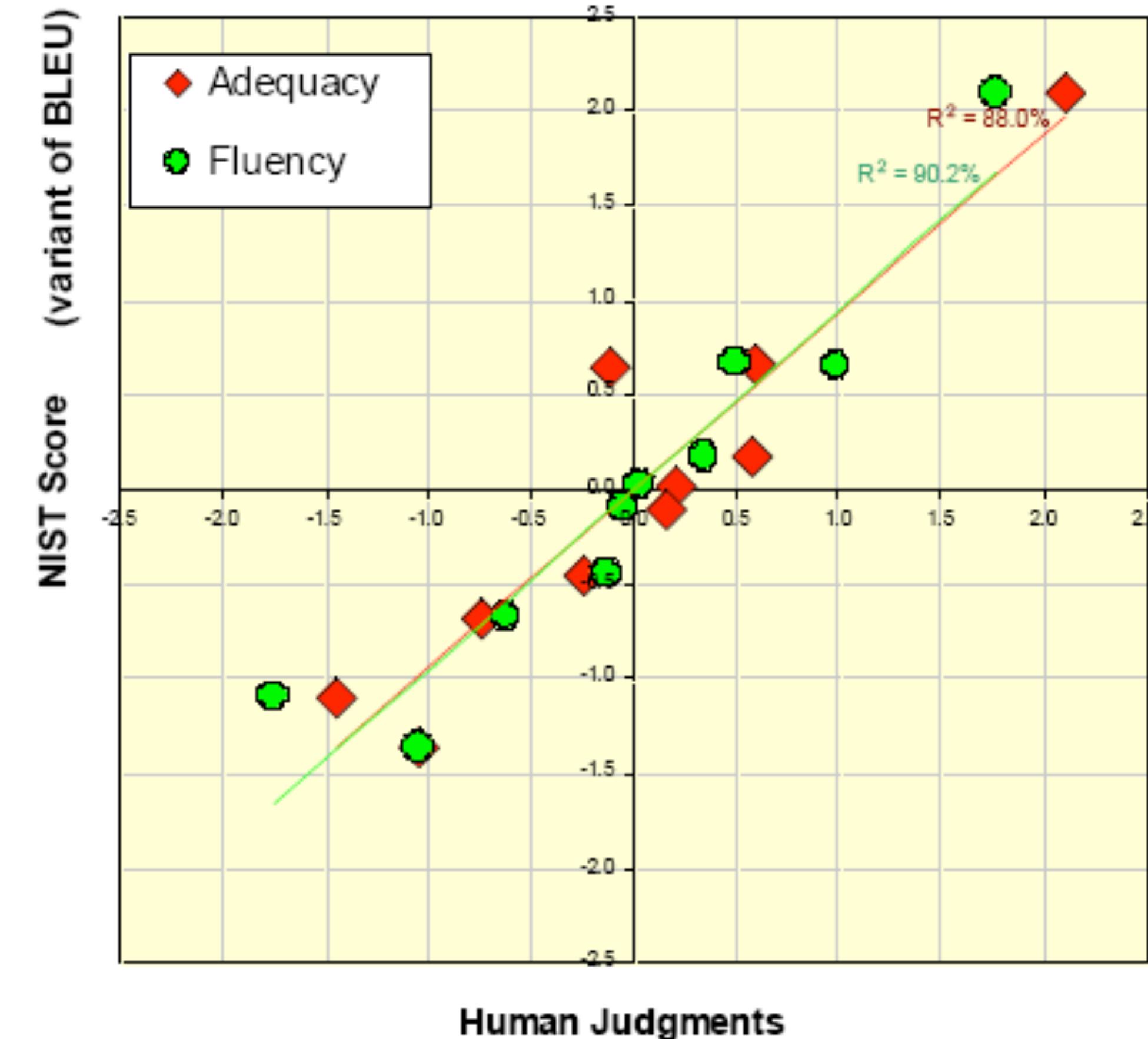
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- ▶ Does this capture fluency and adequacy?

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



Word Alignment

Word Alignment

- ▶ Input: a bitext, pairs of translated sentences

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

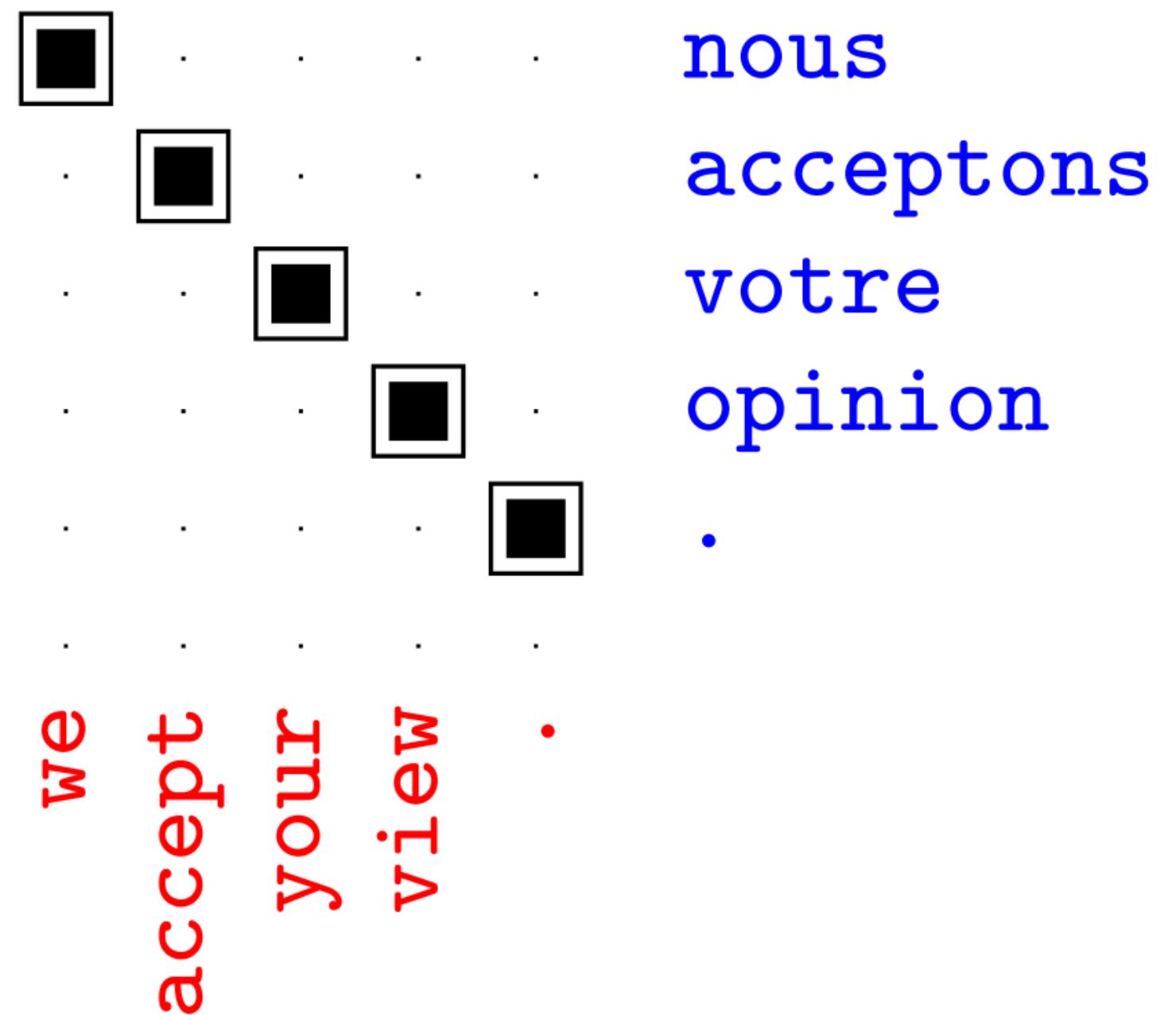
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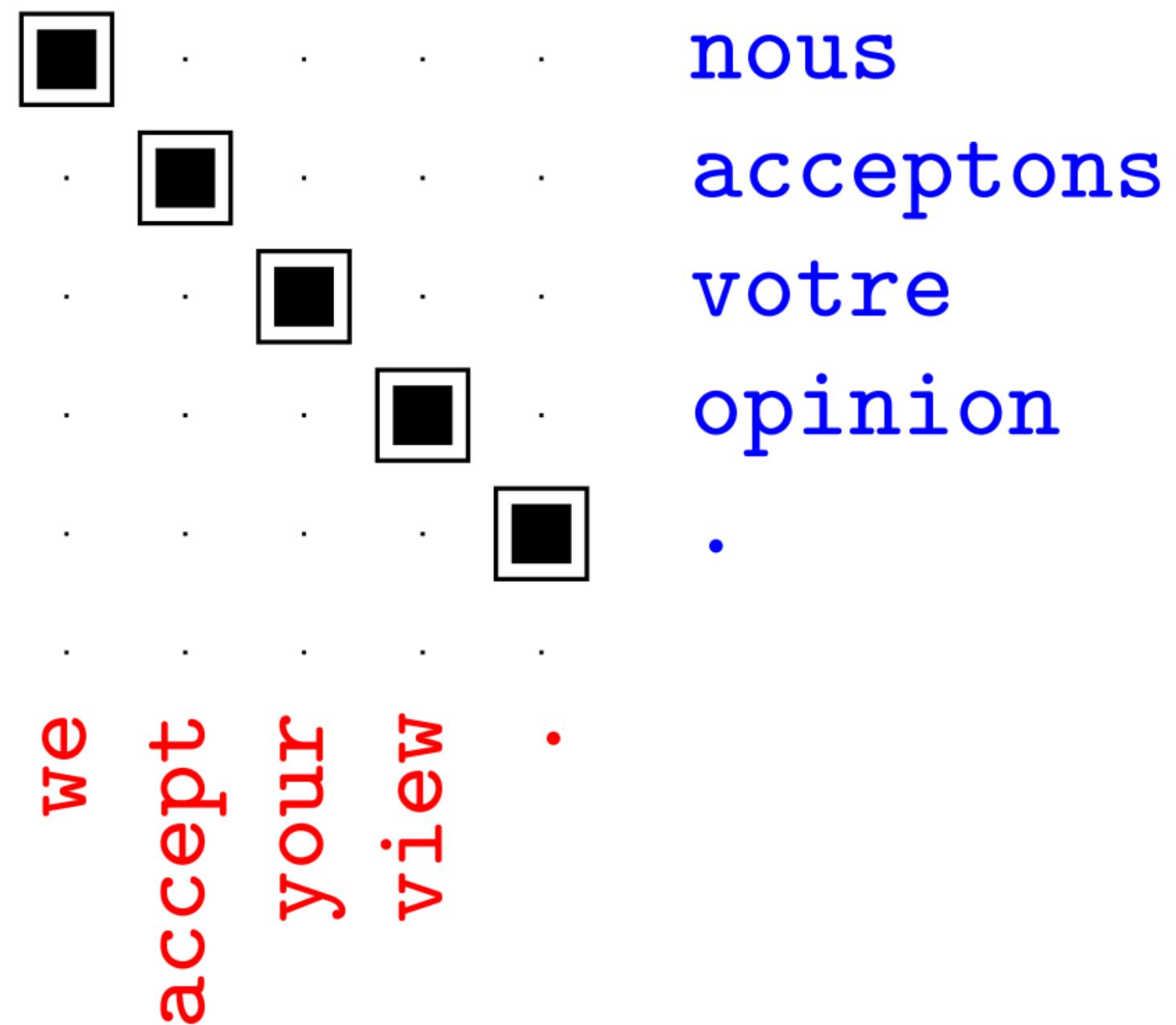
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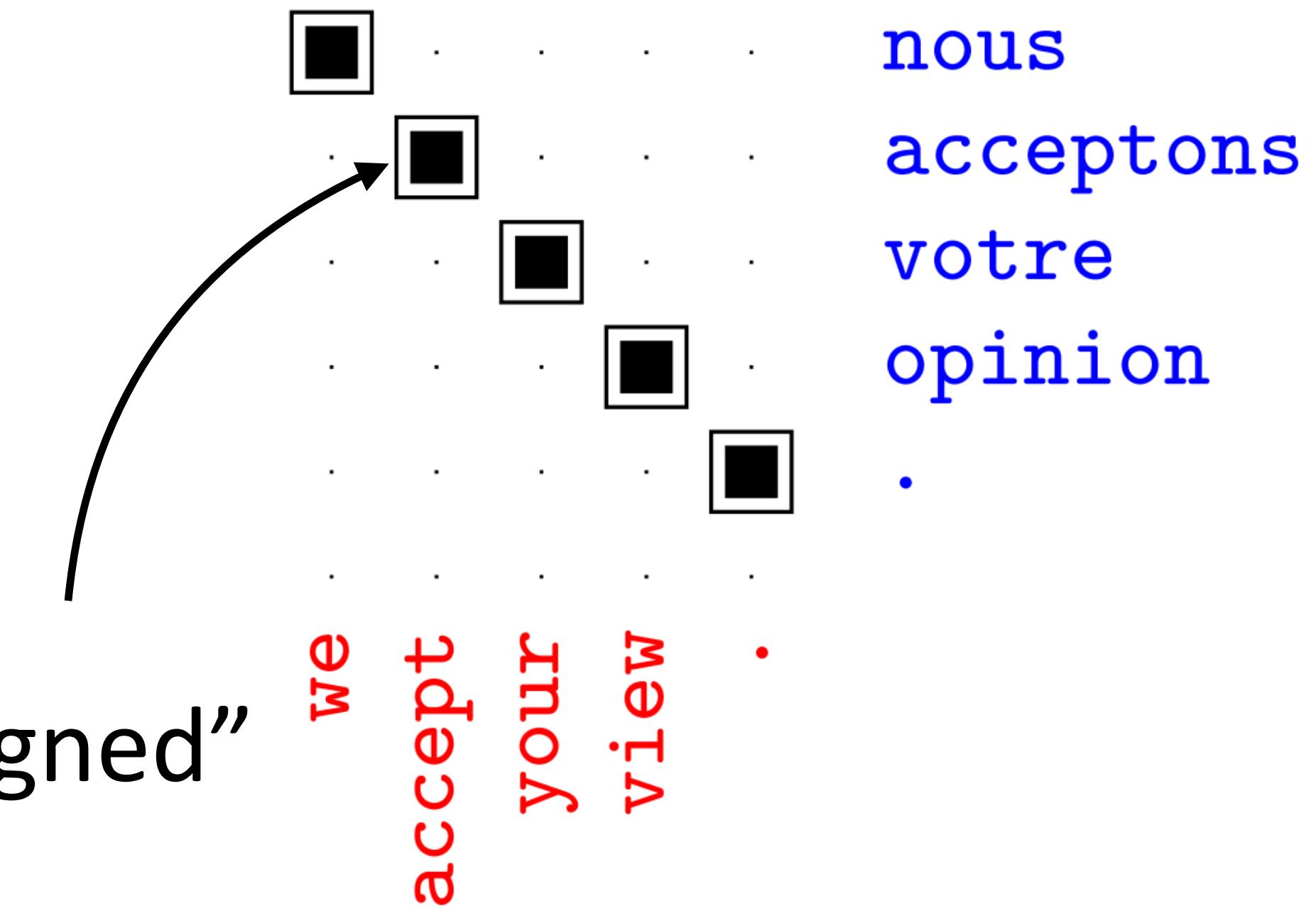
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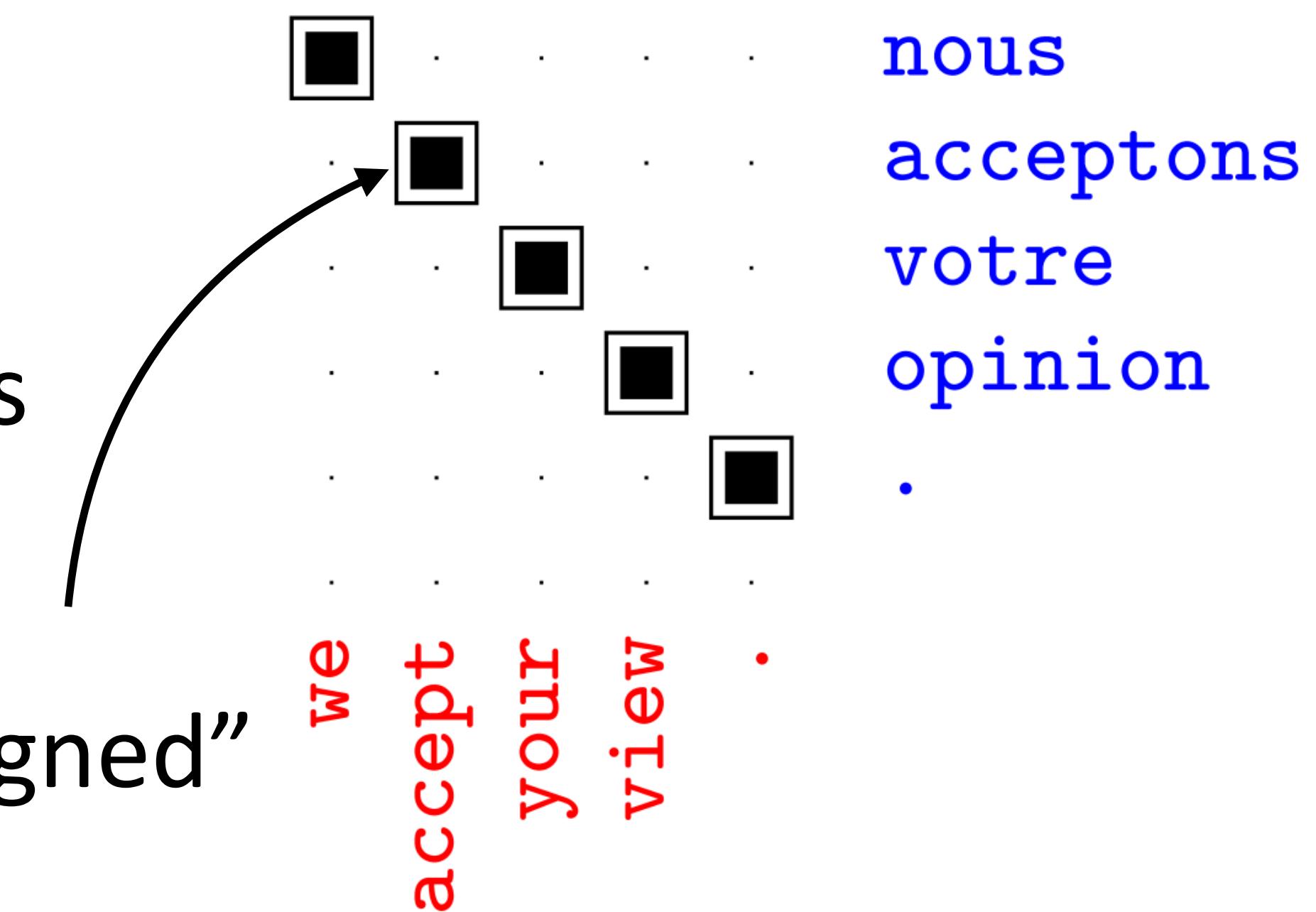
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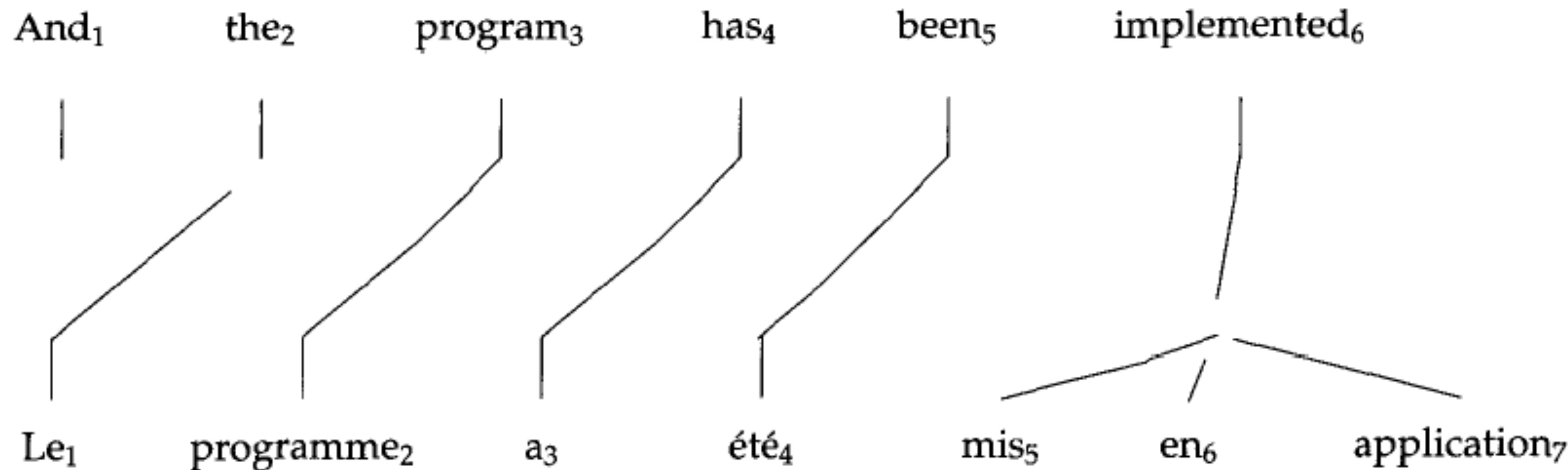
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- ▶ We will see how to turn these into phrases

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1-to-Many Alignments



Word Alignment

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- ▶ Latent variable model:
$$P(f|e) = \sum_a P(f, a|e) = \sum_a P(f|a, e)P(a)$$
- ▶ 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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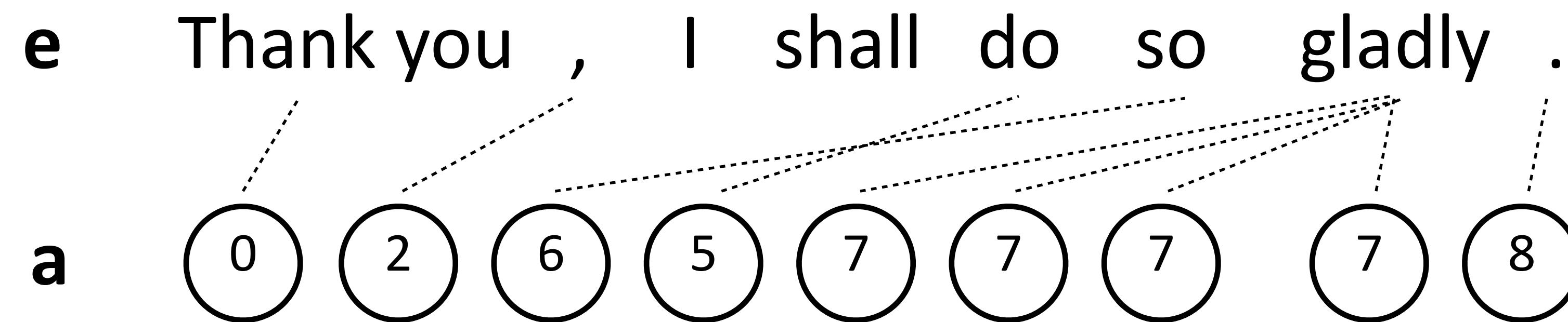
$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \prod_{i=1}^n P(f_i|e_{a_i})P(a_i)$$

e Thank you , I shall do so gladly .

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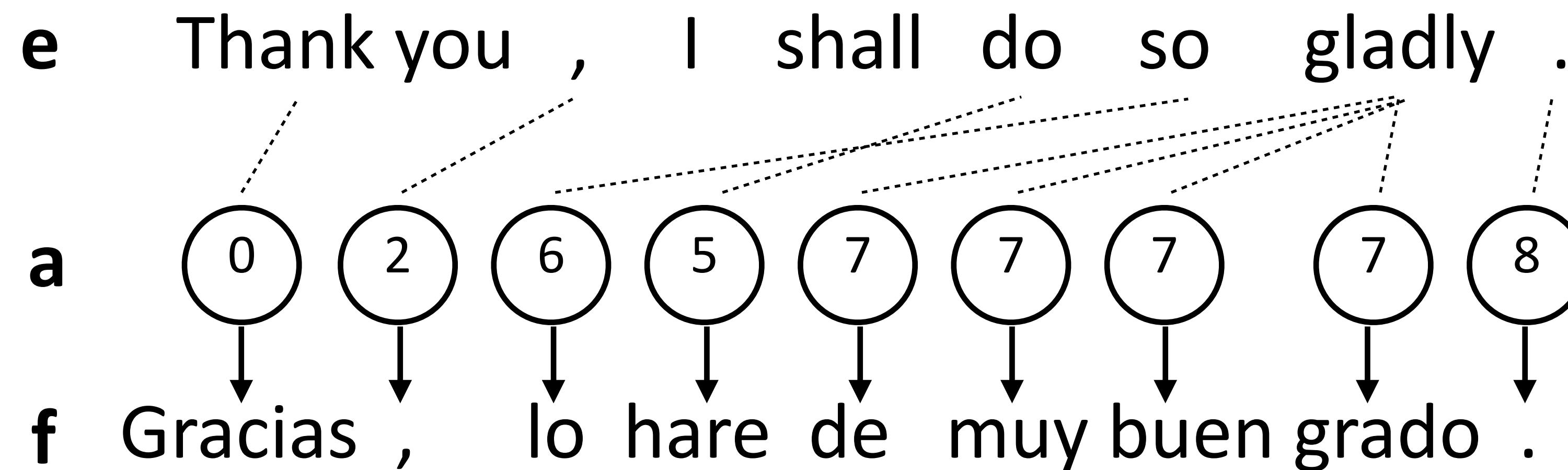
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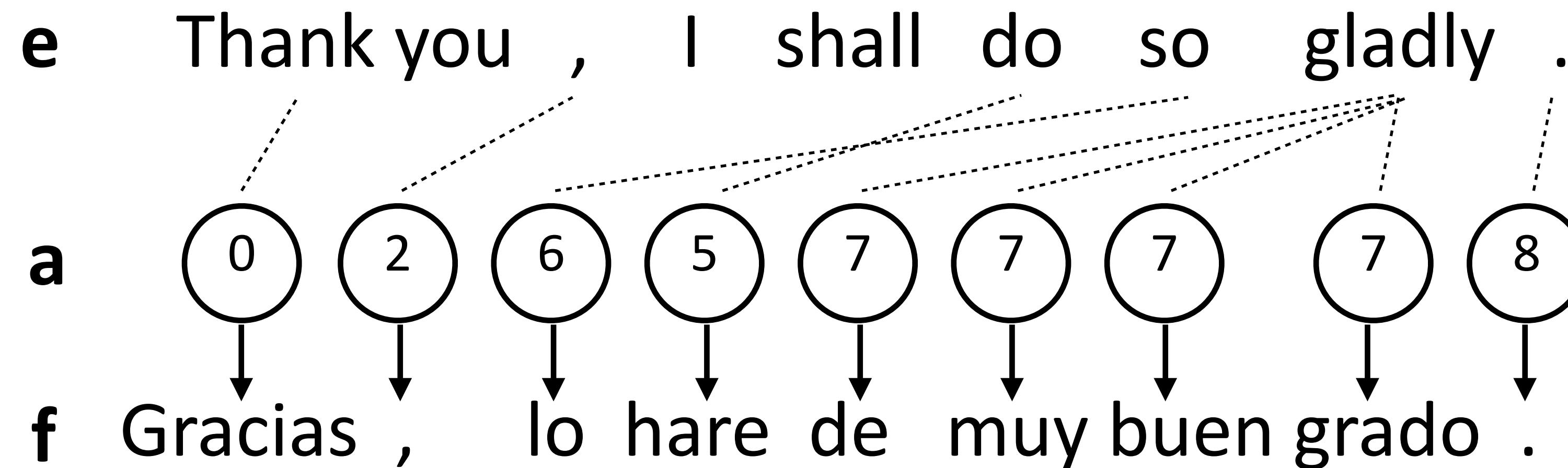
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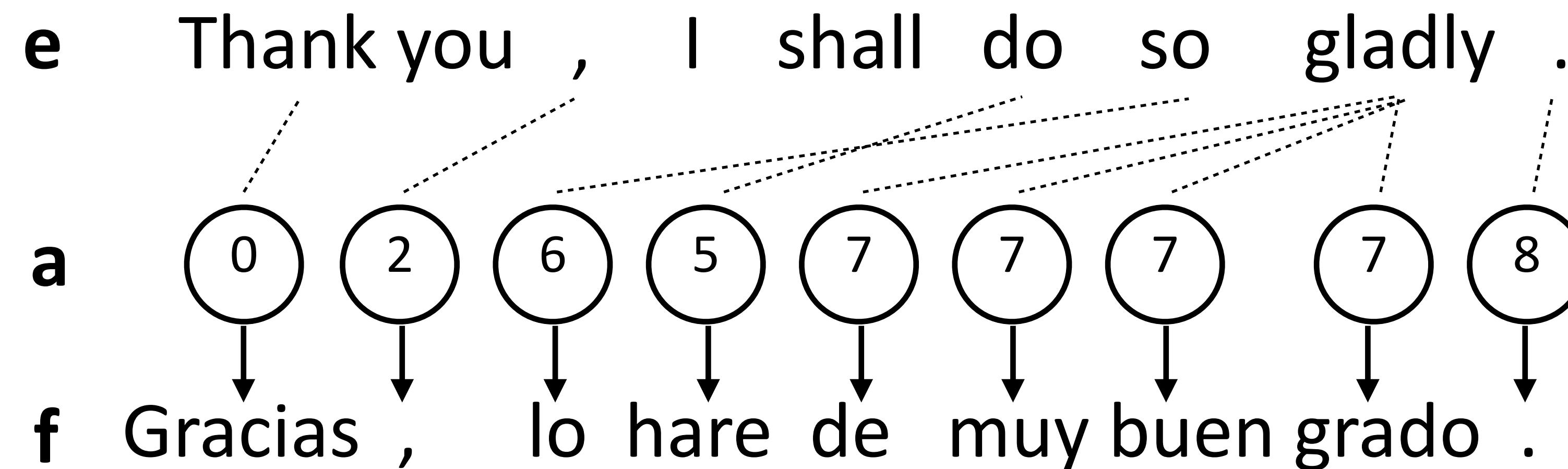


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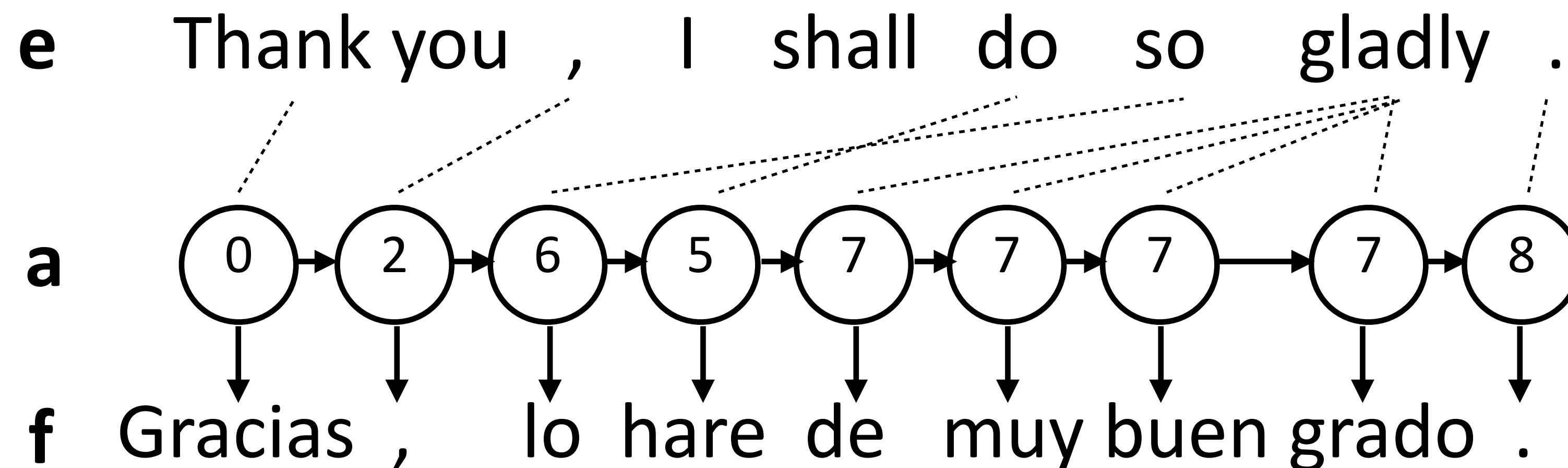
- Set $P(a)$ uniformly (no prior over good alignments)
- $P(f_i | e_{a_i})$: word translation probability table

Brown et al. (1993)

HMM for Alignment

- ▶ Sequential dependence between a's to capture monotonicity

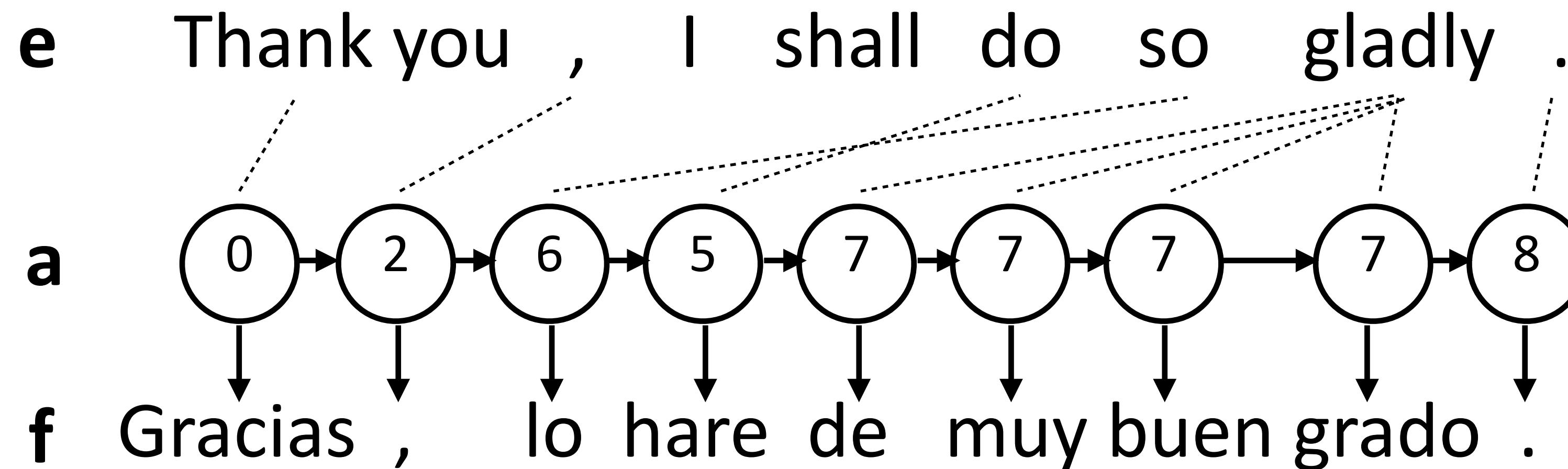
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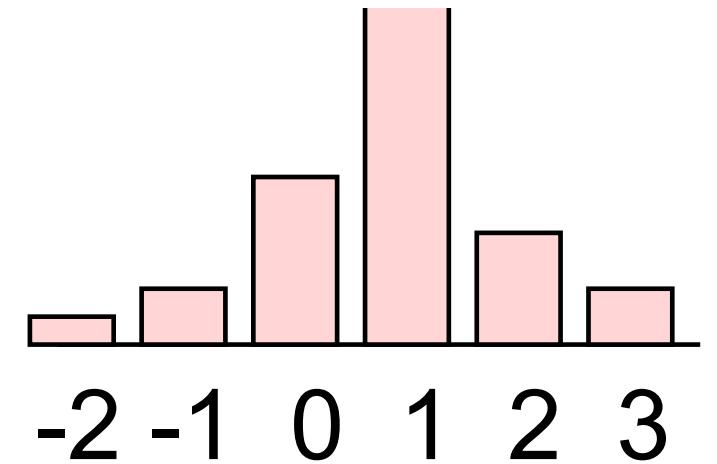
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- ▶ Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$

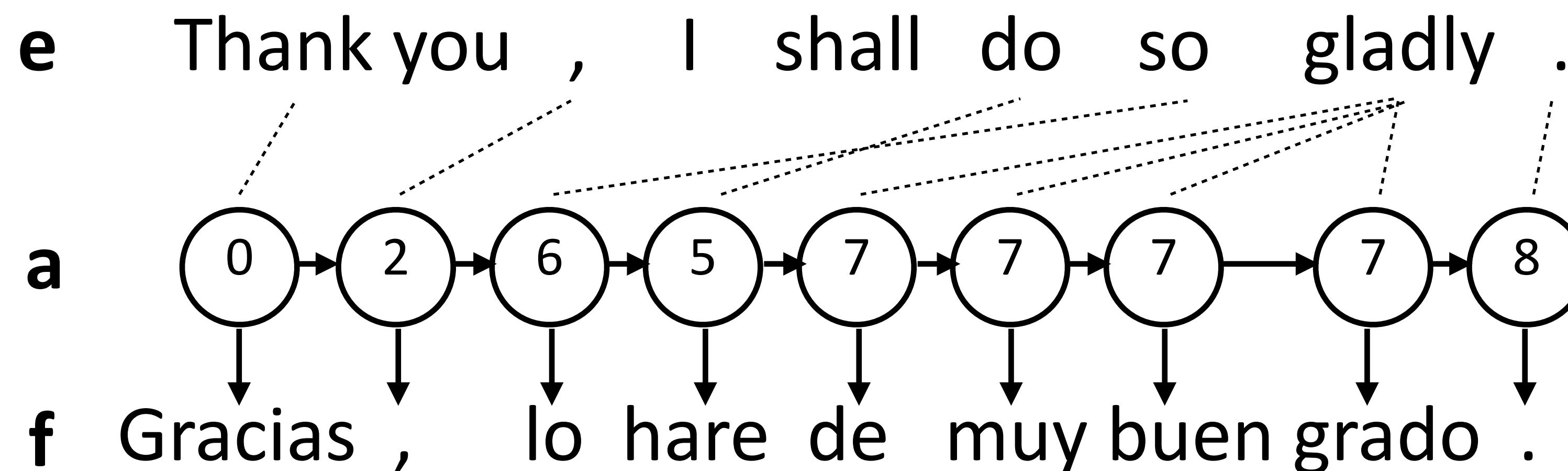


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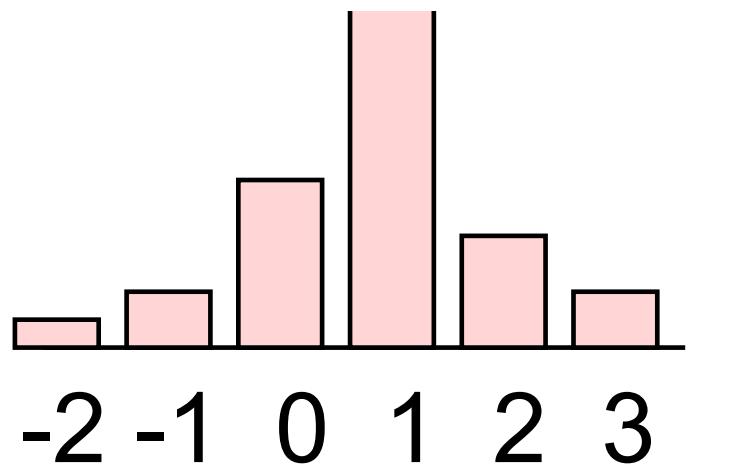
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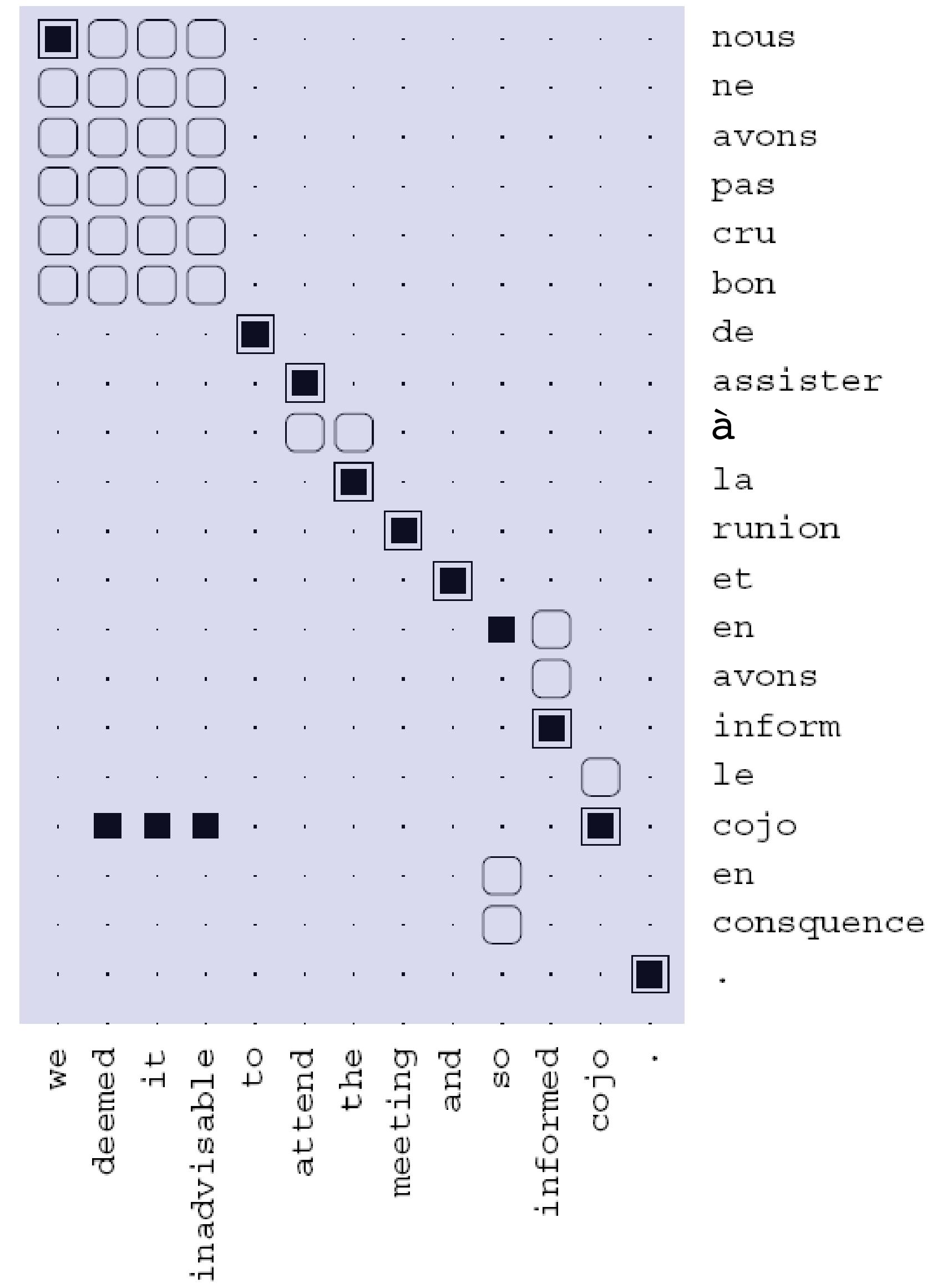
- ▶ Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$
- ▶ $P(f_i | e_{a_i})$: same as before



Brown et al. (1993)

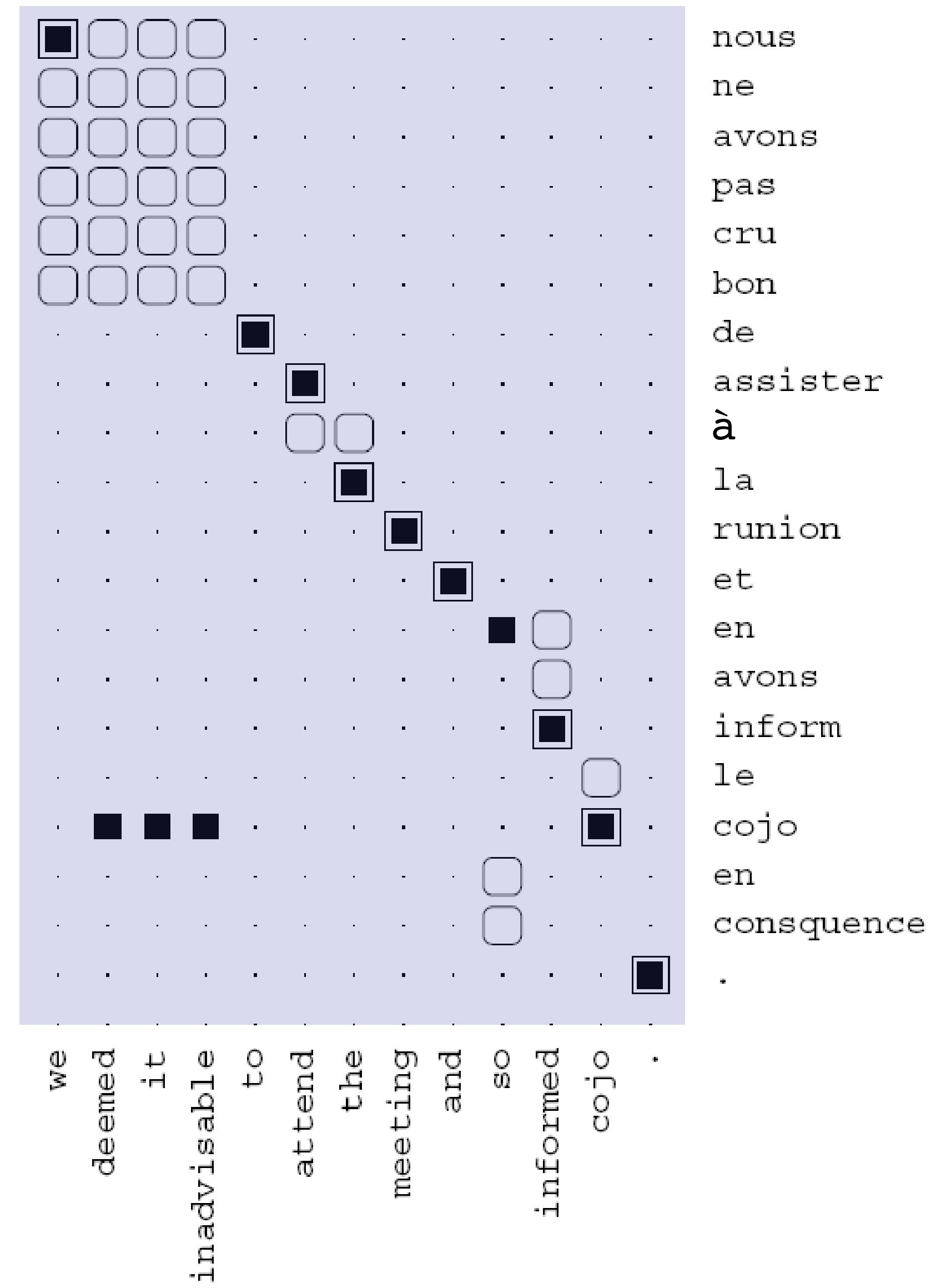
HMM Model

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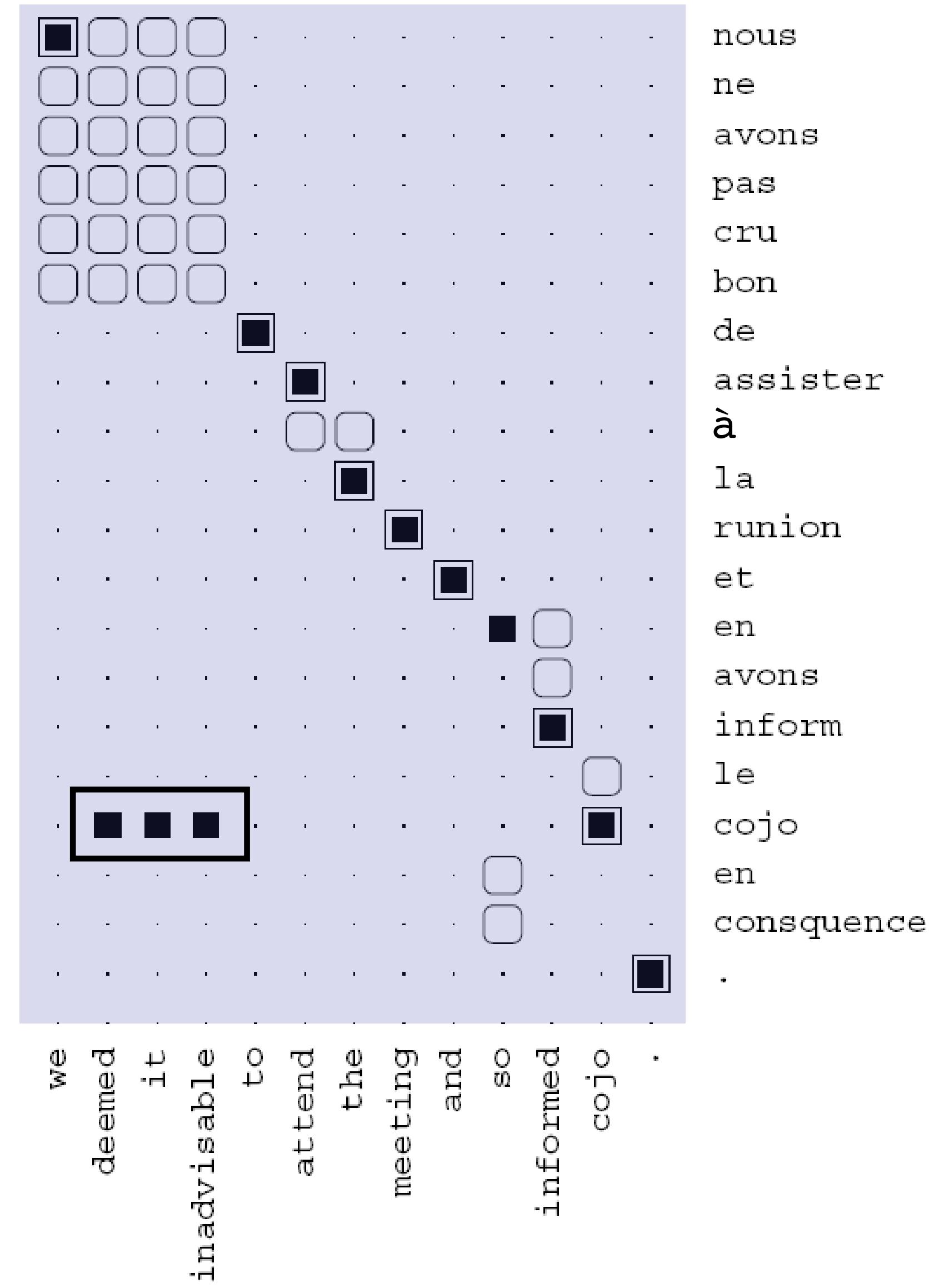
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HMM Model

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



Evaluating Word Alignment

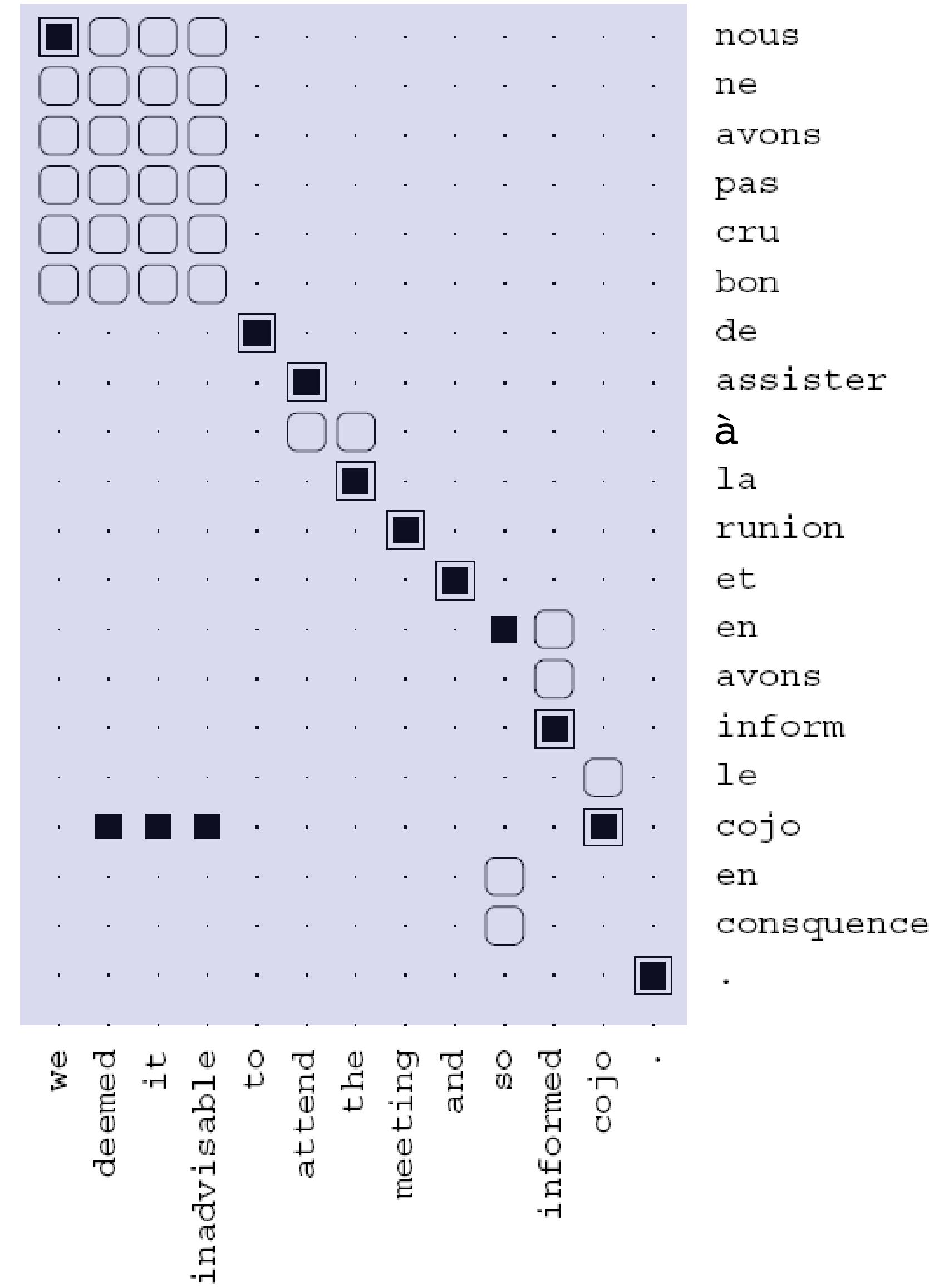
- ▶ “Alignment error rate”: use labeled alignments on small corpus

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

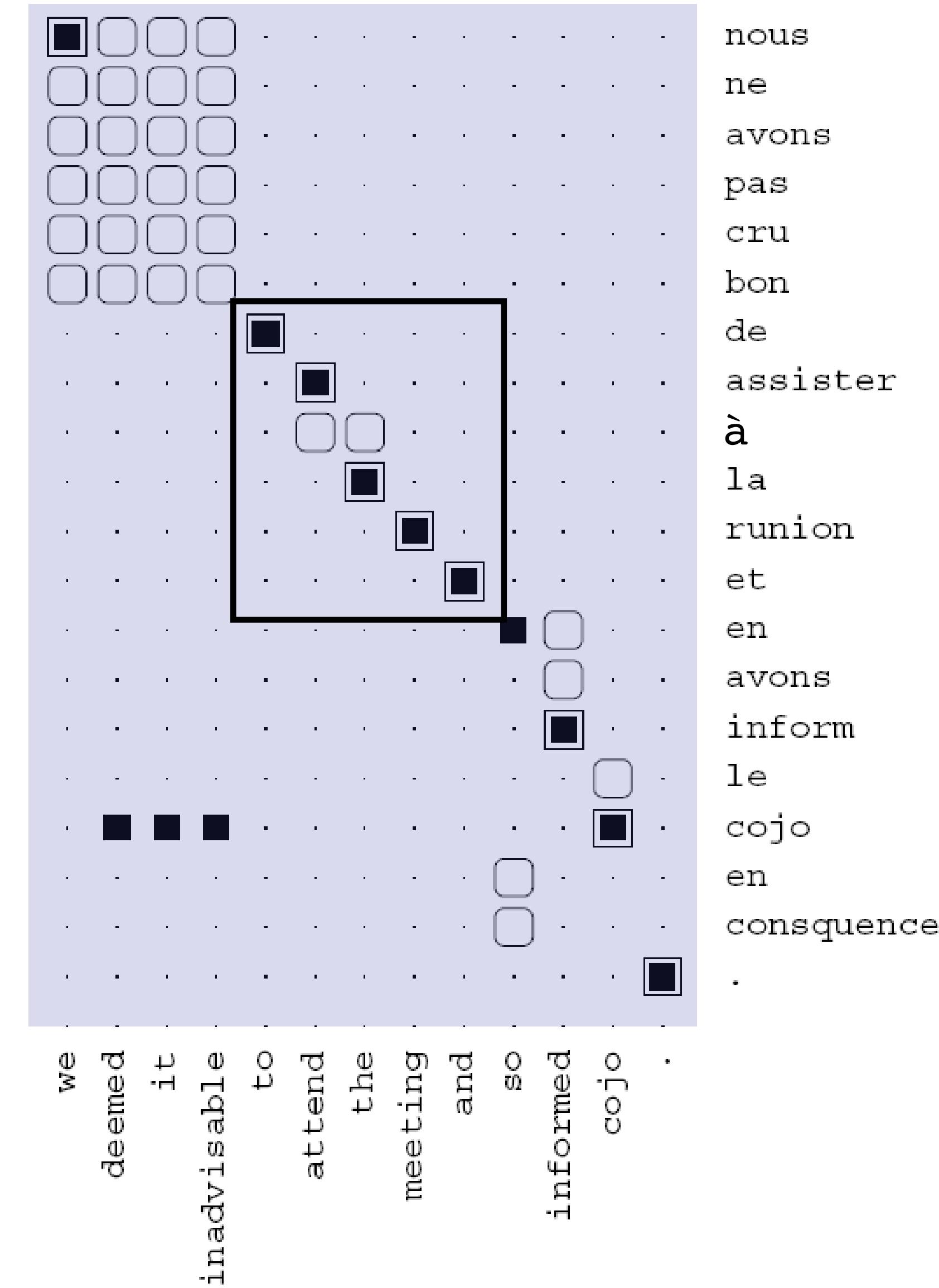
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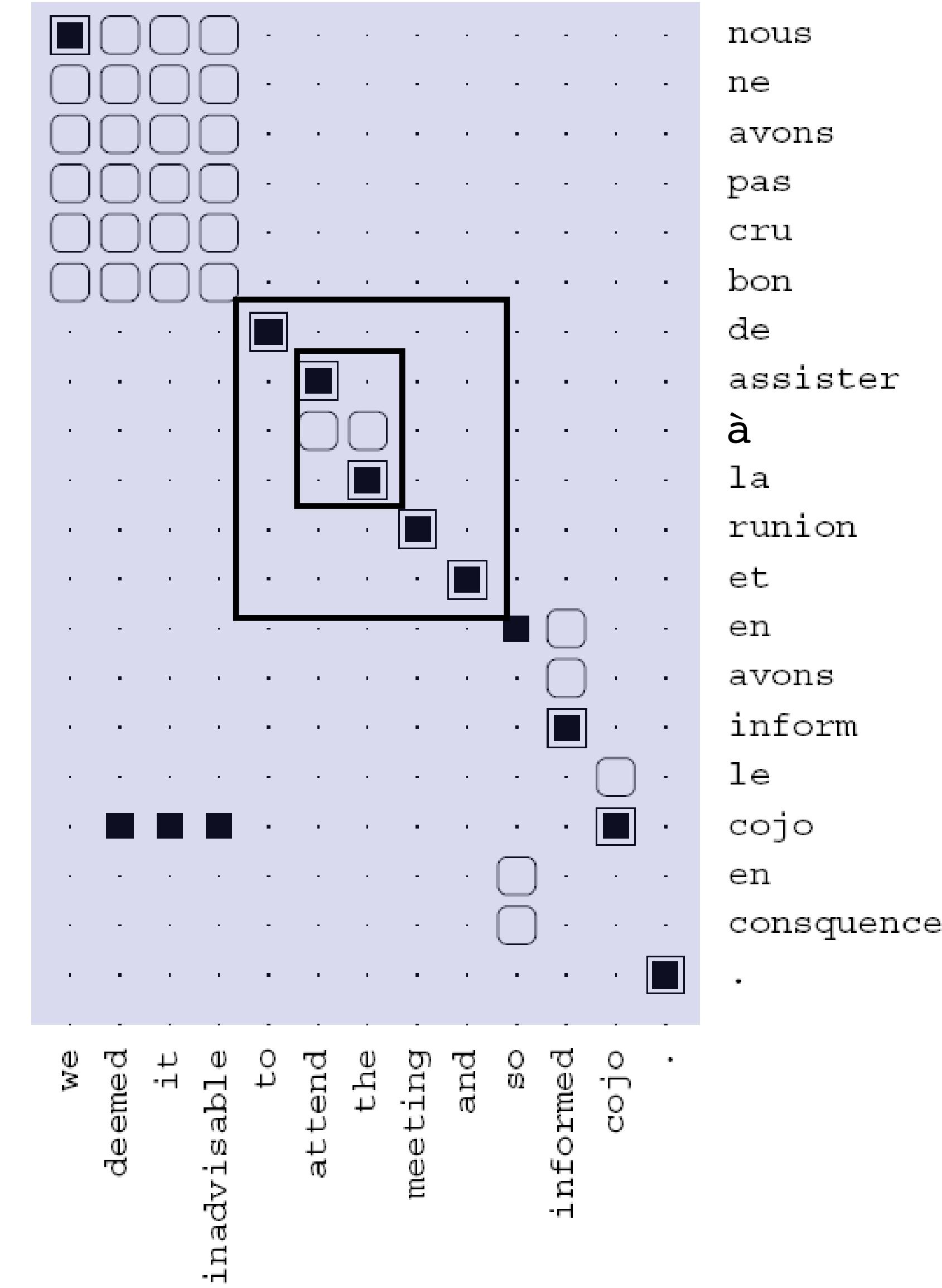
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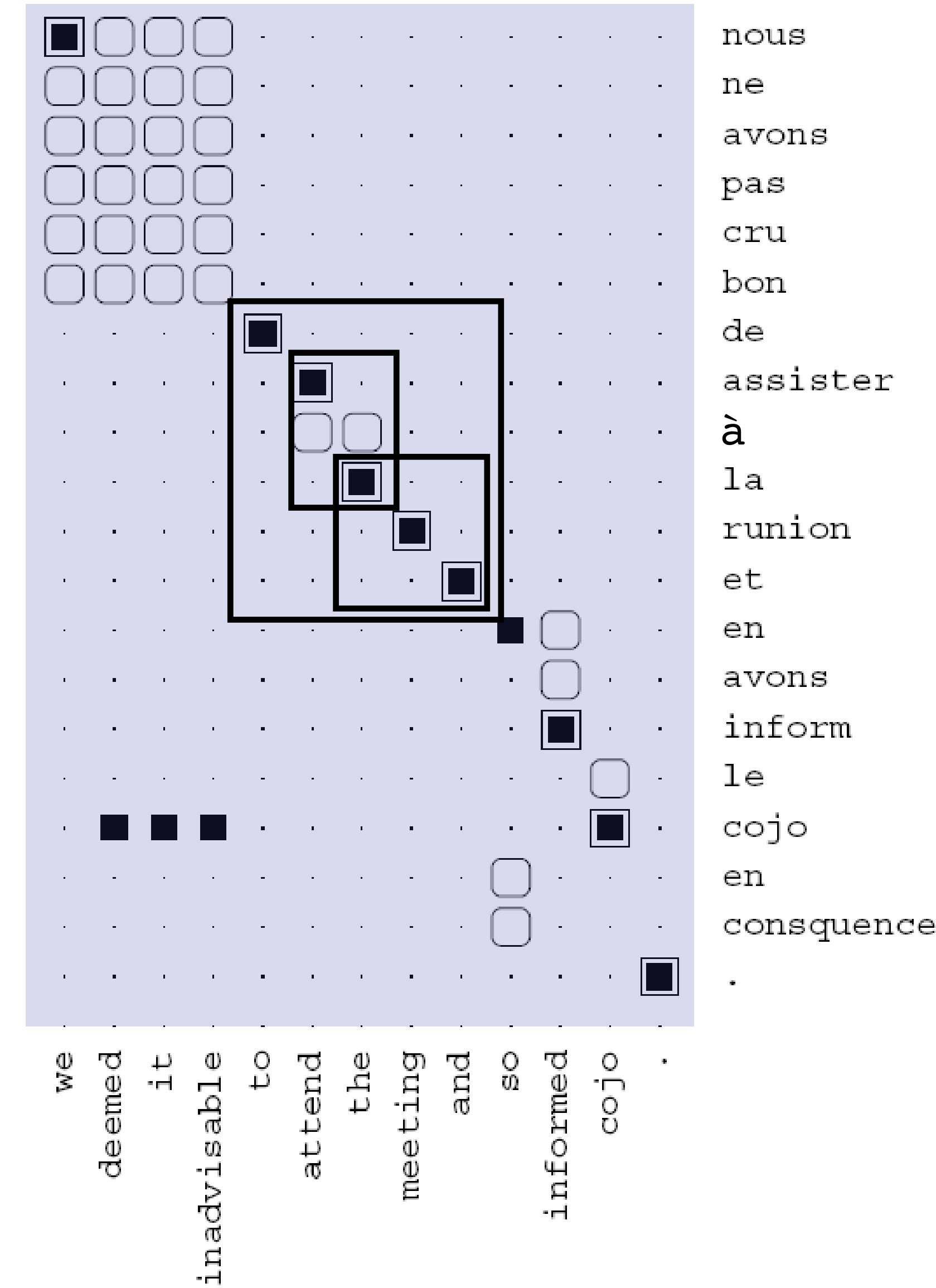
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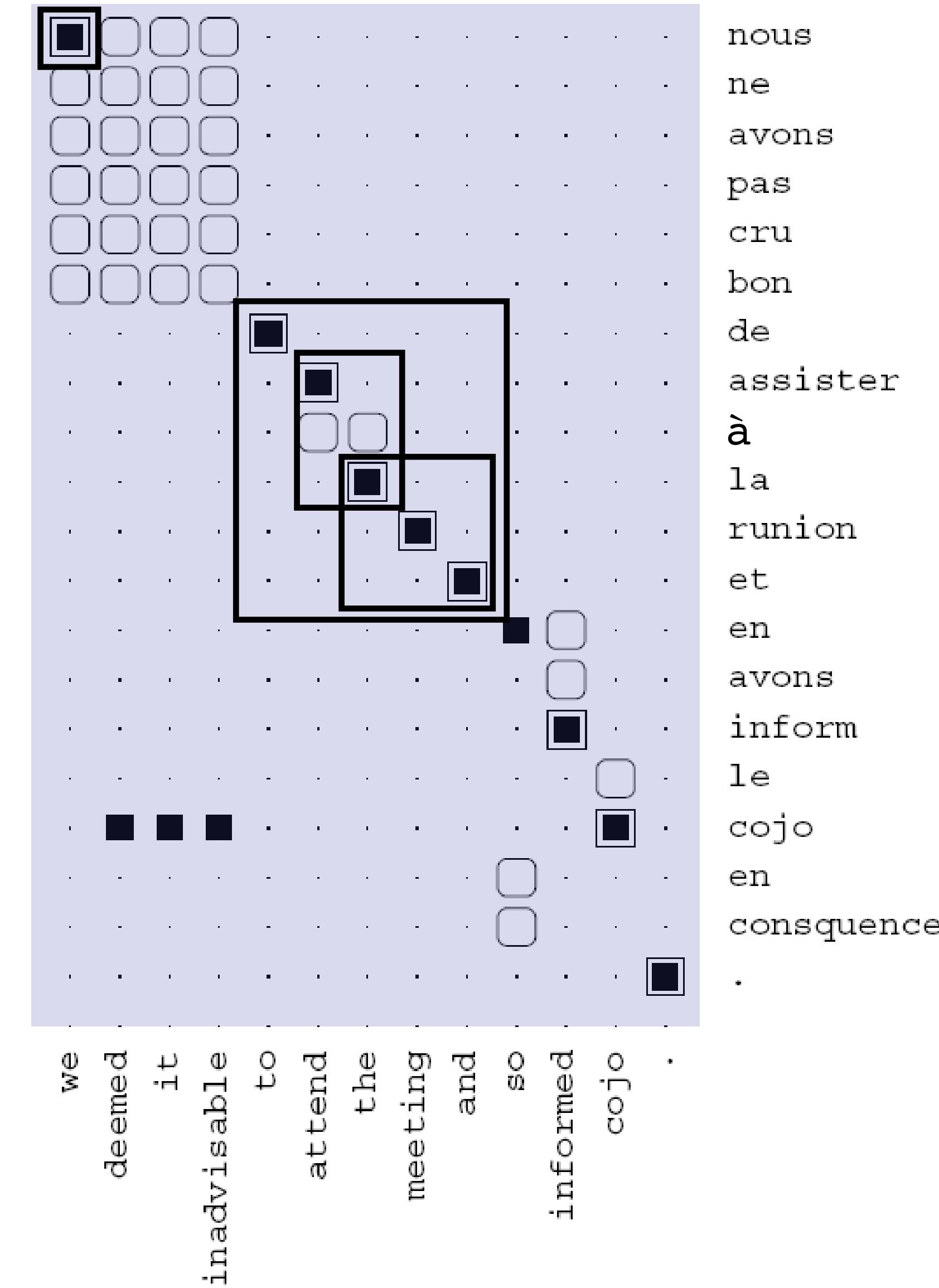
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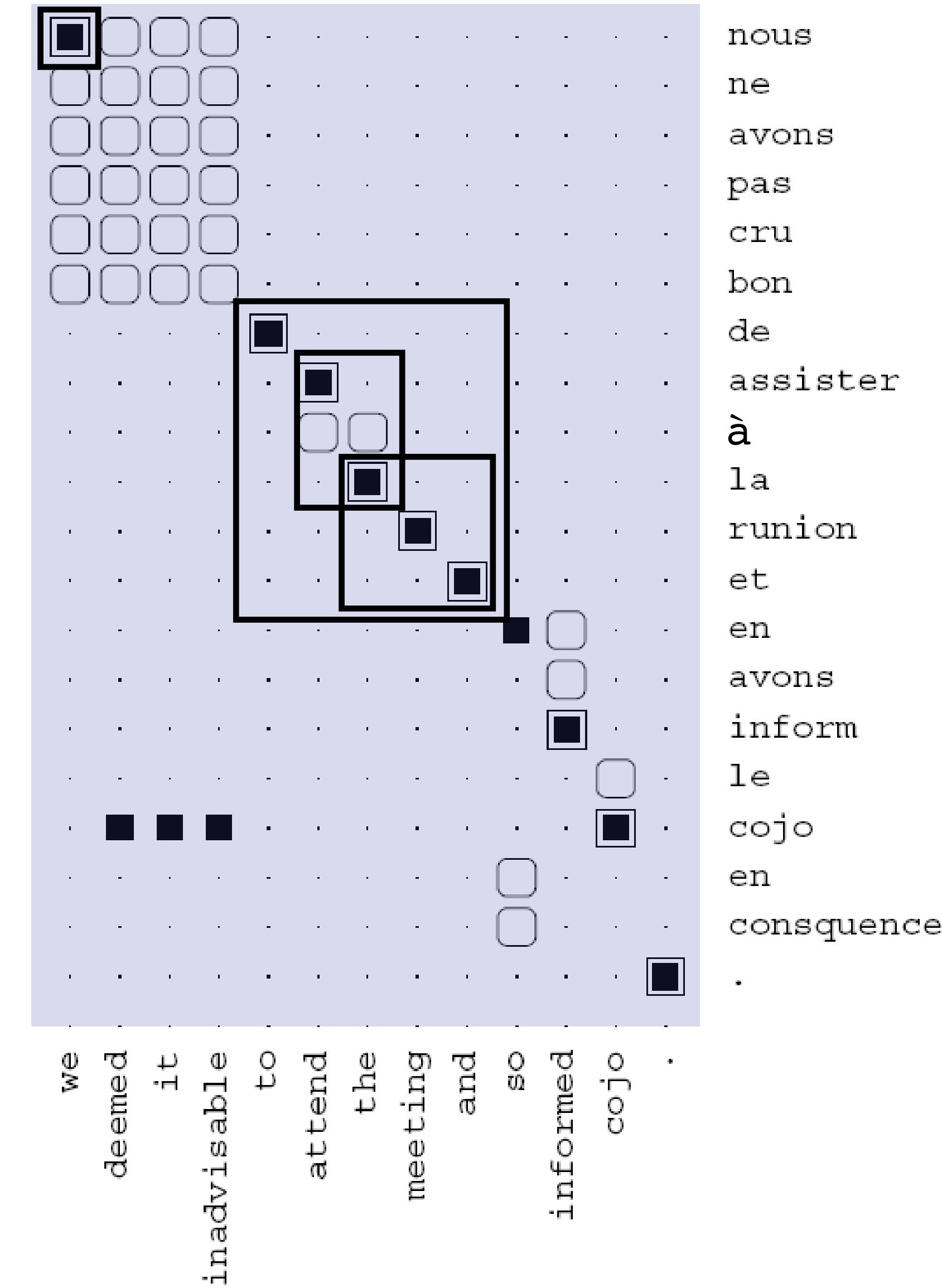
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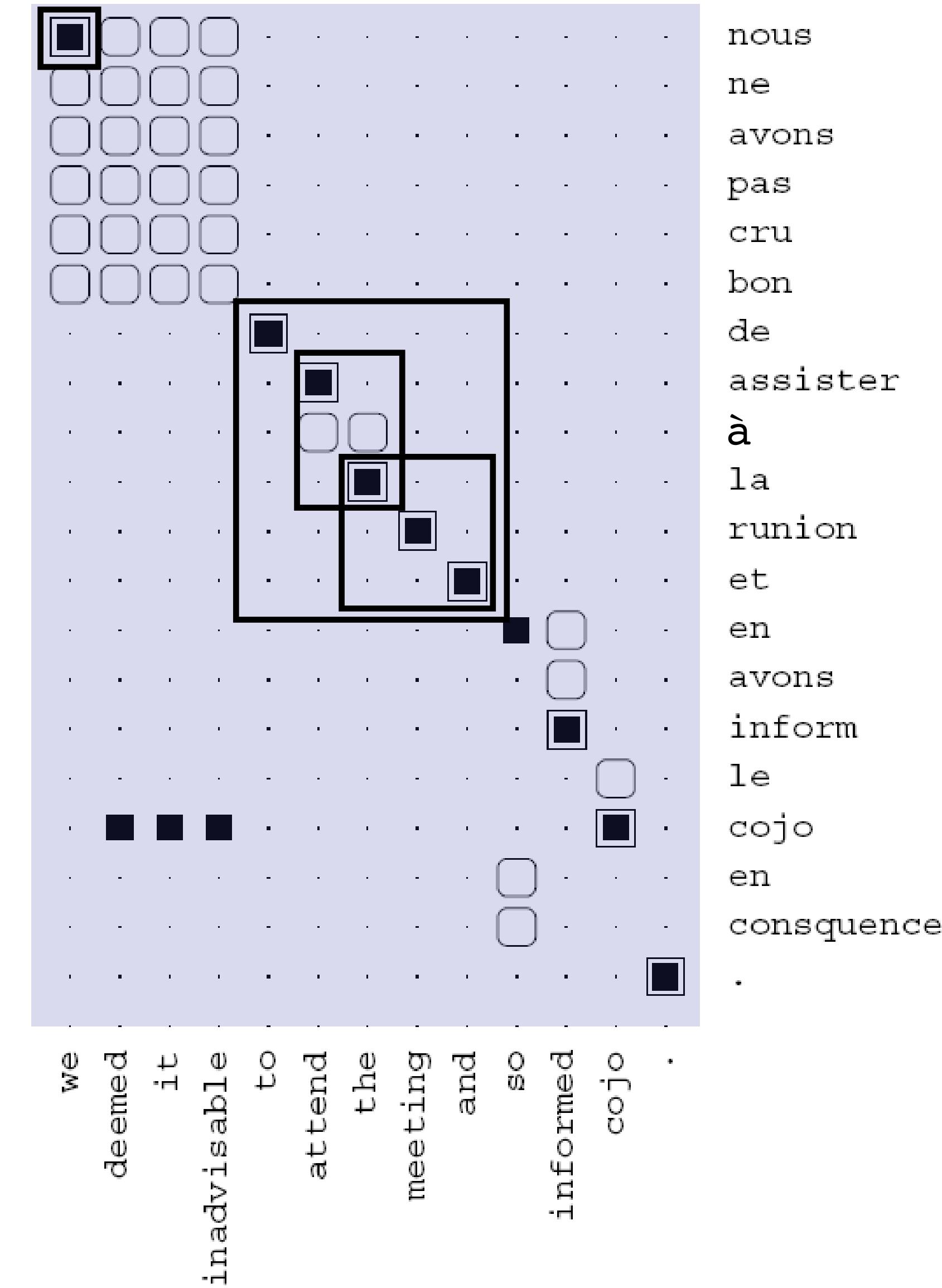
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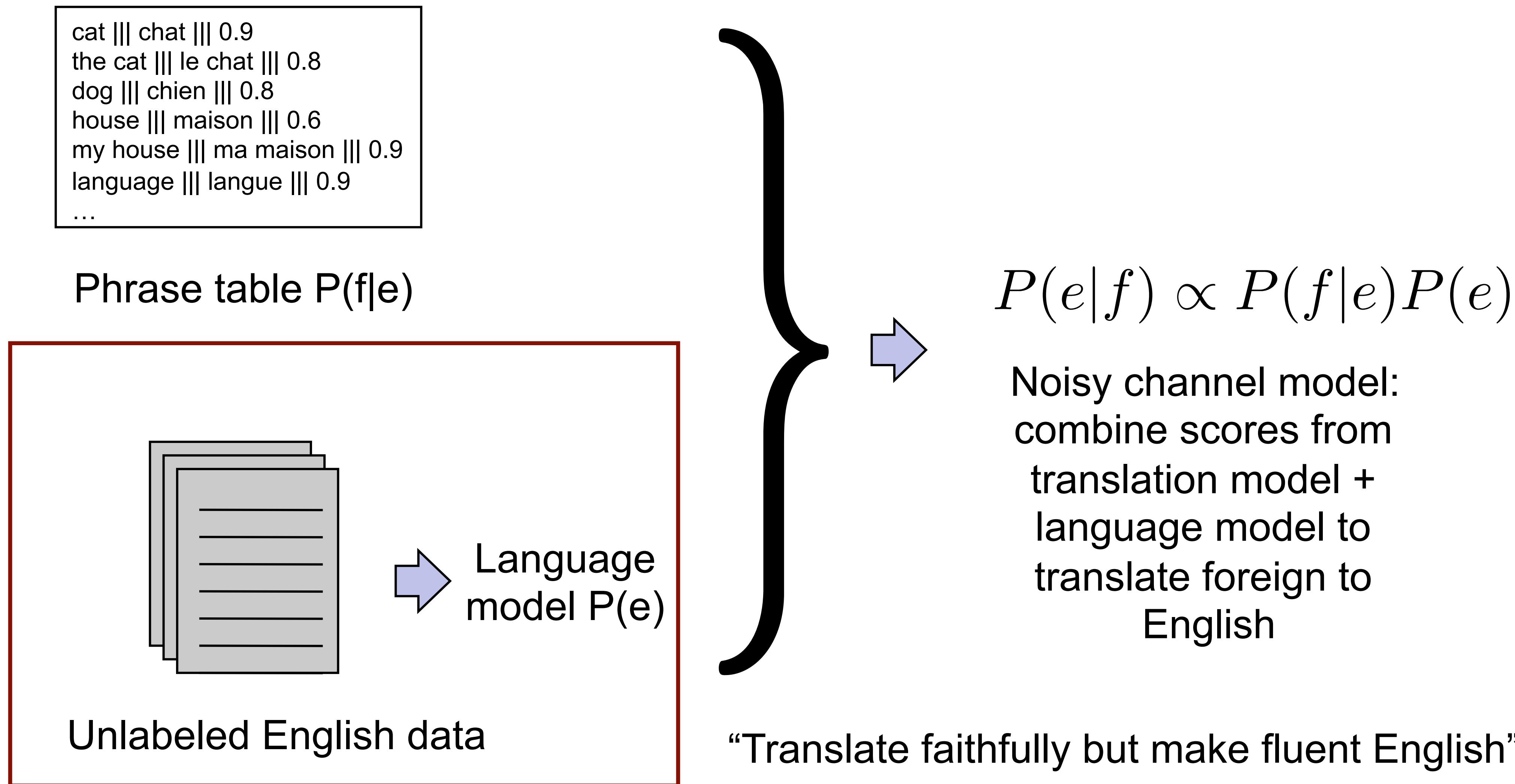
...

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



Language Modeling

Phrase-Based MT



N-gram Language Models

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- ▶ 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

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

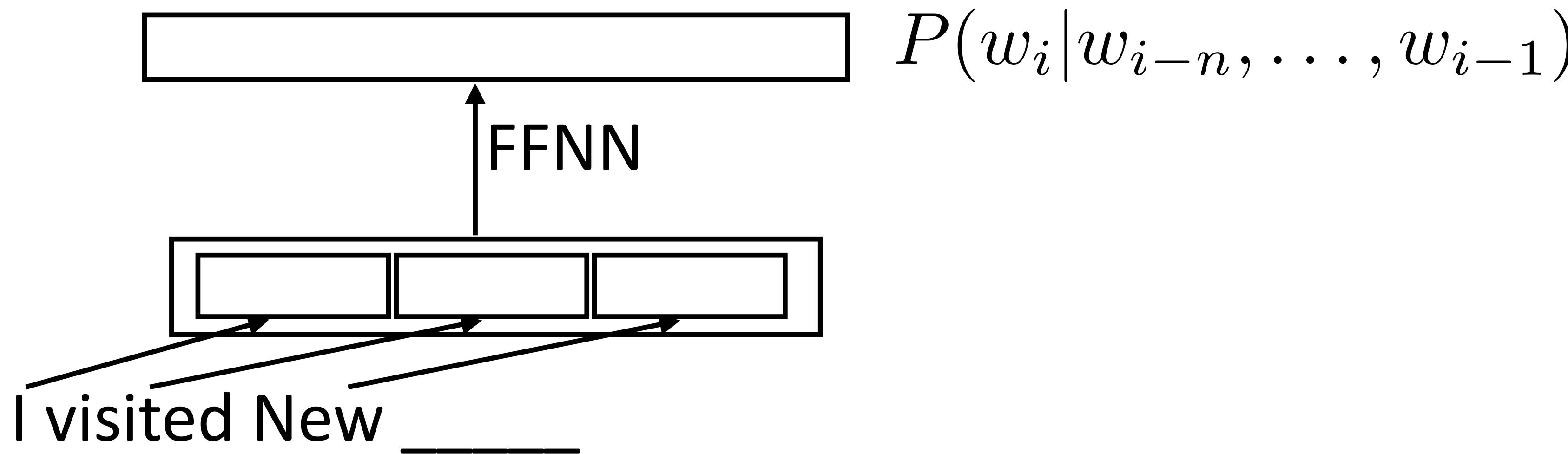
- ▶ Make it fit in memory by *delta encoding* scheme: store deltas instead of values and use variable-length encoding

Neural Language Models

- ▶ Early work: feedforward neural networks looking at context

Neural Language Models

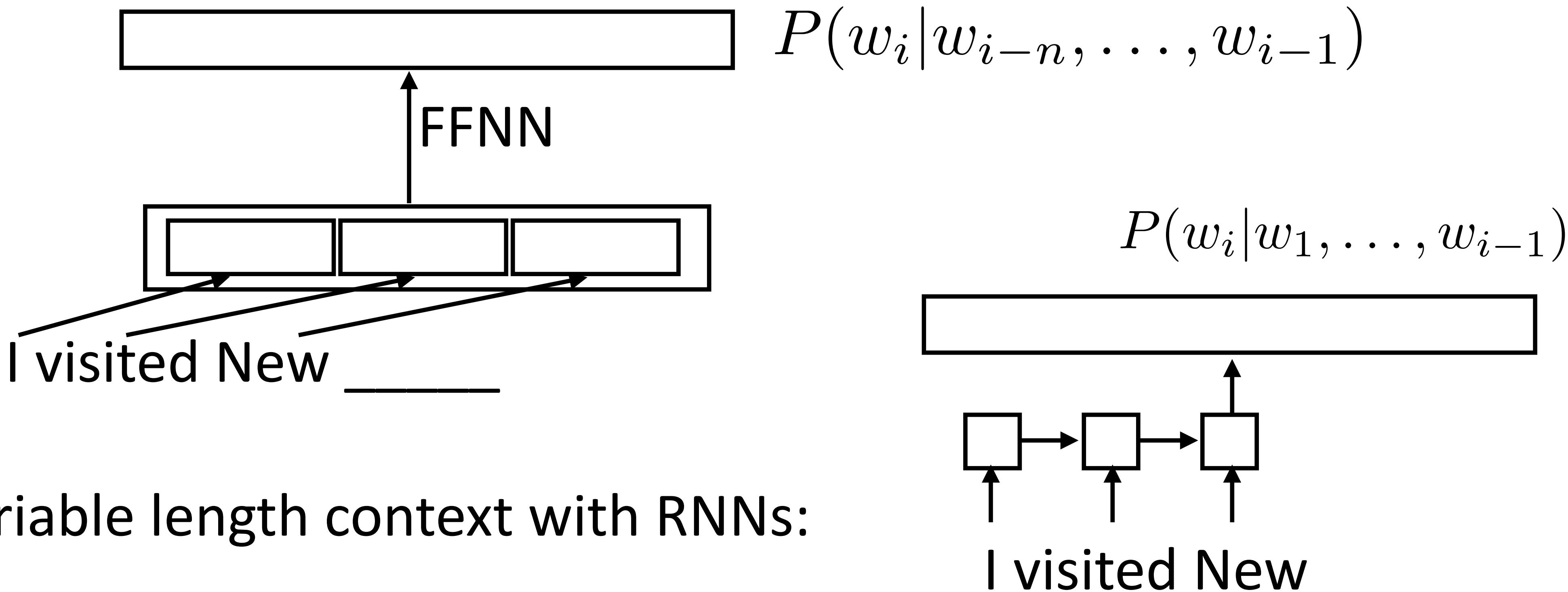
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Mnih and Hinton (2003)

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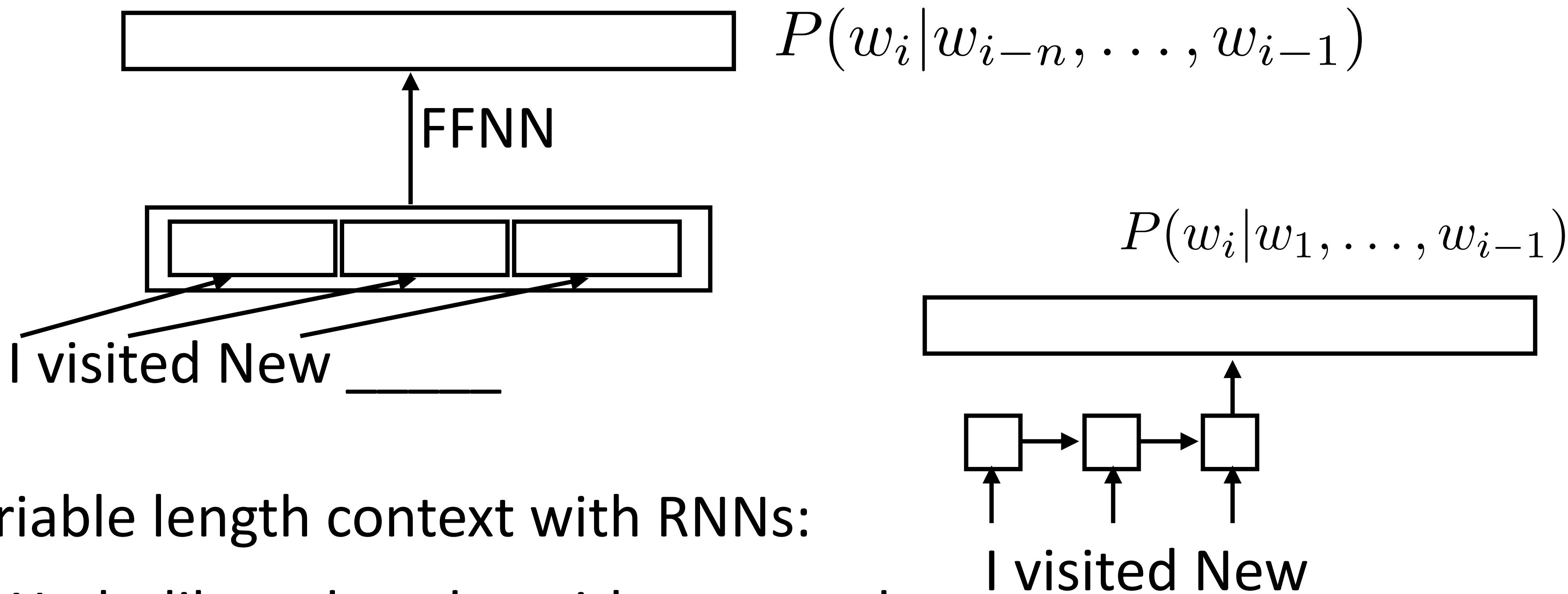


- ▶ Variable length context with RNNs:

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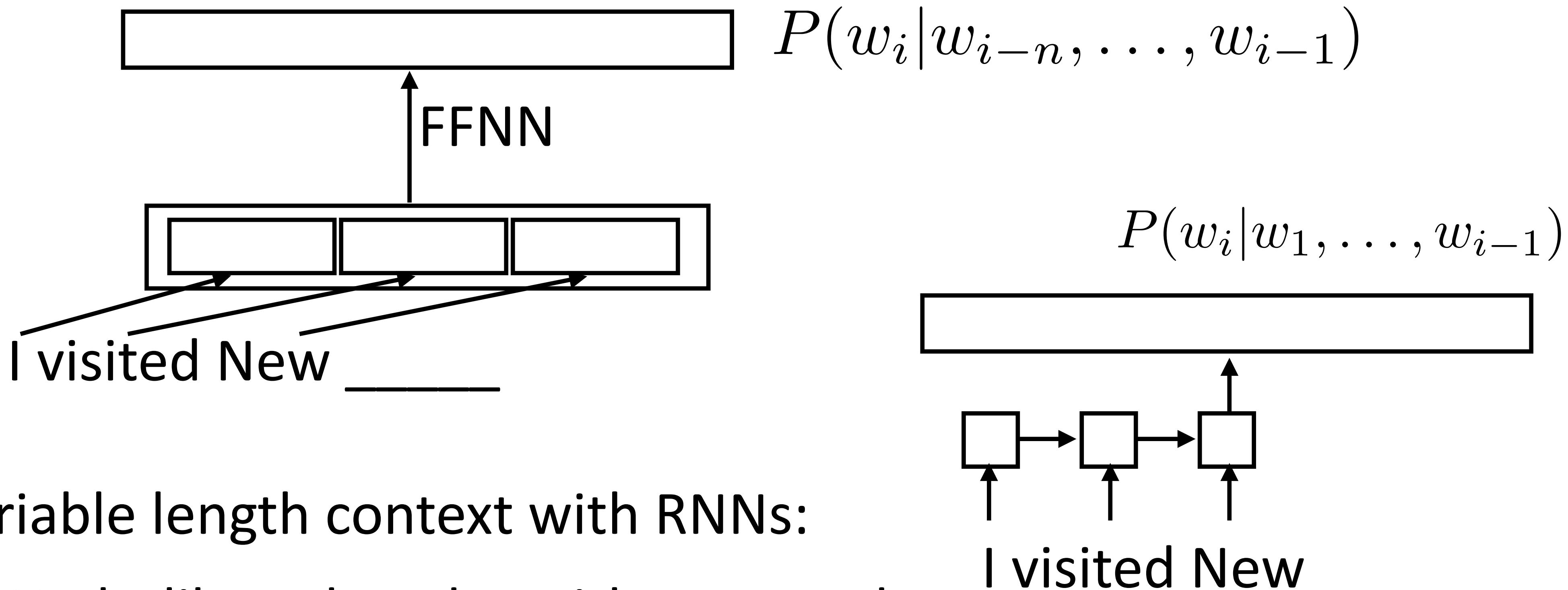


- ▶ Variable length context with RNNs:
 - ▶ Works like a decoder with no encoder

Mnih and Hinton (2003)

Neural Language Models

- ▶ Early work: feedforward neural networks looking at context



- ▶ 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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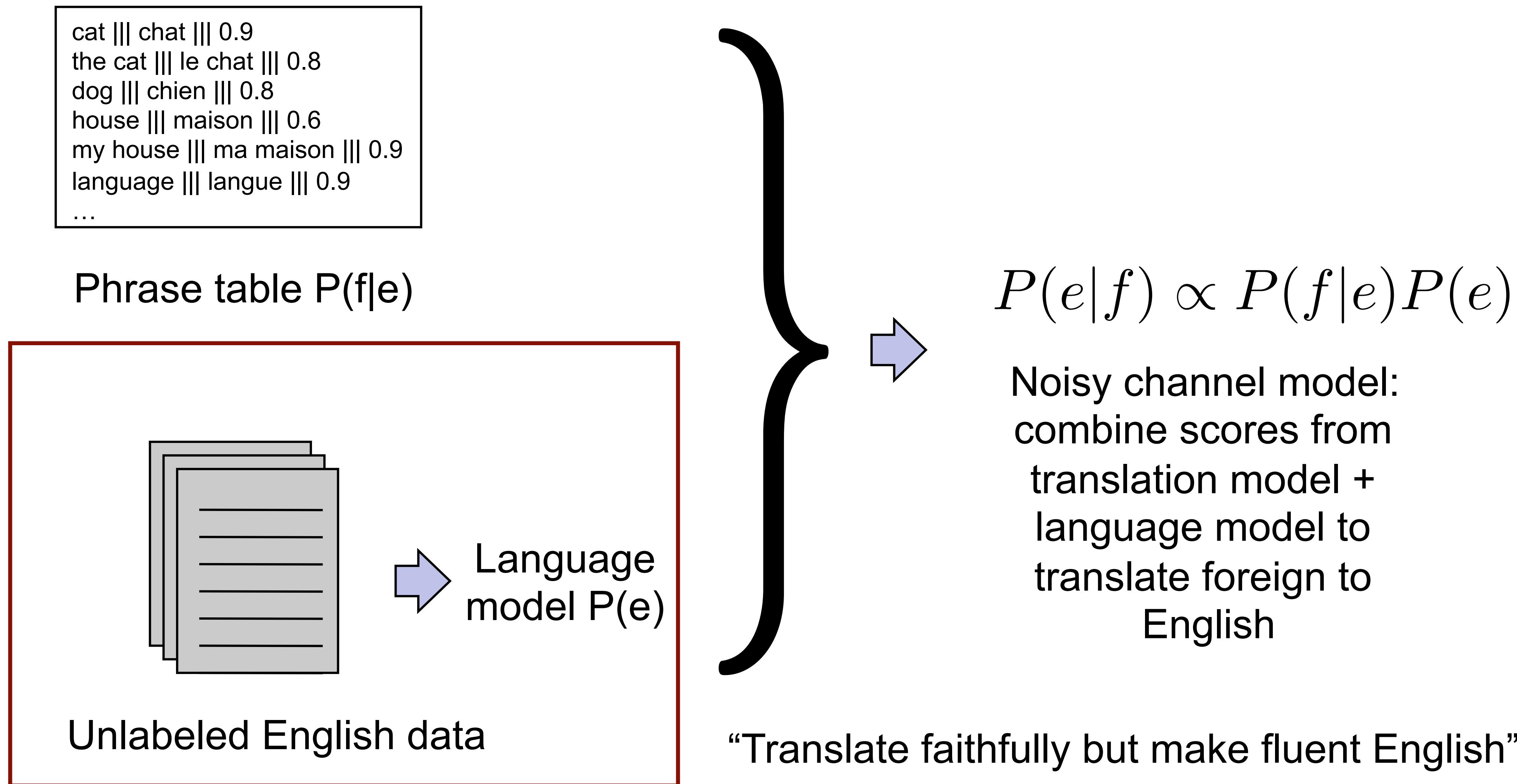
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- ▶ Melis et al.: many neural LM improvements from 2014-2017 are subsumed by just using the right regularization (right dropout settings). So LSTMs are pretty good

Phrase-Based MT



Decoding

Phrase-Based Decoding

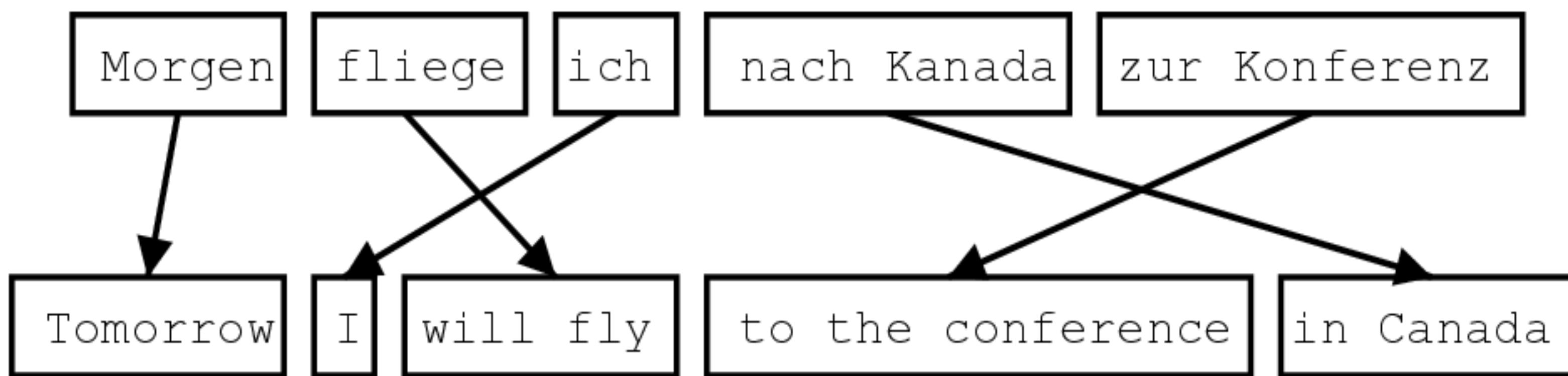
- ▶ Inputs:
 - ▶ Language model that scores $P(e_i|e_1, \dots, e_{i-1}) \approx P(e_i|e_{i-n-1}, \dots, e_{i-1})$
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Phrase lattices are big!

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			

Phrase-Based Decoding

- ▶ Input

lo haré | rápidamente |.

- ▶ Translations

I'll do it | quickly |.

quickly | I'll do it |.

- ▶ Decoding objective (for 3-gram LM)

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

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

The decoder...

tries different segmentations,

translates phrase by phrase,

and considers reorderings.

Monotonic Translation

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<u>Mary</u>	<u>not</u>	<u>give</u>	<u>a</u>	<u>slap</u>	<u>to</u>	<u>the</u>	<u>witch</u>	<u>green</u>
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- If we translate with beam search, what state do we need to keep in the beam?

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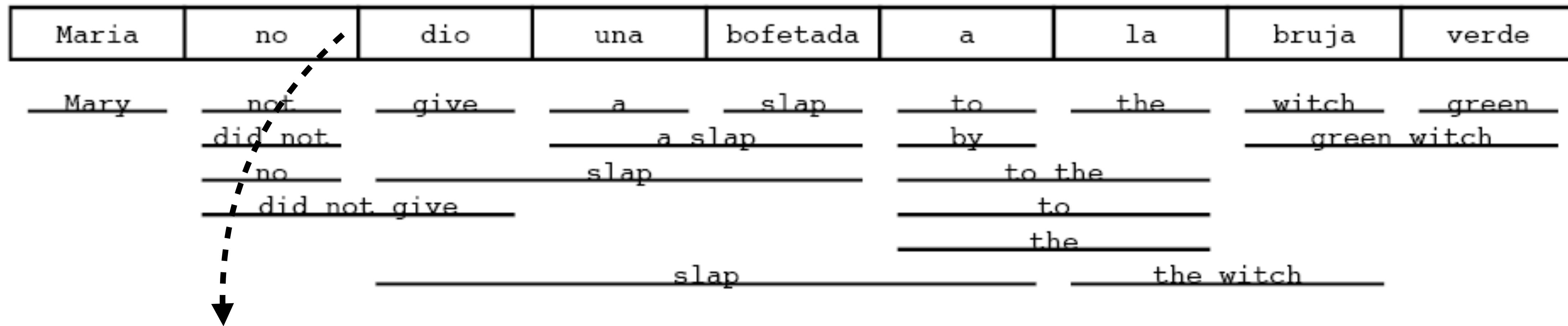
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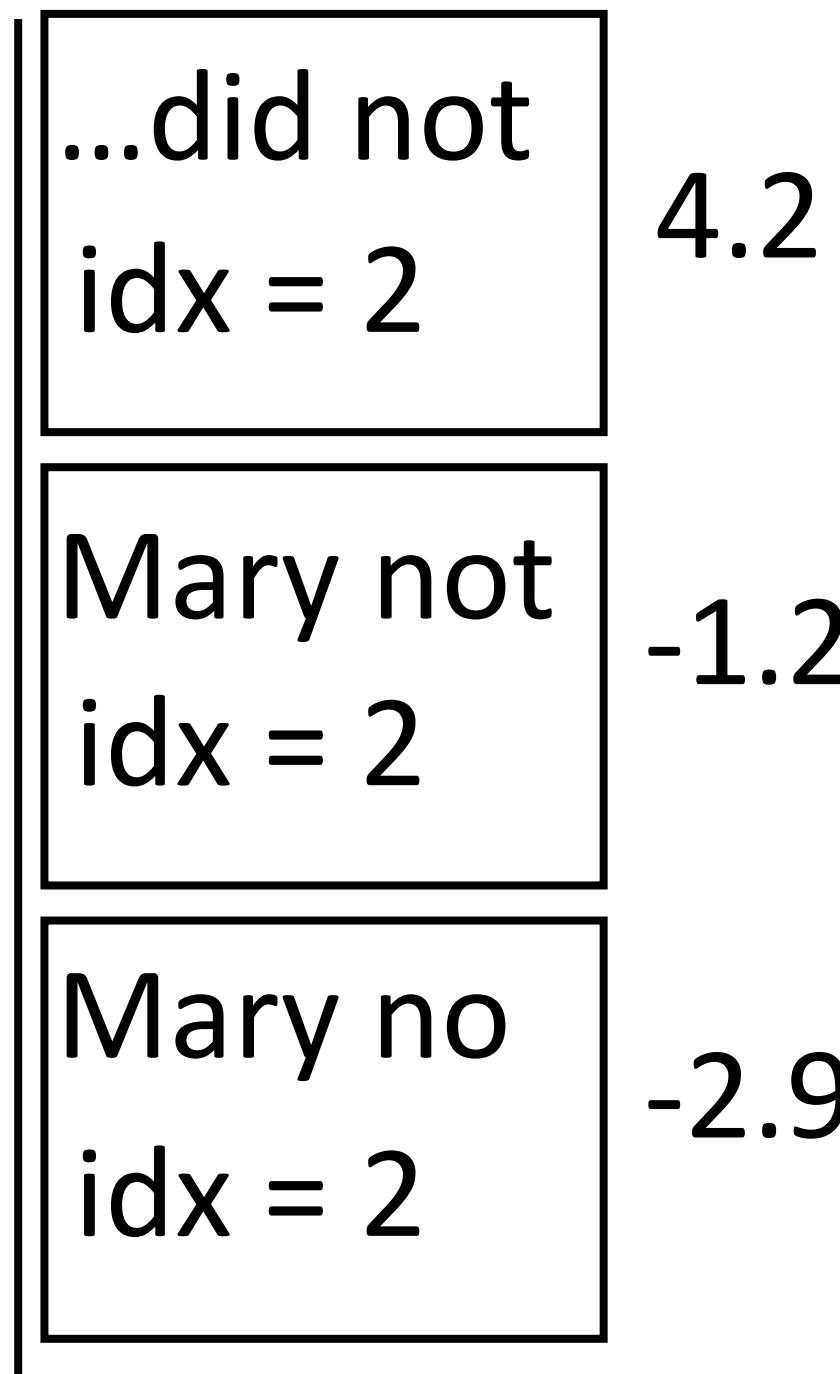
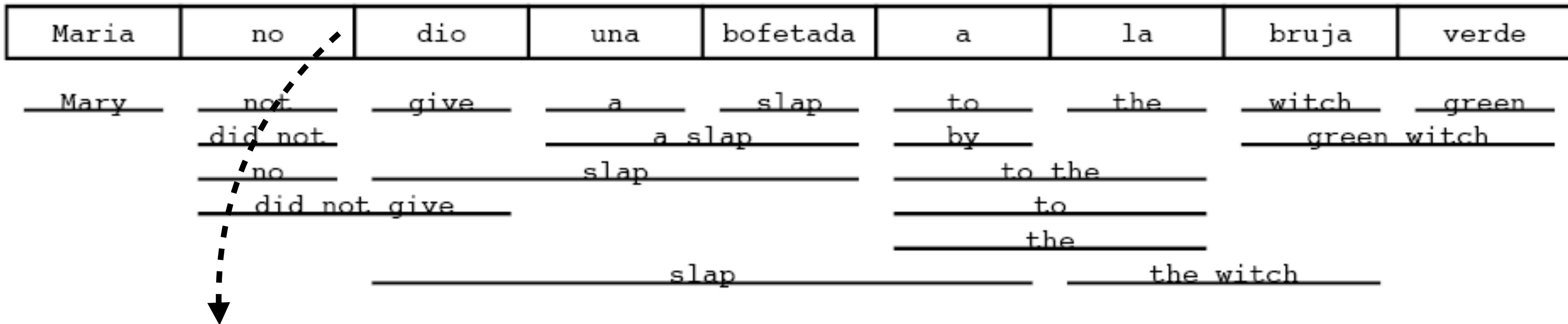
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- ▶ What words have we produced so far?
- ▶ When using a 3-gram LM, only need to remember the last 2 words!

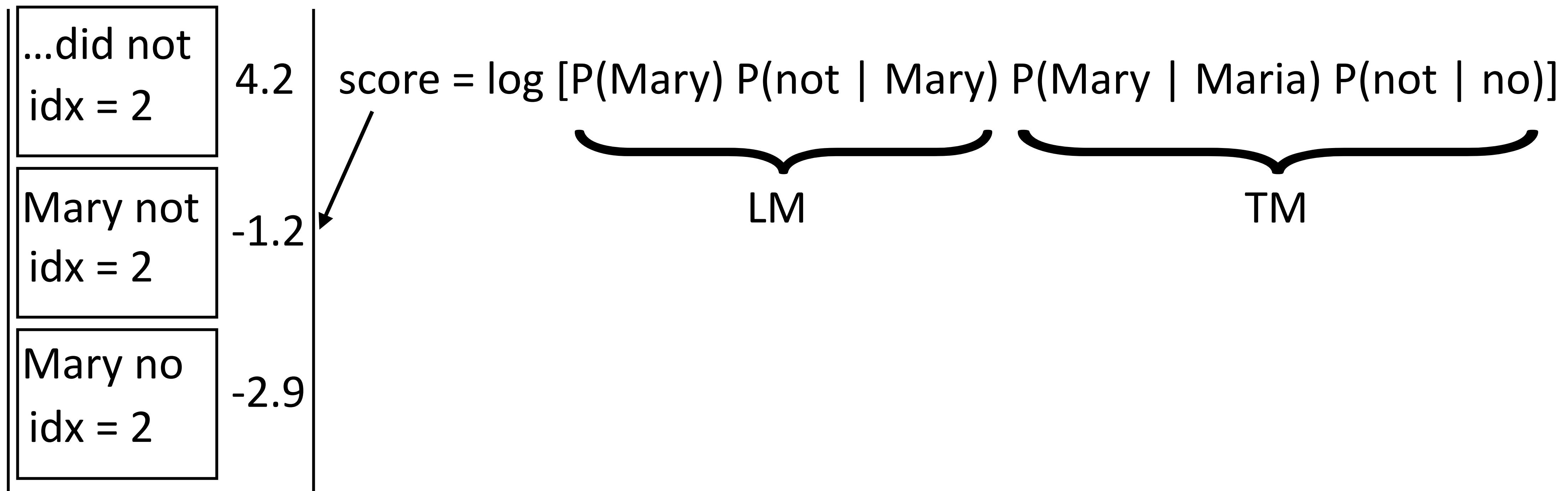
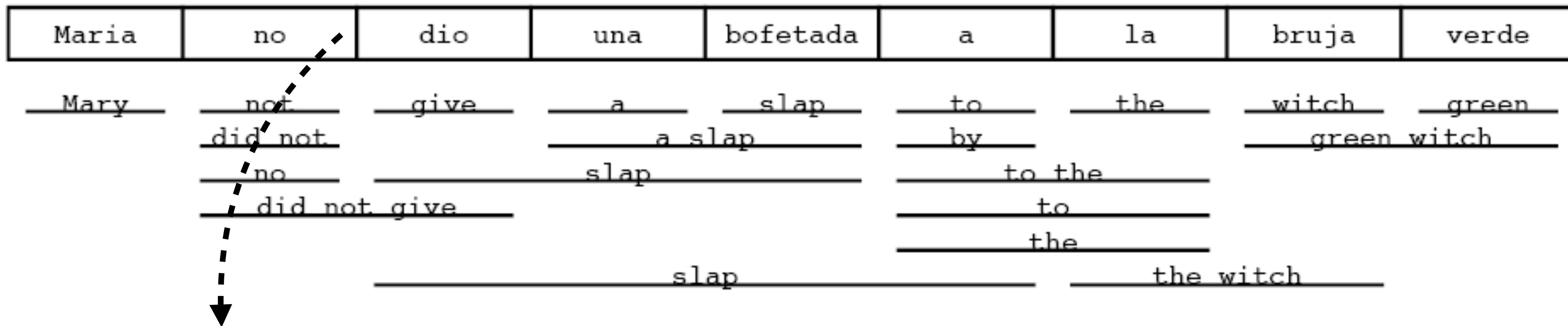
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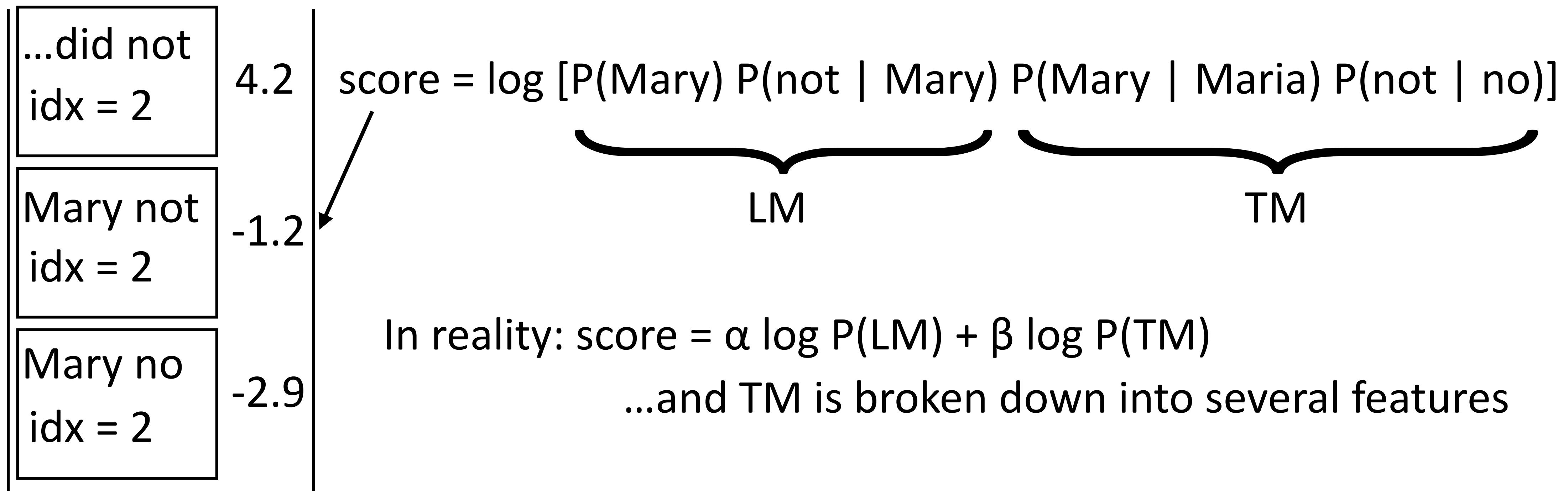
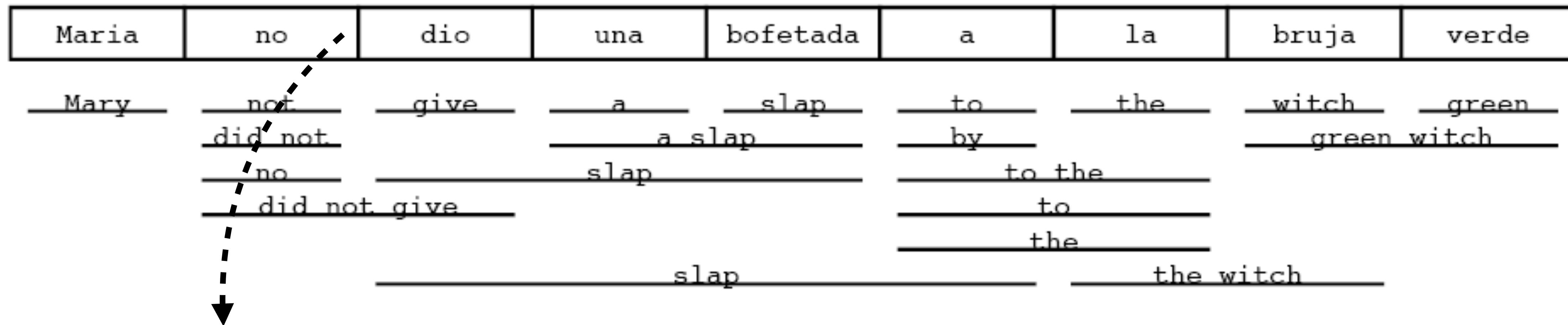
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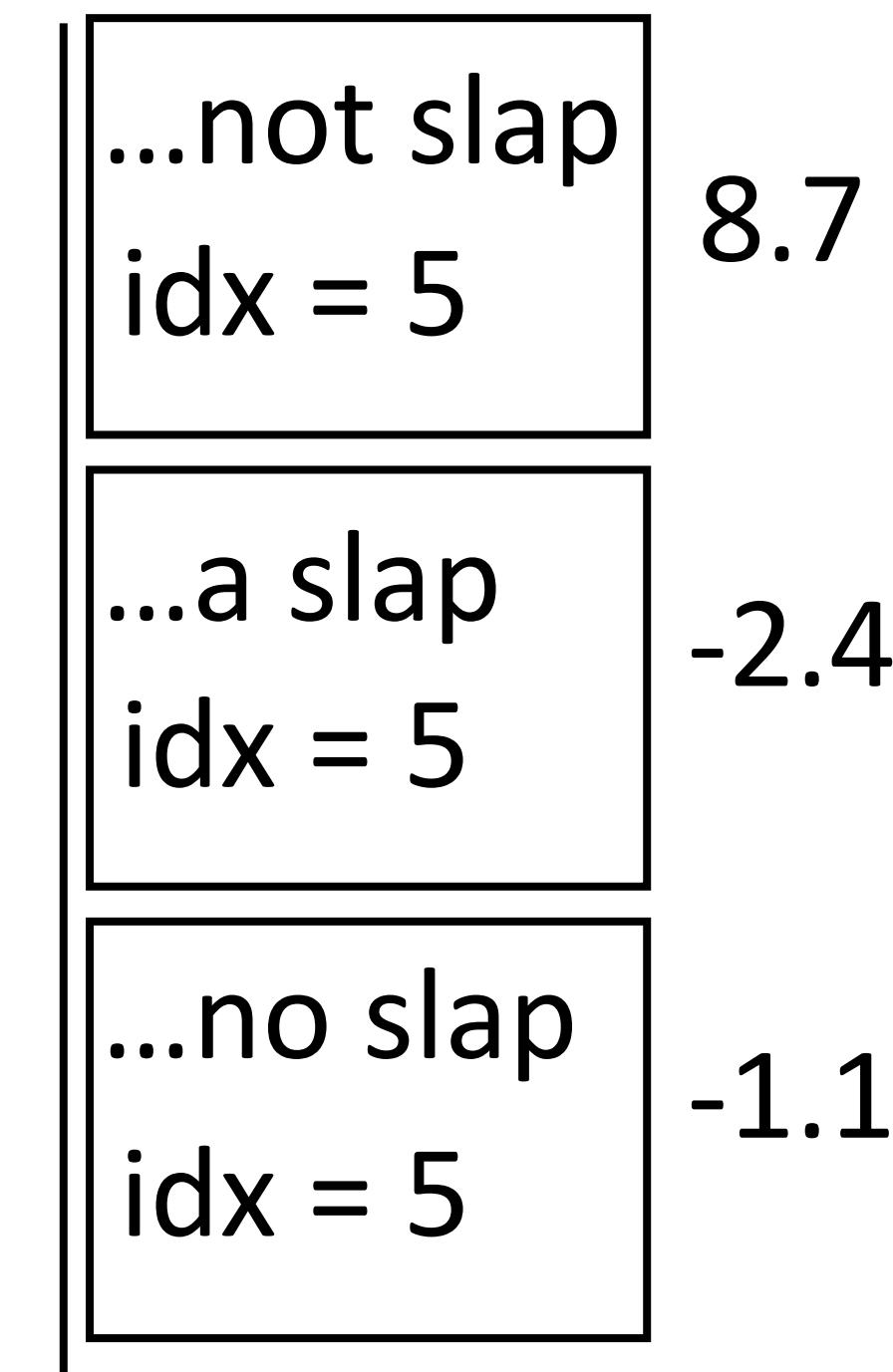
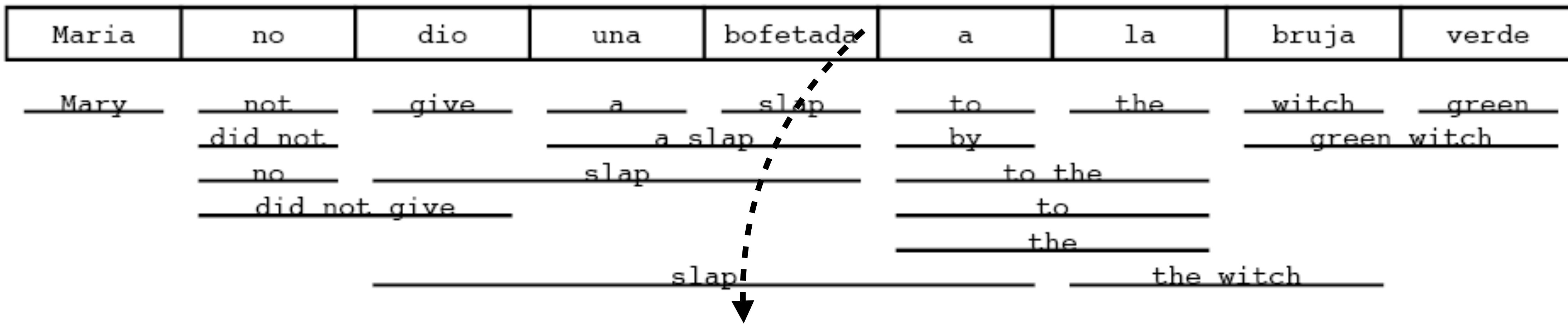
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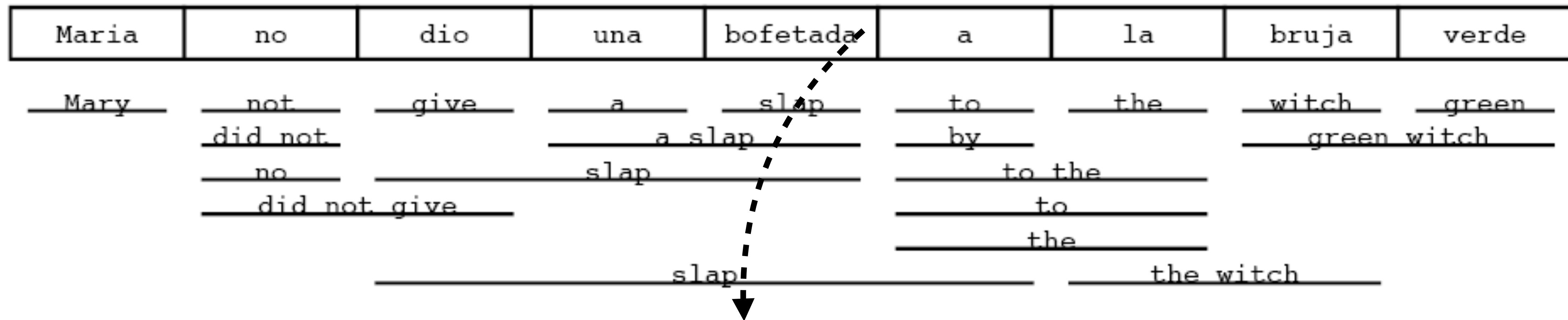
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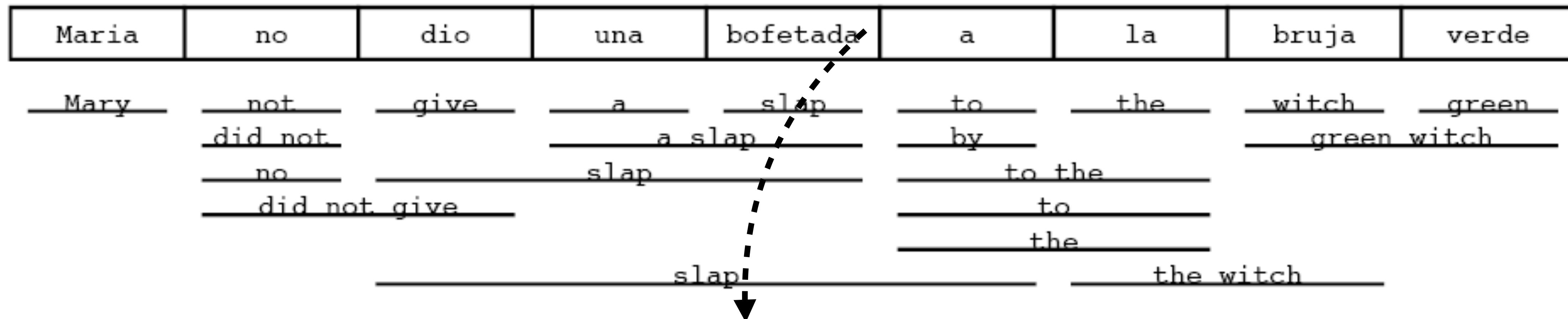
Monotonic Translation



...not slap idx = 5	8.7
...a slap idx = 5	-2.4
...no slap idx = 5	-1.1

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

Monotonic Translation



...not give
idx = 3

una bofetada ||| a slap

...not slap
idx = 5

8.7

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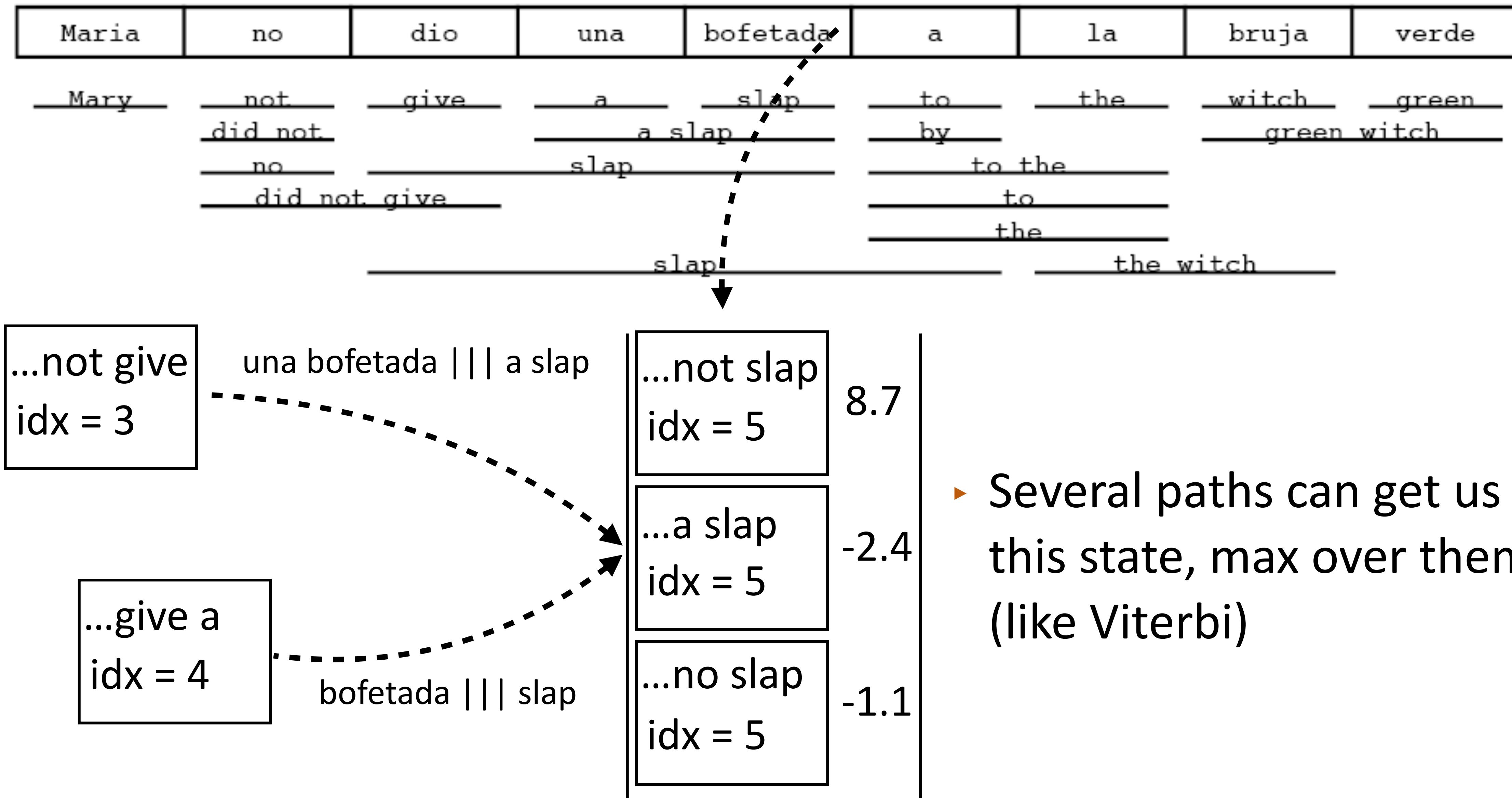
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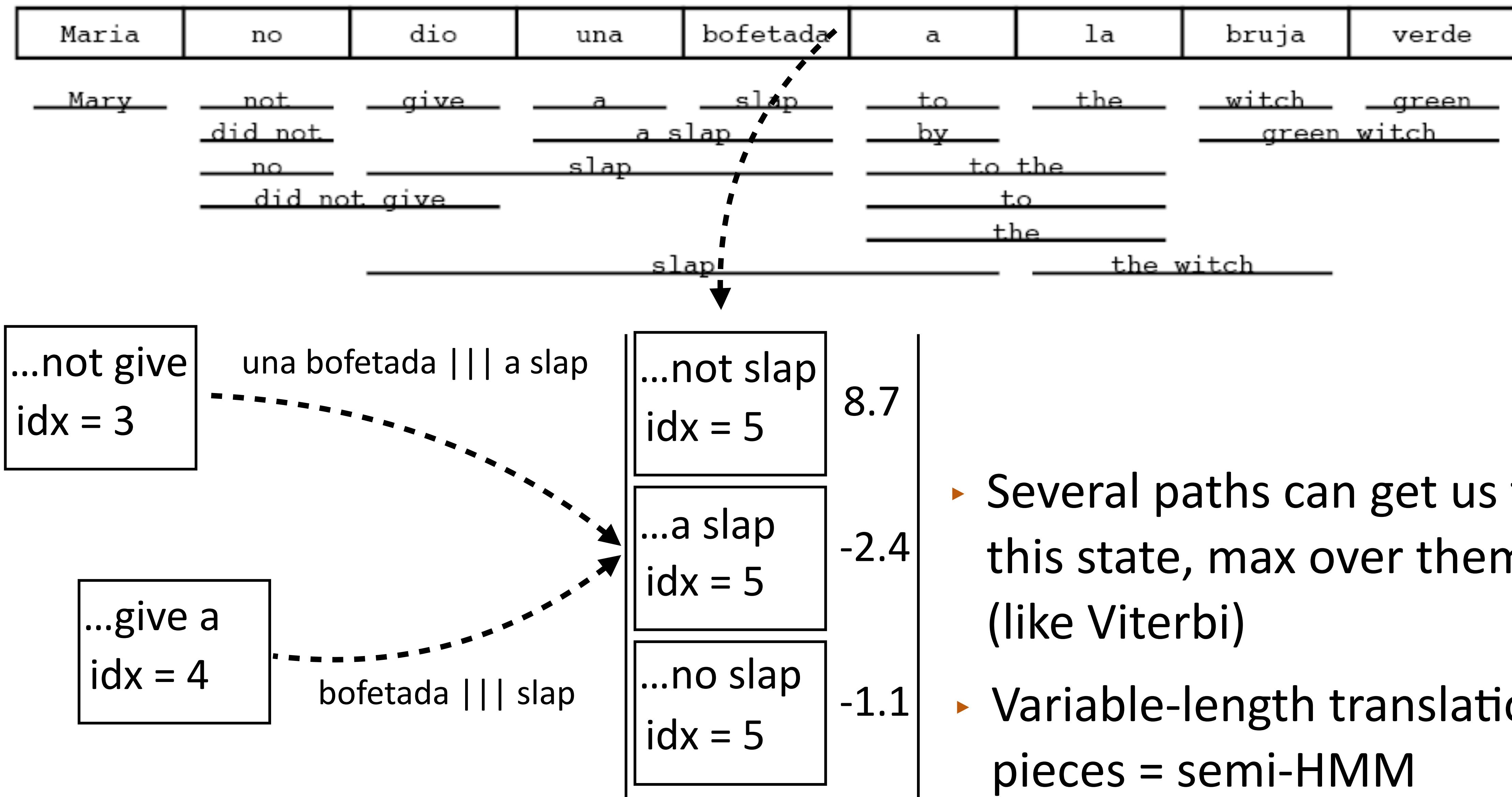
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Non-Monotonic Translation

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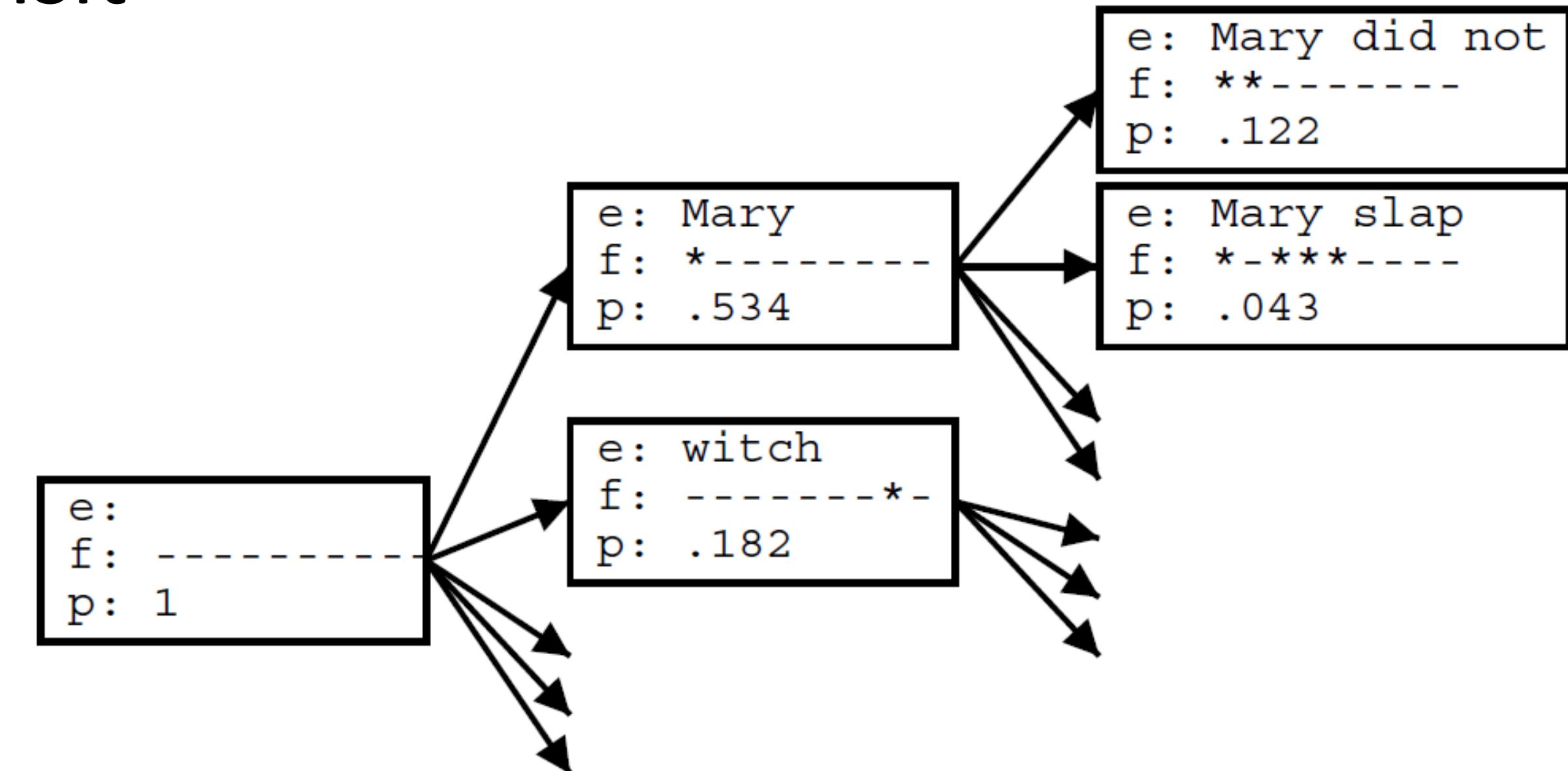
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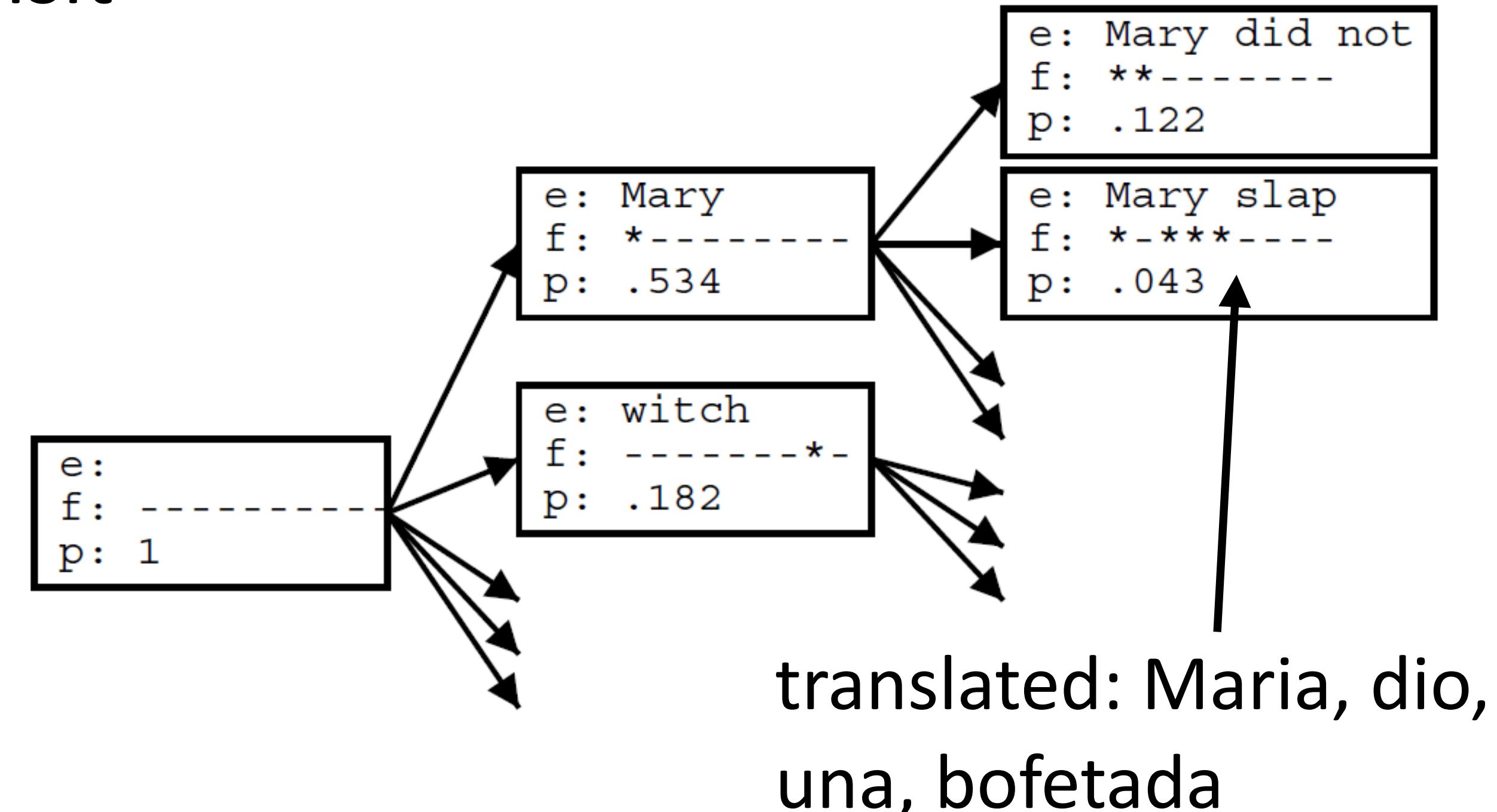
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						<u>the</u>		
				<u>slap</u>			<u>the witch</u>	

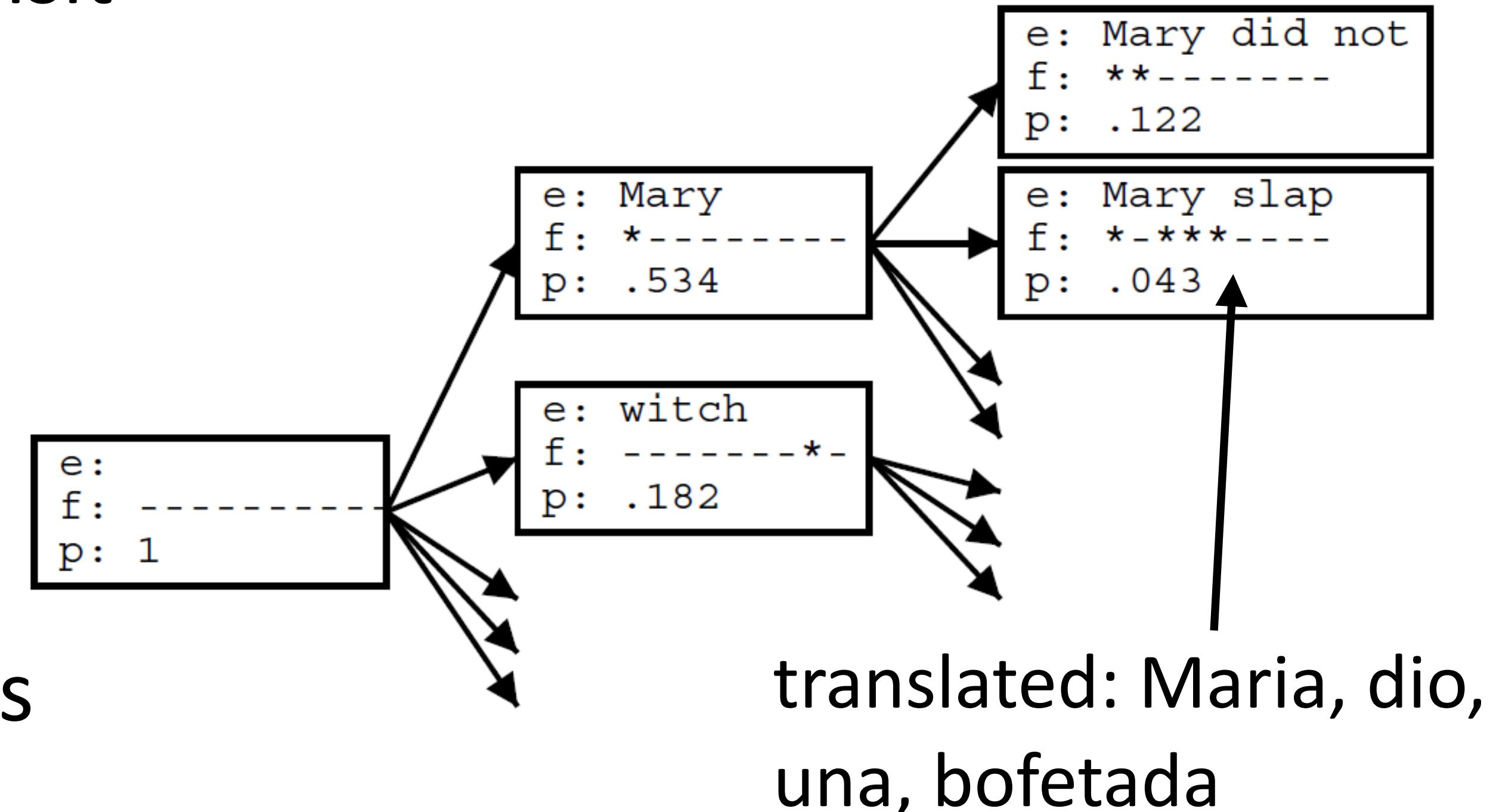
- ▶ Non-monotonic translation: can visit source sentence “out of order”
- ▶ State needs to describe which words have been translated and which haven’t



Non-Monotonic Translation

Maria	no	dio	una	bofetada	a	la	bruja	verde
<u>Mary</u>	<u>not</u>	<u>give</u>	<u>a</u>	<u>slap</u>	<u>to</u>	<u>the</u>	<u>witch</u>	<u>green</u>
	<u>did not</u>			<u>a slap</u>		<u>by</u>		<u>green witch</u>
	<u>no</u>			<u>slap</u>		<u>to the</u>		
						<u>to</u>		
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- ▶ 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



Training Decoders

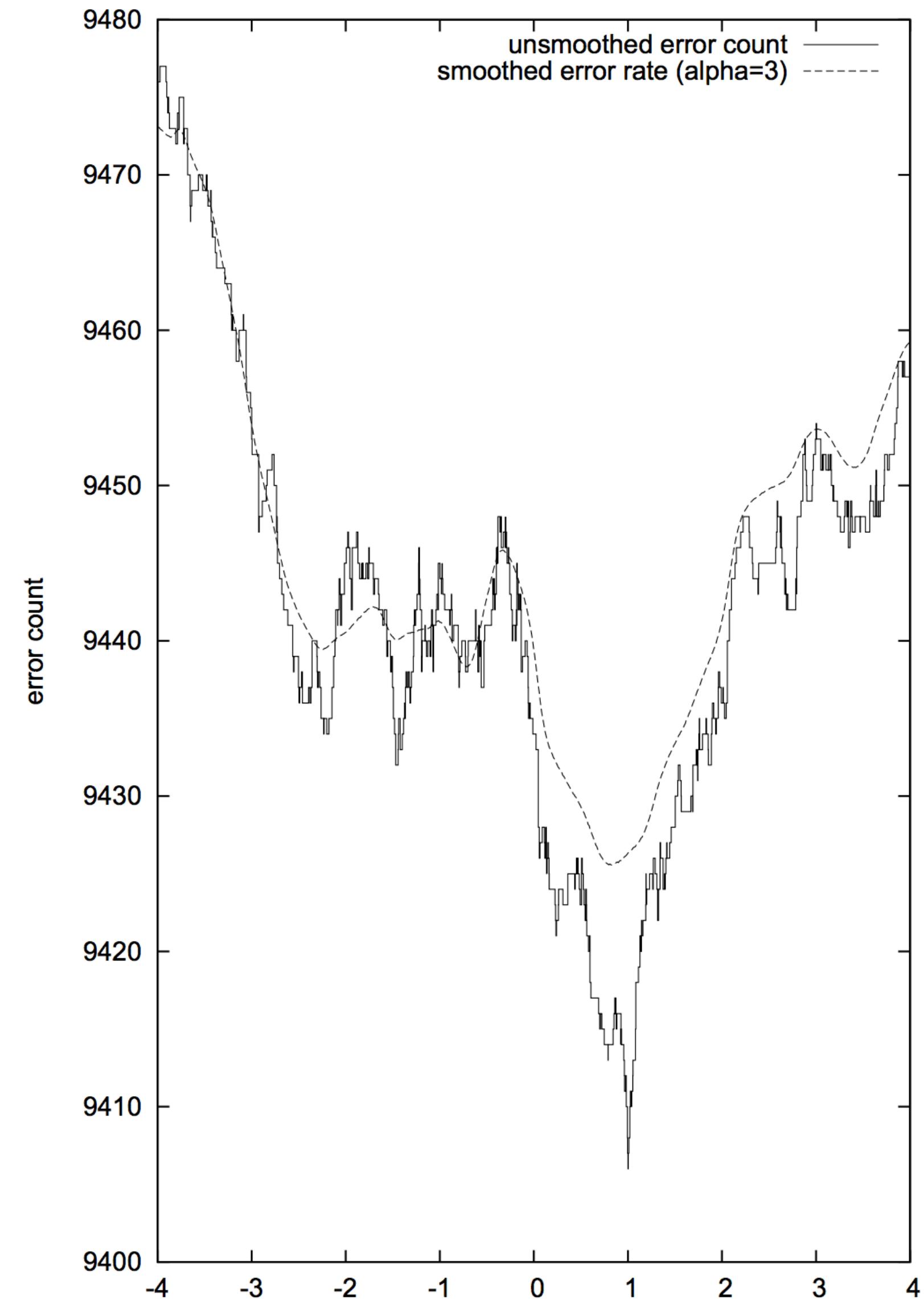
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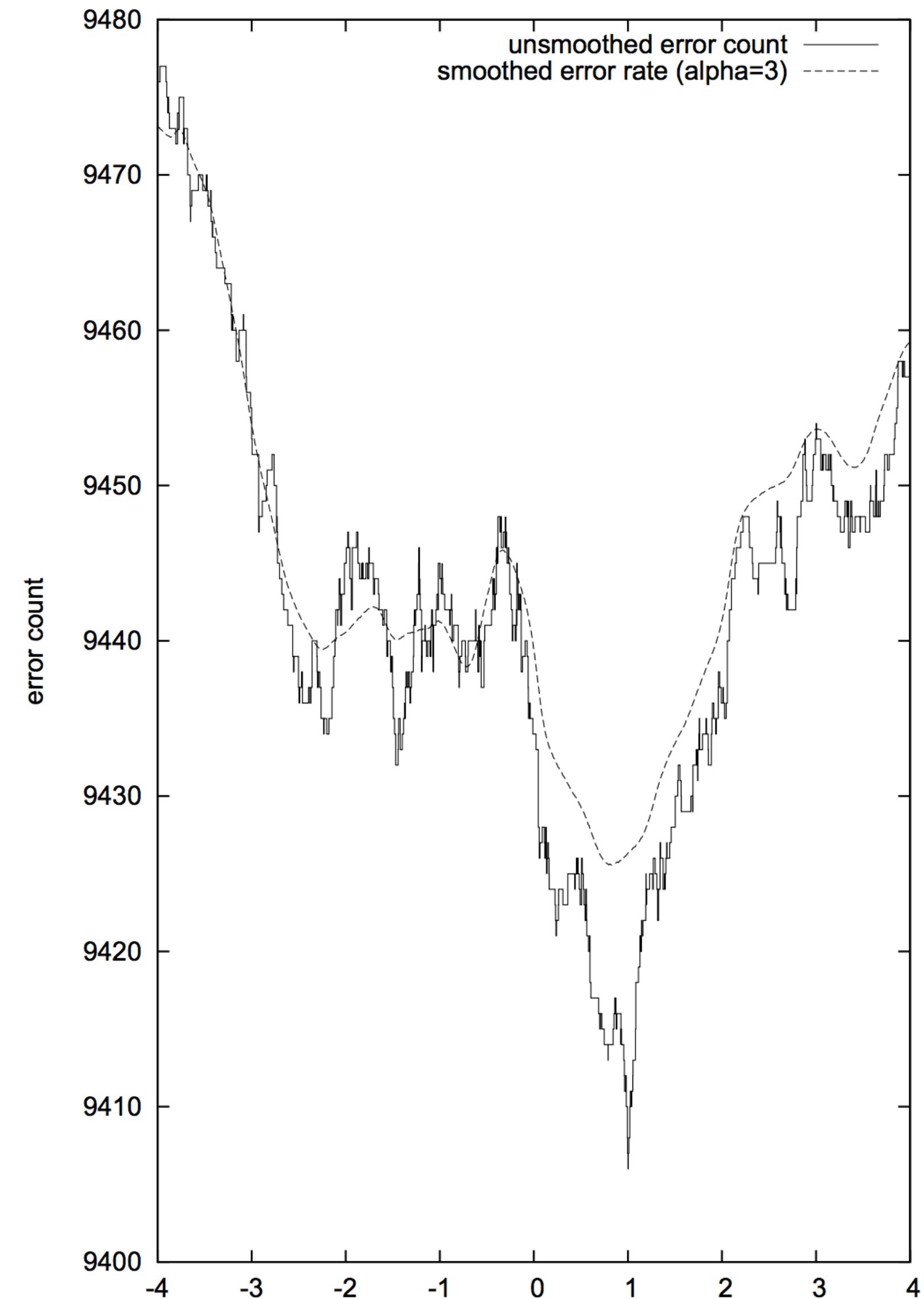


Training Decoders

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

...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

Syntax

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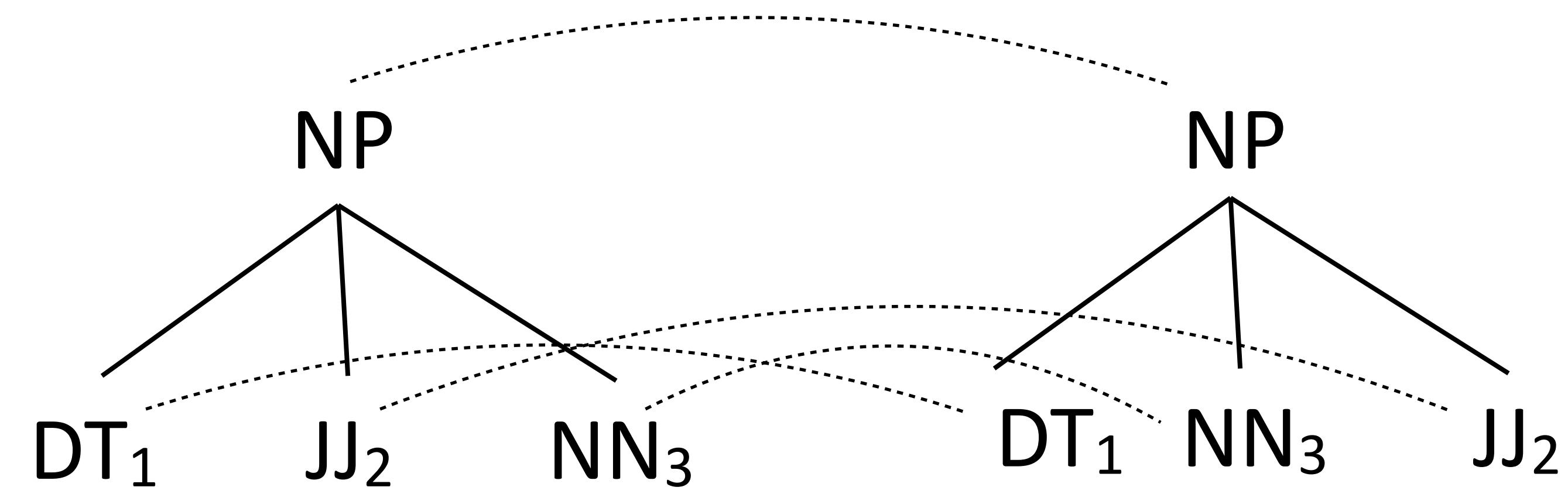
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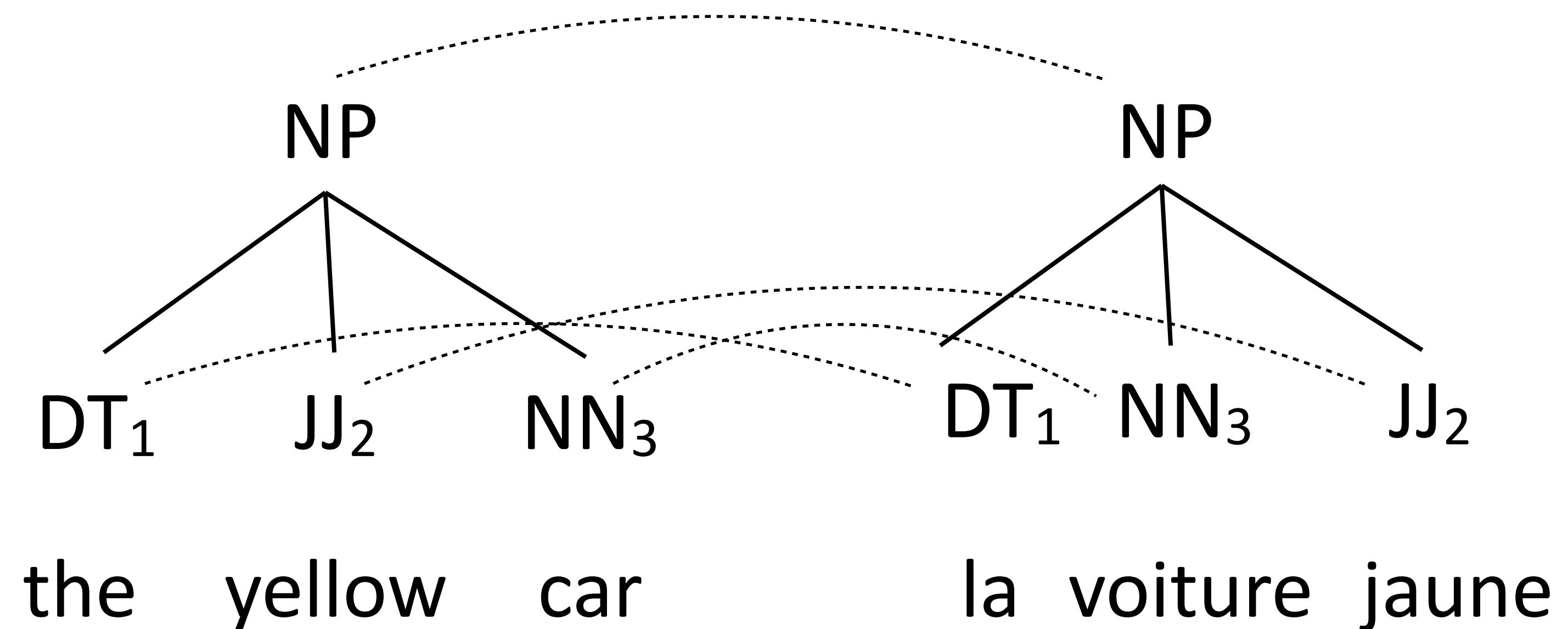
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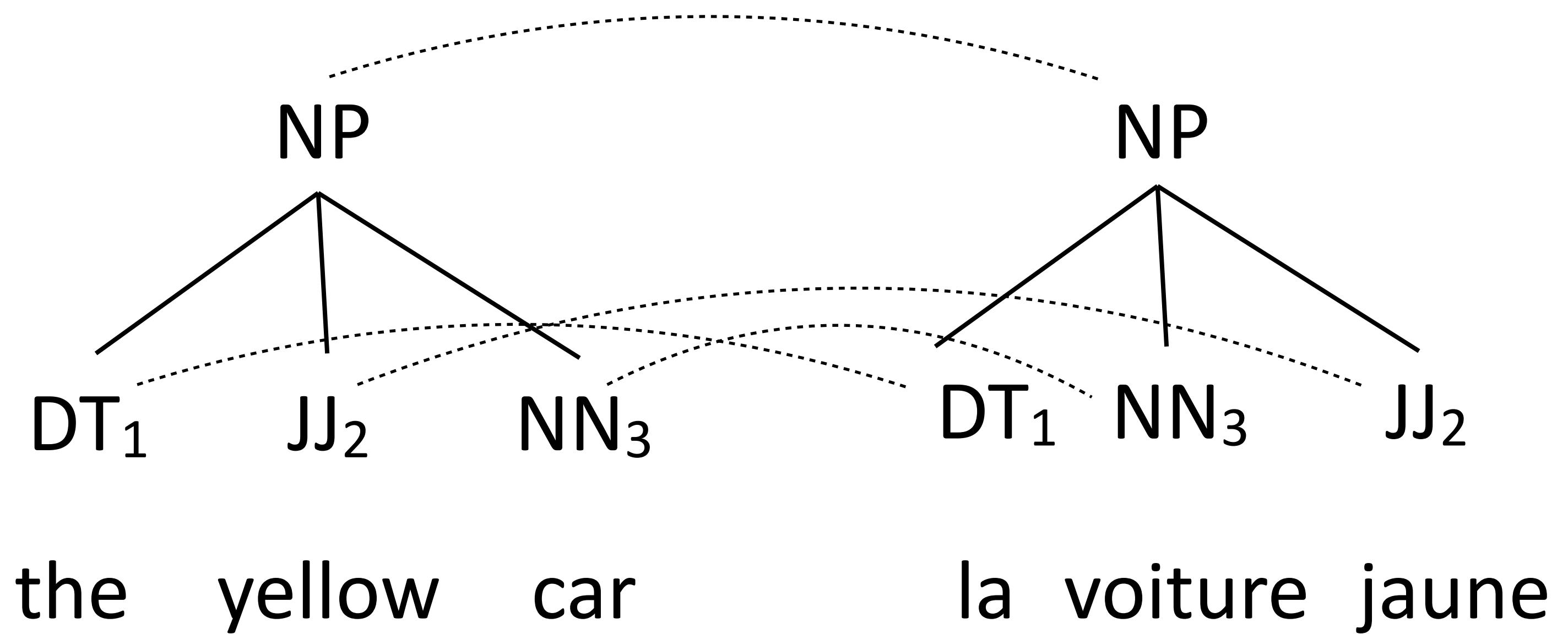
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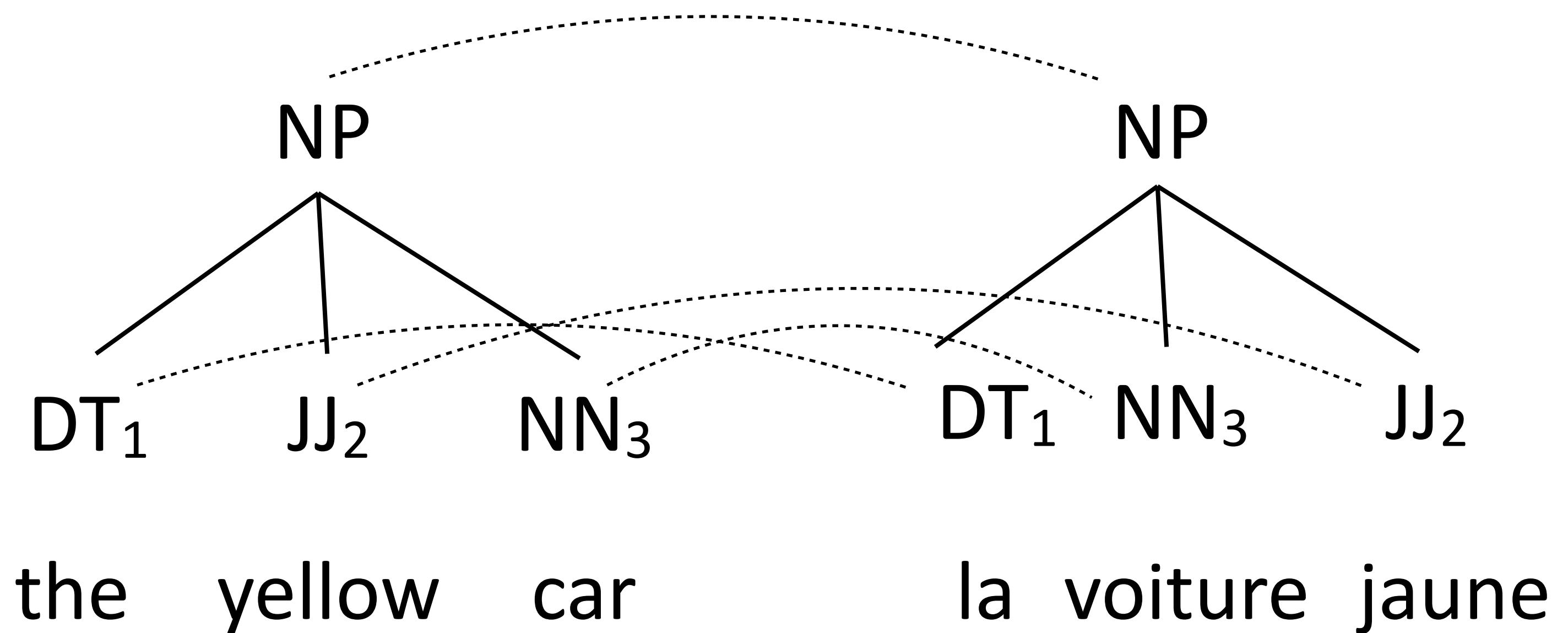
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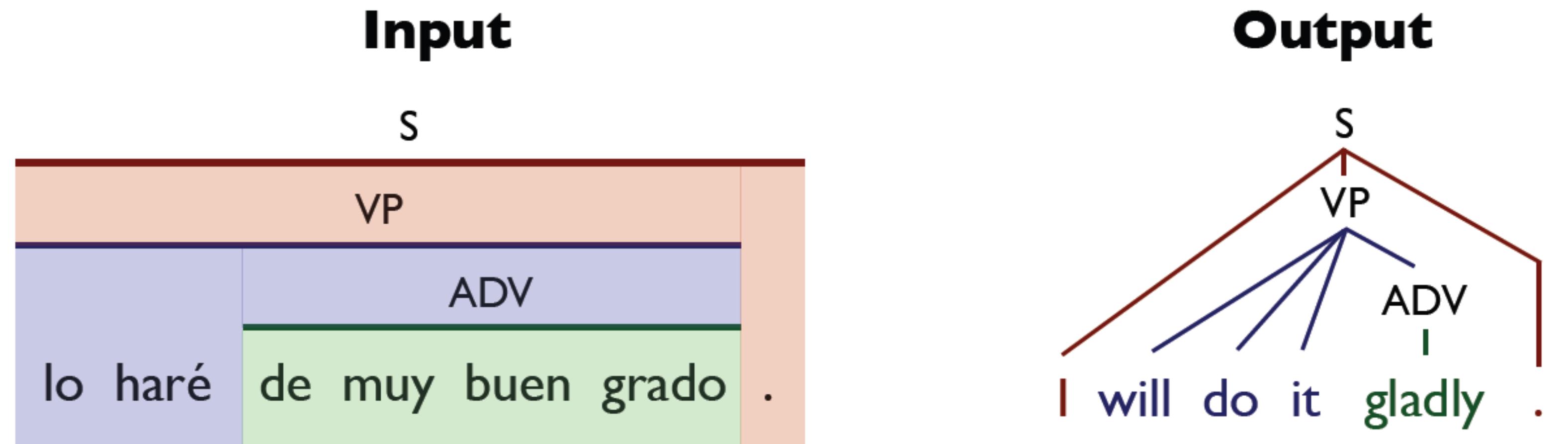
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- ▶ Translation = parse the input with “half” of the grammar, read off the other half
- ▶ Assumes parallel syntax up to reordering

Syntactic MT



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

Grammar

$$S \rightarrow \langle VP . ; I VP . \rangle \quad \text{OR} \quad S \rightarrow \langle VP . ; you VP . \rangle$$
$$VP \rightarrow \langle lo\haré\ ADV ; will\do\it\ ADV \rangle$$
$$S \rightarrow \langle lo\haré\ ADV . ; I will\do\it\ ADV . \rangle$$
$$ADV \rightarrow \langle de\muy\buen\grado ; gladly \rangle$$

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