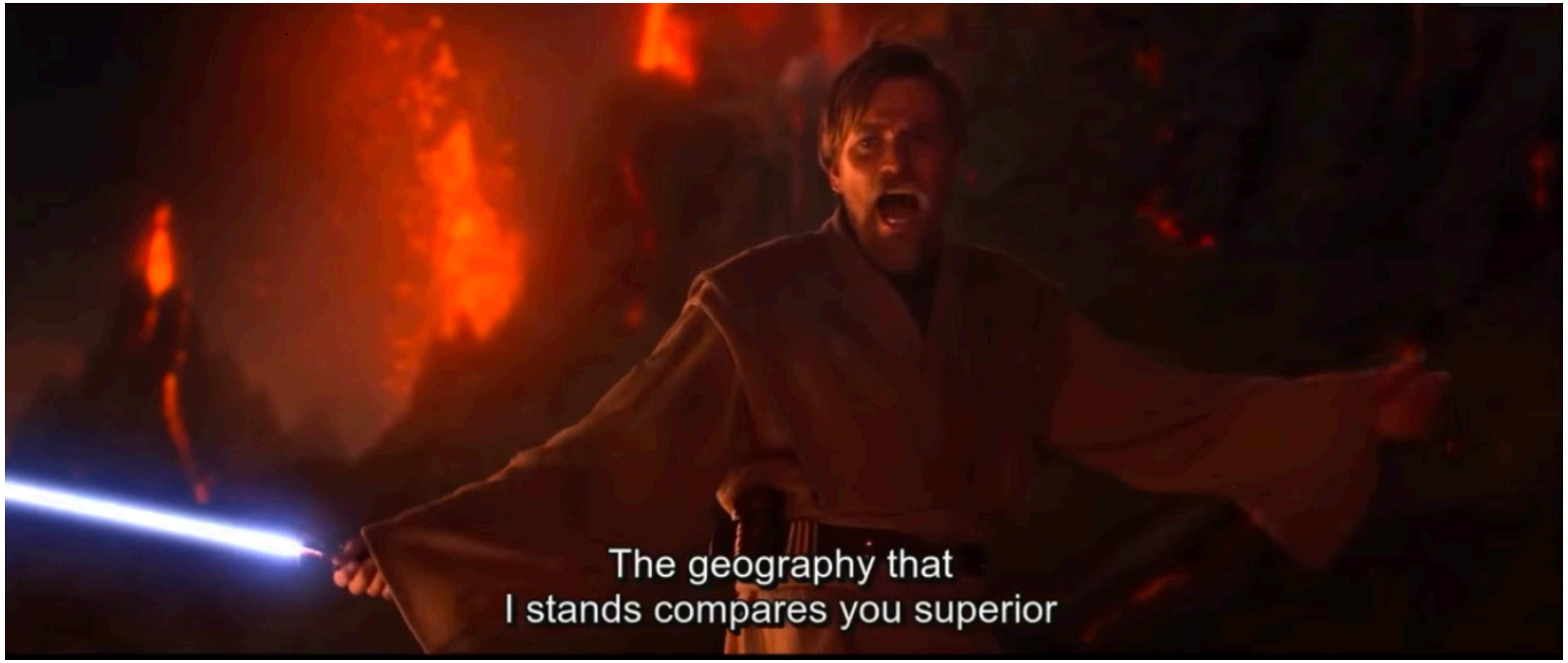
# CS388: Natural Language Processing

## Lecture 17: Machine Translation 1




Star Wars The Third Gathers: The Backstroke of the West
(subtitles machine translated from Chinese)

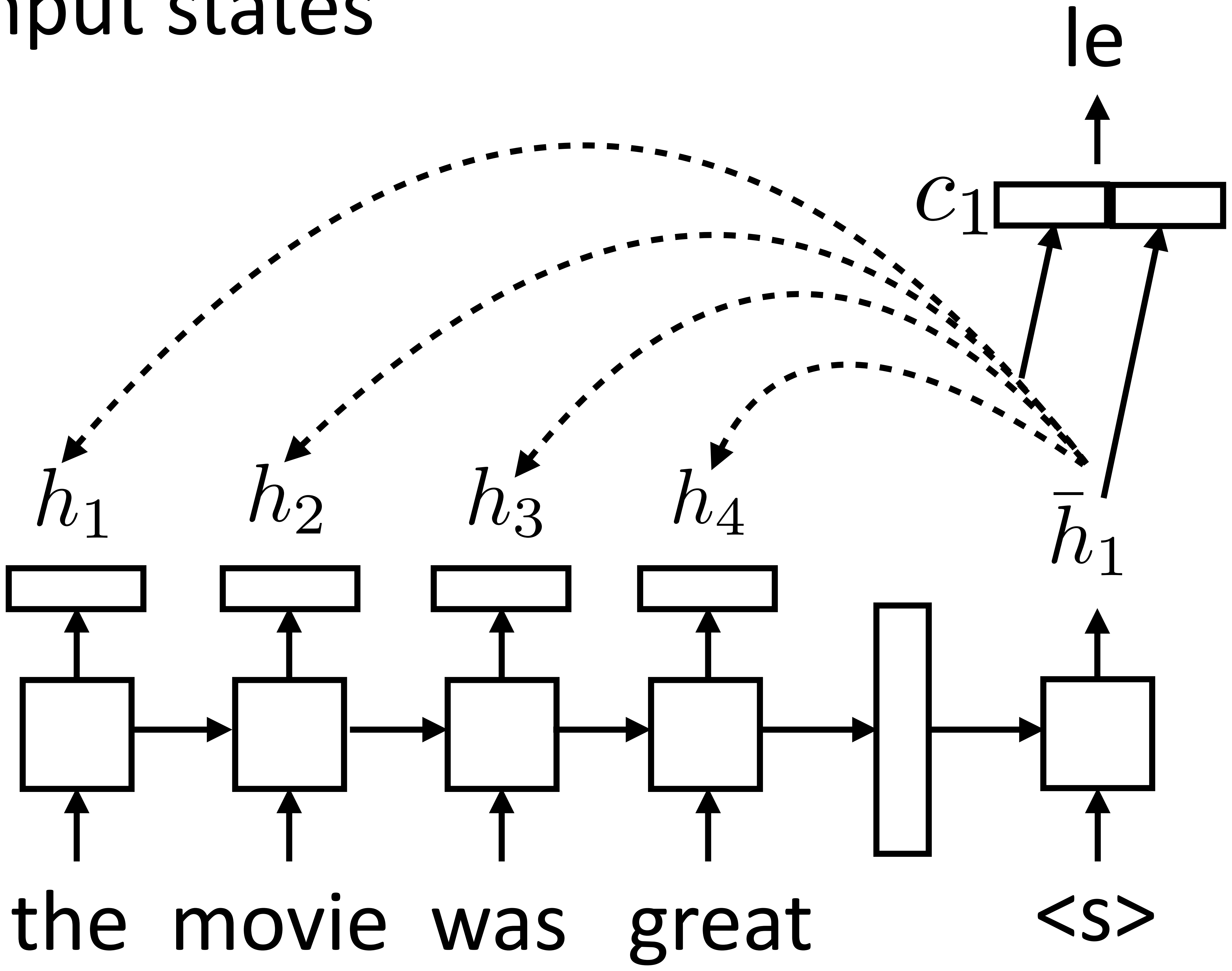
Greg Durrett

TEXAS
The University of Texas at Austin

Some slides adapted from Dan Klein, UC Berkeley

# Recall: Attention

- For each decoder state, compute weighted sum of input states



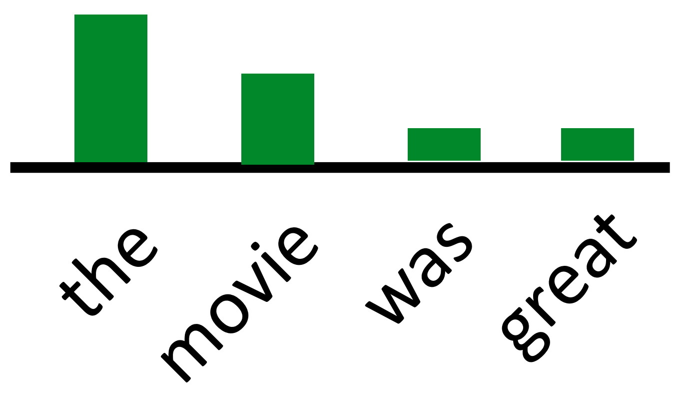

- No attn: $P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h}_i)$

$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W[c_i; \bar{h}_i])$$

$$c_i = \sum_j \alpha_{ij} h_j$$

- Weighted sum of input hidden states (vector)

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

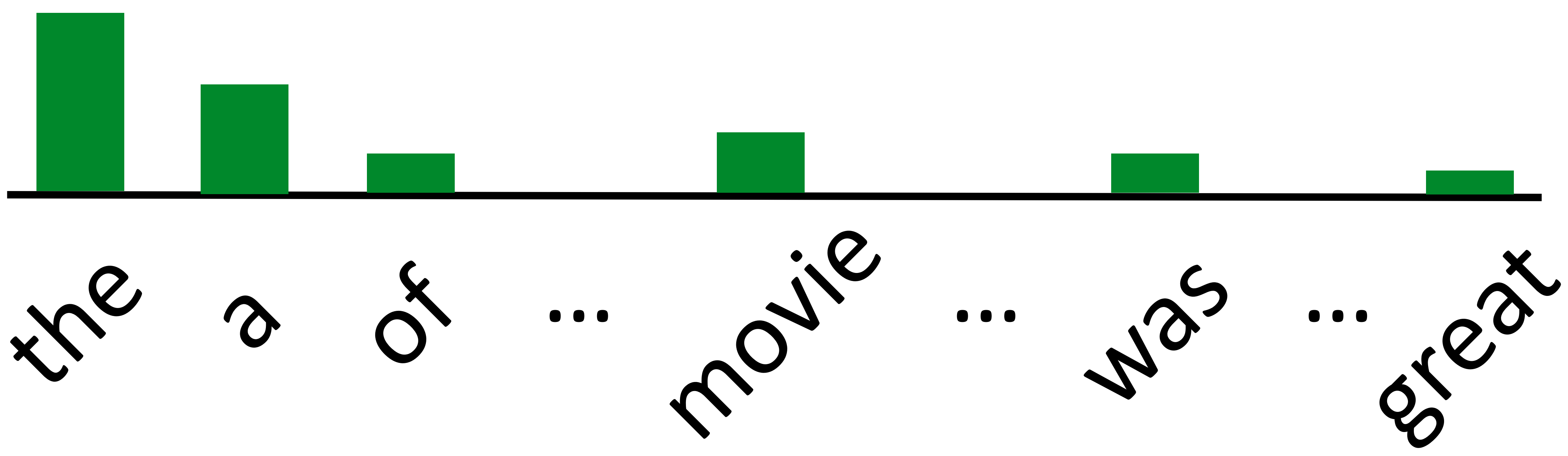



$$e_{ij} = f(\bar{h}_i, h_j)$$

- Some function $f$ (TBD)

# Recall: Pointer Networks

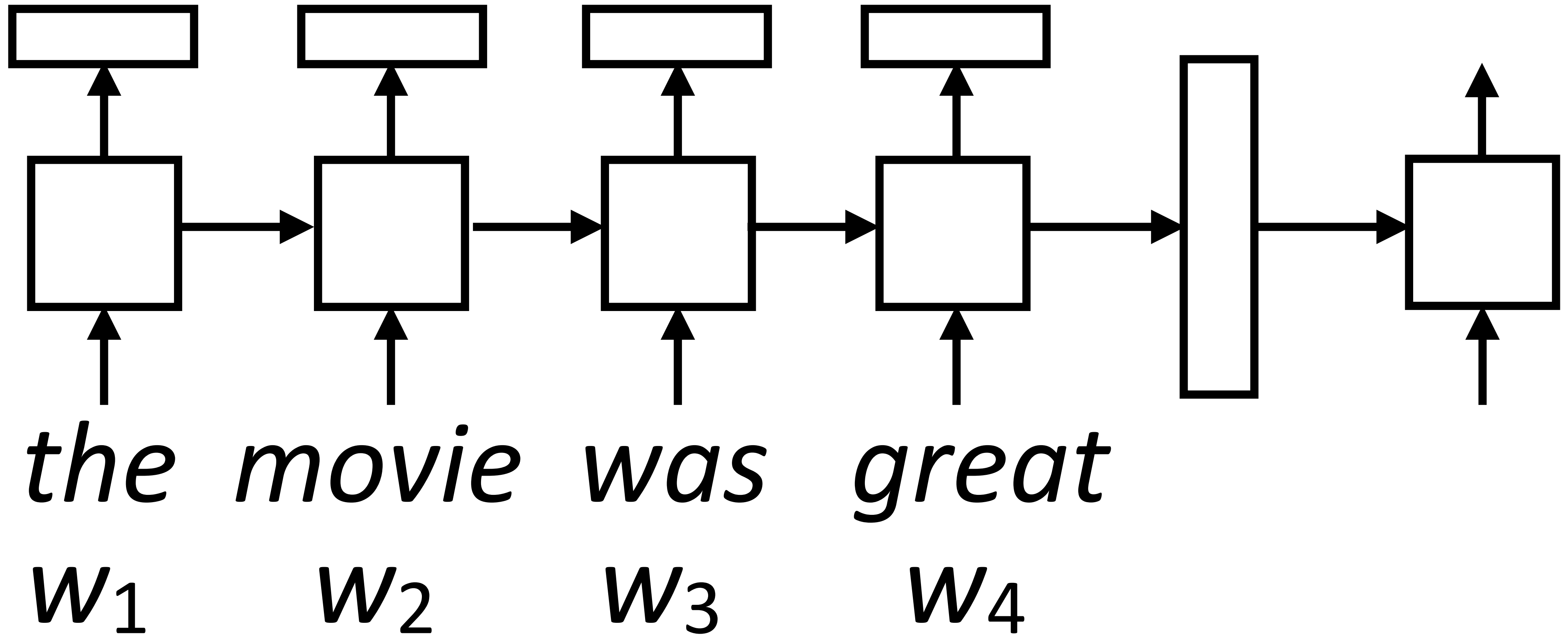
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W[c_i; \bar{h}_i])$$

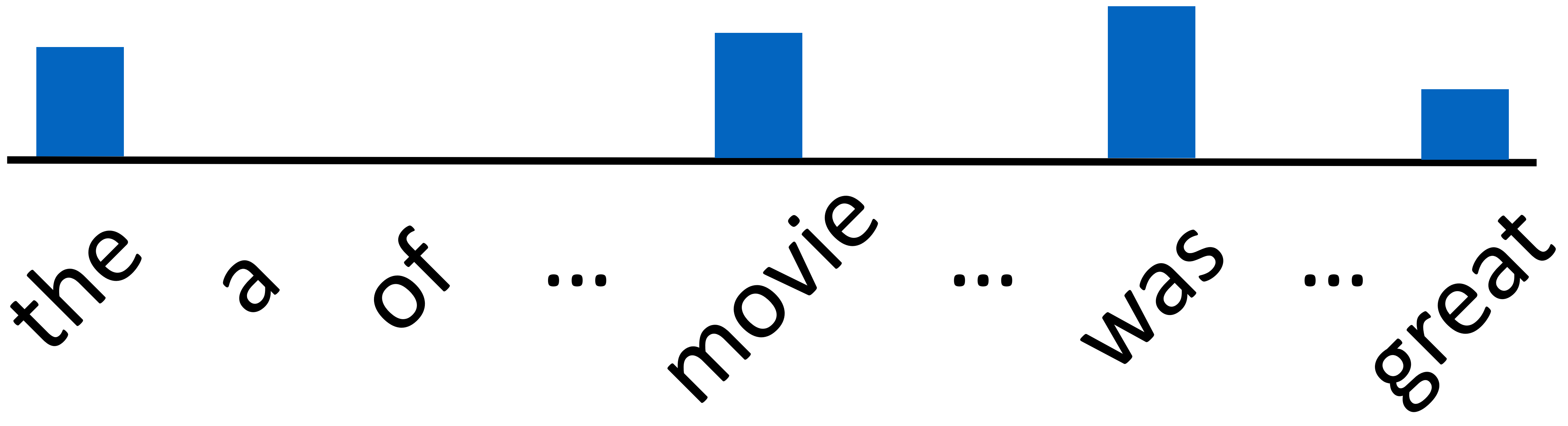



- Standard decoder ($P_{\text{vocab}}$): softmax over vocabulary, all words get >0 prob

- Pointer network: predict from *source words* instead of *target vocab*

$$P_{\text{pointer}}(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) \propto \begin{cases} h_j^\top V \bar{h}_i \text{ if } y_i = w_j \\ \text{0 otherwise} \end{cases}$$



# This Lecture

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

# MT Basics

# MT


People's Daily, August 30, 2017

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

# MT Ideally

- *I have a friend* => `∃x friend(x,self)` => *J'ai un ami*

  *J'ai une amie* (friend is female)

  - May need information you didn't think about in your representation
  - Hard for semantic representations to cover everything

- 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

# MT in Practice

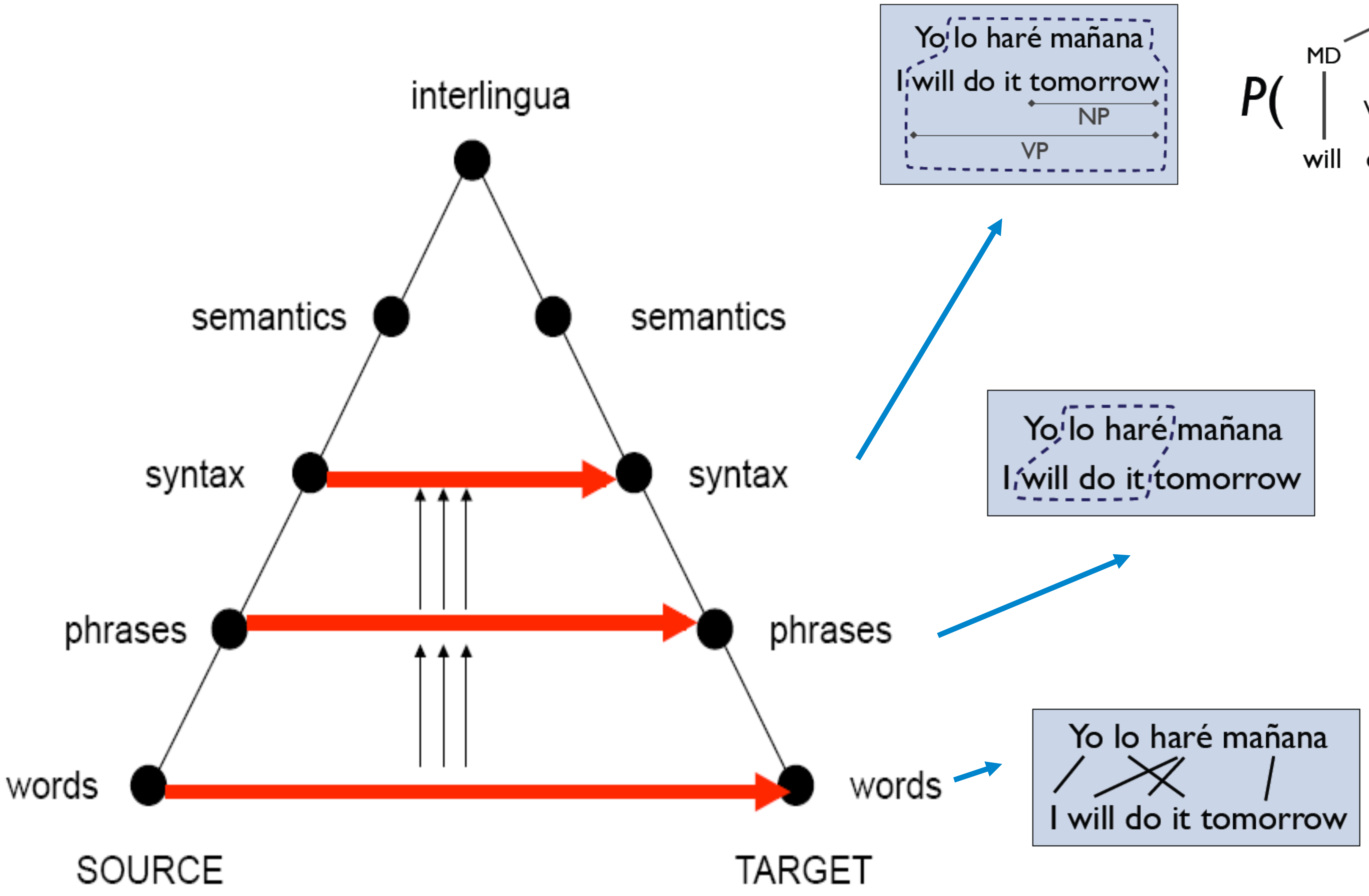
- Bitext: this is what we learn translation systems from

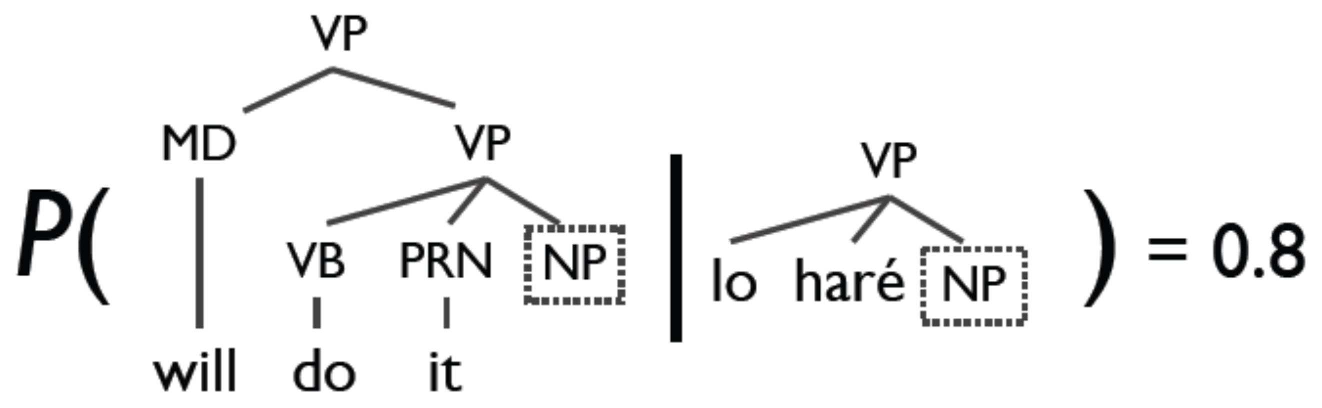
| | |
|---|---|
| Je fais un bureau | I'm making a desk |
| Je fais une soupe | I'm making soup |
| Je fais un bureau | I make a desk |
| Qu'est-ce que tu fais? | What are you making? |

- What are some translation pairs you can identify? How do you know?

- What makes this hard? Not word-to-word translation
  Multiple translations of a single source (ambiguous)

# 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

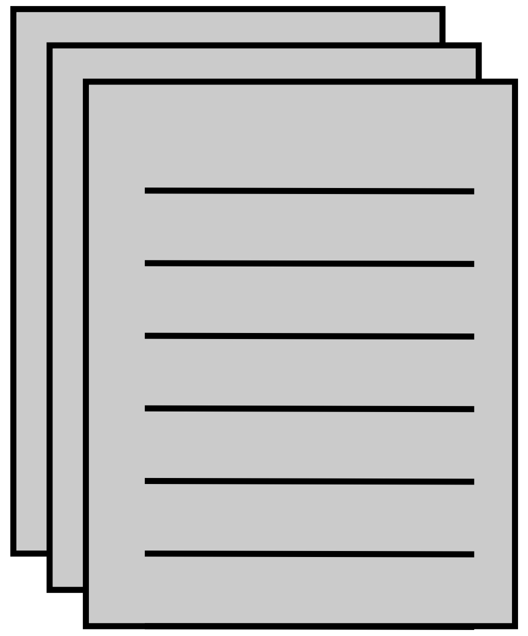
# Phrase-Based MT

- Key idea: translation works better the bigger chunks you use
- Remember phrases from training data, translate piece-by-piece and stitch those pieces together to translate
  - 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"

# Evaluating MT

- Fluency: does it sound good in the target language?
- Fidelity/adequacy: does it capture the meaning of the original?
- BLEU score: geometric mean of 1-, 2-, 3-, and 4-gram *precision* vs. a reference, multiplied by brevity penalty (penalizes short translations)

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right).$$

- Typically $n$ = 4, $w_i$ = 1/4

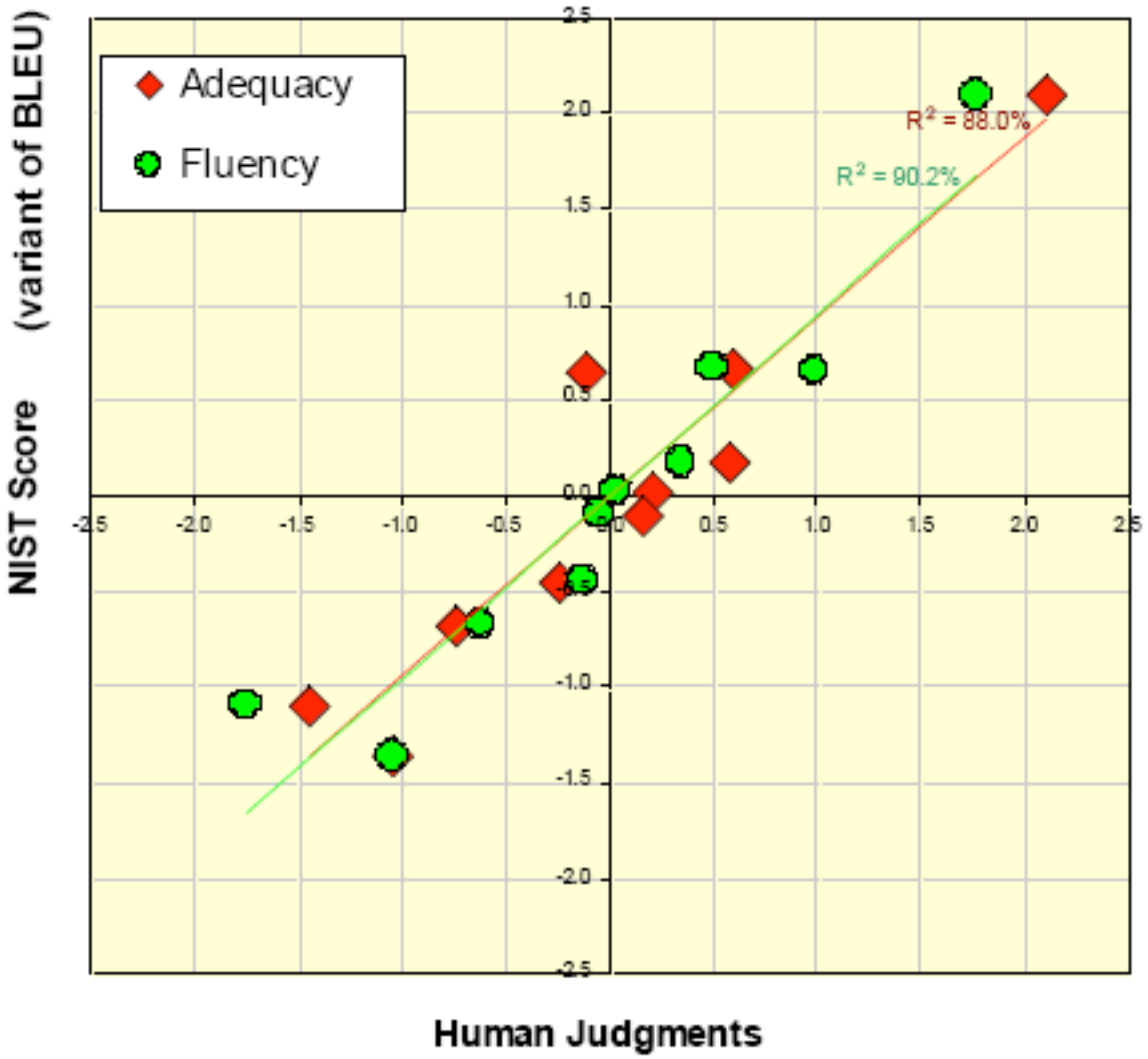
$$\text{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}.$$

r = length of reference
c = length of prediction

- Does this capture fluency and adequacy?

# BLEU Score

- At a *corpus* level, BLEU correlates pretty well with human judgments
- Better methods with human-in-the-loop
- If you're building real MT systems, you do user studies. In academia, you mostly use BLEU




slide from G. Doddington (NIST)

# Word Alignment

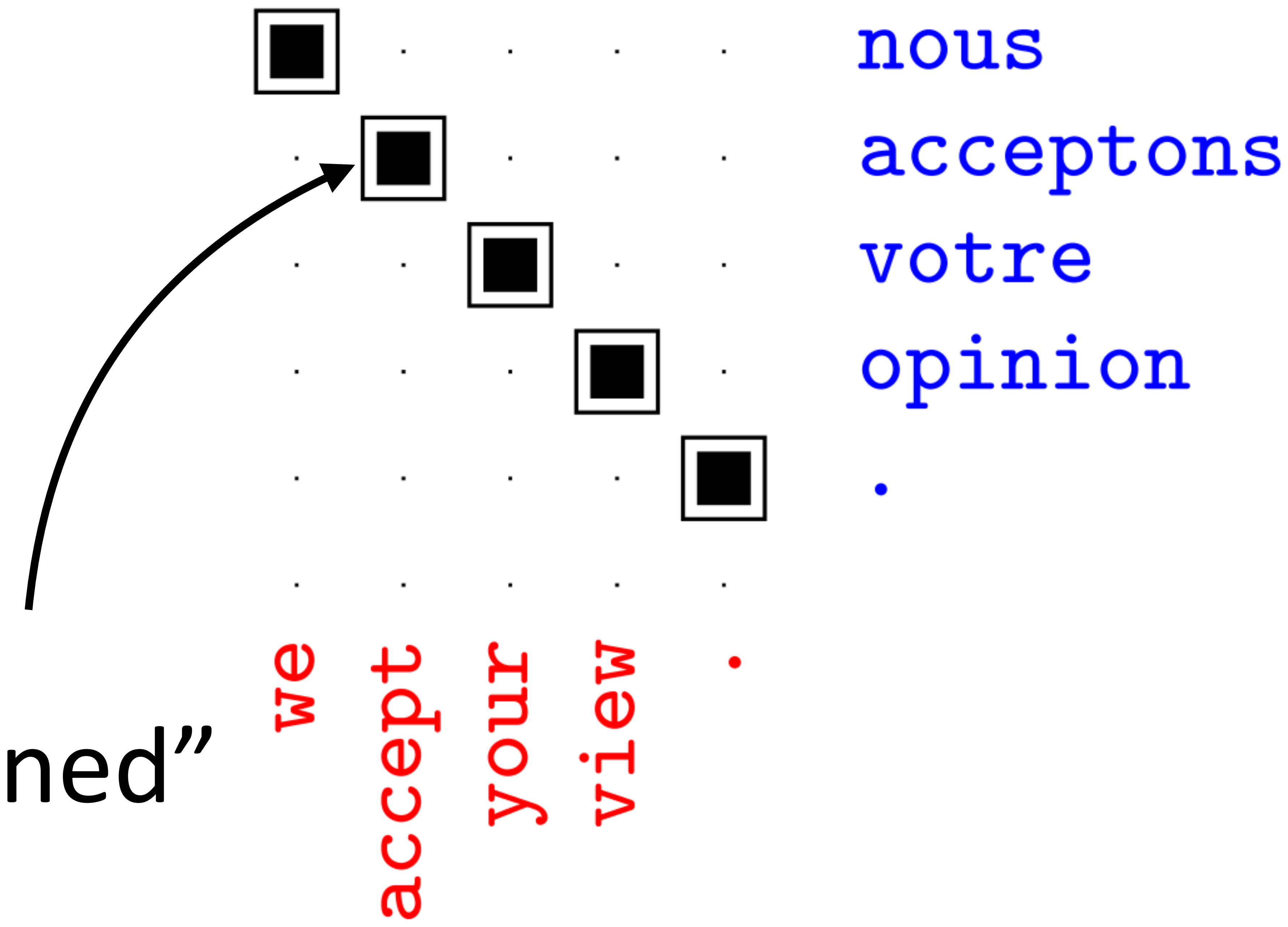
# Word Alignment

- Input: a bitext, pairs of translated sentences

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

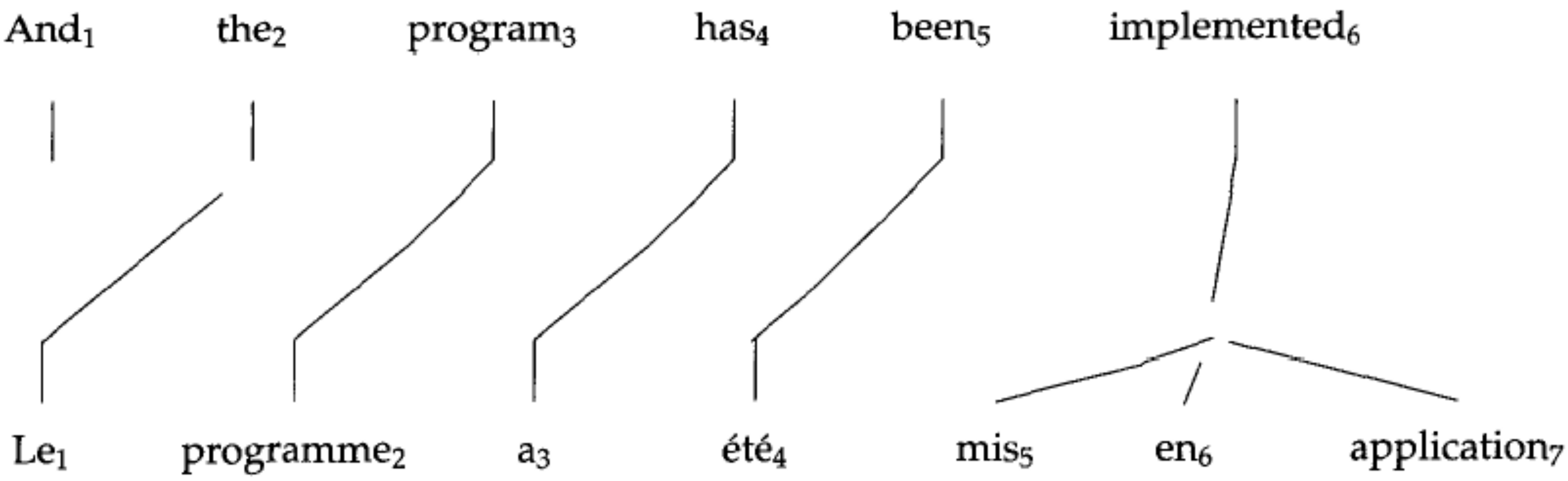
  nous allons changer d'avis ||| we are going to change our minds

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




"accept and acceptons are aligned"

# 1-to-Many Alignments



# Word Alignment

- Models P(**f**|**e**): probability of "French" sentence being generated from "English" sentence according to a model

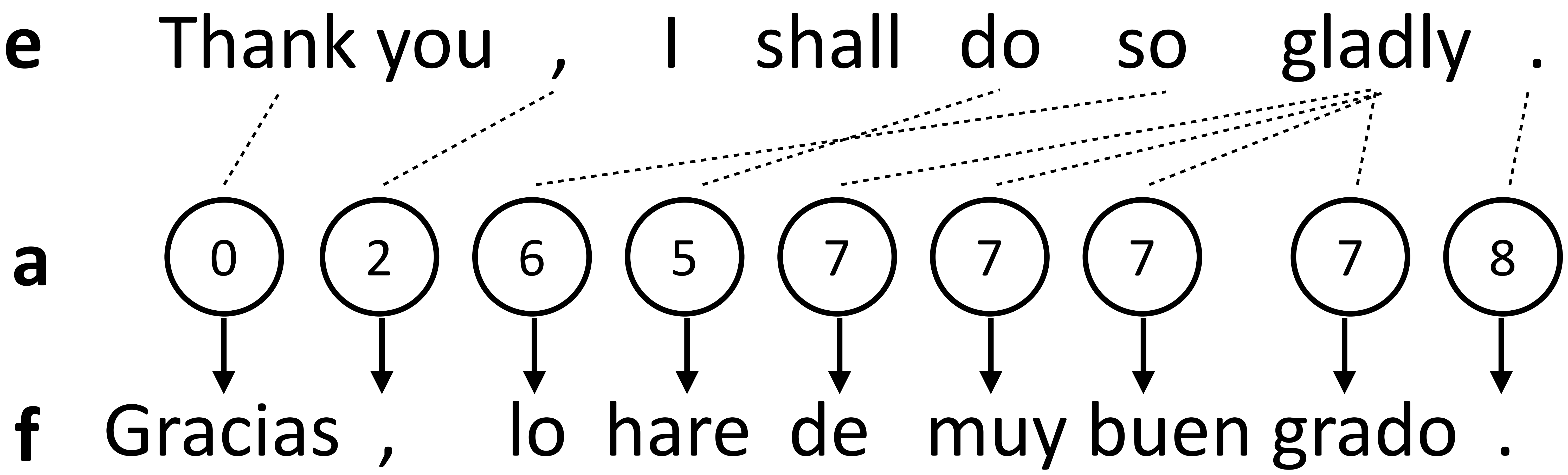
- Latent variable model: $P(\mathbf{f}|\mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}|\mathbf{a}, \mathbf{e}) P(\mathbf{a})$

- 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

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



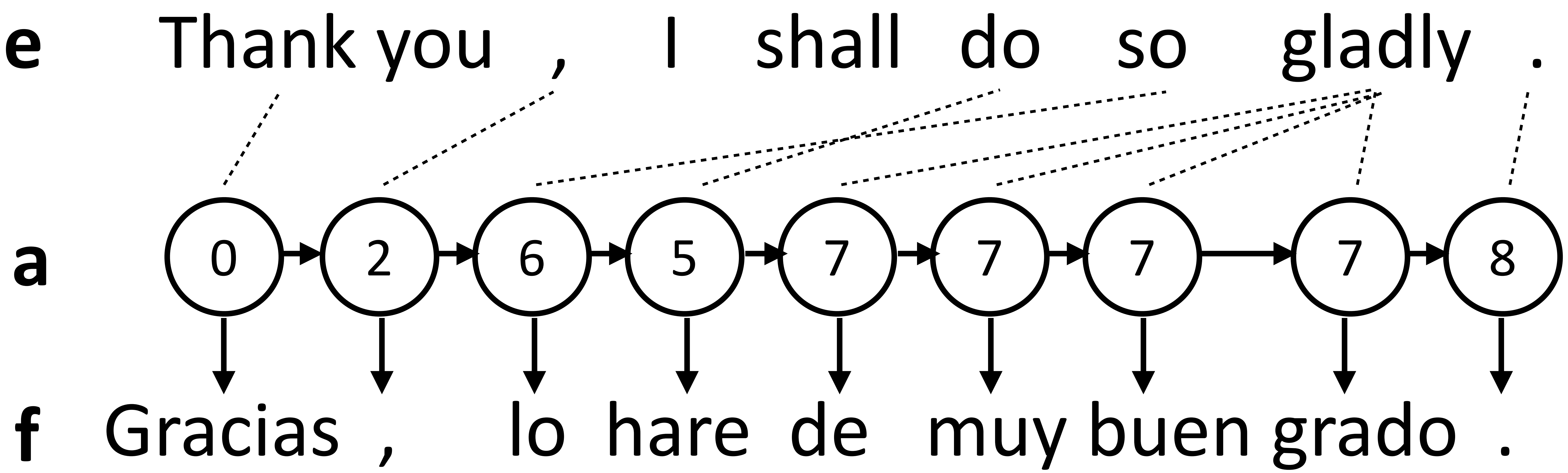

- Set P(a) uniformly (no prior over good alignments)
- $P(f_i|e_{a_i})$: word translation probability table

Brown et al. (1993)

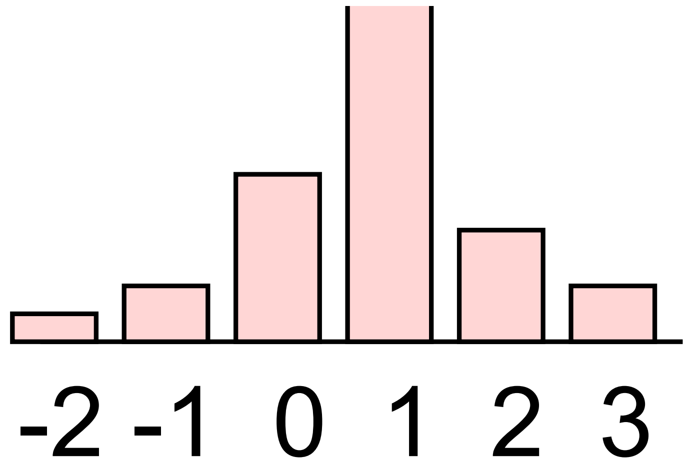
# HMM for Alignment

- Sequential dependence between a's to capture monotonicity

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




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

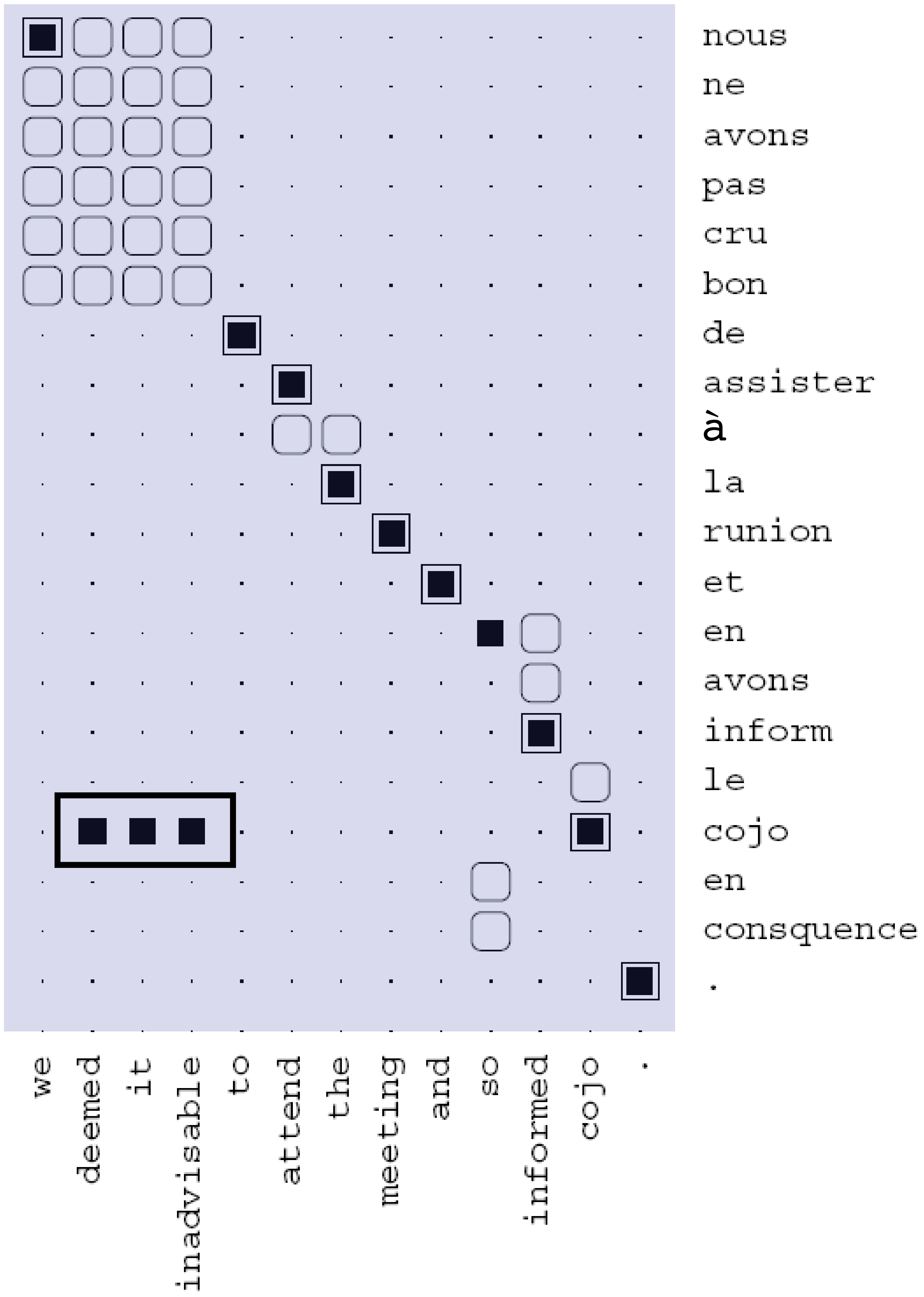



- $P(f_i|e_{a_i})$: same as before

Vogel et al. (1996)

# 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

  d'assister à la reunion et ||| to attend the meeting and

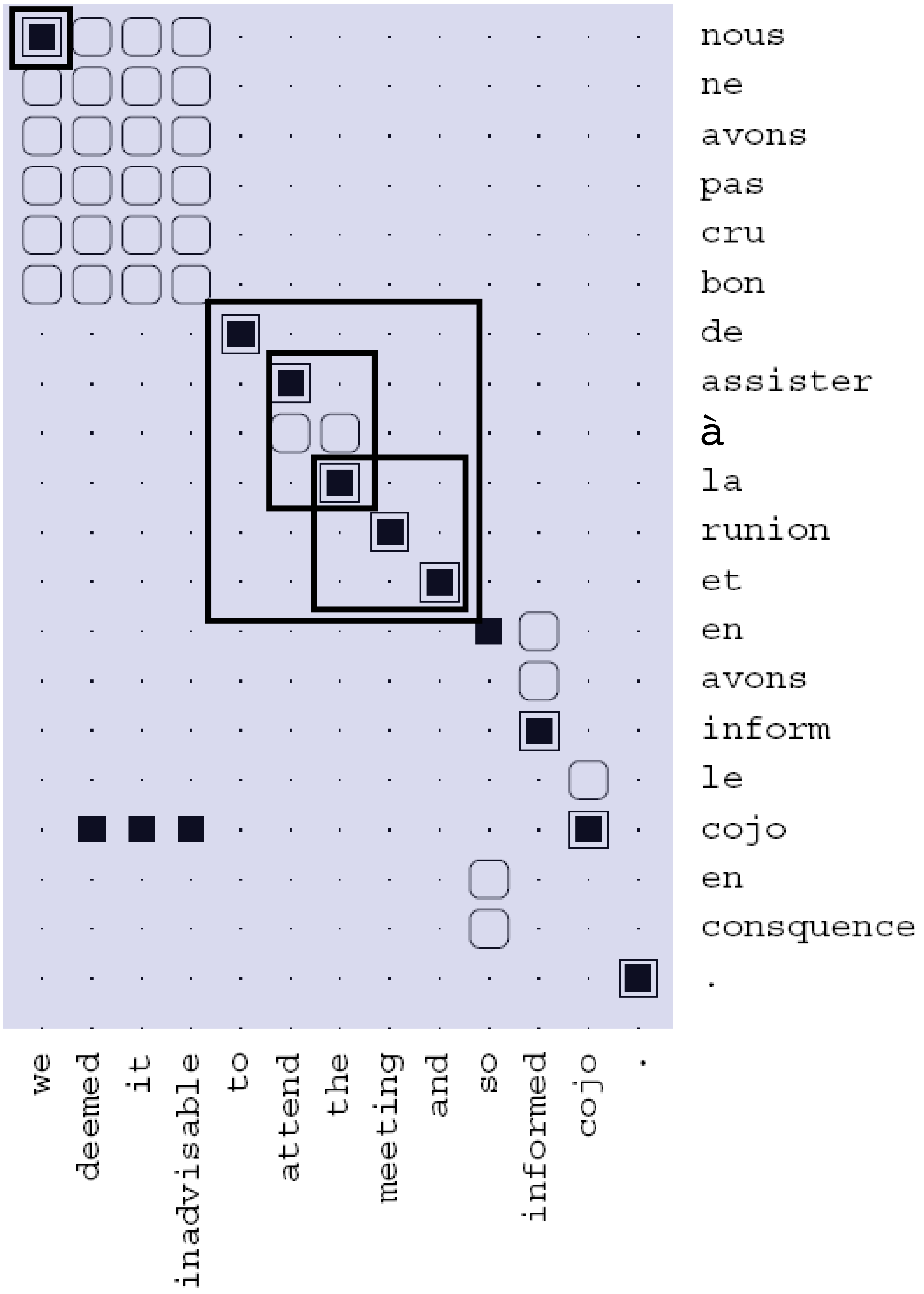
  assister à la reunion ||| attend the meeting

  la reunion and ||| the meeting and

  nous ||| we

  …

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



# Decoding

# Recall: *n*-gram Language Models

$$P(\mathbf{w}) = P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)\ldots$$

- *n*-gram models: distribution of next word is a multinomial conditioned on previous *n*-1 words $P(w_i|w_1, \ldots, w_{i-1}) = P(w_i|w_{i-n+1}, \ldots, w_{i-1})$

I visited San ______ put a distribution over the next word

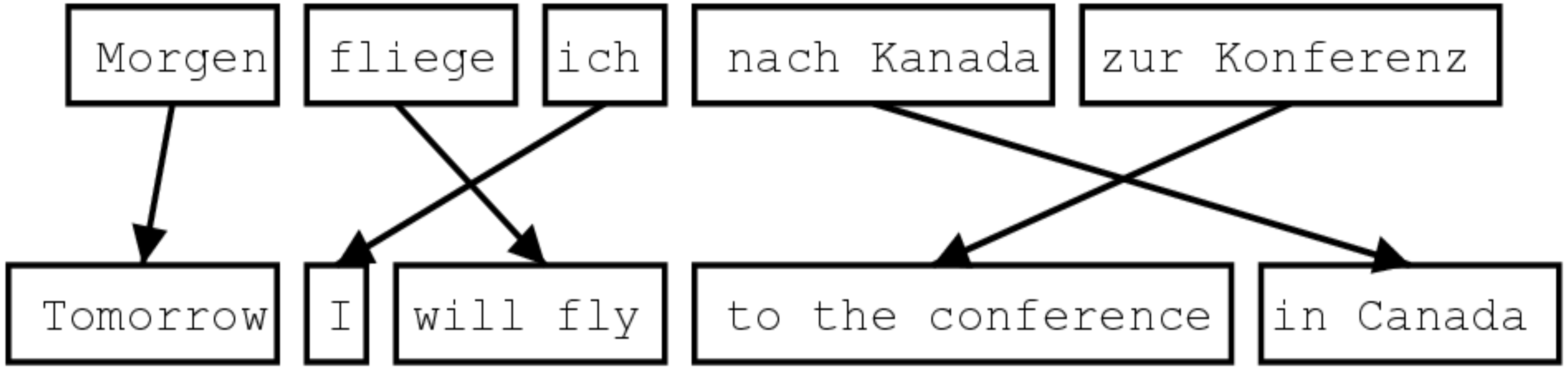
$$P(w|\text{visited San}) = \frac{\text{count}(\text{visited San}, w)}{\text{count}(\text{visited San})}$$

Maximum likelihood estimate of this 3-gram probability from a corpus

- Typically use ~5-gram language models for translation

# Phrase-Based Decoding

- Inputs:
  - n-gram language model: $P(e_i|e_1,\ldots,e_{i-1}) \approx P(e_i|e_{i-n-1},\ldots,e_{i-1})$
  - Phrase table: set of phrase pairs (**e**, **f**) with probabilities P(**f**|**e**)
- What we want to find: **e** produced by a series of phrase-by-phrase translations from an input **f**, possibly with reordering:



# 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.*

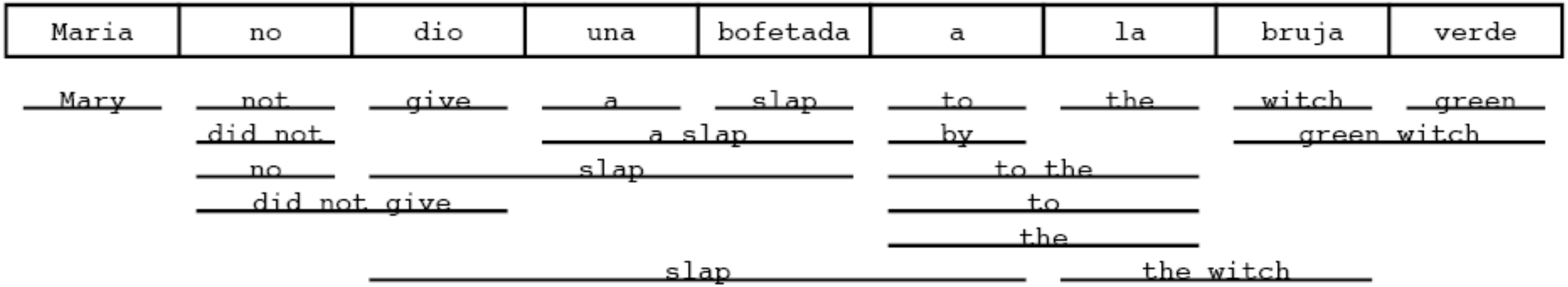
$$\arg\max_{\mathbf{e}} \left[ P(\mathbf{f}|\mathbf{e}) \cdot P(\mathbf{e}) \right]$$

- 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

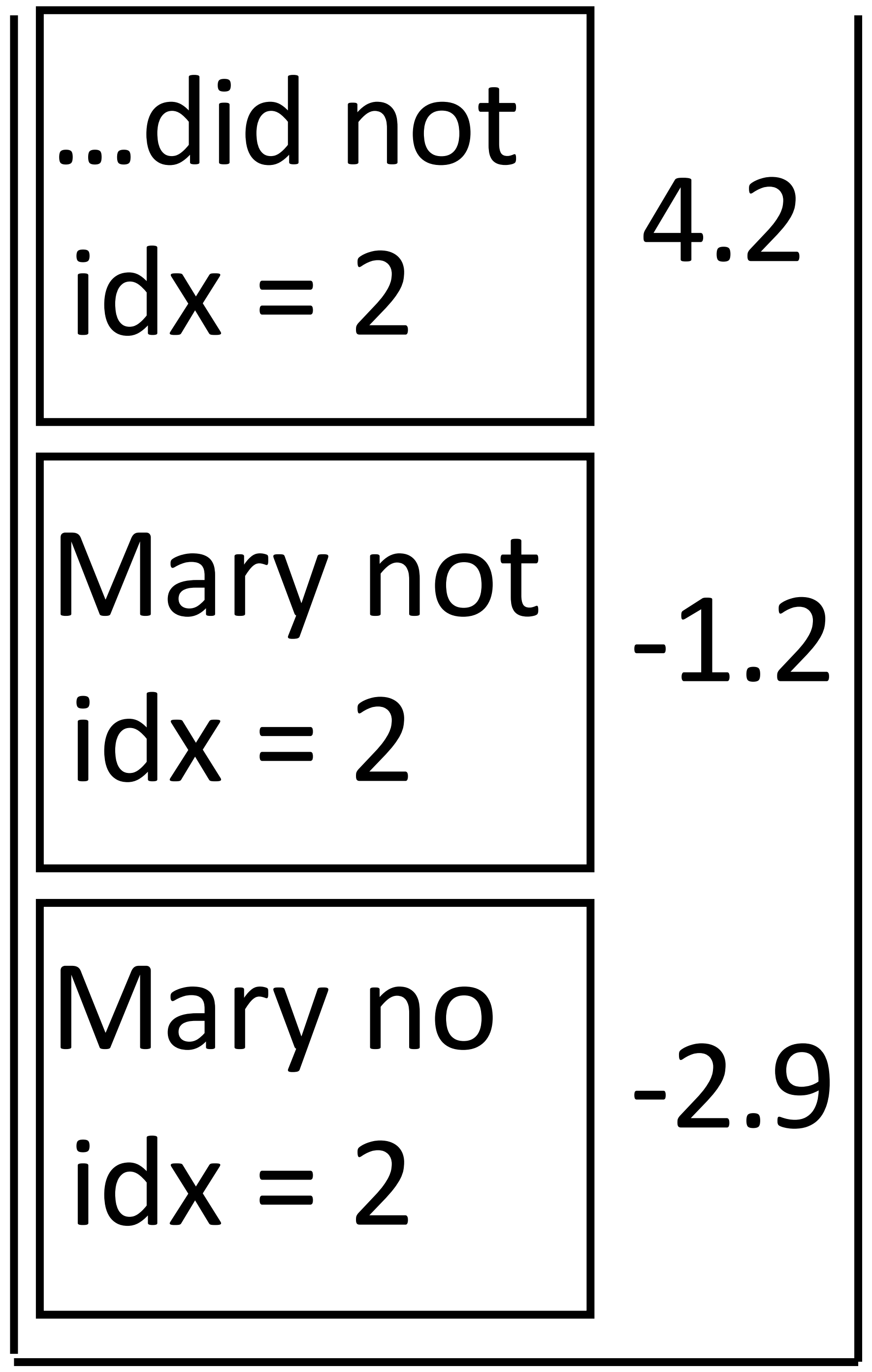



- If we translate with beam search, what state do we need to keep in the beam?
  - What have we translated so far?
  - What words have we produced so far?
  - When using a 3-gram LM, only need to remember the last 2 words!

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

Koehn (2004)

# Monotonic Translation

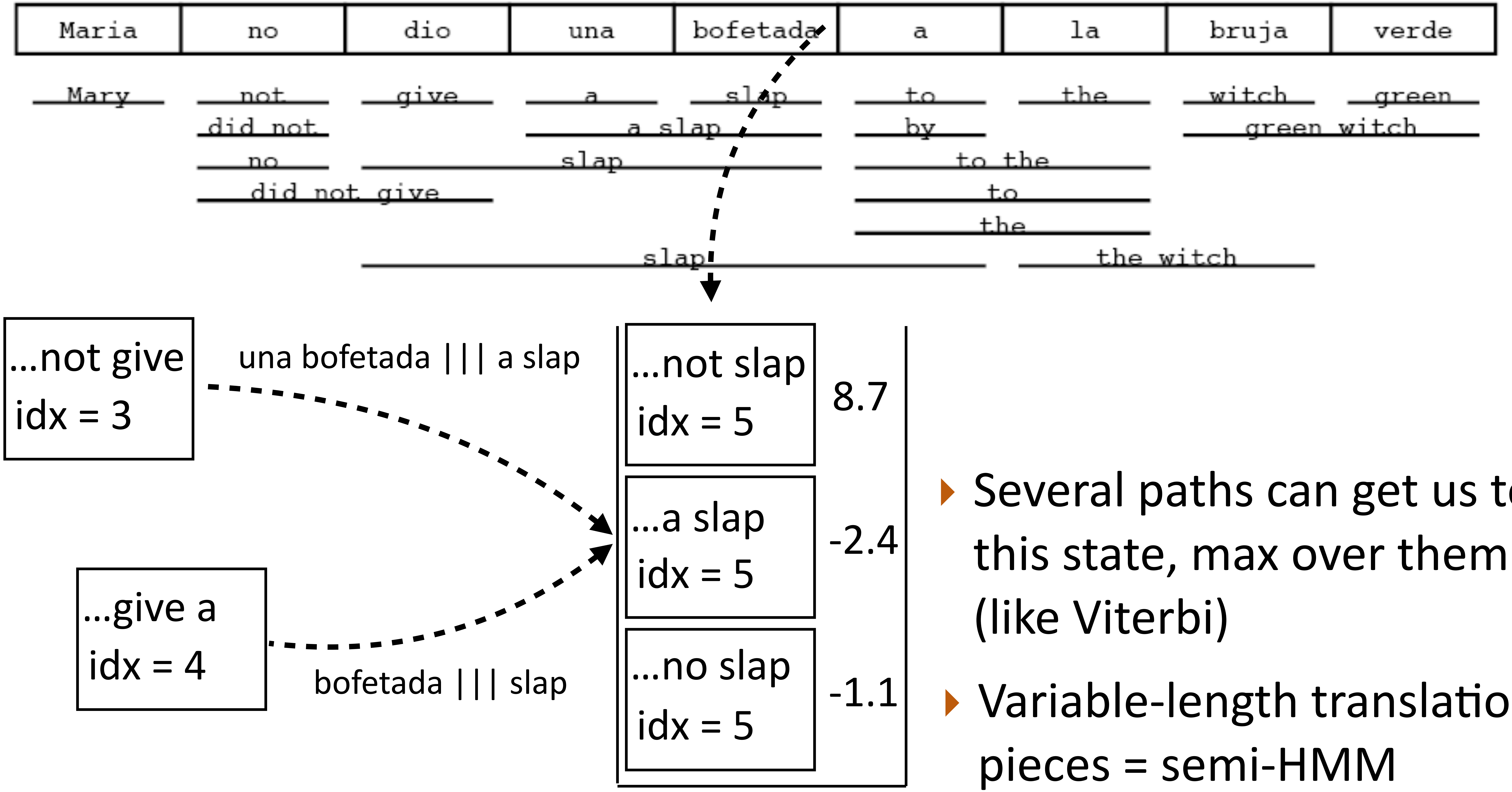

$$\text{score} = \log [\underbrace{P(\text{Mary})\, P(\text{not} \mid \text{Mary})}_{\text{LM}}\ \underbrace{P(\text{Maria} \mid \text{Mary})\, P(\text{no} \mid \text{not})}_{\text{TM}}]$$

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

...and TM is broken down into several features

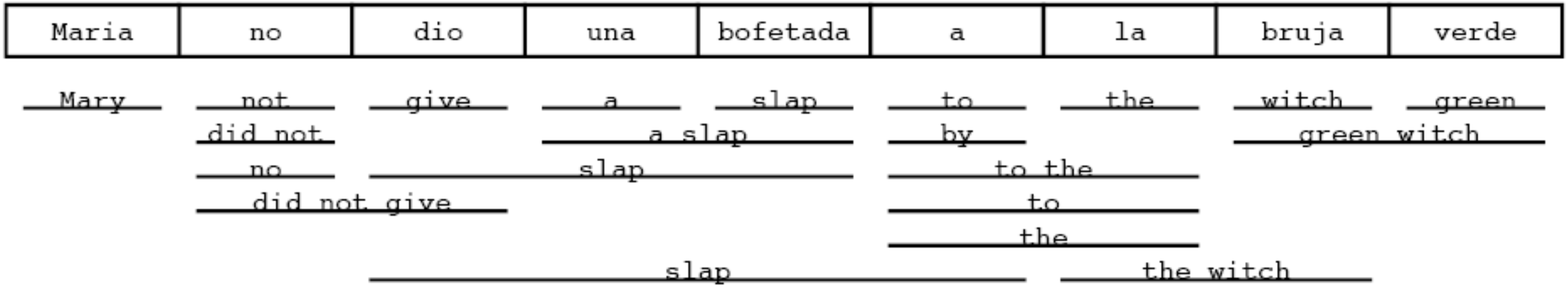
Koehn (2004)

# Monotonic Translation

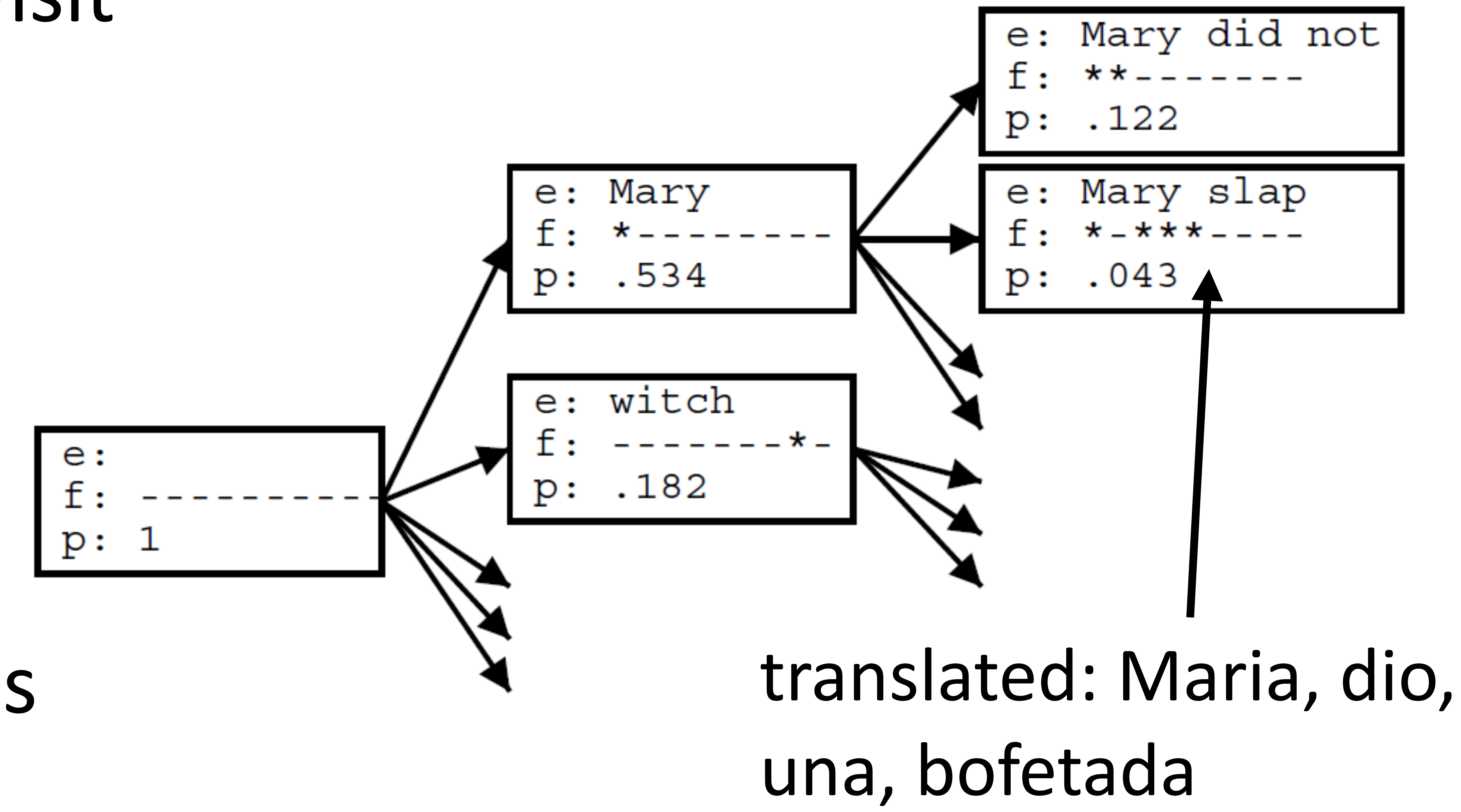



- Several paths can get us to this state, max over them (like Viterbi)
- Variable-length translation pieces = semi-HMM

# 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



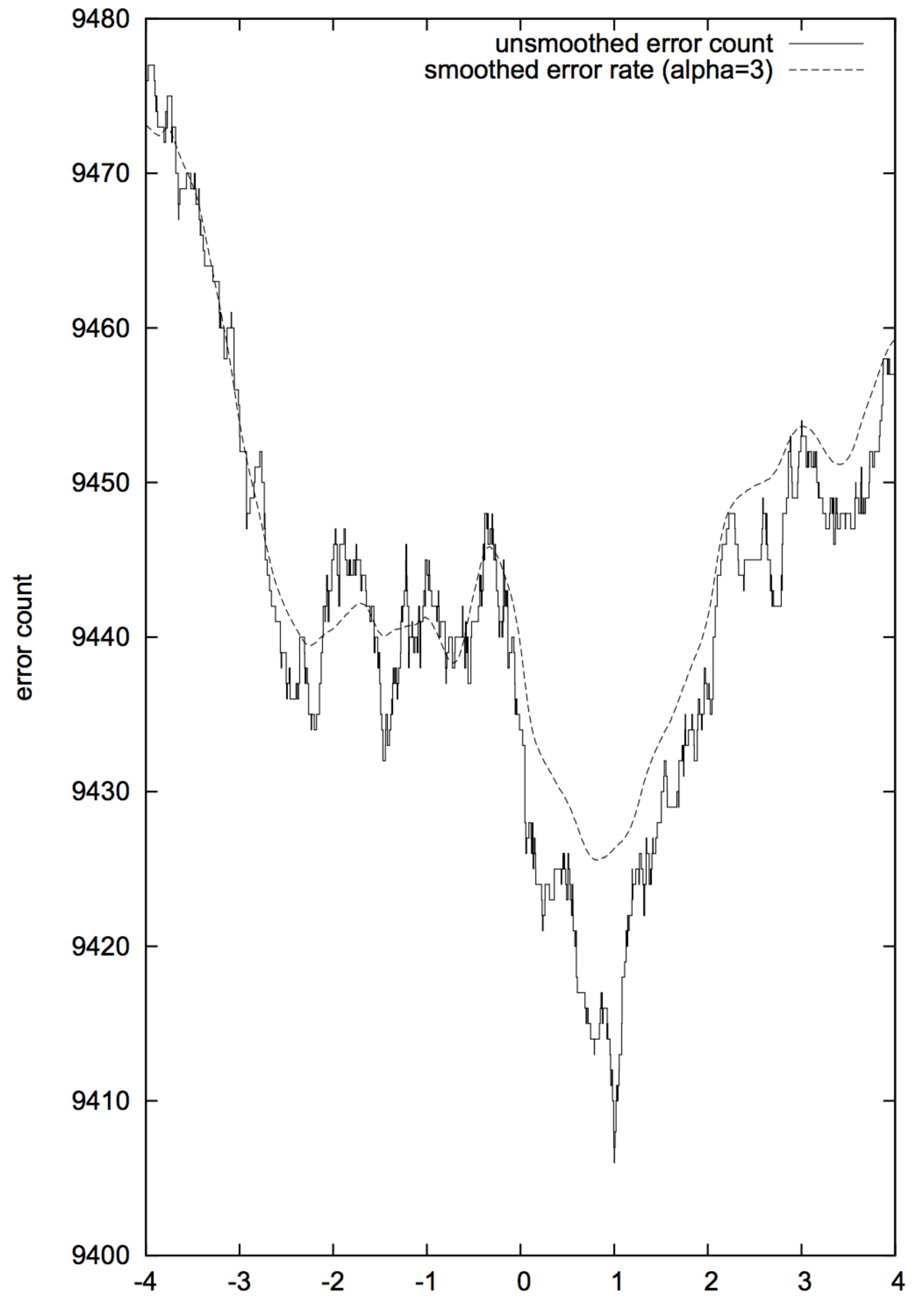
# Training Decoders

score = α log P(LM) + β log P(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

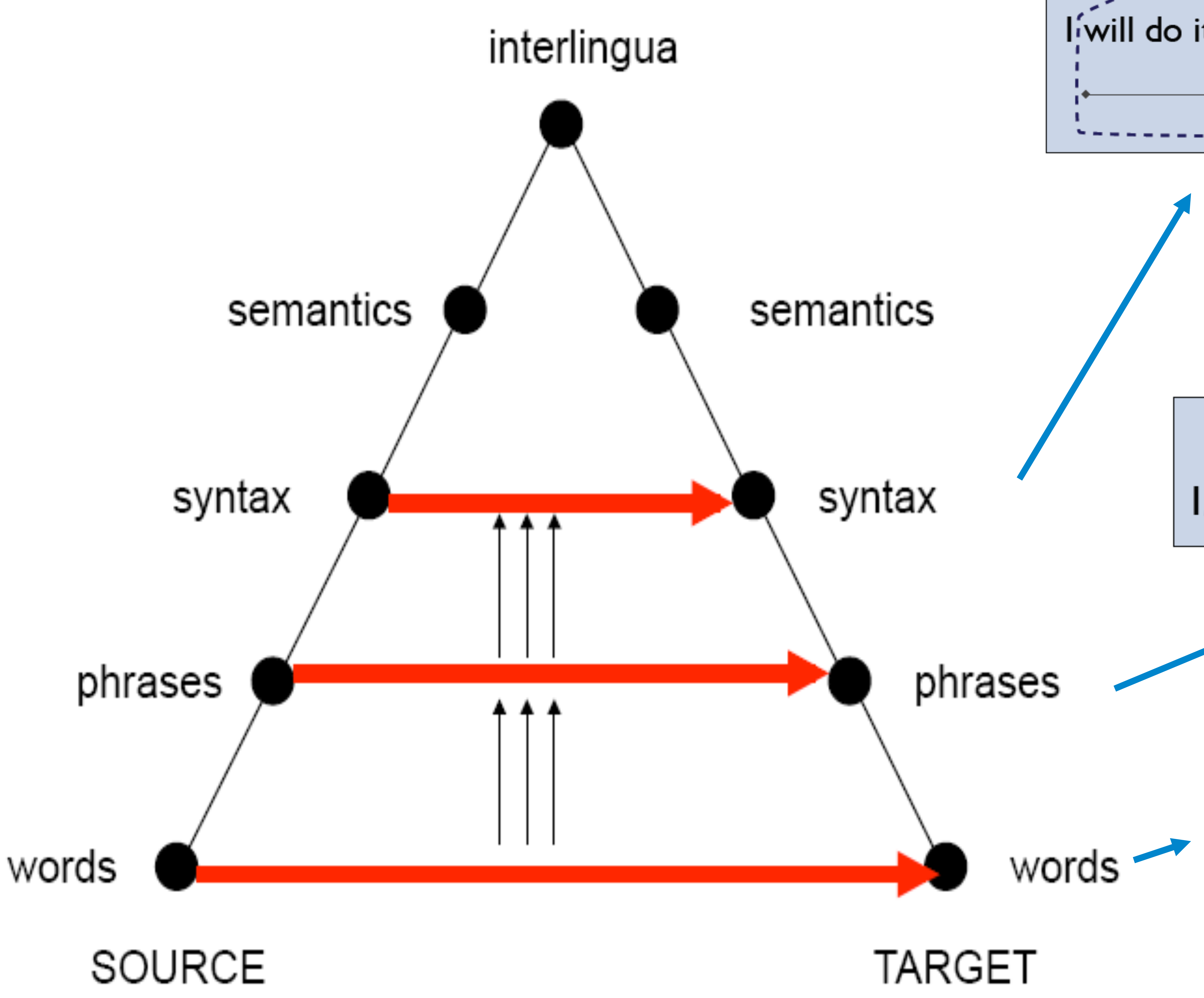


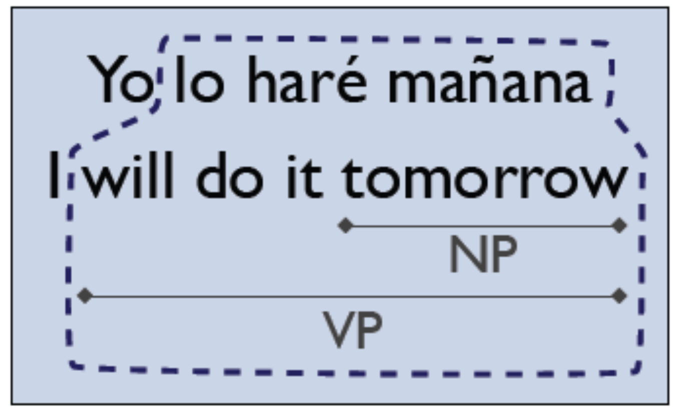
# Moses

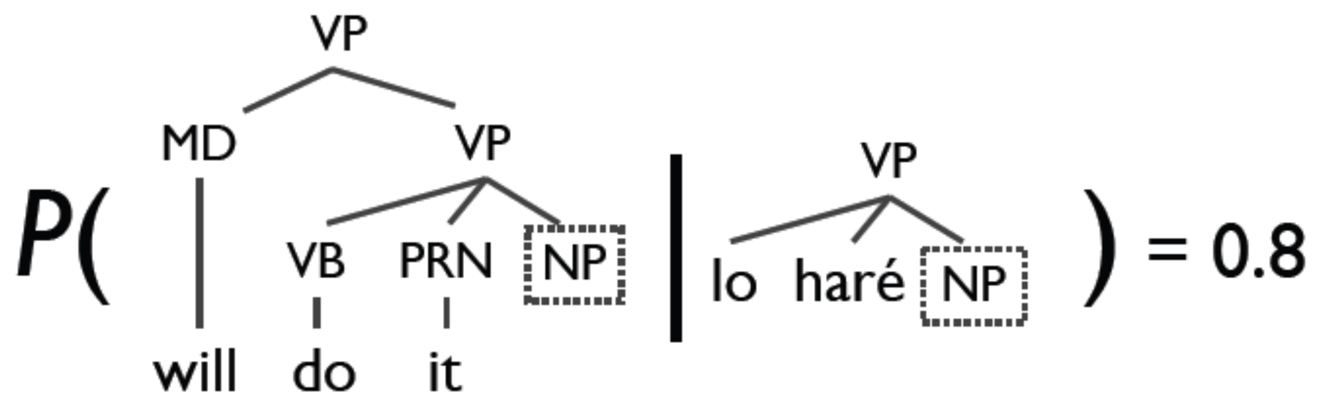
- Toolkit for machine translation due to Philipp Koehn + Hieu Hoang
  - Pharaoh (Koehn, 2004) is the decoder from Koehn's thesis
- Moses implements word alignment, language models, and this decoder, plus *a ton* more stuff
  - Highly optimized and heavily engineered, could more or less build SOTA translation systems with this from 2007-2015
- Next time: results on these and comparisons to neural methods

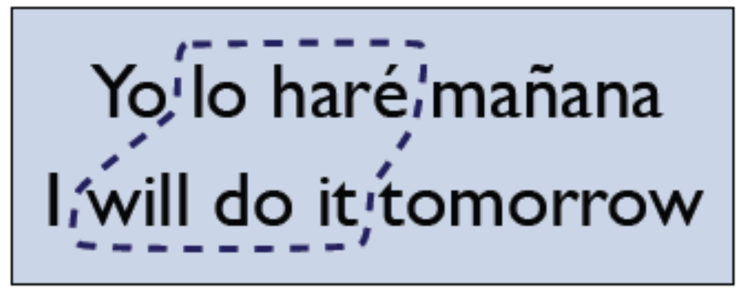
# Syntax

# Levels of Transfer: Vauquois Triangle

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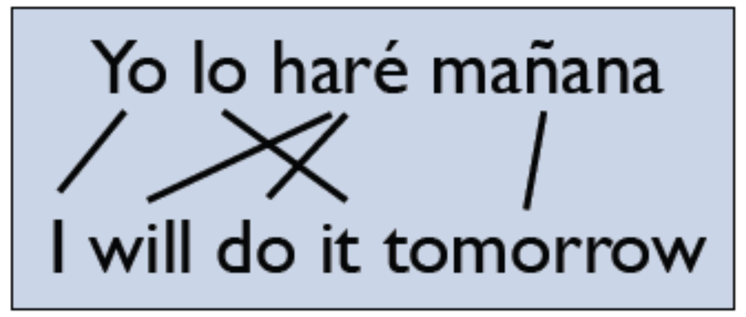



| *English* (E) | *P*( E \| mañana ) |
|---|---|
| tomorrow | 0.7 |
| morning | 0.3 |

- Is syntax a “better” abstraction than phrases?

Slide credit: Dan Klein

# Syntactic MT

- Rather than use phrases, use a *synchronous context-free grammar*

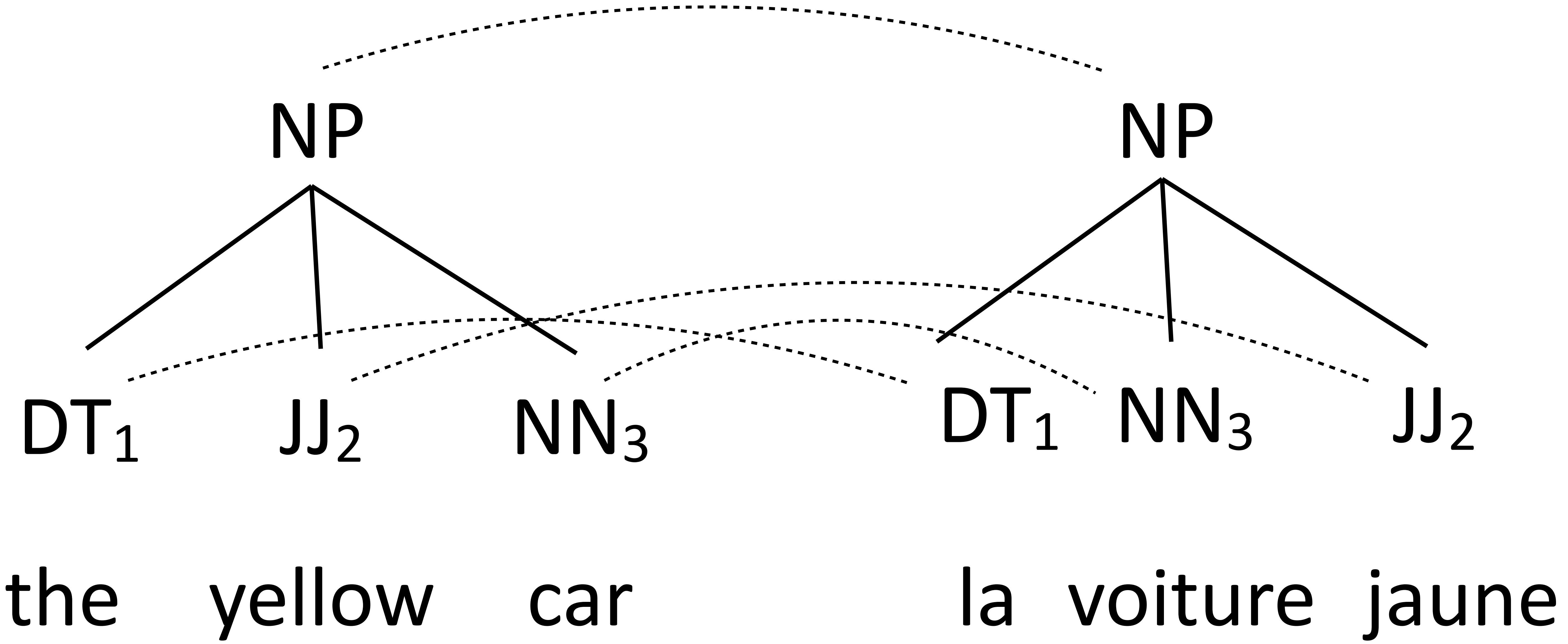
$NP \rightarrow [DT_1\ JJ_2\ NN_3;\ DT_1\ NN_3\ JJ_2]$

$DT \rightarrow$ [the, la]

$DT \rightarrow$ [the, le]

$NN \rightarrow$ [car, voiture]

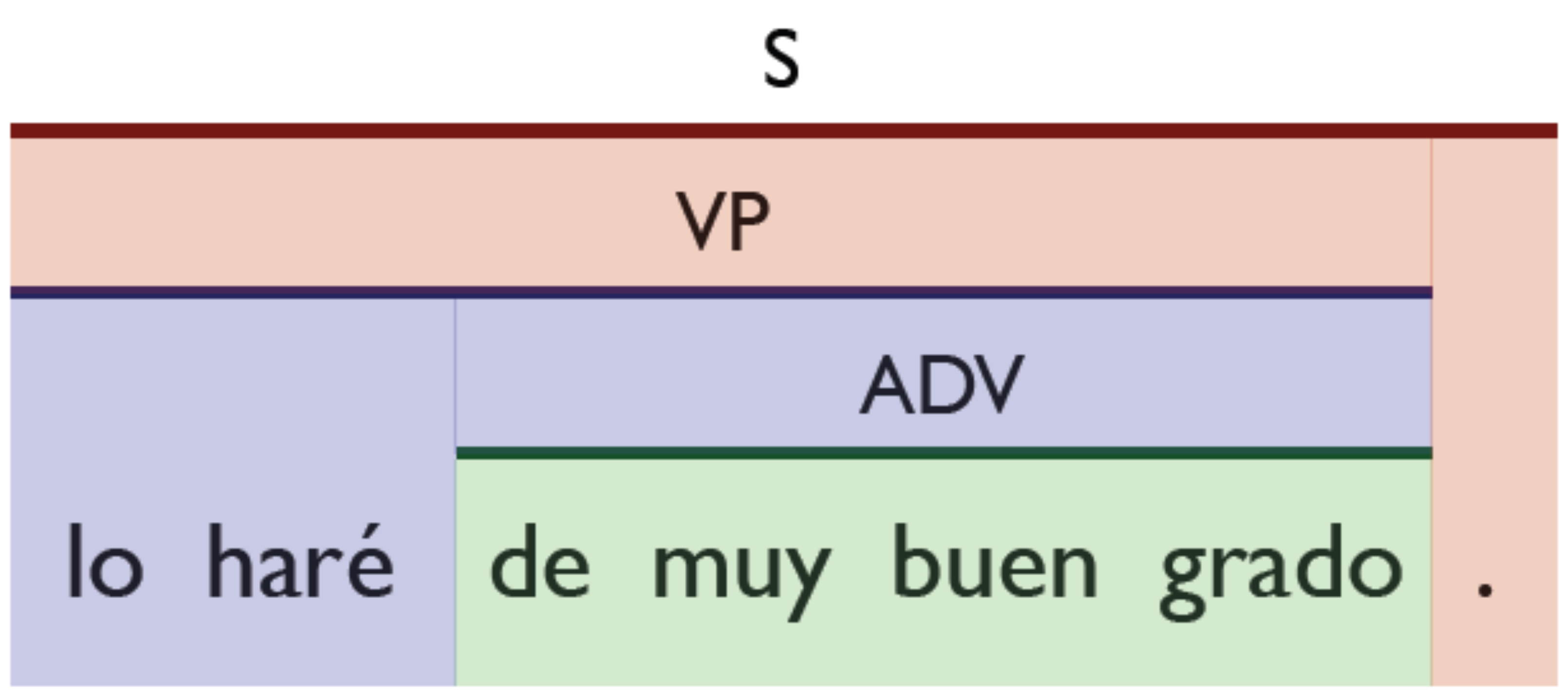
$JJ \rightarrow$ [yellow, jaune]



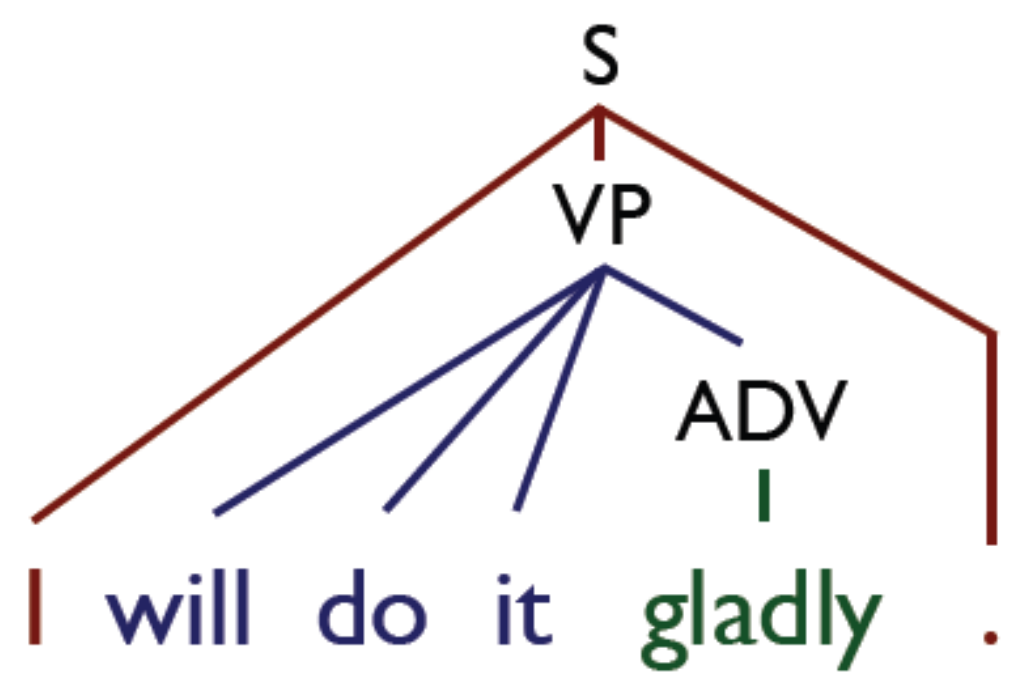

- Translation = parse the input with "half" of the grammar, read off the other half
- Assumes parallel syntax up to reordering

# Syntactic MT

**Input**




**Output**




- 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