

Course Wrap Up



Machine Translation Lecture 26

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Website: mt-class.org/penn

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Statistical Machine Translation

Develop a statistical **model** of translation that can be learned from **data** and used to **predict** the correct English translation of new foreign sentences.

Lexical Translation Models

$$p(e_i \mid f_{a_i})$$

$$\hat{p}_{\text{MLE}}(e \mid \text{Haus}) = \begin{cases} 0.696 & \text{if } e = \text{house} \\ 0.279 & \text{if } e = \text{home} \\ 0.014 & \text{if } e = \text{shell} \\ 0.011 & \text{if } e = \text{household} \\ 0 & \text{otherwise} \end{cases}$$

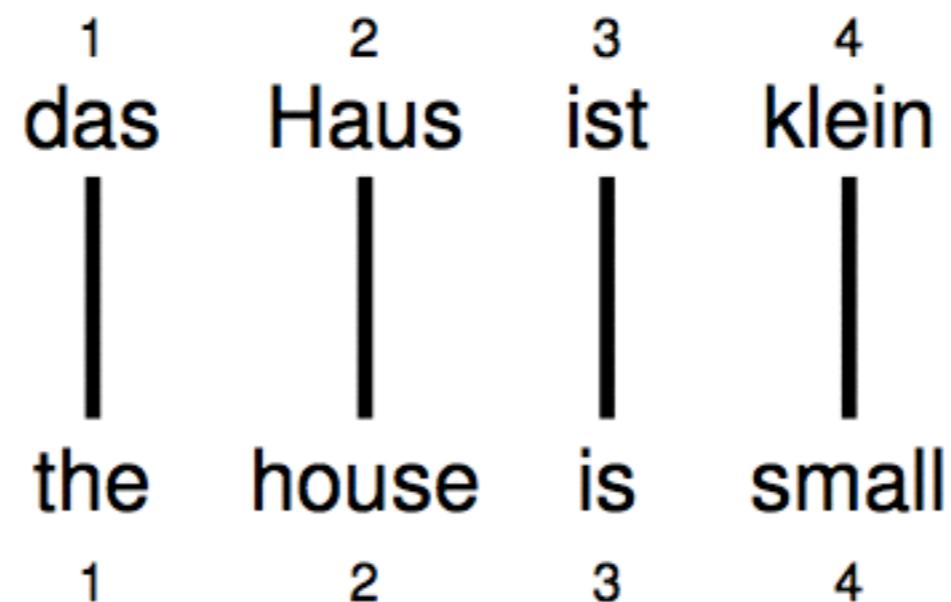
Lexical Translation Models

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0, n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^m p(e_i \mid f_{a_i})$$

Alignment \times Translation \mid Alignment

Alignment

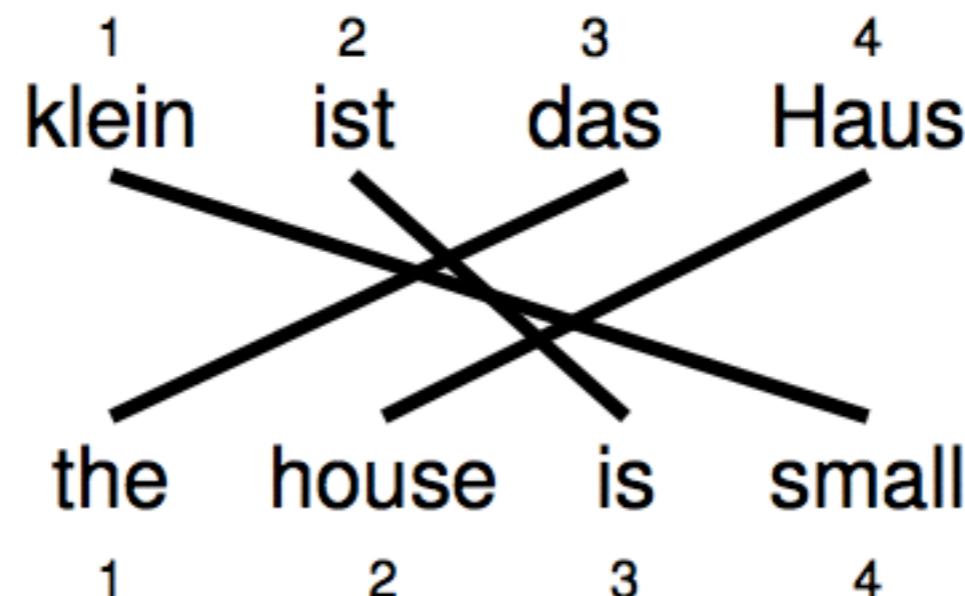
- Alignments can be visualized by drawing links between two sentences, and they are represented as vectors of positions:



$$\mathbf{a} = (1, 2, 3, 4)^\top$$

Reordering

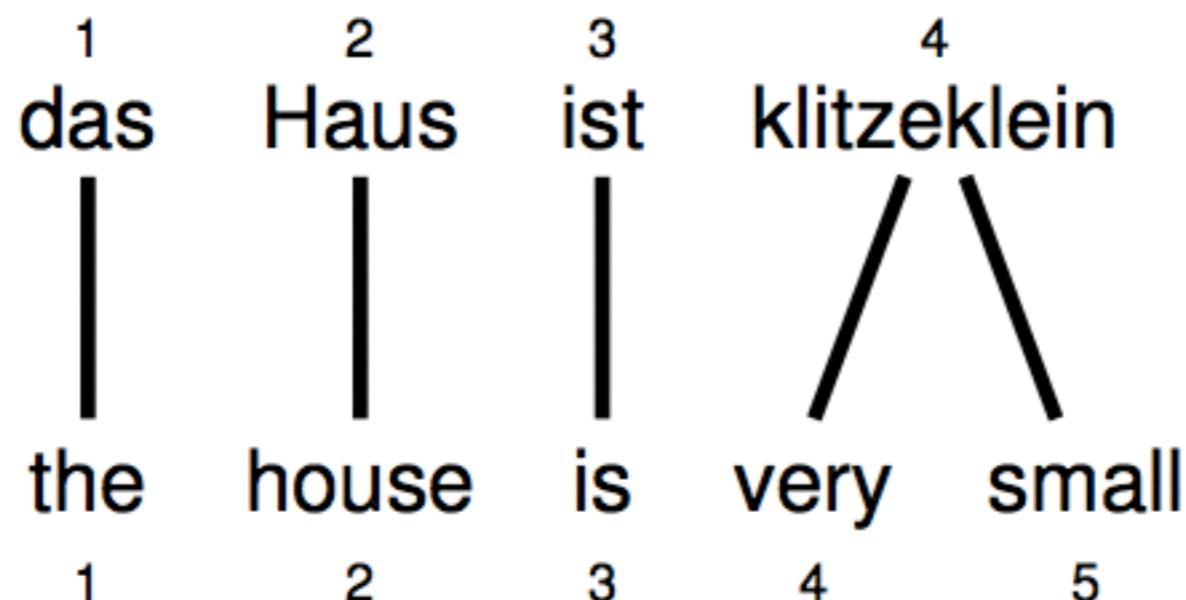
- Words may be reordered during translation.



$$\mathbf{a} = (3, 4, 2, 1)^\top$$

One-to-many Translation

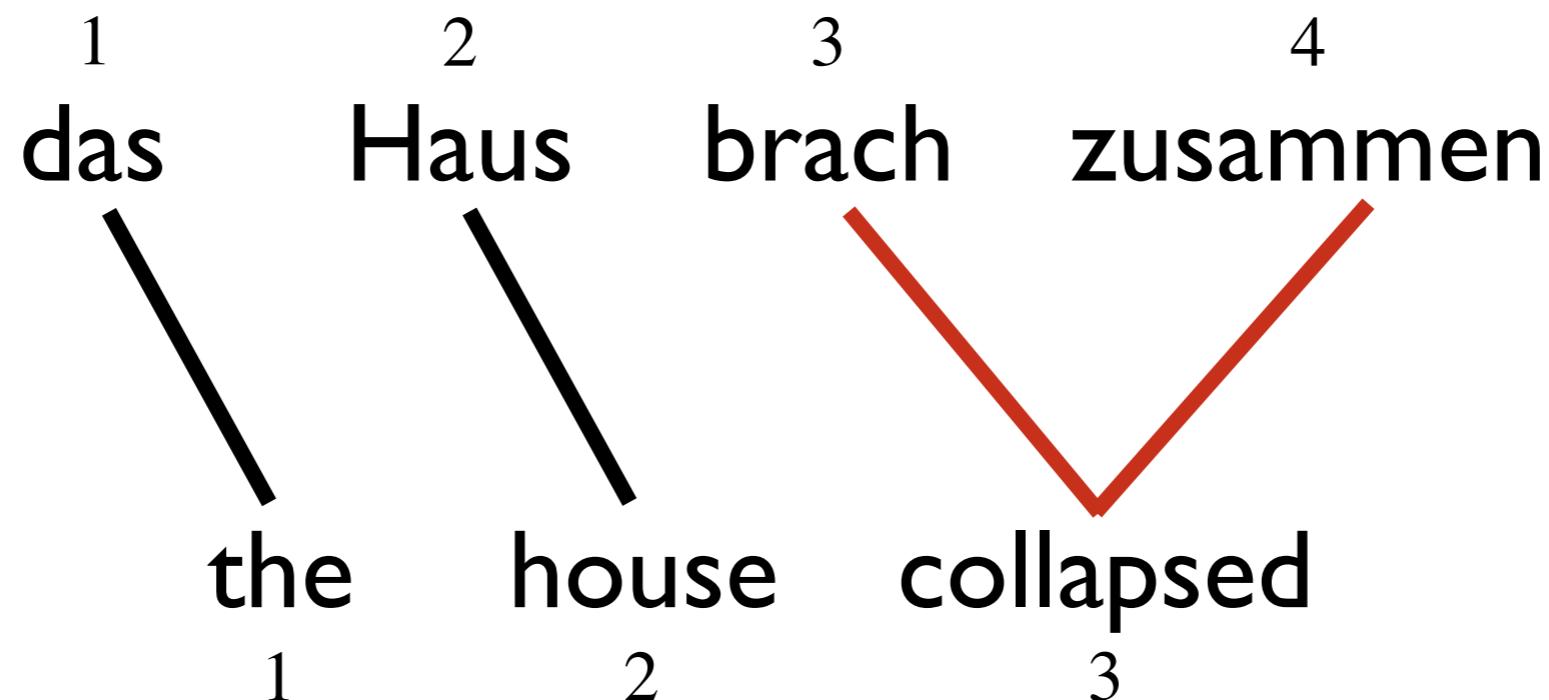
- A source word may translate into more than one target word



$$\mathbf{a} = (1, 2, 3, 4, 4)^\top$$

Many-to-one Translation

- More than one source word may not translate as a unit in lexical translation



$\mathbf{a} = ???$

$\mathbf{a} = (1, 2, (3, 4)^\top)^\top ?$

IBM Model I

- Simplest possible lexical translation model
- Additional assumptions
 - The m alignment decisions are independent
 - The alignment distribution for each a_i is uniform over all source words and NULL

for each $i \in [1, 2, \dots, m]$

$$a_i \sim \text{Uniform}(0, 1, 2, \dots, n)$$

$$e_i \sim \text{Categorical}(\theta_{f_{a_i}})$$

Historical Note

IBM Models

Renaissance



“The validity of a statistical (information theoretic) approach to MT has indeed been recognized, as the authors mention, by Weaver as early as 1949. And was universally recognized as mistaken by 1950 (cf. Hutchins, MT – Past, Present, Future, Ellis Horwood, 1986, p. 30ff and references therein). The crude force of computers is not science. The paper is simply beyond the scope of COLING.”

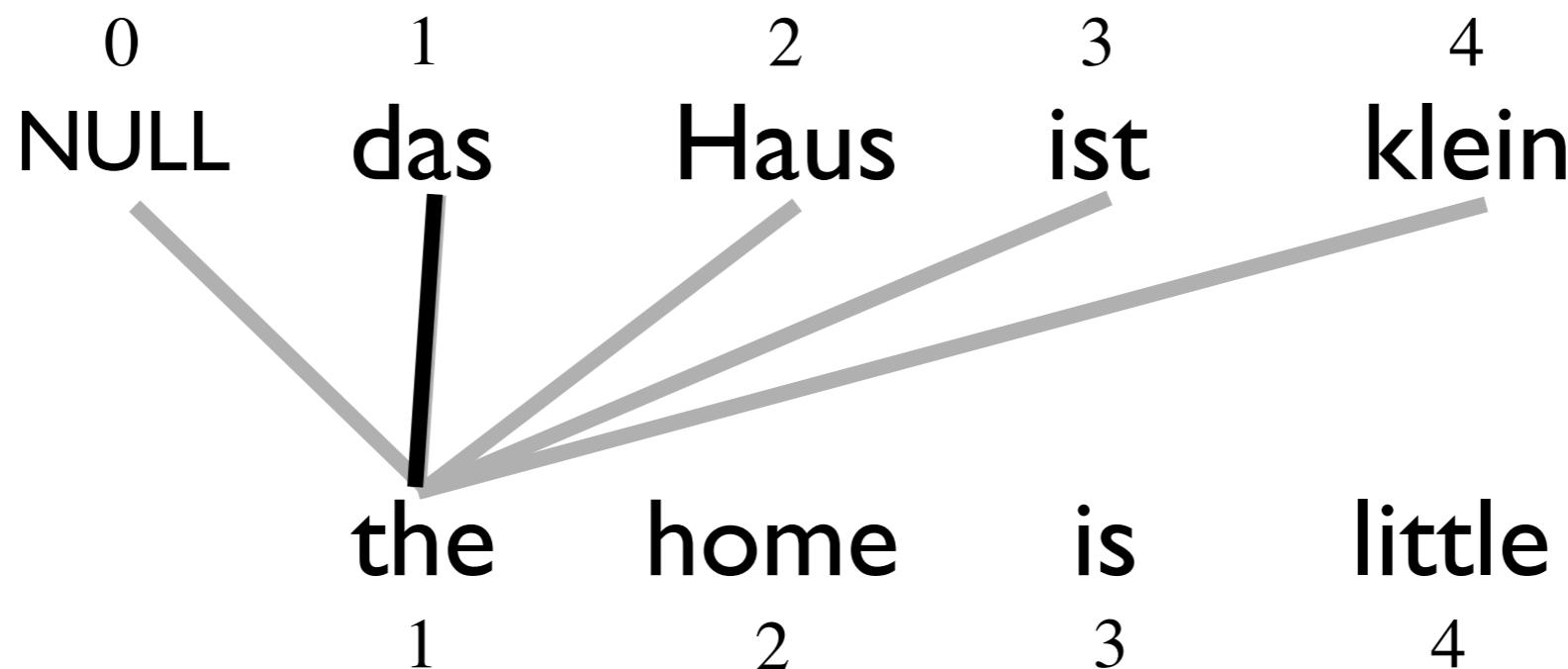


Fred Jelinek
(1932-2010)

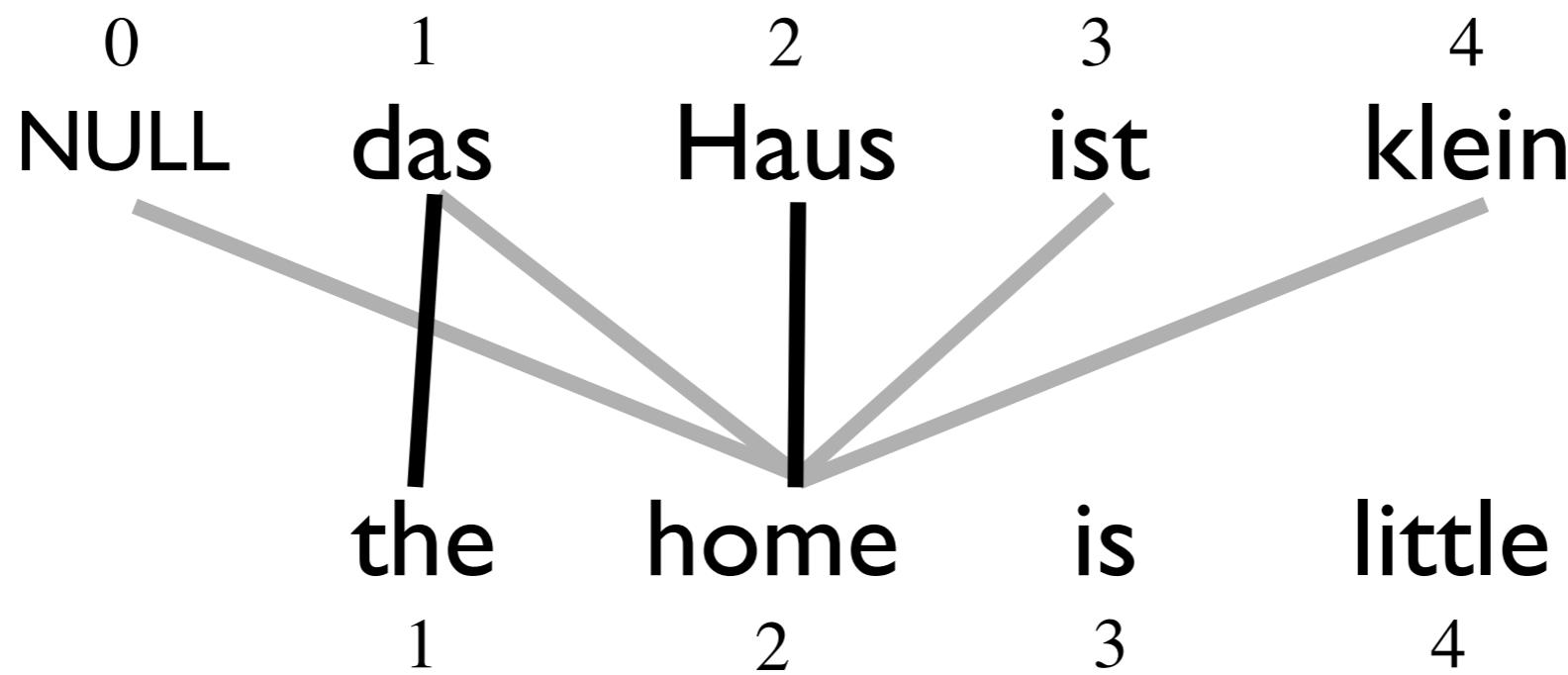


The Center For Language
and Speech Processing
at the Johns Hopkins University

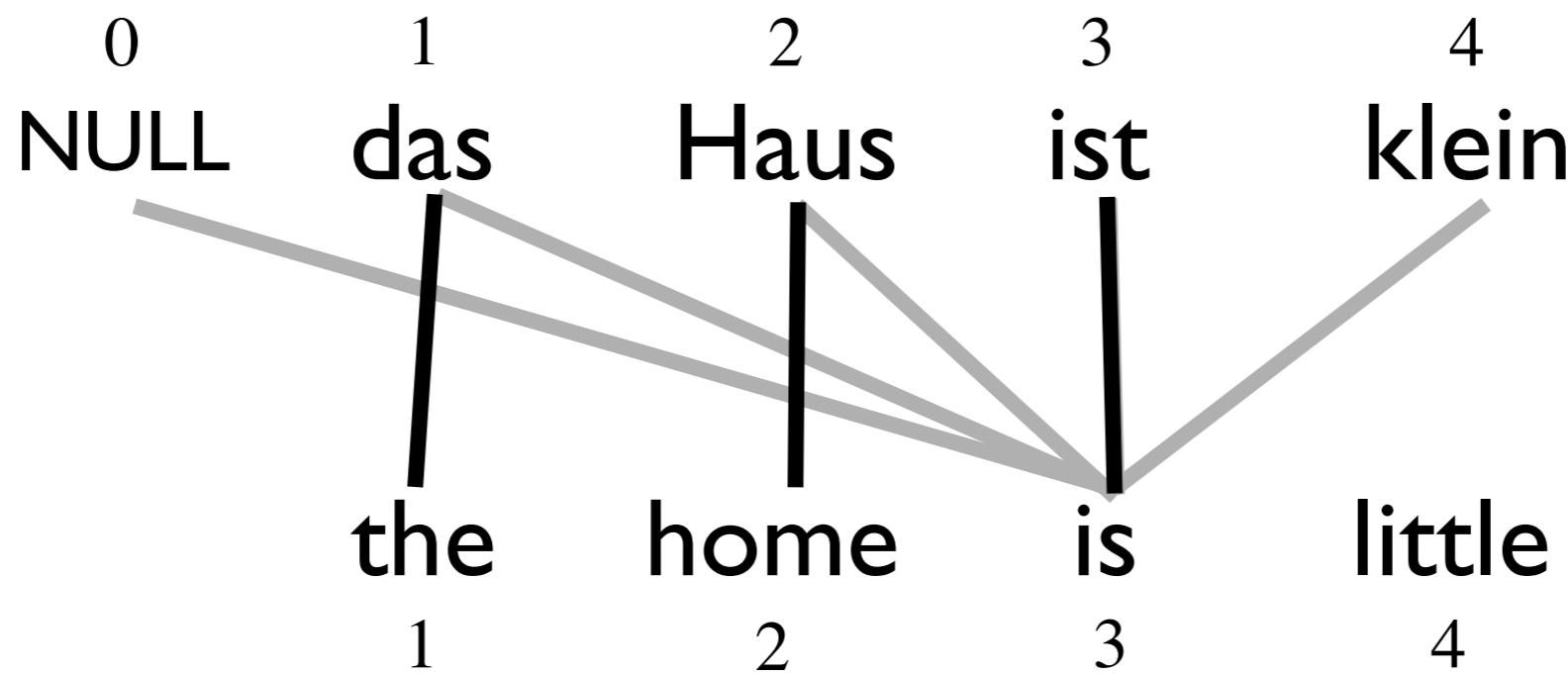
Finding the Viterbi Alignment



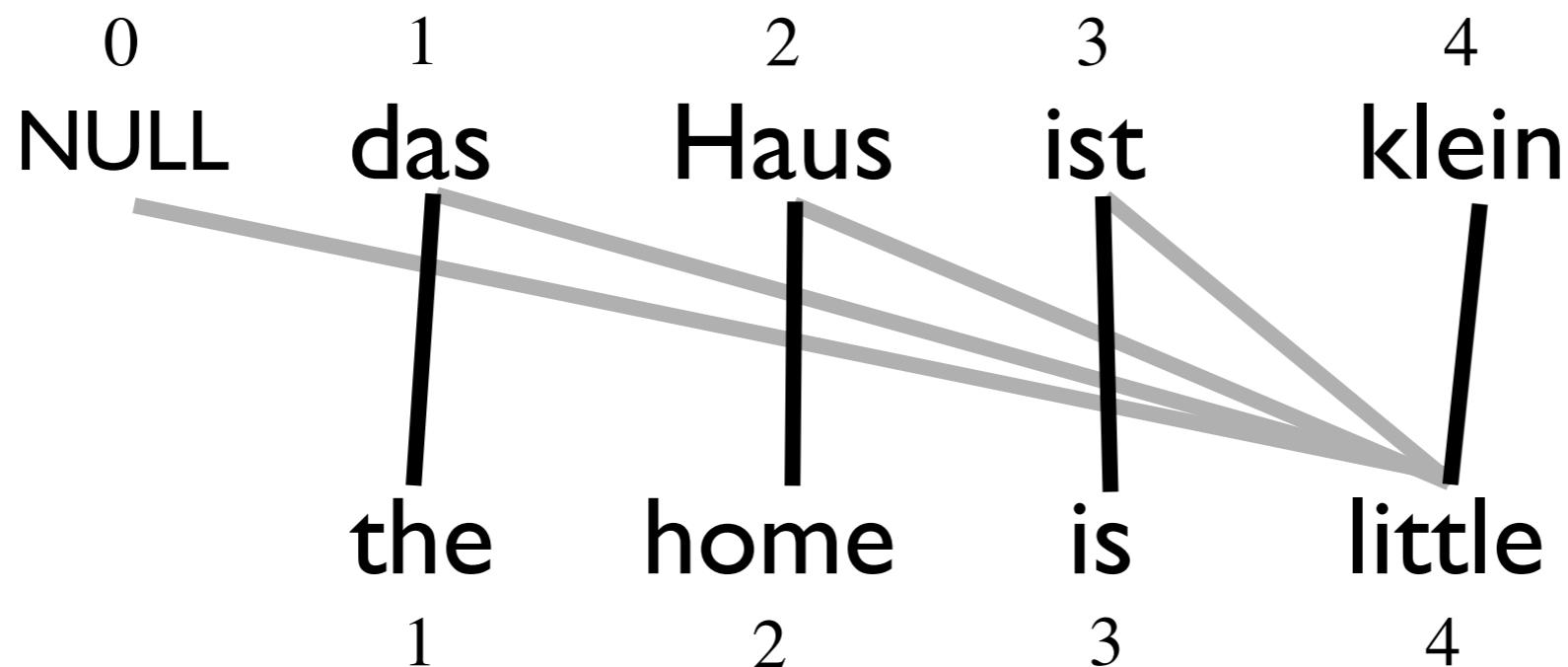
Finding the Viterbi Alignment



Finding the Viterbi Alignment

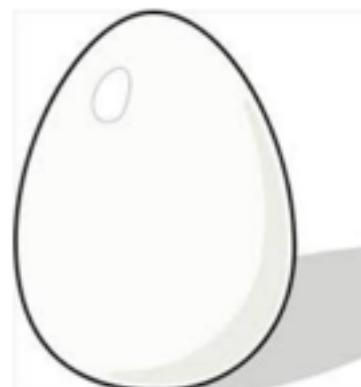
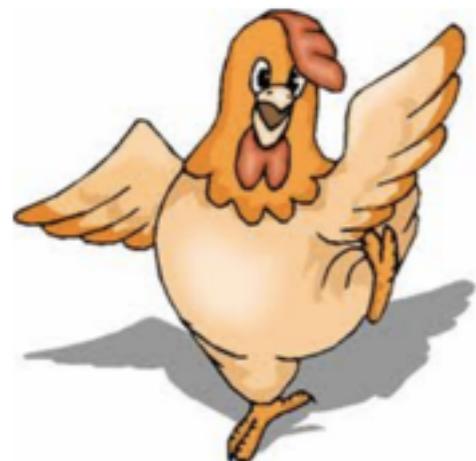


Finding the Viterbi Alignment



Learning Lexical Translation Models

- How do we learn the parameters $p(e | f)$
- “Chicken and egg” problem
 - If we had the alignments, we could estimate the parameters (MLE)
 - If we had parameters, we could find the most likely alignments



You implemented your
own word aligner

Phrase-based Translation

- What are the atomic units?
 - Lexical translation: words
 - Phrase-based translation: phrases
- Benefits
 - many-to-many translation
 - use of local context in translation
- Standard model used by Google, Microsoft ...

Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

$$p(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} \mid \bar{\mathbf{e}})$$

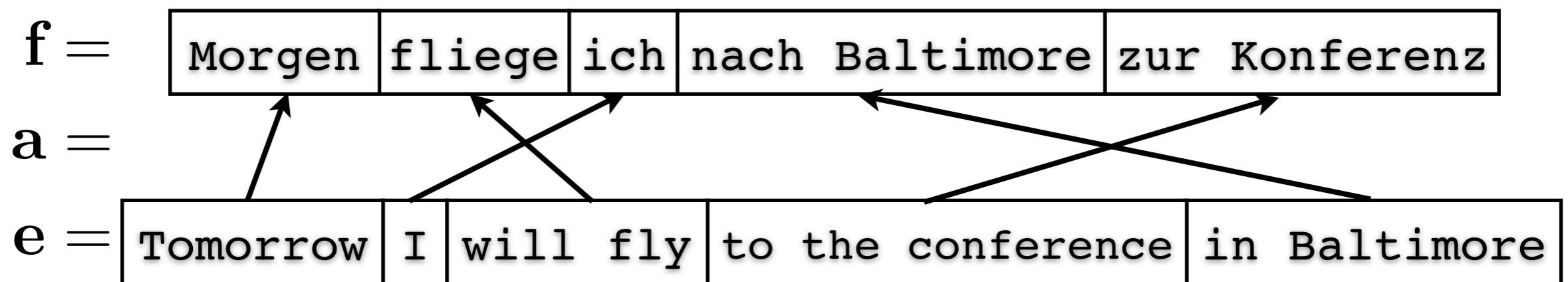
$\mathbf{f} =$ Morgen fliege ich nach Baltimore zur Konferenz

$\mathbf{e} =$ Tomorrow I will fly to the conference in Baltimore

Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

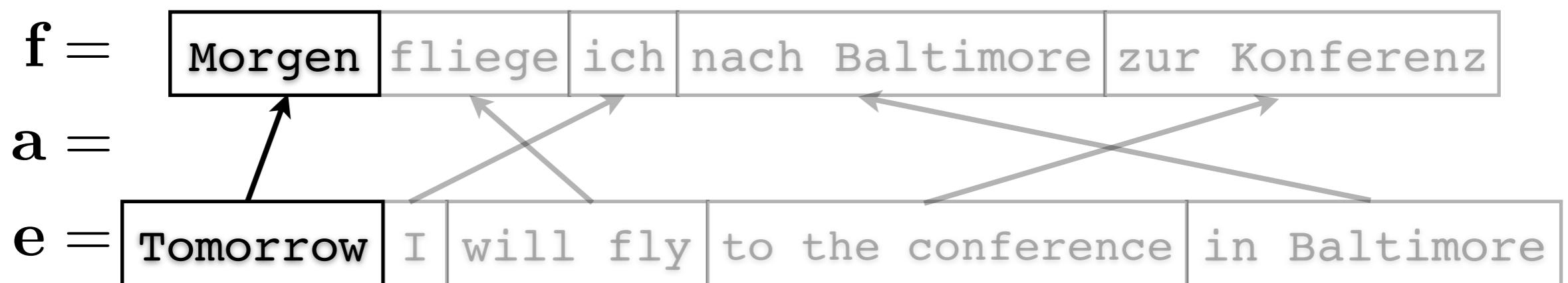
$$p(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} \mid \bar{\mathbf{e}})$$



Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

$$p(\mathbf{f}, \mathbf{a} | \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} | \bar{\mathbf{e}})$$

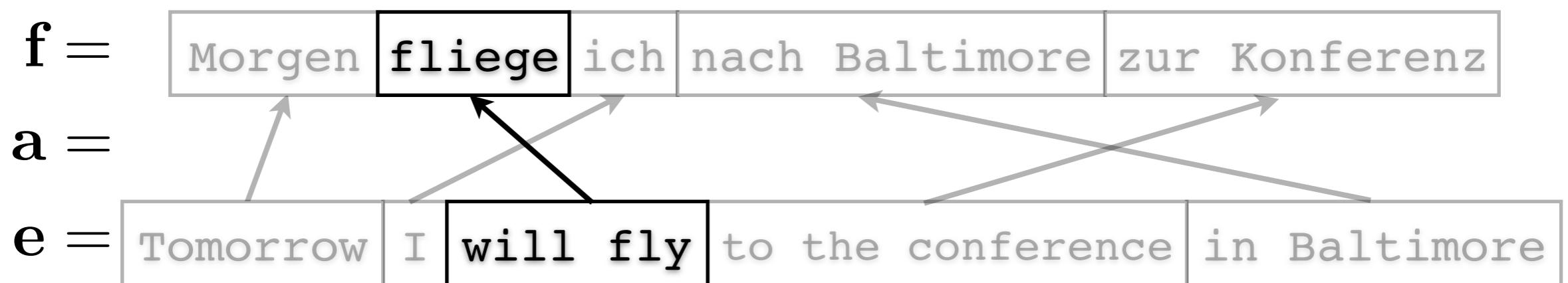


$p(\text{Morgen} | \text{Tomorrow})$

Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

$$p(\mathbf{f}, \mathbf{a} | \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} | \bar{\mathbf{e}})$$

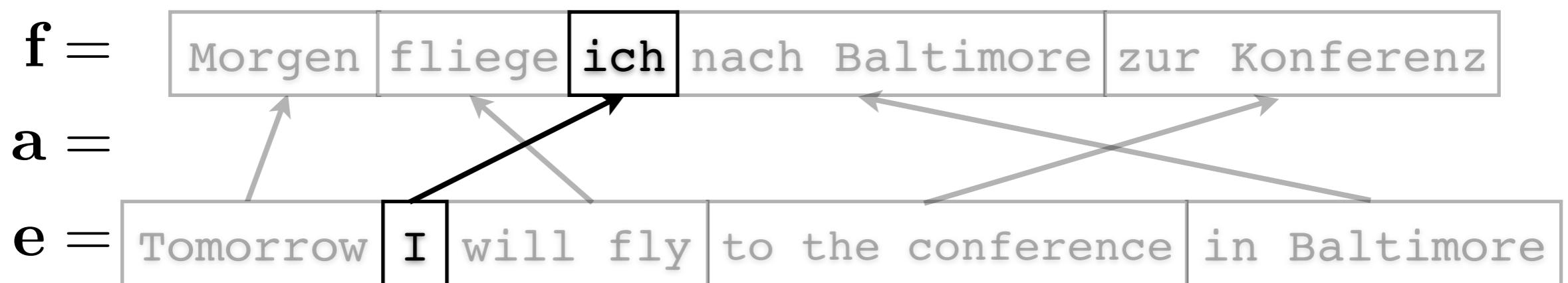


$$p(\text{Morgen}|\text{Tomorrow}) \times p(\text{fliege}| \text{will fly})$$

Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

$$p(\mathbf{f}, \mathbf{a} | \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} | \bar{\mathbf{e}})$$

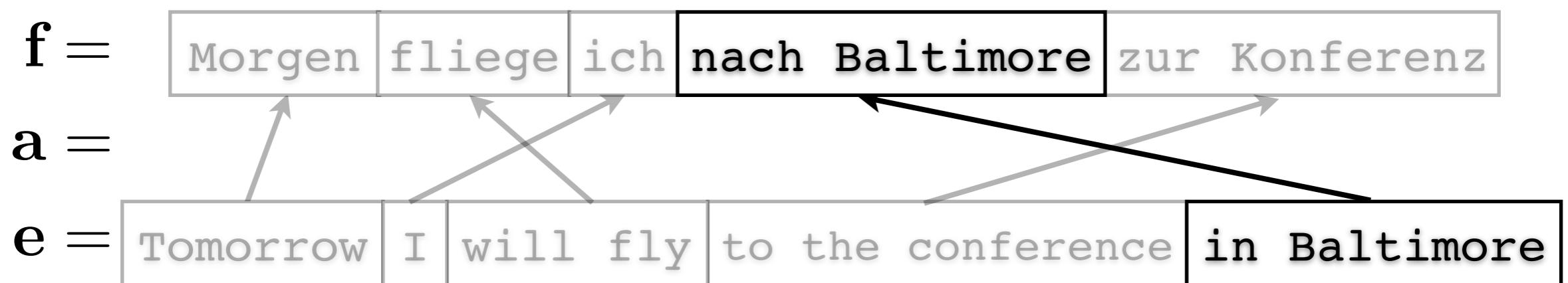


$$p(\text{Morgen}|\text{Tomorrow}) \times p(\text{fliege}| \text{will fly}) \times p(\text{ich}| \text{I})$$

Phrase-based Translation

- With a **latent variable**, we introduce a decomposition into phrases which translate independently:

$$p(\mathbf{f}, \mathbf{a} | \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} | \bar{\mathbf{e}})$$



$$p(\text{Morgen}|\text{Tomorrow}) \times p(\text{fliege}| \text{will fly}) \times p(\text{ich}| \text{I}) \times \dots$$

Phrase-based Translation

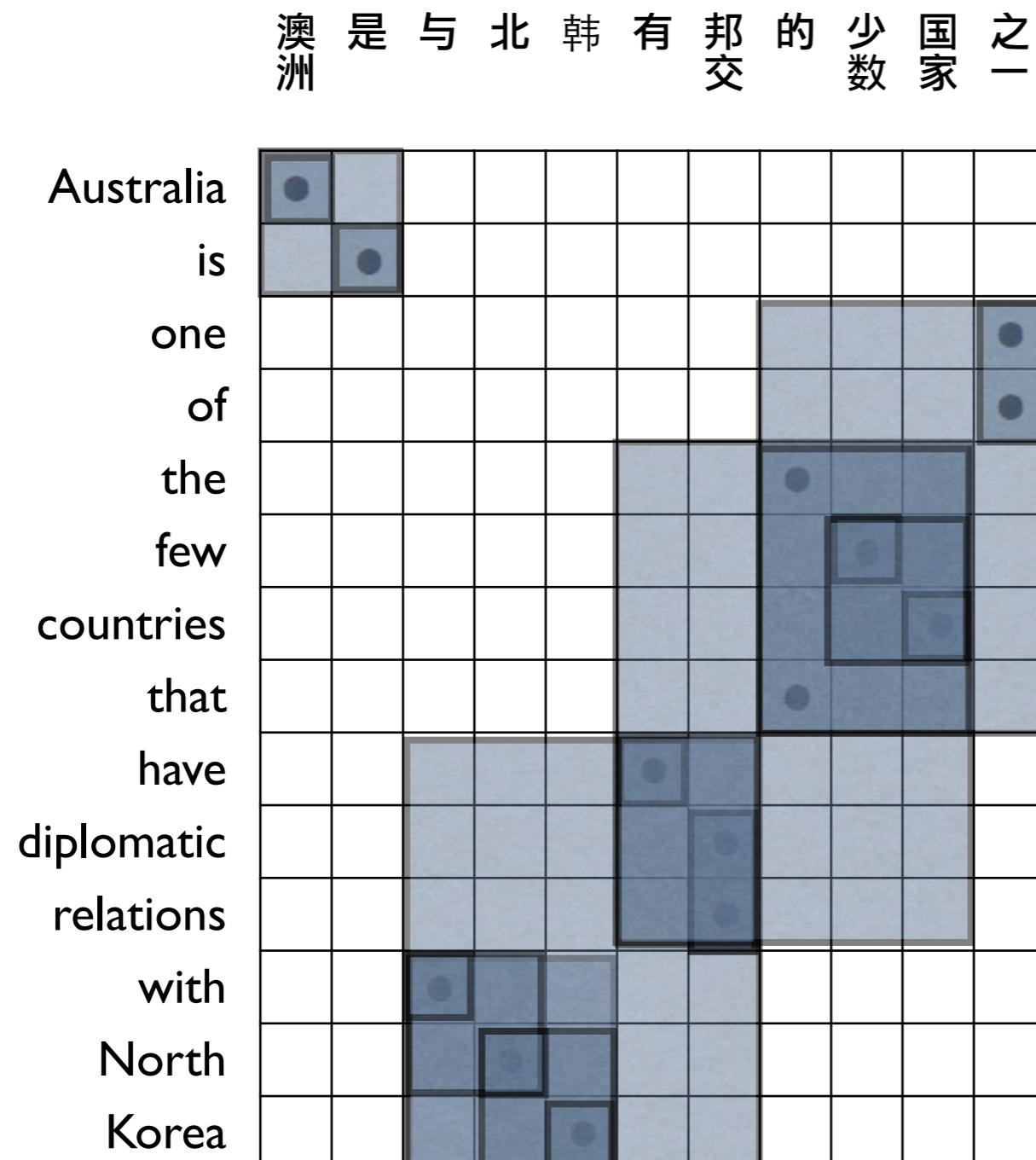
- With a **latent variable**, we introduce a decomposition into phrases which translate **independently**:

$$p(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} \mid \bar{\mathbf{e}})$$

Marginalize to get $p(\mathbf{f} \mid \mathbf{e})$:

$$p(\mathbf{f} \mid \mathbf{e}) = \sum_{\mathbf{a} \in \mathcal{A}} p(\mathbf{a}) \prod_{\langle \bar{\mathbf{e}}, \bar{\mathbf{f}} \rangle \in \mathbf{a}} p(\bar{\mathbf{f}} \mid \bar{\mathbf{e}})$$

Extracting phrase pairs



澳洲, Australia

是, is

之一, one of

少数, few

国家, countries

有, have

邦交, diplomatic relations

与, with

北, North

韩, Korea

澳洲是, Australia is

少数 国家, few countries

有邦交, have diplomatic relations

与北, with North

北韩, North Korea

的少数 国家, the few countries that
与北韩, with North Korea

之一的少数 国家, one of the the few
countries that

与北韩 有邦交, have diplomatic
relations with North Korea

有邦交 的少数 国家, the few countries
that have diplomatic relations

Phrase Tables

\bar{f}	\bar{e}	$p(\bar{f} \bar{e})$
das Thema	the issue	0.41
	the point	0.72
	the subject	0.47
	the thema	0.99
es gibt	there is	0.96
	there are	0.72
morgen	tomorrow	0.9
fliege ich	will I fly	0.63
	will fly	0.17
	I will fly	0.13

Phrases

- Contiguous strings of words
- Phrases are not necessarily syntactic constituents
- Usually have maximum limits
- Phrases subsume words (individual words are phrases of length 1)

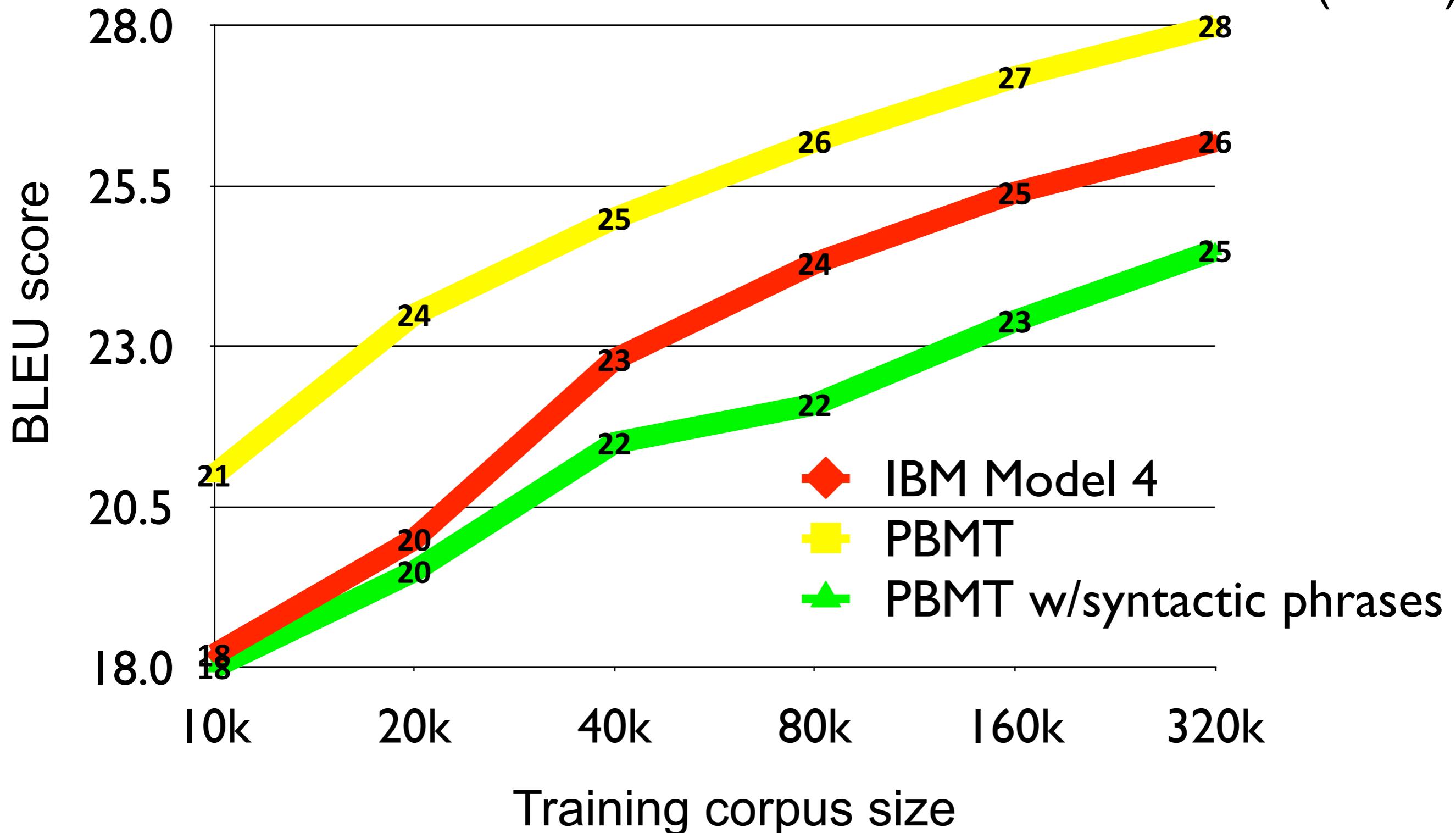
Linguistic Phrases

- Model is not limited to linguistic phrases (NPs, VPs, PPs, CPs...)
- Non-constituent phrases are useful

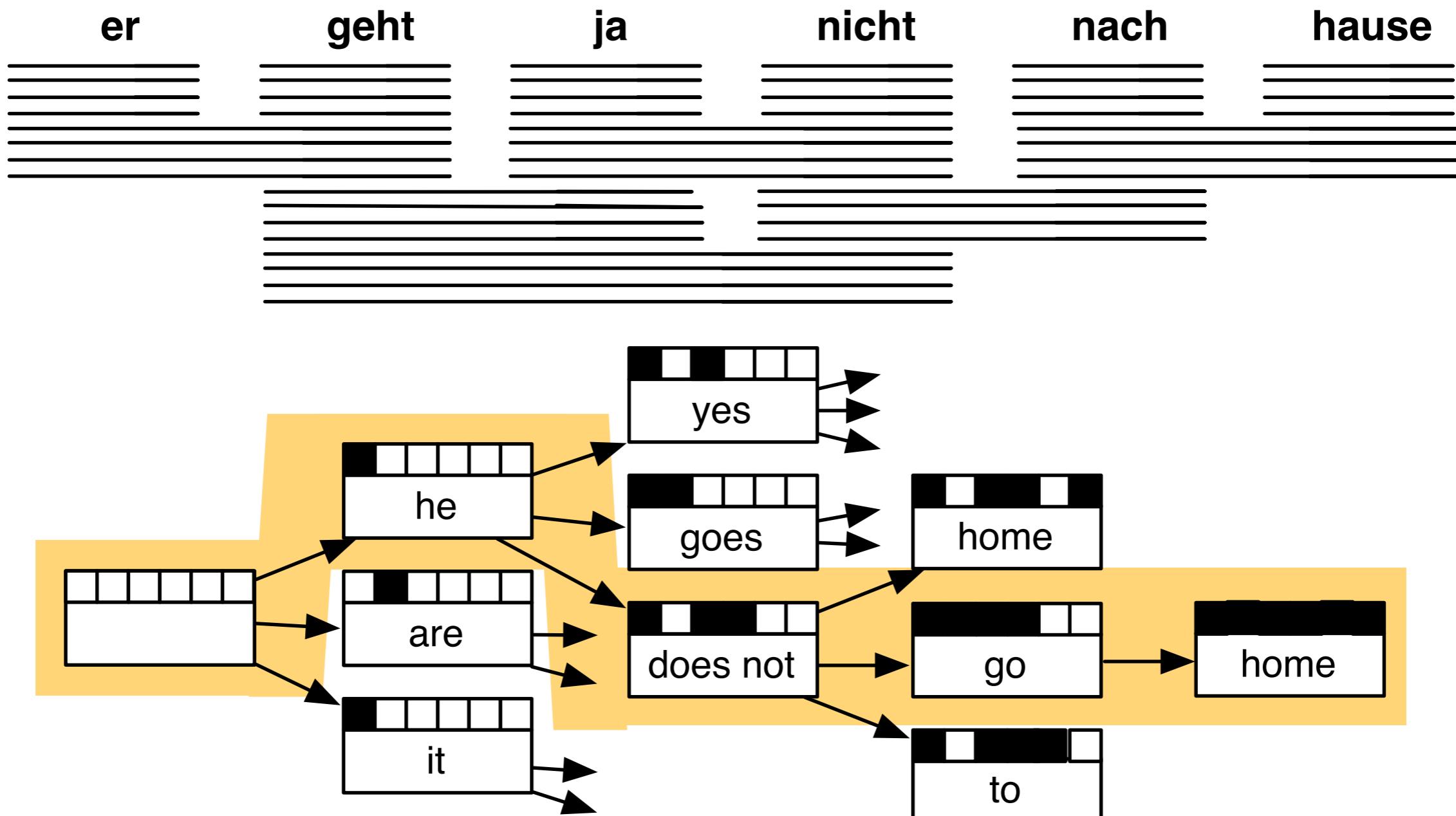
es gibt there is | there are

Syntax hurts

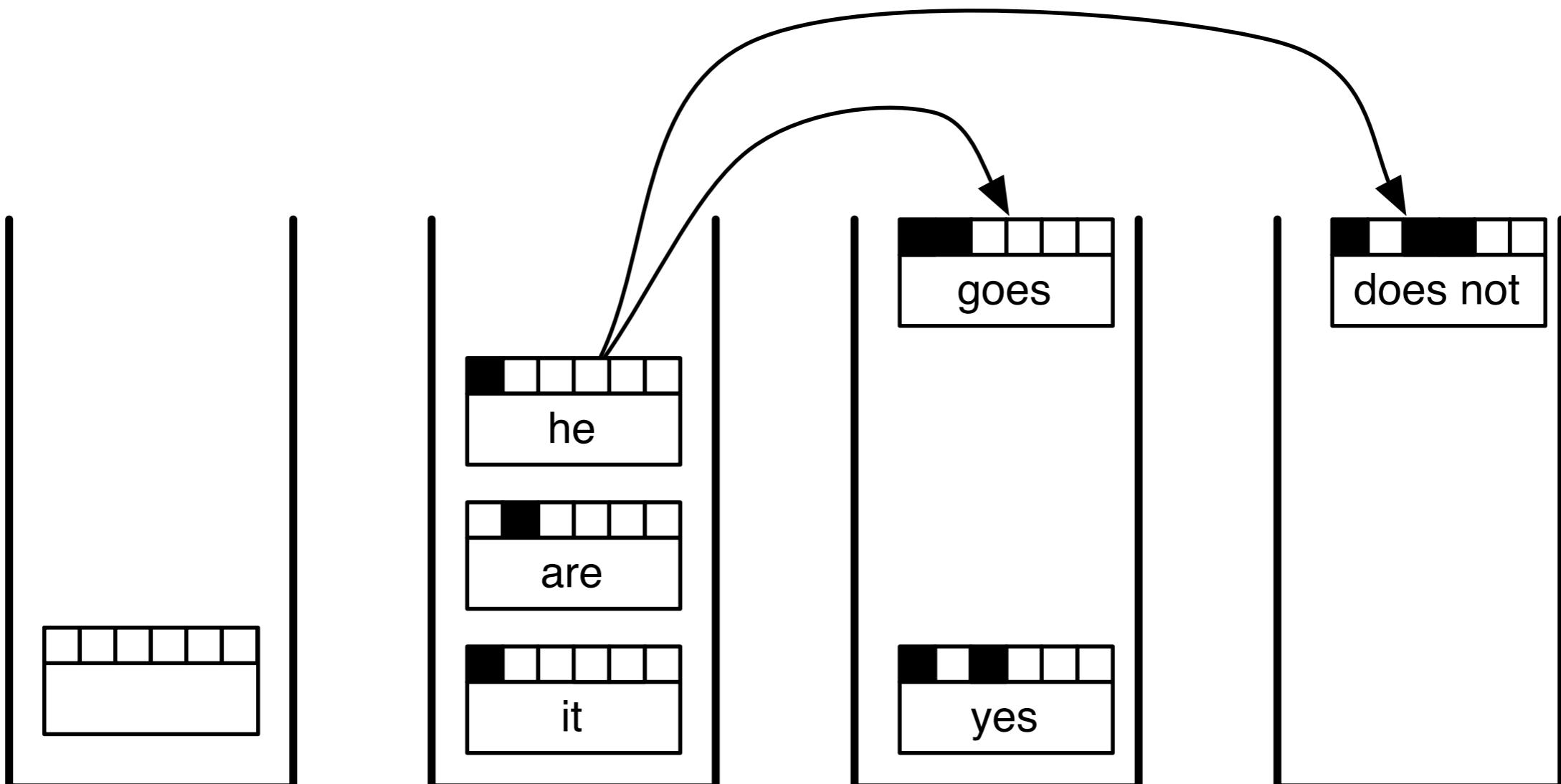
Koehn et al (2003)



Decoding



Decoding



no word
translated

one word
translated

two words
translated

three words
translated

Decoding

```
1: place empty hypothesis into stack 0
2: for all stacks  $0 \dots n - 1$  do
3:   for all hypotheses in stack do
4:     for all translation options do
5:       if applicable then
6:         create new hypothesis
7:         place in stack
8:         recombine with existing hypothesis if possible
9:         prune stack if too big
10:        end if
11:      end for
12:    end for
13:  end for
```

Decoding complexity

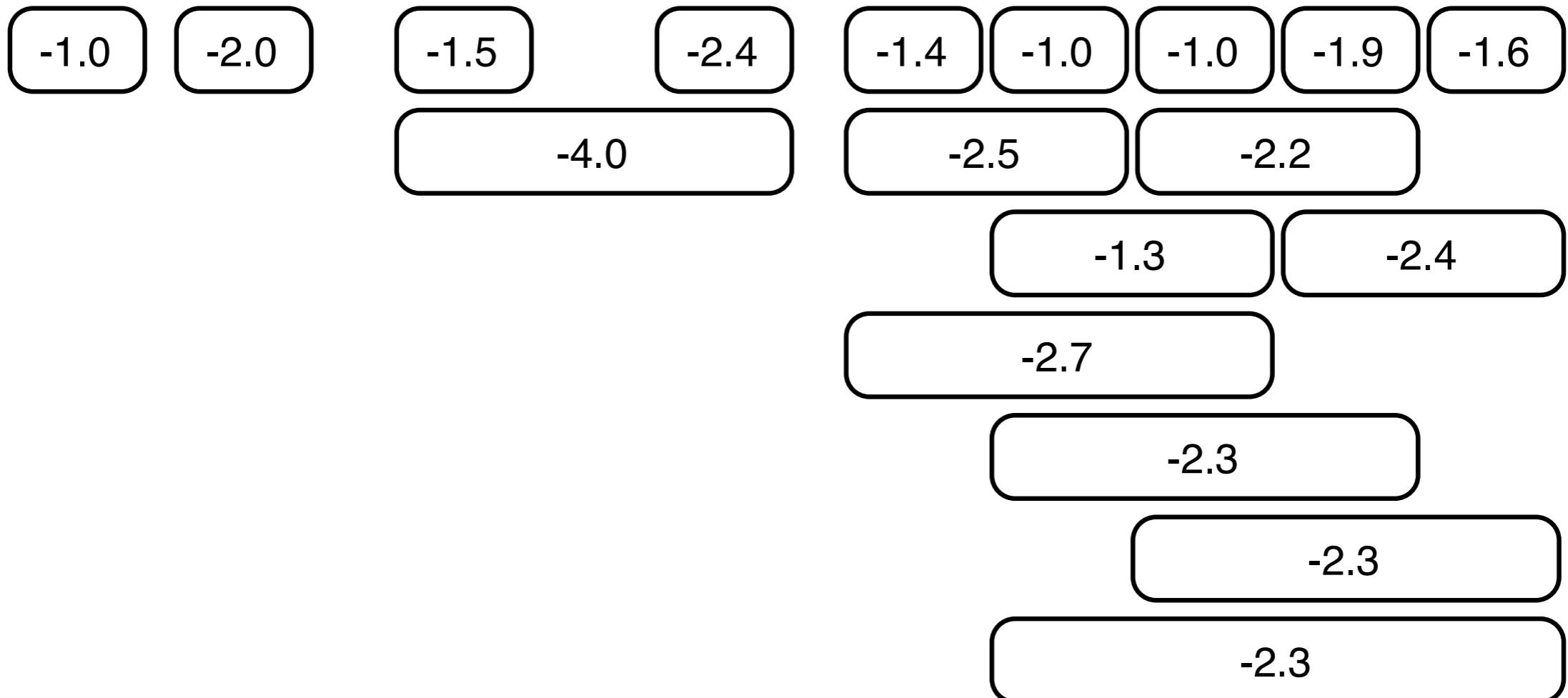
- Finding the best hypothesis is NP-hard
 - Even with no language model, there are an exponential number of states!
 - Solution 1: limit reordering
 - Solution 2: (lossy) pruning

Search Errors

- We are using a **heuristic search** to prune the search space
- There are no guarantees of admissibility (like in A* search)
- We may therefore prune out a partial hypothesis that would have lead to the most probable translation, if we hadn't pruned it early on

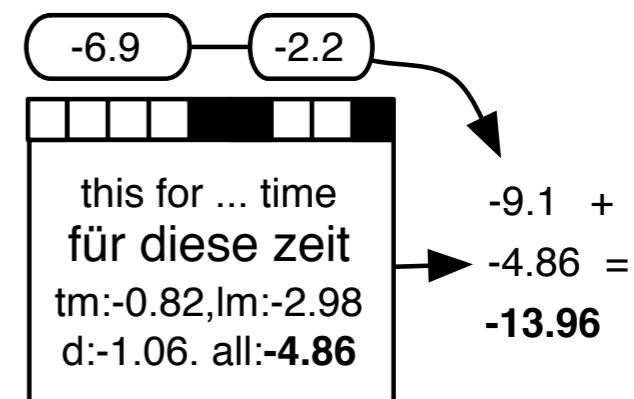
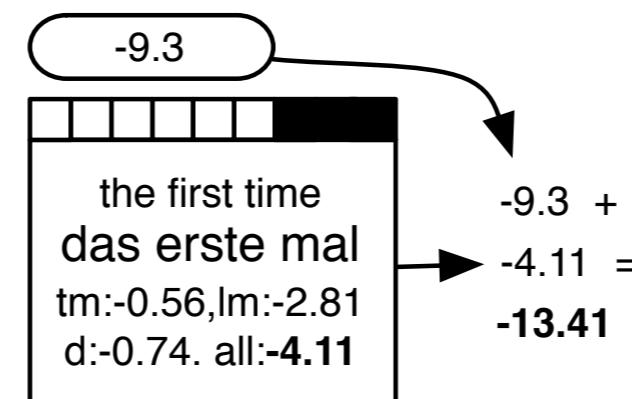
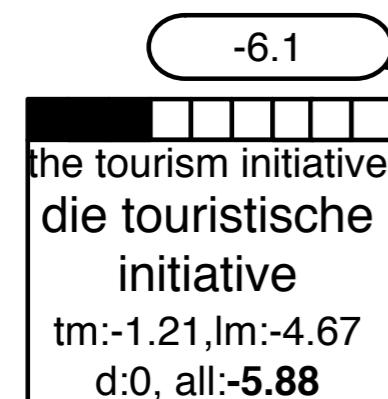
Future Cost Estimation

the tourism initiative addresses this for the first time



Future Cost Estimation

first word	future cost estimate for n words (from first)								
	1	2	3	4	5	6	7	8	9
the	-1.0	-3.0	-4.5	-6.9	-8.3	-9.3	-9.6	-10.6	-10.6
tourism	-2.0	-3.5	-5.9	-7.3	-8.3	-8.6	-9.6	-9.6	
initiative	-1.5	-3.9	-5.3	-6.3	-6.6	-7.6	-7.6		
addresses	-2.4	-3.8	-4.8	-5.1	-6.1	-6.1			
this	-1.4	-2.4	-2.7	-3.7	-3.7				
for	-1.0	-1.3	-2.3	-2.3					
the	-1.0	-2.2	-2.3						
first	-1.9	-2.4							
time	-1.6								



Linguistic Phrases

- Model is not limited to linguistic phrases (NPs, VPs, PPs, CPs...)
- Non-constituent phrases are useful

es *gibt* there is | there are

- Is a “good” phrase more likely to be
[P NP] or [governor P]
Why? How would you figure this out?

You implemented your
own phrase-based
decoder

Evaluating Translation Quality

- Why do we want to do it?
- Want to rank systems
- Want to evaluate incremental changes
- What to make scientific claims

Goals for Automatic Evaluation

- No cost evaluation for incremental changes
- Ability to rank systems
- Ability to identify which sentences we're doing poorly on, and categorize errors
- Correlation with human judgments
- Interpretability of the score

Methodology

- Comparison against reference translations
- Intuition: closer we get to human translations, the better we're doing
- Can't use WER like in speech recognition
 - *This shows how easy it is to recognize speech*
 - *This shows how easy it is to wreck a nice beach*

Problems with WER

- In machine translation there can be many possible (and equally valid) ways of translating a sentence
- *This shows how easy it is to recognize speech*
- *It illustrates how simple it is to transcribe the spoken word*
- Clauses can move around
- *This shows that recognizing speech is easy*

BLEU

- BiLingual Evaluation Understudy
- Uses multiple reference translations
- Look for n-grams that occur anywhere in the sentence

Multiple References

Ref 1	Orejuela appeared calm as he was led to the American plane which will take him to Miami, Florida.
Ref 2	Orejuela appeared calm while being escorted to the plane that would take him to Miami, Florida.
Ref 3	Orejuela appeared calm as he was being led to the American plane that was to carry him to Miami in Florida.
Ref 4	Orejuela seemed quite calm as he was being led to the American plane that would take him to Miami in Florida.

n-gram precision

$$p_n = \frac{\sum_{S \in C} \sum_{ngram \in S} Count_{matched}(ngram)}{\sum_{S \in C} \sum_{ngram \in S} Count(ngram)}$$

**American, Florida, Miami, Orejuela,
appeared, as, being, calm, carry, escorted, he,
him, in, led, plane, quite, seemed, take, that,
the, to, to, to, was , was, which, while, will,
would, , , .**

1-gram precision = 15/18

Hyp

**appeared calm when he was taken to the American
plane , which will to Miami , Florida .**

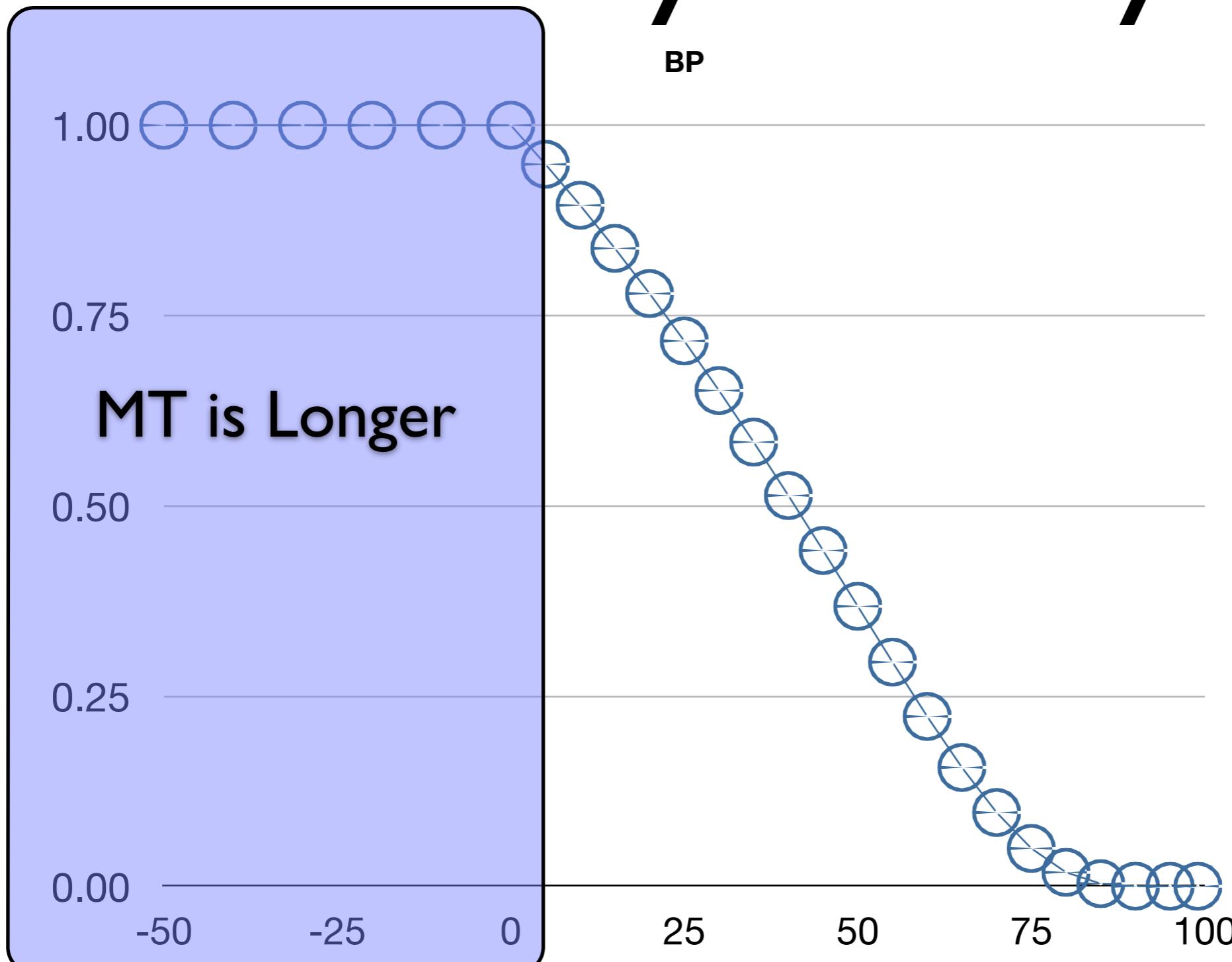
American plane, Florida ., Miami , Miami
in, Orejuela appeared, Orejuela seemed,
appeared calm, as he, being escorted, being
led, calm as, calm while, carry him, escorted
to, **he was**, him to, in Florida, led to, plane
that, plane which, quite calm, seemed quite,
take him, that was, that would, **the American**,
the plane, **to Miami**, to carry, **to the**, was
being, was led, was to, **which will**, while
being, will take, would take, , Florida

2-gram precision = 10/17

Hyp

**appeared calm when he was taken to the American
plane , which will to Miami , Florida .**

Brevity Penalty



Difference with effective reference length (%)

Manual Evaluation

Source: Estos tejidos están analizados, transformados y congelados antes de ser almacenados en Hema-Québec, que gestiona también el único banco público de sangre del cordón umbilical en Quebec.

Reference: These tissues are analyzed, processed and frozen before being stored at Héma-Québec, which manages also the only bank of placental blood in Quebec.

Translation	Rank				
	1	2	3	4	5
	Best				Worst
These weavings are analyzed, transformed and frozen before being stored in Hema-Quebec, that negotiates also the public only bank of blood of the umbilical cord in Quebec.	○	○	○	○	●
These tissues analysed, processed and before frozen of stored in Hema-Québec, which also operates the only public bank umbilical cord blood in Quebec.	○	○	●	○	○
These tissues are analyzed, processed and frozen before being stored in Hema-Québec, which also manages the only public bank umbilical cord blood in Quebec.	○	●	○	○	○
These tissues are analyzed, processed and frozen before being stored in Hema-Quebec, which also operates the only public bank of umbilical cord blood in Quebec.	●	○	○	○	○
These fabrics are analyzed, are transformed and are frozen before being stored in Hema-Québec, who manages also the only public bank of blood of the umbilical cord in Quebec.	○	○	○	●	○

Correlation with Human Judgments

- Kendall's Tau

$$\tau = \frac{\text{num concordant pairs} - \text{num discordant pairs}}{\text{total pairs}}$$

You implemented your
own evaluation metric

Noisy Channel Model

$$\begin{aligned}\mathbf{e}^* &= \arg \max_{\mathbf{e}} p(\mathbf{e} \mid \mathbf{g}) \\&= \arg \max_{\mathbf{e}} \frac{p(\mathbf{g} \mid \mathbf{e}) \times p(\mathbf{e})}{p(\mathbf{g})} \\&= \arg \max_{\mathbf{e}} p(\mathbf{g} \mid \mathbf{e}) \times p(\mathbf{e}) \\&= \arg \max_{\mathbf{e}} \log p(\mathbf{g} \mid \mathbf{e}) + \log p(\mathbf{e})\end{aligned}$$

Noisy Channel Model

$$\mathbf{e}^* = \arg \max_{\mathbf{e}} p(\mathbf{e} \mid \mathbf{g})$$

$$= \arg \max_{\mathbf{e}} \frac{p(\mathbf{g} \mid \mathbf{e}) \times p(\mathbf{e})}{p(\mathbf{g})}$$

$$= \arg \max_{\mathbf{e}} p(\mathbf{g} \mid \mathbf{e}) \times p(\mathbf{e})$$

$$= \arg \max_{\mathbf{e}} \log p(\mathbf{g} \mid \mathbf{e}) + \log p(\mathbf{e})$$

$$= \arg \max_{\mathbf{e}} \underbrace{\begin{bmatrix} 1 \\ 1 \end{bmatrix}^\top}_{\mathbf{w}^\top} \underbrace{\begin{bmatrix} \log p(\mathbf{g} \mid \mathbf{e}) \\ \log p(\mathbf{e}) \end{bmatrix}}_{\mathbf{h}(\mathbf{g}, \mathbf{e})}$$

Log-linear Model

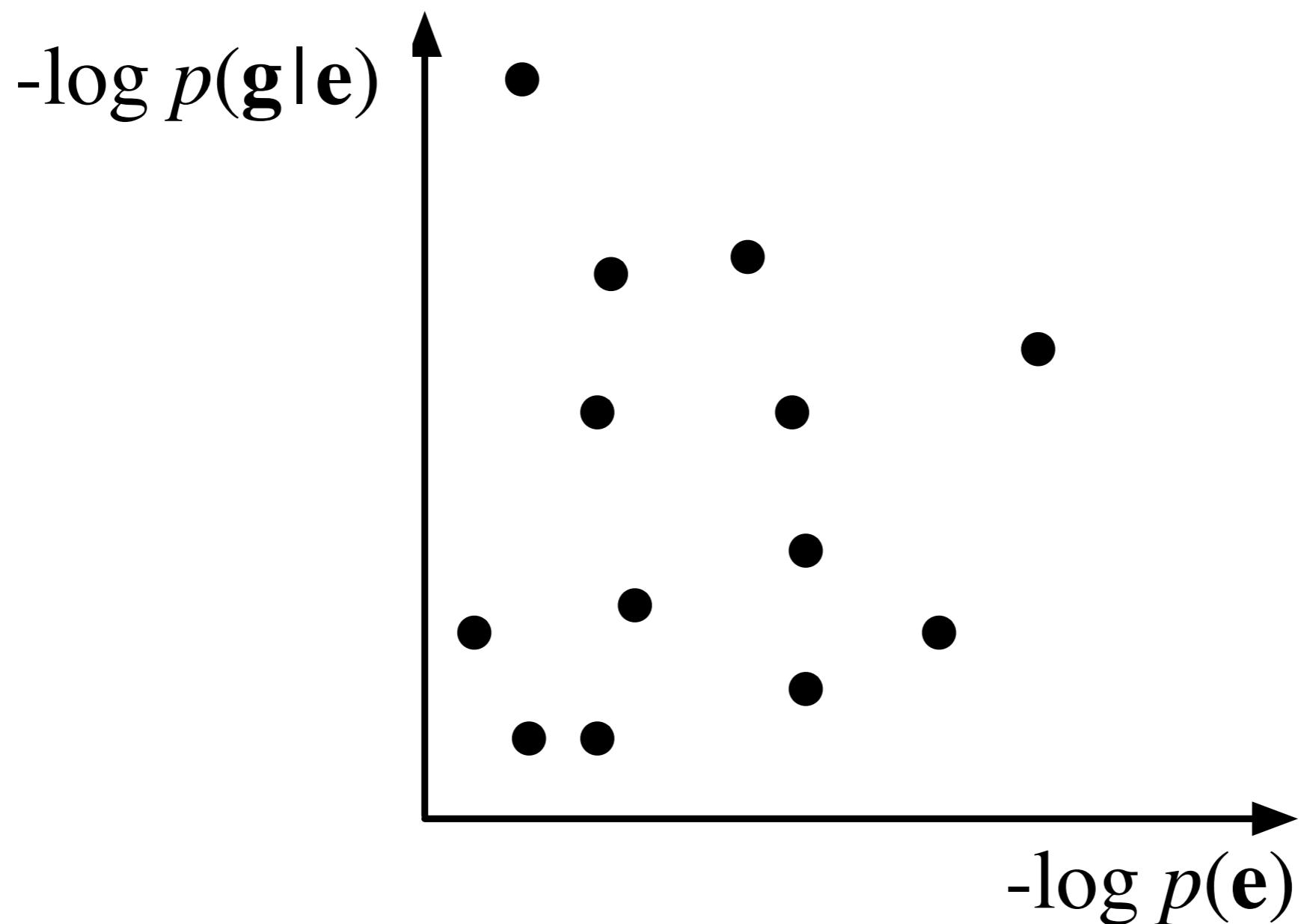
Discriminative modeling

- Depart from generative modeling
- Goal:
 - Directly optimize for translation performance by discriminating between good/bad translation

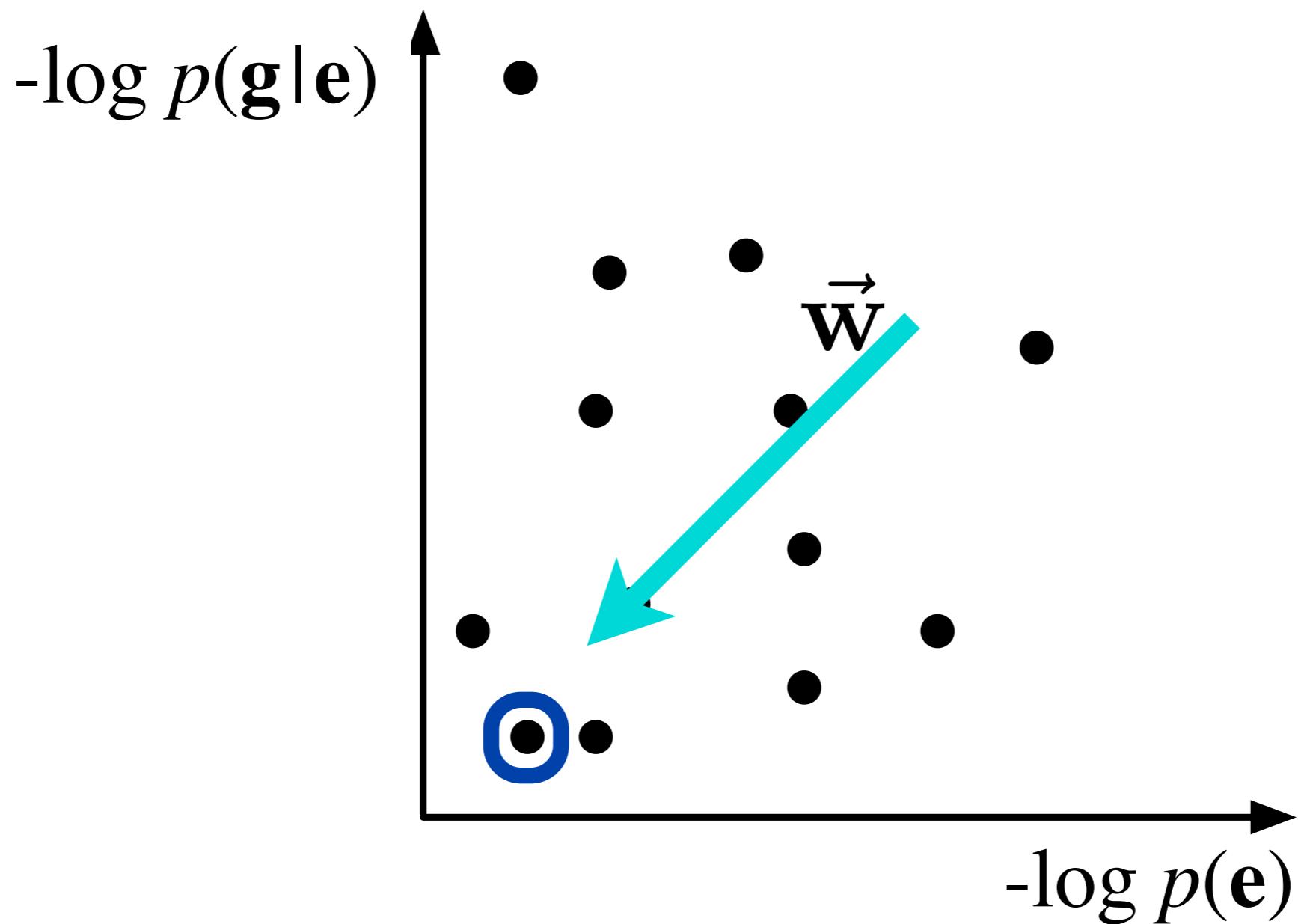
Discriminative modeling

- Represent Possible translations using a set of features h
- Each feature h_i derives from one property of the translation
- Its feature weight w_i indicates its relative importance

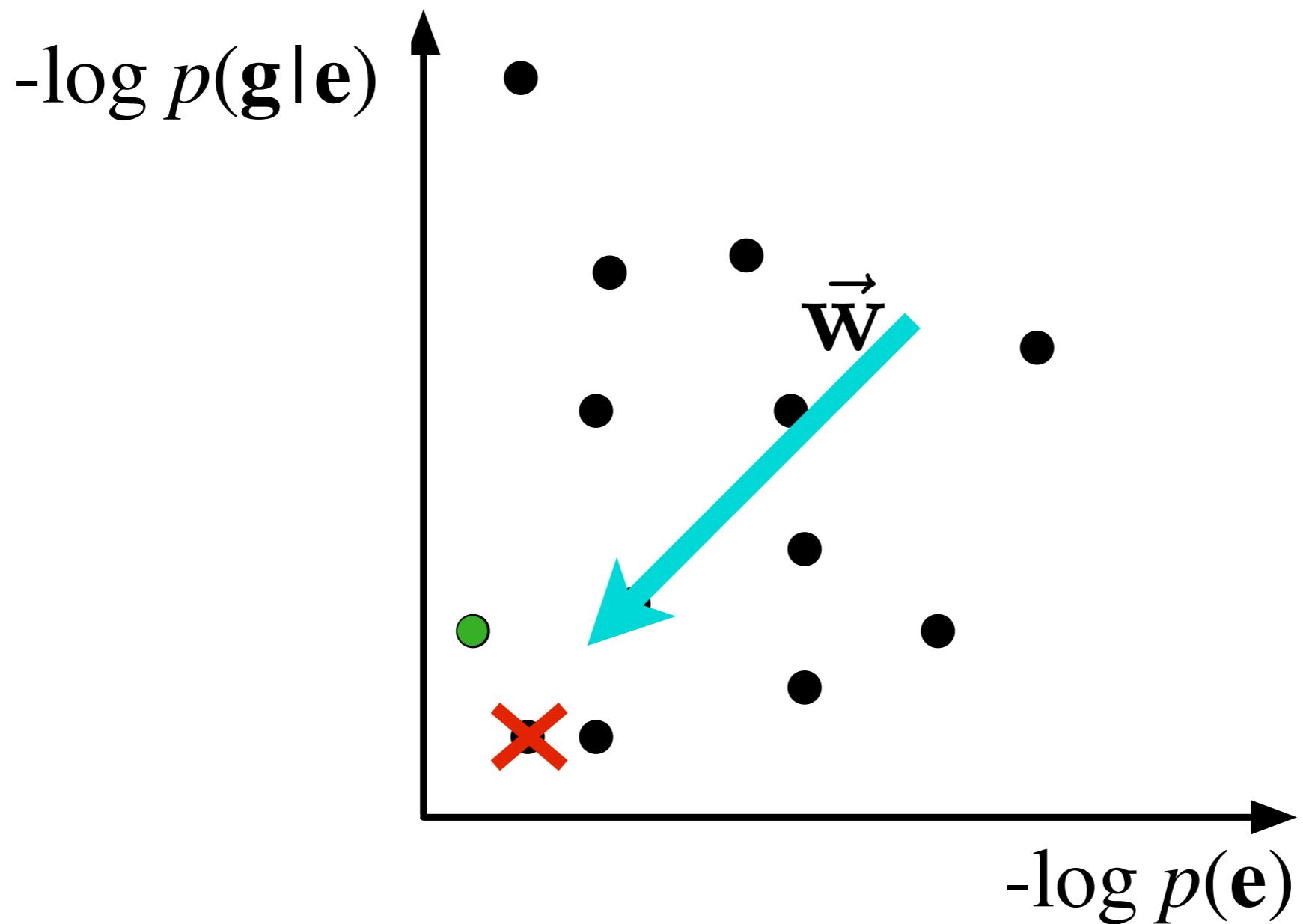
The Noisy Channel



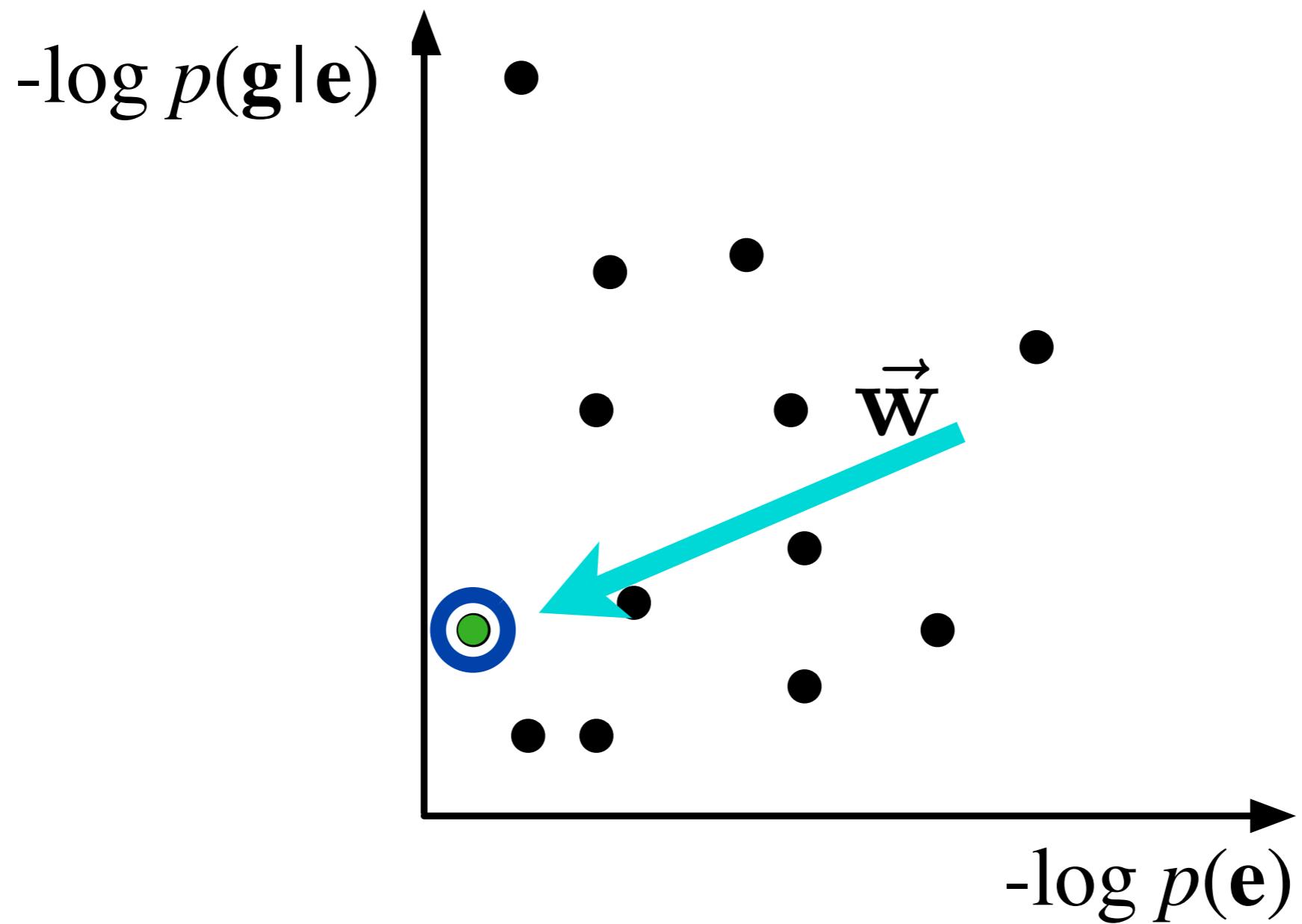
As a Linear Model



As a Linear Model



As a Linear Model

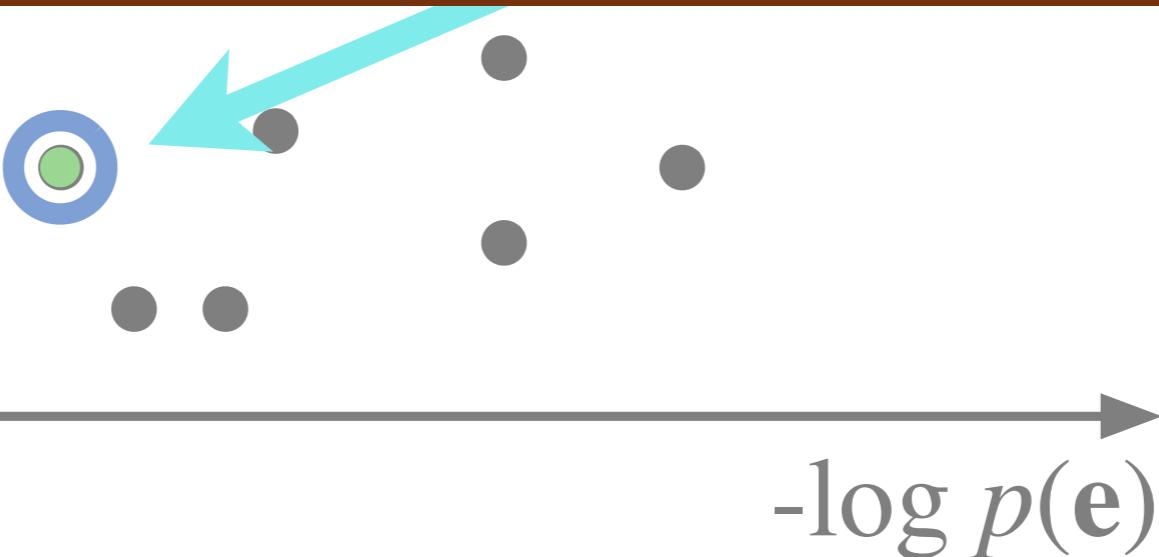


As a Linear Model

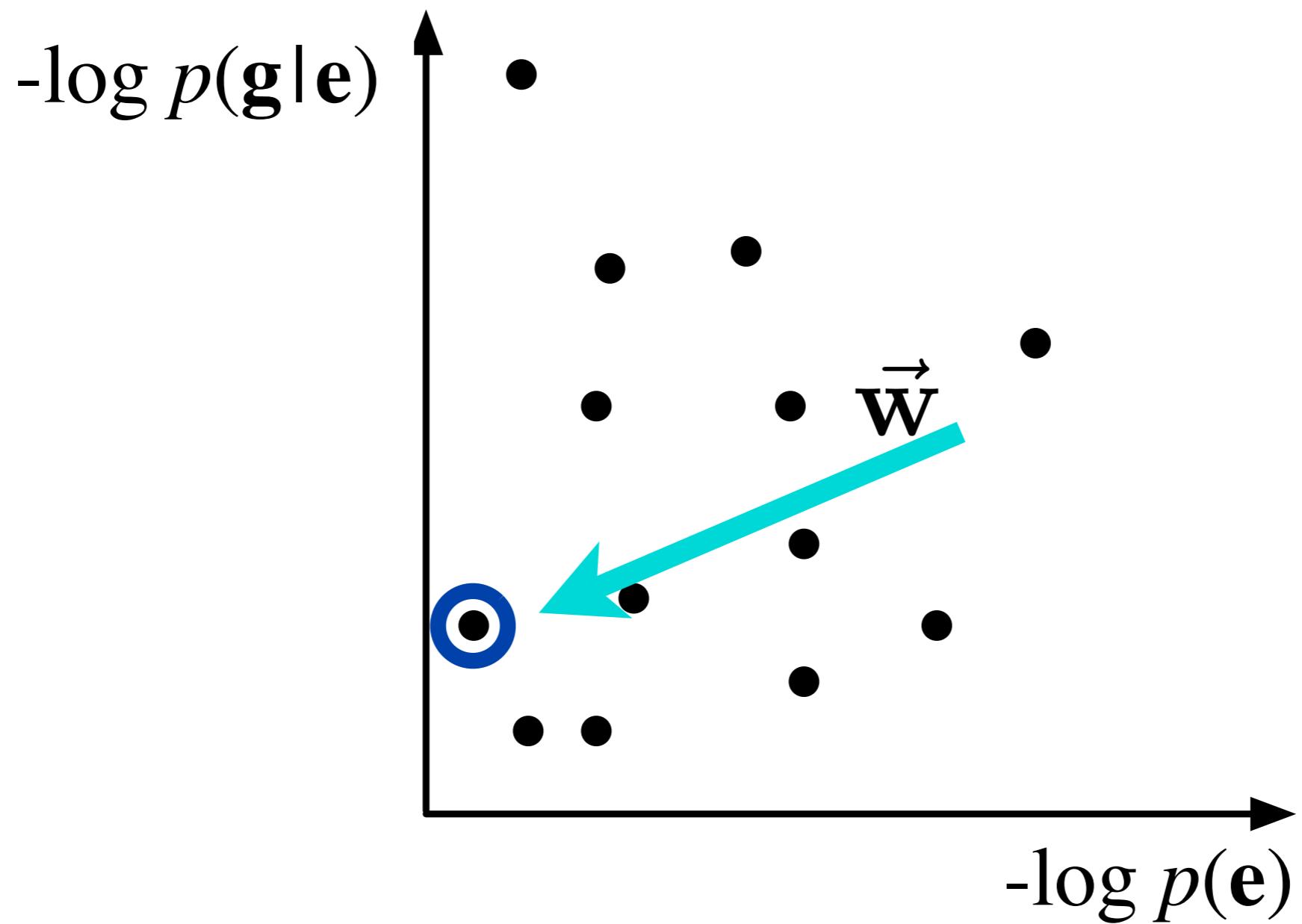
$-\log p(\text{g}|\text{e})$ ↑

Improvement I:

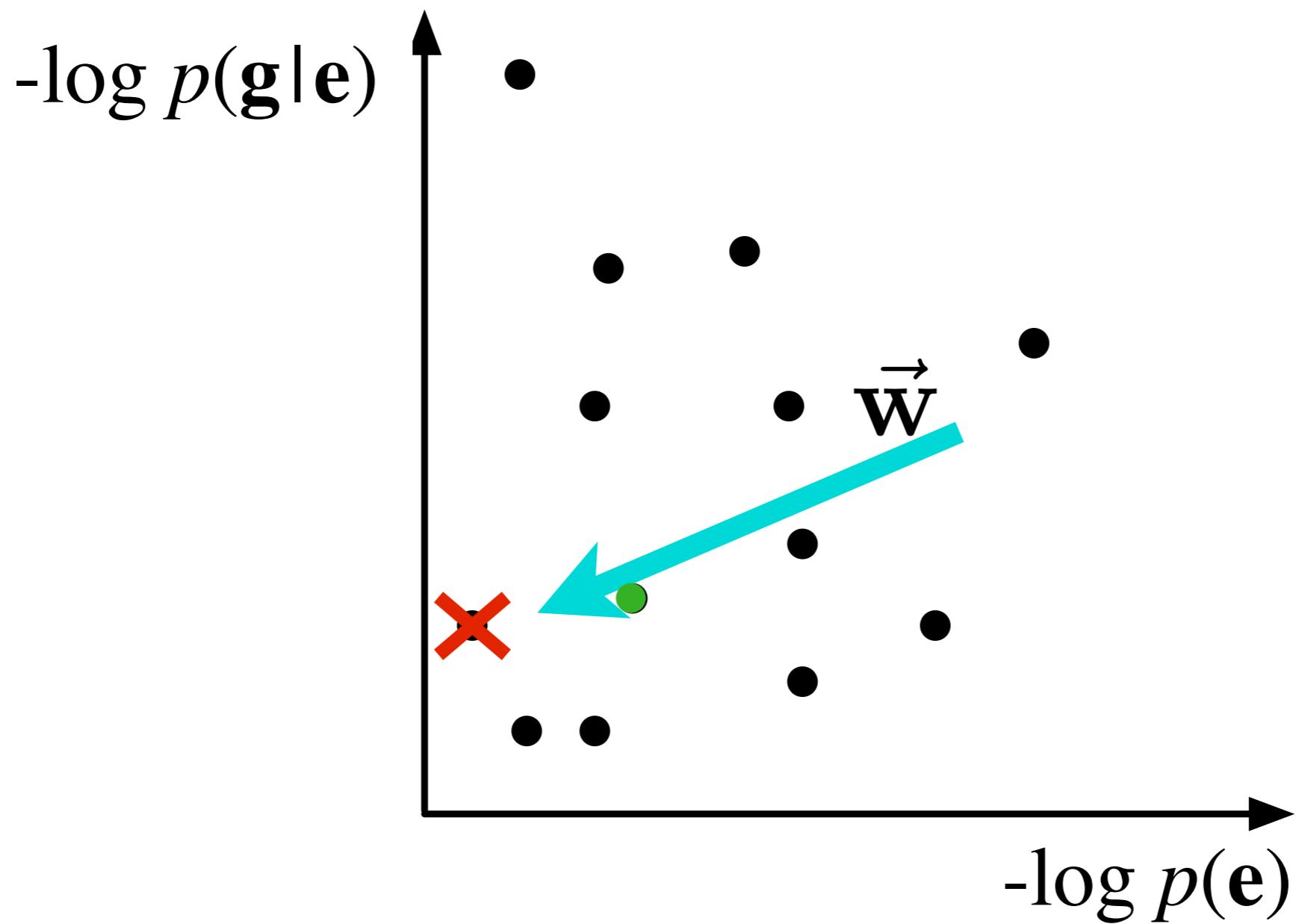
change \vec{w} to find better translations



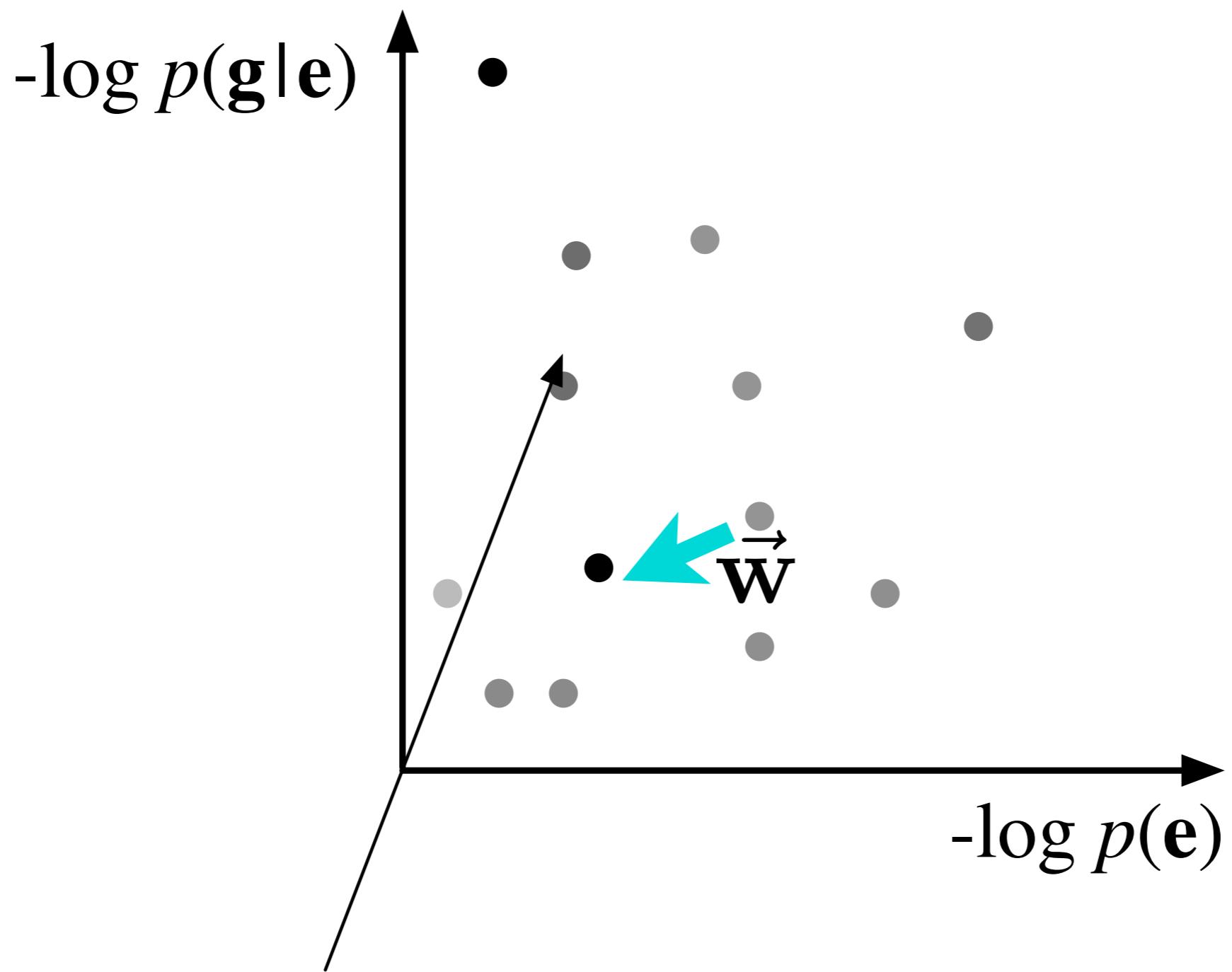
As a Linear Model



As a Linear Model



As a Linear Model

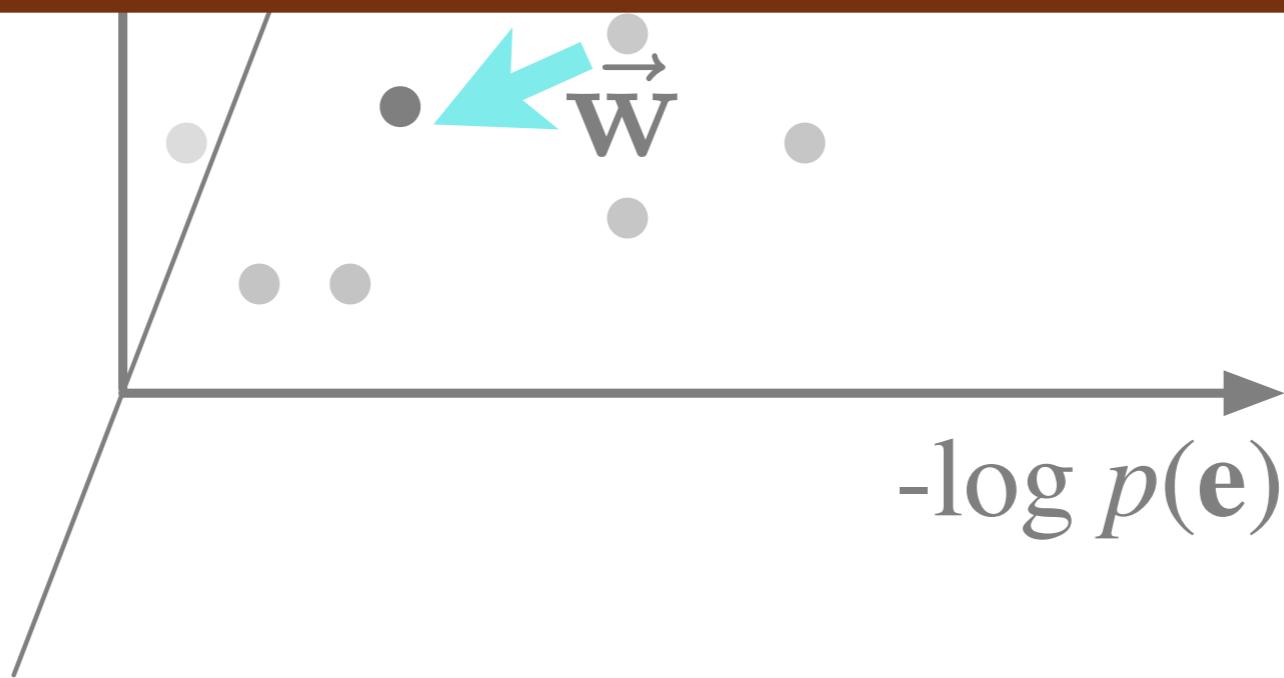


As a Linear Model

$-\log p(\text{gle})$

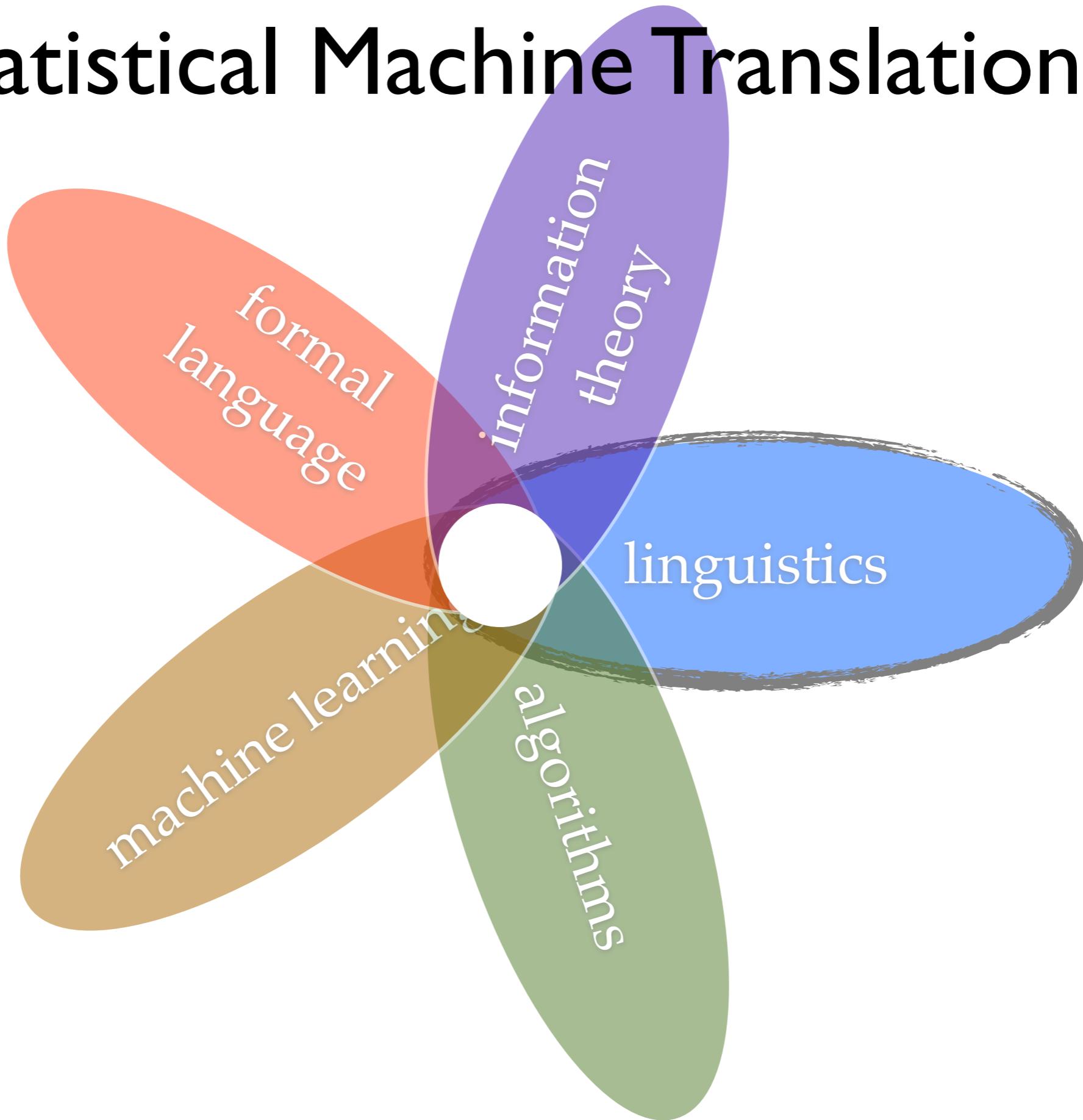
Improvement 2:

Add dimensions to make points separable



You discriminatively
re-ranked n-best
translations

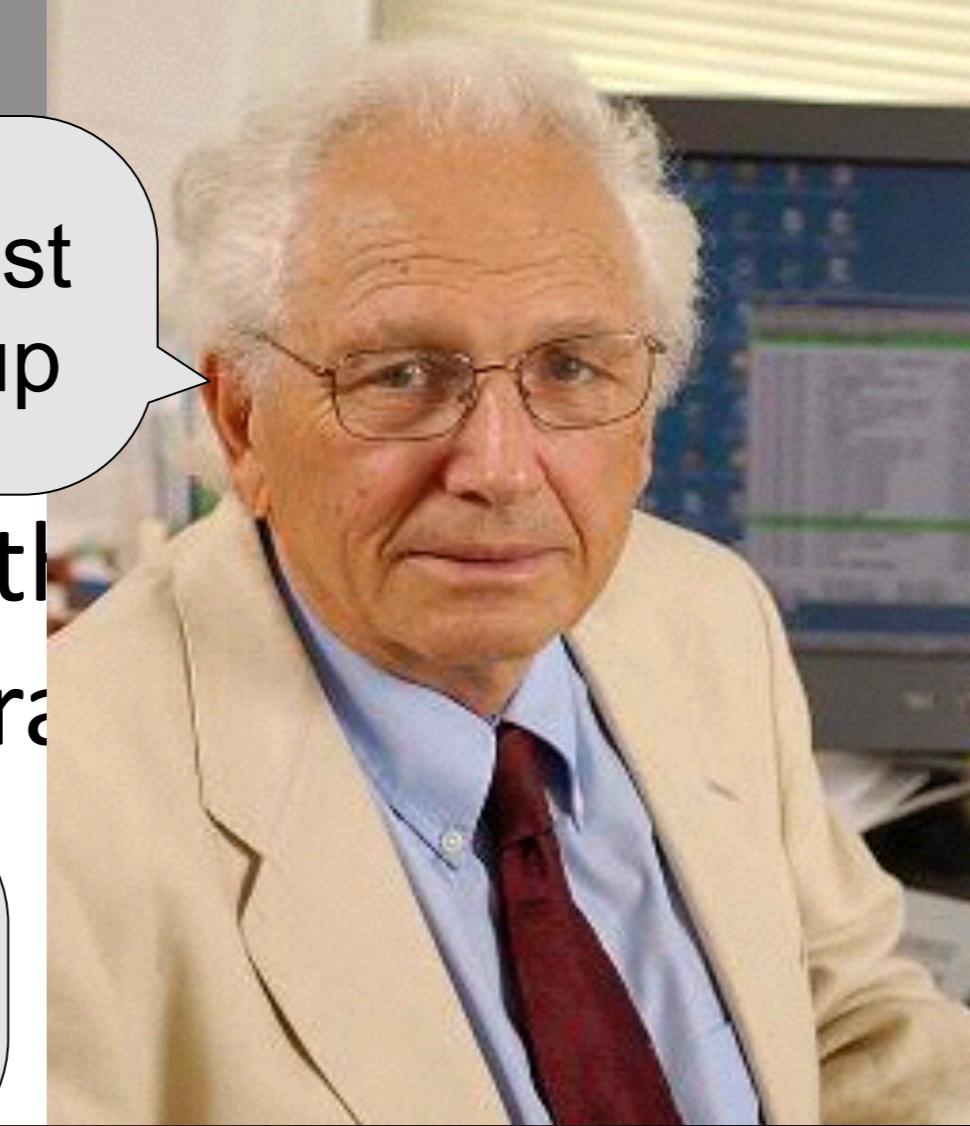
Statistical Machine Translation



Every time I fire a linguist
my performance goes up

- Longstanding debate about whether information can help statistical translation
- Two camps

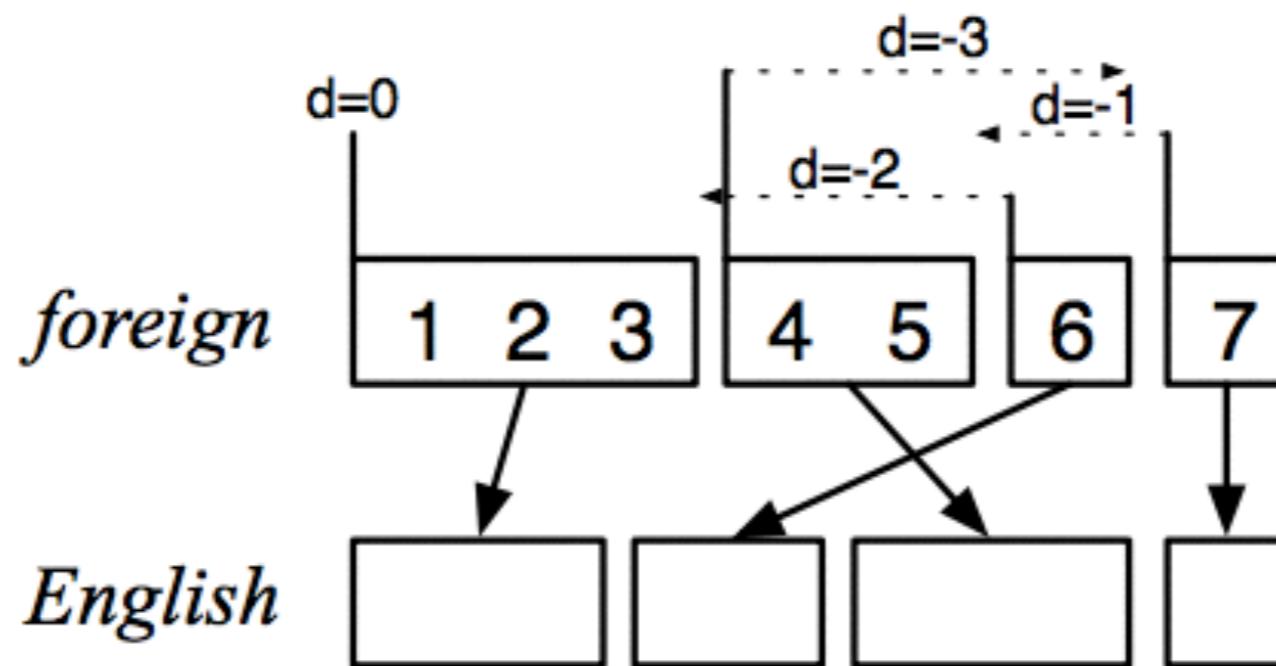
Syntax will improve translation



Simpler data-driven models will always win



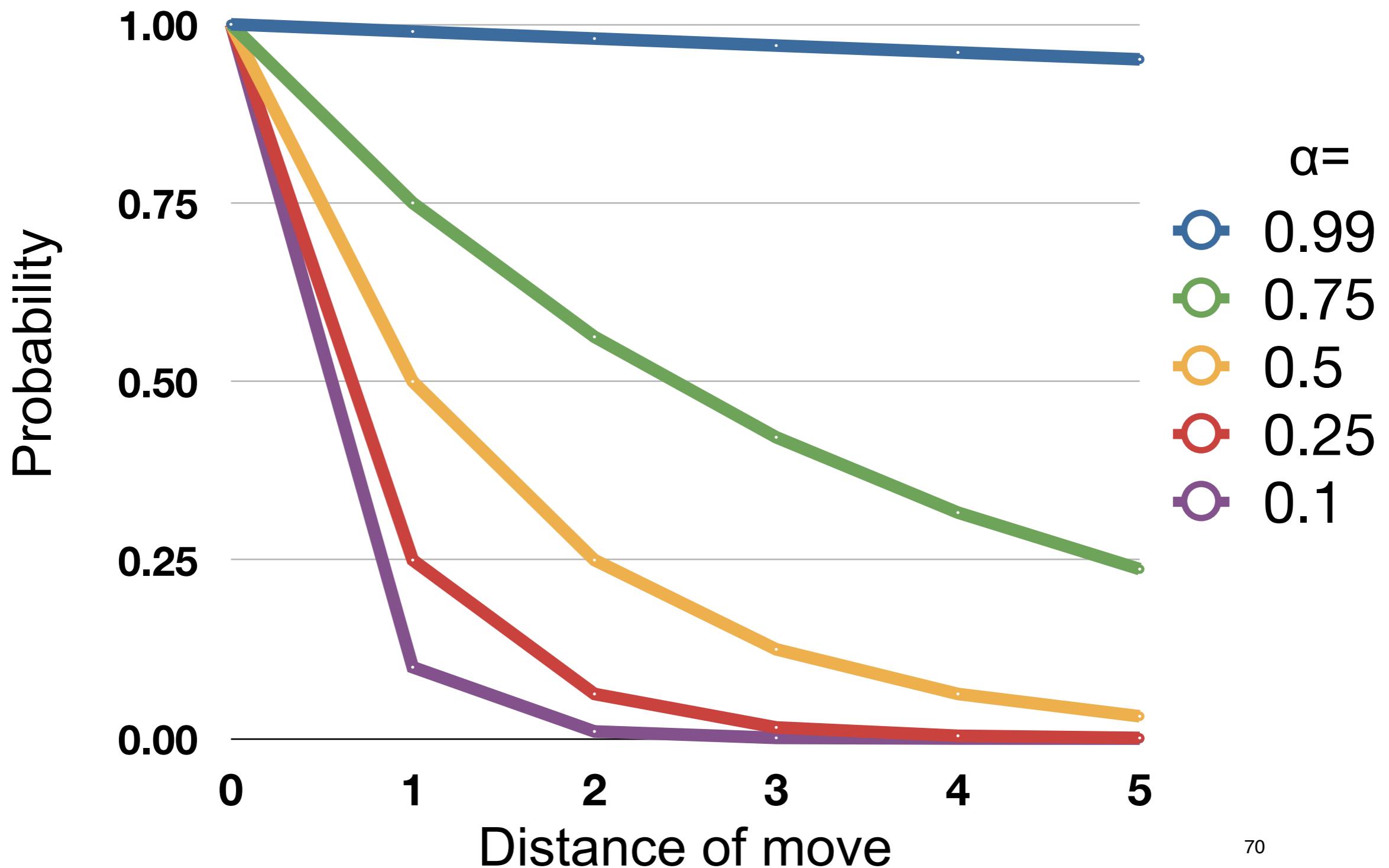
Reordering Model



phrase	translates	movement	distance
1	1–3	start at beginning	0
2	6	skip over 4–5	+2
3	4–5	move back over 4–6	-3
4	7	skip over 6	+1

Scoring function: $d(x) = \alpha^{|x|}$ — exponential with distance

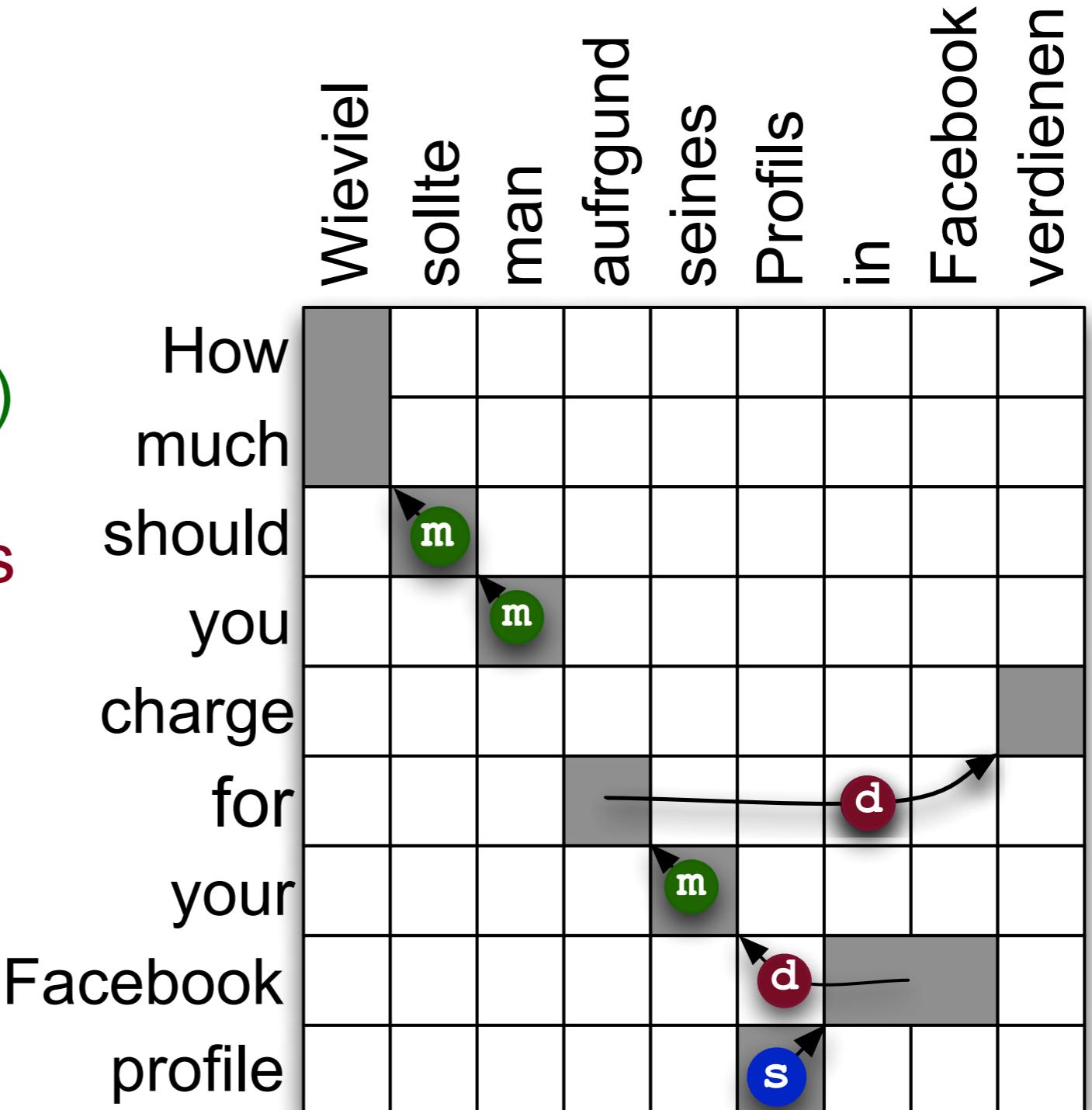
Values of α



Lexicalized Reordering model

m: monotone (keep order)
s: swap order
d: become discontinuous

Reordering features are probability estimates of s, d, and m



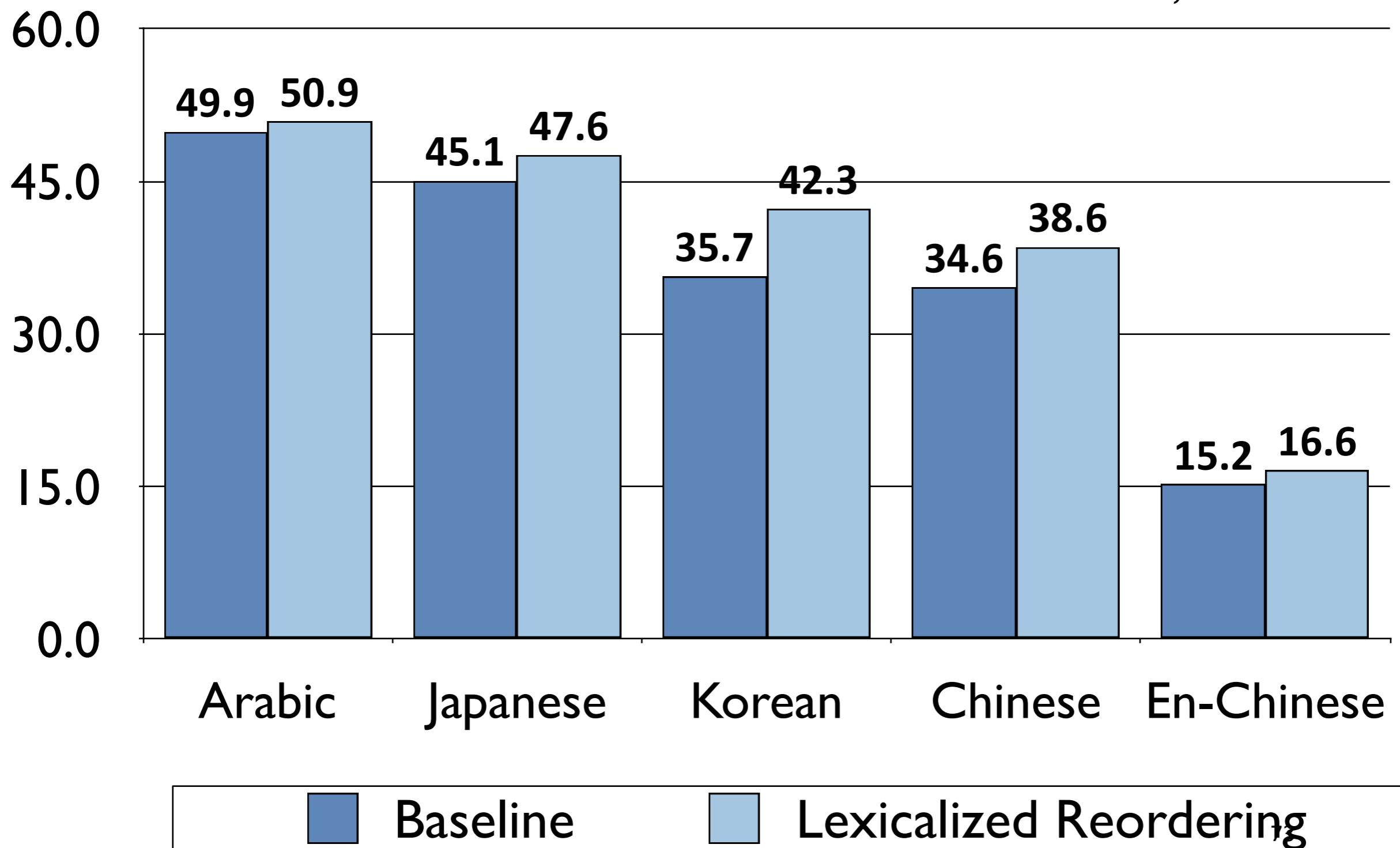
Lexicalized Reordering table

- Identical phrase pairs $\langle f, e \rangle$ as in the phrase translation table
- Contains values for $p(\text{monotone}|e,f)$, $p(\text{swap}|e,f)$, $p(\text{discontinuous}|e,f)$

Source	Translation	$p(m e,f)$	$p(s e,f)$	$p(d e,f)$
natuerlich	of course	0.52	0.08	0.4
natuerlich	naturally	0.42	0.1	0.48
natuerlich	of course ,	0.5	0.001	0.499
natuerlich	, of course	0.27	0.17	0.56

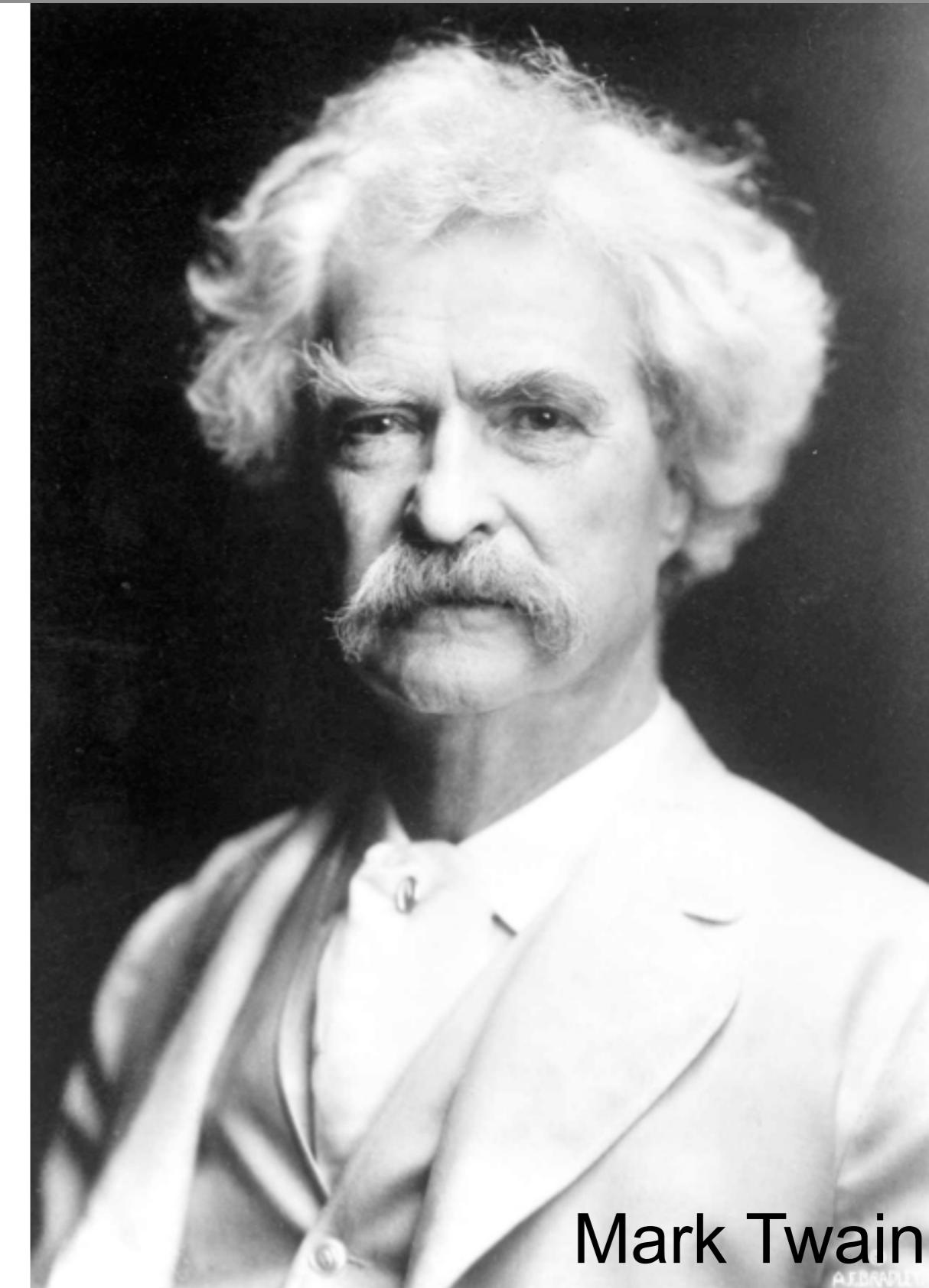
Empirically Better

Koehn et al, IWSLT 2005



The Awful German Language

“The Germans have another kind of parenthesis, which they make by splitting a verb in two and putting half of it at the beginning of an exciting chapter and the OTHER HALF at the end of it. Can any one conceive of anything more confusing than that? These things are called ‘separable verbs.’ The wider the two portions of one of them are spread apart, the better the author of the crime is pleased with his performance.”



Mark Twain

German verbs

Ich **werde** Ihnen den Report **aushaendigen**.
I **will** to_you the report **pass_on**.

Ich **werde** Ihnen die entsprechenden Anmerkungen **aushaendigen**.
I **will** to_you the corresponding comments **pass_on**.

Ich **werde** Ihnen die entsprechenden Anmerkungen am Dienstag **aushaendigen**
I **will** to_you the corresponding comments on Tuesday **pass_on**

Collins' Pre-ordering Model

Step 1: Reorder the source language

Ich **werde** Ihnen den Report **aushaendigen** ,
damit Sie den eventuell uebernehmen **koennen** .

→ Ich **werde aushaendigen** Ihnen den Report ,
damit Sie **koennen uebernehmen** den eventuell .

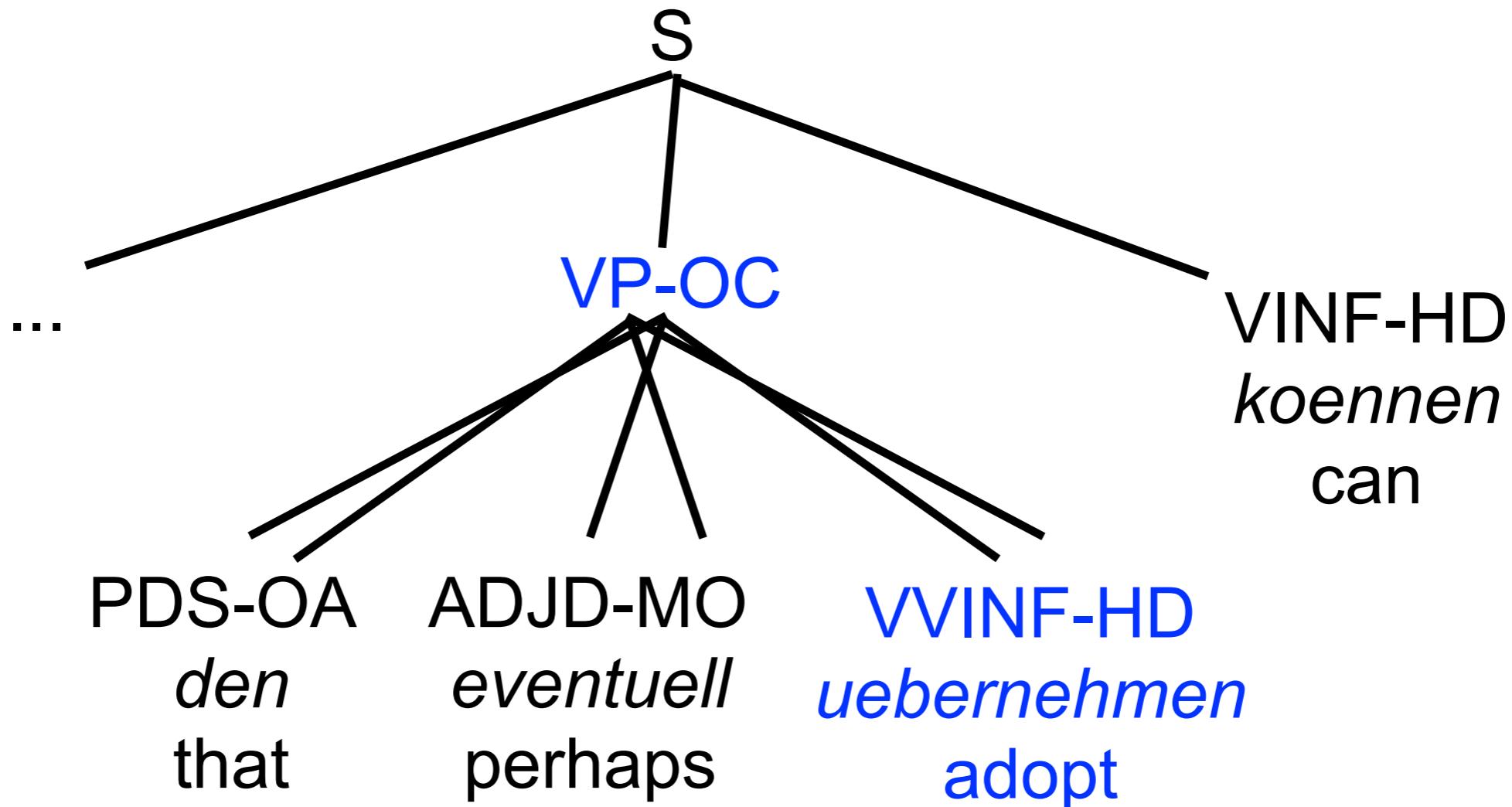
(I **will pass_on** to_you the report, **so_that** you **can adopt** it perhaps .)

Step 2: Apply the phrase-based machine translation pipeline to the reordered input.

Clause Restructuring

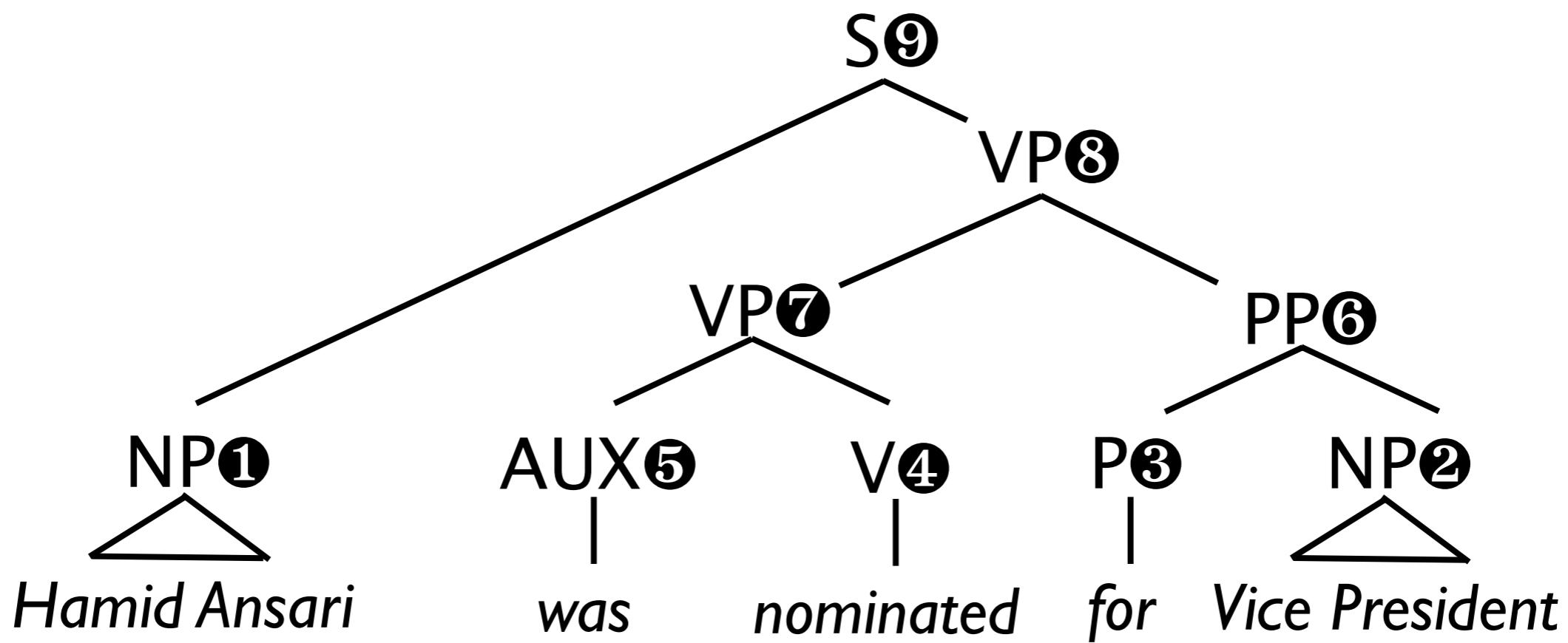
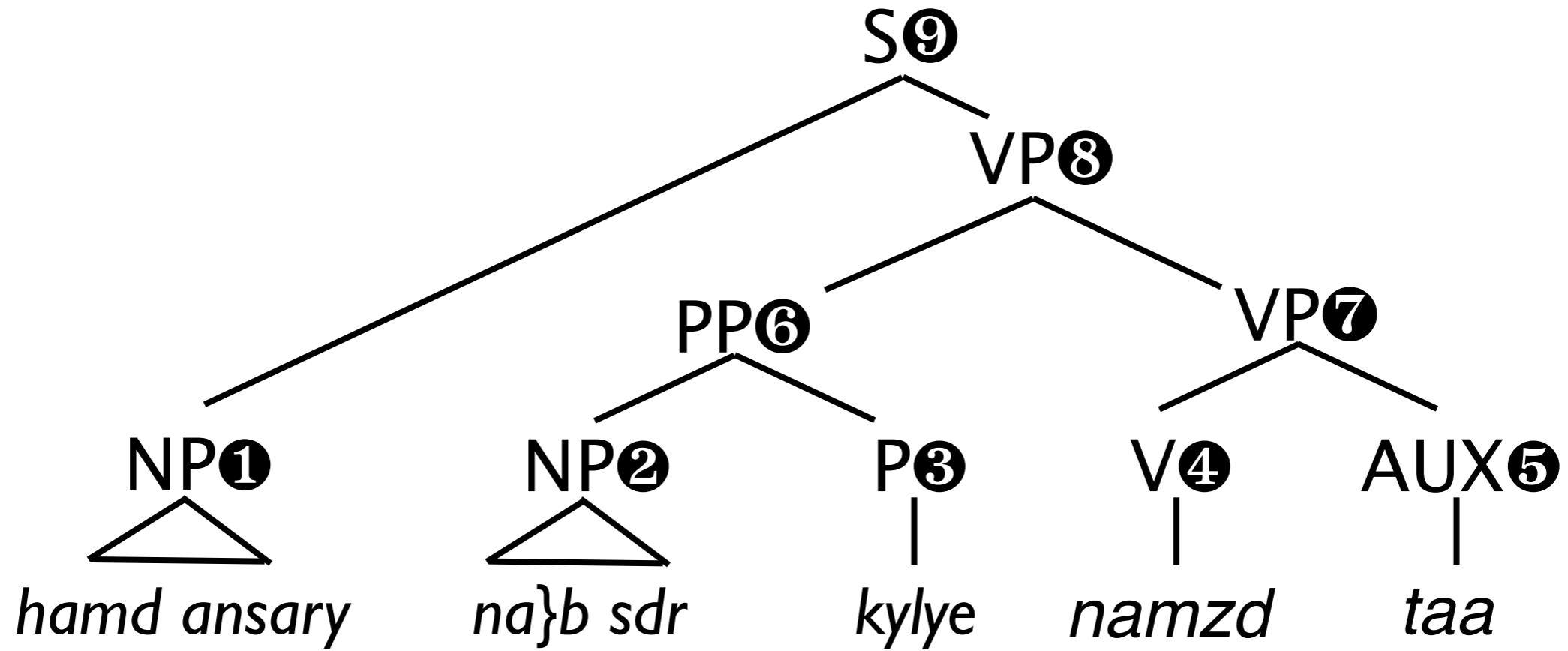
Rule 1: **Verbs are initial in VPs**

Within a VP, move the **head** to the initial position

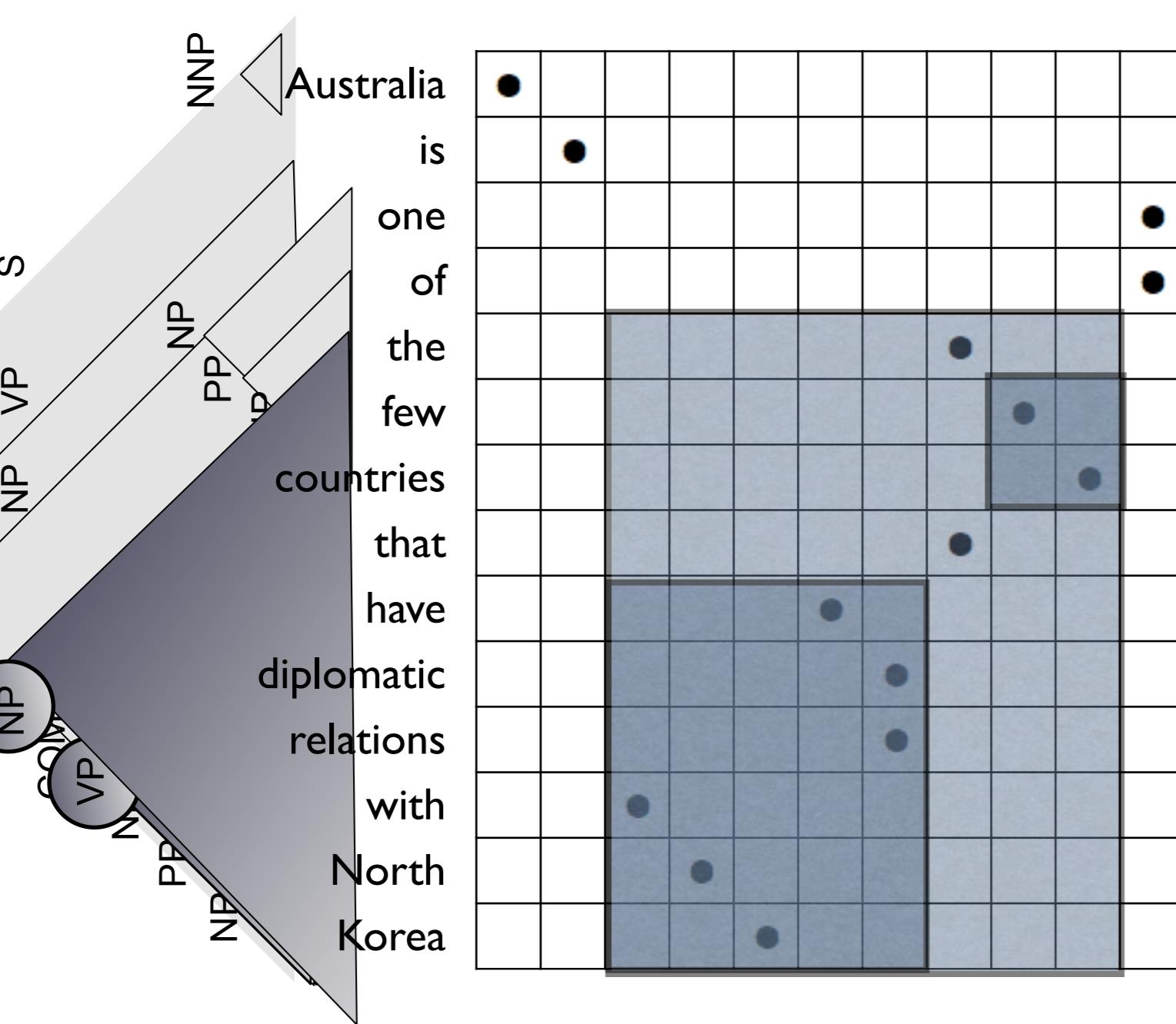


Synchronous Context Free Grammars

- A common way of representing syntax in NLP is through **context free grammars**
- **Synchronous** context free grammars generate pairs of corresponding strings
- Can be used to describe **translation** and **re-ordering** between languages
- SCFGs **translate sentences by parsing them**



Extracting Syntactic Rules



$VP \rightarrow \text{与 北 韩 有 邦 交}$,
have diplomatic relations
with North Korea

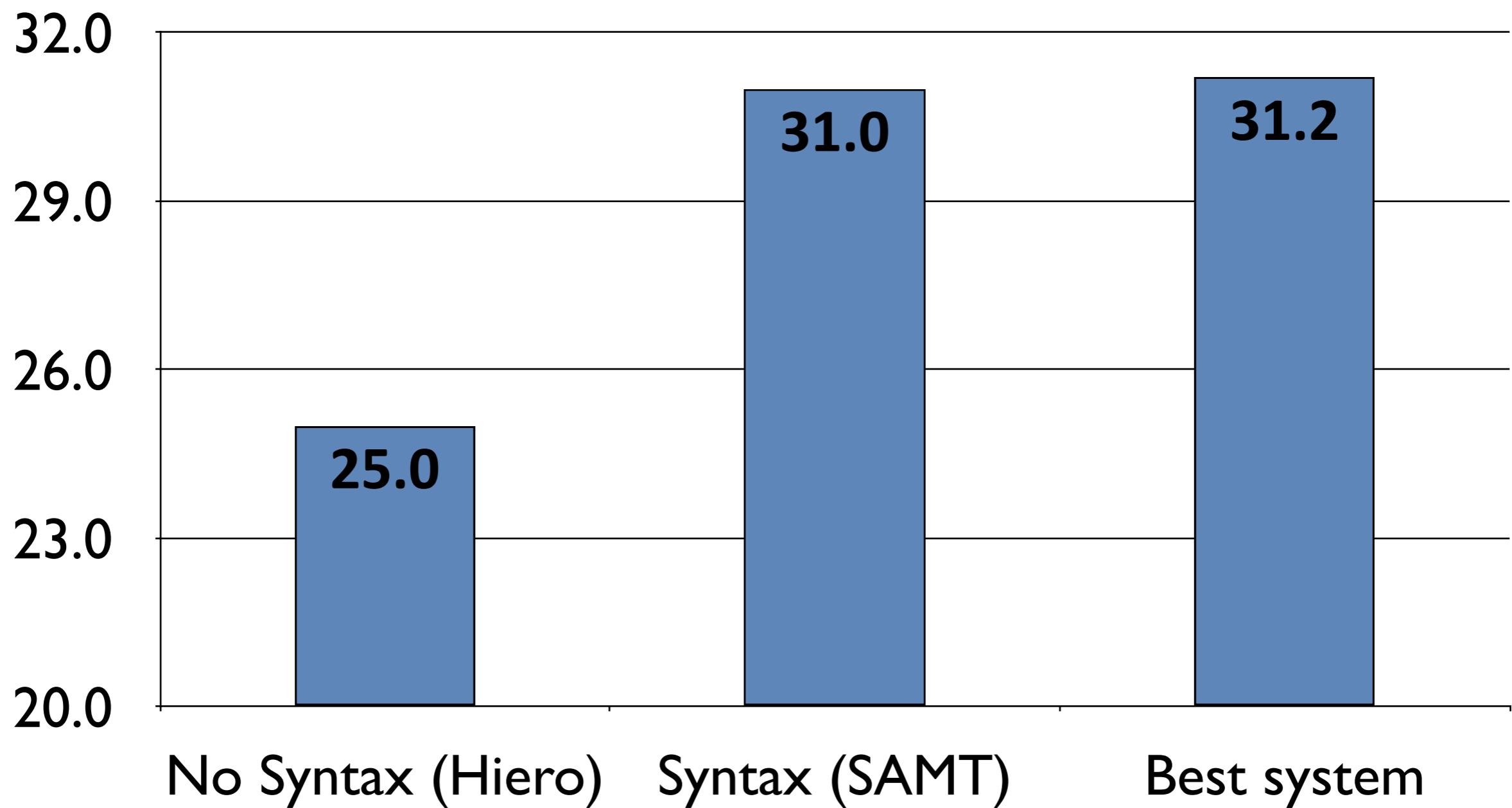
$NP \rightarrow \text{与 北 韩 有 邦 交}$
的 少 数 国 家, the few
countries that have
diplomatic relations with
North Korea

$NP \rightarrow VP$ 的 少 数 国 家,
the few countries that VP

$NP \rightarrow VP$ 的 NP,
the NP that VP

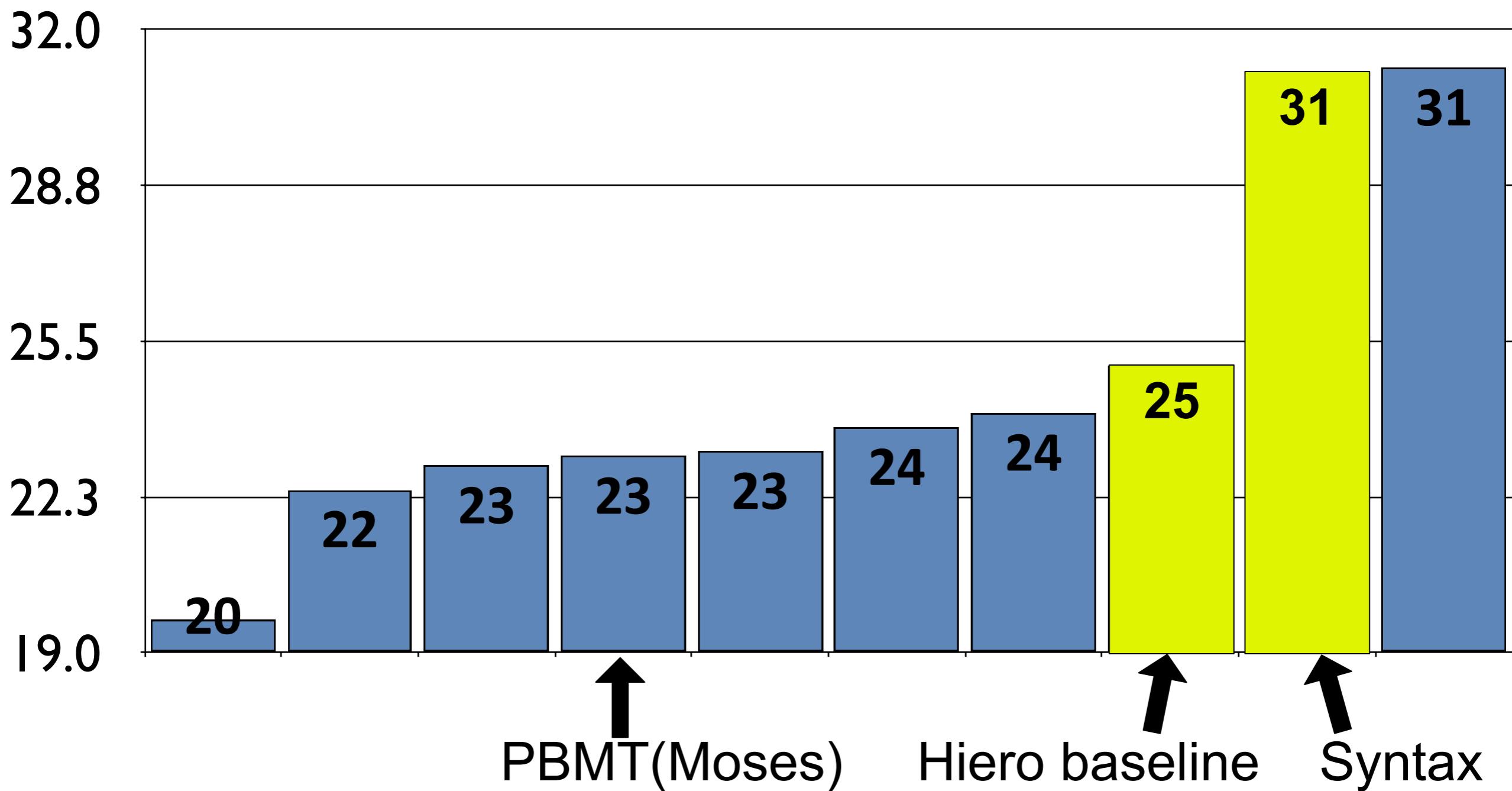
Syntax v. no Syntax

Bleu score on blind NIST Urdu-English test set



State of the Art Urdu Results

All system scores on NIST09 Urdu-English constrained task



Joshua Decoder



- An open source decoder
- Uses synchronous context free grammars to translate
- Implements all algorithms needed for translating with SCFGs
 - grammar extraction (Thrax!)
 - chart-parsing
 - n-gram language model integration
 - pruning, and k-best ⁸³ extraction

History of Decoders



GIZA++ was an open source implementation of the IBM alignment models developed at the 1999 CLSP summer workshop



PHARAOH was a beam search decoder for phrase-based statistical machine translation models



Moses is an open source decoder for phrase-based statistical machine translation models



JosHUa is an open source syntax based SMT models

Advanced Topics

Environment Canada – Take Action for the Environment | Environment Canada – Passons à l'action pour l'environnement – Q

<http://www.ec.gc.ca/education/default.asp?lang=En&n=3AD653> | <http://www.ec.gc.ca/education/default.asp?lang=Fr&n=3AD65317-1>

Environment Canada | Environnement Canada

 Environment Canada | Environnement Canada

Environment Canada

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Passons à l'action pour l'environnement

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- [Habitat et faune](#)
- [Pollution et déchets](#)
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[Divulgation proactive](#)



[L'air](#)



[Changement climatique](#)



[Habitat et faune](#)



Google's efforts

- Number of words of mined English-X parallel text

	baseline	books	web
Czech	27.5M	-	271.9M
French	479.8M	228.5M	4,914.3M
German	54.2M	-	3,787.6M
Hungarian	26.9M	-	198.9M
Spanish	441.0M	15.0M	4,846.8M

- Translation improvements

	baseline	+books	+web
Czech English	21.59	-	29.26 (+7.67)
German English	27.99	-	32.35 (+4.36)
French English	34.26	34.73 (+0.47)	36.65 (+2.39)
Spanish English	43.67	44.07 (+0.40)	46.21 (+2.54)

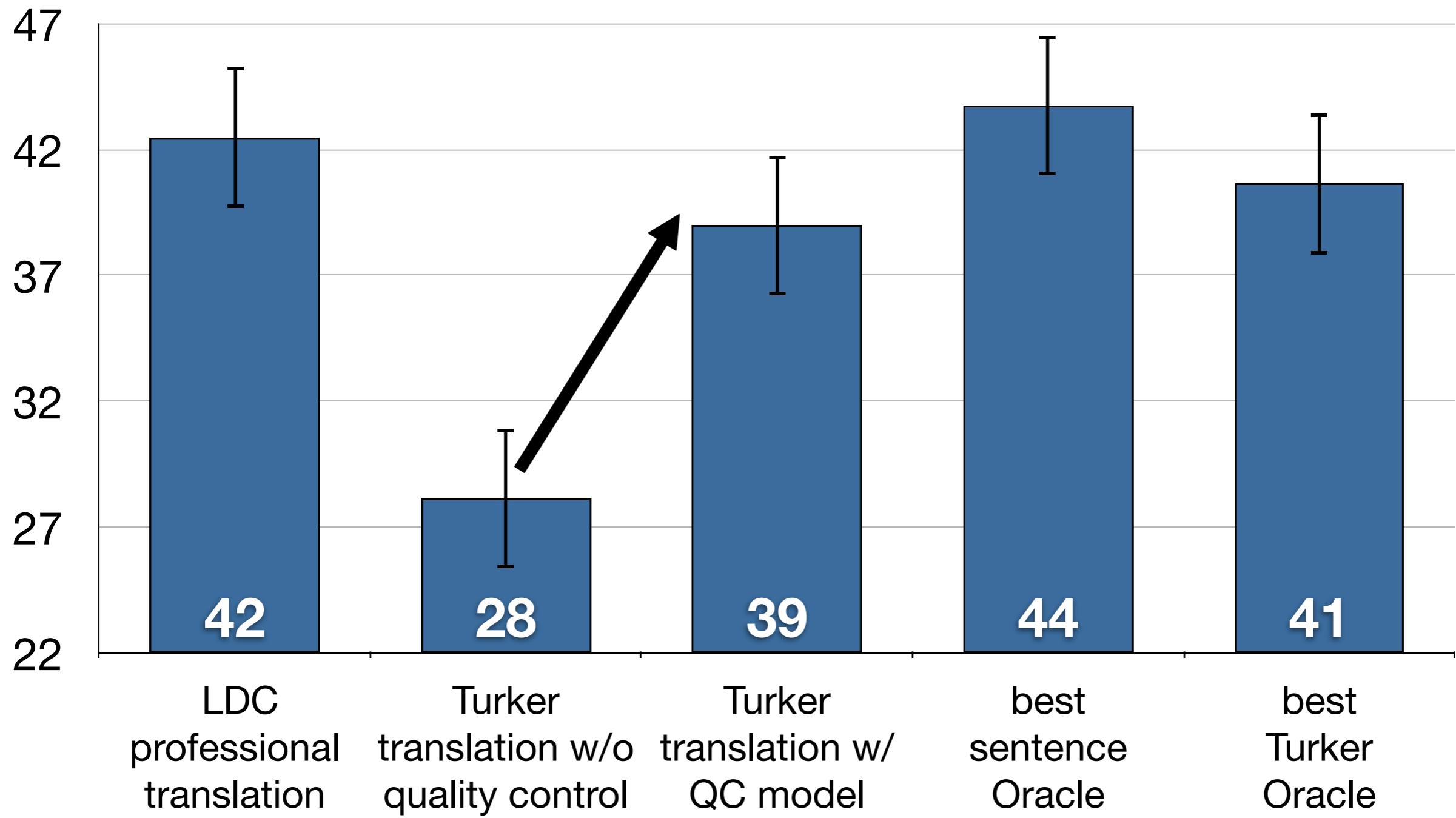
Avoiding dieting to prevent from flu	abstention from dieting in order to avoid Flu	Abstain from decrease eating in order to escape from flue	In order to be safer from flu quit dieting
This research of American scientists came in front after experimenting on mice.	This research from the American Scientists have come up after the experiments on rats.	This research of American scientists was shown after many experiments on mouses.	According to the American Scientist this research has come out after much experimentations on rats.
Experiments proved that mice on a lower calorie diet had comparatively less ability to fight the flu virus.	It has been proven from experiments that rats put on diet with less calories had less ability to resist the Flu virus.	It was proved by experiments the low calories eaters mouses had low defending power for flue in ratio.	Experimentaions have proved that those rats on less calories diet have developed a tendency of not overcoming the flu virus.
research has proven this old myth wrong that its better to fast during fever.	Research disproved the old axiom that " It is better to fast during fever"	The research proved this old talk that decrease eating is useful in fever.	This Research has proved the very old saying wrong that it is good to starve while in fever.

Avoiding dieting to prevent from flu	abstention from dieting in order to avoid Flu	Abstain from decrease eating in order to escape from flue	In order to be safer from flu quit dieting
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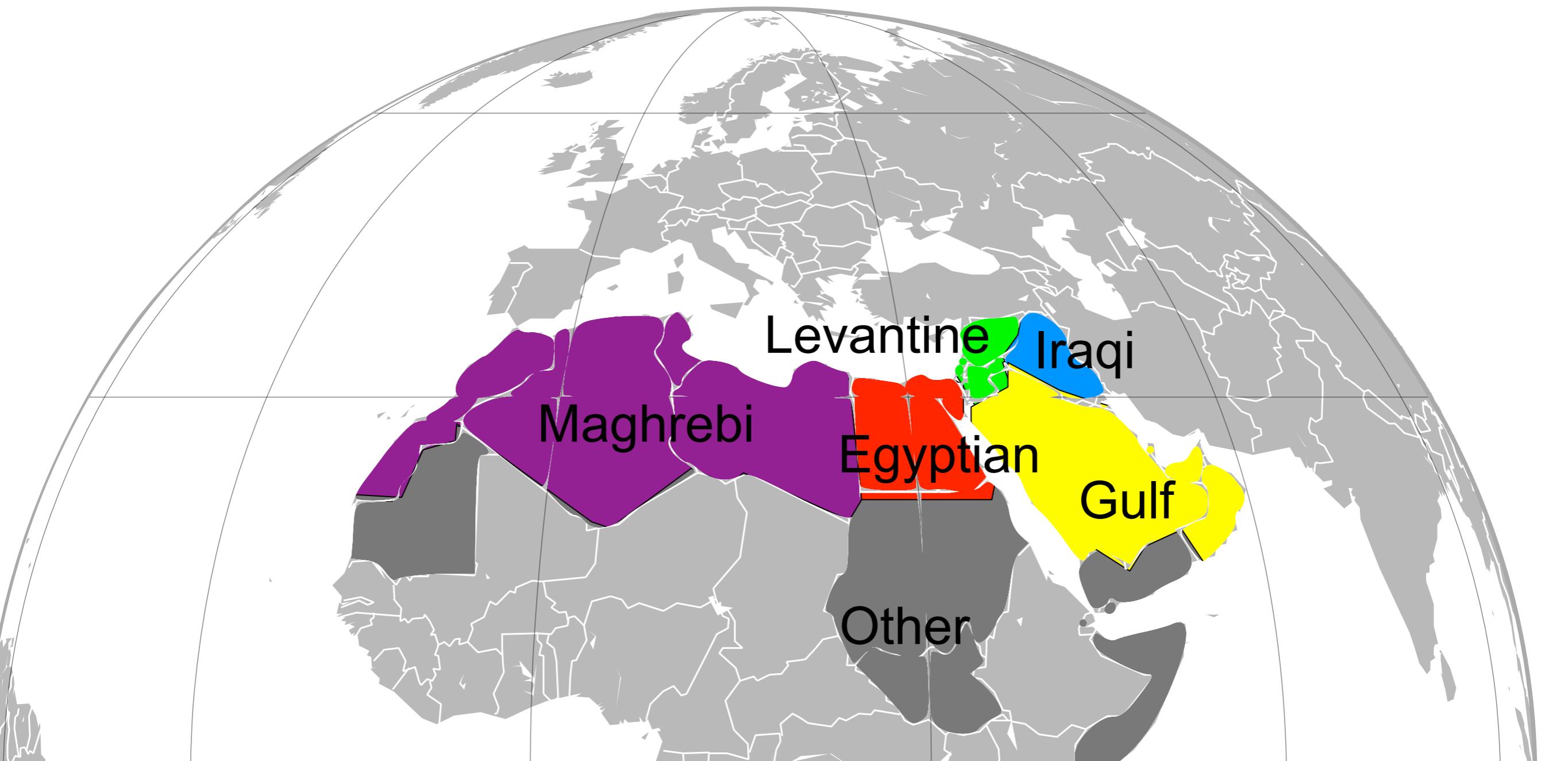
Professional Quality from Non-Professionals

Full details in Zaidan and
Callison-Burch (ACL 2011a)
& Zaidan (PhD Thesis 2012)



Gathering Data about Arabic Dialects

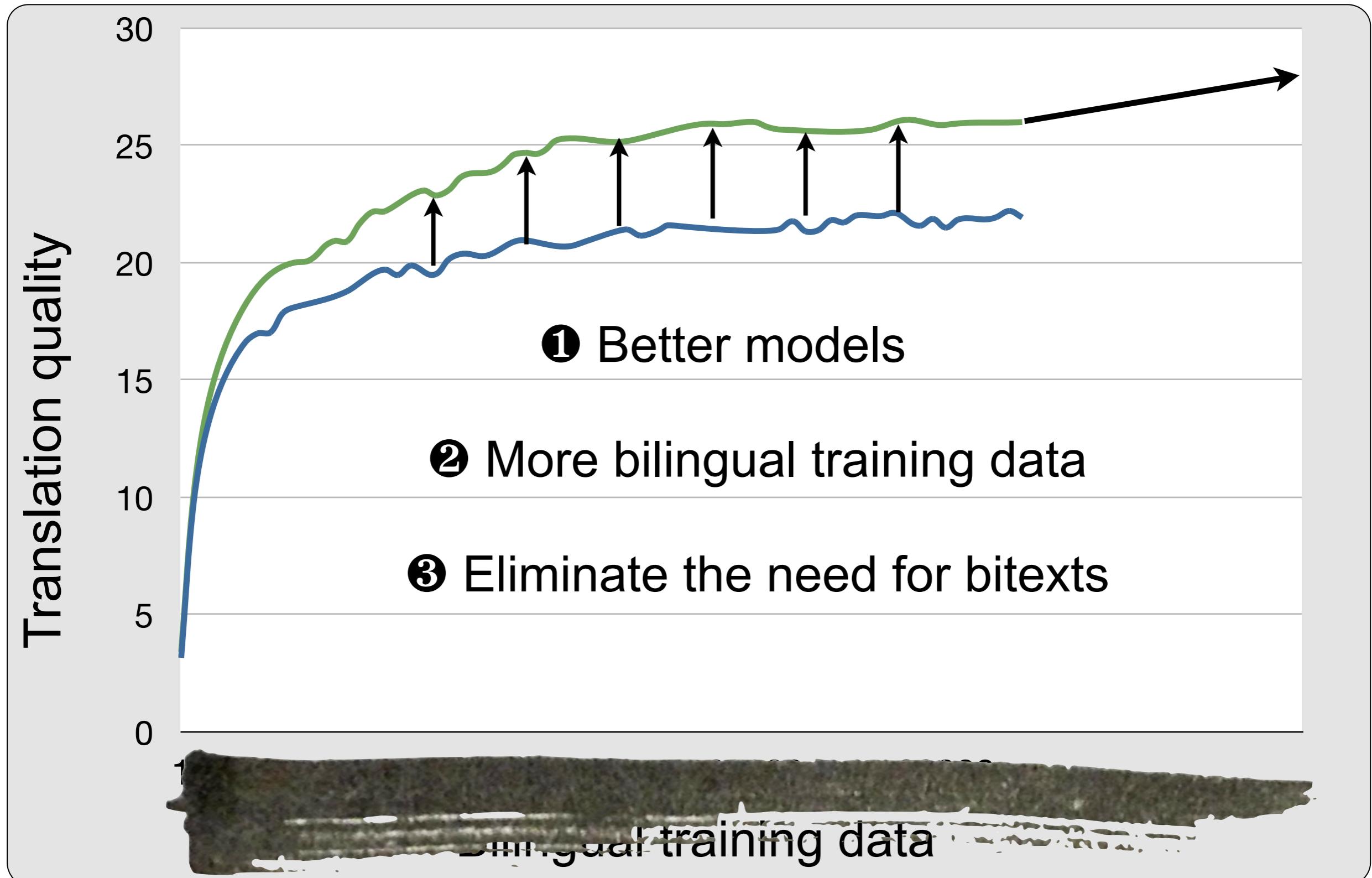
Arabic has **different varieties**. MSA is the standardized form but there are many **distinct regional dialects**.



Examples of Dialect Translation

Dialect Input	MSA system	Dialect system	Reference
EGY انت بتعمل له اعلان ولا ايه ؟ !!	You are working for a declaration and not?	You are making the advertisement for him or what?	Are you promoting it or what?!!
EGY نفسي اطمئن عليه بعد ما شاف الصوره دي	Myself feel to see this image.	I wish to check on him after he saw this picture.	I want to be sure that he is fine after he saw the images.
LEV لهيك الجو كتير كوروول	God you the atmosphere.	This is why the weather is so cool	This is why the weather is so cool
LEV طول بالك عم نمزح	Do you think about a joke long.	Calm down we are kidding	Calm down, we are only kidding

How to Improve Machine Translation



reclamo otra vez cargos políticos

Fue una demostración de fuerza del aparato gremial. Pidió la reelección de Cristina. Pero insistió en que el sindicalismo tenga candidatos en las listas. Para la CGT, hubo 500 mil personas. Para la Policía y la SIDE, unas diez veces menos.

Cristina saludó por carta y envío a sus ministros



Boda Real

Como una película, que vieron dos mil millones

Kate y William salieron desde el Palacio de Buckingham, poco después de casarse. Dieron la mano y se fundieron en un beso. Los invitados, los medios, dieron una imagen impactante. La TV lo transmitió a todo el mundo.

Las Últimas Noticias

8150 Regiones I, II, III, IV y V; 5400 Auto CEX • N° 36.253 • Lunes 2 de mayo de 2011



RIO de PERNAMBUCO



STEVE JOBS O HOMEM QUE DEU ROSTO AO FUTURO

A morte de Steve Jobs, o homem que deu rosto ao futuro, é um momento triste para todos os que admiravam seu trabalho e sua visão. Ele deixou um legado imenso, não só na tecnologia, mas também no design, na inovação e na inspiração. Sua paixão pelo detalhe e pela perfeição é algo que permanecerá com todos nós.



נשיקה

東亞日報

2011年 4月 20日 星期五

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100. 5. cm.

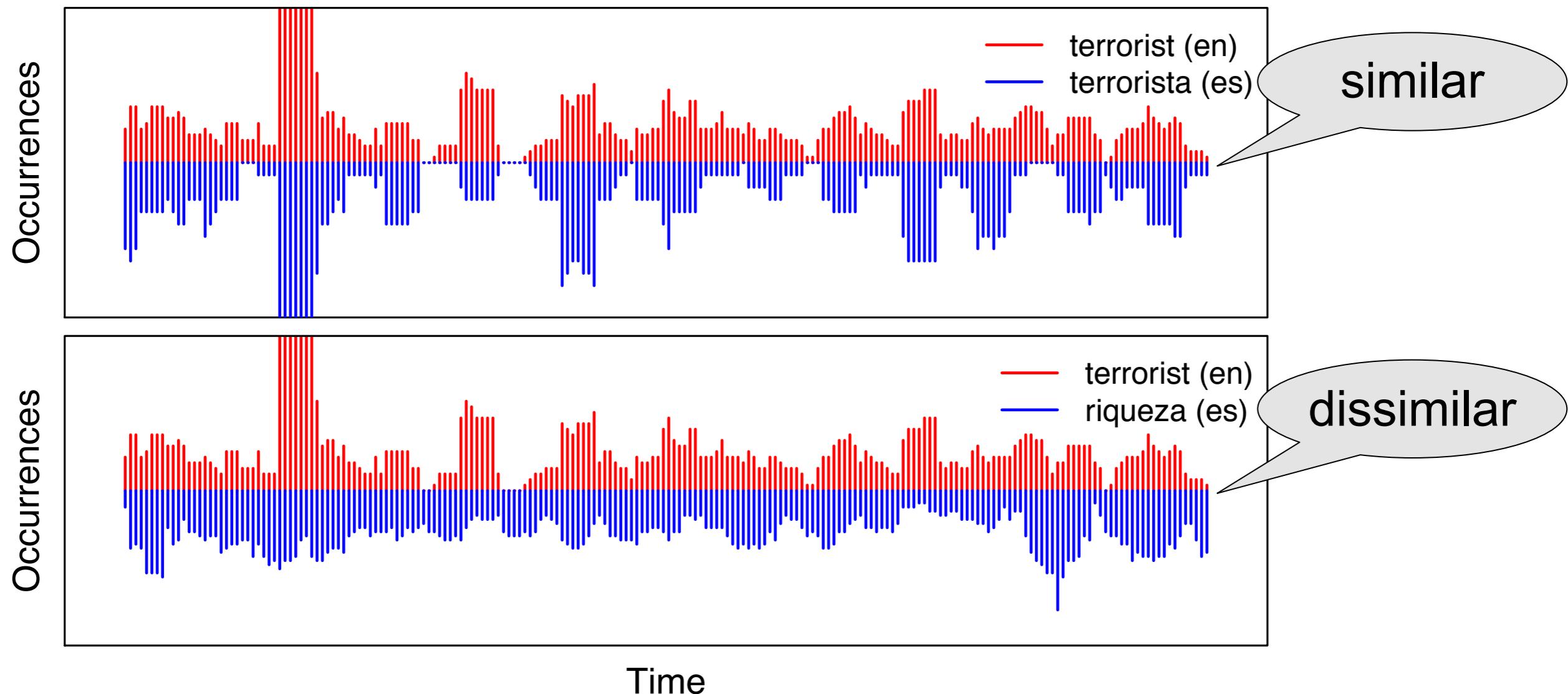
21세기 신데렐라, 왕자님과 임맞춤하다

2011년 4월 20일 목요일

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2011년 4월 20일 목요일

Scoring Translations: Time



Scoring Translations: Time

eólica	estambul	terrorista	vacuno
wind	istanbul	terrorist	beef
renewable	erdogan	terrorism	cattle
solar	turkish	terrorists	bse
sources	turkey	attacks	compulsory
renewables	turks	fight	meat
energy	ankara	attack	cows
energies	membership	terror	veal
electricity	negotiations	acts	cow
photovoltaic	undcp	threat	labelling
grid	talks	september	papayannakis

Paraphrasing

... 5 farmers were thrown into jail in Ireland ...
... fünf Landwirte festgenommen , weil ...
... oder wurden festgenommen , gefoltert ...
... or have been imprisoned , tortured ...

The diagram illustrates the paraphrases for 'thrown into jail'. A central blue box contains the original phrase 'thrown into jail' at the top, followed by three German equivalents: 'festgenommen', 'festgenommen', and 'imprisoned'. Dashed lines connect the first two German words to the first two English words ('thrown' and 'jail'). Dashed lines also connect the third German word to the third English word ('imprisoned').

Many equivalent English expressions

thrown into jail

arrested

be thrown in prison

arrest

detained

been thrown into jail

cases

imprisoned

being arrested

custody

incarcerated

in jail

maltreated

jailed

in prison

owners

locked up

put in prison for

protection

taken into custody

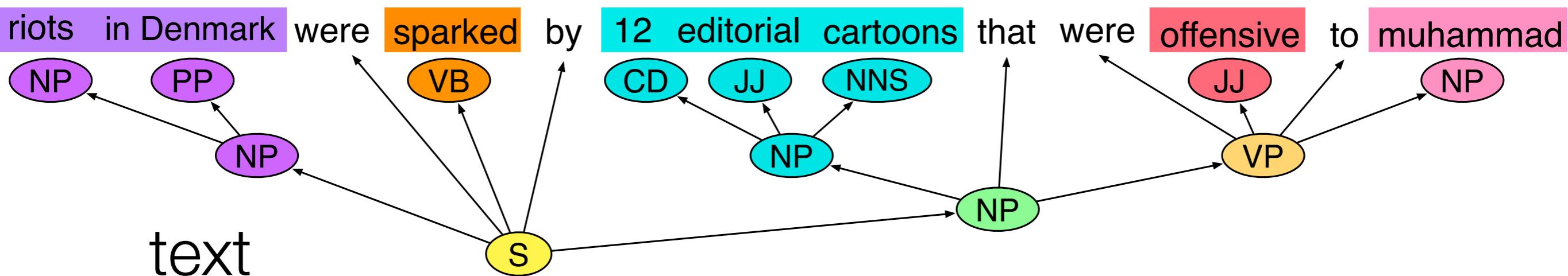
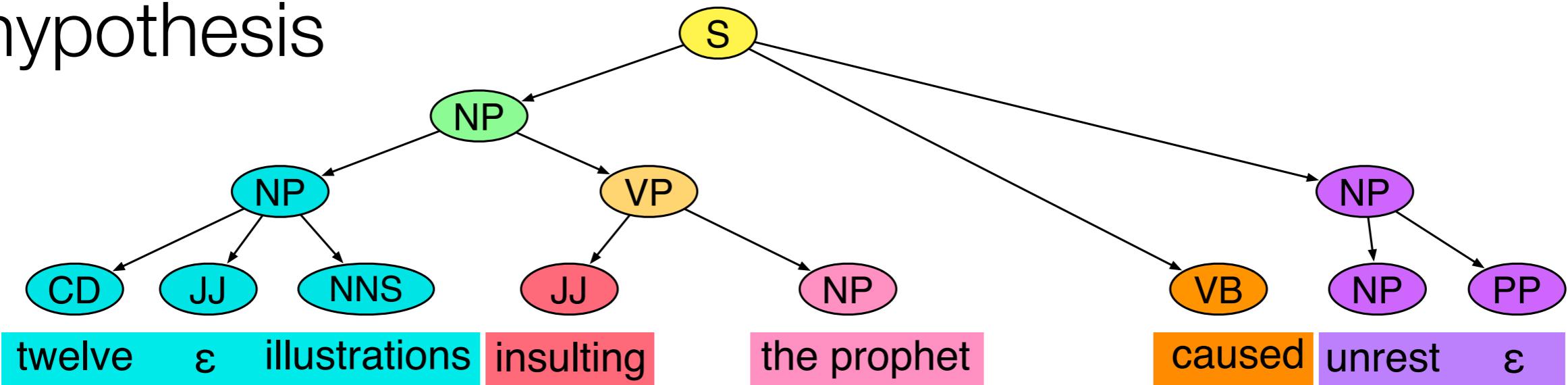
were thrown into jail

thrown

thrown into prison who are held in detention

Natural Language Understanding

hypothesis



Guest Lecturers



Liang Huang
CUNY



Wei Xu
Penn



Matt Post
JHU



Will Lewis
MSR



Christian Buck
Edinburgh



Ken Heafield
Bloomberg

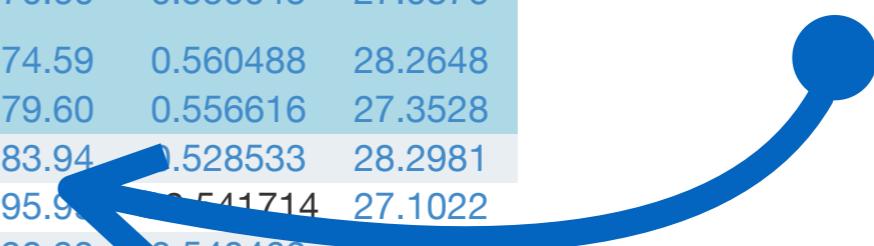
You guys!

Leaderboard

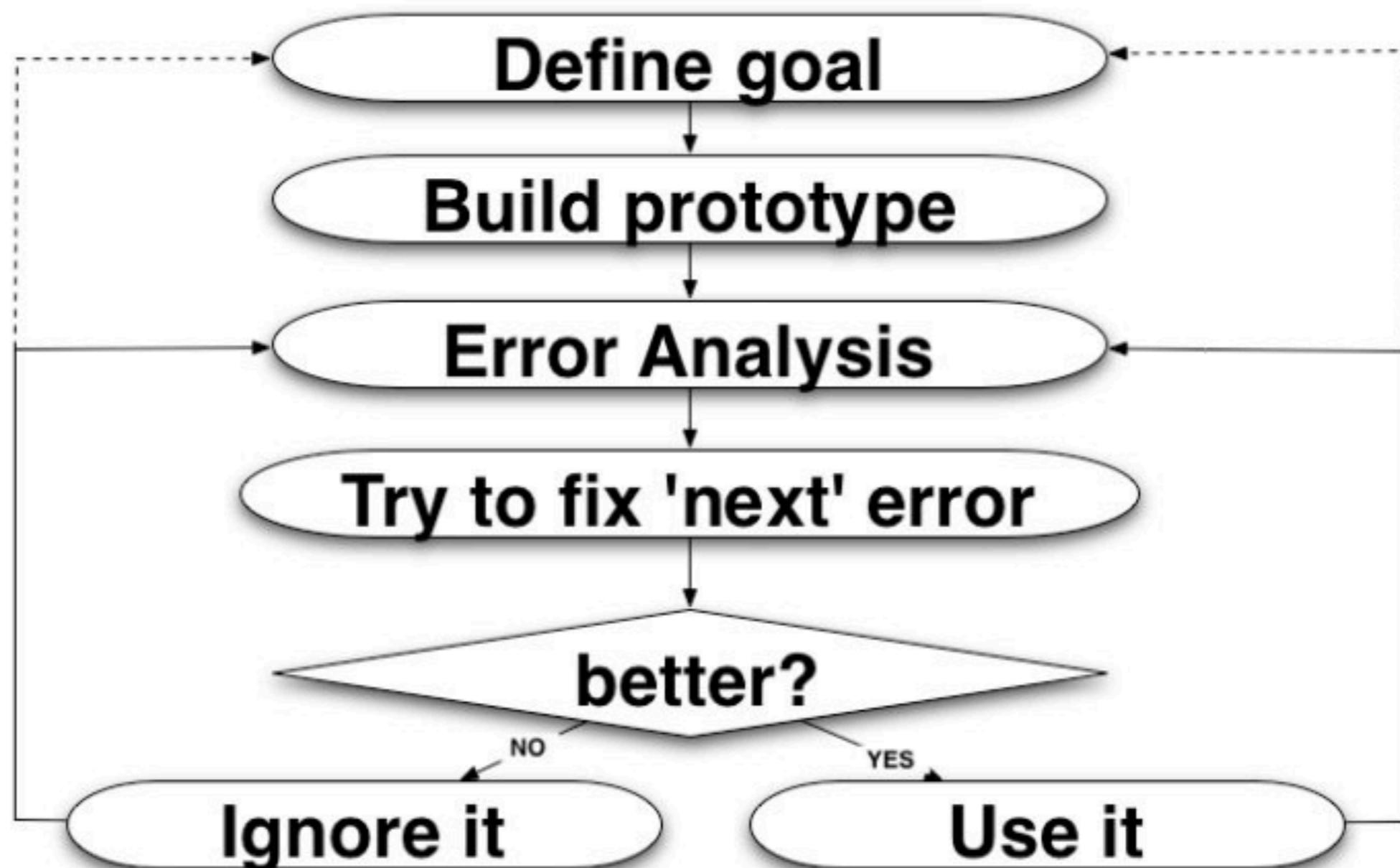


Alias	HW 0 # Correct	HW 1 AER	HW 2 Model Score	HW 3 Accuracy	HW 4 BLEU
okyurp	10	15.12	-1211.39	0.548676	28.3847
do_not_set_yo urself_on_fire	10	18.73	-1224.20	0.540384	27.3337
fly	10	26.94	-1228.65	0.544452	27.9741
@jim	10	16.59	-1229.52	0.547972	27.6029
sogeking	10	18.02	-1230.32	0.556538	28.3220
lilies	10	14.73	-1237.72	0.560918	27.5001
direKt translation	10	21.81	-1238.51	0.541636	28.1127
StopItRon	10	34.04	-1239.82	0.532835	28.1132
Cloud9	10	27.09	-1242.32	0.544687	28.6879
Etaoin Shrdlu	10	19.03	-1242.62	0.539797	28.5747
⌚	10	26.81	-1243.78	0.533657	27.8708
mstag	10	31.41	-1244.77	0.527281	27.5254
Dhrubeel	10	27.59	-1245.83	0.562209	27.9579
Class the MT is.	10	28.32	-1246.62	0.544256	28.5456
Aafikins	10	27.59	-1249.20	0.561818	28.4572
aoc	10	20.51	-1254.07	0.553448	27.4141
sqq	10	25.45	-1254.24	0.555912	28.0958
Kailoofi	10	25.76	-1257.08	0.557868	28.4231
ohayyy	10	26.53	-1263.84	0.538076	27.2392
John E. Mason	10	26.48	-1269.91	0.540345	28.6509
Baby Eigensheep	10	30.60	-1270.60	0.550045	27.0876
Mithrandir	10	27.51	-1274.59	0.560488	28.2648
Chief Relief	10	27.19	-1279.60	0.556616	27.3528
toffl	10	27.40	-1283.94	0.528533	28.2981
luck	10	26.70	-1295.91	0.541714	27.1022
mogjuice	10	31.10	-1298.83	0.540462	27.8550
Madan-Mohan Das	10	23.22	-1299.82	0.537333	23.6436

Moses
(off the shelf):
-1286.92

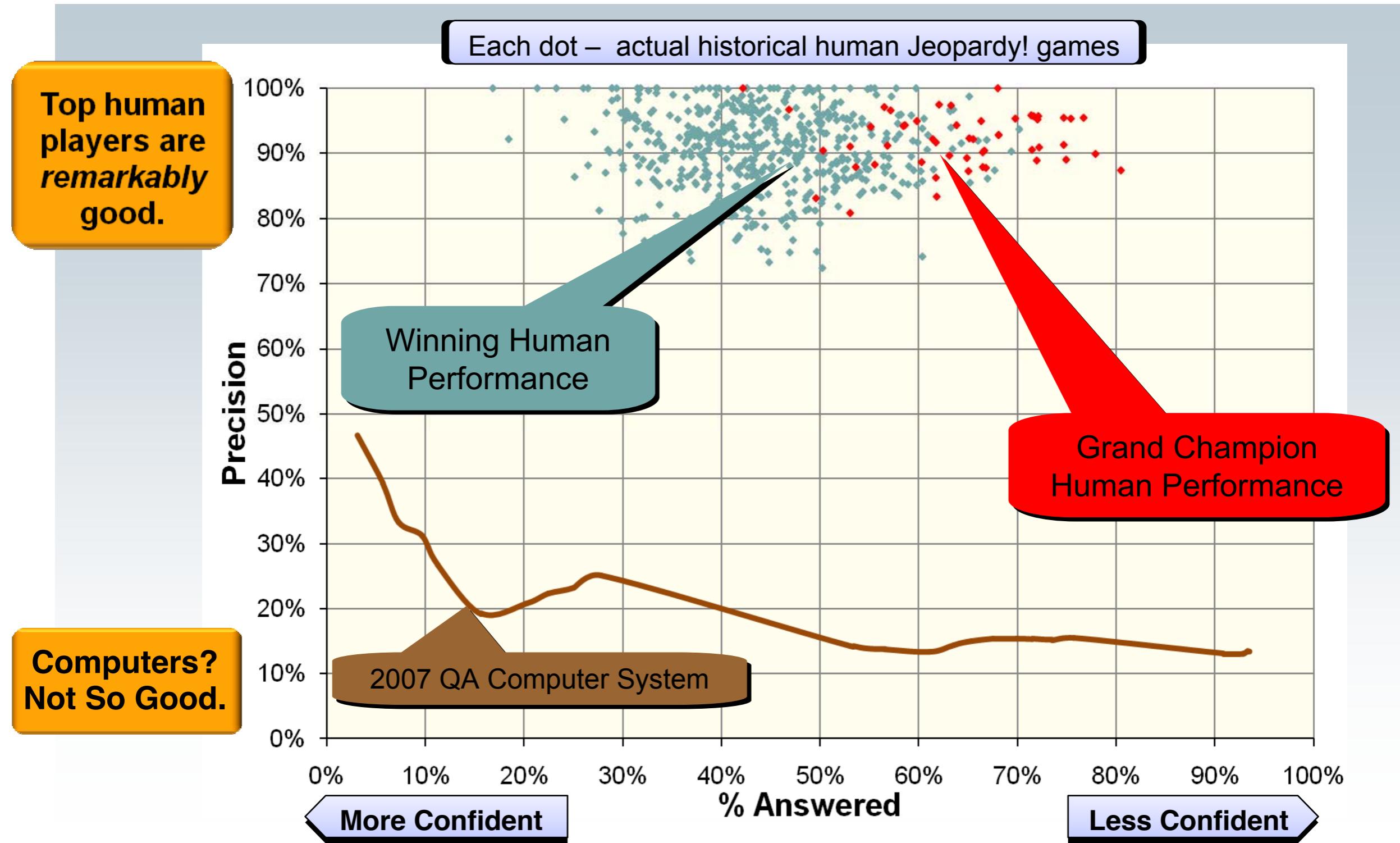


Development Cycle for MT Research

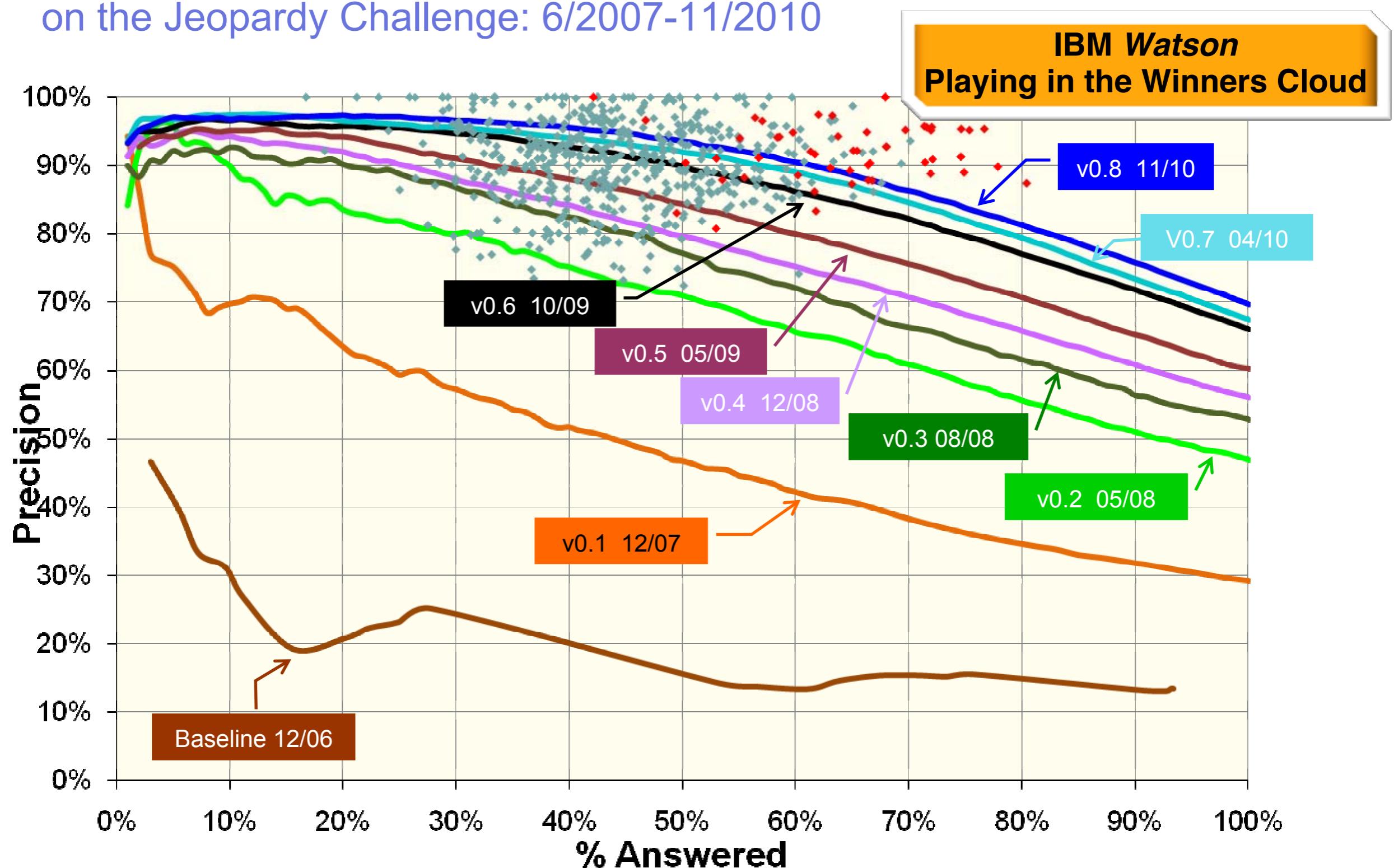


What It Takes to compete against Top Human Jeopardy! Players

Our Analysis Reveals the Winner's Cloud



DeepQA: Incremental Progress in Answering Precision on the Jeopardy Challenge: 6/2007-11/2010



Your term projects did this.

- You defined a challenge problem
- You defined a scoring function that allowed you to plot your progress over time.
- You and your classmates tried different algorithms and developed different models to solve the problem.

What you can do to stay involved

- If you will be back at Penn next year:
 - Take CIS 530 - Computation Linguistics
 - Take CIS 520 - Machine Learning
 - Do an independent research project with me!
- If you're graduating, then stay in touch!

Thanks!

Stay in touch!

email: ccb@cis.upenn.edu

Twitter: [@ccb](https://twitter.com/@ccb)

Facebook: [chris.callisonburch](https://facebook.com/chris.callisonburch)