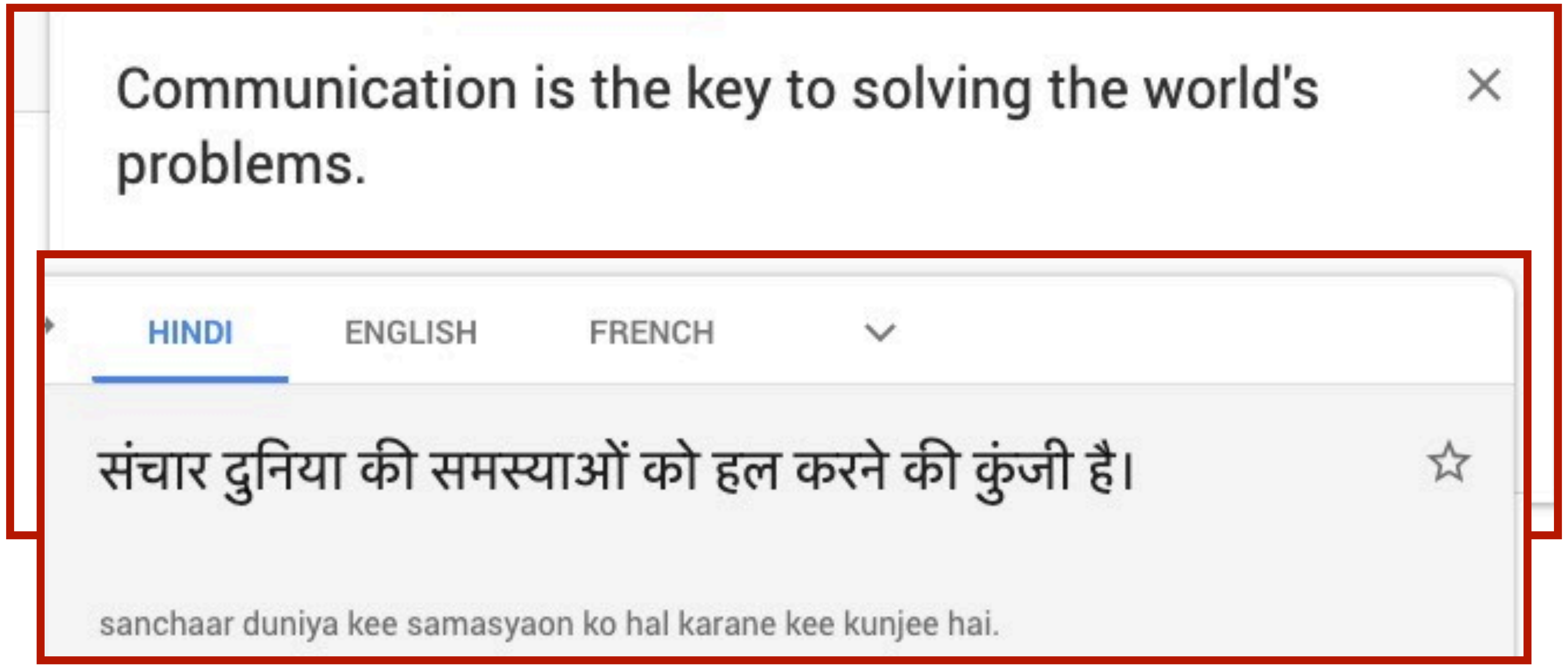
COS 484

L12: Machine Translation

Spring 2022

Translation



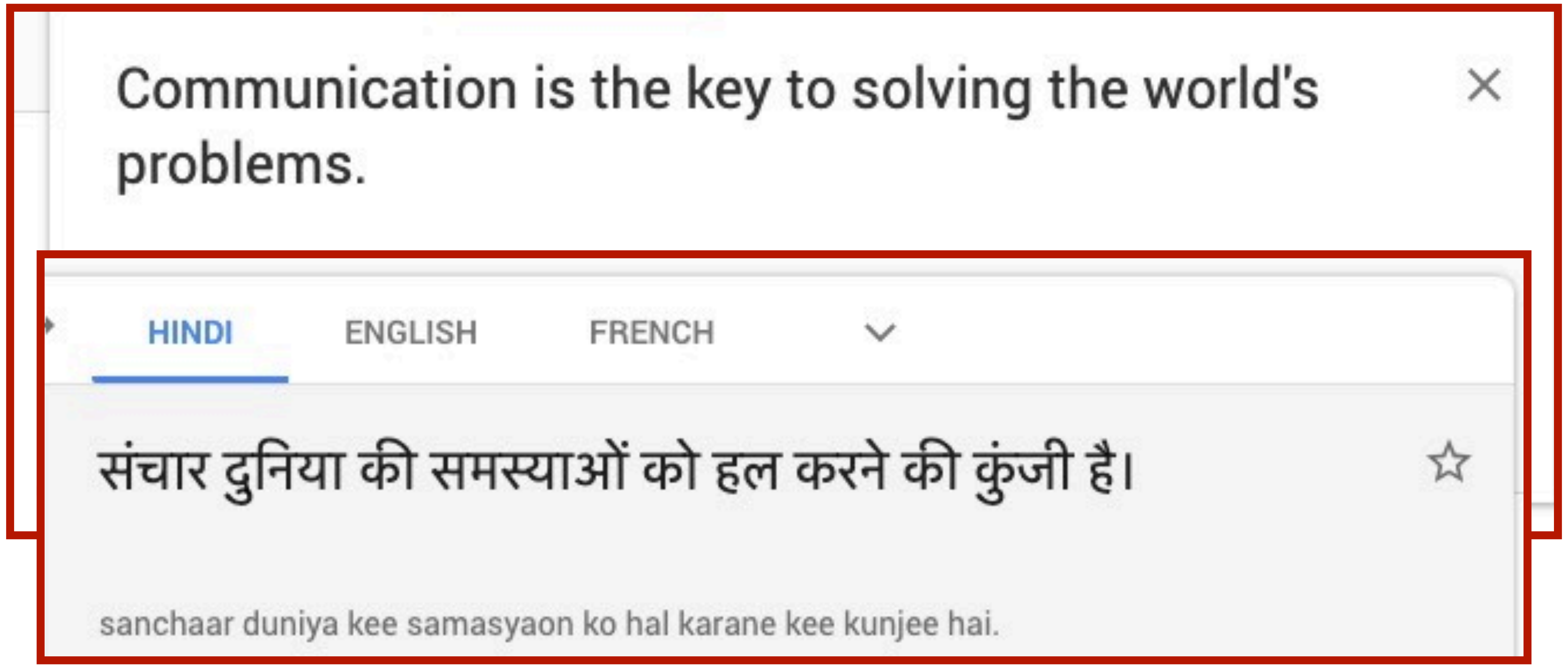
Communication is the key to solving the world's problems.

संचार दुनिया की समस्याओं को हल करने की कुंजी है।

sanchaar duniya kee samasyaon ko hal karane kee kunjee hai.

- One of the "holy grail" problems in artificial intelligence
- Practical use case: Facilitate communication between people in the world
- Extremely challenging (especially for low-resource languages)

Translation



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How many languages do you speak?

A) 1

B) 2

C) 3

D) 4+

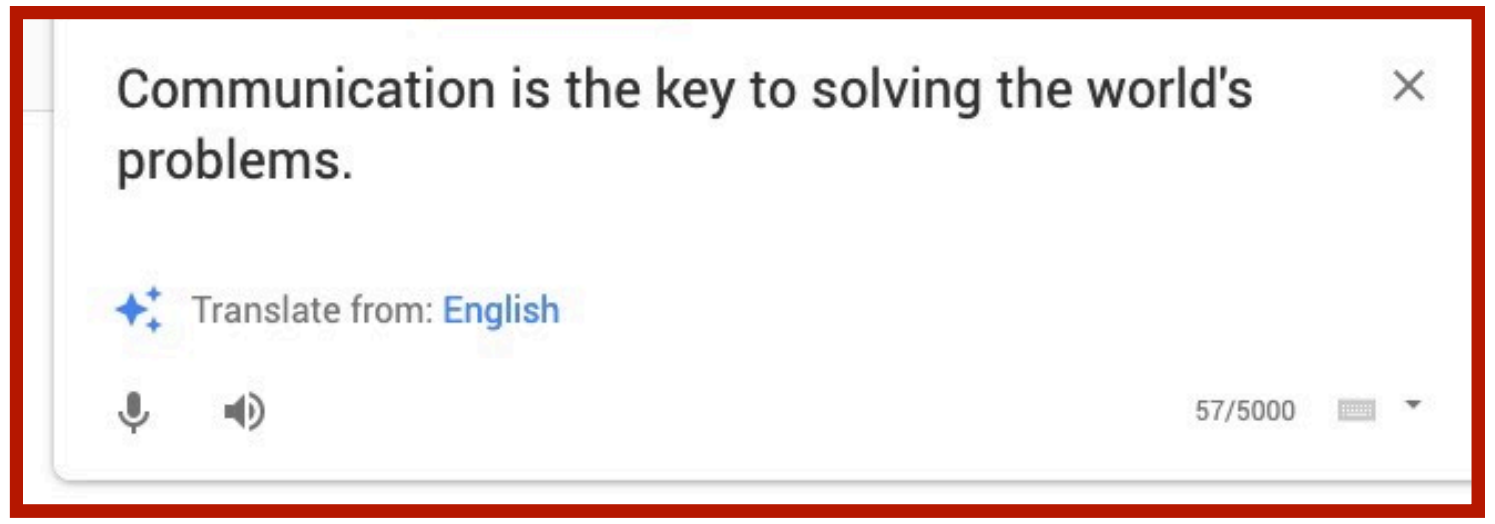
Some translations

- Easy:
  - I like apples ↔ ich mag Äpfel (German)
- Not so easy:
  - I like apples ↔ J'aime les pommes (French)
  - I like red apples ↔ J'aime les pommes rouges (French)
  - *les* ↔ *the* but *les pommes* ↔ *apples*

Basics of machine translation

- Goal: Translate a sentence $\mathbf{w}^{(s)}$ in a **source language (input)** to a sentence in the **target language (output)**
- Can be formulated as an optimization problem:
  - Most likely translation, $\hat{\mathbf{w}}^{(t)} = \arg\max_{\mathbf{w}^{(t)}} \psi\left(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}\right)$
  - where ψ is a scoring function over source and target sentences
- Requires two components:
  - *Learning algorithm* to compute parameters of scoring fn. ψ
  - *Decoding algorithm* for computing the best translation $\hat{\mathbf{w}}^{(t)}$

Source



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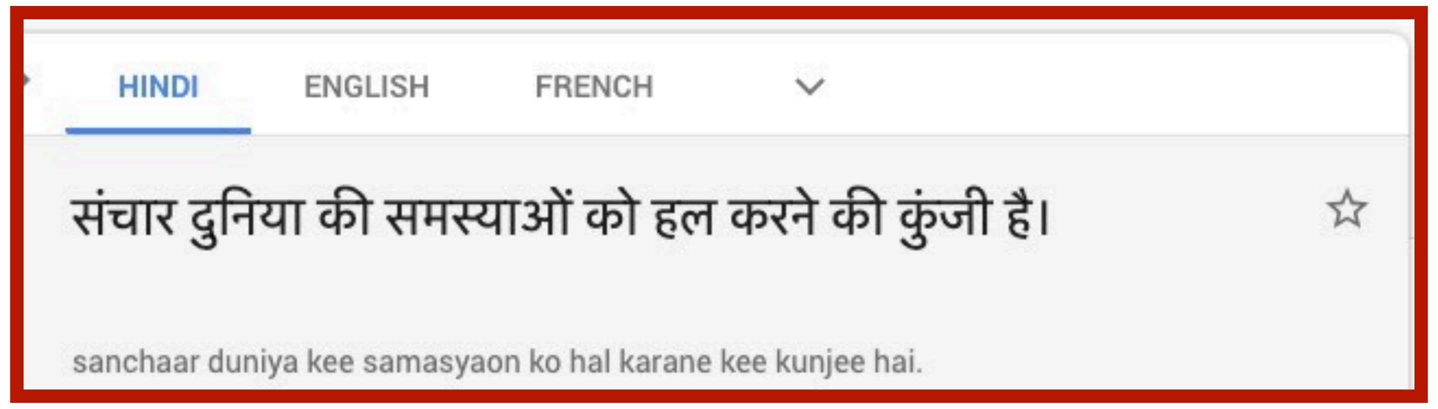

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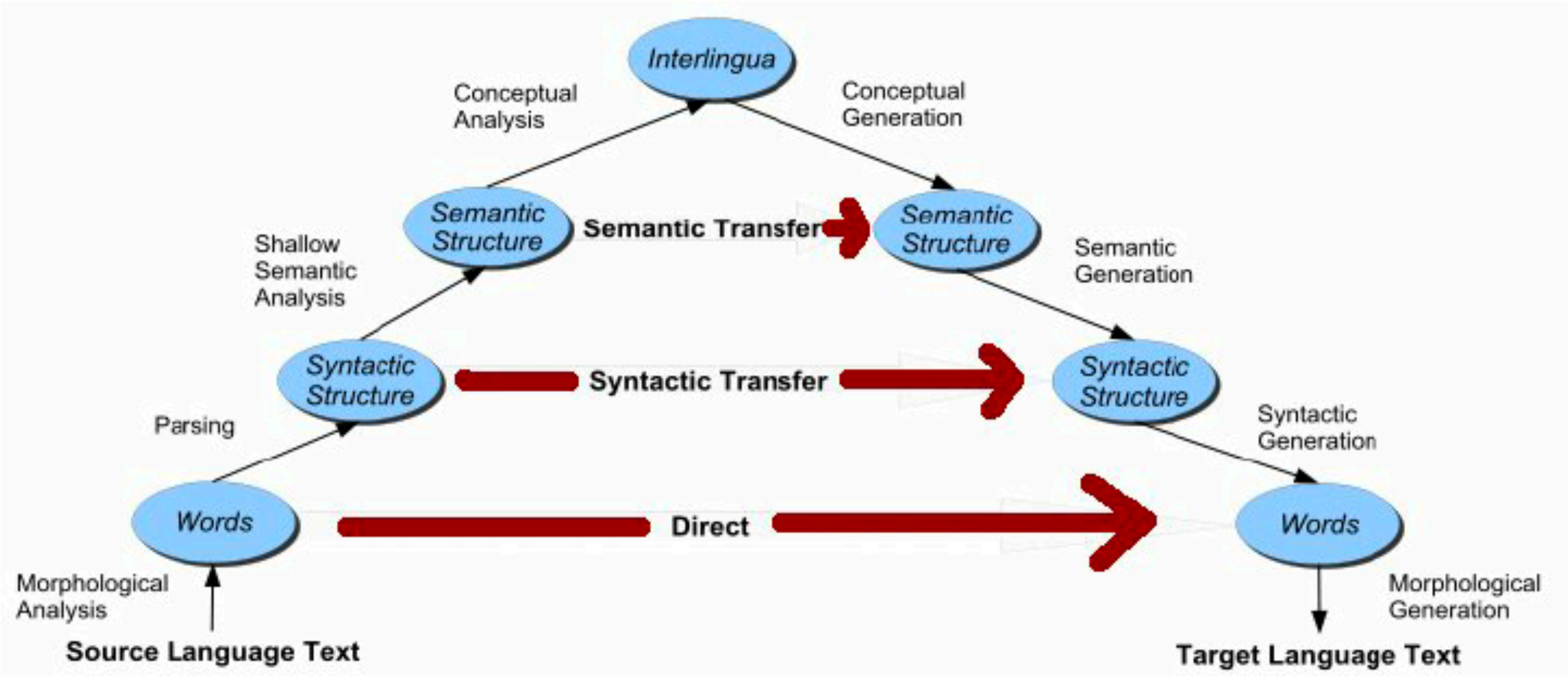
Target

Why is MT challenging?

- Single words may be replaced with multi-word phrases
  - I like apples ↔ J'aime les pommes
- Reordering of phrases
  - I like red apples ↔ J'aime les pommes rouges
- Contextual dependence
  - *les* ↔ *the* but *les pommes* ↔ *apples*

Extremely large output space $\Longrightarrow$ Decoding is NP-hard

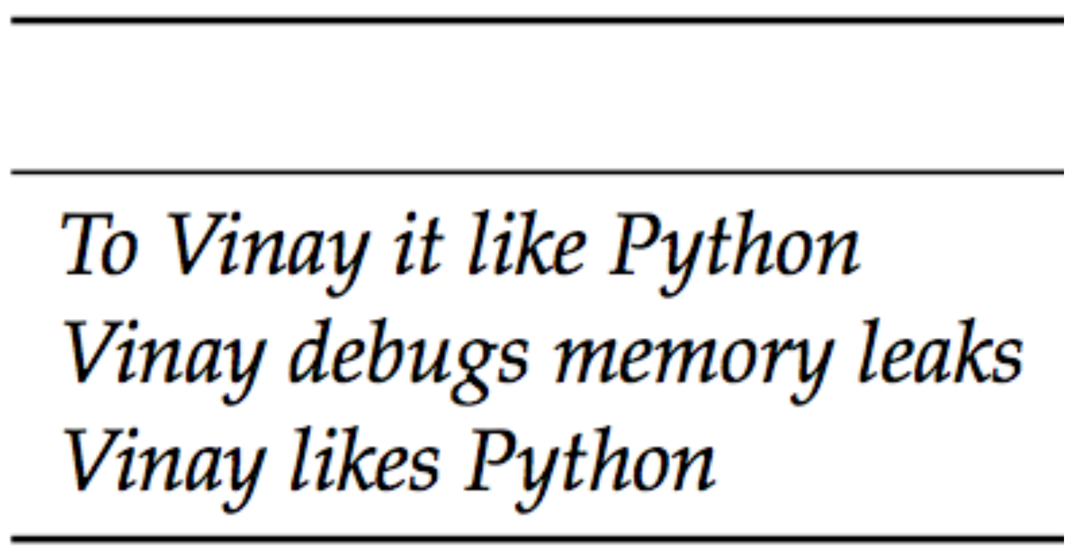
Vauquois Pyramid



- Hierarchy of concepts and distances between them in different languages
- Lowest level: individual words/ characters
- Higher levels: syntax, semantics
- Interlingua: Generic language-agnostic representation of meaning

Evaluating machine translation

- Two main criteria:
  - Adequacy: Translation $\mathbf{w}^{(t)}$ should adequately reflect the linguistic content of $\mathbf{w}^{(s)}$
  - Fluency: Translation $\mathbf{w}^{(t)}$ should be fluent text in the target language



To Vinay it like Python
Vinay debugs memory leaks
Vinay likes Python

Different translations of "*A Vinay le gusta Python*"

Which of these translations is both adequate and fluent?

A) first

B) second

C) third

D) none of them

Evaluating machine translation

- Two main criteria:
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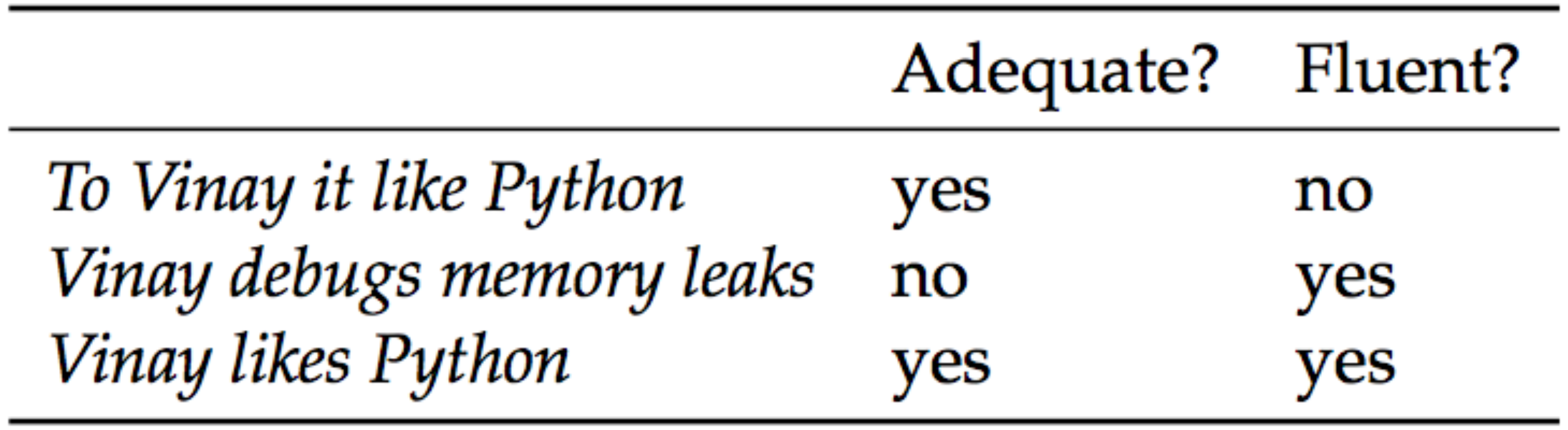


	Adequate?	Fluent?
To Vinay it like Python	yes	no
Vinay debugs memory leaks	no	yes
Vinay likes Python	yes	yes

Different translations of "*A Vinay le gusta Python*"

Which of these translations is both adequate and fluent?

A) first

B) second

[✓ C) third]

D) none of them

Evaluation metrics

- Manual evaluation: ask a native speaker to verify the translation
    - Most accurate, but expensive
- Automated evaluation metrics:
    - Compare system hypothesis with reference translations
    - BiLingual Evaluation Understudy (BLEU) (Papineni et al., 2002):
        - Modified n-gram precision

$$p_n = \frac{\text{number of } n\text{-grams appearing in both } \boxed{\text{reference}} \text{ and } \boxed{\text{hypothesis}} \text{ translations}}{\text{number of } n\text{-grams appearing in the } \boxed{\text{hypothesis}} \text{ translation}}$$

Reference translation

System predictions

BLEU

$$\text{BLEU} = \exp \frac{1}{N} \sum_{n=1}^{N} \log p_n$$

$$p_n = \frac{\text{number of } n\text{-grams appearing in both reference and hypothesis translations}}{\text{number of } n\text{-grams appearing in the hypothesis translation}}$$

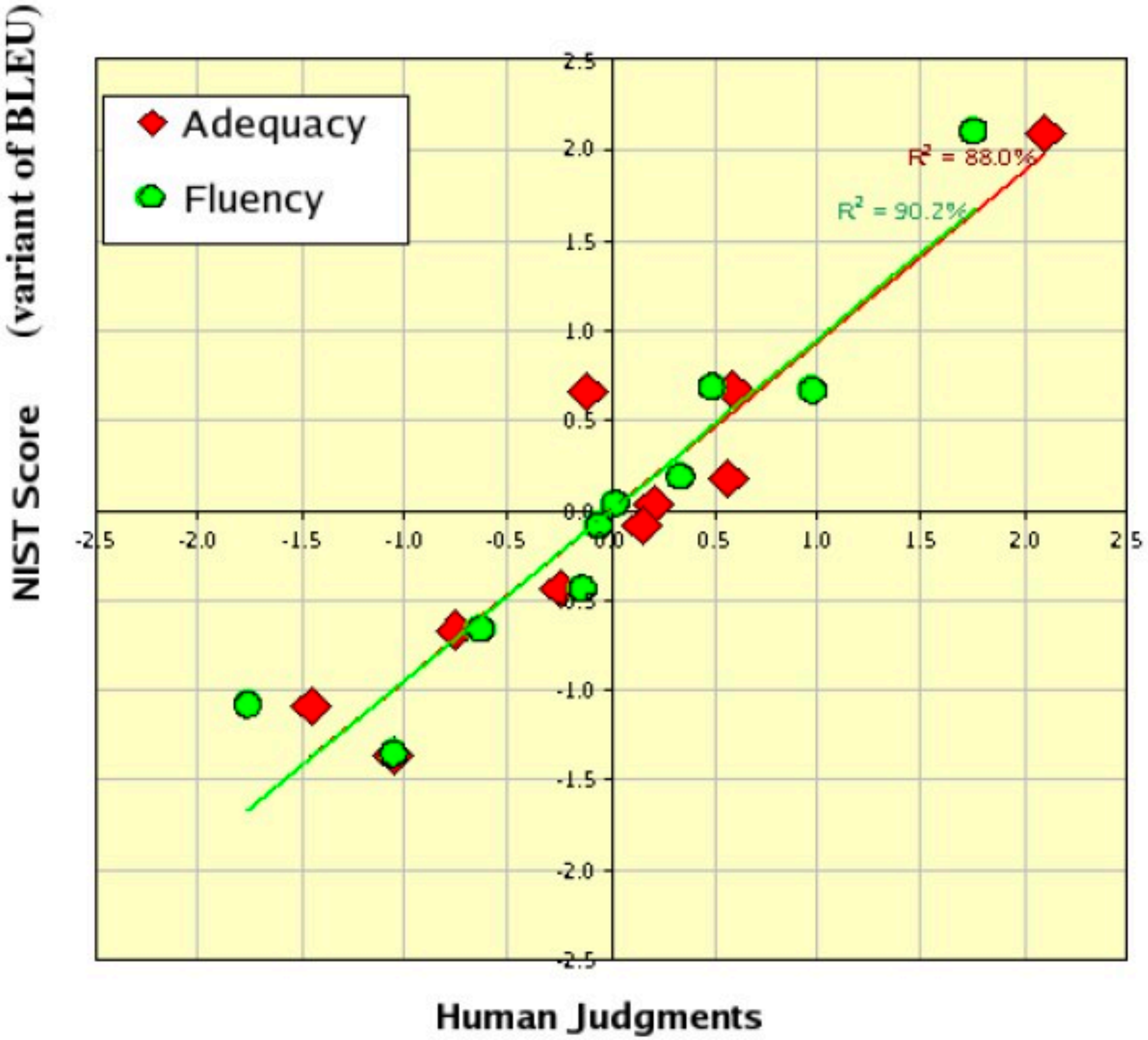
- To avoid $\log 0$, all precisions are smoothed
- Each n-gram in reference can be used at most once
  - Ex. **Hypothesis**: *to to to to to* vs **Reference**: *to be or not to be* should not get a unigram precision of 1
- BLEU-k: average of BLEU scores computed using 1-gram through k-gram.

Problem: Precision-based metrics favor short translations

- Solution: Multiply score with a brevity penalty for translations shorter than reference, $e^{1-r/h}$

BLEU

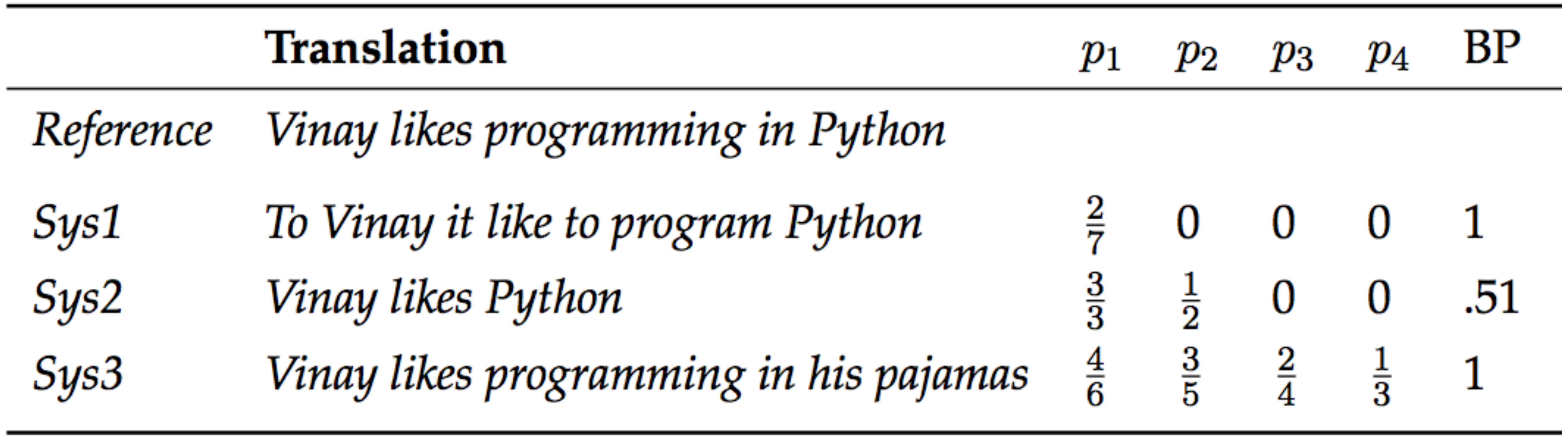
- Correlates with human judgements



(G. Doddington, NIST)

BLEU scores

BP: brevity penalty



	Translation	p_1	p_2	p_3	p_4	BP
Reference	*Vinay likes programming in Python*					
Sys1	*To Vinay it like to program Python*	$\frac{2}{7}$	0	0	0	1
Sys2	*Vinay likes Python*	$\frac{3}{3}$	$\frac{1}{2}$	0	0	.51
Sys3	*Vinay likes programming in his pajamas*	$\frac{4}{6}$	$\frac{3}{5}$	$\frac{2}{4}$	$\frac{1}{3}$	1

Sample BLEU scores for various system outputs

- Alternatives have been proposed:
  - METEOR: weighted F-measure
  - Translation Error Rate (TER): Edit distance between hypothesis and reference

Which of these translations do you think will have the highest BLEU-4 score?

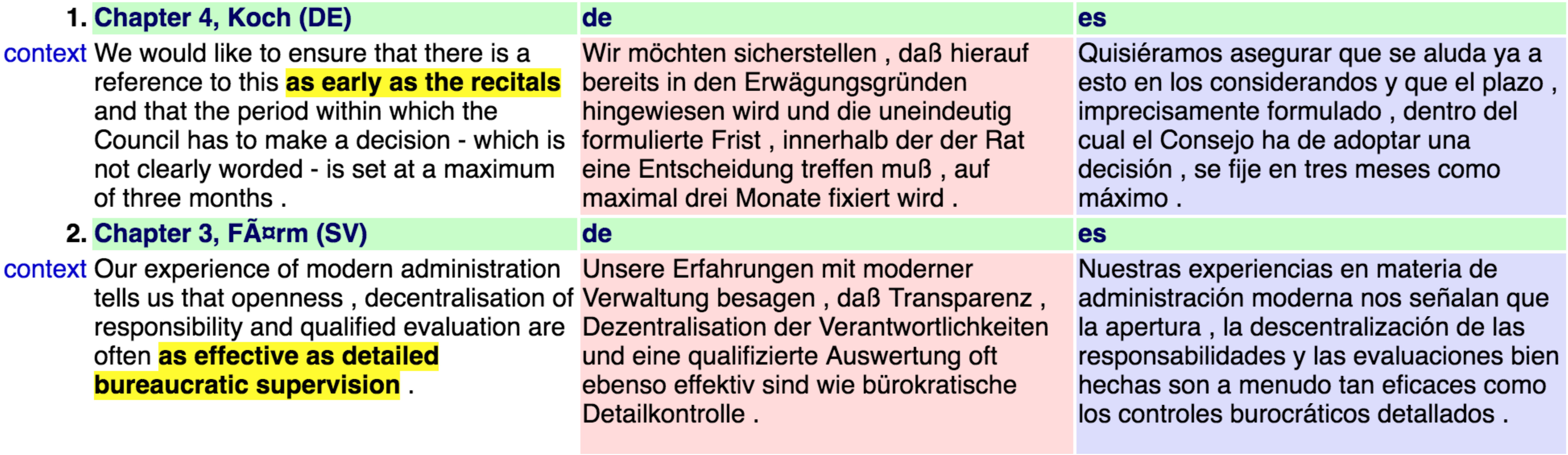
A) sys1

B) sys2

[✓ C) sys3]

Data

- Statistical MT relies requires **parallel corpora (bilingual)**



1.	**Chapter 4, Koch (DE)**	**de**	**es**
context	We would like to ensure that there is a reference to this **as early as the recitals** and that the period within which the Council has to make a decision - which is not clearly worded - is set at a maximum of three months .	Wir möchten sicherstellen , daß hierauf bereits in den Erwägungsgründen hingewiesen wird und die uneindeutig formulierte Frist , innerhalb der der Rat eine Entscheidung treffen muß , auf maximal drei Monate fixiert wird .	Quisiéramos asegurar que se aluda ya a esto en los considerandos y que el plazo , imprecisamente formulado , dentro del cual el Consejo ha de adoptar una decisión , se fije en tres meses como máximo .
2.	**Chapter 3, FÃ¤rm (SV)**	**de**	**es**
context	Our experience of modern administration tells us that openness , decentralisation of responsibility and qualified evaluation are often **as effective as detailed bureaucratic supervision** .	Unsere Erfahrungen mit moderner Verwaltung besagen , daß Transparenz , Dezentralisation der Verantwortlichkeiten und eine qualifizierte Auswertung oft ebenso effektiv sind wie bürokratische Detailkontrolle .	Nuestras experiencias en materia de administración moderna nos señalan que la apertura , la descentralización de las responsabilidades y las evaluaciones bien hechas son a menudo tan eficaces como los controles burocráticos detallados .

(Europarl, Koehn, 2005)

- And lots of it!

- Not easily available for many low-resource languages in the world

Statistical MT

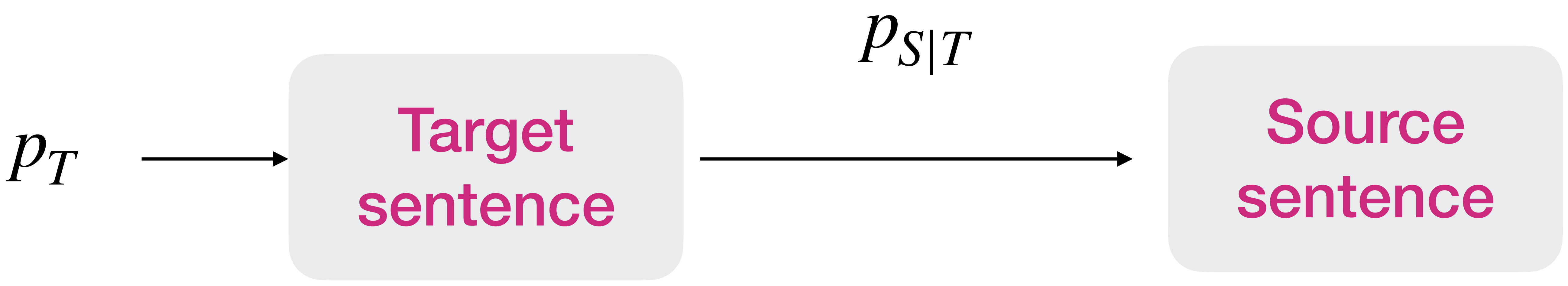
$$\hat{\mathbf{w}}^{(t)} = \arg\max_{\mathbf{w}^{(t)}} \psi\left(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}\right)$$

- We can break down the scoring function ψ as:

$$\psi\left(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}\right) = \underbrace{\psi_A\left(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}\right)}_{\textit{(adequacy)}} + \underbrace{\psi_F\left(\mathbf{w}^{(t)}\right)}_{\textit{(fluency)}}$$

- Allows us to estimate parameters of ψ on separate data
  - ψ_A from aligned bilingual corpora
  - ψ_F from monolingual corpora

Noisy channel model

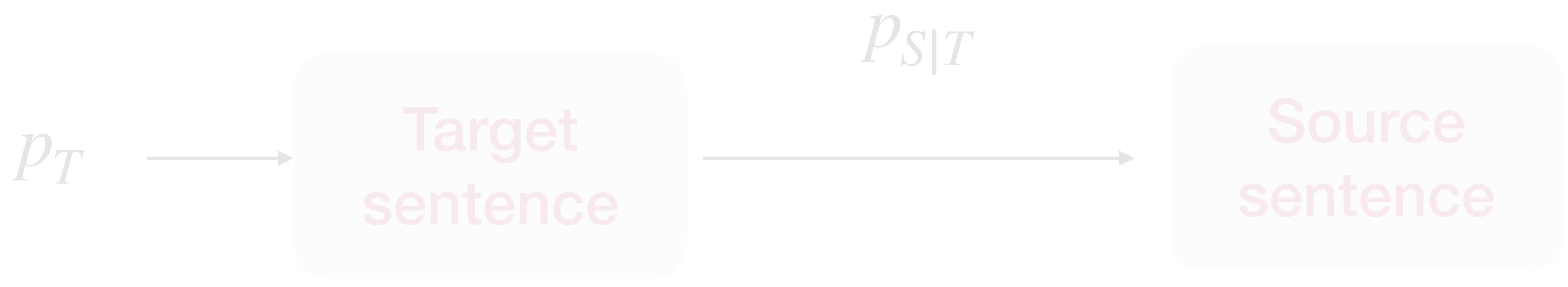


$$
\begin{aligned}
\Psi_A(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) &\triangleq \log \mathrm{p}_{S|T}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}) && \textit{(adequacy)} \\
\Psi_F(\boldsymbol{w}^{(t)}) &\triangleq \log \mathrm{p}_T(\boldsymbol{w}^{(t)}) && \textit{(fluency)} \\
\Psi(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) &= \log \mathrm{p}_{S|T}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}) + \log \mathrm{p}_T(\boldsymbol{w}^{(t)}) = \log \mathrm{p}_{S,T}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}). && \textit{(overall)}
\end{aligned}
$$

- Generative process for source sentence
- Use Bayes rule to recover $w^{(t)}$ that is maximally likely under the conditional distribution $p_{T|S}$ (which is what we want)

$$\arg\max_T p_{T|S} = \arg\max_T \frac{p_T \; p_{S|T}}{p_S}$$

Noisy channel model



$$\begin{aligned}\Psi_A(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) &\triangleq \log \mathrm{p}_{S|T}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}) \\ \Psi_F(\boldsymbol{w}^{(t)}) &\triangleq \log \mathrm{p}_T(\boldsymbol{w}^{(t)}) \\ \Psi(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) &= \log \mathrm{p}_{S|T}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}) + \log \mathrm{p}_T(\boldsymbol{w}^{(t)}) = \log \mathrm{p}_{S,T}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}).\end{aligned}$$

Allows us to use a standalone language model p_T to improve fluency

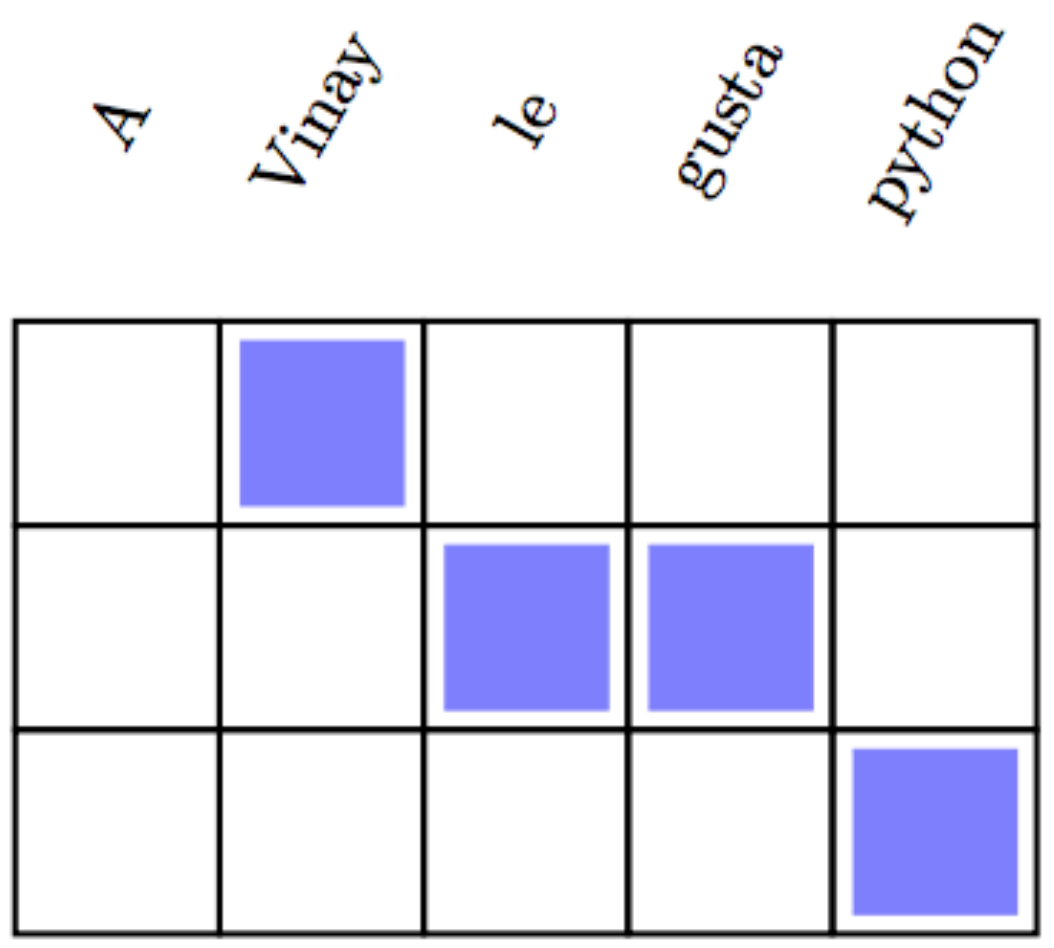
- Use Bayes rule to recover $w^{(t)}$ that is maximally likely under the conditional distribution $p_{T|S}$ (which is what we want)

IBM Models

- Early approaches to statistical MT
- *Key questions:*
  - How do we define the translation model $p_{S|T}$?
  - How can we estimate the parameters of the translation model from parallel training examples?
- Make use of the idea of **alignments**

Alignments

How should we align words in source to words in target?



	A	Vinay	le	gusta	python
Vinay		■			
likes			■	■	
python					■

good $\mathcal{A}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) = \{(A, \varnothing), (\textit{Vinay, Vinay}), (\textit{le, likes}), (\textit{gusta, likes}), (\textit{Python,Python})\}.$

bad $\mathcal{A}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) = \{(\textit{A, Vinay}), (\textit{Vinay, likes}), (\textit{le, Python}), (\textit{gusta}, \varnothing), (\textit{Python}, \varnothing)\}.$

Incorporating alignments

- Let us define the joint probability of alignment and translation as:

$$\begin{aligned}\mathrm{p}(\boldsymbol{w}^{(s)}, \mathcal{A} \mid \boldsymbol{w}^{(t)}) &= \prod_{m=1}^{M^{(s)}} \mathrm{p}(w_m^{(s)}, a_m \mid w_{a_m}^{(t)}, m, M^{(s)}, M^{(t)}) \\ &= \prod_{m=1}^{M^{(s)}} \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}) \times \mathrm{p}(w_m^{(s)} \mid w_{a_m}^{(t)}).\end{aligned}$$

- $M^{(s)}, M^{(t)}$ are the number of words in source and target sentences
- a_m is the alignment of the m^{th} word in the source sentence
  - i.e. it specifies that the m^{th} word in source is aligned to the $a_m{}^{th}$ word in target
- Translation probability for word in source to be a translation of its alignment word

Independence assumptions

$$
\begin{aligned}
\mathrm{p}(\boldsymbol{w}^{(s)}, \mathcal{A} \mid \boldsymbol{w}^{(t)}) &= \prod_{m=1}^{M^{(s)}} \mathrm{p}(w_m^{(s)}, a_m \mid w_{a_m}^{(t)}, m, M^{(s)}, M^{(t)}) \\
&= \prod_{m=1}^{M^{(s)}} \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}) \times \mathrm{p}(w_m^{(s)} \mid w_{a_m}^{(t)}).
\end{aligned}
$$

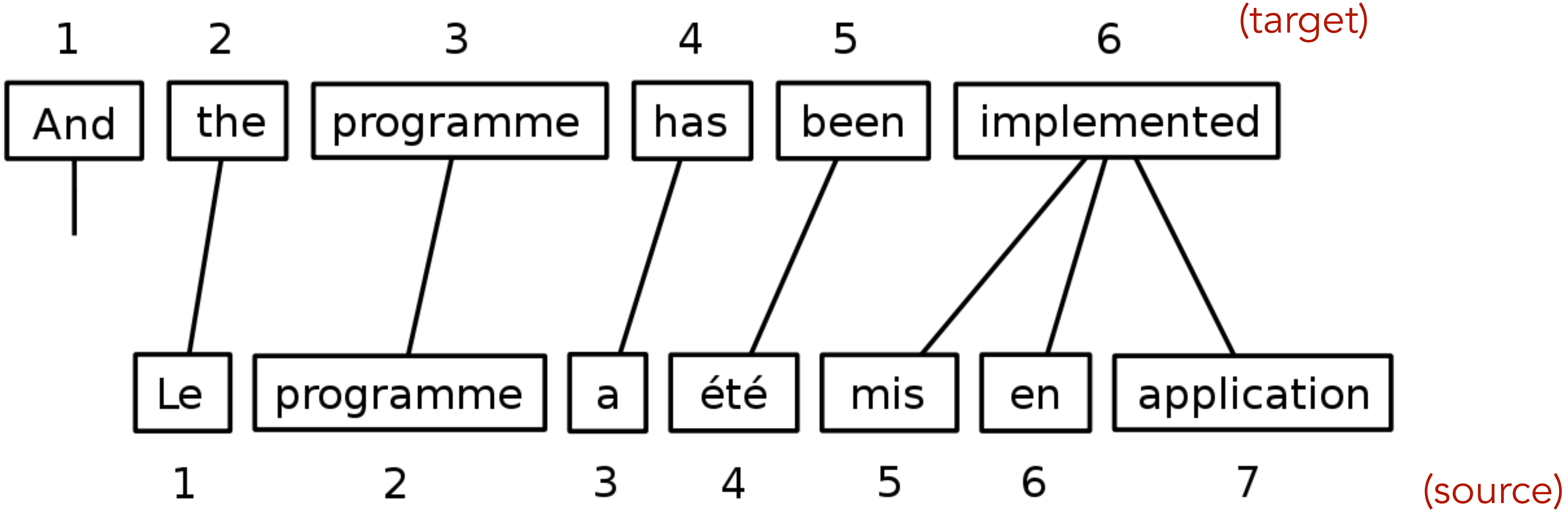
- Two independence assumptions:
  - Alignment probability factors across tokens:

$$\mathrm{p}(\mathcal{A} \mid \boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) = \prod_{m=1}^{M^{(s)}} \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}).$$

  - Translation probability factors across tokens:

$$\mathrm{p}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}, \mathcal{A}) = \prod_{m=1}^{M^{(s)}} \mathrm{p}(w_m^{(s)} \mid w_{a_m}^{(t)}),$$

Limitations

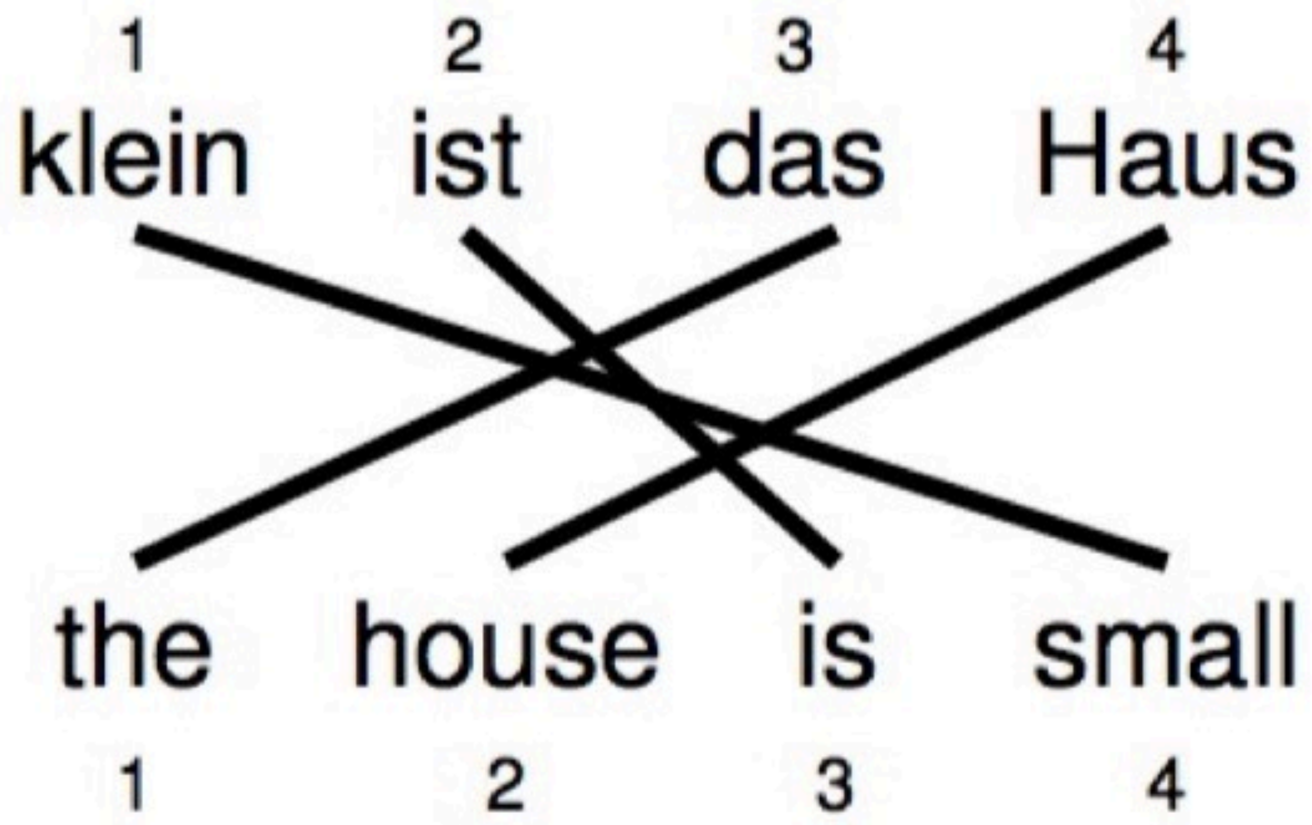


$$a_1 = 2,\ a_2 = 3,\ a_3 = 4,\ldots$$

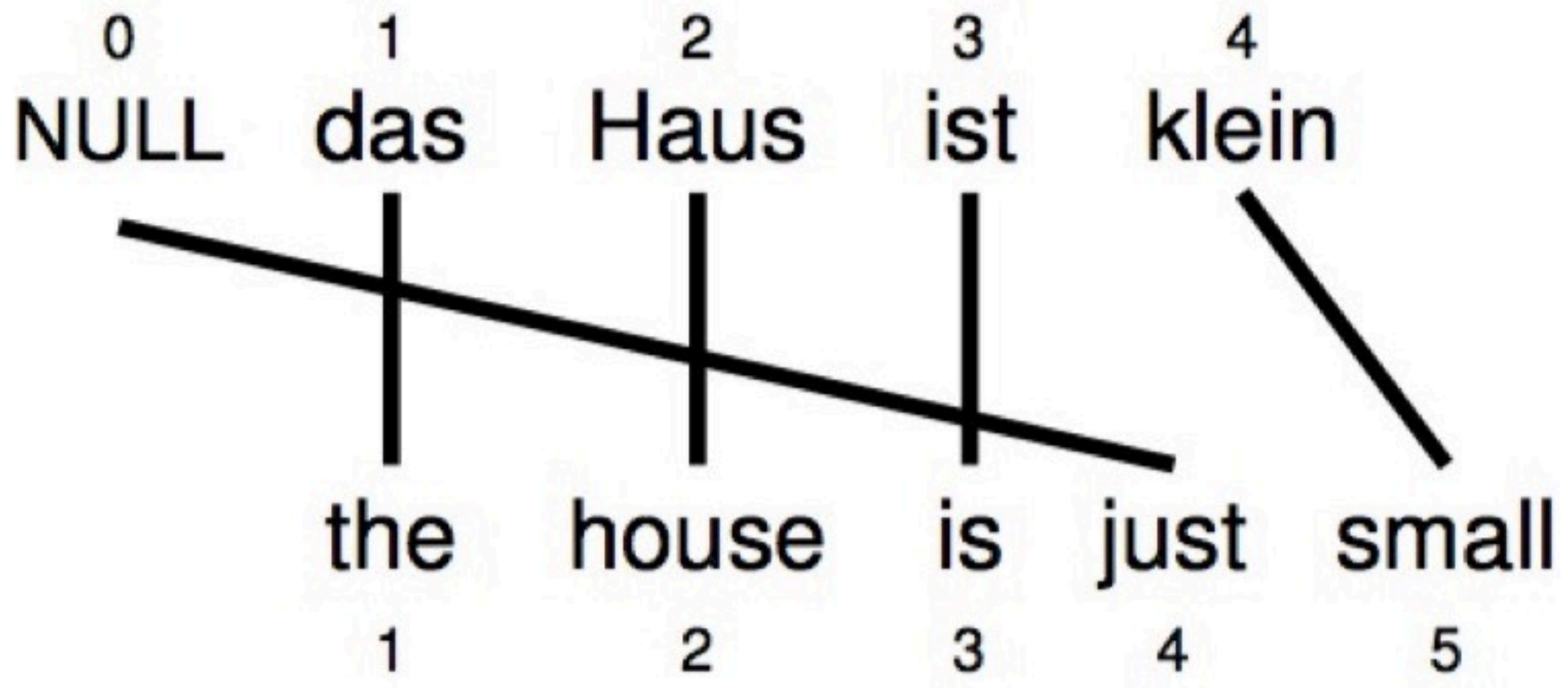
Multiple source words may align to the same target word!

Or a source word may not have any corresponding target.

Reordering and word insertion



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



(target)

(source)

$$\mathbf{a} = (1, 2, 3, 0, 4)^\top$$

Assume extra NULL token

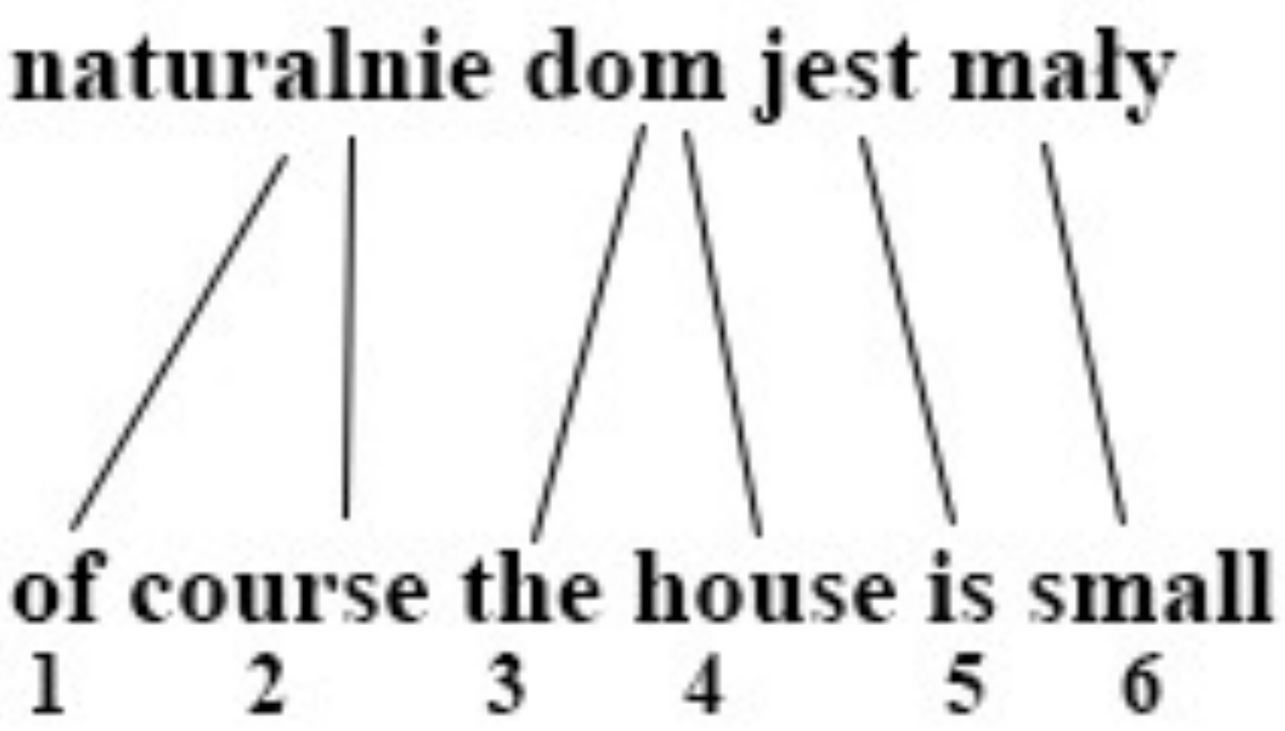
(Slide credit: Brendan O'Connor)

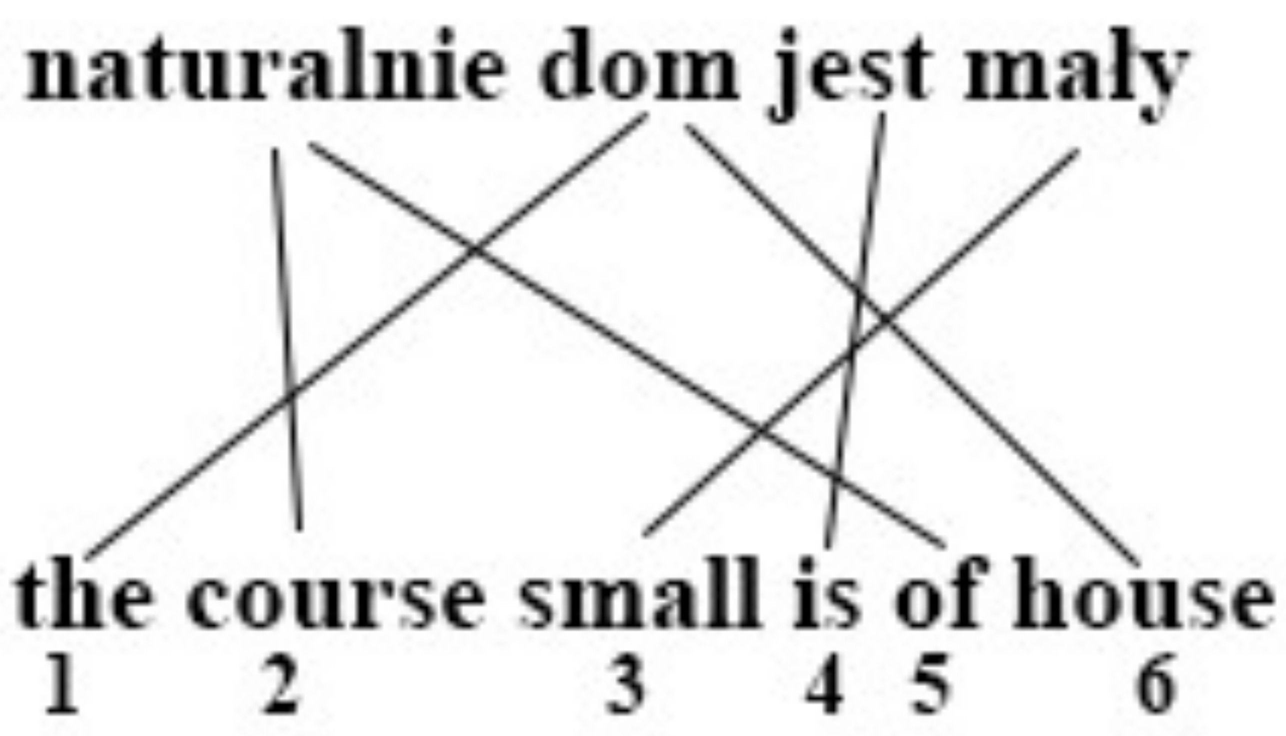
IBM Model 1

- Assume $p(a_m \mid m, M^{(s)}, M^{(t)}) = \dfrac{1}{M^{(t)}}$

- Is this a good assumption?

$$\mathrm{p}(\mathcal{A} \mid \boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) = \prod_{m=1}^{M^{(s)}} \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}).$$





Every alignment is equally likely!

IBM Model 1

- Assume $p(a_m \mid m, M^{(s)}, M^{(t)}) = \dfrac{1}{M^{(t)}}$

- We then have (for each pair of words in source and target):

$$p(w^{(s)}, w^{(t)}) = p(w^{(t)}) \sum_{A} (\frac{1}{M^{(t)}})^{M^{(s)}} \; p(w^{(s)} \mid w^{(t)})$$

- How do we estimate $p(w^{(s)} = v \mid w^{(t)} = u)$?

IBM Model 1

- If we have word-to-word alignments, we can compute the probabilities using the MLE:
  - $p(v \mid u) = \dfrac{count(u, v)}{count(u)}$
  - where $count(u, v)$ = #instances where target word u was aligned to source word v in the training set
- However, word-to-word alignments are often hard to come by

Solution: Unsupervised learning

Expectation Maximization (advanced)

- **(E-Step)** If we had an accurate translation model, we can estimate likelihood of each alignment as:

$$q_m(a_m \mid \boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) \propto \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}) \times \mathrm{p}(w_m^{(s)} \mid w_{a_m}^{(t)}),$$

Remember these are fixed

- **(M Step)** Use expected count to re-estimate translation parameters:

$$p(v \mid u) = \frac{E_q[count(u,v)]}{count(u)}$$

$$E_q\left[\mathrm{count}(u,v)\right] = \sum_m q_m(a_m \mid \boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) \times \delta(w_m^{(s)} = v) \times \delta(w_{a_m}^{(t)} = u).$$

How do we translate?

- We want: $\arg\max_{w^{(t)}} p(w^{(t)} \mid w^{(s)}) = \arg\max_{w^{(t)}} \frac{p(w^{(s)}, w^{(t)})}{p(w^{(s)})}$

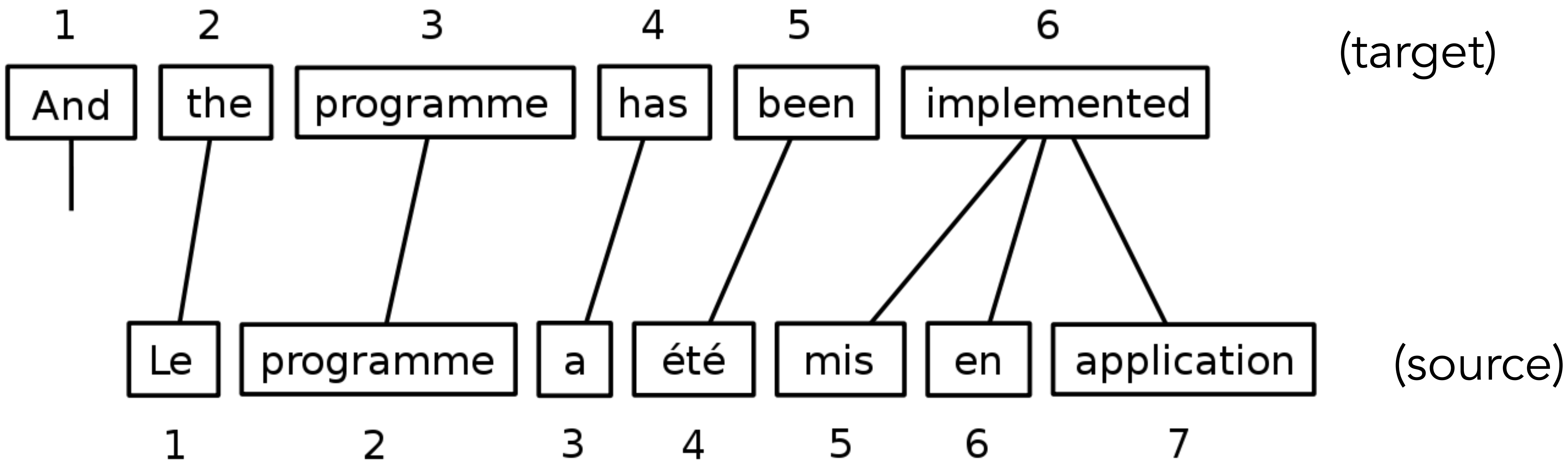
- Sum over all possible alignments:

$$\begin{aligned} \mathrm{p}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) &= \sum_{\mathcal{A}} \mathrm{p}(\boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}, \mathcal{A}) \\ &= \mathrm{p}(\boldsymbol{w}^{(t)}) \sum_{\mathcal{A}} \mathrm{p}(\mathcal{A}) \times \mathrm{p}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}, \mathcal{A}) \end{aligned}$$

- Alternatively, take the max over alignments

- Decoding: Greedy/beam search

Model 1: Decoding



At every step m, pick target word $w_m^{(t)}$ to maximize product of:

1. Language model: $p_{LM}(w_m^{(t)} \mid w_{<m}^{(t)})$
2. Translation model: $p(w_{b_m}^{(s)} \mid w_m^{(t)})$

where b_m is the inverse alignment from target to source

IBM Model 1

- Assume $p(a_m \mid m, M^{(s)}, M^{(t)}) = \frac{1}{M^{(t)}}$
- Each source word is aligned to at most one target word
- We then have:

$$p(w^{(s)}, w^{(t)}) = p(w^{(t)}) \sum_{A} (\frac{1}{M^{(t)}})^{M^{(s)}} \; p(w^{(s)} \mid w^{(t)})$$

Restrictive assumptions

IBM Model 2

- Slightly relaxed assumption:
    - $p(a_m | m, M^{(s)}, M^{(t)})$ is also estimated/learned, not set to constant

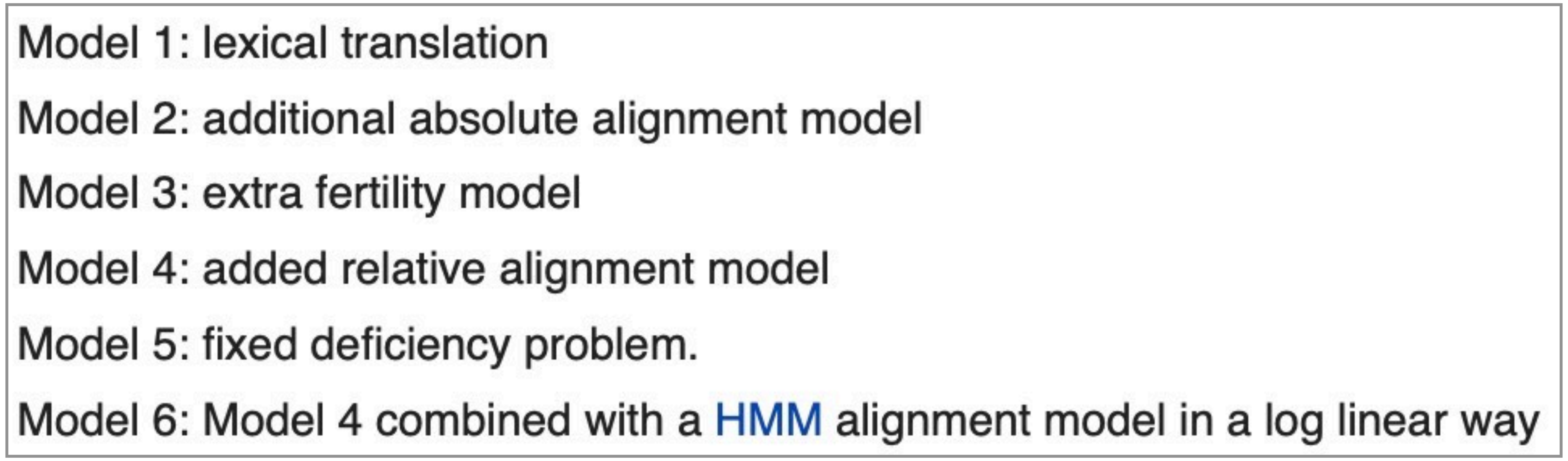
- Some independence assumptions from Model 1 still required:
    - Alignment probability factors across tokens:

$$\mathrm{p}(\mathcal{A} \mid \boldsymbol{w}^{(s)}, \boldsymbol{w}^{(t)}) = \prod_{m=1}^{M^{(s)}} \mathrm{p}(a_m \mid m, M^{(s)}, M^{(t)}).$$

-
    - Translation probability factors across tokens:

$$\mathrm{p}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}, \mathcal{A}) = \prod_{m=1}^{M^{(s)}} \mathrm{p}(w_m^{(s)} \mid w_{a_m}^{(t)}),$$

Other IBM models



Model 1: lexical translation

Model 2: additional absolute alignment model

Model 3: extra fertility model

Model 4: added relative alignment model

Model 5: fixed deficiency problem.

Model 6: Model 4 combined with a HMM alignment model in a log linear way

- Models 3 - 6 make successively weaker assumptions
  - But get progressively harder to optimize
- Simpler models are often used to ‘initialize’ complex ones
  - e.g train Model 1 and use it to initialize Model 2 translation parameters

Phrase-based MT

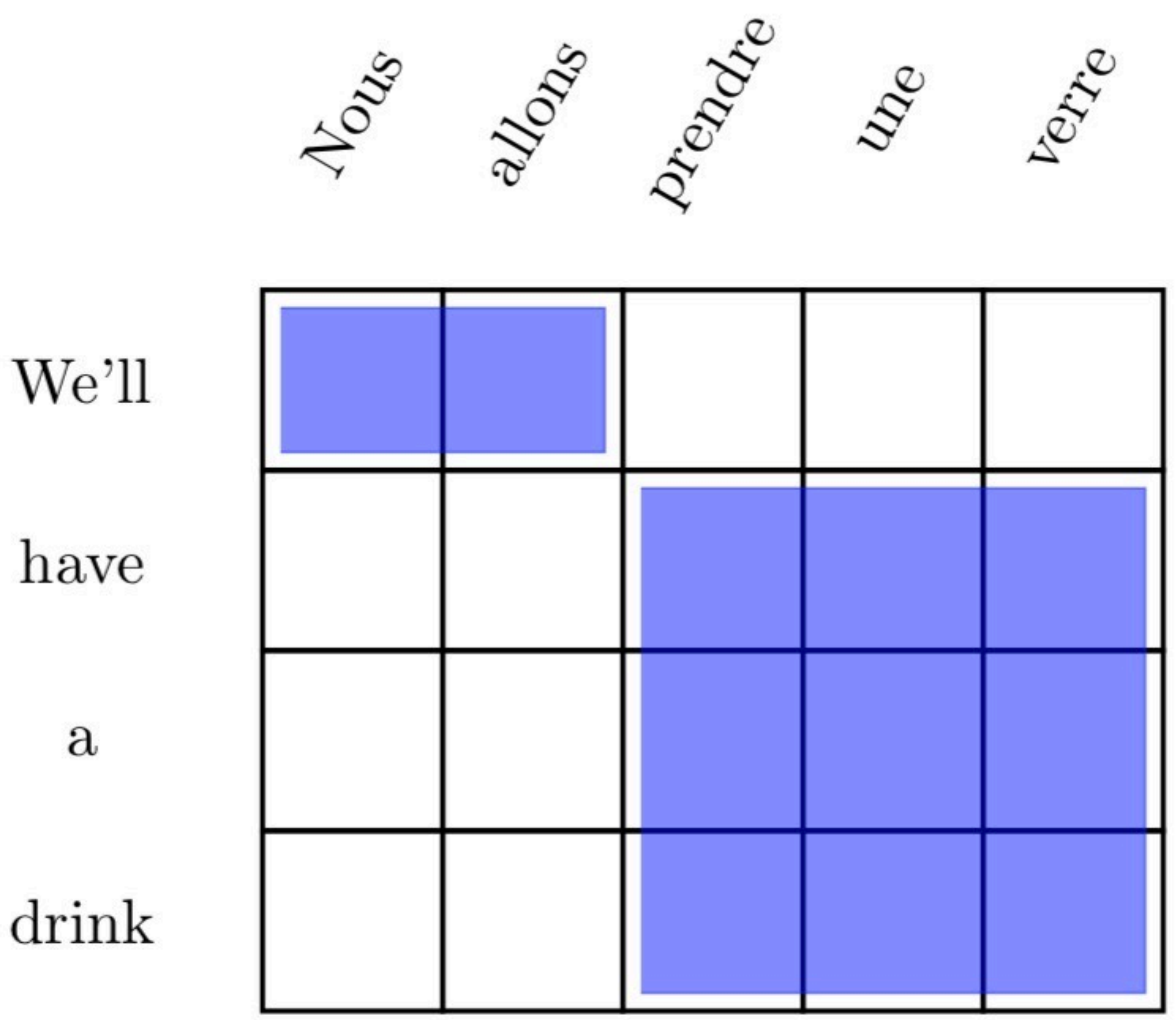
- Word-by-word translation is not sufficient in many cases

Nous allons prendre un verre

(literal) We will take a glass

(actual) We'll have a drink

- Solution: build alignments and translation tables between multiword spans or "phrases"



Phrase-based MT

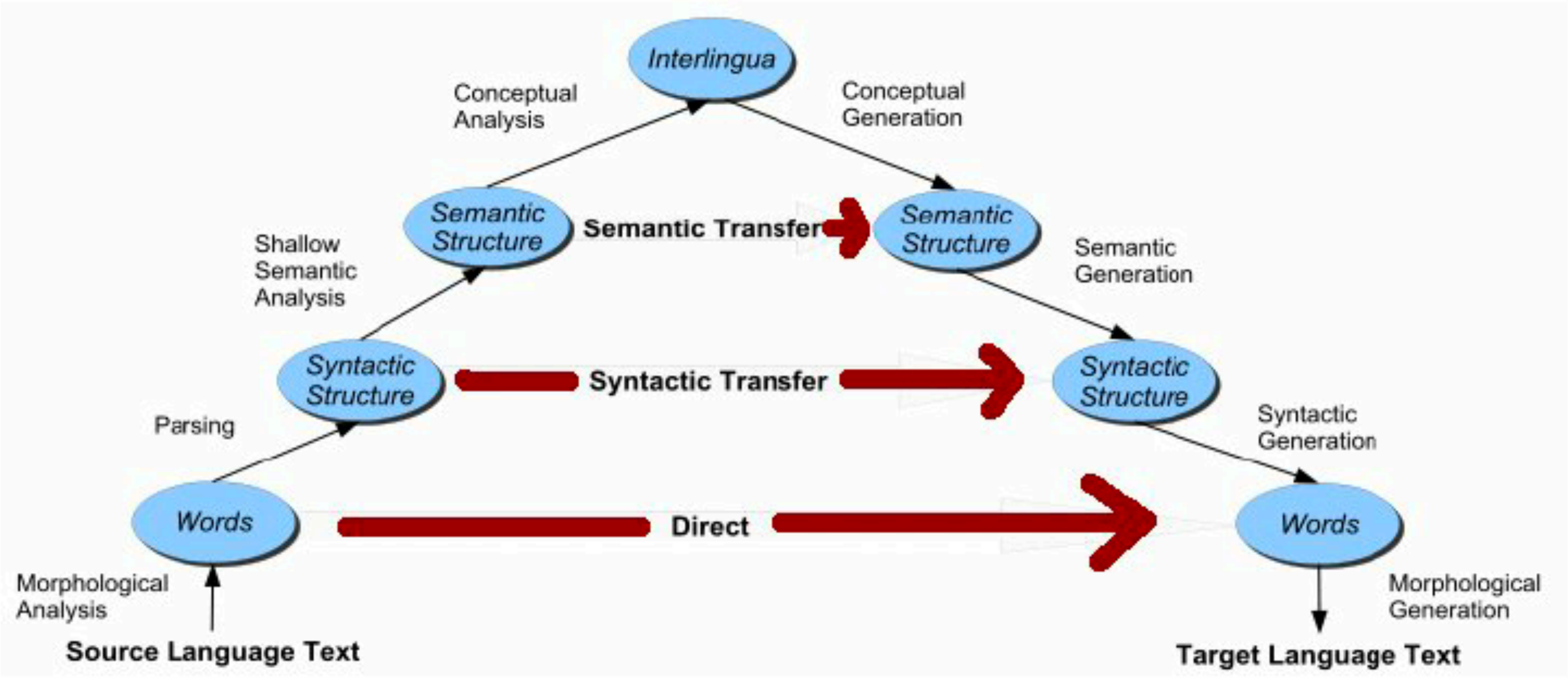
- Solution: build alignments and translation tables between multiword spans or “phrases”

- Translations condition on multi-word units and assign probabilities to multi-word units

- Alignments map from spans to spans

$$\mathrm{p}(\boldsymbol{w}^{(s)} \mid \boldsymbol{w}^{(t)}, \mathcal{A}) = \prod_{((i,j),(k,\ell)) \in \mathcal{A}} \mathrm{p}_{w^{(s)}|w^{(t)}}(\{w_{i+1}^{(s)}, w_{i+2}^{(s)}, \ldots, w_{j}^{(s)}\} \mid \{w_{k+1}^{(t)}, w_{k+2}^{(t)}, \ldots, w_{\ell}^{(t)}\})$$

Vauquois Pyramid



- Hierarchy of concepts and distances between them in different languages
- Lowest level: individual words/ characters
- Higher levels: syntax, semantics
- Interlingua: Generic language-agnostic representation of meaning

Syntactic MT

- Rather than use phrases, use a *synchronous context-free grammar*: constructs "parallel" trees in two languages simultaneously

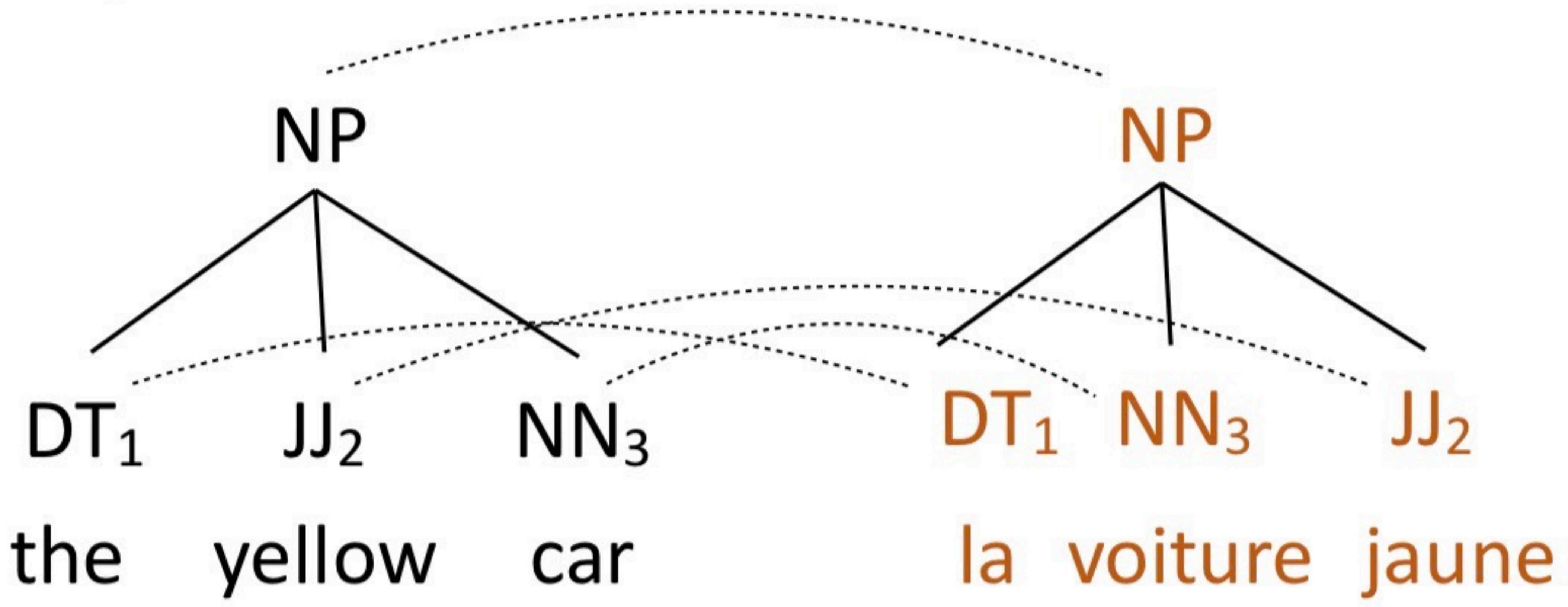
NP → [DT_1 JJ_2 NN_3; DT_1 NN_3 JJ_2]

DT → [the, la]

DT → [the, le]

NN → [car, voiture]

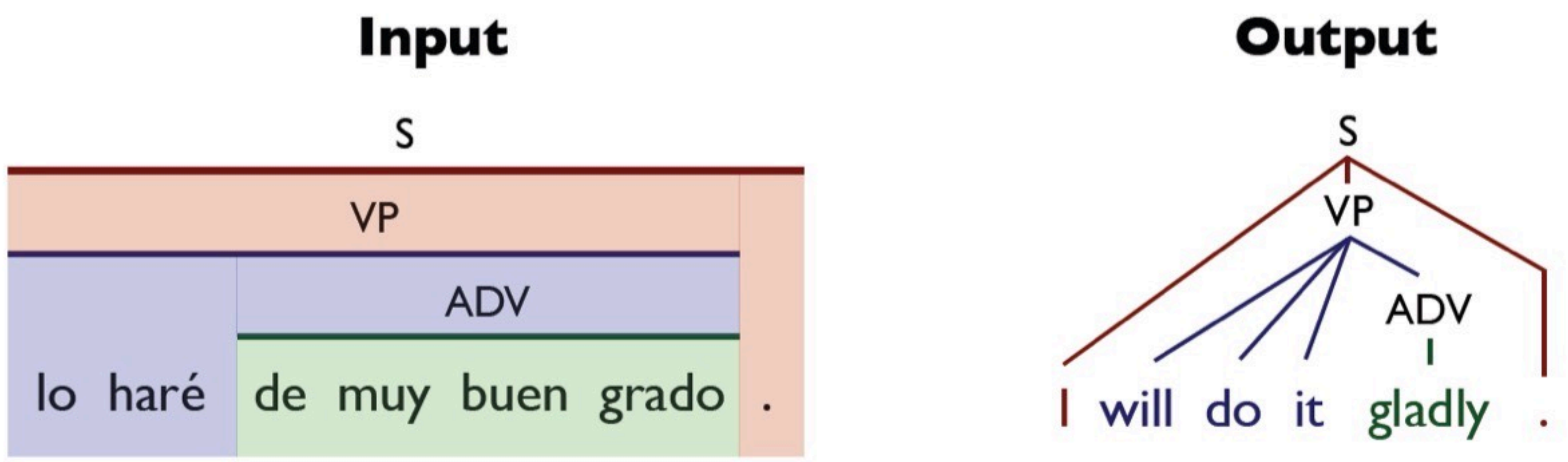
JJ → [yellow, jaune]



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

(Slide credit: Greg Durrett)

Syntactic MT



Input

Output

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 ⟩

- Relax this by using lexicalized rules, like “syntactic phrases”
- Leads to HUGE grammars, parsing is slow

Slide credit: Dan Klein

Next time: Neural machine translation