Machine Translation 1: Word alignments

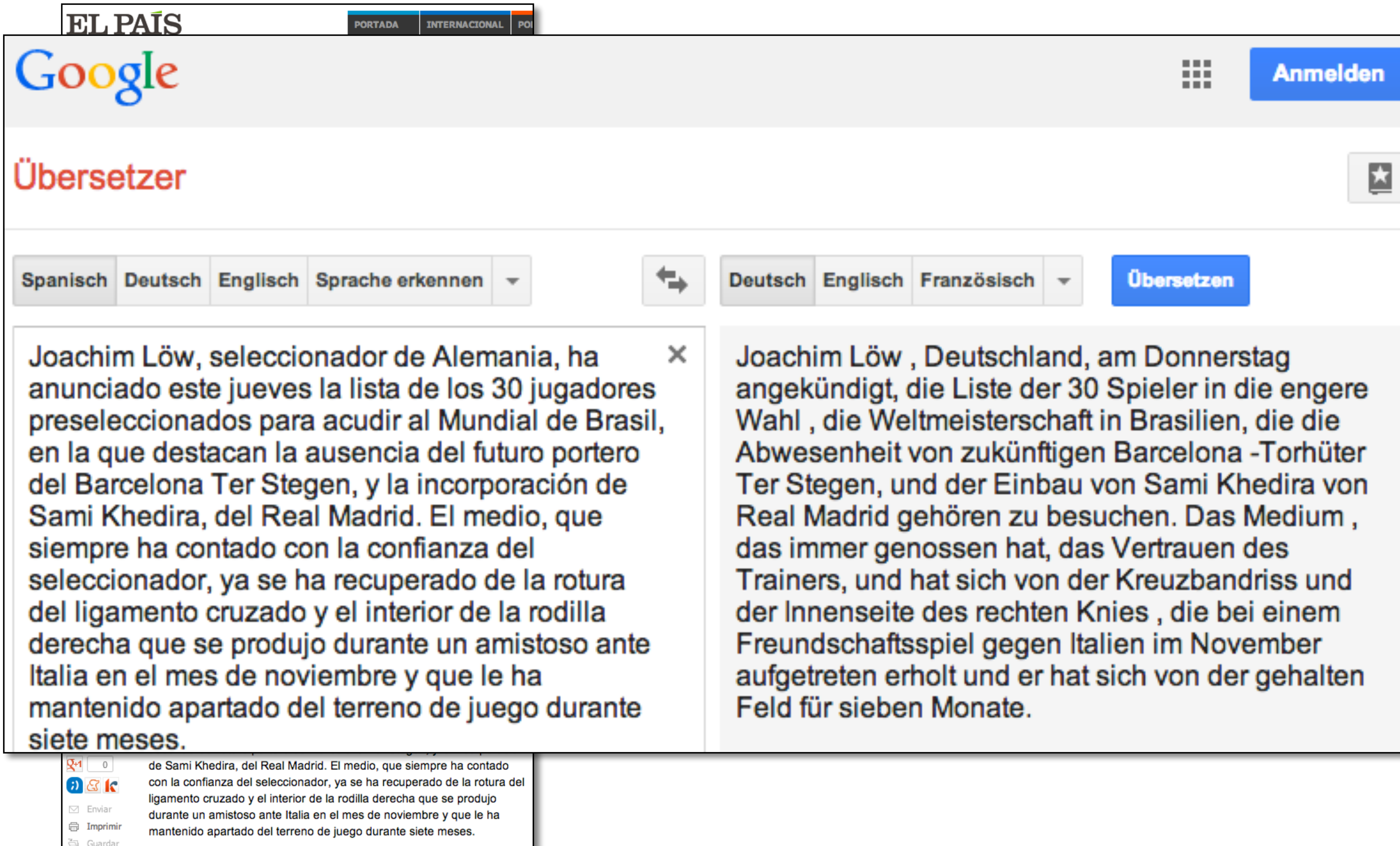
Computational Linguistics

Alexander Koller

20 December 2019

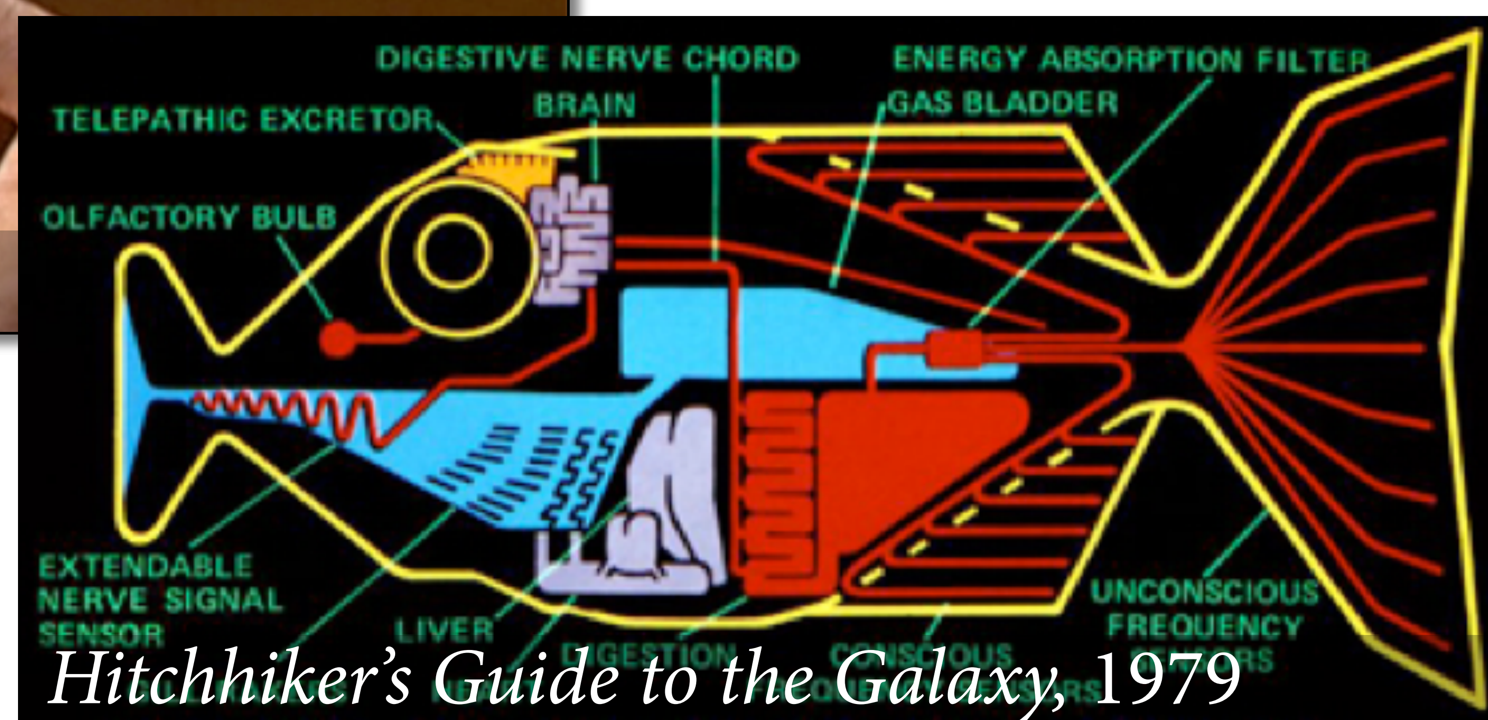
slides contain material from mt-class.org

Google Translate



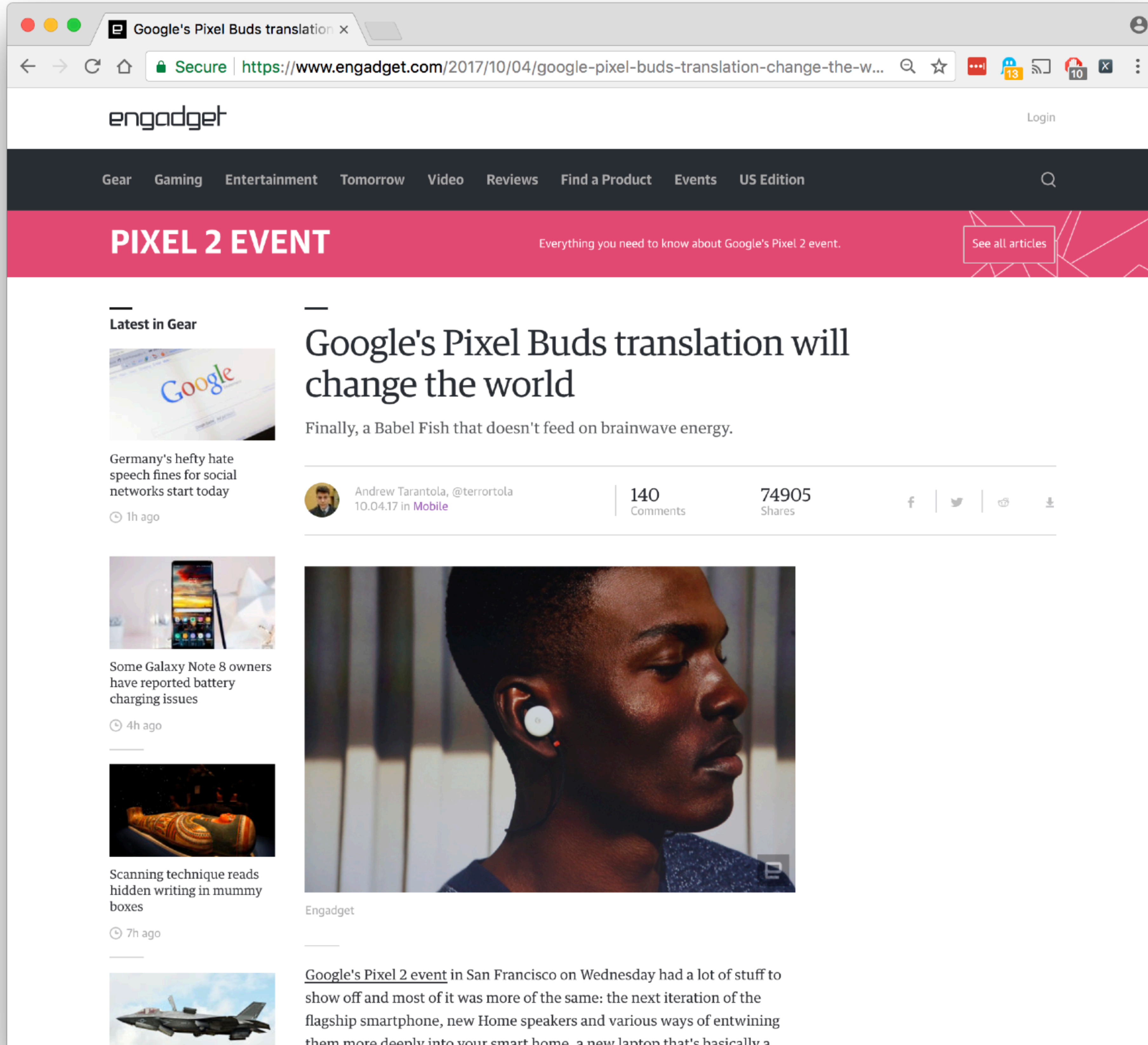
Automatic Translation

Star Trek, 1966



Hitchhiker's Guide to the Galaxy, 1979

Google Pixel Buds, 2017



Google's Pixel Buds translation

Secure https://www.engadget.com/2017/10/04/google-pixel-buds-translation-change-the-w...

engadget

Login

Gear Gaming Entertainment Tomorrow Video Reviews Find a Product Events US Edition

PIXEL 2 EVENT

Everything you need to know about Google's Pixel 2 event.

See all articles

Latest in Gear

Germany's hefty hate speech fines for social networks start today

1h ago

Some Galaxy Note 8 owners have reported battery charging issues

4h ago

Scanning technique reads hidden writing in mummy boxes

7h ago

Google's Pixel Buds translation will change the world

Finally, a Babel Fish that doesn't feed on brainwave energy.

Andrew Tarantola, @terrortola
10.04.17 in Mobile

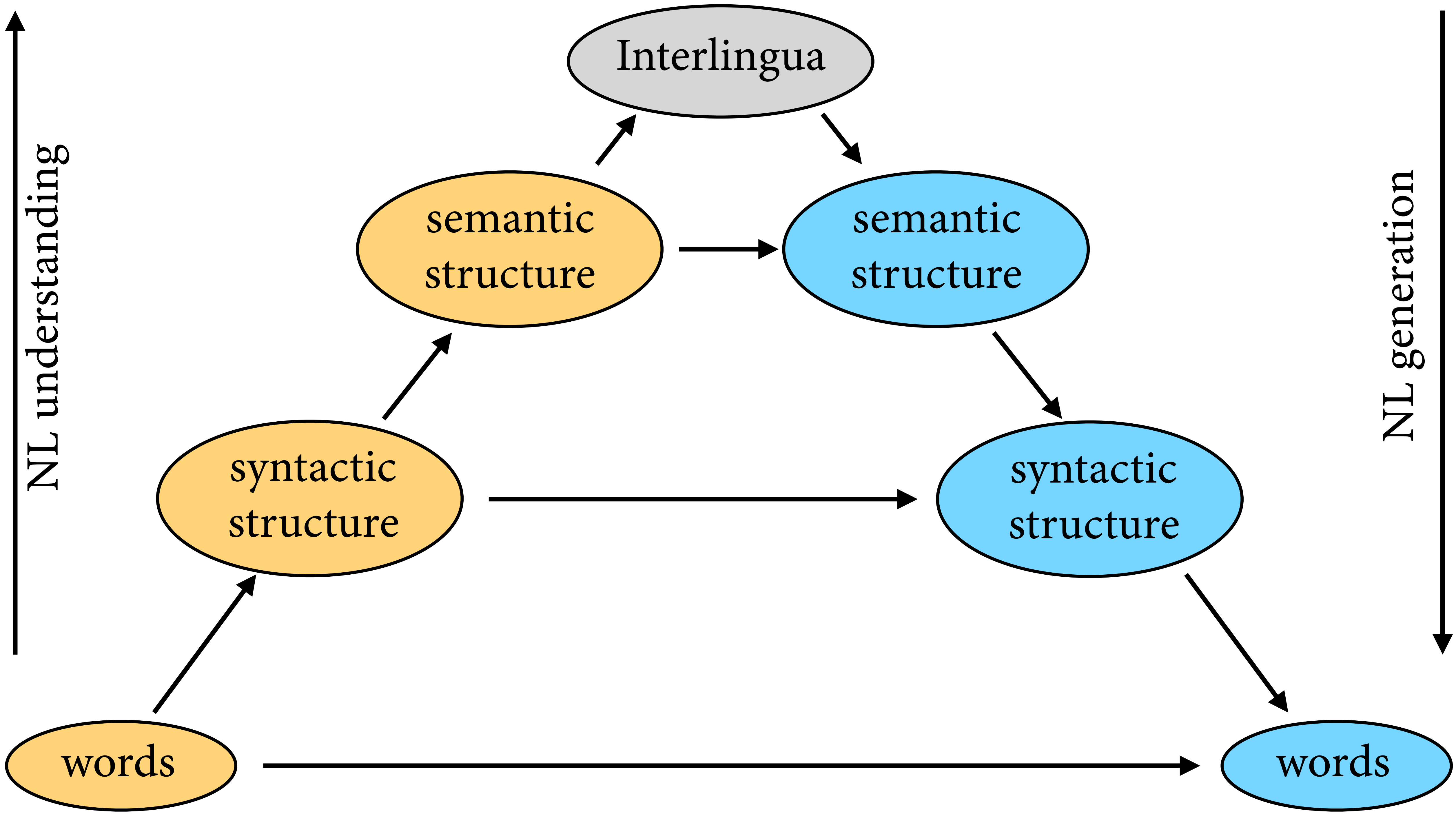
140 Comments

74905 Shares

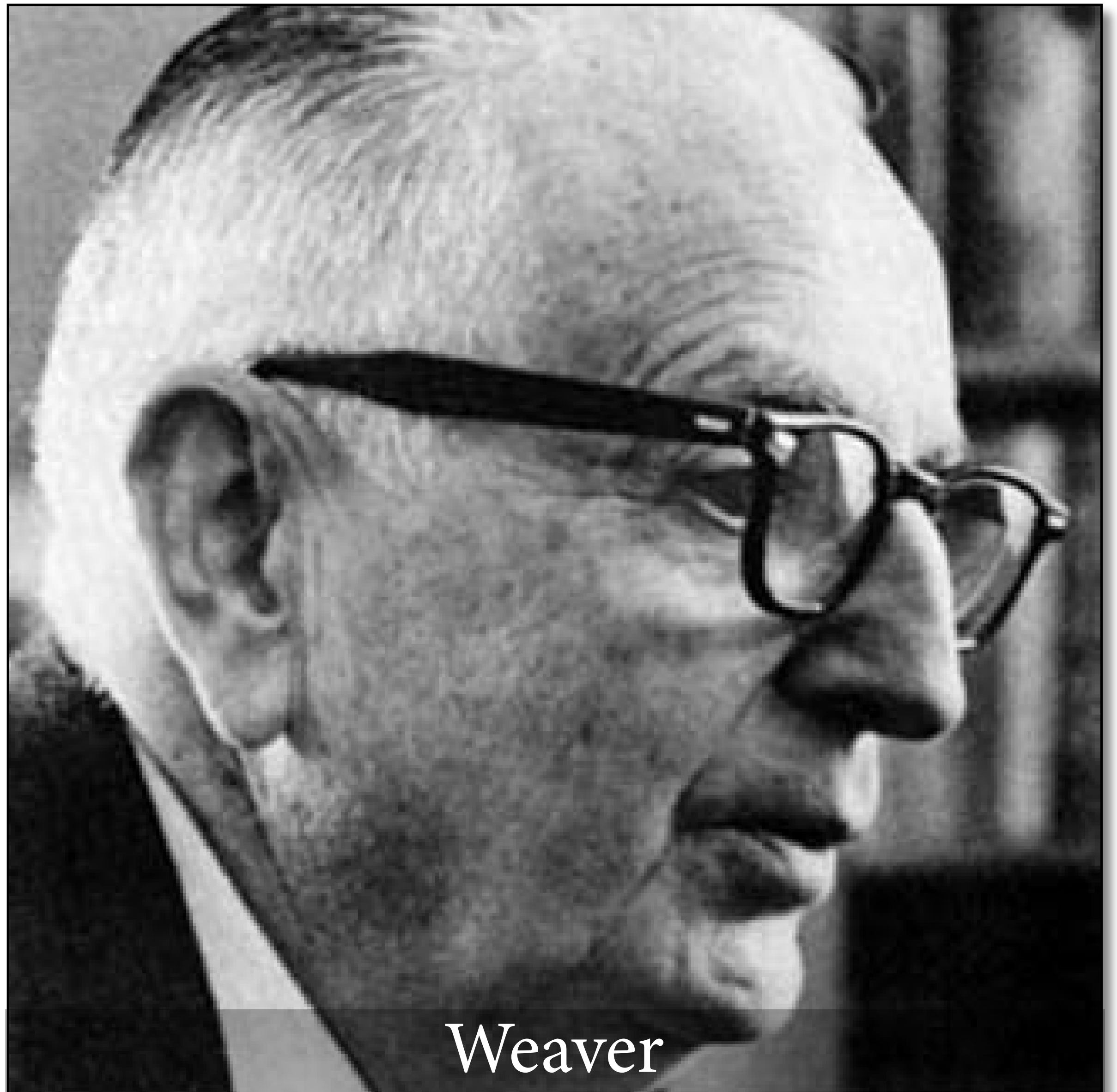
Engadget

Google's Pixel 2 event in San Francisco on Wednesday had a lot of stuff to show off and most of it was more of the same: the next iteration of the flagship smartphone, new Home speakers and various ways of entwining them more deeply into your smart home, a new laptop that's basically a

Classical view on translation



Early History



Weaver

One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography.

When I look at an article in Russian, I say: “This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.”

Warren Weaver to Norbert Wiener (1947)

Types of MT systems

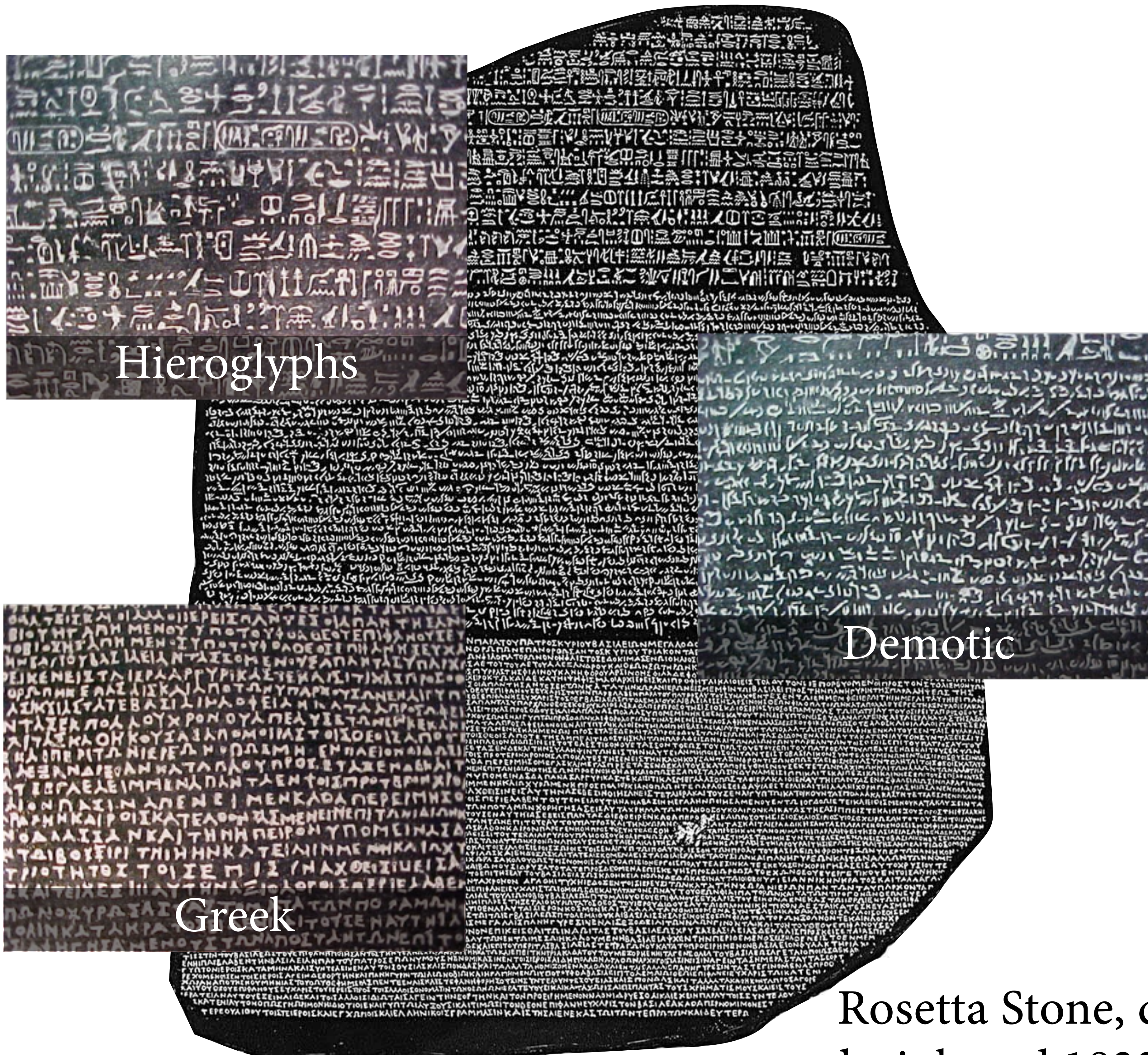
- What’s it for?
  - fully automatic translation
  - support for human translators
- How does it work?
  - rule-based
  - statistical
  - neural
- Neural methods: see “Machine Translation” course.
  Here: elementary statistical methods

Corpora

- Learning translation models requires *parallel corpora:* text in one language with its translation in another.
  - (Except for some really recent work on unsupervised neural MT.)

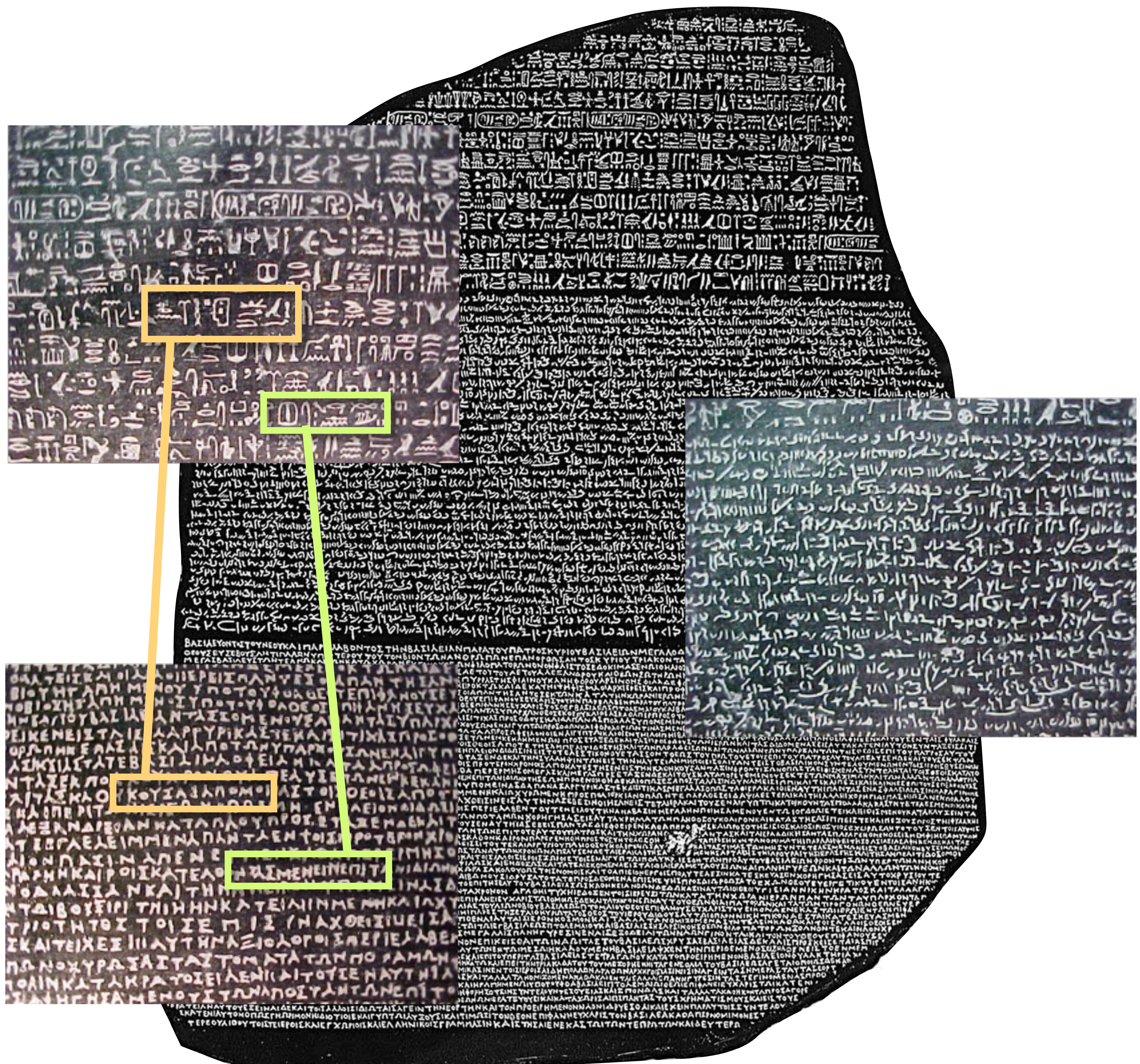
- Popular parallel corpora:
  - Hansards (Canadian parliament): English/French
  - Europarl (European parliament): EU member languages
  - Literary texts with their translations (e.g. bible)

Really Early History



Rosetta Stone, discovered 1799;
deciphered 1822 (Champollion)

Step 1: Lexical Alignment



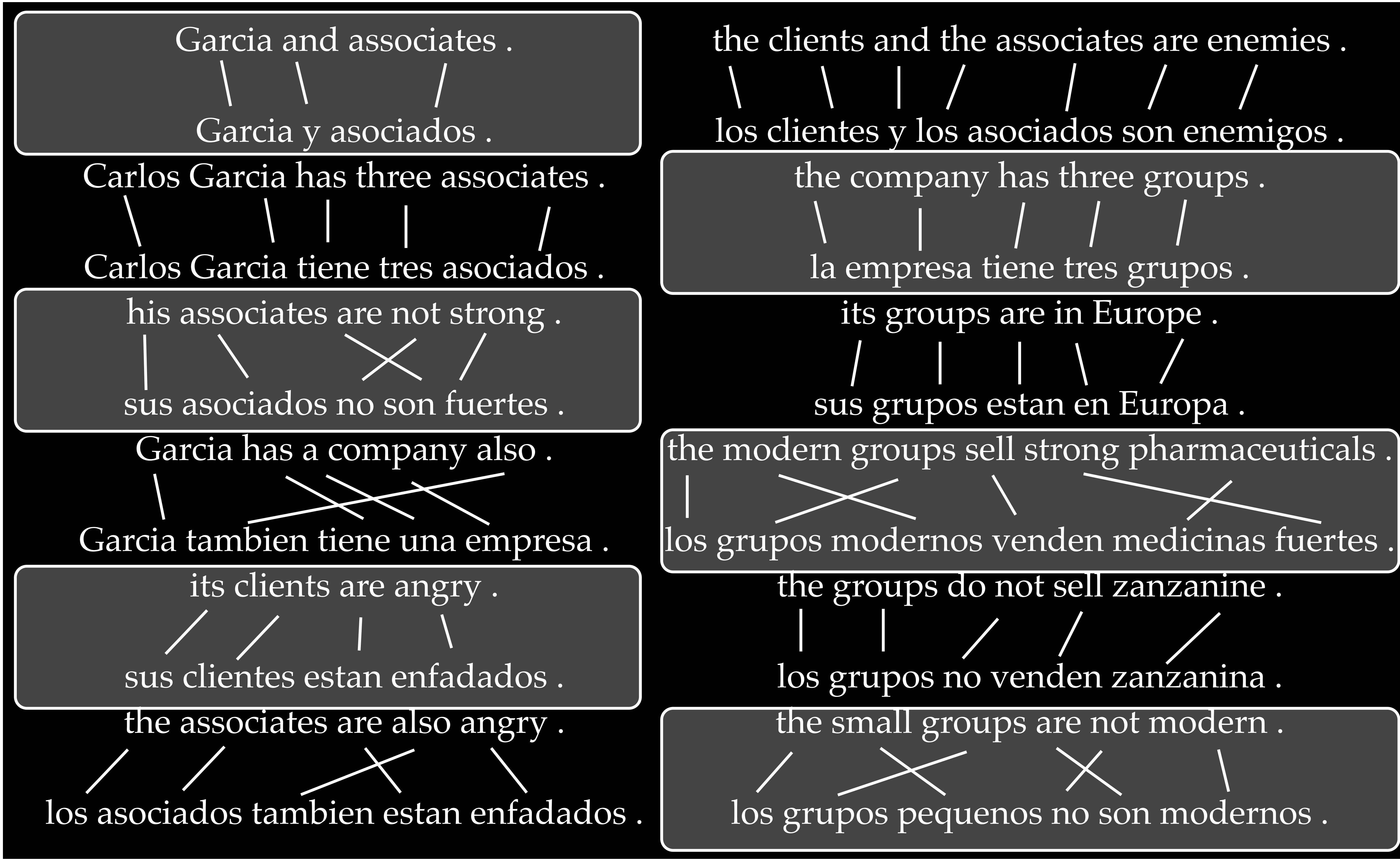
Lexical Translation

- We want to learn a model $P(e \mid f)$:
  - e = "English" word (target language)
  - f = "French" word (original, foreign language)

- Gives a naive translation model for $P(\mathbf{e} \mid \mathbf{f})$.
(Boldface **e**, **f** are English, Foreign sentences.)

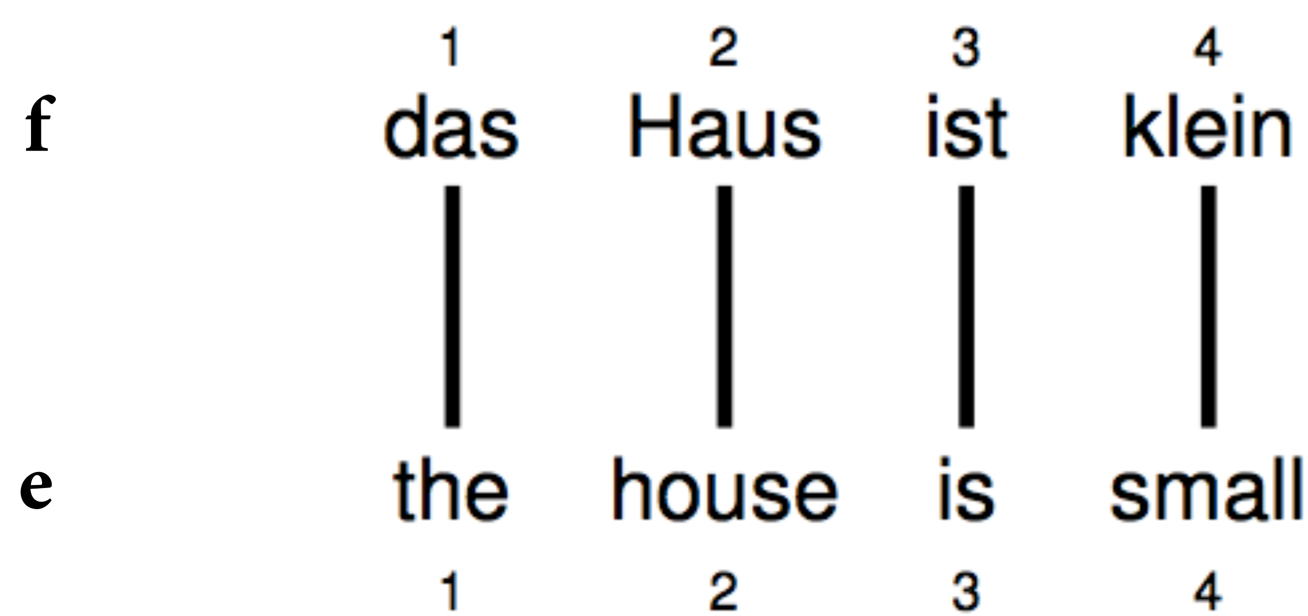
- Linked to idea of *word alignments*.
  - alignments often independently useful
  (e.g. parse tree projection)

Word alignments



Alignment

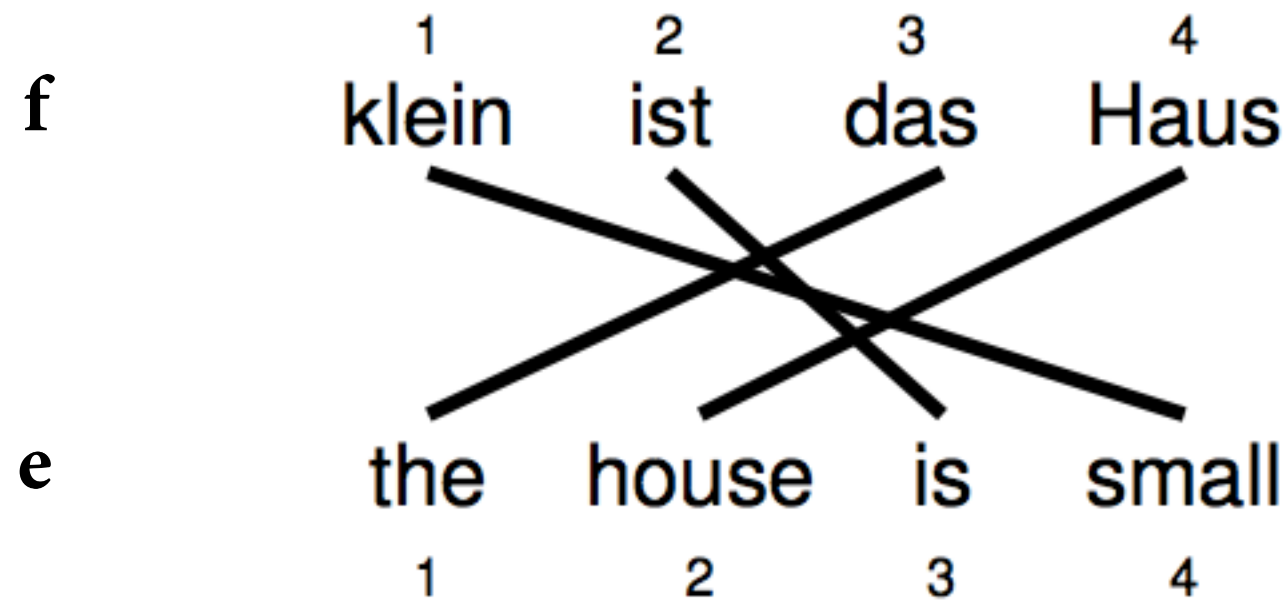
- Alignments can be visualized by drawing links between two sentences, and they are represented as vectors of positions:



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

Reordering

- Words may be reordered during translation.

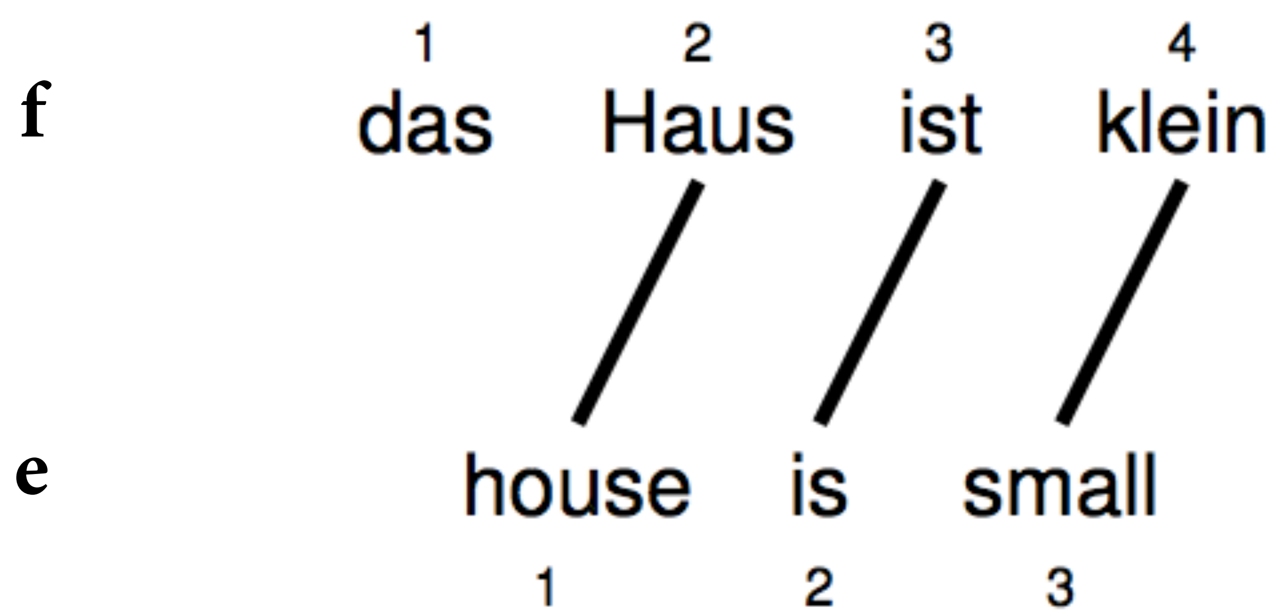


English word #1
aligned with Foreign word #3

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

Word Dropping

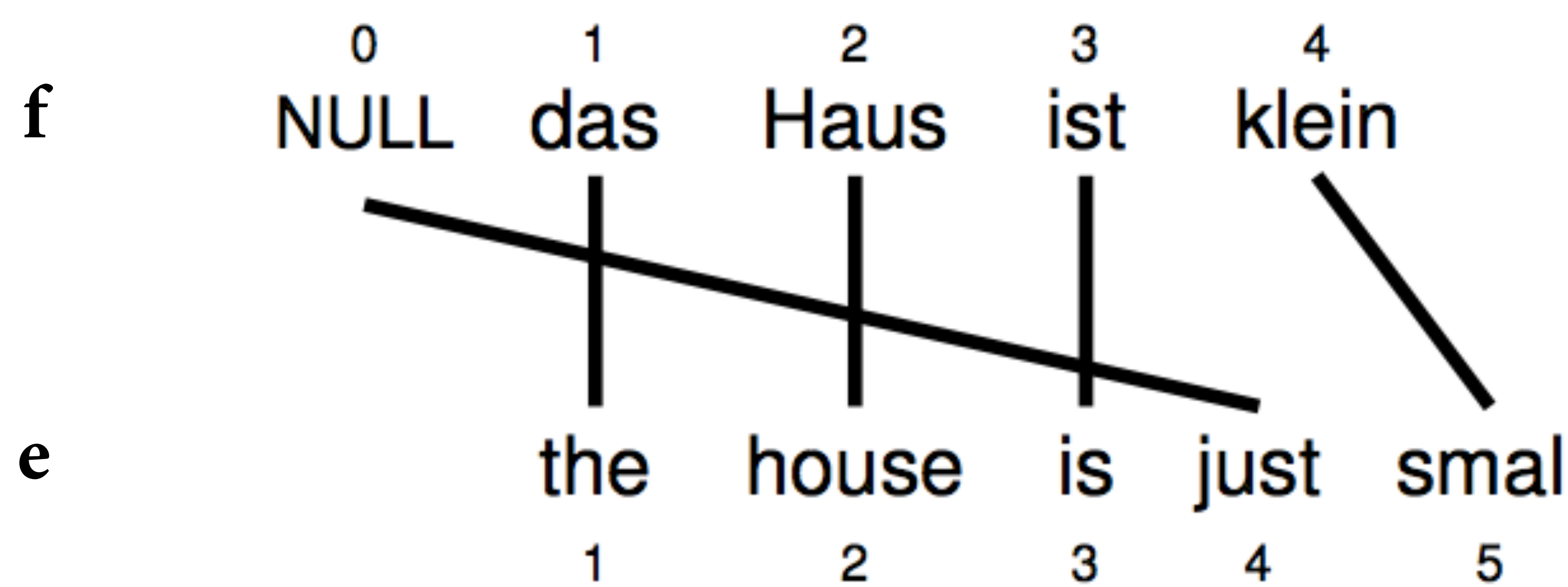
- A source word may not be translated at all
  (“1” does not occur as a_i for any English position i)



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

Word Insertion

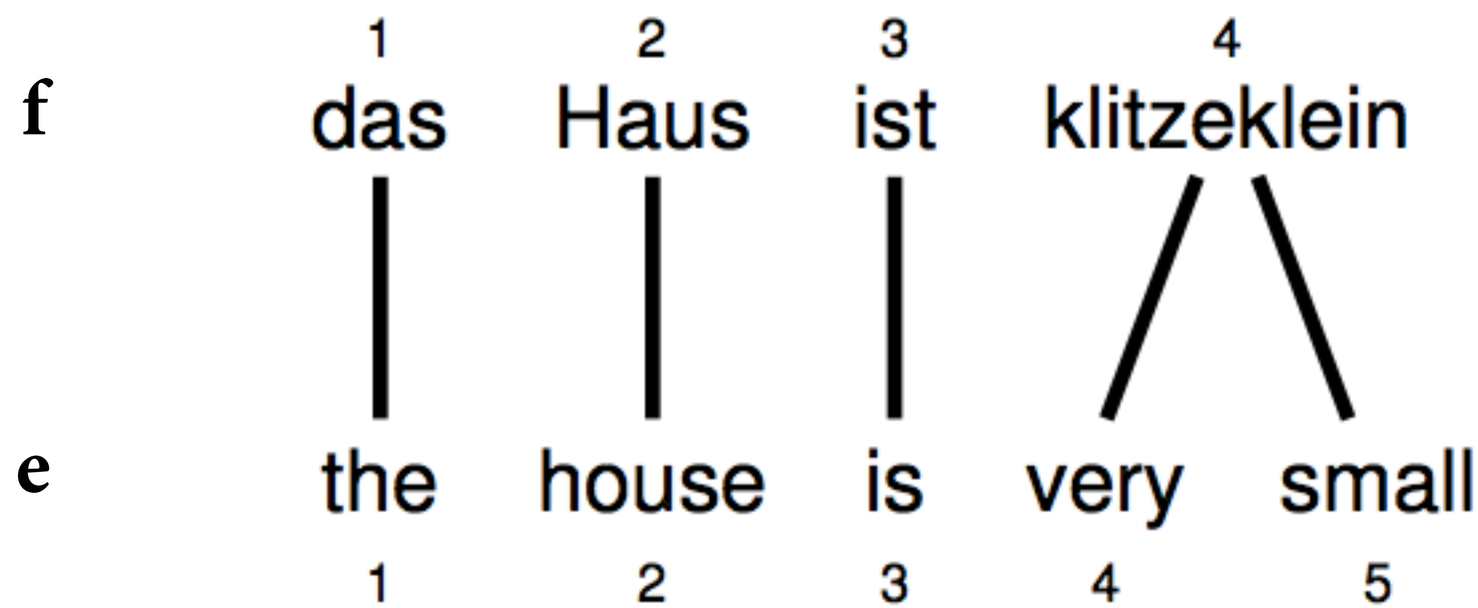
- Words may be inserted during translation
  - English "just" does not have an equivalent
  - record this by aligning with special NULL token at "position 0"



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

One-to-many Translation

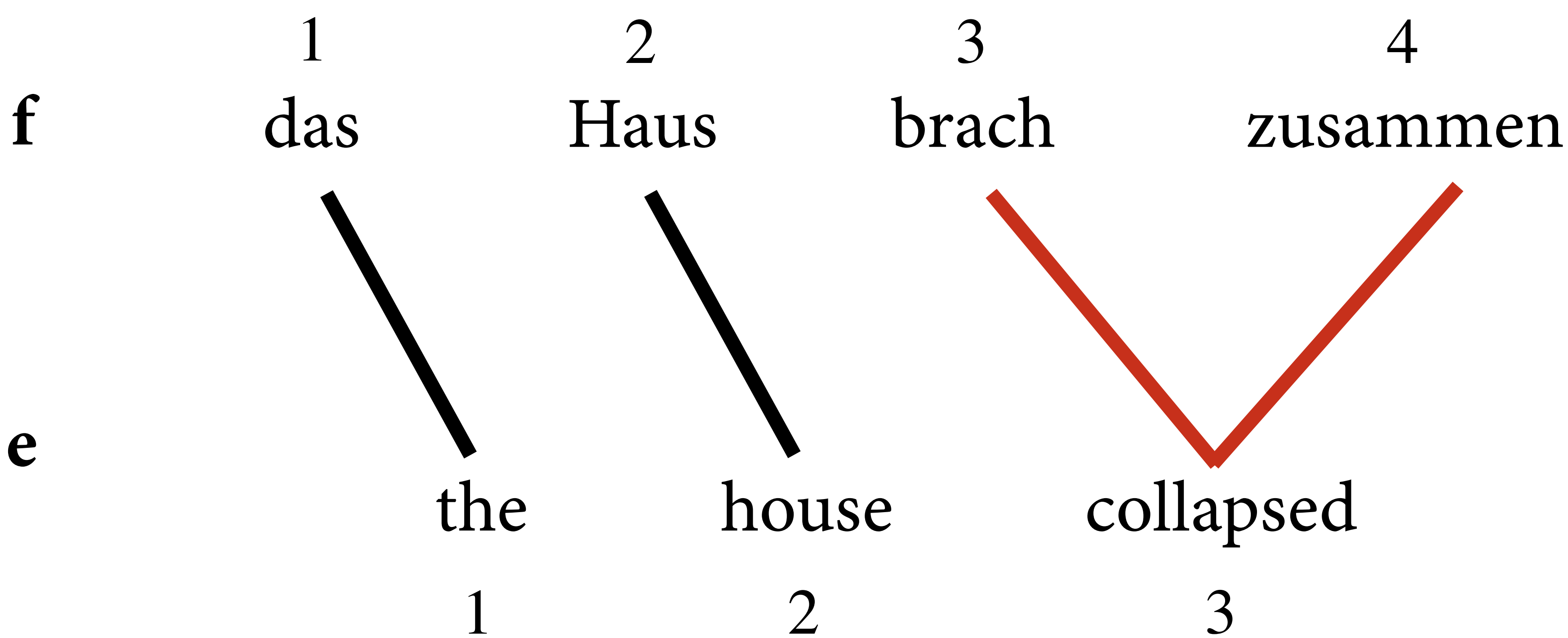
- A Foreign word may translate into *more than one* English word.



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

Many-to-one Translation

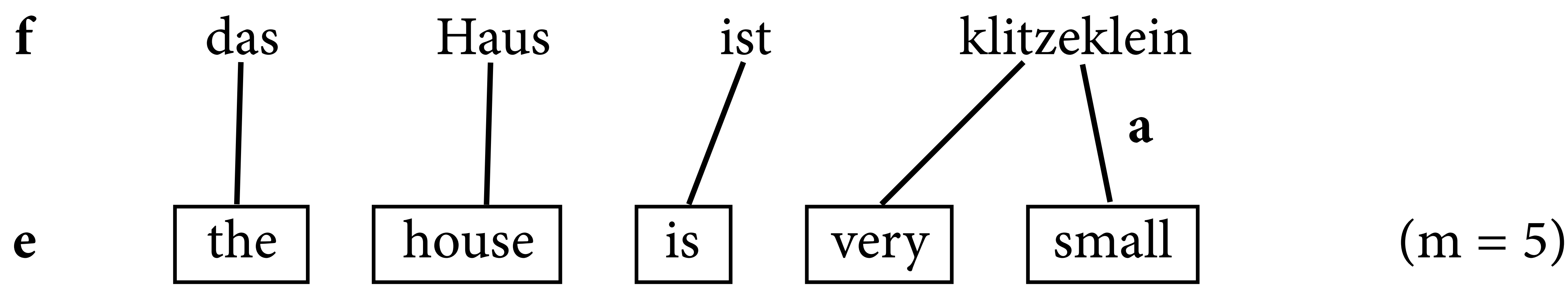
- *More than one* Foreign word may *not* translate into a single English word (can't represent this).



a = ????

Statistical model

- Generative story: Given Foreign string **f** and length m of English string, alignments **a** and English string **e** are generated randomly.



- Model P(**a**, **e** | **f**, m) = P(**a** | **f**, m) * P(**e** | **a**, **f**, m).
  - obtain P(**e** | **f**, m) by marginalizing **a** out → translation
  - obtain P(**a** | **f**, m) by marginalizing **e** out → compute alignments

IBM Model 1

- Simplifying assumptions:
  - The alignment decisions for the m English words are independent.
  - The alignment distribution for each a_i is uniform over all source words and NULL.
  - The English words are generated independently, conditioned only on their aligned Foreign words.

$$\begin{aligned}&\text{for each } i \in [1, 2, \ldots, m]\\ &\qquad a_i \sim \text{Uniform}(0, 1, 2, \ldots, n)\\ &\qquad e_i \sim \text{Categorical}(\boldsymbol{\theta}_{f_{a_i}})\end{aligned}$$

IBM Model 1

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

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

$$e_i \sim \text{Categorical}(\boldsymbol{\theta}_{f_{a_i}})$$

$$P(e_i, a_i \mid \mathbf{f}, m) = \boxed{P(a_i \mid \mathbf{f}, m)} \cdot \boxed{P(e_i \mid a_i, \mathbf{f}, m)} = \boxed{\frac{1}{n+1}} \cdot \boxed{P(e_i \mid f_{a_i})}$$

$$P(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m) = \prod_{i=1}^{m} P(e_i, a_i \mid \mathbf{f}, m) = \prod_{i=1}^{m} \frac{1}{n+1} \cdot P(e_i \mid f_{a_i})$$

$$P(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a}} P(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m)$$

Example

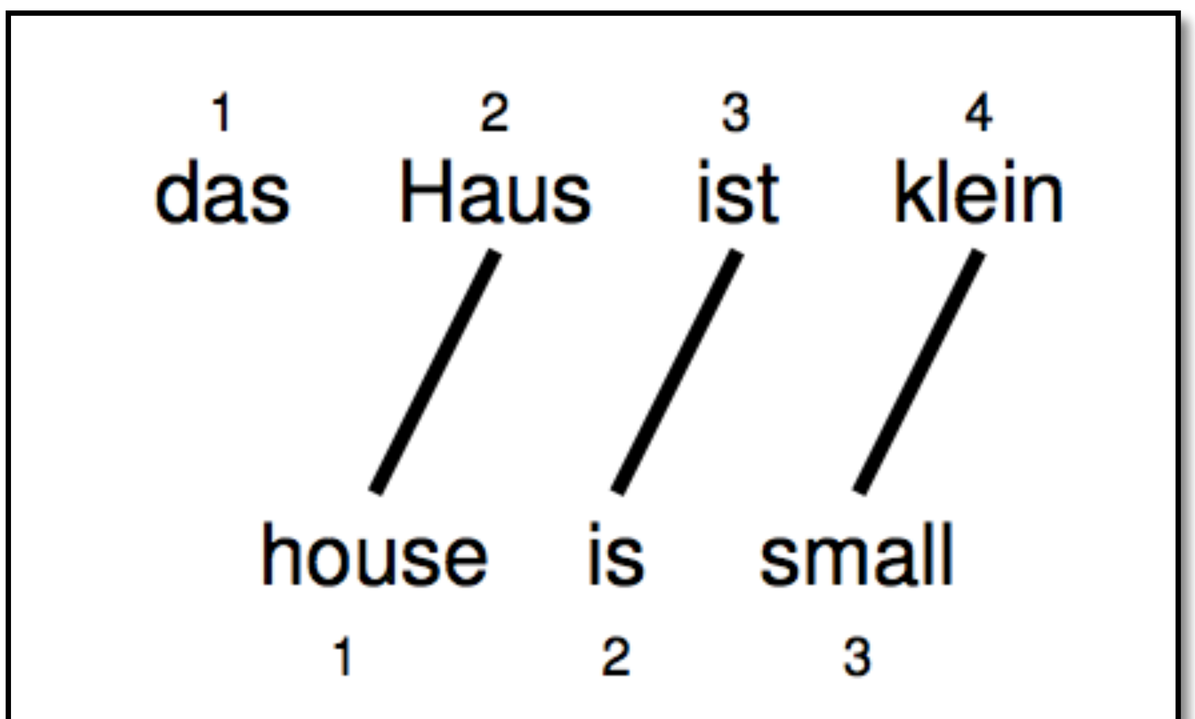
$t(e \mid f) = P(e \mid f)$

das	
e	$t(e\|f)$
the	0.7
that	0.15
which	0.075
who	0.05
this	0.025

Haus	
e	$t(e\|f)$
house	0.8
building	0.16
home	0.02
household	0.015
shell	0.005

ist	
e	$t(e\|f)$
is	0.8
's	0.16
exists	0.02
has	0.015
are	0.005

klein	
e	$t(e\|f)$
small	0.4
little	0.4
short	0.1
minor	0.06
petty	0.04



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

$$
\begin{aligned}
P(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m) = \\
&1/5 * P(\text{Haus}|\text{house}) * \\
&1/5 * P(\text{ist}|\text{is}) * \\
&1/5 * P(\text{small}|\text{klein}) \\
= 1/125 * 0.8 * 0.8 * 0.4 \\
= 0.002
\end{aligned}
$$

Computing best alignments

- Assume that we know parameters P(e | f) and we are given **e** and **f**. What is alignment **a** that maximizes P(**a** | **e**, **f**)?

- Because of independence of $a_1, \ldots, a_m$, can choose best aligned word in **f** for each word in **e** separately.

$$a_i^* = \arg\max_{a_i=0}^{n} \frac{1}{1+n} p(e_i \mid f_{a_i})$$
$$= \arg\max_{a_i=0}^{n} p(e_i \mid f_{a_i})$$

Training

$$p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m) = \prod_{i=1}^{m} \frac{1}{1+n}\, p(e_i \mid f_{a_i})$$

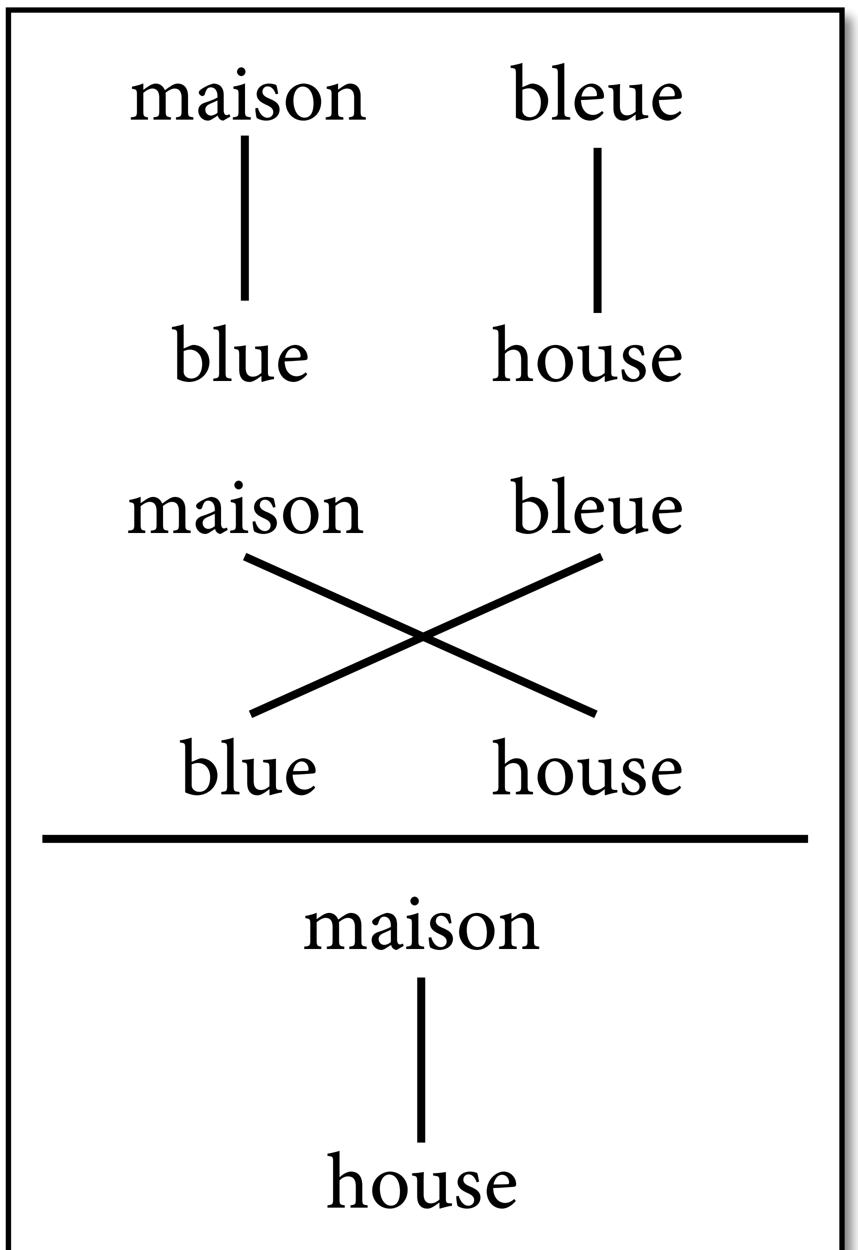
- Parameters of our model: translation probs P(e | f) for any two words e and f.

- If we could observe alignments, then we could just do MLE: C(e aligned with f) / C(f)

- Because we usually only have raw parallel text (no alignments), we need to use EM.
  - estimate counts from estimate of P
  - re-estimate P from estimated counts

EM: An Example

P(e|f)	house	blue
maison	0.5	0.5
bleue	0.5	0.5



$$p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m) = \prod_{i=1}^{m} \frac{1}{1+n}\, p(e_i \mid f_{a_i})$$

*1. Compute P(**e**, **a** | **f**) for each alignment of each sentence pair.*

P($\mathbf{e}_1$, $\mathbf{a}_{11}$ | $\mathbf{f}_1$) = 1/9 * 1/2 * 1/2 = 1/36

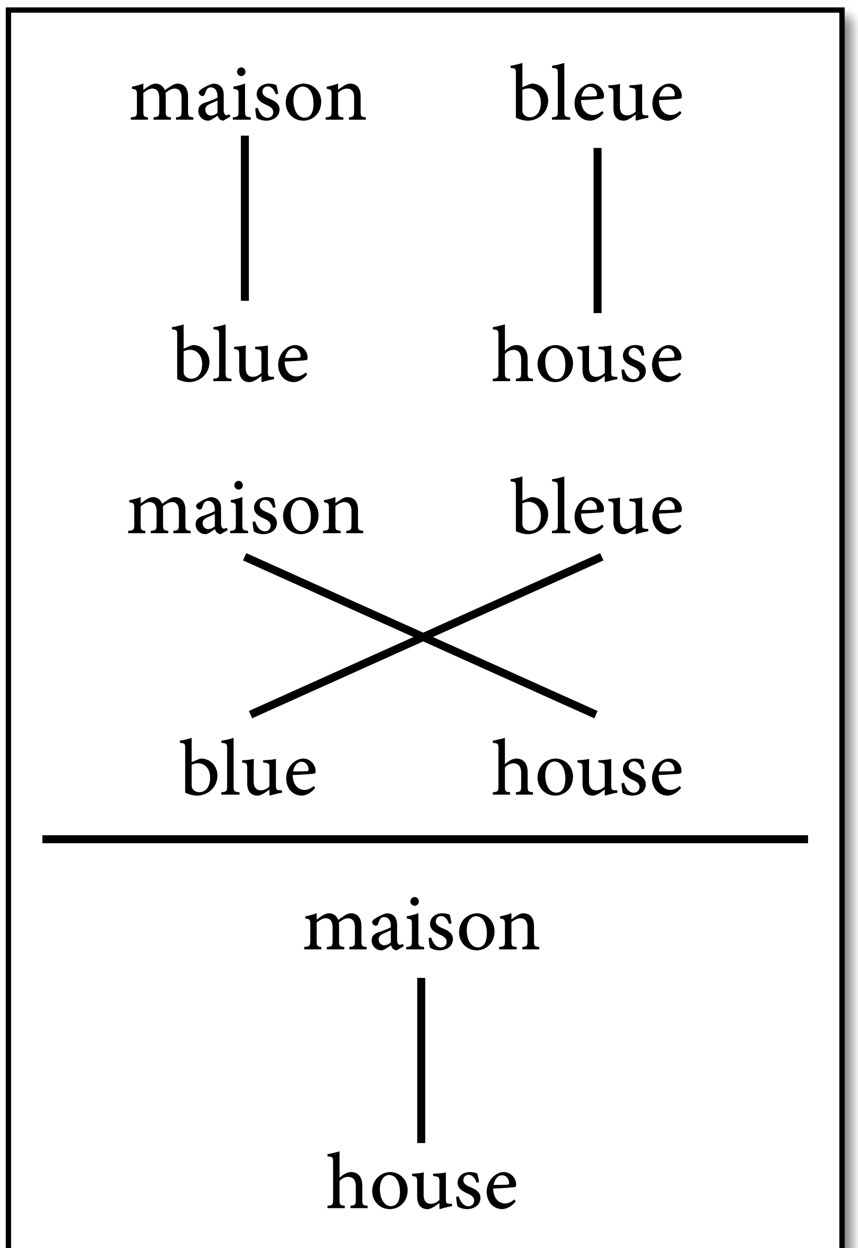
P($\mathbf{e}_1$, $\mathbf{a}_{12}$ | $\mathbf{f}_1$) = 1/9 * 1/2 * 1/2 = 1/36

P($\mathbf{e}_2$, $\mathbf{a}_2$ | $\mathbf{f}_2$) = 1/2 * 1/2 = 1/4

(note: these are not really all alignments)

EM: An Example

P(e|f)	house	blue
maison	0.5	0.5
bleue	0.5	0.5



2. Normalize $P(\boldsymbol{e}, \boldsymbol{a} \mid \boldsymbol{f})$ to yield $P(\boldsymbol{a} \mid \boldsymbol{e}, \boldsymbol{f})$.

$$P(\mathbf{a} \mid \mathbf{e}, \mathbf{f}) = \frac{P(\mathbf{a}, \mathbf{e} \mid \mathbf{f})}{P(\mathbf{e} \mid \mathbf{f})} = \frac{P(\mathbf{a}, \mathbf{e} \mid \mathbf{f})}{\sum_{\mathbf{a}'} P(\mathbf{a}', \mathbf{e} \mid \mathbf{f})}$$

$P(\mathbf{a}_{11} \mid \mathbf{e}_1, \mathbf{f}_1) = 1/2$

$P(\mathbf{a}_{12} \mid \mathbf{e}_1, \mathbf{f}_1) = 1/2$

$P(\mathbf{a}_2 \mid \mathbf{e}_2, \mathbf{f}_2) = 1$

3. collect expected counts

tc	house	blue
maison	3/2	1/2
bleue	1/2	1/2

EM: An Example

*4. Normalize expected counts C(**e**, **f**)*
*by total expected counts C(**f**)*
*to obtain revised translation probs P(**e** | **f**).*

expected counts

tc	house	blue
maison	3/2	1/2
bleue	1/2	1/2

→

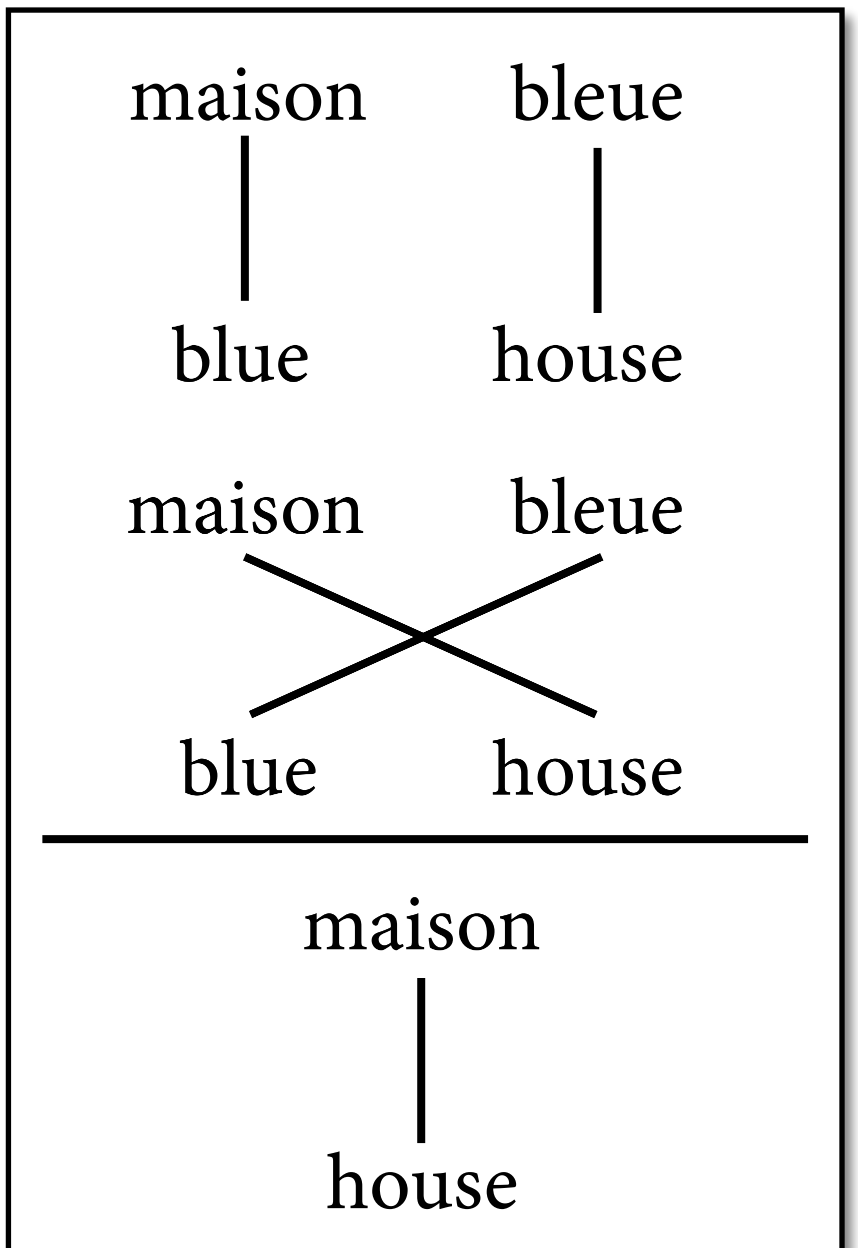
revised translation probs

P(e|f)	house	blue
maison	3/4	1/4
bleue	1/2	1/2

EM: Round Two

P(e|f)	house	blue
maison	3/4	1/4
bleue	1/2	1/2

$$p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m) = \prod_{i=1}^{m} \frac{1}{1+n} \; p(e_i \mid f_{a_i})$$



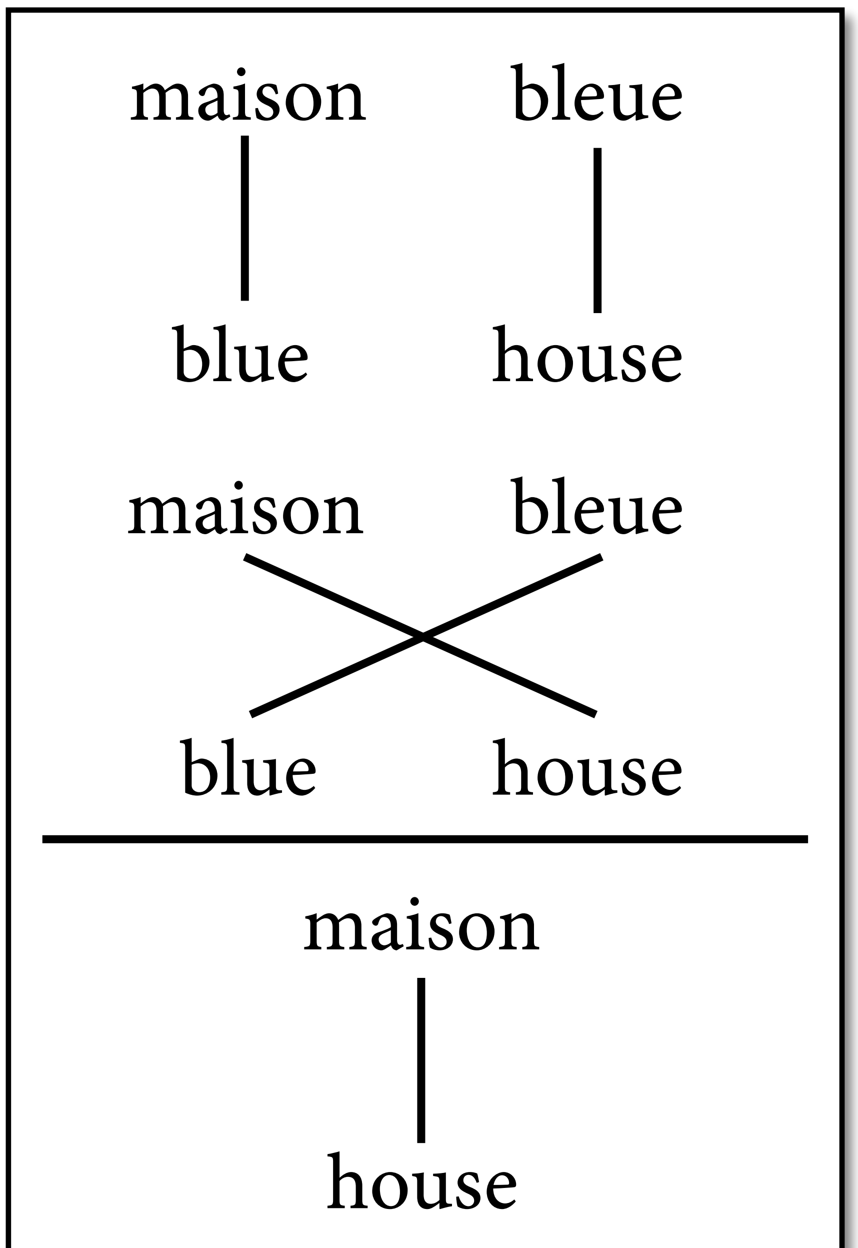
$P(e_1, a_{11} \mid f_1) = 1/9 * 1/4 * 1/2 = 1/72$

$P(e_1, a_{12} \mid f_1) = 1/9 * 3/4 * 1/2 = 3/72$

$P(e_2, a_2 \mid f_2) = 1/2 * 3/4 = 3/8$

EM: Round Two

P(e|f)	house	blue
maison	3/4	1/4
bleue	1/2	1/2



$P(a_{11} \mid e_1, f_1) = 1/4$

$P(a_{12} \mid e_1, f_1) = 3/4$

$P(a_2 \mid e_2, f_2) = 1$

tc	house	blue
maison	7/4	1/4
bleue	1/4	3/4

EM: Round Two

expected counts

tc	house	blue
maison	7/4	1/4
bleue	1/4	3/4

revised translation probs

P(e|f)	house	blue
maison	7/8	1/8
bleue	1/4	3/4

After many iterations:

P(e|f)	house	blue
maison	≈ 1	≈ 0
bleue	≈ 0	≈ 1

Efficient computation

- Computation of P(**a** | **e**, **f**) in E-step is tricky:

$$P(a_i = j \mid \mathbf{e}, \mathbf{f}) = \frac{P(a_i = j, \mathbf{e} \mid \mathbf{f})}{P(\mathbf{e} \mid \mathbf{f})} = \frac{\displaystyle\sum_{\mathbf{a}: a_i = j} \prod_{i'=1}^{m} P(e_{i'} \mid f_{a_{i'}})}{\displaystyle\sum_{\mathbf{a}} \prod_{i'=1}^{m} P(e_{i'} \mid f_{a_{i'}})}$$

- Summation over **a** is exponential in sentence length.

- By clever use of law of distributivity, can rewrite this term so it can be computed in quadratic time.
  See Lopez tutorial on website. (Note flipped **e** and **f**.)

Extensions

- IBM Model 2: P(**a**) not uniform, but implements *reordering model* that prefers alignments in which words stay close to their original position.
- Model 3: adds *fertility model* that predicts the number of English words to which a given f will be aligned. Can't do EM, approximate with sampling.
- Models 4-5: more complicated reordering models.
- Implemented in GIZA++ and successor tools.

Conclusion

- Machine translation: one of the most useful and most challenging disciplines of NLP.
- Today: word alignments.
  - IBM Model 1
  - computing best alignments
  - EM training
  - advanced models
- Next time: let's actually translate something.