CMSC 473/673
Natural Language Processing

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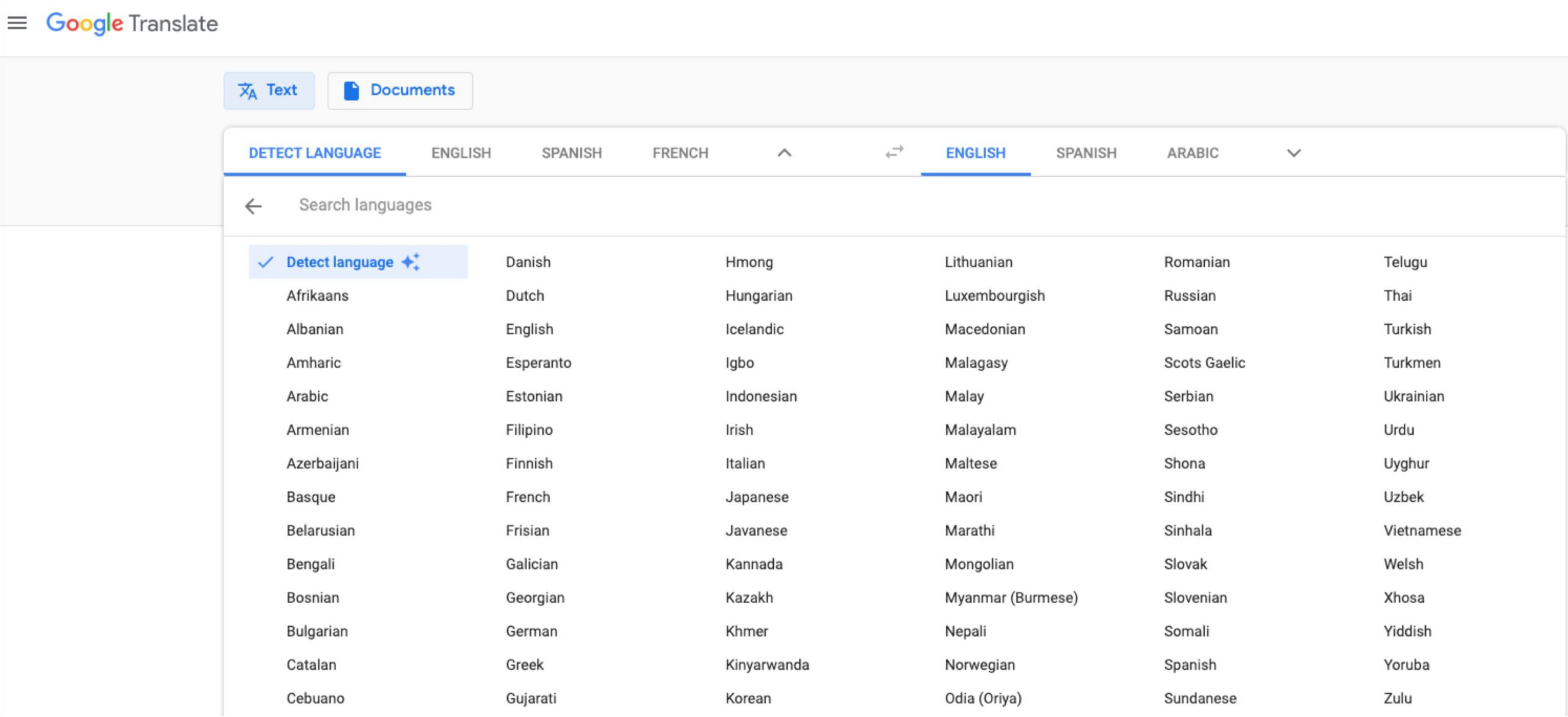
Slides modified from Yulia Tsvetkov & Diyi Yang

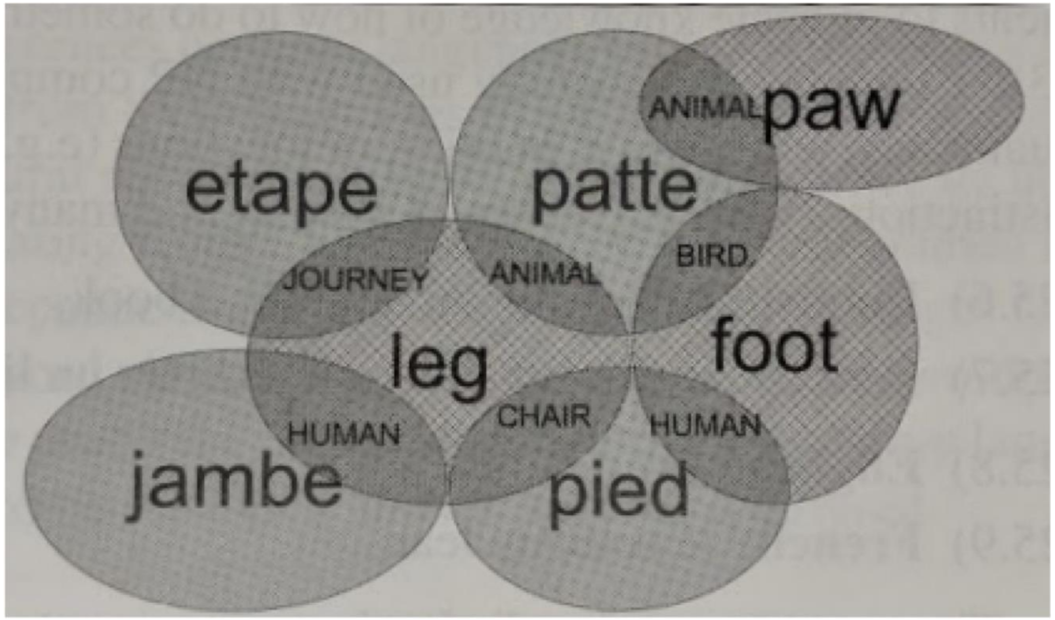
Machine Translation

Tower of Babel


Google Translate
Text
Documents
DETECT LANGUAGE
ENGLISH
SPANISH
FRENCH
ENGLISH
SPANISH
ARABIC
Search languages
Detect language
Afrikaans
Albanian
Amharic
Arabic
Armenian
Azerbaijani
Basque
Belarusian
Bengali
Bosnian
Bulgarian
Catalan
Cebuano
Danish
Dutch
English
Esperanto
Estonian
Filipino
Finnish
French
Frisian
Galician
Georgian
German
Greek
Gujarati
Hmong
Hungarian
Icelandic
Igbo
Indonesian
Irish
Italian
Japanese
Javanese
Kannada
Kazakh
Khmer
Kinyarwanda
Korean
Lithuanian
Luxembourgish
Macedonian
Malagasy
Malay
Malayalam
Maltese
Maori
Marathi
Mongolian
Myanmar (Burmese)
Nepali
Norwegian
Odia (Oriya)
Romanian
Russian
Samoan
Scots Gaelic
Serbian
Sesotho
Shona
Sindhi
Sinhala
Slovak
Slovenian
Somali
Spanish
Sundanese
Telugu
Thai
Turkish
Turkmen
Ukrainian
Urdu
Uyghur
Uzbek
Vietnamese
Welsh
Xhosa
Yiddish
Yoruba
Zulu

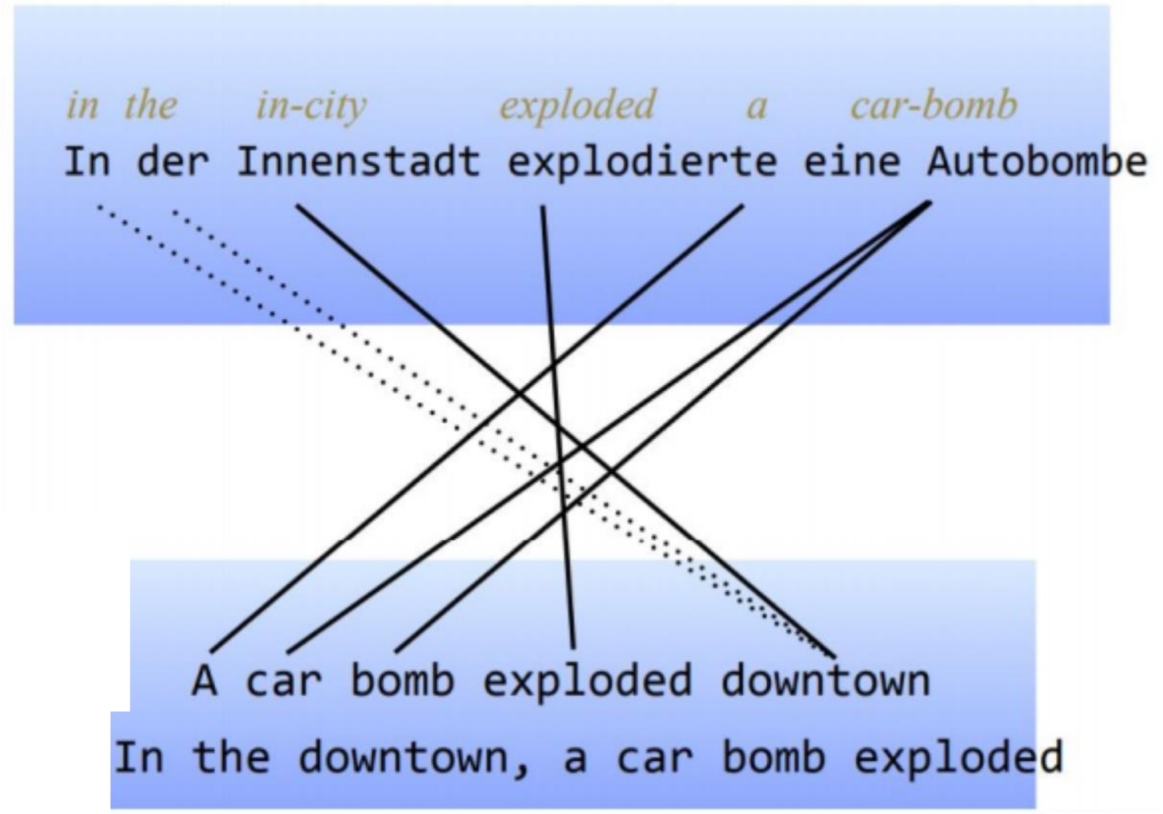
Dictionaries

- English: leg, foot, paw
- French: jambe, pied, patte, etape



Challenges

- Ambiguities
  - Words
  - Morphology
  - Syntax
  - Semantics
  - Pragmatics
- Gaps in data
  - Availability of corpus
  - Commonsense knowledge
- Understanding of context, connotatic social norms, etc



Research Problems

- How can we formalize the process of learning to translate from examples?
- How can we formalize the process of finding translations for new inputs?
- If our model produces many outputs, how do we find the best one?
- If we have a gold standard translation, how can we tell if our output is good or bad?

Two Views Of MT

MT as Code Breaking

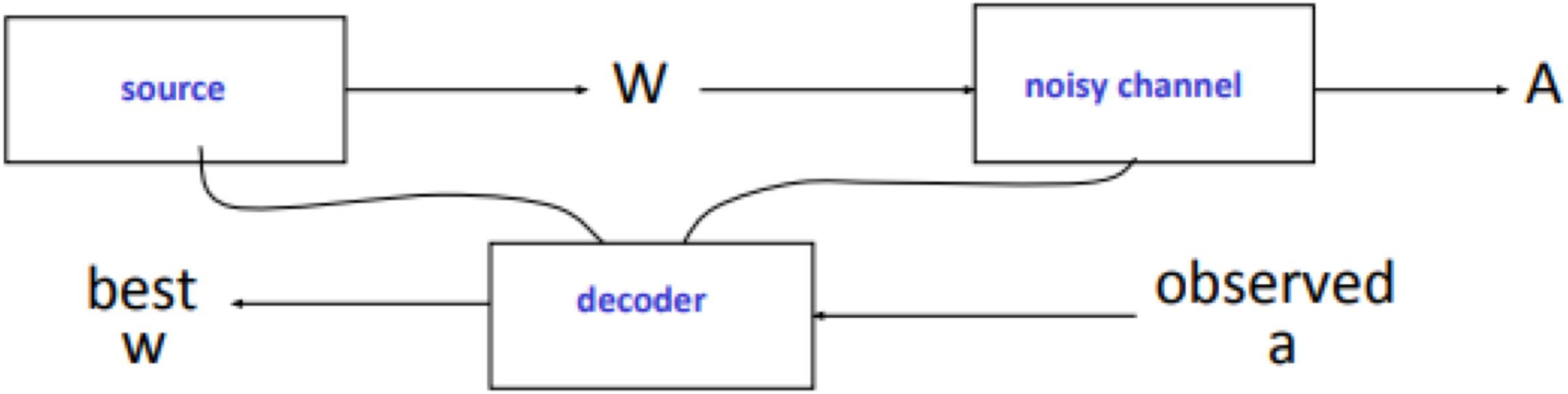
One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: '***This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.***'

Warren Weaver to Norbert Wiener, March, 1947

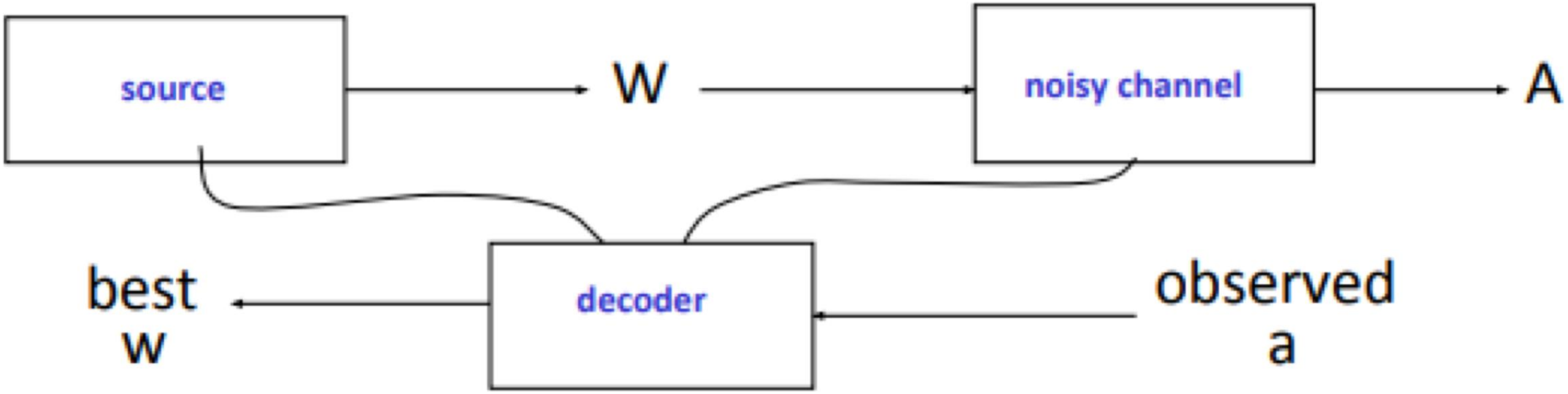
The Noisy-Channel Model

Claude Shannon. "A Mathematical Theory of Communication" 1948.

The Noisy-Channel Model

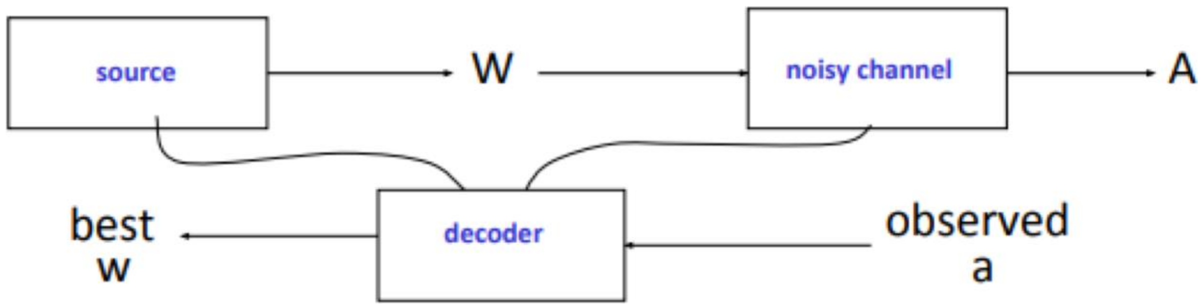


The Noisy-Channel Model



We want to predict a sentence given acoustics: $w^* = \arg\max_w P(w|a)$

The Noisy-Channel Model

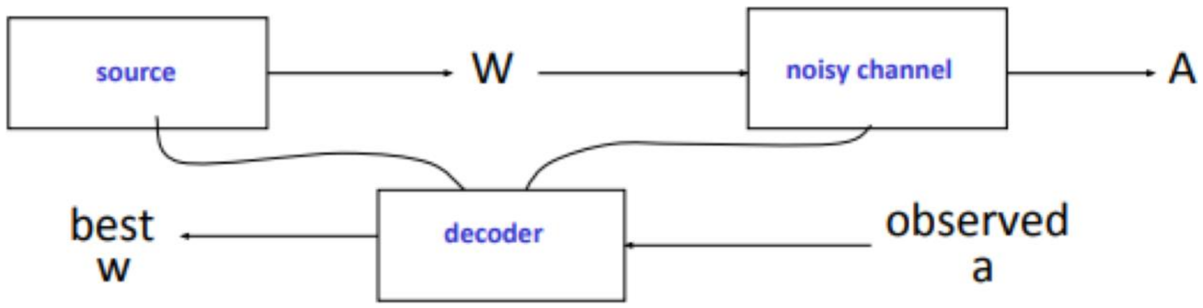


$$
\begin{aligned}
w^* &= \arg\max_{w} P(w|a) \\
&= \arg\max_{w} P(a|w)P(w) \ /P(a) \\
&= \arg\max_{w} \underbrace{P(a|w)}_{\text{Channel model}}\underbrace{P(w)}_{\text{Source model}}
\end{aligned}
$$

Channel model

Source model

The Noisy-Channel Model

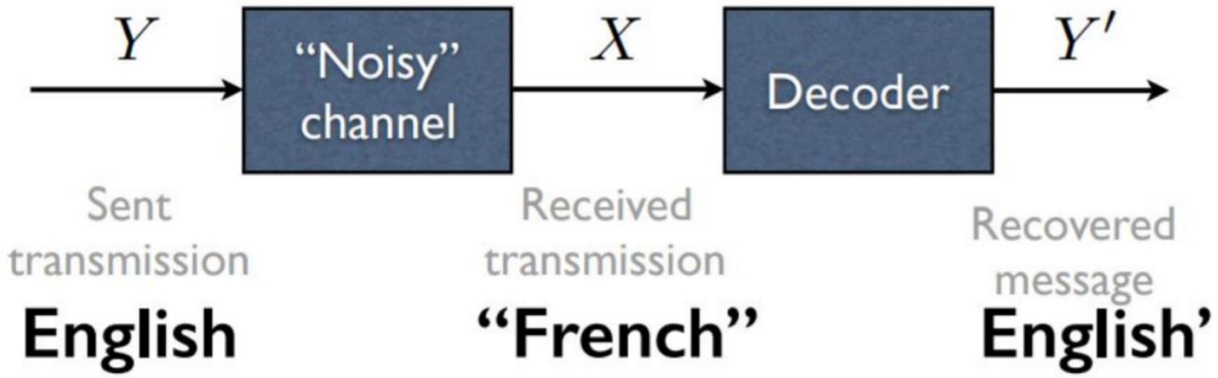


$$w^* = \arg\max_w P(w|a)$$
$$= \arg\max_w P(a|w)P(w) \; / P(a)$$
$$= \arg\max_w P(a|w)P(w)$$

Likelihood
Acoustic model (HMMs)
Translation model

Prior
Language model: Distributions over sequence of words

The Noisy-Channel Model



$$\hat{e} = \arg\max_{e} p_{\varphi}(e) \times p_{\theta}(f|e)$$

Language model

Translation model

MT as Direct Modeling

$$\hat{e} = \arg\max_{e} p_\lambda(e|f)$$

target

source

- One model does everything
- Trained to reproduce a corpus of translations

Two Views of MT

- Code breaking (aka the noisy channel, Bayes rule)
  - I know the target language
  - I have example translations texts (example enciphered data)
- Direct modeling (aka pattern matching)
  - I have really good learning algorithms and a bunch of example inputs (source language sentences) and outputs (target language translations)

Which is Better?

- **Noisy channel -** $p_{\varphi}(e) \times p_{\theta}(f|e)$
  - Easy to use monolingual target language data
  - Search happens under a product of two models (individual models can be simple, product can be powerful)
- **Direct Model -** $p_{\lambda}(e|f)$
  - Directly model the process you care about
  - Model must be very powerful

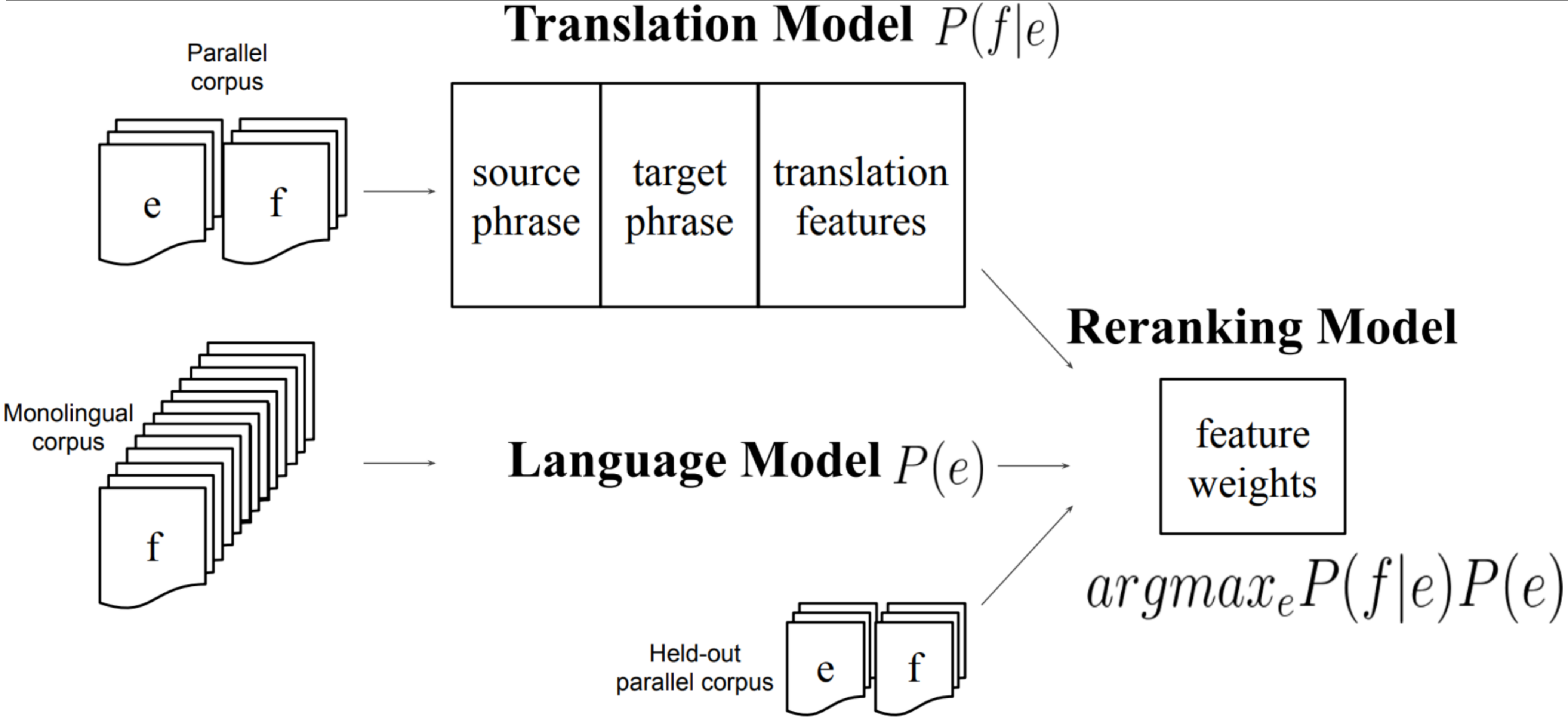
Where are we in 2024?

- Direct modeling is where most of the action is
  - Neural networks are very good at generalizing and conceptually very simple
  - Inference in “product of two models” is hard
- Noisy channel ideas are incredibly important and still play a big role in how we think about translation

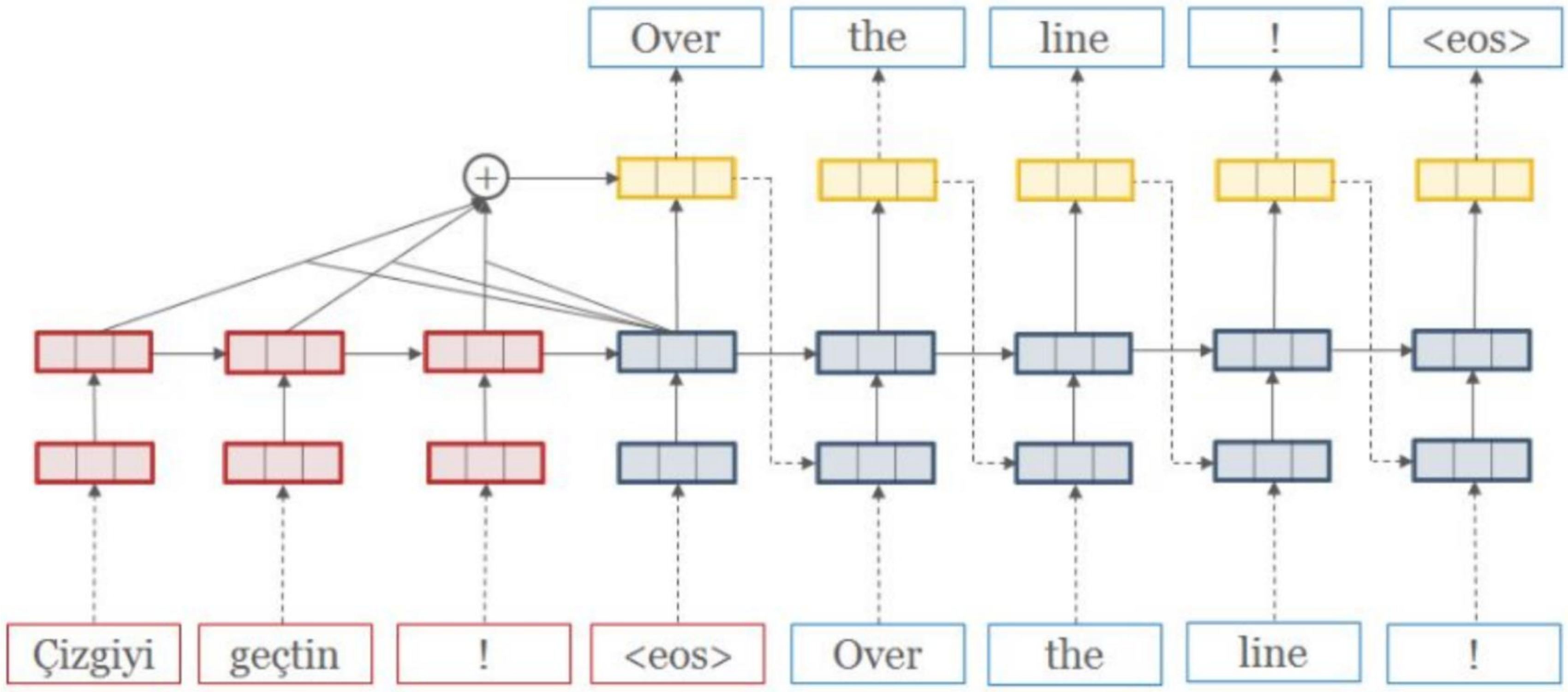
Two Views of MT

- Noisy channel $\hat{e} = \arg\max_{e} p_{\varphi}(e) \times p_{\theta}(f|e)$
- Direct $\hat{e} = \arg\max_{e} p_{\lambda}(e|f)$

Noisy Channel: Phrase-Based MT



Neural MT: Conditional Language Modeling



http://opennmt.net/

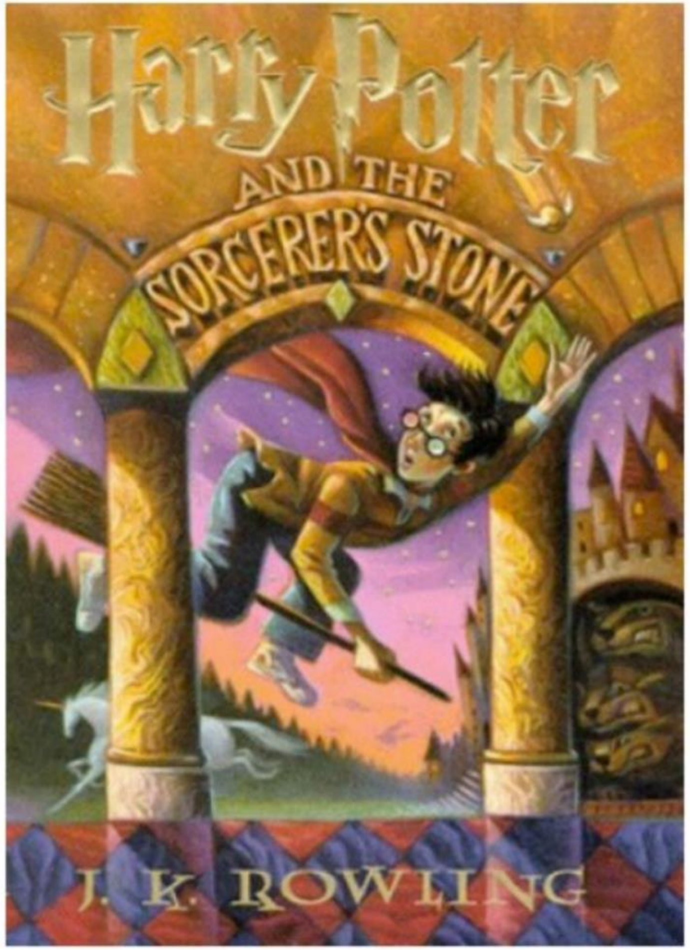
A Common Problem

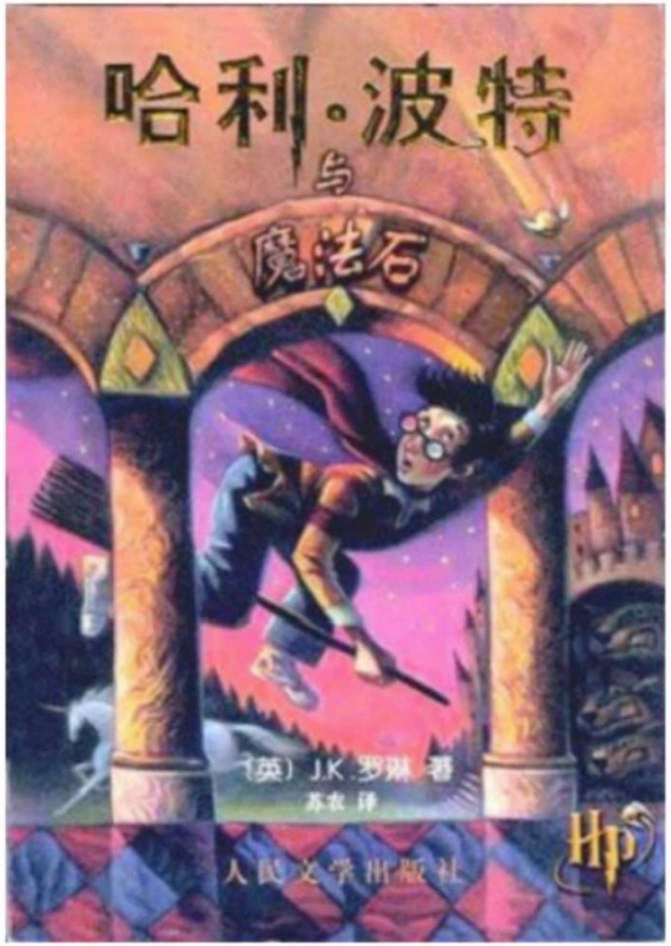
- Noisy channel $\hat{e} = \arg\max_{e} p_{\varphi}(e) \times \boldsymbol{p_{\theta}(f|e)}$
- Direct $\hat{e} = \arg\max_{e} \boldsymbol{p_{\lambda}(e|f)}$

- Both models must assign probabilities to how a sentence in one language translates into a sentence in another language

Learning From Data

Parallel Corpora





Parallel Corpora

CLASSIC SOUPS

			Sm.	Lg.
清燉雞湯	57.	House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)	1.50	2.75
雞飯湯	58.	Chicken Rice Soup	1.85	3.25
雞麵湯	59.	Chicken Noodle Soup	1.85	3.25
廣東雲吞	60.	Cantonese Wonton Soup	1.50	2.75
蕃茄蛋湯	61.	Tomato Clear Egg Drop Soup	1.65	2.95
雲吞湯	62.	Regular Wonton Soup	1.10	2.10
酸辣湯	63.	Hot & Sour Soup	1.10	2.10
蛋花湯	64.	Egg Drop Soup	1.10	2.10
雲蛋湯	65.	Egg Drop Wonton Mix	1.10	2.10
豆腐菜湯	66.	Tofu Vegetable Soup	NA	3.50
雞玉米湯	67.	Chicken Corn Cream Soup	NA	3.50
蟹肉玉米湯	68.	Crab Meat Corn Cream Soup	NA	3.50
海鮮湯	69.	Seafood Soup	NA	3.50

Parallel Corpora (mining parallel data from microblogs Ling et al., 2013)

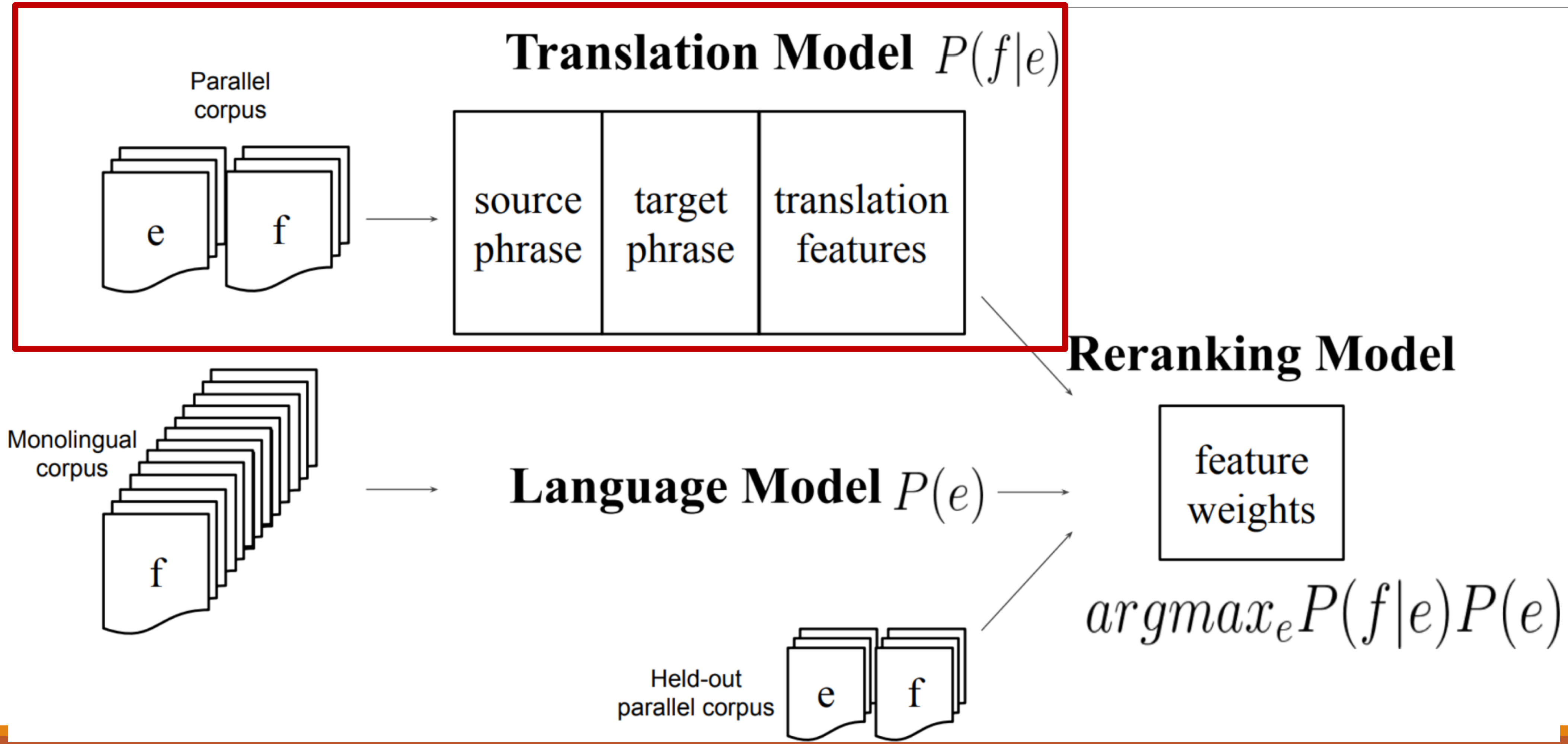
	ENGLISH	MANDARIN
1	i **wanna** live in a wes anderson world	我想要生活在Wes Anderson的世界里
2	Chicken soup, corn never truly digests. **TMI**.	鸡汤吧，玉米神马的从来没有真正消化过.恶心
3	To DanielVeuleman **yea iknw imma** work on that	对DanielVeuleman说，是的我知道，我正在向那方面努力
4	**msg 4** Warren G his **cday** is today 1 **yr** older.	发信息给Warren G，今天是他的生日，又老了一岁了。
5	Where **the hell** have you been all these years?	这些年你**TMD**到哪去了
	ENGLISH	ARABIC
6	It's **gonna** be a warm week!	الاسبو ع **الياي** حر
7	onni this gift only **4 u**	أوني هذة الهدية فقط لك
8	sunset in aqaba **:)**	غروب الشمس في العقبة:)
9	RT @MARYAMALKHAWAJA: there is a call for widespread protests in #bahrain **tmrw**	هناك نداء لظاهرات في عدة مناطق غدا

Table 2: Examples of English-Mandarin and English-Arabic sentence pairs. The English-Mandarin sentences were extracted from Sina Weibo and the English-Arabic sentences were extracted from Twitter. Some messages have been shorted to fit into the table. Some interesting aspects of these sentence pairs are marked in bold.

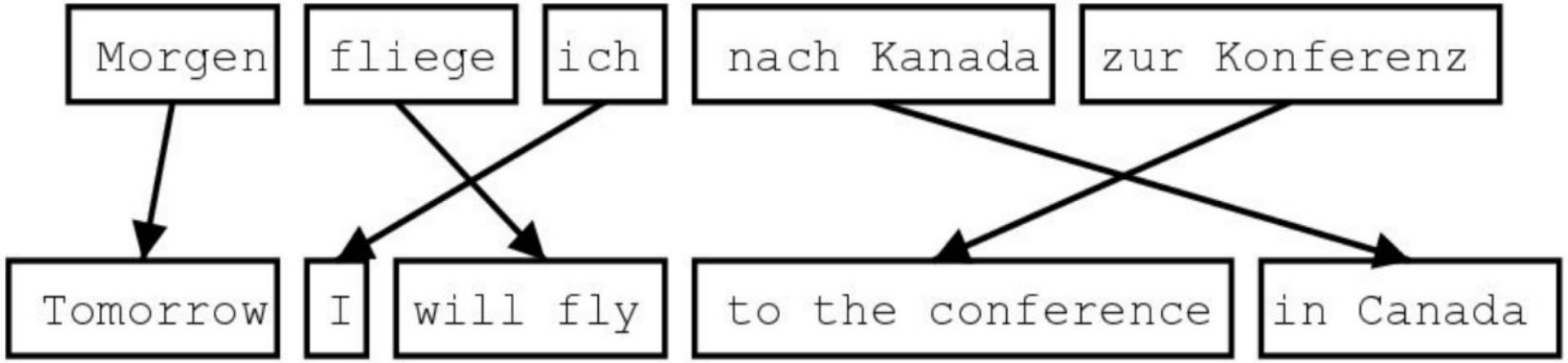
Discussions

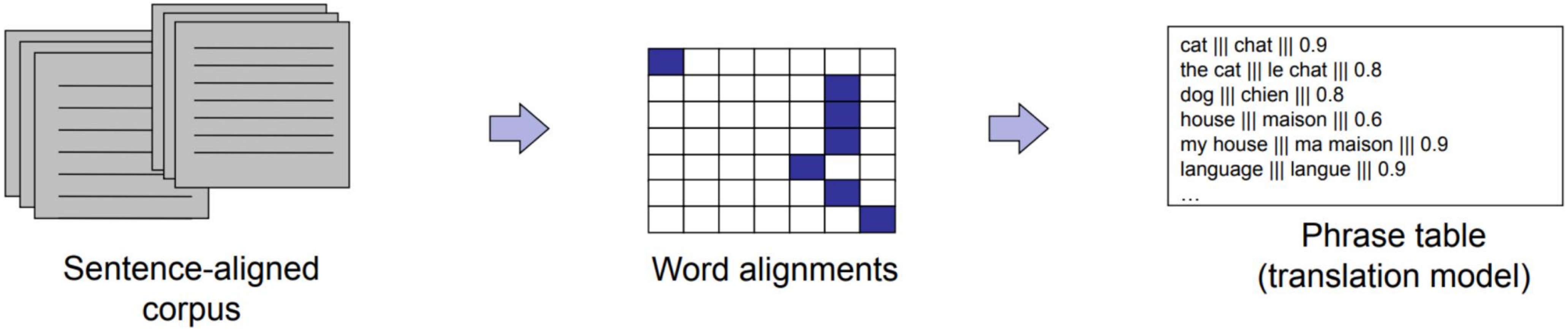
- There is a lot more monolingual data in the world than translated data
- Easy to get about 1 trillion words of English by crawling the web
- With some work, you can get 1 billion translated words of English-French
  - What about Japanese-Turkish?

Phrase-Based MT



Construction of t-table





Word Alignment Models

Lexical Translation

- How do we translate a word? Look it up in the dictionary

  Haus – house, building, home, household, shell

- Multiple translations
  - Some more frequent than others
  - Different word senses, different registers, different functions
  - *House, home* are common
- *Shell* is specialized (the Haus of a snail is a shell)

How Common is Each?

- Look at a parallel corpus (German text along with English translation)

Translation of Haus	Count
house	8000
building	1600
home	200
household	150
shell	50

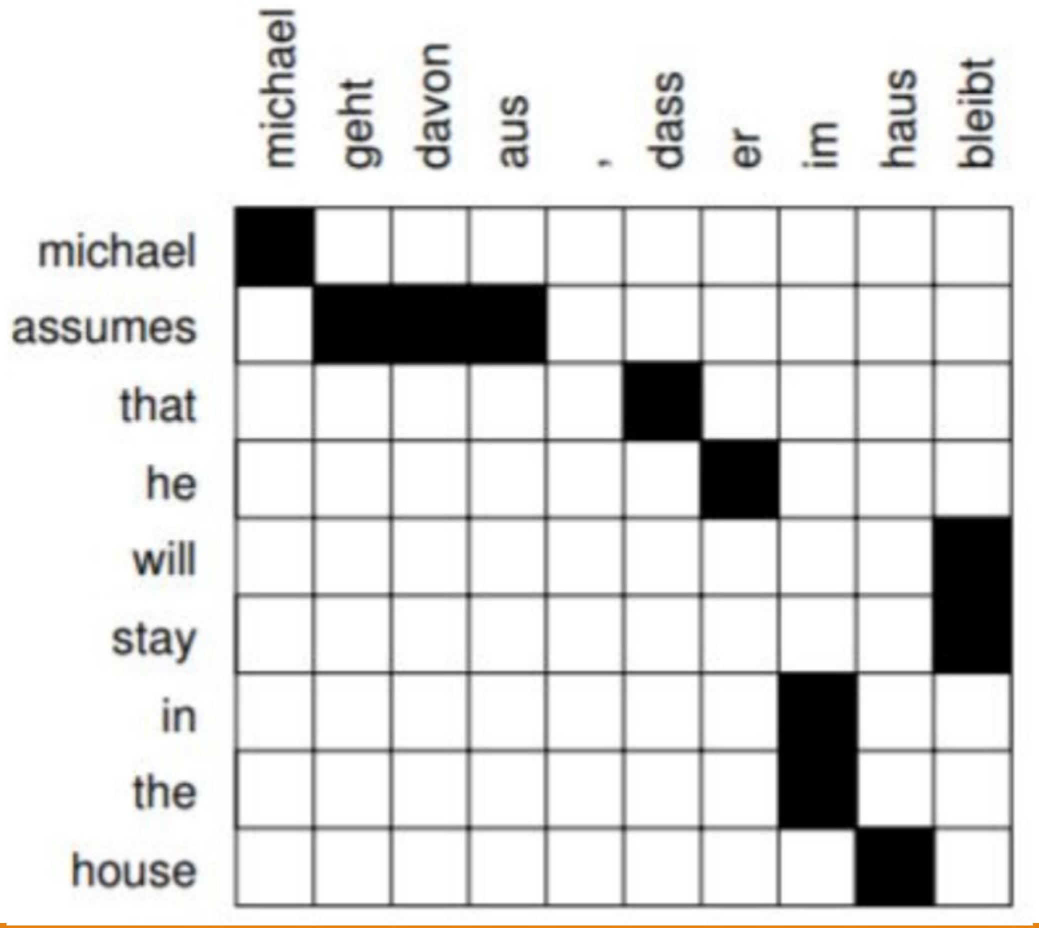
Estimate Translation Probabilities

- Maximum likelihood estimation

$$\hat{p}_{\mathrm{MLE}}(e \mid \texttt{Haus}) = \begin{cases} 0.8 & \text{if } e = \text{house}, \\ 0.16 & \text{if } e = \text{building}, \\ 0.02 & \text{if } e = \text{home}, \\ 0.015 & \text{if } e = \text{household}, \\ 0.005 & \text{if } e = \text{shell}. \end{cases}$$

Word Alignment:

- Given a sentence pair, which words correspond to each other?

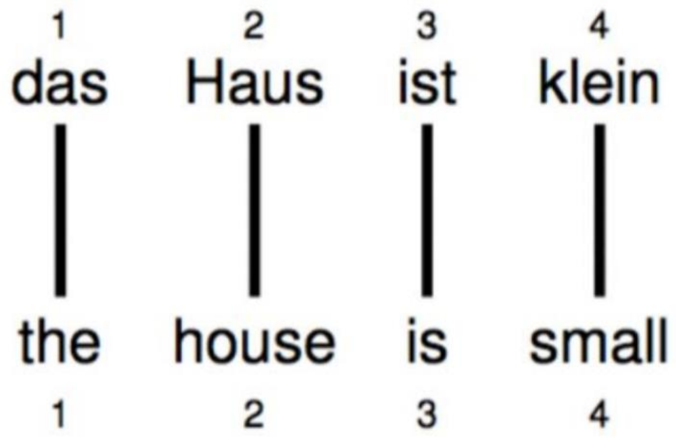


Word Alignment

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

$$\mathbf{f} = \langle f_1, f_2, \ldots, f_n \rangle$$

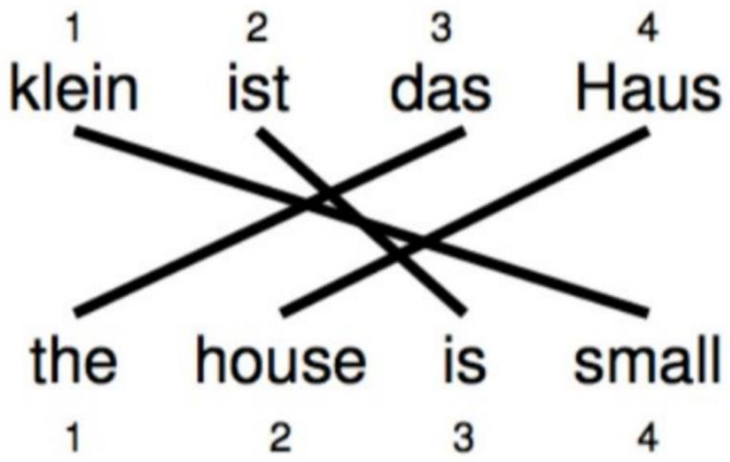
$$\mathbf{e} = \langle e_1, e_2, \ldots, e_m \rangle$$



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

Reordering

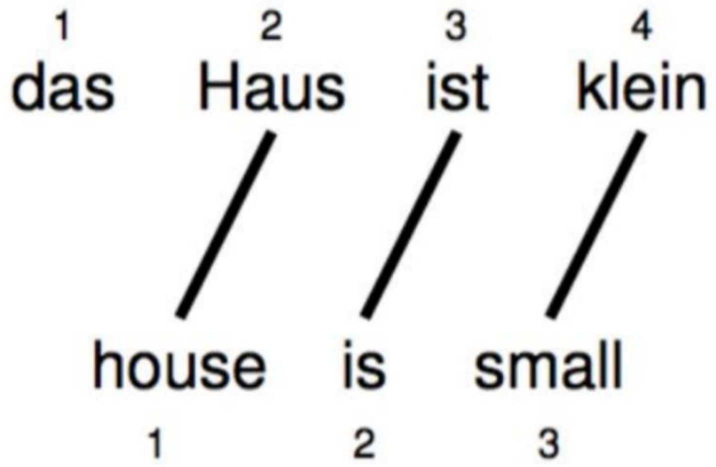
- Words may be reordered during translation



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

Word Dropping

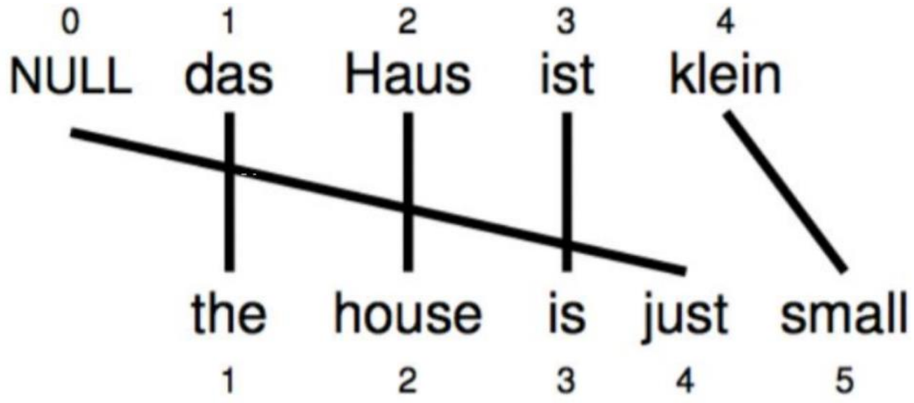
- A source word may not be translated at all



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

Word Insertion

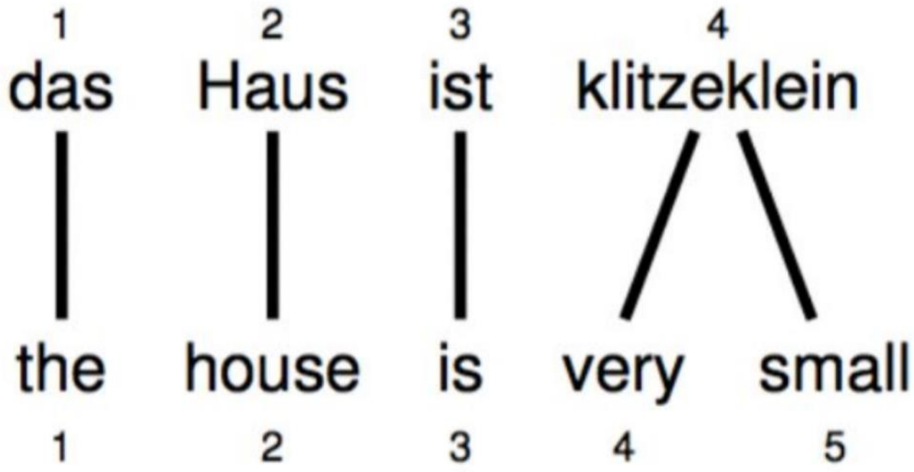
- Words may be inserted during translation
  - English just does not have an equivalent
  - But it must be explained – we typically assume every source sentence contains a NULL token



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

One-to-many Translation

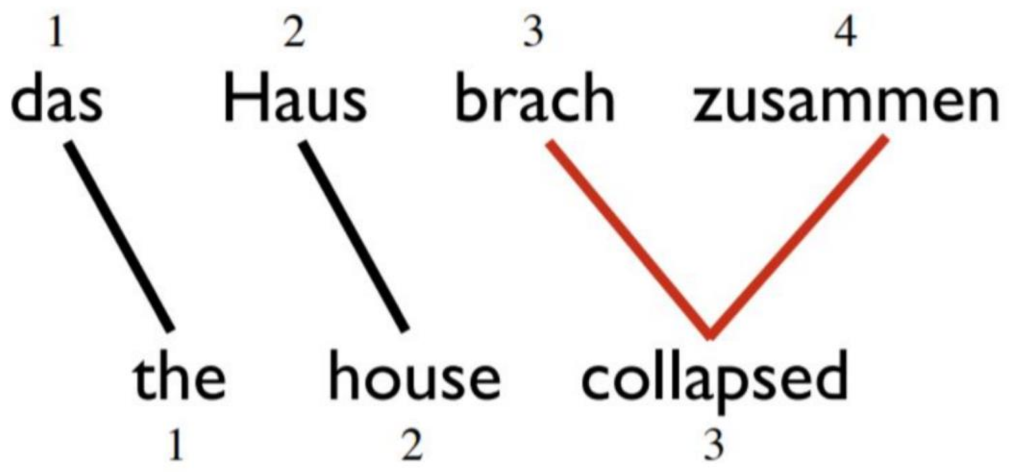
- A source word may translate into more than one target word



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

Many-to-one Translation

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



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

Computing Word Alignments

- Word alignments are the basis for most translation algorithms
- Given two sentences F and E, find a good alignment
- But a word-alignment algorithm can also be part of a mini-translation model itself
- One the most basic alignment models is also a simplistic translation model

IBM Model 1

- Generative model: break up translation process into smaller steps
- Simplest possible lexical translation model
- Additional assumptions
  - All alignment decisions are independent
  - The alignment distribution for each a_i is uniform over all source words and NULL

Lexical Translation

- Goal: a model $p(\boldsymbol{e}|\boldsymbol{f}, m)$
  - Where $\boldsymbol{e}$ and $\boldsymbol{f}$ are complete English and Foreign sentences
  - $\boldsymbol{e} = < e_1, e_2, \ldots, e_m >$
  - $\boldsymbol{f} = < f_1, f_2, \ldots, f_n >$

Lexical Translation

- Goal: a model $p(\boldsymbol{e}|\boldsymbol{f}, m)$
  - Where ***e*** and ***f*** are complete English and Foreign sentences
- Lexical translation makes the following assumptions
  - Each word e_i in ***e*** is generated from exactly one word in ***f***
  - Thus, we have an alignment a_i that indicates which word e_i "came from", specifically it came from f_{a_i}
  - Given the alignments ***a***, translation decisions are conditionally independent of each other and depend only on the aligned source word f_{a_i}

Lexical Translation

- Putting our assumptions together, we have:

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

Alignment × Translation | Alignment

IBM Model 1: P(E|F)

- Translation probability
  - For a foreign sentence $\boldsymbol{f} = (f_1, \ldots, f_{l_f})$ of length l_f
  - To an English sentence $\boldsymbol{e} = (e_1, \ldots, e_{l_e})$ of length l_e
  - With an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \rightarrow I$

$$p(e, a | f) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

  - Parameter ϵ is a normalization constant

Computing P(E|F) in IBM Model 1

$p(a|f)$

$$p(e, a|f) = \boxed{\frac{\epsilon}{(l_f + 1)^{l_e}}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

- A normalization factor, since there are $(l_f + 1)^{l_e}$ possible alignments
- Parameter ϵ is a normalization constant
- The probability of an alignment given the foreign sentence

Computing P(E|F) in IBM Model 1

$$p(e, a|f) = \underbrace{\frac{\epsilon}{(l_f + 1)^{l_e}}}_{p(a|f)} \underbrace{\prod_{j=1}^{l_e} t(e_j | f_{a(j)})}_{p(e|f,a)}$$

$$p(\boldsymbol{e}|\boldsymbol{f}) = \sum_{\boldsymbol{a}} p(\boldsymbol{e}, \boldsymbol{a}|\boldsymbol{f}) = \sum_{\boldsymbol{a}} p(\boldsymbol{a}|\boldsymbol{f}) \times \prod_{j=1}^{l_e} p(e_j | f_{a_j})$$

Example

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

$$
\begin{aligned}
p(e,a|f) &= \frac{\epsilon}{4^3} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\
&= \frac{\epsilon}{4^3} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\
&= 0.0028\epsilon
\end{aligned}
$$

Estimate Translation Probabilities

- Maximum likelihood estimation

$$\hat{p}_{\text{MLE}}(e \mid \texttt{Haus}) = \begin{cases} 0.8 & \text{if } e = \text{house}, \\ 0.16 & \text{if } e = \text{building}, \\ 0.02 & \text{if } e = \text{home}, \\ 0.015 & \text{if } e = \text{household}, \\ 0.005 & \text{if } e = \text{shell}. \end{cases}$$

Estimate Alignments Given t-table

- If we have translation probabilities

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
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klein

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

- The goal is to find the most probable alignment given a parameterized model

Estimating the Alignment

$$p(e, a | f) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

$$\boldsymbol{a}^* = \arg\max_{\boldsymbol{a}} p(\boldsymbol{e}, \boldsymbol{a} | \boldsymbol{f})$$

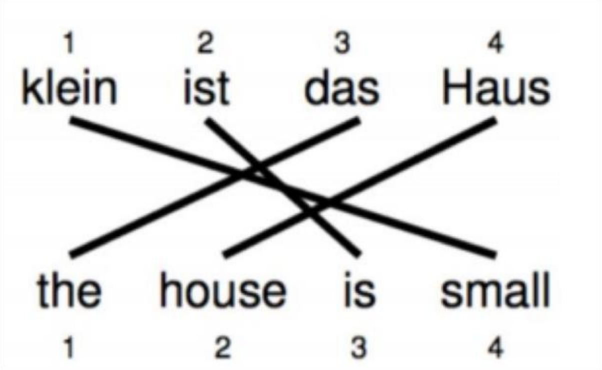
$$= \arg\max_{\boldsymbol{a}} \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

$$= \arg\max_{\boldsymbol{a}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

Since translation choice for each position is independent, the product is maximized by maximizing each term:

$$a_i^* = \arg\max_{a_i=0}^{n} t(e_i | f_{a_i})$$

Learning Lexical Translation Mode



- We'd like to estimate the lexical translation probabilities $t(e \mid f)$ from a parallel corpus but we do not have the alignments
- **Chick and egg problem**
  - If we had the alignments, we could estimate the parameters of our generative model (MLE)
  - If we had the parameters, we could estimate the alignments

klein

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

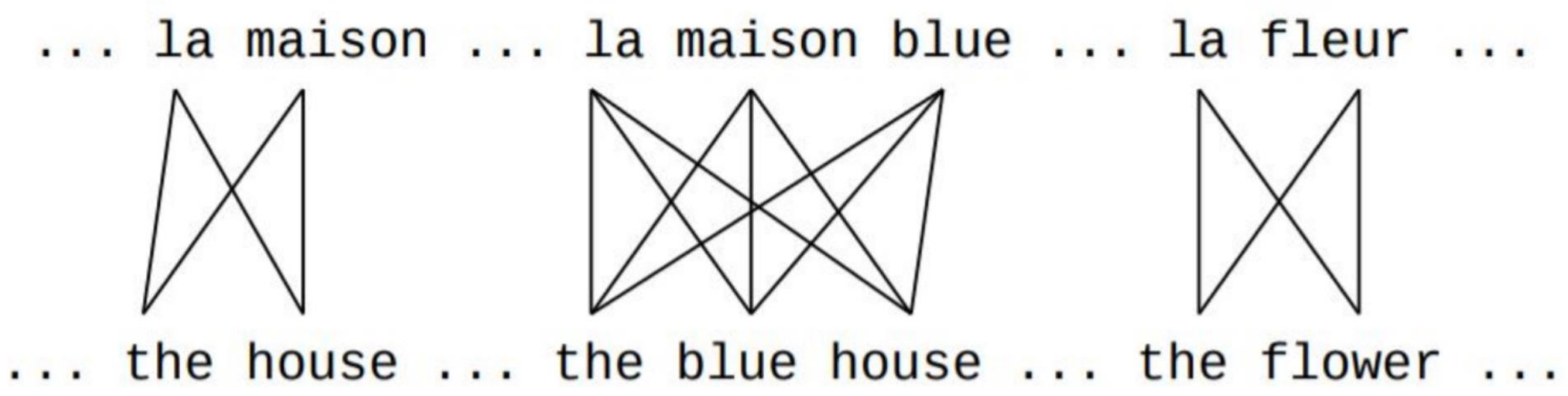
EM Algorithm

- Incomplete data
  - If we had complete data, we could estimate the model
  - If we had the model, we could fill in the gaps in the data

- **Expectation Maximization (EM)** in a nutshell
  1. Initialize model parameters (e.g., uniform, random)
  2. Assign probabilities to the missing data
  3. Estimate model parameters from completed data
  4. Iterate steps 2-3 until convergence

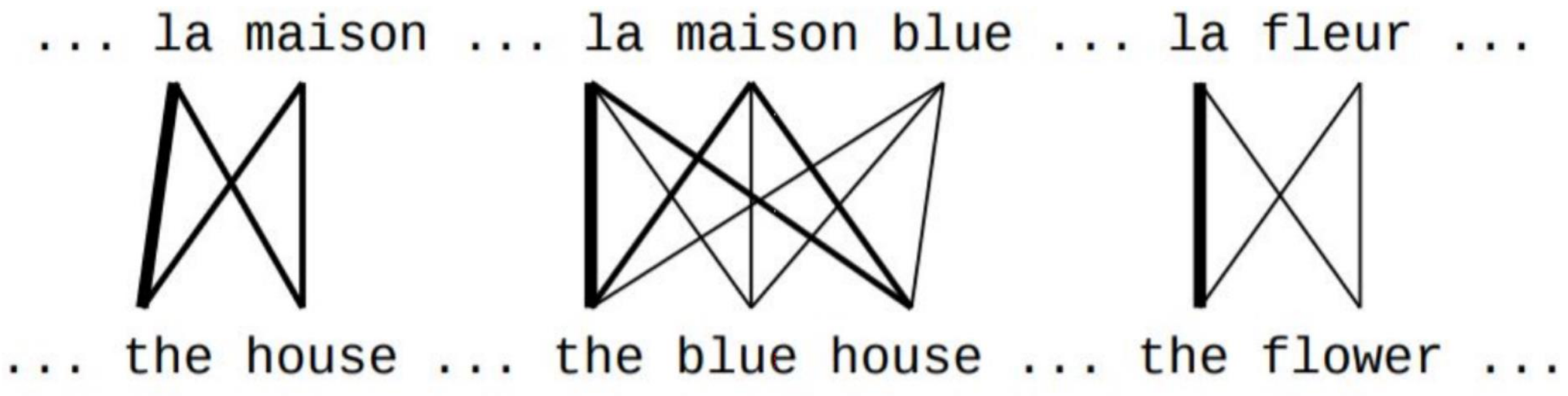
EM Algorithm

Kevin Knight's example



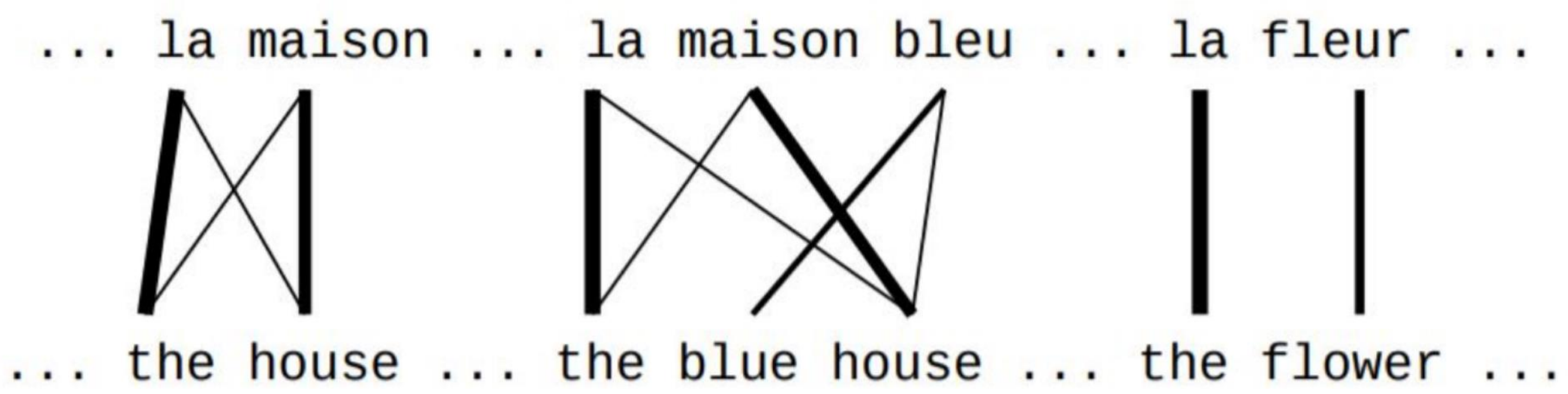
- Initial step: all word alignments equally likely
- Model learns that: e.g., *la* is often aligned with *the*

EM Algorithm



- After one iteration
- Alignments, e.g., between *la* and *the* are more likely

EM Algorithm



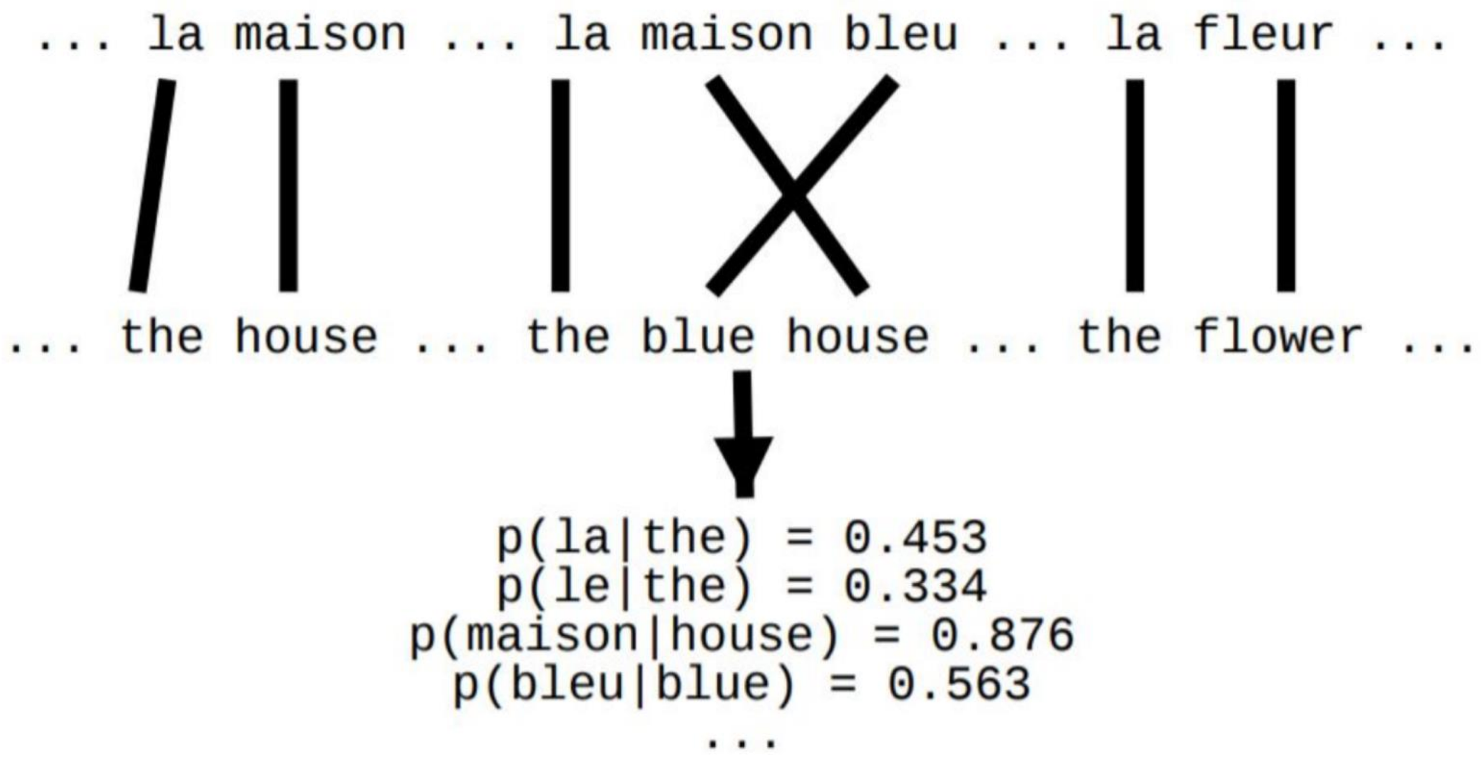
- After another iteration

It becomes apparent that alignments, e.g., between *fleur* and *flower* are more likely

EM Algorithm

- Convergence
- Inherent hidden structure revealed by EM !

EM Algorithm



- **Parameter estimation from the aligned corpus**

Evaluation Metrics

- Manual evaluation is 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

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

BLEU

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

- Two modifications:
  - 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
- Precision-based metrics favor short translations
  - Solution: Multiply score with a brevity penalty (BP) for translations shorter than reference, $e^{1-r/h}$

BLEU Scores

	Translation	p_1	p_2	p_3	p_4	BP	BLEU
Reference	*Vinay likes programming in Python*						
Sys1	*To Vinay it like to program Python*	$\frac{2}{7}$	0	0	0	1	.21
Sys2	*Vinay likes Python*	$\frac{3}{3}$	$\frac{1}{2}$	0	0	.51	.33
Sys3	*Vinay likes programming in his pajamas*	$\frac{4}{6}$	$\frac{3}{5}$	$\frac{2}{4}$	$\frac{1}{3}$	1	.76

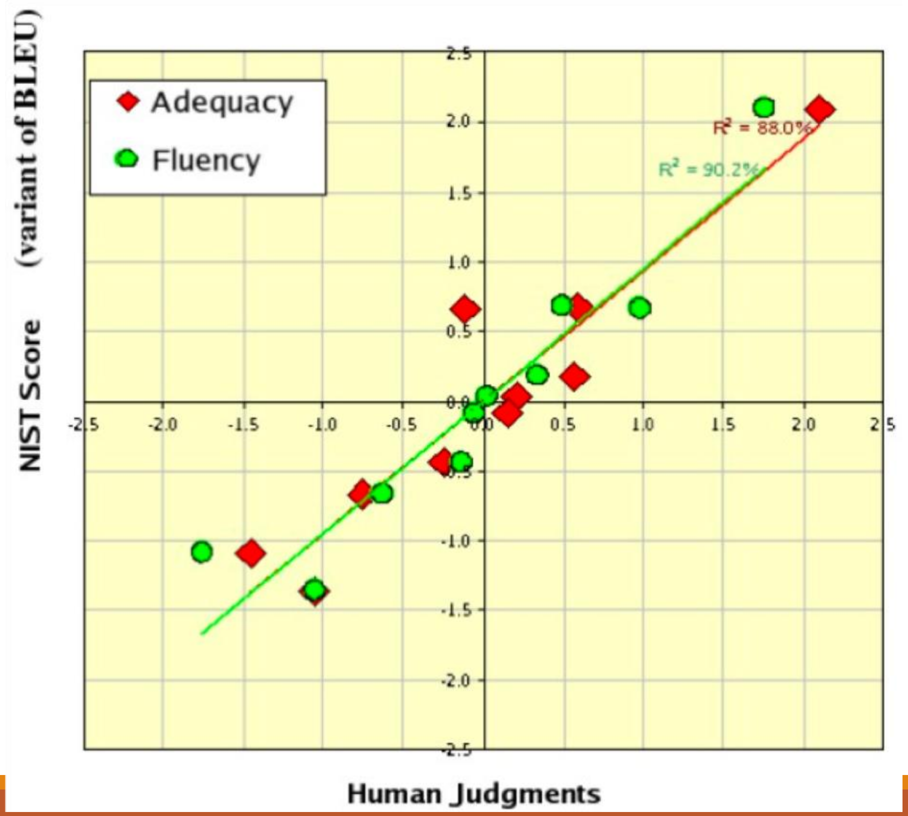
Sample BLEU scores for various system outputs

Other Issues?

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

BLEU

- Correlates somewhat well with human judgments



(G. Doddington, NIST)

Problems with Lexical Translation

- Complexity – exponential in sentence length
- Weak reordering – the output is not fluent
- Many local decisions – error propagation