

Machine Translation

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Learning Objectives

Compare the Noisy Channel Model to Direct Modeling

Consider what to do about uneven parallel corpora

Discover issues with word alignment

Text

Documents

DETECT LANGUAGE

ENGLISH

SPANISH

FRENCH



ENGLISH

SPANISH

ARABIC



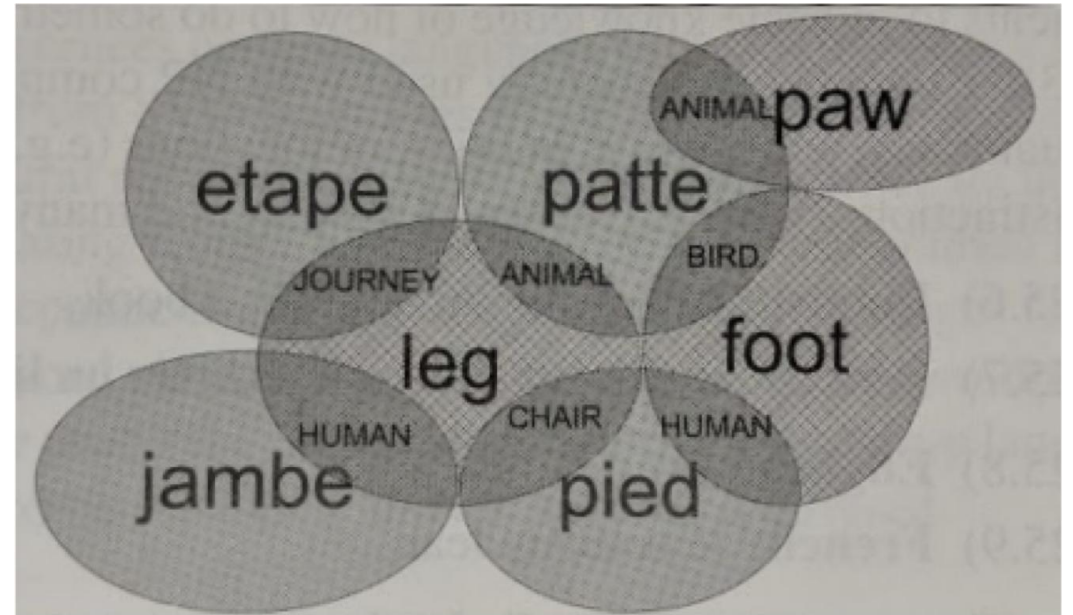
← Search languages

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



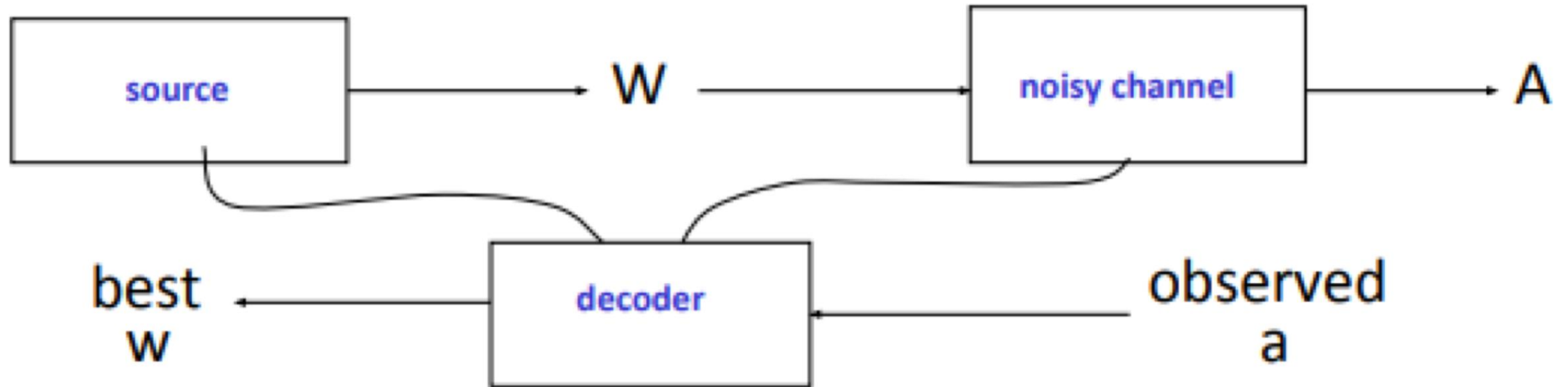
Warren Weaver to Norbert Wiener, March, 1947

The Noisy-Channel Model

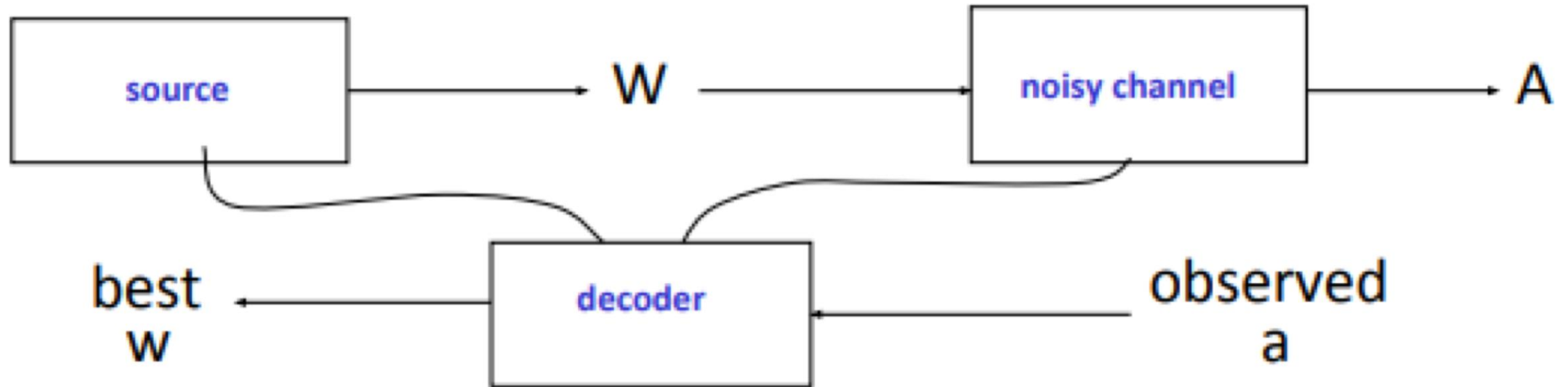


Claude Shannon. "A Mathematical Theory of Communication" 1948.

The Noisy-Channel Model

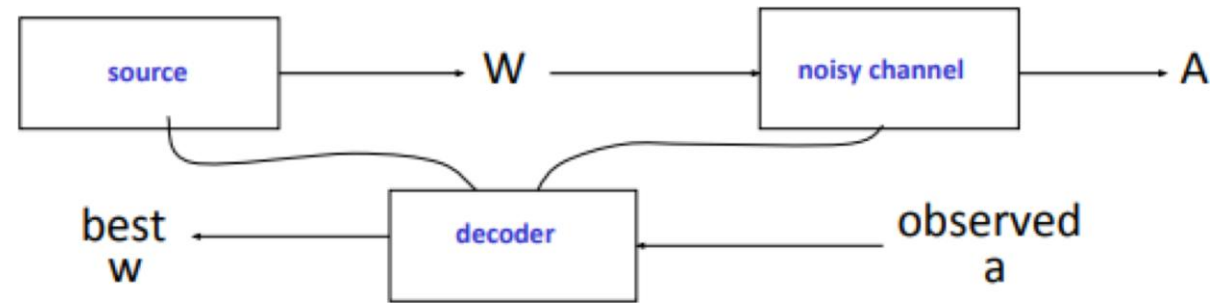


The Noisy-Channel Model



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

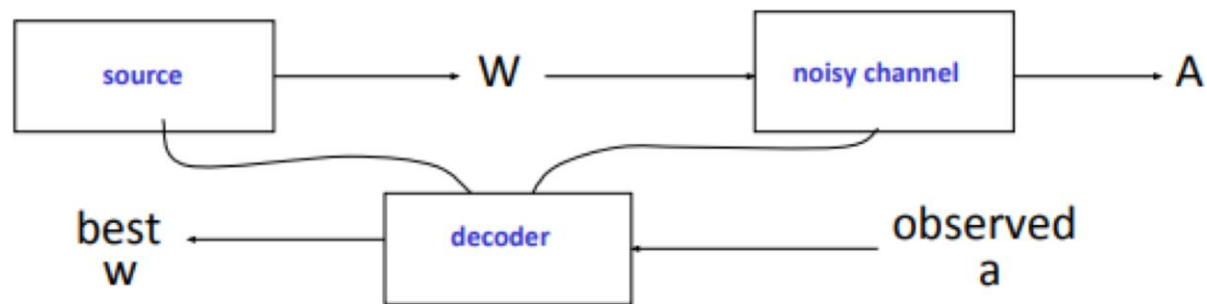
The Noisy-Channel Model



$$\begin{aligned}w^* &= \arg \max_w P(w|a) \\ &= \arg \max_w P(a|w)P(w) / P(a) \\ &= \arg \max_w P(a|w)P(w)\end{aligned}$$

Channel model Source model

The Noisy-Channel Model



$$\begin{aligned} w^* &= \arg \max_w P(w|a) \\ &= \arg \max_w P(a|w)P(w) / P(a) \\ &= \arg \max_w P(a|w)P(w) \end{aligned}$$

Likelihood

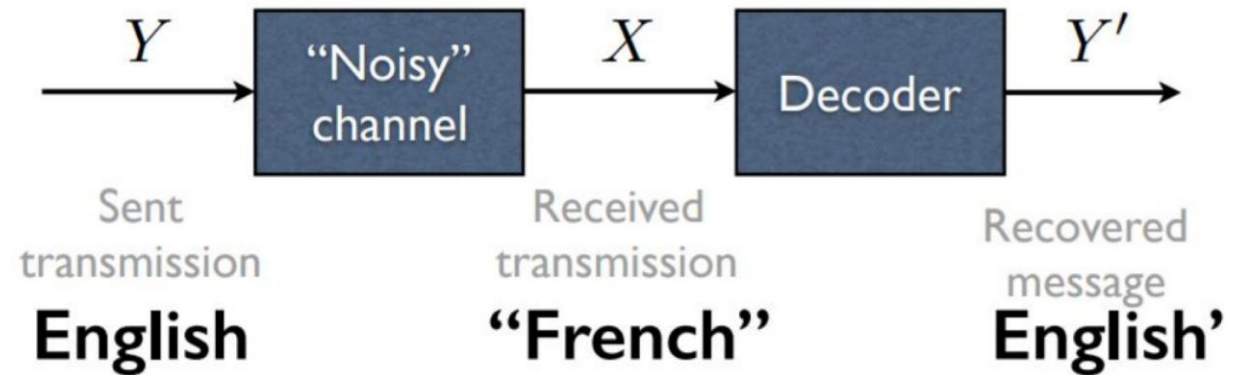
Acoustic model (HMMs)

Translation model

Prior

Language model: Distributions over sequence of words

The Noisy-Channel Model



$$\hat{e} = \arg \max_e p_\phi(e) \times p_\theta(f|e)$$

Language model

Translation model

MT as Direct Modeling

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

The diagram illustrates the direct modeling equation $\hat{e} = \arg \max_e p_\lambda(e|f)$. Two arrows point towards the equation: one from the word "target" (in blue) pointing to the variable e in the maximization, and another from the word "source" (in red) pointing to the variable f in the conditional probability.

- 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?

- Code breaking/Noisy Channel (aka the noisy channel, Bayes rule)

Good if you're translating to multiple languages because you'd only need one LM (and multiple translation models)

- Direct modeling (aka pattern matching)

If language matches the data that you have (by having good data and/or lots of it) or if your model is good at generalizing

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 now?

- **Direct modeling is where most of the action is**

- Neural networks (e.g., transformers) are very good at generalizing and conceptually very simple
- Inference in “product of two models” is hard

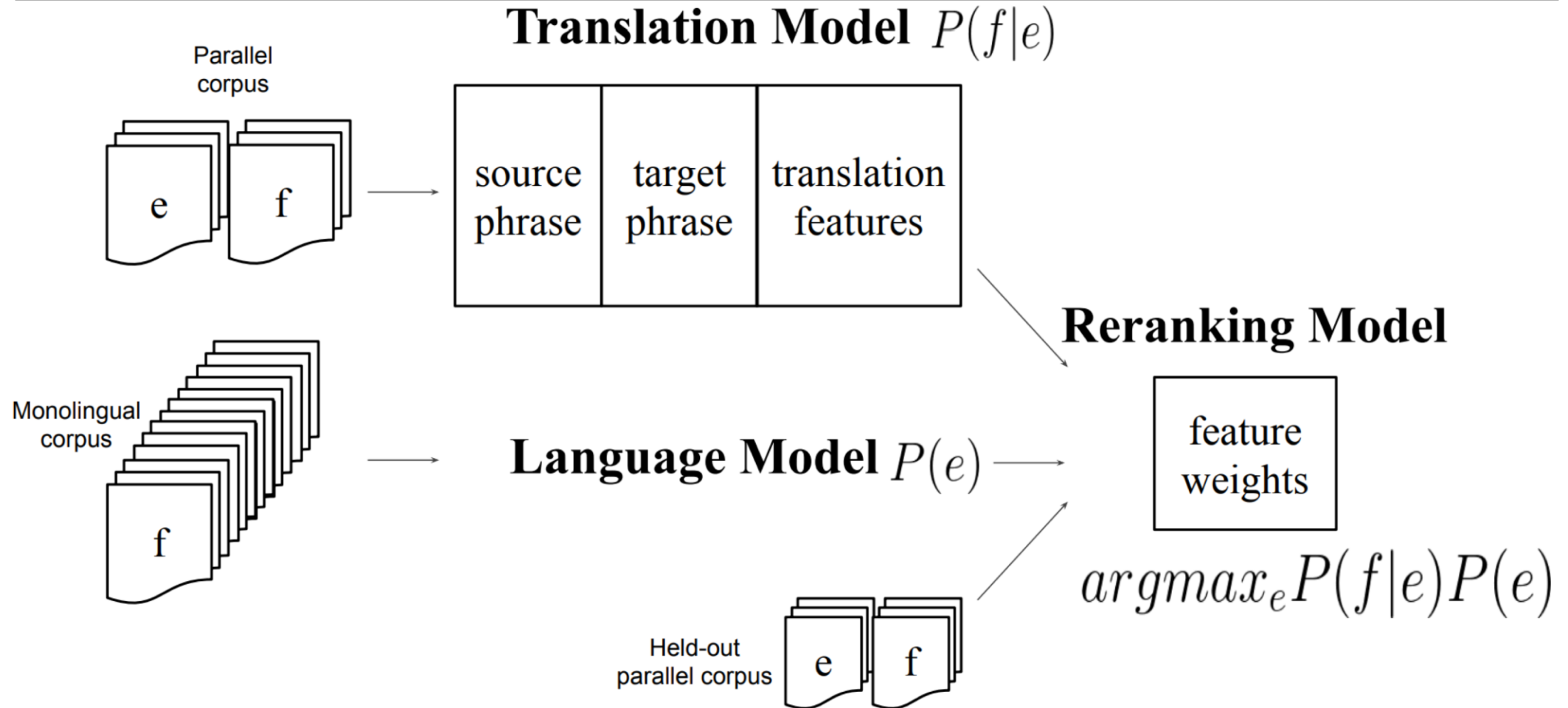
- Noisy channel ideas are incredibly important and still play a big role in how we think about translation

Two Views of MT

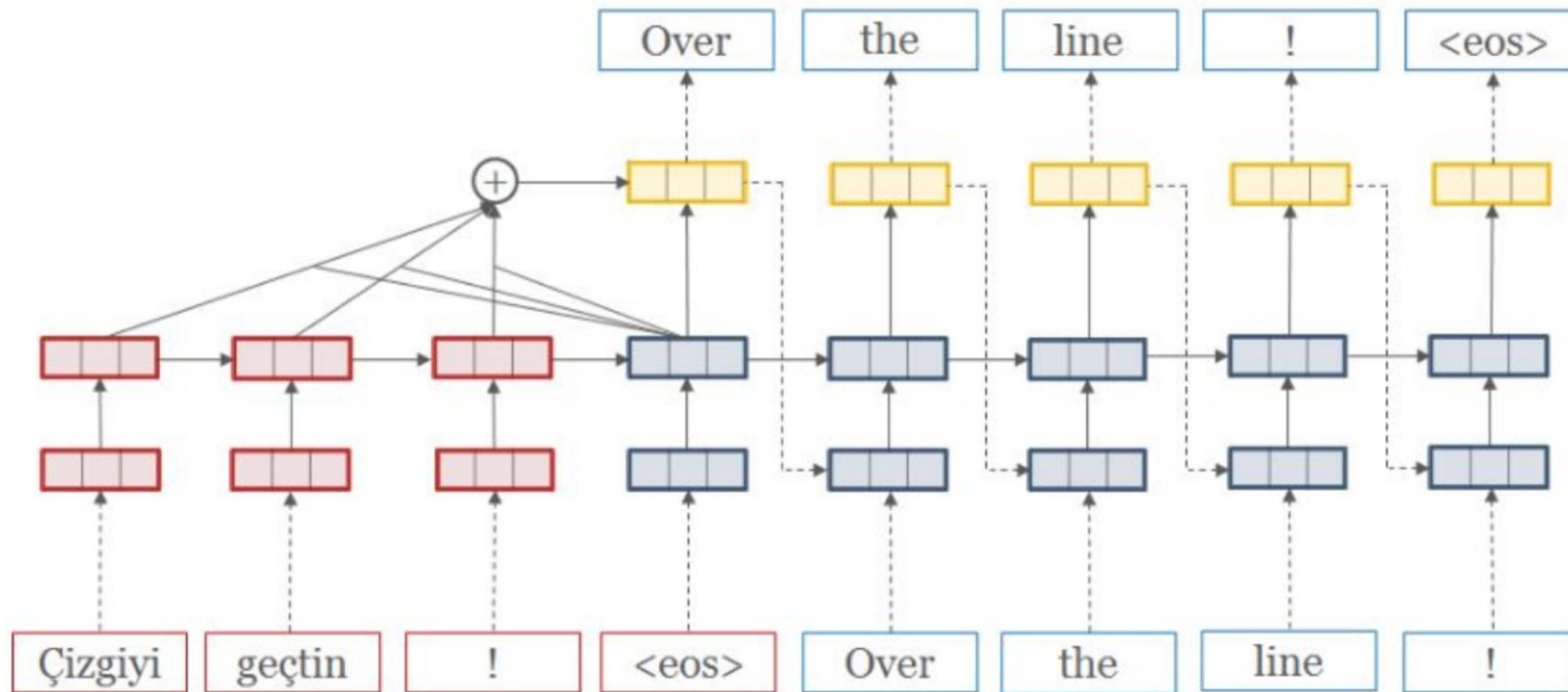
Noisy channel $\hat{e} = \arg \max_e p_\phi(e) \times p_\theta(f|e)$

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

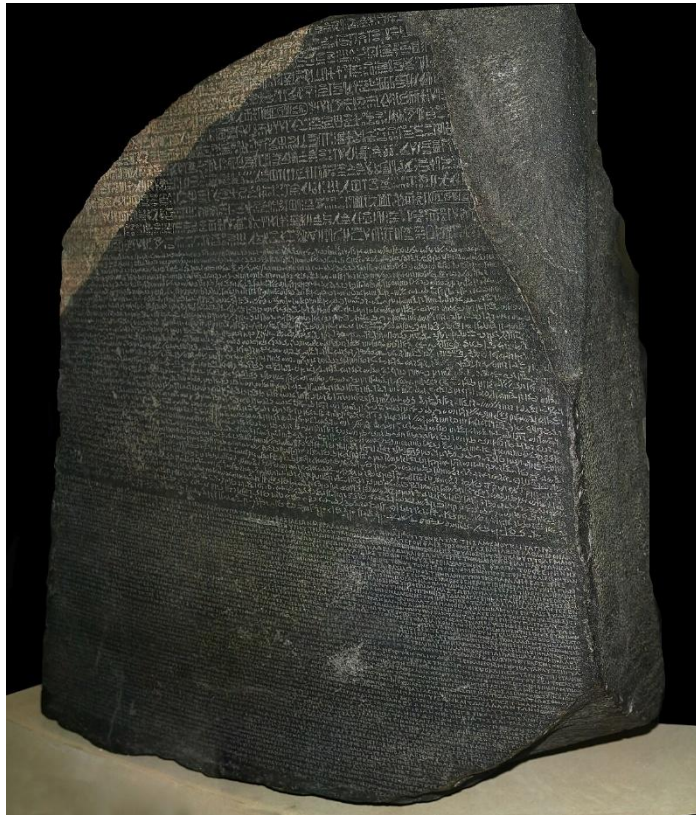
Noisy channel $\hat{e} = \arg \max_e p_\varphi(e) \times p_\theta(f|e)$

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

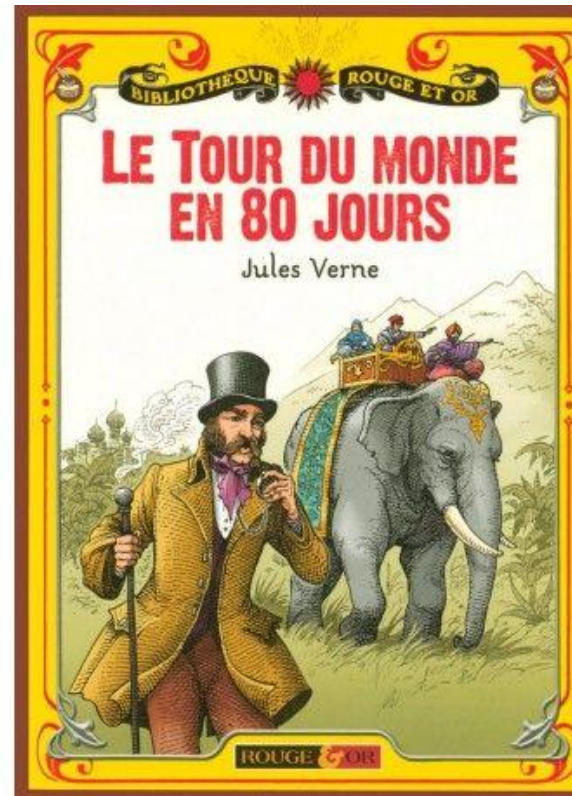
Both models must assign probabilities to how a sentence in one language translates into a sentence in another language

Learning From Data

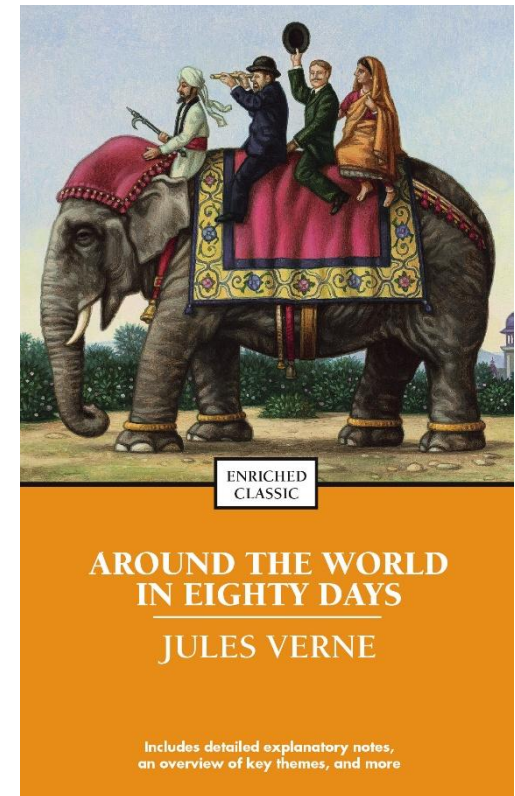
Parallel Corpora



https://en.wikipedia.org/wiki/Rosetta_Stone



<https://www.maarifculture.com>



<https://www.simonandschuster.co.in/books/Around-the-World-in-Eighty-Days/Jules-Verne/Enriched-Classics/9781416534723>

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. 油 | Hot & Sour Soup | 1.10 2.10 |
| 蛋 | 花 | 湯 | 64. | Egg Drop Soup..... | 1.10 2.10 |
| 雲 | 吞 | 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. TML . | 鸡汤吧, 玉米神马的从来没有真正消化过. 恶心 |
| 3 | To Daniel Veuleman yea iknw imma work on that | 对Daniel Veuleman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! | الاسبوع 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 لمظاهرات في عدة مناطق غدا |

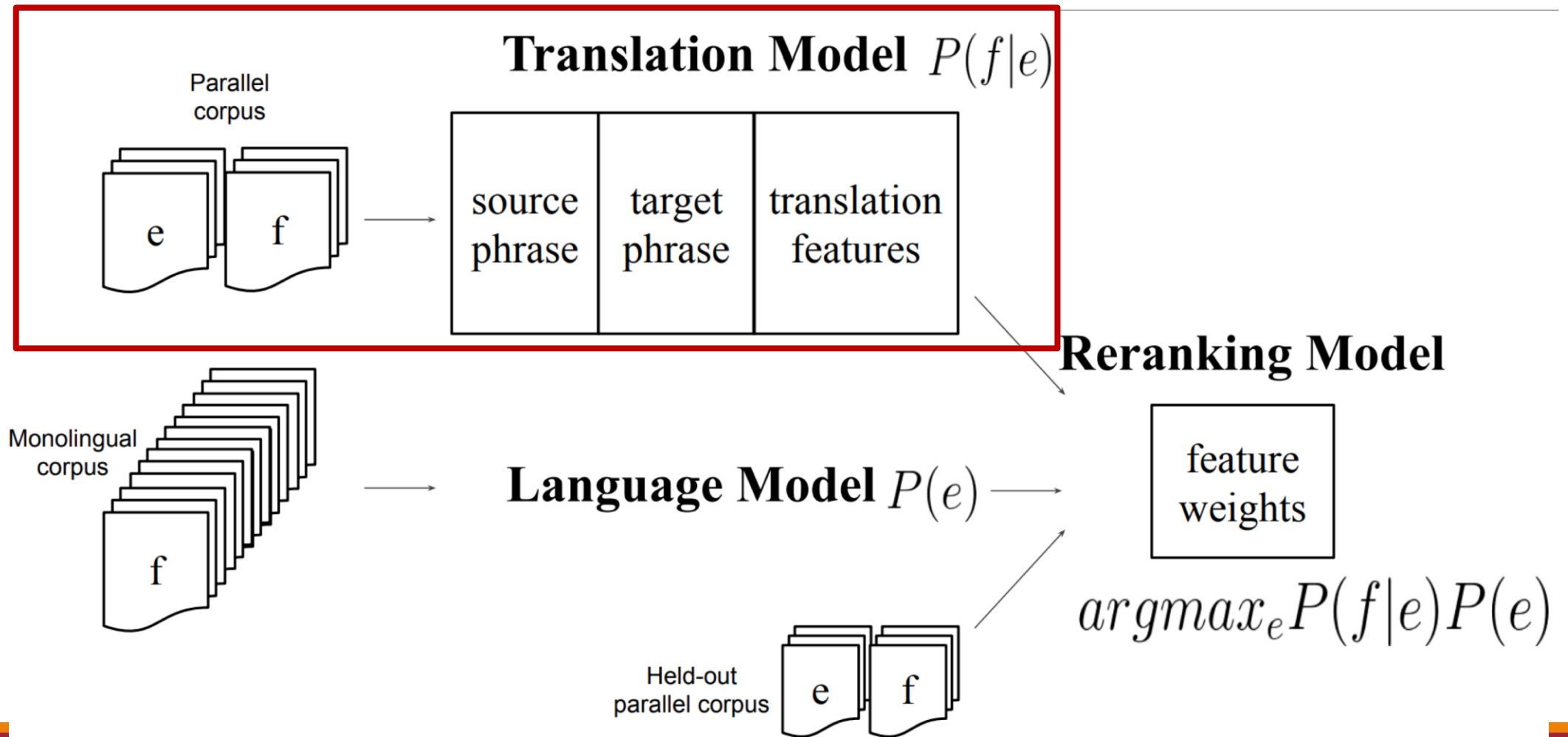
Table 2: Examples of English-Mandarin and English-Arabic sentence pairs. The English-Mandarin sentences were extracted from Sina Weibo and the English-Arabic sentences were extracted from Twitter. Some messages have been shorted to fit into the table. Some interesting aspects of these sentence pairs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

Discussion

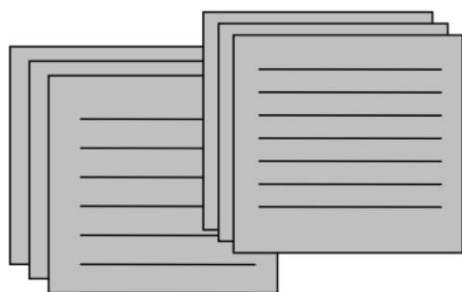
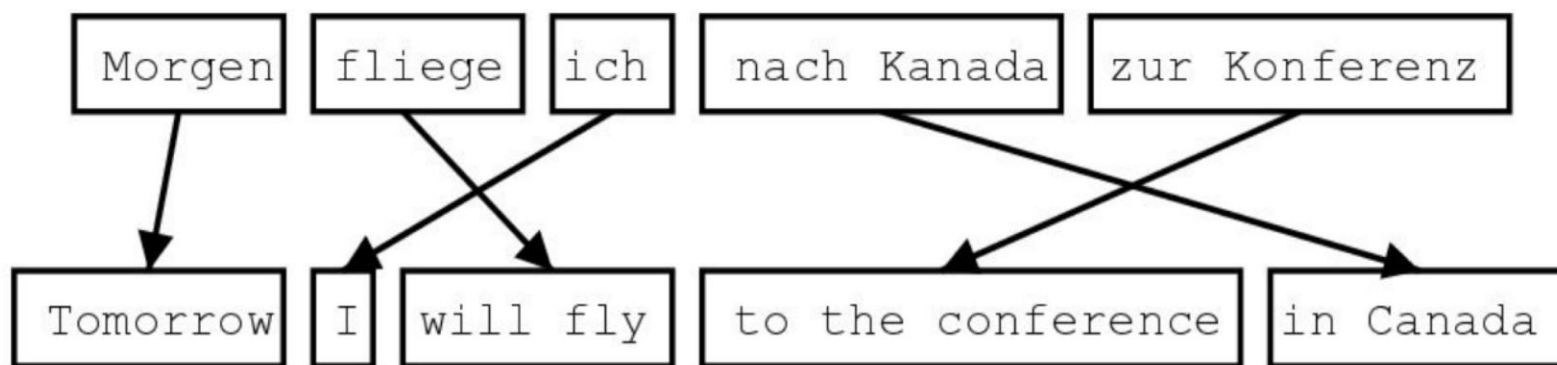
- There is a lot more monolingual data in the world than translated data
- Easy to get about 1 trillion words of English by crawling the web
- With some work, you can get 1 billion translated words of English-French
 - What about Japanese-Turkish?

How can you get around uneven amounts of data?

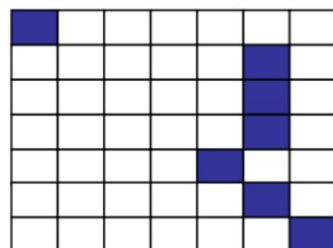
Phrase-Based MT



Construction of t-table



Sentence-aligned corpus



Word alignments



| | | | | |
|----------|--|-----------|--|-----|
| cat | | chat | | 0.9 |
| the cat | | le chat | | 0.8 |
| dog | | chien | | 0.8 |
| house | | maison | | 0.6 |
| my house | | ma maison | | 0.9 |
| language | | langue | | 0.9 |
| ... | | | | |

Phrase table
(translation model)

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

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

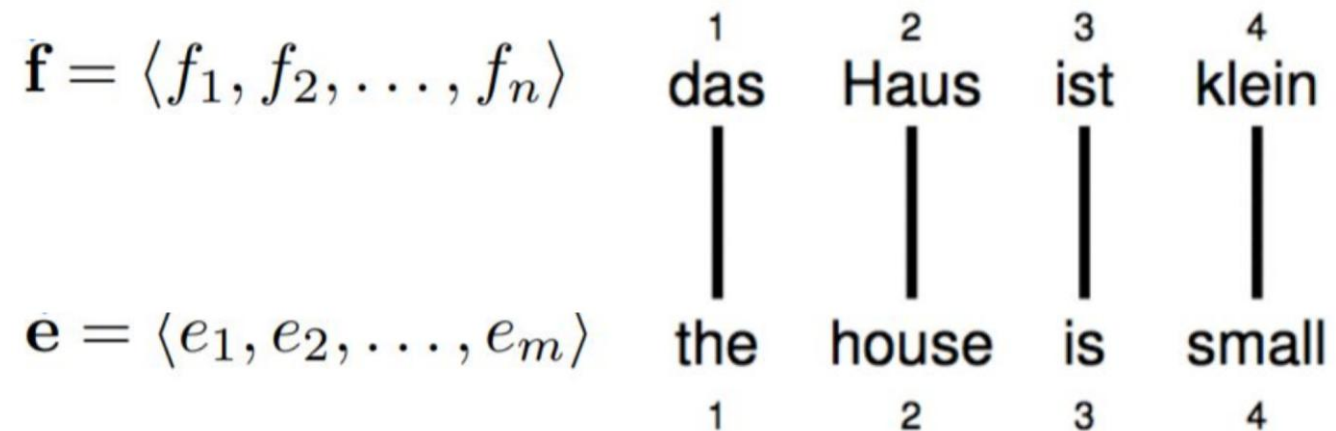
Word Alignment:

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

| | michael | geht | davon | aus | , | dass | er | im | haus | bleibt |
|---------|---------|------|-------|-----|---|------|----|----|------|--------|
| michael | ■ | | | | | | | | | |
| assumes | | ■ | ■ | ■ | | | | | | |
| that | | | | | | ■ | | | | |
| he | | | | | | | ■ | | | |
| will | | | | | | | | | | ■ |
| stay | | | | | | | | | | ■ |
| in | | | | | | | | ■ | | |
| the | | | | | | | | ■ | | |
| house | | | | | | | | | ■ | |

Word Alignment

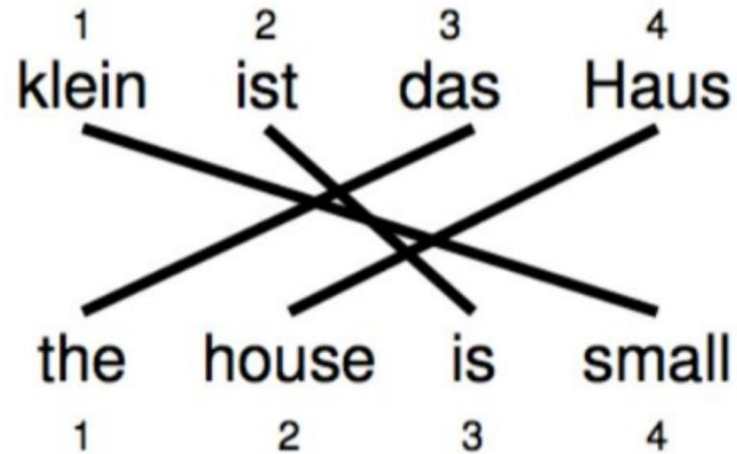
Alignment can be visualized by drawing links between two sentences, and they are represented as vectors of positions



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

Reordering

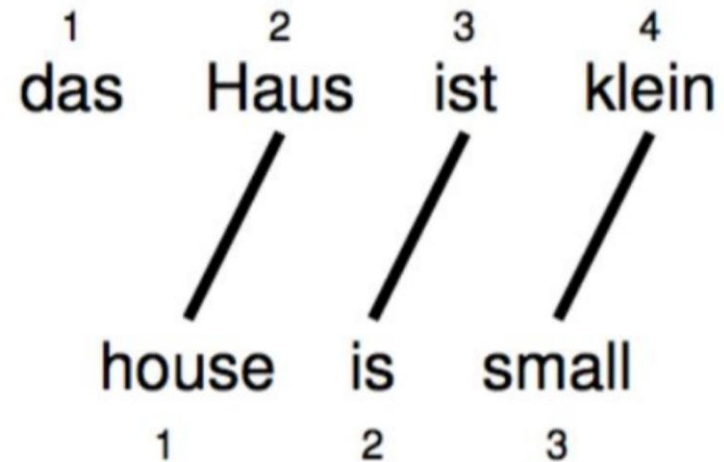
Words may be reordered during translation



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

Word Dropping

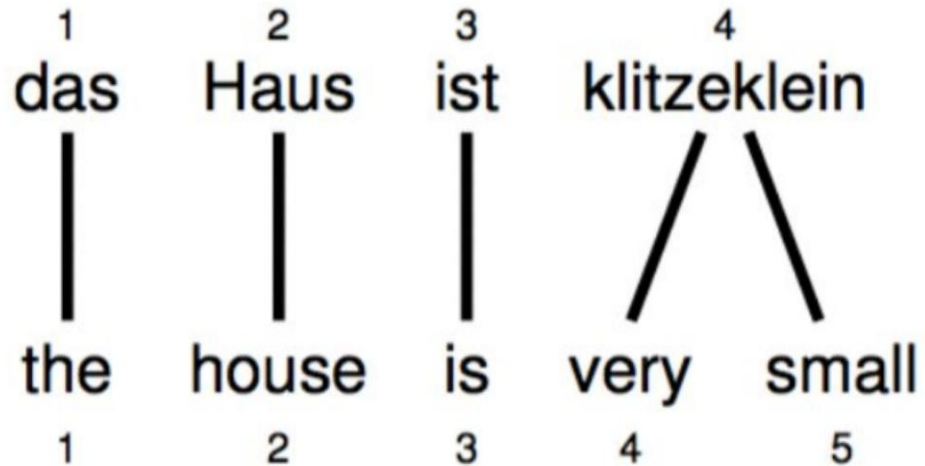
A source word may not be translated at all



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

One-to-many Translation

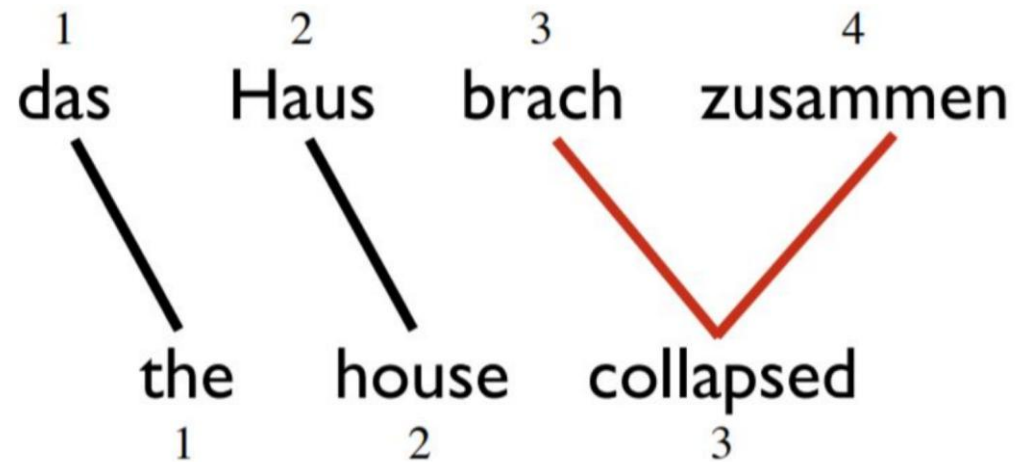
A source word may translate into **more than one** target word



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

Many-to-one Translation

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



$$\mathbf{a} = ???$$

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

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 $p(\mathbf{e}|\mathbf{f}, m)$
 - Where \mathbf{e} and \mathbf{f} are complete English and Foreign sentences
 - $\mathbf{e} = \langle e_1, e_2, \dots, e_m \rangle$
 - $\mathbf{f} = \langle f_1, f_2, \dots, f_n \rangle$

Lexical Translation

- Goal: a model $p(\mathbf{e}|\mathbf{f}, m)$
 - Where \mathbf{e} and \mathbf{f} are complete English and Foreign sentences
- Lexical translation makes the following assumptions
 - Each word e_i in \mathbf{e} is generated from exactly one word in \mathbf{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 \mathbf{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:

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

Alignment × Translation | Alignment

IBM Model 1: $P(E | F)$

■ Translation probability

- For a foreign sentence $f = (f_1, \dots, f_{l_f})$ of length l_f
- To an English sentence $e = (e_1, \dots, e_{l_e})$ 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

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

- 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

$$p(a|f)$$

$$p(e|f,a)$$

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

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

Example

| das | | Haus | | ist | | klein | |
|-------|----------|-----------|----------|--------|----------|--------|----------|
| e | $t(e f)$ | e | $t(e f)$ | e | $t(e f)$ | e | $t(e f)$ |
| the | 0.7 | house | 0.8 | is | 0.8 | small | 0.4 |
| that | 0.15 | building | 0.16 | 's | 0.16 | little | 0.4 |
| which | 0.075 | home | 0.02 | exists | 0.02 | short | 0.1 |
| who | 0.05 | household | 0.015 | has | 0.015 | minor | 0.06 |
| this | 0.025 | shell | 0.005 | are | 0.005 | 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

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

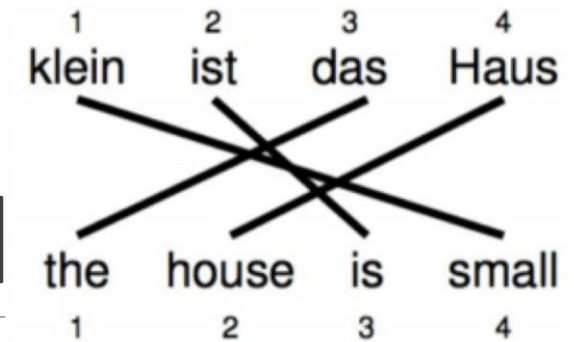
Estimate Alignments Given t-table

- If we have translation probabilities...

| das | | Haus | | ist | | klein | |
|----------|----------|-----------|----------|----------|----------|----------|----------|
| <i>e</i> | $t(e f)$ | <i>e</i> | $t(e f)$ | <i>e</i> | $t(e f)$ | <i>e</i> | $t(e f)$ |
| the | 0.7 | house | 0.8 | is | 0.8 | small | 0.4 |
| that | 0.15 | building | 0.16 | 's | 0.16 | little | 0.4 |
| which | 0.075 | home | 0.02 | exists | 0.02 | short | 0.1 |
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| this | 0.025 | shell | 0.005 | are | 0.005 | petty | 0.04 |

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

Learning Lexical Translation Model



- We'd like to estimate the lexical translation probabilities $t(e | f)$ 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 | $t(e f)$ |
|--------|----------|
| small | 0.4 |
| little | 0.4 |
| short | 0.1 |
| minor | 0.06 |
| petty | 0.04 |

EM Algorithm

■ Incomplete data

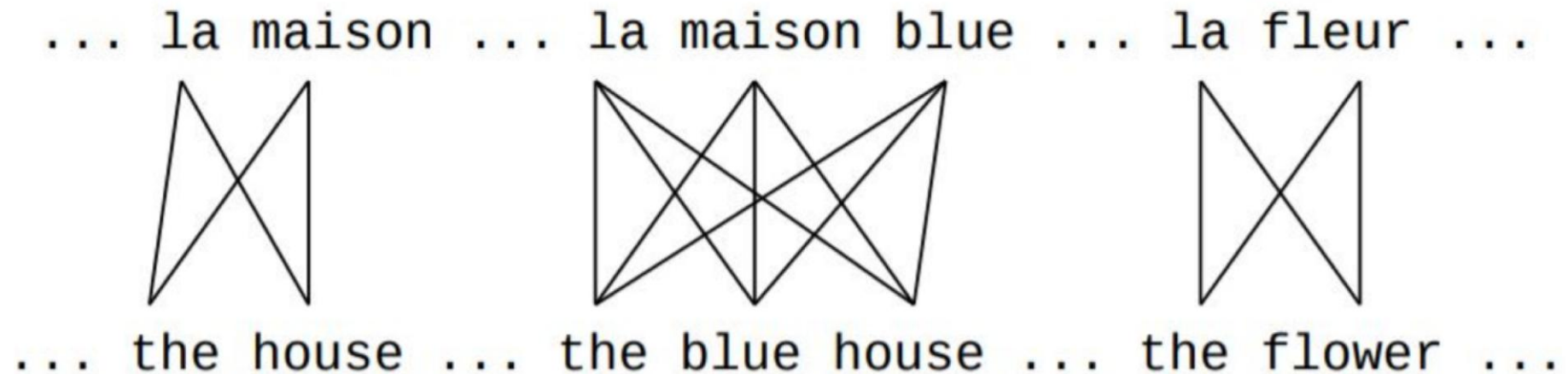
- If we had **complete data**, we could estimate the model
- If we had the **model**, we could fill in the gaps in the data

■ **Expectation Maximization (EM)** in a nutshell

1. Initialize model parameters (e.g., uniform, random)
2. Assign probabilities to the missing data (expectation)
3. Estimate model parameters from completed data (maximization)
4. Iterate steps 2-3 until convergence

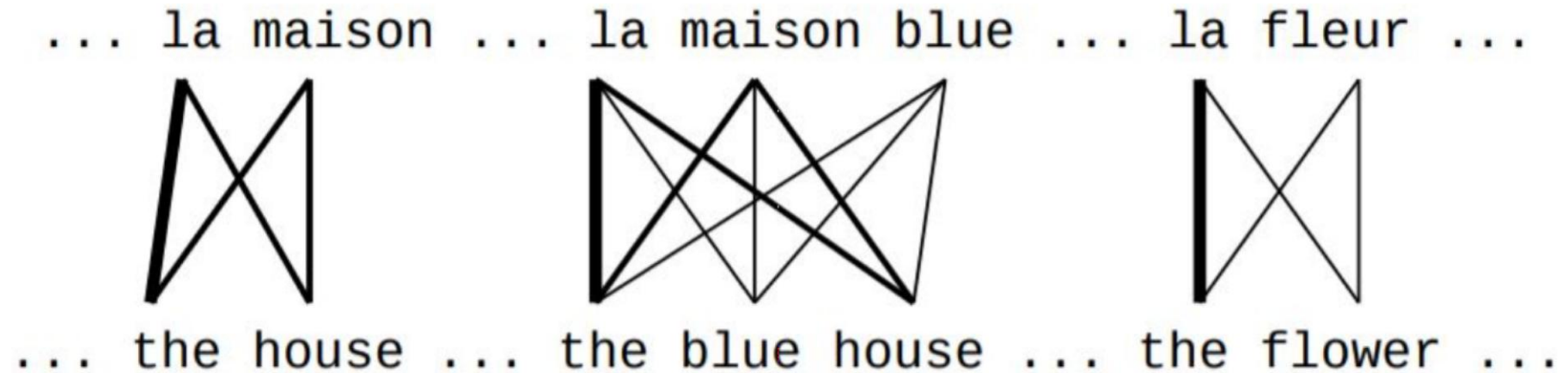
EM Algorithm

Kevin Knight's example



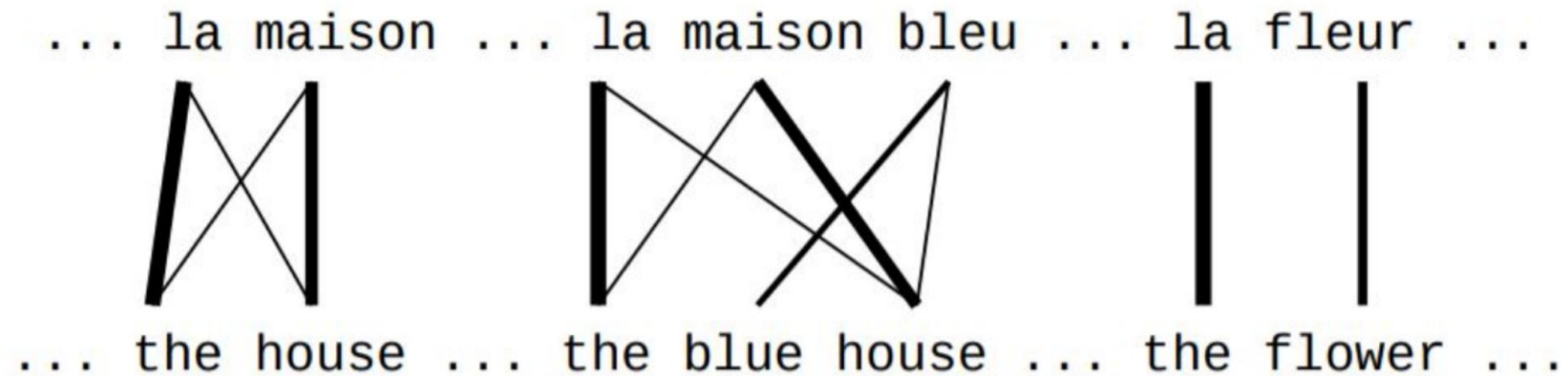
- Initial step: all word alignments equally likely
- Model learns that: e.g., *la* is often aligned with *the*

EM Algorithm



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

EM Algorithm



■ After another iteration

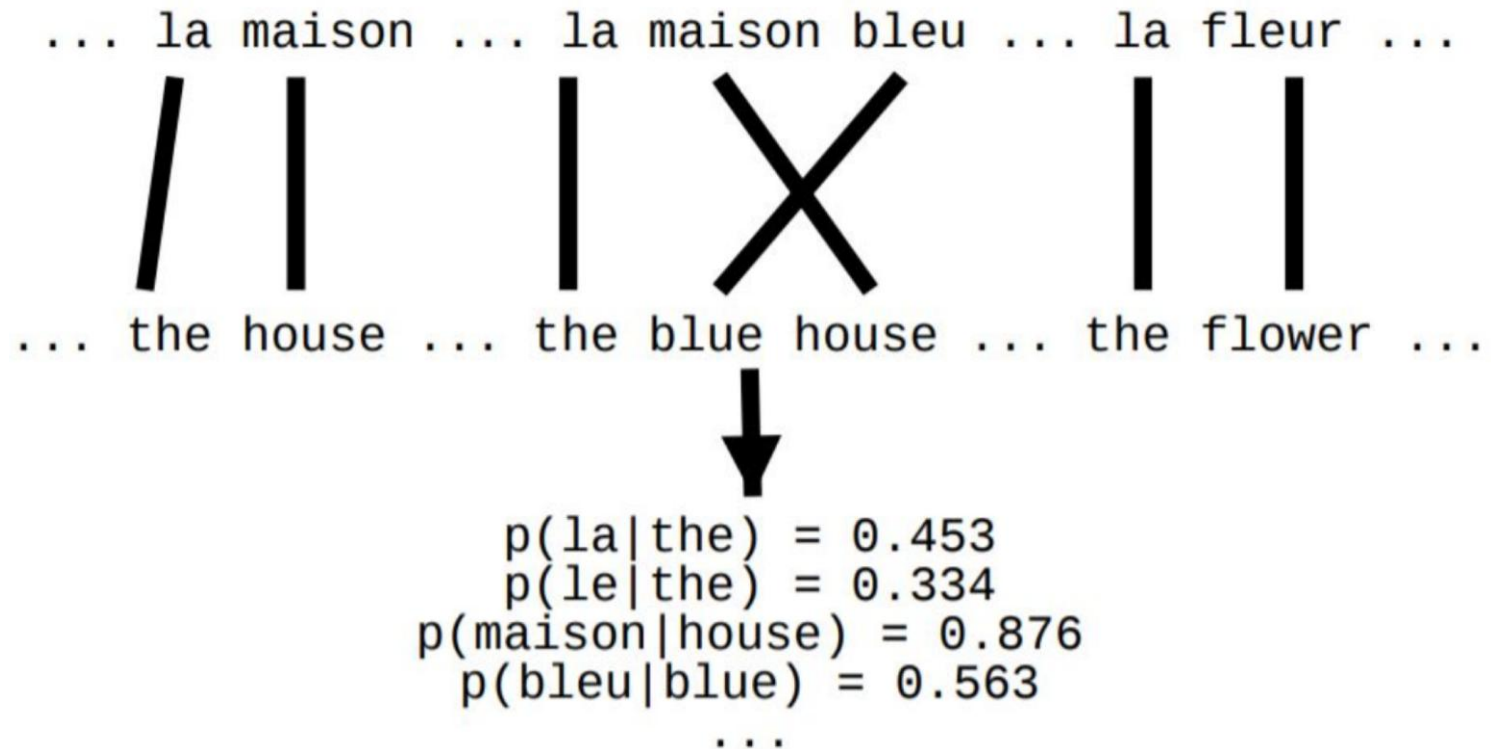
It becomes apparent that alignments, e.g., between *fleur* and *flower* are more likely

EM Algorithm

... la maison ... la maison bleu ... la fleur ...
/ | | X | |
... the house ... the blue house ... the flower ...

- **Convergence**
- Inherent hidden structure revealed by EM !

EM Algorithm



■ **Parameter estimation from the aligned corpus**

Problems with Lexical Translation

- Will struggle with idioms
- Misses longer contexts
- Might have issues with multiple word mappings → not fluent translation
 - Some words might not have 1-1 translation
- Struggles if morphemes change depend on other words in the sentence

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 |
|------------------|---|---------------|---------------|---------------|---------------|-----|------|
| <i>Reference</i> | <i>Vinay likes programming in Python</i> | | | | | | |
| <i>Sys1</i> | <i>To Vinay it like to program Python</i> | $\frac{2}{7}$ | 0 | 0 | 0 | 1 | .21 |
| <i>Sys2</i> | <i>Vinay likes Python</i> | $\frac{3}{3}$ | $\frac{1}{2}$ | 0 | 0 | .51 | .33 |
| <i>Sys3</i> | <i>Vinay likes programming in his pajamas</i> | $\frac{4}{6}$ | $\frac{3}{5}$ | $\frac{2}{4}$ | $\frac{1}{3}$ | 1 | .76 |

Sample BLEU scores for various system outputs

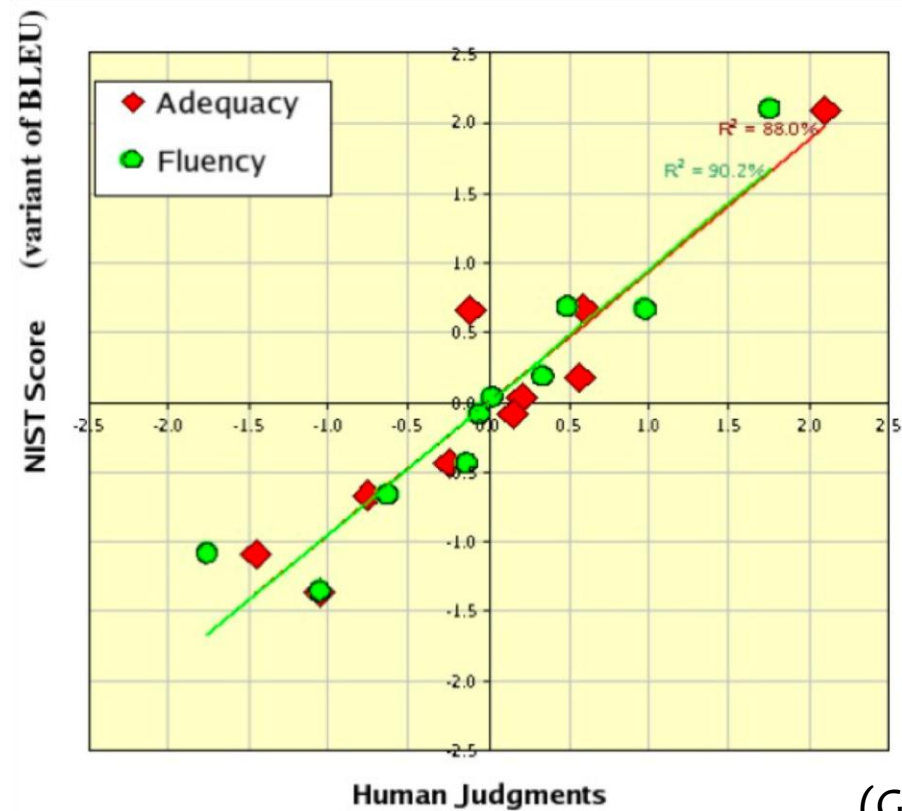
■ Alternatives have been proposed:

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

Other Issues?

BLEU

Correlates somewhat well with human judgments



(G. Doddington, NIST)