Word-based models

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Lexical Translation

- How to translate a word → look up in dictionary

  Haus — house, building, home, household, shell.

- Multiple translations
  - some more frequent than others
  - for instance: house, and building most common
  - special cases: Haus of a snail is its shell

- Note: In all lectures, we translate from a foreign language into English

Collect Statistics

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

Translation of *Haus*	Count
house	8,000
building	1,600
home	200
household	150
shell	50

Estimate Translation Probabilities

Maximum likelihood estimation

$$p_f(e) = \begin{cases} 0.8 & \text{if } e = \text{house}, \\ 0.16 & \text{if } e = \text{building}, \\ 0.02 & \text{if } e = \text{home}, \\ 0.015 & \text{if } e = \text{household}, \\ 0.005 & \text{if } e = \text{shell}. \end{cases}$$

A Model of Translation

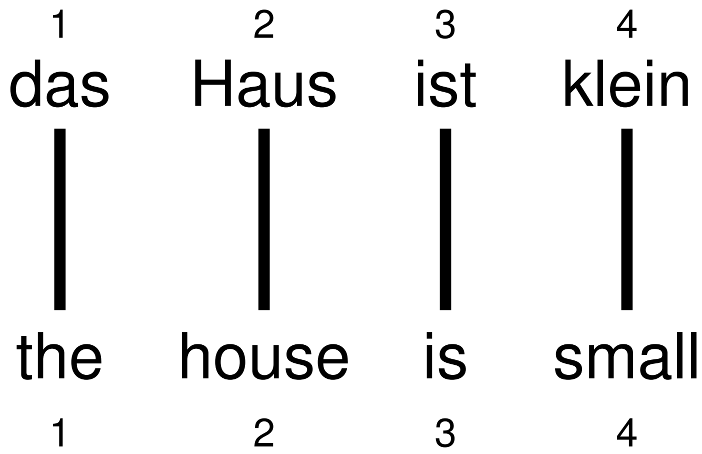
- Goal: build a model $p(\mathbf{e}|\mathbf{f})$
- where $\mathbf{e}$ and $\mathbf{f}$ are complete English and Foreign sentences.
- To help, we'll introduce an alignment a to explain how $\mathbf{f}$ generates $\mathbf{e}$ in terms of word-level translation decisions.

$$p(\mathbf{e}|\mathbf{f}) = \sum_a p(\mathbf{e}, a|\mathbf{f})$$

- If we can learn $p(\mathbf{e}|\mathbf{f})$ from data, we can use it to collect lexical translation probabilities, to align parallel sentences, or to translate new sentences.

Alignment

- In a parallel text (or when we translate), we align words in one language with the words in the other



- Word positions are numbered 1–4

Alignment Function

- Formalizing alignment with an alignment function

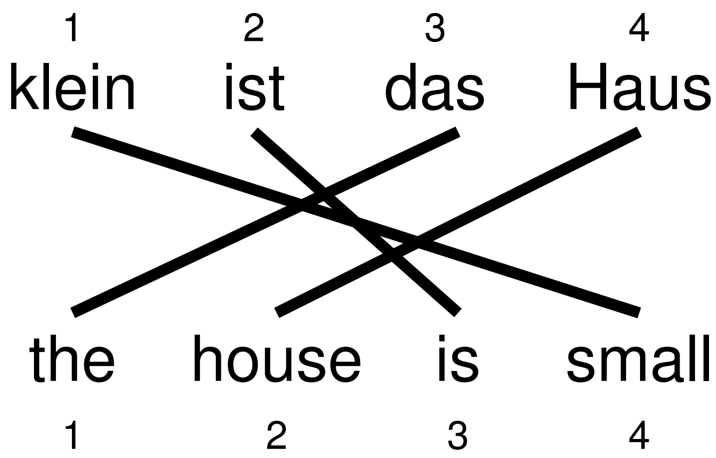
- Mapping an English target word at position i to a German source word at position j with a function $a : i \rightarrow j$

- Example

$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4\}$$

Reordering

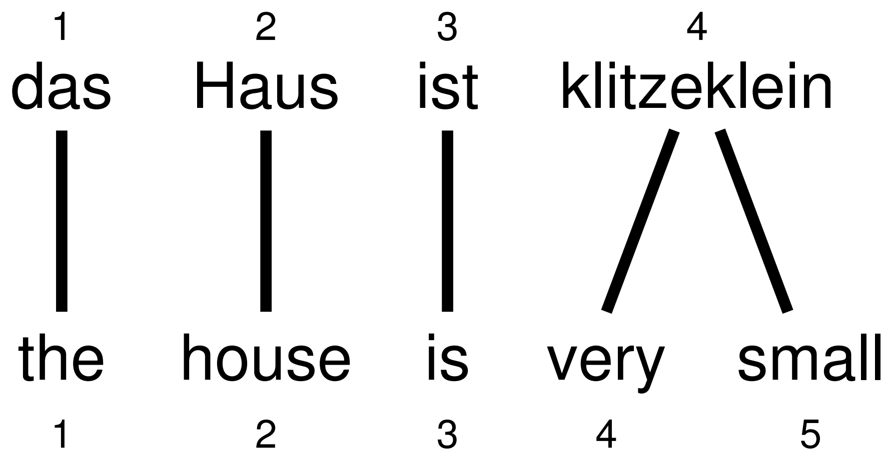
Words may be reordered during translation



$$a : \{1 \rightarrow 3, 2 \rightarrow 4, 3 \rightarrow 2, 4 \rightarrow 1\}$$

One-to-Many Translation

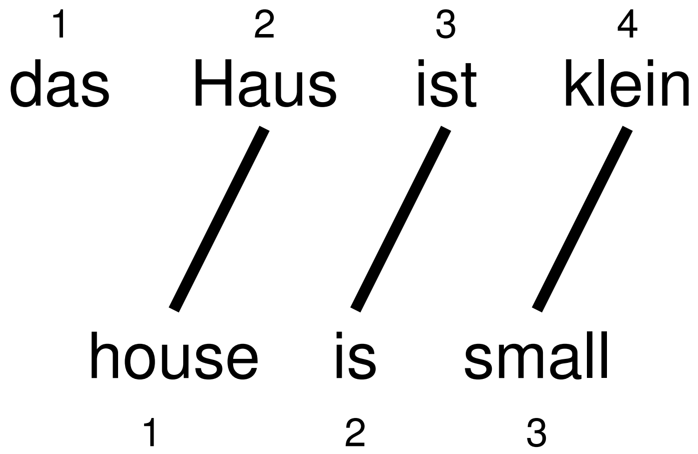
A source word may translate into multiple target words



$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4, 5 \rightarrow 4\}$$

Dropping Words

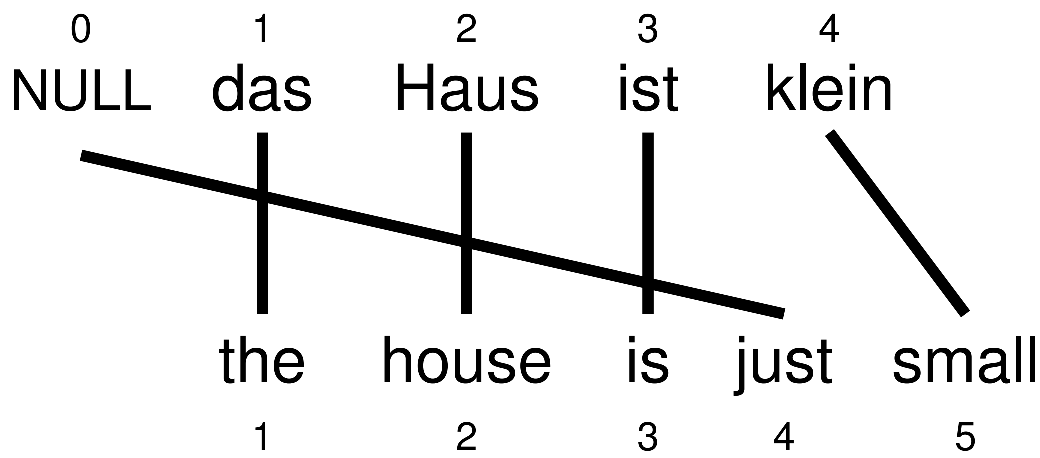
Words may be dropped when translated
(German article das is dropped)



$$a : \{1 \rightarrow 2, 2 \rightarrow 3, 3 \rightarrow 4\}$$

Inserting Words

- Words may be added during translation
  - The English just does not have an equivalent in German
  - We still need to map it to something: special NULL token



$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 0, 5 \rightarrow 4\}$$

IBM Model 1

- Generative model: break up translation process into smaller steps
  - IBM Model 1 only uses lexical translation

- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \to i$

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

  - parameter ϵ is a normalization constant

Start with a German sentence

1	2	3	4
das	Haus	ist	klein

$$p(\mathbf{e}, a|\mathbf{f})$$

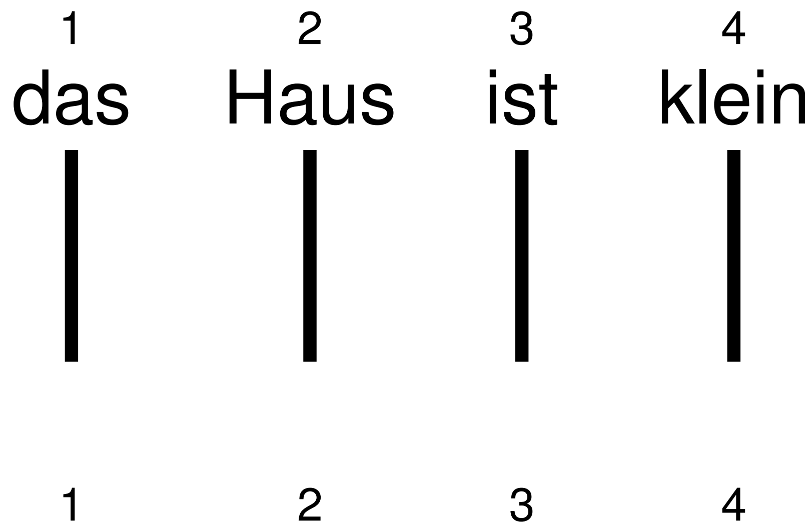
Select length with probability ϵ

1	2	3	4
das	Haus	ist	klein

1	2	3	4

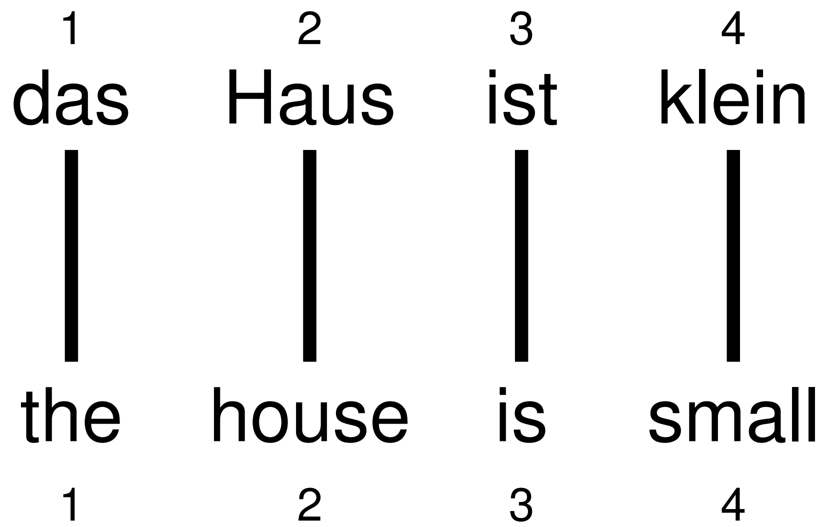
$$p(\mathbf{e}, a|\mathbf{f}) = \epsilon$$

Each position selects a generator



$$p(\mathbf{e}, a|\mathbf{f}) = \frac{\epsilon}{(l_f + 1)^{l_e}}$$

Words are selected according to generators



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

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

$$
\begin{aligned}
p(e,a|f) &= \frac{\epsilon}{4^4} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\
&= \frac{\epsilon}{4^4} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\
&= 0.0007\epsilon
\end{aligned}
$$

Learning Lexical Translation Models

- We would like to estimate the lexical translation probabilities $t(e|f)$ from a parallel corpus

- ... but we do not have the alignments

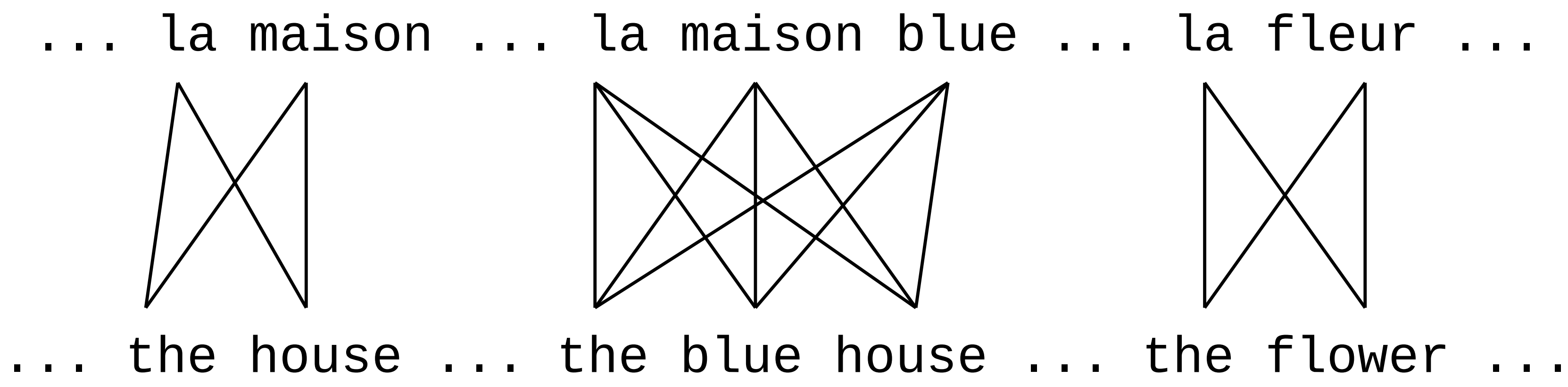
- Chicken and egg problem
  - if we had the *alignments*,
    $\rightarrow$ we could estimate the *parameters* of our generative model
  - if we had the *parameters*,
    $\rightarrow$ we could estimate the *alignments*

EM Algorithm

- Incomplete data
  - if we had *complete data*, would could estimate *model*
  - if we had *model*, we could fill in the *gaps in the data*

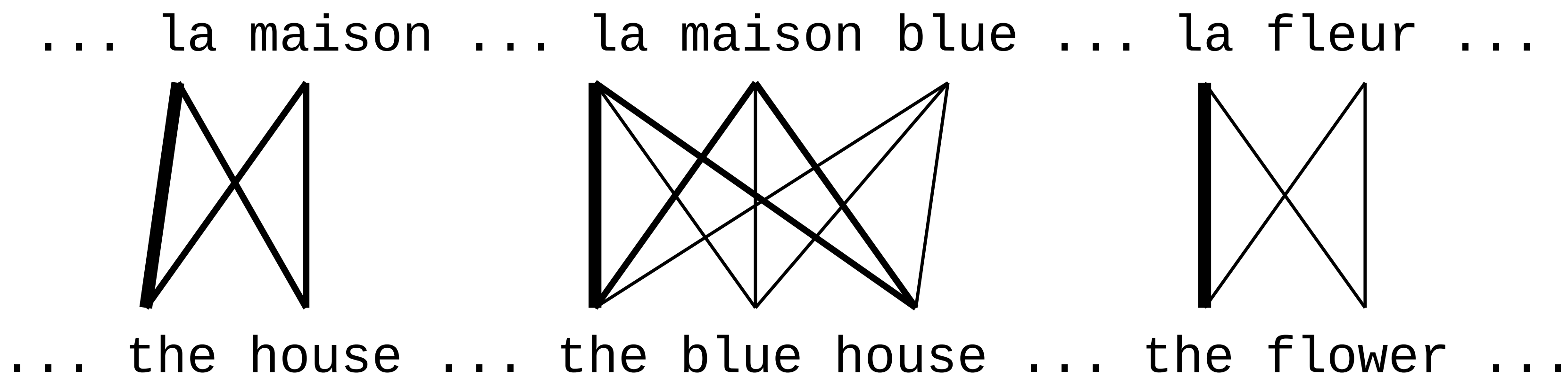
- Expectation Maximization (EM) in a nutshell
  1. initialize model parameters (e.g. uniform)
  2. assign probabilities to the missing data
  3. estimate model parameters from completed data
  4. iterate steps 2–3 until convergence

EM Algorithm



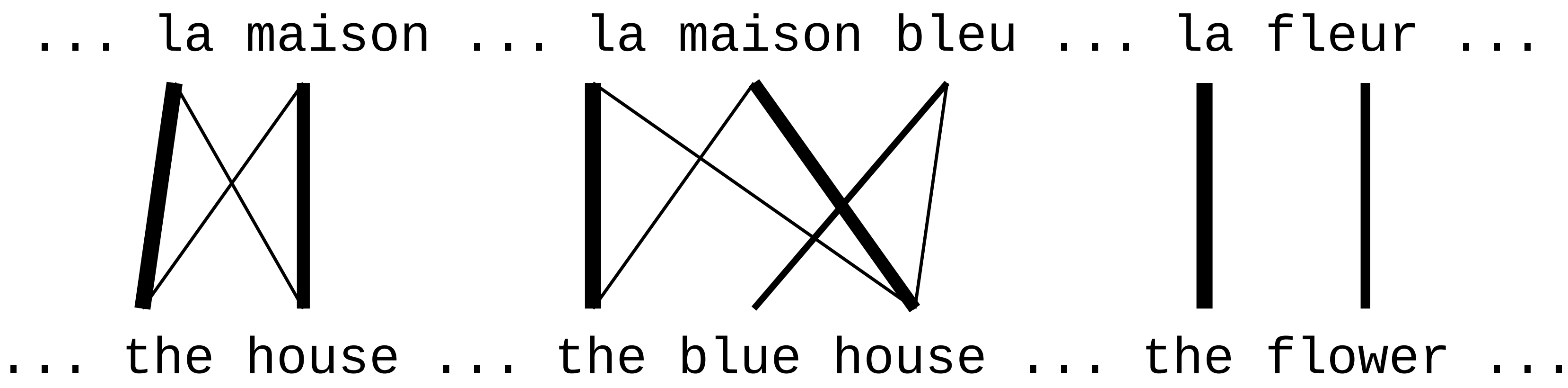
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM Algorithm



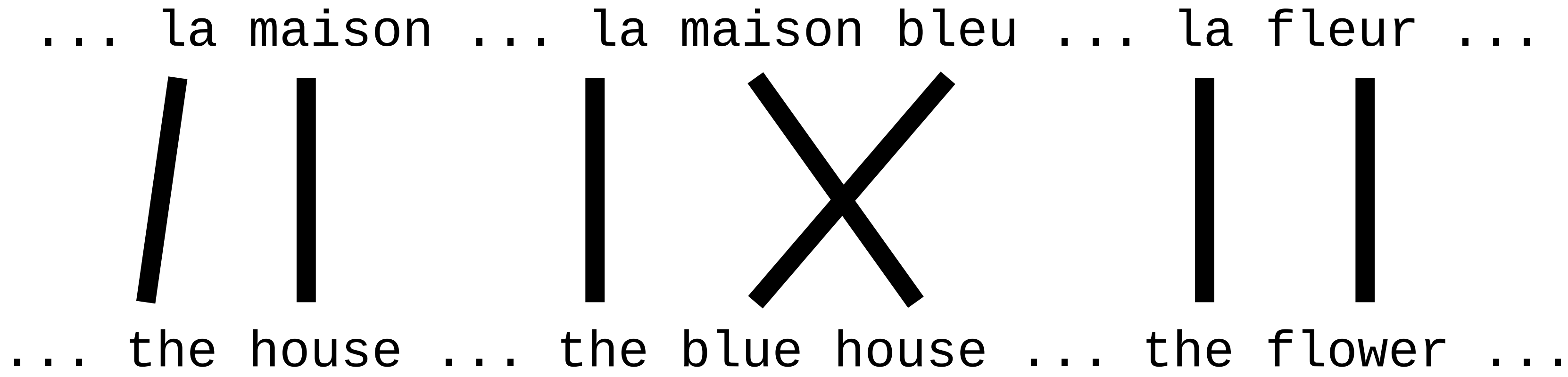
- After one iteration
- Alignments, e.g., between la and the are more likely

EM Algorithm



- After another iteration
- It becomes apparent that alignments, e.g., between fleur and flower are more likely (pigeon hole principle)

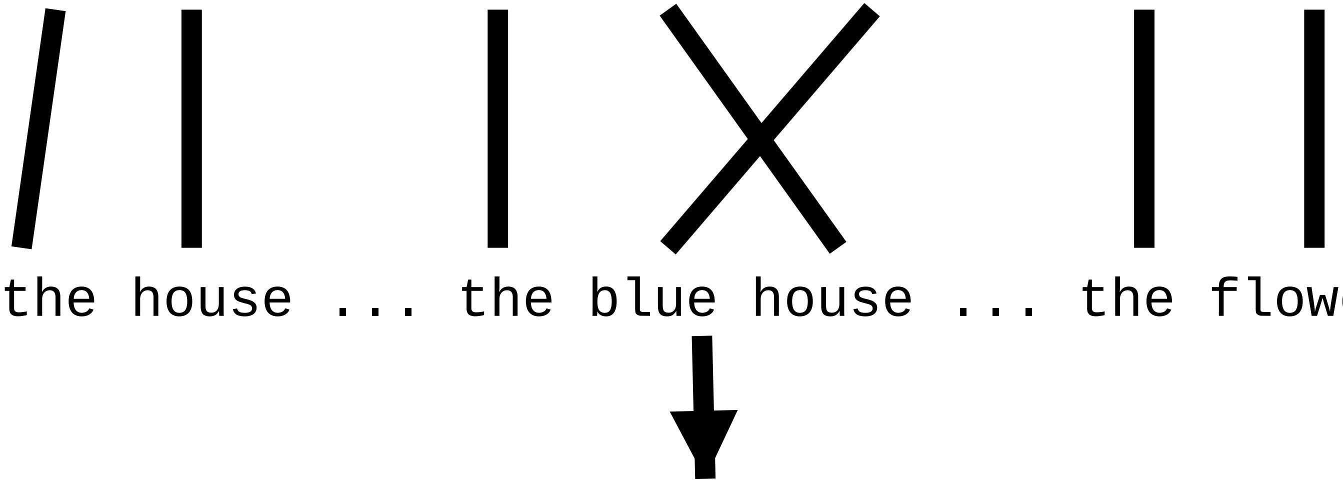
EM Algorithm



- Convergence
- Inherent hidden structure revealed by EM

EM Algorithm

`... la maison ... la maison bleu ... la fleur ...`



`... the house ... the blue house ... the flower ...`

```
p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...
```

- Parameter estimation from the aligned corpus

IBM Model 1 and EM

- EM Algorithm consists of two steps
- Expectation-Step: Apply model to the data
  - parts of the model are hidden (here: alignments)
  - using the model, assign probabilities to possible values
- Maximization-Step: Estimate model from data
  - take assign values as fact
  - collect counts (weighted by probabilities)
  - estimate model from counts
- Iterate these steps until convergence

IBM Model 1 and EM

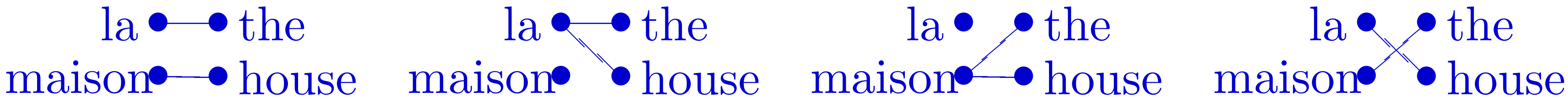
- We need to be able to compute:
  - Expectation-Step: probability of alignments
  - Maximization-Step: count collection

IBM Model 1 and EM

- **Probabilities**

$$p(\text{the}|\text{la}) = 0.7 \qquad p(\text{house}|\text{la}) = 0.05$$
$$p(\text{the}|\text{maison}) = 0.1 \qquad p(\text{house}|\text{maison}) = 0.8$$

- **Alignments**



$$p(\mathbf{e}, a|\mathbf{f}) = 0.56 \qquad p(\mathbf{e}, a|\mathbf{f}) = 0.035 \qquad p(\mathbf{e}, a|\mathbf{f}) = 0.08 \qquad p(\mathbf{e}, a|\mathbf{f}) = 0.005$$

$$p(a|\mathbf{e}, \mathbf{f}) = 0.824 \qquad p(a|\mathbf{e}, \mathbf{f}) = 0.052 \qquad p(a|\mathbf{e}, \mathbf{f}) = 0.118 \qquad p(a|\mathbf{e}, \mathbf{f}) = 0.007$$

- **Counts**

$$c(\text{the}|\text{la}) = 0.824 + 0.052 \qquad c(\text{house}|\text{la}) = 0.052 + 0.007$$
$$c(\text{the}|\text{maison}) = 0.118 + 0.007 \qquad c(\text{house}|\text{maison}) = 0.824 + 0.118$$

IBM Model 1 and EM: Expectation Step

- We need to compute $p(a|\mathbf{e},\mathbf{f})$

- Applying the chain rule:

$$p(a|\mathbf{e},\mathbf{f}) = \frac{p(\mathbf{e},a|\mathbf{f})}{p(\mathbf{e}|\mathbf{f})}$$

- We already have the formula for $p(\mathbf{e},\mathbf{a}|\mathbf{f})$ (definition of Model 1)

IBM Model 1 and EM: Expectation Step

- We need to compute $p(\mathbf{e}|\mathbf{f})$

$$
\begin{aligned}
p(\mathbf{e}|\mathbf{f}) &= \sum_a p(\mathbf{e}, a|\mathbf{f}) \\
&= \sum_{a(1)=0}^{l_f} ... \sum_{a(l_e)=0}^{l_f} p(\mathbf{e}, a|\mathbf{f}) \\
&= \sum_{a(1)=0}^{l_f} ... \sum_{a(l_e)=0}^{l_f} \frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})
\end{aligned}
$$

IBM Model 1 and EM: Expectation Step

$$p(\mathbf{e}|\mathbf{f}) = \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})$$

$$= \frac{\epsilon}{(l_f+1)^{l_e}} \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})$$

$$= \frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} \sum_{i=0}^{l_f} t(e_j|f_i)$$

- Note the trick in the last line
  - removes the need for an exponential number of products

$\longrightarrow$ this makes IBM Model 1 estimation tractable

The Trick

(case $l_e = l_f = 2$)

$$\sum_{a(1)=0}^{2} \sum_{a(2)=0}^{2} = \frac{\epsilon}{3^2} \prod_{j=1}^{2} t(e_j|f_{a(j)}) =$$

$$= t(e_1|f_0)\ t(e_2|f_0) + t(e_1|f_0)\ t(e_2|f_1) + t(e_1|f_0)\ t(e_2|f_2) +$$

$$+ t(e_1|f_1)\ t(e_2|f_0) + t(e_1|f_1)\ t(e_2|f_1) + t(e_1|f_1)\ t(e_2|f_2) +$$

$$+ t(e_1|f_2)\ t(e_2|f_0) + t(e_1|f_2)\ t(e_2|f_1) + t(e_1|f_2)\ t(e_2|f_2) =$$

$$= t(e_1|f_0)\ (t(e_2|f_0) + t(e_2|f_1) + t(e_2|f_2)) +$$

$$+ t(e_1|f_1)\ (t(e_2|f_1) + t(e_2|f_1) + t(e_2|f_2)) +$$

$$+ t(e_1|f_2)\ (t(e_2|f_2) + t(e_2|f_1) + t(e_2|f_2)) =$$

$$= (t(e_1|f_0) + t(e_1|f_1) + t(e_1|f_2))\ (t(e_2|f_2) + t(e_2|f_1) + t(e_2|f_2))$$

IBM Model 1 and EM: Expectation Step

- Combine what we have:

$$\begin{aligned}
p(\mathbf{a}|\mathbf{e},\mathbf{f}) &= p(\mathbf{e},\mathbf{a}|\mathbf{f})/p(\mathbf{e}|\mathbf{f}) \\
&= \frac{\frac{\epsilon}{(l_f+1)^{l_e}}\prod_{j=1}^{l_e} t(e_j|f_{a(j)})}{\frac{\epsilon}{(l_f+1)^{l_e}}\prod_{j=1}^{l_e}\sum_{i=0}^{l_f} t(e_j|f_i)} \\
&= \prod_{j=1}^{l_e} \frac{t(e_j|f_{a(j)})}{\sum_{i=0}^{l_f} t(e_j|f_i)}
\end{aligned}$$

IBM Model 1 and EM: Maximization Step

- Now we have to collect counts

- Evidence from a sentence pair **e,f** that word e is a translation of word f:

$$c(e|f;\mathbf{e},\mathbf{f}) = \sum_a p(a|\mathbf{e},\mathbf{f}) \sum_{j=1}^{l_e} \delta(e,e_j)\delta(f,f_{a(j)})$$

- With the same simplication as before:

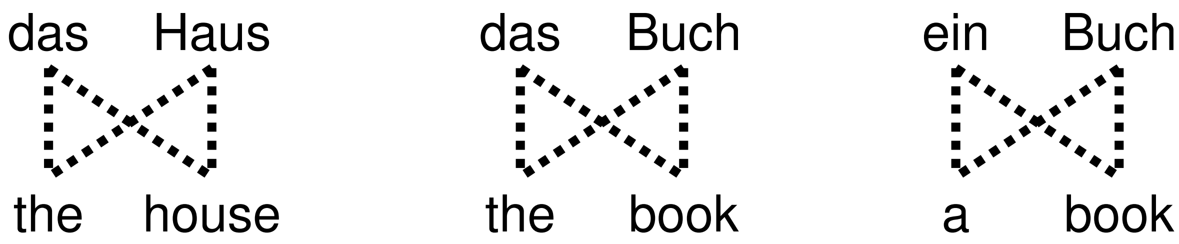
$$c(e|f;\mathbf{e},\mathbf{f}) = \frac{t(e|f)}{\sum_{i=0}^{l_f} t(e|f_i)} \sum_{j=1}^{l_e} \delta(e,e_j) \sum_{i=0}^{l_f} \delta(f,f_i)$$

IBM Model 1 and EM: Maximization Step

After collecting these counts over a corpus, we can estimate the model:

$$t(e|f;\mathbf{e},\mathbf{f}) = \frac{\sum_{(\mathbf{e},\mathbf{f})} c(e|f;\mathbf{e},\mathbf{f}))}{\sum_f \sum_{(\mathbf{e},\mathbf{f})} c(e|f;\mathbf{e},\mathbf{f}))}$$

Convergence



e	f	initial	1st it.	2nd it.	3rd it.	...	final
the	das	0.25	0.5	0.6364	0.7479	...	1
book	das	0.25	0.25	0.1818	0.1208	...	0
house	das	0.25	0.25	0.1818	0.1313	...	0
the	buch	0.25	0.25	0.1818	0.1208	...	0
book	buch	0.25	0.5	0.6364	0.7479	...	1
a	buch	0.25	0.25	0.1818	0.1313	...	0
book	ein	0.25	0.5	0.4286	0.3466	...	0
a	ein	0.25	0.5	0.5714	0.6534	...	1
the	haus	0.25	0.5	0.4286	0.3466	...	0
house	haus	0.25	0.5	0.5714	0.6534	...	1

Perplexity

- How well does the model fit the data?

- Perplexity: derived from probability of the training data according to the model

$$\log_2 PP = -\sum_s \log_2 p(\mathbf{e}_s|\mathbf{f}_s)$$

- Example (ϵ=1)

	initial	1st it.	2nd it.	3rd it.	...	final
$p(\text{the haus}\|\text{das haus})$	0.0625	0.1875	0.1905	0.1913	...	0.1875
$p(\text{the book}\|\text{das buch})$	0.0625	0.1406	0.1790	0.2075	...	0.25
$p(\text{a book}\|\text{ein buch})$	0.0625	0.1875	0.1907	0.1913	...	0.1875
perplexity	4095	202.3	153.6	131.6	...	113.8

Higher IBM Models

IBM Model 1	lexical translation
IBM Model 2	adds absolute reordering model
IBM Model 3	adds fertility model
IBM Model 4	relative reordering model
IBM Model 5	fixes deficiency

- Only IBM Model 1 has global maximum
  - training of a higher IBM model builds on previous model

- Compuationally biggest change in Model 3
  - trick to simplify estimation does not work anymore

  $\rightarrow$ exhaustive count collection becomes computationally too expensive
  - sampling over high probability alignments is used instead

Reminder: IBM Model 1

- Generative model: break up translation process into smaller steps
  - IBM Model 1 only uses lexical translation

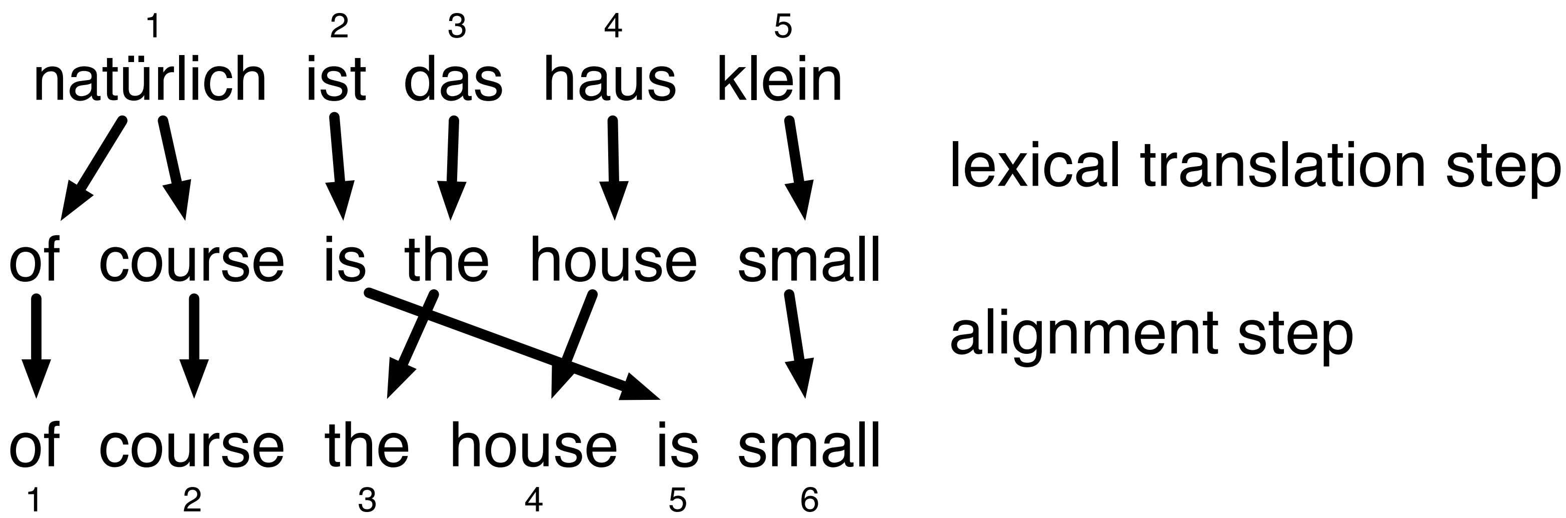
- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \rightarrow i$

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

  - parameter ϵ is a normalization constant

IBM Model 2

Adding a model of alignment



IBM Model 2

- Modeling alignment with an alignment probability distribution

- Translating foreign word at position i to English word at position j:

$$a(i|j, l_e, l_f)$$

- Putting everything together

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

- EM training of this model works the same way as IBM Model 1

Interlude: HMM Model

- Words do not move independently of each other
  - they often move in groups
  - $\rightarrow$ condition word movements on previous word

- HMM alignment model:

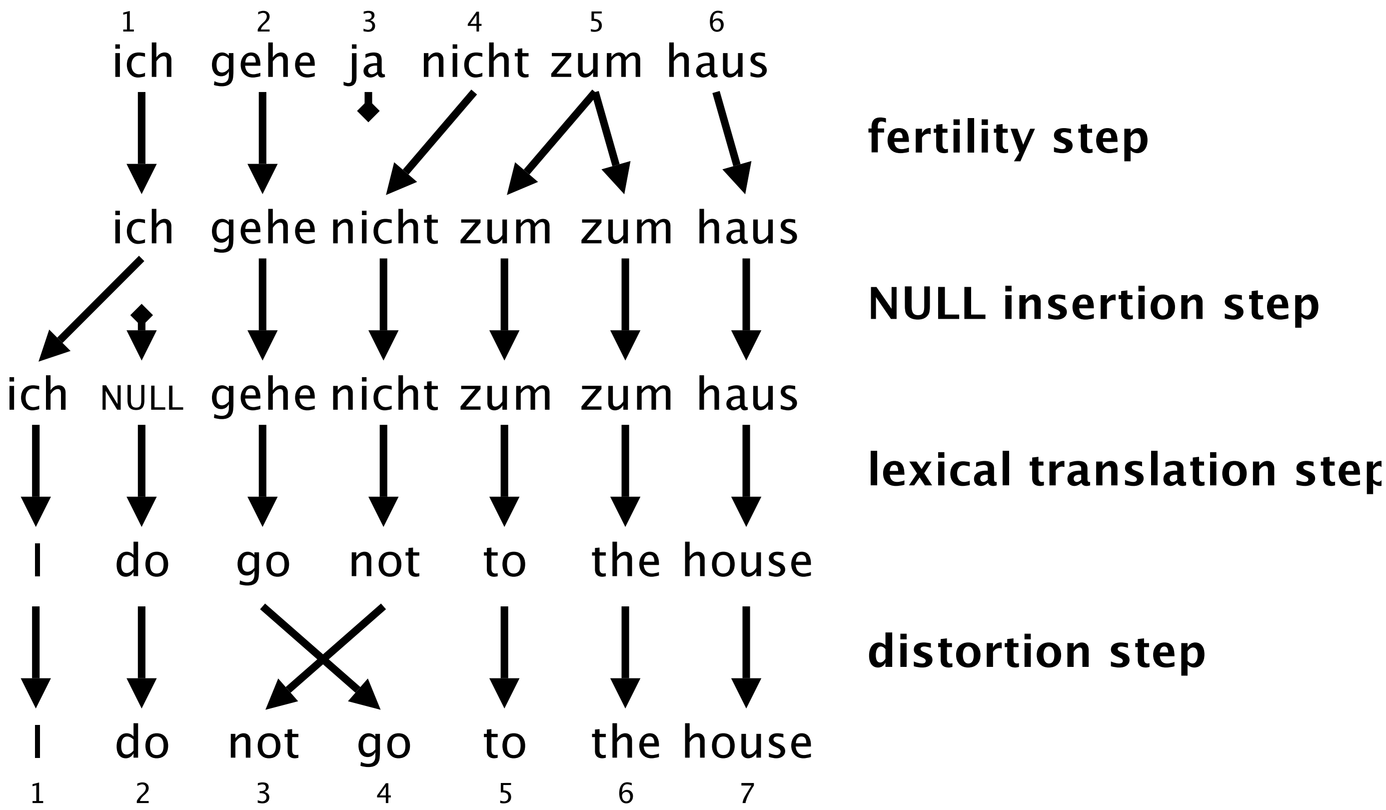
$$p(a(j)|a(j-1), l_e)$$

- EM algorithm application harder, requires dynamic programming

- IBM Model 4 is similar, also conditions on word classes

IBM Model 3

Adding a model of fertilty



IBM Model 3: Fertility

- Fertility: number of English words generated by a foreign word
- Modelled by distribution $n(\phi|f)$
- Example:

$$n(1|\text{haus}) \simeq 1$$
$$n(2|\text{zum}) \simeq 1$$
$$n(0|\text{ja}) \simeq 1$$

Sampling the Alignment Space

- Training IBM Model 3 with the EM algorithm
  - The trick that reduces exponential complexity does not work anymore

  $\rightarrow$ Not possible to exhaustively consider all alignments

- Finding the most probable alignment by hillclimbing
  - start with initial alignment
  - change alignments for individual words
  - keep change if it has higher probability
  - continue until convergence

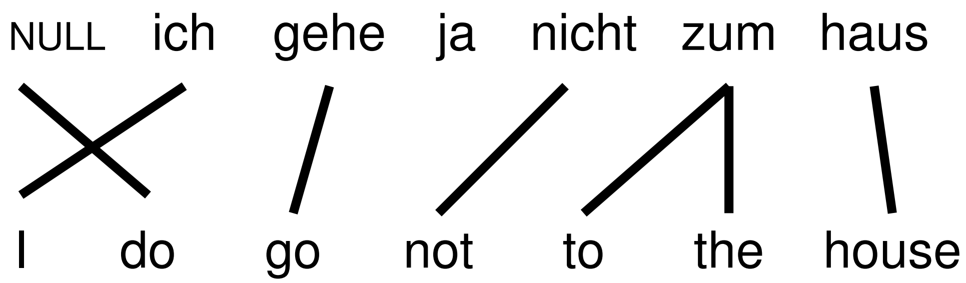
- Sampling: collecting variations to collect statistics
  - all alignments found during hillclimbing
  - neighboring alignments that differ by a move or a swap

IBM Model 4

- Better reordering model
- Reordering in IBM Model 2 and 3
  - recall: $d(j||_i, l_e, lf)$
  - for large sentences (large l_f and l_e), sparse and unreliable statistics
  - phrases tend to move together
- Relative reordering model: relative to previously translated words (cepts)

IBM Model 4: Cepts

Foreign words with non-zero fertility forms cepts
(here 5 cepts)



cept π_i	π_1	π_2	π_3	π_4	π_5
foreign position $[i]$	1	2	4	5	6
foreign word $f_{[i]}$	ich	gehe	nicht	zum	haus
English words $\{e_j\}$	I	go	not	to,the	house
English positions $\{j\}$	1	4	3	5,6	7
center of cept $\odot_i$	1	4	3	6	7

IBM Model 4: Relative Distortion

j	1	2	3	4	5	6	7
e_j	I	do	not	go	to	the	house
in cept $\pi_{i,k}$	$\pi_{1,0}$	$\pi_{0,0}$	$\pi_{3,0}$	$\pi_{2,0}$	$\pi_{4,0}$	$\pi_{4,1}$	$\pi_{5,0}$
$\odot_{i-1}$	0	-	4	1	3	-	6
$j - \odot_{i-1}$	$+1$	-	-1	$+3$	$+2$	-	$+1$
distortion	$d_1(+1)$	1	$d_1(-1)$	$d_1(+3)$	$d_1(+2)$	$d_{>1}(+1)$	$d_1(+1)$

- Center $\odot_i$ of a cept π_i is ceiling(avg(j))
- Three cases:
  - uniform for NULL generated words
  - first word of a cept: d_1
  - next words of a cept: $d_{>1}$

Word Classes

- Some words may trigger reordering → condition reordering on words

$$\text{for initial word in cept: } d_1(j - \odot_{[i-1]} | f_{[i-1]}, e_j)$$

$$\text{for additional words: } d_{>1}(j - \Pi_{i,k-1} | e_j)$$

- Sparse data concerns → cluster words into classes

$$\text{for initial word in cept: } d_1(j - \odot_{[i-1]} | \mathcal{A}(f_{[i-1]}), \mathcal{B}(e_j))$$

$$\text{for additional words: } d_{>1}(j - \Pi_{i,k-1} | \mathcal{B}(e_j))$$

IBM Model 5

- IBM Models 1–4 are *deficient*
  - some impossible translations have positive probability
  - multiple output words may be placed in the same position

  $\longrightarrow$ probability mass is wasted

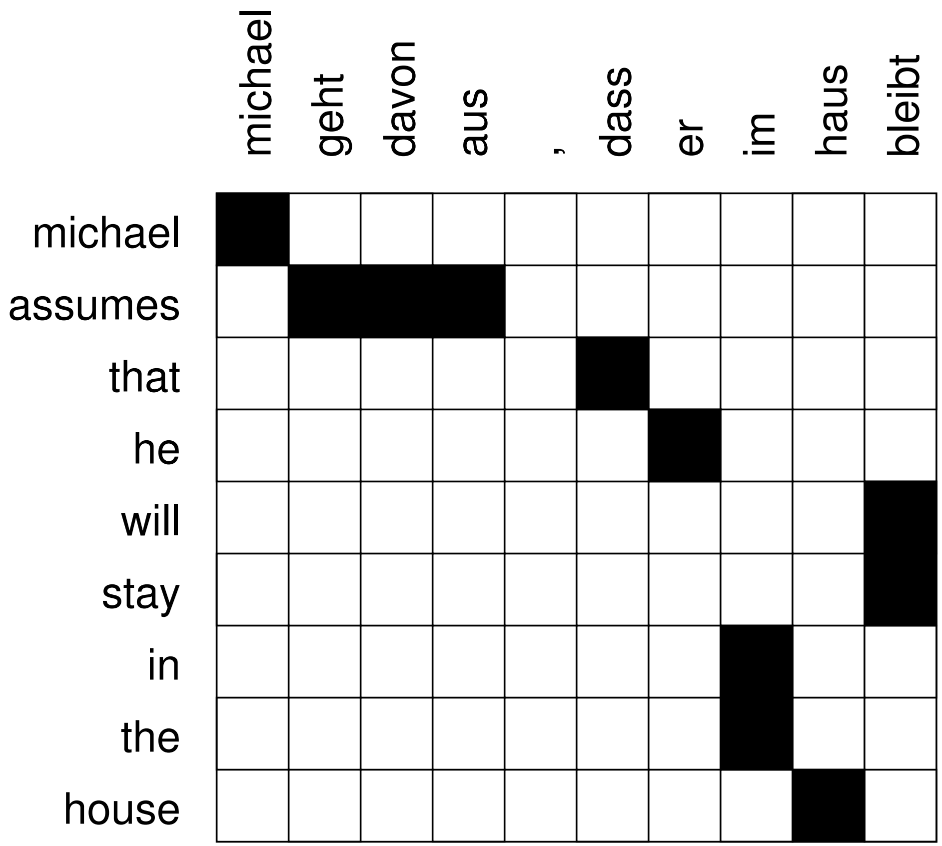
- IBM Model 5 fixes deficiency by keeping track of vacancies (available positions)

Conclusion

- IBM Models were the pioneering models in statistical machine translation
- Introduced important concepts
  - generative model
  - EM training
  - reordering models
- Only used for niche applications as translation model
- ... but still in common use for word alignment (e.g., GIZA++ toolkit)

Word Alignment

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



Measuring Word Alignment Quality

- Manually align corpus with *sure* (S) and *possible* (P) alignment points ($S \subseteq P$)

- Common metric for evaluation word alignments: Alignment Error Rate (AER)

$$\text{AER}(S, P; A) = \frac{|A \cap S| + |A \cap P|}{|A| + |S|}$$

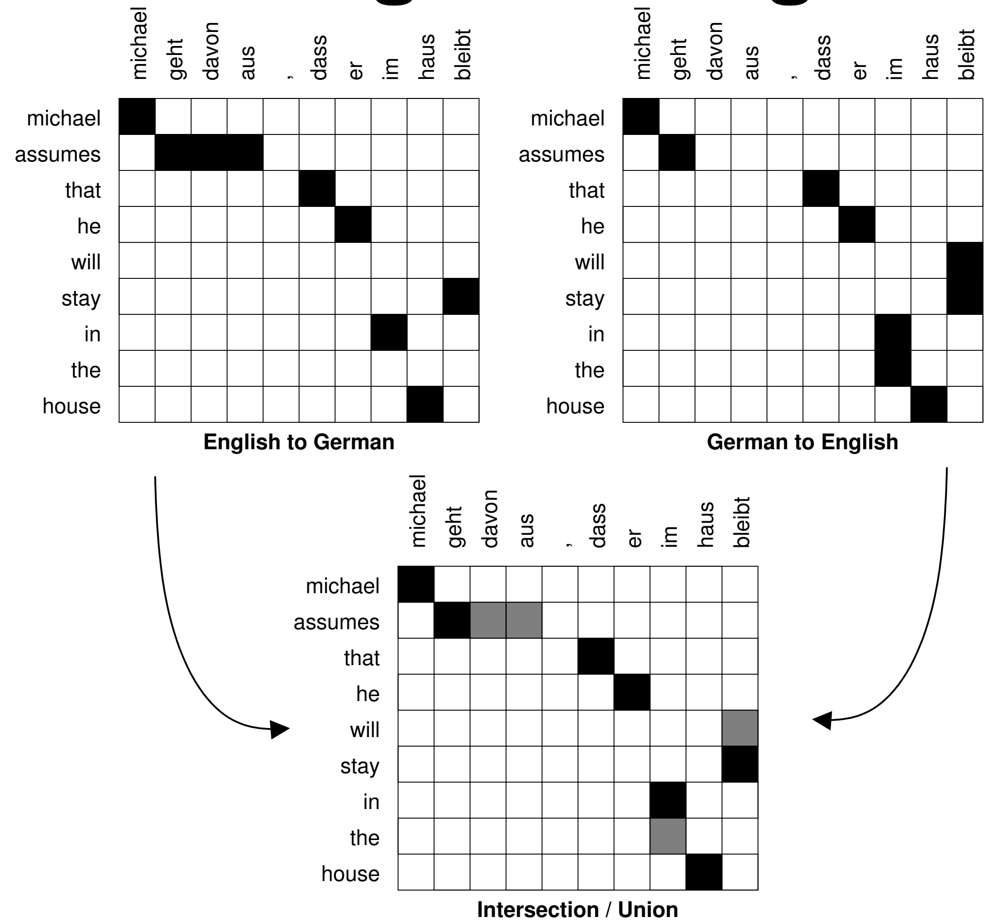
- AER $= 0$: alignment A matches all sure, any possible alignment points

- However: different applications require different precision/recall trade-offs

Word Alignment with IBM Models

- IBM Models create a **many-to-one** mapping
  - words are aligned using an alignment function
  - a function may return the same value for different input (one-to-many mapping)
  - a function can not return multiple values for one input (no many-to-one mapping)
- Real word alignments have **many-to-many** mappings

Symmetrizing Word Alignments



- Intersection of GIZA++ bidirectional alignments
- Grow additional alignment points [Och and Ney, CompLing2003]

Discriminative Training Methods

- Given some annotated training data, supervised learning methods are possible
- Structured prediction
  - not just a classification problem
  - solution structure has to be constructed in steps
- Many approaches: maximum entropy, neural networks, support vector machines, conditional random fields, MIRA, ...
- Small labeled corpus may be used for parameter tuning of unsupervised aligner [Fraser and Marcu, 2007]

Better Generative Models

- Aligning phrases
  - joint model [Marcu and Wong, 2002]
  - problem: EM algorithm likes really long phrases

- Fraser's LEAF
  - decomposes word alignment into many steps
  - similar in spirit to IBM Models
  - includes step for grouping into phrase

Summary

- Lexical translation
- Alignment
- Expectation Maximization (EM) Algorithm
- IBM Models 1–5
  - IBM Model 1: lexical translation
  - IBM Model 2: alignment model
  - IBM Model 3: fertility
  - IBM Model 4: relative alignment model
  - IBM Model 5: deficiency
- Word Alignment