Word-based models

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(adapted from the original slides
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Overview

- IBM Model 1
- IBM Model 2
- IBM Model 3
- IBM Model 4
- IBM Model 5

IBM model 1

- This model generates many different translations for a sentence, each with a different probability
- The estimation is based on the individual words, not on the whole sentence

Generative modeling

- breaks up the process in many smaller steps,
- models these steps with probability distributions,
- and combines the steps into a coherent story

IBM Model 1

- 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 $a : j \rightarrow i$

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

IBM Model 1

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

- The right side is the product over the **lexical translation probabilities** for all l_e generated output words e_j.

IBM Model 1

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

- The left side is a fraction necessary for normalization.
- It uses $(l_f + 1)$ input tokens because we also consider the NULL token.
- There are $(l_f + 1)^{l_e}$ different alignments that map $(l_f + 1)$ input words into l_e output words.
- parameter ϵ is a normalization constant

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

$$\begin{aligned} p(e,a|f) &= \frac{\epsilon}{5^4} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\ &= \frac{\epsilon}{5^4} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\ &= 0.0028\epsilon \end{aligned}$$

Learning the translation probability distributions

- We will learn these probabilities based on sentence-aligned paired texts
- Corpora are not usually word-aligned, just sentence-aligned
- Problem of incomplete data
- Typical problem in machine learning which is usually modeled as a hidden variable

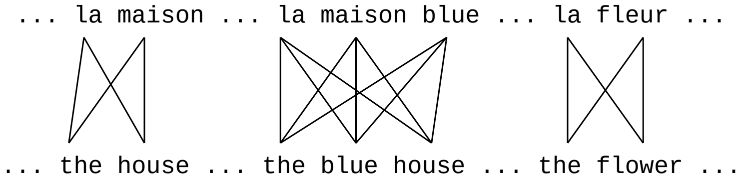
Learning Lexical Translation Models

- 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

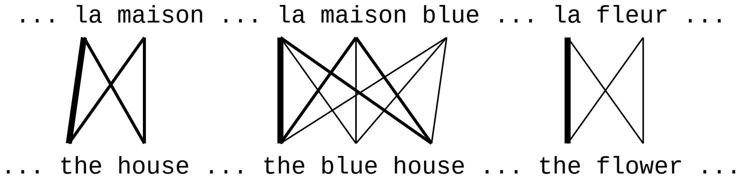
- Incomplete data
  - if we had *complete data*, would could estimate *model*
  - if we had *model*, we could fill in the *gaps in the data*
- Expectation Maximization (EM) in a nutshell
  1. initialize model parameters (e.g. uniform)
  2. assign probabilities to the missing data
  3. estimate model parameters from completed data
  4. iterate steps 2–3 until convergence

EM Algorithm



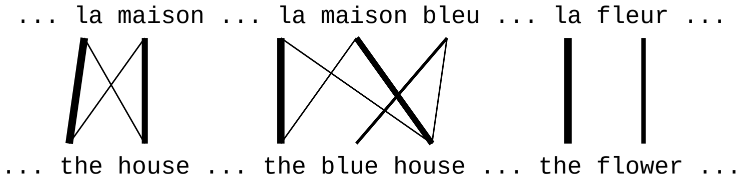
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM Algorithm



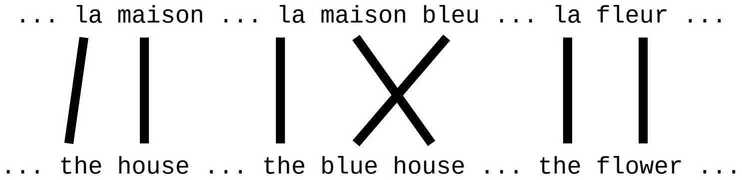
- After one iteration
- Alignments, e.g., between la and the are more likely

EM Algorithm



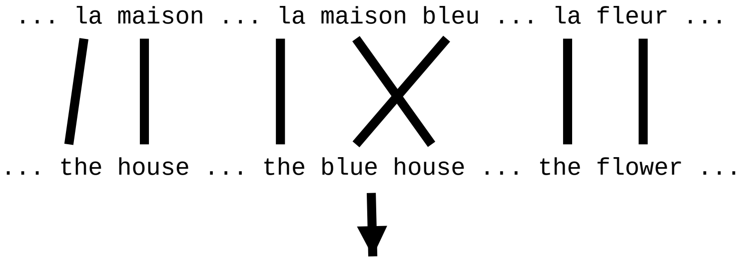
- After another iteration
- It becomes apparent that alignments, e.g., between fleur and flower are more likely

EM Algorithm



- Convergence
- Inherent hidden structure revealed by EM

EM Algorithm




```
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: 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)

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

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

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

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

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

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

  → 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:

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

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

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

- Now we have to collect counts over all possible alignments, weighted by their probabilities
- 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 simplification 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

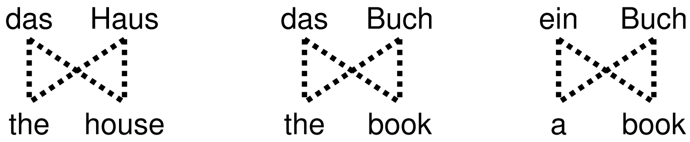
After collecting these counts over a corpus, we can estimate the model:

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

IBM Model 1 and EM: Pseudo-code

```
Input: set of sentence pairs (e, f)
Output: translation prob. t(e|f)
initialize t(e|f) uniformly
while not converged do
    // initialize
    count(e|f) = 0 for all e, f
    total(f) = 0 for all f
    for all sentence pairs (e,f) do
        // compute normalization
        for all words e in e do
            s-total(e) = 0
            for all words f in f do
                s-total(e) += t(e|f)
            end for
        end for
        // collect counts
        for all words e in e do
            for all words f in f do
                count(e|f) += t(e|f) / s-total(e)
                total(f) += t(e|f) / s-total(e)
            end for
        end for
    end for
    // estimate probabilities
    for all foreign words f do
        for all English words e do
            t(e|f) = count(e|f) / total(f)
        end for
    end for
end while
```

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

Convergence of EM

- How can we measure whether our model converged?
- We are building a model for translation and we want it to perform well when translating unseen sentences.

Convergence of EM

Starting with the uniform probabilities:

$$p(\mathit{the\ book} | \mathit{das\ Buch}) = \frac{\epsilon}{2^2}(0.25 + 0.25)(0.25 + 0.25) = 0.0625\epsilon$$

Convergence of EM

After the first iteration:

$$t(e|f) = \begin{cases} 0.5 & \text{if } e = \text{the and } f = \text{das} \\ 0.25 & \text{if } e = \text{the and } f = \text{buch} \\ 0.25 & \text{if } e = \text{book and } f = \text{das} \\ 0.5 & \text{if } e = \text{book and } f = \text{buch} \end{cases}$$

$$p(the\ book|das\ Buch) = \frac{\epsilon}{2^2}(0.5 + 0.25)(0.25 + 0.5) = 0.140625\epsilon$$

Convergence of EM

This will ultimately converge to:

$$t(e|f) = \begin{cases} 1 & \text{if } e = \text{the and } f = \text{das} \\ 0 & \text{if } e = \text{the and } f = \text{buch} \\ 0 & \text{if } e = \text{book and } f = \text{das} \\ 1 & \text{if } e = \text{book and } f = \text{buch} \end{cases}$$

$$p(\textit{the book}|\textit{das Buch}) = \frac{\epsilon}{2^2}(1+0)(0+1) = 0.25\epsilon$$

Perplexity

- How well does the model fit the data?
- Perplexity: derived from probability of the training data according to the model

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

Perplexity

- Example ($\epsilon=1$)

	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

- The perplexity is guaranteed to decrease or stay the same in each iteration.
- In the IBM model 1, the EM training will eventually reach a global minimum.

Ensuring Fluent Output

- Our translation model cannot decide between small and little
- Sometime one is preferred over the other:
  - small step: 2,070,000 occurrences in the Google index
  - little step: 257,000 occurrences in the Google index
- Language model
  - estimate how likely a string is English
  - based on n-gram statistics
    - unigram: when considering a single word (e.g., small)
    - bigram: when considering a sequence of two consecutive words (e.g., small step)
    - trigram: when considering a sequence of three consecutive words (e.g., small step to)

N-gram Language Models

- We break the long sentences into smaller steps for which we can collect sufficient statistics.
- For instance, trigram models (n=3):

$$
\begin{aligned}
p(\mathbf{e}) &= p(e_1, e_2, ..., e_n) \\
&= p(e_1)p(e_2|e_1)...p(e_n|e_1, e_2, ..., e_{n-1}) \\
&\simeq p(e_1)p(e_2|e_1)...p(e_n|e_{n-2}, e_{n-1})
\end{aligned}
$$

N-gram Language Models

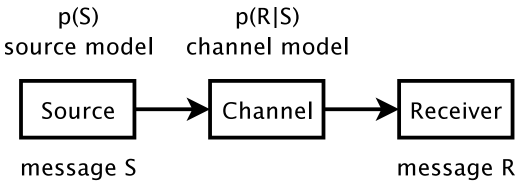
- Statistics can be computed based on both the English dataset of the parallel corpus.
- But also on any text resource in this language (English).

Noisy Channel Model

- We would like to integrate a language model.
- We look for the best translation e for the input foreign sentence f.
- Use use Bayes rule to include $p(e)$:

$$\text{argmax}_{\mathbf{e}}\ p(\mathbf{e}|\mathbf{f}) = \text{argmax}_{\mathbf{e}} \frac{p(\mathbf{f}|\mathbf{e})\ p(\mathbf{e})}{p(\mathbf{f})}$$
$$= \text{argmax}_{\mathbf{e}}\ p(\mathbf{f}|\mathbf{e})\ p(\mathbf{e})$$

Noisy Channel Model



- Applying Bayes rule also called noisy channel model
  - we observe a distorted message R (here: a foreign string **f**)
  - we have a model on how the message is distorted (here: translation model)
  - we have a model on what messages are probably (here: language model)
  - we want to recover the original message S (here: an English string **e**)

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

Reminder: IBM Model 1

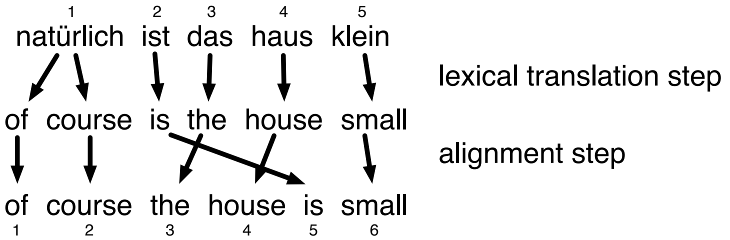
- Generative model: break up translation process into smaller steps
  - IBM Model 1 only uses lexical translation
- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with 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:

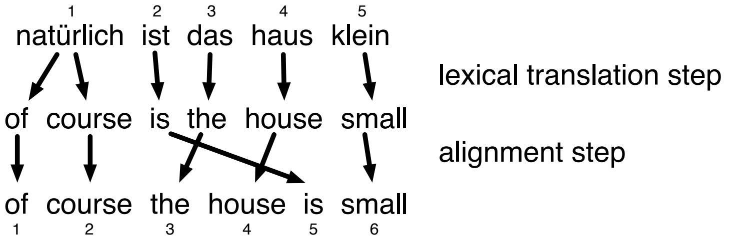


Alignment probability

- We model alignment with an **alignment probability distribution**.
- We translate foreign word at position i to English word at position j:

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

IBM Model 2 - Example



We have a two-step process:

- lexical translation step: translation probability (e.g., $t(is|ist)$)
- alignment step: alignment probability (e.g., $a(2|5, 6, 5)$)

IBM Model 2

- 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

IBM Model 2: Expectation Step

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

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

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

- We use the same trick, just like Model 1

IBM Model 2: Maximization Step

- We can compute the fractional counts for **lexical translations**:

$$c(e|f;\mathbf{e},\mathbf{f}) = \sum_{j=1}^{l_e}\sum_{i=0}^{l_f} \frac{t(e|f)a(i|j,l_e,l_f)\delta(e,e_j)\delta(f,f_i)}{\sum_{i'=0}^{l_f} t(e|f_{i'})a(i'|j,l_e,l_f)}$$

- and the counts for **alignments**:

$$c(i|j;l_e,l_f\mathbf{e},\mathbf{f}) = \frac{t(e_j|f_i)a(i|j,l_e,l_f)}{\sum_{i'=0}^{l_f} t(e|f_{i'})a(i'|j,l_e,l_f)}$$

IBM Model 2

- It is very similar to that for IBM Model 1.
- But we do not initialize the probabilities for $t(e|f)$ and $a(i|j, l_e, l_f)$ uniformly.
  - We get estimations from a few iterations of Model 1 instead.
  - Model 1 is a special case of Model 2 with $a(i|j, l_e, l_f)$ fixed to $\frac{1}{l_f+1}$.

IBM Model 3

fertility step

NULL insertion step

lexical translation step

distortion step

Fertility

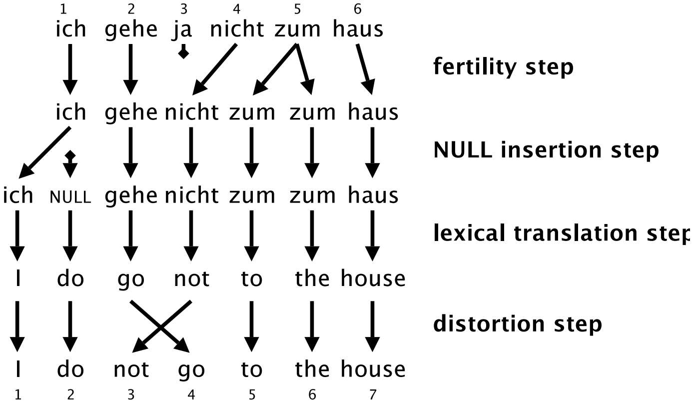
- Fertility: number of English words generated by a foreign word
- Modeled by distribution $n(\phi|f)$, in which $\phi = 0, 1, 2, \ldots$
- Example:

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

Fertility - NULL token

- Modeled by distribution $n(\phi|NULL)$
- This is modeled as a special step as inserted words depends on the sentence length.
  - probability p_1 to introduce a NULL token
  - or probability $p_0 = 1 - p_1$ **not** to introduce a NULL token

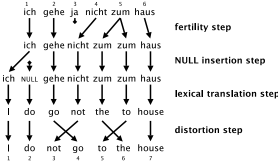
IBM Model 3 - four-step process



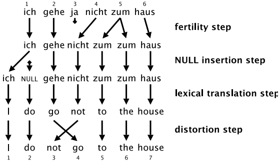
IBM Model 3 - four-step process

- Fertility: modeled by $n(\phi|f)$, e.g., $n(2|zum)$.
- NULL insertion: modeled by p_1 (e.g., NULL insertion after ich), and $p_0 = 1 - p_1$ (e.g., no NULL insertion after nicht).
- Lexical translation: modeled by $t(e|f)$ (Model 1), e.g., translating nicht into not with $p(not|nicht)$.
- Distortion: modeled by $d(j|i, l_e, l_f)$, e.g., distortion of go to gehe with $d(4|2, 7, 6)$.

Distortion instead of alignment



Same translation, same alignment, but in a different way



Distortion instead of alignment

- The alignment function (Models 1 and 2) predicts foreign input word positions conditioned to English output word positions, i.e., from output to input.
- The distortion function (Model 3) predicts output word positions based on input word positions, i.e., from input to output.

Formulation of IBM Model 3

- Fertility: each input word f_i generates ϕ_i output words according to $n(\phi_i|f_i)$.
- NULL Token insertion: its number ϕ_0 depends on the number of output words generated by the input words.
  - Each generated word may insert a NULL token.
  - Number of generated words from foreign input words: $\sum_{i=1}^{l_f} \phi_i = l_e - \phi_0$
  - Probability of generating ϕ_0 words from the NULL token: $p(\phi_0) = \binom{l_e - \phi_0}{\phi_0} p_1^{\phi_0} p_0^{l_e - 2\phi_0}$

Combining the four steps:

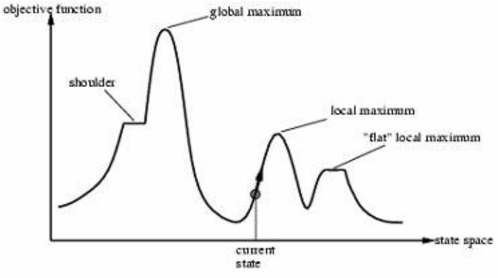
$$
\begin{aligned}
p(\mathbf{e}|\mathbf{f}) &= \sum_a p(e, a|f) \\
&= \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \binom{l_e - \phi_0}{\phi_0} p_1^{\phi_0} p_0^{l_e - 2\phi_0} \\
&\times \prod_{j=1}^{l_f} \phi_i! n(\phi_i|f_i) \\
&\times \prod_{j=1}^{l_e} t(e_j|f_{a(j)}) d(j|a(j), l_e, l_f)
\end{aligned}
$$

- This time we cannot reduce the complexity from exponential to polynomial.

Sampling the Alignment Space

- Training IBM Model 3 with the EM algorithm
  - The trick that reduces exponential complexity does not work anymore
  - → Not possible to exhaustively consider all alignments
- Two tasks:
  - Finding the most probable alignment by **hill climbing**
  - Sampling: collecting additional variations to calculate statistics

Hill climbing



http://www35.homepage.villanova.edu/abdo.achkar/csc8530/proj.htm

Hill climbing

- Finding the most probable alignment by hill climbing
  - start with initial alignment (e.g., Model 2)
  - change alignments for individual words
  - keep change if it has higher probability
  - continue until convergence

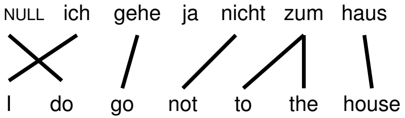
Sampling

- Collecting variations to collect statistics
  - all alignments found during **hill climbing**
  - neighboring alignments that differ by a move or a swap

- 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

The center of a cept is defined as the ceiling of the average of the output word positions for that cept.

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:
  - NULL generated words: uniform distribution
  - first word of a cept: $d_1(j - \odot_{i-1})$
  - next words of a cept: $d_{>1}(j - \pi_{i,k-1})$

Word Classes

- Some words tend to get reordered during translation:
  - For instance, adjective-noun inversion for French/Spanish/Portuguese to English/German, e.g., bruxa verde to green witch.

Word Classes

- Some words may trigger reordering → condition reordering on words

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

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

- Sparse data concerns → cluster words into classes

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

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

- $\mathcal{A}(f)$ and $\mathcal{B}(e)$ functions map words to their word classes.
- Word classes can be part-of-speech tags or derived automatically by clustering words to a fixed number of classes.

Training Model 4

- We also use the hill climbing strategy (just like in Model 3)
- But due to the complexity of the model (distortion, cepts), a hill-climbing method based on Model 3 probabilities is proposed.

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
  - → probability mass is wasted
- IBM Model 5 fixes deficiency by keeping track of **vacant word positions** (available positions)

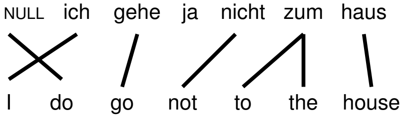
Formalization of IBM Model 5

- Number of vacancies in the English output interval $[1; j]$: v_j
- Distortion probabilities:

$$\text{for initial word in cept:} \quad d_1(v_j | \mathcal{B}(e_j), v_{\odot_{i-1}}, v_{max})$$
$$\text{for additional words:} \quad d_{>1}(v_j - v_{\pi_{i,k-1}} | \mathcal{B}(e_j), v_{max'})$$

- Maximum number of available vacancies: v_{max}
- Number of vacancies at the position of the previously placed English word: $v_{\pi_{i,k-1}}$

IBM Model 5: Example



cept		vacancies							parameters for d_1			
$f_{[i]}$	$\pi_{i,k}$	v_1 I	v_2 do	v_3 not	v_4 go	v_5 to	v_6 the	v_7 house	j	v_j	v_{max}	$v_{\odot_{i-1}}$
NULL	$\pi_{0,1}$	1	**2**	3	4	5	6	7	2	-	-	-
ich	$\pi_{1,1}$	**1**	-	2	3	4	5	6	1	1	6	0
gehe	$\pi_{2,1}$	-	-	1	**2**	3	4	5	4	2	5	0
nicht	$\pi_{3,1}$	-	-	**1**	-	2	3	4	3	1	4	1
zum	$\pi_{4,1}$	-	-	-	-	**1**	2	-	5	1	2	0
	$\pi_{4,2}$	-	-	-	-	-	**1**	2	6	-	-	-
haus	$\pi_{5,1}$	-	-	-	-	-	-	**1**	7	1	1	0

Conclusion

- IBM Models were the pioneering models in statistical machine translation
- Introduced important concepts
  - generative model
  - EM training
  - reordering models
- No longer state of the art models for machine translation...
- ... but still in common use for word alignment (e.g., GIZA++ toolkit)

Summary

- Expectation Maximization (EM) Algorithm
- Noisy Channel Model
- 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

Suggested reading

- Statistical Machine Translation, Philipp Koehn (section 4.1-4.4).