Machine Translation

CL1: Jordan Boyd-Graber

University of Maryland

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COLLEGE OF INFORMATION STUDIES

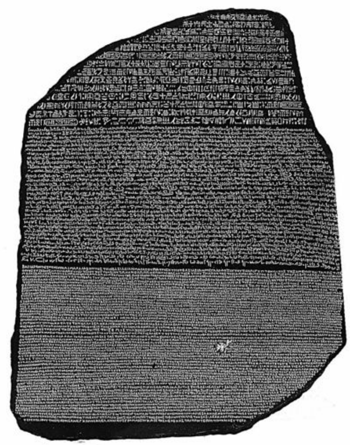
Adapted from material by Philipp Koehn

Roadmap

- Introduction to MT
- Components of MT system
- Word-based models
- Beyond word-based models

Outline

What unlocks translations?



- Humans need parallel text to understand new languages when no speakers are round
- Rosetta stone: allowed us understand to Egyptian
- Computers need the same information

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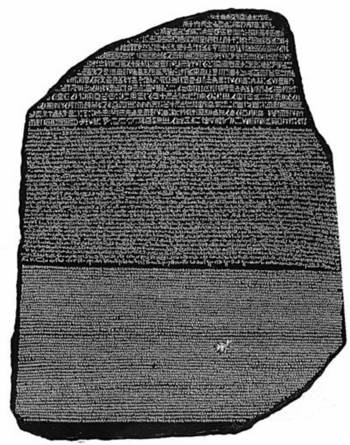
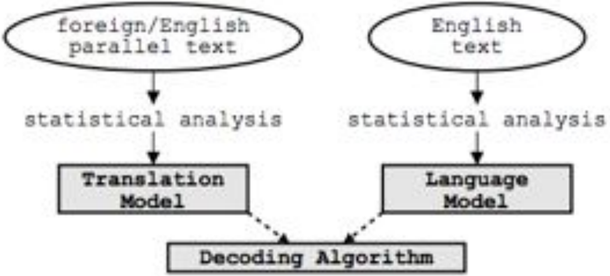


- Humans need parallel text to understand new languages when no speakers are round
- Rosetta stone: allowed us understand to Egyptian
- Computers need the same information
- Where do we get them?
  - Some governments require translations (Canada, EU, Hong Kong)
  - Newspapers
  - Internet

Pieces of Machine Translation System



Terminology

- Source language: $\mathbf{f}$ (foreign)
- Target language: $\mathbf{e}$ (english)

Outline

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

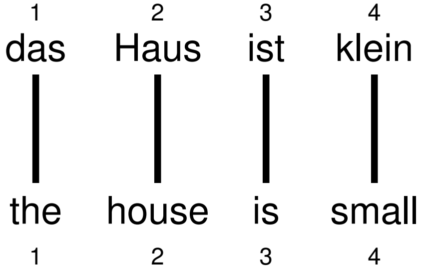
Estimate Translation Probabilities

Maximum likelihood estimation

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

Alignment

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



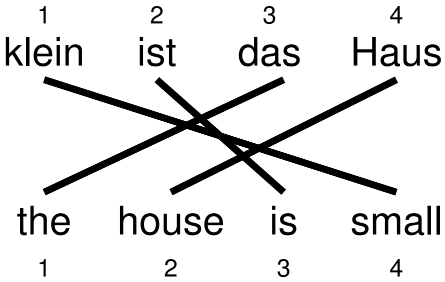
- Word positions are numbered 1–4

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 $a : i \to j$
- Example

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

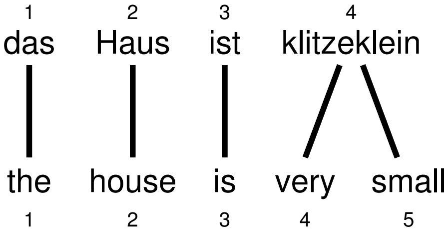
Words may be reordered during translation



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

One-to-Many Translation

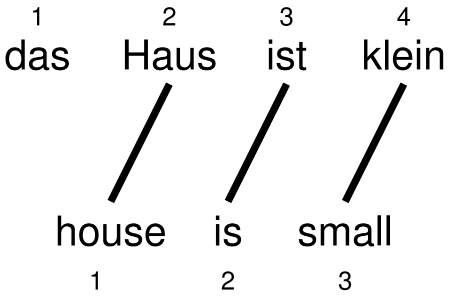
A source word may translate into multiple target words



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

Dropping Words

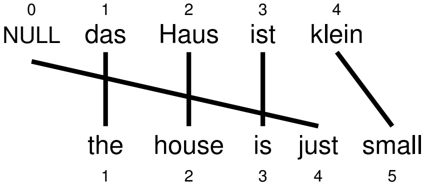
Words may be dropped when translated
(German article das is dropped)



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

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



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

A family of lexical translation models

- A family translation models
- Uncreatively named: Model 1, Model 2, . . .
- Foundation of all modern translation algorithms
- First up: Model 1

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

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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
family	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

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

Outline

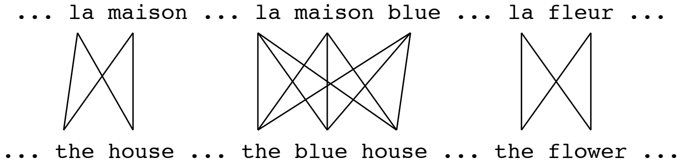
Learning Lexical Translation Models

- 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

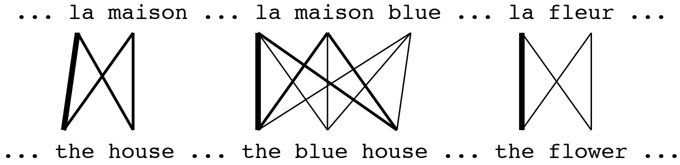
- Incomplete data
  - if we had *complete data*, would could estimate *model*
  - if we had *model*, we could fill in the *gaps in the data*
- Expectation Maximization (EM) in a nutshell
  1. initialize model parameters (e.g. uniform)
  2. assign probabilities to the missing data
  3. estimate model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

EM Algorithm



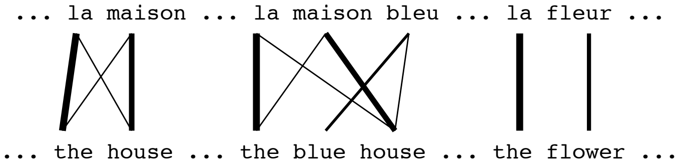
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM Algorithm



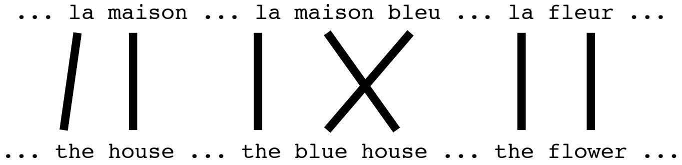
- After one iteration
- Alignments, e.g., between la and the are more likely

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 ...

$$
\begin{aligned}
p(\text{la} \mid \text{the}) &= 0.453 \\
p(\text{le} \mid \text{the}) &= 0.334 \\
p(\text{maison} \mid \text{house}) &= 0.876 \\
p(\text{bleu} \mid \text{blue}) &= 0.563 \\
&\ldots
\end{aligned}
$$

- 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

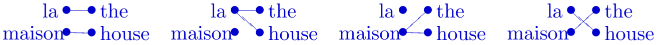
IBM Model 1 and EM

- **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 $p(\mathbf{e}|\mathbf{f})$

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

IBM Model 1 and EM: Expectation Step

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

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

IBM Model 1 and EM: Expectation Step

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

$$p(\mathbf{e}|\mathbf{f}) = \sum_a p(\mathbf{e}, a|\mathbf{f})$$
$$= \sum_{a(1)=0}^{l_f} \cdots \sum_{a(l_e)=0}^{l_f}$$

IBM Model 1 and EM: Expectation Step

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

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

IBM Model 1 and EM: Expectation Step

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

- Note the algebra trick in the last line
  - removes the need for an exponential number of products
  - this makes IBM Model 1 estimation tractable

IBM Model 1 and EM: Expectation Step

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

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The Trick

(case $l_e = l_f = 2$)

$$
\begin{aligned}
\sum_{a(1)=0}^{2} \sum_{a(2)=0}^{2} &= \frac{\epsilon}{3^2} \prod_{j=1}^{2} t(e_j | f_{a(j)}) = \\
&= t(e_1|f_0)\ t(e_2|f_0) + t(e_1|f_0)\ t(e_2|f_1) + t(e_1|f_0)\ t(e_2|f_2) + \\
&\quad + t(e_1|f_1)\ t(e_2|f_0) + t(e_1|f_1)\ t(e_2|f_1) + t(e_1|f_1)\ t(e_2|f_2) + \\
&\quad + t(e_1|f_2)\ t(e_2|f_0) + t(e_1|f_2)\ t(e_2|f_1) + t(e_1|f_2)\ t(e_2|f_2) = \\
&= t(e_1|f_0)\,(t(e_2|f_0) + t(e_2|f_1) + t(e_2|f_2)) + \\
&\quad + t(e_1|f_1)\,(t(e_2|f_1) + t(e_2|f_1) + t(e_2|f_2)) + \\
&\quad + t(e_1|f_2)\,(t(e_2|f_2) + t(e_2|f_1) + t(e_2|f_2)) = \\
&= (t(e_1|f_0) + t(e_1|f_1) + t(e_1|f_2))\,(t(e_2|f_2) + t(e_2|f_1) + t(e_2|f_2))
\end{aligned}
$$

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:

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

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IBM Model 1 and EM: Maximization Step

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

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

IBM Model 1 and EM: Pseudocode

```
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)
        {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)
```

```
while not converged (cont.) do
    {estimate probabilities}
    for all foreign words f do
        for all English words e do
            t(e|f) = count(e|f) / total(f)
```

IBM Model 1 and EM: Pseudocode

initialize $t(e|f)$ uniformly
while not converged **do**
  {initialize}
  $\text{count}(e|f) = 0$ **for all** e, f
  $\text{total}(f) = 0$ **for all** f
  for all sentence pairs (**e**,**f**) **do**
    {compute normalization}
    for all words e in **e** **do**
      $\text{s-total}(e) = 0$
      for all words f in **f** **do**
        $\text{s-total}(e) \mathrel{+}= t(e|f)$
    {collect counts}
    for all words e in **e** **do**
      for all words f in **f** **do**
        $\text{count}(e|f) \mathrel{+}= \frac{t(e|f)}{\text{s-total}(e)}$
        $\text{total}(f) \mathrel{+}= \frac{t(e|f)}{\text{s-total}(e)}$

while not converged (cont.) **do**
  {estimate probabilities}
  for all foreign words f **do**
    for all English words e **do**
      $t(e|f) = \frac{\text{count}(e|f)}{\text{total}(f)}$

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while not converged **do**
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  count$(e|f) = 0$ **for all** e, f
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  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) += $t(e|f)$
    {collect counts}
    for all words e in **e** **do**
      for all words f in **f** **do**
        count$(e|f)$ += $\frac{t(e|f)}{\text{s-total}(e)}$
        total(f) += $\frac{t(e|f)}{\text{s-total}(e)}$

while not converged (cont.) **do**
  {estimate probabilities}
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while not converged (cont.) **do**
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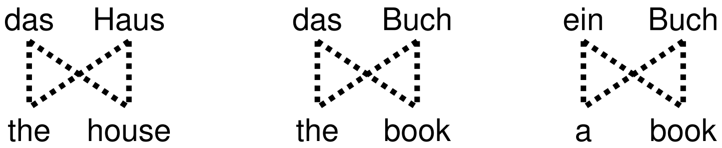
Convergence



e	f	initial	1st it.	2nd it.	...	final
the	das	0.25	0.5	0.6364	...	1
book	das	0.25	0.25	0.1818	...	0
house	das	0.25	0.25	0.1818	...	0
the	buch	0.25	0.25	0.1818	...	0
book	buch	0.25	0.5	0.6364	...	1
a	buch	0.25	0.25	0.1818	...	0
book	ein	0.25	0.5	0.4286	...	0
a	ein	0.25	0.5	0.5714	...	1
the	haus	0.25	0.5	0.4286	...	0
house	haus	0.25	0.5	0.5714	...	1

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

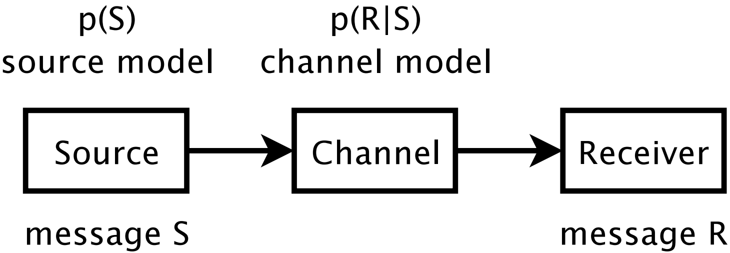
$$
\begin{aligned}
p(\mathbf{e}) &= p(e_1, e_2, \ldots, e_n) \\
&= p(e_1)p(e_2|e_1)\ldots p(e_n|e_1, e_2, \ldots, e_{n-1}) \\
&\simeq p(e_1)p(e_2|e_1)\ldots p(e_n|e_{n-2}, e_{n-1})
\end{aligned}
$$

Noisy Channel Model

- We would like to integrate a language model
- Bayes rule

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

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**)

Outline

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

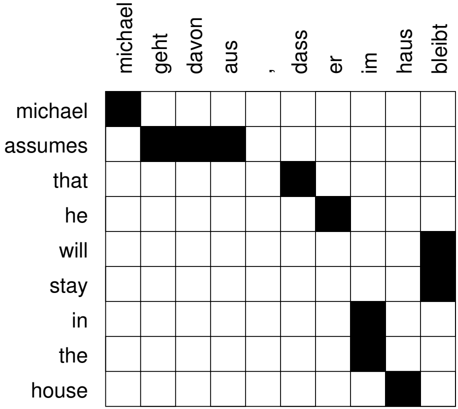
- Only IBM Model 1 has global maximum
  - training of a higher IBM model builds on previous model
- Compuationally biggest change in Model 3
  - trick to simplify estimation does not work anymore
  - $\rightarrow$ exhaustive count collection becomes computationally too expensive
  - sampling over high probability alignments is used instead

Legacy

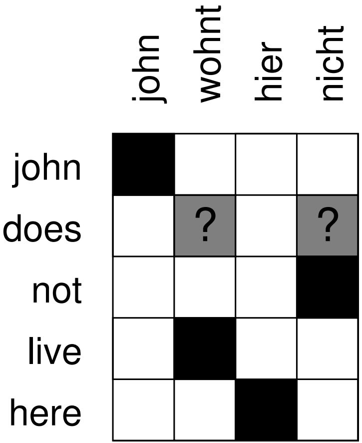
- IBM Models were the pioneering models in statistical machine translation
- Introduced important concepts
    - generative model
    - EM training
    - reordering models
- Only used for niche applications as translation model
- ...but still in common use for word alignment (e.g., GIZA++ toolkit)

Word Alignment

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

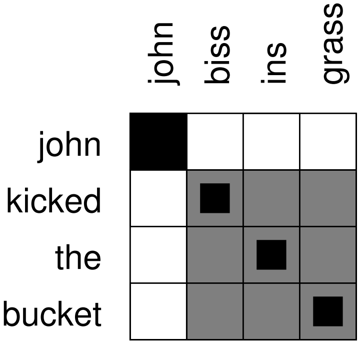


Word Alignment?



Is the English word does aligned to
the German wohnt (verb) or nicht (negation) or neither?

Word Alignment?



How do the idioms kicked the bucket and biss ins grass match up? Outside this exceptional context, bucket is never a good translation for grass

Summary

- Lexical translation
- Alignment
- Expectation Maximization (EM) Algorithm
- Noisy Channel Model
- IBM Models
- Word Alignment

Summary

- Lexical translation
- Alignment
- Expectation Maximization (EM) Algorithm
- Noisy Channel Model
- IBM Models
- Word Alignment
- Much more in CL2!