Natural Language Processing

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anoopsarkar.github.io/nlp-class

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Part 1: Generative Models for Word Alignment
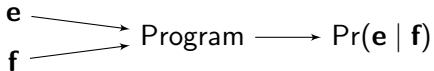
Statistical Machine Translation

Generative Model of Word Alignment

Statistical Machine Translation

Noisy Channel Model

$$\mathbf{e}^* \;=\; \arg\max_{\mathbf{e}} \; \underbrace{\Pr(\mathbf{e})}_{\textbf{Language Model}} \;\cdot\; \underbrace{\Pr(\mathbf{f} \mid \mathbf{e})}_{\textbf{Alignment Model}}$$

Alignment Task

$\mathbf{e}$ ⟶
⟶ Program ⟶ $\Pr(\mathbf{e} \mid \mathbf{f})$
$\mathbf{f}$ ⟶

Training Data

▶ **Alignment Model**: learn a mapping between $\mathbf{f}$ and $\mathbf{e}$.
Training data: lots of translation pairs between $\mathbf{f}$ and $\mathbf{e}$.

Statistical Machine Translation

The IBM Models

- ▶ The first statistical machine translation models were developed at IBM Research (Yorktown Heights, NY) in the 1980s

- ▶ The models were published in 1993:
  Brown et. al. The Mathematics of Statistical Machine Translation.
  Computational Linguistics. 1993.
  http://aclweb.org/anthology/J/J93/J93-2003.pdf

- ▶ These models are the basic SMT models, called:
  IBM Model 1, IBM Model 2, IBM Model 3, IBM Model 4, IBM Model 5
  as they were called in the 1993 paper.

- ▶ We use $\mathbf{e}$ and $\mathbf{f}$ in the equations in honor of their system which translated from French to English.
  Trained on the Canadian Hansards (Parliament Proceedings)

Generative Model of Word Alignment
    Word Alignments: IBM Model 3
    Word Alignments: IBM Model 1
    Finding the best alignment: IBM Model 1
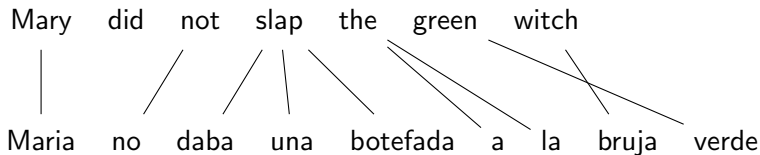   Learning Parameters: IBM Model 1
    IBM Model 2
    Back to IBM Model 3

Generative Model of Word Alignment

- English **e**: Mary did not slap the green witch
- "French" **f**: Maria no daba una botefada a la bruja verde
- Alignment **a**: $\{1, 3, 4, 4, 4, 5, 5, 7, 6\}$
  e.g. $(f_8, e_{a_8}) = (f_8, e_7) = $ (bruja, witch)

Visualizing alignment **a**

Generative Model of Word Alignment

Data Set

- Data set $\mathcal{D}$ of N sentences:
$$\mathcal{D} = \{(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}), \ldots, (\mathbf{f}^{(N)}, \mathbf{e}^{(N)})\}$$

- French $\mathbf{f}$: $(f_1, f_2, \ldots, f_I)$
- English $\mathbf{e}$: $(e_1, e_2, \ldots, e_J)$
- Alignment $\mathbf{a}$: $(a_1, a_2, \ldots, a_I)$
- $\text{length}(\mathbf{f}) = \text{length}(\mathbf{a}) = I$

Generative Model of Word Alignment

Find the best alignment for each translation pair

$$\mathbf{a}^* = \arg\max_{\mathbf{a}} \Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e})$$

Alignment probability

$$
\begin{aligned}
\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) &= \frac{\Pr(\mathbf{f}, \mathbf{a}, \mathbf{e})}{\Pr(\mathbf{f}, \mathbf{e})} \\
&= \frac{\Pr(\mathbf{e}) \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})} \\
&= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} \\
&= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}
\end{aligned}
$$

Generative Model of Word Alignment
  Word Alignments: IBM Model 3
  Word Alignments: IBM Model 1
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  Learning Parameters: IBM Model 1
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  Back to IBM Model 3

Word Alignments: IBM Model 3

Generative "story" for $P(\mathbf{f}, \mathbf{a} \mid \mathbf{e})$

Mary	did	not	slap	the	green	witch	
Mary	not	slap	slap	slap	the	the	green	witch	(fertility)
Maria	no	daba	una	botefada	a	la	verde	bruja	(translate)
Maria	no	daba	una	botefada	a	la	bruja	verde	(reorder)

Word Alignments: IBM Model 3

Fertility parameter

$$n(\phi_j \mid e_j) : n(3 \mid slap); n(0 \mid did)$$

Translation parameter

$$t(f_i \mid e_{a_i}) : t(bruja \mid witch)$$

Distortion parameter

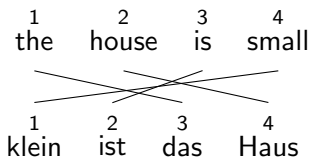$$d(f_{pos} = i \mid e_{pos} = j, I, J) : d(8 \mid 7, 9, 7)$$

Word Alignments: IBM Model 3

Generative model for $P(\mathbf{f}, \mathbf{a} \mid \mathbf{e})$

$$
\begin{aligned}
P(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) &= \prod_{i=1}^{I} n(\phi_{a_i} \mid e_{a_i}) \\
&\times \quad t(f_i \mid e_{a_i}) \\
&\times \quad d(i \mid a_i, I, J)
\end{aligned}
$$

Word Alignments: IBM Model 3

Sentence pair with alignment $\mathbf{a} = (4, 3, 1, 2)$

If we know the parameter values we can easily compute the probability of this aligned sentence pair.

$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) =$

$$
\begin{array}{llll}
n(1 \mid \text{the}) & \times & t(\text{das} \mid \text{the}) & \times & d(3 \mid 1, 4, 4) \times \\
n(1 \mid \text{house}) & \times & t(\text{Haus} \mid \text{house}) & \times & d(4 \mid 2, 4, 4) \times \\
n(1 \mid \text{is}) & \times & t(\text{ist} \mid \text{is}) & \times & d(2 \mid 3, 4, 4) \times \\
n(1 \mid \text{small}) & \times & t(\text{klein} \mid \text{small}) & \times & d(1 \mid 4, 4, 4)
\end{array}
$$

Word Alignments: IBM Model 3

Parameter Estimation

- What is $n(1 \mid \text{very}) = $? and $n(0 \mid \text{very}) = $?
- What is $t(\text{Haus} \mid \text{house}) = $? and $t(\text{klein} \mid \text{small}) = $?
- What is $d(1 \mid 4, 4, 4) = $? and $d(1 \mid 1, 4, 4) = $?

Word Alignments: IBM Model 3

1	2	3	4
the	house	is	small

1	2	3	4
klein	ist	das	Haus

1	2	3	4
the	building	is	small

1	2	3	4
das	Haus	ist	klein

1	2	3	4	5
the	home	is	very	small

1	2	3	4
das	Haus	ist	klitzeklein

1	2	3	4
the	house	is	small

1	2	3	4	5
das	Haus	ist	ja	klein

Parameter Estimation: Sum over all alignments

$$\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \sum_{\mathbf{a}} \prod_{i=1}^{I} n(\phi_{a_i} \mid e_{a_i}) \times t(f_i \mid e_{a_i}) \times d(i \mid a_i, I, J)$$

Word Alignments: IBM Model 3

Summary

- If we know the parameter values we can easily compute the probability $\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e})$ given an aligned sentence pair

- If we are given a corpus of sentence pairs with alignments we can easily learn the parameter values by using relative frequencies.

- If we do not know the alignments then perhaps we can produce all possible alignments each with a certain probability?

IBM Model 3 is too hard: Let us try learning only $t(f_i \mid e_{a_i})$

$$\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \sum_{\mathbf{a}} \prod_{i=1}^{l} n(\phi_{a_i} \mid e_{a_i}) \times t(f_i \mid e_{a_i}) \times d(i \mid a_i, I, J)$$

Generative Model of Word Alignment
    Word Alignments: IBM Model 3
    Word Alignments: IBM Model 1
    Finding the best alignment: IBM Model 1
    Learning Parameters: IBM Model 1
    IBM Model 2
    Back to IBM Model 3

Word Alignments: IBM Model 1

## Alignment probability

$$\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}$$

Example alignment

1	2	3	4
the	house	is	small
|	/	|	|
1	2	3	4
das	Haus	ist	klein

$$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \prod_{i=1}^{I} t(f_i \mid e_{a_i})$$

$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) =$
  $t(\text{das} \mid \text{the}) \times$
  $t(\text{Haus} \mid \text{house}) \times$
  $t(\text{ist} \mid \text{is}) \times$
  $t(\text{klein} \mid \text{small})$

Word Alignments: IBM Model 1

Generative "story" for Model 1

the   house   is   small

das   Haus   ist   klein   (translate)

$$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \prod_{i=1}^{I} t(f_i \mid e_{a_i})$$

Generative Model of Word Alignment
    Word Alignments: IBM Model 3
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Finding the best word alignment: IBM Model 1

Compute the arg max word alignment

$$\hat{\mathbf{a}} = \arg \max_{\mathbf{a}} \Pr(\mathbf{a} \mid \mathbf{e}, \mathbf{f})$$
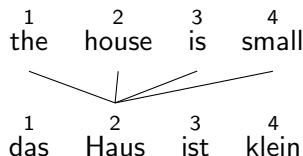
▶ For each f_i in $(f_1, \ldots, f_I)$ build $\mathbf{a} = (\hat{a_1}, \ldots, \hat{a_I})$

$$\hat{a_i} = \arg \max_{a_i} t(f_i \mid e_{a_i})$$

Many to one alignment ✓
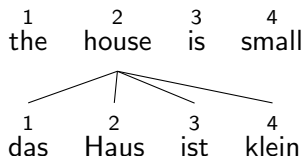
One to many alignment ✗

Generative Model of Word Alignment
   Word Alignments: IBM Model 3
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   Learning Parameters: IBM Model 1
   IBM Model 2
   Back to IBM Model 3

Learning parameters [from P.Koehn SMT book slides]

- ► 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*

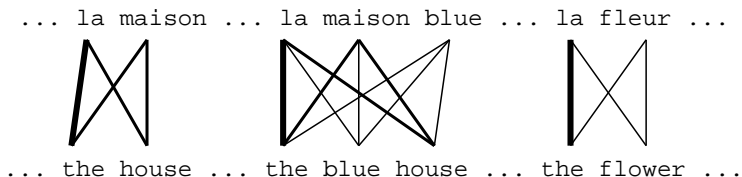# EM Algorithm[from P.Koehn SMT book slides]

- ▶ Incomplete data
    - ▶ if we had *complete data*, we 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
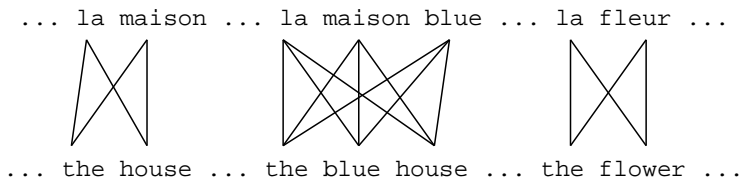
- Initial step: all alignments equally likely
- Model learns that, e.g., *la* is often aligned with *the*

```
... la maison ... la maison blue ... la fleur ...

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

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

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

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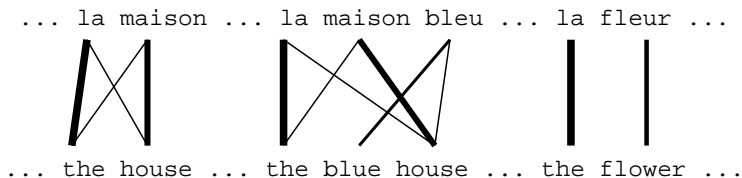
- ► After another iteration
- ► It becomes apparent that alignments, e.g., between *fleur* and *flower* are more likely (pigeon hole principle)

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

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

- ► Convergence
- ► Inherent hidden structure revealed by EM

```
... 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 the EM Algorithm[from P.Koehn SMT book slides]

- ▶ 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 the EM Algorithm[from P.Koehn SMT book slides]

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

Word Alignments: IBM Model 1

Alignment probability

$$
\begin{aligned}
\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) &= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} \\
&= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})} \\
&= \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i})}{\sum_{\mathbf{a}} \prod_{i=1}^{I} t(f_i \mid e_{a_i})}
\end{aligned}
$$

Computing the denominator

▶ The denominator above is summing over J^I alignments

▶ An interlude on how compute the denominator faster ...

Word Alignments: IBM Model 1

Sum over all alignments

$$\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) \;=\; \sum_{a_1=1}^{J} \sum_{a_2=1}^{J} \cdots \sum_{a_I=1}^{J} \prod_{i=1}^{I} t(f_i \mid e_{a_i})$$

Assume (f_1, f_2, f_3) and (e_1, e_2)

$$\sum_{a_1=1}^{2} \sum_{a_2=1}^{2} \sum_{a_3=1}^{2} t(f_1 \mid e_{a_1}) \times t(f_2 \mid e_{a_2}) \times t(f_3 \mid e_{a_3})$$

Word Alignments: IBM Model 1

Assume (f_1, f_2, f_3) and (e_1, e_2): $I = 3$ and $J = 2$

$$\sum_{a_1=1}^{2} \sum_{a_2=1}^{2} \sum_{a_3=1}^{2} t(f_1 \mid e_{a_1}) \times t(f_2 \mid e_{a_2}) \times t(f_3 \mid e_{a_3})$$

$J^I = 2^3$ terms to be added:

$$
\begin{array}{ccccc}
t(f_1 \mid e_1) & \times & t(f_2 \mid e_1) & \times & t(f_3 \mid e_1) & + \\
t(f_1 \mid e_1) & \times & t(f_2 \mid e_1) & \times & t(f_3 \mid e_2) & + \\
t(f_1 \mid e_1) & \times & t(f_2 \mid e_2) & \times & t(f_3 \mid e_1) & + \\
t(f_1 \mid e_1) & \times & t(f_2 \mid e_2) & \times & t(f_3 \mid e_2) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_1) & \times & t(f_3 \mid e_1) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_1) & \times & t(f_3 \mid e_2) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_2) & \times & t(f_3 \mid e_1) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_2) & \times & t(f_3 \mid e_2) &
\end{array}
$$

Word Alignments: IBM Model 1

Factor the terms:

$$(t(f_1 \mid e_1) \times t(f_2 \mid e_1)) \quad \times \quad (t(f_3 \mid e_1) + t(f_3 \mid e_2)) \quad +$$
$$(t(f_1 \mid e_1) \times t(f_2 \mid e_2)) \quad \times \quad (t(f_3 \mid e_1) + t(f_3 \mid e_2)) \quad +$$
$$(t(f_1 \mid e_2) \times t(f_2 \mid e_1)) \quad \times \quad (t(f_3 \mid e_1) + t(f_3 \mid e_2)) \quad +$$
$$(t(f_1 \mid e_2) \times t(f_2 \mid e_2)) \quad \times \quad (t(f_3 \mid e_1) + t(f_3 \mid e_2))$$

$$(t(f_3 \mid e_1) + t(f_3 \mid e_2)) \begin{pmatrix} t(f_1 \mid e_1) & \times & t(f_2 \mid e_1) & + \\ t(f_1 \mid e_1) & \times & t(f_2 \mid e_2) & + \\ t(f_1 \mid e_2) & \times & t(f_2 \mid e_1) & + \\ t(f_1 \mid e_2) & \times & t(f_2 \mid e_2) \end{pmatrix}$$

$$(t(f_3 \mid e_1) + t(f_3 \mid e_2)) \begin{pmatrix} t(f_1 \mid e_1) & \times & (t(f_2 \mid e_1) + t(f_2 \mid e_2)) & + \\ t(f_1 \mid e_2) & \times & (t(f_2 \mid e_1) + t(f_2 \mid e_2)) \end{pmatrix}$$

Word Alignments: IBM Model 1

Assume (f_1, f_2, f_3) and (e_1, e_2): $I = 3$ and $J = 2$

$$\prod_{i=1}^{3} \sum_{a_i=1}^{2} t(f_i \mid e_{a_i})$$

$I \times J = 2 \times 3$ terms to be added:

$$
\begin{array}{lcll}
(t(f_1 \mid e_1) & + & t(f_1 \mid e_2)) & \times \\
(t(f_2 \mid e_1) & + & t(f_2 \mid e_2)) & \times \\
(t(f_3 \mid e_1) & + & t(f_3 \mid e_2)) &
\end{array}
$$

Word Alignments: IBM Model 1

Alignment probability

$$
\begin{aligned}
\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) &= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} \\
&= \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i})}{\sum_{\mathbf{a}} \prod_{i=1}^{I} t(f_i \mid e_{a_i})} \\
&= \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i})}{\prod_{i=1}^{I} \sum_{j=1}^{J} t(f_i \mid e_j)}
\end{aligned}
$$

Learning Parameters: IBM Model 1

1	2		1	2		1	2
the	house		the	book		a	book

1	2		1	2		1	2
das	Haus		das	Buch		ein	Buch

Learning parameters $t(f|e)$ when alignments are known

$$t(das \mid the) = \frac{c(das, the)}{\sum_f c(f, the)} \quad t(house \mid Haus) = \frac{c(Haus, house)}{\sum_f c(f, house)}$$
$$t(ein \mid a) = \frac{c(ein, a)}{\sum_f c(f, a)} \quad t(Buch \mid book) = \frac{c(Buch, book)}{\sum_f c(f, book)}$$

$$t(f|e) = \sum_{s=1}^{N} \sum_{f \to e \in \mathbf{f}^{(s)}, \mathbf{e}^{(s)}} \frac{c(f, e)}{\sum_f c(f, e)}$$

Learning Parameters: IBM Model 1

| 1 | 2 | | 1 | 2 | | 1 | 2 |
| the | house | | the | book | | a | book |

| 1 | 2 | | 1 | 2 | | 1 | 2 |
| das | Haus | | das | Buch | | ein | Buch |

Learning parameters $t(f|e)$ when alignments are *unknown*

| 1 | 2 | | 1 | 2 | | 1 | 2 | | 1 | 2 |
| the | house | | the | house | | the | house | | the | house |

| 1 | 2 | | 1 | 2 | | 1 | 2 | | 1 | 2 |
| das | Haus | | das | Haus | | das | Haus | | das | Haus |

Also list alignments for *(the book, das Buch)* and *(a book, ein Buch)*

Learning Parameters: IBM Model 1

Initialize $t^0(f|e)$

$t(Haus \mid the)$	=	0.25	$t(das \mid house)$	=	0.5
$t(das \mid the)$	=	0.5	$t(Haus \mid house)$	=	0.5
$t(Buch \mid the)$	=	0.25	$t(Buch \mid house)$	=	0.0

Compute posterior for each alignment
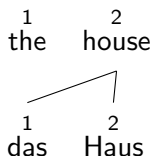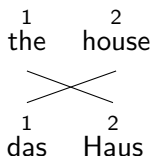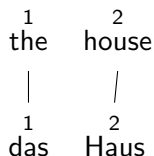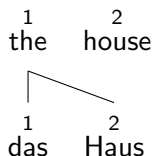
$$\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} = \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i})}{\prod_{i=1}^{I} \sum_{j=1}^{J} t(f_i \mid e_j)}$$

Learning Parameters: IBM Model 1

Initialize $t^0(f|e)$

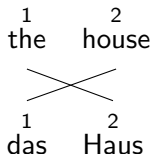|					
$t(Haus \mid the)$	=	0.25	$t(das \mid house)$	=	0.5
$t(das \mid the)$	=	0.5	$t(Haus \mid house)$	=	0.5
$t(Buch \mid the)$	=	0.25	$t(Buch \mid house)$	=	0.0

Compute $\Pr(\mathbf{a}, \mathbf{f} \mid \mathbf{e})$ for each alignment
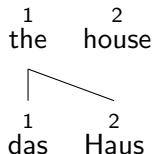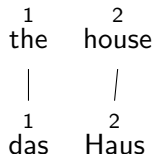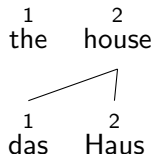
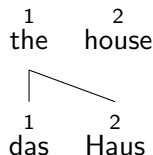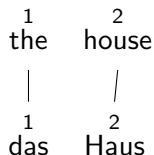| 0.5×0.25	0.5×0.5	0.25×0.5	0.5×0.5
0.125	0.25	0.125	0.25

Learning Parameters: IBM Model 1

Compute $\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{a}, \mathbf{f} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})}$

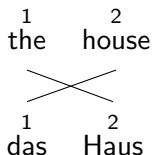$\Pr(\mathbf{f} \mid \mathbf{e}) = 0.125 + 0.25 + 0.125 + 0.25 = 0.75$
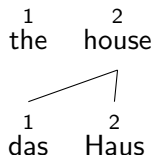

$$\frac{0.125}{0.75} \qquad \frac{0.25}{0.75} \qquad \frac{0.125}{0.75} \qquad \frac{0.25}{0.75}$$
$$0.167 \qquad\qquad 0.334 \qquad\qquad 0.167 \qquad\qquad 0.334$$

Compute fractional counts $c(f, e)$

$c(Haus, the)$	$=$	$0.125 + 0.125$	$c(das, house)$	$= 0.125 + 0.25$
$c(das, the)$	$=$	$0.125 + 0.25$	$c(Haus, house)$	$= 0.25 + 0.25$
$c(Buch, the)$	$=$	0.0	$c(Buch, house)$	$= 0.0$

Learning Parameters: IBM Model 1
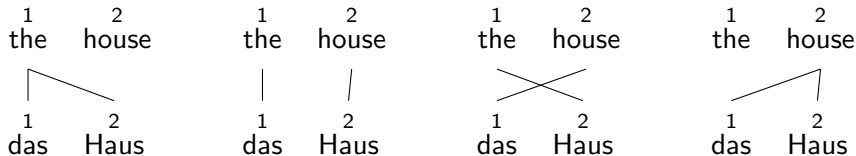
$$\Pr(\mathbf{f} \mid \mathbf{e}) = 0.125 + 0.25 + 0.125 + 0.25 = 0.75$$

Expectation step: expected counts $g(f, e)$

$$g(das, the) = \frac{0.125+0.25}{0.75} \qquad g(das, house) = \frac{0.125+0.25}{0.75}$$
$$g(Haus, the) = \frac{0.125+0.125}{0.75} \qquad g(Haus, house) = \frac{0.25+0.25}{0.75}$$
$$g(Buch, the) = 0.0 \qquad\qquad g(Buch, house) = 0.0$$

Maximization step: get new $t^{(1)}(f \mid e) = \frac{g(f,e)}{\sum_f g(f,e)}$

Learning Parameters: IBM Model 1

Expectation step: expected counts $g(f, e)$

$g(das, the)$	=	0.5	$g(das, house)$	=	0.5
$g(Haus, the)$	=	0.334	$g(Haus, house)$	=	0.667
$g(Buch, the)$	=	0.0	$g(Buch, house)$	=	0.0
total	=	0.834	**total**	=	1.167

Maximization step: get new $t^{(1)}(f \mid e) = \frac{g(f,e)}{\sum_f g(f,e)}$

$t(Haus \mid the)$	=	0.4	$t(das \mid house)$	=	0.43
$t(das, \mid the)$	=	0.6	$t(Haus \mid house)$	=	0.57
$t(Buch \mid the)$	=	0.0	$t(Buch \mid house)$	=	0.0

Keep iterating: Compute $t^{(0)}, t^{(1)}, t^{(2)}, \dots$ until convergence

Parameter Estimation: IBM Model 1

EM learns the parameters $t(\cdot \mid \cdot)$ that maximizes the log-likelihood of the training data:

$$\arg \max_t L(t) = \arg \max_t \sum_s \log \Pr(\mathbf{f}^{(s)} \mid \mathbf{e}^{(s)}, t)$$

- Start with an initial estimate t_0
- Modify it iteratively to get $t_1, t_2, \ldots$
- Re-estimate t from parameters at previous time step t_{-1}
- The convergence proof of EM guarantees that $L(t) \geq L(t_{-1})$
- EM converges when $L(t) - L(t_{-1})$ is zero (or almost zero).

Generative Model of Word Alignment
    Word Alignments: IBM Model 3
    Word Alignments: IBM Model 1
    Finding the best alignment: IBM Model 1
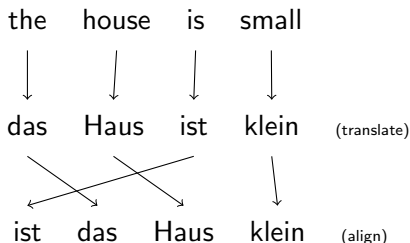   Learning Parameters: IBM Model 1
    IBM Model 2
    Back to IBM Model 3

Word Alignments: IBM Model 2

Generative "story" for Model 2

the   house   is   small

das   Haus   ist   klein   (translate)

ist   das   Haus   klein   (align)

$$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \prod_{i=1}^{I} t(f_i \mid e_{a_i}) \times a(a_i \mid i, I, J)$$
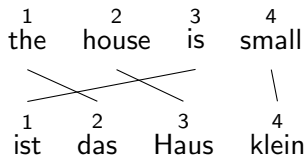
Word Alignments: IBM Model 2

Alignment probability

$$\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}$$

$$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \prod_{i=1}^{I} t(f_i \mid e_{a_i}) \times a(a_i \mid i, I, J)$$

Example alignment

$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) =$
    $t(\mathrm{das} \mid \mathrm{the}) \times a(1 \mid 2, 4, 4) \times$
    $t(\mathrm{Haus} \mid \mathrm{house}) \times a(2 \mid 3, 4, 4) \times$
    $t(\mathrm{ist} \mid \mathrm{is}) \times a(3 \mid 1, 4, 4) \times$
    $t(\mathrm{klein} \mid \mathrm{small}) \times a(4 \mid 4, 4, 4)$

Word Alignments: IBM Model 2

Alignment probability

$$
\begin{aligned}
\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) &= \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} \\
&= \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i}) \times a(a_i \mid i, I, J)}{\sum_{\mathbf{a}} \prod_{i=1}^{I} t(f_i \mid e_{a_i}) \times a(a_i \mid i, I, J)} \\
&= \frac{\prod_{i=1}^{I} t(f_i \mid e_{a_i}) \times a(a_i \mid i, I, J)}{\prod_{i=1}^{I} \sum_{j=1}^{J} t(f_i \mid e_j) \times a(j \mid i, I, J)}
\end{aligned}
$$

Word Alignments: IBM Model 2

Learning the parameters

- ▶ EM training for IBM Model 2 works the same way as IBM Model 1
- ▶ We can do the same factorization trick to efficiently learn the parameters
- ▶ The EM algorithm:
  - ▶ Initialize parameters t and a (prefer the diagonal for alignments)
  - ▶ Expectation step: We collect expected counts for t and a parameter values
  - ▶ Maximization step: add up expected counts and normalize to get new parameter values
  - ▶ Repeat EM steps until convergence.

Generative Model of Word Alignment
    Word Alignments: IBM Model 3
    Word Alignments: IBM Model 1
    Finding the best alignment: IBM Model 1
    Learning Parameters: IBM Model 1
    IBM Model 2
    Back to IBM Model 3

Learning Parameters: IBM Model 3

Parameter Estimation: Sum over all alignments

$$\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \sum_{\mathbf{a}} \prod_{i=1}^{I} n(\phi_{a_i} \mid e_{a_i}) \times t(f_i \mid e_{a_i}) \times d(i \mid a_i, I, J)$$

Sampling the Alignment Space [from P.Koehn SMT book slides]

- ▶ 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
- ▶ 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

Higher IBM Models[from P.Koehn SMT book slides]

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
  - → exhaustive count collection becomes computationally too expensive
  - ▶ sampling over high probability alignments is used instead

Summary

- 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++, mgiza toolkit)

Natural Language Processing

Anoop Sarkar

anoopsarkar.github.io/nlp-class

Simon Fraser University

Part 2: Word Alignment

Word Alignment[from P.Koehn SMT book slides]

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

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*

Measuring Word Alignment Quality [from P.Koehn SMT book slides]

- 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 [from P.Koehn SMT book slides]

- ▶ 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 [from P.Koehn SMT book slides]

- Intersection plus grow additional alignment points
  [Och and Ney, CompLing2003]

Growing heuristic [from P.Koehn SMT book slides]

grow-diag-final(e2f,f2e)

1: neighboring = {(-1,0),(0,-1),(1,0),(0,1),(-1,-1),(-1,1),(1,-1),(1,1)}
2: alignment A = intersect(e2f,f2e); grow-diag(); final(e2f); final(f2e);

grow-diag()

1: **while** new points added **do**
2:   **for all** English word $e \in [1...e_n]$, foreign word $f \in [1...f_n]$, $(e, f) \in A$ **do**
3:     **for all** neighboring alignment points (e_{new}, f_{new}) **do**
4:       **if** (e_{new} unaligned OR f_{new} unaligned) AND
         $(e_{new}, f_{new}) \in$ union(e2f,f2e) **then**
5:         add (e_{new}, f_{new}) to A
6:       **end if**
7:     **end for**
8:   **end for**
9: **end while**

final()

1: **for all** English word $e_{new} \in [1...e_n]$, foreign word $f_{new} \in [1...f_n]$ **do**
2:   **if** (e_{new} unaligned OR f_{new} unaligned) AND $(e_{new}, f_{new}) \in$ union(e2f,f2e)
     then
3:     add (e_{new}, f_{new}) to A
4:   **end if**
5: **end for**

More Recent Work on Symmetrization[from P.Koehn SMT book slides]

- ► Symmetrize after each iteration of IBM Models [Matusov et al., 2004]
    - ► run one iteration of E-step for each direction
    - ► symmetrize the two directions
    - ► count collection (M-step)

- ► Use of posterior probabilities in symmetrization
    - ► generate n-best alignments for each direction
    - ► calculate how often an alignment point occurs in these alignments
    - ► use this posterior probability during symmetrization

Link Deletion / Addition Models[from P.Koehn SMT book slides]

- Link deletion [Fossum et al., 2008]
  - start with union of IBM Model alignment points
  - delete one alignment point at a time
  - uses a neural network classifiers that also considers aspects such as how useful the alignment is for learning translation rules

- Link addition [Ren et al., 2007] [Ma et al., 2008]
  - possibly start with a skeleton of highly likely alignment points
  - add one alignment point at a time

Discriminative Training Methods [from P.Koehn SMT book slides]

- ▶ 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_[from P.Koehn SMT book slides]

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

- Fraser and Marcu: 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
- ▶ 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
- ▶ Word Alignment

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