Statistical Machine Translation — Lecture 3: Word Alignment and Phrase Models

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Overview

- Statistical modeling
- EM algorithm
- Improved word alignment
- Phrase-based SMT

Statistical Modeling

- Learn $P(f|e)$ from a parallel corpus
- Not sufficient data to estimate $P(f|e)$ directly

Statistical Modeling (2)

- Break the process into smaller steps

Statistical Modeling (3)

- Probabilities for smaller steps can be learned

Statistical Modeling (4)

- Generate a story how an English string $e$ gets to be a foreign string $f$
  - choices in story are decided by reference to parameters
  - e.g., $p(\text{bruja}|\text{witch})$
- Formula for $P(f|e)$ in terms of parameters
  - usually long and hairy, but mechanical to extract from the story
- Training to obtain parameter estimates from possibly incomplete data
  - off-the-shelf EM
Parallel Corpora

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

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

- Incomplete data
  - English and foreign words, but no connections between them
- Chicken and egg problem
  - if we had the connections, we could estimate the parameters of our generative story
  - if we had the parameters, we could estimate the connections

In EM Algorithm, we face the problem of incomplete data. If we had the connections, we could estimate the parameters of our generative story. If we had the parameters, we could estimate the connections.

**EM Algorithm**

- **Incomplete data**
  - if we had complete data, we could estimate model
  - if we had model, we could fill in the gaps in the data
- **EM in a nutshell**
  - initialize model parameters (e.g. uniform)
  - assign probabilities to the missing data
  - estimate model parameters from completed data
  - iterate

**Initial step: all connections equally likely**

**Model learns that, e.g., la is often connected with the**

After one iteration

**Connections, e.g., between la and the are more likely**

After another iteration

**It becomes apparent that connections, e.g., between fleur and flower are more likely (pigeon hole principle)**

**Convergence**

**Inherent hidden structure revealed by EM**
EM Algorithm (6)

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

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

\[ p(\text{la} | \text{the}) = 0.453 \]
\[ p(\text{le} | \text{the}) = 0.334 \]
\[ p(\text{maison} | \text{house}) = 0.876 \]
\[ p(\text{bleu} | \text{blue}) = 0.563 \]

- Parameter estimation from the connected corpus

One example

<table>
<thead>
<tr>
<th>das</th>
<th>house</th>
<th>ist</th>
<th>klein</th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>that</td>
<td>who</td>
<td>this</td>
</tr>
<tr>
<td>house</td>
<td>building</td>
<td>household</td>
<td>shell</td>
</tr>
<tr>
<td>small</td>
<td>little</td>
<td>minor</td>
<td>petty</td>
</tr>
</tbody>
</table>

\[ p(\epsilon, a | f) = \frac{\epsilon}{(f + 1)^m} \prod_{j=1}^{m} t(e_j | f_{a(j)}) \]

- What is going on?
  - foreign sentence \( f = f_1 ... f_m \)
  - English sentence \( e = e_1 ... e_l \)
  - each English word \( e_j \) is generated by a English word \( f_{a(j)} \), as defined by the alignment function \( a \), with the probability \( t \)
  - the normalization factor \( \epsilon \) is required to turn the formula into a proper probability function

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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

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IBM Model 1 and EM: Expectation Step

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

\[ p(a | e, f) = \frac{p(e, a | f)}{p(e | f)} \]

We already have the formula for \( p(e, a | f) \) (definition of Model 1)
IBM Model 1 and EM: Expectation Step

- We need to compute \( p(e|f) \)

\[
p(e|f) = \frac{\sum_{a} p(a,e,f)}{\sum_{a} p(a)} \\
- \frac{t + \sum_{a_{i=0}^{m}}^{j}}{t + \sum_{a_{i=0}^{m}}^{j} \prod_{i=0}^{m} n_{f}(a_{i,j})} \\
- \frac{t + \sum_{a_{i=0}^{m}}^{j}}{t + \sum_{a_{i=0}^{m}}^{j} \prod_{i=0}^{m} n_{f}(a_{i,j})} \\
- \frac{t + \sum_{a_{i=0}^{m}}^{j}}{t + \sum_{a_{i=0}^{m}}^{j} \prod_{i=0}^{m} n_{f}(a_{i,j})}
\]

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

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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 \( f \):

\[
c(e|f; e,f) = \sum_{a} p(a|e,f) \sum_{j=1}^{m} \delta(e,e_{j}) \delta(f,f_{a(j)})
\]

- With the same simplification as before:

\[
c(e|f; e,f) = \frac{t(e|f)}{\sum_{j=1}^{m} t(e|f_{a(j)})} \sum_{j=1}^{m} \delta(e,e_{j}) \sum_{i=0}^{t} \delta(f,f_{i})
\]

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IBM Model 1 and EM: Pseudocode

initialize \( t(e|f) \) uniformly

\[
\text{do}
\begin{align*}
\text{set count(e|f) to 0 for all e,f,} \\
\text{set total(f) to 0 for all f,} \\
\text{for all unique words e in e_s,} \\
\text{n_e = count of e in e_s,} \\
\text{total_s = 0,} \\
\text{for all unique words f in f_s,} \\
\text{total_s += count(e|f) * n_e,} \\
\text{for all unique words f in f_s,} \\
\text{n_f = count of f in f_s,} \\
\text{count(e|f) += t(e|f) * n_e * n_f / total_s,} \\
\text{total(f) += t(e|f) * n_e * n_f / total_s,} \\
\text{for all f in domain( total(.))}, \\
\text{for all e in domain( count(.|f) ),} \\
\text{t(e|f) = count(e|f) / total(f),} \\
\end{align*}
\text{until convergence}
\]

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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 |

- Computationally 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
Flaws of Word-Based MT

- Multiple English words for one German word
  
  **one-to-many problem:** Zeitmangel \(\rightarrow\) lack of time
  
  **German:** Zeitmangel erschwert das Problem.
  **Gloss:** LACK OF TIME MAKES MORE DIFFICULT THE PROBLEM.
  **Correct translation:** Lack of time makes the problem more difficult.
  **MT output:** Time makes the problem.

- Phrasal translation
  
  **non-compositional phrase:** erübrigt sich \(\rightarrow\) there is no point in
  
  **German:** Eine Diskussion erübrigt sich demnach
  **Gloss:** A DISCUSSION IS MADE UNNECESSARY ITSELF THEREFORE
  **Correct translation:** Therefore, there is no point in a discussion.
  **MT output:** A debate turned therefore.

**Word Alignment**

- Notion of word alignments valuable
- Trained humans can achieve high agreement
- Shared task at NAACL 2003 and ACL 2005 workshops

**Improved Word Alignments**

- Intersection of GIZA++ bidirectional alignments

**Flaws of Word-Based MT (2)**

- Syntactic transformations
  
  **reordering, genitive NP:** der Sache \(\rightarrow\) for this matter
  
  **German:** Das ist der Sache nicht angemessen.
  **Gloss:** THAT IS THE MATTER NOT APPROPRIATE.
  **Correct translation:** That is not appropriate for this matter.
  **MT output:** That is the thing is not appropriate.

  **object/subject reordering**
  
  **German:** Den Vorschlag lehnt die Kommission ab.
  **Gloss:** THE PROPOSAL REJECTS THE COMMISSION OFF.
  **Correct translation:** The commission rejects the proposal.
  **MT output:** The proposal rejects the commission.

**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)

- But we need many-to-many mappings

**Improved Word Alignments (2)**

- Grow additional alignment points

  [Och and Ney, CompLing2003]
Growing Heuristic

\[ \text{GROW-\textit{DIAG-FINAL}(e2f, f2e)}: \]
\[ \text{neighboring} = \{(-1,0), (0,-1), (1,0), (0,1), (-1,-1), (-1,1), (1,-1), (1,1)\} \]
\[ \text{alignment} = \text{intersect}(e2f, f2e); \]
\[ \text{GROW-\textit{DIAG}()}; \text{FINAL}(e2f); \text{FINAL}(f2e); \]
\[ \text{GROW-\textit{DIAG}():} \]
\[ \text{iterate until no new points added} \]
\[ \text{for foreign word } f = 0 \ldots fn \]
\[ \text{if } (e \text{ aligned with } f) \]
\[ \text{for each neighboring point } (e\text{-new, } f\text{-new}): \]
\[ \text{if } (e\text{-new not aligned and } f\text{-new not aligned}) \text{ and} \]
\[ (e\text{-new, } f\text{-new}) \text{ in union}(e2f, f2e) \]
\[ \text{add alignment point } (e\text{-new, } f\text{-new}) \]
\[ \text{FINAL}(a): \]
\[ \text{for foreign word } f\text{-new} = 0 \ldots fn \]
\[ \text{if } (e\text{-new not aligned or } f\text{-new not aligned}) \text{ and} \]
\[ (e\text{-new, } f\text{-new}) \text{ in alignment } a \]
\[ \text{add alignment point } (e\text{-new, } f\text{-new}) \]

Phrase-Based Translation

- Foreign input is segmented in phrases
  - any sequence of words, not necessarily linguistically motivated
- Each phrase is translated into English
- Phrases are reordered
- See [Koehn et al., NAACL2003] as introduction

Advantages of Phrase-Based Translation

- Many-to-many translation can handle non-compositional phrases
- Use of local context in translation
- The more data, the longer phrases can be learned

How to Learn the Phrase Translation Table?

- Start with the word alignment:

  \[
  \begin{array}{cccc}
  \text{Maria} & \text{no} & \text{daba} \\
  \text{did} & \text{not} & \text{slap} & \text{the} & \text{witch} & \text{green} \\
  \end{array}
  \]

- Collect all phrase pairs that are consistent with the word alignment

Consistent with Word Alignment

- Consistent with the word alignment :=

  \[
  (e, f) \in BP \Rightarrow \forall e_i \in \bar{e}: (e_i, f_j) \in A \rightarrow f_j \in \bar{f} \\
  \text{AND} \forall f_j \in \bar{f}: (e_i, f_j) \in A \rightarrow e_i \in \bar{e}
  \]

(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch), (verde, green)
Word Alignment Induced Phrases (2)

(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch),
(verte, green), (Maria no, Mary did not), (no daba una bofetada, did not slap),
(daba una bofetada a la, slap the), (bruja verde, green witch)

Word Alignment Induced Phrases (3)

(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch),
(verte, green), (Maria no, Mary did not), (no daba una bofetada, did not slap),
(daba una bofetada a la, slap the), (bruja verde, green witch),
(Maria no daba una bofetada, Mary did not slap),
(no daba una bofetada a la, did not slap the), (a la bruja verde, the green witch)

Word Alignment Induced Phrases (4)

(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch),
(verte, green), (Maria no, Mary did not), (no daba una bofetada, did not slap),
(daba una bofetada a la, slap the), (bruja verde, green witch),
(Maria no daba una bofetada, Mary did not slap),
(no daba una bofetada a la, did not slap the), (a la bruja verde, the green witch),
(Maria no daba una bofetada a la, Mary did not slap the),
(daba una bofetada a la bruja verde, slap the green witch)

Word Alignment Induced Phrases (5)

(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch),
(verte, green), (Maria no, Mary did not), (no daba una bofetada, did not slap),
(daba una bofetada a la, slap the), (bruja verde, green witch),
(Maria no daba una bofetada, Mary did not slap),
(no daba una bofetada a la, did not slap the), (a la bruja verde, the green witch),
(Maria no daba una bofetada a la, Mary did not slap the),
(daba una bofetada a la bruja verde, slap the green witch),
(no daba una bofetada a la bruja verde, did not slap the green witch),
(Maria no daba una bofetada a la bruja verde, Mary did not slap the green witch)

Probability Distribution of Phrase Pairs

- We need a probability distribution $\phi(\tilde{f}|\tilde{e})$ over the collected phrase pairs

$\Rightarrow$ Possible choices

- relative frequency of collected phrases:

$$\phi(\tilde{f}|\tilde{e}) = \frac{\text{count}(\tilde{f},\tilde{e})}{\sum \text{count}(\tilde{f},\tilde{e})}$$

- or, conversely $\phi(\tilde{e}|\tilde{f})$

- use lexical translation probabilities

Reordering

- Monotone translation
  - do not allow any reordering
  $\Rightarrow$ worse translations
  - however: limiting reordering to maximum movement helps

- Distance-based reordering cost
  - moving a foreign phrase over $n$ words: cost $\omega^n$

- Lexicalized reordering model
  - $p(\text{monotone}|e,f)$
  - $p(\text{swap}|e,f)$
  - $p(\text{lex}|e,f)$
Log-Linear Models

- IBM Models provided mathematical justification for factoring components together
  \[ p_{LM} \times p_{FM} \times p_{DD} \]
- These may be weighted
  \[ p_{LM}^{\lambda_{LM}} \times p_{FM}^{\lambda_{FM}} \times p_{DD}^{\lambda_{DD}} \]
- Many components \( p_i \) with weights \( \lambda_i \)
  \[ \prod p_i^{\lambda_i} = e^{\sum \lambda_i \log(p_i)} \]
  \[ \log \prod p_i^{\lambda_i} = \sum \lambda_i \log(p_i) \]

Set Feature Weights

- Contribution of components \( p_i \) determined by weight \( \lambda_i \)

- Methods
  - manual setting of weights: try a few, take best
  - automate this process

- Learn weights
  - set aside a development corpus
  - set the weights, so that optimal translation performance on this development corpus is achieved
  - requires automatic scoring method (e.g., BLEU)

Additional Features

- Word count
  - add fixed factor for each generated word
  - if output is too short \( \rightarrow \) add benefit for each word

- Phrase count
  - add fixed factor for each phrase
  - balances use of longer or shorter phrases