CS5740: Natural Language Processing
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IBM Translation Models

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Slides adapted from Michael Collins

The Noisy Channel Model

- Goal: **translate from French to English**
- Have a model $p(e|f)$ to estimate the probability of an English sentence e given a French sentence f
- Estimate the parameters from training corpus
- A noisy channel model has two components:

$p(e)$	**the language model**
$p(f|e)$	**the translation model**

- Giving:

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

and

$$\arg\max_e p(e|f) = \arg\max_e p(e)p(f|e)$$

Overview

- IBM Model 1
- IBM Model 2
- EM Training of Models 1 and 2

IBM Model 1: Alignments

- How do we model $p(f|e)$?
- English sentence e has l words e^1 ... e^l
  French sentence f has m words f^1 ... f^m
- An **alignment** a identifies which English word each French word originated from
- Formally, an alignent a is:

  $\{a_1, \ldots, a_m\}$ where $a_j \in 0 \ldots l$
- There are $(l+1)^m$ possible alignments

IBM Model 1: Alignments

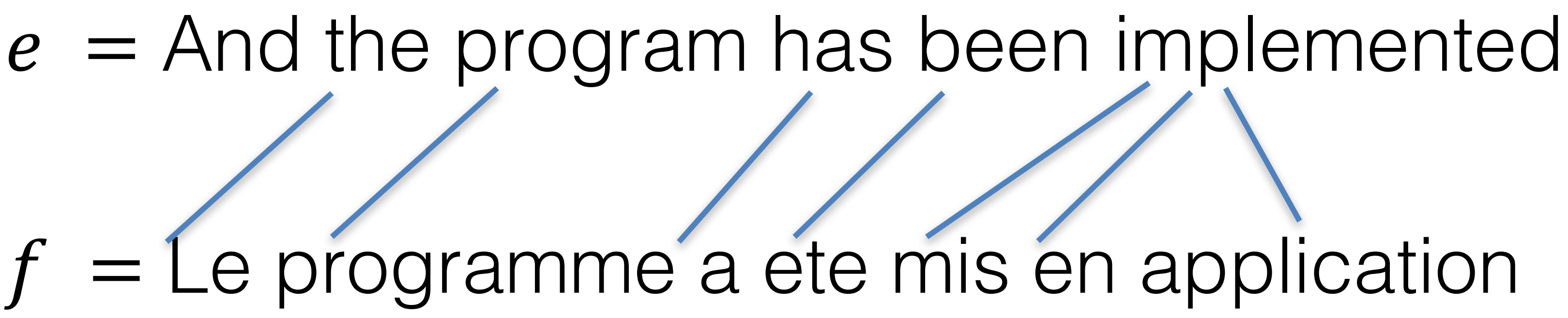
$l = 6, m = 7$

e = And the program has been implemented

f = Le programme a ete mis en application

IBM Model 1: Alignments

$l = 6, m = 7$



e = And the program has been implemented

f = Le programme a ete mis en application

- One alignment is

$$\{2, 3, 4, 5, 6, 6, 6\}$$

IBM Model 1: Alignments

$l = 6, m = 7$

e = And the program has been implemented

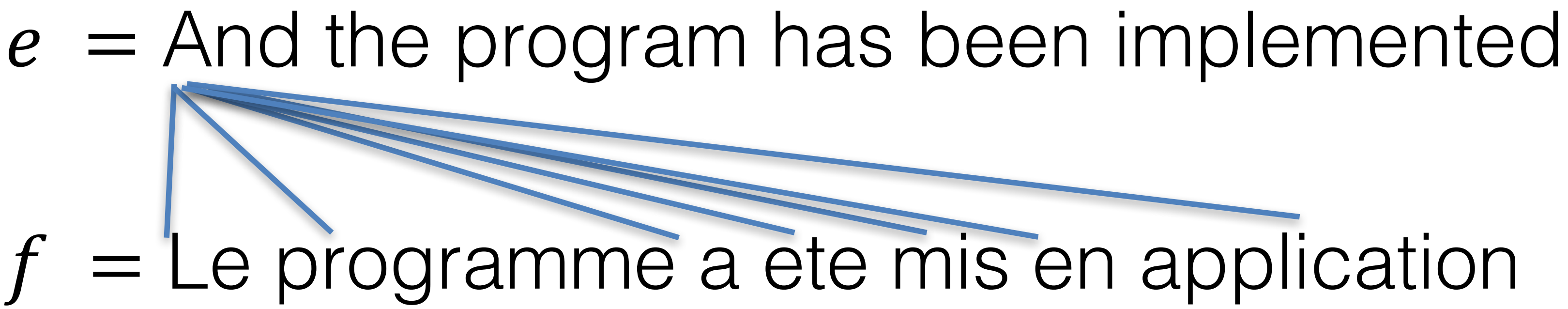
f = Le programme a ete mis en application

- Another (bad!) alignment is

$$\{1, 1, 1, 1, 1, 1, 1\}$$

IBM Model 1: Alignments

$l = 6, m = 7$



e = And the program has been implemented

f = Le programme a ete mis en application

- Another (bad!) alignment is

$$\{1, 1, 1, 1, 1, 1, 1\}$$

Alignments in the IBM Models

- We define two models:

$$\underline{p(a|e,m)} \qquad \underline{p(f|a,e,m)}$$

- Giving:

$$p(f,a|e,m) = \underline{p(a|e,m)}\underline{p(f|a,e,m)}$$

- Also:

$$p(f|e,m) = \sum_{a \in \mathcal{A}} \underline{p(a|e,m)}\underline{p(f|a,e,m)}$$

where A is a set of all possible alignments

Most Likely Alignments

$$p(f, a|e, m) = p(a|e, m)p(f|a, e, m)$$

- We can also calculate:

$$p(a|f, e, m) = \frac{p(f, a|e, m)}{\sum_{a \in \mathcal{A}} p(f, a|e, m)}$$

for any alignment a

- For a given f, e pair, can also compute the most likely alignment (details in notes)
- The original IBM models are rarely used for translation, but still key for recovering alignments

Example Alignment

- French:
  le conseil a rendu son avis , et nous devons à présent adopter un nouvel avis sur la base de la première position .

- English:
  the council has stated its position , and now , on the basis of the first position , we again have to give our opinion .

- Alignment:
  the/le council/conseil has/à stated/rendu its/son position/avis ,/, and/et now/présent ,/NULL on/sur the/le basis/base of/de the/la first/première position/position ,/NULL we/nous again/NULL have/devons to/a give/adopter our/nouvel opinion/avis ./.

IBM Model 1: Alignments

- In IBM Model 1 all alignments a are equally likely:

$$\underline{p(a|e,m)} = \frac{1}{(1+l)^m}$$

- Reasonable assumption?
  - Simplifying assumption, but it gets things started …

IBM Model 1: Translation Probabilities

- Next step: come up with an estimate for

$$p(f|a,e,m)$$

- In Model 1, this is:

$$p(f|a,e,m) = \prod_{j=1}^{m} t(f_j|e_{a_j})$$

IBM Model 1: Example

$l = 6, m = 7$

e = And the program has been implemented

f = Le programme a ete mis en application

$$a = \{2, 3, 4, 5, 6, 6, 6\}$$

IBM Model 1: Example

p(f|e)	And	the	program	has	been	implemented
Le	0.2	0.6	0.1	0.025	0.05	0.025
programme	0.05	0.2	0.45	0.1	0.1	0.1
a	0.1	0.1	0.15	0.2	0.15	0.3
ete	0.05	0.05	0.05	0.05	0.7	0.1
mis	0.2	0.05	0.05	0.05	0.25	0.4
en	0.25	0.1	0.25	0.25	0.1	0.05
application	0.01	0.03	0.01	0.02	0.03	0.9

IBM Model 1: Example

$l = 6, m = 7$

e = And the program has been implemented

f = Le programme a ete mis en application

$$a = \{2, 3, 4, 5, 6, 6, 6\}$$

$$\begin{aligned} p(f|a, e) =& t(\text{Le}|\text{the}) \times t(\text{programme}|\text{program}) \\ & \times t(\text{a}|\text{has}) \times t(\text{ete}|\text{been}) \\ & \times t(\text{mis}|\text{implemented}) \times t(\text{en}|\text{implemented}) \\ & \times t(\text{application}|\text{implemented}) = 0.0006804 \end{aligned}$$

$$p(f, a \mid e, 7) = 8.26186E - 10$$

IBM Model 1: The Generative Process

Translating French→English

To generate a French string $\boldsymbol{f}$ from an English string $\boldsymbol{e}$:

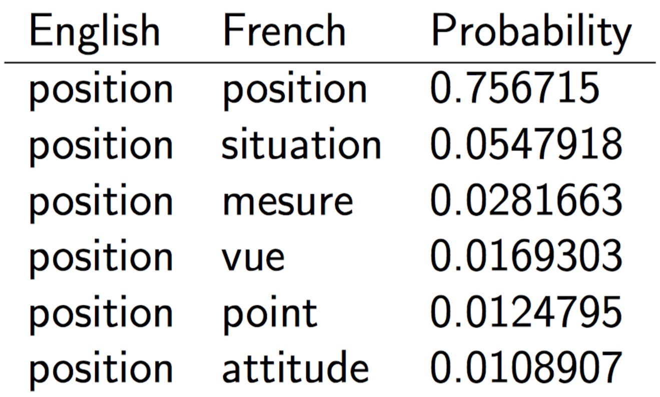
- Step 1: Pick an alignment $\boldsymbol{a}$ with probability $\frac{1}{(l+1)^m}$
- Step 2: Pick the French words with probability

$$\underline{p(f|a,e,m)} = \prod_{j=1}^{m} t(f_j|e_{a_j})$$

The final result:

$$p(f,a|e,m) = \underline{p(a|e,m)} \times \underline{p(f|a,e,m)} = \frac{1}{(1+l)^m} \prod_{j=1}^{m} t(f_j|e_{a_j})$$

Example Lexical Entry



English	French	Probability
position	position	0.756715
position	situation	0.0547918
position	mesure	0.0281663
position	vue	0.0169303
position	point	0.0124795
position	attitude	0.0108907

… de la situation au niveau des négociations de l’ompi …
... of the current position in the wipo negotiations ...

nous ne sommes pas en mesure de décider, …
we are not in position to decide …

... Le point de vue de la commission face à ce problème complexe .
… the commission ‘s position on this complex problem .

Overview

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IBM Model 2

- Only difference: we now introduce alignment distortion parameters

$$q(i|j, l, m)$$

- Probability that j'th French word is connected to i'th English word, given sentence length of e and f are l and m
- Define

$$p(a|e, m) = \prod_{j=1}^{m} q(a_j|j, l, m)$$

where $a = \{a_1, \ldots, a_m\}$

- Gives

$$p(f, a|e, m) = \prod_{j=1}^{m} q(a_j|j, l, m) t(f_j|e_{a_j})$$

Example

$$\begin{aligned} l &= 6 \\ m &= 7 \\ e &= \textsf{And the program has been implemented} \\ f &= \textsf{Le programme a ete mis en application} \\ a &= \{2, 3, 4, 5, 6, 6, 6\} \end{aligned}$$

Example

$$
\begin{aligned}
l &= 6 \\
m &= 7 \\
e &= \text{And the program has been implemented} \\
f &= \text{Le programme a ete mis en application} \\
a &= \{2, 3, 4, 5, 6, 6, 6\}
\end{aligned}
$$

$$
\begin{aligned}
p(a \mid e, 7) \quad = \quad & \mathbf{q}(2 \mid 1, 6, 7) \times \\
& \mathbf{q}(3 \mid 2, 6, 7) \times \\
& \mathbf{q}(4 \mid 3, 6, 7) \times \\
& \mathbf{q}(5 \mid 4, 6, 7) \times \\
& \mathbf{q}(6 \mid 5, 6, 7) \times \\
& \mathbf{q}(6 \mid 6, 6, 7) \times \\
& \mathbf{q}(6 \mid 7, 6, 7)
\end{aligned}
$$

Example

$$
\begin{aligned}
l &= 6 \\
m &= 7 \\
e &= \text{And the program has been implemented} \\
f &= \text{Le programme a ete mis en application} \\
a &= \{2, 3, 4, 5, 6, 6, 6\}
\end{aligned}
$$

$$
\begin{aligned}
p(f \mid a, e, 7) = \; & \mathbf{t}(Le \mid the) \times \\
& \mathbf{t}(programme \mid program) \times \\
& \mathbf{t}(a \mid has) \times \\
& \mathbf{t}(ete \mid been) \times \\
& \mathbf{t}(mis \mid implemented) \times \\
& \mathbf{t}(en \mid implemented) \times \\
& \mathbf{t}(application \mid implemented)
\end{aligned}
$$

IBM Model 2: The Generative Process

Translating French→English

To generate a French string f from an English string e:

- Step 1: Pick an alignment $a = \{a_1, \ldots, a_m\}$ with probability

$$p(a|e,m) = \prod_{j=1}^{m} q(a_j|j,l,m)$$

- Step 2: Pick the French words with probability

$$p(f|a,e,m) = \prod_{j=1}^{m} t(f_j|e_{a_j})$$

The final result:

$$p(f,a|e,m) = p(a|e,m) \times p(f|a,e,m) = \prod_{j=1}^{m} q(a_j|j,l,m) t(f_j|e_{a_j})$$

Recovering Alignments

- If we have parameters q and t, we can easily recover the most likely alignment for any sentence pair

Given a sentence pair

$$e_1, e_2, \ldots, e_l, f_1, f_2, \ldots, f_m$$

define

$$a_j = \arg\max_{a \in \{0 \ldots l\}} q(a|j,l,m) \times t(f_j, e_a)$$

for $j = 1 \ldots m$

e = And the program has been implemented

f = Le programme a ete mis en application

Overview

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The Parameter Estimation Problem

- Input:

$$(e^{(k)}, f^{(k)}), k = 1 \ldots n$$

  Each $e^{(k)}$ is an English sentence, each $f^{(k)}$ is a French sentence

- Output: parameter for

$$t(f|e) \qquad q(i|j, l, m)$$

- A key challenge: we do not have alignments in our training examples

$e^{(100)}$ = And the program has been implemented

$f^{(100)}$ = Le programme a ete mis en application

Parameter Estimation if Alignments are Observed

- Assume alignments are observed in training data
  $e^{(100)}$ = And the program has been implemented

  $f^{(100)}$ = Le programme a ete mis en application
  $a^{(100)}$ = $<2{,}3{,}4{,}5{,}6{,}6{,}6>$
- Training data is

$$(e^{(k)}, f^{(k)}, a^{(k)}), k = 1 \ldots n$$

  Each $e^{(k)}$ is an English sentence, each $f^{(k)}$ is a French sentence, each $a^{(k)}$ is an alignment

- Maximum-likelihood parameter estimates are trivial:

$$t_{ML}(f|e) = \frac{\text{count}(e, f)}{\text{count}(e)} \qquad q_{ML}(j|i, l, m) = \frac{\text{count}(j, i, l, m)}{\text{count}(i, l, m)}$$

Pseudo Code

Input: A training corpus $(f^{(k)}, e^{(k)}, a^{(k)})$ for $k = 1 \dots n$, where $f^{(k)} = f_1^{(k)} \dots f_{m_k}^{(k)}$, $e^{(k)} = e_1^{(k)} \dots e_{l_k}^{(k)}$, $a^{(k)} = a_1^{(k)} \dots a_{m_k}^{(k)}$.

Algorithm:

```
▸ Set all counts $c(\dots) = 0$
▸ For $k = 1 \dots n$
    ▸ For $i = 1 \dots m_k$, For $j = 0 \dots l_k$,
        $c(e_j^{(k)}, f_i^{(k)}) \leftarrow c(e_j^{(k)}, f_i^{(k)}) + \delta(k,i,j)$
        $c(e_j^{(k)}) \leftarrow c(e_j^{(k)}) + \delta(k,i,j)$
        $c(j|i,l,m) \leftarrow c(j|i,l,m) + \delta(k,i,j)$
        $c(i,l,m) \leftarrow c(i,l,m) + \delta(k,i,j)$
      where $\delta(k,i,j) = 1$ if $a_i^{(k)} = j$, 0 otherwise.
```

Output: $t_{ML}(f|e) = \frac{c(e,f)}{c(e)}$, $q_{ML}(j|i,l,m) = \frac{c(j|i,l,m)}{c(i,l,m)}$

Parameter Estimation with the EM Algorithm

- Input: $(e^{(k)}, f^{(k)}), k = 1 \ldots n$

  Each $e^{(k)}$ is an English sentence, each $f^{(k)}$ is a French sentence

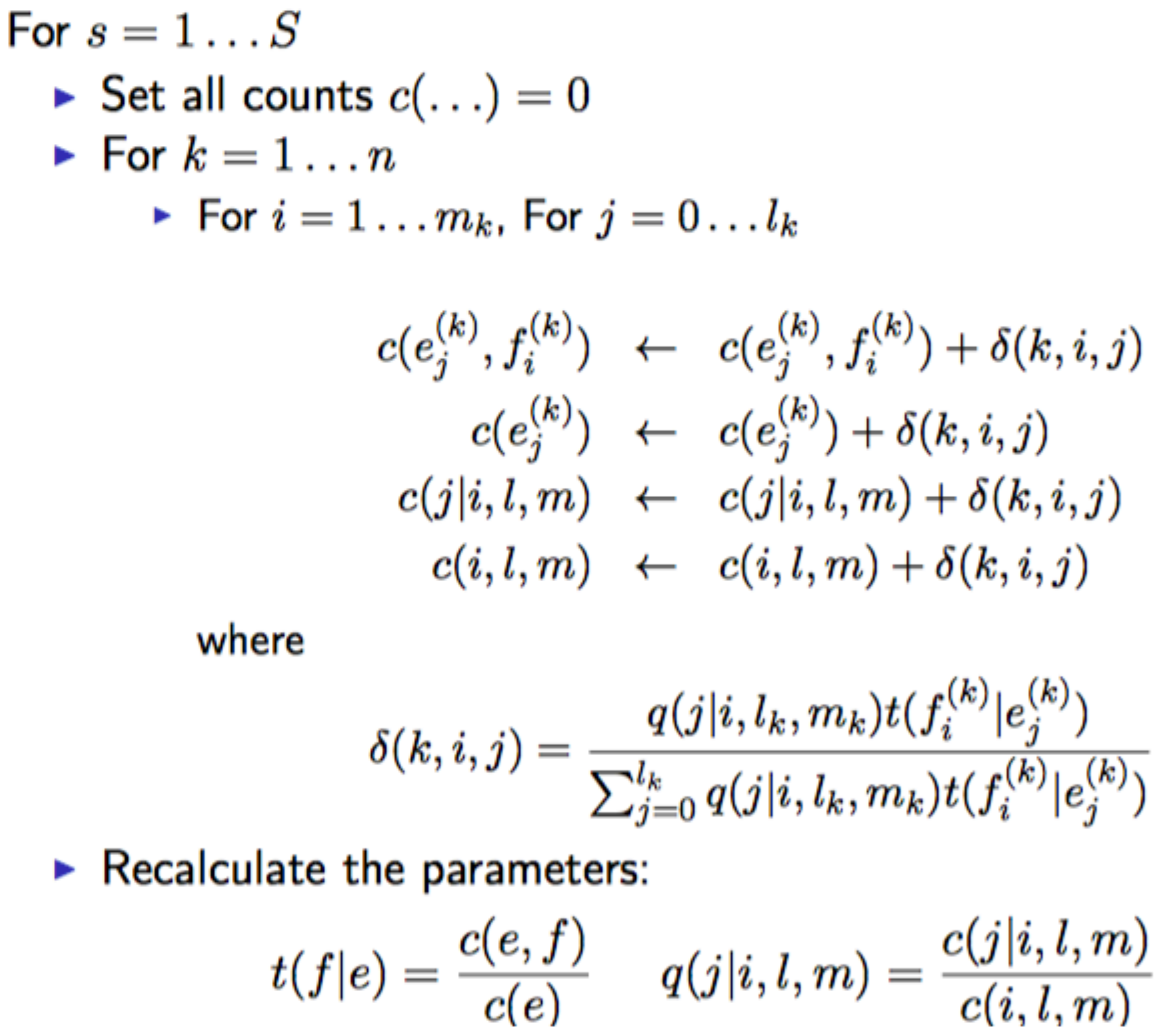
- The algorithm is related to algorithm with observed alignments, but with two key differences:
  - Iterative: start with initial (e.g., random) choice of q and t parameters, at each iteration: compute some "counts" base on data and parameters, and re-estimate parameters
  - The definition of of the delta function is different:

$$\delta(k,i,j) = \frac{q(j|i,l_k,m_k)t(f_i^{(k)}|e_j^{(k)})}{\sum_{j=0}^{l_k} q(j|i,l_k,m_k)t(f_i^{(k)}|e_j^{(k)})}$$

Input: A training corpus $(f^{(k)}, e^{(k)})$ for $k = 1 \ldots n$, where $f^{(k)} = f_1^{(k)} \ldots f_{m_k}^{(k)}$, $e^{(k)} = e_1^{(k)} \ldots e_{l_k}^{(k)}$.

Initialization: Initialize $t(f|e)$ and $q(j|i, l, m)$ parameters (e.g., to random values).

Pseudo Code



```
For $s = 1 \ldots S$
    ▸ Set all counts $c(\ldots) = 0$
    ▸ For $k = 1 \ldots n$
        ▸ For $i = 1 \ldots m_k$, For $j = 0 \ldots l_k$

            $c(e_j^{(k)}, f_i^{(k)}) \leftarrow c(e_j^{(k)}, f_i^{(k)}) + \delta(k, i, j)$
            $c(e_j^{(k)}) \leftarrow c(e_j^{(k)}) + \delta(k, i, j)$
            $c(j|i, l, m) \leftarrow c(j|i, l, m) + \delta(k, i, j)$
            $c(i, l, m) \leftarrow c(i, l, m) + \delta(k, i, j)$

        where

            $\delta(k, i, j) = \frac{q(j|i, l_k, m_k) t(f_i^{(k)}|e_j^{(k)})}{\sum_{j=0}^{l_k} q(j|i, l_k, m_k) t(f_i^{(k)}|e_j^{(k)})}$

    ▸ Recalculate the parameters:

            $t(f|e) = \frac{c(e, f)}{c(e)}$    $q(j|i, l, m) = \frac{c(j|i, l, m)}{c(i, l, m)}$
```

$$\delta(k,i,j) = \frac{q(j|i,l_k,m_k)t(f_i^{(k)}|e_j^{(k)})}{\sum_{j=0}^{l_k} q(j|i,l_k,m_k)t(f_i^{(k)}|e_j^{(k)})}$$

$e^{(100)}$ = And the program has been implemented

$f^{(100)}$ = Le programme a ete mis en application

Pseudo Code

```
For $s = 1 \ldots S$
    ▸ Set all counts $c(\ldots) = 0$
    ▸ For $k = 1 \ldots n$
        ▸ For $i = 1 \ldots m_k$, For $j = 0 \ldots l_k$
            $c(e_j^{(k)}, f_i^{(k)}) \leftarrow c(e_j^{(k)}, f_i^{(k)}) + \delta(k, i, j)$
            $c(e_j^{(k)}) \leftarrow c(e_j^{(k)}) + \delta(k, i, j)$
            $c(j|i, l, m) \leftarrow c(j|i, l, m) + \delta(k, i, j)$
            $c(i, l, m) \leftarrow c(i, l, m) + \delta(k, i, j)$
        where
            $\delta(k, i, j) = \frac{q(j|i, l_k, m_k) t(f_i^{(k)}|e_j^{(k)})}{\sum_{j=0}^{l_k} q(j|i, l_k, m_k) t(f_i^{(k)}|e_j^{(k)})}$
    ▸ Recalculate the parameters:
            $t(f|e) = \frac{c(e, f)}{c(e)}$    $q(j|i, l, m) = \frac{c(j|i, l, m)}{c(i, l, m)}$
```

Justification for the Algorithm

- Input: $$(e^{(k)}, f^{(k)}), k = 1 \dots n$$

  Each $e^{(k)}$ is an English sentence, each $f^{(k)}$ is a French sentence
- The log-likelihood function:

$$L(t, q) = \sum_{k=1}^{n} \log p(f^{(k)} | e^{(k)}) = \sum_{k=1}^{n} \log \sum_{a} p(f^{(k)}, a | e^{(k)})$$

- The maximum-likelihood estimates are:

$$\arg\max_{t,q} L(t, q)$$

- The EM algorithm will converge to a local maximum of the log-likelihood function

Summary

- Key ideas in the IBM translation models:
  - Alignment variables
  - Translation parameters, e.g., t(chien|dog)
  - Distortion parameters, e.g., q(2|1,6,7)
- The EM algorithm: an iterative algorithm for training the q and t parameters
- Once parameters are trained, can recover the most likely alignment on our training examples

$e^{(100)}$ = And the program has been implemented

$f^{(100)}$ = Le programme a ete mis en application