INF5820/INF9820

LANGUAGE TECHNOLOGICAL APPLICATIONS

Jan Tore Lønning, Lecture 5, 19 Sep. 2014
jtl@ifi.uio.no

Today

- Repetition:
  - Statistical machine translation:
    - The noisy channel model
      - IBM model 1
    - Training the intuitive way
- Training – the fast way
- Higher IBM-models

The noisy channel model

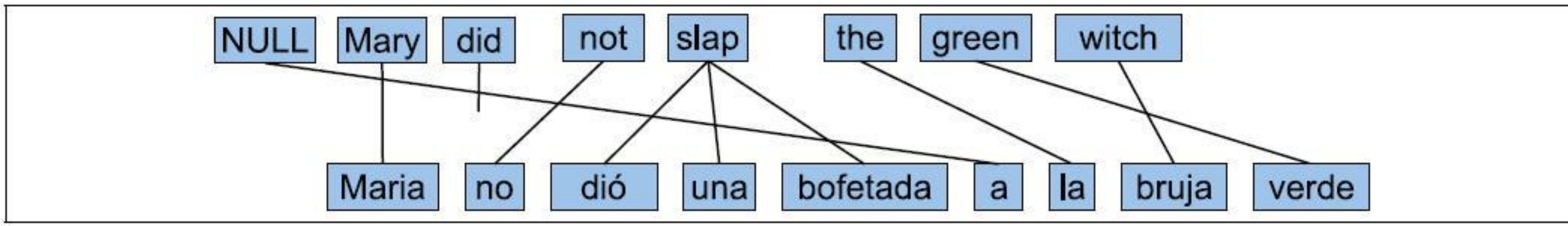
$$\hat{E} = \arg\max_E P(E \mid F)$$

$$= \arg\max_E \frac{P(F \mid E)P(E)}{P(F)}$$

$$= \arg\max_E P(F \mid E)P(E)$$

- Use n-gram language model for P(E)

Alignment



- Length of English string: k (=7)
- Length of foreign string: m (=9)
- An alignment is a vector of length m, each entry a number between 0 and k
- The example:
  - $<a_1, a_2, \ldots, a_9> = <1, 3, 4, 4, 4, 0, 5, 7, 6>$

IBM Model 1

- Consider all possible alignments **a**:

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

- For each alignment use the simplified generative model:

$$P(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})$$

  - ε is a normalisation factor
  - Formula 4.7 in the SMT book
    - (The book goes f→ e, not e → f)

Training – the idea

1. From the translation probabilities, we may estimate alignment probabilities
   - (We do not choose only the best alignment)
2. From alignment probabilities, we may recalculate translation probabilities

- By alternating between (1) and (2), the numbers converge towards better results
- For IBM Model 1 it may be proved that they converge towards a global optimum

Too many alignments

Words, m=k	2	3	4		6		8		10
Align.	9	64	625		117 649		43mill		25 billions

Two ways to describe the algorithm

Intuitive

- Proceed
  - 1. Translation prob
  - 1. Alignment prob
  - 2. Translation prob
  - 2. Alignment prob
  - 3. Translation prob
  - Etc
- J&M, sec 25.6.1, example
- Intractable in practice

Efficient

- Sidestep alignment probs:
  - 1. Translation prob
  - 2. Translation prob
  - 3. Translation prob
  - Etc
- K:SMT, sec 4.2.3, example
- How it gets implemented

Today

- Repetition:
  - Statistical machine translation:
    - The noisy channel model
      - IBM model 1
    - Training the intuitive way
- Training – the fast way
- Higher IBM-models

Training – the intuitive approach

1. Initalize the parameter values $t(f\,|e)$ for pairs of words f and e .
2. For each sentences pair $\boldsymbol{f}$, $\boldsymbol{e}$ calculate the probabilities $P(\boldsymbol{a} \mid \boldsymbol{f}, \boldsymbol{e})$ of all alignments $\boldsymbol{a}$.
3. Collect fractional counts, $tc(f\,|e)$:
   1. First, calculate this, $c(f\,|e\,;\,\boldsymbol{f}, \boldsymbol{e})$ for each sentence $\boldsymbol{f}$, $\boldsymbol{e}$,
   2. Then add over all sentences
4. Calculate the new translation probabilities $t(f\,|e)$
5. Repeat from 2 as long as you like

Training – the efficient approach

1. Initalize the parameter values $t(f\,|e)$ for pairs of words f and e .
2. ~~For each sentences pair $\boldsymbol{f}, \boldsymbol{e}$ calculate the probabilities $P(\boldsymbol{a}\,|\,\boldsymbol{f}, \boldsymbol{e})$ to all alignments $\boldsymbol{a}$.~~
3. Collect fractional counts, $tc(f\,|e)$:
   1. First, calculate this, $c(f\,|e\,;\,\boldsymbol{f}, \boldsymbol{e})$ for each sentence $\boldsymbol{f}, \boldsymbol{e}$,
   2. Then add over all sentences
4. Calculate the new translation probabilities
5. Repeat from 2 as long as you like

IBM Model 1

- Consider all possible alignments **a**:

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

- For each alignment use the simplified generative model:

$$P(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})$$

  - ε is a normalisation factor
  - Formula 4.7 in the SMT book
    - (The book goes f→ e, not e → f)

Necessary simplification

$$P(\mathbf{f} \mid \mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \sum_{\mathbf{a}} \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})$$

$$P(\mathbf{f} \mid \mathbf{e}) = \sum_{a_1=0}^{k} \cdots \sum_{am=0}^{k} \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})$$

- This equals

$$P(\mathbf{f} \mid \mathbf{e}) = \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} \sum_{i=0}^{k} t(f_j \mid e_i)$$

- Because

$$\prod_{j=1}^{m} \sum_{i=0}^{k} c_{j,i} = (c_{1,0} + c_{1,1} + \ldots + c_{1,k})(c_{2,0} + \ldots + c_{2,k}) \cdots (c_{m,0} + \ldots + c_{m,k}) = \sum_{i=0}^{k} \cdots \sum_{i=0}^{k} \prod_{j=1}^{m} c_{j,i}$$

- Reduces the problem from the order $(k+1)^n$ to roughly $k \times n$

Putting this together

- So far

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

$$P(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})$$

$$P(\mathbf{f} \mid \mathbf{e}) = \frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} \sum_{i=0}^{k} t(f_j \mid e_i)$$

- Hence

$$P(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} t(f_j \mid e_{a_j})}{\frac{\varepsilon}{(k+1)^m} \prod_{j=1}^{m} \sum_{i=0}^{k} t(f_j \mid e_i)}$$

- Formula 4.11

$$P(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\prod_{j=1}^{m} t(f_j \mid e_{a_j})}{\prod_{j=1}^{m} \sum_{i=0}^{k} t(f_j \mid e_i)}$$

Fractional counts

Counting for one sentence

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \sum_{\mathbf{a}} \left(p(\mathbf{a} \mid \mathbf{e}, \mathbf{f}) \sum_{j=1}^{m} \delta(f, f_j) \times \delta(e, e_{\mathbf{a}_j}) \right)$$

- (This is a formula for the counting we did last week)
- The part $\sum_{j=1}^{m} \delta(f, f_j) \times \delta(e, e_{\mathbf{a}_j})$

  counts how many times the alignment ***a*** connects a word of the type *f* with one of type e
  - $\delta(a, b) = 1$ if and only if $a = b$, otherwise 0
- We multiply with the probability of this alignment
- And sum over all alignments

Fractional counts

- Counting for one sentence

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \sum_{\mathbf{a}} \left(p(\mathbf{a} \mid \mathbf{e}, \mathbf{f}) \sum_{j=1}^{m} \delta(f, f_j) \times \delta(e, e_{\mathbf{a}_j}) \right)$$

- Substituting in for p(**a** | **e**,**f**)

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \sum_{\mathbf{a}} \left(\frac{\prod_{j=1}^{m} t(f_j \mid e_{\mathbf{a}_j})}{\prod_{j=1}^{m} \sum_{i=0}^{k} t(f_j \mid e_i)} \sum_{j=1}^{m} \delta(f, f_j) \times \delta(e, e_{\mathbf{a}_j}) \right)$$

- and doing some non-trivial calculation:

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \frac{t(f \mid e)}{\sum_{i=0}^{k} t(f \mid e_i)} \sum_{j=1}^{m} \delta(f, f_j) \sum_{i=0}^{k} \delta(e, e_i)$$

Observe:
Directly from t to $c(f|e;\mathbf{e},\mathbf{f})$ without mentioning the ***a***-s

Fractional counts

- Counting over the whole corpus and normalize as before

$$t(f \mid e) = \frac{\sum_{(\mathbf{f},\mathbf{e})} c(f \mid e; \mathbf{f}, \mathbf{e})}{\sum_{f'} \sum_{(\mathbf{f},\mathbf{e})} c(f' \mid e; \mathbf{f}, \mathbf{e})}$$

Example – the efficient way

- Corpus

e_1: Dog barked
f_1: Hund bjeffet

e_2: Dog bit dog
f_2: Hund bet hund

3 English words: dog bit barked
3 foreign words: hund bjeffet bet

Uniform initilaization

t(hund | dog) = 1/3	t(bet | dog) = 1/3	t(bjeffet | dog) = 1/3
t(hund | bit) = 1/3	t(bet | bit) = 1/3	t(bjeffet | bit) = 1/3
t(hund | barked) = 1/3	t(bet | barked) = 1/3	t(bjeffet | barked) = 1/3
t(hund | 0) = 1/3	t(bet | 0) = 1/3	t(bjeffet | 0) = 1/3

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \frac{t(f \mid e)}{\sum_{i=0}^{k} t(f \mid e_i)} \sum_{j=1}^{m} \delta(f, f_j) \sum_{i=0}^{k} \delta(e, e_i)$$

$\mathbf{e}_1$: Dog barked
$\mathbf{f}_1$: Hund bjeffet

$$c(hund \mid barked; \mathbf{e}_1, \mathbf{f}_1) = \frac{t(hund \mid barked)}{\sum_{i=0}^{2} t(f \mid e_i)} \sum_{j=1}^{2} \delta(hund, f_j) \sum_{i=0}^{2} \delta(barked, e_i) =$$

$$\frac{1/3}{\sum_{i=0}^{2} (1/3)} (\delta(hund, hund) + \delta(hund, bjeffet)) \times$$

$$(\delta(barked, 0) + \delta(barked, dog) + \delta(barked, barked)) = 1/3$$

Uniform initilaization

t(hund | dog) = 1/3	t(bet | dog) = 1/3	t(bjeffet | dog) = 1/3
t(hund | bit) = 1/3	t(bet | bit) = 1/3	t(bjeffet | bit) = 1/3
t(hund | barked) = 1/3	t(bet | barked) = 1/3	t(bjeffet | barked) = 1/3
t(hund | 0) = 1/3	t(bet | 0) = 1/3	t(bjeffet | 0) = 1/3

$$c(f \mid e; \mathbf{e}, \mathbf{f}) = \frac{t(f \mid e)}{\sum_{i=0}^{k} t(f \mid e_i)} \sum_{j=1}^{m} \delta(f, f_j) \sum_{i=0}^{k} \delta(e, e_i)$$

e_2: Dog bit dog
f_2: Hund bet hund

$$c(bet \mid bit; \mathbf{e}_2, \mathbf{f}_2) = \frac{t(bet \mid bit)}{\sum_{i=0}^{3} t(bet \mid e_i)} \sum_{j=1}^{3} \delta(bet, f_j) \sum_{i=0}^{3} \delta(bit, e_i) = \frac{1/3}{\sum_{i=0}^{3} (1/3)} \times 1 \times 1 = 1/4$$

$$c(hund \mid dog; \mathbf{e}_2, \mathbf{f}_2) = \frac{t(hund \mid dog)}{\sum_{i=0}^{3} t(hund \mid e_i)} \sum_{j=1}^{3} \delta(hund, f_j) \sum_{i=0}^{3} \delta(dog, e_i) = \frac{1/3}{\sum_{i=0}^{3} (1/3)} \times 2 \times 2 = 1$$

Collect fractional counts

e_1: Dog barked
f_1: Hund bjeffet

Results are the same as the intuitive way

c(hund | dog; f_1, e_1)= 1/3	c(bjeffet | dog; f_1, e_1) = 1/3
c(hund | barked; f_1, e_1) = 1/3	c(bjeffet | barked; f_1, e_1) = 1/3
c(hund | 0; f_1, e_1) = 1/3	c(bjeffet | 0; f_1, e_1) = 1/3

e_2: Dog bit dog
f_2: Hund bet hund

c(hund | dog; f_2, e_2)= 1	c(bet | dog; f_2, e_2) = 1/2
c(hund | bit; f_2, e_2) = 1/2	c(bet | bit; f_2, e_2) = 1/4
c(hund | 0; f_2, e_2) = 1/2	c(bet | 0; f_2, e_2) = 1/4

Step 3.2: Total counts (as before)

$$tc(f \mid e) = \sum_{(\mathbf{f},\mathbf{e})} c(f \mid e; \mathbf{f}, \mathbf{e})$$

tc(hund|dog) = 1+1/3	tc(bet|dog) = 1/2	tc(bjeffet|dog) = 1/3	tc(*|dog)=4/3+1/2+1/3 =13/6
tc(hund|bit) = ½	tc(bet|bit) = ¼	tc(bjeffet|bit) = 0	tc(*|bit)=3/4
tc(hund|barked) = 1/3	tc(bet|barked) = 0	tc(bjeffet|barked) = 1/3	tc(*|barked) =2/3
tc(hund|0) = ½+1/3	tc(bet|0) = 1/4	tc(bjeffet|0) = 1/3	tc(*|0)=17/12

Step 4: new trans. probabilities

$$t(f|e) = \frac{tc(f|e)}{\sum_{f'} tc(f'|e)}$$

e	f	t(f|e)	exact	decimal
0	hund	(5/6)/(17/12)	10/17	0.588235
0	bet	(1/4)/(17/12)	3/17	0.176471
0	bjeffet	(1/3)/(17/12)	4/17	0.235294
dog	hund	(4/3)/(13/6)	8/13	0.615385
dog	bet	(1/2)/(13/6)	3/13	0.230769
dog	bjeffet	(1/3)/(13/6)	2/13	0.153846
bit	hund	(1/2)/(3/4)	2/3	0.666667
bit	bet	(1/4)/(3/4)	1/3	0.333333
barked	hund	(1/3)/(2/3	1/2	0.5
barked	bjeffet	(1/3)/(2/3)	1/2	0.5

Repeat: calculate fractional counts

- Examples

$$c(hund \mid barked; \mathbf{e}_1, \mathbf{f}_1) = \frac{t(hund \mid barked)}{\sum_{i=0}^{2} t(f \mid e_i)} \sum_{j=1}^{2} \delta(hund, f_j) \sum_{i=0}^{2} \delta(barked, e_i) =$$

$$\frac{0.5}{0.588235 + 0.615385 + 0.5} = \frac{0.5}{1.70362} = 0.2934927$$

$$c(hund \mid dog; \mathbf{e}_2, \mathbf{f}_2) = \frac{t(hund \mid dog)}{\sum_{i=0}^{3} t(hund \mid e_i)} \sum_{j=1}^{3} \delta(hund, f_j) \sum_{i=0}^{3} \delta(dog, e_i) =$$

$$\frac{0.615385}{0.588235 + 0.615385 + 0.666667 + 0.615385} \times 2 \times 2 = ?$$

After some iterations

		1st iterat.	2nd iter.	5th iter.	25th iter	100th
0	hund	0.588235				
0	bet	0.176471				
0	bjeffet	0.235294				
dog	hund	0.615385				
dog	bet	0.230769				
dog	bjeffet	0.153846				
bit	hund	0.666667				
bit	bet	0.333333				
barked	hund	0.5				
barked	bjeffet	0.5				

After some iterations

		1st iterat.	2nd iter.	5th iter.	25th iter	100th
0	hund	0.588235	0.647158			
0	bet	0.176471	0.14363			
0	bjeffet	0.235294	0.209212			
dog	hund	0.615385	0.675859			
dog	bet	0.230769	0.237614			
dog	bjeffet	0.153846	0.086527			
bit	hund	0.666667	0.609848			
bit	bet	0.333333	0.390152			
barked	hund	0.5	0.342932			
barked	bjeffet	0.5	0.657068			

After some iterations

		1st iterat.	2nd iter.	5th iter.	25th iter	100th
0	hund	0.588235	0.647158	0.81929		
0	bet	0.176471	0.14363	0.067291		
0	bjeffet	0.235294	0.209212	0.113419		
dog	hund	0.615385	0.675859	0.773893		
dog	bet	0.230769	0.237614	0.214793		
dog	bjeffet	0.153846	0.086527	0.011313		
bit	hund	0.666667	0.609848	0.417491		
bit	bet	0.333333	0.390152	0.582509		
barked	hund	0.5	0.342932	0.097766		
barked	bjeffet	0.5	0.657068	0.902234		

After some iterations

		1st iterat.	2nd iter.	5th iter.	25th iter	100th
0	hund	0.588235	0.647158	0.81929	0.998457	
0	bet	0.176471	0.14363	0.067291	0.000122	
0	bjeffet	0.235294	0.209212	0.113419	0.001421	
dog	hund	0.615385	0.675859	0.773893	0.947458	
dog	bet	0.230769	0.237614	0.214793	0.052541	
dog	bjeffet	0.153846	0.086527	0.011313	0	
bit	hund	0.666667	0.609848	0.417491	0.005351	
bit	bet	0.333333	0.390152	0.582509	0.994648	
barked	hund	0.5	0.342932	0.097766	6.0e-07	
barked	bjeffet	0.5	0.657068	0.902234	0.999999	

After some iterations

		1st iterat.	2nd iter.	5th iter.	25th iter	100th
0	hund	0.588235	0.647158	0.81929	0.998457	1
0	bet	0.176471	0.14363	0.067291	0.000122	0
0	bjeffet	0.235294	0.209212	0.113419	0.001421	0
dog	hund	0.615385	0.675859	0.773893	0.947458	0.966031
dog	bet	0.230769	0.237614	0.214793	0.052541	0.033968
dog	bjeffet	0.153846	0.086527	0.011313	0	0
bit	hund	0.666667	0.609848	0.417491	0.005351	0
bit	bet	0.333333	0.390152	0.582509	0.994648	1
barked	hund	0.5	0.342932	0.097766	6.0e-07	0
barked	bjeffet	0.5	0.657068	0.902234	0.999999	1

Results (perplexitiy)

- Claim: «the numbers converge towards better results»
- Means: for each round

$$\prod_{(\mathbf{e},\mathbf{f})} P(\mathbf{f} \mid \mathbf{e})$$

does not decrease

- For IBM Model 1 it may be proved that they converge towards a global optimum

Today

- Repetition:
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IBM model 2

$$P(\mathbf{f},\mathbf{a}\mid\mathbf{e}) = P(m\mid\mathbf{e})\prod_{j=1}^{m} P(a_j \mid a_1^{j-1}, f_1^{j-1}, m, \mathbf{e}) P(f_j \mid a_1^{j}, f_1^{j-1}, m, \mathbf{e})$$

- *New*
  - $P(a_j \mid a_1^{j-1}, f_1^{j-1}, m, \mathbf{e}) = a(a_j \mid j, m, k)$
    - For a probaility distribution a
    - i.e. it depends on the length of the string and the position
    - (less likely to move far than to stay close)
- As for Model1
  - $P(m\mid\mathbf{e})$ is a constant, independent of *m* and *E*
  - the word translation probability only depends on source word $P(f_j \mid a_1^{j}, f_1^{j-1}, m, \mathbf{e}) = t(f_j \mid e_{a_j})$

Model2

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

- We can do similar steps as for Model1 for expressing P(**f**|**e**) and P(**a**).
- We can do similar simplifications to bypass the exponential number of alignments, and
- Learn the alignment probabilities $a(a_j|j,m,k)$ at the same time as the translation probabilities
- You don't have to learn the details

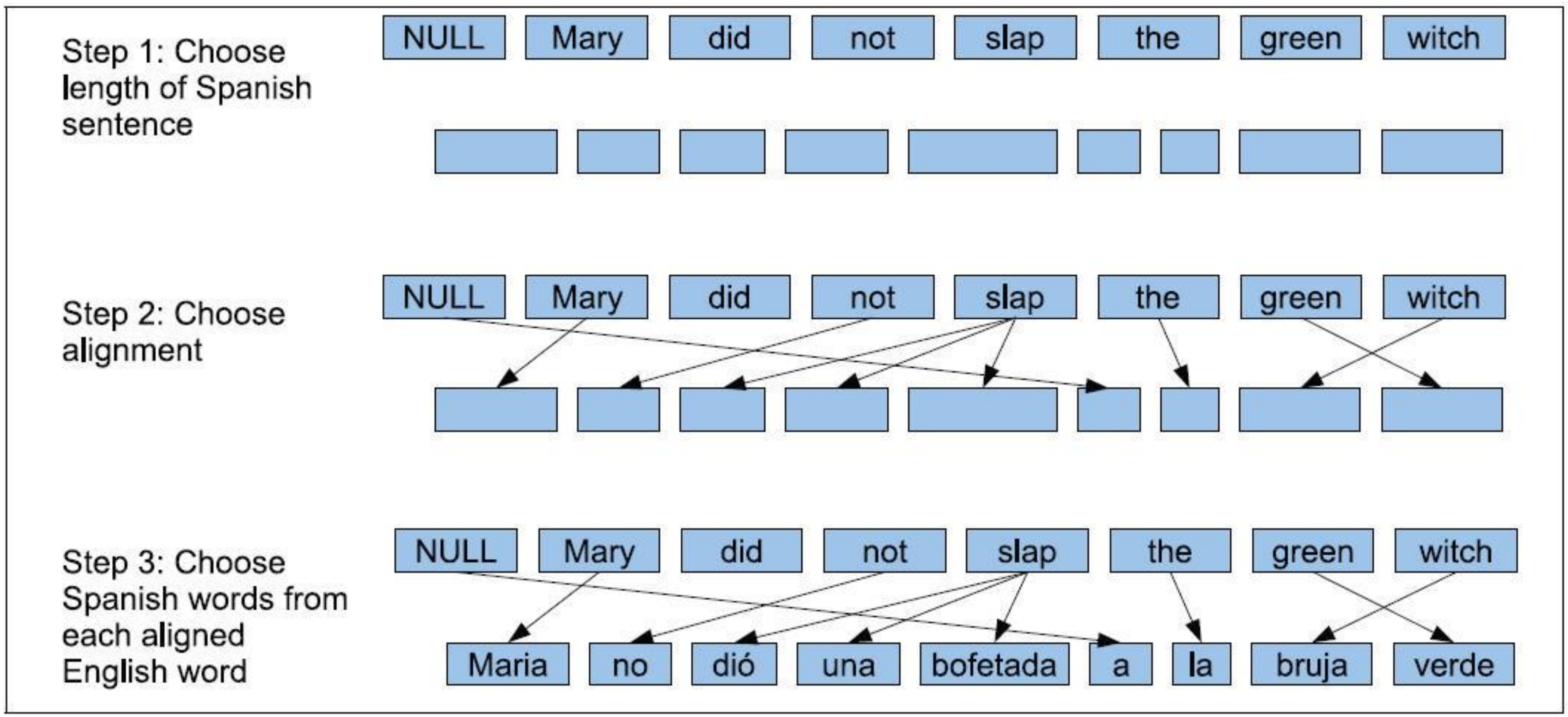
HMM Alignment

$$P(\mathbf{f},\mathbf{a}\mid\mathbf{e}) = P(m\mid\mathbf{e})\prod_{j=1}^{m} P(a_j \mid a_1^{j-1}, f_1^{j-1}, m, \mathbf{e}) P(f_j \mid a_1^{j}, f_1^{j-1}, m, \mathbf{e})$$

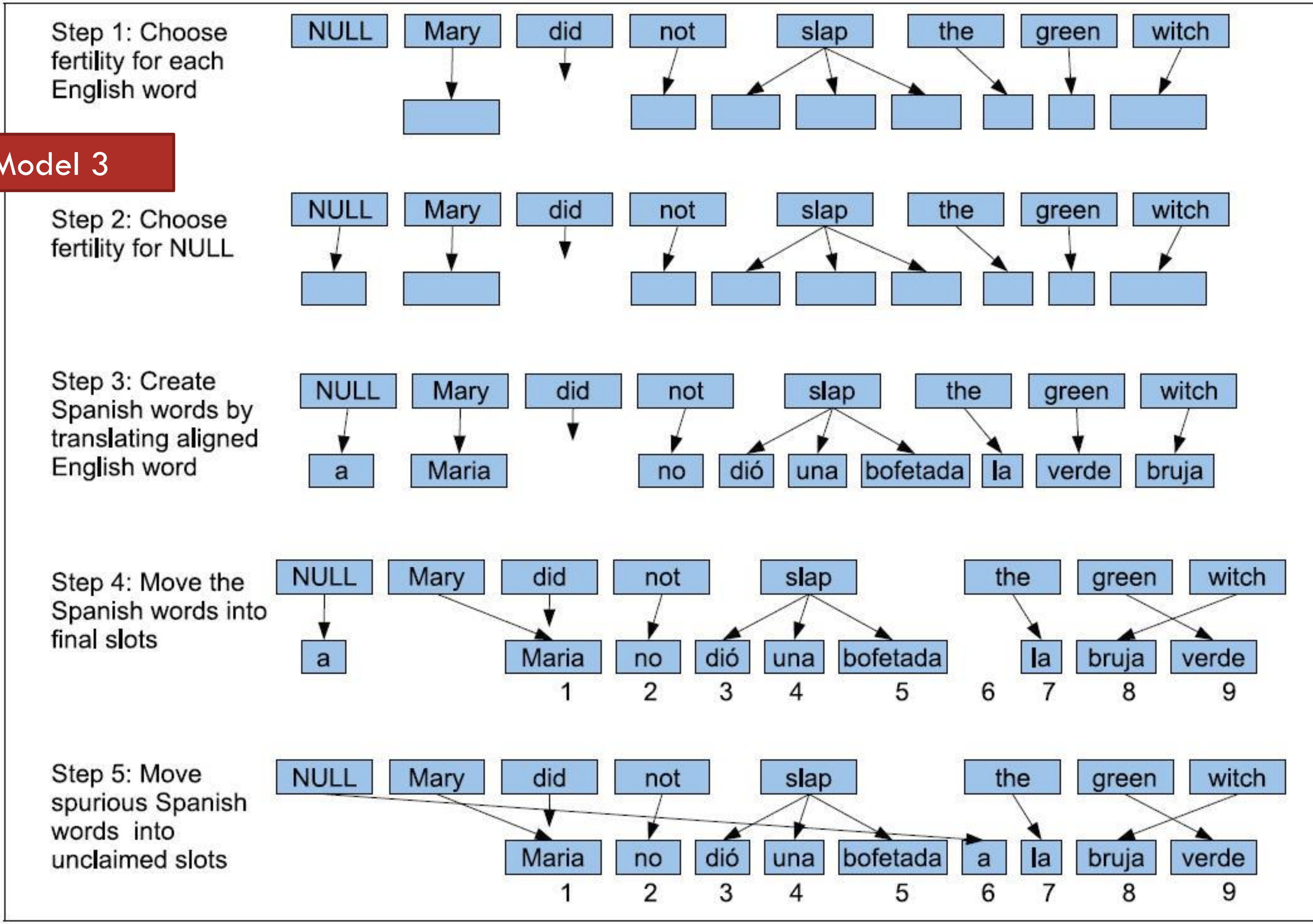
$$P(\mathbf{f},\mathbf{a}\mid\mathbf{e}) = P(m\mid k)\prod_{j=1}^{m} P(a_j \mid a_1^{j-1}, k) t(f_j \mid e_{a_j})$$

- $P(m|k)$ depends on the length *k* of **e**.
- $P(a_j \mid a_1^{j-1}, f_1^{j-1}, m, \mathbf{e}) = P(a_j \mid a_{j-1}, k) = \lambda c(a_j - a_{j-1})$
  - Where word j should come from, depends on where word j-1 came from
  - This is again reduced to probabilities, c, of the distance between a_j and a_{j-1} independently of the actual j.

Model 1 & 2 and HMM alignment



Model 3



Step 1: Choose fertility for each English word
NULL Mary did not slap the green witch
Step 2: Choose fertility for NULL
NULL Mary did not slap the green witch
Step 3: Create Spanish words by translating aligned English word
NULL Mary did not slap the green witch
a Maria no dió una bofetada la verde bruja
Step 4: Move the Spanish words into final slots
NULL Mary did not slap the green witch
a Maria no dió una bofetada la bruja verde
1 2 3 4 5 6 7 8 9
Step 5: Move spurious Spanish words into unclaimed slots
NULL Mary did not slap the green witch
Maria no dió una bofetada a la bruja verde
1 2 3 4 5 6 7 8 9

IBM Model 3: Fertility

- Fertility: number of F words produced by an E word
- Modelled by a distribution $n(x|e)$

Example:
F = Norw.
n(2 | yesterday) ≈ 1
n(1 | to) ≈ 0.8
n(2 | to) ≈ 0.2
n(1 | car) ≈ 1
n(0 | the) ≈ 0.6
n(1 | the) ≈ 0.4

Example:
Norw.→Eng.
n(2 | bilen) ≈ 0.7
n(1 | bilen) ≈ 0.3
n(1 | å) ≈ 0.8
n(0 | å) ≈ 0.2

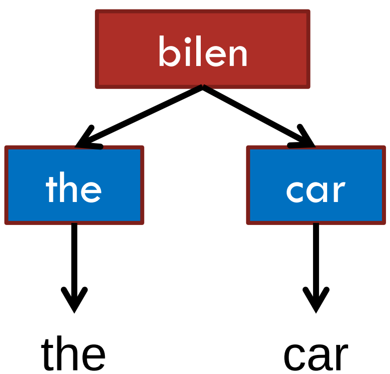
IBM Model 3: Null insertion

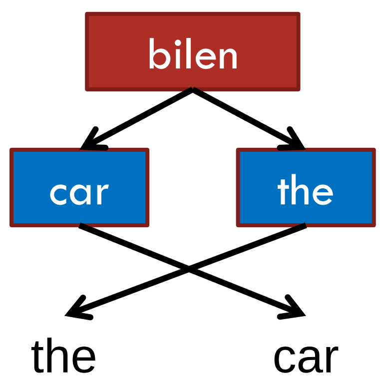
- Modelled by:
- There is a probability p0:
  - After each inserted word there is the probability p0 of not inserting a null-word
  - And a probability p1 = (1-p0) of inserting a null-word
- A rather complex expression for what this contributes into P(a, **f**|**e**) which considers
  - Permutations
  - Length of **f**

IBM Model 3: Distortion

$$d(j \mid a_j, m, k)$$

- A probability distribution which gives the probability of word a_i ending up in position j.
- Similar to alignment in model 2 but:
  - Opposite direction
  - Different choices of words + distortion may correpsond to the same alignment





IBM model 3

$$P(\mathbf{f},\mathbf{a}\,|\,\mathbf{e}) = \prod_{j=1}^{m} t(f_j \,|\, e_{a_j}) \prod_{j=1}^{m} d(j \,|\, a_j, k, m) \times \text{ more}$$

- Where *more* is an expression which counts
  - $n(x \,|\, e_i)$ the right number of times
  - And uses p0 to give the right probability to null-insertion.

Training Model 3

- In principle like Model 1, but
  - The trick to get rid of the alignments does not work
  - Too costly to calculate all alignments
- Strategy
  - Sample and use the most probable alignments
  - Start with alignments for Model 1 and Model 2
  - Use hill-climbing algorithm

Hill-climbing algorithm

- Assign some initial parameter values
- Consider several alternative sets of parameter values in the vicinity of where you are
- Compare the resulting values and choose the parameters which yield the best results
- Repeat

Training model 3

- Model 1: The optimum we find is global
- Model 3 (and model 2):
  - A local optimum does not have to be global
- First run some iterations of Model1 and maybe some iterations of Model 2
- Use the results, in particular the alignment, as input to Model 3
- Hill-climb the space of alignments from here, doing minimal changes.

IBM Model 4

- Better reordering model
- Consider group of words (phrases)
- Distinguish between
  - the placement of the whole group
  - The placement within the group

The IBM-models

- IBM models 1-4 are not true probability models.
- Model 5 fixes this
  - Based of model 4
- We will not consider models 4 and 5
- Phrase Based translation makes use of Model 3