statistical machine translation

Part 2: IBM Model

CSC401/2511 – Natural Language Computing – Spring 2019
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Statistical Machine Translation

- Challenges to statistical machine translation
- Sentence alignment
- IBM model
- Phrase-based translation
- Decoding
- Evaluation

How to use the noisy channel

- How does this work?

$$E^* = \underset{E}{\operatorname{argmax}} P(F|E)P(E)$$

- $P(E)$ is a **language model** (e.g., *N*-gram) and encodes knowledge of word order.
- $P(F|E)$ is a **word-level translation model** that encodes only knowledge on an *unordered* word-by-word basis.

- **Combining** these models can give us **naturalness** and **fidelity**, respectively.

Sentence alignment

- Sentences can also be **unaligned** across translations.
  - E.g., *He was happy.*$_{E1}$ *He had bacon.*$_{E2}$ → *Il était heureux parce qu'il avait du bacon.*$_{F1}$

E_1	F_1
E_2	F_2
E_3	F_3
E_4	F_4
E_5	F_5
E_6	F_6
E_7	F_7
…	

E_1 E_2	F_1
E_3	F_2
E_4	F_3
E_5	F_4 F_5
E_6	F_6
E_7	F_7
…	

Sentence alignment

- We often need to align **sentences** before we can align **words**.

- We'll look at two broad classes of methods:
  1. Methods that only look at **sentence length**,
  2. Methods based on **lexical matches**, or "cognates".

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1. Sentence alignment by length

E_1 E_2	F_1
E_3	F_2
E_4	F_3
E_5	F_4 F_5
E_6	F_6

It's a bit more complicated – see paper on course webpage

We can associate costs with different **types** of alignments.

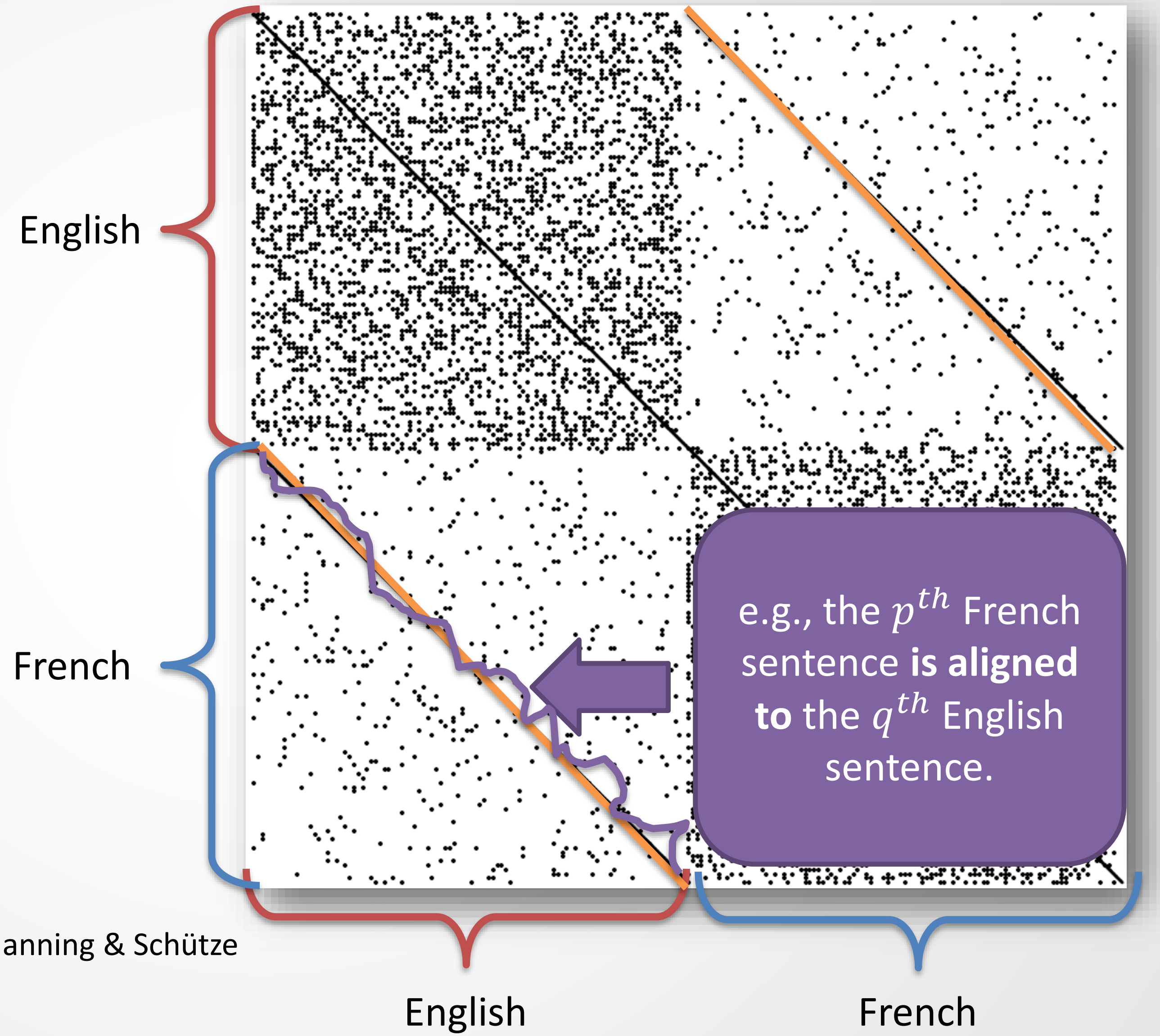
$\boldsymbol{C_{i,j}}$ is the prior cost of aligning i sentences to j sentences.

$$
\begin{aligned}
Cost = {} & Cost\left(\mathcal{L}_{E_1} + \mathcal{L}_{E_2}, \mathcal{L}_{F_1}\right) + C_{2,1} + \\
& Cost\left(\mathcal{L}_{E_3}, \mathcal{L}_{F_2}\right) + C_{1,1} + \\
& Cost\left(\mathcal{L}_{E_4}, \mathcal{L}_{F_3}\right) + C_{1,1} + \\
& Cost\left(\mathcal{L}_{E_5}, \mathcal{L}_{F_4} + \mathcal{L}_{F_5}\right) + C_{1,2} + \\
& Cost\left(\mathcal{L}_{E_6}, \mathcal{L}_{F_6}\right) + C_{1,1}
\end{aligned}
$$

Find distribution of sentence breaks with minimum cost using **dynamic programming**

2a. Church's method

- Church (1993) tracks all **4-graphs** which are identical across two texts.
- Each point along **this path** is considered to represent a **match** between languages.



From Manning & Schütze

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2b. Melamed's method

- $LCS(A, B)$ is the **longest common subsequence** of *characters* (*with gaps allowed*) in words A and B.

- Melamed (1993) measures similarity of words A and B

$$LCSR(A, B) = \frac{length(LCS(A, B))}{\max(length(A), length(B))}$$

  - e.g.,

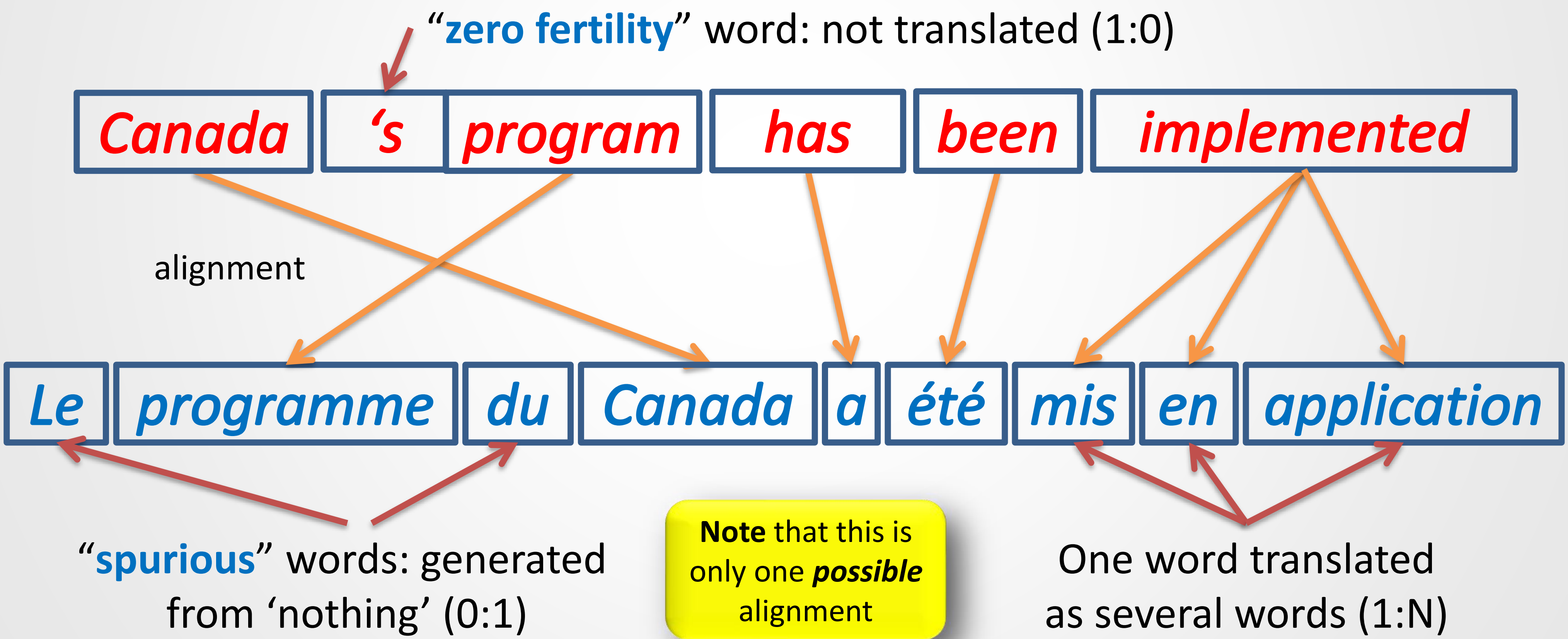
$$LCSR(\boldsymbol{government}, \boldsymbol{gouvernement}) = \frac{10}{12}$$

'LCS Ratio'


word
alignment
sentence
alignment

Word alignment

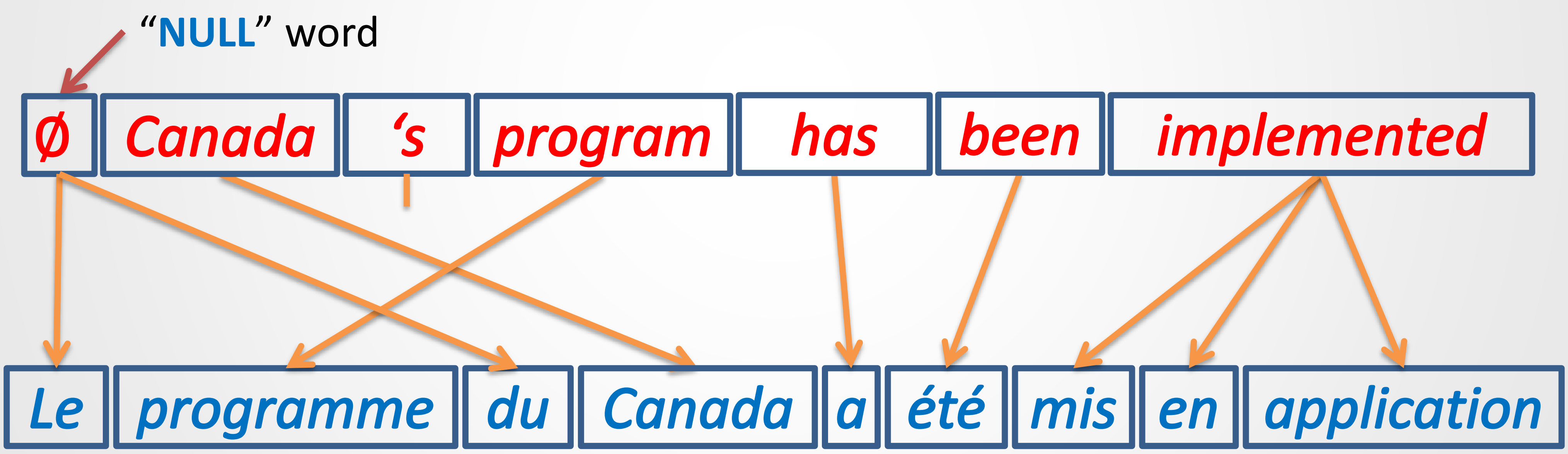
- **Word alignments** can be 1:1, N:1, 1:N, 0:1,1:0,… E.g.,



IBM Model 1

IBM Model 1: the NULL word

- The **NULL** word is an imaginary word that we need to account for the production of spurious words.



IBM Model 1: some definitions

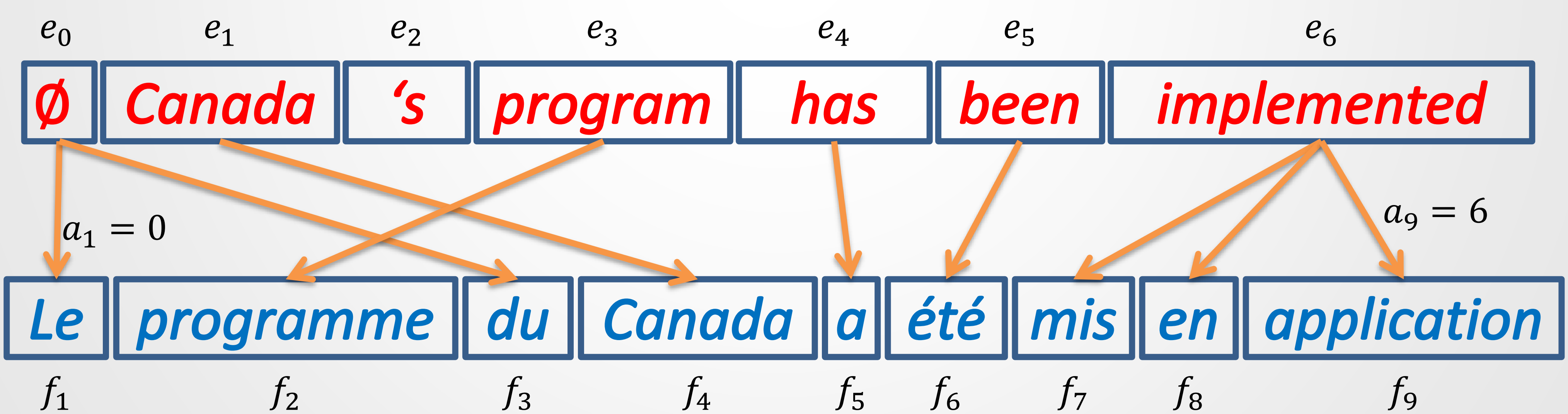
- English sentence E has L_E words, $e_1 \ldots e_{L_E}$,
  plus NULL word, e_0.
- French sentence F has L_F words, $f_1 \ldots f_{L_F}$.

e_0	e_1	e_2	e_3	e_4	e_5	e_6
Ø	*Canada*	*'s*	*program*	*has*	*been*	*implemented*

Le	*programme*	*du*	*Canada*	*a*	*été*	*mis*	*en*	*application*
f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9

IBM Model 1: alignments

- An **alignment**, a, identifies **the English word** that 'produced' **the given French word at each index.**
  - $\boldsymbol{a} = \{\boldsymbol{a_1}, \dots, \boldsymbol{a_{L_F}}\}$ where $a_j \in \{0, \dots, L_E\}$
  - E.g., $\boldsymbol{a} = \{\mathbf{0, 3, 0, 1, 4, 5, 6, 6, 6}\}$



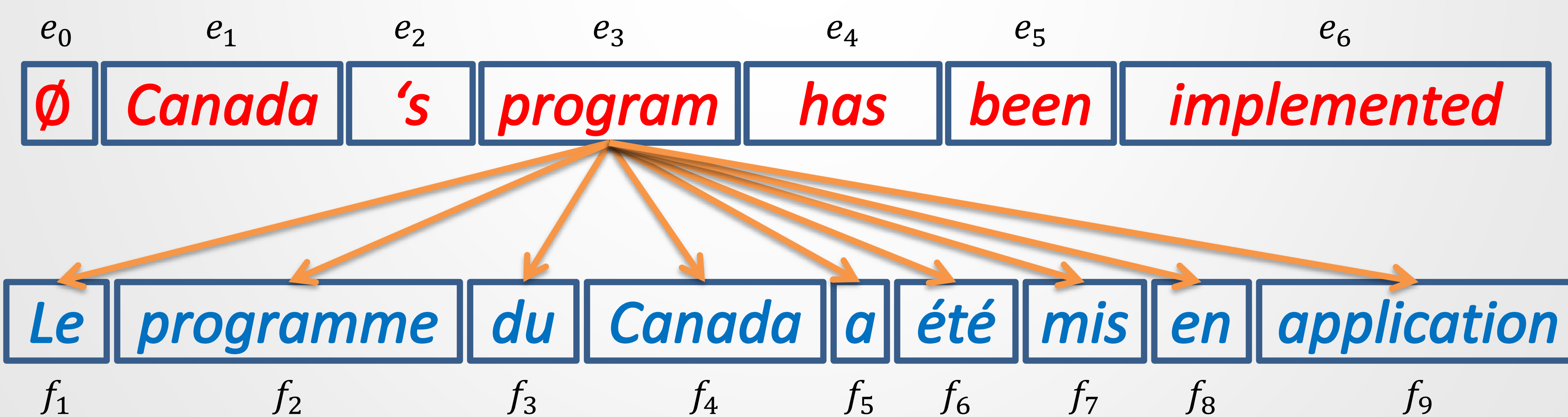
IBM Model 1: alignments

f_1	*Le*	*∅*	e_0
f_2	*programme*	*program*	e_3
f_3	*du*	*∅*	e_0
f_4	*Canada*	*Canada*	e_1
f_5	*a*	*has*	e_4
f_6	*été*	*been*	e_5
f_7	*mis*	*implemented*	e_6
f_8	*en*	*implemented*	e_6
f_9	*application*	*implemented*	e_6

$$\boldsymbol{a} = \{0, 3, 0, 1, 4, 5, 6, 6, 6\}$$

IBM Model 1: alignments

- There are $(L_E + 1)^{L_F}$ possible alignments. (since $\|a\| = L_F$)
- IBM-1 doesn't know that some are *very bad* in reality.
  - E.g., $\boldsymbol{a} = \{3,3,3,3,3,3,3,3,3\}$



IBM Model 1: alignments

- IBM Model 1 assumes that all alignments of E are **equally likely** given only the **length** (not the words) of F.

$$\forall \boldsymbol{a}, P(a|E, L_F) = \frac{1}{(L_E + 1)^{L_F}}$$

Uniform over all possible alignments.

- This is a **major** simplifying assumption, but it gets the process started.

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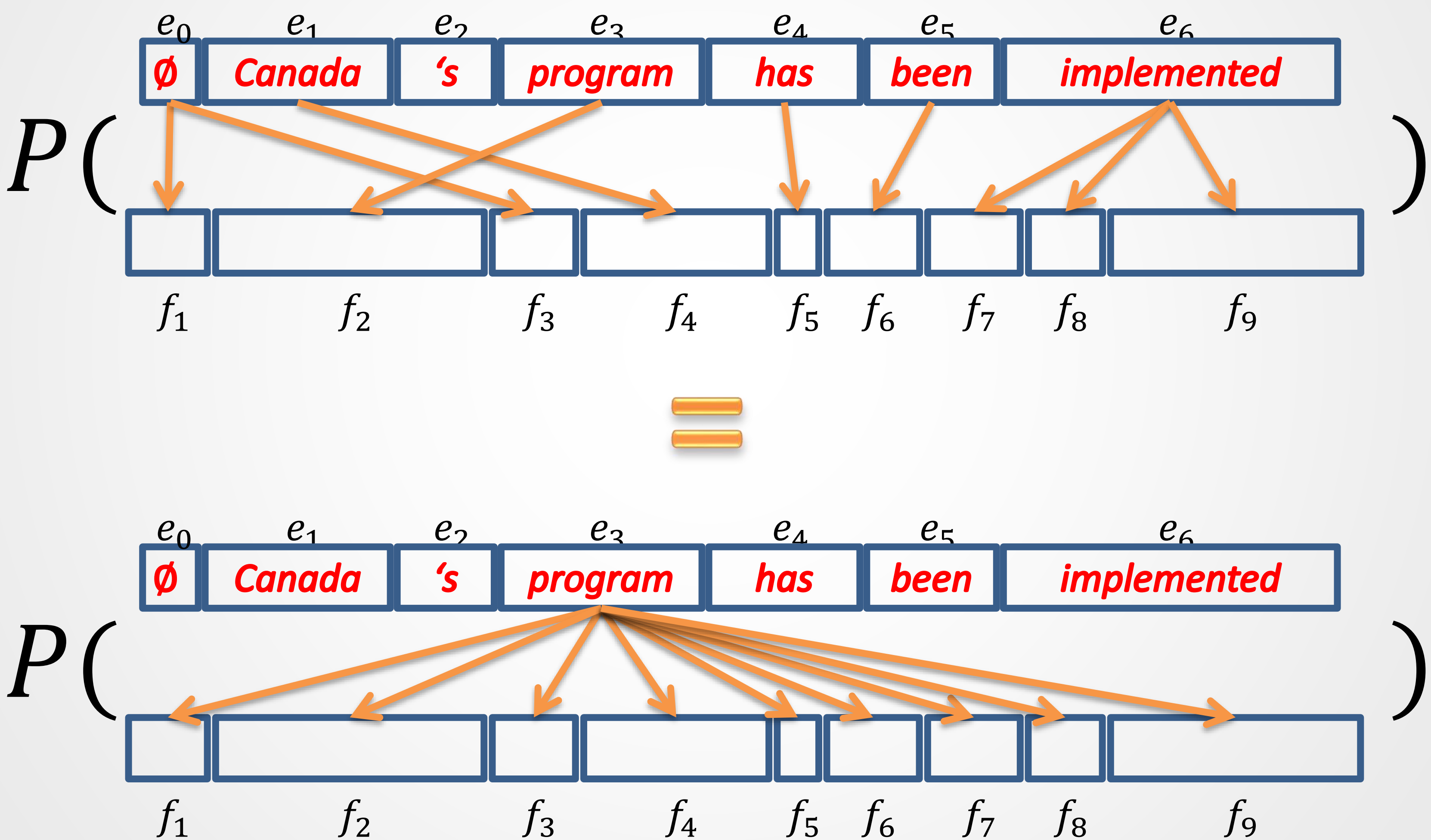
Equally likely alignments *a priori*



IBM Model 1: translation probability

- Given an **alignment** a and an **English sentence** E, what is the probability of a **French sentence** F?

$$P(F|a,E)$$

- In IBM-1,

The probability of the j^{th} French word, given that it was generated from the a_j^{th} English word.

$$P(F|a,E) = \prod_{j=1}^{L_F} P(f_j|e_{a_j})$$

(another simplifying assumption)

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IBM Model 1: translation probability

- E = ***Canada 's program has been implemented***
- $a = \{0,3,0,1,4,5,6,6,6\}$
- F = ***Le programme du Canada à été mis en application***

- $$\begin{aligned} P(F|a,E) = {} & P(Le|\emptyset)P(programme|program) \times \\ & P(du|\emptyset)P(Canada|Canada)P(\text{à}|has) \times \\ & P(\text{été}|been)P(mis|implemented) \times \\ & P(en|implemented) \times \\ & P(application|implemented) \end{aligned}$$

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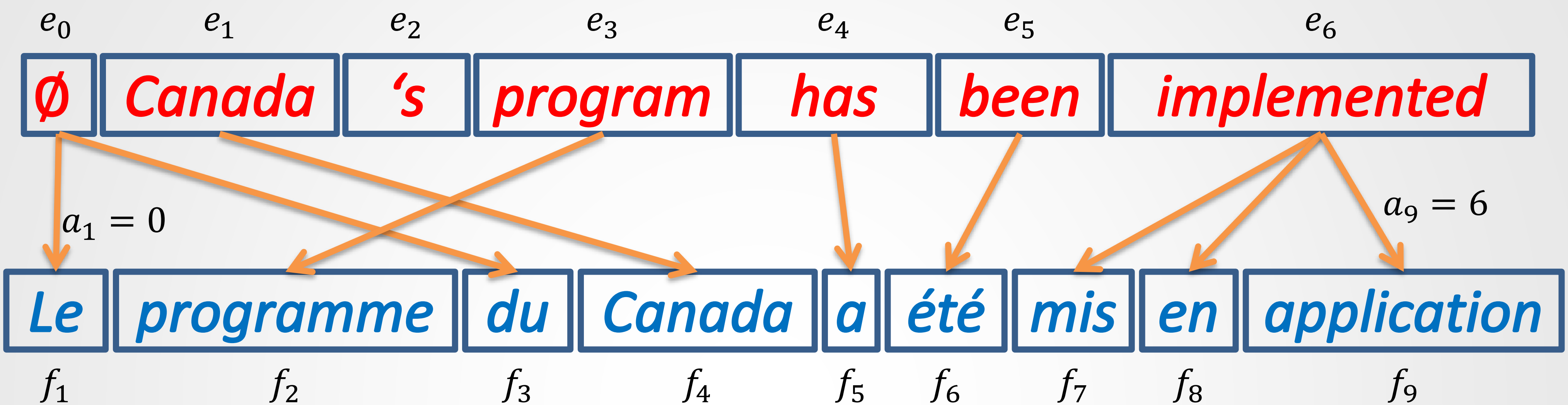
IBM Model 1: translation probability



$$\boldsymbol{a = \{0, 3, 0, 1, 4, 5, 6, 6, 6\}}$$

- $P(F|a, E) = P(Le|Ø)P(programme|program) \times$
  $P(du|Ø)P(Canada|Canada)P(à|has) \times$
  $P(été|been)P(mis|implemented) \times$
  $P(en|implemented) \times$
  $P(application|implemented)$

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IBM Model 1: generation

This is how we imagine English gets corrupted in the noisy channel.

- To **generate** a **French** sentence F **from English** E,
  1. Pick a length of F (with probability $P(L_F)$).
  2. Pick an alignment (with **uniform** probability, $\frac{1}{(L_E+1)^{L_F}}$).
  3. Sample French words with probability

Slide 17

$$P(F|a,E) = \prod_{j=1}^{L_F} P(f_j|e_{a_j})$$

Slide 19

So,

$$P(F,a|E) = P(a|E)P(F|a,E) = \frac{P(L_F)}{(L_E+1)^{L_F}} \prod_{j=1}^{L_F} P(f_j|e_{a_j})$$

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IBM-1: alignment as hidden variable

- If $P(F, a|E)$ describes the process of generating French words *and* alignments from English words…

Remember, the **noisy channel model** states that French words are really encoded English words!

- Then

$$P(F|E) = \sum_{a \in \mathcal{A}} P(F, a|E)$$

where $\mathcal{A}$ is the **set** of **all possible** alignments

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IBM-1: training

- Our **training data** $\mathcal{O}$ is a set of **pairs** of **corresponding** French and English sentences, $\mathcal{O} = \{(F_i, E_i)\}, i = 0..N$.
- If we knew the word alignments, a, learning $P(f|e)$ would be trivial with MLE: $P(f|e) = \frac{Count(f,e)}{Count(e)}$.

  # times aligned
- But the **alignments** are **hidden**. We need to use …

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IBM-1: expectation-maximization

1. **Initialize** translation parameters $P(f|e)$ (e.g., randomly).

2. **Expectation**: Given the current $\theta_k = P(f|e)$, compute the **expected value** of $\boldsymbol{Count}(\boldsymbol{f}, \boldsymbol{e})$ for all words in training data $\mathcal{O}$.

3. **Maximization**: Given the expected value of $\boldsymbol{Count}(\boldsymbol{f}, \boldsymbol{e})$, compute the **maximum likelihood** estimate of $\theta_k = P(f|e)$

IBM-1 EM: Example

- Imagine our training data is

$$\mathcal{O} = \{(blue\ house, maison\ bleue), \\ (the\ house, la\ maison)\}$$

- The vocabularies are

$$\mathcal{V}_E = \{blue, house, the\} \text{ and}$$
$$\mathcal{V}_F = \{maison, bleue, la\}.$$

- For **simplicity**, we consider only 1:1 alignments: there is **no** NULL word, there are **no** zero-fertility words.

IBM-1 EM: Example

- First, we **initialize** our parameters, $\boldsymbol{\theta} = \boldsymbol{P}(\boldsymbol{f}|\boldsymbol{e})$.

- In the **Expectation** step, we compute **expected** counts:
  - $TCount(f, e)$: the total number of times e and f are aligned.
  - $Total(e)$: the total number of e.

    This has to be done in steps by first computing $\boldsymbol{P}(\boldsymbol{F}, \boldsymbol{a}|\boldsymbol{E})$ *then* $\boldsymbol{P}(\boldsymbol{a}|\boldsymbol{F}, \boldsymbol{E})$

- In the **Maximization** step, we perform MLE with the expected counts.

IBM-1 EM: Example initialization

1. Make a table of $P(f|e)$ for all possible pairs f and e.

   Initialize uniformly across rows.

θ_0:

$P(maison\|blue) = \frac{1}{3}$	$P(bleue\|blue) = \frac{1}{3}$	$P(la\|blue) = \frac{1}{3}$
$P(maison\|house) = \frac{1}{3}$	$P(bleue\|house) = \frac{1}{3}$	$P(la\|house) = \frac{1}{3}$
$P(maison\|the) = \frac{1}{3}$	$P(bleue\|the) = \frac{1}{3}$	$P(la\|the) = \frac{1}{3}$

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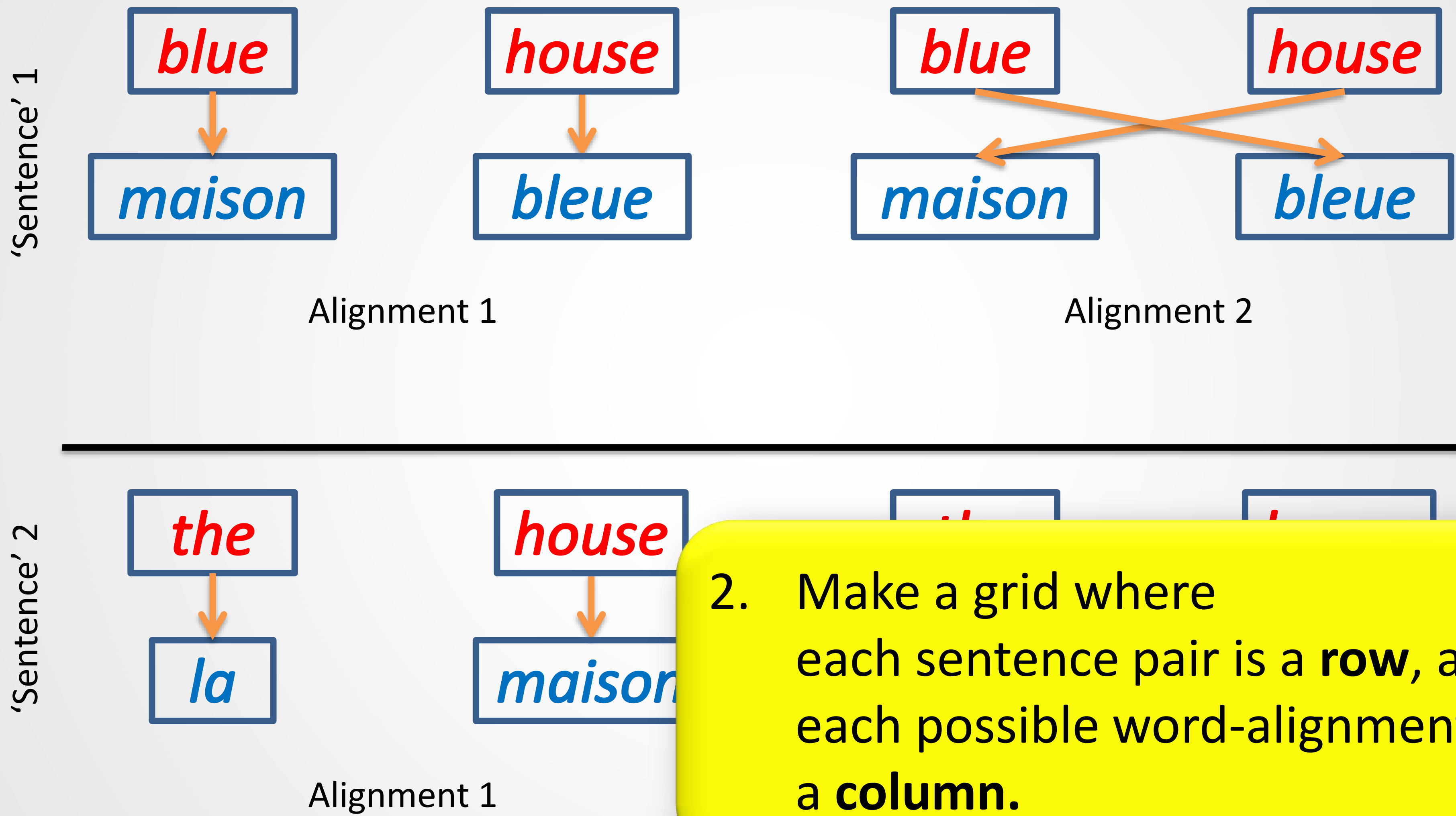
IBM-1 <u>E</u>: compute $P(F|a,E)$



2. Make a grid where
   each sentence pair is a **row**, and
   each possible word-alignment is
   a **column.**

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IBM-1 E: compute $P(F|a,E)$

'Sentence' 1

blue → maison, house → bleue, $a = a_{1,1}$

$$P(F|a,E) = P(maison|blue) \times P(bleue|house) = \frac{1}{3} \cdot \frac{1}{3} = \mathbf{\frac{1}{9}}$$

blue → bleue, house → maison, $a = a_{1,2}$

$$P(F|a,E) = P(bleue|blue) \times P(maison|house) = \frac{1}{3} \cdot \frac{1}{3} = \mathbf{\frac{1}{9}}$$

'Sentence' 2

the → la, house → maison, $a = a_{2,1}$

$$P(F|a,E) = P(la|the) \times P(maison|house) = \frac{1}{3} \cdot \frac{1}{3} = \mathbf{\frac{1}{9}}$$

3 3 **9**

3. For each sentence pair and alignment, compute (slide 19)

$$P(F|a,E) = \prod_{f_j} P(f_j|e_{a_j})$$

IBM-1 <u>E</u>: compute $P(a|E,F)$

- We want the **probability of an alignment** a so that we can compute the **expected** $Count(f_j, e_i)$.

$$P(a|E,F) = \frac{P(F|a,E)}{\sum_{a_i \in \mathcal{A}} P(F|a_i,E)}$$

- This is **not** the same as the probability $P(a|E,L_F)$.
  - i.e., it won't *always* be uniform.

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IBM-1 E: compute $P(a|E,F)$

$$P(a|E,F) = \frac{P(a,E,F)}{P(E,F)} = \frac{P(a,E,F)}{P(E)P(F|E)} = \frac{P(F,a|E)P(E)}{P(E)P(F|E)}$$

$$\overset{(*)}{=} \frac{P(F,a|E)}{\sum_{a_i \in \mathcal{A}} P(F,a_i|E)} \overset{(**)}{=} \frac{P(F|a,E)}{\sum_{a_i \in \mathcal{A}} P(F|a_i,E)}$$

(*) Because $P(F|E) = \sum_{a_i \in \mathcal{A}} P(F, a_i|E)$ (slide 23)

(**) Rewrite $P(F, a|E)$ as on slide 22, and $\frac{P(L_F)}{(L_E+1)^{L_F}}$ cancels out

IBM-1 E: compute $P(a|E,F)$

- We want the **probability of an alignment** a so that we can compute the **expected** $Count(f_j, e_i)$.

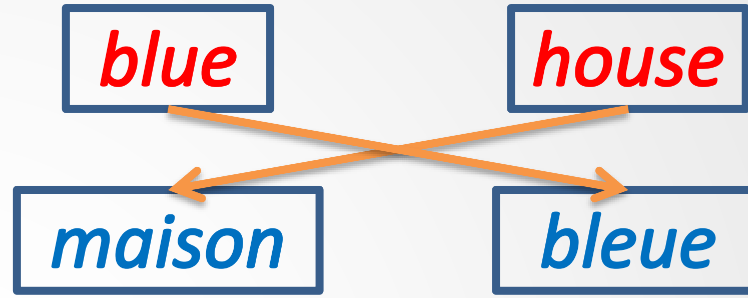
$$P(a|E,F) = \frac{P(F|a,E)}{\sum_{a_i \in \mathcal{A}} P(F|a_i,E)}$$

- This is **not** the same as the probability $P(a|E,L_F)$.
  - i.e., it won't *always* be uniform.

IBM-1 E: compute $P(a|E,F)$

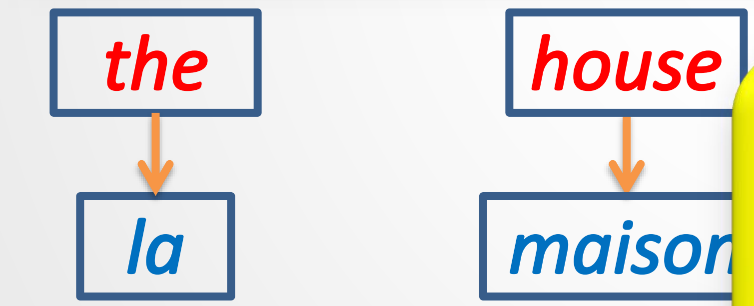
'Sentence' 1

$$P(a|E,F) = \frac{1/9}{1/9 + 1/9} = \frac{1}{2}$$



$$P(a|E,F) = \frac{1/9}{1/9 + 1/9} = \frac{1}{2}$$

'Sentence' 2



$$P(a|E,F) = \frac{1/9}{1/9 + 1/9} = \frac{1}{2}$$

4. For each element in your grid, divide $P(F|a,E)$ by the sum of the row (slide 33).

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IBM-1 E: compute $TCount$

maison and *blue* are aligned only in alignment 1, sentence 1.

$$P(a=1|F_1,E_1)=\frac{1}{2}$$

maison and *house* are aligned in alignment 2, sentence 1.
and
alignment 1, sentence 2

$$P(a=2|F_1,E_1)=\frac{1}{2}$$

$$P(a=1|F_2,E_2)=\frac{1}{2}$$

$TCount(maison, blue) = \frac{1}{2}$	$TCount(bleue, b$	
$TCount(maison, house) = \frac{1}{2}+\frac{1}{2}=1$	$TCount(bleue, hou$ $=?$	$=?$
$TCount(maison, the) =?$		

This is a ***new*** table,
not the $\theta = P(f|e)$ table from before!

5. **For each** possible **word pair** e and f, **sum** $P(a|E,F)$ from step 4 across <u>all alignments and sentence pairs</u> for each instance that e is aligned with f

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IBM-1 E: compute $TCount$

$TCount(maison, blue) = \frac{1}{2}$	$TCount(bleue, blue) = \frac{1}{2}$	$TCount(la, blue) = 0$
$TCount(maison, house) = \frac{1}{2} + \frac{1}{2} = 1$	$TCount(bleue, house) = \frac{1}{2}$	$TCount(la, house) = \frac{1}{2}$
$TCount(maison, the) = \frac{1}{2}$	$TCount(bleue, the) = 0$	$TCount(la, the) = \frac{1}{2}$

IBM-1 E: compute $Total$

E.g., $Total(blue) = \frac{1}{2} + \frac{1}{2} = 1,$

$Total(house) = 1 + \frac{1}{2} + \frac{1}{2} = 2,$ …

$TCount(maison, blue) = \frac{1}{2}$	$TCount(bleue, blue) = \frac{1}{2}$	$TCount(la, blue) = 0$
$TCount(maison, house) = \frac{1}{2} + \frac{1}{2} = 1$	$TCount(bleue, house) = \frac{1}{2}$	$TCount(la, house) = \frac{1}{2}$
$TCount(maison, the) = \frac{1}{2}$		

6. Sum over the rows of this table to get the **total** estimates for **each** English word, e.

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IBM-1 M: Recompute $P(f|e)$

7. Compute $P(f|e) = \frac{TCount(f,e)}{Total(e)}$

   This is your model after iteration 1.

θ_1:

$P(maison\|blue) = \frac{1/2}{1}$	$P(bleue\|blue) = \frac{1/2}{1}$	$P(la\|blue) = \frac{0}{1}$
$P(maison\|house) = \frac{1}{2}$	$P(bleue\|house) = \frac{1/2}{2} = \frac{1}{4}$	$P(la\|house) = \frac{1/2}{2} = \frac{1}{4}$
$P(maison\|the) = \frac{1/2}{1}$	$P(bleue\|the) = \frac{0}{1}$	$P(la\|the) = \frac{1/2}{1}$

IBM-1 EM: Repeat

- You have finished **1 iteration** of EM when you have completed Step 7,
- Go back to Step 2 and repeat.

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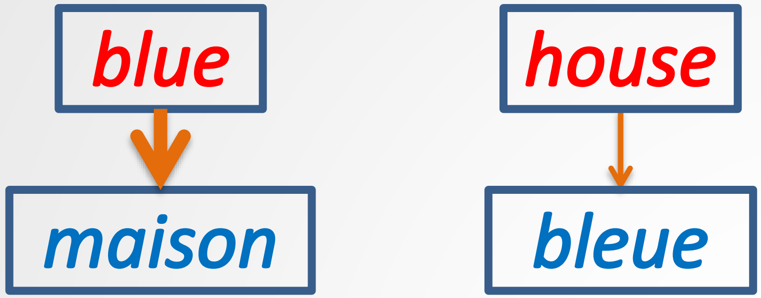
IBM-1 EM: Repeat

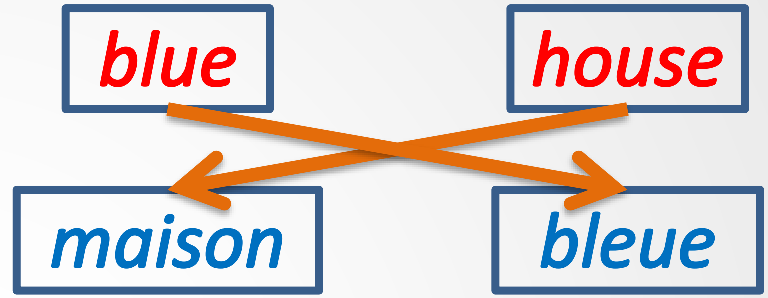
1. ~~Initialize~~ $\cancel{P(f|e)}$
2. Make grid of all possible alignments
3. Compute $P(F|a, E)$ → Products of $P(f|e)$
4. Compute $P(a|E, F)$ → Divide by sum of rows from step 3
5. Compute $TCount$ → Sum relevant probabilities from step 4
6. Compute $Total$ → Sum over rows from step 5
7. Compute $P(f|e) = \frac{TCount(f,e)}{Total(e)}$

IBM-1 E: compute $P(F|a,E)$

‘Sentence’ 1



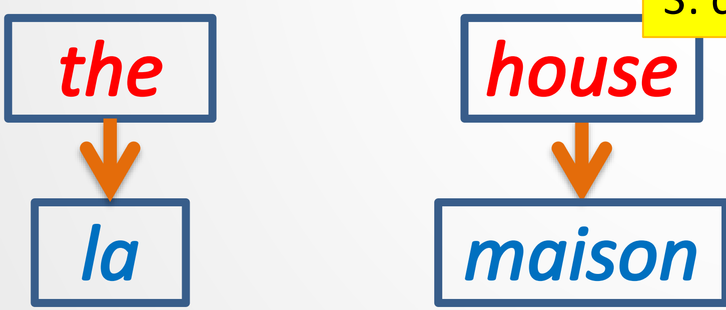
$$P(F|a,E) = P(maison|blue) \times P(bleue|house) = \frac{1}{2} \cdot \frac{1}{4} = \mathbf{\frac{1}{8}}$$



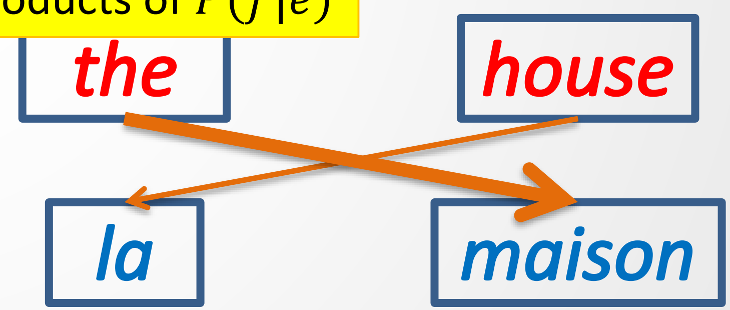
$$P(F|a,E) = P(bleue|blue) \times P(maison|house) = \frac{1}{2} \cdot \frac{1}{2} = \mathbf{\frac{1}{4}}$$

2: make grid
3: compute products of $P(f|e)$

‘Sentence’ 2



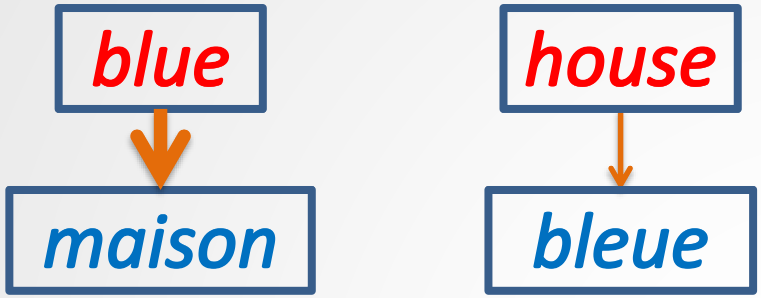
$$P(F|a,E) = P(la|the) \times P(maison|house) = \frac{1}{2} \cdot \frac{1}{2} = \mathbf{\frac{1}{4}}$$

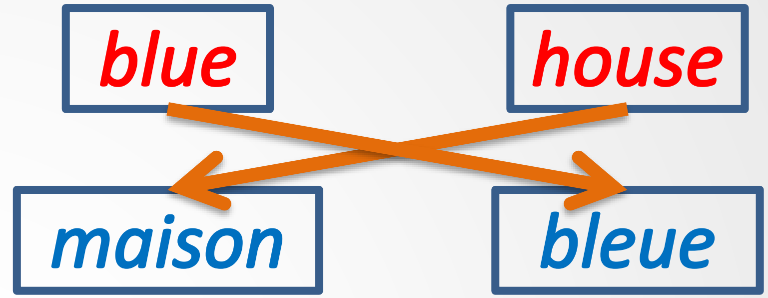


$$P(F|a,E) = P(maison|the) \times P(la|house) = \frac{1}{2} \cdot \frac{1}{4} = \mathbf{\frac{1}{8}}$$

IBM-1 E: compute $P(a|E,F)$

'Sentence' 1



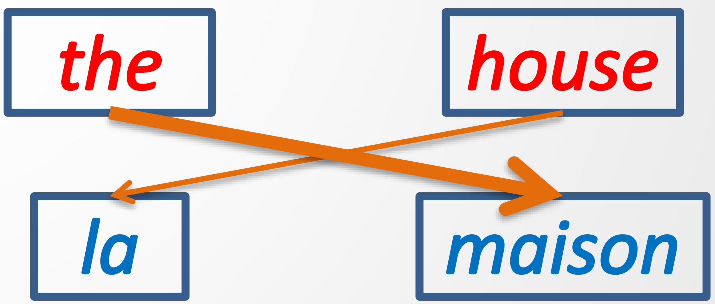


$$P(a|E,F) = \frac{1/8}{1/8 + 1/4} = \mathbf{\frac{1}{3}}$$

$$P(a|E,F) = \frac{1/4}{1/8 + 1/4} = \mathbf{\frac{2}{3}}$$

4: divide by sum of rows in step 3

'Sentence' 2



$$P(a|E,F) = \frac{1/4}{1/4 + 1/8} = \mathbf{\frac{2}{3}}$$

$$P(a|E,F) = \frac{1/8}{1/4 + 1/8} = \mathbf{\frac{1}{3}}$$

IBM-1 E: compute $TCount$ & $Total$

$$Total(blue) = \frac{1}{3} + \frac{2}{3} = 1, \quad Total(house) = \frac{4}{3} + \frac{1}{3} + \frac{1}{3} = 2,$$

$$Total(the) = \frac{1}{3} + \frac{2}{3} = 1$$

5. Compute *TCount* by summing relevant probabilities from step 4
6. Compute *Total* by summing rows

$TCount(maison, blue) = \frac{1}{3}$	$TCount(bleue, blue) = \frac{2}{3}$	$TCount(la, blue) = 0$
$TCount(maison, house) = \frac{2}{3} + \frac{2}{3} = \frac{4}{3}$	$TCount(bleue, house) = \frac{1}{3}$	$TCount(la, house) = \frac{1}{3}$
$TCount(maison, the) = \frac{1}{3}$	$TCount(bleue, the) = 0$	$TCount(la, the) = \frac{2}{3}$

IBM-1 M: Recompute $P(f|e)$

- Compute $P(f|e) = \frac{TCount(f,e)}{Total(e)}$

θ_2:

Ties have been broken
e.g.,
$P(maison|blue)$
$\neq P(bleue|blue)$

$\boldsymbol{P(maison\|blue) = \frac{1/3}{1}}$	$\boldsymbol{P(bleue\|blue) = \frac{2/3}{1}}$	$P(la\|blue) = \frac{0}{1}$
$P(maison\|house) = \frac{4/3}{2} = \frac{2}{3}$	$P(bleue\|house) = \frac{1/3}{2} = \frac{1}{6}$	$P(la\|house) = \frac{1/3}{2} = \frac{1}{6}$
$P(maison\|the) = \frac{1/3}{1}$	$P(bleue\|the) = \frac{0}{1}$	$P(la\|the) = \frac{2/3}{1}$

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Practical note on programming IBM-1

- If you were to code the EM algorithm for IBM-1, you would **not** initialize $\theta = P(f|e)$ uniformly over the **entire** vocabulary.
  - Don't make a $V_F \times V_E$ table with $P(f|e) = 1/\|V_E\|$ X
- This structure would be too **large**.
  - Probabilities would be too **small**.
  - It would take **too much work** to update.
- Rather, initialize a **hash table** over ***possible*** alignments, $\mathcal{M}$. For every English word e, only consider French words f in sentences **aligned** with English sentences containing e.
  - e.g., structure $\mathrm{P}.e.f := P(f|e) = 1/\|\mathcal{M}\|$

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Higher IBM models

IBM Model 1	lexical translation
IBM Model 2	adds absolute **re-ordering model**
IBM Model 3	adds **fertility model**
...	...

- Only IBM Model 1 training reaches a *global maximum*
  - Training of each IBM model **extends** the **next lowest** model.

- **Higher models** become computationally **expensive**.

IBM-2

- **Unlike IBM Model-1**, the placement of a word in, say, Spanish in **IBM Model-2** depends on where its **equivalent** word was in English.
  - IBM-2 captures the intuition that translations should lie roughly "along the diagonal".

	Buenos	dias	,	me	gusta	papas	frías
Good	X						
day		X					
,			X				
I				X			
like					X		
cold							X
potatoes						X	

IBM-2

- IBM Model 2 **builds** on Model 1 by adding a **re-ordering model** defined by **distortion** parameters ***regardless of actual words***.

$D(i|j, \mathcal{L}_E, \mathcal{L}_F)$= the probability that the i^{th} English **slot** is aligned to the j^{th} French **slot**, given sentence lengths $\mathcal{L}_E$ and $\mathcal{L}_F$.

- In IBM Model 2:

$$P(a|E, \mathcal{L}_E, \mathcal{L}_F) = \prod_{j=1}^{\mathcal{L}_F} D(a_j|j, \mathcal{L}_E, \mathcal{L}_F)$$

- Recall that in IBM Model 1,

$$P(a|E, \mathcal{L}_E, \mathcal{L}_F) = \frac{P(\mathcal{L}_F)}{(\mathcal{L}_E + 1)^{\mathcal{L}_F}}$$

IBM-2 – Probability of alignment

- $E =$ *And the program has been implemented*
- $F =$ *Le programme a été mis en application*
- $\mathcal{L}_E = 6$
- $\mathcal{L}_F = 7$
- $a = \{2,3,4,5,6,6,6\}$ (i.e., $f_1 \leftarrow e_2$, $f_2 \leftarrow e_3$,…)

D(2nd English word | 1st French word,…)

- $P(a|E, \mathcal{L}_E, \mathcal{L}_F) = D(2|1,6,7) \times D(3|2,6,7) \times D(4|3,6,7) \times D(5|4,6,7) \times D(6|5,6,7) \times D(6|6,6,7) \times D(6|7,6,7)$

This is independent of the actual **words**.
This cares only about **position**.

IBM-2: generation

- To **generate** a French sentence F from English E,
  1. **Pick an alignment** with probability
     $$\prod_{j=1}^{\mathcal{L}_F} D(a_j|j, \mathcal{L}_E, \mathcal{L}_F)$$
  3. **Sample** French words with probability
     $$P(F|a,E) = \prod_{j=1}^{\mathcal{L}_F} P(f_j|e_{a_j})$$

This is the same $P(f|e)$ as in IBM-1.

So,

$$P(F,a|E) = P(a|E)P(F|a,E) = \prod_{j=1}^{\mathcal{L}_F} D(a_j|j, \mathcal{L}_E, \mathcal{L}_F)P(f_j|e_{a_j})$$

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IBM-2: training

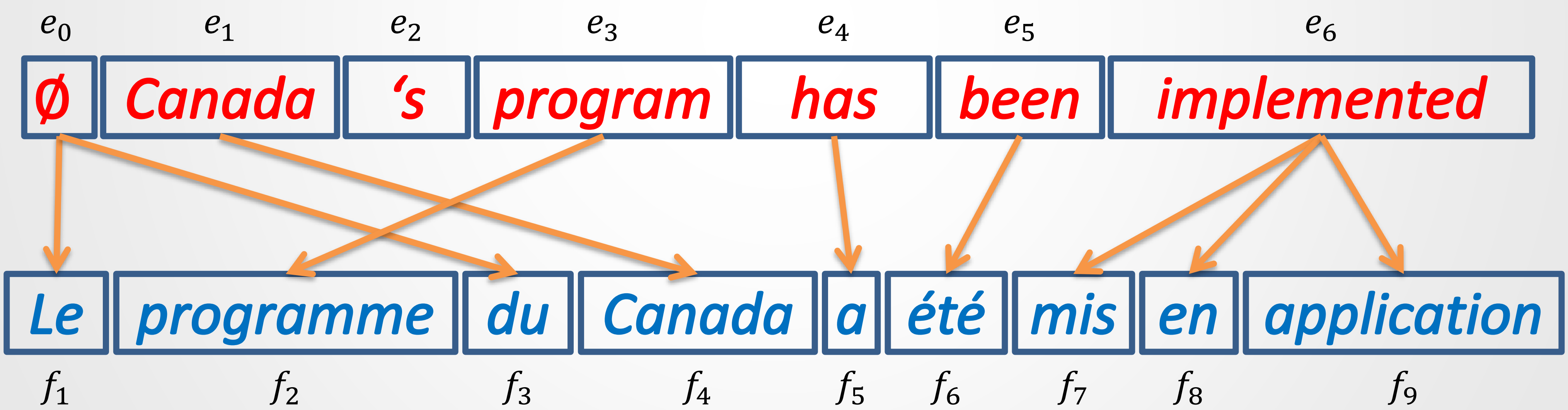
- We use EM, as before with IBM-1 **except** that we need to take the **distortion** into account when computing the probability of an alignment.

- We also need to **learn** the distortion function.

- *Aren't you glad that you don't need to know how to compute EM for IBM-2?*

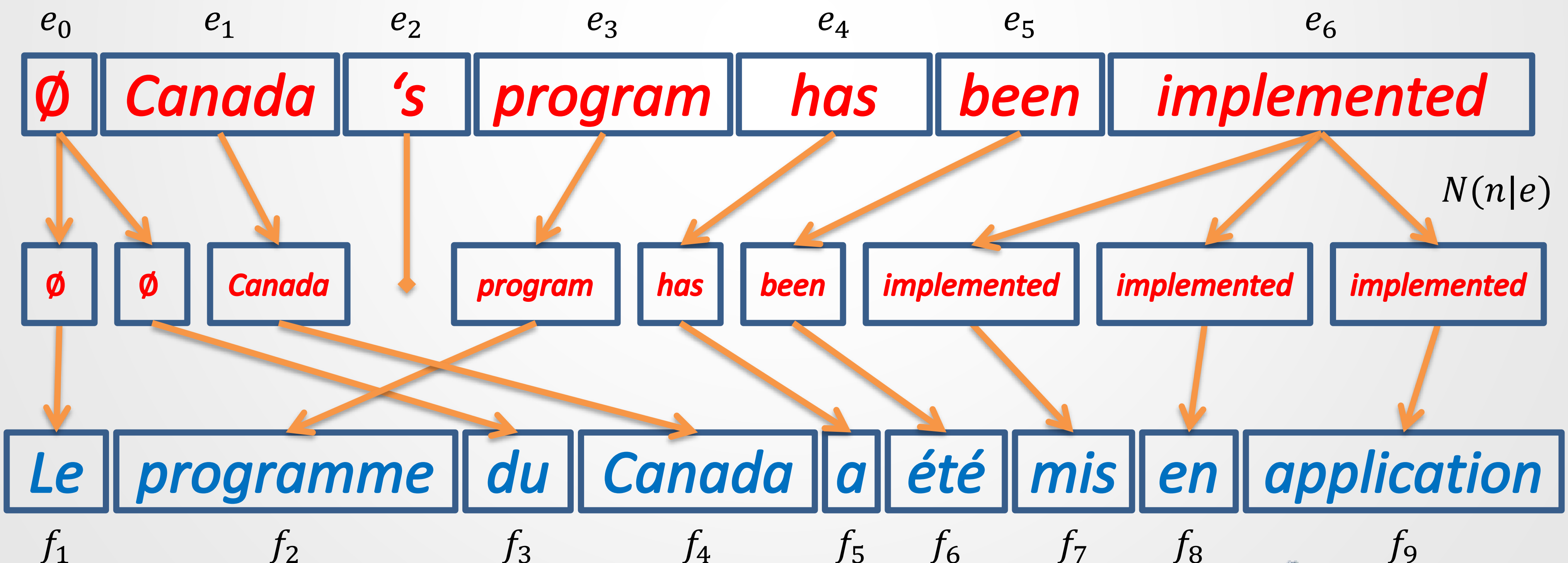
IBM-3

- **IBM Model 3** extends Model 2 by adding a **fertility model** that describes how many French words each English word can produce.
  - In the example below, *implemented* appears to be **more fertile** than *program*.



IBM-3: The generation model

- First, we **replicate** each word according to a new hidden parameter, $\boldsymbol{N}(\boldsymbol{n}|\boldsymbol{e})$, which is the **probability that word *e* produces $\boldsymbol{n}$ words**.
  - We then **re-align** (*with distortion*) and **translate** as we did in IBM-2.



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IBM models

IBM Model 1	lexical translation
IBM Model 2	adds absolute **re-ordering model**
IBM Model 3	adds **fertility model**

Reading

- **Entirely optional**: Vogel, S., Ney, H., and Tillman, C. (1996). *HMM-based Word Alignment in Statistical Translation*. In: Proceedings of the 16th International Conference on Computational Linguistics, pp. 836-841, Copenhagen.

- (optional) Gale & Church "*A Program for Aligning Sentences in Bilingual Corpora*" (on course website)

- **Useful reading on IBM Model-1**: Section 25.5 of the 2nd edition of the Jurafsky & Martin text.
  - 1st edition available at Robarts library.

- **Other**: Manning & Schütze Sections 13.0, 13.1.2 (Gale&Church), 13.1.3 (Church), 13.2, 13.3, 14.2.2