

INF5820/INF9820

LANGUAGE TECHNOLOGICAL APPLICATIONS

Jan Tore Lønning, Lecture 6, 28 Sep. 2016

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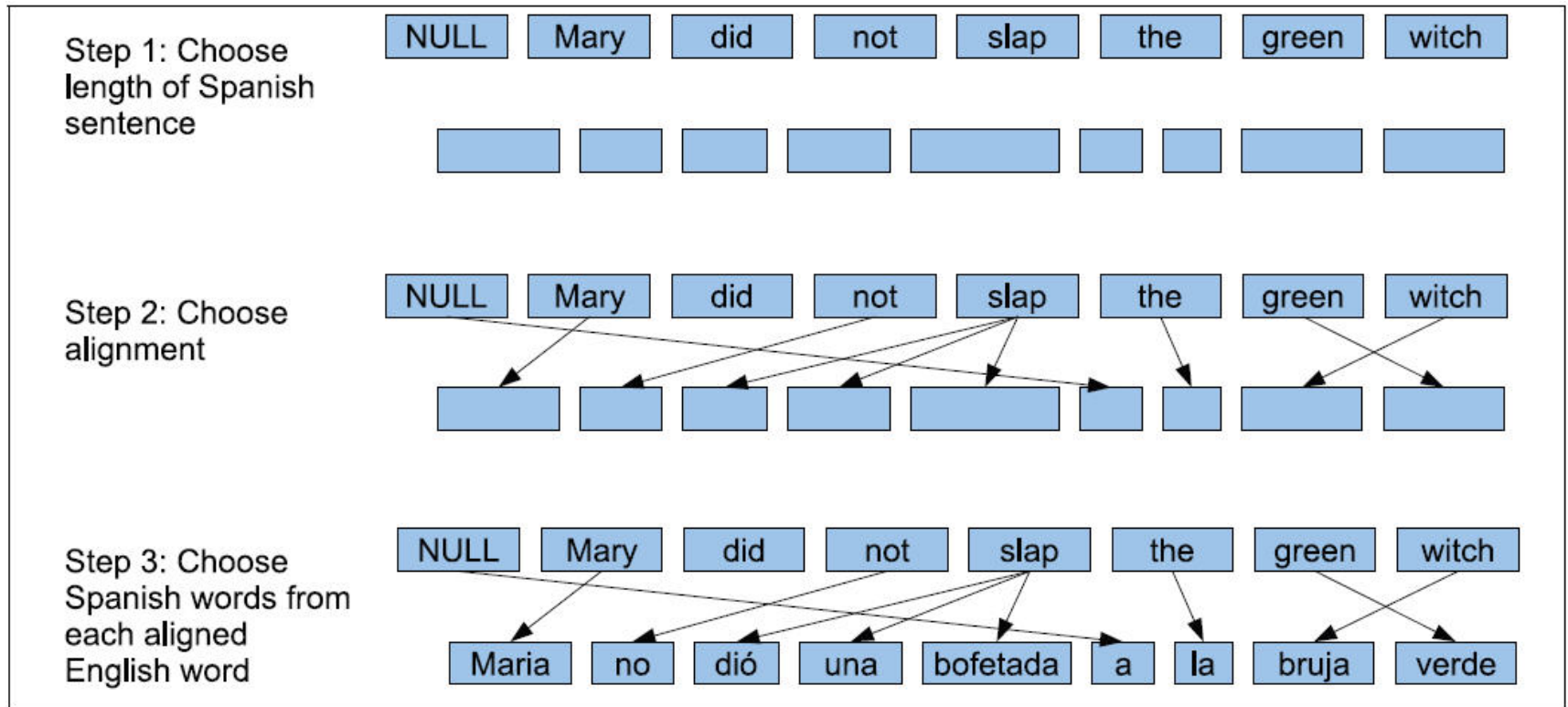
Today

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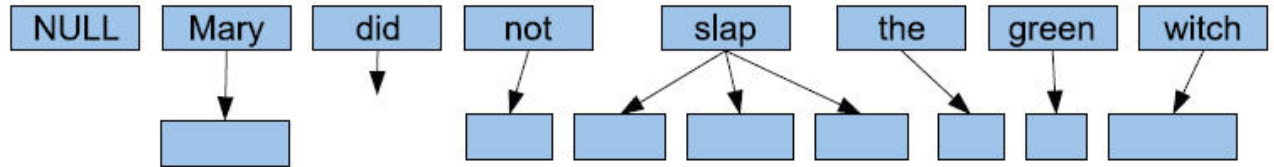
- Repetisjon:
 - ▣ Higher IBM-models: 3, 4, 5
- Phrase-Based Models

Model 1 & 2 and HMM alignment

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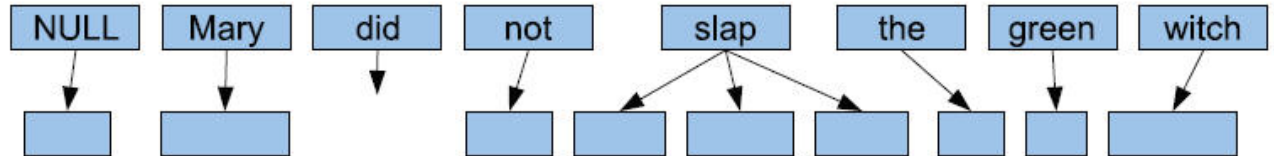


Step 1: Choose fertility for each English word

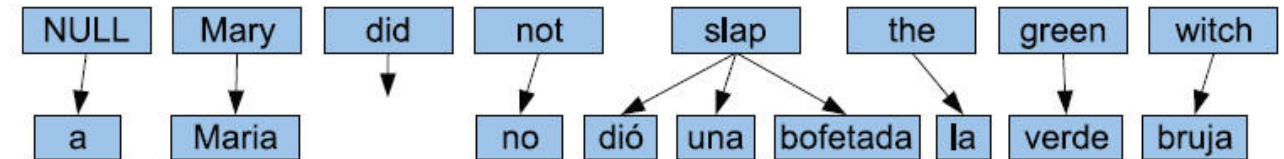


Model 3

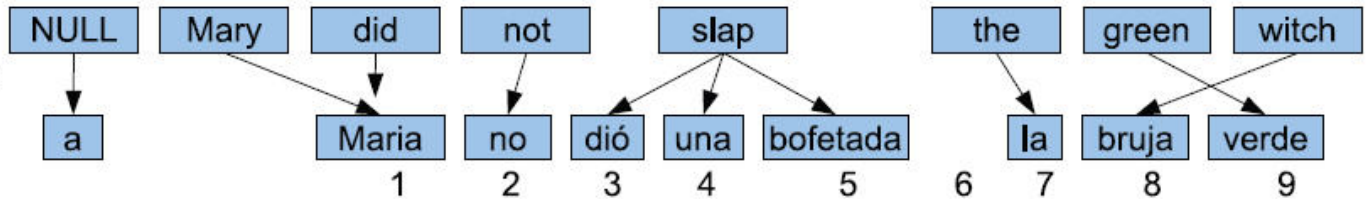
Step 2: Choose fertility for NULL



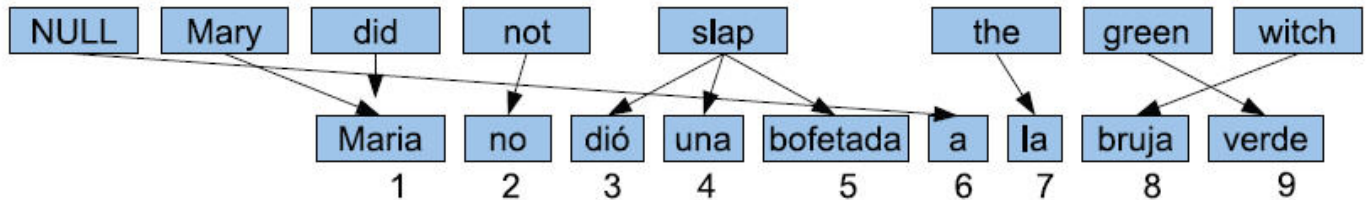
Step 3: Create Spanish words by translating aligned English word



Step 4: Move the Spanish words into final slots



Step 5: Move spurious Spanish words into unclaimed slots



IBM Model 3: Fertility

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

Example:

F = Norw.

$n(2 | \text{yesterday}) \approx 1$

$n(1 | \text{to}) \approx 0.8$

$n(2 | \text{to}) \approx 0.2$

$n(1 | \text{car}) \approx 1$

$n(0 | \text{the}) \approx 0.6$

$n(1 | \text{the}) \approx 0.4$

Example:

Norw. \rightarrow Eng.

$n(2 | \text{bilen}) \approx 0.7$

$n(1 | \text{bilen}) \approx 0.3$

$n(1 | \text{å}) \approx 0.8$

$n(0 | \text{å}) \approx 0.2$

IBM Model 3: Null insertion

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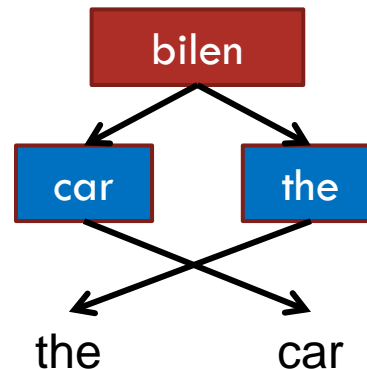
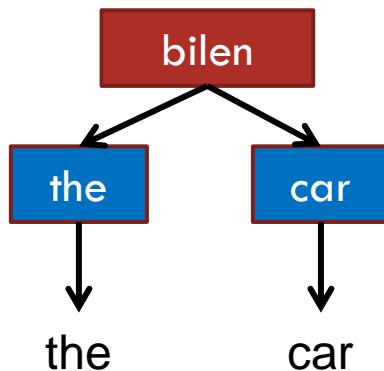
- Modelled by:
- There is a probability p_0 :
 - ▣ After each inserted word there is the probability p_0 of not inserting a null-word
 - ▣ And a probability $p_1 = (1-p_0)$ of inserting a null-word
- A rather complex expression for what this contributes into $P(\mathbf{a}, \mathbf{f} | \mathbf{e})$ which considers
 - ▣ Permutations
 - ▣ Length of \mathbf{f}

IBM Model 3: Distortion

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$$d(j | a_j, m, k)$$

- 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 correspond to the same alignment



IBM model 3

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

- Where *more* is an expression which counts
 - ▣ $n(x | e_i)$ the right number of times
 - ▣ And uses p_0 to give the right probability to null-insertion.

Training Model 3

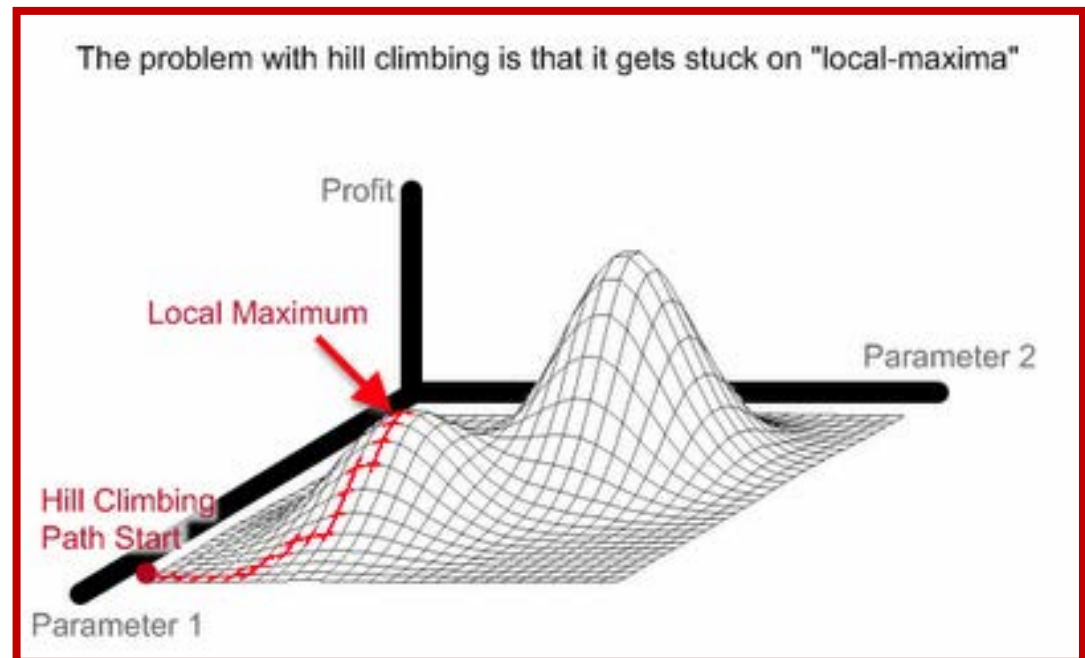
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- In principle like Model 1, but
 - ▣ The trick to get rid of the alignments does not work
 - ▣ Too costly to calculate all alignments
- Strategy
 - ▣ Sample and use the most probable alignments
 - ▣ Start with alignments from Model 1 and Model 2
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

Hill-climbing algorithm

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- Assign some initial parameter values
- Consider (a slightly different) value for one of the parameters and see whether the result is better:
 - ▣ If YES, change the parameter accordingly
- Repeat
 - ▣ (until we do not see big improvements).



Training model 3

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- 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 Model 1 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

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

The IBM-models

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- 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

Today

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- Higher IBM-models: 3, 4, 5
- **Phrase-Based Models**

Phrase alignment

- K. Slides to chapter 4:
 - ▣ 49-51
 - ▣ 53-54

Phrase-Based Models

- K. Slides to chapter 5

