6.863J Natural Language Processing
Lecture 19: Machine translation 3

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The Menu Bar

- Administrivia:
  - Start w/ final projects – (final proj: was 20% - boost to 35%, 4 labs 55%?)
  - *Agenda:*
  - MT: the statistical approach
  - Formalize what we did last time
  - Divide & conquer: 4 steps
    - Noisy channel model
    - Language Model
    - Translation model
    - Scrambling & Fertility; NULL words

Submenu

- The basic idea: moving from Language A to Language B
- The noisy channel model
- Juggling words in translation – bag of words model; divide & translate
- Using n-grams – the Language Model
- The Translation Model
- Estimating parameters from data
- Bootstrapping via EM
- Searching for the best solution

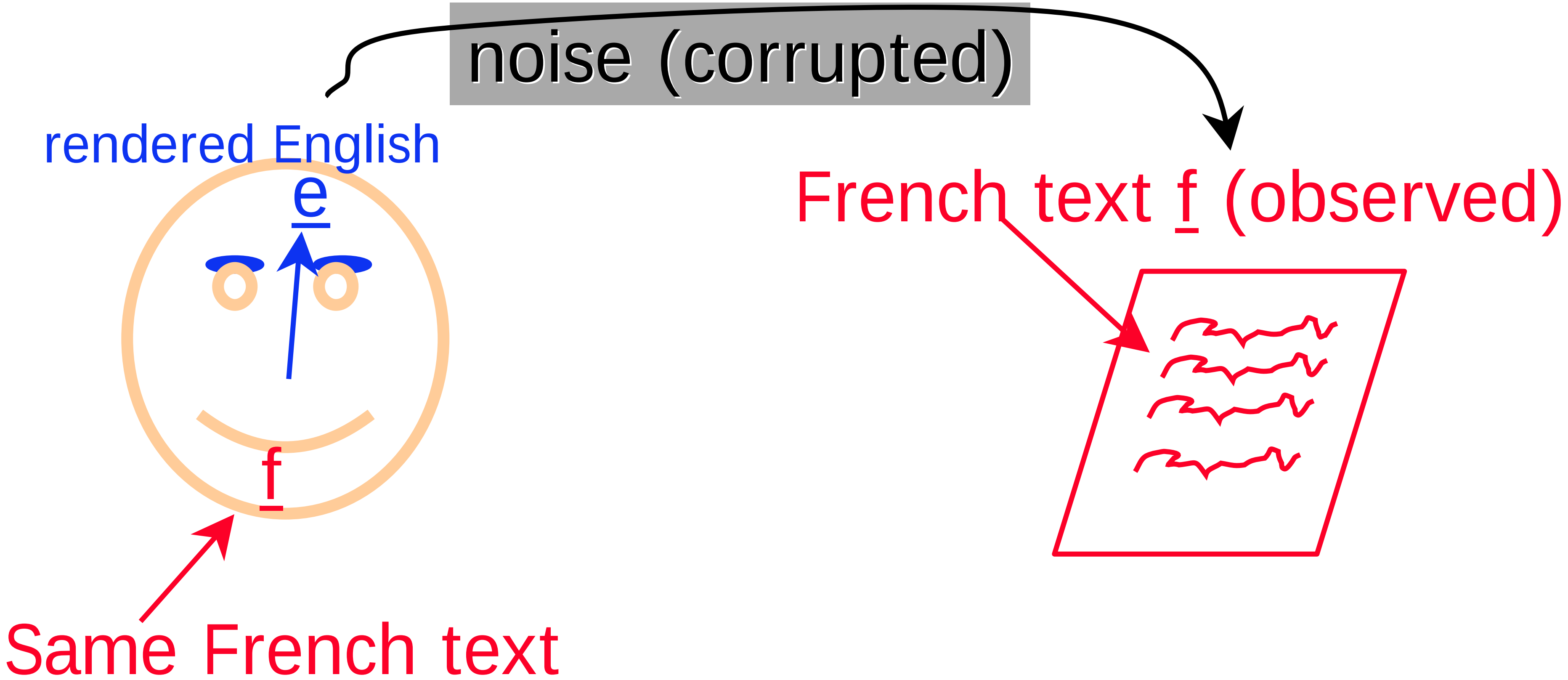
Like our alien system

- We will have two parts:

1. A <u>bi-lingual dictionary</u> that will tell us what e words go w/ what f words
2. A <u>shake-n-bake</u> idea of how the words might get scrambled around

We get these from cycling between alignment & word translations – re-estimation loop on which words linked with which other words

'George Bush' model of translation (noisy channel)



f, e are strings of (french, english) words

IBM “Model 3”

- First to do this, late 80s: Brown et al, “The Mathematics of Statistical Machine Translation”, <u>Computational Linguistics</u>, 1990 (orig 1988 conference) – “Candide”

- We’ll follow that paper & 1993 paper on estimating parameters
- 1993: Brown, Della Pietra, et al, “The mathematics of statistical MT” J. Assoc. Comp. Ling, 19:2, 264-311.

Summary of components – Model 3

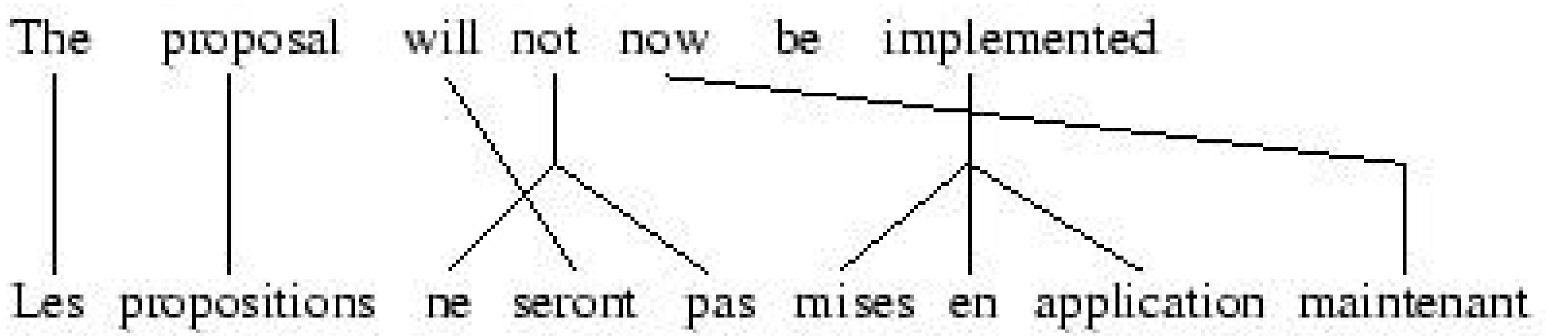
- The language model: P(e)
- The translation model for P(f|e)
  - Word translation t
  - Distortion (scrambling) d
  - Fertility ϕ
- (really evil): null words e_0 and f_0
- Maximize (A* search) through product space

OK, what are the other models?

- Model 1 – just t
- Model 2 – just t & simple d

- What are they for?
- As we'll see – used to pipeline training – get estimates for Model 3

The training data - Hansard



P(les|the)

Q: What do you think is the biggest error source in Hansard?
e.g. which P(f|e), or P(?| e_1 e_0)

A: How about this – P(? | hear, hear) as in “Hear Hear!”

How to estimate?

- Formalize alignment
- Formalize dictionary in terms of P(f|e)
- Formalize shake-n-bake in terms of P(e)
- Formalize re-estimation in terms of the EM Algorithm
  - Give initial estimate (uniform), then up pr's of some associations, lower others

Fundamentals

- The basic equation

$$\hat{e} = \operatorname{argmax} \Pr(e) \Pr(f|e)$$

  - Language Model Probability Estimation - Pr(e)
  - Translation Model Probability Estimation - Pr(f|e)
  - Search Problem - maximizing their product

Finding the pr estimates

- Usual problem: sparse data
  - We cannot create a “sentence dictionary” E $\leftrightarrow$ F
  - we do not see a sentence even twice, let alone once

Let's see what this means

$$P(e) \times P(f|e)$$

Factor 1: Language Model

Factor 2: Translation Model

P(e) – Language model

- Review: it does the job of ordering the English words
- We estimate this from <u>monolingual</u> text
- Just like our alien language bigram data

Bag translation?

- Take sentence, cut into words, put in bag, shake, recover original sentence
- Why? (why: show how it gets order of English language, for P(e) estimate)
- How? Use n-gram model to rank difft arrangements of words:
  - S better than S' if P(S) > P(S')
  - Test: 100 S's, trigram model

Bag results?

- Exact reconstruction (63%)
  - Please give me your response as soon as possible
  - Please give me your response as soon as possible
- Reconstruction that preserves meaning (20%)
  - Now let me mention some of the disadvantages
  - Let me mention some of the disadvantages
- Rest – garbage
  - In our organization research has two missions
  - In our missions research organization has two
- What is time complexity? What K does this use?

Estimating P(e)

- IBM used trigrams
- LOTS of them... we'll see details later
- For now...

P(f|e) - Recall Model 3 story: French mustard

- Words in English replaced by French words, then scrambled
- Let's review how
- Not word for word replacement (can't always have same length sentences)

Alignment as the “Translation Model”

0 1 2 3 4 5 6

- e_0 And the program has been implemented

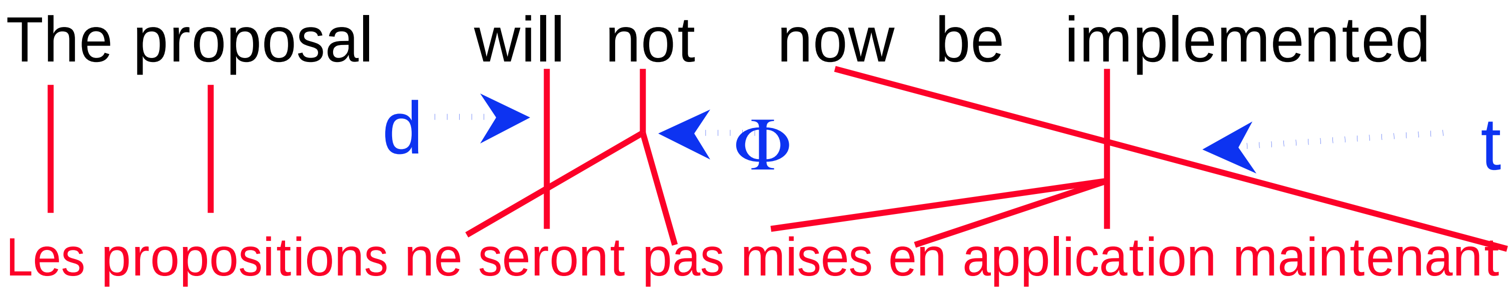
- f_0 Le programme a été mis en application

0 1 2 3 4 5 6 7

- Notation:

f_0(1) Le(2) programme(3) a(4) été(5) mis(6) en(6) application(6) = [2 3 4 5 6 6 6]

Example alignment



4 parameters for P(f|e)

1. Word translation, t
2. Distortion (scrambling), d
3. Fertility, Φ

Spurious word toss-in, p

Notation

- e= English sentence
- f = French sentence
- e_i = i^{th} english word
- f_j = j^{th} french word
- l = # of words in English sentence
- m = # words in French sentence
- a = alignment (vector of integers $a_1 \; a_2 \ldots a_m$ where each a_j ranges from 0 to l)
- a_j = actual English position connected to by the j^{th} French word in alignment a
- e_{aj} = actual English word connected to by the j^{th} French word in alignment a

Φ_i = fertility of English word i (i = 1 to l) given alignment a

OK, what parameters do we need?

- English sentence i= 1, 2, ..., l words
- Look at dependencies in the generative story!
- 3 basic parameters
- Parameter 1: Which f word to generate depends only on English word e that is doing generating
- Example: prob(fromage | monkey)
- Denote these by $t(\tau_i \mid e_i)$

Procrustean bed

1. For each word e_i in the english sentence e, i= 1, 2, ..., l, we choose a fertility $\phi(e_i)$, equal to 0, 1, 2,...[25]

- This value is solely dependent on the English word, not other words or the sentence, or the other fertilities

2. For each word e_i we generate $\phi(e_i)$ French words – not dependent on English context
3. The French words are permuted ('distorted') – assigned a position slot (this is the scrambling phase)

- Call this a distortion parameter $d(i|j)$
- Note that distortion needn't be careful – why?

Fertility

- Prob that <u>monkey</u> will produce certain # of French words
- Denoted $n(\phi_i \mid e_i)$ e.g., n(2|monkey)

Fertility

- The fertility of word i does not depend on the fertility of previous words.
  - Does not always concentrate its probability on events of interest.
- This deficiency is no serious problem.
- It might decrease the probability of all well-formed strings by a constant factor.

Distortion

- Where the target position of the French word is, compared to the English word
- Think of this as distribution of alignment links
- First cut: $d(k|i)$
- Second cut: distortion depends on english and french sentence lengths (why?)
- So, parameter is: $d(k|i, l, m)$

To fix the fertility issue...

- Final Procrustean twist
- Add notion of a Null word that can appear before beginning of english & french sentence, e_0 and f_0
- Purpose: account for ‘spurious’ words like function words (á, la, le, the, ...)
- Example in this case:

Alignment as the "Translation Model"

0 1 2 3 4 5 6

- e_0 And the program has been implemented

- f_0 Le programme a été mis en application

  0 1 2 3 4 5 6 7

- Notation:
  - f_0(1) Le(2) programme(3) a(4) été(5) mis(6) en(6) application(6)=

What about...

- Fertility of Null words?
- Do we want n(2 | null), etc.?
- Model 3: longer S's have more null words... (!) & uses a single parameter p_1
- So, picture is: after fertilities assigned to all the real English words (excluding null), then will generate (perhaps) z French words
- As we generate each french word, throw in spurious French word with probability p_1
- Finally: what about distortion for null words?

Distortions for null words

- Since we can't predict them, we generate the french words first, according to fertilities, and then put null words in spots left over
- Example: if there are 3 null generated words, and 3 empty slots, there are 6 ways for putting them in, so the pr for the distortion is 1/6
- OK, the full monty...

Model 3 in full

1. For each English word $e_{i,}$ i=1,...l, pick fertility Φ_i with probability $n(\Phi_i \mid e_i)$
2. Pick the # of spurious french words ϕ_0 generated from e_0 = null
   - Use probability p_1 and the Σ of fertilities from Step 1
3. Let m be the sum of all the fertilities, incl null = total length of the output french sentence
4. For each i=0,1,...,l & each k=1,2,..., Φ_i pick french translated words τ_{ik} with prob $t(\tau_{ik} \mid e_i)$
5. For each i=1,2,...,l & each k=1,2,... Φ_i pick french target positions with prob d(t | i, l, m)

And 2 more steps

6. [sprinkle jimmies] For each k=1,2,..., Φ_i choose positions in the $\Phi_0 - k + 1$ remaining vacant slots in spots 1,2,...,m, w/ total prob $(1/\Phi_0!)$
7. Output French sentence with words τ_{ik} in the target positions, accdg to the probs $t(\tau_i \mid e_i)$

Model 3 in full

- Has four parameters: t, n, d, p
- t and n are 2-d tables of floating point numbers (words x fertilities)
- d is 1-d table of numbers
- p is just 1 number

- But...where can we can these numbers?
- How do we compute P(f|e)?

Finding parameter values

- Suppose we had the actual step-by-step transform of english sentences into french...
- We could just count: e.g., if did appeared in 24,000 examples and was deleted 15,000 times, then n(0|did)= 5/8
- Word-word alignments can help us here

Alignment as the "Translation Model"

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Alignments help get all estimates

- Compute n : count how many times did connects to 0 french words
- Compute t: count how many times f word connects to e word
- (Note: we assume every french word connects to exactly 1 english word, or null – so never that 2 or more english words jointly give a french word...)
- Also, if 1 english word connects to 2 french words f1 and f2, we don't know whether they were generated in that order, or the reverse...

OK, so how do we get d & p_1?

- Can also get that from aligned pairs
- Every connection in alignment contributes to a particular parameter like d(3 | 2, 5,6)
- Get counts, dc, & normalize:

  $d(3 \mid 2, 5, 6) = dc(3 \mid 2, 5, 6)/\Sigma\, dc(j|2, 5, 6)$

- Finally, p_1 . From alignments, N words in total french corpus, M generated by null.
- So, after each of the N-M real word cases, a spurious word is generated M times, or

  $p_1 = M/N\text{-}M$

Mais...

- We need aligned sentences to get parameter values...
- We need parameter values to get aligned sentences.... i.e., we want to maximize

$$P(a|e,f)$$

comment amorçons-nous?

¿Cómo atamos con correa?

Laying an egg: The magic

- You can actually get estimates from non-aligned sentence pairs!!!
- Exactly as you did in your (ahem) alien assignment

- English & French words that co-occur in sentence translations might/might not be translations, but if we have a rough idea about correspondences, we can get idea about distortion probs… e.g., if first english word/first french word correspond, then what about

  $d(1|1, l,m)$?

The key: alignments

- Suppose we have a single correct alignment for each sentence pair
- We could collect all parameter counts directly
- But we don't...
- Suppose we have 2 equally good looking candidates...
- Then we weight the counts from each by 0.5 (a fractional count)
- In general, many more than this... (Neglecting nulls, if e has length 'l' and f has length 'm', there are 2^{lm} alignments in all)

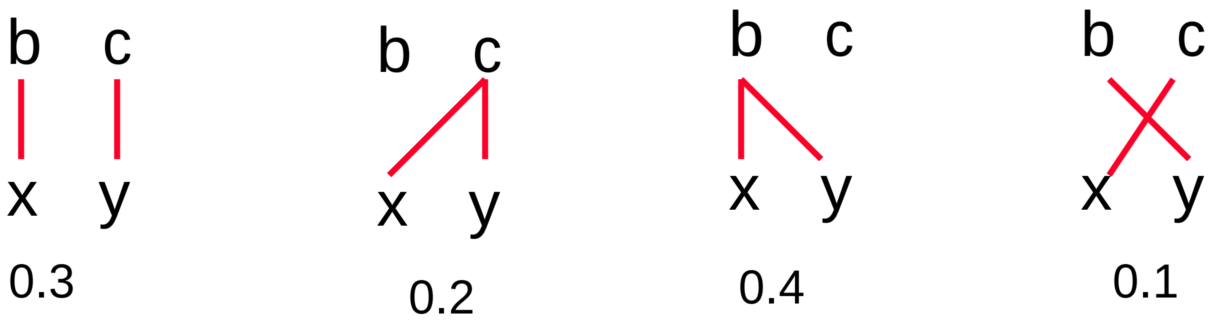
Example: easy as a, b,...

b=blue c= house; x= maison; y=bleue

Can we figure out which alignment works best?

- Idea 1: use alignment <u>weights</u>
- Idea 2: actually use counts as proxies for probabilities

Example



Estimate nc(1|b) =

0.3 +0.1 =0.4

Estimate nc(0|b) = 0.2

Estimate nc(2|b)=0.4

Normalise to get fertility = n(1|b)=0.4/0.4+0.2+0.2 = 0.4

Can do the same to get t(y|b)

Better to compute alignment probabilities

- Let a be an alignment – just a vector of integers
- We want highest P(a|e,f) (e & f are a particular sentence pair)
- What would make alignment more probable?
- If we had the translation t parameters, we could judge – a good alignment ought to connect words that are already known to be high prob translations of one another
- An alignment summarizes (some of) the choices that get made

$P(a,f|e)$

- BUT We can convert $P(a|e,f)$ to:
  $P(a,f|e)/P(f|e)$

- $P(a|e,f) = P(a,e,f)/P(e,f) = ...$

How to compute P(a|f,e) ?

- First term P(a,f|e) can be found from the story of Model 3: start with english string e, blah blah ... get alignment and french string (can have same alignment and two or more different french strings)

- Second term P(f|e) is what we've been after...it is all the ways of producing f, over all alignments, so in fact...

<u>All</u> we need to find is

- $P(f|e)=\Sigma_a P(a,f|e)$
- OK, let's see about this formula

$P(a,f|e)$

- e= English sentence
- f = French sentence
- e_i = i^{th} english word
- f_j = j^{th} french word
- l = # of words in English sentence
- m = # words in French sentence
- a = alignment (vector of integers $a_1\ a_2 \ldots a_m$ where each a_j ranges from 0 to l)
- a_j = actual English position connected to by the j^{th} French word in alignment a
- e_{aj} = actual English word connected to by the j^{th} French word in alignment a
- ϕ_i = fertility of English word i (i = 1 to l) given alignment a

P(a,f|e)

- word translation values implied by alignment & French string

$$P(a,f|e)=\prod_{i=1}^{l} n(f_i \mid e_i) * \prod_{j=1}^{m} t(f_j \mid e_{aj}) * \prod_{j=1}^{m} d(j|a_j, l, m)$$

- We will have to correct this a bit...for the null words...

Adjustments to formula - 4

1. Should only count distortions that involve real english words, not <u>null</u> – eliminate any <u>d</u> value for which $a_j = 0$
2. Need to include probability “costs” for spurious french words – there are Φ_0 null french words, and $m - \Phi_0$ real french words

How many ways to sprinkle in ϕ_0 ‘jimmies’ – pick ϕ_0 balls out of urn that has m-ϕ balls, or, $[(m - \Phi_0)$ choose $\Phi_0]$

Must multiply these choices by prob costs:

- We choose to add spurious word ϕ_0 times, each with probability p_1 so total pr of this is $p_1^{\Phi_0}$
- We choose to <u>not</u> add spurious word $((m - \Phi_0) - \Phi_0)$ times, so total pr of this factor is $p_0^{(m-2\Phi_0)}$

Adjustments – last 2

3. Probability Cost for placing spurious french words into target slots – there are no distortions for the null words, eg, d(j |0, l, m) Instead we put them in at the end, as the final step of generating the french string

   There are $\Phi_0!$ possible orderings, all equally likely, so that adds cost factor of $1/\Phi_0!$

4. For 'fertile' words, e.g., english word x generates french p, q, r – then there are 6 (in general Φ_i) ways to do this (order is not known)

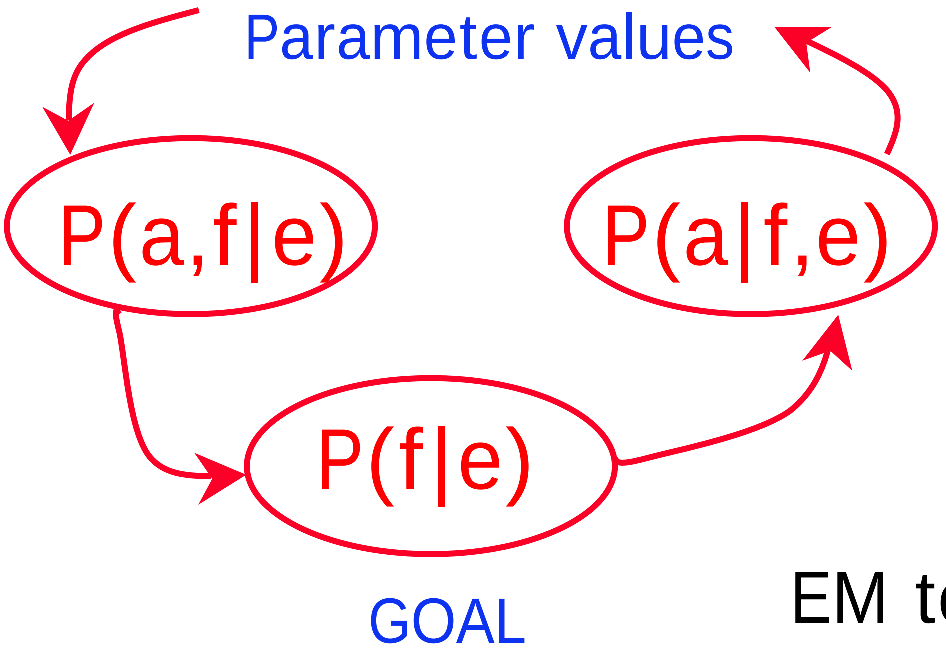
   In general, we must add this factor: $\prod_{i=0}^{l} \Phi_i!$

All boiled down to one math formula…

$$P(a,f|e)=\prod_{i=1}^{l} n(f_i \mid e_i) * \prod_{j=1}^{m} t(f_j \mid e_{aj}) * \prod_{j:a_j<>0}^{m} d(j|a_j, l, m) * \binom{m-\Phi_0}{\Phi_0} * p_0^{(m-2\Phi_0)} * p_1^{\Phi_0}$$

$$* \prod_{i=0}^{l} \Phi_i ! * \left(1 / \Phi_0 \right)$$

Huhn- und Eiproblem?



EM to the rescue!

What is EM about?

- Learning: improve prob estimates
- Imagine game:
- I show you an English sentence e
- I hide a French translation f in my pocket
- You get $100 to bet on French sentences – how you want (all on one, or pennies on lots)
- I then show you the French translation – if you bet $100 on it, you get a lot; even if just 10 cents. But if you bet 0, you lose all your money ($P(f|e)=0$, a mistake!)
- That's <u>all</u> EM learns to do

A question

- If you’re good at this game, would you be a good translator?
- If you’re a good translator, would you be good at this game?

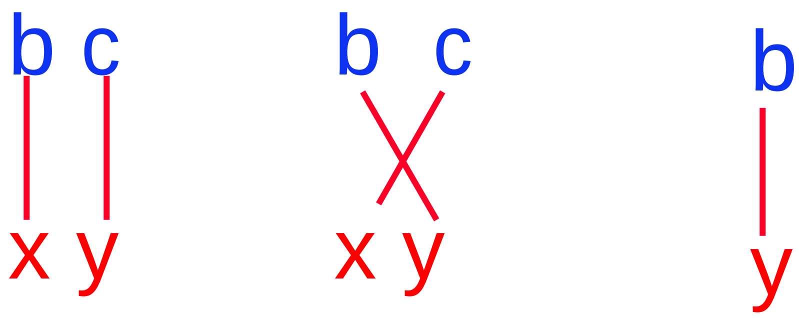
How?

- Begin with uniform parameter values
  - Eg, if 50,000 French words, then $t(f|e)=1/50000$
  - Every word gets same set of fertilities
  - Set $p_1=0.15$
  - Uniform distortion probs (what will these be?)
- Use this to compute alignments
- Use new alignments to refine parameters [Loop until (local) convergence of P(f|e)]

How?

- Corpus: just two paired sentences (english, french)
  - b c/x y & b/y Q: is y a translation of c?
- Assume: Forget about null word, fertility just 1, no distortion;
- So, just 2 alignments for first pair, and one for the second:

Alignments



$$P(a,f|e)= \prod_{i=1}^{l} \cancel{n(f_i \,|\, e_i)} * \prod_{j=1}^{m} t(f_j \,|\, e_{aj}) * \prod_{j=1}^{m} \cancel{d(j|a_j, l, m)}$$

$$\downarrow$$

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

IBM Model1 !

Start to Finish: 4 steps in loop

Initial:
t(x|b) = 0.5
t(y|b) = 0.5
t(x|c) = 0.5
t(y|c) = 0.5

Alignments

2. P(a,f|e)

normalise

3. P(a|e,f)

4. counts tc

5. normalise to get new t's

Final:
t(x|b) = 0.0001
t(y|b) = 0.9999
t(x|c) = 0.9999
t(y|c) = 0.0001

Why does this happen?

- Alignment prob for the crossing case with b connected to y will get boosted
- Because b is also connected to y in the second sentence pair
- That will boost t(b|y), and as side effect will also boost t(x|c), because c connects to x in the same crossed case (note how this is like the game we played)
- Boosting t(x|c) means lowering t(y|c) because they must sum to 1...
- So even though y and c co-occur, wiped out...

EM, step by step (hill climbing)

- Step 1[initial only]: set parameter values uniformly
    - $t(x|b)=1/2$; $t(y|b)=1/2$; $t(x|c)=1/2$; $t(y|c)=1/2$

Loop

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

- Step 2: compute P(a,f|e) for all 3 alignments

b c
x y

P(a,f|e) = ½ * ½ = ¼

b c
x y

P(a,f|e) = ½ * ½ = ¼

b
y

P(a,f|e) = ½ (from original estimate!)

- Step 3: normalise P(a,f|e)/P(f|e) = P(a|e,f)

b c
x y

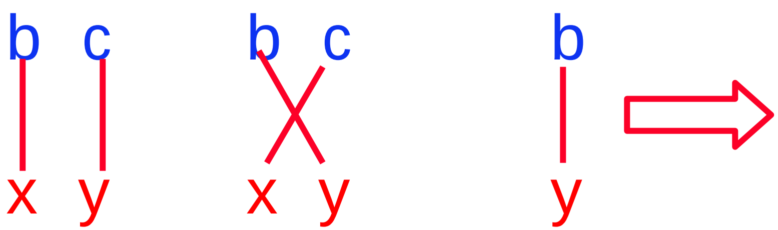
¼/2/4 = ½

b c
x y

¼/2/4 = ½

Loop to Step 2 – update t via counts tc

- (Ps: what is P(a|f,e) for 3rd alignment?
- Step 4: collect fractional counts tc: first local to a single alignment:



tc(x|b)= ½
<u>tc(y|b)= ½ + 1= 3/2</u>
tc(x|c)= ½
tc(y|c) = ½

- Step 5: normalize to get new t values:

t(x|b)= ½/4/2 = 1/4 ← DOWN
t(y|b)= 3/2/4/2 = 3/4 ← UP
t(x|c)= ½/1 = ½
t(y|c) = ½/1 = ½

Cook until done...

- Feed these new t values back to Step 2!

  2^{nd} iteration:

  $$t(x \mid b) = 1/8$$
  $$t(y \mid b) = 7/8$$
  $$t(x \mid c) = 3/4$$
  $$t(y \mid c) = 1/4$$

- EM <u>guarantees</u> that this will monotonically increase P(a,f|e) (but only local maxima)

- EM for Model 3 is <u>exactly</u> like this, but we have difft formula for P(a|f,e) & we collect fractional counts for n, p, d from the alignments

Exercise...

- The blue house / la maison bleue
- The house / la maison
- 6 alignments for sentence 1, two for sentence 2
- Start w/ all t's set to 1/3 – i.e., t(la|the)=1/3...

How good is Model 3?

- Remember gambler?
- How good is Model 3 at this game?

- Distortion – poor description of word order differences – bets on lots of ungrammatical french sentences
- Nothing stops us from choosing target position

Consider

The proposal will not now be implemented

Les propositions ne seront pas mises en application maintenant

ALL map to Position 5

problemas del entrenamiento

- EM not globally optimal
  - Initial condition: might take 1st two words & always link them, then distortion cost small, word-translation costs high
  - EM doesn't know about linguistics!
  - How to fix?
- More seriously: look at iteration
- Over <u>every</u> alignment: $P(f|e)=\Sigma_a P(a,f|e)$
- 20 words by 20 words – gulp
- Solution: iterate only over good-looking ones...
  - How to find best 100 w/o enumerating them all??

parámetros rápidos y sucios

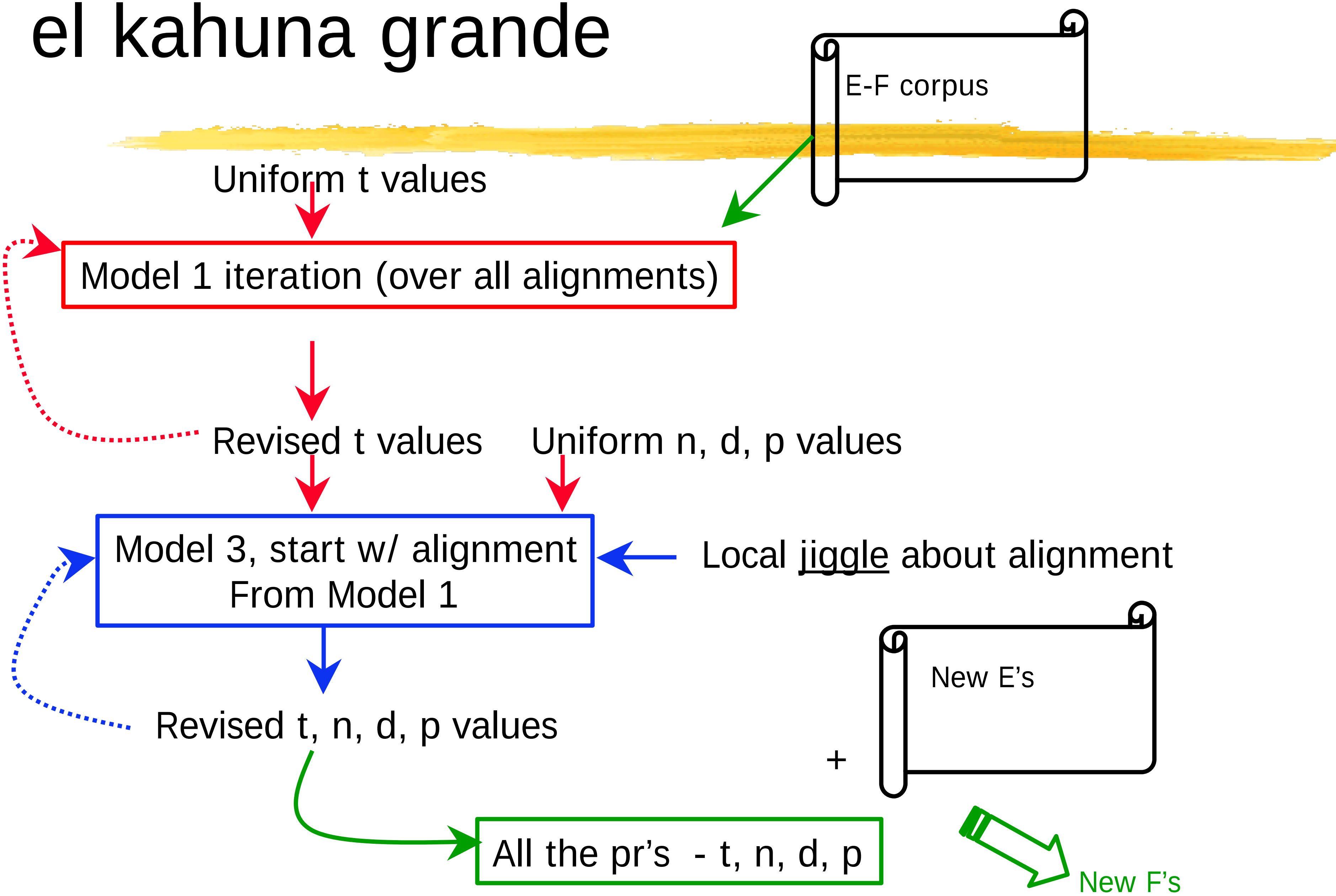
- Can use Model 1 counts from all alignments w/o enumerating them all!
- Model 1 – easy to figure out what best alignment is – quadratic time in l, m
- In fact, it has a single local maximum, since the objective function is quadratic (won't prove this here...)
- Use this to kick-off Model 3

Formula about Model 1

$$\sum_{a} P(a,f|e) = \sum_{a} \prod_{j=1}^{m} t(f_j \mid e_{aj}) = \prod_{j=1}^{m} \sum_{i=0}^{l} t(f_j \mid e_i)$$

Use factoring to do this-
Last expression only takes l+l*m operations

el kahuna grande



Now to the next step...

- Got our P(e), P(f,e)

- To translate given French sentence f, we still need to find the English sentence e that maximizes the product

- Can't search all of these!!!
- How? Basically: A* stack search

Still need

- Unknown words – names & technical terms: use phonetics

- Robert Berwick,... (what does Babelfish do?)

¿Tan qué?

- What did IBM actually do? (datawise)
- Remember the British unemployed?

IBM's actual work

- (Remember the British unemployed)
- 1,778,620 translation pairs
- 28, 850, 104 French words
- T array has 2, 437, 020, 096 entries...
- Final English, French dictionaries have 42,006 and 58, 016 words
- In all, about 100mb of storage needed to calculate the pr's

Iteration	In	→	Out	Surviving pr's	Alignments	Perplexity
1	1	→	2	12,017,609		71,550.56
2	2	→	2	12,160,475		202.99
3	2	→	2	9,403,220		89.41
4	2	→	2	6,837,172		61.59
5	2	→	2	5,303,312		49.77
6	2	→	2	4,397,172		46.36
7	2	→	3	3,841,470		45.15
8	3	→	5	2,057,033	291	124.28
9	5	→	5	1,850,665	95	39.17
10	5	→	5	1,763,665	48	32.91
11	5	→	5	1,703,393	39	31.29
12	5	→	5	1,658,364	33	30.65

the

the

f	t(f|e)	phi	n(phi|e)
le	0.497	1	0.746
la	0.207	0	0.254
les	0.155		
1'	0.086		
ce	0.018		
cette	0.011		

Should

should

f	t(f|e)	phi	(phi|e)
devrait	0.330	1	0.649
Devraient	0.123	0	0.336
devrions	0.109	2	0.014
faudrait	0.073		
faut	0.058		
doit	0.058		
aurait	0.041		
doivent	0.024		
devons	0.017		
devrais	0.013		

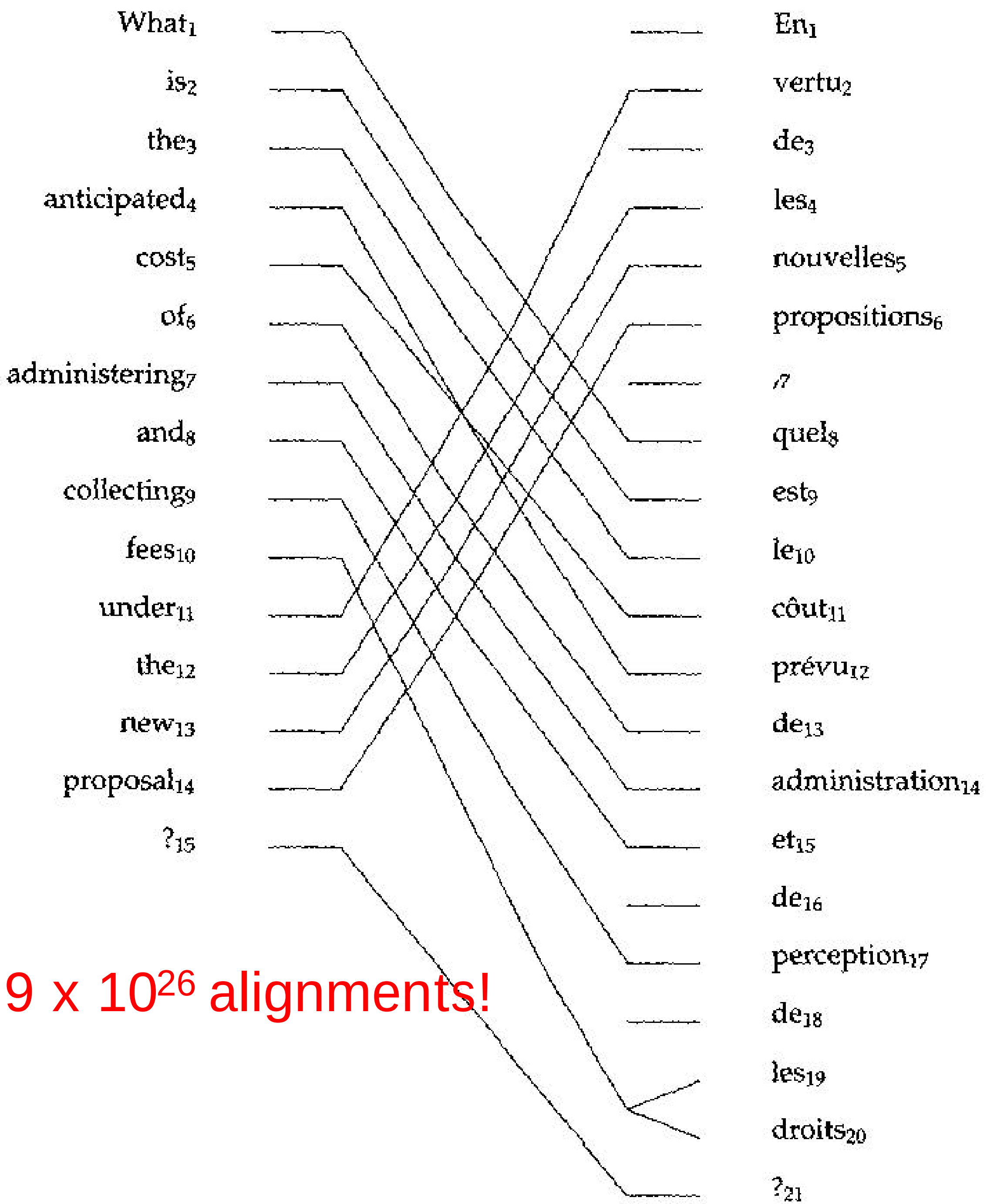
What about...

- In French, what is worth saying is worth saying in many different ways
- He is nodding:
  - Il fait signe qui oui
  - Il fait un signe de la tête
  - Il fait un signe de tête affirmatif
  - Il hoche la tête affirmativement

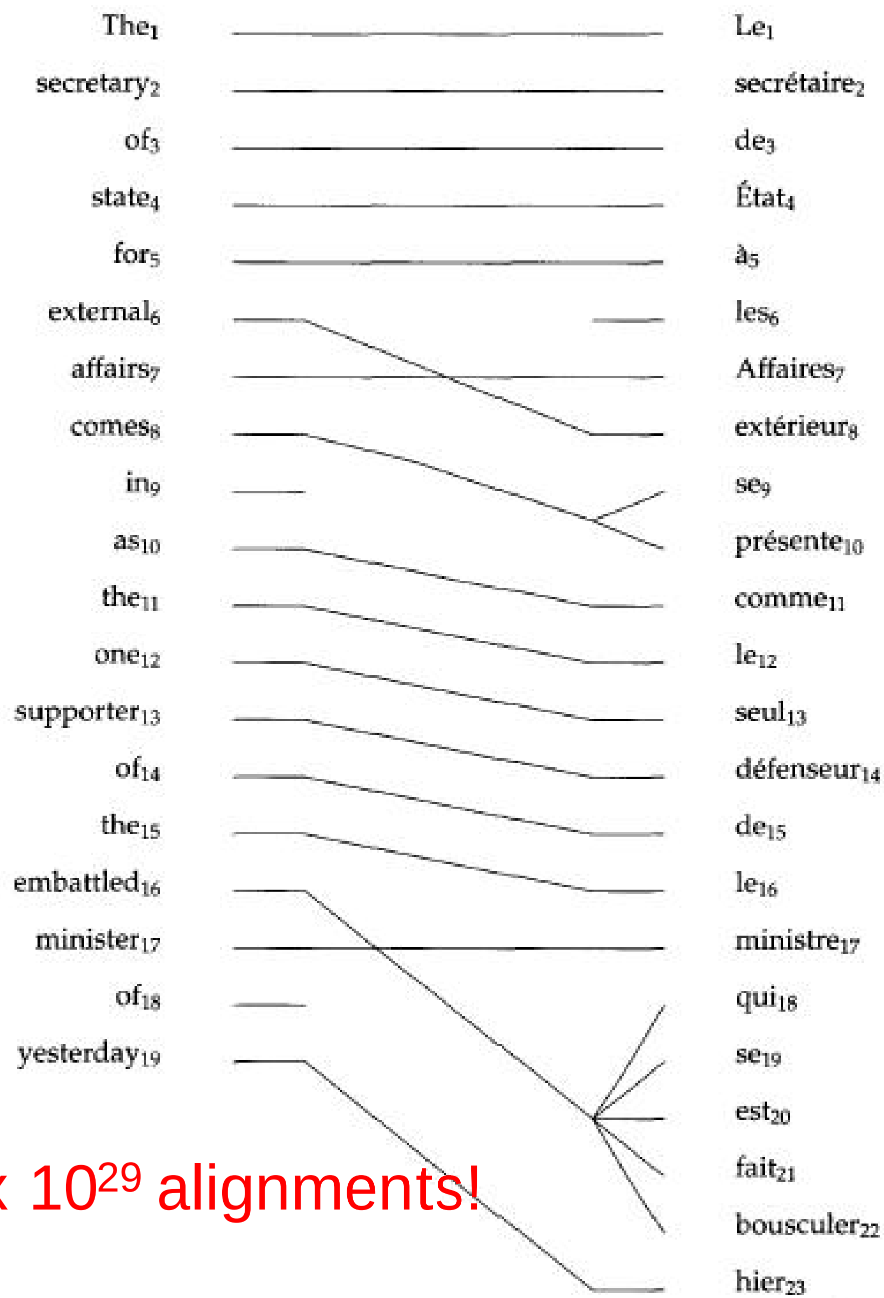
Nodding hill...

nodding

f	t(f|e)	phi	n(phi | e)
signe	0.164	4	0.342
la	0.123	3	0.293
tête	0.097	2	0.167
oui	0.086	1	0.163
fait	0.073	0	0.023
que	0.073		
hoche	0.054		
hocher	0.048		
faire	0.030		
me	0.024		
approuve	0.019		
qui	0.019		
un	0.012		
faites	0.011		

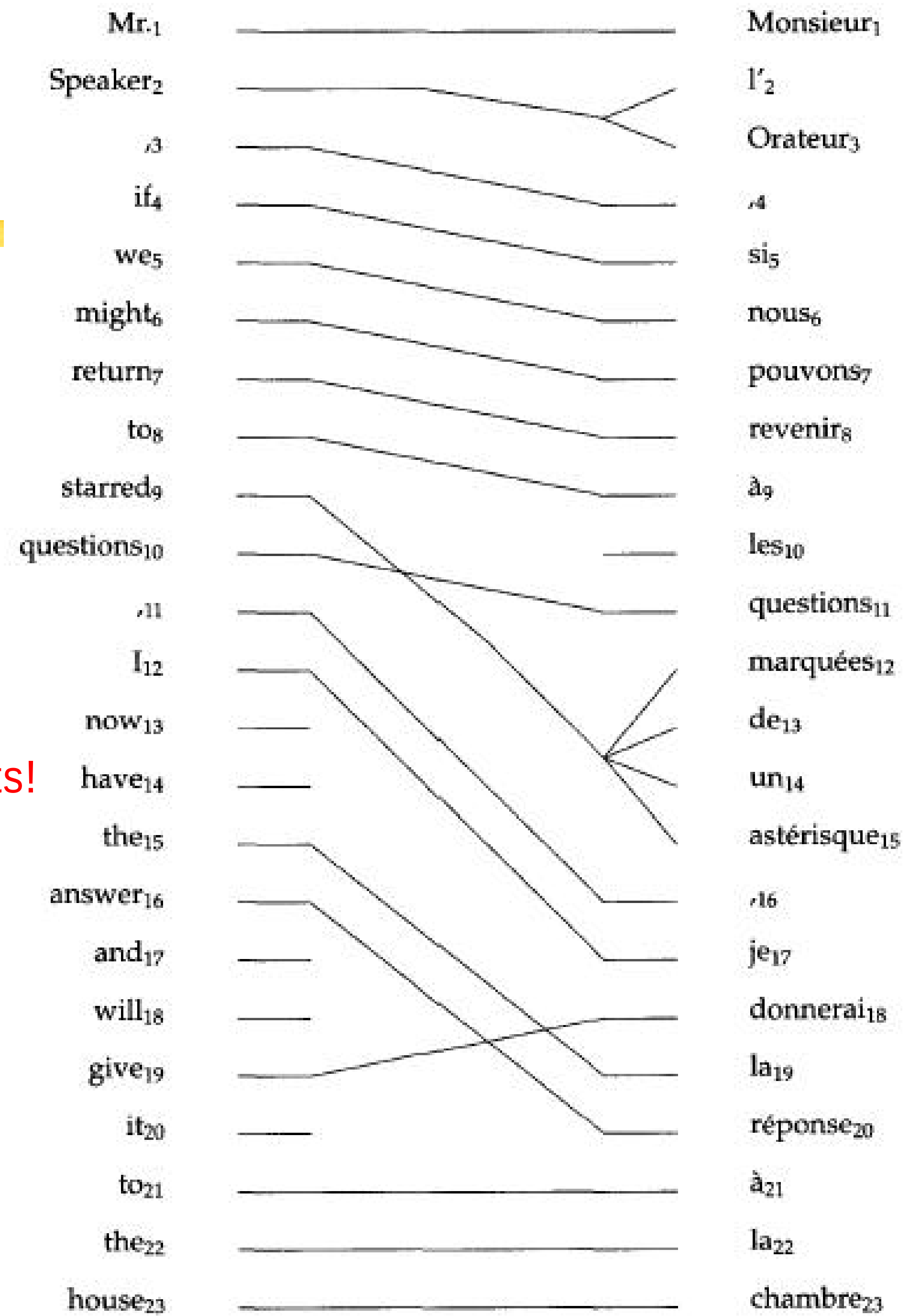


Best of 1.9 x 10^{26} alignments!



Best of 8.4×10^{29} alignments!

5.6 x 10^{31} alignments!



Morals? ¿Moralejas? ? ? ? ? .

- Always works hard – even if the input sentence is one of the training examples
- Ignores morphology – so what happens?
- Ignores phrasal chunks – can we include this? (Do we?)
- What next? Alternative histories...
- Can we include syntax and semantics?
- (why not?)