Statistical NLP

Spring 2007

Lecture 10: Word Alignment

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Machine Translation: Examples

Atlanta, preso il killer del palazzo di Giustizia

ATLANTA - La grande paura che per 26 ore ha attanagliato Atlanta è finita: Brian Nichols, l'uomo che aveva ucciso tre persone a palazzo di Giustizia e che ha poi ucciso un agente di dogana, s'è consegnato alla polizia, dopo avere cercato rifugio nell'alloggio di una donna in un complesso d'appartamenti alla periferia della città. Per tutto il giorno, il centro della città, sede della Coca Cola e dei Giochi 1996, cuore di una popolosa area metropolitana, era rimasto paralizzato.

Atlanta, taken the killer of the palace of Justice

ATLANTA - The great fear that for 26 hours has gripped Atlanta is ended: Brian Nichols, the man who had killed three persons to palace of Justice and that a customs agent has then killed, s' is delivered to the police, after to have tried shelter in the lodging of one woman in a complex of apartments to the periphery of the city. For all the day, the center of the city, center of the Coke Strains and of Giochi 1996, heart of one popolosa metropolitan area, was remained paralyzed.

Machine Translation

Madame la présidente, votre présidence de cette institution a été marquante.
Mrs Fontaine, your presidency of this institution has been outstanding.
Madam President, president of this house has been discoveries.
Madam President, your presidency of this institution has been impressive.

Je vais maintenant m'exprimer brièvement en irlandais.
I shall now speak briefly in Irish .
I will now speak briefly in Ireland .
I will now speak briefly in Irish .

Nous trouvons en vous un président tel que nous le souhaitions.
We think that you are the type of president that we want.
We are in you a president as the wanted.
We are in you a president as we the wanted.

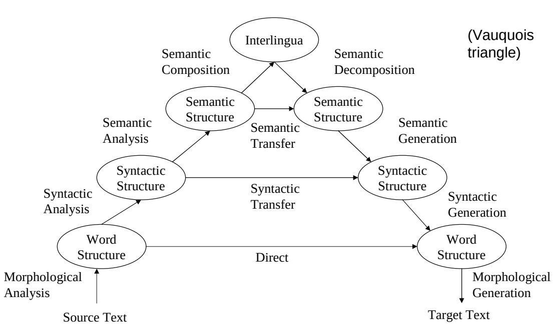
History

- 1950's: Intensive research activity in MT
- 1960's: Direct word-for-word replacement
- 1966 (ALPAC): NRC Report on MT
  - Conclusion: MT no longer worthy of serious scientific investigation.
- 1966-1975: `Recovery period'
- 1975-1985: Resurgence (Europe, Japan)
- 1985-present: Gradual Resurgence (US)

http://ourworld.compuserve.com/homepages/WJHutchins/MTS-93.htm

Levels of Transfer

(Vauquois triangle)



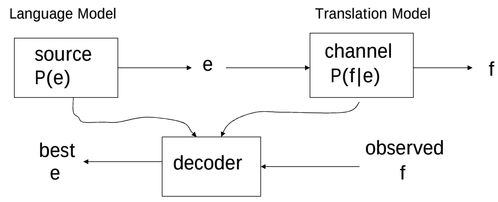
General Approaches

- Rule-based approaches
  - Expert system-like rewrite systems
  - Interlingua methods (analyze and generate)
  - Lexicons come from humans
  - Can be very fast, and can accumulate a lot of knowledge over time (e.g. Systran)
- Statistical approaches
  - Word-to-word translation
  - Phrase-based translation
  - Syntax-based translation (tree-to-tree, tree-to-string)
  - Trained on parallel corpora
  - Usually noisy-channel (at least in spirit)

The Coding View

- "One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.' "
  - Warren Weaver (1955:18, quoting a letter he wrote in 1947)

MT System Components



$$\underset{e}{\operatorname{argmax}} P(e|f) = \underbrace{\underset{e}{\operatorname{argmax}} P(f|e)P(e)}$$

Finds an English translation which is both fluent and semantically faithful to the French source

Today

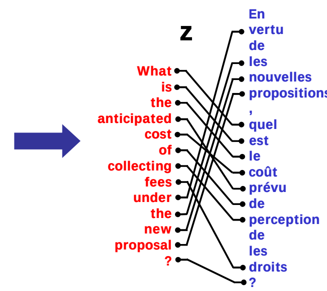
- The components of a simple MT system
  - You already know about the LM
  - Word-alignment based TMs
    - IBM models 1 and 2, HMM model
  - A simple decoder
- Next few classes
  - More complex word-level and phrase-level TMs
  - Tree-to-tree and tree-to-string TMs
  - More sophisticated decoders

Word Alignment

x

What is the anticipated cost of collecting fees under the new proposal?

En vertu des nouvelles propositions, quel est le coût prévu de perception des droits?

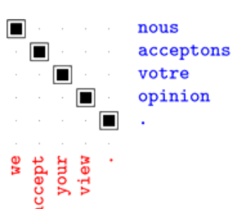


Unsupervised Word Alignment

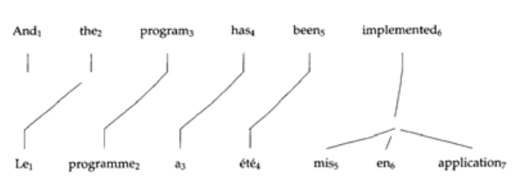
- Input: a ***bitext***: pairs of translated sentences

```
nous acceptons votre opinion .
we accept your view .
```

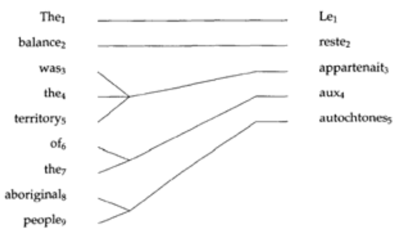
- Output: ***alignments***: pairs of translated words
  - When words have unique sources, can represent as a (forward) alignment function a from French to English positions



1-to-Many Alignments



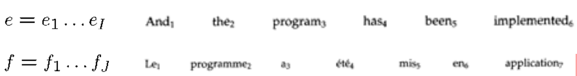
Many-to-1 Alignments



Many-to-Many Alignments

A Word-Level TM?

- What might a model of P(f|e) look like?

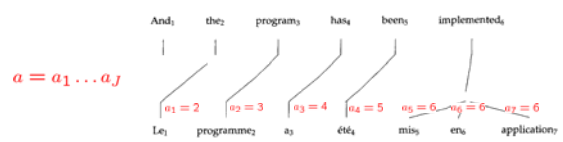


$$P(f|e) = \prod_j \underbrace{P(f_j|e_1 \dots e_I)}_{\text{How to estimate this?}}$$

What can go wrong here?

IBM Model 1 (Brown 93)

- Alignments: a hidden vector called an *alignment* specifies which English source is responsible for each French target word.



$$P(f, a|e) = \prod_j P(a_j = i) P(f_j|e_i)$$
$$= \prod_j \frac{1}{I+1} P(f_j|e_i)$$

$$P(f|e) = \sum_a P(f, a|e)$$

IBM Model 1

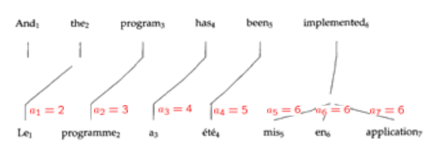
- Obvious first stab: greedy matchings
- Better approach: re-estimated generative models

$$P(f|e) = \sum_a P(f, a|e)$$
$$P(f, a|e) = \prod_j P(a_j = i|e) P(f_j|e_i)$$
$$P(a_j = i|e, f) = \frac{P(f_j|e_i)}{\sum_{i'} P(f_j|e_{i'})}$$

- Basic idea: pick a source for each word, update co-occurrence statistics, repeat

IBM Model 1 [Brown et al, 93]

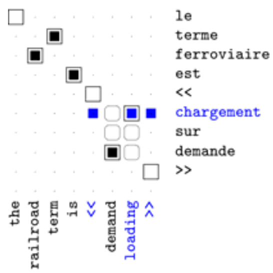
- Alignments: a hidden vector called an *alignment* specifies which English source is responsible for each French target word. $a = a_1 \dots a_J$



$$P(f, a|e) = \prod_j P(a_j = i) P(f_j|e_i)$$
$$= \prod_j \frac{1}{I+1} P(f_j|e_i)$$

Problems with Model 1

- There's a reason they designed models 2-5!
- Problems: alignments jump around, align everything to rare words
- Experimental setup:
  - Training data: 1.1M sentences of French-English text, Canadian Hansards
  - Evaluation metric: alignment error Rate (AER)
  - Evaluation data: 447 hand-aligned sentences



Evaluating TMs

- How do we measure TM quality?
  - Method 1: use in an end-to-end translation system
    - Hard to measure translation quality
    - Option: human judges
    - Option: reference translations (NIST, BLEU scores)
  - Method 2: measure quality of the alignments produced
    - Easy to measure
    - Hard to know what the gold alignments should be
    - May not correlate with translation quality (like perplexity in LMs)

Alignment Error Rate

- Alignment Error Rate

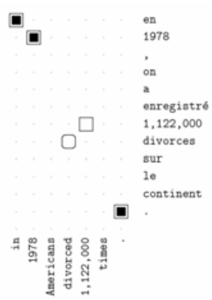
□ = Sure

○ = Possible

■ = Predicted

$$AER(A, S, P) = \left(1 - \frac{|A \cap S| + |A \cap P|}{|A| + |S|}\right)$$

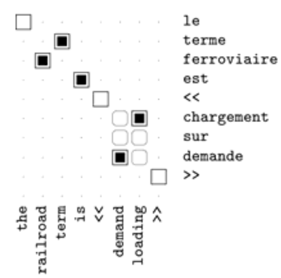
$$= \left(1 - \frac{3+3}{3+4}\right) = \frac{1}{7}$$



Intersected Model 1

- Post-intersection: standard practice to train models in each direction then intersect their predictions [Och and Ney, 03]
- Second model is basically a filter on the first
  - Precision jumps, recall drops
  - End up not guessing hard alignments

Model	P/R	AER
Model 1 E→F	82/58	30.6
Model 1 F→E	85/58	28.7
Model 1 AND	96/46	34.8



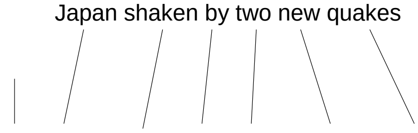
Joint Training?

- Overall:
  - Similar high precision to post-intersection
  - But recall is much higher
  - More confident about positing non-null alignments

Model	P/R	AER
Model 1 E→F	82/58	30.6
Model 1 F→E	85/58	28.7
Model 1 AND	96/46	34.8
Model 1 INT	93/69	19.5

Monotonic Translation

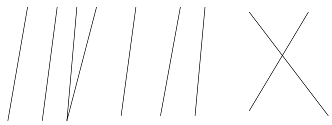
Japan shaken by two new quakes



Le Japon secoué par deux nouveaux séismes

Local Order Change

Japan is at the junction of four tectonic plates



Le Japon est au confluent de quatre plaques tectoniques

IBM Model 2

- Alignments tend to the diagonal (broadly at least)

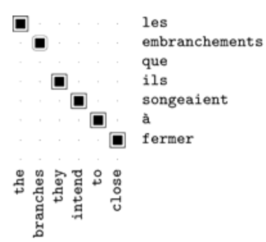
$$P(f,a|e) = \prod_j P(a_j = i|j,I,J)P(f_j|e_i)$$

$$P(i - j\frac{I}{J})$$

$$\frac{1}{Z}e^{-\alpha(i-j\frac{I}{J})}$$

- Other schemes for biasing alignments towards the diagonal:
  - Relative alignment
  - Asymmetric distances
  - Learning a multinomial over distances

Example



EM for Models 1/2

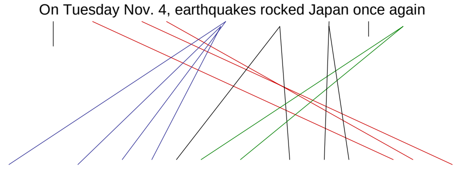
- Model 1 Parameters:
  Translation probabilities (1+2) $P(f_j|e_i)$
  Distortion parameters (2 only) $P(a_j = i|j,I,J)$
- Start with $P(f_j|e_i)$ uniform, including $P(f_j|null)$
- For each sentence:
  - For each French position j
    - Calculate posterior over English positions

$$P(a_j = i|f,e) = \frac{P(a_j = i|j,I,J)P(f_j|e_i)}{\sum_{i'} P(a_j = i'|j,I,J)P(f_j|e'_i)}$$

    - (or just use best single alignment)
    - Increment count of word f_j with word e_i by these amounts
    - Also re-estimate distortion probabilities for model 2
- Iterate until convergence

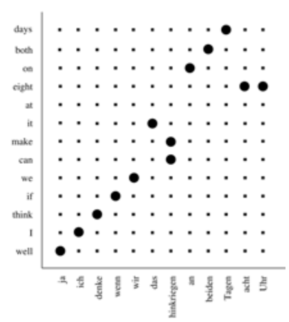
Phrase Movement

On Tuesday Nov. 4, earthquakes rocked Japan once again



Des tremblements de terre ont à nouveau touché le Japon jeudi 4 novembre.

Phrase Movement



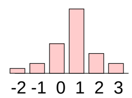
The HMM Model

- Model 2 preferred global monotonicity
- We want local monotonicity:
  - Most jumps are small
- HMM model (Vogel 96)

f	$t(f \mid e)$
nationale	0.469
national	0.418
nationaux	0.054
nationales	0.029

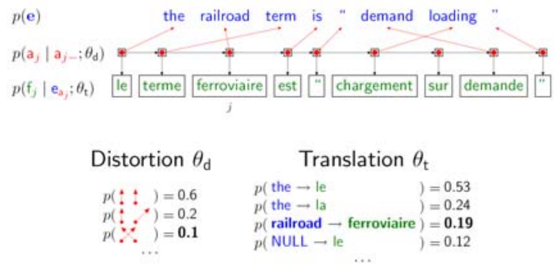
$$P(f,a|e) = \prod_j P(a_j|a_{j-1}) P(f_j|e_i)$$

$$P(a_j - a_{j-1})$$

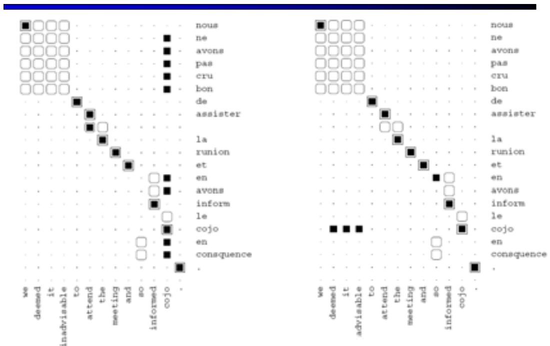


  - Re-estimate using the forward-backward algorithm
  - Handling nulls requires some care
- What are we still missing?

The HMM Model



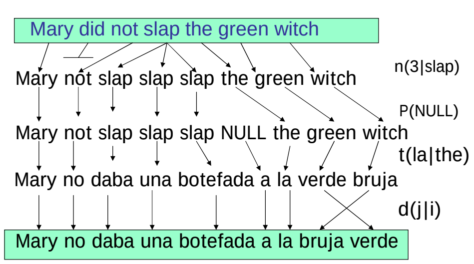
HMM Examples



AER for HMMs

Model	AER
Model 1 INT	19.5
HMM E→F	11.4
HMM F→E	10.8
HMM AND	7.1
HMM INT	4.7
GIZA M4 AND	6.9

IBM Models 3/4/5



[Al-Onaizan and Knight, 1998]

Examples: Translation and Fertility

the

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
le	0.497	1	0.746
la	0.207	0	0.254
les	0.155		
l'	0.086		
ce	0.018		
cette	0.011		

not

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
ne	0.497	2	0.735
pas	0.442	0	0.154
non	0.029	1	0.107
rien	0.011		

farmers

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
agriculteurs	0.442	2	0.731
les	0.418	1	0.228
cultivateurs	0.046	0	0.039
producteurs	0.021		

Example: Idioms

nodding

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
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		

Example: Morphology

should

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
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		

Some Results

- [Och and Ney 03]

Model	Training scheme	0.5K	8K	128K	1.47M
Dice		50.9	43.4	39.6	38.9
Dice+C		46.3	37.6	35.0	34.0
Model 1	1^5	40.6	33.6	28.6	25.9
Model 2	$1^5 2^5$	46.7	29.3	22.0	19.5
HMM	$1^5 H^5$	26.3	23.3	15.0	10.8
Model 3	$1^5 2^5 3^3$	43.6	27.5	20.5	18.0
	$1^5 H^5 3^3$	27.5	22.5	16.6	13.2
Model 4	$1^5 2^5 3^3 4^3$	41.7	25.1	17.3	14.1
	$1^5 H^5 3^3 4^3$	26.1	20.2	13.1	9.4
	$1^5 H^5 4^3$	26.3	21.8	13.3	9.3
Model 5	$1^5 H^5 4^3 5^3$	26.5	21.5	13.7	9.6
	$1^5 H^5 3^3 4^3 5^3$	26.5	20.4	13.4	9.4
Model 6	$1^5 H^5 4^3 6^3$	26.0	21.6	12.8	8.8
	$1^5 H^5 3^3 4^3 6^3$	25.9	20.3	12.5	8.7