

## IBM Models 3/4/5


[Al-Onaizan and Knight, 1998]

## Phrase Movement



## The HMM Model

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

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



Example: Morphology

| should |  |  |  |
| :---: | ---: | ---: | ---: |
| f | $t(f \mid e)$ | $\phi$ | $n(\phi \mid e)$ |
| 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 |  |  |

## Alignment Error Rate

$$
\begin{aligned}
& \text { - Alignment Error Rate } \\
& \square=\text { Sure } \\
& \square=\text { Possible } \\
& \square=\text { Predicted }
\end{aligned}
$$

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

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



## Decoding

- In these word-to-word models
- Finding best alignments is easy
- Finding translations is hard (why?)



## Some Results

- [Och and Ney 03]

| Model | Training scheme | 0.5 K | 8 K | 128 K | 1.47 M |
| :--- | :--- | :--- | :--- | :--- | :--- |
| 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 | $1^{5} 5^{5} 3^{3}$ | 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 |

## Bag "Generation" (Decoding)

Exact reconstruction (24 of 38)
Please give me your response as soon as possible.
$\Rightarrow \quad$ Please give me your response as soon as possible.
Reconstruction preserving meaning (8 of 38)
Now let me mention some of the disadvantages.
$\Rightarrow \quad$ Let me mention some of the disadvantages now.
Garbage reconstruction (6 of 38)
In our organization research has two missions.
$\Rightarrow$ In our missions research organization has two.

## Bag Generation as a TSP

- Imagine bag generation with a bigram LM
- Words are nodes
- Edge weights are P(w|w')
- Valid sentences are Hamiltonian paths
- Not the best news for word-based MT!

(clear)


## IBM Decoding as a TSP



## Decoding, Anyway

- Simplest possible decoder:
- Enumerate sentences, score each with TM and LM
- Greedy decoding:
- Assign each French word it's most likely English translation
- Operators:
- Change a translation
- Insert a word into the English (zero-fertile French)
- Remove a word from the English (null-generated French)
- Swap two adjacent English words
- Do hill-climbing (or annealing)

Greedy Decoding

NULL well heard, it talks a great victory
bien entendu, il parle de une belle victire
NULL well understood, it
translateOneWord(4,he)
bien entendu, il parle de une belle victore .
NULL well understood, he talks about a great victory .
$\left.\right|_{\text {bien }}| | \mid / / / 1$ translateTwoWords(1,quite,2,naturally)
bien entendu, il parle de une belle victoire .
NULL quite naturally
bien entendu, il parie de une belle victoire

## Stack Decoding

- Stack decoding:
- Beam search
- Usually A* estimates for completion cost
- One stack per candidate sentence length
- Other methods:
- Dynamic programming decoders possible if we make assumptions about the set of allowable permutations



## WSD?

- Remember when we discussed WSD?
- Word-based MT systems rarely have a WSD step
- Why not?

| oil |  |  |  |
| :---: | ---: | ---: | ---: |
| $\mathbf{f}$ | $t(f \mid e)$ | $\phi$ | $\boldsymbol{n}(\phi \mid e)$ |
| pétrole | 0.558 | 1 | 0.760 |
| pétrolières | 0.138 | 0 | 0.181 |
| pétrolière | 0.109 | 2 | 0.057 |
| le | 0.054 |  |  |
| pétrolier | 0.030 |  |  |
| pétroliers | 0.024 |  |  |
| huile | 0.020 |  |  |
| Oil | 0.013 |  |  |

