Phrase-based SMT

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April 9, 2015

Content

1. Statistical model
2. Estimation
3. Inference
4. Conclusions
5. Extensions (further reading)

Noisy channel

Bayes rule

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

Inference

$$\hat{E} = \arg\max_{E} P(E)P(F|E)$$

Estimation

- $P(E)$ n-gram LM
- $P(F|E)$ ...

Phrase-based model

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

Let's introduce a bidirectional alignment variable

Bidirectional alignment

Example

		I	have	black	eyes
1	J'	1			
2	ai				
3	les				3
4	yeux				
5	noirs			2	

- $\bar{f}_1 =$ J' ai
- $\bar{e}_1 =$ I have
- $\text{start}_1 = 1$
- $\text{end}_1 = 2$

- $\bar{f}_2 =$ noirs
- $\bar{e}_2 =$ black
- $\text{start}_2 = 5$
- $\text{end}_2 = 5$

- $\bar{f}_3 =$ les yeux
- $\bar{e}_3 =$ eyes
- $\text{start}_3 = 3$
- $\text{end}_3 = 4$

Intuition

$$
\begin{aligned}
P(F|E) &= \sum_A P(A, F|E) \\
&= \sum_A P(\text{segmentation}) \times P(\text{order}) \times P(\text{translation})
\end{aligned}
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	[J'$_1$ ai$_2$] [les$_3$ yeux$_4$] [noirs$_5$]	segmentation

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	$[\text{J'}_1\ \text{ai}_2]$ $[\text{les}_3\ \text{yeux}_4]$ $[\text{noirs}_5]$	segmentation
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	$[\text{I have}]_1$ $[\text{black}]_2$ $[\text{eyes}]_3$	translation

Model and assumptions

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\begin{aligned}
P(F|E) &= \sum_A P(A, F|E) \\
&= \sum_A P(A|E) \times P(F|A, E) \\
&= \sum_A \prod_k \phi(\bar{f}_k|\bar{e}_k)\delta(\text{start}_k - \text{end}_{k-1} - 1)
\end{aligned}
$$

Assumptions

1. uniform alignments (and segmentation)
2. distance-based reordering
3. phrase independence

Estimation

Reordering model

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Phrase translation model

- EM: requires computing **expected counts** of unseen events (phrase alignments) [Marcu and Wong, 2002]
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- EM: requires computing **expected counts** of unseen events (phrase alignments) [Marcu and Wong, 2002]
  DeNero and Klein [2008] proved the problem NP-complete
- Heuristic: view phrase pairs as **observed** irrespective of context or overlap [Koehn et al., 2003]

Phrase pairs from word alignments

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- we extract all of them once, irrespective of derivation

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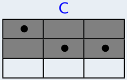

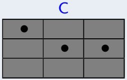

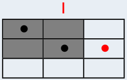

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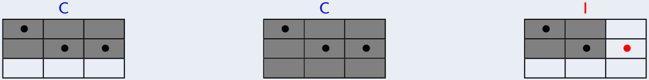

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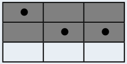

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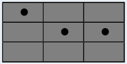

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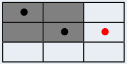

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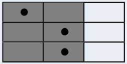

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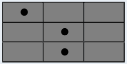

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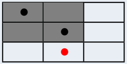

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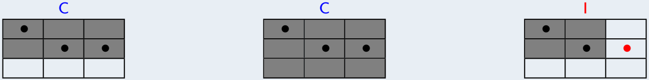

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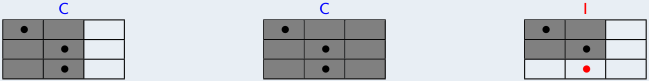

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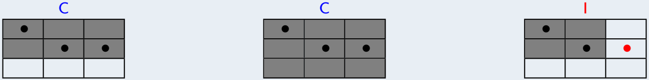

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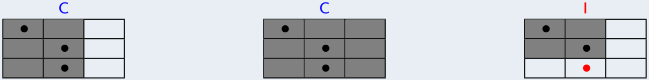

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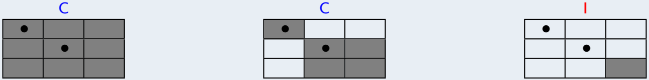

Scoring

Number of times a (consistent) phrase pair is "observed"

$$c(\bar{f}, \bar{e})$$

Relative frequency counting

$$\phi(\bar{f}|\bar{e}) = \frac{c(\bar{f}, \bar{e})}{\sum_{\bar{f}'} c(\bar{f}', \bar{e})}$$

Decoding

Disambiguation problem

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\hat{E} &= \arg\max_{E} P(E)P(F|E) \\
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NP-complete [Sima'an, 2002]

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Viterbi approximation

$$
\hat{E} \approx \arg\max_{E,A} P(E)P(A, F|E)
$$

Viterbi decoding

The alignment space (or space of *derivations*)

- $O(2^n)$ segmentations
- $O(n!)$ permutations
- $O(t^n)$ substitutions

Packed representation using finite-state transducers

$$O(n^2 \times 2^n \times t)$$

NP-complete (TSP) [Knight, 1999, Zaslavskiy et al., 2009]

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- maximum phrase length m: $n^2 \to n \times m$

Complete model

$$P(E)P(F, A|E) = \prod_{j=1}^{|E|} \psi(e_j|e_{j-n+1}^{j-1}) \prod_{i=1}^{|A|} \phi(\bar{f}_i|\bar{e}_i)\delta(\text{start}_i - \text{end}_{i-1} - 1)$$

- alignment space $O(2^d \times n \times t \times m)$
- weighted derivations $O(2^d \times n \times t \times m \times |\Delta|^{k-1})$ where $P(E)$ is a k-gram LM components over Δ^* and $|\Delta| \propto t \times n$

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- pruning: beam search

Wrap up: model

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  Is it a good thing?
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  Do you see why?
- heuristic estimation is straightforward
  Can you guess why it works?

Wrap up: complexity

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- unconstrained reordering: NP-complete

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  Do you think it is sensible to allow all permutations?
- tractability requires an ad-hoc distortion limit
  Do you see the problem here?

Wrap up: reordering

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Nonlocal

- penalised in general
- arbitrarily constrained
  Does it suit every language pair?

Discriminative models

Linear model

$$\text{score}(E, A|F) = \theta^\top h(F, E, A)$$

Features

- language model
- forward translation probability $P(F|E)$
- backward translation probability $P(E|F)$
- forward and backward lexical smoothing
- word penalty
- phrase penalty

Feature weights can be optimised [Och, 2003]

Questions?

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