Phrase-based SMT

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Content

Recap

We looked into Alignment a directional word-based model.

- Parametrisation: Categorical.
- Estimation techniques: EM vs VB.

Recap

We looked into Alignment a directional word-based model.

- Parametrisation: Categorical.
- Estimation techniques: EM vs VB.

We have not look into generation:

- No model of length
- No model of segmentation
- Bad model for translation

Translation

Model:

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

Prediction:

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

Estimation:

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

Word-based SMT

[Brown et al., 1993]

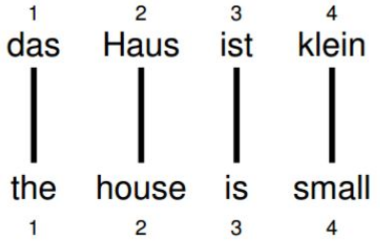

Figure: Koehn [2010]

Limitations of word-based approach

Linguistically

- Can not translate many-to-one or many-to-many
- Compositionality of translation
  multi-word / idiomatic expressions.

Computationally during prediction

- $n!$ permutations in decoding.

Phrase-based model

Change of units: phrase.

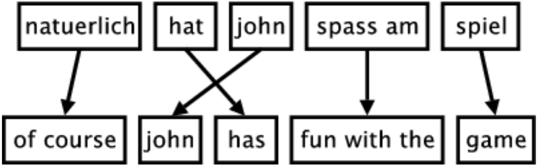

Figure: Koehn [2010]

Phrase-based model

Phrase pairs as translation units

- Capture non-compositional translations.
- Exploit (local) reordering patterns.

Illustration

		I	have	black	eyes
1	J'				
2	ai				
3	les				
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Derivation

Modelling Derivations

$$P(e,d|f) = \frac{\exp(S_\theta(e,d,f))}{\sum_{e'}\sum_{d'}\exp(S_\theta(e',d',f))}$$

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Challenging normalisation.
Large space of derivations:

- Number of segments.
- Number of permutations.
- Number of translations.

Discriminative classifier

- Give up on marginalisation of d
- Give up on probabilistic modelling
- How?

Discriminative classifier

- Give up on marginalisation of d
- Give up on probabilistic modelling
- How?
- If we look at the prediction:

$$
\begin{aligned}
\hat{e}, \hat{d} &= \arg\max_{e,d|f} \log P(e, d|f) \\
&= \arg\max_{e,d|f} S_\theta(e, d, f) - \underbrace{\log \sum_{e'} \sum_{d'} \exp(S_\theta(e', d', f))}_{\text{constant for any}(e,d|f)} \\
&= \arg\max_{e,d|f} S_\theta(e, d, f)
\end{aligned}
$$

Trained discriminatively (e.g. structured perceptron).

Linear model

The score functionS_θ is defined as a linear model.

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where θ are parameters
h are feature functions.

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where θ are parameters
h are feature functions.
Linear model decomposes over phrases.

$$S_\theta(e, d, f) = \theta^T \sum_{i}^{n} \underbrace{h_i(d_i|e, f)}_{\text{local feature function}}$$

Model featurises steps in the derivation independently.

PBSMT Model

- Feature functions $n = 3$
- Translation feature function:

$$h_1 = \log P(\bar{f}|\bar{e})$$

- Language Model feature function:

$$h_2 = \log P(e|e_{\mathsf{past}})$$

- Distortion feature function:

$$h_3 = \log d(\mathsf{start}_k - \mathsf{end}_{k-1} - 1)$$

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- multiple derivations can explain an “observed” phrase pair
- we extract all of them once, irrespective of derivation

Phrase Table

- Goal: Learn phrase translation table from parallel corpus.

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- Three stages:
- Word alignment given IBM.
- Extraction of phrase pairs.
- Phrase scoring.

Phrase extraction

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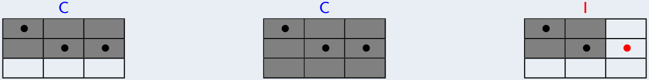

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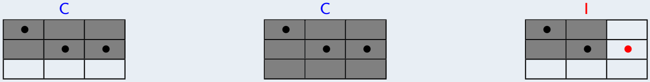

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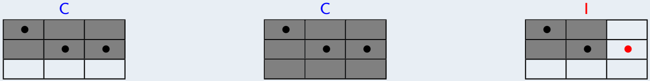

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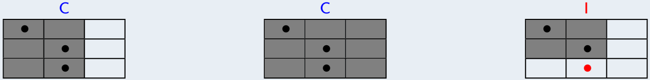

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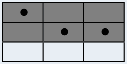
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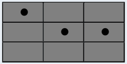
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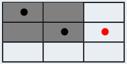

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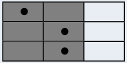
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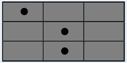
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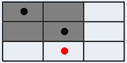

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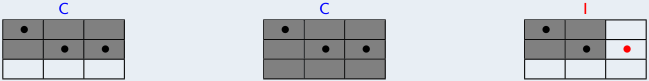

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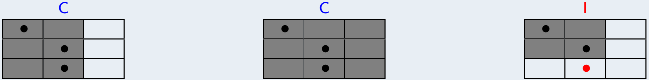

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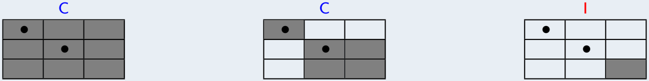


Feature Translation Model

Features

$$\log P(\bar{f}|\bar{e})$$

and

$$\log P(\bar{e}|\bar{f})$$

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

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

Relative frequency counting

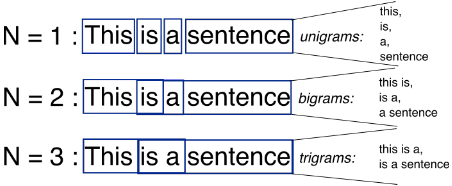
$$\varphi(\bar{f}|\bar{e}) = \frac{c(\bar{f}, \bar{e})}{\sum_{\bar{f}'} c(\bar{f}', \bar{e})}$$

Feature Language Model

Feature n-gram language model

$$\log P(e|e_{\text{past}})$$

Estimated independently on monolingual data.



http://recognize-speech.com/images/Antonio/Unigram.png

Translation Options

- Europarl phrase table: 2727 matching phrase pairs for a sentence.
- Search problem with beam search:
  1. From phrase translation table for all input phrases.
  2. Initial hypothesis: no input words covered, no output produced.
  3. Pick any translation option, create new hypothesis.
  4. Expand hypotheses from created partial hypothesis.
  5. Backtrack from highest scoring complete hypothesis.

Decoding

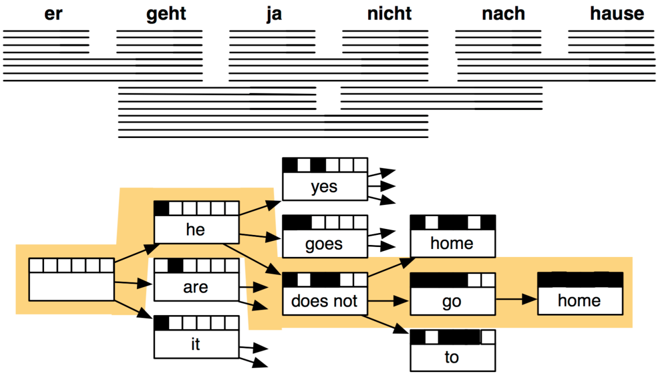


Figure: Koehn [2010]

Questions?

References I

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