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]

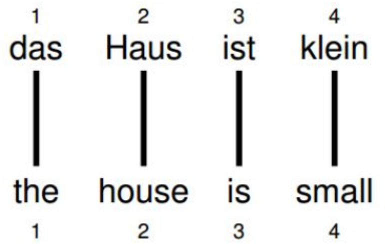

Figure: Koehn [2010]

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.

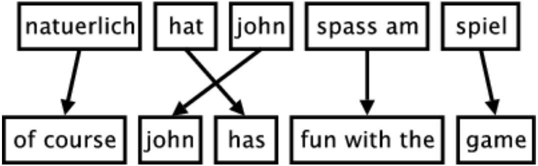

Figure: Koehn [2010]

Phrase-based model

Phrase pairs as translation units

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

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		I	have	black	eyes
1	J’				
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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
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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:

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

- Distortion feature function:

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

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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.

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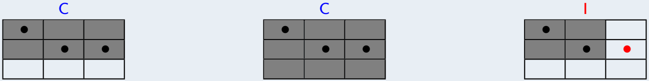

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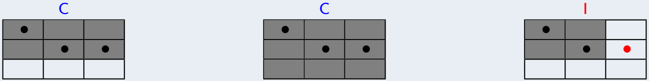

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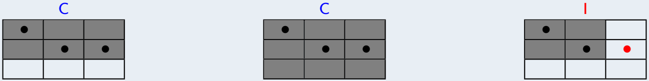

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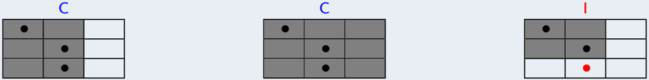

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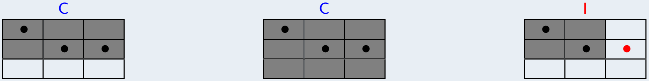

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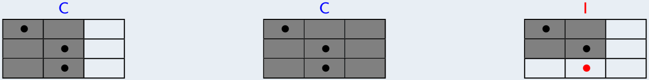

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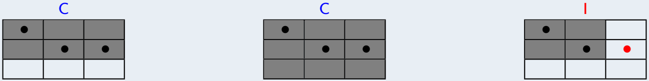

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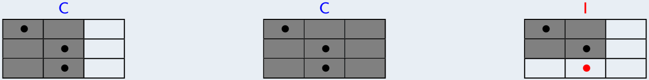

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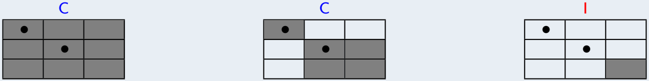


Feature Translation Model

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

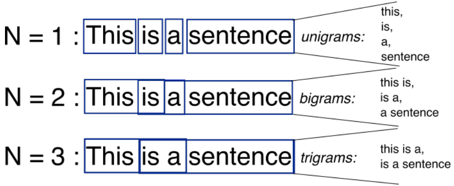
$$\varphi(\bar{f}|\bar{e}) = \frac{c(\bar{f}, \bar{e})}{\sum_{\bar{f}'} c(\bar{f}', \bar{e})}$$

Feature Language Model

Feature n-gram language model

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

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.

Translation Options

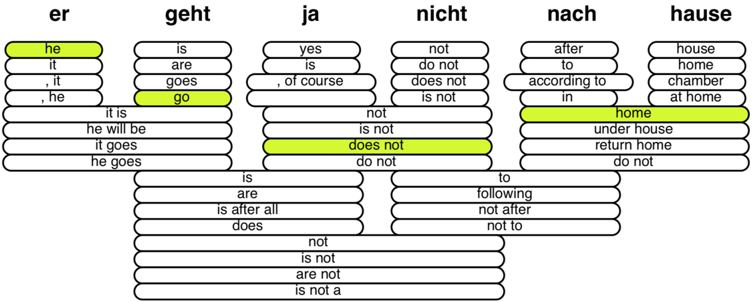


Figure: Koehn [2010]

Decoding

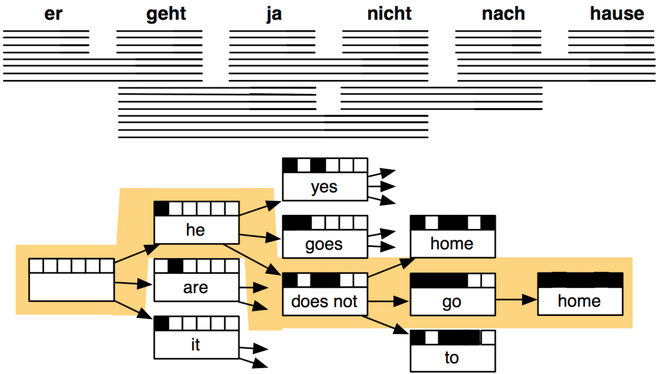


Figure: Koehn [2010]

Questions?

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