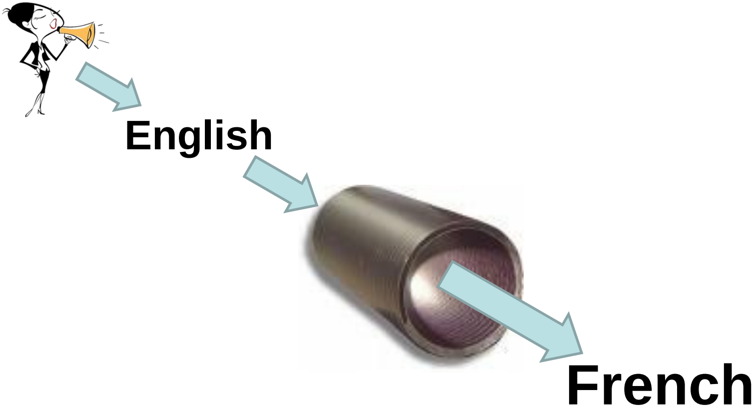
Noisy Channel Framework

$$p(e) \rightarrow e \rightarrow p(f|e) \rightarrow f$$



Noisy Channel Framework

$$\boxed{p(e)} \rightarrow e \rightarrow \boxed{p(f|e)} \rightarrow f$$

$$p(f) = p(e)p(f|e)$$

English

French

Noisy Channel Framework

Applying Bayes' Rule, we have:

$$p(e|f) = \frac{p(e)p(f|e)}{p(f)}$$

Thus:

$$\hat{e} = \operatorname*{argmax}_{e} p(e|f) = \operatorname*{argmax}_{e} p(e)p(f|e)$$

Noisy Channel Framework

$$\hat{e} = \operatorname*{argmax}_{e} p(e)p(f|e)$$

Noisy Channel Framework

$$\hat{e} = \underbrace{\operatorname*{argmax}_{e}}_{\text{Decoder}} \underbrace{p(e)}_{\text{Language Model}} \underbrace{p(f|e)}_{\text{Translation Model}}$$

Noisy Channel Framework

- The *translation model* models how likely it is that *f* is a translations of *e* – **adequacy**.
- The *language model* models how likely it is that *e* is an acceptable sentence – **fluency**.
- The *decoder* searches for the most likely *e*.

We have introduced language models in previouse lectures, here we will mainly focus on translation models and decoding algorithms

Noisy Channel Framework

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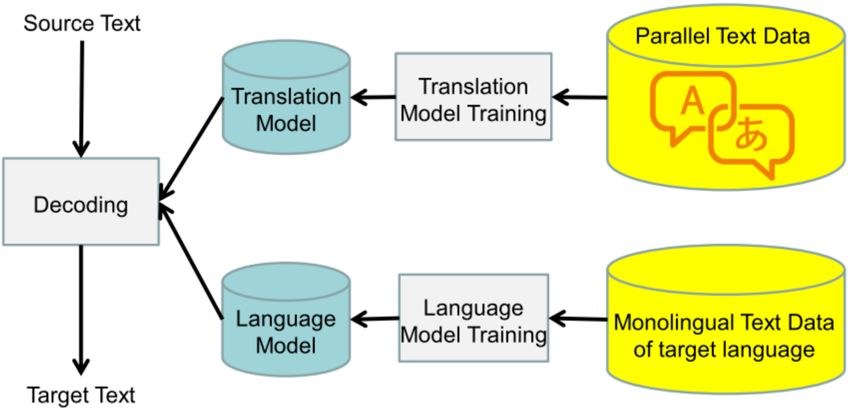
SMT Workflow



Content

Categories of translation models

Various translation models have been proposed, which belong to different categories, according to the language units on which they are built up:

- Word-based models
  - IBM models 1-5
  - HMM models
- Phrase-based models
- Syntax-based models
  - Tree-to-string models
  - String-to-tree models
  - Tree-to-tree models
  - Dependency-based models

IBM Models

IBM researchers proposed 5 models with increased complexity:

- IBM Model 1: only consider lexical translation probabilities
- IBM Model 2: add a absolute reordering model
- IBM Model 3: add a fertility model
- IBM Model 4: add a relative reordering model
- IBM Model 5:

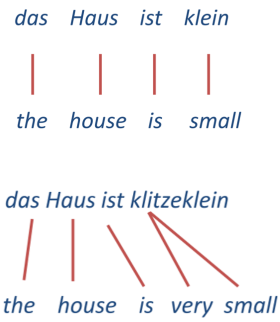
Lexical translation probabilities

English	Chinese	Prob.
a	一	0.2
a	一个	0.4
a	个	0.2
a	一只	0.1
a	一本	0.05
a	...	...

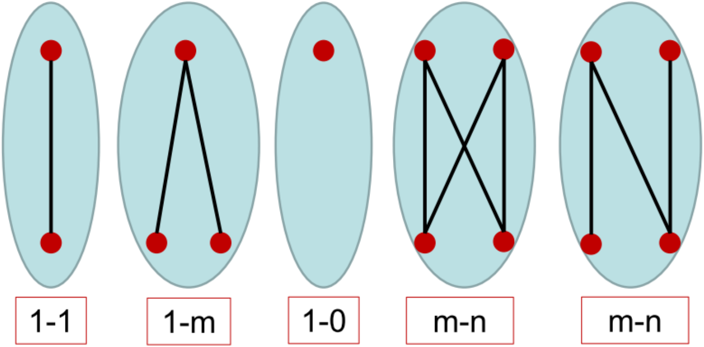
English	Chinese	Prob.
book	书	0.7
book	预定	0.2
book	...	...
take	拿	0.4
take	带走	0.3
take	...	...

Word alignment

- To estimate the word translation probabilities, we need alignment between words in the parallel sentences



Word alignment patterns



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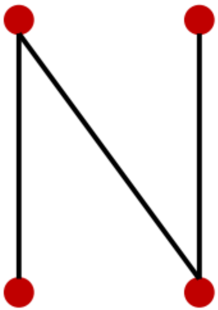
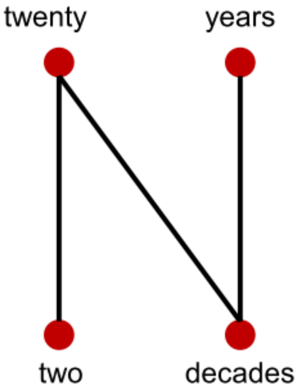


Can you image a word alignment pattern like this?

Word alignment patterns



Can you image a word alignment pattern like this?

Learning lexical translation models

- We would like to estimate the lexical translation probabilities from a parallel corpus...
- but we do not have the alignments:
  - If we had the alignments, we could estimate the lexical translation probabilities.
  - If we had the probabilities, we could estimate the alignments.

Learning lexical translation models

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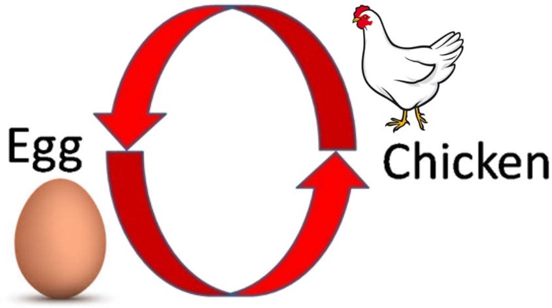
A Paradox



EM Algorithm

- Incomplete data
  - If we had complete data, we could estimate model.
  - If we had the model, we could fill in the gaps in the data.
- Solution: Expectation Maximization (EM) Algorithm
  - Initialize model parameters. (e.g. uniform)
  - Assign probabilities to the missing data. (E-step)
  - Astimate model parameters from completed data. (M-step)
  - Iterate E-step and M-step until the model converges.

How does EM algorithm work?

EM Algorithm consists of two steps:

1. Expectation-Step: Apply model to the data
   - parts of the data are hidden (here: alignments)
   - using the model, assign probabilities of the hidden data to possible values (alignments)
2. Maximization-Step: Estimate new model from data
   - take assigned values as fact
   - collect counts (weighted by probabilities)
   - estimate new model from counts

Iterate the E-step and the M-step until convergence

Example

Consider a parallel corpus containing just two pairs:

blue house	house
maison bleu	maison

How many possible alignments in the first pair?

How many in the second pair?

Example

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blue house	house
maison bleu	maison

How many possible alignments in the first pair?

How many in the second pair?

We will simplify the example by ruling out many-to-one or zero-to-one alignments.

Example

Consider a parallel corpus containing just two pairs:

blue house	house
maison bleu	maison

How many possible alignments in the first pair? 2

How many in the second pair? 1

We will simplify the example by ruling out many-to-one or zero-to-one alignments.

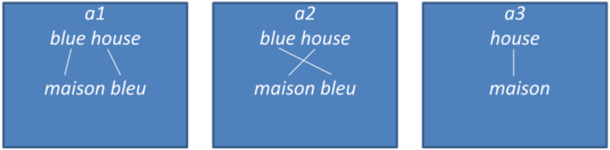
Step 1 (Initialisation)

Set parameter values uniformly.

- t(bleu|house) = 1/2
- t(maison|house) = 1/2
- t(bleu|blue) = 1/2
- t(maison|blue) = 1/2

Step 2 (Expectation)

Compute the probability of all alignments.



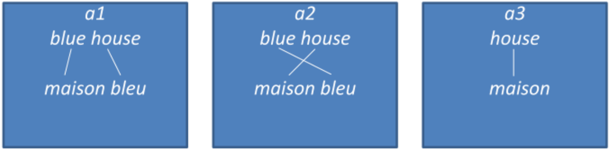
p(a1, maison bleu|blue house) = t(maison|blue) * t(bleu|house) = ½ * ½ = ¼

p(a2, maison bleu|blue house) = t(maison|house) * t(bleu|blue) = ½ * ½ = ¼

p(a3, maison| house) = t(maison|house) = ½

Step 3 (Expectation)

Normalise for all alignments.



p(a1|maison bleu,blue house) = 1/4 ÷ 2/4 = 1/2

p(a2|maison bleu,blue house) = 1/4 ÷2/4 = 1/2

p(a3|maison, house) = 1/2 ÷ 1/2 = 1

Step 4 (Maximisation)

Collect fractional counts

- tc(bleu|house) = 1/2
- tc(maison|house) = 1/2 + 1 = 3/2
- tc(bleu|blue) = 1/2
- tc(maison|blue) = 1/2

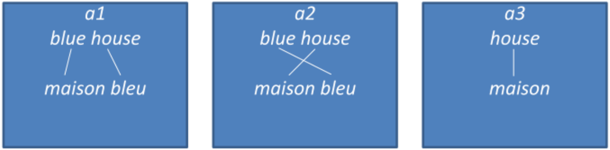
Step 5 (Maximisation)

Normalise fractional counts to yield revised parameter values

- t(bleu|house) = 1/2 ÷ 2 = 1/4
- t(maison|house) = 3/2 ÷ 2 = 3/4
- t(bleu|blue) = 1/2 ÷ 1 = 1/2
- t(maison|blue) = 1/2 ÷ 1 = 1/2

Repeat Step 2 (Expectation)

Compute the probability of all alignments.



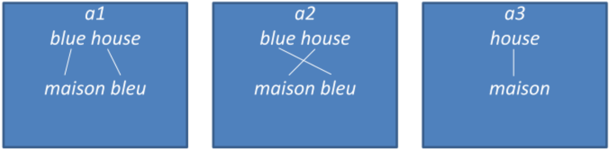
p(a1, maison bleu|blue house) = t(maison|blue) * t(bleu|house) = 1/2 * 1/4 = 1/8

p(a2, maison bleu|blue house) = t(maison|house) * t(bleu|blue) = 3/4 * 1/2 = 3/8

p(a3, maison| house) = t(maison|house) = 3/4

Repeat Step 3 (Expectation)

Normalise for all alignments.



p(a1|maison bleu,blue house) = 1/8 ÷ 4/8 = 1/4

p(a2|maison bleu,blue house) = 3/8 ÷ 4/8 = 3/4

p(a3|maison, house) = 3/4 ÷ 3/4 = 1

Repeat Step 4 (Maximisation)

Collect fractional counts

- tc(bleu|house) = 1/4
- tc(maison|house) = 3/4 + 1 = 7/4
- tc(bleu|blue) = 3/4
- tc(maison|blue) = 1/4

Repeat Step 5 (Maximisation)

Normalise fractional counts to yield revised parameter values

- t(bleu|house) = $1/4 \div 2 = 1/8$
- t(maison|house) = $7/4 \div 2 = 7/8$
- t(bleu|blue) = $3/4 \div 1 = 3/4$
- t(maison|blue) = $1/4 \div 1 = 1/4$

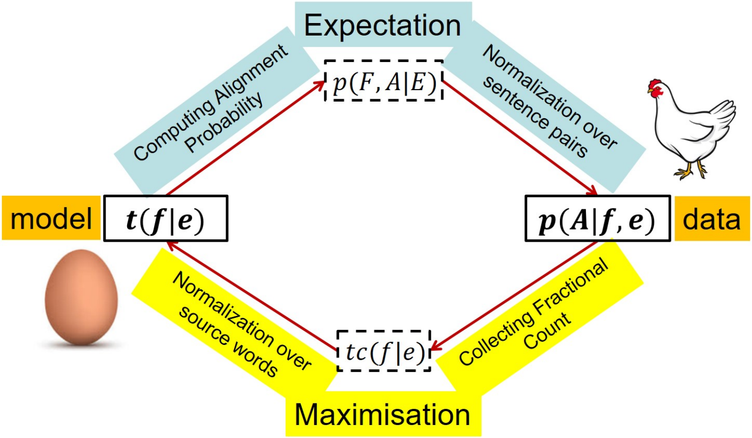
Convergence

Repeating steps 2, 3, 4 and 5 eventually yields:

- t(bleu|house) = 0.0001
- t(maison|house) = 0.9999
- t(bleu|blue) = 0.9999
- t(maison|blue) = 0.0001

It is proved that an EM algorithm is convergent.

EM Algorithm



Content

Shortcomings of word-based SMT

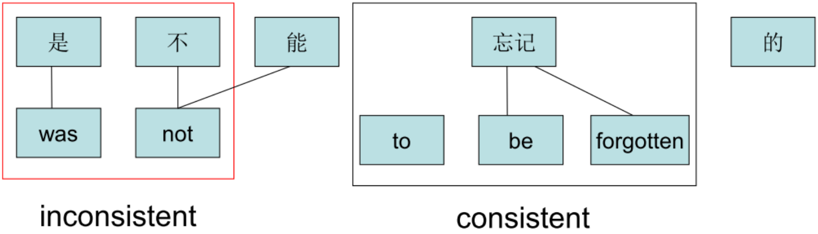
- Word-based translation models do not take into account contextual information for translation decisions
- They are not good at dealing with 1-to-many, many-to-1 and many-to-many translations.

Phrase-based Translation Models

- Phrase-based translate models are proposed to solve the problems for word-based models.
- Phrase-based models translate phrases as atomic units.
- A monolingual phrase can be any contiguous sequence of words in a sentence.
  - A phrase is not necessarily syntactically well-formed
  - A phrase is not necessarily semantically meaningful
- A bilingual phrase pair should be consistent with word alignment.

Bilingual Phrase Pairs

A bilingual phrase pair should be constistent with word alignment:



Bilingual Phrase Pairs

A real example taken from Europarl for the German phrase den Vorschlag:

English	Probability	English	Probability
the proposal	0.6277	the suggestions	0.0114
's proposal	0.1068	the proposed	0.0114
a proposal	0.0341	the motion	0.0091
the idea	0.025	the idea of	0.0091
this proposal	0.0227	the proposal ,	0.0068
proposal	0.0205	its proposal	0.0068
of the proposals	0.0159	it	0.0068
the proposals	0.0159	....	

Learning a phrase translation table

- Task: learn the model from a parallel corpus
- Three stages:
  1. Word alignment: using IBM models or other method
  2. Extraction of phrase pairs
  3. Scoring phrase pairs

Bidirectional word alignment

- With IBM models, each target word can be aligned to at most one source word (patterns supported: 1-0,0-1,1-1,m-1).
- Therefore, it's not possible to end up with an alignment of one target word to many source words (patterns not supported: 1-m, m-m)
- To obtain a word alignment with all possible patterns, a symmetric word alignment algorithm should be adopted.

Bidirectional word alignment

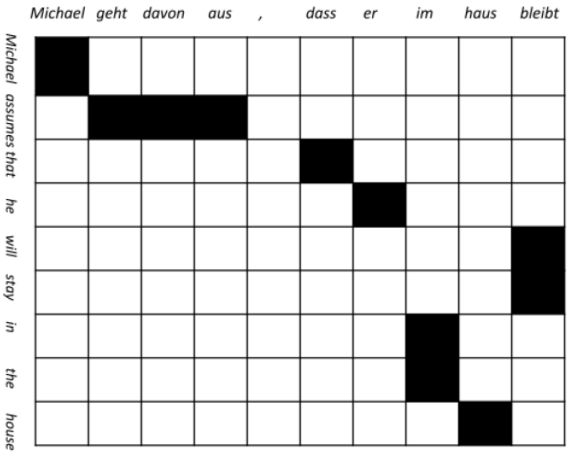
- A typical symmetric word alignment algorithm:
  - Word alignment using IBM Models in one direction.
  - Word alignment using IBM Models in the other direction.
  - Merge the above two alignment results with a certain criterion.

Consistent with word alignment

A phrase pair (e, f) is consistent with a bidirectional word alignment A if and only if:

- For all words $e_i \in e$, if exists an f_j: $(e_i, f_j) \in A$, then $f_j \in f$.
- For all word $f_j \in f$, if exists an e_i: $(e_i, f_j) \in A$, then $e_i \in e$.
- There exists an $e_i \in e$, and an $f_j \in f$: $(e_i, f_j) \in A$

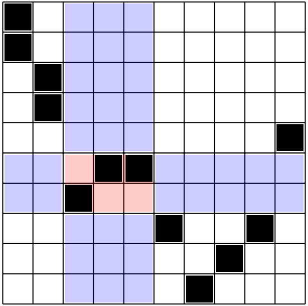
A matrix view of word alignment



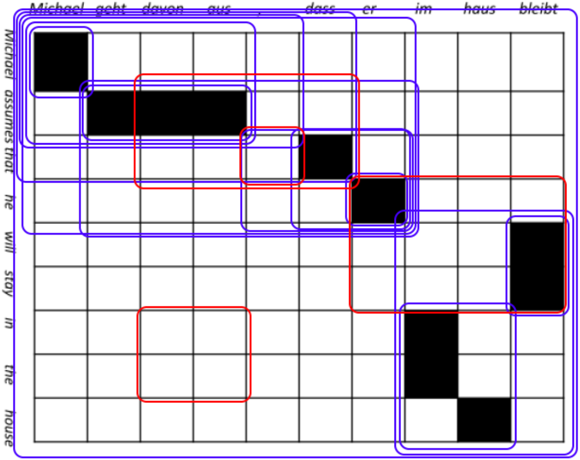
Consistent phrases in the matrix view

A consistent phrase pair defined by the red area should meet the following requirement:

- There should be one or more filled blocks in the red area.
- The blue areas should be all clear.



Phrase pair extraction



Blue box: consistent phrase pairs, Red box: inconsistent phrase pairs

Phrase pair extraction

Phrase pairs extracted from the above example:

- michael assumes | michael geht davon aus ,
- michael assumes | michael geht davon aus
- assumes that | geht davon aus , dass
- assumes that he | geht davon aus , dass er
- that he | , dass er
- that he | dass er
- in the house | im haus
- michael assumes that | michael geht davon aus , dass
- michael assumes that he | michael geht davon aus , dass er
- michael assumes that he will stay in the house | michael geht davon aus , dass er im haus bleibt
- assumes that he will stay in the house | geht davon aus , dass er im haus bleibt
- that he will stay in the house | dass er im haus bleibt ,
- that he will stay in the house | dass er im haus bleibt
- he will stay in the house | er im haus bleibt
- will stay in the house | im haus bleibt