Statistical Machine Translation
A practical tutorial

Cristina España i Bonet
LSI Department
Universitat Politècnica de Catalunya

GF meets SMT
Chalmers University of Technology, Göteborg
1st November, 2010

Overview

Part I: SMT background

$\sim$ 2h

Overview

6. Translation system

7. MT Evaluation basics

8. Evaluation system

Part II: SMT experiments

$\sim$ 2h

Part III: MT evaluation

$\sim$ 45min

Part I

SMT background

Outline

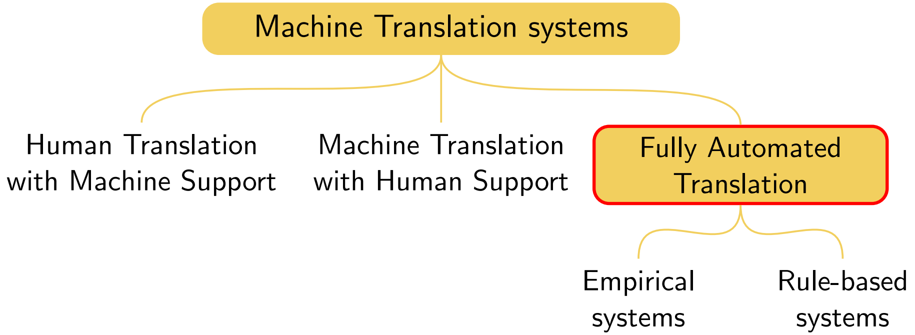
Introduction

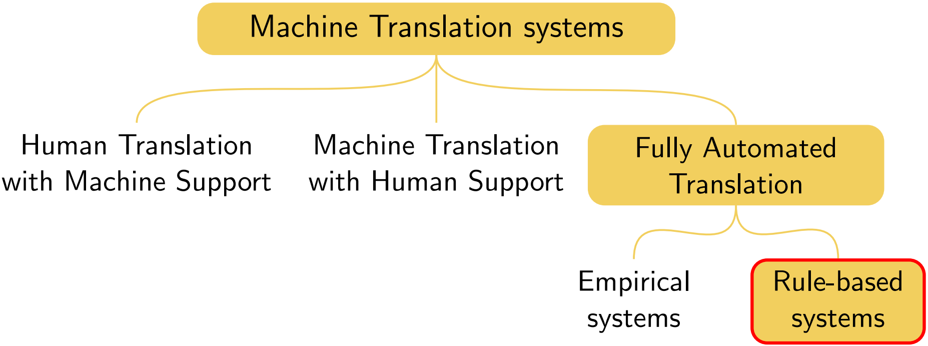
Machine Translation Taxonomy

- Machine Translation systems
  - Human Translation with Machine Support
  - Machine Translation with Human Support
  - Fully Automated Translation

Introduction

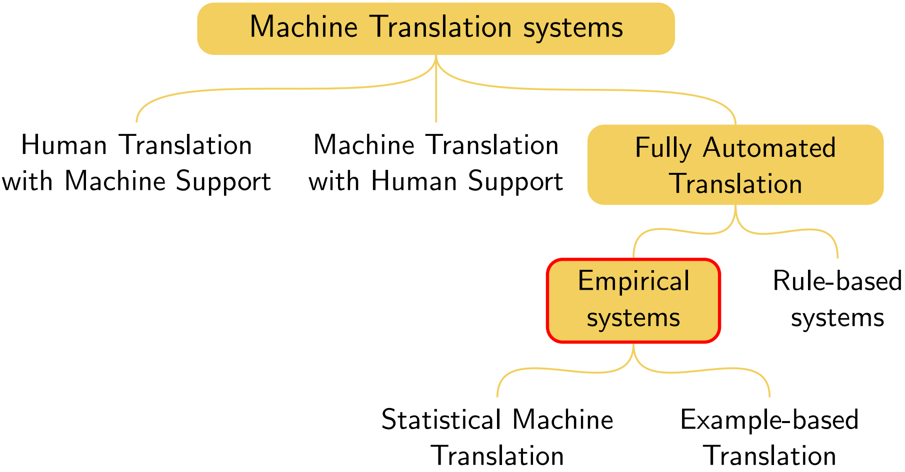
Machine Translation Taxonomy




Machine Translation systems
Human Translation with Machine Support
Machine Translation with Human Support
Fully Automated Translation
Empirical systems
Rule-based systems

Introduction

Machine Translation Taxonomy



Introduction

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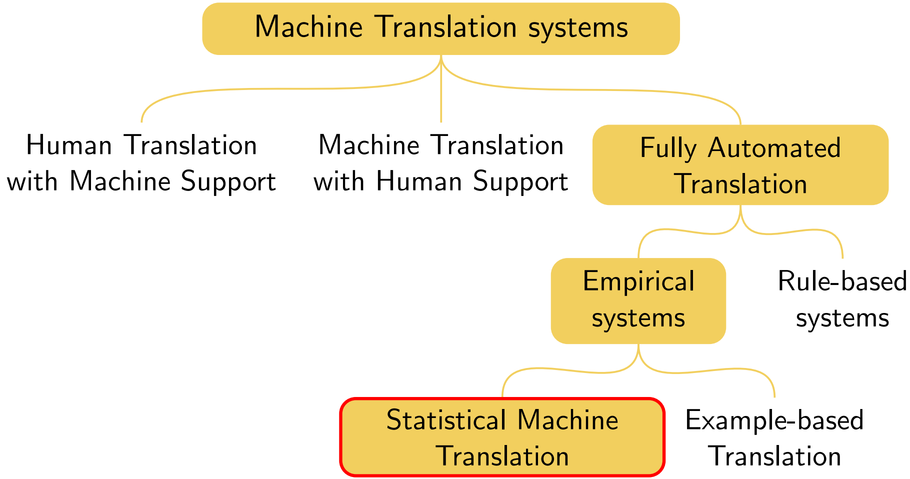

Empirical MT relies on large parallel aligned corpora.

L'objectiu de MOLTO és desenvolupar un conjunt d'eines per a traduir textos entre diversos idiomes en temps real i amb alta qualitat. Les llengües són mòduls separats en l'eina i per tant es poden canviar; els prototips que es construiran cobriran la major part dels 23 idiomes oficials de la UE.

Com a tècnica principal, MOLTO utilitza gramàtiques semàntiques de domini específic i interlingues basades en ontologies. Aquests components s'implementen en GF (Grammatical Framework), un formalisme de gramàtiques on es relacionen diversos idiomes a través d'una sintaxi abstracta comú. El GF s'ha aplicat en diversos dominis de mida petita i mitjana, típicament per tractar fins a un total de deu idiomes, però MOLTO ampliarà això en termes de productivitat i aplicabilitat.

Part de l'ampliació es dedicarà a augmentar la mida dels dominis i el nombre d'idiomes. Una part important és fer la tecnologia accessible per als experts del domini sense experiència amb GFs i reduir al mínim l'esforç necessari per a la construcció d'un traductor. Idealment, això es pot fer només estenent un lexicó i escrivint un conjunt de frases d'exemple.

MOLTO's goal is to develop a set of tools for translating texts between multiple languages in real time with high quality. languages are separate modules in the tool and can be varied; prototypes covering a majority of the EU's 23 official languages will be built.

As its main technique, MOLTO uses domain-specific semantic grammars and ontology-based interlinguas. These components are implemented in GF (Grammatical Framework), which is a grammar formalism where multiple languages are related by a common abstract syntax. GF has been applied in several small-to-medium size domains, typically targeting up to ten languages but MOLTO will scale this up in terms of productivity and applicability.

A part of the scale-up is to increase the size of domains and the number of languages. A more substantial part is to make the technology accessible for domain experts without GF expertise and minimize the effort needed for building a translator. Ideally, this can be done by just extending a lexicon and writing a set of example sentences.

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Aligned parallel corpora numbers

Corpora

Corpus	# segments (app.)	# words (app.)
JRC-Acquis	$1.0 \cdot 10^6$	$30 \cdot 10^6$
Europarl	$1.5 \cdot 10^6$	$45 \cdot 10^6$
United Nations	$3.8 \cdot 10^6$	$100 \cdot 10^6$

Books

Title	# words (approx.)
The Bible	$0.8 \cdot 10^6$
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Outline

SMT, basics

The beginnings, summarised timeline

IBM

CANDIDE system

1988

Candide

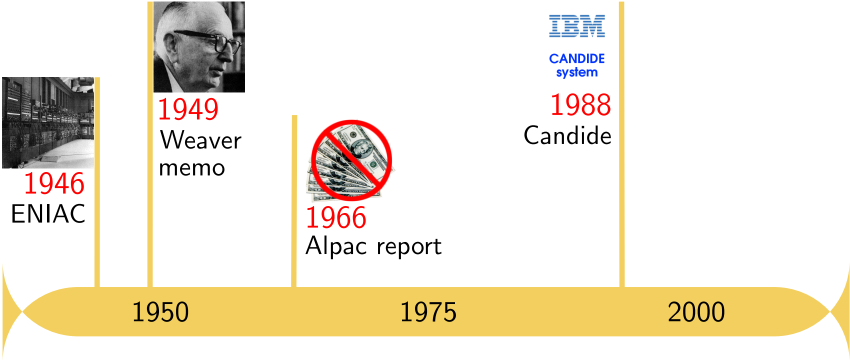
1950

1975

2000

SMT, basics

The beginnings, summarised timeline



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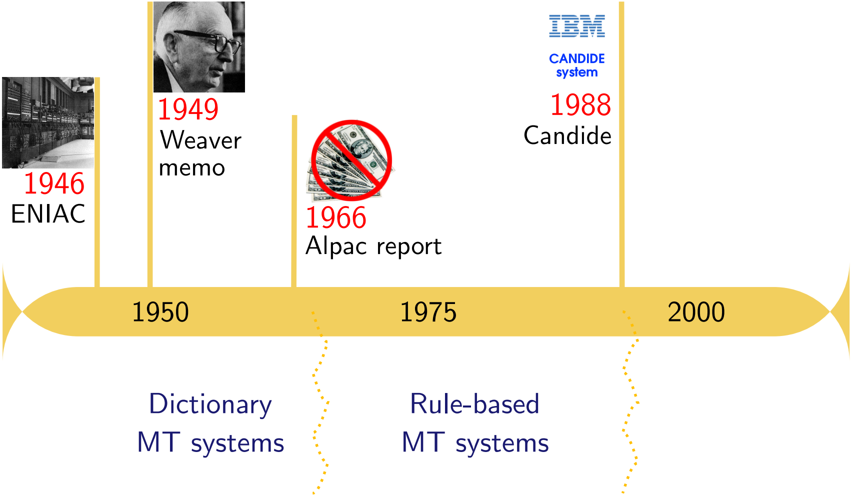

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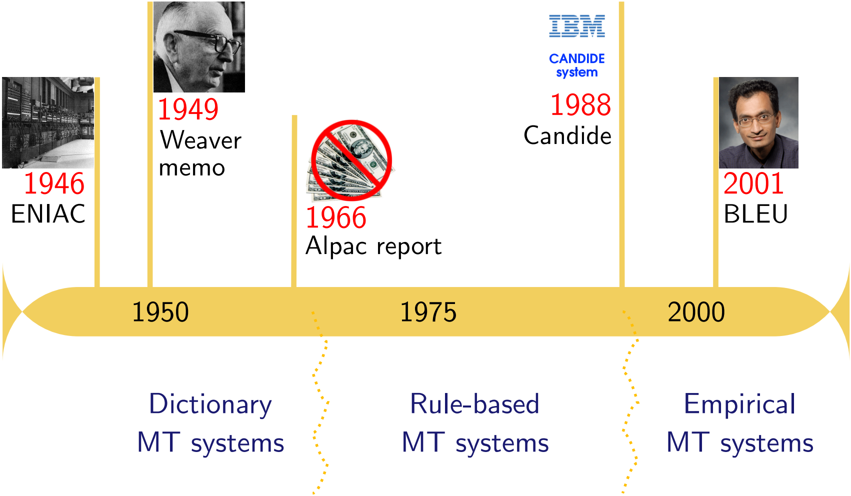
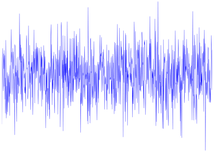
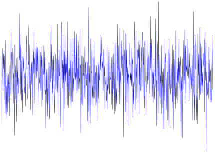


The Noisy Channel as a statistical approach to translation:

Good morning! $\longrightarrow$ 

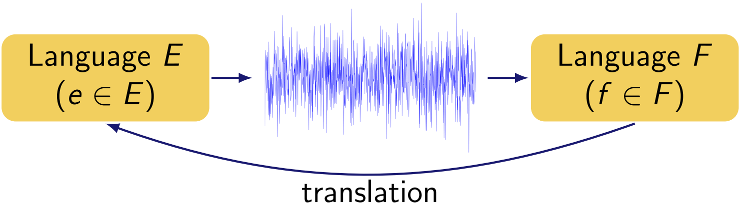
SMT, basics
The Noisy Channel approach

The Noisy Channel as a statistical approach to translation:

Good m  ⟶ Bon jour!

The Noisy Channel as a statistical approach to translation:

e: Good morning! f: Bon jour!



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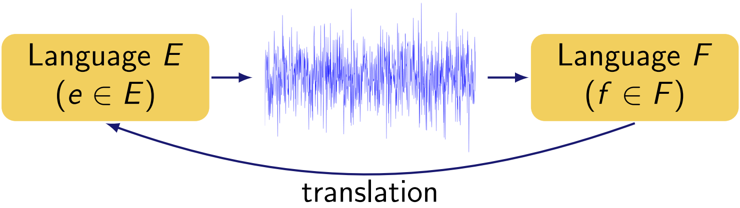

Mathematically:

$$P(e|f)$$

SMT, basics

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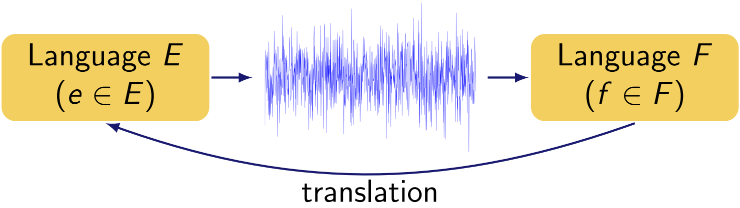

Mathematically:

$$P(e|f) = \frac{P(e)\,P(f|e)}{P(f)}$$

$$T(f) = \hat{e} = \mathrm{argmax}_{\mathrm{e}}\ P(e|f) = \mathrm{argmax}_{\mathrm{e}}\ P(e)\,P(f|e)$$

SMT, basics

Components

$$T(f) = \hat{e} = \mathrm{argmax_e}\ P(e)\, P(f|e)$$

Language Model

- Takes care of fluency in the target language
- Data: corpora in the target language

Translation Model

- Lexical correspondence between languages
- Data: aligned corpora in source and target languages

argmax

- Search done by the *decoder*

SMT, basics

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Language model

$$T(f) = \hat{e} = \mathrm{argmax_e}\ P(e)\, P(f|e)$$

Estimation of how probable a sentence is.

Naïve estimation on a corpus with N sentences:

Frequentist probability of a sentence e: $$P(e) = \frac{N_e}{N_{sentences}}$$

Problem:

- Long chains are difficult to observe in corpora.
  $\Rightarrow$ Long sentences may have zero probability!

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The n-gram approach

The language model assigns a probability $P(e)$ to a sequence of words $e \Rightarrow \{w_1, \ldots, w_m\}$.

$$P(w_1, \ldots, w_m) = \prod_{i=1}^{m} P(w_i | w_{i-(n-1)}, \ldots, w_{i-1})$$

- The probability of a sentence is the product of the conditional probabilities of each word w_i given the previous ones.
- Independence assumption: the probability of w_i is only conditioned by the n previous words.

SMT, components

The language model $P(e)$

Example, a 4-gram model

e: `All work and no play makes Jack a dull boy`

$$
\begin{aligned}
P(e) = {} & P(\texttt{All}|\phi,\phi,\phi)\ P(\texttt{work}|\phi,\phi,\texttt{All})\ P(\texttt{and}|\phi,\texttt{All},\texttt{work}) \\
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where, for each factor,

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Main problems and criticisims:

- Long-range dependencies are lost.
- Still, some *n*-grams can be not observed in the corpus.

Solution

Smoothing techniques:

- Linear interpolation.

$$P(\texttt{and}|\texttt{All},\texttt{work}) = \quad \frac{N_{(\texttt{All},\texttt{work},\texttt{and})}}{N_{(\texttt{All},\texttt{work})}} + \lambda_2 \frac{N_{(\texttt{work},\texttt{and})}}{N_{(\texttt{work})}} + \lambda_1 \frac{N_{(\texttt{and})}}{N_{words}} + \lambda_0$$

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- Back-off models.

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Language model: keep in mind

- Statistical LMs estimate the probability of a sentence from its n-gram frequency counts in a monolingual corpus.
- Within an SMT system, it contributes to select fluent sentences in the target language.
- Smoothing techniques are used so that not frequent translations are not discarded beforehand.

SMT, components

The translation model $P(f|e)$

Translation model

$$T(f) = \hat{e} = \mathrm{argmax_e}\ P(e)\, P(f|e)$$

Estimation of the lexical correspondence between languages.

How can be $P(f|e)$ characterised?

SMT, components

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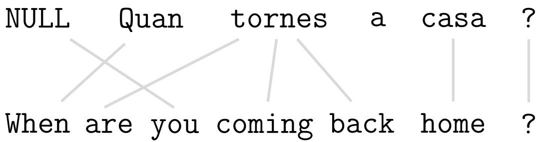

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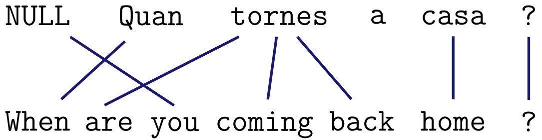

SMT, components

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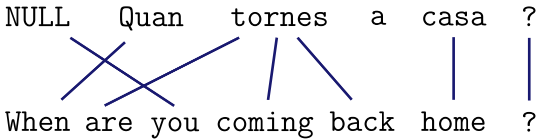


One should at least model for *each word* in the source language:

- Its translation,
- the number of necessary words in the target language,
- the position of the translation within the sentence,
- and, besides, the number of words that need to be generated from scratch.

Word-based models: the IBM models

They characterise $P(f|e)$ with 4 parameters: t, n, d and p_1.

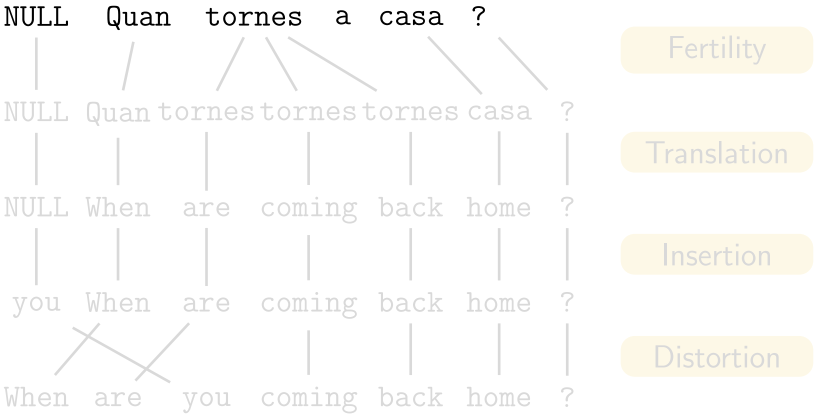
- Lexical probability t
  $t(\texttt{Quan}|\texttt{When})$: the prob. that `Quan` translates into `When`.
- Fertility n
  $n(3|\texttt{tornes})$: the prob. that `tornes` generates 3 words.

Word-based models: the IBM models

They characterise $P(f|e)$ with 4 parameters: t, n, d and p_1.

- Distortion d
  $d(j|i, m, n)$: the prob. that the word in the j position generates a word in the i position. m and n are the length of the source and target sentences.
- Probability p_1
  $p(\texttt{you}|\texttt{NULL})$: the prob. that the spurious word `you` is generated (from `NULL`).

Back to the example:



SMT, components

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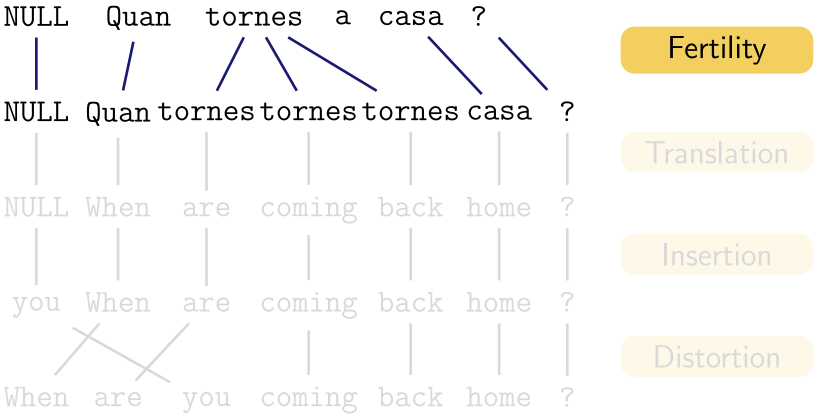

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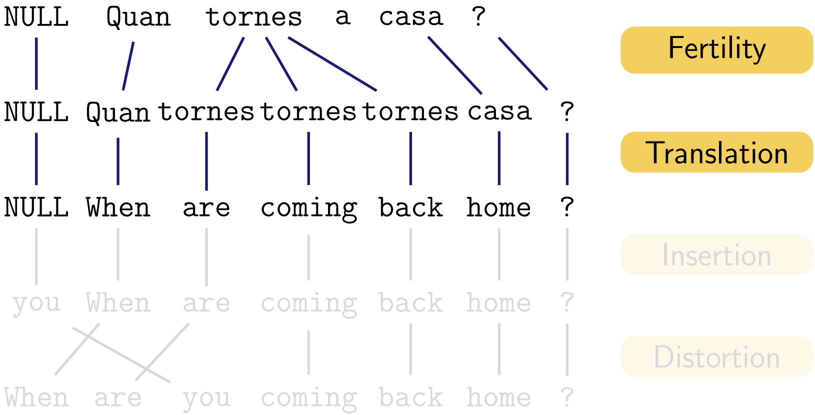

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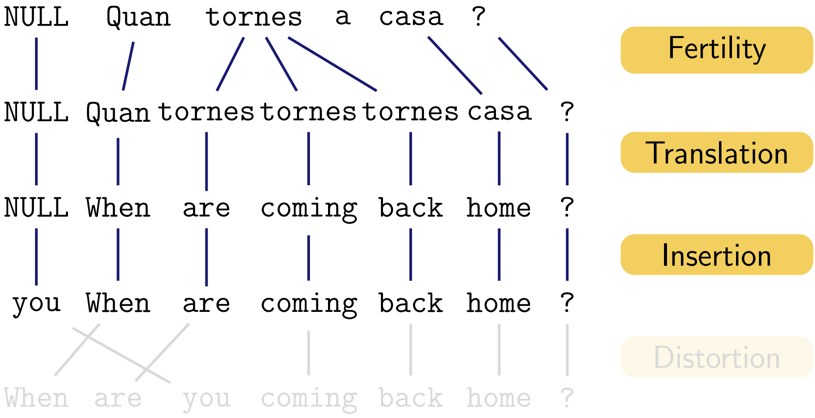

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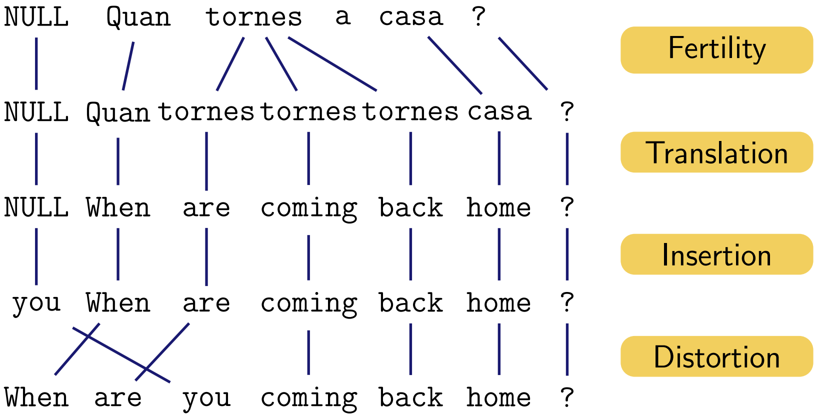

Word-based models: the IBM models

How can be t, n, d and p_1 estimated?

- Statistical model $\Rightarrow$ counts in a (huge) corpus!

But...

- Corpora are aligned at sentence level, not at word level.

Solutions

- Pay someone to align 2 milion sentences word by word.
- Estimate word alignments together with the parameters.

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SMT, components

The translation model $P(f|e)$

Expectation-Maximisation algorithm

Parameter initialisation

↓

Alignment probability calculation

Expectation-Maximisation algorithm

Parameter initialisation

$\downarrow$

Alignment probability calculation

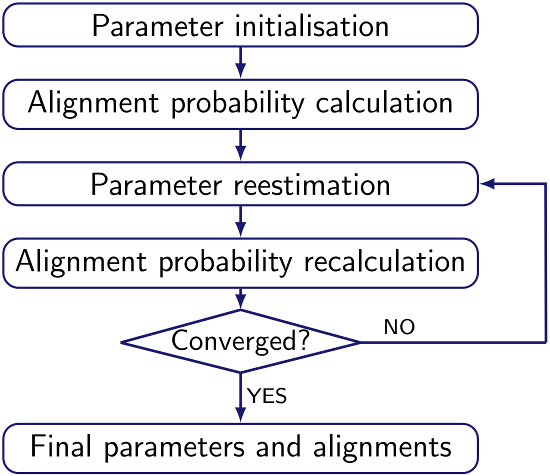
$\downarrow$

Parameter reestimation

$\downarrow$

Alignment probability recalculation

Expectation-Maximisation algorithm



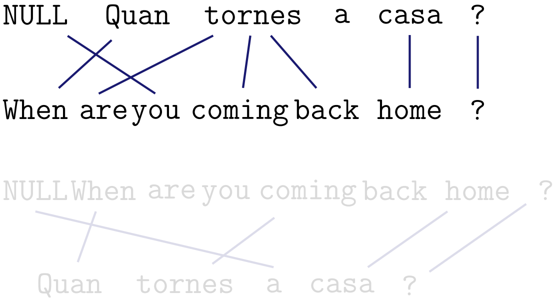
Alignment's asymmetry

The definitions in IBM models make the alignments asymmetric

- each target word corresponds to only one source word, but the opposite is not true due to the definition of fertility.

Catalan to English

English to Catalan



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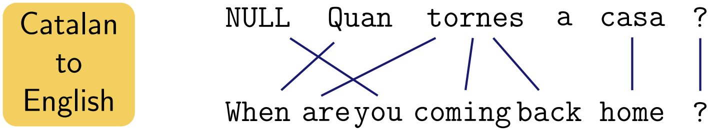

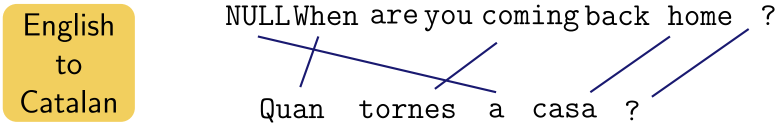

SMT, components

The translation model $P(f|e)$

Graphically:

Catalan to English

SMT, components

The translation model $P(f|e)$

Graphically:

English to Catalan

SMT, components

The translation model $P(f|e)$

Alignment symmetrisation

- Intersection: high-confidence, high precision.

Catalan to English $\bigcap$ English to Catalan

SMT, components

The translation model $P(f|e)$

Alignment symmetrisation

- Union: lower confidence, high recall.

Catalan to English $\bigcup$ English to Catalan

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: ϕ

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David`

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads`

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the`

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the book`

From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the book new.`

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f: `En David llegeix el llibre nou.`

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From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

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e: `David reads the new book.` ✓

f: `En David llegeix el llibre de nou.`

e: `David reads the book of new.` ✗

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e: ϕ

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e: `David reads the book again.`

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From Word-based to Phrase-based models

f: `En David llegeix el llibre` $\boxed{\texttt{nou}}$.

e: `David reads the` $\boxed{\texttt{new}}$ `book.` ✓

f: `En David llegeix el llibre` $\boxed{\texttt{de nou}}$.

e: `David reads the book of new.` ✗

e: `David reads the book` $\boxed{\texttt{again}}$. ✓

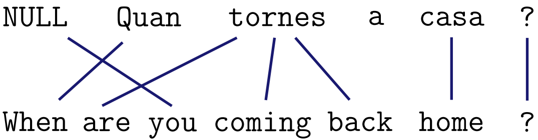
- Some sequences of words usually translate together.
- Approach: take sequences (phrases) as translation units.

What can be achieved with phrase-based models
(as compared to word-based models)

- Allow to translate from several to several words and not only from one to several.
- Some local and short range context is used.
- Idioms can be catched.

SMT, components

The translation model $P(f|e)$



With the new translation units, $P(f|e)$ can be obtained following the same strategy as for word-based models with few modifications:

1. Segment source sentence in phrases.
2. Translate each phrase into the target language.
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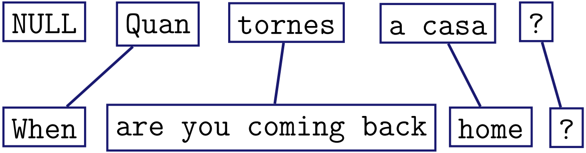

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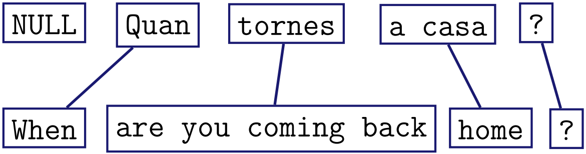

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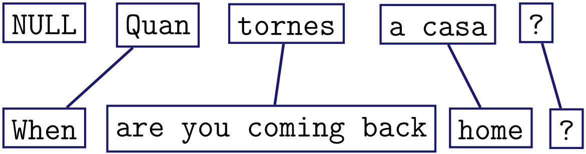

But...

- Alignments need to be done at phrase level

Options

- Calculate phrase-to-phrase alignments $\Rightarrow$ hard!
- Obtain phrase alignments from word alignments $\Rightarrow$ how?

SMT, components

The translation model $P(f|e)$

Questions to answer:

- How do we obtain phrase alignments from word alignments?
- And, by the way, what's exactly a phrase?!

A **phrase is** a sequence of words consistent with word alignment.
That is, no word is aligned to a word outside the phrase.
But a phrase **is not** necessarily a linguistic element.

We do not use the term phrase here in its linguistic sense: a phrase can be any sequence of words, even if they are not a linguistic constituent.

SMT, components

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SMT, components

The translation model $P(f|e)$

Phrase extraction through an example:

(Quan tornes, When are you coming back)

SMT, components

The translation model $P(f|e)$

Phrase extraction through an example:

~~(Quan tornes, When are you coming back)~~

SMT, components
The translation model $P(f|e)$

Phrase extraction through an example:

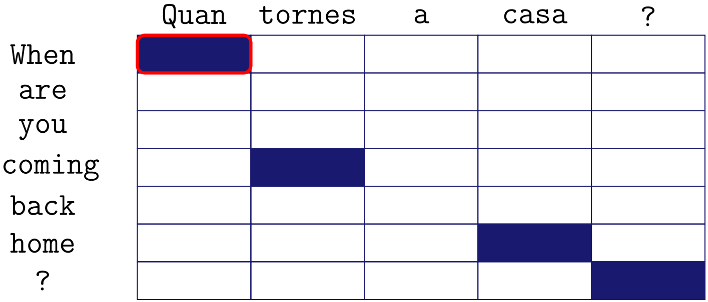
~~(Quan tornes, When are you coming back)~~

(Quan tornes tu, When are you coming back)

SMT, components

The translation model $P(f|e)$

Intersection



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SMT, components

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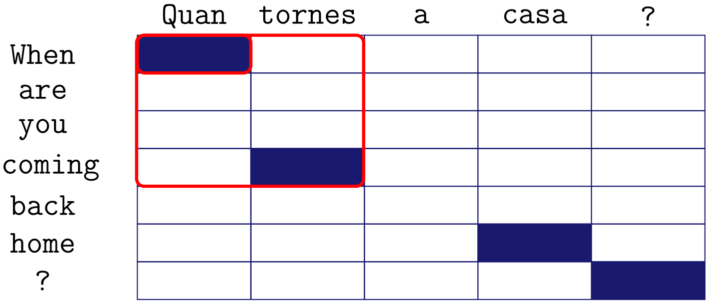

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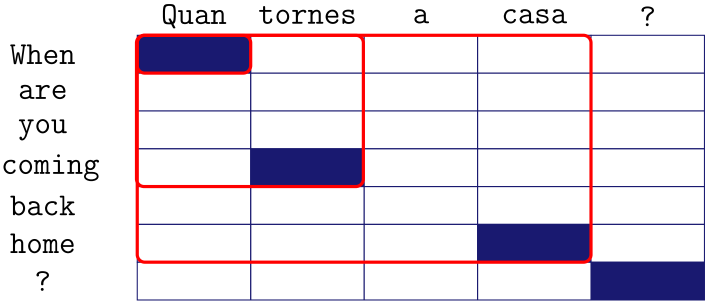

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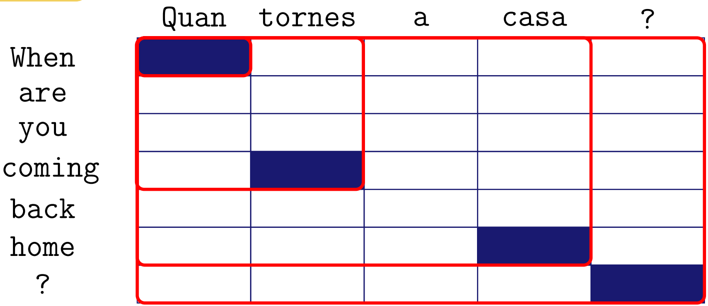

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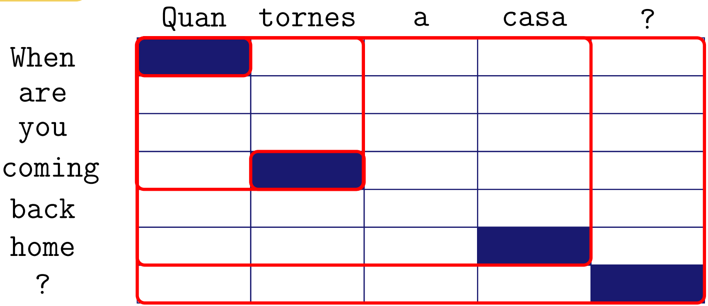

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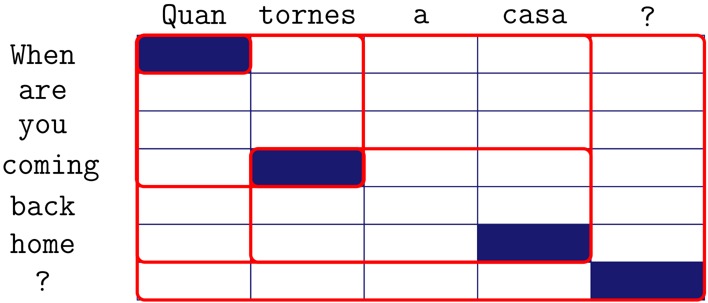

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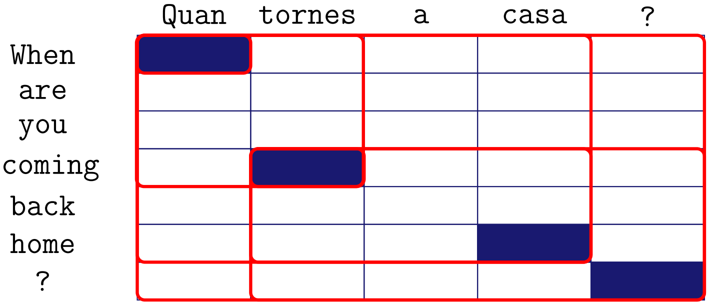

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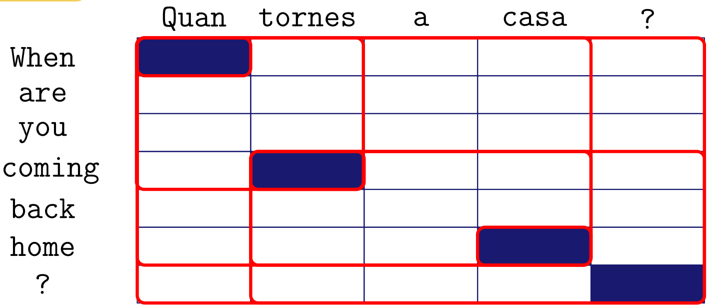

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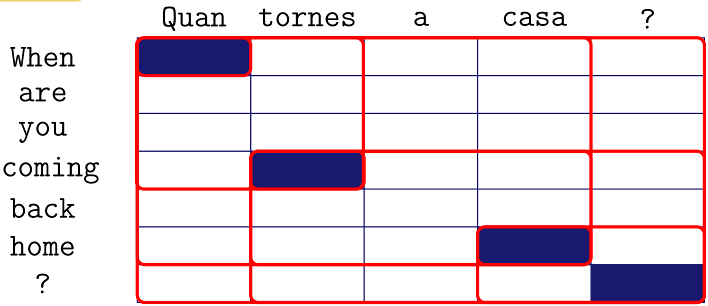

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SMT, components
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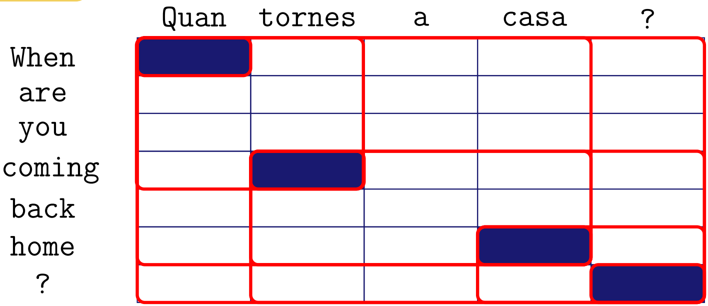

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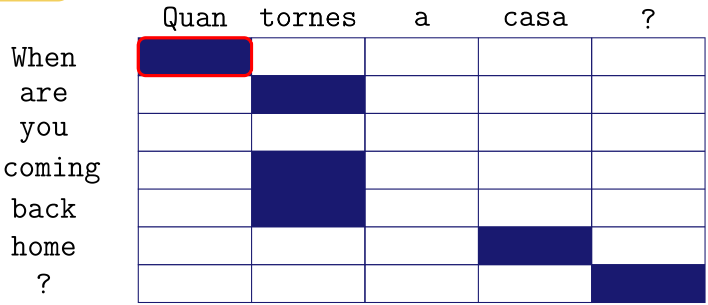
SMT, components

The translation model $P(f|e)$

Union

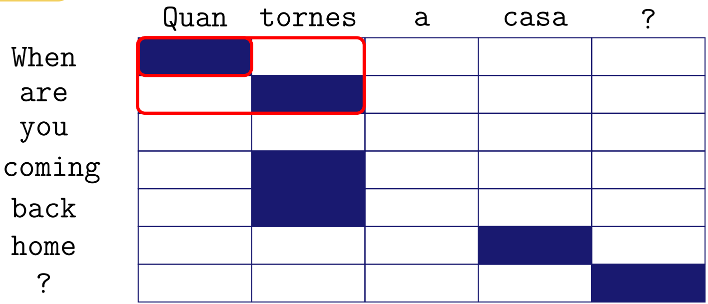


(Quan, When) (Quan tornes, When are) (Quan tornes, When are you coming) (Quan tornes, When are you coming back) (Quan tornes a casa, When are you coming back home) ... (tornes a casa ?, are you coming back home ?) (casa, home) (casa ?, home ?) (?, ?) 21 phrases

SMT, components

The translation model $P(f|e)$

Union



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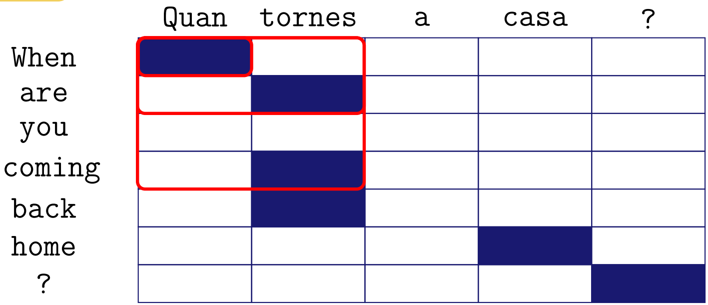

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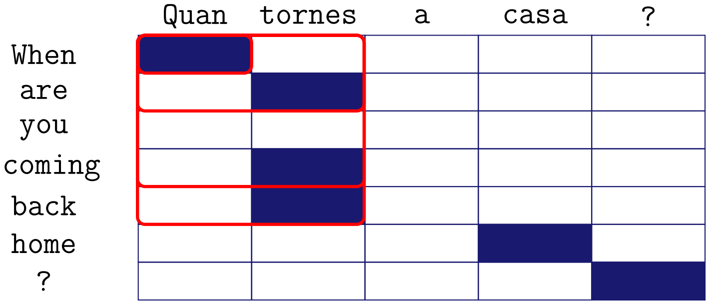

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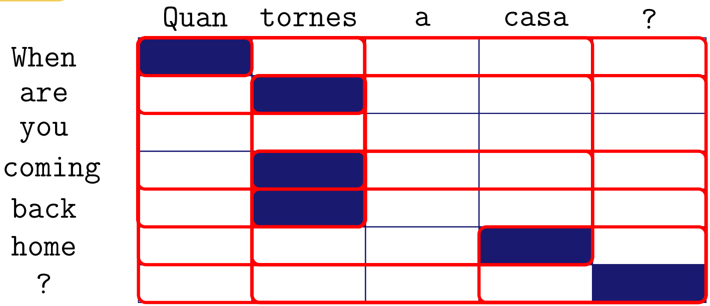

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Phrase extraction

- The number of extracted phrases depends on the symmetrisation method.
  - Intersection: few precise phrases.
  - Union: lots of (less?) precise phrases.
- Usually, neither intersection nor union are used, but something in between.
  - Start from the intersection and add points belonging to the union according to heuristics.

Phrase extraction

- For each phrase-pair (f_i, e_i), $P(f_i|e_i)$ is estimated by frequency counts in the parallel corpus.
- The set of possible phrase-pairs conforms the set of translation options.
- The set of phrase-pairs together with their probabilities conform the translation table.

Translation model: keep in mind

- Statistical TMs estimate the probability of a translation from a parallel aligned corpus.
- Its quality depends on the quality of the obtained word (phrase) alignments.
- Within an SMT system, it contributes to select semantically adequate sentences in the target language.

Decoder

$$T(f) = \hat{e} = \mathrm{argmax}_e\, P(e)\, P(f|e)$$

Responsible for the search in the space of possible translations.

Given a model (LM+TM+...), the decoder constructs the possible translations and looks for the most probable one.

In our context, one can find:

- Greedy decoders. Initial hypothesis (word by word translation) refined iteratively using hill-climbing heuristics.
- Beam search decoders.

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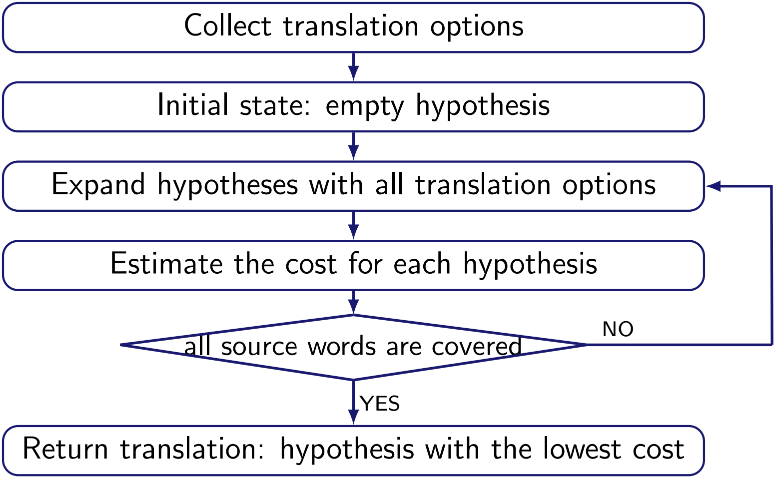
- Beam search decoders. Let's see..

SMT, components

A beam-search decoder

Core algorithm



Example: `Quan tornes a casa`

- Translation options:

  (`Quan`, `When`)
  (`Quan tornes`, `When are you coming back`)
  (`Quan tornes a casa`, `When are you coming back home`)
  (`tornes`, `come back`)
  (`tornes a casa`, `come back home`)
  (`a casa`, `home`)

SMT, components

A beam-search decoder

Example: `Quan tornes a casa`

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  (Quan tornes, When are you coming back)
  (Quan tornes a casa, When are you coming back home)
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  (a casa, home)

- Notation for hypotheses in construction:

  Constructed sentence so far: come back
  Source words already translated: - x - -

SMT, components

A beam-search decoder

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- Translation options:

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(tornes a casa, come back home)
(a casa, home)
```

- Initial hypothesis

Constructed sentence so far: ϕ

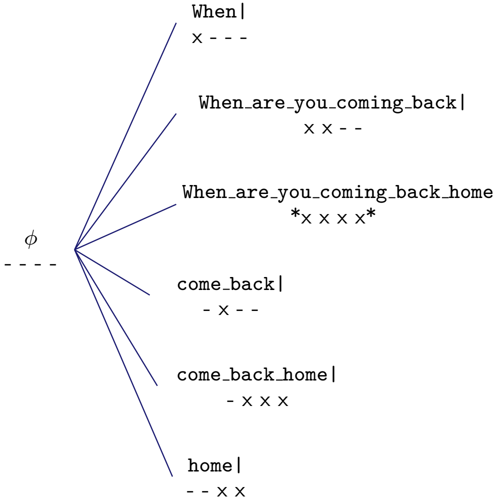
Source words already translated: - - - -

ϕ

- - - -

SMT, components

A beam-search decoder



SMT, components

A beam-search decoder

ϕ
- - - -

When|
x - - -

When_are_you_coming_back|
x x - -

When_are_you_coming_back_home
x x x x

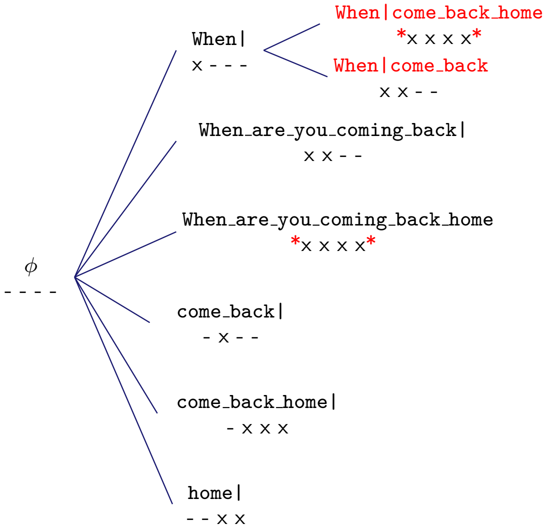
come_back|
- x - -

come_back_home|
- x x x

home|
- - x x

SMT, components

A beam-search decoder



SMT, components

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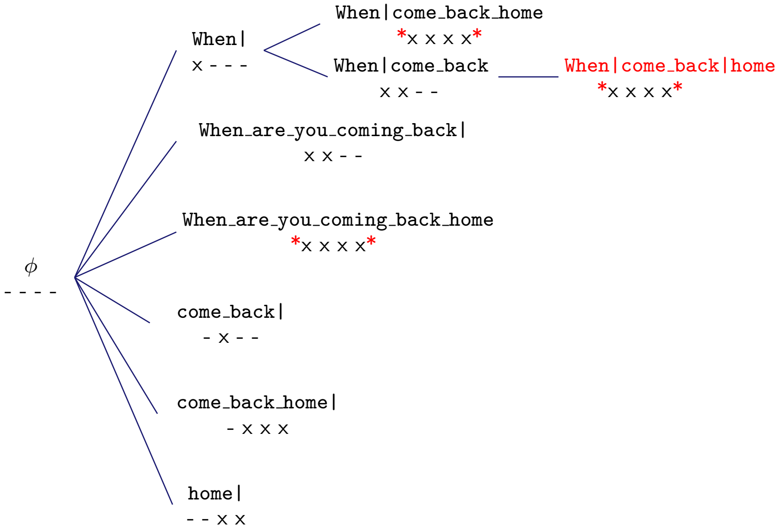
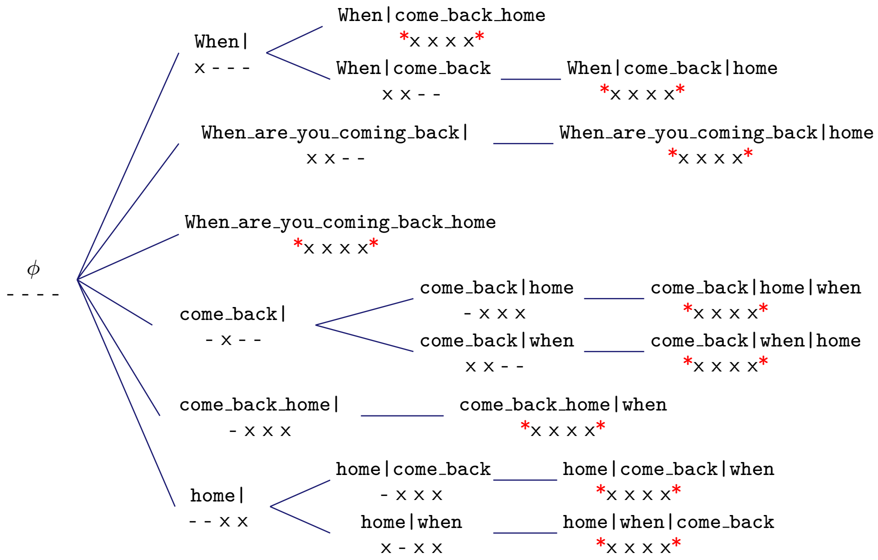


SMT, components

A beam-search decoder



Exhaustive search

- As a result, one should have an estimation of the cost of each hypothesis, being the lowest cost one the best translation.

But...

- The number of hypotheses is exponential with the number of source words.
  (30 words sentence $\Rightarrow$ $2^{30} = 1,073,741,824$ hypotheses!)

Solution

- Optimise the search by:
  - Hypotheses recombination
  - Beam search and pruning

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Hypotheses recombination

Combine hypotheses with the same source words translated, keep that with a lower cost.

When|come_back_home $\Longleftrightarrow$ When|come_back|home

x x x x   x x x x

- Risk-free operation. The lowest cost translation is still there.
- But the space of hypothesis is not reduced enough.

Hypotheses recombination

Combine hypotheses with the same source words translated, keep that with a lower cost.

```
When|come_back_home        When|come_back|home
     x x x x         ⟺          x x x x
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When|come_back_home   ⟺   When|come_back|home
     x x x x                    x x x x
```

- Risk-free operation. The lowest cost translation is still there.
- But the space of hypothesis is not reduced enough.

Beam search and pruning (at last!)

Compare hypotheses with the same number of translated source words and prune out the inferior ones.

What is an inferior hypothesis?

- The quality of a hypothesis is given by the cost so far and by an estimation of the future cost.
- Future cost estimations are only approximate, so the pruning is not risk-free.

Beam search and pruning (at last!)

Strategy:

- Define a beam size (by threshold or number of hypotheses).
- Distribute the hypotheses being generated in stacks according to the number of translated source words, for instance.
- Prune out the hypotheses falling outside the beam.
- The hypotheses to be pruned are those with a higher (current + future) cost.

SMT, components

Decoder

Decoding: keep in mind

- Standard SMT decoders translate the sentences from left to right by expanding hypotheses.
- Beam search decoding is one of the most efficient approach.
- But, the search is only approximate, so, the best translation can be lost if one restricts the search space too much.

Outline

1. Introduction
2. Basics
3. Components
4. The log-linear model
5. Beyond standard SMT

Maximum likelihood (ML)

$$\hat{e} = \mathrm{argmax}_e P(e|f) = \mathrm{argmax}_e \; P(e)\, P(f|e)$$

Maximum entropy (ME)

$$\hat{e} = \mathrm{argmax}_e P(e|f) = \mathrm{argmax}_e \; \exp\left\{\sum \lambda_m \, h_m(f,e)\right\}$$

$$\hat{e} = \mathrm{argmax}_e \log P(e|f) = \mathrm{argmax}_e \; \sum \lambda_m \, h_m(f,e)$$

Log-linear model

SMT, the log-linear model

Motivation

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SMT, the log-linear model

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SMT, the log-linear model

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Log-linear model with

$$h_1(f,e) = logP(e),\ h_2(f,e) = logP(f|e),\ \text{and}\ \lambda_1 = \lambda_2 = 1$$

$\Rightarrow$ Maximum likelihood model

What can achieved with the log-linear model
(as compared to maximum likelihood model)

- Extra features h_m can be easily added...
- ... but their weight λ_m must be somehow determined.
- Different knowledge sources can be used.

SMT, the log-linear model

Features

State of the art feature functions

Eight features are usually used: $P(e)$, $P(f|e)$, $P(e|f)$, $lex(f|e)$, $lex(e|f)$, $ph(e)$, $w(e)$ and $P_d(e,f)$.

- Language model $P(e)$
  $P(e)$: Language model probability as in ML model.
- Translation model $P(f|e)$
  $P(f|e)$: Translation model probability as in ML model.
- Translation model $P(e|f)$
  $P(e|f)$: Inverse translation model probability to be added to the generative one.

State of the art feature functions

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- Translation model $lex(f|e)$
  $lex(f|e)$: Lexical translation model probability.
- Translation model $lex(e|f)$
  $lex(e|f)$: Inverse lexical translation model probability.
- Phrase penalty $ph(e)$
  $ph(e)$: A constant cost per produced phrase.

State of the art feature functions

Eight features are usually used: $P(e)$, $P(f|e)$, $P(e|f)$, $lex(f|e)$, $lex(e|f)$, $ph(e)$, $w(e)$ and $P_d(e,f)$.

- Word penalty $w(e)$
  $w(e)$: A constant cost per produced word.

- Distortion $P_d(e,f)$
  $P_d(\mathrm{ini}_{\mathrm{phrase}_i}, \mathrm{end}_{\mathrm{phrase}_{i-1}})$: Relative distortion probability distribution. A simple distortion model:
  $P_d(\mathrm{ini}_{\mathrm{phrase}_i}, \mathrm{end}_{\mathrm{phrase}_{i-1}}) = \alpha|\mathrm{ini}_{\mathrm{phrase}_i} - \mathrm{end}_{\mathrm{phrase}_{i-1}} - 1|$

State of the art?

Software such as `Moses` makes easy the incorporation of more sophisticated reordering.

From a **distance-based** reordering
(1 feature)

to include orientation information
in a **lexicalised** reordering.
(3-6 features)

SMT, the log-linear model

Digression: lexicalised reordering or distortion

From where and how can one learn reorders?

(are, tornes, monotone)

From where and how can one learn reorders?

(coming back, tornes, swap)

SMT, the log-linear model

Digression: lexicalised reordering or distortion

From where and how can one learn reorders?

(home ?, casa ?, discontinuous)

3 new features estimated by frequency counts:
P_{monotone}, P_{swap} and $P_{\text{discontinuous}}$ (6 when bidirectional).

$$P_{or.}(\text{orientation}|f, e) = \frac{count(\text{orientation}, e, f)}{\sum_{or.} count(\text{orientation}, e, f)}$$

- Sparse statistics of the orientation types $\rightarrow$ smoothing.
- Several variations.

State of the art feature functions

13 features may be used:

- $P(e)$;
- $P(f|e)$, $P(e|f)$, $lex(f|e)$, $lex(e|f)$;
- $ph(e)$, $w(e)$;
- $P_{mon}(o|e,f)$, $P_{swap}(o|e,f)$, $P_{dis}(o|e,f)$,
- $P_{mon}(o|f,e)$, $P_{swap}(o|f,e)$, $P_{dis}(o|f,e)$.

Development training, weights optimisation

- Supervised training: a (small) aligned parallel corpus is used to determine the optimal weights.

$$\hat{e} = \mathrm{argmax_e} \log P(e|f) = \mathrm{argmax_e} \sum \lambda_m \, h_m(f, e)$$

Development training, weights optimisation

Strategies

- Generative training. Optimises ME objective function which has a unique optimum. Maximises the likelihood.
- Discriminative training only for feature weights (not models), or purely discriminative for the model as a whole. This way translation performance can be optimised.
- Minimum Error-Rate Training (MERT).

Development training, weights optimisation

Strategies

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- Minimum Error-Rate Training (MERT).

Minimum Error-Rate Training

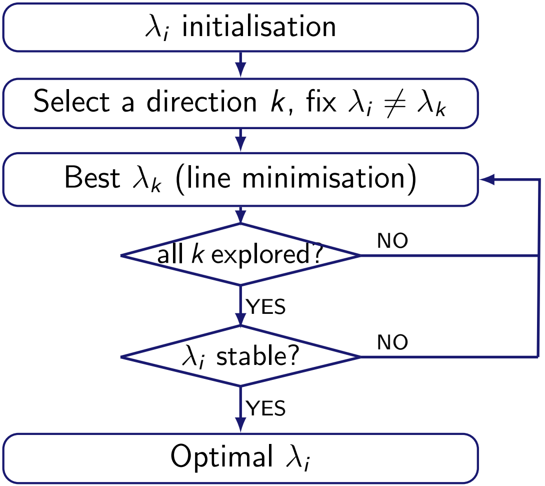
- Approach: Minimise an error function.

But... what's the error of a translation?

- There exist several error measures or metrics.
- Metrics not always correlate with human judgements.
- The quality of the final translation on the metric choosen for the optimisation is shown to improve.
- For the moment, let's say we use BLEU.

(More on MT Evaluation section)

Minimum Error-Rate Training rough algorithm



Log-linear model: keep in mind

- The log-linear model allows to include several weighted features. State of the art systems use 8 real features.
- The corresponding weights are optimised on a development set, a small aligned parallel corpus.
- An optimisation algorithm such as MERT is appropriate for at most a dozen of features. For more features, purely discriminative learnings should be used.
- For MERT, the choice of the metric that quantifies the error in the translation is an issue.

Outline

1. Introduction
2. Basics
3. Components
4. The log-linear model
5. Beyond standard SMT
    - Factored translation models
    - Syntactic translation models
    - Ongoing research

Considering linguistic information in phrase-based models

- Phrase-based log-linear models do not consider linguistic information other than words. This is information should be included.

Options

- Use syntactic information as pre- or post-process (for reordering or reranking for example).
- Include linguistic information in the model itself.
  - Factored translation models.
  - Syntactic-based translation models.

Factored translation models

Extension to phrase-based models where every word is substituted by a vector of factors.

$$(\texttt{word}) \Longrightarrow (\texttt{word}, \texttt{lemma}, \texttt{PoS}, \texttt{morphology}, \ldots)$$

The translation is now a combination of pure translation (T) and generation (G) steps:

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The translation is now a combination of pure translation (T) and generation (G) steps:

$$\begin{array}{cccc} \texttt{lemma}_f & \texttt{PoS}_f & \texttt{morphology}_f & \quad \texttt{word}_f \\ \downarrow \mathsf{T} & \downarrow \mathsf{T} & \downarrow \mathsf{T} & \\ \texttt{lemma}_e & \texttt{PoS}_e & \texttt{morphology}_e & \xrightarrow{\mathsf{G}} \texttt{word}_e \end{array}$$

SMT, beyond standard SMT

Factored translation models

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The translation is now a combination of pure translation (T) and generation (G) steps:

$$\begin{tikzcd}
\texttt{casa}_f \arrow[d, "T"] & \texttt{NN}_f \arrow[d, "T"] & \texttt{fem., plural}_f \arrow[d, "T"] & & \texttt{cases}_f \\
\texttt{house}_e & \texttt{NN}_e & \texttt{plural}_e & \arrow[r, "G"] & \texttt{houses}_e
\end{tikzcd}$$

What differs in factored translation models
(as compared to standard phrase-based models)

- The parallel corpus must be annotated beforehand.
- Extra language models for every factor can also be used.
- Translation steps are accomplished in a similar way.
- Generation steps imply a training only on the target side of the corpus.
- Models corresponding to the different factors and components are combined in a log-linear fashion.

Syntactic translation models

Incorporate syntax to the source and/or target languages.

Approaches

- Syntactic phrase-based based on tree trasducers:
  - Tree-to-string. Build mappings from target parse trees to source strings.
  - String-to-tree. Build mappings from target strings to source parse trees.
  - Tree-to-tree. Mappings from parse trees to parse trees.

Syntactic translation models

Incorporate syntax to the source and/or target languages.

Approaches

- Synchronous grammar formalism which learns a grammar that can simultaneously generate both trees.
  - Syntax-based. Respect linguistic units in translation.
  - Hierarchical phrase-based. Respect phrases in translation.

Syntactic models ease reordering. An intuitive example:

`En David llegeix un llibre nou`

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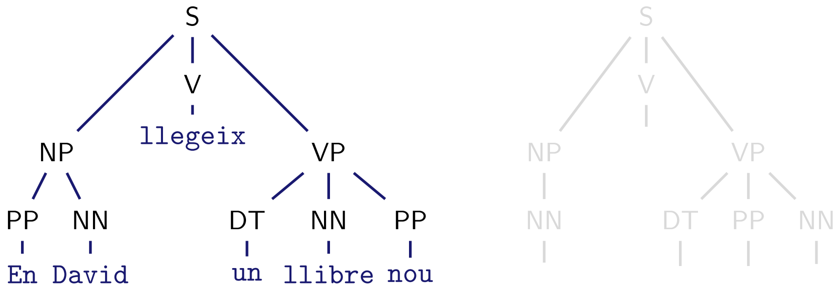

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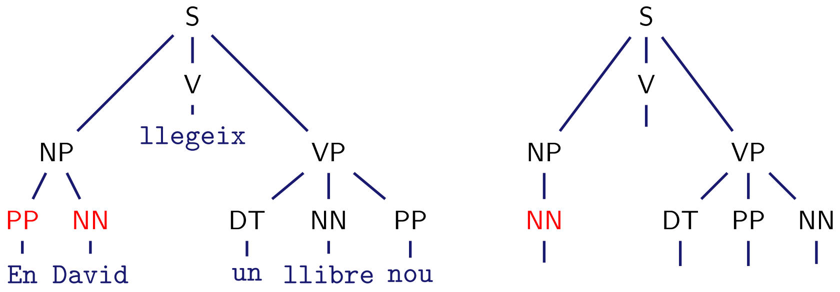

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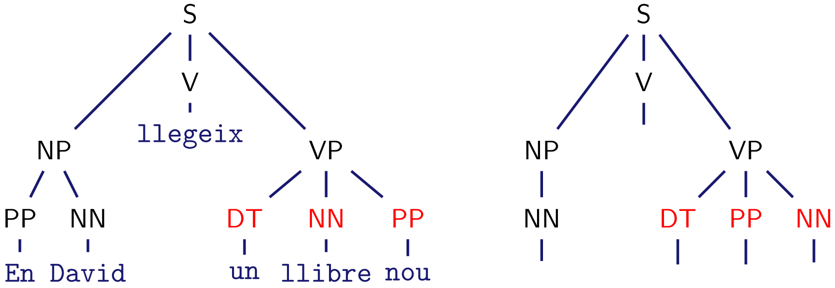

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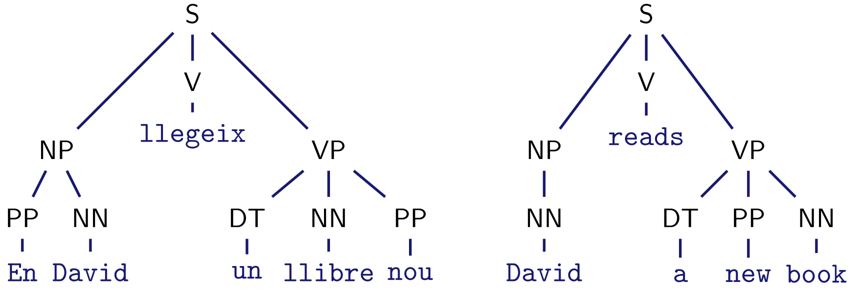


`David reads a new book`

Hot research topics

Current research on SMT addresses known and new problems.

Some components of the standard phrase-based model are still under study:

- Automatic alignments.
- Language models and smoothing techniques.
- Parameter optimisation.

Complements to a standard system can be added:

- Reordering as a pre-process or post-process.
- Reranking of n-best lists.
- OOV treatment.
- Domain adaptation.

Development of full systems from scratch or modifications to the standard:

- Using machine learning.
- Including linguistic information.
- Hybridation of MT paradigms.

Or a different strategy:

- Systems combination.

Beyond standard SMT: keep in mind

- Factored models include linguistic information in phrase-based models and are suitable for morphologically rich languages.
- Syntactic models consider somehow syntaxis and are adequate for language pairs with a different structure of the sentences.
- Current research addresses both new models and modifications to the existing ones.

Part II

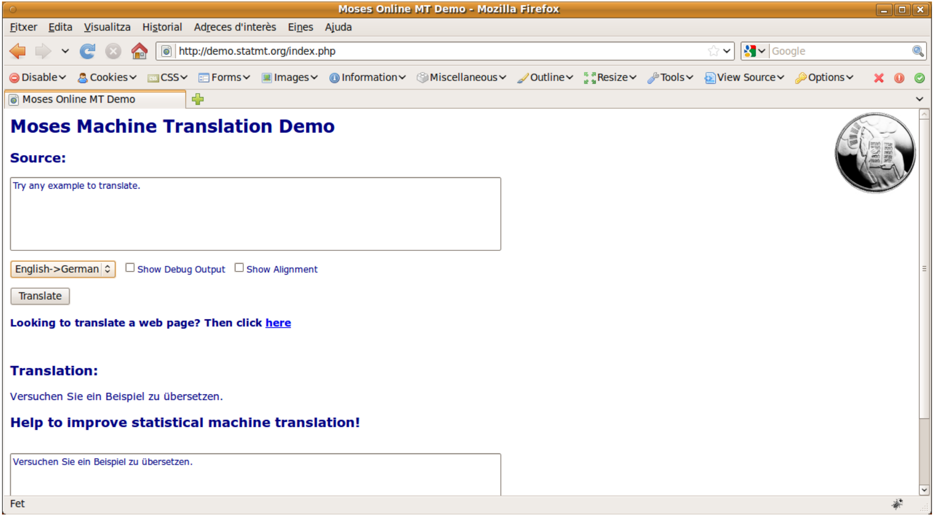
SMT experiments

Outline Part II

6. Translation system
   - Demos
   - Software
   - Steps

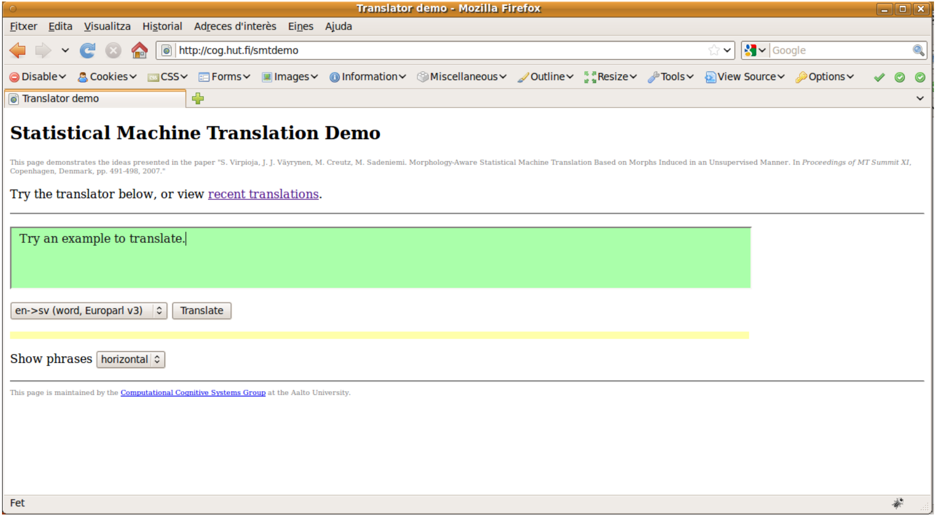
SMT system

Demo: http://demo.statmt.org/



SMT system

Demo: http://cog.hut.fi/smtdemo



Build your own SMT system

1. Language model with `SRILM`.
   http://www-speech.sri.com/projects/srilm/download.htm
2. Word alignments with `GIZA++`.
   http://code.google.com/p/giza-pp/downloads/list
3. And everything else with the `Moses` package.
   http://sourceforge.net/projects/mosesdecoder

1. Download and prepare your data

1. Parallel corpora and some tools can be downloaded for instance from the WMT 2010 web page: http://www.statmt.org/wmt10/translation-task.html

How to construct a baseline system is also explained there: http://www.statmt.org/wmt10/baseline.html

We continue with the Europarl corpus Spanish-to-English.

1. **Download and prepare your data** (cont'd)

2. Tokenise the corpus with WMT10 scripts.
(training corpus and development set for MERT)

```
wmt10scripts/tokenizer.perl -l es < eurov4.es-en.NOTOK.es >
eurov4.es-en.TOK.es
wmt10scripts/tokenizer.perl -l en < eurov4.es-en.NOTOK.en >
eurov4.es-en.TOK.en

wmt10scripts/tokenizer.perl -l es < eurov4.es-en.NOTOK.dev.es >
eurov4.es-en.TOK.dev.es
wmt10scripts/tokenizer.perl -l en < eurov4.es-en.NOTOK.dev.en >
eurov4.es-en.TOK.dev.en
```

1. Download and prepare your data (cont'd)

3. Filter out long sentences with Moses scripts.
(Important for GIZA++)

```
bin/moses-scripts/training/clean-corpus-n.perl eurov4.es-en.TOK es
en eurov4.es-en.TOK.clean 1 100
```

4. Lowercase training and development with WMT10 scripts.
(Optional but recommended)

```
wmt10scripts/lowercase.perl < eurov4.es-en.TOK.clean.es >
eurov4.es-en.es
wmt10scripts/lowercase.perl < eurov4.es-en.TOK.clean.en >
eurov4.es-en.en
```

2. Build the language model

1. Run SRILM on the English part of the parallel corpus or on a monolingual larger one.
(tokenise and lowercase in case it is not)

```
ngram-count -order 5 -interpolate -kndiscount -text
eurov4.es-en.en -lm eurov4.en.lm
```

3. Train the translation model

1. Use the Moses script `train-factored-phrase-model.perl`
   This script performs the whole training:

```
cristina@cosmos:~$ train-factored-phrase-model.perl -help
Train Phrase Model

Steps:  (--first-step to --last-step)
(1) prepare corpus
(2) run GIZA
(3) align words
(4) learn lexical translation
(5) extract phrases
(6) score phrases
(7) learn reordering model
(8) learn generation model
(9) create decoder config file
```

Obre

3. Train the translation model (cont'd)

1. So, it takes a few arguments (and a few time!):

   `bin/moses-scripts/training/train-factored-phrase-model.perl` -**scripts-root-dir** `bin/moses-scripts/` -**root-dir** `working-dir` -**corpus** `eurov4.es-en` -**f** `es` -**e** `en` -**alignment** `grow-diag-final-and` -**reordering** `msd-bidirectional-fe` -**lm** `0:5:eurov4.en.lm:0`

   It generates a configuration file `moses.ini` needed to run the decoder where all the necessary files are specified.

4. Tuning of parameters with MERT

1. Run the Moses script `mert-moses.pl`
   (Another slow step!)

```
bin/moses-scripts/training/mert-moses.pl eurov4.es-en.dev.es
eurov4.es-en.dev.en moses/moses-cmd/src/moses ./model/moses.ini
--working-dir ./tuning --rootdir bin/moses-scripts/
```

2. Insert weights into configuration file with WMT10 script:

```
wmt10scripts/reuse-weights.perl ./tuning/moses.ini <
./model/moses.ini > moses.weight-reused.ini
```

5. Run Moses decoder on a test set

1. Tokenise and lowecase the test set as before.
2. Filter the model with Moses script.
   (mandatory for large translation tables)

```
bin/moses-scripts/training/filter-model-given-input.pl
./filteredmodel moses.weight-reused.ini testset.es
```

3. Run the decoder:

```
moses/moses-cmd/src/moses -f ./filteredmodel/moses.ini <
testset.es > testset.translated.en
```

Part III

Machine Translation Evaluation

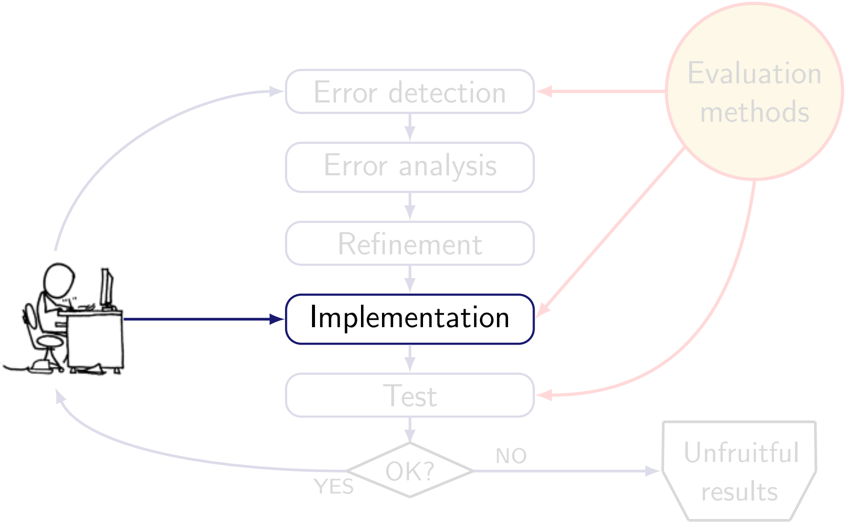
Outline

7. MT Evaluation basics
   - Automatic Evaluation
   - BLEU
   - Limits of lexical similarity

8. Evaluation system

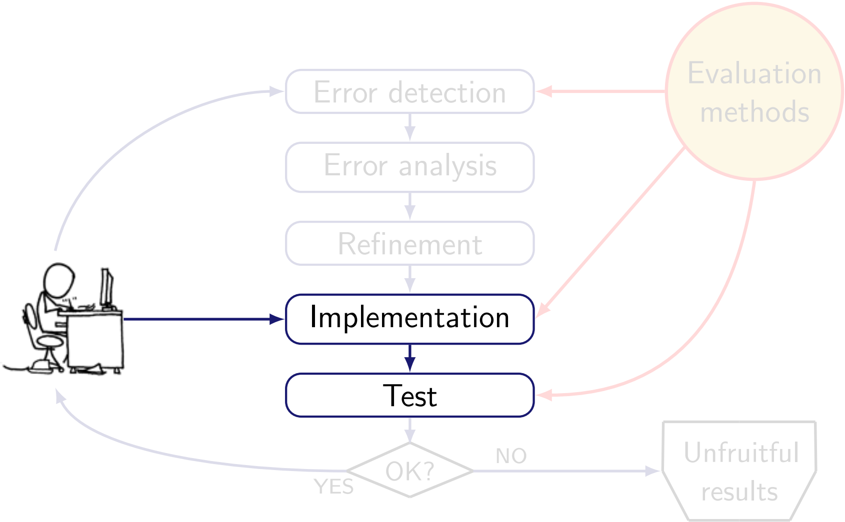
MT Evaluation

Importance for system development



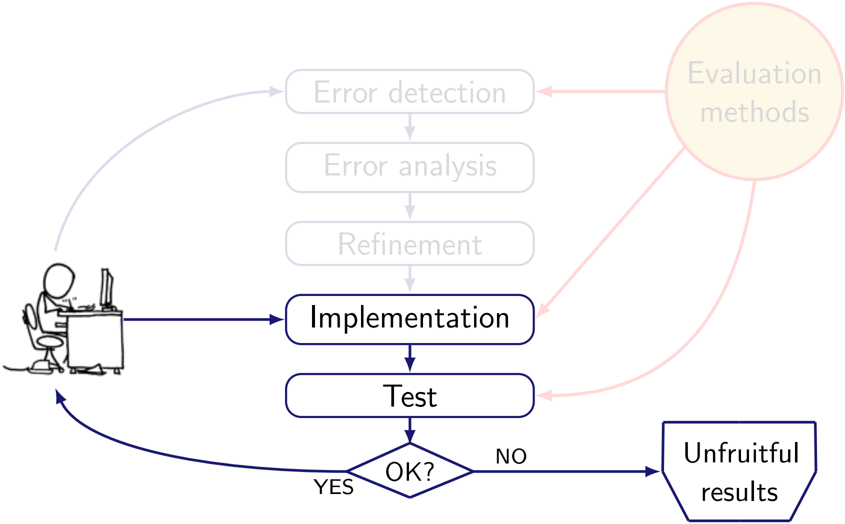
MT Evaluation

Importance for system development



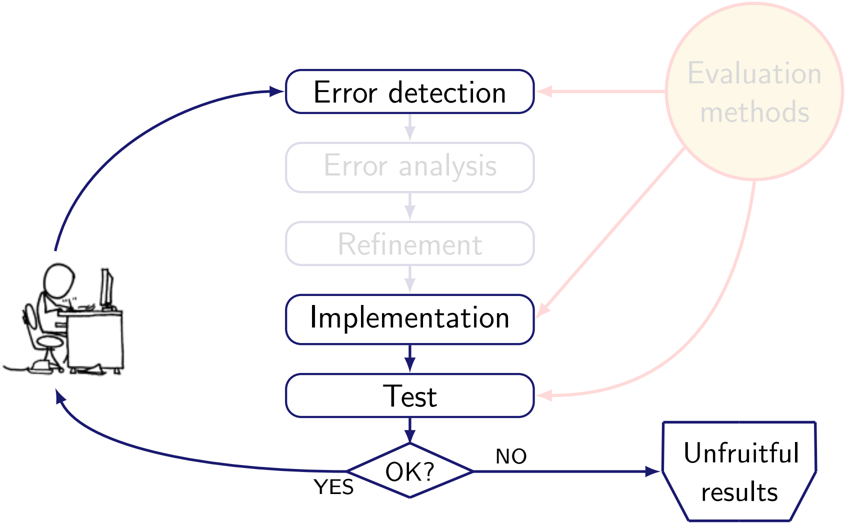
MT Evaluation

Importance for system development



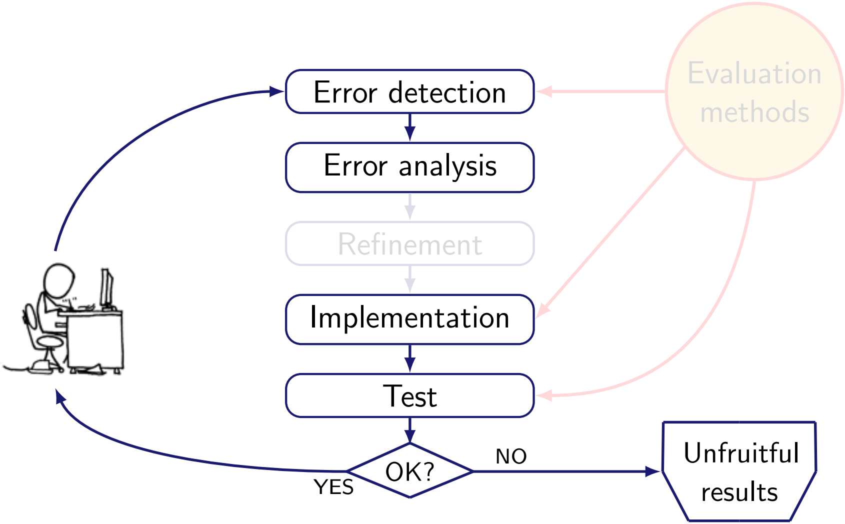
MT Evaluation

Importance for system development



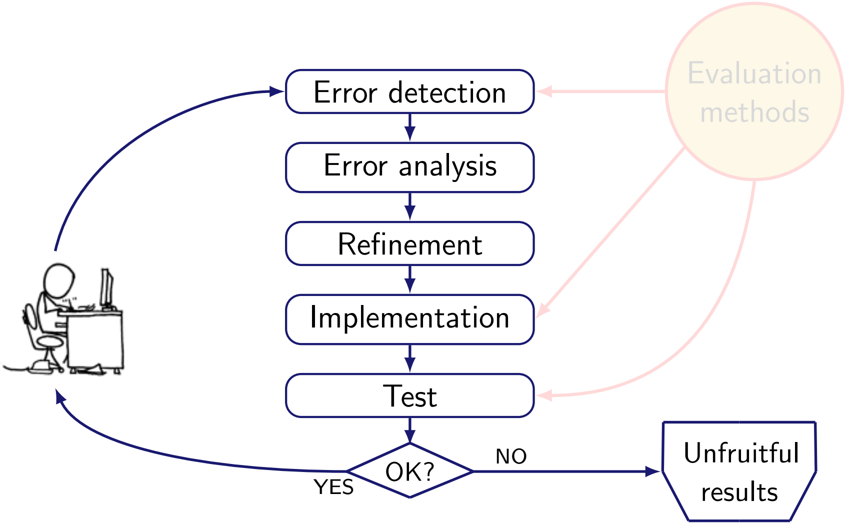
MT Evaluation

Importance for system development



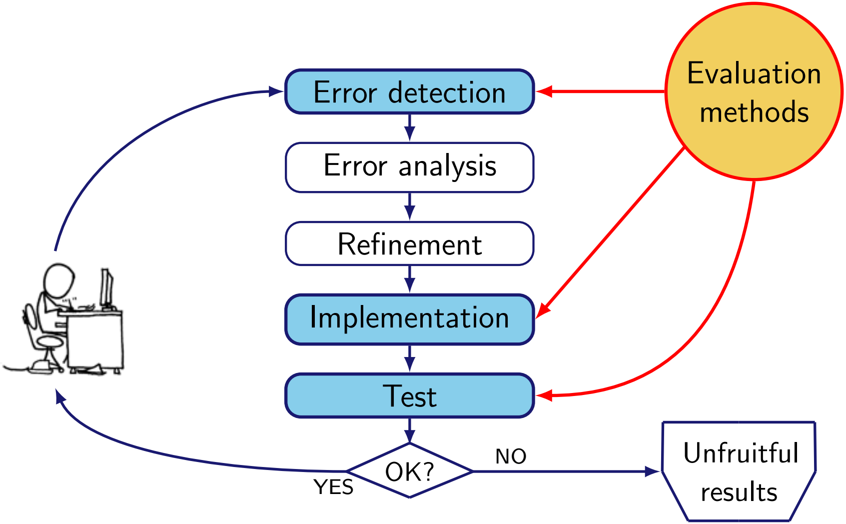
MT Evaluation

Importance for system development



MT Evaluation

Importance for system development



What can achieved with automatic evaluation
(as compared to manual evaluation)

- Automatic metrics notably accelerate the development cycle of MT systems:
  - Error analysis
  - System optimisation
  - System comparison

Besides, they are

- Costless (vs. costly)
- Objective (vs. subjective)
- Reusable (vs. non-reusable)

Metrics based on lexical similarity
(most of the metrics!)

- Edit Distance: WER, PER, TER
- Precision: BLEU, NIST, WNM
- Recall: ROUGE, CDER
- Precision/Recall: GTM, METEOR, BLANC, SIA

Metrics based on lexical similarity
(most of the metrics!)

- Edit Distance: WER, PER, TER
- Precision: BLEU, NIST, WNM
- Recall: ROUGE, CDER
- Precision/Recall: GTM, METEOR, BLANC, SIA

Nowadays, BLEU is accepted as *the standard* metric.

BLEU: a Method for Automatic Evaluation of Machine Translation

Kishore Papineni, Salim Roukos, Todd Ward, Wei-Jing Zhu
IBM Research Division

"The main idea is to use a weighted average of variable length phrase matches against the reference translations. This view gives rise to a family of metrics using various weighting schemes. We have selected a promising baseline metric from this family."

Candidate 1:

`It is a guide to action which ensures that the military always obeys the commands of the party.`

Candidate 2:

`It is to insure the troops forever hearing the activity guidebook that party direct.`

Candidate 1:

`It is a guide to action which ensures that the military always obeys the commands of the party.`

Reference 1:

`It is a guide to action that ensures that the military will forever heed Party commands.`

Reference 2:

`It is the guiding principle which guarantees the military forces always being under the command of the Party.`

Reference 3:

`It is the practical guide for the army always to heed the directions of the party.`

Candidate 1:

`It is a guide to action which ensures that the military always obeys the commands of the party.`

Reference 1:

`It is a guide to action that ensures that the military will forever heed Party commands.`

Reference 2:

`It is the guiding principle which guarantees the military forces always being under the command of the Party.`

Reference 3:

`It is the practical guide for the army always to heed the directions of the party.`

Candidate 2:

`It is to insure the troops forever hearing the activity guidebook that party direct.`

Reference 1:

`It is a guide to action that ensures that the military will forever heed Party commands.`

Reference 2:

`It is the guiding principle which guarantees the military forces always being under the command of the Party.`

Reference 3:

`It is the practical guide for the army always to heed the directions of the party.`

Modified n-gram precision (1-gram)

Precision-based measure, but:

Candidate:
`The the the the the the the.`

Reference 1:
`The cat is on the mat.`

Reference 2:
`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{1+}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{2 +}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{3+}{7}$

Candidate:
`The the the the the the the.`

Reference 1:
`The cat is on the mat.`

Reference 2:
`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{4+}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{5 +}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\quad \text{Prec.} = \dfrac{6+}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

Precision-based measure, but: $\text{Prec.} = \frac{7}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

A reference word should only be matched once.

Algorithm:

1. Count number of times w_i occurs in each reference.
2. Keep the minimun between the maximum of (1) and the number of times w_i appears in the candidate (*clipping*).
3. Add these values and divide by candidate's number of words.

Modified n-gram precision (1-gram)

Modified 1-gram precision:

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

1. $w_i \to \mathrm{The}$
   $\#_{w_i,R1} = 2$
   $\#_{w_i,R2} = 1$
2. $\mathrm{Max}_{(1)}$=2, $\#_{w_i,C} = 7$
   $\Rightarrow$ Min=2
3. No more distinct words

MT Evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu [2001]

Modified n-gram precision (1-gram)

Modified 1-gram precision: $\mathrm{P}_1 =$

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

1. $w_i \rightarrow \mathrm{The}$
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2. $\mathrm{Max}_{(1)}$=2, $\#_{w_i,C} = 7$
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Modified n-gram precision (1-gram)

Modified 1-gram precision: $P_1 = \frac{2}{}$

Candidate:

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1. $w_i \rightarrow$ The
   $\#_{w_i,R1} = 2$
   $\#_{w_i,R2} = 1$
2. $\text{Max}_{(1)}=2$, $\#_{w_i,C} = 7$
   $\Rightarrow$ Min=2
3. No more distinct words

Modified n-gram precision (1-gram)

Modified 1-gram precision: $P_1 = \frac{2}{7}$

Candidate:

`The the the the the the the.`

Reference 1:

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Reference 2:

`There is a cat on the mat.`

1. $w_i \rightarrow \mathrm{The}$
   $\#_{w_i,R1} = 2$
   $\#_{w_i,R2} = 1$
2. $\mathrm{Max}_{(1)}$=2, $\#_{w_i,C} = 7$
   $\Rightarrow$ Min=2
3. No more distinct words

Modified n-gram precision

- Straightforward generalisation to n-grams, P_n.
- Generalisation to multiple sentences:

$$P_n = \frac{\sum_{C \in \{\text{candidates}\}} \sum_{n\text{gram} \in C} Count_{\text{clipped}}(n\text{gram})}{\sum_{C \in \{\text{candidates}\}} \sum_{n\text{gram} \in C} Count(n\text{gram})}$$

low n	high n
adequacy	fluency

Brevity penalty

Candidate:

`of the`

Reference 1:

`It is a guide to action that ensures that the military will forever heed Party commands.`

Reference 2:

`It is the guiding principle which guarantees the military forces always being under the command of the Party.`

Reference 3:

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Brevity penalty

Candidate:

`of the`

$P_1 = 2/2, P_2 = 1/1$

Reference 1:

`It is a guide to action that ensures that the military will forever heed Party commands.`

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Reference 3:

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Brevity penalty

$$\mathrm{BP} = \begin{cases} 1 & \text{if} \quad c > r \\ e^{1-r/c} & \text{if} \quad c \leq r \end{cases}$$

c candidate length, r reference length

- Multiplicative factor.
- At sentence level, huge punishment for short sentences.
- Estimated at document level.

BiLingual Evaluation Understudy, BLEU

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log \mathrm{P}_n\right)$$

- Geometric average of P_n (empirical suggestion).
- w_n positive weights summing to one.
- Brevity penalty.

Paper's Conclusions

- BLEU correlates with human judgements.
- It can distinguish among similar systems.
- Need for multiple references or a big test with heterogeneous references.
- More parametrisation in the future.

Watch out with BLEU implementations!

There are several widely used implementations of BLEU.

(`Moses multi-bleu.perl script, NIST mteval-vXX.pl script, etc.`)

Results differ because of:

- Different tokenisation approach.
- Different definition of *closest reference* in the brevity penalty estimation.

NIST is based on BLEU but:

- Arithmetic average of *n*-gram counts rather than a geometric average.
- Informative *n*-grams are given more weight.
- Different definition of brevity penalty.

Limits of lexical similarity

The reliability of lexical metrics depends very strongly on the heterogeneity/representativity of reference translations.

e: `This sentence is going to be difficult to evaluate.`

Ref1: `The evaluation of the translation is complicated.`
Ref2: `The sentence will be hard to qualify.`
Ref3: `The translation is going to be hard to evaluate.`
Ref4: `It will be difficult to punctuate the output.`

Lexical similarity is nor a sufficient neither a necessary condition so that two sentences convey the same meaning.

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Lexical similarity is nor a sufficient neither a necessary condition so that two sentences convey the same meaning.

Recent efforts to go over lexical similarity

Extend the reference material:

- Using lexical variants such as morphological variations or synonymy lookup or using paraphrasing support.

Compare other linguistic features than words:

- Syntactic similarity: shallow parsing, full parsing (constituents /dependencies).
- Semantic similarity: named entities, semantic roles, discourse representations.

Combination of the existing metrics.

Recent efforts to go over lexical similarity

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- Semantic similarity: named entities, semantic roles, discourse representations.

Combination of the existing metrics.

Much more on the topic in Lluís' seminar:

MT Evaluation

MT Evaluation: keep in mind

- Evaluation is important in the system development cycle. Automatic evaluation accelerates significatively the process.
- Up to now, most (common) metrics rely on lexical similarity, but it cannot assure a correct evaluation.
- Current work is being devoted to go beyond lexical similarity.

Outline

Evaluate the results

1. With BLEU scoring tool. Available as a `Moses` script or from NIST:
   http://www.itl.nist.gov/iad/mig/tools/mtevalv13a-20091001.tar.gz

2. With `IQmt` package.
   http://www.lsi.upc.edu/∼nlp/IQMT/

1. Evaluate the results

1. With BLEU scoring tool in Moses:

```
moses/scripts/generic/multi-bleu.perl references.en <
testset.translated.en
```

2. Evaluate the results on-line

1. OpenMT Evaluation Demo
   http://biniki.lsi.upc.edu/openMT/evaldemo.php

MT Evaluation

Demo: http://biniki.lsi.upc.edu/openMT/evaldemo.php

Part IV

Appendix: References

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