

# Statistical Machine Translation

## A practical tutorial

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MOLTO Kickoff Meeting  
UPC, Barcelona  
11th March, 2010

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

## **Part I: SMT background**

~ 90 minutes

7 Translation system

**Part II: SMT experiments**

8 Evaluation system

~ 30 minutes

9 References

**Part III: References**

## Part I

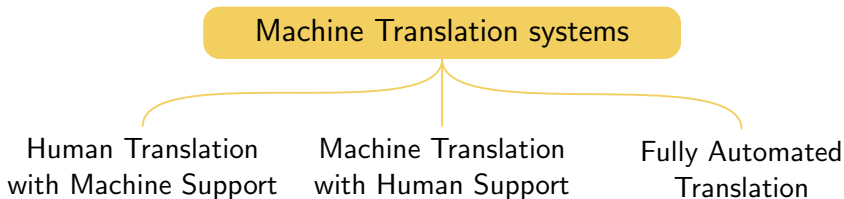
SMT background

# Outline

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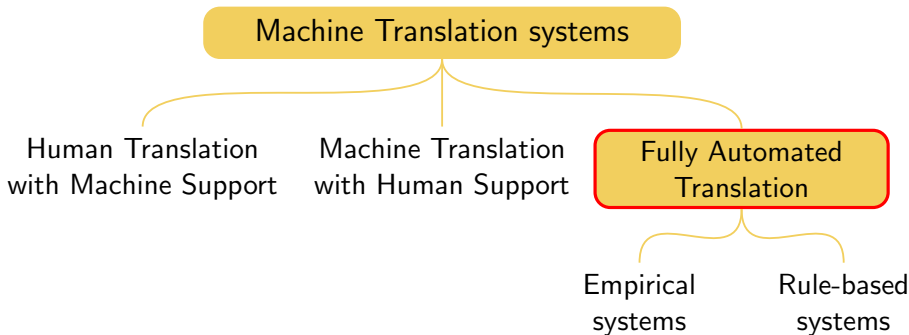
# Introduction

## Machine Translation Taxonomy



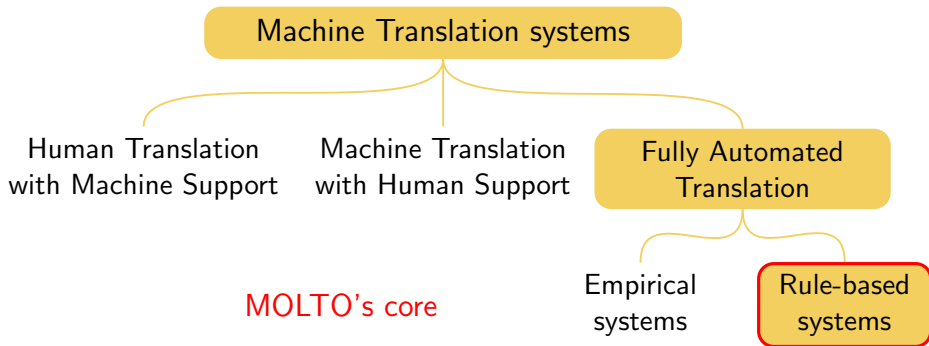
# Introduction

## Machine Translation Taxonomy



# Introduction

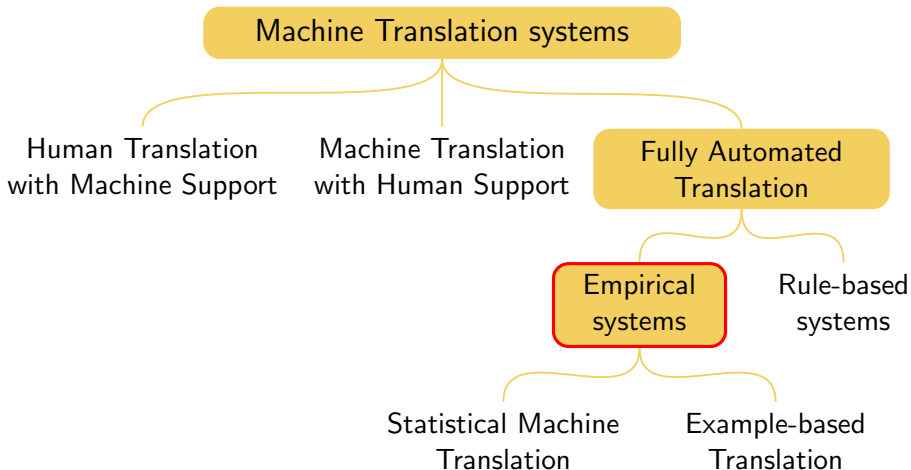
## Machine Translation Taxonomy





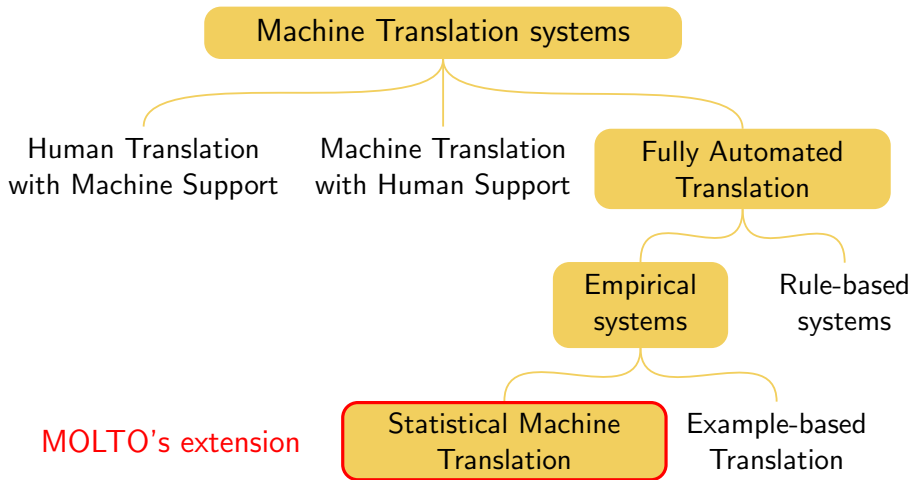
# Introduction

## Machine Translation Taxonomy



# Introduction

## Machine Translation Taxonomy



# Introduction

## Empirical Machine Translation

### 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 construïran cobriran la major part dels 23 idiomes oficials de la UE.

Com a tècnica principal, MOLTO utilitza gramàtiques semàntiques de domini específic i interlingües 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 llexicó 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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# Introduction

## Empirical Machine Translation

### Aligned parallel corpora numbers

#### Corpora

<b>Corpus</b>	<b># segments (app.)</b>	<b># words (app.)</b>
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

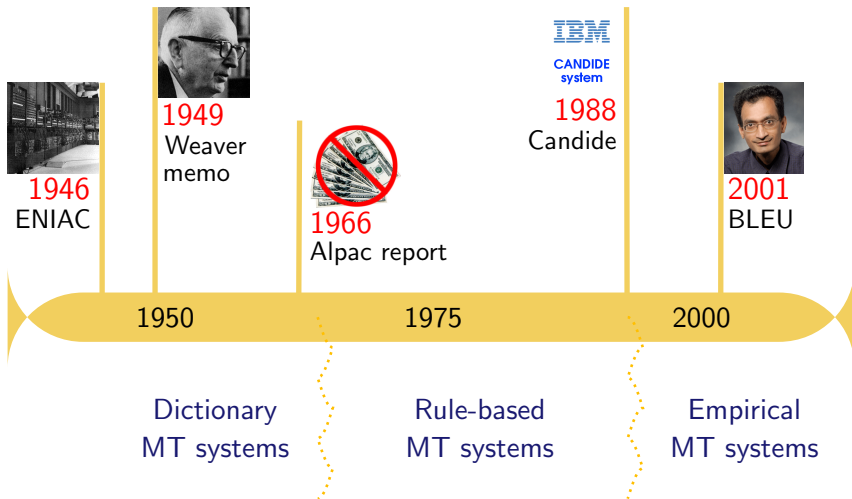
<b>Title</b>	<b># words (approx.)</b>
The Bible	$0.8 \cdot 10^6$
The Dark Tower series	$1.2 \cdot 10^6$
Encyclopaedia Britannica	$44 \cdot 10^6$

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# SMT, basics

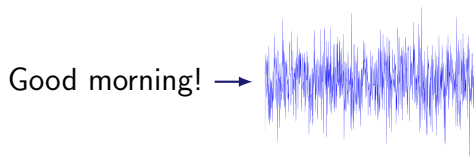
The beginnings, summarised timeline



# SMT, basics

## The Noisy Channel approach

**The Noisy Channel** as a statistical approach to translation:

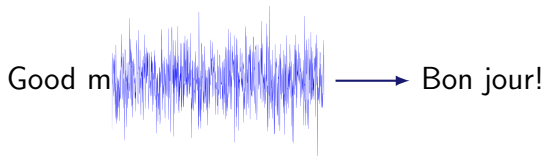




# SMT, basics

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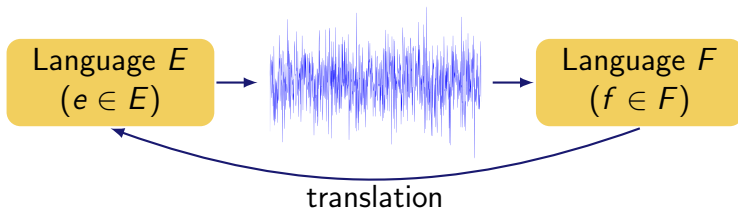
# SMT, basics

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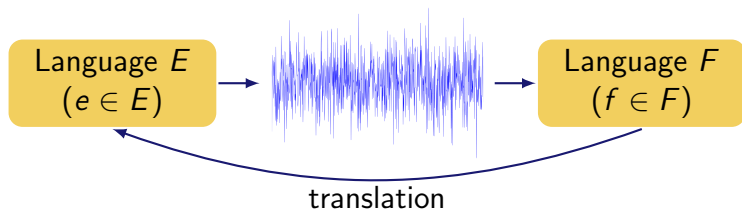
$e$ : Good morning!

$f$ : Bon jour!



# SMT, basics

## The Noisy Channel approach



Mathematically:

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

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

# SMT, basics

## Components

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

### 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*

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  - Translation model
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# SMT, components

The language model  $P(e)$

## Language model

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

Estimation of how probable a sentence is.

Naïve estimation on a corpus with  $N$  sentences:

Frequentist probability  
of a sentence  $e$ :

$$P(e) = \frac{N_e}{N_{\text{sentences}}}$$

Problem:

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



# SMT, components

The language model  $P(e)$

## The n-gram approach

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

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

- 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

$$\begin{aligned} P(e) = & P(\text{All}|\phi, \phi, \phi) P(\text{work}|\phi, \phi, \text{All}) P(\text{and}|\phi, \text{All}, \text{work}) \\ & P(\text{no}|\text{All}, \text{work}, \text{and}) P(\text{play}|\text{work}, \text{and}, \text{no}) \\ & P(\text{makes}|\text{and}, \text{no}, \text{play}) P(\text{Jack}|\text{no}, \text{play}, \text{makes}) \\ & P(\text{a}|\text{play}, \text{makes}, \text{Jack}) P(\text{dull}|\text{makes}, \text{Jack}, \text{a}) \\ & P(\text{boy}|\text{Jack}, \text{a}, \text{dull}) \end{aligned}$$

where, for each factor,

$$P(\text{and}|\phi, \text{All}, \text{work}) = \frac{N_{(\text{All work and})}}{N_{(\text{All work})}}$$

# SMT, components

The language model  $P(e)$

Main problems and criticisms:

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

## Solution

Smoothing techniques:

- Back-off models.
- Linear interpolation:

$$P(\text{and}|\text{All, work}) = \lambda_3 \frac{N_{(\text{All, work, and})}}{N_{(\text{All, work})}} + \lambda_2 \frac{N_{(\text{work, and})}}{N_{(\text{work})}} + \lambda_1 \frac{N_{(\text{and})}}{N_{\text{words}}} + \lambda_0$$

# SMT, components

The language model  $P(e)$

## 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

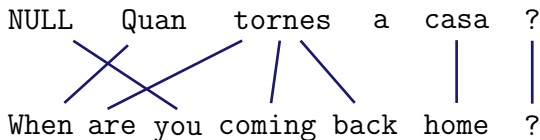
The translation model  $P(f|e)$

## Translation model

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

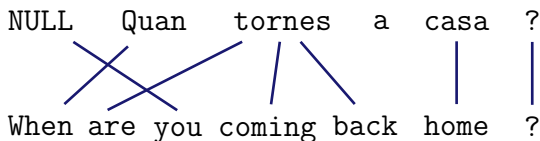
Estimation of the lexical correspondence between languages.

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



# SMT, components

The translation model  $P(f|e)$



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.

# SMT, components

The translation model  $P(f|e)$

## Word-based models: the IBM models

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

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

# SMT, components

The translation model  $P(f|e)$

## Word-based models: the IBM models

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

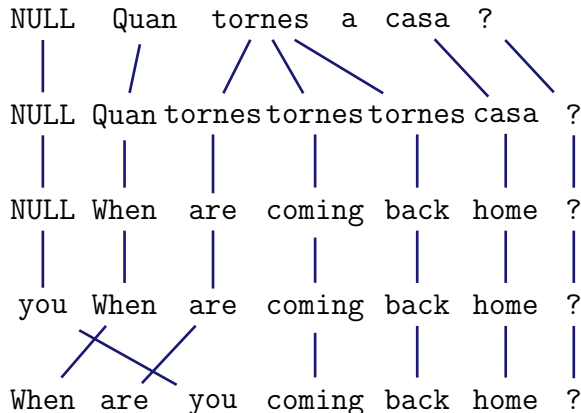
- Distortion  $d$   
 $d(j|i, m, n)$ : the prob. that the word in the  $j$  position generates a word in the  $i$  position.  $m$  and  $n$  are the length of the source and target sentences.
- Probability  $p_1$   
 $p(\text{you}|\text{NULL})$ : the prob. that the spurious word  $\text{you}$  is generated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



# SMT, components

The translation model  $P(f|e)$

Back to the example:



Fertility

Translation

Insertion

Distortion

# SMT, components

The translation model  $P(f|e)$

## 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.

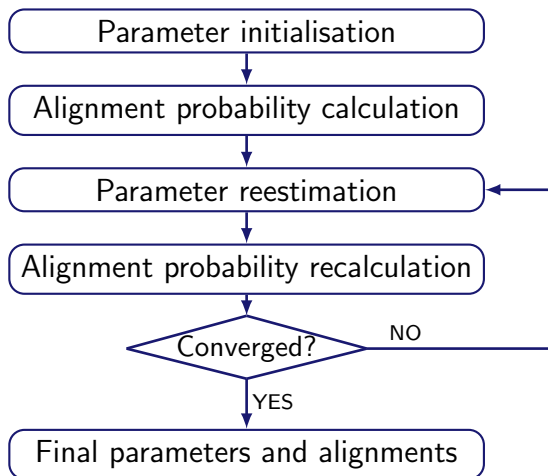
Solutions

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

# SMT, components

The translation model  $P(f|e)$

## Expectation-Maximisation algorithm



# SMT, components

The translation model  $P(f|e)$

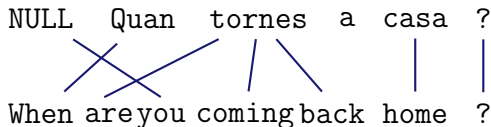
## Alignment's asymmetry

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**.

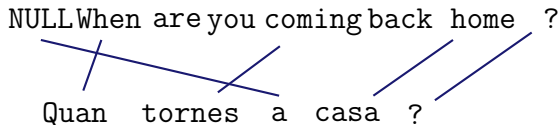
Catalan  
to  
English

NULL Quan tornes a casa ?  
When are you coming back home ?



English  
to  
Catalan

NULL When are you coming back home ?  
Quan tornes a casa ?



# SMT, components

The translation model  $P(f|e)$

Graphically:

	NULL	Quan	tornes	a	casa	?
NULL						
When						
are						
you						
coming						
back						
home						
?						

Catalan to English

# SMT, components

The translation model  $P(f|e)$

Graphically:

	NULL	Quan	tornes	a	casa	?
NULL						
When						
are						
you						
coming						
back						
home						
?						

English to Catalan

# SMT, components

The translation model  $P(f|e)$

Alignment symmetrisation

- Intersection: high-confidence, high precision.

	NULL	Quan	tornes	a	casa	?
NULL						
When						
are						
you						
coming						
back						
home						
?						

Catalan to English  $\cap$  English to Catalan

# SMT, components

The translation model  $P(f|e)$

Alignment symmetrisation

- Union: lower confidence, high recall.

	NULL	Quan	tornes	a	casa	?
NULL						
When						
are						
you						
coming						
back						
home						
?						

Catalan to English  $\cup$  English to Catalan



# SMT, components

The translation model  $P(f|e)$

## From Word-based to Phrase-based models

f: En David llegeix el llibre nou.

e:  $\phi$  David reads the new book ✓

f: En David llegeix el llibre de nou.

e:  $\phi$  David reads the book of new ✗

e:  $\phi$  David reads the book again ✓

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

# SMT, components

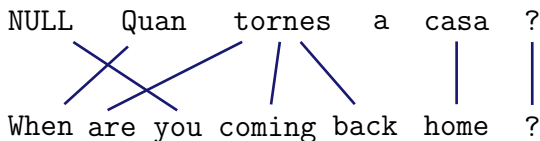
The translation model  $P(f|e)$

## **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 caught.

## SMT, components

The translation model  $P(f|e)$

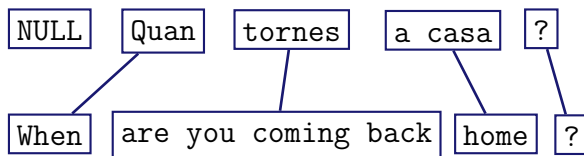


With the new translation units,  $P(f|e)$  can be obtained following the **same strategy** as for word-based models with few modifications:

- 1 Segment source sentence in phrases.
- 2 Translate each phrase into the target language.
- 3 Reorder the output.

# SMT, components

The translation model  $P(f|e)$

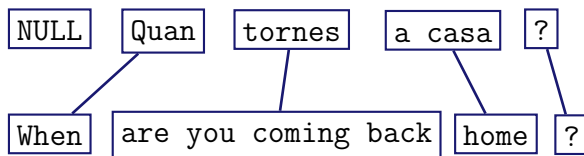


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# SMT, components

The translation model  $P(f|e)$



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.<sup>1</sup>

---

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

The translation model  $P(f|e)$

**Phrase extraction** through an example:

	Quan	tornes	tu	a	casa	?
When						
are						
you						
coming						
back						
home						
?						

(Quan tornes, When are you coming back)

# SMT, components

The translation model  $P(f|e)$

**Phrase extraction** through an example:

	Quan	tornes	tu	a	casa	?
When						
are						
you						
coming						
back						
home						
?						

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



# SMT, components

The translation model  $P(f|e)$

**Phrase extraction** through an example:

	Quan	tornes	tu	a	casa	?
When						
are						
you						
coming						
back						
home						
?						

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

(Quan tornes tu, When are you coming back)

# SMT, components

The translation model  $P(f|e)$

## Intersection

	Quan	tornes	a	casa	?
When					
are					
you					
coming					
back					
home					
?					

(Quan, When) (Quan tornes, When are you coming) (Quan tornes a casa, When are you coming back home) (Quan tornes a casa ?, When are you coming back home ?) (tornes, coming) (tornes a casa, coming back home) (tornes a casa ?, coming back home ?) (casa, home) (casa ?, home ?) (?, ?) 10 phrases

# SMT, components

The translation model  $P(f|e)$

## Union

	Quan	tornes	a	casa	?
When					
are					
you					
coming					
back					
home					
?					

(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  $P(f|e)$

## 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.

# SMT, components

The translation model  $P(f|e)$

## 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**.

# SMT, components

The translation model  $P(f|e)$

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.

# SMT, components

## Decoder

### Decoder

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

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.

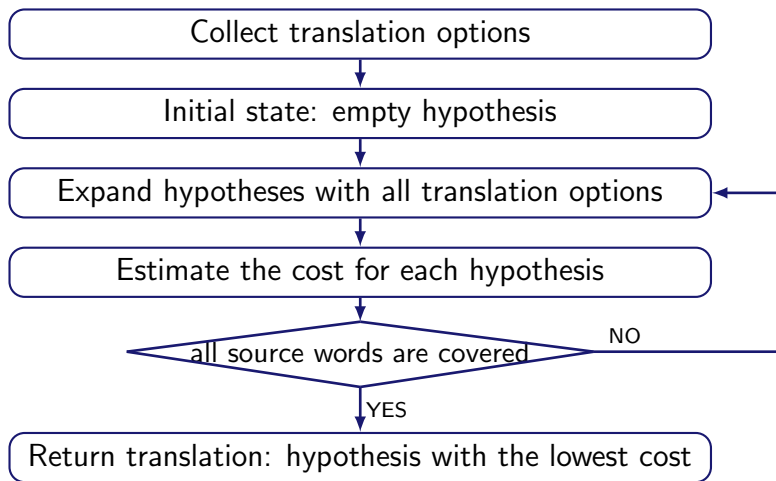
In our context, one can find:

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

# SMT, components

A beam-search decoder

## Core algorithm





# SMT, components

A beam-search decoder

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

- 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)

- Notation for hypotheses in construction:

Constructed sentence so far:            come back

Source words already translated:        - x - -

# SMT, components

A beam-search decoder

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)

- Notation for hypotheses in construction:

Constructed sentence so far:            come back

Source words already translated:        - **X** - -

# SMT, components

A beam-search decoder

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)

- Initial hypothesis

Constructed sentence so far:

$\phi$

Source words already translated:

- - - -

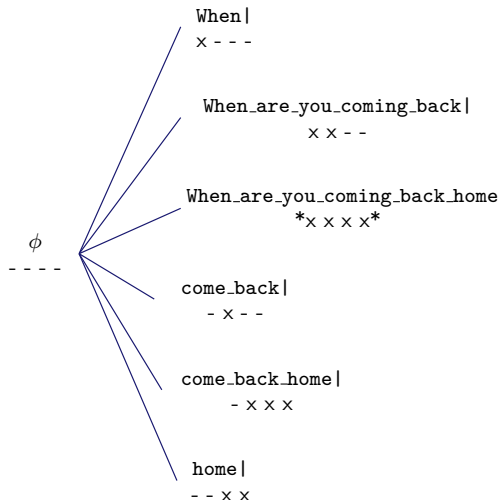
# SMT, components

A beam-search decoder

$\phi$   
-----

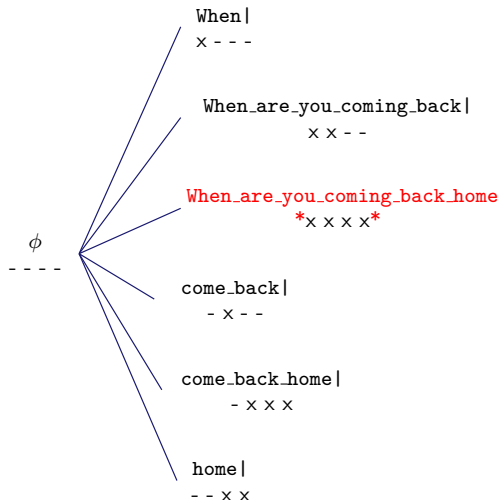
# SMT, components

## A beam-search decoder



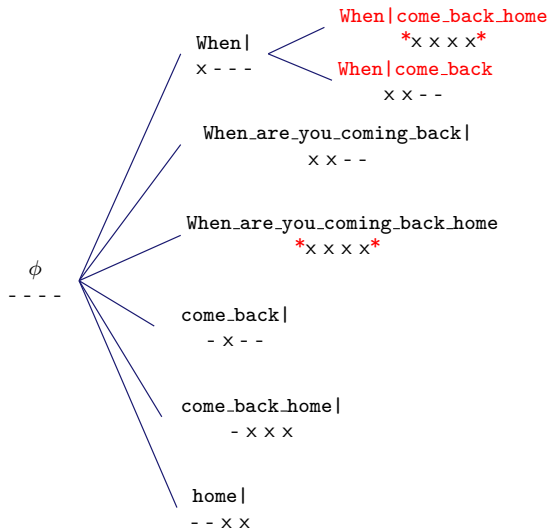
# SMT, components

## A beam-search decoder



# SMT, components

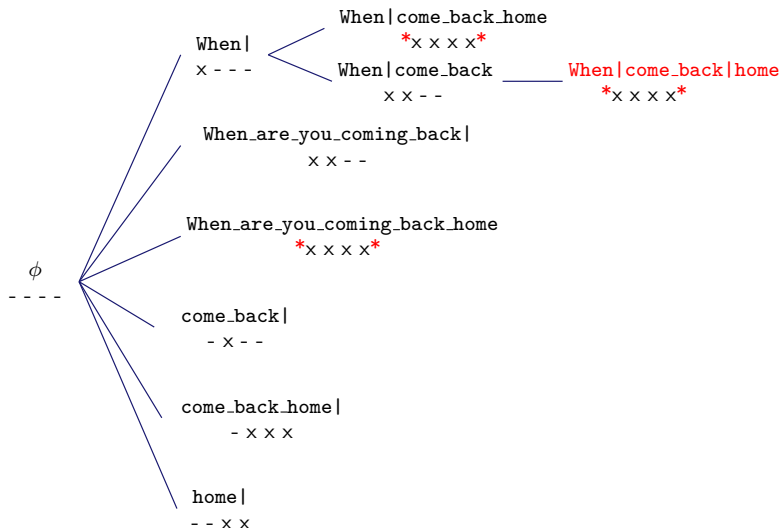
## A beam-search decoder





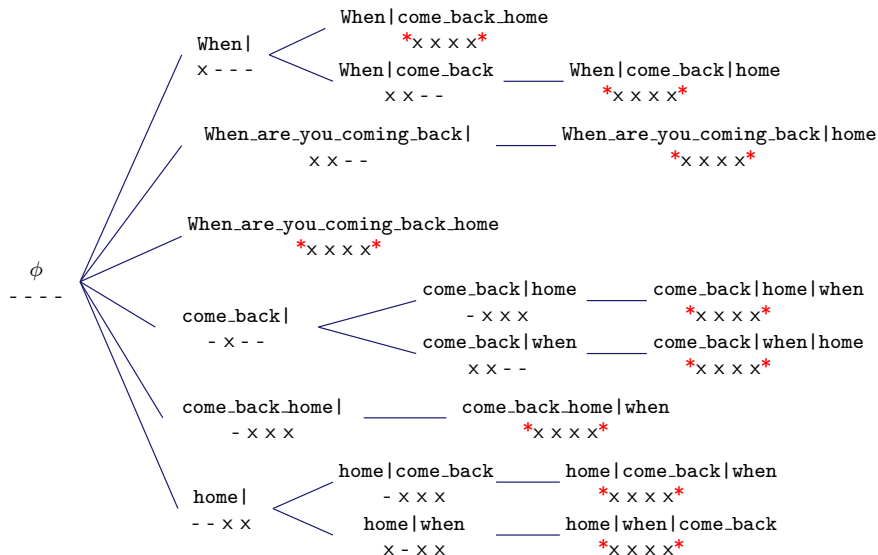
# SMT, components

## A beam-search decoder



# SMT, components

## A beam-search decoder



# 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

# SMT, components

A beam-search decoder

## Hypotheses recombination

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

When | come\_back\_home  $\iff$  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.

# SMT, components

A beam-search decoder

## 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**.

# SMT, components

A beam-search decoder

## 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
- 6 MT Evaluation



# SMT, the log-linear model

## Motivation

### Maximum likelihood (ML)

$$\hat{e} = \operatorname{argmax}_e P(e|f) = \operatorname{argmax}_e P(e) P(f|e)$$

### Maximum entropy (ME)

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

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

Log-linear model

# SMT, the log-linear model

## Motivation

### Maximum likelihood (ML)

$$\hat{e} = \operatorname{argmax}_e P(e|f) = \operatorname{argmax}_e P(e) P(f|e)$$

### Maximum entropy (ME)

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

Log-linear model with

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

$\Rightarrow$  Maximum likelihood model

# SMT, the log-linear model

## Motivation

### **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**  $\lambda_m$  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.

# SMT, the log-linear model

## Features

### State of the art feature functions

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

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

# 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  $P_d(e, f)$ .

- Word penalty  $w(e)$   
 $w(e)$ : A constant cost per produced word.
- Distortion  $P_d(e, f)$   
 $P_d(\text{ini}_{\text{phrase}_i}, \text{end}_{\text{phrase}_{i-1}})$ : Relative distortion probability distribution. A simple distortion model:  
$$P_d(\text{ini}_{\text{phrase}_i}, \text{end}_{\text{phrase}_{i-1}}) = \alpha |\text{ini}_{\text{phrase}_i} - \text{end}_{\text{phrase}_{i-1}} - 1|$$

# SMT, the log-linear model

## Weights optimisation

### Development training, weights optimisation

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

### 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).

# SMT, the log-linear model

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- **Minimum Error-Rate Training (MERT).**

# SMT, the log-linear model

## Minimum Error-Rate Training (MERT)

### Minimum Error-Rate Training

- Approach: Minimise an error function.

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

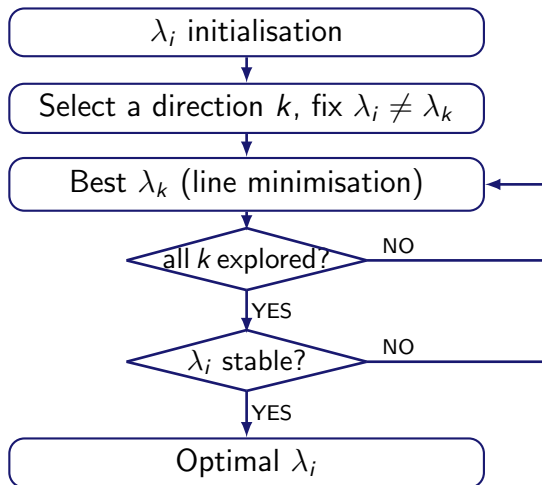
- There exist several error measures or metrics.
- Metrics not always correlate with human judgements.
- The quality of the final translation on the metric chosen for the optimisation is shown to improve.
- For the moment, let's say we use BLEU.

(More on MT Evaluation section)

# SMT, the log-linear model

## Minimum Error-Rate Training (MERT)

### Minimum Error-Rate Training rough algorithm



# SMT, the log-linear model

## The log-linear model

### 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
- 6 MT Evaluation

# SMT, beyond standard SMT

Including linguistic information

## **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.

# SMT, beyond standard SMT

## Factored translation models

### Factored translation models

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

$$(\text{word}) \implies (\text{word}, \text{lemma}, \text{PoS}, \text{morphology}, \dots)$$

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

# SMT, beyond standard SMT

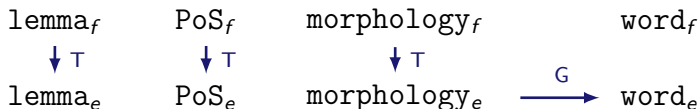
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# SMT, beyond standard SMT

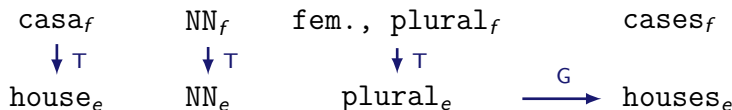
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The translation is now a combination of pure **translation** (T) and **generation** (G) steps:



# SMT, beyond standard SMT

## Factored translation models

### **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.

# SMT, beyond standard SMT

## Syntactic translation models

### 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.

# SMT, beyond standard SMT

## Syntactic translation models

### **Syntactic translation models**

Incorporate syntax to the source and/or target languages.

### Approaches

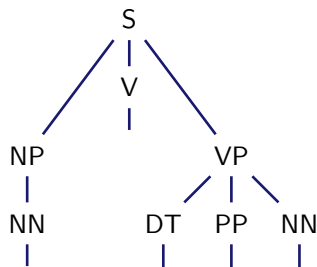
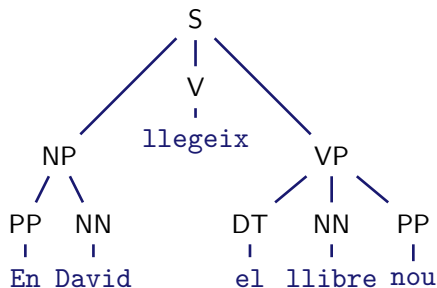
- Synchronous grammar formalism which learns a grammar that can simultaneously generate both trees.
  - ▶ **Syntax-based**. Respect linguistic units in translation.
  - ▶ **Hierarchical phrase-based**. Respect phrases in translation.

# SMT, beyond standard SMT

Syntax-based translation models

Syntactic models ease reordering. An intuitive example:

En David llegeix un llibre nou

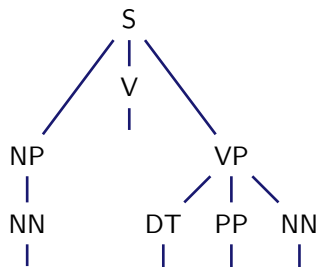
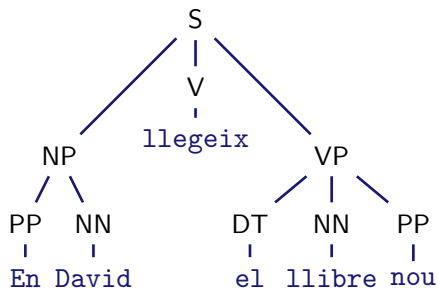


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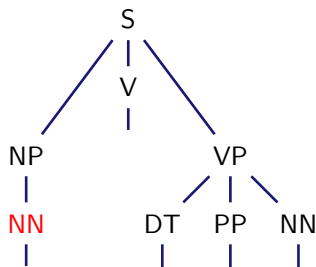
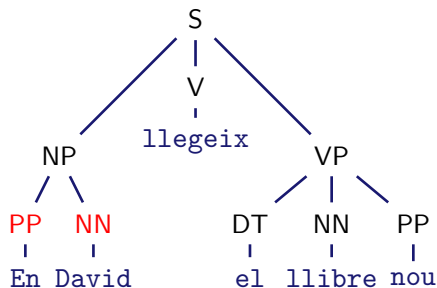


# SMT, beyond standard SMT

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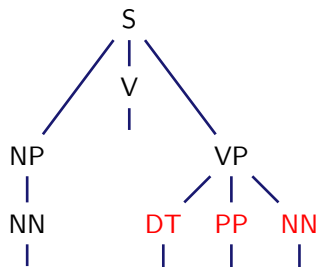
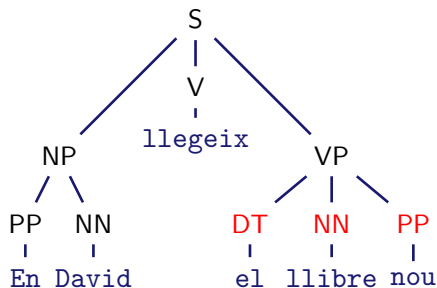


# SMT, beyond standard SMT

Syntax-based translation models

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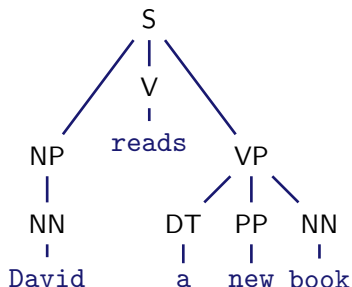
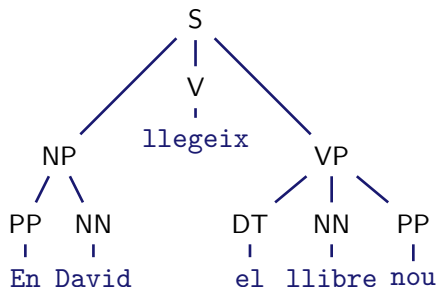


# SMT, beyond standard SMT

## Syntax-based translation models

Syntactic models ease reordering. An intuitive example:

En David llegeix un llibre nou



David reads a new book

# SMT, beyond standard SMT

Ongoing research

## 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.

# SMT, beyond standard SMT

Ongoing research

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.

# SMT, beyond standard SMT

## Ongoing research

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.

# SMT, beyond standard SMT

Including linguistic information

## Beyond standard SMT: keep in mind

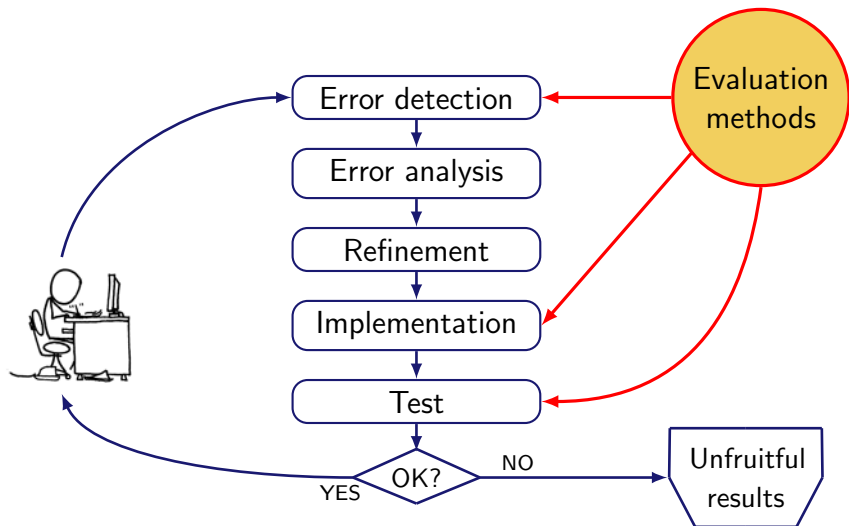
- Factored models include linguistic information in phrase-based models and are suitable for morphologically rich languages.
- Syntactic models consider somehow syntax and are adequate for language pairs with a different structure of the sentences.
- Current research addresses both new models and modifications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

# Outline

- 1 Introduction
- 2 Basics
- 3 Components
- 4 The log-linear model
- 5 Beyond standard SMT
- 6 MT Evaluation**

# MT Evaluation

Importance for system development



# MT Evaluation

## Automatic evaluation

### **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)



# MT Evaluation

## Lexical similarity

### **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

# MT Evaluation

## Lexical similarity

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- 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.

# MT Evaluation

## Lexical similarity

### 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 neither a sufficient nor a necessary condition so that two sentences convey the same meaning.

# MT Evaluation

## Lexical similarity

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Ref4: It will `be difficult to` punctuate the output.

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

# MT Evaluation

Ongoing research

**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.

# MT Evaluation

## Summary

### MT Evaluation: keep in mind

- Evaluation is important in the system development cycle. Automatic evaluation accelerates significantly 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.

# Thanks!

A last alignment

Gràcies a

en Jesús Giménez

per

algunes transparències

Thanks to

Jesús Giménez

for

some of the material



?



## Part II

### SMT experiments

### 7 Translation system

- Software
- Steps

### 8 Evaluation system

- Software
- Steps

## 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

- ➊ 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 >  
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```

```
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



### 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 lowercase 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 -config ./filteredmodel/moses.ini  
-input-file testset.es > testset.translated.en
```

## Evaluate the results

- ❶ With BLEU scoring tool. Available as a Moses script or from NIST:

<http://www.itl.nist.gov/iad/mig/tools/mtevalv13a-20091001.tar.gz>

- ❷ With IQmt package.

<http://www.lsi.upc.edu/~nlp/IQMT/>

# MT Evaluation

## Steps

### 1. Evaluate the results

- 1 With BLEU scoring tool in Moses:

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

# MT Evaluation

## Steps

### 2. Evaluate the results on-line

- ① OpenMT Evaluation Demo

<http://biniki.lsi.upc.edu/openMT/evaldemo.php>

## Part III

### Appendix: References

## History of SMT

- Weaver, 1949 [Wea55]
- Alpac Memorandum [Aut66]
- Hutchins, 1978 [Hut78]
- Slocum, 1985 [Slo85]

## The beginnings, word-based SMT

- Brown et al., 1990 [BCP<sup>+</sup>90]
- Brown et al., 1993 [BPPM93]



## **Phrase-based model**

- Och et al., 1999 [OTN99]
- Koehn et al, 2003 [KOM03]

## **Log-linear model**

- Och & Ney, 2002 [ON02]
- Och & Ney, 2004 [ON04]

## **Factored model**

- Koehn & Hoang, 2007 [KH07]

## **Syntax-based models**

- Yamada & Knight, 2001 [YK01]
- Chiang, 2005 [Chi05]
- Carreras & Collins, 2009 [CC09]

## **Discriminative models**

- Carpuat & Wu, 2007 [CW07]
- Bangalore et al., 2007 [BHK07]
- Giménez & Màrquez, 2008 [GM08]

## **Language model**

- Kneser & Ney, 1995 [KN95]

## **MERT**

- Och, 2003 [Och03]

## **Domain adaptation**

- Bertoldi and Federico, 2009 [Och03]

## Reordering

- Crego & Mariño, 2006 [Cn06]
- Bach et al., 2009 [BGV09]
- Chen et al., 2009 [CWC09]

## Systems combination

- Du et al., 2009 [DMW09]
- Li et al., 2009 [LDZ<sup>+</sup>09]
- Hildebrand & Vogel, 2009 [HV09]

## **Alternative systems in development**

- Blunsom et al., 2008 [BCO08]
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- Chiang et al., 2009 [CKW09]
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## Evaluation

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<http://people.csail.mit.edu/people/koehn/publications/tutorial2003.pdf>

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[http://www.medar.info/conference\\_all/2009/Tutorial\\_3.pdf](http://www.medar.info/conference_all/2009/Tutorial_3.pdf)

- Lopez, 2008 [Lop08]

- Giménez, 2009 [Gim08]

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