# Practical introduction to Statistical Machine Translation

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GF Summer School, Fraueninsel

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# *Overview*

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

**Part I: SMT background**

$\sim$ 120min

# *Overview*

6. Translation system

7. MT Evaluation basics

8. Evaluation system

**Part II: SMT experiments**

from 30min to...

**Part III: MT evaluation**

$\sim$ 45min

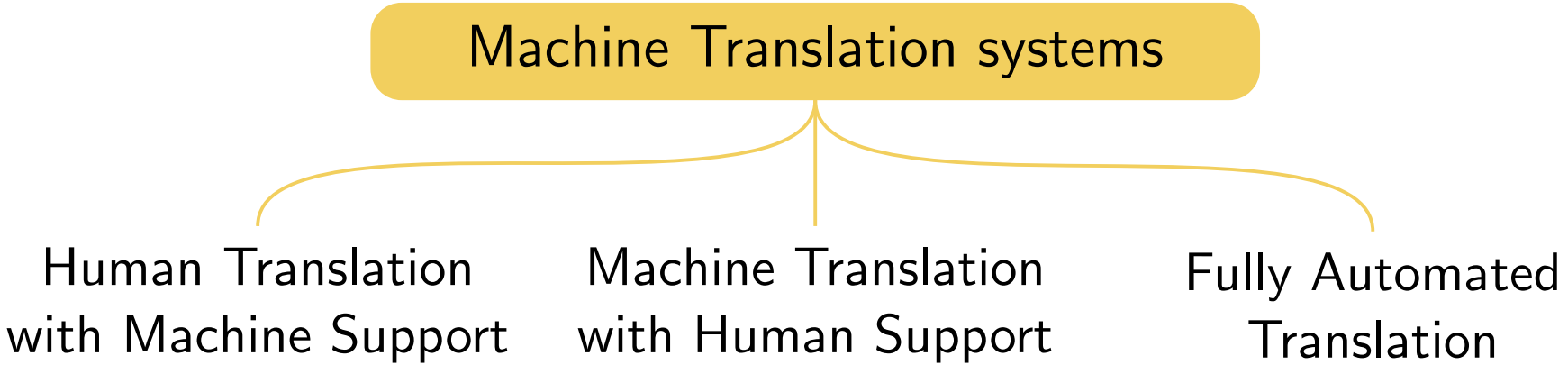
# Part I

# SMT background

# *Outline*

# Introduction

## Machine Translation Taxonomy



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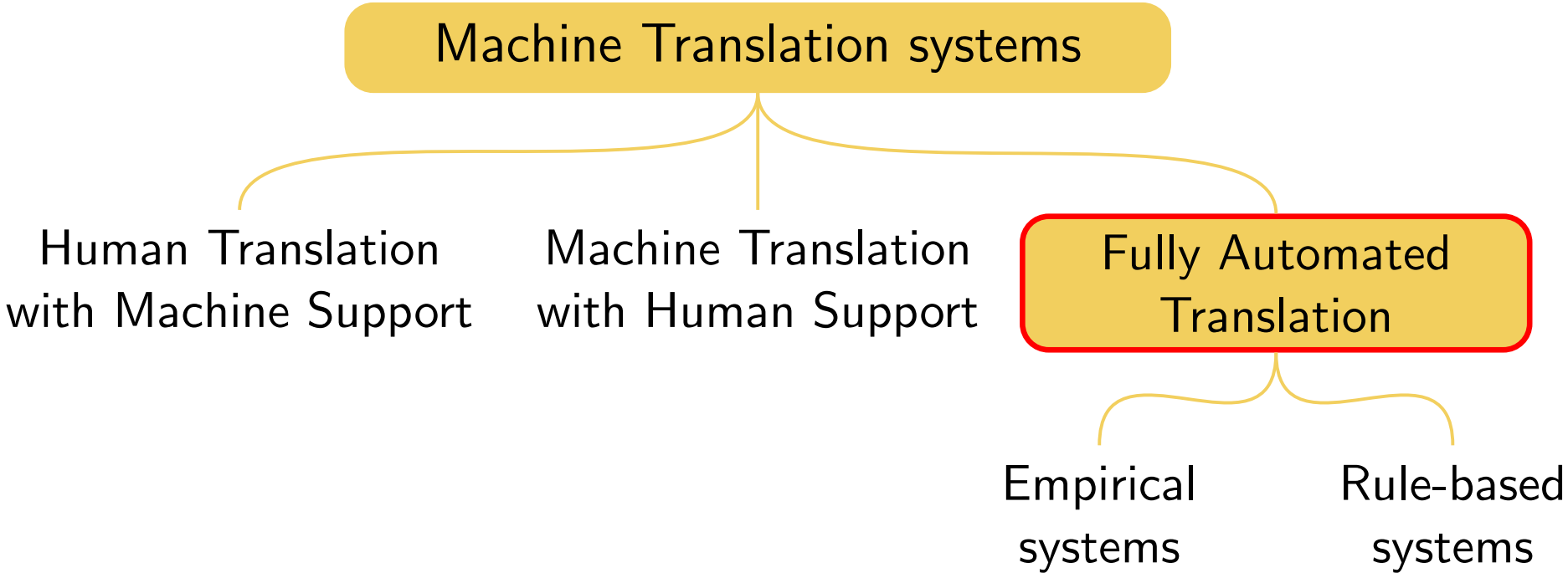

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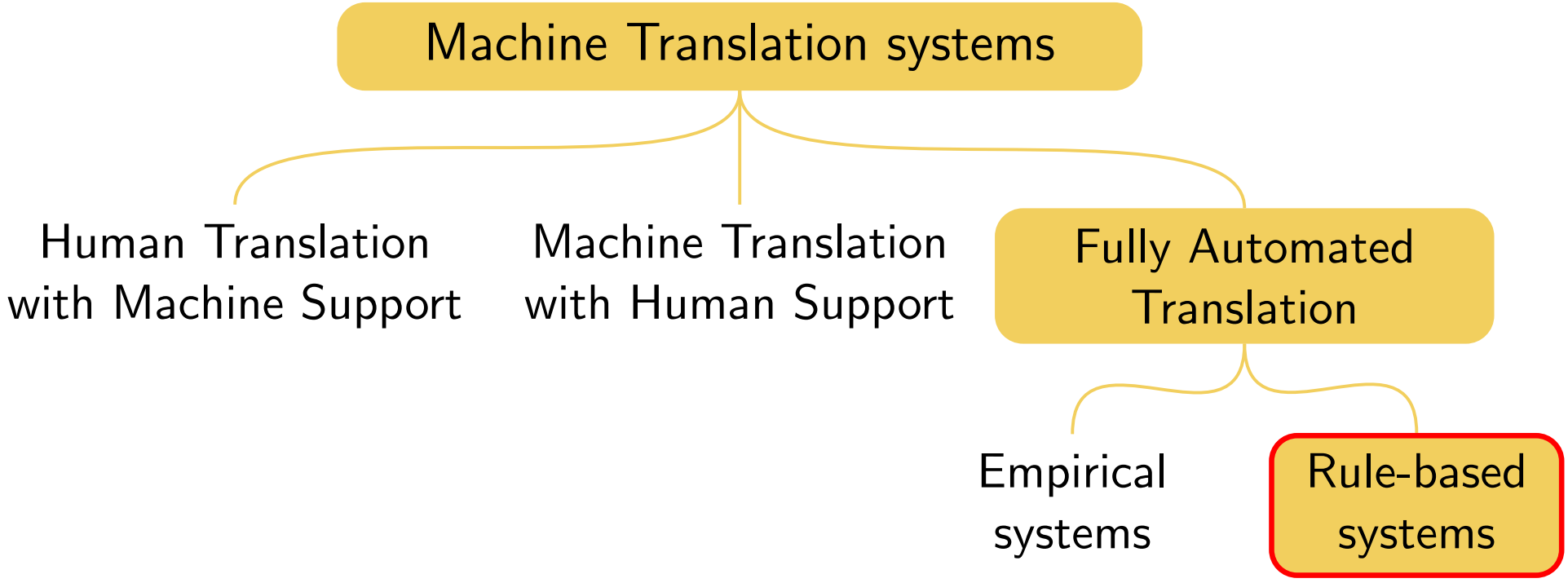

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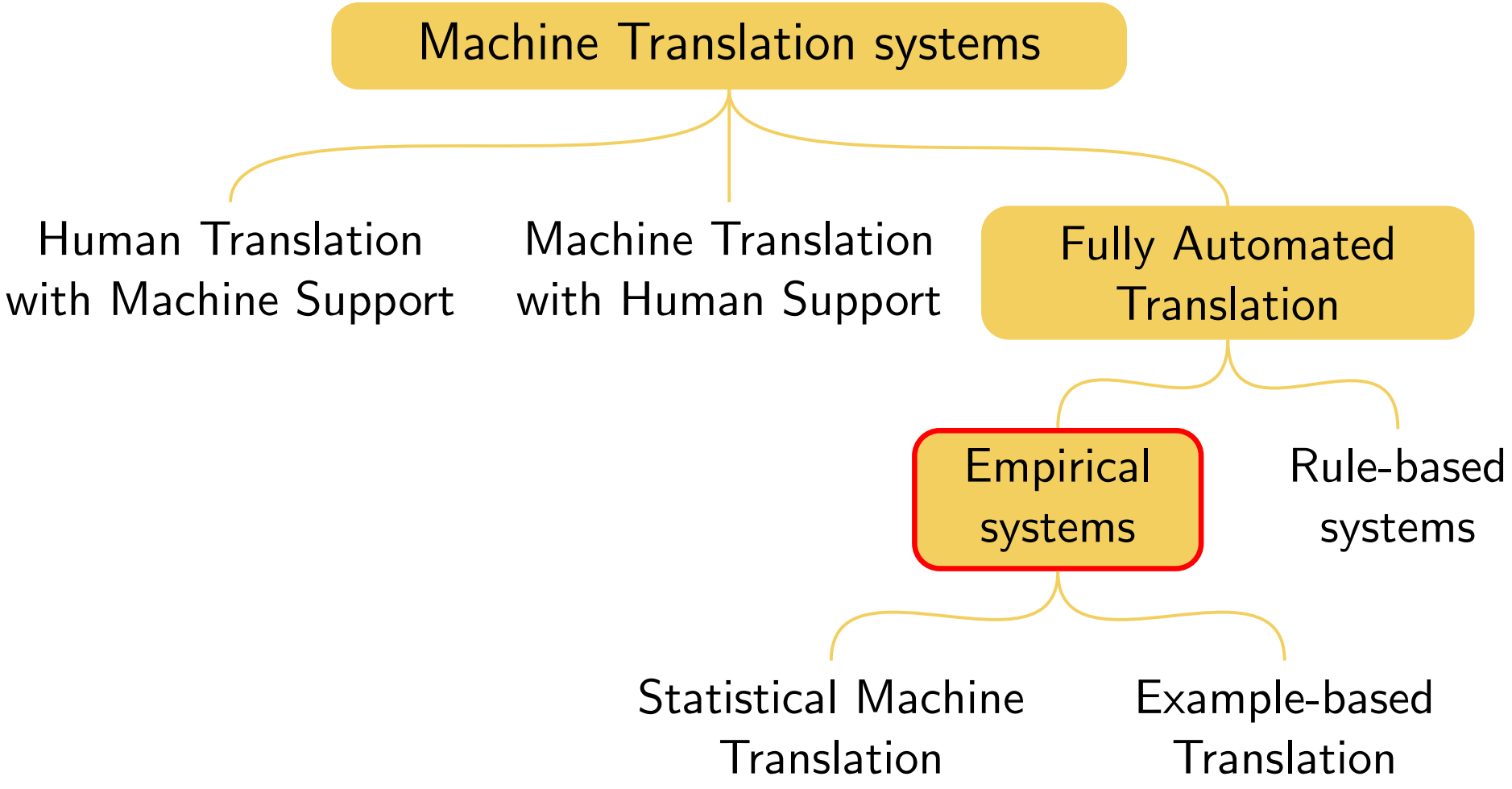

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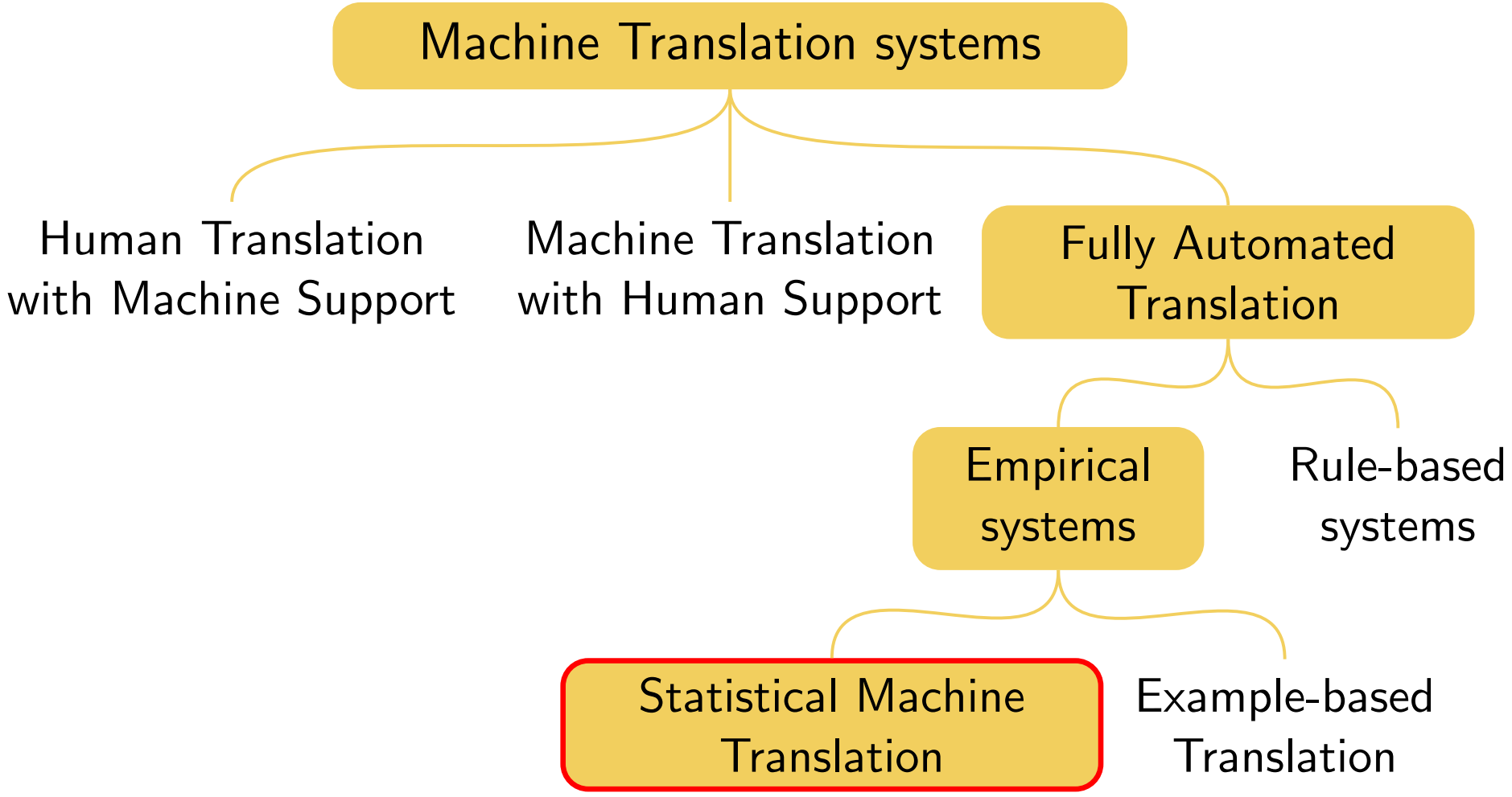
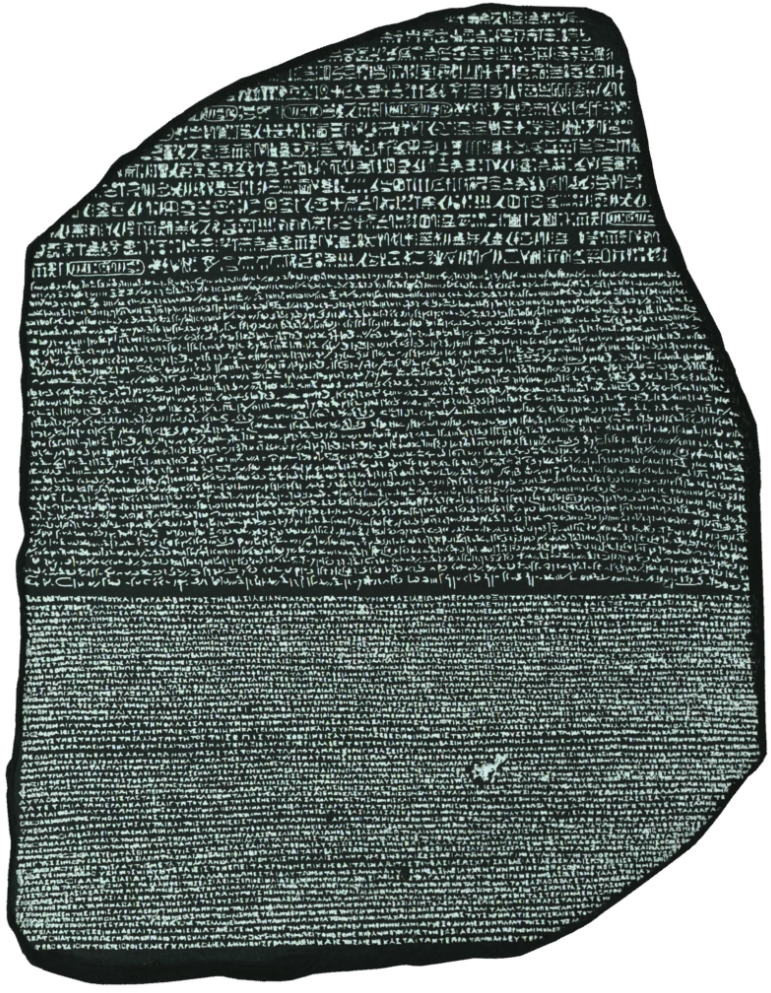


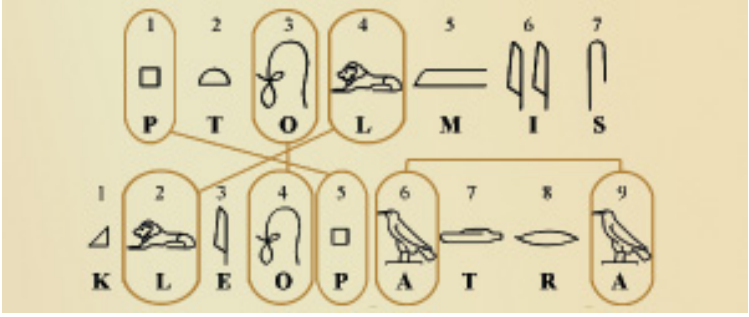
# Introduction

## Empirical Machine Translation

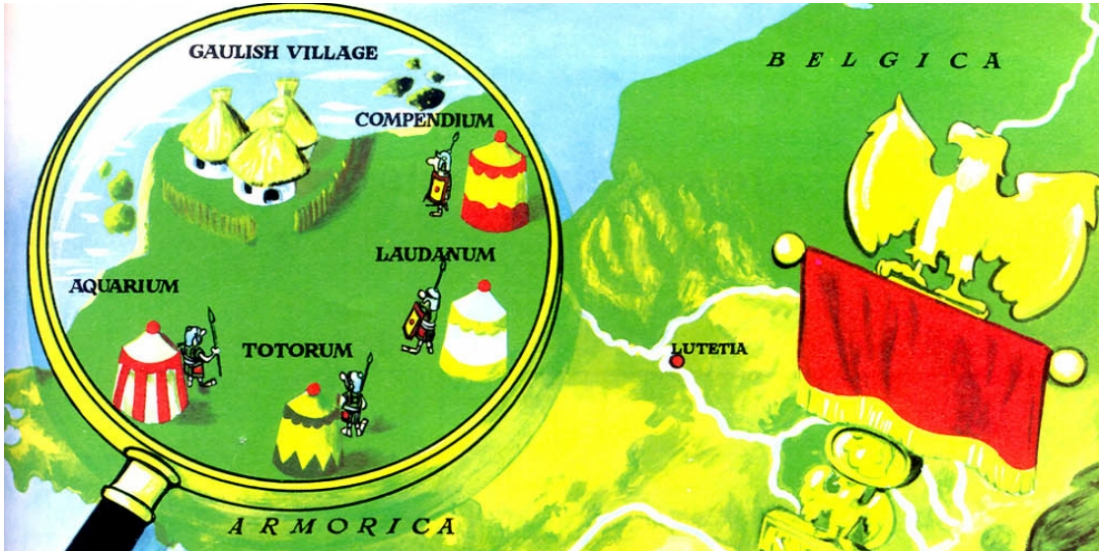
Empirical MT relies on aligned corpora



**Empirical MT relies on aligned corpora**



# Empirical MT relies on large parallel aligned corpora




Som a l'any 50 abans de Crist. Tota la Gàl·lia és ocupada pels romans... Tota? No! Un llogaret del Nord habitat per gals indomables rebutja una i altra vegada ferotgement l'invassor. La vida doncs no és gens planera per als legionaris romans dels petits campaments de Babaòrum, Aquàrium, Laundànum i Petibònum...

The year is 50 B.C. Gaul is entirely occupied by the Romans. Well, not entirely... One small village of indomitable Gauls still holds out against the invaders. And life is not easy for the Roman legionaries who garrison the fortified camps of Totorum, Aquarium, Laudanum and Compendium...

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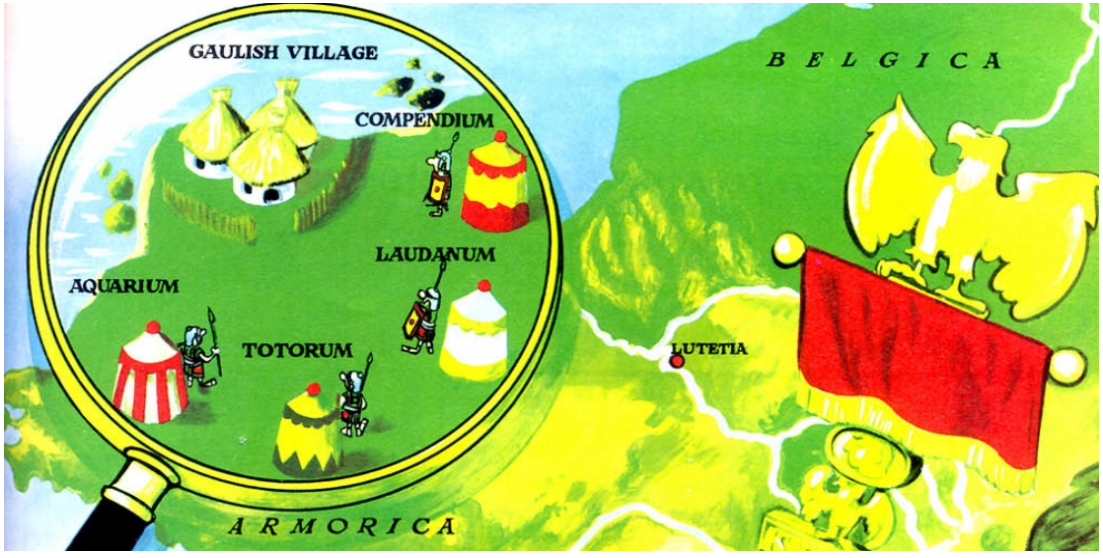


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Astèrix. És l'heroic petit guerrer d'aquestes aventures, viu com una centella i enginyosament astut. Per això sempre li són encomanades les missions més perilloses. Extrau la seva terrorífica força de la beguda màgica inventada pel druida Panoràmix.

Obèlix. És l'antic inseparable d'Astèrix. Fa de repartidor de menhirs i li agrada d'allò més la carn de porc senglar. És capaç d'abandonar-ho tot per tal de seguir Astèrix en una nova aventura. Sobretot si no hi manquen els senglars i fortes batusses.

Copdegarròtix. És el cap de la tribu. Majestuós, valent i desconfiat alhora, el vell guerrer ès respectat pels seus homes i temut pels seus enemics. Tan sols una cosa li fa por: que el cel li pugui caure damunt del cap! Però, tal com ell mateix acostuma a dir, "Qui dia passa, any empeny!".

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Asterix, the hero of these adventures. A shrewd, cunning little warrior; all perilous missions are immediately entrusted to him. Asterix gets his superhuman strength from the magic potion brewed by the druid Getafix...

Obelix, Asterix's inseparable friend. A menhir delivery-man by trade; addicted to wild boar. Obelix is always ready to drop everything and go off on a new adventure with Asterix - so long as there's wild boar to eat, and plenty of fighting.

Finally, Vitalstitistix, the chief of the tribe. Majestic, brave and hot-tempered, the old warrior is respected by his men and feared by his enemies. Vitalstitistix himself has only one fear; he is afraid the sky may fall on his head tomorrow. But as he always says, "Tomorrow never comes".

## Aligned parallel corpora: Numbers

**Corpora**

| Corpus | # segments (app.) | # words (app.) |
|---|---|---|
| JRC-Acquis | $1.0 \cdot 10^6$ | $30 \cdot 10^6$ |
| Europarl | $2.0 \cdot 10^6$ | $55 \cdot 10^6$ |
| United Nations | $10.7 \cdot 10^6$ | $300 \cdot 10^6$ |

**Books**

| Title | # words (approx.) |
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## In practice

### WMT13 parallel data

| Corpus | # segments | # tokens |
|---|---|---|
| Europarl ENG | 1,928,274 | 52,048,855 |
| Europarl SPA | 1,928,274 | 53,996,661 |
| News Commentary ENG | 155,615 | 3,901,839 |
| News Commentary SPA | 155,615 | 4,364,802 |
| United Nations ENG | 10,749,388 | 283,672,192 |
| United Nations SPA | 10,749,388 | 318,045,340 |
| Total (ENG+SPA) | 25,666,554 | 716,029,689 |

http://www.statmt.org/wmt13/translation-task.html

# Comment

## The "In practice" section

**In practice**

Shows real examples of the previous theory, always from freely available data/software:

- Data: `www.statmt.org/wmt13/`
- Software: `SRILM`, `GIZA++` & `Moses`

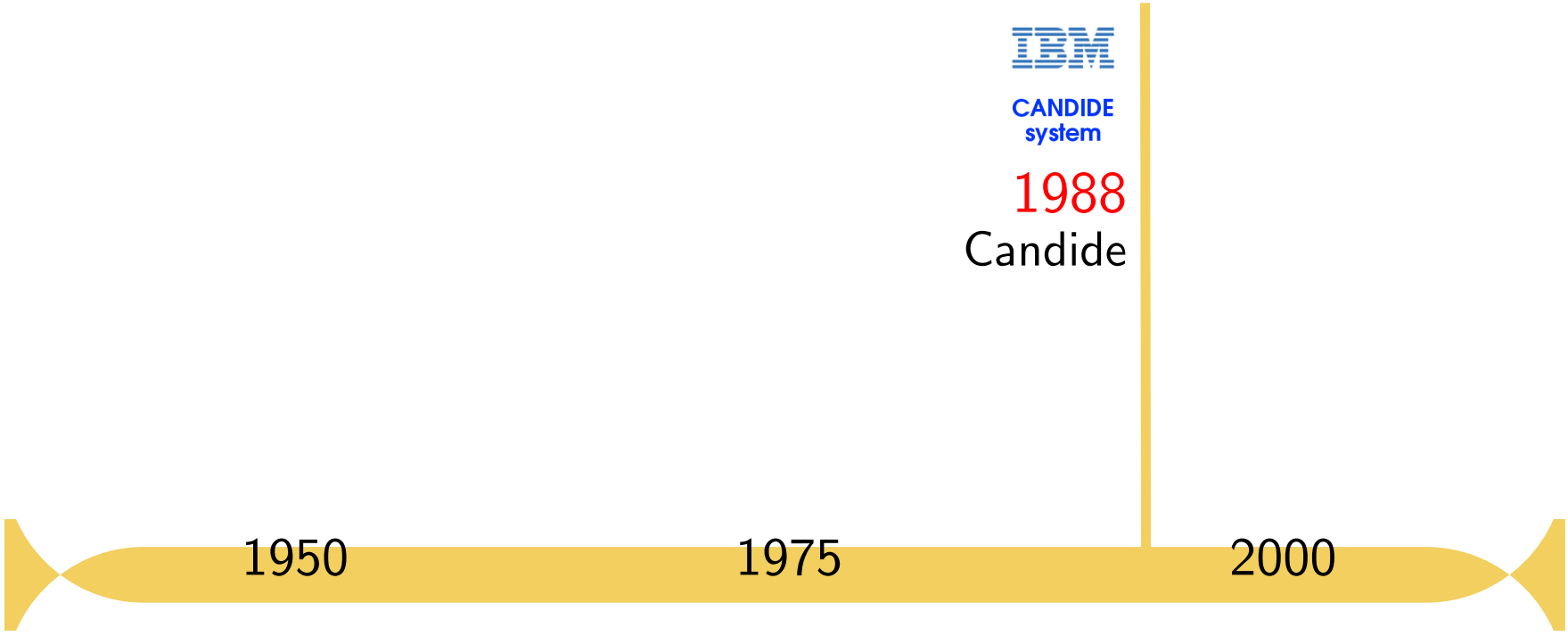
Standard tools, but not exclusive

More on the hands on!

# *Outline*

# SMT, basics

## The beginnings, summarised timeline



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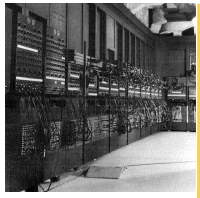
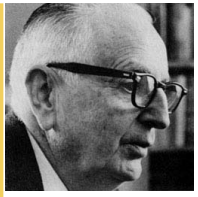


1946
ENIAC



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Weaver
memo

1966
Alpac report

IBM
CANDIDE
system

1988
Candide

1950 1975 2000

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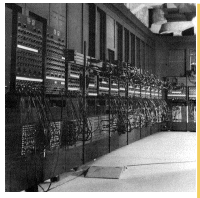

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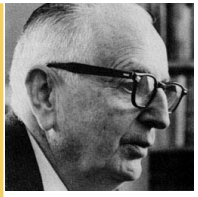

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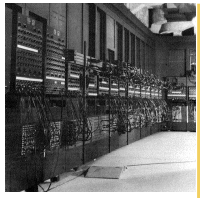

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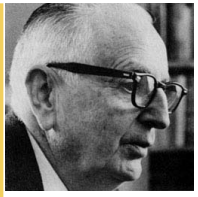

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Empirical
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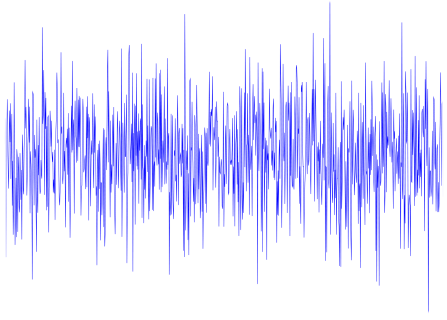
# SMT, basics

## The Noisy Channel approach

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

Good morning! → 

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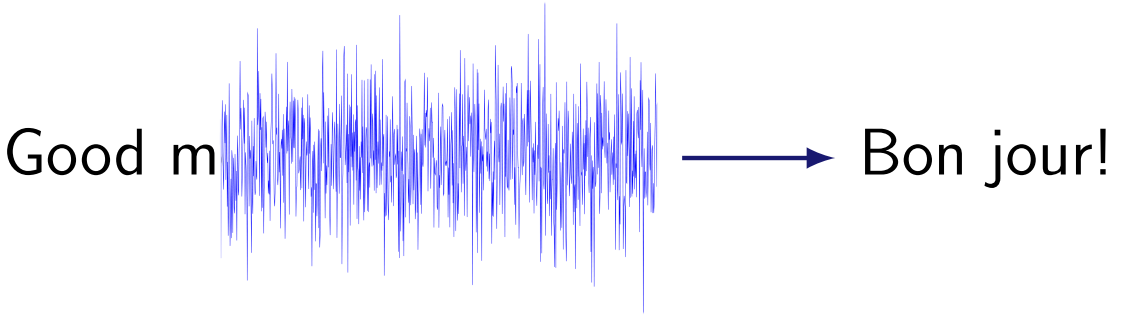

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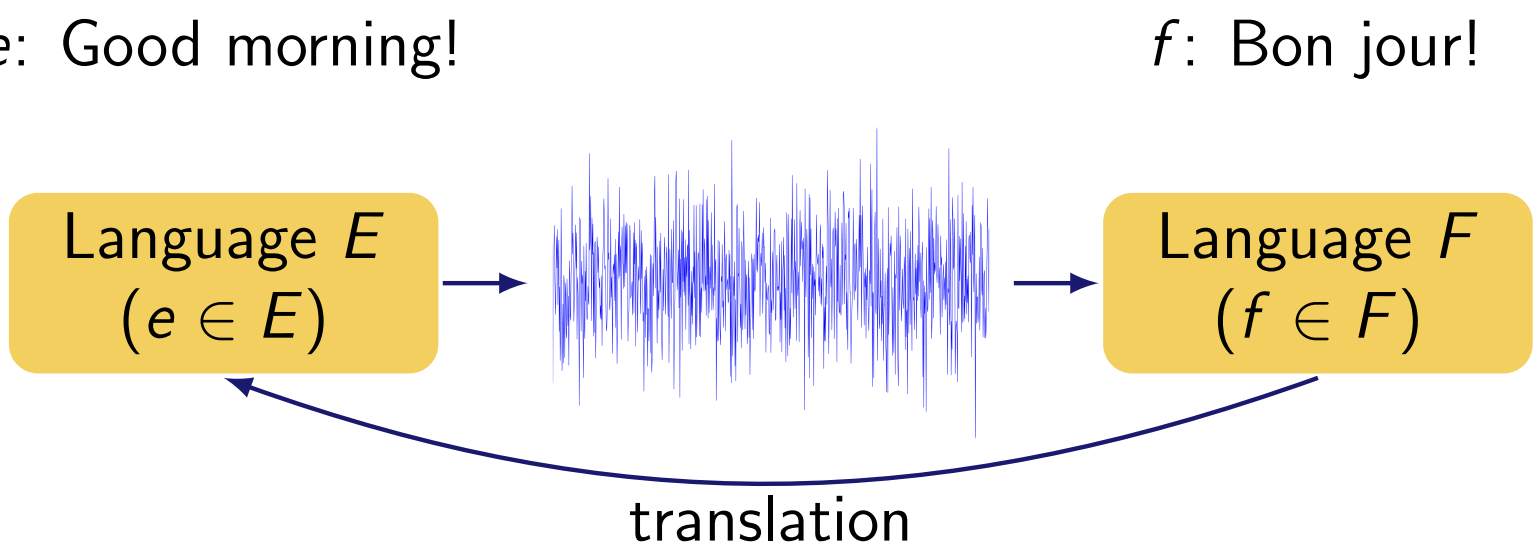

# SMT, basics

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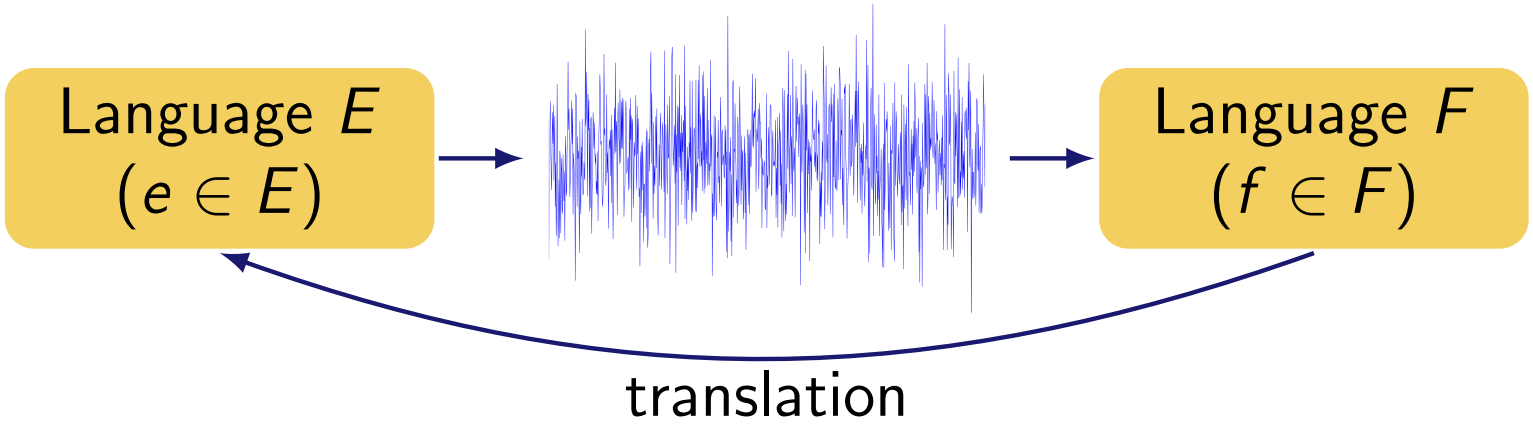


Mathematically:

$$P(e|f)$$

# SMT, basics

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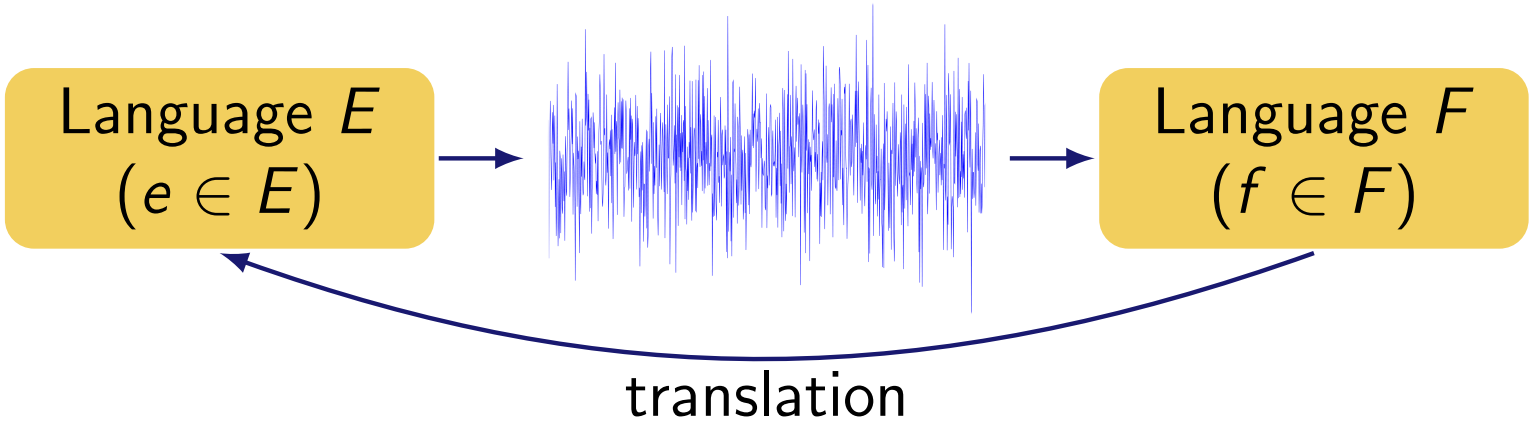


Mathematically:

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

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

# SMT, basics

## Components

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

### 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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# 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 $e$:

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

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`

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

where, for each factor,

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

# SMT, components

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### Example, a 4-gram model

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

$$P(e) = P(\texttt{All}|\phi,\phi,\phi)\ P(\texttt{work}|\phi,\phi,\texttt{All})\ P(\texttt{and}|\phi,\texttt{All},\texttt{work})$$
$$P(\texttt{no}|\texttt{All},\texttt{work},\texttt{and})\ P(\texttt{play}|\texttt{work},\texttt{and},\texttt{no})$$
$$P(\texttt{makes}|\texttt{and},\texttt{no},\texttt{play})P(\texttt{Jack}|\texttt{no},\texttt{play},\texttt{makes})$$
$$P(\texttt{a}|\texttt{play},\texttt{makes},\texttt{Jack})P(\texttt{dull}|\texttt{makes},\texttt{Jack},\texttt{a})$$
$$P(\texttt{boy}|\texttt{Jack},\texttt{a},\texttt{dull})$$

where, for each factor,

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

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# SMT, components

## The language model $P(e)$

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.

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

# SMT, components

## The language model $P(e)$

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- Still, some $n$-grams can be not observed in the corpus.

### Solution

Smoothing techniques:

- Linear interpolation.
- Back-off models.

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# SMT, components

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# SMT, components

## The language model $P(e)$

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.

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

# SMT, components

## The language model $P(e)$

**In practice,**

```
cluster:/home/quest/corpus/lm> ls -lkh

-rw-r--r-- 1  emt ia   507M   mar  3 15:28 europarl.lm
-rw-r--r-- 1  emt ia    50M   mar  3 15:29 nc.lm
-rw-r--r-- 1  emt ia   3,1G   mar  3 15:33 un.lm

cluster:/home/quest/corpus/lm> wc -l

  15,181,883   europarl.lm
   1,735,721   nc.lm
  82,504,380   un.lm
```

# SMT, components

## The language model $P(e)$

```
cluster:/home/quest/corpus/lm> more nc.lm


\data\
ngram 1=655770
ngram 2=11425501
ngram 3=10824125
ngram 4=13037011
ngram 5=12127575

\1-grams:
-3.142546 ! -1.415594
-1.978775 " -0.9078496
-4.266428 # -0.2729652
-3.806078 $ -0.3918373
-3.199419 % -1.139753
-3.613416 & -0.6046973
-2.712332 ’ -0.6271471
-2.268107 ( -0.6895114
```

# SMT, components

## The language model $P(e)$

```
\2-grams:
 -1.08232 concierto ,
-1.093977 concierto . -0.2378127
-1.747908 concierto ad
-1.748422 concierto cobraria
-0.8927398 concierto de
-1.744176 concierto europeo
-1.740879 concierto internacional
-1.635606 concierto para
-1.744787 concierto regional

...

\5-grams:
-0.8890668 no son los unicos culpables
-1.396196 no son los unicos problemas
-0.7550655 no son los unicos que
-1.240193 no son los unicos responsables
```

# 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

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

Estimation of the lexical correspondence between languages.

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

# SMT, components

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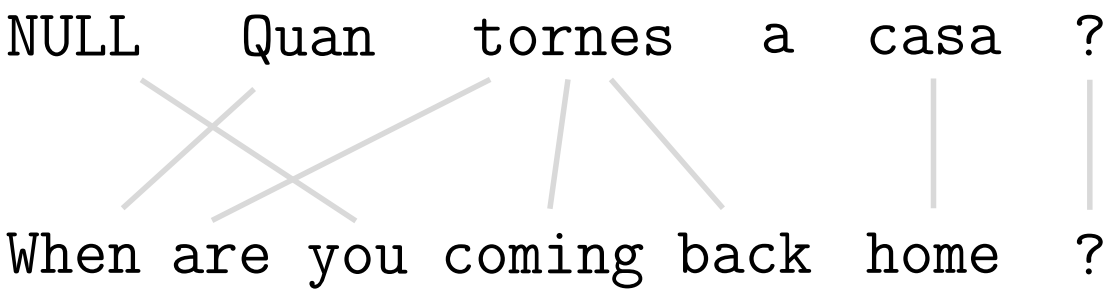

# SMT, components

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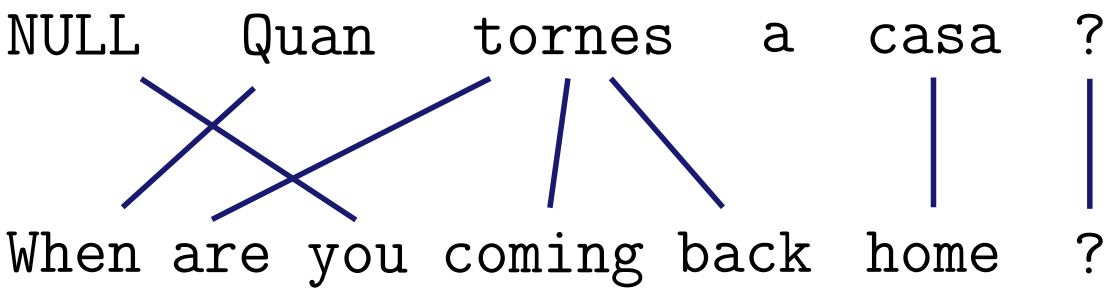
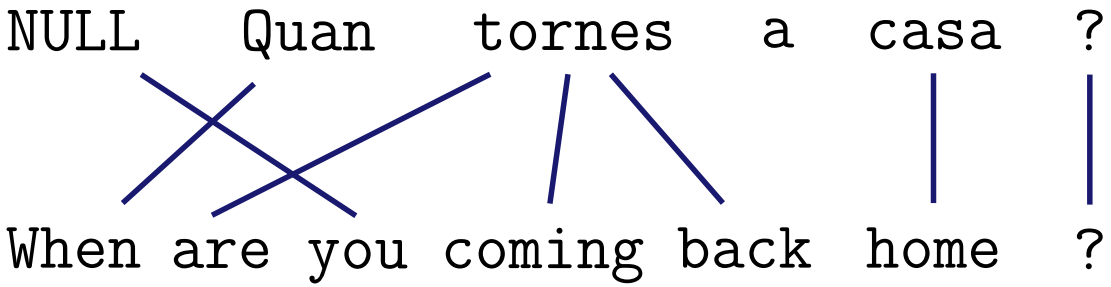


# SMT, components

## 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 $t$
  $t(\texttt{Quan}|\texttt{When})$: 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**

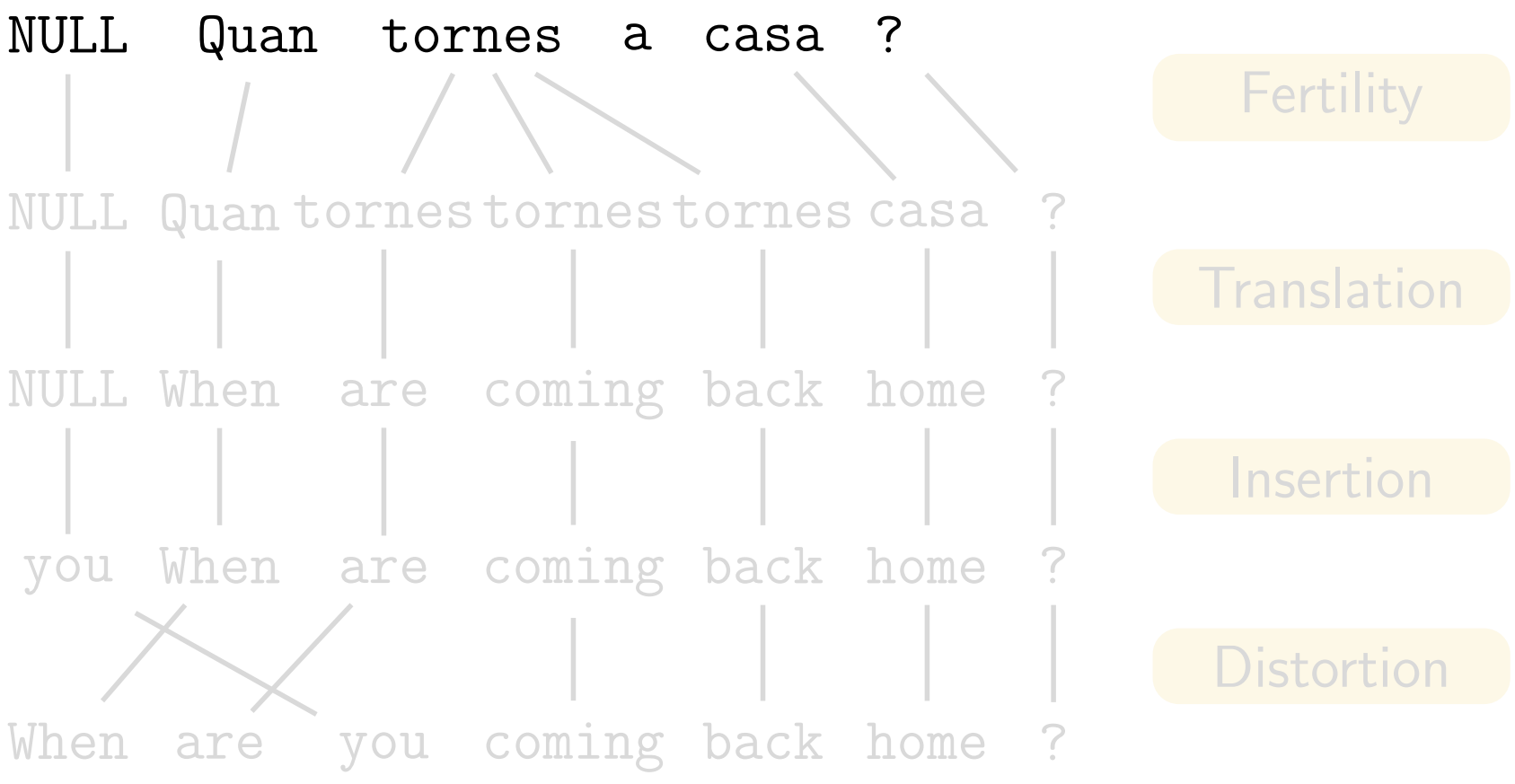
They characterise $P(f|e)$ with 4 parameters: $t$, $n$, $d$ and $p_1$.

- 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`).

# SMT, components

## The translation model $P(f|e)$

Back to the example:



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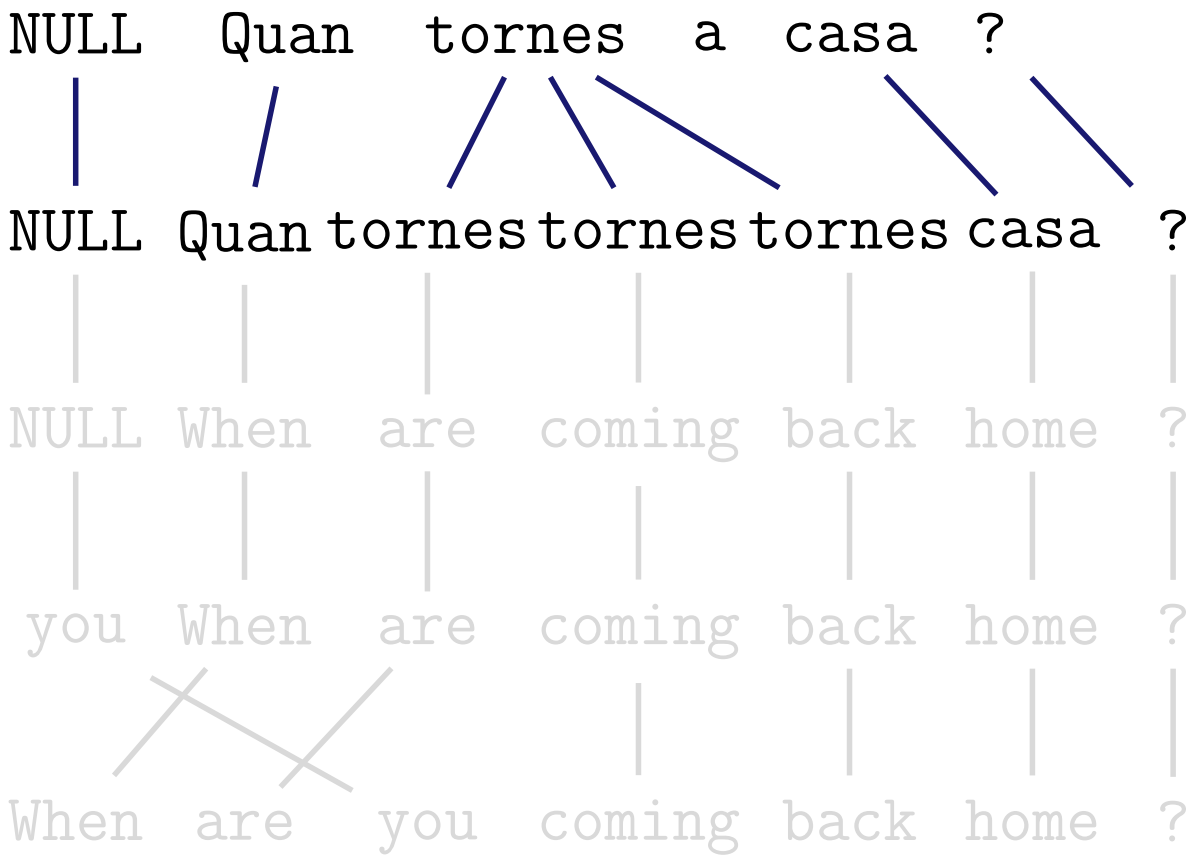

# SMT, components

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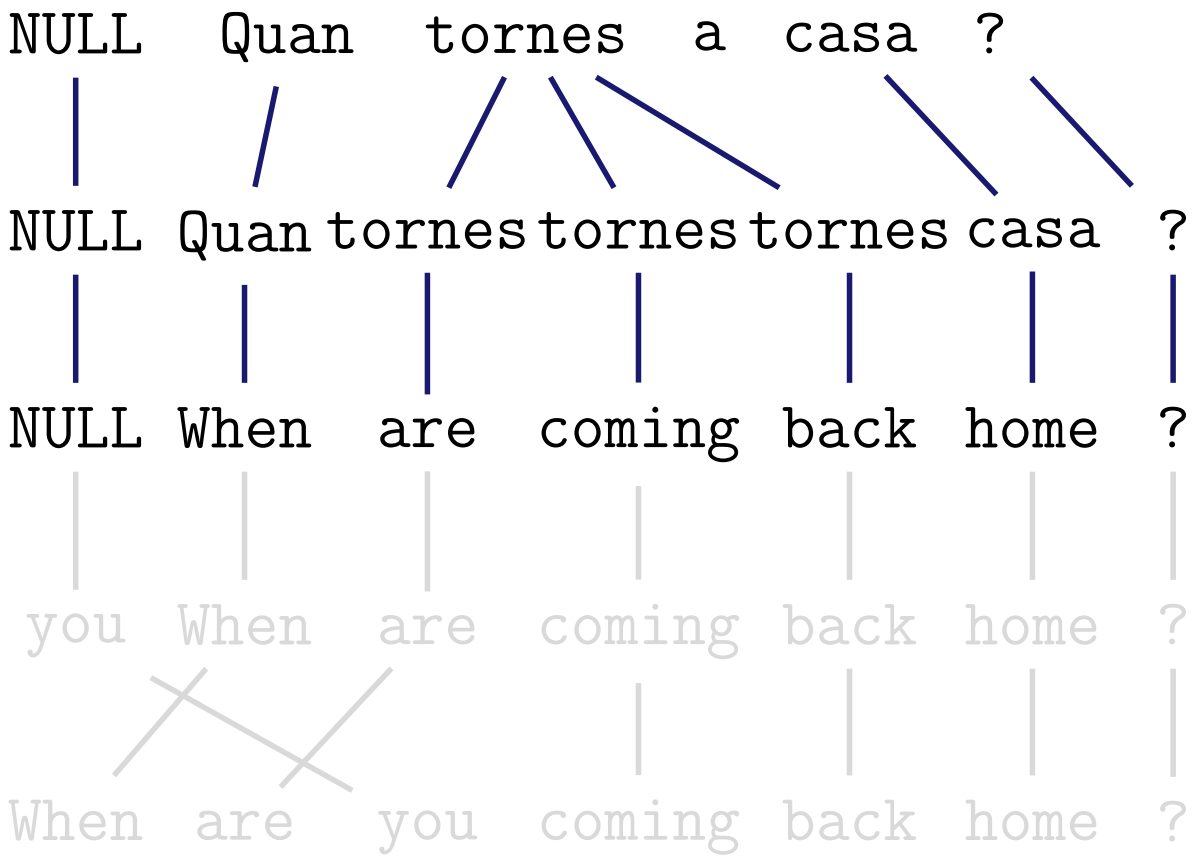

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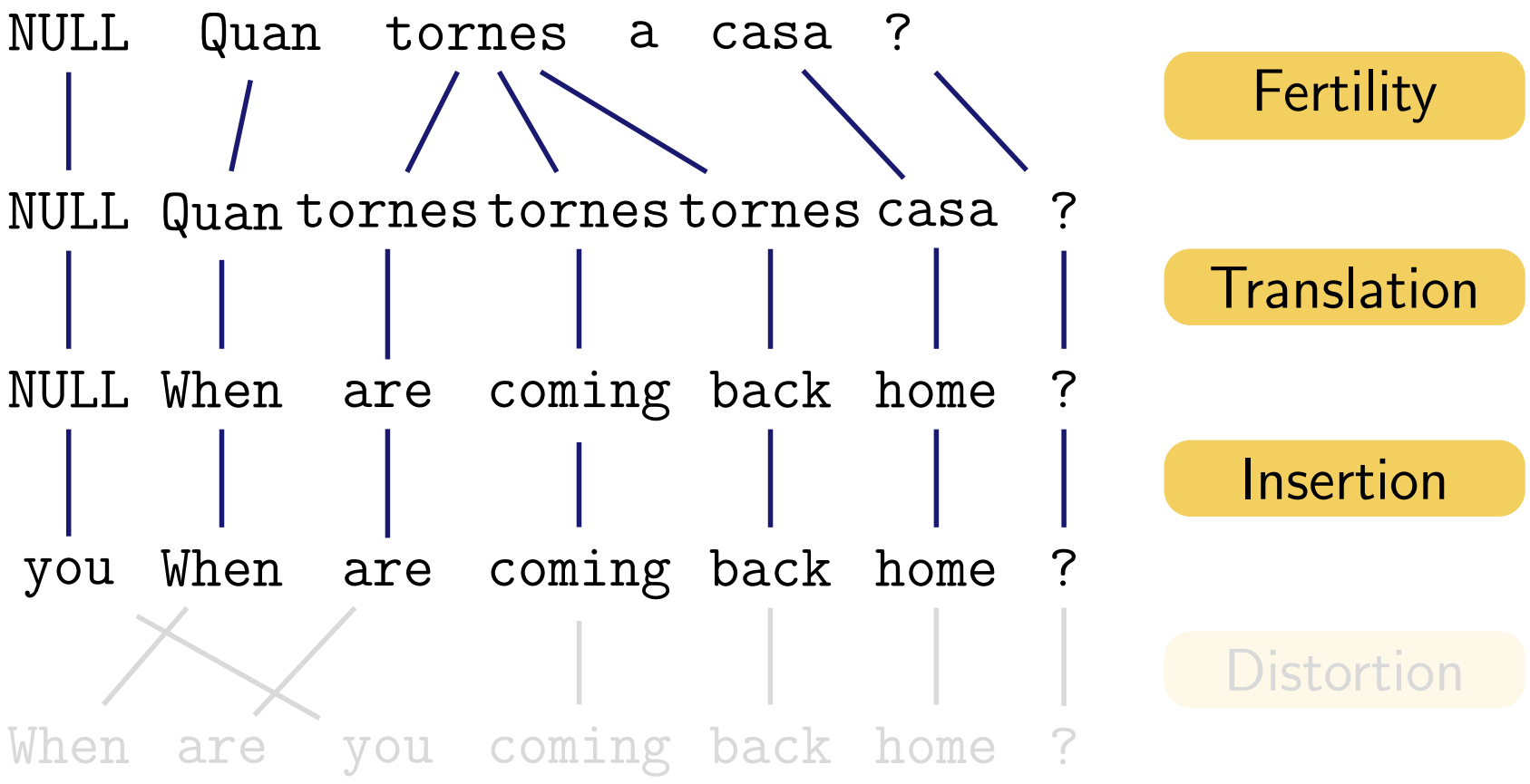

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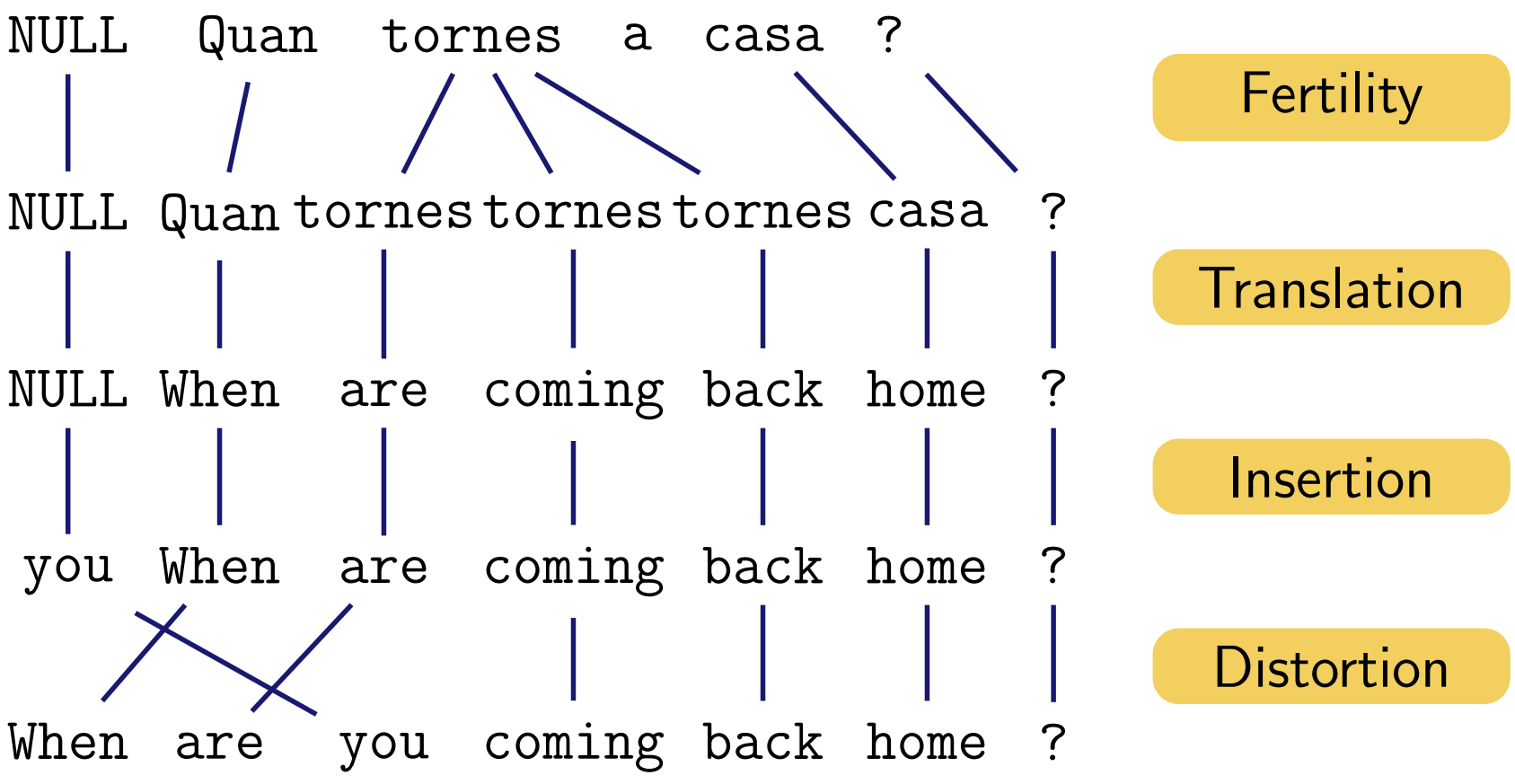

# SMT, components

## 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.

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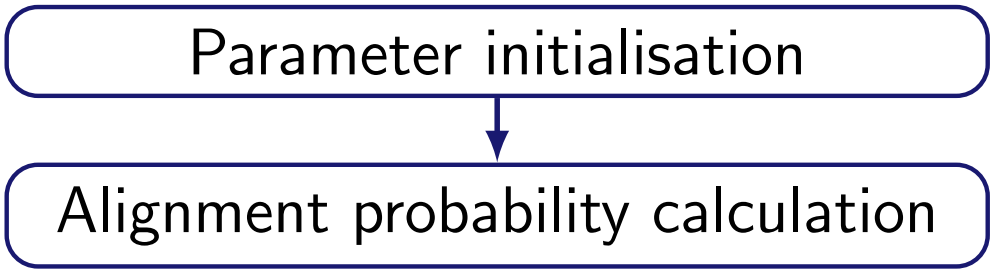
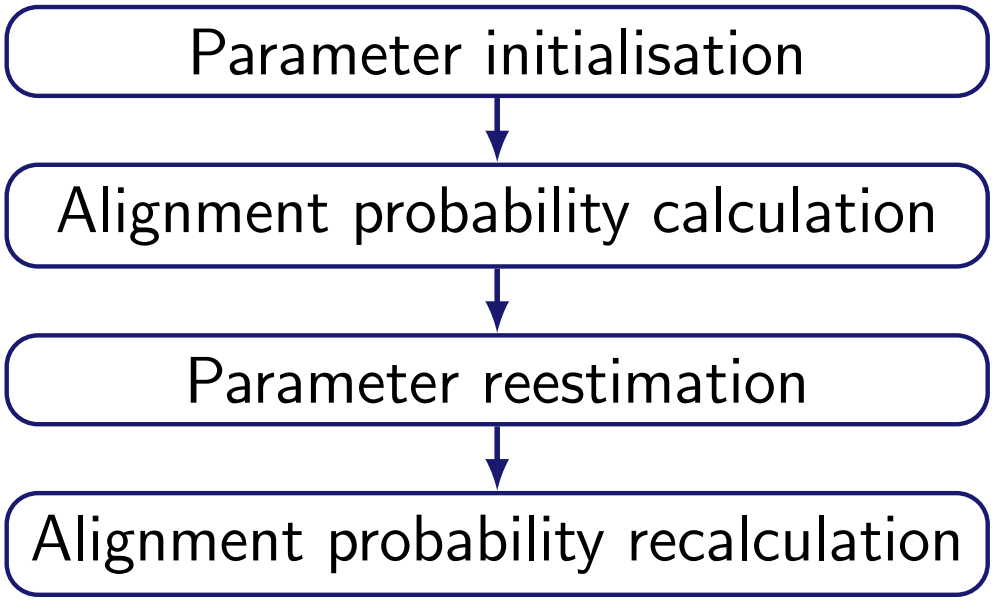
**Expectation-Maximisation algorithm**



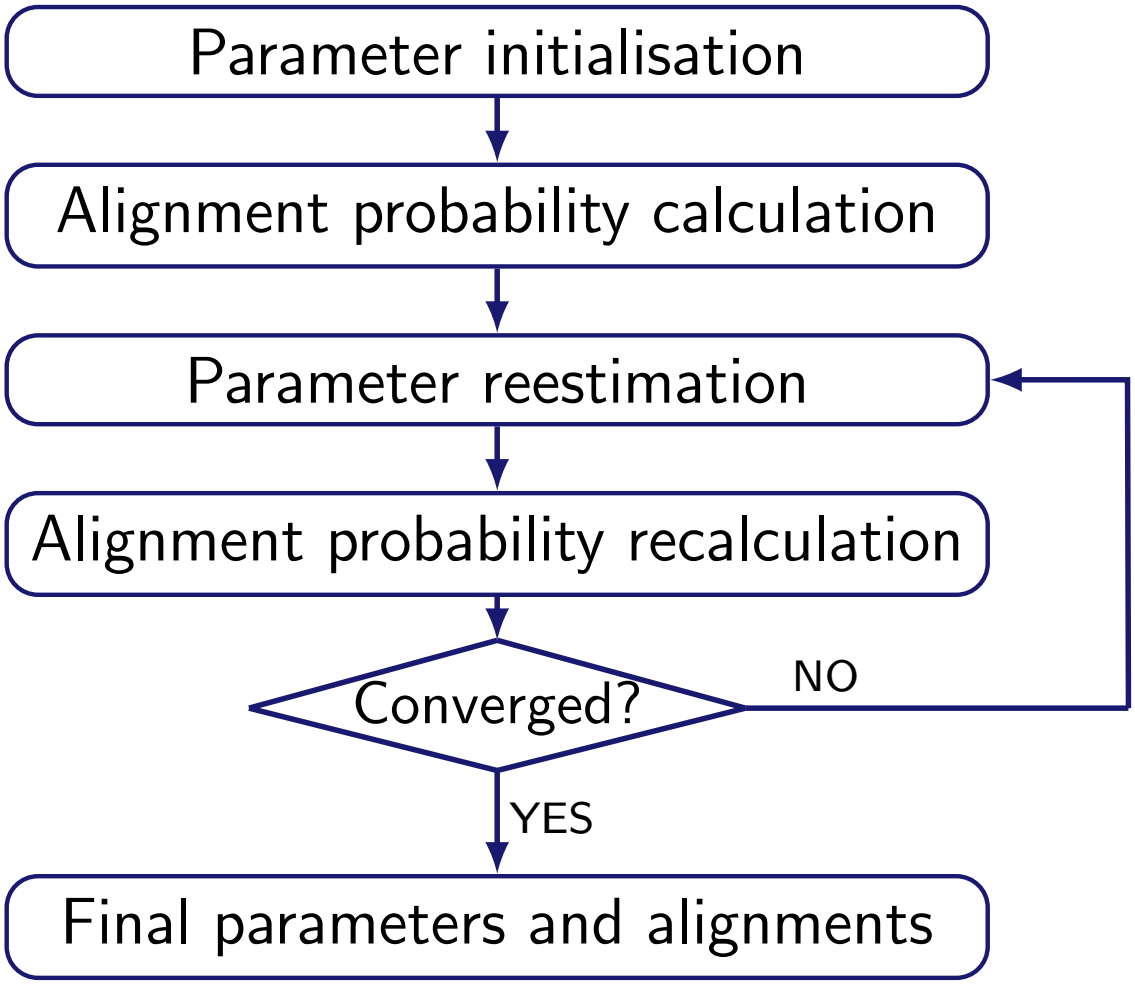
# SMT, components

## The translation model $P(f|e)$

**Expectation-Maximisation algorithm**



## Expectation-Maximisation algorithm

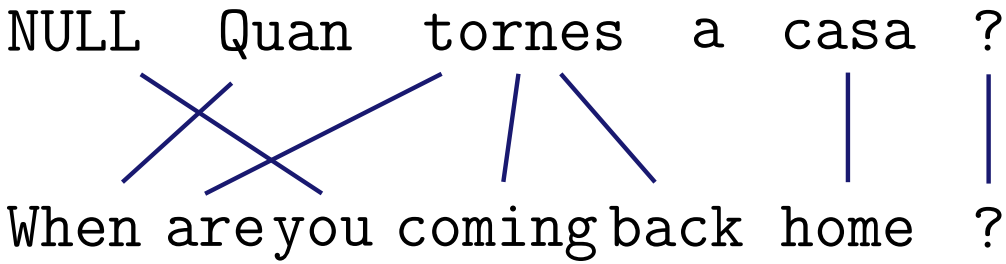


## Alignment's asymmetry

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

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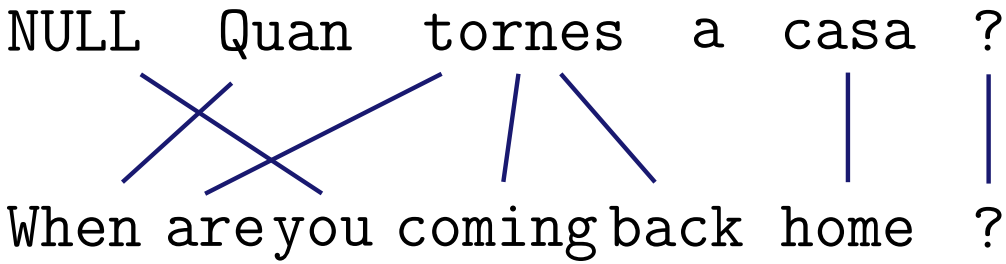
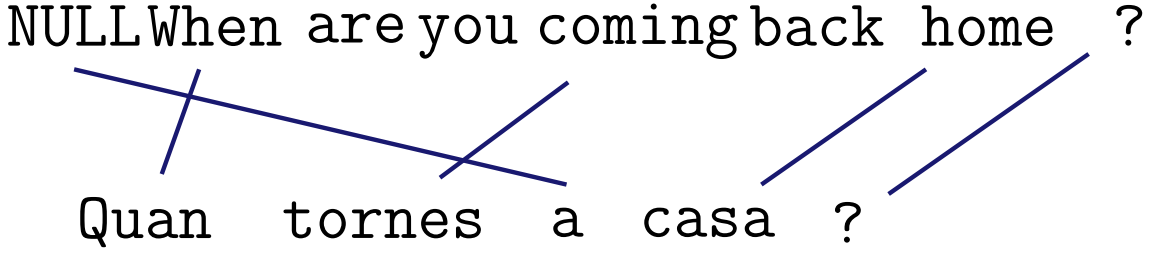



English to Catalan



# 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

# SMT, components

## The translation model $P(f|e)$

**In practice,**

```
cluster:/home/moses/giza.en-es> zmore en-es.A3.final.gz
```

```
# Sentence pair (1) source length 5 target length 4 alignment score: 0.00015062
resumption of the session
NULL ({ }) reanudacion ({ 1 }) del ({ 2 3 }) periodo ({ }) de ({ }) sesiones ({ 4 })

# Sentence pair (2) source length 33 target length 40 alignment score: 3.3682e-61
i declare resumed the session of the european parliament adjourned on friday 17
december 1999 , and i would like once again to wish you a happy new year in the
hope that you enjoyed a pleasant festive period .
NULL ({ 31 }) declaro ({ 1 }) reanudado ({ 2 3 }) el ({ 4 }) periodo ({ }) de ({ })
sesiones ({ 5 }) del ({ 6 7 }) parlamento ({ 9 }) europeo ({ 8 }) , ({ })
interrumpido ({ 10 }) el ({ }) viernes ({ 12 14 }) 17 ({ 11 13 }) de ({ }) diciembre
({ 15 }) pasado ({ }) , ({ 16 }) y ({ 17 }) reitero ({ 21 }) a ({ 23 }) sus ({ 30 })
senorias ({ }) mi ({ 18 }) deseo ({ 24 }) de ({ }) que ({ 33 }) hayan ({ 25 34 35 })
 tenido ({ }) unas ({ 19 20 }) buenas ({ 26 36 }) vacaciones ({ 22 27 28 29 32 37 38
 39 }) . ({ 40 })
```

# SMT, components

## The translation model $P(f|e)$

**In practice,**

```
cluster:/home/moses/giza.es-en> zmore es-en.A3.final.gz
```

```
# Sentence pair (1) source length 4 target length 5 alignment score: 1.08865e-07
reanudacion del periodo de sesiones
NULL ({ 4 }) resumption ({ 1 }) of ({ 2 }) the ({ }) session ({ 3 5 })

# Sentence pair (2) source length 40 target length 33 alignment score: 1.88268e-50
declaro reanudado el periodo de sesiones del parlamento europeo , interrumpido el
viernes 17 de diciembre pasado , y reitero a sus senorias mi deseo de que hayan
tenido unas buenas vacaciones .
NULL ({ 5 10 }) i ({ }) declare ({ 1 }) resumed ({ 2 }) the ({ 3 }) session ({ 4 6 })
of ({ 7 }) the ({ }) european ({ 9 }) parliament ({ 8 12 }) adjourned ({ 11 }) on
({ 15 }) friday ({ 13 }) 17 ({ 14 }) december ({ 16 17 }) 1999 ({ }) , ({ 18 }) and
({ 19 }) i ({ }) would ({ }) like ({ }) once ({ }) again ({ }) to ({ 21 }) wish ({ })
you ({ }) a ({ }) happy ({ }) new ({ }) year ({ }) in ({ 26 }) the ({ }) hope ({ }
) that ({ 27 }) you ({ }) enjoyed ({ 20 }) a ({ }) pleasant ({ 22 23 24 25 28 29 })
festive ({ 30 31 32 }) period ({ }) . ({ 33 })
```

# SMT, components

## The translation model $P(f|e)$

```
cluster:/home/moses/model> more aligned.grow-diag-final


0-0 1-1 1-2 2-3 4-3

0-0 0-1 1-1 1-2 2-3 3-4 5-4 6-5 6-6 8-7 7-8 11-8 10-9 13-10 14-10 12-11
13-12 12-13 15-14 17-15 18-16 23-17 19-20 20-22 24-23 21-29 26-32 27-33
27-34 30-35 28-36 31-36 29-37 30-37 31-37 31-38 32-39
```

# SMT, components

## The translation model $P(f|e)$

```
cluster:/home/moses/model> more lex.e2f

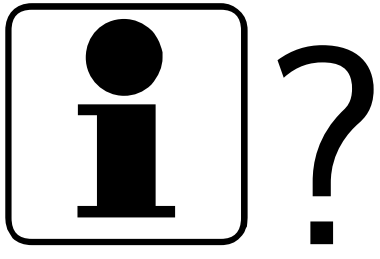
tuneles tunnels 0.7500000
tuneles transit 0.2000000
estructuralmente weak 1.0000000
estructuralmente structurally 0.5000000
destruido had 0.0454545
para tunnels 0.2500000
sean transit 0.2000000
transito transit 0.6000000
...

cluster:/home/moses/model> more lex.f2e

tunnels tuneles 0.7500000
transit tuneles 0.2500000
weak estructuralmente 0.5000000
structurally estructuralmente 0.5000000
...
```

# SMT, components

## The translation model $P(f|e)$

?

?

## 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: $\phi$

## 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.`

## From Word-based to Phrase-based models

f: En David llegeix el llibre nou.

e: David reads the book new. $\sim$

## From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the new book.` ✓

## From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the new book.` ✓

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

## From Word-based to Phrase-based models

f: `En David llegeix el llibre nou.`

e: `David reads the new book.` ✓

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

e: $\phi$

## From Word-based to Phrase-based models

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.

e: David reads the new book. ✓

f: En David llegeix el llibre de nou.

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e: David reads the book again.

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f: `En David llegeix el llibre nou.`

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f: En David llegeix el llibre nou.

e: David reads the new book. ✓

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e: David reads the book of new. ✗

e: David reads the book again. ✓

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

# SMT, components

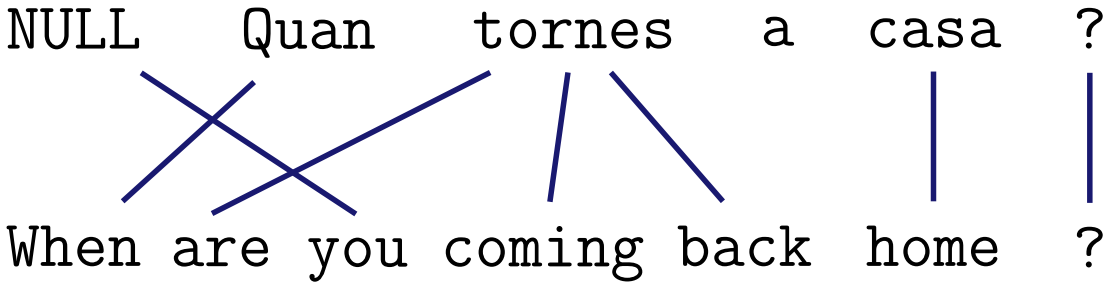
## The translation model $P(f|e)$

**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 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.
3. Reorder the output.

# SMT, components

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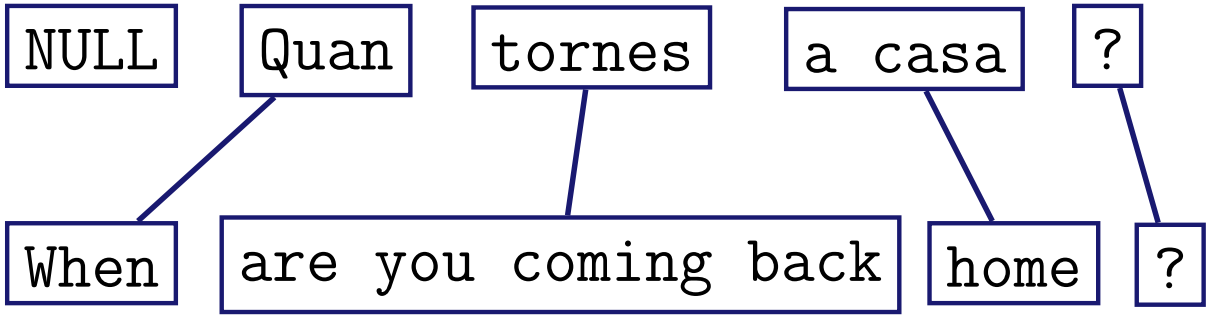


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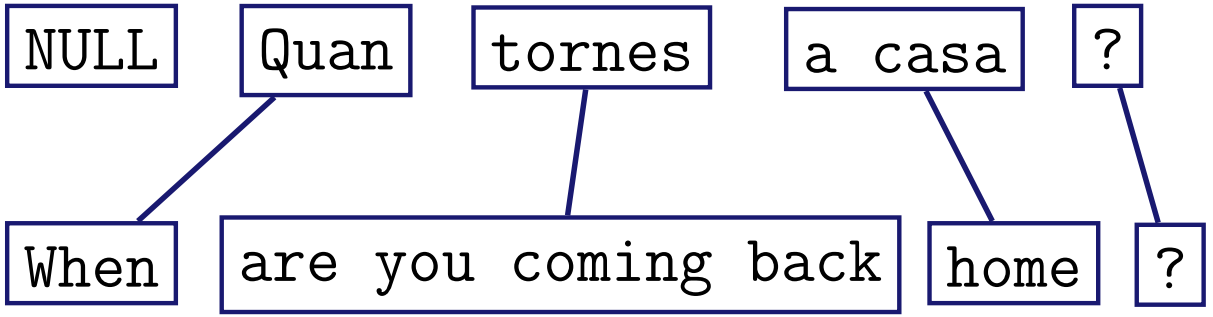


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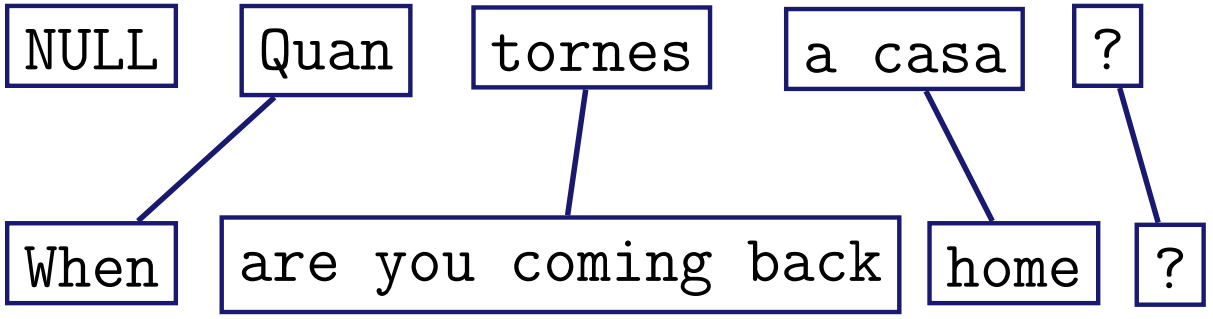


But...

- 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

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# SMT, components

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[1] 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, When are you coming back)

# SMT, components

## The translation model $P(f|e)$

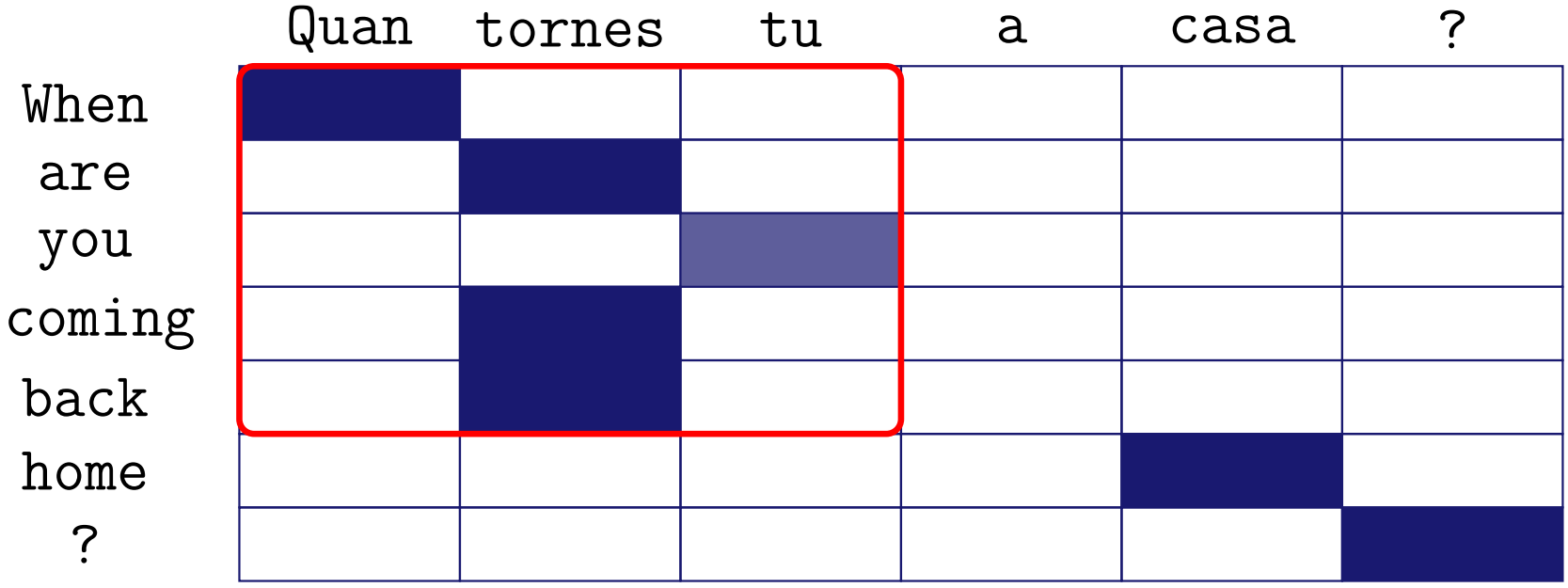
**Phrase extraction** through an example:


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

# SMT, components

## The translation model $P(f|e)$

**Phrase extraction** through an example:



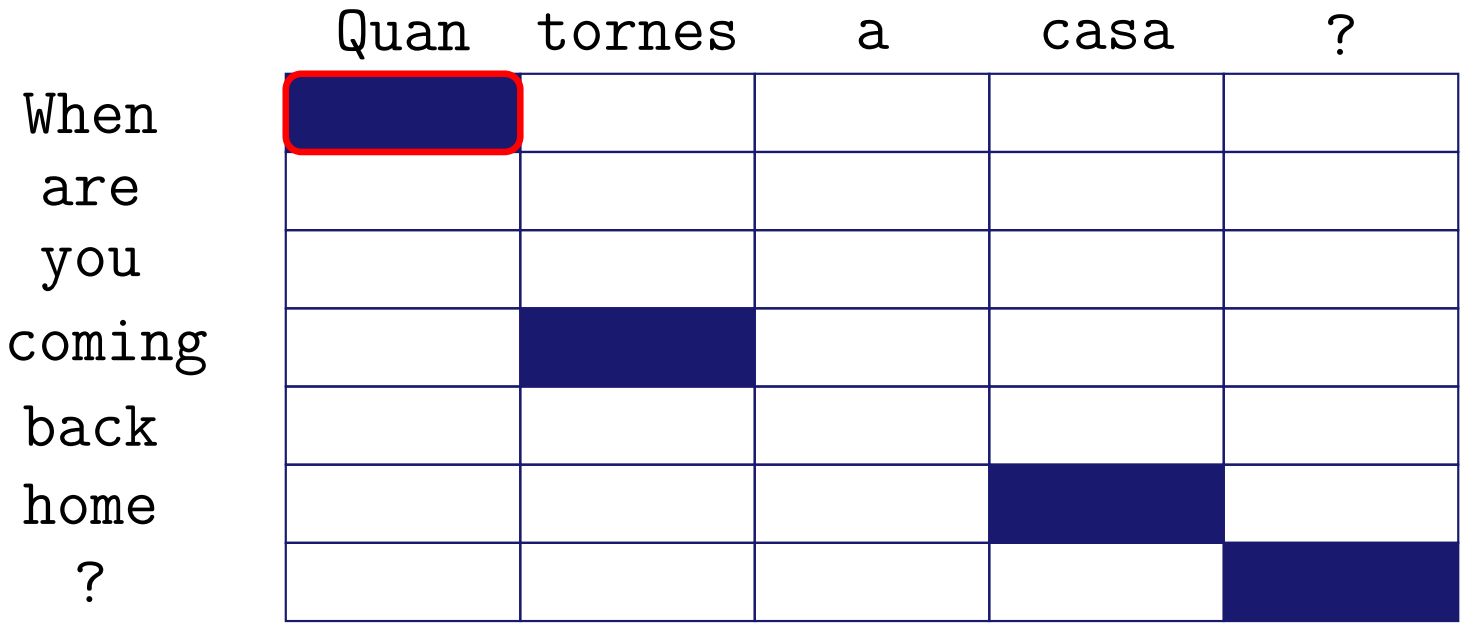

~~(Quan tornes, When are you coming back)~~

(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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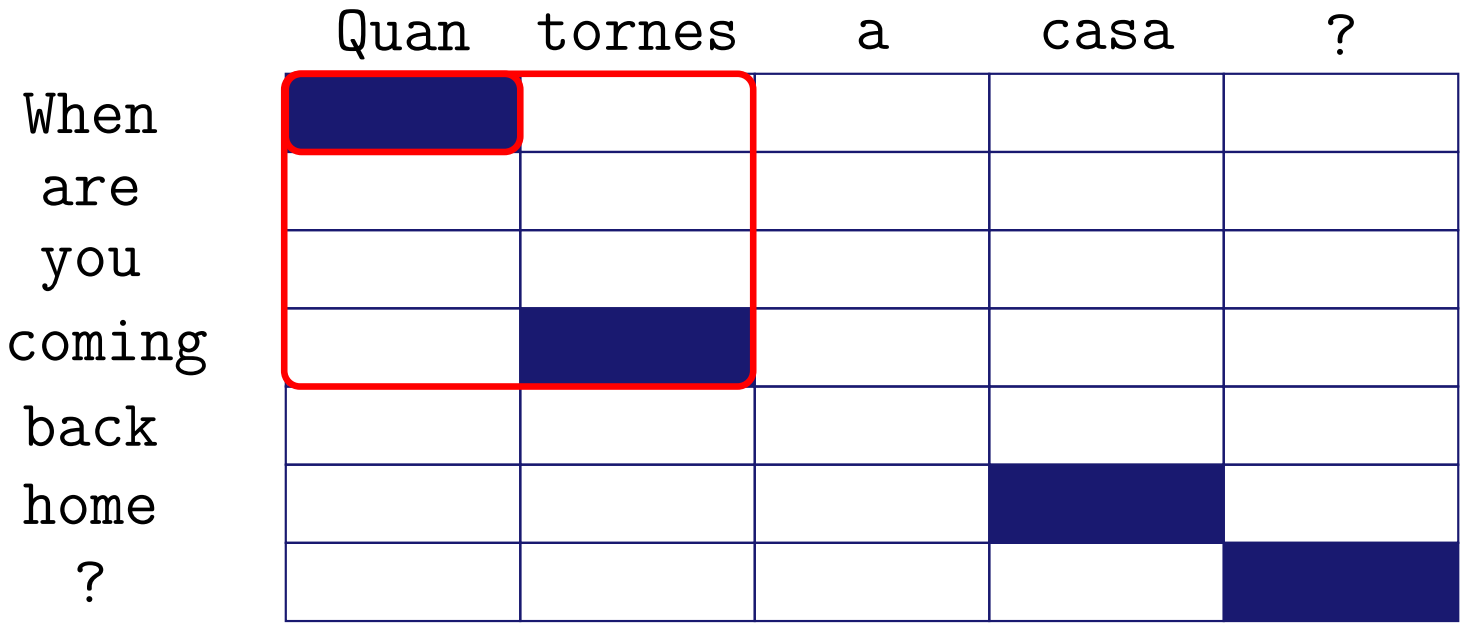


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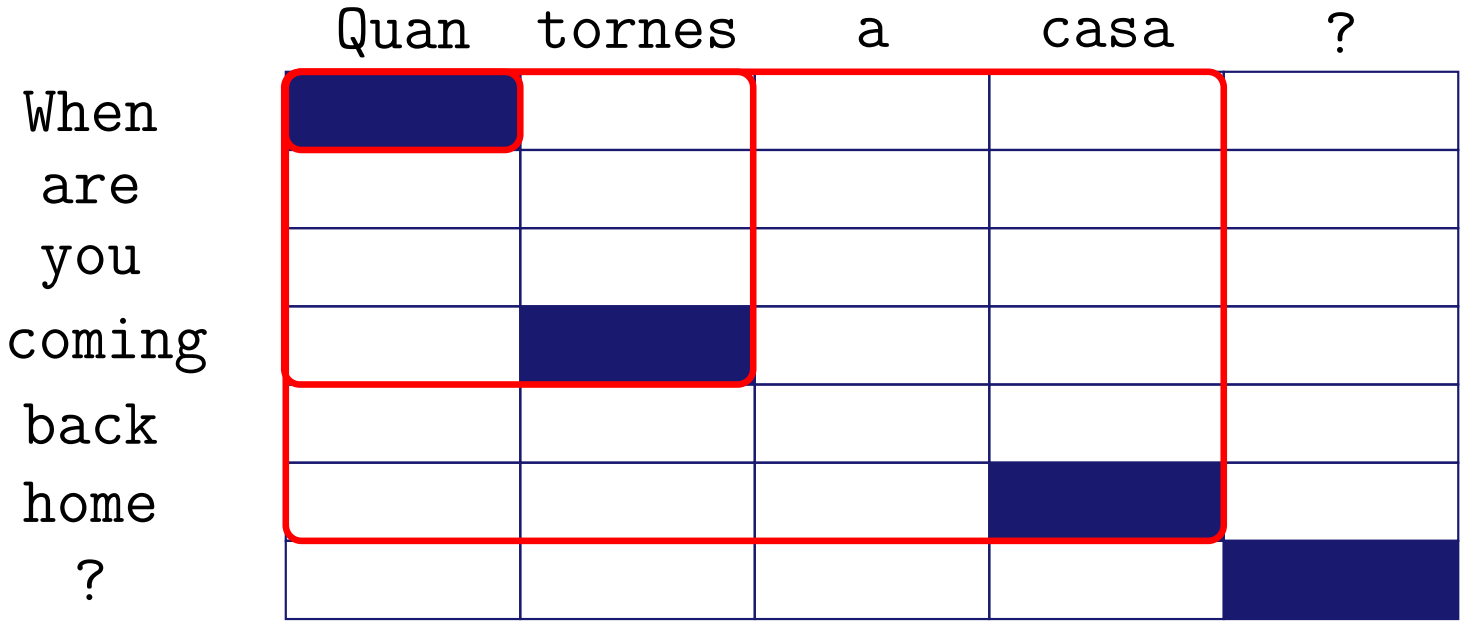


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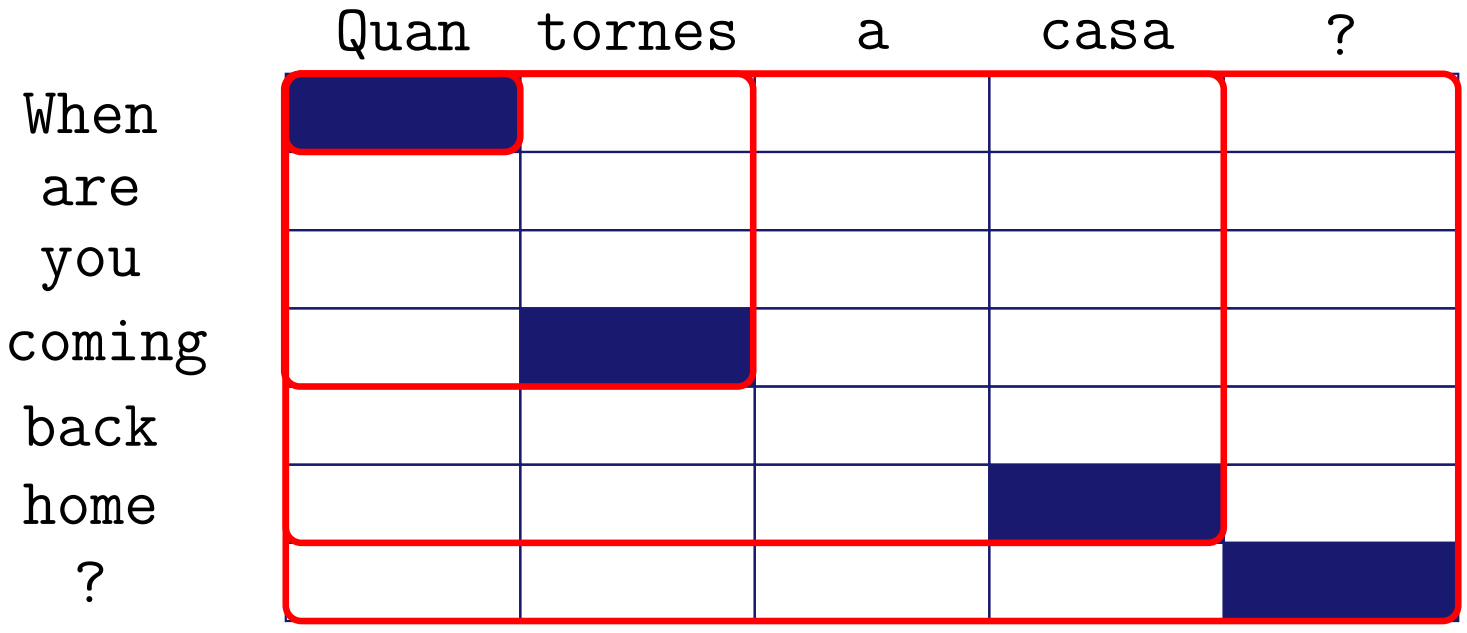


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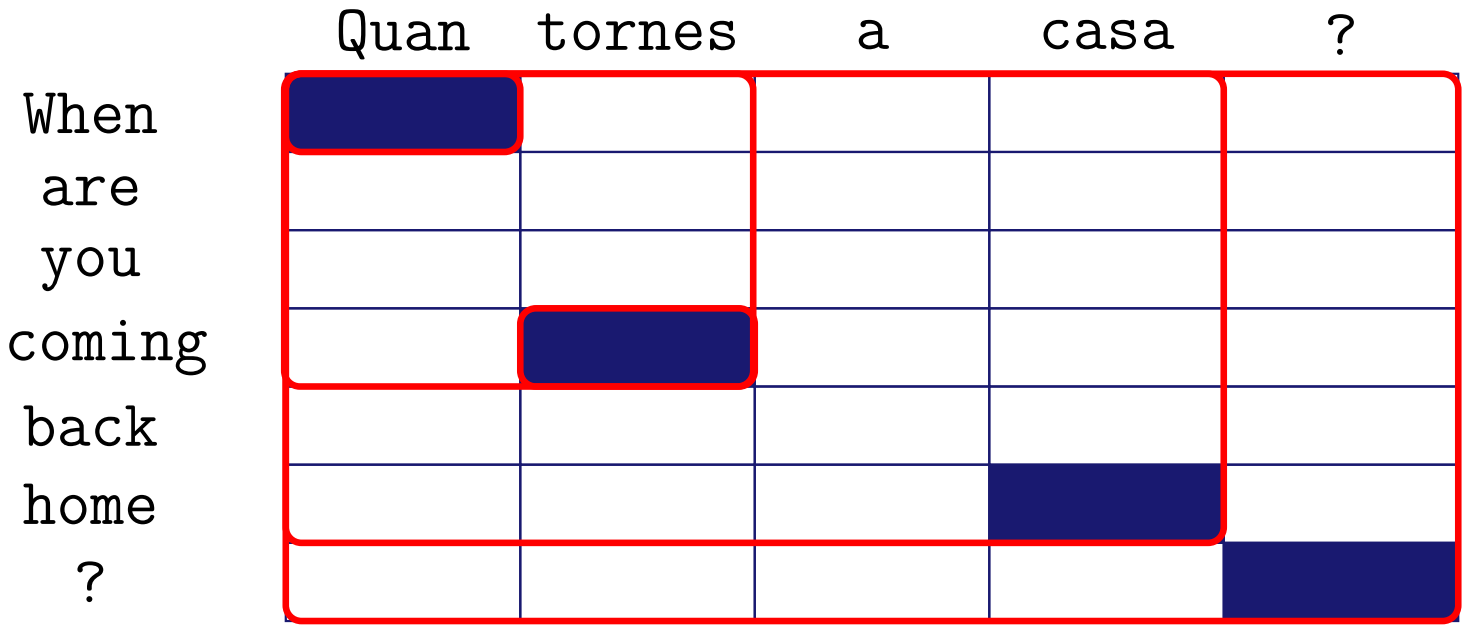


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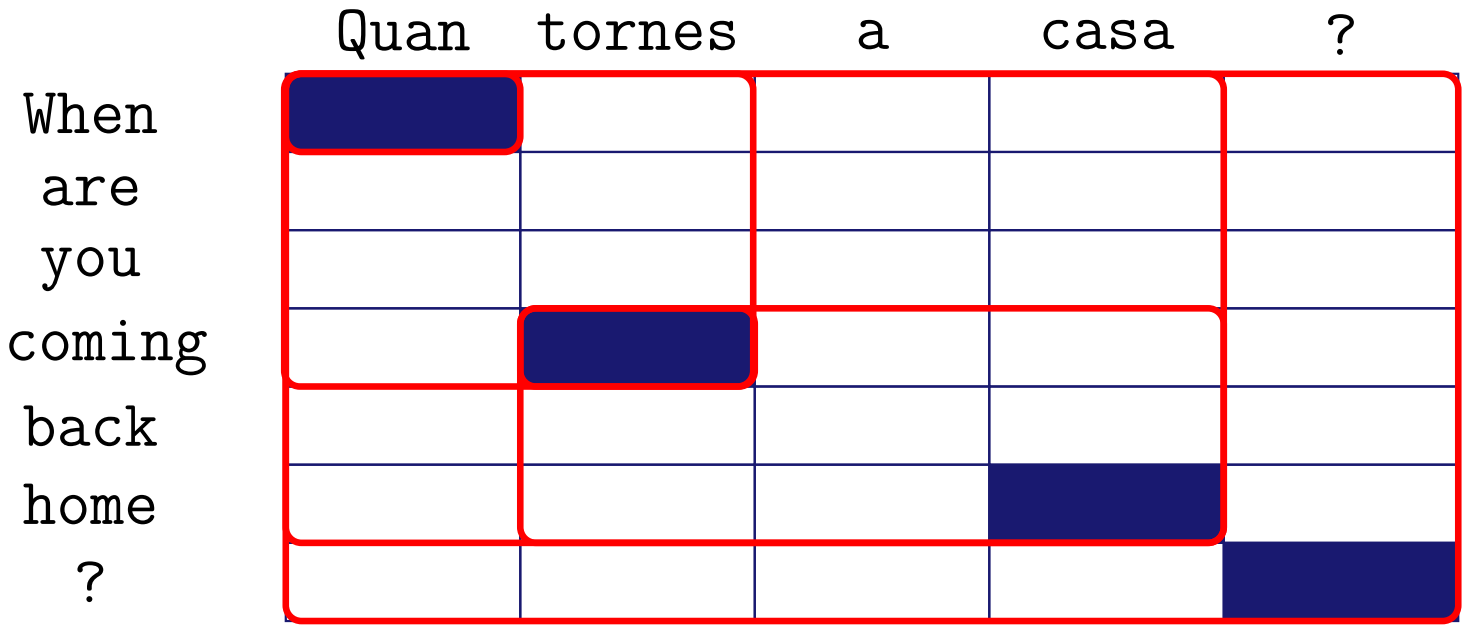


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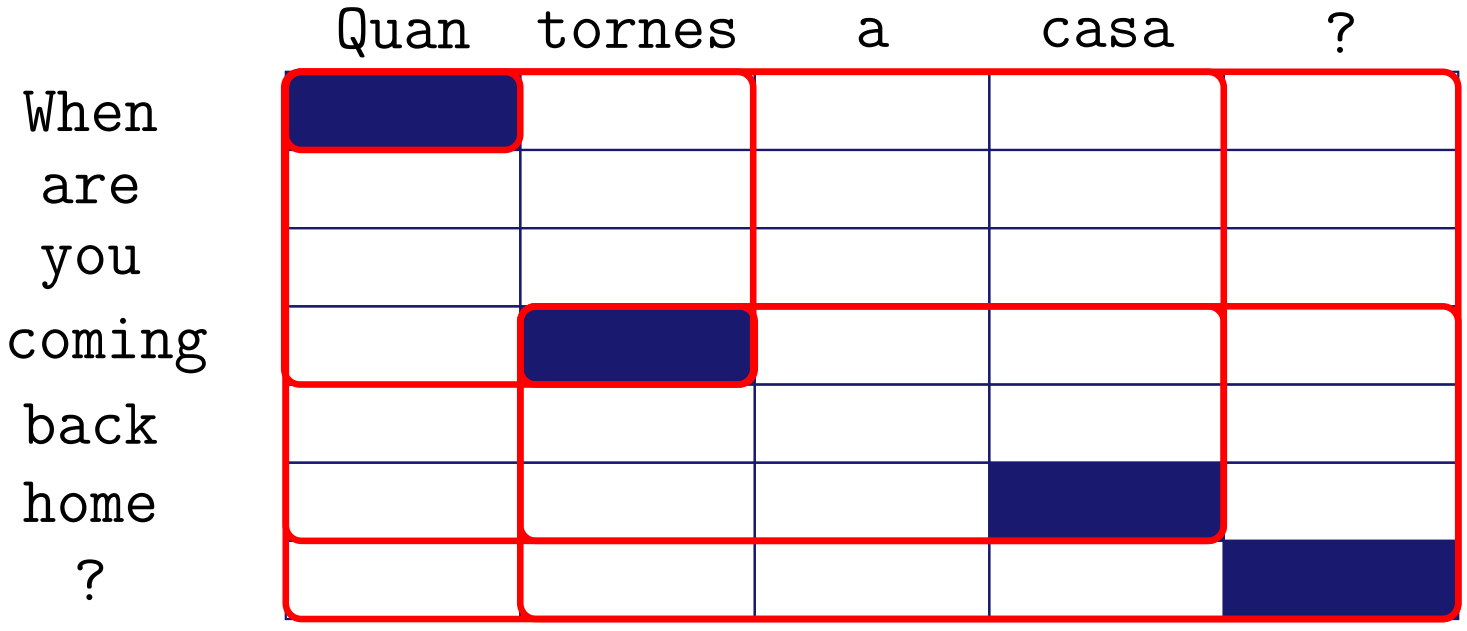


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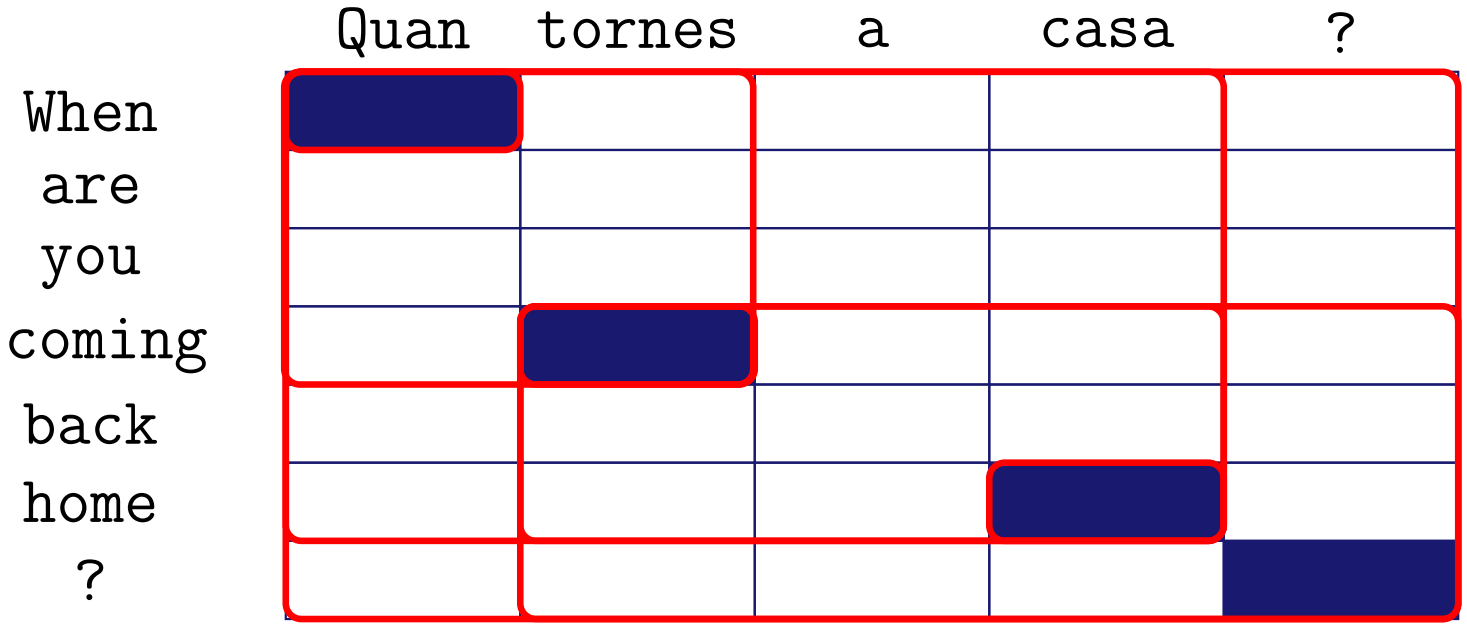


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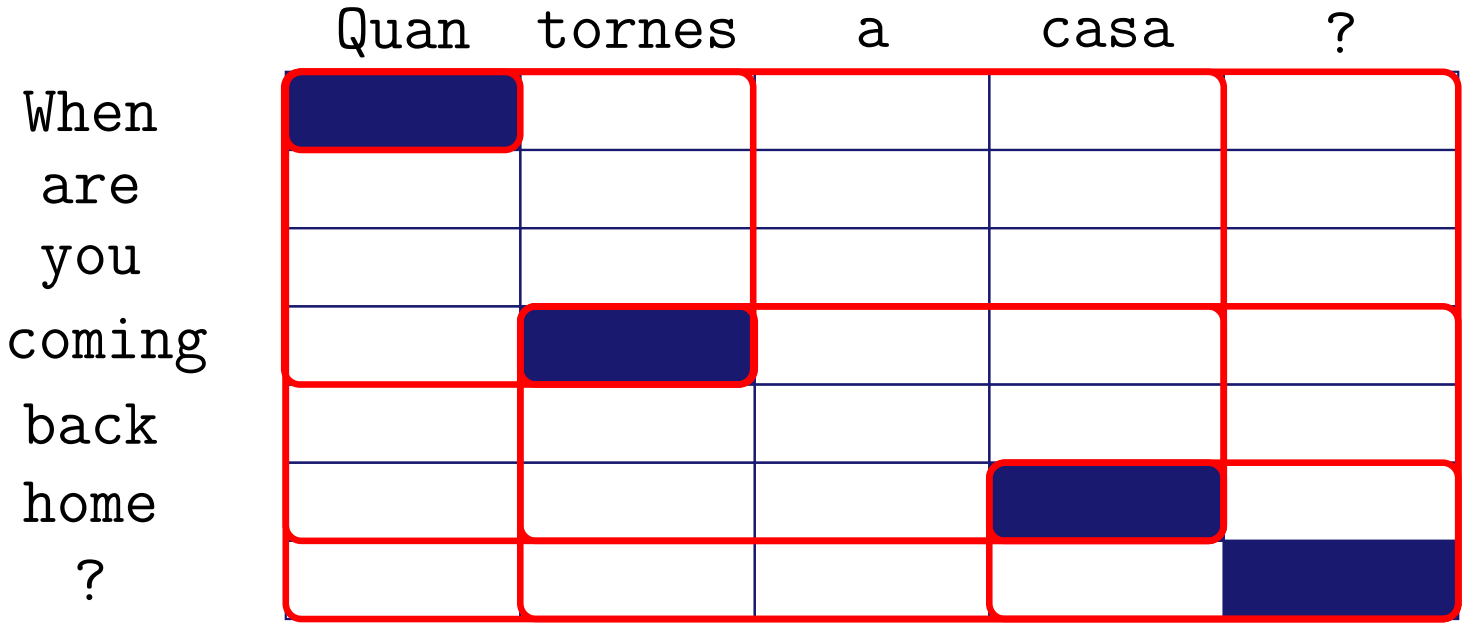


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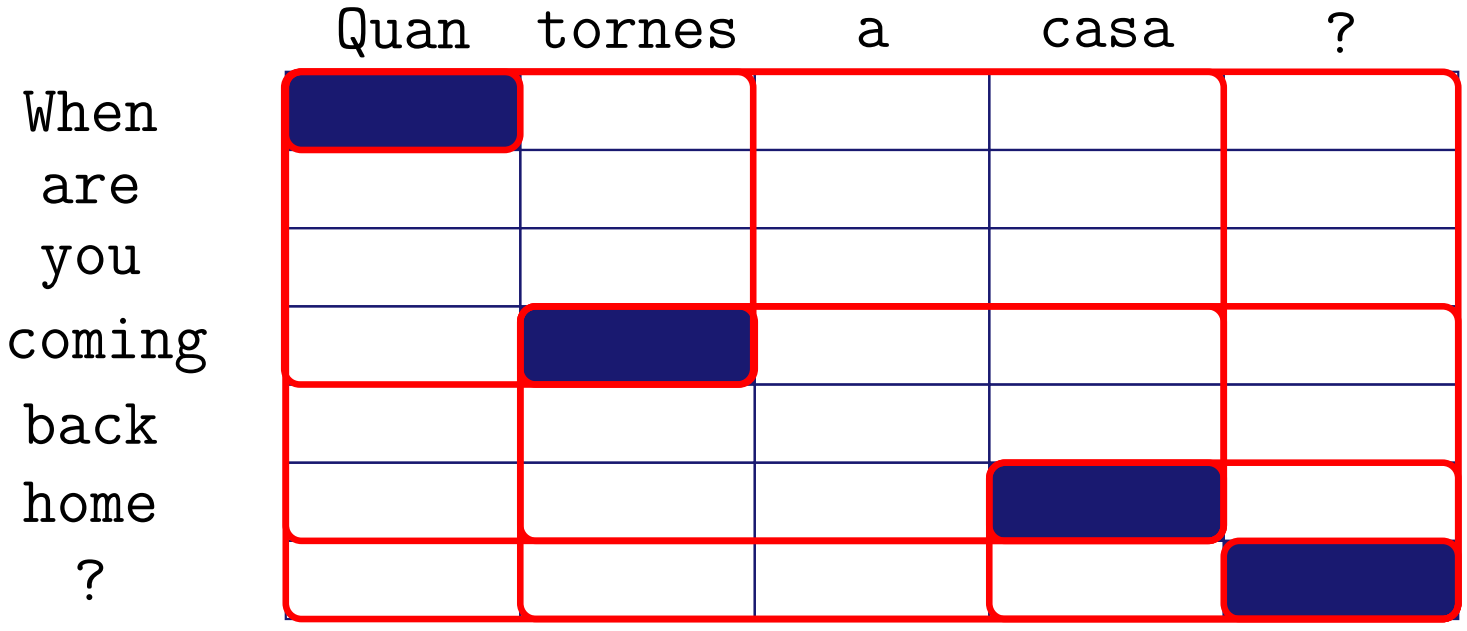


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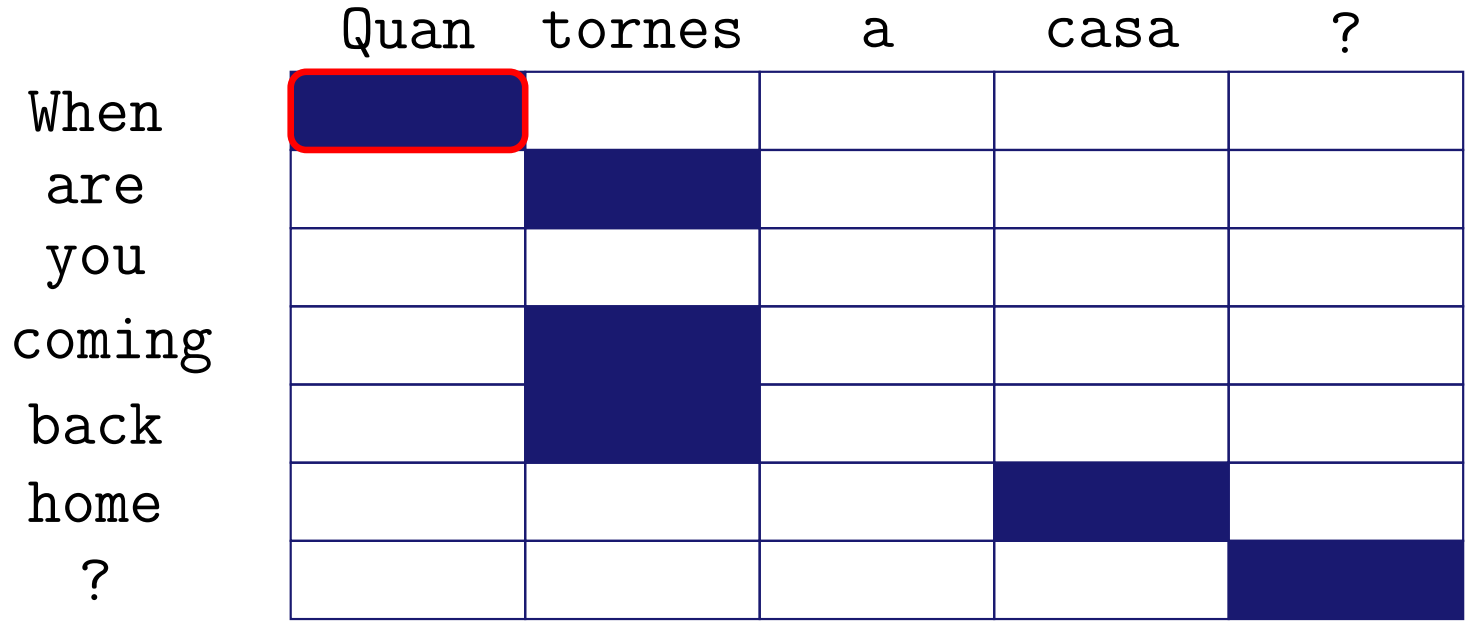
# SMT, components

## The translation model $P(f|e)$

**Union**

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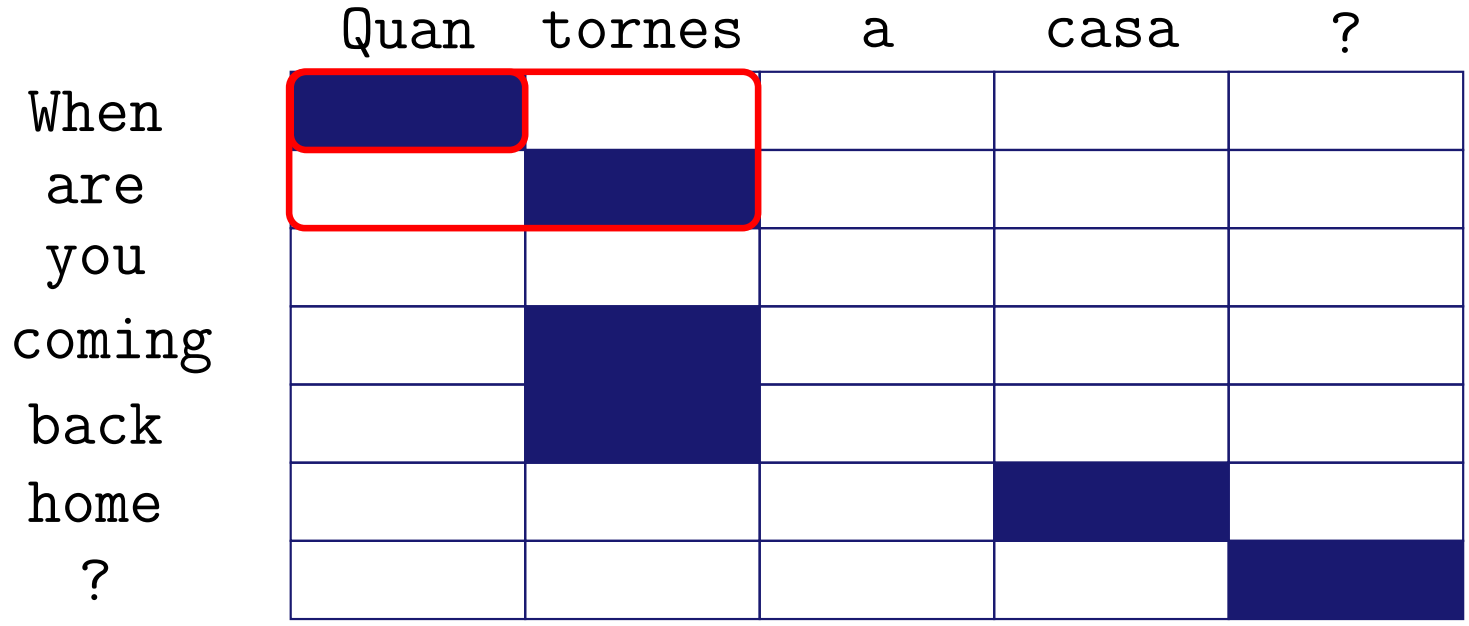


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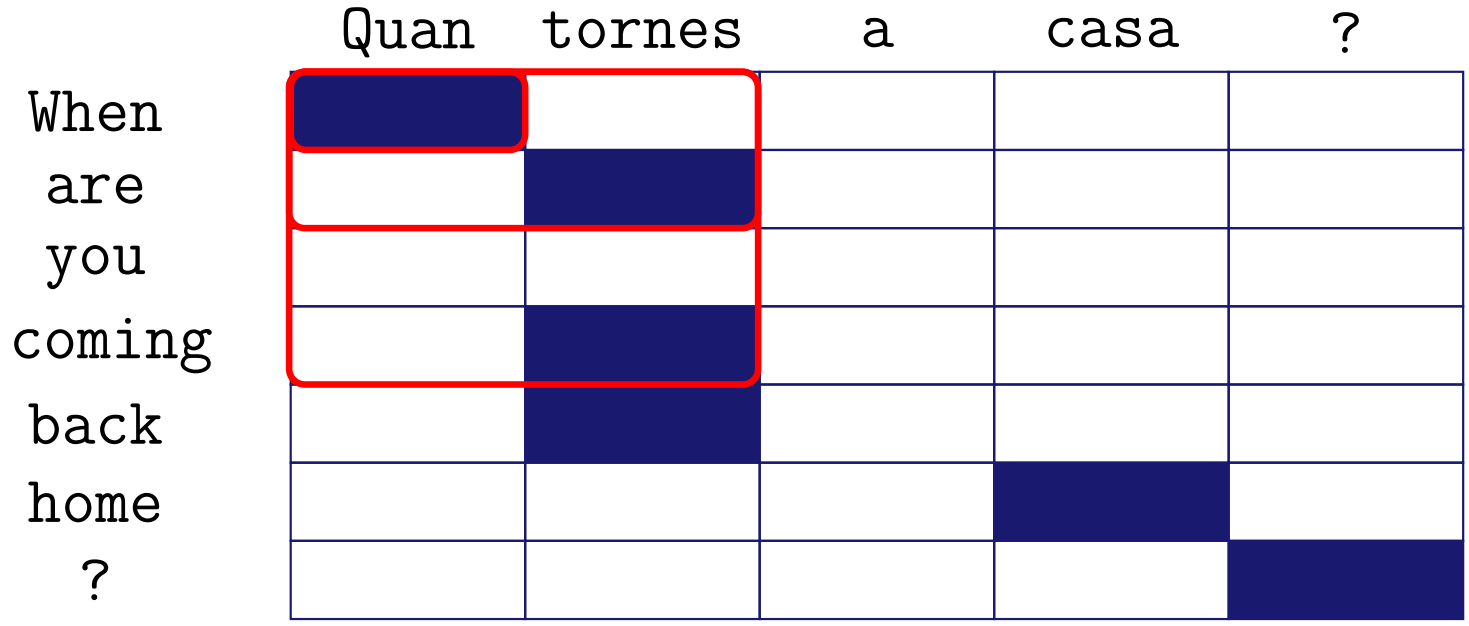


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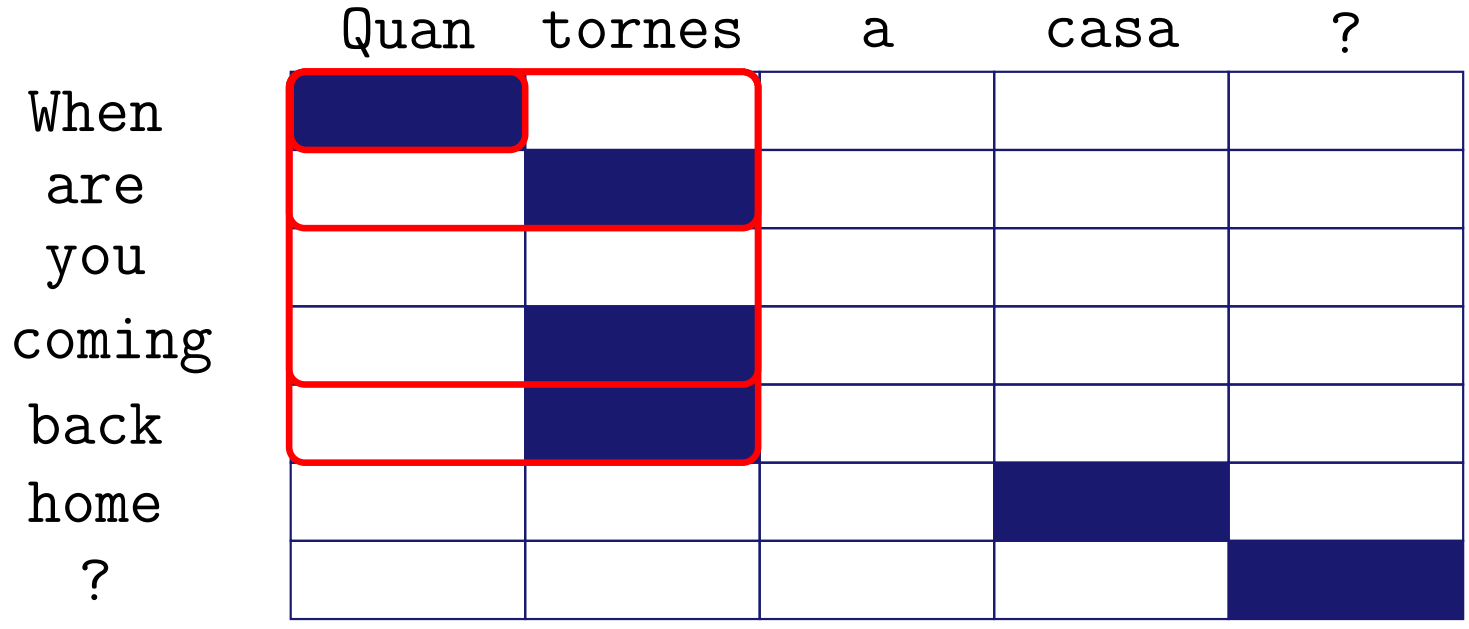


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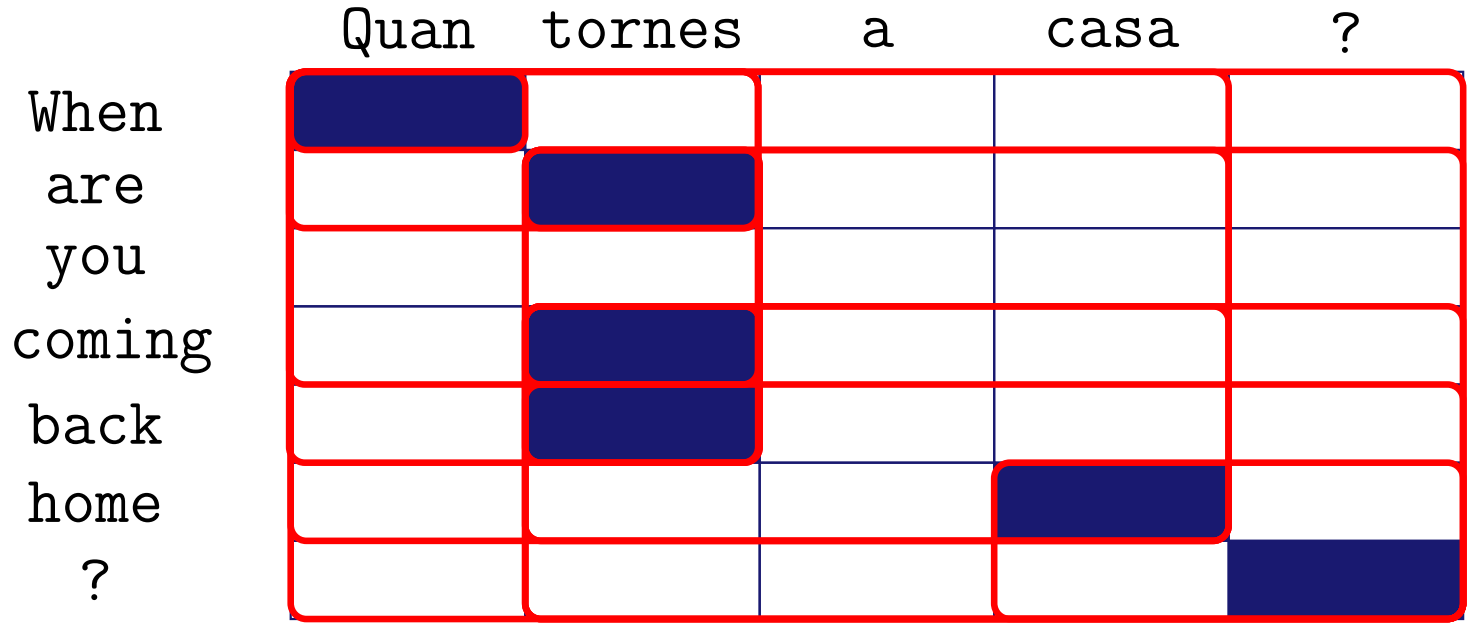


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## Phrase extraction

- 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.

# SMT, components

## The translation model $P(f|e)$

**In practice,**

```
cluster:/home/moses/model> zmore extract.gz

reanudacion ||| resumption ||| 0-0
reanudacion del ||| resumption of the ||| 0-0 1-1 1-2
reanudacion del periodo de sesiones ||| resumption of the session ||| 0-0 1-1 1-2 2-3 4-3

cluster:/home/moses/model> zmore extract.inv.gz

resumption ||| reanudacion ||| 0-0
resumption of the ||| reanudacion del ||| 0-0 1-1 2-1
resumption of the session ||| reanudacion del periodo de sesiones ||| 0-0 1-1 2-1 3-2 3-4

cluster:/home/moses/model> zmore extract.o.gz

reanudacion ||| resumption ||| mono mono
reanudacion del ||| resumption of the ||| mono mono
reanudacion del periodo de sesiones ||| resumption of the session ||| mono mono
```

# SMT, components

## The translation model $P(f|e)$

```
cluster:/home/moses/model> zmore phrase-table.gz
```

```
be consistent ||| coherentes ||| 0.0384615 0.146893 0.0833333 0.0116792 2.718 ||| 1-0 ||| 26 12
be consistent ||| sean coherentes ||| 0.2 0.00022714 0.0833333 0.0916808 2.718 ||| 0-0 1-1 ||| 5 12
be consistent ||| sean consistentes ||| 0.5 0.000104834 0.0833333 0.0785835 2.718 ||| 0-0 1-1 ||| 2 12
be consistent ||| ser coherente ||| 0.5 0.0204044 0.166667 0.569957 2.718 ||| 0-0 1-1 ||| 4 12
be consistent ||| ser consecuente ||| 1 0.000340072 0.0833333 0.759942 2.718 ||| 0-0 1-1 ||| 1 12
be consistent ||| ser consistente ||| 1 0.00850183 0.5 0.633285 2.718 ||| 0-0 1-1 ||| 6 12
consistent when ||| coherente cuando se ||| 1 0.00783857 1 0.329794 2.718 ||| 0-0 1-1 1-2 ||| 1 1
consistent ||| adecuado ||| 0.00512821 0.0112994 0.00671141 0.009009 2.718 ||| 0-0 ||| 195 149
consistent ||| coherencia ||| 0.137931 0.0282486 0.0268456 0.0847458 2.718 ||| 0-0 ||| 29 149
consistent ||| constante ||| 0.0333333 0.0112994 0.0134228 0.0307692 2.718 ||| 0-0 ||| 60 149
consistent ||| constantes ||| 0.0625 0.0056497 0.00671141 0.047619 2.718 ||| 0-0 ||| 16 149
...
```

# 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.

# SMT, components

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# SMT, components

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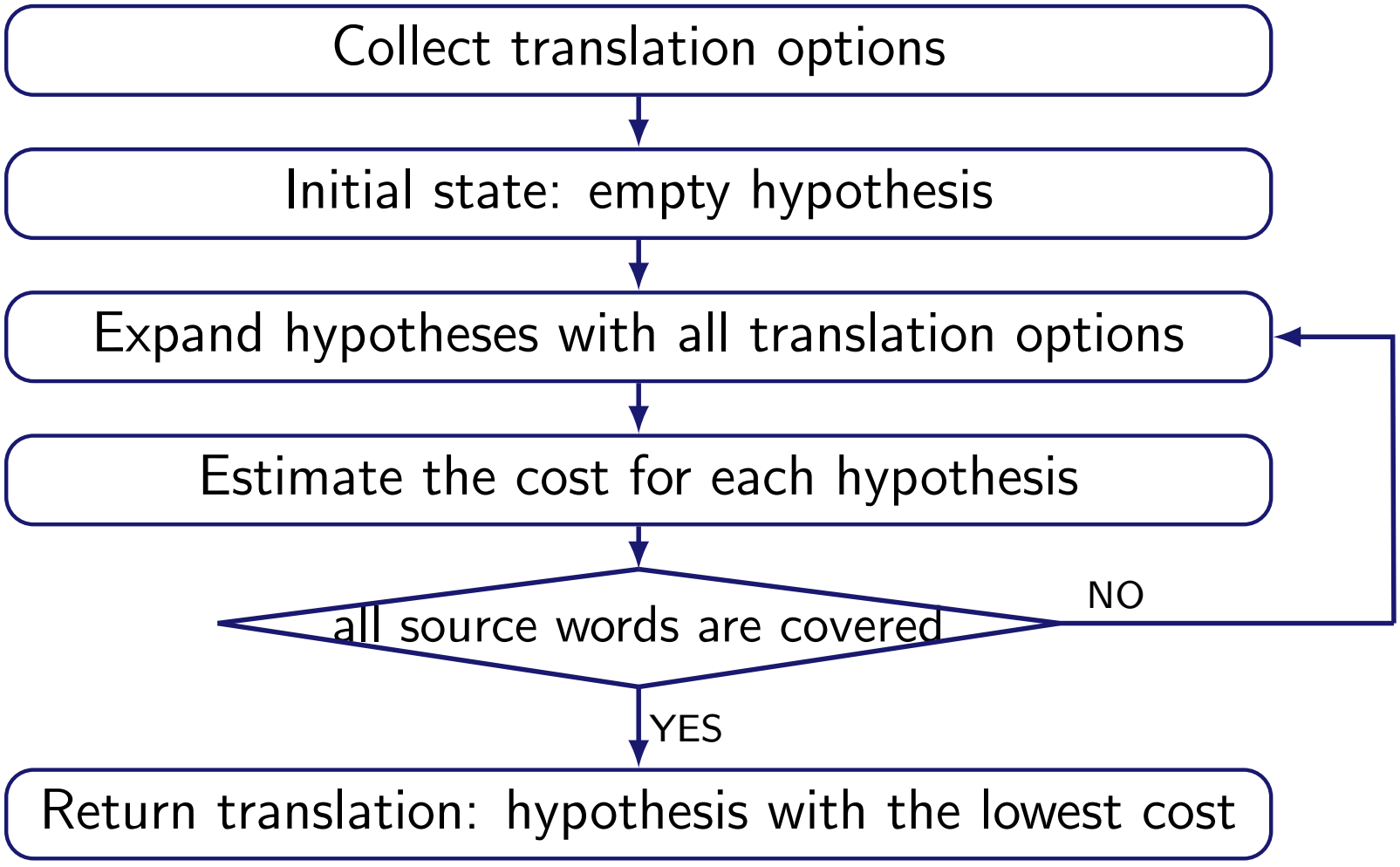
- Beam search decoders. Let's see..

# 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

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

  Constructed sentence so far: $\phi$

  Source words already translated: - - - -

# SMT, components

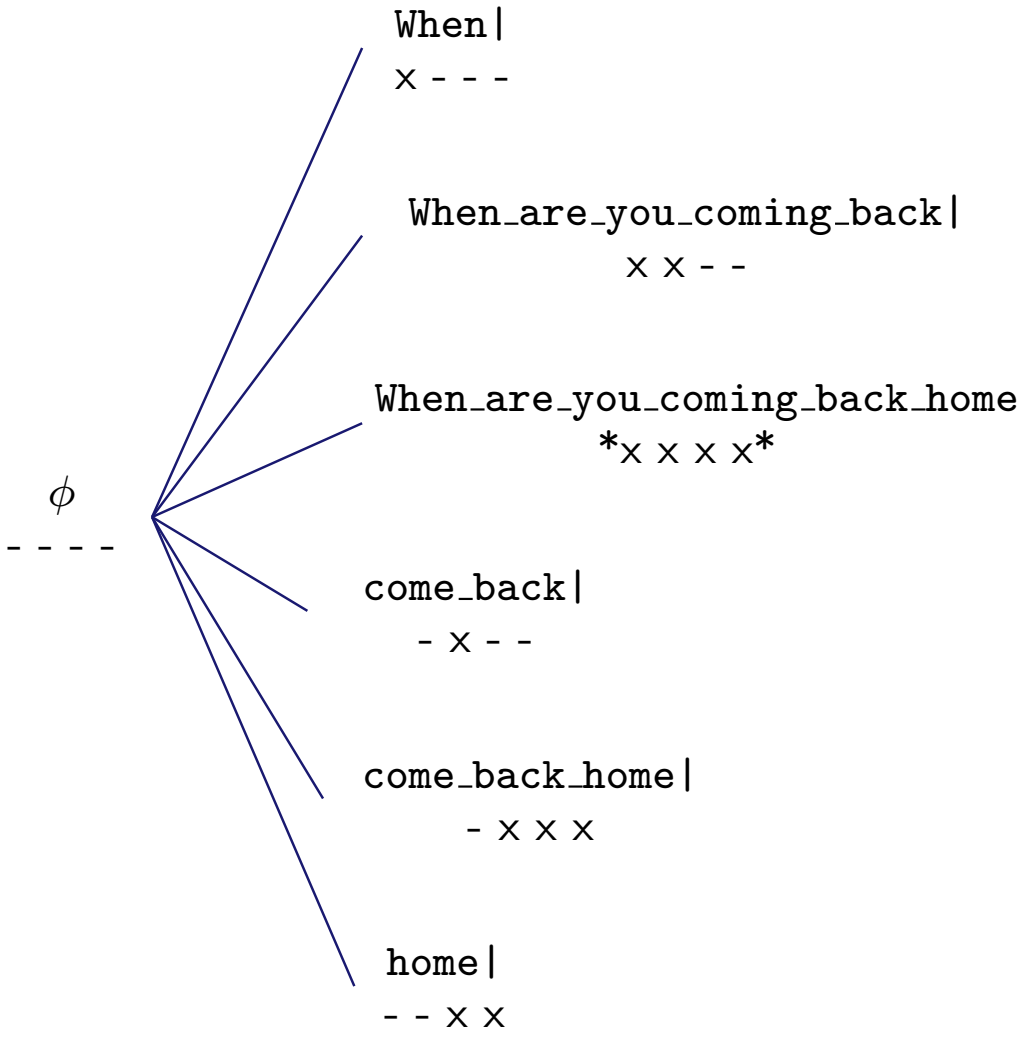
## A beam-search decoder

$\phi$

- - - -

# SMT, components

## A beam-search decoder



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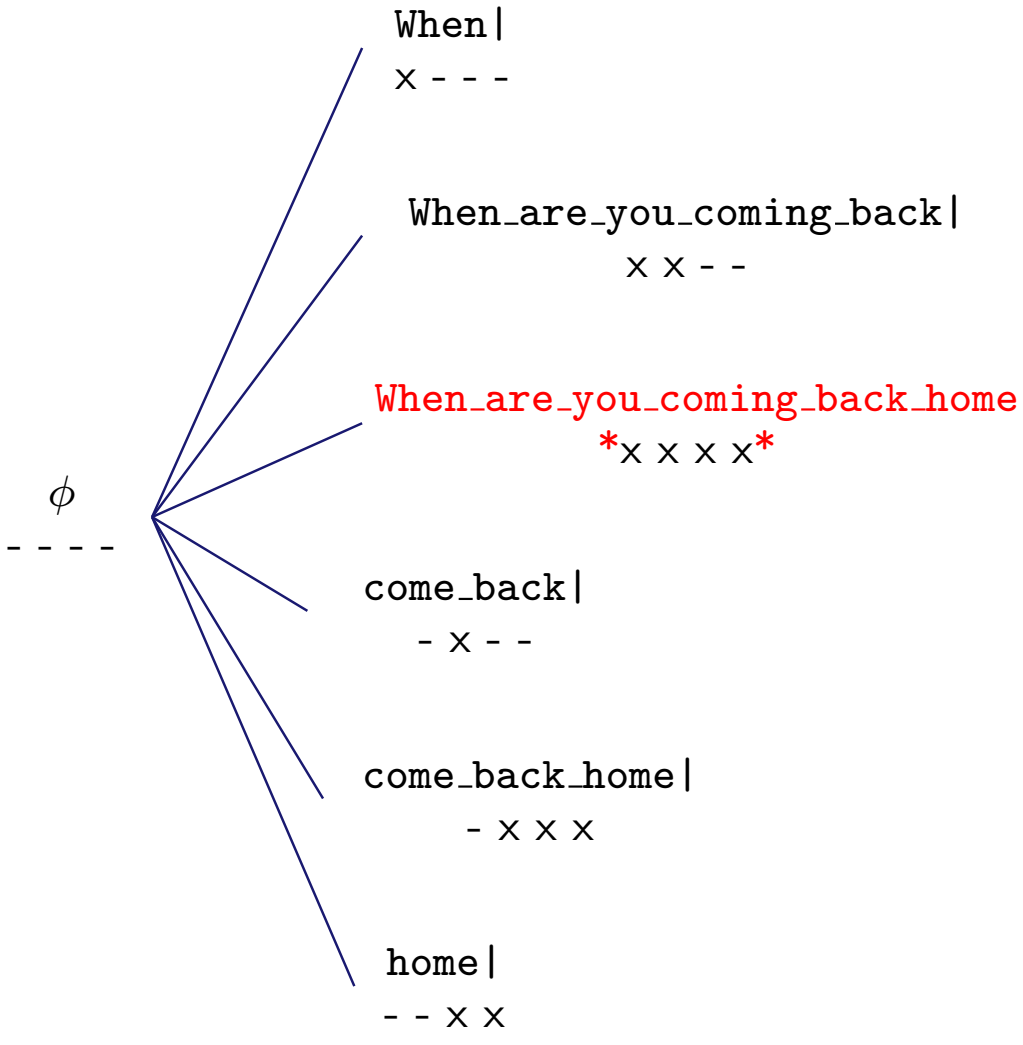

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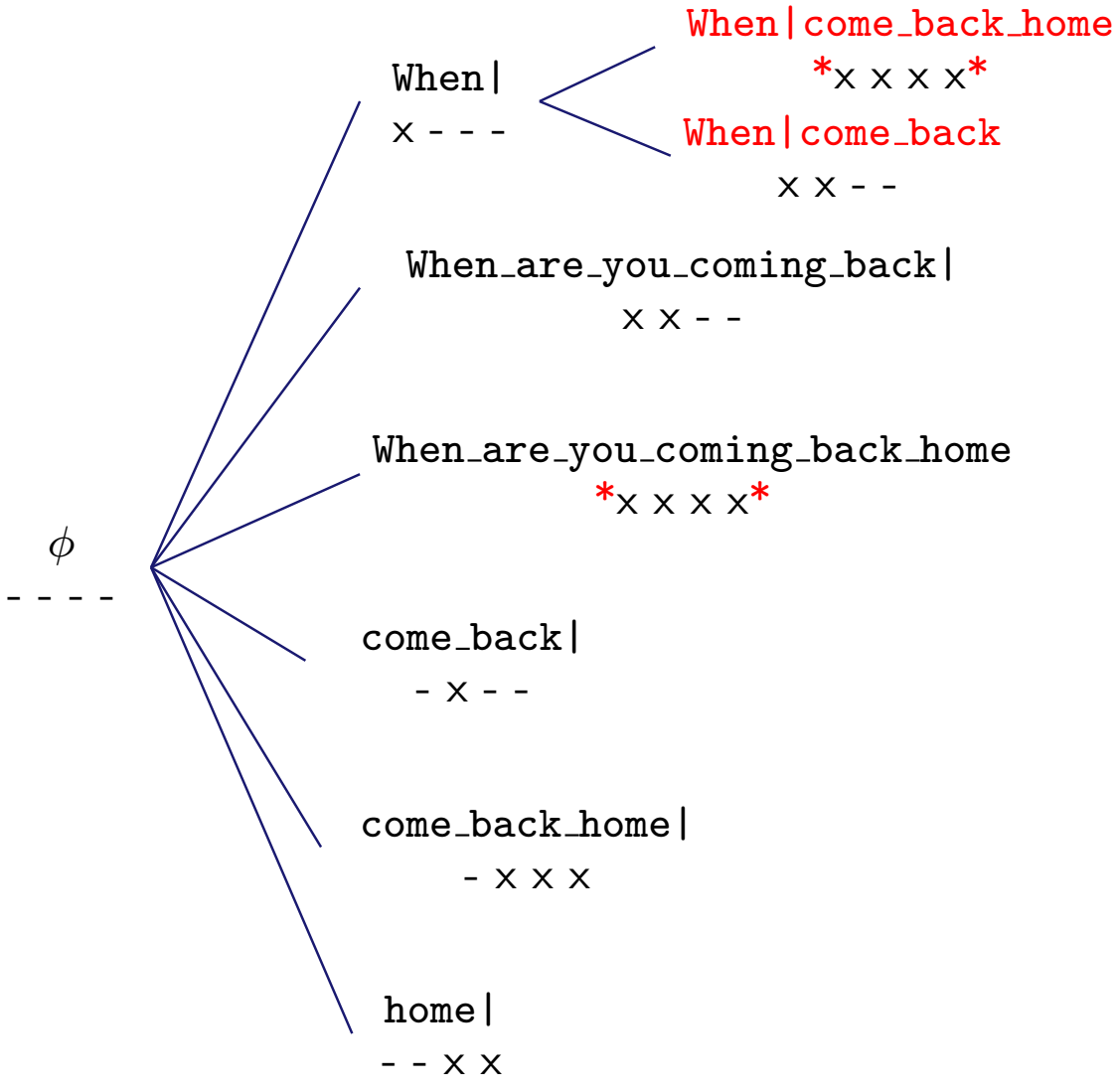

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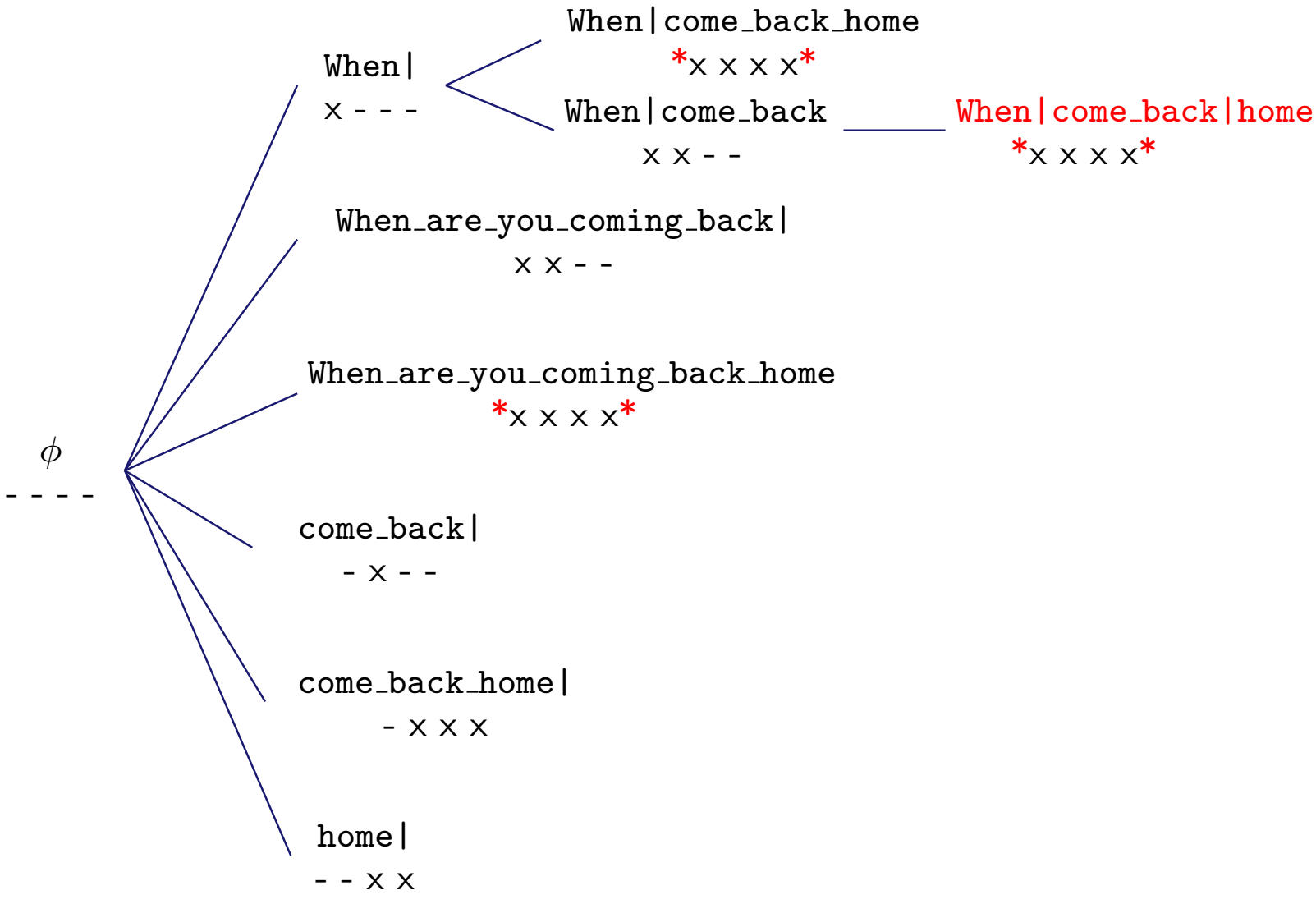

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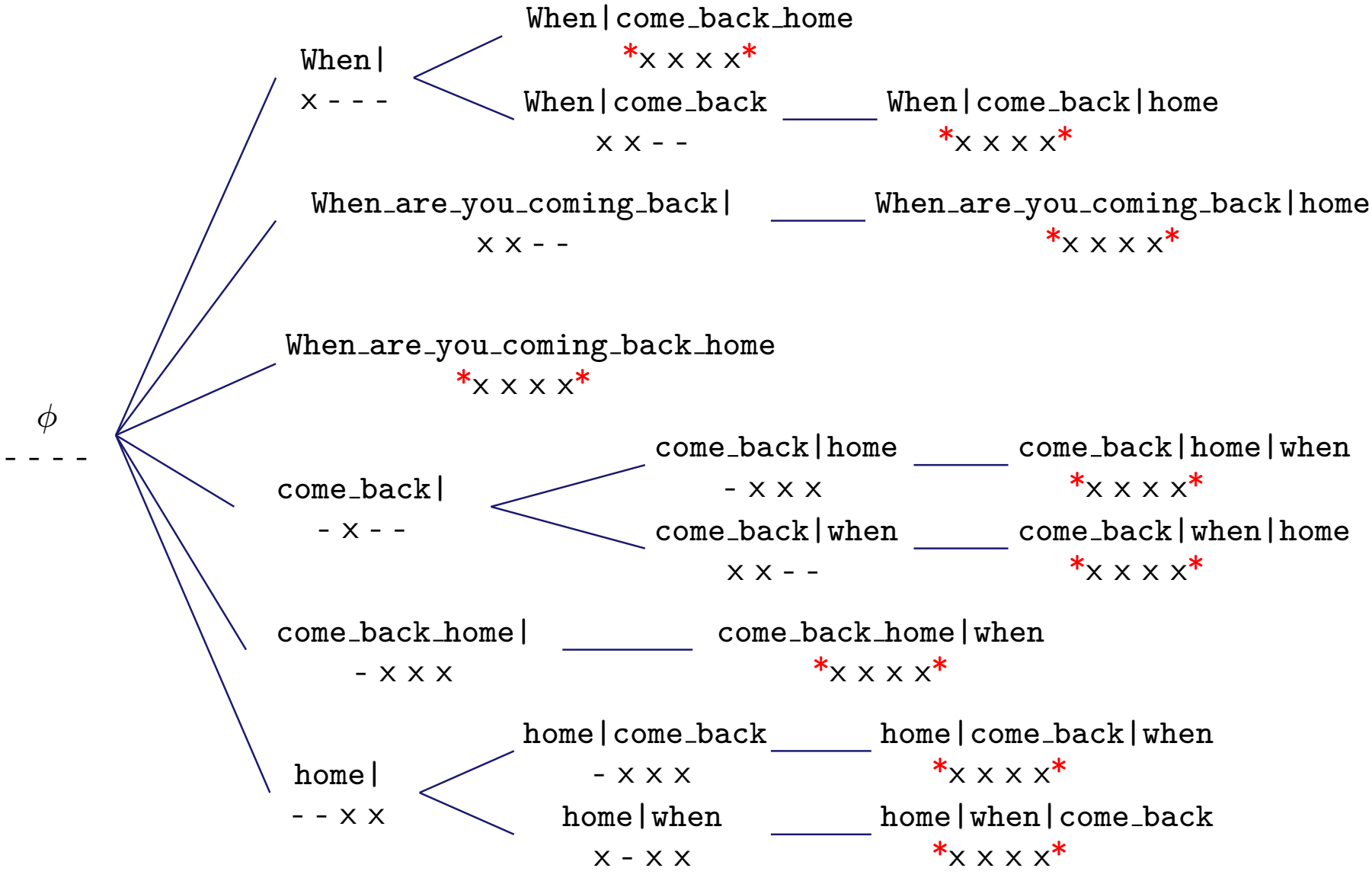

# SMT, components

## 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.




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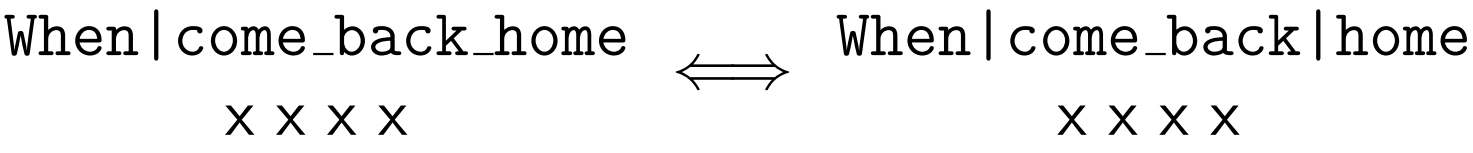


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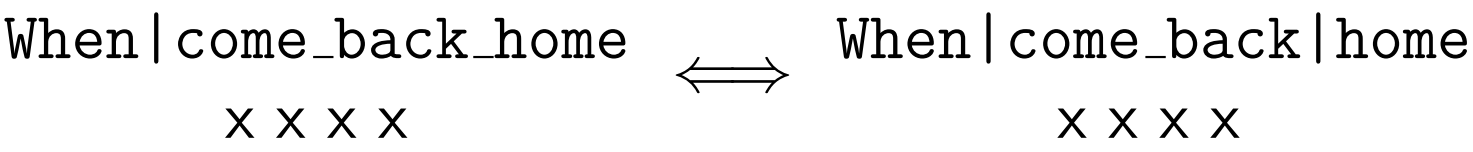


- Risk-free operation. The lowest cost translation is still there.
- But the space of hypothesis is not reduced enough.

**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*

# SMT, the log-linear model

## Motivation

**Maximum likelihood (ML)**

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

**Maximum entropy (ME)**

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

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

**Log-linear model**

# SMT, the log-linear model

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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

# 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: $P(e)$, $P(f|e)$, $P(e|f)$, $lex(f|e)$, $lex(e|f)$, $ph(e)$, $w(e)$ and $P_d(e, f)$.

- 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.

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

# SMT, components

## The translation model $P(f|e)$

**In practice,**

```
cluster:/home/moses/model> zmore phrase-table.gz
```

```
be consistent ||| coherentes ||| 0.0384615 0.146893 0.0833333 0.0116792 2.718 ||| 1-0 ||| 26 12
be consistent ||| sean coherentes ||| 0.2 0.00022714 0.0833333 0.0916808 2.718 ||| 0-0 1-1 ||| 5 12
be consistent ||| sean consistentes ||| 0.5 0.000104834 0.0833333 0.0785835 2.718 ||| 0-0 1-1 ||| 2 12
be consistent ||| ser coherente ||| 0.5 0.0204044 0.166667 0.569957 2.718 ||| 0-0 1-1 ||| 4 12
be consistent ||| ser consecuente ||| 1 0.000340072 0.0833333 0.759942 2.718 ||| 0-0 1-1 ||| 1 12
be consistent ||| ser consistente ||| 1 0.00850183 0.5 0.633285 2.718 ||| 0-0 1-1 ||| 6 12
consistent when ||| coherente cuando se ||| 1 0.00783857 1 0.329794 2.718 ||| 0-0 1-1 1-2 ||| 1 1
consistent ||| adecuado ||| 0.00512821 0.0112994 0.00671141 0.009009 2.718 ||| 0-0 ||| 195 149
consistent ||| coherencia ||| 0.137931 0.0282486 0.0268456 0.0847458 2.718 ||| 0-0 ||| 29 149
consistent ||| constante ||| 0.0333333 0.0112994 0.0134228 0.0307692 2.718 ||| 0-0 ||| 60 149
consistent ||| constantes ||| 0.0625 0.0056497 0.00671141 0.047619 2.718 ||| 0-0 ||| 16 149
...
```

**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)

# SMT, the log-linear model

## Digression: lexicalised reordering or distortion

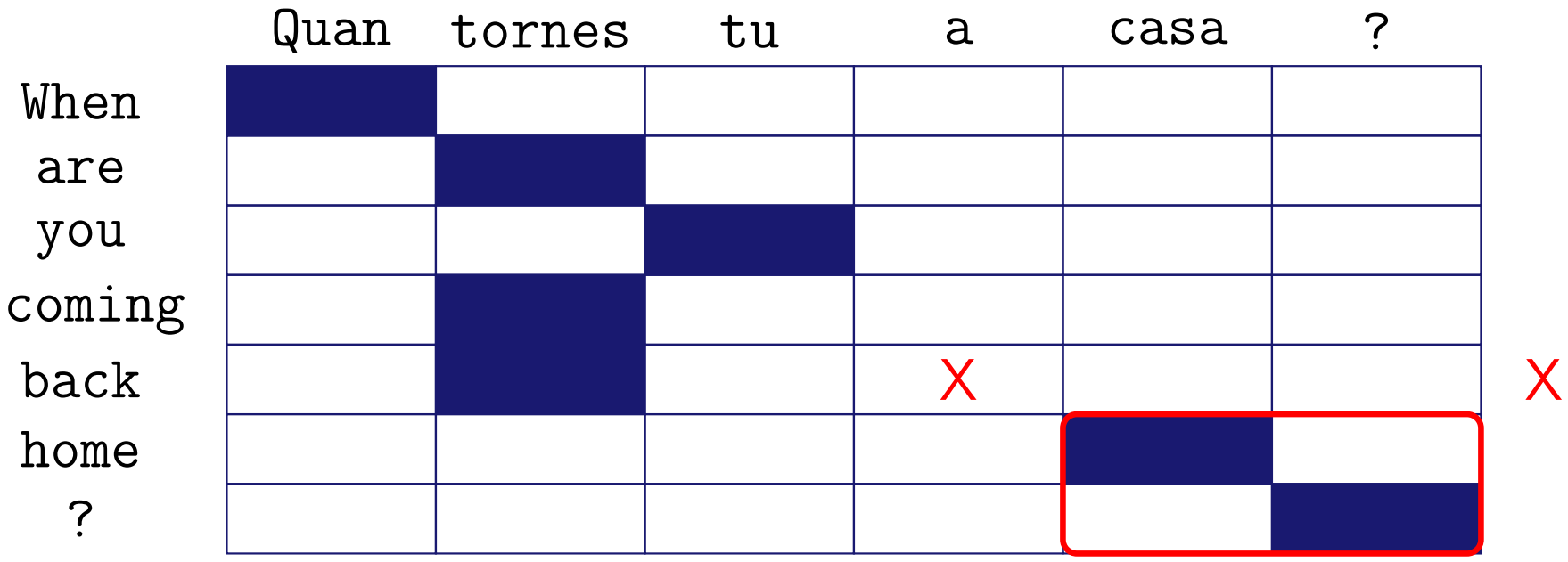
From where and how can one learn reorders?


(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)

# SMT, the log-linear model

## Digression: lexicalised reordering or distortion

3 new features estimated by frequency counts:
$P_{\text{monotone}}$, $P_{\text{swap}}$ 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.

# SMT, components

## The translation model $P(f|e)$

**In practice,**

```
cluster:/home/moses/model> zmore extract.o.gz

resumption ||| reanudacion ||| mono mono
resumption of the ||| reanudacion del ||| mono mono
resumption of the session ||| reanudacion del periodo de sesiones ||| mono mono
de la union ||| union ' s ||| swap swap
competencia de la union ||| union ' s competition ||| swap other
...

cluster:/home/moses/model> zmore reordering-table.wbe-msd-bidirectional-fe.gz

a resumption of the s ||| se reanudara el periodo de s ||| 0.200 0.200 0.600 0.600 0.200 0.200
resumption of the s ||| reanudacion del periodo de s ||| 0.995 0.002 0.002 0.995 0.002 0.002
the resumption of the s ||| la continuacion del periodo de s ||| 0.142 0.142 0.714 0.714 0.142 0.142
the resumption of the s ||| la reanudacion del periodo de s ||| 0.818 0.090 0.090 0.818 0.090 0.090
...
```

# SMT, components

## The translation model $P(f|e)$

```
cluster:/home/moses/model> wc -l *

   493,896,818 phrase-table
   493,896,818 reordering-table.wbe-msd-bidirectional-fe



cluster:/home/moses/model> ls -lkh *

-rw-r--r-- 1 emt ia 57G mar 3 14:01 phrase-table
-rw-r--r-- 1 emt ia 55G mar 3 14:08 reordering-table.wbe-msd-bidirectional-fe
```

# SMT, the log-linear model

## Features

**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).

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- Minimum Error-Rate Training (MERT).

## Minimum Error-Rate Training

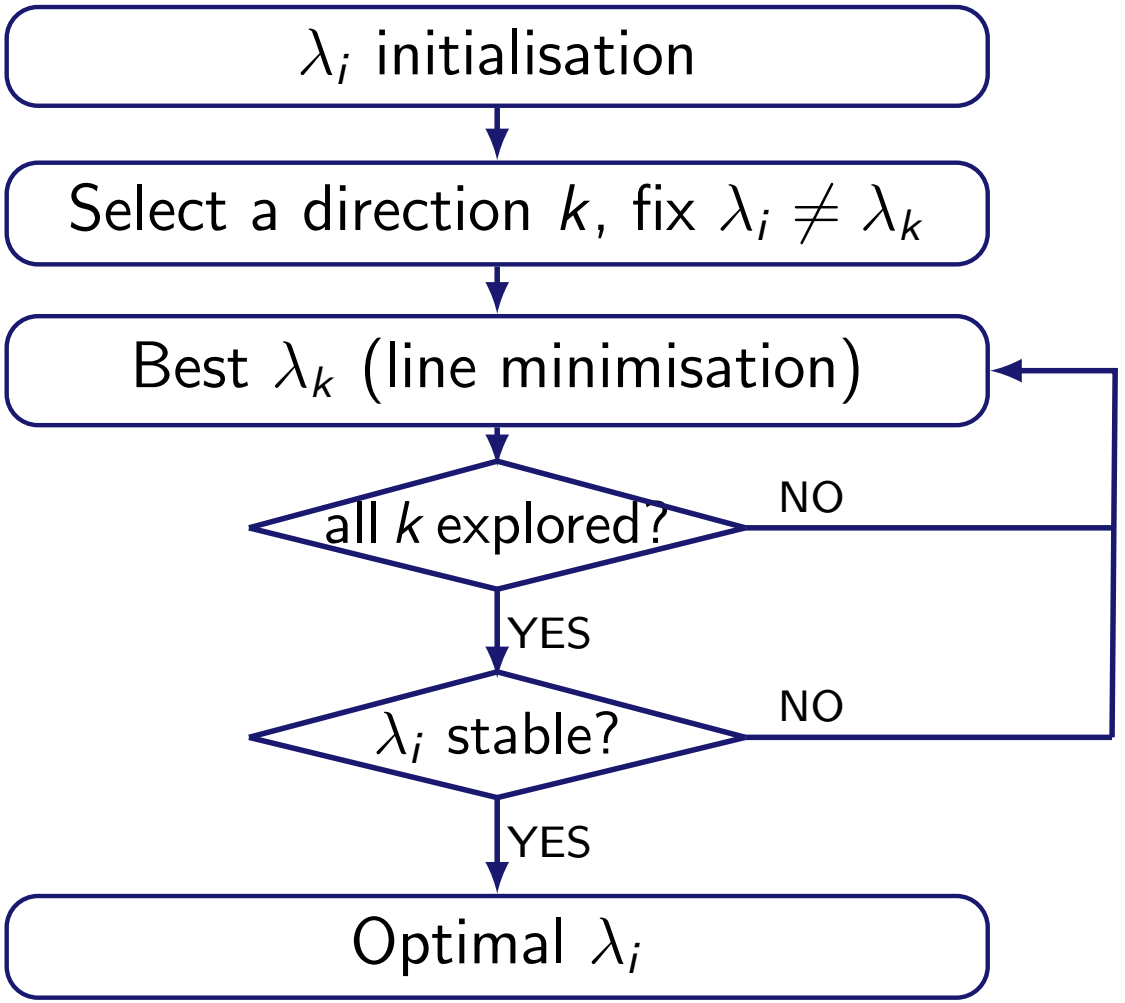
- Approach: Minimise an error function.

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

# 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.

**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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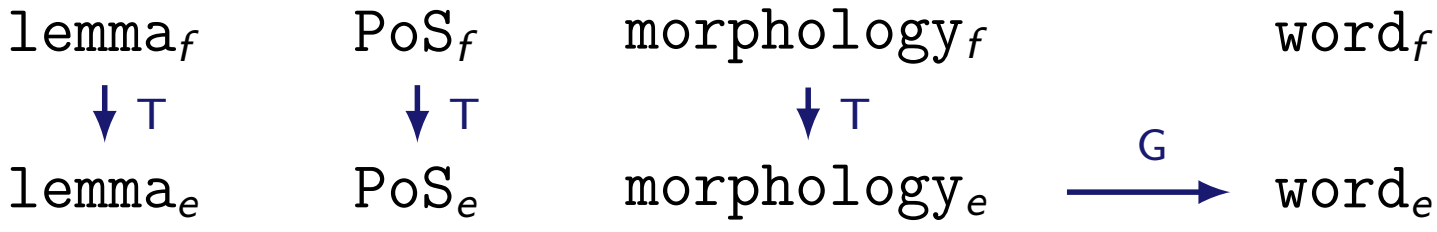

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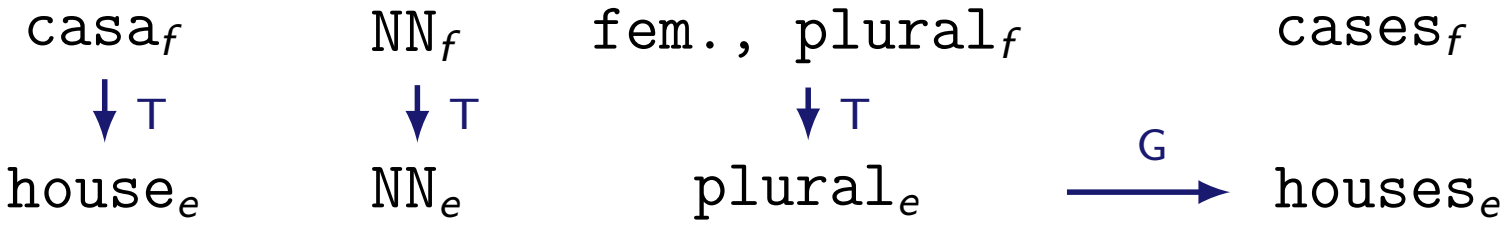

**What differs in factored translation models**
(as compared to standard phrase-based models)

- 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.

# SMT, beyond standard SMT

## Syntax-based translation models

Syntactic models ease reordering. An intuitive example:

En David llegeix un llibre nou

# SMT, beyond standard SMT

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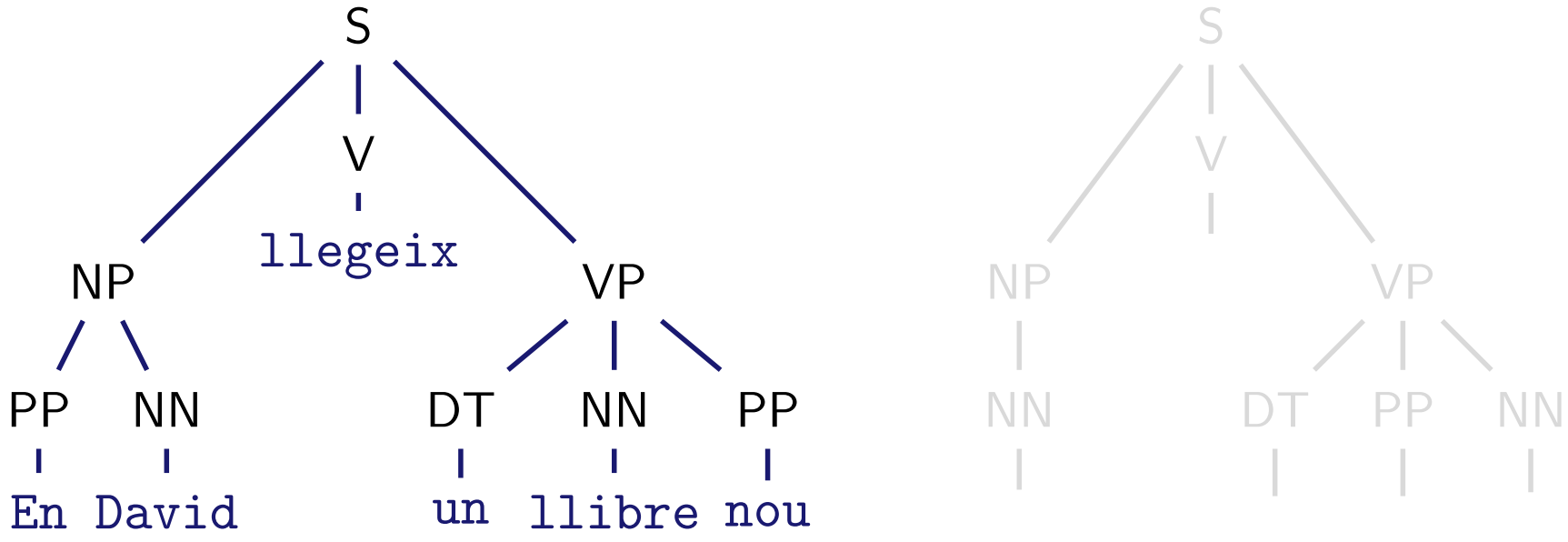

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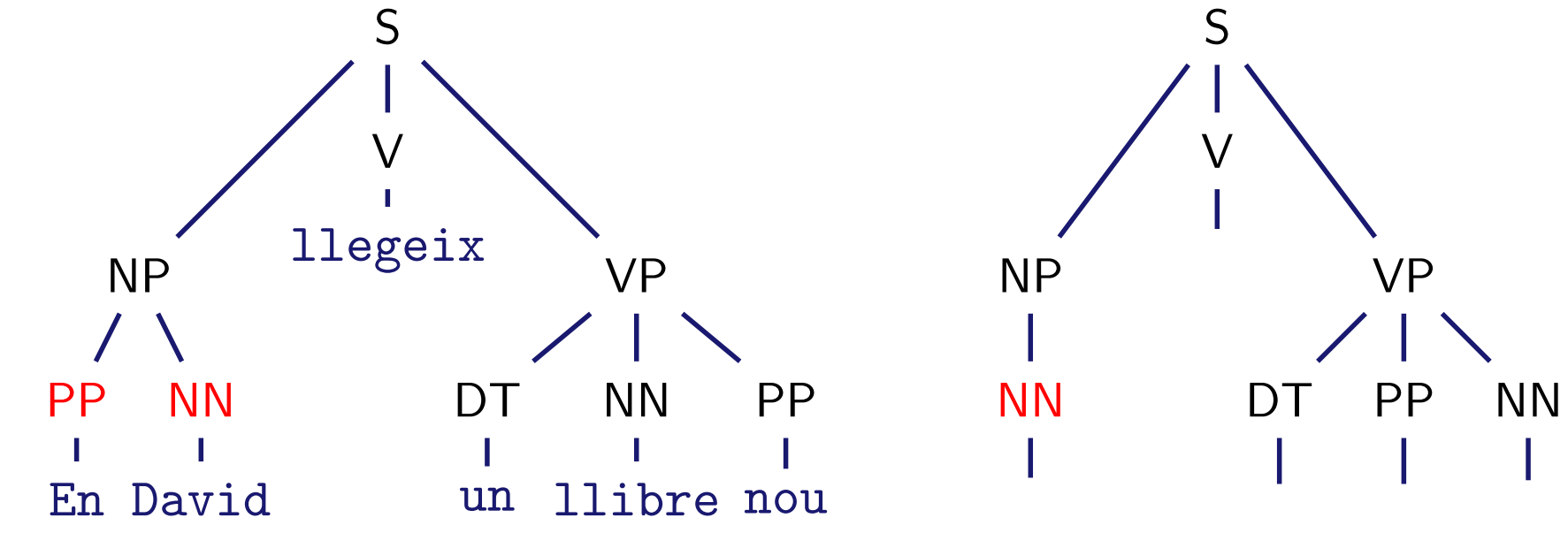

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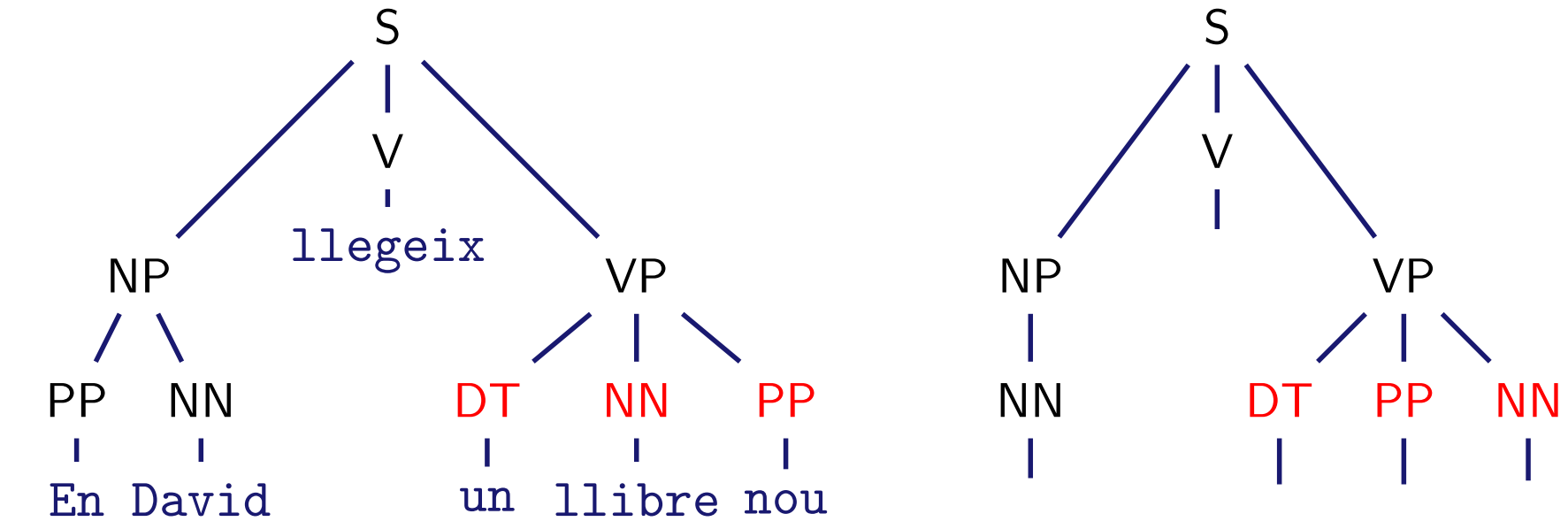

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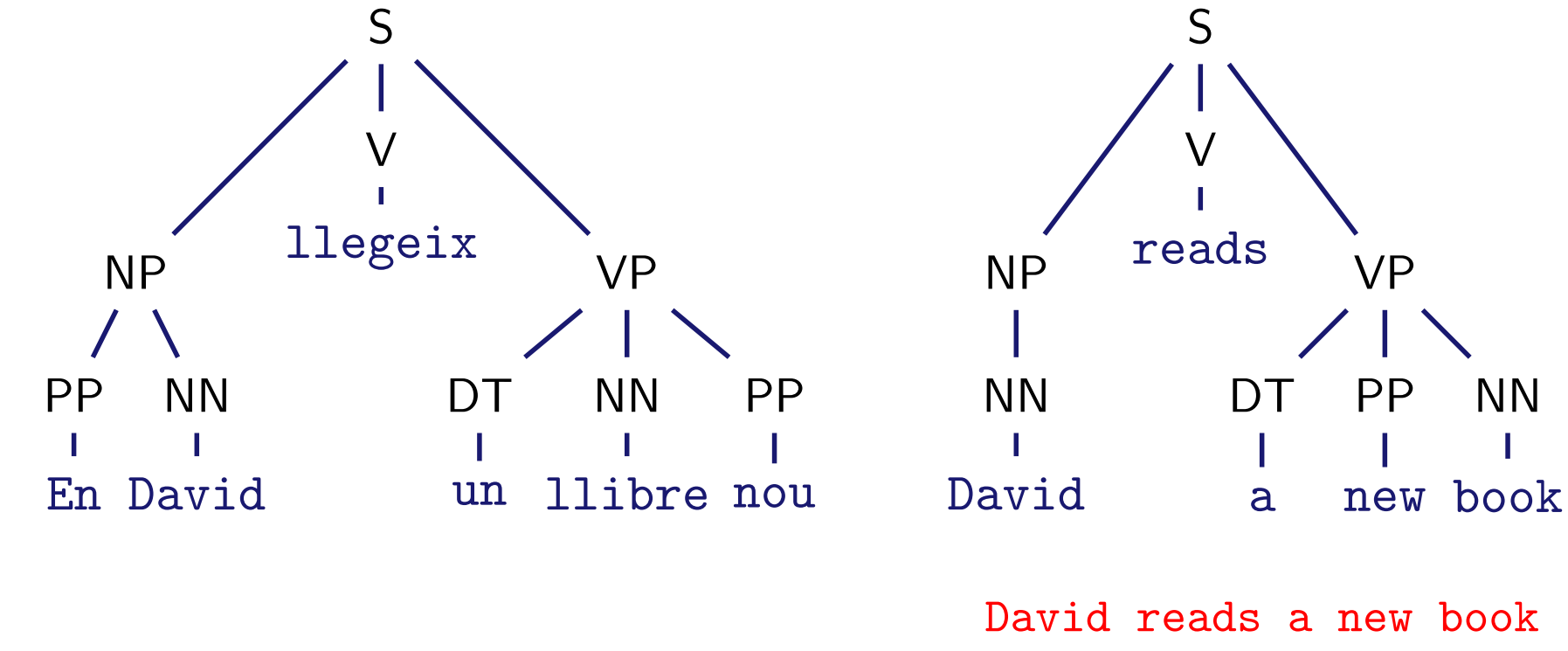


# SMT, beyond standard SMT

## 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 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

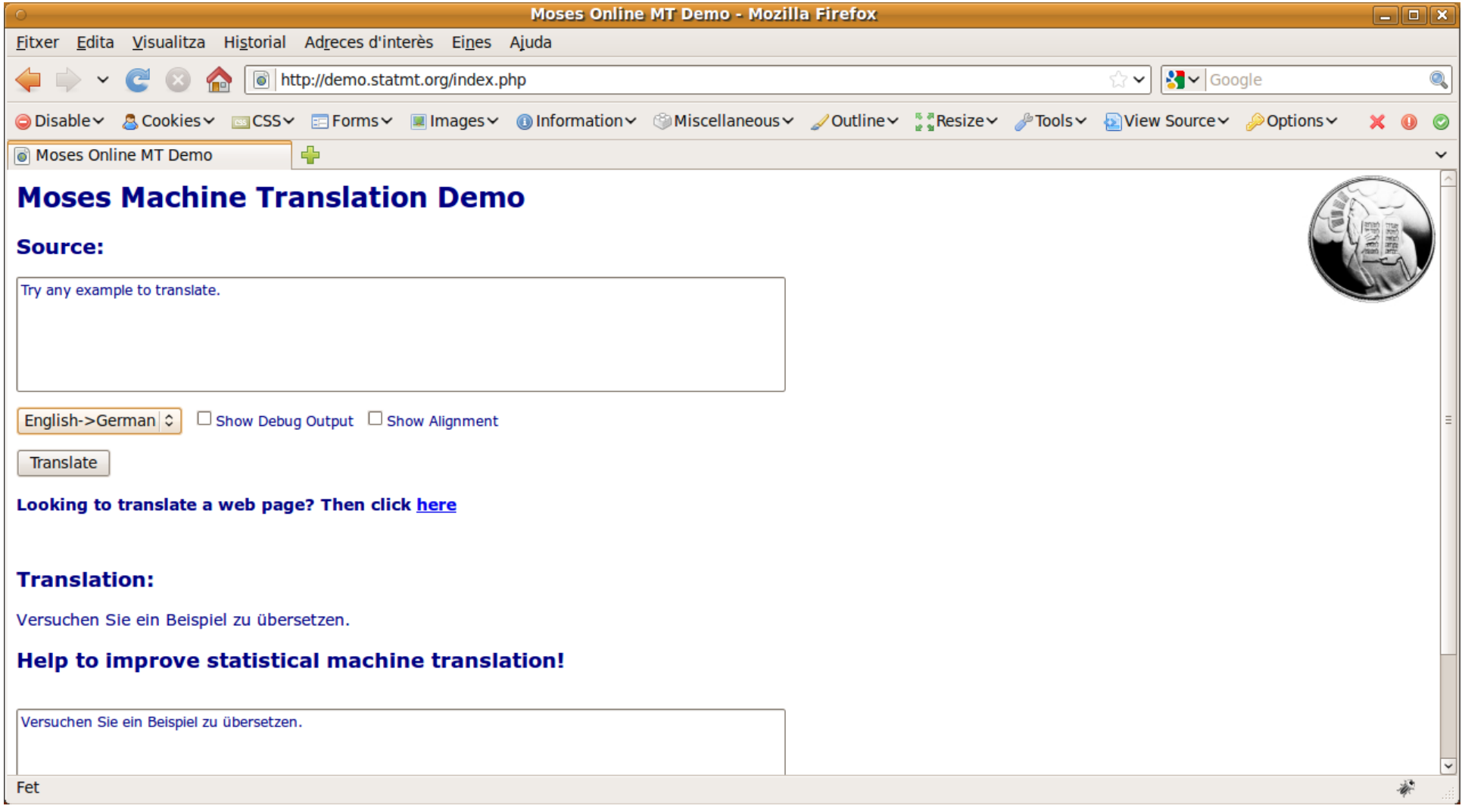
# SMT experiments

# *Outline Part II*

6. Translation system
   - Demos
   - Software
   - Steps

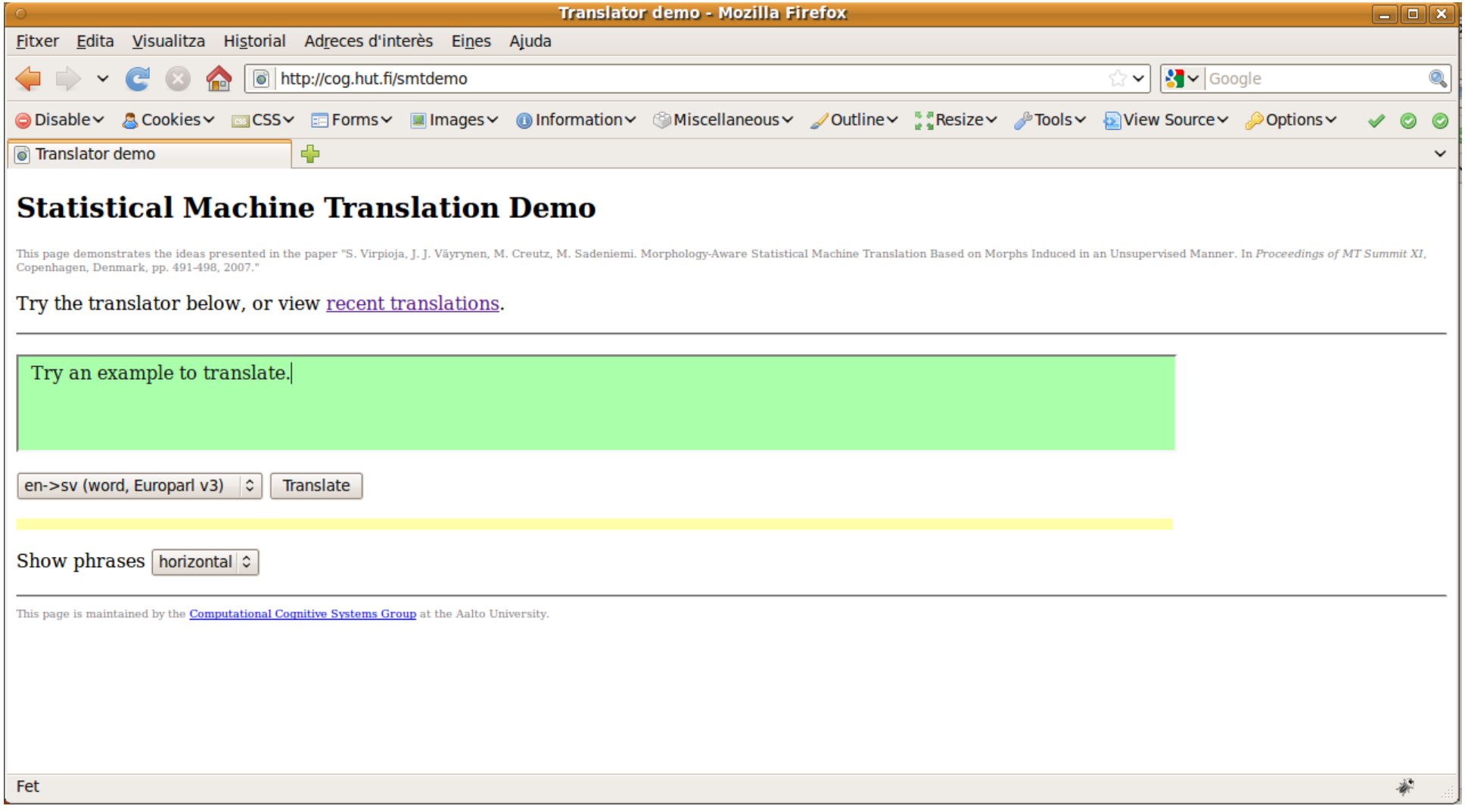
# SMT system

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.html
2. Word alignments with `GIZA++`.
   http://code.google.com/p/giza-pp/downloads/list
3. And everything else with the `Moses` package.
   https://github.com/moses-smt/mosesdecoder

## 1. Download and prepare your data

1. Parallel corpora and some tools can be downloaded for instance from the WMT 2013 web page: http://www.statmt.org/wmt13/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-model.perl`
   This script performs the whole training:

```
train-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!):

```
moses-scripts/training/train-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!)

   ```
   moses-scripts/training/mert-moses.pl eurov4.es-en.dev.es
   eurov4.es-en.dev.en mosesdecoder/bin/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)

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

3. Run the decoder:

```
mosesdecoder/bin/moses -f ./filteredmodel/moses.ini < testset.es >
testset.translated.en
```

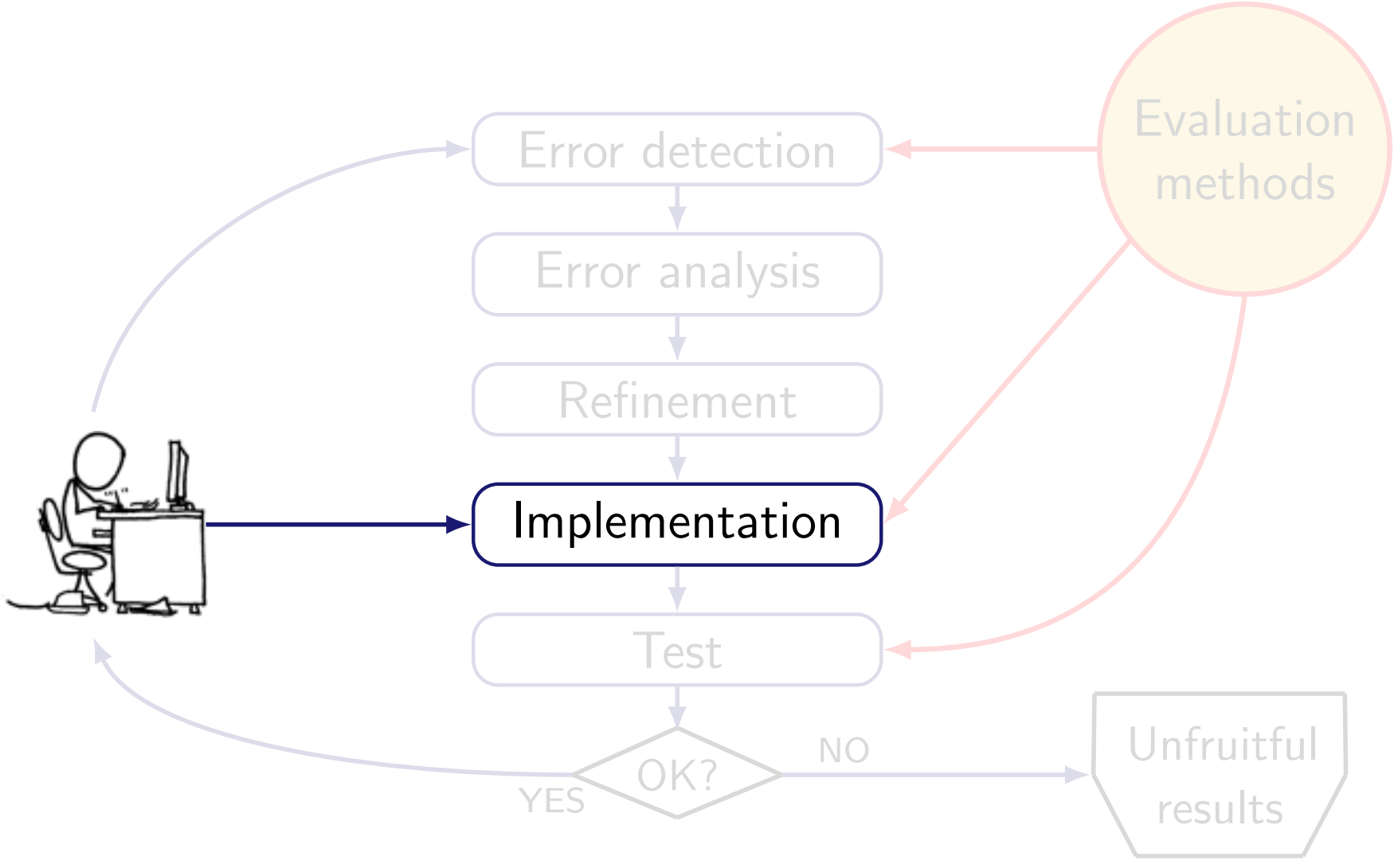
# Part III

# MT Evaluation

# *Outline*

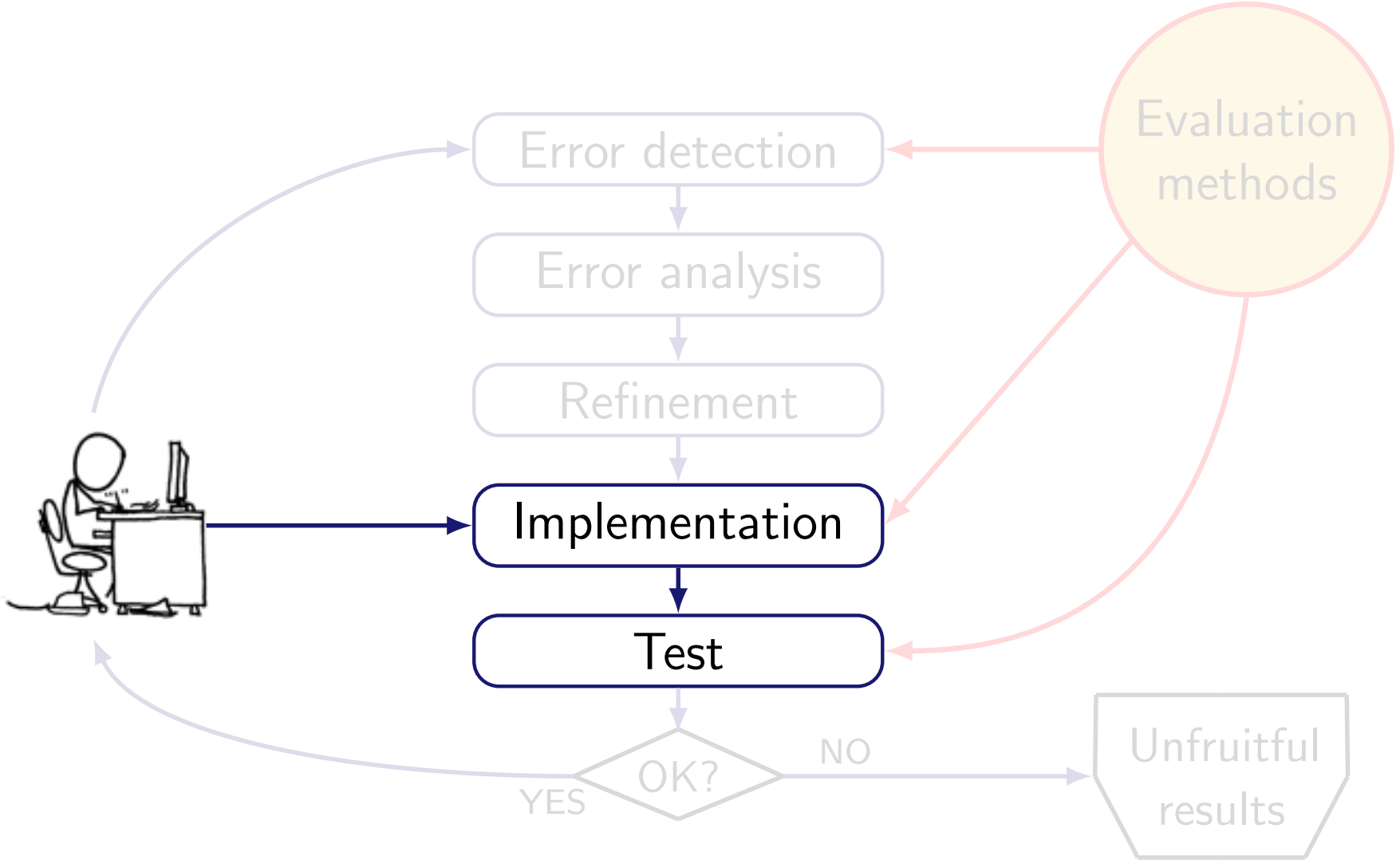
# MT Evaluation

## Importance for system development



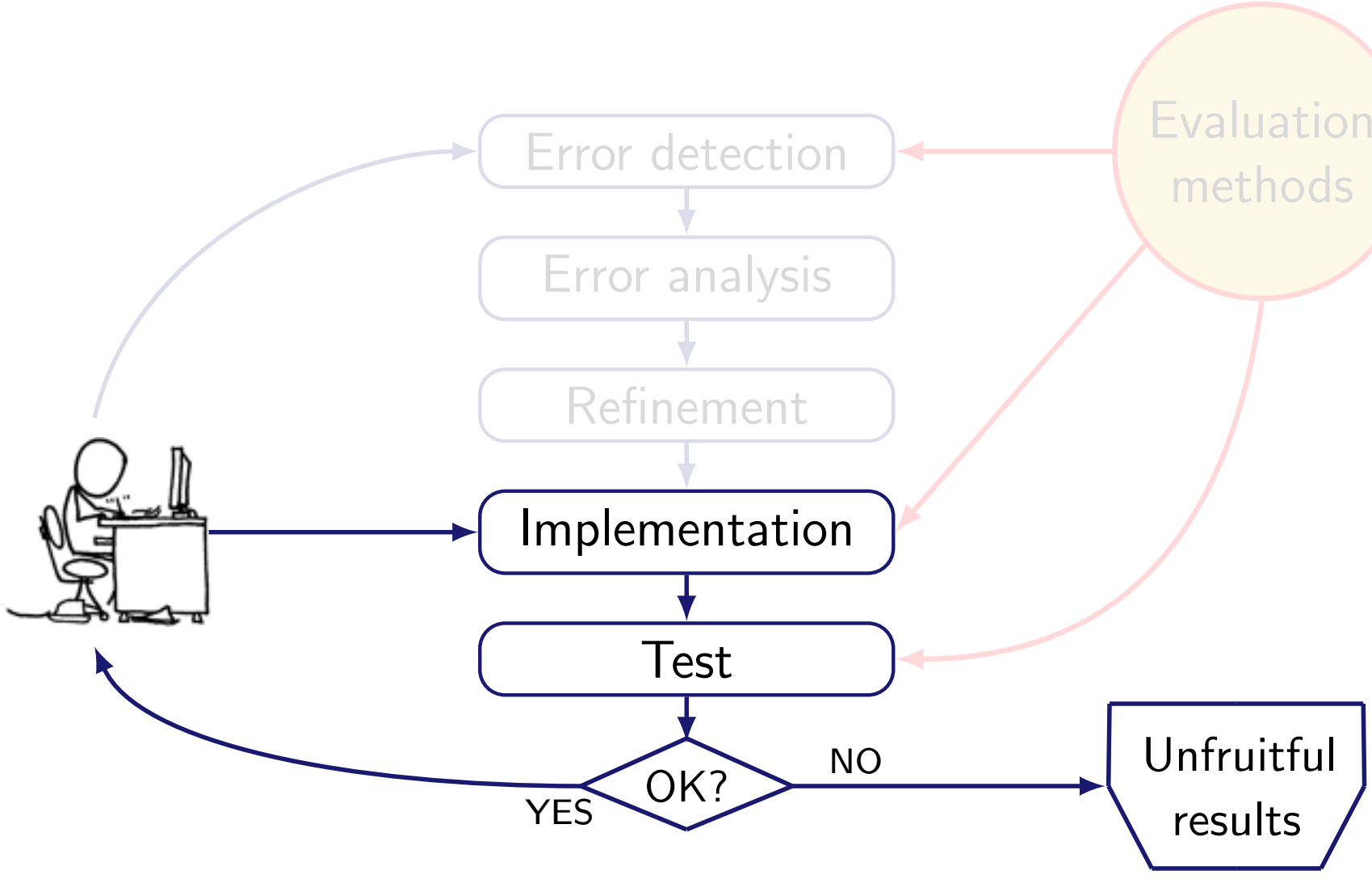
# MT Evaluation

## Importance for system development



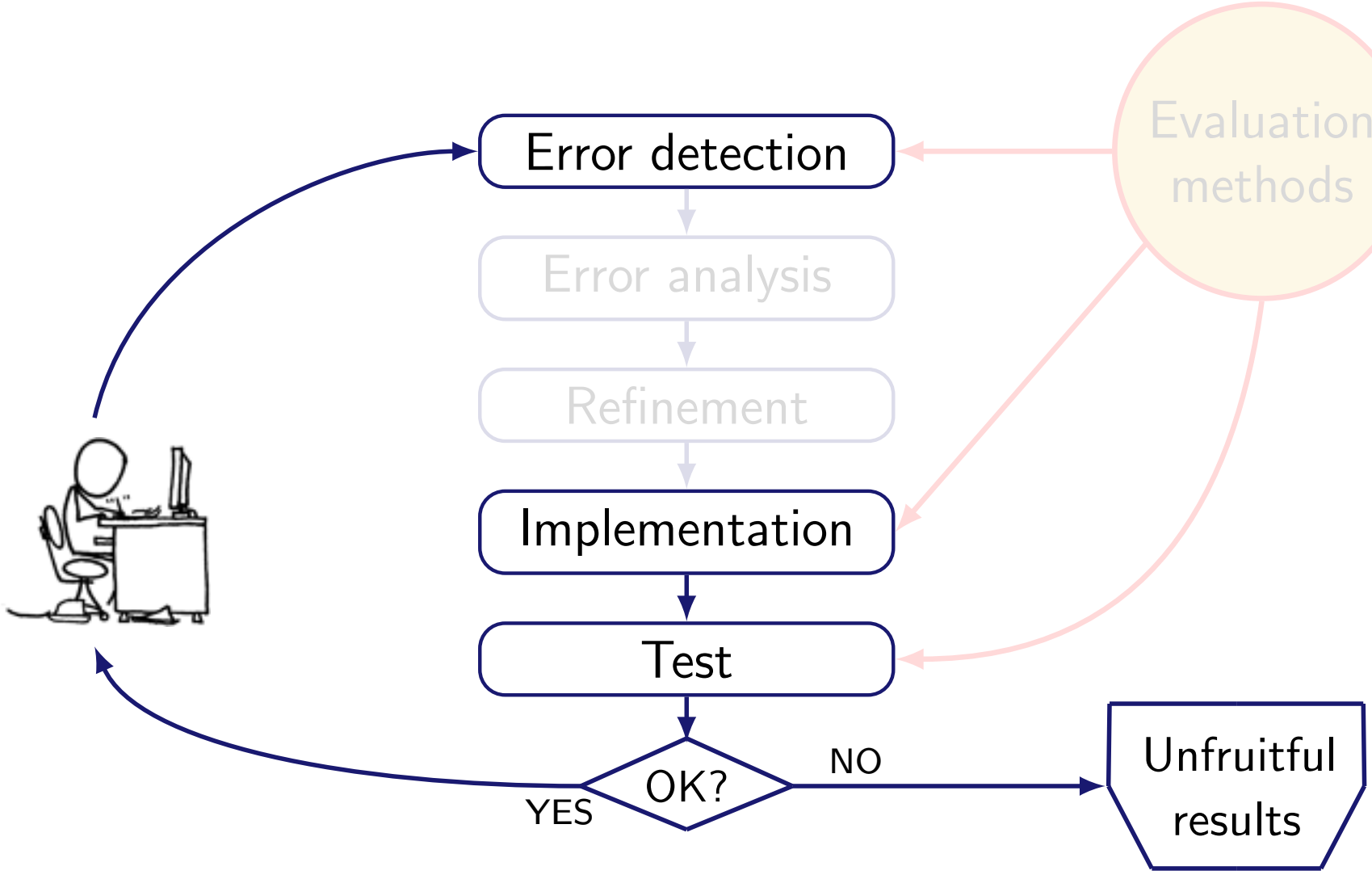
# MT Evaluation

## Importance for system development



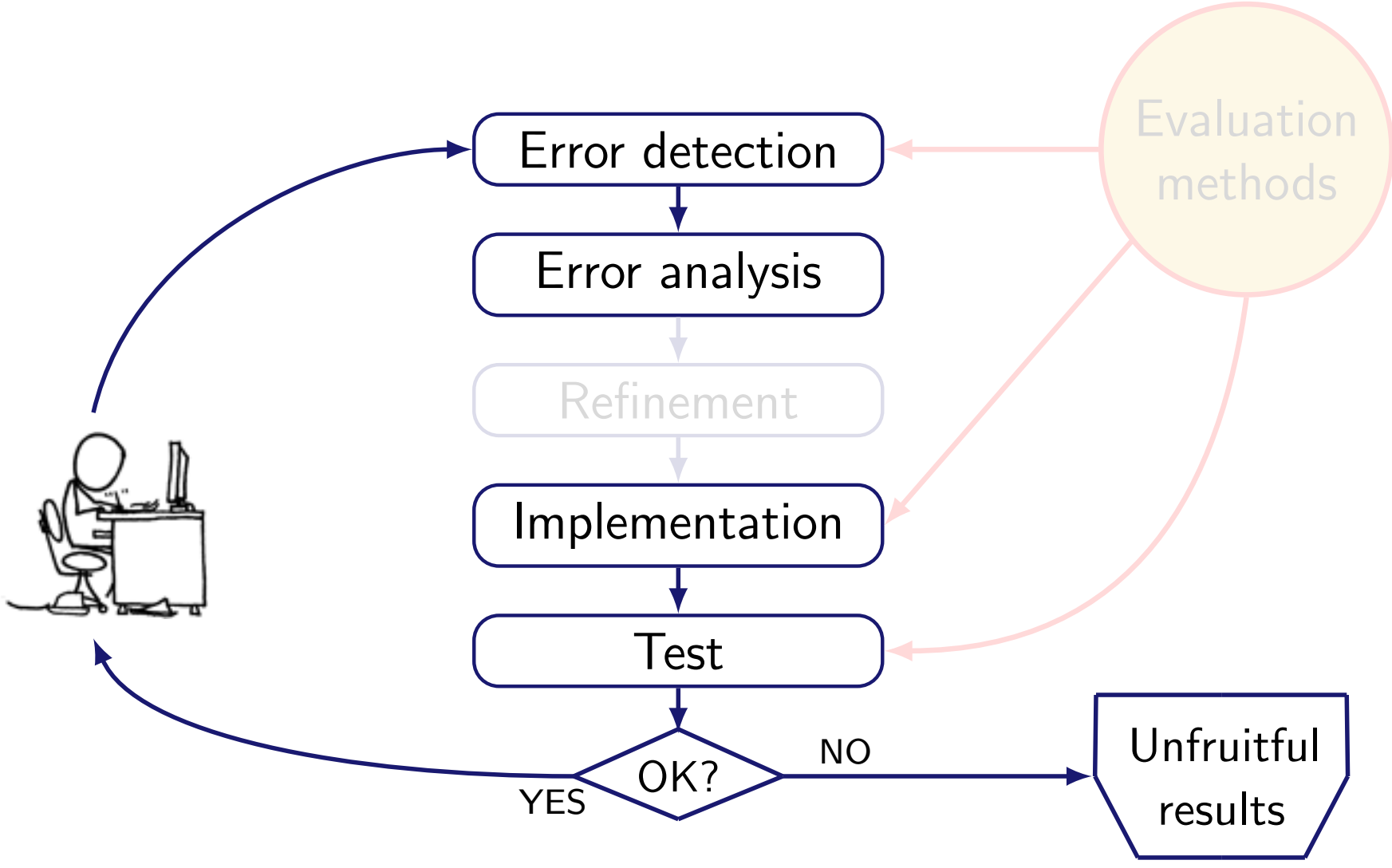
# MT Evaluation

## Importance for system development



# MT Evaluation

## Importance for system development



# MT Evaluation

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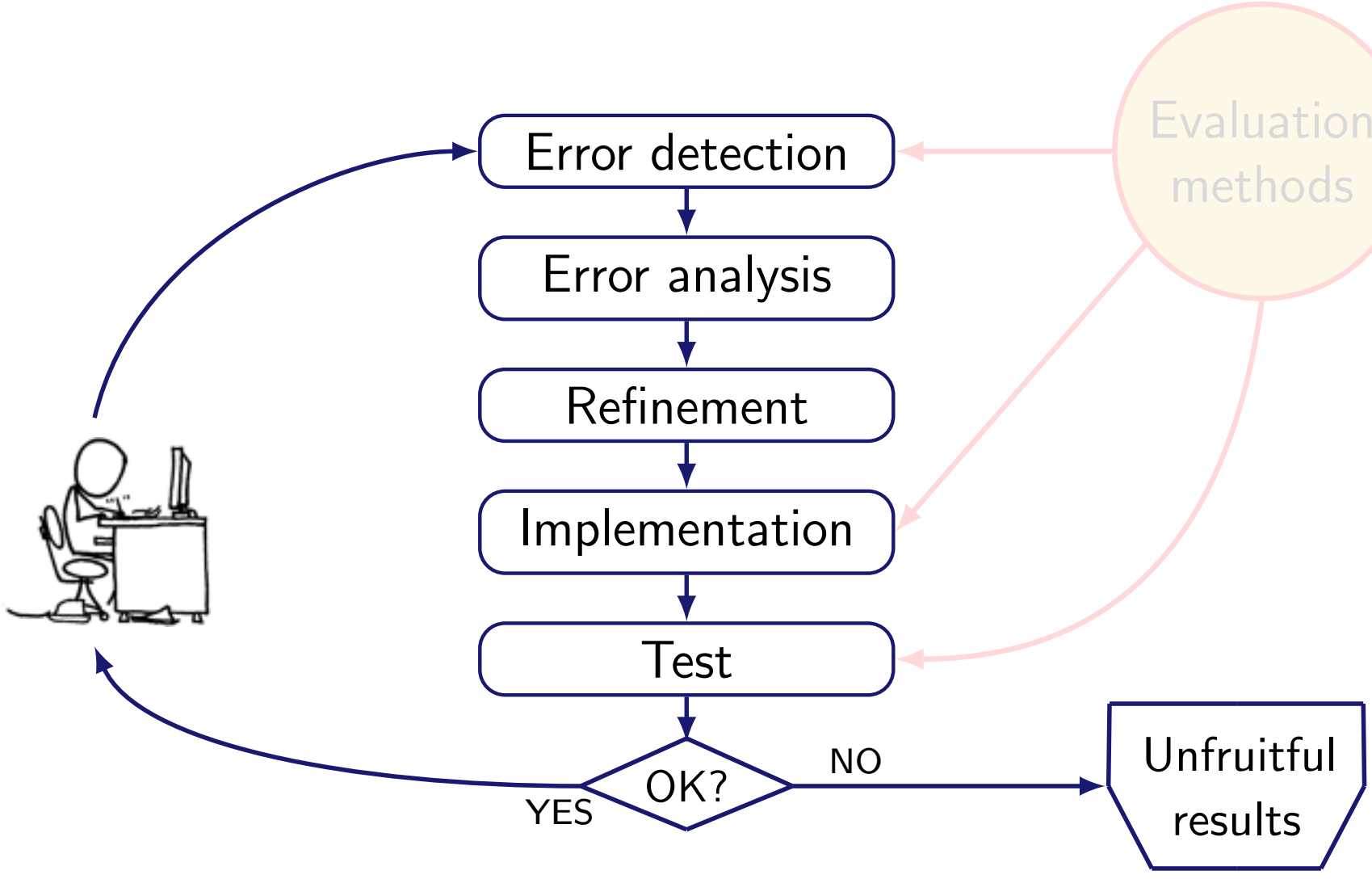
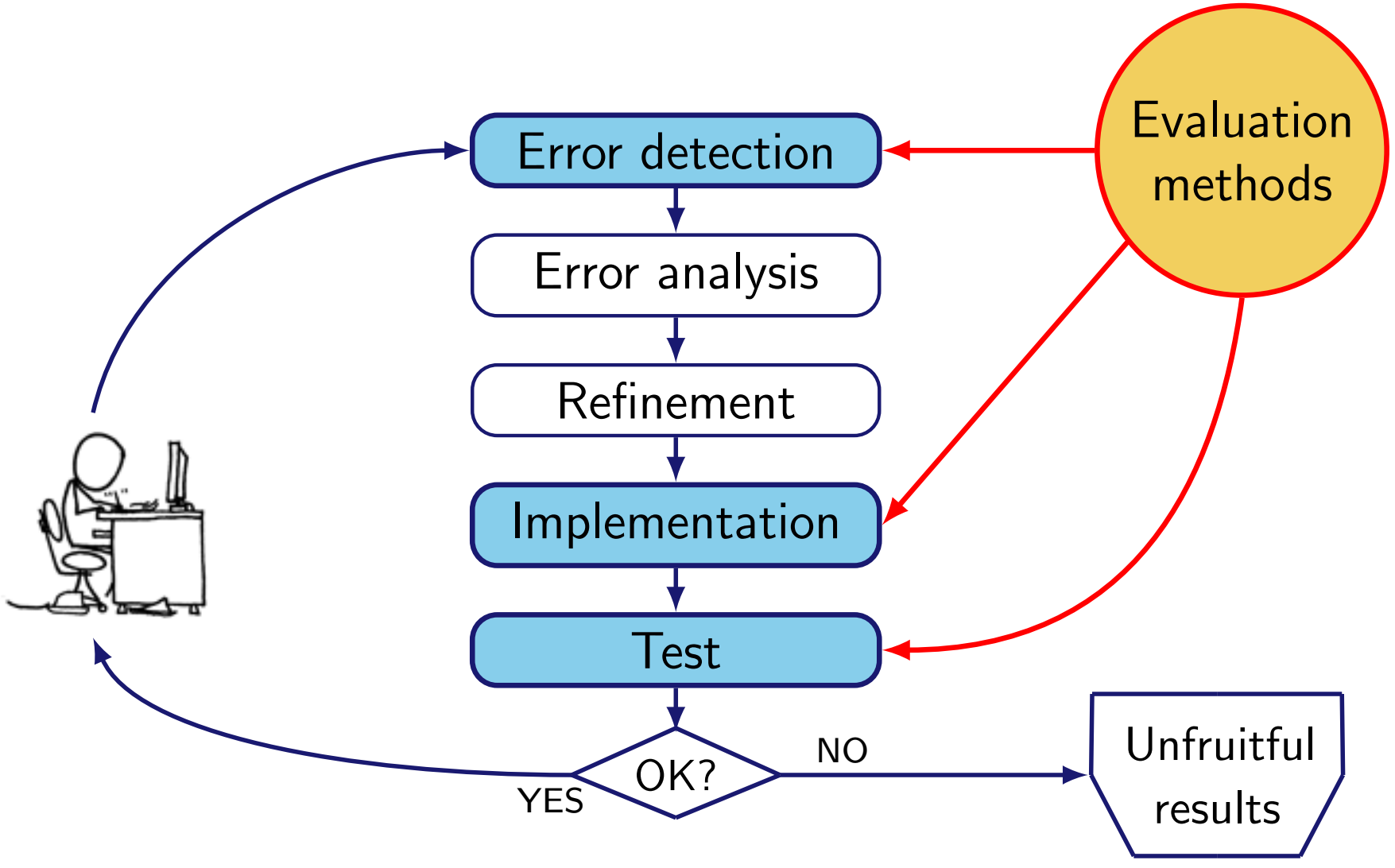


# MT Evaluation

## 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.

# MT Evaluation

## IBM BLEU 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."

# MT Evaluation

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

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.`

# MT Evaluation

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

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.

# MT Evaluation

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

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.

# MT Evaluation

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

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.

# MT Evaluation

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

**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.`

# MT Evaluation

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

**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.

# MT Evaluation

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

**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.`

# MT Evaluation

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

**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.

# MT Evaluation

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

**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.

# MT Evaluation

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

**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.

# MT Evaluation

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

**Modified n-gram precision** (1-gram)

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

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.

# MT Evaluation

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

**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.

# MT Evaluation

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

**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.

# MT Evaluation

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

**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. $w_i \rightarrow$ 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

# MT Evaluation

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

**Modified n-gram precision** (1-gram)

Modified 1-gram precision: $P_1 =$

Candidate:

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Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.

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

# MT Evaluation

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

**Modified n-gram precision** (1-gram)

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

Candidate:

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## Modified n-gram precision

- Straightforward generalisation to $n$-grams, $\mathrm{P}_n$.
- Generalisation to multiple sentences:

$$\mathrm{P}_n = \frac{\sum_{C \in \{\text{candidates}\}} \sum_{n\text{gram} \in C} \mathit{Count}_{\text{clipped}}(n\text{gram})}{\sum_{C \in \{\text{candidates}\}} \sum_{n\text{gram} \in C} \mathit{Count}(n\text{gram})}$$

low $n$
adequacy

high $n$
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:

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

# MT Evaluation

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

### 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.

Reference 2:

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# MT Evaluation

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

**Brevity penalty**

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

$c$ candidate length, $r$ reference length

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

# MT Evaluation

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

**BiLingual Evaluation Understudy, BLEU**

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

- Geometric average of $\text{P}_n$ (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.

# MT Evaluation

## IBM BLEU vs. NIST BLEU vs. ...

**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.

# MT Evaluation

## NIST metric

**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 clause 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.

# MT Evaluation

## Ongoing researh

**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

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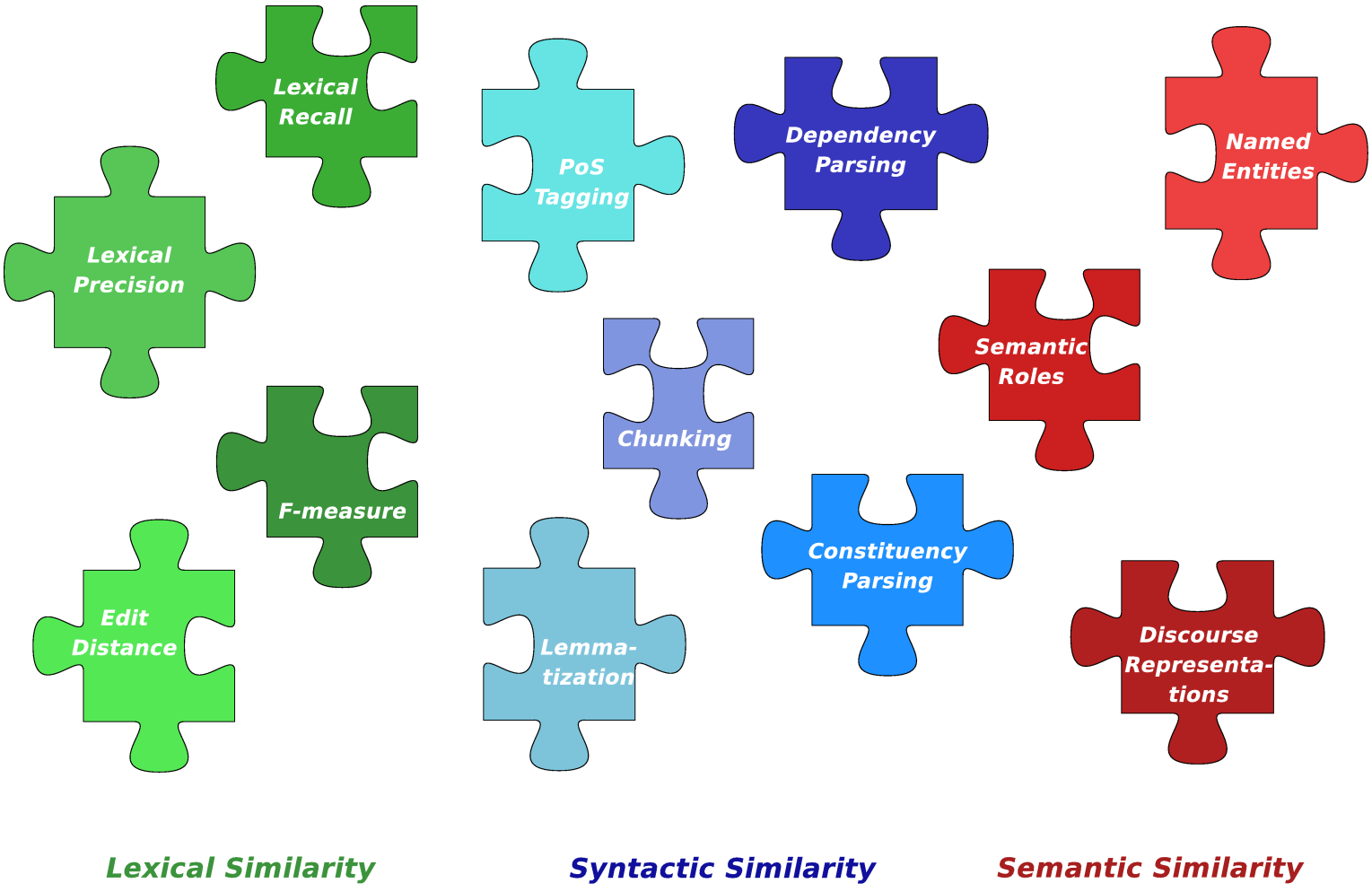
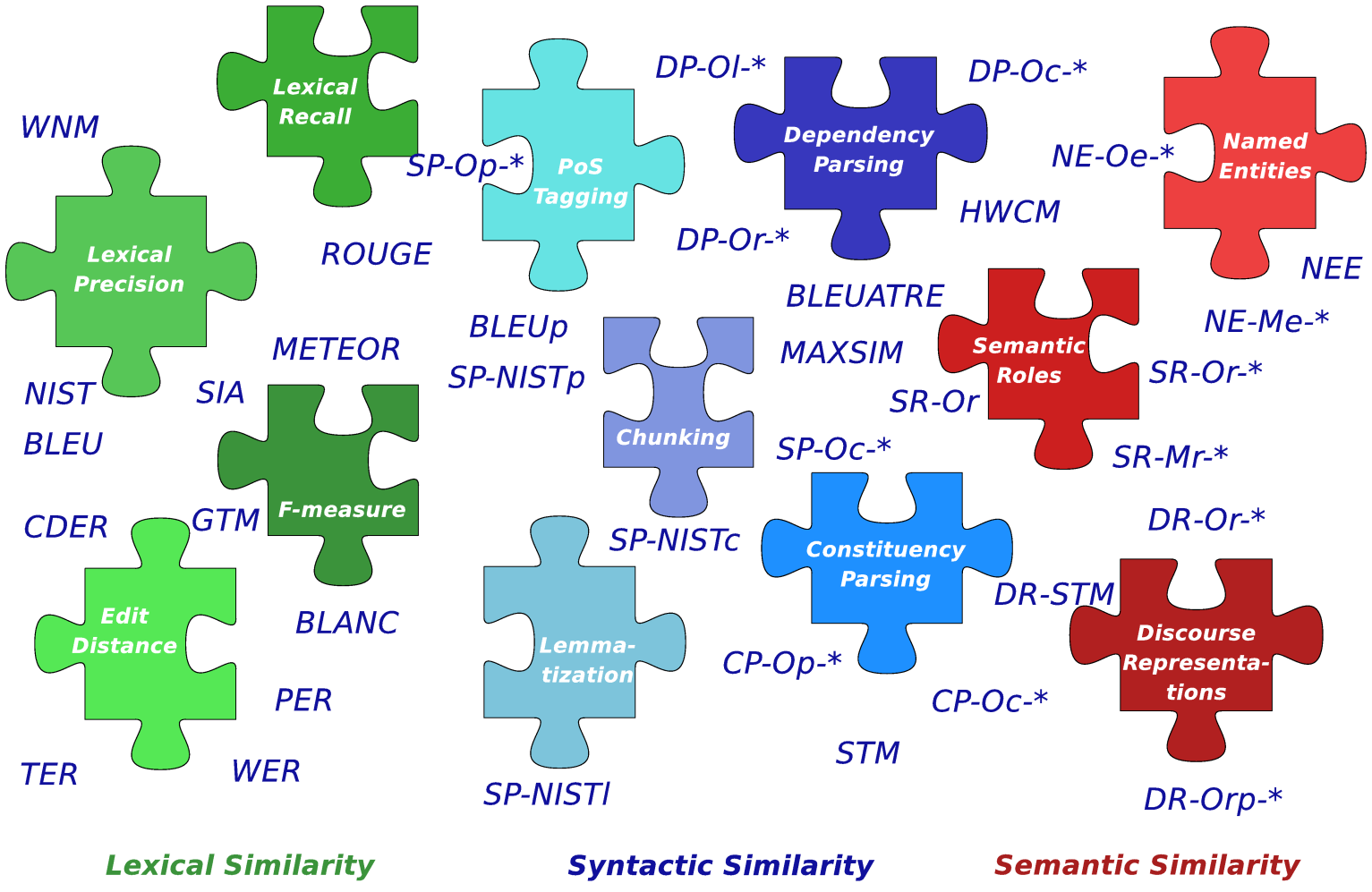
# MT Evaluation

## Towards Heterogeneous Automatic MT Evaluation



# MT Evaluation

## Towards Heterogeneous Automatic MT Evaluation



# ASIYA

Asiya has been designed to assist both **system** and metric **developers** by offering a rich repository of metrics and meta-metrics.

`http://nlp.lsi.upc.edu/asiya/`

# MT Evaluation

## Summary

### 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 `Asiya` package: http://nlp.lsi.upc.edu/asiya/

# 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

1. With the `Asiya` toolkit:

```
Asiya.pl -eval single,ulc -g sys Asiya.config
```

```
input=raw

SRCLANG=de
TRGLANG=en
SRCCASE=cs
TRGCASE=cs

#SRC ================================================
src=./data/patsA61P.test.de
#REF ================================================
ref=./data/patsA61P.test.en
#OUT ================================================
sys=./data/patsA61P.test.trans.de2en
sys=./data/patsA61P.test.trad.google.de2en
sys=./data/patsA61P.test.trad.bing.de2en
#-----------------------------------------------------
```

# MT Evaluation

## Steps

1. With the `Asiya` toolkit:

   `Asiya.pl -eval single,ulc -g sys Asiya.config`

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input=raw

SRCLANG=de
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sys=./data/patsA61P.test.trad.google.de2en
sys=./data/patsA61P.test.trad.bing.de2en
#-----------------------------------------------------
```

# MT Evaluation

## System evaluation with Asiya

```
Asiya.pl -eval single,ulc -m metrSet Asiya.config
```

```
SRCLANG=de
TRGLANG=en

#SRC ================================================
src=./data/patsA61P.test.de
#REF ================================================
ref=./data/patsA61P.test.en
#OUT ================================================
sys=./data/patsA61P.test.trans.de2en
#-----------------------------------------------------

metrSet=1-PER 1-TER 1-WER BLEU-4 CP-Oc-* CP-Op-* CP-STM-9 DP-HWC-c-4
DP-HWC-r-4 DP-HWC-w-4 DP-Oc-* DP-Ol-* DP-Or-* DR-Or-* DR-Orp-* DR-STM-9
GTM-1 GTM-2 GTM-3 MTR-exact MTR-stem MTR-wnstm MTR-wnsyn NE-Me-* NE-Oe-*
NE-Oe-** NIST-5 RG-L RG-S* RG-SU* RG-W-1.2 SP-Oc-* SP-Op-* SP-cNIST-5
SP-iobNIST-5 SP-lNIST-5 SP-pNIST-5 SR-Mr-* SR-Mrv-* SR-Or SR-Or-* SR-Orv
```

# MT Evaluation

## Metrics in Asiya (English)

```
------------------------------------------------------------------------------------------------------------------------
METRIC NAMES
------------------------------------------------------------------------------------------------------------------------
668 metrics are available for language 'en'

METRICS = { -PER, -TER, -TERbase, -TERp, -TERp-A, -WER, BLEU, BLEU-1, BLEU-2, BLEU-3, BLEU-4, BLEUi-2, BLEUi-3, BLEUi-4, CP-Oc(*), CP-Oc(ADJP), CP-Oc(ADVP), CP-Oc(CONJP), CP-Oc(FRAG), CP-Oc(INTJ), CP-Oc(LST), CP-Oc(NAC), CP-Oc(NP), CP-Oc(NX), CP-Oc(O), CP-Oc(PP), CP-Oc(PRN), CP-Oc(PRT), CP-Oc(QP), CP-Oc(RRC), CP-Oc(S), CP-Oc(SBAR), CP-Oc(SINV), CP-Oc(SQ), CP-Oc(UCP), CP-Oc(VP), CP-Oc(WHADJP), CP-Oc(WHADVP), CP-Oc(WHNP), CP-Oc(WHPP), CP-Oc(X), CP-Op(#), CP-Op($), CP-Op(''), CP-Op((), CP-Op()), CP-Op(*), CP-Op(,), CP-Op(.), CP-Op(:), CP-Op(CC), CP-Op(CD), CP-Op(DT), CP-Op(EX), CP-Op(F), CP-Op(FW), CP-Op(IN), CP-Op(J), CP-Op(JJ), CP-Op(JJR), CP-Op(JJS), CP-Op(LS), CP-Op(MD), CP-Op(N), CP-Op(NN), CP-Op(NNP), CP-Op(NNPS), CP-Op(NNS), CP-Op(P), CP-Op(PDT), CP-Op(POS), CP-Op(PRP$), CP-Op(PRP), CP-Op(R), CP-Op(RB), CP-Op(RBR), CP-Op(RBS), CP-Op(RP), CP-Op(SYM), CP-Op(TO), CP-Op(UH), CP-Op(V), CP-Op(VB), CP-Op(VBD), CP-Op(VBG), CP-Op(VBN), CP-Op(VBP), CP-Op(VBZ), CP-Op(W), CP-Op(WDT), CP-Op(WP$), CP-Op(WP), CP-Op(WRB), CP-Op(``), CP-STM-1, CP-STM-2, CP-STM-3, CP-STM-4, CP-STM-5, CP-STM-6, CP-STM-7, CP-STM-8, CP-STM-9, CP-STMi-2, CP-STMi-3, CP-STMi-4, CP-STMi-5, CP-STMi-6, CP-STMi-7, CP-STMi-8, CP-STMi-9, DP-HWCM_c-1, DP-HWCM_c-2, DP-HWCM_c-3, DP-HWCM_c-4, DP-HWCM_r-1, DP-HWCM_r-2, DP-HWCM_r-3, DP-HWCM_r-4, DP-HWCM_w-1, DP-HWCM_w-2, DP-HWCM_w-3, DP-HWCM_w-4, DP-HWCMi_c-2, DP-HWCMi_c-3, DP-HWCMi_c-4, DP-HWCMi_r-2, DP-HWCMi_r-3, DP-HWCMi_r-4, DP-HWCMi_w-2, DP-HWCMi_w-3, DP-HWCMi_w-4, DP-Oc(*), DP-Oc(a), DP-Oc(as), DP-Oc(aux), DP-Oc(be), DP-Oc(c), DP-Oc(comp), DP-Oc(det), DP-Oc(have), DP-Oc(n), DP-Oc(postdet), DP-Oc(ppspec), DP-Oc(predet), DP-Oc(prep), DP-Oc(saidx), DP-Oc(sentadjunct), DP-Oc(subj), DP-Oc(that), DP-Oc(u), DP-Oc(v), DP-Oc(vbe), DP-Oc(xsaid), DP-Ol(*), DP-Ol(1), DP-Ol(2), DP-Ol(3), DP-Ol(4), DP-Ol(5), DP-Ol(6), DP-Ol(7), DP-Ol(8), DP-Ol(9), DP-Or(*), DP-Or(amod), DP-Or(amount-value), DP-Or(appo), DP-Or(appo-mod), DP-Or(as-arg), DP-Or(as1), DP-Or(as2), DP-Or(aux), DP-Or(be), DP-Or(being), DP-Or(by-subj), DP-Or(c), DP-Or(cn), DP-Or(comp1), DP-Or(conj), DP-Or(desc), DP-Or(dest), DP-Or(det), DP-Or(else), DP-Or(fc), DP-Or(gen), DP-Or(guest), DP-Or(have), DP-Or(head), DP-Or(i), DP-Or(inv-aux), DP-Or(inv-have), DP-Or(lex-dep), DP-Or(lex-mod), DP-Or(mod), DP-Or(mod-before), DP-Or(neg), DP-Or(nn), DP-Or(num), DP-Or(num-mod), DP-Or(obj), DP-Or(obj1), DP-Or(obj2), DP-Or(p), DP-Or(p-spec), DP-Or(pcomp-c), DP-Or(pcomp-n), DP-Or(person), DP-Or(pnmod), DP-Or(poss), DP-Or(post), DP-Or(pre), DP-Or(pred), DP-Or(punc), DP-Or(rel), DP-Or(s), DP-Or(sc), DP-Or(subcat), DP-Or(subclass), DP-Or(subj), DP-Or(title), DP-Or(vrel), DP-Or(wha), DP-Or(whn), DP-Or(whp), DPm-HWCM_c-1, DPm-HWCM_c-2, DPm-HWCM_c-3, DPm-HWCM_c-4, DPm-HWCM_r-1, DPm-HWCM_r-2, DPm-HWCM_r-3, DPm-HWCM_r-4, DPm-HWCM_w-1, DPm-HWCM_w-2, DPm-HWCM_w-3, DPm-HWCM_w-4, DPm-HWCMi_c-2, DPm-HWCMi_c-3, DPm-HWCMi_c-4, DPm-HWCMi_r-2, DPm-HWCMi_r-3, DPm-HWCMi_r-4, DPm-HWCMi_w-2, DPm-HWCMi_w-3, DPm-HWCMi_w-4, DPm-Oc(*), DPm-Oc(.....), DPm-Ol(*), DPm-Ol(1), DPm-Ol(2), DPm-Ol(3), DPm-Ol(4), DPm-Ol(5), DPm-Ol(6), DPm-Ol(7), DPm-Ol(8), DPm-Ol(9), DPm-Or(*), DPm-Or(.....), DR-Fr(*), DR-Frp(*), DR-Ol, DR-Or(*), DR-Or(*)_b, DR-Or(*)_i, DR-Or(alfa), DR-Or(card), DR-Or(drs), DR-Or(eq), DR-Or(imp), DR-Or(merge), DR-Or(named), DR-Or(not), DR-Or(or), DR-Or(pred), DR-Or(prop), DR-Or(rel), DR-Or(smerge), DR-Or(timex), DR-Or(whq), DR-Or-(dr), DR-Orp(*), DR-Orp(*)_b, DR-Orp(*)_i, DR-Orp(alfa), DR-Orp(card), DR-Orp(dr), DR-Orp(drs), DR-Orp(eq), DR-Orp(imp), DR-Orp(merge), DR-Orp(named), DR-Orp(not), DR-Orp(or), DR-Orp(pred), DR-Orp(prop), DR-Orp(rel), DR-Orp(smerge), DR-Orp(timex), DR-Orp(whq), DR-Pr(*), DR-Prp(*), DR-Rr(*), DR-Rrp(*), DR-STM-1, DR-STM-2, DR-STM-3, DR-STM-4, DR-STM-4_b, DR-STM-4_i, DR-STM-5, DR-STM-6, DR-STM-7, DR-STM-8, DR-STM-9, DR-STMi-2, DR-STMi-3, DR-STMi-4, DR-STMi-5, DR-STMi-6, DR-STMi-7, DR-STMi-8, DR-STMi-9, DRdoc-Ol, DRdoc-Or(*), DRdoc-Or(*)_b, DRdoc-Or(*)_i, DRdoc-Or(alfa), DRdoc-Or(card), DRdoc-Or(dr), DRdoc-Or(drs), DRdoc-Or(eq), DRdoc-Or(imp), DRdoc-Or(merge), DRdoc-Or(named), DRdoc-Or(not), DRdoc-Or(or), DRdoc-Or(pred), DRdoc-Or(prop), DRdoc-Or(rel), DRdoc-Or(smerge), DRdoc-Or(timex), DRdoc-Or(whq), DRdoc-Orp(*), DRdoc-Orp(*)_b, DRdoc-Orp(*)_i, DRdoc-Orp(alfa), DRdoc-Orp(card), DRdoc-Orp(dr), DRdoc-Orp(drs), DRdoc-Orp(eq), DRdoc-Orp(imp), DRdoc-Orp(merge), DRdoc-Orp(named), DRdoc-Orp(not), DRdoc-Orp(or), DRdoc-Orp(pred), DRdoc-Orp(prop), DRdoc-Orp(rel), DRdoc-Orp(smerge), DRdoc-Orp(timex), DRdoc-Orp(whq), DRdoc-STM-1, DRdoc-STM-2, DRdoc-STM-3, DRdoc-STM-4, DRdoc-STM-4_b, DRdoc-STM-4_i, DRdoc-STM-5, DRdoc-STM-6, DRdoc-STM-7, DRdoc-STM-8, DRdoc-STM-9, DRdoc-STMi-2, DRdoc-STMi-3, DRdoc-STMi-4, DRdoc-STMi-5, DRdoc-STMi-6, DRdoc-STMi-7, DRdoc-STMi-8, DRdoc-STMi-9, Fl, GTM-1, GTM-2, GTM-3, METEOR-ex, METEOR-pa, METEOR-st, METEOR-sy, NE-Me(*), NE-Me(ANGLE_QUANTITY), NE-Me(DATE), NE-Me(DISTANCE_QUANTITY), NE-Me(LANGUAGE), NE-Me(LOC), NE-Me(MEASURE), NE-Me(METHOD), NE-Me(MISC), NE-Me(MONEY), NE-Me(NUM), NE-Me(ORG), NE-Me(PER), NE-Me(PERCENT), NE-Me(PROJECT), NE-Me(SIZE_QUANTITY), NE-Me(SPEED_QUANTITY), NE-Me(SYSTEM), NE-Me(TEMPERATURE_QUANTITY), NE-Me(TIME), NE-Me(WEIGHT_QUANTITY), NE-Oe(*), NE-Oe(**), NE-Oe(ANGLE_QUANTITY), NE-Oe(DATE), NE-Oe(DISTANCE_QUANTITY), NE-Oe(LANGUAGE), NE-Oe(LOC), NE-Oe(MEASURE), NE-Oe(METHOD), NE-Oe(MISC), NE-Oe(MONEY), NE-Oe(NUM), NE-Oe(O), NE-Oe(ORG), NE-Oe(PER), NE-Oe(PERCENT), NE-Oe(PROJECT), NE-Oe(SIZE_QUANTITY), NE-Oe(SPEED_QUANTITY), NE-Oe(SYSTEM), NE-Oe(TEMPERATURE_QUANTITY), NE-Oe(TIME), NE-Oe(WEIGHT_QUANTITY), NIST, NIST-1, NIST-2, NIST-3, NIST-4, NIST-5, NISTi-2, NISTi-3, NISTi-4, NISTi-5, Ol, Pl, ROUGE-1, ROUGE-2, ROUGE-3, ROUGE-4, ROUGE-L, ROUGE-S*, ROUGE-SU*, ROUGE-W, Rl, SP-Oc(*), SP-Oc(ADJP), SP-Oc(ADVP), SP-Oc(CONJP), SP-Oc(INTJ), SP-Oc(LST), SP-Oc(NP), SP-Oc(O), SP-Oc(PP), SP-Oc(PRT), SP-Oc(SBAR), SP-Oc(UCP), SP-Oc(VP), SP-Op(#), SP-Op($), SP-Op(''), SP-Op((), SP-Op()), SP-Op(*), SP-Op(,), SP-Op(.), SP-Op(:), SP-Op(CC), SP-Op(CD), SP-Op(DT), SP-Op(EX), SP-Op(F), SP-Op(FW), SP-Op(IN), SP-Op(J), SP-Op(JJ), SP-Op(JJR), SP-Op(JJS), SP-Op(LS), SP-Op(MD), SP-Op(N), SP-Op(NN), SP-Op(NNP), SP-Op(NNPS), SP-Op(NNS), SP-Op(P), SP-Op(PDT), SP-Op(POS), SP-Op(PRP$), SP-Op(PRP), SP-Op(R), SP-Op(RB), SP-Op(RBR), SP-Op(RBS), SP-Op(RP), SP-Op(SYM), SP-Op(TO), SP-Op(UH), SP-Op(V), SP-Op(VB), SP-Op(VBD), SP-Op(VBG), SP-Op(VBN), SP-Op(VBP), SP-Op(VBZ), SP-Op(W), SP-Op(WDT), SP-Op(WP$), SP-Op(WP), SP-Op(WRB), SP-Op(``), SP-cNIST, SP-cNIST-1, SP-cNIST-2, SP-cNIST-3, SP-cNIST-4, SP-cNIST-5, SP-cNISTi-2, SP-cNISTi-3, SP-cNISTi-4, SP-cNISTi-5, SP-iobNIST, SP-iobNIST-1, SP-iobNIST-2, SP-iobNIST-3, SP-iobNIST-4, SP-iobNIST-5, SP-iobNISTi-2, SP-iobNISTi-3, SP-iobNISTi-4, SP-iobNISTi-5, SP-lNIST, SP-lNIST-1, SP-lNIST-2, SP-lNIST-3, SP-lNIST-4, SP-lNIST-5, SP-lNISTi-2, SP-lNISTi-3, SP-lNISTi-4, SP-lNISTi-5, SP-pNIST, SP-pNIST-1, SP-pNIST-2, SP-pNIST-3, SP-pNIST-4, SP-pNIST-5, SP-pNISTi-2, SP-pNISTi-3, SP-pNISTi-4, SP-pNISTi-5, SR-Fr(*), SR-MFr(*), SR-MPr(*), SR-MRr(*), SR-Mr(*), SR-Mr(*)_b, SR-Mr(*)_i, SR-Mr(A0), SR-Mr(A1), SR-Mr(A2), SR-Mr(A3), SR-Mr(A4), SR-Mr(A5), SR-Mr(AA), SR-Mr(AM-ADV), SR-Mr(AM-CAU), SR-Mr(AM-DIR), SR-Mr(AM-DIS), SR-Mr(AM-EXT), SR-Mr(AM-LOC), SR-Mr(AM-MNR), SR-Mr(AM-MOD), SR-Mr(AM-NEG), SR-Mr(AM-PNC), SR-Mr(AM-PRD), SR-Mr(AM-REC), SR-Mr(AM-TMP), SR-Mrv(*), SR-Mrv(*)_b, SR-Mrv(*)_i, SR-Mrv(A0), SR-Mrv(A1), SR-Mrv(A2), SR-Mrv(A3), SR-Mrv(A4), SR-Mrv(A5), SR-Mrv(AA), SR-Mrv(AM-ADV), SR-Mrv(AM-CAU), SR-Mrv(AM-DIR), SR-Mrv(AM-DIS), SR-Mrv(AM-EXT), SR-Mrv(AM-LOC), SR-Mrv(AM-MNR), SR-Mrv(AM-MOD), SR-Mrv(AM-NEG), SR-Mrv(AM-PNC), SR-Mrv(AM-PRD), SR-Mrv(AM-REC), SR-Mrv(AM-TMP), SR-Nv, SR-Ol, SR-Or, SR-Or(*), SR-Or(*)_b, SR-Or(*)_i, SR-Or(A0), SR-Or(A1), SR-Or(A2), SR-Or(A3), SR-Or(A4), SR-Or(A5), SR-Or(AA), SR-Or(AM-ADV), SR-Or(AM-CAU), SR-Or(AM-DIR), SR-Or(AM-DIS), SR-Or(AM-EXT), SR-Or(AM-LOC), SR-Or(AM-MNR), SR-Or(AM-MOD), SR-Or(AM-NEG), SR-Or(AM-PNC), SR-Or(AM-PRD), SR-Or(AM-REC), SR-Or(AM-TMP), SR-Or_b, SR-Or_i, SR-Orv, SR-Orv(*), SR-Orv(*)_b, SR-Orv(*)_i, SR-Orv(A0), SR-Orv(A1), SR-Orv(A2), SR-Orv(A3), SR-Orv(A4), SR-Orv(A5), SR-Orv(AA), SR-Orv(AM-ADV), SR-Orv(AM-CAU), SR-Orv(AM-DIR), SR-Orv(AM-DIS), SR-Orv(AM-EXT), SR-Orv(AM-LOC), SR-Orv(AM-MNR), SR-Orv(AM-MOD), SR-Orv(AM-NEG), SR-Orv(AM-PNC), SR-Orv(AM-PRD), SR-Orv(AM-REC), SR-Orv(AM-TMP), SR-Orv_b, SR-Orv_i, SR-Ov, SR-Pr(*), SR-Rr(*) }
```

## 2. Evaluate the results on-line

1. Asiya Interface

   http://asiya.lsi.upc.edu/demo/asiya_online.php

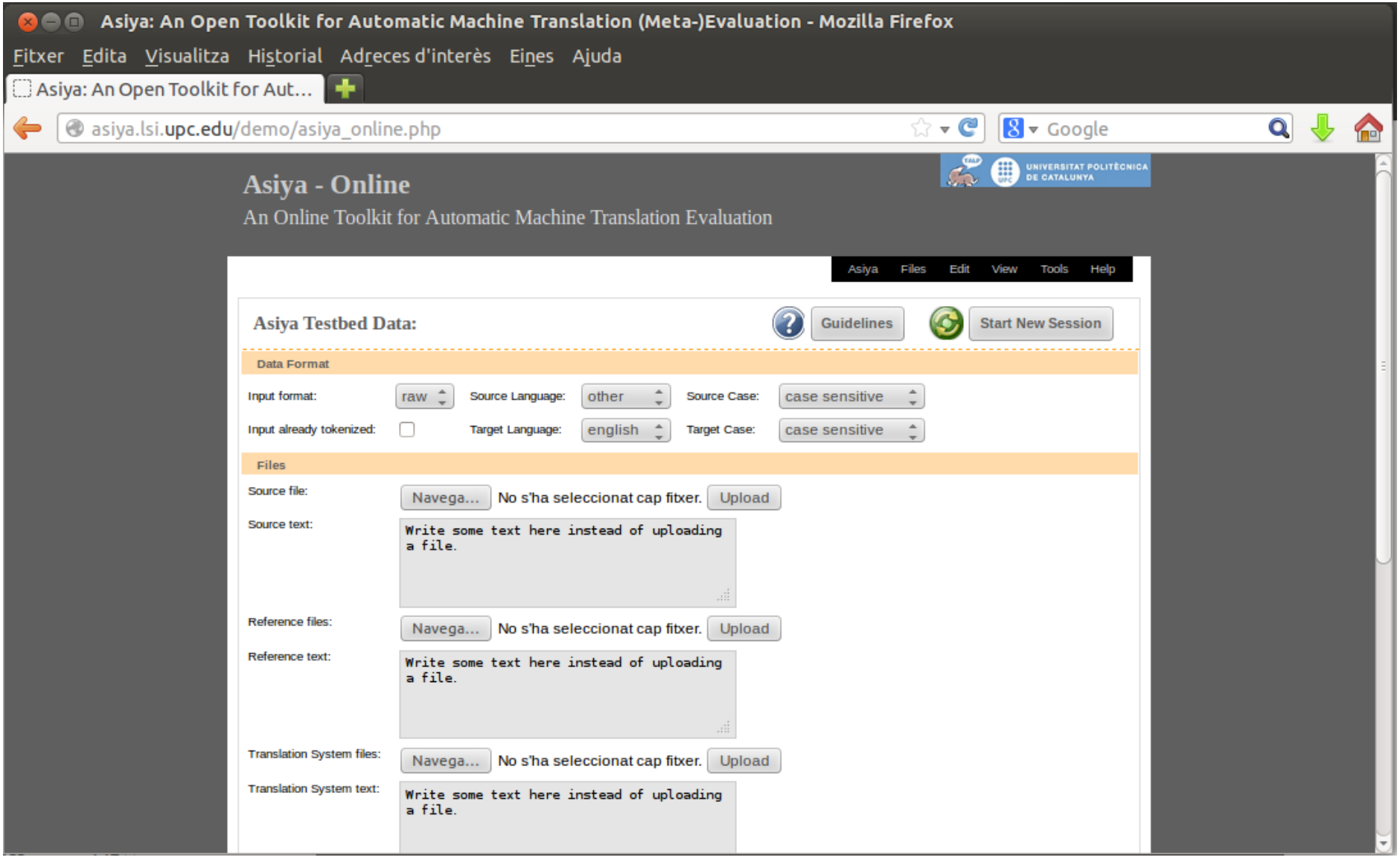
**3. Analise the results on-line**

1. t-Search Interface

   http://asiya.lsi.upc.edu/demo/tsearch_upload.php

# MT Evaluation

Demo: http://asiya.lsi.upc.edu/demo/asiya_online.php



# MT Evaluation

## An experiment: http://asiya.lsi.upc.edu/demo/userexperiment.php

**Was it easy?**

1. Prepared experiment

   http://asiya.lsi.upc.edu/demo/userexperiment.php

# Part IV

# Appendix: References

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