Statistical Machine Translation
A practical tutorial

Cristina España i Bonet
LSI Department
Universitat Politècnica de Catalunya

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

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

Part I: SMT background

≈ 2h
Overview

6 Translation system

7 MT Evaluation basics

8 Evaluation system

Part II: SMT experiments

~ 2h

Part III: MT evaluation

~ 45min
Part I

SMT background
Outline

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

Machine Translation Taxonomy

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

Machine Translation Taxonomy

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

Machine Translation Taxonomy

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

Machine Translation Taxonomy

Machine Translation systems

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

Empirical systems

- Statistical Machine Translation

Rule-based systems

- Example-based Translation
Empirical MT relies on large parallel aligned corpora.

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.
Empirical MT relies on large parallel aligned corpora.

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<tr>
<th>Corpus</th>
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4. The log-linear model
5. Beyond standard SMT
SMT, basics

The beginnings, summarised timeline

1950  1975  2000

1946 ENIAC
1949 Weaver memo
1966 Alpac report
Dictionary MT systems
Rule-based MT systems
2001 BLEU
Empirical MT systems
SMT, basics

The beginnings, summarised timeline

- 1946: ENIAC
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- 1988: Candide
- 2001: BLEU
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Dictionary MT systems
Rule-based MT systems
Empirical MT systems
The Noisy Channel as a statistical approach to translation:

Good morning! →
SMT, basics
The Noisy Channel approach

The Noisy Channel as a statistical approach to translation:

Good m   →   Bon jour!
The Noisy Channel as a statistical approach to translation:

\[ e: \text{Good morning!} \quad \rightarrow \quad f: \text{Bon jour!} \]
Mathematically:

\[ P(e|f) \]
Mathematically:

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

$$T(f) = \hat{e} = \arg\max_e P(e|f) = \arg\max_e P(e) P(f|e)$$
SMT, basics

Components

\[ T(f) = \hat{e} = \arg\max_e P(e) P(f|e) \]

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*
\[ T(f) = \hat{e} = \arg\max_e P(e) P(f|e) \]

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\[ \text{argmax} \]

- Search done by the \textit{decoder}
Outline

1. Introduction
2. Basics
3. Components
   - Language model
   - Translation model
   - Decoder
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The language model $P(e)$

Language model

$$T(f) = \hat{e} = \arg\max_e P(e) P(f|e)$$

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.
  - Long sentences may have zero probability!
Language model

\[ T(f) = \hat{e} = \arg\max_e P(e) P(f|e) \]

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The language model $P(e)$

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Estimation of how probable a sentence is.

Naïve estimation on a corpus with $N$ sentences:

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

Problem:

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

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

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 $P(e)$

Example, a 4-gram model

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

$$P(e) = P(\text{All}|\phi, \phi, \phi) \cdot P(\text{work}|\phi, \phi, \text{All}) \cdot P(\text{and}|\phi, \text{All}, \text{work})$$
$$\cdot P(\text{no}|\text{All}, \text{work}, \text{and}) \cdot P(\text{play}|\text{work}, \text{and}, \text{no})$$
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SMT, components

The language model $P(e)$

Example, a 4-gram model

\begin{align*}
e & : \text{All work and no play makes Jack a dull boy} \\

P(e) &= P(\text{All}|\phi,\phi,\phi) \cdot P(\text{work}|\phi,\phi,\text{All}) \cdot P(\text{and}|\phi,\text{All},\text{work}) \\
& \quad \cdot P(\text{no}|\text{All},\text{work},\text{and}) \cdot P(\text{play}|\text{work},\text{and},\text{no}) \\
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\end{align*}

where, for each factor,

\begin{align*}
P(\text{and}|\phi,\text{All},\text{work}) &= \frac{N(\text{All work and})}{N(\text{All work})}
\end{align*}
Example, a 4-gram model

\[ e: \textcolor{red}{\text{All work and no play}} \text{ makes } \textcolor{red}{\text{Jack a dull boy}} \]

\[
P(e) = P(\text{All}|\phi,\phi,\phi) \cdot P(\text{work}|\phi,\phi,\text{All}) \cdot P(\text{and}|\phi,\text{All,work}) \\
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**Example, a 4-gram model**

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

$$P(e) = P(\text{All}|\phi, \phi, \phi) \cdot P(\text{work}|\phi, \phi, \text{All}) \cdot P(\text{and}|\phi, \text{All}, \text{work})$$

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where, for each factor,

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Example, a 4-gram model

e: All \underline{work} \underline{and} no \underline{play} makes Jack a dull boy

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where, for each factor,
\[ P(\text{and}|\phi,\text{All},\text{work}) = \frac{\text{\textit{N}}(\text{All work and})}{\text{\textit{N}}(\text{All work})} \]
Example, a 4-gram model

\[ P(e) = P(\text{All}|\phi,\phi,\phi) \times P(\text{work}|\phi,\phi,\text{All}) \times P(\text{and}|\phi,\text{All,work}) \]
\[ \times P(\text{no}|\text{All,work,and}) \times P(\text{play}|\text{work,and,no}) \]
\[ \times P(\text{makes}|\text{and,no,play}) \times P(\text{Jack}|\text{no,play,makes}) \]
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SMT, components

The language model $P(e)$

Example, a 4-gram model

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Example, a 4-gram model

\( e: \text{All work and no play makes Jack a dull boy} \)

\[
\begin{align*}
P(e) &= P(\text{All} | \phi, \phi, \phi) \times P(\text{work} | \phi, \phi, \text{All}) \times P(\text{and} | \phi, \text{All}, \text{work}) \times \\
& \quad P(\text{no} | \text{All}, \text{work}, \text{and}) \times P(\text{play} | \text{work}, \text{and}, \text{no}) \times \\
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e: All work and no play makes Jack a dull boy

\[ P(e) = P(\text{All}|\phi,\phi,\phi) \cdot P(\text{work}|\phi,\phi,\text{All}) \cdot P(\text{and}|\phi,\text{All},\text{work}) \]
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where, for each factor,

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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:

- Linear interpolation.

\[
P(\text{and}|\text{All, work}) = \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
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Smoothing techniques:

- Linear interpolation.
- Back-off models.

$$P(\text{and}|\text{All, work}) = \frac{N(\text{All, work, and})}{N(\text{All, work})} + \lambda_2 \frac{N(\text{work, and})}{N(\text{work})} + \lambda_1 \frac{N(\text{and})}{N(\text{words})} + \lambda_0$$
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Smoothing techniques:

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P(\text{and}|\text{All, work}) = \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
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Main problems and criticisms:

- Long-range dependencies are lost.
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Solution

Smoothing techniques:

- Linear interpolation.

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

$$T(f) = \hat{e} = \arg\max_e P(e) P(f|e)$$

Estimation of the lexical correspondence between languages.

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

NULL Quan tornes a casa ?

When are you coming back home ?
SMT, components
The translation model \( P(f|e) \)

**Translation model**

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NULL  Quan tornes a casa ?

When are you coming back home ?

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 \text{Quan} translates into \text{When}.

- **Fertility $n$**
  
  $n(3|\text{tornes})$: the prob. that \text{tornes} generates 3 words.
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 you is generated (from NULL).
SMT, components
The translation model $P(f|e)$

Back to the example:

NULL  Quan  tornes  a  casa  ?

NULL  Quan  tornes  tornes  tornes  casa  ?

NULL  When  are  coming  back  home  ?

you  When  are  coming  back  home  ?

When  are  you  coming  back  home  ?
SMT, components

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Back to the example:

NULL Quan tornes a casa ?

NULL Quan tornestornestornes casa ?

NULL When are coming back home ?

you When are coming back home ?

When are you coming back home ?
SMT, components
The translation model $P(f|e)$

Back to the example:

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Fertility
Translation
Insertion
Distortion
SMT, components
The translation model $P(f|e)$

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When are you coming back home ?
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- **Fertility**
- **Translation**
- **Insertion**
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Word-based models: the IBM models

How can be \( t, n, d \) and \( p_1 \) estimated?

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

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

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

The translation model $P(f|e)$

**Expectation-Maximisation algorithm**

1. Parameter initialisation
2. Alignment probability calculation

Next step: Converged?

- **NO**
- **YES**

Final parameters and alignments
SMT, components
The translation model $P(f|e)$

Expectation-Maximisation algorithm

- Parameter initialisation
- Alignment probability calculation
- Parameter reestimation
- Alignment probability recalculation
SMT, components
The translation model $P(f|e)$

Expectation-Maximisation algorithm

1. Parameter initialisation
2. Alignment probability calculation
3. Parameter reestimation
4. Alignment probability recalculation
5. Converged?
   - NO
   - YES
6. Final parameters and alignments
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 ?
Alignment’s asymmetry

The definitions in IBM models make the alignments asymmetric:

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the opposite is not true due to the definition of fertility.

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<tr>
<th>Catalan to English</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NULL Quan tornes a casa ?</td>
<td>When are you coming back home ?</td>
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</table>

<table>
<thead>
<tr>
<th>English to Catalan</th>
<th></th>
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<tbody>
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<td>NULL When are you coming back home ?</td>
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</table>
SMT, components
The translation model $P(f|e)$

Graphically:

<table>
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<tr>
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<th>NULL</th>
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Catalan to English
SMT, components
The translation model $P(f|e)$

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English to Catalan
### Alignment symmetrisation

- **Intersection**: high-confidence, **high precision**.

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```

Catalan to English \(\cap\) English to Catalan
### Alignment symmetrisation

- **Union**: lower confidence, high recall.

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Catalan to English $\cup$ English to Catalan
SMT, components

The translation model $P(f|e)$

**From Word-based to Phrase-based models**

$$f: \text{En David llegeix el llibre nou.}$$
From Word-based to Phrase-based models

f: En David legeix el llibre nou.
e: φ
From Word-based to Phrase-based models

f: En **David** llegeix el llibre nou.
e: **David**
SMT, components
The translation model $P(f|e)$

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

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

*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: ✓
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: David reads the book again.

f: En David llegeix el llibre de nou.

e: David
From Word-based to Phrase-based models

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f: En David llegeix el llibre de nou.
e: David reads the book of
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: David reads the book of new.
SMT, components
The translation model $P(f|e)$

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: David reads the book of new. ✗
From Word-based to Phrase-based models

f: En David llegeix el llibre nou.
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SMT, components
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SMT, components
The translation model $P(f|e)$

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From Word-based to Phrase-based models

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- Some sequences of words usually translate together.
- Approach: take sequences (phrases) as translation units.
What can be achieved with phrase-based models (as compared to word-based models)

- Allow to translate from several to several words and not only from one to several.
- Some local and short range context is used.
- Idioms can be 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 $P(f|e)$

- **NULL**
- Quan
- ternes
- a casa
- ?

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

The translation model $P(f|e)$

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

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

**Phrase extraction** through an example:

<table>
<thead>
<tr>
<th>When you are coming back home?</th>
<th>Quan tornes</th>
<th>tu</th>
<th>a</th>
<th>casa</th>
<th>?</th>
</tr>
</thead>
</table>

(Quan tornes, When are you coming back)
SMT, components
The translation model $P(f|e)$

Phrase extraction through an example:

When are you coming back home?

When are you coming back?

(Quan tornes, When are you coming back)
Phrase extraction through an example:

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(Quan tornes, When are you coming back)
(Quan tornes tu, When are you coming back)
SMT, components

The translation model $P(f|e)$

### Intersection

<table>
<thead>
<tr>
<th>When</th>
<th>are</th>
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<th>back</th>
<th>home</th>
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<tr>
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(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 $P(f|e)$

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### SMT, components

The translation model $P(f|e)$

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SMT, components

The translation model $P(f|e)$

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

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SMT, components

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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 $P(f|e)$

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**

\[ T(f) = \hat{e} = \arg\max_e P(e) P(f|e) \]

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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- **Beam search decoders.** Let’s see..
Core algorithm

1. Collect translation options
2. Initial state: empty hypothesis
3. Expand hypotheses with all translation options
4. Estimate the cost for each hypothesis
5. Check if all source words are covered
   - If NO, go back to step 3
   - If YES, return translation: hypothesis with the lowest cost
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)
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Notation for hypotheses in construction:

Constructed sentence so far: come back
Source words already translated: - x --
Example: Quan tornes a casa

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  - (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

ϕ
When are you coming back home?

* x x x *

When

x - - -

When_are_you_coming_back

x x - -

When_are_you_coming_back_home

* x x x *

come_back

- x - -

come_back_home

- x x x

home

- - x x
When are you coming back home?

\( \phi \)
When are you coming back home

When|come_back_home
    *x x x x*

When|come_back
    x x - -

When_are_you_coming_back|
    x x - -

When_are_you_coming_back_home
    *x x x x*

come_back|
- x - -

come_back_home|
- x x x

home|
- - x x
SMT, components
A beam-search decoder
SMT, components
A beam-search decoder

\[
\phi
\]

- - - -

When|come_back_home

* x x x *

When|come_back when

x x - -

When|come_back home

* x x x *

When_are_you_coming_back| come_back home

x x - -

When_are_you_coming_back| home

* x x x *

When|come_back home

* x x x *

come_back| home

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come_back| when

x x - -

* x x x *

come_back home

* x x x *

come_back_home

* x x x *

come_back home| when

- x x x

* x x x *

home| come_back

- x x x

* x x x *

home| when

x - x x

* x x x *
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

Exhaustive search

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Hypotheses recombination

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

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

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

\[
\text{When|come_back_home} \iff \text{When|come_back|home}
\]

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

\[
\text{When|come\_back\_home} \quad \leftrightarrow \quad \text{When|come\_back|home}
\]

- 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.
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
SMT, the log-linear model

Motivation

**Maximum likelihood (ML)**

\[ \hat{e} = \arg\max_e P(e|f) = \arg\max_e P(e)P(f|e) \]

**Maximum entropy (ME)**

\[ \hat{e} = \arg\max_e P(e|f) = \arg\max_e \exp \left\{ \sum \lambda_m h_m(f, e) \right\} \]

\[ \hat{e} = \arg\max_e \log P(e|f) = \arg\max_e \sum \lambda_m h_m(f, e) \]

Log-linear model
SMT, the log-linear model
Motivation

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Log-linear model
SMT, the log-linear model

**Motivation**

### Maximum likelihood (ML)

\[ \hat{e} = \arg\max_e P(e|f) = \arg\max_e P(e) P(f|e) \]

### Maximum entropy (ME)

\[ \hat{e} = \arg\max_e P(e|f) = \arg\max_e \exp \left\{ \sum \lambda_m h_m(f, e) \right\} \]

### Log-linear model

\[ \hat{e} = \arg\max_e \log P(e|f) = \arg\max_e \sum \lambda_m h_m(f, e) \]
SMT, the log-linear model

Motivation

**Maximum likelihood (ML)**

\[
\hat{e} = \arg\max_e P(e|f) = \arg\max_e P(e) \cdot P(f|e)
\]

**Maximum entropy (ME)**

\[
\hat{e} = \arg\max_e \log P(e|f) = \arg\max_e \sum \lambda_m h_m(f, e)
\]

Log-linear model with

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

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

- Extra features $h_m$ can be easily added...
- ... but their weight $\lambda_m$ 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: $P(e)$, $P(f|e)$, $P(e|f)$, $\text{lex}(f|e)$, $\text{lex}(e|f)$, $\text{ph}(e)$, $w(e)$ 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.
State of the art feature functions

Eight features are usually used: \( P(e), P(f|e), P(e|f), \text{lex}(f|e), \text{lex}(e|f), ph(e), w(e) \) 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:
  
  \[
  P_d(\text{ini}_{\text{phrase}_i}, \text{end}_{\text{phrase}_{i-1}}) = \alpha|\text{ini}_{\text{phrase}_i} - \text{end}_{\text{phrase}_{i-1}} - 1|
  \]
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)
From where and how can one learn reorders?

<table>
<thead>
<tr>
<th></th>
<th>Quan</th>
<th>tornes</th>
<th>tu</th>
<th>a</th>
<th>casa</th>
<th>?</th>
</tr>
</thead>
<tbody>
<tr>
<td>When</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>are</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>you</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>coming</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>back</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>home</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(are, tornes, monotone)
From where and how can one learn reorders?

(coming back, tornes, swap)
From where and how can one learn reorders?

<table>
<thead>
<tr>
<th></th>
<th>Quan</th>
<th>tornes</th>
<th>tu</th>
<th>a</th>
<th>casa</th>
<th>?</th>
</tr>
</thead>
<tbody>
<tr>
<td>When are you coming back home?</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

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

- Sparse statistics of the orientation types $\rightarrow$ smoothing.
- Several variations.
State of the art feature functions

13 features may be used:

- \( P(e) \);
- \( P(f|e), P(e|f), \text{lex}(f|e), \text{lex}(e|f) \);
- \( ph(e), w(e) \);
- \( P_{\text{mon}}(o|e,f), P_{\text{swap}}(o|e,f), P_{\text{dis}}(o|e,f) \);
- \( P_{\text{mon}}(o|f,e), P_{\text{swap}}(o|f,e), P_{\text{dis}}(o|f,e) \).
Supervised training: a (small) aligned parallel corpus is used to determine the optimal weights.

\[ \hat{e} = \arg \max_e \log P(e|f) = \arg \max_e \sum \lambda_m h_m(f, e) \]
Development training, weights optimisation

Strategies

- **Generative training.** Optimises ME objective function which has a unique optimum. Maximises the likelihood.

- **Discriminative training** only for feature weights (not models), or purely discriminative for the model as a whole. This way translation performance can be optimised.

- Minimum Error-Rate Training (MERT).
Development training, weights optimisation

Strategies

- **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).**
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

1. λᵢ initialisation
2. Select a direction $k$, fix $\lambda_i \neq \lambda_k$
3. Best $\lambda_k$ (line minimisation)
4. all $k$ explored?
   - NO
   - YES
5. $\lambda_i$ stable?
   - NO
   - YES
6. Optimal $\lambda_i$
SMT, the log-linear model

The log-linear model allows to include several weighted features. State of the art systems use 8 real features.

The corresponding weights are optimised on a development set, a small aligned parallel corpus.

An optimisation algorithm such as MERT is appropriate for at most a dozen of features. For more features, purely discriminative learnings should be used.

For MERT, the choice of the metric that quantifies the error in the translation is an issue.
Outline

1. Introduction
2. Basics
3. Components
4. The log-linear model
5. Beyond standard SMT
   - Factored translation models
   - Syntactic translation models
   - Ongoing research
Considering linguistic information in phrase-based models

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

\[(\text{word}) \rightarrow (\text{word, lemma, PoS, morphology, ...})\]

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

\[(\text{word}) \rightarrow (\text{word, lemma, PoS, morphology, ...})\]

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

\[
\begin{align*}
\text{lemma}_f & \quad \downarrow T \\
\text{PoS}_f & \quad \downarrow T \\
\text{morphology}_f & \quad \downarrow T \\
\text{word}_f & \\
\text{lemma}_e & \quad \text{PoS}_e & \quad \text{morphology}_e & \quad \text{word}_e \\
\end{align*}
\]
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.

\[(\text{word}) \rightarrow (\text{word}, \text{lemma}, \text{PoS}, \text{morphology}, ...)\]

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

\[
\begin{align*}
\text{casa}_f & \quad \text{NN}_f \quad \text{fem.}, \text{plural}_f \quad \text{cases}_f \\
\downarrow T & \quad \downarrow T & \quad \downarrow T \\
\text{house}_e & \quad \text{NN}_e \quad \text{plural}_e & \quad \rightarrow \quad \text{houses}_e
\end{align*}
\]
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.
Syntactic models ease reordering. An intuitive example:

**En David llegeix un llibre nou**
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
Syntax-based translation models

Syntactic models ease reordering. An intuitive example:

En David llegeix un llibre nou

```
S  
|  
V  
|  
 llegeix
|  
NP
|  
|  
PP | NN
|  
|  
En David
```

```
S  
|  
V  
|  
 VP
|  
|  
DT | NN | PP
|  
|  
un | llibre | nou
```

```
S  
|  
V  
|  
 VP
|  
|  
NN
|  
|  
DT | PP | NN
```
Syntactic models ease reordering. An intuitive example:

*En David llegeix un llibre nou*
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
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.
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.
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.
Part II

SMT experiments
Translation system
- Demos
- Software
- Steps
SMT system
Demo: http://demo.statmt.org/

Moses Machine Translation Demo

Source:

Try any example to translate.

Source:

Looking to translate a web page? Then click here

Translation:

Versuchen Sie ein Beispiel zu übersetzen.

Help to improve statistical machine translation!

Versuchen Sie ein Beispiel zu übersetzen.
SMT system
Demo: http://cog.hut.fi/smtdemo

Statistical Machine Translation Demo


Try the translator below, or view recent translations.

Try an example to translate.

en->sv (word, Europarl v3)  Translate

Show phrases horizontal

This page is maintained by the Computational Cognitive Systems Group at the Aalto University.
Build your own SMT system

1. Language model with SRILM.

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

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)

   ```
   ```
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)

   ```
   ```
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
   ```
SMT system

Steps

3. Train the translation model

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)

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
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 -f ./filteredmodel/moses.ini <  
   testset.es > testset.translated.en
   ```
Part III

Machine Translation Evaluation
7  MT Evaluation basics
   • Automatic Evaluation
   • BLEU
   • Limits of lexical similarity

8  Evaluation system
MT Evaluation
Importance for system development

Evaluation methods

- Error detection
- Error analysis
- Refinement

Implementation

Test

OK? YES NO

Unfruitful results
MT Evaluation
Importance for system development

- Error detection
- Error analysis
- Refinement
- Implementation
- Test

Evaluation methods

Unfruitful results

OK? YES NO
MT Evaluation
Importance for system development

Evaluation methods

Error detection
Error analysis
Refinement

Implementation

Test

OK? YES NO

Unfruitful results
MT Evaluation
Importance for system development

Evaluation methods

Error detection
Error analysis
Refinement
Implementation
Test

Evaluation methods

Unfruitful results

YES
OK?
NO

Implementation

Error detection

Evaluation methods
MT Evaluation
Importance for system development

- Error detection
- Error analysis
- Refinement
- Implementation
- Test

Evaluation methods

YES

OK?

NO

Unfruitful results
MT Evaluation

Importance for system development

Error detection → Error analysis → Refinement → Implementation → Test → OK?

Evaluation methods

YES

Unfruitful results

NO
MT Evaluation
Importance for system development

- Error detection
- Error analysis
- Refinement
- Implementation
- Test

Evaluation methods

Unfruitful results

YES

NO

OK?
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

Nowadays, BLEU is accepted as the standard metric.
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

Nowadays, BLEU is accepted as *the standard* metric.
BLEU: a Method for Automatic Evaluation of Machine Translation
Kishore Papineni, Salim Roukos, Todd Ward, Wei-Jing Zhu
IBM Research Division

“The main idea is to use a weighted average of variable length phrase matches against the reference translations. This view gives rise to a family of metrics using various weighting schemes. We have selected a promising baseline metric from this family.”
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.
Candidate 1:

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

Reference 1:

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

Reference 2:

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

Reference 3:

It is the practical guide for the army always to heed the directions of the party.
Candidate 1:

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

Reference 1:

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

Reference 2:

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

Reference 3:

It is the practical guide for the army always to heed the directions of the party.
Candidate 2:

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

Reference 1:

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

Reference 2:

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

Reference 3:

*It is the practical guide for the army always to heed the directions of the party.*
Modified n-gram precision (1-gram)

Precision-based measure, but:

Candidate:
\[
\text{The the the the the the the the.}
\]

Reference 1:
\[
\text{The cat is on the mat.}
\]

Reference 2:
\[
\text{There is a cat on the mat.}
\]
Modified n-gram precision (1-gram)

Precision-based measure, but:

\[
\text{Prec. } = \frac{1 + \frac{1}{7}}{}
\]

Candidate:

The the the the the the the the.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.
**Modified n-gram precision** (1-gram)

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

**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: \[ \text{Prec.} = \frac{3 + 7}{7} \]

Candidate:

The the the the the the the the.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.
Modified n-gram precision (1-gram)

Precision-based measure, but:

\[
\text{Prec.} = \frac{4 + \frac{1}{7}}{7}
\]

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)

Precision-based measure, but:

\[ \text{Prec.} = \frac{5 + 7}{7} \]

Candidate:

The the the the the the the the.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.
Modified n-gram precision (1-gram)

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

Candidate:
\textbf{The the the the the the the the}.

Reference 1:
\textbf{The} cat is on the mat.

Reference 2:
\textbf{There is a cat on the mat.}
Modified n-gram precision (1-gram)

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

Candidate:
\begin{quote}
   The the the the the the the the.
\end{quote}

Reference 1:
\begin{quote}
   The cat is on the mat.
\end{quote}

Reference 2:
\begin{quote}
   There is a cat on the mat.
\end{quote}
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 minimum 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 the.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.

1. $w_i \rightarrow \text{The}$
   $\# w_i, R_1 = 2$
   $\# w_i, R_2 = 1$

2. $\text{Max}_{(1)} = 2$, $\# w_i, C = 7$
   $\Rightarrow \text{Min} = 2$

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: $P_1 = \frac{\sum_{w_i \in \text{C}} \min(|w_i|, |R_1|, |R_2|)}{|\text{C}|}$

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. $w_i \rightarrow \text{The}$
   $\#w_i,R_1 = 2$
   $\#w_i,R_2 = 1$

2. $\max_{(1)} = 2$, $\#w_i,C = 7$
   $\Rightarrow \min = 2$

3. No more distinct words
Modified n-gram precision (1-gram)

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

Candidate:

The the the the the the the the

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.

1. $w_i \rightarrow$ The
   $\#w_i, R_1 = 2$
   $\#w_i, R_2 = 1$

2. $\text{Max}_{(1)} = 2, \#w_i, C = 7$
   $\Rightarrow \text{Min} = 2$

3. No more distinct words
**Modified n-gram precision** (1-gram)

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

Candidate:

The the the the the the the.

Reference 1:

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. \( \text{Max}(1)=2, \ \#w_{i,C} = 7 \)
   \( \Rightarrow \text{Min}=2 \)

3. No more distinct words
Modified n-gram precision

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

$$P_n = \frac{\sum_{C \in \{\text{candidates}\}} \sum_{\text{ngram} \in C} \text{Count}_{\text{clipped}}(\text{ngram})}{\sum_{C \in \{\text{candidates}\}} \sum_{\text{ngram} \in C} \text{Count}(\text{ngram})}$$

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.
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:
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.
Brevity penalty

\[
BP = \begin{cases} 
1 & \text{if } c > r \\
\frac{1}{e^{1-r/c}} & \text{if } c \leq r
\end{cases}
\]

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

\[
\text{BLEU} = \text{BP} \cdot \exp \left( \sum_{n=1}^{N} w_n \log P_n \right)
\]

- Geometric average of $P_n$ (empirical suggestion).
- $w_n$ positive weights summing to one.
- Brevity penalty.
Paper’s Conclusions

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

There are several widely used implementations of BLEU.
(Moses multi-bleu.perl script, NIST mteval-vXX.pl script, etc.)

Results differ because of:

- Different tokenisation approach.
- Different definition of closest reference in the brevity penalty estimation.
NIST is based on BLEU but:

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

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

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

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

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

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Lexical similarity is nor a sufficient neither a necessary condition so that two sentences convey the same meaning.
Recent efforts to go over lexical similarity

Extend the reference material:

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

Compare other linguistic features than words:

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

Combination of the existing metrics.
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- Semantic similarity: named entities, semantic roles, discourse representations.

Combination of the existing metrics.
Much more on the topic in Lluís’ seminar:

MT Evaluation
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.
Outline

7 MT Evaluation basics

8 Evaluation system
   - Software
   - Steps
   - Demo
Evaluate the results

1. With BLEU scoring tool. Available as a Moses script or from NIST:
   http://www.itl.nist.gov/ia六个/mig/tools/mtevalv13a-20091001.tar.gz

2. With IQmt package.
   http://www.lsi.upc.edu/~nlp/IQMT/
1. Evaluate the results

With BLEU scoring tool in Moses:

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

Steps

2. Evaluate the results on-line

OpenMT Evaluation Demo

http://biniki.lsi.upc.edu/openMT/evaldemo.php
OpenMT Evaluation Demo
Linguistic Features towards Heterogeneous Automatic MT Evaluation

Translation quality aspects are heterogeneous and diverse, involving, in general, many different linguistic dimensions. However, most automatic evaluation methods in use today rely on partial quality assumptions, such as lexical similarity. This introduces a bias in the development cycle which in some cases has been reported to carry very negative consequences. In order to tackle this methodological problem, we explore a novel path towards heterogeneous automatic MT evaluation. We have compiled a rich set of specialized similarity metrics operating at different linguistic levels (lexical, syntactic and semantic). We have also studied how the scores conferred by different metrics may be integrated into a single measure of quality, without having to adjust their relative importance.

This demo allows you to obtain automatic evaluation scores according to a selected set of metric representatives, together with ULC combined score (i.e., arithmetic mean) over a heuristically defined set of metrics.

Instructions:

- Select the target language. The metric set will depend on this choice. Currently, linguistic features are only supported for English. For other languages, the metric set limits to the lexical dimension.
- Type test cases in the text areas below:
  - at least one, and up to five, candidate translations.
  - at least one, and up to five, reference translations.
  - text areas must contain one test case per line up to a maximum of ten.
- Click on the “Go Evaluate!” button at the right.
  - Execution should take between one and five minutes for English, and just a few seconds for other languages.

Target Language: English

Go Evaluate!
Part IV

Appendix: References
History of SMT

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- Slocum, 1985 [Slo85]

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- Brown et al., 1990 [BCP+90]
- Brown et al., 1993 [BPPM93]
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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]
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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]
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Language model

- Kneser & Ney, 1995 [KN95]

MERT

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Domain adaptation

- Bertoldi and Federico, 2009 [Och03]
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- Bach et al., 2009 [BGV09]
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Systems combination

- Du et al., 2009 [DMW09]
- Li et al., 2009 [LDZ+09]
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- Canisius & van den Bosch, 2009 [CvdB09]
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- Shen et al., 2009 [SXZ+09]
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