

Introduction to Machine Translation Evaluation

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Wait!

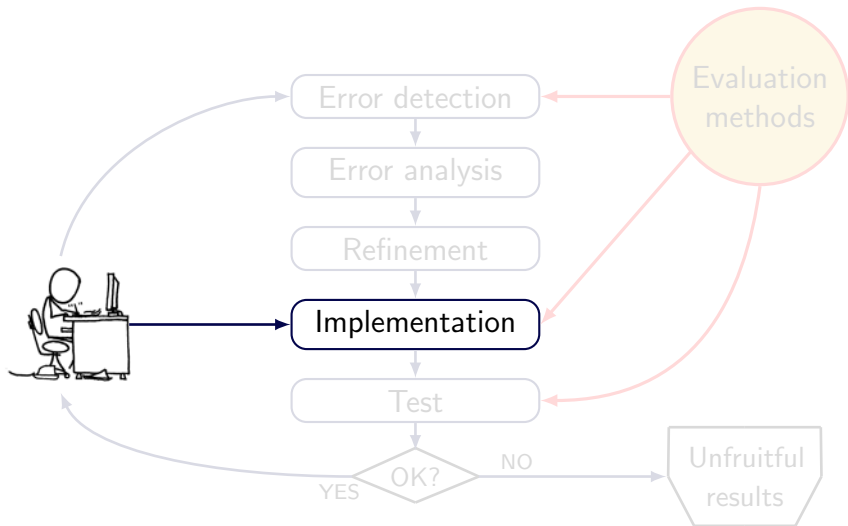
Thanks to
Meritxell González and **Lluís Màrquez**
for some of the slides

Outline

- 1 Basics
- 2 Manual Evaluation
- 3 Automatic Evaluation
- 4 Tools
- 5 References

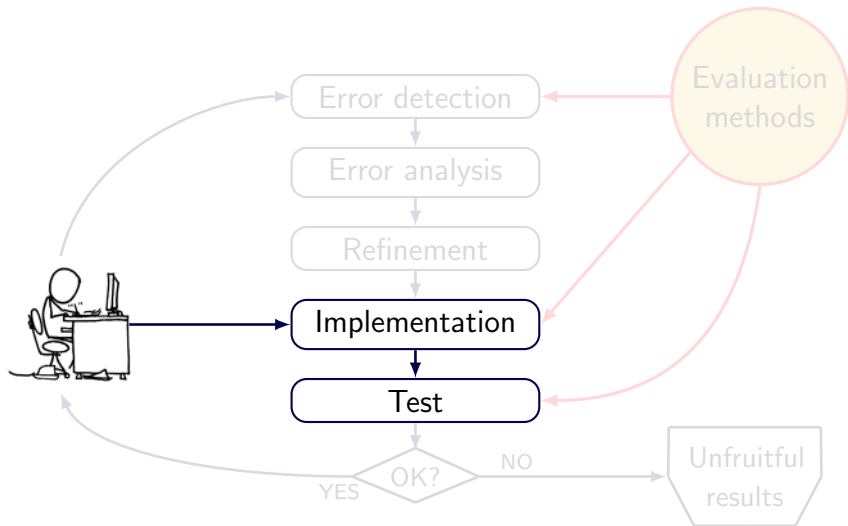
MT Evaluation

Importance for system development



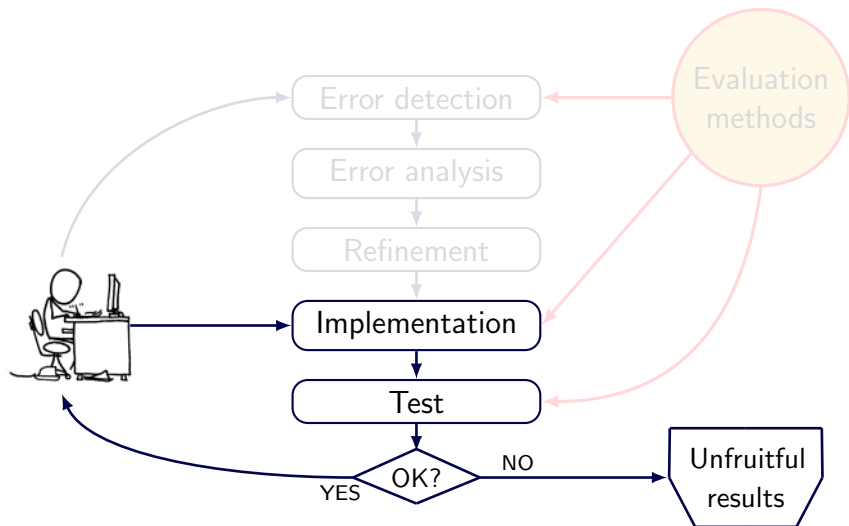
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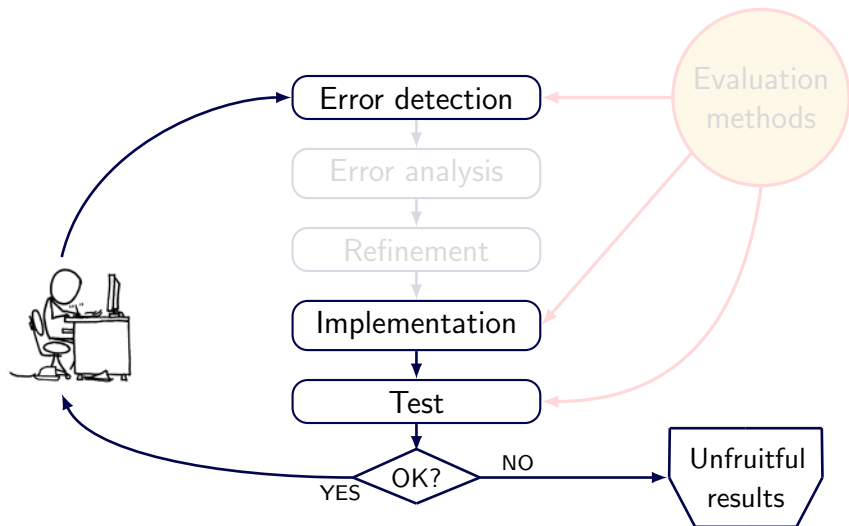
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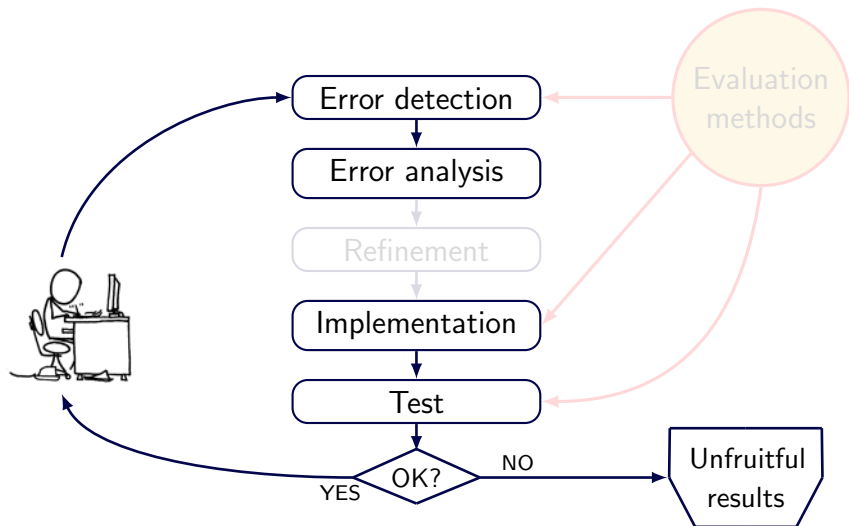
MT Evaluation

Importance for system development



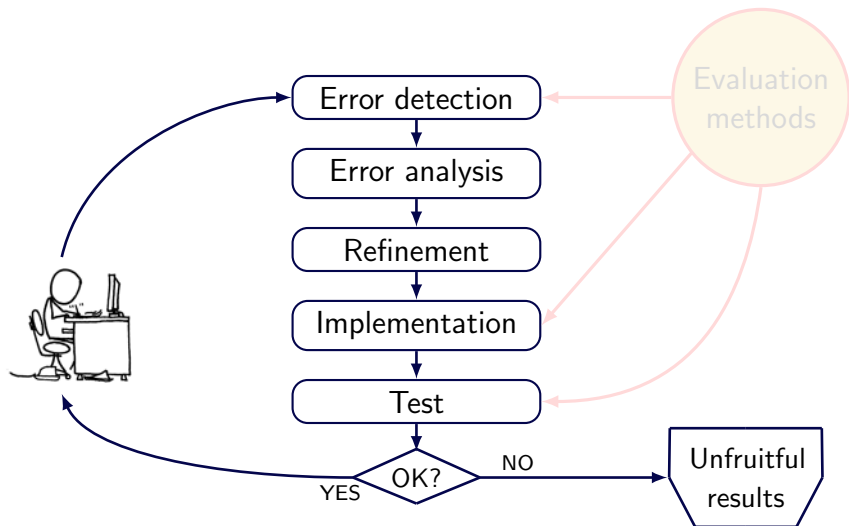
MT Evaluation

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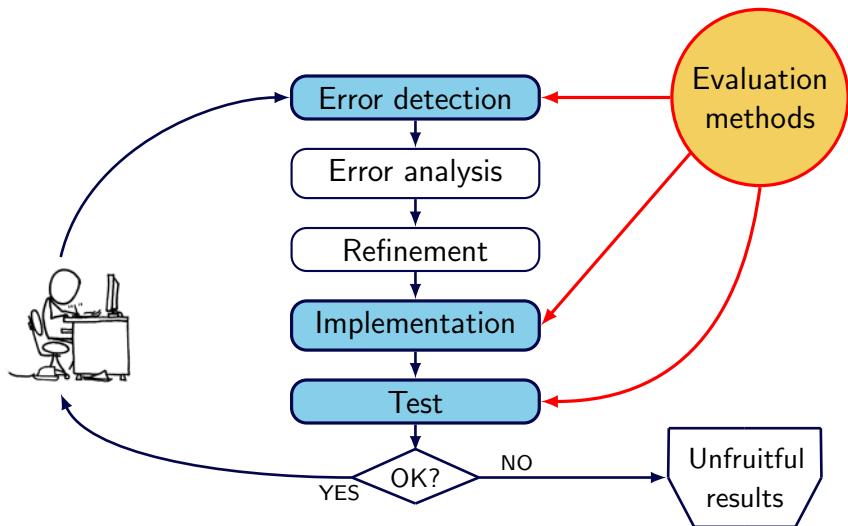
MT Evaluation

Importance for system development



MT Evaluation

Importance for system development



MT Evaluation

Automatic vs. 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

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MT Evaluation

Automatic vs. Manual evaluation

Risks of Automatic Evaluation

- **System overtuning:** when system parameters are adjusted towards a given metric
- **Blind system development:** when metrics are unable to capture actual system improvements
- **Unfair system comparisons:** when metrics are unable to reflect difference in quality between MT systems

MT Evaluation

How can we evaluate translations?

Machine Translation is an open NLP task

- The correct translation is not unique
- The set of valid translations is not small
- Translation correctness is not black and white
- Quality aspects are heterogeneous

MT Evaluation

Quality aspects

Adequacy (or Fidelity) Does the output convey the same meaning as the input sentence? Is part of the message lost, added, or distorted?

Fluency (or Intelligibility) Is the output fluent? This involves both grammatical correctness and idiomatic word choices.

Post–edition effort Time required to *repair* the translation, number of key strokes, etc.

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- 1 Basics
- 2 Manual Evaluation
 - Likert scales
 - Rankings
 - Pros, cons and agreements
- 3 Automatic Evaluation
- 4 Tools
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Manual Evaluation

Human annotations

Likert scales – TAUS recommendation

Adequacy How much of the meaning expressed in the gold-standard translation or the source is also expressed in the target translation?

- 4 Everything
- 3 Most
- 2 Little
- 1 None

Fluency To what extent is a target side translation grammatically well informed, without spelling errors and experienced as using natural/intuitive language by a native speaker?

- 4 Flawless
- 3 Good
- 2 Disfluent
- 1 Incomprehensible

Manual Evaluation

Human annotations

Likert scales – NIST example

Adequacy I How much of the meaning expressed in the Reference translation is also expressed in the System translation?

7-point scale ranging from 1 (None) to 7 (All)

Adequacy II Does the Machine translation mean essentially the same as the Reference translation?

Yes/No, Adequacy I > 4
No, Adequacy II ≤ 4

Manual Evaluation

Human annotations

Ranking – Pair-wise comparison

Annotators chose the best system, given the source and target sentence, and 2 anonymised random systems.

Ranking

Annotators rank n anonymised systems, randomly selected and randomly ordered.

Manual Evaluation

Appraise

Appraise

(Federmann 2012)

Хотите светящегося в темноте мороженого?

Британский предприниматель создал первое в мире светящееся в темноте мороженое с помощью медузы.

— Source

Fancy a glow-in-the-dark ice cream? A British entrepreneur has created the world's first glow-in-the-dark ice cream - using jellyfish.

— Reference

Best ← Rank 1 ● Rank 2 ● Rank 3 ● Rank 4 ● Rank 5 ● → Worst

You do want ice cream luminous in the darkness?

— Translation 1

Best ← Rank 1 ● Rank 2 ● Rank 3 ● Rank 4 ● Rank 5 ● → Worst

You want to glowing in the dark ice cream?

— Translation 2

Best ← Rank 1 ● Rank 2 ● Rank 3 ● Rank 4 ● Rank 5 ● → Worst

You want the luminous in the dark ice cream?

— Translation 3

Best ← Rank 1 ● Rank 2 ● Rank 3 ● Rank 4 ● Rank 5 ● → Worst

Want luminous in the dark ice cream?

— Translation 4

Best ← Rank 1 ● Rank 2 ● Rank 3 ● Rank 4 ● Rank 5 ● → Worst

Want to illuminate the Dark with Ice Cream?

— Translation 5

Manual Evaluation

Appraise

” **Appraise** is an open-source tool for manual evaluation of Machine Translation output.”

Appraise allows to collect **human judgments** on translation output, implementing annotation tasks such as

- translation quality checking;
- ranking of translations;
- error classification;
- manual post-editing.

Manual Evaluation

Pros & Cons

- Likert scales have to be defined
- 4-, 5-, 7, 10-point likert scales have been used
- The concept of ranking is easy
- Ranks provide less information
- Agreement among annotators (common!)

Manual Evaluation

Interannotator Agreement

Cohen's kappa coefficient, κ (Cohen, 1960)

$$\kappa = \frac{Pr(\text{agreement}) - Pr(\text{expected})}{1 - Pr(\text{expected})}$$

Kappa **interpretation** (Landis & Kogh, 1977)

0.0–0.2	slight
0.2–0.4	fair
0.4–0.6	moderate
0.6–0.8	substantial
0.8–1.0	almost perfect

Manual Evaluation

Interannotator Agreement

More details:

[https://staff.fnwi.uva.nl/r.fernandezrovira/teaching/
MoLProject2011/annotation-reliability.pdf](https://staff.fnwi.uva.nl/r.fernandezrovira/teaching/MoLProject2011/annotation-reliability.pdf)

(slides 6-14)

Manual Evaluation

Interanotator Agreement

Workshop on statistical machine translation, **WMT13**

- Inter- κ only slight or fair
- Even Intra- κ only fair or moderate

	Inter- κ	Intra- κ
CZ-EN	0.244	0.479
EN-CZ	0.168	0.290
DE-EN	0.299	0.535
EN-DE	0.267	0.498
ES-EN	0.277	0.575
EN-ES	0.206	0.492
FR-EN	0.275	0.578
EN-FR	0.231	0.495
RU-EN	0.278	0.450
EN-RU	0.243	0.513


Human-targeted Translation Error Rate, HTER

Annotator Post-edition of the candidate translation to have the same meaning as a reference translation with as few edits as possible

Evaluation TER with the candidate translation and the post-edited reference

$$HTER = \frac{\text{Substitutions} + \text{Insertions} + \text{Deletions} + \text{Shifts}}{\text{ReferenceWords}}$$

Wait!

A close-up photograph of a typewriter keyboard. The focus is on a single key that has been pressed, showing the word "Questions?" in a dark, monospaced font. The key itself is a light-colored, possibly plastic or metal, with a slightly worn surface. Above the key, the metal frame of the typewriter is visible, featuring a series of small, evenly spaced holes. The background is a solid, bright yellow color, which contrasts sharply with the dark, textured elements of the typewriter.

Questions?

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- 1 Basics
- 2 Manual Evaluation
 - Likert scales
 - Rankings
 - Pros, cons and agreements
- 3 Automatic Evaluation
 - Lexical metrics
 - BLEU
 - Limits of lexical similarity
 - METEOR
- 4 Tools
 - Software
 - Demo
- 5 References

MT Evaluation

Automatic evaluation

Setting Compute **similarity** between system's output and one or several reference translations

Challenge The similarity measure should be able to discriminate whether the two sentences convey the same meaning (**semantic equivalence**)

Automatic 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

Automatic evaluation

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(most of the metrics!)

- **Edit Distance:** WER, PER, TER
- **Precision:** **BLEU**, NIST, WNM
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Nowadays, BLEU is accepted as *the standard* metric.

Automatic 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.”

Automatic 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.

Automatic 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.

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Candidate 1:

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Reference 1:

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Reference 3:

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

Automatic 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.

Automatic 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.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.

Automatic 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.

Reference 1:

The cat is on the mat.

Reference 2:

There is a cat on the mat.

Automatic 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.

Automatic 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.

Automatic 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.

Automatic 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.

Automatic 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.

Automatic 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.

Automatic 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 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.

Automatic 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:

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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

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Modified n-gram precision (1-gram)

Modified 1-gram precision: $P_1 =$

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Modified n-gram precision (1-gram)

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

Candidate:

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Reference 1:

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Reference 2:

There is a cat on the mat.

① $w_i \rightarrow \text{The}$
 $\#_{w_i, R1} = 2$
 $\#_{w_i, R2} = 1$

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

③ No more distinct words

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Modified n-gram precision (1-gram)

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

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Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Modified n-gram precision

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

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

low n
adequacy

high n
fluency

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Brevity penalty

Candidate:

of the

Reference 1:

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Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Brevity penalty

Candidate:

of the

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

Reference 1:

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Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

Brevity penalty

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

c candidate length, r reference length

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

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

BiLingual Evaluation Understudy, BLEU

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

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

Automatic evaluation

IBM BLEU: Papineni, Roukos, Ward and Zhu (2001)

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.

Automatic 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.

Wait!

A close-up photograph of a typewriter keyboard. The focus is on a single key that has the word "Questions?" typed on it in a dark, monospaced font. The key is surrounded by other keys, some of which are visible in the background but out of focus. The lighting is dramatic, highlighting the texture of the keys and the raised letters.

Questions?

Automatic 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

Lexical similarity

Limits of lexical similarity

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

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

Ref1: The evaluation of the 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 neither a sufficient nor a necessary condition so that two sentences convey the same meaning.

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

Limits of lexical similarity

Beyond 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.

Extending the reference material

METEOR, Banerjee and Lavie (2005)

Metric for Evaluation of Translation with Explicit ORdering

$$METEOR = (1 - Pen)F_{\alpha}$$

$$F_{\alpha} = \frac{PR}{\alpha P + (1 - \alpha)R}$$

Precision and **Recall**
weighted harmonic mean

$$Pen = \gamma \left(\frac{\text{chunks}}{\text{mapped unigrams}} \right)^{\beta}$$

Penalty factor, penalises
non-contiguous matches

Matches: exact, lemma, synonym, paraphrase

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Combination of the existing metrics.

Limits of lexical similarity

Comparing other linguistic features than words

Candidate:

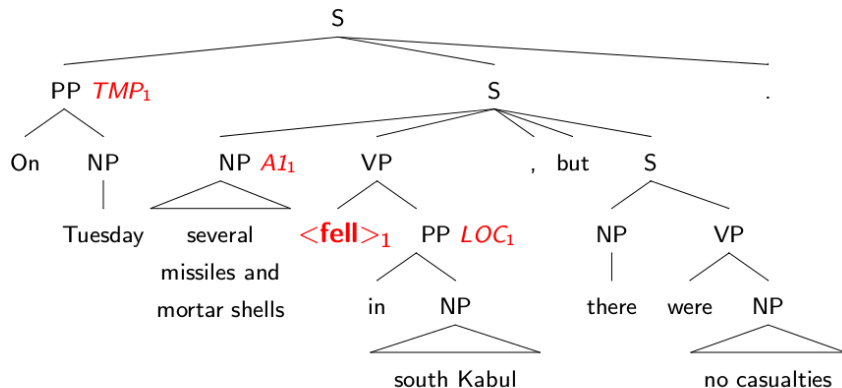
On Tuesday several missiles and mortar shells fell in south Kabul, but there were no casualties.

Reference:

Several rockets and mortar shells fell today, Tuesday, in south Kabul without causing any casualties.

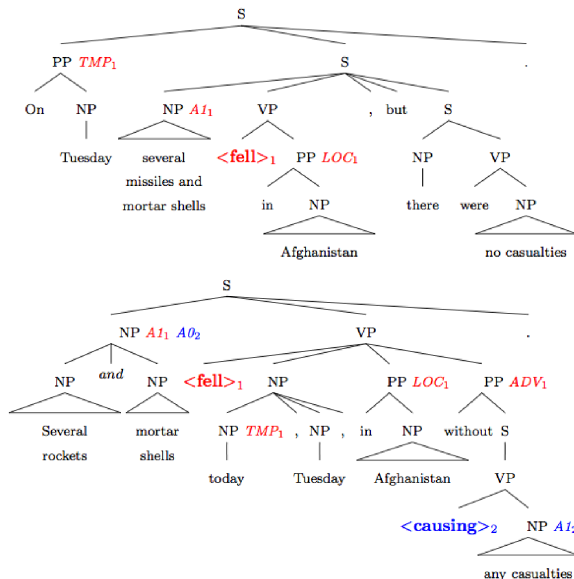
Limits of lexical similarity

Comparing other linguistic features than words



Limits of lexical similarity

Comparing other linguistic features than words



Limits of lexical similarity

Comparing other linguistic features than words

Overlap

Generic similarity measure among Linguistic Elements.
Inspired by the Jaccard similarity coefficient.

Linguistic element (LE): abstract reference to any possible type of linguistic unit, structure, or relationship among them.

- For instance: POS tags, word lemmas, NPs, syntactic phrases
- A sentence can be seen as a bag (or a sequence) of LEs of a certain type
- LEs may embed

Limits of lexical similarity

Comparing other linguistic features than words

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Limits of lexical similarity

Comparing other linguistic features than words

$$O(t) = \frac{\sum_{i \in (\text{items}_t(\text{cand}) \cap \text{items}_t(\text{ref}))} \text{count}_{\text{cand}}(i, t)}{\sum_{i \in (\text{items}_t(\text{cand}) \cup \text{items}_t(\text{ref}))} \max(\text{count}_{\text{cand}}(i, t), \text{count}_{\text{ref}}(i, t))}$$

t is the LE type

'cand': candidate translation

'ref': reference translation

$\text{items}_t(s)$: set of items occurring inside LEs of type t

$\text{count}_s(i, t)$: occurrences of item i in s inside a LE of type t

Limits of lexical similarity

Comparing other linguistic features than words

Coarser variant: **micro-averaged overlap over all types**

$$O(\star) = \frac{\sum_{t \in T} \sum_{i \in (\text{items}_t(\text{cand}) \cap \text{items}_t(\text{ref}))} \text{count}_{\text{cand}}(i, t)}{\sum_{t \in T} \sum_{i \in (\text{items}_t(\text{cand}) \cup \text{items}_t(\text{ref}))} \max(\text{count}_{\text{cand}}(i, t), \text{count}_{\text{ref}}(i, t))}$$

T : set of all LE types associated to the given LE class

Limits of lexical similarity

Beyond lexical similarity

Extend the reference material:

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

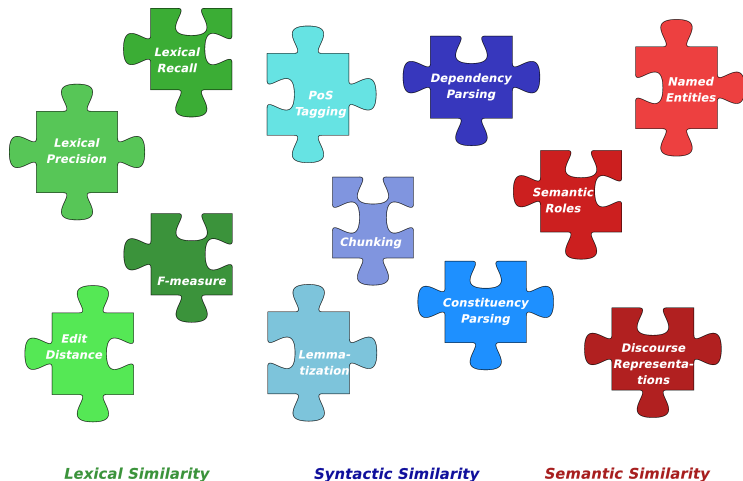
Compare other linguistic features than words:

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

Combination of the existing metrics.

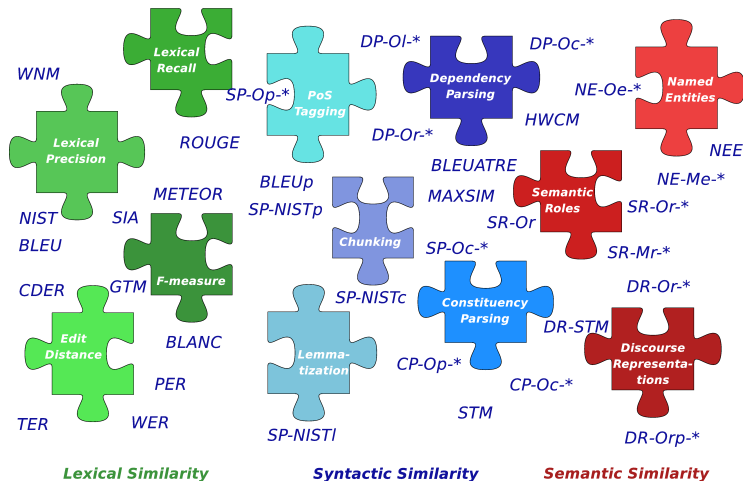
Limits of lexical similarity

Combination of the existing metrics



Limits of lexical similarity

Combination of the existing metrics



Limits of lexical similarity

Combination of the existing metrics

- Different measures capture **different aspects** of similarity suitable for combination
- The most simple approach: **ULC**

Uniformly averaged **linear combination** of measures (ULC):

$$\text{ULC}_M(\text{cand}, \text{ref}) = \frac{1}{|M|} \sum_{m \in M} m(\text{cand}, \text{ref})$$

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MT Evaluation

Summary

- Evaluation is important in the system development cycle. Automatic evaluation accelerates significantly the process.
- Manual evaluation is still necessary but shows low agreements among annotators
- 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.

Wait!

A close-up photograph of a typewriter keyboard. The focus is on a single key that has the word "Questions?" typed on it in a dark, monospaced font. The key is surrounded by other keys, some of which are visible in the background but out of focus. The lighting is dramatic, highlighting the texture of the paper and the metallic parts of the typewriter.

Questions?

Outline

- 1 Basics
- 2 Manual Evaluation
- 3 Automatic Evaluation
- 4 Tools**
 - Software
 - Demo
- 5 References

Evaluate your translations

- 1 With BLEU scoring tool. Available as a Moses script or from NIST:
<ftp://jaguar.ncsl.nist.gov/mt/resources/mteval-v13a.pl>
- 2 With Asiya package:
<http://asiya.cs.upc.edu>

ASIYA

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

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

Tools

In practice

- 1 With BLEU scoring tool in Moses:

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

Tools

In practice

② 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
```

```
#-----
```

Tools

In practice

② With the Asiya toolkit:

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sys=./data/patsA61P.test.trad.google.de2en
```

```
sys=./data/patsA61P.test.trad.bing.de2en
```

```
#-----
```

Tools

In practice

```
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-0c-* CP-0p-* CP-STM-9 DP-HWC-c-4
DP-HWC-r-4 DP-HWC-w-4 DP-0c-* DP-0l-* DP-0r-* DR-0r-* DR-0rp-* 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-0c-* SP-0p-* SP-cNIST-5
SP-iobNIST-5 SP-lNIST-5 SP-pNIST-5 SR-Mr-* SR-Mrv-* SR-Or SR-Or-* SR-Orv
```

Tools

In practice

METRIC NAMES

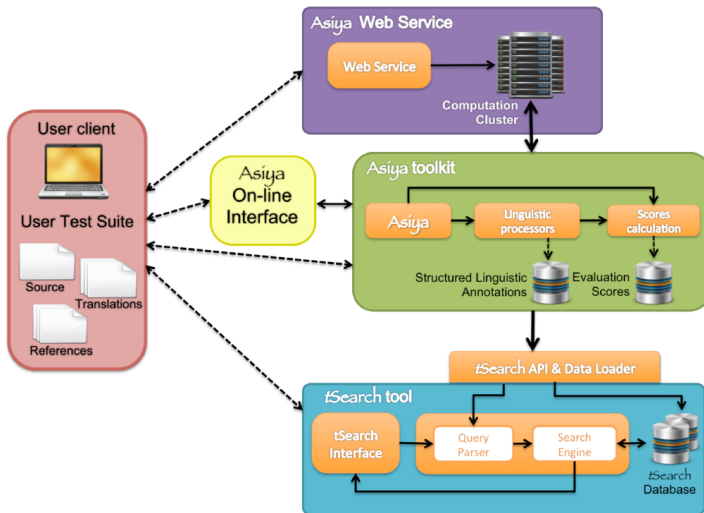
668 metrics are available for language 'en'

[illegible][illegible]

Tools

On-line evaluation

Asiya interfaces



Evaluate the results on-line

- 1 Asiya Interface

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

Analyse 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

The screenshot shows a web browser window titled "Asiya: An Open Toolkit for Automatic Machine Translation (Meta-)Evaluation - Mozilla Firefox". The address bar shows the URL asiya.lsi.upc.edu/demo/asiya_online.php. The page header includes navigation links: Fitxer, Edita, Visualitza, Historial, Adreces d'interès, Enllaços, and Ajuda. The main heading is "Asiya - Online" with the subtitle "An Online Toolkit for Automatic Machine Translation Evaluation". A logo for "UNIVERSITAT POLITÈCNICA DE CATALUNYA" is visible in the top right. Below the header is a menu bar with "Asiya", "Files", "Edit", "View", "Tools", and "Help". The main content area is titled "Asiya Testbed Data:" and includes a "Data Format" section with dropdown menus for "Input format" (raw), "Source Language" (other), "Source Case" (case sensitive), "Input already tokenized" (checkbox), "Target Language" (english), and "Target Case" (case sensitive). There are also buttons for "? Guidelines" and "Start New Session". The "Files" section contains four rows, each with a "Source file:" label, a "Navega..." button, a "No s'ha seleccionat cap fitxer." message, and an "Upload" button. Each row also has a "Source text:" label and a text area containing the placeholder text "Write some text here instead of uploading a file.".

Asiya: An Open Toolkit for Automatic Machine Translation (Meta-)Evaluation - Mozilla Firefox

Fitxer Edita Visualitza Historial Adreces d'interès Enllaços Ajuda

Asiya: An Open Toolkit for Aut... +

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

Google

Asiya - Online

An Online Toolkit for Automatic Machine Translation Evaluation

UNIVERSITAT POLITÈCNICA DE CATALUNYA

Asiya Files Edit View Tools Help

Asiya Testbed Data: ? Guidelines Start New Session

Data Format

Input format: raw Source Language: other Source Case: case sensitive

Input already tokenized: ☐ Target Language: english Target Case: case sensitive

Files

Source file: Navega... No s'ha seleccionat cap fitxer. Upload

Source text: Write some text here instead of uploading a file.

Reference files: Navega... No s'ha seleccionat cap fitxer. Upload

Reference text: Write some text here instead of uploading a file.

Translation System files: Navega... No s'ha seleccionat cap fitxer. Upload

Translation System text: Write some text here instead of uploading a file.

Introduction to Machine Translation Evaluation Outline

- 1 Basics
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Machine Translation Evaluation Resources and Methods: A Survey

Lifeng Han, Derek F. Wong, Lidia S. Chao

<https://arxiv.org/pdf/1605.04515v7.pdf>

Manual Evaluation

- Cohen, 1960 [Coh60]
- Landis & Koch, 1977 [LK77]
- Federmann 2012 [Fed12]

Automatic Evaluation

- Papineni, 2002 [PRWZ02]
- Doddington, 2002 [Dod02]
- Banerjee & Alon Lavie, 2005 [BL05]
- Giménez & Amigó, 2006 [GA06]

Metrics I

- WER [NOLN00]
- PER [TVN⁺97]
- TER [SDS⁺06]

Metrics II

- BLEU [PRWZ02]
- NIST [Dod02]
- METEOR [BL05]
- ROUGE [LO04]

Metrics III

- GTM [MGT03]
- BLANC [Dod02]
- CDER [LUN06]
- ULC [GA06]

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Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Micciulla, , and John Makhoul.
A Study of Translation Edit Rate with Targeted Human Annotation.
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C. Tillmann, S. Vogel, H. Ney, A. Zubiaga, and H. Sawaf.
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