Introduction to Machine Translation Evaluation

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Wait!

Thanks to

Meritxell Gonzàlez and **Lluís Màrquez**

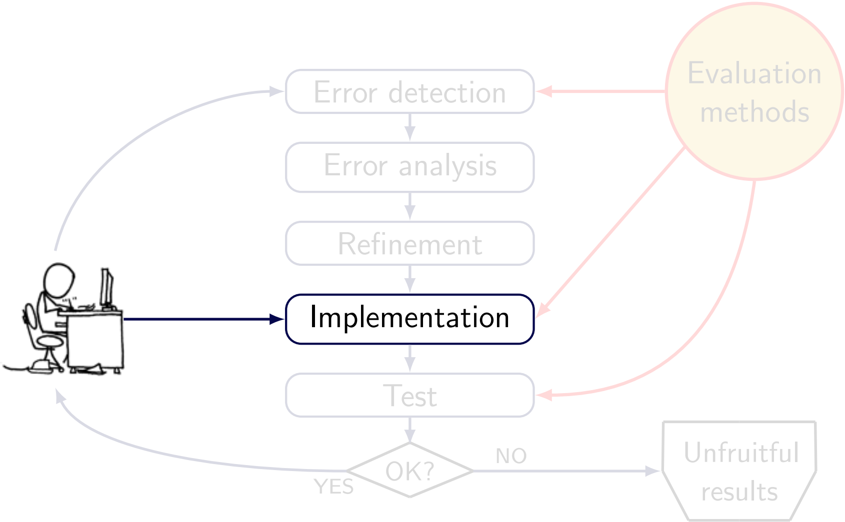
for some of the slides

Outline

1. Basics
2. Manual Evaluation
3. Automatic Evaluation
4. Tools

MT Evaluation

Importance for system development



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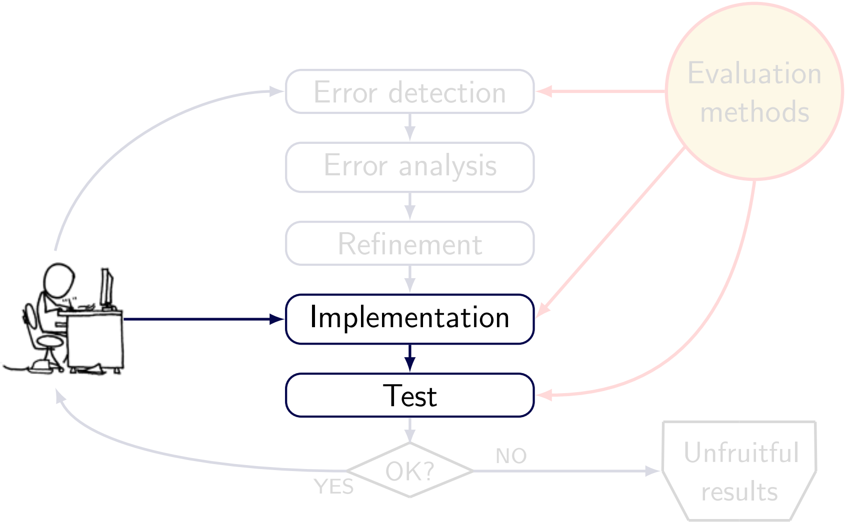

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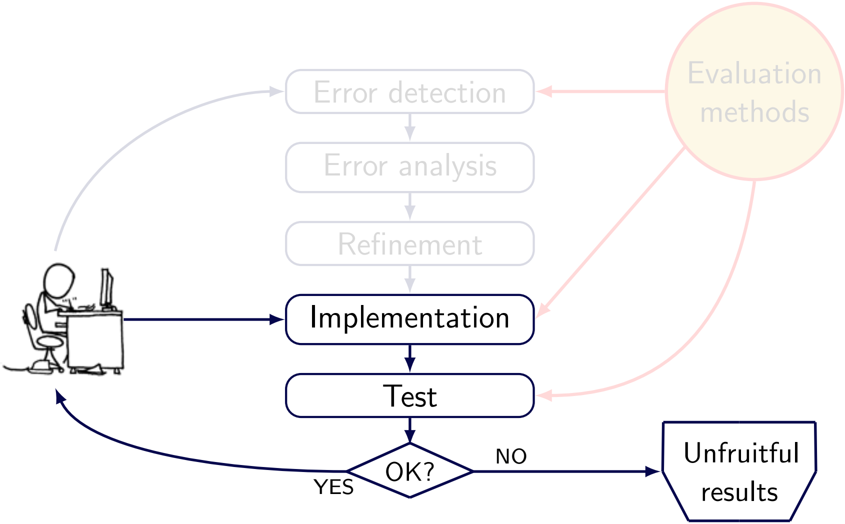

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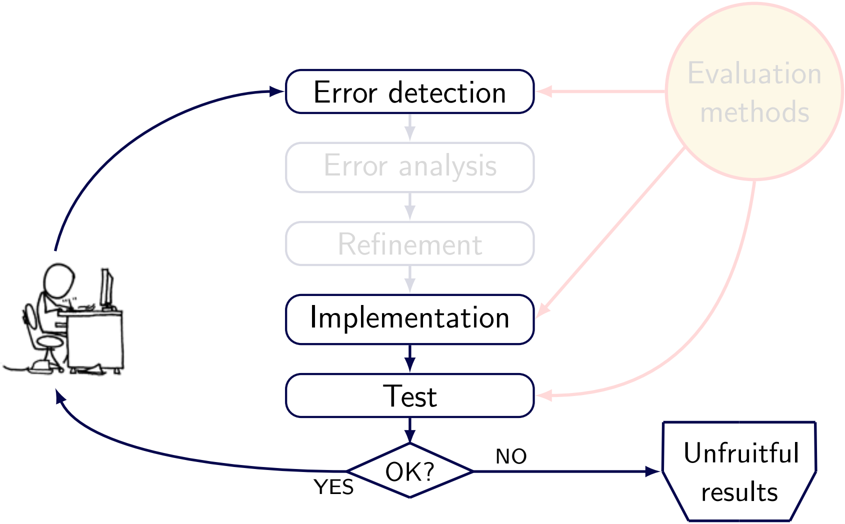

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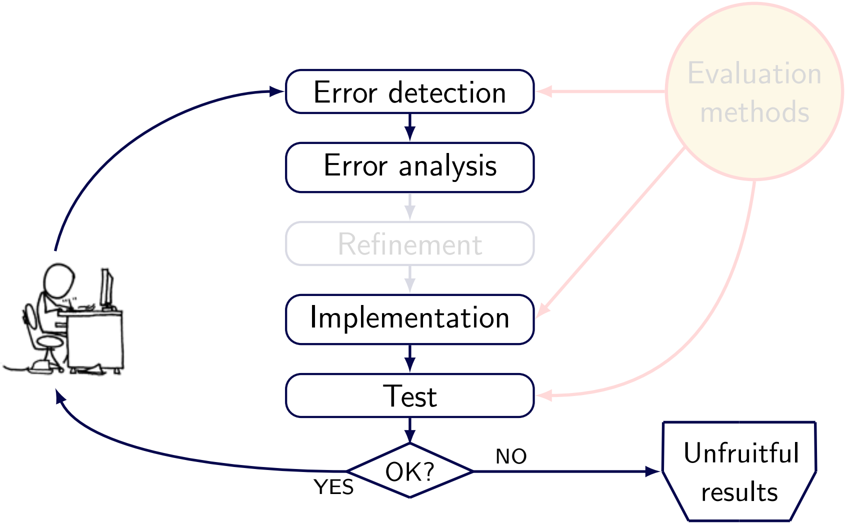

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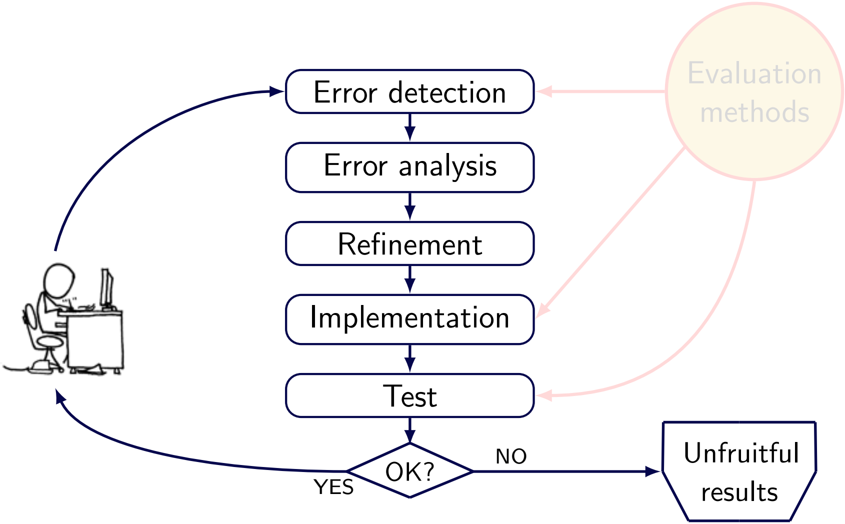

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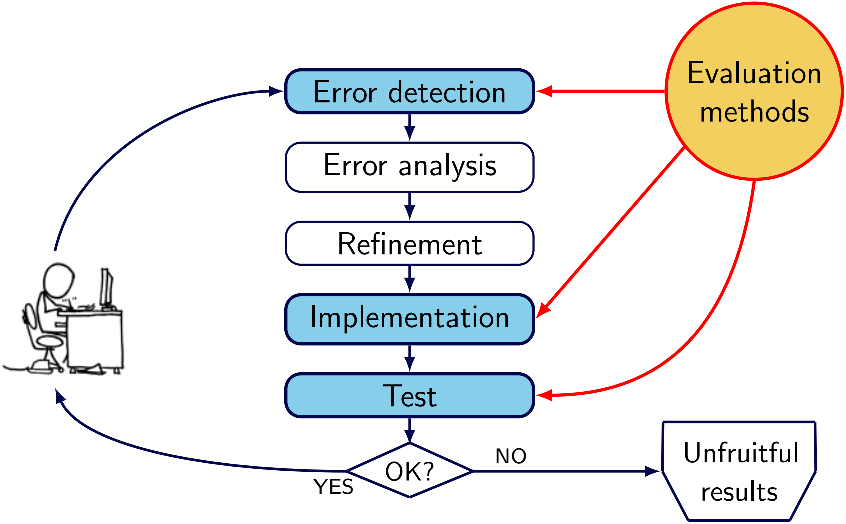

Automatic metrics notably **accelerate the development** cycle of MT systems:

- Error analysis
- System optimisation
- System comparison

Besides, they are

- **costless** (vs. costly),
- **objective** (vs. subjective),
- **reusable** (vs. non-reusable)

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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

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

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.

Outline

1 Basics

2 Manual Evaluation
- Likert scales
- Rankings
- Pros, cons and agreements

3 Automatic Evaluation

4 Tools

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

https://www.taus.net/think-tank/best-practices/evaluate-best-practices/adequacy-fluency-guidelines

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

http://www.itl.nist.gov/iad/mig/tests/metricsmatr/2008/results/correlationResults.html

Manual Evaluation

Human annotations

Ranking – Pair-wise comparison

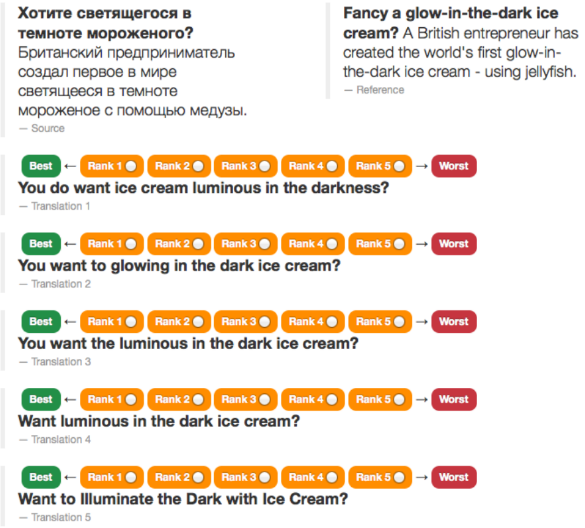
Annotators chose the best system, given the source and target sentence, and 2 anonymised random systems.

Ranking

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

Manual Evaluation

Appraise



Appraise
(Federmann 2012)

"**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!)

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

More details:

`https://staff.fnwi.uva.nl/r.fernandezrovira/teaching/MoLProject2011/annotation-reliability.pdf`

(slides 6-14)

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!

Outline

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

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**)

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

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- **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."

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.
```

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

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Reference 3:

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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.`

Modified n-gram precision (1-gram)

Precision-based measure, but:

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

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

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

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

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

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

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

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

Candidate:

```
The the the the the the the.
```

Reference 1:

```
The cat is on the mat.
```

Reference 2:

```
There is a cat on the mat.
```

Modified n-gram precision (1-gram)

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

Candidate:

`The the the the the the the.`

Reference 1:

`The cat is on the mat.`

Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

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

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.`

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:

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Reference 2:

`There is a cat on the mat.`

Modified n-gram precision (1-gram)

A reference word should only be matched once.

Algorithm:

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

Modified n-gram precision (1-gram)

Modified 1-gram precision:

Candidate:

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Reference 1:

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Reference 2:

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

Modified n-gram precision (1-gram)

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

Candidate:

`The the the the the the the.`

Reference 1:

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

Modified n-gram precision

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

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

low n	high n
adequacy	fluency

Brevity penalty

Candidate:

`of the`

Reference 1:

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

Reference 2:

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Brevity penalty

Candidate:

`of the`

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

Reference 1:

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Brevity penalty

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

c candidate length, r reference length

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

BiLingual Evaluation Understudy, BLEU

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

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

Paper's Conclusions

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

Watch out with BLEU implementations!

There are several widely used implementations of BLEU.

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

Results differ because of:

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

Wait!

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.

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

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

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

*P***recision** and *R***ecall** 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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Limits of lexical similarity

Comparing other linguistic features than words

Candidate:

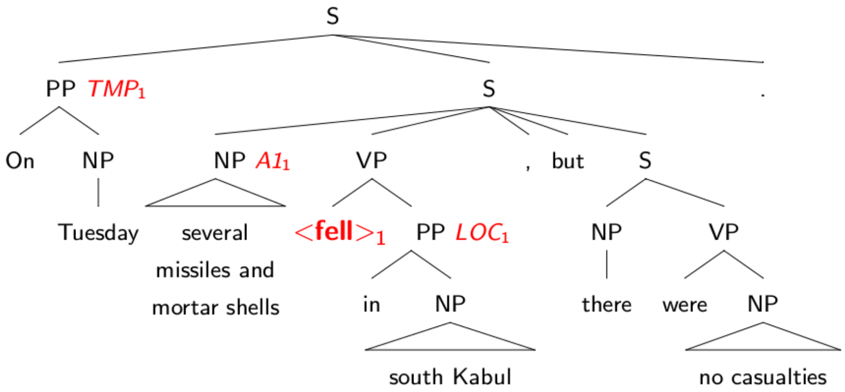
`On Tuesday several missiles and mortar shells fell in south Kabul, but there were no casualties.`

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



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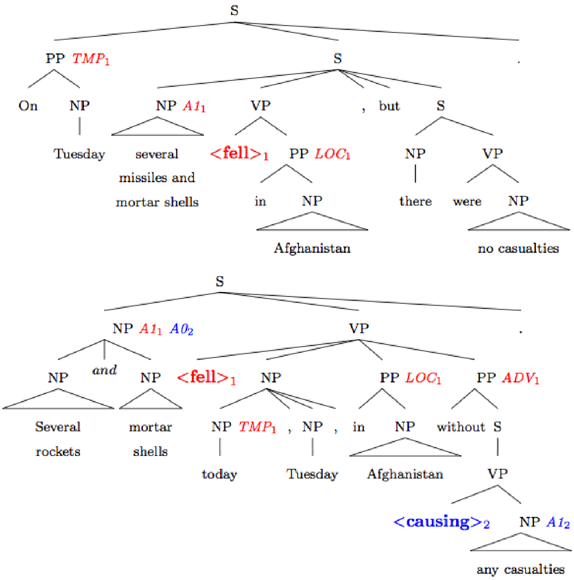

Limits of lexical similarity

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

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Limits of lexical similarity

Comparing other linguistic features than words

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

t is the LE type

'cand': candidate translation

'ref': reference translation

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

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

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

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

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

Extend the reference material:

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

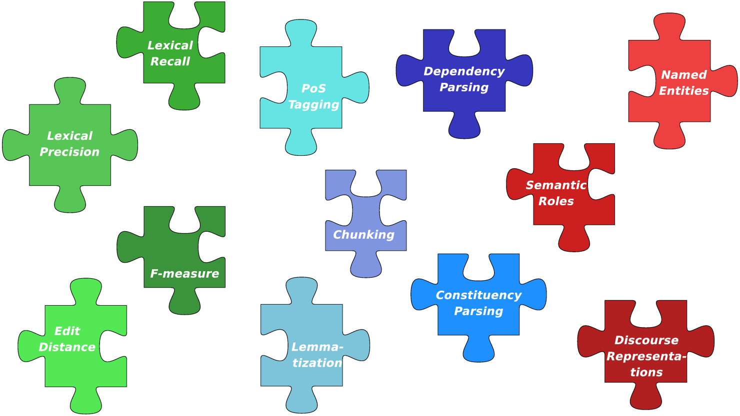
Compare other linguistic features than words:

- 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

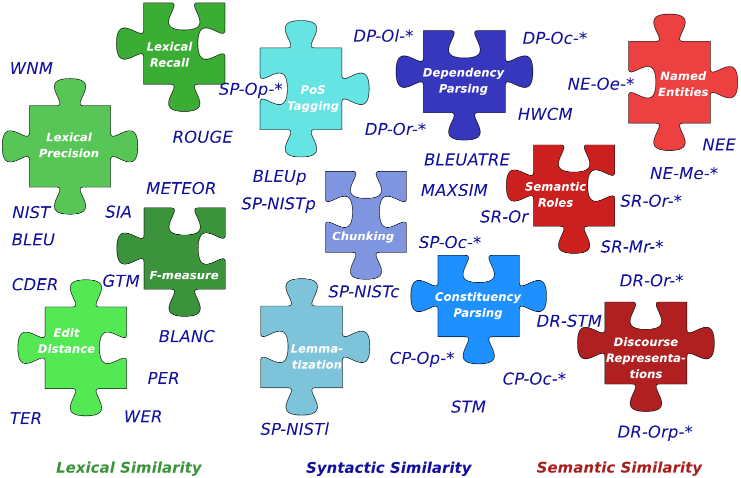
Combination of the existing metrics



Lexical Similarity *Syntactic Similarity* *Semantic Similarity*

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):

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

Limits of lexical similarity

Combination of the existing metrics

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- The most simple approach: **ULC**

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

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

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

Outline

1 Basics

2 Manual Evaluation

3 Automatic Evaluation

4 Tools
- Software
- Demo

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
```

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:

   `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

```
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
```

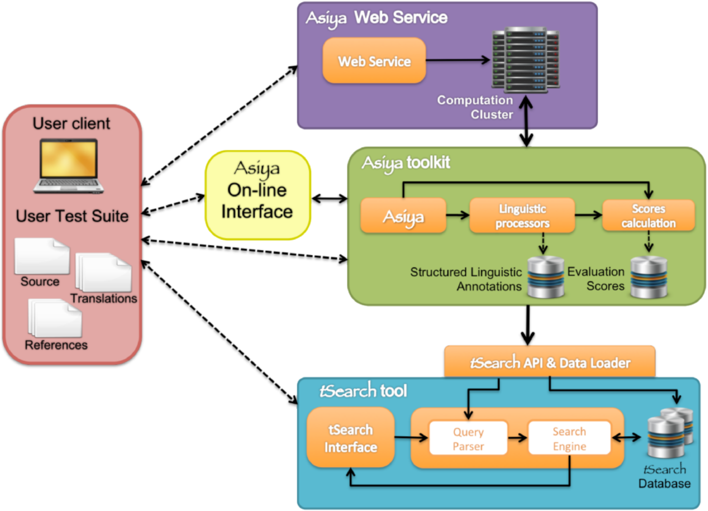
Tools

In practice

```
-------------------------------------------------------------------------------------------------------------------------------------------
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(FRA
G), 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-HWC
M_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(postd
et), 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(car
d), 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(pr
ed), 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, DR
doc-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), DR
doc-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-s
y, 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-O
e(*), 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_Q
UANTITY), 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, S
P-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-iobNI
ST-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-M
r(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(A
1), 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-O
rv(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(*) }
```

Asiya interfaces



Evaluate the results on-line

1. Asiya Interface

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

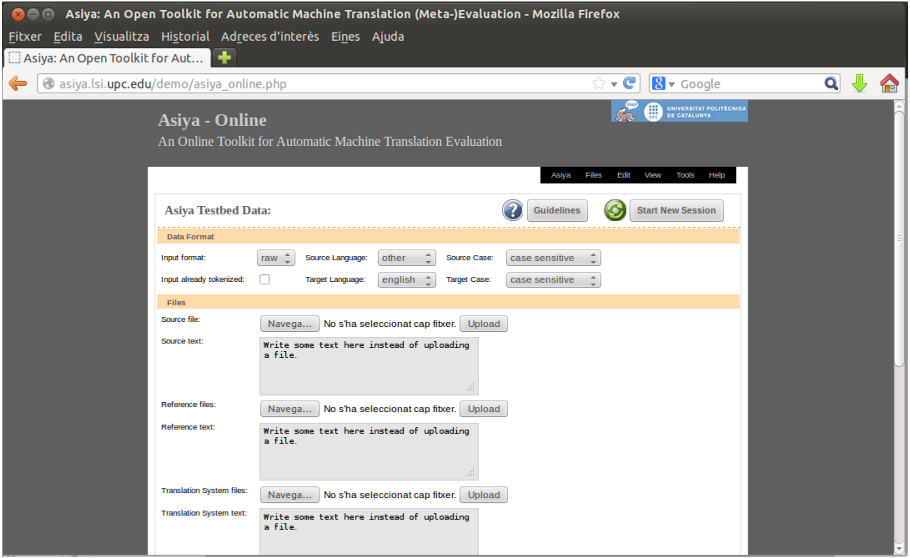
Analise the results on-line

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



Introduction to Machine Translation Evaluation

Cristina España-Bonet
UdS & DFKI

Summer Semester 2018
30th May 2018

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Manual Evaluation

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

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Automatic Evaluation

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

References

Metrics I

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

Metrics II

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

References

Metrics III

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

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