

In search of an acceptability/
unacceptability threshold
in machine translation post-editing
automated metrics

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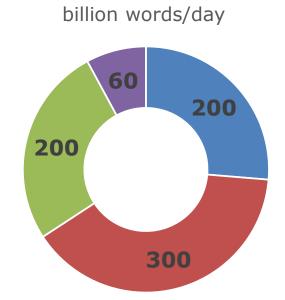
AMTA, October 2020

Why MT?





'Machines translate more in a day than all human translators on the planet combined can do in a year'





MT main use cases and drivers







Translation for understanding: raw MT / light postediting

E-commerce platforms
Forums and user reviews
Support pages
Communication apps



To cut costs and/or improve deadlines: light / full post-editing

MT at CPSL

SMT: Moses, ModernMT

NMT: Marian, 3rd-party platforms

RBMT: Apertium

Generic systems and

Domain-based systems:

- Life sciences
- Medical devices
- Automotive
- Technical













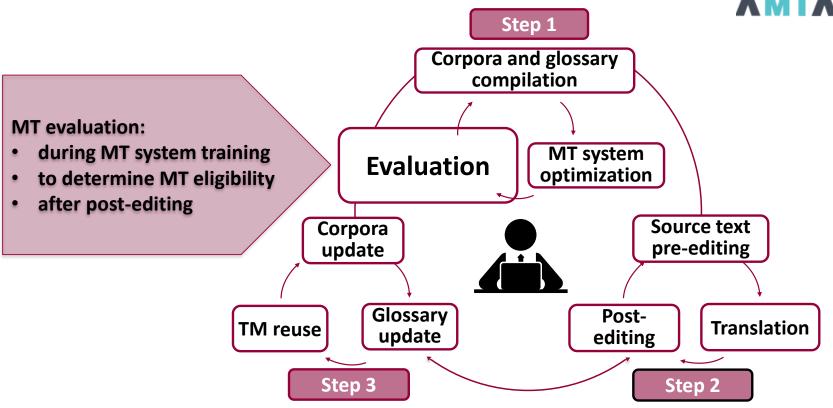




Translator-centered MT workflow







Rico, Celia. 2017. La formación de traductores en traducción automática. Revista Tradumàtica. Tecnologies de la traducció, 15, pages 75-96









Holistic (adequacy/fluency) scoring
Perceived PE effort scoring



Reference-based metrics (BLEU, edit distance, (H)TER...)



Productivity tests: post-editing time



Analytical: all/main errors, categorized

MT feedback template

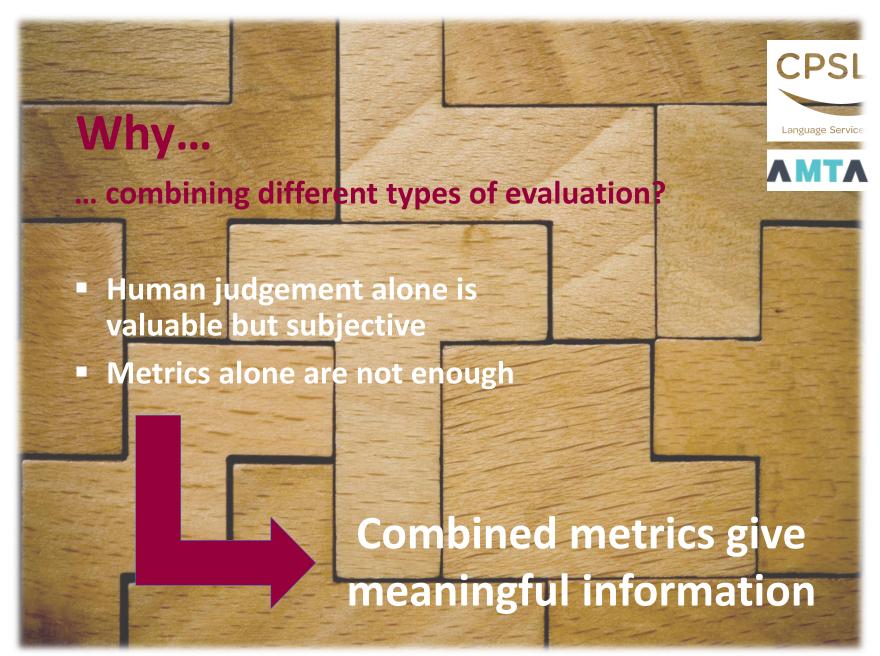




MT raw output feedback



Project ref.	Source	Raw MT output	Post-edited text	Error Category (drop-down menu)	Error Subcategory (drop-down menu)	Severity (drop-down menu)	Comments
			Overa	accuracy language terminology style country_standards layout query implementation client edit	ck		
			output to 4 (be	Please score the MT raw output quality from 1 (worst) to 4 (best): Please leave a comment on the post-editing task:			



Why...



... searching for an acceptability threshold?



- Define goals when training systems
- Know when to retrain a system
- Cherry-picking projects for MT
- Avoid discussions on remuneration

What % of edit distance is acceptable/unacceptable for post-editing?





AMTA

On acceptability:

 Castilho, S. (2016): "Measuring Acceptability of Machine Translated Enterprise Content". Dublin City University, Dublin, Ireland.

On correlation between automated metrics and human judgement:

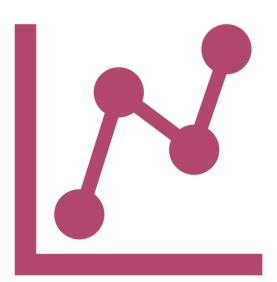
- Fomicheva, M.; Specia, L. (2019); "Taking MT Evaluation Metrics to Extremes: Beyond Correlation with Human Judgments". On *Computational Linguistics*, Association for Computational Linguistics, Stroudsburg, USA.
- Scarton, C.; Forcada, M.; Esplà-Gomis, M.; Specia, L. (2019): "Estimating postediting effort: a study on human judgements, task-based and reference-based metrics of MT quality". Proceedings of IWSLT 2019, Hong Kong, China.

Description of study





- 29 evaluations
 - ☐ Automated metrics: edit distance (Levenshtein algorithm from nltk.metrics)
 - ☐ Human evaluation after post-editing: PE effort perceived (1-4 Likert scale)
- ☐ 3 MT systems: Marian, Google Translate Basic and GT Advanced
- ☐ Evaluators' profile: professional post-editors
- ☐ 10 language combinations and 6 subject areas
- ☐ Limitations:
 - ☐ Usually only 1 post-editor (and evaluator) per project
 - ☐ Likert scores are subjective
 - Metrics result from comparing with the final version (sometimes there is an extra review)
 - ☐ Too few evaluations

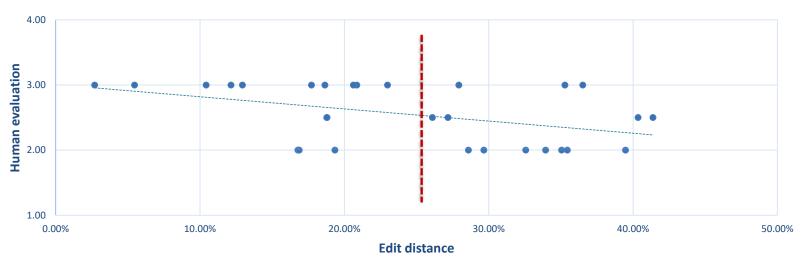








Distribution between human scores and edit distance



Interpretation

Raw MT output scores: 2-3

Most edit distances: 15%-45%

- Correlation? A high edit distance usually has a low score, and the other way around (but note the exceptions)
- According to the specific comments,
 3 is usually related to good quality,
 whereas 2 seems to be closer to
 unacceptability







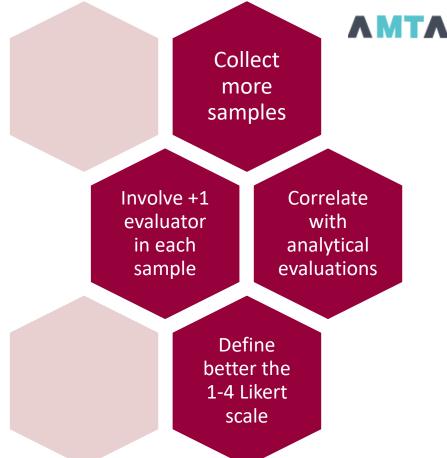
with an edit distance
> 30%, post-editors
expect an improvement
of the raw MT output
in the next job

Ideas for further study









Questions?

Thank you!



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