AMTA VIRTUAL 2020

The 14th Conference of
The Association for Machine Translation
in the Americas

www.amtaweb.org

PROCEEDINGS

Vol. **2**: MT **User** Track

Editors:

Janice Campbell & Dmitriy Genzel (Commercial Users)
Ben Huyck & Patricia O'Neill-Brown (Government Users)

Welcome to the 14th Biennial Conference of the Association for Machine Translation in the Americas

– AMTA 2020 Virtual!

AMTA conferences traditionally provide a unique opportunity for academic and commercial researchers to share their results with colleagues as well as to understand real-world user requirements. Business and government participants benefit from updates on leading-edge R&D in MT and have a chance to present and discuss their use cases. At the same time, students who attend gain a broad perspective and understanding of the fascinating field of MT.

This year's conference, however, is significant in at least two aspects. The first is that neural machine translation (NMT) has become a de facto standard in research and industry. At our last conference in March of 2018, generic NMT systems had just begun to be widely used during the preceding year, but it was later in 2018 that customizable NMT systems became widely available, enabling many companies, governments, and other organizations to benefit from an even higher level of MT quality for their specific applications. Since then, NMT customization and usage across the spectrum from individual translators to large corporations has continued to snowball.

The second aspect has been more of a difficulty than an advantage. The COVID-19 pandemic has resulted in transforming AMTA 2020 from an in-person event at a spectacular venue in Orlando, Florida to a completely online conference. While this transformation has presented many unique challenges, we now see some silver linings in this cloud. Without the need to travel and its associated costs, our attendance numbers have doubled from previous years, and participation has come from around the globe. We have been fortunate to receive tremendous support from our many sponsors, for which we are most grateful. Notably, Microsoft has provided their Teams platform to support the virtual conference sessions.

I wish to offer my sincerest thanks to our conference organizing committee, without whom this virtual conference would not have taken place. They have worked long hours to organize and prepare for this unique format, navigating uncharted waters and overcoming various roadblocks. I trust that all who attend will benefit from the results of their diligent efforts.

Steve Richardson
AMTA President

Introduction

Commercial Track

The Commercial MT Users and Translators Track at AMTA 2020 features twenty-two presentations from enterprises and individuals who supply or implement machine translation. These include technology and language service providers, as well as a host of commercial entities seeking to leverage the benefits of machine translation for better customer engagement.

A common theme that runs through many of the presentations this year is the use of metrics, such as MTPE and Quality Estimation, and setting acceptability thresholds therefor. The goals are to continually improve and interactively adapt models, and predict quality in order to increase language and content coverage, enhance linguists' productivity, ensure end-user trust, or even forego post editing, in some cases. Presentations explore novel applications of MT such as in building multilingual datasets; creating input for select NLP tasks; and translation memory alignment.

On the business side are presentations that explore the challenges an enterprise might face in adopting machine translation and in using technology and metrics to find the best engines or brands to meet their use cases. A unique approach to measuring the Return on Investment for adopting MT is detailed. Students put to the test various NMT claims to determine if valid or hype.

Whether a buyer or supplier, more organizations are building their own engines, thanks to a multitude of toolkits and available training data. Domain customization is the norm. Presentations discuss how to use metadata in source to fine tune customization and they detail strategies for handling tags and placeholders to achieve better output results.

On the practical side, there are presentations on scaling up MT specifically for software and continuous localization scenarios in order to reduce or delay human intervention and still achieve maximum customer impact.

Finally, what bodes for the very near future? Presenters offer that it is identifying and resolving societal biases encoded in machine learning systems, or simultaneously translating speech.

The Commercial Track Co-Chairs

Janice Campbell
Dmitriy Genzel

Government Track

The AMTA 2020 Government and Military MT Stakeholders Track brings together machine translation users, developers, and researchers in government, military and public service worldwide. The proceedings include eight presentations covering a broad range of topics. Two of these presentations include papers that provide in-depth detail and context to the presentations.

Several submissions describe how to effectively use MT in government, as well as how to augment human translation efforts, including the use of complementary NLP tools such as Speech-to-Text (STT) technologies. Others describe the practical application, insertion and measurement of MT into government space. One discusses video to text MT for sign language. Another presentation describes a custom MT engine trained using US Government data to assist with the COVID-19 crisis.

This track is made possible by the hard work and contributions of many individuals. We would like to thank Steve Richardson and all members of the conference committee for their organizational support, Jennifer Doyon and the rest of the organizing committee for guidance on the government track, and all of the AMTA 2020 authors and reviewers.

The Government Track Co-Chairs

Benjamin Huyck
Patricia O'Neill-Brown

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Commercial Track

Government Track

RWS Moravia Operationalizing Machine Translation Quality Estimation (QE)

Miklós Urbán,
Senior Solutions Architect

Maribel Rodríguez,
Language Technology Deployment Manager

www.rws.com/moravia

Agenda

- Introduction
- Methodology
- Potential Business Cases
- Technical Setup
- Conclusions

RWS Moravia

Quality estimation is a method used to automatically provide a quality indication for machine translation output without depending on human reference translations. In more simple terms, it’s a way to find out how good or bad the translations are that are produced by an MT system without human intervention.

Yet in the machine translation space, there’s evidence to show that good quality estimation eases the burden on human editors. With an automated system that highlights mistakes before the human process even begins, the editors can zero in on the areas of a piece of content that most likely need attention.

https://www.forbes.com/sites/forbestechcouncil/2019/01/24/why-quality-estimation-is-the-missing-link-for-machine-translation-adoption
https://tech.ebayinc.com/engineering/machine-translation-the-basics-of-quality-estimation/

The Challenge

With so many different approaches to QE out there and so many variables, **how can we**:

- Evaluate QE performance for different QE options, customers, content types, languages, etc.?
- Identify the business cases that could bring value to RWS Moravia and our clients?
- Figure out when is the right time to implement QE in a specific workflow?
- Continue to monitor the performance of QE after it has been implemented?

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How to Evaluate QE?

RWS Moravia

Common Methodology

Pre-translate the content using MT

Obtain both pre-production MT QE and post-production TER scores

Compare QE score with actual TER score

Analyze the results

Considerations:

- Post-editors are not exposed to QE
- QE initially runs in the background
- Production may apply different workflows
- Translation is not analyzed for over-editing or under-editing

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Input Metric | Quality Estimation

- Quality estimation is available from multiple sources
- QE is based on machine learning algorithms
- To make results comparable, we convert QE results to a 4-choice numeric score system

  - **100%** means QE predicts good raw MT quality
  - **67%** means QE predicts some editing is needed
  - **33%** means QE predicts more editing is needed
  - **0%** means QE predicts poor raw MT quality

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Input Metric | Translation Edit Rate (TER)

- Suited to quantify the post-editing effort
- RWS Moravia has been using TER in production for over a decade
  - Number of edits needed to modify raw MT to produce a final translation
  - TER = edits / reference word count
    - where edits = insertions, deletions, substitutions and shifts
  - The closer the score is to 0, the less post-editing effort is assumed
- We round TER scores to multiples of 10%

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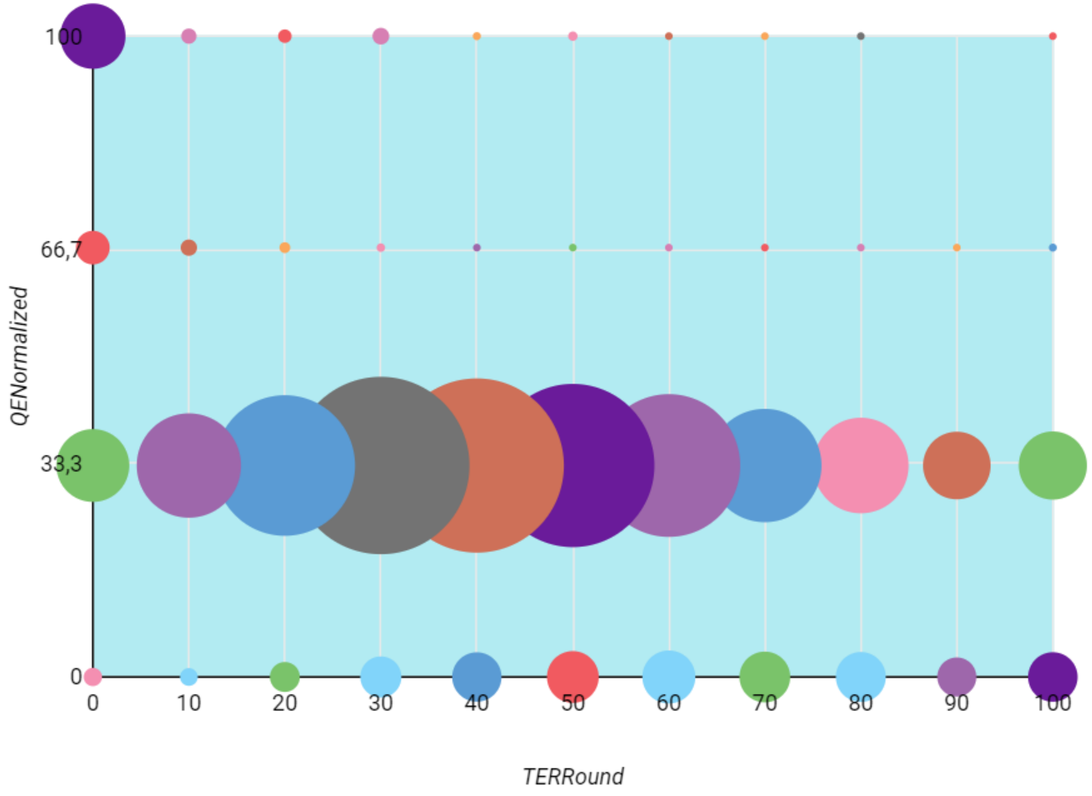
How to Use the Data?

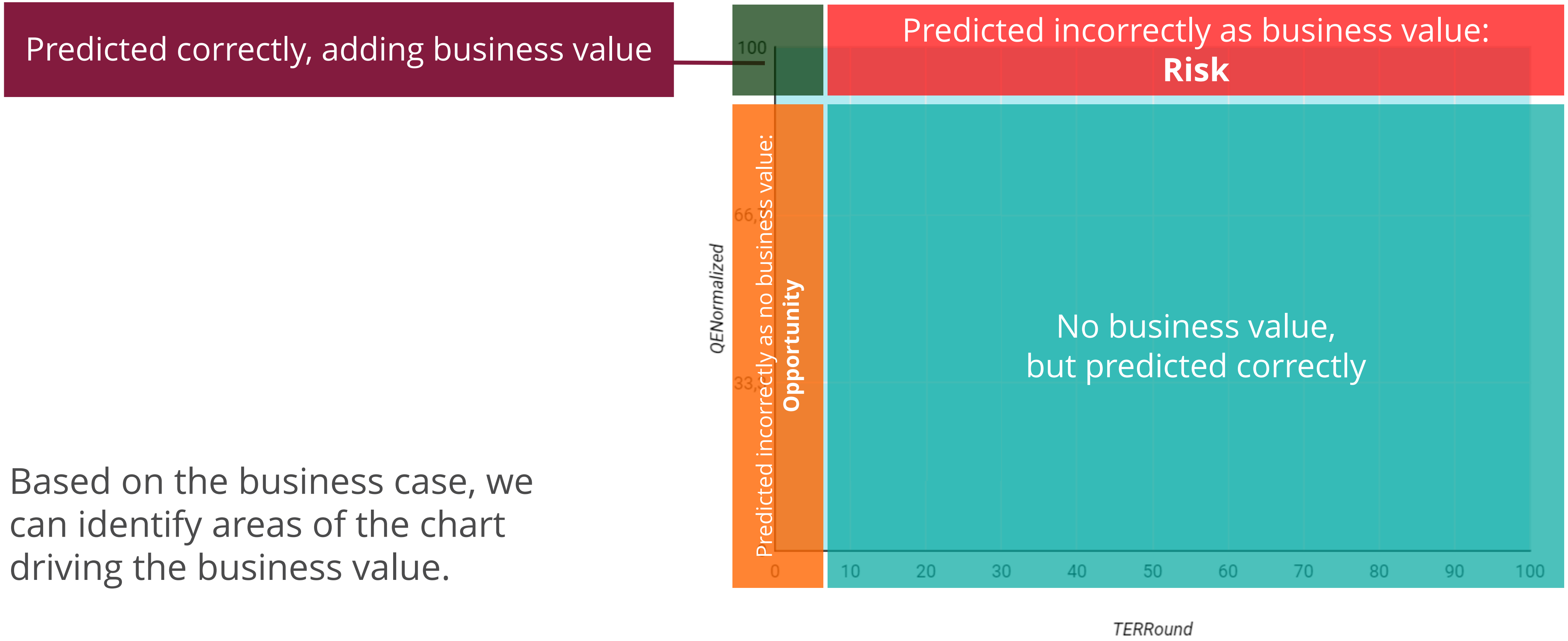


Each segment can be plotted on a chart

We created a bubble chart with:

- Y-axis: QE score
- X-axis: TER score
- Size of bubble: number of segments

Interpreting the Bubble Chart



Based on the business case, we can identify areas of the chart driving the business value.

Output Metrics

$$\text{Accuracy} = \frac{\text{True Positive} + \textbf{True Negative}}{\text{Total}}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \textbf{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \textbf{False Negative}}$$

$$\text{F1} = \frac{2 \text{ x Precision x Recall}}{\text{Precision} + \text{Recall}}$$

Predicted value	Actual value: +	Actual value: -
+	**True positive** QE=100 TER=0	**False positive** QE=100 TER>0
-	**False negative** QE<100 TER=0	**True negative** QE<100 TER>0

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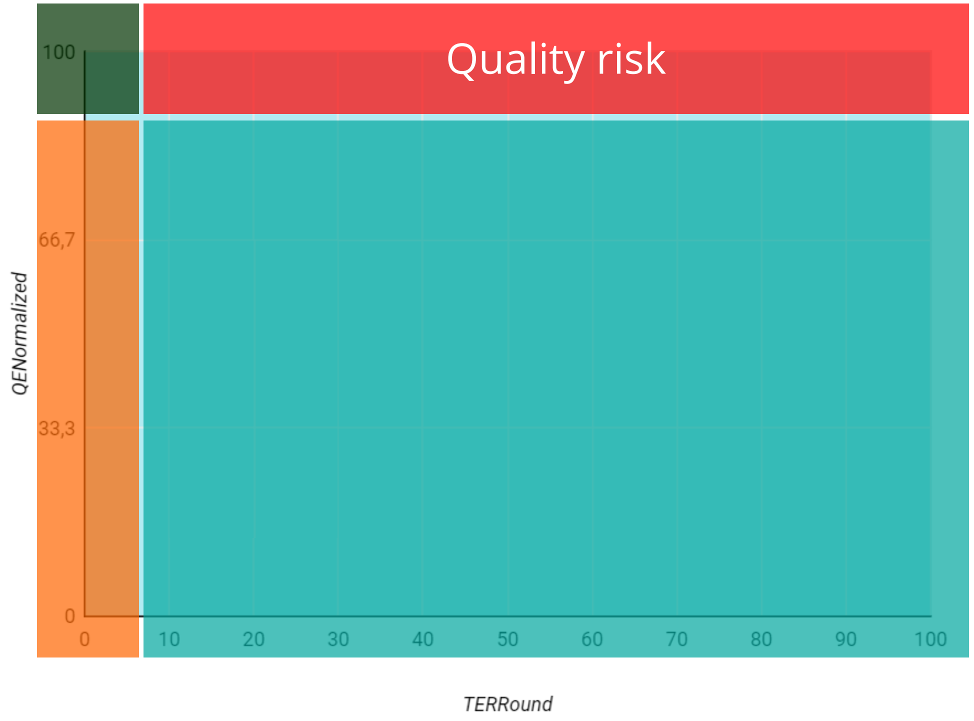
What Are the Business Cases?

Take Advantage of Good MT Segments

- Eliminate post-editing or apply a light post-editing workflow for good raw MT segments (up to 30% of segments)
- Quality risk for false positives
- We expect a high proportion of non-edited segments to be identified, keeping the quality risk close to zero



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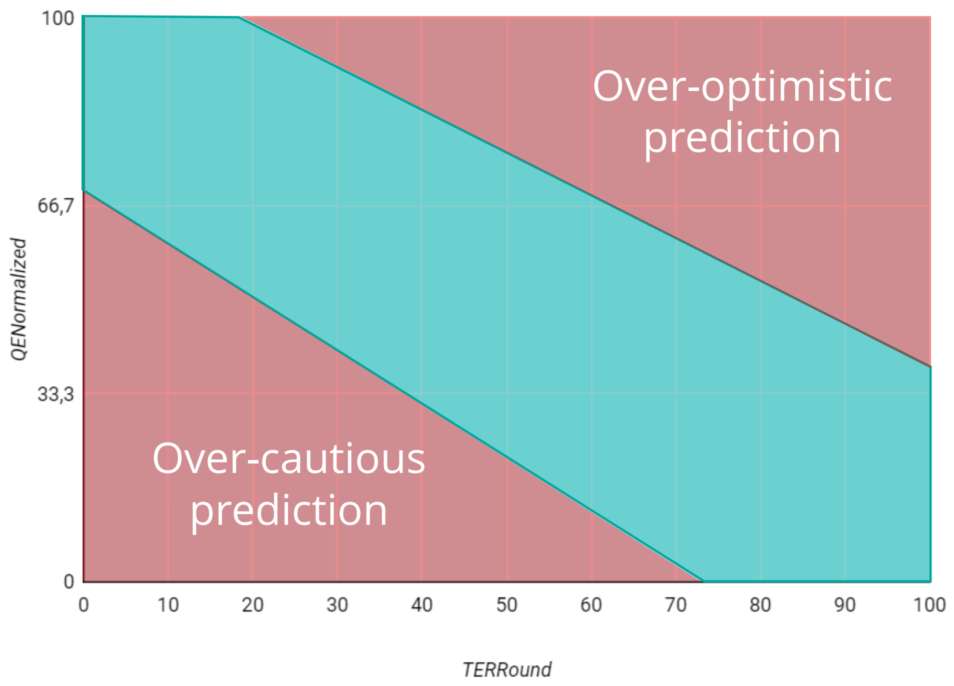
Remove Burden of Reading Poor MT

- Does it really increase productivity?
- Risk of deleting good MT
- We expect a high proportion of poor-quality raw MT to be discarded with minimal loss of good MT

Assessing MT Quality and Applying Fair, Pre-production Pricing

- A good accuracy could allow MT quality measurement without human reference
- High accuracy (95+%) could allow pricing to be based on QE



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Road to Operationalization

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Considerations

- Multiple QE sources
  - Choose the best option that fits our purposes
- QE performance may depend on multiple factors
  - Language pair
  - Client
  - Content type
- We need to establish reproducible metrics that can be measured over a large sample

Pilot

- No. of customers: **1**
- Content types: **2**
- Language pairs: **17**
- Experiment duration: **8 months**

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Pilot Results

- Methodology enabling:
  - Consistent evaluation of QE technology and tracking its progress
  - Monitoring results against preset thresholds before going live
- Automated dataflow solution
  - Evaluation of usability of different QE systems
  - Data insights through dashboards
- Findings
  - Dependency of QE performance across languages and content types
  - Technology still evolves and shows improved performance over time

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How to Set up Continuous Tracking?

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Technical Setup

After populating raw MT into the CAT tool, the QE prediction was run and scores were stored

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Technical Setup

Post-editors completed
the task in the translation tool
without being exposed to QE

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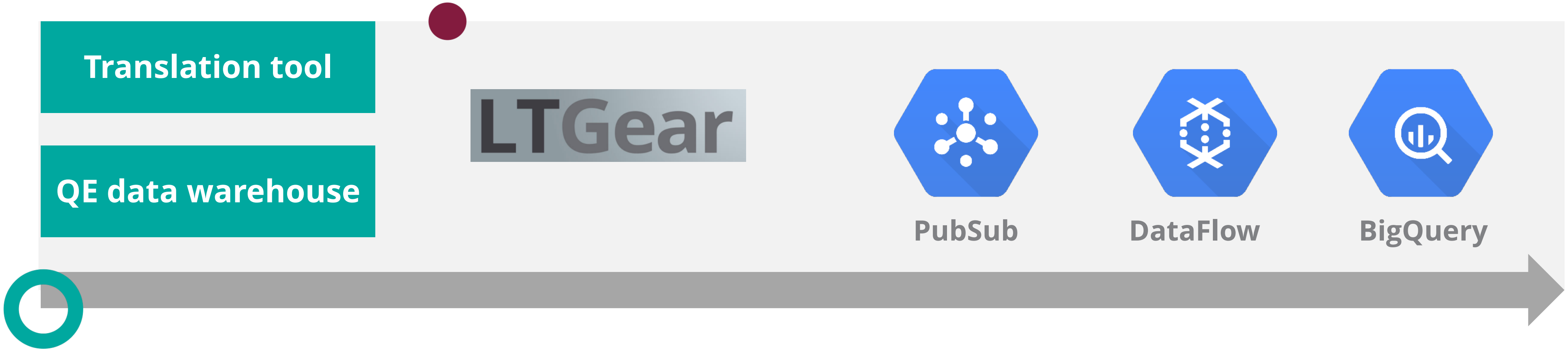
Technical Setup

We created a streaming data solution that:

- Takes segment data from the production environment
- Runs the segment through the TER score evaluation in our proprietary software, LTGear
- Matches the QE data stored earlier for the segment
- Streams this data into the bigdata infrastructure of Google Cloud



Technical Setup

- For each segment, we store its coordinates, timestamp, language pair, client and domain metadata and the MT QE and TER results in BigQuery
- Google Data Studio dashboards help us track and analyze the results

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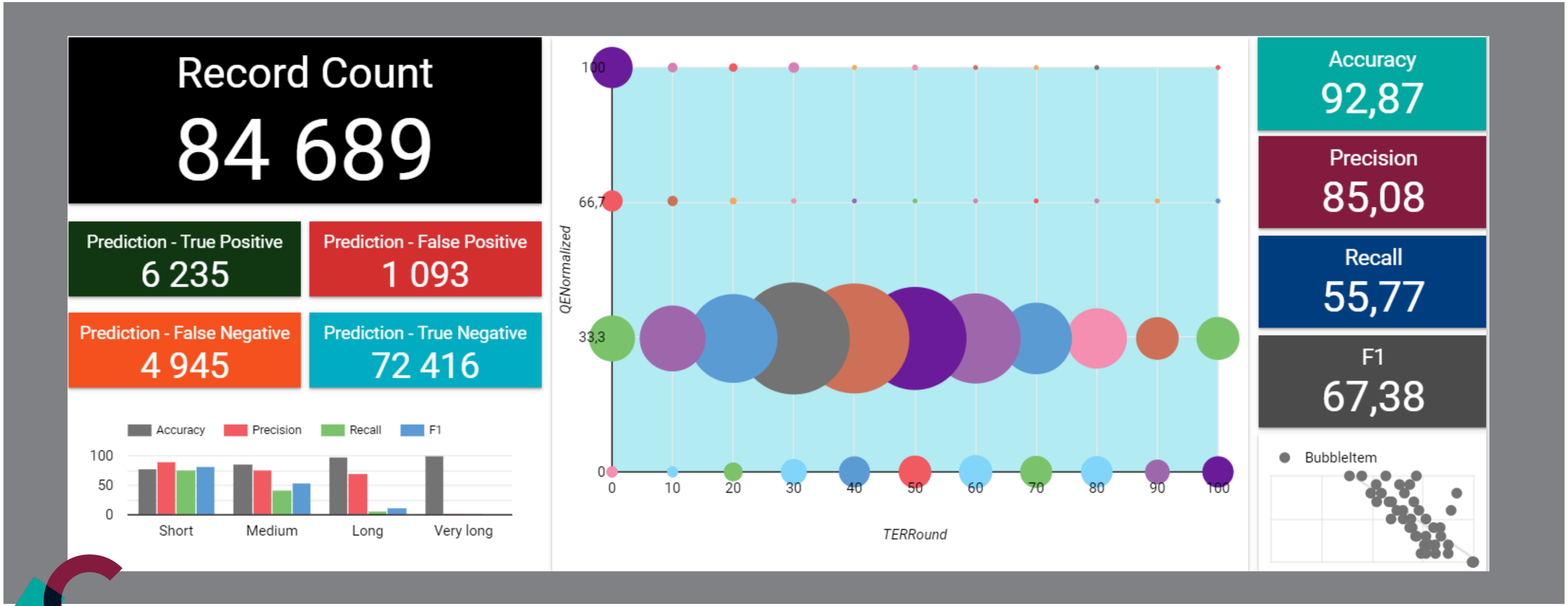
Sample Dashboard



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Conclusions

Conclusions

- QE shows improvement over time and is approaching production readiness in a large LSP setting
- QE performance is highly dependent on language pair and content type
- Robust solution to track performance of QE predictions against post-production metrics is needed
- Thanks to the framework we have put in place, we now have the means to easily monitor the aggregated data in a continuous stream and compare the performance of multiple QE sources

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Some Questions We Are Really Eager to Answer

- Does it make sense to include segment length beside QE to refine the precision of predictions?
- Is quality retained for high-ranking QE segments that will likely get less attention?
- Do post-editors start from scratch for low-ranking QE segments?
- Is productivity enhanced compared to a workflow without QE?

RWS Moravia

Acknowledgement to All the Team Members that Participated in This Research

Tomáš Burkert
Solutions Architect

Tomáš Fulajtár
MT Researcher

Miklós Urbán
Senior Solutions Architect

Maribel Rodríguez
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RWS Moravia

Q&A

Thank you

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

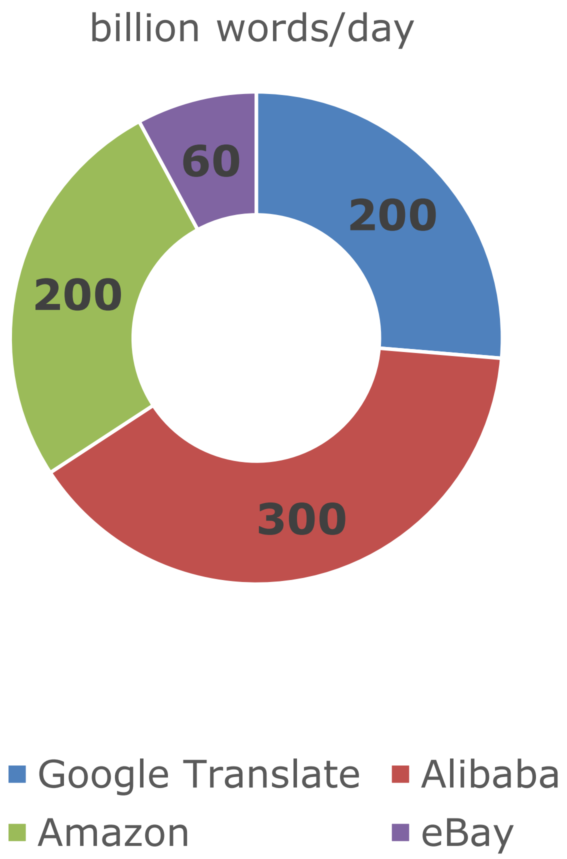
Lucía Guerrero
Machine Translation Specialist, CPSL

AMTA, October 2020

Why MT?

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

Nimdzi Research/TAUS, 2018



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

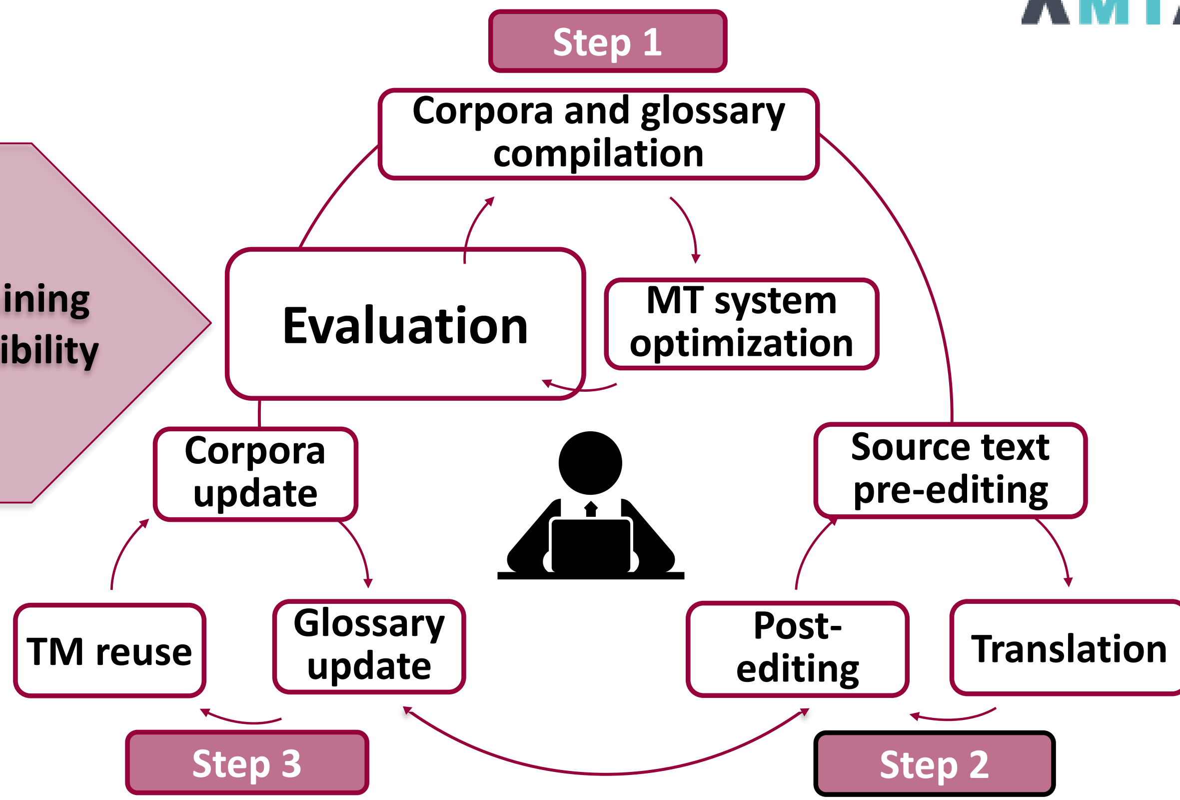
SMT: Moses, ModernMT
NMT: Marian, 3rd-party platforms
RBMT: Apertium

Generic systems
and
Domain-based systems:

- Life sciences
- Medical devices
- Automotive
- Technical

Translator-centered MT workflow

MT evaluation:
- **during MT system training**
- **to determine MT eligibility**
- **after post-editing**



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

MT evaluation

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

CPSL Language Services

AMTA

MT raw output feedback

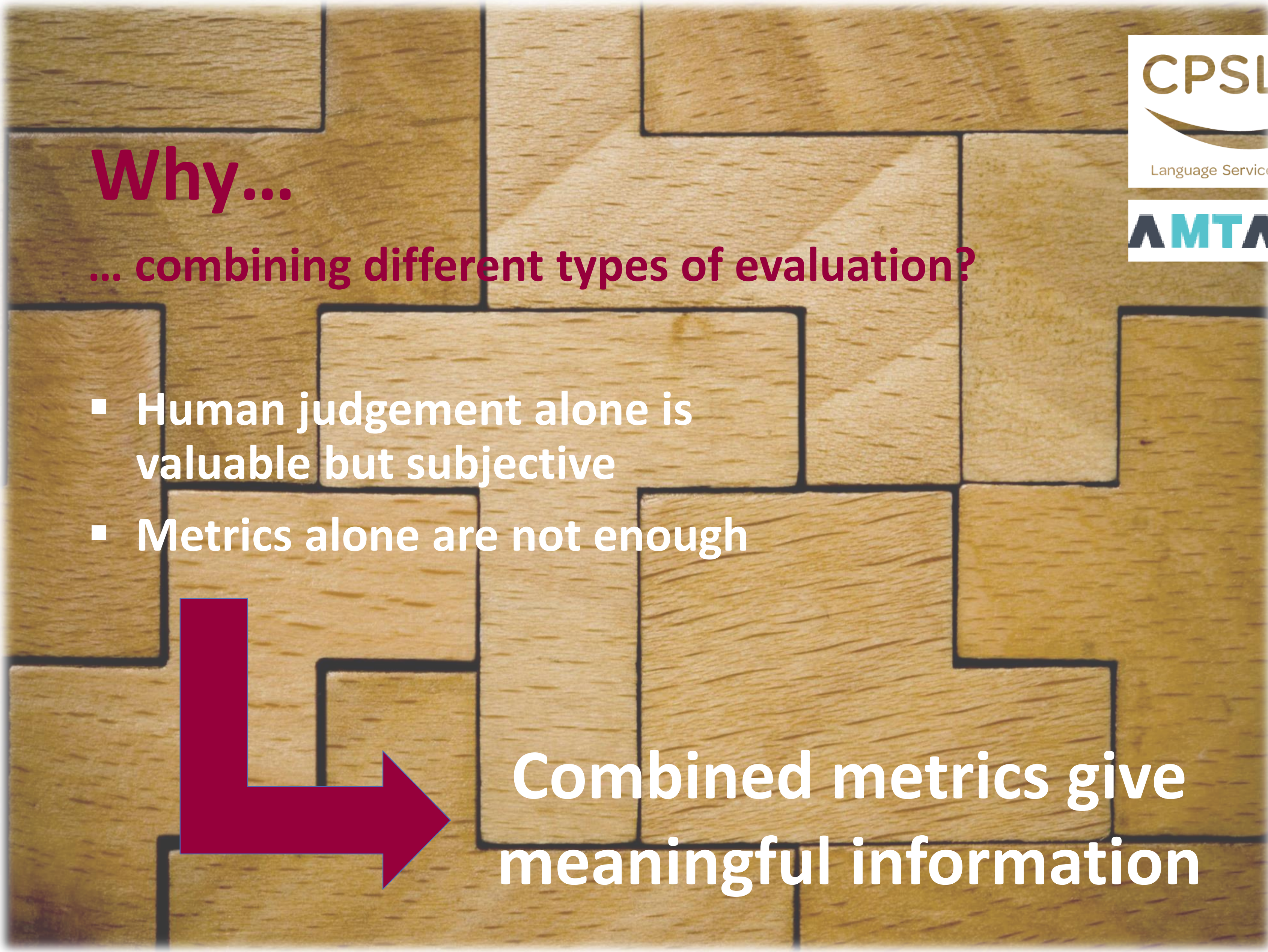
CPSL Language Services

Project ref.	Source	Raw MT output	Post-edited text	Error Category (drop-down menu)	Error Subcategory (drop-down menu)	Severity (drop-down menu)	Comments

accuracy
language
terminology
style
country_standards
layout
query implementation
client edit

Overall feedback

Please score the MT raw output quality from 1 (worst) to 4 (best):	
Please leave a comment on the post-editing task:	


CPSL
Language Service
AMTA
Why…
… combining different types of evaluation?
Human judgement alone is valuable but subjective
Metrics alone are not enough
Combined metrics give meaningful information

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?

CPSL Language Services

AMTA

Previous studies

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 post-editing effort: a study on human judgements, task-based and reference-based metrics of MT quality”. Proceedings of IWSLT 2019, Hong Kong, China.

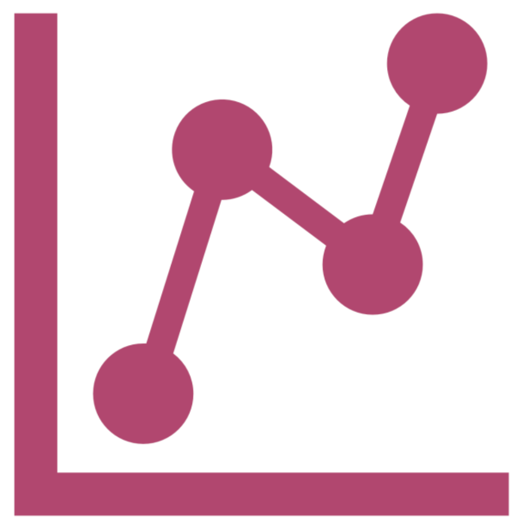
Hypothesis:

50% is too high as an edit distance threshold to define acceptability of MT raw output

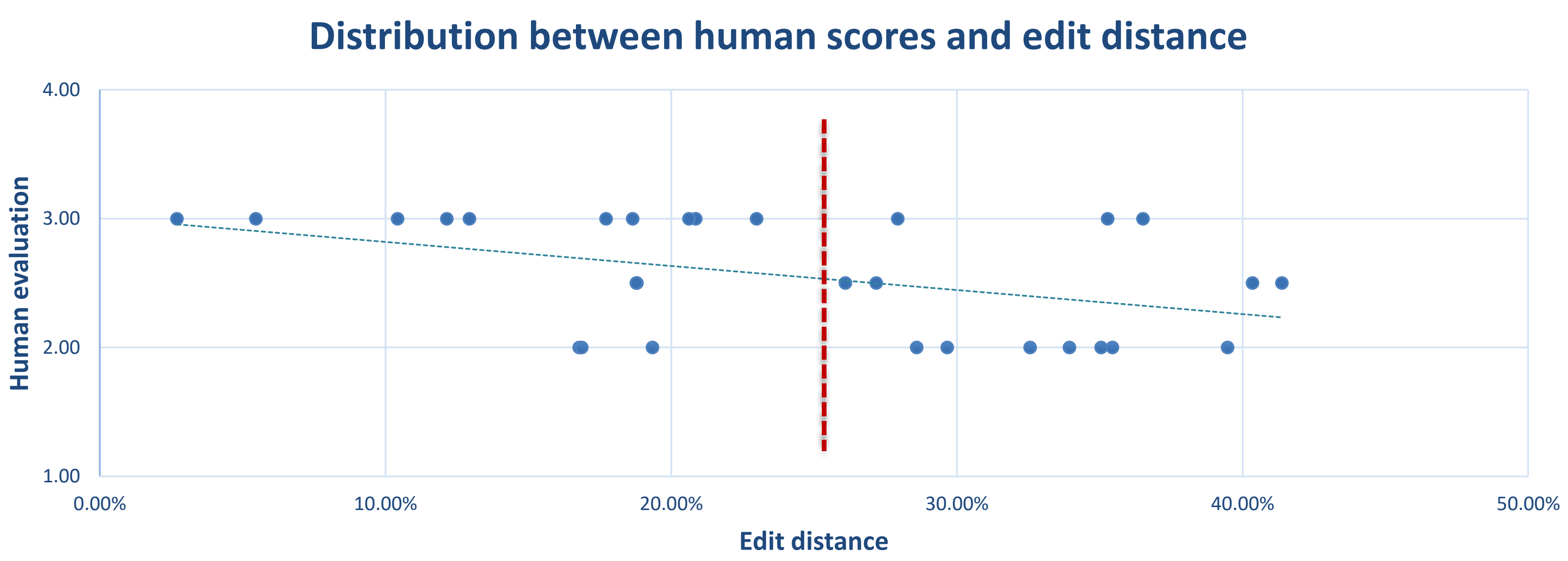
Description of study

- 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



Correlation table

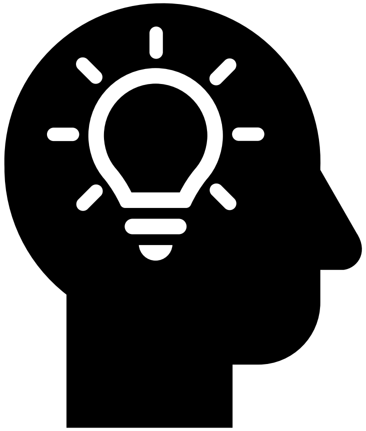


Interpretation

- 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

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

Ideas for further study



Collect more samples

Involve +1 evaluator in each sample

Correlate with analytical evaluations

Define better the 1-4 Likert scale

Questions?

Thank you!

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A Survey of Qualitative Error Analysis for Neural Machine Translation Systems

Denise Diaz
Joint work with Vishrav Chaudhary, James Cross, Ahmed El-Kishky, Philipp Koehn

What prompts this study?

- Internet and social media are proliferating rapidly
- Communication and information need to be available to a wide audience in many different languages
- MT has become widely adopted

End-user trust is the goal

With this wide adoption, it has become important to understand where MT models excel and where they struggle in order to improve MT models and ensure end-user trust (Lommel, 2018).

2020 MT Challenges - **Problematic translations**

Problematic translations are those that are **misleading** and may:

- Carry health, safety, political, legal or financial implications

or

- Introduce toxic language not present in source

Qualitative analytic evaluation

- Specific common errors found in neural machine translations (NMT) on the FB platform

- Problematic errors since these are the riskiest of the bunch

Why a qualitative analysis is important

While automatic metrics such as BLEU capture the average case for how well a MT model translates sentences, they don't give insight into *which linguistic aspects* MT models struggle with.

In this qualitative analysis, we investigated MT samples with native speakers so we could review the *linguistic aspects* of MT errors.

Categorizing errors and making a challenging test set is the first step in benchmarking and improving MT performance in linguistic aspects.

10 Language families, 33 languages

Altaic
Turkish

Afro-Asiatic
Semitic
Amharic
Arabic
Hebrew
Cushitic
Somali
Chadic
Hausa

Niger Congo
Zulu

Sino-Tibetan
Chinese

Japanese
Japanese

Austronesian
Tagalog

Austro-Asiatic
Vietnamese

Kra-Dai
Lao

Dravidian
Kannada
Malayalam
Tamil

Indo-European
Balto Slavic
Belarusian
Russian
Bulgarian
Germanic
Swedish
German
Norwegian
Romance
Catalan
French
Italian
Portuguese
Spanish
Indo-Iranian
Farsi
Pashto
Indo-Aryan
Hindi
Marathi
Sinhalese
Urdu

Why we chose these languages

Languages our model supports

Native language informant availability

Diverse language families

High, mid and low resource languages

Error categories

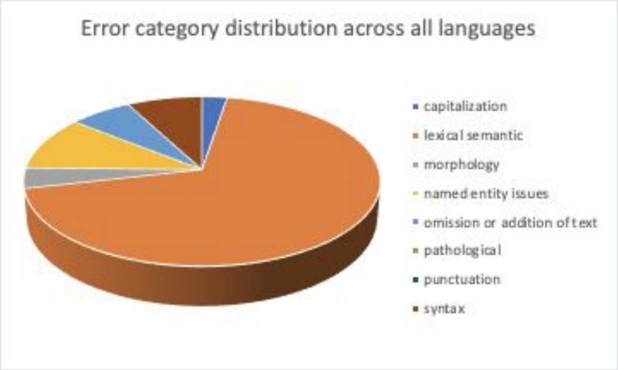
1. Lexical-semantic
2. Named entity issues
3. Morphology
4. Syntax
5. Omission or addition of text
6. Punctuation
7. Capitalization
8. Pathological

★ synthetic samples for illustration

★ no user data is displayed for privacy reasons

Error category average percentages - all languages

Lexical semantic Word ambiguity Noisy source Unknown words Code-switching Dialectal variants	30.00%
Named entity issues	4.00%
Omission or addition of text	7.00%
Pathological translations	3.00%
Syntax	3.00%
Morphology	2.00%
Capitalization	1.00%
Punctuation	0.01%



Lexical semantic

Broad triggers for inappropriate lexical choices in MT include:

- **Word ambiguity**
- **Idiomatic expressions**
- **Phrasal verbs**
- **Noisy source**
    - Misspellings / typos
    - Reduplicated letters
    - Typographical substitution
- **Unknown words**
    - Abbreviations
    - Neologisms or archaic words
    - Vernacular
- **Code switching**
- **Dialectal variants of lexical items**

THIS WAS THE MOST PREVALENT ERROR CATEGORY ACROSS ALL 33 LANGUAGES WITH AN AVERAGE OF 30%. IN THESE INSTANCES THE MODEL WAS UNABLE TO OUTPUT AN APPROPRIATE LEXICAL CHOICE TO MATCH THE SOURCE, THUS DERAILING THE MEANING OF TRANSLATIONS.

Word ambiguity

"Learning how to disambiguate ambiguous words is one of the most difficult and most important challenges in MT." (Popovic, 2018)

NOT MUCH CONTEXT, JUST A NAMED ENTITY!

Source Portuguese	Target English	Desired English output
Morro de São Paulo	*I die of São Paulo*	*Morro de São Paulo*

MORE CONTEXT HELPED THE MODEL TO DISAMBIGUATE FROM THE VERB FORM TO THE NOUN

Source Portuguese	Target English
Vou para o Morro de São Paulo	*I'm going to São Paulo hill*

Idiomatic expressions

Source English	Target Italian	Desired Italian output
Twist my arm!	*Girami il braccio!*	*Non devi convincermi!*

Phrasal verbs

The model sometimes does not recognize phrasal verbs, verbs that are accompanied by a particle or more.

The particles flanking the verb tend to nuance or even change the original meaning of the verb within the phrase, confusing the model.

Source English	Target Spanish	Expected Spanish output
Could you break down those dance moves?	*Podrías romper esos movimientos de baile?*	*Podrías mostrar esos movimientos de baile?*

Noisy source: typos

Source French	Target English	Desired English output
Occupez vous de vis enfants	*English: Take care of kids screws*	*Take care of your kids*

Unknown words: vernacular, neologisms, abbreviations

Vernacular, also current neologism

Abbreviation

Source English	*Decoded*	*Target Spanish*
steezy	*Style with ease*	*Steezy*
TMI	*Too much information*	*tmi tmi*

Dialectal differences

- Phonetic:

English term	IPA transcription with stressed back vowel /ɑ/	IPA transcription with stressed front vowel, /æ/
pajamas	*pə ˈdʒɑː ˌməz*	*pə ˈdʒæː ˌməz*

- Semantic:

Source: British English vernacular	(equivalent Standard American English)	French output:
Dying for a fag!	*Dying for a smoke!*	*Je meurs d'envie d'une tapette*

2. Named entity issues

"Named entities have proven to be some of the most difficult lexical items for the model to tackle." (Ugawa et al., 2018)

Arabic: أم كلثوم

English: *The mother of Kalthoum*

Desired output: *Oum Kalthoum*

NE issues occurred on average 4% across all languages

3. Morphology

English: *Cool down the brake system, cool it!*

Portuguese: *Esfrie o sistema de freio, esfrie!*

THE PRONOUN FOR "IT" IS ABSENT

Desired output: *Esfrie o sistema de freio, esfrie-o!*

Morphological errors occurred 2% on average across languages

4. Syntax

Source Spanish	Target English	Desired English output
disponibles relojes originales en cali	*Original Cali watches available*	*Original watches available in Cali*

3% average across all languages

5. Omission or addition of text

Source Spanish	English output	Desired English output
Dr. Núñez 👨🏾‍⚕️	*Dr.* 👨🏾 ⚕️	*Dr. Núñez* 👨🏾‍⚕️

7% average across all languages

6. Punctuation

English source	Target Arabic	Desired Arabic output
Wow!	!واو	واو!

.09% across all languages

7. Capitalization

Source English	Target Italian	Desired Italian output
Vivaldi's Four Seasons!	*Le quattro stagioni di Vivaldi!*	*Le Quattro Stagioni di Vivaldi!*

2% incidence across all languages

8. Pathological errors

- ➢ Nonsensical or ludicrous
- ➢ Problematic, introducing language that is confusing or even potentially dangerous

- Stuttering
- Toxic language not present in source
- A reversal in polarity or sentiment
- Health or safety risks due to misinformation
- Mistranslated named entities
- Changed units/time/date/numbers

"*With pathological errors the model renders an aberrant output, untethered from source, displaying what are known in industry as hallucinating errors.*" (Koehn and Knowles, 2017; Stahlberg, 2020).

Pathological translation samples

	Source Italian	Target English	Desired English output
NONSENSICAL BUT NOT TOXIC	*Congratulazioni!* 🥂	*I'm sorry!* 🥂	*Congratulations* 🥂
TOXIC LANGUAGE IS INTRODUCED	*È deceduto Antonio*	*F..k Antonio*	*Antonio passed away*

	Source English	Target Italian	Backtranslation	Desired output Italian
STUTTERING OF ADDITIONAL TEXT	J. Hill I think	Ciao. Ciao. Hill, credo	Hi. Hi. Hill, think	J. Hill credo

Machine translation is continuously improving!

- Source phrases sampled last year no longer display many of the original errors from 2018-2019!

WITH CONTINUOUS TRAINING

- MT models continue to improve with more training data

but

- They need to keep improving in order to ensure optimal end-user trust!

What is next?

1. Developing techniques to improve translations for named entities
2. Developing techniques for profanity aware translation (false positives)
3. Developing techniques for translating into morphologically-rich languages.
    a. Small changes in morphology can mean important changes in meaning
4. Curating a new dataset that includes a variety of errors described today
    a. In addition to BLEU, evaluate MT performance on these error types


thank you
danke
謝謝
ngiyabonga
شكراً جزيلاً
рахмат
teşekkür ederim
Баярлалаа
спасибо
gracias
dank je
merci
obrigado
bedankt
dziękuję
go raibh maith agat
mochchakkeram
sukriya
kop khun krap
terima kasih
감사합니다
ありがとう
arigatô
dakujem
мерси
grazie
takk
tapadh leat
hvala
maururu
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mersi
kia ora
barka
welalin
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spas
faafetai lava
vinaka
спасибі
blagodaram
misaotra
matondo
paldies
grazzi
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хвала
asante
manana
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Q & A

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Unbabel

6th October 2020

AMTA 2020

COMET - Deploying a New State-of-the-art MT Evaluation Metric in Production

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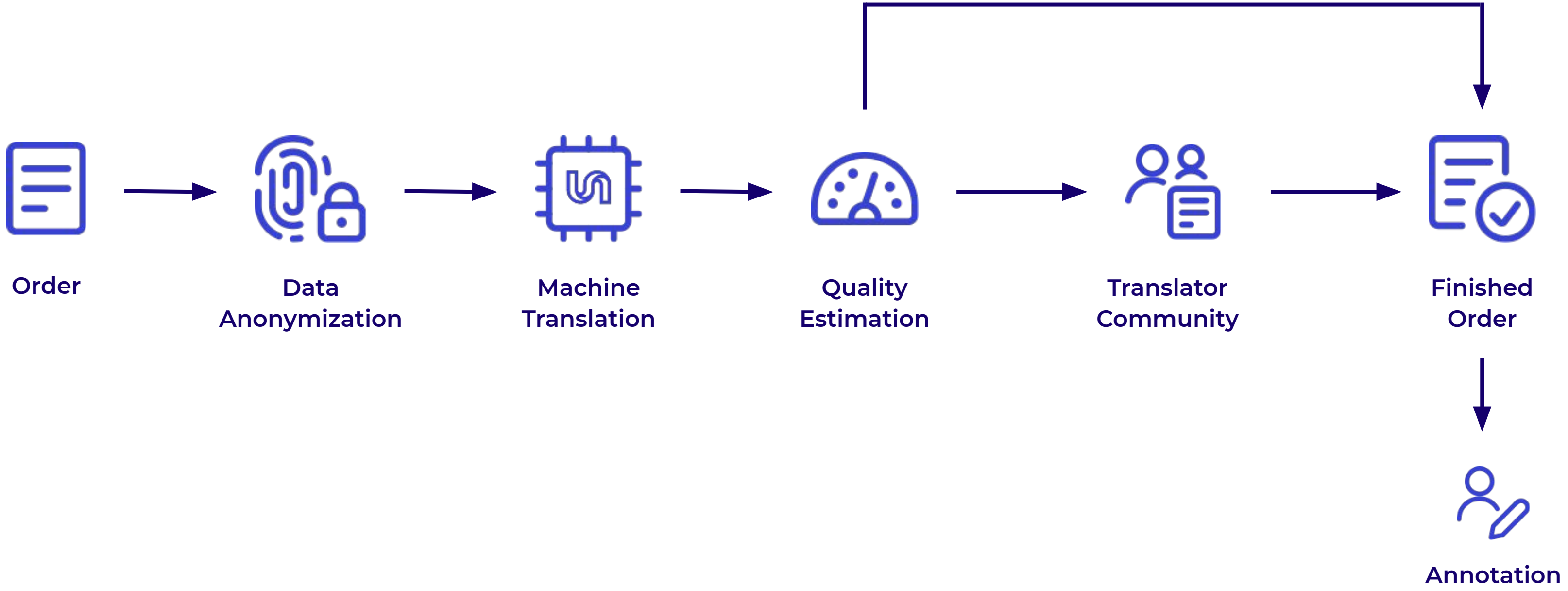
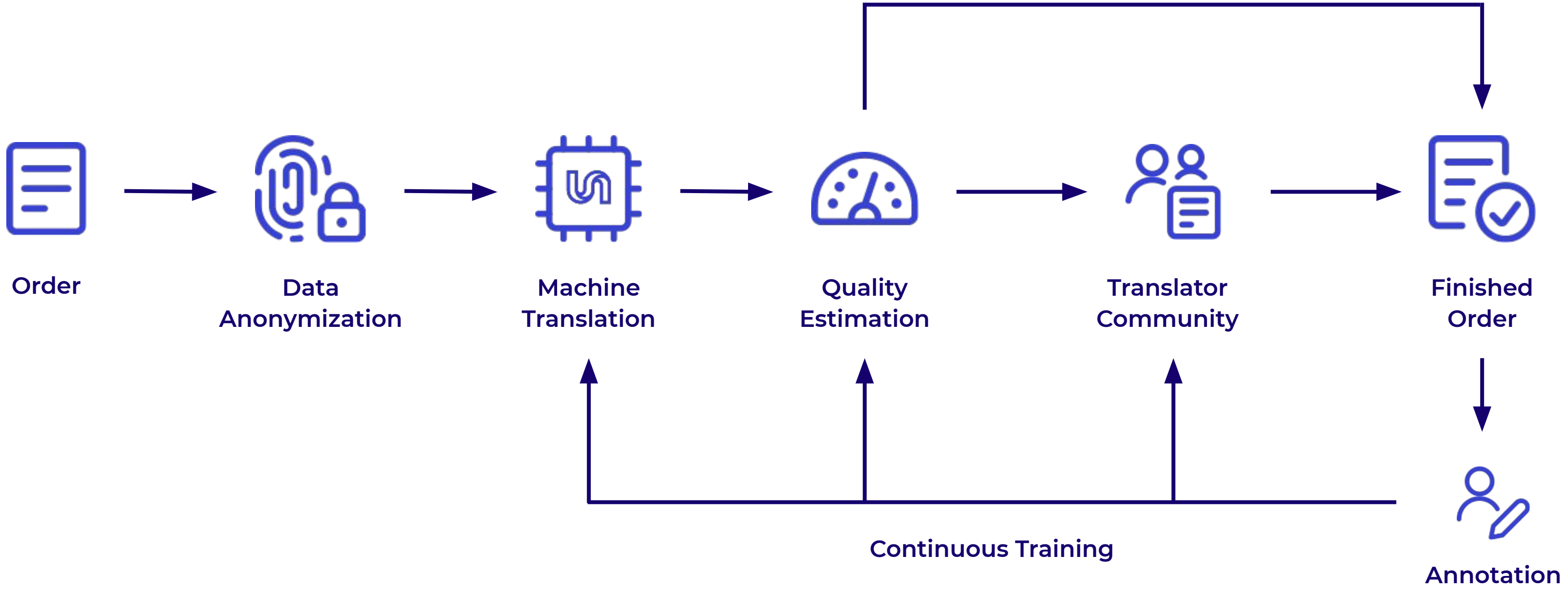
Why is Automatic Evaluation important at Unbabel?

Unbabel’s Translation Pipeline



Unbabel's Translation Pipeline



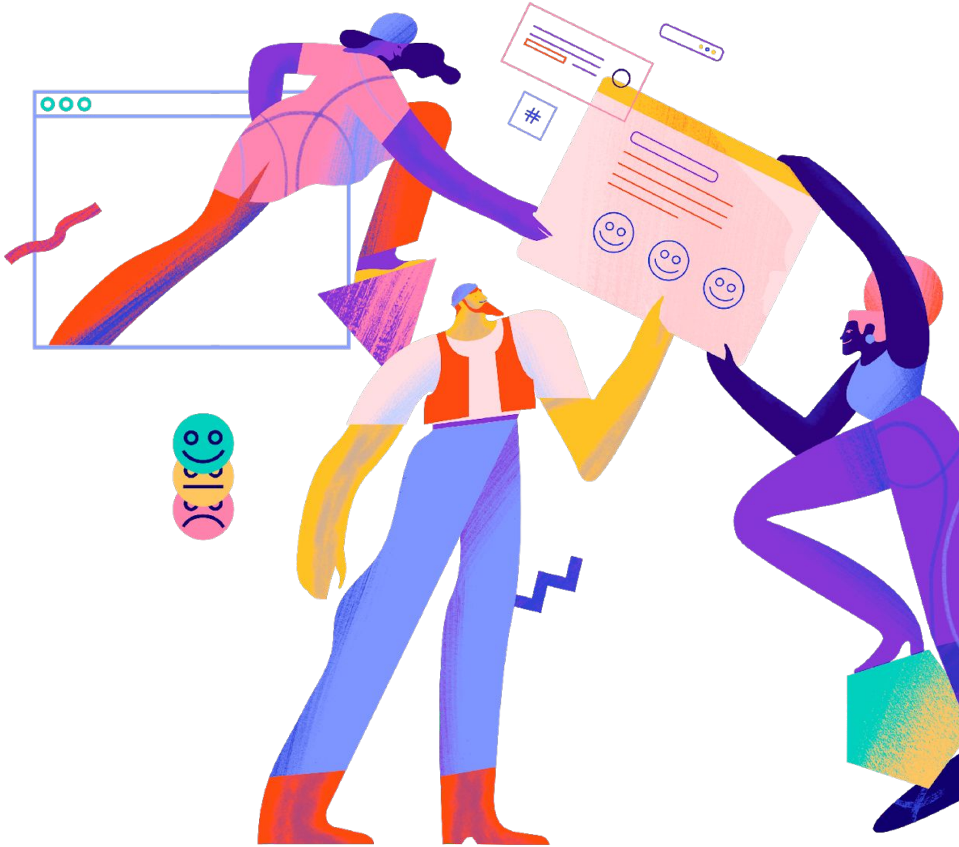
Evaluation at Unbabel

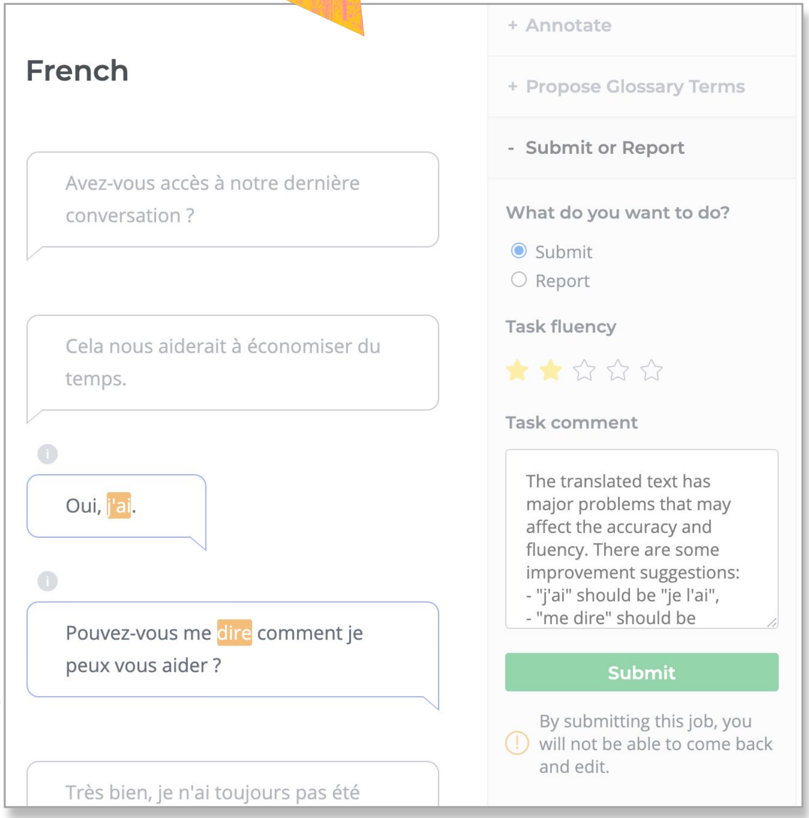
We process high volumes of translations using highly specialized models for customer service solutions in a wide range of domains.

Our MT engines are continually retrained to ensure that we maintain the highest quality of translation and robustness to new content.

How do we know that MT Engine A is better than MT Engine B?

- Our engineers and scientists rely on existing metrics such as BLEU and METEOR to make initial modelling decisions
- We leverage our community of linguists to provide human evaluation using MQM





Multidimensional Quality Metrics (MQM)

Our primary method of evaluating MT quality involves sending batches of translations to our community for annotation.

We ask annotators to highlight errors according to an internal error typology (for things like ‘style’, ‘content and ‘accuracy’) and rank the error as either **minor, major** or **critical.**

We then calculate a segment-level score as a function of the **number** and **severity** of errors in the translation. Post-edition by our community of editors provides us with a ‘gold-standard’.

What’s wrong with using existing metrics like BLEU?

Automatic VS Human evaluation of MT

VS.

Automatic (BLEU)

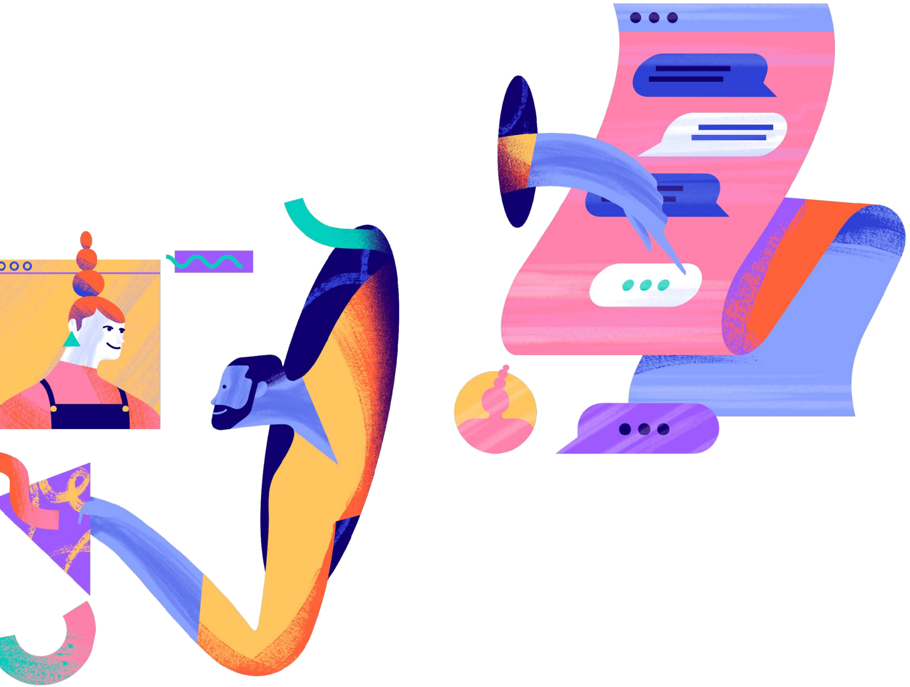
PRO: Allows our scientists and engineers to iterate quickly over MT models

CON: Less reliable and not sensitive to granular error

Human (MQM)

PRO: More reliable and sensitive to nuanced error

CON: Slow and expensive



Inability to differentiate high-performing systems

Much of the time in developing or retraining MT engines we are comparing two systems or versions of the same system that already perform very well. The gap in performance of the two iterations might be very small.

One of the key findings of the WMT 2019 Metrics Shared Task was that **even modern metrics struggle to successfully rank high-performing systems**.

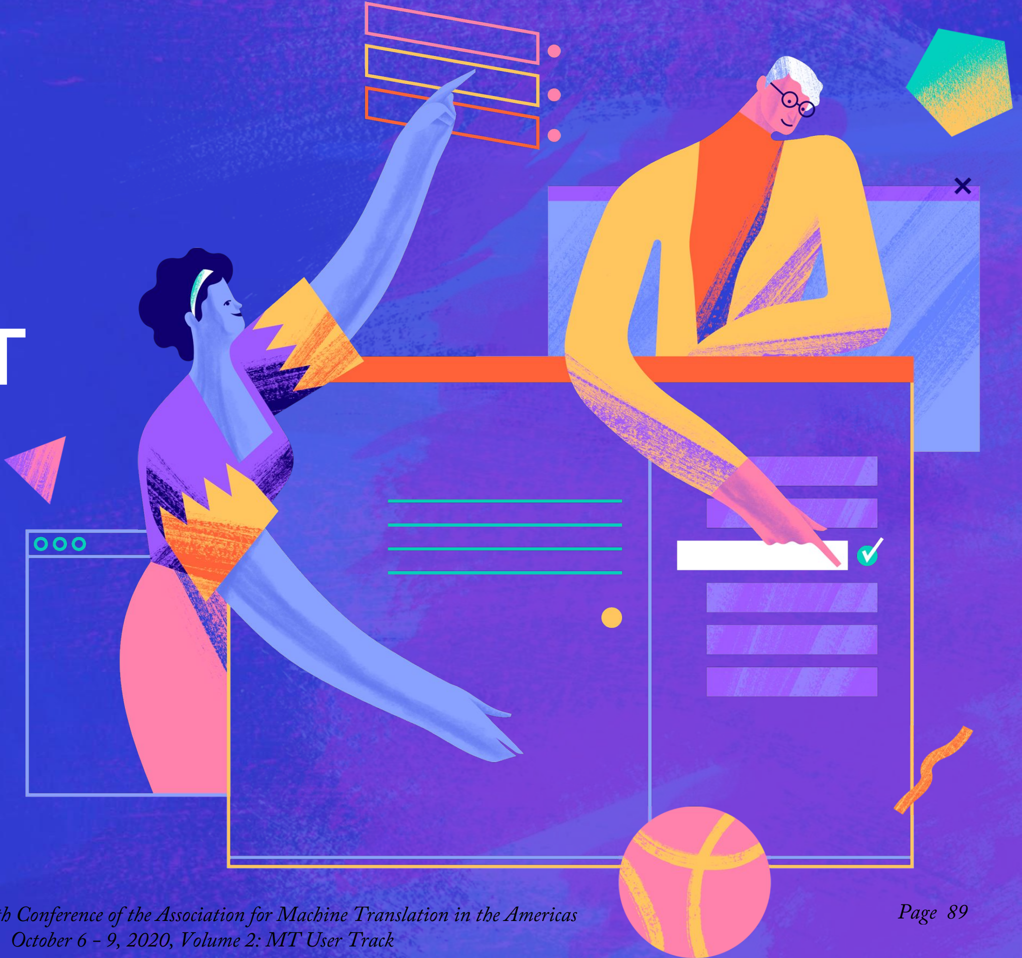
Correlation with Human Judgement

In general, metrics such as BLEU and METEOR (based on n-gram matches with a reference translation) correlate poorly with human judgement.

What does this mean for us and our customers?

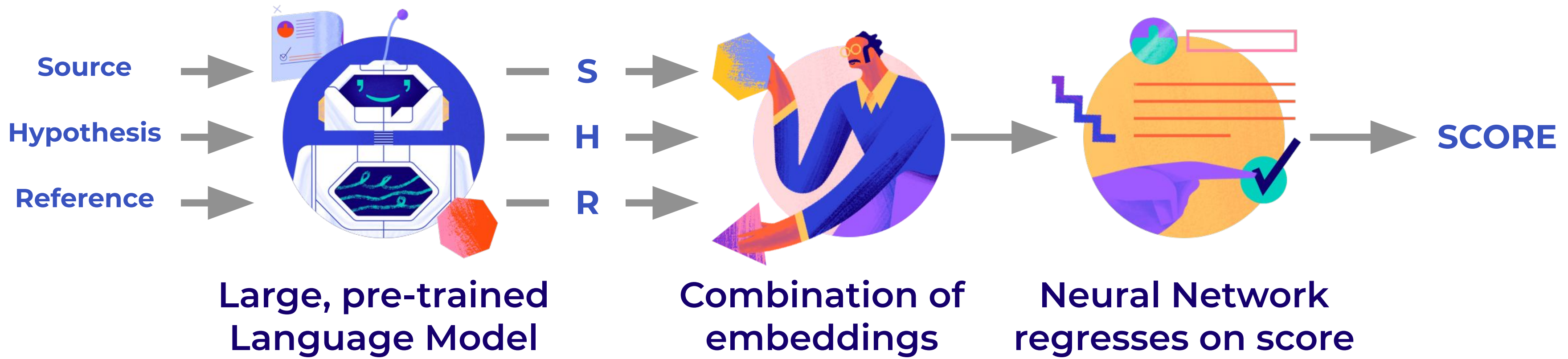
- Modelling decisions are poorly informed and often don't align with human opinion
- Cost of verifying and rectifying modelling decisions is huge
- Degradation of performance downstream results in unhappy customers

COMET: A neural framework for MT evaluation



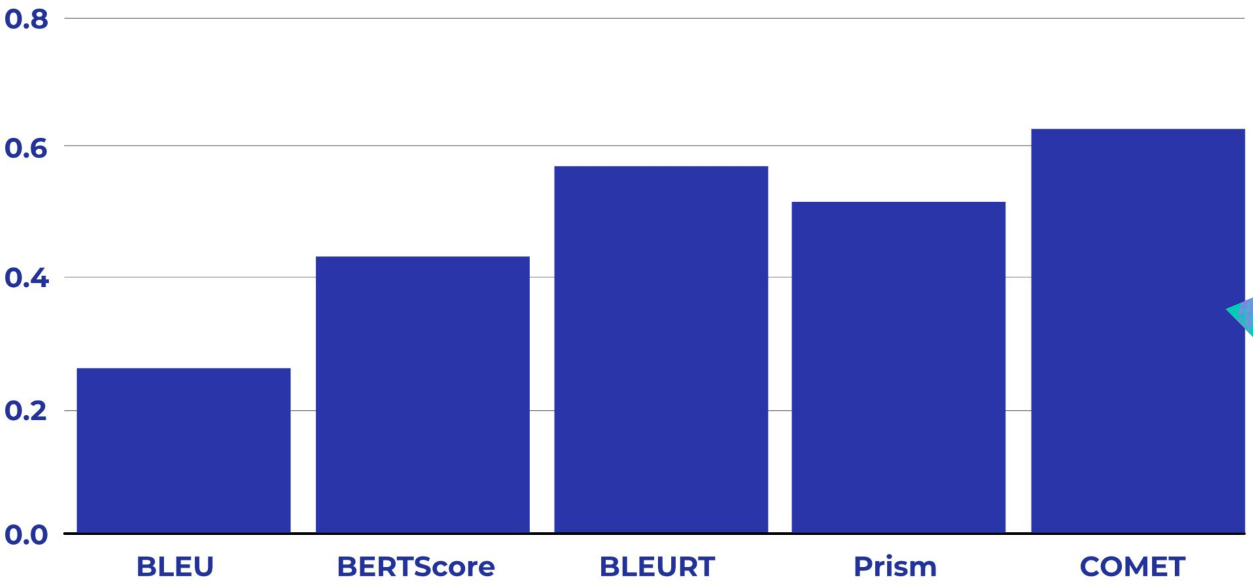
6 October 2020

COMET: Basic Modelling Approach



COMET: Performance

Kendall's Tau on segment level WMT 19 Metrics Shared Task

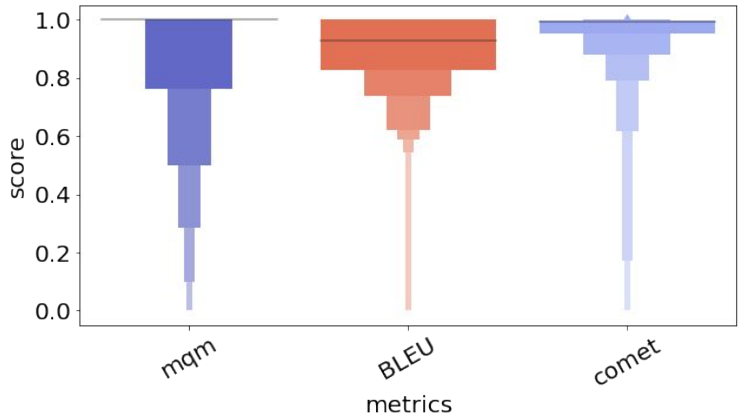


COMET: Strengths and weaknesses

EN-PT_BR

SRC: "Is there anything else I can help with?"
REF: "Existe mais alguma coisa com a qual eu possa ajudar?"
MT: "Posso ajudar com mais alguma coisa?"

MQM	100
BLEU	0.5696
COMET	0.9689



COMET can capture semantic similarities even where there is lexical disparity.

COMET has a tendency to overestimate which presents a challenge for interpretation

COMET: The Importance of Good References

EN-DE

Reference*	Adequacy	r (1-ref)	r (2-refl)
WMT	85.3	**0.523**	-
AR	86.7	0.539	**0.555**
WMTp	81.8	0.470	**0.529**
ARp	80.8	0.476	**0.537**

More references doesn't, necessarily, mean a higher correlation.

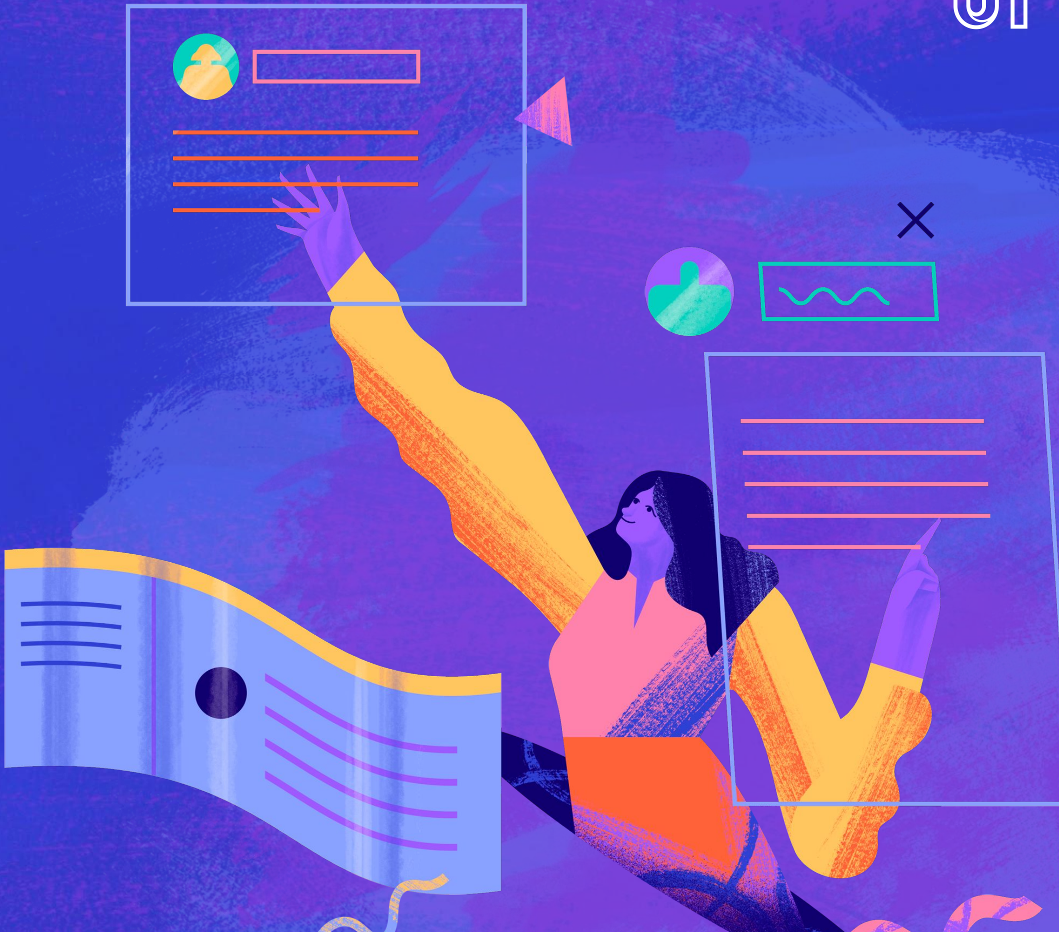
DE-EN

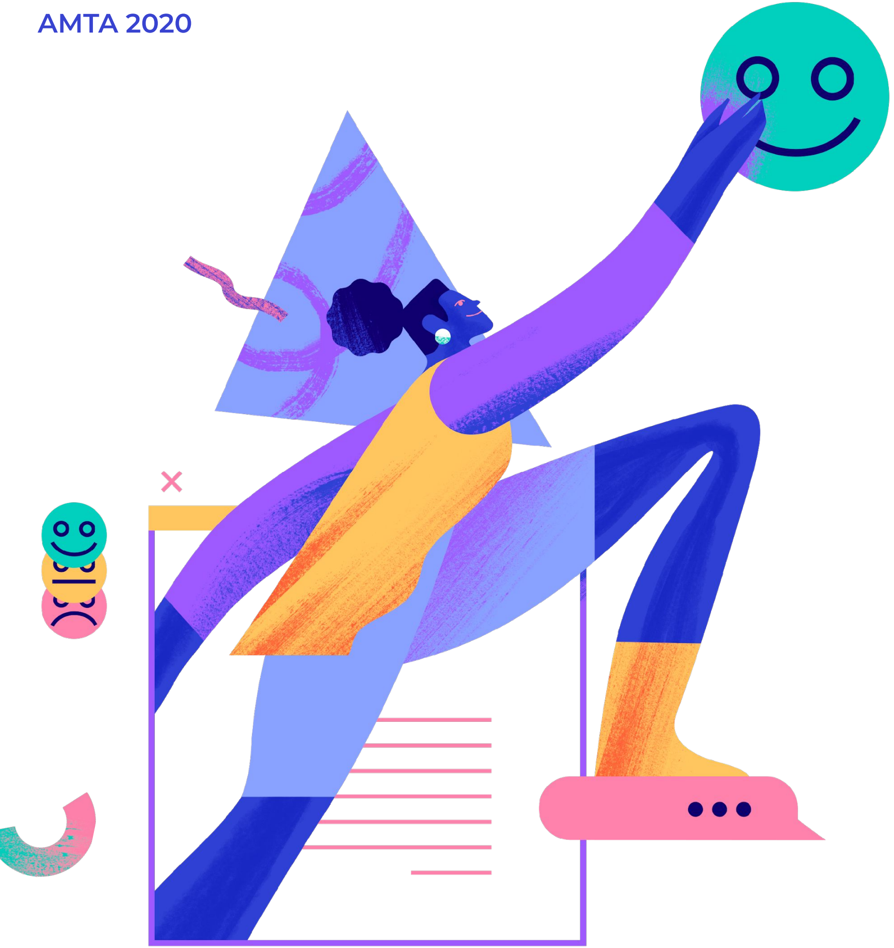
Reference	r (1-ref)	r (2-refl)
WMT	**0.42**	-
ALT	0.34	**0.40**

Using more references can even hurt the correlation!

* *Data from Freitag et al (2020)* - https://arxiv.org/pdf/2004.06063.pdf

Evaluating COMET metrics for deployment





How do we know that COMET is good enough?

We started by assessing the different use cases for COMET internally and realized that these fall into two fairly distinct categories:

- **Single model evaluation** - we just want a score to tell us how well our model is doing
- **Dual model comparison** - particularly in retrainings, we have two systems (usually very close in performance) and we want to know which is better

What do we want out of COMET?

High Quality Assurance

If our ultimate goal is high quality translation, we want to ensure that our engineers have the best tools to make well-informed modelling decisions. Fundamentally we want a metric that performs better than BLEU.

Low Risk Cost Reduction

Having humans verify our engine deployment with MQM annotation is not cost effective or scaleable. We want a metric that aligns well enough with human judgement that we can make deployment decisions based on COMET alone.

Tiered Evaluation

In light of the above we defined a tiered system of evaluation whereby we calculate a Pearson's *r* correlation score on internal test sets to assess how closely the metric aligns with MQM. We start by figuring out what we think is an **acceptable risk margin** which we set at **+/-0.1 Pearson**

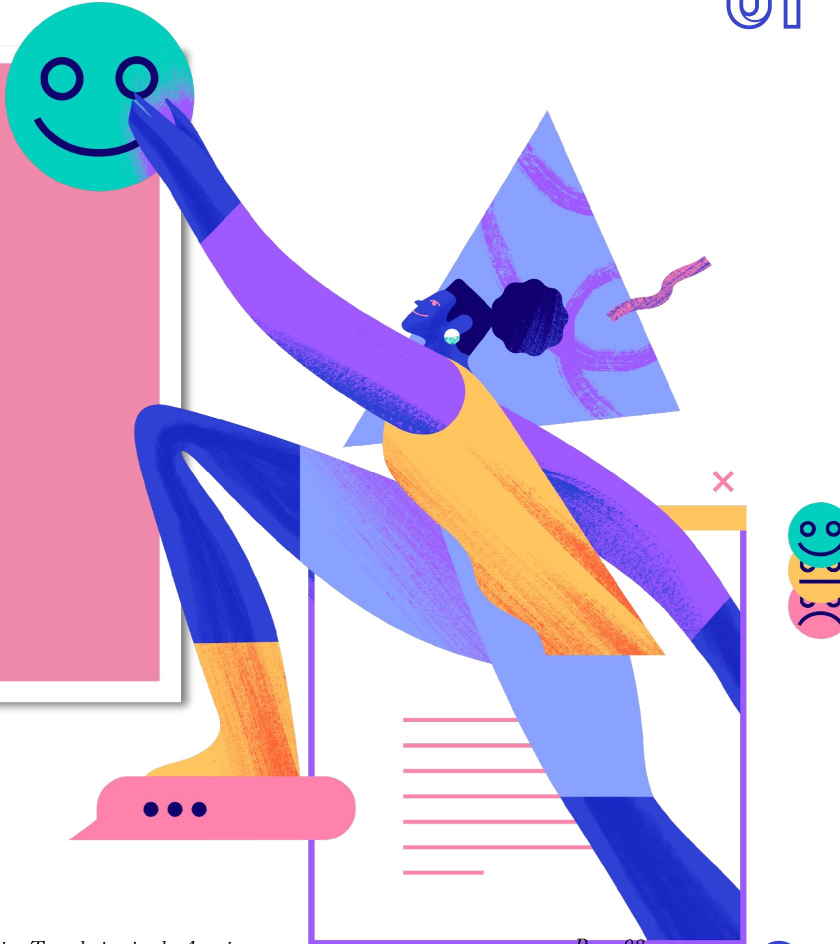
TIER 1 (near enough to human parity)

- Internal analysis revealed that human annotators correlate with each other at around 0.6-0.7 Pearson
- **Does COMET achieve a Pearson of >0.5** (i.e. is it within our risk margin of human agreement)?

TIER 2 (better than BLEU)

- **Does COMET perform better than BLEU** at a level exceeding our risk margin?

en-zh	en-ja	en-id	en-bg
en-fi	en-ko		en-hu
en-ro	en-cs		
en-es	en-es		
en-nl	en-vi		
en-ru	en-da		
en-pl	en-fr		
en-no	en-tr		
en-de	en-pt		
en-sv	en-it		
en-th			



Tiered LPs for out of English Ticket Products

No Language left behind

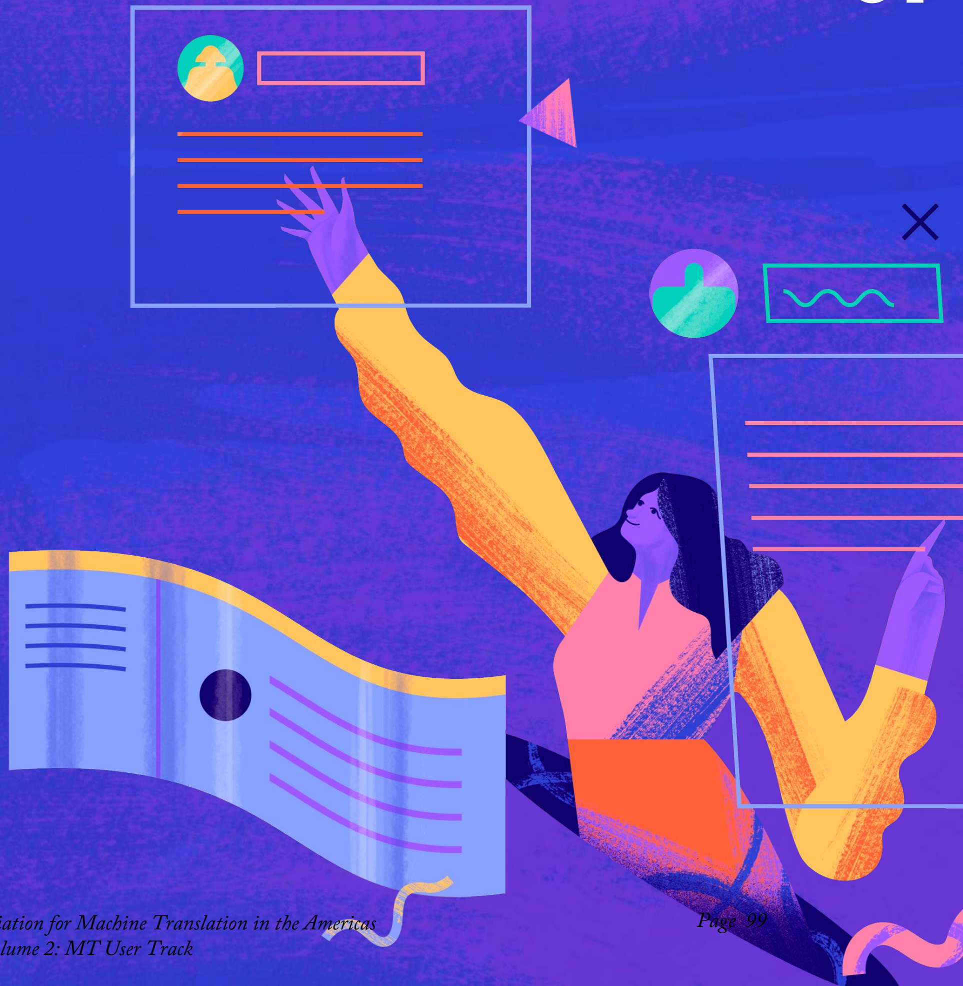
The ideal scenario for COMET is that it puts us in a postition where all of our products can rely on COMET scores without the need for human annotation (i.e. that all LPs land in Tier 1).

For LPs in Tier 2:

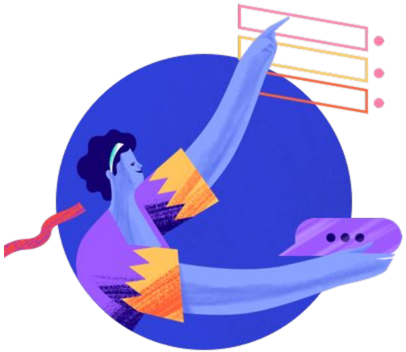
- We are actively seeking opportunities to improve COMET performance on these LPs. This involves both general model improvement and augmentation of our datasets.

For other LPs:

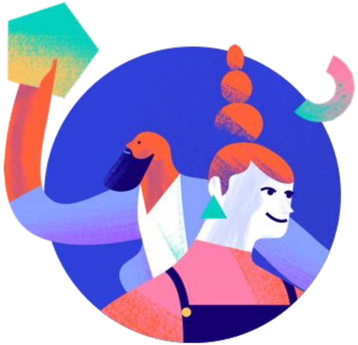
- Where we don't have data for existing LPs we rely on our editors to generate more data for testing and training.



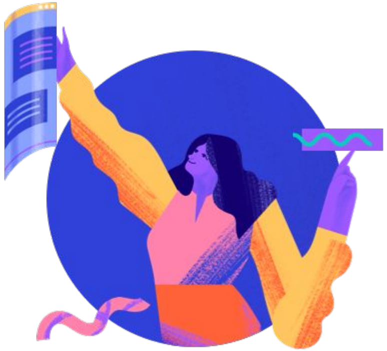
Evaluation Process



Identify products and language pairs across the business and collect data sufficient to give a reasonably reliable Pearson's r score



Evaluate iterations of COMET across settings and compare results with human assessments



Based on our tiered evaluation scheme, assess reliability of COMET in each use case and iterate until we are satisfied of the impact of the model

Deploy the best model and provide clear information to our engineers about how and where to use COMET

COMET in deployment

To provide an extra layer of certainty and trust in COMET for our engineers, we are implementing **statistical significance testing** in our retrainings evaluation.

In deciding whether to deploy a retrained system we apply a bootstrapped t-test for significance to determine, with a 95% confidence interval, that the new system is better than the old.

We also complement our COMET evaluation with a range of other metrics to ensure that our engineers have a full toolkit when making modelling decisions.

What to do when metrics disagree?

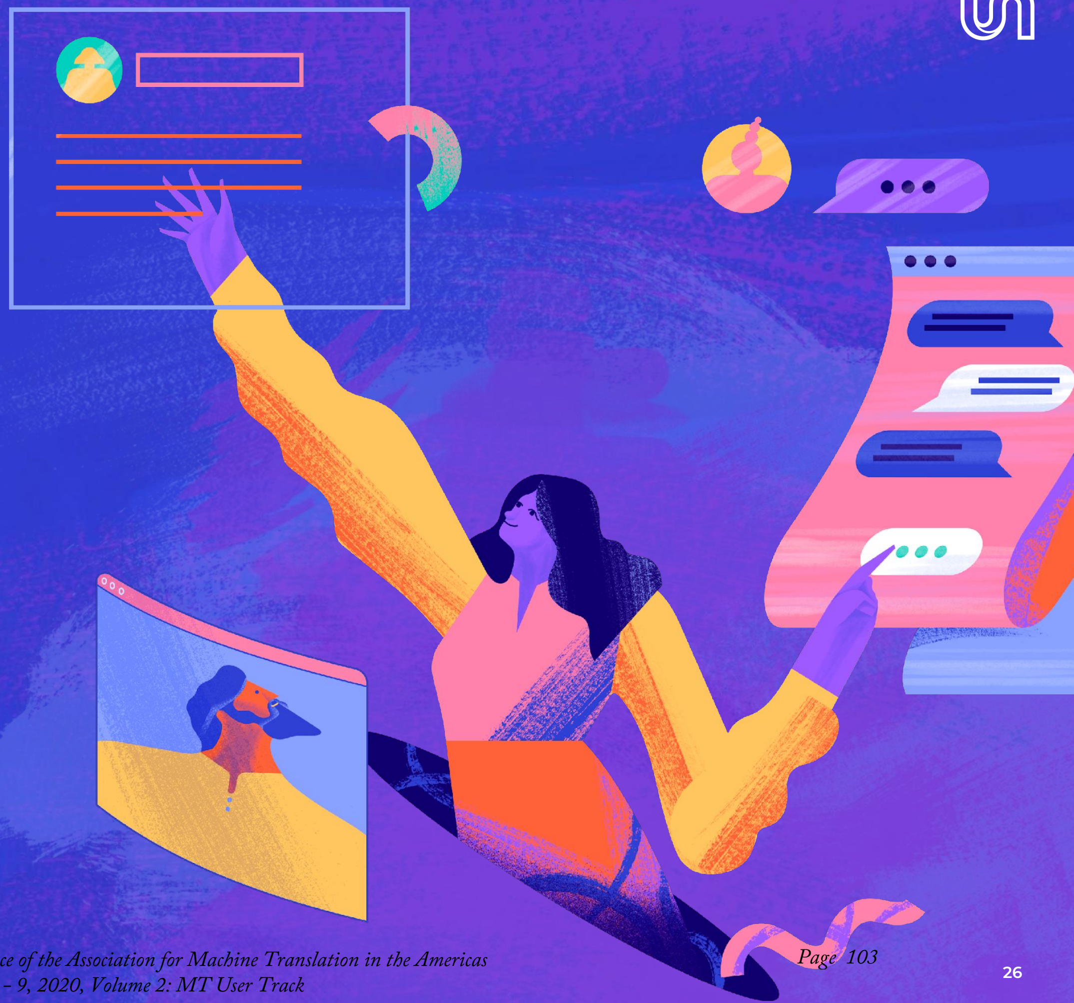
It is important to note that even where metrics like BLEU don't correlate well with human judgement, their input is still valuable, if only because metrics based on lexical similarity tell us something unique from metrics such as COMET which are more grounded in semantics.

As such we encourage our engineers to look at a variety of metrics including BLEU, METEOR, TER, BERTScore and COMET to get a fuller picture of what our models are doing.

Where all metrics agree the decision to deploy is black and white. Where it isn't:

- **COMET and other semantic metrics (e.g. BERTScore) agreeing? Good chance that MT is semantically accurate**
- **COMET disagrees with everyone? Check the magnitude of the difference before discarding and consider the statistical significance of the improvement**

Keeping tabs on COMET over time



How do we continue to adapt COMET?

As the range of products and languages at Unbabel grows, we need to ensure that COMET is keeping up.

With COMET in production, we are developing a procedure to re-evaluate COMET on a rolling basis by sampling retrainings for annotation with MQM.

We are also coordinating with product managers to anticipate future product and language demand and perform evaluations and adaptation on new data.

Outside of Unbabel

We we plan to release an open source version of the COMET framework to benefit the wider MT community, and we are hopeful that development will continue over the next year.

The code will be available at:

https://github.com/Unbabel/COMET

Key takeaways

Metrics in a commercial setting:

- Automatic metrics like BLEU are of limited use
- Adaptive evaluation frameworks trained to correlate well provide an attractive solution
- Our COMET framework is publicly available

Evaluating Metrics:

- Metrics can have different use cases and applications
- A tiered evaluation method can help to align expectations
- Considering the statistical significance of modelling decisions can be insightful

Questions?

Craig Stewart

Research Scientist

Unbabel

Thank you

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Unbabel

Unbabel

Scaling up automatic translation for software: reduction of post-editing volume with well-defined customer impact

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AMTA 2020

Microsoft

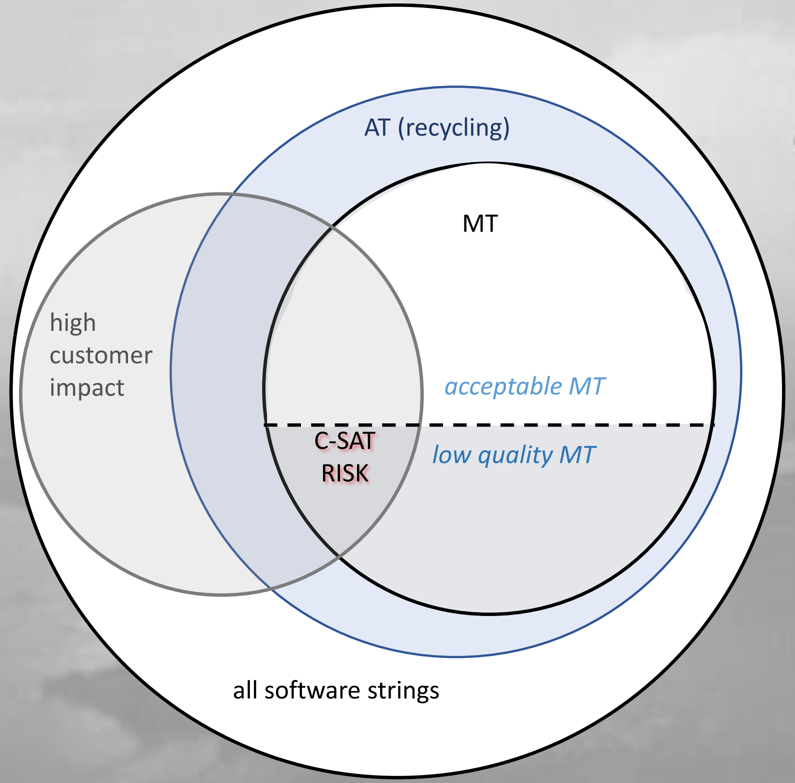
Automatic Translation for software (AT4SW)

Challenge
- Publish more MT for software without human review, with minimal customer impact
- MT quality is highly variable, both within and across languages

Approach
- Safe velocity: sw workflow with configurable constraints and quality gates
- Quality Estimation (QE) enables us to predict MT translation quality
- Workflow tuned to limit low quality MT to 10% of translation volume

Outcomes
- MT now used for 9% of published software translation volumes across 37 languages
- No notable negative impact on customer sat

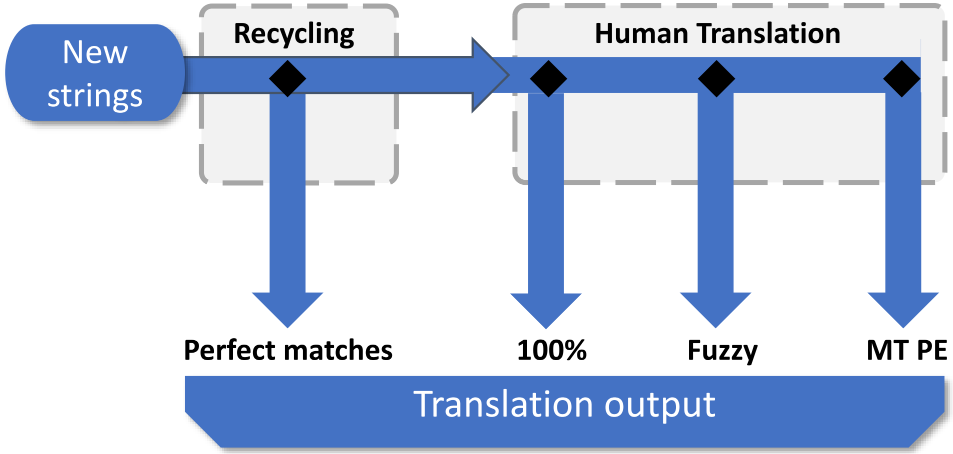
Safe Velocity: managing risk



Automatic Translation (AT) for sw levers to maximize MT usage, with minimal SAT impact
- Improve MT and Optimize Quality Estimation (QE) to reduce low quality MT
- Protect high customer impact strings: exclusion, length thresholding
- Listen and respond to customer feedback

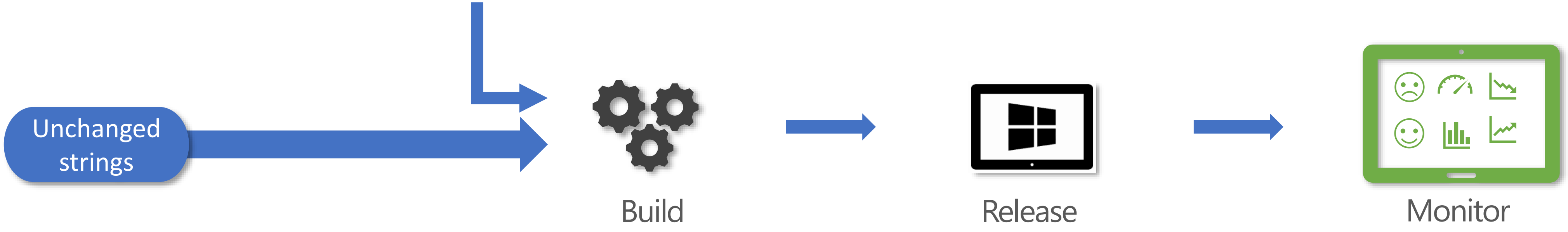
Software UI

Workflow



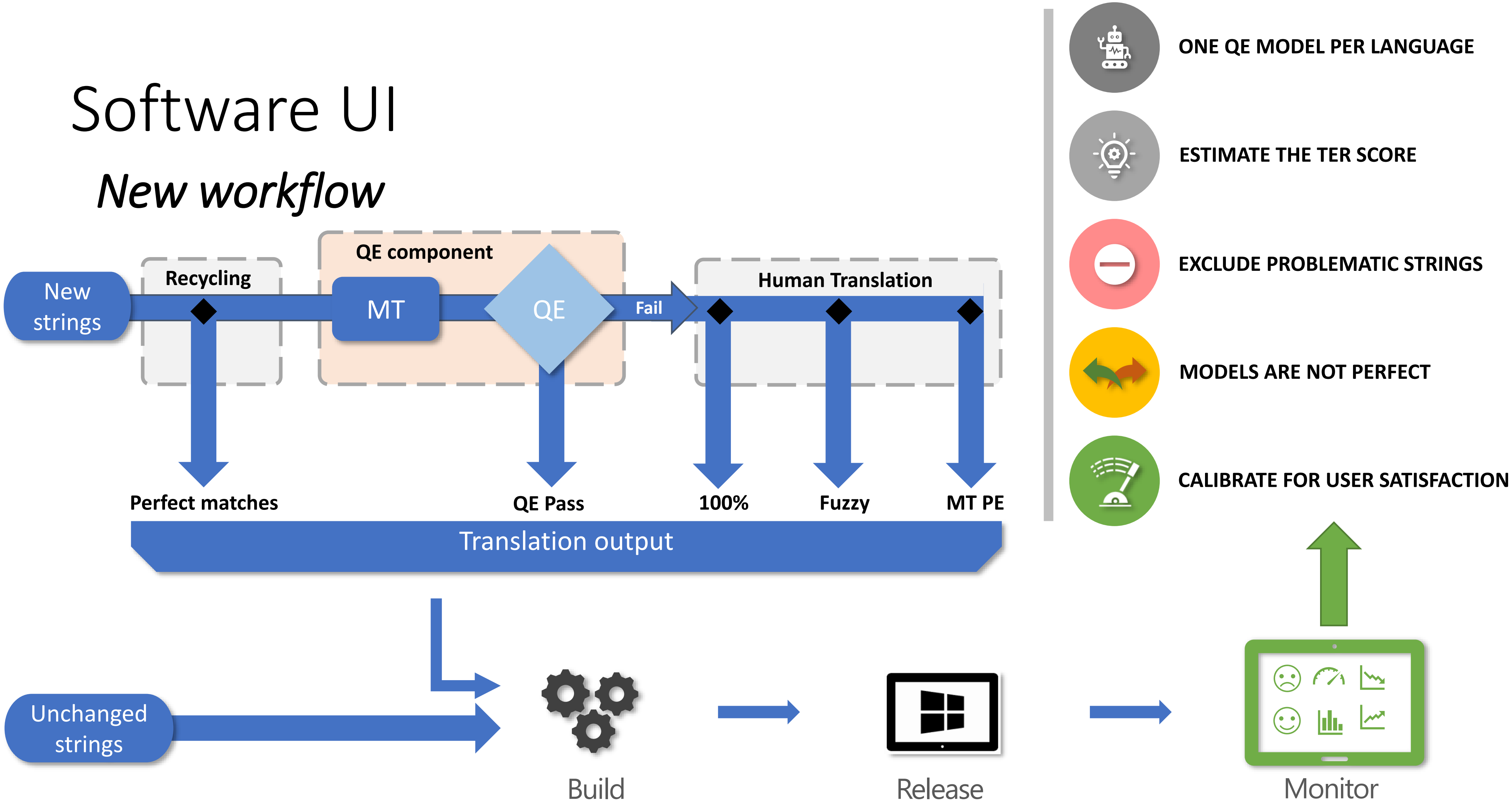
- **CORE TO USER EXPERIENCE**
- **HIGH AMBIGUITY / MAJORITY OF SEGMENTS ARE SHORT (<5 WORDS)**
- **SPECIFIC TRANSLATION CONSTRAINTS (PLACEHOLDERS, COMPLEX PATTERNS…)**

CAN WE DETECT WHEN MT IS GOOD ENOUGH AND DOES NOT REQUIRE POST EDITING?



Software UI

New workflow



Exclusion for High Customer Impact

Why a need for exclusion?
- MT output quality can vary between string type/context & languages
- Some UI strings need get Human Review, as the risk of customer impact is high

Marketing	What's New	Legal
Welcome to Office Your place to create, communicate, collaborate, and get great work done.	"**Starting from scratch is hard**. QuickStarter automatically creates an outline for your topic of choice with suggested talking points and designs that **make your presentation pop**"	"By checking this box and entering your name below, you represent that you have read and understand above agreement, have authority to bind Customer, and that Customer agrees to be bound by the Agreement terms and the websites therein."

Mechanisms for exclusion
- By resource: targeting specific words and phrases in strings, resource names, or developer comments
- By feature: not suitable or ready for MT, such as 'What's New', or resource groups with complex formatting

Initial target for exclusion: up to 20% of new words per month

Quality and customer impact: Error rate

We manage MT quality based on error rate: % of predicted low quality MT

- Based on volume of new words per product and month
- Assumption is users will tolerate a certain ratio of low-quality translations, without significant impact on customer satisfaction
- Historical human translation Linguistic Quality Assurance fail rate is 5%, by string
- MT error rate threshold, per product, language and month, is set to 10%, by word count – this is the amount of low-quality MT we tolerate

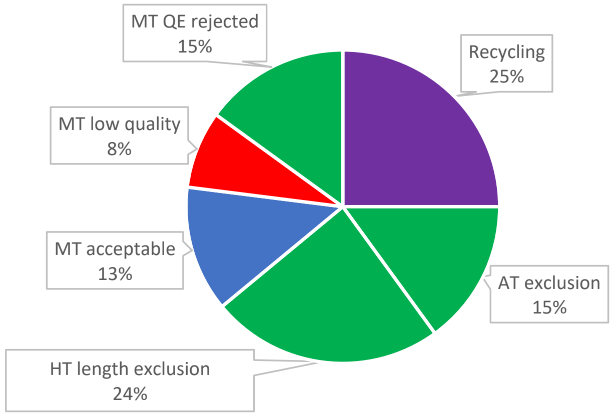
We use Quality Estimation (QE) to estimate the error rate

- Feature based ML model based on Quest++, trained on 100k+ segments /language
- MT low quality strings are those with a TER score >0.3, as predicted by QE
- QE threshold is calibrated per language, taking precision and throughput into account, against the 10% error rate

Calibration and MT error rate

Maximize AT volume against a MT error rate

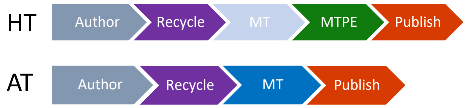
- Recycle rate for contextual (perfect match) recycling
- High customer impact exclusion (AT exclusion)
- Length threshold for MT – we exclude short strings, <8 words
- QE precision and throughput per language
- This allows us to intentionally publish some low-quality MT



Example: QE threshold set to not exceed the error rate

- We select the QE threshold for the right balance of throughput and precision, to hit the target error rate given volume in scope
- In the example, 36% of volume is in scope for MT. A QE threshold of 0.42 results in throughput of 58% and precision of 62%, and an 8% error rate

Green areas show HT workflow.
Purple AT workflow for recycling
Blue & Red AT workflow for MT



Scaling out AT4SW to a wider range of products

Goal for FY20: (Jul-19 to June-20) – expand AT4SW from Office to Windows products

Key Question: Would existing QE models provide sufficient accuracy, or need retraining?

- QE initially trained on Office product range, 2+ years worth of Post-edit data

Outcome: QE precision for Windows products sufficient to maintain MT volume level similar to Office products

- Good indication that our QE models are robust
- Office and Windows products are of a similar/overlapping domain

MT model training, evaluation, bug-fixing

- AT4SW makes use of Microsoft Translator custom models
- Automation and analytics in place to train and evaluate models for 90+ languages, for multiple domains

- Custom MT pre and post-processing in place for tag protection
- Custom training cleanup tools, aligned with pre-processing tools, to ensure we train on the same format text we process at runtime

- Monitoring of quality, analysis of post-editing, and collaboration with Translator team on bug-fixing

Development and optimization

- MT audit rate: measuring error rate in production
  - QE score assigned to all MTd strings, including those that get post-edited
  - Actual TER scores used to calculate Audit Rate: in production edit rate
  - Preliminary results indicate QE predicted scores and error rate is achieved in production

- AT4SW optimization to increase volume against error rate
  - Word count threshold reduction from 10 to 8 words in scope for MT QE

- Reduction of validation failures for MT by integrating upstream string information (dev comments) on placeholders

Summing up: 2 years on...

60M — **FLOW OF 60 MILLION WORDS PER YEAR DISTRIBUTED ACROSS 37 LANGUAGES**

0.4M — VOLUME OF WORDS "QE PASSED" EACH MONTH

9% — PROPORTION OF WORDS SET TO "QE PASSED"

79% — CUSTOMER SATISFACTION SCORES STABLE

NO SIGNIFICANT INCREASE OF DSAT BY LANGUAGE

Challenges

EXCLUSIONS & TERMINOLOGY

PRODUCT SPECIFIC TUNING

ACTIONABLE FEEDBACK

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Q & A

Auto MT Quality Prediction Solution and Best Practice

York Jin & Martin Xiao

Oct. 2020

vmware

Agenda

01 Program overview

02 Data collection and model training

03 Perfect MT scenario

04 Inference acceleration

05 Future works

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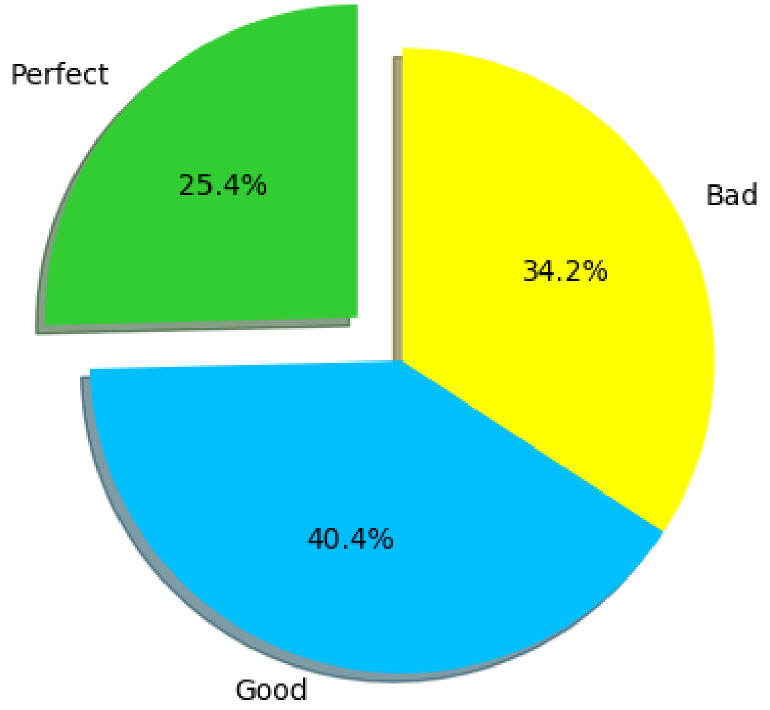
Program overview

Why prediction is needed



Perfect: PE% = 0 **Good**: 0 < PE% < 20% **Bad**: PE% > 20%

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Program overview

POC

- Data collection
- Data washing
- Conceptual design
- Result analyze
- Prove of concept

Model fine- tune

- Added source English as feature(English + MT as input, PE as the label)
- Added regression to get linear output
- Generated training data from fuzzy/ICE
- Validation framework (correlation scatter diagram with actual PE etc.)
- Trained models

Deploy to Stag.

- Model validation by real data
- Load balancing by using multiple instances
- Model performance against 25,000 new words project (5-10 in average)
- Quality index invented and patent applied

Deploy to Prod.

- Model size reduction
- Further validate the model by running pilot projects
- Deploy trained models in DECC (CPU only, with load balancer)
- OpenVINO inference accelerator (CPU)
- Tensor RT ML inference accelerator validation (GPU)
- Exclusion rules
- Integration with TMS

Scenarios

- Perfect MT scenario
- RAW MT quality auto scoring scenario
- Engine quality auto evaluation scenario

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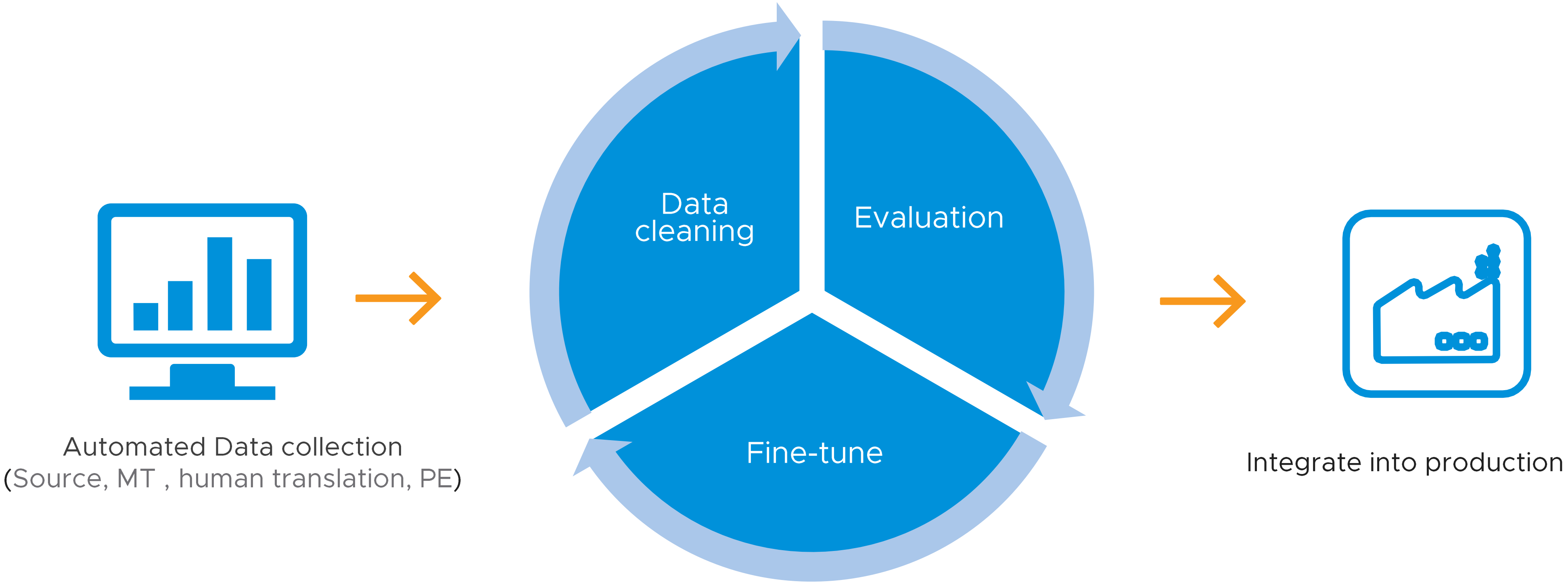
Data collection and model training



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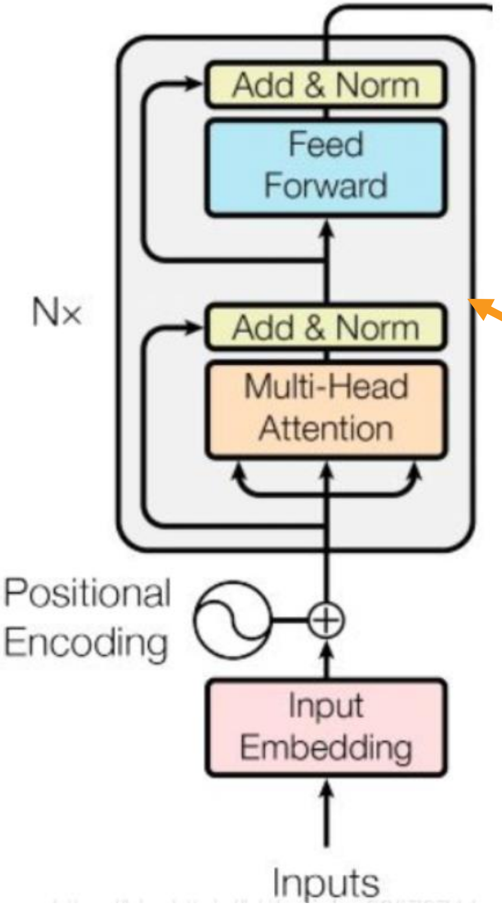
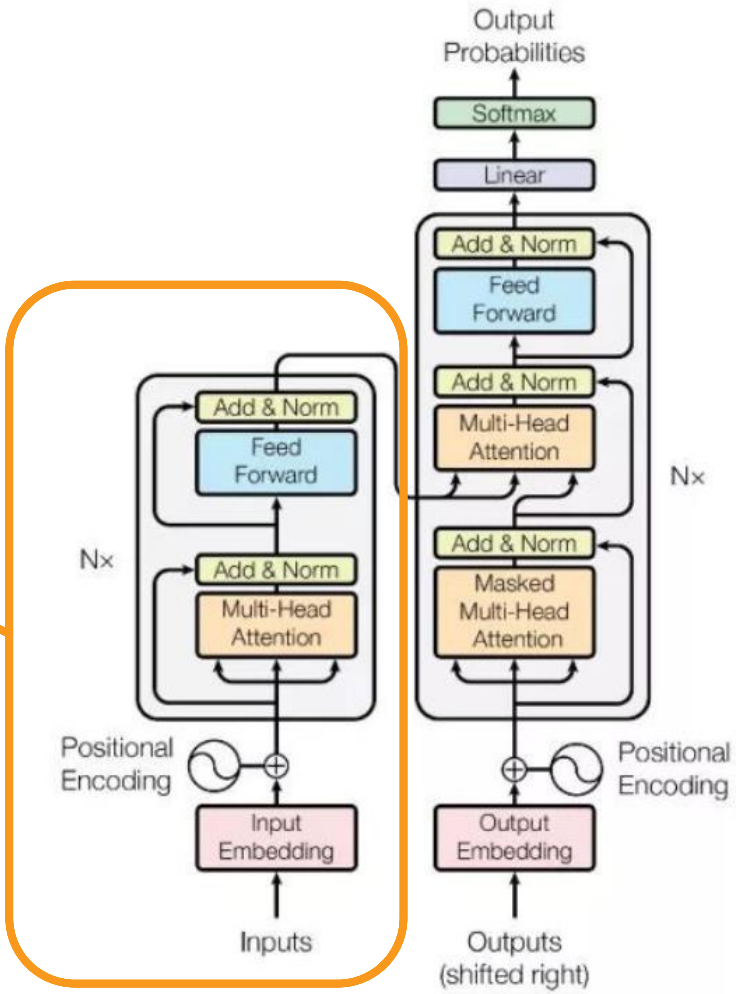
Data collection and model training

Algorithm – Transformer





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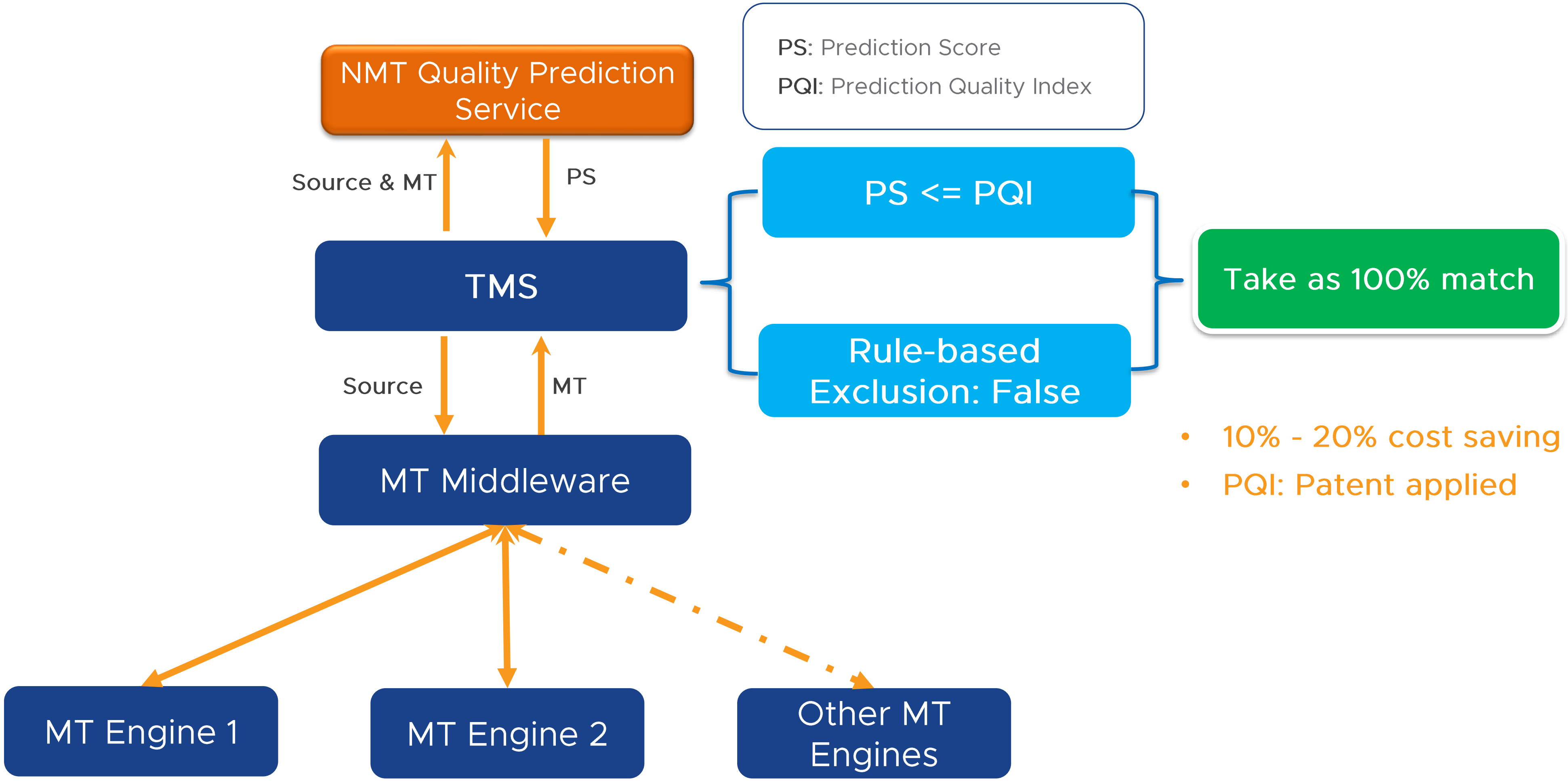
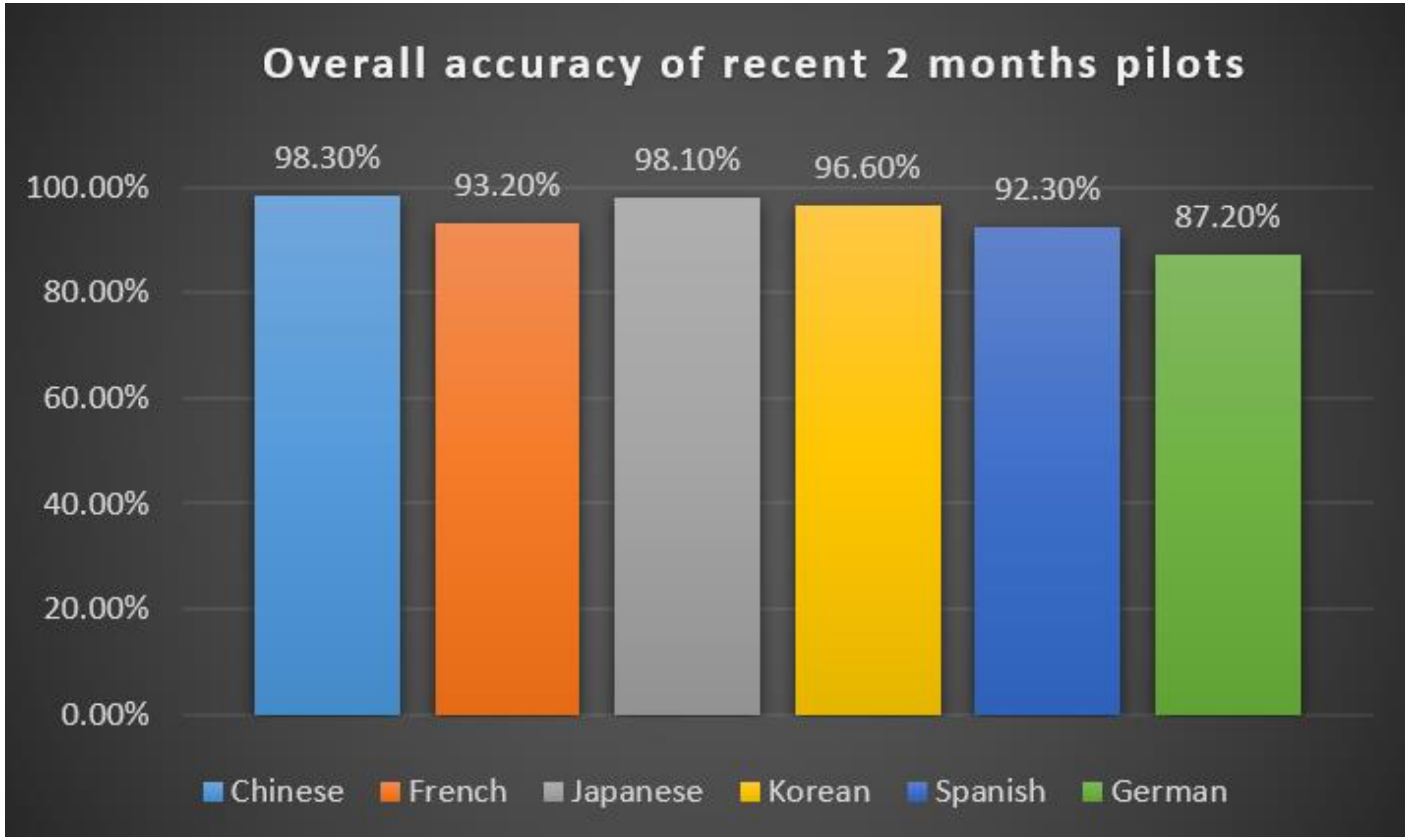
Perfect MT scenario



- 10% - 20% cost saving
- PQI: Patent applied

Perfect MT Scenario

Overall accuracy



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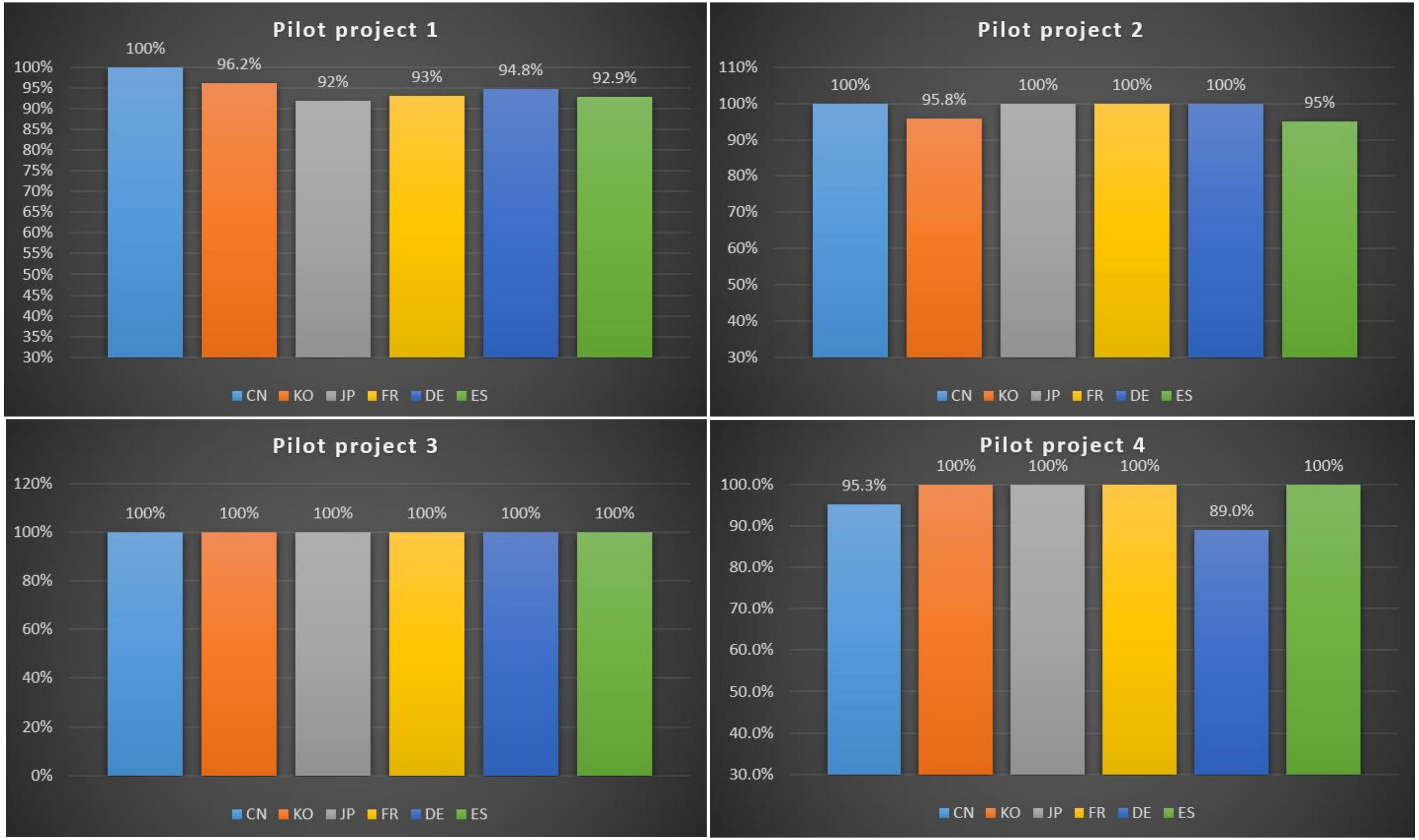
Perfect MT Scenario



Perfect MT Scenario

Typical prediction failure example

DE golden MT that human linguist marked as “bad”:

Source:

Directory sync is handled by the connector component of the service and can only be enabled on one connector instance at a time.

MT:

Die Verzeichnissynchronisierung wird von der Konnektorkomponente des -Diensts durchgeführt und kann jeweils nur auf einer Konnektorinstanz aktiviert werden.

Human MTPE:

Die Verzeichnissynchronisierung wird von der Connector-Komponente des Diensts durchgeführt und kann jeweils nur auf einer Connector-Instanz aktiviert werden.

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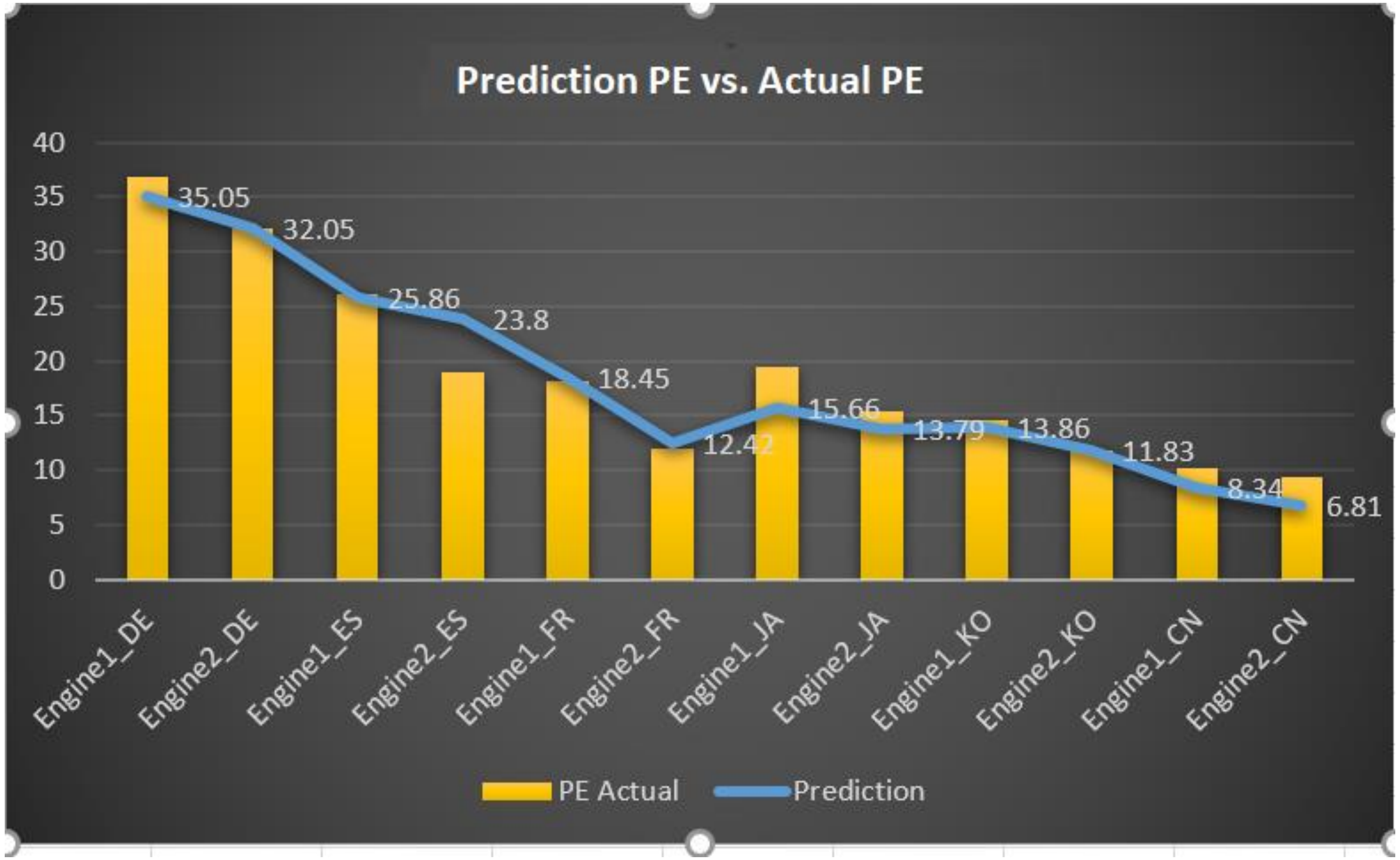
Prediction PE vs. Actual PE



ML Model Inference Acceleration Solutions

Inference time comparison

CPU without acceleration:

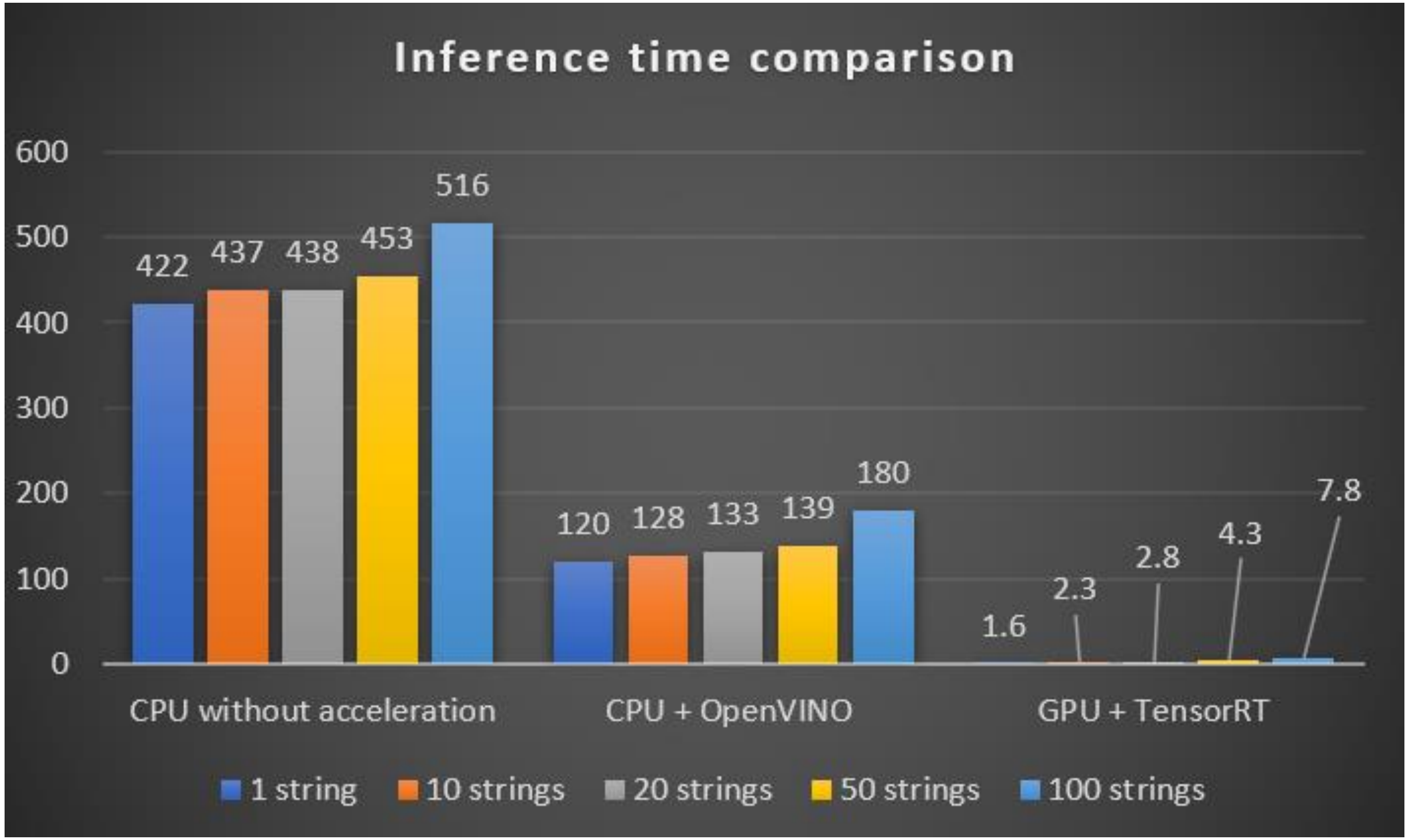
400 ms/string

CPU + OpenVINO

130 ms/string, 3 x

GPU + TensorRT:

2.8 ms/string, 140 x



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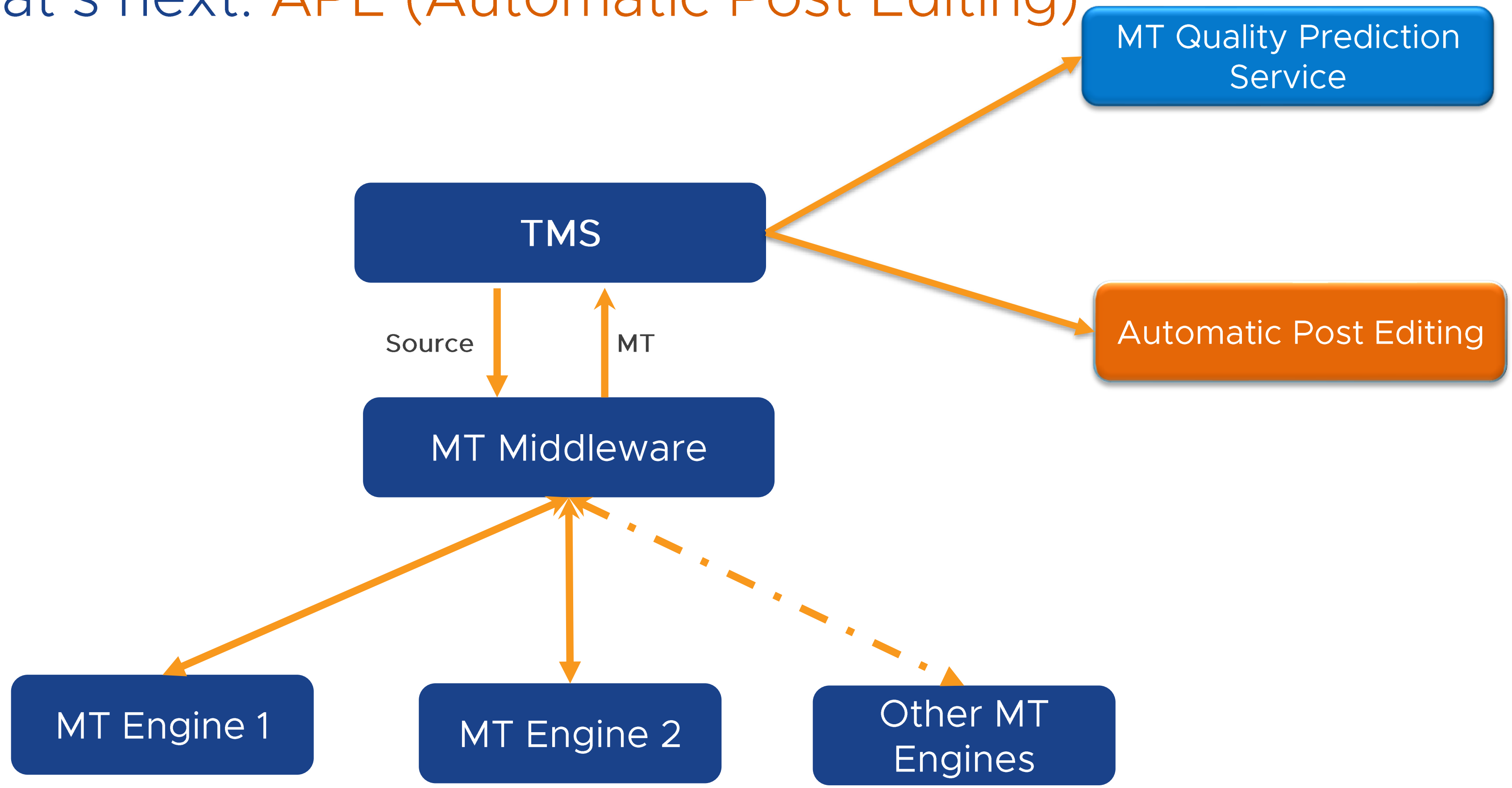
What's next: APE (Automatic Post Editing)



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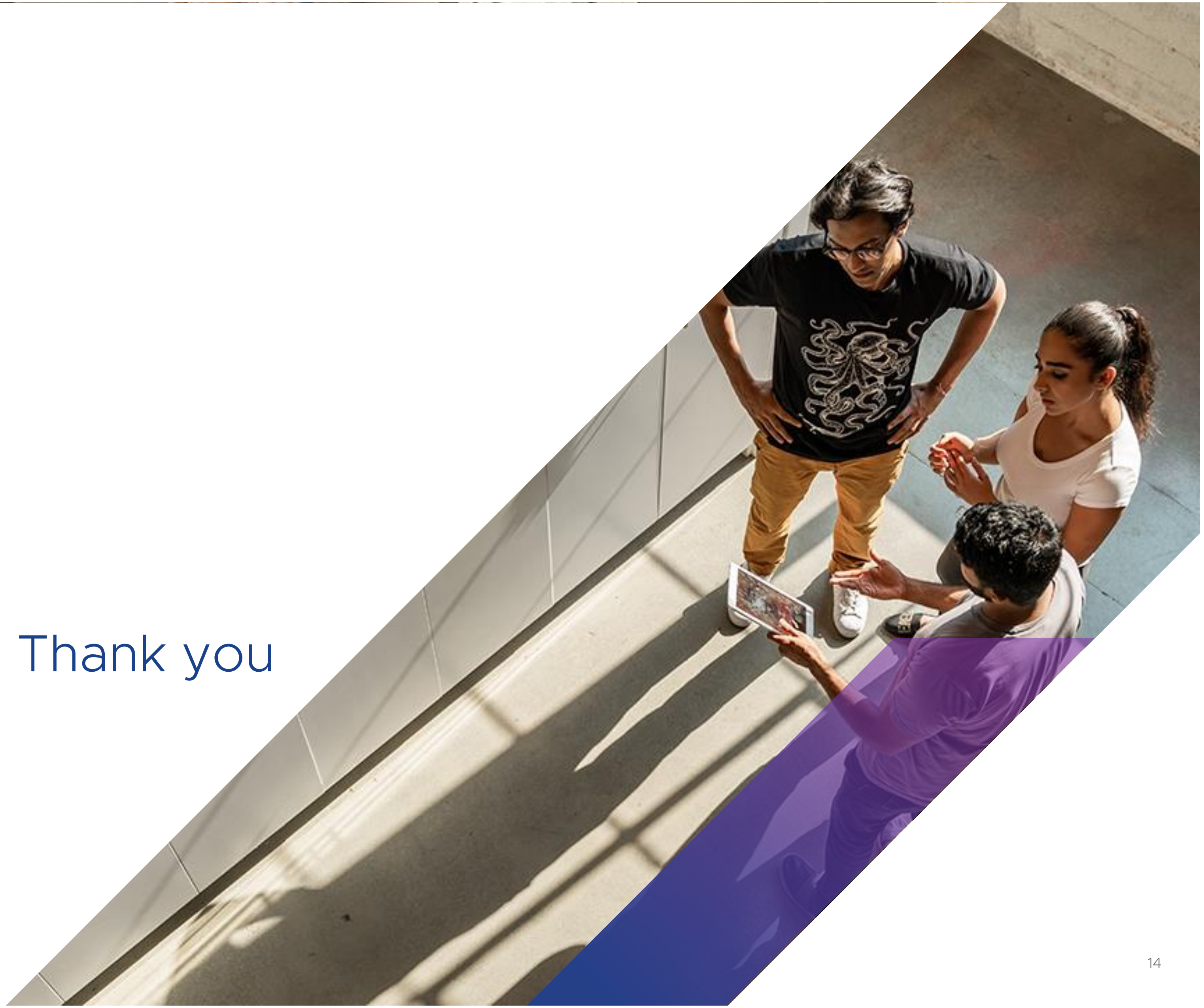
Q&A

Thank you



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A language comparison of Human Evaluation and Quality Estimation

Silvio Picinini - eBay
Adam Bittlingmayer - ModelFront

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MT Quality

Human Evaluation

Quality scores by human linguists

Quality Estimation

Quality scores by machine

No reference translation used

Also called “confidence score” and “risk prediction”

Aggregated for automatic quality *evaluation*

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Goals

“How does machine QE correlate with human evaluation?”

- Compare line-level and aggregate numbers

“What causes differences between QE and human evaluation?”

- Analyse QE line-level issues
    - Get insights for QE

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Human Evaluation

The content:

- 200 segments
    - Various lengths
    - With and without placeholders/tags
- 4 MT outputs per language - one customized
- 2 languages - pt-BR and es-CO

Three expert evaluators per language - reliable results

Scores range from 1 to 4 stars - normalized to 0-100

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Quality Estimation

Generic production system - no custom data, no locales, no context, used for many use cases

Originally a Risk Prediction (0% good, 100% bad), which includes *source-side ambiguity*

Risk is reversed to become QE score (0 bad, 100 good)

Very convenient, but challenging for the QE system to match humans operating with many more inputs.

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Numbers

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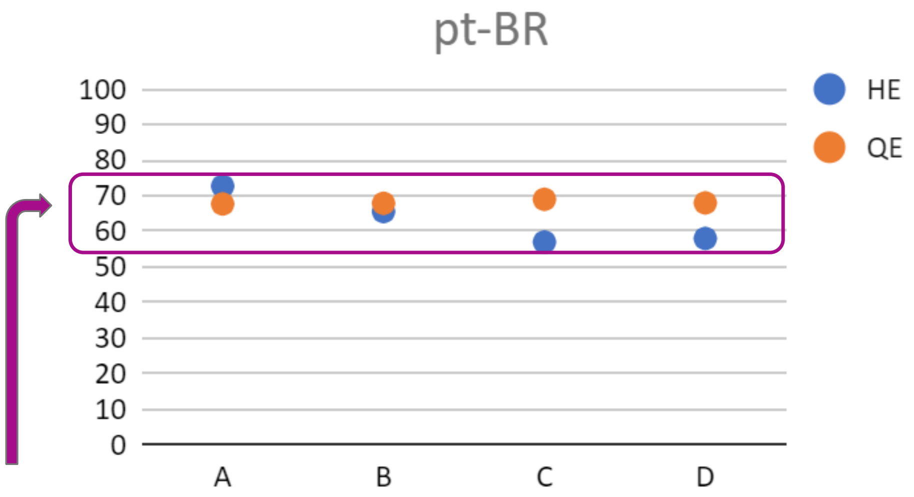
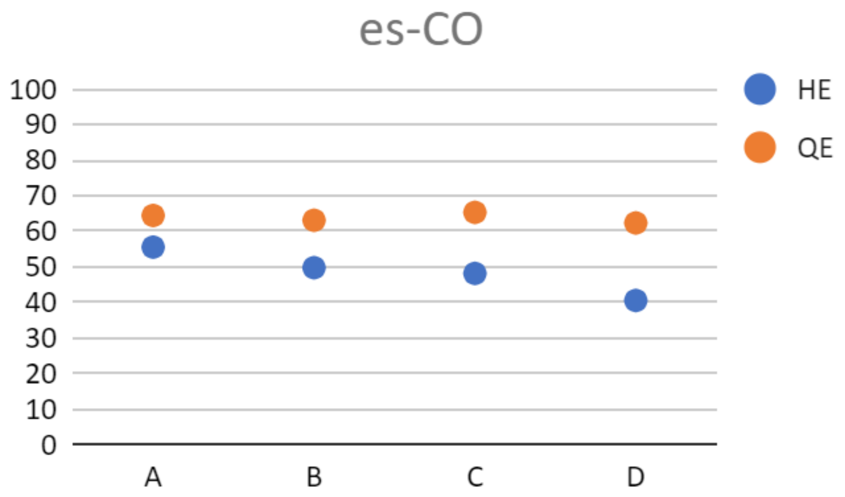
Comparison for the set

QE for pt-BR was closer to the HE, es-CO was a little further

QE was close to the best HE and further away for the worse





The QE is within a narrow range close to the HE. This is a good result.

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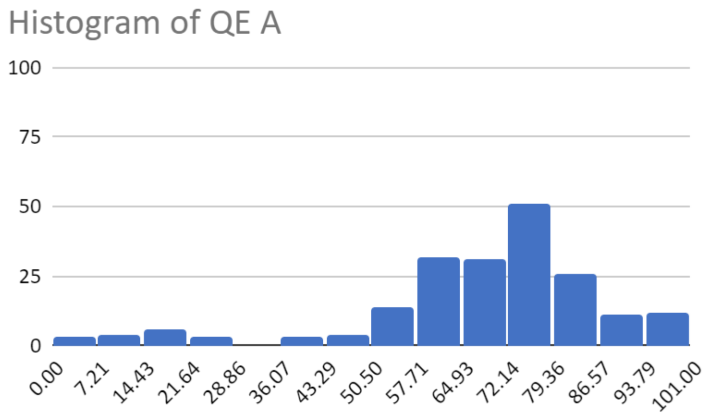
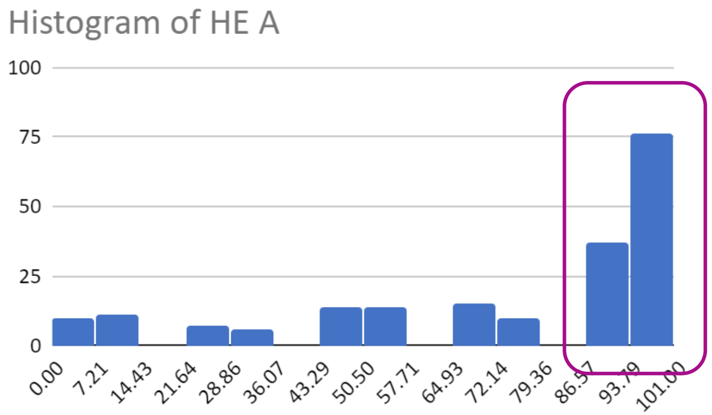
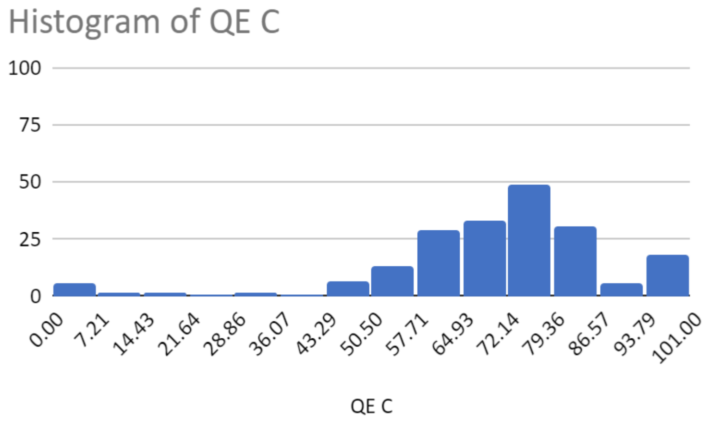
Comparison QE HE histograms - pt-BR

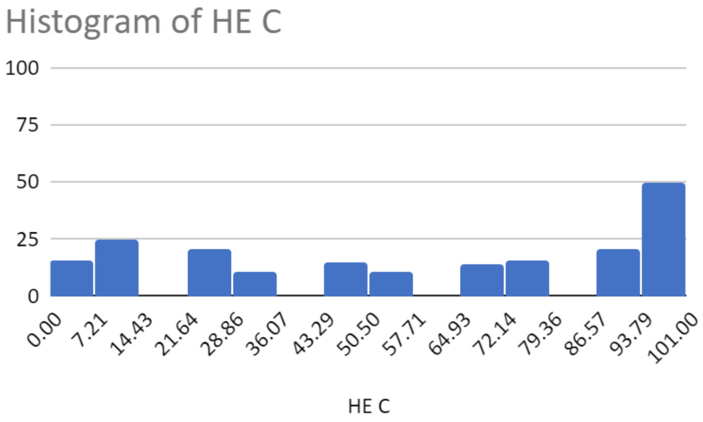




QE better for best MT

Mostly misses the concentration of near perfect.





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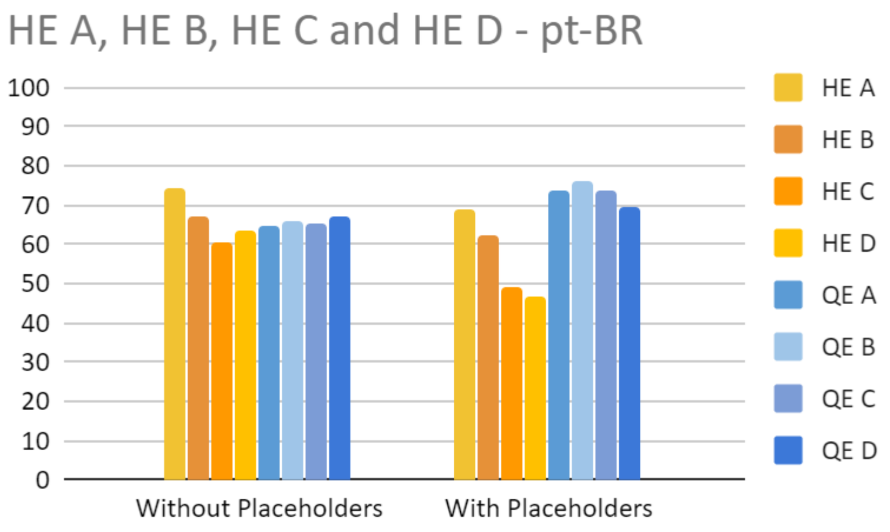
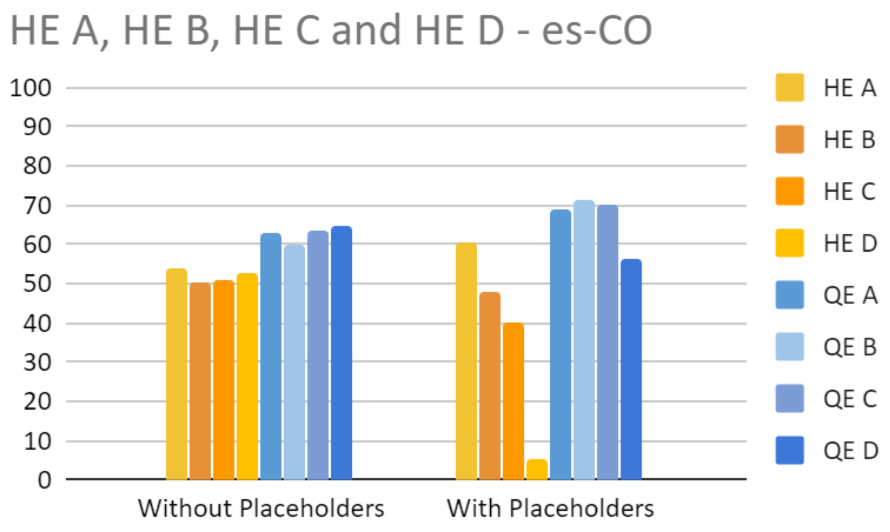
Comparison for Placeholders

HE had lower scores for segments with placeholders - in { } format

QE had higher results with placeholders





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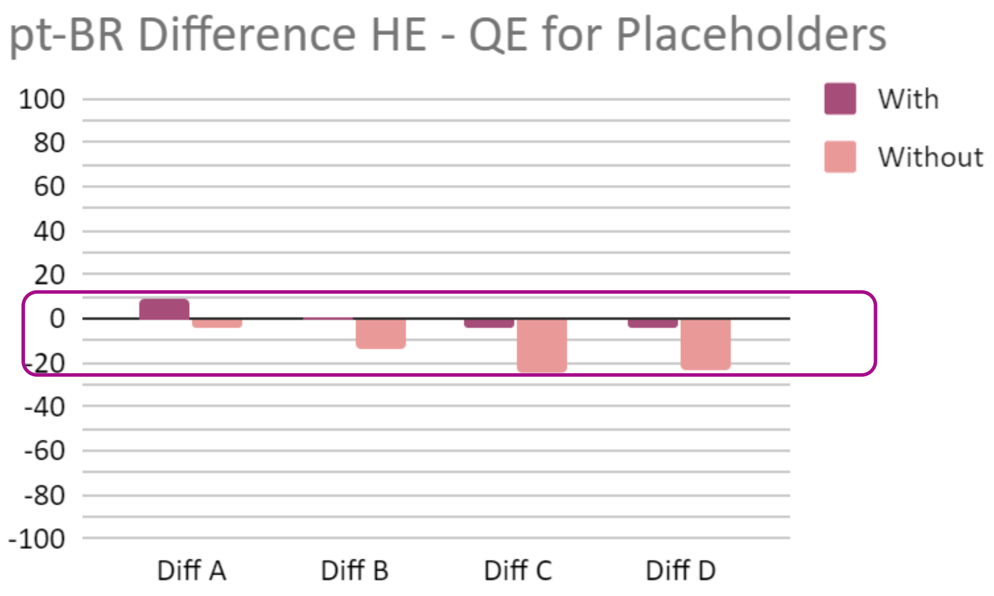
Comparison for differences HE - QE

QE in general overestimates the quality (most differences are negative)

The worst the HE, the greater the difference to the QE



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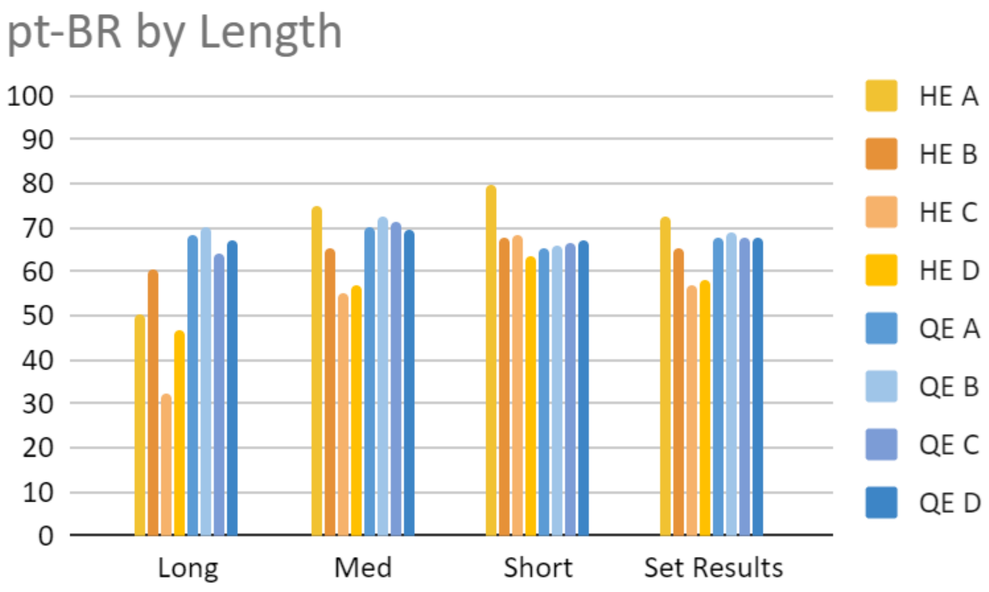
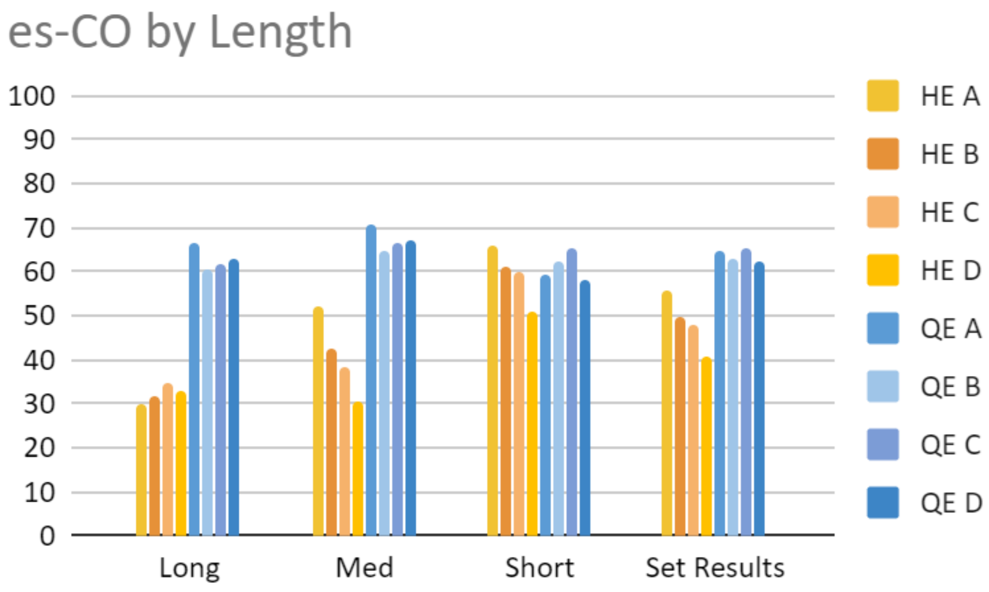
Comparison for Length

HE clearly scored Long < Med < Short

QE did not differentiate, but results for Short are close





Language Issues

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Language Issues

Where we looked:

- HE is much higher than QE - QE **underestimates** quality

- HE is much lower than QE - QE **overestimates** quality

- HE has a wide range of values among the 4 MT outputs (shows **varied translations**, from good to bad)

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Examples

If we don't hear back, this request will be closed on {1} and the hold on this transaction will be removed.	Si no recibimos una respuesta, esta solicitud se cerrará el {1} y se borrará la cuenta de esta transacción.

Mistranslation: the meaning changed from “the hold on the transaction will be removed” (positive) to “the account will be erased” (negative).

HE:11
QE:89

The HE noticed that but the QE did not.

If we don't hear back, this request will be closed on {1} and the hold on this transaction will be removed.	Si no recibimos respuesta, esta solicitud se cerrará el {1} y se eliminará la retención de esta transacción.

Examples

Click to learn about Top Rated Sellers	Clique para saber mais sobre vendedores nível Top

Glossary SRC	Glossary TGT
Top Rated Seller	Vendedor nível Top

Terminology: eBay has a specific terminology for “Top Rated Seller”, which includes the use of an “untranslated” word Top.

HE:92
QE:8

The QE may see this as a possible defect and rate the translation low. HE is aware that in our context the translation is perfect.

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Examples

Silver shooting star for feedback score from 1,000,000 or more	Estrela de tiro de prata para a pontuação de feedback de 1 milhão ou mais

Idioms and figurative meaning:

The expression "shooting star" was translated as "a star of the activity of shooting a gun".

HE:11
QE:66

Basketball? Also a shooting star.

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Examples

{1}Not a registered user{2}	{1} Não é um utilizador registado {2}

Locale: One MT is more influenced by data from European Portuguese. The MT above contains two examples of that.

HE:0
QE:81

{1}Not a registered user{2}	{1}Não é um usuário cadastrado{2}

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Examples

A decision has been made about the dispute that was filed by {1}.	Uma decisão foi feita sobre A disputa que foi registrada em {1}.

Placeholders: they introduced an ambiguity for the MT, which was clear for HE. The source says "filed by {1}" and it means "filed by a person". The MT and the QE thought that it meant "filed by this date".

HE:0
QE:97

A decision has been made about the dispute that was filed by {1}.	Foi tomada uma decisão sobre a disputa que foi apresentada por {1}.

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Examples

PostePay	Envío postal
PostePay	PostePay

Untranslatable:

The name of a service was translated as “Postal shipping”.

The HE noticed that, the QE somewhat.

HE:0
QE:24

Postepay
Semplicemente, il futuro

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Examples

We're aware of this issue and are working to fix it as soon as possible.	Este problema y estamos tratando de solucionar el problema lo antes posible.

Omission:

The translation just says “This issue”, omitting “We’re aware of”.

HE:11
QE:96

We're aware of this issue and are working to fix it as soon as possible.	Somos conscientes de este problema y estamos trabajando para solucionarlo lo antes posible.

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Language Issues

What are some of the reasons for discrepancy between HE and QE?

- Mistranslations not recognized
- Terminology
- Idioms and figurative meaning
- Locale
- Placeholders
- Untranslatables
- Omissions

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Takeaways

- The main generic QE system has aggregate scores in a similar range as HE. This is promising.
- Customization is key to QE for evaluation, to shape the output to the custom translation and evaluation guidelines
- Findings in custom data can help improve accuracy on non-custom errors
- QE is a rising technology that will be widely present in many MT uses in the near future

Future step: Use a trained engine

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Acknowledgements

Our thanks to the language experts that worked on this:

Melany Laterman and Patricia Lawler

eBay Language Specialists

for Brazilian Portuguese and Latin American Spanish

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Questions?

Thanks
Obrigado
Gracias

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Machine Translation quality across demographic dialectical variation in Social Media

Adi Renduchintala and Dmitriy Genzel
Facebook AI

Biases in Machine Learning

- Machine learning systems can encode harmful societal biases.
- Widespread use of machine learning systems amplify these biases.

Biases in Machine Learning (in NLP)

- Machine learning systems can encode harmful societal biases
- Widespread use of machine learning systems amplify these biases.

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}$$

Bolukbasi et al. Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Advances in neural information processing systems, 2016

Biases in Machine Learning (in Vision)

- Machine learning systems can encode harmful societal biases
- Widespread use of machine learning systems amplify these biases.

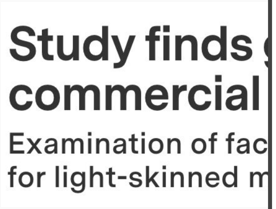
Study finds gender and skin-type bias in commercial artificial-intelligence systems

Examination of facial-analysis software shows error rate of 0.8 percent for light-skinned men, 34.7 percent for dark-skinned women.

http://gendershades.org/ &
news.mit.edu

Biases in Machine Learning (in Vision)

- Machine learning systems can encode harmful societal biases
- Widespread use of machine learning systems amplify these biases.


Study finds
commercial
Examination of fac
for light-skinned m

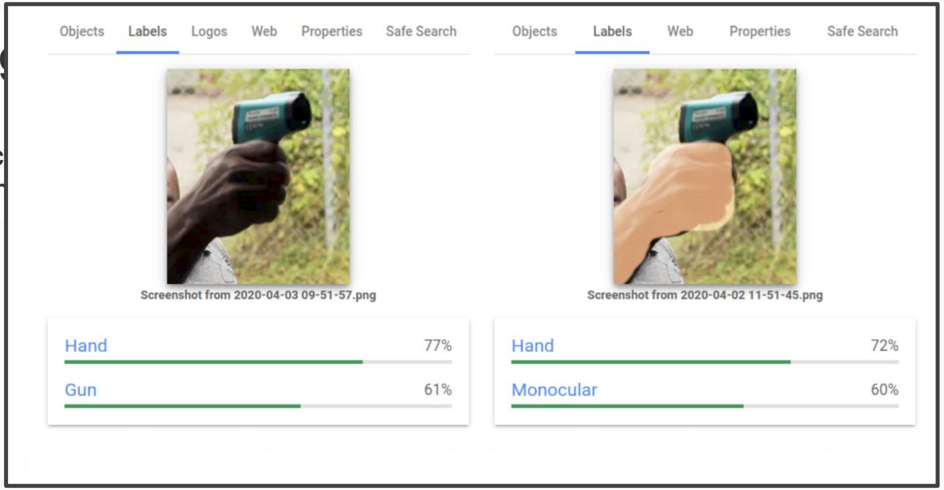


Image Credit:
@bjnagel &
algorithmwatch.org

Biases in Machine Learning (in Vision)

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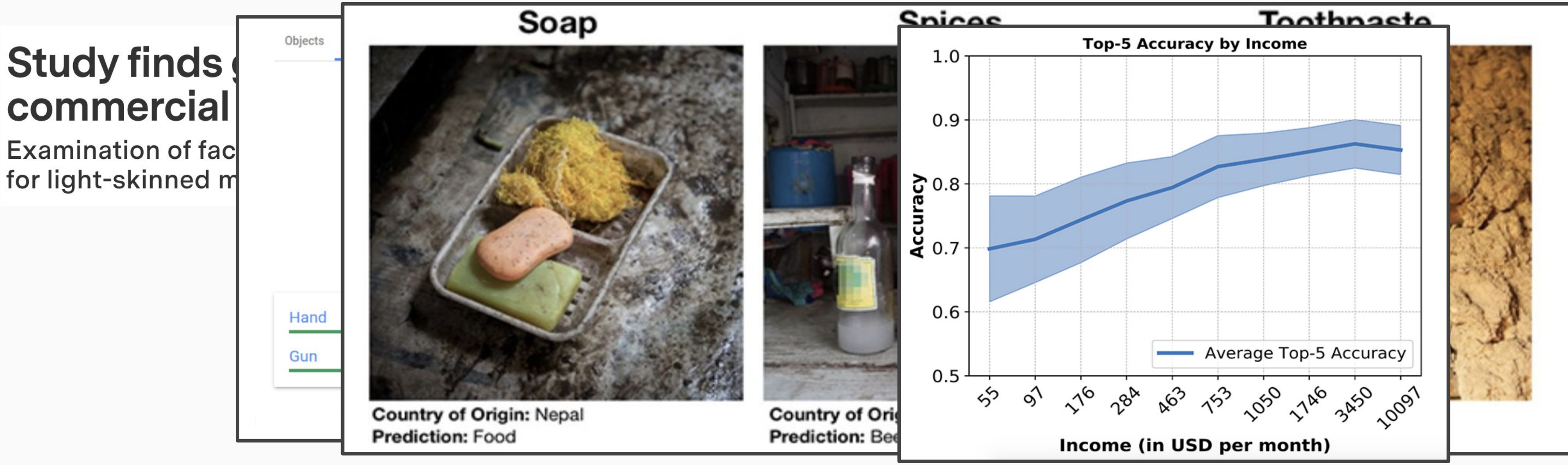

Biases in Machine Learning (in ASR)

- Machine learning systems can encode harmful societal biases
- Widespread use of machine learning systems amplify these biases.

There Is a Racial Divide in Speech-Recognition Systems, Researchers Say

Technology from Amazon, Apple, Google, IBM and Microsoft misidentified 35 percent of words from people who were black. White people fared much better.

Biases in Machine Learning (in MT?)

- Machine learning systems can encode harmful societal biases
- Widespread use of machine learning systems amplify these biases.

Goal: Investigate if modern machine translation systems amplify racial biases?

Proposal

- Use twitter posts which have demographic dialect information associated.
- Translate these tweets with 3 “off-the-shelf” machine translation models
- Do we notice disparity in translation quality?

Data

- We use data that was released in **prior work** by:
  - Blodgett, et al. *Demographic dialectal variation in social media: A case study of African-American English.* EMNLP, 2016
- This data was automatically annotated with racial dialectal labels by the same authors.

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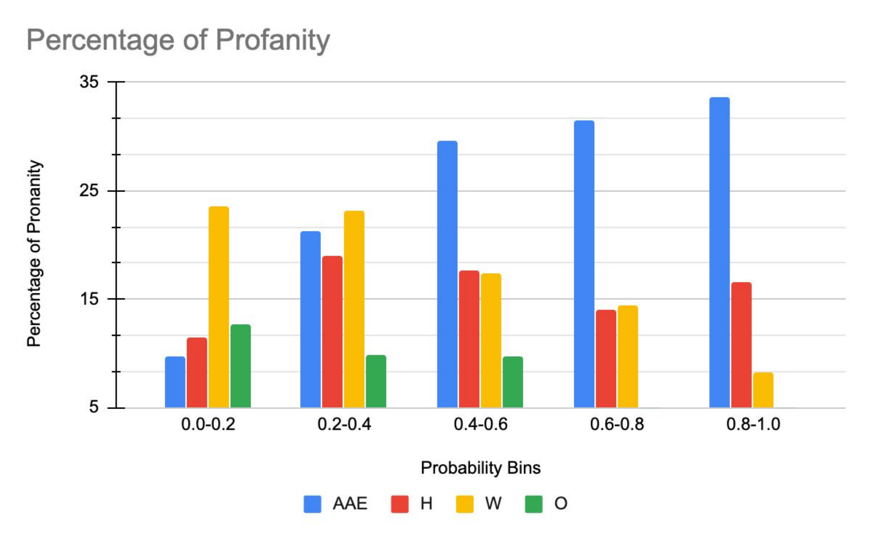
  - Blodgett, et al. *Demographic dialectal variation in social media: A case study of African-American English.* EMNLP 2016
- This data was ⚠️ **automatically annotated** ⚠️ with racial dialectal labels by the same authors.
  - A weakly supervised mixed-membership model was used.
  - The authors generated a posterior distribution over 4 categories for each tweet:
    - African-American English (AAE)
    - Hispanic English (H)
    - White-aligned English (W)
    - Other

Data

Examples	AAE	H	W
Either yu gone get yo fkn life or get out my fkn life	0.82	0.004	0.142
When you got somebody good, you hold on to ' em .	0.45	0.016	0.527
My sister asked me if the lions are in the playoffs..	0.011	0.023	0.965
I'm too sad to stay up and im tired and i have church so night	0.006	0.873	0.12

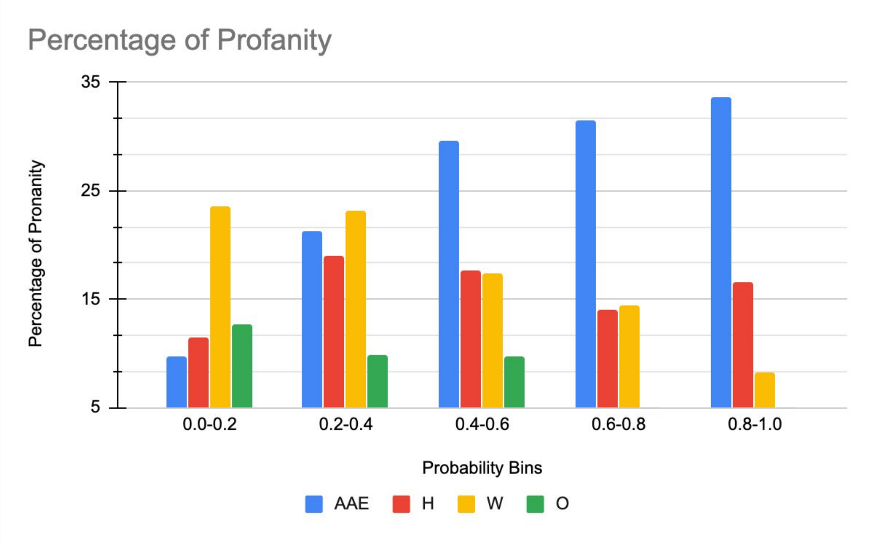
Profanity and Predictions

- The weakly supervised model seems to think that profanity is a feature of the AAE dialect.
- This is not observed in any of the other dialects.
- we filter out all tweets with profanity, to not be influenced by the weakly supervised model's (potentially) spurious correlations.



Data Challenges

- The dataset definitely has some flaws (correlating profanity with a demographic dialect is one example)
- However, the lack of expert annotated data to conduct analysis of this nature is also an issue.

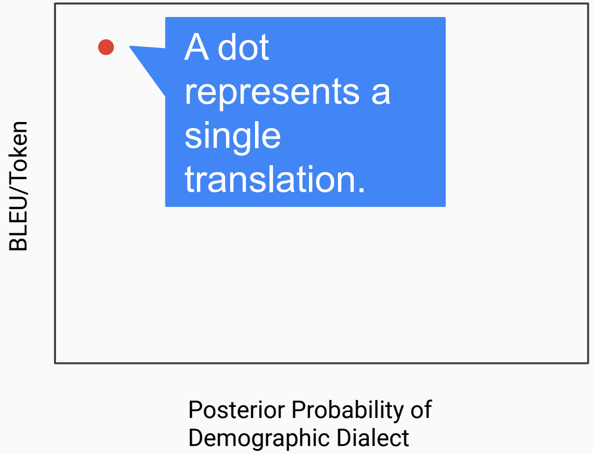


Experimental Setup

- For each category we subdivide the tweets into 5-bins based on the posterior probability (0.0 - 0.2, 0.2 - 0.4, ... 0.8 - 1.0)
- From each bin in each category we sample ~30 tweets and have then translated into French by professional translators.
- We then used 3 "off-the-shelf" translation systems to translate the ~600 tweets using an English->French model.
- We plot the quality of the translation against the posterior probability of being a demographic category.

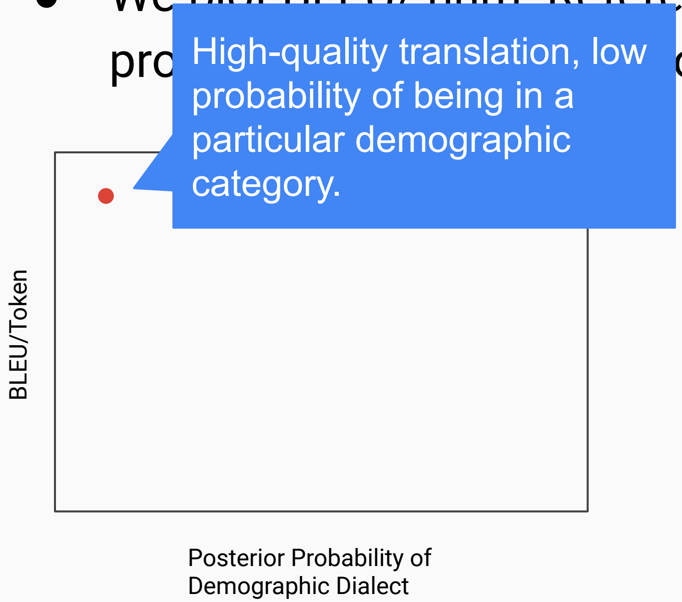
Results

- We plot BLEU/ (num. Reference-tokens) along the y-axis and the posterior probability of the tweet belonging to a demographic dialect category.



Results

- We plot BLEU/ num_Reference-tokens along the y-axis and the posterior pro onging to a demographic dialect category.



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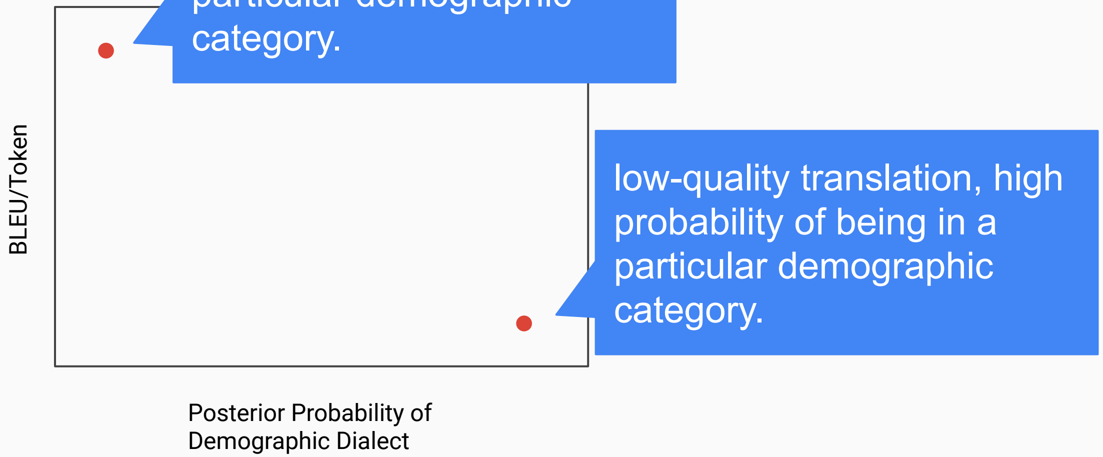

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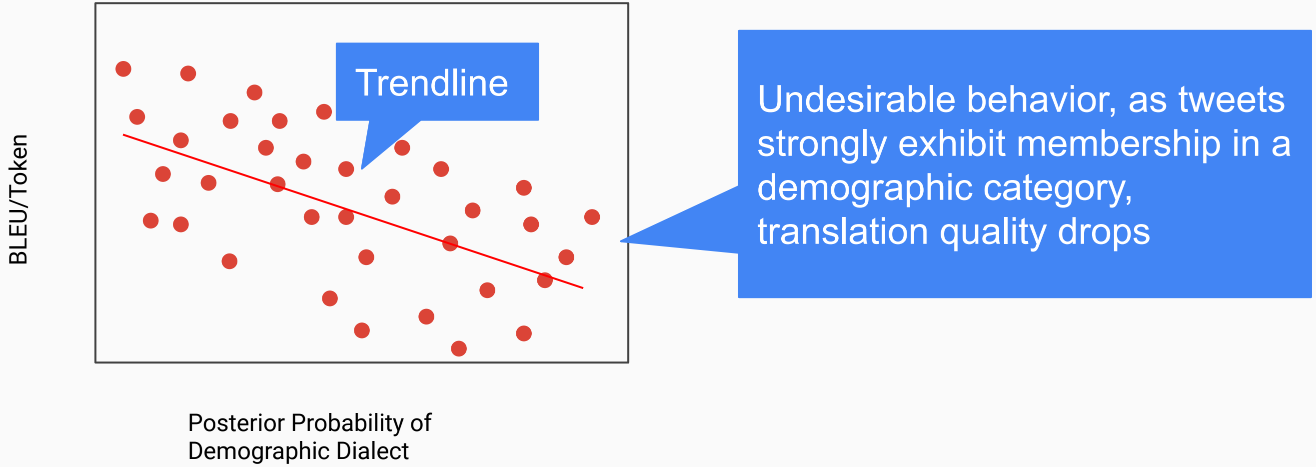

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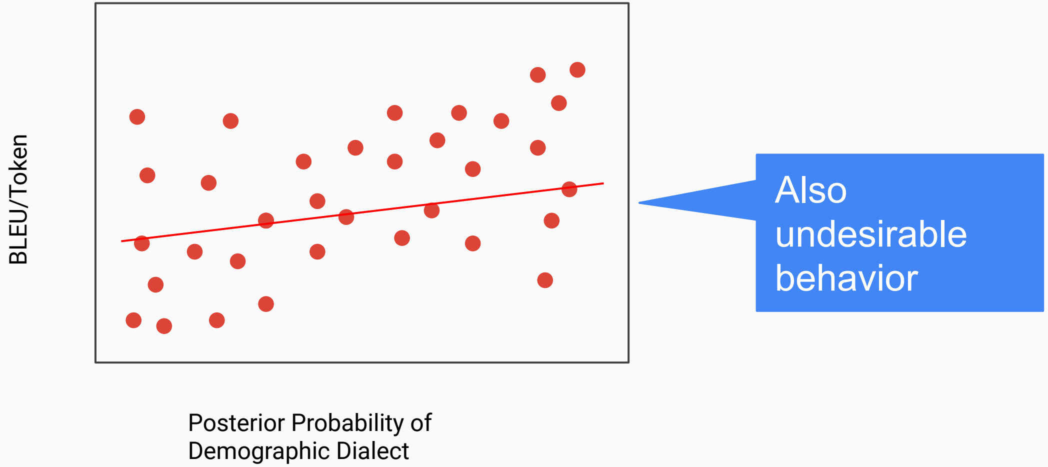

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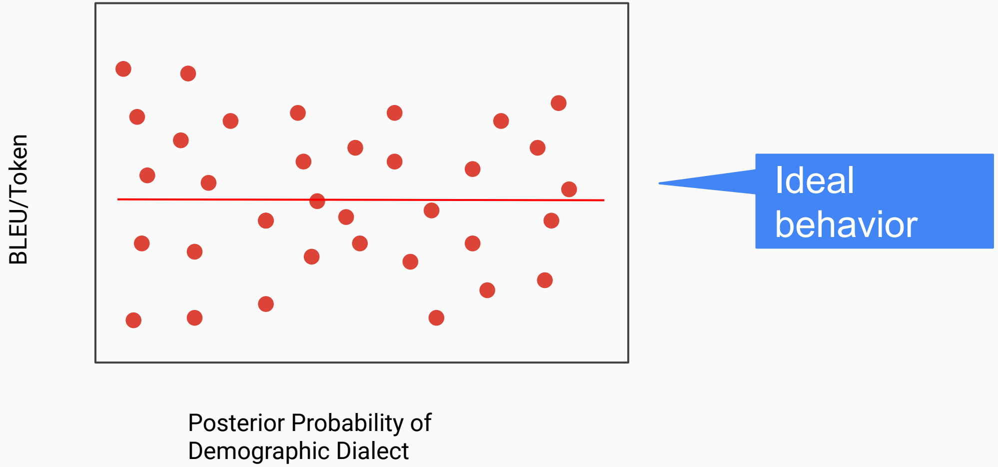
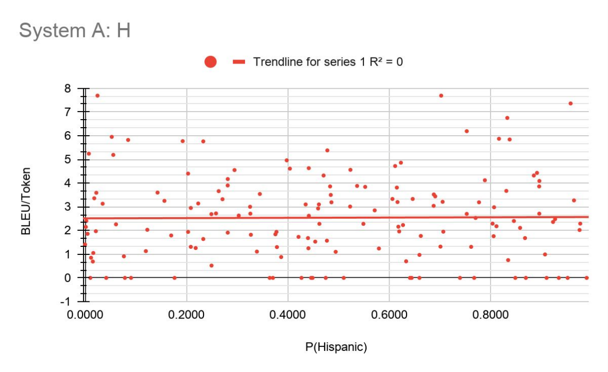
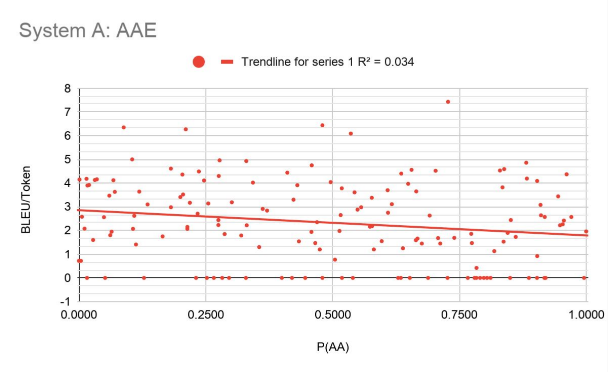
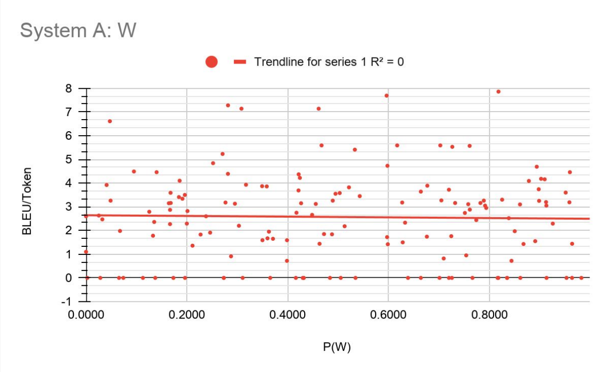


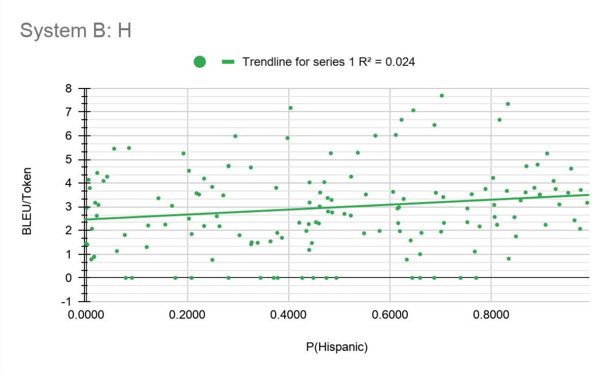
Results

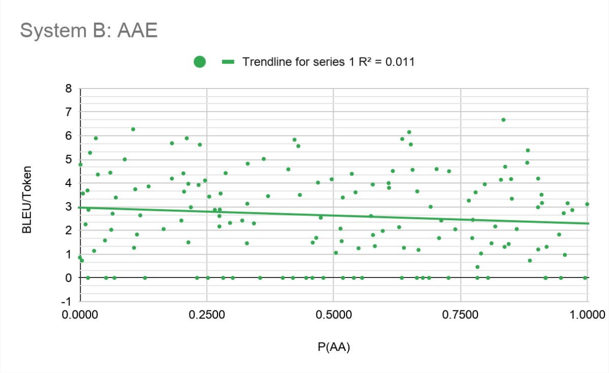

System A: H
Trendline for series 1 R² = 0
BLEU/Token
P(Hispanic)
8
7
6
5
4
3
2
1
0
-1
0.0000
0.2000
0.4000
0.6000
0.8000

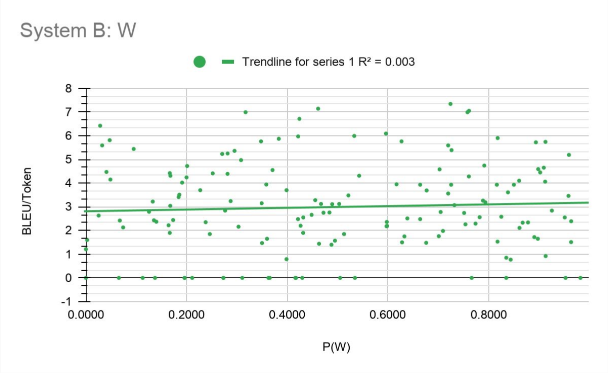

System A: AAE
Trendline for series 1 R² = 0.034
BLEU/Token
P(AA)
8
7
6
5
4
3
2
1
0
-1
0.0000
0.2500
0.5000
0.7500
1.0000


System A: W
Trendline for series 1 R² = 0
BLEU/Token
P(W)
8
7
6
5
4
3
2
1
0
-1
0.0000
0.2000
0.4000
0.6000
0.8000

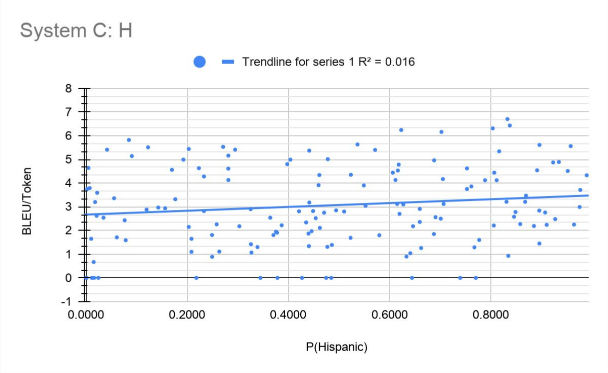
Results

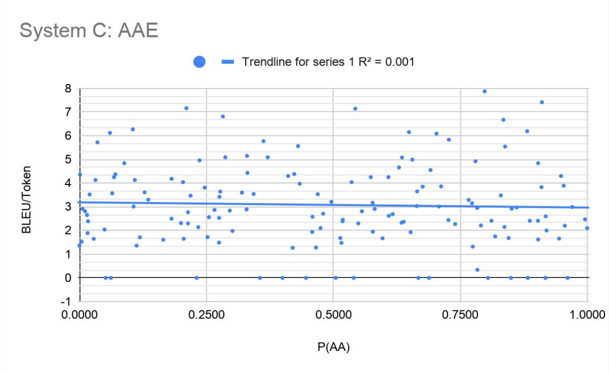

System B: H
Trendline for series 1 R² = 0.024
BLEU/Token
P(Hispanic)

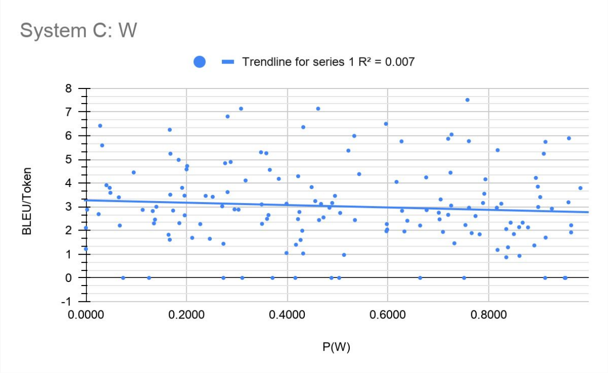

System B: AAE
Trendline for series 1 R² = 0.011
BLEU/Token
P(AA)


System B: W
Trendline for series 1 R² = 0.003
BLEU/Token
P(W)

Results


System C: H
Trendline for series 1 R² = 0.016
BLEU/Token
P(Hispanic)


System C: AAE
Trendline for series 1 R² = 0.001
BLEU/Token
P(AA)


System C: W
Trendline for series 1 R² = 0.007
BLEU/Token
P(W)

Conclusion

- Our experiments suggest that modern NMT systems exhibit undesirable behavior when dealing with input associated with AAE dialects.
- Further work is needed to understand this phenomenon better. Ideally, analysis should be conducted on expert annotated data.
- Our hope is that this work is a call to action to consider this a serious problem and mitigate the amplification of biases via AI systems.
- One concrete recommendation is to include analysis like this into model evaluation.

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CAPITA Translation and interpreting Simplifying complex global communications

"Making the business case for adopting MT"

14th biennial conference of the AMTA

Rodrigo Cristina

October 2020

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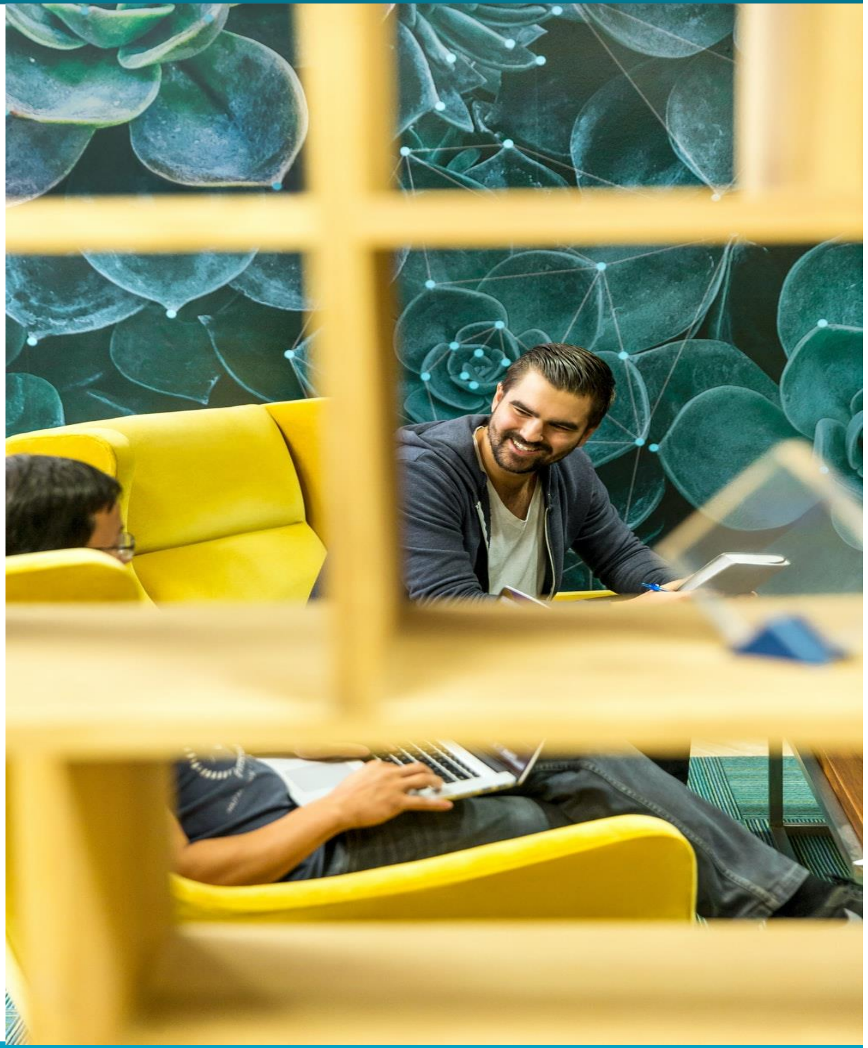
Delivering value.
Understanding ROI.



We understand

The complexity of your organisation

The challenges to mitigate risk and avoid liability

The impact our work has on brand and reputation

We drive cost efficiencies in everything that we do to make sure that you always achieve the expected return on your investment.

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MT @ Capita TI - SmartMATE

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Traditional Language Service Providers

- Low development capabilities
- Immature post editing language resources
- Low security

MT

Traditional MT Technology Providers

- Little or no language capabilities
- Low capitalisation - financially weak
- Little integration with translation workflows

SmartMATE

Translation technology suite

10 years

of MT development and research projects

Integrated with secure localization workflow

Access to large pool of specialised translators & post-editors

High corporate governance and financial strength

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The omnipresent problem

Localization ROI is traditionally complex to measure, many times subjective

The budget holder and the localization manager don’t always speak the same language

Tough and frustrating conversations to secure the budget
Localization is all about building bridges between people that speak different languages

Why not apply the same principle?

CAPITA

The NPV (Net Present Value) approach

- Investment analysis framework used since the 1950's
- The NPV is one of the most widely used tools in investment analysis.
- Quantifiable => better quality localization business cases
- Easier conversations and less frustration
- Potentially higher success rate
- Not the "silver bullet" but a clearer framework to discuss ROI for MT programs

"Win-Win"

MT ROI measurement model – key components/concepts

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I_0	CF	(1+RR)
initial investment (The number to beat)	Investment's annual net cashflow (revenues and savings – running costs)	the discount factor; return rate of best available investment alternative

Net present value (NPV) is an investment analysis methodology that measures the difference between the initial project investment and the net present value of cash flows generated by that investment over a period of **time**, using the **DCF (Discounted Cash Flow)** methodology.

The following formula is used to calculate the NPV: $NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+rr)^n} - I_0$

Decision criteria:
If NPV > 0 then invest
If NPV < 0 then do not invest

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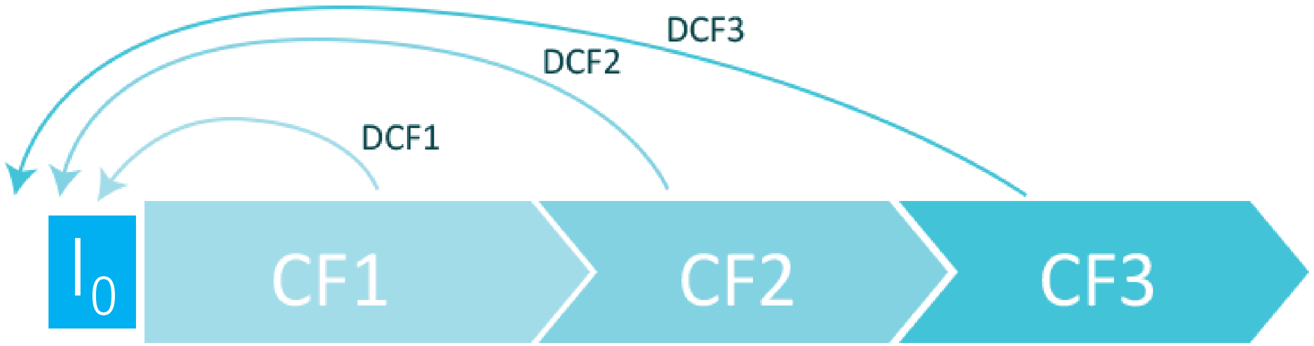
Time and **DCF** in the **NPV** model

- Time and DCF (Discounted Cash Flow) are key concepts in understanding the model’s dynamic
- 1$ today is different from 1$ tomorrow (inflation, interest rate)



NPV model applied to MT – how does it work?

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I_0

deployment investment for MT program

- Annual license for year 1
- Hosting costs year 1
- Software deployment costs
- Includes data cleansing and language asset optimisation (TMs, glossaries and monolingual content) and make them available for engine creation
- Includes building and setting up the engines for production and gisting purposes
- Includes testing and evaluating the best engine options (on real projects)
- Includes fine tuning the chosen engine before the “go live” stage
- Includes any integration required

CF

annual net cashflow (return and savings – running costs)

Return and savings:

- Includes the PEMT savings effect on current translation rates
- Includes the effect of faster time to market for your products that will generate more sales
- Includes savings based on an Enterprise MT service managed solution

Annual costs:

- Includes building new engines for new languages
- Includes retraining of the existing ones
- Add specific features (for example a specific glossary for a specific product line)
- Annual licenses for years 2 and 3
- Engine hosting for subsequent years

(1+RR)

return rate of best available option

What would you alternatively do with the funds available to optimise your localisation output and what return rate you would expect from it.

- For example, the cost of an authoring tool to improve TM matching that would save you 10%
- The estimated return of another (best) available MT option
- The estimated return of training the technical writing team to improve source content
- Return of cleaning and optimising the language assets (TMs, glossaries)
- Return of hiring additional internal translators

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$$\mathrm{NPV} = \frac{CF_1}{(1+rr)} + \frac{CF_2}{(1+rr)^2} + \frac{CF_3}{(1+rr)^3} - \mathrm{I}_0$$

Like in any investment project, there are a number of assumptions we have to make, namely that the MT program will reach its maturity in 3 years. This is debatable but our data gives us some hints in that direction.

Decision criteria:
If NPV > 0 then invest on MT
If NPV < 0 then do not invest in MT

Proceedings of the 14th Conference of the Association for Machine Translation in the Americas
October 6 - 9, 2020, Volume 2: MT User Track

MT ROI measurement model – client case

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Context:

- Large European Manufacturer with global footprint
- Mature and centralised localisation model
- Localising tech pubs content into 20+ languages
- Increasing volumes in top 10 languages
- Long-time user of a translation management system
- Mature terminology management (high quality glossaries)
- Large amount of content stored in translation memories
- TEP applied to technical content
- Average volume per language 800000 words
- TM leverage 68%
- New words: 32% of total
- Average NW rate 0.145$ + 5% PM fee (top 10 languages)

- **Evaluating deploying a global MT program across 10 of the 20 languages**
- **Evaluating other mutually exclusive investments (authoring tool and TM clean-up)**
- **Client wants to know the MT program's expected ROI => sell internally**

MT ROI measurement model – client case

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I_0 – Initial investment

- Year 1 software license
- Client's language assets preparation, cleansing and optimisation
- Building several customised candidate engines
- Testing and evaluating engine performance - Automatic and Human evaluation (DQF)
- Detailed findings report
- Pre deployment systems configuration
- Engine deployment costs
- Total initial investment 93000$ (all languages)

MT ROI measurement model – client case

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MT program Annual benefits and costs (Annual Net Cash Flow $)

Benefits (Cash inflow)

- Expected annual savings in NW rates through PEMT is 25% (92800$ across all 10 languages)
- LSP PM fee decrease from 5% to 3% (9540$ savings across all 10 languages)
- **Annual MT running benefits 102340$**

Costs (Cash outflow)

- MT license annual cost (unlimited use)
- Engine retraining (all 10 languages, once a year)
- Annual Hosting cost (10 engines)
- **Annual MT running costs 44000$**

Benefits of the alternative investment to MT program (discount factor rr in %)

- New authoring tool, will increase TM matching/leverage in 9%
- Major review/cleaning TMs and glossaries, estimated 13% more leverage from TMs
- 22% better matching is estimated to produce **8% of budget savings per language**

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MT ROI measurement model – client case

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$$NPV = \frac{CF_1}{(1+rr)} + \frac{CF_2}{(1+rr)^2} + \frac{CF_3}{(1+rr)^3} - I_0$$

$$NPV = \frac{(102340\$-44000\$)}{(1+8\%)} + \frac{(102340\$-44000\$))}{(1+8\%)^2} + \frac{(102340\$-44000\$))}{(1+8\%)^3} - 93000\$$$

$$NPV = 57347.84\$ \text{ (ROI for Global MT Program)}$$

$$NPV > 0 \text{ the decision is to move ahead with the MT program}$$

Notes:

rr is 8% and represents the expected return of the alternative investment

I_0 - All initial costs of the MT program

CF_1 (Savings – yearly costs) will be (102340\$–44000\$ = 58340\$)

CF_2 (Savings – yearly costs) will be (102340\$–44000\$ = 58340\$)

CF_3 (Savings – yearly costs) will be (102340\$–44000\$ = 58340\$)

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THANK YOU!

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Flexible Customization of a Single Neural Machine Translation System with Multi-dimensional Metadata Inputs

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Abstract

Advances in neural machine translation (NMT) technology not only significantly raised machine translation quality for general-purpose, out-of-the-box systems, but also provided a way for additional input signals to an NMT model to effectively influence its output for a given translation unit, so that a single NMT system can serve different customer needs. At the same time, language service providers, media companies, and other businesses started to systematically store metadata associated with their translatable content. In this work, we show how these metadata can be used both for training and at inference time to flexibly customize a given NMT system to produce somewhat different translations of the same translation unit. The metadata as an extra input to NMT can enable such customization across multiple dimensions and at different levels of input granularity: for individual documents or their collections, for a given post-editing session of a professional translator, or even for individual sentences.

1 Introduction

The following meta-information can be "mixed in" to influence the translation output of a single neural machine translation system:

- Domain, genre, and topic can be provided either in terms of fixed labels (e.g. "patents", "contracts", "news"), or can be inferred as topic embeddings from the content of the given or similar document(s).
- In a multilingual NMT model, the language (variety) or dialect metadata not only augments the representation of corresponding input documents or sentences, but can also specify the desired target language or dialect. Post-editing tools can implement a flexible switch between supported languages/dialects for mixed-language text or speech input.
- Document-level context of different size (e.g. previous/next N sentences) can be "turned on" for better word disambiguation and pronoun resolution.
- Machine translation (MT) output length can be influenced without significant information loss. This is important in applications like subtitling and software localization where translations sometimes have to fit into a given fixed-size template.
- Translation style can be adjusted with a simple "switch" between (binary) classes (e.g. with/without profanities; informal vs. formal "you" forms in languages like German).

- The gender of the speaker/author may be important for a correct, unbiased translation in target languages like Czech where past tense verb forms have different endings depending whether a male or a female is talking about his or her actions. In speech translation, speaker gender labels can be inferred automatically from the upstream speech recognition. Post-editing applications can pre-fetch translations of all styles and genders so that a post-editor can instantaneously switch from e.g. a formal to informal translation with a single click.

- Finally, document- or user-specific terminology glossary entries can accompany each translation request to the NMT system so that for any matched source-language glossary entry it has to produce the translation from the glossary. The challenge here is how to generate this translation in a grammatically correct form, which is especially difficult for morphologically rich target languages.

All of these customizations of a single NMT model are very much suitable for commercial settings. Instead of deploying multiple different NMT models for each domain, style, length, dialect, etc., ideally we deploy a single system. Thus, not only we save on computational resources, reducing the environmental footprint of the MT technology. We also save time and machine and human power necessary for fine-tuning or otherwise adapting each of these customized systems, save on measures to counteract over-fitting, organization of parallel deployment and elaborate load balancing, etc.

In the following section, we will give an overview in which ways additional meta-information can flow into the training and inference of a single NMT system. In Section 3 we will revisit the above meta-information types and show, in many cases supported by experimental findings and/or examples, as well as citations of related work, the positive influence of meta-information on translation quality. We will also provide tips for a practical implementation of metadata-based "switches" in MT applications such as post-editing tools.

2 Using Meta-information for NMT Customization

The meta-information accompanying a source sentence or document can be incorporated into the NMT training in different ways.

The most straightforward way that does not require any changes to the NMT architecture is the use of source-side pseudo-tokens, usually in the beginning of a sentence, that correspond to a (discrete) meta-information. Pseudo-tokens are most widely used in multilingual systems (Johnson et al., 2017; Ha et al., 2016) with multiple target languages: the pseudo-token with the language code, such as `@es@`, signals that a translation into a particular language, in this case Spanish, is desired. Pseudo tokens were also successfully used for specifying the translation style (Sennrich et al., 2016) and for domain adaptation (Tars and Fishel, 2018). Alternatively, pseudo-tokens can be used as prefix constraints in the beginning of the (generated) target sentence (Takeno et al., 2017).

The disadvantage of pseudo-tokens is that they only encode one piece of information, and their influence on the produced NMT output is limited, especially in cases where the differentiating power of the additional meta-information is small, e.g. when the meta-information encodes domains/topics which are similar. In such cases it is advisable to use factored machine translation and encode the extra meta-information as an additional factor for each source word (García-Martínez et al., 2016; Wilken and Matusov, 2019). In this way, the meta-information will have a stronger influence, since the NMT encoder would then be able to learn for which words the meta-information factor is more important than for the other words. For some types of meta-information, like speaker gender, the factor (e.g. male/female gender) can be assigned to the relevant words only (e.g. personal pronouns and verbs whose translation may be different depending on the speaker/author gender). All other words in this case can be assigned a third, "neutral" value.

When the meta-information about a sentence or document is automatically predicted with a certain probability, it is advisable to directly include this probability into the NMT training. Thus, in case of genre prediction, assuming 20 different genres, the additional input can be a 20-dimensional vector with probabilities for each genre given the input source sentence or document. This dense representation can then be associated with a genre embedding and included in the NMT architecture in a variety of ways, e.g. via a separate attention component to the genre/topic embedding. A stronger influence of meta-information on the decoder can be achieved by concatenating each current state with the genre/topic embedding before the next decoder state is predicted. Details can be found e.g. in (Chen et al., 2016).

At inference time, we assume that the extra meta-data is provided by the user/customer or is automatically generated by an upstream component (such as speaker gender classifier or a topic classifier). At training time, the meta-information can also be already available (e.g. domain of a document or a whole collection of documents, language or language variety, or even style). This is especially true of recent customer-specific data, since a lot of companies, language service providers in particular, have started to pay attention to consistent storage of meta-data that accompanies their translation content. Other types of meta-information can be directly computed for each pair of parallel sentences in the training data, like the length ratio between the source and the target sentence which can be used to classify translations into short, medium-length, and long (see Section 4). Or, it can be derived using regular expressions or more complex tools such as syntactic parsers and part-of-speech taggers. A "garbage" class can be assigned to sentences which do not match any of the regular expressions. See Section 3.1 for more details.

For more complex types of meta-information that is not available for a given set of parallel training sentence pairs, a classifier can be trained that predicts this information either on the sentence-level or document-level. To reduce error propagation, the vector of posterior probabilities for all the predicted classes can be directly used in NMT as opposed to the first-best predicted label. For example, the genre and topic of a document can be predicted automatically with a trained classifier, but also e.g. its dialect or language variety. External monolingual labeled data can be used to select the label set and train the classifier. Usually, the classifier is trained for the source language so that it can be applied both at training time and at inference time as described above. More elaborate approaches such as the work of Zeng et al. (2018) jointly model NMT with monolingual attention-based classification tasks (in this particular case, domain classification).

3 Types of Customization

3.1 Style

The style or tone of a translation is very important for its acceptance. Thus, it is not appropriate to use an informal style in legal documents, etc. At the same time, a formal, polite style can not be used in translations of movie dialogs, chat messages, and other cases with colloquial language.

A single NMT system can be trained to support multiple styles. In what style the translation is generated depends on the additional input (selector) from the user, also called side constraints (Sennrich et al., 2016; Feely et al., 2019). In our experiments with English as the source language, we differentiated in particular between a formal style that uses a polite version of the second-person pronoun "you" (which is different from the informal pronoun in many languages such as German, Russian, French, Greek, etc.). The parallel training data was partitioned into 3 classes based on whether the formal or informal version of the pronoun was used in the target language sentence, or none at all. For corpora where document identity was available

System	BLEU [%]
AppTek baseline	27.9
AppTek style token informal	28.7
AppTek style token formal	26.7
On-line G 2020-06-18	21.8
On-line B 2020-06-18	27.3

Table 1: BLEU scores in % on an English-to-Greek subtitle test set of 50K running words, 5.5K sentences (held-out for the AppTek systems).

source	I am at your service.
formal	Ich stehe **Ihnen** zu Diensten.
informal	Ich stehe zu **deinen** Diensten.
source	I see you all are interested in media and subtitling.
formal	Ich sehe, **Sie** alle interessieren sich für Medien und Untertitelung.
informal	Ich sehe, **ihr seid** alle an Medien und Untertitelung interessiert.
source	Please hold the balls in your hands.
formal	Bitte **halten Sie** die **Bälle** in **Ihren** Händen.
informal	Bitte **halte** die **Eier** in **deinen** Händen.

Table 2: Translation examples for English-to-German NMT with formal vs. informal meta-information provided as pseudo-tokens. All of the NMT-generated translations are correct for these examples.

for each sentence, we assigned the whole document to the formal/informal class if the majority of its target sentences contained the formal/informal pronoun. This is a simple, yet effective rule-based approach; for a more sophisticated method, cf. (Niu and Carpuat, 2019).

We experimented with two language pairs: English-to-German and English-to-Greek. In both cases we used state-of-the-art NMT systems trained with Transformer architectures using millions of sentence pairs. For English-to-Greek, the MT quality as measured with the BLEU score (Papineni et al., 2002) on a held-out test set of movie subtitles (Table 1) shows that our systems compare favorably to two major online translation providers. The style information was provided to the system as a pseudo-token (one of 3) both at training and at inference time. At inference time, we always used either the formal or the informal pseudo-token for all sentences in the test set. Since the test set mostly includes popular movies with informal style, the improvement in BLEU when using the informal style token was expected.

We let a professional Greek-native translator check the output of the baseline system that does not use style tokens, compared to the systems that use the formal or informal style token. This was done on a subset of a held-out subtitle file that contains informal dialogs. Whereas no quantitative evaluation was conducted, the translator noted a generally good quality of all outputs. She found that the grammatical part of style adaptation, i.e. the correct second-person pronouns, seemed to work, with the formal version using mostly the formal form, correctly per the style chosen, despite the informal material it was applied on. She also noted that "the vocabulary choices in the MT output depending on the style chosen were fascinating". This underlines the other interesting aspect of style transfer: although not explicitly modelled when partitioning the training data, the vocabulary choice for the informal vs. formal style seems to correlate with the usage of the second-person pronouns.

Similar findings were made for English-to-German. Examples of formal vs. informal style are given in Table 2. Note that both singular and plural second-person pronouns (including

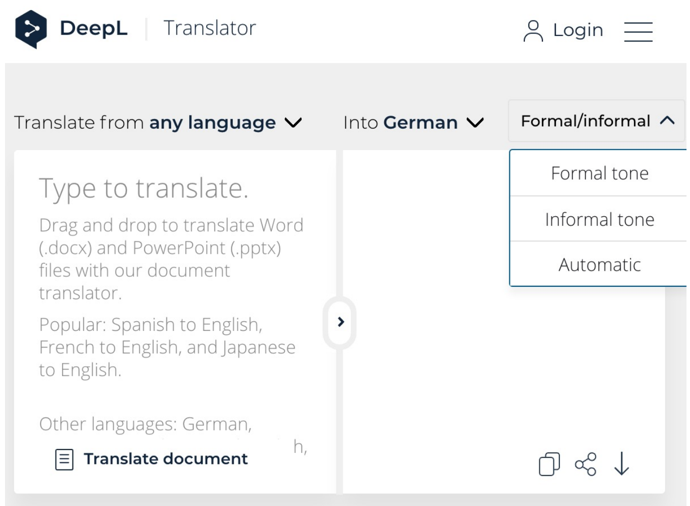

Figure 1: An example of a style switch menu in the on-line UI of the MT provider deepl.com (screenshot from August 28, 2020).

possessive ones) are translated correctly w.r.t. the requested style (`Ihnen` vs. `deinen`, `Sie` vs. `ihr`), correct auxiliary verb forms corresponding to these pronouns are used. The sentence structure is in some cases significantly different. The last anecdotal example in Table 2 where in case of the informal style the English word "balls" is translated in its profane meaning into "Eier" shows that style adaptation and transfer is also about lexical choice and meaning disambiguation. In particular, it is also possible to introduce additional constraints on the style, e.g. informal without obscene language, informal with obscene language, etc.

In practical applications of post-editing by professional translators the information about style can be provided for the whole document in advance before NMT is used to translate the document. However, in many cases style can change within a given document. For example, subtitles of a given film can include formal dialogs using the polite form of "you" as well as informal dialogs (or dialogs with a child) using the informal second-person pronouns. A button in the user interface can be implemented to help the post-editor instantly switch the translation of a single sentence to a different style when he or she notices such style changes. Of course, multiple translations for different styles would have to be pre-fetched in the background in order for this to work seamlessly.

Buttons or menu items for style switches in on-line translation tools for free text translation have started to appear already, as illustrated in Figure 1.

3.2 Domain, Genre and Topic

Domain, genre, and topic are almost synonyms in the sense that they refer to sometimes minuscule, sometimes large differences in content, combined with stylistic differences which are much harder to grasp or explain than the formal/informal style differences. Yet any information about such "world context" that goes beyond the context of the given and surrounding sentences is very important for correct translation, both by humans and by machines. For some genres it is all about correct terminology translation, whereas for others the differences are more subtle.

Usually, no fixed definitions or taxonomy of domains and genres are available. Nevertheless, the sources of monolingual and bilingual data often give a hint at the genre and domain. Yet in many cases especially the parallel data is crawled from multiple sources, often individ-

source	You need an **apple product** to obtain the best shape.
prose	Du brauchst ein **Apfelprodukt**, um die beste Form zu bekommen.
manuals	Sie brauchen ein **Apple-Produkt**, um die beste Form zu erhalten.
source	The bushing 20 is inserted in a **hole** 21 of the cover 12 of the **base** 11.
news texts	Die Buchse 20 wird in ein **Loch** 21 des Deckels 12 der **Basis** 11 eingesetzt.
patents	Die Buchse 20 ist in eine **Bohrung** 21 des Deckels 12 des **Sockels** 11 eingesetzt.
source	He came here to look for **food**.
documentary	Er kam her, um nach **Nahrung** zu suchen.
talks	Er kam her, um nach **Essen** zu suchen.

Table 3: Examples of translations by the same NMT system which change depending on additional meta-information about the input genre (English-to-German).

ual sentence pairs are taken from an unknown bilingual document or are even extracted from non-parallel, comparable corpora. Furthermore, genre can slightly vary even within a single document, or can be a new genre that has traces of the previously observed genres. Also, we would like that at inference time the genre/domain is either provided by the user, or automatically predicted for a given input sentence or document, or is not provided (and then the NMT system falls back to genre-agnostic translation). Most closely related work to our approach is by Kobus et al. (2017).

In our experiments, we decided to focus on genres. Some of them were defined in international MT research projects like GALE (Olive et al., 2011): newswire text, web (blog) text, broadcast news and conversations. We identified further genres based on the available English data. These include chat messages and comments, e-commerce product descriptions, customer product reviews, subtitles (film dialogs), documentary subtitles, emails, government texts, legal texts, software and hardware manuals, marketing material, military-related texts, non-fiction books, fiction (prose), poetry, patents, religious texts, educational (school) material, scientific texts including research papers, as well as parliamentary speeches and public talks.

We sampled 10M English sentences per genre and trained a bidirectional 1-layer LSTM classifier to predict the genre labels on a sentence level. The classifier obtained an accuracy of 77% on a held-out set of 6000 sentences that contained 250 sentences of each genre.

As mentioned in Section 2, the best way to integrate the genre information would be to change the architecture to include the predicted genre distribution as an embedding vector. In preliminary experiments, however, we converted this prediction into a single label using a heuristic – if a single label was predicted with a probability of more than 0.5, we assigned this label to a given training sentence pair. In cases when none of the labels had such a high probability, we assigned a “no genre” label. We then used this label as a pseudo-token similarly to the style pseudo-tokens described in Section 3.1.

We trained an English-to-German system with genre pseudo-tokens and first verified that its quality as measured with BLEU on multiple test sets with different domains did not significantly degrade as compared to a baseline system that does not use any pseudo-tokens. For this sanity check, we prepended each sentence with the “no genre“ pseudo-token. Then, we manually checked the system performance on a number of examples.

Generally, the effect of using just the pseudo token was minimal - the translation in many cases remained the same. That is why in our future work we would like to explore a stronger signal from the predicted genre distribution. However, if there was significant change in the output, it was always in the right direction for our examples, as can be observed in Table 3. In some cases, though, a more fine-grained distinction between genres may be desirable, leading to prediction of a topic distribution/profile of a given sentence or document. For instance, to

System	BLEU [%]
baseline	35.5
concatenate in training	36.3
concatenate in training + inference	37.0
on-line G 2020-06-18	33.2
on-line D 2020-08-12	34.9

Table 4: Translation results for MT with extended context on the English-to-German subtitle test set of 2378 sentences, 18K running words.

disambiguate the translation of "Apple" it is not enough to know whether the system deals with prose or marketing content, since in almost all of the defined genres both the fruit and the brand meaning can occur with high frequency. Topic modeling usually requires unsupervised clustering methods to obtain the right number of topics with as little overlap in their distributed representations as possible. In some applications like e-commerce, however, fine-grained topic taxonomies are already defined (e.g. for product categories and sub-categories) and can be used directly as supervising labels (Chen et al., 2016).

3.3 Extended Context

Topic modeling flows into the research on extended context for NMT and is related to document-level translation. Recently, there have been advances in this area, showing that additional context in the form of encoded previous and subsequent sentences from the same document is beneficial for improved MT quality (Werlen et al., 2018; Kim et al., 2019). In particular it can help with pronoun resolution (Müller et al., 2018). We argue that it is also possible to train a single NMT system that can either consume the additional context or can translate a single sentence without it, depending on the user request.

Table 4 summarizes the results of our experiments for English-to-German. In all cases we follow the simple concatenation approaches of Tiedemann and Scherrer (2017) and Junczys-Dowmunt (2019). We concatenate subsequent sentences appearing consecutively in the same document (subtitles for a single film) if the resulting sequence does not exceed a certain number of tokens (50). Multiple sentences on source and target side are concatenated using a special symbol `@sep@` so that the NMT system learns to generate such separator symbols. The concatenated data is added to the original training data; thus some of the sentences appear in the training data twice: on their own and concatenated with surrounding sentences. The test data is augmented in a similar way, except every sentence is translated exactly once.

AppTek's baseline state-of-the-art English-to-German system was trained on ca. 20M sentence pairs, including subtitle data. As can be inferred from Table 4, its performance on a held-out subtitle test set is better in terms of BLEU than when translating with two major on-line MT services. After augmentation via concatenation of some of the sentences which had document information associated with them, the total number of lines in the training data increased to 39M.

We observed significant increases in BLEU from doing the concatenation in training only, which shows that the proposed method does not harm the baseline translation quality. When short sentences are concatenated at inference time, the translation quality increases further. A detailed analysis of sentences of different lengths showed that in particular translations of very short segments benefited from the context of the previous and next sentences. The absolute BLEU improvement for sentences of length one (individual words) was 11% absolute, and for sentences of length from 2 to 9 words it was 2% absolute. But even for long sentences, a marginal BLEU score improvement was observed.

source	I found a watch and returned it to the owner.
pseudo-token male	Naš**el** jsem hodinky a vrátil je majiteli.
pseudo-token female	Naš**la** jsem hodinky a vrátil**a** je majiteli.

Table 5: An example of two translations into Czech of the same sentence by a single NMT system, the first time with the gender meta-information "male", the second time with the gender meta-information "female".

For real-life use, this means that an MT application can be programmed to use the additional document-level context (or simply put, the context of the surrounding sentences) on demand, when the context of a given sentence is not enough as determined by some objective criterion, the simplest of which can be input sentence length.

3.4 Speaker/Author Gender

In some languages, the morphological realizations of certain parts-of-speech depend on the gender of the speaker/author. Examples include past-tense singular verb forms in Russian, Czech, etc. When translating from languages such as English where this is mostly not the case, the NMT system chooses one of the gender-specific forms. With the absence of supporting gender-relevant context (e.g. "she said" vs. "he said"), it makes its decision mostly based on the examples that were observed in training. Usually, but not always, the training data is biased towards male word forms. Biased or not, however, an incorrect word form in the automatically generated translation is annoying and yet hard to fix; it can appear again and again throughout a given text or speech that, for instance, is a first-person narrative with many forms starting with the pronoun "I".

To explicitly use the information about the speaker or the author, we again propose to partition the training data into "male", "female", and "neutral" sentence pairs depending whether or not the corresponding male or female word forms are used throughout the target sentence (almost) exclusively. We realize that such a method requires many heuristics, but in the absence of data labeled with speaker gender that was used in related research of Vanmassenhove et al. (2018) it is difficult to come up with a better solution.

So far, we conducted only preliminary experiments for English-to-Czech, using 3 types of pseudo-tokens as described above. Table 5 shows an example where the correct gender forms are used in the Czech translation when the information about gender is provided to the system. This is a step in the right direction. We envision that especially for applications involving speech translation, speaker gender can be automatically predicted with high confidence and passed on to NMT for use as an additional signal. Also, in personalized translation applications, the correct gender can be set by the app user, and then her/his texts and messages would be translated from English using the right gender form of a given target language.

3.5 Length

In some applications it is desirable to control the length of MT output, as measured in words or characters, while minimizing any information loss. For instance, subtitle templates are usually created in the source language and have a fixed number of subtitles with a fixed duration of their appearance on the screen. Thus, a translation of a sentence in a subtitle that is significantly longer than the original sentence can only be inserted without changing the template by using more than the allowed number of lines per subtitle (usually two). This means that a faster reading speed is necessary to finish reading the text before the subtitle disappears, and should be avoided as much as possible. That is why shorter translations (from English) are preferred.

Another application is translation of user interface elements/menus in a software compo-

source	¿No te vas a sentir incómodo?
baseline	You're not gonna feel uncomfortable?
shortened	Won't you be uneasy?
source	Se llevan muy bien y la verdad es que me da mucha pena.
baseline	They get along very well, and the truth is, I feel very sorry for them.
shortened	They get along very well and I'm really sorry.
source	De ninguna manera me sentiré incómodo ni tengo problema en verla.
baseline	There's no way I'm gonna feel uncomfortable and I don't have a problem seeing her.
shortened	There's no way I'll feel uncomfortable or have a problem seeing her.

Table 6: Examples of translations shortened by N-best list rescoring aimed at penalizing long translations (Spanish-to-English subtitles).

nent. There, the maximum length may be technically limited by the width of the menu or a text field.

A number of research publications appeared recently which target length control, starting with the seminal work on length control in encoder-decoder architectures by Kikuchi et al. (2016). In (Lakew et al., 2019), the pseudo-tokens for short, medium, and long translations are assigned at training time. These labels are derived from the length ratios between each training source sentence and its target language translation. At inference time, the user provides the desired label, e.g. requesting a short translation. An approach with length constraints learned end-to-end in an unsupervised way is presented by (Niehues, 2020).

Another method that we tested tailored specifically to subtitle translation is to re-score the N-best output of the NMT system using a linear combination of the original NMT model score and a score derived from the the length of an N-best list hypothesis and the duration of the subtitle in which the source sentence, and thus also its translation, is to appear on the screen.

Since for judging the translation quality in cases of e.g. shortened MT output it is not reasonable to use the original reference translations created without such length constraints for computation of automatic MT error measures, we only conducted a small-scale manual evaluation of the resulting output.

We translated the content of 64 subtitles from Spanish to English with AppTek's state-of-the-art NMT system, performing N-best list rescoring aimed at penalizing all translations with a reading speed of 17 chars or more per second[1]. As a result, the average reading speed of the file reduced from 19.3 to 17.23 chars/s and the number of frames with a reading speed of more than 20 chars/s dropped from 33 to 13.

A professional translator noted that the shorter automatic translation versions "are mostly great, exactly what a subtitler would do". In very few cases, they do change the meaning, which is not acceptable, but can usually be fixed by quick post-editing.

Table 6 shows examples of translations shortened with the above approach, for which the meaning of the translation did not change.

3.6 Language Variety and Multilinguality

Multilingual NMT systems have shown to be effective in using parallel training data from high-resource language pairs to improve the quality of translation from or to a low-resource language (Firat et al., 2016; Johnson et al., 2017).

In case of multiple target languages, it is often sufficient to use a pseudo-token at the beginning of the source sentence that signals to what language it should be translated. With this

[1]The reading speed is defined as the subtitle length in characters (e.g. a maximum of 2 lines with a maximum of 42 characters per line) divided by the subtitle duration (usually 2-5 seconds).

simple approach, already an acceptable level of MT quality can be reached. Thus, a multilingual system can be viewed also a customization of a single NMT system with meta-information about the target language.

At AppTek, we use the multilingual approach also for language varieties or dialects, following also the work of Lakew et al. (2018). The main challenge is how to partition the training data: in most cases no reliable information about the used dialect is available, and automatic dialect prediction is a hard task. Following a pragmatic approach for English-to-Spanish translation of movie subtitles, we labeled those film subtitles in the training data as European Spanish which contained words and phrases used only in Spain. The rest was labeled as Latin American Spanish. We then trained a multilingual system with the two labels. Our customers can choose the language variety via an API parameter and obtain a possibly different translation for a given sentence using the same system. More details can be found in Matusov et al. (2019).

In case of multilingual, dialectal, or even mixed-language input, it is possible to train an NMT model which is sensitive to the meta-information about the input language or dialect. Again, in practical applications, such as computer-assisted translation from Arabic to English, a general translation can be generated prior to post-editing (assuming e.g. Modern Standard Arabic or MSA), together with translations for (a subset of) the Arabic dialects. Then, the professional translator can change the MT in the post-editing window when she or he notices that the language switched from MSA to a dialect. This can happen in particular when someone's dialectal speech is quoted in a news article written in MSA.

At the same time, for such multilingual or multi-dialect many-to-one systems it is advisable to use a "garbage" label which is associated randomly with a subset of the training data in any language or dialect. Providing this label may help when the dialect or language of the input is not known, or it is a mixed-language input. For instance, AppTek's multilingual NMT system that can translate from any of 12 Slavic languages into English is also able to translate mixed-language sentences like the following one which is a mix of Ukrainian and Russian (typical for messages and speech of a significant part of the population of Ukraine). Хлопці были у меня дома, но про дівчин они ничего не пліткували is correctly translated as "The boys were at my house, but they didn't say anything about the girls." (Ukrainian words in the otherwise Russian sentence are Хлопці, дівчин, and пліткували).

3.7 Glossaries

Terminology glossary entries or translation memory matches can accompany each translation request to an NMT system so that for any matched entry the translation from the glossary is forced to be used in-context in the MT system output. This so called glossary transfer or override is another user-specific customization of a given NMT system and can be implemented in professional post-editing UIs by e.g. giving the user the possibility to upload a glossary prior to populating the output window with the automatic translation. In other cases the glossary can be automatically created in a computer-assisted translation environment by memorizing past user translation corrections and choices.

In its simplest form, glossary transfer "as is", i.e. the exact copy of the target side of the glossary entry, is implemented using placeholder tokens. In training, a source word or phrase is replaced by such a placeholder token; the same token replaces the (consecutive sequence of) words in the target sentence which are word-aligned to this particular source word or phrase. If there are multiple replacements within a given sentence pair, different placeholder tokens are used. Thus, a system learns to translate (and thus also correctly position, if reordering is involved) a given placeholder token to itself in all cases.

At inference time, a matched glossary entry in the source sentence is replaced with such a placeholder token in preprocessing, and then the same token in the generated translation is replaced with the target side of the corresponding glossary entry in postprocessing. The obvious disadvantage of this approach is that the context in the form of the glossary entry itself is lost during translation, since it is generalized to the placeholder token.

More complex algorithms involve encoding of the desired target translation in the source sentence using special markers (Dinu et al., 2019). Other methods try to use constrained decoding (Hasler et al., 2018) or NMT-internal attention mechanisms to override the translation of the next word if the current focus of the attention is on the corresponding matched source glossary entry (Dahlmann et al., 2017). With such approaches it is not guaranteed that the desired translation from the glossary will be used, but at the same time, it is possible that the system will learn that the glossary translation has to be used in a morphological form that is different from the (base) form present in the glossary because of the surrounding context.

To illustrate the basic approach and the challenges that the more advanced approaches can rarely master, we present two examples. In the first one, the sentence `Jack, when are you going back to Vienna?` is correctly translated into German as `Jack, wann fahren Sie zurück nach Wien?`. However, this translation is not correct if Vienna is referring to a city in the United States. Here, the simple approach of the "as is" glossary override via placeholder tokens can already enforce a glossary entry `Vienna` $\rightarrow$ `Vienna`. In the second example for English-to-Russian translation, the sentence `The Hatter put the Dormouse's head in a teapot and winked to the March Hare` from *Alice in Wonderland* by Lewis Carol can be translated with the help of the following glossary[2]:

```
Doormouse == Sonya
March Hare == Martovskiy Zayats
Hatter == Shlyapnik
```

However, the Russian translations of these fictional characters are given in the nominative case, whereas in a translation of the sentence some of them must be used in other cases with different suffixes/endings: "Shlyapnik polozhil golovu Son**i** v chainik i podmignul Martovsk**omu** Zay**tsu**". The changed suffixes are marked in bold. To the best of our knowledge, state-of-the-art glossary transfer methods for NMT are not able to satisfactorily address this task of glossary override for morphologically rich languages, which opens up possibilities for future work.

4 Conclusion

In this paper, we provided an overview of different customization opportunities so that a single neural machine translation system can be trained to accept additional meta-information as input and thus produce different translations of a given sentence based on the additional metadata. We showed how meta-information about style, genre, topic, and speaker/author gender can be obtained from customer databases or derived automatically, and then used in training and at inference to produce better, in-context translations with correct style, grammar, and correct word sense disambiguation. We discussed how extra context in the form of surrounding sentences from the same document can be "turned on" to improve the translation of a given sentence. Furthermore, we showed that translation length can be effectively controlled if necessary without significant information loss. We also showed how customization works in the context of multilinguality, language varieties and dialects, and even mixed-language input. Finally, we elaborated on the practical applications of single customizable NMT systems in several usage scenarios, with focus on user interfaces for efficient MT post-editing.

Of course, it is possible to combine all or some of the different types of metadata inputs described in this paper in a single NMT system. Our future plans are to train such a system and successfully use it for AppTek's customers.

[2]Transliteration of Russian is used here for better understanding.

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Customized Neural Machine Translation Systems for the Swiss Legal Domain

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Abstract

This paper describes Tilde's work on the development of a Neural Machine Translation (NMT) platform for Hieronymus, a Switzerland-based boutique legal and financial translation provider, giving particular attention to the increase in efficiency as regards internal translation processes, as well as NMT's impact on the customer experience of their partners. The NMT tool was developed by combining a set of domain-adapted NMT systems with a customized translation platform, both of which were built and developed by Tilde. The central aim of the solution is to assist Hieronymus translators and to create LexMachina, a secure, do-it-yourself NMT solution for Swiss lawyers. The current paper outlines the workflow used to collect, filter, clean, normalize, and pre-process data for the NMT systems, as well as the methods utilized to train and adapt the NMT systems for Hieronymus. The current paper also sheds light on the needs of Tilde's partner, from approaches to resolving the challenges they faced to the implementation process itself.

1 Introduction

As a steadily growing company in a highly competitive language service industry, Tilde's partner, Hieronymus[1], was eager to adopt an innovative Neural Machine Translation (NMT) strategy to ensure its long-term growth while vastly improving the translation customer experience, as well as gaining the loyalty of their customers via a 'self-service' tool made to cover their needs. Much to their surprise the absence of readily available solutions on the market coupled with the Swiss-specific language context posed considerable challenges when adopting the chosen NMT strategy. Namely, language tools and NMT systems required by Hieronymus had to account for the linguistic specifics of Switzerland's local languages: Swiss-German, Swiss-French and Swiss-Italian. Unsurprisingly, most of the parallel data available for NMT training is in standard German, French, and Italian. Furthermore, Hieronymus' interests lie translation for highly-technical domains: criminal law, tax law, banking, and finance. The NMT systems used by Hieronymus must therefore be able to deliver reliable and trustworthy translations of highly technical domain-specific terminology. Additionally, the NMT systems must be fully integrated into their translation workflows, so as to boost both the internal and external opera-

[1] www.hieronymus.ch

tional efficiency. The NMT integration sought to provide Hieronymus with a competitive edge by streamlining the translation processes while enhancing quality and terminological accuracy.

Another priority of Hieronymus' NMT development was to offer a new product to their clients, mainly law firms, it being a way to enhance the customer experience. Central to this new product was a self-service legal machine translation infrastructure that their partners could independently access with the guarantee of full confidentiality and the ”Swiss touch”—two essential elements for Hieronymus' clients.

With the above elements in mind, Tilde combined its language and client-oriented approach with the latest, AI-driven natural language processing technology to develop *LexMachina* [2]. The development of LexMachina was a joint effort between Tilde and Hieronymus, where much attention was placed on the selection and preparation of the right data, as well as the testing and improvement of the same. *LexMachina* is a customized translation platform that guarantees the security and confidentiality throughout the translation process. It has been launched as a collection of 10 customized NMT systems and will be extended to include new domain-specific NMT systems in the near future.

The platform is based on the Tilde MT platform (Pinnis et al., 2018) and LetsMT technology (Vasiļjevs et al., 2012). It supports multiple input formats and maintains tag and formatting integrity when translating documents. Additionally, the translation platform integrates Hieronymus translation memories (TMs), supports integration of NMT systems into the most commonly used computer-assisted translation (CAT) tools, and allows for integration of the NMT engines into Microsoft Outlook. As a result, the *LexMachina* platform allows Swiss lawyers to instantly translate legal documents in the necessary confidential environment while reaping the benefits of customized NMT technologies. The solution developed by Tilde and Hieronymus may also be adapted to the specific needs of Swiss banks, insurance companies and major advisory and accounting companies.

All NMT systems were tailor-made to conform to Hieronymus' requirements regarding Swiss local language and domain-specific terminology. To that end, we set out to acquire, classify, and align Swiss domain data, reviewing the main details and preparing the correct training formula for the customization thereafter. As a result, alongside Hieronymus, we developed generic Swiss legal engines. Further development on this project will see the release of additional Swiss legal engines specialized in various sub-domains (criminal law, financial law, tax law, etc.).

The current paper describes the development of *LexMachina*, and how Hieronymus leveraged their machine translation capability to increase both productivity and efficiency, allowing them to streamline translation processes and become the first provider to offer a do-it-yourself, legal machine translation solution for Swiss lawyers. In presenting this use case, we bring to light the details of the technological, infrastructural, and linguistic challenges we have experienced, and indeed overcome, while creating and implementing this NMT project. The application of the developed NMT systems aim at facilitating the vision of Tilde's partner, and enable the desired innovation with the creation of customized NMT systems and a self-service translation platform.

2 Requirements

Hieronymus' demand for NMT solutions were not satisfied with those currently available on the market. Most available engines are based on standard German, French, and Italian, omitting essential local elements such as punctuation, vocabulary, lexicon, style, register, grammar structure, and terminology. These differences between Swiss local and standard languages were of particular concern to Hieronymus' customers, among which are local law firms, banks, in-

[2] `www.lex-machina.ch`

surance companies, and other financial institutions, all of which consider the accuracy of terminology essential.

Thus Hieronymus presented Tilde with a list of requirements that the NMT and translation platform had to meet to be considered adapted to their customers' needs. These needs were primarily a question of data; the NMT systems should be built using in-domain terminology, such as legislative acts and laws, and financial and tax content, adapting them to the specificities of the Swiss-German, Swiss-French, and Swiss-Italian languages.

Due to the nature of work of Hieronymus' customers, all information and documents had to be translated securely. Specifically, it was paramount that the MT system guarantee the confidentiality of sensitive data at all times, and that all data be stored within a Swiss infrastructure environment never to be transferred outside of Switzerland. To reinforce the confidentiality of the translation process, the NMT engines and the *LexMachina* translation platform are hosted in a secure, Swiss-based cloud environment controlled by Hieronymus.

To address the above requirements, Tilde and Hieronymus developed *LexMachina*. *LexMachina* is a set of adapted NMT systems which are integrated into a customized translation platform based on Tilde's MT platform. *LexMachina* provides the following functionalities:

- translation of text snippets (words, sentences, up to several paragraphs);
- translation of documents by preserving formatting and document formats;
- translation of websites by preserving website structure and design;
- CAT tool plug-ins for SDL Tradus Studio and Wordbee.

3 Machine Translation Systems

A typical development cycle of domain-specific MT systems involves MT training on general domain data and adaptation on domain-specific data. The Hieronymus case is different, as the final quality and appropriateness of the MT systems depend not only on their ability to translate domain-specific texts, but also on their being tailored to Swiss language specificities. The following section (3.1) describes how we tackled additional challenges posed by data sparsity, which is result of both occupying a niche domain and Swiss language needs.

3.1 Data Collection

To develop NMT systems for the Swiss legal domain, we used three types of data:

- **Publicly available parallel corpora**. Most publicly available parallel data comprise texts in standard French, Italian, and German. These data are not necessarily of Swiss origin and usually do not contain texts of Swiss German, Swiss Italian, and Swiss French. However, such data are available in large proportions and can help to form baseline models. The largest of such is available from the DGT Translation Memories (Steinberger et al., 2012), Digital Corpus of the European Parliament (Hajlaoui et al., 2014), the Tilde MODEL corpus (Rozis and Skadiņš, 2017), Europarl (Koehn, 2005), and other sources available from the Tilde Data Library[3].
- **Parallel data crawled and extracted from legal-domain Web sites** of institutions of Swiss origin. Having four official languages, many Swiss institutions provide multilingual information on their Websites, making it a valuable asset for machine translation. Therefore, we crawled public institution websites using a parallel data crawler, downloaded

[3] https://www.tilde.com/products-and-services/data-library

monolingual documents, and performed cross-lingual alignment with consecutive parallel data extraction to acquire parallel corpora.

- **Translation memories from Tilde's partner**. The in-domain data that were used to fine-tune NMT systems were provided by Hieronymus, thereby ensuring that the trained NMT systems are tailored specifically to the Swiss language context.

3.2 NMT System Training and Domain Adaptation

For the training of NMT models, we use the Marian NMT toolkit (Junczys-Dowmunt et al., 2018) as it provides the most efficient implementation for training and inference of any standard NMT model. We use Marian's standard configuration[4] of the *transformer-base* model (Vaswani et al., 2017). We select training batch sizes dynamically so that they fit in a workspace of 9,000-22,500 MB (depending on GPU specification). We train models with early stopping (Prechelt, 1998), using ten consecutive evaluations with no improvement in translation quality on the development set as the stopping criterion. The high level view of NMT system training:

1. First, pre-process all data using Tilde's parallel data pre-processing pipeline (Pinnis et al., 2018), which involves custom-made processes for parallel data filtering, normalization, non-translatable entity identification, tokenization, and truecasing, as well as standard processes for word splitting, and cross-lingual word alignment.

2. Then, for each domain, we perform careful data selection. We split data into four parts: out-of-domain colloquial data, out-of-domain formal language data, out-of-domain Swiss data, in-domain Swiss data. All Swiss data are up-sampled while the colloquial data are down-sampled or discarded. See Table 1 for the summary of training data size for each language pair.

3. Before training, we separate random subsets of 2000 and 1000 parallel sentences from the in-domain Swiss data to be used as development and evaluation data sets, respectively.

4. To make MT models more robust against incomplete or incorrect input, we synthesize additional training data by randomly replacing 1-3 content words in sentences with a placeholder (Pinnis et al., 2017).

5. We train baseline Transformer NMT models with guided alignment using the Marian NMT toolkit. We provide subword-unit-based statistical alignments as an additional input data stream for learning guided alignments, which are important for formatting-rich document translation and integration in computer-assisted translation tools.

6. Finally, we adapt the systems, thereby ensuring conformity to Swiss language specificities and style. Domain adaptation is performed using a 1-1 mix of in-domain Swiss data with an equal amount randomly sampled from the remaining data.

3.3 NMT System Quality

Figure 1 gives results of automatic evaluation of translation quality of *LexMachina* MT systems using BLEU (Papineni et al., 2002) metric. The performance of publicly available Google Translate general domain systems is given for the reference. Results show that *LexMachina* MT systems yield substantially better quality (12.3 BLEU higher on average) than the publicly available counterparts. The substantial difference in performance suggests that the strategy to approaching Hieronymus' requirements for Swiss language and domain-specific MT systems as a two-fold domain adaptation problem has been successful.

[4]https://github.com/marian-nmt/marian-examples/tree/master/transformer

			Baseline Data		Domain Adaptation Data	
			Parallel	**Synthetic**	**Parallel**	**Synthetic**
FR	↔	**EN**	53.5	50.7	0.24	0.22
DE	↔	**IT**	15.1	13.4	0.17	0.14
IT	↔	**FR**	16.6	16.2	0.17	0.16
FR	↔	**DE**	9.6	7.6	1.8	1.4

Table 1: Training data sizes in millions of sentences.

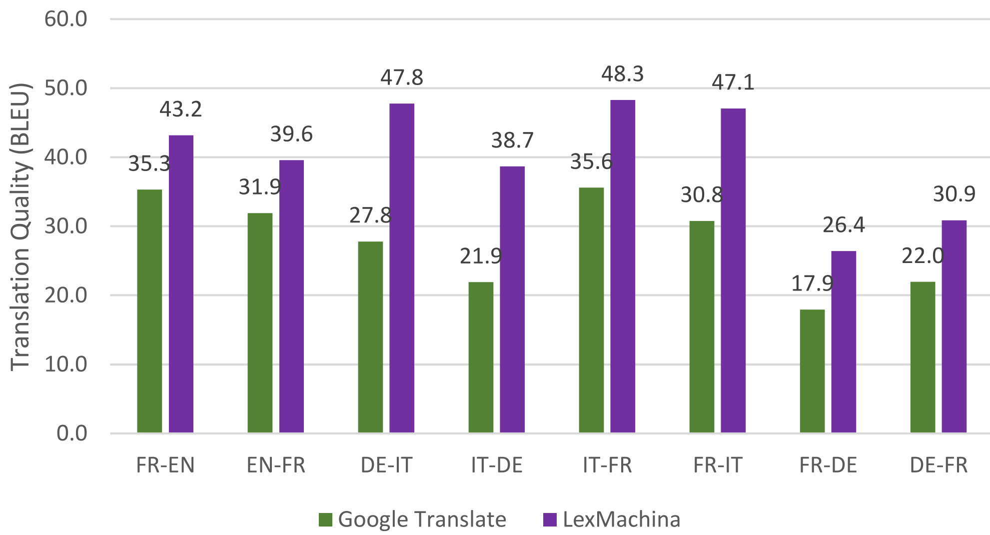

Figure 1: Results of automatic evaluation of translation quality measured in BLEU scores. *LexMachina* in-domain MT systems compared against publicly available general domain MT systems by Google Translate. The comparison was made in February 2020.

4 Implementation

The implementation process for the project was divided in four steps: 1) a pilot to assess NMT capabilities for one language pair, 2) NMT system training, 3) development of the *LexMachina* platform, and 4) deployment of the *LexMachina* platform in Hieronymus' infrastructure. The pilot allowed us to better understand the domain, identify data sources, and establish the domain adaptation strategy for NMT system training. Once satisfied with the results of the pilot, we trained all remaining NMT systems using the strategy established in the pilot phase. The NMT systems were at first deployed on the Tilde MT platform to allow instant access to testing and evaluation of the NMT systems and features of the MT platform. All systems were tested and custom-tweaked by adjusting data pre-processing and post-processing rules. The platform was simultaneously developed according to Hieronymus' requirements. Finally, the platform was deployed in a Switzerland-based, secure data center to comply with the security requirements of Hieronymus and their customers.

The project allowed Hieronymus to reach the following milestones:

- to integrate custom NMT engines in their workflow, which allows their translators to increase productivity and efficiency;

- to become the first provider to offer a self-service, legal machine translation solution for Swiss lawyers;
- to become the first provider to offer a fully secure NMT solution deployed in the Swiss Azure cloud for banks, insurance companies, and major advisory and accounting companies.

5 Conclusions

In response to growing interest from the Swiss banking and insurance industry, both of which want their own specialized NMT engines, Hieronymus and Tilde have developed a common solution to cater for the industry's urgent NMT needs – the current *LexMachina* infrastructure is a proof-of-concept. As a result of the joint project between both parties, Hieronymus can build on the deployed solution and offer on-premises custom NMT engines using both precious corpora developed by Hieronymus, as well as Tilde's extensive experience in setting-up secure infrastructures. Custom-made NMT solutions will allow banks, insurance companies, and large consulting and accounting firms to reduce their translation costs by 30%-50%, improving the quality and speed of delivery - all while maintaining security and confidentiality.

6 Acknowledgements

We would like to acknowledge the contribution, support, and involvement of Hieronymus in the project described in this paper, especially to Orane Laeri and Lauren Spencer, who managed the project on Hieronymus' side. We would also like to thank our colleagues Roberts Rozis, Valters Šics, Igors Zotovs and Viktorija Kononova for their contribution to the project described in this paper.

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RWS
Moravia

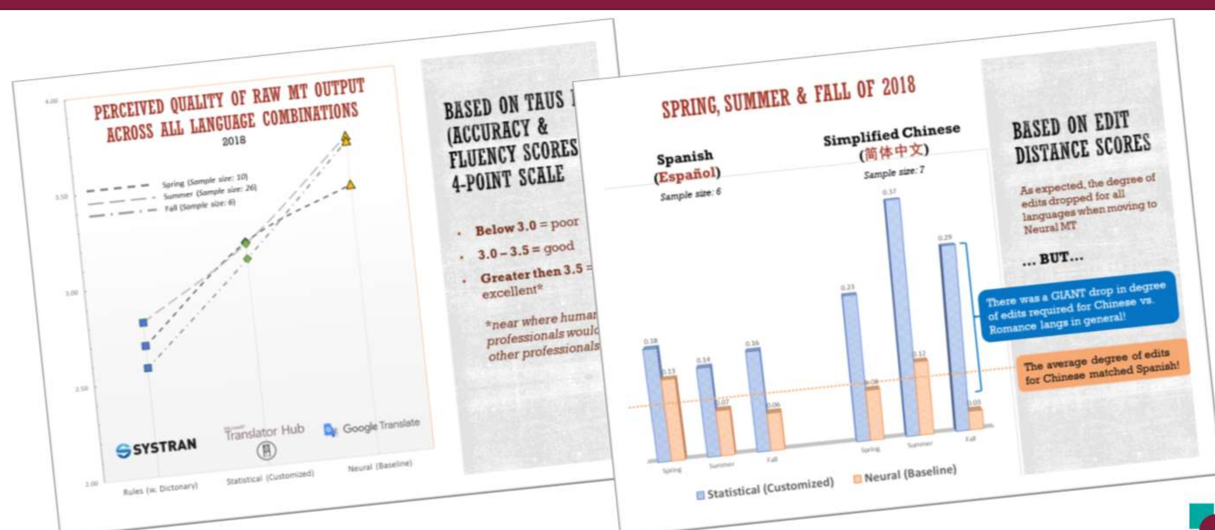
Machine Translation Hype

Crash-Tested by Translation Students

www.rws.com/moravia

1

Since 2016 I have been treating the last four weeks of my *Translation Technology* course as a testing laboratory…

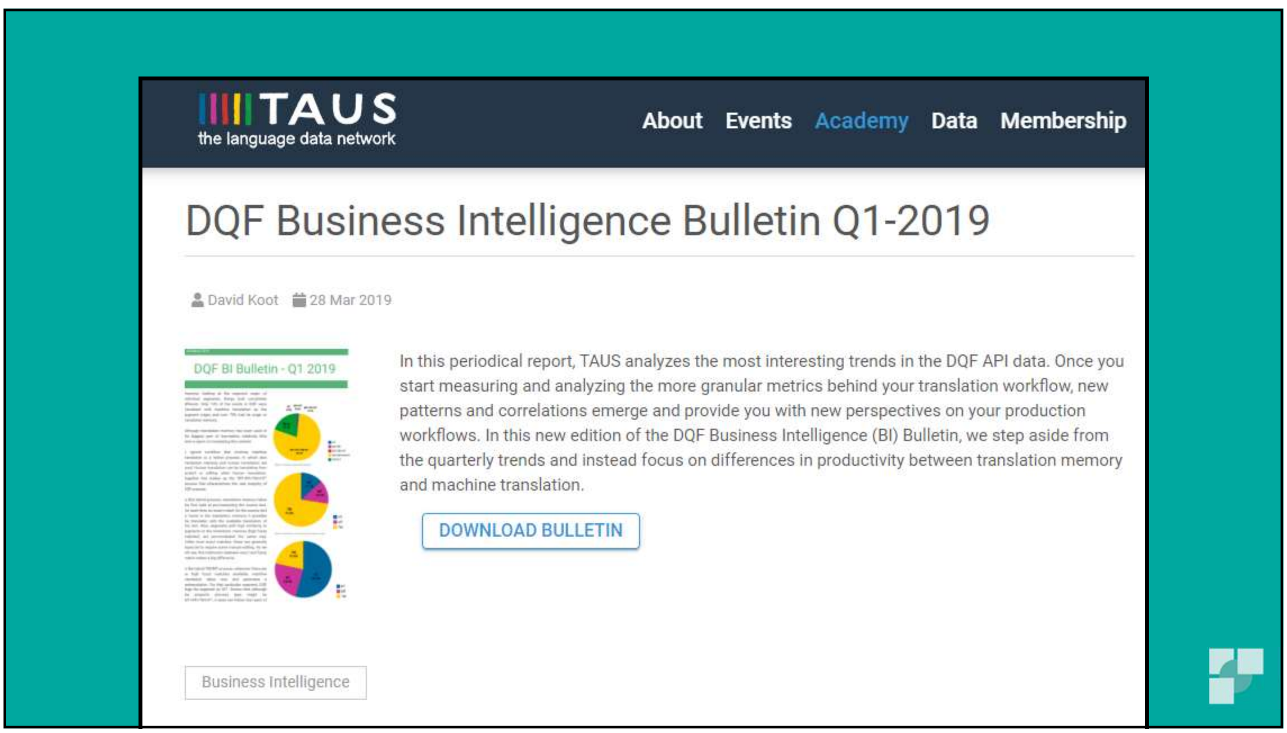


2

So what to test next?

¯_(ツ)_/¯

3



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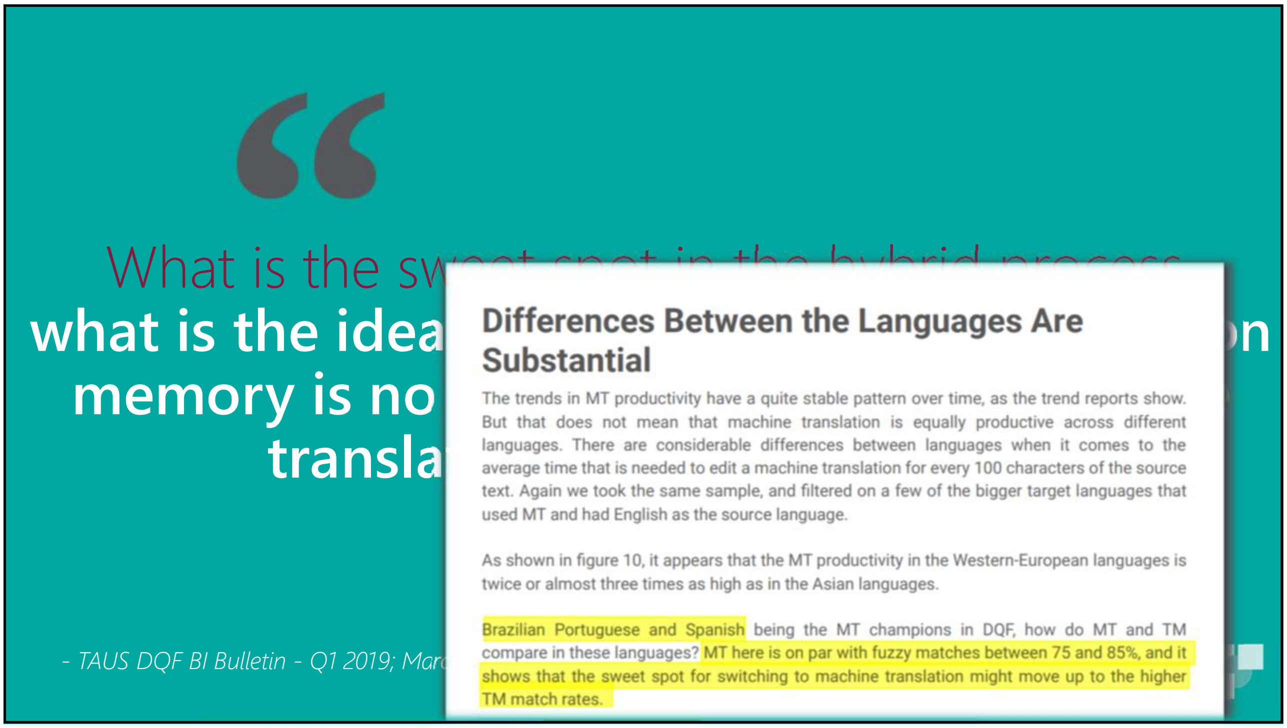
What is the sw
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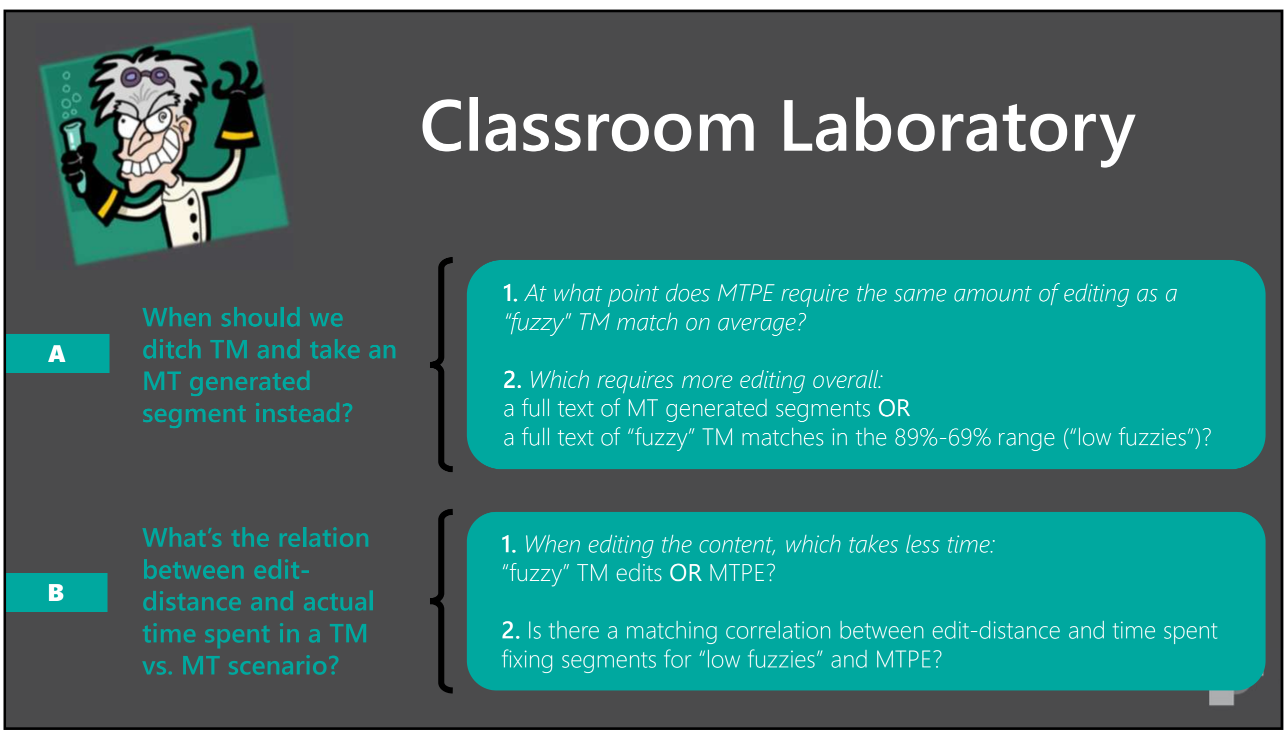
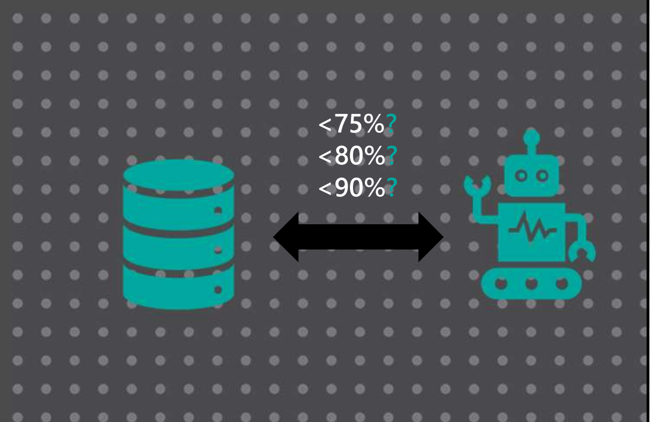
- TAUS DQF BI Bulletin - Q1 2019; Mar
Differences Between the Languages Are Substantial
The trends in MT productivity have a quite stable pattern over time, as the trend reports show. But that does not mean that machine translation is equally productive across different languages. There are considerable differences between languages when it comes to the average time that is needed to edit a machine translation for every 100 characters of the source text. Again we took the same sample, and filtered on a few of the bigger target languages that used MT and had English as the source language.
As shown in figure 10, it appears that the MT productivity in the Western-European languages is twice or almost three times as high as in the Asian languages.
Brazilian Portuguese and Spanish being the MT champions in DQF, how do MT and TM compare in these languages? MT here is on par with fuzzy matches between 75 and 85%, and it shows that the sweet spot for switching to machine translation might move up to the higher TM match rates.

5


Classroom Laboratory
A
When should we ditch TM and take an MT generated segment instead?
1. At what point does MTPE require the same amount of editing as a "fuzzy" TM match on average?
2. Which requires more editing overall:
a full text of MT generated segments OR
a full text of "fuzzy" TM matches in the 89%-69% range ("low fuzzies")?
B
What's the relation between edit-distance and actual time spent in a TM vs. MT scenario?
1. When editing the content, which takes less time:
"fuzzy" TM edits OR MTPE?
2. Is there a matching correlation between edit-distance and time spent fixing segments for "low fuzzies" and MTPE?

6

Experiment A



When should we ditch TM and take an MT generated segment instead?

www.rws.com/moravia

RWS Moravia

7

Methodology

- 8 students; en-US > 3 target language groups (*es-419 (es-LA), zh-CN, zh-TW*)
- There are 22 source segments in total split equally into "Set A" and "Set B"
- All are *full* sentences from older (2015 or earlier) Apple iOS documentation (pulled from PDFs) with an average length of 15 wds
- For **TM**, pre-populate with fuzzy matches in the 89%-69% range (avg. match across Set A = 79%; Set B = 78%)
- For MT, pre-populate with Google Translate generated sentences
- One student *per language* will complete Set A with a "fuzzy match TM" and Set B as MTPE; the other student will do the reverse. Then they will switch.
- Edit distance will be measured for every segment
- NOTE: Students can be unpredictable on occasion, so the official Apple translations were added as a "control group" to minimize this risk

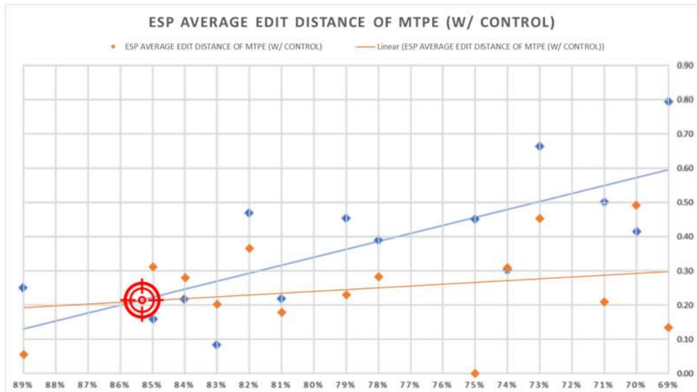
For every language…

	Student 1	Student 2
MT	Set B - 161 wds - 11 sentences; avg. 15 wds long	Set A
Fuzzies TM	Set A - 165 wds - 11 sentences; avg. 15 wds long	Set B

9

1 At what point does MTPE require the same amount of editing as a fuzzy TM match on average?

- Organize segments by original TM match categories
- Calculate location of point based on average edit-distance for total sampled segments by language
- Do this both for fuzzy TM edited & MTPE segments
- Plot the trendlines for both
- Find intersection



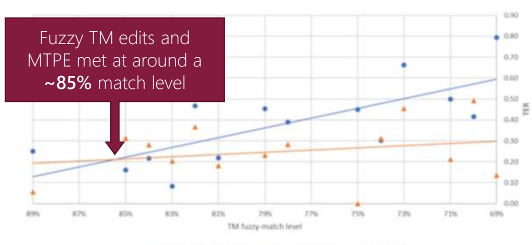
Sample size per graphed point	2	3	7	3	5	8	5	2	2	3	5	2	3	5

Organized by TM Fuzzy Segment Match Category

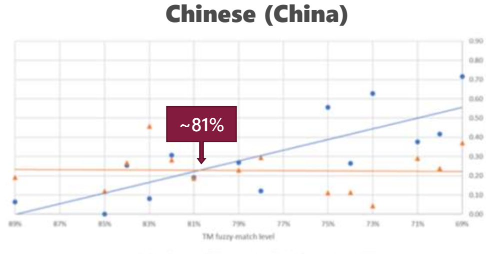
10

At what point does MTPE require the same amount of editing as a fuzzy TM match on average?

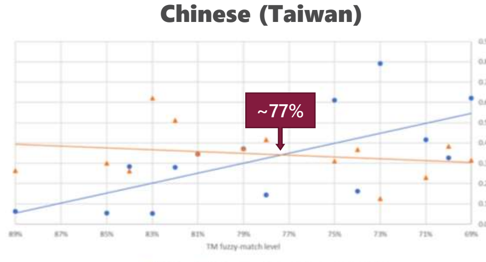
Spanish (LatAm)



Chinese (China)



Chinese (Taiwan)



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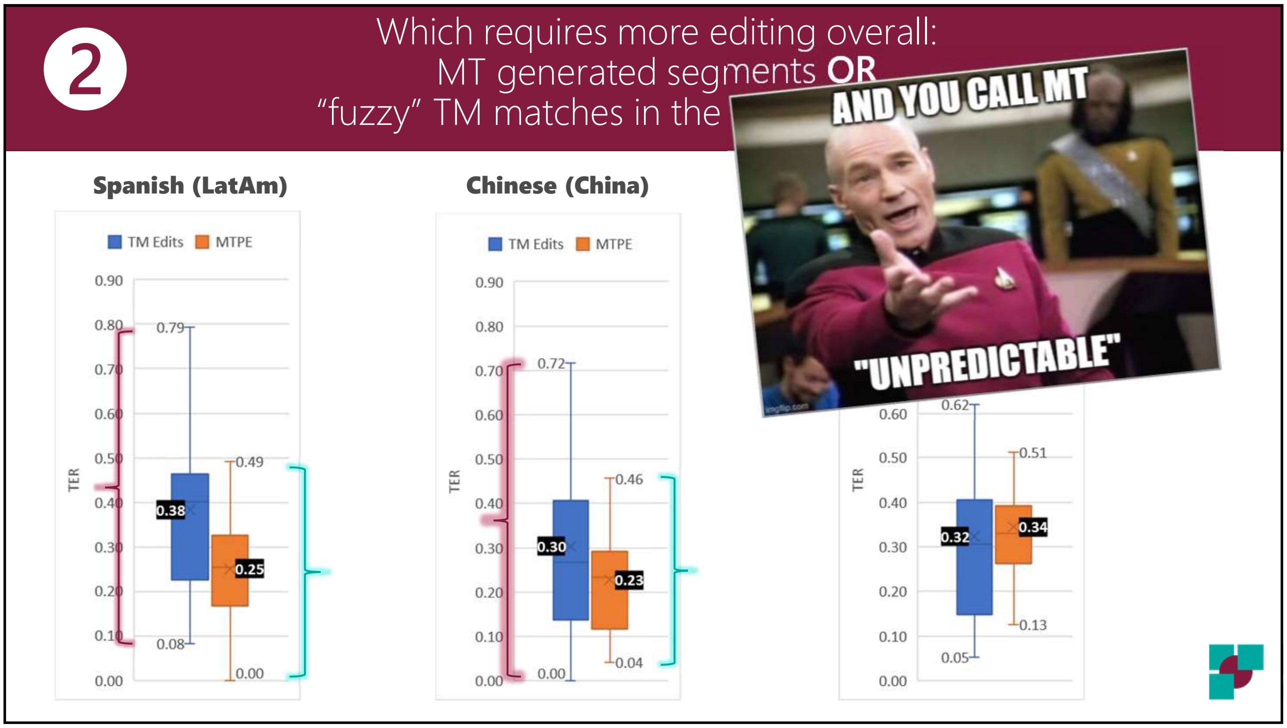
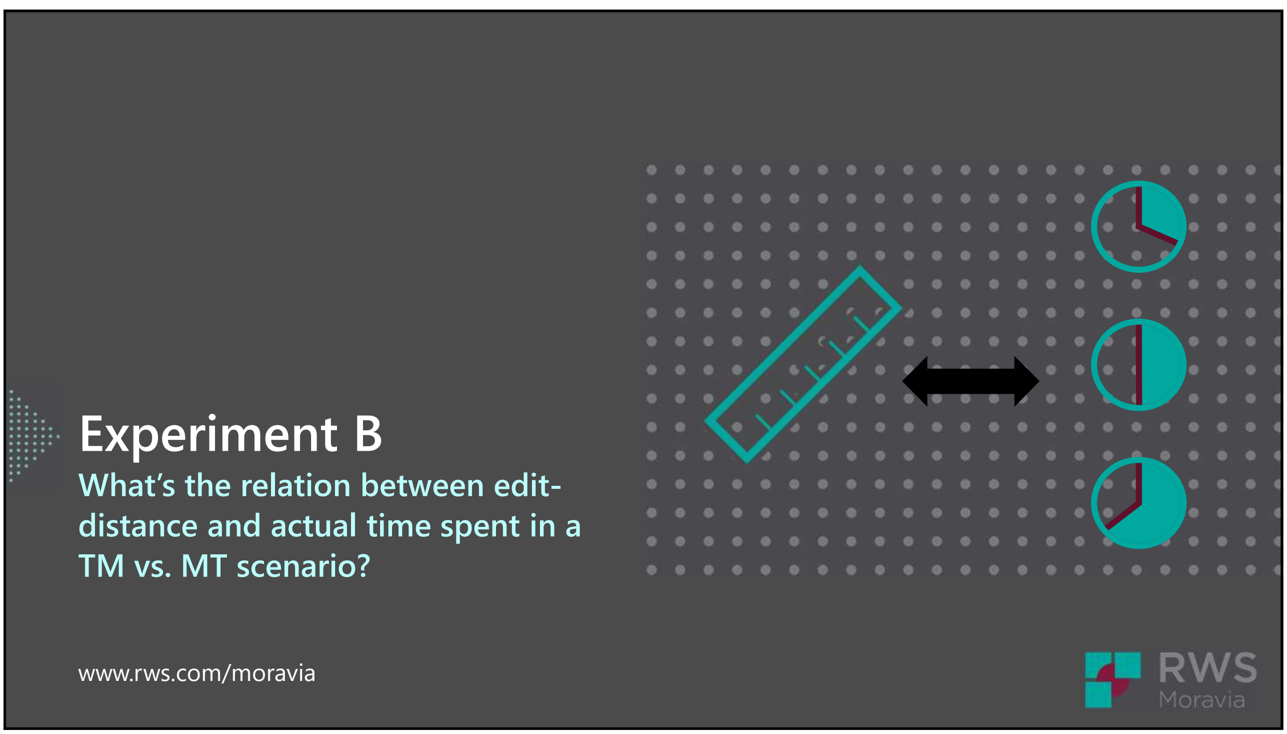

2
Which requires more editing overall:
MT generated segments OR
"fuzzy" TM matches in the
AND YOU CALL MT
"UNPREDICTABLE"
Spanish (LatAm)
Chinese (China)
TM Edits
MTPE
TER
0.79
0.38
0.08
0.49
0.25
0.00
0.72
0.30
0.00
0.46
0.23
0.04
0.62
0.32
0.05
0.51
0.34
0.13

13


Experiment B
What's the relation between edit-distance and actual time spent in a TM vs. MT scenario?
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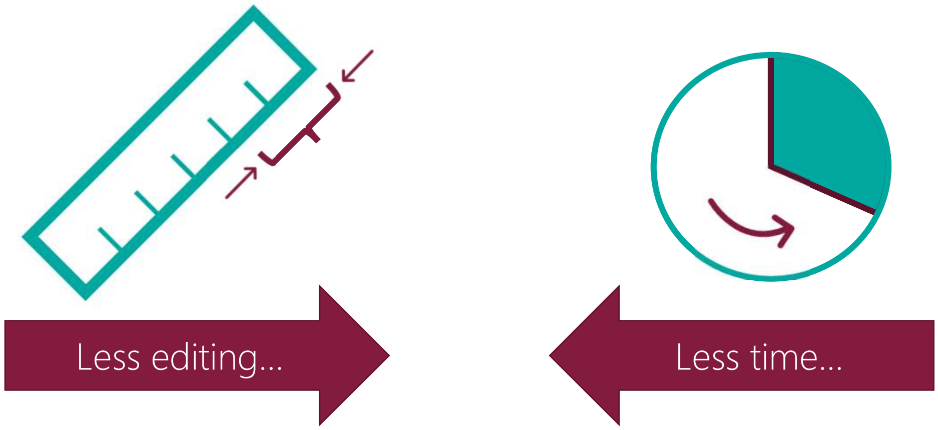
RWS
Moravia

16

Why this test?

Our “knee jerk” reaction when seeing less edit distance is…



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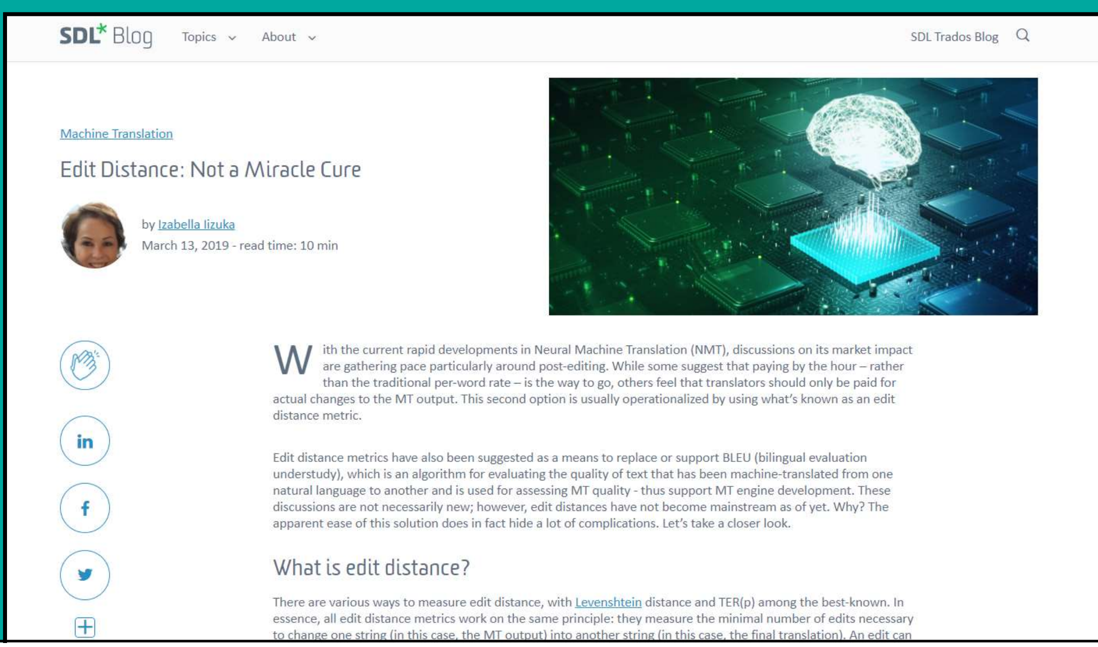

SDL* Blog Topics About SDL Trados Blog

Machine Translation

Edit Distance: Not a Miracle Cure

by Izabella Iizuka
March 13, 2019 - read time: 10 min

With the current rapid developments in Neural Machine Translation (NMT), discussions on its market impact are gathering pace particularly around post-editing. While some suggest that paying by the hour – rather than the traditional per-word rate – is the way to go, others feel that translators should only be paid for actual changes to the MT output. This second option is usually operationalized by using what’s known as an edit distance metric.

Edit distance metrics have also been suggested as a means to replace or support BLEU (bilingual evaluation understudy), which is an algorithm for evaluating the quality of text that has been machine-translated from one natural language to another and is used for assessing MT quality - thus support MT engine development. These discussions are not necessarily new; however, edit distances have not become mainstream as of yet. Why? The apparent ease of this solution does in fact hide a lot of complications. Let’s take a closer look.

What is edit distance?

There are various ways to measure edit distance, with Levenshtein distance and TER(p) among the best-known. In essence, all edit distance metrics work on the same principle: they measure the minimal number of edits necessary to change one string (in this case, the MT output) into another string (in this case, the final translation). An edit can

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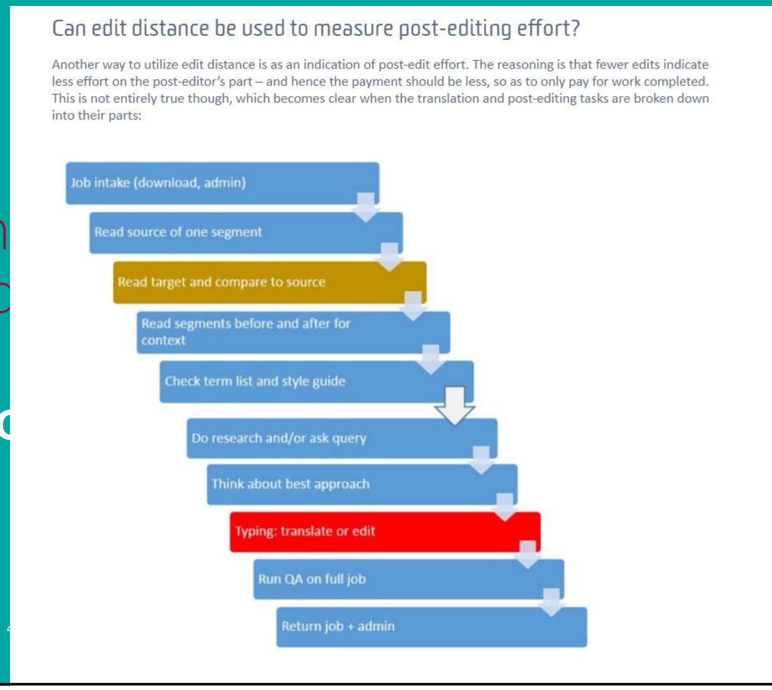
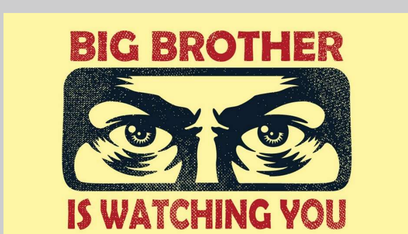
- Edit Distance: Not a Miracle Cure; March



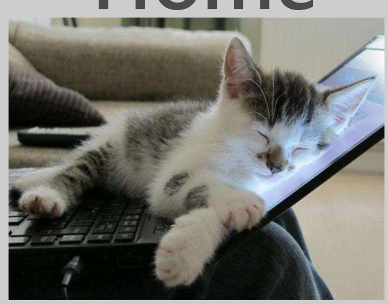
19

My one advantage in measuring for time…

Classroom



Home

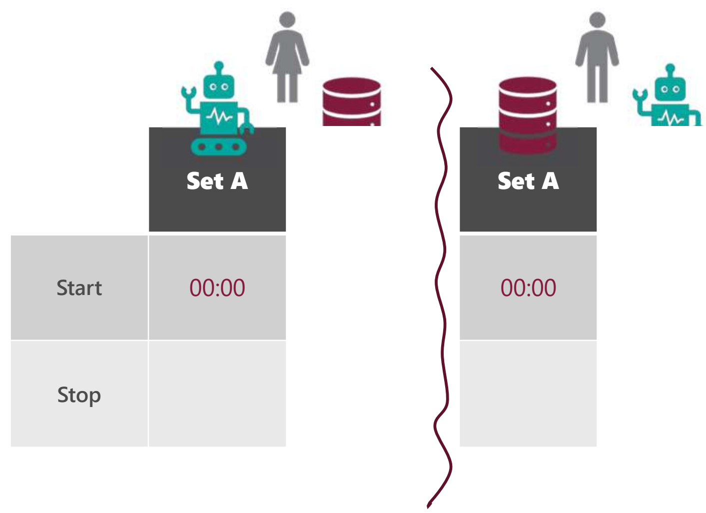


20

Methodology

- Begin stopwatch at start of translation with each set
- Pause timer and call instructor over when…
  - All segments confirmed
  - All terminology checks against the term database were cleared out (or personally verified as a "non-error")
  - All other automated quality checks that could be cleared out were completed (*capitalization, punctuation, number mismatches, etc*).
- If issue was spotted, unpause the timer and call instructor over again when fixed.
- Instructor writes down time of completion
- NOTE: there is no "control group" for this experiment

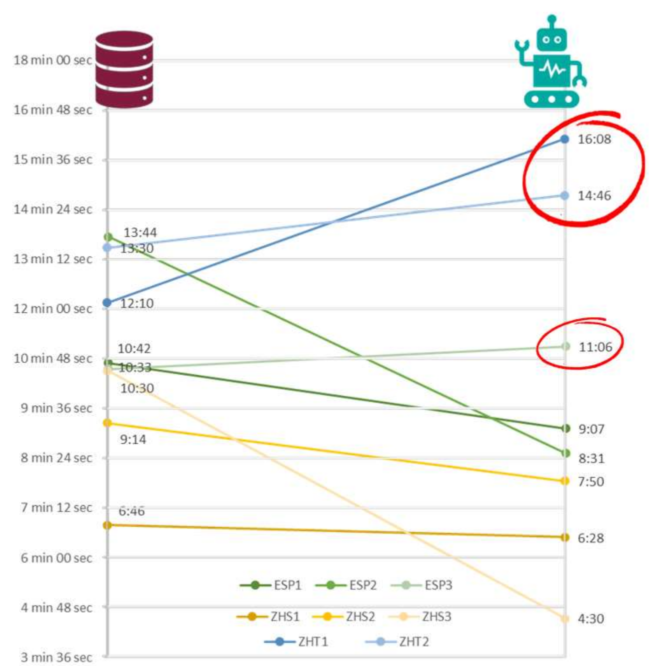
Every student has a stopwatch (i.e., phone) so easy to accommodate



22

1

When editing ~160 wds / 11 sentences of content, which takes less time:
"fuzzy" TM edits (89%-69%)
or **MTPE**?



23

More time... More editing?

When asked "why" they spent more time on MTPE than TM edits...

"TM was easier because the sections to change are clearly marked so I only needed to cut out minor sections."

ESP3

TM	MT
.20	.22

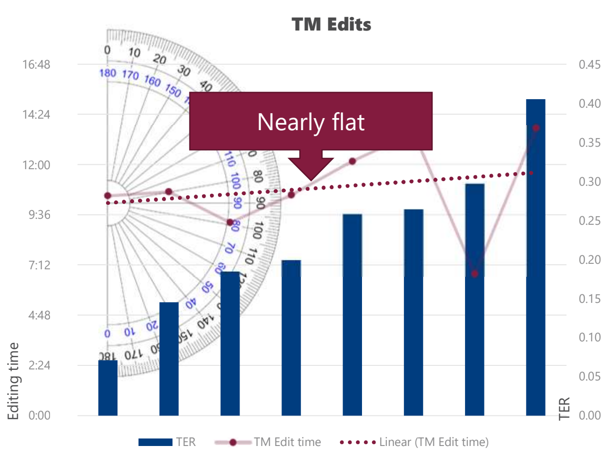
"spent a lot of time looking up the proper terms for Taiwan since the MT kept giving Chinese for mainland China, but in traditional characters."

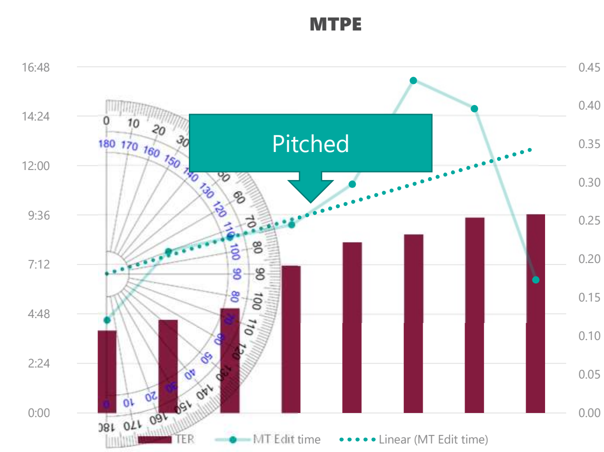
ZHT1 & ZHT2

TM	MT
.26	.23
.26	.25

24

2 Is there a matching correlation between edit-distance and time spent fixing segments for both "low fuzzies" and MTPE?

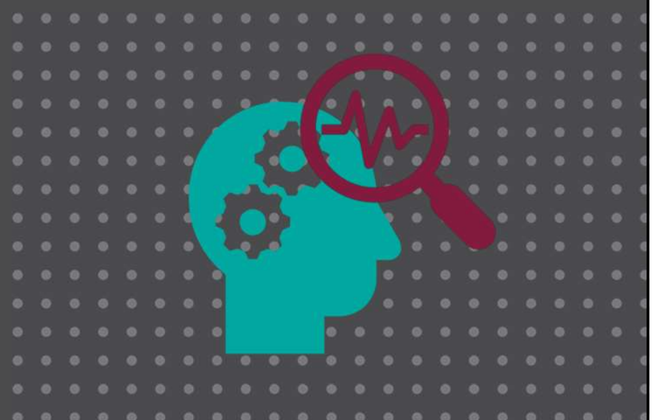




***No matter the level of editing, the time spent is fairly constant.* Conclusion: It's faster to figure out what to edit with TM fuzzies.**

..whereas with MT, time spent does goes up with increasing edit-distance.

26



Subjective Experiments

What's the "experience" when working with MT?

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RWS Moravia

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What did you prefer?

PE of wholly generated raw MT output OR
a trained "adaptive" MT system where you had control over the output

Nearly 50/50 in a show of hands every year since 2016

…those who prefer "adaptive MT" are nearly always Romance language speakers

28

I've mixed the reference translations in with raw MT from 4 major engines.
Which do you think is human?

Students are given homework the week before to provide multiple sentences of human-made content (bilingual) that *they believe* will be "tough" for MT.

Poor Tom Fool, yonder behind the wagon, mumbling his bone with the honest family which lives by his tumbling.	可憐的湯姆·帕爾，馬車後面的遠處，他的骨頭與他的翻滾生活的誠實家庭喃喃自語。	可憐的湯姆·傻瓜，就在馬車後面，嘴裡咕噥著他的骨頭和靠他跌倒生活的誠實家庭。	可憐的湯姆·富爾（Tom Fool）身處馬車後面，與誠實的家庭糊塗骨頭，誠實的家庭靠他的翻滾生活。	可憐的湯姆·愚人，在馬車後面，喃喃自語與誠實的家庭，這是由他的翻滾。	再過去是可憐的小丑湯姆躲在貨車後頭帶著一家老小啃骨頭，這些老實人就靠他翻筋斗賺來的錢過活。
The young lady's countenance, which had before worn an almost livid look of hatred, assumed a smile that perhaps was scarcely more agreeable.	只是這笑容比起方才惡狠狠鐵青的臉色來，也好看不了多少。	這位年輕女士的臉容，曾經穿著一種幾乎鮮豔的仇恨外表，假設一個微笑，也許幾乎沒有比較愉快。	這位年輕女士的面容，以前帶著近乎憤怒的神情，露出了一絲可能更討人喜歡的微笑。	這位年輕女士的臉上以前帶著幾分仇恨的鐵青色，現在露出了一種也許再好不過討人喜歡的微笑。	這位年輕女士的容顏曾帶過幾乎幾乎是充滿生氣的仇恨表情，但露出了微笑，這也許簡直讓人難以接受。
The world is a looking-glass, and gives back to every man the reflection of his own face.	這世界是一面鏡子，每個人都可以在裡面看見自己的影子。	這個世界是一個展望的玻璃，並將自己臉上的反射回饋給每個人。	世界是一面鏡子，把自己臉上的倒影還給每個人。	這個世界是一個窺視鏡，並且將每個人的面孔反射給每個人。	世界是一個看起來玻璃，並回饋每個人自己的臉的反射。
A very stout, puffy man, in buckskins, and Hessian boots, with several immense neckcloths that rose almost to his nose.	他穿著鹿皮褲子，筒上有流蘇的靴子，圍著好幾條寬大的領巾，幾乎直聳到鼻子。	一個非常健壯，浮腫的男人，穿著鹿皮，黑森靴，幾條幾乎高到鼻子的大領巾。	一個非常粗壯，浮腫的人，在雄鹿，和黑森靴子，與幾個巨大的頸布，幾乎上升到他的鼻子。	一個非常粗壯，浮腫的男人，在牛皮和黑森靴子，幾乎上升到他的鼻子幾乎巨大的領口。	一個非常矮胖，矮胖的人，穿著鹿皮和黑森州的靴子，幾條巨大的圍巾圍在他的鼻子上。

Fall 2019 = 1st time students in a language group (Spanish) chose MT generated output over the human reference text

29

I'm looking for your ideas…

30

Q&A

31

STAR

Your single-source communication partner for products and services

AMTA VIRTUAL 2020

Use MT to Simplify and Speed Up Your Alignment for TM creation

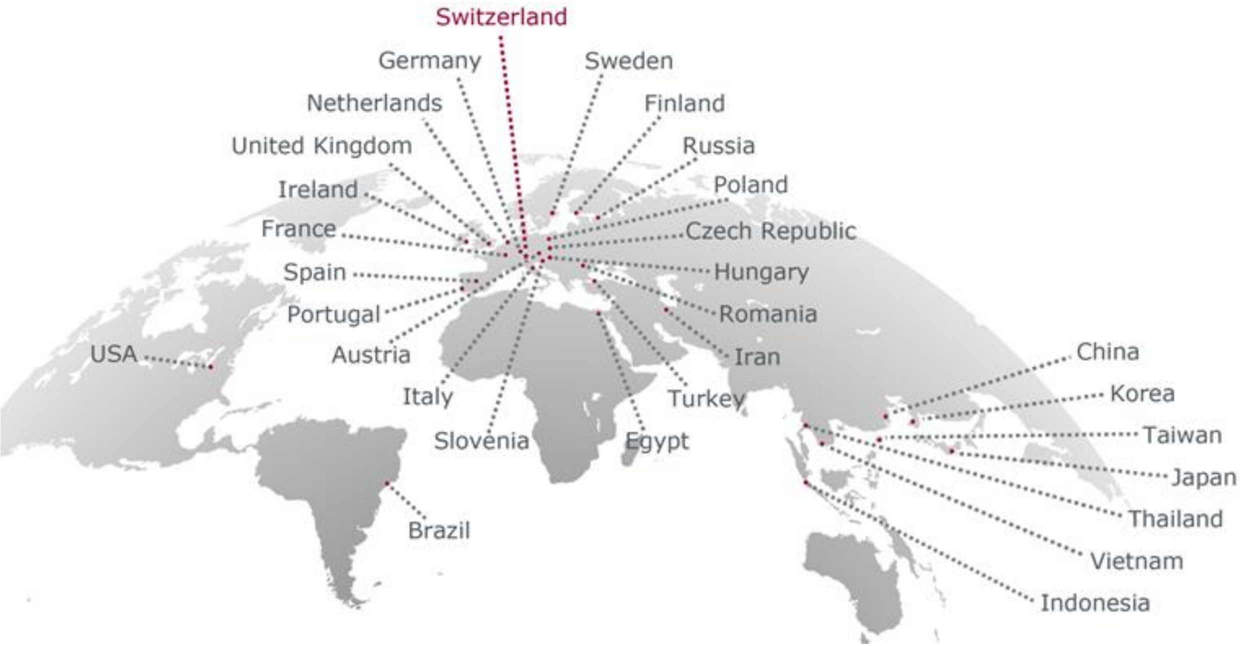
Judith Klein, STAR Group

Judith.Klein@star-group.net

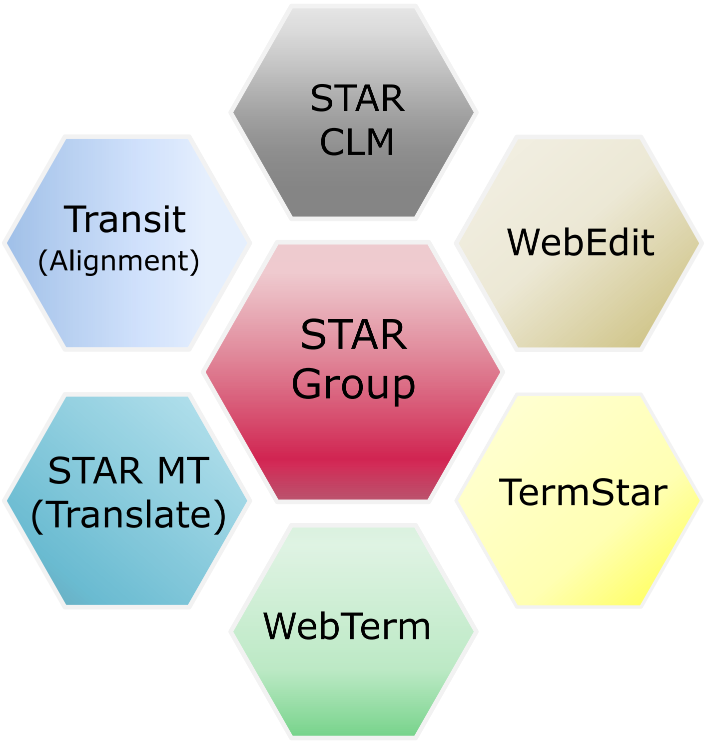
- Motivation
- TMs for CAT Tools
- MT-based Alignment
- Workflow for MT-Aligned TM
- Conclusion

STAR Group (since 1984)

- Translation Services & Translation Technology



STAR's Translation Technology

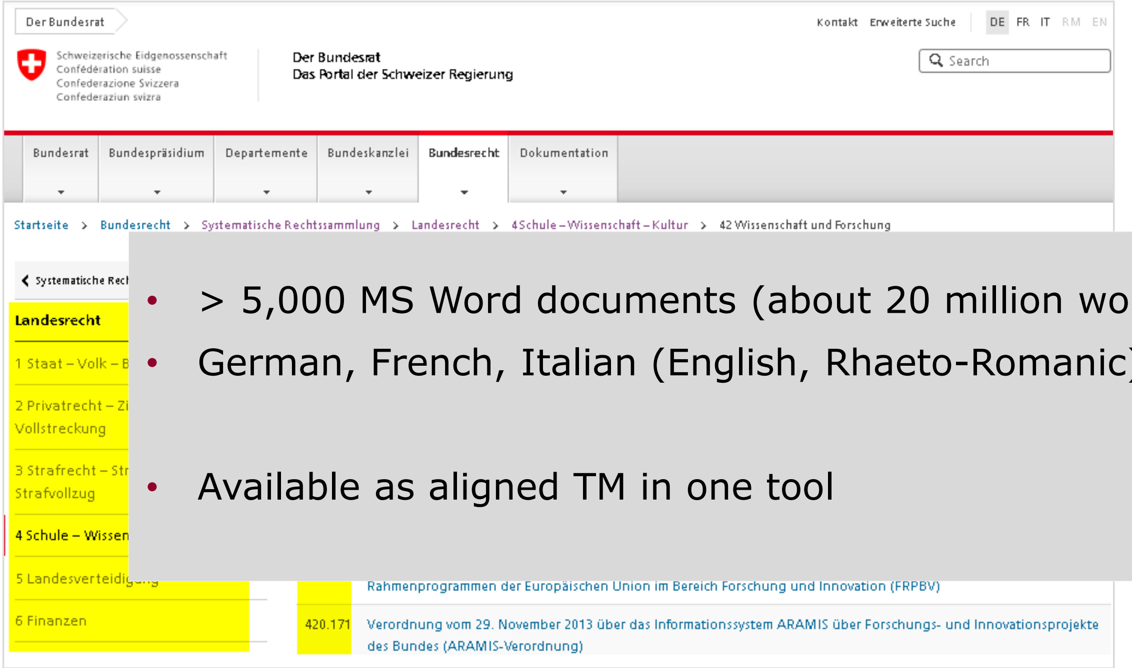


Swiss Federal Administration (Bund)

- 8 departments, 80 offices, 450 language experts
  - Federal Chancellery (BK)
  - Foreign Affairs (EDA)
  - Home Affairs (EDI)
  - Finance (EFD)
  - Justice and Police (EJPD)
  - Environment, Transport, Energy and Communications (UVEK)
  - Defense, Civil Protection and Sport (VBS)
  - Economic Affairs, Education and Research (WBF)
- German, French, Italian, Rhaeto-Romanic, English
- Different tools
- Huge amounts of language resources (translation pools, termbases)

Systematic Collection of Legislation (SR)

Systematic Collection of Legislation (SR)

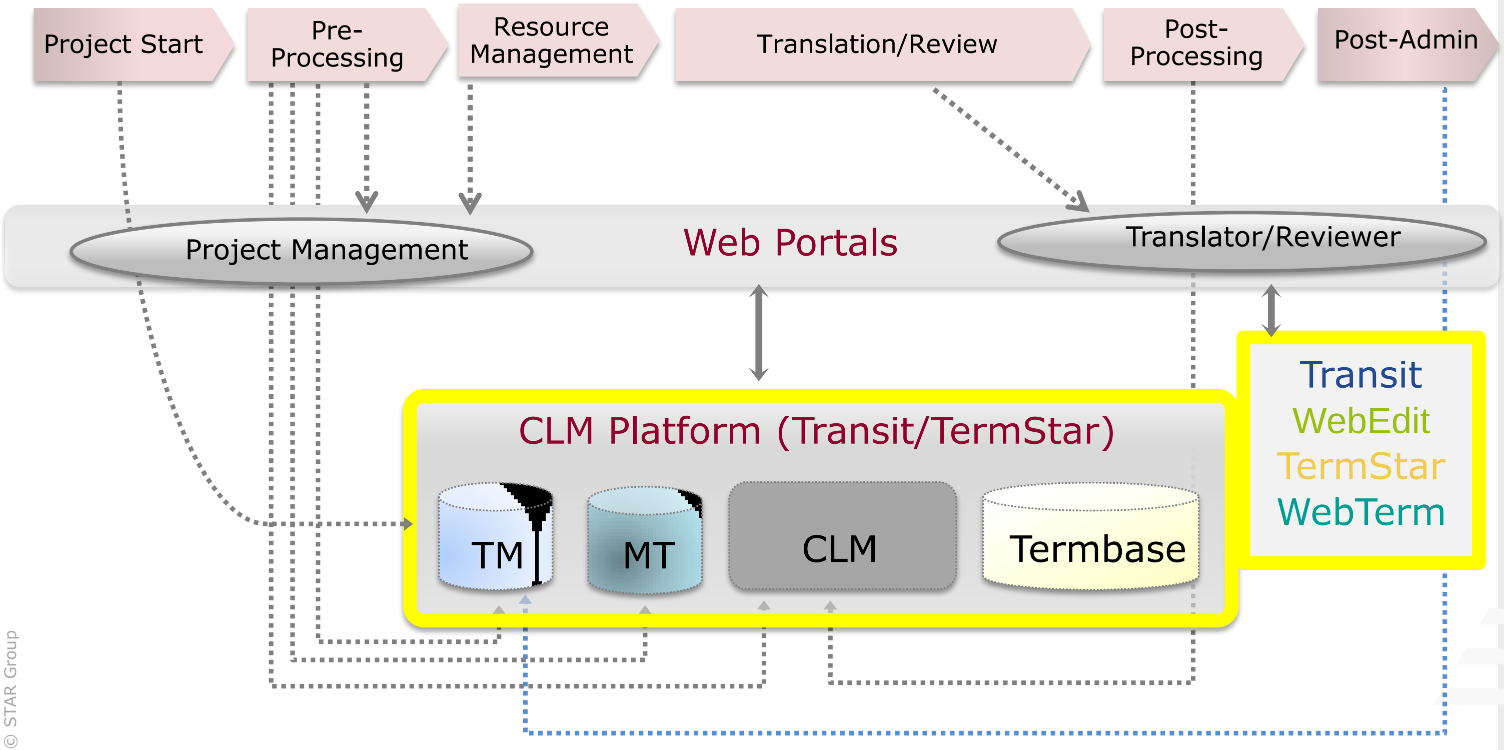


- > 5,000 MS Word documents (about 20 million words)
- German, French, Italian (English, Rhaeto-Romanic)
- Available as aligned TM in one tool

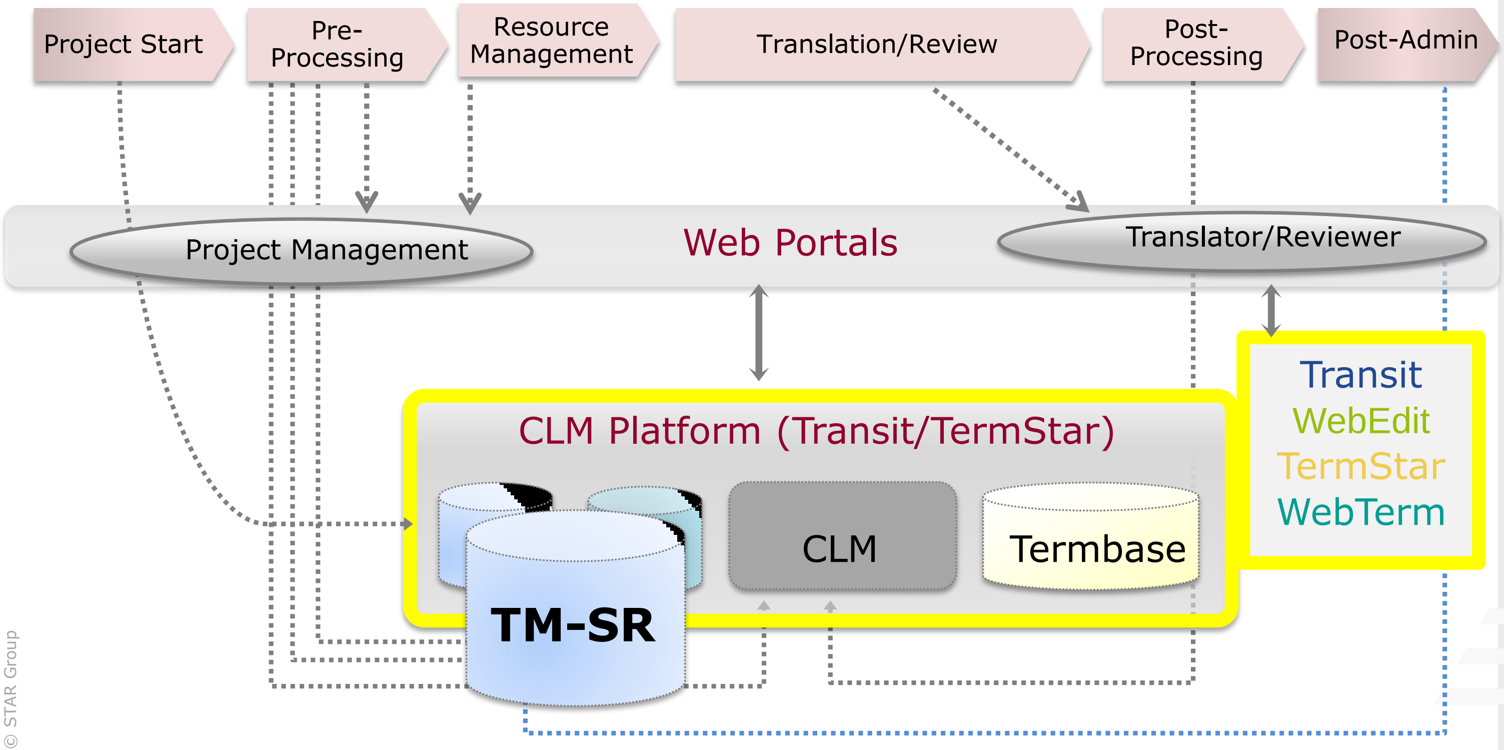
SR as TM for all Departments

- Aim
  - Multi-lingual and multi-directional translation memory
  - Access for all departments in the same way
  - Use in CAT tool for all search functions
- Solution
  - Standard translation workflow solution
  - Fully automated machine alignment
  - Fully automated update-workflow every three month

Standard Translation Workflow Solution

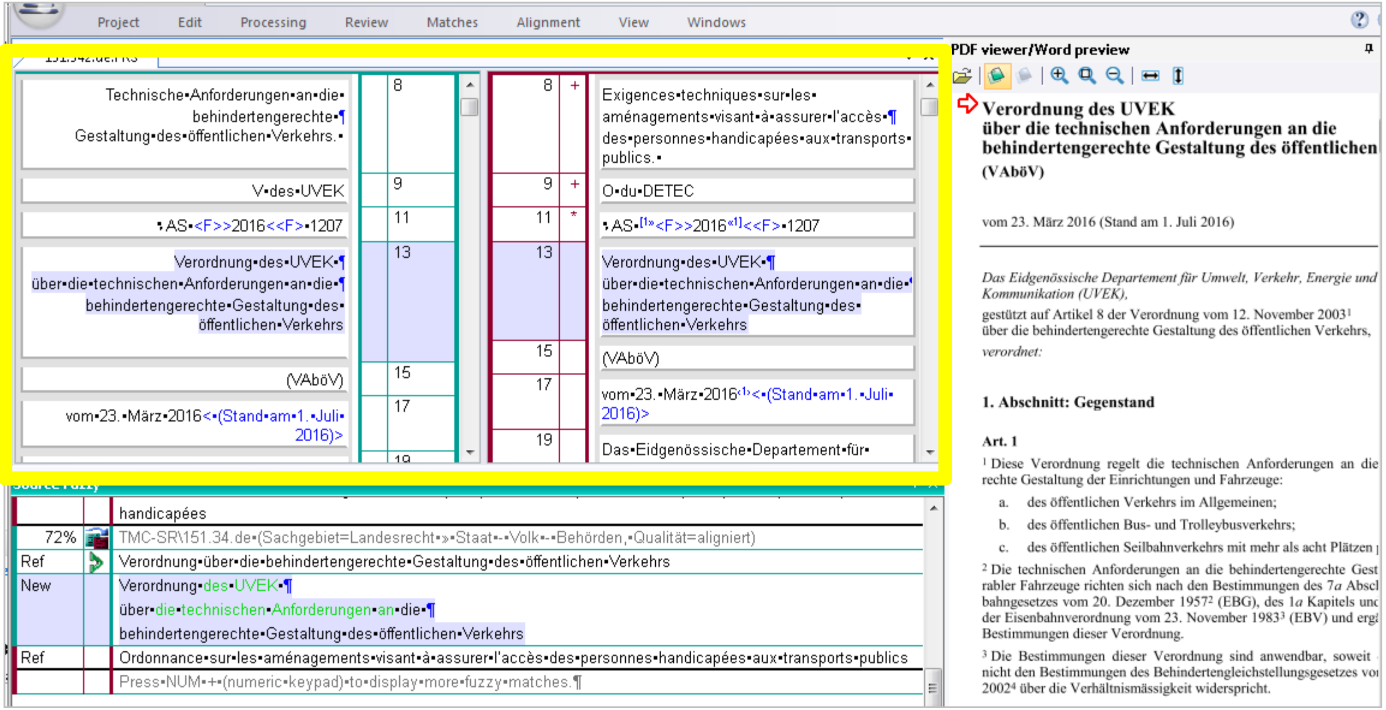


Standard Translation Workflow Solution

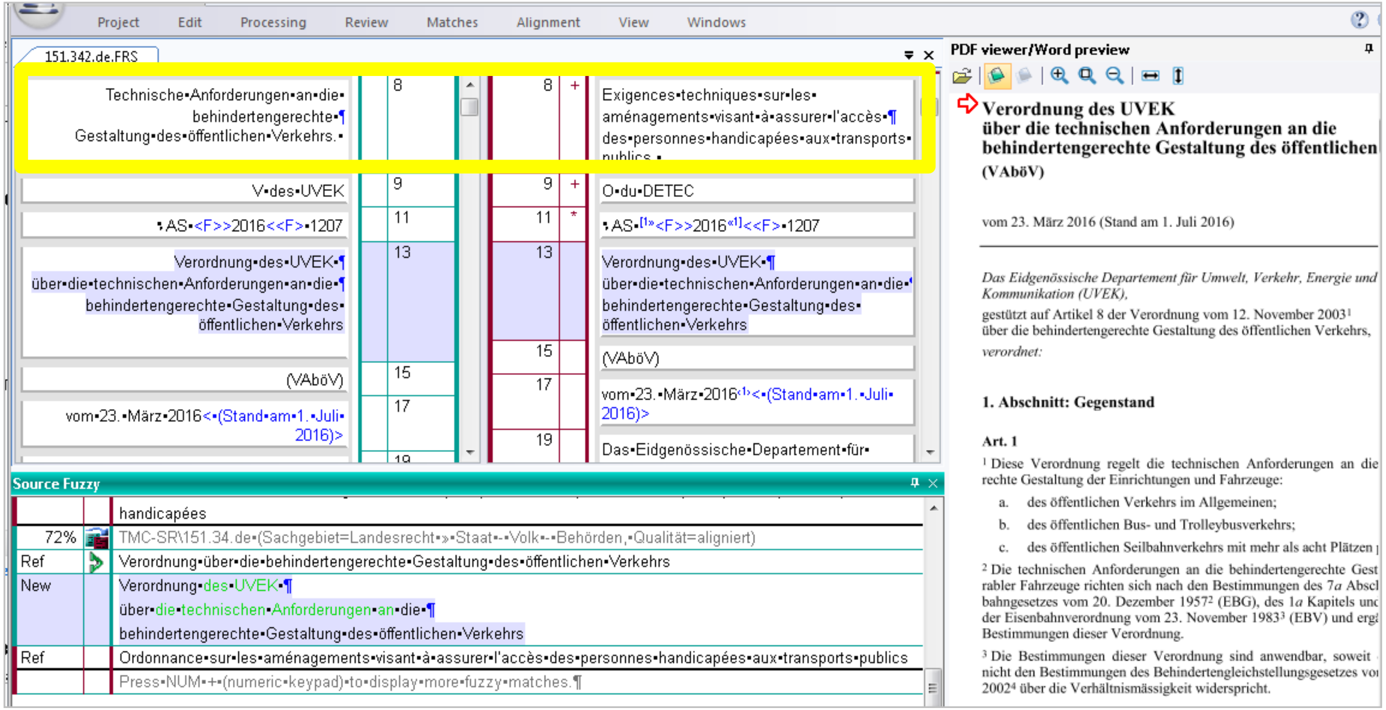


10

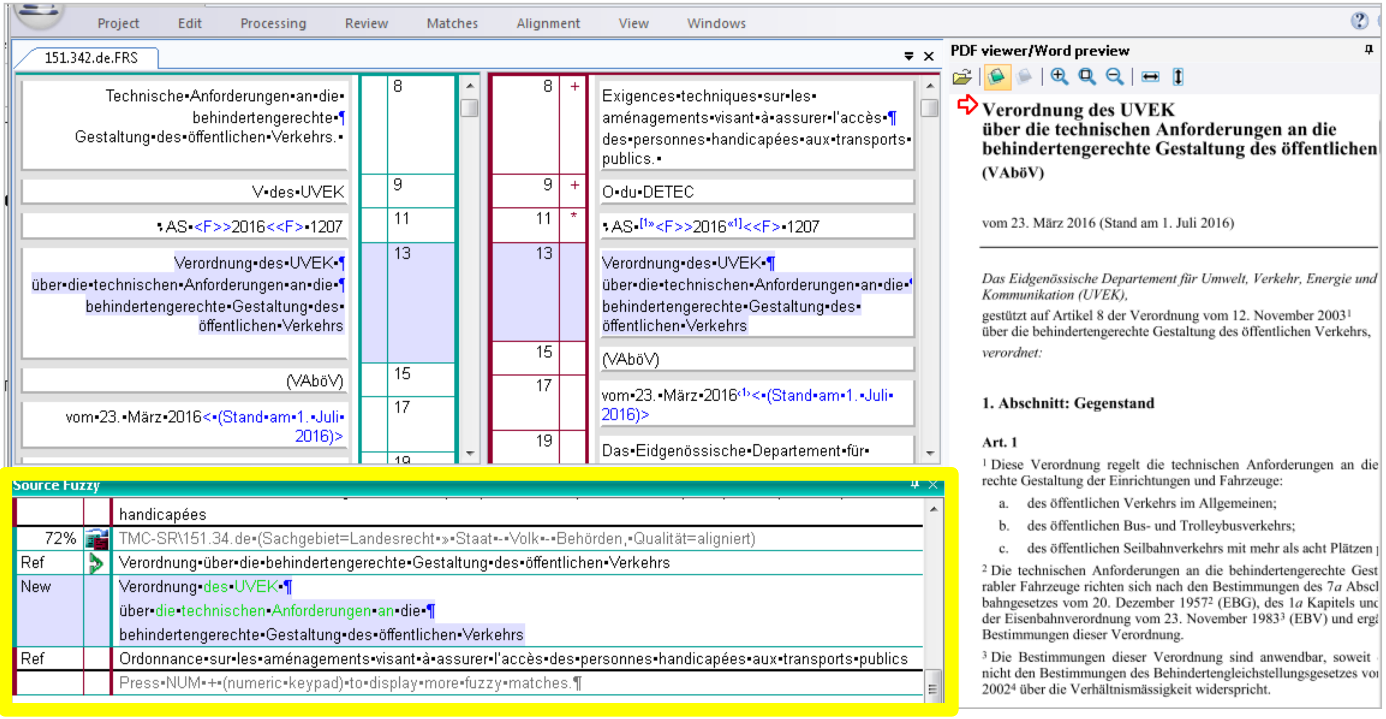
CAT Tool – Segments & Document Context



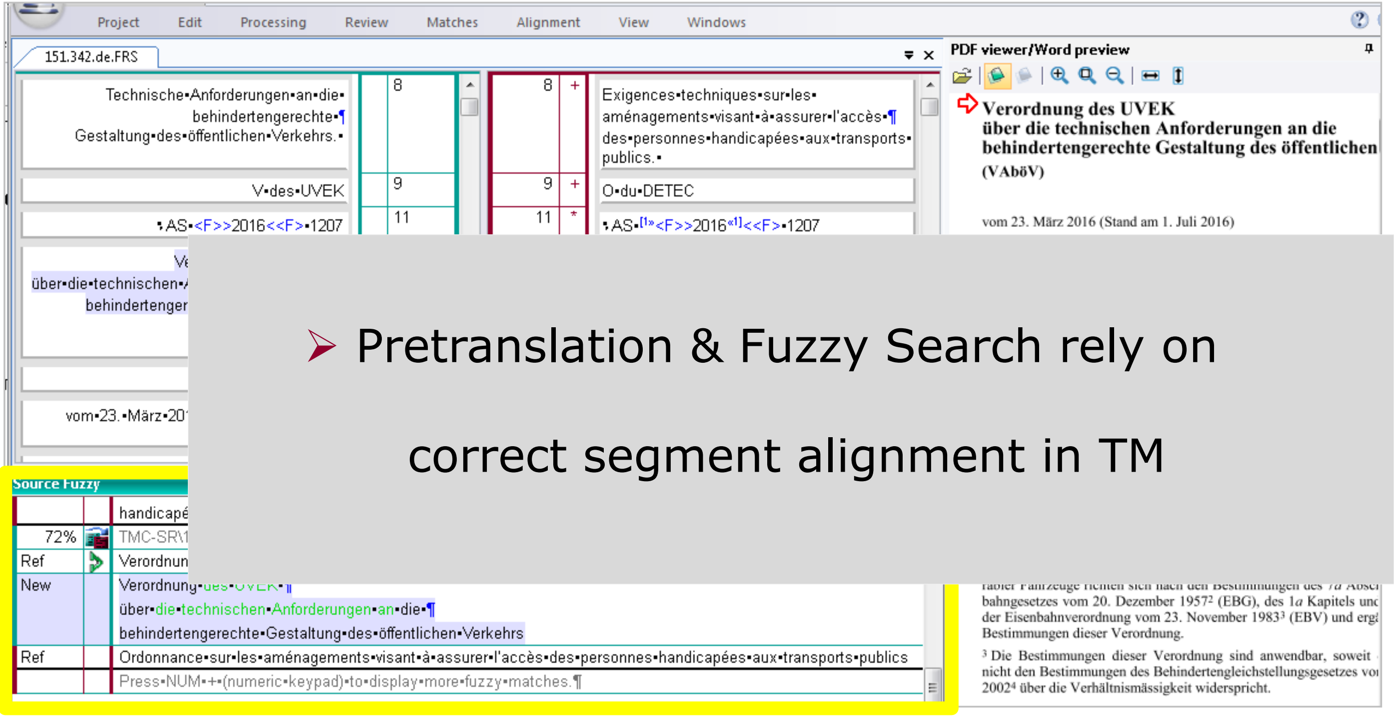
CAT Tool – 100% Matches & Pretranslation



CAT Tool – Fuzzy Matches

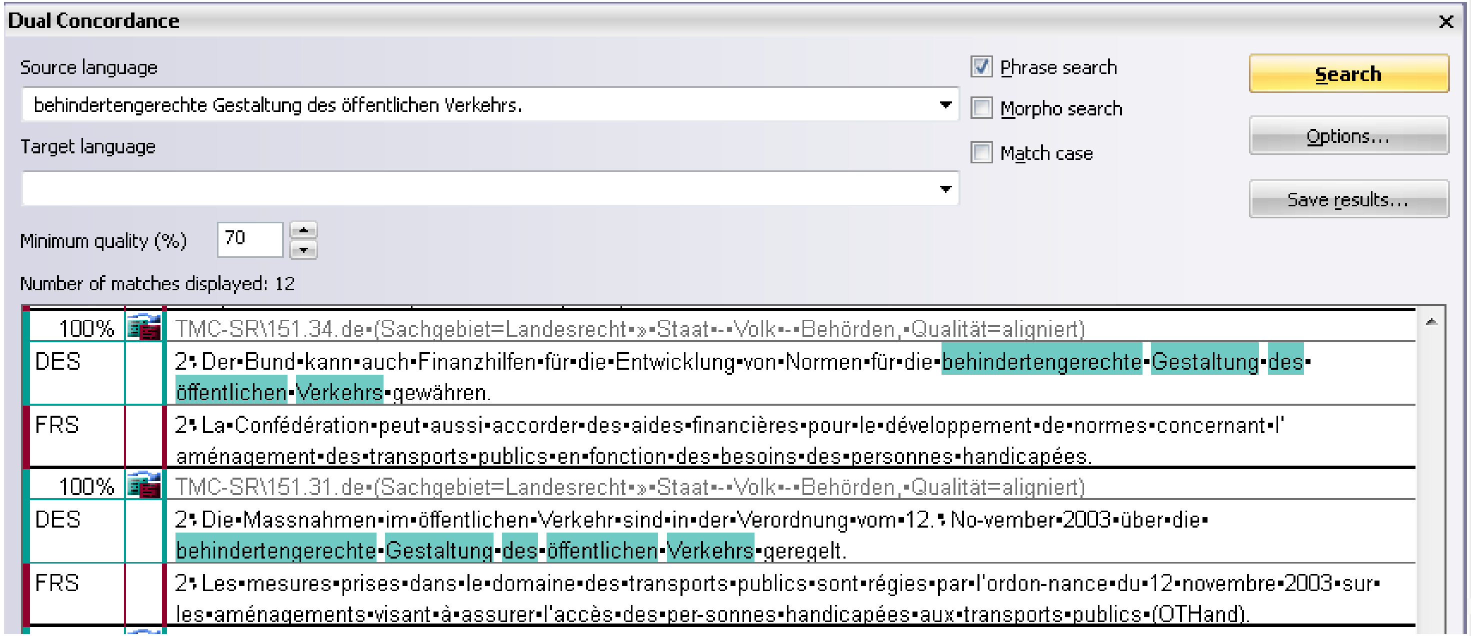


CAT Tool

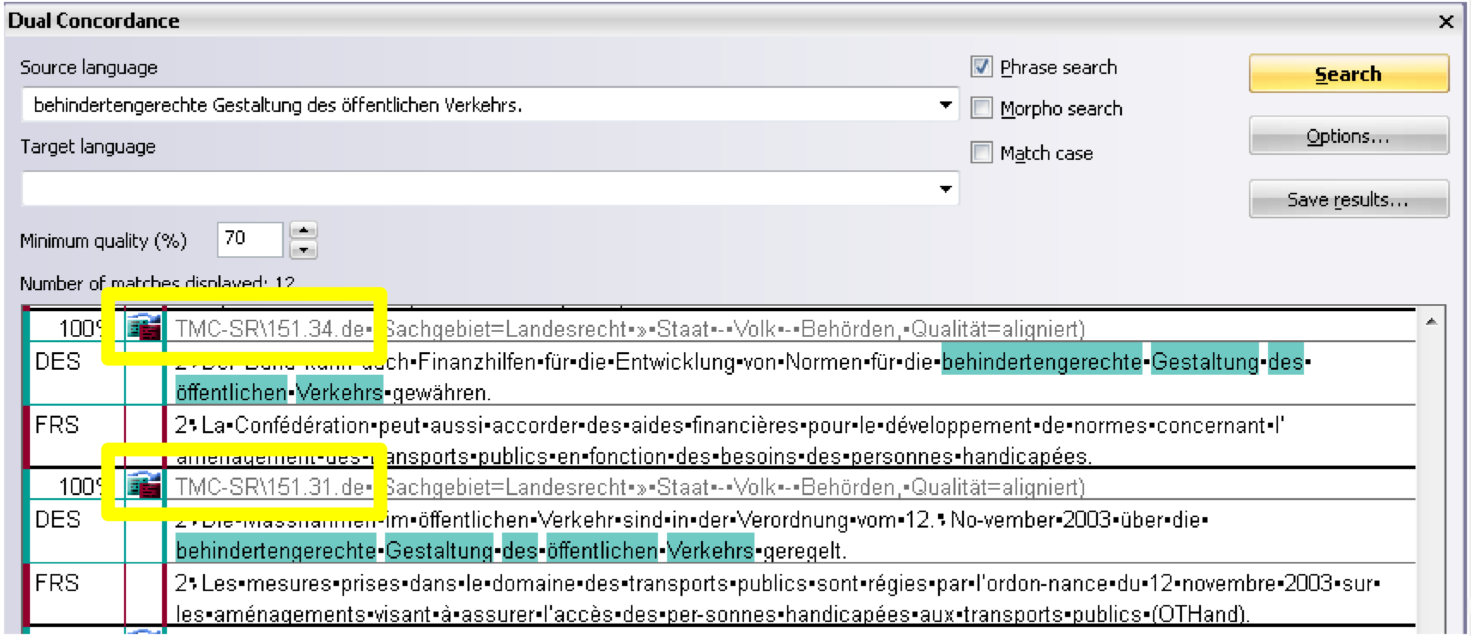


➢ Pretranslation & Fuzzy Search rely on correct segment alignment in TM

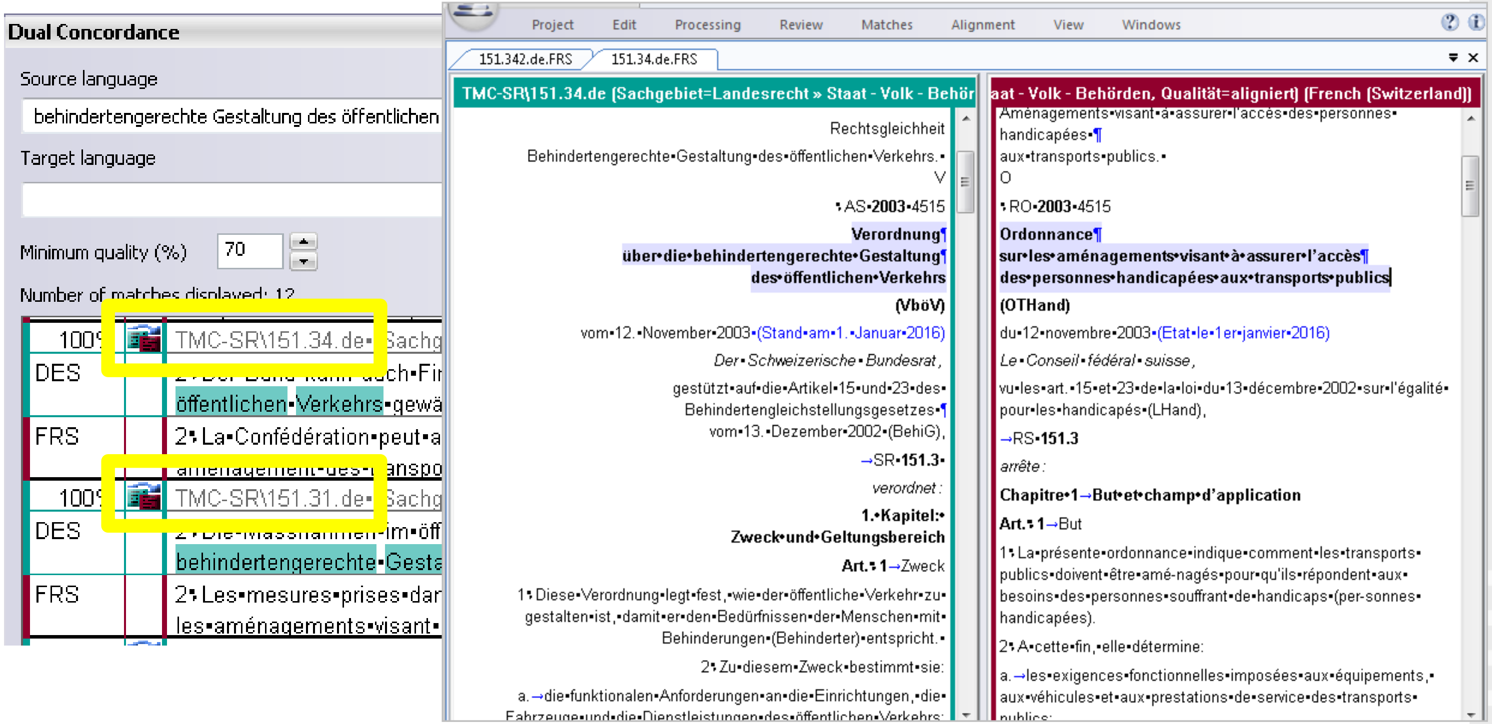
CAT Tool – Concordance Search



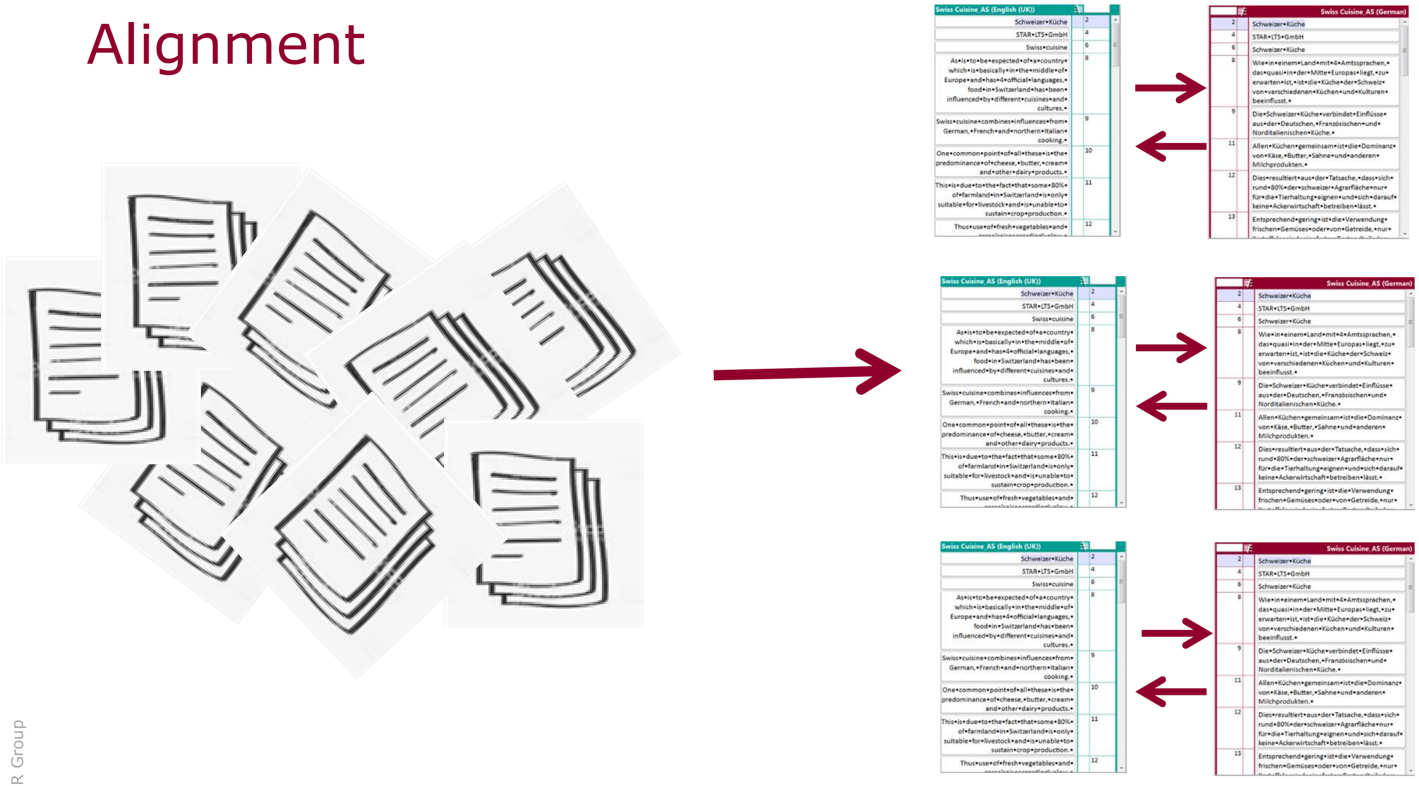
CAT Tool – Concordance Search



CAT Tool – Matches & Document Context



Alignment



Why not MT instead?

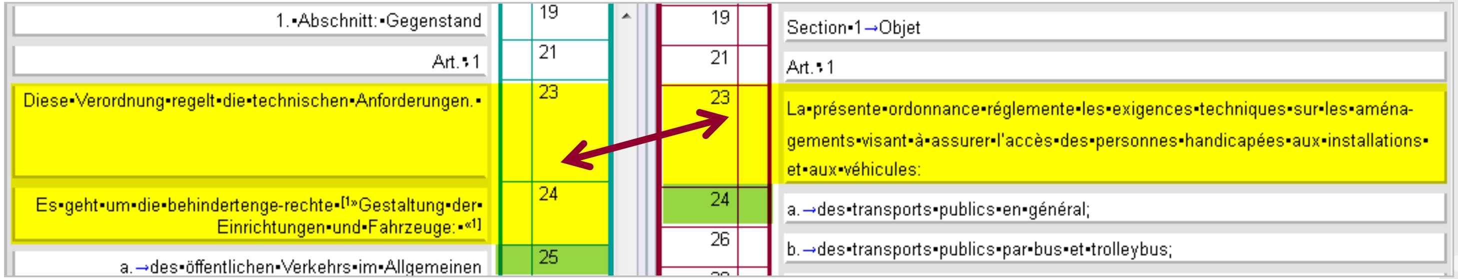
- Documents approved by linguists and law professionals
- Specific terminology usage and meaning depending on sub-areas
- Consistent translation required for same/similar sentences
- Look-up text and translation of specific law (e.g. file 151.342)

- MT often very well – but different
- MT can be identical by chance – but not reliably so

- Systematic Collection of Legislation must be available as it is!

CAT Tool & Alignment

- Formatting
- Linguistic
- 1 <> many, 0<> 1 , different order



CAT Tool & Alignment

- Alignment projects with file alignment
- Import and calculate alignment probability
- Formal (sentence length, numbers, formating, characters,…)
- Lexical (unchanged words, dictionary entries, word lists)

STAR Transit & TM-based Alignment

- Translation Memory segments for alignment
  - Search in TM for segment that is to be aligned
  - Compare translation from TM with alignment candidate
  - Use similarity score as most important value for probability
  - Transit fuzzy algorithms to calculate the similarity

- But – no TM available for the Systematic Collection of Legislation

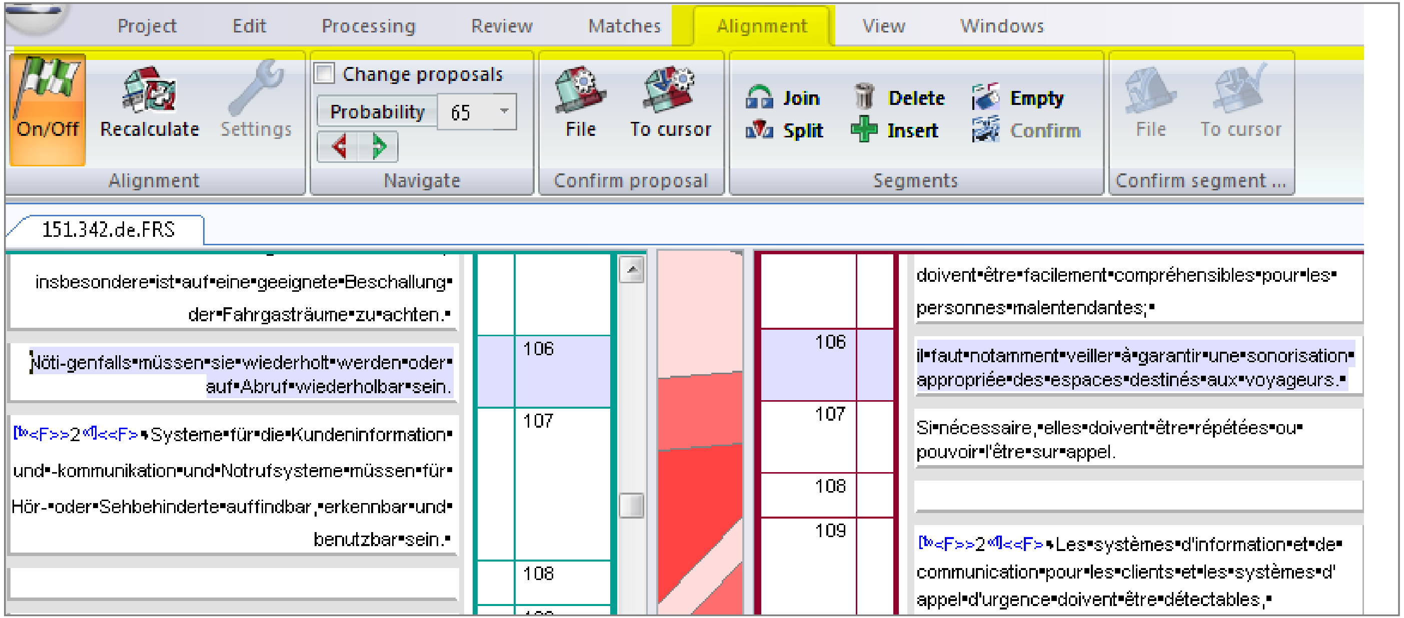
STAR Transit & MT-based Alignment

- Use MT !
- Transit fuzzy algorithm as with TM segments
  - MT-based sentence alignment (Sennrich & Volk, AMTA 2010)
  - BleuAlign used in BiTextor within Paracrawl project

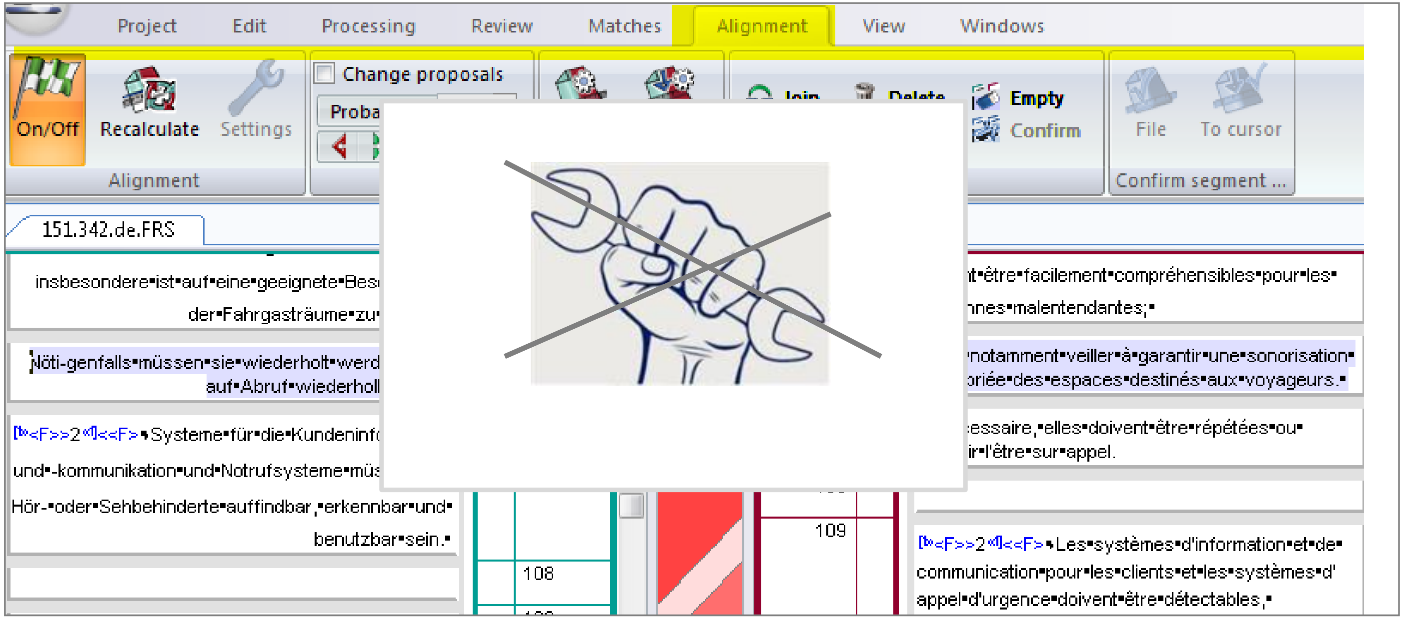
- MT quality per se not so important
- Similarity to decide if two sentences are translation of each other

- MT interfaces available
- MT system selection (DeepL)

Interactive Alignment



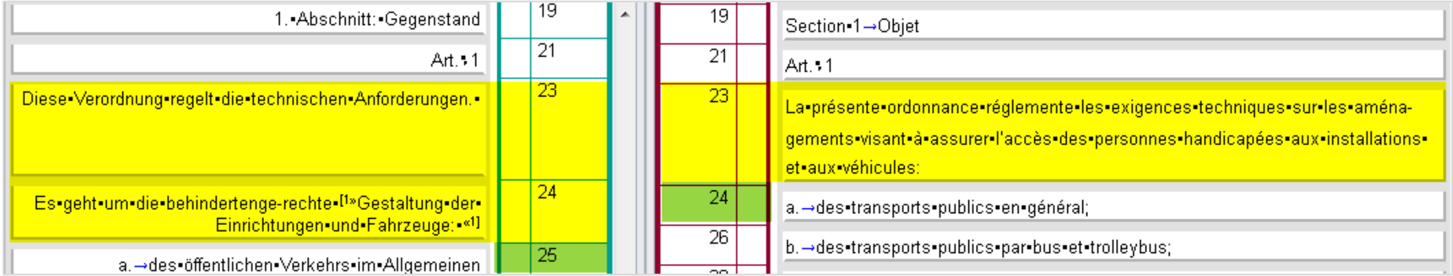
Interactive Alignment

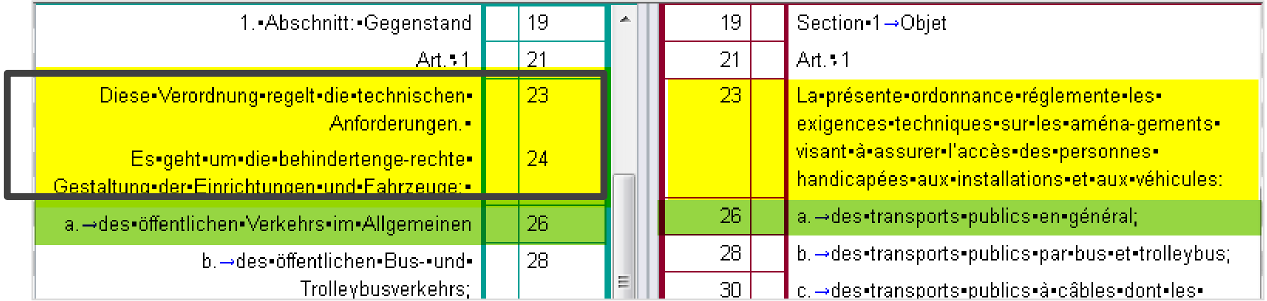


Machine Alignment in Transit

- One environment, no separate tool necessary
  - Transit & Alignment tool for project specification
  - Transit MT interface for fast processing
- Steps:
  - Import, machine translation, translation comparison, calculation
  - Automatic alignment
    - top-down process
    - paragraph tags as anchors
    - 100% similarity as strongest anchors within paragraphs

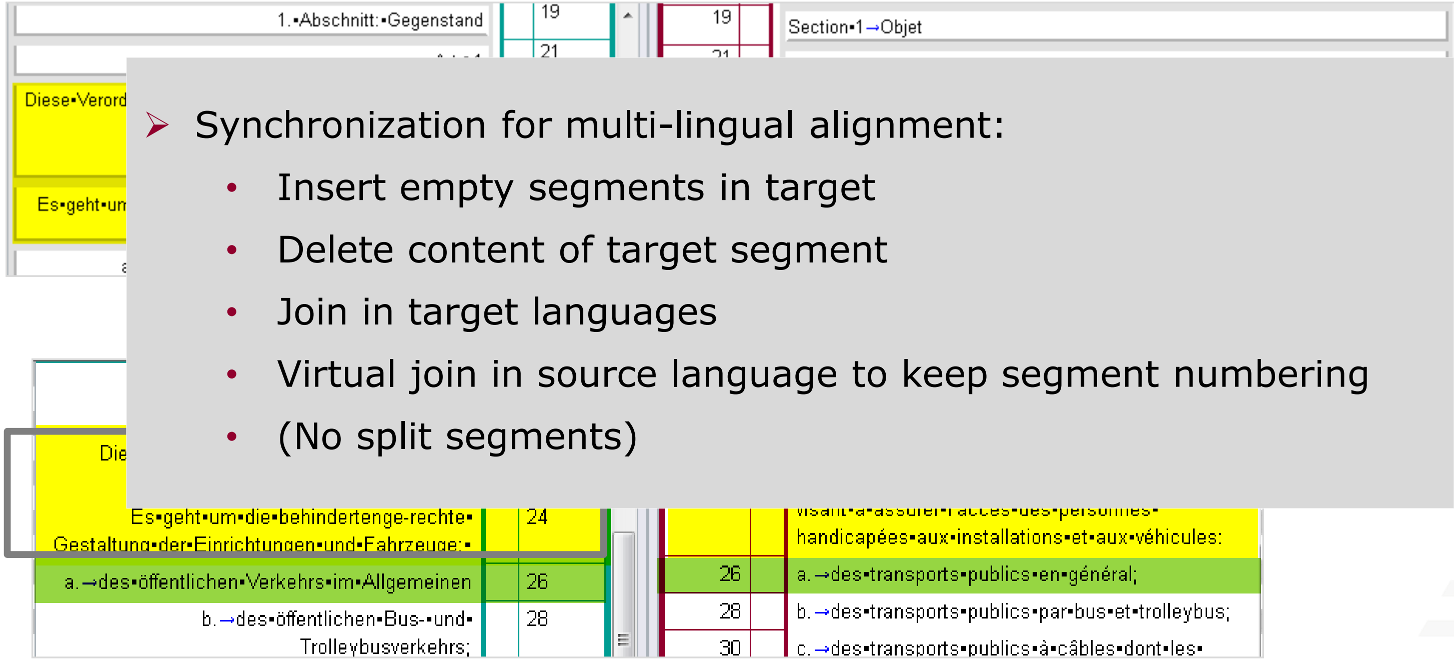
Machine Alignment



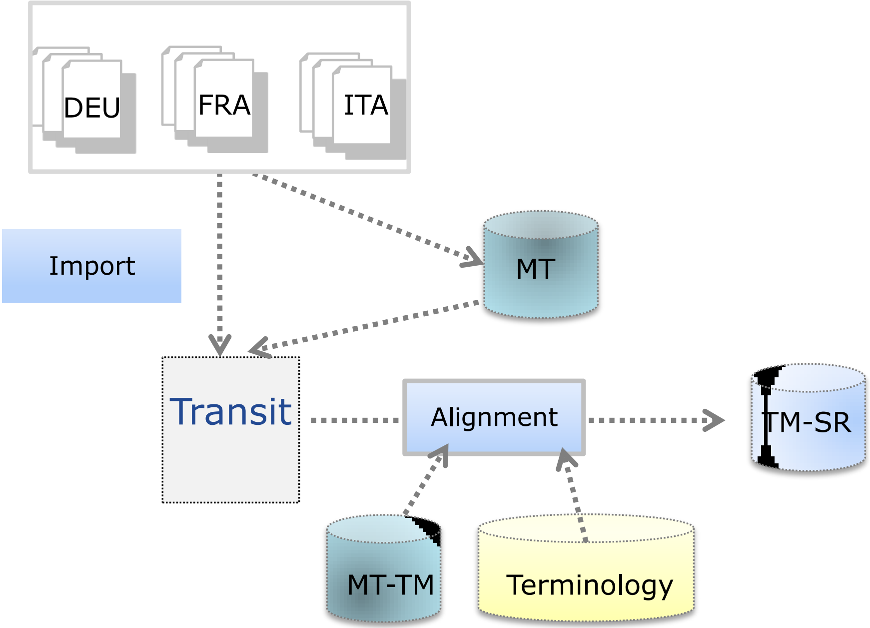


Machine Alignment

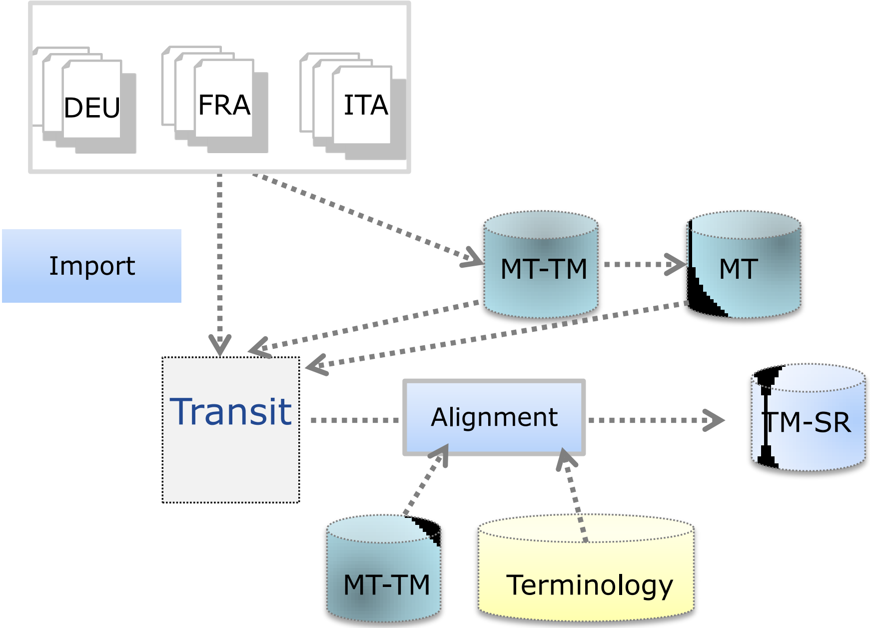
- Synchronization for multi-lingual alignment:
  - Insert empty segments in target
  - Delete content of target segment
  - Join in target languages
  - Virtual join in source language to keep segment numbering
  - (No split segments)



Workflow for MT-Aligned TM-SR



Workflow for MT-Aligned TM-SR

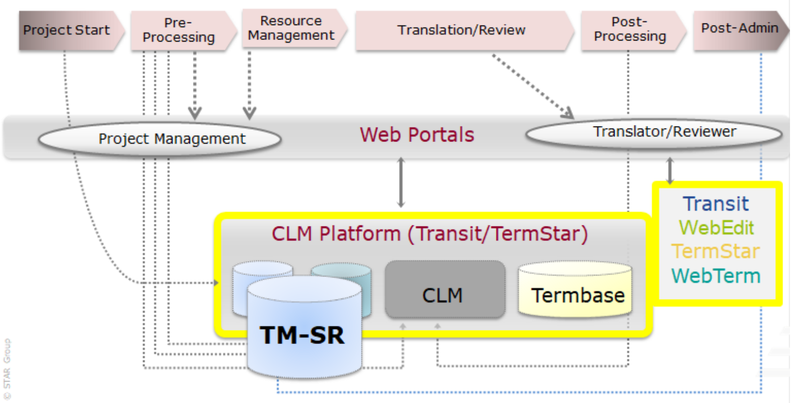


Workflow for MT-Aligned TM-SR

- Delta process for next delivery
  - Automatic file comparison
  - Only new and modified documents are processed
  - Deleted files automatically deleted from TM-SR

Conclusion

- Machine alignment integrated Transit feature
- Smooth interaction of Transit, Alignment tool and MT interface
- Random evaluation of machine aligned documents promising
- Use for search functions in CAT tool possible but restricted
- TM-SR is available for all users in standard translation environment



STAR

Your single-source communication partner for products and services

AMTA VIRTUAL 2020

Thank you!

Judith Klein, STAR Group

Judith.Klein@star-group.net

Selection of MT Systems in Translation Workflows

Aleš Tamchyna

October 8, 2020

MEMSOURCE

OUTLINE

- Introduction, motivation
- MT Quality Across Domains
- Approaches to MT Selection
- Conclusion

INTRODUCTION

- MT quality has been steadily improving in the past few years

- MT can be very beneficial in translation
  - In some scenarios, MT can be used with little or no post-editing
  - MT can be a useful starting point for post-editing

- There are many commercial MT providers to choose from
  - Quality of MT systems varies across languages or domains
  - It is difficult to decide ahead of time which system is optimal for a project

ABOUT MEMSOURCE

- Cloud-based translation management system
- Customers use Memsource to manage the localization process and to produce translations
- We want to provide high-quality MT by default so that our users can benefit from MT as much as possible

MT Quality Across Domains

MEMSOURCE

METHODOLOGY

- Domains were defined using unsupervised machine learning on aggregate customer data, labels assigned manually
    - For non-English source languages, internal MT into English is applied first

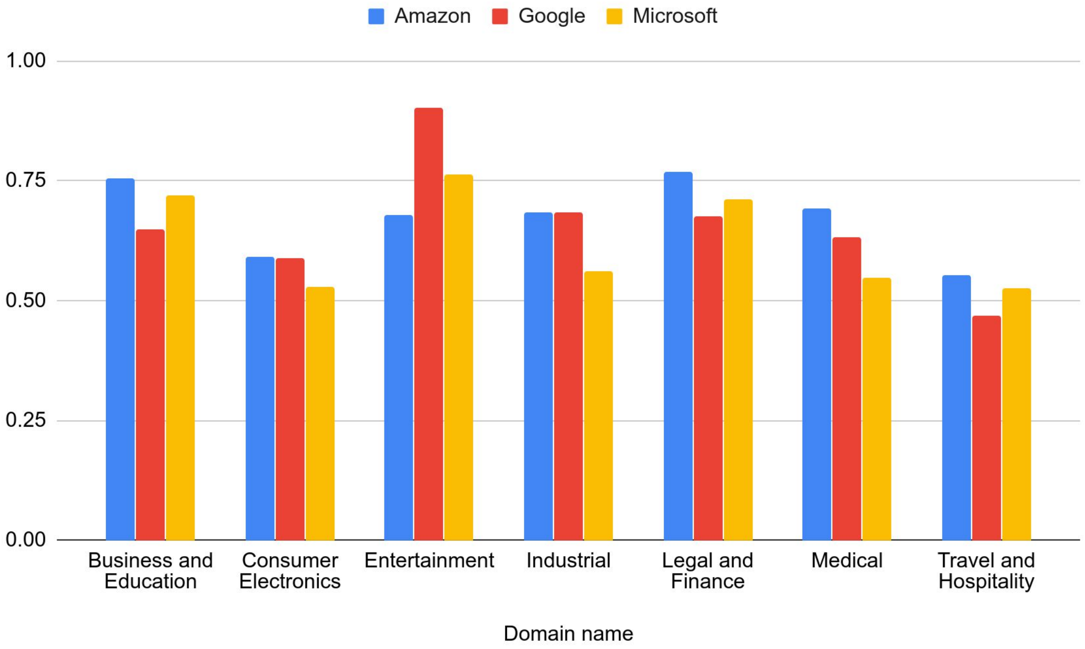
- Domains contain data from multiple customers

- MT engines are assigned to documents using Memsource Translate
    - Eliminates bias of customer preference for specific engines
    - Given enough data points, we can assume inputs for each MT system are i.i.d.

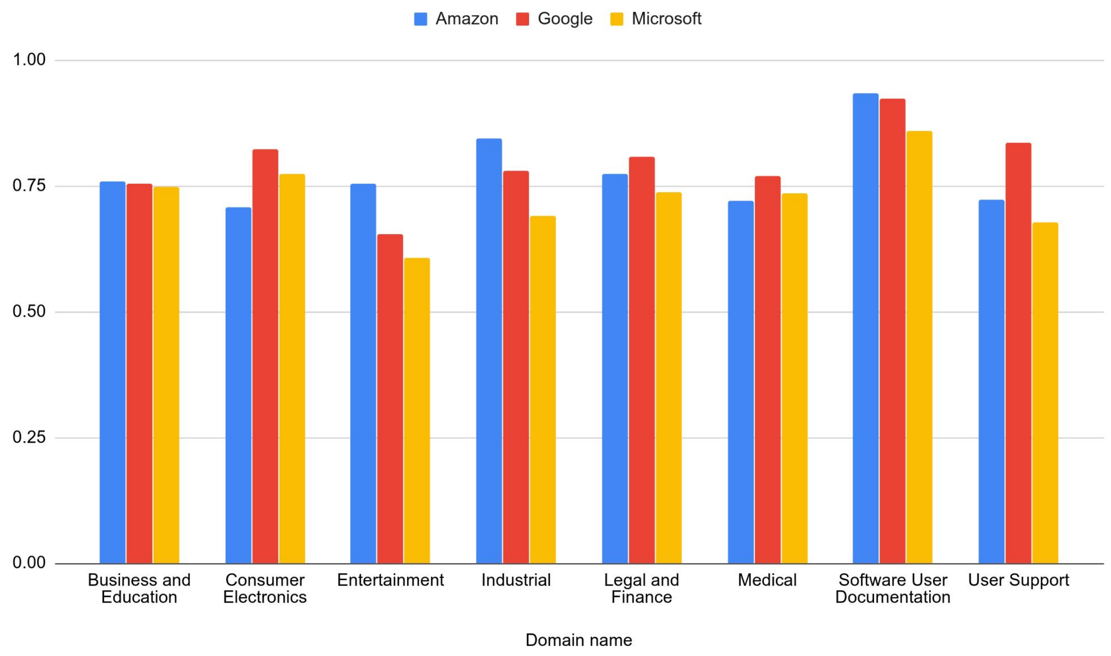
DOMAINS

Domain	Keywords
Medical	'study', 'patients', 'patient', 'treatment', 'dose', 'mg', 'clinical'
Travel and Hospitality	'km', 'hotel', 'guests', 'room', 'accommodation'
Business and Education	'team', 'business', 'work', 'school', 'students',
Legal and Finance	'agreement', 'company', 'contract', 'services', 'financial'
Software User Documentation	'click', 'select', 'data', 'text', 'view', 'file',
Consumer Electronics	'power', 'battery', 'switch', 'sensor', 'usb',
User Support	'please', 'email', 'account', 'domain', 'contact',
Cloud Services	'network', 'server', 'database', 'sql', 'data'
Industrial	'mm', 'pressure', 'valve', 'machine', 'oil'
Software Development	'value', 'class', 'type', 'element', 'string'
Entertainment	'game', 'like', 'get', 'love', 'play', 'go', '

RESULTS: ENGLISH-RUSSIAN

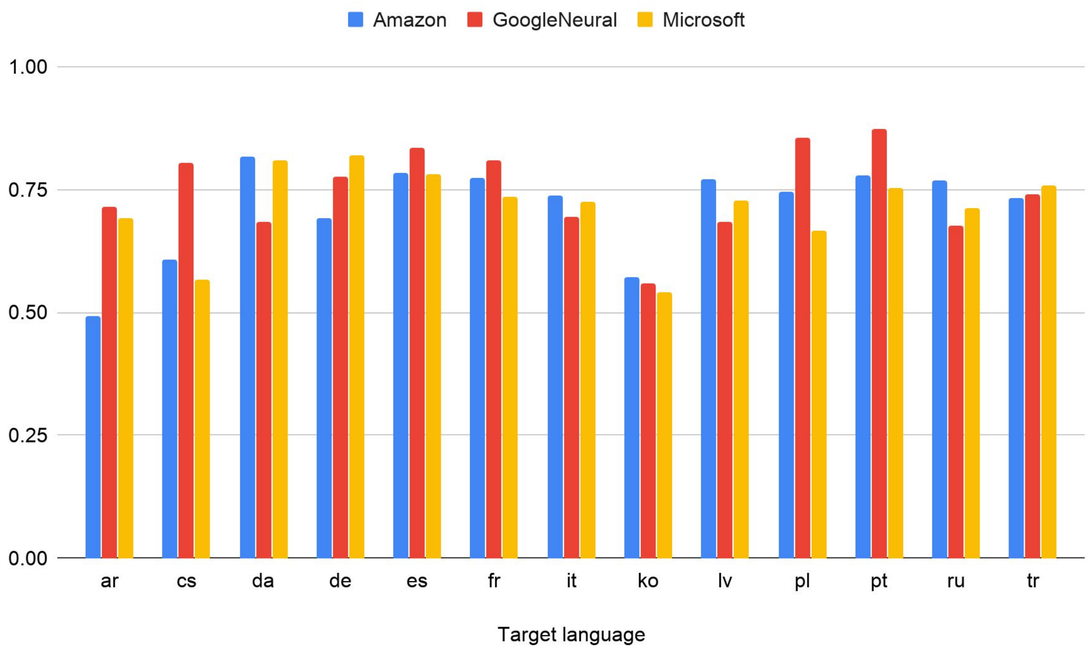


RESULTS: ENGLISH-FRENCH



RESULTS: SINGLE DOMAIN, MULTIPLE LANGUAGES

Domain: Legal and Finance



IMPORTANCE OF SELECTING OPTIMAL MT ENGINES

- Given that all MT systems perform relatively well, does it matter which system is used?

- Sanchez-Torron and Koehn, 2016 show that *“for each 1-point increase in BLEU, there is a PE [post-editing] time decrease of 0.16 seconds per word, about 3-4%”.*

    - There is a clear correlation between MT quality and translator productivity.
    - The exact number may be different today due to specifics of NMT.

Approaches to MT Selection

MEMSOURCE

PILOT STUDY

- High-level overview:
    - Create a sample dataset from the project
    - Translate the sample using multiple MT engines
    - Linguists are asked to post-edit the samples
    - Measure required amount of post-editing, time

- Robust, sound method but costly. Only makes sense for large projects/customers.
    - Needs to be re-done for every project (potential of data drift).

MT QUALITY ESTIMATION

- Similar to pilot study but no manual post-editing.
- High-level overview:
  - Create a sample dataset from the project
  - Translate the sample using multiple MT engines
  - Measure MT quality using MTQE (manual translation is not required)
- Quick, cheap but still requires some manual steps (data preparation, evaluation).
  - Needs to be re-done for every project.
- MTQE may not be reliable enough for some domains/language combinations.

MULTI-ENGINE MT

- Since multiple MT engines are available, use all of them.
  - MT system combination, not selection

- There are methods and for combining multiple MT outputs into a single translation, see e.g. Heafield and Lavie 2010, Freitag et al. 2014, Zhou et al. 2017

- More difficult to implement, costly (all engines used for all inputs), potentially the most robust option.

MACHINE-LEARNING BASED SELECTION

- Use ML directly for recommending optimal MT engines based on translated content
- Only the selected MT engine is used (reduced costs)
- Fully automated for users, no manual steps are involved

- Commercial solutions:
  - Memsource Translate
  - Smartling MT Auto Select
  - Intento Smart Routing*

- Academic work is limited
  - At this conference though: Naradowsky et al. 2020, Machine Translation System Selection from Bandit Feedback

** It is not clear whether recommendations are based on ML or rather static benchmarks.*

MEMSOURCE TRANSLATE

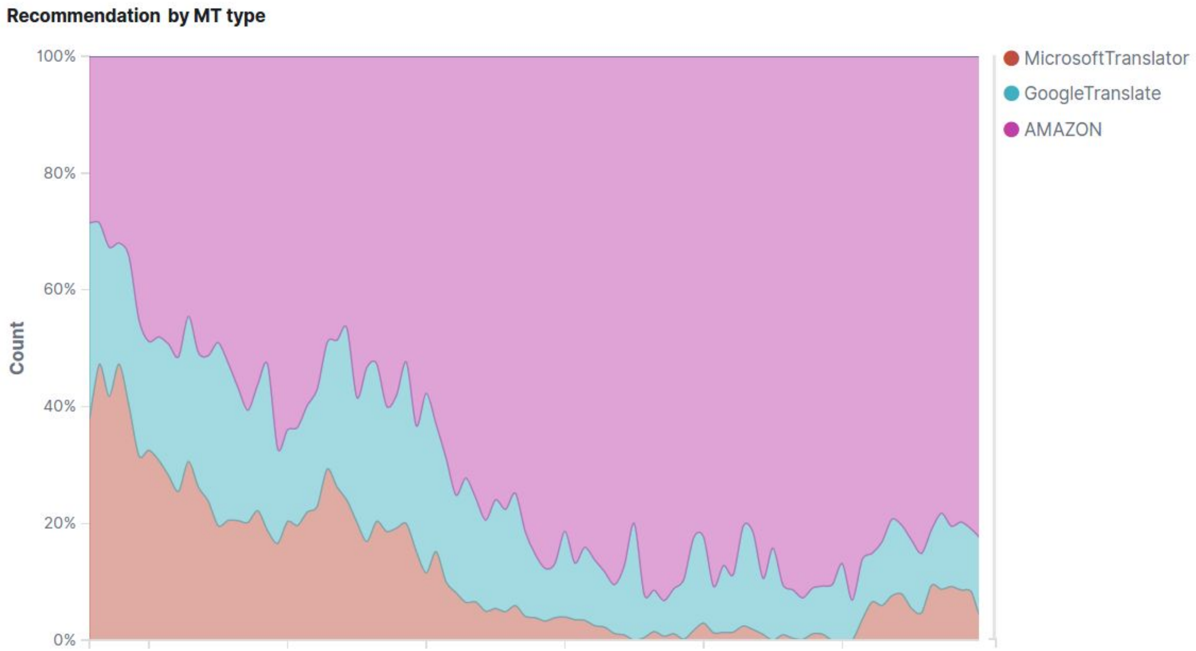
- Automated selection of optimal MT system based on language pair and domain
- For every input document:
  - Analysis of content → domain label
  - Recommendation of MT system based on MT engine statistics
  - Once manual post-editing is completed, MT score is calculated → estimate update

- Recommendations driven by a standard algorithm for Bayesian multi-armed bandits
  - Model is continuously learning and improving
  - MT engine statistics are based on more than 100K documents (and growing)

- Simple, interpretable, fully automated
- A flexible framework, supports custom MT engines

RECOMMENDED SYSTEMS IN TIME

English-Spanish, domain: User support



Conclusion

MEMSOURCE

CONCLUSION

- MT can be very useful in localization

- Considerations:
  - Landscape of MT providers difficult to navigate
  - MT system quality varies across languages but also across domains
  - MT systems evolve over time

- Various approaches to MT selection exist
  - Manual evaluations work well for large, well-defined projects
  - Machine learning can allow to automate the process

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THANK YOU
Q&A

MEMSOURCE

Beyond MT: Opening Doors for an NLP Pipeline

Alex Yanishevsky

Senior Manager, AI Deployments

AMTA 2020 VIRTUAL 2020

Overview

Primary Use Cases of MT

MT for NLP Pipeline

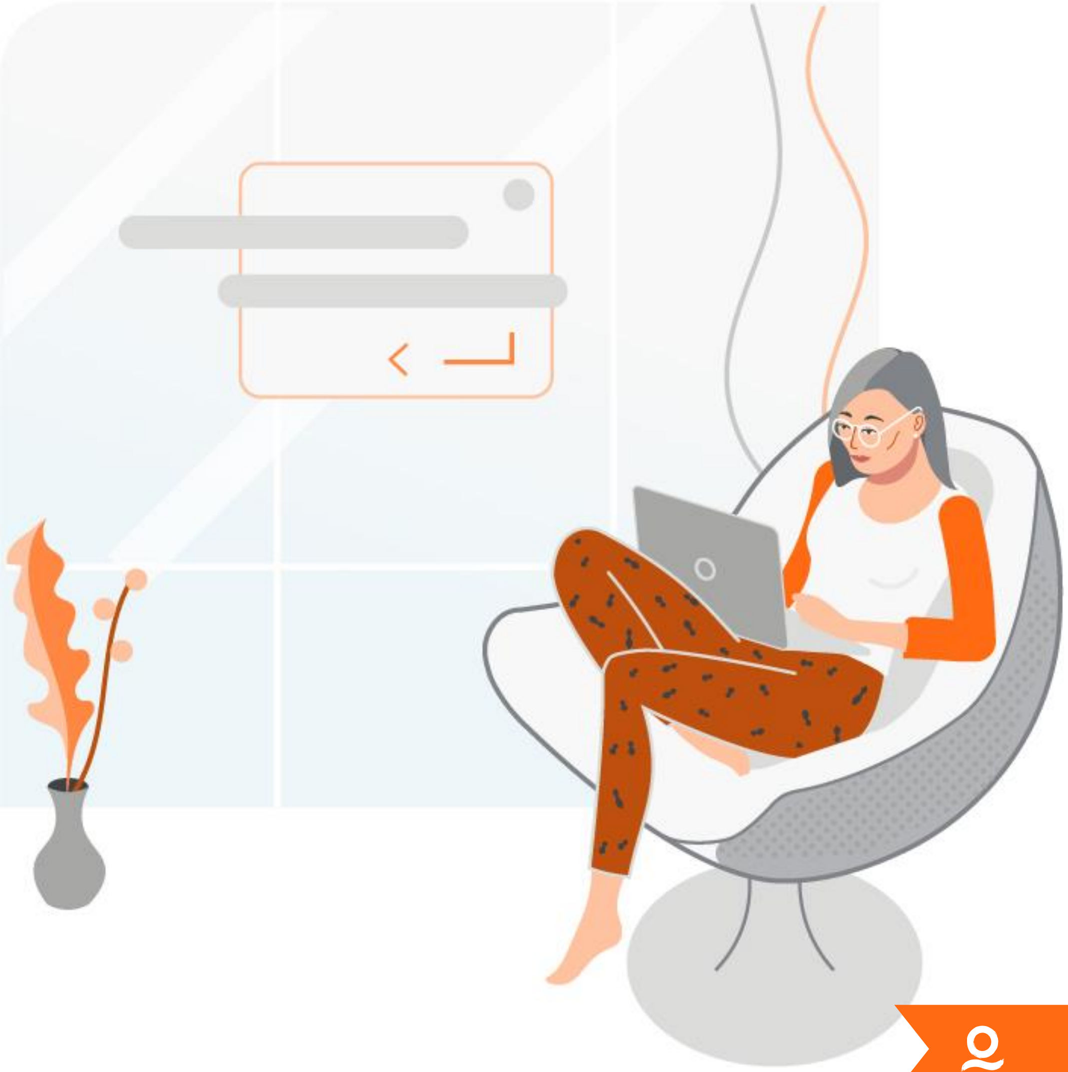
- Why?
- Before MT: Language identification
- After: MT Quality Estimation
- After MT: Social Listening
- After MT: Named Entity Recognition
- After MT: Dependency Parsing
- After MT: Keyword Search

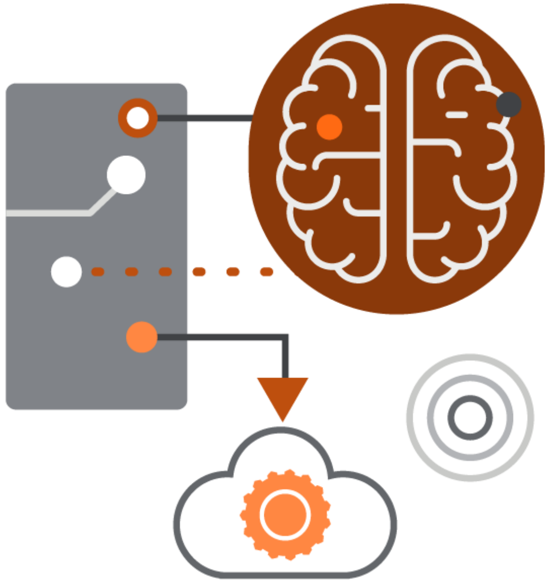
Case Studies

Primary Use Cases of MT

Primary Use Cases of MT

- From and into English
- Generic or trained engines (domain, product, etc.)
- Informational (raw MT) including chat, forums, knowledge bases
- Post-editing (light, medium, full)
- Via MT connectors in TMS or CAT tools
- MT Quality Estimation





MT for NLP Pipeline

Why?

- Many NLP packages (such as NTLK, Stanford CoreNLP or spaCy) not available or lag behind for non-English languages, e.g. readability for Flesch-Kincaid, POS tagging, dependency parsing, named entity recognition, stemming, lemmatization
- Insufficient data to train models

Source: Memsource, AMTA 2020, Session C14

- Domains were defined using unsupervised machine learning on aggregate customer data, labels assigned manually
  - For non-English source languages, internal MT into English is applied first

NLP Pipeline

- Before MT: Language identification
- Machine Translation (generic or trained)
- After: MT Quality Estimation
- After MT: Social Listening
- After MT: Named Entity Recognition*
- After MT: Dependency Parsing
- After MT: Keywords

* Can also be done Before MT

Before MT:
Language Identification

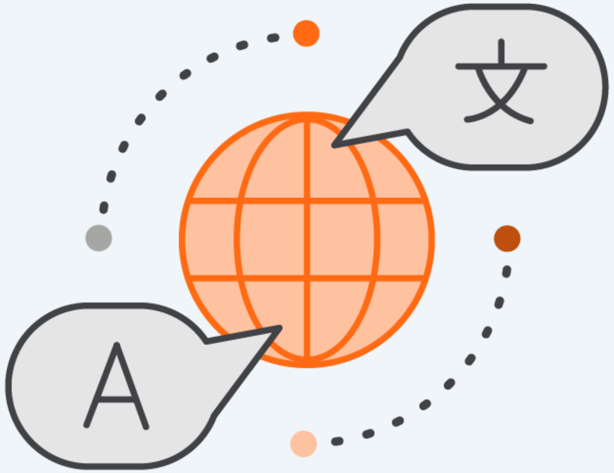
For some domains such as litigation, a file or email may be multi-lingual. Thus, we need a way to identify the language(s) and pass them to MT in one request.

How to deal with this?

Language ID suite with **five** algorithms and majority polling Identification, MT and reassembly on a segment basis.

Example

Программное обеспечение защищено законодательством и международными соглашениями об авторском праве, а также законодательством и соглашениями о защите интеллектуальной собственности. Программное обеспечение не продается, а предоставляется в пользование по лицензии. Puede activar cierto software mediante una clave de licencia proporcionada por el servicio de soporte técnico de Luminex, enviando un mensaje a support@luminexcorp.com o llamando al 1-877-785-2323 o al 1-512-381-4397. 경기 부천에 있는 쿠팡 물류센터 관련 신종 코로나바이러스 감염증(코로나19) 환자가 급속도로 늘어나자, 정부는 내달 14일까지 수도권 내 모든 다중이용시설 운영을 한시적으로 중단하기로 했다. 다만, 수도권 내 초·중·고 등교 수업은 중지 없이 진행된다.



After MT: Quality Estimation

1. Readability
2. Adherence to style based on language models, edit distance, word embeddings
3. Segment length (word and character)
4. Complex words
5. Part of speech tagging
6. Build predictive models based on salient features

After MT: Social Listening

Brand Health

Evaluating public perception of brand and/or products.

Industry Insights

Analyzing discussions or hashtags related to specific industry.

Competitive Analysis

Analyzing competing brands or products.

Campaign Analysis and Event Monitoring

- Evaluating public perception of a campaign.
- Monitoring audience responses to a conferences and/or events.

After MT: Named Entity Recognition*

Recognition (Identification)
Deanonymization
Reassembly

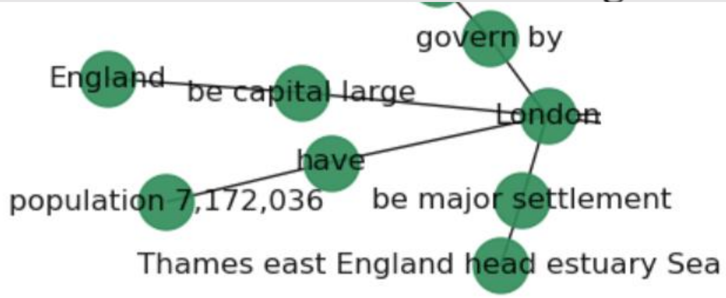
GDPR Compliance
HIPAA Compliance
Responsive (hot) document for litigation

* Can be done before MT

After MT: Dependency Parsing

1. What is it?
2. How to do it? Dependency Parse Tree, Head-Dependent
3. Why do it?

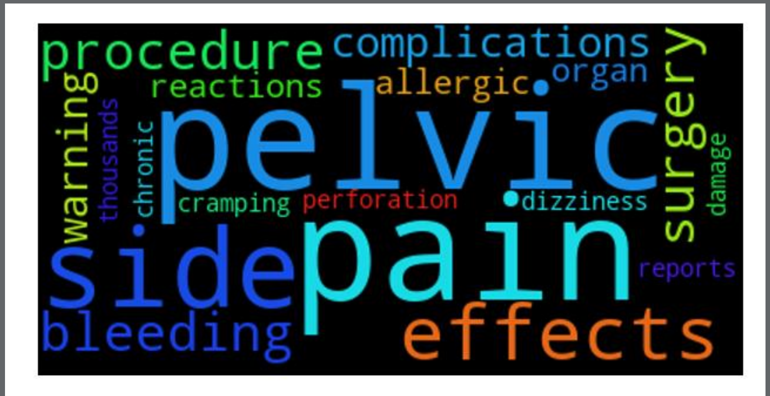
Relation	Examples with *head* and **dependent**
NSUBJ	**United** *canceled* the flight.
DOBJ	United *diverted* the **flight** to Reno.



Source: https://medium.com/data-science-in-your-pocket/dependency-parsing-associated-algorithms-in-nlp-96d65dd95d3e

After MT:
Keyword Search

- An example of a word cloud with salient terms for side effects of a drug



Case Studies

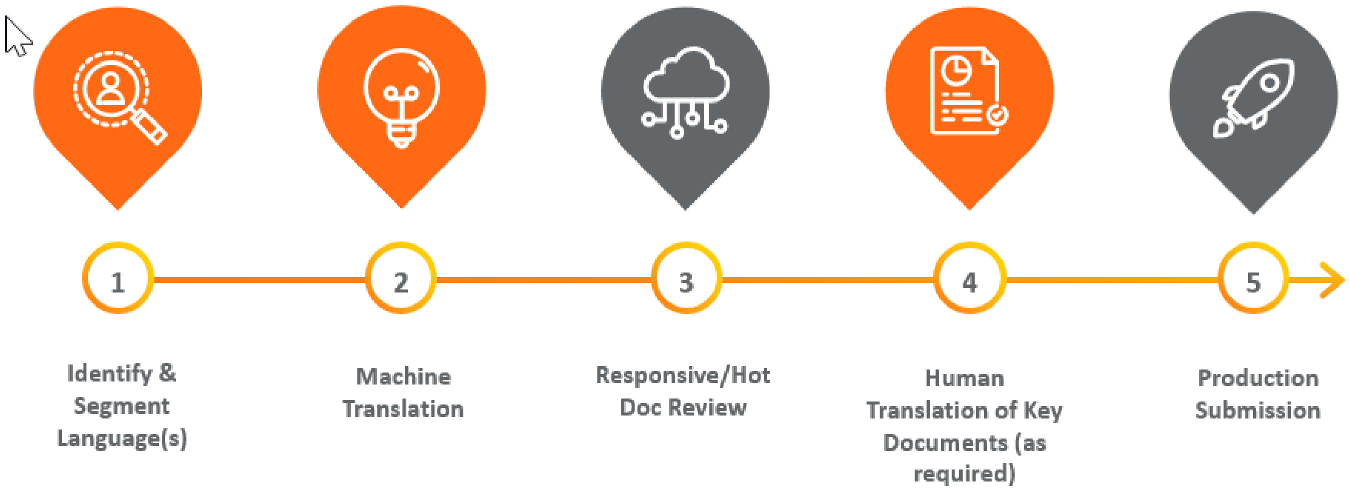
CASE STUDY

Litigation

Over 200 Million
words translated

Challenge

- Quick MT turnaround on 20K plus documents



Results

- Over 1 million USD saved versus human translation
- Saved over 2 months versus human translation
- Targeted selection of responsive documents

CASE STUDY

Life Sciences

Challenge

- Social listening for FR and ES
- Monitor responses of patients taking medication on social media channels

Solution

- Normalization of UGC
- Named Entity Recognition
- Customized sentiment analysis models including parsing ironic and sarcastic comments

Results

- Respond to patients’ concerns
- Monitor and take action on adverse side effects
- Geographical, product and context distributions

Thank you

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welocalize

AMTA VIRTUAL 2020

Building A Multi-Purpose MT Portfolio

INTENTO

AGENDA

Multi-Purpose MT?

—

MT usage scenarios and requirements

—

Case Study 1: **Entity Protection**

—

Case Study 2: **Custom Terminology**

—

Case Study 3: **Tone of Voice**

—

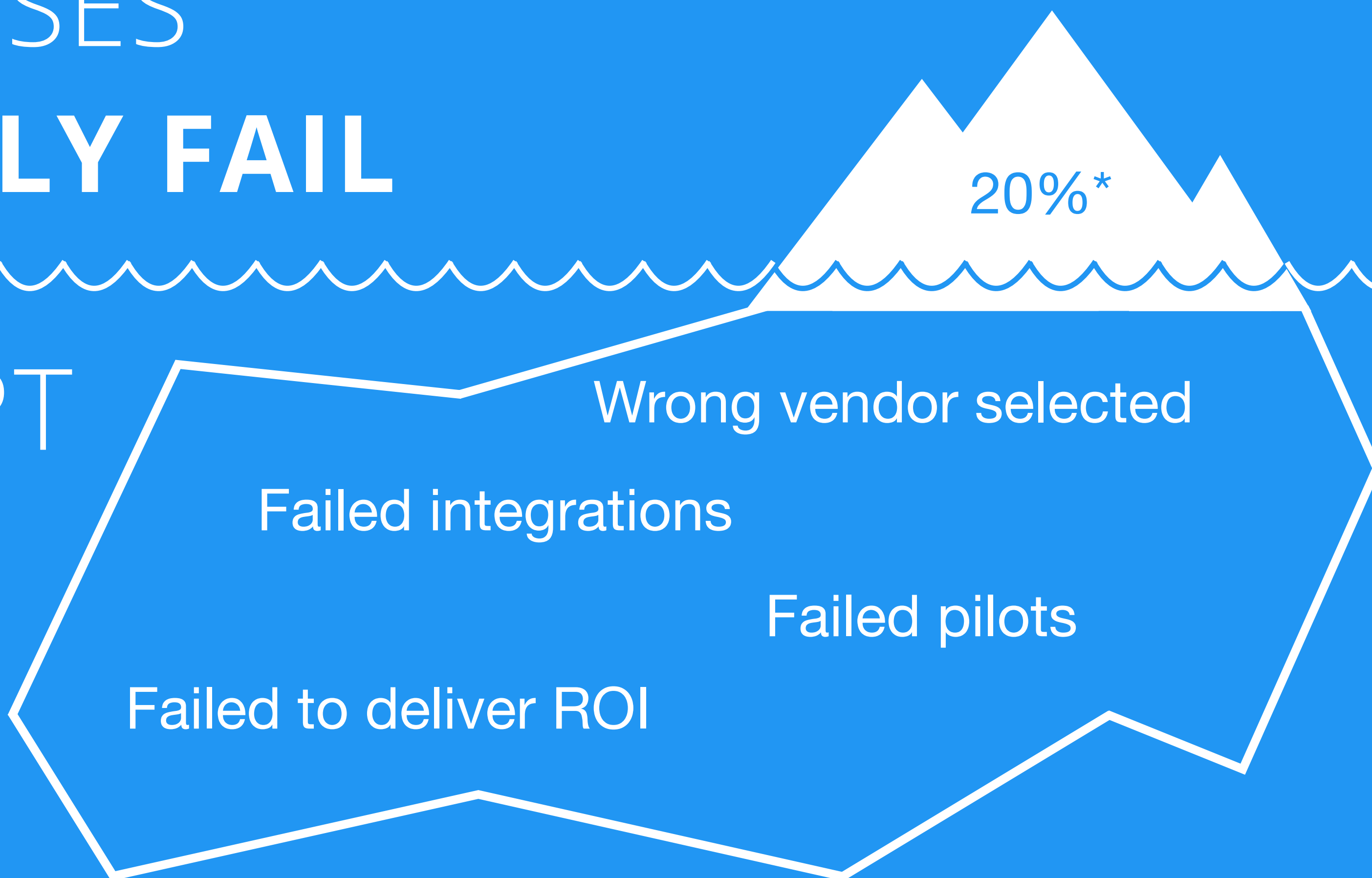
Key Takeaways

Intento

MULTI-PURPOSE MT?

ENTERPRISES
MASSIVELY FAIL

TO ADOPT
AI

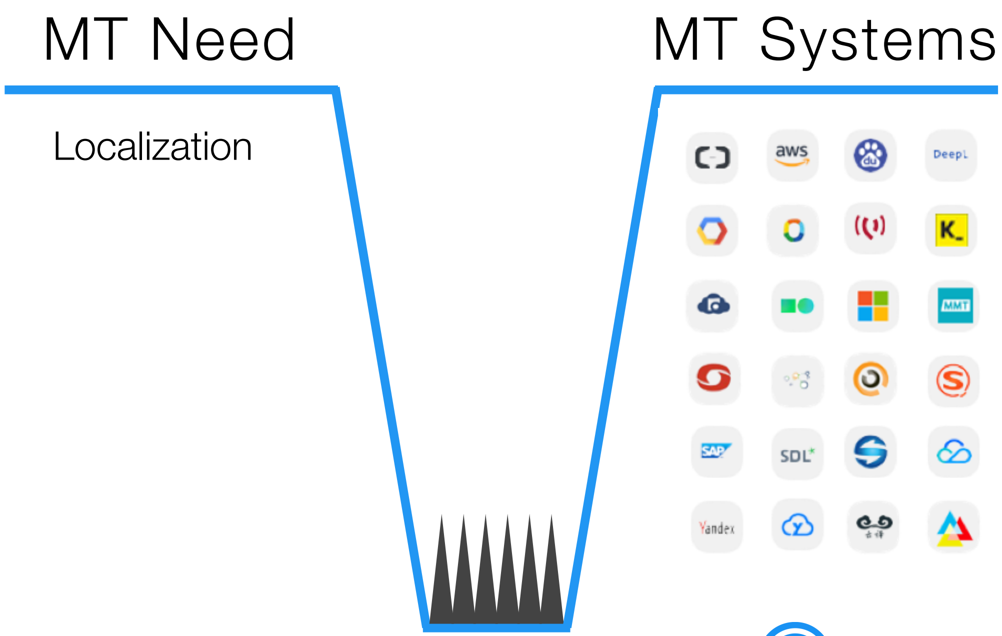


* Share of US companies with successful AI deployment
(*Deloitte State of Cognitive Survey 2017*)

INTENTO

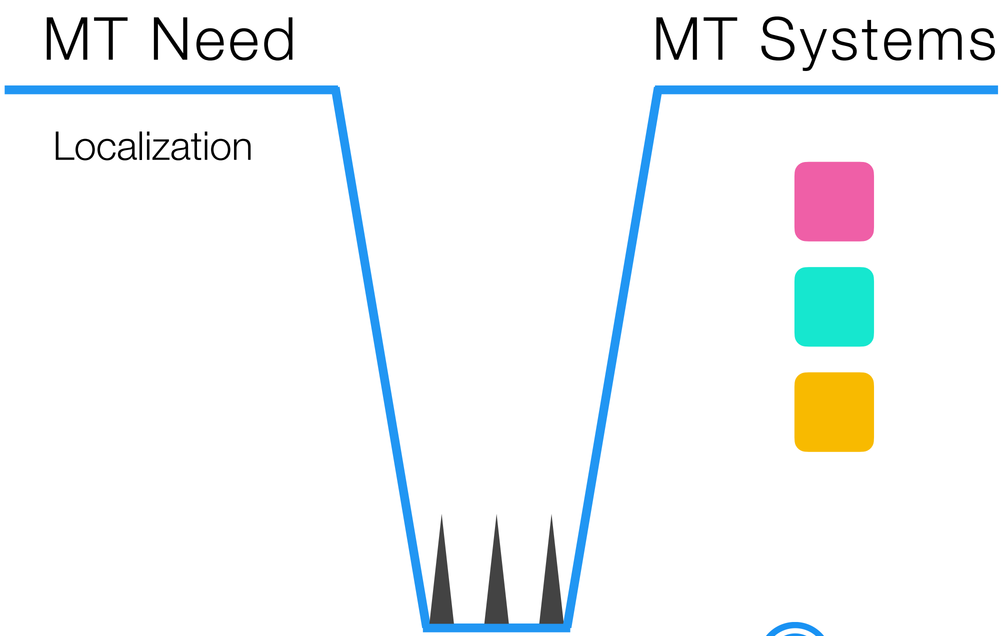
BRIDGING THE GAP BETWEEN
MT CAPABILITIES AND ADOPTION

MT Procurement



BRIDGING THE GAP BETWEEN MT CAPABILITIES AND ADOPTION

MT Procurement



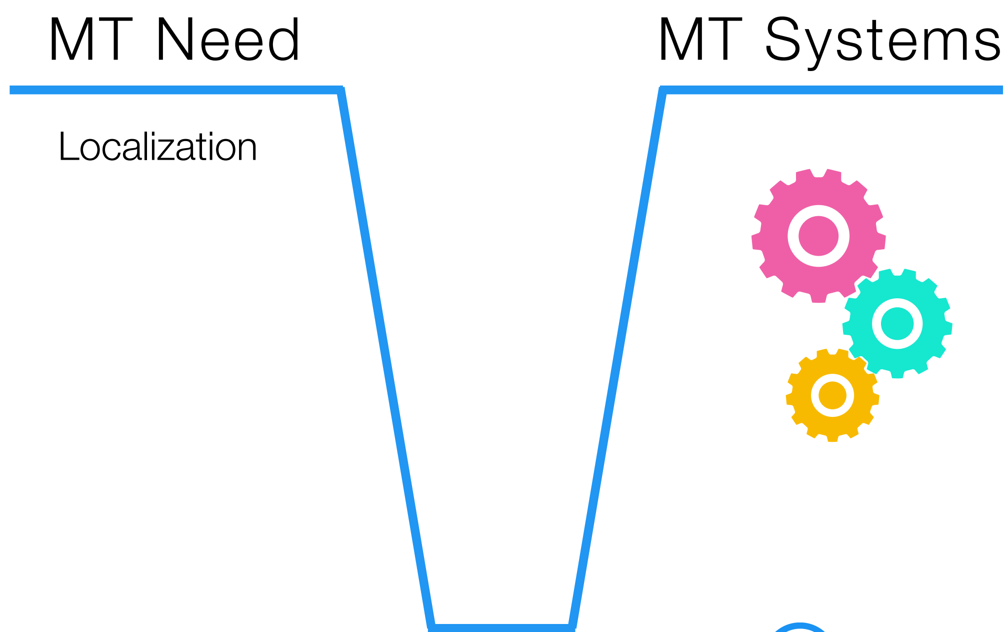
Intento

BRIDGING THE GAP BETWEEN
MT CAPABILITIES AND ADOPTION

MT Procurement

—

MT Curation



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BRIDGING THE GAP BETWEEN MT CAPABILITIES AND ADOPTION

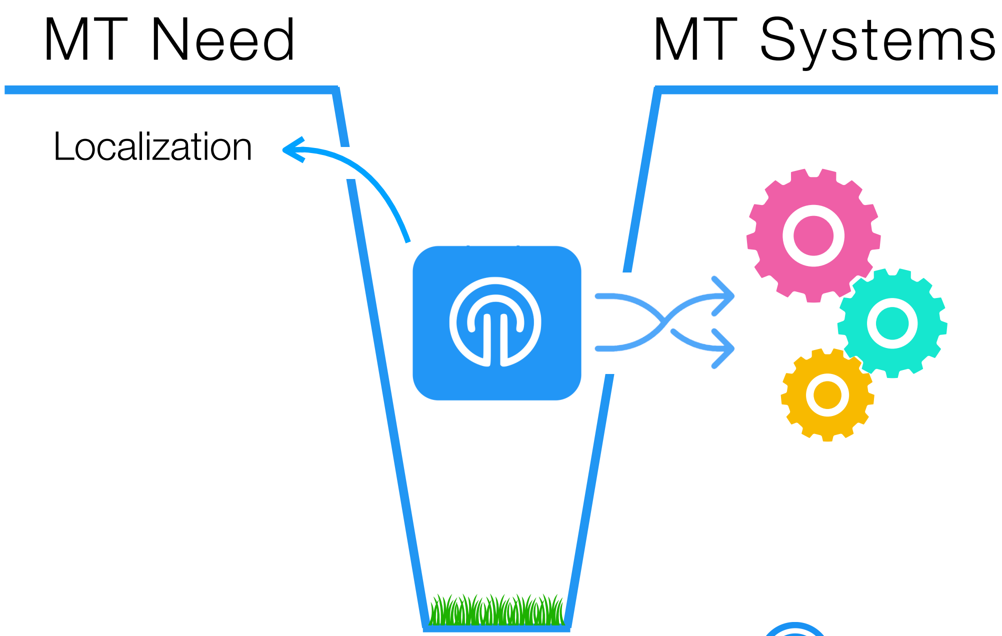
MT Procurement

—

MT Curation

—

Multi-Engine MT



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BRIDGING THE GAP BETWEEN MT CAPABILITIES AND ADOPTION

MT Procurement

—

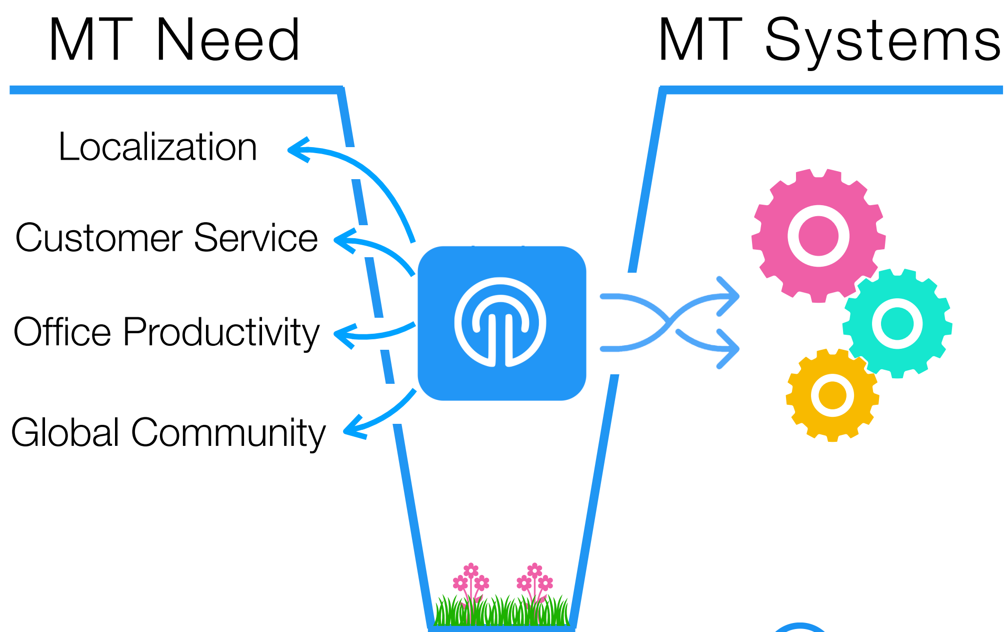
MT Curation

—

Multi-Engine MT

—

Multi-Purpose MT



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MULTI-PURPOSE MT

Instant ROI on the investments already made

—

Combining resources of multiple stakeholders to benefit everyone

—

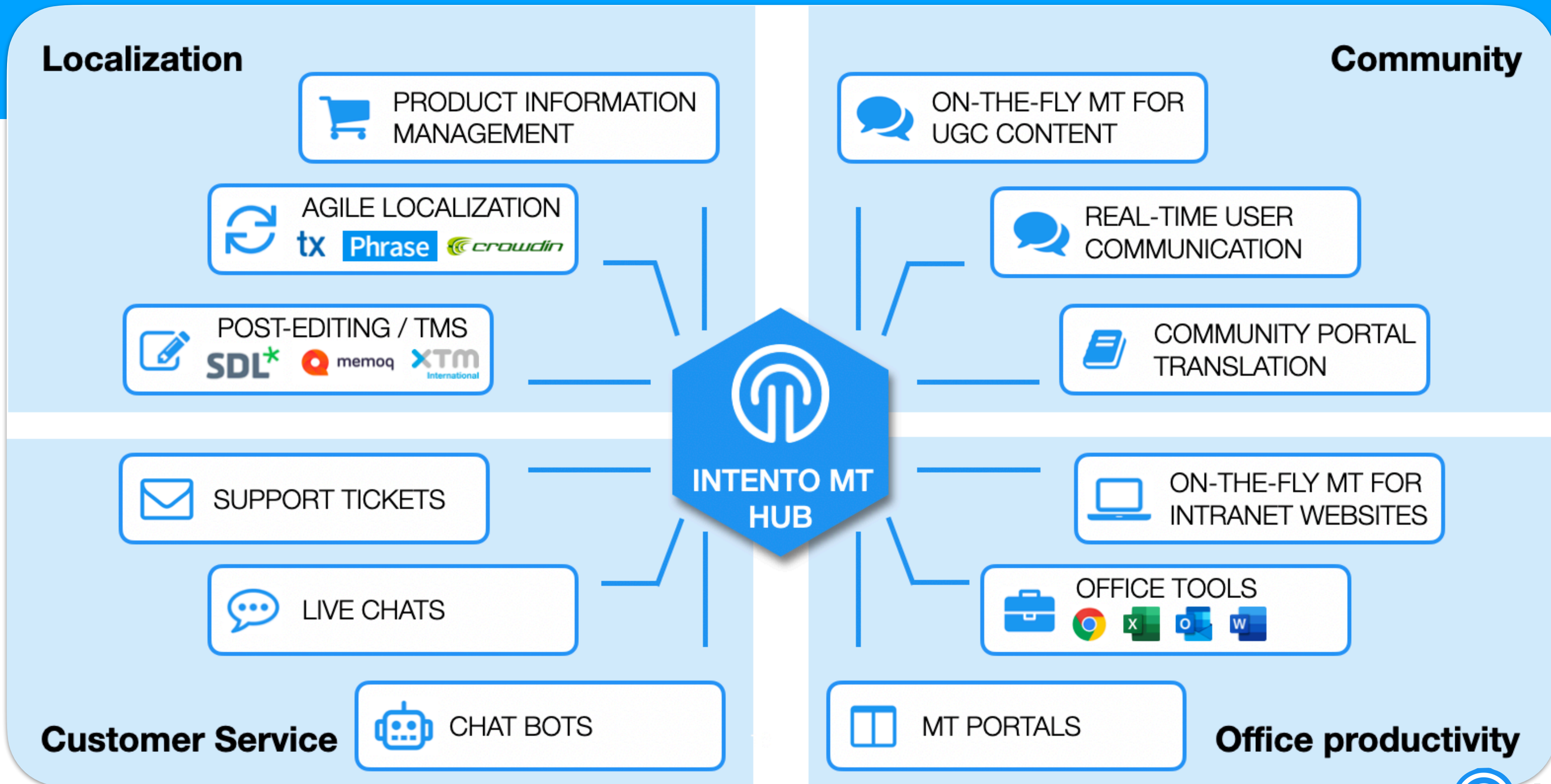
MT Requirements beyond the objective linguistic quality

—

Optimizing for features may compromise the quality

MT USAGE SCENARIOS AND REQUIREMENTS

MULTI-PURPOSE MT



MULTI-PURPOSE MT

REQUIREMENTS BEYOND QUALITY

large text translation

—

batch translation

—

latency and jitter

—

tolerance to bad source

—

language detection

—

tag support

multilingual source

—

profanity control

—

metadata protection

—

entity protection

—

custom terminology

—

tone of voice consistency

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ADDITIONAL CHALLENGES
WITH SPECIFIC COMBINATIONS

large text translation + HTML support

—

source language detection + multilingual source

—

…

MT REQUIREMENTS MATRIX

EVERY CASE HAS ITS OWN NEEDS

	large text translation	batch translation	latency and jitter	tolerance to bad source	language detection	tag support	multilingual source	profanity control	metadata protection	entity protection	custom terminology	tone of voice control
Post-editing / TMS		●				●					●	
Support tickets	●				●		●	●	●	●	●	
Live chats			●	●	●			●		●	●	●
Chatbots			●	●	●	●		●		●	●	●
On-the-fly UGC		●	●	●	●	●	●	●		●		●
Real-time communication			●	●						●		●
Knowledge bases	●					●			●		●	

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MT REQUIREMENTS MATRIX

SAMPLE

ALSO

different for inbound and outbound…

	large text translation	batch translation	latency and jitter	tolerance to bad source	language detection	tag support	multilingual source	profanity control	metadata protection	entity protection	custom terminology	tone of voice control
Post-editing / TMS		●				●					●	
● Support tickets	●				●		●	●	●	●	●	
● Live chats			●	●	●			●		●	●	●
● Chatbots			●	●	●	●		●		●	●	●
On-the-fly UGC		●	●	●	●	●	●	●		●		●
Real-time communication			●	●						●		●
Knowledge bases	●					●			●		●	

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MT REQUIREMENTS SUPPORT
BY POPULAR MT ENGINES

● supported

○ support or its quality depends on the language pair / model

	large text translation	batch translation	latency and jitter	tolerance to bad source	language detection	tag support	multilingual source	profanity control	metadata protection	entity protection	custom terminology	tone of voice control
Amazon Translate	●		○	○	○	○	○		○	○	●	
Google Translate Advanced	●	●	○	○	○	○	○		○	○	●	
DeepL Pro API	●	●	○	○	○	○	○		○	○		●
IBM Watson Translator	●	●	○	○	○	○	○		○	○	●	
Microsoft Text Translator		●	○	○	○	○	○	●	○	○	●	
ModernMT		●	○	○	○	○	○		○	○		
Systran PNMT	●	●	○	○	○	○	○		○	○	●	

CASE STUDY 1:

ENTITY PROTECTION

ENTITY PROTECTION
SOME SAMPLES

Simplest cases: protecting email, URLs, phone numbers, file paths

—

Crucial for Customer Service

—

Easily broken by MT

Source text (English)	Machine Translation
I just want to let you know about a spam mail I have received on Friday - it's in D:\Drv\Prt\Epson\Universal driver x64\ABC6\eeecu120m.inf	Я просто хочу уведомить вас о спаме, который я получил в пятницу - он здесь D:\Drv\Prt\Epson**Универсальный драйвер** x64\ABC6\eeecu120m.inf
It has been Ivan Mitrich (ASAP, email.some+plus@example.com.tr) from Belgrad, but in the future it will be me.	Bio je to Ivan Mitrich (ASAP, email.some+plus@**ekample**.com.tr) iz Belgrada, ali u budućnosti to ću biti ja.
Would you like to help with a new phone for the ABC department - (772) 194 59 65 ext 4406/4408).	Desideri aiutarti con un nuovo telefono per il dipartimento ABC - (772) 194 59 65 ext **406**/4408).
You must submit such a request via ABC-portal, attached link: www.example.com/en/submit	Deve enviar o pedido de tal atraves do ABC-portal, link anexo: www.example.com/**pt**/submit

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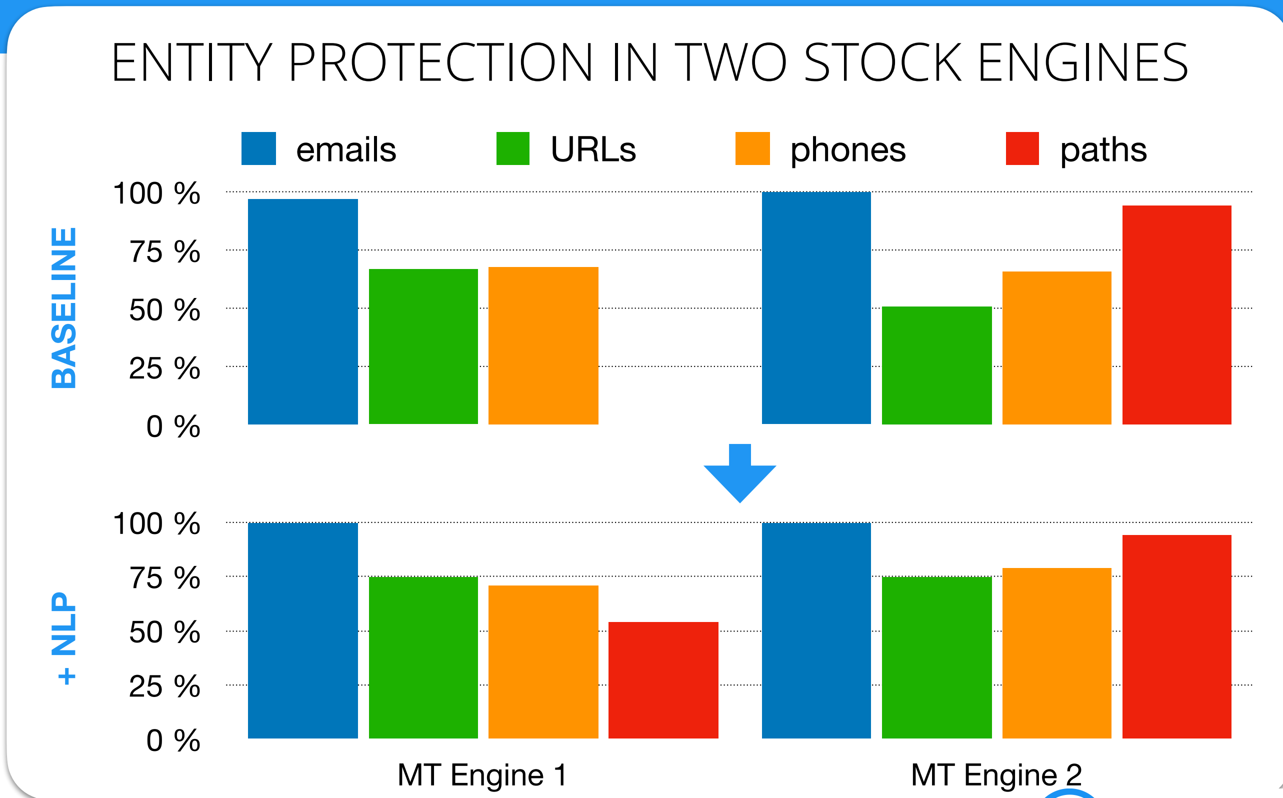
ENTITY PROTECTION
EXPERIMENTAL RESULTS

Selecting the MT based on the default entity protection may compromise the quality

What if we enforce protection via MT-agnostic NLP?



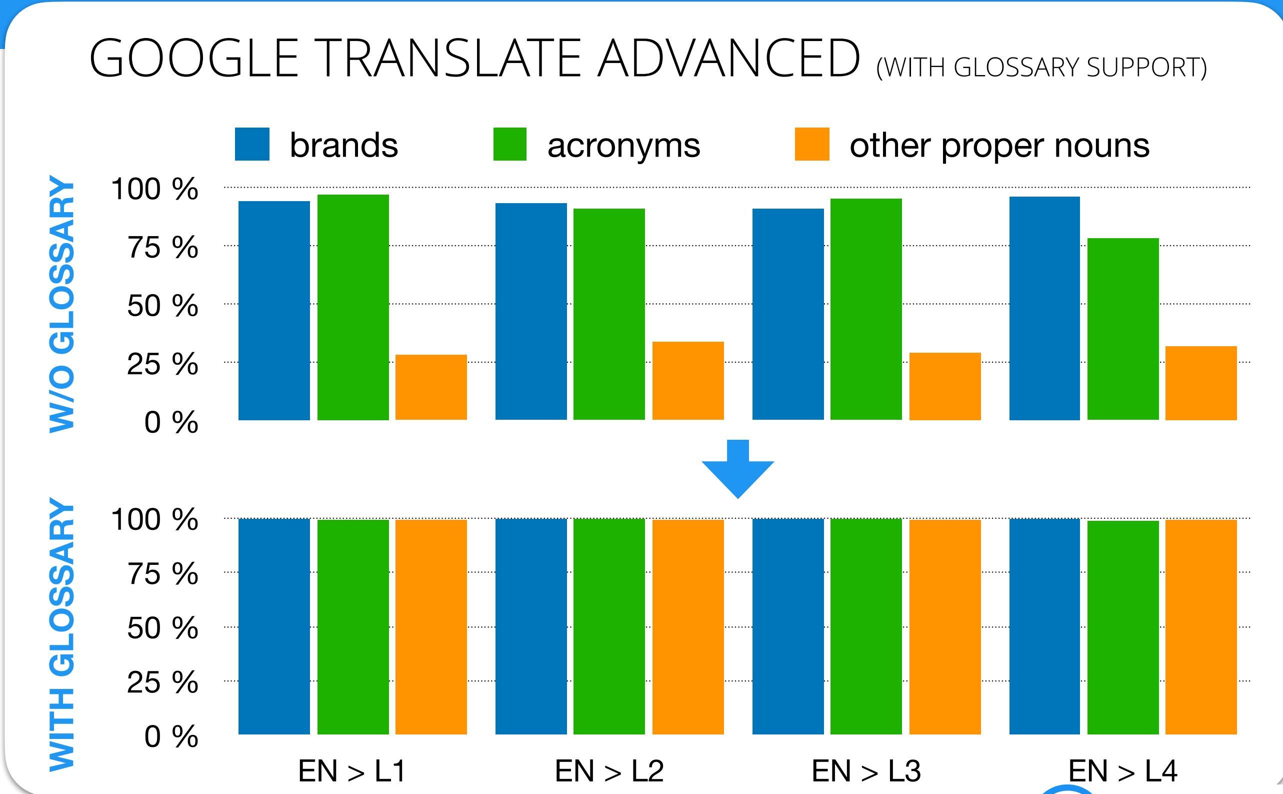
CASE STUDY 2:
CUSTOM TERMINOLOGY

CUSTOM TERMINOLOGY
IMPROVES FIDELITY

Simplest cases: enforcing acronyms, brand names and other proper nouns.

—

Without Custom Terminology support, NMT easily breaks them.



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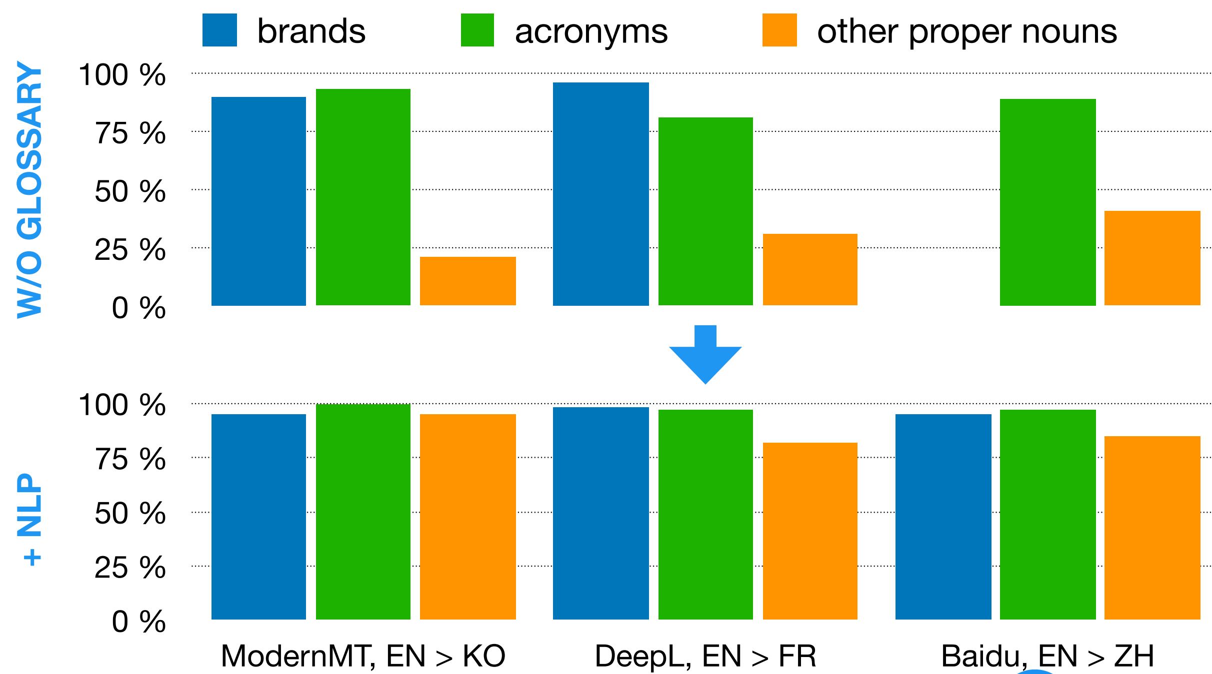
CUSTOM TERMINOLOGY
IMPROVES FIDELITY

Selecting the MT engine by the custom terminology support may compromise MT Quality

MT-agnostic glossary on a top of NMT

STOCK MT ENGINES **WITHOUT** GLOSSARY SUPPORT



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CASE STUDY 3:
TONE OF VOICE CONTROL

TONE OF VOICE CONTROL
SAMPLES FROM SUPPORT CHATS

Formal vs. Informal

—

Crucial for Live Chats

—

Baseline MT engines are not consistent

Source text (English)	Machine Translation (German)	COMMENT
Can you share your screen?	Können Sie Ihren Bildschirm freigeben?	FORMAL
Could you help me?	Kannst du mir helfen?	INFORMAL
Make sure you report any of these issues.	Stellen Sie sicher, dass Sie eines dieser Probleme melden.	FORMAL
Can you give an example?	Kannst du ein Beispiel geben?	INFORMAL

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TONE OF VOICE CONTROL
DEFAULT MT OUTPUT

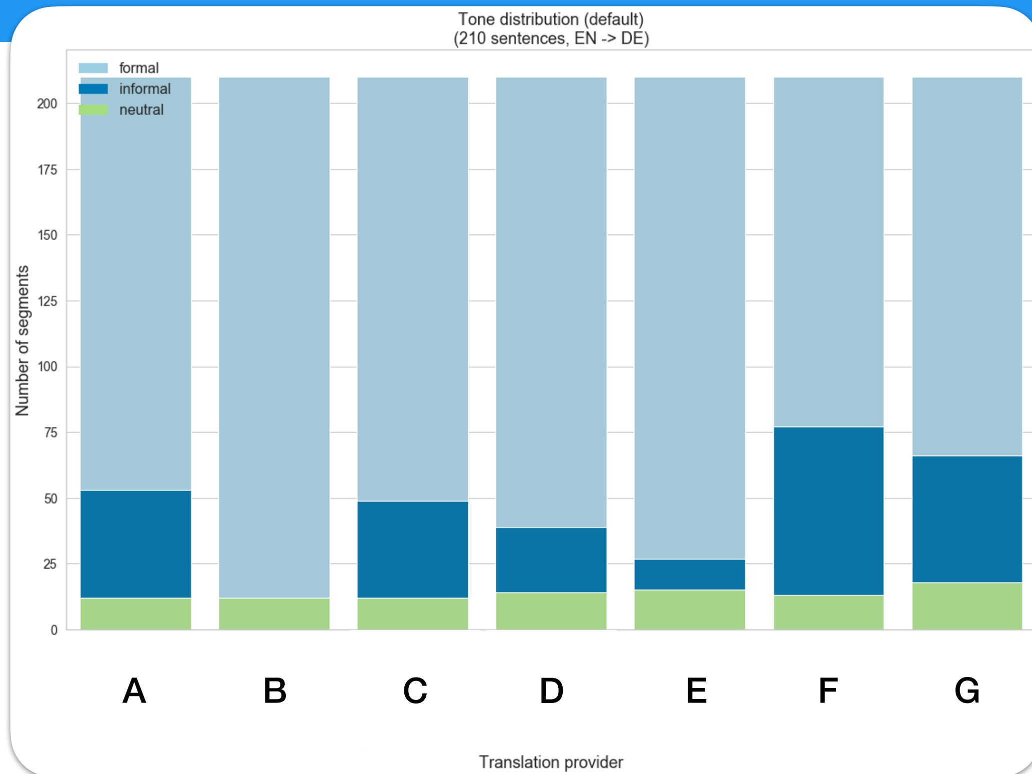
English to German

—

210 segments

—

stock models



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TONE OF VOICE CONTROL
HOW TO MAKE IT INFORMAL?

Option 1: Use DeepL with formality=less (99.5% accuracy)

What if you need a custom model and terminology, or another MT has better linguistic quality for you?

—

Option 2: Generate synthetic training data, hoping translations become more informal

Expensive and time-consuming, also introduces bias into the model

—

Option 3: MT-agnostic NLP

Works to a certain extent, provides a wider choice of MT engines

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TONE OF VOICE CONTROL
MT-AGNOSTIC ADJUSTMENT

English to German

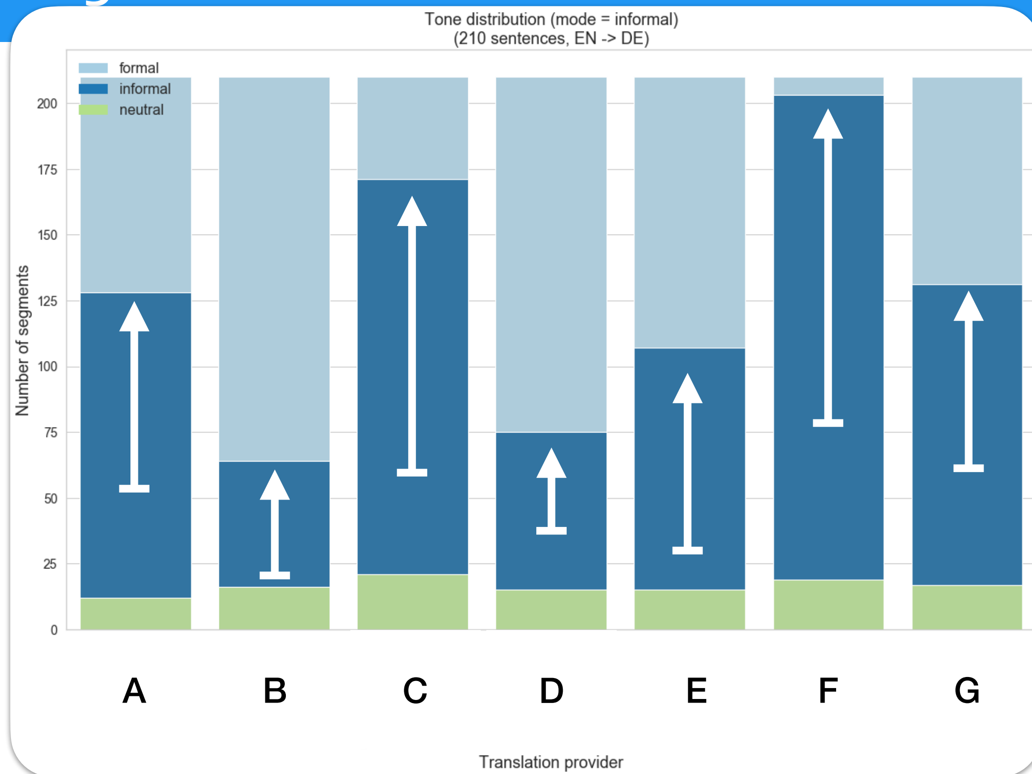
—

210 segments

—

stock models

let's make it more
INFORMAL



TONE OF VOICE CONTROL
MT-AGNOSTIC ADJUSTMENT

English to German

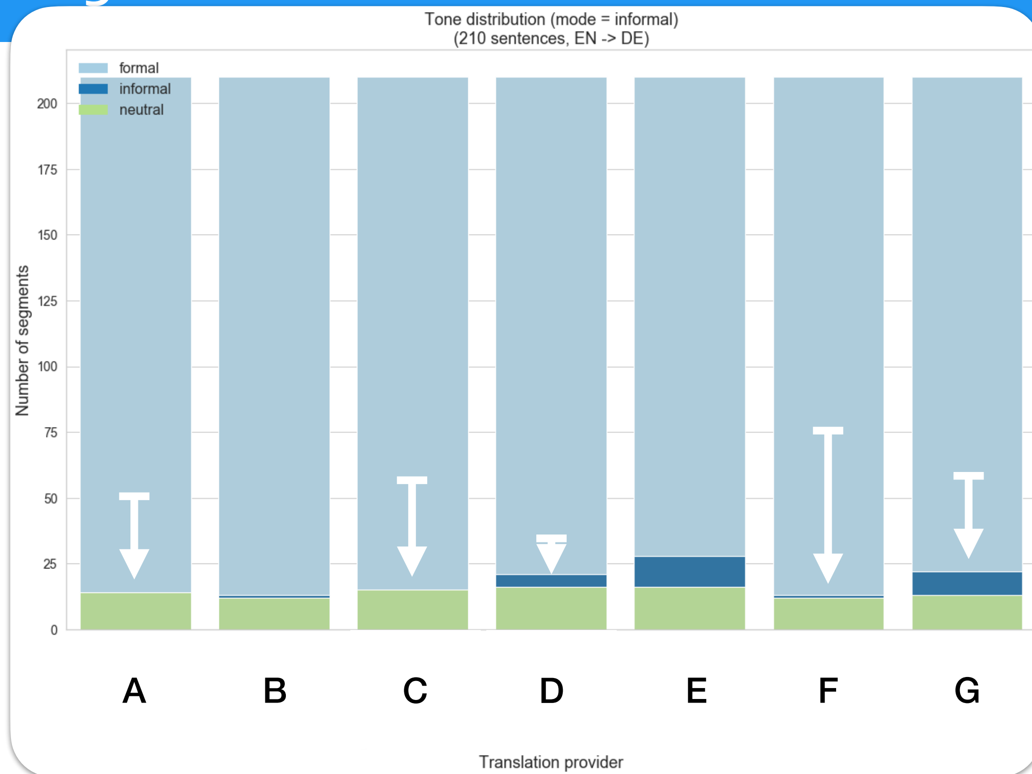
—

210 segments

—

stock models

let's make it more
FORMAL



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KEY TAKEAWAYS

Multi-Purpose MT brings an instant ROI on the MT investment already made.

—

Different use cases impose multiple requirements beyond the linguistic quality.

—

Meeting the requirements takes either the right MT engine choice or clever engineering.

—

We do both, by implementing MT-agnostic fine tuning algorithms to avoid compromising the MT quality.


AMTA 2020
VIRTUAL 20
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Simultaneous Speech Translation in Google Translate

Jeff Pitman <jrp@google.com>

For animations, see: t.co/mz6oZiLEP4

Google Research

Agenda

01 Overview

02 Long-form Audio Input

03 Streaming Translation

04 Streaming Text-to-Speech

05 Putting It Together

Google Research

01

Overview

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Conversational Turn-taking

2011

Components

- ASR
- MT
- TTS

Model Orchestration

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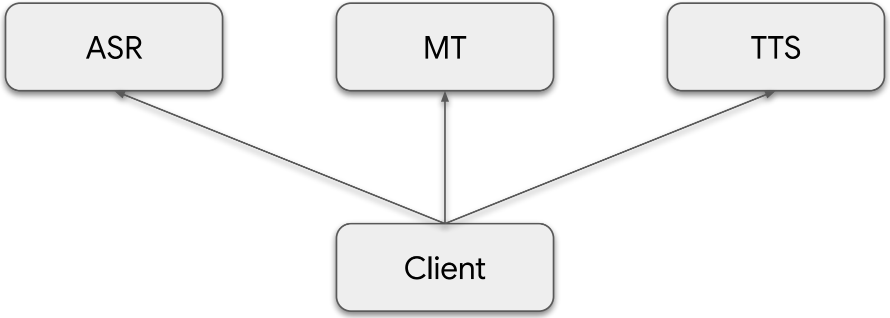
Client-based Model Orchestration



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(Low) Latency is a feature.

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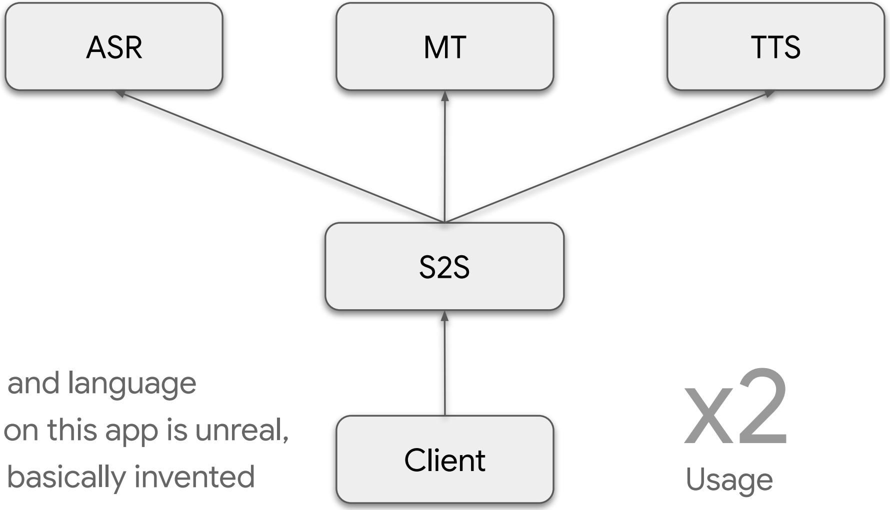
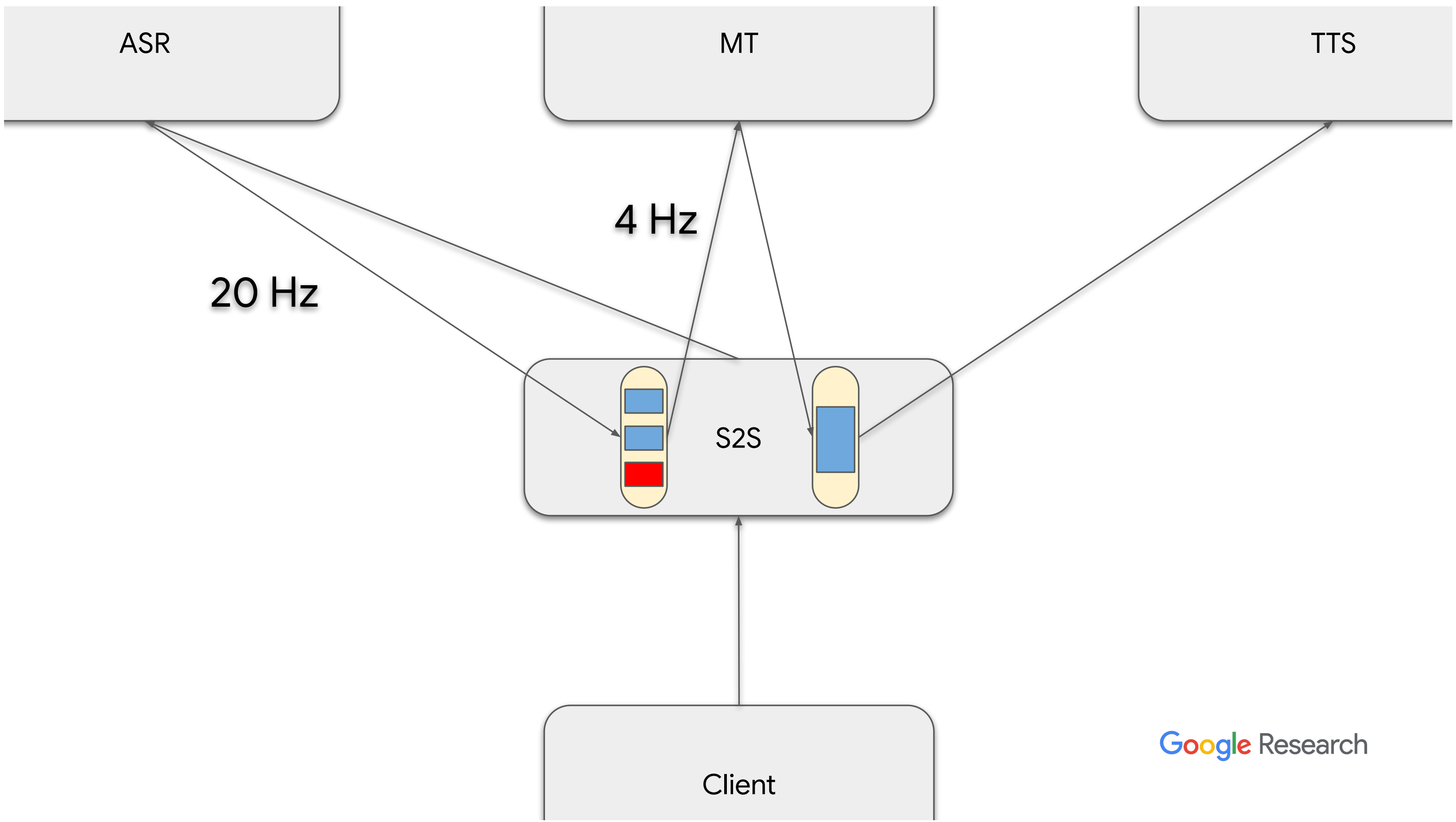
Server-based Model Orchestration



❞ The speech to text and language translation feature on this app is unreal, I think you lot have basically invented the babelfish

x2
Usage

Google Research


ASR
MT
TTS
4 Hz
20 Hz
S2S
Client
Google Research

3100

milliseconds at 95%, previously

950

milliseconds at 95%, now

500

milliseconds at 90%, now

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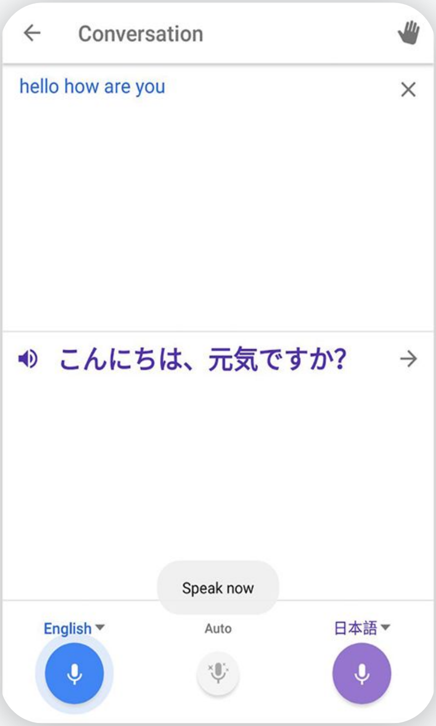
User experience

Input interactions

- Tap and hold
- Quick tap
- Auto mic



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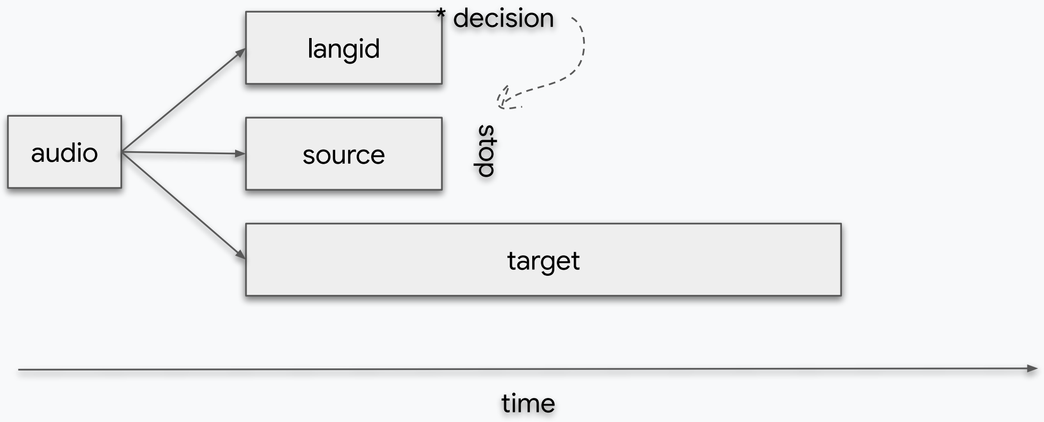
Auto Mic



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What if we kept the microphone on?

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02

Long-form Audio Input

Codecs

The Timeout

ASR Model training

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Codecs

AMR-WB[1] only worked well with clean recording environments and at close distance to the microphone.

Opus[2] @24kbps performed just as well as uncompressed audio. Ended up using 32kbps.

1. [Adaptive Multi-rate Wideband]
2. [Opus]

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The Timeout

Problem: ASR limited to 30 second sessions. But, anything could cause a disconnection.

Solution[1]: Maintain audio buffer on client to stitch sessions together.

1. live-transcribe-speech-engine

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ASR Model

Key insight was to move to models trained on long-form audio.

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03

Streaming Translation

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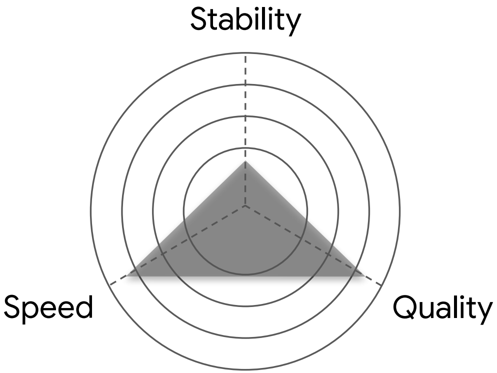

Google Research

UX Research

Participants thought that the instability of the text results were disruptive.

Without preparation, professional interpreters are roughly 60% to 70% accurate in simultaneous interpretation.

Research[1] has shown that audiences get uncomfortable if results take too long.

1. Lee, T.-H. 2002. “Ear voice span in English into Korean simultaneous interpretation.” Meta 47 (4): 596–606.

> “The sentence continues to change while I’m reading it and it is making me nervous.”

Participant

Use case	ASR	TTS	Overall experience
Lecture	⚠️	✔️	⚠️
Museum tour	⚠️	❌	⚠️
Walking city tour	⚠️	❌	⚠️
Boat / Bus tour	❌	⚠️	❌
Airport	❌	✔️	❌

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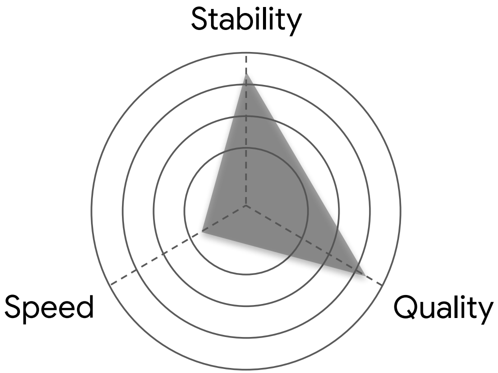

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Tech. Research

We can re-use off-the-shelf ASR and NMT systems by using edit distance heuristics to stabilize prefixes.

We can further improve stabilization by making NMT prefix-aware. Beam search is then constrained on prefixes.

We evaluate performance using a metrics triple of BLEU, Voice-to-eye Latency, and Erasure (flickering rate).

Monotonic Infinite Lookback Attention for Simultaneous Machine Translation

Naveen Arivazhagan* Colin Cherry* Wolfgang Macherey Chung-Cheng Chiu
Semih Yavuz Ruoming Pang Wei Li Colin Raffel
Google

arXiv:1906.05218v1 [cs.CL] 12 Jun 2019

RE-TRANSLATION STRATEGIES FOR LONG FORM, SIMULTANEOUS, SPOKEN LANGUAGE TRANSLATION

Naveen Arivazhagan*, Colin Cherry*, Te I, Wolfgang Macherey, Pallavi Baljekar and George Foster

arXiv:1912.03393v2 [cs.CL] 7 Apr 2020

Re-translation versus Streaming for Simultaneous Translation

Naveen Arivazhagan,* Colin Cherry,* Wolfgang Macherey and George Foster
Google Research
{navari,colincherry,wmach,fosterg}@google.com

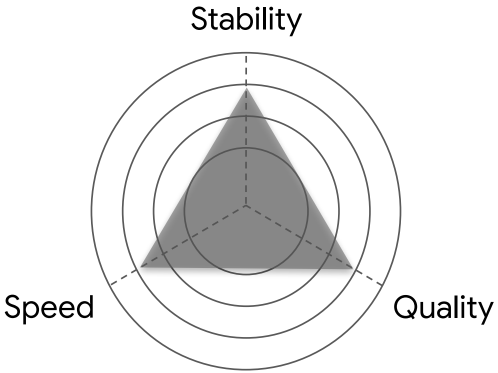
arXiv:... [cs.CL] 14 Apr 2020

Abstract

There has been great progress in improving streaming machine translation, a simultaneous paradigm where the system appends to a growing hypothesis as more source content becomes available. We study a related problem in which revisions to the hypothesis beyond strictly appending words are permitted. This is suitable for applications such as live captioning an audio feed. In this setting, we compare custom streaming approaches to re-translation, a straightforward strategy where each new source token triggers a distinct translation from scratch. We find re-translation to be as good or better than state-of-the-art streaming systems, even when operating under constraints that allow very few revisions.

however, the prohibition against revising output is overly stringent.

The ability to revise previous partial translations makes simply re-translating each successive source prefix a viable strategy. Compared to streaming models, re-translation has the advantage of low latency, since it always attempts a translation of the complete source prefix, and high final-translation quality, since it is not restricted to preserving previous output. It has the disadvantages of higher computational cost, and a high revision rate, visible as textual *instability* in an online translation display. When revisions are an option, it is unclear whether one should prefer a specialized streaming model, or a re-translation strategy.



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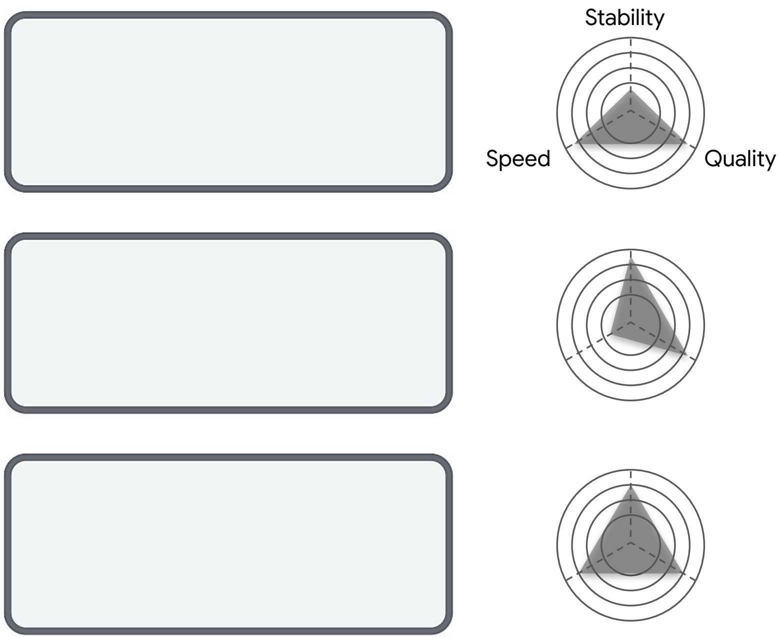

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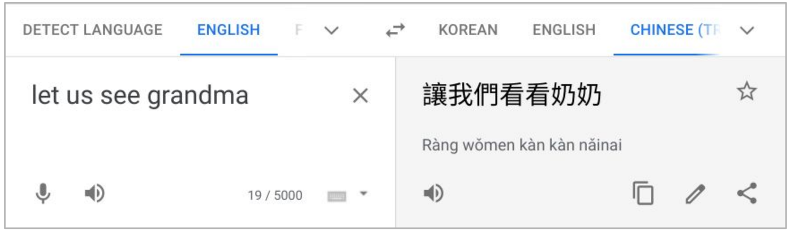
Unspoken Punctuation



+8 BLEU

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04

Streaming Text-to-Speech

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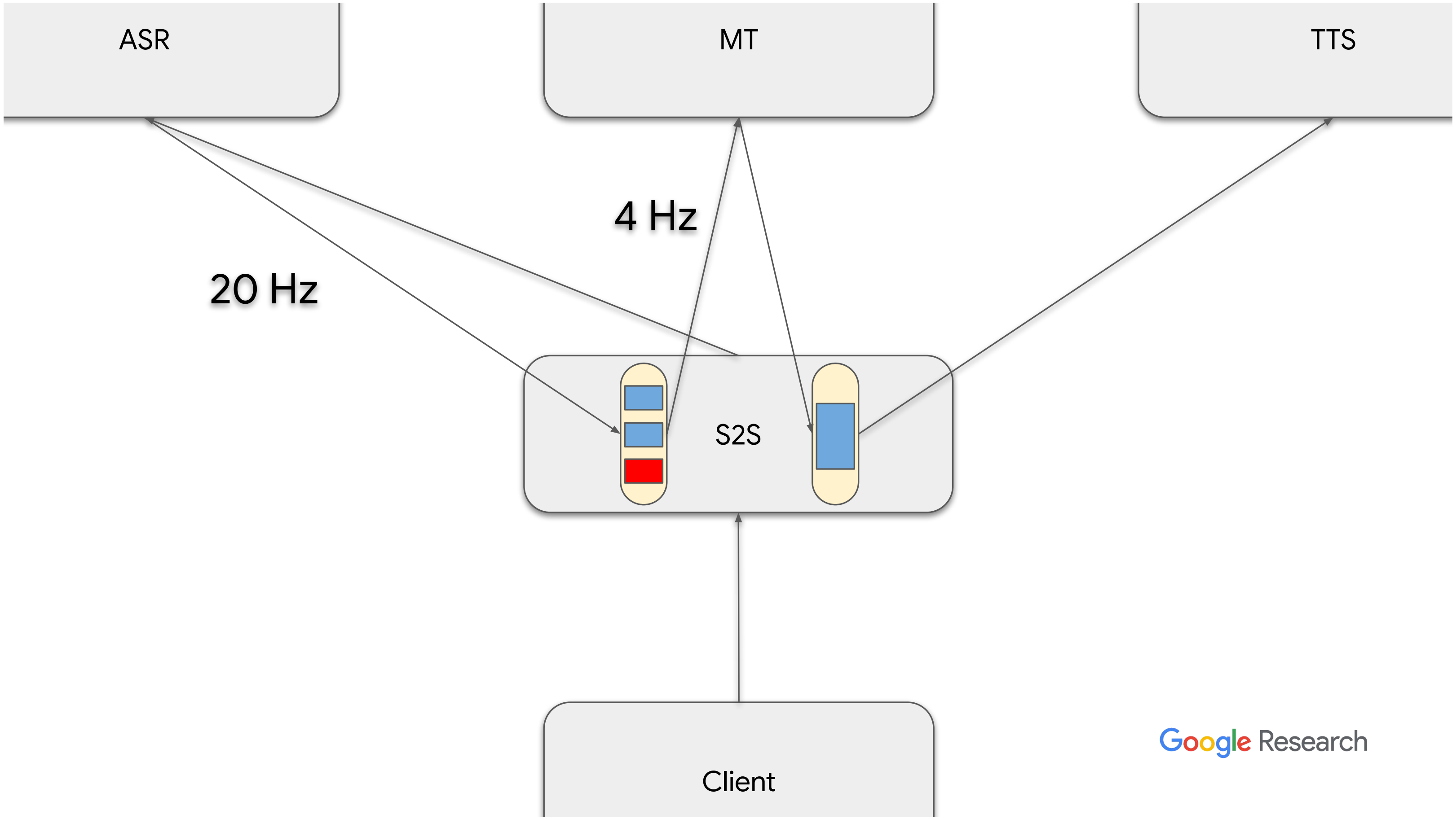

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Goals

Voice-to-ear Latency

Prosody

Pure VUI?

Google Research

Voice-to-ear

Slow finality of ASR results

Short-form ASR models

TTS Speed

Google Research

Prosody

TTS Speed

Length limitations

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Pure Voice UI

Quality

Navigation

Google Research

05

Putting It Together

Evaluation

Results

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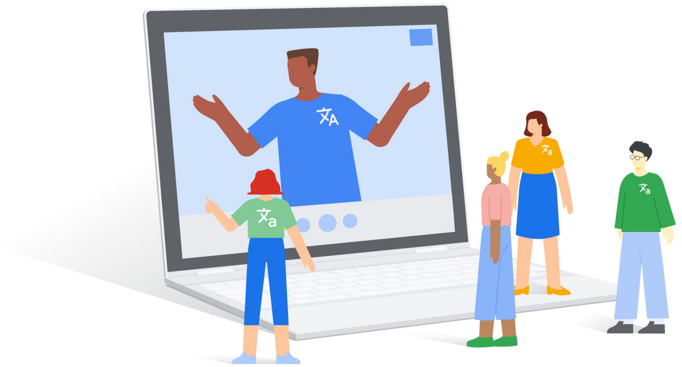
Evaluation

We wanted to see if human judgement in a controlled environment can help make launch decisions.



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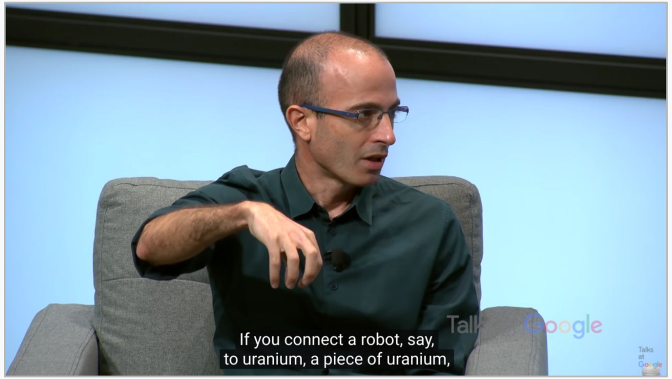
Initial setup

Asked 3 bilingual raters to watch original video, read final and static NMT output, answer adequacy/fluency and gist questions.



Lorem ipsum dolor sit amet, consectetur adipiscing elit. Praesent quis dolor lacus. Orci varius natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. In eu mi placerat, facilisis tellus vitae, efficitur nisi. Nulla placerat placerat sem, tempor vulputate libero suscipit sed. Mauris sit amet massa eu justo dignissim pharetra. Praesent sapien tortor, ornare et leo nec, aliquet suscipit nisi. Aenean egestas mauris eget hendrerit finibus. In eleifend ex pharetra tellus dignissim.

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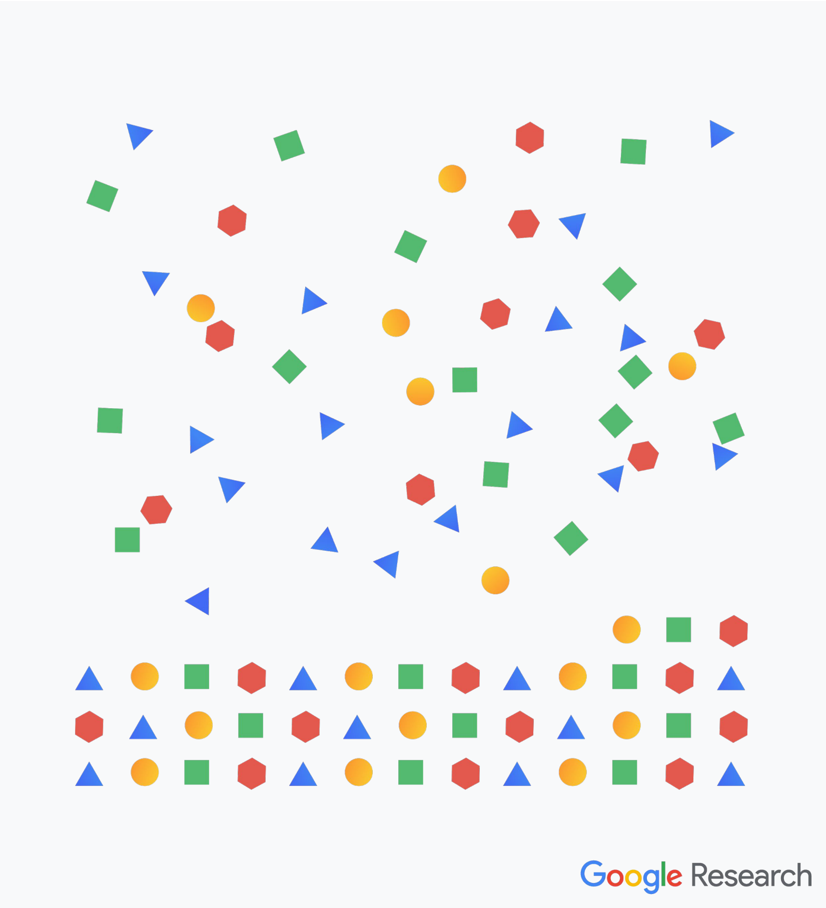
Test set

~100 1-minute publically available videos.

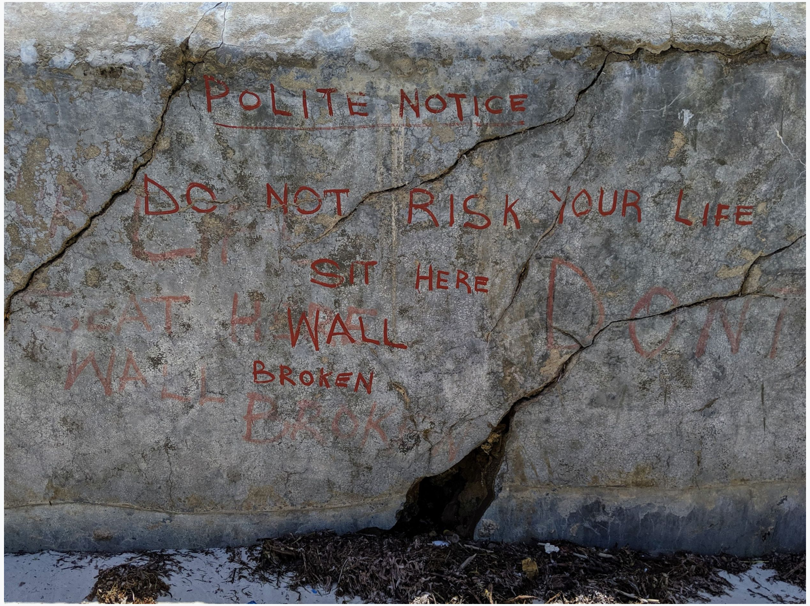
Focused on clean audio with 1 person speaking.



Problems

Domain of test sets misaligned across languages

Raters were not trustworthy .. understanding source language was a bias .. just answering yes to everything was a bias.



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Improvements

Minimized video selection bias with better QC

Minimized bilingual bias by using a monolingual template

Ground truth

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Praesent quis dolor lacus. Orci varius natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. In eu mi placerat, facilisis tellus vitae, efficitur nisi. Nulla placerat placerat sem, tempor vulputate libero suscipit sed. Mauris sit amet massa eu justo dignissim pharetra. Praesent sapien tortor, ornare et leo nec, aliquet suscipit nisi. Aenean egestas mauris eget hendrerit finibus. In eleifend ex pharetra tellus dignissim.

System output

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Praesent quis dolor lacus. Orci varius natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. In eu mi placerat, facilisis tellus vitae, efficitur nisi. Nulla placerat placerat sem, tempor vulputate libero suscipit sed. Mauris sit amet massa eu justo dignissim pharetra. Praesent sapien tortor, ornare et leo nec, aliquet suscipit nisi. Aenean egestas mauris eget hendrerit finibus. In eleifend ex pharetra tellus dignissim.

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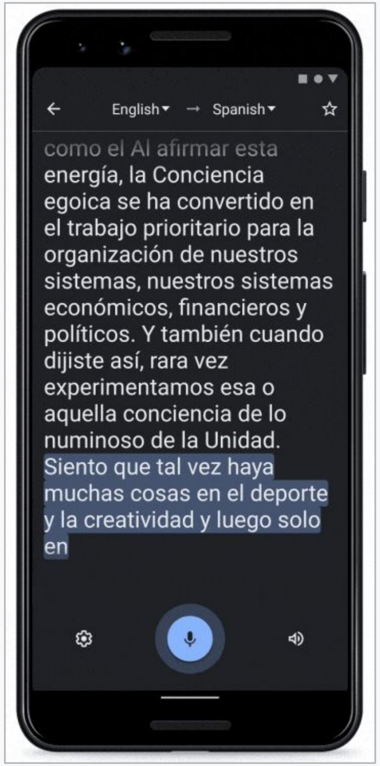
Results

Launched support for 10 languages.

Launched streaming TTS support for Pixel Buds.



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What's next?

Advancing Speech Translation

Long-form Audio Input

Streaming Translation

Streaming Text-to-Speech

Evaluation

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Thank You

Jeff Pitman
Senior Staff Engineering Manager

Deck Props: Shilp Vaishnav, Tom Small, Kannu Mehta, Mengmeng Niu, Bryan Lin, Naveen Ari, Colin Cherry

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Understanding Challenges to Enterprise MT Adoption

Bart Mączyński, VP Machine Learning, SDL

V1.6

Agenda

- Introduction
- New Buyers, New Misconceptions
- The Challenges
  - The Use Case Challenge
  - The Technical Challenge
  - The Linguistic Challenge
- What's Next

SDL*

Introduction

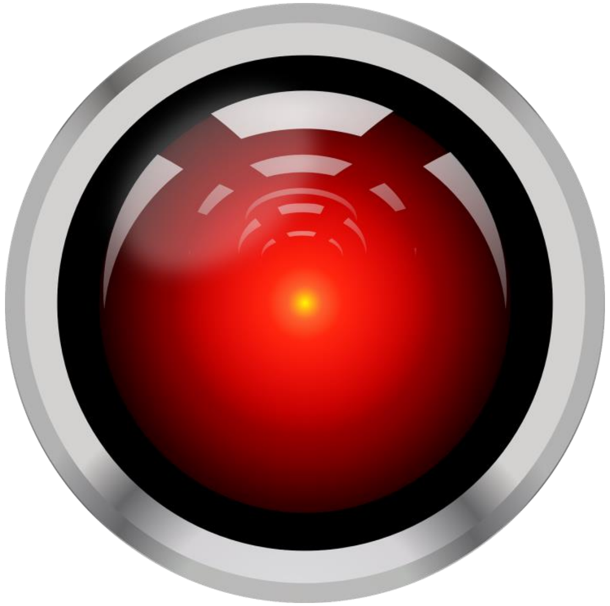
Bart Mączyński

- VP Machine Learning, Solutions Consulting
- Expertise in translation management, TM, MT, terminology systems
- Over 20 years of experience in the field
- Focus on commercial applications of Linguistic AI

Background

Rise of the Machines

- MT is now a viable solution for the enterprise
- Recent advancement opened up new MT use cases
- MT is now directly exposed to new buyer communities
- These new buyers may not have much experience in translation management

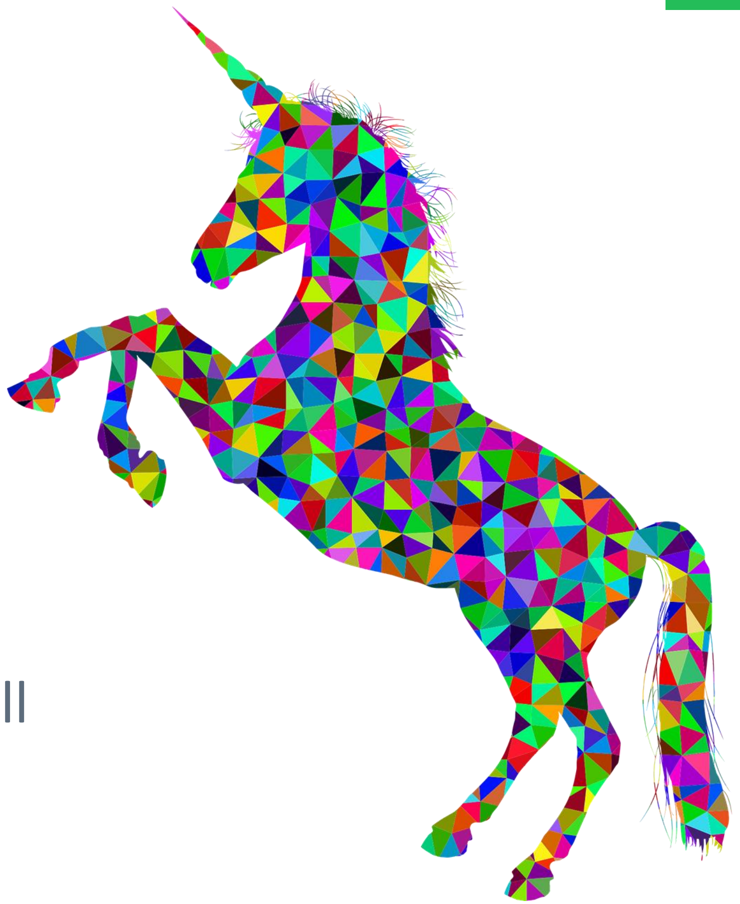


4

New Buyers, New Misconceptions

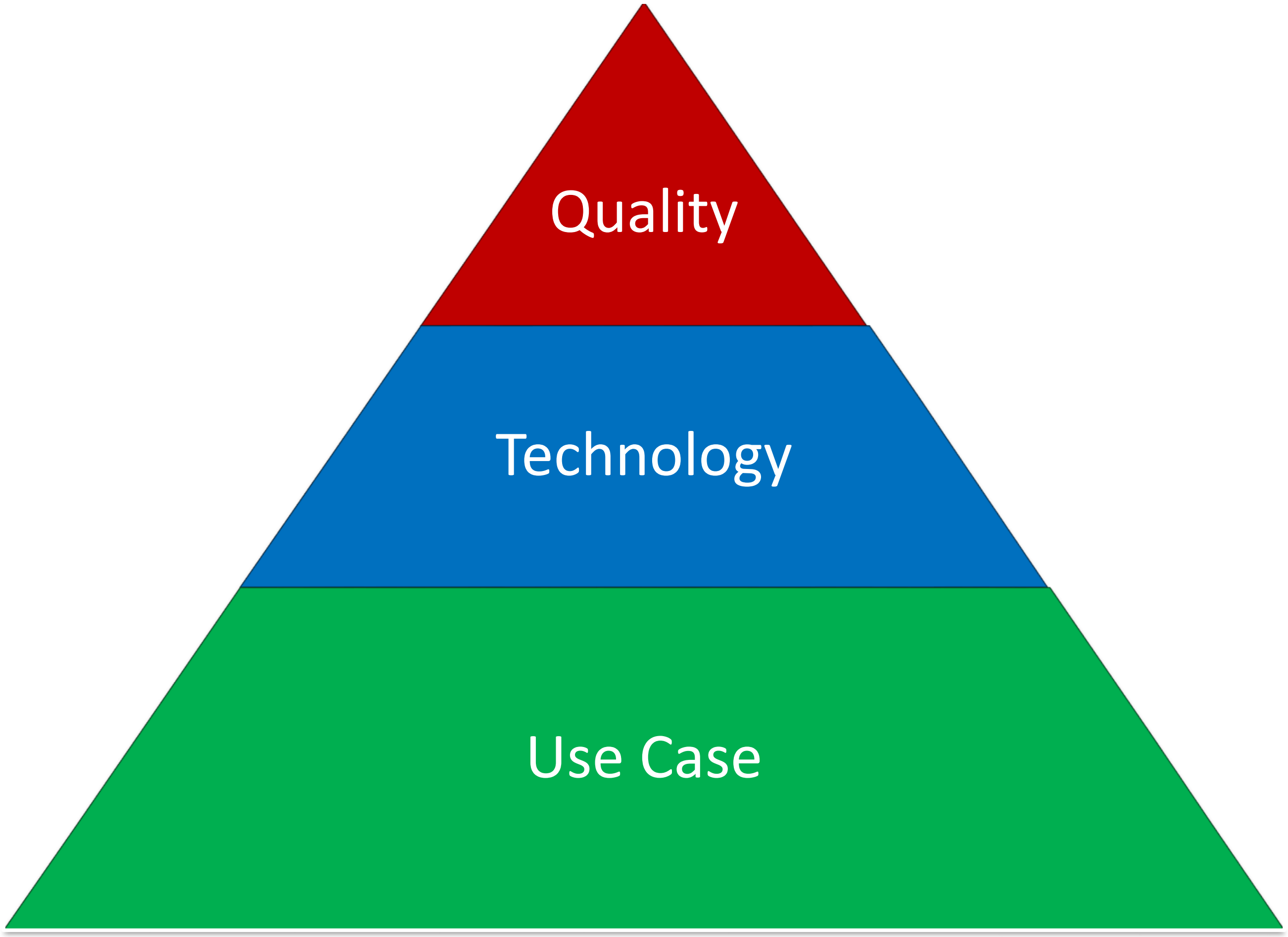
AI, ML, MT Hype

- „MT replaces human translators"
- „MT can learn from what it translates"
- „MT can handle all content"
- „MT quality is amazing across the board"
- „MT is cheap"
- „Anyone can build an MT system"
- „I've read about GPT-3, all my content issues will be solved soon"



SDL

The Three Challenges



SDL*

The Use Case Challenge

The Use Case Challenge

- Understanding if, and how, MT can be utilized
- Providing a pathway to the most optimal translation option

Things to Consider

- Language pair coverage
- Quality
- Volume
- Speed
- Security


Chatbot
Quality
9
8
7
6
5
4
3
2
1
0
Security
Language Coverage
Volume
Speed

SDL


Chatbot
eDiscovery
Quality
9
8
7
6
5
4
3
2
1
0
Language Coverage
Speed
Volume
Security

On-premise vs. Cloud

SDL*


MACH. RM. No.4
UNIT No.3
AHEAD
ASTERN
The Technical Challenge

The Technical Challenge

- Understanding how the MT solution needs to be deployed
- Providing a pathway to acceptable TCO

Things to Consider

- Number of LPs and individual LP scalability
- Translation speed and latency
- Cost of achieving scale (hardware, hosting)
- Flexible licensing model (e.g. for seasonal peaks)
- Integrations and burden of maintenance
- Security and business continuity

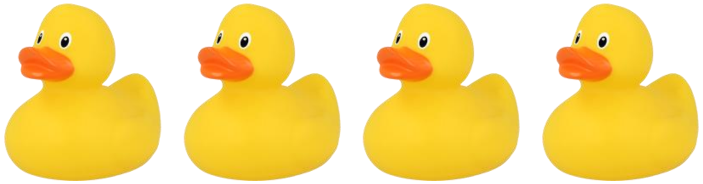

The Linguistic Challenge
14

The Linguistic Challenge

- Understanding the current limits of MT
- Providing a pathway to sufficient quality

Things to Consider

- MT still comes out as too direct and non-idiomatic
- High level of fluency can mask other issues
- Humans excel at detecting extra-textual context
- Even commercial-grade MT systems struggle with messy inputs
- Bias in training data is reflected in MT output



Example 1 – Fluent Nonsense

<u>Phototherapy exposure</u> in this range is used in the treatment of hyperbilirubinemia in newborn children.

<u>Fototerapia ekspozycji</u> w tym zakresie jest stosowana w leczeniu hiperbilirubinemii u noworodków.

fototerapia ekspozycji = phototherapy of exposure

Example 2 – Cross Domain Issues

System 1

Administration should be performed by an individual who has been adequately trained in injection techniques.

Podawanie powinno być wykonywane przez osobę, która została odpowiednio przeszkolona w zakresie technik iniekcji.

Example 2 – Cross Domain Issues

System 2

Administration should be performed by an individual who has been adequately trained in injection techniques.

Podawanie leku powinno być wykonywane przez osobę, która została odpowiednio przeszkolona w zakresie technik wstrzykiwania.

Example 2 – Cross Domain Issues

System 1

System administration should be performed by an individual who has been adequately trained.

Podawanie systemu powinno być wykonywane przez osobę odpowiednio przeszkoloną.

SDL*

Example 2 – Cross Domain Issues

System 2

System administration should be performed by an individual who has been adequately trained.

Administrowanie systemem powinno być wykonywane przez osobę, która została odpowiednio przeszkolona.

Example 3 – Gender Bias

The doctor went home.

The nurse went home.

The professor went home.

The cleaner went home.

[*m*]	Der Arzt ging nach Hause.	Доктор пошел домой.
[*f*]	Die Krankenschwester ging nach Hause.	Медсестра пошла домой.
[*m*]	Der Professor ging nach Hause.	Профессор пошел домой.
[*f*]	Die Putzfrau ging nach Hause.	Уборщица пошла домой.

Example 4 – Imperfect Inputs

This is a test of the emergency alert system.

To jest test systemu alarmowego.

This is a test of the emergency alert system

To jest test systemu alarmowego w sytuacjach awaryjnych

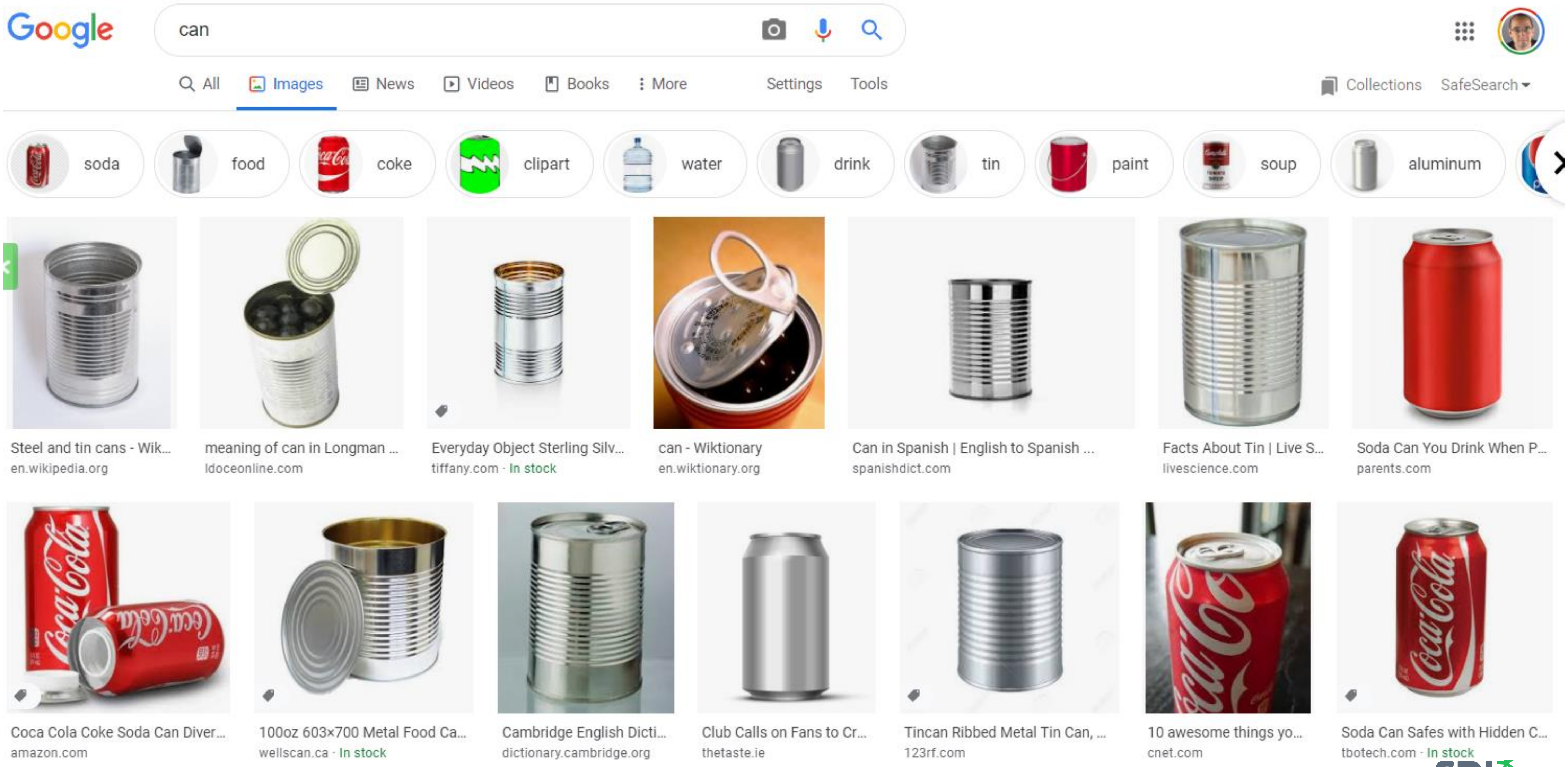
SDL*

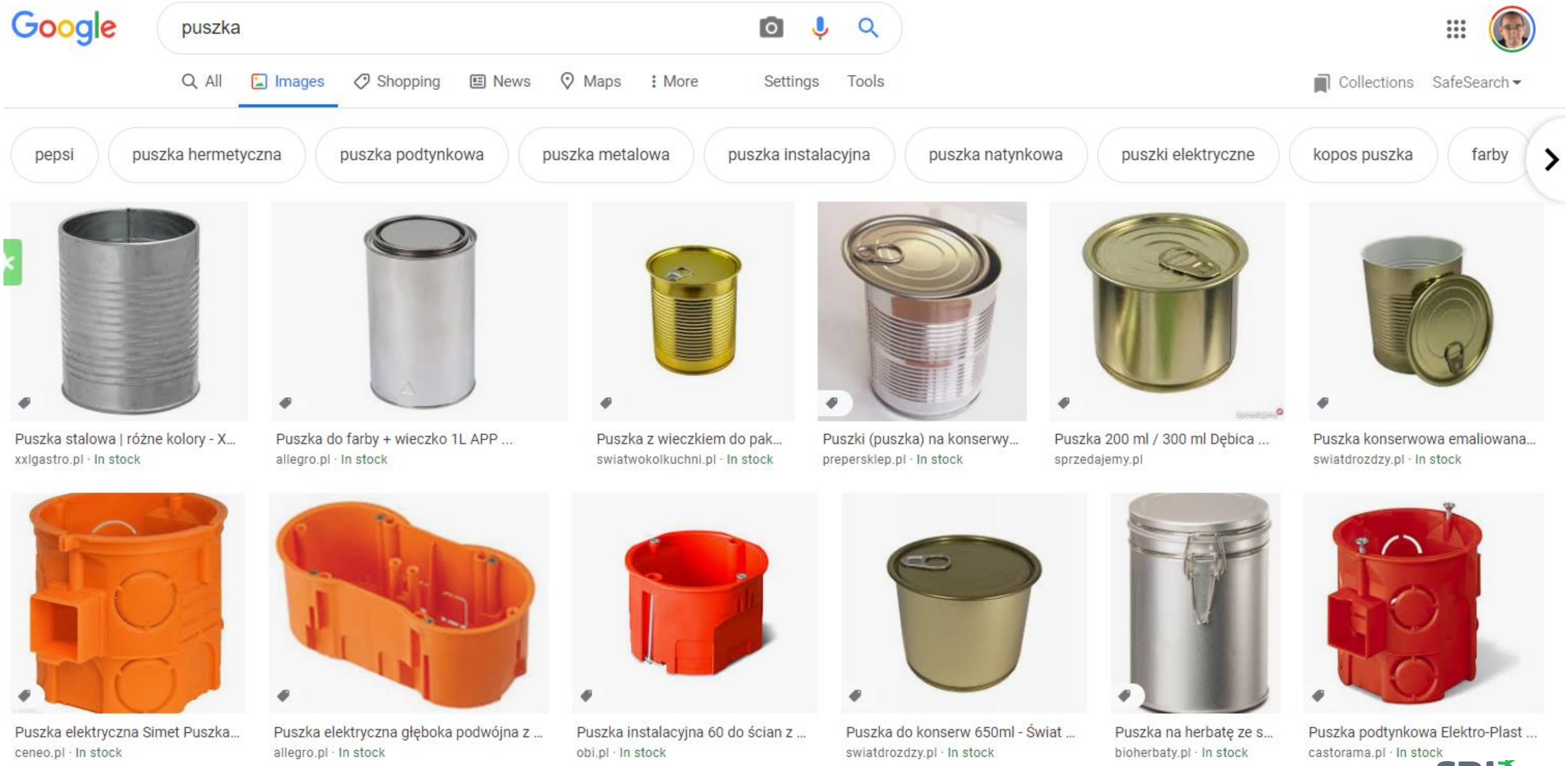
Example 5 – Missing Context

Wymiana puszek i instalacji w starym domu.

Replacement of cans and installations in an old house.

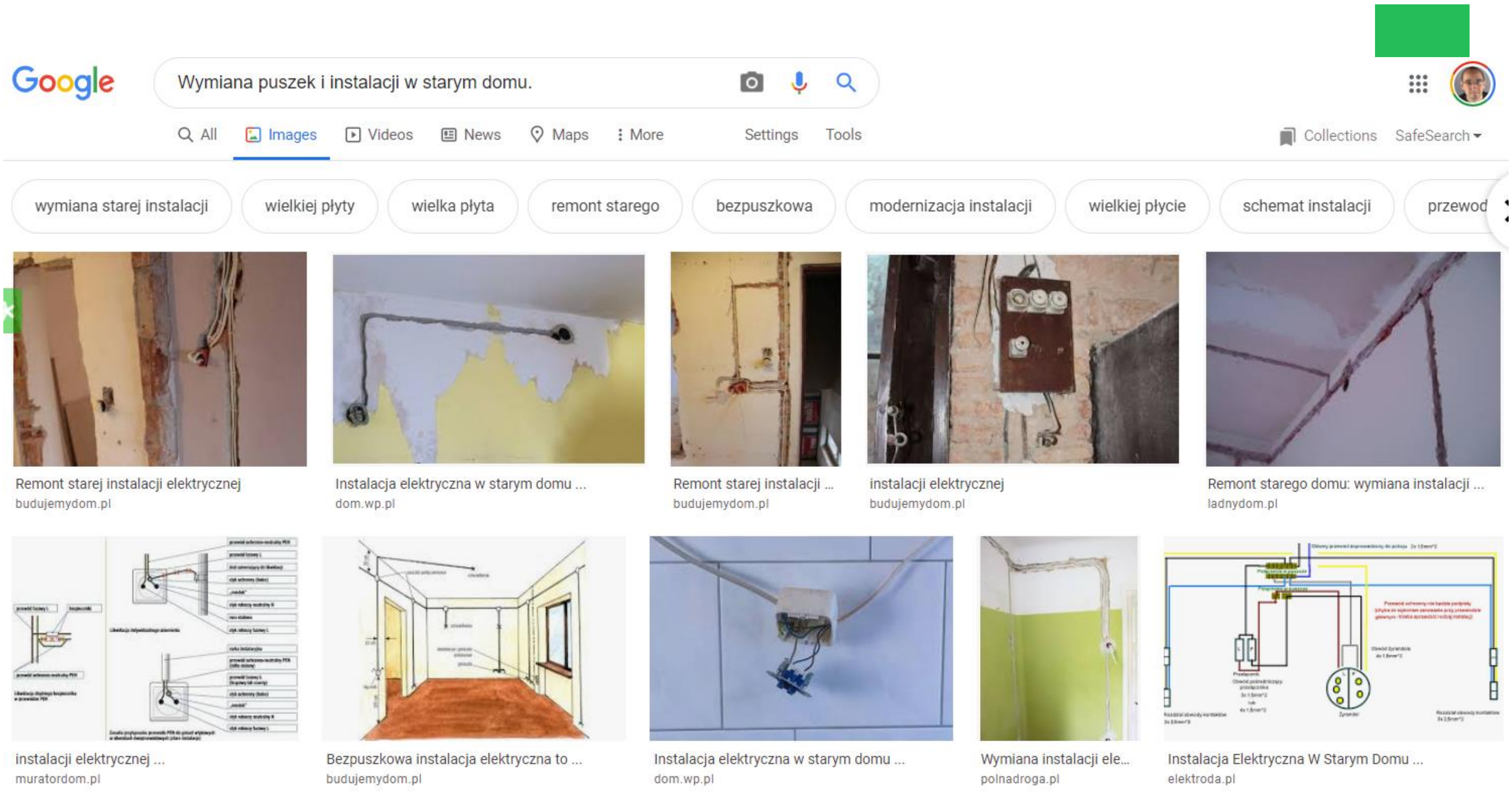
Replacement of junction boxes and wiring in an old house.


Google
can
All
Images
News
Videos
Books
More
Settings
Tools
Collections
SafeSearch
soda
food
coke
clipart
water
drink
tin
paint
soup
aluminum
Steel and tin cans - Wik...
en.wikipedia.org
meaning of can in Longman ...
ldoceonline.com
Everyday Object Sterling Silv...
tiffany.com · In stock
can - Wiktionary
en.wiktionary.org
Can in Spanish | English to Spanish ...
spanishdict.com
Facts About Tin | Live S...
livescience.com
Soda Can You Drink When P...
parents.com
Coca Cola Coke Soda Can Diver...
amazon.com
100oz 603×700 Metal Food Ca...
wellscan.ca · In stock
Cambridge English Dicti...
dictionary.cambridge.org
Club Calls on Fans to Cr...
thetaste.ie
Tincan Ribbed Metal Tin Can, ...
123rf.com
10 awesome things yo...
cnet.com
Soda Can Safes with Hidden C...
tbotech.com · In stock

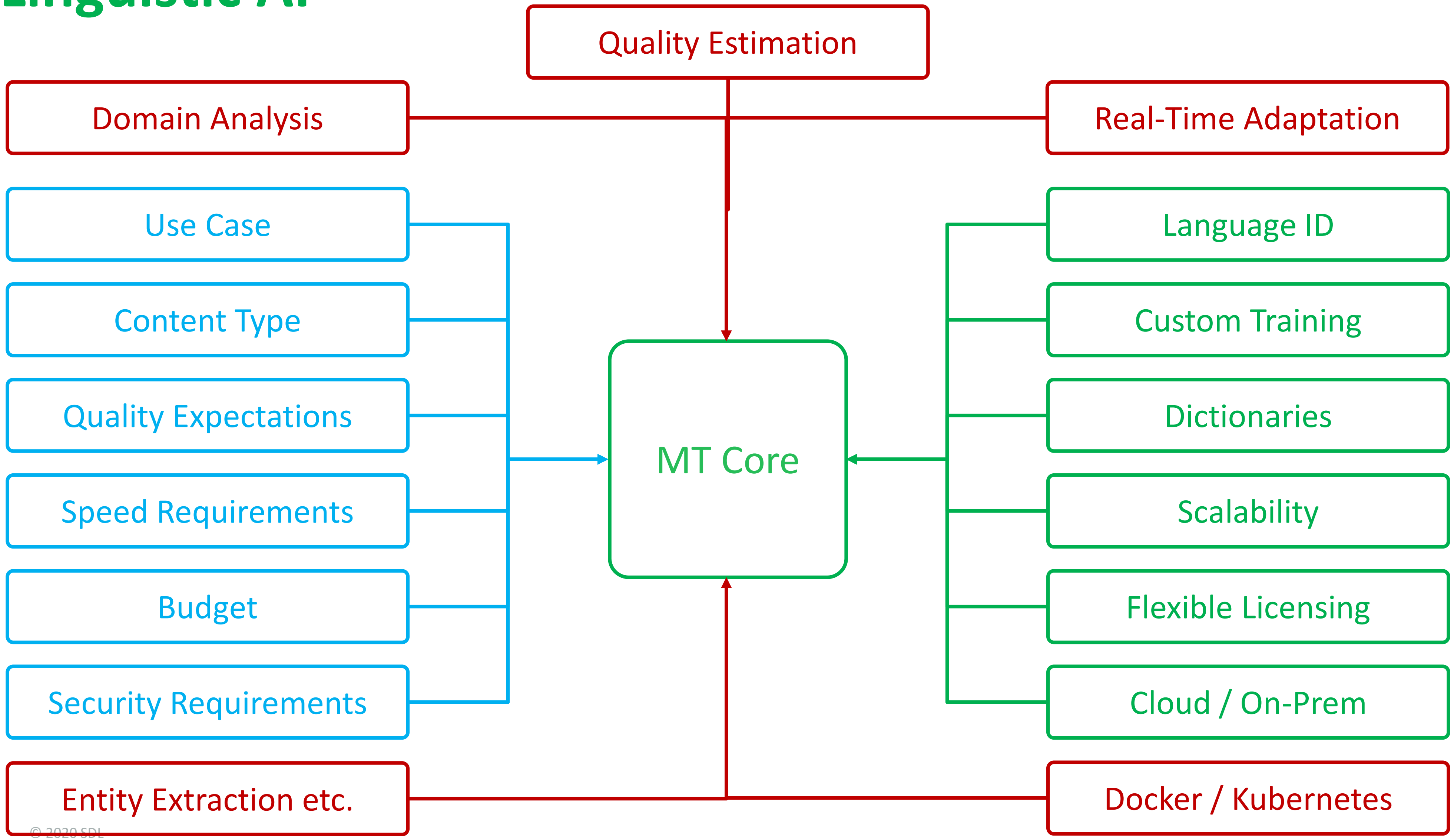


25 © 2020 SDL

SDL


Google
Wymiana puszek i instalacji w starym domu.
All
Images
Videos
News
Maps
More
Settings
Tools
Collections
SafeSearch
wymiana starej instalacji
wielkiej płyty
wielka płyta
remont starego
bezpuszkowa
modernizacja instalacji
wielkiej płycie
schemat instalacji
przewod
Remont starej instalacji elektrycznej
budujemydom.pl
Instalacja elektryczna w starym domu ...
dom.wp.pl
Remont starej instalacji ...
budujemydom.pl
instalacji elektrycznej
budujemydom.pl
Remont starego domu: wymiana instalacji ...
ladnydom.pl
instalacji elektrycznej ...
muratordom.pl
Bezpuszkowa instalacja elektryczna to ...
budujemydom.pl
Instalacja elektryczna w starym domu ...
dom.wp.pl
Wymiana instalacji ele...
polnadroga.pl
Instalacja Elektryczna W Starym Domu ...
elektroda.pl

Linguistic AI



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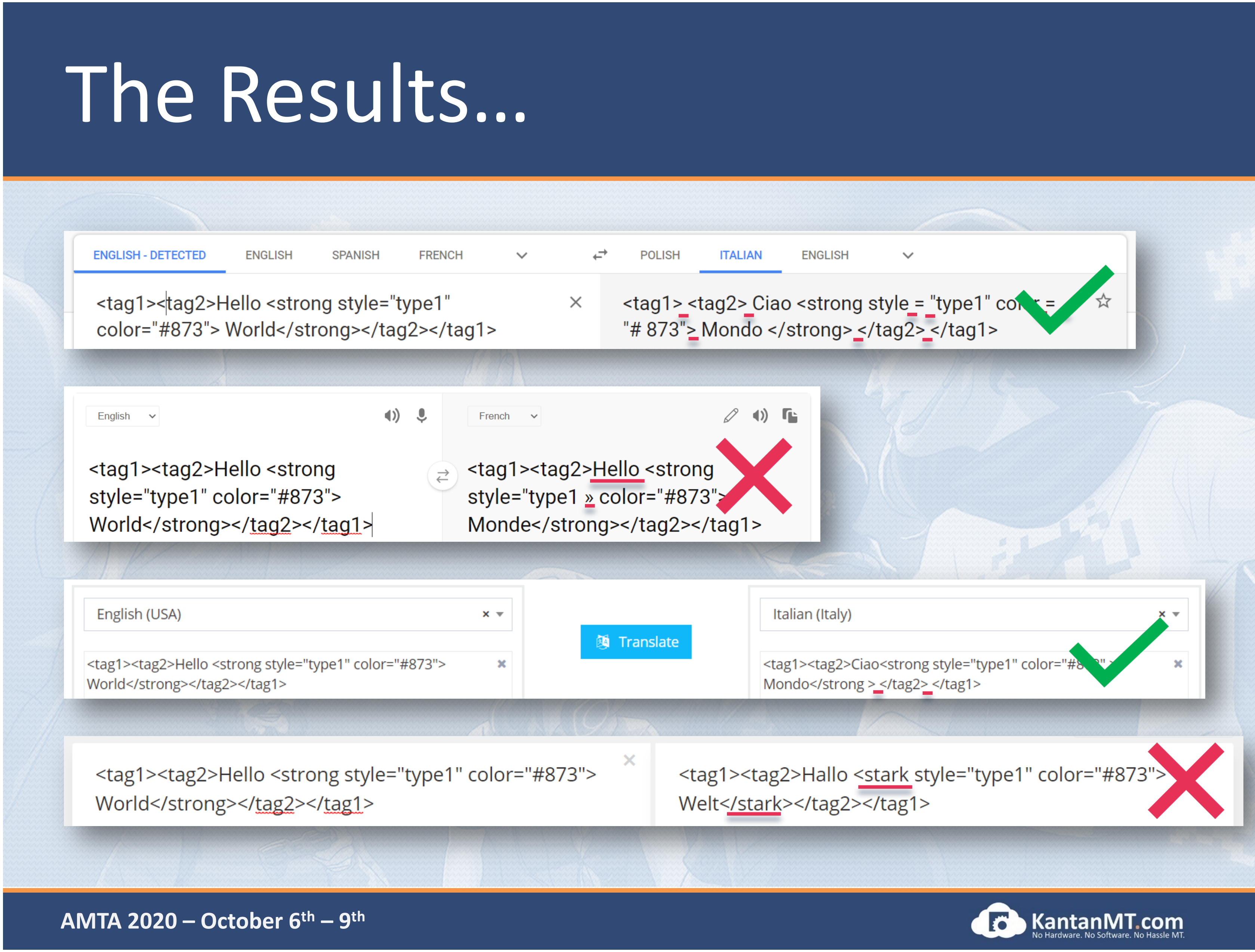
Lexically Constrained Decoding for Sequence Generation

Approaches to support Terms, Tags & Placeholders

The Problem....

original	Hello <g id="1" ctype="x-bold;">World!</g>
after tokenization	Hello < g id = " 1 " ctype = " x-bold ; " > World ! < / g >
after escaping	Hello < g id = " 1 " ctype = " x-bold ; " > World ! < / g >
after lowercasing	hello < g id = " 1 " ctype = " x-bold ; " > world ! < / g >
after translation	guten tag < code < ept id = " 1 " ctype = " " " x-bold ; " > world money < / g > !
after recasing	Guten Tag < Code < ept id = " 1 " ctype = " " " x-bold ; " > World Money < / G > !
after detokenization	Guten Tag < Code < ept id = " 1 " ctype = "" "x-bold;" > World Money < / G >!
after unescaping	Guten Tag < Code < ept id = " 1 " ctype = "" "x-bold;" > World Money < / G >!


The Results…
ENGLISH - DETECTED
ENGLISH
SPANISH
FRENCH
POLISH
ITALIAN
ENGLISH
<tag1><tag2>Hello <strong style="type1" color="#873"> World</tag2></tag1>
<tag1> <tag2> Ciao <strong style = "type1" co = "# 873"> Mondo </tag2> </tag1>
English
French
<tag1><tag2>Hello <strong style="type1" color="#873"> World</tag2></tag1>
<tag1><tag2>Hello <strong style="type1 » color="#873" Monde</tag2></tag1>
English (USA)
Translate
Italian (Italy)
<tag1><tag2>Hello <strong style="type1" color="#873"> World</tag2></tag1>
<tag1><tag2>Ciao<strong style="type1" color="#8 Mondo </tag2> </tag1>
<tag1><tag2>Hello <strong style="type1" color="#873"> World</tag2></tag1>
<tag1><tag2>Hallo <stark style="type1" color="#873"> Welt</stark></tag2></tag1>
AMTA 2020 – October 6th – 9th
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Strategy #1: Structure Forming

- **Subtitling DFXP Format**

```
<p begin="00:01:14:01" end="00:01:17:05">And if that is not enough world championship action,</p>
<p begin="00:01:17:07" end="00:01:21:17">you can pick up the World Championship Pikachu Poké Plush</p>
<p begin="00:01:21:19" end="00:01:23:02">at pokémoncenter.com.</p>
```

Strategy #1: Structure Forming

- **Subtitling DFXP Format**

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<p begin="00:01:14:01" end="00:01:17:05">And if that is not enough world championship action,</p>
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<p begin="00:01:21:19" end="00:01:23:02">at pokémoncenter.com.</p>
```

- **Step 1 - Sentence Forming**

And if that is not enough world championship action, you can pick up the World Championship Pikachu Poké Plush pokémoncenter.com.

Strategy #1: Structure Forming

- **Subtitling DFXP Format**

```
<p begin="00:01:14:01" end="00:01:17:05">And if that is not enough world championship action,</p>
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```

- **Step 1 - Sentence Forming**

And if that is not enough world championship action, you can pick up the World Championship Pikachu Poké Plush at pokémoncenter.com.

- **Step 2 - Translate**

A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship Pikachu Poké Plush na pokémoncenter.com.

Strategy #1: Structure Forming

- **Step 1 - Sentence Forming**

> And if that is not enough world championship action, you can pick up the World Championship Pikachu Poké Plush at pokémoncenter.com.

- **Step 2 – Translate**

> A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship Pikachu Poké Plush na pokémoncenter.com.

- **Step 3 – Reformat & Re-insert**

```
<p begin="00:01:14:01" end="00:01:17:05">И если этого недостаточно для участия в чемпионате мира,</p>
<p begin="00:01:17:07" end="00:01:21:17">вы можете забрать Pikachu Poké Plush Plush</p>
<p begin="00:01:21:19" end="00:01:23:02">pokémoncenter.com.</p>
```

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Strategy #2: Zones & Walls

- **Moses decoder has the concept of**
  - **Forced Translations** – parts of the input sentence can be wrapped in <np> tags and assigned a probability

```
<np translations="Translated Term" prob="1">…</np>
```

  - **Zones**
    - Encapsulates a series of tokens that cannot be individually re-ordered, but can be re-ordered as part of the parent sequence

```
You can pick up the World Championship <zone>Pikachu Poké Plush</zone>
```

  - **Wall**
    - A hard border that tokens cannot cross during re-ordering

Strategy #3: Segmentation

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

Strategy #3: Segmentation

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

And if that is not enough world championship action, you can pick up the World Championship

`<strong>`

Pikachu Poké Plush

`</strong>`

at pokémoncenter.com.

Strategy #3: Segmentation

And if that is not enough world championship action, you can pick up the World Championship

Pikachu Poké Plush

at pokémoncenter.com.

A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship **Pikachu Poké Plush** na pokémoncenter.com.

Strategy #4: Pass Through

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

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Strategy #4: Pass Through

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

And if that is not enough world championship action, you can pick up the World Championship ❶ **Pikachu Poké Plush** ❷ at pokémoncenter.com.

Token	Assigned
❶	
❷	

Strategy #4: Pass Through

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

And if that is not enough world championship action, you can pick up the World Championship ❶ **Pikachu Poké Plush** ❷ at pokémoncenter.com.

Token	Assigned
❶	
❷	

A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship ❶**Pikachu Poké Plush**❷ na pokémoncenter.com.

Strategy #4: Pass Through

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

And if that is not enough world championship action, you can pick up the World Championship ❶ **Pikachu Poké Plush** ❷ at pokémoncenter.com.

Token	Assigned
❶	
❷	

A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship **Pikachu Poké Plush** na pokémoncenter.com.

Strategy #4: Pass Through

Token	Assigned	Token	Assigned
❶		❻	
❷		❼	
❸		❽	
❹		❾	
❺		❿	

Strategy #5: Optimisation

- **Detecting lead/trail tags**

<p><font=“Calibri”><color=“#1234”><size=“10pts”>And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.
</size></color></p>

Strategy #5: Optimisation

- **Detecting lead/trail tags**

<p><font=“Calibri”><color=“#1234”><size=“10pts”>And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com. </size></color></p>

<lead/>And if that is not enough world championship action, you can pick up the World Championship ❶ **Pikachu Poké Plush** ❷ at pokémoncenter.com.**<trail/>**

Token	Assigned
❶	`<strong>`
❷	`</strong>`
Lead	`<p><font="Calibri"><color="#1234"><size="10pts">`
Trail	`</size></color></font></p>`

Which one to work with???

- **Strategy #1**
  - Structure Forming
- **Strategy #2**
  - Zones & Walls
- **Strategy #3**
  - Segmentation
- **Strategy #4**
  - Pass-Thru
- **Strategy #5**
  - Optimisation

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Challenges of Terminology

Basic Levels of Terminology

- **Lexically Constrained Decoding for Sequence Generation**
  - **Level I**
    - Multi-word phrases – non-inflected
    - Nouns, Proper Nouns, Brand or Feature/Service names
    - Can be represented in simple list form

EN	FR	IT	DE
Stakataka	Ama-Ama	Stakataka	Muramura
Snorlax	Ronflex	Snorlax	Relaxo
Trainer	Dresseur	Allenatore	Trainer
Terrakion	Terrakium	Terrakion	Terrakium
Whimsicott	Farfaduvet	Whimsicott	Elfun
Gengar	Ectoplasma	Gengar	Gengar
Tapu Bulu	Tokotoro	Tapu Bulu	Kapu-Toro
Kommo-o	Ékaïser	Kommo-o	Grandiras

  - **Level II**
    - Inflected Multi-word phases
    - Cannot be represented in simple list form
    - Inflected variations to indicate number, grammatical case, or gender

What is a Glossary?

- **Terms in one or more languages**
  - With comments, and usage examples
  - **Industry Glossary**
    - Includes terms that are standard for an industry or subject/domain
    - **Example**: Banking, Cardiology, Automotive, Accounting
  - **Client Glossary**
    - Contains terms that are very specific to a company/client
    - **Example**: eBay, Adobe, BMW
  - **Project Glossary**
    - Used to maintain consistency throughout translation project
    - **Example**: Microsoft Office, Pokemon

iate European Union terminology

https://iate.europa.eu/home

Terms: 7.9 million
Languages: 26

Level #1: Segmentation

And if that is not enough world championship action, you can pick up the World Championship <term>**Pikachu Poké Plush** </term>at pokémoncenter.com.

And if that is not enough world championship action, you can pick up the World Championship

<term>

Pikachu Poké Plush

</term>

at pokémoncenter.com.

Level #1: Segmentation

And if that is not enough world championship action, you can pick up the World Championship

<term>

Pikachu Poké Plush

TermBase Lookup

</term>

at pokémoncenter.com.

A jeśli to nie wystarczy akcja mistrzostw świata, możesz wybrać World Championship **Pikachu Poké Plush** na pokémoncenter.com.

Level #1: Pre-process & Pass-Thru

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

TermBase Lookup

And if that is not enough world championship action, you can pick up the World Championship **<np translations="Pikachu Poké Plush" prob="1"/>** at pokémoncenter.com.

Level #1: Pre-process & Pass-Thru

And if that is not enough world championship action, you can pick up the World Championship **Pikachu Poké Plush** at pokémoncenter.com.

TermBase Lookup

And if that is not enough world championship action, you can pick up the World Championship **<np translations="Pikachu Poké Plush" prob="1"/>** at pokémoncenter.com.

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Thank you…

Building Salesforce Neural Machine Translation System

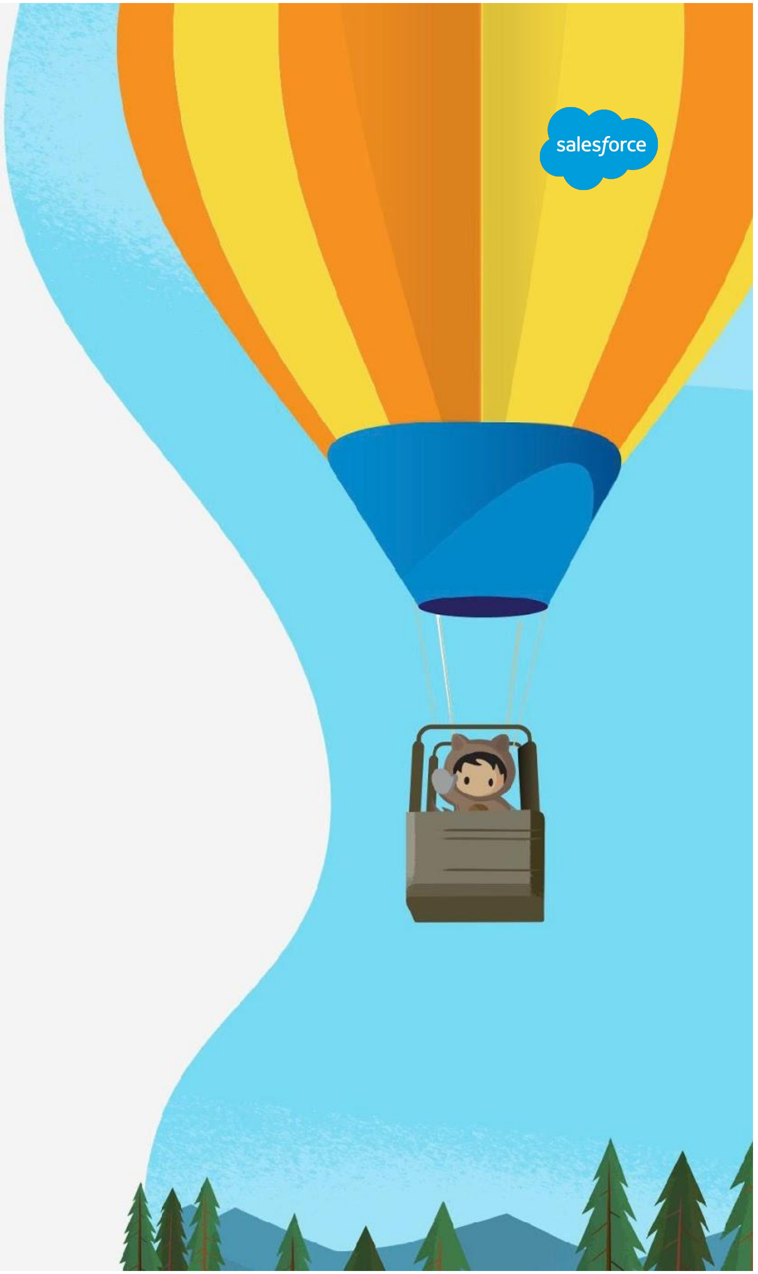
Kazuma Hashimoto, Lead Research Scientist
@ Salesforce Research

Raffaella Buschiazzo, Director, Localization
@ Salesforce R&D Localization

AMTA 2020 Commercial Track

Agenda

- Why invest in machine translation
- Salesforce online help
- What was done: Phase I
  - Technical overview
  - Example flows
- What was done: Phase II
- Roadmap



Why Invest in Machine Translation

A three-year collaboration between R&D Localization and Salesforce Research teams

Interesting research project

- Challenges: difficult MT languages (i.e. Finnish, Japanese), XML tagging.

Improve international customer experience by

- Reducing translation time by enhancing translator's productivity for our online help
- Increasing content accuracy/freshness by publishing updates more frequently
- Re-investing savings into high-value efforts
    - Products and product-related properties
    - Underserved localization content/efforts

Benefits

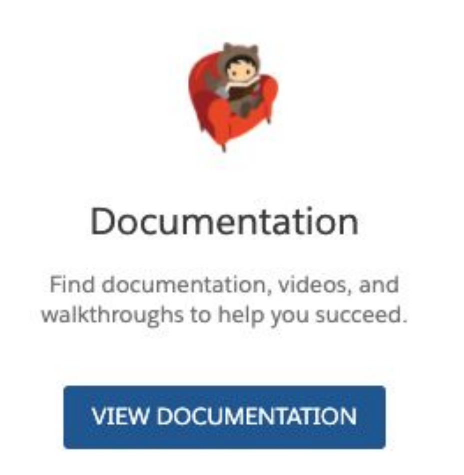
- Increase case deflection through up-to-date content for existing languages
- Increase breadth and depth of localization coverage with more flexibility by market

Salesforce Online Help

Primary target for our MT system

salesforce

- Translated in 16 languages.
- Translations are updated per major release (3 x year).
- New feature/product terminology.
- Structured in DITA XML (200+ tags).



English
Français
Deutsch
Italiano
日本語
Español (México)
Español
中文（简体）
中文（繁體）
한국어
Русский
Português (Brasil)
Suomi
Dansk
Svenska
Nederlands
ภาษาไทย
Norsk

What Was Done: Phase I

Linguistic testing

Built an NMT system on Salesforce domain
- Language-agnostic architecture with models for each language
- Processes whole XML files from English into 16 languages

Completed human evaluations of MTed output
- Japanese, Finnish, German, French Help subsets (500 strings)

Published paper A High-Quality Multilingual Dataset for Structured Documentation Translation (WMT 2019)

Technical Overview

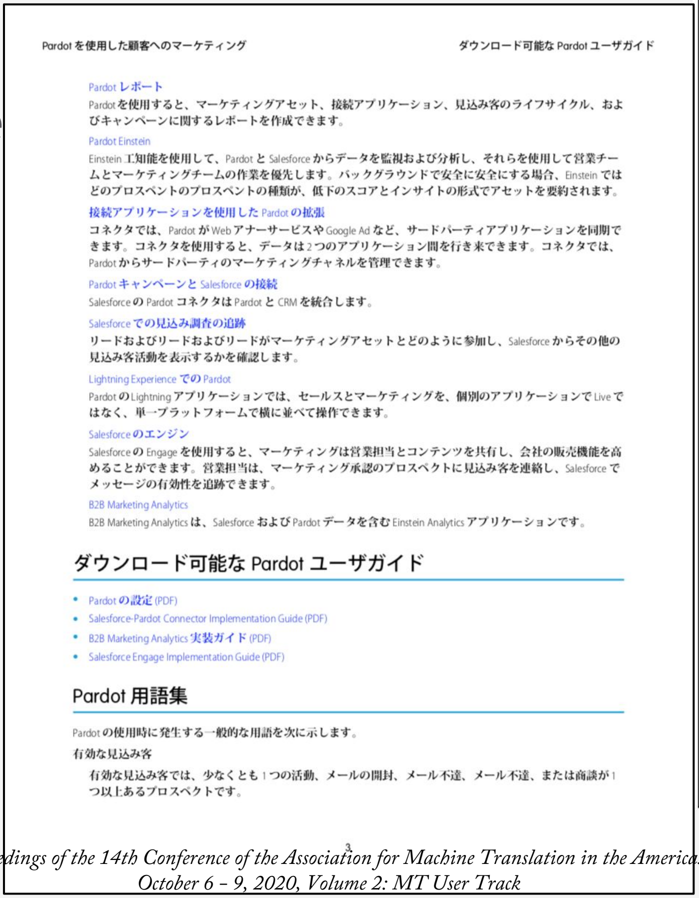
Data and application

Dataset in our paper

- https://github.com/salesforce/localization-xml-mt

Translation of rich-formatted text

- How to preserve the structure



Pardot を使用した顧客へのマーケティング　　　ダウンロード可能な Pardot ユーザガイド

Pardot レポート

Pardot を使用すると、マーケティングアセット、接続アプリケーション、見込み客のライフサイクル、およびキャンペーンに関するレポートを作成できます。

Pardot Einstein

Einstein 工知能を使用して、Pardot と Salesforce からデータを監視および分析し、それらを使用して営業チームとマーケティングチームの作業を優先します。バックグラウンドで安全に安全にする場合、Einstein ではどのプロスペントのプロスペントの種類が、低下のスコアとインサイトの形式でアセットを要約されます。

接続アプリケーションを使用した Pardot の拡張

コネクタでは、Pardot が Web アナーサービスや Google Ad など、サードパーティアプリケーションを同期できます。コネクタを使用すると、データは 2 つのアプリケーション間を行き来できます。コネクタでは、Pardot からサードパーティのマーケティングチャネルを管理できます。

Pardot キャンペーンと Salesforce の接続

Salesforce の Pardot コネクタは Pardot と CRM を統合します。

Salesforce での見込み調査の追跡

リードおよびリードおよびリードがマーケティングアセットとどのように参加し、Salesforce からその他の見込み客活動を表示するかを確認します。

Lightning Experience での Pardot

Pardot の Lightning アプリケーションでは、セールスとマーケティングを、個別のアプリケーションで Live ではなく、単一プラットフォームで横に並べて操作できます。

Salesforce のエンジン

Salesforce の Engage を使用すると、マーケティングは営業担当とコンテンツを共有し、会社の販売機能を高めることができます。営業担当は、マーケティング承認のプロスペクトに見込み客を連絡し、Salesforce でメッセージの有効性を追跡できます。

B2B Marketing Analytics

B2B Marketing Analytics は、Salesforce および Pardot データを含む Einstein Analytics アプリケーションです。

ダウンロード可能な Pardot ユーザガイド

- Pardot の設定 (PDF)
- Salesforce-Pardot Connector Implementation Guide (PDF)
- B2B Marketing Analytics 実装ガイド (PDF)
- Salesforce Engage Implementation Guide (PDF)

Pardot 用語集

Pardot の使用時に発生する一般的な用語を次に示します。

有効な見込み客

有効な見込み客では、少なくとも 1 つの活動、メールの開封、メール不達、メール不達、または商談が 1 つ以上あるプロスペクトです。

3

- Example (a)

English:

You can use this report on your Community Management Home dashboard or in <ph>Community Workspaces</ph> under <menucascade><uicontrol>Dashboards</uicontrol><uicontrol>Home</uicontrol></menucascade>.

Japanese:

このレポートは、[コミュニティ管理] のホームのダッシュボード、または <ph>コミュニティワークスペース</ph>の <menucascade><uicontrol>[ダッシュボード]</uicontrol> <uicontrol>[ホーム]</uicontrol></menucascade> で使用できます。

- Example (b)

English:

Results with both<i>beach</i> and <i>house</i> in the searchable fields of the record.

Japanese:

レコードの検索可能な項目に <i>beach</i> と <i>house</i> の 両方が含まれている結果。

- Example (c)

English:

You can only predefine **this field** to an email address. You can predefine **it** using either T (used to define email addresses) or To Recipients (used to define contact, lead, and user IDs).

Japanese:

この項目はメールアドレスに対してのみ事前に定義できます。
この項目は [宛先] (メールアドレスを定義するために使用) または [宛先受信者] (取引先責任者、リード、ユーザ ID を定義するために使用) のいずれかを使用して事前に定義できます。

Technical Overview

Model

Transformer encoder-decoder (Vaswani et al., 2017)

- Input: XML-tagged text in English
- Output: XML-tagged text in another language
    - **XML-tag-aware tokenizer** is used (based on sentencepiece)
    - e.g.) <uicontrol>New Suite</uicontrol>: Create a suite of test classes that...

      → _ <uicontrol> New _Suite </uicontrol> : _Create _a _suit e _of _test _classes _that...
- \+ copy mechanisms
    - Copy from source is used to **align XML tags**

- Source to be translated (English)

<xref>View a single feed update**</xref>** by clicking the timestamp below the update, *for example*, **<uicontrol>**Yesterday at **12:57 AM</uicontrol>**.

- Retrieved source (English)

In a feed, click the timestamp that appears below the post, *for example*, <uicontrol>Yesterday at 12:57 AM</uicontrol>.

- Retrieved reference (Japanese)

フィード内で、*たとえば*、<uicontrol>**[昨日の** 12:57 AM**]**</uicontrol> **のように、**投稿**の下に**表示される**タイムスタンプ**をクリックします**。**

- Output of the X*rs* model (Japanese)

<uicontrol> [昨日の 12:57 AM] </uicontrol> のように、更新**の下にタイムスタンプ**をクリックして**、<xref>** 1 つのフィード更新を表示**</xref>**します**。**

Technical Overview

System

Training

- Construct our training data from
  - the ***N*-th** release
    - a later version than our published dataset
  - release notes of the new, **(N+1)-th**, release
    - to incorporate translation of new features/context in the new release
    - available for our company's top-tier languages
  - [optional and if applicable] whatever internal parallel data

Translation

- Target English strings that have **little overlap** with our translation memory
- Remove metadata from XML tags
- Run our model for each language
- Align the metadata with the translated strings by using our model's copy mechanism

Human verification and post-editing before publishing the translated online help

Example Flow (1)

Overview

Update basic community settings like your community URL, community name, members, login options, and general preferences in the <TAG id=”1”>Administration</TAG> section of <TAG id=”2”>Experience Workspaces</TAG> or <TAG id=”3”>Community Management</TAG>.

English

Our System

Japanese

<TAG id=”2”>エクスペリエンスワークスペース</TAG>または <TAG id=”3”>[コミュニティ管理]</TAG> の <TAG id=”1”>[管理]</TAG> セクションで、コミュニティ URL、コミュニティ名、メンバー、ログインオプション、一般的な設定など、コミュニティの基本設定を更新します。

Example Flow (2)

Input Preprocessing

Update basic community settings like your community URL, community name, members, login options, and general preferences in the <TAG id=”1”>Administration</TAG> section of <TAG id=”2”>Experience Workspaces</TAG> or <TAG id=”3”>Community Management</TAG>.

Simplify the input

Tag mapping table
<TAG id=”1”>: <ph>
<TAG id=”2”>: <ph>
<TAG id=”3”>: <ph>

Update basic community settings like your community URL, community name, members, login options, and general preferences in the <ph>Administration</ph> section of <ph>Experience Workspaces</ph> or <ph>Community Management</ph>.

Example Flow (3)

Translation by our model

Update basic community settings like your community URL, community name, members, login options, and general preferences in the <ph>Administration</ph> section of <ph>Experience Workspaces</ph> or <ph>Community Management</ph>.

Translation

<ph>エクスペリエンスワークスペース</ph>または <ph>[コミュニティ管理]</ph> の <ph>[管理]</ph> セクションで、コミュニティ URL、コミュニティ名、メンバー、ログインオプション、一般的な設定など、コミュニティの基本設定を更新します。

Example Flow (4)

Tag Alignment

Update basic community settings like your community URL, community name, members, login options, and general preferences in the <ph>Administration</ph> section of <ph>Experience Workspaces</ph> or <ph>Community Management</ph>.

Maximize the product of the copy weights based on one-to-one mapping assumption

English \ Japanese	<ph>_ja	<ph>_ja	<ph>_ja
<ph>_en	0.01	0.05	**0.91**
<ph>_en	**0.92**	0.02	0.01
<ph>_en	0.01	**0.95**	0.01

<ph>エクスペリエンスワークスペース</ph>または <ph>[コミュニティ管理]</ph> の <ph>[管理]</ph> セクションで、コミュニティ URL、コミュニティ名、メンバー、ログインオプション、一般的な設定など、コミュニティの基本設定を更新します。

Example Flow (5)

Output Postprocessing

<ph>エクスペリエンスワークスペース</ph>または <ph>[コミュニティ管理]</ph> の <ph>[管理]</ph> セクションで、コミュニティ URL、コミュニティ名、メンバー、ログインオプション、一般的な設定など、コミュニティの基本設定を更新します。

Tag mapping table
<TAG id="1">: <ph>
<TAG id="2">: <ph>
<TAG id="3">: <ph>

<TAG id="2">エクスペリエンスワークスペース</TAG>または <TAG id="3">[コミュニティ管理]</TAG> の <TAG id="1">[管理]</TAG> セクションで、コミュニティ URL、コミュニティ名、メンバー、ログインオプション、一般的な設定など、コミュニティの基本設定を更新します。

What Was Done: Phase II

Completed 2 pilots

- MTPEd two major releases of help content in Japanese, French, German, Brazilian Portuguese, Mexican Spanish, Swedish, Danish, Norwegian.

Evaluated 500 strings: our system against uncustomized commercially available NMT system

Observations:

- Salesforce NMT is better at outputting sentences with Salesforce writing style.
- Other system is good at outputting generally well-written sentences.
- Most challenging part is translating new features/terminology.
- Including Salesforce Release Notes in training data increased score #1.

Roadmap

- Leveraging publicly available models
  - So far, we used our own data only
  - Fine-tune/customize general models/engines
    - Publicly available pretrained models: mBART, XLM-R, etc.
- Human-in-the-loop training
  - At every release, we can get post-edited strings
  - Can we use the feedback to train another model to refine MT output?
    - Or can we train a model to spot potentially wrong segments to help human post-editing?
- Continual learning
- Extend MT to more online languages and more use cases


thank
you
BLAZE
YOUR
TRAIL
salesforce

SUCCESSFUL TECH TRANSFER OF OF MT RESEARCH IN GOVERNMENT

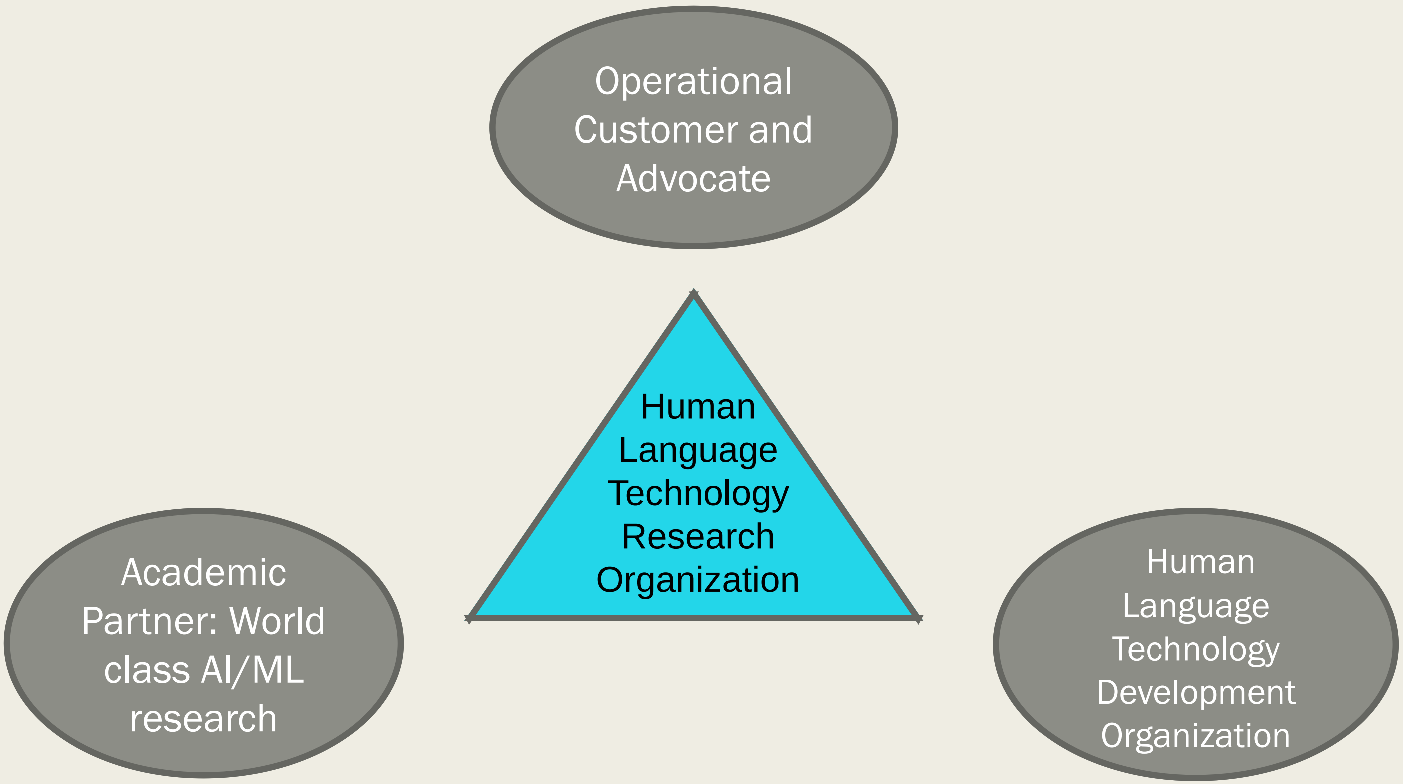
Dr. Kathy Baker
US Dept. of Defense
AMTA
October 9, 2020

Background

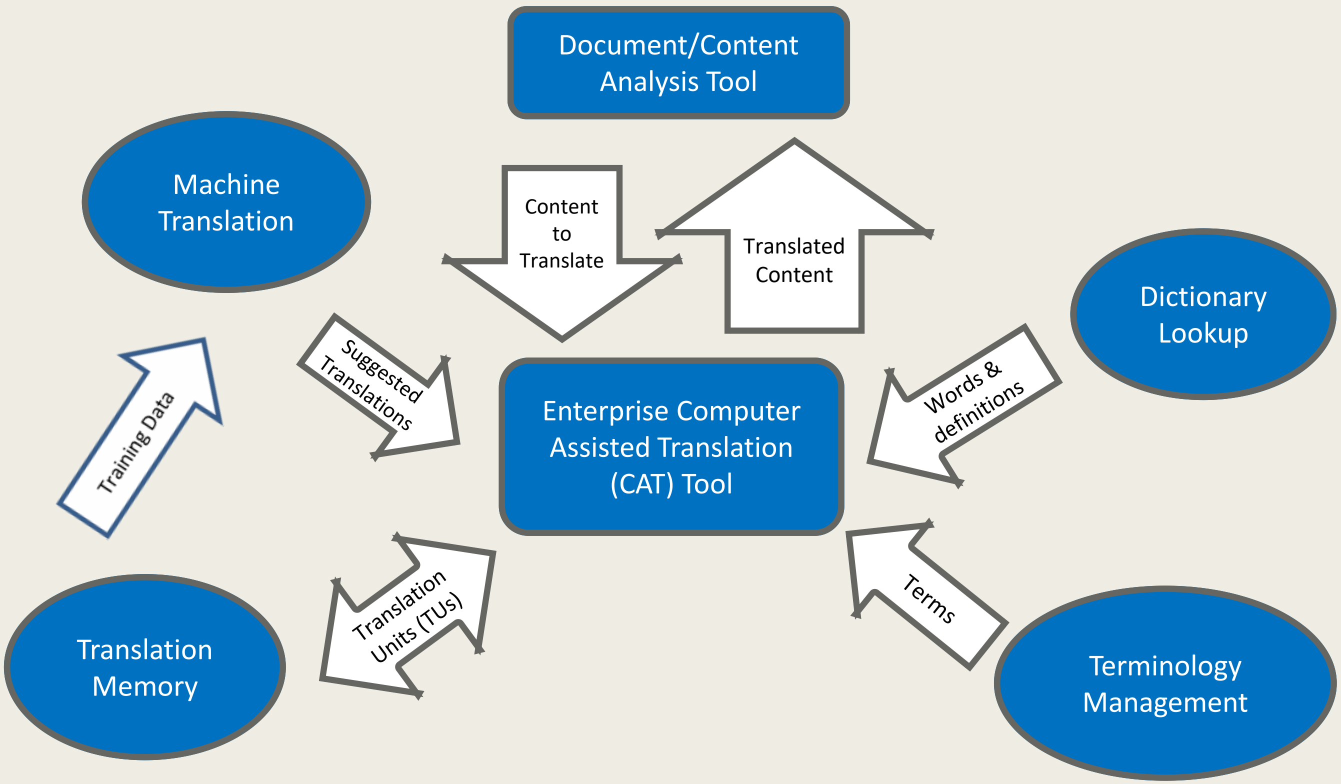
- *Vision* – DoD Agency recognizes Neural Machine Translation (NMT) as a force multiplier for analysis
- In-house HLT Research organization: Cutting edge Artificial Intelligence/Machine Learning (AI/ML)
- “Make vs. buy”– Agency not obligated to productize in-house research
- Key selling point is *access to and understanding of government data sets*

What makes tech transfer successful?

- Partnerships, partnerships, partnerships!



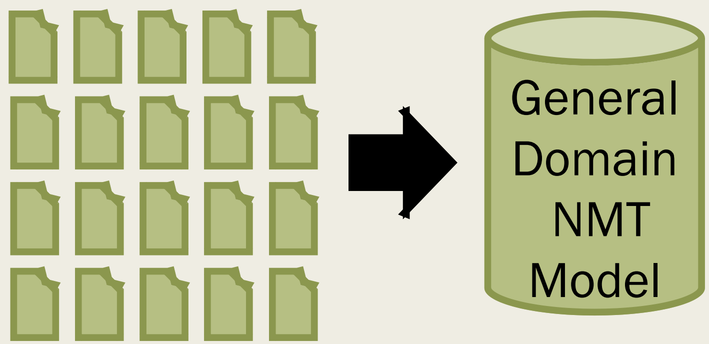
Human Translation Technology Vision



Academic Partnership

- Academic partnership with Johns Hopkins University
- Jump start research in neural MT with "dream team" of academic and industrial experts (Summer 2018 workshop)
- Adapt MT trained on general domain data for your use case with small amounts of highly technological or informal data

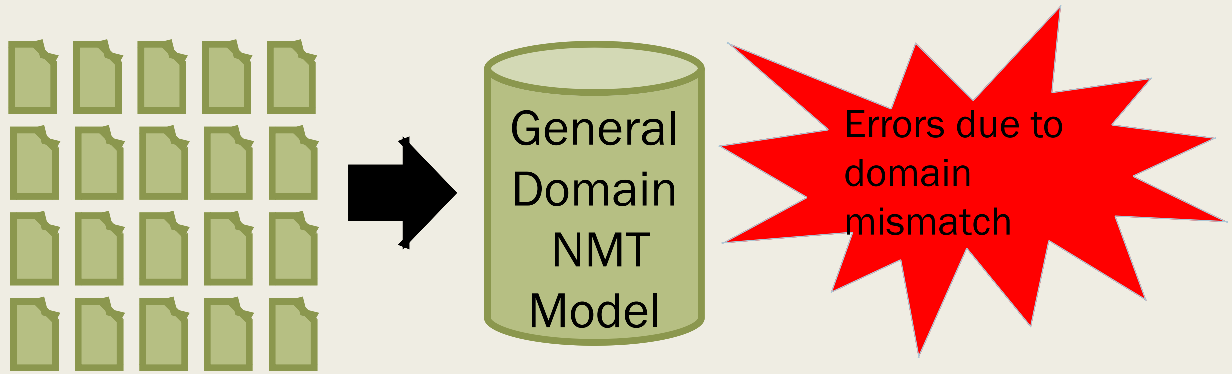
General Domain Training



50M General-domain sentence pairs

General domain: News, parliamentary proceedings, movie subtitles, Wikipedia headlines, etc.

General Domain Training



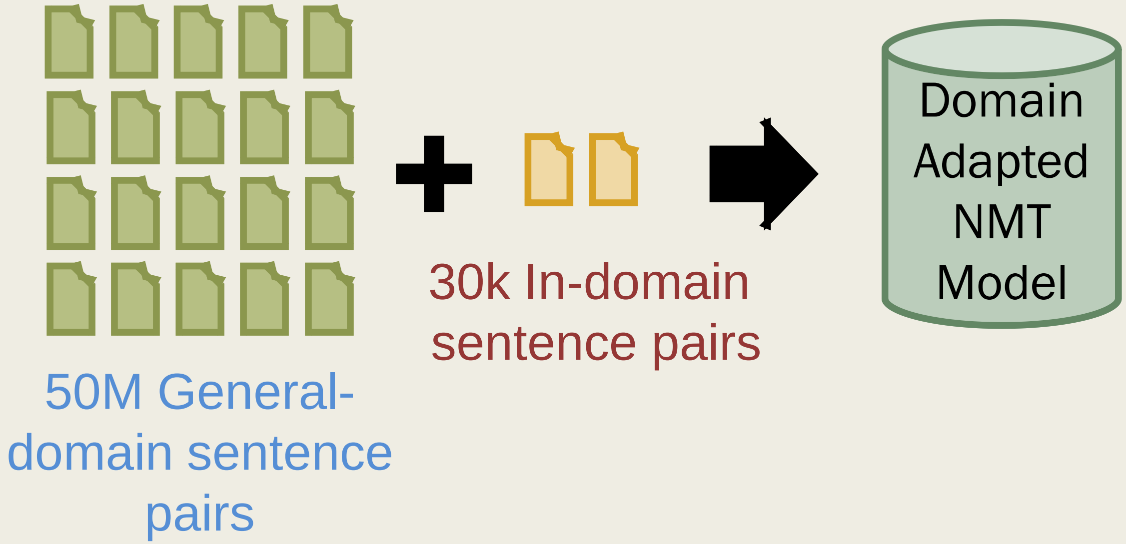
Russian patent example

Input: устройство для сбора воды с последующим её использованием для **стеклоомывателя**
Human: device for collecting water for subsequent use in a **windscreen washer**
System: water collection device and subsequent use for **glazing**

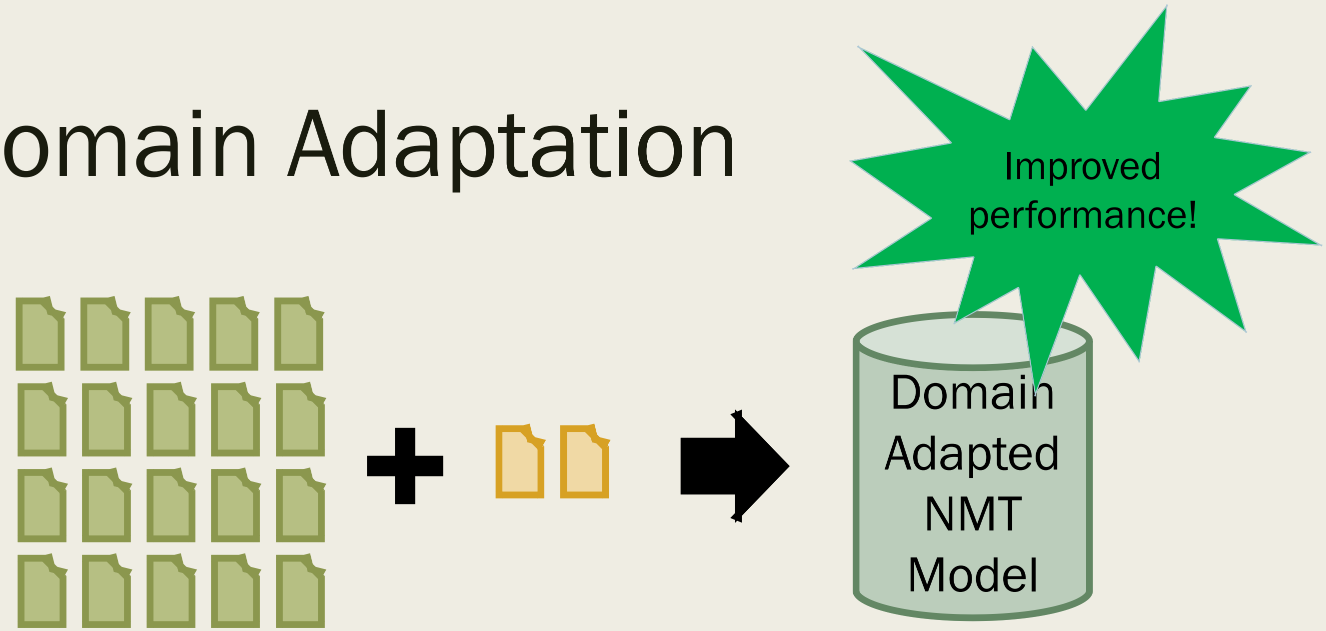
Window glass

British for “windshield”

Domain Adaptation



Domain Adaptation



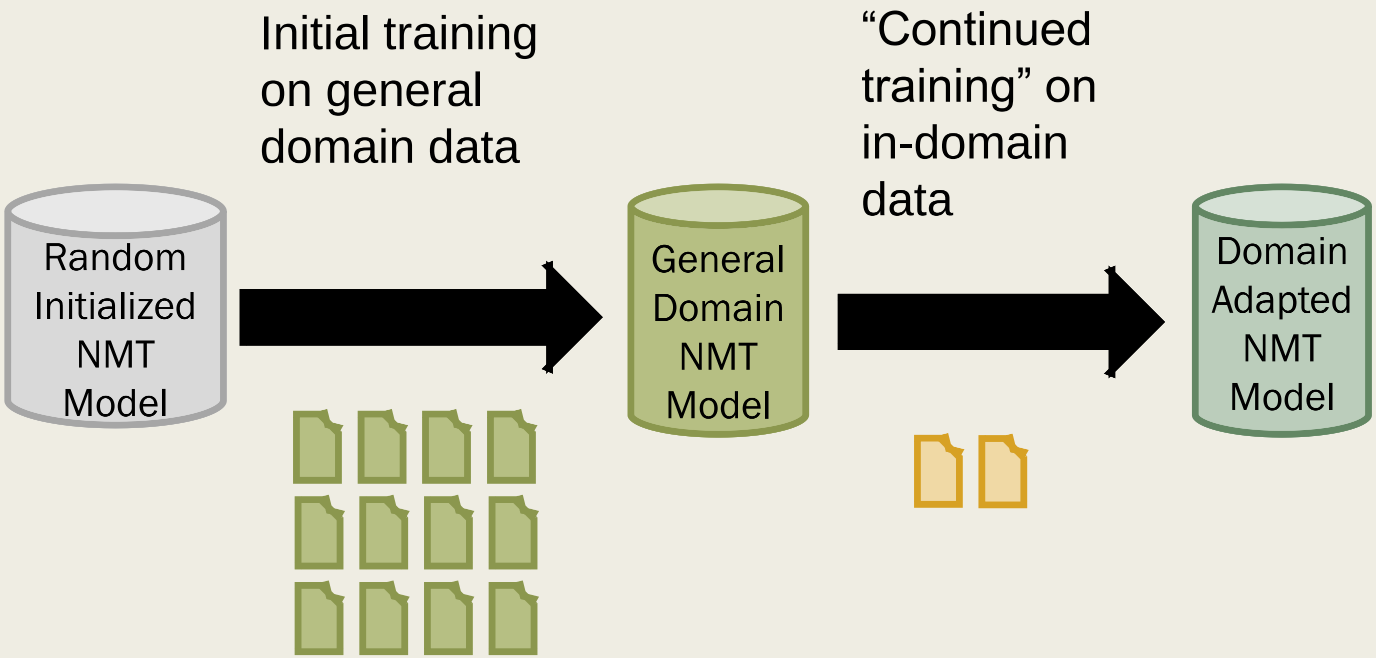
Input: устройство для сбора воды с последующим её использованием для **стеклоомывателя**

Human: device for collecting water for subsequent use in a **windscreen washer**

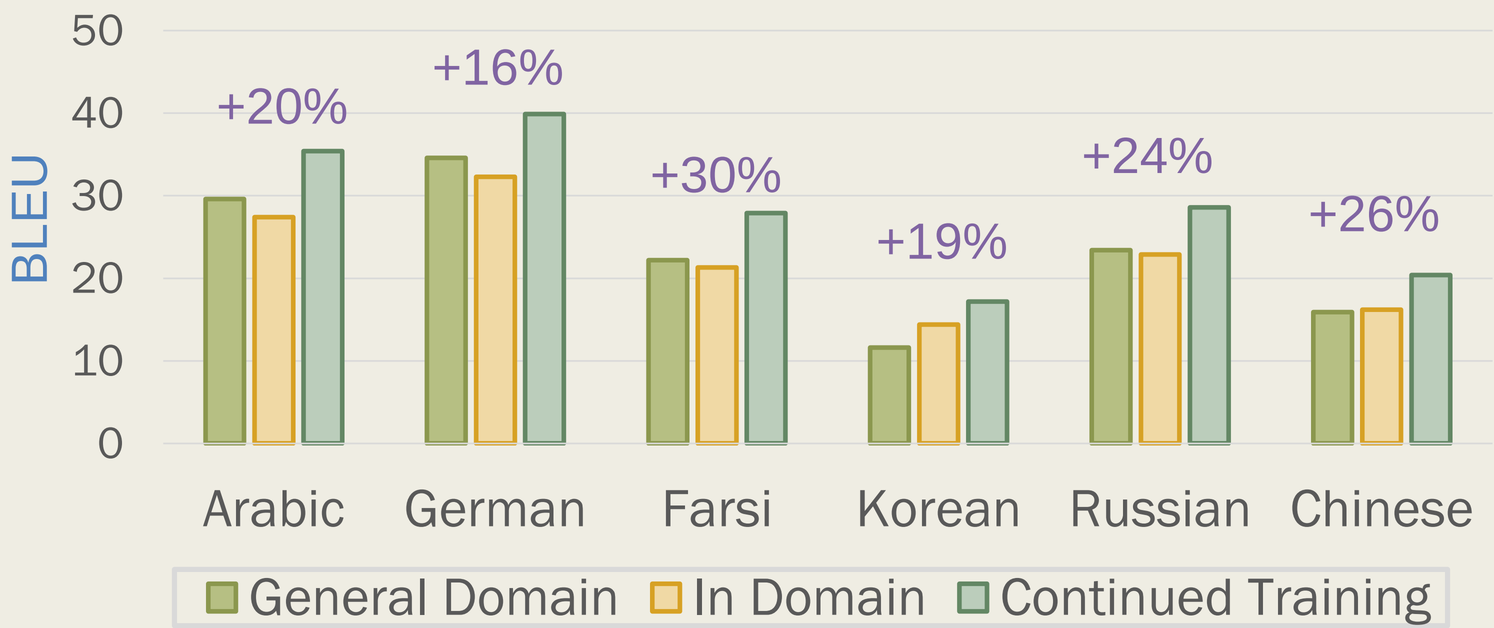
Output: water collecting device with subsequent use thereof for a **windscreen washer**

Continued Training

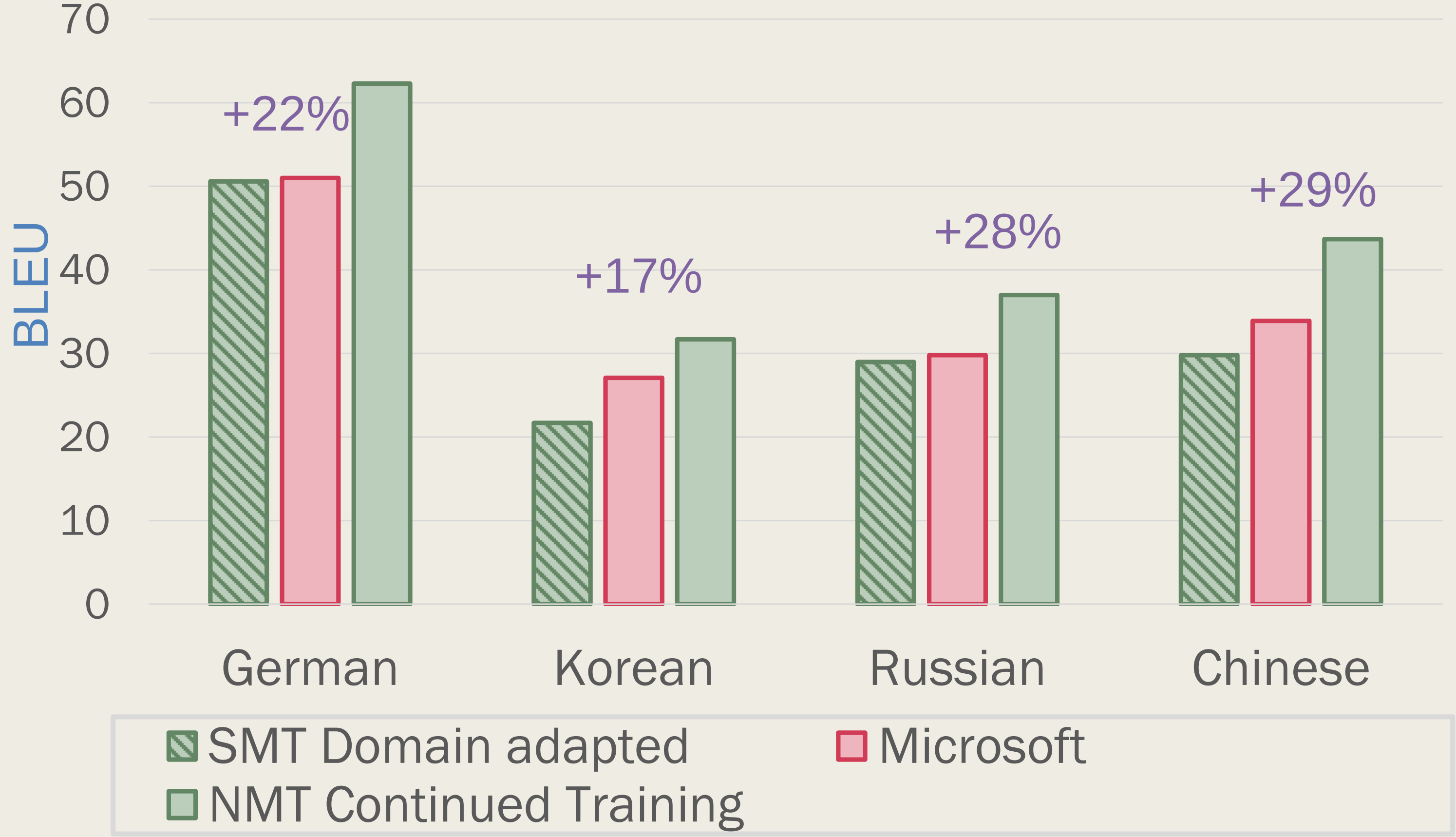
[= “Fine-tuning” in STT literature]



TED Corpus – NMT Continued Training



Patents - NMT vs Statistical MT, Out of box MT



Sample Translations

TED Talk

- **Source:** 我遇到了霍金教授 他说他的梦想是空间旅行
- **Reference:** And I met Professor Hawking, and he said his dream was to travel into space.
- **Agency Baseline:** I ran into Professor Hodgen he saying that his dream was the spatial travel
- **DA-NMT:** I met Professor Hawking who said that his dream was space travel.

Patent

- **Source:** 一种基于纳米滤膜的废有机溶剂处理工艺及系统
- **Reference:** WASTE ORGANIC SOLVENT TREATMENT PROCESS AND SYSTEM BASED ON NANO FILTRATION MEMBRANE
- **Agency Baseline:** One kind based on nanometer filter diaphragm's waste organic solvent processing craft and system
- **DA-NMT:** Waste organic solvent treatment process and system based on nanometer filter film

Operational Partnership

- Customer who understands benefits of research early on contributes
  - *Advocacy*
  - *Funding*
  - *Personnel with language expertise*
  - *Operational Data*

Development Partnership

- HLT Development Organization designed as a "sister org" with common goals for success
- Previous Research successes built up model deployment infrastructure there
  - *Own and provide necessary hardware*
  - *Own the enterprise wrapper for machine translation; no separate User Interface needed*

Open Source Software

- Several well-designed platforms for building neural models
- Cost savings on initial push to Operations (though beware the maintenance tail)
- **Allows control of training data and model building**

Current Status

- Six languages deployed in beta status
- Very well received
- What's left?
  - *Scaling! Throughput, architecture*
  - *More languages*
  - *Tradecraft: Feedback loop from translation at workstation to model retraining*
  - *Modernizing analyst translation interface *in tandem* with deploying to current portal*

Plugging into Trados: Augmenting Translation in the Enclave

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Abstract

The National Virtual Translation Center (NVTC) built an SDL Trados Desktop plugin allowing access to a variety of state-of-the-art machine translation (MT) and transliteration services within its enclave. While Trados users in the open environment have had access to several internet-supplied MT services for some time, this has eluded enclave users. NVTC has had access to an MT portal within its enclave featuring several government and commercial engines in a wide variety of languages, and the plugin now enables users to get results from these engines within Trados, when the translation memory threshold is not met for a translation unit (TU). Translators can customize the order of presentation for the various engines for their language, including whether they want the engine at the top of the list to automatically populate target TU halves. In addition, NVTC has added an automated transliteration feature by which a user can highlight a proper name in the source text and ask for it to be transliterated either as a person or place name; the automated transliteration service will then populate the target text with a transliteration according to the appropriate scheme. Together, the MT and transliteration functionality constitute an important advance in the transition from baseline computer-assisted translation (CAT) to augmented translation (AT), where a fuller range of human-language technology (HLT) services are placed at translators' disposal, ideally within the CAT tool itself. In both the translation and transliteration cases, translators can post-edit the automatically produced information directly within Trados. This paper documents the user pilot of the plugin that assessed user acceptance variables such as preferences for specific MT engines and interface configuration options. The pilot results also provide data points that shed light on productivity and quality impacts of post-editing in NVTC's environment.

1. Introduction

The mission of the National Virtual Translation Center (NVTC) is to "provide timely and accurate translation services to support national intelligence priorities and protect our nation and its interests."[1] In support of that mission, NVTC has constantly sought to employ and improve the state of the art in computer-assisted translation (CAT) technology. We will describe the baseline CAT environment at NVTC. Following that, we will introduce the notion of Augmented Translation (AT), which is an evolution of CAT that introduces an array of human

[1] https://www.fbi.gov/about/leadership-and-structure/intelligence-branch/national-virtual-translation-center

language technologies (HLT) into the CAT workflow. In particular, we will describe two CAT enhancements: one for machine translation (MT), and the other for automated transliteration. We will then describe a user pilot employing the machine translation enhancement and its effectiveness and acceptance within our translator community. Finally, we will touch upon next steps in the further evolution of AT.

2. Computer-Assisted Translation

NVTC's main CAT tool is SDL Trados 2019 (Trados) coupled with SDL Trados GroupShare 2020 (GroupShare). Trados facilitates verbatim translation of a wide range of document types by leveraging translation memories (TMs) and termbases (TBs). The TMs and TBs are stored on a GroupShare server so that a geographically dispersed community of linguists (NVTC's term for human translators) can use and modify them simultaneously. This CAT environment is situated on an isolated government network which does not have connectivity to the internet. While this enclave provides security, it does pose challenges in terms of access to software and language resources.

3. Augmented Translation

Augmented Translation emerged as a notion in 2017 in publications by CSA Research[2] and Deloitte (Eggers et al., 2017). According to CSA, "Just as 'augmented reality' uses AI [artificial intelligence] to enrich individuals' access to relevant information about their surroundings, this transformation provides linguists with more context and guidance for their projects." The Deloitte group situates AT within a program of improving government processes by incorporating AI into them. They establish a hierarchy of levels of evolution of the incorporation of AI into workflows: relieve, split up, replace, augment. In the most evolved "augment" approach to translation, "translators use automated translation tools to ease some of their tasks, such as suggesting several options for a phrase, but remain free to make choices. This increases productivity and quality while leaving the translator in control of the creative process and responsible for aesthetic judgments."

In practical terms, AT is an evolution from CAT where additional HLT and project management (PM) services are seamlessly available to participants in the translation workflow. CSA mentions neural adaptive machine translation available in the CAT process as a key feature of AT. They mention that this is available both in Lilt and SDL's BeGlobal, which are part of a set of plugins offered for Trados under the rubric of Automated Translation,[3] which include access to machine translation from both SDL and Google.

Another class of HLTs CSA envisages as part of AT is Automated Content Enrichment (ACE). ACE appears to be relevant encyclopedic information that can be made available within CAT. Although not explicitly mentioned by CSA, automated transliteration is a function important to NVTC that we propose to incorporate within our local instantiation of AT.

3.1. Machine Translation Plugin

SDL's Automated Translation plugin works on the open internet where there is access to Google Translate and SDL's Language Cloud. Since part of NVTC's CAT workflow takes

[2] https://csa-research.com/Insights/ArticleID/140/Augmented-Translation-Powers-up-Language-Services
[3] https://docs.sdl.com/783545/577209/sdl-trados-studio/automated-translation

place in an enclave, those MT sources are not accessible. However, NVTC has access to Symphony, which is an MT portal featuring several state-of-the-art commercial-off-the-shelf (COTS) and government-off-the-shelf (GOTS) MT engines. The portal has both a graphical user interface (GUI) as well as application programming interface (API) access. GUI users can paste in foreign language text and get English translations using each featured engine (or a subset). Both the GUI and API features offer optional text language identification as a preliminary step to translation. NVTC sought to provide access to Symphony in Trados via a plugin.

SDL has a free software development kit (SDK)[4] that developers can use to build their own plugins, and an active developer and user Community[5] which serves as a forum for discussion. NVTC engaged The MITRE Corporation, which had developed Symphony, to develop the plugin prototype. Similar to the other Automated Translation plugins, the Trados Symphony Plugin allows users to add MT engines from Symphony to their projects alongside other translation resources. Figure 1 shows the Trados editor window with plugin. When no TM match for a given source phrase is found above a user-specified threshold, the MT engines are displayed for the selected segment at the top of the editor window. Users are able to select which available engines are displayed and in what order. The engine in first position can also optionally autopopulate the target side of the editor or the user can choose to start with empty segments when no TM match is found. In this case, users are able to use mouse or keyboard to paste any of the MT results to the target segment for post-editing as they see fit.

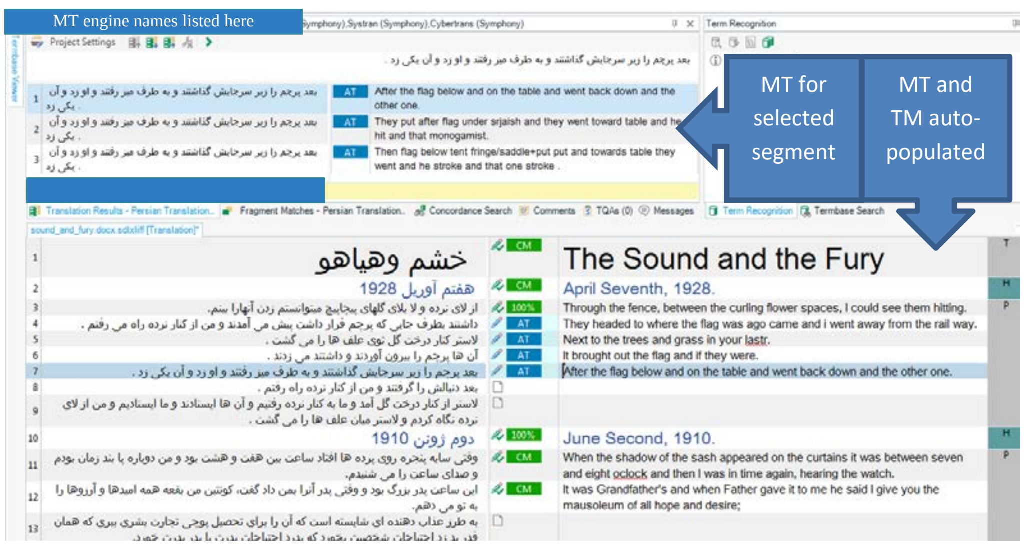

Figure 1. Trados editor with MT plugin

3.2. Automated Transliteration Plugin

Since NVTC's workflow involves the translation of multiple languages into English, the notion of transliteration is important. Transliteration refers to rendering foreign names and places, among other things, from foreign alphabets into the English alphabet. NVTC's Style Guide requires that person names be transliterated according to the Intelligence Community (IC)

[4] https://appstore.sdl.com/language/developers/sdk.html
[5] https://community.sdl.com/

standard for each language, and that place names be transliterated according to the Board of Geographic Names (BGN) transliteration standard for languages where those standards exist.[6]

In order to assist linguists with generating transliterations according to the standards, NVTC has employed the Rosette Name Translator (RNT, transliterator in our parlance) from Basis Technology.[7] Although RNT is available in Symphony, it was thought that incorporating its functionality directly into Trados would facilitate linguists' use of the tool. Accordingly, a second version of the machine translation plugin was created to include access to RNT. RNT supports several different transliteration standards including IC and BGN, and the plugin can be configured to recognize a preferred standard for each language.

Figure 2 shows examples of the transliteration selection windows inside the Trados editor. First the user right-clicks on a selected person or place name in the source text which pulls up a Trados menu where the user chooses whether to transliterate the name as a person or place. In the case of multiple possible transliterations, the linguist selects the most correct one and it is placed at the next position in the target text, which the linguist can then post-edit. A user-configurable option causes the preferred transliteration for a language to automatically populate the target side of the Trados editor after the linguist selects whether it is a person or a place name.

3.3. Global Plugin Configuration

The MT and transliteration functionalities are now incorporated in a single plugin whose behavior is governed by a configuration file in a JavaScript Object Notation (JSON)[8] format. The

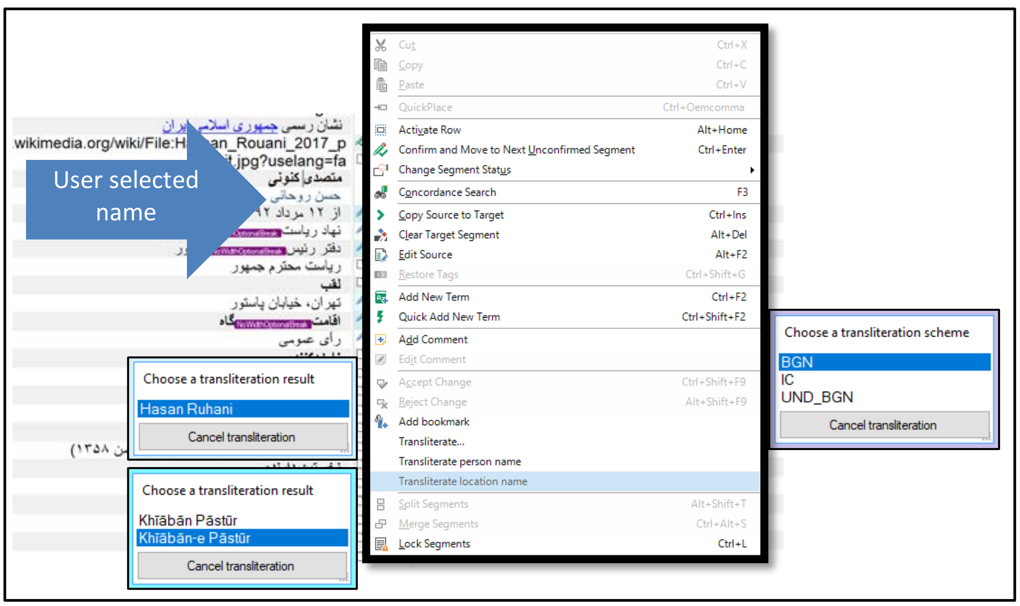

Figure 2. Sample transliteration plugin interface windows

configuration file has sections for both MT and transliteration and has been specified once for

[6] https://geonames.nga.mil/gns/html/romanization.html
[7] https://www.basistech.com/text-analytics/rosette/name-translator/
[8] https://www.json.org/json-en.html

NVTC, so linguists do not need to modify it. One challenge that was resolved by this configuration approach was interoperability issues caused by the wide variation in language naming conventions. The configuration file maps between language name variants used by the various MT vendors, RNT, Trados and NVTC. The language name mapping ensures that each of the plugin technologies delivers the correct language-specific functionality to the user. For transliteration, the configuration file specifies what the NVTC-approved person and place name schemas are for each language.

The project and user specific configuration options for MT and transliteration are described in sections 3.1 and 3.2.

4. Operational Pilot

From October 2019 to February 2020, NVTC conducted an operational pilot using the Symphony Trados (machine translation) plugin. The pilot participants used the MT-only version one plugin since alpha testing on version two with transliteration features was not complete until near the end of the pilot period. The pilot was fully integrated into NVTC's day-to-day operations with the linguists using the plugin on regularly assigned operational work. The pilot linguists were not required to complete extra tasks or reporting for the pilot aside from attending an initial training and then completing one or two fifteen-minute surveys. This approach provided ample opportunity to assess how full operational use of the plugin would impact linguists and their work, but somewhat limited the measurements that could be collected. For example, we did not stage translation of similar documents for comparison with and without the plugin or have linguists retranslate prior work completed with terminology and translation memory support only. These sorts of staged tests can allow detailed productivity comparisons and help determine whether linguists were over- or under-editing MT. Instead, this pilot focused on: 1) gauging whether the plugin could be integrated into NVTC's workflow effectively, 2) the readiness of the MT and plugin interface to enable post-editing of MT, and 3) identifying which configuration and implementation approaches are most effective.

The pilot involved 11 linguists who translated 43 documents in nine languages: Arabic, Chinese, English, Farsi, French, Korean, Russian, Spanish and Turkish. The most prevalent domains across pilot documents were defense, engineering, cyber and economics. Many of the source documents were MS Word or other text-based documents, but spreadsheets, PowerPoint slides and OCR output documents were also included in the pilot. The pilot included documents that were suspected to be non-ideal for MT but represented typical NVTC operational work.

The primary data collection for pilot results was a user survey (see Appendix A for the complete user survey). Fourteen surveys were collected. One linguist dropped out of the pilot before completing a survey because of an operational work change, and linguists participating in the pilot for longer periods of time completed a second identical survey later in the pilot. To the extent possible, finished translations, source documents and full MT output for all available engines were collected to calculate bilingual evaluation understudy (BLEU) scores in order to gain insights into any correlation between BLEU scores and post-editing machine translation (PEMT) outcomes.

4.1. Introducing Post-editing to Operational Linguists

Motivation for the pilot arose from previous shortcomings with PEMT on NVTC operational data, due primarily to available MT engines. For example, a 2016 NVTC PEMT study indicated that available MT would perform poorly on NVTC data and study participants experienced productivity declines when post-editing MT (Richerson, 2016). By 2018, when the idea of a custom MT Trados plugin was conceived, neural machine translation was on the rise and MT with significantly improved performance was beginning to be available to government. Furthermore, the plugin user interface would be designed to provide several variant MT results as a resource to linguists without requiring PEMT. In cases where MT quality is poor, the user would be able to start with empty target translation cells when no TM match is available. In this case, there would be no time lost to deleting inadequate MT results or lengthy post-editing, but MT results would now be visible and potentially save time by allowing the linguist to get the gist of a segment or discover alternative wording that would not have been available without MT. The MT autopopulation feature, on the other hand, would be useful when MT performs well on a document. In these cases, PEMT of a target segment that would be otherwise empty has the potential to result in significant productivity gains. This final conclusion is based on studies of productivity gains from PEMT of high-quality MT versus starting from scratch in commercial settings (Escartin, 2015).

Before rolling out the plugin operationally for this pilot, it was important to show that the plugin would be accepted by users and improve translation outcomes. Additionally, we hoped to gather information about how to most effectively use the plugin by answering questions about the best approach to configuring the linguist MT environment. The linguists who participated in the pilot all had prior SDL Trados experience but were not screened for prior PEMT experience. Linguists were trained using custom training that included PEMT best practices from the TAUS MT Post-editing Guidelines[9].

One key objective of the pilot user survey was gaining insight into optimizing plugin configurations for the users. One set of survey questions was aimed at determining whether it was better to autopopulate MT into the target translation window so that linguists must either post-edit the segment or delete it—or instead to simply leave the linguists to view the MT options, using the mouse or keyboard command to bring the displayed MT into the translation window as needed. Other questions related to the linguists' preferred display order of MT engines and choice of MT engine(s).

4.2. PEMT Acceptance and Preferences

All pilot linguists' surveys reported that the plugin was helpful, and many described specific benefits such as reduced time to complete translations. All linguists found it helpful to have the alternative MT engine results display as a reference and most indicated that seeing the different variants saved them time in either word or grammar choices. For certain documents, however, the survey indicated that the plugin was less helpful due to poor MT outputs.

Eight of the 11 linguists chose to try having the MT autopopulated at least part of the time. Linguists reported completely deleting anywhere from 20 – 100% of autopopulated MT segments depending on the document and language. On average, the linguists chose to post-edit 36% of the autopopulated sentences during the pilot and for the other 64%, they used the MT as a reference and wrote the sentence themselves from scratch. Of the linguists who chose to never autopopulate the MT segments, all but one indicated that they sometimes pasted an MT segment and post-edited it depending on the quality of the MT output.

4.3. MT Quality

The Symphony MT portal provides MT from three different commercial providers in addition to one GOTS MT system. For two of the commercial providers, Symphony initially hosted both

[9] https://www.taus.net/think-tank/reports/postedit-reports/taus-post-editing-guidelines

a new neural MT system and an older non-neural system. One of the older solutions was removed part way through the pilot meaning that up to five MT engines were available via the plugin throughout the pilot depending on the language. The default configuration for the plugin displayed MT results in the order provided in Table 1. Since the plugin allows autopopulating of MT results from the first displayed engine only, linguists could request they be re-ordered. The surveys asked the linguists to rate each MT engine on a five-point scale with five reflecting the highest quality. Note that the default ordering of MT options within the CAT display could have influenced linguist judgment since it is generally easiest to use the first option.

Solution Name	**No. of Raters**	**Average User Rating**	**Average BLEU**
COTS MT A (neural)	10	4.3	31.6
COTS MT B (neural)	8	3.38	26.7
COTS MT C (neural)	7	4.14	28.6
COTS MT D	7	2.86	19.6
COTS MT E	4	3.5	N/A[10]
GOTS MT F	5	2.4	10.68

Table 1. Linguist judgment of available MT versus BLEU

In addition to survey data reflecting linguist judgment of the MT, BLEU scores were calculated on each of the available MT outputs for 27 of the 43 documents translated during the pilot. This involved saving full document MT from each available MT engine and then using the finished translation as the reference document for the BLEU calculation. We used the finished translation as the sole reference translation in the BLEU calculations, and consequently scores are likely lower than would be achieved using multiple reference translations.

BLEU results are shown in Table 1 alongside the ratings linguists provided via survey. A correlation between BLEU and linguist ratings is apparent by inspection of the table and noting that both measures rank the MT solutions in the same order. This in turn confirms that BLEU roughly maps to the NVTC pilot linguists' judgment of which MT results were useful.

The ratings in Table 1 are averages across all languages but there is significant variation in scores across and within languages. For example, COTS MT B (neural) achieved the highest BLEU scores for Chinese documents, but the scores varied from 13.2 to 39.9 between documents. This means that the tradeoff decision of whether to post-edit or use MT only as a reference will vary depending on the document even within one language.

In the 2016 NVTC study on post-editing, the BLEU scores of the MT used ranged from 9.05 to 14.98. One of the conclusions of that study was that improved MT was needed for effective post-editing, and now that has become a reality with BLEU scores peaking over 60 for some of the language/document combinations in this pilot. Furthermore, that study only covered strict post-editing where the MT was only available through prepopulating in the target translation blocks. The option, provided by the new plugin, of displaying several MT options without prepopulating, provides a viable solution for cases where the MT is performing poorly on a particular group of documents.

[10] COTS MT E was decommissioned prior to the end of pilot, which prevented collection of full MT outpluts for BLEU calculations.

5. Conclusions and Future Work

Overall, the pilot results of the Trados Symphony plugin were favorable. The CAT integrated PEMT interface, the display of multiple MT results to provide alternatives, and the increasing quality of available MT led to overall user acceptance of the plugin during the pilot. The pilot demonstrated that the plugin can be implemented and PEMT adopted without disruption to the existing NVTC workflow and provided information to support successful adoption of the plugin at NVTC. To the extent that the pilot results turn out to be predictive, it is likely that around 35% of plugin enabled translation will be PEMT, potentially resulting in productivity gains due to linguists choosing PEMT when the MT only needs light post-editing. The other 65% of plugin enabled translations will benefit from the addition of MT output as a reference. The results data provided a wealth of information that can be further analyzed for more granular NVTC-specific insights beyond the scope of this paper.

One important conclusion of the pilot is a reaffirmation of the need to provide training to linguists on post-editing best practices to enable them to make good decisions such as when it is worth performing PEMT versus translating from scratch with MT used for reference purposes. Despite recent dramatic improvement in MT quality, the pilot showed that MT still performs poorly in many cases. Follow-on work to better identify those cases where MT fails can enable a two-pronged approach:1) identifying in advance whether or not a document is a good candidate for PEMT could facilitate plugin configuration decisions and increase efficiency, and 2) identifying and prioritizing languages and domains for MT improvement could increase the benefit of MT over time.

The plugin transliteration features, while not operationally assessed during the pilot due to development timing, are integrated into version two of the plugin to be operationally tested in 2021. NVTC is considering other efforts in the direction of AT, including the possible incorporation of named entity recognition (NER) into Trados. The form this might take is that person and place names would be identified on the source side of the editor and colored differently, thus facilitating linguists' subsequent identification of the names and use of the transliteration features of the plugin.

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Appendix A: Symphony Trados Plugin Pilot User Survey

Name:
Date:
Project ID:
What language are you translating from?
What language are you translating into?
Domain/Genre of Source Document:

If MT was prepopulated

1) Did you delete any of the MT segments and translate from scratch?
2) If you answered yes to question one, approximately what percentage of MT segments did you delete?
3) Please describe the most helpful and/or unhelpful aspects of post editing MT?

If MT was not prepopulated

4) Did you insert any of the MT results into the target segments instead of translating from scratch?
5) If you answered yes to question four, which translation engine results did you insert most often?
6) If you answered yes to question four, please describe the most helpful and unhelpful aspect of post editing MT.

All pilot users

7) Did you find it helpful to have MT results displayed as a reference?
8) Please rate the quality of each MT engine where a rating of 5 is fantastic and 1 is awful.
9) Did you (or a PM or LTT rep) change the setting for MT display at any point while you were using it?
10) If you answered yes to question nine, please indicate what change was made and why.
11) Overall, did you find the MT output helpful, and if yes, how?

PEMT in the Public Sector: Discovery, Scoping, and Delivery

Konstantine Boukhvalov and Eileen Block
ManpowerGroup Public Sector, Inc

ManpowerGroup™

ManpowerGroup Public Sector

- **25+** years supporting commercial and government clients in over 200 languages and dialects
  - Translation and l10n, transcription, interpretation, language technology support, linguist placements, multimedia analysis and reporting
- **Super user of Human Language Technology (HLT)**
  - 20 years customizing language automation/HLT tools in 60 languages to achieve efficiencies, process voluminous materials, and provide cost savings
  - Leverage and adapt commercial products and combined tools to optimize technology to best meet customers' needs
  - Translation Management System (TMS), Machine Translation (MT), CAT/Localization Tools, Authoring, eLearning, Desktop Publishing/Graphics Design, Audio/Video Production, Lexical Data Management, Optical Character Recognition

Presentation Objective

- Concerns about protecting data and challenges with implementation and measuring ROI have historically prevented public sector clients from using MT, CAT, and TMS
- We will show how our team successfully met client objectives while addressing data protection concerns to develop a practical, domain-specific Post-Edited Machine Translation (PEMT) solution to enable implementation by Public Sector clients.

Key Takeaways:

- How to develop a customized PEMT solution for Public Sector
- How to build and optimize TM corpora for statistical and neural MT training
- How to measure technological and procedural efficiencies for overall program success and scalability

Historical HLT Challenges for Public Sector (PS) Clients

- **Limited HLT use due to various contract constraints**
  - ➢ No co-mingling of data, no data in cloud
  - ➢ No data (TM/TB) retention
  - ➢ CONUS resources with citizenship, various clearance levels
    - HLT use was not widespread among PS linguist base (freelance)

- **No process automation**
  - – Longer production timelines
  - – Project-based translation

Early Steps

- Secure isolated **IT infrastructure**
- Dedicated **enterprise-level CAT** setup
- **Centralized TM/TB**
- Training for resources, e.g. **CAT-trained linguists/project managers**
- **TM/TB corpora** included as a **deliverable**

Case Study

- **Objective:** Translate multiple domain-specific content streams with more automation and increased speed
- Large-volume legacy material alignment
- Geographically dispersed workforce
    - ➢MGPS
    - ➢Client stakeholders
    - ➢Linguists

Program Requirements

- Centralized HLT Resources
  - Projects
  - Integrated Domain-Specific Machine Translation
  - Translation Memories/TermBases
  - Tech Support/Strict IT Infrastructure Requirements
- Integrated Project Management
- Data and Personnel Security
  - Dedicated HLT resource instance
  - Controlled human access
- Continuous MT improvement cycle
- Process automation
- Seamless integration of cloud and local-install HLT solutions

ANSWER?
Cloud-Based Post-Edited Machine Translation

- Post-Editing CAT/MT hybrid solution in an integrated TMS environment

- The Benefits of PEMT
  - ➢Faster processing time than CAT alone
  - ➢Greater consistency of terminology and style
  - ➢Future leveraging and ROI
  - ➢Workflow customization and efficiency

Define Stakeholders and Budget

- Dedicate a representative team of production experts – include the client!
  - Get early buy-in from the future production team
  - Start building the TMS operations culture
  - Let the production-side stakeholders define a business case and the best solution
- Align Budget and HLT options
  - Define Scope and Level of Effort - manage budget and expectations
  - Calculate HLT costs (CAT/TMS/MT)
  - Determine IT setup (local install vs. SaaS)

Challenge

There are a growing number of strong HLT solutions. How do you select the right one, and how do you implement effectively?

Choosing/Validating the Right Solution

- Perform preliminary research
  - *What do I need?*
  - *What are my options (commercial/custom/open source)?*
  - *What are my community peers saying?*
- Choose solution candidates
- Set up orientation calls with solution developers
  - *Identify dedicated contacts for technical and contractual questions*
  - *Explore data security options for data and support*

Choosing/Validating the Right Solution (cont.)

- Create an evaluation matrix
  - *Use the same criteria to evaluate all products*
  - *Standard criteria include:*
    - Key features
    - Benefits
    - Shortcomings
    - Technical and contract support
    - Deployment options
    - Costs

PUT THE DATA ASIDE –
TIME FOR WHITEBOARDING!

Whiteboard Your Workflows

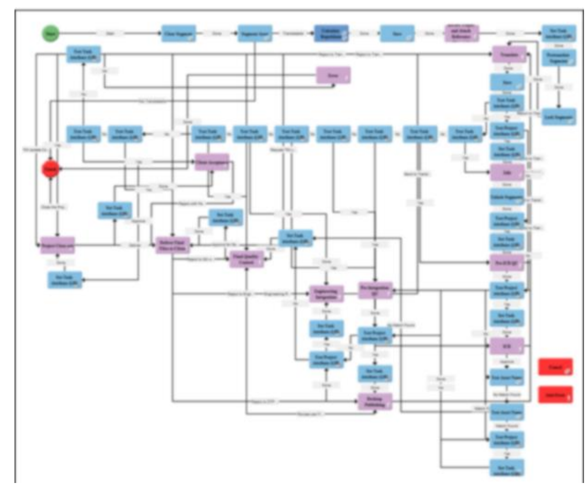
- Define and document/update existing production processes
- Do *not* adjust workflows based on the solutions’ limitations
  - *If it doesn’t fit, it’s not right for you*
- Generate a master workflow that addresses the variations
  - *Define production steps as “required” or “optional”*
- Whiteboard other business requirements/expectations
  - *Manage expectations*

See What "Fits" – Select and Acquire

- Combine your research with your master workflow and business requirements
- Identify the solution that provides the most value
- Generate TMS/MT Selection Report:
    - Fund the acquisition and deployment
    - Maintain technology knowledgebase
    - Validate your decision
- Finalize the deployment plan
- Minimize the time between the acquisition and production deployment

Initial Configuration

- Master production workflow
- Sample business rules
- Sample linguistic resources (TMs, TBs, baseline MT)
- Optional/custom components and workflow steps (forms, fields, etc.)
- Production pilot
  - ➢ *Test the workflow, not just the filters*



Document TMS/PEMT Production Procedures – Role-Specific Instructions

- Project Managers
  - ➢ *Production*
  - ➢ *Offline procedures*
- Linguist Users
  - ➢ *Production*
- Client Users
  - ➢ *Portal access/request*
  - ➢ *Production*
- Other Production Roles (as applicable)

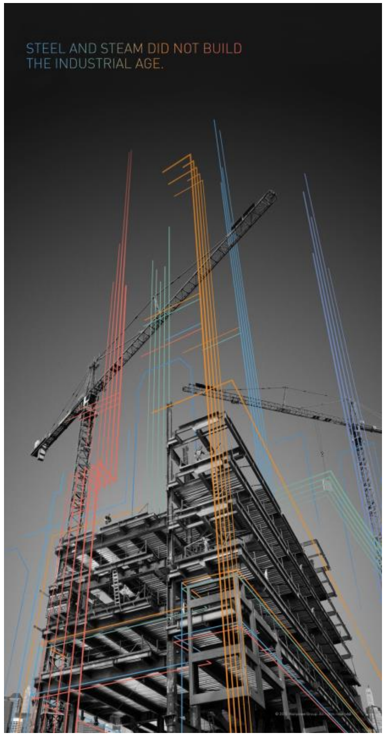
Develop and Implement Training

Client stakeholder participation and buy-in is key to project success.

- Develop a reusable curriculum
- Provide a general system overview
- Provide role-specific training

Production Deployment

- Configure and deploy client portal and other auxiliary components
- Align legacy content
- Optimize TM corpora for MT training
  - Segmentation
  - Markup
- Perform initial training of Domain-Specific MT engines/language pairs
- Perform first automated and human evaluation of MT – start measuring

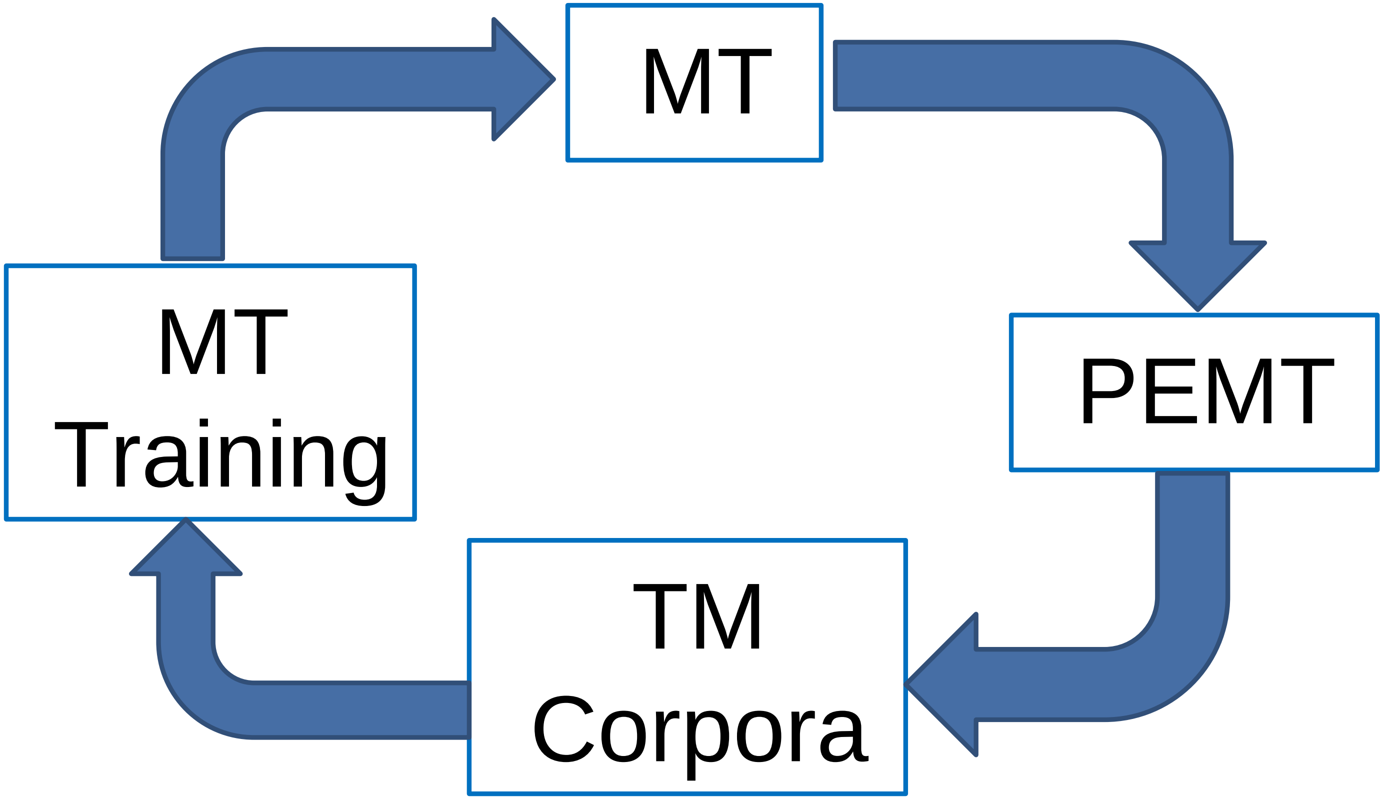


Start PEMT!!!

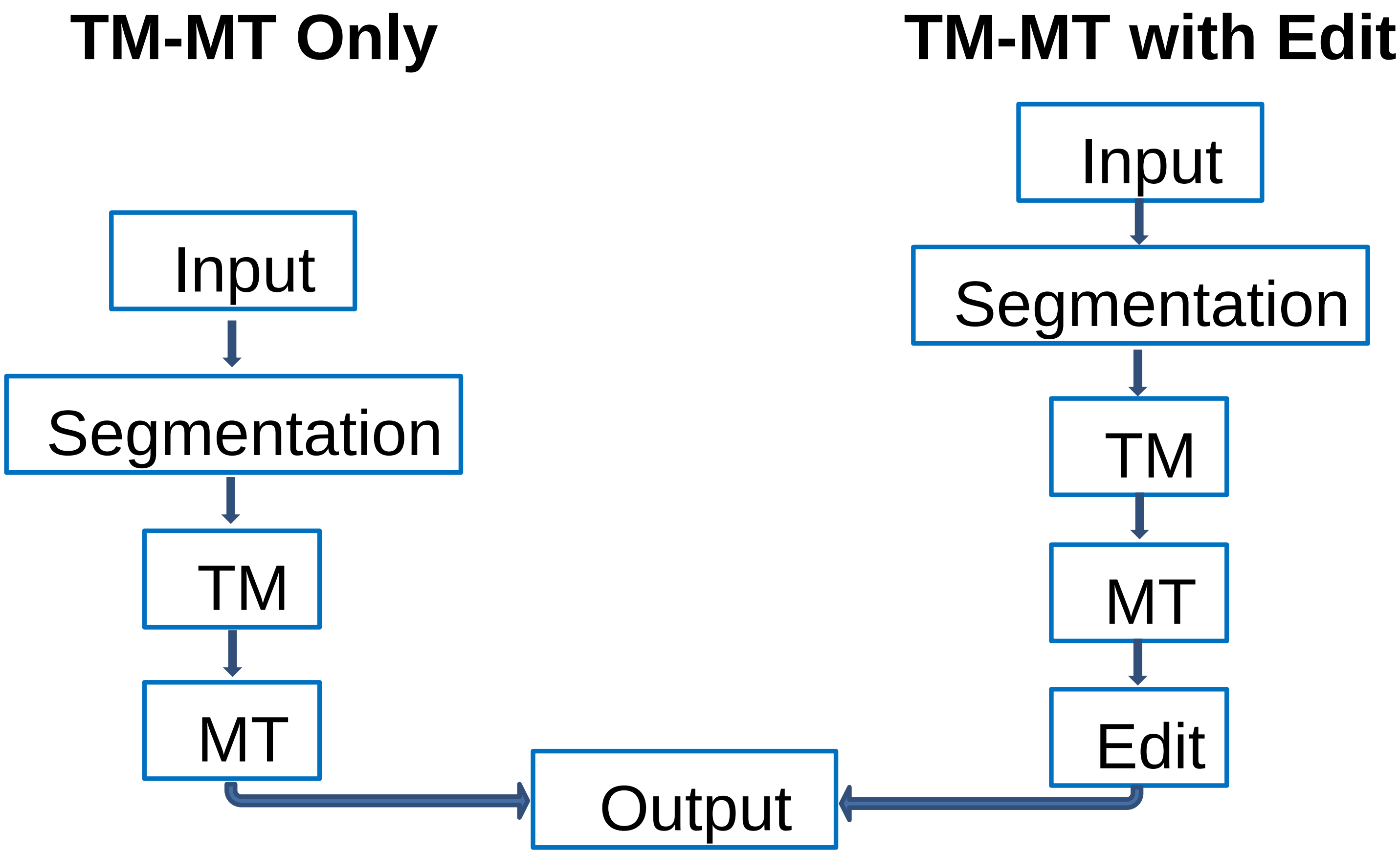
- Start production for the selected Task Orders/Programs

- Adjust configuration, procedures, and documentation, as applicable
  - *Deliver the updates to the appropriate parties*

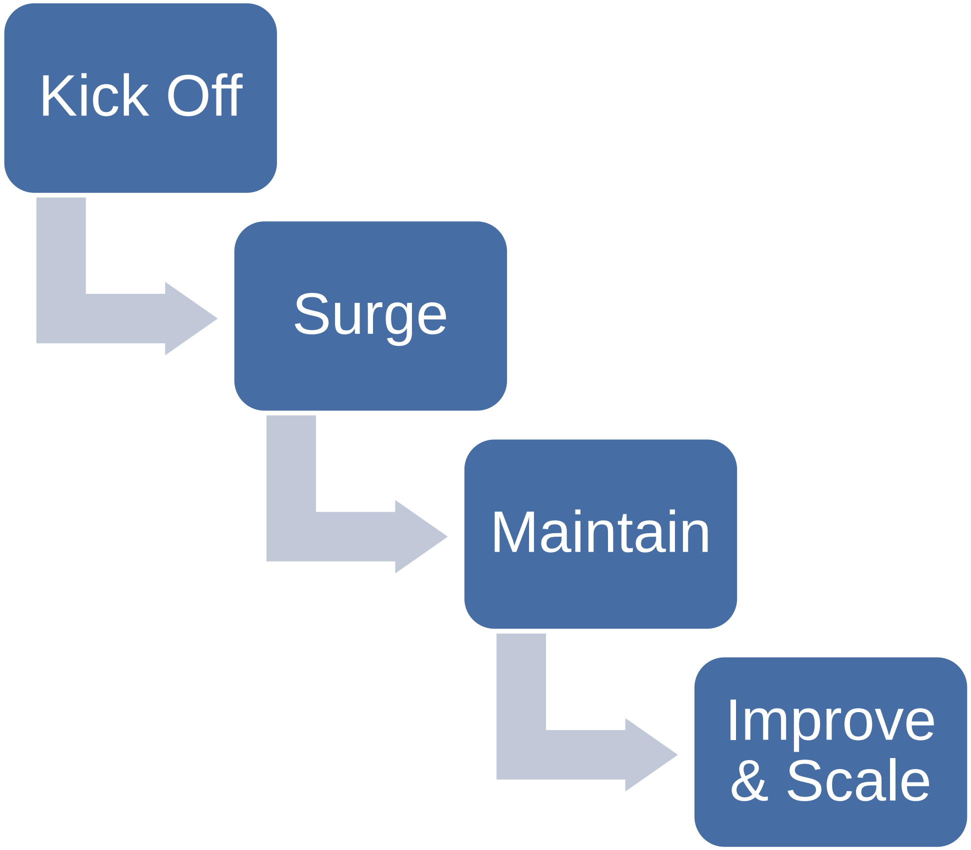
Continuous MT Improvement Cycle



Additional Automated Workflow Options



Program Launch



Kick Off

- **Review Statement of Work (SOW)**
  - Hold kick-off meeting to set expectations, and clarify parameters and assumptions with stakeholders
- **Inform Stakeholders – before, during, after kickoff!**
  - "Engineer for success" with source selection, MT training corpus
  - Manage expectations for productivity, timeline
  - Confirm client's priorities, preferences, and level of involvement
- **Set Goals and Key Performance Indicators (KPIs)**
  - Linguist productivity
  - Tool effectiveness

Surge

- **Build a Team**
  - Linguists, Engineers, PM
- **Train**
  - PEMT objectives and workflow
  - Client-specific tools and style guides
  - HLT tools/resources including CAT, TMS, TM/TB, MT
- **Baseline**
  - Translate sample set of material (larger = better) outside of PEMT environment to measure productivity sans HLT
- **Document / Track Everything!**
  - Client communications
  - Workflow adjustments
  - Technology data
  - Performance data

Maintain

- **Prioritize Knowledge Sharing**
  - Training materials, lessons learned, documentation
  - Meet regularly
- **Monitor, Report, Adjust**
  - Provide reports and recommendations monthly
  - Metrics
- **Evaluate Linguists' Performance**
  - Define and share performance and productivity metrics based on collected data
- **Review Client Level of Engagement**
  - Client involved too much or too little?
  - Client requests within contract scope?

Improve & Scale

- **Monitor technology developments and provide recommendations as necessary**
  - Escalate questions/issues to software developers as needed
  - Test and troubleshoot
  - Receive PM and linguist feedback on potential implementations
- **Evaluate MT output monthly; experiment and make adjustments as needed**
  - Capture qualitative and quantitative data
- **Communicate success stories and lessons learned**
  - Continually demonstrate ROI
- **Scale with additional domains and locales**
  - Ensure HLT solution can accommodate growth and address locale-specific criteria

Recap

- Review historical challenges
- Describe big picture and take incremental steps
- Receive client buy-in
- Customize the HLT solution -- one size does not fit all
- Document/track for reusability and scalability
- Develop talent through training
- Ask for client feedback and evaluate your success
- Continue to improve

Future Enhancements

- Neural MT Non-Formal Language Support
- Post-MT Automated Editing
- Dynamic Learning NMT
- Substring tokenization
- Integrated speech-to-text supported by TMS/CAT/MT

Thank you

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U.S. ARMY COMBAT CAPABILITIES DEVELOPMENT COMMAND – ARMY RESEARCH LABORATORY

Shareable TTS Components

Dr. Steve LaRocca

Computer Scientist and Team Lead

Battlefield Information Systems Branch

DISTRIBUTION STATEMENT GOES HERE

20 AUG 2020

The Team

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TEXT-TO-SPEECH (TTS)

- **A system that converts written text to audible speech**

- **TTS is an important enabling language component**
  - For Speech-to-Speech systems (ASR → MT → TTS)
  - For information delivery tools such as 'talking books'
  - Ultimately, every language community needs a TTS capability

- **USG has relied on commercial TTS software**
  - Licensed commercial products are cumbersome
  - Recent growth in neural computing for TTS with open tools
  - New prospects for more and better shareable TTS components

- **Publicly available neural implementations of TTS, such as Ito's implementation of Google's Tacotron, make creating one's own shareable components easier**

MAKING A SHAREABLE TTS COMPONENT

- **Recent neural (deep learning) methods simplify data preparation**
  - Google's 2017 Tacotron project followed by Keith Ito's implementation
- **Keith Ito's "LJ English" model built with 24 hours of training data**
  - ARL has developed Android Arabic TTS capability using deep learning methods and only 10 hours of training data
- **Compute time and computer resource requirements are substantial**
  - Aging GPU equipment not up to the task, not compatible with current libraries
- **Shareable data and shareable software is an important aspect**
  - ARL is using single speaker data based on in-house translation materials and VOA-type newswire as prompts
- **Neural TTS computes a spectrogram, then renders that data as synthesized speech using a vocoder**

4

OUR WORK TO DATE

- **Zak Al Sagheer: created 10 hour Arabic dataset**
  Trained (K. Ito) Arabic Tacotron model
  Trained Arabic Tacotron2 model
  Trained more Arabic models: current success using FastSpeech 2
  Trained vocoders using Arabic data and neural methods.

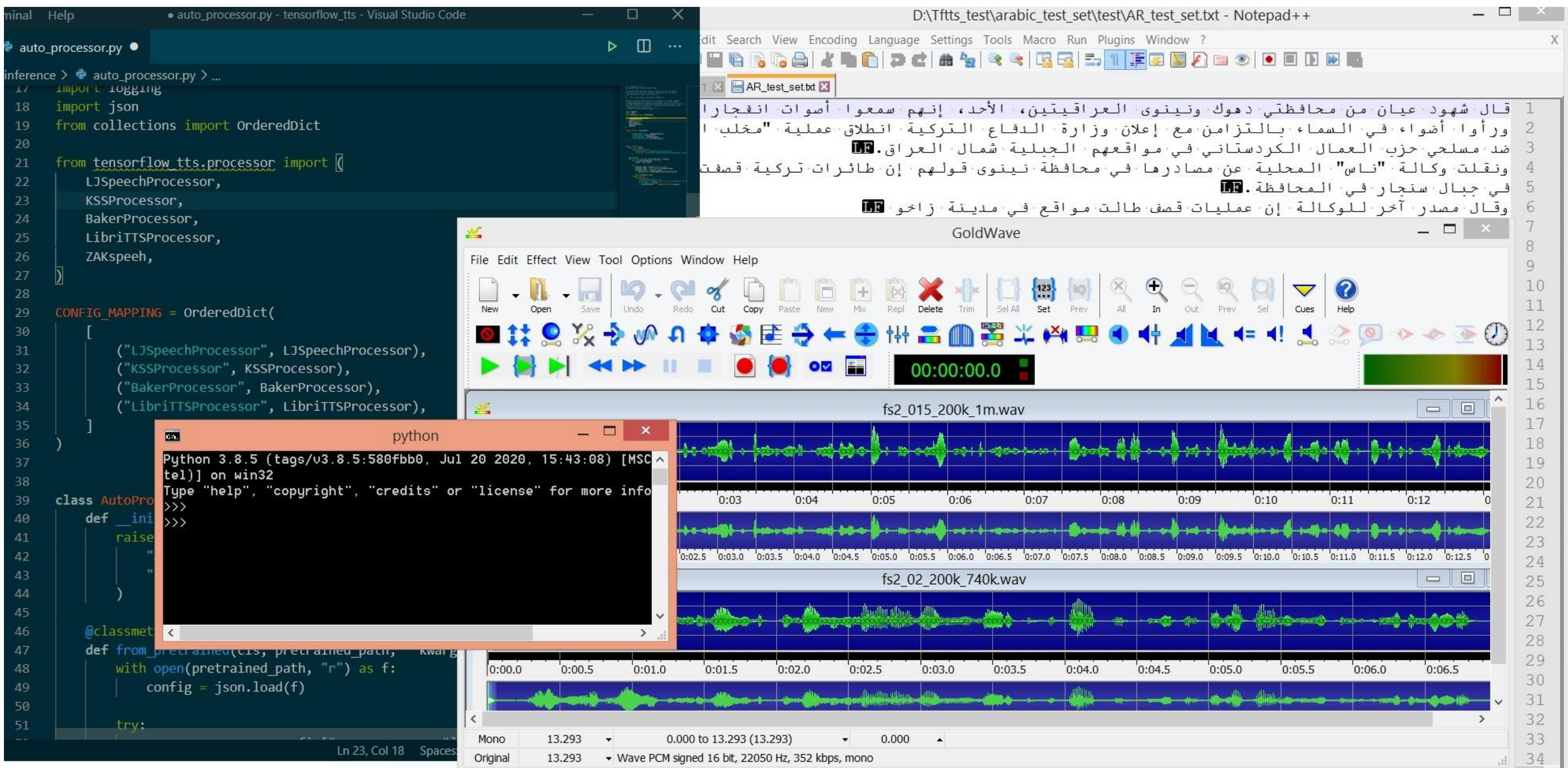
- **Hazrat Jahed: created 10 hour Pashto dataset**

- **UTTC (Vince Iglehart and Jerral Murray):**
  Learned Python programming
  Trained (K. Ito) Tacotron English model
  Conducted experiments (formal vs. informal text; full vs. ablated dataset)
  Surveyed possibilities for Northern Ute and/or Lakota dataset → TTS model

- **Gerry Cervantes provided Android expertise, TensorFlow, tflite**

LET'S SYNTHESIZE SOME ARABIC!

- **Demonstration by Zakariya (Zak) Al Sagheer**



6

A UTTC PERSPECTIVE: GOALS/CHALLENGES

- **Tacotron experiment this summer: small data results in a worse model**
- **Implications for building TTS models for under-resourced/under-documented languages**
- **Creating data resources for some of these languages: Northern Ute, Lakota**
- **Challenges for TTS models that are based on Native American language data**
- **TTS models offer new capabilities for communities**

UNITED TRIBES TECHNICAL COLLEGE

TTS FOR ACADEMICS

- **Teaching materials: introduction to STEM, computational linguistics for linguists and language enthusiasts alike**
- **Second language acquisition: empowering students to practice pronunciation outside the classroom**
- **Experimental materials: a component of the experimental paradigm and a better way to administer instructions to bilingual participants/those with weaker literacy**
- **Language documentation/revitalization: bridging the gap between reading and speaking**
- **Accessibility: free/easy access to screen-readers in many languages for a diverse student body**

GOALS

- Extend the Ito implementation of Tacotron to build models for additional languages: Pashto, Native American languages, which can be shared. For free.

- Make these models transparent and well-documented so that they are easily modified to serve the needs of the military, the academy, and language communities

CONCLUSION

- **Speech technology including TTS serves military interests because it aids in the communication between Soldiers and local nationals who may not have a language in common or an interpreter available**
- **Speech technology including TTS serves Native American communities because it can help to preserve and revitalize Native American languages**

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A Tale of Eight Countries or the EU Council Presidency Translator in Retrospect

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Abstract

In this paper, we describe the development of the EU Council Presidency Translator, a machine translation solution first introduced during the EU Council Presidency of Latvia. We further analyze how the EU Council Presidency Translator has been used across seven presiding member states starting from H2'2017 onwards. Our findings show that usage of different translation tools has depended on the technological readiness level of the presiding member state. Nevertheless, Presidency Translator usage statistics indicated an upwards trend in the volume of words translated monthly, suggesting increasing popularity of the machine translation based solution. Our analysis further indicates that the machine translation services are used continuously after the periods of presidencies they were developed for conclude. These findings suggest the usefulness of the Presidency Translator above and beyond the needs of the period of the presidency.

1 Introduction

Large international organizations face the challenge of language barriers in their everyday work; thus, it is not surprising that they show a strong interest in machine translation (MT). The Pan American Health Organization (PAHO) has developed their MT system already in 1980, starting with English and Spanish and later extending to Portuguese (Aymerich, 2005). The World Intellectual Property Organization (WIPO) has developed its MT tool, WIPO Translate, for ten languages (Pouliquen, 2017) and primary use it for patent translation but also offer it to other UN bodies (Pouliquen et al., 2013) and international organizations, such as the International Monetary Fund (IMF), Food and Agriculture Organization (FAO), International Telecommunication Union (ITU), and World Trade Organization (WTO) (Pouliquen, 2016). The European Patent Office has cooperated with Google by providing its data and using Google Translate technologies for patent search.

European Commission (EC) started to use a customized version of the MT system Systran in 1976, becoming one of the first large-scale adopters of MT(Petrits, 2001). In 2010, the European Commission began to develop its MT system based on the Moses toolkit and released it as the MT@EC tool in 2013 with support for all 24 official languages of the European Union (EU) (Eisele et al., 2011). In 2017, EC migrated its MT platform to neural MT (NMT) technologies and renamed the service to eTranslation. MT@EC and its successor eTranslation are used by thousands of translators employed by EC, European Parliament, European Committee of the Regions, European Court of Justice, European Central Bank, and other European institutions and bodies. It is also available for any public administration of EU member states and has recently been opened for European small and medium-sized businesses.

As the key European Union decision-maker, the Council of the European Union negotiates and adopts EU laws, coordinates member states' policies, develops the EU's common foreign and security policy, concludes international agreements, and adopts the EU budget. The functioning of the Council is organized by EU member states in 6 months long rotating order. As a result, new presiding member state-specific MT solutions are also developed and deployed biannually. In this paper, we describe the development of the EU Council Presidency Translator and its inception during the EU Council Presidency of Latvia as well as analyze its usage statistics and patterns across seven presiding member states starting H2'2017 onwards. Our analysis shows that while the reliance on different translation tools depends on each member state's technological readiness, there is a strong upwards trend in the volume of words translated monthly. Furthermore, the MT systems developed for the EU Council Presidency Translator are used continuously after presidencies of member states conclude, suggesting their usefulness above and beyond the needs of the period of the presidency.

2 Solution Genesis

The member state holding the presidency organizes and chairs hundreds of formal and informal meetings in the country of the rotating presidency. Planning these meetings and disseminating their outcomes involves extensive communication and requires the preparation of many thousands of documents, communiques, press releases, and social media entries. These meetings, communications, documents, and information materials are inherently multilingual because the EU has 27 member states (28 before Brexit) and 24 official languages. Language equality is cemented in the EU founding documents ensuring equal rights to use any of the EU's official languages. Still, the translation demand for the EU Council Presidency is so high that it is challenging to reach this language equality in practice. As a result, not all information is available in all the languages, or non-critical translations are provided with a significant delay.

Machine translation as a solution for the EU Council presidency's translation needs was initially proposed for the Latvian presidency, which took place during the first half of 2015. This was the first time Latvia was assuming the presiding role at the EU Council with its accompanying complex challenges for this relatively small country. The proposal of language technology company Tilde to try leveraging the multilingual challenges with an MT solution was met positively, opening an opportunity to develop and trial custom MT systems and tools. The solution's primary focus was to support delegates, visitors, and journalists attending presidency events in Latvia to access local information and help country residents follow up presidency information. The Latvian national language technology platform hugo.lv was used as the provider of MT systems for translation between Latvian and English (Vasiļjevs et al., 2014). A specialized desktop interface was developed for the translation of text snippets, documents, and websites. Translation applications for iOS, Android, and Windows Phone platforms were provided for mobile users. Two translation kiosks were set up at the central venue of the presidency in the newly opened National Library of Latvia, drawing the attention of presidency event participants. Although no formal assessment was carried out, the feedback from visitors, presidency staff, and journalists was overwhelmingly positive, particularly about the possibility of receiving an instant translation of full documents preserving their formatting, and getting a translation of local websites.

The success at Latvia's EU Council Presidency encouraged to apply to the European Commission with a project proposal to develop a full-fledged solution for the succeeding presidencies. Two projects were co-funded by the Connecting Europe Facility program supporting six presidencies - Estonia (H2'2017), Bulgaria (H1'2018), Austria (H2'2018), Romania (H1'2019), Finland (H2'2019), and Croatia (H1'2020). The German Federal Foreign Office funds the current solution for the German EU Council Presidency (H2'2020). For every presidency, Tilde cooperated with strong national partners – Institute for Bulgarian Language, University of Vienna, Research Institute for Artificial Intelligence of the Romanian Academy, Finland's Prime Minister's Office, and the University of Zagreb. The EU Council Presidency Translator was initially launched at the Tallinn Digital Summit of EU heads of state or government on September 29, 2017.

3 EU Council Presidency Translator

The EU Council Presidency Translator includes tools and features to target several user groups:

- professional translators to speed up their work by using MT post-editing;
- presidency staff and delegates to translate documents preserving their formatting;
- journalists to support the preparation of multilingual materials and access local websites;
- citizens of EU countries to access the presidency website and other materials in their mother tongue.

It is an online tool in which functionality, interface, and design are customized for every presidency's specific requirements. It includes specifically developed MT systems for the primary translation directions of each EU Council Presidency and supports all official EU languages by integrating European Commission eTranslation systems. The Presidency Translator's essential advantages are synchronous translation in real-time (as opposed to the asynchronous service of the public eTranslation) in a secure environment.

We further describe the EU Council Presidency Translator by looking at its functionality (see Section 3.1), technical architecture (see Section 3.2), and the different types of MT systems it provides (see Section 3.3).

3.1 Functionality

Throughout the years the EU Council Presidency Translator, its functionalities and usage have evolved significantly. The latest, EU Council Presidency in Germany, taking place between July 1st and December 31st, 2020, is benefiting from the widest range of features allowing users to translate from/to all official languages of the European Union. The functionality includes:

- **An online translation workspace** that provides text snippet, Web page, and formatting-rich document[1] translation functionality[2] that is available to every visitor, delegate, and public administration translator of the current and previous EU Council presidencies. The text snippet translation interface is integrated also with EuroTermBank[3] (Vasiljevs et al., 2008), the largest termbase in Europe. When entering terms in the text snippet translation form, translations are automatically provided from EuroTermBank.
- **A computer-assisted translation (CAT) tool plug-in for SDL Trados Studio**, which is available to public administration translators.

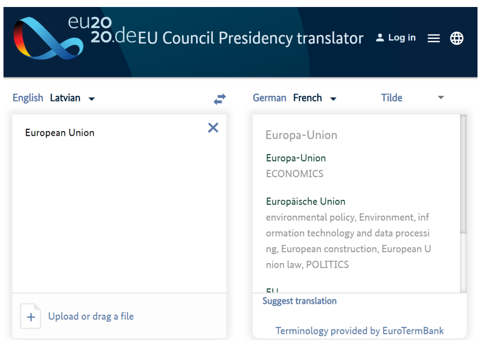
[1]The EU Council Presidency Translator supports translation of *.doc, *.docx, *.xlsx, *.pptx, *.odt, *.odp, *.ods, and *.rtf documents.

[2]https://presidencymt.eu

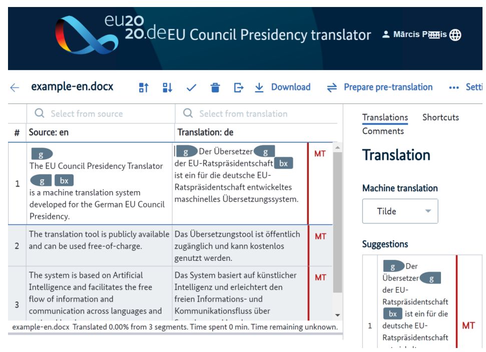
[3]https://www.eurotermbank.com/

(a) Text translation.

(b) Document translation.



(c) Term translation look-up.



(d) Online CAT tool interface.

Figure 1: Examples of the graphical user interface of the EU Council Presidency Translator developed for the German EU Council Presidency (source: `https://presidencymt.eu`).

- **A website translation widget**, which can be integrated into the website of each EU Council Presidency, thereby enabling access to the content of the website for all EU citizens in their native languages. In 2020, the website translation widget is integrated into the website of the German EU Council Presidency[4] and provides translations to all official languages of the European Union from either German or English.
- **An online CAT environment for non-professional translators**, which allows translating formatting-rich documents and provides translation memory (TM) functionality. When translating documents, translation suggestions are automatically provided by the EU Council Presidency Translator's MT systems and user's private translation memory. Additionally, to MT and TM suggestions, users can search terminology in EuroTermBank. Similarly to professional CAT tools, the online CAT environment also allows pre-translating documents using MT or TM, thereby improving translation productivity even further.

Examples of the graphical user interface from the online translation workspace and the online CAT environment are depicted in Figure 1.

The EU Council Presidency Translator allows deploying and integrating custom and third party MT systems. Before the German EU Council Presidency, the EU Council Presidency Translator provided access to generic MT systems from eTranslation[5] (the MT service devel-

[4] `https://www.eu2020.eu`
[5] `https://ec.europa.eu/cefdigital/wiki/display/CEFDIGITAL/eTranslation`

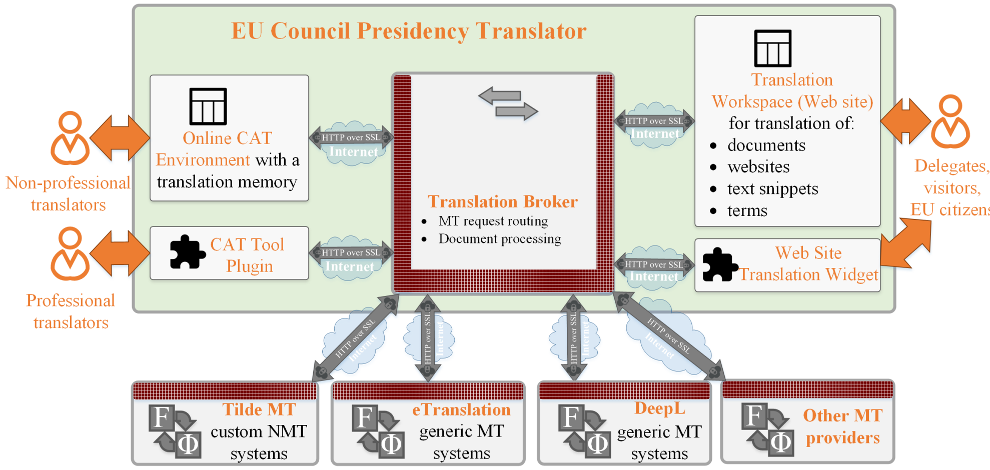


Figure 2: The technical architecture of the EU Council Presidency Translator (an updated diagram from Pinnis and Kalniņš (2018) to reflect the EU Council Presidency Translator for the German EU Council Presidency).

oped and maintained by the European Commission) and custom NMT systems developed by Tilde. For the German EU Council Presidency, The EU Council Presidency Translator has been extended to provide access to generic MT systems developed by DeepL[6] and custom NMT systems developed by the German Research Center for Artificial Intelligence[7] (DFKI).

Users benefit from this user-friendly platform when translating texts, documents, or web content. The EU Council Presidency Translator provides a secure environment for confidential translations as all data transfers are encrypted, and all data are stored within safe data centers within the European Union.

3.2 Architecture

The EU Council Presidency Translator has been developed as a cloud-based solution that consists of three types of components:

1. **MT systems** that are deployed on Tilde MT or third party cloud-based infrastructures. The custom NMT systems that are tailored for each EU Council Presidency are deployed on Tilde MT[8] Pinnis et al. (2018b). Generic systems are provided by eTranslation and for the German EU Council Presidency also by DeepL.

2. **An MT system broker** (or proxy) that processes all translation requests and distributes them to the different custom and generic MT system providers, as well as handles formatting-rich document translation. The MT system broker exposes both a translation segment translation API and a document translation API.

3. **Various translation interfaces** that provide access to MT systems. For instance, the CAT tool plugin for SDL Trados Studio, the online translation workspace for text snippet, document, website translation, and term translation look-up, the website translation widget, and the online CAT environment that provides CAT tool functionality for non-professional translators.

[6]https://www.deepl.com/
[7]https://www.dfki.de/
[8]https://tilde.com/mt

The technical architecture of the EU Council Presidency Translator was first published by (Pinnis and Kalniņš, 2018). In this paper, we update the architecture (see Figure2) to reflect the latest developments for the German EU Council Presidency. As depicted in Figure2, all data between all components are transferred using secure (SSL-encrypted) connections.

3.3 Machine Translation Systems

The EU Council Presidency Translator provides access to custom and generic MT systems. Since the first launch of the EU Council Presidency Translator in 2017, the custom MT systems have been developed using NMT methods. However, NMT technologies have improved during the past three years; therefore, the EU Council Presidency Translator features NMT systems that have been developed using different NMT technologies.

First custom NMT systems for the Estonian EU Council Presidency (back in 2017 and 2018) were trained using Nematus (Sennrich et al., 2017), an NMT toolkit that allowed us to develop recurrent neural network-based NMT models with multiplicative long short-term memory (MLSTM) units (Krause et al., 2016; Pinnis et al., 2017). The models were deployed in Tilde MT using the AmuNMT decoder (Junczys-Dowmunt et al., 2016), which is faster than Nematus and allows using models trained with Nematus. At the end of 2018, we re-trained the models of the Estonian EU Council Presidency using Transformer (Vaswani et al., 2017) models from the Sockeye NMT toolkit (Hieber et al., 2017). We selected Sockeye as it allowed us to train the best-performing NMT systems at the WMT 2018 shared task on news translation for EN↔ET (Bojar et al., 2018; Pinnis et al., 2018a). However, as Sockeye was relatively slow and did not have features necessary for high-quality formatting-rich document translation, all other NMT systems were developed using the Marian NMT toolkit (Junczys-Dowmunt et al., 2018). Marian provides support for guided alignments that are necessary to support formatting-rich document translation. A list that shows which NMT toolkits were used for the different custom NMT systems of the EU Council Presidency Translator is given in Table 1.

Custom NMT systems for all EU Council presidencies were trained using domain-specific MT system training recipes. Baseline models were trained using both in-domain and out-of-domain data, after which NMT models were fine-tuned on in-domain (presidency-specific) datasets. The in-domain datasets depending on each presidency were collected by Tilde, provided by project partners, or EU Council Presidency offices in the different countries.

To provide translations from/to other languages that are not listed in Table 1, the EU Council Presidency Translator integrates generic NMT systems from eTranslation and for the German EU Council Presidency also from DeepL. The generic systems are mostly intended for delegates of events of EU Council Presidencies and EU citizens that do not necessarily speak the languages in which information is provided in the various events and the website of the particular EU Council Presidency. On the other hand, the custom NMT systems are mostly intended to assist translators and public administration employees of each respective EU Council Presidency.

4 Usage Analysis

The EU Council Presidency Translator has been in active use for over three years (since July, 2017). During this time, we have accumulated usage statistics from the different translation interfaces. These statistics allow us to assess, which functionality aspects are the most needed, analyze the adoption of the EU Council Presidency Translator within the different EU Council Presidencies, and plan further improvements to the EU Council Presidency Translator. Further, we provide an analysis of the overall usage statistics (see Section 4.1) as well as country-specific statistics (see Section 4.2).

NMT Toolkit	NMT Architecture	Language pairs
Nematus/AmuNMT	MLSTM	EN↔ET (till 2018), EN↔BG, EN↔DE (for Austrian Presidency)
Sockeye	Transformer	EN↔ET (since 2018)
Marian	Transformer	EN↔DE (since 2020), EN↔RO, EN↔FI, FI↔SV, ET↔FI, EN↔HR, DE↔IT, DE↔ES, DE↔PL, DE↔FR

Table 1: NMT toolkits and NMT model architectures used to develop custom NMT systems for the EU Council Presidency Translator.

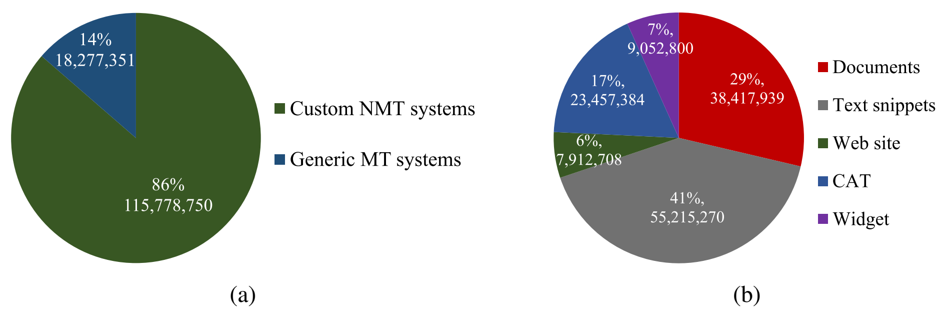


Figure 3: Total number of words translated by the EU Council Presidency Translator grouped by different interface types (left) and MT system types (right).

4.1 Overall Usage Statistics

From the beginning of July, 2017 till August 26, 2020, the EU Council Presidency Translator has processed a total of 4.25 million translation requests from all the different translation interfaces. This amounts to a total of 12.16 million translated sentences or 134.06 million translated words.

As seen in Figure 3a, custom NMT systems that have been developed for each EU Council Presidency have translated 115.8 million words or 86% of the total translation volume. Generic systems that are provided by eTranslation and for the German Presidency also by DeepL have translated 18.3 million words, which amount to 14% of the total translation volume. The proportion of generic systems is slowly increasing since the introduction of the widget for EU Council Presidency websites during the German EU Council Presidency (see Figure 4).

Figure 3b shows that the most used translation interface types are text snippet translation (amounting to 41% of all translated words), formatting-rich document translation (amounting to 29% of all translated words), and CAT tools (amounting to 17% of all translated words). However, note that the widget was introduced only for the German EU Council Presidency. If we look at the overall statistics from July and August of 2020 (See Figure 5 for absolute word counts and Figure 6 for relative proportions), we see that the widget has processed 30% and 34% of all translated words in July and August respectively. We expect it to become the most used translation interface going forward. The website of the German EU Council Presidency[9] provides human-curated content in three languages - German, English, and French. Information in all other official EU languages is provided through the MT widget. The statistics (see Fig-

[9]`https://eu2020.eu`

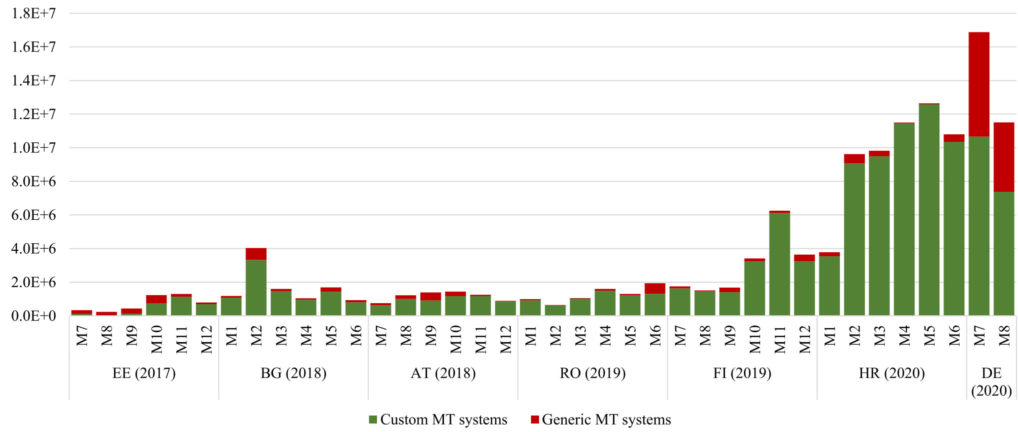


Figure 4: Translated words per month using custom NMT systems and general MT systems (ISO 3166 country codes identify each Presidency)

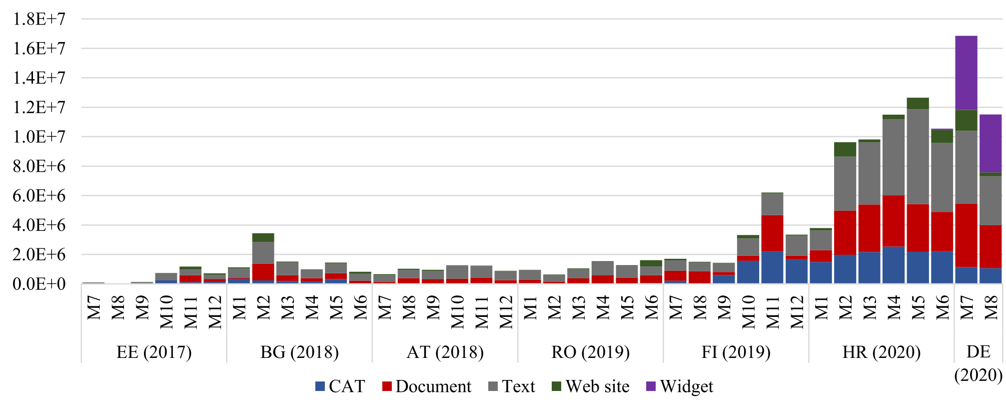


Figure 5: Translated words per month for different interface types for all MT systems of the EU Council Presidency Translator (ISO 3166 country codes identify each Presidency)

ure 7) show that EU citizens use this functionality to acquire content in their native languages, which means that there is a crucial need for EU Council Presidencies to provide content in all official languages of the European Union.

Figure 5 also shows that the EU Council Presidency Translator's usage has increased significantly over the last three presidencies (Finnish, Croatian, and German). When the EU Council Presidency Translator was introduced during the Estonian Presidency, it translated an average of 0.7 million words in a month. During the Bulgarian Presidency, the usage increased to 1.7 million words per month. Then, during the Austrian and Romanian presidencies, the usage dropped to 1.2 to 1.3 million words per month respectively. During the Finnish and Croatian presidencies, the usage increased to an average of 3.0 and 9.7 million words per month. Finally, the German EU Council Presidency during the first two months averages at 14.2 million words translated per month.

For the Romanian presidency, the explanation of a lower translation volume is that there was a funding gap between the first and second projects. This meant that the custom systems for the Romanian EU Council Presidency were available with a three-month delay and dissemination activities were carried out only in the second half of the Presidency. This consequently

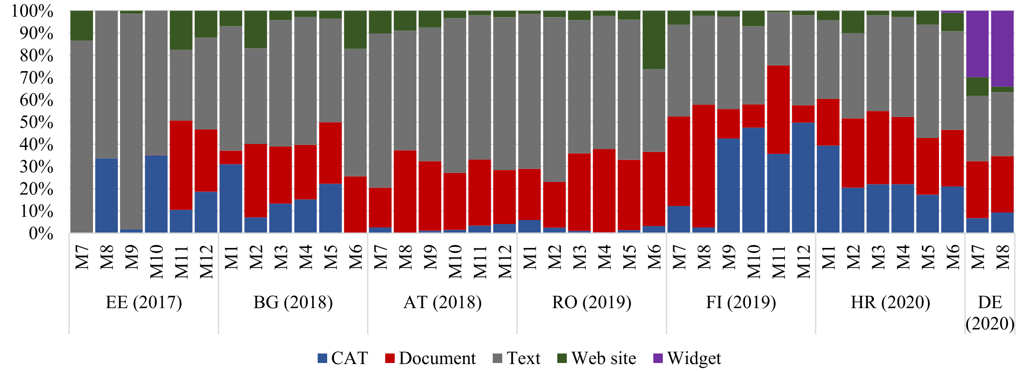


Figure 6: Proportion of translated words per month for different interface types for all MT systems of the EU Council Presidency Translator (ISO 3166 country codes identify each Presidency).

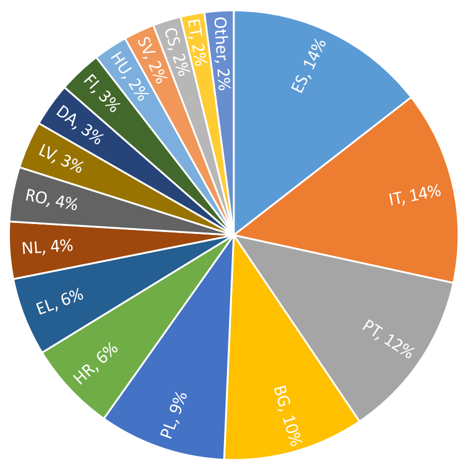


Figure 7: Target languages used through the translation widget that is integrated in the website of the German EU Council Presidency.

resulted in a lower activity by public administration translators from Romania. However, as country-specific statistics (see Section 4.2) show, activity increased at the end of Romania's Presidency.

4.2 Country-Specific Usage Statistics

An aspect of the EU Council Presidency Translator that we are particularly interested in analyzing is how the EU Council Presidency Translator has been adopted in the different EU Council presidencies. For this, we analyze the statistics of the custom MT systems that have been developed for each individual Presidency. The lists of language pairs for each particular Presidency are listed in Table 2.

Figure 8 depicts the statistics (in terms of the proportion of translated words per month) of the custom MT systems. It is evident that during the Estonian, Bulgarian, Finnish, and Croatian presidencies the most used MT systems were the custom MT systems of those presidencies. However, during the Austrian and Romanian presidencies Bulgarian and Estonian Presidency

Presidency	Translation directions
Estonian	ET↔EN
Bulgarian	BG↔EN
Austrian	DE↔EN
Romanian	RO↔EN
Finnish	FI↔EN, FI↔SV, and FI↔ET
Croatian	HR↔EN
German	DE↔EN, DE↔ES, DE↔FR, DE↔IT, and DE↔PL

Table 2: Translation directions for which custom NMT systems were developed for each EU Council Presidency.

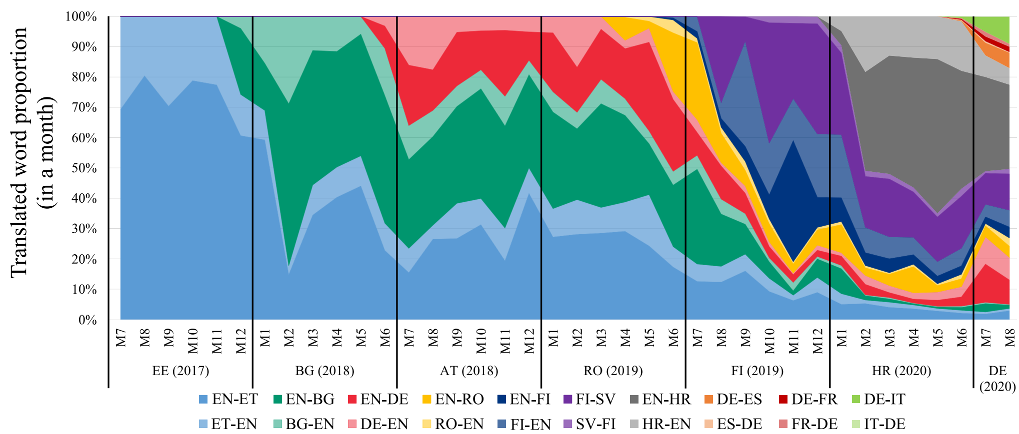


Figure 8: Proportion of translated words per month for different custom NMT systems (ISO 3166 country codes identify each Presidency)

translators continued to use the systems more intensively. For the German EU Council Presidency, it is yet too early to tell, which will be the most used MT systems. It is also interesting to note that since Finland has two official languages, the most used MT system during the Finnish EU Council Presidency was the one translating from Finnish into Swedish.

To better understand the levels of adoption of the EU Council Presidency Translator during each Presidency, we further analyze language pairs of each Presidency individually and for the time frame of each Presidency. We do this because the public administration translators of each particular Presidency continue using the EU Council Presidency Translator also after the presidencies conclude.

Figures 9 and 10 depict the usage of custom NMT systems of each individual Presidency within the Presidency's time frame in absolute and relative numbers respectively. The statistics show that the EU Council Presidency Translator's CAT tool plugin was used by public administration translators of Estonian, Austrian, Romanian, And German EU Council presidencies. However, the small absolute numbers show that the public administration translators from Austria did not use the EU Council Presidency Translator effectively and the Romanian translators (as explained above) started using the system only close to the conclusion of their presidency. That being said, we see that public administration translators from Romania have started using the EU Council Presidency Translator closer to the conclusion of the Presidency and our statistics show that translators continue benefiting from the EU Council Presidency Translator also

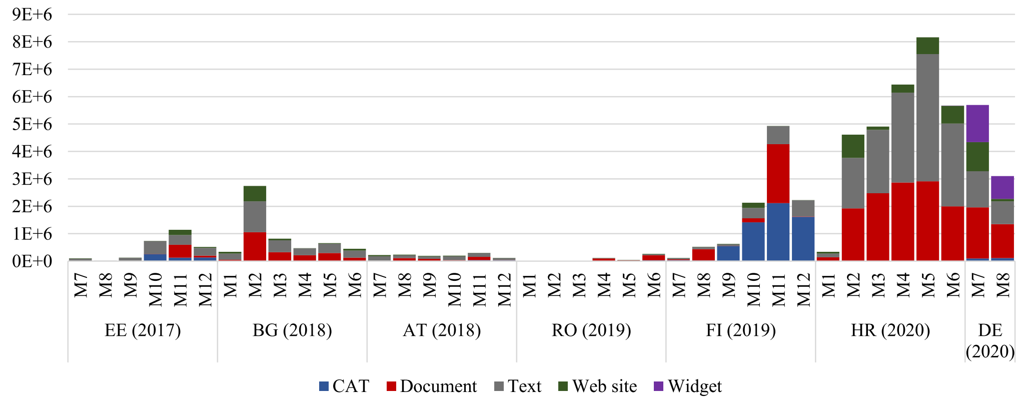


Figure 9: Translated words per month for different interface types for only the custom MT systems of each EU Council Presidency (ISO 3166 country codes identify each Presidency)

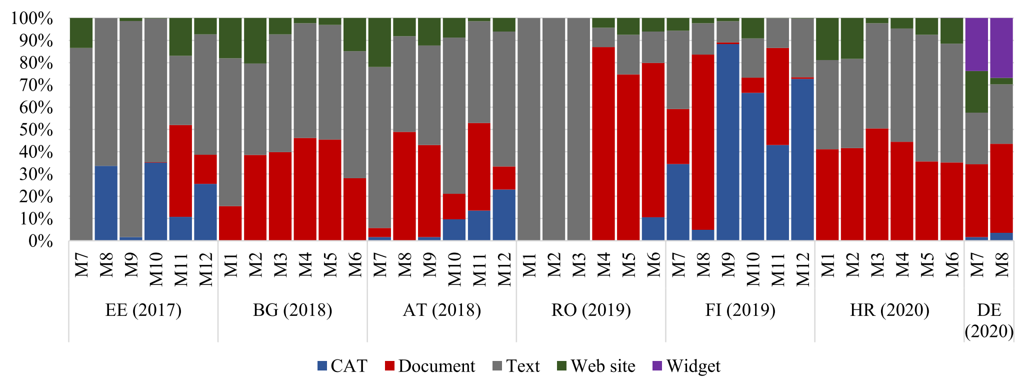


Figure 10: Proportion of translated words per month for different interface types for only the custom MT systems of each EU Council Presidency (ISO 3166 country codes identify each Presidency)

long after the Romanian EU Council Presidency.

Our statistics show that public administration translators in Finland are benefiting from the EU Council Presidency Translator the most. During the Finnish EU Council Presidency, CAT tool requests amount to a total of 55% of all translated words (10.5 million words in total) using the custom NMT systems of the Finnish EU Council Presidency.

Although public administration translators from Bulgaria and Croatia did not utilize CAT tool interfaces, absolute statistics show that the custom systems have been used intensively using other interface types (text snippet translation and document translation particularly). Even more, the custom NMT systems of the Croatian EU Council Presidency are the most used NMT systems to date accounting for a total of 31% of all translated words. This shows that although there are different translation practices established in different countries, the EU Council Presidency Translator's functionality can cater to every Presidency.

5 Conclusions

In the paper, we presented the EU Council Presidency Translator, a secure cloud-based solution that integrates MT systems from different MT providers and implements a wide spectrum of interfaces for end-users (i.e., a web-based translation workspace for text, document, and website translation, an online CAT tool for non-professional translators, an SDL Trados Studio plugin for professional translators, and a website translation widget that enables access to the official website of the German EU Council Presidency in all official languages of the European Union). We discussed its mission to assist EU Council Presidencies by allowing delegates and visitors of events of EU Council Presidencies as well as EU citizens to access information that is shared through the official websites of the EU Council Presidencies as well as by assisting translators (both professional and non-professional) of public administrations in their translation tasks.

Based on aggregated statistics of the usage of the EU Council Presidency Translator, we showed that our solution (having translated a total of 134.06 million words) has been a valuable asset to its users and is heavily utilized on daily bases (with well over 10 million words translated monthly for the last five months) through all types of interfaces. The statistics also allowed us to analyze how the EU Council Presidency Translator has been adopted in different countries. The results showed that Estonia utilized all available translation interfaces. In contrast, Bulgaria did not use CAT tool interfaces, nonetheless, it increased the monthly translated word count. Austria did not fully utilize the benefits of the EU Council Presidency Translator. Due to a funding gap, Romania did not have all the features available during the most active phase of its presidency, however, we see that its translators continue benefiting from the EU Council Presidency Translator even long after the conclusion of the Presidency. Finland showed to have the highest technological readiness level for translation automation. Yet, Croatia utilized the platform most heavily (by mostly translating documents and text snippets and not using the CAT tool plugin), and Germany, although at the beginning of its Presidency, shows to utilize all translation interfaces and reaches usage levels on par or better than Croatia.

We have shown that the EU Council Presidency Translator has been successful in pursuing its mission, and we believe that it will serve many EU Council Presidencies in the future.

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DragonFly

ASL- English MT

October 9, 2020

2020 AMTA Virtual Conference
Government Track

DragonFly

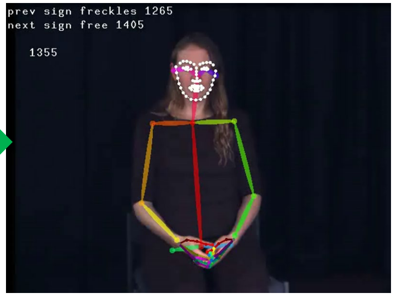
- Technology to enable the deaf and hearing to seamlessly communicate with one another without the assistance of an interpreter
  - Automated Machine Translation (MT) capabilities for enabling communication between speakers of American Sign Language (ASL) and English
  - Dragonfly will operate on the majority of IOS and ANDROID wearable devices including smart phones, tablets, and smart watches

Face-to-Face… Naturally… Anytime… Anywhere…

ASL Signer to English

Smart device captures the video of the sign

Sign is processed and recognized by DragonFly



ASL is translated into English

FREE

Text is displayed and the audio is voiced aloud

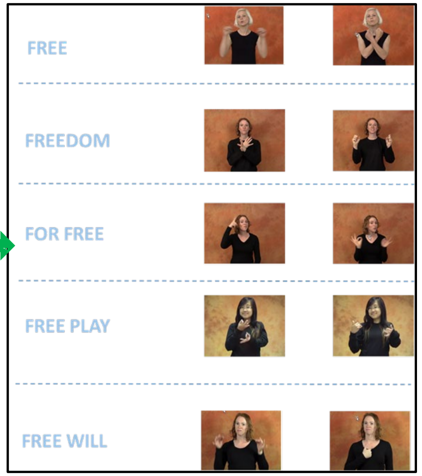
FREE

English Speaker to ASL

Spoken voice is captured by DragonFly

Speech is converted to English text

English to ASL translation performed



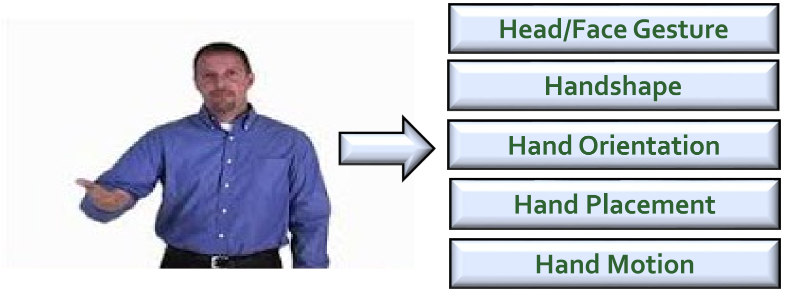
Text and Signing Avatar displayed to user

ASL Translation Challenges

Sign/Signer Variability

Distinct language with broad sign variation across signers

Signal Complexity



Sensor Variability

e.g. 2D/3D, fixed/mobile sensors

Session Variability

e.g. observation angle

Data Availability

- Limited availability of well annotated ASL<->English content

5

What we did

- Integrated the ASL Recognizer (ASLR) into an automated MT system that can be used in real time ad-hoc communications between signers and non-signers

- Implemented deep learning-based models (in OpenMT)
  - ASL video-to-ASL symbol sequence classifier
  - ASL symbol sequence-to-English sentence generator
  - ASL video-to-English sentence generator

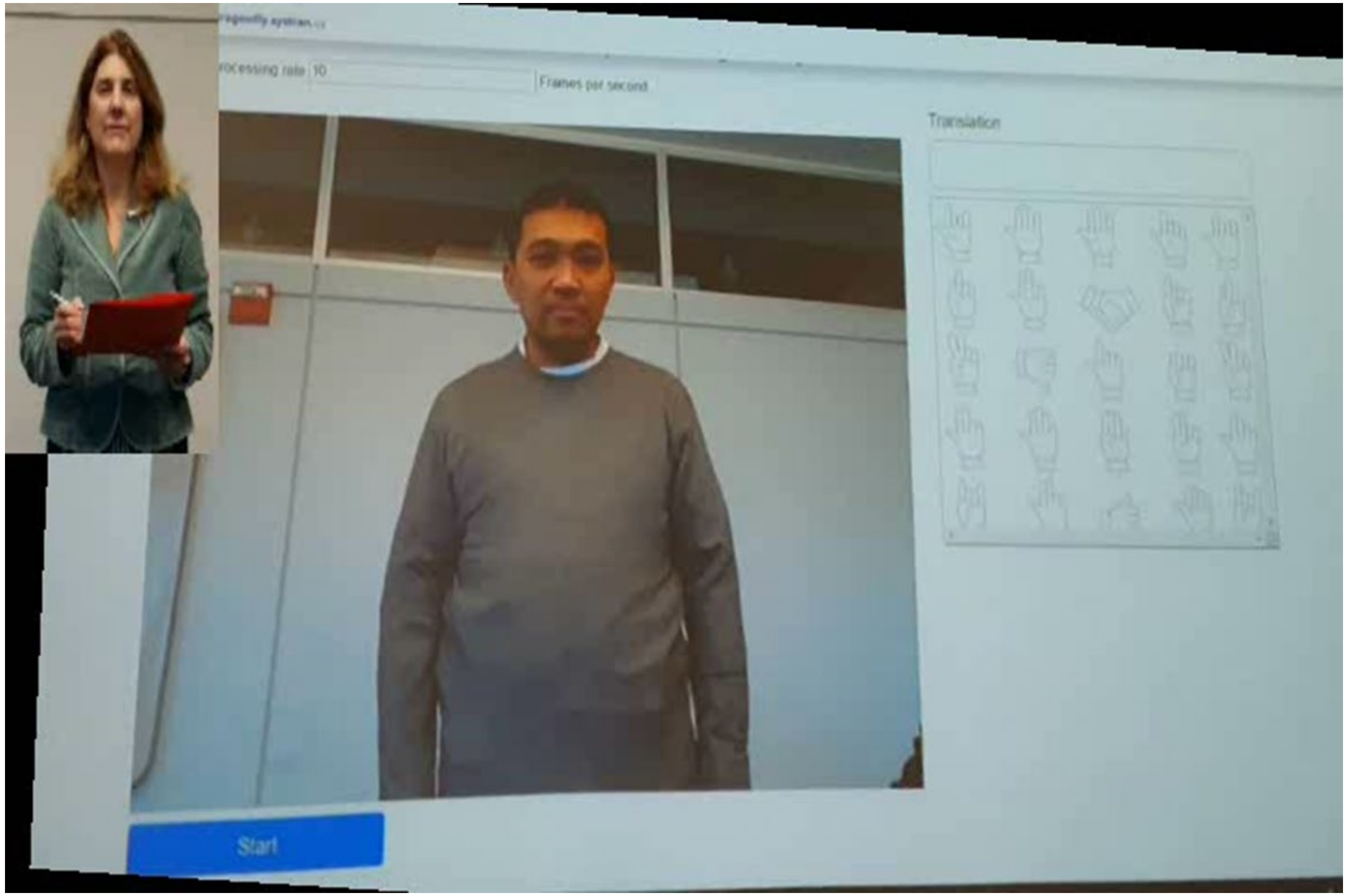
What we did - Continued

- Leveraged sources in addition to BU and Purdue data (e.g. closed-captioned ASL from The Sign Language Channel)
- Created and incorporated the use of computer-generated Synthetic Data to augment training data
- Development and testing of a Handheld Prototype

Handheld Prototype

- Web-based application
- ASL Video captured in real time on Smartphone or Tablet
- Seamlessly transmitted to Amazon Cloud for processing
- English MT text delivered and displayed in chat window
- Text-to-speech performed locally

Cafe DragonFly Demo



Proceedings of the 14th Conference of the Association for Machine Translation in the Americas
October 6 - 9, 2020, Volume 2: MT User Track

What we learned

- Computer generated Synthetic Data improved overall ASLR performance
  - Per sign raw recognition improved over 10% in initial testing
  - Key driver is using "valid" synthetic data to train the models
- Dramatically improved the speed and accuracy of ASLR
- However, we encountered both classic neural net and synthetic data validation challenges

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Neural Net Challenges

- MT Output Errors
  - Error Types typical of neural net encoder-decoder architecture model for low resource languages (Vardaro et. al 17 September 2019:Informatics, Koponen et.al 2019: Machine Translation).
    - Substitution
      - Input: “I want hamburger without mayonnaise, please.”
      - Output: “I will have a chicken sandwich without mayonnaise please.”
    - Reordering /Addition
      - Input: “I want cheeseburger and soup, please.”
      - Output: “I will have soup, cheeseburger and french fries please.”
    - Omission
      - Input: “I want hotdog with ketchup and mustard, please .”
      - Output: “I want hotdog with ketchup and mustard, ________.”
    - Addition /Substitution
      - Input: “I want cheeseburger with extra spinach .”
      - Output: “I want cheese pizza with extra spinach and bacon .”

Sequence-to-Sequence Challenges

- Lack of scalability: inability to easily add new words
  - Multiple training sentences required for each flavor of ice cream
    - I want chocolate ice cream
    - I want vanilla ice cream
    - I want strawberry ice cream, etc.
    - Some words characterized as only nouns so unable to say "peach Ice cream"
  - Multiple permutations required for each sentence instead of for individual words (want, would, love, like chocolate, vanilla, milk, pudding)
    - I want chocolate ice cream; I would like chocolate milk, I love chocolate,
    - I want chocolate pudding, I like vanilla pudding, I like chocolate milk, etc.

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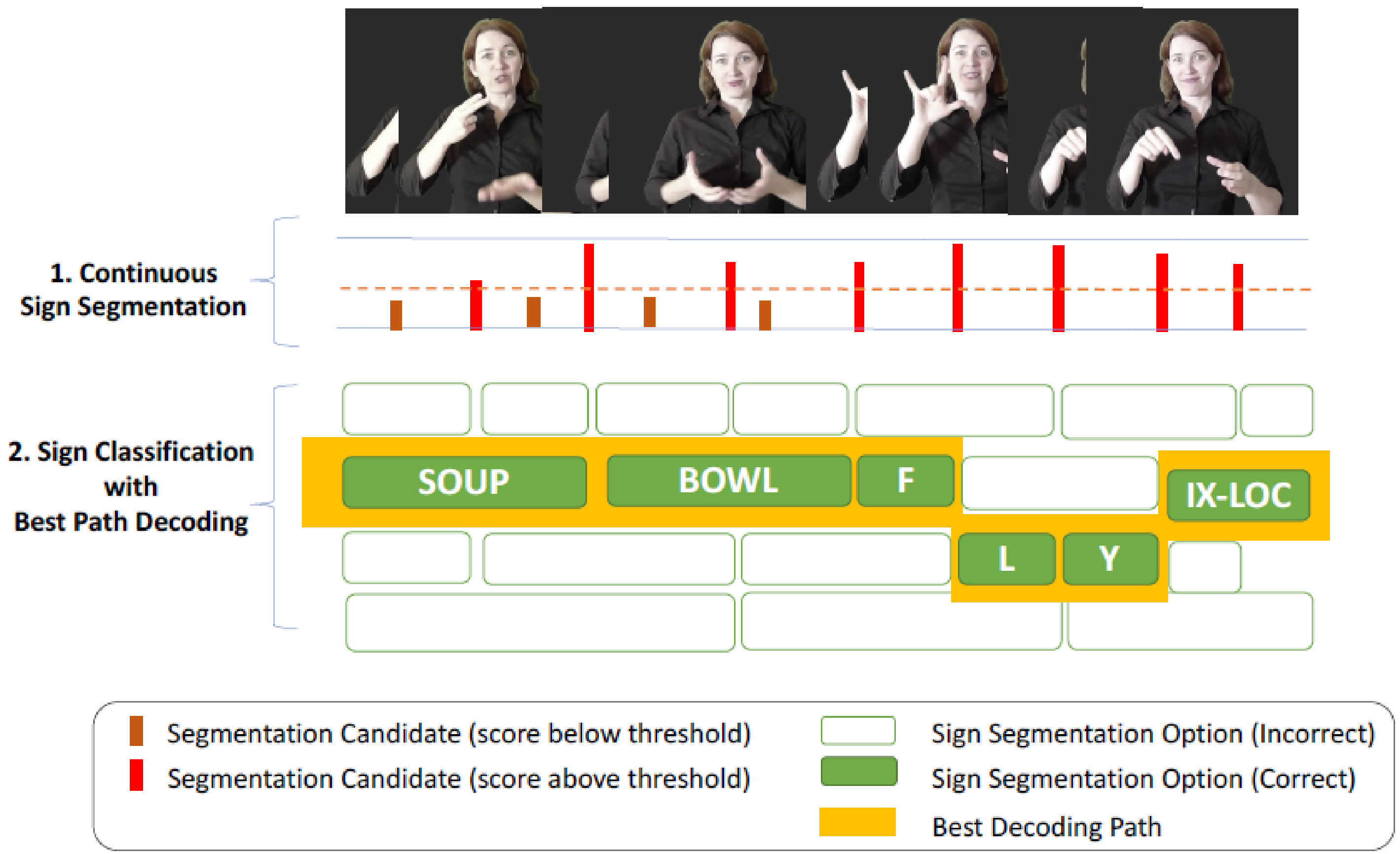
Continuous Sign Recognition



Continuous Sign Recognition Approach with Explicit Sign Segmentation and Sign Classification Steps

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Sign Segmentation Process

(Khan 2014; Farag & Brock 2019), and

Future Plans

- Full scale development, test and evaluation of hand-held operational prototypes
- Platform (iOS, Android, and Windows) and browser (Chrome, Firefox, and Edge) compatibility and user field testing
- Incorporation of ASL avatar for signing synthesis
- Commercial partnerships for product delivery

Questions

Why is it So Hard to Compare Translation Evaluations and How Can Standards Help?

AMTA 2020

9 October 2020

Jennifer DeCamp

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AMTA

Why is it so Hard to Develop Comparable Translation Evaluations and How Can Standards Help?

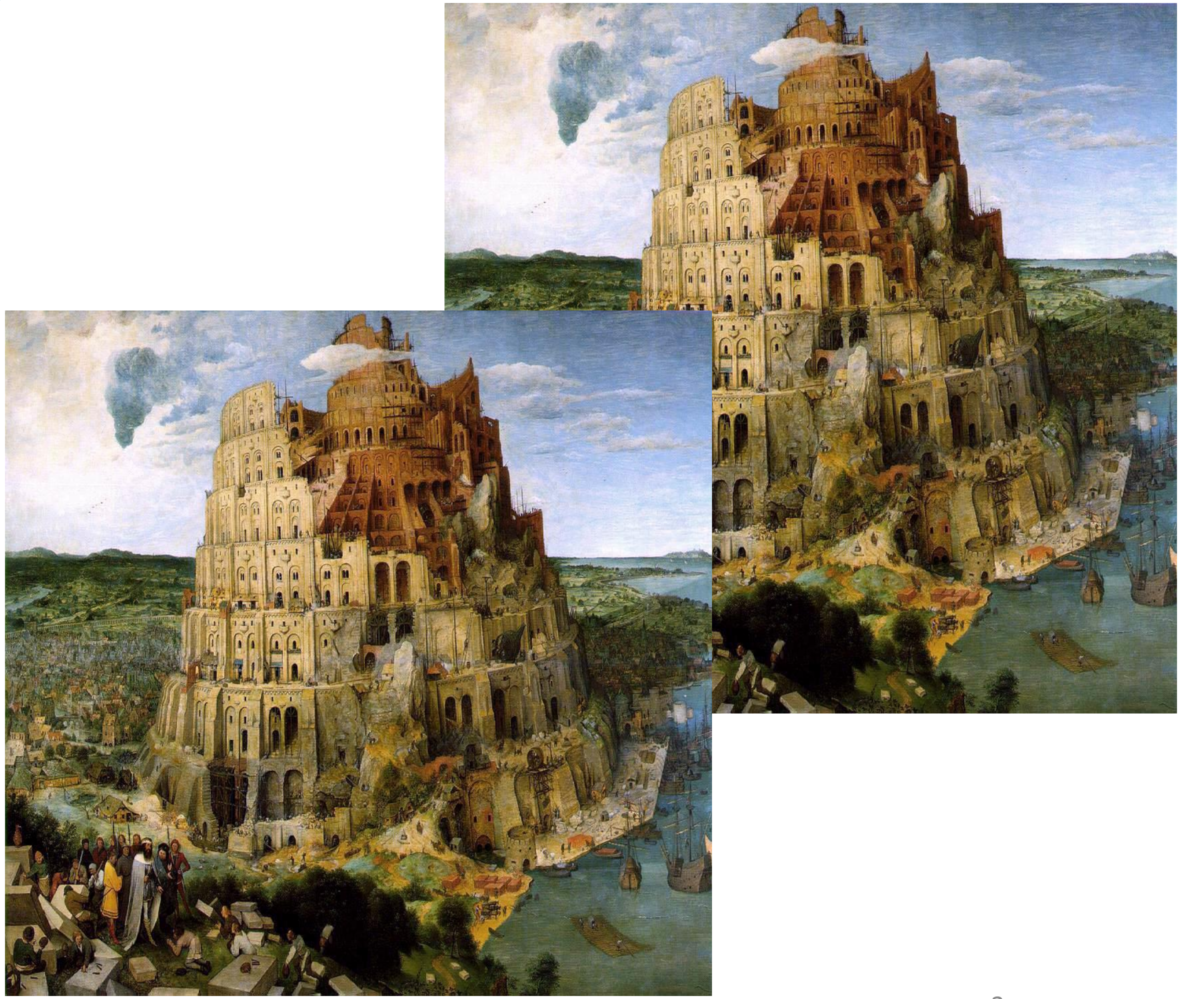
There are several standards and guidelines that may be relevant to MT and that are in use or anticipated to be ready for use this year, including *ASTM 2475 Translation Quality Requirements*, *ASTM WK46396 Analytic Evaluation of Translation Quality*, *ISO 17100 Translation services — Requirements for translation services*, and the Interagency Language Roundtable Skill Level Descriptions for Translation Performance.

This presentation reviews these standards and guidelines and discusses how they can be applied to evaluation of MT, whether HT, MT, or some combination. Such comparisons may include: a new version of MT with the previous version; one company's MT with that of another company, one product with another product; a language service provider's performance in one year vs. another, or one organization with another. The presentation also addresses gaps and provides recommendations, including to for become involved with improving these standards and thus improving MT evaluation.

Why Is It So Hard to Develop Comparable Translation Evaluations?

1. Variation in the translations
   - Languages, dialects, registers, domains
   - Genres
   - Cultural information
   - Processes
   - Tools
   - Purposes
   - Terminology
   - Need for reliability
   - Etc.

2. Variation in translation evaluations
   - Purposes
   - Requirements
   - Methods
   - Tools
   - Terminology
   - Need for reliability
   - Etc.



Purposes for Translation Evaluation

1. Development progress and direction
2. Acquisition
    - Write and administer contracts
        - *48 Code of Federal Regulations (CFR) § 15.101-2 - Lowest price technically acceptable source selection process*: The evaluation factors and significant subfactors that establish the requirements of acceptability shall be set forth in the solicitation.
    - Make decisions
        - Obtain
        - Upgrade
        - Replace
3. Management
    - Deploy resources
    - Determine performance
        - Track performance over time
        - Benchmark
4. Determine quality of deliverable
    - Send it for revision
    - Deliver it to the customer

4

Types of Evaluation

- Product
  - Reference
    - Human translation
  - No reference
    - Impact in workflow (e.g., impact to entity extraction)
    - Detailed error analysis
      - *ATA Certification Scoring*
      - *ASTM WK46396 Analytic Evaluation of Translation Quality*
- Process
  - *ISO 17100 Translation services — Requirements for translation services*
  - *ASTM 2575 Requirements for Translation Evaluation*
  - Skill descriptions by ILR, DLPT, ACTFL, etc.
- Outcome
  - Impact of the translation (e.g., in comparison with source text)

5

Methods and Tools

"Current approaches to Machine Translation (MT) or professional translation evaluation, both automatic and manual, are characterized by

- *A high degree of fragmentation, heterogeneity and a lack of interoperability between methods, tools and data sets.*
- *As a consequence, it is difficult to reproduce, interpret, and compare evaluation results"* *(G. Rehm et al, 2016)*

Standards

- *ASTM WK46396 Analytic Evaluation of Translation Quality*
- *ASTM 2575 Requirements for Translation Evaluation*
- ISO and ASTM efforts in terminology management

6

Meet Customer Requirements

Translator or Language Service Provider	“What the customer wants”
Customer	“100% accuracy, fast, cheap”
MT Developer	“As good as a human”

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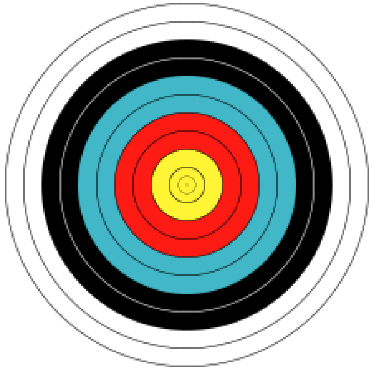
Quality/Target



- Announcements of NMT equaling or exceeding human performance
  - As good as human translators (i.e., humans hired from a translation company)
  - “If they did that work at my company, they wouldn’t be working for me for long” (owner of translation company at last AMTA meeting)
- But anyone can self-declare as a translator; any company can self-declare as a translation company
- And in the above methods, evaluators are not doing translator tasks
- Plus extensive issues with use of reference translations
  - Can’t always use a reference translation (e.g., to determine whether a translation is ready to submit to a client)
  - Get different results with different reference translations or different number of reference translations or references from a different part of the translation pair
  - Numbers often not meaningful at quality levels needed for deliverables
  - Usually reviewed by people with no understanding of context
  - Provides little or no information on WHAT is wrong
  - May penalize for different terminology or word order
  - Etc.

A. Lommel (2016)

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What Humans?

- American Translators Association (ATA) Certification
  - Focused on perhaps too high a level
  - Too time-consuming for most applications
  - Not available for many languages
  - Directory of translators with certification and resumes listed on ATA home page http://www.atanet.org
- *ISO 17100:2015 Translation Services – Requirements for Translation Services*
  - Human translation (no technology), with an amendment to cover requirements in the U.S., Canada, and several other countries
  - CHF 118 (=UDS 128.40)
  - Britain's Institute of Translation and Interpreting (ITI) has created a translator "qualification" for meeting requirements for translators
  - U.S. and others have proposed having a new standard to better meet the needs for certification
- Defense Foreign Language Proficiency Test (DLPT) and American Council on the Teaching of Foreign Languages (ACTFL) Scores

Institute of Translation and Interpreting

9

Interagency Language Roundtable
Skill Descriptions for Translation Performance

- **Level 2+ (Limited Performance)**

  Can render straightforward texts dealing with everyday matters that include statements of fact as well as some judgments, opinion, or other elements which entail more than direct exposition, but do not contain figurative language, complicated concepts, complex sentence structures, or instances of syntactic or semantic skewing.

- **Level 3 (Professional Performance)**

  Can translate texts that contain not only facts but also abstract language, showing an emerging ability to capture their intended implications and many nuances. Such texts usually contain situations and events which are subject to value judgments of a personal or institutional kind, as in some newspaper editorials, propaganda tracts, and evaluations of projects.

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Interagency Language Roundtable
Skill Descriptions for Translation Performance

Level 4+ (Professional Performance Plus)

- Can successfully apply a translation methodology to translate texts that contain highly original and special purpose language (such as that contained in religious sermons, literary prose, and poetry). At this level, a successful performance requires not only conveying content and register but also capturing to the greatest extent all nuances intended in the source document. Expression is virtually flawless.

Level 5 (Professional Performance)

- Can successfully translate virtually all texts, including those where lack of linguistic and cultural parallelism between the source language and the target language requires precise congruity judgments and the ability to apply a translation methodology. Expression is flawless.

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How can Standards Help in MT Evaluation?

1. Can provide a better understanding of the information needed by decision makers
   - Target level
   - Requirements
2. Can help provide a broader framework for structuring an evaluation
   - Broader information
   - Authority
3. Can improve communication through this framework and through standardized terminology

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Recommendations

1. Work towards a common framework
   - Employ standardized terminology
   - Employ interoperability standards for exchange of data
   - Carefully test and document results
2. Become more specific
   - Look at customer requirements for translation and translation evaluation
   - Reduce ambiguity re “human”
3. Educate the customer on
   - Requirements and opportunities training
   - On the impact of evaluation methods on certain types of translation
4. Participate in developing standards
   - ASTM
   - ISO

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Images

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Using Contemporary US Government Data to Train Custom MT for COVID-19

Achim Ruopp

Polyglot Technology LLC

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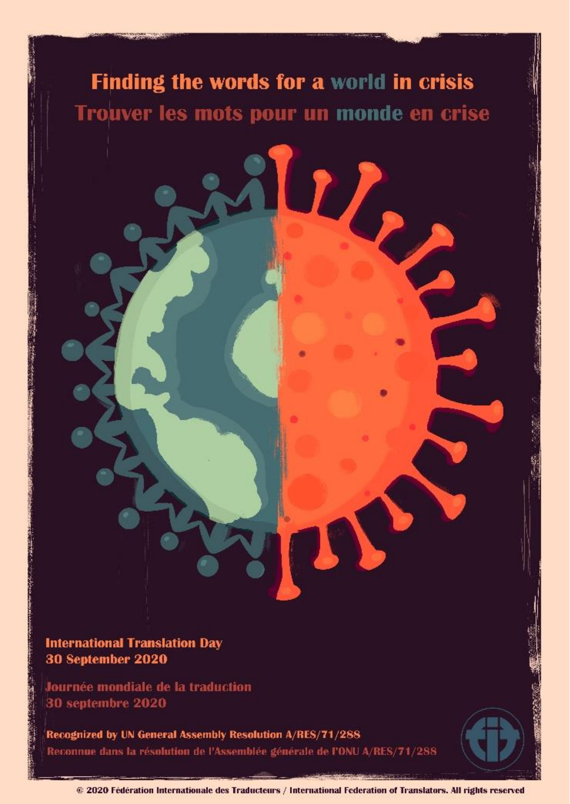
Translation’s Role in the COVID-19 Crisis



- Gretchen McCulloch’s article “Covid-19 Is History’s Biggest Translation Challenge” in WIRED
  - Communicating health information is an essential factor in addressing this crisis
  - Familiar issue that MT currently only supports 100+ languages
    - Languages with millions of speakers are unsupported
    - Long tail of thousands of human languages are unsupported/endangered
  - Some issues with register in the high resource languages
    - Japanese translation of “Wash your hands” in tone of a parent instructing a child
  - People want to gist information in their languages – accurate MT can help to address disinformation
- Translators without Borders did great work in previous health crises like Ebola, but scope of COVID-19 is unprecedented

The Translation Community Coming Together

- TAUS Corona Virus Corpora
  - English↔French/German/Italian/Spanish/Chinese/Russian
  - Translation data (mainly) selected from existing parallel corpora with a COVID-19 specific English query corpus
    - ~ 200k-900k segments
    - Creative Commons Attribution-NonCommercial 4.0 license
  - SYSTRAN built custom COVID-19 MT systems using the data
  - The MT broker Intento
    - did an extensive human evaluation/post-editing study with a test subset of the data https://try.inten.to/mt-evaluation-covid-domain
    - is creating a custom routing for COVID-19 content in their platform
    - customized MT with the TAUS Corona Virus Corpora
      - For only 2 out of 7 language pairs did the custom MT systems outperform the stock engines
      - Possible explanation provided by Intento: medical domain is wide – data might require clustering
      - Alternative customization with just a bilingual glossary failed

The Translation Community Coming Together

- Translation Initiative for COVID-19 aka TICO-19
  - Partners
    - academia: Carnegie Mellon University, Johns Hopkins University
    - industry: Amazon, Appen, Facebook, Google, Microsoft, Translated
    - non-profit: Translators without Borders
      - Strong track record communicating in previous crises (e.g. Ebola, Rohinga refugee crisis) and working with the non-profit organizations
      - Also runs COVID-19 Community Translation Program
  - Data
    - TICO-19 Translation Benchmark
      - 30 English documents with 3071 segments/69.7k words translated to 36 languages
      - English→Amharic, Arabic (Modern Standard), Bengali, Chinese (Simplified), Dari, Dinka, Farsi, French (European), Hausa, Hindi, Indonesian, Kanuri, Khmer (Central), Kinyarwanda, Kurdish Kurmanji, Kurdish Sorani, Lingala, Luganda, Malay, Marathi, Myanmar, Nepali, Nigerian Fulfulde, Nuer, Oromo, Pashto, Portuguese (Brazilian), Russian, Somali, Spanish (Latin American), Swahili, Congolese Swahili, Tagalog, Tamil, Tigrinya, Urdu, Zulu
    - COVID-19 specific translated terminologies (from Facebook and Google)
    - Creative Commons CC0 licensed
  - See website for links to many other COVID-19 related data projects (language data and beyond)

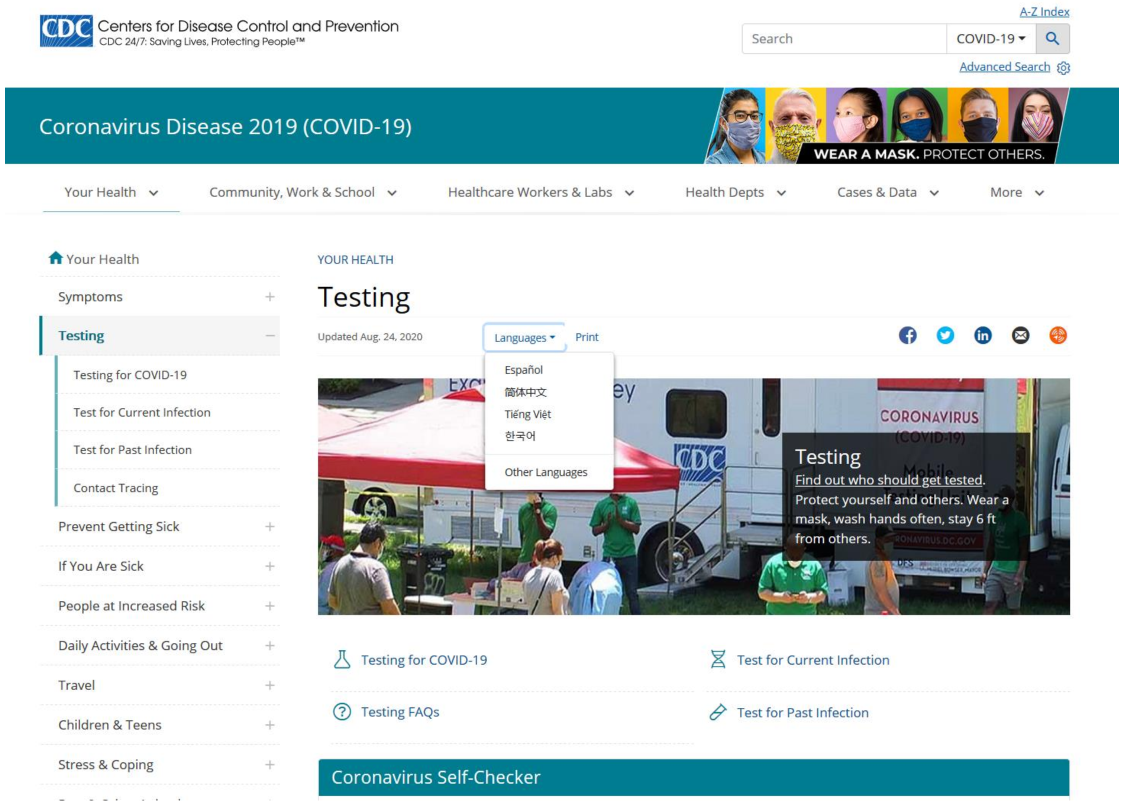
TICO-19 Translation Benchmark Diversity

Data Source	Example
CMU	are you having any shortness of breath?
PubMed	The basic reproductive number (R0) was 3.77 (95% CI: 3.51-4.05), and the adjusted R0 was 2.23-4.82.
Wikinews	By yesterday, the World Health Organization reported 1,051,635 confirmed cases, including 79,332 cases in the twenty four hours preceding 10 a.m. Central European Time (0800 UTC) on April 4.
Wikivoyage	Due to the spread of the disease, you are advised not to travel unless necessary, to avoid being infected, quarantined, or stranded by changing restrictions and cancelled flights.
Wikipedia	Drug development is the process of bringing a new infectious disease vaccine or therapeutic drug to the market once a lead compound has been identified through the process of drug discovery.
Wikisource	The federal government has identified 16 critical infrastructure sectors whose assets, systems, and networks, whether physical or virtual, are considered so vital to the United States that their incapacitation or destruction would have a debilitating effect on security, economic security, public health or safety, or any combination thereof.

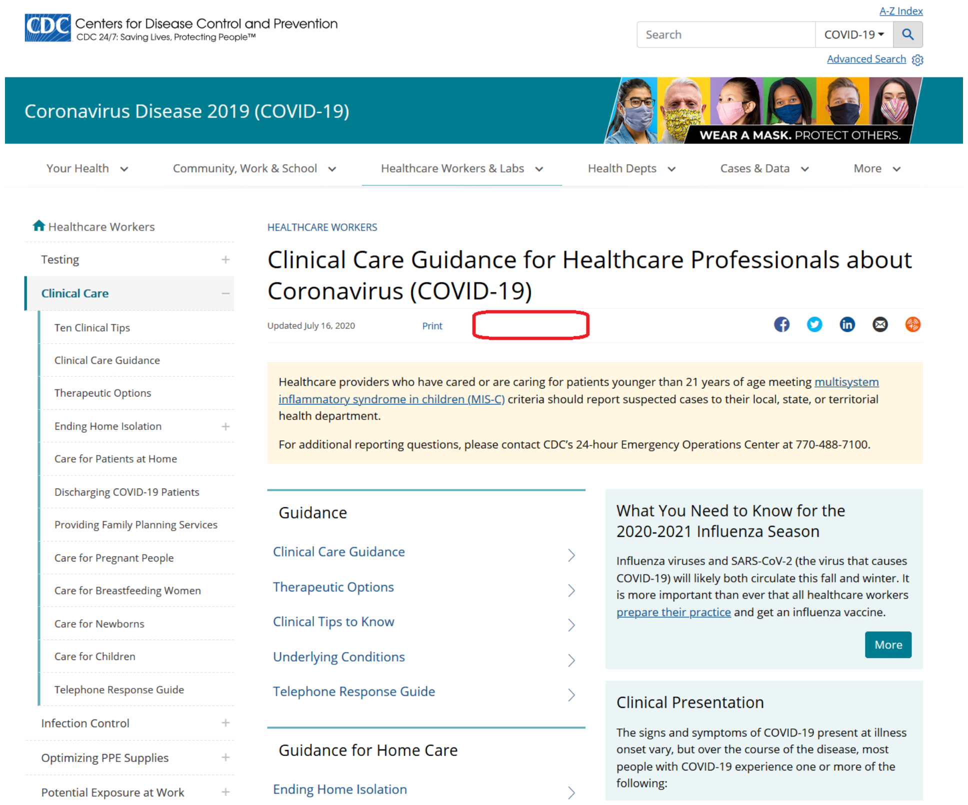
Table 2: Samples of the English source sentences for the TICO-19 benchmark.

Anastasopoulos, A., Cattelan, A., Dou, Z.-Y., Federico, M., Federmann, C., Genzel, D., . . . Tur, S. (2020). TICO-19: the Translation Initiative for COvid-19. arXiv, 2007.01788v2.

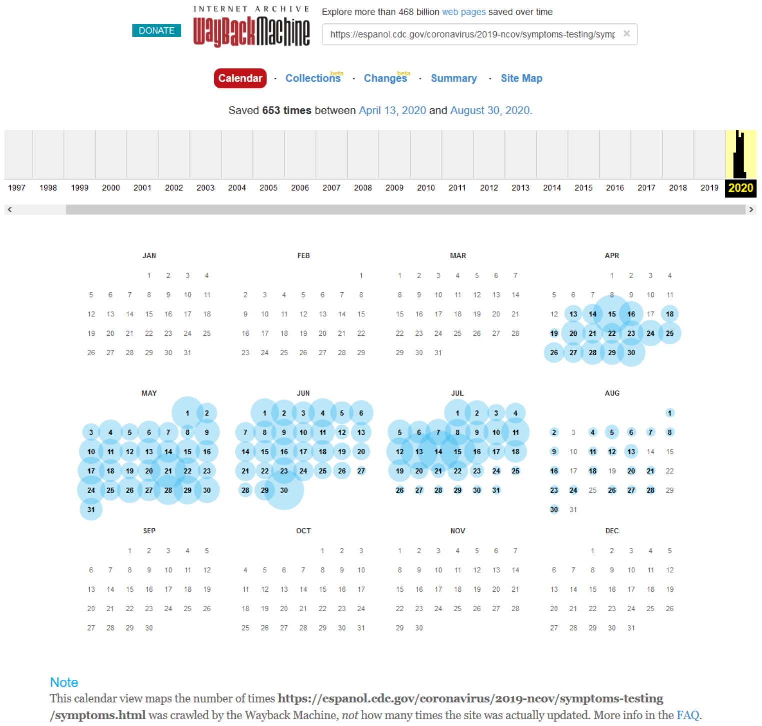
Opportunity: Centers For Disease Control and Prevention COVID-19 Website



Information for Medical Professionals is not Translated



CDC COVID-19 Site Updates



- Site frequently updated
- Crawled on June 24, 2020 and July 24, 2020
  - June 24 crawl yielded the most parallel data of the two
- Data represents translation practices of COVID-19 health info, but not ground truth about COVID-19 virus!

Data Statistics for CDC COVID-19 Parallel Data

- Non-deduplicated (in TMX with context)

English→	Segments	Source words	Target words	Target characters
Spanish (US)	79,106	538,842	696,471	
Vietnamese	79,757	550,066	895,573	
Korean	78,824	537,204	428,979	
Chinese	70,423	508,297		2,958,795

- Deduplicated & shuffled (TSV)

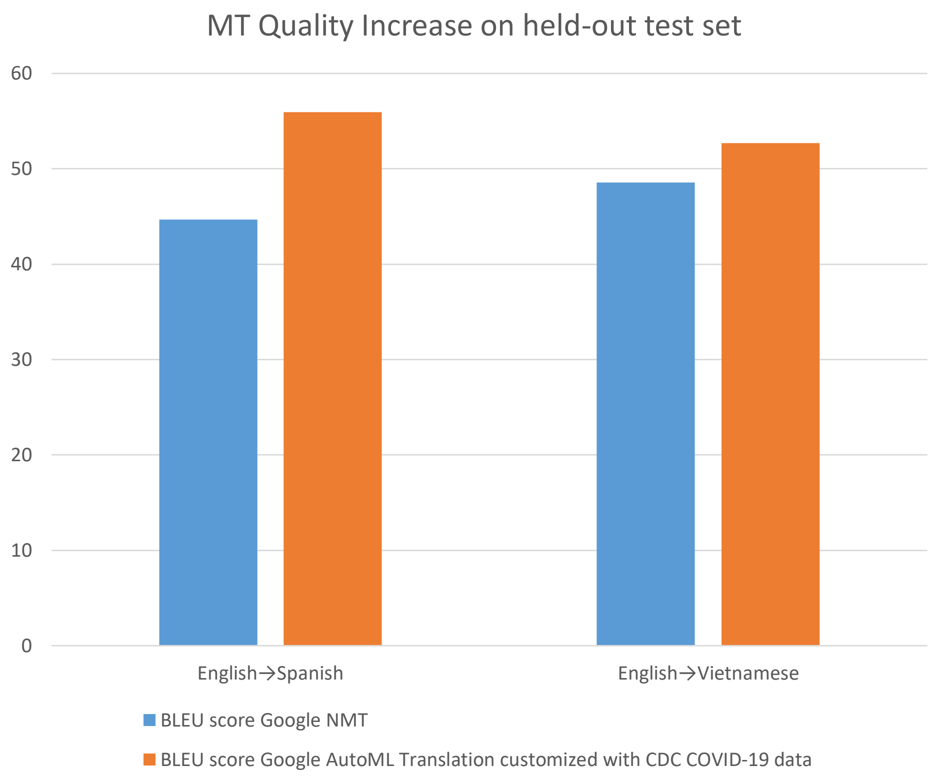
English→	Segments	Source words	Target words	Target characters
Spanish (US)	15,803	248,780	310,223	
Vietnamese	15,849	249,006	380,113	
Korean	16,532	262,393	197,402	
Chinese	11,911	254,876		1,413,993

- Volume in between TAUS Corona Virus Corpus and TICO-19
  - Test/validation/fine tuning data
  - Data with document context in TMX
    - Document context
      - original segment order
      - source-document property groups segments
      - Better: XLIFF (used in WMT)
    - Creation date
      - Better: webpage update date
- Custom crawling code based on Bitextor
  - Non-customized ParaCrawl/Bitextor contains only 5 English-Spanish segments from the CDC in the latest September 2020 release
- Additional medium resource languages/language variants covered
  - US-Spanish (≈ LatAm-Spanish?)
  - Vietnamese
  - Korean

CDC COVID-19 Parallel Data Licensing

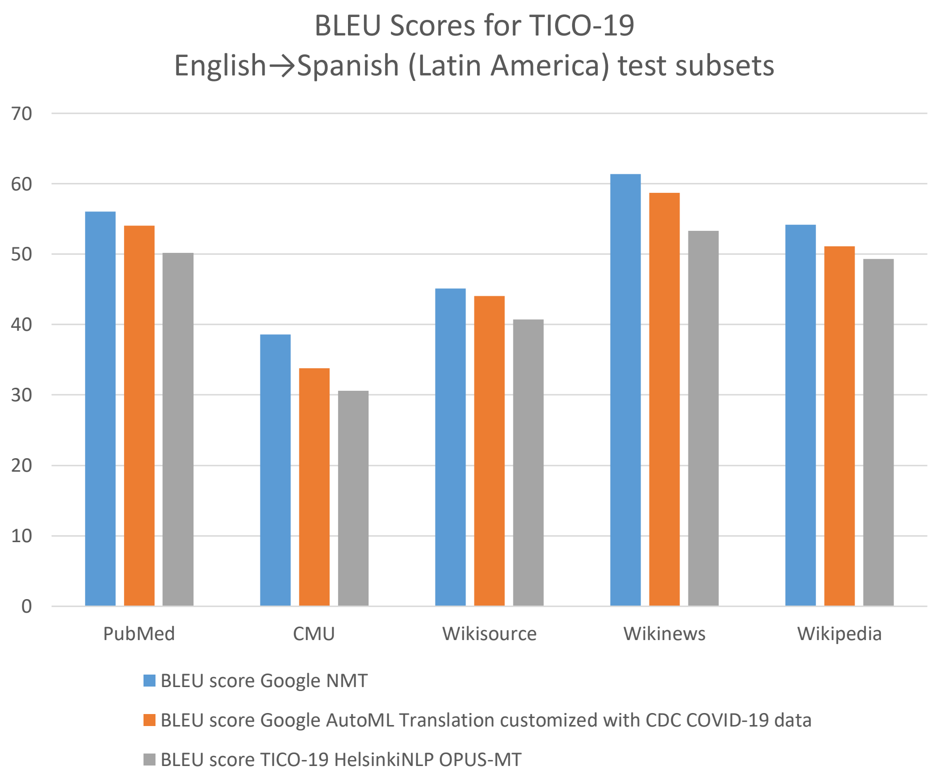
- Content
  - Public domain
  - Disclaimer: Source: CDC; Reference to specific commercial products, manufacturers, companies, or trademarks does not constitute its endorsement or recommendation by the U.S. Government, Department of Health and Human Services, or Centers for Disease Control and Prevention; The public domain material is available on the agency website https://www.cdc.gov/ for no charge.
- Database/database structure, i.e. TMX/TSV
  - Made available under the Open Data Commons Attribution License: http://opendatacommons.org/licenses/by/1.0

Google AutoML Translation Customized with CDC COVID-19 Parallel Data



- Significant BLEU score increases over already high baselines
  - English→Spanish +11.27
  - English→Vietnamese +4.1
  - Confirmed results with TER and BERTScore
- Enables increased productivity in post-editing scenario
- More appropriate raw machine translations of new or revised CDC COVID-19 content

Google AutoML Translation Customized with CDC COVID-19 Parallel Data



- Customized system performs worse with TICO-19 translation benchmark
- Hypotheses
  - Medical domain is wide
  - COVID-19 is not that "novel" from the health information translation perspective
  - Domain mismatch/overfitting to CDC data
    - Topic
    - **Modality** – TICO-19 corpora contain transcribed speech (CMU)
    - **Register**: Level of politeness – translator/project dependent
    - Intent – consistent
    - Style – translator/project dependent
    - **Language variant**

Larger Lessons – Future Research

- For high/medium resource languages
  - MT suppliers have now optimized Transformer-based NMT
    - Many ambiguities already resolved (especially intra-sentence ambiguities)
    - MT systems robust to variations in domain
  - Additional improvements for medium resource languages from transfer learning from other languages/massively multilingual systems
  - Research on using document-level context

⇒ It becomes harder and harder to beat the baseline models with custom MT!

Larger Lessons – Future Research

- Test/development data becomes ever more important - we can't detect if we beat the baseline if we don't specify what we expect!
  - Evaluation data is as crucial as evaluation measures
  - Development sets, e.g. for training data selection, cannot be source-only anymore
  - Opens a great opportunity to include linguists – human-in-the-loop MT
    - For the post-editing use case some MT suppliers already build this into their workflow: Lilt, ModernMT, Unbabel
  - MT suppliers need to improve guidance which data sets are sufficient/good – manual experimentation is tedious/expensive

Larger Lessons – Future Research

- Low resource languages still suffer from lack of language resources
  - Again coming into clear focus in the COVID-19 crisis – resource light approaches unlikely to help
  - Investment needed – public/private?

Other Parallel Corpora from Polyglot Technology LLC

- Healthcare.gov
  - Healthcare/health insurance content
  - English→Spanish
  - Blog article from May 2019
- US Department of State news releases/announcements
  - English→Arabic, Spanish, Farsi, French, Hindi, Indonesian, Portuguese, Russian, Urdu, Vietnamese, Chinese
- Custom Crawling