

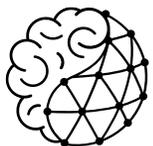
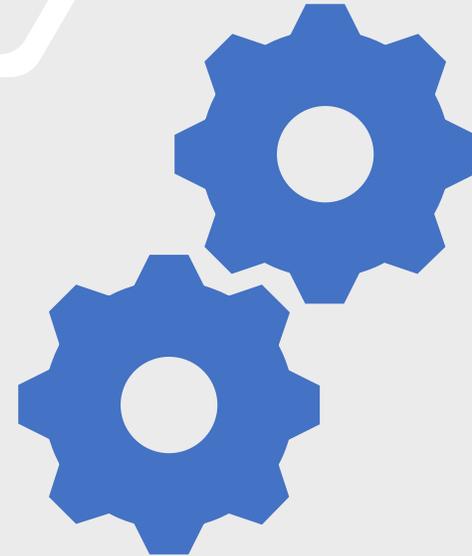
Quality Estimation for Machine Translation

(QE4MT)

Diptesh Kanojia

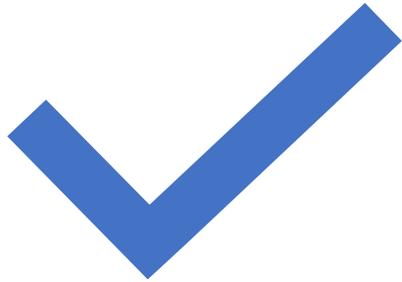


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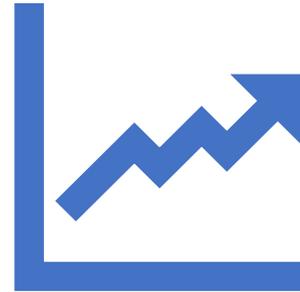


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Research Domains



Evaluation



Improvements

Research Domains



Evaluation



Improvements

Why Estimate?



BLEU scores have become a de-facto standard when it comes to evaluation of machine generated text (translation/summarization/...)

Criticized for low co-relation with human evaluation of machine translated output (Reiter, 2018)

Other statistical measures, like BLEU, do not take 'semantics' into account.



Need for a **measure which takes a more 'meaningful' comparison** into account.



Distributional Semantics (word embeddings) provide a viable method to compare source input with target side output.

Quality Estimation

Input

- Source side text
- Target side text

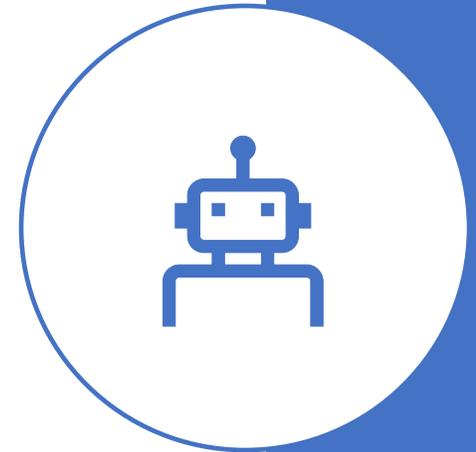
Output

- Score on a scale of 0-100*

No more reliance on parallel data for evaluation

Building Upon The *QueST*

- Early adoption of QE research was based on models produced using QuEst/QuEst++.
 - TransQuEst (Ranasinghe et. al., 2020) provides a reliable framework for building Quality Estimation (QE) models for many language pairs.
 - Research on QE is growing as new language pair data is introduced.
-
- However, our research begets questions on the **reliability** and **robustness** of these systems in evaluating MT output.



Errors in Machine Translation

Hallucination

Text with a significant word count.

Text which contains special characters.

Negation

Ignore the present of 'not', 'neither', 'none' in some cases.

Incorrect use of upper/lower case letters

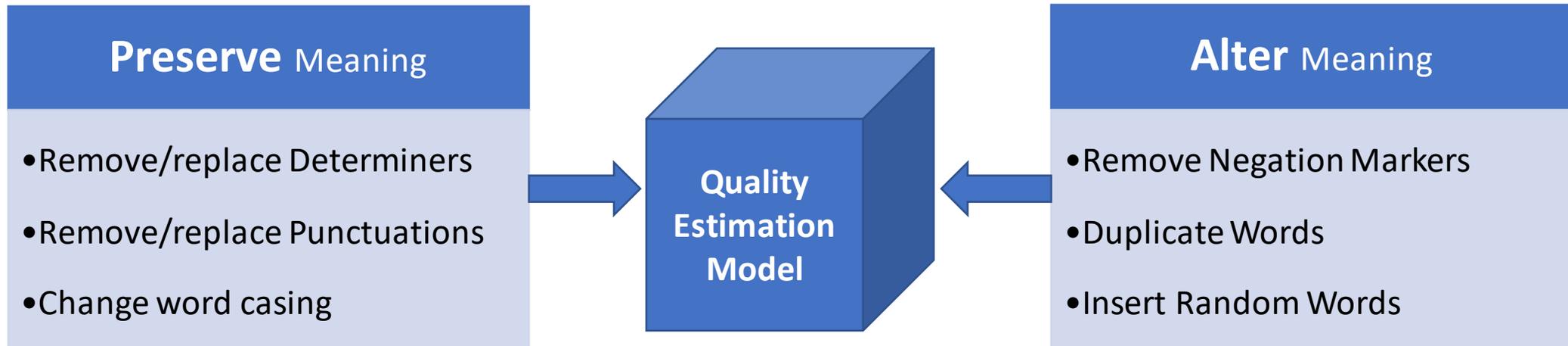
Terms are written in upper case, depending on the context (King/king), but an MT system is unable to detect when to do this

Untranslated acronyms

WHO (World Health Organization), which, in Spanish is OMS (Organización Mundial de la Salud)

Linguistic Perturbations

An initial study which posed questions over the adequacy of the machine translated text and **evaluated the performance of QE models using linguistic perturbations.**



Outcomes



State-of-the-art (SoTA) QE models are able to capture errors many errors and penalize accordingly.



Robust to meaning preserving changes
Unreliable performance when meaning is altered by machine translation output



There are many issues to consider:

- Removal of negation does not render a very different score.
- Replacing words with their antonyms had practically no effect on many examples.
- and then some more...



Unlike other multilingual natural language processing applications; multilingual QE models do not perform as well as models trained on a single language pair.

Limitations and Future Directions

- Resource restricted scenario
 - Use of automated methods to generate perturbed examples restricted us to use of data from language pairs where English was used.
 - Observations on five language pairs.
- A further limitation in exploring/creating tools for other languages in this space is non-availability of datasets for which these tools would possibly be designed.
- Therefore, **let us first create the QE datasets.**



Indian Languages – Low-resource?

- **No datasets for Quality Estimation** for Indian languages.
- Training a quality estimation **model requires ‘direct assessment’ scores from human annotators.**
 - Native speakers of Indian languages like Marathi, Hindi, Tamil, *etc.* who understood English.
- **No leaderboard** for the larger language understanding paradigm, let alone Quality Estimation.
- However, **embeddings models and language models including multilingual variants have been produced** from recent research.
- **Large monolingual and parallel corpora** for many Indian languages/pairs (including English).

Recent and Upcoming Datasets

Indo-Aryan Language Family

- English – Marathi Quality Estimation
 - Released at Conference for Machine Translation (WMT) 2022 Quality Estimation Shared Task.
- English – Hindi Quality Estimation
 - Data Collection ongoing
- English – Gujarati
- English – Bengali
- English – Assamese

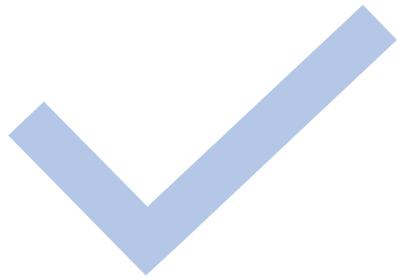
Dravidian Language Family

- English – Tamil
- English – Telugu
- English – Kannada

Further Research

- **Multi-tasking QE models** which perform sentence and word-level QE at the same time.
- **QE models which are robust to linguistic perturbations** generated synthetically.
- **Multilingual QE model** for Indian Languages
- **Document-level Quality Estimation** for English-Tamil

Research Domains



Evaluation



Improvements

Automatic Post-Editing

Indo-Aryan Language Family

- English – Marathi Post-edits
 - Released at Conference for Machine Translation (WMT) 2022 [APE Shared Task](#).
- English – Hindi Post-edits

Dravidian Language Family

- English – Tamil

Other
Collaborations



Thank you!

Questions at the end of the panel.



d.kanojia@surrey.ac.uk

References

- Ehud Reiter; A Structured Review of the Validity of BLEU. *Computational Linguistics* 2018; 44 (3): 393–401.
doi: https://doi.org/10.1162/coli_a_00322
- Ranasinghe, T., Orasan, C., & Mitkov, R. TransQuest: Translation Quality Estimation with Cross-lingual Transformers. In *Proceedings of the 28th International Conference on Computational Linguistics*.