On the Value of Machine Translation Adaptation

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MT, DT, DTMT

- **Domain tuning (DT): Tailoring a machine translation (MT) system to (ideally) better translate the kinds of data users want to translate.**
  - Training MT using data that is representative of a topic's subject matter (e.g., scientific and technical literature)
  - Adding terminology that is relevant to that subject matter

- **Does DTMT improve the quality of MT output?**
  - *What do you mean by 'improve'?*
- **If so, what's the best way to go about DT?**
  - *What do you mean by 'best'?*
- **What are the trade-offs for different approaches to DT?**
  - *Oh, and is it worth the effort?*

What We Collected

- Chinese-English parallel texts in the cyber domain
- 10 abstracts (with a total of roughly 70 segments) were selected for a task-based evaluation.
- Three additional translations were produced for each test segment for a total of four reference translations.

What We Thought

- **Hypothesis 1**. DT improves the quality of machine translation output over baseline capabilities, as measured by automatic evaluation metrics.
- **Hypothesis 2.** Human translation time can be reduced by requiring human translators to post-edit the output of DTMT systems.
- **Hypothesis 3.** The linguistic quality of the target language document can be improved by requiring human translators to post-edit the output of DTMT systems.

What We Measured

- Automatic evaluation across all four domains
  - MT evaluation scores with and without DT
    - BLEU, METEOR, ROUGE, WER, TER
- Task-based evaluation for a subset of the Cyber data
  - MT evaluation scores for 10 experimental conditions (next slide)
    - BLEU, METEOR, ROUGE, WER, TER
    - HTER (Human-mediated translation error rate)
    - Relative translation rates – Total time to complete a translation (in minutes) relative to the length (number of characters) of the source Chinese text
    - Translator judgments – Questionnaire responses about MT utility and quality
    - Quality control (QC) judgments for translated segments
      - Ratings for meaning and grammaticality
      - Counts of missing and incorrectly translated terms

What We Tested

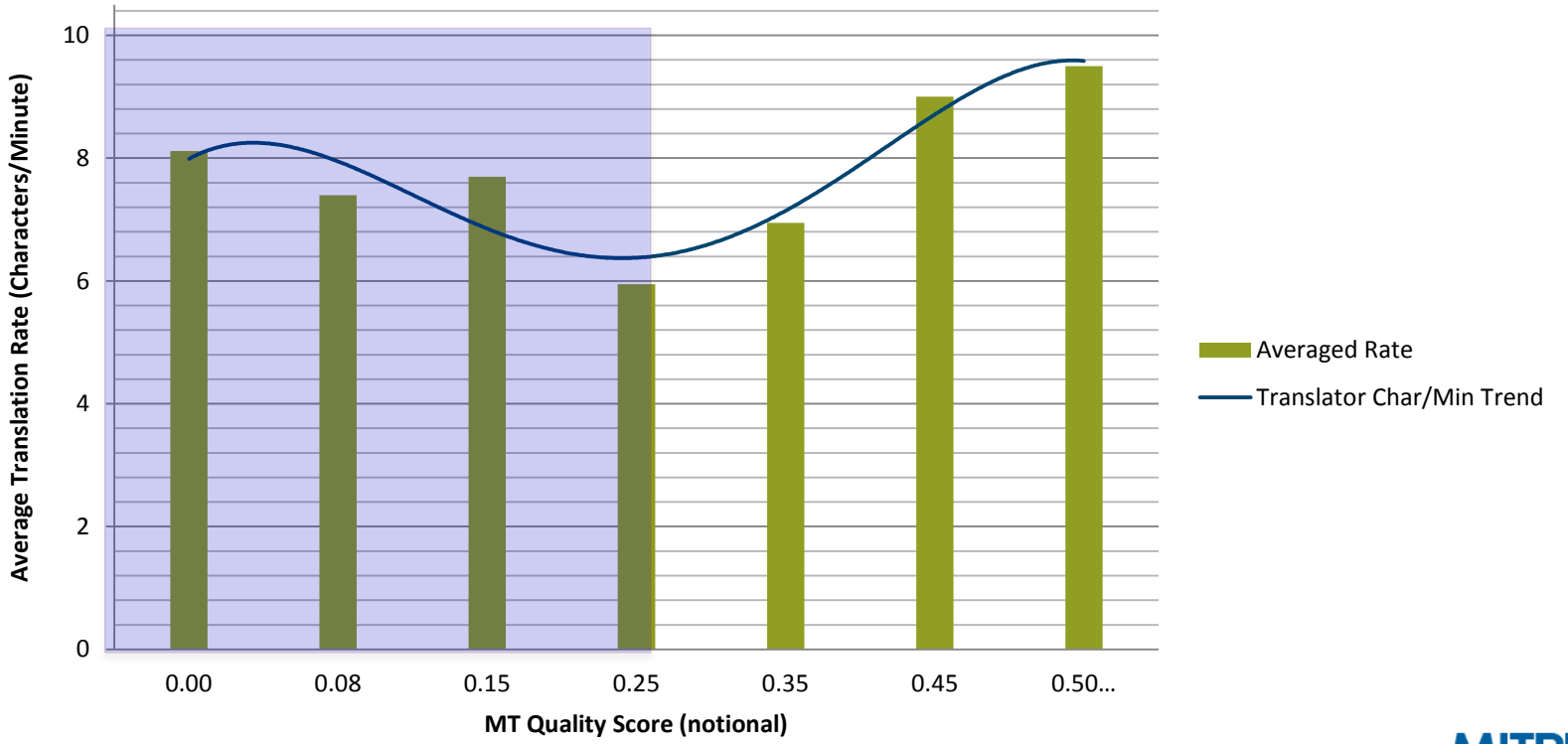
- Types of DT:
  - Statistical MT models: Training a custom engine using parallel, domain-specific data
  - Domain-specific glossaries: Lightweight adaptation with terms
- The MT systems: Two commercial off-the-shelf MT engines
- The experimental conditions:
  - For each MT system
    - **Baseline**. Translation using the MT engine without any DT.
    - **Lexicon**. Translation using the MT engine plus lightweight DT with a found domain-specific lexicon.
    - **Parallel Data**. Translation using the MT engine plus a statistically retrained engine based on the training data.
    - **Lexicon + Parallel Data**. Translation using the MT engine with a statistically retrained engine and a found lexicon.
  - Plus:
    - **Source Language + Term Highlighting**. Manual translation that does not use MT but does use a domain-specific lexicon for highlighting found terms with glosses
    - **Source Language Text Only**. Manual translation with no MT or term highlighting.

What We Found

- **Hypothesis 1**. DT improves the quality of machine translation output over baseline capabilities, as measured by automatic evaluation metrics.
  - DT did improve the automatic scores, but the BLEU scores never improved above the mid 20s.
- **Hypothesis 2.** Human translation time can be reduced by requiring human translators to post-edit the output of DTMT systems.
  - Results neither support or refute this hypothesis. Translation rates were faster for some MT conditions and slower for others.
  - Translators were slowest on output from the two MT conditions with the most involved DT (i.e., DT combining an MT engine trained on domain-specific data and a domain-specific glossary).
  - Translation times for source texts enhanced with term glosses were about the same or slower than those for translating the source texts from scratch.
- **Hypothesis 3.** The linguistic quality of the target language document can be improved by requiring human translators to post-edit the output of DTMT systems.
  - There was a clear pattern of improving (i.e., decreasing) HTER scores with customization for one MT engine, but a mixed pattern with the other MT engine. But this does not speak to the final translation quality after post-editing.
  - Translators' own opinions of the quality of the resulting translations were largely that MT had no effect.
  - Additional adequacy, fluency and error data have been collected but not yet analyzed.

What We Suspected

- Baseline MT might be of such low quality that the meaning may simply not be recoverable from the output provided.
- Translators have no option but to start from scratch, even when asked to post-edit.
- DT might improve the quality of the MT output but only enough to cause translators to take more time to consider the output rather than discarding it out of hand.



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What We Did Next

- The work raised more questions than it answered about the relationship between automated metrics, MT quality and the usefulness of MT for operationally focused tasks, so we…
  - proposed a workshop!
- (We also began follow-on work with a different language pair and data that might put us on a different starting point on the quality-productivity curve.)