The place of automatic evaluation metrics in external quality models for machine translation

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What is translation evaluation?

- Given
  - a sentence $S_n$ in a source language
  - a sentence $T_n$ in a target language

- Determine
  - a score $s(S_n, T_n)$ such as
    - $s = 1$ iff $T_n$ is a **perfect** translation of $S_n$
    - $s = 0$ iff $T_n$ is clearly not a translation of $S_n$
    - $s(S_n, T_n) > s(S_n, T_k)$ iff
      - $T_n$ is a **better** translation of $S_n$ than $T_k$
Issues and answers

- What does “better translation” mean?
  - go and ask **people** (= language users)

- Could \( s \) be computed **automatically**, directly from \( S_n \) and \( T_n \)?
  - *but this is also the goal of MT!*
  - so, could \( s \) be approximated? with what supplementary knowledge?

- A consistently high \( s \) is **not the only** desirable property of an MT system
  - \( \rightarrow \) **FEMTI**
Plan

- A principled view of MT evaluation: FEMTI
  - quality models: characteristics, attributes, metrics

- Two types of justifications for automatic MT evaluation metrics
  - structural reasons ("glass-box")
  - empirical reasons ("black-box")

- Empirical distance-based metrics
  - arguments for or against them

- Task-based evaluation
  - proposal for automatic task-based evaluation
Principled view of MT evaluation: FEMTI

- **FEMTI**: Framework for the evaluation of MT, started within the ISLE project
  
  [http://www.issco.unige.ch/femti](http://www.issco.unige.ch/femti)

- Two classifications / surveys
  - characteristics of the context of use
  - quality characteristics and metrics

- Helps to define evaluation plans
  - support interfaces: specify context of use, then generate contextualized quality model
Important ISO-inspired notions

- ISO/IEC 9126 and 14598, SQUARE framework
- Quality
  - “the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs” (ISO/IEC 9126)
  - decomposed into quality characteristics, then into measurable attributes, each with internal/external metrics
  - six categories of quality characteristics: functionality, reliability, usability, efficiency, maintainability, portability
- Metric
  - “a measurement is the use of a metric to assign a value (i.e., a measure, be it a number or a category) from a scale to an attribute of an entity” (ISO/IEC 14598)
FEMTI refinement of ISO quality characteristics for MT  
(Hovy, King & Popescu-Belis, 2002)

2.1 Functionality

2.1.1 Accuracy
- 2.1.1.1 Terminology
- 2.1.1.2 Fidelity / precision
- 2.1.1.3 Well-formedness
  - 2.1.1.3.1 Morphology
  - 2.1.1.3.2 Punctuation errors
  - 2.1.1.3.3 Lexis / Lexical choice
  - 2.1.1.3.4 Grammar / Syntax
- 2.1.1.4 Consistency

2.1.2 Suitability
- 2.1.2.1 Target-language suitability
  - 2.1.2.1.1 Readability
  - 2.1.2.1.2 Comprehensibility
  - 2.1.2.1.3 Coherence
  - 2.1.2.1.4 Cohesion
- 2.1.2.2 Cross-language / Contrastive
  - 2.1.2.2.1 Style
  - 2.1.2.2.2 Coverage of corpus-specific phenomena

2.1.3 Interoperability

2.1.4 Functionality compliance

2.1.5 Security
FEMTI refinement of ISO quality characteristics for MT (Hovy, King & Popescu-Belis, 2002)

2.2 Reliability
   2.2.1 Maturity
   2.2.2 Fault tolerance
   2.2.3 Crashing frequency
   2.2.4 Recoverability
   2.2.5 Reliability compliance

2.3 Usability
   2.3.1 Understandability
   2.3.2 Learnability
   2.3.3 Operability
      2.3.3.1 Process management
   2.3.4 Documentation
   2.3.5 Attractiveness
   2.3.6 Usability compliance

2.4 Efficiency
   2.4.1 Time behaviour
      2.4.1.1 Overall Production Time
      2.4.1.2 Pre-processing time
      2.4.1.3 Input to Output Tr. Speed
      2.4.1.4 Post-processing time
         2.4.1.4.1 Post-editing time
         2.4.1.4.2 Code set conversion
         2.4.1.4.3 Update time
   2.4.2 Resource utilisation
      2.4.2.1 Memory usage
      2.4.2.2 Lexicon size
      2.4.2.3 Intermediate file clean-up
      2.4.2.4 Program size

2.5 Maintainability
   2.5.1 Analysability
   2.5.2 Changeability
      2.5.2.1 Ease of upgrading multilingual aspects
      2.5.2.2 Improvability
      2.5.2.3 Ease of dictionary update
      2.5.2.4 Ease of modifying grammar rules
      2.5.2.5 Ease of importing data
   2.5.3 Stability
   2.5.4 Testability
   2.5.5 Maintainability compliance

2.6 Portability
   2.6.1 Adaptability
   2.6.2 Installability
   2.6.3 Portability compliance
   2.6.4 Replaceability
   2.6.5 Co-existence

2.7 Cost (Introduction, Maintenance, Other)
Examples of metrics from FEMTI

- For <2.1.1.2 Fidelity>
  - assessment of the correctness of the information transferred by human judges

- For <2.4.1.3 Input to Output Translation Speed>
  - number of translated words per unit of time

- For <2.1.3.2 Punctuation errors>
  - percentage of correct punctuation marks

- For <2.5.2.3 Ease of dictionary update>
  - time OR effort necessary to update dictionary

- Some metrics require human judges that cannot be replaced with software (#1 above)
- Some metrics can be applied both by human judges or software (#2), but software is more precise & cheaper
- Some require human judges or complex software (#3)
- Some metrics require human users of the system (#4)
This workshop: “Automatic procedures in MT evaluation”

- Underlying assumption: look only at automatic metrics for the quality of MT output such as BLEU, WER, etc.

→ FEMTI Part II, under <2.1 Functionality>

- current metrics require human judges
- could they all be automated? No obvious solutions!
Place of automatic metrics in FEMTI

- Do automatic metrics which were independently proposed belong in FEMTI? Where?

- If a function \( s(S, T) : SL \times TL \rightarrow [0; 1] \) is to be called a quality metric, one should indicate what quality it measures
  - it must be possible to integrate this (external) quality into the ISO/FEMTI classification, most likely under &lt;Functionality&gt;, if not present yet
Two types of justifications for automatic MT evaluation metrics (1/2)

○ Structural = “glass-box”
  ● the definition of the score $s$ indicates that it measures the same quality attribute as a recognized metric applied by humans
  → hence place $s$ in FEMTI under the same quality attribute

○ An infrequent justification...
Two types of justifications for automatic MT evaluation metrics (2/2)

- Empirical (and frequent) justification = “black-box”
  - the values of score \( s \) on a given test set are statistically correlated with a recognized metric applied by human judges → assume that the two metrics measure the same quality

- Reverse engineering: how to construct such a score \( s \)?
  - start with a set of MT sentences that are already scored by humans according to a metric \( s_h \), i.e. start with a large set of triples \( (S_n, T_n, s_h(n)) \)
  - train a statistical model to approximate \( s_h \) and then estimate its error using cross-validation → new automatic metric!

- But this is the same problem as statistical MT! \( (s_h = 1) \)
  - too difficult... → need to use supplementary information about correct translation(s) of the evaluation data set
Trainable distance-based metrics

- Distance-based NLP evaluation
  - the evaluation data set (test set) contains desired output associated to the input data
  - evaluation metrics are defined as distances between a system’s output and the desired output, averaged over all items of input data

- Situation for MT
  - no unique desired output for an input sentence
  - frequent proposal: compute a distance between a system’s output and a sample of correct outputs (often up to 4)
  - replace score $s(S_n, T_n)$ with $d(\{T_{\text{ref}(1)}, \ldots, T_{\text{ref}(4)}\}, T_n)$
Graphical representation

$x = MT$ output to be evaluated

$x = Sample\ of\ correct\ translations\ of\ sentence\ \textit{S}_n\ (reference\ translations)$

Distance to sample

Real distance

All possible sentences

All correct translations of sentence $\textit{S}_n$
Training automatic metrics

- How to construct a distance-based automatic metric $d$?
  - start with a set of machine-translated sentences ($T_n$) that are already scored by humans according to a metric $s_h$
  - each source sentence is accompanied by reference translation(s)
  - i.e. start with a large set of t-uples ($\{T_{ref(1)}, \ldots, T_{ref(k)}\}, T_n, s_h(n)$)

- Find a distance $d$ that approximates $s_h$
  - that is, $d($\{T_{ref(1)}, \ldots, T_{ref(k)}\}, T_n) \approx s_h(n)$

- Essential point: role of (machine) learning
  - either the statistical model $d$ was explicitly trained to approximate $s_h$
  - or several distances $d_i$ were tried & the one closest to $s_h$ was selected
  - in both cases, error of the model was estimated using cross-validation
Advantages and drawbacks of trainable (empirical) distance-based metrics

- **Advantages**
  - low application cost
  - high speed
  - reproducible (vs. human judges who may vary)

- **Drawbacks**
  - correlation with reference (human) metric holds mainly for data that is similar to the training (or validation data)
    → unknown behavior for different (unseen) types of data
  - unclear/variable correlation with ISO-style qualities
  - need training data (which may have imperfect inter-judge agreement)
An alternative: task-based evaluation

- Measure utility of MT output for a given task
  - e.g. performance of human subjects on a task using human vs. machine-translated text
  - closer to ISO’s quality in use
  - increasingly popular as limits of BLEU become visible

+ OK if system intended for specific application
  - Expensive, time-consuming

- Idea
  - automatic task-based evaluation
  - use MT output for another NLP module for which good automatic metrics are available
    - e.g. reference resolution, document retrieval
Conclusions: two views of the future

○ Utilitarian view
  ● a “better” system means only “better adapted to the users who wish to pay for it” – no absolute metrics
  ● task-based metrics do work, and could be automated
  ● but could this really be the whole story?

○ Cognitive view
  ● why did the quest for MT evaluation metrics become just another NLP problem?
    ○ with machine learning techniques, annotated data, etc.
  ● the invariants of translation aren’t well understood
    ○ good candidates for ground truth
    ○ components of meaning: logical form, inferences