Exploiting Objective Annotations for Measuring Translation Post-editing Effort

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**MT**: Events of a magnitude unprecedented Mongols claiming their rights have occurred last week in this autonomous region, according to the Information Centre on Human Rights in Shouth Mongolia, an organization based in the States U.S., where universities and public spaces open air were banned from several cities, fearing the power to Beijing more than any protest rallies in the spirit of movements which have stirred recent months the world Arabic.

**SRC**: Des manifestations d’une ampleur sans précédent de Mongols réclamant le respect de leurs droits se sont produites la semaine dernière dans cette région autonome, selon le Centre d’information sur les droits de l’homme en Mongolie du Sud, une organisation installée aux États-Unis, où des universités et des espaces publics en plein air étaient interdits d’accès dans plusieurs villes, le pouvoir à Pékin redoutant plus que tout des rassemblements de protestation dans l’esprit des mouvements qui ont agité ces derniers mois des pays du monde arabe.
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- It may be faster to translate some segments from scratch.
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- Distinguishing bad from good translations allows fairer cost schemes.

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Quality Estimation

**Features** extracted from:
- MT output
- Source text
- Monolingual corpora: source or/and target
- Bilingual corpora
- MT system (CE)

**Annotations** reflecting translation quality

Train a machine **learning algorithm** to produce a model for a certain:
- Language pair
- MT system
- *(Ideally)* Text domain & genre
- *(Ideally)* Human translator
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Related Work

- CE metrics may provide a score for each:
  - word or phrase [GF03, UN05, KN06]
  - sentence [BFF\(^+\)04, Qui04, STC\(^+\)09, SRT10, HM\(_v\)GW10, SF10]
  - document [SE10]

- Quality annotation can be derived using:
  - Automatic MT evaluation metrics [BFF\(^+\)04]
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- Human annotation can be expensive and subjective
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1. Introduction
2. Quality Estimation
3. Related Work
4. Goals
5. Datasets
6. Results
7. Conclusions
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Measure the post-editing time for unseen sentence translations predicted as “good quality” according to QE models learnt based on different types of human annotation:

- Absolute scores reflecting post-editing effort
- Edit distance between automatic and post-edited translations (HTER)
- Post-editing time

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Hypothesis is that **simpler, cheaper, more transparent** and **more objective** annotations can have a more straightforward interpretation for post-editing purposes.
Datasets

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  - **fr-en news-test2009**: 2,525 French news sentences and their translations into English (BLEU = 0.2447)
  - **en-es news-test2010**: 1,000 English news sentences and their translations into Spanish (BLEU = 0.2830)
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- Translators also scored the original translation according to its post-editing effort:
Datasets - Annotation

- **Post-editing effort score** \((\text{effort})\): a discrete score:
  
  1. requires complete retranslation
  2. post editing still quicker than retranslation
  3. very little post editing needed
  4. fit for purpose
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- **Post-editing time** \((time)\): average number of seconds to post-edit each word in the sentence
Quality Estimation Framework

- Similar to that proposed by [SF10], with SVM for regression: epsilon-SVR algorithm with radial basis function kernel from the LIBSVM package [CL01], with the parameters $\gamma$, $\epsilon$ and cost optimized.

- 80 shallow, MT system-independent features:
  - source & target sentence lengths and their ratios
  - source & target sentence type/token ratio
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- percentage of 1 to 3-grams in the source sentence belonging to each frequency quartile of a source corpus
- average number of translations per source word in the sentence (given by GIZA++ tables), unweighted/weighted by the (inverse) frequency of words
- percentages of numbers, content-/non-content words in the source & target sentences
- number of mismatching opening/closing brackets and quotation marks in the target sentence
- percentages & number of mismatches of some superficial constructions between the source and target sentences: brackets, punctuation symbols, numbers
Results
Average Human Scores

| Dataset | Average Human Score |
|---------|---------------------|
| fr-en   | HTER                |
|         | effort              |
|         | time snt            |
|         | 0.201 ↓             |
|         | 2.834 ↑             |
|         | 24.095 ↓            |
| en-es   | HTER                |
|         | effort              |
|         | time snt            |
|         | 0.349 ↓             |
|         | 2.441 ↑             |
|         | 98.692 ↓            |

- Translators have different level of experience: en-es translator is more experienced.
- Translators followed different strategies: fr-en translator read the source before the time measurement started.
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Prediction Error and Correlation

- Spearman’s rank coefficient with human scores
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- Spearman’s **rank coefficient** with human scores
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**Root Mean Squared Error** (RMSE) for regression error

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| Dataset | RMSE $\downarrow$ | Spearman $\uparrow$ |
|---------|------------------|---------------------|
| **fr-en** | | |
| HTER effort | 0.155 ± 0.011 | 0.366 ± 0.047 |
| time | 0.662 ± 0.022 | 0.459 ± 0.034 |
| time | 0.651 ± 0.040 | 0.455 ± 0.052 |
| **en-es** | | |
| HTER effort | 0.178 ± 0.006 | 0.281 ± 0.102 |
| time | 0.549 ± 0.028 | 0.367 ± 0.096 |
| time | 1.970 ± 0.250 | 0.298 ± 0.024 |
**Goal**: measure number of words that can be post-edited in a fixed amount of time in translations selected according to each QE model.
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**Quality predictions** generated using the 3 variations of the QE models
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Task-based Evaluation

Predicted scores can be used to directly **filter out bad quality translations**:

- Setting a threshold on estimated scores: [STW+09], [HMvGW10]

We evaluate the **ranking of translations** using QE scores from alternative models in order to answer:

1. Which annotation type yields models that allow ranking sentences so that selecting the top ranked sentences can maximize the number of words that can be post-edited per second?
2. Using such models to rank sentences and selecting the top ranked sentences, is it possible to **post-edit more words** as compared to post-editing sentences without any ranking in a given slot of time?
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**Task-based Evaluation**

- **4 subsets of 600 translations** randomly selected from each unseen dataset
  - Translations in **3 subsets ranked using each QE model** so that the best translations appear first
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- Translators asked to post-edited as many sentences as possible in each of 4 “tasks” on different days:
  - **1 hour per task**
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- Variation: **effort** in en-es datasets: 43% “good” (4-3), 57% “bad” (1-2)
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- Variation: **effort** in en-es datasets: 43% “good” (4-3), 57% “bad” (1-2)
## Results

### Task-based Evaluation

| Dataset | Sentences/h | Words/s |
|---------|-------------|---------|
| fr-en   |             |         |
| T1: HTER | 65          | 0.96    |
| T2: effort | 97         | 0.91    |
| T3: time  | 82          | 1.09    |
| T4: unsorted | 55       | 0.75    |
| en-es   |             |         |
| T1: HTER | 38          | 0.41    |
| T2: effort | 71         | 0.43    |
| T3: time  | 69          | 0.57    |
| T4: unsorted | 33       | 0.32    |

- **Post-editing only top translations** acc. to any QE model: more words post-edited per second than post-editing any translation
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Exploiting Objective Annotations for Measuring Translation Post-editing Effort

Lucia Specia

Outline

1. Introduction
2. Quality Estimation
3. Related Work
4. Goals
5. Datasets
6. Results
7. Conclusions
We have presented experiments with alternative ways of annotating translation quality for building QE models.

Explicit and subjective annotations used in previous work, post-editing effort, are worse than simpler and more objective metrics, in particular time.

These can be obtained as a by-product of having humans post-editing a reasonably small number of translations.

Translators are different: QE model for each human translator (MT system, language pair).
Conclusions

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In real world scenarios translators would have to translate all sentences - not only the top ranked ones.

A reliable model can help distinguishing sentences that are worth post-editing from those that should be translated in order to:

- Increase productivity by preventing translators from spending time reading bad quality translations.
- Minimize translators’ frustration with trying to post-edit bad quality translations.

Datasets are available for download.
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Future work

- Combine these algorithms with techniques to establish **thresholds on the predicted scores**
- Design a **post-editing tool** that can incorporate quality predictions for translations from different MT/TM systems
- Analyze **changes in the behavior of translators** as they gain more experience with the task of post-editing, especially wrt post-editing time
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