Translation Quality Assessment: Evaluation and Estimation

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"MT Evaluation is better understood than MT" (Carbonell and Wilks, 1991)

Outline

- 1 Translation Quality
- QTLaunchPad Project
- Quality Estimation
- 4 State of the art in QE
- 5 Open issues



Outline

Translation Quality

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- Adequate?
- Easy to post-edit?

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- Quality for whom?
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 - Other applications (e.g. CLIR)
- Quality for what?
 - Internal communications
 - Dissemination (publishing)
 - Gisting (Google Translate)
 - Draft translations (light vs heavy post-editing)
 - MT system improvement (diagnosis)

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- sys Six-hours battery, **30 minutes** to full charge last.

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ref The battery lasts 6 hours and it can be **fully recharged** in **30 minutes**.

sys Six-hours battery, **30 minutes** to full charge last.

- Ok for gisting meaning preserved
- Very costly for post-editing if style is to be preserved

How do we measure quality?

- Human metrics: error counts (which?), ranking, acceptability, 1-N fluency/adequacy
- Automatic metrics based on human references: (BLEU, METEOR, TER, etc.
- Semi-automatic metrics based on **post-editions**: HTER, PE time, eye-tracking, etc.

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- Automatic metrics without references: quality estimation

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QTLaunchPad project

http://www.qt21.eu/launchpad/

- Multidimensional Quality Metrics (MQM) based on a specification
- Machine and human translation quality
- Manual and (semi-)automatic assessment
- Takes quality of source text into account
- MT system improvement, gisting, dissemination, etc.



Quality Estimation

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Conclusions

Multidimensional Quality Metrics (MQM)

Issues selected based on a given **specification** (dimensions):

- Language/locale
- Subject field/domain
- Terminology
- Text Type
- Audience
- Purpose
- Register
- Style
- Content correspondence
- Output modality, ...

Quality Estimation

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Multidimensional Quality Metrics (MQM)

Issue types (core):



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Conclusions

Multidimensional Quality Metrics (MQM)

Issue types: http://www.qt21.eu/launchpad/content/ high-level-structure-0

Combining issue types: $TQ = 100 - AccP - (FluP_T - FluP_S) - (VerP_T - VerP_S)$

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Quality = **How much effort to fix it?**

Quality = What's this translation's MQM score?

Framework



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Framework

Main components to build a QE system:

- Definition of quality: what to predict
- (Human) labelled data (for quality)
- Features
- Machine learning algorithm

Definition of quality

- Predict 1-N absolute scores for adequacy/fluency
- Predict 1-N absolute scores for post-editing effort
- Predict average post-editing time per word
- Predict relative rankings
- Predict relative rankings for same source
- Predict percentage of edits needed for sentence
- Predict word-level edits and its types
- Predict **BLEU**, etc. scores for document

Datasets

- **SHEF** (several): http://staffwww.dcs.shef.ac.uk/ people/L.Specia/resources.html
- LIG (10K, fr-en): http://www-clips.imag.fr/geod/ User/marion.potet/index.php?page=download
- LMSI (14K, fr-en, en-fr, 2 post-editors): http://web.limsi.fr/Individu/wisniews/ recherche/index.html





QuEst

Goal: framework to explore features for QE

- Feature extractors for 150+ features of all types: Java
- Machine learning: Gaussian Processes & scikit-learn toolkit (Python), with wrappers for a number of algorithms, grid search, feature selection



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Quality	Year	Languages
1-5 subjective scores	WMT12	en-es
Ranking all sentences best-worst	WMT12/13	en-es
HTER scores	WMT13	en-es
Post-editing time	WMT13	en-es
Word-level edits: change/keep	WMT13	en-es
Word-level edits: keep/delete/replace	WMT13	en-es
Ranking 5 MTs per source	WMT13	en-es; de-en

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• Evaluation metric:

$$\mathsf{MAE} = \frac{\sum_{i=1}^{N} |H(s_i) - V(s_i)|}{N}$$

Baseline system

Features:

- number of tokens in the source and target sentences
- average source token length
- average number of occurrences of words in the target
- number of punctuation marks in source and target sentences
- LM probability of source and target sentences
- average number of translations per source word
- % of source 1-grams, 2-grams and 3-grams in frequency quartiles 1 and 4
- % of seen source unigrams

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SVM regression with RBF kernel with the parameters γ , ϵ and C optimised using a grid-search and 5-fold cross validation on the training set

Translation Quality

State of the art in QE

Open issues Conclus

Results - scoring sub-task (WMT12)

System ID	MAE	RMSE
 SDLLW_M5PbestDeltaAvg 	0.61	0.75
UU_best	0.64	0.79
SDLLW_SVM	0.64	0.78
UU_bltk	0.64	0.79
Loria_SVMlinear	0.68	0.82
UEdin	0.68	0.82
TCD_M5P-resources-only*	0.68	0.82
Baseline bb17 SVR	0.69	0.82
Loria_SVMrbf	0.69	0.83
SJTU	0.69	0.83
WLV-SHEF_FS	0.69	0.85
PRHLT-UPV	0.70	0.85
WLV-SHEF_BL	0.72	0.86
DCU-SYMC_unconstrained	0.75	0.97
DFKI_grcfs-mars	0.82	0.98
$DFKI_{cfs}$ -plsreg	0.82	0.99
UPC_1	0.84	1.01
DCU-SYMC_constrained	0.86	1.12
UPC_2	0.87	1.04
TCD_M5P-all	2.09	2.32

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Results - scoring sub-task (WMT13)

System ID	MAE	RMSE
 SHEF FS 	12.42	15.74
SHEF FS-AL	13.02	17.03
CNGL SVRPLS	13.26	16.82
LIMSI	13.32	17.22
DCU-SYMC combine	13.45	16.64
DCU-SYMC alltypes	13.51	17.14
CMU noB	13.84	17.46
CNGL SVR	13.85	17.28
FBK-UEdin extra	14.38	17.68
FBK-UEdin rand-svr	14.50	17.73
LORIA inctrain	14.79	18.34
Baseline bb17 SVR	14.81	18.22
TCD-CNGL open	14.81	19.00
LORIA inctraincont	14.83	18.17
TCD-CNGL restricted	15.20	19.59
CMU full	15.25	18.97
UMAC	16.97	21.94

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• Relative scores

- Different task altogether
- WMT13: better results than reference-based metrics

Annotation costs

Active learning to select subset of instances to be annotated (Beck et al., ACL 2013)



Curse of dimensionality

Feature selection to identify relevant info for dataset (Shah et al., MT Summit 2013)



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Common feature set identified, but **nuanced subsets** for specific datasets

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Do users prefer detailed estimates (sub-sentence level) or an overall estimate for the complete sentence or not seeing bad sentences at all?

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- Too much information vs hard-to-interpret scores
- IBM's Goodness metric

Source	التقليد والمحاكاة والذوبان	ِ نفسك في سر داب	عن زيد و عمر و فلا تحشر	أنت مختلف تمامأ
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MT output you totally different from zaid amr, and not to deprive yourself in a basement of imitation and assimilation .

you totally different from zaid amr, and not to deprive yourself in We predict and visualize a basement of imitation and assimilation .

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MATECAT project investigating it

Feature engineering

Two families of features missing in current work:

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- Can we predict human translation quality?

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Don't panic, you can help!

Two (sub-) QuEst projects at MTM-2013 :-)

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- Interesting open issues: join the QuEst projects!