Quality Estimation of Machine Translation

Recent advances, Challenges and Software

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Outline

1. Introduction
   - Structure of the tutorial
   - Quality estimation
2. Variants
   - Sentence-level QE
   - Word-level QE
   - Document-level QE
3. Conclusions
4. Practice
   - QuEst
   - QuEst++
   - Feature Extractor module
   - Machine Learning module

Theory

- Introduction to QE
- Sentence, word, document-level QE
  - Labels
  - Features
  - ML algorithms
  - Results
  - Challenges and future work
- Does QE help improve productivity?

Practice

- Code and installation (dependencies)
- How to run code on existing example
- How to set up a new experiment
- How to implement a new feature
- How to add a new machine learning algorithm

Definition

- Approaches to **predict** the quality of a language output application – no access to “true” output for comparison

- **(Machine) translation**: predict the quality of translation without access to a reference translation
  - **Quality**: fluency, adequacy, post-editing effort, etc.
  - **General method**: supervised machine learning on quality features + labels

- Circa 2001 - **Confidence Estimation**
  - How **confident** MT system is in a translation
  - Mostly word-level prediction from SMT internal features

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  - Mostly word-level prediction from SMT internal features
- **Now**: popular area, challenging research, commercial interest

Motivations

MT: The King closed hearings Monday with Deputy Canary Coalition Ana Maria Oramas González -Moro, who said, in line with the above, that "there is room to have government in the coming months," although he did not disclose prints Rey about reports Francesco Manetto. Monarch Oramas transmitted to his conviction that ' soon there will be an election" because looks unlikely that Rajoy or Sanchez can form a government.

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SRC: El Rey cerró las audiencias del lunes con la diputada de Coalición Canaria Ana María Oramas González-Moro, quien aseguró, en la línea de los anteriores, que "no hay ambiente de tener Gobierno en los próximos meses", aunque no desveló las impresiones del Rey al respecto, informa Francesco Manetto. Oramas transmitió al Monarca su convicción de que "pronto habrá un proceso electoral", porque ve poco probable que Rajoy o Sánchez puedan formar Gobierno.

Motivations

Target:
site security should be included in **sex education** curriculum for students

Source:
场地安全性教育应纳入学生的课程

Reference:
site security **requirements** should be included in the **education** curriculum for students

By Google Translate

Motivations

Target:
the road boycotted a friend ... indian robin hood killed the poor after 32 years of prosecution.

Source:
مقتل روبن هود الهندي.. قاطع الطريق صديق الفقراء بعد 32 عاما من الملاحقة

Reference:
death of the indian robin hood, highway robber and friend of the poor, after 32 years on the run.

By Google Translate

Uses

Quality = **Can we publish it as is?**

Quality = **Can a reader get the gist?**

Quality = **Is it worth post-editing it?**

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

Quality = **Which words need fixing?**

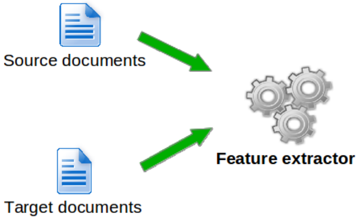
Quality = **Which version of the document is more reliable?**

General method

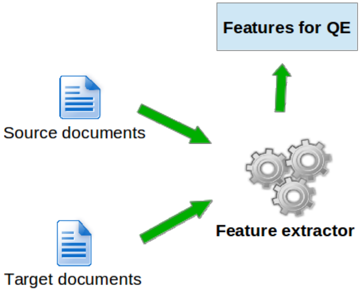
Source documents

Target documents

General method



General method



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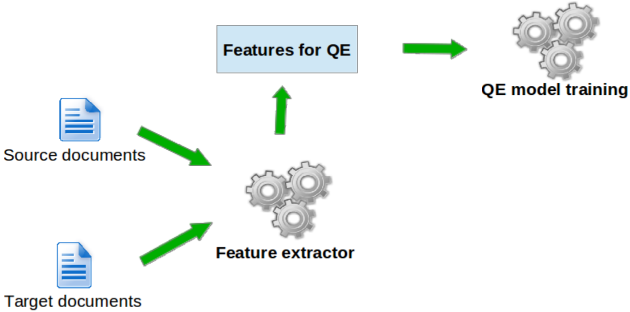

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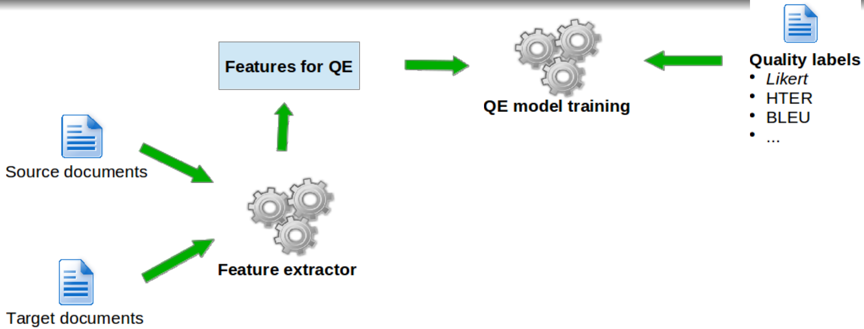

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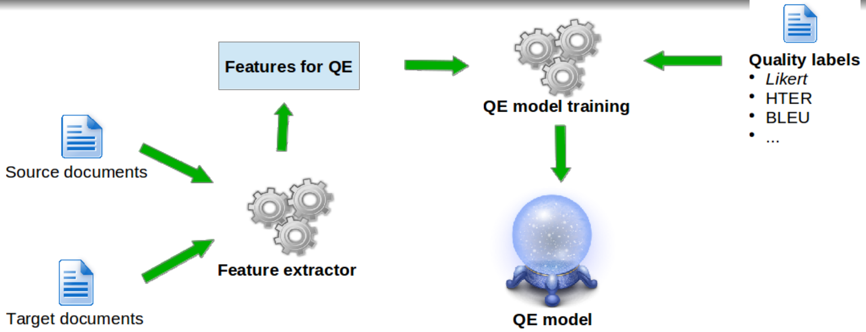

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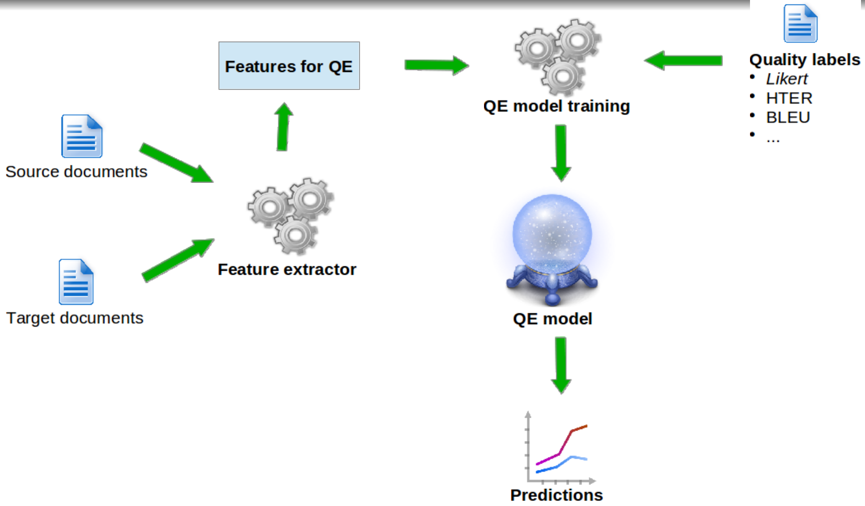

General method

Main components to build a QE system:

1. Definition of quality: **what to predict**
2. (Human) labelled **data** (for quality)
3. **Features**
4. Machine learning **algorithm**

Quality

Different users, different needs

Ref: Do **not** buy this product, it's their craziest invention!

MT: Do buy this product, it's their craziest invention!

Quality

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- **Severe** if end-user does not speak source language
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Ref: The **battery** lasts **6 hours** and it can be **fully recharged** in **30 minutes**.
MT: **Six-hour 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**.
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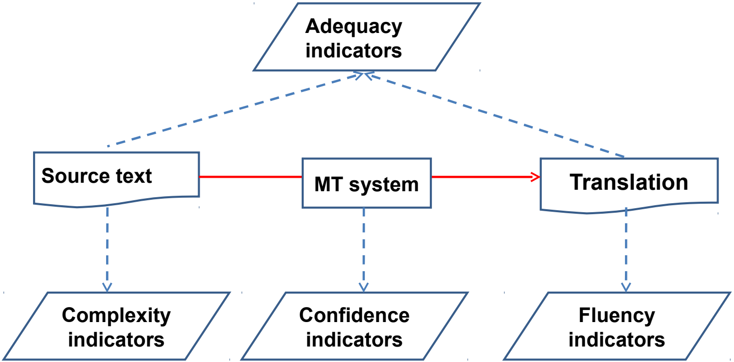
- **Ok** for gisting - meaning preserved
- **Very costly** for post-editing if style is to be preserved

Features


Adequacy indicators
Source text
MT system
Translation
Complexity indicators
Confidence indicators
Fluency indicators

Sentence-level QE

- Most popular level
  - MT systems work at sentence-level
  - PE is done at sentence-level
- Easier to get labelled data
- Practical mainly for **post-editing purposes**
- Wide range of features possible: sentence-wide, sentence within document, words in sentence

Labels

- Old work: predict NIST, TER, BLEU against independently created reference
- **Explicit**:
  - Predict 1-N absolute scores for **adequacy/fluency**
  - Predict 1-N absolute scores for **post-editing effort**
  - Predict **good/bad** score for whatever purpose
  - Predict **relative rankings** for same/different sources, by one or more MT systems
- **Implicit**:
  - Predict average post-editing **time** per word
  - Predict **percentage of edits** needed for sentence

Features

MT **system-independent** features:

- **SF - Source complexity features**:
  - source sentence length
  - source sentence type/token ratio
  - average source word length
  - source sentence 3-gram LM score
  - percentage of source 1 to 3-grams seen in the MT training corpus

Features

MT system-independent features:

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  - source sentence type/token ratio
  - average source word length
  - source sentence 3-gram LM score
  - percentage of source 1 to 3-grams seen in the MT training corpus
- **TF - Target fluency features**:
  - target sentence 3-gram LM score
  - translation sentence length
  - proportion of mismatching opening/closing brackets and quotation marks in translation
  - coherence of the target sentence

Features

- **AF - Adequacy features**:
  - ratio of number of tokens btw source & target and v.v.
  - absolute difference btw no tokens in source & target
  - absolute difference btw no brackets, numbers, punctuation symbols in source & target
  - ratio of no, content-/non-content words btw source & target
  - ratio of nouns/verbs/pronouns/etc btw source & target
  - proportion of dependency relations with constituents aligned btw source & target
  - difference btw depth of the syntactic trees of source & target
  - difference btw no pp/np/vp/adjp/advp/conjp phrase labels in source & target
  - difference btw no 'person'/'location'/'organization' (aligned) entities in source & target
  - proportion of matching base-phrase types at different levels of source & target parse trees

Features

- **Confidence** features:
  - score of the hypothesis (MT global score)
  - size of nbest list
  - using n-best to build LM: sentence n-gram log-probability
  - individual model features (phrase probabilities, etc.)
  - maximum/minimum/average size of the phrases in translation
  - proportion of unknown/untranslated words
  - n-best list density (vocabulary size / average sentence length)
  - edit distance of the current hypothesis to the center hypothesis
  - Search graph info: total hypotheses, % discarded / pruned / recombined search graph nodes
- Other: **average quality prediction for words in sentence**

http://www.quest.dcs.shef.ac.uk/quest_files/features_blackbox

http://www.quest.dcs.shef.ac.uk/quest_files/features_glassbox

Algorithms

- Mostly **regression** algorithms (SVM, GP)
- Binary **classification**
- **Kernel** methods perform better
- **Tree kernel** methods for syntactic trees
- Advanced approaches: online learning, multi-task learning

Results

WMT15:

- English → Spanish
- Predicting HTER [0-100]
- One MT system
- News
- Crowdsourced annotations
- Training/dev: $11,271/1,000$ <source, MT, PE, HTER>
- Test: $1,817$ <source, MT>

Results

WMT15:

System ID	**MAE** ↓
English-Spanish	
• RTM-DCU/RTM-FS+PLS-SVR	13.25
• LORIA/17+LSI+MT+FILTRE	13.34
• RTM-DCU/RTM-FS-SVR	13.35
• LORIA/17+LSI+MT	13.42
• UGENT-LT3/SCATE-SVM	13.71
UGENT-LT3/SCATE-SVM-single	13.76
SHEF/SVM	13.83
Baseline SVM	**14.82**
SHEF/GP	15.16

• = winning submissions - top-scoring and those which are not significantly worse.
Gray area = systems that are not significantly different from the baseline.

Results

Did we do better than **WMT14**?

System ID	**MAE** ↓
English-Spanish	
• FBK-UPV-UEDIN/WP	12.89
• RTM-DCU/RTM-SVR	13.40
• USHEFF	13.61
RTM-DCU/RTM-TREE	14.03
DFKI/SVR	14.32
FBK-UPV-UEDIN/NOWP	14.38
SHEFF-lite/sparse	15.04
MULTILIZER	15.04
Baseline SVM	**15.23**
DFKI/SVRxdata	16.01
SHEFF-lite	18.15

Results

WMT15:

Pearson correlation (Graham, 2015) = DeltaAvg's ranking

System ID	**Pearson's r ↑**
• LORIA/17+LSI+MT+FILTRE	0.39
• LORIA/17+LSI+MT	0.39
• RTM-DCU/RTM-FS+PLS-SVR	0.38
RTM-DCU/RTM-FS-SVR	0.38
UGENT-LT3/SCATE-SVM	0.37
UGENT-LT3/SCATE-SVM-single	0.32
SHEF/SVM	0.29
SHEF/GP	0.19
Baseline SVM	**0.14**

Challenges and future work

- **Data**: how to obtain objective labels, for different languages and domains, which are comparable across translators? $\rightarrow$ **By product of PE**
- How to deal with **biases** from annotators (or domains)? $\rightarrow$ Multi-task learning
- How to **adapt** models over time? $\rightarrow$ Online (multitask) learning

Word-level QE

Some **applications** require fine-grained information on quality:

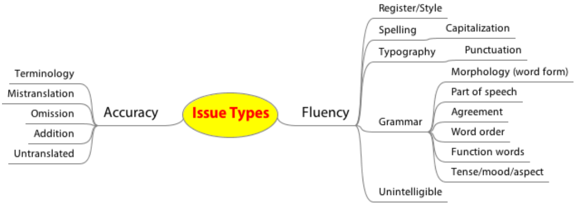
- Highlight words that need fixing
- Inform readers of portions of sentence that are not reliable

Seemingly a **more challenging task**

- A quality label is to be predicted for each target word
- Sparsity is a serious issue
- Skewed distribution towards GOOD
- Errors are interdependent

Labels

- Predict binary **GOOD/BAD** labels
- Predict general **types of edits**:
  - Shift
  - Replacement
  - Insertion
  - Deletion is an issue
- Predict specific errors. E.g. **MQM** in WMT14

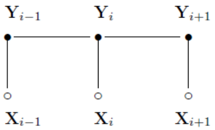


Features

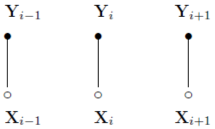
- target token, its left & right token
- source token aligned to target token, its left & right tokens
- boolean dictionary flag: whether target token is a stopword, a punctuation mark, a proper noun, a number
- dangling token flag (null link)
- LM of n-grams with target token t_i: (t_{i-2}, t_{i-1}, t_i), (t_{i-1}, t_i, t_{i+1}), (t_i, t_{i+1}, t_{i+2})
- order of the highest order n-gram which starts/ends with the source/target token
- POS tag of target/source token
- number of senses of target/source token in WordNet
- pseudo-reference flag: 1 if token belongs to pseudo-reference, 0 otherwise

Algorithms

- **Sequence labelling** algorithms, like **CRF**



- **Classification** algorithms: each word tagged independently



- **DNN**: multilayer perceptron with bilingual word embeddings
  - Linear combination with classifier on standard features (**WMT15**

Results

WMT15:

- English $\rightarrow$ Spanish, one MT system, News
- Labelling done with TERCOM:
  - OK = unchanged
  - BAD = insertion, substitution
- Data: <source word, MT word, OK/BAD label>

	Sentences	Words	**% of BAD words**
Training	11,271	257,548	19.14
Dev	1,000	23,207	19.18
Test	1,817	40,899	18.87

Challenge: skewed class distribution

Results

WMT15:

- Mostly interested in finding errors
- Precision/recall preferences depend on application
- Rare classes should not dominate

Evaluation metric: weighted average $F1$ of "BAD" class

Baseline introduced:

- CRF classifier with 25 features

Results

System ID	weighted F_1 All ↑	F_1 **BAD** ↑	F_1 OK ↑
English-Spanish			
• UAlacant/OnLine-SBI-Baseline	71.47	43.12	78.07
• HDCL/QUETCHPLUS	72.56	43.05	79.42
UAlacant/OnLine-SBI	69.54	41.51	76.06
SAU/KERC-CRF	77.44	39.11	86.36
SAU/KERC-SLG-CRF	77.4	38.91	86.35
SHEF2/W2V-BI-2000	65.37	38.43	71.63
SHEF2/W2V-BI-2000-SIM	65.27	38.40	71.52
SHEF1/QuEst++-AROW	62.07	38.36	67.58
UGENT/SCATE-HYBRID	74.28	36.72	83.02
DCU-SHEFF/BASE-NGRAM-2000	67.33	36.60	74.49
HDCL/QUETCH	75.26	35.27	84.56
DCU-SHEFF/BASE-NGRAM-5000	75.09	34.53	84.53
SHEF1/QuEst++-PA	26.25	34.30	24.38
Baseline (always BAD)	0.599	31.76	0.00
UGENT/SCATE-MBL	74.17	30.56	84.32
RTM-DCU/s5-RTM-GLMd	76.00	23.91	88.12
RTM-DCU/s4-RTM-GLMd	75.88	22.69	88.26
Baseline CRF	**75.31**	**16.78**	**88.93**
Baseline (always OK)	72.67	0.00	89.58

Results

Did we do better than **WMT14**?

System ID	weighted F_1 All ↑	F_1 **BAD** ↑
Baseline (always OK)	50.43	0.00
Baseline (always BAD)	18.71	**52.53**
• FBK-UPV-UEDIN/RNN	62.00	**48.73**
LIMSI/RF	60.55	47.32
LIG/FS	63.55	44.47
LIG/BL ALL	63.77	44.11
FBK-UPV-UEDIN/CRF	62.17	42.63
RTM-DCU/RTM-GLM	60.68	35.08
RTM-DCU/RTM-GLMd	60.24	32.89

Challenges and future work

- **Data**:
  - Labelling is very expensive → by product of post-editing
  - Labelling from post-editing not reliable → need better alignment methods
  - Data sparsity and skewness are hard to overcome →
    - **Injecting errors** or **filtering positive cases**
    - DNNs for generalisation - but require large datasets
- Errors are rarely isolated – how to model **interdependencies**? → **Phrase-level QE - WMT16**

Document-level QE

- Prediction of a single label for **entire documents**
- **Assumption**: quality of a document is more than the simple aggregation of its sentence-level quality scores
  - While certain sentences are perfect in isolation, their combination in context may lead to an incoherent document
  - A sentence can be poor in isolation, but good in context as it may benefit from information in surrounding sentences
- **Feature engineering** is challenging: few processing tools for discourse-wide information
  - Topic and structure of document
  - Relationship between its sentences/paragraphs
- Parallel data with **doc-level markup** not commonly found

Labels

- Notion of **quality** is very subjective
  - Human labels are difficult and too expensive to get
  - No datasets with human labels are available.
- Predict **METEOR, BLEU** against independently created reference
- Either as:
  - Absolute score, or
  - Relative ranking of translations by one or more MT systems

Features

- aggregation or doc-level counts of **sentence-level features**
- word/lemma/noun repetition in source/target doc
- ratio of word/lemma/noun repetition btw source & target docs
- number of pronouns in source/target doc
- number of discourse connectives of type *Expansion*, *Temporal*, *Contingency*, *Comparison* and *Non-discourse*
- number of EDU (elementary discourse units) breaks in source/target doc
- number of RST (Rhetorical Structure Theory) *Nucleus* relations in source/target doc
- number of RST *Satellite* relations in source/target doc
- **average quality prediction for sentences in docs**

Algorithms

- Same as for sentence-level
- Tree kernels for discourse parser trees

Results

WMT15:

- English → German, German → English
- **Paragraphs** from all WMT13 translation task MT systems
- 800 for training; 415 for test
- Average METEOR scores in data [0,1]:

	EN-DE		DE-EN	
	AVG	STDEV	AVG	STDEV
METEOR (↑)	0.35	0.14	0.26	0.09

ps.: it is possible that variation (STDEV) is more affected by the difference in MT systems than the difference in quality or the fact that it's paragraphs. E.g. EN-DE doc-level 1 MT system, AVG = 0.39 and STDEV 0.058

Results

System ID	MAE ↓
English-German	
• RTM-DCU/RTM-FS-SVR	7.28
• RTM-DCU/RTM-SVR	7.5
USAAR-USHEF/BFF	9.37
USHEF/QUEST-DISC-REP	9.55
Baseline SVM	10.05
German-English	
• RTM-DCU/RTM-FS-SVR	4.94
RTM-DCU/RTM-FS+PLS-SVR	5.78
USHEF/QUEST-DISC-BO	6.54
USAAR-USHEF/BFF	6.56
Baseline SVM	7.35

Results

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Baseline SVM	0.12
German-English	
• RTM-DCU/RTM-FS-SVR	0.52
RTM-DCU/RTM-FS+PLS-SVR	0.39
USHEF/QUEST-DISC-BO	0.10
USAAR-USHEF/BFF	0.08
Baseline SVM	0.06

Challenges and future work

- BLEU-style metrics are not ideal to be used as labels
  - They have well known limitations as evaluation metrics
  - They were designed to evaluate **different MT systems** and not different documents produced by the same MT system
- Ideal **quality label** should take into account purpose of translation $\rightarrow$
  - **Two-stage post-editing**: isolate document-level problems
  - **Reading comprehension assessment**: how much of the MT text is understandable by humans
- Better **features** are needed for discourse information at different levels
  - micro units (lexical, EDUs)
  - macro units (sentences, paragraphs)

QE in practice

Does QE help?

- (Specia, 2011) **Time to post-edit** subset of sentences predicted as "low PE effort" **vs** time to post-edit random subset of sentences

Language	no QE	QE
fr-en	0.75 words/sec	**1.09** words/sec
en-es	0.32 words/sec	**0.57** words/sec

QE in practice

Does QE help?

- (Huang et al., 2014) **Productivity increase** of 10% at IBM when translation is supported by the estimates of a QE system
- Comparison between using MT suggestions with predicted QE labels against not using MT at all

QE in practice

Does QE help?

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- Comparison btw post-editing with and without QE
- Predictions shown with binary colour codes (**green** vs **red**)

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Does QE help?

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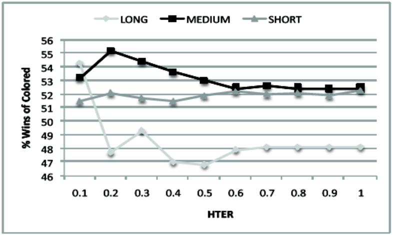
- Comparison btw post-editing with and without QE
- Predictions shown with binary colour codes (**green** vs **red**)

Average PET (sec/word)	colored	8.086	$p = 0.33$
	grey	9.592	
% Wins of colored	51.7		$p = 0.039$



Next round - WMT16

- Large datasets collected as part of QT21: 15K segments
- EN-DE as starting point
- Post-editing by professionals
- Document-level: new annotation schemes by humans

`http://www.statmt.org/wmt16/quality-estimation-task.html`

Conclusions

- Different metrics for: different purposes/users, different needs, different notions of **quality**
- **Quality estimation**: learning of these different notions, based on labelled data
- Estimates can be used in **real applications**
- Estimates have been shown to help
- **Commercial** interest: IBM, Multilizer, SLD, KantanMT, Xerox, ...
- **Advanced topics**: multi-task learning, phrase-level QE, pipelined prediction, DNNs, etc.
- **Utility of QE** in practice: needs to be further validated

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Goal: framework to explore features for QE

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Goal: framework to explore features for QE

- **Feature extractors**: for 150+ features of all types: Java
- **Machine learning**: wrappers for a number of algorithms in the scikit-learn toolkit, grid search, feature selection: Python

Open source: `http://www.quest.dcs.shef.ac.uk/`

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New release: word and document-level feature extraction and machine learning added

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- **Feature extractors**: 40 features for word-level and 79 features for document-level
- **Machine learning**: support to Conditional Random Fields (CRF) added for word-level models
- **Another important improvement**: changes on the core functionalities

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  - Perl 5 (or above)
  - SRILM
  - Tokenizer and Truecaser (from Moses toolkit)

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  - Perl 5 (or above)
  - SRILM
  - Tokenizer and Truecaser (from Moses toolkit)
- **Word-level features**
  - Stanford Core NLP 3.5.1 models
  - Stanford Core NLP Spanish model
  - Universal WordNet plugin

Basic Usage - Word-level

```
java -cp QuEst++.jar:lib/* shef.mt.WordLevelFeatureExtractor
-lang <<lang_source>> <<lang_target>>
-input <<input_source>> <<input_target>>
-alignments <<alignment_file>>
-config <<config_file>>
```

Basic Usage - Sentence-level

```
java -cp QuEst++.jar shef.mt.SentenceLevelFeatureExtractor
-tok -case true
-lang <<lang_source>> <<lang_target>>
-input <<input_source>> <<input_target>>
-config <<config_file>>
```

Basic Usage - Document-level

java -cp QuEst++.jar shef.mt.**DocLevelFeatureExtractor**
-tok -case true
-lang <<lang_source>> <<lang_target>>
-input <<input_source>> <<input_target>>
-config <<config_file>>

Input files

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Input files

- **Word and sentence levels**: file with one sentence per line
- **Document level**: file with paths for documents

Files from source and target should have the same number of lines

Folders

- **src**: source code
- **lang_resources**: folder containing all language resources required for the features
- **lib**: external libraries needed for feature extraction
- **config**: configuration files for running QuEst++
- **input**: auxiliary input folder
- **output**: output folder

Adding a new feature

- Example with **sentence-level** feature extractor

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- New feature: **complex words per sentence** (averaged by the length of sentence)

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Adding a new feature

- Example with **sentence-level** feature extractor
- New feature: **complex words per sentence** (averaged by the length of sentence)
- Language Resource: **list of simple words** (LSW)
- **Idea**: count words not in the LSW and normalise by number of words in the sentence

Adding a new feature

- **Creating a processor for the new feature**
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Adding a new feature

- **Creating a processor for the new feature**
  - Package: **shef.mt.tools**
  - Function: prepare resources to be used by features
  - Extends **ResourceProcessor** class: add the resources to the sentence (**processNextSentence** method)
  - It is useful because a **unique processor** can be used by several features

Adding a new feature

- **Create a new Java class called ComplexWordsProcessor.java**
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  - Package: **shef.mt.tools**
  - Extends: ResourceProcessor class
  - Read the LSW and store it on a ArrayList

Adding a new feature

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Adding a new feature

- **Creating a class for the new feature**
  - Package: **shef.mt.features.impl.bb**
  - Extends **Feature** class: **run** method - feature extraction itself
  - Feature classes are usually named following a number order (e.g. Feature1001, Feature1002)

Adding a new feature

- **Create a new Java class called Feature7001.java**
  - Package: **shef.mt.features.impl.bb**

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Adding a new feature

- **Create a new Java class called Feature7001.java**
    - Package: **shef.mt.features.impl.bb**
    - Extends: **Feature** class
    - Get the ArrayList from the **ComplexWordsProcessor** class and calculate the feature

Adding a new feature

- **Create a new Java class called Feature7001.java**
  - Package: **shef.mt.features.impl.bb**
  - Extends: **Feature** class
  - Get the ArrayList from the **ComplexWordsProcessor** class and calculate the feature
  - Also define the resource that will be required for this feature

Adding a new feature

- **Feature configuration file**
  - Folder: **config/features**

Adding a new feature

- **Feature configuration file**
  - Folder: **config/features**
  - XML file with the featureset that will be executed

Adding a new feature

- **Feature configuration file**
  - Create a file named **features_complex_words.xml** inside the folder **config/features**

Adding a new feature

- **Feature configuration file**
  - Create a file named **features_complex_words.xml** inside the folder **config/features**
  - Add the new feature to this file

Adding a new feature

- **Configuration file**
  - Folder: **config**

Adding a new feature

- **Configuration file**
  - Folder: **config**
  - For sentence-level: **config.sentence-level.properties**

Adding a new feature

- **Configuration file**
  - Folder: **config**
  - For sentence-level: **config.sentence-level.properties**
  - Contains basic configuration for the system and paths to resources and tools

Adding a new feature

- **Configuration file**
  - Add the resource **source.simplewords** to the configuration file

Adding a new feature

- **Configuration file**
  - Add the resource **source.simplewords** to the configuration file
  - Change the option **featureConfig** to the path to **features_complex_words.xml**

Adding a new feature

- **SentenceLevelProcessorFactory.java**
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Adding a new feature

- **SentenceLevelProcessorFactory.java**
  - Package: **shef.mt.tools**
  - Function: create all processors required by the features
  - Only generate processors that will be used (improvement of QuEst++)
  - It is the connection between features and configuration file

Adding a new feature

- **SentenceLevelProcessorFactory.java**
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Adding a new feature

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  - Add an **if** block containing the calling to a method called **getComplexWordsProcessor**

Adding a new feature

- **SentenceLevelProcessorFactory.java**
  - Package: **shef.mt.tools**
  - Add an **if** block containing the calling to a method called **getComplexWordsProcessor**
  - Implement **getComplexWordsProcessor** method

Build

- NetBeans 8.1
- ant "-Dplatforms.JDK_1.8.home=/usr/lib/jvm/java-8-<<version>>"

Run

```
java -cp QuEst++.jar
shef.mt.SentenceLevelFeatureExtractor
-tok -case true
-lang <<lang_source>> <<lang_target>>
-input <<input_source>> <<input_target>>
-config <<config_file>>
```

Check the file output.txt inside output/test

System requirements

- **Python 2.7.6** (or above - only 2.7 stable distributions)

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- **scikit-learn** (version 0.15.2)
- **PyYAML**

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- **scikit-learn** (version 0.15.2)
- **PyYAML**
- GPy
- CRFsuite

Folders

- **learning**: main folder
- **config**: configuration files
- **src**: source code files
- **data**: example data (same format as output of feature extractor) + scores

Run

python src/learn_model.py config/<<config_file>>

Machine learning algorithms

- SVR
- SVC
- LassoCV
- LassorLars
- LassorLarsCV
- GP (implemented using GPy - need some code update)
- CRF (implemented using CRFsuite)

Adding a machine learning algorithm

Exemple using an algorithm from scikit-learn

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- Algorithm: **Ridge**: Linear least squares with l2 regularization

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- Package: **sklearn.linear.model.Ridge**

Adding a machine learning algorithm

Exemple using an algorithm from scikit-learn

- Algorithm: **Ridge**: Linear least squares with l2 regularization
- Package: **sklearn.linear.model.Ridge**
- **Idea**: include the algorithm on the available code

Adding a machine learning algorithm

learn_model.py

- Main class of QuEst++ machine learning module

Adding a machine learning algorithm

learn_model.py

- Main class of QuEst++ machine learning module
- Method: **set_learning_method(config, X_train, y_train)**

Adding a machine learning algorithm

learn_model.py

- Main class of QuEst++ machine learning module
- Method: **set_learning_method(config, X_train, y_train)**
- Create estimators for the new algorithm

Configuration file

- Folder: **config**

Configuration file

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- Files follows the YAML format

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- Open the file **svr.cfg** to see an example

Configuration file

- Folder: **config**
- Files follows the YAML format
- Open the file **svr.cfg** to see an example

Create a new file called ridge.cfg and follow the structured YAML to provide parameters for the model

Run

python src/learn_model.py config/ridge.cfg

Quality Estimation of Machine Translation

Recent advances, Challenges and Software

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Alicante, 21 January 2016