Phrase-level Quality Estimation for Machine Translation

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Quality Estimation

Quality Estimation – determination of the quality of an automatically translated segment without reference translation.

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Sentence-level quality estimation:

C'est mon chat.

My dog likes chocolate.
This is my cat.

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Document-level quality estimation:

Il a besoin de toilettage régulier car le poil du Maine Coon est un poil, mi-long, il ne faut pas être allergique! Il a aussi besoin d'un, shampoing tout les mois, et d'un dégraissant tout les deux mois (ou, avant les expositions). Il existe d'ailleurs des shampoings pour, sublimer les couleurs (comme le blanc ou le noir par exemple).

He needs regular grooming for the coat of Maine Coon is a semi-long hair, it should not be allergic! He also needs a shampoo every month, and a degreasing agent every two months (or before exposure). There are also shampoos to sublimate the colors (like white or black for example).

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Phrase-level QE: Motivation

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Machine Translation errors are not independent

Source:	A beautiful flower
Machine Translation:	Un bel arbre

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Machine Translation:	~~Un~~ ~~bel~~ ~~arbre~~
Post-edition:	Une belle fleur

3 errors

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Machine Translation:	Un bel arbre
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Phrase-level QE: Motivation

Machine Translation errors are not independent

Machine Translation:	Un bel arbre	*Wrong choice of word*
Post-edition:	Une belle fleur	

Phrase-level QE: Motivation

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Machine Translation:	Un bel arbre	*Wrong*
Post-edition:	Une belle fleur	*agreement*

Phrase-level QE: Motivation

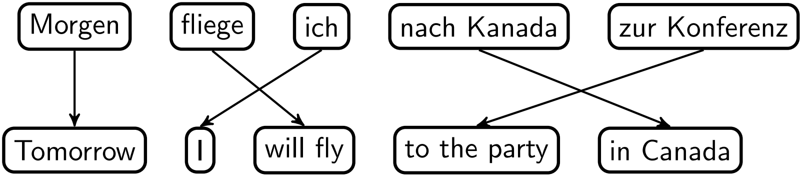
Machine Translation errors are not independent

Machine Translation:	Un bel arbre
Post-edition:	Une belle fleur

1 phrase-level error

Phrase-level QE: Motivation

The majority of Machine Translation systems are phrase-level



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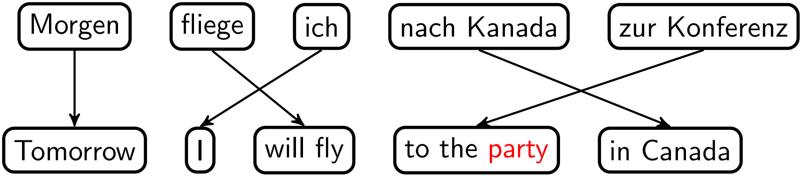

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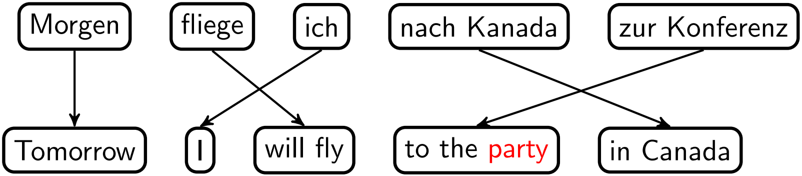

BAD

Phrase-level QE: Challenges

Problems:

- No information on phrase borders
- No definition of "phrase"
- All labels are word-level
- Optimal features for phrase-level QE are unknown

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Sub-tasks:

- Segment sentences into phrases
- Retrieve phrase-level labels
- Find well-performing phrase-level features

Data segmentation

Available data:

- Source sentence
- Automatically translated sentence
- Post-edition of automatic translation
- Word-level labelling of automatic translation (OK/BAD)

Approach: re-decoding of the data.

Decoder-based segmentation: source-target

Joint segmentation of source and target sentences with **constrained decoding**

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Source:	Well ‖ , things ‖ got even more inappropriate ‖ !
Target:	Bueno ‖ , las cosas ‖ se pusieron aún más inadecuado ‖ !

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Target:	Bueno ‖ , las cosas ‖ se pusieron aún más inadecuado ‖ !

Pros
Correspondence between source and target phrases

Contras
Phrases are too long

Decoder-based segmentation: target

Independent decoding of target side

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- Translate target side with target-to-source SMT system

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Well , things got even more inappropriate !

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Well , || things got || even more || inappropriate || !

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Pros

Shorter phrases

Contras

Unreliable source phrases:

- depend on alignments
- don't guarantee source coverage

Labelling

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Optimistic: majority labelling

[Mostly	good	phrase]	[mostly	bad	phrase]
OK	OK	BAD	OK	BAD	BAD
	$\Downarrow$			$\Downarrow$	
	OK			**BAD**	

Labelling

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[Mostly	good	phrase]	[mostly	bad	phrase]
OK	OK	BAD	OK	BAD	BAD
	⇓			⇓	
	OK			**BAD**	

Pessimistic: 30% bad words

[Bad	enough	phrase]	[not	enough	bad	phrase]
OK	OK	BAD	OK	OK	OK	BAD
	⇓			⇓		
	BAD			**OK**		

Labelling

Optimistic: majority labelling

[Mostly	good	phrase]	[mostly	bad	phrase]
OK	OK	BAD	OK	BAD	BAD

$\Downarrow$ **OK** $\Downarrow$ **BAD**

Pessimistic: 30% bad words

[Bad	enough	phrase]	[not	enough	bad	phrase]
OK	OK	BAD	OK	OK	OK	BAD

$\Downarrow$ **BAD** $\Downarrow$ **OK**

Super-pessimistic: any phrase with a bad word is bad

[Good	phrase]	[bad	phrase]	[yet	another	bad	phrase]
OK	OK	BAD	OK	OK	OK	BAD	OK

$\Downarrow$ **OK** $\Downarrow$ **BAD** $\Downarrow$ **BAD**

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Language pair: English – Spanish

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- WMT-15: 11,000 sentences, post-edited

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Feature sets:

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- Word2Vec word embeddings
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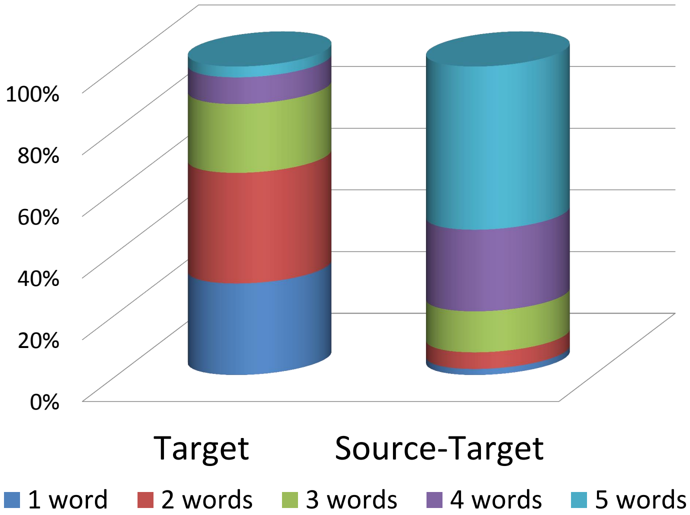
Training methods:

- Conditional Random Fields
- Random Forest

Segmentation properties



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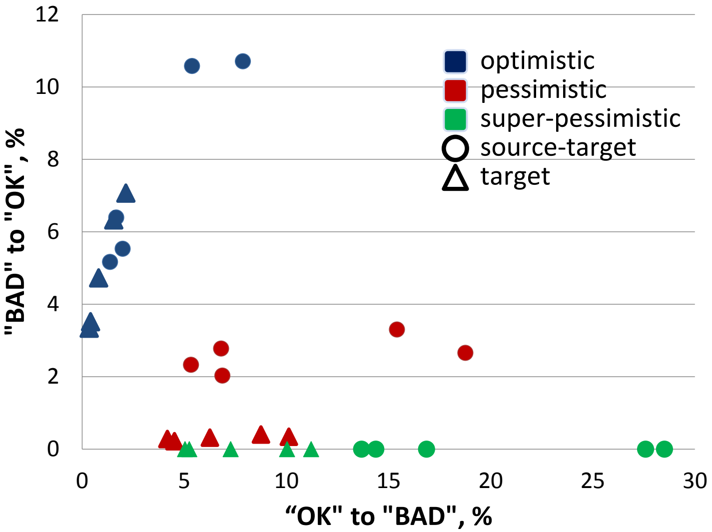
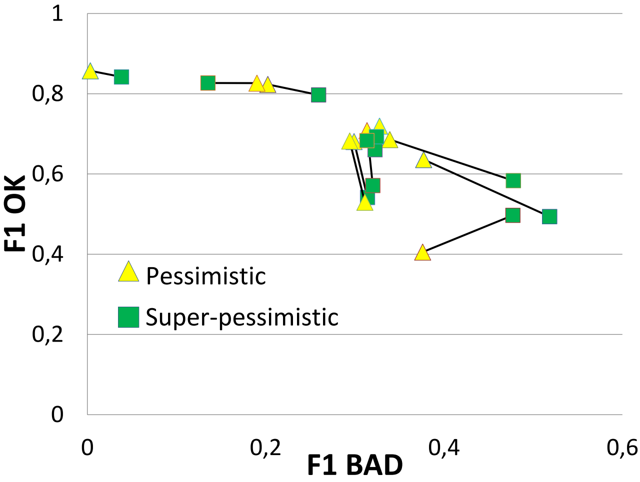
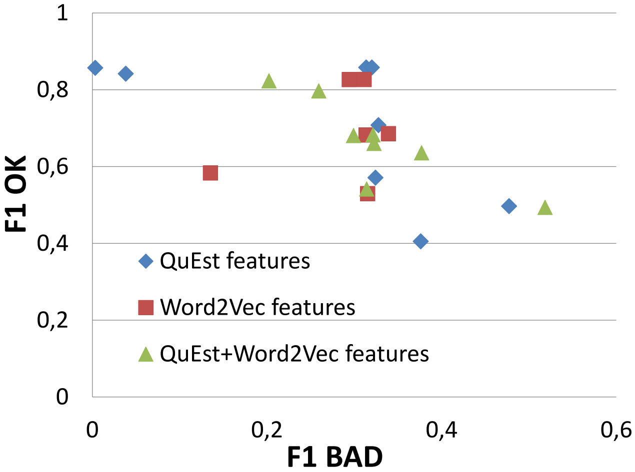


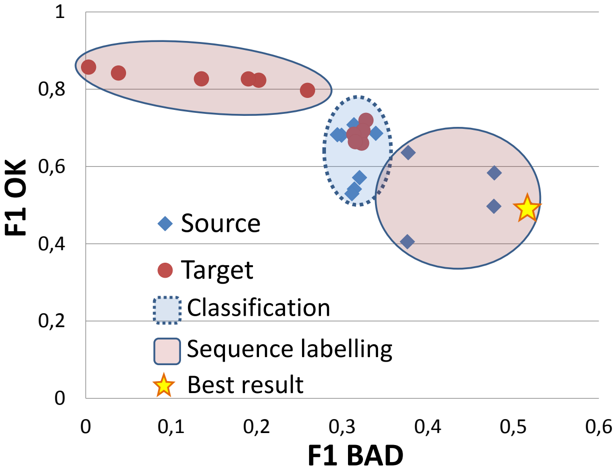
Optimal parameters: labelling



Optimal parameters: features



Optimal parameters: segmentation and training algorithms



Comparison with word-level systems

WMT-14 systems

System	F_1-**BAD** ↑	F_1-OK	Weighted F1
phrase-wmt-14	62.76	39.07	56.80
Baseline-all-bad	52.52	0.0	18.7
FBK-UPV-UEDIN	48.72	69.33	61.99
LIG	44.47	74.09	63.54

Comparison with word-level systems

WMT-15 systems

System	F_1-**BAD** ↑	F_1-OK	Weighted F1
phrase-wmt-15	51.84	49.38	51.08
UAlacant	43.12	78.07	71.47
SHEF-word2vec	38.43	71.63	65.37
Baseline-all-bad	31.75	0.0	5.99
Baseline	16.78	88.93	75.31

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- phrase-level QE model for MT
- decoder-based sentence segmentation techniques
- features: **sentence-level** and word embeddings
- training methods: **CRF** and Random Forest
- phrase-level systems outperform word-level systems

Thank you