

# Quality Estimation for Machine Translation: different users, different needs

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JEC Workshop

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# Quality Estimation for Machine Translation: different translators, same needs

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# Why are you not (yet) using MT?

❑ Why do you use translation memories?

❑ Perfect translations?

The screenshot displays the SDL Studio Online 2011 interface. The main window shows a translation results table for the document 'SDL Product Overview (Translation | EN-US > DE)'. A red circle highlights a specific row in the table, indicating a 100% match. The table contains the following data:

ID	Source Text	Match %	Target Text
1	When new content is written and submitted for translation SDL TMS automatically checks the content against previously translated content using the latest patented technology and advanced linguistic processing.	100%	Wenn neue Inhalte Inhalte mittels neuer Sprachverarbeitung davon bereits übersetzt.
5900	enables corporations to centralise all multilingual assets into a centralised repository.	100%	SDL TMS ermöglicht es Unternehmen, alle mehrsprachigen Inhalte in einer zentralisierten Datenbank zu speichern.
5901	When new content is written and submitted for translation SDL TMS automatically checks the content against previously translated content using the latest patented technology and advanced linguistic processing.	100%	Wenn neue Inhalte in die Übersetzung eingebracht werden, überprüft SDL TMS diese Inhalte mittels neuer Sprachverarbeitungstechnologie und ermittelt, wie viel davon bereits übersetzt wurde.
5902	Any content matched is delivered back translated, whilst new content requiring translation is automatically delivered down into the translation supply chain for human translation.	100%	Alle mehrsprachigen Inhalte in der Datenbank werden automatisch ausgegeben, neu zu übersetzende Inhalte werden dem normalen Übersetzungsprozess gegeben.
5903	For more information about SDL TMS please visit our translation management section.	100%	Weitere Informationen über SDL TMS finden Sie in der Rubrik „Translation Management“.
5904	SDL Knowledge-based Translation System (SDL KbTS™)		SDL Knowledge-based Translation System (SDL KbTS™)
5905	Provides high-quality translations, accelerated time-to-market and reduced total cost for the world's leading brands.	82%	SDL KbTS™ liefert führenden Unternehmen weltweit qualitativ hochwertige Übersetzungen, beschleunigt die Time-to-Market und ermöglicht eine Reduzierung der Gesamtkosten.
5906	The power of the solution lies in the combination of sophisticated machine translation technology with other translation automation	100%	Der Vorteil der Lösung liegt in der Kombination hochentwickelter maschineller Übersetzungstechnologie mit weiteren automatisierten

# Outline

- ❑ **Quality Estimation (QE)** for Machine Translation (MT)
- ❑ **Applications**
- ❑ General **approach**
- ❑ What **aspect of quality** we want to estimate and **how to represent it**
- ❑ How we **assess** quality estimation systems

# QE for MT

□ **Goal**: given the output of an MT system for a given input, provide an estimate of its **quality**

□ **Motivations**: assessing the quality of translations is

□ **Time consuming, tedious, not worth it**

Une interdiction gouvernementale sur la non-UE conjoints étrangers de moins de 21 à venir au Royaume-Uni, qui a été introduit par le Labour en 2008 et vise un partenaire étranger de l'extérieur de l'UE ne pouvait pas se joindre à leurs partenaires au Royaume-Uni si elles étaient moins de 21 ans, est illégale, disent les juges haut.

□ **Not always possible**

个非欧盟国家的外国配偶来英国 □是在 2008 年由工党推出 □意味美

# QE for MT

## □ Main applications:

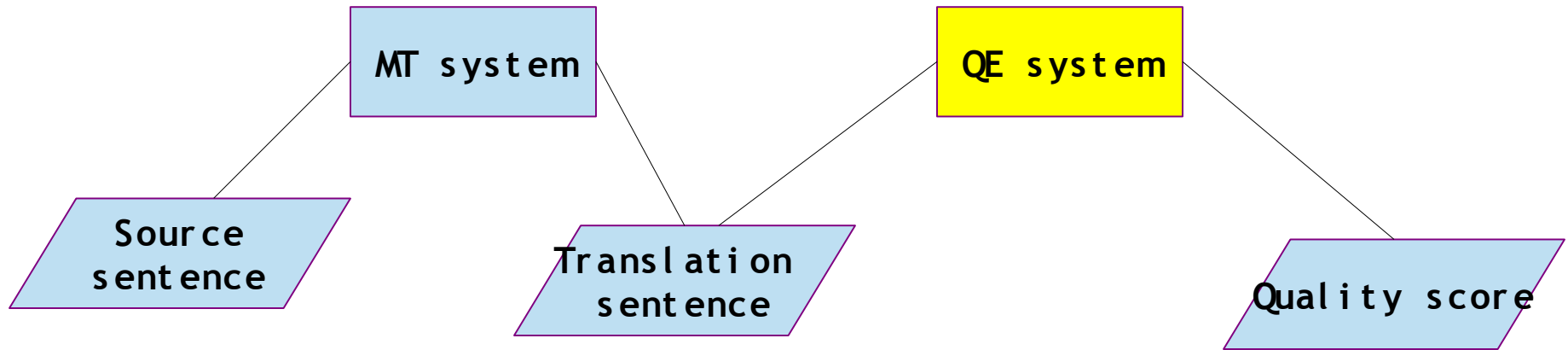
Is it worth providing this translation to a professional translator for post-editing?

Should this translation be highlighted as “not reliable” to a reader?

Given multiple translation options for a given input  
can we select the best one?

Is this sentence good enough for publishing as is?

# QE for MT



- Different from MT evaluation (BLEU, NIST, etc):
  - ◆ MT system in use, translating **unseen text**
  - ◆ Translation unit: **sentence** → not about **average quality**
  - ◆ **Independent** from MT system (post-MT)

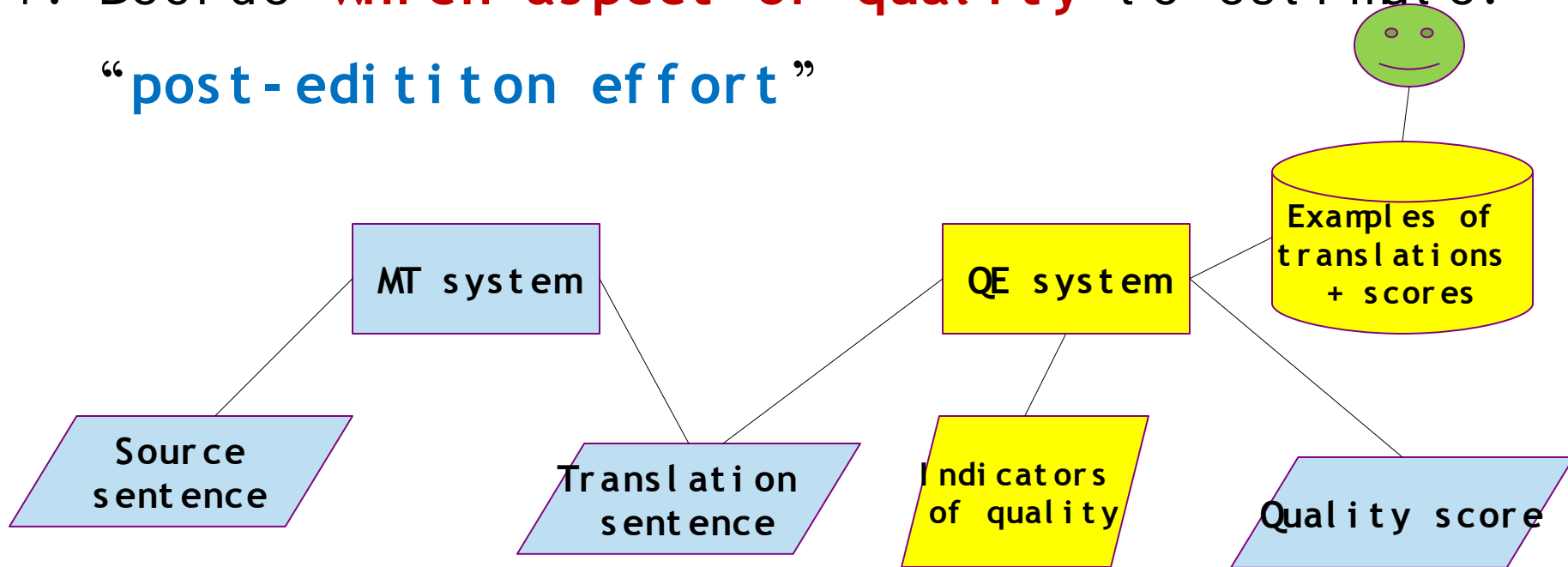
# General approach

1. Decide **which aspect of quality** to estimate
2. Decide **how to represent** this aspect of quality
3. Collect **examples** of translations with different levels of quality
4. Identify and extract **indicators** that represent this quality
5. Apply an algorithm to induce a **model** to predict quality scores for new translations
6. **Evaluate** this model on new translations



# General approach

1. Decide **which aspect of quality** to estimate:  
“**post-edition effort**”



represent this quality

5. Apply an algorithm to induce a model to predict quality

# How is quality defined?

1. **Good** vs **bad** translations: good for what?  
(Blatz et al. 2003)
2. **MT1** vs **MT 2**: is MT1 better than MT2. Yes,  
but is MT1 good enough? (Blatz et al. 2003; He et  
al., 2010)
3. **Perfect** vs **not perfect** translations: can we  
publish this translation as is? (Soricut and  
Echiabi 2010)

Define “quality” in terms of post-editing  
effort

4. Which translations are **good enough** for post-

# How is quality defined?

What levels of quality can we expect from an MT system?

1. **Perfect**: no post-editing needed at all
2. **Good**: some post-editing needed, but **faster/easier** than translating from scratch
3. **Bad**: too much post-editing needed, **faster/easier** to translate from scratch

We expect the machine to estimate this well,  
but can humans do it well?

# How is quality defined?

The court said that the rule was unjustified.

La cour a déclaré que la règle était injustifiée.

"I basically felt like I'd been exiled from my country and in forcing him to leave they'd also forced me to leave," she said.

"J'ai essentiellement ressenti si j'avais été exilé de mon pays et dans le forçant à quitter leur pays m'a aussi forcé de partir", dit -

# How is quality defined?

Tomrrow, and tomrrow, and tomrrow,  
Creeps in this petty pace from day to day,  
To the last syllable of recorded time;  
And all our yesterdays have lighted fools  
The way to dusty death. Out, out, brief  
candle! ...

Pour demain, et demain, et demain,  
Creeps dans cette petite cadence de jour en  
jour,  
Pour la dernière syllabe du temps enregistré;  
Et tous nos hiers ont éclairé les fous  
Le chemin de la mort poussiéreuse. Dehors,  
dehors, bougie bref! ...

# How do humans perform?

Humans are good at identifying **perfect** translations, as well as terribly **bad** translations

But medium quality translations are more difficult: “**good enough**” depends on the translator

- **Very experienced** translators: may prefer only close to perfect translations
- **Less experienced** translators: may benefit from

# How do QE systems perform?

- ◆ **Humans:** agreement on **en-es Europarl**: 85% (prof., 2 an.)
- ◆ **Humans:** agreement on **en-pt subtitles** of TV series: 850 sentences (non prof., 3 an.)
  - 351 cases (41%) have **full** agreement
  - 445 cases (52%) have **partial** agreement
  - 54 cases (7%) have **null** agreement

- ◆ Agreement by score

Score	Full	Partial
4	59%	41%
3	35%	65%
2	23%	77%
1	50%	50%

# How do QE systems perform?

simplify the task, if we know how experienced the translator is: binary problem -> **good**

Languages	MT system	Accuracy	Most frequent score	Sentence length
en-es	MT1	70%	52%	36%
en-es	MT2	77%	74%	21%
en-es	MT3	66%	57%	30%
en-es	MT4	94%	94%	70%



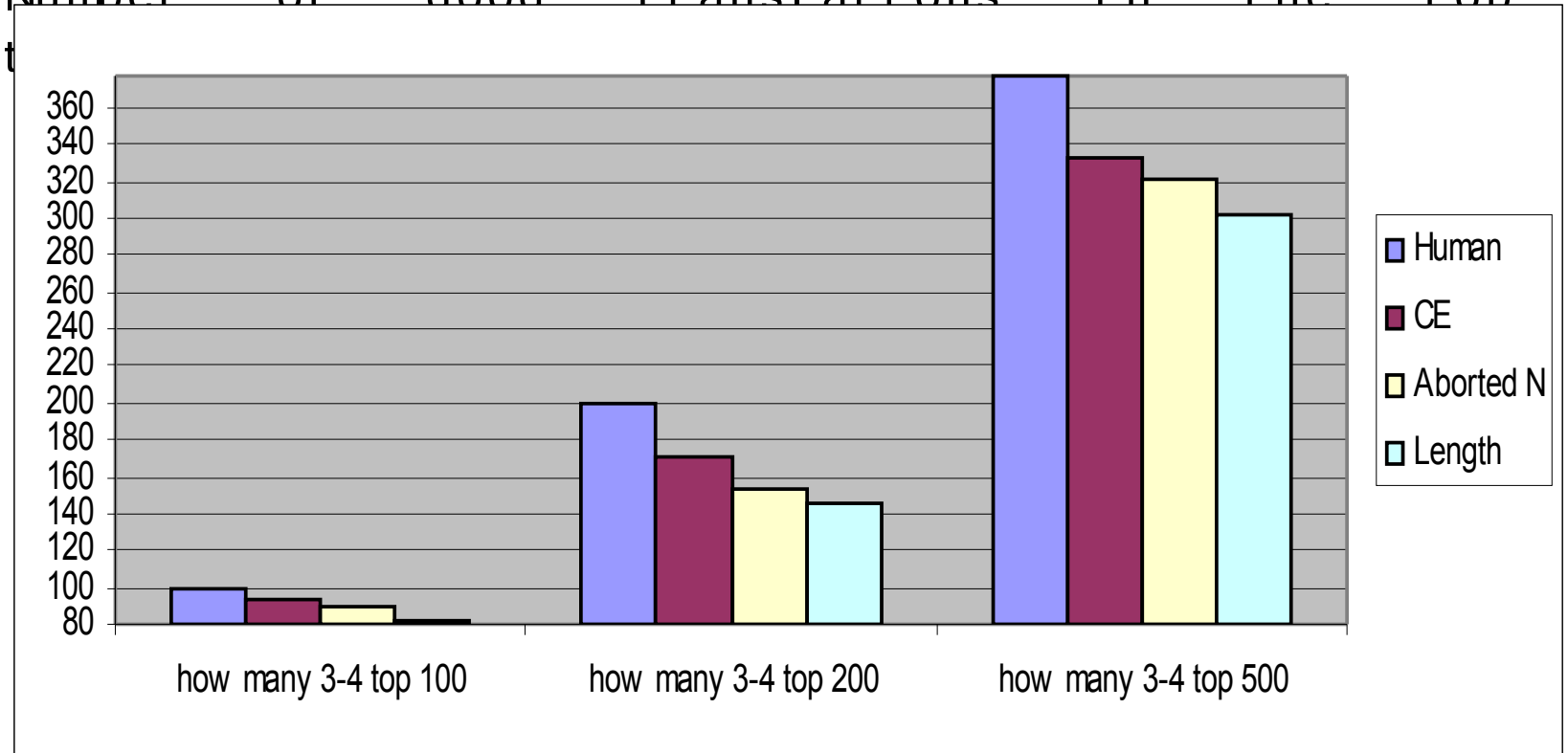
# How do QE systems perform?

- ◆ Evaluation in terms of **classification accuracy** → clear
  - Upper bound = 100%
  - 50% = we are selecting 50% of the bad cases as good / of the good cases as bad
- ◆ **Is ~70% accuracy enough?**
- ◆ A different perspective: **precision/recall** by category:
  - How many bad translations the system says are good (**false rate**)
  - How many good the system says are bad (**miss rate**)

# How do QE systems perform?

- Selecting only good translations: [3-4] (en-es)

◆ Number of good translations in the top  $n$



# Are 2/4 discrete scores enough?

- We want to estimate: 1, 2 or 1, 2, 3, 4
- It's like saying you can get, from a TM:
  - Only **0% match** or **100% match**
  - Or the following (fuzzy) match levels: **0%**, **50%**, **75%**, **100%**
- Isn't there anything in between?

Estimate a continuum: a real  
number in  $[1, 4]$

# Estimating a continuous score

## ■ English-Spanish Europarl data

◆ 4 SMT systems, 4 sets of 4,000 translations

## ■ Quality score: 1-4

1: requires complete retranslation	2: a lot of post-editing needed, but quicker than retranslation
3: a little post-editing needed	4: fit for purpose

Languages	MT System	Error
en-es	MT1	0.653
en-es	MT2	0.718
en-es	MT3	0.706
en-es	MT4	0.603

# Is a number in [1, 4] informative?

Can we see this number as a fuzzy match level?

- Not really... How much work to do on a 3.2 translation?

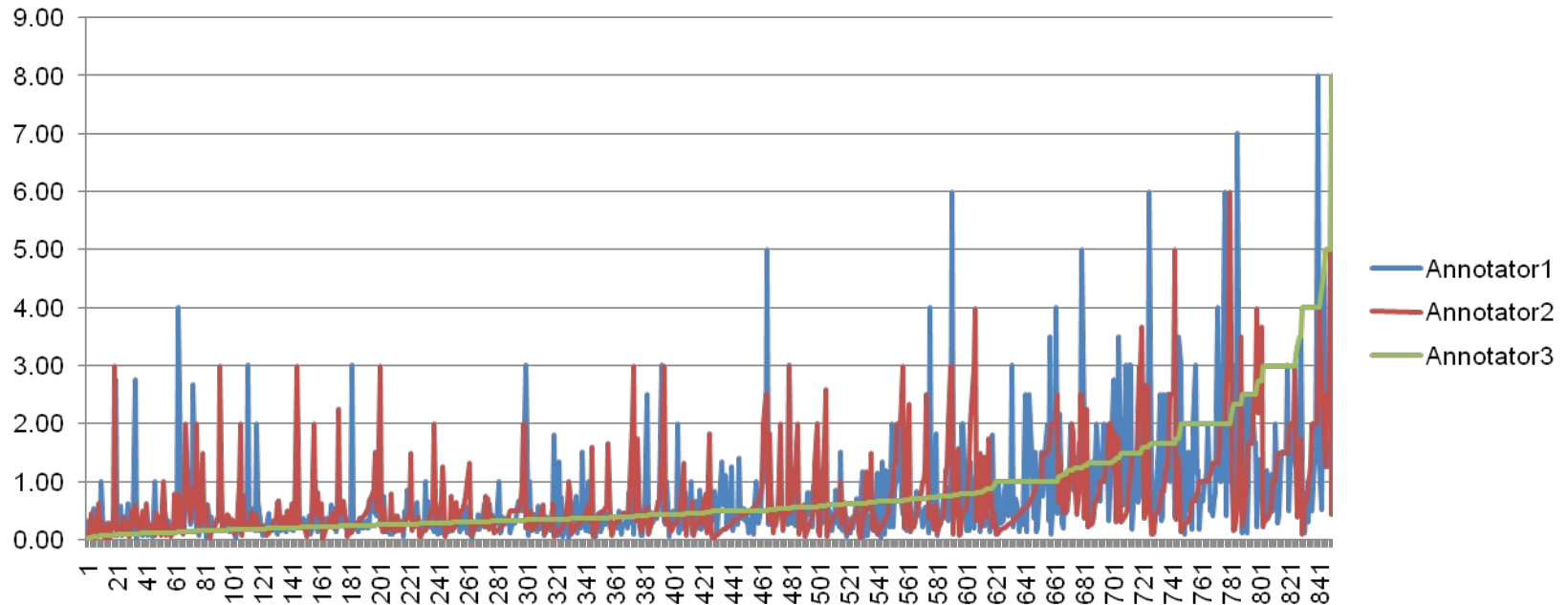
Try more objective ways of representing quality:

$$\text{HTER} = \frac{\# \text{ edits}}{\# \text{ words in post-edited version}}$$

- **Edit distance (HTER):** distance (in [0, 1]) between original MT and post-edited version. What is the proportion of edits (words) will I have to perform to correct

# Is a number in [1, 4] informative?

- **Time** : how many seconds will it take to post-edit this sentence?
  - **Time varies** considerably from annotator to annotator



This annotation is **cheap** and **easy** to obtain if translators already post-edit MT

# Other ways of representing quality

- **English-Spanish, French-English** news articles
- 1,500-2,500 translations
- Quality scores:
  - ◆ Score1 = HTER
  - ◆ Score2 = [1-4]
  - ◆ Score3 = time
- Annotation **tool** to collect data from translators

# Other ways of representing quality

## ■ Results

- ◆ Each model trained on examples from a **single translator**

Dataset		Error ↓
fr-en	Distance	0.16
	[1-4]	0.66
	Time	0.65
en-es	Distance	0.18
	[1-4]	0.55
	Time	1.97



# Other ways of representing quality

- So we are **almost** happy:
  - ◆ We can estimate an aspect of quality that is clear and objective (time, distance) ✓
- But do these error metrics say something about how good the QE model is? Or which model is better? ✗

# Evaluation by ranking

Rank translations by their QE scores (best first)

Based on the quality of the MT system for a small development data, find the percentage of “**good enough**” translations, using any annotation scheme. E.g. 30% of the translations are good

Measure improvement of top 30% according to QE scores:

- ◆ Compare **average quality of full dataset**

# Evaluation by ranking

Languages	Delta [ 1- 4 ] ↑	Delta Distance ↓ [ 0, 1 ]	Delta Time ↓ ( sec/ word )
fr -en (70% good)	0.07	-0.02	-0.11
en -es (40% good)	0.20	-0.06	-0.19

Languages	Delta [ 1- 4 ] ↑	Delta Distance ↓ [ 0, 1 ]	Delta Time ↓ ( sec/ word )
fr -en	0.16	-0.04	-0.20
en -es	0.15	-0.04	-0.26

25%, 50% and 75%

# Extrinsic evaluation by ranking

measure **post-editing time** to correct **top 30% translations** selected according to QE scores

- Compare it against post-editing time of **randomly selected 30% translations**

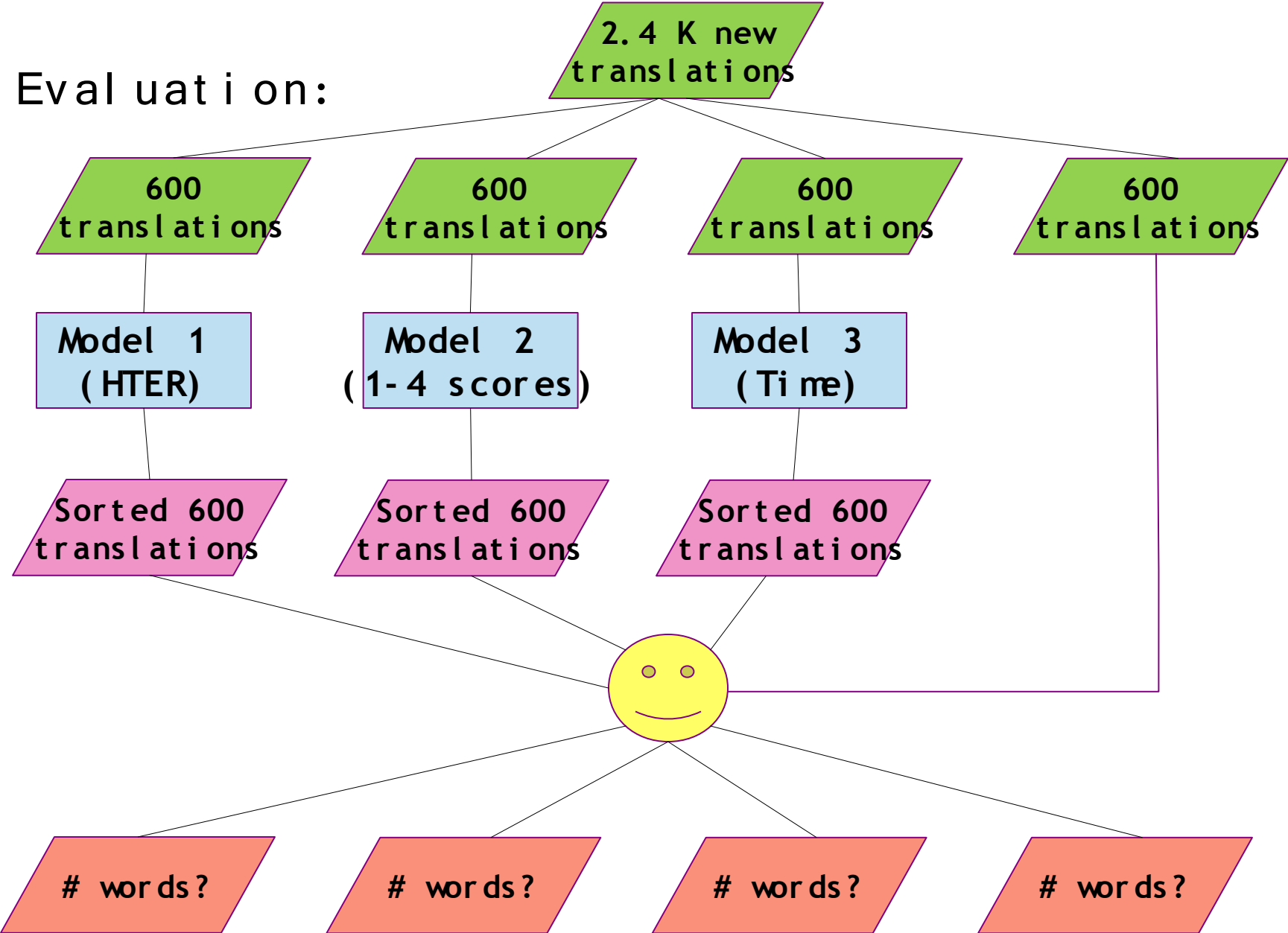
If can't decide on the %, measure **number of words that can be post-edited in a fixed amount of time** from best to worse

translations ranked according to QE model

- Compare it against number of words post-

# Extrinsic evaluation by ranking

■ Evaluation:



# Extrinsic evaluation by ranking

- Post-editing in 1 hour :

MT System / Dataset	Wbr ds / secon d
S6 fr-en HTER (0-1)	0.96
S6 fr-en [1-4]	0.91
S6 fr-en time (sec/word)	<b>1.09</b>
<hr/>	
MT System / Dataset	Wbr ds / secon d
S7 en-es HTER (0-1)	0.41
S7 en-es [1-4]	0.43
S7 en-es time (sec/word)	<b>0.57</b>
S7 en-es no CE	<b>0.32</b>

# Extrinsic evaluation by ranking

summing up:

- ◆ The aspect of quality we estimate is clear (time, distance)
- ◆ The number of ranking-based (esp. something about extrinsic how good a



# How about other users?

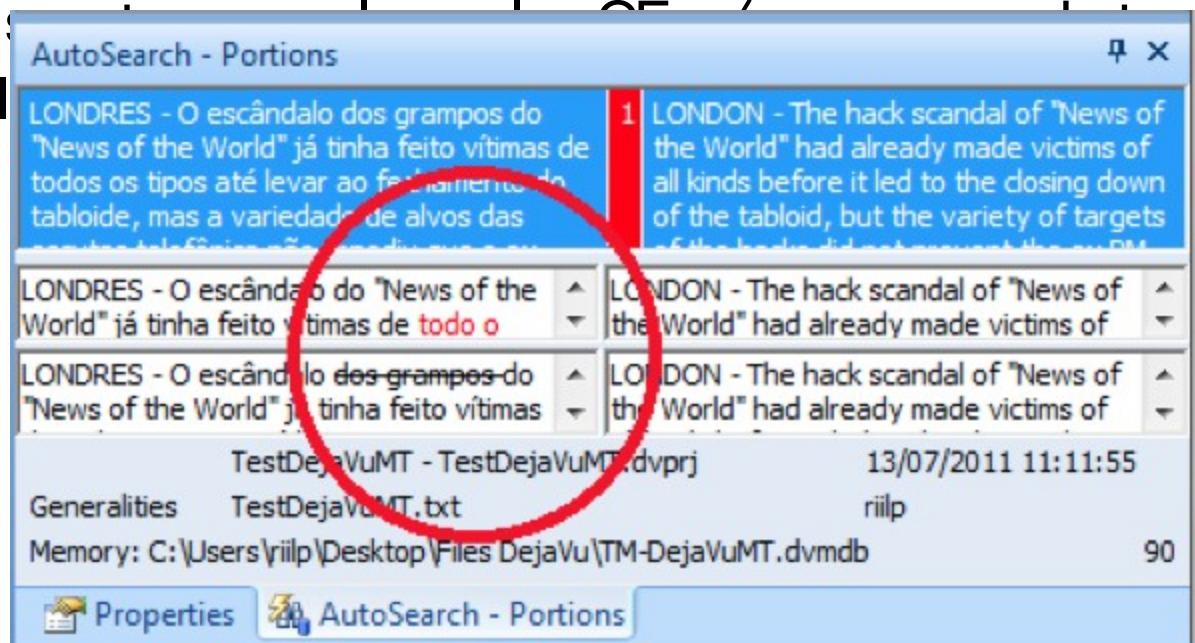
- Post-editing time/distance/[1-4] scores have a good (pearson) correlation:
  - ◆ **Distance** and **[1-4]** = **0.75 - 0.82**
  - ◆ **Time** and **[1-4]** = **0.50 - 0.60**  
(the smaller values are when scores are given by different translators)
- If we correlate post-editing **time/distance** and [1-4] scores reflecting **adequacy** (not post-editing effort)
  - ◆ **Distance** and **[1-4] Adequacy** = **0.55**
  - ◆ **Time** and **[1-4] Adequacy** = **0.40**



# Is this enough?

- Is an accurate QE system at the sentence level enough?
- QE should also indicate, for sentences that are not perfect, **what the bad parts are**
- ◆ Sub-... QE... action in

translation



(Xiong et al. 2010): Link grammar: mostly words

# Concl usi ons

- It is possible to estimate the quality of MT systems with respect to **post-editing needs**
- Measuring and estimating post-editing **time** seems to be the best way to **build** and **evaluate** QE systems
  - ◆ **Translator-dependent** measure: build a model per translator or project the time differences
  - ◆ Extrinsic evaluation using time is **expensive**, not feasible to compare many QE systems
  - ◆ Alternative: **intrinsic ranking-based**

# Concl usi ons

- QE is a relatively **new area**
- It has a great potential to make MT more **useful** to end-users:
  - ◆ Translation: minimize post-editing time, allow for fair pricing models
  - ◆ Localization: keep the “brand” of the product /company
  - ◆ Gisting: avoid misunderstandings
  - ◆ Dissemination of large amounts of content, e.g.: user reviews

# Advertisement:

## ■ Shared task on QE

- ◆ Most likely with **WMT** at NAACL, June 2012
- ◆ **Sentence-level**: classification, regression and ranking

## ■ We will provide:

- ◆ Training sets annotated for quality
- ◆ Baseline feature sets
- ◆ Baseline systems to extract features
- ◆ Test sets annotated for quality

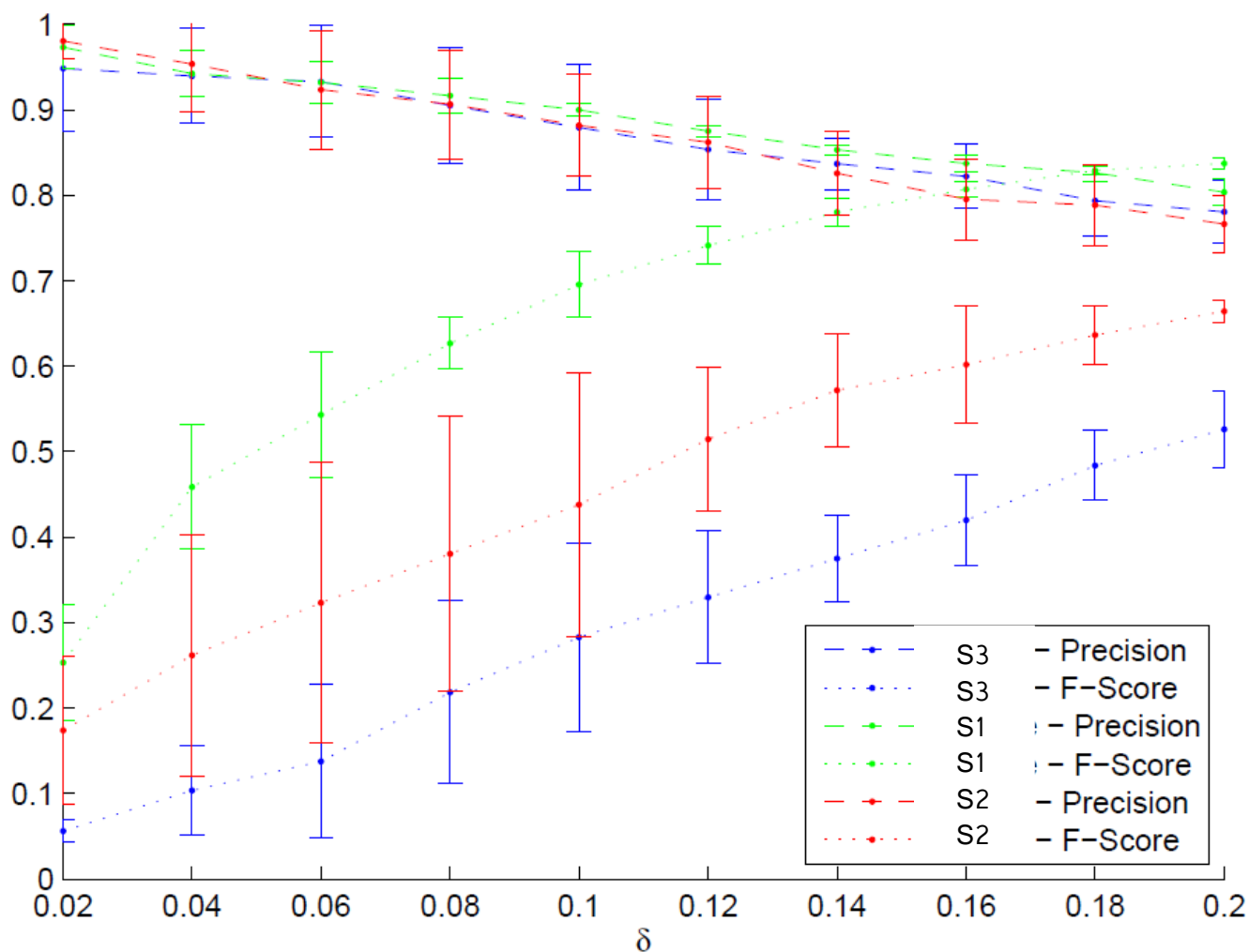
# Questions?

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# En- Es Europarl - [1- 4]

- Regression + Confidence Machines to define the splitting point according to expected conf



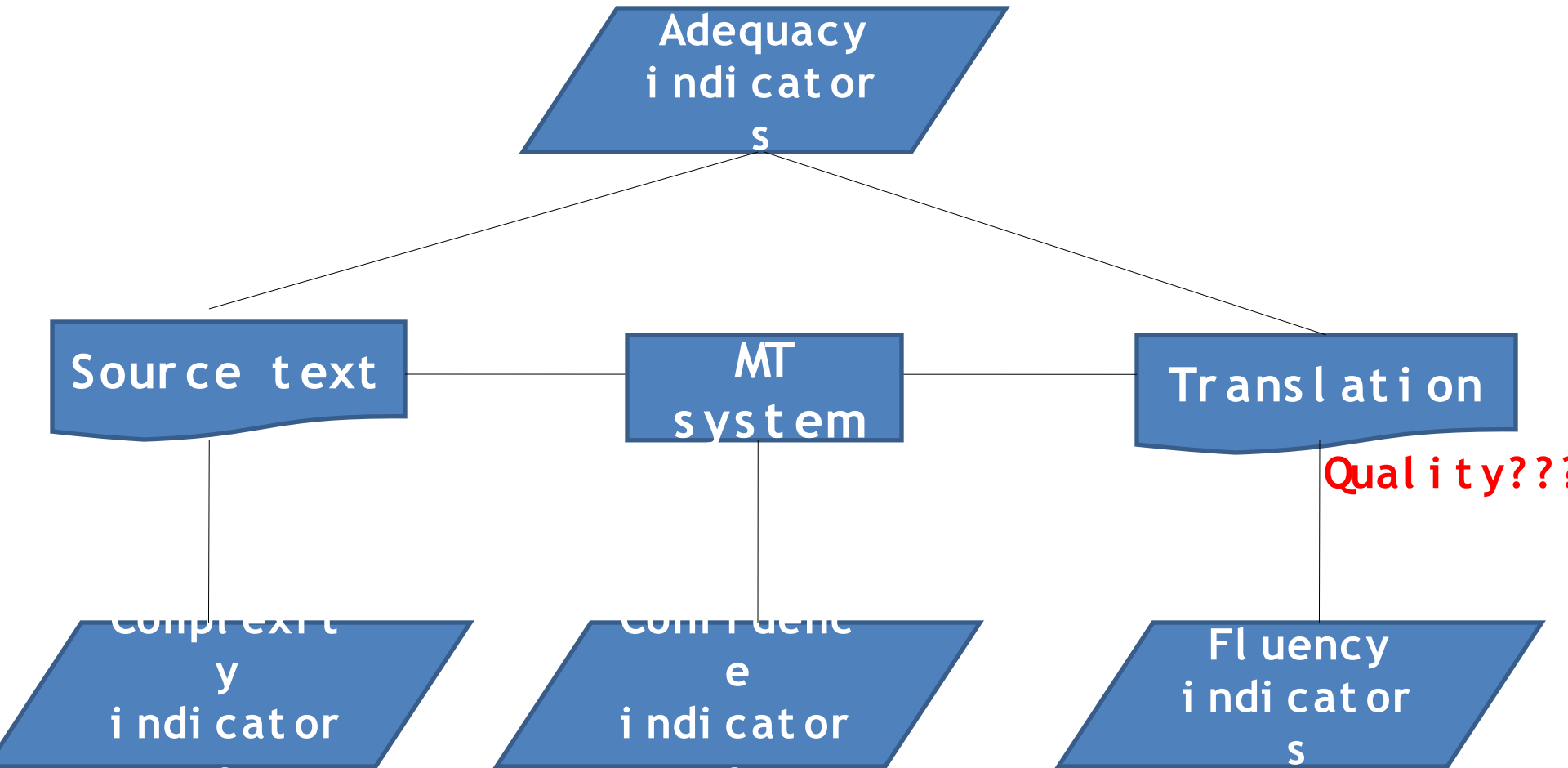
$\tau = 3$

# En-Es Europarl - [1-4]

- QE score x MT metrics: Pearson's correlation across datasets produced by different MT systems:

Test set	Training set	Pearson QE and human
S3 en-es	S1 en-es	0.478
	S2 en-es	0.517
	S3 en-es	0.542
	S4 en-es	0.423
S2 en-es	S1 en-es	0.531
	S2 en-es	0.562
	S3 en-es	0.547
	S4 en-es	0.442

# Features



- Shallow vs linguistically motivated
- MT system dependent vs independent



# Source features

- ❑ Source sentence length
- ❑ Language model of source
- ❑ Average number of possible translations per source word
- ❑ % of n-grams belonging to different frequency quartiles of the source side of the parallel corpus
- ❑ Average source word length
- ❑ ...

# Target features

- ❑ Target sentence length
- ❑ Language model of target
- ❑ Proportion of untranslated words
- ❑ Grammar checking
- ❑ Mismatching opening/closing brackets, quotation symbols
- ❑ Coherence of the target sentence
- ❑ ...

# MT features (confidence)

- SMT model global score and internal features
  - Distortion count, phrase probability, ...
- % search nodes aborted, pruned, recombined ...
- Language model using n-best list as corpus
- Distance to centre hypothesis in the n-best list
- Relative frequency of the words in the translation in the n-best list
- Ratio of SMT model score of the top translation to the sum of the scores of all hypothesis in the n-best list
- ...

# Source-target features

- Ratio between source and target sentence lengths
- Punctuation checking (target vs source)
- Correct translation of pronouns
- Matching of phrase/POS tags
- Matching of dependency relations
- Matching of named entities
- Matching of semantic role labels
- Alignment of these and other linguistic markers
- ...

# MT system selection

## ■ Approach:

- ◆ Train QE models for each MT system (individually)
- ◆ Use all MT systems to **translate** each input segment
- ◆ **Estimate** the QE score for each alternative translation
- ◆ **Select** the translation with the highest CE score

## ■ Experiments:

- ◆ **En-Es Europarl [1-4] datasets**, 4 MT systems

## ■ Results:

# How do QE systems perform?

- Selecting only good translations: [3-4] (en-es)

- ◆ Average human scores in the top N translations:

