

MT Evaluation Basics

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Machine Translation
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Evaluating MT

- What do we want to know?
 - How good is the MT output?
 - Is a system useful?
 - Is one system better than another?
 - What errors does it make?

Evaluating MT

- Why do we want to evaluate MT? E.g. to help it get better ...:

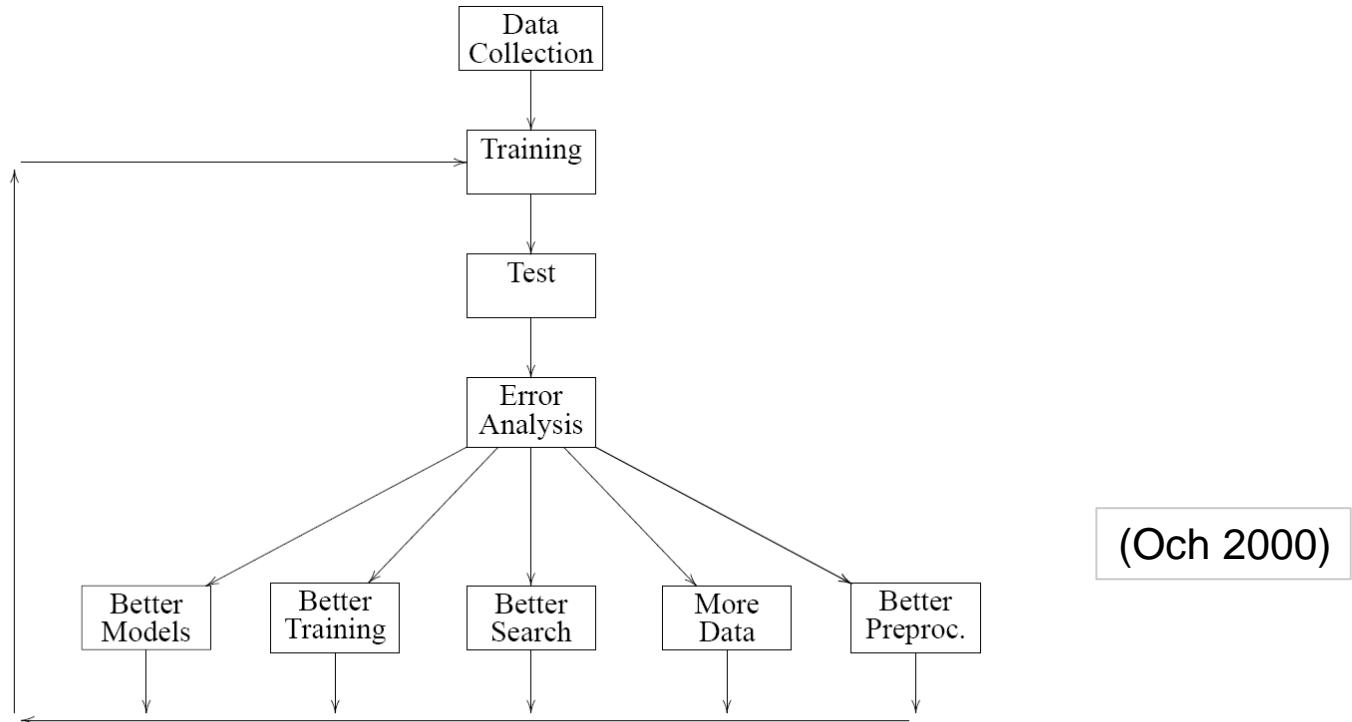


Figure 3.1: Development cycle of a statistical MT system.

Evaluating MT

- What do we want to know?
 - How good is the MT output?
 - Is a system useful?
 - Is one system better than another?
 - What mistakes does it make?

- When is a translation a good translation?
 - Equivalent in meaning to source text: **Adequacy**
 - Fluent in target language: **Fluency**

Evaluating MT

- What do we want to know?
 - How good is the MT output?
 - Is a system useful?
 - Is one system better than another?
 - What mistakes does it make?
- When is a translation a good translation?
 - Equivalent in meaning to source text: **Adequacy**
 - Fluent in target language: **Fluency**
- What do we compare with? How many good translations are there?
- Is there a single “best” translation?

Ten Translations of a Chinese Sentence

这个 机场 的 安全 工作 由 以色列 方面 负责 .

Israeli officials are responsible for airport security.

Israel is in charge of the security at this airport.

The security work for this airport is the responsibility of the Israel government.

Israeli side was in charge of the security of this airport.

Israel is responsible for the airport's security.

Israel is responsible for safety work at this airport.

Israel presides over the security of the airport.

Israel took charge of the airport security.

The safety of this airport is taken charge of by Israel.

This airport's security is the responsibility of the Israeli security officials.

(a typical example from the 2001 NIST evaluation set)

Evaluating MT

- How do we evaluate MT?
 - Manual (“human”, “subjective”)
 - Automatic (“objective”)
- Quality (overall, a number like BLEU, TER, human score etc.)
- Diagnostic (what goes wrong, linguistic analysis)
- Scoring
- Ranking
- Intrinsic
- Extrinsic

Evaluating MT

- How do we evaluate MT?
 - Manual (“human”, “subjective”)
 - Automatic (“objective”)
- Manual/human/”subjective” (+ intrinsic)
 - Human professional translators
 - People proficient in source and target language at stake
 - People who only understand target but have access to a reference
 - The Crowd ... turkers ...
- Often very time consuming and expensive
- Not easy to reproduce: rater/inter-annotator agreement
- MT output hard to rate ... (sometimes subtle, sometimes bad ...)
- Still: the **yardstick**, the gold-standard, the **ideal** ...

Human Evaluation

- How good/bad, general quality, scoring
 - rating on a scale or absolute rating = assigning a **score** to a translation
 - comparing two translations and deciding which of the two is better or worse
- What is wrong: **diagnostic evaluation** ...

Human Evaluation: Scoring

□ Guidelines

□ Adequacy (Scale of 5) (~ “meaning”)

- 5 = All meaning
- 4 = Most meaning
- 3 = Much meaning
- 2 = Little meaning
- 1 = none

□ Fluency (Scale of 5) (~ “grammar”)

- 5 = Flawless (English)
- 4 = Good (English)
- 3 = Non-native (English)
- 2 = Disfluent (English)
- 1 = Incomprehensible

Human Evaluation: Scoring

□ Guidelines

□ Adequacy (Scale of 5) (≈ “meaning”)

- 5 = All meaning
- 4 = Most meaning
- 3 = Much meaning
- 2 = Little meaning
- 1 = none

Very hard to operationalise!

□ Fluency (Scale of 5) (≈ “grammar”)

- 5 = Flawless (English)
- 4 = Good (English)
- 3 = Non-native (English)
- 2 = Disfluent (English)
- 1 = Incomprehensible

Judge Sentence

You have already judged 14 of 3064 sentences, taking 86.4 seconds per sentence.

Source: les deux pays constituent plutôt un laboratoire nécessaire au fonctionnement interne de l'ue .

Reference: rather , the two countries form a laboratory needed for the internal working of the eu .

Translation	Adequacy	Fluency
both countries are rather a necessary laboratory the internal operation of the eu .	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> 1 2 3 4 5	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input checked="" type="radio"/> 1 2 3 4 5
both countries are a necessary laboratory at internal functioning of the eu .	<input type="radio"/> <input type="radio"/> <input checked="" type="radio"/> <input type="radio"/> <input type="radio"/> 1 2 3 4 5	<input type="radio"/> <input type="radio"/> <input checked="" type="radio"/> <input type="radio"/> <input type="radio"/> 1 2 3 4 5
the two countries are rather a laboratory necessary for the internal workings of the eu .	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input checked="" type="radio"/> <input type="radio"/> 1 2 3 4 5	<input type="radio"/> <input type="radio"/> <input type="radio"/> <input checked="" type="radio"/> <input type="radio"/> 1 2 3 4 5
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Annotator: Philipp Koehn Task: WMT06 French-English	<input type="button" value="Annotate"/>	
Instructions	5= All Meaning 4= Most Meaning 3= Much Meaning 2= Little Meaning 1= None	5= Flawless English 4= Good English 3= Non-native English 2= Disfluent English 1= Incomprehensible

Human Evaluation: Scoring

- Very hard to do for humans
- Juggle 5 (possibly equally miserable or good) automatic translations (for possibly long sentences)
- With respect to 2 dimensions on a scale of 5 each ...
- Poor inter-annotator/rater agreement!
- Many data points (raters) + statistics = good results possible ...

- Don't know yet **what** is wrong
- **why** a system is good or bad
- ...

Judge Sentence

You have already judged 14 of 3064 sentences, taking 86.4 seconds per sentence.

Source: les deux pays constituent plutôt un laboratoire nécessaire au fonctionnement interne de l'ue .

Reference: rather , the two countries form a laboratory needed for the internal working of the eu .

Translation	Adequacy	Fluency
both countries are rather a necessary laboratory the internal operation of the eu .	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5
both countries are a necessary laboratory at internal functioning of the eu .	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5
the two countries are rather a laboratory necessary for the internal workings of the eu .	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5
the two countries are rather a laboratory for the internal workings of the eu .	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5
the two countries are rather a necessary laboratory internal workings of the eu .	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5	Ⓐ Ⓑ Ⓒ Ⓓ Ⓔ 1 2 3 4 5
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Human Evaluation: Ranking

3-Way Ranking

Appraise Overview Status Logout "cfedermann"

001/200

Thanks to grant funding (subsidy of 2.8 million) they were able to purchase equipment and for the period of two years provide qualified personnel and operation. The European Union announces having allocated in 2010 2.2 thousand million Euros, a good token of observance of its promise of 7.2 thousand million Euros in 2012.
 — Source

Dank dieser Finanzierung (Zuschüsse in Höhe von 2, 8 Mio. CZK) konnten die notwendigen Einrichtungen und die Ausstattung beschafft werden und für die Dauer von 2 Jahren ist für qualifiziertes Personal und für den Betrieb gesorgt. Die EU verkündet, im Jahre 2010 2,2 Milliarden Euro freigesetzt zu haben, was sie auf den richtigen Weg zur Respektbezahlung ihres Engagements von 7,2 Milliarden im Jahre 2012 bringt.
 — Reference

Dank Subventionsfinanzierung (Subvention von 2.8 Millionen) konnten sie Ausstattung kaufen und sorgen für den Zeitraum von zwei Jahren für qualifiziertes Personal und Operation.

— Translation A

Dank Subventionsfinanzierung (Subvention von 2.8 Millionen) waren sie fähig, um Ausstattung zu kaufen, und sorgen für den Zeitraum von zwei Jahren für qualifiziertes Personal und Operation.

— Translation B

A > B
 A = B
 A < B

Human Evaluation: Diagnostic

- What is wrong/diagnostic evaluation: error classifications (Vilar et al. 2006):

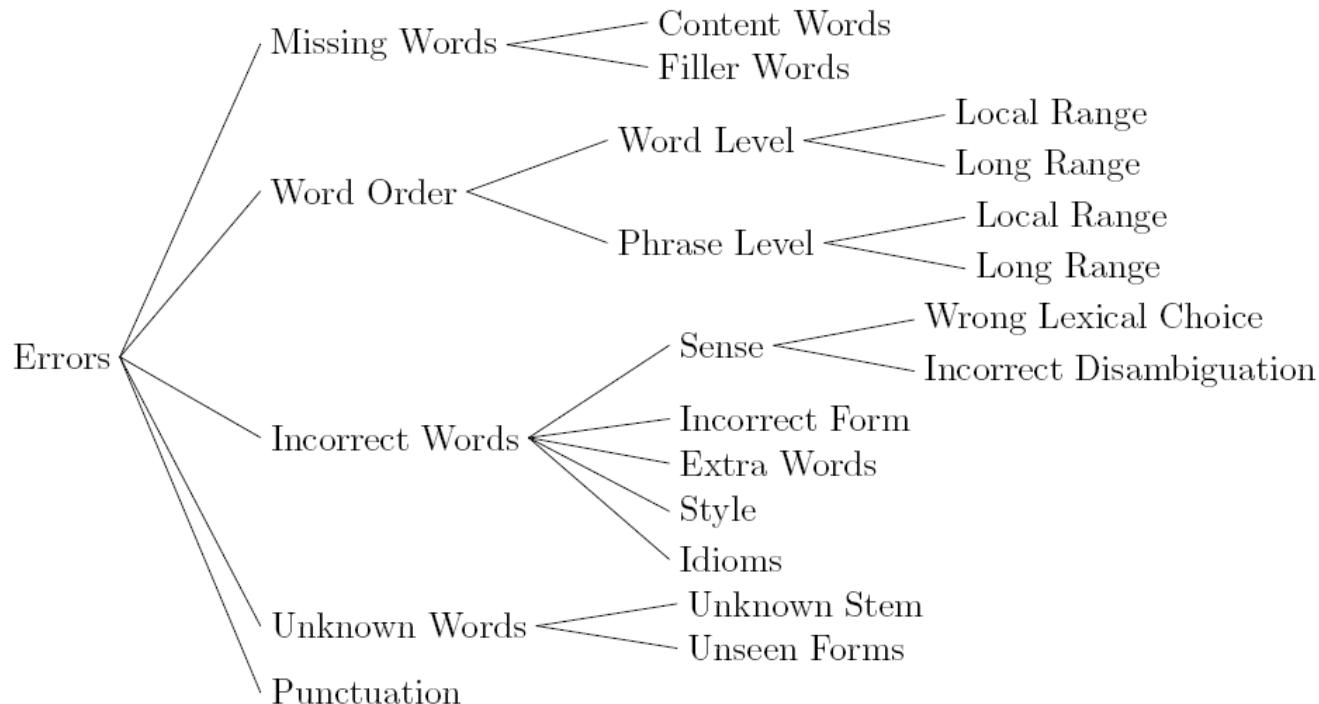
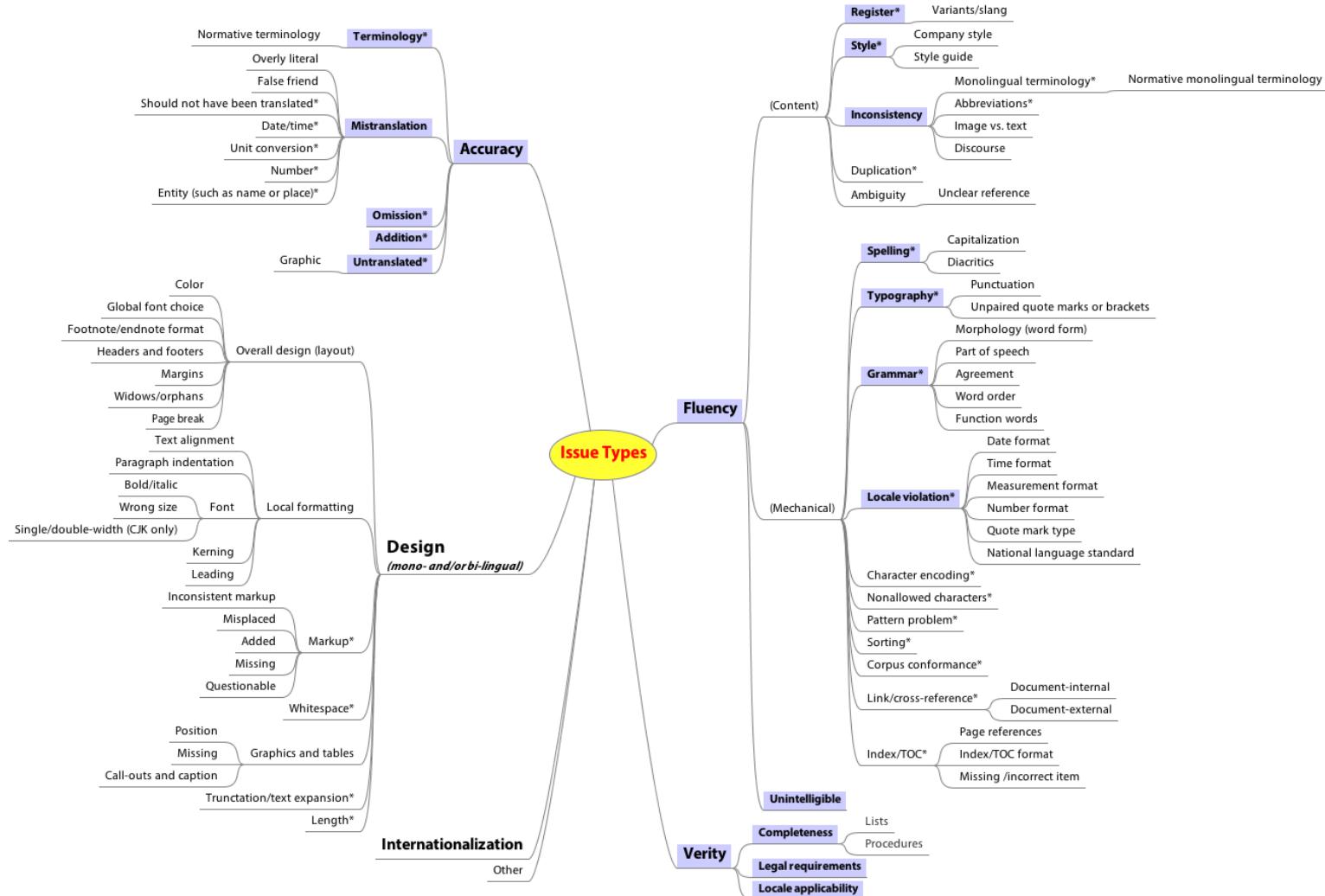


Figure 1: Classification of translation errors.

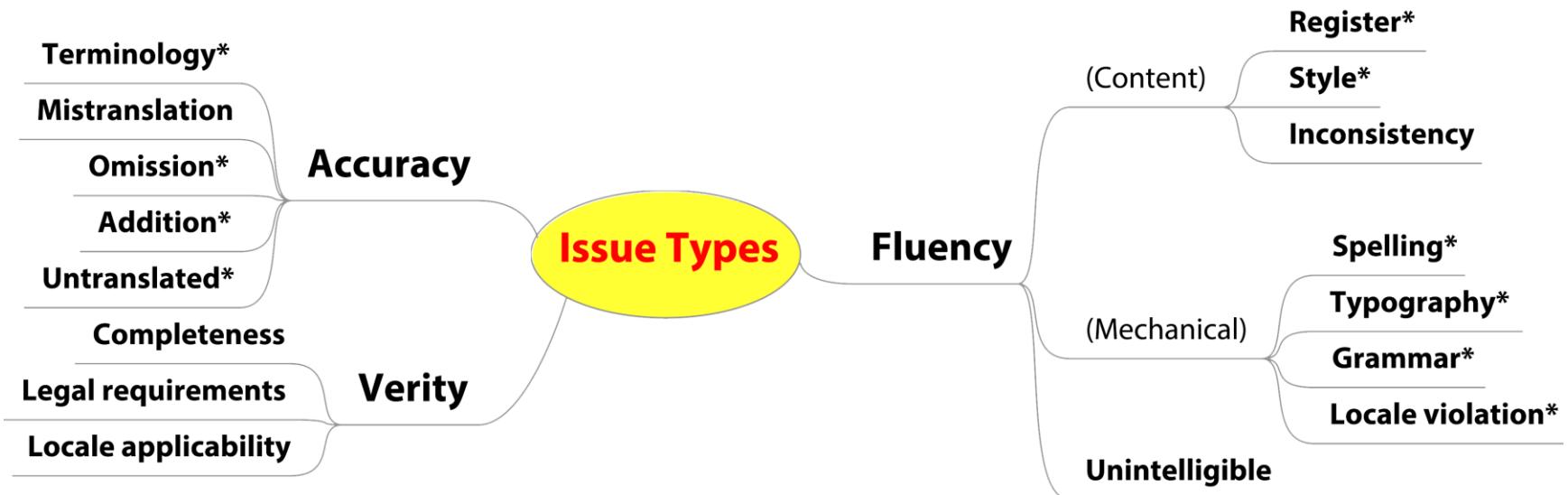
Human Evaluation: Diagnostic

□ Error classification MQM QTLaunchPad (Lommel et al. 2013):



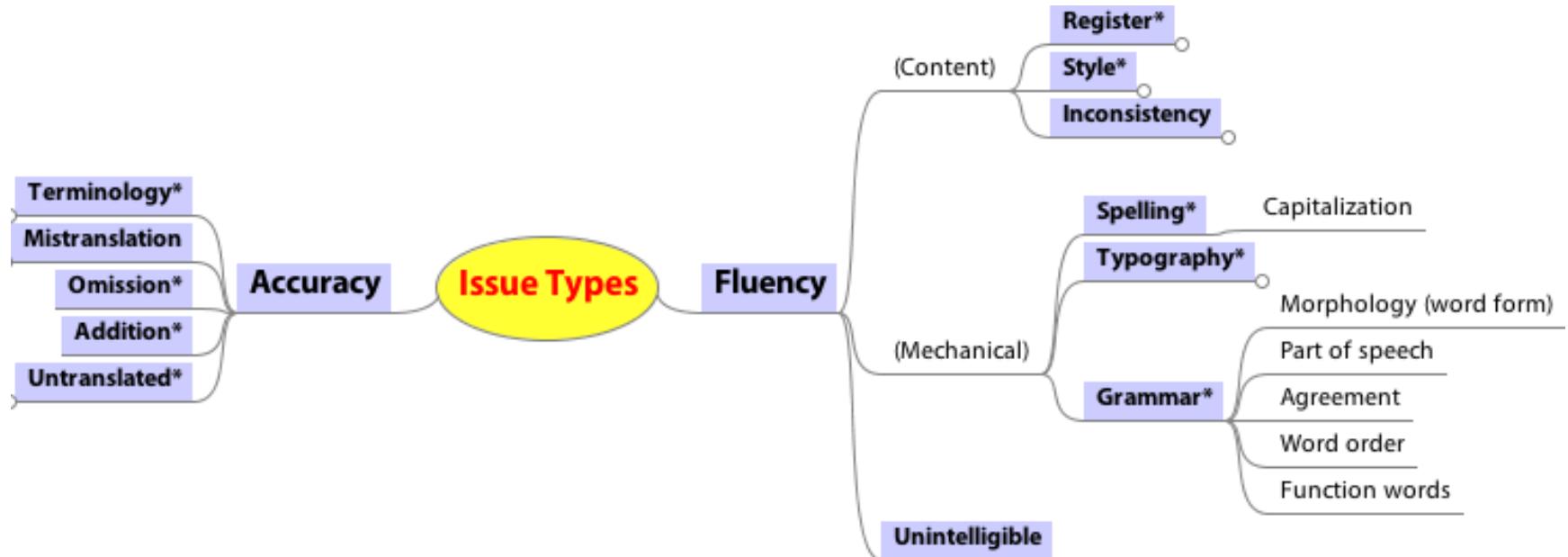
Human Evaluation: Diagnostic

- Error classification **MQM Core** QTLaunchPad (Lommel et al. 2013):



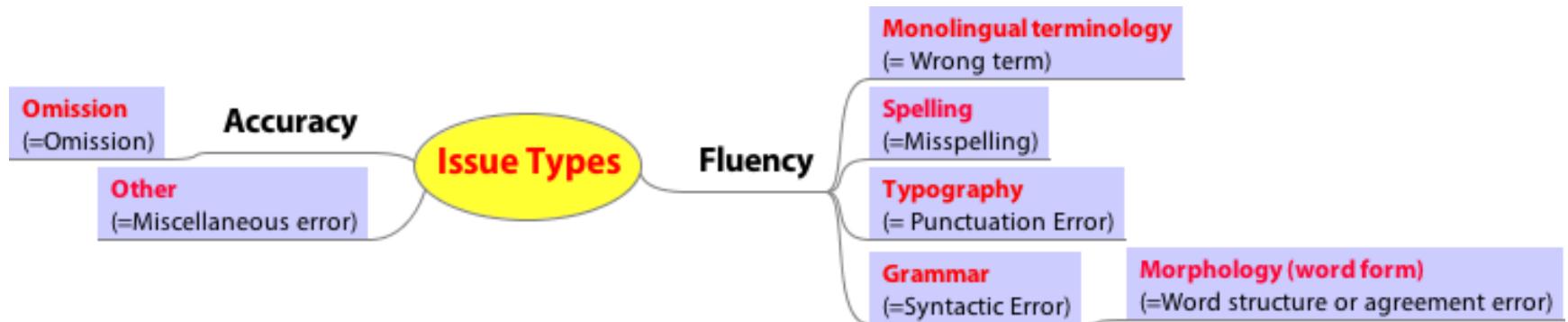
Human Evaluation: Diagnostic

- Error classification **MQM MT Subset** (Lommel et al. 2013):



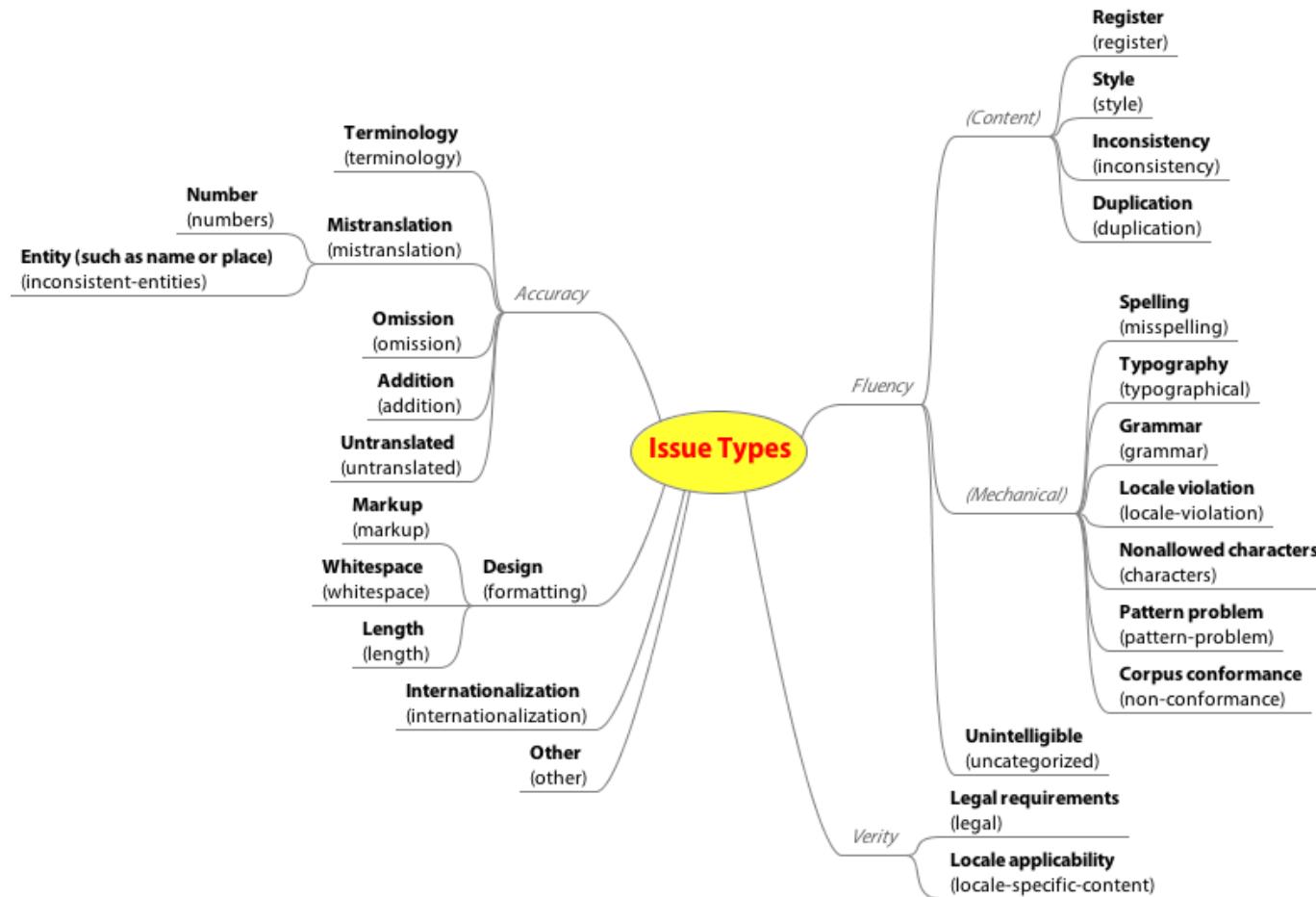
Human Evaluation: Diagnostic

- Error classification MQM mapping to SAE J2450 (Lommel et al. 2013):



Human Evaluation: Diagnostic

- Error classification MQM mapping to ITS 2.0 (Lommel et al. 2013):



Human Evaluation

We have seen quite a few variants

- Fluency/Adequacy (with score on Likert scale): **scoring**
 - Complex, high granularity, inter- and intra-rater agreement, time consuming
- Simple **ranking**: better, worse, same
 - Easier, faster, but still very time consuming
- Many data points and statistics needed: “direct assessment”

Don't know what's wrong! Diagnostic evaluation:

- **Error typology/annotation**: Vilar et al. 2006, MQM, DQF, ..
 - Time consuming, expensive, low rater agreement ...

Human Evaluation

We have seen quite a few variants

- Fluency/Adequacy (with **score** on Likert scale)
- Simple **ranking**: better, worse, same ... and from the pairwise rankings we can compute overall rankings (= scores)
- Error annotation: Vilar et al. 2006, MQM, DQF, ..

- Can you think about another way/dimension?

Human Evaluation

We have seen quite a few variants

- Fluency/Adequacy (with **score** on Likert scale)
- Simple **ranking**: better, worse, same ... and from the pairwise rankings we can compute overall rankings (= scores)
- Error annotation: Vilar et al. 2006, MQM, DQF, ..

- Can you think about another way/dimension?

- **Intrinsic** vs. **extrinsic** evaluation (**extrinsic** = task-based)

Human Evaluation: Extrinsic

- Intrinsic vs. extrinsic evaluation (task-based)
- Extrinsic evaluation: “external” task
- Given two MT systems A and B, the better one is the one that e.g. requires less human post-editing (correction) to eliminate mistakes and produce a good translation ...
- Extrinsic Task: translation and post-editing
- Better = less time = less effort = less cost ...
- Other possible extrinsic tasks: e.g. answer questions from the translation, ... many others possible

Human Evaluation:

- Scoring – ranking, diagnostic, ..., intrinsic – extrinsic etc.
- Time consuming
- Expensive
- Difficult to define and operationalise
- Hard to reproduce: low inter- and intra-rater agreement
- Hard to scale: though see crowd-sourcing (Chris Callison-Burch papers, [Yvette Graham et al. papers on Direct Assessment](#))

- Still: human eval. indispensable and the yardstick
- All “serious” MT shared tasks/competitions (such as WMT, IWSLT, NIST, ...) do a human evaluation track

- and, of course, they also do **automatic evaluation** ...

Automatic Evaluation

- The basic idea:
 - Given a human professional **reference translation** (or **several reference translations**), compare MT output against **this**
 - How?
 - How similar are they?
-
- Word-, n-gram-, character-, **string-overlap** (surface similarity ...)
 - **F-measure**, **BLEU**, ..., **chrF3**, ...
 - More sophisticated stuff (not just surface string matching based)
 - Stemming, morphological analysis, synonyms, paraphrases, syntactic and semantic structure, etc. **METEOR**
 - There are also **edit-distance** based metrics: **TER**, **characTER**, ...
 - Neural methods: **ReVaL**, ...

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: Israeli officials responsibility of airport safety

Automatic Evaluation: F-Measure

Reference: **Israeli officials** are responsible for **airport** security
System A: **Israeli officials** responsibility of **airport** safety

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: Israeli officials responsibility of airport safety

- Word overlap: precision, recall and f-measure
- Precision: how many words in MT output are correct (in ref)?
- Recall: how many of the words in reference are in the MT output?
- F-measure: harmonic mean of precision and recall

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: Israeli officials responsibility of airport safety

- Word overlap: precision, recall and f-measure
- Precision: how many of the words in output are correct (in ref)?

$$\frac{\text{\# correct words in output}}{\text{\# total words in output}} = \frac{3}{6} = 0.5$$

- Recall: how many of the words in reference are in the output?

$$\frac{\text{\# correct words in output}}{\text{\# total words in reference}} = \frac{3}{7} = 0.43$$

- F-measure: harmonic mean of precision and recall

$$f_score = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = 0.46$$

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: Israeli

- Why not precision alone?

Automatic Evaluation: F-Measure

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System A: Israeli

- Why not precision alone?
- Precision: how many of the words in output are correct (in ref)?

$$\frac{\# \text{ correct words in output}}{\# \text{ total words in output}} = \frac{1}{1} = 1$$

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: Israeli

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$$f_score = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = 0.25$$

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: “dump of all the words in MT vocabulary/lexicon ...”

- Why not recall alone?

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: “dump of all the words in MT vocabulary/lexicon ...”

- Why not recall alone?
- Recall: how many of the words in reference are in the output?

$$\frac{\text{\# correct words in output}}{\text{\# total words in reference}} = \frac{7}{7} = 1$$

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security
System A: “dump of all the words in its vocabulary/lexicon ...”

- Why not recall alone?

- Recall: how many of the words in reference are in the output?
$$\frac{\text{\# correct words in output}}{\text{\# total words in reference}} = \frac{7}{7} = 1$$

- Precision: how many of the words in output are correct?
$$\frac{\text{\# correct words in output}}{\text{\# total words in output}} = \frac{7}{50,000}$$

Automatic Evaluation: F-Measure

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System A: “dump of all the words in its vocabulary/lexicon ...”

- Why not recall alone?
- Recall: how many of the words in reference are in the output?

$$\frac{\text{\# correct words in output}}{\text{\# total words in reference}} = \frac{7}{7} = 1$$

- Precision: how many of the words in output are correct?

$$\frac{\text{\# correct words in output}}{\text{\# total words in output}} = \frac{7}{50,000}$$

- F-score: harmonic mean of precision and recall

$$f_score = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \approx 0.00006$$

Precision, Recall, F-Score, Accuracy ...

		Predictions	
		true	false
Ground Truth	true	<i>tp</i>	<i>fn</i>
	false	<i>fp</i>	<i>tn</i>

$$P = \frac{tp}{tp + fp}$$

$$R = \frac{tp}{tp + fn}$$

$$F = \frac{2 \times P \times R}{P + R}$$

$$Acc = \frac{tp + tn}{tp + tn + fp + fn}$$

Automatic Evaluation: F-Measure

-
- Reference: Israeli officials are responsible for airport security
- System A: Israeli officials responsibility of airport safety
- System B: airport security Israeli officials are responsible
- System C: security Israeli are officials responsible airport

Automatic Evaluation: F-Measure

- Reference: Israeli officials are responsible for airport security
- System A: Israeli officials responsibility of airport safety
- System B: airport security Israeli officials are responsible
- System C: security Israeli are officials responsible airport

	System A	System B	System C
precision	0.50	1.00	1.00
recall	0.43	0.86	0.86
f-score	0.46	0.92	0.92

Automatic Evaluation: F-Measure

- Reference: Israeli officials are responsible for airport security
- System A: Israeli officials responsibility of airport safety
- System B: airport security Israeli officials are responsible
- System C: security Israeli are officials responsible airport

	System A	System B	System C
precision	0.50	1.00	1.00
recall	0.43	0.86	0.86
f-score	0.46	0.92	0.92

- Problem: f-measure can reward unintelligible word salad in C if individual words are O.K. ...
- Fails to reflect What?

Automatic Evaluation: F-Measure

Reference: Israeli officials are responsible for airport security

System A: Israeli officials responsibility of airport safety

System B: airport security Israeli officials are responsible

System C: security Israeli are officials responsible airport

	System A	System B	System C
precision	0.50	1.00	1.00
recall	0.43	0.86	0.86
f-score	0.46	0.92	0.92

- Problem: f-measure can reward unintelligible word salad in C if individual words are O.K. ...
- Fails to reflect word order !!!

Automatic Evaluation: BLEU

Reference: Israeli officials are responsible for airport security

System A: Israeli officials responsibility of airport safety

System B: airport security Israeli officials are responsible

System C: security Israeli are officials responsible airport

- Look at n-gram overlap, not just word overlap

Automatic Evaluation: BLEU

Reference:	Israeli officials are responsible for airport security
System A:	Israeli officials responsibility of airport safety
System B:	airport security Israeli officials are responsible
System C:	security Israeli are officials responsible airport

- Look at **n-gram overlap**, not just word overlap
- **n-gram precision** ($n = 1 \dots 4$) times a brevity penalty (“recall”)

$$BLEU := \min(1, \exp(1 - \frac{|reference|}{|output|})) \left(\prod_{n=1}^4 n - gram\ precision \right)^{\frac{1}{4}}$$

- $BLEU = 0$ if the hypothesis does not have **at least one** matching n-gram for any one of the $n = 1 \dots 4$: systems A and C!

Automatic Evaluation: BLEU

- Reference: Israeli officials are responsible for airport security
- System A: Israeli officials responsibility of airport safety
- System B: airport security Israeli officials are responsible
- System C: security Israeli are officials responsible airport

$$BLEU := \min(1, \exp\left(1 - \frac{|reference|}{|output|}\right)) \left(\prod_{n=1}^4 n - gram\ precision\right)^{\frac{1}{4}}$$

$$\left(\prod_{n=1}^4 n - gram\ precision\right)^{\frac{1}{4}} = \left(\frac{6}{6} \times \frac{4}{5} \times \frac{2}{4} \times \frac{1}{3}\right)^{\frac{1}{4}} = 0.1333^{\frac{1}{4}} = 0.60$$

$$\min\left(1, \exp\left(1 - \frac{|reference|}{|output|}\right)\right) = \min\left(1, \exp\left(1 - \frac{7}{6}\right)\right) = 0.87$$

$$BLEU_B = 0.87 \times 0.60 = 0.52$$

Automatic Evaluation: BLEU

Reference: Israeli officials are responsible for airport security

System A: Israeli officials responsibility of airport safety

System B: airport security Israeli officials are responsible

System C: security Israeli are officials responsible airport

	System A	System B	System C
f-score	0.46	0.92	0.92
BLEU	0	0.52	0

- Problem: BLEU assigns 0 to many hypotheses ...
- Meant to work on document, not individual sentence, level
- sBLEU for sentence level ... (smoothed BLEU)

Automatic Evaluation: BLEU

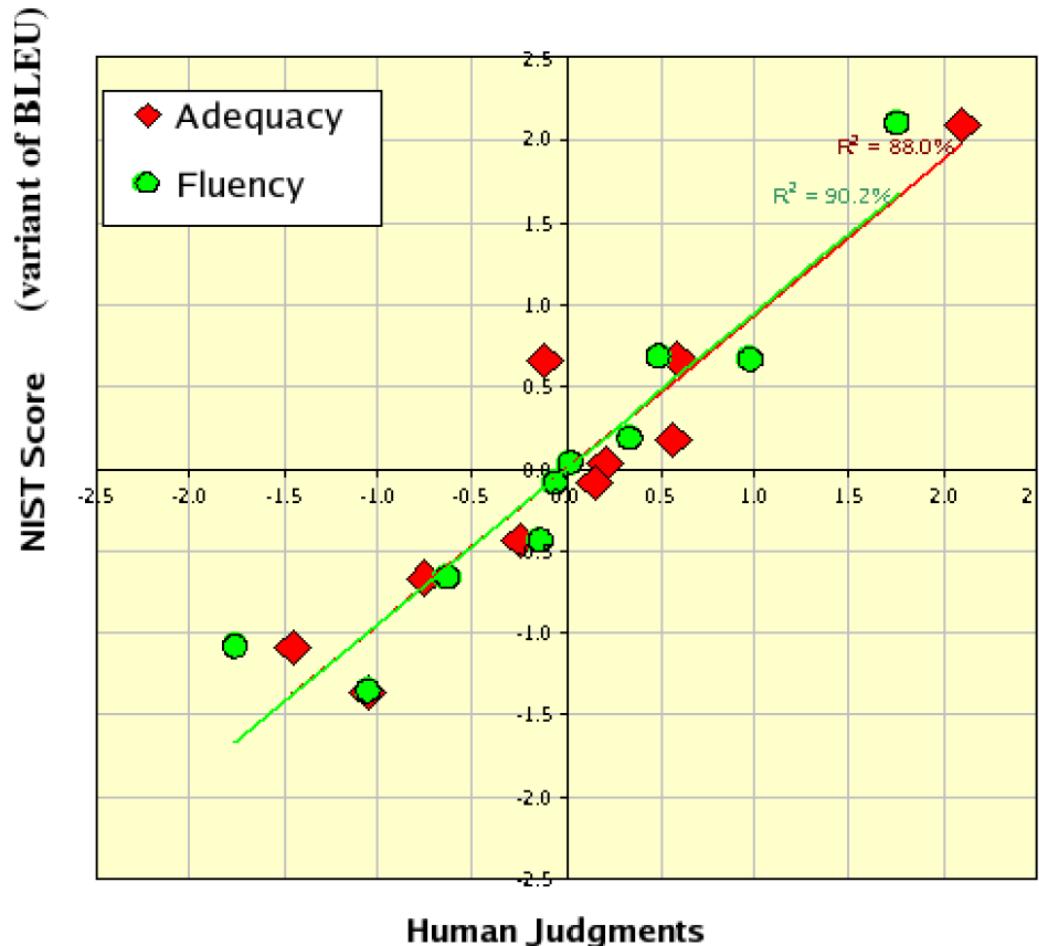
$$BLEU := \min(1, \exp(1 - \frac{|reference|}{|output|})) \left(\prod_{n=1}^4 n - gram\ precision \right)^{\frac{1}{4}}$$

- Fancy way of writing BLEU:

$$BLEU := \min(1, \exp(1 - \frac{|reference|}{|output|})) \left(\exp \left(\sum_{n=1}^4 \lambda_n \times \log(n - gram\ prec) \right) \right)^{\frac{1}{4}}$$

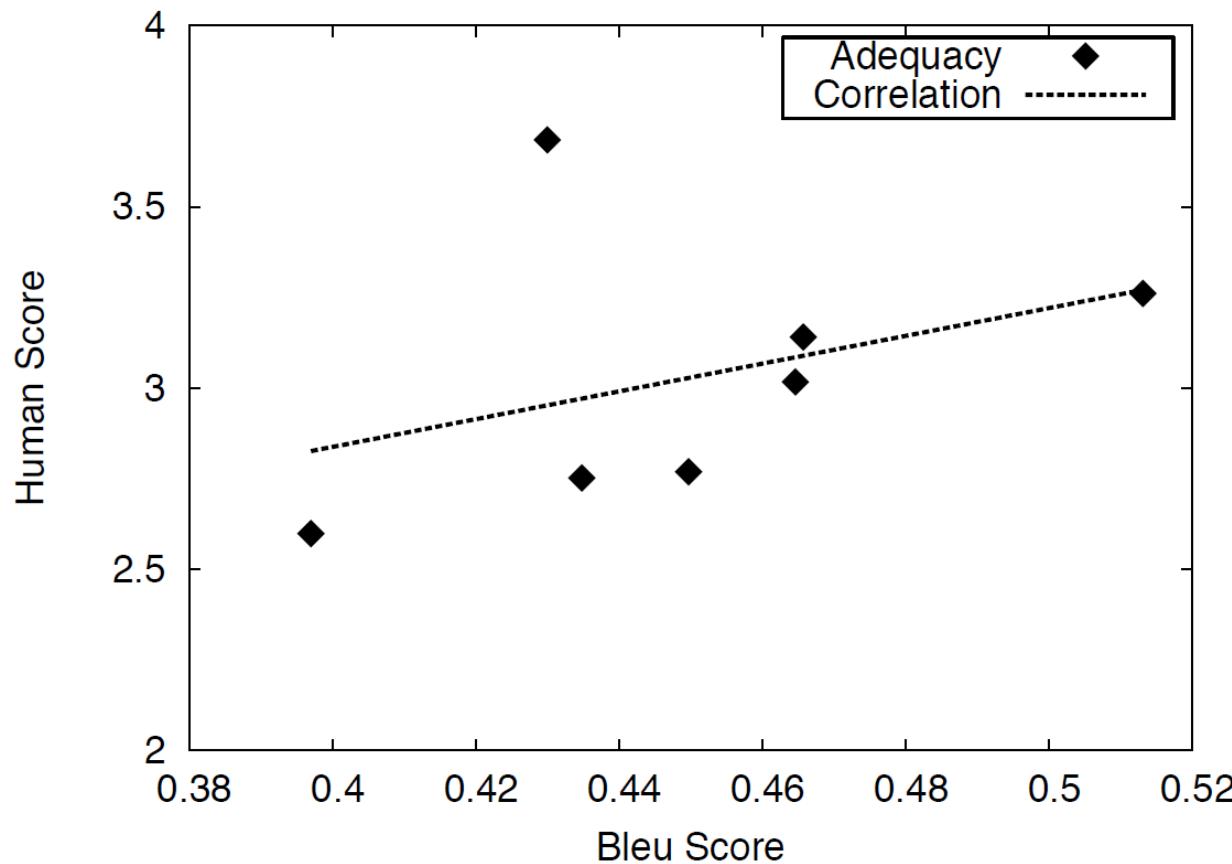
- Taking log of n-gram prec, summing over them and using inverse function of log: e ...
- λ_i usually 1...

Correlation with Human Judgement



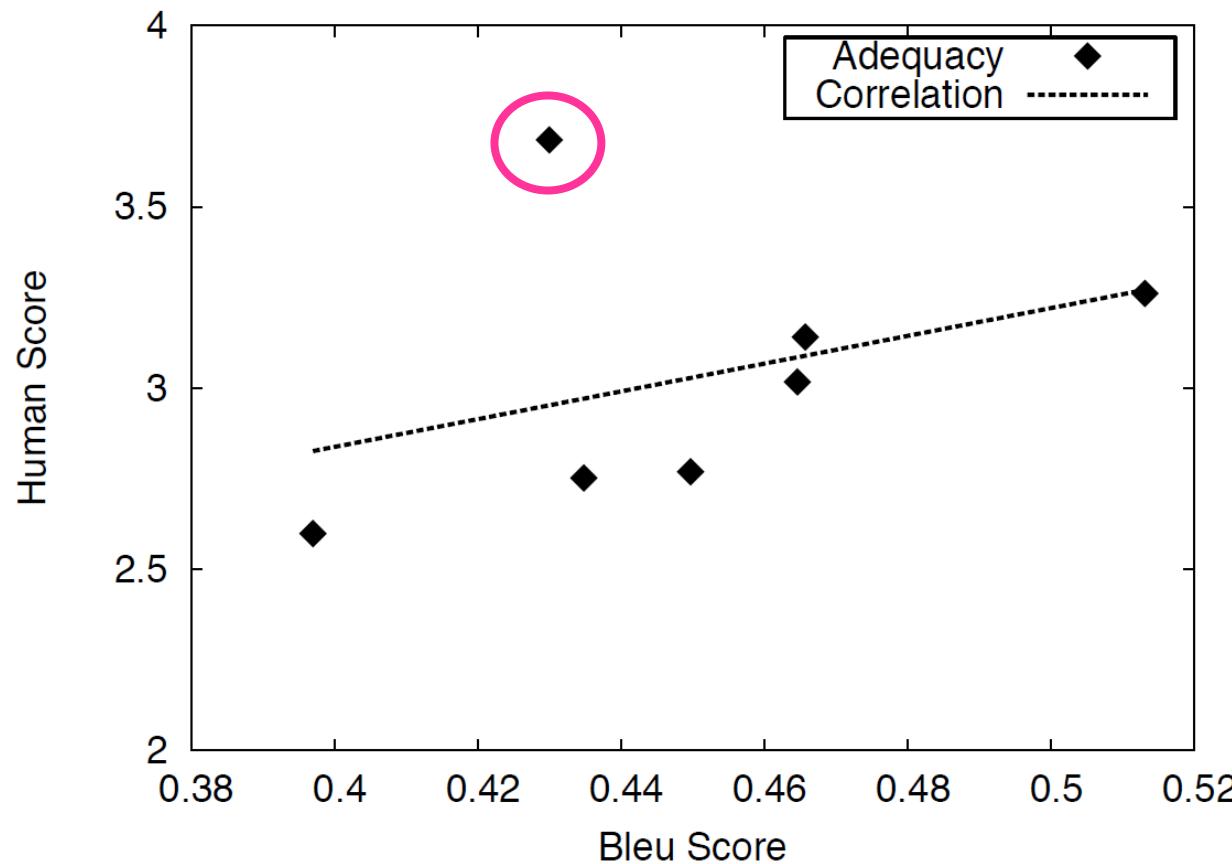
Evidence of Shortcomings of Automatic Metrics

Post-edited output vs. statistical systems (NIST 2005)



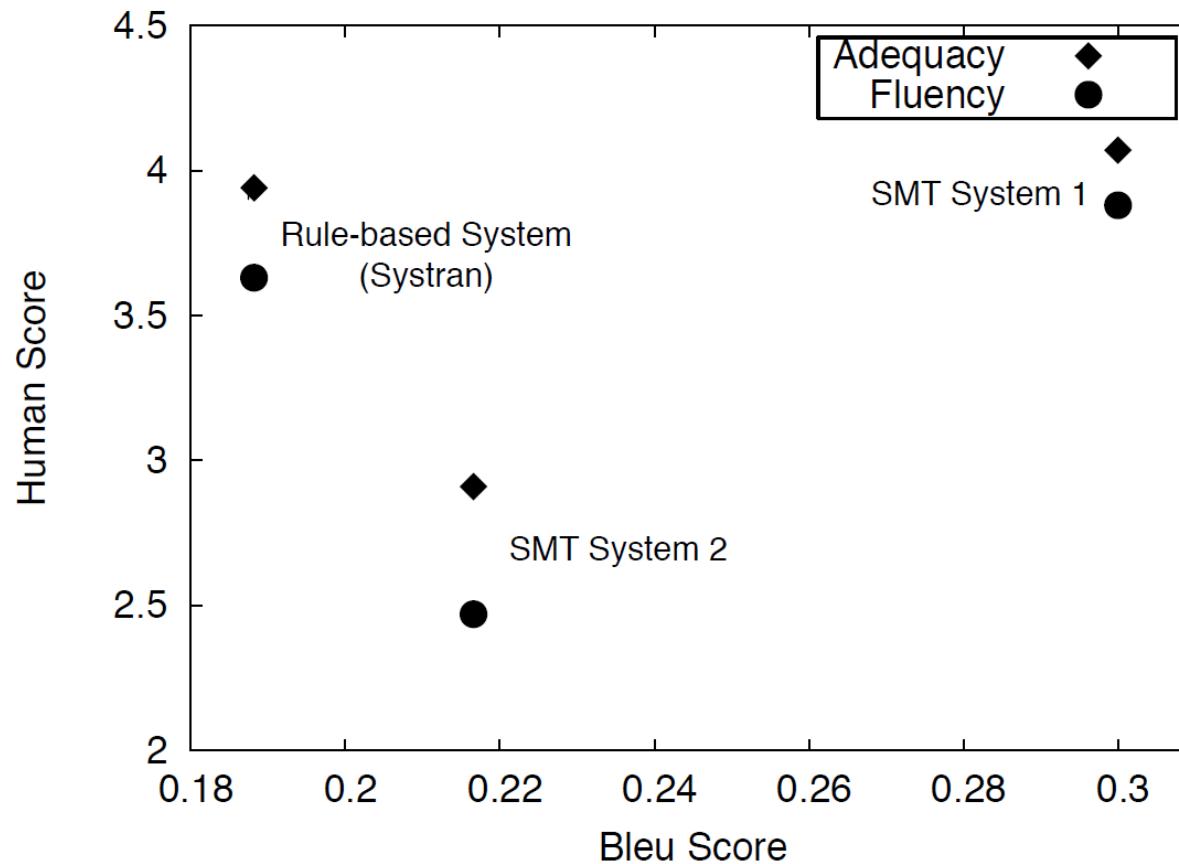
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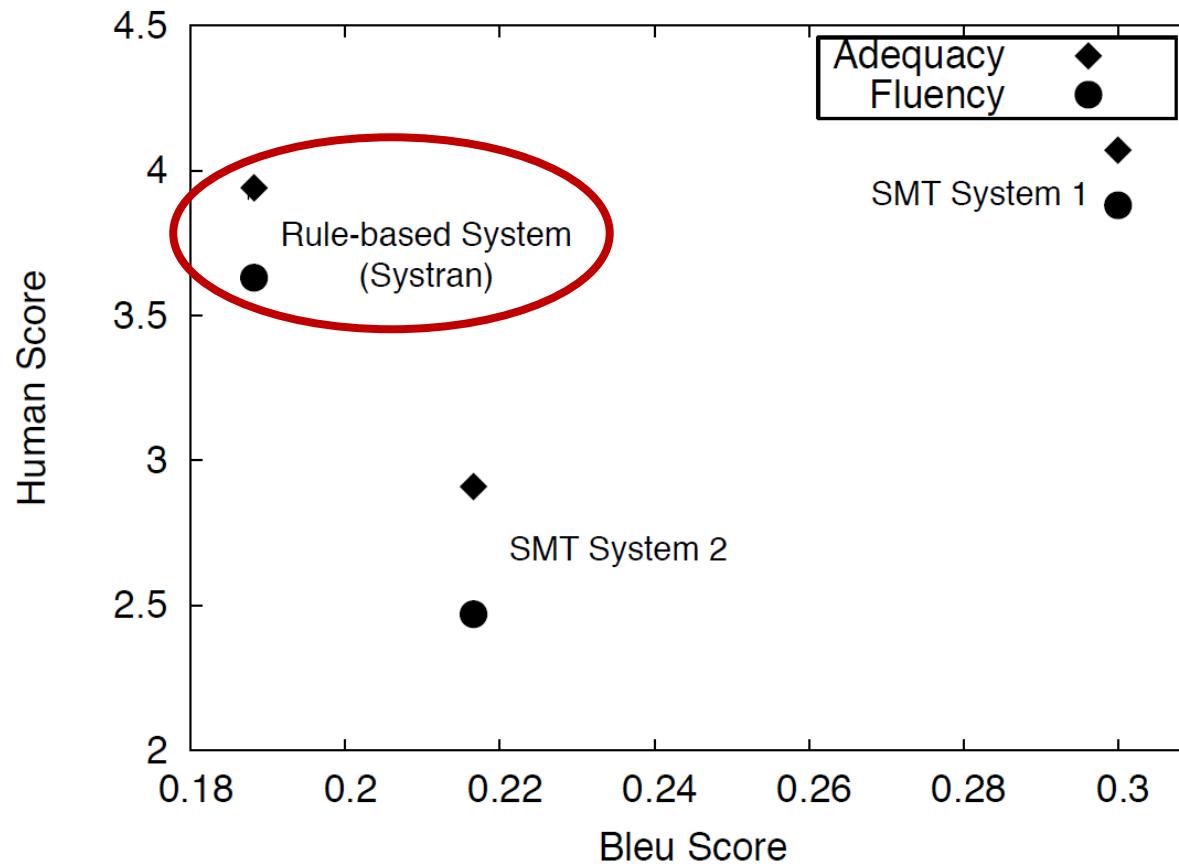
Evidence of Shortcomings of Automatic Metrics

Rule-based vs. statistical systems



Evidence of Shortcomings of Automatic Metrics

Rule-based vs. statistical systems



String-based Automatic MT Evaluation Metrics

- Consistent
- Treat all words as strings: no difference between function and content words, morphological variants ...
- Do not consider global grammaticality
- Do not consider meaning

*Yesterday John resigned from the company
John quit the company yesterday*

- Punishes perfect paraphrases
- Scores by themselves do not mean much
- Don't tell you what is wrong ...
- Human translators often score fairly low on BLEU

Automatic MT Evaluation Metrics

- But: we could in principle use many references ... expensive again ...
- BLEU (n-gram), METEOR (stemming, paraphrases), TER (edit-distance based), dependency-based MT evaluation measures (Karolina Owczarzak), MEANT, chrF3 character- rather than word-token based measures (Maja Popovich), BEER (trainable), neural MT evaluation measures like ReVal (Rohit Gupta et al.), based on recursive neural networks, ... a very active area of research: YiSi-1/2, BERTscore
- Quality Estimation (QE, as opposed to MT evaluation): estimate/predict quality (BLEU/TER scores, post-editing effort) without reference ... !!! (papers by Lucia Specia a good starting point): Lucia Specia, Carolina Scarton, Gustavo Paetzold. “Quality Estimation for Machine Translation”. Synthesis Lectures on Human Language Technologies September 2018

Human Evaluation:

- Time Consuming
- Expensive
- Difficult to define and operationalise
- Hard to reproduce: inter-rater agreement
- Hard to scale: though see crowd-sourcing (Chris Callison-Burch papers) and (Yvette Graham's papers on [Direct Assessment](#), which is used pretty much as standard for human crowd eval)
- Still: indispensable and the yardstick
- All “serious” MT shared tasks/competitions (such as WMT, IWSLT, NIST, ...) do a human evaluation track
- and, of course, they also do automatic evaluation: [BLEU](#), [TER](#), [Meteor](#) ([chrF3](#), [character](#), [Beer](#), ...)
- [WMT Metrics Matter](#) shared task

Some References to Start Out in MT Evaluation

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Precision, Recall, F-Score, Accuracy ...

		Predictions	
		true	false
Ground Truth	true	tp	fn
	false	fd	tn