89688: Statistical Machine Translation

Lecture 2: Evaluation

March 2020

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Computer Science Department
Bar Ilan University

Based in part on slides from Edinburgh University's MT class


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“More has been written about machine translation evaluation than about machine translation itself.”

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Yorick Wilks

Why evaluate?

Why evaluate?

- Rank competing systems

English→German		
Ave.	Ave. z	System
90.3	0.347	Facebook-FAIR
93.0	0.311	Microsoft-WMT19-sent-doc
92.6	0.296	Microsoft-WMT19-doc-level
90.3	0.240	HUMAN
87.6	0.214	MSRA-MADL
88.7	0.213	UCAM
89.6	0.208	NEU
87.5	0.189	MLLP-UPV
87.5	0.130	eTranslation
86.8	0.119	dfki-nmt
84.2	0.094	online-B
86.6	0.094	Microsoft-WMT19-sent-level
87.3	0.081	JHU
84.4	0.077	Helsinki-NLP

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June 8 and 9, 2006

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Why evaluate?

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- Make incremental improvements
  - More data?

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- Rank competing systems
- Make incremental improvements
  - More data?
  - Different preprocessing?

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Why evaluate?

- Rank competing systems
- Make incremental improvements
  - More data?
  - Different preprocessing?
  - Different hyperparameters?

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Why evaluate?

- Rank competing systems
- Make incremental improvements
  - More data?
  - Different preprocessing?
  - Different hyperparameters?
- Evaluate new ideas

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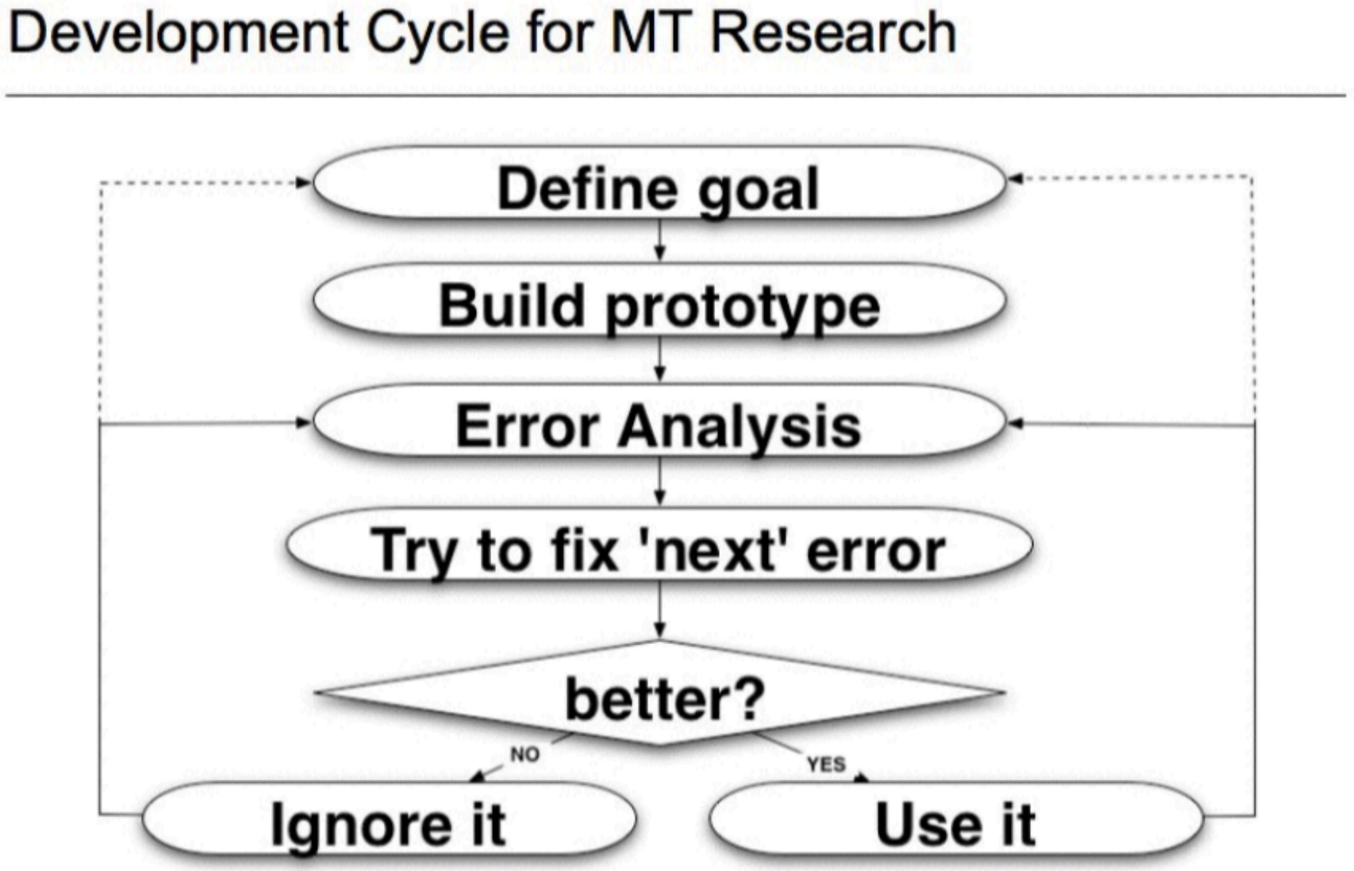
Why evaluate?

Why evaluate?

Evaluation enables progress



What is a good translation?

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What is a good translation?

- Transitions from one language to another

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- Transitions from one language to another
- Preserves the meaning

What is a good translation?

- Transitions from one language to another
- Preserves the meaning
- Fluent?

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- Transitions from one language to another
- Preserves the meaning
- Fluent?
- Preserves style?

What is a good translation?

- Transitions from one language to another
- Preserves the meaning
- Fluent?
- Preserves style?
- What else?

How can we *measure* this?

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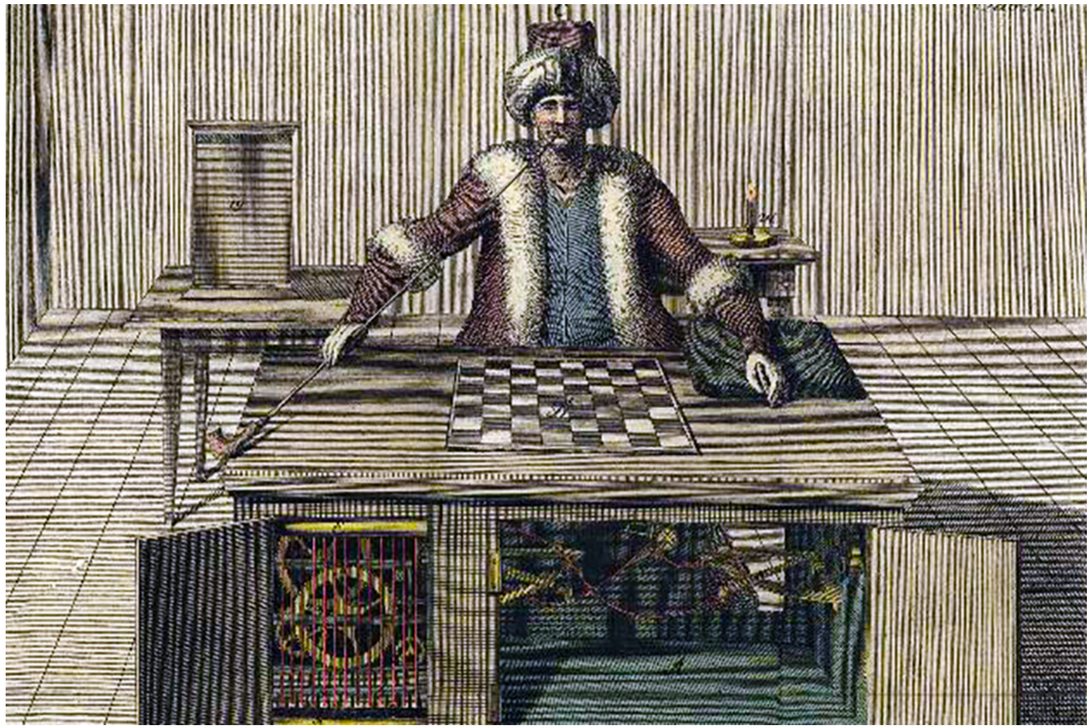

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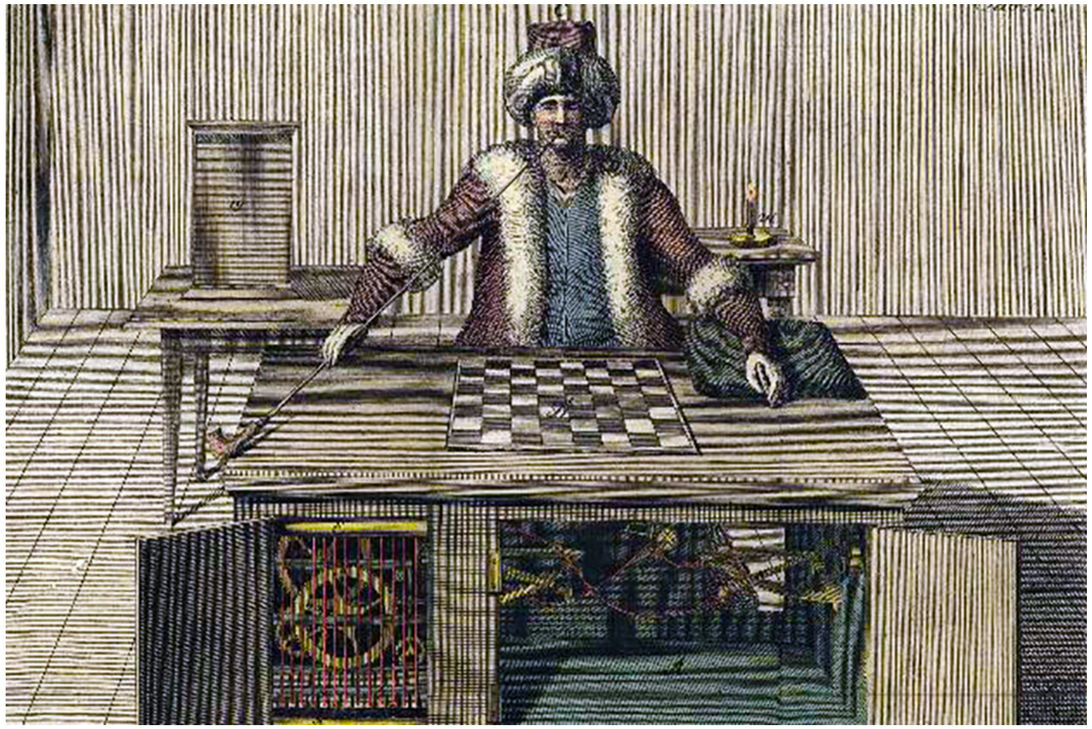

How can we *measure* this?

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	Human	Automatic

How can we *measure* this?

	Human	Automatic
Accurate	Yes	Sometimes…

How can we *measure* this?

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Speed	Slow	Fast

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Subjectivity	Subjective	Objective

How can we *measure* this?

	Human	Automatic
Accurate	Yes	Sometimes…
Speed	Slow	Fast
Price	Expensive	Cheap
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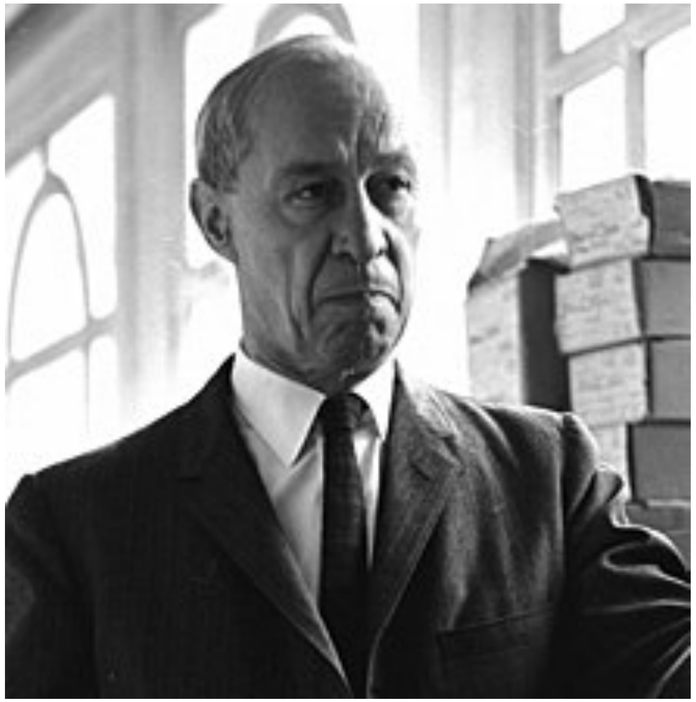
Reproducible	No	Yes

Human Evaluation Methods

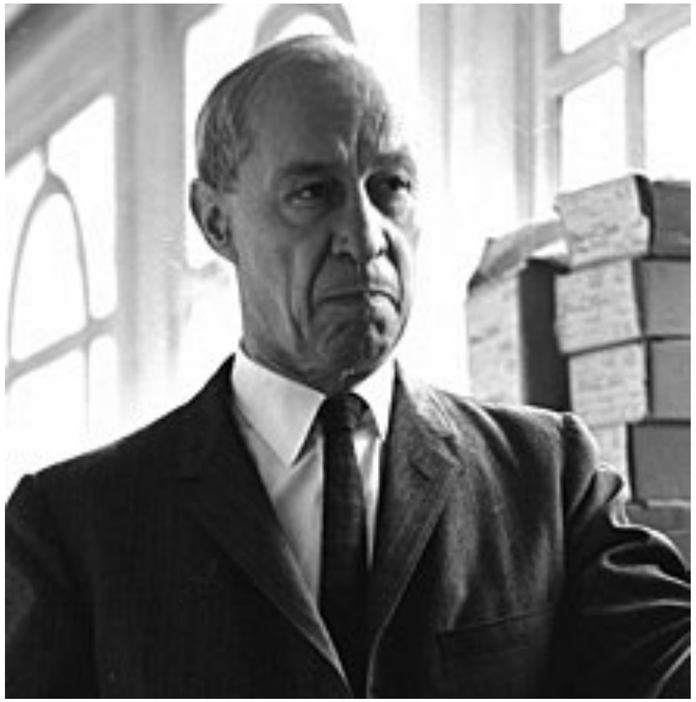
The Likert Scale

The Likert Scale



Rensis Likert

The Likert Scale



Rensis Likert

Website User Survey

1. The website has a user friendly interface.

strongly agree — agree — neutral — disagree — strongly disagree

2. The website is easy to navigate.

strongly agree — agree — neutral — disagree — strongly disagree

3. The website's pages generally have good images.

strongly agree — agree — neutral — disagree — strongly disagree

4. The website allows users to upload pictures easily.

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5. The website has a pleasing color scheme.

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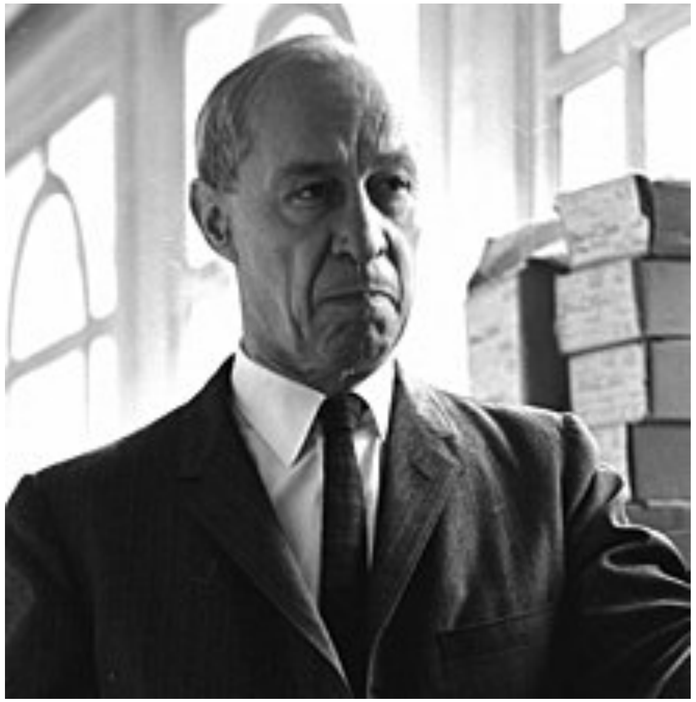
The Likert Scale

- WMT 06’ - WMT 07’



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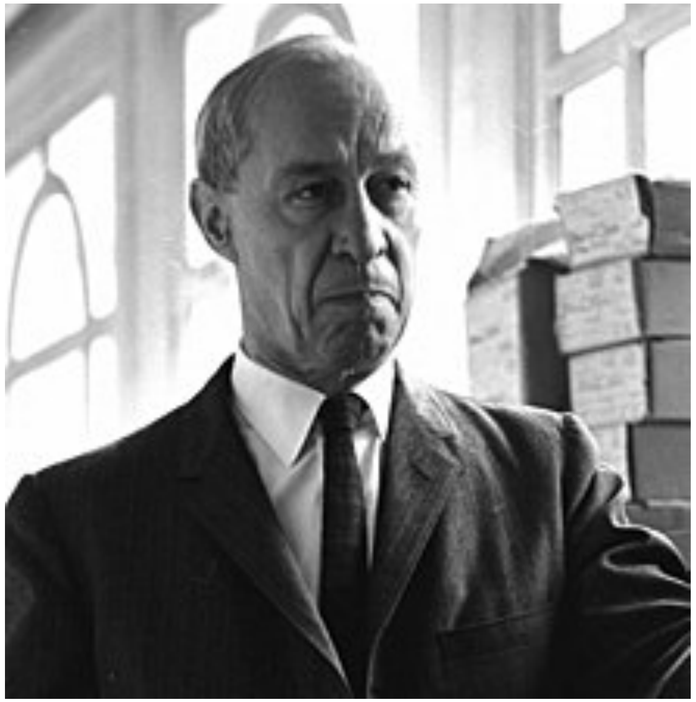

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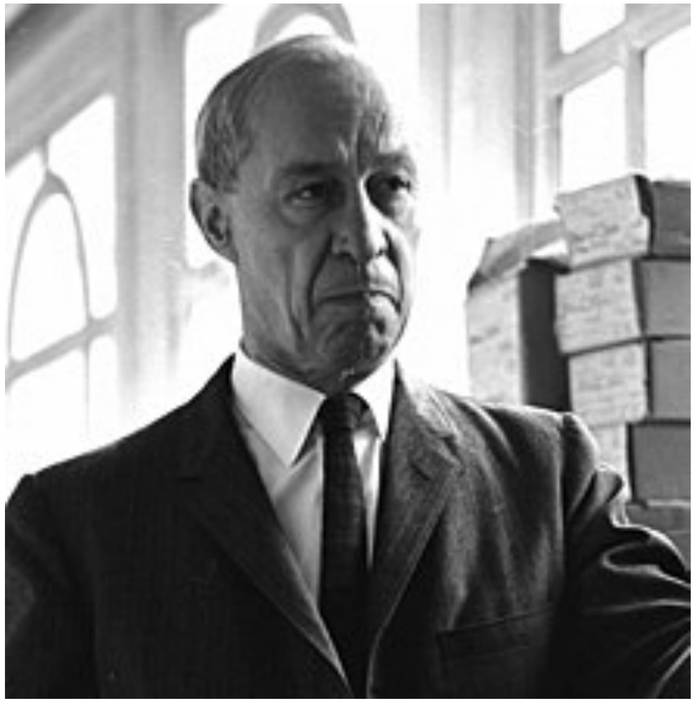

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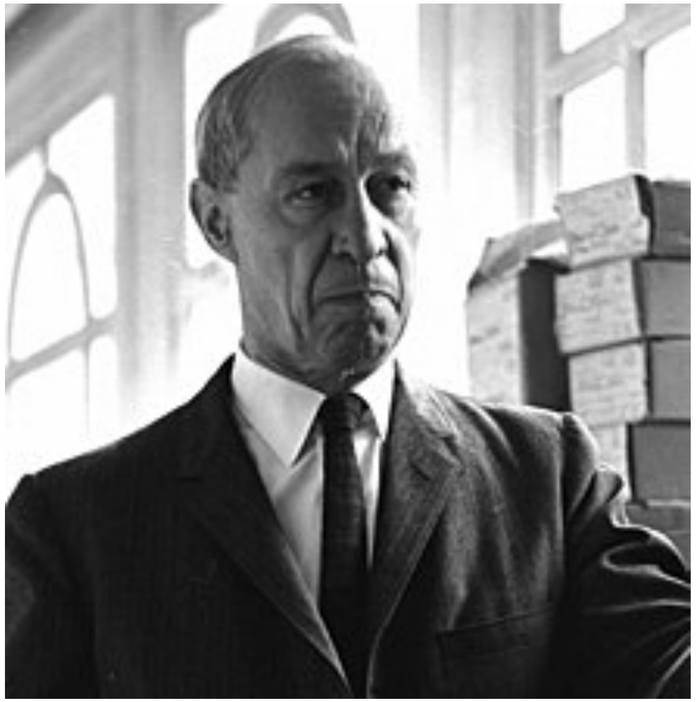

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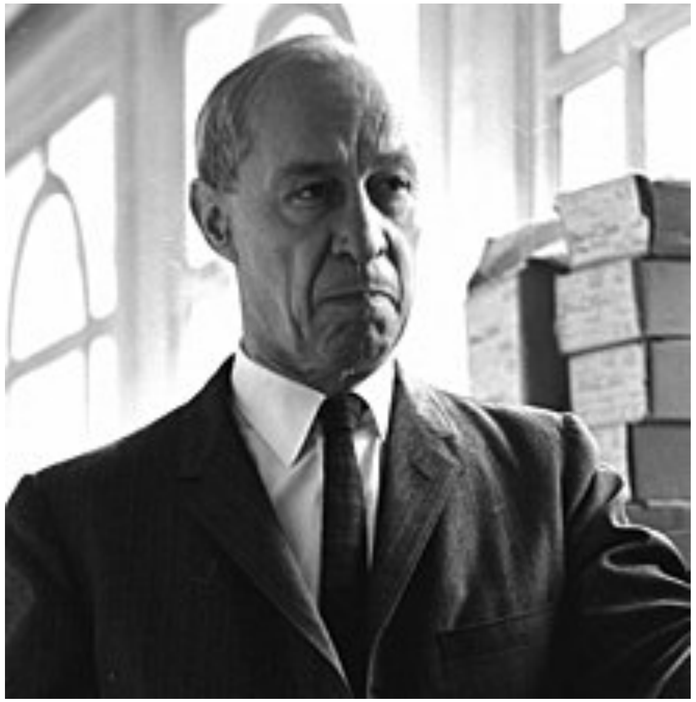

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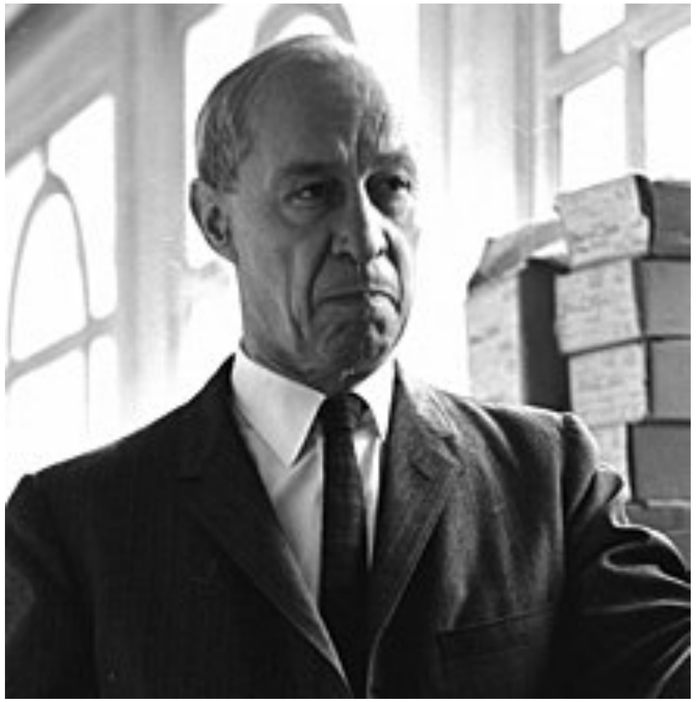

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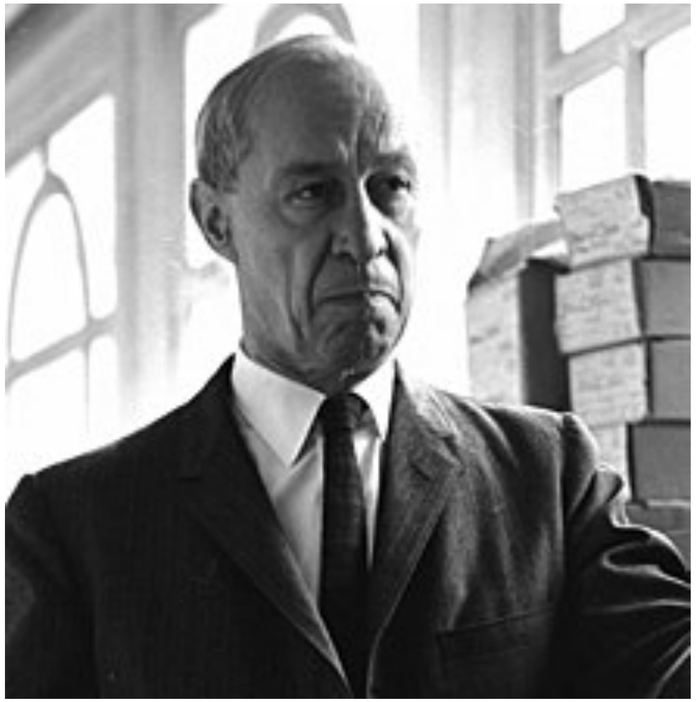

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- WMT 07’-WMT 16’

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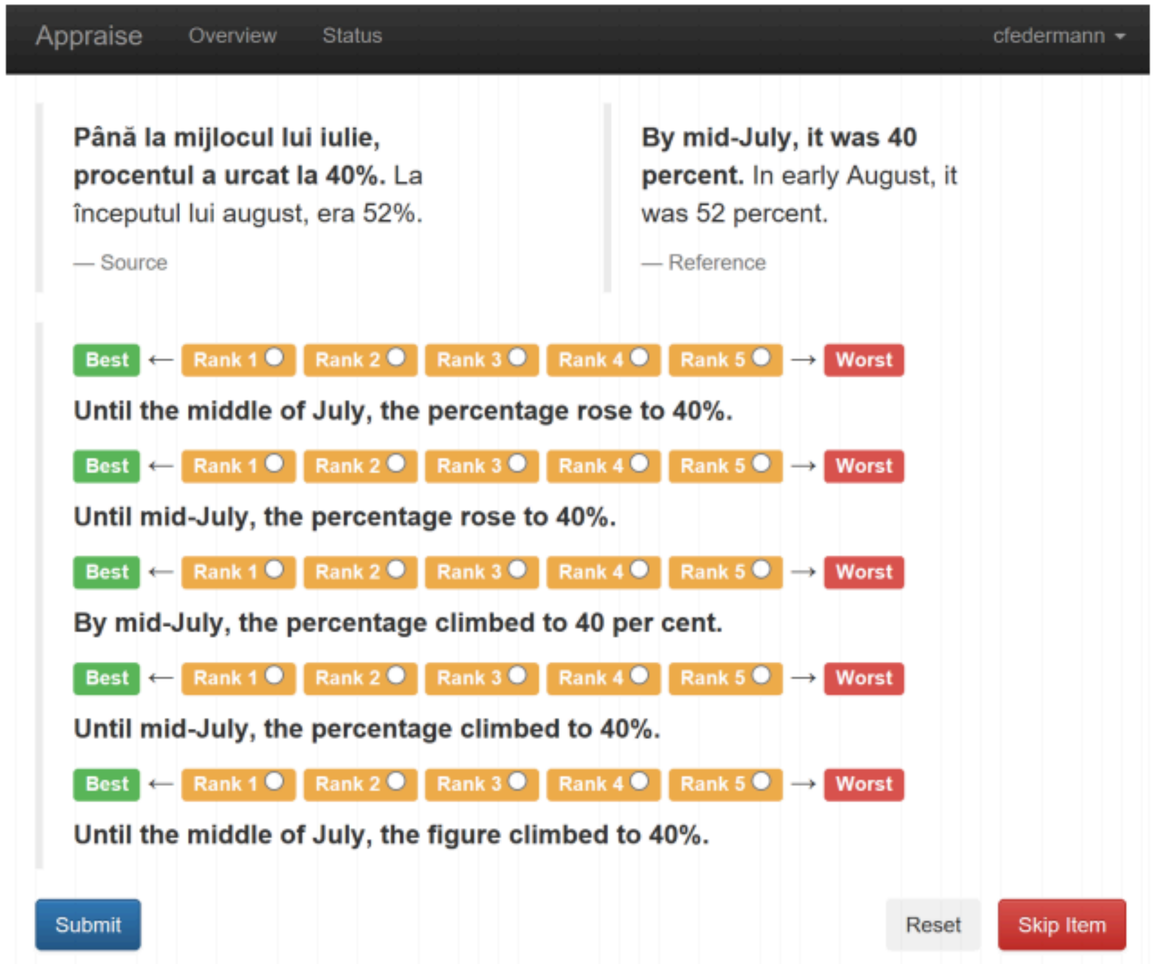
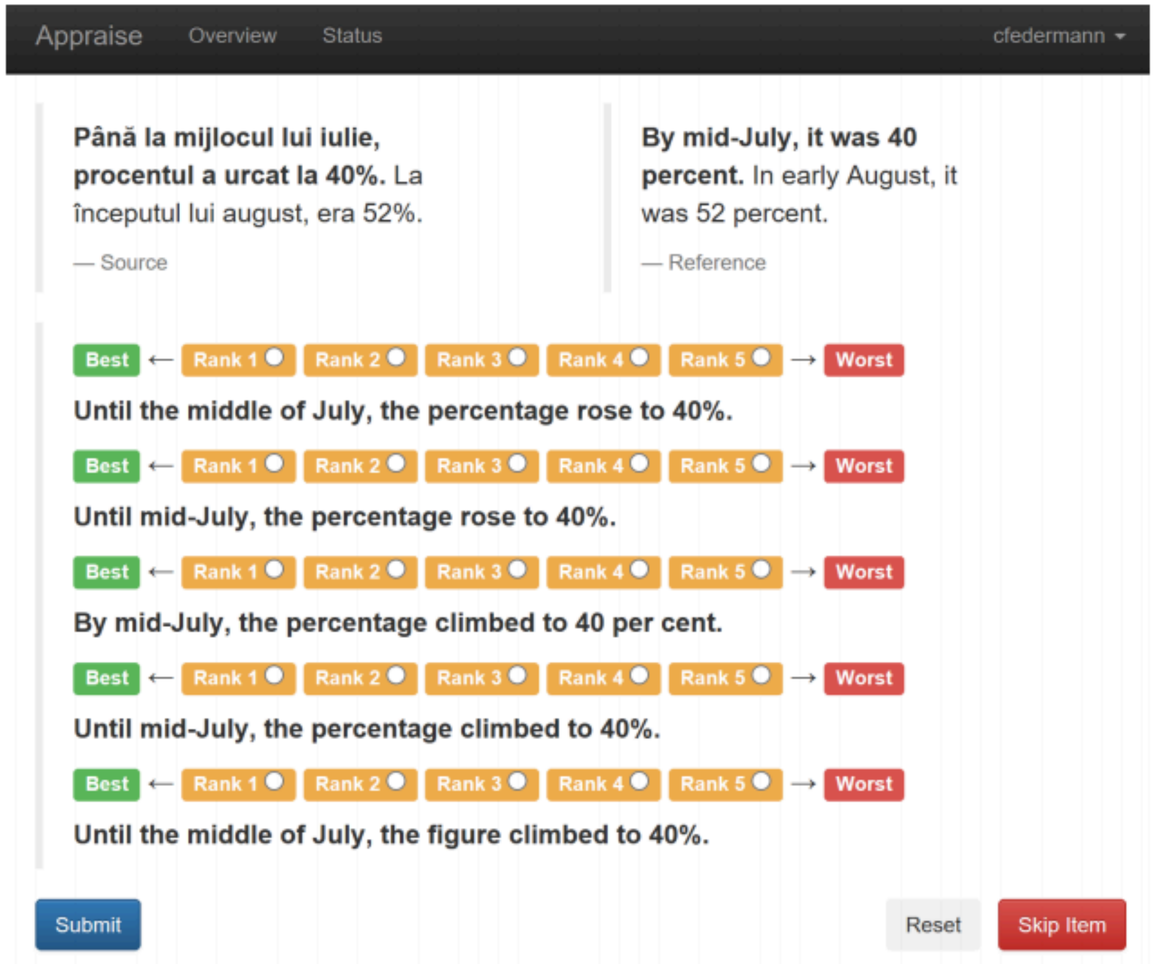
- Each rater ranks 5 systems



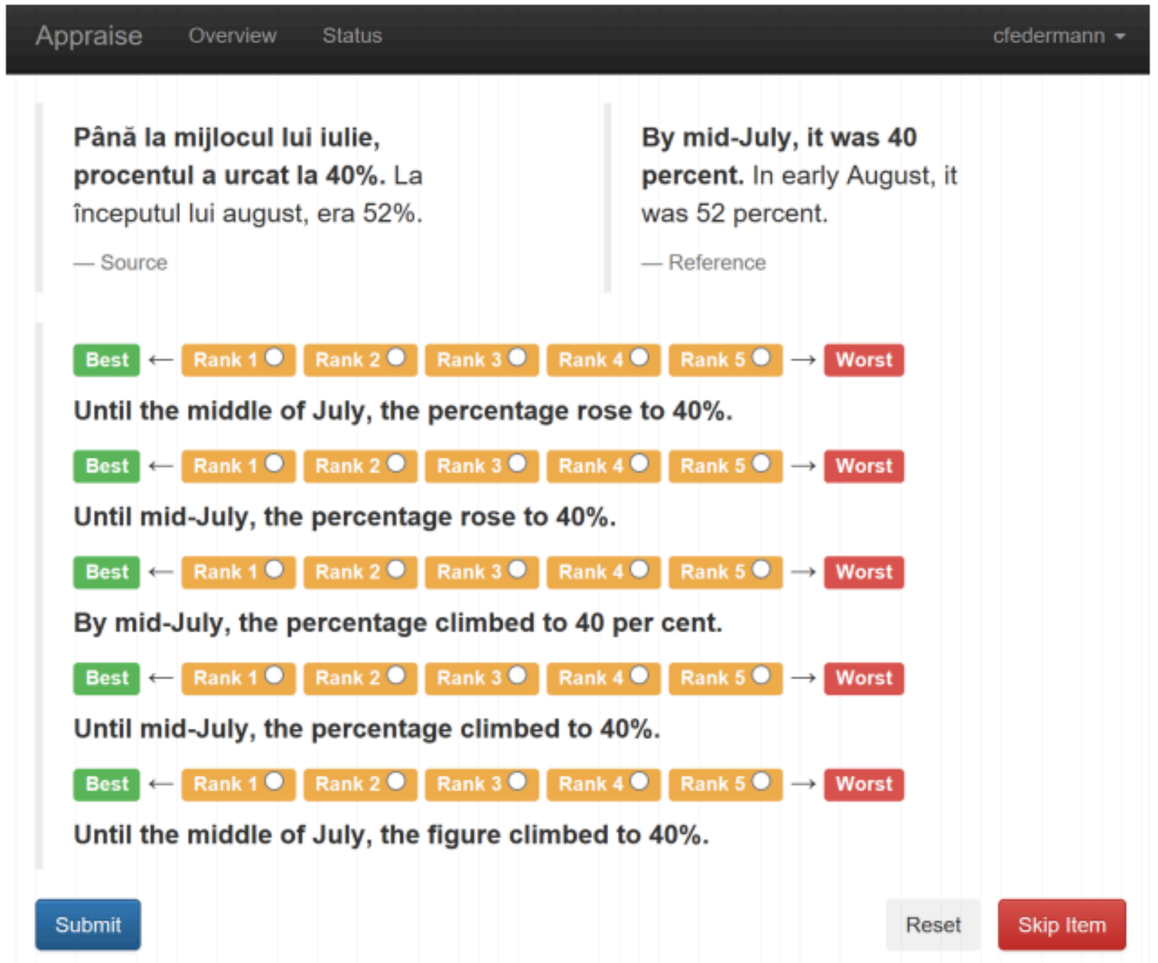
Relative Ranking

- WMT 07’-WMT 16’
- Each rater ranks 5 systems
- Produces pairwise rankings



Relative Ranking

- WMT 07’-WMT 16’
- Each rater ranks 5 systems
- Produces pairwise rankings
- Feed to the TrueSkill (or other) algorithm to obtain final rankings



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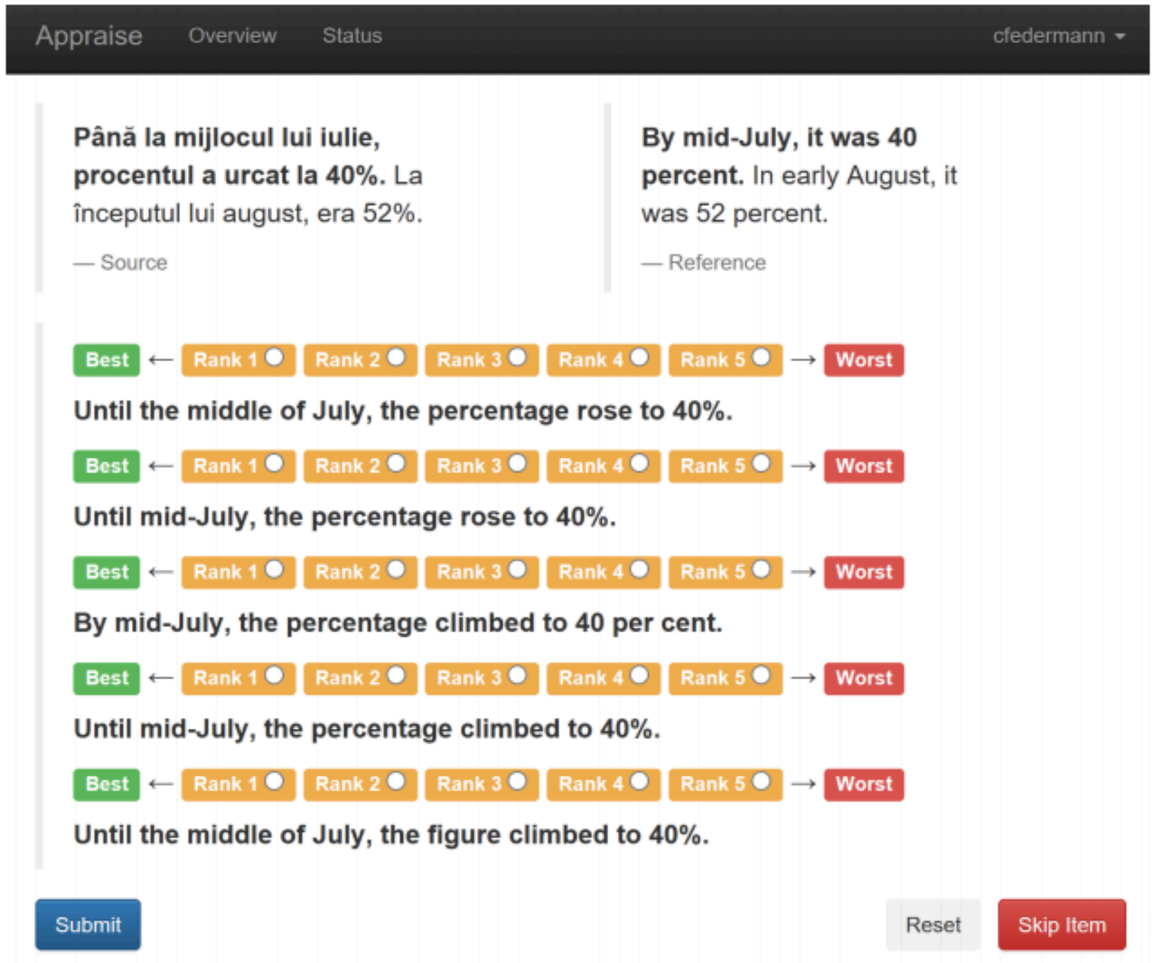

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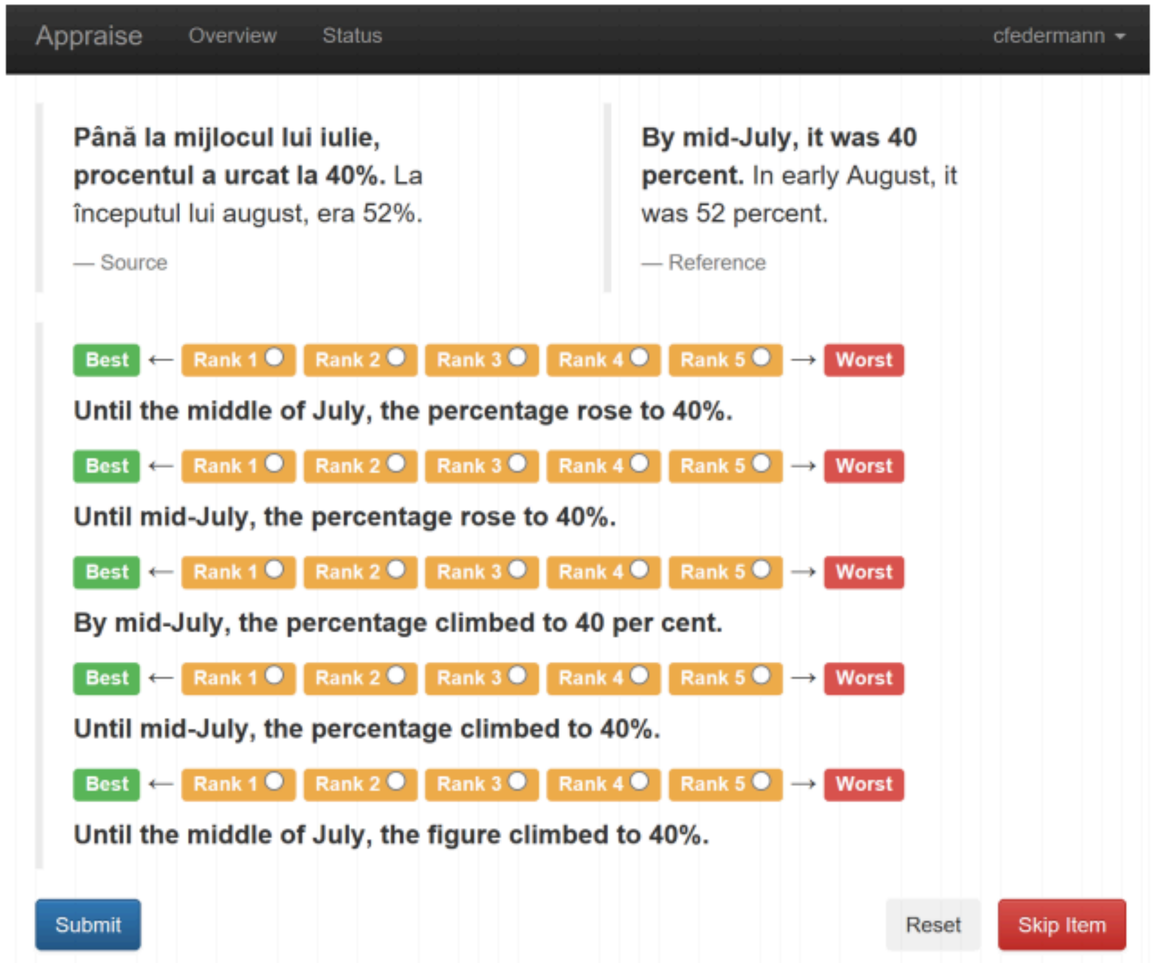

Direct Assessment: Monolingual

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- WMT 16’-WMT 19’

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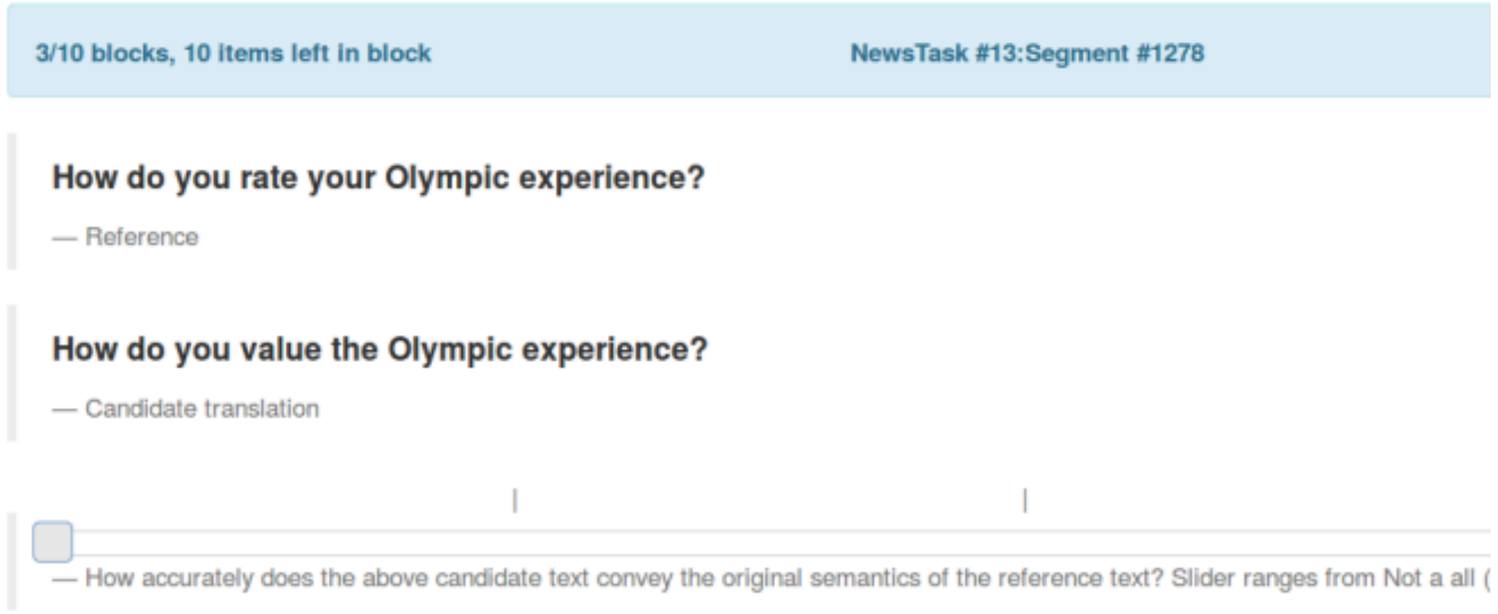
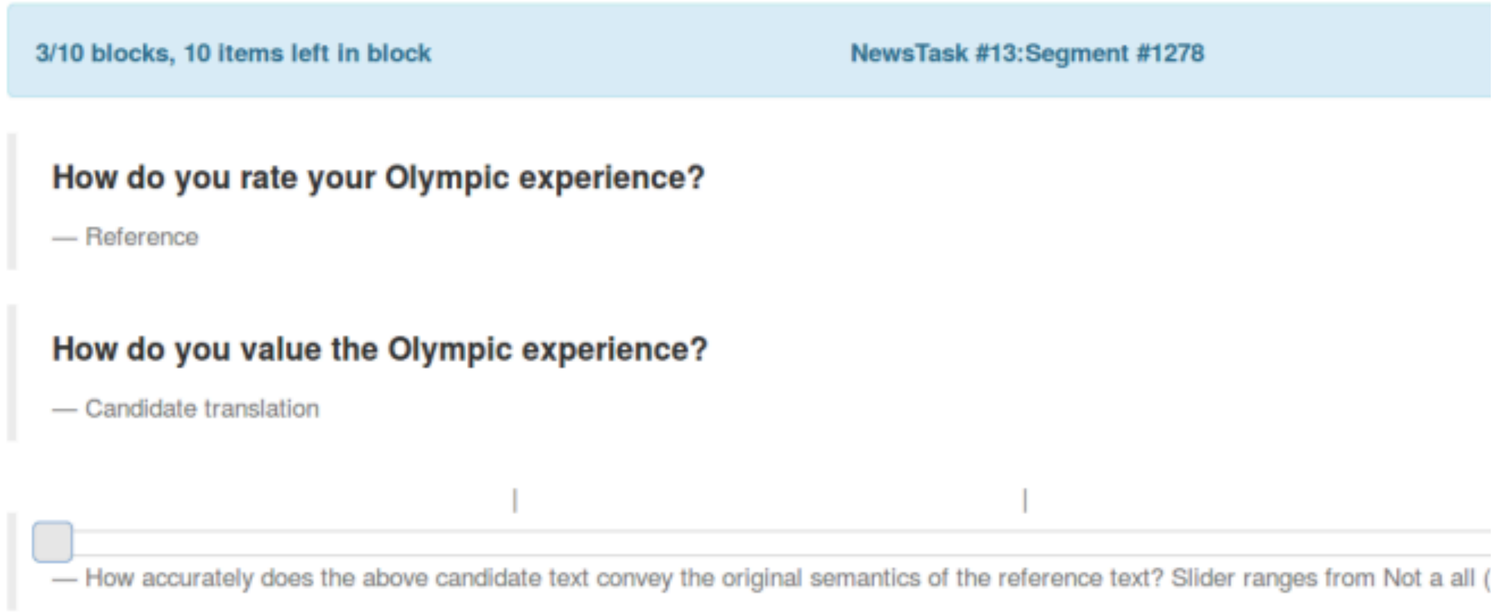
- WMT 16’-WMT 19’



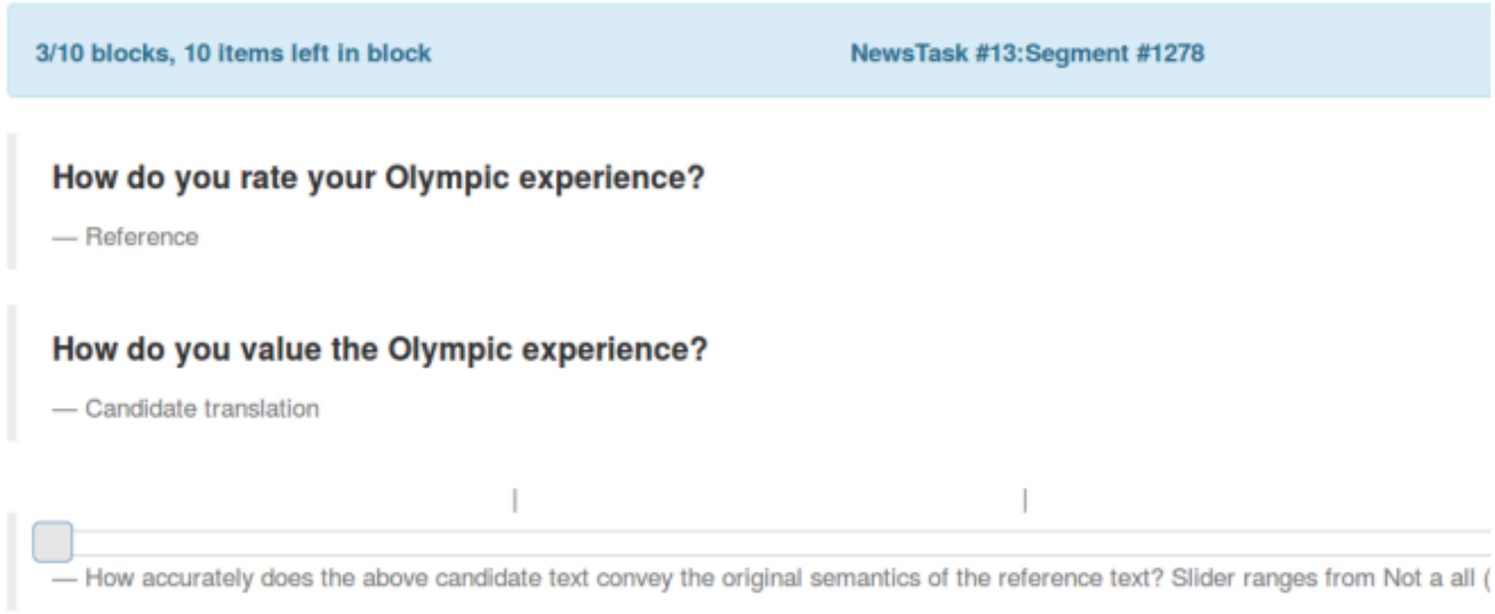
Direct Assessment: Monolingual

- WMT 16’-WMT 19’
- Scores are standardised according to each individual worker’s overall mean and standard deviation



Direct Assessment: Monolingual

- WMT 16’-WMT 19’
- Scores are standardised according to each individual worker’s overall mean and standard deviation
- the overall score of a system is the mean (standardised) score of its translations



Direct Assessment: Monolingual

- WMT 16’-WMT 19’
- Scores are standardised according to each individual worker’s overall mean and standard deviation
- the overall score of a system is the mean (standardised) score of its translations
- Adequacy is main, fluency used to break ties

Direct Assessment: Bilingual

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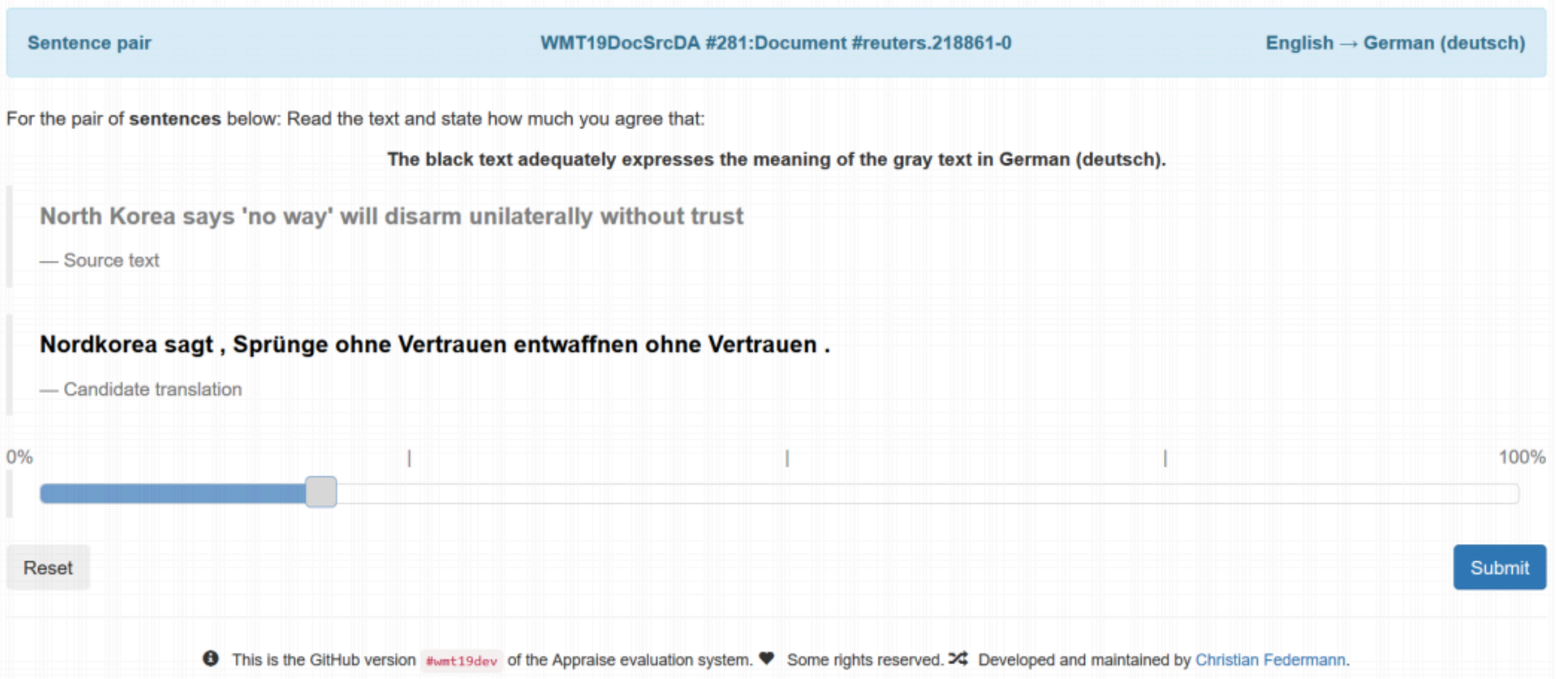
- WMT 18’-WMT 19’

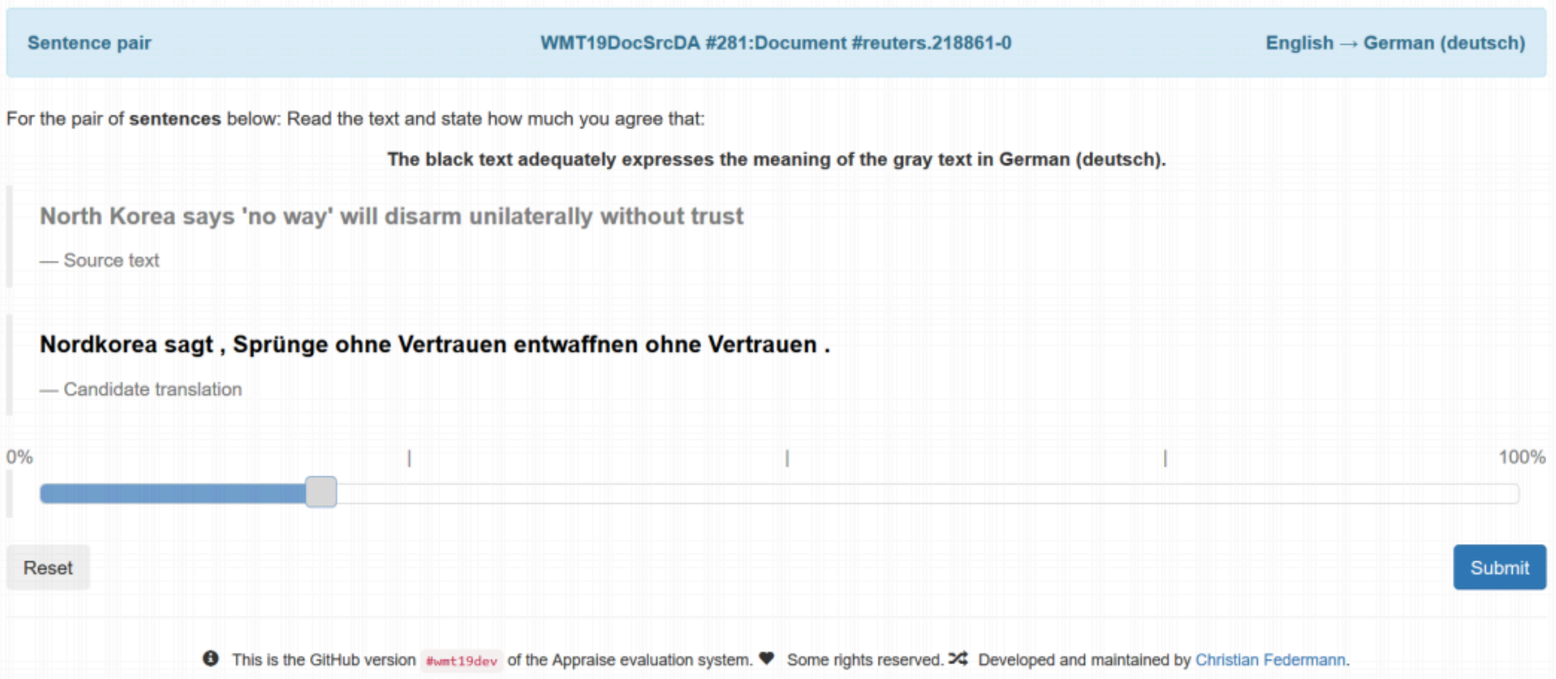
Direct Assessment: Bilingual

- WMT 18’-WMT 19’
- Use a source sentence instead of a reference sentence (“source-based”)



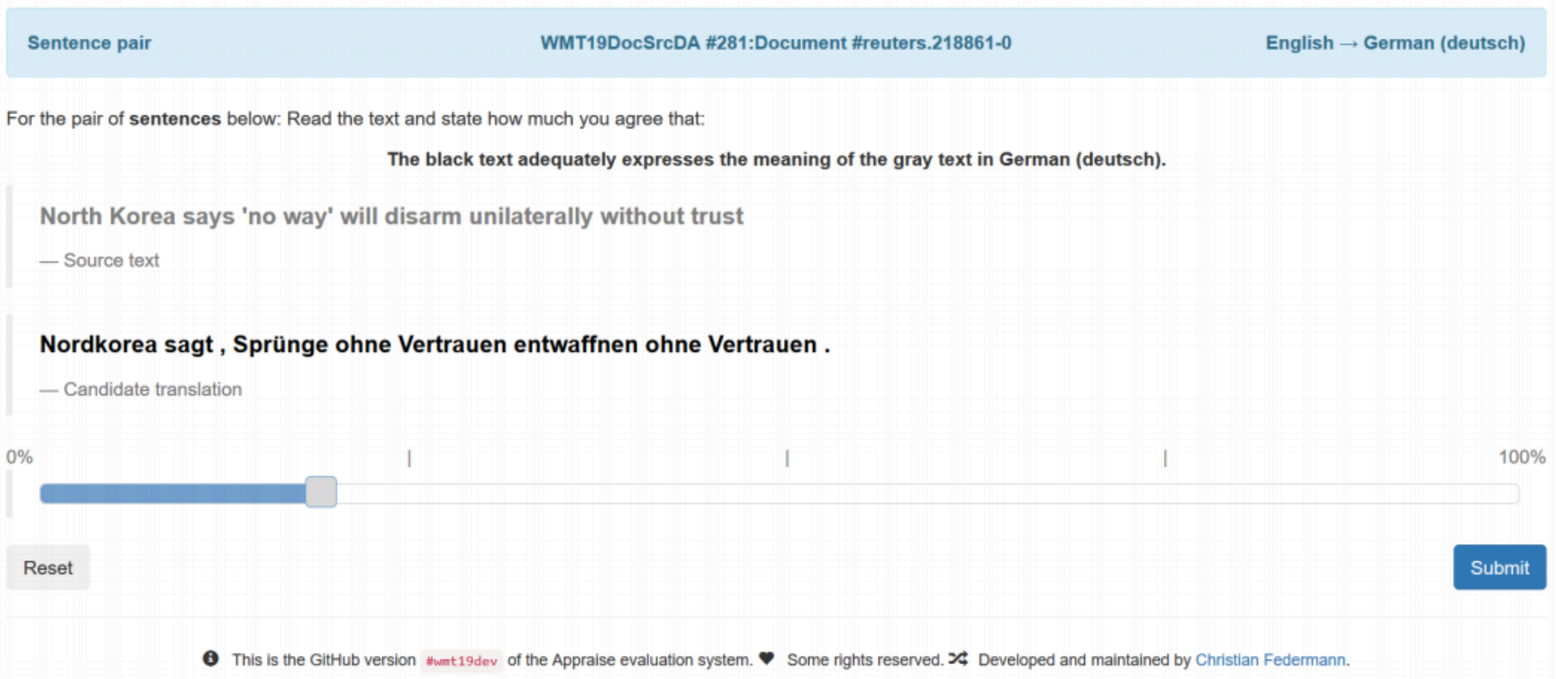
Direct Assessment: Bilingual

- WMT 18’-WMT 19’
- Use a source sentence instead of a reference sentence (“source-based”)
- Main motivation: enables to measure “human performance”



Direct Assessment: Bilingual

- WMT 18’-WMT 19’
- Use a source sentence instead of a reference sentence (“source-based”)
- Main motivation: enables to measure “human performance”
- **Are we there yet?**



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English→Czech

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2	79.8	0.521	UEDIN
	78.6	0.483	NEWSTEST2018-REF
4	68.1	0.128	ONLINE-B
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81.6	0.146	Facebook-FAIR
81.5	0.136	RWTH-Aachen
79.0	0.136	MSRA-MADL
79.9	0.121	online-B
79.0	0.086	JHU
80.1	0.067	MLLP-UPV
79.0	0.066	dfki-nmt
78.0	0.066	UCAM
76.6	0.050	online-A
78.4	0.039	NEU
79.0	0.027	HUMAN
77.4	0.011	uedin
77.9	0.009	online-Y
74.8	0.006	TartuNLP-c
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- For 3 out of 9 (De-En, En-De, En-Ru) language pairs, MT systems were tied or better than the reference translations
  - **For sentence-level MT in high-resource settings, we can see some signs for human parity!**
- However, for document level evaluation, the human translations are still significantly better, unlike in 2018

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DR+DC

Ave.	Ave. z	System
84.0	0.915	HUMAN
76.4	0.537	CUNI-Transformer-T2T-2019
76.7	0.528	CUNI-Transformer-T2T-2018
73.7	0.474	CUNI-DocTransformer-T2T
69.7	0.299	CUNI-DocTransformer-Marian
70.0	0.234	uedin
60.0	−0.098	TartuNLP-c
59.9	−0.169	online-Y
57.3	−0.314	online-B
54.7	−0.368	online-G
47.7	−0.619	online-A
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Automatic Evaluation Methods

BLEU

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- “**Bil**ingual **E**valuation **U**nderstudy”

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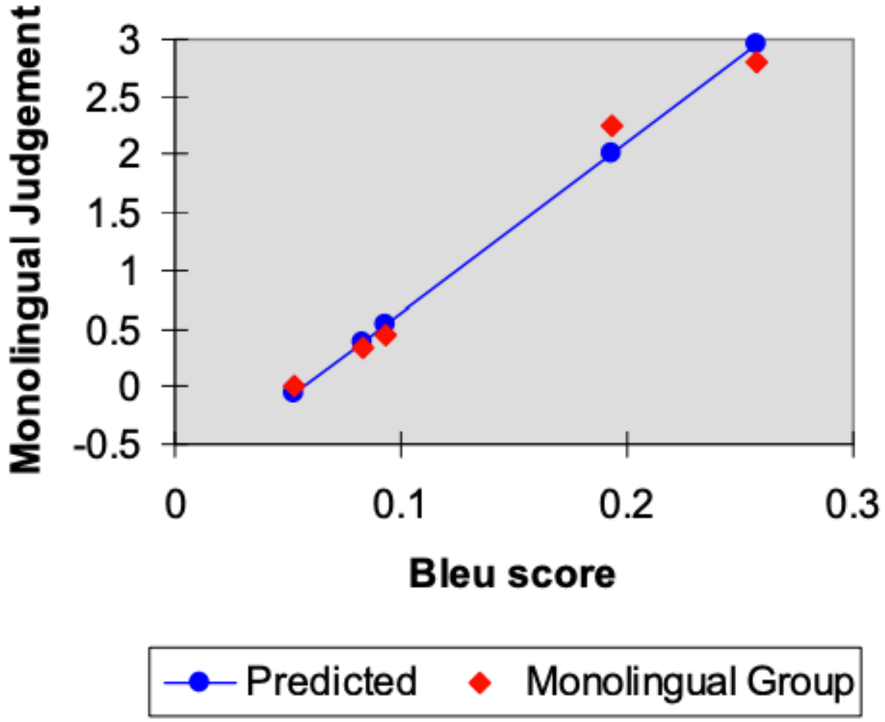

BLEU - How it works?

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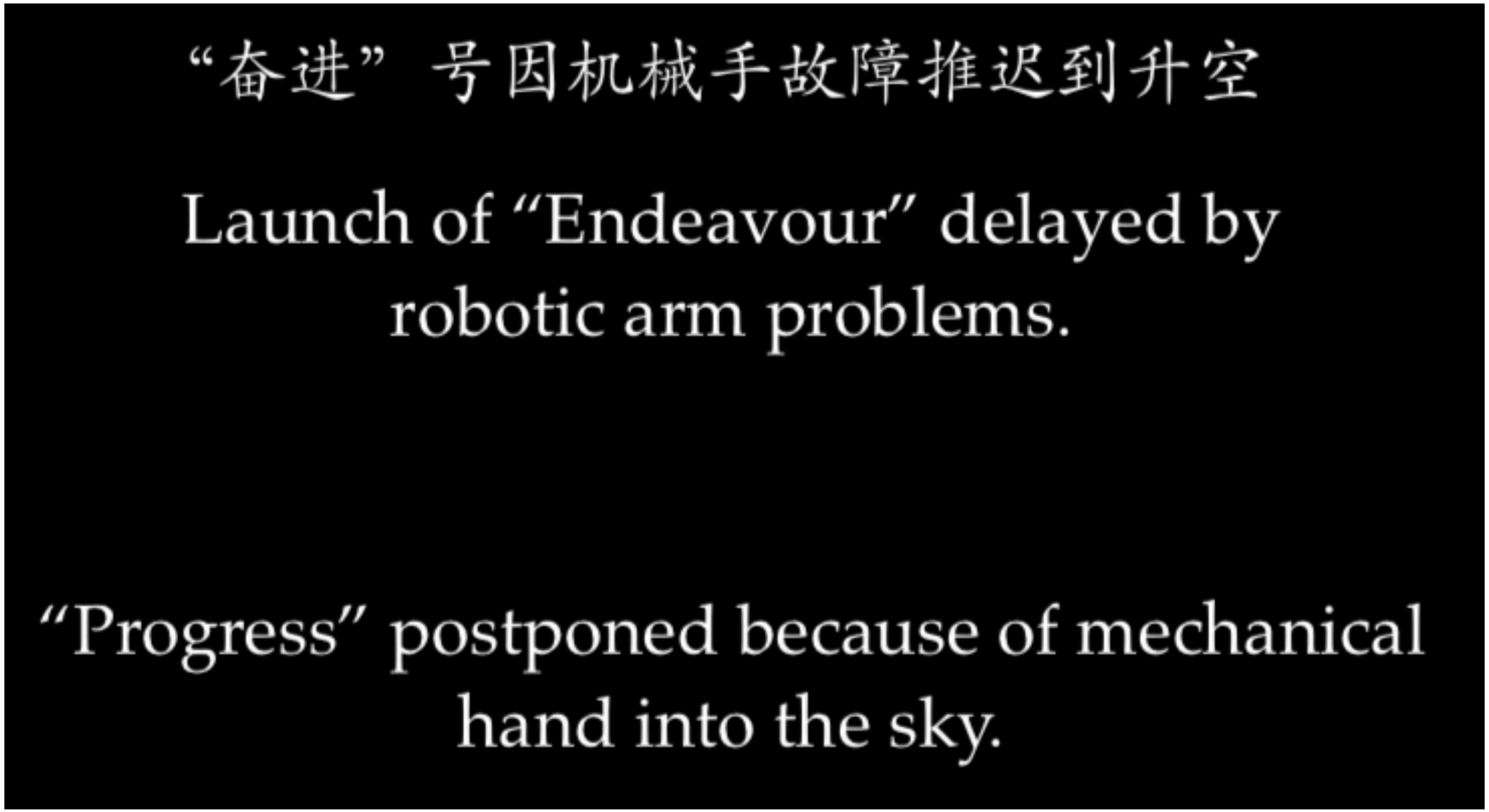

BLEU - How it works?

Although the northern wind shrieked across the sky , it was still very clear .

However , the sky remained clear under the strong north wind .

Refresh - Precision/Recall

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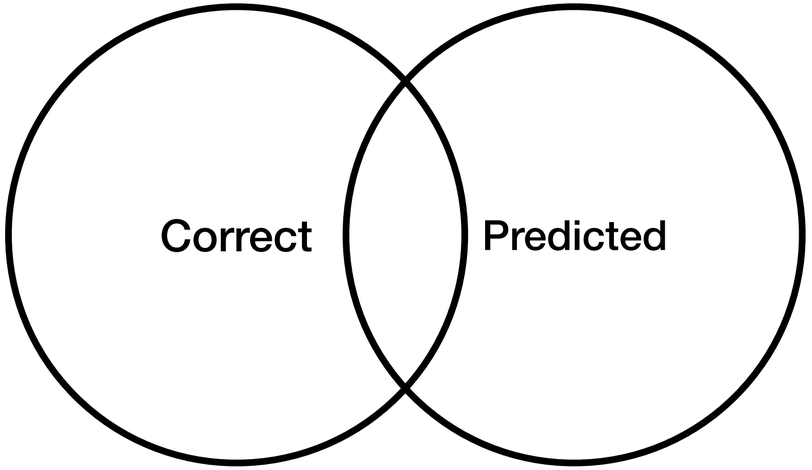

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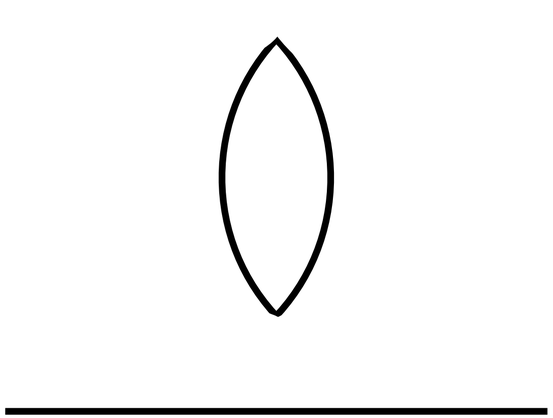

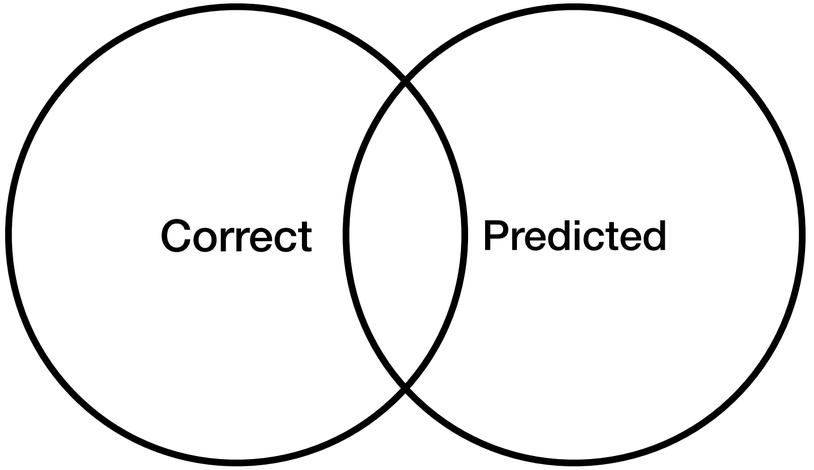

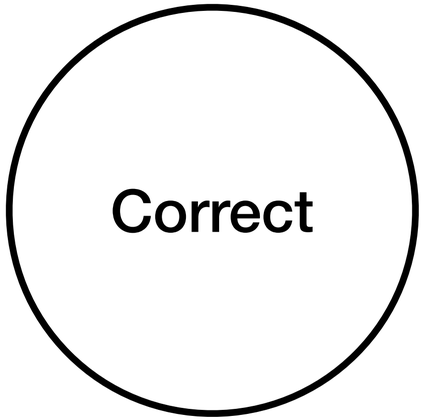

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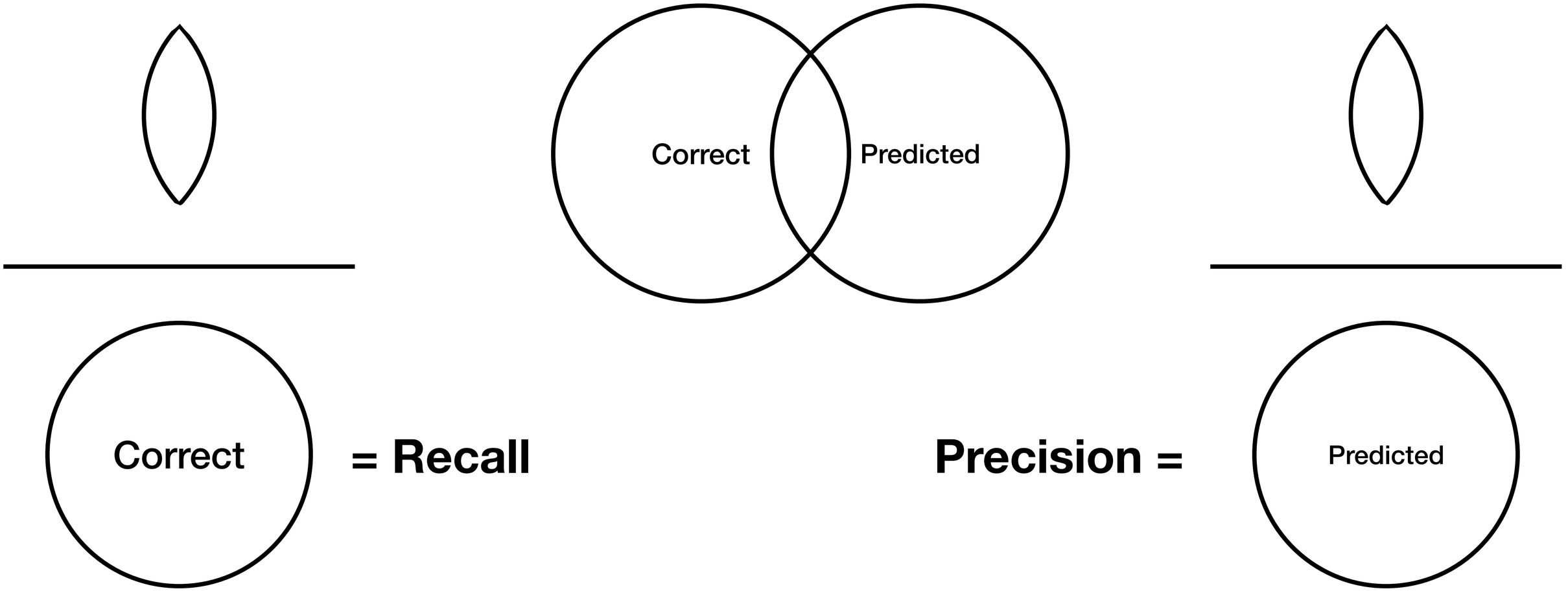

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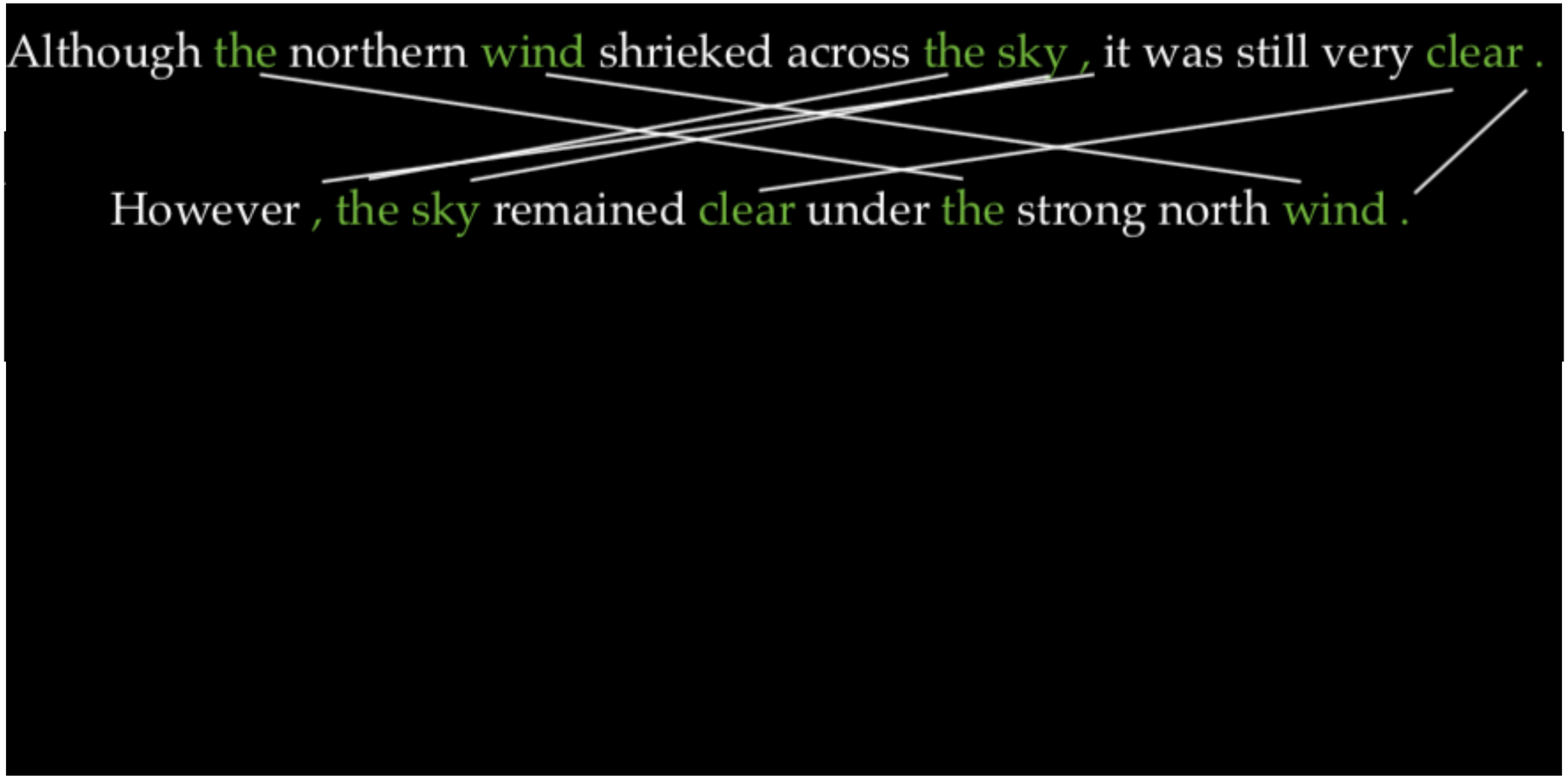

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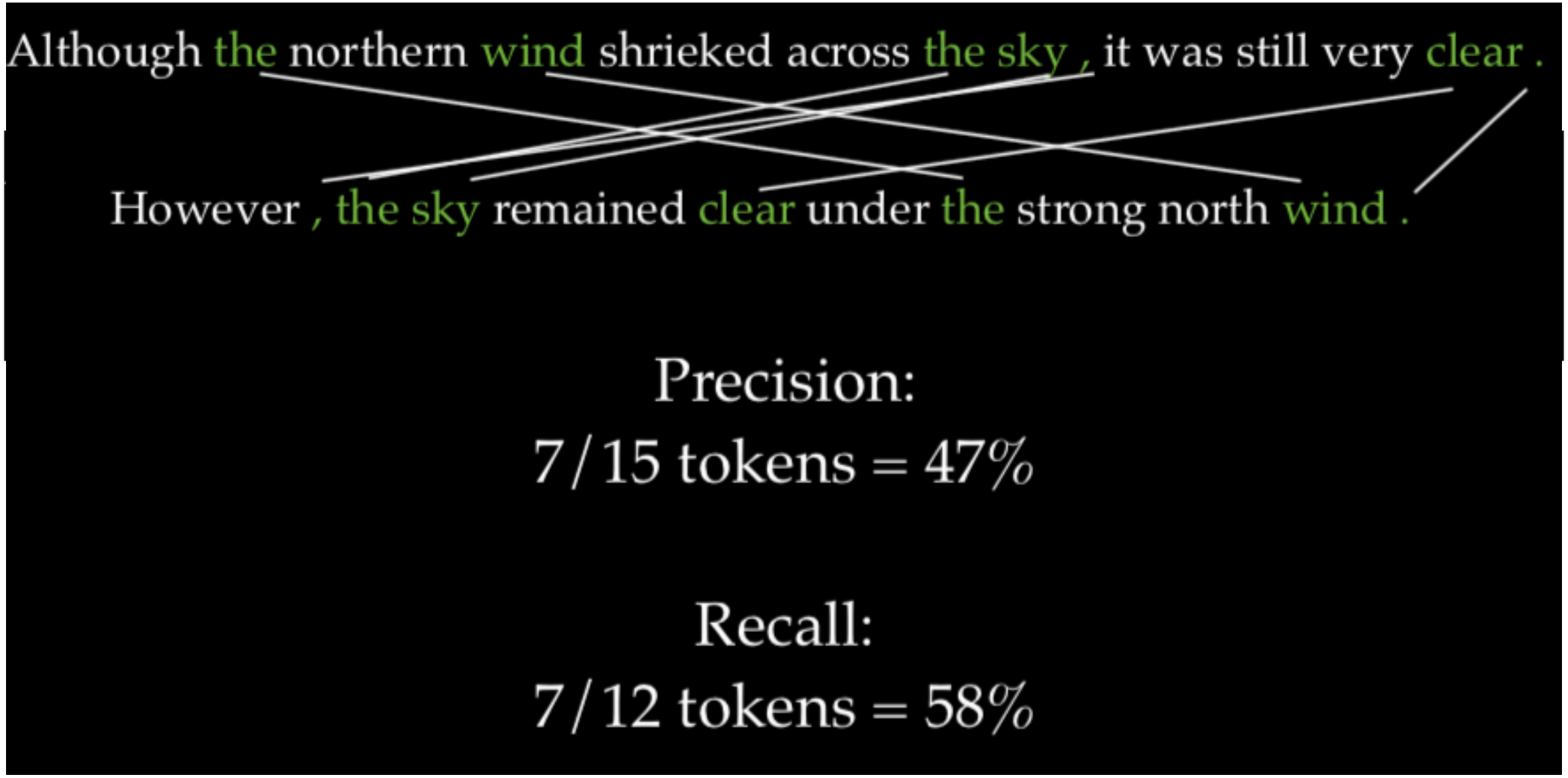

BLEU - How it works?

Precision: 11/15 tokens

Although the northern wind shrieked across the sky , it was still very clear .

However , the sky remained clear under the strong north wind .

Although a north wind was howling , the sky remained clear and blue .

The sky was still crystal clear , though the north wind was howling .

Despite the strong northerly winds , the sky remains very clear .

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4/14 bigrams

1/13 trigrams

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Precision: 3/1 tokens

2/2 bigrams

1/1 trigrams

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Brevity Penalty - punish if candidate is too short

$$\text{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}$$

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BLEU score

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right), w_n = 1/N$$

BLEU - Discussion

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- Can we compare BLEU scores across systems?

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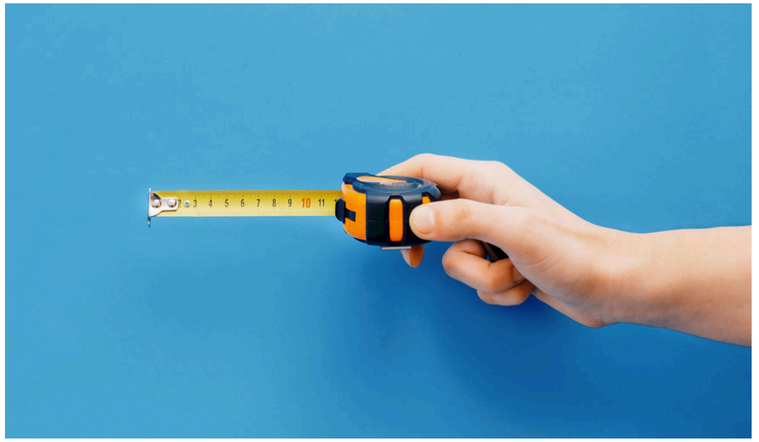
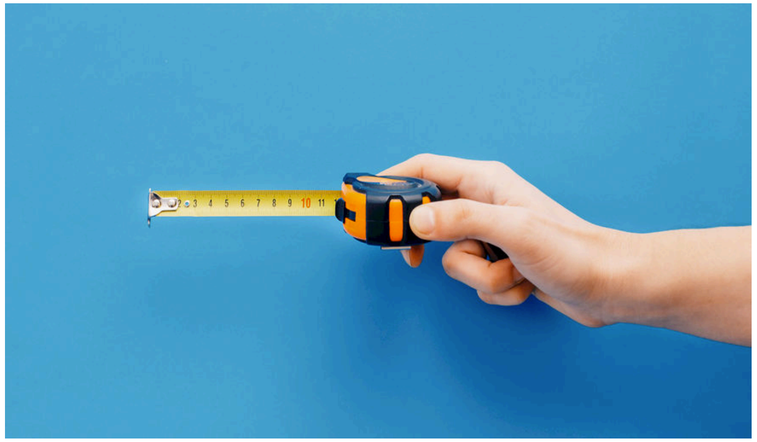
Summary



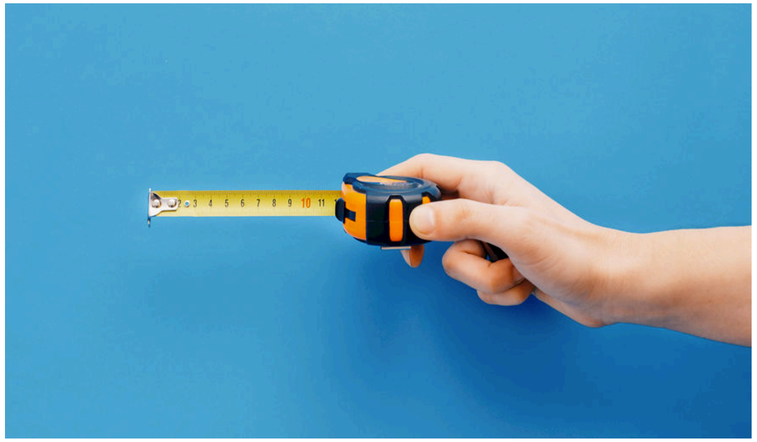
Summary

- Evaluation is very important!



Summary

- Evaluation is very important!
- Human evaluation is best, but:



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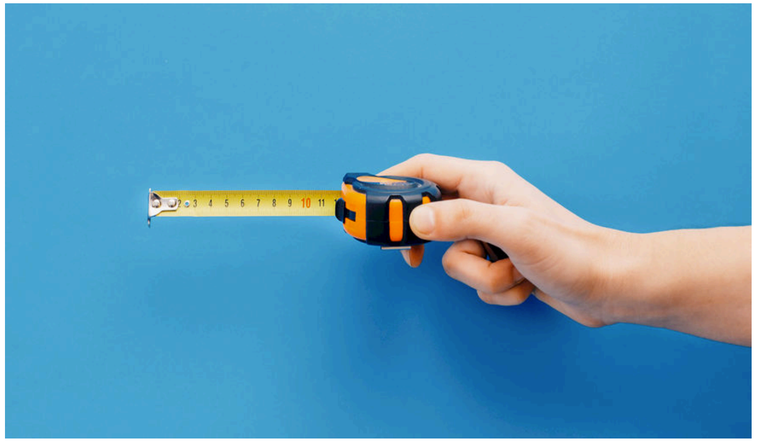
  - Expensive, slow, subjective



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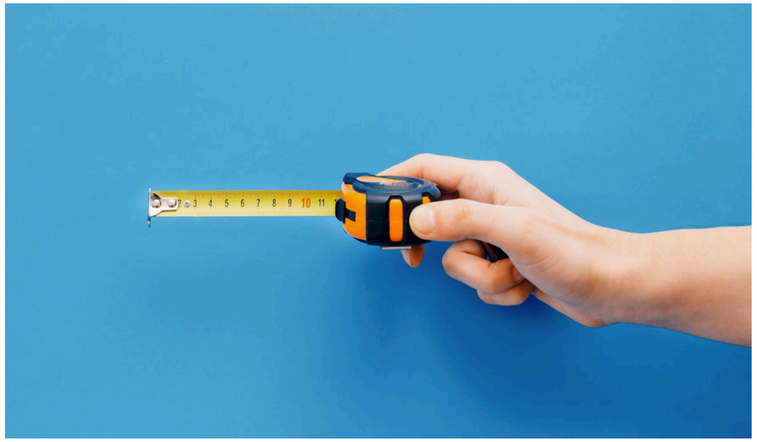

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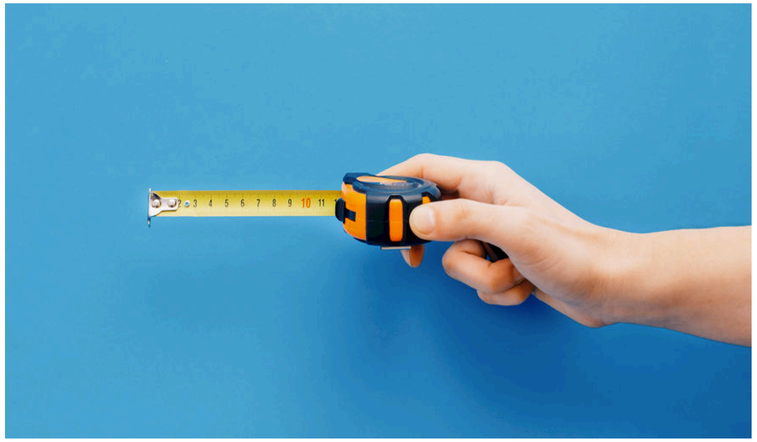
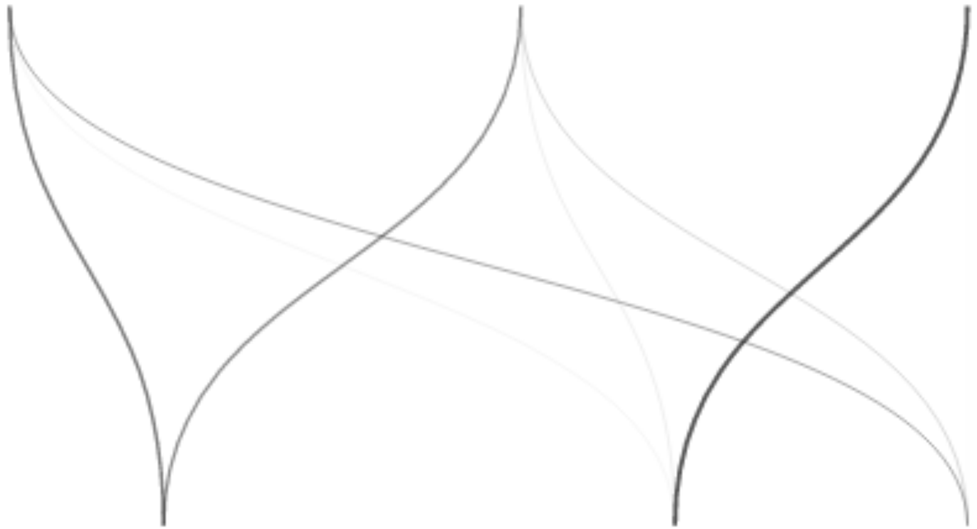
- Evaluation is very important!
- Human evaluation is best, but:
  - Expensive, slow, subjective
- Automatic evaluation is cheap, fast and objective!
  - BLEU is not perfect, but very popular



Any Questions ?



Questions diverses ?