Evaluation of really good Grammatical Error Correction

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Executive Summary

The issue

As grammatical error correction (GEC) systems become more capable, how do we evaluate their performance?

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Improvement of Swedish second language learner texts, using a palette of different GEC methods.

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Results

Automatic metrics have different biases, we suggest evaluating by measuring changes during post-editing.

Approaches

Discrete errors

- Goal: identify, categorize and correct discrete errors.
- GEC tools: fits well with traditional NLP pipeline of POS tagging, morphological analysis, parsing.
- Characteristics: conservative, any change that is not an official 'error' counts as a mistake.
- Evaluation: comparison to error annotations.

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Holistic improvement

- Goal: make the text more native-like.
- GEC tools: more suited for generative neural models.
- Characteristics: may edit the text considerable, multiple very different outputs may all be considered appropriate.
- Evaluation: that’s the question...

Evaluations

- Reference-based
  - Requires one or more target versions of each text
  - Sometimes includes additional error annotations
  - GLEU: text similarity to reference(s), similar to MT
  - ERRANT: similarity of the *types* of edits made, compared to the reference(s)

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- Reference-free
  - Focus on the end result: is the final text acceptable?
  - Typically judged by a language model
  - Separate module needed to guard against changing semantics (meaning preservation)
  - SOME: weighs together fluency, grammaticality and meaning preservation scores from different models
  - Scribendi: LM score + surface level check for similarity in content

Evolution of evaluations

- Consider the failure modes of traditional GEC systems:
  - failure to detect an error, which is left unchanged (no effect on precision)
  - false positive, making a **small** unnecessary change
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- Favored by most reference-free metrics (anti-conservative bias)
- How do these biases affect actual GEC systems? What can we do about them?

The playing field

- Three categories of GEC systems:
  - Rule-based (Granska)
  - Translation-based (from artificially corrupted text)
  - LLM-based (GPT-3.5)
- Human 'systems':
  - Minimal: minimal edits to achieve grammaticality
  - Fluent: minimal edits to achieve native-like fluency
  - Free: any edits to achieve native-like fluency and idiomaticity

Human evaluation

- Anchor point: human minimal (only one with access to context beyond sentence)
- Humans annotate the following for each system output:
  - Grammaticality score (1–4)
  - Fluency score (1–4)
  - Meaning preservation score (1–4)
  - Post-edited output, which must achieve the maximal score for all three scores above

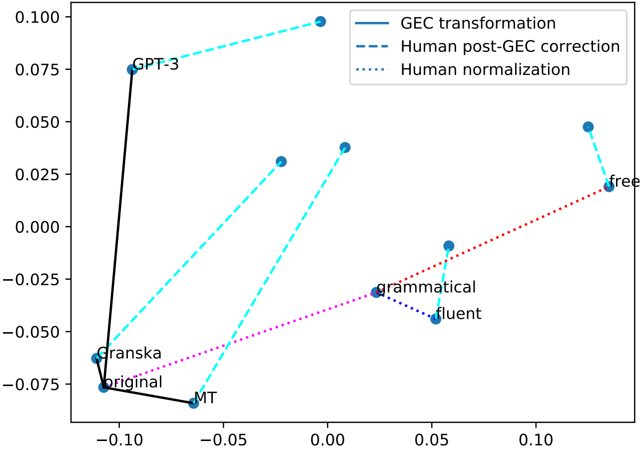
What metric to use?

- Our suggestion: distance to post-edited version
- One 'reference' per system output
- Including human corrections (human free/fluent) provides a baseline for differences of opinion
- We use normalized Levenshtein distance for simplicity
- Others could be used, including ERRANT-like for more detailed semi-automatic analysis
- Main disadvantage: expensive (but LLMs could be useful in some settings)

Normalized Levenshtein distance

	CEFR level			
System	All	A	B	C
Granska	0.126	0.119	0.180	0.079
MT	0.113	0.095	0.158	0.087
GPT-3.5	0.076	0.068	0.112	0.050
Human fluent	0.034	0.034	0.045	0.022
Human free	0.029	0.030	0.034	0.025

Map of edits



Pairwise normalized Levenshtein distance matrix reduced to 2-D by MDS

Reference-based (GLEU)

	CEFR level			
System	All	A	B	C
Uncorrected	0.44	0.29	0.17	0.53
Granska	0.47	0.35	0.24	0.55
MT	0.57	0.48	0.38	0.63
GPT-3.5	0.63	0.60	0.52	0.65
Human minimal	1.0	1.0	1.0	1.0

Reference-free (Scribendi)

System	CEFR level All	A	B	C
Uncorrected	0	0	0	0
Granska	0.03	0.08	0.11	-0.01
MT	0.51	0.57	0.68	0.43
GPT-3.5	0.69	0.70	0.83	0.65
Human minimal	0.68	0.67	0.77	0.65

Conclusions

- Different types of automated metrics have their problems:
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  - possibility of fine-grained analysis
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- Manual post-editing is an appealing alternative:
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- LLM-based GEC sets a new state of the art for Swedish

Resources

- Annotation tool and guidelines
- Annotated and post-edited Swedish GEC system outputs
- https://github.com/robertostling/gec-evaluation