Russian Learner Corpus:

Towards Error-Cause Annotation for L2 Russian

Outline

- RLC: Russian Learner Corpus
- RLC-GEC: Annotated subset of RLC
- RLC-Crowd: Crowdsourced corrections
- RLC-ERRANT: Automatic error annotation

Russian Learner Datasets

RULEC-GEC (Rozovskaya and Roth, 2019)	12,480 sentences Essays written by English-speaking learners of Russian	Automatic error classification tool
RU-Lang8 (Trinh and Rozovskaya, 2021)	48,260 sentences (4,412 re-annotated) Data from Lang8 language-learning website	(Rozovskaya, 2022)
ReLCo (Katinskaia <i>et al.</i> , 2022)	22,370 sentences Data from exercises performed using the Revita language-learning system	RuERRANT

The annotation systems are mainly based on grammatical features of individual words.

Russian Learner Corpus (RLC)

(Rakhilina et al. 2016)

- Essays written by heritage speakers and L2 learners of Russian
- 48 dominant languages
- Over 190,000 sentences (2,200,000 tokens)
- Half of RLC is manually corrected and annotated
- Available through a search interface at http://web-corpora.net/RLC/

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Example: Error Boundaries

Ремонт делает этим (instr) великолепным (instr) зданием (instr) идеальным для жилья. Ремонт делает это (acc) великолепное (acc) здание (acc) идеальным для жилья. Renovation makes this gorgeous building perfect for living.

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- The noun is in the wrong case.
- The determiner and adjective are also in the wrong case, but they agree with the noun.
- This is a single error in government (not three errors).

Example: Noun Endings

(быть) друг → другом (instr)
 (be a) friend

(является) поэмом → поэмой (instr)
 (is a) poem

(хлеб с) моцарелли → моцареллой (instr)
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- and makes annotation hard to automate.

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- RLC-Test
 - 204 sentences
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- Five corrections per sentence may not be enough.
- May be good as is for training or fine-tuning machine-learning GEC models.
- A valuable resource for studying users' correction strategies, the visibility of errors across various types, etc.

Error-annotation tool following the rule-based approach of ERRANT (Bryant et al. 2017).

Input: A sentence and its correction

Output: A list of edits classified into RLC types

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```
Orig: [4, 5, 'полезней'], Cor: [4, 5, 'полезным'], Type: 'Com'
Orig: [6, 8, 'при том'], Cor: [6, 7, 'притом'], Type: 'Space+Ins'
```

Error Extraction

- Alignment based on Damerau-Levenshtein distance,
- followed by rule-based merging of some adjacent edits

Example

If adjacent words in the original sentence share the number and case different from those in the corrected sentence, this is a single error.

Ремонт делает этим (sg instr.) великолепным (sg instr) зданием (sg instr) идеальным для жилья. Ремонт делает это (sg acc) великолепное (sg acc) здание (sg acc) идеальным для жилья.

```
Orig: [2, 5, 'этим великолепным зданием'], Cor: [2, 5, 'это великолепное здание'], Type: 'Gov'
```

Error Classification

- A simplified version of the RLC tagset is used.
- Each edit is assigned a single tag.
- Tag assignment is rule-based.
- Rules are applied sequentially.
- The first rule that fires defines the tag.

WO, CS, Brev, Tense, Passive, Num, Gender, Nominative/Gov/AgrCase, AgrNum, AgrPers, AgrGender, Refl, Asp, Impers, Com, Mode, Hyphen+Ins, Hyphen+Del, Space+Ins, Space+Del, Conj, Ref, Prep, Graph, Infl, Lex, Constr, Ortho, Morph, Ortho, Misspell

Nominative/Gov/AgrCase

этим (Det sg instr) великолепным (Adj sg instr) зданием (Adj sg instr)

→ это (Det sg acc) великолепное (Adj sg acc) здание (Adj sg acc)

Nominative/Gov/AgrCase

- → это (Det sg acc) великолепное (Adj sg acc) здание (Adj sg acc)
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Gov otherwise.

Experimental Evaluation

We tested RLC-ERRANT on RLC-Test.

- Overall accuracy: 0.58
- Many classification errors are due to incorrectly determined morphological categories, especially for non-existing words.
- Orthographic errors are often hard to differentiate from morphological errors.
- Training a machine-learning classifier can help here.

Tag	Precision	Recall
Lex	0.70	0.77
Ortho	0.73	0.10
Gov	0.91	0.75
Constr	0.62	0.38
Prep	0.97	0.78
Ref	0.76	0.81
Asp	0.71	0.71
Conj	0.77	0.87

Conclusion

We released

https://github.com/Russian-Learner-Corpus

- Two L2 Russian datasets with over 30,000 sentences each
 - RLC-GEC is linguistically annotated
 - RLC-Crowd contains 200K+ crowdsourced corrections, at least five per sentence
- RLC-ERRANT, an error annotation tool for RLC error tagging system

Plans

- Make other parts of RLC publicly available
- Analyze the crowdsourced data for users' correction strategies
- Use the data to train or fine-tune machine-learning models
- Improve the performance of RLC-ERRANT using machine learning