Automatic Classification of Russian Learner Errors

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Abstract
Grammatical Error Correction systems are typically evaluated overall, without taking into consideration performance on individual error types because system output is not annotated with respect to error type. We introduce a tool that automatically classifies errors in Russian learner texts. The tool takes an edit pair consisting of the original token(s) and the corresponding replacement and provides a grammatical error category. Manual evaluation of the output reveals that in more than 93% of cases the error categories are judged as correct or acceptable. We apply the tool to carry out a fine-grained evaluation on the performance of two error correction systems for Russian.

Keywords: grammatical error correction, Russian, error classification

1. Introduction
In the field of Grammatical Error Correction (GEC), similarly to Machine Translation, evaluation is performed by first producing edits (token deletions, insertions, and replacements) needed to transform the source sentence into its corrected counterpart. This is done by aligning the two sentences. A gold edit is an edit between a source sentence and its reference, i.e. a corrected version produced by a human annotator. A proposed (system) edit is an edit between a source sentence and the corrected version proposed by the automatic system, or system hypothesis. A correct edit is an edit in the intersection of gold and proposed edits. Below we show a sample (source, reference) pair, a possible alignment, and the resulting gold edits: “realistic” → “realistic”, “a” → “are”, and “are” → “were”.

• Source: The settings are very realistic and the actors had a great performance.

• Ref.: The settings were very realistic and the actors had great performance.

When annotating and correcting learner data, annotators can also be asked to categorize the resulting gold edits. For the example above, the edits would be classified as verb tense, spelling, and missing determiner. Classifying system edits generated by neural machine translation frameworks that are being used today is not trivial, as these systems are not restricted in the type of edits that can be made (Susanto et al., 2014; Yuan and Briscoe, 2016; Hoang et al., 2016; Junczys-Dowmont and Grundkiewicz, 2016; Mizumoto and Matsumoto, 2016; Jianshu et al., 2017; Chollampatt and Ng, 2018).

As the system edits are not labeled for linguistic type, it is not possible to perform type-based evaluation. Type-based evaluation would be extremely useful, as it could help provide directions for making further progress in system development by allowing one to focus on and improve performance on specific error types. Furthermore, the resulting error categories can be used in language learning applications, to provide educational feedback. Finally, automatic type classification allows for a standardization of multiple GEC datasets (Bryant et al., 2017). For instance, various GEC corpora in English (e.g. FCE (Yannakoudakis et al., 2011) and CoNLL (Ng et al., 2014)) have different error classification schemas, which can be unified using automatic error typing.

Recently, Bryant et al. (2017) introduced ERRANT, an error annotation toolkit for English, designed to extract edits from a pair of the original and corrected sentences and classify these according to a rule-based framework. Grammatical error types are assigned based on rules that rely on the part-of-speech (POS) of original and corrected token(s), as opposed to manually designed error categories. A key advantage of a rule-based approach over a canonical automatic one of training a classifier is that this approach is not tied to a specific error classification schema, which can vary significantly among datasets in the same language (Bryant et al., 2017). ERRANT is widely used for fine-grained evaluation and error analysis in English GEC (Bryant et al., 2019).

Our approach is inspired by ERRANT and adapted to the specific challenges of a language with rich morphology, such as Russian. We develop a rule-based classification framework, which uses POS and morphological information to classify edits. Manual evaluation of the resulting edits with 2 raters and on 2 learner corpora shows that the edits are judged as correct or acceptable on average 93.5% of the time. We use the tool to perform fine-grained evaluation of two GEC systems using two learner corpora. Type-based evaluation allows us to identify performance differences between the two models, as well as to determine the sets of “easy” and “challenging” errors for the cur-
2. Automatic Error Typing

2.1. Learner datasets

We perform experiments using two datasets of Russian learner data manually corrected for errors: the RULEC-GEC corpus (Rozovskaya and Roth, 2019) (henceforth RULEC) and another dataset of Russian learner writing that has been recently collected from the online language learning platform Lang-8 (Mizumoto et al., 2011) and annotated by native speakers. We refer to this dataset as RU-Lang8 (Trinh and Rozovskaya, 2021).

RU-Lang8 is collected from the Lang-8 website and contains data from learners of a variety of foreign languages. The size of the Russian subcorpus is 633,000 tokens. A subset of that (54,000 tokens) has been manually corrected by expert annotators and split into development and test. The RU-Lang8 corpus differs from RULEC: the latter consists of essays written on a University setting in a controlled environment, while the Lang-8 data was collected online; the majority of texts are short paragraphs or questions posed by learners. To compare to RULEC, we show in Table 1 the error rates, i.e. the percentage of the erroneous tokens in the data. RU-Lang8 data has significantly higher error rates than both foreign and heritage parts of RULEC (Table 1). We attribute this to the overall higher proficiency level of the RULEC corpus writers.

2.2. Automatic edit extraction

Before the edits can be categorized, they need to be extracted using pairs of original and corrected sentences. This is essentially an alignment problem, where the start and end position of each edit need to be identified. Table 2 shows a pair of original and corrected sentence and a sample alignment that includes three edits: (1) merging the first two tokens всé-таки → всé-таки, (2) merging tokens 4 and 5 не плохо → не плохо and (3) inserting missing preposition не → на. We note that this is not a unique alignment. For example, inserting the missing preposition can be represented as скрипке → на скрипке.

In the humanly-corrected data, edit boundaries are typically already known, however, for automatically-corrected data this is not the case. Thus, automatic edit extraction is necessary to identify boundaries of the proposed edits.

Several attempts have been made at automatic edit extraction. Swanson and Yamangil (2012) used Levenshtein distance, but it does not align multi-token edits, i.e. edits where there is more than one token on either side. Felice et al. (2016) proposed a rule-based linguistically-motivated alignment algorithm. It includes both generic and English-specific rules combined with the Damerau-Levenshtein (DL) algorithm and showed the effectiveness of the approach compared to Levenshtein distance.

We evaluate the rule-based strategy (excluding rules that are English-specific) and the Levenshtein distance. We compare the quality of the automatically-extracted edits against the gold humanly-generated edits in Table 3. Surprisingly, the Levenshtein distance performs reasonably well on the Russian datasets, obtaining F-scores of 81-87% on the RU-Lang8 and RULEC datasets, respectively (on the English datasets it achieved an F-score of 60%). The rule-based strategy is better on RULEC by 2 points and is a 7-point improvement on RU-Lang8.

Overall, results on edit extraction on Russian are slightly better than on English. This may be due to the fact that single-token edits account for a higher percentage of Russian edits (91.4% in RULEC and 93.8% in RU-Lang8). This is not a unique alignment. For example, inserting the missing preposition can be represented as скрипке → на скрипке.

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Table 1: Error rates in RULEC (foreign and heritage speakers shown separately) and in RU-Lang8. Error rates refer to the percentage of tokens that have been modified.

| Corpus          | Total words | Incorrect words | Error rate (%) |
|-----------------|-------------|-----------------|----------------|
| RULEC (Foreign) | 164,071     | 11,343          | 6.9            |
| RULEC (Herit.)  | 42,187      | 1,705           | 4.0            |
| RU-Lang8 (dev)  | 23,138      | 3,605           | 15.6           |
| RU-Lang8 (test) | 31,603      | 3,558           | 11.3           |

Table 2: Sample alignment between original and corrected sentence. The source and the target token(s) in each edit are shown in red and blue, respectively.

| Dataset       | Method     | Edit Extraction | P  | R  | F  |
|---------------|------------|-----------------|----|----|----|
| RULEC         | Lev.       |                 | 88.0| 85.9| 87.0|
|               | DL-Rules   |                 | 91.0| 88.1| 89.5|
| RU-Lang8      | Lev.       |                 | 82.8| 80.1| 81.4|
|               | DL-Rules   |                 | 91.4| 86.1| 88.7|

Table 3: Performance of different edit extraction methods. Lev stands for Levenshtein distance; DL-Rules stands for Damerau-Levenshtein distance and linguistically-motivated rules.
Since Russian is a morphologically-rich language, we rely on the grammatical categories within each major POS tag and generate all possible morphological analyses. In the remainder of the paper, we use the DL-rules method of edit extraction.

### 2.3. Automatic type prediction

Error type classification in English relies on the POS information of the edit tokens (Bryant et al., 2017). Since Russian is a morphologically-rich language, we rely on the grammatical categories within each major POS (V(erb), N(ount), A(djective)). This approach follows closely the error categories adopted for the manual annotation in Rozovskaya and Roth (2019).

**Overview of the rules**  The complete description of rules is presented in Table 4. The pseudocode is presented in Appendix Algorithm 1. We adhere to the morphological properties within each major POS category (A, N, V); otherwise the POS tag is used to assign error type (preposition, pronoun, adverb, etc.). The original and corrected tokens are pre-processed with a morphological analyzer (Sorokin, 2017). Given a word token, the analyzer produces the token’s base form and generates all possible morphological analyses. Each morphological analysis consists of a concatenation of all the relevant grammatical categories. For nouns and adjectives, the categories are gender (masculine/feminine/neuter), number (singular/plural), and declension (6 cases). For verbs, the categories include aspect (perfective/imperfective), voice (active/reflexive), number (singular/plural), gender (masculine/feminine/neuter), person (1st, 2nd, 3rd), tense (past/present/future), voice (active/reflexive), and may include additional categories, such as gerund or participle. Many Russian words do not have a unique analysis (we discuss this further below).

| (1) Determine the original token(s) (O) and the corrected token(s) (C). Check whether O and C are in the dictionary. |
| (2) If O is not in the dictionary, assign category **Spelling**. |
| (3) Deletions and Insertions: A single-token insertion or deletion is categorized based on the token’s POS. Exceptions are nouns, verbs, and adjectives that are assigned the category Insert or Delete. Insertion or deletion of a punctuation symbol (,.?) is treated as Punctuation error. |
| (4) Replacements |
| (a) Replacing one punctuation symbol with another is Punctuation category. |
| (b) If O/C is not in the dictionary, the error category is based on POS tag of the token, e.g. NO/AO/VO (Noun/Other). Note that other POS categories are closed-class and thus words that are not in the dictionary can only be a noun, verb, or adjective/adverb. |
| (c) Determine POS tags of O and C tokens. If one of the tokens has more than one POS tags select those that match. If POS tags do not match, the error category is either Lexical or Morphology (see below). |
| (d) If POS categories match but base words are different, error category is Lexical or Morphology (see below) for N, V, and A. All other words are assigned error type based on POS tag. |
| (e) Distinguish between Morphology and Lexical errors: different POS tags or different base forms for A, N, or V. Compute the length of the longest common prefix (or suffix) in O and C. If its greater than or equal to the half of the O or C (whichever is less), the error type is Morphology. The intuition here is the stem word is most likely the same, and the error involves incorrect affixation (e.g., ). |
| (f) For O and C that share the same POS tag and base form, error type is assigned based on the mismatch between linguistic categories within the specific POS tag. For example, if both O and C are nouns, the values of the categories gender, case, and number are compared. If the values for number are different, for instance, the error category assigned is NN. Multiple categories are assigned if more than one category does not match. |
| (g) Verb aspect errors: In addition to category mismatch as in (f), the aspectual value of the verb is determined based on a list of verb that lists all pairs of corresponding verbs (perfective/imperfective). This is needed since the morphological analysis maps verbs that share the same stem but different aspectual forms to different base forms. Using the aspect list allows us to identify pairs of verbs that, even though they do not share the same base form, they differ only in the aspect category and thus we classify these as Aspect errors. |
| (h) Verb voice errors: These are difficult to identify as these are not mapped to the same base form. We thus check for the specific endings that signal the passive (reflexive) verbs (собрать (“get something ready”) → собраться-ся (“get oneself ready”). The ending -ся signals reflexive form. |

Table 4: Error classification rules. O stands for original token, and C stands for corrected token.

in RU-Lang8), while in English, these account for 71-81%. A lot of multi-token edits in English are phrasal verbs, verbs with auxiliaries, and missing possessive markers on nouns. These categories are typically expressed in Russian via morphological markers. In the remainder of the paper, we use the DL-rules method of edit extraction.
Table 5: List of automatic error types and their distribution in the RULEC and RU-Lang8 corpora.

| Error type                  | RULEC Gold count | RULEC Rel. Freq. | RU-Lang8 Gold count | RU-Lang8 Rel. freq. |
|-----------------------------|------------------|------------------|---------------------|---------------------|
| Spelling                    | 965              | 18.3             | 739                 | 21.8               |
| Lex. choice                 | 819              | 15.5             | 497                 | 14.8               |
| Punc.                       | 592              | 11.2             | 277                 | 8.2                |
| Prep.                       | 333              | 6.3              | 236                 | 7.0                |
| Replace                     | 381              | 7.2              | 185                 | 5.5                |
| Insert                      | 252              | 4.8              | 144                 | 4.3                |
| Delete                      | 94               | 1.8              | 117                 | 3.5                |
| Adv.                        | 78               | 1.5              | 90                  | 2.7                |
| Conj.                       | 77               | 1.5              | 78                  | 2.3                |
| Part.                       | 56               | 1.1              | 36                  | 1.1                |
| Morph.                      | 110              | 2.1              | 30                  | 0.9                |
| Noun case                   | 339              | 6.4              | 217                 | 6.4                |
| Noun case/Noun number       | 423              | 8.1              | 144                 | 4.3                |
| Noun number                 | 29               | 0.6              | 14                  | 0.4                |
| Noun other                  | 13               | 0.3              | -                   | -                   |
| Noun (all)                  | 804              | 15.2             | 382                 | 11.3               |
| Verb aspect                 | 50               | 1.0              | 82                  | 2.4                |
| Verb other                  | 68               | 1.3              | 75                  | 2.2                |
| Verb agreement              | 134              | 2.5              | 73                  | 2.2                |
| Verb tense                  | 12               | 0.2              | 16                  | 0.5                |
| Verb voice                  | 45               | 0.9              | 12                  | 0.4                |
| Verb (all)                  | 324              | 6.1              | 264                 | 7.8                |
| Adj. case                   | 101              | 1.9              | 62                  | 1.8                |
| Adj. gender                 | 69               | 1.3              | 70                  | 2.1                |
| Adj. other                  | 128              | 2.4              | 83                  | 2.5                |
| Adj. number                 | 55               | 1.0              | 49                  | 1.4                |
| Adj. (all)                  | 370              | 7.0              | 275                 | 8.1                |

and the target tokens, the error category is determined based on the property that has different values in the source and target tokens. For example, given an edit that involves two nouns that share the same base form, a noun case error is assigned if the number and gender properties match, but the case values do not.

Several error types require additional checks – morphology, lexical choice, and spelling. If a source token is not in the dictionary, we consider the edit to be a spelling mistake. Insertions and deletions that involve open-class words (N, V, A) are marked as Insert and Delete, respectively. Otherwise, an inserted or deleted token is assigned the error type based on its POS tag.

Lexical change errors involve single-token edits that do not share a stem, while Replace errors are mistakes that involve multi-token replacements.

**Challenges specific to Russian: Morphology errors**

Word morphology errors include edits where the source and the target token share the same stem but incorrect word formation. Some of the mistakes in this category result in words that are not valid Russian words (due to an incorrect word formation suffix), and, since these

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4 We use a large native corpus of Russian (250M tokens collected over the web) to build a dictionary of valid Russian words.

5 Morphology errors also occur in English, but in Russian, arguably, these are more common and challenging due to more options of morphological formation.
Table 6: Manual evaluation of the automatically assigned error categories by each rater and each dataset on a set of 100 edits, randomly selected.

| Rater | RULEC | RU-Lang8 |
|-------|-------|----------|
|       | Good  | Accept. | Bad  | Good  | Accept. | Bad  |
| 1     | 70    | 25      | 5    | 88    | 8       | 4    |
| 2     | 63    | 25      | 12   | 83    | 12      | 5    |

Table 7: Results on the test of the models trained on learner and synthetic data. Best result for each test set is in bold.

| Model | RULEC | RU-Lang8 |
|-------|-------|----------|
|       | P     | R | F₀.₅ | P | R | F₀.₅ |
| CNN   | 55.8  | 26.6 | 45.7 | 57.9 | 26.8 | 47.0 |
| Transf.| 63.3  | 27.5 | **50.2** | 55.3 | 28.5 | 46.5 |

This ambiguity can be resolved in most cases by considering sentential context, however, we only look at token edits in isolation. Such cases are problematic, as, depending on the analysis chosen, a different mismatch in the grammatical category between the source and the target tokens will be identified (either number or case). For such edits, we predict both noun case and noun number error categories. A manual evaluation of 31 ambiguous cases shows that 64.5% of these are errors in case, while 22.6% are errors in noun number, and 12.9% have errors in both number and case.

**Manual evaluation of automatic error typing** We perform a manual evaluation of the rule-based classifier, following the approach in Bryant et al. (2017) used to evaluate the performance of ERRANT. 100 randomly chosen edits from gold reference files are manually evaluated by two independent native annotators as “Good”, “Acceptable”, or “Bad”. “Good” means the chosen error type was the most appropriate for the given edit; “Acceptable” means that the chosen type was appropriate but not the optimum, and “Bad” means not appropriate.

The results of the evaluation are shown in Table 6. In all cases, with the exception of RU-Lang8 and rater 2, at least 95% of the predicted error types were judged as acceptable. These results are comparable to those reported for English. However, note that, unlike with ERRANT, our evaluation excludes trivial error categories, such as Punctuation, Insertion, and Deletion errors. A complete list of the error categories and statistics on the two learner datasets are shown in Table 5.

### 3. Type-Based Evaluation

We now apply the automatic error classification to the outputs of two GEC models applied two learner corpora: RULEC and RU-Lang8. The models that make use of state-of-the-art techniques: a Convolutional Encoder-Decoder Neural Network (CNN) (Chollam-patt and Ng, 2018) and a Transformer model (Naplava and Straka, 2019). We train the CNN model using the same hyperparameter values. The Transformer achieved the highest F-score on the RULEC corpus in the literature.

Both of the models use the training and dev portions of RULEC as learner data, and similar amounts of native data with synthetic errors. Overall performance of the two models on each of the two benchmark corpora is shown in Table 7. Observe that the transformer model outperforms CNN on RULEC by almost 5 points, however, on the RU-Lang8 corpus the two models perform similarly.

We show type-based performance of the models on RULEC and RU-Lang8 in Tables 8 and 9, respectively. For both datasets, highest results are achieved on spelling mistakes (F-scores between 60% and 70%). This is followed by errors related to grammar on nouns, verbs, and adjectives (F-scores of 40-60%). The Transformer model also does well on preposition errors, while the CNN model performs well on punctuation mistakes.

Regarding performance differences between the models, the Transformer does better on RULEC in almost all error categories, with the exception of punctuation. However, on RU-Lang8, both models perform similarly on errors related to nouns, verbs, and adjectives, with the CNN model being slightly ahead, which suggests that the Transformer may be overfitting towards RULEC more strongly than the CNN model. Finally, the most challenging error categories for both models are lexical choice, replacement and insertion errors.

To summarize, the type-based analysis indicates that the models currently have difficulty correcting mistakes that involve major changes that go beyond character-level modifications.

### 4. Conclusion

We describe a tool for automatic classification of learner errors in Russian. The classification is based on POS (similar to English) but also incorporates additional constraints specific to Russian. We believe this tool can be easily modified to fit another (morphologically-rich) language. The tool has been evaluated on two Russian learner datasets with encouraging results. Using the tool, we have also conducted type-based evaluation of two state-of-the-art GEC systems. Type-based evaluation can assist in making progress on developing robust GEC systems. In particular, we showed that beyond spelling mistakes and select grammar errors that require character-level modifications, current systems do not do well on major learner misuse that requires more global lexical changes. This tool can also be used to inform language learners and provide feedback with explanations.

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6This is one common ambiguity but is not the only one.

7Replacements refer to multi-token lexical changes.
| Error type | CNN P  | CNN R  | CNN F0.5 | Transformer P  | Transformer R  | Transformer F0.5 |
|------------|--------|--------|----------|----------------|----------------|------------------|
| Spelling   | 66.2   | 53.9   | 63.3     | 75.93          | 63.73          | 73.13            |
| Lex. choice| 46.3   | 3.0    | 12.1     | 67.07          | 13.43          | 37.29            |
| Punc.      | 54.8   | 23.3   | **43.1** | 42.71          | 6.93           | 21.01            |
| Replace    | 0.00   | 0.00   | 0.00     | 2.30           | 1.05           | 1.86             |
| Prep.      | 25.2   | 8.1    | 17.7     | 70.25          | 25.53          | **52.02**        |
| Morph.     | 20.0   | 1.8    | 6.7      | 51.61          | 14.55          | **34.19**        |
| Insert     | 0.0    | 0.0    | 0.0      | 17.39          | 6.35           | **12.90**        |
| Delete     | 75.0   | 3.2    | 13.6     | 38.24          | 13.83          | **28.26**        |
| Noun (all) | 61.1   | 38.4   | 54.6     | 72.0           | 36.4           | **60.2**         |
| Verb (all) | 54.5   | 20.4   | 40.8     | 71.5           | 38.0           | **60.8**         |
| Adj. (all) | 50.0   | 21.6   | 39.6     | 64.1           | 29.5           | **51.9**         |

Table 8: Evaluation by error type on the RULEC corpus.

| Error type | CNN P  | CNN R  | CNN F0.5 | Transformer P  | Transformer R  | Transformer F0.5 |
|------------|--------|--------|----------|----------------|----------------|------------------|
| Spelling   | 66.9   | 45.8   | 61.3     | 70.3           | 63.3           | **68.8**         |
| Lex. choice| 38.8   | 3.8    | 13.7     | 50.00          | 13.68          | **32.7**         |
| Punc.      | 67.1   | 39.0   | **58.6** | 44.4           | 5.8            | 19.0             |
| Prep.      | 49.2   | 14.0   | 32.7     | 76.2           | 20.3           | **49.2**         |
| Replace    | 0.0    | 0.0    | 0.0      | 9.6            | 10.3           | **9.7**          |
| Morph.     | 0.0    | 0.0    | 0.0      | 50.0           | 16.7           | **35.7**         |
| Insert     | 25.0   | 2.1    | 7.8      | 12.2           | 6.2            | **10.2**         |
| Delete     | 76.5   | 11.1   | **35.1** | 39.2           | 17.1           | 31.1             |
| Noun (all) | 69.6   | 41.9   | **61.4** | 70.5           | 35.1           | 58.7             |
| Verb (all) | 54.8   | 19.3   | 40.1     | 49.1           | 21.2           | 38.9             |
| Adj. (all) | 74.8   | 33.5   | **60.0** | 66.4           | 34.5           | 56.1             |

Table 9: Evaluation by error type on the RU-Lang8 corpus.

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Appendix
Algorithm 1
Error Type Classification Algorithm

**Input:** Source token(s) s, target token(s) t, baseform dictionary BaseD containing all basic wordforms and their POS tags as keys, and a list of all possible morphological analyses and corresponding wordforms; wordform dictionary WordD containing a morphological form as key and a list of possible analyses with corresponding POS tags as values; list of word aspect pairs AspectD listing perfective/imperfective verb pairs; list of punctuation symbols PUNC

**Output:** error type // Set list of grammatical categories
gram_cats=[’case’,’number’,’gender’,’tense’,’aspect’,’voice’,’form’,’finite’]

// Handle split and merge errors
if t equals s.replace(’ ’,”) or s equals t.replace(’ ’,”) then
return Spelling
end if

// If source or target contain more than one token, set error to Replace
if len(s.split())>1 or len(t.split())>1 then
return Replace
end if

// Punctuation errors
if s in PUNC or t in PUNC then
return Punctuation
end if

// Spelling errors if source word not in dictionary
if s not in WordD then
return Spelling
end if

// Missing token errors
if s is empty then
Initialize POS(target) ← None
POS(target) = WordD[t] if t in WordD
if POS(target) in {Adj,Noun,Verb} then
return Insert
else
return POS(target)
end if
end if

// Extraneous token errors
if t is empty then
Initialize POS(source) ← None
POS(source) = WordD[s] if s in WordD
if POS(source) in {Adj,Noun,Verb} then
return Delete
else
return POS(source)
end if
end if

// Get list of all baseforms and their corresponding POS tags for source token
Initialize pos_list(source) ← None
Initialize baseform_list(source) ← None
pos_list(source) = WordD[s].postags()
baseform_list(source) = WordD[s].baseforms()

// Handle errors where target word not in dictionary
if t not in WordD then
POS(source) = WordD[s]
if POS(source) in {Adj,Noun,Verb} then
return POS(source)+’ : O’
else
return POS(source)
end if
end if

// Get list of all baseforms and their corresponding POS tags for target token
Initialize pos_list(target) ← None
Initialize baseform_list(target) ← None
pos_list(target) = WordD[t].postags()
baseform_list(target) = WordD[t].baseforms()

// Find common POS of source and target tokens
Initialize pos ← None
Initialize baseform_t ← None
for pos pos_t in pos_list(target) do
if pos in pos_list(source) then
base_s=WDic[s].getbase(pos)
base_t=WDic[t].getbase(pos)
end if
end for
if pos not in {Adj,Noun,Verb} then
return pos
end if

// Check if s and t share a common prefix or suffix that is at least half of min(len(s),len(t))+1
if pos equals None then
Lcom = 1 + min(len(s),len(t))
if Lcom≥4 and (s[0:Lcom] equals t[0:Lcom] or s[-Lcom:] equals t[-Lcom:]) then
return M
else
return L
end if
end if

if shared POS is not an Adj., Noun, or Verb then
if pos not in {Adj,Noun,Verb} then
return pos
end if

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Algorithm 1

Error Type Classification Algorithm: Part II

Input: Source token(s) s, target token(s) t, baseform dictionary BaseD containing all basic wordforms and their POS tags as keys, and a list of all possible morphological analyses and corresponding wordforms; wordform dictionary WordD containing a morphological form as key and a list of possible analyses with corresponding POS tag as values; list of verb aspect pairs AspectD listing perfective/imperfective verb pairs; list of punctuation symbols PUNC

Output: error type

Handle verb voice errors – confusing active and reflexive forms
if pos equals V
for ending en in {ся,сь}
do
if base(s)+en equals base(t) or base(s) equals base(t)+en then
return VV
end if
end for
end if

Handle verb aspect errors using verb aspect table of perfective/imperfective verb pairs
if pos equals V then
if base(s) in DAspect and base(t) in DAspect[base(s)] then
return VA
end if
end if

Source and target have same POS, different baseforms – check if it could be an M error
if s and t share a common prefix or suffix that is at least half of min(len(s),len(t))+1
Lcom = 1 + min(len(s),len(t))
if Lcom ≥ 4 and (s[−Lcom:] equals t[−Lcom:] or s[−Lcom:] equals t[Lcom:−]) then
return M
else
return L
end if

Get all morph. variants of baseform with chosen POS; note that here source and target share the same baseform and POS
morpho_variants=BaseD[pos+':'+baseform(s)]
cat_values={}
for gr in gram_cats do
cat_values[gr]=
cat_values[gr][0]=cat_values[gr][2]=
cat_values[gr][1]=cat_values[gr][3]=0
end for
for var in morpho_variants do
word=var.word()
if word in {s,t} then
gram_cats_word=var.values()
for c in gram_cats_word do
append parameter value for the corresponding (source or target) wordform
if c_val not in cat_values[c_name][index] then
cat_values[c_name][index]+=':'+c_val
end if
end for
end if
end for

Handle errors where verb infinitival form is confused with tensed form
if inf equals 1 then
return VINF
end if
Algorithm 1
Error Type Classification Algorithm: Part III

Input: Source token(s) $s$, target token(s) $t$, baseform dictionary $BaseD$ containing all basic wordforms and their POS tags as keys, and a list of all possible morphological analyses and corresponding wordforms; wordform dictionary $WordD$ containing a morphological form as key and a list of possible analyses with corresponding POS tag as values; list of verb aspect pairs $AspectD$ listing perfective/imperfective verb pairs; list of punctuation symbols $PUNC$

Output: error type

//Compare values of grammatical categories for source and target, where POS is either adjective, noun, or verb; and set error category based on the category where the values in source and target differ

cats_N = {'case':'NC','num':'NN','gen':'NG'}
cats_V = {'aspect':'VA','tense':'VT','num':'VNG','gen':'VNG','per':'VNG','voice':'VV','other':'VO','case':VO'}
cats_A = {'case':'AC','num':'AN','gen':'AG','form':AO'}
error_type=""

for gr in cat_values do
    if (pos equals N and gr in cats_N) or (pos equals A and gr in cats_A) or (pos equals V and gr in cats_V) then
        if pos equals N then
            diff_val=cats_Ngr
        else if pos equals A then
            diff_val=cats_Agr
        else if pos equals V then
            diff_val=cats_Vgr
        end if
        if diff_val not in error_type then
            error_type+=diff_val+','
        end if
    end if
    values=cat_values[gr][0].split(':') //Check if source and target wordforms share same parameter value
    for val in values do
        if (val not equal "") and (val in cat_values[gr][2]) then
            cat_values[gr][1]=0
            Break
        end if
    end for
    //If source and target wordforms do not share the value for given parameter, set error type to this parameter
    if (val not equal "") and (val in cat_values[gr][2]) then
        cat_values[gr][1]=0
        Break
    end if
end for

if error_type equals "" then
    error_type=pos+':O'
end if

return error_type