Fine-Tuning OCR Error Detection and Correction in a Polish Corpus of Scientific Abstracts

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Abstract. The paper explores the idea of detecting and correcting post-OCR errors in a corpus of Polish scientific abstracts by first evaluating several available spellchecking approaches and then reusing one of the rule-based solutions to eliminate frequent errors most likely resulting from technical problems of the OCR process. The fine-tuning consisted in removing word breaks, rejecting corrections which change the case of the output, removing unnecessary spaces between word segments and restoring Polish letters replaced with spaces whenever the correction resulted in a valid Polish word. The obtained system proved competitive with language model-based solutions.

Keywords: OCR post-correction · POSMAC corpus · Polish

1 Introduction

The process of OCR may result in errors — that's a trivial observation. Lewandowski [4][1] mentions various factors contributing to unsatisfactory recognition rate of OCR, e.g. thinness of paper causing the contents of the back page to break through during scanning, imprecisions of print caused by the wear of the printing press or discontinuities in the letters, discolouration or damage caused during use. Various compensation mechanisms may be applied already at the stage of recognition but if the process is not supervised, many errors may remain.

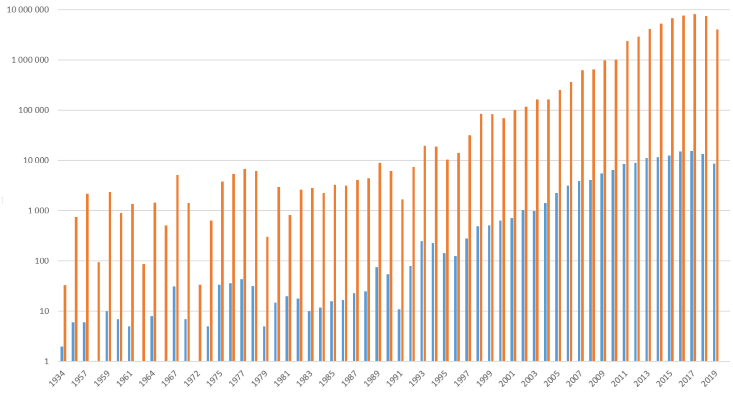
This is also the case with The Polish Open Science Metadata Corpus (POSMAC) [6][2], a new source of scientific articles (abstract and full texts) acquired from the Polish Library of Science (LoS)[3]. The corpus contains over 142K files with over 55M words dated between 1934 and 2020 (with uneven distribution, see Figure 1 for details), coming from over 900 Polish scientific journals and books, in most cases scanned and OCR-ed. The nature of the process influenced the content: the texts have been recognized in various periods, by heterogeneous teams and using methods varying from journal to journal so the spectrum of encountered errors can be wide.

[1] See also `http://www.djvu.com.pl/galeria/UJ/Gazety_czasopisma.php`

[2] `http://clip.ipipan.waw.pl/POSMAC`

[3] `https://bibliotekanauki.pl/`

Fig. 1. Document and word count per year in POSMAC



POSMAC is currently being included in the set of CURLICAT[4] corpora [8] which motivates us to attempt to raise its quality by eliminating as many spelling errors as possible while trying not to introduce the new ones. This leads to our first conclusion that precision is what should matter most in the task while other measures such as recall are not that important (following the rule: "correct as much as you can but only when you are certain that the change will not result in an error"). Secondly, due to the large size of the corpus the corrections need to be applied in an automated manner.

These two requirements define our setup: we need to reuse or construct a precision-oriented non-interactive spellchecking tool for Polish which will be used to process the POSMAC corpus. To be able to select the tool we will be carrying out the small-scale evaluation on a manually corrected subset of the corpus.

2 Available Approaches

Since "most of the spelling approaches strongly depend on the specifics of the language and are hard to adapt to another language or a different application" [1], we decided to review several recent spellchecking initiatives specific to Polish and try to validate existing approaches before implementing a new one. Below we list the most available spellchecking tools reused in our experiment.

- LanguageTool is definitely the most popular error correction tool for Polish[5]. It is a multilingual grammar, style, and spell checker, recently made available in its non-interactive form as a CLARIN-PL service Speller[6].

[4] `https://curlicat.eu/`

[5] `https://languagetool.org/`

[6] `https://ws.clarin-pl.eu/speller`

Speller also claims to use spaCy[7], a robust Python NLP library and AutoCorrect[8], a spelling corrector in Python that currently supports 12 languages including Polish.

- Symspell is another CLARIN-PL spellchecking service for Polish[9], using a fast symmetric delete spelling correction algorithm which provides single word and compound word-aware multi-word spelling correction as well as word segmentation of noisy text. The service integrates the original solution by Wolf Garbe[10] with the frequency dictionary generated from the KGR10 collection[11].
- ED 3 pl tool [13] has been developed for the most recent spellchecking task for Polish, i.e. PolEval 2021 Task 3: Post-correction of OCR results[12] [3]. The solution was based on a sequence-to-sequence model using T5 architecture [7] and a publicly available plT5 Large language model for Polish[13]. ED 3 pl ranked second-best in the PolEval Task 3.
- Another group of tools worth testing are popular grammar and spellcheckers integrated with office applications such as Microsoft Word or Google Docs. They are not intended for non-interactive use and they do not have an autocorrect feature integrated into their regular interfaces but such behaviour can be simulated with macros replacing each detected problem with the first available suggestion (if there is any). For Microsoft Word, we used a Jay Freedman's macro[14] replacing spelling errors with the first suggestion while for Google Docs the first suggestion was selected manually (see Figure 2).

3 Evaluation of the Out-of-the-Box Solutions

Several metrics have been proposed for the evaluation of spellcheckers, e.g. word error rate (WER), used to rank the submissions in the PolEval 2021 Task 3 (see. e.g. [2] for review of different methods). Still, according to [1], "the most common evaluation metric is classification accuracy". The authors mention the fact that "only the best candidate from the suggestion list is considered, and order and count of the other proposed correction candidates are insignificant" as a disadvantage of this method and point out that "it is not suitable for evaluating an interactive system". Since our setup is non-interactive and best-candidate-only, we decided to select the classification-based method as our main ranking

[7] `https://spacy.io/`

[8] `https://github.com/filyp/autocorrect`

[9] `https://ws.clarin-pl.eu/symspell`

[10] `https://github.com/wolfgarbe/SymSpell`

[11] `https://huggingface.co/clarin-pl/fastText-kgr10`

[12] `http://2021.poleval.pl/tasks/task3`

[13] `https://huggingface.co/allegro/plt5-large`

[14] `https://answers.microsoft.com/en-us/msoffice/forum/all/how-to-accept-all-autocorrect-suggestions-in/e8de0d2c-5429-4a48-8f0c-c62c0f69c717`.

```
Sub AcceptSpellingSuggestions()
    Dim er As Range
    For Each er In ActiveDocument.SpellingErrors
        If er.GetSpellingSuggestions.Count > 0 Then
            er.Text = er.GetSpellingSuggestions.Item(1).Name
       End If
    Next
End Sub
```

Fig. 2. Jay Freedman's macro for simulating non-interactive spelling correction in Microsoft Word

criterion and perform a detailed investigation of precision, recall and accuracy of the systems evaluated on a subset of POSMAC corpus.

Even though "it is virtually impossible to compare the performance of state-of-the-art spelling correction systems", as authors of [1] state, they report a range of results for various evaluation corpora and different languages. The best reported precision value is 97.8 for modern Greek, recall — 99.2 for Arabic Newspaper Corpora and accuracy — 95.72 for Chinese OCR Medical Records.

3.1 Development and Evaluation Sets

To prepare for the task, 1000 randomly selected sentences[15] from the POSMAC corpus were reviewed. This resulted in the development of an initial categorization of errors, used in further annotation. The error types mostly concern spelling; punctuation errors were not intended to be corrected[16].

For the evaluation, we randomly selected another set of sentences from the corpus and performed their manual correction. The annotator was instructed to mark error types with previously defined codes attached in square brackets to affected words. The process was supposed to finish after finding 500 errors which resulted in selecting 385 sentences. After carrying out the second pass to verify its results, several annotations were corrected (e.g. undetected missing diacritics in rare place names, missing error codes for corrections etc.) after consulting the PDF sources of articles from the Library of Science to resolve ambiguous interpretations. The final evaluation set eventually contains 10 871 words and 517 errors. Table 1 presents the categorization of errors with examples and counts of each error type.

After the first pass, the code set contained one more mark, `[?]`, used to signal „other errors", unable to categorize by the annotator. There was only one instance marked, i.e. *Saw1g* which was resolved in the second pass to *Sawąg*

[15] Detected automatically in the process of linguistic annotation with Concraft disambiguating tagger [9] which in some rare cases resulted in several true sentences treated as a single one.

[16] Compare e.g. `https://languagetool.org/development/api/org/languagetool/rules/Categories.html`.

Table 1. Error categorization

Code	Explanation	Example	Correct form	Count
[D]	diacritic missing	sie	się	272
[-]	missing chracter	dziaania	działania	103
[+]	extra character	zajmniemy	zajmiemy	46
[S]	unnecessary space	oczyszczaln i	oczyszczalni	45
[T]	typo	zostaliWmy	zostaliśmy	20
[G]	words glued together	któryw	który	20
[C]	uppercase instead of lowercase or vice versa	zamoyskim	Zamoyskim	7
[P]	excessive punctuation	uniwersalne, narzędzie	uniwersalne narzędzie	2
[M]	metathesis, i.e. replacement of two adjacent letters	szkalnych	szklanych	1
Any				**517**

(a typo in the name of the lake) by consulting the PDF source. Unclear cases, e.g. missing diacritics in proper names, as in *Damieckiej* (most likely *Damięckiej*), were intentionally kept consistent with the source.

3.2 Evaluation Method and Results

As stated before, standard classification notions and metrics were used:

	words changed	**words left alone**
words with incorrect spelling	*tp* (true positives: corrected errors)	*fn* (false negatives: errors but not corrected)
words spelt correctly	*fp* (false positives: not errors but corrected)	*tn* (true negatives: not errors and not corrected)

$$Precision = \frac{tp}{tp+fp} \qquad Accuracy = \frac{tp+tn}{tp+tn+fp+fn}$$

$$Recall = \frac{tp}{tp+fn} \qquad F_1 = \frac{2 \cdot tp}{2 \cdot tp+fp+fn}$$

The calculations were performed by applying the Merge algorithm[17] for three-way comparison of word-aligned ORIG (original sample), GOLD (manually corrected sample) and SYS (system output) files and interpreting its output by counting:

[17] `https://metacpan.org/pod/Algorithm::Merge`

- tp when *ORIG != GOLD* and *SYSTEM = GOLD*
- fn when *ORIG != GOLD* and *SYSTEM != GOLD*
- fp when *ORIG = GOLD* and *SYSTEM != GOLD*
- tn when *ORIG = GOLD* and *SYSTEM = GOLD*

Table 2 presents the results of the evaluation. Even though the accuracy of most solutions seems sufficiently high, the precision is not satisfactory, most likely because of the scientific character of the texts. We will take a closer look at this issue in the next section. The low score of Symspell must result from its improper configuration since even a simple rule correcting just one error in the set can reach higher overall accuracy.

Table 2. Error correction statistics for all investigated settings; bold means best

Tool name	**tp**	**fp**	**P**	**R**	**F$_1$**	**A**
Symspell	85	1136	6.96	14.78	9.47	85.79
Microsoft	298	436	40.60	56.87	47.38	93.98
Speller	310	243	56.06	59.50	57.73	95.87
Google	403	**206**	**66.17**	68.19	67.17	96.42
ED 3 pl	**407**	214	65.54	**70.54**	**67.95**	**96.50**

4 Qualitative Error Analysis

The specificity of scientific data defines several requirements for the correction process. The ideal system should not attempt to correct citations including person names, foreign words and symbols. It needs to keep brackets, dashes and quotation marks in place and should not replace the word with its edit-distantly equivalent. All these problems were observed with the reviewed systems in varied intensity. We present the most characteristic features of each system and some interpretations below. Table 3 presents selected results for various error types which illustrate the differences between various approaches.

4.1 Symspell

The particularly low score of the CLARIN-PL configuration of Symspell results mostly from unnecessary spaces introduced around quotation marks and brackets, e.g. *(Kadrow 2010; Kadrow 2011a)* → *mężczyzn(Kadrow 2010; Kadrow 2011a)* or *„trojki”* → *„ trojki ”* but also in unexpected places such as date ranges, e.g. *330–347* → *330–3 47*. Since brackets are frequently used to mark citations in scientific texts, the number of such errors is high.

While the solution was most effective in removing word-break hyphens, at the same time, it was wrongly removing minus characters used as dashes or properly

Table 3. Sample error correction results for categories from Table 1; bold values are correct

Error	**Correct value**	Speller	Symspell
zamoyskim	**Zamoyskim**	**Zamoyskim**	zamoyskim
poary	**pożary**	pory	poary
sie	**się**	**się**	sie
któryw	**który w**	który	**który w**
oczyszczaln i	**oczyszczalni**	oczyszczalń i	**oczyszczalni**
zostaliWmy	**zostaliśmy**	**zostaliśmy**	zostali W my
zajmniemy	**zajmiemy**	**zajmiemy**	zajmniemy
dzia a	**działań**	dnia a	dzia a

Error	ED 3 pl	Google	Microsoft
zamoyskim	zamoyskim	zamoyskim	**Zamoyskim**
poary	poary	**pożary**	opary
sie	**się**	**się**	**się**
któryw	**który w**	**który w**	który
oczyszczaln i	oczyszczania i	**oczyszczalni**	oczyszczalń i
zostaliWmy	**zostaliśmy**	zostaliŚmy	**zostaliśmy**
zajmniemy	zajmniemy	**zajmiemy**	**zajmiemy**
dzia a	działania	dzia a	dziab a

used hyphens in compound words, e.g. *bułgarsko-polskich* → *bułgarsko polskich* or symbols, e.g. *W(1-3)* → *W(13)*.

Symspell was also unnecessarily normalizing the case in acronyms, e.g. *MChAT-u* → *Mchatu* and was over creative in correcting proper names such as person names, again frequently used in citations, e.g. *Januszko-Szkiel* → *Janusz koszkiel*.

4.2 Microsoft spellchecker

Microsoft spellchecker seems not to take into account any context information (beyond the word boundaries) which results in prioritizing existing words over other corrections, e.g. *wahan iami* → *wahań iłami*. This also concerns wrongly hyphenated words, e.g. changing *me-chanicznych* → *me-chemicznych* while just removing the hyphen would result in a perfectly correct word (which all other solutions discovered). This also concerns splitting unknown words into in-vocabulary segments as in *estymaty* → *estyma ty*.

The method is not frequency-based since *Krola* (EN: *the king* without a diacritic) is corrected to *Krolla* (a rare inflected proper name) instead of *Króla*.

4.3 Speller

Similarly to Microsoft spellchecker, the CLARIN-PL configuration of Speller consequently searches for Polish words to replace the foreign ones, e.g. *Polská*

Praha aneb Jak se z půlky stala polka → *Polská Praha Anek Jak se z pułku stała polka* and corrects out-of-vocabulary words by replacing them with in-vocabulary guesses, even in obvious cases e.g. *nawią zując* → *nawie żyjąc*. The model is capable of removing words, e.g. *okazały się być bardzo trwałe* → *okazały się bardzo trwałe*, usually resulting in errors.

4.4 Google spellchecker

Google model is most likely trained on a large corpus without a dictionary which results in replacing less frequent (and thus missing from its limited vocabulary) and unknown words with their similar equivalents, e.g. *pielonych* (a valid rare form) → *zielonych*. Unfortunately, this also leads to acronym-unfriendly behaviour, i.e. changing *CMCU* → *MCU* (while other models keep it unchanged).

Google model also seems to take into account the local context which sometimes results in errors, e.g. changing proper singular forms to plural ones when a closer word is plural: *Okres*$_{\text{SG}}$*, gdy Bałabanow zrealizował swoje pierwsze filmy*$_{\text{PL}}$*, był*$_{\text{SG}}$ (EN: *the period*$_{\text{SG}}$ *when Balabanow completed his first films*$_{\text{PL}}$ *was*$_{\text{SG}}$) → *Okres*$_{\text{PL}}$*, gdy Bałabanow zrealizował swoje pierwsze filmy*$_{\text{PL}}$*, były*$_{\text{PL}}$ (EN: *the period*$_{\text{SG}}$ *when Balabanow completed his first films*$_{\text{PL}}$ *were*$_{\text{PL}}$).

4.5 ED 3 pl

ED 3 pl, based on transformer architecture, was very effective in replacing out-of-word hyphens (wrongly used to indicate pauses) with proper dashes or correcting HTML character entities: *J&oacute;zef* → *Józef* (later removed from evaluation as an obvious conversion problem). The system (as the only one) could also effectively glue together words split into several segments, e.g. *pod ję tą* → *podjętą*.

The generative character of the system was sometimes creating unnecessary effects such as replacing correct words with their synonyms, e.g. *zaprezentowano* → *przedstawiono* (EN: *present*) but sometimes also fuzzynyms, e.g. *studenci* (EN: *students*) *to absolwenci* (*graduates*). In this first case, the behaviour of the system might not be perceived as invalid by a user while the second is obviously wrong. There were several similar cases of this type, e.g. *2002–2012* → *2002–12* which is another valid way of expressing the year range. At the same time the changes were often unpredictable and wrong, particularly concerning years in citations, e.g. *(Pękala 1984)* → *(Pękala 1983)*. Some changes were also corrupting valid words, e.g. *innowacyjności* → *innowacjości*.

5 Reuse and Recycle

The solution we propose intends to build on the results of Speller by making several adjustments to its corrections to eliminate false positives based on the character of our corpus. Taking into account the specifics of scientific texts (see Section 4) and its OCR provenance, we intend to:

1. remove word breaks (surprisingly, still present)
2. reject corrections which change the case of the output
3. remove unnecessary spaces between word segments
4. restore Polish letters which were replaced with spaces due to potential technical problems.

The two first methods are language-independent while the other two require a dictionary lookup to verify whether the proposed correction results in an existing word. For this purpose, we used the list of Polish inflected word forms made available by the creators of the morphological analyser Morfeusz[18] [10]. The dictionary comes in two flavours, based on PoliMorf [11] and The Grammatical Dictionary of Polish (SGJP) [12]. Each dictionary contains over 600K unique word forms absent from the other one (see Table 4) so a joint version was created to broaden the coverage.

Table 4. Counts of unique word forms in various dictionaries

Dictionary	**Word form count**
PoliMorf 2014	3 800 454
PoliMorf 2022	4 876 026
SGJP 2022	4 909 741
PoliMorf 2022 + SGJP 2022	5 336 228

5.1 Pre-processing

Since word breaks resulting from splitting the word between lines (e.g. *jako-ści*) still seem to appear in the Speller results and frequently result in changes applied to word segments independently, we decided to correct them in the pre-processing step.

Due to the high number of named entities in scientific texts (mostly person names in citations) it seemed worthwhile to test how keeping all words starting with an uppercase character would influence the results.

For cases when a word was split into two segments a mechanism glueing them together was applied when a resulting word was found in the joint dictionary of Polish word forms.

5.2 Adding Missing Polish Letters

Missing diacritics or in-word letters have already been added by existing rules of LanguageTool integrated with Speller. Still, there are cases when a Polish letter has been removed in the OCR process and space was output in its

[18] `http://morfeusz.sgjp.pl/download/`, version 20220410.

place, e.g. *wyznacza a* instead of *wyznaczała*. Again, as with broken words, for LanguageTool this means applying separate correction mechanisms to each segment individually rather than guessing the missing letter and concatenating it with the segments in the text.

The correction procedure subsequently investigated all Polish letters and attempted to join two-word segments with each of them. When a resulting word was found in the joint dictionary, the correction was applied. The operation was limited to in-word Polish letters, without adding them before or after the word which could also be the case of an error. This idea was not tested because it would by all means result in many errors since e.g. Polish *ę* or *ł* correspond to inflectional patterns, e.g. *robi*$_{\texttt{fin:sg:ter:imperf}}$ / *robię*$_{\texttt{fin:sg:pri:imperf}}$ / *robił*$_{\texttt{praet:sg:m1.m2.m3:ter:imperf}}$.

5.3 Evaluation of the Proposed Solution

The proposed solution was evaluated in stages; the results of this process are presented in Table 5. Since each step is independent of the others, the influence of the underlying method on the obtained scores can be easily calculated. Values of the three best original systems are given for reference.

Table 5. Four-step improvement of Speller results

Tool name	**tp**	**fp**	**P**	**R**	**F$_1$**	**A**
Speller	310	243	56.06	59.50	57.73	95.87
Google	403	206	66.17	68.19	67.17	96.42
Ed 3 pl	**407**	214	65.54	70.54	67.95	96.50
Speller						
+ preprocessing	328	235	58.26	62.00	60.07	96.03
+ keep uppercase	325	179	64.48	60.63	62.50	96.45
+ glue words	345	**166**	67.51	63.19	65.28	96.66
+ add missing Polish letters	379	181	**67.68**	**72.05**	**69.80**	**97.01**

At the end of the day, the record number of hits still belongs to Ed 3 pl system, but all other scores were subsequently raised by each next variant of the corrector. What is particularly important is the lowest number of false alarms raised, yet still far from making the tool usable without supervision.

6 Conclusions and Future Work

The presented solution shows how rule-based systems can still compete with language model-based solutions in a specialised setting to reduce the number of false positives and raise the precision of the system. Since the nature of errors detected by these two types of solutions varies, one of the next steps could be combining them in an ensemble or by creating a hybrid solution. But even with the current solution, several improvements can be made, e.g. detecting the language of the content to avoid correcting fragments in a foreign language or old Polish, paying attention to punctuation, dates and symbols.

What could also help analyse the results and fine-tune its subcomponents could be the calculation of our scores for each category of errors independently. Finer-grained categorization of errors could also be carried out, e.g. typos split into standard characters, Polish characters or frequent OCR errors such as confusing lowercase *l* with *1* and uppercase *I* or omitted characters into spaces vs. letters. In turn, standard measures could be calculated for each error subtype and the algorithm could be fine-tuned for different periods or scientific journals.

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