Lexical Normalization of User-Generated Medical Forum Data

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Abstract

In the medical domain, user-generated social media text is increasingly used as a valuable complementary knowledge source to scientific medical literature. The extraction of this knowledge is complicated by colloquial language use and misspellings. Yet, lexical normalization of such data has not been addressed properly. This paper presents an unsupervised, data-driven spelling correction module for medical social media. Our method outperforms state-of-the-art spelling correction and can detect mistakes with an $F_0.5$ of 0.888. Additionally, we present a novel corpus for spelling mistake detection and correction on a medical patient forum.

1 Introduction

In recent years, user-generated data from social media that contains information about health, such as patient forum posts or health-related tweets, has been used extensively for medical text mining and information retrieval (IR) (Gonzalez-Hernandez et al., 2017). This user-generated data encapsulates a vast amount of knowledge, which has been used for a range of health-related applications, such as the tracking of public health trends (Sarker et al., 2016) and the detection of adverse drug responses (Sarker et al., 2015). However, the extraction of this knowledge is complicated by non-standard and colloquial language use, typographical errors, phonetic substitutions, and misspellings (Clark and Araki, 2011; Sarker, 2017; Park et al., 2015). Thus, social media text is generally noisy and this is only aggravated by the complex medical domain (Gonzalez-Hernandez et al., 2017).

Despite these challenges, text normalization for medical social media has not been explored thoroughly. Medical lexical normalization methods (i.e. abbreviation expansion (Mowery et al., 2016) and spelling correction (Lai et al., 2015; Patrick et al., 2010)) have mostly been developed for clinical records or notes, as these also contain an abundance of domain-specific abbreviations and misspellings. However, social media text presents distinct challenges, such as colloquial language use, (Gonzalez-Hernandez et al., 2017; Sarker, 2017) that cannot be tackled with these methods.

The most comprehensive benchmark for general-domain social media text normalization is the ACL W-NUT 2015 shared task (Baldwin et al., 2015). The current state-of-the-art system for this task is a modular pipeline with a hybrid approach to spelling, developed by Sarker (2017). Their pipeline also includes a customizable back-end module for domain-specific normalization. However, this back-end module relies, on the one hand, on a standard dictionary supplemented manually with domain-specific terms to detect mistakes and, on the other hand, on a language model of generic Twitter data to correct these mistakes. For domains that have many out-of-vocabulary (OOV) terms compared to the available dictionaries and language models, such as medical social media, this is problematic.

Manual creation of specialized dictionaries is an unfeasible alternative: medical social media can be devoted to a wide range of different medical conditions and developing dictionaries for each condition (including laymen terms) would be very labor-intensive. Additionally, there are many different ways of expressing the same information and the language use in the forum evolves over time. Consequently, hand-made lexicons may get outdated (Gonzalez-Hernandez et al., 2017). In this paper, we present an alternative: a corpus-driven spelling correction approach. We address two research questions:

1. To what extent can corpus-driven spelling correction reduce the out-of-vocabulary rate in medical social media text?

\[1\text{https://noisy-text.github.io/norm-shared-task.html} \]
2. To what extent can our corpus-driven spelling correction improve accuracy of health-related classification tasks with social media text?

Our contributions are (1) an unsupervised data-driven spelling correction method that works well on specialized domains with many OOV terms without the need for a specialized dictionary and (2) the first corpus for evaluating mistake detection and correction in a medical patient forum.²

Our method is designed to be conservative and to focus on precision to mitigate one of the major challenges of correcting errors in domain-specific data: the loss of information due to the ‘correction’ of already correct domain-specific terms. We hypothesize that a dictionary-based method is able to retrieve more mistakes than a data-driven method, because all terms not included in the dictionary are classified as mistakes, which will probably include all non-word errors. However, we also expect that a dictionary-based method will misclassify more correct terms as mistakes, because any domain-specific terms not present in the dictionary will be classified incorrectly.

2 Related work

Challenges in correcting spelling errors in medical social media A major challenge for correcting spelling errors in small and highly specialized domains is a lack of domain-specific resources. This complicates the automatic creation of relevant dictionaries and language models. Moreover, if the dictionaries or language models are not domain-specific enough, there is a high probability that specialized terms will be incorrectly marked as mistakes. Consequently, essential information may be lost as these terms are often key to knowledge extraction tasks (e.g. a drug name) and to specialized classification tasks (e.g. does the post contain a side effect of drug X?).

This challenge is further complicated by the dynamic nature of language on medical social media: in both the medical domain and social media novel terms (e.g. a novel drug name) and neologisms (e.g. group-specific slang) are constantly introduced. Unfortunately, professional clinical lexicons are also unsuited for capturing the domain-specific terminology on forums, because laypersons and health care professionals express health-related concepts differently (Zeng and Tse, 2006).

Another complication is the frequent misspellings of key medical terms, as medical terms are typically difficult to spell (Zhou et al., 2015). This results in an abundance of common mistakes in key terms, and thus, a large amount of lost information if these terms are not handled correctly.

Lexical normalization of generic social media In earlier research, text normalization for social media was mostly unsupervised or semi-supervised e.g. (Han et al., 2012) due to a lack of annotated data. These methods often pre-selected and ranked correction candidates based on phonetic or lexical string similarity (Han et al., 2012, 2013). Han et al. (2013) additionally used a trigram language model trained a large Twitter corpus to improve correction. Although these methods did not rely on training data to correct mistakes, they did rely on dictionaries to determine whether a word needed to be corrected (Han et al., 2012, 2013). The opposite is true for modern supervised methods, which rely on training data but not on dictionaries. For instance, the best performing method at the ACL W-NUT shared task of 2015 used canonical forms in the training data to develop their own normalization dictionary (Jin, 2015). The second and third best performing methods were also supervised and used deep learning to detect and correct mistakes (Leemam-Munk et al., 2015; Min and Mott, 2015) (for more detail on W-NUT systems see Baldwin et al. (2015)). Since specialized resources (appropriate dictionaries or training data) are not available for medical forum data, a method that relies on neither is necessary. We address this gap.

Additionally, recent approaches often make use of language models, which require a large corpus of comparable text from the same genre and domain (Sarker, 2017). This is however a major obstacle for employing such an approach in niche domains. Since forums are often highly specialized, the resources that could capture the same language use are limited. Nevertheless, if comparable corpora are available, language models can contribute to effectively reducing spelling errors in social media (Sarker, 2017) due to their ability to capture the context of words and to handle the dynamic nature of language.

3 Data

Medical forum data For evaluating spelling correction methods, we use an international pa-
Table 1: Raw data without punctuation. IQR: Interquartile range

|       | GIST forum | Reddit forum |
|-------|------------|--------------|
| # Tokens | 1,255,741  | 4,520,074    |
| # Posts  | 36,277     | 274,532      |
| Median post length (IQR) | 20 (35) | 11 (18) |

Table 1: Raw data without punctuation. IQR: Interquartile range

Annotated data Spelling mistakes were annotated for 500 randomly selected posts from the GIST data. Real word errors and split or concatenation errors were not included, because we are not interested in syntactic or semantic errors (Ku- kich, 1992). In addition, we considered each word independent of its content, because word bigrams or trigrams are sparse in the small forum collections (Verberne, 2002). Each token was classified as a mistake (1) or not (0) by the first author. A second annotator checked if any of the mistakes were false positives. 53 unique mistakes were found: Their corrections were annotated individually by two annotators. Annotators were provided with the complete post in order to determine the correct word. The initial absolute agreement was 89.0%. If a consensus could not be reached, a third assessor was used to resolve the matter. These 53 mistakes and their corrections form the test set for evaluating spelling correction methods.

Spelling error frequency corpus Since by default all edits are weighted equally when calculating Levenshtein distance, we needed to compute a weighted edit matrix in order to assign lower costs and thereby higher probabilities to edits that occur more frequently in the real world.

Specialized vocabulary for cancer forums To be able to calculate the number of out-of-vocabulary terms in two cancer forums, a specialized vocabulary was created by merging the standard English lexicon CELEX (Burnage et al., 1990) (73,452 tokens), the NCI Dictionary of Cancer Terms (National Cancer Institute) (6,038 tokens), the generic and commercial drug names from the RxNorm (National Library of Medicine (US)) (3,837 tokens), the ADR lexicon used by Nikfarjam et al. (2015) (30,846 tokens) and our in-house domain-specific abbreviation expansions (DSAE) (42 tokens) (see Preprocessing for more detail). As many terms overlapped with those in CELEX, the total vocabulary consisted of 118,052 tokens (62.2% CELEX, 5.1% NCI, 26.1% ADR, 6.5% RxNorm and <0.01% DSAE).

Data sets for external validation We obtained six public classification data sets that use health-related social media data. They were retrieved from the data repository of Dredze and the shared tasks of Social Media Mining 4 Health workshop (SMM4H) 2019. The data sets sizes range from 588 to 16,141 posts (see Table 2).

6Two errors overlapped between the sets
7Due to a limited number of words of length 17, 311 instead of 320 words were added
8http://norvig.com/ngrams/count_1edit.txt
9http://www.cs.jhu.edu/~mdredze/data/
10https://healthlanguageprocessing.org/smm4h/challenge/
| Data set                                      | Task                                           | Size     | Positive (%) | Negative (%) |
|----------------------------------------------|------------------------------------------------|----------|--------------|--------------|
| Task 1 SMM4H 2019*                           | Presence adverse drug reaction                 | 16,141   | 8.7          | 91.3         |
| Task 4 SMM4H 2019*                           | Personal health mention of flu vaccination     | 6,738    | 28.3         | 71.7         |
| Flu Vaccination Tweets (Huang et al., 2017)   | Relevance to topic flu vaccination             | 3,798    | 26.4         | 73.6         |
| Twitter Health (Paul and Dredze, 2009)       | Relevance to health                            | 2,598    | 40.1         | 59.9         |
| Task 4 SMM4H 2019*                           | Personal health mention of having flu          | 1,034    | 54.4         | 45.6         |
| Zika Conspiracy Tweets (Dredze et al., 2016)  | Contains pseudo-scientific information         | 588      | 25.9         | 74.1         |

Table 2: Six classification data sets of health-related Twitter data. *SMM4H: Social Media Mining 4 Health workshop

![Sequential processing pipeline](image)

Figure 1: Sequential processing pipeline

4 Methods

Preprocessing To protect the privacy of users, in-text person names were replaced as much as possible using a combination of the NLTK names corpus and part-of-speech tags (NNP and NNPS). Additionally, URLs and email addresses were replaced by the strings -url- and -email- using regular expressions. Furthermore, text was lower-cased and tokenized using NLTK. The first modules of the normalization pipeline of Sarker (2017) were employed: converting British to American English and normalizing generic abbreviations (see Figure 1). Some forum-specific additions were made: Gleevec (British variant: Glivec) was included in the British-American spelling conversion and one generic abbreviation expansion that clashed with a domain-specific one was substituted (i.e. ‘temp’ defined as temperature instead of temporary). Moreover, the abbreviations dictionary by Sarker (2017) was lower-cased. Lastly, domain-specific abbreviations were expanded with a lexicon of 42 non-ambiguous abbreviations, generated based on 500 randomly selected posts from the GIST forum and annotated by a domain expert and the first author.  

Spelling correction We used the method by Sarker (2017) as a baseline for spelling correction. Their method combines normalized absolute Levenshtein distance with Metaphone phonetic similarity and language model similarity. For the latter, distributed word representations (skip-gram word2vec) of three large Twitter data sets were used. In this paper, we used only the DIEGO LAB Drug Chatter Corpus (Sarker and Gonzalez, 2017a), as it was the only health-related corpus of the three. We also use a purely data-driven spelling correction method for comparison: Text-Induced Spelling Correction (TISC) developed by Reynaert (2005). It compares the anagrams of a token to those in a large corpus of text to correct mistakes. These two methods are compared with simple absolute and relative Levenshtein distance and weighted versions of both. To evaluate the spelling correction methods, the accuracy (i.e. the percentage of correct corrections) was used. The weights of the edits for weighted Levenshtein distance were computed using the log of the frequencies of the Norvig corpus. We used the log to ensure that a 10x more frequent error does not become 10x as cheap, as this would make infrequent errors too improbable. In order to make the weights inversely proportional to the frequencies and scale the weights between 0 and 1 with lower weights signifying lower costs for an edit, the following transformation of the log frequencies was used: Weight Edit Distance = 1/(1+log(Frequency)).

Spelling mistake detection We manually constructed a decision process, inspired by the work by Beeksma et al. (2019), for detecting spelling mistakes (See Figure 2). The decision process uses the corpus frequency relative to that of the token and the similarity to the token. The underlying idea is that if a word is either common within the domain-specific language or there is no simi-
lar enough candidate available, it is unlikely to be a mistake. A relative threshold enables us to capture more common mistakes.

To ensure generalisability, we opted for an unsupervised, data-driven method that does not rely on the construction of a specialized vocabulary. Candidates are considered in order of frequency. Of the candidates with the highest similarity score, the first is selected. The spelling correction ignores numbers and punctuation.

To optimize the decision process, a 10-fold cross validation grid search was conducted with a grid of 2 to 10 (steps of 1) for the minimum multiplication factor of the corpus frequency and a grid of 0.05 to 0.15 (steps of 0.01) for the minimum similarity. The choice of grid was based on previous work by Walasek (2016) and Beeksma et al. (2019). The loss function used to tune the parameters was the $F_{0.5}$ score, which places more weight on precision than the $F_1$ score. We believe it is more important to not alter correct terms, than to retrieve incorrect ones.

**Spelling correction candidates** For evaluating the mistake detection process, spelling correction candidates are derived from the data itself using the corpus frequency and similarity thresholds. For internal and external validation, candidates are also derived from the data itself. However, for comparing the spelling correction methods, the words of the specialized vocabulary for cancer forums (see section 3) were used as correction candidates in order to evaluate the methods independently of the vocabulary present in the data.

**Internal validation** The percentage of out-of-vocabulary (OOV) terms is used as an estimation of the quality of the data: less OOV-terms and thus more in-vocabulary (IV) terms is a proxy for cleaner data. As the correction candidates are derived from the data itself, one must note that words that are not part of CELEX may also be transformed from IV to OOV. The forum text was lemmatised prior to spelling correction. OOV analysis was done manually.

**External validation** Text classification was performed with default sklearn classifiers: Stochastic Gradient Descent (SGD), Multinomial Naive Bayes (MNB) and Linear Support Vector Machine (SVC). Uni-grams were used as features. A 10-fold cross-validation was used to determine the average score and paired t-test was applied to determine significance of the absolute difference. Only the best performing classifier is reported per data set. For the shared tasks of the SMM4H workshop, only the training data was used.

To evaluate our method on generic social media text, we used the test set of the ACL W-NUT 2015 task (Baldwin et al., 2015). The test set consists of 1967 tweets with 2024 one-to-one, 704 one-to-many, and 10 many-to-one mappings. We did not need to use the training data, as our method is unsupervised. For comparison, the $F_1$ score on the W-NUT training data was 0.562.

5 Results

5.1 Spelling correction

The state-of-the-art method for generic social media performed poorly on medical social media with an accuracy of only 20.8% (see Table 3). A second established data-driven approach, TISC, also performed poorly (24.5%). The best performing baseline method on our spelling corpus was Relative Weighted Edit distance (RWE) (62.3%). As eight corrections did not occur in the CELEX, the upper bound was 84.9%.

One of the reasons for the low accuracy of Sarker’s method may be the absence of correct terms (e.g. gleevec) in the language model it employs. This potential complication was already highlighted by Sarker (2017) in their own paper. Similarly, the large corpus of English news texts, which TISC relies on, may not contain the right terms or may not be comparable enough as a language model to our domain-specific data set.

In contrast, the key to the success of weighted edit distance methods is likely the incorporation of probabilities for 1-edit errors. This matches the intuition that certain errors are easier to make than others. For example, someone is more likely to wrongly spell sutent as sutant than as mutant (see Table 4). Such weighted methods indirectly integrate different types of possible errors, such as typo- and orthographical errors. The relative

| Method                        | Accuracy |
|-------------------------------|----------|
| Sarker’s method               | 20.8 %   |
| TISC                          | 24.5 %   |
| Absolute Edit distance (AE)   | 56.6 %   |
| Relative Edit distance (RE)   | 56.6 %   |
| Absolute Weighted Edit distance (AWE) | 54.7 % |
| Relative Weighted Edit distance (RWE) | 62.3 % |
| Upper bound                   | 84.9 %   |

Table 3: Accuracy of spelling correction methods
variant, as opposed to the absolute weighted edit distance, can counterbalance cheap deletions and additions, as can be seen for the mistake stomach (See Table 4).

5.2 Detecting spelling mistakes

The grid search results in two criteria for correction candidates: (1) a minimum of 2 times the relative corpus frequency of the token and (2) a maximum similarity score of 0.08 (see Figure 2). This combination attains the maximum F0.5 score for all 10 folds.

On the test set, the decision process has an F0.5 of 0.888. Its precision is high (0.90). Although the recall of a generic dictionary (i.e. CELEX) is maximal (1.0), its precision is low (0.464). This indicates, as hypothesized, that a dictionary-based method can retrieve more of the mistakes, but also will identify many correct terms as mistakes. Some examples of false positives were: ‘oncologist’, ‘gleevec’ and ‘colonoscopy’. See Table 6 for some examples of errors made by our decision process.

The accuracy of the RWE method is further increased by 1.8% point by filtering the correction candidates using the preceding decision process, as is done in the full spelling module. The upper limit for spelling correction also increased from 84.9% to 92.5% by using candidates from the data instead of a specialized dictionary.

5.3 Effect on OOV rate

The reduction in OOV-terms was higher for the GIST (0.50%) than for the Reddit forum (0.27%) (See Figure 3). As expected, it appears that in-vocabulary terms are occasionally replaced with out-of-vocabulary terms, as the percentage of altered words is higher than the reduction in OOV (0.67% vs 0.50% for the GIST and 0.44% vs 0.27% for the Reddit forum).

Interestingly, the initial OOV count before spelling correction of the GIST forum is almost double that of the sub-reddit on cancer. This could be explained by the more specific nature of the forum: it may contain more words that are excluded from the dictionary, despite it being tailored to the cancer domain. This again underscores the limitations of dictionary-based methods.

Some of the most frequent corrections made in the GIST forum data were medical terms (e.g. gleevec, scan). Thus, although the overall reduction in OOV-terms may seem minor, our approach appears to target medical concepts, which are highly relevant for knowledge extraction tasks.

Besides correcting mistakes in medical terms, our method also normalizes variants of medical terms (e.g. metastatic to metastasis). This is possibly a result of the corpus frequency comparison between tokens and candidates, which favors more prevalent variants.

Concerning the 50 most frequent remaining OOV terms, only a small proportion of them are in fact non-word spelling errors (e.g. ‘wa’), although slang words (e.g ‘ya’) could arguably also be part of this category (see Table 7). A significant portion consists of real words (e.g. ‘online’, ‘website’, ‘stressful’) not present in the specialized dictio-
Figure 3: Percentage of OOV-terms in two cancer forums pre- and post-spelling correction.

Figure 4: Most frequent mistakes and corrections in the GIST forum.

nary. Upon manual inspection, the abbreviations frequently refer to treatments (e.g. ‘rai’), mutation types (e.g. ‘nf’) or hospitals (e.g. ‘ucla’). Importantly, also some drug names are considered OOV (e.g. ‘ativan’). Since they can be essential for downstream tasks, it is promising that they have not been altered by our method.

5.4 External evaluation

As can be seen in Table 8, the spelling correction does not lead to significant changes in the F1 score for five of the six tasks. For the Twitter Health classification task, the improvement is significant with a p-value of 0.041 according to a paired t-test.

In general, these changes are of the same order of magnitude as those made by the normalization pipeline of Sarker (2017). Moreover, the % of alterations due to spelling correction is comparable to that of the two cancer-related forums (see Figure 3). Although the overall classification accuracy on Task 1 of the SMM4H workshop is low, this is in line with the low F1 score (0.522) of the best performing system on the comparable task in 2018 (Weissenbacher et al., 2018).

Neither the goal of the task, the relative amount of corrections nor the initial result seem to correlate with the change in F1 score. Unlike in Sarker (2017), the improvements also do not seem to increase with the size of the data. The imbalance of the data may be associated with the change in accuracy to some extent: the two most balanced data sets show the largest increase (see Table 2). Further experiments would be necessary to elucidate if this is truly the case.

As can be seen in Table 9, our method does not perform well on generic social media text. In comparison, Sarker (2017)’s method attained state-of-the-art results with a F1 of 0.836 on the ACL W-NUT 2015, but functioned poorly for medical social media (see Table 3). Thus, the success on one does not imply success on the other and consequently, normalisation of generic social media text and of domain-specific social media text appear different to the extent that they necessitate different approaches.

6 Discussion

Relative weighted edit distance outperforms both Sarker’s method and other edit distance metrics with an accuracy of 62.3%. The accuracy is increased by a further 1.8% point if correction candidates are filtered with the criteria of the preceding decision process. This decision process is also capable of identifying mistakes with an F0.5 of 0.888 and a high precision (0.90).

The spelling correction method led to an overall reduction in OOV-terms of 0.50% and 0.27% for two cancer-related forums. Although the reduction of OOV-terms may seem minor, relevant medical terms appear to be targeted (see Figure 4) and, additionally, many of the remaining OOV-terms are not spelling errors (see Table 7). Further-

| GIST forum | Reddit |
|---|---|
| Spelling error | 3 | 1 |
| Real word | 11 | 21 |
| Abbreviation | 14 | 9 |
| Slang | 6 | 13 |
| Name of person or hospital | 14 | 2 |
| Drug name | 1 | 4 |
| Not English | 1 | 0 |
| TOTAL | 50 | 50 |

Table 7: Analysis of 50 most frequent remaining OOV in two cancer forums.
Table 8: Mean classification accuracy before normalization (prenorm), after normalization (postnorm) and after spelling correction (postspell) for six health-related classification tasks. Only the results for the best performing classifier per data set are reported. MNB: Multinomial Naive Bayes; SVC: Linear Support Vector Classification.

| Data set               | Classifier | Pre norm F<sub>1</sub> | Post norm F<sub>1</sub> | Post spell F<sub>1</sub> | Change* | % of words corrected |
|------------------------|------------|-------------------------|-------------------------|--------------------------|---------|----------------------|
| Task 1 SMM4H 2019      | SVC        | 0.410                   | 0.413                   | 0.417                    | +0.006  | 1.1                  |
| Task 4 SMM4H 2019 Flu vaccine | MNB        | 0.780                   | 0.781                   | 0.782                    | +0.001  | 0.47                 |
| Flu Vaccination Tweets | SVC        | 0.939                   | 0.938                   | 0.941                    | +0.002  | 0.83                 |
| Twitter Health         | MNB        | 0.702                   | 0.708                   | 0.713                    | +0.010* | 0.64                 |
| Task4 SMM4H Flu infection | MNB      | 0.784                   | 0.792                   | 0.795                    | +0.011  | 0.29                 |
| Zika Conspiracy Tweets | MNB        | 0.822                   | 0.818                   | 0.811                    | -0.011  | 1.1                  |

Table 9: Results for unconstrained systems of ACL W-NUT 2015

|                | F<sub>1</sub> | Precision | Recall |
|----------------|--------------|-----------|--------|
| Sarker’s method (Sarker, 2017) | **0.836** | **0.880** | 0.796  |
| IHS_RD (Supranovich and Patsepnia, 2015) | 0.827 | 0.847 | **0.808** |
| USZEGED (Berend and Tasnádi, 2015) | 0.805 | 0.861 | 0.756  |
| BEKLI (Beckley, 2015) | 0.757 | 0.774 | 0.742  |
| LYGROUP (Doval Mosquera et al., 2015) | 0.531 | 0.459 | 0.630  |
| Our method | 0.522 | 0.646 | 0.577  |

more, our method was designed to be conservative and to focus on precision to mitigate one of the major challenges of correcting errors in domain-specific data: the loss of information due to the ‘correction’ of correct domain-specific terms. The marginal change in task-based classification accuracy may be due to the fact that classification tasks do not rely strongly on individual terms, but on all words combined. This could also explain the lack of a correlation between the amount of alterations and the change in F<sub>1</sub> score. We plan to evaluate these results further by analysing both the corrections and the classification errors.

We speculate that our method will have a larger impact on named entity recognition (NER) tasks. Unfortunately, NER benchmarks for health-related social media are limited. We have investigated three relevant NER tasks that were publicly available: CADEC (Karimi et al., 2015), ADR-Miner (Nikfarjam et al., 2015), and the ADR extraction task of the SMM4H 2019. For all three tasks, extracted concepts could be matched exactly to the forum posts, thus negating the potential benefit of normalization. The exact matching can perhaps be explained by the fact that data collection and extraction from noisy text sources such as social media typically rely on keyword-based searching (Sarker and Gonzalez, 2017b).

Our study has a number of limitations. Firstly, the use of OOV-terms as a proxy for quality of the data relies heavily on the vocabulary that is chosen and, moreover, does not allow for differentiation between correct and incorrect substitutions. Consequently, we also test whether our method can improve classification accuracy on various tasks. Secondly, our method is currently targeted specifically at correcting non-word errors and is thus unable to correct real word errors. Thirdly, our evaluation data set for developing our method is small: a larger evaluation data set would allow for more rigorous testing. Nonetheless, as far as we are aware, our corpora are the first for evaluating mistake detection and correction in a medical patient forum. We welcome comparable data sets sourced from various patient communities for further refinement and testing of our method.

7 Conclusion and future work

Our data-driven, unsupervised spelling correction can improve the quality of text data from medical forum posts from two cancer-related forums. Our method may also be useful for user-generated content in other highly specific and noisy domains, which contain many OOV compared to available dictionaries. Future work will include extending the pipeline with modules for named entity recognition, automated relation annotation and concept normalization.

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