Benefits of Data Augmentation for NMT-based Text Normalization of User-Generated Content

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Abstract

One of the most persistent characteristics of written user-generated content (UGC) is the use of non-standard words. This characteristic contributes to an increased difficulty to automatically process and analyze UGC. Text normalization is the task of transforming lexical variants to their canonical forms and is often used as a pre-processing step for conventional NLP tasks in order to overcome the performance drop that NLP systems experience when applied to UGC. In this work, we follow a Neural Machine Translation approach to text normalization. To train such an encoder-decoder model, large parallel training corpora are required. However, obtaining large data sets with UGC and their normalized version is not trivial, especially for languages other than English. In this paper, we explore how to overcome this data bottleneck for Dutch, a low-resource language. We start off with a small publicly available parallel Dutch data set comprising three UGC genres and compare two different approaches. The first is to manually normalize and add training data, a money and time-consuming task. The second approach is a set of data augmentation techniques which increase data size by converting existing resources into synthesized non-standard forms. Our results reveal that, while the different approaches yield similar results regarding the normalization issues in the test set, they also introduce a large amount of over-normalizations.

1 Introduction

Social media text are considered important language resources for several NLP tasks (Van Hee et al., 2017; Pinto et al., 2016; Zhu et al., 2014). However, one of their most persistent characteristics is the use non-standard words. Social media texts are considered a type of written user-generated content (UGC) in which several language variations can be found as people often tend to write as they speak and/or write as fast as possible (Vandekerckhove and Nobels, 2010). For instance, it is typical to express emotions by the use of symbols or lexical variation. This can be done in the form of the repetition of characters or flooding (woooow), capitalization (YEY!), and the productive use of emoticons. In addition, the use of homophonous graphemic variants of a word, abbreviations, spelling mistakes or letter transpositions are also used regularly (Eisenstein et al., 2014).

Since NLP tools have originally been developed for and trained on standard language, these non-standard forms adversely affect their performance. One of the computational approaches which has been suggested to overcome this problem is text normalization (Sproat et al., 2001). This approach envisages transforming the lexical variants to their canonical forms. In this way, standard NLP tools can be applied in a next step after normalization (Aw et al., 2006). Please note that for some NLP applications, e.g. sentiment analysis, it might be beneficial to keep some ‘noise’ in the data. For example, the use of flooding or capital letters could be a good indicator of the emotion present in the text (Van Hee et al., 2017). However, for applications aiming at information extraction from text, normalization is needed to help to improve the performance of downstream NLP tasks (Schulz et al., 2016). Kobus et al. (2008) introduced three metaphors to refer to these normalization approaches: the spell checking, automatic speech recognition and machine translation metaphors.

In this paper, the focus will be on the machine translation metaphor. One of the most conventional approaches is to use Statistical Machine Translation (SMT) techniques (Kauffmann, 2010; De Clercq et al., 2014; Junczys-Dowmunt and Grundkiewicz, 2016), in particular using
the Moses toolkit (Koehn et al., 2007). However, neural networks have proven to outperform many state-of-the-art systems in several NLP tasks (Young et al., 2018). Especially the encoder-decoder model with an attention mechanism (Bahdanau et al., 2014) for recurrent neural networks (RNN) has lead to a new paradigm in machine translation, i.e., Neural MT (NMT) (Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015; Sennrich et al., 2016a).

Many works have adopted and applied these techniques to the normalization task (Ikeda et al., 2016; Mandal and Naman, 2018; Lusetti et al., 2018) some of them outperforming the SMT approach. However, it is well-known that these neural systems require a huge amount of data in order to perform properly (Ikeda et al., 2016; Saito et al., 2017). When it comes to translation these data even have to be parallel and should thus consist of aligned source and target sentences. Unfortunately, when it comes to UGC text normalization there is a lack of parallel corpora in which UGC is considered the source language and its standardized form the target language. Furthermore, the problem even exacerbates when working with low-resourced languages.

In this work, we follow an NMT approach to tackle text normalization of Dutch UGC and explore how to overcome this parallel data bottleneck for Dutch, a low-resource language. We start off with a publicly available tiny parallel Dutch data set comprising three UGC genres and compare two different approaches. The first one is to manually normalize and add training data, a money and time-consuming task. The second approach consists in a set of data augmentation techniques which increase data size by converting existing resources into synthesized non-standard forms. Our results reveal that the different setups resolve most of the normalization issues and that automatic data augmentation mainly helps to reduce the number of over-generalizations produced by the NMT approach.

In the following section, we discuss related work on MT-based text normalization as well as data augmentation techniques. In section 3, we discuss the two approaches to augment the available data: manual annotations of new sentence pairs and augmentation techniques. The data used for our experiments are also explained in detail. Section 4 gives an overview of the experiments and results, whereas section 5 concludes this work and offers prospects for future work.

2 Related Work

Previous research on UGC text normalization has been performed on diverse languages using different techniques ranging from hand-crafted rules (Chua et al., 2018) to deep learning approaches (Ikeda et al., 2016; Sproat and Jaitly, 2016; Lusetti et al., 2018). Three different metaphors were introduced by Kobus et al. (2008) to refer to these normalization approaches. That is the automatic speech recognition (ASR), spell checking, and translation metaphors. The ASR approach exploits the similarity between social media text and spoken language. Several works have followed this methodology, mostly combining it with the others (Beaufort and Rockhaut, 2010; Xue et al., 2011; Han and Baldwin, 2011). In the spell checking approach, corrections from noisy to standard words occurs at the word level. Some approaches have treated the problem by using dictionaries containing standard and non-standard words (Clark and Araki, 2011). However, the success of this kind of systems highly depends on the coverage of the dictionary. Since social media language is highly productive and new terms constantly appear, it is very challenging and expensive to continuously keep such a dictionary up to date.

In this work, we consider the normalization task as a Machine Translation problem and treat noisy UGC text as the source language and its normalized form as the target language. In the past, several works have also used this approach and there are two leading paradigms: Statistical and Neural Machine Translation.

Statistical Machine Translation (SMT) models, especially those trained at the character-level, have proven highly effective for the task because they capture well intra-word transformations (Pennell and Liu, 2011). Besides, they have the advantage of being effective when small training data is provided, thanks to their small vocabulary size. Kaufmann (2010), for example, followed a two step approach for the normalization of English tweets. First, they pre-processed the tweets to remove as much noise as possible, and then they used Moses to convert them into standard English. Moses is a statistical machine translation package which can produce high quality translations from one lan-
| Source Sentence | Target Sentence | English Translation |
|-----------------|-----------------|---------------------|
| iz da muzieksgool vnavnd ? kwt da niemr . | is dat muzieschool vanavond ? ik weet dat niet meer . | is that music school tonight? I don’t know that anymore. |
| wa is je msn k en e nieuwe msn omda k er nie meer op graal . xxx | wat is je msn ik heb een nieuwe msn omdat ik er niet meer op geraak . xx | what is your msn i have a new msn because i can’t get it anymore. xx |
| @renskedemaessc dm me je gsmnummer eens ;-) | <user> doormail me je gsmnummer eens <emoji> | <user> mail me your cellphone number once <emoji> |

Table 1: Source and target pairs as parallel data for a machine translation approach.

Recently, neural networks have proven to outperform many state-of-the-art systems in several NLP tasks (Young et al., 2018). The encoder-decoder model for recurrent neural networks (RNN) was developed in order to address the sequence-to-sequence nature of machine translation and obtains good results for this task (Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015). The model consist of two neural networks: an encoder and a decoder. The encoder extracts a fixed-length representation from a variable-length input sentence, and the decoder generates a correct translation from this representation. Some works on text normalization have followed the same approach (Lusetti et al., 2018; Cho et al., 2014). In 2016, Sproat and Jaitly (Sproat and Jaitly, 2016) presented a challenge to the research community: given a large corpus of written text aligned to its normalized spoken form, train an RNN to learn the correct normalization function. Although their work focuses on the Text to Speech (TTS) use case of text normalization, they compared prior work of text normalization for TTS (Rao et al., 2015; William Chan, 2016) and also discuss the problems that arise when using neural networks for text normalization. They made clear that although RNNs were often capable to produce surprisingly good results and learn some complex mappings, they are prone to make errors like reading the wrong number, or substituting hours for gigabytes. This makes them risky to apply in a TTS system. Lusetti et al. (2018) performed NMT text normalization over Swiss German WhatsApp messages and compared it to a state-of-the-art SMT system. They revealed that integrating language models into an encoder-decoder framework can outperform the character-level SMT methods for that language.

Although the encoder-decoder model has shown its effectiveness in large datasets, it is much less effective when only a small number of sentence pairs is available (Sennrich et al., 2016b; Zoph et al., 2016). Automatic data augmentation is commonly used in vision and speech and can help train more robust models, particularly when using smaller datasets (Chatfield et al., 2014; Taylor and Nitschke, 2017). Fadaee et al. (2017) present Translation Data Augmentation (TDA), a method to improve the translation quality for low resource pairs (English to German and German to English). Their approach generates new sentence pairs containing rare words in new, synthetically created contexts.

Data augmentation techniques have therefore also been applied to outperform text normalization for low-resourced languages. For example, Ikeda et al. (2016) performed text normalization at the character level for Japanese text and proposed a method for data augmentation using handcrafted rules. Their method transformed existing resources into synthesized non-standard forms using the rules proposed in the work of Sasano et al. (2015). They proved that the use of the synthesized corpus improved the performance of Japanese text normalization. Saito et al. (2017) also proposed two methods for data augmentation in order to improve text normalization. Unlike the previous work, the proposed method did not use prior knowledge to generate synthetic data at the

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*Source Sentence*:

iz da muzieksgool vnavnd ? kwt da niemr .
wa is je msn k en e nieuwe msn omda k er nie meer op graal . xxx
@renskedemaessc dm me je gsmnummer eens ;-) 

*Target Sentence*:

is dat muzieschool vanavond ? ik weet dat niet meer .
wat is je msn ik heb een nieuwe msn omdat ik er niet meer op geraak . xx
<user> doormail me je gsmnummer eens <emoji>

*English Translation*:

is that music school tonight? I don’t know that anymore. 
what is your msn i have a new msn because i can’t get it anymore. xx
<user> mail me your cellphone number once <emoji>
character and morphological level. Instead, they proposed a two-level data augmentation model that converted standard sentences to dialect sentences by using extracted morphological conversion patterns. Their experiments using an encoder-decoder model for Japanese, performed better than SMT with Moses after the data augmentation.

3 Methodology

Our objective is to go from noisy to standard text and we tackle this normalization problem using an NMT approach. Sequence-to-Sequence (seq2seq) models have been used for a variety of NLP tasks including machine translation obtaining state-of-the-art results (Luong et al., 2015; Young et al., 2018). As in general MT, a translation model is trained on parallel data consisting of pairs \((x, y)\) of source sentences/words (= social media text) and their corresponding target equivalents (= standard text). Table 1 lists some examples of the noisy data we are dealing with.

3.1 NMT Approach

In this approach, both input and output sentences are going in and out of the model. As described in the literature overview, the model consists of two neural networks: an encoder and decoder (See Figure 1).

The encoder extracts a fixed-length representation from a variable-length input sentence \((A B C D)\), and the decoder generates a correct translation from this representation \((X Y Z)\). In the figure, \(<eos>\) marks the end of a sentence. The encoder-decoder model is trained on a parallel corpus consisting of source sentences aligned with their normalized form.

We relied on OpenNMT\(^2\) to train our encoder-decoder model. OpenNMT is an open source (MIT) initiative for neural machine translation and neural sequence modeling (Klein et al., 2017). The main system is implemented in the Lua/Torch mathematical framework, and can easily be extended using Torch’s internal standard neural network components. We used the version of the system with the basic architecture which consists of an encoder using a simple LSTM recurrent neural network. The decoder applies attention over the source sequence and implements input feeding (Luong et al., 2015).

3.2 Evaluation Metric

To evaluate the results of the normalization, we calculated Word Error Rate (WER) and Character Error Rate (CER) over the three genres. WER is a metric derived from the Levenshtein distance (Levenshtein, 1966), working at the word level. Character Error Rate (CER), instead, works at the character level. These metrics take into account the number of insertions (INS), deletions (DEL) and substitutions (SUBS) that are needed to transform the suggested string into the manually normalized string. The metrics are computed as follows:

\[
\text{WER} = \frac{INS_w + DEL_w + SUBS_w}{N_w}
\]
\[
\text{CER} = \frac{INS_c + DEL_c + SUBS_c}{N_c}
\]

where \(N_w\) is the number of words in the reference and \(N_c\) represents the number of characters.

The higher the value, the higher the number of normalization operations needed to obtain the target sentence.

3.3 Overcoming Data Sparsity

Since our focus is on Dutch, our starting point is an existing Dutch corpus comprising three UGC genres, which were manually normalized (Schulz et al., 2016). The genres represented in this corpus are the following:

- Tweets (TWE), which were randomly selected from the social network.
- Message board posts (SNS), which were sampled from the social network Netlog, which was

\(^2\)http://opennmt.net
a Belgian social networking website targeted at youngsters.

Text messages (SMS), which were sampled from the Flemish part of the SoNaR corpus (Treurniet et al., 2012).

This corpus is, to our knowledge, the only freely available parallel normalization dataset for Dutch.

Table 2 presents the number of parallel sentences in each genre and the number of words before and after normalization. The WER and CER values computed between the original and target parallel sentence pairs are also shown. These values were calculated per sentence and averaged over the data set. As can be observed, the Dutch tweets (TWE) required hardly any normalization (with a WER of 0.09 and a CER of 0.047). This can be explained by the fact that this platform has mainly been mainly adopted by professionals in Belgium who write in a more formal style (Schulz et al., 2016).

![Table 2: Dutch parallel corpora data statistics.](image)

On the other hand, we observe that the text messages (SMS) required most normalization (with a WER and CER score of 0.27 and 0.117, respectively). Table 2 also reveals that the corpus amounts to only a few hundred parallel sentences. NMT models often fail when insufficient data is provided (Ikeda et al., 2016; Saito et al., 2017). Because of that, we believe that the mentioned data would not be enough to successfully train a RNN model.

Under these conditions, we decided to experimentally verify which approach works best in order to overcome this data sparsity problem. Our objective is to find out whether annotating more data or using a set of data augmentation techniques is more beneficial and leads to better results.

### Collecting More Data

First, we sampled and manually annotated ten thousand additional sentences for each of the three genres. We sampled SMS from the Flemish part of the SoNaR corpus (Treurniet et al., 2012). For the TWE genre, new data were retrieved by crawling Twitter using the Twiqs software, which was specifically designed to crawl Dutch tweets from Twitter. We used emoticons as keyword for the crawling process in order to collect text in which noisy words were present to some extent. For the SNS genre we relied on text collected from the social networking site ASKfm (Van Hee et al., 2018), where users can create profiles and ask or answer questions, with the option of doing so anonymously. ASKfm data typically consists of question-answer pairs published on a user’s profile.

For all genres we made sure that there were no duplicates in the texts. Each message was also lowercased and tokenized using the NLTK tokenizer prior to annotation, and the annotators also had to check the tokenization of the sentences. Besides this, hashtags, usernames and emoticons were replaced with a placeholder. All data was then normalized following the procedure described in Schulz et al. (2016). Table 3 shows the size of the newly annotated data in terms of the number of sentences and tokens for each genre. The WER and CER values give an insight into the normalization needed for each of the genres.

![Table 3: Parallel corpora data statistics after new annotations.](image)

As can be derived from Table 3, TWE remains the least noisy genre, whereas the SNS genre is now the noisiest one with higher WER and CER values.

### Applying Data Augmentation Techniques

A less time-consuming way to overcome data sparsity is to investigate the added value of data augmentation. A rudimentary way to augment the existing data is to simply add monolingual standard data to both the source and target side of the corpus. This implies providing a large number of standard Dutch sentences from which the model can learn the standard word use. This type of data augmentation, however, is very primitive and, although it could probably provide good training...
data to learn the standard form of sentences, the non-canonical form of the words would be heavily (and even more so than in the beginning) underrepresented in the training data.

In order to address this problem, we took our initial parallel data as starting point for the data augmentation. Since we want to obtain more instances of non-canonical words and their corresponding normalized forms, we first relied on pretrained embeddings to replace the standard words by similar ones. These embeddings where trained on Flemish newspapers and magazines data collected from 1999 to 2014 in the Mediargus Archives, which can be accessed through GoPress Academic.6

In a second step, we applied an additional data augmentation technique, starting from the user-generated text in it. In Table 4, we illustrate this augmentation technique, starting from the user-generated text: *jaaa sws toch :) hij is echt leuk* (yes anyway *<emoji>* he is really nice). It is important to emphasize that we only replaced words that were already in their standard form in both the source and target side of the corpus. The replacements were made using the most similar words from the embeddings, using a similarity threshold with a value equal or greater than 0.5.

In the upper part of Table 4 the standard words in the source and target sentences are placed in cursive. In the middle and lower part, the bold words show the replacement for the standard words based on the embeddings. Please note that this replacement sometimes caused a (slight) change in the semantics of the sentence, as in *jaaa sws toch <emoji> hij blijft echt leuk*. However, since we are only dealing with lexical normalization, we argue that this is not an issue for the task.

In a second step, we applied an additional data augmentation technique which produces new abbreviations on the source side of the parallel corpus. We made use of a dictionary of about 350 frequent abbreviations appearing in social media texts, such as *lol* (laughing out loud) and *aub* for *alstublieft* (you are welcome) (Schulz et al., 2016).

Table 5 exemplifies this technique. It first lists two examples of newly generated sentences using the embeddings after which the abbreviations step is applied, leading to two additional new sentences.

### 3.4 Experimental Setup

To conduct the experiments, both approaches were applied in several steps and combinations.

The first round of experiments (Setup 0), which we will consider as the baseline system, consisted in applying the NMT architecture to the original small Dutch parallel corpus, as presented in Table 2. We performed 10-fold cross validation experiments to ensure that each part of the dataset would be used once as training and test set. For the remaining experiments (see Setup 1 to 3 below), this entire small dataset was used as held-out test set in order to find out which approach works best for overcoming data sparsity.

| Sentences | Source | Target | Embed. | Abbr. | English |
|-----------|--------|--------|--------|-------|---------|
| *jaaa sws toch <emoji> hij is echt leuk* | *jaaa sws toch <emoji> hij is echt leuk* | *jaa sowieso toch <emoji> hij is echt leuk* | *jaaa sws maar <emoji> hij is gewoon leuk* | *jaa sws dus <emoji> hij is inderdaad tof* | *yes anyway but/so <emoji> he/himself is really/just/indeed nice/cool* |

| Sentences | Source | Target | Embed. | Abbr. | English |
|-----------|--------|--------|--------|-------|---------|
| *jaa sowieso toch <emoji> hij is echt leuk* | *jaa sowieso toch <emoji> hij is echt leuk* | *jaa sowieso toch <emoji> hij is echt leuk* | *jaa sowieso <emoji> hij is inderdaad tof* | *jaa sws dus <emoji> hij is idd tof* | *yes anyway but/so <emoji> he/himself is really/just/indeed nice/cool* |

| INS | DEL | SUBS | SUM |
|-----|-----|------|-----|
| TWE | 1118 | 934 | 355 | 2407 |
| SNS | 2483 | 2238 | 1021 | 5742 |
| SMS | 4209 | 508 | 758 | 5475 |

Table 6: Operations needed at the character level to normalize the test set for each genre.

6https://bib.kuleuven.be/english/ub/searching/collections/belgian-press-database-gopress-academic
Table 6 shows the number of insertions (INS), deletions (DEL) and substitutions (SUBS) that are needed to transform the source sentences of the test set into manually normalized ones. The last column of the table shows the overall number of operations that would need to be solved by the systems.

The new annotations as presented in Table 3 were used for training (Setup 1). In a next step, we trained the NMT model on the data obtained by first applying the embeddings technique to the newly annotated data (Setup 2) and then together with the abbreviation step (Setup 3).

Table 7: Parallel corpora data statistics for each experimental setup.

| #Sent. | # Words |
|--------|---------|
| TWE    |         |
| 1      | 5190    | 124578  | 122165  |
| 2      | 697441  | 20692213| 20416466|
| 3      | 853465  | 26316110| 26002836|
| SNS    |         |
| 1      | 8136    | 108127  | 110326  |
| 2      | 577281  | 21120858| 21499465|
| 3      | 835091  | 70337827| 71257870|
| SMS    |         |
| 1      | 7626    | 111393  | 113846  |
| 2      | 615195  | 15356594| 15669683|
| 3      | 766946  | 22066532| 22651464|

Table 7 shows the number of parallel training sentences and words in the original and target sides of each setup for each genre.

4 Experiments

As we explained before, the goal of our work is to experimentally verify which approach works best to overcome the data sparsity problem for a low-resourced language such as Dutch UGC: annotating more data or using data augmentation techniques.

Figure 2 presents the WER results for each genre with the different experimental setups and Figure 3 the CER results. As expected, the 10-fold cross validation experiments on the tiny original datasets (Setup 0) leads to bad results. The system’s output consisted of sentences of the type <emoji>, de, ..., <emoji>. These are random repetitions of the most represented tokens in the training data like ik (I in English), punctuation marks or <emoji> labels. The system was thus unable to learn from such a small dataset.

Table 8 shows some examples of sentences which were normalized using the proposed NMT approach.

However, the approach still produces a large number of odd normalizations. For example, in the second sentence in Table 8, the system was unable to correctly normalize some of the words. For instance, the word byyy (there) was incorrectly normalized as the verb gedragen (behave). Furthermore, the system also produced odd translations of words that already were in their standard form. For example, the word tammy, which is a proper name, is changed into toevallig (accidentally) and the word u (you) was duplicated in 50% WER and CER reduction for the SMS genre. The data augmentation techniques (Setup 2 and 3) seem to further affect the normalization results. For the SNS and SMS genre, the WER and CER significantly decreases with the data augmentation technique relying on embeddings. However, when more noise is introduced to the data set (Setup 3) this adversely affects the WER and CER values for all genres.

With the results of Setups 2 and 3 compared to the original WER values of our test set (see Table 2) we observe that the normalization task was not solved at all as the WER values are almost always higher. Only for the SMS genre, the results are somewhat similar, with WERs of 0.25 and 0.27 for setups 2 and 3 respectively.

4.1 Error Analysis

Table 8 shows some examples of sentences which were normalized using the proposed NMT approach.

However, the approach still produces a large number of odd normalizations. For example, in the second sentence in Table 8, the system was unable to correctly normalize some of the words. For instance, the word byyy (there) was incorrectly normalized as the verb gedragen (behave). Furthermore, the system also produced odd translations of words that already were in their standard form. For example, the word tammy, which is a proper name, is changed into toevallig (accidentally) and the word u (you) was duplicated in.
Table 8: Examples of original (src), predicted (norm) and target (tgt) sentences using the NMT approach. An English translation is also provided.

| src sent. | norm sent. | tgt sent. | English |
|-----------|------------|-----------|---------|
| haha zekr mdaje n vriend vn matti zyt! <emoji> x | haha zeker omdat je een vriend van matti zijt! <emoji> x | haha zeker omdat je een vriend van matti zijt! <emoji> x | haha certainly because you are a friend of matti! <emoji> x |
| eeh ik sta dr nie byyyy <emoji> I y mis je | he ik sta er niet gedragen <emoji> love you mis je | he ik sta er niet bij <emoji> love you mis je | he i am not there <emoji> love you miss you |
| jonge tammy, k u | jongen toevallig, ik u | jongen tammy, ik u | boy tammy, me you |

Table 9: Number of solved operations at the character level after normalization for each genre.

| Setup | Test | SNS | INS | DEL | SUBS | SUM |
|-------|------|-----|-----|-----|------|-----|
| 0     | 1118 | 934 | 355 | 2407 |
| 1     | 1101 | 930 | 351 | 2382 |
| 2     | 1099 | 924 | 330 | 2353 |
| 3     | 1105 | 917 | 326 | 2348 |
| Setup 0 | 2454 | 2225 | 992 | 5671 |
| Setup 1 | 2468 | 2220 | 995 | 5683 |
| Setup 2 | 2366 | 2092 | 968 | 5426 |
| Setup 3 | 2366 | 2141 | 971 | 5478 |
| Setup 0 | 4107 | 505 | 727 | 5339 |
| Setup 1 | 4094 | 483 | 700 | 5277 |
| Setup 2 | 4099 | 470 | 709 | 5278 |
| Setup 3 | 4090 | 468 | 710 | 5268 |

Ideally, the number of operations after normalization should be reduced to zero. As can be derived from the Table 9 many cases where correctly
normalized by the systems. However, we can also observe that at the same time a large number of over-normalizations is introduced (Figures 2 and 3). Regarding data augmentation, we conclude that these techniques mainly help to reduce the number of over-normalizations.

5 Conclusions and Future Work

In this article, we have applied text normalization to Dutch written user-generated content from different genres: text messages, message board posts and tweets. We followed a Neural Machine Translation approach to solve the task and investigated different data augmentation techniques to tackle the problem of data sparsity. Results show that for most of the genres, augmenting the data by using pretrained embeddings helped to reduce the errors introduced by the NMT approach. On the other hand, for most of the genres Setup 0, i.e. training the NMT system on the small in-domain data set, solved most of the normalization problems in the test set.

Regarding the quality of the normalization, despite many of the non-standard words being correctly normalized, the system also produced odd translations, which is a common error using encoder-decoder architectures (Sproat and Jaitly, 2016). This is reflected in the number of over-normalizations that are produced by the system. With respect to these errors, we believe that following a modular approach that helps to solve the remaining errors, instead of only using NMT, could lead to a better performance.

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