A Fine-grained Error Analysis of NMT, PBMT and RBMT Output for English-to-Dutch

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Abstract
This paper presents a fine-grained error comparison of the English-to-Dutch translations of a commercial neural, phrase-based and rule-based machine translation (MT) system. For phrase-based and rule-based machine translation, we make use of the annotated SCATE corpus of MT errors, enriching it with the annotation of neural MT errors and updating the SCATE error taxonomy to fit the neural MT output as well. Neural, in general, outperforms phrase-based and rule-based systems especially for fluency, except for lexical issues. On the accuracy level, the improvements are less obvious. The target sentence does not always contain traces or clues of content being missing (omissions). This has repercussions for quality estimation or gisting operating only on the monolingual level. Mistranslations are part of another well represented error category, comprising a high number of word-sense disambiguation errors and a variety of other mistranslation errors, making it more complex to annotate or post-edit.

Keywords: machine translation, error classification, bilingual corpus

1. Introduction
Since 2016, the landscape of automated translation has substantially changed with the arrival of neural machine translation (NMT). The output quality of this newest system is a hot topic for research at the moment. It has already been compared with the previous state-of-the-art phrase-based machine translation (PBMT) engines and even with rule-based machine translation (RBMT) engines, focusing on the overall performance by applying various automatic metrics, by manual ranking and scoring (Shterionov, Casanellas, Superbo, & O’Dowd, 2017), post-editing or manual error classification (Bentivogli, Bisazza, Cettolo, & Federico, 2016). The scope of the studies range from one to multiple language directions (Toral and Sánchez-Cartagena, 2017; Klubička, Toral, and Sánchez-Cartagena, 2017; Bojar et al., 2016). Unlike previous work, where engines are developed in research institutes or test suites are built for evaluation, in this paper, we take a different angle by using commercial MT systems and real-life texts from different genres, and thus bring more ecological validity into the field.
In this article, we compare the output of commercial NMT, PBMT and RBMT systems for English to Dutch. Since it provides a detailed overview of the types of errors, we want to discover if the findings for other language pairs apply to English-to-Dutch as well, identify the actual improvements that NMT systems bring to automated translation and get a grip on their potential shortcomings.

2. Related Work
This analysis is carried out in the framework of the SCATE project (Tezcan, Hoste, & Macken, 2017b) and draws on its corpus of PBMT and RBMT errors. We used SCATE’s error taxonomy to annotate the same sentences, this time translated by Google’s Neural Machine Translation (GNMT)1.
A substantial part of the research in the field focuses on the language pair English-German. For English to German, Bentivogli et al. (2016) found that NMT output contains less lexical, morphological and word-order errors, which leads to a lower overall post-editing effort. However, according to the authors, the performance of NMT degraded more quickly for longer sentences. Popović (2017) looked into both the overall performance and the specific language-related issues for German-English, using the output of the best NMT and a PBMT engine which participates in the WMT 2016 shared news translation task. The BLEU score and ChrF-score2 for NMT were higher than for the PBMT output in both language directions. She manually annotated a subset of 264 sentences for English-to-German and 204 for German-to-English extracted from the total corpus of 3000 sentences. In her study, the number of correct sentences was remarkably higher for the NMT system than for the PBMT system. As for the language-specific issues, NMT outperformed the PBMT system in terms of verb aspects (form, order and omission), articles, English noun collocations and German compounds, as well as phrase structure. This led to improved fluency. Burchardt et al. (2017) use a test suite drawn from grammatical resources, and online lists, consisting of typical translation errors, to compare the output of different NMT, PBMT and RBMT systems. This very controlled, difficulty-isolating method, showed a higher intra-system output variation among NMT systems. They also found that NMT scores best on composition, function words, long-distance dependency, multiword expressions, subordination and verb valence. Ambiguity, tense and mood of verbs, on the other hand, are handled best by RBMT systems. Terminology and named entities, finally, form the mainstay of PBMT systems based on their results. By using a similar challenge-set approach, Isabelle, Cherry, and Foster (2017) focus on short sentences that contain one particular language phenomenon at a time, which reveals the strengths and weaknesses of NMT compared to PBMT for English to French. The controlled input in both studies is both a strength and a trade-off for ecological validity. Language-specific errors hardly ever occur in isolation. The performance of systems can differ if multiple difficulties need to be handled in the same sentence.

1 MT output generated in June 2017.
2 Character n-gram F-score (Popovic, 2015)
3 The Dutch Parallel Corpus comprises two additional text types that were not used by SCATE: administrative texts and instructive texts.

4 Systran Enterprise Edition, version 7.5

5 http://brat.nlplab.org/
Table 2: Correct sentences in MT output

Table 2 illustrates that the NMT output surpasses the other systems. One third of the sentences has been translated correctly by NMT, while this rate is much lower for RBMT and PBMT.

5.1 Accuracy errors

Accuracy concerns the transfer of information and meaning from source to target language. The following main categories can be distinguished: mistranslation, do-not-translate (DNT), untranslated, addition, omission, and mechanical. 6 ‘Mistranslations’ comprise all errors for which the source content has been translated incorrectly (the subcategories will be mentioned below). The label ‘DNT’ is used for instances in which one or more source words have been translated unnecessarily, e.g. for proper names. ‘Addition’ refers to errors in which the target content is not present in the source, while for ‘omission’ some source content is absent in the target sentence. All mistakes concerning non-meaning (mostly punctuation errors only visible on bilingual level) fall under the category ‘mechanical’.

Table 3: Overview of the number of accuracy errors

Table 3 shows that overall, NMT scores better on accuracy than previous systems. However, upon closer inspection, it becomes evident that PBMT handles DNT issues better than NMT. This comes as no surprise, since most of the DNT errors are instances of proper names, a reported strength of PBMT (Burchardt et al., 2017). We also observe that RMBT output contains the fewest omissions. The main category ‘mistranslation’ is obviously a tough nut to crack for automated translation, as it is the category with the highest number of accuracy errors in all three systems, urging us to dig a little deeper.

5.1.1 Mistranslation errors

‘Mistranslation’ refers to incorrectly translated source content and is subdivided in the following subcategories: multiword expressions (MWE), part of speech (POS), sense, partial and other. The label ‘partial’ is used for partial translations of verbs (especially for Dutch, separable verbs). The container ‘other’ comprises mistranslations of the verb tense and voice, or the number (noun/ verb). To cover the instances for which the target word(s) could never be a plausible translation of the given source word, we introduce the label “semantically unrelated”. An example:

EN: … to build the first ever dynamic billboard to grace the streets of Glasgow.
NL: … om het eerste dynamische billboard te bouwen om de straten van Glasgow te grazen.

In the sentence above ‘grace’ is translated by ‘grazen’, the Dutch equivalent of ‘to graze’. This new category reveals a high number of semantically unrelated mistranslations in the NMT output, an error that does not occur in RBMT and only rarely in PBMT output.

Table 4: Differentiation of mistranslation errors

Table 4 further illustrates the improvement that NMT has made on almost all mistranslation categories, except for ‘other’.

5.1.2 Omissions

Castilho et al. (2017) reported the problem of omissions in NMT output. When scanning the error statistics in Table 5, we can see that also in our data set, NMT makes fewer omission errors than PBMT. However, the ratio of omitted words per omission error is much higher in NMT than in PBMT and RMBT.

Table 5: The number of omission errors compared to the number of words per omission error

Looking back at the corpus, we see that the nature of the omission errors has changed. Often, the NMT output does not provide any clues that source content has been omitted. Wu et al. (2016) already commented: “MT systems sometimes produce output sentences that do not translate all parts of the input sentence – in other words, they fail to completely ‘cover’ the input, which can result in surprising translations”.

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6The actual SCATE taxonomy also includes the categories ‘terminology’, ‘source’ and ‘other’, but these are left out here as there were no occurrences for any of the three systems.
except for the label ‘multiple errors’, which is used when an accumulation of fluency errors on a text span makes it hard to identify the error separately. Table 7 gives an overview of the fluency performance of the different systems.

![Table 7: Overview of the number of fluency errors](image)

As previous research confirms, fluency is handled best by NMT for English-Dutch as well. The improvements are enormous for all categories, except for lexicon, which, therefore, draws our attention.

5.2.1 Lexicon

Lexical errors are split into two subcategories: ‘non-existent’ and ‘lexical choice’. The latter distinguishes ‘content words’ from ‘function words’. Table 8 gives an overview of all the lexical errors in the MT output. From the results in Table 8, it is clear that NMT makes much more lexical choice errors than PBMT, but it is actually only the content words that cause difficulties. For function words, NMT scores best.

![Table 8: Subdivision of lexical choice errors](image)

In many instances, the category ‘Fluency-Lexical Choice’ occurs together with an accuracy error for ‘Mistranslation-Sense-Content word’. This type of fluency error is the clue that source content has not been rendered correctly.

5.2.2 Grammar

Another well represented fluency error category is grammar. Comparing the three paradigms, we see the progress that has been made. A further subdivision of this category is presented in Table 9.

![Table 9: Subdivision of grammar errors](image)

It is worthwhile to take a look into ‘extra words’. Table 10 shows the newly added ‘repetition’ subcategory to label words or word groups that are unnecessarily repeated. The rest category ‘other’ contains all other extra words in the
target sentences, that should not be there. An example of repetition is illustrated below:

EN: Located above Glasgow Central Station, on the corner of Union Street and Gordon Street, the 55 square metre LED screen faces directly onto Renfield street--the second largest retail location in the United Kingdom, and is visible across a range of over 600 metres.

NL: Het 55 vierkante meter LED-scherm ligt boven het central station van Glasgow, op de hoek van Union Street en Gordon Street. Het scherm heeft een oppervlakte van 55 meter en is direct zichtbaar op Renfield Street, de tweede grootste winkelplaats in het Verenigd Koninkrijk.

The words in bold in the source sentence have been translated in 2 places (also in bold) in the target sentences. A subdivision of all extra word errors is presented in Table 10.

|                  | RBMT | PBMT | NMT |
|------------------|------|------|-----|
| Extra words      | 162  | 99   | 46  |
| Repetition       | 9    | 6    | 15  |
| Other            | 153  | 93   | 31  |

Table 10: Subdivision of ‘grammar extra words’ errors

Although NMT has less superfluous words in its output, it has a higher number of repetitions of one or more words than the other systems.

5.3 Long sentences

In literature, long sentences have been reported as a weakness of NMT systems. Bentivogli et al. (2016) found that the performance of NMT degraded faster with increased segment length. Toral and Sánchez-Cartagena (2017) confirmed this negative correlation and even reported that PBMT outperforms NMT for sentences consisting of 40 or more words.

|                  | RBMT | PBMT | NMT |
|------------------|------|------|-----|
| Long sentences   |      |      |     |
| # Errors         | 446  | 335  | 157 |
| # Target words   | 1791 | 1749 | 1677|
| # Unique annotated words | 821 | 685 | 195 |
| % Erroneous words| 46%  | 39%  | 12% |
| Short sentences  |      |      |     |
| # Errors         | 230  | 175  | 104 |
| # Target words   | 969  | 958  | 950 |
| # Unique annotated words | 225 | 228 | 113 |
| % Erroneous words| 23%  | 24%  | 12% |

Table 11: Performance on long sentences (min. 40 words) compared to short sentences (max. 10 words)

Table 11 shows us that NMT still outstrips PBMT for long sentences. In fact, two of the 38 long sentences in our corpus were translated without errors by NMT. PBMT and RBMT produced no correct long sentences. For the sake of completeness, we include the performance of all engines on all 145 short sentences found in our corpus as well. In addition to the number of errors, Table 11 also presents the number of target words and the number of unique annotated words for each system. In the number of unique annotated words, every erroneous word is only counted once, even though it might be annotated multiple times in the same sentence.

The percentage of wrong words in long and short sentences in our subset for NMT is the same. The expected degradation of NMT performance in long sentences, doesn’t hold (anymore). To overcome the accumulation of errors in longer sentences in NMT, different architectures have been examined and tested (Barone, Helcl, Sennrich, Haddow, & Birch, 2017) and all kinds of attentional mechanisms have been investigated (Luong, Pham, & Manning, 2015) and implemented. The GNMT’s architecture has also been enhanced by a bi-directional encoder for the bottomlayer only, allowing for a maximum possible parallelisation during computation (Wu et al., 2016).

6. Conclusions and outlook

In this paper we compared the NMT output with RBMT and PBMT translations, providing an overview of the strengths and weaknesses of NMT. We explained why we expect that NMT output is more difficult to post-edit, by elaborating on the special and less transparent character of some types of NMT errors. Omissions and mistranslations that are semantically unrelated to the source, will be a future challenge, especially for all activities that only take the translation product into account (e.g. gisting and quality estimation of MT output).

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