Translationese in Machine Translation Evaluation

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Abstract

The term translationese has been used to describe the presence of unusual features in translated text. In this paper, we provide a detailed analysis of the adverse effects of translationese on machine translation evaluation results. Our analysis shows evidence to support differences in text originally written in a given language relative to translated text and this can potentially negatively impact the accuracy of machine translation evaluations. For this reason we recommend that reverse-created test data be omitted from future machine translation test sets.

In addition, we provide a re-evaluation of a past high-profile machine translation evaluation claiming human-parity of MT, as well as analysis of the since re-evaluations of it. We find potential ways of improving the reliability of all three past evaluations. One important issue not previously considered is the statistical power of significance tests applied in past evaluations that aim to investigate human-parity of MT. Since the very aim of such evaluations is to reveal legitimate ties between human and MT systems, power analysis is of particular importance, where low power could result in claims of human parity that in fact simply correspond to Type II error. We therefore provide a detailed power analysis of tests used in such evaluations to provide an indication of a suitable minimum sample size of translations for such studies.

Subsequently, since no past evaluation that aimed to investigate claims of human parity ticks all boxes in terms of accuracy and reliability, we rerun the evaluation of the systems claiming human parity. Finally, we provide a comprehensive checklist for future machine translation evaluation.

1 Introduction

Human-translated text is thought to display features that deviate to some degree from those of text originally composed in the that language. Baker et al. (1993) report that translated text can: be more explicit than the original source, less ambiguous, simplified (lexical, syntactically and stylistically); display a preference for conventional grammaticality; avoid repetition; exaggerate target language features; as well as display features of the source language. The term translationese has often been used to describe the presence of such phenomenon in translated text.

Standard evaluation protocol in Machine Translation (MT) comprises system tests on a sample of human-translated text. Since creating this human-translated text is expensive, re-use of test sets for both directions of translation is commonplace, without regard to whether source or target contain features of translationese. For example, translation shared tasks at the Conference on Machine Translation (WMT) (Bojar et al., 2018) generally test translation between a given language pair as depicted in Figure 1 for testing Chinese to English translation. Portion (a) of the test data (accounting for approximately 50% of sentences) is made up of text that originated in Chinese and was human-translated into English, while portion (b) (i.e. the remaining 50%), was translated in the opposite direction, originating in English with manual translation into Chinese. The motivation for creating the test data in this way is to create test sets for both directions simultaneously (so at no extra cost).

Although translationese has been cited as a likely confound in MT evaluation results in the past (Toral et al., 2018; Läubli et al., 2018), to the best of our knowledge, no detailed investigation into the impact of translationese on the accuracy
of MT evaluation has been reported to date. With this aim, we examine the degree to which translationese phenomena may impact human and automatic evaluation results in MT. We firstly examine past results of WMT shared tasks, a main venue for MT evaluation, and reveal that although system rankings are overall very similar for human evaluation of forward and reverse test data, in a small number of cases system rankings diverge to a more serious degree. For example, for Turkish-English translation at WMT-18 forward and reverse system rankings correlate at only $r = 0.703$ in one case. Besides human evaluation, much more concerning is the divergence in forward and reverse rankings when BLEU is relied upon for evaluation of systems, where the correlation can be as low as 0.106 in the worst case.

Subsequently, we provide a reassessment of a human evaluation previously criticized for including reverse-created test data that claimed human parity of Chinese to English MT. We reveal insights into additional potential sources of inaccuracy of conclusions beyond the presence of translationese with the aim of preventing future inaccuracies. To this end, we provide a concise and clear checklist of considerations that should be taken into account when planning or reviewing MT evaluations.

2 Related Work

Hassan et al. (2018) provide one of the earliest claims in MT of systems achieving human-parity in terms of the quality of translations. Läubli et al. (2018) and Toral et al. (2018) both question the reliability of conclusions due to it following the 50/50 set-up of test data creation (shown in Figure 1), highlighting the inclusion of reverse-created test data as a likely confound. Läubli et al. (2018) and Toral et al. (2018) repeat the human evaluation of translations produced by Hassan et al. (2018) only for test data that originated in the source language and with some additional distinctions.

Firstly, and making a positive change, both Läubli et al. (2018) and Toral et al. (2018) include more context than the original sentence-level evaluation, the former now asking human judges to assess entire documents, and the latter involving assessment of MT output sentences in the order that they appeared in original documents. Secondly, both reassessments again move away from the evaluation method employed in Hassan et al. (2018), Direct Assessment (Graham et al., 2016), and revert to an older method of human evaluation, relative ranking, no longer used at WMT for evaluation of systems.

In addition, in both re-evaluations, besides use of older evaluation methodologies, another concern is that they were limited to only a small number of human judges with low levels of inter-annotator agreement. Therefore, although both re-evaluations improved the methodology employed in two respects, by eliminating reverse-created test data and including more context, both potentially include other sources of inaccuracy, such as lack of reliability of human judges when human evaluation takes the form of relative ranking (Callison-Burch et al., 2007, 2008, 2009, 2010, 2011, 2012; Bojar et al., 2013, 2014, 2015, 2016).

Furthermore, Toral et al. (2018) employ Trueskill to reach the conclusion that the MT system in question has not achieved human performance, and although Trueskill has been used in past WMT evaluations to produce system rankings, its aim is to minimize the number of judgments required to produce those rankings when resources are limited. Results may not be directly comparable with results of standard statistical significance tests therefore, now current practice at WMT evaluations.

Finally, neither Toral et al. (2018) nor Läubli et al. (2018) discuss statistical power of significance tests used to distinguish the performance of system and human, an important aspect of evaluation and one of particular importance with respect to evaluations that aim to investigate claims of human parity, where Type II error could result in false claims.

Besides criticisms already made of the human evaluation in Hassan et al. (2018), an additional aspect of importance not yet highlighted is the proportion of distinct translations that were included.
in the original human-parity evaluation of systems, a consideration that also relates strongly to the question of statistical power. In most MT human evaluations, it is not feasible to evaluate the full test set of sentences for all systems and it is common to instead evaluate a sample of translations, usually drawn at random from the test data. In current WMT evaluations, for example, translations of all test sentences produced by all participating systems are pooled and a random sample are human-evaluated. This method ensures that as great a number as possible of distinct test sentences are evaluated. Alongside system performance estimates, WMT also reports the number of distinct test sentences evaluated, \( n \), and it is this number that they consider the sample size used for statistical significance tests subsequently used to draw conclusions about which competing systems outperform others. For example, all else being equal, a difference in system performance estimates for a pair of systems computed from a larger set of distinct translations is interpreted as more reliable.

Other MT human evaluations, despite claims of following WMT human evaluation methodology, have diverged from this method of sample size computation, however, including the human-parity evaluation of Hassan et al. (2018) and Läubli et al. (2018). For example, although a large sample of human judgments is reported as \( n \geq 1,827 \) per system in Hassan et al. (2018), firstly this number in fact included quality control check translations, generally removed from data before computing sample sizes. More importantly however, very high numbers of repeat evaluations of the same translations were included in the human-parity evaluation of Hassan et al. (2018). In other words, a very low number of distinct test sentences were in fact human evaluated despite reporting a large sample size. The method of computing sample size therefore diverges from that reported of WMT evaluations in a small but important way. The sample size reported instead corresponds to the total number of human ratings collected as opposed to distinct test sentences (as in WMT evaluations). In this current work, we make this important distinction explicit by referring to the number of distinct test sentences evaluated as \( n \) and the number of human judgments collected as \( N \). We also recommend this distinction be made and adopted as common practice in future human evaluations of MT.

Table 1 shows results reproduced from the Hassan et al. (2018) data set, where we now report both the number of human judgments collected, \( N \), and the number of distinct test sentences included, \( n \), in addition to adding separate results for forward and reverse-created test data. Only when tested on the less legitimate reverse direction data does MT now appear to outperform human translation. Nonetheless, when interpreting results in Table 1, it is important to remember, however, that the reliability of even the conclusions drawn from forward-created test data only is still uncertain however, due to the small \( n \), as only 92 distinct translations were in fact included in the evaluation claiming human parity. It remains a possibility that, for example, had the number of distinct test sentences evaluated been higher that distinct conclusions would also be drawn.

Since the original human evaluation in Hassan et al. (2018) was hampered by low numbers of distinct test sentences and both subsequent re-evaluations hampered by somewhat outdated human evaluation methodologies and low inter-annotator agreement levels between human judges, we rerun the evaluation using the original translation data included in Hassan et al. (2018) with entirely up-to-date WMT human evaluation methodology in addition to ensuring that a sufficiently large sample of distinct translations are assessed by human judges. We also take into account the very legitimate criticism made by both Toral et al. (2018) and Läubli et al. (2018) and include document-level context in the human evaluation. Furthermore, since no previous evaluation has included statistical power analysis, prior to running our own human evaluation, we examine the power of significance tests to estimate a suitable sample size to decrease the likelihood of Type II error leading to conclusions of human parity due to the application of a low powered test.

Prior to rerunning the evaluation, we examine potential issues for MT evaluation when test data created in the reverse direction to testing. Despite being identified by Toral et al. (2018) and Läubli et al. (2018) as a serious cause of concern in MT evaluations, to the best of our knowledge no previous study exists that examines in detail the degree to which reverse-created test data may have skewed past results. The sections that follow therefore include an investigation into the issue of
translationese in MT evaluation, in addition to a re-evaluation of Hassan et al. (2018) data with all potential sources of criticism, in terms of test data and evaluation methodology, now taken into account and corrected.

In other work, past MT evaluations have investigated the effect of using translated and original data for training statistical machine translation (SMT) systems (Lambersky et al., 2012), revealing that training data created via translation, as opposed to data sourced from text originally written in a given language, achieves better results for systems in some cases.

3 Translationese

When testing MT systems it seems more natural to test systems in the forward direction: by taking text that genuinely originated in the source language, inputting it to a given MT system, and comparing the output with human translation of the same sentences. However, as described previously, as an artifact of WMT evaluations being carried out in both translation directions, it is common in MT evaluation for only around 50% of test sentences to be created in the forward direction with the remaining created in the reverse direction to testing, or even select test data without taking into account test data creation direction.

It is thought however that using reverse-created test data makes the evaluation unrealistically easy (Toral et al., 2018; Läubli et al., 2018), because in real-world MT scenarios, input text is unlikely to very often comprise text that has already been translated from the target language. Due to the possibility that the portion of test data created in the reverse direction could artificially boost MT evaluation results, we investigate with past evaluation data the degree to which this is actually the case. We therefore compare results of systems when test data is split according to the creation direction and examine differences in scores for systems in terms of both human and automatic metrics.

3.1 Human Evaluation

In order to examine differences in human evaluation results for MT systems with respect to the presence of translationese as a possible confound, we firstly examine systems participating in past evaluation campaigns at WMT-17 and WMT-18, where direct assessment (DA) was employed.

| System                  | Ave. | z    | n   | N  |
|-------------------------|------|------|-----|----|
| Reference-HT            | 67.1 | 0.185| 92  | 828|
| Combo-5                 | 64.8 | 0.048| 92  | 828|
| Combo-6                 | 64.3 | 0.042| 92  | 828|
| Combo-4                 | 64.3 | 0.023| 92  | 828|
| Reference-PE            | 64.1 | 0.020| 92  | 828|
| Reference-WMT           | 61.1 | −0.144| 92  | 828|
| Sogou                   | 56.2 | −0.345| 92  | 828|
| Online-A-1710           | 50.9 | −0.580| 92  | 828|
| Online-B-1710           | 48.5 | −0.717| 92  | 828|

Table 1: Results of Hassan et al. (2018) for forward, reverse and both test set creation directions reproduced from published data set. N is the number of human judgments collected for that system while n is the number of distinct translations assessed for that system. Reference-HT are human translations created by Hassan et al., 2018), Reference-PE are the outputs of an online MT system after human correction, Reference-WMT are the original WMT reference translations.
Table 2: Effect size for all systems included in Hassan et al. (2018) as the official human evaluation measure.\(^1\) We compute two separate human evaluation scores for each system. Firstly, for each individual system, we compute its forward DA score, comprising the average DA score computed only for test sentences that were created in the same direction as testing. Secondly, a corresponding reverse DA score is computed as the average DA score for MT output sentences corresponding to test data created in the opposite direction to testing. Then, to examine the extremity to which MT human evaluation results may differ when systems are tested in the reverse as opposed to forward direction, we subtract a given system’s forward DA score (expected to be lower than its reverse counterpart) from its reverse DA score (expected to be higher than its forward counterpart). This provides the difference in human DA scores for each system, with positive differences expected in general since reverse-created test data is thought to be an artificially easier test for MT systems.

Figure 2 shows the distribution of DA score differences (reverse DA – forward DA) for all systems participating in WMT-17 and WMT-18 news translation shared task broken down by language pair, where positive differences for systems indicate a higher human evaluation score when systems are tested in the reverse direction relative to the corresponding forward direction DA score.

\(1\)Prior to 2017, the method of human evaluation employed at WMT was relative ranking, where a preference between competing pairs of translations was provided by human judges, only recording whether or not the one translation was considered better or worse than the other. This method of human evaluation cannot be used to analyze absolute quality judgments for the reverse and forward test data as we do with DA scores.
Figure 2: Differences in human evaluation DA scores for test sentences created in the reverse direction to testing and those created in the same/forward direction to testing broken down by language pair, showing that reverse human evaluation scores higher than forward ones in almost all cases. PHI: there is a lot of white space in the bottom half of this chart - maybe cut it off

Russian to English translation, up to the largest and substantial average difference of 18.04 for English-Latvian.

It is important when carrying out such a comparison, however, to consider the degree to which splitting DA scores in the way we have done here really provides a good and valid comparison. One thing to consider is human assessors and, more specifically, was there any difference in human assessors between forward and reverse DA scores? For example, if human evaluation of forward and reverse test sentences were carried out by two different groups of human assessors, this damages the validity of the comparison, since differences in forward and reverse scores could be caused to some unknown degree by differences in human judge scoring strategies as opposed to differences in text. Human evaluation at WMT thankfully includes randomization of test sentences that distributes close to equal proportions of forward and reverse test sentences to each human judge however, and this ensures that differences in human judge scoring strategies will not negatively impact the validity of our comparison of forward and reverse scores.

Another worthwhile consideration is how splitting the test data may or may not impact the intended interpretation of DA scores. The fact that DA scores are simply a straightforward average of absolute scores for sentences, however, ensures that splitting human evaluation results for forward and reverse direction testing does not change the interpretation of each separate human score, since both remain a simple average of sentence scores.

A final consideration about the validity of our comparison of forward and reverse DA scores is the fact that splitting the test data does of course result in two distinct sets of test sentences. It is possible therefore that there remains something we have not taken into account about a given set of sentences (besides its creation direction) that could impact the difficulty of translation, such as a more difficult topic in the forward direction as opposed to the reverse direction. However, although the test sentences in the forward and reverse sets are distinct sentences, the fact that both sets are randomly selected news articles helps provide a sufficiently valid comparison.

In the section that follows, we will compare BLEU scores for the forward and reverse direc-
tions, which, as we will see, comprises a less straightforward comparison than human evaluation DA scores.

### 3.2 BLEU

Besides human evaluation, the performance of MT systems is often measured using automatic metrics, the most common of which remains to be the BLEU score (Papineni et al., 2002), and we therefore compare forward and reverse BLEU scores for systems participating in past evaluation campaigns. Figure 2 shows a box plot of absolute differences in BLEU scores for systems (reverse BLEU — forward BLEU) participating in WMT news translation tasks from 2015 to 2018, and Table 4 shows differences in terms of mean and standard deviation, as well as proportions of systems with a higher reverse than forward BLEU score for the same set of systems.

Somewhat surprisingly, results in Figure 3 and Table 4 do not display the same trend of higher reverse scores observed in human evaluation results in Section 3.1. Counter expectation there is a clear mix of positive and negative BLEU score differences for several language pairs, as forward BLEU scores are higher than equivalent reverse BLEU scores (cs-en, en-cs, en-de, en-et, fi-en, lv-en, ro-en, ru-en, en-ru, zh-en and en-zh).

As mentioned previously, however, comparison of BLEU scores is not as straightforward as human evaluation and there are further consideration to be made before drawing conclusions from the mix of positive and negative absolute BLEU score differences described above. For example, the fact that splitting the test set into forward and reverse directions creates two test sets comprised of distinct sentences is likely to impact how each distinct BLEU score should be interpreted, as BLEU is not a simple arithmetic average of sentence scores (like human evaluation DA scores) but rather the geometric mean of 4-gram precision combined with a brevity penalty. An important difference that could impact BLEU score interpretation, for example, could be sentence length, a large divergence resulting in forward and reverse BLEU scores becoming not entirely comparable.

To investigate differences in sentence length between forward and reverse test data, Figure 4 shows sentence length distributions for WMT-15–WMT-18 test sets firstly for all non-English languages and Figure 5 shows equivalent distributions for English test sets. For non-English languages (Figure 4), there is a clear trend for text that genuinely originated in a given language to have shorter sentences than those translated from English into that language, and this could be artifact, for example, of translated text being found to be more explicit than the original source and less ambiguous (Baker et al., 1993). The only exception to this trend of longer translated text exists for Latvian test data, where sentence length distributions for both text originating in Latvian and text translated from English to Latvian unusually have very similar sentence length distributions.

For English text (Figure 5), in general sentence length distributions appear to depend on the source language, with sentence length of text originating in English being lower than English text originating in Chinese and Latvian but longer than text originating in all remaining non-English languages. In summary, our analysis indicates that in general translationese is shorter than text originating in a given language.

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|       | R>F (%) | F>R (%) | R–F µ | R–F σ | n  |
|-------|---------|---------|-------|-------|----|
| lv-en | 11.1    | 88.9    | −2.00 | 2.12  | 9  |
| zh-en | 33.3    | 66.7    | −2.52 | 6.54  | 30 |
| fi-en | 42.1    | 57.9    | −0.06 | 2.85  | 38 |
| ru-en | 47.5    | 52.5    | 0.90  | 5.53  | 40 |
| cs-en | 48.6    | 51.4    | 1.13  | 6.78  | 37 |
| tr-en | 76.0    | 24.0    | 4.38  | 5.45  | 25 |
| et-en | 78.6    | 21.4    | 2.30  | 2.12  | 14 |
| de-en | 100.0   | 0.0     | 10.03 | 4.92  | 50 |
| en-de | 1.6     | 98.4    | −6.34 | 3.39  | 63 |
| en-zh | 36.0    | 60.0    | 0.02  | 1.63  | 25 |
| en-cs | 52.7    | 47.3    | 0.56  | 3.35  | 55 |
| en-ru | 65.0    | 35.0    | 3.09  | 5.82  | 40 |
| en-et | 71.4    | 28.6    | 0.86  | 1.21  | 14 |
| en-tr | 84.0    | 12.0    | 2.53  | 2.56  | 25 |
| en-fi | 87.2    | 12.8    | 3.07  | 2.31  | 47 |
| en-lv | 100.0   | 0.0     | 8.12  | 2.50  | 17 |

Table 4: Comparison of BLEU scores of MT systems participating in WMT-15 – WMT-18 for test data created in the same/forward (F) and reverse (R) direction, where R>F (%) = the proportion of systems with a reverse BLEU score greater than its forward score for precisely the same test scenario; R–F µ = mean of the difference in reverse and forward BLEU scores; R–F σ = standard deviation of the difference in reverse and forward BLEU scores; n = number of MT systems.

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2Since Chinese language text has no direct equivalent to sentence length in the other languages, we omit it from this part of the analysis.
Figure 3: Differences in BLEU scores for systems participating in WMT-15–WMT-18 news translation task computed for test sentences created in the reverse direction to testing and those created in the same/forward direction to testing broken down by language pair, showing a mix of positive and negative differences in BLEU scores depending on test set creation direction.

Figure 4: Sentence length distribution in test data of WMT-15–WMT-18 news translation task for text in non-English languages, where, for example, cs<en depicts text originating in English that was manually translated into Czech; cs<cs depicts text that genuinely originated in Czech; colors depict text in the same language; note that plots are intentionally cropped in favor of providing better detail of differences in median scores at the cost of omitting some outliers. PHI: maybe not use "cs<cs" but just "cs" since here is no "<" happening.
follows we examine relative differences in scores for pairs of systems instead of absolute differences for individual systems. In this way, it is possible to compute BLEU score differences on the same test sentences for pairs of systems before examining the extremity of such differences for each language direction.

3.3 Relative Differences

To overcome issues caused by comparison of reverse and forward BLEU being different test sentences is to compare scores primarily for reverse-created test data separately from forward-created test data.

Besides absolute differences in BLEU scores for individual systems, we should also consider how the differences in BLEU scores that occur when we change from forward to reverse test data correspond to one another, i.e. how changes in scores correspond from one system to another. For example, for an individual competition, the problems associated with test data creation are more problematic if they occur differently for different systems participating in the same competition and less severe if they affect all systems equally, as system scores are mainly interpreted relative to one another. To investigate this further, we examine relative changes in BLEU scores for pairs of systems, and compare BLEU score changes for all pairs of systems participating in the same evaluation campaign.

The scatter plot in Figure 7 shows relative differences in BLEU scores when we change from forward to reverse test data for all pairs of systems participating in WMT-15–WMT-18. The absence of systems in the upper-left and lower-right quadrants reassuringly shows that although extreme changes in BLEU scores do occur when test set creation direction is altered, the changes are at least somewhat systematic in the sense that when a difference in BLEU scores occurs (a drop or increase when we change from forward to reverse test data), it occurs similarly for pairs of systems. However, the although there is a diagonal orientation in the plot, it still is somewhat worryingly broad and it remains possible that inclusion of reverse test data could bias BLEU scores in different ways for different types of systems.

In terms of human evaluation, the scatter plot in Figure 8 shows relative differences in human scores for all pairs of systems in WMT-17–
WMT-18. Again, the absence of systems in the upper-left and lower-right quadrants shows a similar trend for human evaluation, where relative differences in DA scores for pairs of systems correspond very closely when we change from reverse to forward-created test data.

In summary, examination of absolute differences in human scores revealed almost across the board higher human scores when systems are tested on data created in the reverse direction to testing, while BLEU scores showed a mix of higher and lower reverse scores for test set creation directions. Although it is important to understand the changes in absolute scores that should be expected, relative differences in performance are more important, as these directly impact conclusions about what systems and methods outperform others. More reassuring than absolute differences in BLEU scores, relative differences correspond quite well between pairs of competing systems. The correspondence of relative differences for pairs of systems was extremely close for human evaluation and this provides evidence of the validity of conclusions made in past human evaluations of MT that included reverse test data. However the spread in Figure 7 appear to suggest that system rankings could still change if we measure forward
Figure 8: Differences in Human evaluation DA scores for pairs of systems participating in WMT-17–WMT-18 news translation task computed for test sentences created in the reverse and forward directions, where “Reverse Human Difference” = reverse DA – reverse DA for a pair of MT systems and “Forward Human Difference” = forward DA – forward DA for the same pair of MT systems.

vs reverse BLEU, and although the corresponding DA graph (Figure 8 is much narrower (which is good) but there still could be changes in ranking. We therefore include further analysis that provides a direct comparison of system rankings for past evaluations in terms of both BLEU and human evaluation.

## 4 System Rankings

Tables 5(a), 5(b) and 5(c) show the Kendall’s $\tau$ rank correlation of forward and reverse BLEU scores for systems participating in WMT-15–WMT-18 individual competitions, in addition to Pearson and Spearman correlations of same. As can be seen, the correspondence between forward and reverse rank correlation of systems according to BLEU varies considerably across different evaluation test sets, from as low as a $\tau$ of 0.2, where BLEU score rankings are extremely different depending on test data creation direction, up to a $\tau$ of 1.0, where rank correlation is identical (cs-en; fi-en newstest2017; fi-en; en-cs newstest2018).

Similarly, Table 6 shows the correlation of rankings of human evaluation data, where Kendall’s $\tau$ correlations of forward and reverse test data also

| Language Pair | $r$ | $\rho$ | $\tau$ |
|---------------|-----|--------|--------|
| en-ru         | 0.838 | 0.498 | 0.405 |
| fi-en         | 0.900 | 0.873 | 0.670 |
| ru-en         | 0.903 | 0.934 | 0.821 |
| en-fi         | 0.911 | 0.842 | 0.689 |
| en-de         | 0.932 | 0.891 | 0.717 |
| de-en         | 0.952 | 0.879 | 0.769 |
| cs-en         | 0.985 | 0.832 | 0.717 |
| en-cs         | 0.995 | 0.963 | 0.880 |

| Language Pair | $r$ | $\rho$ | $\tau$ |
|---------------|-----|--------|--------|
| ro-en         | 0.489 | 0.679 | 0.524 |
| en-de         | 0.787 | 0.545 | 0.421 |
| tr-en         | 0.795 | 0.783 | 0.667 |
| en-ru         | 0.809 | 0.252 | 0.182 |
| fi-en         | 0.845 | 0.820 | 0.648 |
| en-fi         | 0.875 | 0.889 | 0.735 |
| en-tr         | 0.881 | 0.850 | 0.722 |
| en-ro         | 0.945 | 0.930 | 0.818 |
| ru-en         | 0.945 | 0.697 | 0.600 |
| en-cs         | 0.954 | 0.598 | 0.466 |
| de-en         | 0.958 | 0.818 | 0.644 |
| cs-en         | 0.961 | 0.655 | 0.504 |

| Language Pair | $r$ | $\rho$ | $\tau$ |
|---------------|-----|--------|--------|
| en-zh         | 0.608 | 0.601 | 0.367 |
| zh-en         | 0.646 | 0.838 | 0.667 |
| en-lv         | 0.861 | 0.860 | 0.735 |
| cs-en         | 0.865 | 1.000 | 1.000 |
| lv-en         | 0.879 | 0.883 | 0.778 |
| en-ru         | 0.890 | 0.750 | 0.667 |
| tr-en         | 0.901 | 0.927 | 0.778 |
| en-de         | 0.933 | 0.718 | 0.567 |
| de-en         | 0.937 | 0.836 | 0.673 |
| en-tr         | 0.939 | 0.976 | 0.929 |
| ru-en         | 0.942 | 0.817 | 0.611 |
| en-cs         | 0.961 | 0.945 | 0.842 |
| en-fi         | 0.969 | 0.944 | 0.848 |
| fi-en         | 0.988 | 1.000 | 1.000 |

| Language Pair | $r$ | $\rho$ | $\tau$ |
|---------------|-----|--------|--------|
| tr-en         | 0.106 | 0.314 | 0.200 |
| en-zh         | 0.570 | 0.445 | 0.333 |
| cs-en         | 0.579 | 0.700 | 0.600 |
| zh-en         | 0.771 | 0.616 | 0.442 |
| en-tr         | 0.897 | 0.611 | 0.546 |
| en-de         | 0.938 | 0.741 | 0.583 |
| de-en         | 0.954 | 0.897 | 0.750 |
| fi-en         | 0.963 | 1.000 | 1.000 |
| en-et         | 0.966 | 0.978 | 0.912 |
| en-ru         | 0.966 | 0.983 | 0.944 |
| ru-en         | 0.986 | 0.857 | 0.714 |
| en-fi         | 0.981 | 0.986 | 0.939 |
| et-en         | 0.985 | 0.978 | 0.912 |
| en-cs         | 0.990 | 1.000 | 1.000 |

Table 5: Pearson ($r$), Spearman ($\rho$) and Kendall’s $\tau$ correlation of forward and reverse BLEU scores of all systems participating in WMT-15–WMT-18 news translation task; language pairs ordered from lowest to highest Pearson correlation.
Table 6: Pearson ($r$), Spearman ($\rho$) and Kendall’s $\tau$ correlation of forward and reverse Human DA scores of all systems participating in WMT-17 – WMT-18 news translation task; language pairs ordered from lowest to highest Pearson correlation.

|        | $r$  | $\rho$ | $\tau$ |
|--------|------|--------|--------|
| zh-en  | 0.935| 0.903  | 0.758  |
| ru-en  | 0.939| 0.883  | 0.778  |
| de-en  | 0.949| 0.909  | 0.782  |
| en-cs  | 0.952| 0.952  | 0.857  |
| en-lv  | 0.952| 0.904  | 0.765  |
| cs-en  | 0.957| 1.000  | 1.000  |
| lv-en  | 0.958| 0.817  | 0.722  |
| en-zh  | 0.972| 0.967  | 0.889  |
| en-ru  | 0.977| 0.939  | 0.822  |
| en-de  | 0.979| 0.921  | 0.771  |
| fi-en  | 0.979| 1.000  | 1.000  |
| tr-en  | 0.983| 0.927  | 0.822  |
| en-fi  | 0.989| 0.902  | 0.788  |
| en-tr  | 0.992| 1.000  | 1.000  |

Table 7 shows the statistical power, the probability of identifying a significant difference when one exists, of the statistical test applied in WMT evaluations, Wilcoxon rank-sum test, for a range of effect and sample sizes ($n$), where for the pur-

range from little correspondence for tr-en newstest2018 at 0.4 in the worst case to identical system rankings $\tau$ of 1.0 in five cases (cs-en; fin-en; en-tr newstest2017; en-ru; en-cs newstest2018).

In overall summary, our analysis of differences in both BLEU and human evaluation scores reveals differences in system rankings when tested on reverse and forward-created test data, differences substantial in some cases. Subsequently we have confirmed the validity of suspicions raised about potential lack of reliability of test data raised by Toral et al. (2018) and Läubli et al. (2018) caused by inclusion of reverse-created test data. However, as stated previously, both reassessments of Hassan et al. (2018) include the

5 Re-evaluation of Human Parity Claims

As mentioned previously in Section 2, past re-evaluations of human parity claims were hampered by low inter-annotator agreement levels, employment of older human evaluation technologies than the original, treatment of Trueskill clus-

ters to draw conclusions of statistical significance and lack of statistical power analysis for planned sample size, while the original evaluation itself suffered severely from inclusion of reverse-created data we have shown to be problematic, as well as a very low number of distinct translations included in the evaluation.

In our re-evaluation of the original, we firstly carry out statistical power analysis so that in the case of encountering any ties between systems or indeed human and system, that tests used to draw conclusions have sufficient statistical power to avoid human-parity claims that in fact simply correspond to a Type II error. Statistical power is of particular importance when considering document-level evaluation due to the fact that gathering ratings of documents as opposed to sentences requires substantially more annotator time and for this reason is likely to result in a reduction in the number of assessments collected in any evaluation. For example, Läubli et al. (2018) included as few as 55 documents in their re-evaluation of Hassan et al. (2018). Our concern about a potential substantial reduction in sample size in future document-level evaluations is well-founded therefore, especially considering standard segment-level MT human evaluations commonly include a sample of 1,500 segments. In the case of Läubli et al. (2018) this corresponds to an extreme reduction of approximately 96% to the sample size. Since the very nature of the question being investigated involves a potential tie between human and machine, such a small sample size is a serious risk to the reliability of conclusions drawn simply due to its impact in terms of statistical power.

For this reason, prior to running our re-evaluation, we run power analysis to investigate an appropriate sample size that will result in sufficiently powerful tests. As a rough guide to what constitutes sufficient statistical power, we borrow the five-eighty convention from the behavioural sciences that provides a balance between Type I versus Type II error, where significance and power levels are set at 0.05 and 0.8 respectively (Cohen, 1988).
pose of the test the appropriate effect size is the probability of the translations of system A being scored lower than those of system B. As shown in Table 7 for the usual sample size employed in WMT evaluations, 1,500, statistical power even for closely performing systems, where the probability of the translations of system A being scored lower than those of system B is 0.47, statistical power is still above 0.8. For such pairs of systems, however, if we were to employ the smaller sample size of 55 documents, as in Läubli et al. (2018), the power of the test to identify a significant differences falls as low as 0.081, approaching one tenth of acceptable statistical power levels.

In order to further put into context the closeness in human performance of systems we can expect to encounter in our planned re-evaluation, we examine the effect size for pairs of systems in the original. Table 8 shows the effect size for all pairs of systems included in Hassan et al. (2018). If we take, for example, the effect size between the top two runs, Ref-HT and Combo-5 of 0.435, we can roughly see from Table 7 that the likelihood of identifying a significant difference at this effect size ranges from as low as 0.188 for a sample size of 55 and only reaches an acceptable level above 0.8 at sample size 385. Since the test set used in Hassan et al. (2018) included a far lower number of test documents however, basing our evaluation on document ratings would lead to low statistical power and likely result in Type II errors cause by this small sample size.

A good compromise between fully document-level evaluation, where only ratings of documents are collected, and fully segment-level evaluations, in which segments are presented to human judges in isolation of the document, is collection of ratings of segments with the wider document context available to the human assessor and have the segments evaluated in their original order. In this way, a sufficient sample size can still be achieved to ensure appropriate levels of statistical power with the added aim of human judges being able to take into account the quality of translations within the wider document context. Although Toral et al. (2018) did not specifically indicate statistical power analysis as their particular motivation, this segment-rating document-context approach appears to be that which they employed.

We therefore plan our re-evaluation as follows:

- Collect segment ratings for documents produced by a single system within the correct document context;
- Aim to collect direct assessments of a sufficient number of translations exceeding the minimum acceptable sample size in terms of power analysis, approximately 385 distinct translations;
- Use \( n \), the number of distinct translations as opposed to repeat human assessments as the sample size;
- Employ Direct Assessment, the most up to date technology for this purpose and that employed by WMT for the official results since 2017, a method shown to produce highly repeatable results;
- Only employ forward-created test data;
- Only draw conclusions specific to Chinese to English translation and news domain;
- Produce clusters with a standard significance test, Wilcoxon rank-sum test.

### 5.1 Re-evaluation Results

Direct Assessment (DA) HITs were set up and run as in WMT human evaluations on Mechanical Turk but with the distinction of segments being evaluated in the correct order in which they appeared in a document, comprising an initial set of results, which we refer to as segment rating + document context (SR+DC). In addition to the segment rating workers were additionally shown entire documents and asked to rate them, providing a secondary set of results for comparison purposes. We refer to these fully document-level results as document rating + document context (DR+DC) configuration. As is usual in DA evaluations, translations were rated in a 0–100 rating scale and quality control was applied.

131 workers participated producing a total of 13,214 assessments of translations, of which 6,606 (49.99%) were from workers who passed DA’s quality control checks.

Table 9 shows results of our re-evaluation of the top systems originally included in Hassan et al. (2018), where REF-HT is the original set of human translations produced by Hassan et al. (2018).
than that of the system in a given column; systems and data taken from Hassan et al. (2018) human evaluation.

Table 7: Statistical Power of two-sided Wilcoxon Rank Sum Test for a range of sample and effect sizes; power > 0.8 highlighted in bold.

| n   | Ref-HT | Combo-5 | Combo-6 | Combo-4 | Ref-PE | Ref-WMT | Sogou | Online-A | Online-B |
|-----|--------|---------|---------|---------|--------|---------|-------|----------|----------|
| 10  | 0.788  | 0.718   | 0.659   | 0.586   | 0.512  | 0.438   | 0.367 | 0.300    | 0.243    |
| 20  | 0.750  | 0.690   | 0.613   | 0.537   | 0.454  | 0.385   | 0.313 | 0.250    | 0.196    |
| 50  | 0.800  | 0.730   | 0.650   | 0.577   | 0.507  | 0.437   | 0.367 | 0.300    | 0.243    |
| 100 | 0.850  | 0.780   | 0.709   | 0.637   | 0.574  | 0.507   | 0.437 | 0.367    | 0.300    |

Table 8: Effect size, probability of a translation produced by the system in a given row receiving a lower DA score than that of the system in a given column; systems and data taken from Hassan et al. (2018) human evaluation.
Table 9: Re-evaluation of human-parity-claimed Chinese to English system of Hassan et al. (2018); * denotes system that significantly outperforms all lower ranked systems according to a two-sided Wilcoxon rank-sum test $p < 0.05$.

6 Conclusion

In this work, we explore issues relating to the reliability of machine translation evaluations. Firstly, we provide a detailed analysis of how translationese phenomena can adversely affect machine translation results. Our analysis of text that originated in a given language compared to that which had been created via human translation showed that in general translated text is longer than text originally written in a given language. Besides having different characteristics, in terms of the legitimacy of machine translation evaluation results, our analysis provides sufficient evidence that translationese is a problem for evaluation of systems, in particular in terms of comparison of system performance with automatic metrics such as BLEU. This results in our first recommendation in future MT evaluations to avoid the use of test data that was created via human translation from another language.

As described in Section 2, no previous work aiming to provide more certainty about conclusions of human parity in MT ticked all boxes. We therefore provided some missing analysis that should be included in the planning stage of future human evaluations of MT, particularly relevant to document-level evaluation that aims to investigate human-parity of MT. This analysis includes one of statistical power that will be useful as a reference for future MT evaluations to reduce the likelihood of future claims of human parity resulting from statistical ties produced from tests with low
Finally, since evaluation of machine translation systems now involves several different criteria required to produce accurate and reliable results, we provide the following MT evaluation checklist for planning upcoming MT evaluations:

1. Test data creation direction – reverse-created data should be avoided as it can potentially lead inaccurate results in particular in terms of BLEU scores;

2. Human judge reliability – either ensure high inter-annotator agreement levels or employ a method of human evaluation that has been shown to provide repeatable results such as Direct Assessment;

3. Testing level (e.g. document or sentence) – conclusions possible to be drawn from results are limited to the amount of context provided to human judges;

4. Test language pairs – only draw conclusions with reference to the tested language pairs;

5. Test domain – only draw conclusions with reference to the tested language domain;

6. Translation sample size (n) – numbers of distinct translations to be assessed should be planned prior to running a given evaluation to ensure sufficient statistical power (at least 80%); n should be reported and employed as the sample size for significance testing as opposed to the number of assessments;

7. Human judgment sample size (N) – numbers of assessments should also be reported;

8. Meaningful overall statistic employed to distinguish performance of systems;

9. Clustering via standard statistical significance testing.

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