Automatic Reference-Based Evaluation of Pronoun Translation
Misses the Point

Liane Guillou
University of Edinburgh
School of Informatics
Scotland, United Kingdom
lguillou@inf.ed.ac.uk

Christian Hardmeier
Uppsala University
Dept. of Linguistics and Philology
Uppsala, Sweden
christian.hardmeier@lingfil.uu.se

Abstract
We compare the performance of the APT and AutoPRF metrics for pronoun translation against a manually annotated dataset comprising human judgements as to the correctness of translations of the PROTEST test suite. Although there is some correlation with the human judgements, a range of issues limit the performance of the automated metrics. Instead, we recommend the use of semi-automatic metrics and test suites in place of fully automatic metrics.

1 Introduction
As the general quality of machine translation (MT) increases, there is a growing interest in improving the translation of specific linguistic phenomena. A case in point that has been studied in the context of both statistical (Hardmeier, 2014; Guillou, 2016; Loaiciga, 2017) and neural MT (Bawden et al., 2017) is that of pronominal anaphora. In the simplest case, translating anaphoric pronouns requires the generation of corresponding word forms respecting the grammatical constraints on agreement in the target language, as in the following English-French example, where the correct form of the pronoun in the second sentence varies depending on which of the (equally correct) translations of the word bicycle was used in the first:

(1) a. I have a bicycle. It is red.
   b. J’ai un vélo. Il est rouge. [ref]
   c. J’ai une bicyclette. Elle est rouge. [MT]

However, the problem is more complex in practice because there is often no 1 : 1 correspondence between pronouns in two languages. This is easily demonstrated at the corpus level by observing that the number of pronouns varies significantly across languages in parallel texts (Mitkov and Barbu, 2003), but it tends to be difficult to predict in individual cases.

In general MT research, significant progress was enabled by the invention of automatic evaluation metrics based on reference translations, such as BLEU (Papineni et al., 2002). Attempting to create a similar framework for efficient research, researchers have proposed automatic reference-based evaluation metrics specifically targeting pronoun translation (Hardmeier and Federico, 2010; Werlen and Popescu-Belis, 2017). In this paper, we study the performance of these metrics on a dataset of English-French translations and investigate to what extent automatic evaluation based on reference translations can provide useful information about the capacity of an MT system to handle pronouns. Our analysis clarifies the conceptual differences between AutoPRF and APT, uncovering weaknesses in both metrics, and investigates the effects of the alignment correction heuristics used in APT. By using the fine-grained PROTEST categories of pronoun function, we find that the accuracy of the automatic metrics varies across pronouns of different functions, suggesting that certain linguistic patterns are captured better in the automatic evaluation than others. We argue that fully automatic wide-coverage evaluation of this phenomenon is unlikely to drive research forward, as it misses essential parts of the problem despite achieving some correlation with human judgements. Instead, semi-automatic evaluation involving automatic identification of correct translations with high precision and low recall appears to be a more achievable goal. Another more realistic option is a test suite evaluation with a very limited scope.

2 Pronoun Evaluation Metrics for MT
Two reference-based automatic metrics of pronoun translation have been proposed in the literature. The first (Hardmeier and Federico, 2010)
is a variant of precision, recall and F-score that measures the overlap of pronouns in the MT output with a reference translation. It lacks an official name, so we refer to it as AutoPRF following the terminology of the DiscoMT 2015 shared task (Hardmeier et al., 2015). The scoring process relies on a word alignment between the source and the MT output, and between the source and the reference translation. For each input pronoun, it computes a clipped count (Papineni et al., 2002) of the overlap between the aligned tokens in the reference and the MT output. The final metric is then calculated as the precision, recall and F-score based on these clipped counts.

Werlen and Popescu-Belis (2017) propose a metric called Accuracy of Pronoun Translation (APT) that introduces several innovations over the previous work. It is a variant of accuracy, so it counts, for each source pronoun, whether its translation can be considered correct, without considering multiple alignments. Since word alignment is problematic for pronouns, the authors propose an heuristic procedure to improve alignment quality. Finally, it introduces the notion of pronoun equivalence, assigning partial credit to pronoun translations that differ from the reference translation in specific ways deemed to be acceptable. In particular, it considers six possible cases when comparing the translation of a pronoun in MT output and the reference. The pronouns may be: (1) identical, (2) equivalent, (3) different/incompatible, or there may be no translation in: (4) the MT output, (5) the reference, (6) either the MT output or the reference. Each of these cases may be assigned a weight between 0 and 1 to determine the level of correctness.

3 The PROTEST Dataset

We study the behaviour of the two automatic metrics using the PROTEST test suite (Guillou and Hardmeier, 2016). It comprises 250 hand-selected personal pronoun tokens taken from the DiscoMT2015.test dataset (Hardmeier et al., 2016) and annotated according to the ParCor guidelines (Guillou et al., 2014). Pronouns are first categorised according to their function:

- anaphoric: I have a bicycle. It is red.
- event: He lost his job. It was a shock.
- pleonastic: It is raining.
- addressee reference: You’re welcome.
- and then subcategorised according to mor-phosyntactic criteria, whether the antecedent is a group noun, whether the antecedent is in the same or a different sentence, and whether an addressee reference pronoun refers to one or more specific people (deictic) or to people in general (generic).

Our dataset contains human judgements on the performance of eight MT systems on the translation of the 250 pronouns in the PROTEST test suite. The systems include five submissions to the DiscoMT 2015 shared task on pronoun translation (Hardmeier et al., 2015) – four phrase-based SMT systems AUTO-POSTEDIT (Guillou, 2015), uu-HARDMEIER (Hardmeier et al., 2015), IDIAP (Luong et al., 2015), uu-TIEDEMANN (Tiedemann, 2015), a rule-based system ITS2 (Loáiciga and Wehrli, 2015), and the shared task baseline (also phrase-based SMT). Two NMT systems are included for comparison: LIMSI (Bawden et al., 2017) and NYU (Jean et al., 2014).

Manual evaluation was conducted using the PROTEST graphical user interface and accompanying guidelines (Hardmeier and Guillou, 2016). The annotators were asked to make judgements (correct/incorrect) on the translations of the pronouns and antecedent heads whilst ignoring the correctness of other words (except in cases where it impacted the annotator’s ability to make a judgement). The annotations were carried out by two bilingual English-French speakers, both of whom are native speakers of French. Note that our human judgements differ in important ways from the human evaluation conducted for the same set of systems at DiscoMT 2015 (Hardmeier et al., 2015), which was carried out by non-native speakers over an unbalanced data sample using a gap-filling methodology.

4 Accuracy versus Precision/Recall

There are three ways in which APT differs from AutoPRF: the scoring statistic, the alignment heuristic in APT and the definition of pronoun equivalence.

APT is a measure of accuracy: It reflects the proportion of source pronouns for which an acceptable translation was produced in the target. AutoPRF, by contrast, is a precision/recall metric on the basis of clipped counts. The reason for using precision and recall given by Hardmeier and Federico (2010) is that word alignments are not 1 : 1, and each pronoun can therefore be linked to multiple elements in the target language, both in the refer-
Table 1: Comparison of APT scores with human judgements over the PROTEST test suite

| Score | APT-A | APT-B | PROTEST |
|-------|-------|-------|---------|
| Alig. cor. | + | – | + | – | |
| Reference | 1.000 | 1.000 | 1.000 | 1.000 | 0.920 |
| BASELINE | 0.544 | 0.536 | 0.574 | 0.566 | 0.660 |
| IDIAP | 0.496 | 0.496 | 0.528 | 0.528 | 0.660 |
| UU-TIED. | 0.532 | 0.532 | 0.562 | 0.562 | 0.680 |
| UU-HARD. | 0.528 | 0.520 | 0.556 | 0.548 | 0.636 |
| POSTEDIT | 0.492 | 0.492 | 0.532 | 0.532 | 0.668 |
| ITS2 | 0.436 | 0.428 | 0.462 | 0.454 | 0.472 |
| LIMSI | 0.364 | 0.364 | 0.388 | 0.388 | 0.576 |
| NYU | 0.424 | 0.420 | 0.456 | 0.452 | 0.616 |

Table 2: Correlation of APT and human judgements

| Category | APT Cases | Human Assess. | Disagreement |
|----------|-----------|---------------|--------------|
| Anaphoric | 1 | 2 | 3 | ✓ | × | % |
| intra sjb it | 112 | 13 | 68 | 133 | 60 | 42/193 | 21.8 |
| intra nsbj it | 52 | 1 | 25 | 65 | 13 | 12/78 | 15.4 |
| inter sjb it | 99 | 17 | 95 | 130 | 81 | 56/211 | 26.5 |
| inter nsbj it | 18 | 0 | 7 | 6 | 19 | 12/25 | 48.0 |
| intra they | 115 | 0 | 86 | 133 | 68 | 30/201 | 14.9 |
| inter they | 117 | 0 | 94 | 118 | 93 | 43/211 | 20.4 |
| sg they | 52 | 0 | 58 | 72 | 38 | 48/110 | 43.6 |
| group /they | 45 | 0 | 35 | 57 | 23 | 26/80 | 32.5 |
| Event it | 125 | 38 | 89 | 157 | 95 | 56/252 | 22.2 |
| Pleonastic it | 155 | 49 | 46 | 216 | 34 | 40/250 | 16.0 |
| Generic you | 105 | 0 | 62 | 166 | 1 | 61/167 | 36.5 |
| Deictic sg you | 85 | 0 | 43 | 126 | 2 | 41/128 | 32.0 |
| Deictic pl you | 81 | 0 | 7 | 87 | 1 | 6/88 | 6.9 |
| Total | 1,161 | 118 | 715 | 1,466 | 528 | 473/1,994 | 23.7 |

Table 3: Number of pronouns marked as correct/incorrect in the PROTEST human judgements, as identical (1), equivalent (2), and incompatible (3) by APT, and the percentage of disagreements, per category

5 Effects of Word Alignment

APT includes an heuristic alignment correction procedure to mitigate errors in the word alignment between a source-language text and its translation (reference or MT output). We ran experiments to assess the correlation of APT with human judgements, with and without the alignment heuristics.

Table 1 displays the APT results, with and without the alignment heuristics, and the proportion of pronouns in the PROTEST test suite marked as correctly translated. We computed APT scores for two different weight settings: 1 APT-A uses weight 1 for identical matches and 0 for all other cases. APT-B uses weight 1 for identical matches, 0.5 for equivalent matches and 0 otherwise.

There is little difference in the APT scores when we consider the use of alignment heuristics. This is due to the small number of pronouns for which alignment improvements are applied for most systems (typically 0–9 per system). The exception is the ITS2 system output for which 18 alignment improvements are made. For the following systems we observe a very small increase in APT score for each of the two weight settings we consider, when alignment heuristics are applied: UU-HARDMEIER (+0.8), ITS2 (+0.8), the BASELINE (+0.8) and NYU (+0.4). However, these small improvements are not sufficient to affect the system rankings.

6 Metric Accuracy per Category

Like Werlen and Popescu-Belis (2017), we use Pearson’s and Spearman’s correlation coefficients to assess the correlation between APT and our human judgements (Table 2). Although APT does correlate with the human judgements over the PROTEST test suite, the correlation is weaker than that with the DiscoMT gap-filling evaluations re-
ported in Werlen and Popescu-Belis (2017). Table 1 also shows that the rankings induced from the PROTEST and APT scores are rather different.

We also study how the results of APT (with alignment correction) interact with the categories in PROTEST. We consider a pronoun to be measured as correct by APT if it is assigned case 1 (identical) or 2 (equivalent). Likewise, a pronoun is considered incorrect if it is assigned case 3 (incompatible). We compare the number of pronouns marked as correct/incorrect by APT and by the human judges, ignoring APT cases in which no judgement can be made: no translation of the pronoun in the MT output, reference or both, and pronouns for which the human judges were unable to make a judgement due to factors such as poor overall MT quality, incorrect word alignments, etc. The results of this comparison are displayed in Table 3.

At first glance, we can see that APT disagrees with the human judgements for almost a quarter (23.72%) of the assessed translations. The distribution of the disagreements over APT is very skewed and ranges from 9% for case 1 to 34% for case 2 and 46% for case 3. In other words, APT identifies correct pronoun translations with good precision, but relatively low recall. We can also see that APT rarely marks pronouns as equivalent (case 2).

APT performs particularly poorly on the assessment of pronouns belonging to the anaphoric inter-sentential non-subject “it” and anaphoric singular “they” categories. In general, there are three main problems affecting anaphoric pronouns (Table 4). 1) APT does not consider pronoun-antecedent head agreement so many valid alternative translations involving personal pronouns are marked as incompatible (case 3), but as correct by the human judges. 2) Substitutions between pronouns are governed by much more complex rules than the simple pronoun equivalence mechanism in APT suggests. 3) APT does not consider the use of impersonal pronouns such as ce in place of the feminine personal pronoun elle or the plural forms ils and elles.

As with anaphoric pronouns, APT incorrectly marks some pleonastic and event translations as equivalent in disagreement with the human judges. Other common errors arise from 1) the use of alternative translations marked as incompatible by APT but correct by the human judges, for example il (personal) in the MT output when the reference contained the impersonal pronoun cela or ça (25 cases for pleonastic, 6 for event), or 2) the presence of il in both the MT output and reference which APT marked as identical but the human judges marked as incorrect (3 cases for pleonastic, 16 event).

Some of these issues could be addressed by incorporating knowledge of pronoun function in the source language, pronoun antecedents, and the wider context of the translation surrounding the pronoun. However, whilst we might be able to derive language-specific rules for some scenarios, it would be difficult to come up with more general or language-independent rules. For example, il and ce can be anaphoric or pleonastic pronouns, but il has a more referential character. Therefore in certain constructions that are strongly pleonastic (e.g. clefts) only ce is acceptable. This rule would be specific to French, and would not cover other scenarios for the translation of pleonastic it. Other issues include the use of pronouns in impersonal constructions such as il faut [one must/it takes] in which evaluation of the pronoun requires consideration of the whole expression, or transformations between active and passive voice, where the perspective of the pronouns changes.

### Table 4: Common cases of disagreement for anaphoric, pleonastic, and event reference pronouns

| Category                  | V   | E   | I   | O   |
|---------------------------|-----|-----|-----|-----|
| Anaphoric                 |     |     |     |     |
| intra-sent. subj. it      | 26  | 9   | 7   | –   |
| intra-sent. non-subj. it  | –   | –   | –   | 12  |
| inter-sent. subj. it      | 32  | 5   | 19  | –   |
| inter-sent. non-subj. it  | 12  | –   | –   | –   |
| intra-sent. they          | 26  | –   | 2   | –   |
| inter-sent. they          | 41  | –   | 2   | –   |
| singular they             | 47  | –   | –   | 1   |
| group it/they             | 24  | –   | –   | 2   |
| Event it                  | –   | 16  | 40  |     |
| Pleonastic it             | –   | 11  | 29  |     |

V: Valid alternative translation  I: Impersonal translation  E: Incorrect equivalence  O: Other

7 Conclusions

Our analyses reveal that despite some correlation between APT and the human judgements, fully automatic wide-coverage evaluation of pronoun translation misses essential parts of the problem. Comparison with human judgements shows that APT identifies good translations with rela-
tively high precision, but fails to reward important patterns that pronoun-specific systems must strive to generate. Instead of relying on fully automatic evaluation, our recommendation is to emphasise high precision in the automatic metrics and implement semi-automatic evaluation procedures that refer negative cases to a human evaluator, using available tools and methods (Hardmeier and Guillou, 2016). Fully automatic evaluation of a very restricted scope may still be feasible using test suites designed for specific problems (Bawden et al., 2017).

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