Pronoun Translation in English–French Machine Translation: An Analysis of Error Types

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Abstract

Pronouns are a long-standing challenge in machine translation. We present a study of the performance of a range of rule-based, statistical and neural MT systems on pronoun translation based on an extensive manual evaluation using the PROTEST test suite, which enables a fine-grained analysis of different pronoun types and sheds light on the difficulties of the task. We find that the rule-based approaches in our corpus perform poorly as a result of oversimplification, whereas SMT and early NMT systems exhibit significant shortcomings due to a lack of awareness of the functional and referential properties of pronouns. A recent Transformer-based NMT system with cross-sentence context shows very promising results on non-anaphoric pronouns and intra-sentential anaphora, but there is still considerable room for improvement in examples with cross-sentence dependencies.

1. Introduction

Pronoun translation still poses serious challenges for machine translation (MT) systems despite years of research \cite{1,2,3,4}. This can be ascribed to a combination of factors including an incomplete understanding of the problem, evaluation difficulties, and the fact that low system performance is often obscured by the presence of many trivial problem instances. While the generally increased fluency of neural MT (NMT) creates hope that NMT may perform better on this task than statistical MT (SMT), this has not been convincingly shown as yet. In this paper, we investigate the difficulties that pronouns create for MT with the help of a detailed manual analysis of a corpus of MT output covering rule-based, SMT and NMT systems. Our study sheds light on the problems inherent in pronoun translation and its manual evaluation, and on the relative performance of different types of MT systems on different types of pronouns.

Our contributions include the manual annotation and assessment of the performance of nine English–French MT systems against the PROTEST test suite, a comparison with the manual evaluation from the DiscoMT 2015 shared task (for a subset of the systems), and a detailed corpus study highlighting some of the common categories of errors revealed in a meta-evaluation of the human judgements. The results of our study confirm that pronoun translation remains a serious problem for rule-based, statistical and neural MT. They strengthen previous results indicating that rendering pronouns in translation requires modelling both functional and referential properties \cite{3}, and reveal severe weaknesses in previous modelling attempts that only addressed these problems in part. We find that neural MT does not automatically resolve the problem of pronoun translation. While early NMT approaches fail to outperform SMT on pronouns, a recent Transformer-based NMT system \cite{5} achieves very promising results for non-anaphoric pronouns and intra-sentential anaphora, but still performs relatively poorly on examples with cross-sentence dependencies despite explicit attempts to model inter-sentential context.

2. The PROTEST Test Suite

PROTEST \cite{6} is a test suite designed to evaluate pronouns in MT. It consists of 250 pronouns categorised following a two-level schema. The pronouns in PROTEST were selected from the DiscoMT2015.test dataset \cite{7}, a collection of TED talk transcripts \cite{8} and their translations. The corpus is manually annotated with pronoun properties and links between pronouns and their antecedents \cite{8}. At the top level the categories capture pronoun function. Anaphoric pronouns refer to an antecedent. Event reference pronouns may refer to a verb, verb phrase, clause, or an entire sentence. Pleonastic pronouns, in contrast, do not refer to anything. Addressee reference pronouns are used to refer to the reader/audience:

\begin{itemize}
  \item \textit{anaphoric}: I have a bicycle. \textit{It} is red.
  \item \textit{event}: He lost his job. \textit{It} came as a total surprise.
  \item \textit{pleonastic}: It is raining.
  \item \textit{addressee reference}: \textit{You’re} welcome.
\end{itemize}

More fine-grained categories are derived from additional annotated features: the pronoun’s surface form, singular vs. plural use, subject vs. non-subject position, and whether the antecedent is a group noun, an anaphoric pronoun is inter- or intra-sentential, and an addressee reference pronoun refers to specific people (deictic) or to people in general (generic).

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3. Data Set

The core part of our data set consists of one rule-based MT and four SMT systems that participated in the shared task on pronoun translation at DiscoMT 2015 \cite{9}. We complement this data set by adding the output of an SMT baseline and three NMT systems.

The DiscoMT 2015 pronoun translation shared task \cite{9} studied English–French MT, paying special attention to the translation of the English pronouns *it* and *they*. Of the six submissions, four were phrase-based SMT systems, each trained on the shared task data, comprising Europarl \cite{10}, News Commentary version 9 and the shuffled news corpora from WMT 2007–2013 \cite{11}, and the WIT^3 corpus of TED talks \cite{12}. These four systems differ in the components that are specific to pronoun translation. IDIAP \cite{13} and AUTO-POSTEDIT \cite{14} employ a two-pass strategy to detect and amend incorrect pronoun translations. UU-TIEDEMANN \cite{15} does not attempt to resolve pronominal anaphora explicitly, instead it employs a cross-sentence n-gram model over determiners and pronouns to bias the model towards selecting correct pronouns. UU-HARDMEIER \cite{9} includes a neural network classifier for pronoun prediction trained with latent anaphora resolution. The fifth system, ITS2 \cite{16}, is a rule-based system with syntax-based transfer and an anaphora resolution component influenced by Binding Theory. An SMT baseline system implemented with Moses \cite{17} is included in the data set with the label BASELINE.

Following the recent shift in focus from SMT to NMT, we also assess the performance of NMT systems on pronoun translation. We extend our corpus with three NMT systems provided to us by researchers from leading NMT groups. The first (LIMSI) is the *s-hier* system described in paper \cite{18}. It was trained on OpenSubtitles2016 data \cite{19}, and is designed to exploit context from previous source and target sentences when translating discourse phenomena (including pronouns). The second (NYU) is based on the NMT baseline described in \cite{20}. It is trained on the official training data from WMT 2014 \cite{11}. It should be noted that the WIT^3 data set of TED talks, which can be considered in-domain for the PROTEST test suite, is not included in the training data of the LIMSI and NYU systems. The third NMT system (YANDEX) is an English-French version of a system developed for English–Russian \cite{5}. It is based on the Transformer NMT architecture \cite{21} and uses context from the preceding sentence to improve the translation of discourse phenomena. It is trained on a subset of the Europarl, News Commentary, and TED data from the DiscoMT 2015 shared task. We also include the reference translation as an upper bound to system performance.

4. PROTEST Annotation

The MT system translations of the test suite pronouns were manually evaluated using the PROTEST graphical user interface (GUI) \cite{22}. The annotator is presented with the original English sentence together with up to five sentences of context and the corresponding MT system translation. The pronoun to be annotated is highlighted in the English sentence, and its translation (found via source-target word-alignments) is highlighted if available. If the pronoun is anaphoric, its antecedent head and translation are also highlighted.

The translation of each pronoun in the test suite by each MT system (a translation example) is annotated according to the PROTEST guidelines \cite{22}. The focus of the annotation is on the pronouns and their antecedents, which are marked as either correct or incorrect. Other words in the translation are not evaluated, except if the translation is so bad that pronoun evaluation is impossible. Additionally, tags are used to indicate common issues such as *bad translations* or *incorrect word alignments*. The annotations were carried out by two bilingual English-French speakers, both of whom are native speakers of French.

5. Inter-Annnotator Agreement

A random sample of 228 translation examples, stratified by pronoun category and annotated by both annotators, was used to calculate inter-annotator agreement (IAA). The remainder (2,272 examples) was divided between the two annotators. As the NMT systems were added to the analysis later, no NMT examples are present in the IAA set.

The IAA scores were calculated using Cohen’s Kappa \cite{23}. The agreement scores are 0.71 for pronouns (*good agreement*) and 0.58 for antecedents (*moderate agreement*). The annotators disagreed on the annotation of 22/228 (12.28\%) pronouns and 8/140 (5.71\%) antecedents. An examination of the confusion matrices reveals only one notable difference: in half of the disagreements (13 cases) annotator 1 marked a pronoun translation as correct, and annotator 2 marked it as incorrect, possibly indicating that one of the annotators was slightly stricter. We conclude that although the level of agreement is reasonable, the manual annotation of pronouns and antecedents is far from easy. The 31 examples in the IAA set for which the annotators disagree on the annotation of the pronoun, antecedent, or both, were resolved through adjudication by one of the authors of this study.

6. Comparison with DiscoMT 2015 Manual Evaluation

In the DiscoMT 2015 shared task, performance was evaluated using human judgements from a gap-filling task in which the pronoun translation in the MT output was obscured and the annotator was asked to suggest which French pronoun(s) would be suitable given the surrounding MT context. The set of examples was different from PROTEST and focused only...
We then re-computed the official accuracy metric, named Acc+OTHER scores from DiscoMT 2015 computed over the Acc+OTHER in the DiscoMT 2015 evaluation [24], for the provided correct suggestions, but failed to list the correct gap-filling data set. It included 16 incorrect cases and 11 errors. Errors occur disproportionately often in the DiscoMT cases (75.9%). 30 cases (11.1%) differ due to annotation errors that the PROTEST and DiscoMT assessments agree in 205 six MT systems, for a total of 270 judgements. We find both evaluations. The overlap comprised 45 examples from evaluation methods, we studied the examples common to systems both beat the examples of incomplete annotations, where the annotators providing, and AUTO-POSTEDIT fares better (cf. Table 3).

Table 1: Comparison between the DiscoMT 2015 and PROTEST manual evaluations

|                | PROTEST | DiscoMT | official DiscoMT |
|----------------|---------|---------|-----------------|
|                | it/they | 195 ex. | 210 ex.         |
| BASELINE       | 0.590   | 0.631   | 0.676           |
| IDIAP          | 0.600   | 0.595   | 0.657           |
| UU-TIEDEMANN   | 0.610   | 0.615   | 0.643           |
| UU-HARDMEIER   | 0.566   | 0.544   | 0.581           |
| AUTO-POSTEDIT  | 0.595   | 0.528   | 0.543           |
| ITS2           | 0.380   | 0.394   | 0.419           |

Table: Comparison between the DiscoMT 2015 and PROTEST manual evaluations

on subject instances of it and they.

To compare our results with the original shared task evaluation, we first identified a PROTEST-style category for each pronoun example in the DiscoMT 2015 evaluation set (210 pronouns) using the manual annotations in DiscoMT2015.test. We then re-computed the official accuracy metric, named Acc+OTHER in the DiscoMT 2015 evaluation [24], for the systems contained in the original DiscoMT data set, restricting the pronoun examples to those with categories matching the set used in the PROTEST evaluation (leaving 195 pronouns in total). Table 1 shows the Acc+OTHER scores on the reduced set of 195 pronouns and on the 205 it/they pronouns from the PROTEST test suite (after removing all instances of you). For reference, we also include the original Acc+OTHER scores from DiscoMT 2015 computed over the full evaluation set.

The system rankings are very different when Acc+OTHER on the reduced set of 195 pronouns is compared to the proportion of correctly translated pronouns in the reduced set of 205 PROTEST pronouns. The UU-TIEDEMANN and IDIAP systems both beat the BASELINE according to PROTEST rankings, and AUTO-POSTEDIT fares better (cf. Table 3).

To gain more insight into the differences between the evaluation methods, we studied the examples common to both evaluations. The overlap comprised 45 examples from six MT systems, for a total of 270 judgements. We find that the PROTEST and DiscoMT assessments agree in 205 cases (75.9%). 30 cases (11.1%) differ due to annotation errors. Errors occur disproportionately often in the DiscoMT gap-filling data set. It included 16 incorrect cases and 11 examples of incomplete annotations, where the annotators provided correct suggestions, but failed to list the correct pronoun selected by the MT system. The PROTEST data set had 3 obviously incorrect annotations. The remaining 35 cases (13.0%) reflect problems of the annotation task, such as incorrect word alignments, disagreement about whether to accept its without overt antecedents or annotation differences in disfluent translations.

The comparison of the two evaluation procedures shows that the ranking of systems is sensitive to the choice of examples. The original DiscoMT evaluation used a random selection of pronoun examples designed to approximate the distribution of pronouns in naturally occurring text. PROTEST, by contrast, contains a stratified sample covering specific types of pronoun use. Which selection strategy is more useful in practice must be decided from case to case based on the purpose of the evaluation. Another noteworthy point is the high number of annotation errors found in the DiscoMT evaluation. On the one hand, the incomplete annotations reveal a weakness of the gap-filling evaluation procedure, which was designed to avoid priming the annotators with the output of the MT systems, but comes at the expense of an increased risk of missing valid alternatives. The large number of outright annotation errors, on the other hand, demonstrates the dangers of using annotators that are not native speakers of the target language. Finally, a relatively large number of disagreements seems to be inherent in the task and shows that the evaluation of pronouns in the context of disfluent MT output is not always a well-defined problem.

7. MT Corpus Study

In this section, we present an overview of system performance based on the human judgements collected during annotation over the PROTEST test suite. Table 2 details the number of correctly translated antecedent heads and those translations which could not be evaluated due to more general problems. Table 3 shows a summary of the judgements on the pronoun translations.

In addition, we manually looked through the 821 examples in the data set in the anaphoric, event and pleonastic categories that were labelled as incorrect or rejected due to general problems by the annotators, and created another level of synthesis of the results by categorising the errors into different types according to the most important problem in the translation. This meta-evaluation was performed by one of the authors of this study, a native speaker of German with good knowledge of English and French.

The tags assigned in this meta-evaluation are always based on a reassessment of the examples, so the counts per category do not tally exactly with the counts of the main analysis, even for identical tags. They fall into four broad categories: Acceptable means that the pronoun translations were judged to be acceptable even though they had been rejected in the initial annotation. Most of these examples are due to incorrect automatic word alignments between the source and the translations. In such cases, the first-pass annotators had been instructed not to label the pronoun translations as correct so that the word-aligned data set could be used as a source of correct examples in other experiments. The acceptable category also includes some examples where the initial annotator had missed a valid different reading (e.g., by interpreting a pronoun as encoding abstract instead of concrete anaphora), but we did not question the native speakers’ acceptability judgements where no such alternative reading was available.

The second category includes examples where the main problem was a general mistranslation or disfluency in the translation (bad translation), with the omission of a large part
Table 2: Antecedent translations marked as correct, and supplementary information, per system

| Examples | antecedent correct | bad translation | incorrect | alignment | missing text |
|----------|--------------------|------------------|-----------|-----------|-------------|
| Reference| 139                | 1                | 0         | 0         |             |
| BASELINE | 123                | 7                | 9         | 0         |             |
| AUTO-POSTED | 140            | 3                | 0         | 0         |             |
| UU-HARDMEIER | 134         | 2                | 9         | 0         |             |
| IDIAP    | 125                | 7                | 9         | 0         |             |
| ITS2     | 107                | 4                | 34        | 0         |             |
| UU-TIEDEMANN | 127      | 8                | 6         | 0         |             |
| LIMSI    | 108                | 2                | 30        | 55        |             |
| NYU      | 125                | 9                | 9         | 3         |             |
| YANDEX   | 135                | 2                | 12        | 0         |             |

Table 2: Antecedent translations marked as correct, and supplementary information, per system

of the sentence as a special case (missing text). The third category comprises translations with errors in gender or number agreement, or both.

In the final category, wrong pronoun type, the type of pronoun output by the MT system was not compatible with the structure or semantics of the target sentence. Typical examples are the use of a French personal pronoun like il/elle where a demonstrative like ce or cela would have been appropriate, or vice versa. This category also includes the use of feminine pronouns as pleonastics, or pleonastic uses of il (acceptable in many, but not all cases) that were judged as incorrect by our native speaker annotators.

7.1. Comparison of Functional Categories

Table 4 shows the most common error types found in the data for each of the pronoun categories. Note that the examples in the test suite were the same for all systems and many of the systems made similar errors on the same examples. This should be kept in mind when interpreting the numbers in this table.

In theory, a translation can also be grammatical while not containing a direct translation of the source pronoun. Whilst we found very few examples of this type in the dataset, we should stress that the rarity of such examples in the dataset does not imply that this is not a relevant translation strategy. Rather, this type of alternation is beyond the capabilities of current MT systems, and examples where it would have been appropriate are likely to have ended up in another error category.

Clear patterns are visible in Table 4. In the anaphoric it categories, there is a split between subject and non-subject pronouns. Bad translation is very common for non-subject pronouns, and this frequently means that the pronouns are simply omitted by the MT systems. This happens far less frequently for subject it, where gender agreement is the most important problem, followed by wrong pronoun type, which in this category usually means that ce or another demonstrative was chosen where a personal pronoun would have been appropriate. The patterns for inter- and intra-sentential it are very similar, but the inter-sentential category has more wrong pronoun type cases. One possible explanation is that in the inter-sentential examples sentences often start with it’s, inviting confusion with pleonastic it. The context of the intra-sentential examples tends to include clues like content-bearing verbs that disambiguate the pronoun function more strongly.

In the intra- and inter-sentential anaphoric they categories, gender agreement is also the most prevalent source of errors, especially in the inter-sentential case. This is not unexpected, as gender marking of plural pronouns is known to be a challenging problem for MT to such an extent that accuracy on these cases has even been used as a benchmark metric in previous work [25]. There are also some cases of number agreement errors. In the intra-sentential category, most of these stem from a single example in the test suite. It involves the pronoun someone, which is correctly referred to with singular they in English, but requires singular agreement in French. The number agreement examples in the inter-sentential category are spread over different examples, and we could not discern any clear patterns.

In the singular they category, bad translation and number agreement stand out as the most common error types, whereas the errors in the group it/they categories are distributed quite evenly over different types. Nevertheless, the two categories exhibit similar problems. Many of these examples involve a named entity in one sentence referred to by the pronoun they, usually translated as ils, in the next sentence. There are two main problems, one of translation and one of evaluation. First, it turns out that some of the named entity antecedents pose a real challenge to the MT systems. It is very common for multi-word named entities to be spectacularly mistranslated. For names like ‘Deep Mind’ or ‘National Ignition Facility’, the MT systems produce pseudo-compositional translations that can hardly be recognised as proper names in the output, let alone assigned to a particular gender. As a result, the annotators struggled to determine what pronoun should be used to refer to the entity in the next sentence. The second problem, related to evaluation, is that the annotators reportedly find it difficult to assess whether or not ils can be a correct translation of they in these examples. Both annotators agree that referring to the named entities in question with ils is considered ungrammatical in French and sounds much less natural than the literally equivalent English pattern. Such examples are the main source of the number agreement errors in these categories. Still, in some cases the annotators are reluctant to categorically label the translations as unacceptable as this pronoun use is occasionally encountered in informal French speech.

In the event it category, wrong pronoun type is by far the most common source of errors. In almost all of these
### Table 3: Pronoun translations marked as correct, per system

|          | anaphoric | event pleonastic | addressee reference |
|----------|-----------|------------------|---------------------|
|          | intra     | inter            | intra               |
|          | subj.     | non-subj.        | subj. non-subj.     |
| Examples | 25        | 15               | 25                  |
| Reference| 25        | 15               | 20                  |
| BASELINE | 15        | 5                | 12                  |
| AUTO-POSTEDIT | 18    | 10               | 12                  |
| UU-HARDMEIER | 14   | 7                | 12                  |
| IDIAP    | 13        | 6                | 16                  |
| ITSG2    | 9         | 6                | 12                  |
| UU-TIEDEMAN | 15   | 3                | 13                  |
| LIMSI    | 10        | 6                | 10                  |
| NYU      | 15        | 8                | 17                  |
| YANDEX   | 23        | 12               | 21                  |
|          |           |                  | total               |
|          |           |                  | count               |
|          |           |                  | percentage          |
| Average  | 97        | 76               | 10                  |

### Table 4: Meta-evaluation: Common error sources

|          | anaphoric | event pleonastic |
|----------|-----------|------------------|
|          | intra     | inter            |
|          | subj. non-subj. | subj. non-subj. |     |
| acceptable | 16        | 19               |
| bad translation | 21   | 37               |
| missing text | 11    | 5                |
| gender agreement | 43   | 50               |
| number agreement | 1    | 1                |
| gender and number | –    | –                |
| wrong pronoun type | 5    | 8                |
| total      | 97        | 76               |

Table 3: Pronoun translations marked as correct, per system

Table 4: Meta-evaluation: Common error sources
cases, the English pronoun it was translated with the French personal pronoun il or, occasionally, elle or ils. The correct choice in these cases would usually have been the demonstrative pronoun cela or ça. This confirms that pronoun choice in translation depends in a crucial way on the function of the pronoun [3], and suggests that pronoun function identification [26] may be useful for MT.

Finally, in the pleonastic it category, wrong pronoun type and bad translation are the most common error sources. However, this error category is probably over-represented in our data set, as many of the systems specifically manipulate pronouns in an imperfect attempt to improve phenomena like gender agreement. In the pleonastic category, the uninformed “default” translation of the pronouns is often correct, and there is a great risk of introducing errors by making changes to it. This is reflected by the fact that the performance of the BASELINE system is among the best in this category (see Table 3). The BASELINE did not have any instances of wrong pronoun type in the meta-evaluation, and there were only two cases of bad translation.

### 7.2. Comparison Across MT Systems

The data collected in our study also allows us to make a comparison across the rule-based, SMT, and NMT systems represented in the data set.

Our manual evaluation procedure depends on word alignments between pronouns and their translations. For the SMT systems, word alignments were obtained directly from the MT decoder. For the rule-based and NMT systems, we rely on automatic word alignments generated retrospectively using GIZA++ [27]. We reject the option of using the output of the attention model for NMT systems as it is known that attention and word alignment may dramatically diverge [28]. Retrospectively computed alignments are clearly less accurate than those output by a decoder. As a result, the number of examples that could not be annotated correctly because of incorrect word alignment is very high, especially for the ITS2 and LIMSI systems (Table 2).

We start by noting that only 230 out of 250 pronouns in the reference translation were deemed to be correctly translated (Table 3). In general, the problems in the reference translation are not very severe. They include typographical errors (e.g., elle/lelles and il/ils are sometimes confused because they share the same pronunciation) and a few cases where the reference structure in the translation was subtly altered in a way that the annotators did not accept.

The bulk of the systems (BASELINE, IDIAP, UU-TIEDEMANN, UU-HARDMEIER, AUTO-POSTEDIT) are phrase-based SMT systems built using the same technology and training data. As the shared task focused on pronoun translation, all systems except for the BASELINE are extended in some way to handle pronouns in specific ways. Nevertheless, none of the systems manages to reduce the number of gender agreement or wrong pronoun type problems below the BASELINE. In fact, some of the systems achieved noticeably worse results. Compared to the rule-based and NMT systems, a high number of examples are tagged for missing pronouns.

ITS2 is the only purely rule-based system in the corpus. The pronoun-related rules of the system are restricted in the sense that English personal pronouns in subject position are always rendered with one of the French personal pronouns il, elle, ils or elles. The demonstratives ça, cela and ce were never produced. This strategy was not accepted by our annotators, resulting in an extraordinarily high number of wrong pronoun type annotations. A similar observation can be made about AUTO-POSTEDIT, an SMT system with rule-based postprocessing. Like ITS2, it relies on rules that do not produce the full range of pronouns (avoiding ça and cela) and is penalised for that in the evaluation.

The three NMT systems exhibit rather different performance. LIMSI has fewer examples tagged for gender agreement and wrong pronoun type errors than NYU. Unfortu-

|                | Reference | BASELINE | IDIAP | UU-TIEDEMANN | UU-HARDMEIER | AUTO-POSTEDIT | ITS2 | LIMSI | NYU | YANDEX | Total |
|----------------|-----------|----------|-------|--------------|--------------|---------------|------|-------|-----|--------|-------|
| acceptable     | 14        | 12       | 6     | 8            | 8            | 6             | 27   | 8     | 12  | 9      | 110   |
| bad translation| 1         | 28       | 31    | 32           | 23           | 22            | 24   | 12    | 34  | 12     | 219   |
| missing text   |           |          |       |              |              |               | 50   | 1     | 51  |        |       |
| gender agreement| 5         | 28       | 29    | 27           | 40           | 30            | 30   | 17    | 25  | 23     | 254   |
| number agreement| 2         | 6        | 1     | 3            | 4            | 1             | 6    | 3     | 5   | 2      | 33    |
| gender and number| 1         | 1        | 4     | –            | 1            | 2             | 4    | –     | 1   | 1      | 15    |
| wrong pronoun type| 2         | 12       | 12    | 12           | 14           | 22            | 39   | 7     | 16  | 3      | 139   |
| total          | 25        | 87       | 83    | 82           | 90           | 83            | 130  | 97    | 94  | 50     | 821   |

Table 5: Meta-evaluation: Error types per system
nately, this cannot be unequivocally interpreted as evidence of better performance because LIMSI produced a very high number of truncated sentences (labelled missing text), later found to be a result of poorly aligned sentence pairs in the OpenSubtitles2016 dataset, and it is likely that it avoided many potential errors simply by failing to produce any output at all.

The YANDEX system, a recent NMT system that builds on the Transformer NMT architecture and models the current sentence together with one previous sentence of context, performs much better on the test suite than all the other systems in our corpus. This indicates that an up-to-date NMT can have an edge over most previous MT technology when it comes to pronoun translation. It is also noteworthy that the YANDEX system has much fewer cases of wrong pronoun type than the other systems, a fact that can primarily be put down to much better performance on the event it category.

Interestingly, however, the system performs much better on the intra-sentential anaphoric categories than the inter-sentential ones. This suggests that the Transformer architecture has a real advantage over recurrent NMT models in propagating agreement information within the scope of a sentence and that the additional context (of the previous sentence) available to the YANDEX model is not being harnessed to its full potential. In fact, 43 of the 55 instances of anaphoric inter-sentential pronouns in PROTEST have antecedents in the previous sentence, but only 18 of these are correctly translated by the system. This result contrasts with the reported claims of a noticeable improvement in the translation of inter-sentential anaphoric pronouns with the original English–Russian YANDEX system. A more detailed study of this discrepancy must be left to future work.

8. Discussion

By re-evaluating a corpus of MT systems that had already been manually evaluated in a different way for DiscoMT 2015, our study touches on questions of both MT evaluation and MT performance. It also reveals some information about the pronoun uses that are most problematic for MT.

8.1. MT Evaluation

The evaluation of pronoun translation in an MT context is surprisingly challenging. This is not immediately obvious, and in fact some earlier work on discourse in MT focused on pronouns specifically because they were supposed to be easier to evaluate than other aspects of discourse coherence such as lexical choice. Problems arise in two ways. First, pronoun usage in corpus data is often less clear-cut than one might expect, with sometimes vague reference and occasional violations of the rules of gender and number agreement imposed by prescriptive grammar. Second, MT output is often disfluent in various ways. Since pronouns have very little semantic content other than their context-dependent referential properties, they become extremely difficult to interpret and judge once the context is disturbed. Our comparison of the DiscoMT gap-filling and the PROTEST test suite evaluation reveals problems of both kinds. It also shows the danger of using non-native speakers as evaluators, resulting in a high number of annotation errors despite best efforts. General-purpose MT evaluation methods such as those used at WMT arguably focus more on the adequacy of content words and may be more robust to minor disfluencies. The effect of pronoun translation on general-purpose human MT evaluation is an interesting follow-up problem for future work.

8.2. MT Performance

Gender agreement was long assumed to be the most important problem that needed to be addressed to solve the issue of pronoun translation. This was eventually recognised to be insufficient, and Guillou suggested that the function of pronouns was another important factor affecting their translation. Our evaluation results confirm that both of these factors play an important role. In our study, gender agreement is by far the most common error type for anaphoric pronouns. Beyond doubt, resolution and maintenance of coreference relations are essential problems that must be tackled in MT research. At the same time, many pronoun choice errors can be attributed to an incorrect identification of pronoun function. These errors are especially frequent among anaphoric pronouns with non-nominal antecedents, categorised as event pronouns in PROTEST. It seems, therefore, that noun-noun coreference does not provide sufficient information for the correct translation of arbitrary pronouns. To generate correct translations, the function of the input pronouns, and to the extent they are identified as anaphoric, the type of anaphoric reference they encode, must be taken into consideration. Among the systems in our data set, the YANDEX system stands out by achieving much better disambiguation between anaphoric and event pronouns. It is an interesting question for future work whether this is primarily due to the Transformer architecture or to the additional context encoder in the system, and whether this disambiguation capability can be harnessed to improve other NLP tasks such as coreference resolution.

So far, non-subject position pronouns have received little attention from the SMT community. We find that the typical error patterns in this category differ significantly from those of pronouns in subject position. The abysmal performance of the MT systems for non-subject inter-sentential anaphora, where only one system translated more than one item correctly, may to some extent be a result of random variation due to the very small sample size (5 examples per system). However, the results in the intra-sentential category are also very low, pointing to serious difficulties in the translation of these pronouns. The dominant cause of error for non-subject pronouns is omission in the target language. For the phrase-based SMT systems, this may be due to unreliable automatic word alignments of these pronouns. Word alignment is difficult both because the French direct object pronouns

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3Personal communication with Rachel Bawden.
are homonymous with the more frequent definite articles and because of word reordering between post-verbal English and pre-verbal French object pronouns. The rule-based and NMT systems do not perform significantly better on this category, but the YANDEX system achieves an improvement, especially in the intra-sentential case and probably due to the Transformer architecture. Specifically for non-subject pronouns, it also achieves better results than the other system in the inter-sentential case, but the number of examples of this kind in PROTEST is too small to make a definitive statement, especially since we fail to observe a corresponding improvement for inter-sentential subject pronouns.

Our corpus contains one completely rule-based MT system (ITS2) and one SMT system with rule-based post-editing (AUTO-POSTEDIT). The overall performance of the two systems differs greatly, but both of them generate a large number of pronouns of incorrect type (e.g., personal pronouns instead of demonstratives; Table 5). This is likely because the rule-based component of both systems emits only a restricted subset of all possible target-language pronouns; in particular, neither system will ever generate the French demonstrative ça/cela for an English personal pronoun. This suggests that the complexity of the rule-based components in the MT systems we evaluated is insufficient.

8.3. Pronoun Use

Our study does not focus primarily on the linguistic constraints of pronoun use, however, it is worth highlighting those aspects that pose particular problems for MT and its evaluation. Whilst there is a clear correlation between the semantic plurality of an entity and number marking on the associated linguistic expressions, this correlation is not absolute, and quite frequently actual and grammatical number diverge. Typical examples in English are the use of they referring to group nouns or to individuals of unknown gender. The constraints governing the use of such forms are highly language-dependent. Our annotators agree that they are distinctly less natural in French, even though they do occur occasionally in informal speech. For practical MT, this has two implications. First, we cannot assume that linguistic properties such as number marking will be consistent in a coreference chain or invariant under translation. Second, while literal translations may sometimes work despite cross-linguistic differences in language use, they will be perceived as unnatural especially if frequent.

9. Conclusions

We have evaluated the quality of pronoun translation in a corpus of translations generated by different types of MT systems using a test suite of examples that is balanced to cover different uses of pronouns. Our results demonstrate that pronouns are problematic for all of the MT technologies we considered. In particular, we find no evidence that the adoption of neural methods in MT by itself leads to significantly better performance on this type of problem. Our results do suggest, however, that the latest generation of Transformer-based NMT models are better at handling cases of intra-sentential anaphora and at identifying the functional properties of pronouns. However, the advantage of a context encoder, a major contribution of the YANDEX system, is less clear, as the system fails to outperform previous technology even in those cases where the required information is available in the scope of the context sentence. It is therefore too early to suggest that NMT has solved the problem of pronoun translation, but the results are encouraging.

We find two major sources of pronoun translation errors in our English–French corpus. First, lacking awareness of pronoun function causes confusion between, primarily, personal pronouns and demonstratives in the target language. Second, lacking awareness of the referential properties of the pronouns results in incorrect gender and number agreement. We recommend that system developers address both of these factors, as simple heuristic approaches can demonstrably lead to decreased performance.

We also highlight that the evaluation of pronoun translation is in itself a difficult problem, as evidenced by the disagreement between the two manual evaluation methods applied to the DiscoMT data set. As an alternative to fully automatic evaluation we recommend the use of semi-automatic methods in combination with hand-crafted test suites or challenge sets.

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