Repairing Pronouns in Translation with BERT-Based Post-Editing

Reid Pryzant
Stanford University
rpryzant@stanford.edu

Abstract

Pronouns are important determinants of a text’s meaning but difficult to translate. This is because pronoun choice can depend on entities described in previous sentences, and in some languages pronouns may be dropped when the referent is inferable from the context. These issues can lead Neural Machine Translation (NMT) systems to make critical errors on pronouns that impair intelligibility and even reinforce gender bias. We investigate the severity of this pronoun issue, showing that (1) in some domains, pronoun choice can account for more than half of a NMT systems’ errors, and (2) pronouns have a disproportionately large impact on perceived translation quality. We then investigate a possible solution: fine-tuning BERT on a pronoun prediction task using chunks of source-side sentences, then using the resulting classifier to repair the translations of an existing NMT model. We offer an initial case study of this approach for the Japanese-English language pair, observing that a small number of translations are significantly improved according to human evaluators.

1 Introduction

Neural machine translation (NMT, Sutskever et al. (2014); Bahdanau et al. (2015) systems make frequent mistakes on pronouns, especially for languages like Japanese (our object of focus, Müller et al. (2018)). This is because pronoun choice may depend on contextual information beyond that of the source sentence. In Japanese these words can even be dropped, which forces MT systems to infer pronouns as part of the translation process. Figure 1 gives an example.

This pronoun issue has been well studied in the machine translation community (Guillou et al., 2019; Stanovsky et al., 2019; Schiebinger, 2013; Vanmassenhove et al., 2019b). Prior work includes context-aware translation (Voita et al., 2018; Miculicich et al., 2018; Wang et al., 2019b), zero-pronoun translation (Tan et al., 2019; Wang et al., 2019a), and anaphora resolution (Stojanovski and Fraser, 2019; Luong and Popescu-Belis, 2017). Many of these approaches achieve progress by designing specialized models that are trained from scratch with relatively scarce document-aligned parallel corpora.

This research note adds to this body of work by offering (1) an investigation into the severity of this pronoun issue, and (2) preliminary steps towards an alternative approach for combating the issue, one which aims to be model-agnostic and require only a small amount of document-level data.

We begin with a pair of surveys. We study critical errors while translating Japanese biographical Wikipedia pages into English, finding that a majority of errors are due to pronoun choice. Next we compare pronoun-corrected translations to randomly corrected translations, finding that pronouns have a disproportionately large impact on perceived translation quality.
Figure 2: Pronouns are a critical source of error and bias for these English translations of Japanese-language biographies.

We then propose a method for improving pronoun translation. Inspired by prior methods in statistical machine translation (Nakaiwa, 1999; Guillou, 2015; Taira et al., 2012; Kudo et al., 2015; Russo et al., 2012), we fine-tune BERT (Devlin et al., 2018) to produce target-side pronouns from chunks of source-side sentences. Then, motivated by recent work suggesting the applicability of post-editing for NMT (Chollampatt et al., 2020; Alvarez et al., 2019), we use the BERT classifier to repair pronouns in existing translations.

Last, we offer a case study of the proposed method, using an initial prototype system to translate Japanese documents into English. Only a small percent of typical test sets are relevant and our gains in BLEU are modest (owing to the small syntactic changes required to fix pronouns). However, human evaluation results suggest that the repaired translations are significantly preferable to their initial prototypes.

2 Motivation

2.1 Error Analysis

Here we seek to understand the degree to which pronouns degrade NMT performance. Biographical Wikipedia pages have a high density of pronouns and thus suggest the maximal extent of this degradation. For each person on the 2019 Time 100 Most Influential People list, we took the lead paragraph of their Japanese Wikipedia page and translated it into English using Google Translate. We then evaluated sentences according to a five-point JPO criterion (Nakazawa et al., 2016; Pryzant et al., 2018). The majority (62%) of critical errors (translations rated between 1 and 2 points) could be traced to pronoun choice (Table 1, Figure 2). We conclude that pronouns, having contextual dependencies and being dropped in some languages, significantly inhibit modern NMT’s performance. This aligns with findings from previous research (Schiebinger, 2013; Voigt and Jurafsky, 2012; Hughes, 2018).

2.2 Pronoun Importance

Next we use a novel analytic technique to estimate the importance of pronouns for a good translation:

1. Use Google Translate to produce English translations of the Japanese test sets used in Section 5.
2. Select those translations which contained at least one pronoun-related error; these are “prototype” translations.
3. Create one “repaired” translation by manually correcting pronouns in the prototypes.
4. Create an alternative repair by fixing random non-pronouns in the prototype (Figure 3). Segments are selected for correction with probability $p = 0.12$, which yielded the same reference BLEU score as the output of step #3.

We proceeded to show each translation to professional bilingual human evaluators. They were asked to rate the quality of each repaired translation relative to the prototype on a 5-point scale. Randomly repaired translations did not change translation quality (-0.17 ± 0.23 points), but pronoun-repaired translations were significantly improved (+0.57 ± 0.13), suggesting that pronouns have an outsized effect on perceived translation quality.

3 Pronoun Repair Module

Next we propose an initial step towards repairing pronouns in translation. The method seeks

| Error Type | % |
|------------|---|
| Pronoun (missing) | 33 |
| Pronoun (wrong) | 29 |
| Verb | 16 |
| Article/determiner/noun/preposition | 8 |
| Other (fluency, conjugation, etc) | 14 |

Table 1: Proportion of critical error types on biographical Wikipedia articles.
Figure 3: Top: we compare the quality of raw prototype translations, translations where the pronouns are repaired, and translations where words besides pronouns are repaired. Bottom: our random repair procedure uses the diff of the reference and translation, building a new translation by selecting a random reference segment.

3.1 Pronoun Prediction Classifier

For the first part of the module we fine-tune BERT (Devlin et al., 2018) to predict pronouns occurring in the English target text from chunks of Japanese source sentences. These pronoun targets are coded as a categorical variables, with one value per pronoun. For example, if the target text was “She was elected in 1997” than this classifier would be trained to predict “she” from a set of possible pronouns.

Concretely, let \( D = \{ (s_0, t_0), \ldots, (s_n, t_n) \} \) be a document of \( n \) consecutive source-target sentence pairs. We select \( (s_{i-l}, \ldots, s_i, \ldots, s_{i+r}) \), a chunk of source sentences centered around \( s_i \), and prepend the [CLS] token. We then encode the concatenation of these sentences using BERT, select the vector corresponding to the [CLS] token \( b^{[CLS]} \) and use this to predict the probability of each pronoun occurring in the target:

\[
\hat{p} = [\hat{p}_1, \ldots, \hat{p}_c] = softmax(W^\top b^{[CLS]})
\]

Where \( W \in \mathbb{R}^{b \times c} \) is a matrix of learned parameters, \( b \) is the BERT vector size, and \( c \) is the number of pronouns under consideration. We train all parameters, including BERT, with the standard negative cross-entropy loss: \( \sum_j -p_j \log \hat{p}_j \). Our prediction targets \( p_j \) are a one-hot representation of the correct pronoun occurring in the target-side sentence \( t_i \).

For this initial case study, we restrict our label space to the personal pronouns: [“I”, “you”, “he”, “she”, “they”, “we”]. We perform this restriction by sub-setting our training data to only include sentences with one of these pronouns.\(^3\)

3.2 Editing Submodule

The pronoun editing submodule uses the pronoun predicted by BERT to override words in an existing translation. It works by (1) replacing pronoun(s) in the prototype, then (2) re-inflecting any dependent verbs to match the new pronoun in person, case, number and gender. We use a morphological analyzer\(^4\) and a database of English inflections (Sánchez-Gutiérrez et al., 2018) to find and re-inflect these dependent verbs. Linguistic scenarios that follow different rules were manually coded\(^5\)

We improve the precision of this process with a Laplace-smoothed ngram language model trained on web text (Islam and Inkpen, 2009). If, after rewriting, the perplexity of the new sentence increases by some percent threshold \( \tau \), then we ignore the edit.

Note that this procedure is not robust to errors in translation where the number of pronouns in the prototype does not match that of the reference. In practice, such cases are infrequent (16.3% occurrence) and symptomatic of deeper issues (e.g. when the prototype and target have different grammatical voice). Our preliminary case study leaves this to future work.

4 Experiments

We proceed to offer a limited and preliminary case study of the proposed pronoun repair module. We use the module to repair translations of Wikipedia pages and subtitles. Our results indicate that while only a small number of examples are relevant, people significantly prefer repaired translations to the original machine translation output.

\(^3\)We leave to future work the exploration of multiple or no pronouns per label.
\(^4\)https://cloud.google.com/natural-language/
\(^5\)For example, English pronouns may follow special rules in the presence of contractions, gerunds, and negated forms.
4.1 Protocol

Modeling. We initialize our BERT model using the publicly released BERT-Base multilingual and cased parameters. We use the WordPiece tokenization model and vocabulary from the same release to tokenize our data (Wu et al., 2016).

Unless otherwise stated, all vectors which are not pretrained are of size 256. We train with a batch size of 32 and optimize with Adam and a learning rate of 3e-5 (Kingma and Ba, 2014). We fine-tune BERT with three epochs over the training data. NMT models in Section 5 were trained for 40 epochs before testing, using Adam for nonlinear optimization, a learning rate of 3e-4, and gradient clipping whenever norms exceed 2.0. Unless stated otherwise, all context windows are of size $\ell = 4, r = 0$.

Evaluation. We report average performance over 5 experimental replicates and seeds. Similar to Isabelle et al. (2017), we report BLEU on edited examples, which means that the subset of evaluated examples could vary, but in practice we found the results of Section 5 were consistent across different data samples. The proportion of modified examples is given as CR (change rate) in Section 5. For human evaluation, we used a 7-point Likert scale (Albaum, 1997) and inter-annotator agreement was moderate to substantial (Cohen’s kappa of 0.64). We report the percent increase in translation quality relative to the pre-edit prototype.

Data. We evaluate our pronoun module using two datasets, each sampled down to 200,000 train and 10,000 test examples, noting that this represents one to two orders of magnitude less document-aligned data than other context-aware MT studies (Tiedemann and Scherrer, 2017; Voita et al., 2018; Wang et al., 2019a). OpenSubtitles: here we train and test on a corpus of movie and TV show subtitles (Lison and Tiedemann, 2016). OpenSubtitles Kyoto: here we train on a corpus of crawled multilingual web pages and test on the Kyoto Wikipedia Corpus (Neubig et al., 2011). Note that BERT, having been pre-trained on Wikipedia, may have previously seen these data, a nuance we do not investigate for the sake of brevity.

5 Results

First, we investigate the relationship between context size and pronoun prediction performance (5). We find that left-hand context helps pronoun prediction but right-hand context does not. This aligns with the findings of Voita et al. (2018).

Next, we evaluate end-to-end translation performance, finding that the proposed module boosts translation quality for a small number of sentences.

---

*https://github.com/google-research/bert
For the Kyoto data (Table 3), though our BLEU gains are modest (+0.91), the translations are a significant 21% better according to human evaluators. This highlights the importance of pronouns for a good translation. For OpenSubtitles (Table 2), we find that attaching the pronoun module improves all of the baselines’ translations.

Notably, the change rate (proportion of initial test set translations that our post-editing system modified) is quite low for both datasets, pointing to both the sparsity of relevant examples in the data and also the brittle inflexibility of the initial rule-based prototype.

| System     | Original | +P-MOD | CR (%) |
|------------|----------|--------|--------|
| RNMT+      | 13.28    | 13.46  | 16.35  |
| aNMT       | 15.93    | 16.13  | 10.09  |
| aNMT + B   | 14.54    | 14.86  | 17.09  |
| aNMT + M   | 15.50    | 15.73  | 12.21  |
| aNMT + C   | 16.11    | 16.33  | 11.11  |

Table 2: OpenSubtitles corpus results. The “Original” and “+P-MOD” columns correspond to BLEU score before and after attaching the proposed pronoun module. Adding the pronoun module helped every baseline system.

| System     | BLEU | Human | CR (%) |
|------------|------|-------|--------|
| RNMT+      | 13.80| –     | –      |
| +BERT      | 14.30*| –     | 2.32   |
| +Rewriter  | 14.58| +16.73%*| 1.01 |
| +LM (P-MOD)| 14.71| +21.02%*| 0.93 |

Table 3: Kyoto corpus results showing the results of an ablation test. We see successive gains as we add pronoun prediction with direct word substitution (+BERT), re-inflecting dependant verbs (+Rewriter), and language model filtering (+LM). Human evaluation scores reflect how much translation quality improved over the RNMT+ baseline (bigger is better) among changed examples. Asterisks indicate statistical significance.

6 Analysis

Attention scores. Similar to (Clark et al., 2019) we investigate the module’s attention distributions by averaging across the attention heads of BERT’s top transformer layer (Table 6). The model attends closely to pronouns and proper nouns like names. Interestingly, the model also attends strongly to tokens like [SEP] (aligning with Clark et al. (2019)’s findings) and dates, which may encode summaries of local content.

Per-pronoun performance of the BERT classifier in P-MOD results are given in Table 5. Like other work in the pronoun prediction space, we observe that our data are highly skewed (Sebastiáni, 2015; Rabinovich et al., 2016; Loáiciga et al., 2017; Vanmassenhove et al., 2019a). Masculine pronouns numerically dominate (and are often confused with) their feminine counterparts. Precision and recall is also low for “we,” possibly because “we” has common editorial usages where the referent is implicit, e.g. “this Osaka is not the Osaka we know today” (Evans, 1980).

Error analysis. We categorized the system’s severe errors: test set translations where human evaluators gave a rating of 1 on a 7-point scale. Some errors were hard to explain (20%), or due to issues like data noise (9%), poor reinflection (8%), and insufficient context (7%). However a majority (55%) of the most severe errors made by the model belonged to one of these three categories:

1. Ambiguous Examples (19%). Pronoun choice can be subjective, and we found cases where raters simply disagreed with the model’s predictions.

Table 4: Tokens with the highest average attentional scores across the Kyoto test set.

| Token | Meaning | Score |
|-------|---------|-------|
| [SEP] |         | 0.180 |
| I     | pronoun (EN) | 0.063 |
| 598   | date     | 0.041 |
| 俺    | name     | 0.036 |
| 314   | date     | 0.034 |
| 関    | name     | 0.017 |

Table 5: Per-pronoun performance on each test set. For each pronoun we report precision (P) and recall (R) for the proposed P-MOD as well as the proportion of labels belonging to this class (%).
2. **Misused context** (18%). These are cases where the model is confused by a portion of the context. For example, when referring back to a man named 竹川直枝 (Naoe Takegawa), the model’s self-attention is focused on the character 枝 when incorrectly predicting “she”; 枝 was often a part of female names in Japanese antiquity.

3. **Model bias** (18%). Though our module helps reduce the number of biased and stereotype-driven mistakes (e.g. referring to female politicians as “he”) it fails to eliminate them.

7 Conclusion

This research note presented a limited case study in (1) quantifying the importance of pronouns in translation and (2) using a separately trained BERT classifier to improve pronouns in translation. First, our findings indicate that pronouns are a source of critical error and, despite their relative scarcity, are important determinants of translation quality. Second, our results suggest that the proposed approach can achieve consistent gains in BLEU and significant increases in translation quality according to human evaluators. This finding comes with a cautionary observation: our preliminary rewriting module yielded a system which is only applicable to a small percentage of typical test sets. We encourage future work to improve the approach with more robust methods that are capable of handling arbitrary combinations of pronouns, and broader evaluation using pronoun-rich challenge sets (Isabelle et al., 2017; Stanovsky et al., 2019; Nagata and Morishita, 2020).

8 Acknowledgements

We thank Dan Jurafsky and Tetsuji Nakagawa, Melvin Johnson and Hideto Kazawa for their direction throughout the project. We also thank Kellie Webster, Apu Shah, Macduff Hughes and Wei Wang for their advice.

References

Gerald Albaum. 1997. The likert scale revisited. *Market Research Society. Journal.*, 39(2):1–21.

Sergi Alvarez, Antoni Oliver, and Toni Badia. 2019. Does nmt make a difference when post-editing closely related languages? the case of spanish-catalan. In *Proceedings of Machine Translation Summit XVII Volume 2: Translator, Project and User Tracks*, pages 49–56.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. *International Conference on Learning Representations (ICLR)*.

Denny Britz, Quoc Le, and Reid Pryzant. 2017. Effective domain mixing for neural machine translation. In *Proceedings of the Second Conference on Machine Translation*, pages 118–126.

Mia Xu Chen, Orhan Firat, Ankur Bapna, Melvin Johnson, Wolfgang Macherey, George Foster, Lilian Jones, Niki Parmar, Mike Schuster, Zhifeng Chen, et al. 2018. The best of both worlds: Combining recent advances in neural machine translation. *arXiv preprint arXiv:1804.09849*.

Shamil Chollampatt, Raymond Hendy Susanto, Liling Tan, and Ewa Szymanska. 2020. Can automatic post-editing improve nmt? *Empirical Methods in Natural Language Processing (EMNLP)*.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D Manning. 2019. What does bert look at? an analysis of bert’s attention.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Gareth Evans. 1980. Pronouns. *Linguistic inquiry*, 11(2):337–362.

Liane Guillou. 2015. Automatic post-editing for the discomt pronoun translation task. In *Proceedings of the Second Workshop on Discourse in Machine Translation*, pages 65–71.

Liane Guillou, Christian Hardmeier, Preslav Nakov, Sara Stynne, Jörg Tiedemann, Yannick Versley, Mauro Cettolo, Bonnie Webber, and Andrei Popescu-Belis. 2019. Findings of the 2016 wmt shared task on cross-lingual pronoun prediction. *First Workshop on Machine Translation (WMT)*.

Macduff Hughes. 2018. Keynote: Machine translation beyond the sentence. In *Proceedings of the 13th Conference of the Association for Machine Translation in the Americas (Volume 2: User Papers)*.

Kenji Imamura and Eiichiro Sumita. 2019. Recycling a pre-trained bert encoder for neural machine translation. *Proceedings of the 3rd Workshop on Neural Generation and Translation (EMNLP)*.

Pierre Isabelle, Colin Cherry, and George Foster. 2017. A challenge set approach to evaluating machine translation. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.
Aminul Islam and Diana Inkpen. 2009. Real-word spelling correction using google web it 3-grams. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 3-Volume 3, pages 1241–1249. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. International Conference on Learning Representations (ICLR).

Taku. Kudo, H. Ichikawa, and Hideto Kazawa. 2015. Language independent null subject prediction for statistical machine translation. In Annual meeting of Natural language Processing (in Japan).

Pierre Lison and Jörg Tiedemann. 2016. OpenSubtitles2016: Extracting large parallel corpora from movie and tv subtitles.

Sharid Loáiciga, Sara Stymen, Preslav Nakov, Christian Hardmeier, Jörg Tiedemann, Mauro Cettolo, and Yannick Versley. 2017. Findings of the 2017 discomt shared task on cross-lingual pronoun prediction. In The Third Workshop on Discourse in Machine Translation.

Minh-Thang Luong, Hieu Pham, and Christopher D Manning. 2015. Effective approaches to attention-based neural machine translation. Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP).

Ngoc-Quang Luong and Andrei Popescu-Belis. 2017. Machine translation of Spanish personal and possessive pronouns using anaphora probabilities. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL), CONF. Association for Computational Linguistics.

Lesly Miculicich, Dhananjay Ram, Nikolaos Pappas, and James Henderson. 2018. Document-level neural machine translation with hierarchical attention networks. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP).

Mathias Müller, Annette Rios, Elena Voita, and Rico Sennrich. 2018. A large-scale test set for the evaluation of context-aware pronoun translation in neural machine translation. Association for Computational Linguistics.

Masaaki Nagata and Makoto Morishita. 2020. A test set for discourse translation from Japanese to English. In Proceedings of The 12th Language Resources and Evaluation Conference, pages 3704–3709.

Hiromi Nakaiwa. 1999. Automatic extraction of rules for anaphora resolution of Japanese zero pronouns in Japanese–English machine translation from aligned sentence pairs. Machine translation, 14(3-4):247–279.

Toshiaki Nakazawa, Manabu Yaguchi, Kiyotaka Uchimoto, Masao Utiyama, Eiichiro Sumita, Sadao Kurohashi, and Hitoshi Ishahara. 2016. Aspec: Asian scientific paper excerpt corpus. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 2204–2208.

Graham Neubig, Yosuke Nakata, and Shinsuke Mori. 2011. Pointwise prediction for robust, adaptable Japanese morphological analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2, pages 529–533. Association for Computational Linguistics.

Reid Pryzant, Yongjoo Chung, Dan Jurafsky, and Denny Britz. 2018. Jesc: Japanese-English subtitle corpus. Language Resources and Evaluation Conference (LREC).

Reid Pryzant, Richard Diehl Martínez, Nathan Dass, Sadao Kurohashi, Dan Jurafsky, and Diyi Yang. 2020. Automatically neutralizing subjective bias in text. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 480–489.

Ella Rabinovich, Shachar Mirkin, Raj Nath Patel, Lucia Specia, and Shuly Wintner. 2016. Personalized machine translation: Preserving original author traits. EACL.

Lorenza Russo, Sharid Loáiciga, and Asheesh Gulati. 2012. Improving machine translation of null subjects in Italian and Spanish. In Proceedings of the Student Research Workshop at the 13th Conference of the European Chapter of the Association for Computational Linguistics, pages 81–89.

Claudia H Sánchez-Gutiérrez, Hugo Mailhot, S Hélène Deacon, and Maximiliano A Wilson. 2018. Morphlex: A derivational morphological database for 70,000 English words. Behavior research methods, 50(4):1568–1580.

Londa Schiebinger. 2013. Machine translation: Analyzing gender. Case study, Gendered Innovations. Gendered Innovations Project webpage: https://genderedinnovations.stanford.edu/case-studies/nlp.html.

Fabrizio Sebastiani. 2015. An axiomatically derived measure for the evaluation of classification algorithms. In Proceedings of the 2015 International Conference on The Theory of Information Retrieval, pages 11–20. ACM.

Gabriel Stanovsky, Noah A Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine translation. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL).

Dario Stojanovski and Alexander Fraser. 2019. Improving anaphora resolution in neural machine translation using curriculum learning. In Proceedings
Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In Advances in neural information processing systems, pages 3104–3112.

Hirotoshi Taira, Katsuhito Sudoh, and Masaaki Nagata. 2012. Zero pronoun resolution can improve the quality of j-e translation. In Proceedings of the Sixth Workshop on Syntax, Semantics and Structure in Statistical Translation, pages 111–118.

Xin Tan, Shaohui Kuang, and Deyi Xiong. 2019. Detecting and translating dropped pronouns in neural machine translation. In CCF International Conference on Natural Language Processing and Chinese Computing, pages 343–354. Springer.

Jörg Tiedemann and Yves Scherrer. 2017. Neural machine translation with extended context. Proceedings of the Third Workshop on Discourse in Machine Translation (DiscoMT).

Eva Vanmassenhove, Christian Hardmeier, and Andy Way. 2019a. Getting gender right in neural machine translation. 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP).

Eva Vanmassenhove, Dimitar Shterionov, and Andy Way. 2019b. Lost in translation: Loss and decay of linguistic richness in machine translation. 17th Machine Translation Summit (MTSummit2019).

Rob Voigt and Dan Jurafsky. 2012. Towards a literary machine translation: The role of referential cohesion. In Proceedings of the NAACL-HLT 2012 Workshop on Computational Linguistics for Literature, pages 18–25.

Elena Voita, Pavel Serdyukov, Rico Sennrich, and Ivan Titov. 2018. Context-aware neural machine translation learns anaphora resolution. Association for Computational Linguistics (ACL).

Longyue Wang, Zhaopeng Tu, Xing Wang, and Shuming Shi. 2019a. One model to learn both: Zero pronoun prediction and translation. Proceedings of the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP).

Xing Wang, Zhaopeng Tu, Longyue Wang, and Shuming Shi. 2019b. Exploiting sentential context for neural machine translation. arXiv preprint arXiv:1906.01268.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.