Neural Machine Translation Doesn’t Translate Gender Coreference Right Unless You Make It

Danielle Saunders and Rosie Sallis and Bill Byrne
Department of Engineering, University of Cambridge, UK
{ds636, rs965, wjb31}@cam.ac.uk

Abstract

Neural Machine Translation (NMT) has been shown to struggle with grammatical gender that is dependent on the gender of human referents. Many existing approaches to this problem seek to control gender inflection in the target language by explicitly or implicitly adding a gender feature to the source sentence, usually at the sentence level.

In this paper we propose schemes for incorporating explicit word-level gender inflection tags into NMT. We explore the potential of this gender-inflection controlled translation when the gender feature can be determined from a human reference, assessing on English-to-Spanish and English-to-German translation.

We find that simple existing approaches can over-generalize a gender-feature to multiple entities in a sentence, and suggest an effective alternative in the form of tagged coreference adaptation data. We also propose an extension to assess translations of gender-neutral entities from English given a corresponding linguistic convention in the inflected target language.

1 Introduction

Translation into languages with grammatical gender involves correctly inferring the grammatical gender of all entities in a sentence. In some languages this grammatical gender is dependent on the social gender of human referents. For example, in the Spanish translation of the sentence ‘This is the doctor’, ‘the doctor’ would be either ‘el médico’, masculine, or ‘la médica’, feminine. Since the noun refers to a person the grammatical gender inflection should be correct for a given referent.

In practice many NMT models struggle at generating such inflections correctly (Sun et al., 2019), often instead defaulting to gender-based social stereotypes (Prates et al., 2019) or masculine language (Hovy et al., 2020). For example, an NMT model might always translate ‘This is the doctor’ into a sentence with a masculine inflected noun: ‘Este es el médico’.

Such behaviour can be viewed as translations exhibiting gender bias. By ‘bias’ we follow the definition from Friedman and Nissenbaum (1996) of behaviour which ‘systematically and unfairly discriminate[s] against certain individuals or groups of individuals in favor of others.’ Specifically, translation performance favors referents fitting into groups corresponding to social stereotypes, such as male doctors. Such systems propagate the allocational harm of erasure to referents – for example, a non-male doctor might be incorrectly gendered by a translation of the above example (Crawford, 2017). System users also experience representational harms via the reinforcement of stereotypes associating occupations with a particular gender, as well as lower quality of service in receiving grammatically incorrect translations (Abbasi et al., 2019).

A common approach to this problem in NMT is the use of gender features, implicit or explicit. The gender of one or more words in a test sentence is determined from external context (Vanmassenhove et al., 2018; Basta et al., 2020) or by reliance on ‘gender signals’ from words in the source sentence such as gendered pronouns. That information can then be used when translating. Such approaches combine two distinct tasks: identifying the gender inflection feature, and then applying it to translate words in the source sentence. These feature-based approaches make the unstated assumption that if we could correctly identify that, e.g., the doctor in the above example should be female, we could inflect entities in the sentence correctly, reducing the effect of gender bias.

Our contribution is an exploration of this assumption. We propose a scheme for incorporating an explicit gender inflection tag into NMT, particu-
larly for translating coreference sentences where the reference gender label is known. Experimenting with translation from English to Spanish and English to German, we find that simple existing approaches overgeneralize from a gender signal, incorrectly using the same inflection for every entity in the sentence. We show that a tagged-coreference adaptation approach is effective for combatting this behaviour. Although we only work with English source sentences to extend prior work, we note that this approach can be extended to source languages without inherent gender signals like gendered pronouns, unlike approaches that rely on those signals.

Existing work in NMT gender bias has focused on the translation of sentences based on binary gender signals, such as exclusively male or female personal pronouns. This excludes and erases those who do not use binary gendered language, including but not limited to non-binary individuals (Zimman, 2017; Cao and Daumé III, 2020). We therefore explore applying tagging to indicate gender-neutral referents, and produce a WinoMT set to assess translation of coreference sentences with gender-neutral entities.

Intuitively, if gender tagging does not perform well when it can use the label determined by human coreference resolution, it will be even less useful when a gender label must be automatically inferred. Conversely, gender tagging that is effective in this scenario may be beneficial when the user can specify the gendered language to use for the referent, such as Google Translate’s translation inflection selection (Johnson, 2018), or for translations where the grammatical gender to use for all human referents is known.

1.1 Related work

Variations on a gender tag or signal for machine translation have been proposed in several forms. Vanmassenhove et al. (2018) incorporate a ‘speaker gender’ tag into training data, allowing gender to be conveyed at the sentence level. However, this does not allow more fine-grained control, for example if there is more than one referent in a sentence. Similar approaches from Voita et al. (2018) and Basta et al. (2020) infer and use gender information from discourse context. Moryossef et al. (2019) also incorporate a single explicit gender feature for each sentence at inference. Miculicich Werlen and Popescu-Belis (2017) integrate coreference links into machine translation reranking to improve pronoun translation with cross-sentence context. Stanovsky et al. (2019) propose NMT gender bias reduction by ‘mixing signals’ with the addition of pro-stereotypical adjectives.

Saunders and Byrne (2020) treat gender bias as a domain adaptation problem by adapting to a small set of synthetic sentences with equal numbers of entities using masculine and feminine inflections. We also interpret this as a gender ‘tagging’ approach, since the gendered terms in the synthetic dataset give a strong signal to the model. In this work we extend the synthetic datasets made available by these authors to explore this effect further.

Other approaches to reducing gender bias effects involve adjusting the word embeddings either directly (Escude Font and Costa-jussá, 2019) or by training with counterfactual data augmentation (Zhao et al., 2018; Zmigrod et al., 2019). We view these approaches as orthogonal to our proposed scheme: they have similar goals but do not directly control inference-time gender inflection at the word or sentence level.

2 Assessing and controlling gender inflection

We wish to investigate whether a system can translate into inflected languages correctly given the reference gender label of a certain word. Our proposed approach involves fine-tuning a model on a synthetic set of sentences which have gender tags. At test time we assign the reference gender label to the words whose gender inflection we wish to control.

2.1 Gender bias assessment

WinoMT (Stanovsky et al., 2019) is a test set for assessing the presence of gender bias in translation from English to several gender-inflected languages. Each of 3888 test sentence contains two human entities, one of which is coreferent with a pronoun. 1826 of these sentences have male primary entities, 1822 female and 240 neutral. The first test sentence in WinoMT is:

*The developer argued with the designer because she did not like the design.*

We only tag the primary entity in test sentences.
### Table 1: Examples of the tagging schemes explored in this paper. Adjective-based sentences (e.g. ‘the tall woman finished her work’) are never tagged. For neutral target sentences, we define synthetic placeholder articles `<DEF>` and noun inflections `<W_END>`, as well as a placeholder possessive pronoun for German `<PRP>`

| Name | English source | German target | Spanish target |
|------|----------------|----------------|----------------|
| S&B  | the trainer finished his work  
  the trainer finished her work  
  the trainer finished their work | der Trainer beendete seine Arbeit  
  Trainerinnen beendeten ihre Arbeit  
  Trainer beendeten ihre Arbeit | el entrenador terminó su trabajo  
  la entrenadora terminó su trabajo  
  el entrenador terminó su trabajo |
| V1   | the trainer `<M>` finished his work | der Trainer beendete seine Arbeit | el entrenador terminó su trabajo |
| V2   | the trainer `<F>` finished the work | die Trainerin beendete ihre Arbeit | la entrenadora terminó su trabajo |
| V3   | the trainer `<M>` and the choreographer `<M>` finished the work | `<DEF>` Trainer `<W_END>` und der Choreograf beendeten die Arbeit | `<DEF>` entrenador `<W_END>` y el coreógrafo terminaron el trabajo |

During evaluation WinoMT extracts the hypothesis translation for ‘the developer’ by automatic word alignment and assesses its gender inflection in the target language. The main objective is high overall accuracy – the percentage of correctly inflected primary entities.

We note a comment by Rudinger et al. (2018), who develop a portion of the English WinoMT source sentences, that such schemas ‘may demonstrate the presence of gender bias in a system, but not prove its absence.’ In fact high WinoMT accuracy can be achieved by using the labeled inflection for both entities in a WinoMT test sentence, even though only one is specified by the sentence.

We therefore produce a test set for the WinoMT framework to track the gender inflection of the secondary entity in each original WinoMT sentence (e.g. ‘the designer’ in the above example). We measure second-entity inflection correspondence with the gender label, which we refer to as L2. High L2 suggests that ‘the designer’ would also have feminine inflection in a translation of the above example, despite not being coreferent with the pronoun.

We are particularly interested in cases where L2 increases over a baseline, or high ΔL2. Many factors may contribute to a baseline system’s L2, but we are specifically interested in whether adding gender features affects only the words they are intended to affect. High ΔL2 indicates a system learning to over-generalize from available gender features. We consider this as erasing the secondary referents, and therefore as undesirable behaviour.

#### 2.2 Adaptation to gender-feature datasets

Saunders and Byrne (2020) propose reducing gender bias effects quickly by model adaptation to sets of 388 simple synthetic sentences with equal numbers of male and female entities. A gendered-alternative-lattice rescoring scheme avoids catastrophic forgetting. The sentences follow a template:

*The [entity] finished [his/her] work.*

In one set the *entity* is always a profession (e.g. ‘doctor’). In the other it is either *[adjective]* `[man|woman]` (e.g. ‘tall man’) or a profession that does not occur in WinoMT source sentences (e.g. ‘trainer’). We use the latter set to minimize the confounding effects of vocabulary memorization.

It is possible to extract natural text with gendered entities, for example using GeBioToolkit (Costajussà et al., 2020). The synthetic dataset is more suited to our work for two reasons: it has been shown to allow strong accuracy improvements on WinoMT, and it has a predictable format that can easily be augmented with gender tags. We leave the more complicated scenario of extracting and tagging natural adaptation data to future work.

As well as the unchanged S&B synthetic adaptation set, we propose three gender-tagged variations, which we illustrate in Table 1. In the first, V1, we add a gender tag following professions only (we do not tag adjective-based sentences since ‘man’ and ‘woman’ are already distinct words in English).

For the second, V2, we use the same tagging scheme but note that the possessive pronoun offers a gender signal that may conflate with the tag, so change all examples to ‘... finished the work’.

The third, V3, is the same as V2 but in each profession-based sentence a second profession-based entity with a different gender inflection tag is added. This is intended to discourage systems from over-generalizing one tag to all sentence entities.

#### 2.3 Exploring gender-neutral translation

We wish to extend previous machine translation coreference research to the translation of gender-neutral language, which may be used by non-binary
individuals or to avoid the social impact of using gendered language (Zimman, 2017; Misersky et al., 2019). Recently Cao and Daumé III (2020) have encouraged inclusion of non-binary referents in NLP coreference work. Their study focuses heavily on English, where gender-neutral language such as singular *they* is in increasingly common use (Bradley et al., 2019); the authors acknowledge that ‘some extensions ... to languages with grammatical gender are non-trivial’.

In particular, existing NMT gender bias test sets typically analyse behaviour in languages with grammatical gender that corresponds to a referent’s gender. Translation into these languages is effective in highlighting differences in translation between masculine and feminine referents, but these languages also often lack widely-accepted conventions for gender-neutral language (Ackerman, 2019; Hord, 2016).

We therefore explore a proof-of-concept scheme for translating tagged neutral language into inflected languages by introducing synthetic gender-neutral placeholder articles and noun inflections in the target language. For example, we represent the gender-neutral inflection of ‘*el entrenador*’ (the trainer) as ‘<DEF> entrenador<END>’

A variety of gender-neutral inflections have been proposed for various grammatically gendered languages, such as *e* or *x* Spanish noun inflections instead of masculine *o* and feminine *a* (Papadopoulos, 2019; Shroy, 2016). Our intent is not to prescribe which should be used, but to explore an approach which in principle could be extended to various real inflection schemes.

We construct additional ‘neutral-augmented’ versions of the adaptation sets described in 2.2, adding ‘*The [adjective] person finished [their] the work*’ sentences to the adjective-based sets and sentences like ‘*The trainer <N> finished [their] the work*’ to the profession-based sets, with synthetic placeholder articles <DEF> and inflections <END> on the target side of profession sentences. We give examples for Spanish and German in Table 1. We also construct a neutral-label-only version of WinoMT containing the 1826 unique binary templates filled with they/them/their. We report results on the original and neutral-augmented sets separately for ease of comparison with prior work.

### 3 Experiments

We use baseline Transformer models, BPE vocabularies, synthetic datasets and baseline rescoring gendered-alternative lattices made available by Saunders and Byrne (2020) and follow their adaptation scheme, assessing on English-to-German and English-to-Spanish translation. We define gender tags as unique vocabulary items which only appear in the source sentence. We adapt to synthetic data with minibatches of 256 tokens for 64 training updates, which we found gave good results when fine-tuning on the S&B datasets. The V3 sets have about 30% more tokens and the neutral-augmented sets about 50% more: we increase the number of adaptation steps accordingly for these cases.

For all results we rescore the baseline system gendered-alternative lattices with the listed model. This constrains the output hypothesis to be a gender-inflceted version of the original baseline hypothesis, allowing minimal degradation in BLEU while letting gender inflections in the hypothesis translation be varied for potentially large WinoMT accuracy increases. For the gender-neutral experiments we add synthetic inflections and articles to the lattices.

We wish to improve coreference without loss of general translation quality, and so assess BLEU on a separate, untagged general test set. For ease of comparison with previous work, we report general translation quality on the test sets from WMT18 (en-de) and WMT13 (en-es), reporting cased BLEU using SacreBLEU2 (Post, 2018).

#### 3.1 Measured improvements in gender accuracy are often accompanied by over-generalization

Table 2 gives BLEU score and primary-entity accuracy for the original, binary versions of synthetic adaptation sets described in section 2.2. WinoMT test sentences have primary entities tagged with their gender label if the adaptation set had tags, and are unlabeled otherwise. We note that lattice rescoring keeps the general test set score within 0.3 BLEU of the baseline, and focus on the variation in WinoMT performance.

Primary-entity WinoMT accuracy does increase significantly over the baseline for all adaptation schemes. V3, which gives coreference examples, is particularly effective for en-es, while V2, which contains a single entity, is more effective for en-de.

---

2BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+v.1.4.8
### Table 2: Test BLEU, WinoMT primary-entity accuracy (Acc), and change in second-entity label correspondence ∆L2. We adapt the baseline to a set without tags (S&B), or to one of the binary gender-inflection tagging schemes (V1, V2, V3). ‘Labeled WinoMT’ indicates whether WinoMT primary entities are tagged with their reference gender label. All results are for rescoring the baseline system gendered-alternative lattices with the listed model.

| System | Labeled WinoMT | en-de | en-es |
|--------|----------------|-------|-------|
|        | BLEU | Acc  | ∆L2  | BLEU | Acc  | ∆L2  |
| Baseline | ×   | 42.7 | 60.1 | -   | 27.8 | 49.6 |
| S&B    | ×   | 42.4 | 82.3 | 27.4 | 27.7 | 66.3 |
| V1     | ✓   | 42.5 | 81.7 | 26.6 | 27.7 | 69.0 |
| V2     | ✓   | 42.5 | 84.1 | 24.2 | 27.5 | 70.9 |
| V3     | ✓   | 42.6 | 77.4 | 1.1  | 27.5 | 80.6 |

### Table 3: WinoMT accuracy and change in second-entity label correspondence for the adaptation schemes in Table 2 when WinoMT source sentences are or are not tagged with the primary entity’s gender label.

| System | Unlabeled WinoMT | Labeled WinoMT | en-de | en-es |
|--------|-----------------|----------------|-------|-------|
|        | BLEU | Acc  | ∆L2  | BLEU | Acc  | ∆L2  |
| Baseline | 60.1 | -   | -   | 49.6 | -   | -   |
| S&B    | 82.3 | 27.4 | -   | 66.3 | 29.7 | -   |
| V1     | 81.5 | 26.6 | 81.7 | 26.6 | 67.3 | 29.6 |
| V2     | 71.2 | 9.2  | 84.1 | 24.2 | 52.1 | 3.5  |
| V3     | 57.5 | -5.8 | 77.4 | 1.1  | 47.9 | -2.5 |

This may reflect the difference in baseline quality: the stronger en-de baseline is more likely to have already seen multiple-entity sentences.

We also report ∆L2, the change in the secondary entity’s label correspondence compared to the baseline. High ∆L2 implies that the model is over-generalizing a gender signal intended for the primary entity to the secondary entity. In other words, the gender signal intended for the primary entity has a very strong influence on the translation of the secondary entity. ∆L2 does indeed increase strongly from the baseline for the S&B and V1 systems, confirming our suspicion that these models trained on sentences with a single entity simply learn to apply any gender feature to both entities in the test sentences indiscriminately.

Remarkably, for adaptation to S&B and V1 datasets we found that the secondary entity is inflected to correspond with the pronoun more often than the primary entity which is labeled as coref-erent with it. A possible explanation is that the secondary entity occurs at the start of the sentence in about two thirds of test sentences, compared to about one third for the primary entity. Adapting to single-entity test sets may encourage the model to simply inflect the first entity in the sentence using the gender signal.

For V2, where the source possessive pronoun is removed and the tag is the only gender signal, ∆L2 still increases significantly, although less than for V1. This indicates that even if the only signal is a gender tag applied directly to the correct word, it may be wrongly taken as a signal to inflect other words. The V3 scheme is the most promising, with a 17% increase in accuracy for en-de and a 30% increase for en-es corresponding to very small changes in L2, suggesting this model minimizes over-generalization from gender features beyond the tagged word.

### 3.2 Labeled and unlabeled test sentences

Table 3 lists accuracy and ∆L2 with and without WinoMT source sentence labelling for the same systems as Table 2. V1 gives similar performance to S&B with and without WinoMT labelling. Removing the possessive pronoun as in V2 decreases accuracy compared to V1 without labelling and slightly increases it with labelling, suggesting removing the source pronoun forces the model to rely on the gender tag.

Accuracy under V2 and V3 improves dramatically when gender labels are added to WinoMT primary entities. Without labels V2 and V3 accuracies improve far less or not at all. This is unsurprising, since in the V2 and V3 datasets the gender tag is the only way to infer the correct target inflection. Nevertheless some accuracy improvement is still possible with neither tags nor possessive pronouns, possibly because the model ‘sees’ more examples of profession constructions in the target language.

Without test set labels, the V3 system has negative ∆L2, implying that the second entity’s inflec-
Table 4: Primary-entity accuracy and second-entity label correspondence \( \Delta L_2 \) on a neutral-label-only extension of WinoMT. Here, adaptation sets and lattices are augmented with synthetic neutral articles and nouns.

| System  | Labeled WinoMT | en-de \( L_2 \) | en-es \( L_2 \) |
|---------|----------------|----------------|----------------|
| Baseline| ×              | 2.7            | 4.2            |
| S&B     | ×              | 13.5 28.8      | 6.4 3.9        |
| V1      | ✓              | 27.3 28.2      | 25.4 25.1      |
| V2      | ✓              | 23.0 39.6      | 32.1 27.5      |
| V3      | ✓              | 20.2 18.7      | 38.8 10.0      |

The primary entity corresponds to the primary entity label less often than for the baseline. This is not necessarily bad, as they are still low absolute values. Small absolute \( \Delta L_2 \) indicates that added primary-entity gender signals have little impact on the secondary entity relative to the baseline, which is the desired behaviour. Small negative values are therefore better than large positive values.

### 3.3 Gender-neutral translation

In Table 4 we report on systems adapted to the neutral-augmented synthetic sets, evaluated on the neutral-only WinoMT set. We use test labeling for all cases where models are trained with tags – as with the binary experiments we found that performance was otherwise poor.

Unsurprisingly, the baseline model is unable to generate the newly defined gender-neutral articles or noun inflections – the non-zero accuracy is a result of existing WinoMT sentences with neutral entities like ‘someone’. Adapting on the neutral-augmented S&B set does little better for en-es, although it gives a larger gain for en-de. This discrepancy may be because the only neutral gender signal in the S&B source sentences is from the possessive pronoun *their*. In Spanish, which has one gender-neutral third-person singular possessive pronoun, *their* has the same Spanish translation as *his* or *her* and therefore does not constitute a strong gender signal. By contrast in German we add a synthetic singular gender-neutral pronoun, which indicates neutral gender even without tags.

Adding a gender tag significantly improves primary entity accuracy. As with Table 2, there is little difference in labeled-WinoMT performance when the possessive pronoun is removed. Also as previously, the V3 set shows far less over-generalization in terms of \( \Delta L_2 \) than the other tagged schemes.

We note that primary-entity accuracy is relatively low compared to results for the original WinoMT set. We consider this unsurprising since the model has never encountered most of the neutral-inflected occupation terms before, even during adaptation, due to the lack of overlap between the adaptation and WinoMT test sets. However, it does suggest that more work remains for introducing novel gender inflections for NMT.

### 4 Conclusions

Tagging words with target language gender inflection is a powerful way to improve accuracy of translated inflections. This could be applied in cases where the correct grammatical gender to use for a given referent is known, or as monolingual coreference resolution tools improve sufficiently to be used for automatic tagging. It also has potential application to new inflections defined for gender-neutral language.

However, there is a risk that gender features will be used in an over-general way. Providing a strong gender signal for one entity can cause harm by erasing other entities in the same sentence, unless a model is specifically trained to translate sentences with multiple entities. In particular we find that our V3 system, which is trained on multiple-entity translation examples, allows good performance while minimizing peripheral effects.

We conclude by emphasising that work on gender coreference in translation requires care to ensure that the effects of interventions are as intended, as well as testing scenarios that capture the full complexity of the problem, if the work is to have an impact on gender bias.

### Acknowledgments

This work was supported by EPSRC grants EP/M508007/1 and EP/N509620/1 and has been performed using resources provided by the Cambridge Tier-2 system operated by the University of Cambridge Research Computing Service\(^3\) funded by EPSRC Tier-2 capital grant EP/P020259/1.

---

\(^3\)http://www.hpc.cam.ac.uk
References

Mohsen Abbasi, Sorelle A Friedler, Carlos Scheidegger, and Suresh Venkatasubramanian. 2019. Fairness in representation: quantifying stereotyping as a representational harm. In Proceedings of the 2019 SIAM International Conference on Data Mining, pages 801–809. SIAM.

Lauren Ackerman. 2019. Syntactic and cognitive issues in investigating gendered coreference. Glossa: a journal of general linguistics, 4(1).

Christine Basta, Marta R. Costa-jussà, and Josè A. R. Lauro. 2020. Providing gender-specific translations in Google Translate. (accessed: Aug 2020).

Lesly Miculich Werlen and Andrei Popescu-Belis. 2017. Using coreference links to improve Spanish-to-English machine translation. In Proceedings of the 2nd Workshop on Coreference Resolution Beyond OntoNotes (CORBON 2017), pages 30–40, Valencia, Spain. Association for Computational Linguistics.

Julia Misersky, Asifa Majid, and Tineke M Snijders. 2019. Grammatical gender in German influences how role-nouns are interpreted: Evidence from erps. Discourse Processes, 56(8):643–654.

Amit Moryossef, Roei Aharoni, and Yoav Goldberg. 2019. Filling gender & number gaps in neural machine translation with black-box context injection. In Proceedings of the First Workshop on Gender Bias in Natural Language Processing, pages 49–54, Florence, Italy. Association for Computational Linguistics.

Benjamin Papadopoulos. 2019. Innovaciones al género morfológico en el Español de hablantes genderqueer (morphological gender innovations in Spanish of genderqueer speakers). eScholarship, University of California.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Belgium, Brussels. Association for Computational Linguistics.

Marcelo OR Prates, Pedro H Avelar, and Luís C Lamb. 2019. Assessing gender bias in machine translation: a case study with google translate. Neural Computing and Applications, pages 1–19.

Rachel Rudinger, Jason Naradowsky, Brian Leonard, and Benjamin Van Durme. 2018. Gender bias in coreference resolution. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 8–14, New Orleans, Louisiana. Association for Computational Linguistics.

Danielle Saunders and Bill Byrne. 2020. Reducing gender bias in neural machine translation as a domain adaptation problem. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7724–7736, Online. Association for Computational Linguistics.

Alyx J Shroy. 2016. Innovations in gender-neutral french: Language practices of nonbinary french speakers on twitter. Ms., University of California, Davis.

Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine
Tony Sun, Andrew Gaut, Shirlyn Tang, Yuxin Huang, Mai ElSherief, Jieyu Zhao, Diba Mirza, Elizabeth Belding, Kai-Wei Chang, and William Yang Wang. 2019. Mitigating gender bias in natural language processing: Literature review. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1630–1640, Florence, Italy. Association for Computational Linguistics.

Eva Vanmassenhove, Christian Hardmeier, and Andy Way. 2018. Getting gender right in neural machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3003–3008, Brussels, Belgium. Association for Computational Linguistics.

Elena Voita, Pavel Serdyukov, Rico Sennrich, and Ivan Titov. 2018. Context-aware neural machine translation learns anaphora resolution. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1264–1274, Melbourne, Australia. Association for Computational Linguistics.

Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2018. Gender bias in coreference resolution: Evaluation and debiasing methods. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 15–20, New Orleans, Louisiana. Association for Computational Linguistics.

Lal Zimman. 2017. Transgender language reform: Some challenges and strategies for promoting trans-affirming, gender-inclusive language. Journal of Language and Discrimination, 1(1):83–104.

Ran Zmigrod, Sabrina J. Mielke, Hanna Wallach, and Ryan Cotterell. 2019. Counterfactual data augmentation for mitigating gender stereotypes in languages with rich morphology. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1651–1661, Florence, Italy. Association for Computational Linguistics.