Faithful Target Attribute Prediction in Neural Machine Translation

Xing Niu, Georgiana Dinu, Prashant Mathur, Anna Currey
Amazon AI Translate
{xingniu,gddinu,pramathu,ancurrey}@amazon.com

Abstract
The training data used in NMT is rarely controlled with respect to specific attributes, such as word casing or gender, which can cause errors in translations. We argue that predicting the target word and attributes simultaneously is an effective way to ensure that translations are more faithful to the training data distribution with respect to these attributes. Experimental results on two tasks, uppercased input translation and gender prediction, show that this strategy helps mirror the training data distribution in testing. It also facilitates data augmentation on the task of uppercased input translation.

1 Introduction
Neural Machine Translation (NMT) (Bahdanau et al., 2015; Vaswani et al., 2017) has become the leading MT technology, bringing discussions of human parity and even super-human performance (Hassan et al., 2018; Barrault et al., 2019). Despite impressive advances in general translation quality, MT is not a solved problem: among other issues, NMT models make errors in attributes of interest, such as making biased word gender prediction (Vanmassenhove et al., 2018; Stanovsky et al., 2019; Moryossef et al., 2019) or generating incorrectly cased output given noisy or perturbed input (Berard et al., 2019; Niu et al., 2020).

The variation in MT performance along various dimensions of quality as defined by these attributes is rooted in the largely opportunistically sourced parallel data, where such attributes can be over- or under-represented. Manipulating the training data distribution is a popular way to address the problem, based on the assumption that a model predicts the same attribute distribution as that of its training data. Unfortunately, this is not guaranteed; training data skewness may even be amplified (Zhao et al., 2017; Vanmassenhove et al., 2021).

We argue that effective training data manipulation requires model predictions to be faithful to the distribution of attributes of interest. Faithfulness with respect to an attribute can be defined as preserving the training distribution of that attribute in inference predictions. We show that factored NMT—simultaneously predicting the target word and attributes—is effective for increasing faithfulness of translations to the training data distribution. To the best of our knowledge, this is the first work connecting factored NMT with models’ faithfulness to the training data.

We study two token-level attributes—casing and gender—in two different tasks: uppercased text translation and gender prediction of professions. While modeling these two attributes with factored NMT has been shown to improve translation quality (Koehn and Hoang, 2007; Sennrich and Haddow, 2016; Berard et al., 2019; Wilken and Matúsov, 2019; Stafanović et al., 2020), we focus on evaluating models’ faithfulness across various training data distributions, simulating the uncertainty of natural data. Results using simultaneous attribute prediction show that the translation output better mirrors the training distribution with respect to the attributes modeled: e.g., casing preservation ratio in inference matches the ratio in training.

We also demonstrate a novel and practical use case for leveraging a more faithful model: it enables easier development of data augmentation, a popular way to manipulate the training distribution along specific dimensions. In the task of uppercased text translation, we show that models with simultaneous attribute prediction and vocabulary space factoring are more robust to the size of augmented data (i.e., no unexpected quality degradation when augmenting with relatively little data).

2 Factored NMT
Bilmes and Kirchhoff (2003) and Alexandrescu and Kirchhoff (2006) introduced factored language models to deal with data sparsity and increase the generalization power of language models. They
represent a word as a vector of factors \( \{ f_1, \ldots, f_n \} \) (e.g., stem, word class) and explicitly model the probabilities of the vector sequences. In MT, factored models have been used to enrich phrase-based MT or NMT with linguistic features (Koehn and Hoang, 2007; García-Martínez et al., 2016). They reduce the output space by decomposing surface words \( y \) on different dimensions, such as lemma and morphological tags, and maximize \( P(y|\mathbf{x}) = \prod_{i=1}^{n} P(f_i|y^<t, \mathbf{x}) \). Factors are recombined to obtain the surface word. The term “factor” has also been applied more generally to adding features to the source or target, as input or as auxiliary prediction functions even when the vocabulary space is not actually factored, i.e., \( f_1 \) is the surface word. (Koehn and Hoang, 2007; Sennrich and Haddow, 2016).

A similar line of work, target attribute prediction in NMT, falls under the paradigm of simultaneous prediction tasks (Caruana, 1997). The additional training signal for predicting target attributes encourages the model to disentangle and leverage the attribute information more explicitly. Besides using factored NMT, this has also been done through inline concatenation of attributes to words (Nädejde et al., 2017; Berard et al., 2019), which can achieve similar translation quality but increases the length of the generated sequence.

### 3 Experiments

We conduct experiments with two token-level attributes: uppercase style and gender of nouns. Capitalization conventions vary from language to language and often reflect content-specific style conventions, with all-caps commonly used for titles or to indicate tone of voice (McCulloch, 2020). Although less represented in the data, translation (e.g., stem, word class) and explicitly model the probabilities of the vector sequences. In MT, factored models have been used to enrich phrase-based MT or NMT with linguistic features (Koehn and Hoang, 2007; García-Martínez et al., 2016). They reduce the output space by decomposing surface words \( y \) on different dimensions, such as lemma and morphological tags, and maximize \( P(y|\mathbf{x}) = \prod_{i=1}^{n} P(f_i|y^<t, \mathbf{x}) \). Factors are recombined to obtain the surface word. The term “factor” has also been applied more generally to adding features to the source or target, as input or as auxiliary prediction functions even when the vocabulary space is not actually factored, i.e., \( f_1 \) is the surface word. (Koehn and Hoang, 2007; Sennrich and Haddow, 2016).

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### 3.1 Uncertain Attribute Distribution

**Uppercased Input Translation:** All-uppercase text is rare in many MT corpora, and the attribute of uppercasing is not always preserved from source to target. For example, ParaCrawl v7.1 (Bañón et al., 2020) is a corpus crawled from various domains and is a representative corpus for building generic MT systems without controlling specific data attributes. In its EN–DE parallel set, only 2.1% of English (EN) tokens and 1.7% of German (DE) tokens are uppercased. Among 16K all-uppercase EN sentences, merely 1.8% of their corresponding DE sentences preserve all-uppercasing (we denote this as uppercasing preservation ratio, UPR). While other languages contain the same magnitude of ratio of uppercased tokens, UPR varies across language pairs (e.g., 19% for DE–FR).

We simulate the uncertainty of uppercasing preservation with controlled EN–DE ParaCrawl training data. First, we subsample 5M sentence pairs and lowercase all text.\(^1\) Then, we select 2% of pairs and uppercase the source sentences. This yields roughly 2% uppercased source tokens, which approximates the true ratio of uppercased tokens in the raw data. Next, for these 2% we vary UPR from 0% to 100% in increments of 20%. We compare four methods differing in the usage of

\[ P(y|\mathbf{x}) = \prod_{i=1}^{n} P(f_i|y^<t, \mathbf{x}) \]

\[ \text{UPR} \]

\[ y \text{ (surface)} \]

| task | \( y \) (surface) | \( f_1 \) (word) | \( f_2 \) (attribute) |
|------|-----------------|-----------------|-----------------|
| case | NEURAL          | neural          | uppercase       |
| gender | chanteuse     | chanteuse     | feminine        |

Table 1: Attributes are disentangled from the surface words. For case, words are lowercased to factor out casing information; for gender, \( y \) and \( f_1 \) are identical.

We implement simultaneous target attribute prediction using factored NMT as exemplified in Table 1. While different implementations of target factors exist (García-Martínez et al., 2016; Shi et al., 2020), we opt for the Sockeye NMT toolkit (Domhan et al., 2020). It predicts target words \( f_1 \) and attributes \( f_2 \ldots n \) with independent output layers, and the embeddings of the word and attributes are summed for the next decoder step. It incorporates the dependency between words and attributes by time-shifting attributes so that attributes at position \( t \) are predicted at \( t+1 \).

\[ \text{UPR} \]

\[ y \text{ (surface)} \]

\[ f_1 \text{ (word)} \]

\[ f_2 \text{ (attribute)} \]

\[ y \text{ (surface)} \]

\[ f_1 \text{ (word)} \]

\[ f_2 \text{ (attribute)} \]

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\(^1\)Preliminary analyses show that subsampling the training data does not change observations, but it can speed up experimentation and alleviate the environmental impact of our computations of 72 models (Strubell et al., 2019).
For an effective evaluation, we disentangle casing from content and report both case-insensitive SacreBLEU (Post, 2018) and uppercased output tokens ratio in Figure 1. The ratio of uppercased output tokens among all output tokens approximates UPR in prediction when the source test sentences are all-uppercased. Considering content translation measured by case-insensitive BLEU, when target factors are used (i.e., both and target), models are not sensitive to the uncertainty of UPR (Figure 1a). More importantly, with simultaneous target attribute prediction, models predict uppercased tokens with closer probability to that of the training data (Figure 1b).

**Gender Prediction:** To further verify the hypothesis that simultaneously predicting the target attribute leads to more faithful attribute distribution, we also analyze gender information in words (i.e., gender markers) by investigating EN–FR models when translating professions grouped by their diverse natural occurrence in the training data.

EN–FR models are trained with 50M subsampled ParaCrawl sentence pairs. Gender markers for all target words are annotated using spaCy. All text is lowercased to exclude casing variations for easier analysis of gendered word distribution. We use lowercased WMT newstest13 for development and lowercased newstest14 for sanity check. The baseline model gets 36.6 BLEU while the model with target factors gets 36.5 BLEU, and the difference is not statistically significant.

To evaluate if the gender distribution of translated professions matches that of the training data, we create a test set as follows: we aggregate English occupations out of context from three lists collected by Rudinger et al. (2018), Zhao et al. (2018), and Prates et al. (2020) and request both masculine and feminine French translations from paid professional translators, obtaining triples such as \{singer, chanteur (masc), chanteuse (fem)\}. This yields a set of 353 gender-distinct translation pairs for which phrases in each pair appear at least five times in total in the training data. We use our NMT models to score these paired translations via forced decoding (Sennrich, 2017) and pick the gender with a higher translation probability in a pair.

Next, we sort French translation pairs by the training masculine ratio, i.e.,

\[
\text{count(masculine)} \over \text{count(masculine)} + \text{count(feminine)}
\]

where \text{count(masculine)} is the count of the masculine French translation in the training data (and similarly for feminine). We evenly split these pairs into 15 bins. For each bin, we report the average training masculine ratio (on the \(x\)-axis) and the ratio of NMT models picking the masculine translation (on the \(y\)-axis) in Figure 2. These data points approximate gender distribution for training vs. that of the model prediction. We find that using target factors brings the predicted masculine ratio

\footnote{\url{https://spacy.io/}}

\footnote{Although we use a wide variety of professions, for 325 of the 353 professions, the masculine translation occurs more often than the feminine translation in our training data. We provide detailed description in Appendix E and release this test set at \url{https://github.com/amazon-research/gendered-profession-translations}.}
closer to the training masculine ratio by reducing 11% MSE from 0.037.\footnote{We do not test source factors because English largely lacks grammatical gender distinctions. We leave improving in-context gender translation as future work: see preliminary results in Appendix F.}

3.2 Data Augmentation (DA)

With uncertain attribute distribution in the training data, obtaining the desired distribution in the output (e.g., always preserving source case) will be uncertain as well. A practical solution is to manipulate the training distribution using data augmentation, for example by uppercasing a portion of the training data and adding it to the training.

For a faithful model, it should be easier to alter the prediction distribution with DA. We demonstrate this on the aforementioned 5M subsampled EN–DE ParaCrawl data but with original casing where we vary the size of augmented data from $2^{-5}\%$ to $2^{5}\%$ of the original training data. As before, we report case-insensitive BLEU and ratio of uppercased output tokens in Figure 3.

Figure 3b shows that target factor models better preserve source uppercasing when augmented with a small amount of casing-matched data, as they are more faithful to augmented data. Surprisingly, Figure 3a shows (and Figure 1a hints) that content translation quality for source and none drops significantly even with tiny (e.g., $2^{-5}\%$) augmented data. Target factors never suffer from this, no matter the initial quality (i.e., 0% DA).

We hypothesize that, except when using both source and target factors, the uppercased token embeddings (which are part of the uppercased language model) are not well-trained and not well-aligned with the lowercased token embeddings before DA.

To verify this, we separate lowercased and uppercased tokens into two groups and calculate group centroids in the embedding space. The cosine similarities between these two centroids are shown in Figure 3c. The increasing trend of embedding similarities can partially explain the initial quality degradation when target factors are not used: models quickly shift to producing uppercased tokens when augmented with a small amount of data, but the uppercased target language model is under-trained, leading to low quality.

This demonstrates that factored MT is crucial for robust DA, and using both source and target factors is optimal to achieve both good content translation and casing preservation with minimal
We showed that this leads to translations that are more faithful to the training distribution. When applied to uppercased input, the method is robust to uncertainty in training distributions and enables data augmentation that is more stable. We leave extensions of this work to the future, including investigating joint attribute distributions and other data manipulation techniques, such as up/down-sampling.

4 Conclusion and Future Work

We investigated the simultaneous prediction of target attributes and translations focusing on two attributes: casing of words and gender of professions. We showed that this leads to translations that are more faithful to the training distribution. When applied to uppercased input, the method is robust to uncertainty in training distributions and enables data augmentation that is more stable. We leave extensions of this work to the future, including investigating joint attribute distributions and other data manipulation techniques, such as up/down-sampling.

References

Andrei Alexandrescu and Katrin Kirchhoff. 2006. Factored neural language models. In Proceedings of the Human Language Technology Conference of the NAACL, Companion Volume: Short Papers, pages 1–4, New York City, USA. Association for Computational Linguistics.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations.

Marta Bahón, Pinzhen Chen, Barry Haddow, Kenneth Heafield, Hieu Hoang, Miquel Esplà-Gomis, Mikel L. Forcada, Amir Kamran, Faheem Kirefu, Philipp Koehn, Sergio Ortiz Rojas, Leopoldo Pla Sempere, Gema Ramírez-Sánchez, Elsa Sarriás, Marek Strelec, Brian Thompson, William Waites, Dion Wiggins, and Jaume Zaragoza. 2020. ParaCrawl: Web-scale acquisition of parallel corpora. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4555–4567, Online. Association for Computational Linguistics.

Loïc Barrault, Magdalena Biesialśka, Ondřej Bojar, Marta R. Costa-jussá, Christian Federmann, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Matthias Huck, Eric Joanos, Tom Kocmi, Philipp Koehn, Chi-kiu Lo, Nikola Ljubešić, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Santanu Pal, Matt Post, and Marcos Zampieri. 2020. Findings of the 2020 conference on machine translation (WMT20). In Proceedings of the Fifth Conference on Machine Translation, pages 1–55, Online. Association for Computational Linguistics.

Loïc Barrault, Ondřej Bojar, Marta R. Costa-jussá, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. 2019. Findings of the 2019 conference on machine translation (WMT19). In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 1–61, Florence, Italy. Association for Computational Linguistics.

Alexandre Berard, Ioan Calapodescu, Marc Dymetman, Claude Roux, Jean-Luc Meunier, and Vassilina Nikoulina. 2019. Machine translation of restaurant reviews: New corpus for domain adaptation and robustness. In Proceedings of the 3rd Workshop on Neural Generation and Translation, pages 168–176, Hong Kong. Association for Computational Linguistics.

Jeff A. Bilmes and Katrin Kirchhoff. 2003. Factored language models and generalized parallel backoff. In Companion Volume of the Proceedings of HLT-NAACL 2003 - Short Papers, pages 4–6.

Rich Caruana. 1997. Multitask learning. Machine Learning, 28(1):41–75.

Tobias Domhan, Michael Denkowski, David Vilar, Xing Niu, Felix Hieber, and Kenneth Heafield. 2020. The sockeye 2 neural machine translation toolkit at AMTA 2020. In Proceedings of the 14th Conference of the Association for Machine Translation in the Americas (Volume 1: Research Track), pages 110–115, Virtual. Association for Machine Translation in the Americas.

Mercedes García-Martínez, Loïc Barrault, and Fethi Bougares. 2016. Factored neural machine translation architectures. In Proceedings of the 13th International Workshop on Spoken Language Translation, Seattle, US.

Hany Hassan, Anthony Aue, Chang Chen, Vishal Chowdhary, Jonathan Clark, Christian Federmann, Xuedong Huang, Marcin Junczys-Dowmunt, William Lewis, Mu Li, Shujie Liu, Tie-Yan Liu, Renqian Luo, Arul Menezes, Tao Qin, Frank Seide, Xu Tan, Fei Tian, Lijun Wu, Shuangzhi Wu, Yingce Xia, Dongdong Zhang, Zhirui Zhang, and Ming Zhou. 2018. Achieving human parity on automatic chinese to english news translation. Computing Research Repository, arXiv:1803.05567.

Philipp Koehn and Hieu Hoang. 2007. Factored translation models. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), pages 868–876, Prague, Czech Republic. Association for Computational Linguistics.

Gretchen McCulloch. 2020. Because Internet: Understanding how Language is Changing. Penguin Random House.

Amit Morossyef, Roee 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.

Maria Nádejde, Siva Reddy, Rico Sennrich, Tomasz Dwojak, Marcin Junczys-Dowmunt, Philipp Koehn, and Alexandra Birch. 2017. Predicting target language CCG supertags improves neural machine translation. In Proceedings of the Second Conference on Machine Translation, pages 68–79, Copenhagen, Denmark. Association for Computational Linguistics.

Xing Niu, Prashant Mathur, Georgiana Dinu, and Yaser Al-Onaizan. 2020. Evaluating robustness to input perturbations for neural machine translation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8538–8544, Online. Association for Computational Linguistics.

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, Brussels, Belgium. Association for Computational Linguistics.

Marcelo O. R. Prates, Pedro H. C. Avelar, and Luís C. Lamb. 2020. Assessing gender bias in machine translation: a case study with google translate. Neural Computing and Applications, 32(10):6363–6381.

Ofir Press and Lior Wolf. 2017. Using the output embedding to improve language models. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 157–163, Valencia, Spain. Association for Computational Linguistics.

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.

Rico Sennrich. 2017. How grammatical is character-level neural machine translation? assessing MT quality with contrastive translation pairs. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 376–382, Valencia, Spain. Association for Computational Linguistics.

Rico Sennrich and Barry Haddow. 2016. Linguistic input features improve neural machine translation. In Proceedings of the First Conference on Machine Translation: Volume 1, Research Papers, pages 83–91, Berlin, Germany. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Xuewen Shi, Heyan Huang, Ping Jian, and Yi-Kun Tang. 2020. Case-sensitive neural machine translation. In Advances in Knowledge Discovery and Data Mining - 24th Pacific-Asia Conference, volume 12084 of Lecture Notes in Computer Science, pages 662–674. Springer.

Artūrs Stafanovičs, Mārcis Pinnis, and Toms Bergmannis. 2020. Mitigating gender bias in machine translation with target gender annotations. In Proceedings of the Fifth Conference on Machine Translation, pages 629–638, Online. Association for Computational Linguistics.

Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1679–1684, Florence, Italy. Association for Computational Linguistics.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. 2019. Energy and policy considerations for deep learning in NLP. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3645–3650, 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.

Eva Vanmassenhove, Dimitar Shterionov, and Matthew Gwilliam. 2021. Machine translationese: Effects of algorithmic bias on linguistic complexity in machine translation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2203–2213, Online. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, pages 5998–6008.

Patrick Wilken and Evgeny Matusov. 2019. Novel applications of factored neural machine translation. Computing Research Repository, arXiv:1910.03912.
Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2017. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2979–2989, Copenhagen, Denmark. 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.

A Data Pre-Processing

We tokenize all training and development data using the Sacremoses tokenizer, except the French data, which is tokenized alongside with the morphological annotation by spaCy. Words are segmented using byte pair encoding (BPE, Sennrich et al., 2016) with 32K operations. Source and target subwords share the same vocabulary.

For experiments involving casing attributes, we true-case the training data to reduce the vocabulary before training BPE models but recover the original cases after applying BPE segmentation. The true-case of a word is simply its most frequent case variation.

B Factor Deduction

We consider four case factors, namely uppercased, capitalized, lowercased, and undefined (e.g., punctuations). Factors are deducted at the subword level, so we prohibit BPE merge operations that lose case information, such as Wi@@ and Fi are not merged no matter how frequent WiFi is.

We consider three gender factors annotated by spaCy, namely masculine, feminine, and unknown. Gender is associated with each word, so we broadcast the annotation to all its subwords.

C NMT Model Configuration

We build NMT models with the Transformer-base architecture (Vaswani et al., 2017) except we use 20 encoder layers and 2 decoder layers as recommended by Domhan et al. (2020). The source embeddings, target embeddings, and the output layer’s weight matrix are tied (Press and Wolf, 2017). Training is done on 8 GPUs with Sockeye 2’s large batch training. It has an effective batch size of 262,144 tokens, a learning rate of 0.00113 with 2000 warmup steps and a reduce rate of 0.9, a checkpoint interval of 125 steps, and learning rate reduction after 8 checkpoints without improvement. After an extended plateau of 60 checkpoints, the 8 checkpoints with the lowest validation perplexity are averaged to produce the final model parameters.

D Generating German Nouns

We have demonstrated that using both source and target factors is the best option in the application of translating uppercased input with data augmentation.

One may argue that this model could just learn to copy all source factors to the target. We examine this by testing the generated casing of nouns in German. In German, nouns are always capitalized while it is not the case in English, so the model needs to predict nouns’ casing based on some information beyond the source casing. We extracted 4,403 test pairs from newstest2011 to newstest2020, where the German side has 4 times more capitalized tokens than the English side. Results show that all 48 models we investigated (4 factor configurations × 12 augmented data sizes) yield almost the same case-sensitive BLEU ($26.76 \pm 0.15$) and ratio of capitalized tokens (30.38 $\pm$ 0.04%) on this subset. It indicates that all methods, including both, learn to predict German nouns’ casing well, and it is not hurt by augmenting only uppercased data.

E Human Translation of Professions

Combining three profession lists collected by Rudinger et al. (2018), Zhao et al. (2018), and Prates et al. (2020) yields 1054 distinct English gender-neutral professions. Professions can be either single words (e.g., singer) or phrases (e.g., flight attendant). We request both masculine and feminine French translations from paid professional translators. The instruction to translators contains examples: “If the profession is driver we would like both conducteur and conductrice. Ideally we want equivalent masculine and feminine words if such equivalents exist (so not chauffeur and conductrice).” All translations were done by a single translator and QA’d by a second trans-
Table 2: Baseline and target factor models are evaluated on WinoMT. Target factors improve across all four WinoMT subsets: masculine $F_1$, feminine $F_1$, pro-stereotypical accuracy, and anti-stereotypical accuracy.

|                                      | WinoMT ($F_1$/Accuracy) |
|--------------------------------------|--------------------------|
| baseline                             | 62.2 53.3 70.6 44.7      |
| target factors                       | 64.4 61.3 77.3 48.2      |


In-Context Gender Translation

We also evaluate EN–FR models on WinoMT (Stanovsky et al., 2019) to assess the translation accuracy of professions in context. This data set contains examples of professions for which the gender is disambiguated by the context, such as mover in The secretary asked the mover when she is available. Results show that simultaneously predicting gender markers improves gender translation across all subsets (Table 2). We hypothesize that the context-conditioned gender distribution in the training data is better preserved, because the training loss of gender prediction additionally encourages the model to attend more to the context, hence disambiguate the gender better. We leave the verification as future work.