# A Natural Diet: Towards Improving Naturalness of Machine Translation Output

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## Abstract

Machine translation (MT) evaluation often focuses on accuracy and fluency, without paying much attention to translation style. This means that, even when considered accurate and fluent, MT output can still sound less *natural* than high quality human translations or text originally written in the target language. Machine translation output notably exhibits lower lexical diversity, and employs constructs that mirror those in the source sentence. In this work we propose a method for training MT systems to achieve a more natural style, i.e. mirroring the style of text originally written in the target language. Our method tags parallel training data according to the naturalness of the target side by contrasting language models trained on natural and translated data. Tagging data allows us to put greater emphasis on target sentences originally written in the target language. Automatic metrics show that the resulting models achieve lexical richness on par with human translations, mimicking a style much closer to sentences originally written in the target language. Furthermore, we find that their output is preferred by human experts when compared to the baseline translations.

**Source** Es wird befürchtet, dass die Opferzahlen noch deutlich in die Höhe gehen.

**Translationese** It is feared that the number of victims will increase significantly.

**Natural** It is feared that the death toll will rise significantly.

Figure 1: Example De→En translations: This work sets the goal to generate more natural translations like *death toll/rise* in comparison to literal translations like *number of victims/increase*.

## 1 Introduction

Machine translation has made tremendous progress in recent years with the advent of neural methods (Bahdanau et al., 2015; Vaswani et al., 2017). This is especially true for language pairs with a large amount of available bilingual text for training (Barrault et al., 2020a). However MT output still can be improved: it currently trails human translators in expert evaluation (Toral et al., 2018; Freitag et al., 2021) and its language is perceived as poorer and more synthetic (Vanmassenhove et al., 2021). In this work, we aim to produce machine translation output that has a more *natural* style.

Although difficult to define precisely, we consider a translation to be natural if it is an adequate and fluent translation, whose style matches that of high quality monolingual text. Such a translation should contain few translationese constructs and use a rich vocabulary. This is exemplified in Figure 1. The translationese sentence uses the construct "number of victims", which is a literal translation for the German "Opferzahlen". Although correct (i.e. adequate and fluent), "death toll" shows a much more natural word choice for this translation.

Our objective in this paper is to study how the naturalness of machine translation output can be improved. In particular, we focus on how available measures can guide the translation process towards this goal. There have been several studies analyzing the naturalness of generated texts (see Section 2), but in contrast we concentrate on actively improving this aspect by modifying how NMT output is produced.

Our methodology follows a simple intuition: training data whose target side resembles high-quality text naturally written in the target language can bring model outputs closer to this style of text. We exploit the fact that bilingual training sets typically mix examples originating from both translation directions: source-to-target and target-to-source. We rely on contrasting language models (LMs) (Manning and Schütze, 1999; Moore and Lewis, 2010) to identify natural data: we train separate models on target-language data known to be translations, and on data known to be mostly originally written in the target language. We then use these LMs to tag parallel training data as having a natural or translated target side. Comparing to hard filtering of the data, tagging offers more flexibility without sacrificing coverage (Caswell et al., 2019).

Our contributions are as follows: (1) We use contrastive language model scoring to separate natural from translated text. (2) We demonstrate that optimizing BLEU scores on tgt-original test sets while avoiding high BLEU scores on src-original test set is a valid strategy to improve the naturalness of MT output. (3) We show that our more natural MT output is more similar to natural sentences based on lexical diversity. (4) Human evaluations show that the style of our more natural translations are preferred by humans, albeit with minimal loss in translation accuracy.

## 2 Related Work

### 2.1 Translationese

Translations differ from text originally written in the target language due to a combination of factors that may include the intentional use of explicitation and normalization, or unintentional lexical or structural artifacts. The style resulting from the combination of these factors is often referred to as *translationese*. The effects of translationese in training data on MT quality and evaluation have been investigated by many authors (Kurokawa et al., 2009; Lembersky et al., 2012; Toral et al., 2018; Zhang and Toral, 2019; Graham et al., 2020; Freitag et al., 2019; Edunov et al., 2020; Freitag et al., 2020b). Several papers (Kurokawa et al., 2009; Koppel and Ordan, 2011; Shen et al., 2019; Riley et al., 2020) proposed to train classifiers to detect translationese sentences in monolingual corpora. Similar to our work, Kurokawa et al. (2009) used their classifier to preprocess MT training data, but they removed target-original pairs while we emphasize them. Lembersky et al. (2012) kept both types of data but introduced entropy-based measures that allowed their phrase-based decoder to favor lower entropy translationese entries. Riley et al. (2020) used a convolutional classifier to distinguish natural from translationese text. We train contrastive language models to partition the training data into original and translated sentences to bias the model to generate more natural translations.

### 2.2 Training Data Tagging for NMT

We use tags to differentiate subsets of the training data, with the objective of training a model that will decode differently depending on the tag provided at inference. This strategy has been explored with various objectives in prior work. Tagging to control inference has notably been used to indicate target language in multilingual models (Johnson et al., 2016), formality level (Yamagishi et al., 2016), politeness (Sennrich et al., 2016a), gender from a gender-neutral language (Kuczmarski and Johnson, 2018), backtranslation (Caswell et al., 2019), as well as to produce domain-targeted translation (Kobus et al., 2017). Shu et al. (2019) use tags at training and inference time to increase the syntactic diversity of their output while maintaining translation quality; similarly, Agrawal and Carpuat (2019) and Marchisio et al. (2019) use tags to control the reading level (simplicity/complexity) of the output.

### 2.3 Evaluation of Naturalness

Evaluation of MT usually focuses on accuracy and/or fluency (Barrault et al., 2020a; Läubli et al., 2020). Recent work has started to look at the richness and complexity of MT output. Vanmassenhove et al. (2019, 2021) address the effects of statistical bias on language generation. They assess lexical diversity and sophistication, and conclude that the translations produced by MT systems are consistently less diverse than the original training data, containing more frequent patterns and fewer infrequent ones. Toral (2019) compared MT output with human generated translations and found that there is a measurable difference between the two. In this work we use the diversity metrics introduced by Vanmassenhove et al. (2021) to demonstrate that we can build an MT system with lexical diversity similar to human translations (HT). We also incorporate the findings of Freitag et al. (2019), and show how to reliably evaluate more natural translations on target-original test sets while allowing the model to decrease BLEU scores on source-original test sets.

## 3 Approach

Our first objective is to distinguish text originally written in the target language (natural text) from translations. For that purpose, we train a pair of sentence-level language models to contrast their likelihood, a proven method for domain adaptation (Moore and Lewis, 2010; Axelrod et al., 2011).

These language models are then used to tag MT training data as natural target (`<nat>`) or translationese target (`<trans>`), in order to train an MT system which can favor natural hypotheses.

### 3.1 Inferring Naturalness Tags

Our natural language model is trained on the monolingual newscrawl dataset from WMT (Barrault et al., 2020a). This data consists of web-crawled sentences from newspapers and other news sites from the countries speaking the corresponding language (e.g. Germany, Austria and Switzerland for German). Although it is not unusual to have contributions from foreign reporters or even translations of articles from foreign newspapers, we expect that the majority of the data collected this way will be natural text.

Our translationese LM is trained on machine-translated newscrawl data, as a proxy for human translated data. This approach does not require finding large amounts of existing text in the target language known to be translations, which is a challenging problem as the necessary metadata is not available for most corpora.

For our language models, we use a decoder-only transformer architecture comparable to *transformer-big* (Vaswani et al., 2017). We classify new sentences by thresholding the difference in average log probability under the two models.

For training our MT system we label each bilingual training example by prepending a special token in the source sentence denoting the class of the target sentence (`<nat>` or `<trans>`). At inference, we favor natural generation by prepending the natural token (`<nat>`) to the input. We call these models *natural-to-natural* (N2N) as their ultimate purpose is to translate natural source sentences into natural target sentences.

### 3.2 Synthetic and Topical Biases

The training corpus for our translation LM is synthetically generated using MT in order to bypass the difficulty of tracing the translation direction in true parallel data. This is not ideal for our purpose since machine and human translations might differ, and we are primarily interested in identifying human translated text. In other words, our LM training condition (train on MT) differs from the inference condition (identify HT). Prior to training our translation LM, we measured the lexical characteristics of each type of text using the metrics from (Vanmassenhove et al., 2021), as shown in Table 1. This table has two main messages: First, MT and HT are similar to each other and both are quite different from natural text (NAT), which motivates our use of MT data for LM training as a proxy for HT. Second, a clear difference between the lexical diversity between HT and natural test (NAT) can be seen across all metrics. This supports our intuition that the MT output can be made be more natural and lexically diverse by putting more emphasis on training data with natural target side.

One counter-intuitive finding in Table 1 is that NAT sentences actually have less inflectional diversity than HT and MT, as measured by $H$ and $D$. It is unclear why this should be the case, but it could be due the news commentary domain of the dataset (newstest2011-2019) we used to measure these metrics, which has perhaps a more consistent style and more careful editing than the data used for Vanmassenhove et al. (2021)'s experiments, which were conducted over the entire training set.

Topical bias might also arise with our strategy. Our translated data originates from source language news and focuses on topics of interest to a source-language speaker, while our natural data originates from target language news and therefore focuses on topics of interest to a target-language speaker. These differences are not necessarily problematic in our case (or might even be beneficial) but it might be worthwhile to investigate solutions to topical biases in later work.

## 4 Experimental Setup

We experiment on the WMT news translation tasks for evaluation (Bojar et al., 2016; Barrault et al., 2020b), focusing on the German↔English language pair. For this language pair there is abundant training data available, and MT systems achieve high quality translations. This is a good setting for our work since improving naturalness becomes a worthwhile endeavor only if high accuracy and fluency levels are reached.

### 4.1 Training Data

We use news-commentary-v15, paracrawl-v5.1, europarl-v10 and commoncrawl as training corpora (see Table 2). Noisy data is filtered out with contrastive data selection as proposed by Wang et al. (2018). Finally, we add back-translated data (Sennrich et al., 2016b) from the monolingual newscrawl (2007-2018) dataset for each

| model | B1↓ | B2 | B3↑ | TTR↑ | Yule's I↑ | MTLD↑ | H↑ | D↓ | PTF↓ | CDU↓ | SynTTR↑ | cLM ↓ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Diversity Metrics | | | | | | | | | | | |
| MT | 68.55 | 6.31 | 25.13 | 0.1028 | 0.9375 | 144.07 | 12.64 | 92.22 | 0.7637 | 0.3938 | 0.1587 | 1.21 |
| HT | 68.25 | 6.30 | 25.44 | 0.1184 | 1.3980 | 148.08 | 12.93 | 92.00 | 0.7450 | 0.3781 | 0.1621 | 1.16 |
| NAT | 65.98 | 6.12 | 27.90 | 0.1553 | 2.9612 | 169.93 | 11.13 | 93.04 | 0.7133 | 0.3861 | 0.2108 | 0.77 |

Table 1: En→De: Diversity metrics calculated on the concatenation of newstest2011-2020 (∼25k sentences). HT scores are calculated on the src-orig half while NAT is calculated on the tgt-orig half. The cLM shows the ratio between the contrastive translationese and natural LMs. The arrows by the metric names indicate the desired behaviour towards more natural style. B2 does not have a clear desired behaviour.

target language, and mark synthetic source sentences with an additional special tag on the source side (`<bt>`) (Caswell et al., 2019).

## 4.2 Automatic Evaluation

### 4.2.1 Translation Quality

We use sacreBLEU (Post, 2018)[1] to automatically evaluate translation quality with BLEU, with the primary goal of improving scores on the *target-original* test sets. Since 2019, all WMT test sets have been composed only of source original (src-orig) sentence pairs. To create target original (tgt-orig) sets, we just flip the source and target of the test sets for the reverse direction. In previous years, the WMT test sets were a mixture of source- and target-original texts, each human-translated into the other language. For these years we split the test sets based on their original language and report results on the two subsets. Optimizing MT systems on these two settings can yield very different conclusions.

**src-orig** Beyond a certain level, BLEU scores on src-orig test sets are biased in favor of simpler and more literal translations (Freitag et al., 2020b); increasing scores above this threshold can have a negative impact on translation quality. Consequently, our goal is to avoid very high src-orig BLEU scores while increasing tgt-orig scores, a strategy that Freitag et al. (2020a) have demonstrated to be effective for improving translation quality.

**tgt-orig** Freitag et al. (2019); Edunov et al. (2020) found that MT systems trained with back-translated training data mostly improve on tgt-orig test sets. One explanation is that backtranslation increases the fluency and naturalness of MT output, a property that can more easily be measured by comparing to natural target-language text than typical human translations, which have lower lexical diversity. Contrary to src-original test sets, generating literal, simple translation output decreases BLEU scores on tgt-orig test sets and cannot be used as a strategy to inflate BLEU scores. To further our main goal of generating more natural translations, we focus on improving BLEU scores on tgt-orig test sets.

### 4.2.2 Diversity Scores

Vanmassenhove et al. (2021) proposed a series of metrics to measure the lexical diversity of a text. They range from known measures like type-to-token ratio (TTR) or the entropy of word forms given a lemma, to novel metrics that analyse synonym frequencies. They show that MT text has a lower degree of diversity than human-generated text but do not distinguish between original text and HT.

We refer the reader to the original paper for the metric definitions. For better interpretability, in the results table we provide an indication of the desired direction for each metric.. Note however that our goal is *not* to optimize these metrics, rather we want to build an MT system whose output is most similar to natural sentences. To illustrate this, assume we have a "translation model" that just generates random words. Such a system will certainly score high in diversity metrics (e.g. it will have a high entropy), but the resulting text will certainly not be natural. In fact, for a few metrics, our baseline system already gets a "better" score than natural sentences. Thus, for those metrics we should steer them in the "wrong" direction to achieve a style most closely to natural sentences.

We used the implementation provided by the authors except for the "Synonym Frequency Analysis" metrics, which we reimplemented using an in-house synonym dictionary. Note also that some of these metrics are sensitive to the corpus size they

[1] sacreBLEU signatures: BLEU+case.mixed+lang.LP +numrefs.1+smooth.exp+SET+tok.13a+version.1.5.1

are applied on (e.g. TTR, the type-to-token ratio, decreases as the corpus size increases). Thus not all numbers are in the same range as the results reported by Vanmassenhove et al. (2021).

### 4.3 Human Evaluation

We hired 4 professional translators and conducted 2 types of human evaluations to evaluate (a) overall translation quality, and (b) the naturalness of our MT output. We randomly chose 62 documents (comprising roughly 1,000 sentences) from the src-original halves of newstest2019 for human evaluation to avoid human translated source sentences (Läubli et al., 2020).

**Quality** We measure quality with an in-context version of MQM (Lommel et al., 2014) which mimics the setup proposed in Freitag et al. (2021). This includes using the same error categories, severity levels and error weighting schema, which were adapted for the MT use case. As suggested in the study, we weight each major error with 5 and each minor error with 1, except for minor punctuation errors which get a score of 0.1.

**Naturalness** The preferred setup to evaluate naturalness is to present two translations of the same source sentence to native speakers without showing the actual source sentence. We then ask the raters whether they prefer one of the outputs or rate them equally based on naturalness and natural phrasing. We emphasize that this evaluation is carried out in a monolingual manner, as showing the source can bias the human judges towards the translation that mimics the original sentence, as it is easier to evaluate.

### 4.4 Training Details

We train transformer models with the transformer-big (Vaswani et al., 2017) architecture. All our models are trained for 250k updates with a batch size of 32k sentences. The baseline system uses only the `<bt>` tags, our proposed system (denoted as N2N) is enhanced with the `<nat>` and `<trans>` tags described above. During inference, in order to produce more natural output we tag the input sentence with the `<nat>` tag. For comparison purposes, we also analyze the output of the test sets when using the `<trans>` tag instead.

## 5 Experimental Results

Due to space constraints and German being the more morphologically rich language, we focus our

| | size | NAT |
|---|---|---|
| news-commentary | 251k | 15.3% |
| commoncrawl | 1.5M | 39.6% |
| europarl | 452k | 44.1% |
| paracrawl | 54.7M | 30.4% |
| newscrawl-de | 271M | 92.0%* |

Table 2: En→De: Training data statistics and fraction of natural target sentences. *This fraction is overestimated since this set is used for LM training.

analysis mainly on the English→German (En→De) translation direction, but we provide translation results for the reverse direction (De→En) as well.

### 5.1 Naturalness Classification

Our naturalness classifier contrasts the natural and translation LMs introduced in Section 3. We need to find a threshold to be able to classify the training data based on their target side as natural or translation. We chose 0.95 for both directions, resulting in $\sim 90\%$ sentence-level classification accuracy on newstest2018. Table 1 (last column) shows the contrastive language model (cLM) scores for the concatenation of newstest 2011-20 for En→De for natural, (human) translated (HT) and machine translated (MT) sentences and shows that 0.95 seems a reasonable decision.

Table 2 reports the fraction of data classified as natural for each subset of the German side of our training corpus along with subset sizes. The fraction of natural target sentences per dataset varies between 30.4% and 44.1%, except for newscrawl-de (92.3%) which is our training set to define natural language and news commentary (15.3%) which mostly seems to have translations on the target side. The $44.1\%$ of natural German sentences for Europarl is probably an overestimate and reflects the high quality of the translations in this particular corpus. Overall, the parallel corpora have less than 50% natural target sentences which means that the training data in this translation direction is dominated by translated text on the target side.

Table 3 shows the diversity metrics on a 15k sample of the training data. We can clearly see that the sentences considered natural are more lexically diverse than the sentences marked as translations, suggesting a valid classification by our model. Note that, as pointed out above, the lack of labelled data hinders reporting classification accuracy measures for the training data.

| classified | B1↓ | B2 | B3↑ | TTR↑ | Yule's I↑ | MTLD↑ | H↑ | D↓ | PTF↓ | CDU↓ | SynTTR↑ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TRANS | 70.74 | 6.98 | 22.28 | 0.0918 | 0.9484 | 211.73 | 15.13 | 90.75 | 0.7296 | 0.3528 | 0.1328 |
| NAT | 68.91 | 7.16 | 23.93 | 0.1103 | 1.3501 | 303.05 | 14.94 | 90.69 | 0.7140 | 0.3726 | 0.1636 |

Table 3: En→De: Diversity metrics calculated on a 15k sample of the classified training data.

### 5.2 Translation Results

We evaluate three types of translations: the output of a regular baseline MT system and the outputs of our natural-to-natural (N2N) system trained with tags, decoding with either the <nat> or the <trans> tag. BLEU scores are reported in Table 4. We report average scores over all test sets (newstest 2011 through 2020), separate results for each set can be found in the appendix.

Focusing on En→De, for the src-orig half of the test sets, we obtain an average drop of 4.6 BLEU points when using the <nat> tag. For src-orig data, the references are translated text and the BLEU evaluation does not strongly reward text which does not adopt a translation style. When we instruct the system to produce translationese text using the <trans> tag, we recover the BLEU score of the baseline system. We thus have a clear indication that the system is learning to produce different texts depending on the given tag. This behaviour is consistent across all test sets, it is not just an effect due to averaging (see the Appendix for the detailed numbers).

We now turn our attention to the results on target-original data. In this situation the BLEU scores show a behaviour opposite to the previous case. Using the <nat> tag for translation, we get an improvement of 1.0 BLEU on average compared to the baseline. Remember that for this condition, the original text is on the target side, i.e. on the references we are evaluating against. This is thus an indication that we are indeed generating text that is closer to human natural text. When switching to <trans> translation, we see a drop of 2.4 points.

For the opposite direction we see a similar trend for both conditions (right part of Table 4).

### 5.3 Lexical Diversity Scores

In Section 5.2 we showed how BLEU scores change when applying our proposed method, and we observed an improvement on the target-original test sets, which may indicate improved naturalness in the output text. This evaluation setting is however artificial since it relies on translated source text while MT systems generally need to translate text originally written in the source language. We thus turn to a more detailed analysis of the produced translations, focusing on the src-original test sets.

Table 5 shows the diversity metrics computed on the concatenation of all the source-original test sets. It can be seen that the N2N system gets diversity scores much closer to ones calculated on natural sentences (NAT) when compared to the baseline system in all categories. In fact, it even obtains better scores than the human translations for some of them. We do not claim to outperform humans on translation quality: natural text shows certain characteristics that can be measured by these metrics, but improving on these metrics alone does not necessarily imply better translations. However, these results combined with the metrics from the previous section are positive indicators which motivate a human evaluation.

## 6 Human Evaluation

### 6.1 MQM

We carry out a human evaluation using the MQM framework (Lommel et al., 2014), which provides a detailed categorization of errors found in the text. The evaluation was carried out by professional translators. The results comparing the baseline output with the output of our N2N models with <nat> tag can be found in Tables 6 and 7.

Looking into the error categorization for En→De, we see a clear advantage of the N2N system for the style metrics, halving the number of major errors and reducing the number of minor errors by one third. The number of grammar errors has also been significantly reduced, from 56 minor errors in the baseline system to 29 in the N2N system, although with an increase of 6 major errors. For N2N we observe an increase in minor punctuation errors (mainly repetition of punctuation signs) and spelling errors, which can be traced back to the German orthography reform: the N2N seems to prefer the old writing form[2] which is now officially considered incorrect.[3]

[2] E.g. the N2N seems to generate more occurrences of "daß" instead of "dass".

[3] These errors could easily be corrected in a rule-based

| | | En→De | | De→En | |
|---|---|---|---|---|---|
| | | src-orig | tgt-orig | src-orig | tgt-orig |
| Base | | 38.0 | 37.0 | 36.4 | 45.4 |
| N2N | `<nat>` | 33.4 | 38.0 | 31.8 | 46.3 |
| | `<trans>` | 38.0 | 34.6 | 36.3 | 43.4 |

Table 4: Average BLEU scores for the WMT news datasets from 2011 to 2020.

| Mode | | B1↓ | B2 | B3↑ | TTR↑ | Yule's I↑ | MTLD↑ | H↑ | D↓ | PTF↓ | CDU↓ | SynTTR↑ | cLM ↓ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| En→De | | | | | | | | | | | | | |
| NAT | | 65.98 | 6.12 | 27.90 | 0.1553 | 2.9612 | 169.93 | 11.13 | 93.04 | 0.7133 | 0.3861 | 0.2108 | 0.77 |
| HT | | 68.25 | 6.30 | 25.44 | **0.1184** | **1.3980** | 148.08 | **12.93** | **92.00** | 0.7450 | **0.3781** | 0.1621 | 1.16 |
| Base | | 68.55 | 6.31 | 25.13 | 0.1028 | 0.9375 | 144.07 | 12.64 | 92.22 | 0.7637 | 0.3938 | 0.1587 | 1.21 |
| N2N | `<nat>` | **67.48** | 6.21 | **26.31** | 0.1099 | 1.1672 | **156.19** | 12.56 | 92.26 | **0.7363** | 0.3915 | **0.1744** | **1.11** |
| | `<trans>` | 68.53 | 6.32 | 25.16 | 0.1031 | 0.9446 | 145.88 | 12.72 | 92.17 | 0.7646 | 0.3948 | 0.1588 | 1.22 |
| De→En | | | | | | | | | | | | | |
| NAT | | 70.17 | 7.61 | 22.22 | 0.0835 | 0.7706 | 100.32 | 10.54 | 93.39 | 0.7888 | 0.3872 | 0.1847 | 0.83 |
| HT | | 71.28 | 7.66 | 21.06 | 0.0878 | 0.6884 | 92.52 | 9.44 | 94.05 | **0.7752** | **0.4194** | 0.2431 | 1.14 |
| Base | | 70.97 | 7.70 | 21.34 | 0.0982 | 0.8278 | 92.38 | 9.45 | 94.03 | 0.8023 | 0.4294 | 0.2399 | 1.25 |
| N2N | `<nat>` | **69.88** | 7.60 | **22.53** | **0.1057** | **1.0220** | **98.49** | **9.76** | **93.84** | 0.7813 | 0.4283 | **0.2592** | 1.14 |
| | `<trans>` | 70.97 | 7.71 | 21.32 | 0.0979 | 0.8235 | 93.42 | 9.46 | 94.02 | 0.8026 | 0.4280 | 0.2378 | 1.25 |

Table 5: En→De: Diversity metrics computed on the concatenation of newstest2011 to newstest2020, source-original test sets. Both the base and the N2N include backtranslated data. The arrows by the metric names indicate the desired behaviour towards more natural style. B2 does not have a clear desired behaviour.

For the accuracy errors, we also see an important reduction of mistranslation errors, from 79 to 26, but at the cost of increasing the number of major errors from 44 to 51. The other categories show comparable results between the two systems. Looking at the total number of errors, we see that the total number of errors decreases for the N2N system, from 508 for the baseline to 407 for the N2N system. The shift in errors is however not uniform across major and minor errors: while we achieve a drop of 30% in the number of minor errors (from 395 to 275), we increase the number of major errors by 16% (from 113 to 132). Overall, using the weighting approach proposed by (Freitag et al., 2021),[4] N2N achieves a better global score of 0.88, compared to 0.91 for the baseline system.

For the De→En translation direction, the results are mixed: we again obtain an important reduction in the number of minor style and grammar errors, but with with a slight increase of major errors. However the number of accuracy errors is also increased, which leads to a worse global score for the N2N system (0.49 vs. 0.55).

post-processing step.

[4]This weighting approach has been adapted for the machine translation use case, and differs from the standard weighting scheme used for human-produced translations.

### 6.2 Side-by-side

The MQM analysis shows that the N2N system is able to produce grammatically better sentences, with some slight degradation in accuracy when compared with the baseline system. But, as pointed out before, a *natural* text might require more than grammatical and fluent text. In order to judge the naturalness, we carry out an additional evaluation where we present the translations produced by the baseline system and the N2N system to native speaker crowdworkers, and ask them to choose the better sounding one. Since MQM already judges the accuracy of the translations, this evaluation is *monolingual* and focuses solely on the naturalness of the sentences. Showing the source sentence may steer the human judges to choose the translation that is closer to it, as it is easier to judge, and we wanted to avoid this bias. The results can be found in Table 8. It can be seen that the human evaluators do have a preference for sentences generated by our N2N system. The difference is particularly important for the De→En translation direction. Some example translations are given in the Appendix.

| | base | | <nat> | |
|---|---|---|---|---|
| | M | m | M | m |
| Acc/Mistrans. | 44 | 79 | 51 | 26 |
| Acc/Omission | 6 | 0 | 2 | 0 |
| Acc/Addition | 3 | 1 | 1 | 1 |
| Acc/Untranslated | 3 | 6 | 8 | 4 |
| Fl/Grammar | 14 | 56 | 20 | 29 |
| Fl/Register | 3 | 9 | 0 | 4 |
| Fl/Inconsistency | 0 | 2 | 1 | 0 |
| Fl/Punctuation | 0 | 57 | 2 | 72 |
| Fl/Spelling | 0 | 1 | 0 | 13 |
| Fl/Display | 1 | 10 | 8 | 4 |
| St/Awkward | 14 | 143 | 7 | 95 |
| Ter/Inappr. | 25 | 31 | 29 | 27 |
| Other | 0 | 0 | 1 | 2 |
| Total Errors | 113 | 395 | 132 | 275 |
| Global Score | 0.91 | | 0.88 | |

Table 6: MQM scores for English-to-German of the baseline model compared to our N2N model with <nat> decode. The global score is a weighted combination of the error counts of all the categories. Lower scores are better. Major errors are under the 'M' column, minor errors under the 'm' column. Abbreviations are as follows: "Acc": Accuracy, "Fl": Fluency, "St": Style, "Ter": Terminology.

| | base | | <nat> | |
|---|---|---|---|---|
| | M | m | M | m |
| Acc/Mistrans. | 6 | 4 | 9 | 14 |
| Acc/Omission | 6 | 3 | 11 | 12 |
| Acc/Addition | 0 | 0 | 3 | 4 |
| Acc/Untranslated | 3 | 2 | 0 | 2 |
| Fl/Grammar | 1 | 31 | 4 | 9 |
| Fl/Register | 0 | 0 | 0 | 0 |
| Fl/Inconsistency | 4 | 3 | 2 | 2 |
| Fl/Punctuation | 1 | 3 | 5 | 4 |
| Fl/Spelling | 1 | 1 | 4 | 1 |
| Fl/Display | 0 | 0 | 0 | 2 |
| St/Awkward | 12 | 119 | 16 | 75 |
| Ter/Inappr. | 18 | 10 | 19 | 13 |
| Other | 0 | 0 | 0 | 0 |
| Source Error | 3 | 0 | 2 | 0 |
| Locale/Date | 0 | 1 | 0 | 0 |
| Total Errors | 55 | 177 | 75 | 138 |
| Global Score | 0.49 | | 0.55 | |

Table 7: MQM scores for German-to-English of the baseline model compared to our N2N model with <nat> decode. Refer to Table 6 for a list of abbreviations.

| Lang. | Preferences (%) | | | Num. |
|---|---|---|---|---|
| | <nat> | neutral | base | Ratings |
| EnDe | 33.3 | 41.3 | 25.4 | 1000 |
| DeEn | 44.6 | 29.3 | 26.1 | 1000 |

Table 8: Human Evaluation: natural side-by-side of the baseline model compared to our N2N model with <nat> decode.

## 7 Conclusion

We propose a method for achieving more natural translations, i.e. translations which adopt a style closer to text originally written in the target language. Using contrastive language model scoring we classify our training data depending on whether the target side was originally written in the target language or whether it is a translation. This information is given to the translation system via an input tag, so that we can bias the generation process towards producing output closer to natural text. We demonstrate that building an MT system focusing on natural translations can be evaluated by optimizing BLEU on target-original test sets while avoiding high BLEU scores on src-original test sets. Through automatic metrics we show that the N2N method achieves lexical diversity closer to that of natural sentences indicative of more natural text. Indeed, human evaluations show that the produced translations are preferred by human judges when asked to choose the more natural translation. There is some drop in translation accuracy, as shown by the MQM analysis, however this can be an acceptable trade-off for some applications. For example, when considering post-editing, a more natural initial proposal will most certainly result in a more natural final output, while accuracy errors are usually easier to detect and fix for human post-editors.

The main contribution of this work lies in highlighting the potential for more natural translations by appropriate manipulation of the training data and evaluation measures. Our approach for using this information through tagging is a good first step, but it is a straightforward data manipulation. Other techniques that modify the model architecture or training objective may allow us to achieve the same improvements in naturalness without loss in translation accuracy.

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# A Additional Results

## A.1 Accuracy of Contrastive LM

The accuracy of the contrastive language model for all test sets for English→German are shown in Table 9. The accuracy is mostly around 90% for all test sets. In 2020, the test sets have been generated on the paragraph-level which could be the reason for the lower precision on the natural half. Some of the reference translations in earlier years have been post-edited from MT output which could be the reason why newstest2011 and newstest2013 have lower accuracy numbers for the natural sentences.

## A.2 Per Test-set Results

Table 10 shows BLEU results for each separate test. It can be seen that all test set exhibit the same behaviour: increase tgt-orig and decrease in src-orig when using `<nat>`, the opposite for `<trans>`.

## A.3 Results Without Backtranslation

Table 11 shows BLEU scores for the English→German translation direction, without using backtranslated data. We confirm that the N2N system using the `<nat>` also outperforms the baseline system on the tgt-original condition, while obtaining worse BLEU scores on the src-original evaluation. Using the `<trans>` tag, the score of the baseline system on the src-orig conditional is recovered.

Comparing the base system from Table 11 with the base system in the original paper, we see that the addition of backtranslated data, which is by construction natural on the target side, also behaves differently for the two evaluation conditions. Although it achieves improvements for both source and target original data, for the source-original condition it is only a minor improvement of 0.5 BLEU. On the other hand, for the target-original data we see a big gain of 3.1 points, further pointing towards the fact that the system generates more natural text.

# B Translation Examples

Table 12 shows translation examples for the German-to-English translation direction. The N2N translations have a more natural sentence structure when compared to the baseline translations. Further, N2N uses wordings that are more typically in natural written English text.

| | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|
| NAT | 77.9% | 91.3% | 67.8% | 91.5% | 91.8% | 92.7% | 88.1% | 91.7% | 93.0% | 76.6% | 86.2% |
| HT | 81.4% | 87.7% | 79.4% | 86.6% | 85.7% | 94.6% | 87.2% | 97.1% | 93.6% | 93.7% | 88.7% |

Table 9: English→German: Accuracy for all test sets.

| | | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base | | 29.9 | 35.9 | 33.1 | 32.1 | 37.5 | 43.9 | 36.4 | 53.8 | 44.0 | 33.6 | 38.0 |
| N2N | <nat> | 27.4 | 31.5 | 30.9 | 30.0 | 34.0 | 36.1 | 32.0 | 44.5 | 37.8 | 29.9 | 33.4 |
| | <trans> | 30.0 | 35.2 | 33.3 | 32.4 | 37.9 | 44.1 | 36.3 | 53.1 | 44.1 | 33.1 | 38.0 |

(a) En→De: Source original side of test sets.

| | | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base | | 33.3 | 33.5 | 42.8 | 37.5 | 31.7 | 39.4 | 32.8 | 45.8 | 41.8 | 31.1 | 37.0 |
| N2N | <nat> | 33.2 | 35.0 | 43.2 | 38.3 | 33.5 | 40.6 | 34.0 | 46.5 | 43.1 | 32.5 | 38.0 |
| | <trans> | 31.1 | 30.9 | 40.7 | 34.3 | 30.0 | 36.7 | 30.8 | 42.1 | 39.4 | 30.1 | 34.6 |

(b) En→De: Target original side of the test sets.

| | mode | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base | | 36.0 | 35.8 | 42.0 | 35.3 | 29.2 | 37.9 | 34.0 | 39.5 | 41.7 | 32.6 | 36.4 |
| N2N | <nat> | 33.5 | 32.7 | 36.9 | 29.9 | 25.3 | 32.5 | 30.3 | 33.9 | 34.5 | 28.3 | 31.8 |
| | <trans> | 36.3 | 35.2 | 42.1 | 34.9 | 29.2 | 37.8 | 33.6 | 39.8 | 41.7 | 32.7 | 36.3 |

(c) De→En: Source original side of test sets.

| | | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base | | 39.2 | 44.1 | 39.6 | 39.9 | 44.0 | 54.9 | 47.2 | 58.6 | 48.2 | 38.1 | 45.4 |
| N2N | <nat> | 40.0 | 44.5 | 40.1 | 42.8 | 44.5 | 54.8 | 47.5 | 58.1 | 49.7 | 41.0 | 46.3 |
| | <trans> | 37.7 | 42.3 | 37.7 | 38.8 | 42.2 | 51.6 | 45.5 | 55.3 | 46.0 | 36.8 | 43.4 |

(d) De→En: Target original side of the test sets.

Table 10: BLEU scores for the WMT news datasets translation direction.

| | | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base system | | 30.0 | 35.0 | 32.4 | 31.4 | 37.0 | 43.3 | 35.8 | 53.2 | 44.2 | 32.6 | 37.5 |
| N2N | <nat> | 28.0 | 31.1 | 29.9 | 29.2 | 33.3 | 36.4 | 31.7 | 44.9 | 38.1 | 29.7 | 33.2 |
| | <trans> | 29.9 | 34.9 | 32.5 | 30.9 | 36.8 | 43.2 | 36.1 | 53.7 | 44.4 | 32.0 | 37.4 |

(a) Source-original, no backtranslated data.

| | | nt11 | nt12 | nt13 | nt14 | nt15 | nt16 | nt17 | nt18 | nt19 | nt20 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base system | | 30.8 | 29.0 | 41.1 | 34.3 | 30.2 | 35.8 | 30.1 | 41.9 | 37.2 | 28.6 | 33.9 |
| N2N | <nat> | 32.2 | 31.3 | 42.6 | 35.7 | 30.9 | 36.6 | 31.0 | 42.6 | 38.6 | 29.6 | 35.1 |
| | <trans> | 30.5 | 29.2 | 40.3 | 32.0 | 28.3 | 34.0 | 28.4 | 39.2 | 36.1 | 27.9 | 32.6 |

(b) Target-original, no backtranslated data.

Table 11: BLEU scores for the English→German translation direction, without backtranslated data.

| | |
|---|---|
| Source | Es wird befürchtet, dass die Opferzahlen noch deutlich in die Höhe gehen. |
| Baseline | It is feared that the number of victims will increase significantly. |
| N2N | It is feared that the death toll will rise significantly. |
| Source | Der Neubau sollte möglichst freundlich und hell gestaltet werden, damit sich die Bewohner darin wohlfühlen können, so der Architekt. |
| Baseline | The new building should be designed as friendly and bright as possible so that the residents can feel comfortable in it, according to the architect. |
| N2N | According to the architect, the new building should be made as friendly and bright as possible so that the residents can feel at ease in it. |
| Source | Deren effektivste Aktion bestand in einem frühzeitigen Wechsel. |
| Baseline | Their most effective action was an early change. |
| N2N | Their most effective action was to switch early. |
| Source | Musiker wie Janet Jackson, John Legend, Shawn Mendes und Cardi B haben bei einem gemeinsamen Konzert im New Yorker Central Park für mehr Engagement im Kampf gegen Armut und Krankheiten geworben. |
| Baseline | Musicians such as Janet Jackson, John Legend, Shawn Mendes and Cardi B have campaigned for more commitment in the fight against poverty and disease at a joint concert in New York's Central Park. |
| N2N | Musicians such as Janet Jackson, John Legend, Shawn Mendes and Cardi B joined forces at a concert in New York's Central Park to promote greater commitment to fighting poverty and disease. |
| Source | Bundesgesundheitsminister Jens Spahn hat sich für eine Neuregelung der Organspende ausgesprochen. |
| Baseline | Federal Health Minister Jens Spahn has spoken out in favour of a new regulation on organ donation. |
| N2N | Jens Spahn, Germany's Minister of Health, has called for a new regulation of organ donation. |
| Source | Grüß war schon vor zwei Jahren als damals 14-Jähriger in Bielefeld dabei. |
| Baseline | Grüß was already there two years ago as a 14-year-old in Bielefeld. |
| N2N | Grüß was in Bielefeld, Germany two years ago when he was 14 years old. |

Table 12: Example translations for the German→English direction.