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Identifying Weaknesses in Machine Translation Metrics Through Minimum Bayes Risk Decoding: A Case Study for COMET

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Abstract

Neural metrics have achieved impressive correlation with human judgements in the evaluation of machine translation systems, but before we can safely optimise towards such metrics, we should be aware of (and ideally eliminate) biases toward bad translations that receive high scores. Our experiments show that sample-based Minimum Bayes Risk decoding can be used to explore and quantify such weaknesses. When applying this strategy to COMET for en→de and de→en, we find that COMET models are not sensitive enough to discrepancies in numbers and named entities. We further show that these biases are hard to fully remove by simply training on additional synthetic data and release our code and data for facilitating further experiments.¹

1 Introduction

Recently, neural machine translation evaluation metrics have reached better correlation scores with human evaluators than surface-level metrics like BLEU (Papineni et al., 2002). In particular, COMET (Rei et al., 2020a) has shown significant potential as a leading evaluation metric both in shared tasks (Mathur et al., 2020; Freitag et al., 2021b) and other studies on machine translation evaluation metrics (Kocmi et al., 2021). The main benefits of such neural metrics are that they do not rely on surface-level similarity to a reference translation and that some of them operate in a multilingual representation space. This also allows for comparing translations to the source sentence.

A recent evaluation as part of the WMT 2021 metrics shared task (Freitag et al., 2021b) suggests that neural metrics are also less susceptible to many weaknesses of earlier non-neural metrics, e.g. an antonym in the translation hurting the BLEU score exactly the same amount as a synonym. However,

it is still unclear whether or not these metrics also introduce new biases that are harder to detect since they are essentially “black box” metrics that do not explain why a certain score is attributed to a translation. Failing to identify these biases in neural metrics could lead the community to optimise towards metric “blind spots”, either directly through reward-based training methods such as Minimum Risk Training (Shen et al., 2016), or more slowly by basing modelling choices on metric scores. It is therefore worthwhile to find new means to uncover weaknesses of neural machine translation metrics.

In this paper, we show that sampling-based Minimum Bayes Risk (MBR) decoding - where a pool of samples are compared against each other using a machine translation evaluation metric as a utility function - can render blind spots of these metrics more observable. When applying COMET as the utility function, we find many examples where a translation hypothesis is chosen that contains different numbers or named entities than the source and reference (see examples in Table 1). Through a targeted sensitivity analysis, we identify that these are indeed weaknesses of COMET and we show that it can be hard to remove them from the model.

Our contributions are the following:

- We propose to use sample-based MBR decoding to explore and measure weaknesses of neural machine translation evaluation metrics.
- We find that COMET is not sensitive enough to number differences and mistranslations of named entities when translating from de↔en.
- We show that simply retraining COMET on synthetic data is not enough to fully eliminate these blind spots.

2 Related Works

How to best evaluate machine translation models has been a long-standing question in the research

¹<https://github.com/ZurichNLP/mbr-sensitivity>

<code>src</code>	Schon drei Jahre nach der Gründung verließ Green die Band 1970 .
<code>ref</code>	Green left the band three years after it was formed, in 1970 .
<code>MBR_{chrF++}</code>	Already three years after the foundation, Green left the band in 1970 .
<code>MBR_{COMET}</code>	Three years after the creation, Green left the band in 1980 .
<code>src</code>	[...] Mahmoud Guemama’s Death - Algeria Loses a Patriot [...], Says President Tebboune .
<code>ref</code>	[...] Mahmoud Guemamas Tod - Algerien verliert einen Patrioten [...], sagt Präsident Tebboune .
<code>MBR_{chrF++}</code>	[...] Mahmoud Guemamas Tod - Algerien verliert einen Patriot [...], sagt Präsident Tebboune .
<code>MBR_{COMET}</code>	[...] Mahmud Guemamas Tod - Algerien verliert einen Patriot [...], sagt Präsident Tebboene .

Table 1: Examples of MBR decoding outputs with chrF++ and COMET as utility metrics. The outputs chosen with COMET indicate less sensitivity towards discrepancies in numbers and named entities.

community. Ideally, we could employ humans to judge the quality of different models but this is time-consuming, costly and requires trained professionals. Various automatic machine translation metrics have been proposed over the years that typically compare a machine translation output to a reference sentence according to surface-level similarity (Papineni et al., 2002; Popović, 2015) or on a shallow semantic level (Banerjee and Lavie, 2005).

With the rise of contextual embeddings and large multilingual Transformer language models, metrics that map translations and references into the same latent space and compare the cosine similarity between them (Lo, 2020) or use them as inputs to predict a score (Sellam et al., 2020; Rei et al., 2020a) have become popular. Such neural metrics have been shown to agree more with human evaluation than previously popular metrics such as BLEU (Papineni et al., 2002) or chrF (Popović, 2015).

However, these neural metrics can also introduce new biases that we are not yet aware of (Hanna and Bojar, 2021). In this paper, we aim to find a way to identify such weaknesses via Minimum Bayes Risk (MBR) decoding. While MBR decoding was a frequently used decoding strategy in the days of statistical machine translation (Goel and Byrne, 2000; Kumar and Byrne, 2004; Tromble et al., 2008), it has only recently gained traction in the context of neural machine translation. Eikema and Aziz (2020) argue that MBR decoding using samples as hypotheses results in an unbiased candidate pool in contrast to beam search outputs which maximise the probability under the model. Indeed, if the machine translation model generating the samples is strong enough, humans prefer MBR-decoded hypotheses selected with BLEURT (Sellam et al., 2020) as the utility function over beam search outputs (Freitag et al., 2022).

Müller and Sennrich (2021) further show that MBR outputs can inherit biases from the utility function, for example, the length bias (Nakov et al., 2012) when BLEU is used as the utility function. Consequently, it stands to reason that MBR decoding can also be used to uncover new biases of metrics that are used as utility functions, as we will show in this work.

3 Minimum Bayes Risk Decoding

Traditionally, maximum a posteriori (MAP) decoding is used in the context of neural machine translation. The goal is to find the translation hypothesis h_i among all possible hypotheses H that is most probable under the translation model given the source sentence x and the model parameters θ :

$$y^* = \operatorname{argmax}_{h_i \in H} p_{\text{model}}(h_i|x, \theta) \quad (1)$$

In practice, it is not feasible to consider every possible hypothesis. Beam search offers a popular and effective approximation.

In contrast, MBR decoding aims to find a translation that minimises the expected cost (risk) of choosing a candidate translation h_i , assuming that we have some loss function L to compare the candidate to a true translation h_j , and access to the true probability distribution P :

$$y^* = \operatorname{argmin}_{h_i \in H} \sum_{h_j \in H} P(h_j|x) L(h_i, h_j) \quad (2)$$

Since we do not have access to the true probability distribution P , and cannot exhaustively sum over all possible translations H , we have to make several approximations. First, we select a subset of all possible hypotheses H as candidate translations C to make the computation tractable. Eikema

and Aziz (2020) suggest drawing ancestral samples from the translation model as a set of unbiased candidates, and we follow this sampling-based MBR approach. Ancestral samples s are created by sampling the next token w from the translation model according to the probability distribution over the vocabulary V at each time step t :

$$s_t = s_{t-1} + \underset{w_i \in V}{\text{sample}}(p_{\text{model}}(w_i|x, s_{t-1}, \theta)) \quad (3)$$

The probability distribution is conditioned on the source sentence x and the previously produced output tokens s_{t-1} . For each ancestral sample s , this sampling continues until the end-of-sentence symbol is sampled as the next token w .

Second, we need to create an additional set of “support hypotheses” S that serve as an approximation to the unknown true translation. The set of candidates C and the set of support hypotheses S can be created separately but in this work, we follow Eikema and Aziz (2020) and let our translation model produce a set of 100 ancestral samples that are used both as candidates and support ($C = S$).

Third, we need to define a loss function L . In practice, we often substitute the loss function for a similarity function where higher values are better. Such a “utility function” u is then used to search for the translation h_i that maximises the expected utility or – to paraphrase – is most similar to all hypotheses in the support set S :

$$y^* = \underset{h_i \in C}{\text{argmax}} \frac{1}{|S|} \sum_{h_j \in S} u(h_i, h_j) \quad (4)$$

Any automatic machine translation evaluation metric can be used as the utility function u . Eikema and Aziz (2021) find that BEER (Stanojević and Sima’an, 2014) works best among a range of non-neural metrics. More recently, Freitag et al. (2022) compare several metrics as utility functions in a human evaluation of MBR-decoded outputs where the neural metric BLEURT (Sellam et al., 2020) clearly outperforms non-neural metrics. In this paper, we explore the use of another neural evaluation metric as the utility function, namely COMET. Since the reference-based COMET model takes the source, a translation hypothesis and a reference (approximated in MBR decoding with another hypothesis) as input, our formulation of MBR decoding now takes into account the source sentence x :

$$y^* = \underset{h_i \in C}{\text{argmax}} \frac{1}{|S|} \sum_{h_j \in S} u(x, h_i, h_j) \quad (5)$$

For an efficiency-related discussion of our implementation, please refer to Section 4.3.

4 Experiment Setup

4.1 Translation Model

To be able to generate samples, we train two Transformer Base machine translation models (Vaswani et al., 2017) using the `nematus`² (Sennrich et al., 2017) framework, one from de→en and one from en→de. We follow Eikema and Aziz (2021) and use all available parallel data from the WMT 2018 news shared task (Bojar et al., 2018) except for Paracrawl as training data. This amounts to 5.9 million sentence pairs. After deduplication, we have approximately 5.6 million training examples.

Both models are trained for 250k updates and we choose the best checkpoint based on the BLEU score as evaluated on `newstest2017` using SacreBLEU (Post, 2018). We compute a joint subword vocabulary of size 32k with byte pair encoding (Sennrich et al., 2016) using the SentencePiece implementation (Kudo and Richardson, 2018). During training and decoding, the maximum sequence length is set to 200 tokens.

Our models are built with 6 encoder layers, 6 decoder layers, 8 attention heads with an embedding and hidden state dimension of 512 and a feed-forward network dimension of 2048. For regularisation, we use a dropout rate of 0.1 for BPE-dropout (Provilkov et al., 2020) during training, for the embeddings, for the residual connections, in the feed-forward sub-layers and for the attention weights. We train with tied encoder and decoder input embeddings as well as tied decoder input and output embeddings (Press and Wolf, 2017) and apply exponential smoothing of model parameters (decay 10^{-4}) (Junczys-Dowmunt et al., 2018). Following previous work on MBR decoding (Eikema and Aziz, 2020), we train without label smoothing.

For optimisation, we use Adam (Kingma and Ba, 2015) with standard hyperparameters and a learning rate of 10^{-4} . We follow the Transformer learning schedule described in (Vaswani et al., 2017) with a linear warm-up over 4,000 steps. Our token batch size is set to 16,348 and we train on 4 NVIDIA Tesla V100 GPUs.

²github.com/EdinburghNLP/nematus

4.2 COMET Models

We experiment with two COMET models that were trained towards two different regression objectives:

- `wmt20-comet-da` (Rei et al., 2020b), developed for the WMT 2020 metrics shared task (Mathur et al., 2020) and trained to predict Direct Assessment (DA) (Graham et al., 2017) scores.
- `wmt21-comet-mqm` (Rei et al., 2021), developed for the WMT 2021 metrics shared task (Freitag et al., 2021b) and trained to predict MQM scores (Freitag et al., 2021a) based on the Multidimensional Quality Metrics (MQM) methodology (Uszkoreit and Lommel, 2013).

4.3 MBR Decoding Implementations

For non-neural metrics, we use the MBR decoding implementation³ provided by Eikema and Aziz (2021). We use only unique samples such that no hypothesis is assigned a higher average MBR score simply because it perfectly matches one or multiple hypotheses in the support.⁴ In our experiments, we use chrF++ (Popović, 2017) and BLEU as non-neural metrics. For BLEU, the implementation internally uses SacreBLEU (Post, 2018)⁵.

For our experiments with COMET, we adapt the official COMET implementation⁶ and implement an option for MBR decoding. Since COMET first creates a pooled sentence representation of the source and each of the two hypotheses before constructing a single vector from these representations and passing it through a regression layer, it is crucial that the implementation does not naively call COMET on every hypothesis pair. Instead, we encode the source sentence and hypotheses **only once** with XLM-R (Conneau et al., 2020) and then score all combinations of hypothesis pairs in parallel.

4.4 Evaluation Data

We decide to use the test sets from the WMT 2021 news shared task (Akhbardeh et al., 2021) as our evaluation data. This dataset brings two major benefits to our analysis:

- In the `de↔en` directions, it provides at least two references for every source sentence. This

allows us to compare how much MBR scores differ between two equivalent human translation alternatives as a reference point.

- This dataset was not part of the training data of the `wmt20-comet-da` and `wmt21-comet-mqm` COMET models which avoids the risk that the models have seen scores for similarly erroneous translations of these source sentences before.

There are 1000 sentence triplets (source, two human translations) for `de→en` where we use translation A as our reference and translation B as an alternative translation and 1002 sentence triplets for `en→de` where we use translation C as our reference and translation D as an alternative translation.

5 Exploration of MBR-Decoded Outputs

We employ sampling-based MBR decoding as a strategy to identify weaknesses in evaluation metrics that are used as utility functions. We believe that – in addition to general errors – we may also find other errors that can stem from two sources:

First, since samples are often of lower quality than hypotheses produced with beam search, neural metrics may behave unexpectedly when faced with errors that occur less frequently in beam search based machine translation outputs on which they were trained. Second, in MBR decoding, we compare a candidate translation hypothesis to a pseudo-reference (another hypothesis) instead of an actual reference. This is also something neural metrics were neither trained on nor designed to do.

We are most interested in general errors and errors of the first type since the second type is only relevant for MBR decoding itself. Therefore, we conduct additional experiments in Section 6 to distinguish between these two sources for the errors we identify below. Note that errors of the second type may become more important to investigate as MBR decoding becomes more prevalent or if we evaluate against multiple translation hypotheses instead of references (Fomicheva et al., 2020).

In our experiments, we first manually compare MBR-decoded outputs that were chosen with two different evaluation metrics as the utility function: chrF++ and COMET. For COMET, we notice several cases where the chosen hypothesis contains numbers and named entities that do not match with the source and the reference, even though the majority of samples in the support set contain the correct

³<https://github.com/Roxot/mbr-nmt>

⁴Using all samples does not affect our results.

⁵Using floor smoothing with a smoothing value of 0.1.

⁶<https://github.com/Unbabel/COMET>

	Numbers				Named Entities			
	de-en		en-de		de-en		en-de	
reference	93.24		93.46		n/a		n/a	
alternative	94.83	+ 1.59	95.66	+ 2.20	73.73		77.66	
beam search	95.91	+ 2.67	95.73	+ 2.27	71.55	- 2.18	70.03	- 7.63
MBR chrF++	91.22	- 2.02	93.43	- 0.03	67.59	- 6.14	62.44	-15.22
MBR bleu	93.88	+ 0.64	91.37	- 2.09	65.14	- 8.59	62.50	-15.16
MBR wmt20-comet-da	90.34	- 2.90	89.14	- 4.32	65.33	- 8.40	54.17	- 23.49
MBR wmt21-comet-mqm	82.35	- 10.89	77.10	- 16.36	58.15	- 15.58	53.31	- 24.35
MBR retrain-comet-da	92.65	- 0.59	90.17	- 3.29	66.48	- 7.25	60.48	- 17.18

Table 2: Results of the automatic evaluation. F1-scores (%) for number and named entity matches and F1-score changes compared to the reference for numbers and alternative translation for named entities. F1-scores that increased after retraining COMET are marked in green.

numbers and named entities. Two examples are shown in Table 1.

To test if these findings apply at scale, we run an automatic evaluation. For numbers, we use regular expressions to identify numbers in the MBR-decoded outputs. We measure the overlap between numbers in the source and the translation with the F1-score. We decide to compare to the source to be able to compute the overlaps for the reference and the alternative human translation as well. The results can be seen in the left part of Table 2. For named entities, we use spaCy⁷ (Honnibal et al., 2020) to identify entities of type “person”. Here, we compute the F1-scores to measure the overlap to the reference rather than to the source (as done for numbers) since the named entity recognition (NER) models are different for English and German. The results are shown in Table 2 on the right.

These simple automatic “gold” annotations produce false positives⁸, which explains why neither the reference nor the alternative reference (for named entities) achieves an F1-score of 100%. However, this approximate method is sufficient to expose the large gap between the reference translation, the beam search output, and the output with MBR decoding with surface-level metrics and with COMET. We perform a manual error analysis of all numbers that our evaluation script identifies as errors for the MBR decoded outputs. The false positive rate is similar for all three utility func-

tions: Around 3% of all numbers that occur either in the source or the translation are mistakenly identified as number mismatches. In contrast, the percentage of genuine errors increases: MBR bleu has a true negative rate of 4.4%, MBR chrF++ of 4.6%, MBR wmt20-comet-da of 7.2% and MBR wmt21-comet-mqm of 16.6% (computed jointly over de↔en). Thus, the wide gap caused with COMET as the utility function is due to genuine number mismatches, not paraphrasing.

Consequently, these results indicate that MBR decoding with the COMET metrics chooses more erroneous translations with respect to these criteria than with the two non-neural metrics or compared to beam search decoding. Interestingly, the wmt21-comet-mqm model performs considerably worse than the wmt20-comet-da model in this analysis. Oracle experiments where we choose the sample closest to the two references according to different metrics (see Appendix B) show smaller F1-score differences between both COMET models and the non-neural metrics but they still perform worse, particularly compared to chrF++.

It is worth noting that the beam search output has the highest F1-score of all tested decoding strategies. This suggests that mistranslations of numbers and named entities do not occur as frequently in beam search outputs and COMET’s insensitivity to numbers and named entities could therefore be less harmful when evaluating beam search outputs. However, Wang et al. (2021) recently showed that state-of-the-art research models and commercial NMT systems still struggle with numerical translations even when decoding with beam search. Such

⁷English: en_core_web_lg, German: de_core_news_lg

⁸For example, translating “3 pm” in the source to “15:00” is a valid translation, but would be counted as a mistake with the automatic number matching. Similarly, numbers translated as numerals are counted as errors, e.g. “15” and “fifteen”.

mistranslations may also occur more frequently in out-of-domain and low-resource settings and therefore, we argue that this insensitivity of COMET is not only harmful for sampling-based MBR decoding but also when evaluating beam search output.

This automatic evaluation has strengthened the findings in our manual exploration that wrong number and named entity translations are recurring problems. To better quantify how sensitive COMET models are toward these error types, we propose to perform an MBR-based sensitivity analysis in the next section.

6 MBR-Based Sensitivity Analysis

Our findings in the previous section stand in contrast to the corrupted reference analysis performed as part of the WMT 2021 metrics shared task (Freitag et al., 2021b) where COMET mostly preferred the correct alternative human translation to one with swapped numbers when comparing to the reference. In reality, we will seldom have a hypothesis pool with a perfect translation and variants of it that only differ in one aspect. Ideally, evaluation metrics should be able to order translation hypotheses with many different error types according to their severity. Therefore, it makes sense to compare how much metrics punish different error types.

Since our previous analysis showed that many samples with number and named entity mismatches are chosen in MBR decoding, this indicates that COMET is not as sensitive to these error types as to other errors. To further support this finding, we propose to look more closely at how COMET behaves with different error types. As described in Section 3, in MBR decoding, every candidate translation is assigned a score that represents the average similarity to the support hypotheses. Consequently, if the support is kept constant and a targeted change is made to a candidate translation, the difference in this MBR score indicates how sensitive the utility function was towards this change. We term this an “MBR-based sensitivity analysis”.

To measure COMET’s sensitivity towards changes in numbers and named entities, we create a candidate pool that consists of the reference translation and several changed variants. Note that the support still contains the same 100 samples that were used to find the MBR-decoded outputs described in Section 5. In particular, we make the following targeted changes to the reference to measure the sensitivity towards each change:

- **num_{add}**: one digit is added to a number at a random position.
- **num_{del}**: one digit is removed from a number at a random position.
- **num_{sub}**: one digit is substituted with another digit in a number at a random position.
- **num_{whole}**: one entire number is substituted with another number.
- **NE_{add}**: one letter is added to a named entity at a random position.
- **NE_{del}**: one letter is removed from a named entity at a random position.
- **NE_{sub}**: one letter is substituted with another letter in a named entity at a random position.
- **NE_{whole}**: a named entity is substituted with another named entity.

As reference points, we also apply the same types of changes to random nouns in the reference:

- **noun_{add}**: one letter is added to a random noun at a random position.
- **noun_{del}**: one letter is removed from a random noun at a random position.
- **noun_{sub}**: one letter is substituted with another letter in a random noun at a random position.
- **noun_{whole}**: a random noun is substituted with another noun.

Additionally, our candidate pool contains the following hypotheses to be used as controls:

- **alternative**: the second human reference provided as part of the WMT 2021 news shared task simulating an alternative translation.
- **copy**: the original, unchanged source sentence simulating a model that simply copied the source to the decoder side.
- **hallucination**: a sentence that is completely unrelated to the source and randomly picked from a larger corpus.

We use the same tools to identify numbers and named entities as in Section 5 to create these perturbations of the reference. For each newly created candidate, we compute the difference to the

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns	Samples	Ref.	
de-en	add	-0.047	-0.054	-0.255	-0.086	-0.101	-0.385	altern.	0.022	
	del	-0.048	-0.044	-0.214	-0.085	-0.079	-0.314	copy	-0.593	-0.472
	sub	-0.024	-0.056	-0.270	-0.041	-0.119	-0.410	hallucin.	-1.277	-1.907
	whole	-0.064	-0.122	-0.320	-0.111	-0.212	-0.496			
en-de	add	-0.024	-0.053	-0.160	-0.057	-0.108	-0.257	altern.	-0.014	
	del	-0.037	-0.044	-0.113	-0.063	-0.078	-0.215	copy	-1.449	-1.350
	sub	-0.011	-0.064	-0.180	-0.019	-0.113	-0.295	hallucin.	-1.560	-2.055
	whole	-0.040	-0.103	-0.347	-0.079	-0.173	-0.509			
average	-0.037	-0.068	-0.232	-0.068	-0.123	-0.360				

Table 3: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE) compared to the controls (alternative translation, copy of the source or hallucination). The numbers show the average difference to the MBR score for the reference (left) and 1-best beam search output (right) when using `wmt20-comet-da` as the utility function. Red means the sensitivity for random nouns is larger than for both numbers and named entities.

MBR score of the reference. We then average those differences across sentences for each perturbation type. The results for the sensitivity analysis with the `wmt20-comet-da` model can be seen in the left part of Table 3. We focus here on the `wmt20-comet-da` model since this is currently the model the authors recommend to use.⁹

The controls, i.e. alternative translation, copied sentence and hallucination, behave as expected. The MBR score difference to the hallucination is by far the largest, followed by the copied source. For the alternative reference, we see the smallest MBR score difference.¹⁰ More importantly, all targeted changes to *numbers* or *named entities* result in a much smaller difference in MBR score compared to changes to the *random nouns*. This shows that COMET is not as sensitive to such discrepancies as it should be since such mistranslations can drastically alter the meaning. Both BLEU and chrF++ are more sensitive to changes to numbers and named entities than to random nouns (see Appendix C).

Following our discussion of error sources at the beginning of Section 5, it is a valid concern that if we were to compare the candidates to high-quality support translations rather than samples, COMET may be more sensitive toward number and named

entity differences as there would be fewer other discrepancies between the candidates and the support. To test if this is the case, we repeat the sensitivity analysis but now use the two alternative references as the support instead of the 100 samples that were used before. The candidates are formed by applying the same perturbations as before to the 1-best beam search output instead of the reference. This mimics an oracle setup. The results for this experiment are shown in the middle of Table 3. Note that we cannot compare to an alternative translation for the beam search output in this setup.

The differences in the MBR score of the unperturbed beam search output are generally larger in this setup, which indicates that COMET is indeed more sensitive to errors when used as intended, i.e. with high-quality translations and correct references. However, we can still see that the perturbations made to random nouns result in much larger differences than perturbations made to numbers or named entities. This indicates that the problem cannot be attributed to the MBR decoding setting and low-quality pseudo-references alone.

7 COMET Retraining

One possible explanation for the low sensitivity of COMET to perturbations of numbers and named entities is that these errors are too rare in the WMT outputs used to train COMET. We decide to retrain COMET on the original training data plus added synthetic data on which we perform the same perturbations as described in Section 6. The idea is that the newly trained model is more sensitive to-

⁹<https://github.com/Unbabel/COMET/blob/master/METRICS.md>

¹⁰Note that this is due to averaging over sentences where the alternative sometimes gets a higher, sometimes a lower score. The average absolute difference is 0.111 which shows that the difference to the alternative of an individual sentence can be much larger.

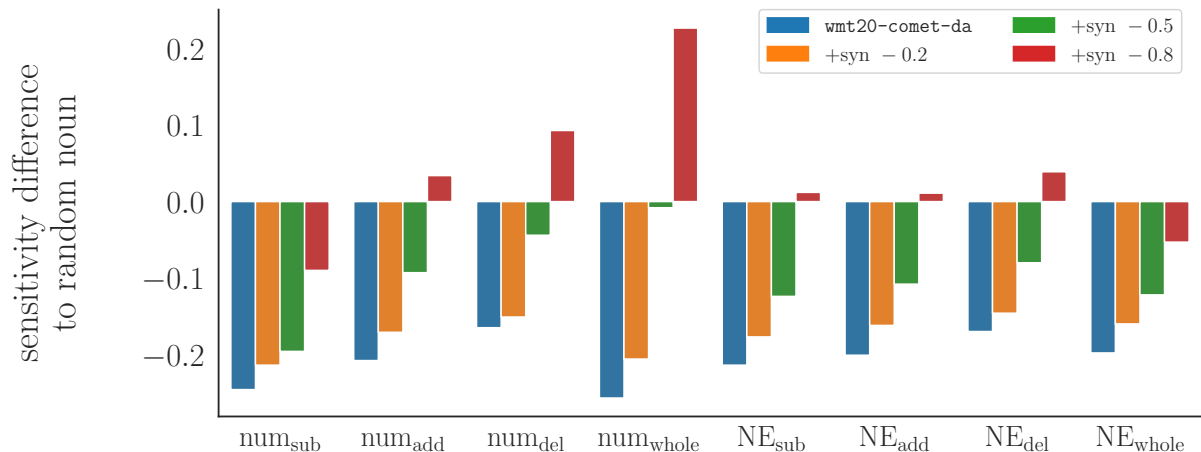


Figure 1: Difference in sensitivity to the same error type applied to a random noun for the de-en test set with samples as support. Comparing the original `wmt20-comet-da` to three retrained models, with different amounts subtracted from the original score for synthetic examples (-0.2, -0.5 and -0.8).

ward named entity or number mismatches between the translation and its reference and/or source.

To retrain the `wmt20-comet-da` model, we use the data from the WMT metrics shared tasks collected in the years 2017 to 2019 (Bojar et al., 2017; Ma et al., 2018, 2019) as training data. For every `de`→`en` or `en`→`de` system output that contains a number or a named entity, we randomly apply one of the perturbations described in Section 6 (except for the perturbations of random nouns and whole named entities). To encourage COMET to punish such synthetically inserted mismatches, we modify the scores of the original examples by subtracting a penalty from the z-score of the Direct Assessment (DA) score. We retrain three different models with penalties of -0.2, -0.5 and -0.8 respectively. Within every experiment, the penalty is the same for all error classes. The resulting $\sim 61k$ synthetic training examples are then added to the $\sim 640k$ original examples which means that roughly 10% of the data are synthetic.¹¹

We follow the hyperparameter suggestions in Rei et al. (2020b) for retraining COMET but we do not perform model averaging. The models are trained for two epochs and the hyperparameters are listed in Appendix A. We ensure that the retrained models still perform as well as the original model on the WMT 2020 metrics shared task (Mathur et al., 2020). The average difference in system-level Pearson correlation to the original COMET model lies within 0.006 for all three penalties. The full results can be found in Appendix F.

¹¹We also trained models with larger amounts of synthetic data but did not see an improvement (see Appendix E).

The effects of retraining with different penalties can be seen in Figure 1 (tables in Appendix D). Subtracting -0.2 from the original scores for synthetic examples can slightly reduce the difference between the MBR scores for numbers / named entities and random nouns with the same error types. Retraining with -0.5 subtracted from the original score improves this further but still cannot close this gap completely. With a penalty of -0.8, we now see a larger sensitivity to numbers and named entities than to random nouns for several error types. However, the difference to random nouns is still rather high for substituting a digit in numbers.

When repeating the automatic analysis from Section 5 with the penalty -0.8 model, we see that retraining does improve the F1-scores (see last row in Table 2). However, the retrained COMET model can still not beat non-neural utility functions which indicates that it is still less sensitive to mismatches in numbers and named entities.

From this experiment, we conclude that removing such blind spots from COMET - once identified - might need more effort than simply training on additional synthetic data. We hypothesise is that the XLM-R component learns very similar representations for numbers and rare words like named entities during pretraining which could be hard to reverse with finetuning only. Lin et al. (2020) show that pretrained language models are surprisingly bad at guessing the correct number from context (e.g. "A bird usually has [MASK] legs.") which supports this hypothesis. Several other works also find that task-specific models often struggle with numbers and named entities such as in summar-

sation (Zhao et al., 2020) or question answering (Dua et al., 2019; Kim et al., 2021). We leave a more extensive analysis of biases in the human evaluation training data (e.g. unpunished number mismatches) and further experiments on weakness-targeted training for future work.

8 Conclusion

Identifying weaknesses of neural machine translation evaluation metrics becomes more important as these essentially “black box” evaluation tools become more popular and are optimised towards during model development. We show that MBR decoding can be used to explore biases of such metrics. Through a case study, we show that COMET is relatively insensitive to mistranslated numbers and named entities. This can be seen both in the MBR-decoded output which contains a higher number of these errors compared to beam search (or MBR with other utility functions) and in an MBR-based sensitivity analysis which compares the differences in MBR scores that arise when such errors are introduced to a candidate translation. We also show that this insensitivity is not simply the result of insufficient training data containing such errors: retraining COMET with additional synthetic data did not fully alleviate this weakness.

While errors related to number and named entity translation were very salient in our exploration, we do not claim that this case study is exhaustive. In our manual analysis, we also see anecdotal evidence of polarity errors and nonsensical German compounds. We hope our findings motivate further research into identifying and mitigating biases of neural machine translation metrics – we envision that actively searching for biases in neural metrics, for example by using them as utility functions in MBR, could become an important step during metric development.

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for Science IT team at the University of Zurich.

Ethical Considerations

In our work, we only use publicly available toolkits and datasets and do not collect any additional data. Our experiments also do not involve human annotators (other than ourselves). The main contribution of our paper is a new approach for identifying weaknesses in neural machine translation evaluation metrics using MBR decoding. We believe this approach is largely beneficial to the research community as a tool to investigate “blind spots” of metrics and we do not see any immediate risks.

Limitations

We limited our analysis in this work to the en \leftrightarrow de translation directions and one machine translation evaluation metric, namely COMET. Consequently, we cannot draw any conclusions on whether the identified weaknesses are specific to COMET or also apply to other neural machine translation evaluation metrics and language pairs. We leave such exploration for future work. While our approach for identifying weaknesses in evaluation metrics is readily applicable to other surface-level or neural metrics, the runtime for MBR decoding can explode if the similarity computation cannot be parallelised or the size of the sample pool is increased. However, since our proposed approach is a tool for metric analysis and is not intended to be run regularly, we believe an increased runtime is not obstructive.

Another limitation is that we do not use a state-of-the-art machine translation model (in terms of data size) to generate the samples for our metric analysis. This does, however, not limit our findings that COMET is not as sensitive to number and named entity differences as it should be. Even if machine translation models may produce fewer mistakes of this nature in the future, eliminating such weaknesses remains relevant, for example, if COMET is used for Minimum Risk Training.

Finally, while our experiments indicate that weaknesses related to number and named entity changes cannot easily be eliminated by retraining on synthetic data, alternative strategies to create or retrain on synthetic data may be more successful.

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A Hyperparameters for COMET Retraining

We list all hyperparameters used for training the `retrain-comet-da` models with different penalties in Tables 4. Each model was trained on 1 NVIDIA Tesla V100 GPU.

Hyperparameter	Value
<code>nr_frozen_epochs</code>	1
<code>keep_embeddings_frozen</code>	True
<code>optimizer</code>	Adam
<code>encoder_learning_rate</code>	1.0e-05
<code>learning_rate</code>	3.0e-05
<code>layerwise_decay</code>	0.95
<code>encoder_model</code>	XLM-RoBERTa
<code>pretrained_model</code>	xlm-roberta-large
<code>pool</code>	avg
<code>layer</code>	mix
<code>dropout</code>	0.1
<code>batch_size</code>	2
<code>accumulate_grad_batches</code>	8
<code>hidden_sizes</code>	3072, 1536
<code>load_weights_from_checkpoint</code>	null
<code>min_epochs</code>	2
<code>max_epochs</code>	2

Table 4: Hyperparameters used to retrain `wmt20-comet-da`.

B Oracle Results for Automatic Analysis

In MBR, we use machine translation metrics in an unintended way since we compare translation hypotheses against other hypotheses rather than a reference translation. To check if the results for the COMET models in our automatic analysis stem from this train-test mismatch, we also run an oracle experiment. Rather than comparing all samples against each other with MBR, we choose the sample that is most similar to the human reference translations. The results can be seen in Table 5. Most error rates are better in the oracle setup compared to the MBR setup. Especially, the error rates for the COMET models are now closer to the non-neural metrics. However, the gap to chrF++ is still rather large, especially for named entities.

C MBR-based Sensitivity Analysis for BLEU and chrF++

The MBR-based sensitivity analysis can also be used to compare COMET to non-neural metrics. The results when using BLEU or chrF++ as the utility function can be seen in Table 6 and Table 7 re-

spectively. We can see that with BLEU the changes made to random nouns result in smaller MBR differences than changes to numbers or named entities. For chrF++, the changes to random nouns result in smaller MBR differences than changes to named entities but slightly larger differences than changes to numbers. The cause for this may be that numbers are often shorter than named entities or nouns and a change will affect fewer n-grams. For random nouns, there may be many possible alternative translations in the samples and the references. If the random noun does not occur in the sentence we compare to, making a change to it will not affect the BLEU score and only partially the chrF++ score which can explain these results.

D Retraining with Different Penalties

Tables 8, 9, 10 show the results of the sensitivity analysis for the retrained models with penalties of -0.2, -0.5 and -0.8 respectively. The difference between the sensitivity scores for numbers / named entities and for random nouns becomes smaller as the penalty increases. With a penalty of -0.8, we see that for most error types the sensitivity scores for random nouns are either lower than either (blue) or both (green) for numbers and named entities. Note that the differences in MBR score compared to the reference (left) and the 1-best beam search output (right) also become larger as the penalties increase. However, this does not affect on the models' ability to score real translations as we confirm in Section F.

E Retraining with Different Amounts of Synthetic Data

Aside from varying the penalties for retraining COMET (see Appendix D), we can also vary the amount of synthetic data. Using the best performing penalty from before (0.8), we run experiments with 0%, 10%, 25%, 40%, 55%, 70%, 85% and 100% synthetic data for retraining COMET. Note that 0% corresponds to the original `wmt20-comet-da` model and 10% corresponds to `retrain-comet-da` in the main paper experiments. We evaluate these models based on two factors: 1) the average difference in sensitivity between the number and named entity error types and the random nouns (corresponding to an average over the individual columns in Figure 1) and 2) the change in Pearson correlation compared to `wmt20-comet-da`. The first measure indicates

	Numbers				Named Entities			
	de-en		en-de		de-en		en-de	
reference	93.24		93.46		n/a		n/a	
alternative	94.83	+ 1.59	95.66	+ 2.20	73.73		77.66	
beam search	95.91	+ 2.67	95.73	+ 2.27	71.55	- 2.18	70.03	- 7.63
Oracle chrF++	91.91	- 1.33	93.64	+ 0.18	69.54	- 4.19	63.59	-14.07
Oracle bleu	90.77	- 2.47	92.05	- 1.41	65.73	- 8.00	60.16	-17.50
Oracle <small>wmt20-comet-da</small>	90.83	- 2.41	88.79	- 4.67	65.64	- 8.09	56.41	-21.25
Oracle <small>wmt21-comet-mqm</small>	91.35	- 1.89	86.01	- 7.45	64.75	- 8.98	55.98	-21.68

Table 5: Results of the automatic evaluation. “Oracle” means choosing the sample closest to the two reference translations. F1-scores (%) for numbers and named entities and F1-score changes compared to the reference for numbers and alternative translation for named entities.

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns	Samples	Ref.	
de-en	add	-1.80	-1.80	-1.20	-4.92	-5.62	-4.41	altern.	1.11	
	del	-1.70	-1.79	-1.20	-4.84	-5.62	-4.41	copy	-5.87	-21.43
	sub	-1.78	-1.84	-1.19	-5.10	-5.78	-4.44	hallucin.	-6.71	-22.75
	whole	-1.80	-2.28	-1.25	-4.92	-6.64	-4.46			
en-de	add	-1.62	-1.41	-0.88	-4.10	-3.56	-2.73	altern.	-0.33	
	del	-1.65	-1.37	-0.88	-4.24	-3.58	-2.73	copy	-6.02	-20.06
	sub	-1.57	-1.41	-0.86	-4.09	-3.71	-2.75	hallucin.	-6.71	-21.14
	whole	-1.62	-1.72	-0.90	-4.10	-4.41	-2.79			
average		-1.69	-1.70	-1.05	-4.54	-4.87	-3.59			

Table 6: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE). Average difference to MBR score for reference (left) and 1-best beam search output (right) when using BLEU as the utility function. Green means both numbers and named entities have higher sensitivity than random nouns.

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns	Samples	Ref.	
de-en	add	-1.18	-1.66	-1.20	-2.18	-2.91	-2.55	altern.	0.32	
	del	-1.52	-1.99	-1.41	-2.53	-3.30	-2.94	copy	-17.18	-32.94
	sub	-1.54	-2.00	-1.47	-2.74	-3.53	-3.07	hallucin.	-22.82	-43.39
	whole	-1.91	-4.85	-2.50	-3.25	-8.57	-5.27			
en-de	add	-0.88	-1.25	-0.80	-2.28	-2.04	-1.52	altern.	-0.73	
	del	-1.10	-1.47	-0.94	-1.89	-2.37	-1.78	copy	-19.13	-32.68
	sub	-1.08	-1.51	-0.96	-1.87	-2.44	-1.81	hallucin.	-24.96	-42.11
	whole	-1.33	-3.72	-1.98	-2.28	-5.81	-3.68			
average		-1.32	-2.31	-1.41	-2.38	-3.87	-2.83			

Table 7: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE). Average difference to MBR score for reference (left) and 1-best beam search output (right) when using chrF++ as the utility function. chrF++ scores are mapped to 0-100 scale for better comparison to BLEU. Green means both numbers and named entities have higher sensitivity than random nouns, blue means at least one is higher than random nouns.

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns	Samples	Ref.	
de-en	add	-0.059	-0.067	-0.230	-0.116	-0.135	-0.386	altern.	0.021	
	del	-0.048	-0.053	-0.199	-0.092	-0.105	-0.326	copy	-0.778	-0.690
	sub	-0.028	-0.065	-0.242	-0.054	-0.146	-0.403	hallucin.	-1.081	-1.720
	whole	-0.082	-0.127	-0.287	-0.151	-0.250	-0.493			
en-de	add	-0.040	-0.044	-0.153	-0.083	-0.107	-0.260	altern.	-0.015	
	del	-0.046	-0.038	-0.117	-0.080	-0.083	-0.211	copy	-1.513	-1.625
	sub	-0.015	-0.051	-0.169	-0.034	-0.111	-0.277	hallucin.	-1.402	-1.891
	whole	-0.055	-0.106	-0.353	-0.109	-0.197	-0.541			
average	-0.047	-0.069	-0.219	-0.090	-0.108	-0.362				

Table 8: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE) compared to the controls (alternative translation, copy of the source or hallucination). The numbers show the average difference to the MBR score for the reference (left) and 1-best beam search output (right) when using `retrain-comet-da` with a **penalty of -0.2** as the utility function. Red means the sensitivity for random nouns is larger than for both numbers and named entities.

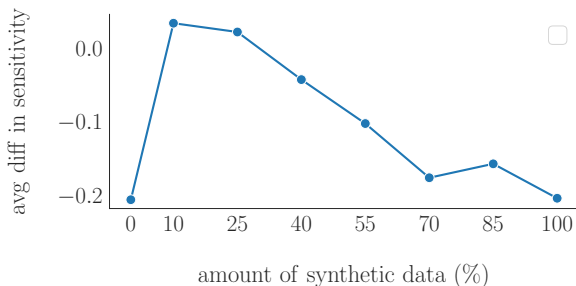


Figure 2: The average difference in sensitivity between the noun/named entity error categories and their corresponding random noun error categories. The x-axis shows how the difference changes as the amount of synthetic data is increased.

how the retrained models’ sensitivity to numbers and named entities changes compared to random nouns with increased synthetic data. The second measure shows whether an increased amount of synthetic data reduces the agreement with human judgements (this is computed as described in Appendix F).

Figure 2 shows that with an increased percentage of synthetic data, the difference between sensitivity towards nouns and named entities and towards random noun changes first becomes smaller (at 10% synthetic). When we further increase the amount of synthetic data, this improvement gradually decreases as the model sees less and less contrasting examples and more and more only examples with number mismatches.

Increasing the amount of synthetic data during retraining also has an effect on the correlation with

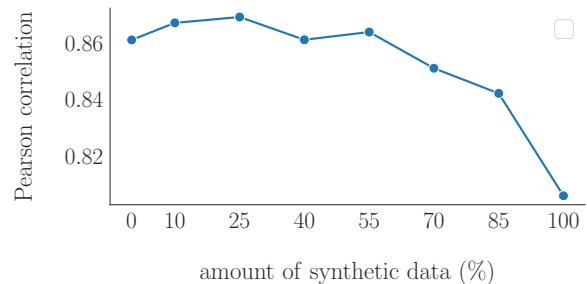


Figure 3: The correlation with human judgements evaluated as described in Appendix F. The x-axis shows how the correlation changes as the amount of synthetic data is increased.

human judgements. We show this in Figure 3. Similarly to the difference in sensitivity, the correlation with human judgements also improves with small amounts of synthetic data (10% and 25%) but then decreases slowly as the amount of synthetic data is increased further. These additional experiments show that using 10% of synthetic data is a sensible choice for our main experiments.

F Correlation with Human Evaluators

We use our retrained `retrain-comet-da` models to score all systems that are part of the WMT 2020 metrics shared task evaluation (Mathur et al., 2020).¹² Then, we use the official evaluation script¹³ from the WMT 2020 shared task to com-

¹²We run the `run_ref_metrics.sh` script provided at https://drive.google.com/drive/folders/1n_alr6WFQZfw4dcAmyxow4V8FC67XD8p

¹³<https://github.com/WMT-Metrics-task/wmt20-metrics>

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns	Samples	Ref.	
de-en	add	-0.243	-0.229	-0.337	-0.417	-0.382	-0.523	altern.	0.026	
	del	-0.217	-0.180	-0.261	-0.380	-0.295	-0.410	copy	-0.471	-0.409
	sub	-0.152	-0.223	-0.347	-0.256	-0.402	-0.542	hallucin.	-1.076	-1.724
	whole	-0.312	-0.197	-0.320	-0.529	-0.374	-0.521			
en-de	add	-0.224	-0.210	-0.231	-0.405	-0.379	-0.379	altern.	-0.017	
	del	-0.197	-0.156	-0.148	-0.319	-0.261	-0.262	copy	-1.142	-1.133
	sub	-0.129	-0.196	-0.250	-0.213	-0.352	-0.392	hallucin.	-1.370	-1.895
	whole	-0.275	-0.196	-0.339	-0.493	-0.351	-0.516			
average	-0.219	-0.198	-0.279	-0.377	-0.350	-0.511				

Table 9: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE) compared to the controls (alternative translation, copy of the source or hallucination). The numbers show the average difference to the MBR score for the reference (left) and 1-best beam search output (right) when using `retrain-comet-da` with a **penalty of -0.5** as the utility function. Red means the sensitivity for random nouns is larger than for both numbers and named entities, blue means at least one is higher than random nouns and green means both numbers and named entities have higher sensitivity than random nouns.

pute the system-level Pearson correlation for our retrained models. The results can be seen in Table 11. We also ensure that evaluation setup results in the same scores as in the WMT 2020 publication (Mathur et al., 2020) when we use `wmt20-comet-da` to score the systems. For most language pairs, all models reach an almost identical correlation with human assessments.

		Samples as Support			References as Support			Controls		
		Numbers	NEs	Nouns	Numbers	NEs	Nouns		Samples	Ref.
de-en	add	-0.435	-0.412	-0.401	-0.706	-0.687	-0.617	altern.	0.024	
	del	-0.385	-0.331	-0.293	-0.655	-0.526	-0.450	copy	-0.306	-0.234
	sub	-0.305	-0.547	-0.394	-0.472	-0.667	-0.614	hallucin.	-1.225	-1.962
	whole	-0.547	-0.267	-0.320	-0.889	-0.495	-0.539			
en-de	add	-0.381	-0.337	-0.337	-0.657	-0.635	-0.575	altern.	-0.015	
	del	-0.355	-0.254	-0.230	-0.614	-0.457	-0.402	copy	-0.852	-0.755
	sub	-0.264	-0.322	-0.351	-0.437	-0.585	-0.570	hallucin.	-1.498	-2.046
	whole	-0.470	-0.271	-0.370	-0.827	-0.484	-0.550			
average	-0.393	-0.343	-0.337	-0.657	-0.567	-0.540				

Table 10: Effects of randomly adding, substituting or deleting a digit in a number or a letter in a noun or named entity (NE) compared to the controls (alternative translation, copy of the source or hallucination). The numbers show the average difference to the MBR score for the reference (left) and 1-best beam search output (right) when using `retrain-comet-da` with a **penalty of -0.8** as the utility function. Red means the sensitivity for random nouns is larger than for both numbers and named entities, blue means at least one is higher than random nouns and green means both numbers and named entities have higher sensitivity than random nouns.

		<u>wmt20-comet-da</u>	<u>retrain-comet-da</u>		
			-0.2	-0.5	-0.8
en-cs	0.978	0.981	0.981	0.981	
en-de	0.972	0.971	0.965	0.963	
en-ja	0.974	0.987	0.974	0.982	
en-pl	0.981	0.983	0.985	0.983	
en-ru	0.925	0.863	0.900	0.918	
en-ta	0.944	0.948	0.949	0.954	
en-zh	0.007	0.026	0.034	0.049	
en-iu	0.860	0.861	0.851	0.873	
cs-en	0.783	0.799	0.798	0.808	
de-en	0.998	0.996	0.995	0.997	
ja-en	0.964	0.966	0.968	0.968	
pl-en	0.591	0.570	0.570	0.563	
ru-en	0.923	0.924	0.921	0.925	
ta-en	0.880	0.888	0.887	0.890	
zh-en	0.952	0.952	0.942	0.951	
iu-en	0.852	0.878	0.866	0.880	
km-en	0.971	0.981	0.981	0.974	
ps-en	0.941	0.951	0.949	0.945	
avg diff		+0.0016	-0.0006	+0.0060	

Table 11: Pearson correlation of to-and-from-English system-level COMET scores with DA human assessments. Last row shows the average difference to the original `wmt20-comet-da` model. Results with `wmt20-comet-da` corresponding to “COMET” in Tables 5 and 6 in Mathur et al. (2020).