Minimum Bayes Risk Decoding with Neural Metrics of Translation Quality

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Abstract

This work applies Minimum Bayes Risk (MBR) decoding to optimize diverse automated metrics of translation quality. Automatic metrics in machine translation have made tremendous progress recently. In particular, neural metrics, fine-tuned on human ratings (e.g. BLEURT, or COMET) are outperforming surface metrics in terms of correlations to human judgments. Our experiments show that the combination of a neural translation model with a neural reference-based metric, BLEURT, results in significant improvement in automatic and human evaluations. This improvement is obtained with translations different from classical beam-search output: these translations have much lower likelihood and are less favored by surface metrics like BLEU.

1 Introduction

Neural sequence-to-sequence models constitute the state-of-the-art for machine translation. These models estimate the probability of a target sentence given a source sentence. At inference, it is commonplace to approximate the maximum-a-posteriori (MAP) hypothesis with beam search in order to output a sentence with (close to) the highest probability given the provided source.

This strategy assumes that the sentences with the highest estimated probabilities should also be the translations with the highest quality as measured by humans. This assumption can be questioned based on two observations: (i) Neural Machine Translations (NMTs) generated by beam search are ranked below human translations in professional evaluations (Freitag et al., 2021a) while (ii) the NMT model itself considers human translations much less likely than its beam outputs (Ott et al., 2018). These observations clearly show that estimated probability and translation quality do not always correlate. An example is given in Table 1 where beam search generates a translation using mostly frequent words which results in inaccuracies. The two correct human translations contain infrequent words and phrases with low estimated probabilities based on the model.

These observations do not in themselves suggest an alternative to likelihood in selecting better hypotheses. For that, we look at recent progress in automated evaluation. Recently introduced utility metrics, such as BLEURT (Sellam et al., 2020a) or COMET (Rei et al., 2020), estimate human judgements \( u(h, r) \) from a candidate translation \( h \) and a reference human translation \( r \) with a neural network. These learned metrics have shown higher correlation with human judgments compared to traditional metrics based on lexical overlap such as BLEU (Papineni et al., 2002) and METEOR (Banerjee and Lavie, 2005). BLEURT and COMET have also been shown by the WMT metric task Freitag et al. (2021b) to perform better than YiSi (Lo, 2020) which measures overlap in a neural embedding space. BLEURT and COMET are able to evaluate hypotheses with different word choices, sentence structures and lengths compared to the reference translations. Unlike overlap-based metrics like BLEU, these metrics do not necessarily prefer the most likely tokens to increase the chance of covering n-grams in the reference translations (Freitag et al., 2020). When comparing a model output \( h \) and an alternative human reference \( r' \), BLEU and BLEURT behave differently. While BLEU often estimates the quality of the model output \( h \) to be much higher than the alternative human translation \( r' \) (BLEU(h, r) > BLEU(r', r)), BLEURT and COMET typically prefer the human translation over the MT output (BLEURT(h, r) < BLEURT(r', r)). This behavior generally agrees with professional raters (Toral, 2020).

These observations suggest selecting model hypotheses likely to have a high quality score with
| system     | translations                                      | logP |
|------------|--------------------------------------------------|------|
| source     | Der Ausbruch sei „mit Ansage“ gekommen.           | -2.82|
| MAP/ beam  | The outbreak came "with announcement".           | -2.82|
| human-A    | The outbreak occurred “predictably”.             | -18.1|
| human-B    | The outbreak happened “on cue.”                  | -18.74|

Table 1: Example of De→En translations generated by NMT or humans. Human translations get a low model estimated probability (logP) as they do not generate the most frequent and direct translation.

respect to learned neural utility metrics should bring the quality of MT output closer to that of human translations. For that, we rely on Minimum Bayes Risk (MBR) decoding (Kumar, 2004). MBR starts with a set of sampled hypotheses from an MT model and finds the candidate which has the highest average utility when each hypothesis in the set is used as a pseudo-reference.

This MBR strategy has several potential pitfalls. First, the expectation of utility under the model distribution is used as a proxy to the expectation under the true underlying (human translator) distribution. This means that a high divergence between these two distributions will affect MBR (Pitfall 1: model quality). Second, the utility metric might be unreliable in areas of the space where it has not been evaluated (e.g., with low quality, low probability pseudo-references). This might cause its expectation to be very different from single point evaluations with high quality human references (Pitfall 2: utility validity over the reference space). Third, even if MBR discovers hypotheses with high utility with respect to actual human references, there is no guarantee that these hypotheses will receive high human judgments since these hypotheses are not necessarily close to the conditions for which the utility metrics have been designed (Pitfall 3: utility validity over the hypothesis space).

This paper evaluates MBR decoding for multiple utility functions and measures whether their predictions indeed improve the actual utility with respect to human references. We show that an NMT model based on the transformer-big architecture and BLEU, CHRF, YISI, and BLEURT successfully avoid Pitfall 1 and 2. We also study the robustness of these conclusions with respect to the number of considered samples and model size. We then conduct a human evaluation of MBR hypotheses with high estimated utility according to different metrics to assess Pitfall 3. We show that MBR decoding using BLEU as a utility metric slightly improves over beam search decoding, even though the difference between these two translations are minor. In contrast, MBR using BLEURT as a utility metric generates translations further away from beam output. These translations are given significantly higher human quality ratings compared to beam search and the other MBR hypotheses.

Our contributions can be summarized as follows:

- We are the first to use neural metrics – YISI and BLEURT – as utility functions during MBR decoding.
- We run a human evaluation with professional translators to assess the quality of MBR decode using different utilities.
- We show that MBR using BLEURT outperforms beam search decoding according to human judgments from experts.
- We further demonstrate that MBR decoding with BLEURT results in less likely translations which are lexically different from both beam output and MBR output relying on overlap-based utilities.

2 Related Work

Minimum Bayes Risk decoding (Berger, 1985) was first introduced for speech recognition to replace MAP inference with a process to provide a prediction likely to minimize the edit distance (word/phone error rate) with unobserved labels (Kumar and Byrne, 2004). The same idea was later applied to bilingual word alignment (Kumar and Byrne, 2002) and machine translation (Kumar and Byrne, 2004). MBR was used to maximize overlap metrics such as BLEU (Papineni et al., 2002) with statistical MT systems (Kumar and Byrne, 2004; Smith and Eisner, 2006; Tromble et al., 2008). After the advent of neural machine translation (Sutskever et al., 2014), most methods re-
lied on beam search to approximate MAP decoding (Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017). The question of optimizing utility metrics of interest such as BLEU was also explored. Approaches based on structured risk minimization (Edunov et al., 2018) or reinforcement learning (Bahdanau et al., 2017; Leblond et al., 2021) considered modifying the training procedure. Alternatively, MBR was also considered for inference (Eikema and Aziz, 2020; Müller and Sennrich, 2021; Eikema and Aziz, 2021).

The application of MBR to neural MT has focused on maximizing classical metrics, either overlap-based (BLEU, METEOR or CHRF) or linear combinations of these such as BEER (Stanojević and Sima’an, 2014). Our work builds upon recent advances in the automatic evaluation of MT (Mathur et al., 2020) which has shown the emergence of learned utility metrics based on neural networks. We consider using neural metrics for MBR, which has not been done before. These metrics are neural networks which consider a pair of sentences (a hypothesis and a reference) or a triplet of sentences (a source, a hypothesis and a reference) and output a real-valued score estimating the quality of the hypothesis. They rely on pre-trained monolingual or multilingual neural language models. The first generation of neural utility metrics uses neural models to extract pre-trained sentence and word representations to compute distances indicative of semantic proximity, e.g., BERTSCORE and YSi (Zhang* et al., 2020; Lo, 2019). Later, a second generation of neural utilities proposed to fine-tune neural models on human judgements, either through regression or ranking tasks. These approaches, such as BLEURT and COMET (Sellam et al., 2020a; Rei et al., 2020), have shown better correlation with human judgments (Mathur et al., 2020).

3 Method

3.1 Minimum Bayes Risk Decoding

MBR relies on two essential components: a machine translation model and a utility metric. The translation model $P_{\text{model}}(y|x)$ estimates the probability of any target segment $y$ given a source segment $x$. The utility metric $u(h, r)$ estimates quality of a candidate translation $h$ given a reference translation $r$.

Given a set of hypotheses $\mathcal{H}$, we would like to select the best hypothesis according to its expected utility with respect to the distribution over human references in the space of all sequences $\Omega$, i.e.

$$h^{\text{best}} = \arg \max_{h \in \mathcal{H}} \mathbb{E}_{r \sim P_{\text{human}}(\cdot|\cdot)} \left\{ u(h, r) \right\}$$

$$= \arg \max_{h \in \mathcal{H}} \sum_{r \in \Omega} u(h, r) P_{\text{human}}(r|x).$$

Since $P_{\text{human}}(r|x)$ is unknown, we need to rely on the model estimate instead, i.e.

$$h^{\text{model}} = \arg \max_{h \in \mathcal{H}} \sum_{y \in \Omega} u(h, y) P_{\text{model}}(y|x) \quad (2)$$

This substitution assumes that the model provides a good approximation for the true underlying (human translation) distribution. As integrating over $\Omega$, the space of all sequences, is intractable, MBR relies on a finite sample estimate by sampling a set of pseudo references $\mathcal{H}_{\text{model}}$ from $P_{\text{model}}(\cdot|x)$. This yields,

$$h^{\text{MBR}} = \arg \max_{h \in \mathcal{H}} \frac{1}{|\mathcal{H}_{\text{model}}|} \sum_{y \in \mathcal{H}_{\text{model}}} u(h, y). \quad (3)$$

Commonly, one relies on the same set of model hypotheses for $\mathcal{H}$ (candidate pool) and $\mathcal{H}_{\text{model}}$ (pseudo-references), i.e. $\mathcal{H} = \mathcal{H}_{\text{model}}$. In that case, growing $\mathcal{H}_{\text{model}}$ has two beneficial effects: a larger set provides a better approximation of the expected utility (reducing finite sample variance) while the maximum over a finite candidate pool obviously increases as the candidate pool grows.

Growing $\mathcal{H}_{\text{model}}$ is however computationally costly, both to obtain hypotheses and to evaluate their cross-utility. Hypotheses are sampled through ancestral sampling (Robert et al., 2004) from a neural machine translation model, and the cost of sampling is linear in the size of the set. Cross-utility can involve evaluating a large neural network as well and the cost of utility computation is generally quadratic in the size of the set.

3.2 Utility Metrics

The automatic evaluation of machine translation is an active area of research (Mathur et al., 2020; Freitag et al., 2021b). MBR decoding centrally relies on a reference-based utility metric: its goal is to identify a hypothesis with a high estimated utility (expectation under model distribution) with the hope that a high estimated utility translates into a high actual utility (with respect to a human reference), which itself should translate to a high human quality judgment. We experiment with utilities from different families of metrics:
Lexical Overlap: BLEU

BLEU (Papineni et al., 2002) measures lexical overlap as the geometric mean of the precision of \( n \)-gram matches with \( n \leq 4 \) on the corpus level and adds a brevity penalty to penalize low recall hypotheses. As MBR decoding requires segment-level scores, we use add-one smoothed sentence-level BLEU (sBLEU) (Lin and Och, 2004) during MBR decoding as an approximation. We use SacreBLEU (Post, 2018) for reporting corpus-level BLEU scores\(^1\).

Lexical Overlap: CHRF

We use CHRF (Popović, 2015) as an additional lexical overlap metric. CHRF uses character \( n \)-grams instead of word \( n \)-grams to compare the MT output with the reference. For CHRF we use the SacreBLEU sentence_chrf function (with default arguments\(^2\)).

Embedding-based Overlap: YISI

We also evaluate MBR decoding with neural utilities which has not been done before. We rely on Yisi-1-BERT (Lo, 2020) to represent first generation neural metrics, i.e., metrics focusing on embedding-based overlap and not fine-tuned on human judgements. This metric relies on BERT (Devlin et al., 2019) to compute in-context word embeddings and then perform bi-directional alignments of \( n \)-gram matches in the embedding space to compute an F-score. For our experiments, we rely on base-cased BERT for English language evaluation and the multilingual model MBERT for other languages. We use our in-house reimplementation of YiSi.

Neural, fine-tuned: BLEURT

We rely on BLEURT to represent second generation neural metrics, i.e., metrics not focusing on overlap but fine-tuned on human judgments instead. BLEURT is a regression model and relies on a learned embedding of the concatenation of the hypothesis and the reference translation. One of the strengths of BLEURT is that it can evaluate translations of different sentence structure, wording and length in an unbiased fashion, as it is not focusing on any kind of overlap. This was one of our main motivations to revisit MBR decoding with neural metrics. We conducted experiments on two versions of BLEURT.

- **BLEURT v0.1**

BLEURT v0.1 is a cased version of BLEURT (Sellam et al., 2020b) that is based on RemBERT (Chung et al., 2020). The model was pre-trained on more than 110 languages, and jointly fine-tuned on 13 target languages using the z-normalized WMT human evaluation data from 2015-2018.

- **BLEURT v0.2**

BLEURT v0.2 is a joint model for all language pairs that is based on RemBERT. In addition to the fine-tuning data used for BLEURT v0.1, it also uses the WMT human evaluation data from 2019 and synthetic examples which consists for identities, alternative references, and random sentence pairs. Motivation for the latter was improved performance on very bad translations, a scenario frequently observed when scoring a candidate list during MBR decoding. Furthermore, BLEURT v0.2 is trained on the raw WMT data (on a 0-100 scale) instead of the z-normalized data. This change encourages better transfer learning between the language pairs and the human ratings of different years as the raw scores represent an absolute quality signal. Z-normalized scores on the other hand are usually normalized per year and language pair and highly depend on the quality of the other systems in this year’s evaluation. Z-scores are not directly comparable between years and language pairs which makes transfer learning quite difficult. As a consequence, the metric is (softly) bound to a range of \([0, 100]\).

4 Experimental Setup

4.1 Data and Model

We run experiments on two language pairs: English→German (En→De) and the reverse direction German→English (De→En) with models trained on WMT training data (Barrault et al., 2019). We use news-commentary-v15, paracrawl-v5.1, europarl-v10 and commoncrawl as training corpora with ~57 million training examples after filtering out noisy data with contrastive data selection as proposed by Wang et al. (2018). We also remove sentences longer than 250 tokens and sentence pairs with a source/target ratio exceeding 1.5.
We use newstest2019 as our dev set to pick checkpoints and newstest2021 (Barrault et al., 2021) as our test set. For newstest2021, we have two reference translations (Ref-C and Ref-D for En→De and Ref-A and Ref-B for De→En).

4.2 Model

We use the transformer implementation in lingvo (Shen et al., 2019), using a model similar to the transformer-big setting (Vaswani et al., 2017). The model has 6 encoder and 6 decoder layers, model dimension size of 1,024, hidden dimension size of 8,192, and the number of multi-attention heads is 16. Our models use a vocabulary of 32k subword units (Kudo and Richardson, 2018). We train the models until convergences for around 300,000 updates with a batch size of 43,000. These are trained without label smoothing to produce more reliable probability estimates. This slightly drops accuracy by 0.5 BLEU points on both language pairs when compared to a model using label smoothing. We run beam search with beam size of 4 and length penalty as described in Equation 10 in Wu et al. (2016) using $\alpha=0.5$. We do not use coverage penalty as this does not improve the results. For MBR decoding, we generate 1,000 samples via ancestral sampling for each source sentence.

4.3 Human Evaluation

We run two different human evaluations in this paper. For our main results, we run a human evaluation based on the Multidimensional Quality Metrics (MQM) methodology (Uszkoreit and Lommel, 2013) with professional translators. Freitag et al. (2021a) showed that this human evaluation is more reliable than typical scalar-value evaluation using crowd-workers. For ablation studies, we use a scalar-value human evaluation with professional translators similar to what is typically implemented in WMT as this human evaluation setup is cheaper and less time consuming.

4.3.1 MQM

We hired 9 professional translators (4 for En→De and 5 for De→En) and measure translation quality with an document context version of MQM (Lommel et al., 2014) which mimics the setup proposed in Freitag et al. (2021a). This includes using the same error categories, severity levels and error weighting schema. 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. The final segment-level score is an average over scores from all annotators. We refer the reader to Freitag et al. (2021a) for the details on error categories and annotator instructions.

4.3.2 pSQM

In some of our ablation experiments, we conduct a human evaluation via profesiosnal Scalar Quality Metric (Freitag et al., 2021a). This evaluation presents each source and translated segment from a document in a table row, asking professional translators to pick a rating from 0 through 6. The rater can scroll up or down to see all the other source/translation segments from the document. The final score for each of the systems is an average over their segment-level scores. We run pSQM evaluations in our ablation studies for En→De with 3 professional translators.

5 Experimental Results

In this section, we discuss the main results of our study. First, we look into the automatic scores to investigate if MBR results in higher actual utility scores when estimating the expectation of the same utility. Second, we look into the human evaluation results to investigate how well the improvements in utility scores can transfer to human judgements.

5.1 Automatic Evaluation

MBR decoding chooses the translations with the highest estimated utility in a candidate list with the hope that this translation also gets a high actual utility score with respect to a human reference. We run MBR decoding with the utilities sBLEU, CHRF, YISI, BLEURT v0.1 and BLEURT v0.2. We verify whether our NMT model is accurate enough for its candidate list to serve as a proxy for the human distribution. Experimental results with a 1,000 candidate list generated by ancestral sampling are summarized in Table 2 and Table 3. For all utilities, the hypotheses with the highest estimated utility can generate a higher actual utility (bold, underlined numbers) when compared to the beam search output. This shows that the expectation of utility under the model distribution is a good proxy for the actual utility with respect to a human translation.

Interestingly, MBR with overlap-based metrics (sBLEU, CHRF, YISI) prefers high log likelihood
Table 2: Actual utility, log-likelihood (logP) and MQM score for different MBR methods and beam search on newstest2021 En→De computed with human reference Ref-C. All MQM results labelled with † are significantly better than beam search based on PERM-BOTH significance testing (Deutsch et al., 2021) with p=0.001.

| Method   | Automatic Evaluation | Model logP | Human Eval |
|----------|-----------------------|------------|------------|
|          | BLEU | sBLEU | CHRF | YISI | BL.1 | BL.2 |          |            |
| Human Transl. | Ref-D | 31.5 | 31.6 | 60.9 | 84.7 | 37.1 | 75.6 | -38.0 | 0.388†    |
| Beam 4   | 34.3 | 34.2 | 62.5 | 85.3 | 26.8 | 71.6 | -11.5 | 2.030 |
|          | sBLEU | 34.7 | 34.8 | 62.5 | 85.4 | 23.4 | 70.5 | -11.2 | 1.855 |
|          | CHRF | 34.2 | 34.3 | 64.1 | 85.7 | 25.8 | 71.4 | -13.2 | 2.139 |
|          | YISI | 34.2 | 34.3 | 62.8 | 86.0 | 26.4 | 71.6 | -11.4 | 2.445 |
|          | BLEURT v0.1 | 29.2 | 29.4 | 60.0 | 84.3 | 40.1 | 75.0 | -7.1  | 0.323 |
|          | BLEURT v0.2 | 25.4 | 26.0 | 57.7 | 83.1 | 41.2 | 78.2 | -12.2 | 0.272 |

Table 3: Actual utility of different MBR methods on newstest2021 De→En. Actual utility is computed with respect to reference A. This table is the equivalent of Table 2 for En→De.

| Method   | Automatic Evaluation | Model logP | Human Eval |
|----------|-----------------------|------------|------------|
|          | BLEU | sBLEU | CHRF | YISI | BL.1 | BL.2 |          |            |
| Human Transl. | Ref-B | 29.5 | 30.4 | 57.7 | 82.8 | 38.3 | 75.4 | -23.0 | 0.447 |
| Beam 4   | 33.1 | 34.2 | 61.2 | 84.1 | 41.1 | 75.2 | -6.1  | 0.345 |
|          | sBLEU | 33.3 | 34.7 | 61.1 | 84.1 | 40.1 | 75.0 | -7.1  | 0.323 |
|          | CHRF | 32.5 | 34.1 | 62.2 | 84.2 | 41.7 | 75.3 | -8.0  | 0.380 |
|          | YISI | 32.6 | 33.8 | 60.8 | 84.4 | 41.5 | 75.1 | -7.7  | 0.307 |
|          | BLEURT v0.1 | 28.2 | 29.7 | 58.5 | 82.9 | 41.9 | 77.3 | -11.8 | 0.302 |
|          | BLEURT v0.2 | 28.4 | 30.0 | 58.2 | 82.9 | 41.2 | 78.2 | -12.2 | 0.272 |

hypotheses, with \( \log P \) similar to MAP decodes. Rewarding reference overlap – even with an embedding distance in the case of YISI – favors the most common wording with the highest chance to match the surface form or embedding of a phrase in the reference translation. The BLEURT metrics on the other hand do not rely on overlap evaluation and can reward less frequent translations. BLEURT selects alternative translations, which are not scored highly by overlap metrics like BLEU and which are not among the highest likelihood (\( \log P \)) sentences according to the underlying NMT model.

5.2 Human Evaluation

Automatic metric results are encouraging but need to be confirmed with human assessments. We ran MQM-based human evaluations with professional translators for all MBR decoding outputs, beam search and one human translation. MQM generates an interpretable error score (lower is better) and a score of 1 is equivalent to an average of one minor error per sentence, while a score of 5 is equivalent to an average of 1 major error. The MQM results in Table 2 and Table 3 show that MBR decoding with BLEURT clearly outperforms beam search decoding and MBR decoding with sBLEU, CHRF and YISI, demonstrating that when comparing different decoding strategies, model probability and actual human assessment poorly correlate. Interestingly, MBR using BLEU as the utility function is also better than beam search decoding, while CHRF and YISI are ranked below beam search for at least one language pair.

We have to mention that the human translation for En→De outperforms all machine generated translations. For De→En, the human translation is ranked behind all machine generated translations. We looked into the ratings and confirm that the human translation contains critical errors (this is in line with the official WMT21 human evaluation (Barrault et al., 2021), showcasing how important it is to generate a good human translation when comparing MT with humans.

6 Ablation

We run ablation experiments to better understand the properties of MBR. We will mostly focus on
experiments for English→German due to space and cost constraints.

6.1 Smaller Model
The candidate lists used by MBR in the main results section (Section 5) were generated by an NMT model using 375 million parameters similar to the transformer-big architecture. We raise the question if MBR using BLEURT v0.2 still avoids Pitfall 1 and outperforms beam search when using a candidate list that is generated by a weaker model that is trained with 93 million parameters (model dimension size of 512, hidden dimension size of 2,048, and 8 transformer heads) similar to the transformer-base architecture. Experimental results can be seen in Table 4. We can see that the performance drops by 2 BLEU and 2 BLEURT points when comparing the beam hypotheses of the two different NMT models, indicating that the smaller model is indeed of lower quality.

| Model               | BLEU | BLEURT | pSQM |
|---------------------|------|--------|------|
| Transformer-big     | 34.3 | 71.6   | 4.47 |
| Beam                | 25.4 | 79.0   | 4.67 |
| Transformer-base    | 32.2 | 69.7   | 4.31 |
| Beam                | 21.8 | 70.5   | 3.55 |
| E=base; max=big     | 23.5 | 76.2   | n/a  |
| MBR-BL.2            | 23.5 | 73.0   | n/a  |

Table 4: Candidate list generation with either transformer-big or transformer-base model. The last column shows pSQM human evaluations results (higher is better). The results demonstrate that MBR needs a good model to outperform beam search.

Even though MBR outperforms beam decoding by 0.8 BLEURT points on the transformer-base model, the gap is much smaller than what we observe with the bigger model (7.4 BLEURT points). This already indicates that MBR is less effective on the smaller model, and the candidate list might not be good enough as a proxy for human references. We run a human evaluation comparing the two decoding algorithms on the small model and find that translation quality actually drops for the small setup when using MBR decoding. This shows that MBR requires a good quality candidate list to outperform beam search.

MBR uses the candidate list in two ways: (i) as a candidate pool from which it picks the hypothesis with the maximum estimated Bayes risk (max step) and (ii) as a list of pseudo-references to calculate the expected risk for each entry in the candidate pool (E step). It is not required that both operations use the same list. We run MBR decode using the candidate list of the small model on the E side and the candidate list of the larger model on the max side and vice versa. The BLEURT v0.2 results in the last two rows of Table 4 show that the candidate list generated by the smaller model has a larger negative effect when used on the max operation compared to using it on the E side only. Overall, the results show that it is not sufficient to use the candidate list of the smaller model on either the E or the max operation.

6.2 Candidate List Size
All our MBR decoding results in the main results section (Section 5) rely on a candidate list size of 1,000 generated by ancestral sampling. Generating 1,000 candidates and computing $1,000 \times 1,000 = 1$M BLEURT scores for each source sentence is computationally costly and would not be practical at scale. We explore two different strategies to prune the candidate list via either (i) random sampling, or (ii) based on the model probabilities (logP). Similar to Section 6.1, we can apply the pruning strategies to either the E list, the max list or both lists. Experimental results can be seen in Figure 1.

There are three major insights: (i) if we prune both operations in MBR, randomly down-sampling the candidate list size to a size of 8 (En→De) or 13 (De→En) already outperforms beam decoding based on BLEURT. (ii) We can aggressively sub-sample the candidate list used for the expectation (E). For En→De, we observe major improvements over beam search decoding, shrinking the candidate list to 5 on the E side, resulting in only $5 \times 1,000 = 5,000$ BLEURT computations for a single source sentence. This confirms the findings of Section 6.1 that we rely more on the quality and size of the candidate pool on the maximization step than on the expectation. (iii) The results in Figure 1 suggest that the MBR output most likely further improves when increasing the candidate list size beyond 1,000. This is different from beam search where accuracy gains are typically not achieved by growing beam size beyond a small number (< 10).

6.3 Oracle Experiments
We conduct oracle experiments to evaluate how the MBR hypotheses compare with selecting the best hypothesis with respect to a human ref-
Figure 1: Effect of different candidate list sizes on MBR decode with utility BLEURT v0.2 by either randomly sampling or choosing the candidates with the highest logP. We can reduce the number of candidates either only on the maximization or the expectation step alone or tight the two lists together. The graph shows that randomly subsampling the candidate list outperforms choosing candidates based on logP. Another evidence that we want the translations to steer away from the most probable translations. Further, pruning via sampling on the expectation side is more effective than reducing the candidate pool on the maximization side.

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We consider two scenarios: selecting and evaluating a hypothesis with the same human reference, or selecting a hypothesis with a first reference before evaluating it with a second, different reference. The second method considers the selection reference and the evaluation reference as two independent samples of the human translation space. This avoids biasing selection to translation choices specific to the evaluation conditions.

Table 5 reports these results. In the different reference scenario, MBR performs better than the cross human selection, e.g., selecting the best hypotheses with Ref-C yields a BLEURT score of 0.774 with Ref-D which is lower than 0.789, the BLEURT score of MBR with Ref-D. It is remarkable that the inter-translator variability in single reference automated evaluation causes more damage in oracle selection than the drop due to swapping human references for model estimates.

Table 6 shows percentiles of the rankings of the selected translations among the candidate list as ranked by BLEURT v0.2 (BL.2). The percentiles are calculated on the 1002 test queries of Newstest2021 En→De. A smaller value indicates that the chosen candidate is also preferred by the actual Ref-C BLEURT metric. This table shows that MBR provides more stable quality estimates than single references.


| Method          | Reference-based Evaluation | COMET-QE   | Model | pSQM ↑ |
|-----------------|----------------------------|-----------|-------|--------|
|                 | BLEU | CHRF | YISI | BL.1 | BL.2 | 2020 | 2021 | logP |        |
| Human Transl.   | 31.5 | 60.9 | 84.7 | 37.1 | 75.6 | 39.7 | 11.4 | -38.0 | n/a    |
| Beam 4          | 34.3 | 62.5 | 85.3 | 26.8 | 71.6 | 36.0 | 10.9 | -11.5 | 4.47   |
| MBR             | BLEURT v0.2                   | 25.4 | 57.7 | 83.1 | 43.9 | 79.0 | 43.4 | 10.8 | -24.4 | 4.67   |
| Reranking       | COMET-QE-20                   | 20.1 | 52.2 | 80.7 | 10.2 | 39.8 | 60.6 | 11.9 | -31.7 | 4.05   |
|                 | COMET-QE-21                   | 15.2 | 44.3 | 76.9 | -12.4 | 63.1 | 43.5 | 12.8 | -32.8 | 3.44   |

Table 7: Reranking results with COMET-QE on Newstest2021 En→De. Actual utility is computed with respect to reference C. pSQM are human evaluation results on the same sentences (higher is better).

6.4 Comparison to QE Metrics

Similar to reference-based metrics, reference-free Quality Estimation (QE) metrics have made huge improvements in the last years and show promising performance for some language pairs and test sets (Mathur et al., 2020). We pose the question whether a QE metric alone is sufficient to rerank the candidate list that we usually use for MBR decoding. The obvious advantage is that we only need \( N \) (\( N \) being the size of the candidate list), instead of \( N \times N \) metric calculations. We present results with two different QE metrics: COMET-QE-20 (Rei et al., 2020) and COMET-QE-21 (Rei et al., 2021). These two metrics were the best QE metrics based on the two most recent WMT metric tasks (Mathur et al., 2020; Freitag et al., 2021b). Experimental results for En→De and De→En can be seen in Table 7.

Both reranking experiments show similar patterns: The QE-based reranking outputs outperform beam search and MBR with BLEURT v0.2 on both QE-metrics. Nevertheless, we can see that most reference-based metrics set the QE-based reranked output below both the beam search and the MBR output. When looking into the translations, we observed that some sentences in the QE-based reranking approach contain translations with crucial errors or the translation is unrelated to the source. The human evaluation results in Table 7 confirm our impression that the reranked translations are of much lower quality and contain huge errors.

7 How Different are Beam and MBR Hypotheses?

In Section 5, we observed that the model probabilities of the MBR output using BLEURT v0.2 is much lower when compared to the beam search output. We want to further characterize the differences between these two decoding algorithms.

7.1 Cross BLEU

BLEU measures the lexical overlap between a hypothesis and a reference translation. It can also be used to measure the lexical similarity of two alternative machine translations. In that case, BLEU does not assess translation quality but surface proximity between sentences.

Cross BLEU scores of our MBR outputs with our MAP decode and the best submissions in WMT21 can be seen in Table 8. BLEU scores lower than 50 are highlighted in the table. Our MAP hypothesis, the WMT21 submissions, and our MBR hypotheses using BLEU, CHRF, or YISI have high cross-BLEU which shows that they yield similar translations. The MBR output using BLEURT and the human translations have low cross-BLEU with all MAP hypotheses which means that they use different words and sentence structures. It is worth highlighting that the two human translations are as different from each other as they are to our MBR output using BLEURT.

7.2 MQM Error Categories

In addition to an overall quality score, MQM provides individual error labels with category and severity information. Table 9 reports major error counts for the most frequent categories, excluding categories with similar counts from beam and MBR. This table shows a clear advantage for the MBR output for four categories. Specifically, the number of errors in the category Terminology/Inappropriate for context which is problematic for En→De shows a reduction of one third with MBR.

8 Conclusion

In this work, we explored an alternative to the commonly used beam search decoding algorithm typically used in NMT. We run Minimum Bayes Risk (MBR) decoding to optimize BLEU, CHRF,
Table 8: Overlap (cross-BLEU) between beam search output from different systems, our MBR hypotheses and human references on newstest2021 En → De. Lower cross-Bleu means lower word overlap between 2 translations. Facebook (Tran et al., 2021), Online-W and UEdin (Chen et al., 2021) are submissions of the WMT21 evaluation campaign. BLEURT v0.1 and v0.2 are shortened BL.1, BL.2. We observe that the beam search output and MBR with BLEU, CHRF, and YISI form a cluster of similar translations, while human references and the MBR output with BLEURT (in particular BLEURT v0.2) are different. Cross-BLEUs lower than 50 are highlighted in green.

| Beam  | BLEU | CHRF | YISI | BL.1 | BL.2 | Human |
|-------|------|------|------|------|------|-------|
| Beam  |      |      |      |      |      |       |
| Facebook | 59.5 | 67.6 | 56.9 | 55.6 | 54.0 | 42.0  |
| Online-W | 59.4 | 56.4 | 53.9 | 52.9 | 52.8 | 42.6  |
| UEdin | 67.6 | 56.5 | 62.1 | 59.5 | 57.4 | 43.7  |
| Ours | 57.0 | 54.0 | 62.2 | 77.0 | 71.9 | 39.8  |
| MBR   |      |      |      |      |      |       |
| BLEU  | 55.6 | 53.0 | 59.6 | 73.5 | 76.8 | 50.7  |
| CHRF  | 53.9 | 52.8 | 57.4 | 73.4 | 72.1 | 50.6  |
| YISI  | 54.2 | 51.9 | 57.9 | 76.7 | 72.2 | 50.4  |
| BL.1  | 43.3 | 42.6 | 43.7 | 50.6 | 50.6 | 50.3  |
| BL.2  | 35.0 | 34.7 | 35.3 | 39.9 | 40.0 | 39.5  |
| Human |      |      |      |      |      |       |
| Ref-C | 42.0 | 41.4 | 38.0 | 34.6 | 34.3 | 34.1  |
| Ref-D | 38.5 | 40.4 | 35.7 | 33.9 | 33.2 | 28.7  |

Table 9: Number of major errors for selected categories for the MQM human evaluation.

|                  | En→De | De→En |
|------------------|--------|--------|
| Terminology/Inappropriate for context | 151 | 98 | 7 | 6 |
| Accuracy/Mistranslation | 70 | 58 | 33 | 23 |
| Style/Awkward | 66 | 46 | 10 | 5 |
| Accuracy/Omission | 18 | 7 | 0 | 0 |

YISI and two versions of BLEURT. Our experimental results showed that MBR decoding using BLEURT as utility function results in translations that significantly outperform beam search decoding based on both automatic and human evaluation. We showed that the resulting translations are significantly different from both the beam search decode and MBR decoding output using one of the other overlap-based metrics as utility function, and have a much lower model probability.

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