Quality-Aware Decoding for Neural Machine Translation

Anonymous ACL submission

Abstract

Despite the progress in machine translation quality estimation and evaluation in the last years, decoding in neural machine translation (NMT) is mostly oblivious to this and centers around finding the most probable translation according to the model (MAP decoding), approximated with beam search. In this paper, we bring together these two lines of research and propose *quality-aware decoding* for NMT, by leveraging recent breakthroughs in reference-free and reference-based MT evaluation through various inference methods like N-best reranking and minimum Bayes risk decoding. We perform an extensive comparison of various possible candidate generation and ranking methods across four datasets and two model classes and find that quality-aware decoding consistently outperforms MAP-based decoding according both to state-of-the-art automatic metrics (COMET and BLEURT) and to human assessments.

1 Introduction

The most common procedure in neural machine translation (NMT) is to train models using maximum likelihood estimation (MLE) at training time, and to decode with beam search at test time, as a way to approximate maximum-a-posteriori (MAP) decoding. However, several works have questioned the utility of model likelihood as a good proxy for translation quality (Koehn and Knowles, 2017; Ott et al., 2018; Stahlberg and Byrne, 2019; Eikema and Aziz, 2020). In parallel, significant progress has been made in methods for quality estimation and evaluation of generated translations (Specia et al., 2020; Mathur et al., 2020b), but this progress is (by large) not yet reflected in either training or decoding methods. Exceptions such as minimum risk training (Shen et al., 2016; Edunov et al., 2018) come at a cost of more expensive and unstable training, often with modest quality improvements.

An appealing alternative is to modify the decoding procedure only, separating it into two stages:

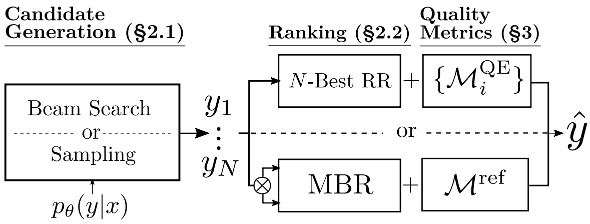

Figure 1: Quality-aware decoding framework. First, translation candidates are *generated* according to the model. Then, using reference-free and/or reference-based MT metrics, these candidates are *ranked*, and the highest ranked one is picked as the final translation.

candidate generation (§2.1; where candidates are generated with beam search or sampled from the whole distribution) and *ranking* (§2.2; where they are scored using a quality metric of interest, and the translation with the highest score is picked). This strategy has been explored in approaches using N-best reranking (Ng et al., 2019; Bhattacharyya et al., 2021) and minimum Bayes risk (MBR) decoding (Shu and Nakayama, 2017a; Eikema and Aziz, 2021; Müller and Sennrich, 2021). While this previous work has exhibited promising results, it has mostly focused on optimizing lexical metrics such as BLEU or METEOR (Papineni et al., 2002; Lavie and Denkowski, 2009), which have limited correlation with human judgments (Mathur et al., 2020a; Freitag et al., 2021a). Moreover, a rigorous apples-to-apples comparison among this suite of techniques and their variants is still missing, even though they share similar building blocks.

Our work fills these gaps by asking the question:

> "*Can we leverage recent advances in MT quality evaluation to generate better translations? If so, how can we most effectively do so?*"

To answer this question, we systematically explore NMT decoding using a suite of ranking procedures. We take advantage of recent state-of-the-art learnable metrics, both reference-based, such as COMET and BLEURT (Rei et al., 2020a; Sellam et al., 2020), and reference-free (also known as *quality estimation*; QE), such as TransQuest and OpenKiwi (Ranasinghe et al., 2020; Kepler et al., 2019). We compare different ranking strategies under a unified framework, which we name **quality-aware decoding** (§3). First, we analyze the performance of decoding using N-best reranking, both *fixed* according to a single metric and *learned* using multiple metrics, where the coefficients for each metric are optimized according to a reference-based metric. Second, we explore ranking using reference-based metrics directly through MBR decoding. Finally, to circumvent the expensive computational cost of the latter when the number of candidates is large, we develop a two-stage ranking procedure, where we use N-best reranking to pick a subset of the candidates to be ranked through MBR decoding. We explore the interaction of these different ranking methods with various candidate generation procedures including beam search, vanilla sampling, and nucleus sampling.

Experiments with two model sizes and four datasets (§4) reveal that while MAP-based decoding appears competitive when evaluating with lexical-based metrics (BLEU and ChrF), the story is very different with state-of-the-art evaluation metrics, where quality-aware decoding shows significant gains, both with N-best reranking and MBR decoding. We perform a human-study to more faithfully evaluate our systems and find that, while performance on learnable metrics is not always predictive of the best system, quality-aware decoding usually results in translations with higher quality than MAP-based decoding.

2 Candidate Generation and Ranking

We start by reviewing some of the most commonly used methods for both candidate generation and ranking under a common lens.

2.1 Candidate Generation

An NMT model defines a probability distribution $p_\theta(y|x)$ over a set of hypotheses $\mathcal{Y}$, conditioned on a source sentence x, where θ are learned parameters. A translation is typically predicted using MAP decoding, formalized as

$$\hat{y}_{\text{MAP}} = \underset{y \in \mathcal{Y}}{\arg\max} \ \log p_\theta(y|x). \quad (1)$$

In words, MAP decoding searches for the most probable translation under $p_\theta(y|x)$, *i.e.*, the mode of the model distribution. Finding the exact $\hat{y}_{\text{MAP}}$ is intractable since the search space $\mathcal{Y}$ is combinatorially large, thus, approximations like **beam search** (Graves, 2012; Sutskever et al., 2014) are used. However, it has been shown that the translation quality *degrades* for large values of the beam size (Koehn and Knowles, 2017; Yang et al., 2018; Murray and Chiang, 2018; Meister et al., 2020), with the empty string often being the true MAP hypothesis (Stahlberg and Byrne, 2019).

A stochastic alternative to beam search is to *draw samples* directly from $p_\theta(y|x)$ with ancestral sampling, optionally with variants that truncate this distribution, such as top-k sampling (Fan et al., 2018) or p**-nucleus sampling** (Holtzman et al., 2020) – the latter samples from the smallest set of words whose cumulative probability is larger than a predefined value p. Deterministic methods combining beam and nucleus search have also been proposed (Shaham and Levy, 2021).

Unlike beam search, sampling is not a search algorithm nor a decision rule – it is not expected for a single sample to outperform MAP decoding (Eikema and Aziz, 2020). However, samples from the model can still be useful for alternative decoding methods, as we shall see. While beam search focus on high probability candidates, typically similar to each other, sampling allows for more *exploration*, leading to higher candidate *diversity*.

2.2 Ranking

We assume access to a set $\bar{\mathcal{Y}} \subseteq \mathcal{Y}$ containing N candidate translations for a source sentence, obtained with one of the generation procedures described in §2.1. As long as N is relatively small, it is possible to (re-)rank these candidates in a post-hoc manner, such that the best translation maximizes a given metric of interest. We highlight two different lines of work for ranking in MT decoding: first, N**-best reranking**, using reference-free metrics as features; second, **MBR decoding**, using reference-based metrics.

2.2.1 N-best Reranking

In its simplest form (which we call *fixed* reranking), a *single* feature f is used (*e.g.*, an estimated quality score), and the candidate that maximizes this score is picked as the final translation,

$$\hat{y}_{\text{F-RR}} = \underset{y \in \bar{\mathcal{Y}}}{\arg\max} \ f(y). \quad (2)$$

When *multiple* features $[f_1, \ldots, f_K]$ are available, one can tune weights $[w_1, \ldots, w_K]$ for these features to maximize a given reference-based evaluation metric on a validation set (Och, 2003; Duh and Kirchhoff, 2008) – we call this *tuned* reranking. In this case, the final translation is

$$\hat{y}_{\text{T-RR}} = \arg\max_{y \in \bar{\mathcal{Y}}} \ \sum_{k=1}^{K} w_k f_k(y). \tag{3}$$

2.2.2 Minimum Bayes Risk (MBR) Decoding

While the techniques above rely on *reference-free* metrics for the computation of features, MBR decoding uses *reference-based* metrics to rank candidates. Unlike MAP decoding, which searches for the most probable translation, MBR decoding aims to find the translation that maximizes the expected *utility* (equivalently, that minimizes *risk*, Kumar and Byrne 2002, 2004; Eikema and Aziz 2020). Let again $\bar{\mathcal{Y}} \subseteq \mathcal{Y}$ be a set containing N hypotheses and $u(y, y^*)$ a utility function measuring the similarity between a hypothesis $y \in \mathcal{Y}$ and a reference $y^* \in \bar{\mathcal{Y}}$ (*e.g*, an automatic evaluation metric such as BLEU or COMET). MBR decoding seeks for

$$\hat{y}_{\text{MBR}} = \arg\max_{y^* \in \bar{\mathcal{Y}}} \ \underbrace{\mathbb{E}_{Y \sim p_\theta(y|x)}[u(Y, y^*)]}_{\approx \ \frac{1}{M}\sum_{j=1}^{M} u(y^{(j)}, y^*)}, \tag{4}$$

where in Eq. 4 the expectation is approximated as a Monte Carlo (MC) sum using model samples $y^{(1)}, \ldots, y^{(M)} \sim p_\theta(y|x)$.[1] In practice, the translation with the highest expected utility can be computed for each hypothesis $y^* \in \bar{\mathcal{Y}}$ by comparing it to all the other hypotheses in the set.

3 Quality-Aware Decoding

While recent works have explored various combinations of candidate generation and ranking procedures for NMT (Lee et al., 2021; Bhattacharyya et al., 2021; Eikema and Aziz, 2021; Müller and Sennrich, 2021), they suffer from two limitations:

- The ranking procedure is usually based on simple lexical-based metrics (BLEU, chrF, METEOR). Although these metrics are well established and inexpensive to compute, they correlate poorly with human judgments at segment level (Mathur et al., 2020b; Freitag et al., 2021b).
- Each work independently explores N-best reranking or MBR decoding, making unclear which method produces better translations.

In this work, we hypothesize that using more powerful metrics in the ranking procedure may lead to better quality translations. We propose a unified framework for ranking with both reference-based (§3.1) and reference-free metrics (§3.2), independently of the candidate generation procedure. We explore four methods with different computational costs for a given number of candidates, N.

Fixed N-best Reranker. An N-best reranker using a single reference-free metric (§3.2) as a feature, according to Eq. 2. The computational cost of this ranker is $\mathcal{O}(N \times C_{\mathcal{M}^{\text{QE}}})$, where $C_{\mathcal{M}^{\text{QE}}}$ denotes the cost of running an evaluation with a metric $\mathcal{M}^{\text{QE}}$.

Tuned N-best Reranker. An N-best reranker using as features *all* the reference-free metrics in §3.2, along with the model log-likelihood $\log p_\theta(y|x)$. The weights in Eq. 3 are optimized to maximize a given reference-based metric $\mathcal{M}^{\text{ref}}$ using MERT (Och, 2003), a coordinate-ascent optimization algorithm widely used in previous work. The decoding cost is $\mathcal{O}(N \times \sum_i C_{\mathcal{M}_i^{\text{QE}}})$ for all metrics $\{\mathcal{M}_i^{\text{QE}}\}$.

MBR Decoding. Choosing as the utility function a reference-based metric $\mathcal{M}^{\text{ref}}$ (§3.1), we estimate the utility using a simple Monte Carlo sum, as shown in Eq. 4. The estimation requires computing pairwise comparisons and thus the cost of running MBR decoding is $\mathcal{O}(N^2 \times C_{\mathcal{M}^{\text{ref}}})$.

N-best Reranker → MBR. Using a large number of samples in MBR decoding is expensive due to its quadratic cost. To circumvent this issue, we explore a *two-stage* ranking approach: we first rank all the candidates using a tuned N-best reranker, followed by MBR decoding using the top M candidates. The computational cost becomes $\mathcal{O}(N \times \sum_i C_{\mathcal{M}_i} + M^2 \times C_{\mathcal{M}^{\text{ref}}})$. The first ranking stage *prunes* the candidate list to a smaller, higher quality subset, making possible a more accurate estimation of the utility with less samples, and potentially allowing a better ranker than *plain* MBR for almost the same computational budget.

3.1 Reference-based Metrics

Reference-based metrics are the standard way to evaluate MT systems; the most used ones rely on the lexical overlap between hypotheses and reference translations (Papineni et al., 2002; Lavie

[1] We also consider the case where $y^{(1)}, \ldots, y^{(M)}$ are obtained from nucleus sampling or beam search. Although the original MC estimate is unbiased, these ones are biased.

and Denkowski, 2009; Popović, 2015). However, lexical-based approaches have important limitations: they have difficulties recognizing correct translations that are paraphrases of the reference(s); they ignore the source sentence, an important indicator of meaning for the translation; and they do not always correlate well with human judgments, particularly at segment-level (Freitag et al., 2021b).

In this work, apart from BLEU and chrF, we use the following state-of-the-art trainable reference-based metrics for both ranking and performance evaluation of MT systems:

- BLEURT (Sellam et al., 2020; Pu et al., 2021b), trained to regress on human direct assessments (DA; Graham et al. 2013). We use the largest multilingual version, *BLEURT-20*, based on the RemBERT model (Chung et al., 2021).

- COMET (Rei et al., 2020a), based on XLM-R (Conneau et al., 2020), trained to regress on quality assessments such as DA using both the reference and the source to assess the quality of a given translation. We use the publicly available model developed for the WMT20 metrics shared task (*wmt20-comet-da*).

These metrics have shown much better correlation at segment-level than previous lexical metrics in WMT metrics shared tasks (Mathur et al., 2020b; Freitag et al., 2021b). Hence, as discussed in §2.2, they are good candidates to be used either *indirectly* as an optimization objective for learning the tuned reranker's feature weights, or *directly* as a utility function in MBR decoding. In the former, the higher the metric correlation with human judgment, the better the translation picked by the tuned reranker. In the latter, we approximate the expected utility in Eq. 4 by letting a candidate generated by the model be a reference translation – a suitable premise *if* the model is good in expectation.

3.2 Reference-free Metrics

MT evaluation metrics have also been developed for the case where references are not available – they are called *reference-free* or *quality estimation* (QE) metrics. In the last years, considerable improvements have been made to such metrics, with state-of-the-art models having increasing correlations with human annotators (Freitag et al., 2021b; Specia et al., 2021). These improvements enable the use of such models for ranking translation hypotheses in a more reliable way than before.

In this work, we explore four recently proposed reference-free metrics as features for N-best reranking, all at the sentence-level:

- COMET-QE (Rei et al., 2020b), a reference-free version of COMET (§3.1). It was the winning submission for the QE-as-a-metric subtask of the WMT20 shared task (Mathur et al., 2020b).

- TransQuest (Ranasinghe et al., 2020), the winning submission for the sentence-level DA prediction subtask of the WMT20 QE shared task (Specia et al., 2020). Similarly to COMET-QE this metric predicts a DA score.

- MBART-QE (Zerva et al., 2021), based on the mBART (Liu et al., 2020) model, trained to predict both the *mean* and the *variance* of DA scores. It was a top performer in the WMT21 QE shared task (Specia et al., 2021).

- OpenKiwi-MQM (Kepler et al., 2019; Rei et al., 2021), based on XLM-R, trained to predict the *multidimensional quality metric* (MQM; Lommel et al. 2014).[2] This reference-free metric was ranked second on the QE-as-a-metric subtask from the WMT 2021 metrics shared task.

4 Experiments

4.1 Setup

We study the benefits of quality-aware decoding over MAP-based decoding in two regimes:

- A high-resource, unconstrained, setting with *large* transformer models (6 layers, 16 attention heads, 1024 embedding dimensions, and 8192 hidden dimensions) trained by Ng et al. (2019) for the WMT19 news translation task (Barrault et al., 2019), using English to German (EN $\rightarrow$ DE) and English to Russian (EN $\rightarrow$ RU) language pairs. These models were trained on over 20 million parallel and 100 million back-translated sentences, being the winning submissions of that year's shared task. We consider the non-ensembled version of the model and use *newstest19* for validation and *newstest20* for testing.

- A more constrained scenario with a *small* transformer model (6 layers, 4 attention heads, 512 embedding dimensions, and 1024 hidden dimensions) trained from scratch in *Fairseq* (Ott et al.,

[2] MQM annotations are expert-level type of annotations more fine-grained then DA, with individual errors annotated.

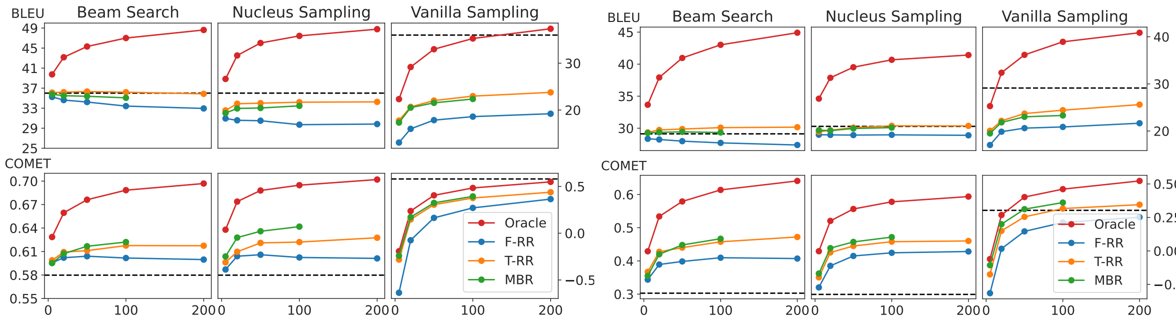

Figure 2: Values for BLEU (top) and COMET (bottom) for EN → DE as we increase the number of candidates for different generation and ranking procedures, as well as oracles with the respective metrics, for the *large* (left) and *small* (right) models. Baseline values are marked with a dashed horizontal line.

2019) on the smaller IWSLT17 datasets (Cettolo et al., 2012) for English to German (EN → DE) and English to French (EN → FR), each with a little over 200k training examples. We chose these datasets because they have been extensively used in previous work (Bhattacharyya et al., 2021) and smaller model allows us to answer questions about how the training methodology affects ranking performance (see § 4.2.2). Further training details can be found in Appendix A.

We use beam search with a beam size of 5 as our decoding baseline. For tuned N-best reranking, we use Travatar's (Neubig, 2013) implementation of MERT (Och, 2003) to optimize the weight of each feature, as described in §3.2. Finally, we evaluate each system using the metrics discussed in §3.1, along with BLEU and chrF (Popović, 2015).

4.2 Results

Overall, given all the metrics, candidate generation, and ranking procedures, we evaluate over 150 systems per dataset. We report subsets of this data separately to answer specific research questions, and defer to Appendix B for additional results.

4.2.1 Impact of Candidate Generation

First, we explore the impact of the candidate generation procedure and the number of candidates.

Which candidate generation method works best, beam search or sampling? We generate candidates with beam search, vanilla sampling, and nucleus sampling. For the latter, we use $p = 0.6$ based on early results showing improved performance for all metrics.[3] For N-best reranking, we use up to 200 samples; for MBR decoding, due to the quadratic computational cost, we use up to 100.

Figure 2 shows BLEU and COMET for different candidate generation and ranking methods for the EN → DE WMT20 and IWSLT17 datasets, with increasing number of candidates. To assess the performance *ceiling* of the rankers, we also report results with an *oracle* ranker for the reported metrics, picking the candidate that maximizes it. For the *fixed* N-best reranker, we use COMET-QE as a metric, albeit the results for other reference-free metrics are similar. Performance seems to scale well with the number of candidates, particularly for vanilla sampling and for the *tuned* N-best reranker and MBR decoder – this is in line with the findings of previous work (Lee et al., 2021; Müller and Sennrich, 2021). However, all the rankers using vanilla sampling severely under-perform the baseline in most cases (we will come back to this in §4.2.2). In contrast, the rankers using beam search or nucleus sampling are competitive or outperform the baseline in terms of BLEU, and greatly outperform it in terms of COMET. For the larger models trained on WMT20, we see that the performance according to the lexical metrics degrades with more candidates. In this scenario, rankers using candidates generated by nucleus sampling seem to have an edge over the ones that use beam search for COMET.

Based on the findings above, and due to generally better performance of COMET over BLEU for MT evaluation (Kocmi et al., 2021), in following experiments we use nucleus sampling with the *large* model and beam search with the *small* model.

4.2.2 Impact of Label Smoothing

How does label smoothing affect candidate generation? Label smoothing (Szegedy et al., 2016) is a regularization technique that redistributes proba-

[3] We picked nucleus sampling over top-k sampling because it allows varying support size and has outperformed top-k in text generation tasks (Holtzman et al., 2020).

	Large (WMT20)				Small (IWSLT)			
	BLEU	chrF	BLEURT	COMET	BLEU	chrF	BLEURT	COMET
Baseline	**36.01**	63.88	0.7376	0.5795	29.12	56.23	0.6635	0.3028
F-RR w/ COMET-QE	29.83	59.91	0.7457	0.6012	27.38	54.89	0.6848	0.4071
F-RR w/ MBART-QE	32.92	62.71	0.7384	0.5831	27.30	55.62	0.6765	0.3533
F-RR w/ OpenKiwi	30.38	59.56	0.7401	0.5623	25.35	51.53	0.6524	0.2200
F-RR w/ Transquest	31.28	60.94	0.7368	0.5739	26.90	54.46	0.6613	0.2999
T-RR w/ BLEU	35.34	63.82	0.7407	0.5891	**30.51**	**57.73**	0.7077	0.4536
T-RR w/ BLEURT	33.39	62.56	0.7552	0.6217	30.16	57.40	0.7127	0.4741
T-RR w/ COMET	34.26	63.31	0.7546	0.6276	30.16	57.32	0.7124	0.4721
MBR w/ BLEU	34.94	63.21	0.7333	0.5680	29.25	56.36	0.6619	0.3017
MBR w/ BLEURT	32.90	62.34	0.7649	0.6047	28.69	56.28	0.7051	0.3799
MBR w/ COMET	33.04	62.65	0.7477	0.6359	29.43	56.74	0.6882	0.4480
T-RR+MBR w/ BLEU	35.84	**63.96**	0.7395	0.5888	30.23	57.34	0.6913	0.3969
T-RR+MBR w/ BLEURT	33.61	62.95	**0.7658**	0.6165	29.28	56.77	**0.7225**	0.4361
T-RR+MBR w/ COMET	34.20	63.35	0.7526	**0.6418**	29.46	57.13	0.7058	**0.5005**

Table 1: Evaluation metrics for EN $\rightarrow$ DE for the *large* and *small* model settings, using a *fixed* N-best reranker (F-RR), a *tuned* N-best reranker (T-RR), MBR decoding, and a two-stage approach.

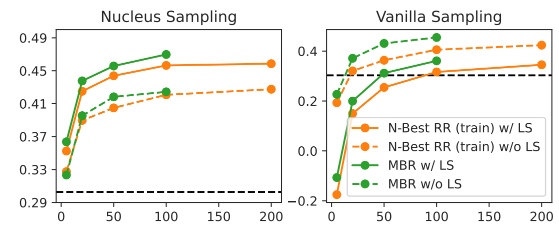

Figure 3: COMET scores for EN $\rightarrow$ DE (IWSLT17) for models trained with and without label smoothing.

bility mass from the gold label to the other target labels, typically preventing the model from becoming overconfident (Müller et al., 2019). However, it has been found that label smoothing negatively impacts model fit, compromising the performance of MBR decoding (Eikema and Aziz, 2020, 2021). Thus, we train a small transformer model without label smoothing to verify its impact in the performance of N-best reranking and MBR decoding. Figure 3 shows that disabling label smoothing really helps when generating candidates using vanilla sampling. However, the performance *degrades* for candidates generated using nucleus sampling when we disable label smoothing, hinting that the pruning mechanism of nucleus sampling may help mitigate the negative impact of label smoothing in sampling based approaches. Even without label smoothing, vanilla sampling is not competitive with nucleus sampling or beam search with label smoothing, thus, we do not experiment further with it.

4.2.3 Impact of Ranking and Metrics

We now investigate the usefulness of the metrics presented in §3 as features and objectives for ranking. For N-best reranking, we use all the available candidates (200) while, for MBR, due to the computational cost of using 100 candidates, we report results with 50 candidates only (we found that ranking with *tuned* N-best reranking with $N = 100$ and MBR with $N = 50$ takes about the same time). We report results in Table 1, and use them to answer some specific research questions.

Which QE metric works best in a fixed N-best reranker? We consider a *fixed* N-best reranker with a single reference-free metric as a feature (see Table 1, second group). While none of the metrics allows for improving the baseline results in terms of the lexical metrics (BLEU and chrF), rerankers using COMET-QE or MBART-QE outperform the baseline according to BLEURT and COMET, for both the *large* and *small* models. Due to the aforementioned better performance of these metrics for translation quality evaluation, we hypothesize that these rankers produce better translations than the baseline. However, since the sharp drop in the lexical metrics is concerning, we will verify this hypothesis in a human study, in §4.2.4.

How does the performance of a tuned N-best reranker vary when we change the optimization objective? We consider a *tuned* N-best reranker using as features *all* the reference-free metrics introduced in §3.2, and optimized using MERT. Table 1 (third group) shows the results for EN $\rightarrow$ DE. For the *small* model, all the rankers show improved results over the baseline for all the metrics. In particular, optimizing for BLEU leads to the best results in terms of the lexical metrics, while optimizing for BLEURT leads to the best performance in terms of the others. Finally, optimizing for COMET leads to similar performance than optimizing for BLEURT. For the *large* model, although none of the rerankers is able to outperform the baseline in terms of the lexical metrics, one can see similar trends as before in terms of BLEURT and COMET.

How does the performance of MBR decoding vary when we change the utility function? Table 1 (fourth group) shows the impact of the utility function (BLEU, BLEURT, or COMET). For the *small* model, using COMET leads to the best performance according to all the metrics except BLEURT (for which the best result is attained when optimizing itself). For the *large* model, the best result according to a given metric is obtained when using that metric as the utility function.

How do (tuned) N-best reranking and MBR compare to each other? Looking at the third and fourth groups in Table 1 we see that, for the *small* model, N-best reranking seems to perform better than MBR decoding in terms of all the evaluation metrics, including the one that was used as the utility function in MBR decoding. The picture is less clear for the *large* model, with MBR decoding achieving best values for a given fine-tuned metric when using it as the utility; this comes at the cost of worse performance according to the others metrics, hinting at a potential "*overfitting*" effect. Overall, N-best reranking seems to have an edge over MBR decoding. We will further clarify this question with human evaluation in § 4.2.4.

Can we improve performance by combining N-best reranking with MBR decoding? The results in Table 1 show that, for both the *large* and the *small* model, the two-stage ranking approach described in §3 leads to the best performance according to the fine-tuned metrics. In particular, the best result is obtained when the utility function is the same as the evaluation metric. These results suggest that a promising research direction is to seek more sophisticated pruning strategies as a preprocessing step for MBR decoding.

4.2.4 Human Evaluation

Which metric correlates more with human judgments? How risky is it to optimize a metric and evaluate on a related metric? Our experiments suggest that, overall, *quality-aware* decoding produces translations with better performance across most metrics than *MAP-based* decoding. However, for some cases (such as fixed N-best reranking and most results with the *large* model), there is a concerning "metric gap" between lexical-based and fine-tuned metrics. While the latter have shown to correlate better with human judgments, previous work has not attempted to explicitly optimize these metrics, and doing so could lead to ranking systems that learn to exploit "pathologies" in these metrics rather than improving translation quality.

To investigate this hypothesis, we perform a human study across all four datasets. We ask annotators to rate, from 1 (no overlap in meaning) to 5 (perfect translation), the translations produced by the 4 *ranking* systems mentioned §3, as well as the baseline translation and the reference. Further details can be found in Appendix C. We choose COMET-QE as the feature for the fixed N-best ranker and COMET as the optimization metric and utility function for the tuned N-best reranker and MBR decoding, respectively. The reasons for this are two-fold: (1) they are currently the reference-free and reference-based metrics with highest reported correlation with human judgments (Kocmi et al., 2021), (2) we saw the largest "metric gap" for systems based on these metrics, hinting of a potential "overfitting" problem (specially since COMET-QE and COMET are similar models).

Table 2 shows the results for the human evaluation, as well as the automatic metrics. Overall, we see that when fine-tuned metrics are explicitly optimized for, their correlation with human judgments decreases and they are no longer reliable indicators of system-level ranking. This is especially notable for the fixed N-best reranker with COMET-QE, which outperforms the baseline in terms of COMET in every single scenario, but results in markedly lower quality translations. However, despite the potential for overfitting these metrics, we find that *tuned* N-best reranking, MBR, and their combination consistently achieve better translation quality than the baseline, especially with the small model. In particular, N-best reranking seems to result in better translations than MBR, however their combination is the best system in two of four LPs.

5 Related Work

Reranking. Inspired by the work of Shen et al. (2004) on discriminative reranking for SMT, Lee et al. (2021) trained a large transformer model us-

	EN-DE (WMT20)					EN-RU (WMT20)				
	BLEU	chrF	BLEURT	COMET	Human R.	BLEU	chrF	BLEURT	COMET	Human R.
Reference	-	-	-	-	4.51	-	-	-	-	4.07
Baseline	**36.01**	**63.88**	0.7376	0.5795	4.28	**23.86**	51.16	0.6953	0.5361	3.62
F-RR w/ COMET-QE	29.83	59.91	0.7457	0.6012	4.19	20.32	49.18	0.7130	0.6207	3.25
T-RR w/ COMET	34.26	63.31	**0.7546**	0.6276	**4.33**	22.42	50.91	**0.7243**	0.6441	3.65
MBR w/ COMET	33.04	62.65	0.7477	0.6359	4.27	23.67	51.18	0.7093	0.6242	3.66
F-RR + MBR w/ COMET	34.20	63.35	0.7526	**0.6418**	4.30	23.21	**51.26**	0.7238	**0.6736**	**3.72**†
	EN-DE (IWSLT17)					EN-FR (IWSLT17)				
Reference	-	-	-	-	4.38	-	-	-	-	4.00
Baseline	29.12	0.6635	56.23	0.3028	3.68	38.12	0.6532	63.20	0.4809	3.92
F-RR w/ COMET-QE	27.38	0.6848	54.89	0.4071	3.67	35.59	0.6628	60.90	0.5553	3.63
T-RR w/ COMET	**30.16**	**0.7124**	**57.32**	0.4721	**3.90**†	**38.60**	**0.7020**	**63.77**	0.6392	4.05†
MBR w/ COMET	29.43	0.6882	56.74	0.4480	3.79†	37.77	0.6710	63.24	0.6127	4.05†
F-RR + MBR w/ COMET	29.46	0.7058	57.13	**0.5005**	3.83†	38.33	0.6883	63.53	**0.6610**	**4.09**†

Table 2: Results for automatic and human evaluation. Top: WMT20 (large models); Bottom: IWSLT17 (small models). Methods with † are statistically significantly better than the baseline, with $p < 0.05$.

ing a reranking objective to optimize BLEU. Our work differs in which our rerankers are much simpler (a single feature or a linear combination of features) and therefore can simply be tuned on a validation set; and we use more powerful quality metrics instead of BLEU. Similarly, Bhattacharyya et al. (2021) learned an energy-based reranker to assign lower energy to the samples with higher BLEU scores. While the energy model plays a similar role to a QE system (the higher the quality, the lower the energy), our work differs in two ways: we use an existing, pretrained QE model instead of training a dedicated reranker, making our approach applicable to any MT system without requiring further training; and the QE model is trained to predict human assessments, rather than BLEU scores. Leblond et al. (2021) compare a reinforcement learning approach to some reranking approaches (but not MBR decoding, as we do). They investigate the use of reference-based metrics and, for the reward function, a reference-free metric based on a modified BERTScore (Zhang et al., 2020). This new multilingual BERTScore is not fine-tuned on human judgments as COMET and BLEURT and it is unclear what its level of agreement with human judgments is. Another line of work is *generative reranking*, where the reranker is not trained to optimize an evaluation metric directly, but rather as a generative noisy-channel model (Yu et al., 2017; Yee et al., 2019; Ng et al., 2019).

Minimum Bayes Risk Decoding. MBR decoding (Kumar and Byrne, 2002, 2004) has recently been revived for NMT using candidates generated with beam search (Stahlberg et al., 2017; Shu and Nakayama, 2017b) and sampling (Eikema and Aziz, 2020, 2021; Müller and Sennrich, 2021). However, a comparison with N-best re-ranking was missing in these works, a gap our paper fills. A related line of work is *minimum risk training* (MRT; Smith and Eisner 2006; Shen et al. 2016), which *trains* models to minimize risk, allowing arbitrary non-differentiable loss functions (Edunov et al., 2018; Wieting et al., 2019) and avoiding exposure bias (Wang and Sennrich, 2020; Kiegeland and Kreutzer, 2021). However, MRT is considerably more expensive and difficult to train and the gains are often small. Incorporating our quality metrics in MRT is an exciting research direction.

6 Conclusions and Future Work

We leverage recent advances in MT quality estimation and evaluation and propose *quality-aware decoding* for NMT. We explore different candidate generation and ranking methods, with a comprehensive empirical analysis across four datasets and two model classes. We show that, compared to MAP-based decoding, quality-aware decoding leads to better translations, according to powerful automatic evaluation metrics and human judgments.

There are several directions for future work. Our ranking strategies, while leading to higher accuracies, are substantially more expensive, particularly when used with costly evaluation metrics such as BLEURT and COMET. While reranking-based pruning before MBR decoding was found helpful, additional strategies such as caching encoder representations and distillation of BERT-based metrics (Pu et al., 2021a) are promising directions.

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Supplemental Material

A Training Details

For the experiments using IWSLT17, we train a *small* transformer model (6 layers, 4 attention heads, 512 embedding dimensions, and 1024 hidden dimensions) from scratch, using *Fairseq* (Ott et al., 2019). We tokenize the data using SentencePiece(Kudo and Richardson, 2018), with a joint vocabulary with 20000 units. We train using the Adam optimizer (Kingma and Ba, 2015) with $\beta_1 = 0.9$ and $\beta_2 = 0.98$ and use an inverse square root learning rate scheduler, with an initial learning rate of 5×10^{-4} and with a linear warm-up in the first 4000 steps. For models trained with label smoothing, we use the default value of 0.1.

B Additional Results

For completeness, we include in Table 3 results to evaluate the impact of the metrics presented in §3 as features and objectives for ranking using the other language pairs: EN $\rightarrow$ RU (large model) and EN $\rightarrow$ FR (small model).

	Large (WMT20)				Small (IWSLT)			
	BLEU	chrF	BLEURT	COMET	BLEU	chrF	BLEURT	COMET
Baseline	23.86	51.16	0.6953	0.5361	38.12	63.20	0.6532	0.4809
F-RR w/ COMET-QE	20.32	49.18	0.7130	0.6207	35.59	60.90	0.6628	0.5553
F-RR w/ MBART-QE	22.39	50.59	0.6993	0.5481	36.68	62.17	0.6593	0.5091
F-RR w/ OpenKiwi	20.88	48.72	0.7040	0.5688	32.03	55.68	0.5996	0.2581
F-RR w/ Transquest	21.60	50.14	0.7060	0.5836	36.02	62.26	0.6681	0.5397
T-RR w/ BLEU	23.87	**51.51**	0.7042	0.5669	**39.10**	**64.22**	0.6968	0.6189
T-RR w /BLEURT	22.84	51.25	0.7265	0.6470	38.60	63.76	0.7042	0.6405
F-RR w/ COMET	22.42	50.91	0.7243	0.6441	38.60	63.77	0.7020	0.6392
MBR w/ BLEU	24.03	51.12	0.6938	0.5393	37.97	63.13	0.6484	0.4764
MBR w/ BLEURT	23.01	50.87	0.7314	0.5984	37.29	62.82	0.6886	0.5361
MBR w/ COMET	23.67	51.18	0.7093	0.6242	37.77	63.24	0.6710	0.6127
T-RR+MBR w/ BLEU	**24.11**	51.44	0.6967	0.5482	38.96	64.04	0.6781	0.5636
T-RR+MBR w/ BLEURT	23.18	51.30	**0.7344**	0.6277	37.43	63.14	**0.7092**	0.5961
T-RR+MBR w/ COMET	23.21	51.26	0.7238	**0.6736**	38.33	63.53	0.6883	**0.6610**

Table 3: Evaluation metrics for EN $\rightarrow$ RU for the *large* model setting and EN $\rightarrow$ FR for *small* model settings, using a *fixed* N-best reranker (F-RR), a *tuned* N-best reranker (T-RR), MBR decoding, and a two-stage approach.

C Human Study

In order to perform human evaluation, we recruited professional translators who were native speakers of the target language on the freelancing site Upwork.[4] 300 sentences were evaluated for each language pair, sampled randomly from the test sets after a restriction that sentences were no longer than 30 words. All translation hypotheses for a single source sentence were first deduplicated, and then shown to the translator side-by-side in randomized order to avoid any ordering biases.

Sentences were evaluated according to a 1-5 rubric slightly adapted from that of Wieting et al. (2019):

1. There is no overlap in the meaning of the source sentence whatsoever.
2. Some content is similar but the most important information in the sentence is different.
3. The key information in the sentence is the same but the details differ.
4. Meaning is essentially equal but some expressions are unnatural.
5. Meaning is essentially equal and the sentence is natural.

[4] https://upwork.com. Freelancers were paid a market rate of 18-20 US dollars per hour, and finished approximately 50 sentences in one hour.