Rethinking Round-trip Translation for Machine Translation Evaluation

Anonymous ACL submission

Abstract

Automatic evaluation on low-resource language translation suffers from a deficiency of parallel corpora. Round-trip translation could be served as a clever and straightforward technique to alleviate the requirement of the parallel evaluation corpus. However, there was an observation of negative correlations between the evaluation scores by forward and round-trip translations in the era of statistical machine translation (SMT). In this paper, we first revisit the round-trip translation evaluation and unveil its long-standing misunderstanding is essentially caused by copying mechanism. After removing copying mechanism in SMT, round-trip translation scores can reflect the forward translation performance. Then, we demonstrate the rectification is overdue as round-trip translation could benefit multiple machine translation evaluation tasks. To be more specific, round-trip translation could be used i) to predict corresponding forward translation scores; ii) to identify adversarial competitors in shared tasks via cross-system verification; and iii) to improve the performance of the recently advanced quality estimation model.

1 Introduction

Thanks to the recent progress of neural machine translation (NMT) and large-scale multilingual corpora, machine translation (MT) systems have achieved remarkable performances on high- to medium-resource languages (Fan et al., 2021; Pan et al., 2021; Goyal et al., 2022a). However, the development of MT technology on low-resource language pairs still suffers from insufficient data for training and evaluation (Aji et al., 2022; Siddhant et al., 2022). Recent advanced multilingual pre-trained language model explores the methods trained on monolingual data, using data augmentation and denoising auto-encoding method (Xia et al., 2019; Liu et al., 2020). However, high-quality parallel corpora are still required for evaluating translation quality. Such requirement is especially resource-consuming when working on *i)* hundreds of underrepresented low-resource languages (Bird and Chiang, 2012; Joshi et al., 2019; Aji et al., 2022) and *ii)* translations for specific domains (Li et al., 2020; Müller et al., 2020).

In order to mitigate the deficiency of parallel corpora, conducting Round-trip Translation (RT) could be a promising method for training data augmentation and evaluation solely on the monolingual corpus. RT entails two components, one forward translation (FT), and the other backward translation (BT). FT translates a given sentence in the source language A to a sentence in target language B, then the output sentence from FT are translated back to language A via a back translation system. However, the existing literature demonstrates that the automatic evaluation score on RT (RT-SCORE) unfortunately fails to reflect the score of FT quality (FT-SCORE) on statistical machine translation (SMT) and rule-based machine translation (RMT) systems (Huang, 1990; Koehn, 2005; Somers, 2005; Zaanen and Zwarts, 2006). This understanding impedes the usage of RT for MT evaluation on monolingual data, until some recent empirical discovery of RT could be helpful for quality estimation (QE) using sentence embeddings (Moon et al., 2020; Crone et al., 2021). In this work, we revisit the dispute on the usefulness of RT-SCORE in the era of SMT versus NMT. The main reason is due to the fact that SMT (and RMT) usually incorporate implicitly reversible rules in their translation. For example, copying unrecognized tokens forward to target languages is sometimes penalized by FT evaluation while it is usually awarded by RT evaluation. Extensive experiments are conducted to demonstrate the effect of copying mechanism on SMT. Later, we illustrate strong correlations between FT-SCOREs and RT-SCOREs on various MT systems, including NMT and SMT without the copying mechanism.

The finding sets the basis of using RT-SCORE

for MT evaluation. Three application scenarios in MT evaluation have been investigated to show the effectiveness of RT-SCORE. Firstly, RT-SCOREs can be used to predict FT-SCOREs via training a simple but effective linear regression model on several hundred languages pairs. The prediction performance is robust in evaluating transferred MT systems and unseen language pairs including low-resource languages. Then, a cross-system check (`X-Check`) mechanism is introduced to RT evaluation for real-world MT shared tasks. By leveraging the estimation from multiple translation systems, `X-Check` manages to identify those adversarial competitors, which rely heavily on the copy strategy. Finally, RT-SCOREs are proved effective in improving the performance of a recently advanced quality estimation model.

2 Related Work

Reference-based Machine Translation Evaluation Metric. Designing high-quality automatic evaluation metric for translation is one of the fundamental challenges in MT research. Most existing metrics largely rely on parallel corpora to provide aligned texts as references (Papineni et al., 2002; Lin, 2004). One can compare translated outputs against references to estimate the performance of MT systems. The string-based metrics incorporate lexical matching rate for translation quality, such as BLEU (Papineni et al., 2002), ChrF (Popović, 2015) and TER (Snover et al., 2006). In addition, metrics using pre-trained language models to estimate the semantic relevance of texts, such as BERTScore (Zhang et al., 2020) and BLEURT (Sellam et al., 2020), are demonstrated to match human evaluation (Kocmi et al., 2021). Some reference-based evaluation metrics require supervised training to work well (Mathur et al., 2019; Rei et al., 2020). While these automatic evaluation metrics are widely applied in MT evaluation, they fail in the low-resource language translation scenarios where there are no ground-truth parallel references (Mathur et al., 2020). Our work paves the way towards reference-free evaluation for MT.

Reference-free Quality Estimation. In recent years, there has been a surge of interest in designing QE metrics, which aims to predict translation quality from human expert judgement without the access to parallel reference translations in the run-time (Specia et al., 2010, 2013; Bojar et al., 2014; Zhao et al., 2020). Recent focus on QE is mainly based on human evaluation approaches, direct assessment (DA) and post-editing (PE), where researchers intend to train models on numerous human evaluation score features to estimate MT quality. Despite few unsuccessful early QE works towards predicting automatic evaluation metric (Blatz et al., 2004), current QE metrics generally require human-annotated DA and PE data at sentence level for training on the target languages pairs. Recent progresses, YiSi-2 (Lo, 2019), COMET-QE-MQM (Rei et al., 2021), to name a few, demonstrate their effectiveness on `WMT` shared tasks. Our work follows a zero-shot setting for low-resource translation quality evaluation, meaning there is no need for data in the tested language pairs to train our predictors.

3 Revisiting Round-trip Translation

3.1 Evaluation on Round-trip Translation

Given machine translation systems, $\mathcal{T}_{A\to B}$ and $\mathcal{T}_{B\to A}$, between two languages (L_A and L_B), and a monolingual corpus $\mathcal{D}_A = \{a_i\}_{i=1}^N$, FT transforms a_i to $b_i' = \mathcal{T}_{A\to B}(a_i)$ and BT translates it back to A, $a_i' = \mathcal{T}_{B\to A}(\mathcal{T}_{A\to B}(a_i))$. FT and BT constitute a round-trip translation (RT).

The evaluation scores on round-trip translation (RT-SCORE) with regard to an automatic evaluation metric $\mathcal{M}$ is

$$\text{RT-SCORE}^{\mathcal{M}}_{A\circlearrowright B} = \frac{1}{N}\sum_{i=1}^{N}\mathcal{M}(\mathcal{T}_{B\to A}(\mathcal{T}_{A\to B}(a_i)), a_i) \quad (1)$$

where `sacreBLEU`, `spBLEU`, `chrF` and `BERTScore` are target metrics $\mathcal{M}$ in our discussion.

On the other hand, traditional MT evaluation on parallel corpus is

$$\text{FT-SCORE}^{\mathcal{M}}_{A\to B} = \frac{1}{N}\sum_{i=1}^{N}\mathcal{M}(\mathcal{T}_{A\to B}(a_i), b_i) \quad (2)$$

given a (virtual) parallel corpus $\mathcal{D}_{A||B} = \{(a_i, b_i)\}_{i=1}^N$. The main research question is whether FT-SCOREs are correlated to therefore could be predicted by RT-SCOREs.

3.2 RT Evaluation on Statistical Machine Translation

The previous analysis on the automatic evaluation scores from RT and FT shows that they are negatively correlated. Such a long-established understanding started from the era of RMT (Huang,

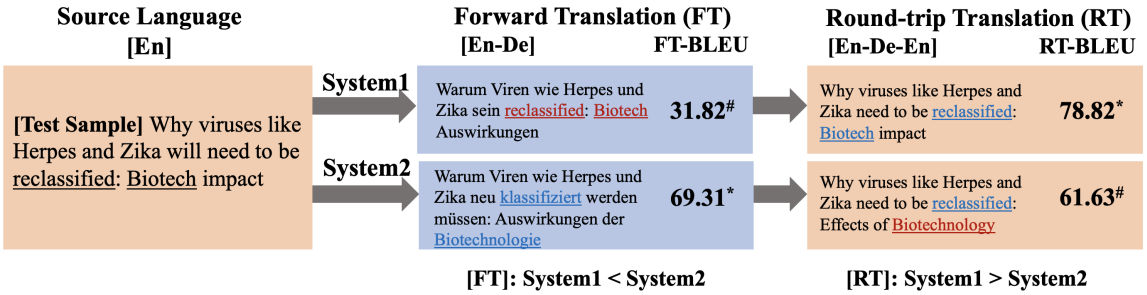


Figure 1: The comparison of the forward translation (FT) and round-trip translation (RT) performance of two translation systems, System 1 and System 2 are based on Statistical Machine Translation (SMT) and Neural Machine Translation (NMT), respectively. The conflict conclusions by FT Scores (System 1 $<$ System 2) and RT Scores (System 1 $>$ System 2) are attributed to the translation of the underlined words, 'reclassified' and 'Biotech'.

1990) and lasted through SMT (Koehn, 2005; Somers, 2005) and prevented the usage of RT to MT evaluation. We argue that the negative observations are probably due to the selected SMT models involve some reversible transformation rules, e.g., copying unrecognized tokens in translation. As an example illustrated in Figure 1, the MT System 1 works worse than its competing System 2, as System 1 fails to translate 'reclassified' and 'Biotech'. Instead, it decides to copy the words in source language (En) directly to the target outputs. During BT, System 1 manages to perfectly translate them back without any difficulty. For System 2, although translating 'Biotechnologie' (De) to 'Biotechnology' (En) is adequate, it is not appreciated by the original reference in this case. Consequently, the rankings of these two MT systems are flipped according to their FT and RT scores. Previous error analysis study on SMT (Vilar et al., 2006) also mentioned that the unknown word copy strategy is one of the major causes resulting in the translation errors. We therefore argue that the reversible transformation like word copy could have introduced significant bias to the previous experiments on SMT (and RMT). Then, we conduct experiments to replicate the negative conclusion. Interestingly, removing the copying mechanism can almost perfectly resolve the negation in our experiments.

3.3 Experiments and Analysis

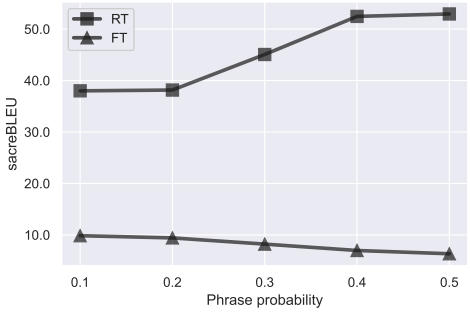
We compare RT and FT on SMT following the protocol by Somers (2005); Koehn (2005). `Moses` (Koehn and Hoang, 2009) is utilized to train phrase-based MT systems (Koehn et al., 2003), which were popular in the SMT era.[1] We train SMT systems on `News-Commentary v8` (Tiedemann, 2012), as suggested by `WMT` organizers (Koehn and Monz, 2006). We test our systems on four language pairs (de-en, en-de, cs-en, and en-cs) in the competition track of `WMT` 2020 Translation Shared Tasks (Barrault et al., 2020), namely news track `WMT2020-News`. RT-SCOREs and FT-SCOREs are calculated based on `sacreBLEU` in this section. Then, we use Kendall's τ to verify the correlation of RT-SCOREs and FT-SCOREs (Kendall, 1938). We train five systems using different phrase dictionary by varying phrase probability threshold from 0.1, to 0.5. The higher threshold indicates the smaller phrase table and hence a better chance of processing unknown words by the corresponding MT systems. During translation inference, we consider two settings for comparison, one drops the unknown words and the other one copies these tokens to the outputs. Hence, we end up having two groups of five outputs from various SMT systems.

Lang. Pair	K. τ ↑		Improv.
	w/ cp	w/o cp	
de-en	-1.00	1.00	2.00
en-de	-1.00	1.00	2.00
cs-en	-1.00	1.00	2.00
en-cs	-1.00	1.00	2.00

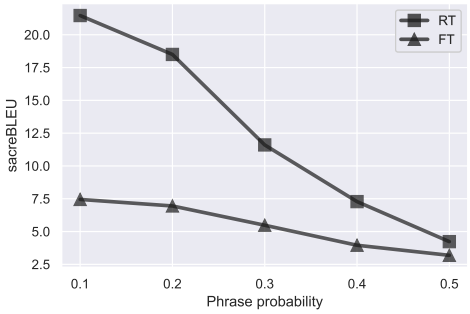
Table 1: Comparison between RT-SCORE and FT-SCORE on two groups of systems with copying (w/ cp) and without copying (w/o cp) unknown words using Kendall's τ on four language pairs.

In Table 1, we examine whether the relevance between RT-SCOREs and FT-SCOREs on five SMT systems. The performance is measured by Kendall's τ. The correlation is essentially decided by the copying mechanism. Specifically, their correlation turns to perfectly positive for those systems not allowed copying. In Figure 2, we further visualize RT-SCOREs and FT-SCOREs of five SMT

[1] We follow the baseline setup in the Moses' tutorial in http://www2.statmt.org/moses/?n=Moses.Baseline.



(a) FT vs RT on SMT with word copy.



(b) FT vs RT on SMT without word copy

Figure 2: Comparison between RT-SCOREs$^{\texttt{sacreBLEU}}_{A\circlearrowright B}$ (FT) and FT-SCOREs$^{\texttt{sacreBLEU}}_{A\to B}$ (RT) on *en-de*, based on SMT varying by phrase probability thresholds.

systems on en-de translation. Two lines in Figure 2.a provides negative correlation, while those two in Figure 2.b are clearly positively correlated.

Now, we discuss the rationality of using RT evaluation for NMT systems, by comparing the reliance of copying mechanism in NMT and SMT. For NMT, we choose MBART50-M2M (Tang et al., 2020), which covers 50 languages of cross-lingual translation. Exactly matched words in outputs from the input words are considered copying, although the system may not intrinsically intend to copy them. In Table 2, we observe that copying frequency is about two times in SMT than NMT. Although NMT systems may copy some words during translation, most of them are unavoidable, e.g., we observe that most of these copies are proper nouns whose translation are actually the same words in target language. In contrast, the copied words in SMT are more diverse and many of them could be common nouns.

4 Predicting FT-SCORE using RT-SCORE

In this section, we validate whether FT-SCOREs could be predicted by RT-SCOREs. Then, we examine the robustness of the predictor on unseen language pairs and transferred MT models.

Lang. Pair	Avg. Copy (%)	
	SMT	NMT
de-en	17.39	9.28
en-de	21.47	9.54

Table 2: Comparison of word copy frequency between SMT and NMT on two language pairs. We calculate average percentage of copy (Avg. Copy) per sentence. We use `Moses` with the phrase probability threshold of 0.4 for SMT.

4.1 Regression on RT-SCORE

Here, we construct a linear regressor f to predict FT-SCOREs of a target translation metric $\mathcal{M}$ by corresponding RT-SCOREs,

$$\text{FT-SCORE}^{\mathcal{M}}_{A\to B} \approx f_{\mathcal{M}}(\text{RT-SCORE}^{\mathcal{M}^*}_{A\circlearrowright B}, \text{RT-SCORE}^{\mathcal{M}^*}_{B\circlearrowright A}). \quad (3)$$

$\mathcal{M}^*$ indicates that multiple metrics could be used to construct the input features. We utilize RT-SCORE from both sides of a language pair as our primary setting, as using more features usually provides better prediction performance (Xia et al., 2020). We introduce a linear regressor for predicting FT-SCORE,

$$f_{\mathcal{M}}(\mathbf{S}) = \mathbf{W}_1 \cdot \mathbf{S}^{\mathcal{M}^*}_{A\circlearrowright B} + \mathbf{W}_2 \cdot \mathbf{S}^{\mathcal{M}^*}_{B\circlearrowright A} + \beta \quad (4)$$

where $\mathbf{S}^{\mathcal{M}^*}_{A\circlearrowright B}$ and $\mathbf{S}^{\mathcal{M}^*}_{B\circlearrowright A}$ are RT-SCORE features used as inputs of the regressor[2]. $\mathbf{W}_1$, $\mathbf{W}_2$ and β are the parameters of the prediction model optimized by supervised training. [3]

In addition, when organizing a new shared task, say `WMT`, collecting a parallel corpus in low-resource language could be challenging and resource-intensive. Hence, we investigate another setting that utilizes merely the monolingual corpora in language A or B to predict FT-SCORE,

$$\text{FT-SCORE}^{\mathcal{M}}_{A\to B} \approx f'_{\mathcal{M}}(\text{RT-SCORE}^{\mathcal{M}^*}_{A\circlearrowright B}),$$
$$\text{FT-SCORE}^{\mathcal{M}}_{A\to B} \approx f'_{\mathcal{M}}(\text{RT-SCORE}^{\mathcal{M}^*}_{B\circlearrowright A}). \quad (5)$$

We will compare and discuss this setting in our experiments on `WMT`.

[2]We use $\mathcal{M}^* = \mathcal{M}$ as our primary setting, as it is the most straightforward and effective method to construct features. In addition, we discuss the possibility to improve the regressor by involving more features, in Appendix F.3.

[3]Implementation details can be found in Appendix D.

4.2 Experimental Setup

4.2.1 Datasets

We conduct experiments on the large-scale multilingual benchmark, FLORES-101, and WMT machine translation shared tasks. FLORES-AE33 is for training and testing on languages and transferred MT systems. WMT is for testing on real-world shared tasks in new domains.

FLORES-AE33. We extract FLORES-AE33, which contains parallel data among 33 languages, covering 1,056 (33×32) language pairs, from a curated subset of FLORES-101 (Goyal et al., 2022a). We select these languages based on two criteria: *i)* We rank languages given the scale of their bi-text corpora; *ii)* We prioritize the languages covered by WMT2020-News and WMT2020-Bio. As a result, FLORES-AE33 includes 7 high-resource languages, 16 medium-resource languages and 10 low-resource languages, with more details in Appendix A.

Then, we partition these 33 languages into two sets, *i)* the languages that are utilized in training our models (TRAIN+TEST[4]) and *ii)* the others are employed used for training the predictors but considered for test purpose only (TEST). We include 20 languages to TRAIN+TEST, with 7 high-resource, 7 medium-resource and 6 low-resource. The rest 13 languages fall into TEST, with 9 medium-resource and 4 low-resource. Combining these two categories of languages, we obtain three types of *language pairs* in FLORES-AE33.

Type I contains pairs of languages in TRAIN+TEST, where a train set and a test set are collected and utilized independently. For each language pairs, we collect 997 training samples and 1,012 test samples. The test set of **Type II** is more challenging than that of **Type I** set, where the language pairs in this set are composed of one language from TRAIN+TEST set and the other language from TEST set. **Type III**'s test set is the most challenging one, as all its language pairs are derived from TEST languages. **Type II** and **Type III** sets are designed for test purpose, and they will not be used for training predictors. Overall, **Type I**, **Type II** and **Type III** sets contain 380, 520, and 156 language pairs, respectively.

WMT. We collect corpora from the translation track to evaluate multiple MT systems on the same test sets. We consider their ranking based on FT-SCORE with metric $\mathcal{M}$ as the ground truth. We choose the competition tracks in WMT 2020 Translation Shared Tasks (Barrault et al., 2020), namely news track WMT2020-News and biomedical track WMT2020-Bio. We consider *news* and *bio* as new domains, compared to our training data FLORES-101 whose contents are mostly from Wikipedia.

4.2.2 Neural Machine Translation Systems

We experiment with five MT systems which support most of the languages appearing in FLORES-AE33 and WMT. Except MBART50-M2M, we adopt M2M-100-BASE and M2M-100-LARGE (Fan et al., 2021), which are proposed to conduct many-to-many MT without explicit pivot languages, supporting 100 languages. GOOGLE-TRANS (Wu et al., 2016; Bapna et al., 2022)[5] is a commercial translation API, which was considered as a baseline translation systems in many previous competitions (Barrault et al., 2020). Meanwhile, we also include a family of bilingual MT models, OPUS-MT (Tiedemann and Thottingal, 2020), sharing the same model architecture MARIAN-NMT (Junczys-Dowmunt et al., 2018). We provide more details about these MT systems in Appendix C.

4.2.3 Automatic MT Evaluation Metrics

We consider sacreBLEU, spBLEU (Goyal et al., 2022b), chrF (Popović, 2015) and BERTScore (Zhang et al., 2020) as the primary automatic evaluation metrics (Freitag et al., 2020). All these metrics will be used and tested for both input features and target FT-SCORE. The first two metrics are differentiated by their tokenizers, where sacreBLEU uses Moses (Koehn and Hoang, 2010) and spBLEU uses SentencePiece (Kudo and Richardson, 2018). Both evaluation metrics were officially used in WMT21 Large-Scale Multilingual Machine Translation Shared Task (Wenzek et al., 2021). While sacreBLEU works for most language tokenizations, spBLEU shows superior effectiveness on various language tokenizations, especially the performance on low-resource languages (Goyal et al., 2022a). More details of these metrics are described in Appendix B

[4] Both train and test sets of our corpus will have these languages.

[5] We queried GOOGLE-TRANS API in August, 2022.

4.3 Experiments and Analysis

Following our discussion in the last section on SMT, we conduct similar experiments using our new multilingual NMT systems on **Type I** test set of FLORES-AE33. We observe highly positives correlation between FT-SCOREs and RT-SCOREs, measured by Pearson's r (Benesty et al., 2009). Please refer to Appendix F.1 for more details. Then, we train regressors on RT-SCOREs and conduct experiments to examine their performance on various challenging settings.

MT System	Trans. Metric	Type I		
		MAE ↓	RMSE ↓	P. r ↑
MBART50-M2M	sacreBLEU	1.80	2.70	0.94
	spBLEU	2.13	2.99	0.94
	chrF	3.51	4.53	0.96
	BERTScore	4.98	7.07	0.88
M2M-100-BASE	sacreBLEU	3.86	5.82	0.95
	spBLEU	3.97	5.72	0.96
	chrF	6.06	7.53	0.96
	BERTScore	4.35	6.32	0.91
GOOGLE-TRANS	sacreBLEU	4.09	5.60	0.93
	spBLEU	4.22	5.62	0.87
	chrF	5.70	6.90	0.93
	BERTScore	2.87	3.66	0.80

Table 3: The results of predicted FT-SCOREs of MBART50-M2M, M2M-100-BASE and GOOGLE-TRANS on **Type I** test set based on different translation evaluation metrics (Trans. Metric). *MAE: Mean Absolute Error, RMSE: Root Mean Square Error, P. r: Pearson's r.

4.3.1 Transferability of Regressors

We firstly investigate the transferability of our regressors from two different aspects, transferred MT systems and unseen language pairs. We also evaluate the regressor on different scales of language resources, in Appendix F.2.

Settings. We train our regressors on **Type I** train set of FLORES-AE33 based on the translation scores from MBART50-M2M. In order to assess system transferability, we test three models, MBART50-M2M, M2M-100-BASE and GOOGLE-TRANS, on **Type I** test set. In terms of the language transferability, we consider FT-SCOREs of MBART50-M2M (a seen MT system in training) and M2M-100-BASE (an unseen MT system in training) on **Type II** and **Type III** test sets in FLORES-AE33. **Type II** and **Type III** language pairs respectively include one and two unseen languages for each pair. We vary our experiment on four metrics, sacreBLEU, spBLEU, chrF and BERTScore. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Pearson's r are calculated to evaluation the difference between the predicted scores and the gold FT-SCOREs.

Discussion. In Table 3, we present the performance of the regressor across various translation systems and evaluation metrics. We first analyze the results on MBART50-M2M, which is seen in training. The absolute errors between predicted scores and ground-truth FT-SCOREs are relatively small with regard to MAE and RMSE. Meanwhile, the correlation between prediction and ground truth is strong, with all Pearson's r above or equal to 0.88. This indicates that ranking the predicted scores is rational. The results of M2M-100-BASE and GOOGLE-TRANS demonstrate the performance of predictors on *unseen* systems. Although the overall errors are higher than those of MBART50-M2M without system transfer, Pearson's r scores are at the competitive level, indicating a similar ranking capability on unseen systems. Meanwhile, our model obtains adequate language transferability results, as demonstrated in Table 4. Notably, our regressor performs well on low-resource translation (see Appendix F.2), which corroborates our claim about the significance of RT to FT for low-resource languages.

4.3.2 Predicting FT-SCOREs on WMT

With the basis of high transferabilities of the regressors, we conduct experiments on WMT shared tasks, namely WMT2020-News, which includes10 language pairs.

Settings. We have involved five MT systems, MBART50-M2M, M2M-100-BASE, M2M-100-LARGE, OPUS-MT and GOOGLE-TRANS.[6] In addition to MAE, RMSE and Pearson's r, we introduce Kendall's τ (Kendall, 1938) to measure the rank correlation coefficient of the MT systems, via comparing the ranking of our model predictions and the actual ranking based on FT-SCORE. We are aware of the cases that collecting corpora in target languages for competitions might be significantly complex, which means only a monolingual corpus is available for evaluation. Thus, we train predictors f' using single RT-SCOREs in Equation 5 on **Type I** train set. Note that this experiment covers several challenging settings, such as transferred

[6] We have contacted the competitors to WMT2020-News. However, we have not received enough valid MT systems to increase the number of competitors. We will show the robustness of our method to a larger number of pseudo-competitors in Appendix F.4.

MT System	Trans. Metric	Type II			Type III		
		MAE ↓	RMSE ↓	P. r ↑	MAE ↓	RMSE ↓	P. r ↑
MBART50-M2M	sacreBLEU	1.36	1.97	0.93	0.81	0.95	0.96
	spBLEU	1.61	2.19	0.93	1.20	1.38	0.94
	chrF	3.80	4.89	0.95	3.04	3.89	0.95
	BERTScore	4.67	6.38	0.88	5.08	6.88	0.87
M2M-100-BASE	sacreBLEU	3.10	4.16	0.95	2.99	3.76	0.94
	spBLEU	3.24	4.18	0.96	3.18	3.88	0.95
	chrF	5.53	6.70	0.95	5.42	6.54	0.93
	BERTScore	4.38	6.51	0.83	4.29	6.65	0.80

Table 4: The results of predicted FT-SCOREs of MBART50-M2M (a *seen* MT system) and M2M-100-BASE (an *unseen* MT system) on **Type II** and **Type III** (with *unseen* languages) test sets based on different translation evaluation metrics (Trans. Metric).

Lang. Pair	$A \circlearrowright B$				$B \circlearrowright A$				$A \circlearrowright B$ & $B \circlearrowright A$			
	MAE ↓	RMSE ↓	K. τ ↑	P. r ↑	MAE ↓	RMSE ↓	K. τ ↑	P. r ↑	MAE ↓	RMSE ↓	K. τ ↑	P. r ↑
cs-en	4.01	4.34	0.20	0.45	8.92	9.08	0.60	0.91	8.53	8.71	0.60	0.88
de-en	13.23	13.26	0.80	0.95	1.69	1.77	0.80	0.95	1.26	1.38	0.80	0.96
de-fr	10.45	10.53	1.00	0.99	1.72	2.05	0.80	0.97	1.59	1.93	1.00	0.97
en-cs	6.96	7.49	0.20	0.25	1.39	1.79	0.60	0.94	1.25	1.80	0.60	0.95
en-de	2.96	4.00	0.40	0.59	2.29	2.70	1.00	0.92	2.75	3.12	1.00	0.93
en-ru	1.98	2.40	0.20	0.40	7.41	7.53	0.40	0.85	7.48	7.60	0.60	0.86
en-zh	2.96	3.93	0.20	0.19	1.36	1.60	0.80	0.80	1.23	1.50	0.80	0.82
fr-de	2.89	3.70	0.80	0.90	2.99	3.56	1.00	0.94	2.59	3.17	1.00	0.93
ru-en	9.83	9.97	1.00	0.78	1.16	1.72	0.80	0.85	1.44	1.78	0.80	0.88
zh-en	12.44	12.77	0.00	0.26	3.04	3.55	0.20	0.50	2.62	3.56	0.20	0.50
Average	6.77	7.24	0.48	0.58	3.20	3.54	0.70	0.86	3.07	3.41	0.74	0.87

Table 5: The results of our predictors on ranking the selected MT systems on WMT2020-News shared tasks.

MT systems, unseen languages in training, single source features, and transferred application domains. Another set of results on WMT2020-Bio can be found in Appendix F.5.

Discussion. In Table 5, we display the results on WMT2020-News.[7] Although MAE and RMSE vary among experiments for different language pairs, the overall correlation scores are favorable. Pearson's r values on all language pairs are above 0.5, showing strong ranking correlations. While prediction performances on $A \circlearrowright B$ have some variances among different language pairs, the results of the experiments using $B \circlearrowright A$ are competitive to those using both $A \circlearrowright B$ and $B \circlearrowright A$ features, showing the feasibility of predicting FT-SCORE using monolingual data. We conclude that our regression-based predictors can be practical in ranking MT systems in WMT-style shared tasks.

5 Cross-system Round-trip Translation

In this section, we first validate RT evaluation on WMT2020-News with $A \circlearrowright B$ direction. One of the advantages of RT is that multiple MT systems could be used to verify the performance of other systems via checking the $N \times N$ combinational RT results from these N systems, coined X-Check. Finally, we demonstrate that the predicted automatic evaluation scores could be further improved via multi-system cross-check.

[7]The results on WMT2020-Bio are reported in Appendix F.5

5.1 Cross-system Validation for Competitions

Given FT MT systems $\{\mathcal{F}_i\}_{i=1}^{N}$, BT MT systems $\{\mathcal{B}_i\}_{i=1}^{M}$, and a regression model $\mathcal{M}$ on predicting the target metric, we can estimate the translation quality of i-th FT system on j-th BT system:

$$\mathbb{S}_{i,j} = f_{\mathcal{M}}(\mathcal{B}_j(\mathcal{F}_i(x)), x),$$

where $\mathbb{S} = \{\mathbb{S}_{i,j}\}_{N \times M}$. The estimated translation quality of $\mathcal{F}_i$ is the average score of the i-th column,

$$\overline{\mathbb{S}}_{i,:} = \frac{1}{M} \sum_{j=1}^{M} \mathbb{S}_{i,j}.$$

Note that the same number of FT and BT systems are considered for simplicity, i.e. $N = M$.

5.2 Experiments and Analysis

Settings. We conduct experiments on WMT2020-News similar to Section 4.3.2. We rank the system-level translation quality via the regressor trained on RT-SCORE$^{\text{spBLEU}}$. We challenge the evaluation paradigm by introducing some adversarial MT systems, e.g., SMT with copying mechanism. Specifically, we introduce basic competition scenarios with 3-5 competitors to the shared task, and we consider different numbers of adversarial systems, namely *i)* no adversary; *ii)* one adversarial SMT with word copy; *iii)* two adversarial SMT systems with word copy. We provide details of two SMT systems in Appendix F.6. The experiments with adversarial

# Sys.	Method	No Adversary		One adversarial SMT				Two adversarial SMTs			
		K. τ ↑	**P. r** ↑	**Hit@1** ↑	**Avg. Rank** ↓	**K. τ** ↑	**P. r** ↑	**Hit@2** ↑	**Avg. Rank** ↓	**K. τ** ↑	**P. r** ↑
3	Sing-Check	0.07	0.17	0.50	2.00	0.33	0.51	0.00	4.75	-0.15	-0.30
	X-Check	0.47	0.43	1.00	1.00	0.33	0.98	1.00	1.50	0.55	0.98
4	Sing-Check	0.33	0.37	0.25	2.75	0.40	0.39	0.00	5.75	-0.03	-0.33
	X-Check	0.57	0.81	1.00	1.00	0.60	0.97	1.00	1.50	0.70	0.98
5	Sing-Check	0.48	0.58	0.25	3.25	0.30	0.25	0.00	6.75	-0.05	-0.40
	X-Check	0.42	0.52	1.00	1.00	0.50	0.93	1.00	1.50	0.62	0.92

Table 6: Results of the competition between 3 to 5 honest competitors, with a combination of additional adversarial competing systems (No Adversary, One adversarial SMT ($X = 0.1$) w/ copy, Two adversarial SMTs ($X = 0.1$ and $X = 0.5$) w/ copy). We measure the identifiability of the adversarial MT systems by Hit@K, where K is decided by the number of adversarial systems. We also report the average ranking (Avg. Rank.) of the adversarial systems, and correlation scores, Kendall's τ and Pearson's r.

systems are conducted on four language pairs, cs-en, de-en, en-cs and en-de, as the corresponding adversarial systems were trained in Section 3.3.

Discussion. We also observe that the overall system ranking could be severely affected by the adversarial systems, according to Pearson's r and Kendall's τ. The adversarial systems are stealthy among normal competitors, according to Hit@K and Avg. Rank. X-Check evidently successfully identifies these adversarial systems in all our experiments and manages to improve the correlation scores significantly.

6 RT-SCOREs for Quality Estimation

In this section, we demonstrate that the features acquired by round-trip translation benefit quality estimation (QE) models.

Dataset. QE was firstly introduced in WMT11 (Callison-Burch et al., 2011), focusing on automatic methods for estimating the quality of neural machine translation output at run-time. The estimated quality should align with the human judgment on the word and sentence level, without accessing to the reference in the target language. In this experiment, we perform sentence-level QE, which aims to predict human direction assessment (DA) scores. We use DA dataset collected from 2015 to 2021 by MT News Translation shared task coordinators. The *train set* contains 33 diverse language pairs and a total of 574,186 tuples with source, hypothesis, reference and direct assessment z-score. We construct the *test* set by collecting DA scores on *zh-en* (82,692 segments) and *en-de* (65,045 segments), as two *unseen* language pairs.

Experimental Setup. Firstly, we extract RT features RT-sacreBLEU, RT-spBLEU and RT-chrF. Then, we examine whether QE scores could be predicted by these RT features using linear regression models. We train the regressors using Equation 5 with only $A \circlearrowright B$ features. Finally, a combination of COMET-QE-DA scores and RT-SCOREs are investigated to acquire a more competitive QE scorer.

QE model	zh-en		en-de	
	K. τ ↑	**P. r** ↑	**K. τ** ↑	**P. r** ↑
RT-sacreBLEU	15.17	21.76	11.83	19.71
RT-spBLEU	13.55	18.30	11.49	19.00
RT-chrF	15.52	21.74	13.57	22.93
RT-ALL	15.53	21.74	13.52	22.87
COMET-QE-DA	32.83	46.91	42.71	64.36
+ RT-ALL	**32.87**	**46.92**	**42.74**	**64.42**

Table 7: Comparisons of RT-SCORE for QE. RT-ALL refers to the combination of RT-sacreBLEU, RT-spBLEU and RT-chrF. COMET-QE-DA + RT-ALL incorporates both COMET-QE-DA and all RT-SCOREs.

Discussion. Both Kendall's τ and Pearson's r provide consistant results in Table 7. The models merely using RT-SCOREs could be used to predict DA scores. We also observe that RT-SCOREs can further boost the performance of COMET-QE-DA. We believe RT-SCOREs advances QE research and urge more investigation in this direction.

7 Conclusion

This paper revisits the problem of estimating FT quality using RT scores. The negative results from previous literature are basically caused by the heavy reliance of copy mechanism in traditional statistical machine translation systems. Then, we conduct comprehensive experiments to show the corrected understanding on RT benefits several relevant MT evaluation tasks, such as predicting FT metrics using RT scores, filtering out unreliable MT competitors for WMT shared tasks, and enhancing state-of-the-art QE systems. We believe our work will inspire research on reference-free evaluation on low-resource machine translation and natural language generation.

Limitations

Although we have observed positive correlation between FT-SCOREs and RT-SCOREs and conduct experiments to predict FT-SCOREs using RT-SCOREs, their relation could be complicated and non-linear. We encourage future research to investigate various RT-SCORE features and more complex machine learning models for better prediction models. Although we have examined the prediction models on low-resource languages in `FLORES-101`, we have not tested those very low-resource languages out of these 101 languages. We suggest auditing FT-SCORE prediction models on a small validation dataset for any new low-resource languages in future applications.

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A Dataset Construction

Resource	Language	Scale	Usage
High	English	-	TRAIN+TEST
	Spanish	315M	TRAIN+TEST
	French	289M	TRAIN+TEST
	German	216M	TRAIN+TEST
	Portuguese	137M	TRAIN+TEST
	Russian	127M	TRAIN+TEST
	Italian	116M	TRAIN+TEST
Medium	Dutch	82.4M	TRAIN+TEST
	Turkish	41.2M	TRAIN+TEST
	Polish	40.9M	TRAIN+TEST
	Chinese	37.9M	TRAIN+TEST
	Romanian	31.9M	TRAIN+TEST
	Greek	23.7M	TRAIN+TEST
	Japanese	23.2M	TRAIN+TEST
	Czech	23.2M	TEST
	Finnish	15.2M	TEST
	Bulgarian	10.3M	TEST
	Lithuanian	6.69M	TEST
	Estonian	4.82M	TEST
	Latvian	4.8M	TEST
	Hindi	3.3M	TEST
	Javanese	1.49M	TEST
	Icelandic	1.17M	TEST
Low	Tamil	992K	TRAIN+TEST
	Armenian	977K	TEST
	Azerbaijani	867K	TEST
	Kazakh	701K	TRAIN+TEST
	Urdu	630K	TEST
	Khmer	398K	TRAIN+TEST
	Hausa	335K	TRAIN+TEST
	Pashto	293K	TRAIN+TEST
	Burmese	283K	TEST
	Gujarati	160K	TRAIN+TEST

Table 8: The statistics of FLORES-AE33. 20 languages are used in both training and test (TRAIN+TEST), the other 13 languages are used in test only (TEST).

We provide the statistics of all languages covered by FLORES-AE33, categorised by different scale of the resource (high, medium and low) and usage purpose (TRAIN+TEST and TEST) in Table 8. Scale is counted by the amount of bi-text data to English in FLORES-101 (Goyal et al., 2022a).

B Automatic Evaluation Metrics for Translation

For BERTScore, Deberta-xlarge-mnli (He et al., 2021) is used as the backbone pre-trained language model, as it is reported to have a satisfactory correlation with human evaluation in WMT16. While sacreBLEU, spBLEU and chrF are string-based metrics, BERTScore is model-based. The selection of these metrics is on the basis that they should directly reflect the translation quality. We calculate those scores via open-source toolboxes, EASYNMT[8], SACREBLEU-TOOLKIT[9] and BERTSCORE[10]. We use word-level 4-gram for sacreBLEU and spBLEU, character-level 6-gram for chrF, and F_1 score for BERTScore by default.

C Machine Translation Systems

MBART50-M2M. MBART50-M2M (Tang et al., 2020) is a multilingual translation model with many-to-many encoders and decoders. The model is trained on 50 publicly available language corpora with English as a pivot language.

M2M-100-BASE & M2M-100-LARGE. These two models are one of the first non-English-centric multilingual machine translation systems, which are trained on 100 languages covering high-resource to low-resource languages. Different from MBART50-M2M, M2M-100-BASE and M2M-100-LARGE (Fan et al., 2021) are trained on parallel multilingual corpora without an explicit centering language.

OPUS-MT. OPUS-MT (Tiedemann and Thottingal, 2020) is a collection of one-to-one machine translation models which are trained on corresponding parallel data from OPUS using MARIAN-NMT as backbone (Junczys-Dowmunt et al., 2018). The collection of MT models support 186 languages.

GOOGLE-TRANS. GOOGLE-TRANS (Wu et al., 2016; Bapna et al., 2022) is an online Translation service provided by Google Translation API, which supports 133 languages. The system is frequently involved as a baseline system by WMT shared tasks (Barrault et al., 2020).

D Implementation Details

Regressor. We use the linear regression model tool by Scikit-Learn[11] with the default setting for the API.

[8] https://github.com/UKPLab/EasyNMT.
[9] https://github.com/mjpost/sacrebleu.
[10] https://github.com/Tiiiger/bert_score.
[11] https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

MT Systems. We adopt `EasyNMT`[12] for loading MBART50-M2M, M2M-100-BASE, M2M-100-LARGE and OPUS-MT for translation.

Computational Resource and Time. In our experiment, we collect the translation results and compute their FT-SCORE and RT-SCORE on multiple single-GPU servers with Nvidia A40. Overall, it cost us about three GPU months for collecting translation results by all the aforementioned MT systems.

E Measurement

We evaluate the performance of our predictive model via the following measurements:

Mean Absolute Error (MAE) is used for measuring the average magnitude of the errors in a set of predictions, indicating the accuracy for continuous variables.

Root Mean Square Error (RMSE) measures the average magnitude of the error. Compared to MAE, RMSE gives relatively higher weights to larger error.

Pearson's r correlation (Benesty et al., 2009) is officially used in `WMT` to evaluate the agreement between the automatic evaluation metrics and human judgement, emphasizing on the translation consistency. In our paper, the metric evaluates the agreement between the predicted automatic evaluation scores and the ground truth.

Kendall's τ correlation (Kendall, 1938) is another metric to evaluate the ordinal association between two measured quantities.

F Supplementary Experiments

F.1 Correlation between FT-SCOREs and RT-SCOREs on `FLORES-AE33`

Settings. We experiment with MBART50-M2M and M2M-100-BASE on **Type I** test set of `FLORES-AE33` by comparing their RT-SCORE$^{\mathcal{M}}_{A\circlearrowright B}$, RT-SCORE$^{\mathcal{M}}_{B\circlearrowright A}$ and FT-SCORE$^{\mathcal{M}}_{A\to B}$ using multiple translation metrics $\mathcal{M}$, `sacreBLEU`, `spBLEU`, `chrF` and `BERTScore`. We measure their correlations by computing Pearson's r (Benesty et al., 2009) of (RT-SCORE$^{\mathcal{M}}_{A\circlearrowright B}$, FT-SCORE$^{\mathcal{M}}_{A\to B}$) and (RT-SCORE$^{\mathcal{M}}_{B\circlearrowright A}$, FT-SCORE$^{\mathcal{M}}_{A\to B}$). Note that our experiment is beyond English-centric, as all languages are permuted and equally considered.

Discussion. The overall correlation scores are reported in Table 9. Our results indicate at least moderately positive correlations between all pairs of RT-SCOREs and FT-SCOREs. Moreover, we observe that RT-SCORE$_{B\circlearrowright A}$ is generally more correlated to FT-SCORE than RT-SCORE$_{A\circlearrowright B}$, leading to strongly positive correlation scores. We attribute the advantage to the fact that $\mathcal{T}_{A\to B}$ serves as the last translation step in RT-SCORE$_{B\circlearrowright A}$. We visualize more detailed results of correlation between FT-SCOREs and RT-SCOREs on **Type I** language pairs in `FLORES-101`, in Figure 3 (MBART50-M2M) and Figure 4 (M2M-100-BASE).

F.2 Regressors on Language Resources

In Tables 11 and 12, we provide detailed performance of our regressor on language pairs of different resources categories on `FLORES-AE33`, with RT-SCOREs of MBART50-M2M and M2M-100-BASE respectively. Specifically, we split the three categories based on Table 8, which are high, medium and low. The evaluated regressor is the same as the one tested in Sections 4.3.1 and 4.3.2. The results of two tables show that our regressor is able to predict FT-SCOREs with small errors, and reflect the relative orders among FT-SCOREs, with high transferability across language pairs and MT systems.

F.3 Improve Prediction Performance Using More Features

Settings. We introduce two extra features, MAX-4 COUNT and REF LENGTH,[13] to enhance the prediction of `spBLEU`. MAX-4 COUNT is the counts of correct 4 grams, and REF LENGTH is the cumulative reference length. We follow the similar procedure in **RQ2**, using the same measurements to evaluate the predictor performance on MBART50-M2M and M2M-100-BASE across three types of test sets in `FLORES-AE33`.

Results. Table 10 shows the results of those models with additional features. Both features consistently improve our basic models, and the performance can be further boosted by incorporating both features. We believe that more carefully designed

[12] https://github.com/UKPLab/EasyNMT

[13] MAX-4 COUNT and REF LENGTH are "counts" and "ref_len" in https://github.com/mjpost/sacrebleu/blob/master/sacrebleu/metrics/bleu.py.

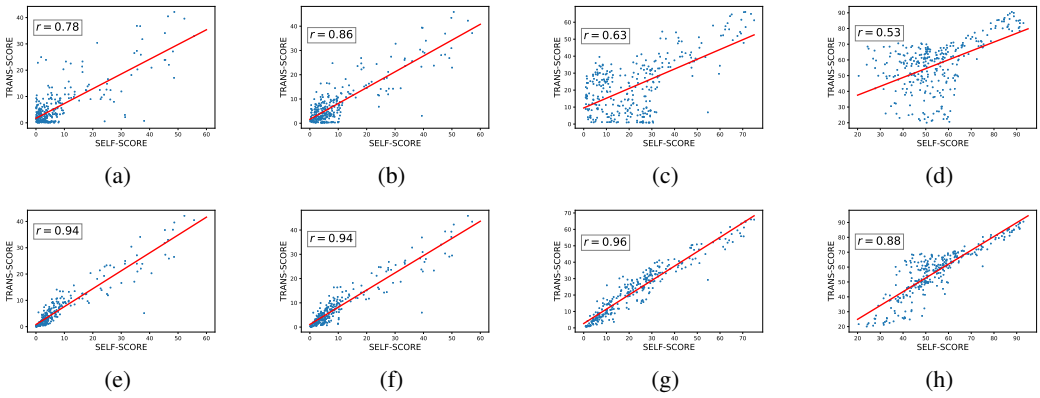

Figure 3: The first row is the correlations between RT-SCORE$^{\mathcal{M}}_{A\circlearrowright B}$ and FT-SCORE$^{\mathcal{M}}_{A\to B}$ on MBART50-M2M using (a) `sacreBLEU`, (b) `spBLEU`, (c) `chrF` and (d) `BERTScore`. The second row is the correlations between RT-SCORE$^{\mathcal{M}}_{B\circlearrowright A}$ and FT-SCORE$^{\mathcal{M}}_{A\to B}$ on MBART50-M2M using (e) `sacreBLEU`, (f) `spBLEU`, (g) `chrF` and (h) `BERTScore`. All experiments with overall Pearson's r.

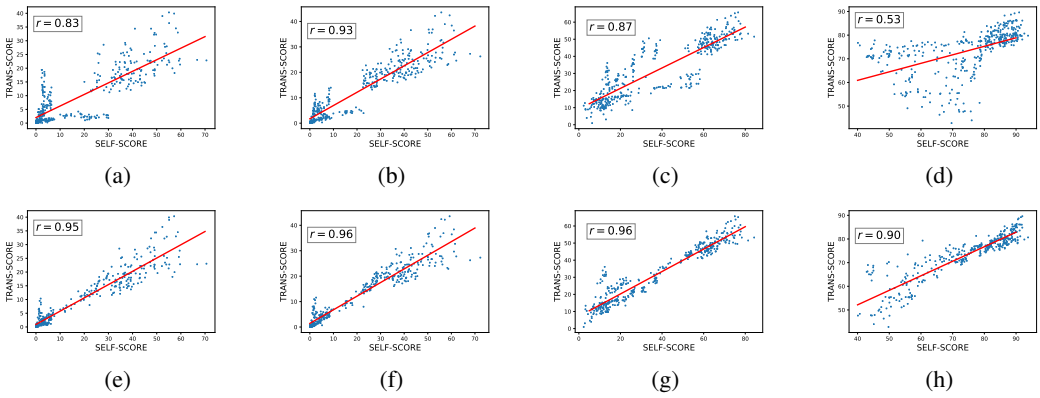

Figure 4: The first row is the correlations between RT-SCORE$^{\mathcal{M}}_{A\circlearrowright B}$ and FT-SCORE$^{\mathcal{M}}_{A\to B}$ on M2M-100-BASE using (a) `sacreBLEU`, (b) `spBLEU`;, (c) `chrF` and (d) `BERTScore`. The second row is the correlations between RT-SCORE$^{\mathcal{M}}_{B\circlearrowright A}$ and FT-SCORE$^{\mathcal{M}}_{A\to B}$ on M2M-100-BASE using (e) `sacreBLEU`, (f) `spBLEU`, (g) `chrF` and (h) `BERTScore`. All experiments with overall Pearson's r.

MT System	Comparison	sacreBLEU	spBLEU	chrF	BERTScore
MBART50-M2M	$A \to B$ vs. $A \circlearrowright B$	0.78	0.86	0.63	0.53
	$A \to B$ vs. $B \circlearrowright A$	0.94	0.94	0.96	0.88
M2M-100-BASE	$A \to B$ vs. $A \circlearrowright B$	0.83	0.93	0.87	0.53
	$A \to B$ vs. $B \circlearrowright A$	0.95	0.96	0.96	0.90

Table 9: Pearson's r between FT-SCORE$^{\mathcal{M}}_{A\to B}$ and RT-SCORE$^{\mathcal{M}}$ (both $A \circlearrowright B$ and $B \circlearrowright A$) using different automatic evaluation metrics $\mathcal{M}$ on **Type I** test set of `FLORES-AE33`.

MT System	Self-Trans Feature	Type I			Type II			Type III		
		MAE ↓	RMSE ↓	r ↑	MAE ↓	RMSE ↓	r ↑	MAE ↓	RMSE ↓	r ↑
MBART50-M2M	spBLEU (basic model)	2.13	2.99	0.94	1.61	2.19	0.93	1.20	1.38	0.94
	+ MAX-4 COUNT	2.01	2.92	0.94	1.54	2.15	0.94	1.12	1.34	0.94
	+ REF LENGTH	2.07	2.96	0.94	1.61	2.21	0.93	1.17	1.45	0.94
	+ MAX-4 COUNT & REF LENGTH	2.00	2.92	0.94	1.53	2.16	0.94	1.08	1.33	0.95
M2M-100-BASE	spBLEU (basic model)	3.97	5.72	0.96	3.24	4.18	0.96	3.18	3.88	0.95
	+ MAX-4 COUNT	2.95	4.00	0.96	2.74	3.67	0.95	2.82	3.62	0.93
	+ REF LENGTH	3.61	5.32	0.96	2.93	3.92	0.96	2.90	3.67	0.94
	+ MAX-4 COUNT & REF LENGTH	2.95	4.10	0.96	2.71	3.65	0.95	2.79	3.59	0.93

Table 10: The results of using auxiliary features to `spBLEU` for training predictors. We test the performance of MBART50-M2M and M2M-100-BASE cross language pairs in **Type I**, **Type II** and **Type III** of `FLORES-AE33`.

	MAE			RMSE			P. r		
	H.	M.	L.	H.	M.	L.	H.	M.	L.
H.	3.17	2.90	2.70	4.02	3.74	4.07	0.94	0.94	0.77
M.	1.51	1.37	1.77	1.95	1.78	2.29	0.97	0.85	0.22
L	1.22	1.27	1.16	1.39	1.43	1.36	0.97	0.87	0.78

Table 11: The results of predicted FT-SCOREs of MBART50-M2M on nine sets of language pairs, categorized by different scale of the resources, High (H.), Medium (M.) and Low (L.). The three categories in rows are source languages, and the ones in columns are target languages. We report Mean Average Error (MAE), Root Mean Square Error (RMSE) and Pearson's r.

	MAE			RMSE			P. r		
	H.	M.	L.	H.	M.	L.	H.	M.	L.
H.	8.72	5.41	3.50	10.82	6.45	4.52	0.51	0.80	0.67
M.	4.86	4.01	2.93	4.71	1.78	4.09	0.86	0.90	0.69
L	1.70	1.67	1.24	1.39	1.86	1.51	0.98	0.97	0.80

Table 12: The results of predicted FT-SCOREs of M2M-100-BASE on nine sets of language pairs, categorized by different scale of the resources, High (H.), Medium (M.) and Low (L.). The three categories in rows are source languages, and the ones in columns are target languages. We report Mean Average Error (MAE), Root Mean Square Error (RMSE) and Pearson's r.

features and regression models could potentially boost the performance of our predictors.

F.4 WMT2020-News with Synthetic Competitors

We increase the scale of competitors to WMT2020-News by introducing pseudo competitors. To mimic the number of a conventional WMT task, we vary 17 forward translation systems by randomly dropping 0% to 80% (with a step of 5%) tokens from the outputs of GOOGLE-TRANS. Then, we utilize the vanilla GOOGLE-TRANS to translate these synthetic forward translation results back to the source language. We conduct experiments on *de-fr*, *en-ta* and *zh-en*, representing those *non-En to non-En*, *En to non-En* and *non-En to En* language pairs.

The results in Table 13 demonstrate the predictors' performances on ranking the pseudo competitors on WMT2020-News based on spBLEU features. The overall ranking errors on 17 MT systems are small on all three selected language pairs.

F.5 Ranking Experiments on WMT2020-Bio

We display the experimental results on WMT2020-Bio in the Table 14. The overall performance is positive, while it is relatively

Langauge Pair	MAE ↓	RMSE ↓	K. τ ↑	P. r ↑
de-fr	2.21	2.67	1.00	0.98
en-ta	0.88	0.98	1.00	0.99
zh-en	1.69	2.37	1.00	0.99
Average	1.59	2.01	1.00	0.99

Table 13: Results of prediction and ranking on translation quality of WMT2020-News synthetic data for three language pairs.

worse than the results of WMT2020-News reported in Table 5. We attribute this to the fact that the $\mathcal{M}$ used on WMT2020-Bio are calculated on document, while our regression models rely on sentence-level translation metrics in training. The large granularity difference of text may result in a distribution shift.

Langauge Pair	$B \circlearrowright A$				$A \circlearrowright B$ & $B \circlearrowright A$			
	MAE ↓	RMSE ↓	K. τ ↑	P. r ↑	MAE ↓	RMSE ↓	K.τ ↑	P. r ↑
de-en	10.96	11.06	0.80	0.75	10.15	10.21	0.80	0.76
en-de	5.41	5.69	0.80	0.63	5.94	6.06	0.80	0.63
en-es	6.42	7.95	0.80	0.82	6.31	7.42	0.80	0.83
en-fr	4.03	6.27	0.40	0.19	3.68	5.86	0.40	0.20
en-it	6.13	6.92	0.40	0.56	5.94	6.58	0.40	0.57
en-ru	4.16	5.62	0.20	0.46	4.20	5.18	0.20	0.49
en-zh	2.17	2.73	0.20	-0.04	2.21	2.59	0.00	0.02
es-en	6.58	8.17	0.60	0.75	6.23	7.48	0.80	0.79
fr-en	6.12	8.02	0.60	0.66	5.77	7.13	0.60	0.67
it-en	6.33	7.94	0.60	0.50	5.90	7.13	0.60	0.56
ru-en	5.94	8.51	0.40	0.18	5.51	7.81	0.20	0.23
zh-en	5.67	8.15	0.20	0.22	5.18	7.48	0.20	0.23
Average	5.83	7.25	0.50	0.47	5.59	6.74	0.48	0.50

Table 14: Results of our predictors on ranking the selected MT systems on WMT2020-Bio shared tasks.

F.6 Benign MT systems and Adversarial MT Systems for X-Check

The selection of the benign systems is:

- **3 Systems:** OPUS-MT, M2M-100-LARGE and MBART50-M2M;
- **4 Systems:** OPUS-MT, M2M-100-LARGE,M2M-100-BASE and MBART50-M2M;
- **5 Systems:** GOOGLE-TRANS, OPUS-MT, M2M-100-LARGE,M2M-100-BASE and MBART50-M2M.

SMT ($X = 0.1$). We train the SMT system on News-Commentary v8 with the max phrase length 4 and the phrase table probability threshold of 0.1.

SMT ($X = 0.5$). We train the SMT system on News-Commentary v8 with the max phrase length 4 and the phrase table probability threshold of 0.5.

SMT($X = 0.1$) tends to copy fewer words than SMT($X = 0.5$), due to the larger phrase table size filtered by lower prebability threshold.