RETHINKING THE REASONABILITY OF THE TEST SET FOR SIMULTANEOUS MACHINE TRANSLATION

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ABSTRACT

Simultaneous machine translation (SimulMT) models start translation before the end of the source sentence, making the translation monotonically aligned with the source sentence. However, the general full-sentence translation test set is acquired by offline translation of the entire source sentence, which is not designed for SimulMT evaluation, making us rethink whether this will underestimate the performance of SimulMT models. In this paper, we manually annotate a monotonic test set based on the MuST-C English-Chinese test set, denoted as SiMuST-C. Our human evaluation confirms the acceptability of our annotated test set. Evaluations on three different SimulMT models verify that the underestimation problem can be alleviated on our test set. Further experiments show that finetuning on an automatically extracted monotonic training set improves SimulMT models by up to 3 BLEU points.

Index Terms— Machine Translation, Simultaneous Machine Translation Evaluation

1. INTRODUCTION

Recently, remarkable progress has been made by simultaneous machine translation (SimulMT) models [1, 2], consisting of streaming translation models [3, 4] that do not revise translations and re-translation models [5, 6] with revision. Streaming translation models either adopt fixed policies [3, 7, 8] or adaptive policies [1, 2, 4, 9, 10] to find the READ-WRITE paths and need to balance translation quality and latency. Retranslation models re-translate each successive source prefix to revise previous partial translations, requiring careful control of the flicker in the translation [11, 12]. However, there is a thought-provoking phenomenon. Most SimulMT models are evaluated on the general full-sentence translation test set, which is acquired by translating the full source sentence offline. Yet the SimulMT models must generate translations without reading the full source sentences. This makes us wonder: is it reasonable to evaluate the performance of SimulMT models with the general full-sentence translation test set?

Model	BLEU		AP	
	Score	$\Delta(\%)$	Score	$\Delta(\%)$
Wait-k (AL=6.08)	24.1	24.90%	78%	14 10%
Wait-k (AL=1.09)	18.2	-24.2%	67%	-14.170
Re-trans (NE=1.00)	25.2	-23.4%	75%	-13.3%
Re-trans (NE=0.09)	19.3		65%	

Table 1: Comparison between automatic and human evaluation.

To explore this question, we compare the automatic and human evaluation results of the Wait-k and Re-trans models on the MuST-C test set. In Table 1, the translation quality of the Wait-k and Re-trans models degrades rapidly as latency and flicker decrease, and the BLEU scores of both models with low latency and few flickers are 24.2% and 23.4% lower than those with high latency and many flickers, respectively. Note that Δ stands for the quality drop rate, lower AL [3] value means lower latency, lower NE value [6] means fewer flickers, and AP is human acceptability [13, 14]. A total of 200 sentences are randomly sampled from the test set for human evaluation¹. Surprisingly, we find that both for the Wait-kand Re-trans models, the quality drop rates in human scoring is only 13~14%, which is much lower than those of BLEU scores. Therefore, the general full-sentence translation test set indeed underestimates the ability of the SimulMT model.

Intuitively, SimulMT models usually generate monotonic translations due to limited source information. However, the long-distance reordering in the general full-sentence translation test set leads to the problem that the test set underestimates the SimulMT model. [15, 16] show that the monotonic data and the monotonic training method could improve translation quality at low latency. [17, 18, 19] collect real-world interpretation data, which have serious omission because the interpretation task is extremely challenging and exhausting for human. To this end, we devise a new annotation method performed on text streams, which has no limitation in time or memory for annotators². Our annotation method is applied to the MuST-C [20, 21] English-Chinese test set³. Comparative experiments on three different SimulMT models show that the underestimation problem can be alleviated on our annotated

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¹The evaluator has extensive experience and qualification with TEM-8 (Test for English Majors-Band 8).

 $^{^2} The annotators have extensive experience and qualification with TEM-8. <math display="inline">^3 SiMuST-C$ is available at https://github.com/XiaoMi/SiMuST-C.

test set. Moreover, finetuning on a monotonic dataset automatically extracted from the training set improves SimulMT models by up to 3 BLEU points on our annotated test set.

2. METHOD

2.1. Human Annotation

Our annotation is performed on text streams. Initially, no words in the source sentence are exposed to the annotator. The annotater starts with reading the first source word, then he/she chooses either the READ or WRITE action per step. READ means the annotator reads the next source word, and WRITE means the annotator translates and outputs a target word. Once the full source sentence has been read, the annotator finishes the current sentence. An example is given in Table 2, the source and target streams are recorded during annotation. We also make an agreement with annotators that the target words that have already been written cannot be revised.

Source Streams	Target Streams	Actions
And		R(And)
And this	this 这	this R(this) W(这)
And this made	this make 这使	make R(made) W(使)
And this made me	this make me 这使我	me R(me) W(我)
And this made me sad	this make me sad 这 使 我 难过	sad R(sad) W(难过)

Table 2: An example of streaming annotation. R and W representthe READ and WRITE actions performed by annotators, respectively.The contents in parentheses indicate what annotators read and write.**2.2.** Automatic Extraction

Drawing on AR_k defined by [15], we design a metric to measure the monotonicity of parallel sentence pairs. Given a sentence pair $X = [x_1, x_2, ..., x_i, ...]$ and $Y = [y_1, y_2, ..., y_j, ...]$, we use the tool SimAlign [22] to calculate the word alignment As. The presence of (x_i, y_j) in As means that the i^{th} word in the source sentence is aligned with the j^{th} word in the target sentence. i - j > 0 indicates that anticipation [3] occurs, which means that the j^{th} target word is aligned with the source word that has not yet been seen. Assume n = |As|, Average Anticipation (AA) is computed:

$$AA = \frac{1}{n} \sum_{(x_i, y_j) \in As} \max{(i - j, 0)}$$
(1)

We first calculate the AA score of each sentence pair in the training set and then select sentence pairs with AA scores of 0. We believe that these sentence pairs are relatively monotonic and do not contain long-distance reordering, which is used to finetune the SimulMT models.

3. EXPERIMENTS

3.1. Datasets

We use the English-Chinese dataset from MuST-C release $v2.0^4$, where the training and development sets consist of

Src.1	There are 68 million people estimated to be in wheelchairs world- wide				
OrigRef	worldwide estimate have 68 million wheelchair users 世界上 估计 有 6千8百万 轮椅 使用者				
MonoRef	there are 68 million, estimate there are 68 million use 有6800万人, 估计 有6800万人 使用 wheelchair worldwide 較椅, 在全世界范围内				
Src.2	Who are these cousins?				
OrigRef	these cousin is what animal 这些 近亲 是些什么 动物				
MonoRef	who are these cousin 谁 是 这些 堂兄妹				

 Table 3: Examples of test-orig and test-mono.

358, 853 and 1, 349 sentence pairs, respectively. The original test set tst-COMMON contains 2,841 sentence pairs, denoted as test-orig, and the reference is called OrigRef. Human annotation is performed on the source of test-orig to build a monotonic test set called test-mono, and the reference is marked as MonoRef. Examples in Table 3 show the difference between OrigRef and MonoRef. Sacremoses⁵ and Jieba⁶ are employed for English tokenization and Chinese word segmentation. Byte pair encoding [23] is applied with 32k operations. For the first example, the word "worldwide" is translated at the end in the MonoRef, which is more consistent with the word order in the source sentence compared to the OrigRef, so the MonoRef has better monotonicity. In the second example, the OrigRef is actually obtained by segmenting the documentlevel translation into sentences, so translations may depend on the context, such as "animal," whereas the MonoRef is a sentence-level translation, which can only translate information in the source sentence and is more in line with the prediction of machine translation models.

3.2. Models

We employ the following three models to compare the performance of the SimulMT models on test-orig and test-mono:

- Wait-k: Streaming translation models trained with fixed latency (*k*=13 for reported results), proposed by [3].
- **GMA**: Streaming translation models trained with an adaptive-policy strategy, proposed by [9].
- **Re-trans**: Re-translation models, conventional transformer trained on the mixture of the original training set and prefix pairs [12], with biased beam search proposed by [6].

Wait-*k* and GMA are used to evaluate the streaming translation model, and Re-trans is for evaluating the re-translation model. All models are implemented based on fairseq [24] with the transformer_iwslt_de_en setting.

3.3. Metrics

To explore the availability of our annotated test set, we conduct analysis from three aspects: quality, latency, and stability. The BLEU [25] scores on both test-orig and test-mono are

⁴https://ict.fbk.eu/must-c-release-v2-0/

⁵https://github.com/alvations/sacremoses

⁶https://github.com/fxsjy/jieba



Fig. 1: BLEU-AL curves of streaming translation methods, including Wait-*k*, and GMA models. Greedy denotes the general full-sentence translation model decodes with beamsize of 1.

Metrics	test-orig	test-mono
Human Score ↑	4.24	4.08
$AP\uparrow$	92.7%	89.7%
$AA\downarrow$	1.47	0.77
$AL\downarrow$	15.65	2.71

Table 4: Comparison between test-orig and test-mono.

calculated by SacreBleu [26], and denoted as BLEU-Orig and BLEU-Mono, respectively. Since the reference stream is also recorded during the annotation process, we can calculate the BLEU score of the intermediate translation, denoted as BLEU-Stream. Following [3] and [6], Average Lagging (AL) and Normalized Erasure (NE) are adopted to measure the latency and the stability, respectively.

3.4. Analytical Experiments

3.4.1. Applicability and Monotonicity

For the two test sets, test-orig and test-mono, 200 sentences are randomly sampled, then three annotators separately rate the acceptability of translations in the range of [1, 5], and finally, translations with a score of at least 3 are considered acceptable. The average human score and average acceptability (AP) rates on both test sets are listed in Table 4. It can be seen that the acceptability ratio of test-mono is comparable to test-orig, confirming the high quality of our annotated test-mono. AA is calculated according to Equation 1, reflecting the monotonicity of the reference translation, and the smaller value means the better monotonicity. The AL of test-orig is counted by the number of words in the source sentence, and the AL of test-mono is calculated based on the number of waiting words per WRITE action during the annotation process. Both AA and AL scores are averaged over the test set. Table 4 shows that test-mono has lower AL and AA scores than test-orig, which indicates that test-mono is an online annotated test set and has better monotonicity. In conclusion, test-mono is of high quality and more monotonic.

3.4.2. Quality and Latency

We leverage the BLEU-AL curves to show the trade-off between the quality and latency of the SimulMT model. As shown in Figure 1, BLEU-Orig, BLEU-Mono, and normalized scores on the test sets are calculated separately. Note that, as explained in Section 3.1, the BLEU scores of SimulMT models on test-mono are higher than those on test-orig.

In Figures 1a and 1b, the Wait-k model performs better than the GMA model when evaluated on test-orig and test-mono, the Wait-k model has a higher BLEU score in each AL regime. The GMA model performs poorly, possibly due to the reordering in English-Chinese parallel data, which makes it difficult to learn the best READ/WRITE path. The quality drop of the Wait-k model in high-latency regime can be observed in Figure 1b, which is caused by the decrease in data monotonicity as more source information is read. For comparability across different test sets, we compute the Norm-Score to normalize the BLEU scores across different test sets. For each test set, the BLEU score of the full-sentence translation is regarded as the base value (marked as grey dash lines in Figures 1a and 1b), and the BLEU scores of SimulMT models are divided by the base value to get the Norm-Score. As shown in Figure 1c, in the low-latency regime, the Wait-k model performs significantly better on test-mono than on test-orig. This significant improvement indicates that the translation quality at low latency is seriously underestimated by test-orig. It can be concluded that test-mono provides evaluation results more consistent with human evaluation, without underestimation caused by long-distance reordering.

3.4.3. Quality and Stability

The results of the re-translation methods are shown in Figure 2. We draw BLEU-NE curves to show the quality-stability trade-off. Both BLEU-Orig and BLEU-Mono decrease as NE becomes lower. We apply the same normalization method to compare the BLEU scores on test-orig and test-mono. As shown in Figure 2c, the normalized scores on test-mono are shown in a solid line and scores on test-orig are shown in a dash line. The solid line achieves higher scores, especially in the few-flicker regime, which is consistent with the results of quality and latency analysis in Section 3.4.2. The results of the re-translation methods provide further evidence that our test-mono is more consistent with human evaluation.



Fig. 2: BLEU-NE curves of re-translation strategy. Lower NE means better stability. Beam denotes the general full-sentence translation.



Fig. 3: Finetuning results of Wait-k and GMA models. Wait-k-FT and GMA-FT denote the finetuned models. The lower AA means better monotonicity.



Fig. 4: BLEU-steam vs.AL of streaming translation models.

3.4.4. Steaming Evaluation

The BLEU-Stream evaluation is shown in Figure 4. The BLEU-Stream scores reach the highest value when AL is about 3.5 then decrease as latency becomes higher. This is different from other BLEU-AL curves because the target streams may have many blank or short translation in high-latency regime. The BLEU-Stream score may provide us with a reference latency regime, which is close to the delay of manual annotation.

3.4.5. Finetuning

To enhance the monotonicity of SimulMT models, we select 42,000 sentence pairs with no anticipation from the original training corpus, denoted as the monotonic corpus. On the monotonic corpus, we finetune the Wait-k and GMA models for 2,000 steps. And we calculate the AA scores (Equation 1) of the hypotheses generated by models for monotonicity evaluation. Figure 3a shows that the AA scores of the Wait-k and GMA models are both significantly lower after finetuning, meaning the monotonicity improvement of SimulMT models when optimized by the monotonic corpus.

Figure 3b and Figure 3c present the impact of finetuning to BLEU scores. After finetuning, for both Wait-k and GMA models, the BLEU-Orig grows a little bit in low-latency regime and decreases in higher-latency regime. The BLEU-Mono of the Wait-k and GMA models, on the other hand, improves dramatically. In particular, when evaluated by BLEU-Mono, the GMA model is improved by more than 3 points, and the latency gets lower at each δ setting [9]. This notable improvement may suggest that the monotonic corpus is much easier for the GMA model to learn the READ/WRITE strategy. As the finetuning benefits the monotonicity of SimulMT models, our test-mono can better reflect this improvement because of its better monotonicity. So the test-mono performs better in evaluating the monotonicity of SimulMT models.

4. CONCLUSION

We design a streaming annotation method to annotate a monotonic test set based on the MuST-C English-Chinese test set. Human evaluation and experiments prove that our SiMuST-C is of high quality and has better monotonicity. Besides, the automatically extracted monotonic training set can help SimulMT models generate monotonic translations and also significantly improve the model's performance. Overall, our annotated monotonic test set is more suitable for the evaluation of English-Chinese simultaneous machine translation.

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