DECISION ATTENTIVE REGULARIZATION TO IMPROVE SIMULTANEOUS SPEECH TRANSLATION SYSTEMS

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ABSTRACT

Simultaneous Speech-to-text Translation (SimulST) systems translate source speech in tandem with the speaker using partial input. Recent works have tried to leverage the text translation task to improve the performance of Speech Translation (ST) in the offline domain. Motivated by these improvements, we propose to add Decision Attentive Regularization (DAR) to Monotonic Multihead Attention (MMA) based SimulST systems. DAR improves the read/write decisions for speech using the Simultaneous text Translation (SimulMT) task. We also extend several techniques from the offline domain to the SimulST task. Our proposed system achieves significant performance improvements for the MuST-C English-German (EnDe) SimulST task, where we provide an average BLUE score improvement of around 4.57 points or 34.17% across different latencies. Further, the latency-quality tradeoffs establish that the proposed model achieves better results compared to the baseline.

Index Terms— Simultaneous Translation, Speech Translation, Regularization, Multitask Learning, Monotonic Attention

1. INTRODUCTION

Simultaneous Translation systems alternate between read/write decisions when trying to translate from one language to another using streaming input. They aim to produce high-quality outputs with as little latency with respect to the source as possible. These systems find huge applications in settings such as live subtitle generation and real-time interpretation. Initial approaches such as wait-\(k\) [1] use a fixed policy, where the read/write decisions are pre-decided, and the model starts to output after waiting for \(k\) input units. Recent approaches use monotonic attention to learn a flexible policy. Different variants of monotonic attention have been proposed such as Monotonic Hard Attention [2], Monotonic Chunkwise Attention (MoChA) [3], Monotonic Infinite Lookback Attention (MILk) [4] and Monotonic Multihead Attention(MMA) [5]. The most recent of them, MMA, replaces the soft attention in the transformer [6] model with MILk-like monotonic attention.

Traditionally, the Simultaneous text Translation (SimulMT) task has a better performance compared to the Simultaneous Speech-to-Text Translation (SimulST) due to data abundance and the relative difficulty associated with speech inputs. However, simultaneous interpretation is more suited for conversational settings where the input is speech. In this work, we use the relatively easier and data abundant SimulMT task as an auxiliary task to improve the performance of SimulST systems.

Since the speech translation task suffers from data scarcity, many proposed approaches in the offline domain try to tackle this issue. [7], [8] train ST with auxiliary tasks such as text translation and Automatic Speech Recognition (ASR) to train better models. Online Knowledge Distillation (KD) [9] approach uses the text translation model as a teacher to train the student speech model. [9] also proposes Cross-Attentive Regularization (CAR) to improve the speech representations by bringing them closer to the representations of the corresponding text.

Motivated by these improvements in the offline ST domain, we propose to add Decision Attentive Regularization (DAR) to leverage the SimulMT task to improve SimulST performance. The read/write decisions in MMA-based SimulST systems are guided by the monotonic attention energies learned during training. Hence, DAR uses the attention energies corresponding to the text to improve the decision policy for the SimulST task, thus enabling the model to take better read/write decisions. We also extend the recently proposed techniques to the MMA-based SimulST models. Our contributions can be summarized as follows:

1. We introduce a novel Decision Attentive Regularization (DAR) which aids the read/write decisions of SimulST using the SimulMT task.

2. We extend offline speech translation techniques such as data augmentation, pre-training, knowledge distillation,
We use Online KD and CAR losses proposed in [9]. The weight given to the DAL loss, while the latency-variance parameter controls the latency among the reading decisions taken by the SimulST model. In order to motivate early write decisions, we use the Differentiable Average Lagging (DAL) loss proposed in [4] to penalize excessive read decisions.

The latency-average ($\lambda_{avg}$) hyperparameter controls the weight given to the DAL loss, while the latency-variance ($\lambda_{var}$) parameter controls the variance among the reading speed of different attention heads through the head divergence loss. It ensures that the read/write decisions taken by different heads do not diverge. Since, we use MMA-IL for our experiments, we set $\lambda_{var} = 0$. Henceforth, in this paper $\lambda$ refers to $\lambda_{avg}$ or the latency-average parameter.

### 2. Online KD & CAR

We use Online KD and CAR losses proposed in [9]. The Online KD loss computes the cross-entropy loss between the SimulST output and SimulMT output distribution. CAR loss intends to make the speech representations close to the text representations by calculating the difference between the two at the output of the encoder. In this work, we incorporate these methods into the SimulST model since they have been proven to be beneficial in the offline ST domain.

### 2.2. Decision Attentive Regularization

We propose to add Decision Attentive Regularization (DAR) to improve the read/write decisions taken by the SimulST model. For MMA, the decision policy is decided by the monotonic energy (me) between the decoder and encoder states. For a particular attention head, MMA computes a probability $p_{ij}$ which determines whether the $i_{th}$ target uses the $j_{th}$ source step during inference. In the following equations, $e$ represents the encoder output, $y$ is the target, and $z$ determines whether the model reads ($z = 0$) or writes ($z = 1$).

\[
\begin{align*}
me_{i,j} &= \text{MonotonicEnergy}(y_{i-1}, e_j) \\
p_{i,j} &= \text{Sigmoid}(me_{i,j}) \\
z_{i,j} &= \text{Bernoulli}(p_{i,j})
\end{align*}
\]

The read/write decisions rely on the amount of information contained in the source sequence and the word orders of the source and target languages. Hence, we expect an ideal SimulST system to take similar read/write decisions as an ideal SimulMT system. Due to the complexity associated with speech inputs, it is easier to learn the read/write decisions from the text data. Therefore, we use the monotonic energies of the SimulMT model to guide the decision policy of the SimulST model implicitly.

DAR computes the similarity between the monotonic energies of the SimulST and SimulMT models. However, we cannot compute this loss directly since the attention energies corresponding to speech ($A^s$) and text ($A^t$) have different sizes. Similar to [9], we use self-attention and cross-attention operations with respect to the text attention to obtain representations $A^{s \rightarrow t}$ and $A^{t \rightarrow s}$ which have the same size. Finding the $\mathcal{L}^2$ distance between these reconstructed representations serves as the similarity metric between the attention energies.

A particular training example consists of input speech and transcript (MT input) in the source language and target text in the output language. Let $K$ and $L$ denote the length of speech and text representations at the output of the encoder. The monotonic attention energy matrices for speech and text for the $h_{th}$ head are defined as follows:

\[
\begin{align*}
A^s_h &= (att^s_{h,1}, att^s_{h,2}, \ldots, att^s_{h,K}) \\
A^t_h &= (att^t_{h,1}, att^t_{h,2}, \ldots, att^t_{h,L})
\end{align*}
\]

We stack attention energies from different heads as follows:

\[
\begin{align*}
A^s &= [A^s_1, A^s_2, \ldots, A^s_H] = (a^s_1, a^s_2, \ldots, a^s_{K \times H}) \\
A^t &= [A^t_1, A^t_2, \ldots, A^t_H] = (a^t_1, a^t_2, \ldots, a^t_{L \times H})
\end{align*}
\]

Next, we use similarity matrix $S$ to obtain $A^{s \rightarrow t}$ via cross-attention between $A^s$ and $A^t$. Similarly, we use self attention to reconstruct the $A^{t \rightarrow s}$ from $A^t$.

\[
A^{s \rightarrow t} = A^s \cdot \text{softmax}(S)
\]

\[
s_{i,j} = a^s_i \cdot a^t_j / \|a^s_i\|_2 \|a^t_j\|_2
\]

Finally, the DAR loss is computed as follows: $(sg$ - stop gradient operator)

\[
\mathcal{L}_{DAR}(\theta_s) = \frac{1}{L \times H} \|A^{s \rightarrow t} - sg[A^{t \rightarrow s}]\|_2^2
\]

The overall loss $\mathcal{L}(\theta_s, \theta_t)$ combines the negative log likelihood (NLL), KD, CAR, DAR, and the latency loss (DAL), where $\theta_s$ and $\theta_t$ are speech and text model parameters.

\[
\mathcal{L}(\theta_s, \theta_t) = (1 - \alpha)\mathcal{L}_{NLL}(\theta_s) + \alpha \mathcal{L}_{KD}(\theta_s, \theta_t) \\
+ \beta \mathcal{L}_{CAR}(\theta_s) + \gamma \mathcal{L}_{NLL}(\theta_t) \\
+ \delta \mathcal{L}_{DAR}(\theta_s, \theta_t) + \lambda \mathcal{L}_{DAL}(\theta_s, \theta_t)
\]
3. EXPERIMENTAL SETTINGS

3.1. Datasets & Preprocessing

**Speech Translation:** We used the English-German (En-De) portion of the MuST-C [10] dataset. It consists of 230k training examples, 1.4k dev examples, and 2.6k examples in the test set (tst-COMMON). For data augmentation, synthetic speech is generated using sox effects similar to [11].

**Machine Translation:** We used WMT 14 En-De data to train the MT model. Similar to speech data, we generate target texts using WMT 19 winner offline En-De model [12]. KD, CAR, and DAR losses are computed using the parallel text data from the MuST-C En-De dataset.

**Data Preprocessing:** For source speech data, we extract features using 80-dimensional log Mel-filterbank with a step size of 10ms and 25ms window size by using Kaldi [13]. We apply global channel mean and variance normalization. To avoid overfitting, the SpecAugment [14] data augmentation strategy is also applied. Similar to [15], speech transcripts are encoded to phoneme symbols from grapheme using the G2P library. The total vocabulary size for the source speech transcript is 134. For target texts, we use SentencePiece to generate 10k unigram vocabulary [16]. We use original and augmented data in 1:1 proportion by pairing original speech with augmented text and vice versa.

3.2. Implementation Details

The models are implemented using the fairseq [17] toolkit. Our base model is adapted from [18]. We use two 1-dimensional convolutions with a kernel size of 5 and stride set as 2 to reduce the length of incoming speech by a factor of 4. Hence, each encoder state corresponds to 40ms of speech. Since we set the pre-decision ratio as 7, the read/write decisions are taken corresponding to a speech segment size of 280ms during training. We can vary the speech segment size or step size during inference to get different results along the latency-quality curve.

We use an MMA-based transformer model, which consists of a speech encoder (12 layers), text encoder (6 layers), and a joint monotonic decoder (6 layers) shared between the SimulST and SimulMT models. Similar to [9], both speech and text encoders are initialized using pretrained offline ASR encoder and offline MT model encoder, respectively. The top 6 layers of the speech encoder are tied to the text encoder. Similarly, a pretrained offline MT model decoder is used to initialize the decoder weights. All the models are trained using Adam optimizer [19], learning rate set as 0.002 with inverse square root scheduler of 20k warm-up updates.

The model is first trained with KD, MT, and CAR losses for 150 epochs. The proposed model is then finetuned for 10 epochs after adding the DAR loss. Finally, we finetune the model adding the latency loss (Eq. [11]). The loss calculation parameters $\alpha$, $\beta$, $\gamma$ and $\delta$ are set as 0.2 (KD), 0.02 (CAR), 0.5 (MT-NLL loss) and 0.01 (DAR) respectively. To train the model for different latency regimes, we use 3 different values of $\lambda \in \{0.01, 0.05, 0.1\}$. The models before the latency training phase are referred to as $\lambda_0$ models. All the models are trained using 8xA100 GPUs with an update frequency of 4, simulating 32 GPU settings.

4. RESULTS

In this section, we provide the results obtained using various approaches described in Section 2 and 3.1 in the form of latency-quality curves. We use Average Lagging (AL) [18] as our latency metric and case-sensitive detokenized BLEU [20] score to measure the translation quality. In Table 1, we also compare the performance of the models after the initial training phases without the latency loss. It provides the improvements obtained using each approach for the $\lambda_0$ models.

### Table 1. Performance of various approaches: MMA-0 models

| S.No | Method                        | BLEU($\uparrow$) | $\Delta$ BLEU |
|------|-------------------------------|------------------|---------------|
| 1    | Baseline MMA                  | 17.23            | -             |
| 2    | + Data Augmentation           | 19.81            | +2.58         |
| 3    | 1 + Multitask Learning        | 18.90            | +1.67         |
| 4    | + Online KD                   | 19.85            | +0.95         |
| 5    | + CAR                         | 20.10            | +0.25         |
| 6    | + Data Augmentation           | 21.49            | +1.39         |
| 7    | 5 + DAR                       | 20.67            | +0.57         |
| 8    | 6 + DAR                       | 22.35            | +0.86         |

In Fig. 1, we show the effect of data augmentation on the latency-quality curve. The baseline MMA is trained using the same architecture but without any help from the MT task.

4.1. Existing Approaches

As mentioned above, we extend several techniques from the offline ST domain to SimulST. This section discusses the
results obtained using these approaches: data augmentation, Multitask Learning (MTL), online KD, and CAR.

4.1.1. Data Augmentation

As mentioned in Section [3.1] we augment the data using modified speech and generated target text. Data Augmentation provides significant performance gains both for the baseline and the proposed approach. For $\lambda_0$ models, we observe a BLEU score improvement of 2.58 over the MMA baseline, while an improvement of 1.68 (Row 7 vs. Row 8 in Table) for the proposed DAR based model. MMA-Aug refers to the model trained with augmentation. Figure[1] provides the latency-quality tradeoff comparison with the MMA baseline.

4.1.2. Pretraining & Multitask Learning

The baseline MMA model fails to converge without the pretrained ASR encoder. Moreover, using MTL with the SimulMT task boosts the performance of the SimulST model. As we can see in Table MMA-Aug-MT with the SimulMT task provides a BLEU score improvement of 1.67 for the $\lambda_0$ model.

4.1.3. Online KD & CAR

Similar to the offline domain, we observe that both Online KD and CAR improve the performance of the SimulST model. For the $\lambda_0$ model, Online KD provides an improvement of 0.95 BLEU scores over the MTL approach. Further, CAR also provides an improvement of 0.25 BLEU score. Figure[2] provides the latency-quality plot obtained using the model trained with MTL, Online KD, and CAR (referred to as MMA-MT) against the baseline MMA model. It provides consistent improvements as compared to the baseline across different latency regimes. For the $\lambda_0$ models, MMA-MT significantly improves the performance by 2.87 BLEU score (Row 5 vs. Row 1 in Table) over the baseline.

4.2. Proposed Approach: DAR

The results obtained using the proposed Decision Attentive Regularization (DAR) approach have been reported in this section. We also provide the aggregated improvements obtained through various approaches used in this work.

4.2.1. Decision Attentive Regularization

As discussed in the previous sections, DAR loss is designed to improve the read/write decisions for the challenging SimulST task using the relatively easier SimulMT task. The final model (Row 8 in Table) is trained using all the described approaches. MMA-Aug-MT refers to the model trained by adding data augmentation to the MMA-MT model. Finally, MMA-DAR adds the proposed DAR loss on top of MMA-Aug-MT. For $\lambda_0$ models, MMA-DAR provides a BLEU score improvement of 0.57 over the MMA-MT model and 0.86 BLEU score improvement over MMA-Aug-MT. Figure[3] provides the improvements achieved with respect to the latency-quality tradeoff using DAR. It provides improvements in the range of 0.5 ~ 1 BLEU scores consistently across all latency regimes.

5. CONCLUSION

In this work, we leverage the SimulMT task to improve the performance of SimulST system. We extend the existing data augmentation, multitask learning, knowledge distillation, and cross-attentive regularization approaches to monotonic attention-based simultaneous translation models. We propose Decision Attentive Regularization to improve the read/write decision policy for SimulST using the SimulMT task. The proposed approach improves the performance of SimulST systems. Overall, we improve the performance of the baseline by around 35% across different latencies.
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