USST's System for AutoSimTrans 2022

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Outline

- Tracks
- Data and preprocessing
- Text-to-text system
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Tracks

- We participated in two streaming transcription track:
 - Zh→En Translation. (text-to-text)
 - En→Es Translation. (text-to-text)

Streaming transcription	Translation
我	
我下	I
我下面	
我下面来	'm
我下面来讲	
我下面来讲我	going
我下面来讲我们	
我下面来讲我们这	to
我下面来讲我们这段	talk
我下面来讲我们这段故	
我下面来讲我们这段故事	about
我下面来讲我们这段故事。	this story.

Data and preprocessing

Datasets

- Zh→En: We pretrained our MT model on CWMT21 (9.1M) and fine-tined on Baidu Speech Translation Corpus (39K).
- En→Es: We trained our MT model on UN Parallel Coupus (21M).

Preprocessing

- Word Segmentation.
- Length filter.
- Langage identification.
- Deduplication.
- Byte-pair-encoding.

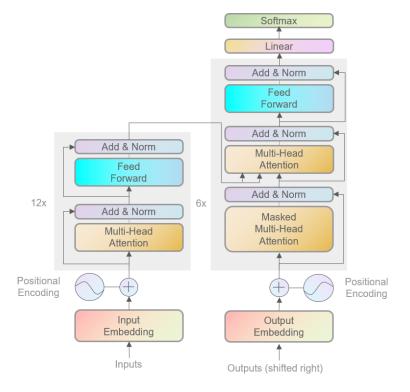
Text-to-text system

• 1. For abtaining rich source representations, we train a Transformer base with 12 layer encoder.

• 2. For stabilize training, we initialize the model with the method mentioned in DeepNet.

```
Encoder
                                                                                                                              Decoder
def deepnorm(x):
                                                                 Architectures
                                                                                           \alpha
    return LayerNorm(x * \alpha + f(x))
                                                                 Encoder-only
                                                                                                         (8N)^{-\frac{1}{4}}
def deepnorm_init(w):
                                                                 (e.g., BERT)
                                                                 Decoder-only
    if w is ['ffn', 'v_proj', 'out_proj']:
                                                                                                                         (2M)^{\frac{1}{4}}
                                                                                                                                   (8M)^{-\frac{1}{4}}
                                                                 (e.g., GPT)
         nn.init.xavier_normal_(w, gain=\beta)
                                                                 Encoder-decoder
    elif w is ['q_proj', 'k_proj']:
                                                                                    0.81(N^4M)^{\frac{1}{16}} 0.87(N^4M)^{-\frac{1}{16}}
                                                                                                                        (3M)^{\frac{1}{4}} (12M)^{-\frac{1}{4}}
                                                                 (e.g., NMT, T5)
         nn.init.xavier_normal_(w, gain=1)
```

Figure 2: (a) Pseudocode for DEEPNORM. We take Xavier initialization (Glorot and Bengio, 2010) as an example, and it can be replaced with other standard initialization. Notice that α is a constant. (b) Parameters of DEEPNORM for different architectures (N-layer encoder, M-layer decoder).



Text-to-text system

 3.For domain adaption, we use in-domain data filtering to mine data from CWMT that is most similar to BSTC, and then mix it with BSTC for fine-tuning.

$$Score(p)_{abs} = |P_I(p) - P_N(p)| \tag{5}$$

• 4. To reduce the latency, we adopt fixed read/write policy wait-k.

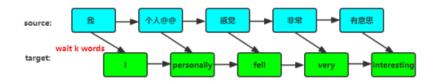


Figure 1: An example of prefix-to-prefix (wait 1).

Conclusion

• 1. This paper describes our text-to-text simultaneous translation system, which uses a deep Transformer to improve translation quality and adopt wait-k policy to reduce latency.

• 3. We plan to research on some dynamic read-write policies in order to better balance quality and latency.

Thank you!