INTEGRATING WHOLE CONTEXT TO SEQUENCE-TO-SEQUENCE SPEECH RECOGNITION

Ye Bai¹,², Jiangyan Yi¹, Jianhua Tao¹,²,³, Zhengkun Tian¹,², Zhengqi Wen¹, Shuai Zhang¹,²

¹NLPR, Institute of Automation, Chinese Academy of Sciences, China
²School of Artificial Intelligence, University of Chinese Academy of Sciences, China
³CAS Center for Excellence in Brain Science and Intelligence Technology, China

ABSTRACT
Because an attention based sequence-to-sequence speech (Seq2Seq) recognition model decodes a token sequence in a left-to-right manner, it is non-trivial for the decoder to leverage the whole context of the target sequence. In this paper, we propose a self-attention mechanism based language model called casual cloze completer (COR), which models the left context and the right context simultaneously. Then, we utilize our previously proposed “Learn Spelling from Teachers” approach to integrate the whole context knowledge from COR to the Seq2Seq model. We conduct the experiments on public Chinese dataset AISHELL-1. The experimental results show that leveraging whole context can improve the performance of the Seq2Seq model.

Index Terms— language modeling, sequence-to-sequence, speech recognition, casual cloze completer, learn spelling from teachers

1. INTRODUCTION
Recently, attention based sequence-to-sequence (Seq2Seq) models have achieved success in automatic speech recognition (ASR) [1, 2]. A common decoder of a Seq2Seq model generates a token sequence in a left-to-right manner, i.e., it only utilizes the left context to predict the next word. Because of this autoregressive property, these decoders are difficult to leverage the right context. The main issue introduced by the left-to-right manner is the error accumulation. This problem generally exists in sequence-to-sequence model for many tasks [3, 4, 5].

Several previous works are proposed to address this issue for Seq2Seq models. A forward-backward searching algorithm was proposed for a Seq2Seq model to decode speech from left to right as well as right to left [4]. However, the three-pass decoding algorithm increases complexity during test stage. A synchronous bidirectional transformer model, which uses left-to-right and right-to-left decoding simultaneously and interactively for machine translation, does not need multi-pass decoding [3]. However, the bidirectional attention computed in parallel makes the model complex. Bidirectional agreement methods, which minimizes discrepancy between a left-to-right decoding Seq2Seq model and a right-to-left one, improves performance of Seq2Seq model for machine translation [6, 7] and end-to-end text-to-speech tasks [5]. However, in these methods, training two Seq2Seq models is not easy. Moreover, the agreement is made between the left-to-right model and the right-to-left model, but the whole sentence context is not leveraged.

In this work, we propose a self-attention based language model called Casual cloze completer (COR), which models the whole context of a sentence. Then, the whole context knowledge is transferred to the Seq2Seq model. Different from previous autoregressive language models [8], COR leverages the left context and the right context simultaneously. And different from previous denoising autoencoder language models, such as BERT [9], COR models position-wise conditional probability for each token directly. We first train COR on external text only data, and then we use our previously proposed “Learn Spelling from Teachers” (LST) training approach to transfer the knowledge from COR to the Seq2Seq speech recognition model [10]. With LST, there’s no extra complexity during test. We conducted experiments on publicly available Chinese speech dataset AISHELL-1. The experimental results demonstrate the effectiveness of leveraging the whole context.

The rest of the paper is organized as follows. Section 2 describes the proposed COR. Section 3 introduces LST method to transfer the knowledge from COR to the Seq2Seq model. Section 4 introduces the related works. Section 5 presents the experiments. Section 6 concludes the paper.

2. CASUAL CLOZE COMPLETER
In this section, we describe the proposed COR, which models the whole sequence context. We first formulate the cloze test problem. And then, we present the COR model architecture.

2.1. Cloze Test
Motivated by previous pre-training language model work BERT [9], we introduce cloze test problem [11]. Fig. 2 shows an example. In cloze test, we predict a token in the sentence in terms of the left context and right context. In this
procedure, the left context and right context, i.e. the whole sequence context, are used simultaneously.

The above procedure can be formulated as follows. Let a token sequence be \( X = [x_1, \ldots, x_T] \), where each \( x \) represents a token in vocabulary, and \( T \) is the sequence length. For a token \( x_t \) at step \( t \), given the left context \( [x_1, \ldots, x_{t-1}] \) and the right context \( [x_{t+1}, \ldots, x_T] \), we would like to predict the probability \( P(x_t | x_1, \ldots, x_{t-1}, x_{t+1}, \ldots, x_T) \).

### 2.2. COR Architecture

We use COR, a neural network, to estimate the above probability for each step in parallel. We use self-attention mechanism to model the token sequence, and predict the probabilities. The self-attention mechanism directly models the long-term dependency between each token in a sequence without recurrent structure, and it can be computed in parallel. Different from BERT [9], we do not introduce [MASK] symbol in to the input sequence to make the token to be predicted do not “see itself”, but directly model the conditional probability. This avoids the mismatch between training and test, because the input sequence does not have [MASK] symbol during test.

The main structure of a transformer block is the same as previous transformer works [12]. First, the scaled dot-product attention aggregates the input \( U = [u_1, \ldots, u_T] \in \mathbb{R}^{T \times D} \) with length \( T \) as follows.

\[
H = \text{softmax}(\frac{QK^T}{\sqrt{D_k}} + M)V,
\]

where \( Q = UW_q, K = UW_k, V = UW_v \).

\( Q \in \mathbb{R}^{T \times D_k}, K \in \mathbb{R}^{T \times D_k}, V \in \mathbb{R}^{T \times D_v} \) denote a query matrix, a key matrix, and a value matrix, respectively. \( D_k \) and \( D_v \) are corresponding dimensionality. \( W_q, W_k, \) and \( W_v \) are corresponding parameter matrices. \( M \in \{0, -\infty \}^{T \times T} \) is the mask matrix to prevent from attending at some positions:

\[
M = \begin{cases} 
-\infty, & \text{mask input} \\
0, & \text{otherwise}
\end{cases}
\]

With matrix \( M \), the attention scores are masked to zero, and this part of input is not used. To allow the model attend from different representation subspaces, we use multi-head version of attention [12]. After attention, a position wise feed-forward network is used as non-linear transformation.

\[
O = \max(HW_1, 0)W_2.
\]

where \( W_1 \in \mathbb{R}^{D_n \times D_{in}} \) and \( W_2 \in \mathbb{R}^{D_{in} \times D} \) are parameter matrices. The residual connections and layer normalization are also used.

The illustration of COR is shown in Fig. 1(a). First, the input token sequence is embedded and added with position embedding. We use sinusoidal position embeddings [12]. Then, two stacks of transformer blocks are used in parallel. The one is a stack of forward transformer blocks to model the left context, and the other is a stack of backward transformer blocks to model the right context. The outputs of the top forward transformer block and the backward transformer block are concatenated together and inputed a fusion transformer block.
The probability of each token at each step is computed with a softmax function. In order to match the target sequence of the downstream speech recognition task, the input sequence of COR is from step 1 to step \( T - 1 \), and the target sequence of COR is from step 2 to step \( T \). Because of this casual property, we name the model as casual cloze completer.

We use three mask mechanism to control the context flows. The illustration of the three different mask matrices is shown in Fig. 1(a). For the forward transformer block, the output at step \( t \) only “see” the left context, i.e. the attention scores from \( t \) to \( T \) are masked to zeros. Note that the target sequence has an offset to the input sequence, so the attention scores also have an offset. Fig. 1(c) shows the context flow for each transformer block. For backward mask, some all-zero-row scores exist, and it makes softmax function illegal. We mask these rows to zeros after softmax.

After optimization, COR predicts the probability distribution on the vocabulary at each time step, given the left context and the right context.

\[
P_{\text{COR}}(k_t|\mathbf{x}_1, \cdots, \mathbf{x}_{t-1}, \mathbf{x}_{t+1}, \cdots, \mathbf{x}_T) = \text{COR}(\mathbf{X}),
\]

(4)

where \( k_t \in 1, \cdots, K \) is the index of the token at step \( t \) in vocabulary, and \( K \) is the vocabulary size.

### 3. LEARN SPELLING FROM TEACHERS

In order to transfer the knowledge from COR to the Seq2Seq speech recognition model, we use our previous work LST training approach [10].

Specifically, let \( P_{\text{S2S}}(k_t|\mathbf{x}_{t-1}, \mathbf{c}_{t-1}, \mathbf{a}; \theta) \) be the probability of the next token at step \( t \), which is estimated by the Seq2Seq model, where \( c_{t-1} \) is the history context of Seq2Seq model, \( a \) is the acoustic features, \( \theta \) represents the parameters. And \( P_{\text{COR}}(k_t|\mathbf{x}_1, \cdots, \mathbf{x}_{t-1}, \mathbf{x}_{t+1}, \cdots, \mathbf{x}_T) \) is estimated by COR, which contains the whole context of the token sequence. We expect the two probabilities as close as possible. So we optimize the following Kullback-Leibler divergence (KLD) \( D_{\text{KL}}(P_{\text{COR}}||P_{\text{S2S}}) \). Because the parameters are fixed during Seq2Seq model training, we can simplify the above KLD to cross-entropy. Moreover, we want to introduce the knowledge from the hard labels of the transcriptions, so we use a coefficient \( \lambda \in [0, 1] \) to combine the standard cross-entropy and the KL divergence. The final loss is

\[
L(\theta) = - \sum_{k_t=1}^{K} (\lambda \delta(k_t, \mathbf{x}_t) + (1 - \lambda) P_{\text{COR}}(k_t|\mathbf{x}_1, \cdots, \mathbf{x}_{t-1}, \mathbf{x}_{t+1}, \cdots, \mathbf{x}_T)) \log P_{\text{S2S}}(k_t),
\]

(5)

where \( \delta(\cdot, \cdot) \) is 1 if the two variables are equal, and 0 otherwise. Because COR is only used during training, there’s no extra complexity during test. The Seq2Seq model is directly used for decoding.

### 4. RELATED WORKS

#### Bidirectional agreement

Several previous works optimize KLD between a left-to-right Seq2Seq model and a right-to-left one [6, 7, 5] to leverage the right context and improve the model performance. In these works, a left-to-right Seq2Seq model and a right-to-left one are trained in advance, and then the right-to-left model provides soft labels to optimize the left-to-right one. Different from these works, we train COR which only leverages target sequence and can model left context and right context simultaneously.

#### Pre-trained language models

Several previous works leverage bidirectional recurrent neural networks [13, 14] or self-attention networks [9, 15] to improve downstream natural language processing tasks. Our proposed method leverages transformers. Different from previous BERT works, we do not use [MASK] symbol but directly model the two-side context. Previous work [16] also uses two stacks of transformers with forward masks and backward masks, and the combination module is a feed-forward network. Different from this work, we leverage fusion transformer block which combines the whole context with self-attention mechanism. Moreover, our goal is to transfer the whole context knowledge to Seq2Seq model, so we introduce casual property, i.e. there is an offset between the input and the target.

### 5. EXPERIMENTS

#### 5.1. Dataset

We use public Mandarin dataset AISHELL-1\(^1\) to evaluate our proposed method [17]. The dataset contains about 150 hours of speech for training, about 15 hours of speech for development, and about 5 hours of speech for test. All the recordings of AISHELL-1 are recorded by 400 speakers.

A subset of CLMAD [18, 19] is used as external text data. It is selected from the whole CLMAD with XenC [20] for matching the domain of AISHELL-1. This subset\(^2\) is the same one which we used in our previous LSTM work [10]. The number of sentences is 30 times larger than the training transcription of AISHELL-1.

#### 5.2. Evaluation Method

Because the proposed is a bidirectional language model, the perplexity cannot be computed. So, we directly compute the cloze completion accuracy to evaluate the performance of the COR. Formally, the cloze completion accuracy is computed as follows:

\[
\text{ACC} = \frac{M}{N}.
\]

(6)

where \( N \) is the total number of tokens in the corpus, and \( M \) is the total number tokens which the model predicts right.

---

\(^1\)http://openslr.org/33/

\(^2\)This subset of the external text has been shared with OneDrive: https://1drv.ms/u/s!Aa8tK7hvUohB6234-V-Z0Qh_Zcc
Because COR uses both the left context and the right context, the completion accuracy is much higher than the unidirectional LMs. We only use the cloze completion accuracy to show the ability of COR. Then, we mainly focus on the downstream ASR task. We use character error rate (CER) to evaluate the performance on Chinese ASR task.

### 5.3. Experimental Setup

We use COR model as teacher model in LST, and the Seq2Seq model is Speech-Transformer [21]. The two models share the same vocabulary. The tokens in the vocabulary are 4230 Chinese characters and three special symbols “<unk>”, “<sos>”, “<eos>” as unknown token, start symbol of a sentence, and a end symbol of a sentence, respectively.

For COR model, we use 512-dimensional embedding for each token, and the model dimensionality is also 512, i.e., \( D \) of \( U \) in Eq. (1). The number of transformer blocks for forward stack and backward stack is 5. Each block has 8 heads for attention, and the dimensionality of the inner transformation is 1024, i.e. \( D_{\text{in}} \) of \( W_1 \) in Eq. (3). We use Adam algorithm and transformer learning rate schedule for optimization [12]. The batch size is 128. We train the model for 4 epochs.

For the Seq2Seq model, we use the same configuration with our previous work LST [10]. The acoustic features are 80-dimension Mel-filter bank features (FBANK). Each frame is spliced with three left frames. The sequence is subsampled every three frames. Both encoder and decoder has 32 blocks. The dimensionality of the model is 512, and the feedforward network of each block has 2048 inner nodes. The number of heads is 8. The optimizer and the learning rate schedule is the same as COR. We train the model for 50 epochs and average the last 7 models as the final one. The sinusoidal position embeddings are also used. For LST training, we use \( \lambda = 0 \) and \( T = 2 \) for COR, and \( \lambda = 0.9 \) and \( T = 5 \) for UniCOR. These hyper-parameters are selected across cross validation. Because COR can provide very accurate soft labels, we do not use hard labels but only use the soft labels provided by COR, i.e. \( \lambda = 0 \).

### 6. Conclusions

This paper proposes a language model called casual cloze completer (COR) which directly leverages whole context to predict a word. A self-attention based network is used to model the left context and the right context simultaneously. We use LST training approach to integrating whole context to Seq2Seq speech recognition systems. The experiments are conducted on public Chinese dataset AISHELL-1. We achieve 8.2% of CER, which demonstrates the effectiveness of the proposed method.

Table 1: Cloze Test Accuracy

| Model                  | Accuracy |
|------------------------|----------|
| UniCOR (transcriptions)| 0.186    |
| COR (transcriptions)   | 0.985    |
| UniCOR (external text) | 0.193    |
| COR (external text)    | 0.996    |

Table 2: Character error rates on AISHELL-1 test set.

| Model                        | CER%  |
|------------------------------|-------|
| Seq2Seq (baseline)           | 10.6  |
| Seq2Seq + Label Smoothing    | 10.0  |
| Seq2Seq + RNNLM LST* [10]    | 9.3   |
| Seq2Seq + UniCOR LST         | 8.7   |
| Seq2Seq + COR LST            | **8.2** |

* is from the literature.
7. REFERENCES

[1] W. Chan, N. Jaitly, Q. Le, and O. Vinyals, “Listen, attend and spell: A neural network for large vocabulary conversational speech recognition,” in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2016, pp. 4960–4964.

[2] C.-C. Chiu, T. N. Sainath, Y. Wu, R. Prabhavalkar, P. Nguyen, Z. Chen, A. Kannan, R. J. Weiss, K. Rao, E. Gonina et al., “State-of-the-art speech recognition with sequence-to-sequence models,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 4774–4778.

[3] L. Zhou, J. Zhang, and C. Zong, “Synchronous bidirectional neural machine translation,” Transactions of the Association for Computational Linguistics, vol. 7, pp. 91–105, 2019.

[4] M. Mimura, S. Sakai, and T. Kawahara, “Forward-backward attention decoder.” Proc. Interspeech 2018, pp. 2232–2236, 2018.

[5] Y. Zheng, X. Wang, L. He, S. Pan, F. K. Soong, Z. Wen, and J. Tao, “Forward-backward decoding for regularizing end-to-end tts,” Interspeech, 2019.

[6] L. Liu, M. Utiyama, A. Finch, and E. Sumita, “Agreement on target-bidirectional neural machine translation,” in Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

[7] Z. Zhang, S. Wu, S. Liu, M. Li, M. Zhou, and T. Xu, “Regularizing neural machine translation by target-bidirectional agreement,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, 2019, pp. 443–450.

[8] T. Mikolov, S. Kombrink, A. Deoras, L. Burget, and J. Černocký, “Rnnlm-recurrent neural network language modeling toolkit,” in Proc. of the 2011 ASRU Workshop, 2011, pp. 196–201.

[9] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

[10] Y. Bai, J. Yi, J. Tao, Z. Tian, and Z. Wen, “Learn spelling from teachers: Transferring knowledge from language models to sequence-to-sequence speech recognition,” Proc. Interspeech 2019, pp. 3795–3799, 2019.

[11] W. L. Taylor, “cloze procedure: A new tool for measuring readability,” Journalism Bulletin, vol. 30, no. 4, pp. 415–433, 1953.

[12] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[13] A. Mousa and B. Schuller, “Contextual bidirectional long short-term memory recurrent neural network language models: A generative approach to sentiment analysis,” in Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics, 2017, pp. 1023–1032.

[14] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, “Deep contextualized word representations,” arXiv preprint arXiv:1802.05365, 2018.

[15] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, and Q. V. Le, “Xlnet: Generalized autoregressive pretraining for language understanding,” 2019.

[16] A. Baevski, S. Edunov, Y. Liu, L. Zettlemoyer, and M. Auli, “Cloze-driven pretraining of self-attention networks,” arXiv preprint arXiv:1903.07785, 2019.

[17] H. Bu, J. Du, X. Na, B. Wu, and H. Zheng, “AIShell-1: An open-source mandarin speech corpus and a speech recognition baseline,” in 20th Conference of the Oriental Chapter of the International Coordinating Committee on Speech Databases and Speech I/O Systems and Assessment (O-COCOSDA). IEEE, 2017, pp. 1–5.

[18] Y. Bai, J. Tao, J. Yi, Z. Wen, and C. Fan, “CLMAD: A chinese language model adaptation dataset,” in The Eleventh International Symposium on Chinese Spoken Language Processing (ISCSLP 2018), 2018.

[19] J. Li and M. Sun, “Scalable term selection for text categorization,” in Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), 2007.

[20] A. Rousseau, “Xenc: An open-source tool for data selection in natural language processing,” The Prague Bulletin of Mathematical Linguistics, vol. 100, pp. 73–82, 2013.

[21] L. Dong, S. Xu, and B. Xu, “Speech-transformer: a no-recurrence sequence-to-sequence model for speech recognition,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5884–5888.