Mask CTC: Non-Autoregressive End-to-End ASR with CTC and Mask Predict

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Abstract

We present Mask CTC, a novel non-autoregressive end-to-end automatic speech recognition (ASR) framework, which generates a sequence by refining outputs of the connectionist temporal classification (CTC). Neural sequence-to-sequence models are usually autoregressive: each output token is generated by conditioning on previously generated tokens, at the cost of requiring as many iterations as the output length. On the other hand, non-autoregressive models can simultaneously generate tokens within a constant number of iterations, which results in significant inference time reduction and better suits end-to-end ASR model for real-world scenarios. In this work, Mask CTC model is trained using a Transformer encoder-decoder with joint training of mask prediction and CTC. During inference, the target sequence is initialized with the greedy CTC outputs and low-confidence tokens are masked based on the CTC probabilities. Based on the conditional dependence between output tokens, these masked low-confidence tokens are then predicted conditioning on the high-confidence tokens. Experimental results on different speech recognition tasks show that Mask CTC outperforms the standard CTC model (e.g., 17.9% WER on WSJ) and approaches the autoregressive model (e.g., 12.1% WER on WSJ) and approaches the autoregressive model.

1. Introduction

Owing to the rapid development of neural sequence-to-sequence modeling [1][2][3], deep neural network (DNN)-based end-to-end automatic speech recognition (ASR) systems have become almost as effective as the traditional hidden Markov model-based systems [4][5][6]. Various models and approaches have been proposed for improving the performance of the autoregressive (AR) end-to-end ASR model with the encoder-decoder architecture based on recurrent neural networks (RNNs) [6][7][8] and Transformers [9][10][11].

Contrary to the autoregressive framework, non-autoregressive (NAR) sequence generation has attracted attention, including the revisitation of connectionist temporal classification (CTC) [12][13] and the growing interest for non-autoregressive Transformer [NAT] [14]. While the autoregressive model requires \(L\) iterations to generate an \(L\)-length target sequence, a non-autoregressive model costs a constant number of iterations \(K(\ll L)\), independent on the length of the target sequence. Despite the limitation in this decoding iteration, some recent studies in neural machine translation have successfully shown the effectiveness of the non-autoregressive models, performing comparable results to the autoregressive models. Different types of non-autoregressive models have been proposed based on the iterative refinement decoding [15], insert or edit-based sequence generation [10][17], masked language model objective [18][19][20], and generative flow [21].

Some attempts have also been made to realize the non-autoregressive model in speech recognition. CTC introduces a frame-wise latent alignment to represent the alignment between the input speech frames and the output tokens [22]. While CTC makes use of dynamic programming to efficiently calculate the most probable alignment, the strong conditional independence assumption between output tokens results in poor performance compared to the autoregressive models [23]. On the other hand, [24] trains a Transformer encoder-decoder in a mask-predict manner [18]: target tokens are randomly masked and predicted conditioning on the unmasked tokens and the input speech. To generate the output sequence in parallel during inference, the target sequence is initialized as all masked tokens and the output length is predicted by finding the position of the end-of-sequence token. However with this prediction of the output length, the model is known to be vulnerable to the output sequence with a long length. At the beginning of the decoding, the model is likely to make more mistakes in predicting long masked sequence, propagating the error to the later decoding steps. [25] proposes Imputer, which performs the mask prediction in CTC’s latent alignments to get rid of the output length prediction. However, unlike the mask-predict, Imputer requires more calculations in each interaction, which is proportional to the square of the input length \(T(>>L)\) in the self-attention layer, and the total computational cost can be very large.

Our work aims to obtain a non-autoregressive end-to-end ASR model, which generates the sequence in token-level with low computational cost. The proposed Mask CTC framework trains a Transformer encoder-decoder model with both CTC and mask-predict objectives. During inference, the target sequence is initialized with the greedy CTC outputs and low-confidence tokens are masked based on the CTC probabilities. The masked low-confidence tokens are predicted conditioning on the high-confidence tokens not only in the past but also in the future context. The advantages of Mask CTC are summarized as follows.

No requirement for output length prediction: Predicting the output token length from input speech is rather challenging because the length of the input utterances varies greatly depending on the speaking rate or the duration of silence. By initializing the target sequence with the CTC outputs, Mask CTC does not have to care about predicting the output length at the beginning of the decoding.

Accurate and fast decoding: We observed that the results of CTC outputs themselves are quite accurate. Mask CTC does not only retain the correct tokens in the CTC outputs but also recovers the output errors by considering the entire context. Token-level iterative decoding with a small number of masks makes the model well-suited for the usage in real scenarios.
2. Mask CTC framework

The objective of end-to-end ASR is to model the joint probability of a $L$-length output sequence $Y = \{y_l \in \mathcal{V} | l = 1, ..., L\}$ given a $T$-length input sequence $X = \{x_t \in \mathbb{R}^D | t = 1, ..., T\}$. Here, $y_l$ is an output token at position $l$ in the vocabulary $\mathcal{V}$ and $x_t$ is a $D$-dimensional acoustic feature at frame $t$.

The following subsections first explain a conventional autoregressive framework based on attention-based encoder-decoder and CTC. Then a non-autoregressive model trained with mask prediction is explained and finally, the proposed Mask CTC decoding method is introduced.

2.1. Attention-based encoder-decoder

Attention-based encoder-decoder models the joint probability of $Y$ given $X$ by factorizing the probability based on the probabilistic left-to-right chain rule as follows:

$$ P_{\text{att}}(Y|X) = \prod_{l=1}^{L} P_{\text{att}}(y_l|y_{<l}, X). \quad (1) $$

The model estimates the output token $y_l$ at each time-step conditioning on previously generated tokens $y_{<l}$ in an autoregressive manner. In general, during training, the ground truth tokens are used for the history tokens $y_{<l}$ and during inference, the predicted tokens are used.

2.2. Connectionist temporal classification

CTC predicts a frame-level alignment between the input sequence $X$ and the output sequence $Y$ by introducing a special $<$blank$>$ token. The alignment $A = \{a_t \in \mathcal{V} \cup \{<\text{blank}\}> | t = 1, ..., T\}$ is predicted with the conditional independence assumption between the output tokens as follows:

$$ P_{\text{ctc}}(A|X) = \prod_{t=1}^{T} P_{\text{ctc}}(a_t|X). \quad (2) $$

Considering the probability distribution over all possible alignments, CTC models the joint probability of $Y$ given $X$ as follows:

$$ P_{\text{ctc}}(Y|X) = \sum_{A \in \beta^{-1}(Y)} P_{\text{ctc}}(A|X), \quad (3) $$

where $\beta^{-1}(Y)$ returns all possible alignments compatible with $Y$. The summation of the probabilities for all of the alignments can be computed efficiently by using dynamic programming.

To achieve robust alignment training and fast convergence, an end-to-end ASR model based on an attention-based encoder-decoder framework is trained with CTC [8][11]. The objective of the autoregressive joint CTC-attention model is defined as follows by combining Eq. (1) and Eq. (2):

$$ \mathcal{L}_{\text{AR}} = \lambda \log P_{\text{ctc}}(Y|X) + (1 - \lambda) \log P_{\text{att}}(Y|X), \quad (4) $$

where $\lambda$ is a tunable parameter.

2.3. Joint CTC-CMLM non-autoregressive ASR

Mask CTC adopts non-autoregressive speech recognition [24] based on a conditional masked language model (CMLM) [15], where the model is trained to predict masked tokens in the target sequence [25]. Taking advantages of Transformer’s parallel computation [26], CMLM can predict any arbitrary subset of masked tokens in the target sequence by attending to the entire sequence including tokens in the past and the future.

CMLM predicts a set of masked tokens $Y_{\text{mask}}$ conditioning on the input sequence $X$ and observed (unmasked) tokens $Y_{\text{obs}}$ as follows:

$$ P_{\text{cmlm}}(Y_{\text{mask}}|Y_{\text{obs}}, X) = \prod_{y \in Y_{\text{mask}}} P_{\text{cmlm}}(y|Y_{\text{obs}}, X), \quad (5) $$

where $Y_{\text{obs}} = Y \setminus Y_{\text{mask}}$. During inference, the ground truth tokens are randomly replaced by a special $<$MASK$>$ token and CMLM is trained to predict the original tokens conditioning on the input sequence $X$ and the unmasked tokens $Y_{\text{obs}}$. The number of tokens to be masked is sampled from a uniform distribution between 1 to $L$ as in [15]. During inference, the target sequence is gradually generated in a constant number of iterations $K$ by the iterative decoding algorithm [15], which repeatedly masks and predicts the subset of the target sequence.

We observed that applying the original CMLM to non-autoregressive speech recognition shows poor performance, having the problem of skipping and repeating the output tokens. To deal with this, we found that jointly training with CTC similar to [8] provides the model with absolute positional information (conditional independence) explicitly and improves the model performance reasonably well. With the CTC objective from Eq. (3) and Eq. (5), the objective of joint CTC-CMLM training for non-autoregressive ASR model is defined as follows:

$$ \mathcal{L}_{\text{NAR}} = \gamma \log P_{\text{ctc}}(Y|X) + (1 - \gamma) \log P_{\text{cmlm}}(Y_{\text{mask}}|Y_{\text{obs}}, X), \quad (6) $$

where $\gamma$ is a tunable parameter.

2.4. Mask CTC decoding

Non-autoregressive models must know the length of the output sequence to predict the entire sequence in parallel. For example, in the beginning of the CMLM decoding, the output length must be given to initialize the target sequence with the masked...
tokens. To deal with this problem, in machine translation, the output length is predicted by training a fertility model [14] or introducing a special $<\text{LENGTH}>$ token in the encoder [15]. In speech recognition, however, due to the different characteristics between the input acoustic signals and the output linguistic symbols, it appeared that predicting the output length is rather challenging, e.g., the length of the input utterances of the same transcription varies greatly depending on the speaking rate or the duration of silence. [24] simply makes the decoder to predict the position of $<\text{EOS}>$ token to deal with the output length. However, they analyzed that this prediction is vulnerable to the output sequence with a long length because the model is likely to make more mistakes in predicting a long masked sequence and the error is propagated to the later decoding, which degrades the recognition performance. To compensate this problem, they use beam search with CTC and a language model to obtain the reasonable performance, which leads to a slow down of the overall decoding speed, making the advantage of non-autoregressive framework less effective.

To tackle this problem regarding the initialization of the target sequence, we consider using the CTC outputs as the initial sequence for decoding. Figure 1 shows the decoding of CTC Mask based on the inference of CTC. CTC outputs are first obtained through a single calculation of the encoder and the decoder works as to refine the CTC outputs by attending to the whole sequence.

In this work, we use “greedy” result of CTC $\hat{Y} = \{\hat{y}_t \in \beta(A) | l = 1, \ldots , L\}$, which is obtained without using prefix search [12], to keep an inference algorithm non-autoregressive. The errors caused by the conditional independence assumption are expected to be corrected using the CMLM decoder. The errors of the last 10 epochs as in [5]. For Mask CTC model, we obtained 12 self-attention layers with convolutional layers units, and 2048 feed-forward inner dimension size. The encoder-decoder architecture as [11], which consists of Transformer self-attention layers with 4 attention heads, 256 hidden units, and 2048 feed-forward inner dimension size. The encoder included 12 self-attention layers with convolutional layers for downsampling and the decoder was 6 self-attention layers. With the mask-predict objective, the convergence for training the Mask CTC model required more epochs (about 200 – 500) than the autoregressive models (about 50 – 100). The final non-autoregressive model was obtained by averaging the model parameters of the last 10 epochs as in [5]. For Mask CTC model, we

### Table 1: Word error rates (WERs) and real time factor (RTF) for WSJ (English).

| Model                  | Iterations | dev93 | eval92 | RTF  |
|------------------------|------------|-------|--------|------|
| Autoregressive         |            |       |        |      |
| CTC-attention [8]      | L          | 14.4  | 11.3   | 0.97 |
| + beam search          | L          | 13.5  | 10.9   | 4.62 |
| Non-autoregressive     |            |       |        |      |
| CTC                    | 1          | 22.2  | 17.9   | 0.03 |
| Mask CTC ($P_{\text{thres}} = 0.0$) | 1        | 16.3  | 12.9   | 0.03 |
| Mask CTC               | 1          | 15.7  | 12.5   | 0.04 |
| Mask CTC               | 5          | 15.2  | 12.2   | 0.05 |
| Mask CTC #mask         | 10         | 15.5  | 12.1   | 0.07 |
| Mask CTC #mask         | 15.4       | 12.1  | 0.13   |      |

| Model                  | Iterations | Dev  | Test |
|------------------------|------------|------|------|
| Autoregressive         |            |      |      |
| CTC-attention [8]      | L          | 35.5 | 35.5 |
| + beam search          | L          | 35.4 | 35.7 |
| Non-autoregressive     |            |      |      |
| CTC                    | 1          | 53.8 | 56.1 |
| Mask CTC ($P_{\text{thres}} = 0.0$) | 1        | 41.6 | 40.2 |
| Mask CTC               | 1          | 41.3 | 40.1 |
| Mask CTC               | 5          | 40.7 | 39.4 |
| Mask CTC               | 10         | 40.5 | 39.2 |
| Mask CTC #mask         | 40.4       | 39.0 |

### Table 2: Word error rates (WERs) for Voxforge (Italian).

| Model                  | Iterations | dev  | Test |
|------------------------|------------|------|------|
| Autoregressive         |            |      |      |
| CTC-attention [8]      | L          | 35.5 | 35.5 |
| + beam search          | L          | 35.4 | 35.7 |
| Non-autoregressive     |            |      |      |
| CTC                    | 1          | 53.8 | 56.1 |
| Mask CTC ($P_{\text{thres}} = 0.0$) | 1        | 41.6 | 40.2 |
| Mask CTC               | 1          | 41.3 | 40.1 |
| Mask CTC               | 5          | 40.7 | 39.4 |
| Mask CTC               | 10         | 40.5 | 39.2 |
| Mask CTC #mask         | 40.4       | 39.0 |

### 3. Experiments

To evaluate the effectiveness Mask CTC, we conducted speech recognition experiments to compare different end-to-end ASR models using ESPnet [28]. The performance of the models was evaluated based on character error rates (CERs) or word error rates (WERs) without relying on external language models.

#### 3.1. Datasets

The experiments were carried out using three tasks with different languages and amounts of training data: the 81 hours Wall Street Journal (WSJ) in English [29], the 581 hours Corpus of Spontaneous Japanese (CSJ) in Japanese [30] and the 16 hours Voxforge in Italian [31]. For the network inputs, we used 80 mel-scale filterbank coefficients with three-dimensional pitch features and applied SpecAugment [22] during model training. For the tokenization of the target, we used characters: Latin alphabets for English and Italian, and Japanese syllable characters (Kana) and Chinese characters (Kanj) for Japanese.

#### 3.2. Experimental setup

For experiments in all of the tasks, we adopted the same encoder-decoder architecture as [11], which consists of Transformer self-attention layers with 4 attention heads, 256 hidden units, and 2048 feed-forward inner dimension size. The encoder included 12 self-attention layers with convolutional layers for downsampling and the decoder was 6 self-attention layers. With the mask-predict objective, the convergence for training the Mask CTC model required more epochs (about 200 – 500) than the autoregressive models (about 50 – 100). The final non-autoregressive model was obtained by averaging the model parameters of the last 10 epochs as in [5]. For Mask CTC model, we
Ground truth instead they favor unannounced checks by roving rather than in house inspectors focusing on critical control points in seafood processing.

Greedy CTC inference instead they favor unannounced checks by roving rather than in house inspectors focusing on critical control points in seafood processing.

Proposed CTC masking & iterative decoding ($P_{\text{thres}} = 0.999, K = 3$) instead they favor unannounced checks by roving rather than in house inspectors focusing on critical control points in seafood processing.

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Figure 2: Decoding example for utterance 44 1e0401i in WSJ eval92. The target sequence is initialized as the CTC outputs and some tokens are replaced with masks (“_”) based on the CTC confidence. Then, the masked tokens are iteratively predicted conditioning on the other unmasked tokens. Red indicates characters with errors and blue indicates ones recovered by Mask CTC decoding.

Table 3: Character error rates (CERs) and sentence error rates (SERs) for CSJ (Japanese).

| Model                  | Eval1  |    |    |    |    |    |    |
|------------------------|--------|----|----|----|----|----|----|
|                        | CER    |    | CER |    |    |    |    |
| Autoregressive         |        |    |    |    |    |    |    |
| CTC-attention          | 6.51   | 59.7 | 4.71 | 59.5 | 5.49 | 44.5 |
| + beam search          | 6.56   | 60.3 | 4.69 | 57.0 | 4.97 | 41.9 |
| Non-autoregressive     |        |    |    |    |    |    |    |
| CTC                    | 6.56   | 58.7 | 4.57 | 55.5 | 4.96 | 40.7 |

Table 3 shows character error rates (CERs) and sentence error rates (SERs) for CSJ. While Mask CTC performed quite close or even better CERs than the autoregressive model, the results showed a little improvement from the simple CTC model, compared to the results of the aforementioned tasks. Since Japanese includes a large number of characters and the characters themselves often form a certain word, the simple CTC model seemed to be dealing with the short dependence between the characters reasonably well, performing almost the same scores without applying Mask CTC. However, when we look at the results in sentence-level, we observed some clear improvements for all of the evaluation sets, again showing that our model effectively recovers the CTC errors by considering the conditional dependence.

These experimental results on different tasks indicate that Mask CTC framework is especially effective on languages having tokens with a small unit (i.e., Latin alphabet and other phonemic scripts). It is our future work for investigating the effectiveness when we use byte pair encodings (BPEs) for the languages with such a small unit.

4. Conclusions

This paper proposed Mask CTC, a novel non-autoregressive end-to-end speech recognition framework, which generates a sequence by refining the CTC outputs based on mask prediction. During inference, the target sequence was initialized with the greedy CTC outputs and low-confidence masked tokens were iteratively refined conditioning on the other unmasked tokens and input speech features. The experimental comparisons demonstrated that Mask CTC outperformed the standard CTC model while maintaining the decoding speed fast. Mask CTC approached the results of autoregressive models; especially for CSJ, they were comparable or even better. Our future plan is to reduce the gap of masking strategies between training using random masking and inference using CTC outputs. Furthermore, we plan to explore the integration of external language models (e.g., BERT) in Mask CTC framework.
5. References

[1] L. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in Proceedings of Advances in Neural Information Processing Systems (NeurIPS), 2014.

[2] D. Bahdanau, K. Cho, and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” in Proceedings of International Conference on Learning Representations (ICLR), 2015.

[3] 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 Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018.

[4] C. Lüscher, E. Beck, K. Irie, M. Kitza, W. Michel, A. Zeyer, R. Schlüter, and H. Ney, “RWTH ASR systems for librispeech: Hybrid vs attention,” in Proceedings of Annual Conference of the International Speech Communication Association (INTERSPEECH), 2019.

[5] S. Karita, X. Wang, S. Watanabe, T. Yoshimura, W. Zhang, N. Chen, T. Hayashi, T. Hori, H. Inaguma, Z. Jiang, M. Somek, N. Yalta, and R. Yamamoto, “A comparative study on Transformer vs RNN in speech applications,” in Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016.

[6] J. K. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, and Y. Bengio, “Attention-based models for speech recognition,” in Proceedings of Advances in Neural Information Processing Systems (NeurIPS), 2015.

[7] W. Chan, N. Jaitly, Q. Le, and O. Vinyals, “Listen, attend and spell: A neural network for large vocabulary conversational speech recognition,” in Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017.

[8] S. Kim, T. Hori, and S. Watanabe, “Joint CTC-attention based end-to-end speech recognition using multi-task learning,” in Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017.

[9] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Proceedings of Advances in Neural Information Processing Systems (NeurIPS), 2017.

[10] R. Dong, S. Xu, and B. Xu, “Speech-Transformer: a no-recurrence sequence-to-sequence model for speech recognition,” in Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018.

[11] S. Karita, N. E. Y. Soplin, S. Watanabe, M. Delcroix, A. Ogawa, and T. Nakatani, “Improving Transformer-based end-to-end speech recognition with connectionist temporal classification and language model integration,” in Proceedings of Annual Conference of the International Speech Communication Association (INTERSPEECH), 2019.

[12] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in Proceedings of International Conference on Machine Learning (ICML), 2006.

[13] J. Libovický and J. Helcl, “End-to-end non-autoregressive neural machine translation with connectionist temporal classification,” in Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP), 2018.

[14] J. Gu, J. Bradbury, C. Xiong, V. O. Li, and R. Socher, “Non-autoregressive neural machine translation,” Proceedings of International Conference on Learning Representations (ICLR), 2018.

[15] J. Lee, E. Mansimov, and K. Cho, “Deterministic non-autoregressive neural sequence modeling by iterative refinement,” in Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP), 2018.

[16] M. Stern, W. Chan, J. Kiros, and J. Uszkoreit, “Insertion Transformer: flexible sequence generation via insertion operations,” in Proceedings of International Conference on Machine Learning (ICML), 2019.

[17] J. Gu, C. Wang, and J. Zhao, “Levenshtein Transformer,” in Proceedings of Advances in Neural Information Processing Systems (NeurIPS), 2019.

[18] M. Ghazvininejad, O. Levy, Y. Liu, and L. Zettlemoyer, “Mask-predict: Parallel decoding of conditional masked language models,” in Proceedings of Conference on Empirical Methods in Natural Language Processing and International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2019.

[19] M. Ghazvininejad, O. Levy, and L. Zettlemoyer, “Semi-autoregressive training improves mask-predict decoding,” arXiv preprint arXiv:2001.08785, 2020.

[20] C. Saharia, W. Chan, S. Saxena, and M. Norouzi, “Non-autoregressive machine translation with latent alignments,” arXiv preprint arXiv:2004.07437, 2020.

[21] X. Ma, C. Zhou, X. Li, G. Neubig, and E. Hovy, “Floow-Seq: Non-autoregressive conditional sequence generation with generative flow,” in Proceedings of Conference on Empirical Methods in Natural Language Processing and International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2019.

[22] A. Graves and N. Jaitly, “Towards end-to-end speech recognition with recurrent neural networks,” in Proceedings of International Conference on Machine Learning (ICML), 2014.

[23] E. Battenberg, J. Chen, R. Child, A. Coates, Y. G. Yi, H. Liu, S. Sathesh, A. Sriman, and Z. Zhu, “Exploring neural transducers for end-to-end speech recognition,” in Proceedings of IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 2017.

[24] N. Chen, S. Watanabe, J. Villalba, and N. Dehak, “Non-autoregressive Transformer automatic speech recognition,” arXiv preprint arXiv:1911.04908, 2019.

[25] W. Chan, C. Saharia, G. Hinton, M. Norouzi, and N. Jaitly, “Impuber: Sequence modelling via imputation and dynamic programming,” arXiv preprint arXiv:2002.08926, 2020.

[26] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proceedings of Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT), 2019.

[27] Y. Goldberg and M. Elhadad, “An efficient algorithm for easy-first non-directional dependency parsing,” in Proceedings of Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT), 2010.

[28] S. Watanabe, T. Hori, S. Karita, T. Hayashi, J. Nishitoba, T. Nakatani, “Improving Transformer-based end-to-end speech recognition with connectionist temporal classification and language model integration,” in Proceedings of Annual Conference of the International Speech Communication Association (INTERSPEECH), 2019.

[29] D. B. Paul and J. M. Baker, “The design for the wall street journal-based CSR corpus,” in Proceedings of Workshop on Speech and Natural Language, 1992.

[30] K. Maekawa, “Corpus of spontaneous Japanese: Its design and evaluation,” in Proceedings of ISCA & IEEE International Conference on Spoken Language Processing and Recognition, 2003.

[31] "Voxforge," [online] http://www.voxforge.org.

[32] D. S. Park, W. Chan, Y. Zhang, C.-C. Chiu, B. Zoph, E. D. Cubuk, and Q. V. Le, “SpecAugment: A simple data augmentation method for automatic speech recognition,” in Proceedings of Annual Conference on the International Speech Communication Association (INTERSPEECH), 2019.

[33] T. Hori, S. Watanabe, and J. Hershey, “Joint CTC/attention decoding for end-to-end speech recognition,” in Proceedings of Annual Meeting of the Association for Computational Linguistics (ACL), 2017.

[34] R. Sennrich, B. Haddow, and A. Birch, “Neural machine translation of rare words with subword units,” in Proceedings of Annual Meeting of the Association for Computational Linguistics (ACL), 2016.