AN EMPIRICAL STUDY OF EFFICIENT ASR RESCORING WITH TRANSFORMERS

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ABSTRACT

Neural language models (LMs) have been proved to significantly outperform classical \(n\)-gram LMs for language modeling due to their superior abilities to model long-range dependencies in text and handle data sparsity problems. And recently, well configured deep Transformers have exhibited superior performance over shallow stack of recurrent neural network layers for language modeling. However, these state-of-the-art deep Transformer models were mostly engineered to be deep with high model capacity, which makes it computationally inefficient and challenging to be deployed into large-scale real-world applications. Therefore, it is important to develop Transformer LMs that have relatively small model sizes, while still retaining good performance of those much larger models. In this paper, we aim to conduct empirical study on training Transformers with small parameter sizes in the context of ASR rescoring. By combining techniques including subword units, adaptive softmax, large-scale model pre-training, and knowledge distillation, we show that we are able to successfully train small Transformer LMs with significant relative word error rate reductions (WERR) through \(n\)-best rescoring. In particular, our experiments on a video speech recognition dataset show that we are able to achieve WERRs ranging from 6.46\% to 7.17\% while only with 5.5\% to 11.9\% parameter sizes of the well-known large GPT model [1], whose WERR with rescoring on the same dataset is 7.58\%.

Index Terms— neural language modeling, transformer, pre-training, knowledge distillation, adaptive softmax

1. INTRODUCTION

Neural networks have been proven to outperform traditional \(n\)-gram language models (LMs) and have achieved state-of-the-art (SOTA) performance in language modeling [2][3][4][5]. This is mainly because \(n\)-gram LMs suffer from data sparsity problems, which makes it difficult to capture large contexts and model long-range dependencies in text. In contrast, neural models overcome these issues with distributed representation learning in a latent semantic space, thus with superior abilities in modeling long-range dependencies and better model performance. However, compared to \(n\)-gram LMs, neural models are computationally expensive and slow, which makes it difficult to be used in first-pass automatic speech recognition (ASR) systems, where search space could be very large. Thus, neural LMs have been mostly used in second-pass rescoring, either through the \(n\)-best lists or lattices generated by the first-pass systems with \(n\)-gram LMs [6][7][8][9][10].

Transformer, which was originally invented in an encoder-decoder framework for machine translation [11], has been popular in natural language processing (NLP). With the usage of self-attention mechanism and residual connections, it allows for successful training of very deep and high capacity networks, resulting in SOTA performance in many NLP tasks [11][12][13][14]. A number of recent works [15][13][16][17] on language modeling also demonstrate the superior ability of deep Transformers over shallow stack of recurrent neural networks such as LSTM [13]. However, these SOTA Transformer models were mostly engineered to have very high capacity with great depth. For example, even the smallest model of OpenAI GPT2 [13] has 24 decoder layers with 345M model parameters. And Irie et al. [17] uses up to 42 and 96 decoder layers for ASR rescoring. Such a large model size makes it unrealistic to directly deploy these models into large-scale applications due to latency and computation resource restrictions, even for second-pass ASR rescoring where the scoring space has been greatly pruned. In addition, smaller model size is important for on-device applications where machine capacity such as memory is usually limited.

In this work, we aim to conduct empirical study on efficient ASR rescoring with Transformers, which is important to put these superior Transformer models into large-scale real-world applications. First of all, we know that a neural LM trained with the standard cross entropy loss contains a softmax layer that involves a summation over the entire output vocabulary. Thus the model size of the softmax layer is proportional to the size of output vocabulary, and larger vocabulary could significantly increase the model size. In order to handle this issue, we propose to combine subword unit models with adaptive softmax. Subword units such as byte pair encoding (BPE) [19] can represent an open vocabulary through a fixed-size vocabulary of character sequences, which is an effective way to reduce model sizes and handle out-of-vocabulary issues. Adaptive softmax [20] is a technique to speed up the softmax layer by assigning larger capacity to more frequent vocabulary units, while smaller capacity to less frequent ones. Thus it can further reduce model sizes from the softmax layer.

For language modeling, it has been observed that higher capacity and depth tends to lead to better metrics with regarding to perplexity (PPL) [17]. Thus existing work mostly focused on training very large models to achieve SOTA performance. In contrast, in this work we switch our focus to train Transformers with small parameter sizes to make them applicable to large-scale applications. In our empirical study, we observe that small Transformer LMs also perform reasonably well with \(n\)-best rescoring. We further propose to leverage a simple yet effective strategy with large-scale model pre-training and fine-tuning to first train powerful teacher models. We then adopt knowledge distillation [21] to transfer knowledge from these teacher models into small student models to further improve their performance.

The main contributions of this paper are summarized as follows:

- We show that subword unit models with different vocabulary sizes can achieve similar performance for ASR rescoring. By combining with adaptive softmax, we can significantly reduce model sizes of Transformer LMs.

- We experiment Transformer LMs with small parameter sizes, and achieve significant word error rate reductions with second-pass \(n\)-best rescoring. Compared to those much
larger models, only slight performance degradation is observed.

- We propose to improve small Transformer LMs with large-scale model pre-training and knowledge distillation, which further reduce PPLs and WERs over models that are trained without using these techniques.
- By combining all of these techniques, we successfully train small Transformer LMs that achieve relative WERRs ranging from 6.46% to 7.17% while only with 5.5% to 11.9% parameter sizes of the well-known large GPT model \cite{6}, whose WERR with rescoring on the same dataset is 7.58%.

2. OUR APPROACH

In this section, we introduce the details of our explored techniques to train small Transformer LMs with the goal of retraining performance of those large models.

2.1. Preliminaries

Given a text corpus $D = \{S_1, \ldots, S_N\}$ with vocabulary $V$, where each $S_i$ is a sequence of text with $k$ word or subword units $S_i = \{w_1^{(i)}, \ldots, w_k^{(i)}\}$, we can train a standard left-to-right neural language model $\Theta$ by maximizing the following objective function:

$$L_{CE}(\Theta) = \sum_i \sum_j \log P(w_j^{(i)}|h_j^{(i)}; \Theta)$$

where the conditional probability $P$ of $w_j^{(i)}$ given its context history $h_j^{(i)}$ and the unnormalized logit $z_j^{(i)}$ is computed as:

$$P(w_j^{(i)}|h_j^{(i)}; \Theta) = \frac{\exp(z_j^{(i)})}{\sum_v \exp(z_v)}$$

From Equation 2 we can see that computation of the normalized probability for each $w_j^{(i)}$ needs to go through a softmax layer that involves a summation over all units in the vocabulary. This could be very computationally inefficient and is a major performance bottleneck for neural LMs with large output vocabularies. In this work, we choose to train neural LMs based on the standard deep Transformer decoder \cite{5}, which consists of a stack of $N$ transformer blocks. Each block contains a self-attention layer for modeling contextual information, and a position-wise feed-forward layer for feature transformation. Residual connection and layer normalization are added between each layer so that lower layer information can be passed to upper layers, which allows for successful training of very deep Transformer networks.

2.2. Subword Unit Models

Large word-level vocabularies are often used in large-scale neural language model training, resulting in significant increase of model size from the softmax layer. Thus an effective way to reduce model size is to directly reduce the size of the output vocabulary. A straightforward method to reduce vocabulary size is to simply group those words with low frequencies into one cluster and replace them by a specific symbol. However, this approach has shown poor performance in handling rare and unknown words \cite{19, 22}.

In order to better handle this challenge, subword unit representations such as byte pair encoding (BPE) \cite{19} and wordpiece model \cite{22} have been proposed with improved performance in many NLP tasks. This approach chooses to divide words into a limited set of subword units, and it can effectively interpolate between word-level inputs for frequent words and character-level inputs for rare words. Thus it is able to achieve a good balance between character-level and word-level models. In this work, we adopt BPE\footnote{https://github.com/glample/fastBPE} for input representations. Different from previous work that normally used a relatively large BPE vocabulary, we also conduct empirical study on the choice of BPE unit sizes and their impact on ASR rescoring.

2.3. Adaptive Softmax

Even though with subword units, it is still computationally inefficient to obtain normalized model predictions through the softmax layer. Extensive study has been conducted to reduce the computational costs from the softmax layer. Existing approaches can roughly be grouped into two categories: (i) modifying the softmax architecture such as through hierarchical softmax \cite{23} to make it more efficient, and (ii) completely removing the softmax layer and utilizing other auxiliary loss such as self-normalization \cite{24, 25} and noise contrastive estimation (NCE) \cite{26, 27}. In this work, we choose to exploit adaptive softmax \cite{28}, an improved approach over hierarchical softmax. It assigns larger capacity to more frequent vocab units and smaller capacity to less frequent ones. Thus it can reduce model size and speed up both model training and inference. By combining with subword unit models, we find that it works effectively to reduce parameter sizes while maintaining model performance.

2.4. Knowledge Distillation

Knowledge distillation (KD) is a model compression technique that is also known as teacher student training, where a small model (student) is trained to match the output of larger models (teachers). More specifically, the student model is learned to minimize a new loss function based on the weighted linear combination of cross-entropy loss with hard labels from training data and Kullback-Leibler (KL) divergence to predicted distributions (soft labels) of teacher models. Formally, we need to modify the objective function as defined in Equation 1 as follows:

$$L(\Theta) = \alpha L_{CE}(\Theta) + (1 - \alpha) L_{KLD}(\Theta)$$

where $L_{KLD}(\Theta)$ is KL divergence loss computed from student and teacher model outputs, $\alpha$ is used to control the balance of the two loss. We optimize the values of $alpha$ and temperature on the development set and find that the optimal values for $alpha$ and temperature is 0.1 and 1.0, respectively. We also completely remove dropouts for student models following the existing study on KD for language modeling \cite{28} as it gives the best performance.

2.5. Pre-training and Fine-tuning

In order to fully leverage the power of knowledge distillation, we need to first successfully train teacher models with superior performance. And existence of high-quality in-domain data is important for this step. However, in many cases it is challenging to obtain adequate in-domain data in a timely fashion due to emergence of new domains or extra annotation costs. Fortunately, there exists abundant general domain text data from diverse sources, including News articles, Wikipedia, and social media posts etc. These general corpuses have played an important role in the successful applications of pre-trained models in natural language understanding...
NLU) tasks [1][2][29]. But different from these existing work on improving NLU with pre-trained Transformers, we study the effectiveness of the pre-training strategy with deep Transformers for ASR rescoring, together with knowledge distillation.

In this work, we first construct a large pre-training corpus that is not domain specific, then we pre-train deep Transformer LMs with high capacity on this corpus. These pre-trained models are then further optimized on the target domain data, and used to guide the learning of small student models.

3. EXPERIMENTAL SETUP

In all experiments of this work, we target to build a strong ASR system for automatic video transcription, which has many downstream applications such as auto-captioning of videos. To evaluate the effectiveness of our proposed approaches, we first gather n-best candidates from the first-pass decoding with our in-house hybrid ASR system, which has achieved state-of-the-art performance on multiple speech recognition datasets [30]. For acoustic modeling, we utilize a multi-layer Latency Controlled Bidirectional LSTM (LC-BLSTM) [31] with grapheme representations. In the first-pass decoding, we use our in-house dynamic decoder [22] with a pruned 5-gram LM. For Transformer LMs, we leverage the PyTorch implementation of Transformer with Adam as optimizer. The n-best candidates are further reranked with additional evidence generated by neural LMs. We optimize all model hyper-parameters in the development set, and use word error rate as the evaluation metric.

Speech Recognition Dataset. We evaluate the effectiveness of our proposed approaches on an in-house English video dataset. It is randomly sampled from the pool of publicly shared videos by users on Facebook platform. This data is completely anonymized, and no user-identifiable information (UII) is access to both transcribers and researchers. We use a total of 943,346 videos as training data, 4,309 videos as development data, and 8,189 videos as testing data. The total duration of this dataset is 13.9K hours, and the total number of tokens in the transcriptions is 144M. It is a challenging dataset as it contains videos from diverse speakers, content topics, and acoustic conditions.

Pre-training Corpus. We construct a large-scale background text corpus for neural LM pre-training from public Facebook user posts, where we randomly sample 105 million posts that users publicly shared on the Facebook platform. We do not have access to any user UII information, and we directly converted the text into BPE and machine reading format for model training.

N-best Rescoring. After we obtain n-best (i.e., n = 50 is used in this work) candidates for each video from the first-pass ASR system. Weighted linear combination is then performed to re-estimate the final ranking score of each n-best candidate $c_i$ through $s(c_i) = s_{am}(c_i) + \alpha s_{gram}(c_i) + (1 - \alpha)s_{lm}(c_i)$, where $s_{am}(c_i)$ is the acoustic score from acoustic model, $s_{gram}(c_i)$ is the estimated probability from the 5-gram LM, and $s_{lm}(c_i)$ is the neural language modeling score. Finally we choose the top ranked candidates as the final ASR output and measure new word error rates on them.

Approaches for Comparison. To empirically study the impact of our strategies, we compare the following approaches:

- n-gram: this is the first-pass ASR system with n-gram LM. By comparing to this baseline, we can understand the impact of ASR n-best rescoring with Transformer LMs.

- Large: this is a rescoring model with a high capacity Transformer LM. Here we follow the popular GPT configuration [1], where the numbers of decoder layers and attention heads are both set as 12. And the dimension of input embeddings, hidden states and feed-forward layers is set as 768, 768 and 3072, respectively. And we choose 25K BPE units as the vocabulary, which is similar to previous work on large-scale Transformer pre-training [12].

- Small one: this is a rescoring model with a smaller Transformer LM, where the number of decoder layers and attention heads is set as 6 and 8, respectively. The dimension of input embeddings, hidden states and feed-forward layers set is as 352, 352 and 1408, respectively.

- Small two: this is another rescoring model with a smaller Transformer LM than Small one. It uses the same numbers of decoder layers and attention heads as Small one, but the dimension of input embeddings, hidden states and feed-forward layers is further reduced to 256, 256 and 1024. For both small Transformers, we experiment with different BPE vocabularies with 10K and 5K units to understand the impact of small vocabularies on ASR rescoring.

4. RESULTS AND DISCUSSION

4.1. Overall Performance

Table [1] shows the overall performance of various approaches on the video dataset. Here we train Transformer Large only on in-domain video transcriptions without adaptive softmax to study the impact of various strategies we explore to train models with small parameter sizes. And both small Transformer LMs are trained with all of our explored strategies, including smaller BPE vocabulary sizes, adaptive softmax, and knowledge distillation from high capacity pre-trained and fine-tuned models.

We can see that n-best rescoring with Transformer LMs is effective to improve speech recognition accuracy. Specifically, rescoring with the Large model achieves 7.58% WERR, showing the effectiveness of rescoring with Transformer LMs. Additionally, the first small model Small one obtains 7.17% and 6.81% WERR with 10K and 5K BPE vocabularies, while they only have 11.9% and 9.6% model sizes of the large model. Furthermore, we can see that the even smaller model Small two still achieves similar speech recognition accuracy, while only with 7.2% and 5.5% parameter sizes of the large model.

We further conduct latency study on a random sample of 5,000 n-best candidates generated from the first-pass ASR system. For each Transformer LM, we run it on the sampled set for 10 times on

Table 1. The overall WER and relative WERR of each approach on the video dataset. “#BPE” denotes the size of BPE output vocabulary, “#Param” represents the number of model parameters of each Transformer LM.

| Approach | #BPE | #Param | WER  | WERR |
|----------|------|--------|------|------|
| n-gram   | -    | -      | 16.88| -    |
| Large    | 25K  | 123.4M | 15.60| 7.58%|
| Small one| 10K  | 14.7M  | 15.67| 7.17%|
| Small one| 5K   | 11.8M  | 15.73| 6.81%|
| Small two| 10K  | 8.9M   | 15.78| 6.52%|
| Small two| 5K   | 6.8M   | 15.79| 6.46%|

2https://github.com/pytorch/fairseq
Table 2. Effect of Sub-word Unit Models and Adaptive Softmax on Transformer Large. “AdaSoft” indicates whether we use adaptive softmax or not.

| #BPE | AdaSoft | #Param | WER |
|------|---------|--------|-----|
| 25K  | No      | 123.4M | 15.60 |
| 25K  | Yes     | 110.0M | 15.58 |
| 10K  | No      | 100.4M | 15.60 |
| 10K  | Yes     | 97.7M  | 15.60 |
| 5K   | No      | 92.7M  | 15.58 |
| 5K   | Yes     | 91.4M  | 15.64 |

Table 3. Effect of Sub-word Unit Models and Adaptive Softmax on Transformer Small two.

| #BPE | AdaSoft | #Param | WER |
|------|---------|--------|-----|
| 25K  | No      | 17.5M  | 15.84 |
| 25K  | Yes     | 13.0M  | 15.85 |
| 10K  | No      | 9.9M   | 15.87 |
| 10K  | Yes     | 8.9M   | 15.91 |
| 5K   | No      | 7.3M   | 15.92 |
| 5K   | Yes     | 6.8M   | 15.97 |

the same CPU machine and compute the average duration of inference time. Our study shows that both small models with 5K or 10K BPE vocabularies can achieve speedup from 7.6x to 8.4x over the large Transformer LM with 25K vocabulary. These results demonstrate that we can successfully train much smaller Transformer LMs that not only significantly improve speech recognition accuracy, but also greatly reduce model inference latency and computational costs.

4.2. Effect of Sub-word Unit Models and Adaptive Softmax

In this section, we aim to study the effect of BPE vocabulary sizes and adaptive softmax on both large and small models. Thus we train both Transformer Large and Small two on in-domain video data, and compare the system performance after rescoring. Table 2 and 3 demonstrate the impact of these two techniques. By comparing the rows with the same BPE vocabularies from these two tables, we can see that adaptive softmax further reduces model sizes while retaining the gains from rescoring, demonstrating its effectiveness to reduce model size from the softmax layer. In addition, by reducing the BPE vocabulary sizes from 25K to 10K or 5K, we can still see that similar speech recognition accuracy is achieved for both models, showing reducing BPE vocabulary sizes is another effective way to reduce model sizes. By combining both techniques, we can reduce the model sizes by 26% for Transformer Large, and 61% for Transformer Small two.

4.3. Effect of Model Pre-training and Knowledge Distillation

To study the joint impact of model pre-training and knowledge distillation, we compare the rescoring performance of Small two models trained on in-domain data with and without knowledge distillation. Table 4 shows the perplexities and word error rates achieved by these models with 10K and 5K BPE vocabularies. We can see that by distilling the knowledge from the pre-trained then fine-tuned teacher models, we can achieve 11.8% and 12.7% perplexity reductions for 10K and 5K vocabularies respectively, and also further reductions on WERs.

We then further compare perplexity and rescoring performance of Transformer Large with and without large-scale model pre-training to understand the impact of pre-training on ASR rescoring. The results are shown in Table 5 for both 10K and 5K vocabularies. Even though we already have a relative large in-domain dataset with 144M tokens for neural LM training, we can easily see that the simple pre-training then fine-tuning strategy is still very effective in reducing perplexities (i.e., 20.7% and 12.7% PPL reductions for both 10K and 5K vocabulary sizes, respectively). The models with pre-training also obtain better rescoring performance, demonstrating the effectiveness of large-scale model pre-training.

5. CONCLUSION AND FUTURE WORK

In this paper, we have studied several techniques including subword units, adaptive softmax, knowledge distillation with large-scale model pre-training to train Transformer LMs with small parameter sizes for efficient ASR rescoring. Our empirical study shows that we can significantly reduce model parameter sizes and improve speech recognition accuracy with n-best rescoring by combining all these explored techniques together. In the future, we plan to explore knowledge distillation with bi-directional teachers models, as well as two-stage distillation in both pre-training and fine-tuning stages.

6. REFERENCES

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