IMPROVING THE TRAINING AND EVALUATION EFFICIENCY OF RECURRENT NEURAL NETWORK LANGUAGE MODELS

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ABSTRACT

Recurrent neural network language models (RNNLMs) are becoming increasingly popular for speech recognition. Previously, we have shown that RNNLMs with a full (non-classed) output layer (F-RNNLMs) can be trained efficiently using a GPU giving a large reduction in training time over conventional class-based models (C-RNNLMs) on a standard CPU. However, since test-time RNNLM evaluation is often performed entirely on a CPU, standard F-RNNLMs are inefficient since the entire output layer needs to be calculated for normalisation. In this paper, it is demonstrated that C-RNNLMs can be efficiently trained on a GPU, using our spliced sentence bunch technique which allows good CPU test-time performance (42× speedup over F-RNNLM). Furthermore, the performance of different classing approaches is investigated. We also examine the use of variance regularisation of the softmax denominator for F-RNNLMs and show that it allows F-RNNLMs to be efficiently used in test (56× speedup on a CPU). Finally the use of two GPUs for F-RNNLM training using pipelining is described and shown to give a reduction in training time over a single GPU by a factor of 1.6×.

***Index Terms*—** language models, recurrent neural network, GPU, speech recognition

1. INTRODUCTION

Recurrent neural network language models (RNNLMs) have shown promising performance improvements in many applications, such as speech recognition [1, 2, 3, 4, 5], spoken language understanding [6, 7, 8], and machine translation [9, 10] .

One key practical issue is slow training speed of standard RNNLMs on standard CPUs. Previously we showed that using the "spliced sentence bunch" technique, which processes many sentences in parallel and performs mini-batch parameter updates, RNNLMs with a full output layer (F-RNNLMs) could be trained efficiently on a GPU [11], resulting in a 27× speed-up over a CPU with a class-based factorised output layer. However, F-RNNLMs are very time-consuming to evaluate (e.g. for lattice-rescoring) on CPUs, and hence techniques that allow fast GPU-based training and efficient CPU-based evaluation are of great practical value.

In this paper we extend our previous work on GPU-based RNNLM training with spliced sentence bunch [11] and present two methods to improve CPU-based evaluation efficiency. First a simple modification is introduced to allow class-based RNNLMs to be trained on GPUs efficiently. Furthermore, different word clustering algorithms are investigated and compared. The second method allows the RNNLM to be used without softmax normalisation during testing, by training with an extra variance regularisation term in the training objective function. This approach was applied on feedforward NNLMs and class-based RNNLMs in previous work [12, 10, 13]. It can also be applied to full output layer RNNLMs. Finally, to further improve training speed, pipelined training using multiple GPUs is explored.

The rest of this paper is structured as follows. Section 2, reviews RNNLMs. Efficient training of class-based RNNLMs is described in Section 3, and variance regularisation in Section 4. Pipelined training of RNNLMs is described in Section 5. Experimental results on a conversational telephone speech transcription task are given in Section 6 and conclusions presented in Section 7.

2. RECURRENT NEURAL NETWORK LMS

In contrast to feedforward NNLMs, recurrent NNLMs [1] represent the full, non-truncated history $h_1^{i-1} =< w_{i-1}, \ldots, w_1 >$ for word w_i using the 1-of-k encoding of the previous word w_{i-1} and a continuous vector v_{i-2} for the remaining context. For an empty history, this is initialised, for example, to a vector of all ones. The topology of the recurrent neural network used to compute LM probabilities $P_{\mathsf{RNN}}(w_i|w_{i-1}, v_{i-2})$ consists of three layers. The full history vector, obtained by concatenating w_{i-1} and v_{i-2}, is fed into the input layer. The hidden layer compresses the information from these two inputs and computes a new representation v_{i-1} using a sigmoid activation to achieve non-linearity. This is then passed to the output layer to produce normalised RNNLM probabilities using a softmax activation, as well as recursively fed back into the input layer to be used as the history when computing the LM probability for the following word $P_{\mathsf{RNN}}(w_{i+1}|w_i, v_{i-1})$. As RNNLMs use a vector representation of full histories, they are mostly used for N-best list rescoring. For more efficient lattice rescoring using RNNLMs, approximation schemes, for example, based on clustering among complete histories [14] can be used.

2.1. Full output layer based RNNLMs (F-RNNLMs)

A traditional RNNLM architecture with an unclustered, full output layer (F-RNNLM) is shown in Figure 1. RNNLMs can be trained using an extended form of the standard back propagation algorithm, back propagation through time (BPTT) [15], where the error is propagated through recurrent connections back in time for a specific

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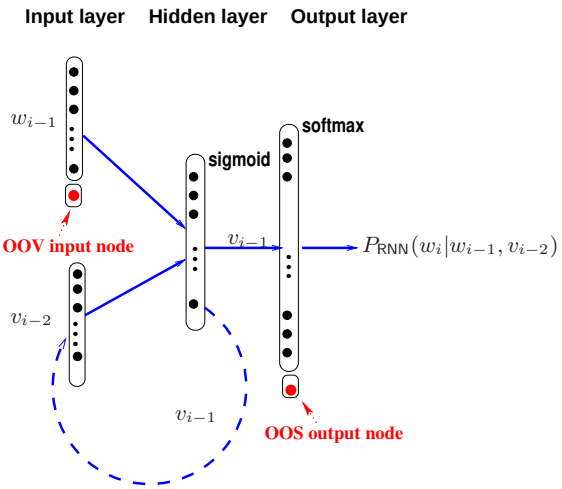

Fig. 1. *A full output layer RNNLM with OOS nodes.*

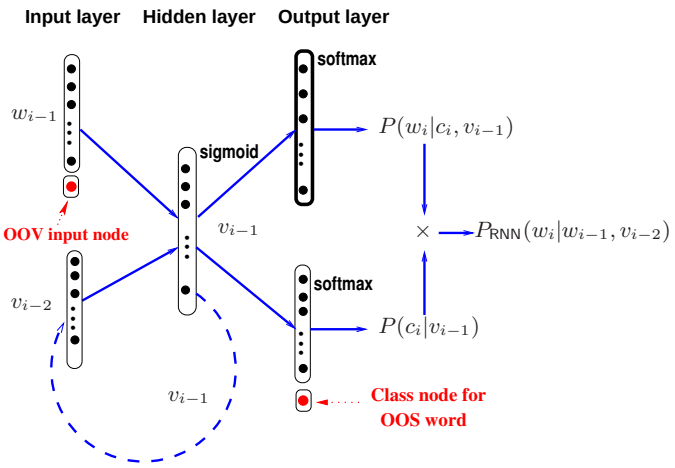

Fig. 2. *A class based RNNLM with OOS nodes.*

number of time steps, for example, 4 or 5 [2]. This allows the recurrent network to record information for several time steps in the hidden layer. To reduce the computational cost, a shortlist [16, 17] based output layer vocabulary limited to the most frequent words can be used. To reduce the bias to in-shortlist words during NNLM training and improve robustness, an additional node is added at the output layer to model the probability mass of out-of-shortlist (OOS) words [18, 19, 14].

2.2. Class Based RNNLMs (C-RNNLMs)

Although F-RNNLMs can be trained and evaluated efficiently using GPUs [11], it is computationally expensive on CPUs due to the normalisation at the output layer. Class based RNNLMs (C-RNNLMs) provide an alternative choice to speedup training and evaluation on CPUs, and adopt a modified RNNLM architecture with a class-based factorised output layer [2]. An illustration of a C-RNNLM is given in Figure 2. Each word in the output layer is assigned to a unique class. The LM probability assigned to a word is factorised into two individual terms.

$$P_{\text{RNN}}(w_i|w_{i-1}, v_{i-2}) \;=\; P(w_i|c_i, v_{i-1})P(c_i|v_{i-1}). \quad (1)$$

The calculation of the word probability is based on only the words from the same class, as well as the class prediction probability. Since the number of classes is normally much smaller than the full output layer size, computation is reduced. It is worth noting that a special case of C-RNNLMs using a single class is equivalent to a traditional, full output layer based F-RNNLM introduced in Section 2.1.

In state-of-the-art ASR systems, NNLMs are often linearly interpolated with n-gram LMs to obtain both a good context coverage and strong generalisation [16, 17, 18, 1, 5, 19]. The interpolated LM probability is given by

$$P(w_i|h_1^{i-1}) \;=\; \lambda P_{\text{NG}}(w_i|h_1^{i-1}) + (1-\lambda)P_{\text{RNN}}(w_i|h_1^{i-1}) \quad (2)$$

where λ is the weight assigned to the n-gram LM distribution $P_{\text{NG}}(\cdot)$, and kept fixed at 0.5 for all RNNLM experiments in this paper. In the above interpolation, the probability mass of OOS words assigned by the RNNLM component is re-distributed with equal probabilities among all OOS words [18, 19].

3. CLASS BASED RNNLMS TRAINING WITH SPLICED SENTENCE BUNCH

Spliced sentence bunch training operates on many sentences in parallel and performs a mini-batch update [11]. F-RNNLMs could be trained efficiently on GPUs due to the large number of computational units. However, a very efficient implementation of C-RNNLMs training with bunch mode is not easy. The data samples in the same bunch may belong to different classes. This requires different sub-matrices to be called and greatly complicates implementation. However, here the aim is to train a C-RNNLM for efficient CPU-evaluation, rather than to provide a speed-up over GPU-based F-RNNLM training. During training, for each parallel stream, only the output of words belonging to the target class are kept before applying softmax from the forward pass, and the outputs for other words are set to zero. By applying this simple modification, C-RNNLMs can be trained on GPUs with bunch mode with a similar computation cost as F-RNNLMs.

It has been shown that the training accuracy and speed are sensitive to word clustering for RNNLM training. In [2], frequency based class was adopted to speedup training. However, it degraded perplexity on the Penn Tree Bank corpus [2, 20]. Word clustering using Brown's classing method [21] was investigated in [20, 22, 23] and improved perplexity results were reported compared to frequency based classes. As well as frequency-based and Brown-like word clustering[1], word clustering derived from a vector-based word representation has also been explored. Each word can be represented by a vector in a low-dimensional space [25] obtained from the matrix associated with the input word and hidden nodes. The similarity of words could be measured by the distance of vectors in the continuous space. For F-RNNLMs, the weight matrix between the hidden nodes could also be used to represent words[2]. A k-means approach is used to cluster words into a specific number of classes in this work and the input and output matrices are obtained from a well-trained F-RNNLM.

[1]We adopted the Brown-like classing method from [24], which is slightly different to the original version in [21].

[2]Most previous work on vector word representations has used an hierarchical output layer.

4. F-RNNLM WITH VARIANCE REGULARISATION

Another type of solution to speedup evaluation of NNLMs has been proposed both in [12] (variance regularisation) and [10] (self-norm). The variance of the softmax log normalisation is added into the objective function for optimisation. If the normalisation term can be regarded as constant at test time, a large speedup can be achieved by avoiding the calculation of the time consuming softmax function. The use of variance regularisation was also explored for RNNLM training in [13], where C-RNNLMs were used and trained sample by sample. In this work, we investigate the use of variance regularisation for F-RNNLMs and train using GPU-based sentence-splice bunch mode. The objective function to be minimised is

$$J^{vr} = J^{ce} + \frac{1}{T}\sum_{i=1}^{N}\sum_{j=1}^{M}\frac{\gamma}{2}(\log Z_j^{(i)} - \overline{LogZ_i})^2 \quad (3)$$

where J^{ce} is the standard cross-entropy (CE) based loss function,

$$J^{ce} = -\frac{1}{T}\sum_{i=1}^{N}\sum_{j=1}^{M}\log P(w_j^{(i)}|h_j^{(i)}) \quad (4)$$

T is the number of training samples and N is the number of bunches in the training corpus and M is the bunch size. Here $Z_j^{(i)}$ is the normalisation term for word w_j in the ith bunch, $\overline{LogZ_i} = \frac{1}{M}\sum_{j=1}^{M}\log Z_j^{(i)}$ is the mean of the log normalisation (Log-Norm) term in the ith bunch. It is worth mentioning that in C-RNNLM training with variance regularisation in [13], the mean of Log-Norm is set to zero directly, which works well for C-RNNLMs. However, it doesn't work well for F-RNNLM training where the number of classes equals one. Hence, it is important to calculate the mean and variance of the Log-Norm term for every bunch.

At test time, the mean of the log normalisation term on a validation set, denoted $\overline{LogZ}$, is calculated. Since the variance of $\overline{LogZ}$ is small, the approximate log probability of predicted words can be calculated as,

$$log(P(w_j|h_j)) = log(\tilde{P}(w_j|h_j)) - \overline{LogZ} \quad (5)$$

where $\tilde{P}(w_j|h_j)$ is the unnormalised probability that can be used at evaluation time. This significantly reduces the computation at the output layer as the normalisation is no longer required.

5. PIPELINED TRAINING OF RNNLMS

The parallelisation of neural network training can be classified into two categories: model parallelism and data parallelism [26]. The difference lies in whether the model or data is split across multiple machines or cores. Pipelined training is a type of model parallelism. It was proposed to speedup the training of deep neural network for acoustic models in [27]. Here, we extend it to the training of RNNLMs. Layers of the network are distributed across different GPUs, and operations on these layers (e.g. forward-pass, BPTT) are executed on their own GPU. It allows each GPU to proceed independently and simultaneously, and communication between layers happens after a parameter update step.

The data flow of pipelined training is shown in Figure 3. The input weight matrix (W0) and output weight matrix (W1) are processed in two GPUs (denoted GPU 0 and GPU 1). For the first bunch in each epoch, the input is forwarded to the hidden layer and the output of hidden layer is copied from GPU 0 to GPU 1. For the 2nd bunch, the input is again forwarded. Simultaneously, GPU 1 forwards the previous bunch obtained from the hidden layer to the output layer, followed by error back propagation and parameter update. The communication (i.e. copy operation) between GPUs happens afterwards. For the following bunches, GPU 0 updates the model parameters using the corresponding error signal and input with BPTT, then forwards the current input bunch. GPU 1 performs successively a forward pass, error back propagation and update . Although there is one bunch update delay for the update of W0, pipelined training can guarantee that the update direction is correct and deterministic for every update.

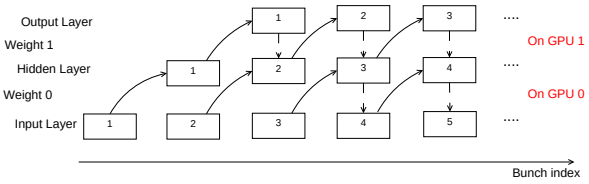

Fig. 3. *Data flow in pipelined training using two GPUs*

6. EXPERIMENTS

In the main part of this section, RNNLMs were evaluated using the CU-HTK LVCSR system for conversational telephone speech (CTS) from the 2004 DARPA EARS evaluation. The acoustic models were trained on approximately 2000 hours of Fisher conversational speech released by the LDC. A 59k recognition word list was used in decoding. The system uses a multi-pass recognition framework. A detailed description of the baseline system can be found in [28]. The 3 hour **dev04** data, which includes 72 Fisher conversations, was used as a test set. The baseline 4-gram LM was trained using a total of 545 million words from 2 text sources: the LDC Fisher acoustic transcriptions, **Fisher**, of 20 million words (weight 0.75), and the University Washington conversational web data [29], **UWWeb**, of 525 million words (weight 0.25). This baseline LM gave a perplexity of 51.8 and a word error rate (WER) of 16.7% on **dev04** measured using lattice rescoring. The **Fisher** data was used to train RNNLMs. A 32k word input layer vocabulary and a 20k word output layer shortlist were used. All RNNLMs were trained in a sentence independent mode. The size of the hidden layer was set to 512, the number of BPTT steps to 5 and the bunch size used was 128. For the C-RNNLMs, 200 classes were used. An NVidia GTX Titan GPU was used for RNNLM training. The CPU experiments used a computer with dual Intel Xeon E5-2670 2.6GHz processors and a total of 16 physical cores. All RNNLMs were interpolated with the baseline 4-gram LM using a fixed weight of 0.5. The 100-best hypotheses extracted from the baseline 4-gram LM lattices were then rescored for performance evaluation. A detailed description of the baseline RNNLM can be found in [11].

6.1. Experiments on C-RNNLMs training

The performance of the bunch mode trained C-RNNLMs described in section 3 were evaluated first. The performance of the three types of word clustering schemes presented in section 3 based on frequency, Brown classing or K-Means based classing were compared in an initial experiment on the Penn Tree Bank (PTB) corpus. In common with previous research reported in [2, 30, 20, 22], sections 0-20 were used as the training data (about 930K words), while sections 21-22 were kept as the validation data (74K) and section 23-24

as the test data (82K). The size of the vocabulary was 10K words. RNNLMs modelling cross-sentence dependency were trained using various word clustering methods with 200 hidden layer nodes, 100 classes and 5 BPTT steps. In practice, the GPU-based bunch mode training speed of C-RNNLMs was found to be close to that of F-RNNLMs. Their respective perplexities (PPLs) were then evaluated. As shown in Table 1, the performance of C-RNNLMs was found to be sensitive to the underlying word clustering scheme being used at the output layer. The C-RNNLM trained with Brown classing gave the lowest perplexity of 127.4 among all C-RNNLMs, though slightly higher than the F-RNNLM. Frequency based C-RNNLMs gave the highest PPL of 135.3.

Word clustering type	PPL
Frequency	135.3
Brown	127.4
K-means on input matrix	132.2
K-means on output matrix	130.6
none	126.1

Table 1. PPL using different word clustering types on the Penn Tree Bank Corpus

Table 2 shows a comparable set of PPL and WER results obtained on the CTS task. As is shown in that table, the K-Means based clustering using the output layer matrix gave the best performance, though it is slightly outperformed by the F-RNNLM in terms of WER. The other three word clustering methods gave comparable error rates. This indicates that using a larger amount of training data, the performance of C-RNNLMs become less sensitive to the word clustering algorithm used.

Word clustering	CTS	
	PPL	WER
Frequency	47.4	15.36
Brown	46.3	15.36
K-means on Input matrix	47.1	15.40
K-means on Output matrix	46.2	15.28
none	46.3	15.22

Table 2. PPL and WER results using different word clustering types

6.2. Experiments on F-RNNLMs with variance regularisation

In this section, the performance of F-RNNLMs trained with variance regularisation is evaluated. The experimental results are shown in Table 3. In practice the training of F-RNNLMs with variance regularisation normally requires one more epoch than CE based training for good convergence. The error rates marked as "WER" in the table are the WER scores measured using normalised RNNLM probabilities, while "WER*" in the last column are obtained using a more efficient, and unnormalised RNNLM probability given in equation (5). The first row of the table gives results without variance regularisation by setting γ to 0. As expected, the WER increased from 15.22% to 16.24% without normalisation. This confirms that the normalisation term computation for the softmax function is crucial when using standard CE trained RNNLMs in decoding. When the variance regularisation term was applied in RNNLM training, the difference between the "WER" and "WER*" metrics was quite small. As expected, when the setting of γ is the increased, the variance of the log normalisation term decreased. When γ was set to 0.4, a WER of 15.28% resulted which is comparable to the baseline CE trained RNNLM, but with much reduced computation at evaluation time.

γ	log(norm)		PPL	WER	WER*
	mean	var			
0.0	15.4	1.67	46.3	15.22	16.24
0.1	14.2	0.12	46.5	15.21	15.34
0.2	13.9	0.08	46.6	15.33	15.35
0.3	14.0	0.06	46.5	15.40	15.30
0.4	14.2	0.05	46.6	15.29	15.28
0.5	14.4	0.04	46.5	15.40	15.42

Table 3. PPL and WER results with variance regularisation. WER* denotes WER using unnormalised RNNLM probability from (5).

Table 4 shows the evaluation speed of a CE-trained C-RNNLM, F-RNNLM and a CE-trained F-RNNLM using variance regularisation on a CPU. As is shown in the table, the C-RNNLM gives a speedup of 42× over the CE trained F-RNNLM baseline. With variance regularisation during F-RNNLM training, a 56× evaluation speedup is obtained compared to the baseline CE-based F-RNNLM.

RNNLMs	Train Crit	Speed (w/s)
F-RNNLM	CE	0.14k
C-RNNLM		5.9k
F-RNNLM	+VR	7.9k

Table 4. Evaluation speed of RNNLMs on CPUs

6.3. Experiments on dual GPU pipelined training of F-RNNLMs

In this section, the performance of a dual GPU based pipelined F-RNNLM training algorithm is evaluated. In the previous experiments, a single NVidia GeForce GTX TITAN GPU (designed for a workstation) was used. For multi-GPU work, two slightly slower NVidia Tesla K20m GPUs housed in the same server were used. Table 5 gives the training speed, PPL and WER results of the pipelined training algorithm. From these results, pipelined training gave a speedup of 1.6× without affecting RNNLM performance.

Model Type	GPU	Train Speed (w/s)	PPL	WER
C-RNN	-	0.37k	46.5	15.31
F-RNN	1xTITAN	9.9k	46.3	15.22
	1xK20m	6.9k		
	2xK20m	11.0k	46.3	15.23

Table 5. Training Speed, PPL and WER results for pipelined training of F-RNNLMs

7. CONCLUSION

Following our previous research on efficient parallelised training of full output layer RNNLMs [11], several approaches have been investigated in this paper to further improve their efficiency at both training and evaluation time: class based RNNLMs were efficiently trained on GPU in a modified spliced sentence bunch mode and gave a 42× reduction in evaluation time; the variance normalised form of RNNLM training scheme produced a 56× speedup at test time; and a pipelined RNNLM training algorithm using two GPUs gave an additional 1.6× acceleration in training speed.

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