A COMPARATIVE STUDY OF BATCH CONSTRUCTION STRATEGIES FOR RECURRENT NEURAL NETWORKS IN MXNET

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ABSTRACT
In this work we compare different batch construction methods for mini-batch training of recurrent neural networks. While popular implementations like TensorFlow and MXNet suggest a bucketing approach to improve the parallelization capabilities of the recurrent training process, we propose a simple ordering strategy that arranges the training sequences in a stochastic alternatingly sorted way. We compare our method to sequence bucketing as well as various other batch construction strategies on the CHiME-4 noisy speech recognition corpus. The experiments show that our alternated sorting approach is able to compete both in training time and recognition performance while being conceptually simpler to implement.

Index Terms: bucketing, batches, recurrent neural networks

1. INTRODUCTION

Neural network based acoustic modeling became the de-facto standard in automatic speech recognition (ASR) and related tasks. Modeling contextual information over long distances in the input signal hereby showed to be of fundamental importance for optimal system performance. Modern acoustic models therefore use recurrent neural networks (RNN) to model long temporal dependencies. In particular the long short-term memory (LSTM) [1] has been shown to work very well on these tasks and most current state-of-the-art systems incorporate LSTMs into their acoustic models. While it is common practice to train the models on a frame-by-frame labeling obtained from a previously trained system, sequence-level criteria that optimize the acoustic model and the alignment model jointly are becoming increasingly popular. As an example, the connectionist temporal classification (CTC) [2] enables fully integrated training of acoustic models without assuming a frame-level alignment to be given. Sequence-level criteria however require to train on full utterances, while it is possible to train frame-wise labeled systems on sub-utterances of any resolution.

Training of recurrent neural networks for large vocabulary continuous speech recognition (LVCSR) tasks is computationally very expensive and the sequential nature of recurrent process prohibits to parallelize the training over input frames. A robust optimization requires to work on large batches of utterances and training time as well as recognition performance can vary strongly depending on the choice of how batches were put together. The main reason is that combining utterances of different lengths in a mini-batch requires to extend the length of each utterance to that of the longest utterance within the batch, usually by appending zeros. These zero frames are ignored later on when gradients are computed but the forward-propagation of zeros through the RNN is a waste of computing power.

A straight-forward strategy to minimize zero padding is to sort the utterances by length and to partition them into batches afterwards. However, there are significant drawbacks to this method. First, the sequence order remains constant in each epoch and therefore the intra-batch variability is very low since the same sequences are usually combined into the same batch. Second, the strategy favors putting similar utterances into the same batch, since short utterances often tend to share other properties. One way to overcome this limitation was proposed within TensorFlow and is also used as recommended strategy in MXNet. The idea is to perform a bucketing of the training corpus, where each bucket represents a range of utterance lengths and each training sample is assigned to the bucket that corresponds to its length. Afterwards a batch is constructed by drawing sequences from a randomly chosen bucket. The concept somehow mitigates the issue of zero padding if suitable length ranges can be defined, while still allowing for some level of randomness at least when sequences are selected within a bucket. However, buckets have to be made very large in order to ensure a sufficiently large variability within batches. On the other hand, making buckets too large will increase training time due to irrelevant computations on zero padded frames. Setting these hyper-parameters correctly is therefore of fundamental importance for fast and robust acoustic model training.

In this work we propose a simple batch construction strategy that is easier to parametrize and implement. The method produces batches with large variability of sequences while at
the same time reducing irrelevant computation to a minimum. In the following sections we are going to give an overview over current batch construction strategies and compare them w.r.t. training time and variability. We will then derive our proposed method and discuss its properties on a theoretical level, followed by an empirical evaluation on the CHiME-4 noisy speech recognition task.

2. RELATED WORK

While mini-batch training was studied extensively for feed-forward networks [3], authors rarely reveal the batch construction strategy they used during training when RNN experiments are reported. This is because the systems are either trained in a frame-wise fashion [4] or because the analysis uses sequences of very similar length as in [5]. We studied in an earlier work [6] how training on sub-sequences in those cases can lead to significantly faster and often also more robust training. In [7] the problem of having sequences of largely varying lengths in a batch was identified and the authors suggested to adapt their proposed batch-normalization method to a frame-level normalization, although a sequence-level normalization sounds theoretically more reasonable. In [8] a curriculum learning strategy is proposed where sequences follow a specific scheduling in order to reduce overfitting.

Modern machine learning frameworks like TensorFlow [9] and MXNet [10] implement a bucketing approach based on the lengths distribution of the sequences. In [11] the authors extend this idea by selecting optimal sequences within each bucket using a dynamic programming technique.

3. BUCKETING IN MXNET

Borrowed from TensorFlow’s sequence training example, MXNet implements bucketing by clustering sequences into bins depending on their length. The size of each bin, i.e. the span of sequence lengths associated with this bin, has to be specified by the user and optimal values depend on the ASR task. The sampling process can be done in logarithmic time, since for each sequence length in the training set a binary search over the bins has to be performed.

In each iteration of the mini-batch training a bucket is then selected randomly. Within the selected bucket a random span of sequences is chosen to be used as data batch. Note that this random shuffling only ensures a large inter-batch variance w.r.t. the sequence length, while the variance within each batch can be small.

Bucketing is especially useful if the RNN model itself does not support dynamic unrolling and is not able to handle arbitrary long sequences but instead requires to store an unrolled version of the network for every possible length. In those cases bucketing allows the framework to assign each batch to the shortest possible unrolled network, while still optimizing the same shared weights.

4. PROPOSED APPROACH

In order to improve the intra-batch variability we propose a stochastic bucketing process. At the beginning of each epoch the utterances are arranged randomly and then partitioned into bins of equal size. Each bin is then sorted in alternating directions such that two consecutive bins are sorted in reverse order to each other. Finally, the constructed ordering is partitioned into batches. The overall algorithm can be summarized as follows:

For each epoch

1. shuffle training data
2. partition resulting sequence into $N$ bins
3. sort each bin $n$ by the utterance length:
   - in ascending order if $n$ is odd
   - in descending order if $n$ is even
4. draw consecutive batches of desired size from the resulting sequence
Due to the initial shuffling and subsequent partitioning the probability for two sequences of any length being put into the same bin is \(\frac{1}{N(N-1)}\), so by increasing the number of bins, the variability within a partition decreases quadratically while the variability among different partitions increases. The alternated sorting approach ensures that utterances at the boundaries of two consecutive bins are of similar length such that the final partitioning into batches requires minimal zero padding.

Figure 1 shows the utterance lengths for random and sorted sequence ordering as well as for bucketing in MXNet and the proposed approach. Note that in the case of bucketing batches are put together by randomly choosing one of the buckets first, so the ordering does not directly represent the final set of batches.

5. EXPERIMENTAL SETUP

The 4th CHiME Speech Separation and Recognition Challenge [12] consists of noisy utterances spoken by speakers in challenging environments. Recording was done using a 6-channel microphone array on a tablet. The dataset revisits the CHiME-3 corpus that was published one year before the challenge took place [13].

We extracted 16-dimensional MFCC vectors as in [14] from the six sub-corpora and used them as features for the neural network models. The context-dependent HMM states were clustered into 1500 classes using a classification and regression tree (CART). We trained a GMM-based baseline model with three state HMM without skip transitions in order to obtain a frame-wise labeling of the training data. A network of three bi-directional LSTM layers followed by a softmax layer was trained to minimize the frame-wise cross-entropy. Optimization was done with the Adam optimizer and a constant learning rate of 0.01. We used MXNet [10] for experiments using the bucketing approach and RETURNN [15] for the other methods.

After training, the state posterior estimates from the neural network are normalized by the state priors and used as likelihoods in a conventional hybrid HMM decoder using the RASR toolkit [16]. A 4-gram LM was used during decoding with a language model scale of 12.

6. EXPERIMENTS

In order to provide some perspective on the impact of temporal context on the CHiME-4 task, we performed experiments on sub-utterance (chunk) which are presented in Table 1. For different sub-utterance lengths, we report the processing speed measured in utterances per second, the memory required and the word error rate (WER) on the evaluation set of the CHiME-4 database. Here we constrained batches to only contain 5,000 frames in total, such that the overall number of updates is constant in all experiments. We can observe that while large speed-ups can be obtained when training is done in this fashion, full-utterance context is required for optimal performance. However, it is worth noting that the memory requirement decreases significantly when sub-utterance training is applied. In particular, for unusually long utterances, sub-utterance training might be the only way to fit the data into GPU memory.

For training on full sequences we conducted experiments with different batch construction strategies. The results are reported in Table 2, where the first two rows show results for trivial sequence ordering methods and the last rows provide a direct comparison of the bucketing approach as it is implemented in MXNet and the alternated sorting approach as proposed in this paper.

As expected, sorting the entire training set by utterance length reduces the required time per epoch to a minimum, while the best overall performance is obtained when utterances are shuffled randomly. Both bucketing and the proposed approach are in between. We can observe that our method is able to reach almost the same recognition performance as using a randomly shuffled sequence ordering, while being almost as fast as the sorted utterance scheduler. This allows for a good trade-off between runtime and system performance.
7. CONCLUSIONS

In this work we presented a novel strategy to construct sequence-level batches for recurrent neural network acoustic model training. While not much attention is given to the topic of batch construction, we demonstrate that different strategies can lead to large variations both in training time and recognition performance. Most deep-learning frameworks rely on a bucketing approach by clustering sequences of similar length into bins and to draw batches from each bin individually. We showed that we can achieve a better runtime performance using a simpler batch design, by partitioning a shuffled sequence order and to sort the partitions in an alternating order. The method was evaluated on the ChiME-4 noisy speech recognition task and compared to standard approaches like random sequence shuffling and the bucketing approach of MXNet, where our method was able to reach a better trade-off between training time and recognition performance while being easier to parametrize than the bucketing method.

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