Approximate Neural Networks for Speech Applications in Resource-Constrained Environments

by

Sairam Arunachalam

A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved May 2016 by the
Graduate Supervisory Committee:

Chaitali Chakrabarti, Co-Chair
Jae-sun Seo, Co-Chair
Yu Cao

ARIZONA STATE UNIVERSITY

August 2016

ABSTRACT

Speech recognition and keyword detection are becoming increasingly popular applications for mobile systems. While deep neural network (DNN) implementation of these systems have very good performance, they have large memory and compute resource requirements, making their implementation on a mobile device quite challenging. In this thesis, techniques to reduce the memory and computation cost of keyword detection and speech recognition networks (or DNNs) are presented.

The first technique is based on representing all weights and biases by a small number of bits and mapping all nodal computations into fixed-point ones with minimal degradation in the accuracy. Experiments conducted on the Resource Management (RM) database show that for the keyword detection neural network, representing the weights by 5 bits results in a 6 fold reduction in memory compared to a floating point implementation with very little loss in performance. Similarly, for the speech recognition neural network, representing the weights by 6 bits results in a 5 fold reduction in memory while maintaining an error rate similar to a floating point implementation. Additional reduction in memory is achieved by a technique called weight pruning, where the weights are classified as sensitive and insensitive and the sensitive weights are represented with higher precision. A combination of these two techniques helps reduce the memory footprint by 81 - 84% for speech recognition and keyword detection networks respectively.

Further reduction in memory size is achieved by judiciously dropping connections for large blocks of weights. The corresponding technique, termed coarse-grain sparsification, introduces hardware-aware sparsity during DNN training, which leads to efficient weight memory compression and significant reduction in the number of computations during classification without loss of accuracy. Keyword detection and speech recognition DNNs trained with 75% of the weights dropped and classified with

5-6 bit weight precision effectively reduced the weight memory requirement by $\sim$95% compared to a fully-connected network with double precision, while showing similar performance in keyword detection accuracy and word error rate.

DEDICATION

To my family for their support

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to Dr. Chaitali Charkrabarti and Dr. Jae-sun Seo for their continuous guidance throughout my research work during the past year. I'm also grateful to Dr. Yu Cao for taking the time to review my work.

I would like to thank Dr. Mohit Shah for his support throughout my research work. He introduced me to speech recognition tools and helped me even after his graduation. I'm grateful to Deepak Kadetotad for his insights into my research and collaboration in the project.

I also thank my parents, brother, friends and roommates for supporting me though the past two years.

I also gratefully acknowledge the financial support provided by Dr. Jae-sun Seo and Dr. Chaitali Chakrabarti.

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Chapter 1

INTRODUCTION

1.1 Speech Recognition, Keyword Detection

Automatic Speech Recognition (ASR) refers to the task of converting speech/audio input to text. Applications for speech recognition include speech-to-text systems (for word processors), personal assistance systems (Apple Siri, Google Now, Amazon Alexa, etc.). Keyword detection refers to the task of detecting specific keywords embedded in speech. Keyword detection can be used to control the front-end in personal assistant systems to trigger a speech recognition engine, or in performing certain actions depending on keyword detected in speech (e.g. "call home").

A speech signal can be modeled as a stationary process in a short time scale (frame) of 25ms. It can also be thought of as a Markov process where the probability of the future outputs depends not only on the current state but also on the previous states. This makes Hidden Markov Models (HMM) (Baker *et al.*, 2009) an appropriate choice to model acoustic information.

There is a vast amount of literature for both speech recognition and keyword detection systems. For speech recognition, the usual process involves using a Hidden Markov Model (HMM) for modeling the sequence of words/phonemes and using a Gaussian Mixture Model (GMM) for acoustic modeling (Su *et al.*, 2010; Sha and Saul, 2006; Juang *et al.*, 1986; Gales and Young, 2008). This modeling can be done using the Expectation-Maximization method. The most likely sequence can be determined from the HMMs by employing the Viterbi algorithm. The GMMs can be implemented in a parallel fashion, but the Viterbi algorithm is inherently sequential.

Keyword detection falls under speech recognition umbrella and is relatively less complex. There are different approaches for detecting a keyword. For instance, the speech recognition system can be used to perform keyword detection. In this approach, first speech recognition is performed and then keywords are detected from the decoded transcription (Miller *et al.*, 2007; Parlak and Saraclar, 2008; Mamou *et al.*, 2007). The drawback for such a method is that it requires the entire phrase to be decoded before the keywords can be detected. The second method involves training separate models for keywords and out-of-vocabulary (OOV) words and detecting keywords based on the likelihood over each model. A separate GMM-HMM is trained for each keyword and the out-of-vocabulary words are modeled using a garbage or filler model (Rohlicek *et al.*, 1989; Rose and Paul, 1990; Wilpon *et al.*, 1991; Silaghi and Bourlard, 1999; Silaghi, 2005). Such a system is suitable in environments where the set of keywords is known beforehand.

1.2 Speech Recognition and Keyword Detection with Neural Networks

Recently, neural network (NN) based methods have shown tremendous success in speech recognition tasks. This success has come after advances made in the field of deep learning (Dahl *et al.*, 2011; Chen *et al.*, 2014). These networks are well-suited to capture the complex and non-linear patterns from the acoustic properties of speech. Detection is performed through feed-forward computation; a matrix-vector multiplication step followed by a non-linear operation at each layer, making it highly suitable for parallel implementations. One such implementation for keyword detection was presented in (Chen *et al.*, 2014), for keyword detection. This system was also shown to outperform the traditional GMM-HMM based approach. While its detection performance was very good, the network was quite large, requiring up to a few million multiplications every few milliseconds as well as large memory banks for storing the weights.

The neural network for a typical speech recognition system is even larger and a straightforward implementation would require huge memory for storing the weights and large number of compute resources. The DNNs in speech recognition are used to predict the probabilities of the different HMM states. Traditionally the GMMs were used to model the relationship between the HMM states (Juang *et al.*, 1986). The GMMs failed to model data that lie on a non-linear manifold in dataspace. Artificial neural networks, trained through backpropagation, have the potential to learn such data representations (Hinton *et al.*, 2012). In our work, the traditional GMM-HMM model is used to derive the target vectors for training the DNN-HMM hybrid system. The DNN based speech model is also shown to outperform the traditional GMM based model (Dahl *et al.*, 2012).

1.3 Problem Definition

The neural networks for speech recognition and keyword detection have large memory and compute resource requirements, making their implementation on a mobile device quite challenging. Keyword detection engine can run as a background service to an ASR in a mobile environment. Since it is always ‘on’, its power consumption has to be very small. Compared to the keyword detection engine, the automatic speech recognition system has very high memory and compute resource requirements. Implementing such a system in a mobile or resource constrained environment is even more challenging. Thus there is a strong need to develop an architectural framework for such applications with the goal of reducing memory footprint and lowering power consumption. In this thesis, low cost neural network architectures for keyword detection and speech recognition have been designed and their performance analyzed.

1.4 Proposed Method

Reduction in memory and power of a neural network can be achieved in many ways such as reducing the number of hidden layers, reducing size of hidden layers, pruning the precision of weights and dropping weights and biases. Methods to reduce the size of the hidden layer and scaling down the precision of the weights and biases have been researched in (Shah *et al.*, 2015). In order to further reduce the memory requirement of the neural network, we propose two approaches. In the first method called weight pruning (detailed in Chapter 3), the connections (weights and biases) are classified as sensitive and insensitive based on the error produced by the connections and the insensitive connections are scaled to a lower precision. In the second approach (detailed in Chapter 4) we drop/remove a large portion of connections within a neural network in a block structure to form a coarse-grain sparse weight matrix. The dropped connections are not stored in the memory, which leads in a reduced memory footprint for the network. The proposed systems are shown to perform at par with a fully connected neural network with floating point architecture while requiring only a small fraction of the memory.

1.5 Contributions

Overall, this thesis makes the following contributions.

- Design of fixed point neural network architecture with 4 hidden layers and 1024 neurons per layer for speech recognition. The weights and biases are represented by 6 bits resulting in memory requirement reducing from 19.53MB to 3.66MB, while maintaining a word error rate of 1.77%.
- Development of an algorithm to classify weights based on their sensitivity and represent insensitive weights with lower precision to reduce memory require-

ment. This method was applied to speech recognition and keyword detection networks resulting in 0.82 -2.12% memory reduction with loss in accuracy by 0.03 AUC and 0.17% reduction in WER, respectively.

- Development of static coarse-grain sparsification technique that can substantially reduce the memory footprint as well as computations when deep neural networks are implemented in hardware with minimal degradation in accuracy.
- A combination of fixed point implementation along with the coarse-grain drop-connect structure reduced the memory requirement of the speech recognition network from 19.53MB to 0.85MB with word error rate of 1.64%.
- A combination of fixed point implementation along with the coarse-grain drop-connect structure reduced the memory requirement of the keyword detection network from 1.81M to 101.26KB with detection accuracy of 0.91 AUC.

1.6 Organization

The reminder of the thesis is organized as follows. In Chapter 2, we discuss the background details of DNN training and its application in speech recognition and keyword detection. A method to prune the weights and biases based on their relative sensitivity is discussed in Chapter 3. In Chapter 4, a coarse-grain sparsification methodology to compress weight memory is described. Finally, the conclusions and future work are presented in Chapter 5.

Chapter 2

BACKGROUND

2.1 Deep Neural Network Structure

A Deep Neural Network (DNN) is an artificial neural network with multiple hidden layers between the input layer and output layer. A simple neural network consisting of a single hidden layer is shown in Figure 2.1. DNNs have shown to be capable of learning complex non-linear relationship present in data. In recent years, DNNs have been implemented for image recognition and speech recognition tasks, significantly outperforming their predecessors performance.

At a high level, a DNN consists of multiple layers of non-linear information processing, where each layer is trained using supervised/unsupervised method (Deng and Yu, 2014). One aspect of DNNs is to learn representation of data from examples. DNNs attempt to learn feature representation of data from supervised learning algorithms and these models can substitute the traditional handcrafted features used in learning algorithms (Song and Lee, 2013).

In a feed-forward DNN, the neurons in one layer of the network are connected to neurons in the next layer. The neurons within a layer are not connected and no cycles are allowed within the network. There are certain architectures where cycles in connections are allowed, but in this thesis we only consider feed-forward networks.

The computations involved in a neuron are described by Eqn. (2.1).

$$n_j = \sum_{i=0}^{N} w_{ij} * x_i + b_j \tag{2.1}$$

where w_{ij} is the weight of the connection between ith neuron in the previous layer

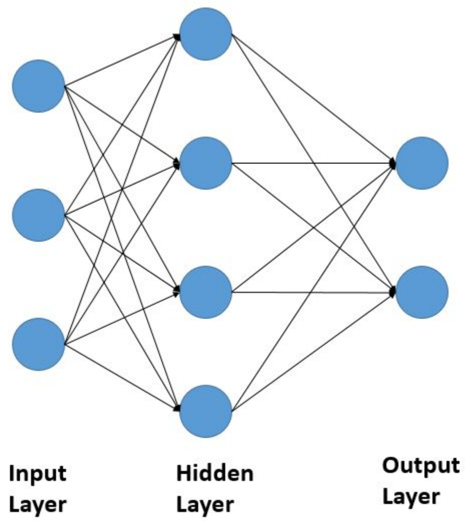


Figure 2.1: A feed-forward neural network with a single hidden layer.

and the jth neuron in the current layer, b_j is the bias value for the current neuron and N is the number of input neurons.

The weighted sum is processed using a non-linear transformation to obtain the output. While any non-linear function can be used to model the neuron output, typically sigmoid (Eqn. (2.2)), ReLU (Eqn. (2.3)) or tanh are used. The ReLU activation best mimics the biological neuron model and is commonly used in recent deep networks.

$$h_j^1 = \frac{1}{(1 + e^{-z_j^1})} \tag{2.2}$$

$$h_j^1 = \max(0, z_j^1) \tag{2.3}$$

The networks with ReLU activation are easier to train and no pre-training is generally required for such networks (Zeiler *et al.*, 2013). Moreover, the ReLU activation requires a simple comparison operation compared to sigmoid or tahn functions. This makes the hardware implementation simple and reduces energy costs associated with

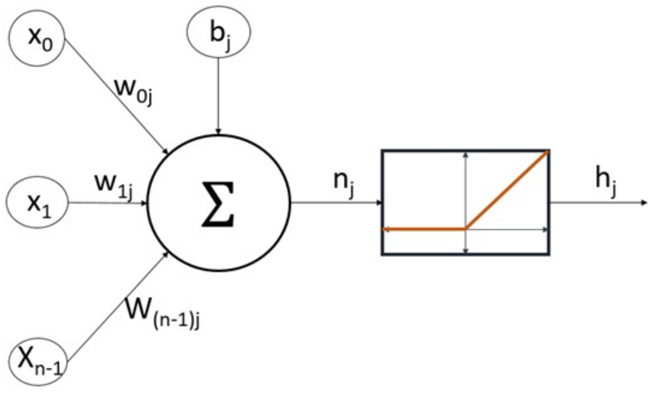


Figure 2.2: A model of a neuron with ReLU activation in a feed-forward neural network architecture.

the network. A sample neuron with the ReLU activation is shown in Figure 2.2.

The output layer of the neural network consists of N_o neurons, where each output represents an output state. In the networks used in this thesis, the output of the neural network represents the posterior probability of the corresponding state in the output layer. To model this behavior of the network, the softmax activation (Eqn. 2.4) is used to model the last layer.

$$o_i = \frac{e^{z_i}}{\sum_{n=1}^{N_o} e^{z_i}} \tag{2.4}$$

Here z_i is the weighted sum of the inputs to the ith neuron in the last layer of the network.

2.2 Training Strategy for DNNs

Typically DNNs are trained using the back-propagation algorithm (Gardner, 1984). This approach is a supervised learning problem where the target outputs of the network are known beforehand. The back-propagation algorithm calculates the error produced by each of the individual weights and biases of the network layer by layer, such that the errors are propagated backwards from the output layer to the input layer.

Mathematically the neural network training aims to achieve the least value for the cost-function associated with the network. Typical cost functions include squared error, cross-entropy, etc. Previous works (Van Ooyen and Nienhuis, 1992) have suggested that the cross-entropy error helps in reducing the training time and improves the convergence of the network parameters. Accordingly we use cross-entropy described in Eqn.(2.5), for the learning process.

$$E = -\sum_{i=1}^{N} t_i * ln(y_i) \tag{2.5}$$

Here N is the size of the output layer, y_i is the ith output node and t_i is the ith target value or label. The mini-batch stochastic gradient method (Gardner, 1984) is used to train the network. The weights are updated using Eqn. (2.6).

$$(w_{ij})_{k+1} = (w_{ij})_k + lr * (m * \Delta(w_{ij})_{k-1} + \Delta(w_{ij})_k) \tag{2.6}$$

where $(w_{ij})_k$ is the w_{ij}th weight during the kth iteration, lr is the learning rate and m is the momentum. The learning rate is kept small. Since the ReLU activation is used, a small learning rate leads to better convergence. A higher learning rate can cause the algorithm not to reach a local minimum but overshoot and not converge at all.

The change in weight is the error produced at the output due to the particular weight. This value is the gradient of the cost of the network output with respect to the weight described in Eqn. (2.7)

$$\Delta(w_{ij})_k = \frac{\partial E}{\partial (w_{ij})_k} \tag{2.7}$$

Here $(w_{ij})_k$ is an element of the weight matrix at layer k and E is the cost-function associated with the neural network.

The momentum method is incorporated into the training procedure with the coefficient m in the weight update equation described in Eqn (2.6) in order to accelerate the convergence of the training algorithm (Sutskever *et al.*, 2013). The key idea in using this method is that the weight change can be stabilized by making non-radical changes by incorporating the previous changes to the weights.

The above training approach is implemented using batches of training input for a number of training iterations over the whole training data (epochs).

2.3 Keyword Detection

2.3.1 Input Features

The speech signal is divided into overlapping signals of short duration (typically 25ms) called frames. The frames from the speech signal are extracted every 10ms. The Mel-Frequency Cepstral Coefficients (Huang *et al.*, 2001) are used to represent meaningful features of the speech frame. For every speech frame, a spectrum in obtained using Fast Fourier Transform (FFT). This is then passed through Mel-filters. Ceptral analysis is performed on these mel-ceptrum to obtain the Mel-frequency Ceptral Coefficient(MFCC) features. Typical ASR systems and keyword detection systems use the first 13 MFCC coefficients.

2.3.2 Data Preparation

The first 13 MFCCs from a frame are augmented with MFCCs of the 15 previous frames and 15 future frames to form a 403-dimension feature vector per frame. The 31 frames with 13 MFCCs/frame corresponds to 310ms of speech. Since the average word duration for this database is 300ms, this choice was deemed to be appropriate for modeling words or sub-word units. Ten keywords were chosen for this work: *ships*, *list*, *chart*, *display*, *fuel*, *show*, *track*, *submarine*, *latitude* and *longitude*. Forced alignment was done using the Kaldi-toolkit (Povey *et al.*, 2011) to obtain the word boundaries. Then each frame was labeled as one of the three categories: a particular keyword, Out Of Vocabulary (OOV) in case the keyword was not in the list above, or silence. The speaker-independent train and test partitions are already specified in the database; there are 109 and 59 speakers in the training and test dataset, respectively. The speech features are z-normalized to zero mean and unit variance for each speaker.

2.3.3 Neural Network Architecture

The DNN used in keyword detection is shown in Figure 2.3. The neural network consists of 2 hidden layers, with 512 neurons per layer. While the number of neurons per layer was 400 (Shah *et al.*, 2015), here we choose 512 due to better performance, and also because a block size that is a power of 2 helps make the coarse-grain sparsification structure efficient. The output layer of the network consists of 12 states, 10 for the 10 keywords, 1 for out-of-vocabulary words and 1 for silence. The neurons in the output layer compute outputs using the softmax function.

The training of this neural network is performed for a fixed number of 6 epochs with a constant learning rate of 0.001 and momentum of 0.8 using a batch size of 500. Here the cost function optimized is the cross-entropy cost

2.3.4 Post Processing

The DNN for the keyword detection network returns the posterior probability that a keyword is present in a given frame. Detecting a keyword on a single frame is not good as the noise in the output signal is very high. As a frame is just a very small

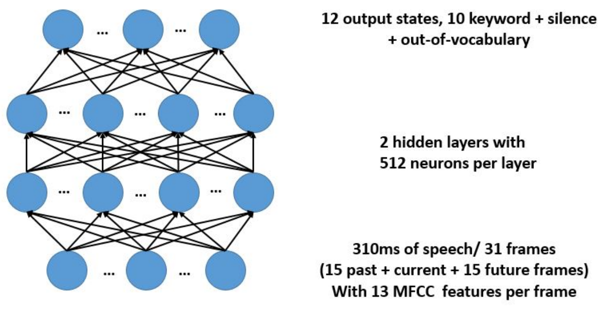

12 output states, 10 keyword + silence + out-of-vocabulary
2 hidden layers with 512 neurons per layer
310ms of speech/ 31 frames (15 past + current + 15 future frames) With 13 MFCC features per frame

Figure 2.3: Neural network architecture for keyword detection consists of 2 hidden layers with 512 neurons per layer. The input feature dimension is 403 and the output dimension is 12 (10 keywords, 1 OOV and 1 silence).

sample of the speech signal, a keyword is likely to span multiple frames and as such the output signal consists of spikes. To reduce the noise in estimation, the estimates are smoothed using a moving average window of W frames. Another sliding window of size C is applied over the smoothed estimates, and if the average probability over the window is greater than a certain threshold the keyword, is said to be present. The values of W and C are varied to find the optimal value. The optimal values were found to be $W = 50$ and $C = 25$(Shah *et al.*, 2015).

2.3.5 Evaluation

In keyword detection, there can be cases where the system predicts that a keyword is present (True Positive) or predicts that a keyword is absent (False Alarm). A good metric to measure the performance of such system is the area under the curve (AUC) of the receiver operator characteristics (ROC) curve (Bradley, 1997). The ROC is the plot between rate of true positive detection and rate of false alarms. The area under this curve represent the probability that the detection system chooses a true positive case over a false alarm.

2.4 Speech Recognition

2.4.1 Input Features

Feature space Maximum Likelihood Linear Regression (fMLLR) is widely used in speech recognition technologies for speaker adaptation. The fMLLR features (Rath *et al.*, 2013) are extracted by applying certain transformations on the MFCC features of the speech signal. Six frames from the neighbourhood of the current frame (3 past frames and 3 future frames) are chosen and the MFCC features of these frames are augmented to the MFCC features of the current frame totalling 13*7 =91 features. These features are then reduced to 40 features by de-correlation and dimensionality reduction using Linear Discriminant Analysis (LDA). These features are further de-correlated using the Maximum Likelihood Linear Transform (MLLT). The fMMLR features can further be spliced in time (5 future frames and 5 past frames) to obtain the final feature vector for each frame in the speech signal. In this thesis, the features are obtained by using Kaldi-toolkit (Povey *et al.*, 2011) and the Kaldi and PDNN scripts (Miao, 2014).

2.4.2 Neural Network Architecture

The DNN used for the speech recognition system is shown in Figure 2.4. This system consists of 4 hidden layers with 1024 neurons per layer. The output of the neural network consists of 1483 HMM states obtained from the baseline GMM-HMM model for the speech recognition system. Similar to the DNN used for keyword detection, the outputs of neurons in the hidden layers are computed using a ReLU activation and the neurons in the output layer use the softmax function to compute the outputs.

The training for this network is performed using a “newbob” approach (Ooi *et al.*,

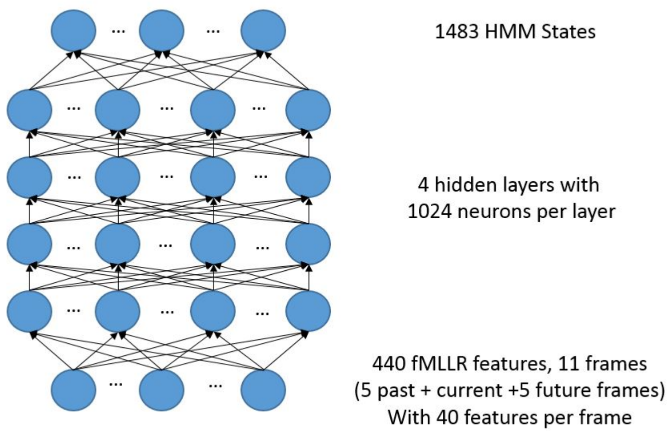

1483 HMM States
4 hidden layers with
1024 neurons per layer
440 fMLLR features, 11 frames
(5 past + current +5 future frames)
With 40 features per frame

Figure 2.4: Neural network architecture for the speech recognition system consists of four hidden layers with 1024 neurons per layer. The input feature dimension is 440 and the output layer consists of 1483 nodes representing the posterior probability of the 1483 HMM states.

2014). We first start with an initial learning rate of 0.08 and momentum of 0.5 . The learning rate is scaled by a factor of 0.5 if the validation error is less than 0.2% between two consecutive epochs. The scaling is repeated for rest of the epochs. The training is stopped when the cross-validation error between two consecutive epochs is less than 0.2%. The batch size used is 256 inputs per iteration. In this learning strategy, the number of epochs is not fixed and can vary for different starting conditions. This results in better and faster convergence of the training algorithm. Essentially it prevents the algorithm from overfitting as training stops if the validation error does not change much.

2.4.3 Post Processing

The posterior probabilities of the frames are obtained from the output layer of the neural network. These probability estimates are divided by the prior probabilities that were obtained for each state from the baseline GMM-HMM model (Bourlard and Morgan, 1994). The scaled estimates are then fed to the Viterbi algorithm to determine the best sequence of phonemes. These phonemes are then used to transcribe the words and sentences for the particular input sequence. The post processing of the neural network output is done using the scripts for the database provided by the Kaldi-toolkit.

2.4.4 Evaluation

To evaluate different speech recognition implementations, we use the Word Error Rate (WER) (Morris *et al.*, 2004) metric. WER is derived from Levenshtien distance, which works at the word level instead of the phoneme level. It is measured as

$$WER = 100 * \frac{(S + D + I)}{N} \tag{2.8}$$

where S is the number of substitutions, D is the number of deletions, I is the number of insertions and N is the number of reference words. In the RM database, the test portion contains 1460 sentences. While the error rates are for the whole system (neural network + HMM), the analysis here focuses only on the neural network part.

2.5 Simulation Setup

For the purpose of developing the speech recognition and keyword detection neural networks, the RM database (Price *et al.*, 1988) is used. This database consists of sentences recorded in a naval resource management task. It consists of 160 speakers (70% male and 30% female evenly over four geographic locations NE-NY, Midland, South, North-West) with varied dialects. The Kaldi toolkit (Povey *et al.*, 2011) is used to train the speech recognition models. The Kaldi-toolkit is an open source software to train speech recognition models. This toolkit provides command line tools to perform various operations including training, decoding and evaluating speech models. The scripts for training the speech models on popular databases are also provided with the toolkit.

Chapter 3

FIXED POINT ARCHITECTURE AND WEIGHT PRUNING

Previous research into reduction of memory for neural network for resource constrained hardware involved using a fixed-point architecture to represent values of weights and biases (Shah *et al.*, 2015). The precision of the weights and biases were kept constant throughout the network for ease of implementation. To further reduce the memory, this thesis proposes to use two sets of precision levels one higher precision and one lower precision level. In this chapter, first a fixed point architecture with constant precision for keyword detection and speech recognition is presented, and then the pruning algorithm that results in minimal degradation in performance is described.

3.1 Fixed-Point NN for Keyword Detection

The neural network for keyword detection consists of two hidden layers with 512 neurons per layer and a output layer with 12 neurons. The input layer consists of 403-D MFCC features. A floating point architecture of this network requires 1.81MB of memory. To reduce this memory requirement, the weights, biases and neuron outputs are represented in fixed-point with fewer bits while keeping the performance of the system comparable to the floating point architecture. The technique to implement the fixed-point architecture is as follows.

First, the precision of the weights and biases of the network are determined. In this step, the neurons in all the layers are kept at 32-bit floating point precision.

The ROC curves for floating point implementations with different number of neurons per hidden layer (256, 512 and 1024 neurons) are shown in Figure 3.1. We see

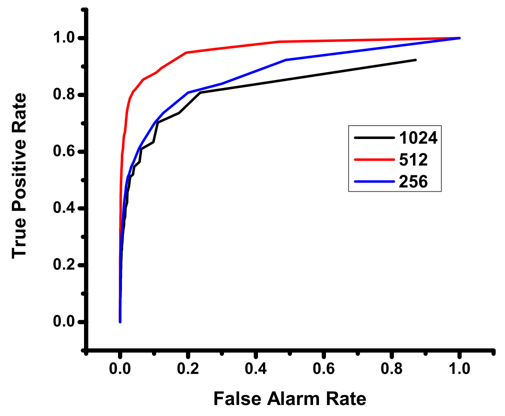


Figure 3.1: A comparison of the average ROC across all keywords between networks with different number of nodes per hidden layer.

that the network with 512 neurons outperforms the other architectures and we use the 512 neurons per hidden layer architecture in this study.

In order to determine the fixed-point precision of the weights and biases, we first derive their histograms. Figure 3.2 shows the histograms of the weights and biases in different layers. It can be seen that all the weights and biases lie in the range $w \in (-4, 4)$. From this we infer that we need 2 integer bits to represent the weights and biases. We also have a sign bit to distinguish between negative and positive values. To find the fractional precision of weights and biases, we sweep the average AUC for various precision levels in the range $B \in \{0, 1, 2, 3\}$. The results of this experiment are shown in Figure 3.3. We see that a fractional precision of 2 bits provides a quality of detection comparable to the floating point implementation. Increase in fractional precision above 2 bits provides negligible gain in performance and decrease in the precision to 1 bit has a drastic impact on the AUC metric. Therefore we choose 2 fractional bits and represent the weights and biases using Q2.2 format.

The inputs (MFCC coefficients) are represented by Q2.13 (16 bits including sign

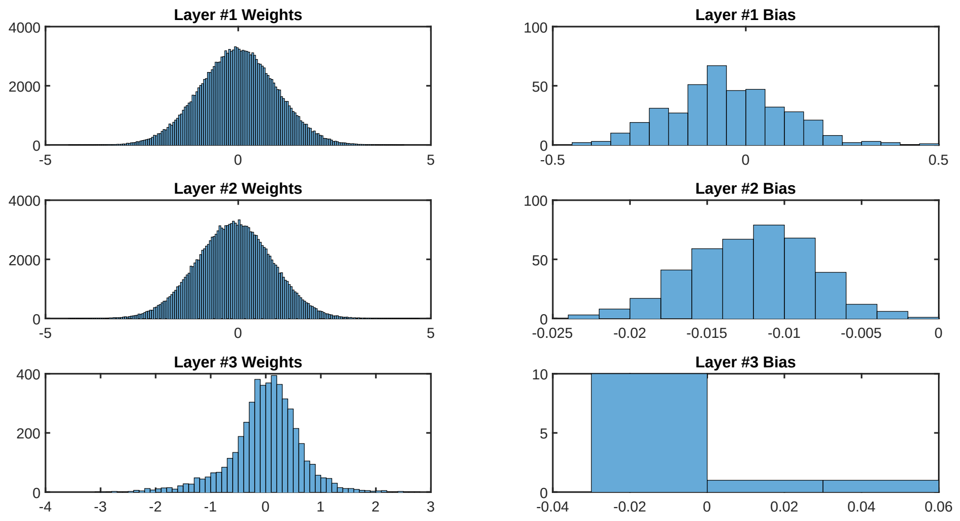


Figure 3.2: Histogram of weights and biases for keyword detection neural network

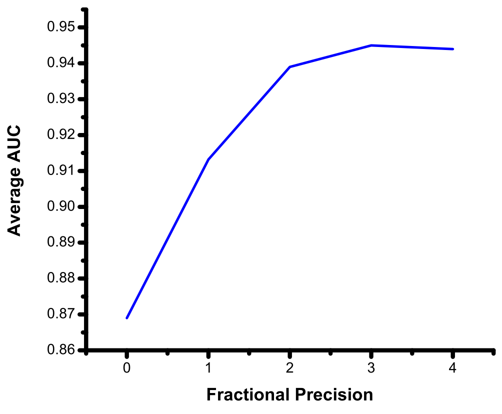


Figure 3.3: Effect of fractional precision of weights and biases on the average AUC for keyword detection network

Table 3.1: AUC and memory requirements of floating and fixed point implementations for keyword detection network

Architecture	AUC	Memory
Floating Point	0.945	1.81MB
Fixed Point Q.2.2	0.939	290.32KB

bit) and the hidden node outputs are represented by Q10.5 (15 bits without a sign bit). The dynamic range of the outputs of the hidden nodes is used to determine the number of integer bits, which is 10. Since the activation function is ReLU, the output is always positive and there is no sign bit. To obtain the number of fractional bits, we choose the fractional precision that results in an AUC comparable to that of the floating point system. Also, to simplify the hardware, the precision (excluding the sign bit) of all the nodes (hidden, input and output) are kept the same. Based on the above criteria, the number of integer bits is 10 and the number of fractional bits is fixed at 5.

3.2 Fixed-Point NN for for Speech Recognition

The neural network for keyword detection consists of four hidden layers with 1024 neurons per layer and an output layer with 1483 neurons. The input layer consists of 440-D fMMLR features. A floating point architecture of this network requires 19.53MB of memory. To reduce this memory requirement, the weights, biases and neuron outputs are represented by a fixed-point architecture with small number of bits provided that the performance of the system is comparable to the floating point architecture.

To determine the precision of the weights, biases and neurons, a methodology similar to that used for the keyword detection algorithm is used here. In order to determine the precision of the weights and biases, we first derive the distribution of weights and biases of each layer of the speech recognition neural network. Figure 3.4 shows the distributions in each of the 5 layers. The weights and biases form a normal distribution centered at 0. The values of the weights and biases are in the range $w \in (-1, 1)$ and so no integer bits are required to represent these values.

The histograms of the weights and biases in Figure 3.4 show that most of the values are near 0. Hence the fractional part of the weights is what determines the recognition performance. Figure 3.5 shows the effect of the precision. The WER drops substantially when changing the precision from 7 bits to 4 bits. This confirms that a 4-bit fractional part is required for the system to perform as well as the baseline floating point implementation. Thus we choose to represent the weights by Q0.5 (6 bits). This results in the weight memory to be of size 3.66MB compared to 19.53MB that is required if the weights are represented in 32-bit floating point.

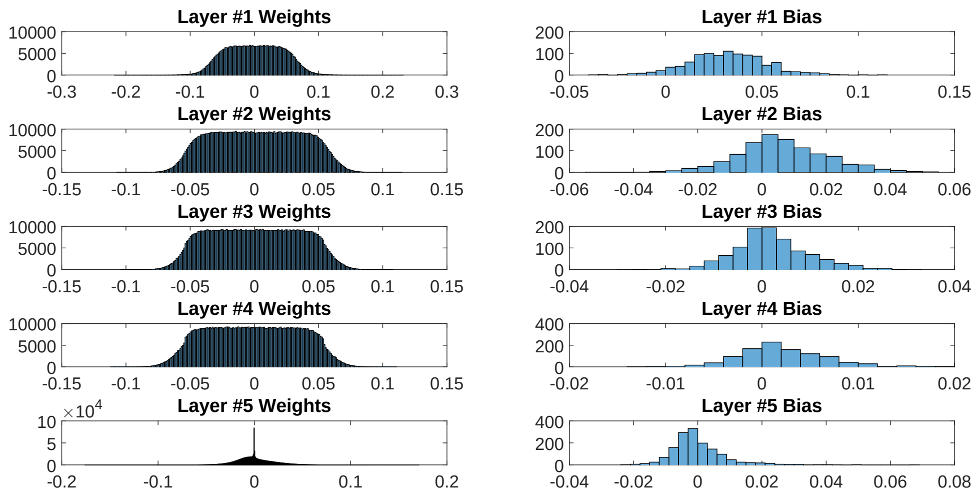


Figure 3.4: Histogram of weights for speech recognition neural network

The inputs (fMLLR features) are represented by Q4.11 (16 bits) and the hidden

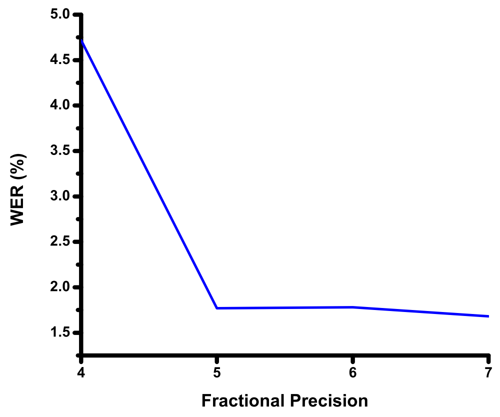


Figure 3.5: Effect of fractional precision of weights on WER for speech recognition network.

nodes are represented by Q10.5 (15 bits).

Table 3.2: WER and memory requirements of floating and fixed-point implementations for speech recognition network.

Architecture	WER(%)	Memory
Floating Point	1.65%	19.53 MB
Fixed Point (Q0.5)	1.77%	3.66 MB

3.3 Weight Pruning

In order to further reduce the required memory, we classify the weights as either sensitive or insensitive. This enables us to represent weights that have a larger effect on the outcome of the network, namely the sensitive ones, with more bits. This method is derived from the work done in (Venkataramani *et al.*, 2014), where each node in a particular layer was approximated based on energy considerations. Instead of approximating each node as done in (Venkataramani *et al.*, 2014), we propose to approximate the weights that aids in reducing the memory footprint.

To derive such an architecture, we need to first identify which connections are sensitive. We achieve weight approximation by piggy-backing on the well known back propagation algorithm that calculates the gradients at different levels of the network by back tracking from the output. We train the network by minimizing the cross-entropy error as described in Section 2.2. Once the trained network is obtained, we once again use the back propagation algorithm on a sample of M inputs to reduce the bias and compensate for bad predictions during classification. In our experiments, we choose the value of M to be 100,000. The errors are used to determine the sensitivity of the connection. In a specific layer, if the error for a particular weight/bias is greater than the threshold, we classify the weight as sensitive and use more bits to represent the value; if the error is below a threshold we deem the weight to be insensitive and we use fewer bits to represent its value. We sweep the threshold values and determine the value that results in minimal loss in quality. No retraining is necessary here as the error produced by incremental retraining will not be high enough to update the already approximated weights.

3.3.1 Results

The above mentioned pruning algorithm is implemented on both the keyword detection and speech recognition neural networks.

In the keyword detection neural network, described in Section 3.1, the weights and biases were represented using Q2.2 format. In order to further reduce the memory requirement, the sensitive weights and biases are represented using Q2.2 and the insensitive weights and biases are represented using Q2.1. Figure 4.2 shows the effect of threshold on the average AUC of such an implementation. For a threshold of 0.4, 52,611 weights and biases are represented using Q2.1 out of a total of 475,660 format resulting in a total memory of 283.89KB.

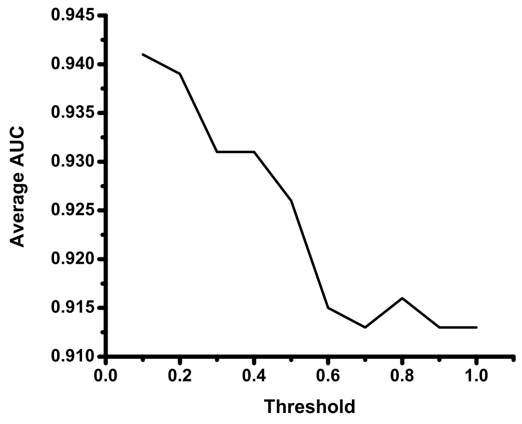


Figure 3.6: Effect of threshold on AUC for keyword detection neural network

In the speech recognition neural network, described in Section 3.2, the weights and biases were represented using Q0.5 format. In order to further reduce the memory requirement, the sensitive weights and biases are represented using Q0.5 and the insensitive weights and biases are represented using Q0.4. Figure 3.7 shows the effect of threshold on the average AUC of such an implementation. For a threshold of 0.4, 226,791 weights and biases are represented using Q0.4 out of a total of 5,120,459 resulting in memory size of 3.63MB.

Table 3.3: Memory Requirement of Networks with Pruned Weights.

Network	**Memory**	**Performance**
Keyword Detection	283.89KB	0.91 (AUC)
Speech Recognition	3.63MB	1.82%(WER)

The results for the weight pruning algorithm are tabulated in Table 3.3. We see that the keyword detection and speech recognition networks perform with minimal

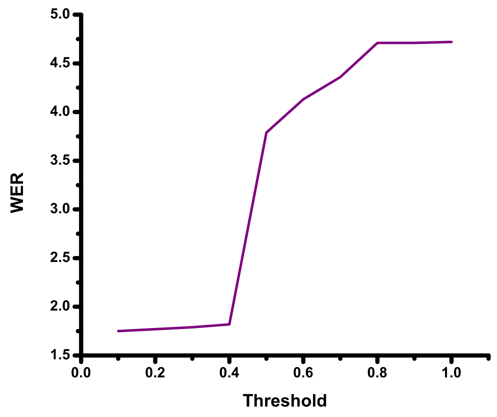


Figure 3.7: Effect of weight pruning threshold on WER for speech recognition network.

degradation of performance with a memory reduction of 0.82% and 2.12%, respectively.

3.4 Conclusions

In this chapter a fully-connected feed-forward fixed point neural network architecture was presented for two key speech applications, namely, keyword detection and speech recognition. Techniques were developed to represent the weights and biases with minimum number of bits to reduce the memory footprint while minimally affecting the detection/recognition performance. With a fixed point architecture the memory requirement of the network was reduced by 83% compared to a naive floating point architecture. This was achieved by using a fixed point implementation using 5 -7 bits. A weight pruning technique was also presented.

Chapter 4

COARSE GRAIN SPARSIFICATION

In this chapter, a hardware-centric methodology to develop neural network with a small memory footprint and computational requirement is described. Such a design is achieved by judiciously dropping large blocks of weights. This method, termed coarse-grain sparsification, resulted in 20x memory compression when tested on neural network architectures for both keyword detection and speech recognition.

4.1 Overview

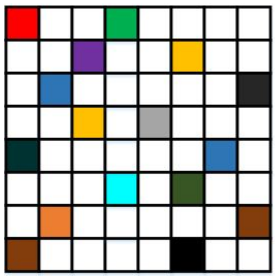
The large memory requirement of the neural network is due to the large weight matrices, which have very large dimensions. For instance, the speech recognition system uses three weight matrices of size 1024×1024, and two matrices each of size 1024×440 and 1024×1483. To reduce memory requirement of a neural network, some of the weights/connections between the layers can be dropped. The challenge is to drop a select set that will not affect the performance of the network adversely. The removal of connections reduces the memory requirement significantly when compared to the weight pruning algorithm. This is because here we are able to remove all the bits for the weights instead of removing only 1 or 2 bits from the weights as in the weight pruning algorithm.

In the rest of this chapter, the coarse-grain sparsification(CGS) technique, that efficiently compresses the memory, is presented. The key idea here is to drop the connections in large blocks (e.g., 64×64, 128×128), and enforce such a constraint in a static manner throughout the training phase of the algorithm. The remaining connections of the network can be efficiently mapped onto SRAM arrays with minimal address information for classification. The blocks of connections are removed with a certain probability (e.g. 75%) during the initialization of the network and this structure is kept constant throughout training and classification phases. This structure is different from the Dropout (Srivastava *et al.*, 2014) and Dropconnect (Wan *et al.*, 2013) architecture that are commonly used in deep learning algorithms to prevent overfitting. Dropout and Dropconnect drop nodes or weights in a dynamic manner in every training iteration. Since the removal of the weights/nodes is dynamic, these approaches do not aid in reducing the memory footprint of the network and the fully connected network is required during classification.

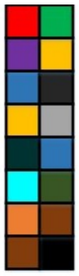
4.2 Block Structure

There exists prior work on partially connected neural networks where some connections between layers have been dropped. Previous approaches drop the weights based on a specific criteria (e.g. if the value is lower than a threshold). Such an approach prevents efficient mapping onto hardware since the weights, as well as the indices of the non-zero weights, have to be stored. To overcome this inefficiency, in our technique, the connections are dropped in large blocks and the weights are dropped on a block-by-block basis. A fully-connected neural network is first initialized and then a certain percentage of the connections are removed block-by-block keeping the number of remaining blocks (e.g. 50%, 75%) constant along either the row or column dimension. Throughout training and classification, the weights in the dropped blocks remain zero. This ensures that there is no memory allocated for these dropped connections, resulting in reduced memory footprint.

Figure 4.1a shows a sample connection matrix with size of 512×512. The matrix is divided into 64 blocks each of size 64×64. The white blocks indicate the absence of connections and the colored blocks indicate the presence of connections. The number



(a) Sample connection matrix of size 512x512 with block size of 64.



(b) Matrix compressed along the column. The martix dimension is 512x128

Figure 4.1: Weight matrix compression

of blocks removed along each row is kept constant so as to obtain efficient compression of memory as shown in Figure 4.1b.

The challenge is to find the appropriate block size and percentage of weight drop that results in the network performing at par with a fully-connected floating point neural network. As the drop percentage of the connections increase, memory requirements reduce. Also, as the size of the block increases, the hardware complexity reduces. The maximum possible block size is related to the percentage of connections removed. For instance, if 50% of the connections are dropped for a connection matrix of size 512×512, the maximum possible block size is 256×256. Ideally we want higher drop rate and larger block sizes since this would result in larger reduction in memory. Experiments are performed to find the best combination of block size and weight drop percentage that reduces the memory size with minimal degradation in the performance.

4.3 Training of Sparse Neural Networks

The training of the neural network with sparse connections is similar to the training algorithm mentioned in Chapter 2. Here we need to account for the dropped connections when performing the forward propagation and the back-propagation in the training algorithm. A connection matrix C is introduced, where the element C_{ij} is a binary variable that represents a connection between ith neuron in one layer and jth neuron in another layer. The connection matrix can take values of either one or zero depending on whether a connection between the neurons across adjacent layers is present or absent.

The training mechanism of the neural network is modified as follows. Eqn. (4.1) describes the modified back-propagation algorithm.

$$(w_{ij})_{k+1} = (w_{ij})_k + C_{ij} * (m * \Delta(w_{ij})_{k-1} - lr * \Delta(w_{ij})_k) \tag{4.1}$$

where $(w_{ij})_k$ is the weight during the kth iteration, C_{ij} is the binary connection coefficient, m is the momentum coefficient and lr is the learning rate. By this method we ensure that only the weights (w_{ij}) present in the network corresponding to $(C_{ij} = 1)$ are updated. The parameters of the training algorithm for both the keyword detection and speech recognition neural network are kept the same as described in Chapter 2.

4.4 Results

In this section, the experimental results are described in detail and the architectural parameters (block size, percentage dropout, precision of neurons, weights and biases) are derived for both keyword detection and speech recognition neural networks.

4.4.1 Keyword Detection

Figure 4.2 shows the effect of block size and percentage drop of the connections on the AUC performance of the floating point keyword detection neural network. The

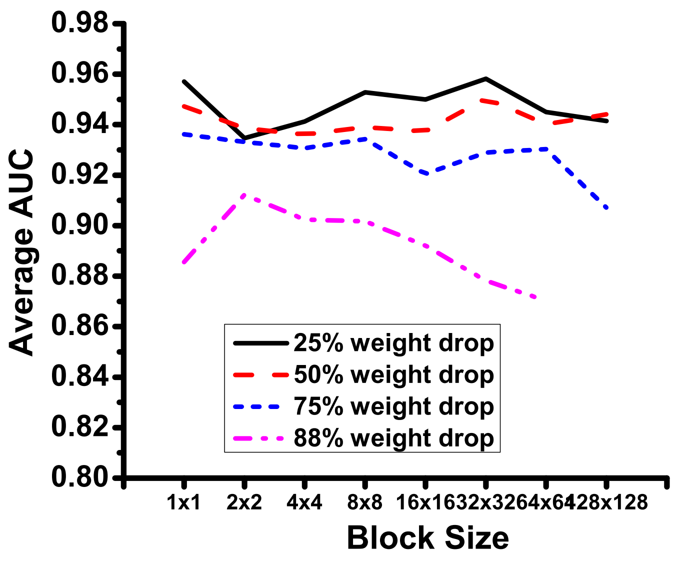


Figure 4.2: Effect of block size and percentage dropout on WER of speech recognition network

percentage drop of the connections are with respect to the two middle layers. We do not drop connections in the last layer since it consists of only 12 nodes and is relatively sensitive. Also since the last layer contributes to 1% of the total weights in the system, any reduction in this layer does not result in substantial reduction in memory requirement. From Figure 4.2, we see that for the same block size, increasing the percentage of dropped connections adversely affects the AUC performance, as expected. When the drop in connections is less than 50%, there is little change in the AUC performance even when the block size is large. However, for larger drops, the AUC performance becomes sensitive to the block size. For instance, the performance of a system with 75% of its weights dropped has an AUC performance loss of up to 0.029 when the block size is 128×128. The AUC performance loss is only 0.015 when the block size is 64×64, and so we use this configuration in our sparse network.

To determine the fixed point precision of the CGS architecture for keyword de-

Table 4.1: AUC and memory requirements of floating and fixed point implementations for keyword detection network

Architecture	AUC	Memory
Floating Point	0.945	1.81MB
Fixed Point Q.2.2	0.940	290.32KB
Proposed CGS (64 block size at 75% dropout)	0.910	101.26KB

tection, the procedure similar to the one mentioned in Chapter 3 is followed. The histogram of the weights and biases is shown in Figure 4.3 and the effect of fractional precision on average AUC is shown in Figure 4.4. From the histogram, the majority of weights and bias values lie in (-4,4) and so 2 integer bits are required. Also the gain in performance for a fractional precision greater than 3 bits is negligible. Therefore we represent the weights and biases using Q2.3 (5 bits including sign bits) representation. The input and hidden layers are represented using the Q2.13 (16 bits including sign bit) and Q10.5 (15 bits without sign bit) respectively.

Table 4.1 compares the memory requirements and the performance of the system for different neural network architectures. We see that there is a small drop in the performance of the proposed architecture compared to both the fixed point and floating point architectures. The proposed CGS architecture requires only 101KB of memory compared to the floating point architecture that requires 1.81MB. This scheme achieves a 18× memory compression with minimal impact to the performance of the system. The ROC curves for the three different architectures shown in Fig. 4.5 are similar. From these results, we conclude that our sparsified architecture performs at a level similar to the floating point architecture, while requiring only a small fraction of the memory required by the fully connected floating point architecture. Moreover

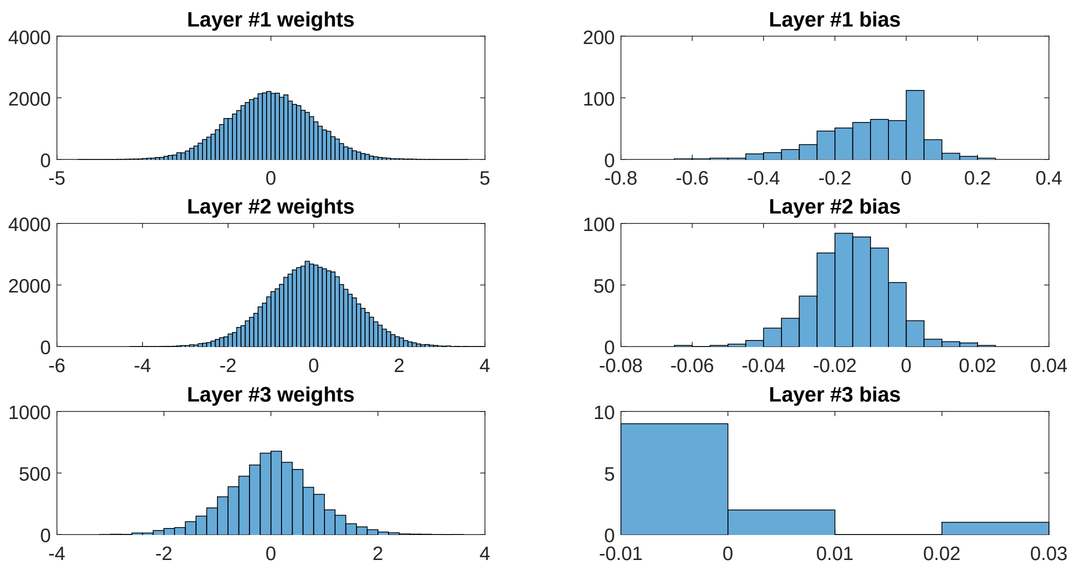


Figure 4.3: Histogram of weights and biases of CGS architecture with 64×64 at 75% drop for keyword detection

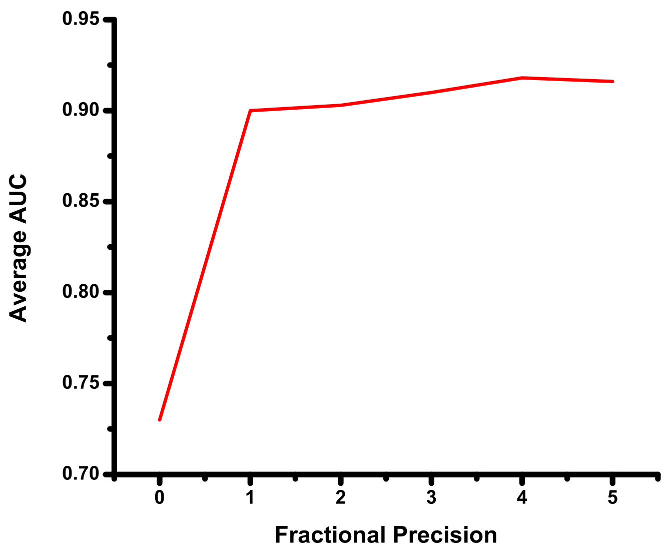


Figure 4.4: Effect of fractional precision of weights and bias on average AUC of keyword detection network for CGS architecture

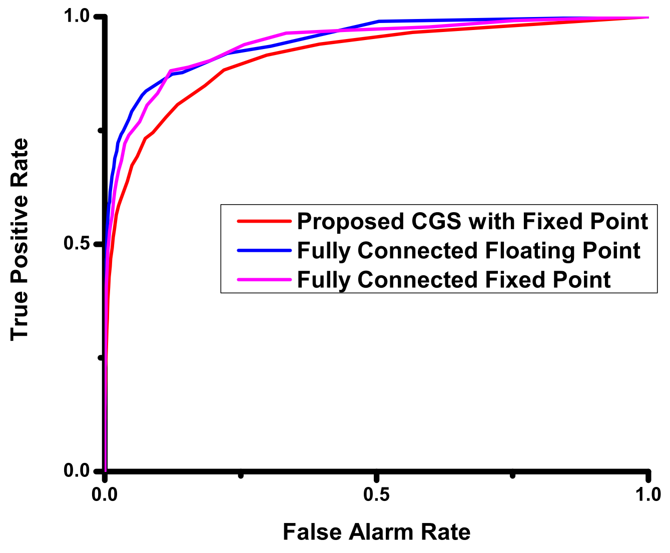


Figure 4.5: ROC Curve of different deep neural network implementations for keyword detection.

with 75% of the weights dropped, we also achieve a 4× reduction in the number of computations, which further reduces the power consumption of the network.

4.4.2 Speech Recognition

Figure 4.6 shows the effect of percentage drop of connections on the WER of the floating point system as a function of the block size. At up to 75% weight drop at all layers of the network, the performance of the system is comparable to the fully connected floating point DNN. Increasing the drop rate to 88% for block sizes larger than 64×64, increases the error rate. Based on this analysis, we choose a drop rate of 75% across all layers with block size of 64×64.

To determine the fixed point precision of the CGS architecture, the procedure similar to the one mentioned in Chapter 3 is followed. The histogram of the weights and biases is shown in Figure 4.7 and the effect of fractional precision on WER is

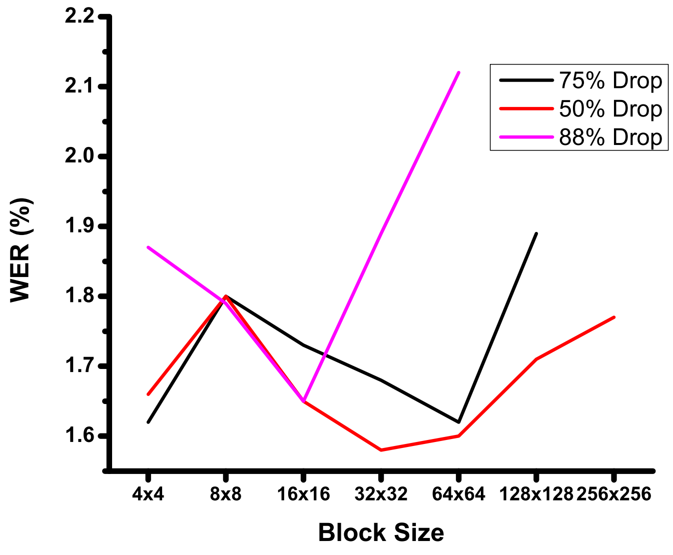


Figure 4.6: Effect of block size and percentage dropout on WER of speech recognition network

shown in Figure 4.8. From the histogram, we see that the majority of weights and bias values lie in (-1,1) and so 0 integer bits are required. Also the gain in performance for a fractional precision greater than 4 bits is negligible. Therefore we represent the weights and biases using Q0.4 (5 bits including sign bits) representation. The input and hidden layers are represented using Q4.11 (16 bits including sign bit) and Q10.5 (15 bits without sign bit) respectively.

Table 4.2 compares the performance of our system with the fully connected floating point and fixed point architectures. The sparse fixed-point DNN using the proposed technique with up to 75% of its connections dropped, has an WER close to that of the floating point fully-connected DNN. The proposed architecture requires memory size of only 0.85MB compared to 19.53MB of a fully connected floating point architecture. Thus, the sparsified fixed point network is able to drop ∼95% of the memory requirement with a small drop in performance. Moreover, with 75% of the weights

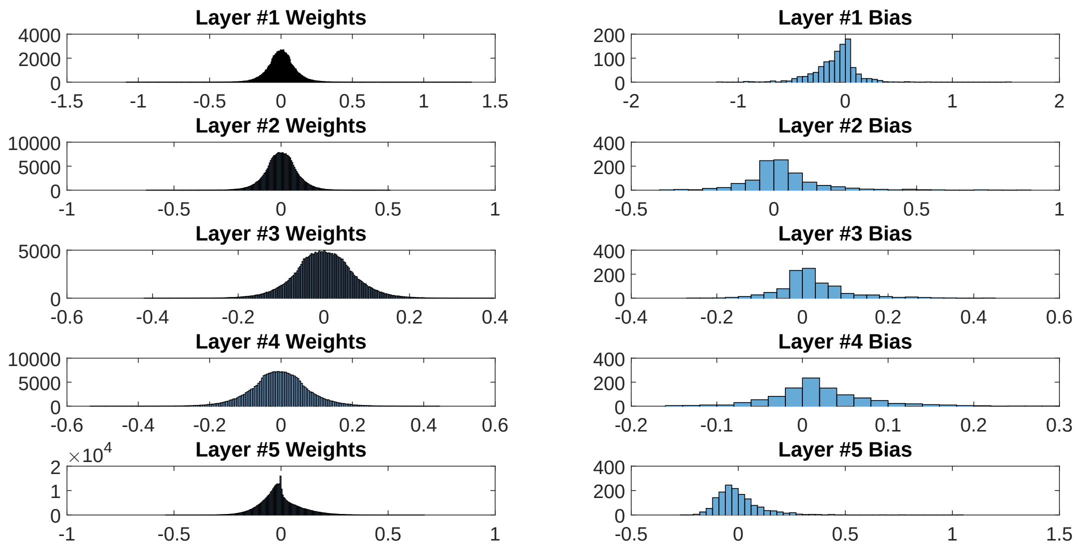


Figure 4.7: Histogram of weights and biases of CGS architecture with 64×64 at 75% drop

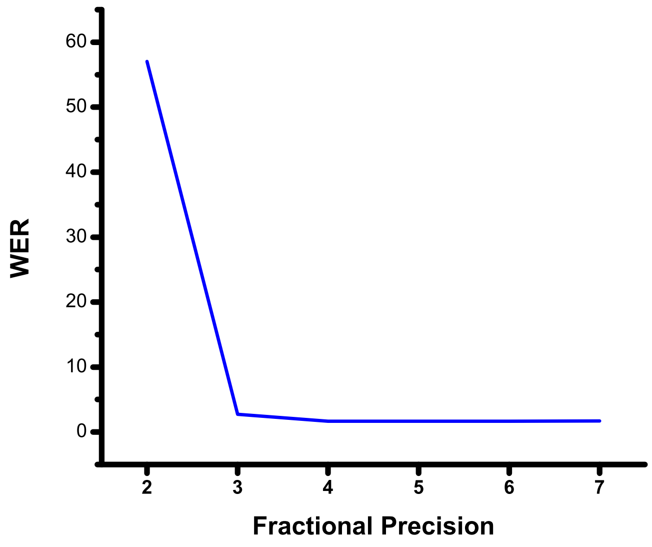


Figure 4.8: Effect of fractional precision of weights and bias on WER of speech recognition system for CGS architecture

Table 4.2: WER and memory requirements of floating and fixed-point implementations for speech recognition network.

Architecture	WER(%)	Memory
Floating Point	1.65%	19.53 MB
Fixed Point (Q0.5)	1.77%	3.66 MB
Proposed CGS (64 block at 75% dropout)	1.64%	0.85MB

dropped, we also achieve a 4× reduction in the number of computations that further reduces the power consumption of the network.

4.5 Conclusions

In this chapter, a block structure was described to efficiently compress weights in a neural network with minimal degradation in the performance. The proposed methodology combined with the fixed point architecture helped achieve a compression rate of $18\times - 23\times$ for keyword detection and speech recognition respectively along with 4× reduction in the number of computations.

Chapter 5

CONCLUSIONS

5.1 Summary

This thesis focused on developing techniques to reduce the memory size in deep networks, specifically in feed-forward neural networks for keyword detection and speech recognition. The neural network for keyword detection consists of 2 hidden layers, with 512 neurons per layer, while the network for speech recognition is much larger with 4 hidden layers and 1024 neurons per layer.

First, techniques were developed to represent the weights and biases with minimum number of bits to reduce the memory footprint while minimally affecting the detection/recognition performance. For keyword detection, where 10 keywords were selected from the RM corpus, experimental results show that there is only a marginal loss in performance when the weights are stored in Q2.2 (5 bits) format. The total memory required in this case is approximately 290KB (compared to 1.81MB if the weights were represented by 32 bit floating point), making it highly suitable for resource constrained hardware devices. On the larger speech recognition network, the memory reduction is even more significant. Here the memory size dropped from 19.53MB to 3.66MB when the weights are represented in Q0.5 (6 bits) format. An additional 0.82%-2.12% reduction (compared to fixed point implementation) can be obtained by representing insensitive weights by lower precision.

Even larger reduction in memory was achieved by dropping connections in blocks. Instead of reducing the precision levels of the individual weights, here the weight connections are removed from the network. We show that the keyword detection and speech recognition networks with 75% of its connections removed performs at a level similar to that of fully connected networks. Application of this technique on fixed point reduced precision implementation, helped reduce the memory requirement by ∼95% compared to a fully connected double precision floating point architecture. Such an architecture also reduces the number of computations by 4×. Therefore, these proposed techniques can substantially reduce the memory and power requirement of resource-constrained devices. As speech recognition becomes more mainstream, the proposed techniques will enable implementation of these networks in mobile and wearable devices.

5.2 Future Work

Future work in this area can be directed towards finding an optimal block selection that maximizes the accuracy of the system. Other approaches include implementing Convolutional Neural Networks (Abdel-Hamid *et al.*, 2014) to analyze the input features. Recently Recurrent Neural Networks (Graves and Jaitly, 2014) have been shown to perform comparable to DNN-HMM systems. These networks have greatly simplified the speech recognition pipeline. Implementing the proposed memory reduction schemes on RNNs can simplify their hardware implementations significantly.

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