Karlsruhe Institute of Technology

Training Deep Neural Networks for Bottleneck Feature Extraction

Master's Thesis of

Jonas Gehring

Interactive Systems Laboratories
Carnegie Mellon University, Pittsburgh, USA
Karlsruhe Institute of Technology, Germany

Advisor:	Prof. Alexander Waibel
Second advisor:	Prof. Florian Metze
Reviewer:	Prof. Alexander Waibel
Second reviewer:	Dr. Sebastian Stüker

Duration: June 2012 – December 2012

KIT – University of the State of Baden-Wuerttemberg and National Research Center of the Helmholtz Association

www.kit.edu

I declare that I have developed and written the enclosed thesis completely by myself, and have not used sources or means without declaration in the text.

Karlsruhe, December 7th, 2012

.....

Jonas Gehring

Abstract

In automatic speech recognition systems, preprocessing the audio signal to generate features is an important part of achieving a good recognition rate. Previous works have shown that artificial neural networks can be used to extract good, discriminative features that yield better recognition performance than manually engineered feature extraction algorithms. One possible approach for this is to train a network with a small bottleneck layer, and then use the activations of the units in this layer to produce feature vectors for the remaining parts of the system.

Deep learning is a field of machine learning that deals with efficient training algorithms for neural networks with many hidden layers, and with automatic discovery of relevant features from data. While most frequently used in computer vision, multiple recent works have demonstrated the ability of deep networks to achieve superior performance on speech recognition tasks as well.

In this work, a novel approach for extracting bottleneck features from deep neural networks is proposed. A stack of denoising auto-encoders is first trained in a layer-wise and unsupervised manner. Afterwards, the stack is transformed to a feed-forward neural network and a bottleneck layer, an additional hidden layer and the classification layer are added. The whole network is then fine-tuned to estimate phonetic target states in order to generate discriminative features in the bottleneck layer.

Multiple experiments on conversational telephone speech in Cantonese show that the proposed architecture can effectively leverage the increased capacity introduced by deep neural networks by generating more useful features that result in better recognition performance. Experiments confirm that this ability heavily depends on initializing the stack of auto-encoders with pre-training. Extracting features from log mel scale filterbank coefficients results in additional gains when compared to features from cepstral coefficients. Further, small improvements can be achieved by pre-training auto-encoders with more data, which is an interesting property for settings where only little transcribed data is available.

Evaluations on larger datasets result in significant reductions of recognition error rates (8% to 10% relative) over baseline systems using standard features, and therefore demonstrate the general applicability of the proposed architecture.

Acknowledgements

First of all, thanks and kisses go to Kristina and our son Max for their love and amazing support in all those years, especially during my stay in Pittsburgh. And nothing would have been possible without our parents, of course.

I like to thank Prof. Alexander Waibel for reaching out to me, providing me with the opportunity to participate in the interACT exchange program and for constant encouragement. Furthermore, I would like to thank to my supervisor at Carnegie Mellon University, Prof. Florian Metze, for providing the continuous support that led me through this thesis; Prof. Ian Lane for GPU computing power in Silicon Valley; Zaid Md Abdul Wahab Sheikh at CMU for testing many a network during this thesis; Dr. Sebastian Stüker for reviewing this work; and Denis Stier for proof-reading.

This work was performed at Carnegie Mellon University in Pittsburgh, Pennsylvania during the interACT student exchange program and supported by a scholarship from the Baden-Württemberg Stiftung.

This work is supported in part by the Intelligence Advanced Research Projects Activity (IARPA) via Department of Defense U.S. Army Research Laboratory (DoD/ARL) contract number W911NF-12-C-0015. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright annotation thereon. Disclaimer: The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of IARPA, DoD/ARL, or the U.S. Government.

Contents

Introduction

During the last decade of research in automatic speech recognition (ASR), the field has faced an enormous number of applications. The growing amount of computational resources available paves the way for using speech recognition in tasks like real-time translation, audio analysis of videos or keyword search in large archives of recordings. With computers and mobile phones becoming increasingly ubiquitous, those systems are gaining importance as providers of natural and intuitive human-computer interfaces. Generally speaking, speech is the fundamental medium of communication between humans, and enabling machines to handle this medium reasonably well is of major concern to researchers. But as the number of applications continues to increase, so do the challenges current systems have to overcome.

While constrained tasks on read speech with limited vocabularies have long been mastered and have led to many successful applications, progress of conventional systems on more difficult problems has been slow over the last decade. Conversational, large-vocabulary speech continues to be a major issue for current systems. Further challenges are caused by inherent variations such as background noise, speaker style or age, accents and more that humans are able to master while machines are still struggling.

Recent works have demonstrated the ability of *deep learning* techniques to bring the performance of recognizers on challenging tasks to the next level. This field deals with the training of powerful models called *deep neural networks*, that are able to effectively handle the plethora of variations that makes classification of raw data like images and speech so difficult. Many algorithms also provide ways to improve performance by leveraging unlabeled data, which is especially attractive for ASR, where preparing training data is still very labor-intense. While the challenges mentioned above have not been fully mastered yet, it has become clear that deep neural networks are going to play an important role in overcoming them.

Most of the work on the application of deep learning to speech recognition has been

done by improving acoustic models that estimate the likelihood of a speech signal given a corresponding symbolic representation like a phoneme sequence. In current systems, this task is performed by hidden Markov models that model the human speech production process. Hybrid systems in which those models are combined with deep neural networks have therefore become popular.

An alternative approach is using neural networks to generate the *input features* used by a conventional system employing a combination of Gaussian mixture models and hidden Markov models for acoustic modeling. This is done by training a network to classify phoneme states and then using the network output (*probabilistic features*) or the activations of a narrow hidden layer (*bottleneck features*) to generate the features for the main system. Applying deep neural networks to this task is appealing, too, because many systems already include support for generating features this way. Furthermore, the behaviour of the remaining system in combination with those features is well-understood, which helps when integrating and comparing different types of networks.

1.1. Contribution

This thesis describes a novel approach of using deep neural networks for bottleneck feature extraction as a preprocessing step for acoustic modeling, and demonstrates its superiority over conventional setups. In particular, it is being shown that the pre-training algorithms popular in the deep learning community produce better neural network models compared to standard methods, and that deeper neural networks result in better performance of the resulting speech recognition system.

The models proposed were evaluated in a state-of-the-art recognition system on challenging real-world tasks with conversational telephone speech in languages that are new to the research community. Additional evaluation on a standard benchmark task shows that the approach presented is generally applicable.

1.2. Layout

The next chapter provides the theoretical background for the main contributions of this work and introduces the relevant concepts of automatic speech recognition, artificial neural networks and deep learning. Chapter three discusses previous work on using deep learning to generate bottleneck features and describes the models, algorithms and training procedures proposed. The fourth chapter documents the experiments done during the course of this thesis and provides an evaluation of the techniques introduced previously. The ASR system and the individual setups used will be described as well. The results are then summarized and discussed in chapter five, followed by an outlook suggesting possible future work.

Detailed mathematical descriptions of the training algorithms used as well as implementation notes regarding the training of neural networks on graphics processors can be found in the respective appendices.

Background

2.1. Automatic Speech Recognition

The term *automatic speech recognition* (ASR) describes the process of extracting a textual representation of spoken words from a sound signal when performed by a machine, e.g. a computer. Usually, the physical signal caused by a human uttering a sequence of words is recording using a microphone and converted to a digital representation of a sound wave. This is the input to the ASR system, which tries to find a sequence of words as close as possible to the ones originally uttered.

The multiple levels of ambiguity present in human communication make ASR a very challenging task. Background noise, noisy channels like telephone lines, speaker variability or conversational ("sloppy") speech pose additional difficulties that even modern systems still struggle with. Nonetheless, speech recognition systems are expected to achieve near-human levels of performance in scenarios like human-machine interfaces.

2.1.1. System Overview

A typical ASR system consists of five major building blocks that are illustrated in Figure 2.1. During *preprocessing*, the digitalized sound signal recorded over a period of time is transformed into a sequence of feature vectors X. The goal of the whole system is to determine the most likely sequence of words W given a sequence of feature vectors X. This is equal to maximizing the a posteriori probability $P(W|X)$, which can be expressed using Bayes' rule as

$$P(W|X) = \frac{P(X|W)P(W)}{P(X)}$$

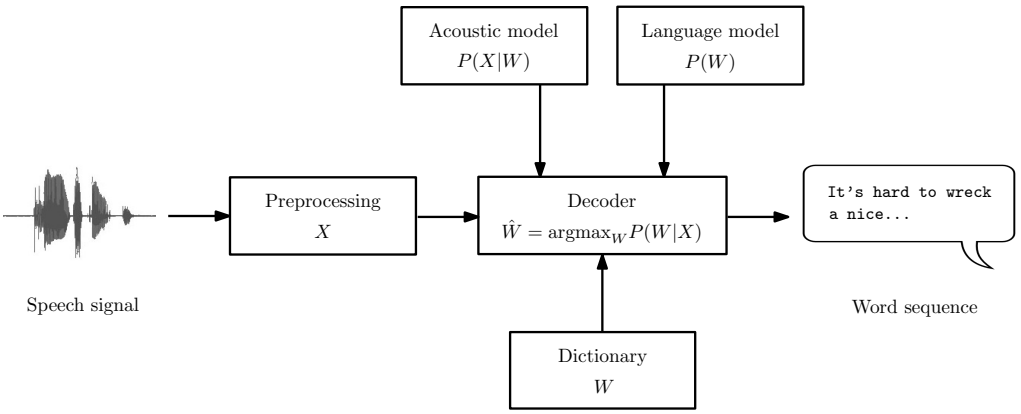


Figure 2.1.: Basic components of a speech recognition system

This maximization is done by the *decoder* and can be formalized as follows:

$$\begin{aligned}\hat{W} &= \text{argmax}_W \, P(W|X) \\ &= \text{argmax}_W \, \frac{P(X|W)P(W)}{P(X)}\end{aligned}$$

The actual numerical value of the maximum is not of interest, so this can be simplified to

$$\hat{W} = \text{argmax}_W \, P(X|W)P(W)$$

The first factor of the product that determines the maximum, $P(X|W)$, is estimated by the *acoustic model*. Given a sequence of words, this describes the likelihood of observing a sequence of feature vectors. $P(W)$ is produced by the *language model* and describes the probability of observing a sequence of words independent of the current feature vectors. Finally, the *dictionary* contains a list of available words, thus restricting the search space of the decoder.

This work deals with the preprocessing part of a speech recognition system, which directly influences the setup and performance of the acoustic model. Therefore, those two components will be described in more detailed below.

2.1.2. Preprocessing

The techniques used for the preprocessing stage are designed to fulfill multiple demands. Foremost, X should contain the relevant information needed to reconstruct the spoken content, although low-dimensional feature vectors are beneficial since they result in a faster computation of the overall system. Algorithms used for acoustic modeling may pose additional restrictions on numerical range or correlation between individual features.

During the history of automatic speech recognition, a large number of preprocessing techniques and features have been proposed. In most cases, the speech signal is sampled by

consecutively computing the response to a short Hamming window, which produces small time frames that are assumed to be periodic signals for further processing. This makes it possible to apply a discrete Fourier transform yielding a power spectrum of isolated sound waves at different frequencies. Commonly, the powers are mapped to the mel scale, which approximates the perception of the human ear.

The most popular features used in ASR systems today are *mel frequency cepstral coefficients*, or MFCCs [DM80]. In order to generate them, the mel coefficients obtained using the technique described above are treated as a signal themselves. A discrete cosine transform is applied to their logarithm, resulting in the individual MFCCs.

Acoustic models usually benefit from increased temporal context per feature vector, so features extracted from consecutive windowed speech segments are concatenated to form a feature frame. Finally, a dimensionality reduction technique such as *linear discriminant analysis* (LDA) produces the final feature vector that is used by the recognition system.

This thesis deals with using *artificial neural networks* to generate discriminative features out of traditional features like mel-scale coefficients or MFCCs. In combination with the traditional GMM/HMM approach introduced in the next section, this is usually referred to as a *tandem system* [HES00], [GKKC07]. This is described in more detail in section 2.2.1 after neural networks have been introduced.

2.1.3. Acoustic Modeling

As described in section 2.1.1, acoustic models are used to estimate the probability that the current sequence of feature vectors are being observed given a sequence of words. Given the multitude of variations regarding speaker style or age, background noises etc. and combining them with additional variations in time makes this a very challenging problem.

In current systems, acoustic modeling is usually approached using *hidden Markov models* (HMMs). HMMs model Markov processes where only the results but not the process producing them can be observed. In the ASR context, the process corresponds to the contraction of muscles in the human vocal tract and the result is the sound captured by a microphone, or feature vectors generated by the preprocessing stage.

The states of the speech production process are commonly modeled as sub-word units such as multi-state phonemes or senones. Since processes modeled with HMMs are assumed to fulfill the Markov property, i.e. that the next state of a process depends on its current state only, each observance is assumed to solely depend on the current state as well. For speech, this means that sub-word units are modeled independent of their temporal context, which does not reflect the reality. In order to overcome this limitation, current systems use *context-dependent* states, where sub-word units with different surrounding units are assigned to different HMM states.

Performing computations with hidden Markov models requires two probability distributions: emission probabilities of the possible results that can be observed and transition

probabilities between the different states of the process. Training algorithms to estimate the latter require existing emission probabilities, which have to be learned separately from the available data. Current systems typically employ *Gaussian mixture models* (GMMs) to estimate the probability that a feature vector corresponds to a specific sub-word unit, that are usually trained using variants of the Expectation-Maximization algorithm.

2.2. Artificial Neural Networks

Artificial neural networks (ANNs) have been of interest to researchers for decades, albeit with varying degrees thanks to repeated waves of popularity and aversion by the scientific community. In 1958, Rosenblatt first introduced *perceptrons*, simple computational units crudely modelled after biological neurons, and a corresponding training procedure for using them as linear classifiers [Ros58]. Decades later, Rumelhardt et al. proposed the backpropagation training algorithm which finally made it possible to train *networks* of perceptrons [RHW86].

In an artificial neural network, a perceptron acts as the basic computational unit and is connected to a certain number of input units, i.e. input data features or the outputs of other perceptrons. A weight vector $\boldsymbol{w}$ is assigned to each of the inputs and is used to compute a weighted sum of the perceptron's respective input unit values. Additionally, a single bias value b is added to the sum that ensures that the neuron can be active (have a positive output) even if the input values are zero. The result is then filtered through an usually non-linear activation function $\sigma(x)$, e.g. the sigmoid function $(1 + e^{-x})^{-1}$, to compute the final output value of the unit.

One of the most common ANN models is the *multi-layer perceptron* (MLP) as shown in Figure 2.2. The components of an input vector $\boldsymbol{x}$ are assigned to the units in the input layer. Perceptrons are then arranged in layers where each unit is connected to units from the previous layer only. The perceptrons in the output layer compute the final output values of the network, which might be class probabilities for a classification problem. The feed-forward computation of a MLP, which simply consists of multiple weighted sums for each perceptron, can be expressed in terms of multiplying the input vector $\boldsymbol{x}$ with a weight matrix $\boldsymbol{W}$ and adding a bias vector $\boldsymbol{b}$ afterwards. Again, a non-linear function is used to compute the final output vector $\boldsymbol{y}$ of a layer. Thus, the whole computation performed by a single layer can be written as

$$\boldsymbol{y} = \sigma\left(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}\right)$$

Training a artificial neural network equals to adjusting its parameters, i.e. the weights and biases, in order to compute the desired outputs for a given number of training vectors. After the network has computed its output for a specific input training vector, the error between the actual output $\boldsymbol{o}$ and the desired output vector $\boldsymbol{t}$ is computed, e.g. using the mean squared error:

$$E\left(\boldsymbol{o}, \boldsymbol{t}\right) = \sum_i \left(o_i - t_i\right)^2$$

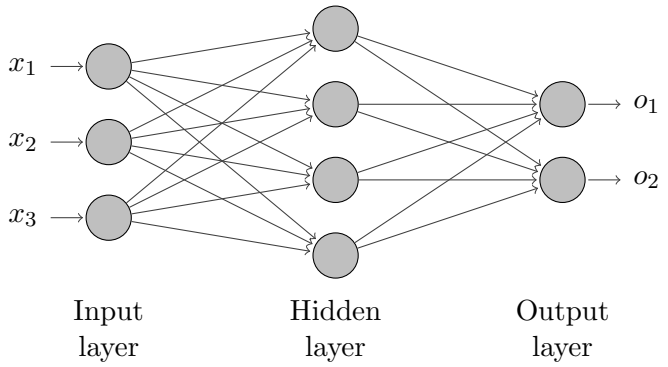


Figure 2.2.: Architecture of a multi-layer perceptron with a single hidden layer.

The backpropagation algorithm is then used to compute first-order gradients for each weight and bias of the network according to the current error. Gradient descent is commonly used to update the parameters by a fraction of their respective gradients. These steps are usually repeated until convergence on a separate dataset is reached, which means that the network does not improve its accuracy any more. The MLP training algorithm used in this work is described in more detail in section 3.2.3.

2.2.1. Tandem Systems for ASR

Throughout the 1980s, a large number of ANN-based speech recognition systems have been proposed [Lip89]. In particular, work has been done to tackle the problem of recognizing sequences, for example with *Time-Delay Neural Networks* [WHH+89] that increase their temporal context in higher layers by applying low-level hidden units at multiple time steps to the input, and *recurrent neural networks* [WS87], in which an internal state is created by using the output of units as their input again. Although highly successful on limited tasks, those approaches were eventually abandoned in favor of hidden Markov models in combination with Gaussian mixtures. In part, this happened because they provided similar performance to small neural networks and algorithms as well as suitable hardware for training large networks was lacking.

Afterwards, multiple ways of combining the strengths of both HMMs and ANNs have been proposed. Bourland & Morgan described a *hybrid system* that employs neural networks for estimating the emission probabilities of sub-word units [BM94]. However, since modeling emission probabilities with Gaussian mixtures was already established and well-understood, and the benefits achieved by using neural networks seemed to be rather small, most researches continued using the GMM/HMM approach. An alternative approach was proposed in the form of *tandem systems*, where neural networks are used to generate discriminative input features at the preprocessing stage of an ASR system [FRB97], [HES00]. These features could be integrated into existing systems, which enabled meaningful comparisons against setups using standard input features.

In [HES00], Hermansky et al. proposed training a neural network to classify an input vector

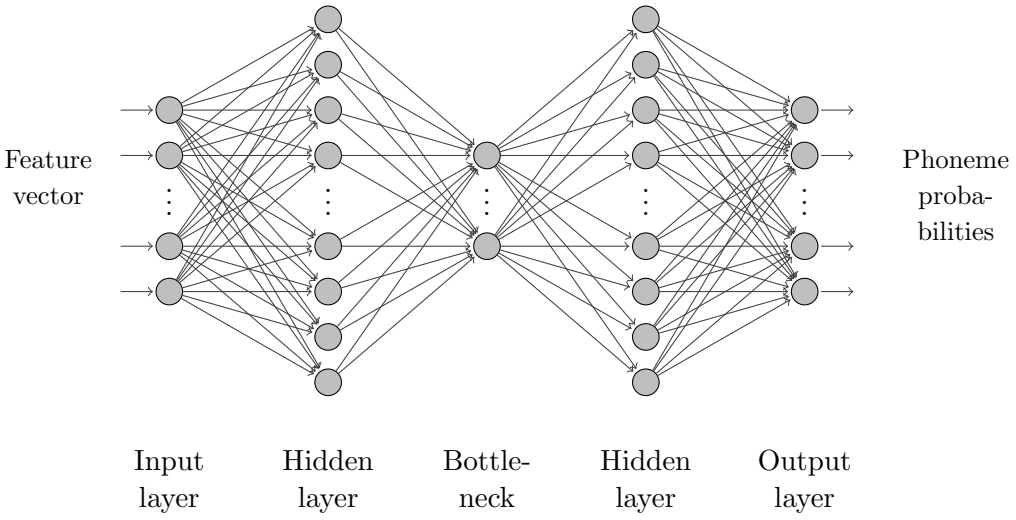


Figure 2.3.: Multi-layer perceptron for bottleneck feature extraction as proposed by Grézl et al.

consisting of MFCCs, MFCC deltas and delta-deltas as one of 24 phonemes. The *tandem features* used by the GMM/HMM system where then generated by taking the outputs of the network without applying the final activation function and orthogonalizing them via primary component analysis (PCA). Hermansky et al. showed that their system performed better than both a standard setup on the same input data and a hybrid approach where the ANN output is directly used by the Hidden Markov Model.

Grézl et al. proposed extracting features from the activations of a very small hidden layer instead of using the network output values [GKKC07]. They trained a 5-layer neural network as a phoneme classifier on windows of coefficients of a discrete cosine transform applied to log-critical band energies. The input features for the ASR system were generated from the activations in the small hidden layer in a similar way as in [HES00] by subsequent dimensionality reduction. It was also noted that combining the bottleneck features with traditional input features can result in further improvements of the recognition rate.

The architecture of the network used by Grézl et al. is illustrated in Figure 2.3. The second, narrow hidden layer which computes the features of interest is called the "bottleneck" layer. Since its size is usually even smaller than the size of the input layer, the main motivation for this architecture is that the neural network is "forced" to learn a compact representation of the input data which is useful for the respective classification task. This principle is similar to early work on auto-encoder neural networks, which have been used for non-discriminative dimensionality reduction, for example [Hin89]. Section 2.3.2.1 contains a more detailed description of auto-encoder networks, although not in the context of reducing the dimensionality of data but as building blocks for deep neural networks.

2.3. Deep Learning

In recent years, *deep learning* has gained a lot of attention in the machine learning community. The general objective of this field is the training of large neural networks with many hidden layers, so-called *deep neural networks* (DNNs). There are multiple reasons why deep networks are attractive. From a theoretical point of view, they are more efficient than shallow ones in the sense that they are able to represent complex functions with exponentially fewer computational elements [Ben09]. In theory, this makes them more suitable for high-dimensional classifications problems with complicated decision manifolds like image classification.

Apart from that, another main motivation for deep architectures is the automatic discovery of feature hierarchies where high-level features are composed of low-level features. For example, in computer vision a feature representing a face might be composed of features for eyes, a nose and more, that in turn are represented as combinations of simple edge detectors. According to current studies, such hierarchies of feature detector neurons are present in primate brains as well, for example in the visual system [SKK+07]. There are also practical benefits in hierarchical architectures, like the re-use of low-level features for new classification tasks and an increased understanding of the resulting networks since one can already expect the appearance of certain kinds of feature detectors.

Many deep learning algorithms are also *unsupervised* in that they do not use labels when training the network. Since accurately labeling training data is a time- and labor-intense task, this is a very attractive property. Especially in speech recognition, where recordings first have to be transcribed by humans, systems can benefit from leveraging unlabeled speech data.

Learning local features with neural networks and combining them in hierarchical models has been pursued by researchers for a long time. The time-delay neural networks introduced by Waibel et al. have already been mentioned in section 2.2.1 [WHH+89]. Later work dealt with general procedures to build, merge and extend hierarchical neural networks in a similar fashion [WSS89]. LeCun & Bengio built upon this work by hard-wiring the idea of location-invariant features into the neural network model [LB95]. Their proposed *Convolutional Neural Network* architecture used convolution operations of small groups of hidden units at multiple stages, which made it possible to train the whole neural network in one pass.

However, until 2006, training deep networks with 3 or more hidden layers was not successful using standard techniques [Ben09]. When starting from a random initialization as usual, the backpropagation algorithm suffers from diluting gradients and is prone to overfitting. Furthermore, the large amount of parameters in a deep neural network requires a huge amount of labeled data for training. In 2006, Hinton et al. proposed a *deep belief network* which used greedy, unsupervised and layer-wise pre-training to successfully build a large network with three hidden layers [HOT06]. In their work, they trained each layer of the

network as a *restricted Boltzmann machine* (RBM) [AHS85]. Their key insight was that unsupervised training can be used to initialize each layer in a local, isolated fashion and that the resulting network can be trained much easier than starting with random weights.

The major part of the work in deep learning makes use of the layer-wise pre-training strategy of Hinton et al. as well. Bengio et al. showed that auto-encoder networks can be used for pre-training instead of restricted Boltzmann machines [BLPL07]. Shortly afterwards, sparse models have been proposed that increase the invariance of learnt features [MRBL07]. Building on earlier ideas by LeCun et al., Lee et al. developed location- and time-invariant convolutional models that can be pre-trained accordingly, focussing explicitly on the ability of hierarchical feature extraction [LGRN09]. Quite recently, those ideas ideas have been applied to harder, large-scale problems and led to breakthroughs in speech recognition [SLY11], [DYDA12], object recognition [LMD+11], [KSH12] and other areas. The following section provides a more detailed overview of current work on applying deep learning to acoustic modeling for ASR.

In order to build deep neural networks, the work at hand utilizes an alternative auto-encoder model proposed by Vincent et al. [VLBM08] which will be introduced section 2.3.2.

2.3.1. Applications to Acoustic Modeling

Deep learning has been applied successfully to the speech recognition domain, in particular to acoustic modeling. This focus may be due to the fact that this stage deals with signal data at a similar level than images, and deep networks showed superior performance on computer vision tasks. Deep neural networks with high modeling power have thus been able to outperform the commonly used Gaussian mixture models in phoneme recognition tasks [HDY+12].

First applications to phoneme recognition have been performed by Mohamed et al. [MDH09], who showed that deep belief networks are able to outperform heavily tuned GMM-based approaches on the TIMIT benchmark, a small dataset of read English speech. Dahl et al. proposed using the *mean-covariance* restricted Boltzmann machine, a model specifically designed to capture correlations between real-valued input data features, for modeling speech data and were able to beat the result of Mohamed et al. by a small margin [DRMH10]. Recently, Abdel-Hamid et al. demonstrated using convolutional, deep neural networks in a hybrid system with a HMM which resulted in further improvement on the TIMIT task [AHMJP12].

Additionally, several recent works have shown that deep learning techniques can be used to increase the performance on large-vocabulary speech recognition tasks as well. Seide et al. reported a huge relative improvement of 33% in terms of recognition rate on the challenging Switchboard task [SLY11], using a similar setup that had previously produced a 16% relative improvement on Bing voice search data [DYDA12]. In their work, they used a hybrid context-dependent DNN/HMM system containing a large 7-layer deep belief

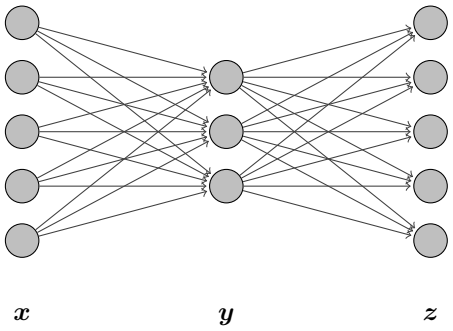


Figure 2.4.: Auto-encoder architecture.

network with 2048 units per hidden layer that was trained on over 300 hours of speech. Their results also suggest that the usual pre-training is not critical, although still beneficial, for recognition performance if enough input data is being used. Jaitly et al. trained deep belief networks on mel-scale filterbank coefficients extracted from 1400 hours of YouTube data [JNSV12]. They were able to improve the recognition rate by 4.5% absolute in comparison to the baseline GMM/HMM system.

2.3.2. Stacked, Denoising Auto-encoders

2.3.2.1. Auto-encoder Neural Networks

Auto-encoders are a special kind of artificial neural networks that are not trained for classification but rather to reconstruct the network input after it has been transformed by a hidden layer. As a result, the hidden layer of a trained auto-encoder provides an alternative representation (encoding) of the input data. If the number of units in the hidden layer is smaller than the number of input features, it is forced to learn a compact and invertible encoding of its input [AHS85], [Hin89]. This corresponds to a non-linear dimensionality reduction.

The architecture of an auto-encoder with a small number of hidden units is shown in Figure 2.4. The model is similar to standard feed-forward neural networks as described in section 2.2, consisting of an input layer, a single hidden layer and an output layer with the same dimensionality as the input layer. Again, the backpropagation algorithm can be used to train the auto-encoder, using the values of the input vector as targets for the output layer.

Auto-encoder networks can also be used for building deep neural networks, which was fast explored by Bengio et al. as an alternative to restricted Boltzmann machines [BLPL07]. As described in section 2.3.2.3, the main idea of this approach is the training of each additional hidden layer as an auto-encoder for the hidden representation of the previous layer. The resulting stack of auto-encoders can then be transformed into a standard, feed-forward neural network.

When building deep neural networks, a dimensionality reduction in the first hidden layer is often not desirable since it results in losing information from the input data that will

be missing when training consecutive layers. Instead, the auto-encoder used for the first layer should learn an *over-complete* representation of its input by having more hidden units than input features. Another motivation for learning a high-dimensionality is that this way, models can learn to *disentangle* the factors of variation present in the original data [VLL+10]. Subsequent models and classifiers might then benefit from such a disentangled representation, where the individual factors extracted can be combined again. However, care must be taken to prevent an over-complete model from learning a trivial identity-like mapping in which every hidden unit is activated by only one input feature. A common technique for learning useful over-complete representations in the context of deep learning includes the addition of a sparsity constraint that forces most of the hidden units to have near-zero activation given a particular training example [MRCL06], [MRBL07].

2.3.2.2. Adding a Denoising Criterion

An alternative approach to extend classic auto-encoders for deep learning purposes has been proposed by Vincent et al. [VLBM08]. In a so-called *denoising auto-encoder* (DAE), the input data is first corrupted by applying random noise to the individual features. Afterwards, the model is trained to reconstruct the *uncorrupted* input from the corrupted input in an auto-encoder-like fashion. In their work, Vincent et al. showed that hidden representations learned from randomly corrupted input differ from the results achieved with standard sparsity constraints and may provide more useful features when adding further layers.

The general idea of adding noise to training examples in order to improve the generalization ability of a neural network is much older. In 1986, Plaut, Nowlan and Hinton added Gaussian noise to artificial data resembling speech signals and reported excellent results [PNH86], but did not perform a direct omparison to training without noise. This was done in numerous further experiments, for example by Elmand and Zipser [EZ88] or Sietsma and Dow [SD91] who could confirm an increased generalization when adding noise to the input data of a network.

Deep neural networks constructed from denoising auto-encoders have been used for image recognition [VLL+10], natural language processing [DGB11] and text sentiment classification [GBB11], for example, with results that demonstrated the competitiveness of the approach compared to other deep learning concepts like deep belief networks. Denoising auto-encoders are also used as the main building blocks in this work, and will be described in more detail in the following.

The individual steps of the computation performed by a denoising auto-encoder are illustrated in Figure 2.5. As noted above, the main difference to normal auto-encoders is the corruption of an input vector $\boldsymbol{x}$. This can be formalized as the application of a stochastic process q_D

$$\tilde{\boldsymbol{x}} \sim q_D(\tilde{\boldsymbol{x}}|\boldsymbol{x})$$

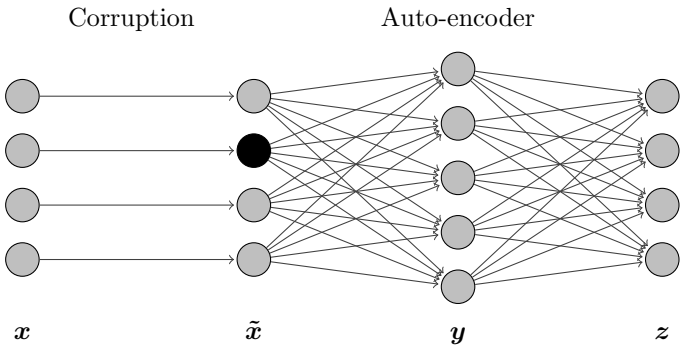


Figure 2.5.: Architecture of a denoising auto-encoder with masking noise. The black color indicates that units are set to zero (masked).

This process effectively adds random noise to individual training examples. Vincent et al. proposed multiple possible noise models [VLL+10]. The most common and straightforward one is *masking noise*, which consists of randomly setting a fraction of the elements of the input vector to zero. Isotropic *Gaussian noise* replaces every element x_i of $\boldsymbol{x}$ with a random sample drawn from a normal distribution with mean x_i and a fixed variance. Finally, *salt-end-pepper noise* sets random elements of $\boldsymbol{x}$ to their minimum or maximum value. While some types of noise can be regardes as more natural choices for a given task, Vincent et al. demonstrated that all types result in learning useful hidden representations.

The corrupted input $\tilde{\boldsymbol{x}}$ is mapped to a hidden representation $\boldsymbol{y}$ using the weight matrix $\boldsymbol{W}$ and the biases $\boldsymbol{b}$ of the nodes in the hidden layer. This is analogous to the computation done for a single layer in a multi-layer perceptrons, including the application of a non-linearity σ_y as well:

$$\boldsymbol{y} = \sigma_y \left(\boldsymbol{W}\tilde{\boldsymbol{x}} + \boldsymbol{b} \right)$$

The reconstruction $\boldsymbol{z}$ can be obtained in a similar manner using the transposed weight matrix and the visible biases $\boldsymbol{c}$, again followed by another activation function:

$$\boldsymbol{z} = \sigma_z \left(\boldsymbol{W}^T \boldsymbol{y} + \boldsymbol{c} \right)$$

Using the same weights for both encoding and decoding poses additional constraints on the model that help to prevent learning trivial representations.

Training a denoising auto-encoder is done in the same manner as training a standard auto-encoder by backpropagating an error signal that compares the original input $\boldsymbol{x}$ to the reconstruction $\boldsymbol{z}$. If the input values represent binary variables or probabilities, e.g. greyscale pixel values between 0 and 1, Vincent et al. suggest using the cross-entropy error term:

$$E\left(\boldsymbol{x}, \boldsymbol{z}\right)_H = \sum_i x_i \log z_i + (1 - x_i) \log z_i$$

However, when dealing with real-valued input, the standard mean squared error is a more adequate choice.

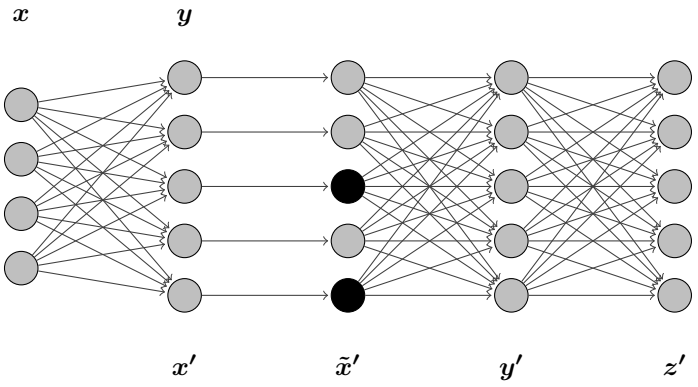


Figure 2.6.: Training a stack of denoising auto-encoders. The hidden representation $\boldsymbol{y}$ of the first DAE is now used as the input $\boldsymbol{x'}$ of the second DAE, which is being corrupted, encoded to $\boldsymbol{y'}$ and reconstructed. Note that the $\boldsymbol{y}$ is computed from the uncorrupted input $\boldsymbol{x}$.

2.3.2.3. Building Deep Neural Networks

Just like standard auto-encoders or restricted Boltzmann machines, denoising auto-encoders can be stacked and used as building blocks for deep neural networks [VLL+10]. This process starts with training a single DAE that is trained to reconstruct corrupted versions of the input data. Afterwards, another DAE is trained on the hidden representation $\boldsymbol{y}$ of the first model, leaving the weights of the first model fixed (see Figure 2.6). During this training, corruption is applied to the input to second DAE only, and *not* to the original input data. This scheme can be continued for the desired number of layers. Each time, auto-encoders computing the input representation for the model that is being trained perform their computation on uncorrupted input.

After each layer has been pre-trained, the hidden representation of the top auto-encoder the whole system can be transformed into a deep neural network. This involves replacing the decoding part of the top-most DAE with a neural network output layer, and using the encoder parts of the remaining auto-encoders to initialize the hidden layers. The resulting network can now be treated like a multi-layer perceptron and fine-tuned with standard backpropagation.

Bottleneck Features from Deep Neural Networks

3.1. Previous Work

For the most part, work on applying deep neural networks to automatic speech recognition dealt with refining acoustic models and language models, and significant improvements could be achieved in those areas. As of now, only few publications examined how *tandem systems* using probabilistic or bottleneck features could be improved with deep learning techniques.

In 2011, Yu & Seltzer pre-trained restricted Boltzmann machines (RBMs) in the usual fashion to form deep belief network for supervised phoneme classification from MFCC input including deltas and delta-deltas [YS11]. They proposed a symmetric architecture where the bottleneck layer is surrounded by an equal number of large, hidden layers on both sides. In their work, they evaluated the effects of pre-training and of using different kinds of labels for supervised training on a business voice search task containing 24 hours of speech. It was shown that unsupervised pre-training resulted in higher recognition accuracy of the whole system, and that using context-dependent senones instead of monophone targets for supervised fine-tuning improved the recognition rate significantly. However, their model failed to profit as expected from increasing the number of hidden layers. They noted that this may be due to their symmetric architecture in which the bottleneck is separated by possibly numerous hidden layers from the classification layer, and therefore receives only weak gradients from the current error. In a more recent work, Mohamed et al. also argued that RBMs are unsuited for modeling highly decorrelated data such as MFCCs and suggested training on log mel scale filterbank coefficients instead [MHP12].

Sainath et al. applied deep belief networks to an auto-encoder bottleneck architecture proposed by Mangu et al. [MKC+11], [SKR12]. First, they trained a DBN to predict

clustered, context-dependent targets given a frame of speaker-adapted PLP features. Afterwards, they trained an auto-encoder network on the DBN outputs that reduced its input data in two steps to 40 features, which were then used as input for the speech recognition system. Their evaluation on two English broadcast news tasks containing 50 and 430 hours of speech resulted in absolute improvements of 1.0% and 0.5% in terms of word error rate over strong baseline systems using the same input features.

In both works, deep learning techniques known to work well on speech data have been directly transfered to tasks previously done by shallow networks obtained by supervised training. This showed the general applicability of these methods and produced valuable insights, e.g. for selecting the targets used for fine-tuning. However, this thesis proposes a different training procedure that combines the advantages of deep neural networks and dimensionality reduction by supervised training. This is done by training a network containing a bottleneck layer in a supervised manner once a deep, high-dimensional representation of the data has been obtained via unsupervised, layer-wise pre-training.

The model for pre-training layers that was selected for this thesis are denoising auto-encoders as described in section 2.3.2. Previous work by Vincent et al. demonstrated their ability to model sound in the context of music genre classification [VLL+10]. Apart from that, I am not aware of any previous work on applying the DAE concept to audio data, in particular to speech recognition.

Most of the work on deep learning for speech recognition was done using deep belief networks built from restricted Boltzmann machines, e.g. acoustic modeling in hybrid DBN/HMM setups (see section 2.3.1). The reasons for choosing denoising auto-encoders instead of an already tested approach for this work are the following: first, training restricted Boltzmann machines on real-valued input like speech is more difficult than on binary data for which they were originally proposed, in the sense that the training algorithm is not very robust and care must be taken to sensibly select correct hyper-parameters like the learning rate and to normalize the input data [Hin10]. Second, this work initially focussed on extracting bottleneck features from MFCC data, which was argued to be unsuitable for training RBMs with [MHP12]. Last, the theoretical and practical simplicity of the auto-encoder setup is appealing, and it was interesting to prove their applicability to model speech data.

3.2. Model Description and Training Procedure

The proposed architecture for bottleneck feature extraction is illustrated in Figure 3.1. First, a number of equally-sized layer is pre-trained as denoising auto-encoders in a greedy, unsupervised fashion in order to generate a useful deep representation of the input data. This is the usual procedure when pre-training a deep neural network that might be used for classification later. Afterwards, a small bottleneck layer, an additional hidden layer and a classification layer are added. The whole model is then fine-tuned to predict phonetic

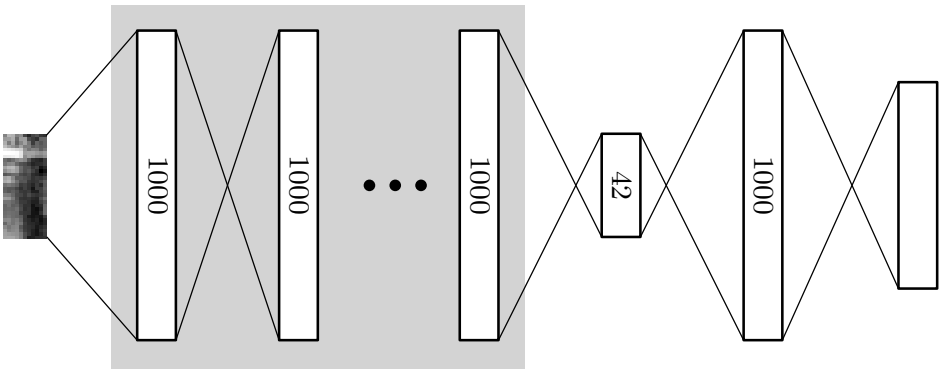


Figure 3.1.: The proposed architecture contains a number of equally-sized layers pre-trained as denoising auto-encoders. The bottleneck, an additional large hidden layer and the classification layer are added prior to supervised fine-tuning.

target states. The resulting network is similar to the one originally proposed in [GKKC07] (Figure 2.3), with the difference that the hidden layer connected to the input is now replaced by a stack of pre-trained denoising auto-encoders.

Please note that the bottleneck layer and the additional hidden layer are *not* pre-trained but instead randomly initialized like in a normal multilayer perceptron. This approach differs from earlier work on generating bottleneck features with deep networks, where the bottleneck layer was pre-trained as well [YS11]. In the experiments performed during this thesis, networks that were fine-tuned with a randomly initialized bottleneck layer consistently performed better than the ones in which all layers had been pre-trained. A possible reason for this is that the dimensionality reduction performed by the bottleneck layer may be too extreme; in the setup used in this work, a 1000-dimensional hidden representation had to be encoded into 42 hidden units. Thus, when pre-training the bottleneck layer, the unsupervised training criterion of minimizing the cross-entropy between input and reconstruction may result in features that are useful for approximate reconstruction from very few units, but not so useful for predicting phoneme states. Consequently, if the representation learned by the bottleneck layer is not useful for the final classification task, pre-training another large hidden layer on this representation will not be helpful either.

Experiments also showed that the proposed approach works better than a symmetric approach with an equal number of hidden layers before and after the bottleneck layer as proposed in [YS11]. The problem of having too many layers that weaken the gradient from the error term computed the output layer as discussed above does not arise, since the neural network capacity is increased by adding more auto-encoder layers only in front of the bottleneck.

The remainder of this section describes the models, the training algorithms and hyper-parameters used in higher detail.

3.2.1. Denoising Auto-Encoders for Speech

In their application of denoising auto-encoders to classification of music genres, Vincent et al. proposed modifying the decoding part of the model accordingly [VLL+10]. They did not apply the usual sigmoid activation function to the output units that make up the reconstruction, which resulted in a linear decoder. Furthermore, since audio data is usually real-valued, they computed the minimum squared error (MSE) between uncorrupted input and linear decoded output in order to generate an error signal for training. These adaptations were applied to the first auto-encoder only, though. Since the sigmoid activation function was still used to compute the values of the hidden units, the input data for the second and subsequent auto-encoders could be considered as representing probabilities, which made it possible to employ the usual combination of sigmoid output units and cross-entropy error training.

In this work, denoising auto-encoders were used to model both MFCC and log mel scale (lMEL) filterbank data, which was extracted from audio data as described in section 3.3.1. After a set of initial experiments on MFCC data were performed, the linear activation of the output units was abandoned in favor of a hyperbolic tangent activation. This seemed suitable, since MFCCs are commonly distributed in a Gaussian-like fashion around 0, and the data at hand had only few outliers with values outside of the $[-1, 1]$ interval. Training with a non-linearity in the decoder also resulted in more stable results regarding the setting of different hyper-parameters. For the lMEL data, which was introduced later in the thesis work, the same model properties were selected and worked well regardless of the slightly different input distribution.

The first DAE employing the tanh activation function for its output units was trained to minimize the mean squared error of its reconstruction, while subsequent auto-encoders were trained using the cross-entropy error term. Following the standard approach, those models used the sigmoid activation function for their output units.

As mentioned in section 2.3.2, it is desirable to learn an over-complete representation from the input when pre-training layers to be used in a deep neural network. At the start of this thesis, several values for the number of hidden units in the first auto-encoder were tested. Using 1000 hidden units turned out to be a good compromise, since smaller layers performed worse and adding more hidden units did not result in significant improvements on the development system but in much longer training time, especially for networks with many hidden layers.

3.2.2. Layer-wise Pre-training

The auto-encoder layers were pre-trained as denoising auto-encoders, each one trained to encode the hidden representation of the previous one (or the input data, in case of the first DAE). All training steps used the same hyper-parameters, except for the error term used to compute gradient updates as discussed above. Prior to training, the weights of an

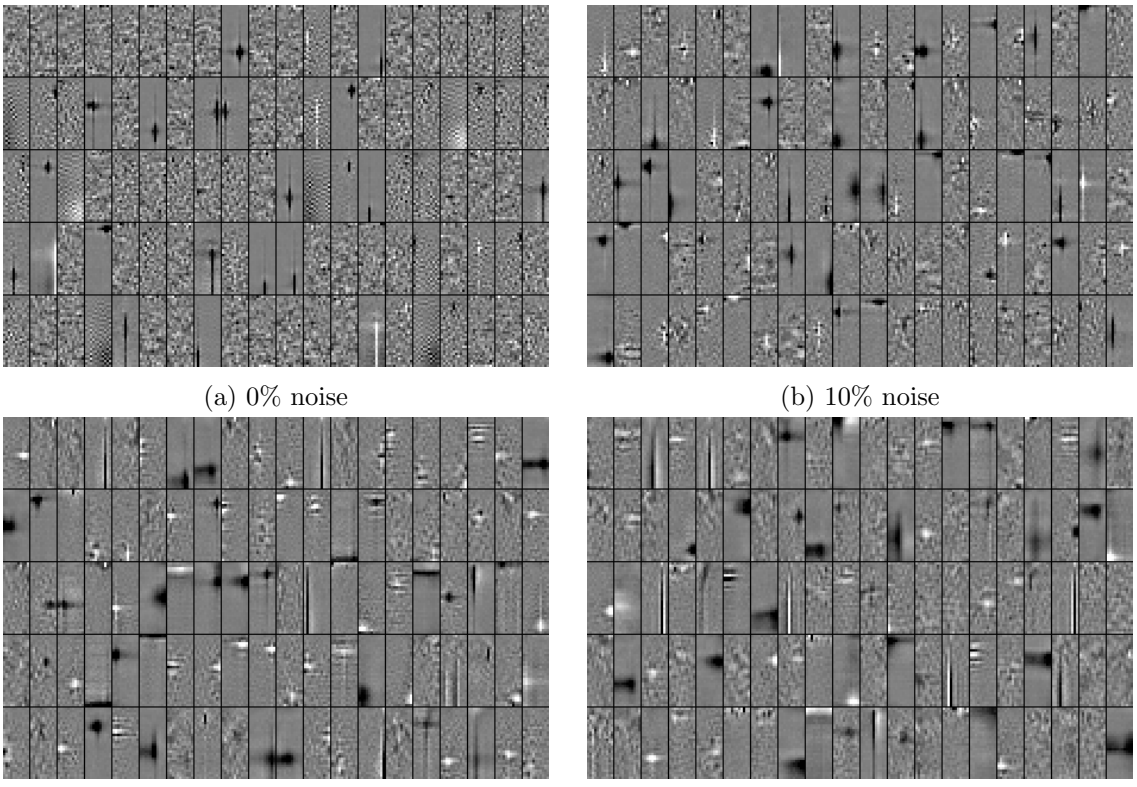
auto-encoder where initialized randomly depending on the size of the model. As suggested by Glorot & Bengio, weights were sampled from a uniform distribution within the interval $\left[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}\right]$, where n equals to the number of visible and hidden units of the model [GB10]. The bias values of the visible and hidden units were all set to zero.

For corrupting the input of the denoising auto-encoder, 20% masking noise was applied to the data, resulting in a random fraction of 20% of input elements being set to zero. As already noted in [VLL+10], changing the number of corrupted elements changes the resulting filters (the weight values can be interpreted as detectors for certain input patterns). Figure 3.2 shows a comparison of learned filters when using different noise levels on lMEL data. The images were generated by plotting the weights of selected hidden units in input space, where a dark pixel indicates a negative weight for the connection of a unit to the respective input element, and a light pixel indicates a positive weight. The weight values were clipped so that white corresponds to a value of 0.5 or higher, black to -0.5 or lower and grey to 0. For the purpose of visualization, the input space is assumed to be two-dimensional: each row inside a rectangle corresponds to a specific frequency on the mel scale. Samples are arranged in columns to form the frames used for network training.

It can be seen that less noise results in more local and more noise in more global filters, which is consistent with the results reported in [VLL+10]. The figure also shows that without applying any noise during training, the model has a hard time learning plausible filters.

Auto-encoder training was done using stochastic mini-batch gradient descent as described in appendix A.3, with a batch size of 64 and a learning rate of 0.01. Each layer was pre-trained on 4 million mini-batches, which resulted in 4 million updates on each parameter and a total of 256 million training examples used (including duplicates caused by iterating multiple times over the dataset). The 44 hours of training data for the development system described in section 4.1.2.1 resulted in a dataset containing about 17 million frames, so slightly more than 15 epochs were needed for pre-training in this case.

The relatively short duration of pre-training with a small learning rate was selected in order to prevent overfitting of the models, which was observed in the form of hidden units that react to only one input feature (Figure 3.3). This tendency emerged in units that did not manage to capture a plausible filter in the beginning. While these detectors might lower the reconstruction error by a tiny margin, they usually indicate a degraded unit not suitable for classification. Additionally, since the data contained outliers not in the image of the tanh activation function used for the visible units of the first auto-encoder, it was desirable to limit the impact of the error signal from those points. This would especially occur later during training, when most of the weights had settled and failure in reconstructing single points would become more apparent.



(a) 0% noise (b) 10% noise

(c) 30% noise (d) 50% noise

Figure 3.2.: Weights of 100 of 500 units of denoising auto-encoders trained on 1 million batches of Cantonese lMEL data, with different levels of masking noise.

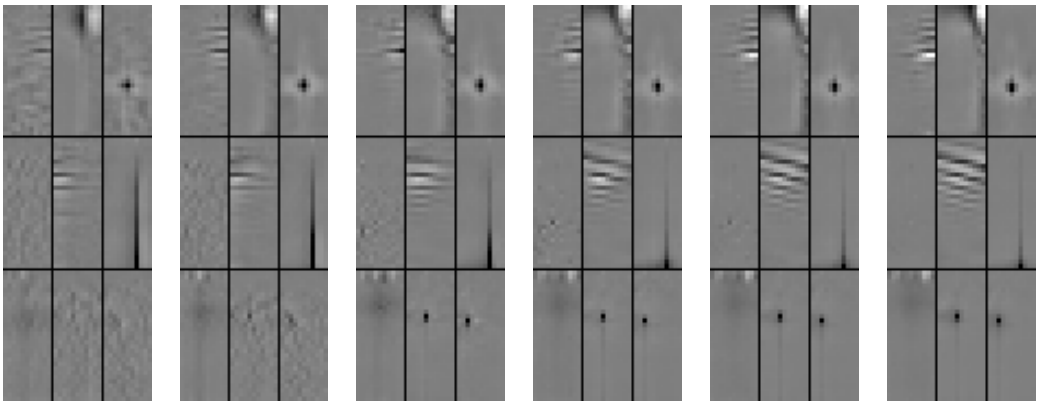
3.2.3. Adding the Bottleneck and Fine-tuning

After pre-training the auto-encoder layers, their resulting weights were used to initialize hidden layers of equal respective size in a multi-layer perceptron. After the last auto-encoder, a small bottleneck layer consisting of 42 units and an additional hidden layer with 1000 units was added. This was followed by a classification layer containing one unit for each phonetic target state in the data (406 for the development system). None of those layers had been pre-trained, but initialized with random weights and zero bias values like the auto-encoders described in the previous section.

In order to be able to predict phoneme states, the *softmax* activation function was used in the classification layer, which takes into account the pre-activation values a_j of neighboring units as well:

$$o_i = \frac{e^{a_i}}{\sum_j e^{a_j}}$$

Finally, the whole network was trained in a supervised manner, again using stochastic mini-batch gradient descent. This time, a larger batch size of 256 examples was selected, as well as a larger learning rate of 0.05. After each epoch, the network's classification accuracy was evaluated on a held-out validation set that contained a random subset of 5% of the available data. The best-performing model on the validation set after 50 epochs of



(a) 2M (b) 4M (c) 8M (d) 12M (e) 16M (f) 20M

Figure 3.3.: Weights for 9 hidden units of a denoising auto-encoder trained on different amounts of mini-batches (in millions). The two units in the lower right corner learned to respond to a single input value (visible as a "dot") instead of capturing a pattern.

training was then selected as the final deep neural network for feature extraction.

3.3. Usage in an Automatic Speech Recognition System

3.3.1. Initial Setup and Training Data Generation

In this work, context-independent acoustic models that work with states of single phonemes using Gaussian mixtures and hidden Markov models were first trained on standard MFCC input features. Fixed-size Hamming windows of 16 ms were applied to the speech signal at a sampling rate of 10 ms, and 13 cepstral coefficients were then extracted as described in section 2.1.2. 11 consecutive MFCC samples were stacked to a form a 143-dimensional vector, which was reduced to 42 final features using linear discriminant analysis (LDA). For the actual training, standard merge-and-split training and maximum likelihood estimation were used. In particular, neither discriminative training nor speaker adaptation were performed.

With the trained acoustic model, the speech data was re-labeled automatically in order to generate more accurate labels. These labels were used to train further context-dependent systems and to extract samples for training the neural networks that would later provide the bottleneck features. MFCC training data was extracted like described above, and log mel coefficients were computed from the signal in a similar manner. For the lMEL data, however, 30 coefficients were used as this was the amount that was previously extracted to compute the 13 MFCC values.

3.3.2. Feature Extraction

For using the bottleneck features in an ASR system, the input data consisting of a frame of log mel scale or MFCC values was extracted from the speech data and provided to

the network. The values of the hidden units in the bottleneck layer are computed and then used as a feature vector for the GMM/HMM acoustic model. In order to get good, decorrelated features, a whole frame of consecutive bottleneck features is extracted and reduced via LDA.

In the setups used in this thesis, the network was trained to extract 42 bottleneck features. The feature vector was formed using a context of 5 past and 5 future samples, resulting in a total of $11 \cdot 42 = 462$ bottleneck features that were then reduced to 42 features as with the standard MFCC data.

The bottleneck features were used to train context-dependent acoustic models only. Initial attempts to use BNFs for context-independent training had failed, presumably because of the different feature space compared to MFCCs. This would have required adjusting the parameters used for generating the polyphone decision tree determining the tying of context-dependent phone states. However, since negligible effects were anticipated by training a context-independent system on bottleneck features, no further work was done to adopt the context clustering stage accordingly.

Experiments

4.1. Baseline Systems

4.1.1. The Janus Recognition Toolkit

For all the experiments performed in this thesis, the Janus recognition toolkit (JRTk, [FGH+97]) was used to extract speech data and to train and evaluate the speech recognition systems. The JRTk provides a flexible architecture for building state-of-the-art recognition systems, with the actual computational flow being determined by Tcl scripts. The actual decoding to determine the performance of the systems trained was done using the IBIS decoder, which is included in the recognition toolkit [SMFW01].

4.1.2. System Configurations

In the following, the individual datasets, acoustic model setups and language models will be described that were used for developing, optimizing and evaluating the proposed architecture. Recognition performance of the respective baseline systems using MFCC features is stated as well; please refer to section 4.2 for an explanation of the performance measures used.

4.1.2.1. Development System

The initial experiments regarding network architectures and the optimization of hyperparameters for neural network training were performed on a comparably small development system. The corresponding dataset consisted of 44 hours of conversational telephone speech from 400 speakers in Cantonese, a language natively spoken in southern pars of China as well as Hong Kong and Macao. This corpus was recently released with identifier "101A" during the IARPA BABEL program [IAR], and is a subset of the full Cantonese dataset "101B" containing 80 hours of speech from 966 speakers.

Acoustic model training for the context-independent system was done as described in section 3.3.1, using MFCC input data and maximum likelihood training. The data used for neural network training was labeled with three states for each phoneme (begin, middle and end), resulting in a total of 406 phonetic targets for this setup.

For the development system, a simple 3-gram language model was used, in which the probability of a single word occurring in a sequence is determined by the two words that appear in front of it. The model was extracted from the transcriptions that had been provided with the data.

The baseline system used as a reference in recognition performance was among the initial system builds on this new and relatively small corpus. With the simple language model described above and using only basic acoustic model training, it achieved a character error rate (CER) of 71.5%. This number was determined by transcribing data from a testing set containing 3.3 hours of speech.

4.1.2.2. Cantonese

Further experiments for optimizing the network architecture were performed on the full "101B" dataset of Cantonese with 80 hours of speech. This system employed a more sophisticated language model, again using 3-grams but interpolating between the corpus data and text extracted from Cantonese Wikipedia articles. The recognition performance of the baseline on MFCC features was 66.4% CER, using a much larger testing set with 20 hours of speech.

4.1.2.3. Tagalog

The Tagalog corpus is another new dataset released by IARPA for the BABEL program, identified as "106B" and containing conversational telephone speech, too. Tagalog is the native language spoken in large parts of the Philippines. In total, the dataset consisted of 69 hours of speech. The system setup was similar to the one used for the full Cantonese dataset and also used a language model interpolating between transcriptions contained in the corpus and text from Wikipedia articles. The baseline system achieved a word error rate (WER) of 72.5% on a test set of 24 hours.

4.1.2.4. Switchboard

In order to evaluate the bottleneck feature setup on a more standard benchmark, an additional system was trained on the Switchboard task [GHM92]. This corpus contains 300 hours of English conversational telephone speech, and is widely used as a benchmark for speech-to-text transcription in the ASR community. As for the development system, acoustic models were trained using maximum likelihood estimation and Viterbi training only. Similarly, the language model used 3-grams extracted from the corpus transcriptions. The MFCC-based baseline system resulted in 39.0% WER.

4.2. Evaluation Criteria

Even though the neural networks used for bottleneck feature extraction were trained to minimize a classification error, their actual classification performance was not of much interest. Instead, networks were compared on the basis of the recognition accuracy that can be achieved by using the generated features. While the classification accuracy of a network in comparison to another one on the same dataset might give hints about the quality of its bottleneck features, training acoustic models and performing decoding on the test set is needed to produce a final result.

The ASR systems used in this work generally measured the recognition performance in *word error rate* (WER). The goal is to measure the difference between the text sequence generated by the system and a reference transcription, which may differ in contents as well as in length. Thus, the word error rate is computed by summing up the word substitutions, insertions and deletions that need to be performed to transform the system output into the reference transcription, normalized by the number of words in the reference:

$$\text{WER} = \frac{\#\text{Substitutions} + \#\text{Insertions} + \#\text{Deletions}}{\#\text{Words in reference}}$$

There is no clear concept of a single word in Cantonese, so the word error rate which relies on word boundary detection is not a very useful performance metric there. Instead, the *character error rate* (CER), which is computed in an analogous manner, was used for the respective systems.

4.3. Experiments on the Development System

The first experiments that have been performed mostly dealt with exploring different types of architectures for bottleneck feature extraction as well as different pre-training schemes. A high-level summary of the relevant outcomes that led to the design decisions made in this thesis is included in the model description in section 3.2. This section describes the systematic comparisons performed after basic model properties and hyper-parameters had already been selected.

4.3.1. Input Data

As noted previously, the proposed architecture was trained to extract bottleneck features from both MFCCs and log mel scale filterbank coefficients (lMEL). In the case of restricted Boltzmann machines, Mohamed et al. argued that MFCCs are unsuited because of their decorrelated nature [MHP12]. Although this limitation was not specifically stated for denoising auto-encoders as used in this work, the idea of applying random corruption to the input values is in part aiming at the discovery of relations between the different elements of an input vector as well.

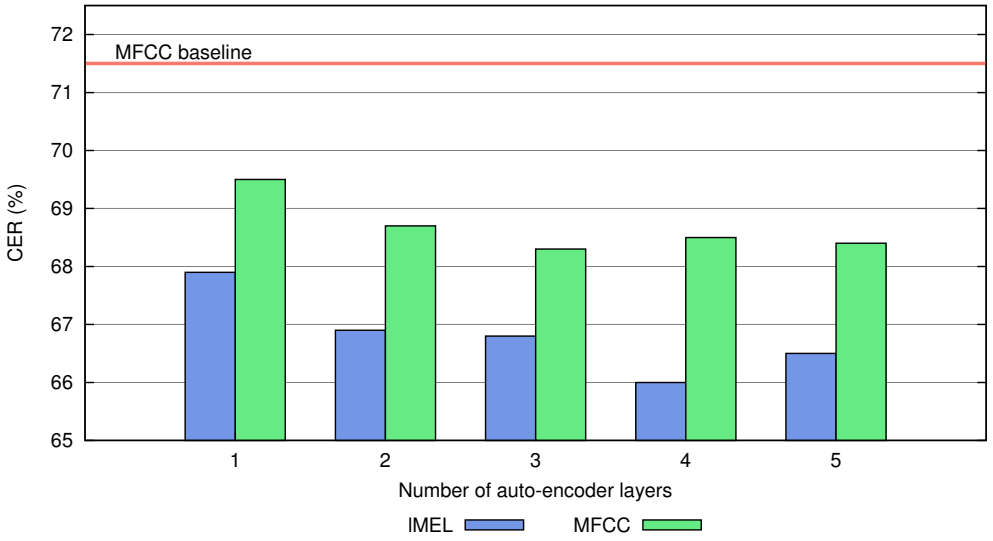


Figure 4.1.: Comparison on character error rates of the development system achieved with bottleneck features extracted from lMEL and MFCC features.

Figure 4.1 compares the resulting recognition accuracies of the development system. Bottleneck features were extracted from either MFCC or lMEL data and by networks with different numbers of pre-trained auto-encoder layers. For clarity, it might be worth noting that a neural network with 4 auto-encoder layers corresponds to a network with 5 layers when used for feature extraction (4 auto-encoders and one bottleneck layer) and to a 7-layer network for unsupervised fine-tuning (4 auto-encoders, the bottleneck layer, the additional hidden and the classification layer).

It can be seen that bottleneck features from both types of data significantly outperform the baseline system trained on MFCCs, and that the recognition accuracy improves as more layers are added to the neural network. Using lMEL data produces a constant performance gain of about 2% CER absolute, which is why the following experiments were not performed on MFCC data any more. For lMEL features, the best character error rate of 66.0% was achieved with a network containing 4 auto-encoders; for MFCCs, using the 3-auto-encoder network resulted in 68.3% CER.

4.3.2. Training on More Data

As Cantonese data was available in the form of two corpora, with the 80-hour "101B" release being a superset of the 44 hours used for training the development system, experiments were performed to find out whether the proposed architecture can make use of additional data. The pre-training stage for initializing the stack of auto-encoder layers employs unsupervised training only, which led to two experiments. One set of networks was pre-trained on the larger "101B" dataset and fine-tuned on the "101A" subset as usual, while another set of networks was both pre-trained and fine-tuned on the larger dataset.

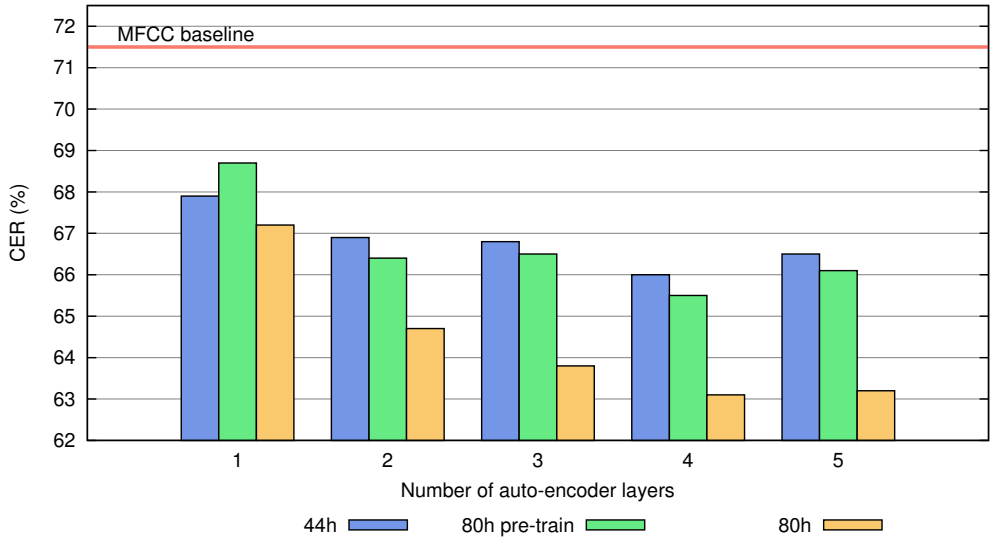


Figure 4.2.: Comparison of recognition performance with networks trained on different amounts of data: 44 h total, 80 h for pre-training and 44 h for fine-tuning, and 80 h for both.

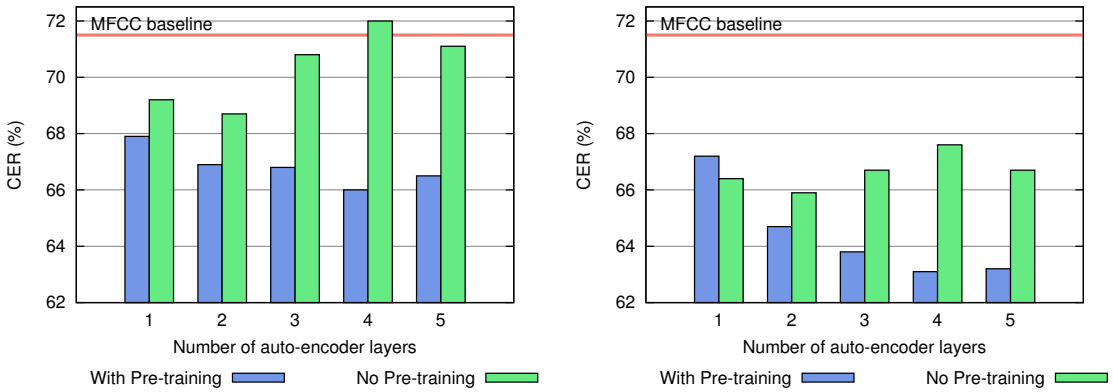
As already noted briefly in section 2.3, the ability to benefit from using unlabeled data is highly desirable in the field of speech recognition. This is because labeling the data is very expensive in both time and labor. For conversational data like the one used in this work, human transcriptions are usually not free of errors, too. On the other hand, obtaining recordings is easy since someone simply has to speak into a microphone.

Figure 4.2 shows the character error rates from the development system when trained on bottleneck features extracted by networks trained with different amounts of lMEL data. Using more data for pre-training did indeed result in slightly but consistently increased recognition performance of about 0.5%, except for the network containing one auto-encoder only. However, by doing unsupervised as well as supervised training on the full dataset, a significantly lower error rate could be achieved. Again, the best results were achieved using a network with 4 auto-encoders: 65.5% CER for pre-training only, and 63.1% CER for pre-training and fine-tuning on 80 hours of data.

4.3.3. Importance of Pre-training

The results from using more data suggested that supervised fine-tuning is the most important part of the training procedure, since using more labeled data resulted in significantly larger gains than using more unlabeled data. Therefore, further experiments were done in order to check whether the pre-training stage was necessary at all. Networks were trained on both Cantonese corpora (44 hours and 80 hours), and the resulting features were evaluated using the development system like before.

The resulting error rates plotted in Figure 4.3 suggest that pre-training is indeed required in order to extract useful bottleneck features when adding more auto-encoder layers to



(a) Networks trained on 44 hours.

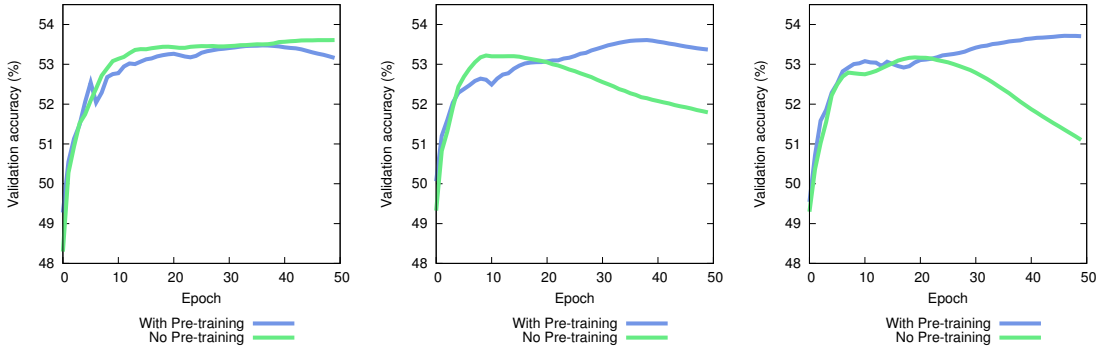
(b) Networks trained on 80 hours.

Figure 4.3.: Comparison of recognition performance on the development system for pre-trained and purely supervised trained neural networks.

the neural network. Training deeper networks with more than two auto-encoder layers without pre-training was counter-productive in that the recognition error rate became higher than when using only one or two layers. When training the network on 80 hours of data, the gap between pre-training and fine-tuning only was less dramatic; features from the network containing only one auto-encoder layer could even achieve a lower error rate when no pre-training was used. However, pre-training was needed as well in order to make use of additional layers.

When taking a look at the classification accuracy on the validation set during network training in Figure 4.4, it becomes clear that without pre-training, the increased modeling power of deeper networks cannot be leveraged. After increasing steadily for a couple of epochs, the validation accuracy reaches a maximum value and drops. However, the accuracy on the training set (not shown) continues to rise, which is an indication for overfitting, i.e. memorizing the training data rather than generalizing from it. In contrast, validation accuracy for pre-trained networks keeps increasing with small interruptions before reaching its maximum in the later part of the training process.

Another indicator for the poor performance of non-pre-trained deep networks is provided by the weights learned in the first auto-encoder layer which is connected to the input speech data. Figure 4.5 shows the weights of units in the first layer after after 50 epochs of supervised fine-tuning, starting from a random initialization. Plotting was done in a similar manner as for Figure 3.2 by arranging the weights in two dimensions where rows correspond to mel scale frequencies and multiple samples (columns) make up a frame of speech data. It can be seen that for networks containing only 1 or 2 auto-encoders in front of the bottleneck layer, the first layer still manages to extract some structure from the input data. The basis for this observation that for a unit to be active (i.e. its weighted sum having a large enough positive value), the signs of the individual input filterbank coefficients have to match those of the weights that are connected to them. Thus, for



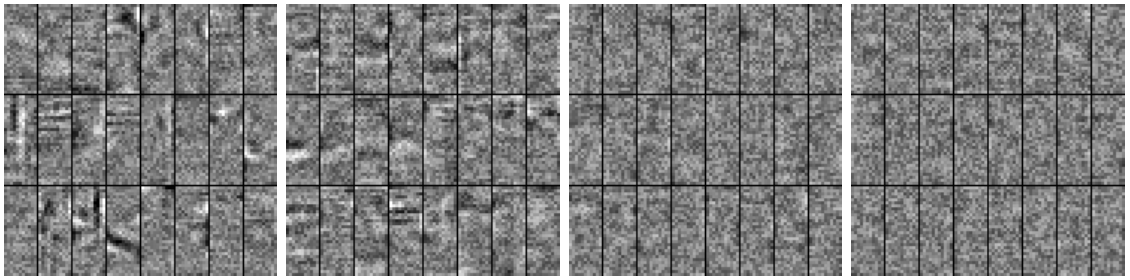
(a) 2 auto-encoders (b) 4 auto-encoders (c) 6 auto-encoders

Figure 4.4.: Classification accuracy on the validation set during supervised fine-tuning, for networks of different size with and without pre-training.

example, a black blob-like shape in the plot indicates that unit detects a blob-like pattern of negative coefficients.

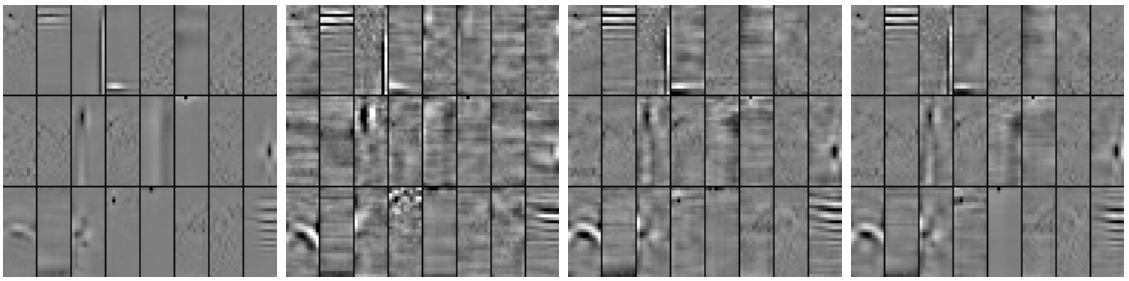
If three or more auto-encoders are placed in the network, the units in the first layer contain weights that are almost completely random and don't appear to detect any specific structure of the input data. Thus, when initialized randomly rather than pre-trained, supervised fine-tuning alone is not sufficient to produce meaningful weights in the first layer.

In comparison, Figure 4.6 shows the weights of some of units in the first layer after supervised fine-tuning of a pre-trained network, and the same weights after pre-training only for reference. After unsupervised pre-training, the first layer already captures meaningful structure of the input data, and supervised training merely adjusts or reinforces the weights for the classification task. As before, the changes occurring in the first layer are smaller for deeper networks, but this time, this does not cause overfitting.



(a) 1 auto-encoder (b) 2 auto-encoders (c) 3 auto-encoders (d) 5 auto-encoders

Figure 4.5.: Final weights of 24 of 1000 units from the first layer of networks trained *without* pre-training on Cantonese lMEL data.



(a) pre-trained only (b) 1 auto-encoder (c) 3 auto-encoders (d) 5 auto-encoders

Figure 4.6.: Final weights of 24 of 1000 units from the first layer of networks trained *with* pre-training on Cantonese lMEL data.

4.4. Evaluation on Larger Systems

To demonstrate the general applicability of the proposed approach for bottleneck feature extraction, additional evaluation was performed on a number of larger datasets. The individual setups have been introduced in section 4.1.2, so in the following, results will be listed and described.

4.4.1. Cantonese

As noted in section 4.1.2.2, the system set up on the full 80 hours of Cantonese data used a stronger language model as well as more training data than the development system. The baseline system trained on MFCCs could thus provide a lower character error rate of 66.4%. Bottleneck features from deep networks containing a different number of auto-encoder layers were used for training, with results as listed in Table 4.1.

Similar to the development system, significant improvements could be achieved over the baseline system. Again, the network containing 4 auto-encoders produced features that resulted in the best recognition performance of 60.3%, a relative improvement of 9.2%. Adding additional layers did not result in further improvements; instead, the character error rate rose slightly.

4.4.2. Tagalog

For the Tagalog corpus, bottleneck features from neural networks with 3, 4 and 5 auto-encoder layers were compared against standard MFCC features, where the baseline achieved

System	**AE Layers**	**CER (%)**
MFCC baseline		66.4
Bottleneck features	3	60.9
	4	60.3
	5	60.5
	6	61.1

Table 4.1.: Results on the 80 hours Cantonese system with features from different networks

System	AE Layers	WER (%)
MFCC baseline		72.5
Bottleneck features	3	65.1
	4	65.2
	5	65.4

Table 4.2.: Results on the Tagalog system with features from different networks.

a word error rate of 72.5%. Table 4.2 lists the error rates for the different-sized networks, with the versions containing 3 and 4 auto-encoders resulting in the best performances of 65.1% WER and 65.2% WER, respectively. This constitutes the largest improvement among the three large-scale evaluations, corresponding to a relative gain of more than 10%. As in previous experiments, adding a fifth auto-encoder did not lower the error rates any further.

4.4.3. Switchboard

As evidence from previous experiments suggested, networks with 4 auto-encoder layers would usually produce the best results. Thus, this configuration was selected for evaluation on the well-known Switchboard corpus. The factor of variation introduced for this experiment was the amount of data used to train the neural network. Even with the GPU implementations made for this work, network training was still time-consuming. Being able to perform a trade-off between system training time and recognition performance might thus be useful in certain settings.

Table 4.3 lists the results obtained on the Switchboard system. Using networks with 4 auto-encoder layers, the recognition rate could be significantly increased in comparison to the 39.0% WER baseline trained on MFCC features. Training the neural network on 60 hours of data yielded a relative improvement of 7.4%. Doubling the amount of training data to 120 hours lowered the error rate by another 0.5%, which is a gain of 8.7% relative compared to the baseline. This also doubled the training time for supervised fine-tuning, increasing the total time spent on training the neural network from 31.1 to 51.7 hours. Time constraints rendered it impossible to train and evaluate a network on 300 hours of data during the course of this thesis. However, the gains observed when training on 120 instead of 60 hours of data suggest that further improvements might be expected by training a neural network on the full dataset.

System		WER (%)	Training Time
MFCC baseline		39.0	–
Bottleneck features	trained on 60 h	36.1	31.1 h
	trained on 120 h	35.6	51.7 h

Table 4.3.: Results on Switchboard with features form 4-auto-encoder networks trained on different amounts of data.

The training times listed in Table 4.3 were obtained by training the networks on a NVIDIA GTX 480 graphics processor, which contains 480 cores running at 700 MHz. For more details regarding the training of neural networks on GPUs, please refer to the respective appendix B.

Conclusion

5.1. Summary

In this work, a new approach for training deep neural networks used for the extraction of bottleneck features has been proposed. In contrast to earlier work regarding bottleneck features, the new network architecture is able to effectively make use of the increased model capacity of deep neural networks by producing features that increase the final recognition accuracy. The techniques presented resulted in significant and consistent improvements over standard MFCC-based systems on datasets in three different languages. The relative improvements in terms of character or word error rate, respectively, were 9.2% CER for Cantonese, 10.3% WER for Tagalog and 8.7% WER on the Switchboard task.

It has been demonstrated that with the proposed architecture, deep neural networks with many layers are able to outperform shallow networks by extracting more useful bottleneck features. However, this ability depends on a suitable training algorithm, and the greedy, layer-wise and unsupervised pre-training strategy popular in deep learning was able to produce models with superior performance. Closer examination of the network learning procedure and the learned weight parameters suggested that without pre-training, deep neural networks tend to overfit and their first layer fails to extract meaningful structure from the training data.

Experiments showed that extracting bottleneck features from log mel scale filterbank coefficients results in better recognition performance compared to features extracted from MFCCs. Further small improvements could be achieved by using more, unlabeled data when pre-training individual layers.

Finally, denoising auto-encoders proved to be robust models for building deep networks and initializing bottleneck networks. Training the models was straightforward and fast, and the performance improvements obtained were equally encouraging than the results reported

in previous works regarding bottleneck features and hybrid systems, which mostly relied on restricted Boltzmann machines for pre-training.

5.2. Discussion

In this thesis, multiple experiments have been performed in order to better understand the influence of neural network topology and input data. For the latter, it could be shown that training the network on log mel scale filterbank coefficients resulted in better recognition performance than training on MFCC frames (see section 4.3.1). This is consistent with findings in by Mohamed et al. regarding restricted Boltzmann machines [MHP12]. In order to actually confirm this for denoising auto-encoders as used in this work, further experiments might need to be performed to rule out the possibility that the performance gains were simply due to the log mel scale features having a higher dimensionality (in this case, 330 compared to of 143 MFCC elements for a single feature vector). This could be done by either reducing the number of mel coefficients or increasing the number of MFCCs used.

In terms of network topology, it could be shown that features extracted from networks with more hidden layers resulted in higher recognition accuracy. This is expected when using a suitable learning algorithm, as increasing the modeling power of the neural network should result in more useful bottleneck features. However, when adding more then 4 auto-encoder layers, no further improvements in terms of recognition rate could be observed. Possible reasons for this include not having enough data available for training networks with such a large number of parameters, or that the denoising auto-encoders in higher levels did not extract very useful features during pre-training.

As described in section 4.3.3, pre-training turned out to be important for extracting useful features with deep neural networks. The gap between recognition rates on features extracted with and without pre-training was less extreme when training the networks on 80 instead of 44 hours. Similar findings have been reported by Seide et al., who noted that in their best configuration regarding a hybrid DNN/HMM setup trained 300 hours, pre-training produced only small gains over networks that were trained in a purely supervised fashion [SLY11]. This suggests that while being generally helpful, unsupervised pre-training might be especially crucial if only little training data is available. Another indicator for this correlation is that while yielding small gains, adding more data for pre-training is not as beneficial as fine-tuning on more data as shown in section 4.3.2.

5.3. Outlook

The recognition setups used in this thesis employed relatively simple algorithms for acoustic modeling and language modeling. Therefore, additional evaluation needs to be done in heavily tuned systems that use discriminative training, speaker adaption and strong

language models, with the hope that the relative gains achieved (9% to 10% relative) will persist. The same is true for systems build on very large corpora that consist of thousands of hours of speech data.

Amongst further experiments are the ones that address the open questions formulated above, for example what constitutes the best input data to extract features from. Apart from that, the network architecture and training procedures proposed provide a solid foundation for further enhancements. It might be interesting to fully evaluate other methods for pre-training the individual layers, with possible candidates being mean-covariance restricted Boltzmann machines [DRMH10] and contractive auto-encoders [RVM+11].

The fine-tuning step could be optimized as well by training the neural network to estimate context-dependent instead of context-independent states, which was reported to improve the resulting features in previous works [YS11], [SKR12]. Furthermore, it might be worthwhile to apply the recently proposed "dropout" training procedure, in which hidden units are randomly omitted from the network in order to prevent overfitting caused by co-adaptation of neurons [HSK+12].

Bibliography

[AHMJP12] O. Abdel-Hamid, A. Mohamed, H. Jiang, and G. Penn, "Applying convolutional neural networks concepts to hybrid NN-HMM model for speech recognition," in *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*. IEEE, 2012, pp. 4277–4280.

[AHS85] D. Ackley, G. Hinton, and T. Sejnowski, "A learning algorithm for boltzmann machines," *Cognitive science*, vol. 9, no. 1, pp. 147–169, 1985.

[BBB+10] J. Bergstra, O. Breuleux, F. Bastien, P. Lamblin, R. Pascanu, G. Desjardins, J. Turian, D. Warde-Farley, and Y. Bengio, "Theano: a CPU and GPU Math Expression Compiler," in *Proceedings of the Python for Scientific Computing Conference (SciPy)*, Jun. 2010, Oral Presentation.

[Ben09] Y. Bengio, "Learning deep architectures for AI," *Foundations and Trends in Machine Learning*, vol. 2, no. 1, pp. 1–127, 2009.

[BLPL07] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," *Advances in neural information processing systems*, vol. 19, p. 153, 2007.

[BM94] H. Bourlard and N. Morgan, *Connectionist speech recognition: a hybrid approach*. Springer, 1994, vol. 247.

[DGB11] Y. Dauphin, X. Glorot, and Y. Bengio, "Large-scale learning of embeddings with reconstruction sampling," in *Proceedings of the Twenty-eighth International Conference on Machine Learning (ICML'11)*, 2011.

[DM80] S. Davis and P. Mermelstein, "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 28, no. 4, pp. 357–366, 1980.

[DRMH10] G. Dahl, M. Ranzato, A. Mohamed, and G. Hinton, "Phone recognition with the mean-covariance restricted boltzmann machine," *Advances in neural information processing systems*, vol. 23, pp. 469–477, 2010.

[DYDA12] G. Dahl, D. Yu, L. Deng, and A. Acero, "Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition," *Audio,*

Speech, and Language Processing, IEEE Transactions on, vol. 20, no. 1, pp. 30–42, 2012.

[EZ88] J. Elman and D. Zipser, "Learning the hidden structure of speech," *The Journal of the Acoustical Society of America*, vol. 83, p. 1615, 1988.

[FGH+97] M. Finke, P. Geutner, H. Hild, T. Kemp, K. Ries, and M. Westphal, "The Karlsruhe-Verbmobil speech recognition engine," in *Acoustics, Speech, and Signal Processing, 1997. ICASSP-97., 1997 IEEE International Conference on*, vol. 1. IEEE, 1997, pp. 83–86.

[FRB97] V. Fontaine, C. Ris, and J. Boite, "Nonlinear discriminant analysis for improved speech recognition," in *Proc. Eurospeech*, vol. 97, 1997, pp. 2071–2074.

[GB10] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the International Conference on Artificial Intelligence and Statistics (AISTATS'10). Society for Artificial Intelligence and Statistics*, 2010.

[GBB11] X. Glorot, A. Bordes, and Y. Bengio, "Domain adaptation for large-scale sentiment classification: A deep learning approach," in *Proceedings of the Twenty-eight International Conference on Machine Learning, ICML*, 2011.

[GHM92] J. Godfrey, E. Holliman, and J. McDaniel, "SWITCHBOARD: Telephone speech corpus for research and development," in *Acoustics, Speech, and Signal Processing, 1992. ICASSP-92., 1992 IEEE International Conference on*, vol. 1. IEEE, 1992, pp. 517–520.

[GKKC07] F. Grézl, M. Karafiat, S. Kontar, and J. Cernocky, "Probabilistic and Bottle-Neck Features for LVCSR of Meetings," in *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, vol. 4, april 2007, pp. IV–757 –IV–760.

[HDY+12] G. Hinton, L. Deng, D. Yu, G. Dahl, A. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. Sainath *et al.*, "Deep neural networks for acoustic modeling in speech recognition," *IEEE Signal Processing Magazine*, 2012.

[HES00] H. Hermansky, D. Ellis, and S. Sharma, "Tandem connectionist feature extraction for conventional HMM systems," in *Acoustics, Speech, and Signal Processing, 2000. ICASSP'00. Proceedings. 2000 IEEE International Conference on*, vol. 3. IEEE, 2000, pp. 1635–1638.

[Hin89] G. Hinton, "Connectionist learning procedures," *Artificial intelligence*, vol. 40, no. 1, pp. 185–234, 1989.

[Hin10] ——, "A practical guide to training restricted boltzmann machines," *Momentum*, vol. 9, p. 1, 2010.

[HOT06] G. Hinton, S. Osindero, and Y. Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527–1554, 2006.

[HSK+12] G. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Improving neural networks by preventing co-adaptation of feature detectors," *arXiv preprint arXiv:1207.0580*, 2012.

[IAR] "IARPA-BAA-11-02," http://www.iarpa.gov/Programs/ia/Babel/babel.html, IARPA.

[J+04] D. Johnson *et al.*, "ICSI Quicknet software package," http://www.icsi.berkeley.edu/Speech/qn.html, 2004.

[JNSV12] N. Jaitly, P. Nguyen, A. Senior, and V. Vanhoucke, "An application of pretrained deep neural networks to large vocabulary conversational speech recognition," Tech. Rep. 001, Department of Computer Science, University of Toronto, Tech. Rep., 2012.

[KSH12] A. Krizhevsky, I. Sutskever, and G. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems*, vol. 25, 2012.

[LB95] Y. LeCun and Y. Bengio, "Convolutional networks for images, speech, and time series," *The handbook of brain theory and neural networks*, vol. 3361, 1995.

[LGRN09] H. Lee, R. Grosse, R. Ranganath, and A. Ng, "Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations," in *Proceedings of the 26th Annual International Conference on Machine Learning*. ACM, 2009, pp. 609–616.

[Lip89] R. Lippmann, "Review of neural networks for speech recognition," *Neural computation*, vol. 1, no. 1, pp. 1–38, 1989.

[LMD+11] Q. Le, R. Monga, M. Devin, G. Corrado, K. Chen, M. Ranzato, J. Dean, and A. Ng, "Building high-level features using large scale unsupervised learning," *arXiv preprint arXiv:1112.6209*, 2011.

[MDH09] A. Mohamed, G. Dahl, and G. Hinton, "Deep belief networks for phone recognition," in *NIPS Workshop on Deep Learning for Speech Recognition and Related Applications*, 2009.

[MHP12] A. Mohamed, G. Hinton, and G. Penn, "Understanding how deep belief networks perform acoustic modelling," in *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*. IEEE, 2012, pp. 4273–4276.

[MKC+11] L. Mangu, H. Kuo, S. Chu, B. Kingsbury, G. Saon, H. Soltau, and F. Biadsy, "The IBM 2011 GALE Arabic speech transcription system," in *Automatic Speech Recognition and Understanding (ASRU), 2011 IEEE Workshop on*. IEEE, 2011, pp. 272–277.

[MRBL07] Y. Marc'Aurelio Ranzato, L. Boureau, and Y. LeCun, "Sparse feature learning for deep belief networks," *Advances in neural information processing systems*, vol. 20, pp. 1185–1192, 2007.

[MRCL06] C. Marc'Aurelio Ranzato, S. Chopra, and Y. LeCun, "Efficient learning of sparse representations with an energy-based model," *Advances in neural information processing systems*, vol. 19, pp. 1137–1144, 2006.

[PNH86] D. C. Plaut, S. J. Nowlan, and G. E. Hinton, "Experiments on learning by back propagation," Carnegie Mellon University, Tech. Rep., 1986.

[RHW86] D. Rumelhart, G. Hintont, and R. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, no. 6088, pp. 533–536, 1986.

[Ros58] F. Rosenblatt, "The perceptron: a probabilistic model for information storage and organization in the brain." *Psychological review*, vol. 65, no. 6, p. 386, 1958.

[RVM+11] S. Rifai, P. Vincent, X. Muller, X. Glorot, and Y. Bengio, "Contractive auto-encoders: Explicit invariance during feature extraction," in *Proceedings of the Twenty-eight International Conference on Machine Learning (ICML'11)*, 2011.

[SD91] J. Sietsma and R. Dow, "Creating artificial neural networks that generalize," *Neural Networks*, vol. 4, no. 1, pp. 67–79, 1991.

[SKK+07] T. Serre, G. Kreiman, M. Kouh, C. Cadieu, U. Knoblich, and T. Poggio, "A quantitative theory of immediate visual recognition," *Progress in Brain Research*, vol. 165, pp. 33–56, 2007.

[SKR12] T. Sainath, B. Kingsbury, and B. Ramabhadran, "Auto-encoder bottleneck features using deep belief networks," in *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*. IEEE, 2012, pp. 4153–4156.

[SLY11] F. Seide, G. Li, and D. Yu, "Conversational speech transcription using context-dependent deep neural networks," in *Proc. Interspeech*, 2011, pp. 437–440.

[SMFW01] H. Soltau, F. Metze, C. Fugen, and A. Waibel, "A one-pass decoder based on polymorphic linguistic context assignment," in *Automatic Speech Recognition and Understanding, 2001. ASRU'01. IEEE Workshop on*. IEEE, 2001, pp. 214–217.

[VLBM08] P. Vincent, H. Larochelle, Y. Bengio, and P. Manzagol, "Extracting and composing robust features with denoising autoencoders," in *Proceedings of the 25th international conference on Machine learning*. ACM, 2008, pp. 1096–1103.

[VLL+10] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *The Journal of Machine Learning Research*, vol. 11, pp. 3371–3408, 2010.

[WHH+89] A. Waibel, T. Hanazawa, G. Hinton, K. Shikano, and K. Lang, "Phoneme recognition using time-delay neural networks," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 37, no. 3, pp. 328–339, 1989.

[WS87] R. Watrous and L. Shastri, "Learning phonetic features using connectionist networks," *The Journal of the Acoustical Society of America*, vol. 81, no. S1, pp. S93–S94, 1987.

[WSS89] A. Waibel, H. Sawai, and K. Shikano, "Modularity and scaling in large phonemic neural networks," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 37, no. 12, pp. 1888–1898, 1989.

[YS11] D. Yu and M. Seltzer, "Improved bottleneck features using pretrained deep neural networks," *Proc. Interspeech 2011*, pp. 237–240, 2011.

Appendix

A. Training Algorithms

In this thesis, backpropagation and gradient descent have been used to train neural networks to minimizing an error term (see section 2.2). Backpropagation enables the propagation of the output error through the network so that each unit gets an error signal corresponding to its contribution to the total error. The gradient of the error signal is then used to update the individual weight and bias values.

A.1. Denoising Auto-encoder

The denoising auto-encoders used in this work performed both encoding and decoding using the same weight parameters ("tied" weights). Thus, the computations described in section 2.3.2.2 can be expanded as follows:

$$\boldsymbol{z} = \sigma_z \left(\boldsymbol{W}^T \boldsymbol{y} + \boldsymbol{c} \right) \tag{A.1}$$

$$= \sigma_z \left(\boldsymbol{W}^T \sigma_y \left(\boldsymbol{W} \tilde{\boldsymbol{x}} + \boldsymbol{b} \right) + \boldsymbol{c} \right) \tag{A.2}$$

Here, $\tilde{\boldsymbol{x}}$ constitutes the corrupted version of the auto-encoder input $\boldsymbol{x}$, $\boldsymbol{z}$ is the reconstruction and $\boldsymbol{W}$ is the weight matrix. σ_y and σ_z are the activation functions for the hidden and output layer, and $\boldsymbol{b}$ and $\boldsymbol{c}$ define the bias values of the hidden and output units, respectively.

For the first auto-encoder layer, the input is given by a frame of real-valued coefficients extracted from speech data, so the mean squared error term was used for training. In vector notation, this term can be formulated as

$$E\left(\boldsymbol{x}, \boldsymbol{z}\right)_2 = \frac{1}{2} \left(\boldsymbol{x} - \boldsymbol{z} \right)^2 \tag{A.3}$$

In order to compute the updates for the weight matrix $\Delta \boldsymbol{W}$, the error term has to be propagated backwards through the network, starting with the output units. The mean squared error is straightforward to differentiate, and the derivative of the hyperbolic tangent used for $\sigma_z(x)$ is given by $(1 - x^2)$. With $\boldsymbol{a}_z = \boldsymbol{W}^T \boldsymbol{y} + \boldsymbol{c}$, the error for the output units is given by:

$$\boldsymbol{\delta}_z = - \left(\boldsymbol{x} - \boldsymbol{z} \right) \left(1 - \boldsymbol{a}_z^2 \right) \tag{A.4}$$

Using the backpropagation algorithm and abbreviating the activation of the hidden units with $\boldsymbol{a_y} = \boldsymbol{W}\tilde{\boldsymbol{x}} + \boldsymbol{b}$, the error term for the hidden layer is given by

$$\boldsymbol{\delta}_y = \left(\boldsymbol{W}^{T^T}\boldsymbol{\delta}_z\right)\sigma'_y\left(\boldsymbol{a}_y\right) \tag{A.5}$$

Differentiating the sigmoid function yields $x \cdot (1 - x)$, so this equals to

$$\boldsymbol{\delta}_y = \left(\boldsymbol{W}\boldsymbol{\delta}_z\right)\boldsymbol{a}_y\left(1 - \boldsymbol{a}_y\right) \tag{A.6}$$

In a fully connected network, the derivatives with respect to the weights are computed by multiplying the error of a layer with its input values [RHW86]. Since the same weight matrix is used to compute $\boldsymbol{y}$ and the reconstruction $\boldsymbol{z}$, the actual derivative for updating the weights is given by the sum of the error terms in Eq. A.4 and Eq. A.6, each multiplied with the respective input values:

$$\frac{\partial E}{\partial \boldsymbol{W}} = \boldsymbol{\delta}_y\tilde{\boldsymbol{x}}^T + \boldsymbol{\delta}_z\boldsymbol{y}^T \tag{A.7}$$

$$= \left(\boldsymbol{W}\boldsymbol{\delta}_z\right)\boldsymbol{a}_y\left(1 - \boldsymbol{a}_y\right)\tilde{\boldsymbol{x}}^T + \left(-\left(\boldsymbol{x} - \boldsymbol{z}\right)\left(1 - \boldsymbol{a}_z^2\right)\boldsymbol{y}^T\right) \tag{A.8}$$

In this work, standard gradient descent was used for training denoising auto-encoders. Thus, weights are updated by subtracting a fraction of the respective derivative as determined by the learning rate η:

$$\Delta\boldsymbol{W} = -\eta\frac{\partial E}{\partial \boldsymbol{W}} \tag{A.9}$$

The hidden and visible bias parameters are updated in a similar manner, with the difference that the propagated error terms are not being multiplied by the input of the layer:

$$\Delta\boldsymbol{b} = -\eta\boldsymbol{\delta}_y \qquad \Delta\boldsymbol{c} = -\eta\boldsymbol{\delta}_z \tag{A.10}$$

In auto-encoders that did not model the input data directly, a cross-entropy error term and a sigmoid activation function for the output units was being used. For this case, the weight updates can be computed in the same way as before. The error term for $\boldsymbol{y}$ stays the same, but the other ones have to be changed accordingly

$$E\left(\boldsymbol{x}, \boldsymbol{z}\right)_H = \boldsymbol{x}\log\boldsymbol{z} + \left(1 - \boldsymbol{x}\right)\log\boldsymbol{z} \tag{A.11}$$

$$\boldsymbol{\delta}_z = \boldsymbol{x} - \boldsymbol{z} \tag{A.12}$$

$$\frac{\partial E}{\partial \boldsymbol{W}} = \left(\boldsymbol{W}\boldsymbol{\delta}_z\right)\boldsymbol{a}_y\left(1 - \boldsymbol{a}_y\right)\tilde{\boldsymbol{x}}^T + \left(\boldsymbol{x} - \boldsymbol{z}\right)\boldsymbol{y}^T \tag{A.13}$$

A.2. Multi-layer Perceptron

After pre-training, the stack of auto-encoder layers was transformed into a standard multi-layer perceptron, and additional layers were being added on top of it. In order to perform

classification of input examples, the output layer contained one unit for each target class and used the softmax activation function to compute the estimated probabilities. Thus, the network assigned the following probability for a vector $\boldsymbol{x}$ belonging to class c:

$$P(C = c \mid \boldsymbol{x}) = o_i = \frac{e^{a_{o_i}}}{\sum_j e^{a_{o_j}}} \tag{A.14}$$

Here, $\boldsymbol{a}_o$ denotes the activation of the output units, which is computed by the hidden layers in a feed-forward manner from the network input $\boldsymbol{x}$. The target vectors $\boldsymbol{t}$ for the network were generated using a 1-of-N coding so that for a target class i, all elements of $\boldsymbol{t}$ are zero except for t_i, which is set to one. For learning, a cross-entropy error function was used:

$$E\left(\boldsymbol{t}, \boldsymbol{o}\right)_H = -\sum_i t_i \log o_i \tag{A.15}$$

When using the softmax activation in combination with a cross-entropy error term, the error term for the output units simplifies to

$$\boldsymbol{\delta}_o = \boldsymbol{t} - \boldsymbol{o} \tag{A.16}$$

This can be used to compute the updates for the output layer weights by multiplication with the output of the previous layer and the learning rate. The contribution of weights from lower layers can then be computed using the backpropagation algorithm as explained in the previous section.

A.3. Stochastic Mini-batch Gradient Descent

For training both denoising auto-encoders and the resulting multi-layer perceptron, a variant of gradient descent called *stochastic mini-batch gradient descent* has been used. Instead of computing the error term for all training examples first and updating the weights afterwards (batch training) or updating the weights after each training example presented (stochastic training), a mini-batch of several examples is passed to the network, which then computes its output and the average error gradients over the mini-batch in order to update its weights.

The mini-batch method has several advantages over the other methods. Most notably, it enables parallel computation of a whole batch of examples, which is particularly desirable when running training algorithms on multi-processor machines or GPUs. Additionally, the gradients obtained are usually smoother than for stochastic training because they are being averaged over several examples.

The size of the min-batches is another hyper-parameter to be chosen, although not a sensitive one. Typically, mini-batches containing between 10 and 1000 examples are used, with a trade-off that for a small number for training examples, training is faster (the network can receive more updates in the same amount of time), but that the resulting gradients for updating the weights are more noisy.

Software	Hardware	Time / Epoch
Quicknet	6-core Intel Xeon	70 min
Theano	6-core Intel Xeon	53 min
Theano	GTX-480	8 min, 52 sec
Theano	GTX-580	7 min, 5 sec

Table B.1.: Comparison of training times per epoch for a 5-layer network containing a bottleneck, using 22 GB of data.

B. Neural Network Training on Graphics Processors

For large and deep networks containing millions of free parameters that are optimized by iterating over gigabytes of training data, graphics processors (GPUs) offer crucial speedups when developing and comparing network architectures or hyper-parameters. Thus, the ability to run training algorithms on GPUs was among the initial objectives of this thesis, and the software used for training the networks had been selected accordingly.

B.1. Software

For implementing the actual training algorithms, Theano, a math expression compiler for Python[1], has been used [BBB+10]. With Theano, mathematical expressions, e.g. for computing the reconstruction of a denoising auto-encoder as in Eq. A.2, can be defined in a symbolic manner. This makes it possible to optimize or differentiate them automatically, and to generate efficient C code. Theano is designed to offer transparent use of GPUs and is currently supporting NVIDIA's CUDA framework[2].

In order to be able to experiment with different training algorithms and to combine individual neural network components, a custom command-line tool has been developed for this thesis. Using Python as well, it makes heavy use of Theano and is thus able to leverage the computational power of GPUs.

Further issues that had to be tackled with custom implementations mostly regarded interoperability with existing software, for example reading data form the training files produced or exporting neural network parameters in suitable formats.

B.2. Training Time

This section aims at providing a short overview over training times that could be achieved by using a GPU implementation. For comparing the times to a different CPU implementation, the Quicknet neural network package has been used [J+04].

Table B.1 lists the time needed for supervised training of a 5-layer neural network with different implementations. This corresponds to the fine-tuning stage when training the

[1] `http://python.org`
[2] `http://www.nvidia.com/object/cuda_home_new.html`

Hardware	Corpus	Data	AEs	Pre-tr.	Fine-tu.	Total
GTX-580	Cantonese "101 A"	44 h, 22 GB	4	11.7 h	10.0 h	21.7 h
			5	15.8 h	11.9 h	1 day, 3 h
			6	20.3 h	13.7 h	1 day, 10 h
GTX-480	Switchboard	120 h, 56 GB	4	16.4 h	35.6 h	2 days, 4 h

Table B.2.: Total training times for pre-training and fine-tuning on different datasets and hardware.

proposed architecture with a single auto-encoder layer on log mel scale filterbank coefficients. For both Quicknet and Theano, a mini-batch size of 256 was used. Training was done using the 44 hours of speech from the development system (Cantonese "101A"), which equaled to 22 GB of data (including silence). The CPU implementations ran on a machine containing 6 Intel Xeon processors running at 2.53 GHz. Via Hyper-threading, they were advertised to applications as 12 distinct cores. The GPU implementation was tested on a NVIDIA GTX-480 with 480 cores at a clock rate of 700 MHz and a GTX-580, which contains 512 cores at 773 MHz.

It can be seen that both Theano implementations outperformed the Quicknet toolkit, and that the training time on GPUs is dramatically faster. A 10-fold speed-up over training with Quicknet could be achieved by automatically generating GPU training code with Theano. For larger networks, the improvements in training time might be even higher, since GPUs are particularly suited to perform the layer-wise computations that occur in multi-layer perceptrons in a highly parallel manner.

Table B.2 shows the individual and total training times for the network setup proposed in thesis, i.e. pre-training a stack of auto-encoder layers and fine-tuning a network with a bottleneck layer afterwards. For the 120 hours of data from the Switchboard task, a NVIDIA GTX480 graphics card was used, which offers slightly worse performance compared to the more recent GTX580.

The table shows that when the number of auto-encoder layers was increased, additional time for pre-training was needed and fine-tuning was a little slower. If the amount of training data was increased, pre-training time hardly suffered since training time is limited by mini-batch updates rather than epochs. However, fine-tuning the neural network for 50 epochs did take proportionally longer.