Modularity and Neural Integration in Large-Vocabulary Continuous Speech Recognition

zur Erlangung des akademischen Grades eines

Doktors der Ingenieurwissenschaften

von der Fakultät für Informatik

des Karlsruher Instituts für Technologie (KIT)

genehmigte

Dissertation

von

Kevin Kilgour

aus Glasgow

Tag der mündlichen Prüfung: 09.06.2015

Erster Gutachter: Prof. Dr. Alexander Waibel

Zweiter Gutachter: Prof. Dr. Florian Metze

Ich erkläre hiermit, dass ich die vorliegende Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe, sowie dass ich die wörtlich oder inhaltlich übernommenen Stellen als solche kenntlich gemacht habe und die Satzung des KIT, ehem. Universität Karlsruhe (TH), zur Sicherung guter wissenschaftlicher Praxis in der jeweils gültigen Fassung beachtet habe.

Karlsruhe, den 21.04.2015

Kevin Kilgour

Abstract

Recent advances in deep neural networks (DNNs) have seen automatic speech recognition (ASR) technology mature and start to become mainstream. Many systems visibly employ ASR technology for services such as voice search and many more systems employ it in back-end systems to index online videos or to generate television subtitles.

Speech recognition is a multifaceted problem that can, and, in order to perform well, must be, tackled at many levels. Deep neural networks are very powerful tools for classification and can be used at the word level to predict the probability of a word in a given context as well as at the phonetic level to classify feature vectors extracted from the speech signal into acoustic units. Deep neural networks can also be used to help extract good features from the speech signal by leveraging their hidden layer's ability to learn new representations of inputs and setting such a hidden layer to the desired feature size.

These separate levels are, however, often addressed independently from one another. This thesis hopes to remedy that problem and presents a modular deep neural network for acoustic unit classification that can combine multiple well trained feature extraction networks into its topology. A word prediction deep neural network is also presented that functions at the lower subword level.

The use of multiple similar and yet still, to a certain extent, complementary features in deep feature extraction networks is investigated and demonstrated to be a good method of feature combination. Using multiple different input features is also shown to improve deep neural networks acoustic units classification ability. Despite the recent advances in deep neural networks the selection of these acoustic units used as classification targets is still performed using older non neural network modeling methods. In this thesis an approach is presented that alleviates this requirement and demonstrates how a deep neural network can be used in lieu of the older method.

The proposed modular deep neural network exploits the already well trained deep feature extraction networks, that can make use of multiple input features, in order to improve its classification ability. In principle, the modular deep neural network design is not limited by the number of different feature extraction networks included within it. This thesis evaluates the inclusion of up to seven of them and compares the results to post recognition combinations of normal deep neural networks using the same variety of input features.

Another problem addressed in the thesis is that of long compound words in German. Speech recognition systems require a vocabulary of all the words they can possibly recognize. The aspect of the the German language to allow multiple words to be combined to form new words results in those words being unrecognizable. The proposed solution uses a subword vocabulary in which some of the subwords are marked with an intraword symbol allowing for a deterministic construction of the fullword sentence after recognition. A neural network that predicts word probabilities is adapted for use at the subword level.

A final neural network is investigated that combines the output of the subword prediction model with the output of the modular deep neural network.

Zusammenfassung

Moderne Spracherkennungssysteme bestehen aus vier Komponenten, der Vorverarbeitung, dem akustischen Modell (AM), dem Sprachmodell (SM) und dem Dekoder. Im Rahmen dieser Arbeit werden diese einzelnen Komponenten durch neuronale Netze ersetzt oder ergänzt. Neuronale Netze haben sich bei einer Vielzahl von Lernaufgaben als sehr nützlich erwiesen. Es wird gezeigt, wie mit einem neuronalen Netz (NN) bessere Merkmalsvektoren aus einer Kombination verschiedener Vorverarbeitungsmethoden gewonnen werden können. Darauf aufbauende, durch modulare neuronale Netze modulierte, akustische Modelle werden untersucht und ihre Leistungsfähigkeit demonstriert. In Verbindung mit einem durch ein neuronales Netz moduliertes Subwortsprachmodell können weitere Verbesserungen erreicht werden. Ein neuronales Netz zum Kombinieren der beiden Modelle im Dekoder wird vorgestellt und analysiert. Die Integration dieser neuronalen Netze in ein Vorlesungsübersetzungssystem wird untersucht und für die dabei auftretenden Probleme werden Lösungen präsentiert. Deutliche Fehlerreduzierungen und Erfolge bei internationalen Evaluationskampagnen belegen die Effektivität dieser Arbeit.

Vorverarbeitung Die Vorverarbeitung extrahiert aus einem Audiosignal eine Sequenz von Merkmalsvektoren. Man kann beobachten, dass Spracherkennungssysteme, die unterschiedliche Vorverarbeitungsmethoden verwenden, unterschiedliche Fehler produzieren. Durch Kombinationsalgorithmen können die Ausgaben solcher Systeme verwendet werden, um eine Gesamthypothese zu erzeugen, die weniger Fehler enthält als die beste Einzelsystemausgabe. Es wird ein neuronales Netz vorgestellt, welches diese Kombination in der Vorverarbeitung durchführt und eine Sequenz von kombinierten Merkmalsvektoren erzeugt. Die Wichtigkeit der verschiedenen Parameter wird experimentell untersucht und optimiert.

Akustische Modellierung Auch in der akustischen Modellierung werden neuronale Netze verwendet. Diese Netze bestehen aus derselben Eingabeschicht wie die Netze der Vorverarbeitung, enthalten aber keinen Bottleneck. Die Ausgabeschicht enthält pro akustischer Einheit ein Neuron. Die besten Netze verwenden ca. 18000 kontextabhängige akustische Einheiten. Es wird gezeigt, wie ein solches Netz modular aufgebaut werden kann, indem zuerst ein Netz zur Bottleneckmerkmalsextraktion über ein Zeitfenster des Audiosignals verschoben mehrfach angewandt wird. Es wird experimentell gezeigt, dass solche Netze die Erkennungsleistung erheblich verbessern und die Fehlerrate um über 10%, im Vergleich zu einem herkömmliches NN-AM, reduzieren können. Des Weiteren wird eine Methode vorgestellt, mit der ohne Gaußsche Mixturmodelle kontextabhängige akustische Einheiten ausgewählt werden können.

Sprachmodellierung In einem weiteren Teil der Arbeit wird ein Subwort-NN-SM gebaut und dessen Fähigkeit analysiert mit den vielen Wortzusammensetzungen im Deutschen umzugehen. Es wird Subwortvokabular ausgewählt werden, das sowohl Subwörter als auch vollständige Wörter enthält. Das Subwort-NN-SM erhält in der Eingabeschicht einen Kontext von drei, als Vektoren kodierte, Subwörtern und berechnet die Wahrscheinlichkeit des Folgesubwortes. Das Subwort-NN-SM erweist sich als deutlich leistungsfähiger als sowohl ein statistisches SM als auch ein normales NN-SM.

Neuronale Kombination aus Sprachmodell und akustischem Modell Der Dekoder verwendet die Ausgaben vom SM und vom AM, um die beste Wortsequenz zu finden. Diese werden normalerweise loglinear mit Gewichten kombiniert, die auf einem Entwicklungsdatensatz optimiert werden. Es wird ein NN vorgestellt, welches diese Kombination übernehmen kann und das nur auf den Trainingsdaten des AMs trainiert ist. Es enthält keine Gewichtungsparameter, die auf einem Entwicklungsdatensatz optimiert werden müssen.

To Kira (& bump)

Acknowledgements

I would like to thank everyone who has supported and helped me during my work on this thesis. In particular I would like to thank Alex Waibel for giving me the opportunity to perform the research leading to this thesis, for his advice, our discussions about neural networks, and for providing me with any equipment that I asked him for. Working at the Interactive Systems Laboratories, first as a HiWi and later as a researcher has been a joy. I would also like to extend my thanks to Prof. Florian Metze for being the co-advisor of my thesis. I always enjoyed my visits to him where he simply made me feel as part of the team.

For getting me interesed in Speech Recognition I would like to thank my former diploma thesis advisor Florian Kraft, who, after we became colleages was still always there for me and helped me learn about speech recognition. And Sebastian Stüker for helping me learn the Janus Recognition Toolkit and being there when I had questions about it. I would like to extend my thanks to all the past and present members of the ASR team with whom I have worked over the years: Jonas Gehring, Michael Heck, Christian Mohr, Markus Müller, Huy Van Nguyen, Bao Quoc Nguyen, Thai Son Nguyen, Christian Saam, Matthias Sperber, Yury Titov and Joshua Winebarger. Speech recognition is a hard problem that is nigh on impossible to tackle alone so thanks for being part of a great team.

As well as the ASR team I would also like to thank the members of the MT and Dialog teams as well as the former research team Mobile Technology with whom I had many fruitful discussion during my time at the lab: Jan Niehues, Eunah Cho, Thanh-Le Ha, Silja Hildebrand, Teresa Herrmann, Christian Fügen, Muntsin Kolss, Narine Kokhlikyan, Thilo Köhler, Mohammed Mediani, Kay Rottmann, Rainer Saam, Maria Schmidt, Carsten Schnober, Isabel Slawik, Liang Guo Zhang, and Yuqi Zhang. In general, the open and inclusive atmosphere in lab has made working on projects across

teams easy and enjoyable. So thank you for being part of a working environment that I enjoy to come to every morning, and to Eunah: thank you for being there for me and for all our fun times. My thanks also goes out to all secretarial, technical, administrative and other support staff: Silke Dannenmaier, Sarah Fünfer, Klaus Joas, Bastian Krüger, Patricia Lichtblau, Margit Rödder, Virginia Roth, and Mirjam Simantzik. Without you this lab would cease to function so thanks for keeping everything running and for your support.

I also have to thank my father and Kira for proofreading and helping to correct this thesis. Thanks go also to my mother, sister and friends for their support and encouragement. And last but not least I would like to thank my, at this moment, pregnant wife Kira for her patience and support when had to stay at work late and over the weekends.

Contents

List of Figures

LIST OF FIGURES

List of Tables

Chapter 1

Introduction

The past decade from 2005 to 2015 has seen automatic speech recognition (ASR) technology mature and become mainstream. As well as many visible applications such as voice search [FHBM06], audio commands on smartphones [Aro11], or the automatic transcriptions of lectures [CFH+13], ASR technology is also used in many backend systems such as indexing online videos or creating subtitles for television programs. While the second set of applications can be processed in multiple steps and with multiple complementary ASR systems using large HPC (High Performance Computing) clusters the first set of applications require a careful balance between accuracy and latency. A simple way to create complementary ASR systems that can increase accuracy when combined is to use several different methods of extracting a sequence of feature vectors from the audio. This feature extraction part of an ASR system is referred to as its front-end. Although many front-ends are fundamentally similar and equally useful, they are still, to some extent, complementary and the outputs of ASR systems trained separately on different front-ends can be combined in such a manner that the combined output contains fewer transcription errors than either of the individual outputs [MBS00a, Fis97]. While very useful, this high level combination method has the disadvantage of requiring multiple ASR systems to be run in parallel. In this thesis an alternative approach is proposed that uses deep neural networks (DNNs) to combine the features in either a multi-feature front-end or in the ASR system's so called acoustic model (AM).

The acoustic model is one of the two main models in an ASR system and estimates the conditional probability that a word sequence produces the sequence of

observed feature vectors that the front-end had extracted from the audio. Until 2013 the dominant approach to acoustic modeling in large vocabulary continuous speech recognition (LVCSR) used hidden Markov models (HMMs) with Gaussian mixture models (GMMs) for estimating their emission probabilities. Recent advances in deep neural networks (DNNs) and in the field of general-purpose computing on graphics processing units (GPGPU) have caused hybrid HMM/DNN AMs to supplant the HMM/GMM AMs as the default acoustic model in state of the art ASR systems [MHL+14]. The use of HMM/DNN AMs can reduce word error rates (WERs) by up to 30% relative [SSS14, DYDA12, HDY+12].

Both HMM/DNN AMs and HMM/GMM AMs have an underlying HMM topology where the states of the HMM correspond to the acoustic units that are modeled using either the GMM or the DNN. The acoustic units chosen as states should be small enough so as not to contain much fluctuation and instead be mostly stationary. This means that the beginning of the acoustic unit should *sound* the same as its end. Phonemes, the basic unit of a language's phonology, do not satisfy this stationary condition. This can clearly be seen in the fact that diphthongs, sounds that begin sounding like one vowel and end sounding like a different vowel, are often considered to be phonemes [Hay11]. A common approach, therefore, is to subdivide the phonemes into multiple parts (e.g. beginning, middle and end) and to use these sub phonemes as states in the HMM. This approach assumes that all instances of a phoneme *sound* similar regardless of their context and is referred to as a context independent (CI) acoustic model. Since phonemes are in fact pronounced differently depending on the proceding and following phonemes, state of the art speech recognition systems instead use context dependent (CD) AMs that model phonemes in a specific phonetic context called polyphones.

Modelling these small acoustic units has the added advantage of allowing speech recognition systems to be able to recognize words for which the training data did not contain any example pronunciations. Instead ASR systems only require a dictionary that describes the words using the selected acoustic units. This is normally done by providing a mapping from each word to a sequence of phonemes. We refer to all these words for which an ASR system has a phonetic mapping as its vocabulary and only words contained in the vocabulary can be recognized by the ASR system. Since the vocabulary cannot possibly contain every word or name that an ASR system may encounter it will produce errors when dealing with so called *out of vocabulary* (OOV)

Words	noch bis Freitag diskutieren die achtundsechzig Abgeordneten <NOISE> ob Wirtschaftswachstum auch umweltfreundlich und dauerhaft geht
Sub-words	noch bis Freitag diskutieren die acht+ und+ sechzig Abgeordneten <NOISE> ob Wirtschafts+ wachstum auch umwelt+ freundlich und dauerhaft geht
Phones	N O CH B I S F R A I T AH K D I S K U T IE ER E2 N ...
Quinphone	*N($,$|O,CH) O($,N|CH,B) CH(N,O|B,I) B(O,CH|I,S) ...*
Generalized Quinphones	*N(12) O(88) CH(2) B(61) I(13) S(41) F(16) R(77) A(9) I(17) ...*
Phones states	N-b N-m N-e O-b O-m O-e CH-b CH-m CH-e B-b B-m B-e ..
Quinphones states	N-b($,$|O,CH) N-m($,$|O,CH) N-e($,$|O,CH) O-b($,N|CH,B) ...
Generalized quinphones states	N-b(17) N-m(2) N-e(8) O-b(76) O-m(19) O-e(38) CH-b(27) ...
Waveform	

Table 1.1: *An example utterance viewed at multiple levels.*

words. Some languages like Turkish or German allow new compound words to be constructed from two or more pre-existing words. The German words *Tee (eng: tea)* and *Kanne (eng: canister)*, for example, can be combined into *Teekanne (eng: teapot)*. In order to deal with these compound words ASR systems can employ a sub-word vocabulary instead of the normal fullword vocabulary.

The goal of this thesis is to apply and evaluate the effectiveness of neural networks at all the levels at which an utterance can be viewed from the waveform / feature level over the phoneme / polyphone state level to the level of sub-words and words. An overview of these different levels is provided in Table 1.1 for an example utterance. The utterance is a segment from the German evening news *Tagesschau* and can be translated as "*until Friday the eighty six delegates will still be discussing <NOISE> if economic growth can be sustainably environmentally friendly*". It contains two compound words *Wirtschaftswachstum (eng: economic growth)* and *umweltfreundlich (eng: environmental friendliness)* as well as the number *achtundsechzig (68)* which in German is written together in one word as *eight-and-sixty*.

This word level is where the language model, the second main model of an ASR system, comes into play and estimates the a priori probability of a word sequence.

This is important because certain words or phrases sound similar and the only way to differentiate them is to look at the linguistic context. Consider the sentence *they're over there*, since *there*, *their* and *they're* are all pronounced identically prior knowledge about their usage in sentences is required in order to decide which word was spoken. In practice this is done by using a model that estimates the probability of the next word based on the preceding few words. Statistical language models that use the last $n-1$ words are called ngram language models and are trained on large amounts of text data that do not necessarily have to have any audio associated with them. Besides ngram language models, neural network based language models have been shown to be very effective at language modeling. In this work the methods of neural networks are applied at the sub-word level and a sub-word neural network language model is developed for German that greatly reduces its OOV and significantly improves the WER.

The next part of Table 1.1 shows the sentence represented at the level of phones and polyphones. Polyphones that consider a context of one phone to the right and one to the left are called tri-phones and when, like here, two phones to the right and left are taken into consideration the polyphone is called a quinphone. The notation *CH(N,O|B,I)* indicates that the center phone *CH* is proceeded by the phones *N* and *O*, and followed by the phones *B* and *I*. On the phone state level the three states beginning, middle and end are marked by appending *-b*, *-m* or *-e* to the phone or quinphone. The phoneset used in this example contains 46 different phonemes with 3 states each as well as an extra silence phoneme modeled using only a single state which results in over 600 million quinphone states.

Training models to robustly estimate the emission probabilities of over 600 million states is impossible given the amounts of acoustic model training data currently available. Most states would have to be estimated using only a few samples and many states would not contain any examples at all in the training corpus. The models would also become very large and unwieldy with the HMM/DNN AM requiring a DNN with a 600 million neuron output layer and 600 million GMMs being necessary for the HMM/GMM AM. Overcoming this problem requires clustering the quinphones into clusters of similarly pronounced quinphones called generalized quinphones (e.g. CH(2) - generalized quinphone with CH as the center phone no. 2) Modeling the generalized quinphones in multiple states can be done by either first clustering the phones into generalized quinphones and then using multiple states per generalized

quniphone or instead by beginning with the phone states and clustering them into generalized quinphone states, often called senons. The second approach is the more popular as it provides more flexibility during clustering [Hua92].

The emission probabilities for each quinphone state in a generalized quinphone state are the same and are learned using all their examples in the training data. This means that the number of clusters chosen to group the quinphones into directly determines the number of GMMs a HMM/GMM AM requires and the size of the output layer in DNN AM. The standard method of clustering is with the help of classification and regression trees (cluster trees) that pose questions regarding the properties of the phonetic context of a phoneme. They require a distance measure between clusters of polyphones in order to choose the best question to ask for any given context. A commonly used distance measure is the weighted entropy distance. This is calculated on the mixture weights from a semi-continuous HMM/GMM system in which a GMM is trained for each polyphone state encountered during training and all polyphone states with the same center state use the same set of Gaussians. An equally powerful alternative approach is presented in this thesis that uses an HMM/DNN AM and allows the weighted entropy distance to be calculated without either training or evaluating any Gaussians.

The leaves of the cluster tree represent the states in the HMM and correspond to the neurons in the output layer of the DNN. The other important aspects of a DNN AM are its topology and the input features on which it is trained. In contrast to the default topology which consists of just a feed forward neural network with an input layer for the features, a number of equally sized hidden layers that are fully connected to their neighbours and an output layer, this thesis proposes a new modular topology. It involves training deep, possibly multi-stream, feature extractors using a multilayer perceptron (MLP) containing a so called bottleneck which is a hidden layer that is reduced in size to the dimension of the desired feature vector. After training, all layers following the bottleneck are discarded. The remaining network maps the input features to so called bottleneck features (BNFs) or to deep bottleneck features (DBNFs). The proposed modular DNN AM uses one or more pretrained DBNF networks and combines the outputs from multiple neighbouring time frames as the input to a further feed forward neural network. During the joint training, weight sharing is used to average the changes accumulated by a DBNF network at various time frames.

Figure 1.1: *3D model of a cortical column in a rat's brain. Source: [OdKB+12]*

The forth and final component that this thesis augments by using neural networks is the decoder that combines the outputs of the AM and the LM in its search for the optimal hypothesis. The decoder intelligently restricts the search because examining all word sequences that can be produced from the ASR system's lexicon would require a prohibitively large amount of computational resources. By combining information from both the LM and AM as well as from other sources it can create a ranking of the most probable hypotheses. The thesis replaces the log-linear combination of AM and LM in the decoder with a neural network combination.

The multi-level view of an utterance is not just necessary for the technical application of an ASR system but also reflects the stages in which human infants acquire their first language. In roughly the first nine months after birth infants learn which phonemes and combinations of phonemes are possible in their native language and begin to lose the ability to discriminate non-native phonemes that are just variants of their native language's phoneme [WT84] (e.g Japanese Infants lose the ability to tell /l/ and /r/ apart). Research has shown that by about twelve months infants are able

to recognize from about a dozen to over a hundred individual words as well as some short phrases like *"come here"* [FDR+94, CBC+95] and their vocabulary will continue to steadily increase. Children learn various simple multi-word utterances from about 1-2 years of age [Bro73] and then from about the age of three begin to understand the structure of sentences [NRP11a]. Both their vocabulary and their knowledge of grammar continues to improve as they grow older.

The deep neural networks used in this work are themselves inspired by the structure of the nervous system. Like their biological counterparts the individual artificial neurons contain a number of inputs from other neurons that can cause them to activate (fire) sending a signal on to their downstream neurons. Figure 1.1 depicts a 3D model of a cortical column, a group of neurons in the cerebral cortex or outer layer of the brain, that appears structurally similar to a feed forward deep neural network.

Despite these similarities and the their biological motivation there are still major differences between the artificial neural networks and biological neural networks that connot be ignored. Artificial neural networks run synchronously in discrete time steps but biological neural networks work asynchronously. Depending on the activation function the output of an artificial neuron can have many possible values whereas real neurons can only either fire or not fire and therefore convey information using the frequency with which they fire. Further differences can be found in the way the weights are learned in artificial neural network and how the connections are formed and pruned in biological neural networks.

The analogy of speech recognition technology to the development of language understanding in humans should not be carried too far. Human brains do not learn language perception in isolation: Speech production and perception complement each other and unlike ASR systems, words are also learned and associated with certain real world objects or actions.

1.1 Contributions

As eluded to earlier this thesis is concerned with the improvement to or introduction of neural networks to the four major components of an ASR system:

- **Front-end:** Existing techniques for deep bottleneck are expanded upon to build multi-stream bottleneck features that combine several different front-ends. Their topologies are optimized and their performances evaluated.

- **Acoustic model:** Introduction of multi-stream deep neural network acoustic models that also combine several different front-ends and improve upon DNNs that only use a single input feature. Modular deep neural network acoustic models are presented which use one or more multi-stream bottleneck networks applied at multiple time frames as the basis of the deep neural network, and are shown to significantly improve the performance of DNN AMs. A method of constructing a cluster tree using a CD DNN AM is described and is shown to be slightly better than the GMM AM based approach. Contributions are also made in the use of singular value decomposition (SVD) in initializing new layers in DNNs, where this thesis evaluates some of its applications and shows how it can both increase the performance of a DNN as well as reduce the number of its parameters.

- **Language model:** A sub-word vocabulary is proposed and shown to be very effective at reducing both the OOV rate and the WER of German ASR systems. A standard approach for building word level language models is adapted and used to build a sub-word neural network language model. An error analysis shows how it noticeably reduces the number of errors from compound words.

- **Decoder:** A combination neural network is designed to optimally combine the outputs of the language model and acoustic model as well as other features such as word count. It is integrated into the ASR system as a replacement for the standard log linear model combination and can be trained directly on the system's training data without the need of a development set to optimize the interpolation parameters.

1.2 Overview and Structure

This thesis is structured as follows. The required theoretical background knowledge is covered in chapter 2 with section 2.1 presenting an overview of neural networks, their training methods and the parameters that affect their performance. An overview of the structure of an ASR system, including a description of its four major components,

is given in section 2.2 as well as an explanation of the metric used to evaluate the performance of ASR systems. The chapter continues with an overview of the related research and concludes by explaining how this thesis fits into the context of that related work.

Chapter 3 explores the speech recognition tasks on which the achievements of the thesis are evaluated, with section 3.4 introducing the data sets on which the WER are measured and section 3.5 examining and analysing the various training corpera. This chapter also discusses the structure of our baseline ASR system in section 3.6 with an overview of our neural network training presented in section 3.7.

Feature extraction using neural networks is discussed in chapter 4. It begins in section 4.1 with an overview of the 4 different features, lMEL, MFCC, MVDR and tonal features used in the following experiments. After a general introduction to bottleneck features the first initial experiments on combining two feature streams, MVDR and MFCC, are discussed in section 4.3. This is followed in section 4.3.2.1 by an investigation into the optimal topology for a deep MVDR+MFCC bottleneck MLP and section 4.3.2.2 where various combinations of the 4 input features are compared to each other. Integration level experiments are performed in section 4.3.3 and section 4.4 presents optimized training strategies for large DBNF based GMM AMs.

Chapter 5 is devoted to the analysis of neural network acoustic models. It begins with an analysis of the effects of different input feature combinations to the deep neural network in section 5.2.1 and moves on to present the modular deep neural network in section 5.2.2. This is followed in section 5.3 by a method of building cluster trees using DNNs and section 5.4 which shows how new hidden layers can be initialized using SVD.

A subword language model is presented in chapter 6. The proposed subword vocabulary, explained in section 6.2.1, is designed to alleviate the errors found in the error analysis in section 6.1. After analyzing the performance on an ngram language model in section 6.2.4 the proposed subword neural network language model is described and evaluated in section 6.3. The chapter is finished with a discussion of the subword vocabulary's integration into the lecture translation system installed at the KIT in section 6.4.

Chapter 7 describes a neural network that can be used to combine the output of an AM and an LM. Its topology is presented in section 7.2 and the error function required to train it is explained in section 7.2.1. The results are then discussed in section 7.3

The thesis in concluded with a short summary in chapter 9 and contains appendices with additional information on the language model data and the backpropagation algorithm as well as a detailed derivative of MMIE error function required to train the combination neural network.

Chapter 2

Theory und Related Work

This chapter briefly lays out the required theoretical foundations in the fields of automatic speech recognition (ASR) and artificial neural networks (ANN) on which the experiments performed in this thesis are based. It covers the design and training of neural networks, explains the parameters that have to be considered when training a neural network and how neural networks can be used in various ASR components. An overview of the structure of an ASR system is given together with an introduction of its major components.

Since neural networks have seen many uses in ASR over the years an overview and description of approaches similar to the ones examined in the thesis is also presented in this chapter followed by a discussion on how this thesis fits into the context of that related work.

2.1 Neural Network Basics

Artificial neural networks are biologically motived statistical models that can be trained using data to solve various different problems such as character recognition, playing backgammon or controlling a robot arm. They consist of a number of individual artificial neurons that are connected to each other, often organized into layers. Some neurons are referred to as input neurons and instead of possessing incoming connections they allow their values to be set, thereby acting as the inputs to the neural network. Analogously output neurons do not forward their output to other neurons but instead present it as the output of the neural network. The character recognition neural

network, for example, might have 1024 input neurons mapped to the pixels of a 32 pixel by 32 pixel image and 26 output neurons, one for each letter in the English alphabet.

2.1.1 Perceptron

A neural network consisting of only a single neuron is called a perceptron. The model has m inputs $x_0..x_m - 1$ that can be real numbers and are connected to the neuron together with an extra input x_m that is always set to +1. Each connection is associated with a weight $w_0..w_m$. The weight w_m that is always connected to +1 is called the bias. The output y of the perceptron is computed by multiplying each input with its connection's weight, adding all these values together and then applying a so called activation function φ.

$$y = \varphi\left(\sum_{j=0}^{m} w_j x_j\right) \tag{2.1}$$

There are many possible activation functions and while the original model proposed by Rosenblatt [Ros57] uses the *heaviside step function* the sigmoid activation is currently more popular due to its useful properties in multilayer neural networks:

$$\varphi_{\texttt{step}}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \tag{2.2}$$

$$\varphi_{\texttt{sig}}(x) = \text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{2.3}$$

The perceptron model is a form of nonparametric supervised classification and requires a set of labeled training examples $(x_1, t_1)..(x_n, t_n)$ on which the optimal weights can be learned. For the original perceptron model using the *Heaviside step function* as the activation function the following weight update rule can be used for all weights w_i:

$$w_i^{s+1} = w_i^s + \eta(t_j - y_j)x_{j,i} \tag{2.4}$$

where y_t is the output of the network for the input x_i, η is the learning rate with $0 < \eta \leq 1$ and s the current iteration. The update rule is repeated either until convergence or for a certain number of iterations. Due to its simplicity the perceptron

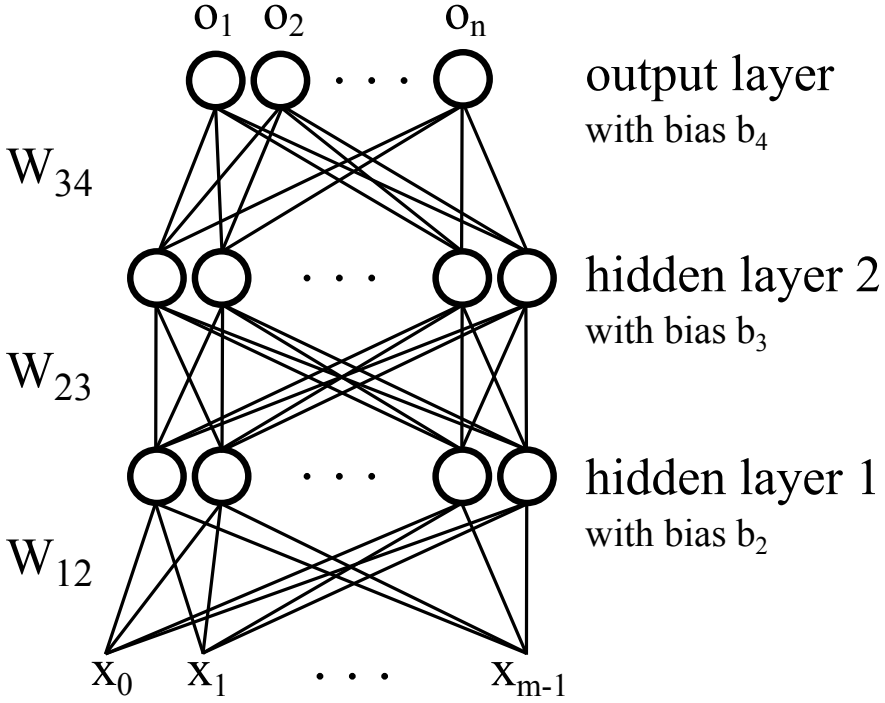


Figure 2.1: *An MLP*

can only solve linearly separable problems and fails at learning even simple nonlinear functions like the XOR function [MS69]. More complicated problems may be tackled with networks of these small neurons.

2.1.2 Multilayer Neural Networks

As well as input and output neurons multilayer neural networks also contain a number of hidden neurons. There are two main categories of multilayer neural networks, feed forward neural networks that only contain connections to neurons whose outputs do not directly or indirectly affect them and recurrent neural networks that can contain neurons connected in loops. A simple type of feed forward neural network is the multilayer perceptron which, like the normal perceptron, has a set of inputs $x_0..x_m - 1$. The inputs are connected to every neuron in the first layer of hidden neurons. The outputs of these neurons are connected to every neuron in the next layer. Two layers with this type of connection between them are said to be fully connected. After one or more hidden layers that are fully connected to each other the network finishes with an output layer that is fully connected to the last hidden layer. As well as the incoming

connections each neuron also has its own bias and activation function.

An example MLP with 2 hidden layers is presented in Figure 2.1. Such MLPs are often referred to as having 4 layers: an input layer, 2 hidden layers and an output layer. Since the input layer doesn't contain any functionality it is often ignored and the network is said to have 3 layers. This thesis uses the more common 4 layer description. If we look at the transition between two layers where the first layer has n_1 neurons and the second layer has n_2 then there will be $n_1 \times n_2$ weights connecting the two layers as well as n_2 biases. Using a vector notation we can write the outputs y_1 of the first layer as $y_1 \in \mathbb{R}^{n_1}$, the outputs y_2 of the second layer as $y_2 \in \mathbb{R}^{n_2}$, the weights $w_{i,j}$ connecting the two layers can be thought of as a matrix $W_{1,2} \in \mathbb{R}^{n_2 \times n_1}$ and the biases as the vector $b_2 \in \mathbb{R}^{n_2}$ allowing their relationship to be expressed using this equation:

$$y_2 = \varphi\left(W_{1,2} \cdot y_1 + b_2\right) \tag{2.5}$$

Applying the activation function φ to a vector is defined as applying it separately to each component. The example MLP in Figure 2.1 can now be described using three weight matrices $W_{1,2}, W_{2,3}, W_{3,4}$ and three vectors b_2, b_3, b_4:

$$h_1 = \varphi\left(W_{1,2} \cdot x + b_2\right) \tag{2.6}$$

$$h_2 = \varphi\left(W_{2,3} \cdot h_1 + b_3\right) \tag{2.7}$$

$$o = \varphi\left(W_{3,4} \cdot h_2 + b_4\right) \tag{2.8}$$

where x is the input vector, h_1 and h_2 are the outputs of the hidden layers and o is the output vector of the MLP. When used for classification it is common to have one output neuron per class and use the *one of n* encoding for the class labels. The *one of n* encoding represents the class j as an n dimensional vector with a 1 in position j and zeros everywhere else. As in the case of the simple perceptron these parameters (weights and biases) have to be trained using a set of labeled training examples $(x_1, t_{x_1})...(x_N, t_{x_N})$ which is typically performed using the backpropagation algorithm.

2.1.3 Backpropagation Algorithm

The backpropagation algorithm is a two phase supervised method for training neural networks by first, in the forward phase, sending examples through the network and accumulating the errors made by the network and then, in the backward phase, propagating the error back though the network while using it to update the network's weights. It is, therefore, sometimes called backward propagation of errors.

A summary of the algorithm is ommited here but can be found in appendex B.

Using the derived δ_k the update rule can now be written as:

$$w_{ji}^{s+1} \leftarrow w_{ji}^{s} + \eta \delta_k x_j i \tag{2.9}$$

This works for any feed forward neural network topology. The algorithm, however, cannot decide how the topology should look, which error function and which activations to use or what to set the learning rate η to. These, so called hyperparameters, have to be optimized independently of the learning algorithm.

2.1.4 Hyperparameters in Neural Networks

Neural networks depend on two types of parameters: weights $\vec{w}$ and Hyperparameters $\vec{\theta}$. Weights $\vec{w}$ can be learned by acquiring a set X of labeled examples and performing backpropagation in order to find the weights $\vec{w}$ that minimize an error function. Hyperparameters have to be *intelligently selected* by the neural network designer before the neural network can be trained. This section will cover three hyperparameters that are relevant to this thesis, the error and activation functions as well as how to choose the best learning rate and why a constant learning rate may not be the best choice.

2.1.4.1 Error Functions

The two most common error functions are the mean squared error (MSE) error function and the cross entropy (CE) error function [B$^+$95]. The MSE error function defined in equation B.1 penalizes large differences more than small differences and performs well on tasks such as function approximation and in cases where the outputs of the NN are real values and do not simply lie between 0 and 1.

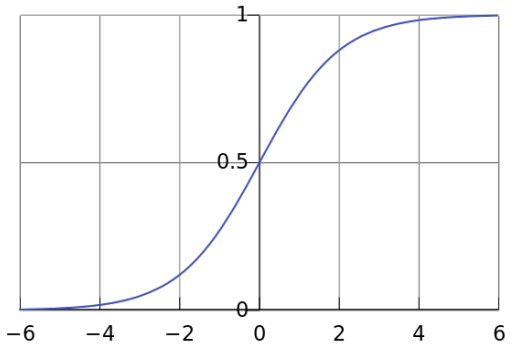


Figure 2.2: *The sigmoid activation function*

The CE error function performs well in classification tasks and is defined as:

$$E_{\mathrm{CD}}(\vec{w}) = -\sum_{x \in X} \sum_{k} [t_{kx} \log(o_{kx}) + (1 - t_{kx}) \log(1 - o_{kx})] \tag{2.10}$$

It has a derivative that when combined with a sigmoid activation function results in a simple update rule. In addition to these error functions chapter 7 also introduces an ASR specific error function.

2.1.4.2 Activation Functions

The identity function can be viewed as the most trivial activation function.

$$\varphi_{\mathrm{linear}}(x) = x \tag{2.11}$$

Also referred to as a *linear activation function* it is often used in combination neurons for function approximation problems. Neural networks that use only linear activation functions can be simplified and replaced by a single perceptron making them unsuitable as the default neuron in multilayer neural networks [MS69].

The *heaviside step function* defined in 2.2 has the major disadvantage that its derivative is almost always equal to 0 which makes it unusable for neural networks trained using backpropagation. The *sigmoid* activation function shown in figure 2.2 can be interpreted as a smoothed version of the step function and is defined as.

$$\varphi_{\mathrm{sig}}(x) = \mathrm{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{2.12}$$

It is easy to differentiate ($\frac{d\varphi(x)}{dx} = \varphi(x)(1-\varphi(x))$) and has a tendency to saturate which happens when the input is either very large or very small thereby putting it in a state where its derivative will be very close to zero which then leads to very small weight updates. Depending upon where and when it happens this saturation effect can have either positive or negative consequences.

The *sigmoid* activation function can be generalized to a group of neurons in such a way that their output sums to one and forms a discrete probability distribution.

$$\varphi_{\text{softmax}}(\text{net}_j) = \frac{e^{\text{net}_j}}{\sum_k e^{\text{net}_k}} \tag{2.13}$$

This is called the softmax activation function and is common in classification tasks where the goal is to use a neural network to find the probability $P(c|f)$ that a particular input f is a member of a certain class c_i.

All real activation functions discussed so far have only had possible output values between 0 and 1. In cases where negative outputs are also required the hyperbolic tangent is often a good choice:

$$\varphi_{\text{tanh}}(x) = tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2.14}$$

It has the added advantage of not changing the mean of the input from 0 if the input already has a mean of 0.

In recent years rectified linear units have become quite popular in deep neural networks [NH10]. They are neurons with an easy to compute activation function:

$$\varphi_{\text{ReLU}}(x) = = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \tag{2.15}$$

A neural network using these neurons will only have about half its neurons active ($\neq 0$) at any particular time making it more sparse than networks not using rectified linear units.

2.1.4.3 Learning Rate Schedule

The learning rate determines by how much a weight parameter is updated each iteration:

$$w_{ji} \leftarrow w_{ji} + \eta\delta_j x_{ji} \tag{2.16}$$

Choosing a constant learning rate can be problematic because if a large learning rate is chosen then it may quickly saturate some of the neurons and it could also lead to the learning algorithm constantly jumping past the minimum. If, on the other hand, a very small learning rate is chosen then the learning procedure will slow down and it may get stuck in a local minimum. For these reasons it is advisable to use a learning rate schedule instead of a constant learning rate.

We can observe that starting with a high learning rate and reducing it later results in our learning algorithm both converging fast and tending to find a better minimum. We can accomplish this using various learning rate strategies:

- **Predetermined piecewise constant learning rate**: Use a predetermined sequence of η_i. After ever epoch (or every n training examples) the learning rate is replaced with the next one in the list. This has the disadvantage that we have to set a whole list of learning rates.

- **Exponentially decaying learning rate**: Multiply an initial learning rate by a constant factor α ($0 < \alpha < 1$) after ever epoch: $\eta_t = \eta_{t-1} * \alpha = \eta_0 * \alpha^t$

- **Performance scheduling**: Periodically measure the error on a cross validation set and decrease the learning rate when the learning routine stops showing improvements on the cross validation set.

- **Weight dependent learning rate methods**: Use a different learning rate for parameter (weight or bias). Algorithms like AdaGrad and AdaDec can be employed to compute and decay η on a per-parameter basis.

- **Newbob learning rate schedule**: The newbob learning rate schedule is a combination of the performance scheduling and exponentially decaying learning rate. At first the learning rate is kept constant and the performance of the neural network is measured on a validation set every epoch (or every n training examples). A soon as the validation error shows that the network's improvement has dropped below a predetermined threshold it switches to an exponentially decaying learning rate schedule and decays the learning rate every epoch. The performance on the validation set is still measured and used as a termination criterion when the network's improvement again dips below a predetermined threshold.

Most of the neural networks trained in this thesis use the Newbob learning rate schedule.

2.1.5 Autoencoders and Pre-Training of Deep Neural Networks

Neural networks with multiple hidden layers are often referred to as deep neural networks (DNNs). Since the introduction of *deep belief networks* (DBN) by Hinton et al. in 2006 [HOT06], DNNs have become very popular in the field of machine learning and have outperformed other approaches in many machine learning and classification tasks making them the default technique for solving complex or high dimensional classification problems [Ben09]. The exact point at which a neural network becomes a deep neural network is not well defined [Sch15] but in general DNNs will have some of the following properties:

- Multiple hidden layers: A neural network requires at least 2 hidden layers in order to be considered deep. In some cases, as in bottleneck feature MLPs, deep neural networks will have at least 4 hidden layers [Geh12]. The multiple hidden layers in a DNN should allow it to represent complex functions with fewer weights than shallow DNNs.

- Large layers: While the individual layers in a DNN may be somewhat smaller than the layers in a shallow NN designed for the same purpose, they will not be multiple orders of magnitude smaller. With multiple fully connected layers the number of weight parameters in a DNN will be quite high: From a few tens of thousands of parameters to well over a few tens of millions of parameters.

- Large training sets: DNNs tend to be trained on large amounts of annotated data. This property is very task dependent and in part related to the necessity of a large amount of data being required to train the large number of parameters.

- Trained on GPUs: The consequence of having many parameters and a large set of training examples is that training becomes very computationally expensive and time consuming. GPU based backpropagation implementations have been shown to be several orders of magnitude faster than basic CPU based implementations [JO+13] allowing networks to be trained in hours or days instead of weeks or

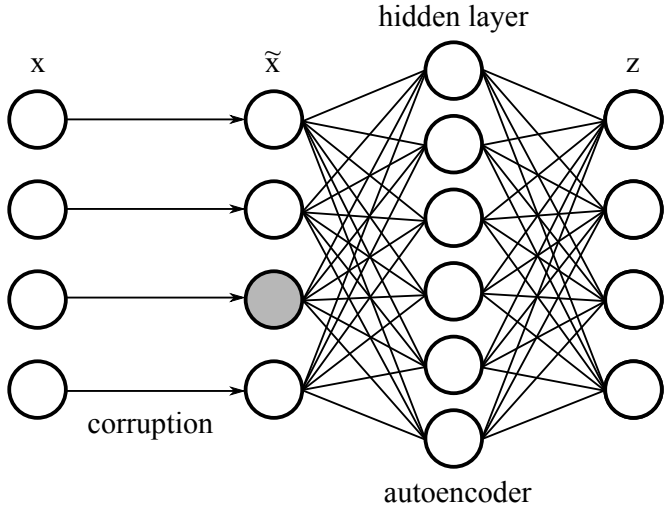


Figure 2.3: *A denoising autoencoder. The input x is corrupted and fed into a neural network that is then trained to undo the corruption.*

months. The faster turnover makes it possible for many more experiments to be performed and more hyperparameter configurations to be examined.

- Pre-training: Neural networks typically use small random values to initialize the weights prior to training with backpropagation. Pre-training involves making use of the training data to intelligently initialize the weights. It is generally performed in an unsupervised manner (without using the labels) and layer-wise. The use of stacked restricted Boltzmann machines (RBMs) [AHS85] was pioneered by Hinton et al. in 2006. They begin by initializing the first hidden layer with an RBM. Once trained the RBMs parameters are frozen and used to map the training data to the feature space of the first hidden layer. The second hidden layer is initialized with another RBM. This procedure is repeated for all hidden layers [HOT06]. Stacked autoencoders can also be used to pretrain DNNs [BLP+07] and can be improved with the use of sparse autoencoders [BC+08] or denoising autoencoders [Geh12]. While DNNs using pretraining have demonstrated some impressive results [DYDA12, SLY11, Le13] other approaches have shown that state-of-the-art DNNs can be trained without using any pretraining methods [HDY+12, VGBP13].

With the exception of some initial experiments on shallow bottleneck MLPs most neural networks used in this thesis can be called deep neural networks. They will

generally have 3 or more hidden layers with at least 600 neurons per hidden layer, and be trained on millions of training examples. All the neural network training setups make use of GPUs. Pre-training is implemented using denoising autoencoders and used consistantly thoughout all the DNN experiments.

An autoencoder is a feed forward neural network that contains a single hidden layer and identically sized input and output layers. It is trained on unlabeled data with the backpropagation algorithm by using the input data as the targets $t_x = x$ in order to learn a different representation of the input data in the hidden layer. If the number of neurons in the hidden layer is less than the dimensionality of the input then the autoencoder functions as a method of dimensionality reduction. After training the output layer, its biases and all weights connecting it to the hidden layer can be discarded and the remaining parts of the network used to map the input data from its original feature space to a new feature space.

A modified type of autoencoder, called a denoising autoencoder (DAE) is shown in figure 2.3 where the data is corrupted prior to being put through the network [VLBM08]. Training a network like this causes it to learn how to reconstruct corrupted input vectors. The corruption c_r is performed by randomly setting a predetermined percentage (r) of the inputs dimensions to zero:

$$\tilde{x} = c_d(x) \tag{2.17}$$

Due to the symmetry of the model the weight transition matrix from the input layer to and from the hidden layer can be tied reducing the number of parameters that have to be learned. The reconstructed output of the DAE is:

$$h_1 = \varphi_{2a}\left(W_{1,2} \cdot \tilde{x} + b_2\right) \tag{2.18}$$

$$z = \varphi_{2b}\left(W_{1,2}^T \cdot h_1 + c_2\right) \tag{2.19}$$

and can be compared to the input x using either the CE error function or the MSE error function. After training, the data can be mapped onto the new feature space learned in the hidden layer

$$x' = \varphi_{2a}\left(W_{1,2} \cdot x + b_2\right) \tag{2.20}$$

and the procedure repeated using x' as the input to the DAE:

$$\tilde{x'} = c_d(x') \tag{2.21}$$

$$h_2 = \varphi_{3a}\left(W_{2,3} \cdot \tilde{x'} + b_3\right) \tag{2.22}$$

$$z' = \varphi_{3b}\left(W_{2,3}^T \cdot h_2 + c_3\right) \tag{2.23}$$

where z' is now compared to x' in this DEA's error function. After all hidden layers have been pre-trained a final classification output layer can be added and the whole stack of autoencoders transformed into a DNN. This setup has been demonstrated to work well in both image recognition [VLL+10] and speech recognition tasks [Geh12]

2.2 Overview of Automatic Speech Recognition

Automatic speech recognition systems aim to extract the sequence of words spoken in an audio signal or audio file. In both cases microphones are used to measure variations in air pressure that are then digitized and either saved to file or sent directly to the ASR system. When the digitized audio is sent directly to the ASR system we talk about online ASR and in the other case, where recorded audio files are processed, it is called offline or batch ASR.

The audio signal or file is then feed to the front-end of an ASR system which analyzes it and converts it into a sequence of feature vectors X. We now wish to find the most probable sequence of words W, given this sequence of feature vectors X.

$$\hat{W} = \underset{W}{\operatorname{argmax}} P(W|X) \tag{2.24}$$

The application of the Bayes' rule to this probability gives us the *fundamental formula of speech recognition*, where the prior probability $p(X)$ of the feature sequence X can be ignored due it being constant for all word sequences.

$$\hat{W} = \underset{W}{\operatorname{argmax}} P(W|X) = \underset{W}{\operatorname{argmax}} \frac{p(X|W)P(W)}{p(X)} \tag{2.25}$$

$$= \underset{W}{\operatorname{argmax}} P(X|W)P(W) \tag{2.26}$$

Individual parts of this formula correspond to the four main components of an ASR that was informally discussed in chapter 1. The front-end extracts the feature vectors

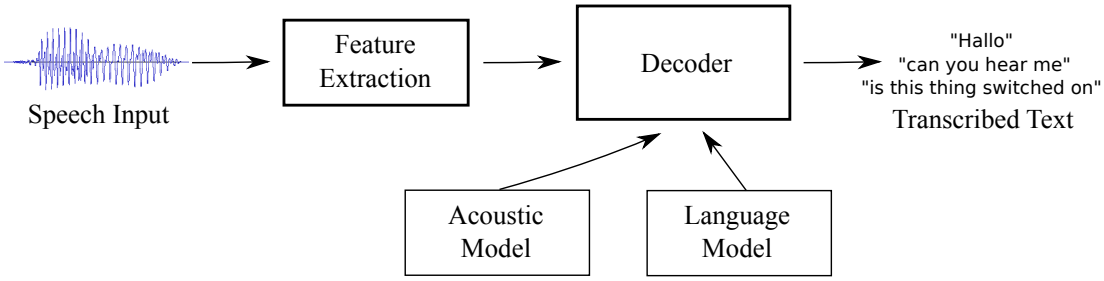


Figure 2.4: *ASR system setup*

X and since they are derived from real world measurement they are said to have been *observed*. The acoustic model estimates the probability $p(X|W)$ that the sequence of feature vectors X is observed given the word sequence W. P(W) is the prior probability of a word sequence independent of the observed sequence of feature vectors X and is estimated in a so called language model. argmax_W corresponds to the decoder that combines the output of the AM and LM and searches for the most probable sequence of words $\hat{W}$. An overview of these components is given in 2.4.

2.2.1 Language Model

The language model estimates the prior probability $P(W)$ of the word sequence $W = w_0 w_1 ... w_N$ and can be broken down into a product of the probabilities of each word w_i occurring, given its context or history $h = w_{i-1} w_{i-2} ... w_0$ which is often approximated to just the last few words.

$$P(W) = \prod_{i=0}^{N} P(w_i | w_{i-1}, w_{i-2}, ..., w_0) \tag{2.27}$$

$$\approx \prod_{i=0}^{N} P(w_i | w_{i-1}, w_{i-2}, ..., w_{i-(n-1)}) \tag{2.28}$$

This is typically done by using n-grams that estimate the probability of a word given the last $n-1$ words. N-gram models are trained using a maximum likelihood estimation on a large corpus of text:

$$P(w_i | w_{i-1}, w_{i-2}, ..., w_{n-1}) = \frac{\#(w_{i-(n-1)}, ..., w_{i-1}, w_i)}{\#(w_{i-(n-1)}, ..., w_{i-1})} \tag{2.29}$$

Depending on the value of n we speak of uni-grams ($n = 1$), bi-grams ($n = 2$), tri-gram ($n = 3$), 4-grams ($n = 4$) and so on. In ASR, language models normally use values of n from about 3 to 5 but even for the smaller bi-grams it would be impossible to find training examples for each word in every possible context, leading to some estimates being 0. Sentences containing these n-grams could never be recognized by the ASR system because the LM would give them a prior probability of 0. Statistical n-gram models use two techniques to combat this problem *discounting* and *smoothing*.

Discounting reduces the probabilities of the nonzero estimates by a small amount and smoothing intelligently redistributes this discounted probability mass across the other the ngrams for which no training example are given. This can be done by backing off to the estimate of a lower order n-gram or even to the unigram if none of the lower order ngrams are non-zero. Alternatively an ngram model can be interpolated with all of its lower order models [CG96].

Neural network language models on the other hand do not suffer from this sparseness problem as they begin by mapping the $n - 1$ words in the history of the n-gram into a continuous vector space such as $\mathbb{R}^m$, where *similar* words are closer together. The $n - 1$ word vectors are concatenated together and used as the input layer to a DNN where the softmax output layer contains a neuron for every word [Sch07]. While more powerful than ngram-LMs NN LMs have some disadvantages: they take at lot longer to train, require a method of word vectorization (embedding), are much slower than ngram-LMs at runtime and it is infeasible to have an output layer that is as large as the typical vocabulary used in LVCSR.

The training time can be reduced by only using the most useful training data and not all the available data. Word embedding can either be performed prior to training the NN using a dedicated algorithm (or external tool like word2vec [MCCD13]) or while training the NN by providing the words using the 1-of-n-encoding and learning a shared projection matrix. When the vocabulary becomes to large for the output layer to handle, it can be reduced to a shortlist that covers 80-95% of the expected words and the remaining words are modeled using a normal n-gram LM [Sch07]. NN LMs can be speeded up a bit during decoding by caching the whole output layer or alternatively, methods exist that can convert them into backoff ngram LMs [AKV+14]. If they are only used in a second pass after all contexts required for an utterance are already known then these can be efficiently precomputed in batch mode.

Two broad catagories of neural networks are used for language modelling, recurrent neural networks [SSN12, MKB+10] where a hidden layer depends on the previous word's hidden layer and the vector representation of the current word to predict its successor and feed forward neural networks [Sch07] which have a fixed input context of word representations.

2.2.2 Acoustic Model

The acoustic model estimates the conditional probability $p(X|W)$ that the sequence of observed feature vectors $X = x_0, ..., x_T$ is produced by the word sequence $W = w_0, ..., w_N$. Its units of modeling are, as discussed in chapter 1, at the subphoneme level which are assumed to be stationary, i.e the observations will be constant for a period time spanned by one or more feature vectors or *frames*. Both common types of acoustic models HMM/DNNs and HMM/GMMs use hidden Markov models to model their structure and to describe how the subphoneme acoustic units are concatenated together to form the sequence of words [Rab89].

2.2.2.1 Hidden Markov Model (HMM)

An HMM models a system where a sequence of visible observations $o_0, o_1, ..., o_T$ depend on an internal sequence of hidden states $s_0, s_1, ..., s_T$. The Markov assumption of this model means that the probability of transitioning to a state depends only on the current state. They are defined over a vocabulary V and a set of states $S = s_1, s_2, ...$ [Fuk13] For each state s_i there is a probability $p(s_j|s_j)$ of transitioning to s_j and each state has an emission probability distribution that describes the emission probabilities of the symbols in the Vocabulary V after transitioning to the state. When applied to ASR systems that vocabulary V is the set of all possible feature vectors, typically $\mathbb{R}^n$. Due to its continuous nature the emission probabilities are estimated using the probability density function $p(x_t|s_t)$. The transition probabilities between the states are defined by the HMM's topology which often limits the possible transitions by setting some of them to 0. In a three state (beginning, middle, end) topology, for example, a particular phoneme's beginning state may only have non-zero connections to itself and to the phoneme's middle state while the end state would have connections to itself and to all other phonemes' beginning states.

A dictionary or lexicon can provide us with a mapping from a word sequence to a sequence of phonemes which we subdivide further resulting in a sequence of subphoneme acoustic units that can each span multiple frames. What is unknown at this point is at which time step the transitions between these states occur. So a given word sequence $W = w_0, ..., w_N$ can be represented by many different possible state sequences $s_0, s_1, ..., s_T$ whose lengths are all the same as the length of the feature vector sequence $x_0, ..., x_T$ because each feature vector has to be emitted by a state in the HMM [Hei10]:

$$p(X|W) = \sum_{S_j \in \mathbb{S}(W)} p(X|S_j) \tag{2.30}$$

where $\mathbb{S}(W)$ is the set of all possible state sequences of W. With $S_j = s_0, ...s_T$ as a possible state sequence we can now separate it into the product of the individual emission and transition probabilities and, when using the Viterbi algorithm [Vit67], the summation over all possible state sequences is approximated by using only the most probable sequence [Hei10].

$$p(X|W) = \sum_{S_j \in \mathbb{S}(W)} \prod_{t=1}^{T} p(x_t|s_t)p(s_t|s_{t-1}) \tag{2.31}$$

$$\approx \max_{S_j \in \mathbb{S}(W)} \{\prod_{t=1}^{T} p(x_t|s_t)p(s_t|s_{t-1})\} \tag{2.32}$$

Depending on the type of AM the emission probabilities $p(x_t|s_t)$ are either estimated with a DNN or with a GMM.

2.2.2.2 HMM/GMM Acoustic Models

For a long time GMM AMs were the de-facto standard for acoustic modeling. Even with the rise of DNN AMs they are still useful in many applications thanks to the many well researched techniques on discriminatively training them [BBdSM86, PKK$^+$08, WW03] or on performing speaker adaptation [GW96]. There are two main variants of HMM/GMM AMs, semi-continuous and fully-continuous models. Semi-continuous HMM/GMM AMs have a global pool (codebook) of M n-dimensional Gaussians $\mathcal{N}_1, ..., \mathcal{N}_M$ with means $\mu_1, ..., \mu_M$ and covariance matrices $\Sigma_1, ..., \Sigma_M$ that are shared between all models. Each state's emission probability is then a weighted sum over all

the Gaussians.

$$p(x_i|s_i) = \sum_{j=1}^{M} a_{ij}\mathcal{N}_j(x_i, \mu_j, \Sigma_j) \tag{2.33}$$

Fully continuous HMM/GMM AMs differ by not having a global pool of Gaussians and instead use a separate set Gaussians for each state.

$$p(x_i|s_i) = \sum_{j=1}^{M} a_{ij}\mathcal{N}_{ji}(x_i, \mu_{ji}, \Sigma_{ji}) \tag{2.34}$$

In some systems both approaches are combined by having codebooks that are shared by only some states, e.g. all variants of a phone state in a CD-AM.

It is beneficial for feature vectors to be augmented by either their differences with neighbouring features or by using a window of feature vectors instead of a single feature vector. In both cases the dimension of the feature vector sequence sent to the ASR system can easily become very large resulting in larger dimensional Gaussians that require more parameters. Dimensionality reduction techniques are therefore required in order to still benefit from the stacked feature vectors without inflating the number of parameters in the GMM AM. A common method for performing this dimensionality reduction is the principal component analysis (PCA) which can be learned without labels and performs a linear transformation of the features into a decorrelated feature space where the first few dimensions contain most of the variance. Linear discriminant analysis (LDA) is an alternative linear approach that is trained with label information and is optimized for class separability [Fuk13]. Chapter 4 will present and expand on another common method that uses an MLP with a small hidden layer for dimensionality reduction.

2.2.2.3 HMM/DNN Acoustic Models

HMM/DNN AMs do not have a problem with large feature vectors and can, without resorting to dimensionality reduction preprocessing steps, even use very large windows of stacked features. They are modeled with a DNN that uses the (stacked) feature vector as the input layer and, after multiple hidden layers, have an output layer whose neurons correspond to the states in the HMM. Using the softmax activation function

in the output layer lets the DNN generate the probability $P(s_i|x_i)$ for each state.

$$P(s_i|x_i) = \frac{p(x_i|s_i)P(s_i)}{p(x_i)} \tag{2.35}$$

The prior probability $p(x_i)$ of the feature vector is generally set to a constant value like 1[RMB+94]. This gives us the following approximation of the emission probability using the output of the DNN and the prior probability of the states [BM94].

$$p(x_i|s_i) \approx \frac{P(s_i|x_i)}{P(s_i)} \tag{2.36}$$

In recent years speech recognition systems have significantly improved due to the use of deep neural networks (DNN) with layer wise pretraining as acoustic models (AM) [DYDA12].

2.2.2.4 Context Dependent Acoustic Models and Cluster Trees

As mentioned in chapter 1 state of the art speech recognition systems use CD-AM due to phonemes being pronounced differently depending on their neighbours. They instead use various types of polyphones, like tri-phones, when the context only includes one left and one right neighbour or quinphones when the context includes two neighbours from each side. This can lead to a large number of possible polyphone states, many of which are never seen in the training data, with many almost identical to each other. Clustering algorithms are used to group these triphone or quinphone states together and reduce the total number of states that have to be modeled. This directly affects the size of the DNN-AM's output layer.

We refer to a decision tree used to cluster the large number of possible polyphones into a manageable number of classes as a cluster tree. The basic procedure requires a set of yes/no questions that can be asked about a phoneme, such as whether it is a vowel or if it is at a word boundary. An example cluster tree, where a set of triphones is split after asking the question *"is the previous phoneme a vowel"* is shown in figure 2.5.

The following steps describe how to build a cluster tree:

1. Go over the alignment and get statistics on all existing polyphones.

2. Begin with all polyphones that have the same center phone clustered into one cluster per HMM state (e.g. beginning, middle, end).

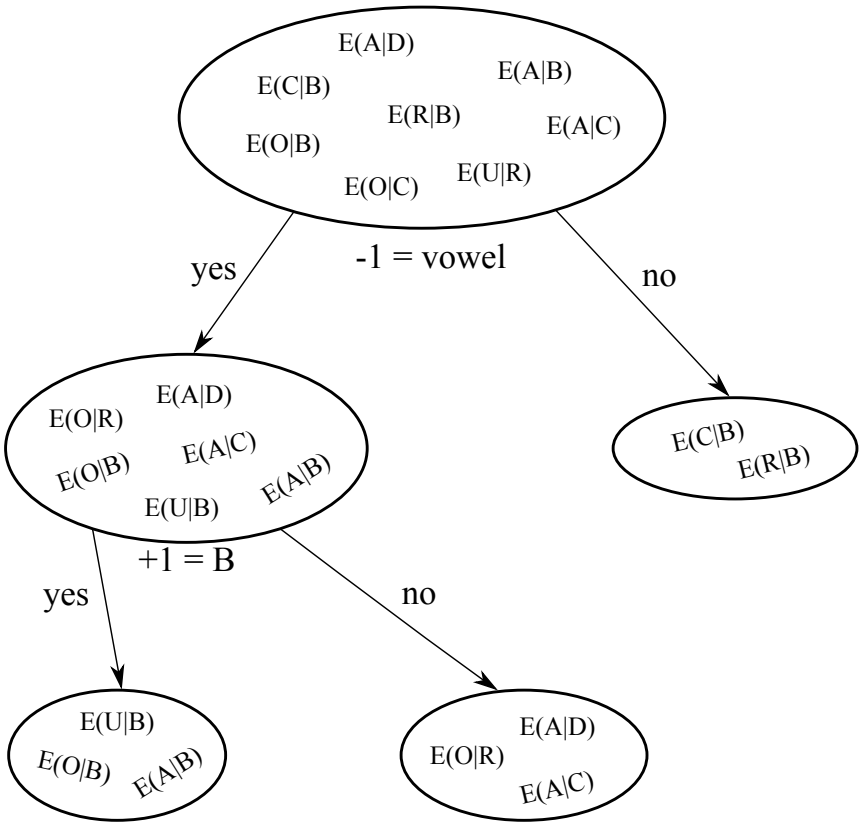


Figure 2.5: *An example cluster tree for the center phone E. The notation $E(A|D)$ indicates that the phone E is preceded by the phone A and followed by the phone D. The question "-1= vowel" asks if the preceding phone is a vowel.*

3. Select a cluster to split. Each yes/no question splits a cluster into two separate clusters. Only take questions into consideration that produce clusters of a minimum size. Find the *best* questions to pose.

4. Split a cluster using the *best* question and repeat from step 3 until all clusters that can be split are split.

5. Prune the tree back until it has the desired number of leaves.

The key point in this procedure is how to find the *best* question. Given two clusters A and B we require a distance metric $d(A, B)$ that is high for good splits and low for bad splits. A common metric is the weighted entropy distance between A and B. It is the entropy difference between both clusters being joined and them being separate.

Let the number of occurrences of each cluster be n_A and n_B, then the weighted entropy distance can be defined as:

$$d(A, B) = (n_A + n_B)H(A \cup B) - n_A H(B) - n_A H(B) \tag{2.37}$$

where $H(A)$ is the entropy of cluster A, $H(B)$ is the entropy of cluster B and $H(A \cup B)$ is the entropy of the merged cluster. Using the equation

$$H(p) = \sum_{i=1}^{k} p(i) \log p(i) \tag{2.38}$$

we can compute the entropy of a k dimensional probability distribution. Furthermore, given probability distributions (over the same probability space) p_A and p_B for both clusters the probability distribution of the merged cluster can be computed as:

$$p_{A \cup B}(i) = \frac{n_A \; p_A(i) + n_A \; p_B(i)}{n_A + n_B} \tag{2.39}$$

The required probability distributions can be defined in multiple ways. One method would be to train a single Gaussian on the training examples belonging to a particular cluster. In this case the probability space would be the feature space. Another approach uses the discrete mixture weights of a shared codebook of Gaussians as the feature space. This GMM based approach requires a semi continuous CI HMM/GMM system, where each phone (monophone) state is modeled using a weighted mixture of a set of Gaussians trained specifically for that phone state. For all polyphone states appearing in the training data derived from the same monophone state a new GMM is trained by only learning the mixture weights and keeping the codebook of the monophone. The normalized mixture weights of the polyphone states can be regarded as the probabilities of a discrete distribution which can be used in the entropy distance measure.

2.2.3 Decoder

The decoder uses the outputs of the LM and AM to find the most probable word sequence given the observed sequence of feature vectors. It is generally limited by a predetermined search vocabulary V and it contains all the possible words the ASR system could potentially recognize. Even for a small search vocabulary the total amount of possible word sequences for a short utterance would be so large that they could not

all be evaluated. A search vocabulary containing 10000 words would allow for 10^{80} possible sentences containing exactly 20 words, which is about the same number as our current best estimate for the total number of atoms in the observable universe. Instead of evaluating every possible hypothesis the decoder builds them up state by state and only follows the most likely partial hypotheses at any time and marks the others as dead ends. The marking of partial hypotheses as dead ends is call pruning and generating new partial hypotheses by evaluating the next possible states of a current partial hypothesis is referred to as expanding it. Partial hypotheses that have neither been pruned nor expanded are considered to still be active.

There are two main types of decoders: synchronous and asynchronous. Asynchronous decoders have a list of the possible partial hypotheses. In each step they expand the best one and sort the new partial expanded hypotheses back into the list. The individual partial hypotheses can have different lengths. In synchronous decoders each time step generates a new set of partial hypotheses based on the partial hypotheses of the previous time step. In both cases the set or list of active partial hypothesis has to be limited by either a maximum size, or through use of a relative cutoff that prunes partial hypotheses that are less probable, the probability of the best partial hypotheses multiplied by a factor or *beam*. Both pruning methods can be combined allowing the decoder to prune a lot and speed up in cases where it is very sure of current best partial hypotheses (their probabilities are much higher than competing ones) and if it is unsure then the maximum amount of partial hypotheses prevents it from slowing down too much.

When computing the probability of partial hypotheses the decoder has to compensate for the fact that while the language model is estimating a real probability $P(W)$ the acoustic model has to deal with $X \in \mathbb{R}^n$ and supplies a continuous probability distribution. As these two values are not directly comparable, a scaling factor has to be applied. Other problems that the decoder has to deal with are the varying utterance lengths, the very small probabilities that occur when many small probabilities are multiplied together and the non-word acoustic events like laughing, coughs or background noise. A further word penalty term can be added to the speech recognition equation to deal with the varying utterance lengths and because the word sequence that maximizes the probability of $P(W|X)$ also maximizes its logarithm $\log P(W|X)$

we can replace the multiplication of the small probabilities with a summation of log probabilities, which we refer to as scores.

$$\begin{aligned}
\hat{W} &= \underset{W}{\operatorname{argmax}}\, P(W|X) = \underset{W}{\operatorname{argmax}}\, P(X|W)P(W) \\
&= \underset{W}{\operatorname{argmax}}\ \log P(W|X) = \underset{W}{\operatorname{argmax}}\ \log(P(X|W)P(W)) \\
&\approx \underset{W}{\operatorname{argmax}}\ \log(P(X|W)P(W)^{\alpha}\ e^{|W|_w\beta}\ e^{|W|_n\gamma}) \\
&= \underset{W}{\operatorname{argmax}}\ \log P(X|W) + \alpha \log P(W) + |W|_w\beta + |W|_n\gamma
\end{aligned}$$

The parameter α is the scaling factor between the language model and the acoustic model, β is the word penalty, γ is a noise penalty which is used instead of the language model score for the non-word acoustic events, $|W|_w$ is the total number of words in the word sequence W and $|W|_n$ is the number of non-word acoustic events which are ignored by the language model [OTI98].

2.3 Related Work

Neural networks have been used in many different forms in ASR in the past 30+ years. Although the late 90s saw them almost uniformly replaced with GMM based ASR systems, in the last decade they have returned to prominence and can be found in the front-end, AM and LM. Especially their use of DNNs with layer wise pretraining as acoustic models AM has lead to a significant improvement in ASR systems.

In many ways this thesis can be seen as a continuation and an extension of the time-delay neural network (TDNN) [WHH$^+$89]. TDNNs are designed to be time invariant and work on sequences of feature vectors. As well as the current feature vector x_t the neurons of the first hidden layer are also connected to a few of the preceding feature vectors $x_{t-1}x_{t-2}, ...$ The *time-delay* procedure is applied at the transition from the first hidden layer to the second hidden layer. The neurons of the second hidden layer also possess connections to the first hidden layer's outputs at the preceding steps.

A second similarity is the TDNN's modular design. Sawai et. all [SMM$^+$91] show how individual TDNN modules can be joined into a *large phonemic TDNN*. They used

9 TDNN modules: 6 consonant class modules, an intra-class module, a silence module and a vowel module. The outputs of the 2nd hidden layers of each of the modules are joined, together with a span of their preceding outputs in a 3rd hidden layer. The final output layer contains 24 neurons, one for each of the 24 phonemes. For continuous speech recognition the output layer is used in an LR parser [Tom85].

TDNNs were also used to demonstrate the effectiveness of training, combining separately trained modules. Each TDNN module can be trained to discriminate between phonemes with small phonetic classes (e.g. voiced stops: B, D & G). Waibel et al. [WHH+87a, WHH+87b] show that two small and easy to train 3-phoneme TDNNs modules can be combined by training a joint second hidden layer while keeping the weights of both modules' first hidden layer constant. They also tried two dimensional shift invariance by sharing along the frequency axis as well as the time axis. Further, combining pre-trained modular networks allows for a faster training time than a normal 6-phoneme TDNN without any degradation in performance [Wai89].

Le Cun [LB95] applied 2-dimensianl time delay networks to images and coined the term CNN. In recent years this approach has been reapplied to speech recognition by again considering the time and frequency to be the two dimensions [SMKR13]. This results again in impressive improvements of 6% to 11% compared to a baseline DNN.

TDNNs address the time dependent nature of speech by incorporating the past outputs of each layer into the inputs of the next layer. An alternative approach to the problem is the use of recurrent neural networks (RNN) which, unlike feed forward neural networks, can contain loops. The input of at least one of an RNN's layers will depend upon its output at a previous time step. In order to still be able to train such networks using backpropagation they can be unrolled through time and trained using weight sharing. This setup is called backpropagation through time (BPTT) [Moz89]. A common RNN variant used in many ASR applications is the long short-term memory (LSTM) [HS97] which addresses the RNNs vanishing gradient problems.

An early application of RNNs to ASR used them to eastimate the emission probabilities in an HMM [Rob94, RHR94]. They trained an RNN with a single layer to predict the probabilities of each phone class. Through their recurrent nature RNNs are aware of the preceding context but unaware of the future context. The authors compensate for this by delaying the output by 4 frames and training separate backwards RNNs on the reversed data. The phone probabilities of both the forward and backward

models are weighted equally and interpolated. This combination of output probabilities can be extended by further RNNs trained on different input features.

A recurrent neural network is used by Plahl et. al to directly combine three different feature streams [PKSN13]. The features are stacked and used as the input to a shallow RNN which is trained to classify the phone targets. In a 2nd step the output layer of the RNN is augmented by its input features, stacked in a window of up to 9 frames and used as the input to a shallow MLP which is also trained to classify phone targets. A GMM-AM is then trained using the output of this MLP.

Both this RNN feature extraction setup and the RNN phone probability estimater rely on having prior knowledge of the sequence labels as states in the HMM. This is lost when an RNN is used to replace the HMM and trained to directly convert a sequence of feature vectors to a sequence of phonemes. In [GFGS06] Graves et al. introduce a method of learning such networks called *connectionist temporal classification*. At each time step the RNN produces a probability distribution over its possible output symbols $P(p|t)$, the language's phonemes and null symbol. Given the input feature vectors of a whole utterance it can generate a probability distribution over all possible phoneme sequences $P(\mathbf{p}|x)$ by summing up the probability of x generating each phoneme sequence or *path*. A sequence of symbols becomes a path after removing subsequent multiple activations of the same symbol and all null symbols. The error function is the log-probability $P(z|x)$ of the RNN producing target phoneme sequences provide by the training data. Using a LSTM-RNN this setup is able to outperform HMM based systems on the phoneme recognition test set TIMIT [GJ14]. In [HCC$^+$14] an RNN based ASR system is presented that outperforms many tradional HMM based system. That paper, however, also clearly demonstrates the current limitations of this approach. In order to compete with state of the are DNNs and CNNs trained on 300hours of data they have to train their RNN on over 2000 hours of data.

Chapter 3

Speech Recognition Tasks

This chapter introduces the datasets on which the approaches presented in the following chapters are trained and tested. Speech recognition systems can be used in a variety of different application scenarios. Although the main focus of this thesis is on the offline recognition of recorded speech like podcasts, the possible application of the developed methods to an online low latency speech recognition task is also investigated. All offline tests are performed on development sets from both the Quaero project and the IWSLT evaluation campaign.

3.1 Quaero

Quaero[1] was a French lead research project running from 2008 to 2013 with German participation. During the project multimedia and multilingual indexing and management tools were developed for automatic analysis, classification, extraction, and exploitation of information. Within the project, work was performed on *search engines for multimedia*, *professional audiovisual asset management*, *personalized video selection and distribution*, *enhancing access services to audiovisual content* [SKK12a] and *digitalization and enrichment of library content*. Basic research organized into the *Core Technology Cluster* (CTC), was performed to supply the target applications with the necessary underlying technologies such as speech recognition.

During the project six evaluations of the participating speech recognition partners were performed from 2008 to 2013. The evaluation sets were typically reused as the

[1] Quaero: http://www.quaero.org

development set for the following year's evaluation which is why the Quaero 2011 development set is referred to as the Quaero 2010 evaluation set (or eval2010) in this thesis.

3.2 International Workshop on Spoken Language Translation (IWSLT)

The International Workshop on Spoken Language Translation (IWSLT)[1] is a workshop that organizes a yearly evaluation campaign on spoken language translation [CNS+13]. In recent years it has focused on the transcription and translation of TED and TEDx talks and operates tracks on machine translation (MT), spoken language translation (SLT) and automatic speech recognition.

TED[2] which stands for *Technology, Entertainment, Design* is a recurring conference where speakers give short 5-20min talks, called TED talks, on a plethora of different topics in English. Due to the prestigious nature of the event the speakers are generally very well prepared and the event is recorded in a very high quality. TEDx conferences are events set up in the same manner as a TED conference but independently organized. TEDx talks and recordings may not necessarily be of the same quality as normal TED talks but the independent organizers can choose to allow the talk in languages other than English like German. TED also hosts the *Open Translation Project* which allows volunteers to help transcribe and translate TED and TEDx talks.

3.3 Lecture Translation

In 2011 the Karlsruhe Institute of Technology became the first university to install an online low-latency lecture translation system [CFH+13]. In 2012 the system began operation in 3 lecture halls and provides students with a textual translation of the lecture to their laptops, tablets or smart phones via a website with a delay that is typically only a few seconds long. Its goal is to help foreign students, who are attending German lectures, to follow the lecture even if they still lack the required level of German proficiency.

[1] IWSLT: http://workshop2014.iwslt.org/
[2] http://www.ted.com/

It is set up in a distributed manner with the only requirements for the lecture hall being internet access, a microphone for the lecturer and a small laptop or pc that streams the audio to a mediator. The mediator then coordinates individual workers that perform the subtasks such as ASR, punctuation prediction and sentence segmentation and MT. The resulting translation is displayed on a website next to the ASR output after it has been post processed by a punctuation prediction component.

3.4 Test Sets

During the course of this thesis experiments were performed on multiple test sets and the techniques developed were also applied to other languages besides German. Most experiments, however, were performed on either the Quaero 2010 evaluation set or the IWSLT 2012 development set. In many cases the experiments were performed on both sets to demonstrate that results of the presented systems are generalizable.

3.4.1 Quaero Test set (eval2010)

The German 2010 Quaero evaluation set [SKK12a] contains 3 hours and 34 minutes of broadcast news (5 files) and conversational speech (6 files). It was collected between the 19th and 26th of March 2010 from NDR, HeuteNews, Tagesschau and SWR2 and contains 135 speakers. 88 of them are male and 45 female. The reference transcriptions contain 32231 words. The results of the systems are measured using WER and reported with an accuracy of two decimal places.

3.4.2 IWSLT TED Test set (dev2012)

With a reference length of 17913 words and a runtime of 2 hours the German IWSLT 2012 development set is a bit smaller then the Quaero test set. It consists of 7 German TEDx talks by 7 separate speakers. The IWSLT evaluation campaign imposes restrictions on the text data that can be used for build language models and only allows sources explicitly listed on the webpage of the evaluation campaign. The relatively small size of the IWSLT 2012 development set means that providing WER with any more accuracy than one decimal place would not be useful because changes there would not have a high likelihood of being significant. With the exception of the initial experiments on shallow BNFs all design decisions were made using test set.

3.5 Training Data

The acoustic and language models trained in this system use data from numerous different sources. This section sheds some light on what data sets exist and where they stem from.

3.5.1 Audio

Well transcribed audio data is hard to come by, especially if it one wishes it to be in a particular domain and language. In order to gather training data for the KIT lecture translation system a large corpus of lectures was gathered in-house, transcribed and translated. In total, 197 hours and 26 minutes of lectures given by 44 lecturers were recorded and 86 hours and 21 minutes of them were transcribed. Most lecturers were male and the majority (185h) of the recorded data stemmed from computer science lectures. While over 110 hours of CS data remained untranscribed only 35 minutes of non-CS data was not transcribed.[SKM+12]. The final transcriptions contained 831k words of which 712k were from CS lectures.

During the course of the Quaero project, audio files collected from publicly available sources, and their transcripts were released in yearly batches. The Quaero project used two types of transcriptions, detailed and quick. Quick transcriptions were automatically preprocessed and segmented into estimated speaker turns which the transcriber did not have to correct while transcribing the audio. Detailed transcriptions on the other hand are correctly segmented into speaker turns and, unlike the quick transcripts, have annotated noises. The whole corpus contains 214 hours of data (detailed: 130:20h / quick 83:45h).

Most of the collected data is in the form of broadcast conversations where multiple people are talking with each person being individually recorded. Talk shows and podcasts are often in this format. A small amount of broadcast news data (*Tagesthemen*, *Tagesschau* and *Heute Journal*) as well as some recordings from the European parliament's plenary sessions are also included. The broadcast conversation data was collected from *NDR*, *SWR2*, *ARD*, *ZDF*, *Radio Eins*, *Dradio* and *SR3*.

A further corpus contains 18 hours and 35 minutes of broadcast news collected from the news program *Tagesschau* prior to 2008.

The Landtag (parliament) of the German state Baden-Württemberg has publicly available transcripts and recordings of their plenary sessions. As well as lacking timestamps the transcripts are also often heavily edited and therefore sometimes only roughly match the recordings. Of the over 400 hours of recordings just over 123 hours of well aligned segments were extracted.

This thesis uses the following collections (databases) of corpora:

- *Lecture DB:* Contains only the lecture corpus.
- *Quaero partial DB:* Contains all the Quaero data released prior to 2012 and the Tagesschau corpus (197:09h).
- *Quaero DB:* Only contains the full Quaero data (214 hours). The Tagesschau corpus is no longer included.
- *Quaero extended DB:* Consists of all the Quaero data released prior to 2012, the Tagesschau corpus and the Landtag corpus (320:09 h)

3.5.2 Text

Although some text corporas, such as those provided by the WMT, are available in a format and encoding that allows them to be used to train an LM most them require some form of preprocessing. Text from websites is generally the hardest to extract clean text from because it may still contain HTML tags, encoding is often incorrect or inconsistent and it sometimes contains English text instead of German. The complete cleaning setup involves:

- **Encoding Normalization:** Large corpora often contain data from different sources with possibly different encodings (e.g utf-8, ISO 8859-1, HTML entities, ...). This can sometimes also be seen on websites where a user can contribute text. It is, therefore, important to perform encoding checking and normalization at the paragraph level and not at the document level. Even then, texts can sometimes be seriously messed up. Sometimes uft-8 encoded files are opened as if their contents were ascii and then converted from ascii to utf-8 and saved again resulting in words like f\xc3\x83\xc2\xBcr (für) Gr\xc3\x83\xc2\xB6\xc3\x83\xc2\x9fer (Größer). Common encoding errors like these can be fixed using a lookup table.

- **Character Normalization:** Sometimes encodings allow for multiple representations of a single character. In utf-8 an *ä*, for example, can either be its own unique letter or it could be the letter *a* with a modifier. A consistent normalization has to be chosen to allow for string comparisons. Punctuation marks almost always require normalization as there are many different types of quotes, dashes etc. It helps to have a predetermined set of punctuation marks and all other punctuation marks are either mapped to one from that set or removed.
- **Identify and remove junk:** If the correct encodings can't be found, the data we are trying to process isn't text, or if it is text but unsuitable for language modeling (e.g. football result, code snippets, ...) then it should be removed.
- **Sentence segmentation:** Language model toolkits generally require one sentence per line. [Koe05]
- **Number normalization:** Text sources tend to have numbers represented using digits which are pronounced differently depending upon what they represent: dates, times, cardinal numbers, etc. This step replaced the digits with their context dependent written form.
- **Word normalization:** acronyms, initialisms, words with hyphens and words with multiple spellings also have to be normalized to a consistent token. Common spelling mistakes can also be corrected.

In most cases preprocessing a raw text source will reduce the number of tokens. Only a fraction of the token in a raw dump of a websites, for example, will turn out to be usable. Some steps like number normalization or word normalization may increase the total number of tokens by replacing a single token like UN with multiple tokens like U. N..

The text corpora used in this thesis originate from many different sources. A full list can be found in Table 3.1 including the raw word counts of the text corpora, their sizes after cleaning and the dates when the original texts included in the corpora were first published. The most notable corpora are:

- **A query based webdump:** This webdump was originally performed in order to collect data for a language model used in human robot interaction[1]. From the

[1]SFB 588 Humanoid Robots: http://www.sfb588.uni-karlsruhe.de

small amount of existing in-domain data 30k short phrases were extracted and used as search terms in an online search engine[1]. The websites in the top search results were downloaded and cleaned.

- **ODP Crawl:** The *Open Directory Project*[2] is a collection of over 4 Million links which have been sorted into over 1 Million relevant categories by human editors and has a hierarchical structure. Volunteer editors extend and maintain the directory. The raw data of the ODP can be downloaded as a large XML file. This corpus contains all the German websites linked to by the ODP in March of 2009. [Kil09]

- **Baden-Württemberg Landtag transcripts:** The state of Baden-Württemberg is the 3rd largest in Germany and this corpus contains the transcripts from the plenary discussions of their state parliament in Stuttgart from the 12th, 13th and the first half of the 14th legislative periods[3].

- **GeneralNews:** An old collection of German news articles first published prior to the 10th of September 1998 from the German Associated Press[4], Agence France-Presse[5], Deutsche Presse-Agentur[6], Frankfurter Allgemeine Zeitung[7] and the Süddeutsche Zeitung[8].

- **LM data from the Quaero project:** Over the course of the Quaero project a large amount a language modeling data was collected mostly from news websites and blogs and then released in multiple stages [LCD+11]. The sources are Zeit Online, Aachener Nachrichten[9], Overblog[10], Bild[11], Nordkurier[12], Spiegel[13],

[1] Google: https://www.google.com
[2] ODP http://www.dmoz.org
[3] BW Landtag: https://www.landtag-bw.de/cms/home/dokumente/plenarprotokolle.html
[4] Acquired by the ddp in 2009 and now operates as the DAPD - Deutscher Auslands-Depeschendienst: https://www.dapd.de/
[5] AFP: https://www.afp.com/
[6] DPA: http://www.dpa.de/
[7] Frankfurter Allgemeine Zeitung: http://www.faz.net/
[8] Süddeutsche Zeitung: http://www.sueddeutsche.de/
[9] Aachener Nachrichten: http://www.aachener-nachrichten.de/
[10] Overblog: https://de.over-blog.com/
[11] Bild: http://www.bild.de/
[12] http://www.nordkurier.de/
[13] Welt: http://www.spiegel.de/

TAZ[1] and Welt[2], many of which were released together as a single corpus, labeled *Various News Websites* in the table.

- **AM data transcripts:** Although very small, the transcripts of the acoustic model training data can be very useful for multiple reasons. Unlike webdumps or newspaper articles it contains actual spoken data and is therefore relevant for LM in ASR systems. The AM training data is often collected in the domain we wish our system to be deployed so it may also be in domain data. This is especially the case for the Quaero task.

- **WMT Data:** The workshop on statistical machine translation organises a yearly evaluation campaign on statistical machine translation and provide both parallel and monolingual data[3].

- **European Language Newspaper Text:** A corpus containing German newspaper articles published by AFP, AP and DP prior to 1995. [GF94]

- **German Political Speeches Corpus:** A corpus of the speeches made by the German presidents from 1984 to 2011 and by the German chancellors from 1998 to 2011. [Bar12]

- **Google Web and Book ngrams:** Unlike the other corpora, the Google web[4] and book[5] ngrams are not provided as raw text but instead as ngram counts.

[1] TAZ: http://www.taz.de/
[2] Welt: http://www.welt.de/
[3] http://www.statmt.org/wmt14/translation-task.html
[4] Google Web 1T 5-gram, 10 European Languages: https://catalog.ldc.upenn.edu/LDC2009T25
[5] Google Books Ngrams: http://storage.googleapis.com/books/ngrams/books/datasetsv2.html

Source Name	from	raw tokens	cleaned tokens
A query based webdump	2008	343.4M	360.1M
ODP Crawl	2008	120.7M	116.9M
Uni Karlsruhe Webpage Crawl	2007-05-25	-	1.4M
Meeting transcriptions	<2005	-	77.4k
KogSys Lecture Notes	2007	-	63.2k
Presentation transcripts	2007	-	13.1k
European Parliament Plenary Session (EPPS)	1996-05-15 to 2003-09-03	27.9M	24.3M
Baden-Württemberg Landtag transcripts	1996 to 2009	16.2M	14.1M
GermNews	1996-11-19 to 2000-01-31	0.92M	0.86M
GeneralNews	<1998-09-10	-	108.1M
Aachener Nachrichten Online	<2010	307.2M	84.0M
Zeit Online	<2000	332.2M	134.0M
Zeit Online	2000 - 2009	354.7M	177.6M
Over-Blog	2007 - 2009	265.6M	135.2M
Zeit Online Forum	2007 - 2009	132.1M	63.7M
Various News Websites	2009-05-11 to 2010-02-28	570.1M	148.8M
Zeit Online	2010	7.6M	7.6M
Aachener Nachrichten Online	2010	18.3M	18.3M
Various News Websites	2010-02-28 to 2010-02-31	40.6M	40.7M
Various News Websites	2011	112.3M	106M
AM data transcripts	<2012	-	1.8M
NewsCrawl (WMT)	2007 - 2013	-	1427.2M
CommonCrawl (WMT)	<2013	-	48.6M
News Commentary (WMT)	<2014	-	4.5M
EuroParl (WMT) [Koe05]	1996-2011	-	47.7M
MultiUN Corpus	2000-2010	5.9M	5.8M
European Language Newspaper Text LDC95T11	<1995	105.4M	92.0M
ECI Multilingual Text LDC94T5	<1995	13.8M	13.7M
HUB5 German Transcripts LDC2003T03	1997	30.6k	19.8k
German Political Speeches Corpus	1984 - 2012	5.6M	5.5M
CALLHOME German Transcripts LDC97T15	<1997	0.23M	0.17M
IWSLT LM Data	<2014	-	2.8M
TED Transcripts Translated	<2014	-	2.6M
Google Web 1T 5-grams LDC2009T25	<2008	-	-
Google Books Ngrams	<1508-2012	-	-

Table 3.1: *List of all text sources*

3.6 Baseline System

The decoding and GMM AM training uses the *Janus Recognition Tool-kit* (JRTk) with the Ibis single pass decoding developed at Karlsruhe Institute of Technology in cooperation with Carnegie Mellon University [SMFW01].

3.6.1 Language Model and Search Vocabulary

The data usage restrictions imposed by the IWSLT campaign result in different text sources being used to train the language models for both tasks which we refer to as the QuaeroLM and the IwsltLM. A full list of which sources went into which LM is provided in appendix A. The tuning set for the QuaeroLM is derived from the acoustic model transcripts of the Quaero data from which roughly 628k words are used. The remaining acoustic model transcripts become a training source. In lieu of the Quaero audio data transcripts the IwsltLM uses the example data provided by the campaign organizers. 240k words of this data are used as the tuning set and the rest used as a training source.

Both the IwsltLM and the QuaeroLM use the same vocabulary method and the same approaches to language model building. Only their text sources and tuning sets differ and all other parameters are kept the same. Some of the larger corpora listed in table 3.1, like the NewsCrawl, are split into multiple smaller text sources based on publication year or source.

For each of these text sources a Witten-Bell smoothed unigram language model is built using the union of the text sources' vocabulary as the language models' vocabulary (global vocabulary). With the help of the maximum likelihood count estimation method described in [VW03] the best mixture weights are found for representing the tuning set's vocabulary as a weighted mixture of the sources' word counts thereby giving us a ranking of all the words in the global vocabulary by their relevance to the tuning set. The top 300k words are then used as the vocabulary.

With the selected vocabulary, a 4gram case sensitive language model with modified Kneser-Ney smoothing is built for each of the used text sources. This is done using the SRI Language Modeling Toolkit [Sto02]. The language models are then interpolated using interpolation weights estimated on the tuning set resulting in a large >10 GByte language model. Because even compressed in an easy to load binary format the language

model uses up a lot memory it is loaded into a region of shared memory which allows multiple decoder instances running on the same server to share it.

All experiments in chapter 4 and chapter 5 are performed using the subword vocabulary developed in chapter 6 but not the neural network subword language model which is the culmination of that chapter.

3.6.2 Acoustic Model

All acoustic models use left to right HMM without skip states where each of the 46 normal phonemes have three HMM states and the silence phoneme has only a single state. The initial cluster tree is built using the method described in section 2.2.2.4 with 6016 leaves.

The baseline GMM AM setup uses codebooks with 128 Gaussians per model. The CD AM is trained using multiple steps. First an LDA trained to reduce the input feature's dimension to 42 then GMM models are trained using *incremental splitting of Gaussians* (MAS) training, followed by the training of a global STC matrix and two rounds of Viterbi training [SKK12a]. All models use *vocal tract length normalization* (VTLN [ZW97]) and feature space constraint MLLR (cMLLR) [FLBG07] speaker adaptive training.

Boosted MMIE (bMMIE), an updated version of MMIE,[PKK$^+$08] where the lattice confusions with the largest phone error are given more weight (*boosted*), in order to improve the discriminative capability of the acoustic model, consistently improves all trained GMM AMs. It is, however, not included in many experiments due its high demand for computational resources. Its consistent gains allow it to be skipped when evaluting front-end features.

The JrTk [SMFW01] is extended with a DNN AM object that implements the same interface to the Ibis decoder as the existing GMM AM. A diverse range of topologies are supported by allowing their computation to be controlled by a tcl script.

3.6.3 System Combination

The outputs of multiple systems can be combined using confusion network combination (cnc) to produce a combined output with a lower error rate. The individual system's lattices are merged into a confusion network which consists of a sequence of slots containing the possible words including the null word that, according to the lattices,

could occur in that part of the utterance. At the same time the posterior probability of each word in a slot is calculated and then used to select the sequence of words that should result in the lowest word error rate [MBS00b].

3.7 Neural Network Training

Some training of shallow MLPs is preformed with a consistent [Joh04] toolkit that allows for fast network training on GPUs. Quicknet, however, can only train networks with up to 3 hidden layers. In order to train networks with more hidden layers an inhouse solution based on Theano[BBB+10] was developed. In his master thesis Jonas Gehring, explored the application of denoising autoencoders as a method of pre-training DNNs for feature extraction. Using Theano he implemented a flexible DNN training setup that included multiple forms of pretraining, various error functions, activation functions and layer types. All DNN experiments trained in chapters 4 through 6 used either this setup or a modified and extended version of this setup. Due to the novel error function and the tight integration with a lattice rescoring setup the DNNs trained in chapter 7 required their own specialized training setup, which was also based on Theano.

Pretraining was consistently performed layerwise using denoising autoencoders. A normal setup would use 2M of mini batches with a corruption of 20%, a constant learning rate and the sigmoid activation function. Because the input data to the network is mean normalized the first denoising autoencoder has to use the tanh activation function in its output layer. It still uses the sigmoid activation function in its hidden layer so that all further layers only have inputs between 0 and 1, allowing them to use the sigmoid activation function in their output layers and the CE error function. The first hidden layer has to use the MSE error function. Pretrained hidden layers can be cached and reused in experiments that only change the output layer or the total number of hidden layers. After pretraining the final layer(s) can be added, with the output layer using the softmax activation function. The full DNN is then fine-tuned using the newbob learning rate schedule.

Chapter 4

Neural Network Feature Extraction

This chapter deals with the uses of neural networks in the feature extraction process. Good features can significantly improve the performance of HMM/GMM AM based ASR systems. The origins of this approach stem from a time when HMM/GMM AMs were fast becoming the dominant approach to acoustic modeling. In 2000 Hermansky et al. [HES00] successfully used the MLP output of a context independent hybrid system as the input to a GMM based AM (Tandem approach). After an error analysis [RGE02] showed that systems using MLP features and systems using cepstral features produced different errors, attempts were undertaken to combine both features at the input level to the GMM. In [BBC+01] PCA is performed independently on both MLP and cepstral features while for [ZCM+04] performing HLDA on the cepstral features and PCA on the MLP features resulted in the best system when using MLLR speaker adaptation. Since these neural network based features are only augmenting the existing cepstral features in the input to the GMMs, techniques designed to improve GMM based systems like MLLR speaker adaptation and MMIE discriminative training can also be leveraged to improve systems using neural network features. Similar approaches have been used to clean up noisy audio signals [TW88]. This chapter starts off with a quick overview of the relevant initial front-end features from which the neural network based features will be extracted and goes on to explain how MLPs can be used to extract so called bottleneck features. Experiments on MVDR in particular show how to make the best use of bottleneck features. Further experiments show how multiple front-end

features can be combined using bottleneck features and improved with the use of deep bottleneck features.

4.1 Features for Speech Recognition

In the past, a myriad of input features have been tested in ASR, and no single feature found to be the best in all circumstances. Input features are often considered to be good if they were simple to compute, discarded irrelevant information, such as who is speaking or where they're speaking, and preserved or enhanced the distinctive properties of the speech signal. In many cases the input features were also required to be robust against distortions like echos or background noises. Many feature extraction algorithms have been inspired by the physiology of the human ear. In the outer ear an incoming sound wave is filtered and focused on the eardrum. The vibrations of which are transmitted, with the help of 3 small bones, to the fluid in the cochlea. Different frequencies of vibrations resonate in different places within the cochlea and cause the hair cells in those places to release a neurotransmitter resulting in neurons of the auditory nerve sending a signal to the brain [Kal15]. This can conceptually be thought of as analogous to a short-time Fourier transform (STFT) of the audio signal, which computes the Fourier transformation on a small window of the audio signal, often referred to as a frame. While human hearing is asynchronous, the STFT performed when extracting features for speech recognition uses a fixed window size (normally 16-32ms) and a fixed frameshift (8-40ms). Plotting the magnitude of an STFT results in a spectrogram where the Y-Axis represents the frequency and the X-axis the time.

4.1.1 Log-MEL Features (lMEL)

Also motivated by the physiology of human hearing is the mel scale developed by [SVN37]. Humans find it easier to distinguish frequency differences at lower frequencies than at higher frequencies. We can assume from this that the lower frequencies contain more speech relevant information. To emulate this a filterbank of triangular window functions is applied to each frame after performing a short-time Fourier transform. The windows are smaller and closer together at lower frequencies and larger and further apart at higher frequencies. Each window function corresponds to a coefficient in the feature vector. The final step involves taking the log of each coefficient. By taking the

logarithm we are able to transform convolutional noise of the audio signal that became multiplicative noise after the Fourier transformation into additive noise that is much easier to handle.

4.1.2 Mel Frequency Cepstral Coefficients (MFCC)

Applying an inverse Fourier transformation to the lMEL features preserves the additive nature of the originally convolutional noise in the cepstrum. Under the assumption that, while the speech signal varies, the noise is constant during an utterance, it can estimated using the average signal over the timeframe of the utterance and compensated by subtracting it from each utterance. A discrete cosine transformation is generally used instead of a the inverse Fourier transformation. Mel frequency ceptral coefficients (MFCC) have established themselves as the most common front end feature in speech recognition.

4.1.3 Minimum Variance Distortionless Response (MVDR) Spectrum

Some alternative feature extraction methods are based on linear predictive coding that aims to estimate samples as a linear combination of the preceding n samples [Her90]. Basic linear prediction tends to overemphasize the harmonic peaks seen in medium and high pitched voices. Minimum variance distortionless response [MR00] (MVDR) solves this problem and is improved by (mel)-warping the frequency axis prior to spectral estimation. This allows for more parameters in the low frequency regions of the spectrum and fewer in the high frequency regions [WM05]. In some circumstances warped Minimum Variance Distortionless Response (MVDR) features for speech recognition have been shown to be better [WMW03] than MFCC features.

4.1.4 Tonal Features

The use of pitch in languages to distinguish between words, their inflections or grammatical meaning is refereed to as tone. Pitch information is generally not considered to be very useful in speech recognition systems for non-tonal languages. Even for tonal languages like Mandarin, Cantonese, and Vietnamese, that use tones to represent phone level distinctions [Bao99] and therefore make them essential to distinguish between words, tonal features only provide a modest boost to performance

[VS09, CW95]. Modeling tones and integrating tonal features into a recognition system is challenging and often optimized to the particularities of the language the system is designed for. [CGM+97, LGL+11].

In non-tonal languages like German and English, pitch can be considered a prosodic feature along with rhythm (phoneme duration) and loudness (acoustic intensity). These are generally only useful for modeling information in speech beyond the word level such as emotion, emphasis or intonation [Pie80, Hir83]. On a word level pitch may contribute a small part to lexical stress but only a small number of word pairs exist that require lexical stress to distinguish them: for example INcline (sloped surface) vs inCLIne (tendency to do something) [Wai88].

In work performed together with Metze, Gehring and others [MSW+13a] various tonal models and methods of integrating tonal features are analyzed on both tonal and non tonal languages. That work reports, for the first time, results of using fundamental frequency variation [LHE08] features for speech recognition of tonal languages.

4.1.4.1 Pitch Features

The pitch features in this work use the approach described by Kjell Schubert in his thesis [Sch98]. The distinguishing information in many tonal languages is not so much the absolute pitch height but more its change or contour. In Mandarin, for example, the word *chūn* contains a flat tone and can be translated into English as *spring*. Simply altering the tone contour to a falling-rising tone (chǔn) changes the meaning of the word to *stupid*. Good tonal features should, therefore, detect rising, falling, or otherwise marked pitch contours.

Kjell's pitch features use dynamic programming over a cepstrogram with a window length of 32 ms to find the best pitch for each frame without exceeding certain constraints, such as the maximum pitch difference between two frames. Using the three right and left neighbours delta and double delta features are computed. Together with an optimal frame-based cross-correlation feature, this results in 8 coefficients.

4.1.4.2 Fundamental Frequency Variation (FFV) Features

Normal pitch features have problems in dealing with silent segments of speech where pitch isn't defined. FFV features, on the other hand, can handle silent segments and have been successful in tasks like speaker verification. A geometric interpretation

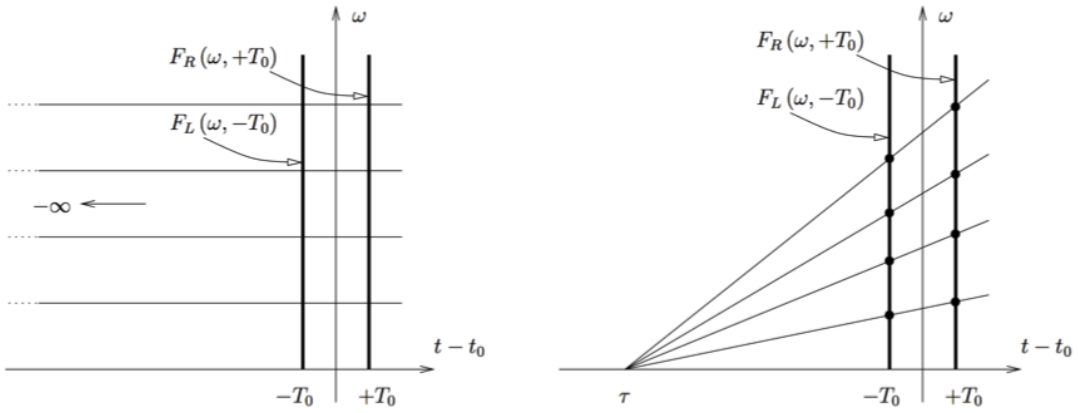


Figure 4.1: *Visualization of Fundamental Frequency Variation (FFV) features, from [LHE08]: The standard dot-product between two vectors (spectra at a distance T_0 each from a center point) is shown as an orthonormal projection onto a point at infinity (left panel), while the proposed "vanishing-point product" for a point τ generalizes to the former when $\tau \to \infty$ (right panel).* Image source: [LHE08]

of FFV features based on the *vanishing-point product* is shown is figure 4.1. For a given center point two spectra at a distance of +- T_0 are combined using a so called *vanishing-point product* that can be interpreted as a generalized dot-product. In the standard dot-product the coefficients of the vectors are multiple pair-wise, with the pair selected by an orthonormal projection to a point at infinity. The *vanishing-point product* (with vanishing point τ: $-\infty < \tau < \infty$) results in a warping of spectra vectors so that the corresponding coefficients lie on lines that intersect at the vanishing point. Varying τ from $-\infty$ to ∞ leads to the FFV spectrum.

The 7 FFV features are derived by applying a filter-bank over the FFV spectrum. A trapezoidal filter in the middle aims to capture flat or constant pitch, two trapezoidal filters slightly to the left and right target slowly changing pitch and two trapezoidal filters further to the left and right try to capture fast changing pitch information. The 5 trapezoidal filters are augmented by 2 rectangular filters at the left and right edges of the spectrum.

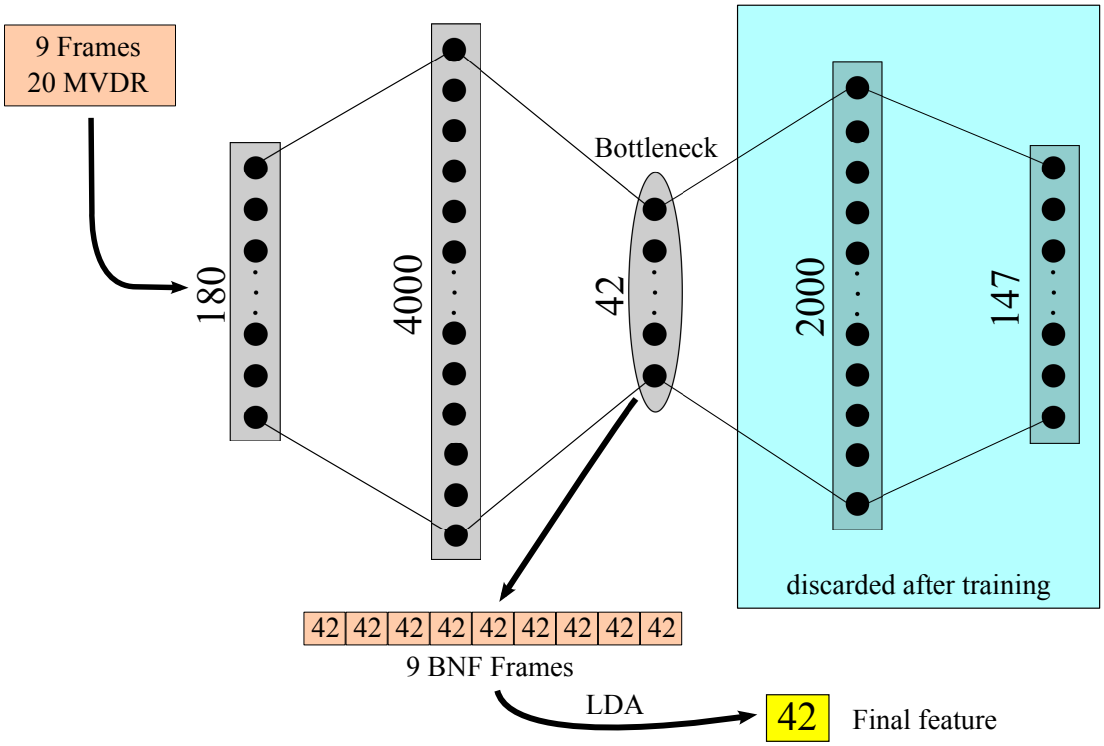


Figure 4.2: *Example MLP architecture (4kx2k): A 9 frame context window, each with 20 wMVDR coefficients is used as the input feature. The 147 node target layer (one node per subphone) and the 2k 3rd hidden layer are discarded after the MLP is trained. A 9 frame context window of the MLP output at the 42 node bottleneck layer is then used as the new 372 dim BNF feature which is reduced back to 42 using an LDA [KTNW13].*

4.2 Bottleneck Features

In MLPs the outputs of a given layer can be thought of as an alternative representation of the input feature vector. A small hidden layer in the middle of an MLP will, therefore, provide compact alternative features, with the number of coefficients being controlled by the number of neurons in the hidden layer. An example of a 5 layer MLP with a bottleneck in its middle layer is shown in figure 4.2. Bottleneck features are discriminativly trained using either context dependent or context independent subphone states as targets. For small (shallow) bottle feature networks the topology is described by listing the sizes of the hidden layers, with an x being used for the bottleneck layer. The bottleneck network in figure 4.2 is referred to as 4kx2k because it contains 4000 neurons in the first hidden layer followed by a bottleneck layer and 2000 neurons in the

final hidden layer.

4.2.1 Related Work

This 5 layer bottleneck MLP was first introduced by Greszl et al. in 2007 [GKKC07] where it was shown to outperform both an HLDA dimensionality reduction on the input features and the posterior phoneme probabilities used by the traditional tandem systems. They saw further improvements by using phone states as targets instead of phones [GF08], using a topology with twice as many neurons in the first hidden layer than in the second hidden layer and by adding delta features to their input.

Temporal Pattern (TRAP) features proposed by Hermansky [HS98] use multiple small MLPs trained on long, (up to 1s) temporal features that each correspond to a frequency band in the spectrum. The individual MLPs can then be joined in a further MLP and its output used as in the tandem system setup. In a similar setup Valente et al. [VVP+07] describe a hierarchical approach to neural feature extraction where an MLP is trained on spectral features spanning a short temporal context. Its output is then combined with spectral features spanning a long temporal context and used as the input to a further MLP. In [PSN10] this approach is extended by adding bottlenecks to both of the MLPs and is shown to be significantly better than a normal bottleneck MLP on the same features, the hierarchical setup without a bottleneck and the TRAP features.

A method of using BNFs to combine multiple feature streams proposed in [PSN11], shows that combining MFCC, PLP and gammatone features in the input layer of an MLP can lead to a system that performs better than the system combination of the lattices of the individual systems. The MLP using the combined input feature also outperforms the best single feature MLP by a small amount. In contrast to this work they, however, only look at shallow networks. Instead they focus on integrating the multiple features into a shallow RNN [PKSN13] trained to classify the phone targets.

In [YS11] bottleneck features are pretrained using stacked restricted Boltzmann machines which improve the performance of the subsequently trained MLP. An approach using denoising autoencoders instead of restricted Boltzmann machines also shows impressive reductions in WER [Geh12]. Both case's setups allow the number of hidden layers prior to the bottleneck layer to be increased and improve the quality of the BNFs.

4.3 Combining Features with a Bottleneck MLP

The initial experiments to ascertain if this approach is feasible and what sort of input contexts should be used are performed on MFCC and MVDR features using a small bottleneck network with only 3 hidden layers. The results of these experiments motivate the setup of the later experiments on combining multiple features using deep bottleneck feature networks.

4.3.1 Experimental Optimization of MFCC+MVDR-BNF Features

Intuitively one may assume that larger input vectors, derived from a larger stack on consecutive frames, should contain more information and should therefore result in better BNFs. Especially when the results of the TRAP features [HS98] are taken into consideration which show that useful information can be found in contexts up to 1s. On the flip side larger input vectors mean more parameters which can also cause problems. In this section the effects of various input feature sizes is examined on MFCC+MVDR-BNF feature networks of different topologies compared with both MVDR-BNF and MFCC-BNF features. Since feature stacking can also be performed in the LDA prior to GMM training the size of the feature stack is also scrutinized.

4.3.1.1 MLP Topology

All MLPs use a 42 node bottleneck as the 2nd hidden layer. The 2k MLPs contain a 2000 node hidden layer between the bottleneck layer and the input layer. This layer has 4000 nodes in the 4kx2k MLPs which also include a 3rd hidden layer with 2000 nodes between the bottleneck and output layers. Further increases in layer sizes decreased the MLPs performance. The ratio of 2:1 between the 1st and 3rd hidden layers is motivated by [GKKC07]. We performed pretraining on the German MLPs by training first on all available German audio data (sets 1+2) and then fine-tuning with only the in-domain data (set 1).

All audio is sampled at 16 kHz with a 16 ms window size, 10 ms frame shift and a frame size of 20 coefficients. Between 1 and 15 consecutive frames are concatenated to form the input of the MLP. To provide a comparison both an MFCC-BNF system and a MVDR-BNF system using the same parameters are trained in parallel for each

feature	topology	1 frame	3 frames	5 frames	7 frames	9 frames	11 frames	13 frames
MFCC-BNF	2k	27.87	23.95	22.86	20.51	22.86	21.92	22.08
MVDR-BNF	2k	27.02	21.26	21.98	21.58	19.92	20.33	20.49
MVDR+MFCC-BNF	2k	25.67	20.38	19.97	19.47	19.58	19.44	19.73
MFCC-BNF	4kx2k	-	-	-	18.52	18.69	18.42	18.36
MVDR-BNF	4kx2k	-	-	-	18.40	18.64	18.79	18.77
MVDR+MFCC-BNF	4kx2k	-	-	-	18.35	18.11	18.81	-

Table 4.1: *LDA test tested on the German Quaero 2010 evaluation data on inputs from 1 to 13 frames.*

MVDR+MFCC BNF system. The inputs for the MVDR+MFCC MLP are derived by concatenating the MVDR and MFCC feature vectors.

The output layer of the MLP is initially set to the number of phone states in our ASR system. This results in an MLP with an output layer containing 147 neurons, an input layer with between 20 and 300 neurons for the MVDR and MFCC MLPs and between 40 and 600 neurons for the MVDR+MFCC MLPs. Using the best context window a further MLP is trained on each input feature where instead of 139 phone states as targets 6016 context dependent phone states are used.

4.3.1.2 MLP Integration

Before the BNF features are used in the GMM acoustic model they are stacked over a short timeframe and an LDA is preformed to reduce the dimension back down to 42. The effect of different window sizes is analyzed by training systems with window sizes from 7 to 13 for the best non-pretrained BNF of each frontend. We did not include discriminative training in our standard AM training setup due its high demand for computational resources. The KIT Quaero 2012 German evaluation system included bMMIE trained models which resulted in our MFCC system improving from 20.69% to 19.90% and our MFCC-BNF system improving from 18.82% to 17.80%. Other systems showed a similar consistent improvement. This observation allows us to compare frontend performance without discriminative training.

feature	topology	9 frames	9 frames pretrained	15 frames	15 frames pretrained
MFCC-BNF	2k	22.86	-	19.83	19.98
wMVDR-BNF	2k	19.92	-	20.28	20.88
wMVDR+MFCC	2k	19.58	-	19.81	19.38
MFCC-BNF	4kx2k	18.69	18.53	18.83	18.45
wMVDR-BNF	4kx2k	18.64	18.18	18.95	18.84
wMVDR+MFCC	4kx2k	18.11	17.81	19.79	18.38

Table 4.2: *Comparison of all 3 frontends with and without pretraining on various input sizes and topologies. Tested on the German Quaero 2010 evaluation data. First published in [KTNW13]*

4.3.1.3 Sytem Training

The MLPs are trained with Quicknet [Joh04] on the *Quaero partial DB*. Using the *Quaero extended DB* which also includes the out of domain and in some cases poorly aligned Landtag corpus degraded the performance of the BNF frontend. The results of discriminately pretraining the MLPs using the *Quaero extended DB* are evaluated by performing one round of training on the *Quaero extended DB* and using the resulting network as the initial network for a second round of training with only the *Quaero partial DB*. The *Quaero partial DB* also proved to be better than the *Quaero extended DB* for training the GMM acoustic model.

4.3.1.4 Results

The analysis of the best LDA context for the BNFs is presented in table 4.1. The very small LDA context values are omitted for the larger 4kx2k networks. The optimum values vary slightly between 7 frames for the small 2k MVDR+MFCC BNF system and 15 frames for the larger 4kx2k MFCC-BNF system. The results of the larger 4kx2k networks seem to vary much less with the size of the LDA context than the smaller 2k systems. All further experiments are performed using an LDA context window of 9 frames.

Table 4.2 shows that pretraining with the *Quaero extended DB* can help improve system performance when used to pretrain the MLPs as described in section 4.3.1.1. For

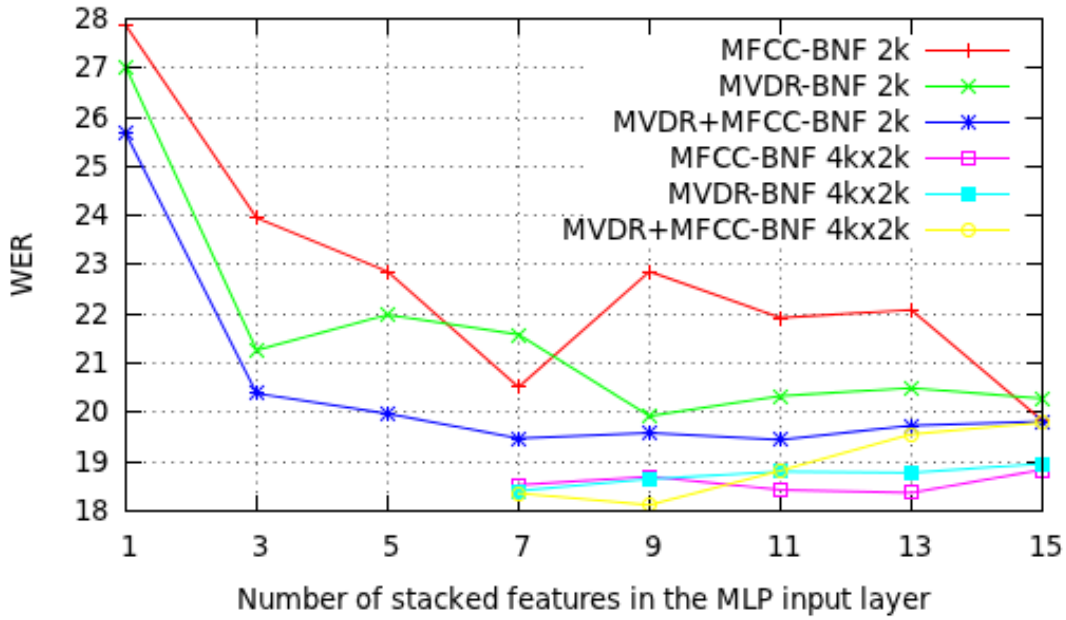


Figure 4.3: *Evaluation of the effects of different input layer dimensions for MFCC-BNF, MVDR-BNF and MVDR+MFCC-BNFs. The 4kx2k topologies were not tested with input sizes smaller than 7 stacked frames. Tested on the German Quaero 2010 evaluation set.*

the 2k setup pretraining either only slightly improves the performance or decreases the performance. The larger 4kx2k BNF are all noticeably improved by using pretraining. The 15 frame MVDR+MFCC frontend, in particular, went from being the worst 15 frame 4kx2k frontend without pretraining to being the best 15 frame 4kx2k with pretraining. In general the trend seems to be that larger MLPs benefit more from pretraining than smaller MLPs.

While the 2k BNFs are tested on context windows of 1-15, the 4kx2k BNFs are only tested on context windows of 7-15 due to the very poor results of the 2k networks on those small contexts. As can be seen in figure 4.3 the smaller context windows of 1-5 perform poorly. With the exception of the 2k-MFCC-BNF system all systems seem to perform best at or around a window size of 9 frames.

As reported in [KTNW13] the results of the single system experiments are compared to baseline MVDR and MFCC systems in table 4.3 and show that all the systems significantly outperform the baseline MFCC system. Compared to the best MFCC-BNF system our best MVDR-BNF system only decreased the WER slightly from 18.53% to

System	WER	Improvement
MFCC baseline	20.67%	-
wMVDR baseline	20.91%	-
MFCC-BNF	18.69%	9.7%
MVDR-BNF	18.64%	9.9%
MVDR+MFCC-BNF	18.11%	12.5%
pretrained MFCC-BNF	18.53%	10.4%
pretrained MVDR-BNF	18.18%	12.1%
pretrained MVDR+MFCC-BNF	17.81%	13.9%

Table 4.3: *Results of our best systems for each frontend with and without pretraining compared to baseline MFCC and MVDR systems. Tested on the German Quaero 2010 evaluation data.*

System	CI targets	CD targets
MFCC-BNF	18.53%	18.24%
MVDR-BNF	18.18%	17.68%
MVDR+MFCC-BNF	17.81%	17.36%

Table 4.4: *Results of our best systems for each frontend on both context independent target and context dependent targets. All systems used supervised pretraining. Tested on the German Quaero 2010 evaluation data.*

18.18% (2% relative) whereas our best MVDR+MFCC system was able to achieve a relative improvement of 3.9% resulting in a decrease of WER from 18.53% to 17.81%.

Further improvements can be achieved in all systems by replacing the context independent phone state target with context dependent phone state targets. This increases the size of the output layer from 139 neurons to 6016 neurons and also drastically increase the training time of the MLPs. The MFCC-BNF is improved by only 0.29% and the other two BNFs (MVDR & MVDR+MFCC) are both improved by about 0.5% absolute. An overview of these results can be seen in table 4.4.

This experimental optimization of MFCC+MVDR-BNF features shows that while MFCC and MVDR features are fundamentally similar and equally useful, they are still, to some extent, complementary and training BNFs on their union can outperform BNFs trained on either feature individually.

4.3.2 Deep Bottleneck based Feature Combination

In the previous section the effects of different sizes of inputs are analyzed on both single feature and multifeature BNF networks. This section expands on those results by increasing the number of hidden layers in the neural networks for BNF extraction and examines the effects of also integrating lMEL and tonal features. We refer to BNFs whose neural networks contain two or more hidden layers prior to the bottleneck layer as deep bottleneck features (DBNF). An example of such a network with 4 hidden layers prior to the bottleneck layer is given in Figure 4.4. The input, output and bottleneck layers remain unchanged but the number of hidden layers between the input layer and the output layer has increased from one to four. In order to avoid increasing the number of parameters too drastically the size of the hidden layers is reduced. The largest network analyzed so far uses an input feature vector of 600 followed by a 4000 neuron hidden layer, a bottleneck layer with 42 neurons, a final smaller hidden layer of 2000 neurons and a 6016 neuron output layer. Since all layers are fully connected the network contains 14 684 000 connections. Adding an extra hidden layer with 4000 neurons just prior to the bottleneck would increase the number of connections by 16 000 000 to 30 684 000, more than doubling them. By reducing the size of the hidden layers to 1200 neurons we can build a deep bottleneck network with 5 hidden layers between the input and the bottleneck that contains only 13 800 000 connections. With the exception of the bottleneck all hidden layers in a DBNF are the same size and the hidden layers prior to the bottleneck are referred to as the main hidden layers. This allows us to name the example network 5x1.2k where the 5 refers to its number of hidden layers and 1.2k refers to its size.

The experiments on DBNFs are evaluated on both the IWSLT dev2012 test set and the Quaero eval2010 test set. Although the results are reported together the tests were initially run on dev2012 and all design decisions based on those results. Only after all DBNF experiments were evaluated on dev2012 are the same models used to evaluate the eval2010 test set. The test sets are dissimilar enough so that improvements and trends that then also show up the in eval2010 can be considered real improvements and not merely test set tuning.

While the results in section 4.3 are obtained using the Quaero 2011 evaluation system the results in this section employ both the Quaero 2012 evaluation system

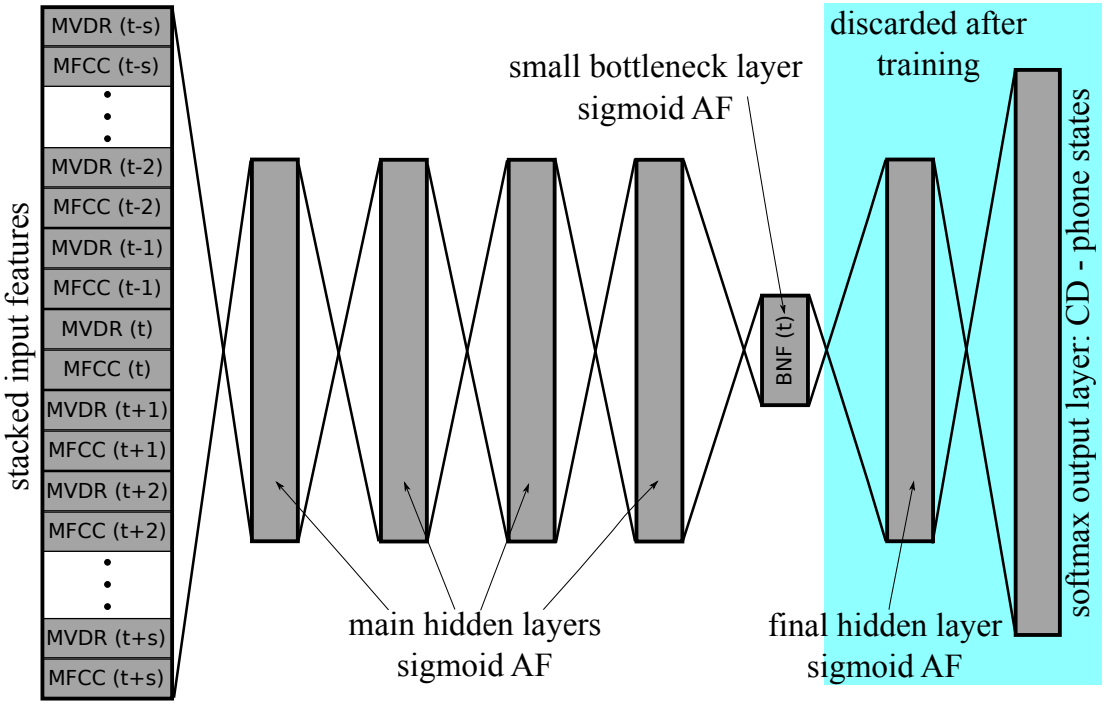


Figure 4.4: *An example DBNF with 4 hidden layers prior to the bottleneck layer*

and the IWSLT 2014 evaluation systems. The *Quaero DB* is used to train the newer systems which contain slightly more AM training data then the *Quaero partial DB* and the frame alignments are performed using using a better AM. The LM of the Quaero 2012 evaluation system contains more data sources and improves on the Quaero 2011 evaluation system's LM. The LM used in the IWSLT 2014 evaluation system is restricted to the data sources permitted by the evaluation campaign organizers. In order to compare the results of this section with the results of the previous section two MVDR+MFCC-DBNF networks with 5 main hidden layers are trained on both the old and new data.

The outcome of this experiment is given in table 4.5 and shows that changing the topology from a BNF with a single hidden layer of 4000 neurons to DBNF with an equivalent number of parameters reduces the WER on our test set by 0.80% absolute from 17.36% to 16.56%. Increasing the size of the hidden layers to 1600 neurons leads to a further WER reduction to 16.42%. Transitioning to the 2012 AM data with the new alignments and using an updated language improves the WER on the Quaero 2010

topology	AM & LM data	eval2010	dev2012
4kx2k	2011	17.36%	-
5x1.2k	2011	16.56%	-
5x1.6k	2011	16.42%	-
5x1.2k	2012	15.53%	20.6%
5x1.6k	2012	15.54%	20.3%

Table 4.5: *Comparison of the 2011 evaluation setup with the 2012 evaluation setup using a DBNF with 1200 or 1600 neurons in the hidden layer. The results on the dev2012 test set are measured with the IWSLTLM and the results on the eval2010 set are measured using the QuaeroLM.*

evaluation set by about 0.9%. While both deep topologies perform equally well on the Quaero 2010 evaluation set the larger 5x1.6k network is 0.3% ahead of 5x1.2k network on the IWSLT development set.

4.3.2.1 Deep MVDR+MFCC Bottleneck Features

As described in [YS11], adding more hidden layers can greatly improve the quality of deep neural networks. Based on the results of [YS11] and [Geh12] that show improvements in single feature BNFs this section explores the effects of applying those techniques to the proposed MVDR+MFCC BNF network. In order to find the optimum topologies for DBNFs this section examines the effects of various layer sizes and tries to determine how deep the network should be.

All networks described in this section are variations of the network depicted in figure 4.4. The smallest uses only two main hidden layers of 1200 neurons and has 9 480 000 connections. Each new hidden layer increases the number of connections proportional to the square of its size: 1 440 000 for the 1200 neuron layer, 2 560 000 for the 1600 neuron layer and 4 000 000 for 2000 neuron hidden layer. The largest network tested has 33 400 000 connections and uses six main hidden layers of 2000 neurons.

In total 15 systems are trained using DBNFs of depths ranging from 2 hidden layers to 6 hidden layers with 3 different sizes of hidden layers and tested on both the 2014 IWSLT development set and the Quaero 2010 evaluation set. In all cases pretraining is performed using the same data (*Quaero DB*) that is also used to both fine-tune the network and to train the GMM AM. After fine-tuning, the two layers following the bottleneck are discarded. The targets for all networks are the 6016 context dependent

Topology	1200		1600		2000	
	eval2010	dev2012	eval2010	dev2012		
2 hidden layers	16.0	20.8	16.0	20.4	15.9	20.7
3 hidden layers	16.0	20.7	15.8	20.4	15.5	20.4
4 hidden layers	15.7	20.6	15.8	20.6	**15.5**	**20.3**
5 hidden layers	15.5	20.6	**15.5**	**20.3**	15.5	20.5
6 hidden layers	15.7	20.8	15.5	20.8	15.5	20.8

Table 4.6: *Results of MVDR+MFCC DBNFs test with 1 to 6 hidden layers and three hidden layer sizes. Tested on both the dev2012 test and eval2010 test set.*

phone states. As a comparison a separate MFCC system is trained on the best two topologies as well as an MVDR system on the 5x1.6k topology.

The results of this experiment, presented in table 4.6, show variations in WER on both test sets of about 0.5%. Networks with only two main hidden layers perform poorer than networks with more hidden layers. Although increasing the number of hidden layers initially results in an improved performance, after reaching an optimal depth it starts to harm the network. The optimal depth is dependent on the size of the hidden layers. For networks with hidden layers containing 1200 or 1600 neurons the optimal depth is 5. The larger networks with 2000 neurons in their hidden layers reach their optimum depth sooner after only 4 hidden layers. The MFCC comparison system with 5 hidden layers containing 1600 neurons each has a WER of 15.95% on the eval2010 test set and 20.8% on the dev2012 test. The same topology using MVDR feature vectors achieved a slightly better WER of 15.84% and 20.6%. The MVDR+MFCC is significantly better than both of these systems with WERs 0.4% and 0.29% lower on the eval2010 test set and on the dev2012 test set 0.5% and 0.3% lower. Significance is at $p < 0.001$ tested using the McNemer's test of significance. Using the 4x2k topology also shows significant improvements for the MVDR+MFCC network.

4.3.2.2 Exploring Additional Features

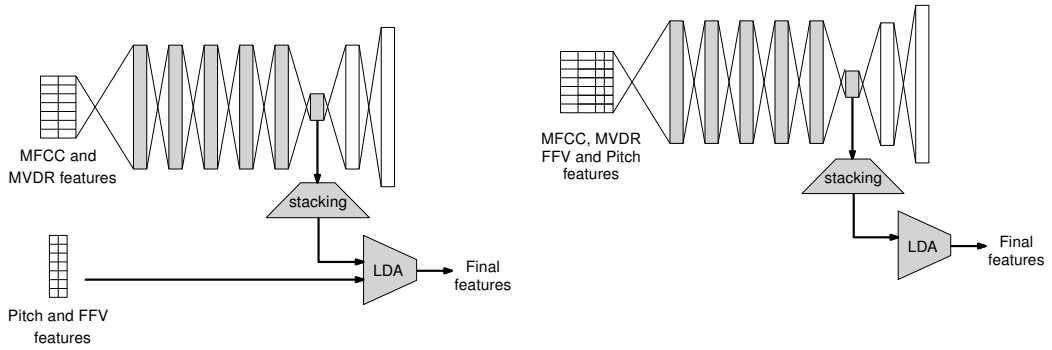
So far this chapter has shown the effectiveness of the MVDR+MFCC multifeature network. This section expands on that network by including further features in the input layer to the MLP and evaluating the gains seen after adding them. All feature combinations are trained using the best two topologies found in the previous

Topology	5x1.6k		4x2k	
	eval2010	dev2012	eval2010	dev2012
MFCC	15.95	20.8	16.07	20.7
+MVDR	15.55	20.3	15.56	20.3
+Tone	15.04	20.2	15.32	20.4
+lMEL	**14.81**	**20.1**	**14.84**	**19.9**
lMEL	15.34	20.4	15.34	20.4
+Tone	15.27	**20.1**	14.95	20.1
MVDR	15.84	20.6	-	-

Table 4.7: *Results of systematically increasing the number of different features used in as the input to MLPs of two different topologies. Results are reported on both the Quaero eval2010 test set and the IWSLT dev2012 test set.*

experiment: the 5x1.6k topology with 5 hidden layers of 1600 neurons each and the 4x2k topology with 4 hidden layers containing 2000 neurons each. The only difference to the preceding experiments are the compositions and sizes of the input features. The single feature MFCC and MVDR MLPs both have 20 coefficients and the merged MVDR+MFCC network has 40 coefficients. Adding the tonal features (7 FFVs and 7 pitch) brings it up to 54 for the MVDR+MFCC+TONE MLP. Since the lMEL feature uses 40 coefficients the lMEL+TONE MLP also has an input of 54. The final MVDR+MFCC+TONE+lMEL network containing all the features has 94 coefficients.

The first four lines in table 4.7 show that starting with MFCC based BNFs and adding more features consistently results in better systems. The only exception is the system using the MFCC+MVDR+TONE (which from now on will be abbreviated as *m2+t*) features and the *4x2k* topology which is 0.1% worse than the same setup without the tonal features test on the dev2012 test set. The exception can be considered an outlier since the same system slightly improves the eval2010 test set by 0.16% to 15.32% from 15.56% for the MVDR+MFCC system and the addition of tonal features to the 5x1.6k MVDR+MFCC system significantly ($p < 0.001$) improves both test sets. The addition of tonal features also improves all the lMEL features using all topologies and on both test sets. Further gains can be seen be using all input features with the MVDR+MFCC+TONE+lMEL (from here on referred to as *m3+t*) achieving the lowest WER rate on all 4 cases. This *m3+t* system improves the best best single feature system which uses lMEL BNF features by about 0.5% and the normal MFCC



(a) *Late integration*

(b) *Early integration as merged network input features*

Figure 4.5: *Late versus early integration of tonal features for acoustic models trained on deep bottleneck features. Source: [MSW+13a]*

BNF system by 0.7% to 1.14%.

4.3.3 Integration Level

So far all features have been integrated into the system as early as possible. The cepstral MFCC, MVDR and the tonal FFV & Pitch features could, however, be combined at different levels. In this section we compare a late integration setup using features joined just prior to being used in the GMM-AM to an early integration setup using merged features for bottleneck feature training.

4.3.3.1 Late: As Parallel Features

The parallel feature setup concatenates FFV and Pitch features with DBNFs extracted from MFCC and MVDR features and stacks them over a 9-frame context. An LDA is used to reduce the feature dimensionality to 42. This setup has the advantage that it allows us to add tonal features to an existing DBNF based ASR system by simply retraining the acoustic model, keeping the number of parameters in the GMM constant.

4.3.3.2 Early: At the MLP Feature Level

It has already been shown that training DBNFs on a concatenation of multiple ASR features can result in improvements compared to BNFs trained on any of the individual features. The merged DBNF training uses a 715-dimensional input vector consisting

of 20 MFCC and 20 MVDR coefficients joined with 7 FFVs and 8 Pitch features and stacked over a 13-frame context window. The remaining DBNF topology and training procedure is unaltered.

4.3.3.3 Integration Level Experiments

In order to ascertain how to optimally integrate the tonal features described in section 4.1.4 tests are performed on Vietnamese, a tonal language instead of one the usual German test sets.

The Vietnamese systems are trained using data released within the IARPA Babel program which consists of about 80 hours of transcribed conversational telephone speech per language. A 3-gram Kneser-Ney smoothed [CG96] language model is trained from the transcripts using the SRILM toolkit [Sto02]. The acoustic models used in this section are trained using GMMs and initialized using a flat start setup based on 6 iterations of EM-training and regeneration of training data alignments. Phonetic contexts are clustered into roughly 10 000 context-dependent quinphone states that also serve as targets for fine-tuning the DBNFs. The flat start and non-DBNF baseline systems use 13 MFCC coefficients that are stacked over 15 frames and reduced to 42-dimensional feature vectors with LDA. Tests are performed on a 2-hour subset of the official 10-hour IARPA Babel development set.

The *Baseline DBNF* systems use 20 MFCC coefficients concatenated with 20 MVDR coefficients, stacked over 13 frames. The deep bottleneck feature network consists of 5 layers containing 1,200 neurons each, followed by the bottleneck layer with 42 neurons, a further hidden layer and the final layer. Layers prior to the bottleneck are initialized with unsupervised pre-training and a stack of denoising auto-encoders [VLL+10]. Fine-tuning is performed for 15-20 epochs using the *newbob* learning rate schedule. The activations of the 42 bottleneck units are stacked over a 9 frame context window and reduced back to 42 features using LDA.

As can be seen in Table 4.8, by performing late integration, systems using parallel features improve on the baseline DBNF systems by 0.7%. Showing improvements of 2.6%, integrating the tonal features early as additional input to the DBNF network performs much better. These integration experiments clearly show that using all features as the input to a bottleneck MLP to be the best stratagy.

System	Tonal Phones
Baseline MFCC	68.9%
Tonal features	65.3%
Baseline DBNF	54.7%
Tonal DBNF (late int.)	54.0%
Tonal DBNF (early int.)	52.1%

Table 4.8: Results obtained on a Vietnamese test set in Word Error Rate (WER). [MSW+13a]

Tonal Features in Non-Tonal Languages The best tonal setup is tested two non-tonal languages, German and English, in order to examine whether or not these potentially superfluous features had a detrimental effect. Table 4.7 already shows that adding tone features actually results in significant gains in German. In an English system, a small improvement of 0.5% from 16.0% to 15.5% could be obtained with this approach. Again, all other parameters are the same for tonal and non-tonal systems.

4.4 Optimized BNF based Acoustic Model Training

Bottleneck features, especially deep bottleneck features are orders of magnitude more computationally expensive to train than traditional MFCC or MVDR features. Optimizing the training of DBNF based GMM AMs is necessary in order to not let their training time increase too much compared to MFCC GMMs and in order to allow for a rapid turnover in DBNF topology experiments. The first optimization technique makes use of the large amount of RAM available to modern HPCs.

In order to achieve an acceptable training time the steps are parallelized by splitting the training data. Interprocess communication is quite low since most steps only require a single final merging procedure. For past systems a shared network memory partition (network-attached storage (NAS)), which all nodes can access was used since this merging can only be done by a single process and all the fragmental results need to be available to that process. This method, however, leads to enormous cluster network traffic and therefore large memory access times.

The new approach uses the nodes' tmpfs, a small RAM disk partition, which can be used by all processes running on one node. Since the tmpfs is in local RAM the

Step	tmpfs	NAS (1 node)	NAS (4 nodes)
LDAs	≈ 16 min	≈ 20 min	≈ 5 min
Samples	≈ 9 min	≈ 68 min	≈ 17 min
MAS	≈ 9 min	≈ 104 min	≈ 26 min
OFS	≈ 116 min	≈ 184 min	≈ 46 min
Viterbi	≈ 54 min	≈ 80 min	≈ 20 min
total	≈ 204 min	≈ 456 min	≈ 114 min

Table 4.9: *Runtime of different training steps comparing use of tmpfs (RAM disk) and shared network memory (NAS). All training steps using tmpfs are run on a single node, training steps using NAS are run on 4 nodes. The middle column, NAS (1 node), was computed from the NAS (4 node) column in order to better demonstrate the resources saved by using tmpfs. Source: [KSM+11]*

access times are short and there is no need to send data over the network. We limit the maximal number of processes per step to the number of cores in a node. Table 4.9 compares the training time of several training steps of a non-BNF system computed on one node with 16 cores using tmpfs to their runtime using shared network memory and more nodes, with an extra column showing the hypothetical runtime of the NAS setup if only a single node is used. It can be seen that most steps are absolutely faster using tmpfs or at least relatively faster according to the number of processes. The steps performed during GMM training involve first training an LDA matrix after which samples are written in order to build the initial GMM models using *incremental splitting of Gaussians* (MAS) training, followed by the training of a global STC matrix and two rounds of Viterbi training. In total the tmpfs approach requires only about half as many cluster node minutes as the NAS approach. The presented numbers are from a time of low cluster traffic. At times of high cluster traffic the NAS approach is slowed down even more.

The second optimization directly addresses the issue raised by the botteneck features. Caching them locally in RAM for the duration of the whole training process means that their increased computational cost only has to be paid once. This, however, comes at the expense of requiring machines with a large amount of RAM. For smaller machines a compromise solution that caches them on a local disk is implemented. Table 4.10 clearly shows that the computation of the DBNF features dominates the GMM training process and that caching the features reduced the training time by a

Step	tmpfs + featCache	tmpfs
LDAs	≈ 195 min	≈ 210min
Samples	≈ 1min	≈ 209min
MAS	≈ 20 min	≈ 23 min
OFS	≈ 8 min	≈ 17 min
Viterbi	≈ 6 min	≈ 265 min
total	≈ 230 min	≈ 724

Table 4.10: *Runtime of different training steps comparing the use of tmpfs (RAM disk) with and without feature caching.*

factor of 3. The system trained uses 4 layer DBNF with MFCC features augmented by tonal features and is trained on 100h of training data using a cluster node with 64 cores and 512 GBytes of RAM.

4.5 Summary

In this chapter a DBNF setup is presented that increases in performance with each added feature. Even tonal features are shown to result in a performance gain in German, a non-tonal language. The topology and parameters for both flat and deep MVDR-MFCC MLPs are optimized. The two best topologies have 5 hidden layers with 1600 neurons each and 4 hidden layers with 2000 neurons each. Compared to a simple MFCC system which has WER of 20.81 on the eval2010 test set the best DBNF system presented here with a WER of 14.81 achieves an improvement of 6% absolute (29% relative). It also improves a MFCC DBNF by 1.14% and the best single feature DBNF by 0.53%. The multifeature DBNF is now a standard system component and used in all languages.

4.5.1 Evaluation Usage

The shallow bottleneck feature techniques from section 4.2 were used in the 2011 Quaero evaluation and contributed to the KIT German and Russian systems outperforming all other submissions. Shortly after the IWSLT 2011 evaluation the approaches were introduced to the English evaluation system which was then able to produce results better than the best submitted evaluation system [KTNW13].

Chapter 5

Neural Network Acoustic Models

This chapter examines acoustic models that use neural networks to estimate their emission probabilities. This approach was first introduced in 1993 by Bourlard [BM94] and is explained in section 2.2.2.3. Initially only phone states or a very small number of context dependent phone states could be used as targets for the neural network. In recent years, with the advent of powerful graphics processing units and NN training algorithms that make use of them [BBB+10], the number of context dependent phone states that can reasonably be used has increased to well over 10 000. The increased output layer size coupled with bigger and deeper networks trained on a lot of data has lead to impressive reductions in WER by up to 30% relative [SSS14, DYDA12, HDY+12]. The multiple feature streams, introduced in chapter 4 as inputs to DBNF networks, are applied to DNNs in this chapter and the actual DBNF networks evaluated there are reused as building blocks for a larger modular DNNs. This chapter also investigates how to train a cluster tree without using a GMM based AM and how SVD based layer initialization can be applied to DNNs.

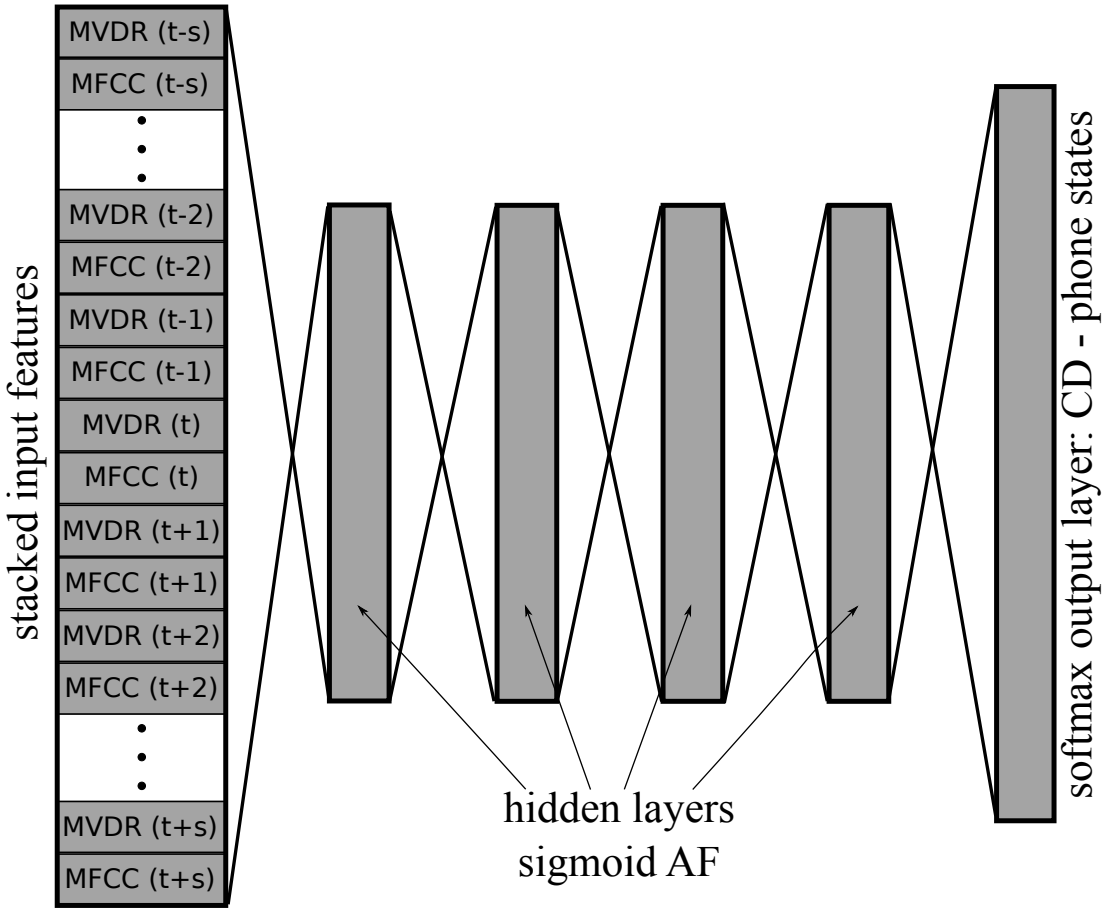


Figure 5.1: *An example of a deep neural network with 4 hidden layers and an output layer with corresponding CD phone states. Its input is a 2s+1 frame window containing both MFCC and MVDR features.*

5.1 Deep Neural Networks

A series of normal single feature DNN experiments are performed in order to ascertain the baseline performance of DNNs on our task and in order to select the best topologies for further experiments. The system used in these experiments is based on the KIT 2013 IWSLT evaluation system [KTNW13]. An example DNN AM is shown in figure 5.1. It has an input layer that uses stacked MVDR+MFCC features in a window spanning from s frames prior to the current frame to s frames after the current time frame, followed by four hidden layers that use the sigmoid activation function. The final output layer where the neurons correspond to the CD phone states uses the softmax

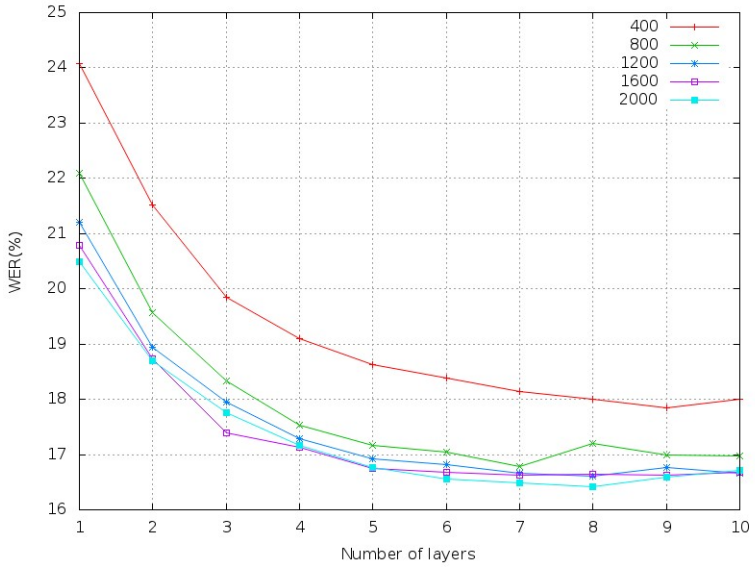


Figure 5.2: *Baseline setup. The sizes of hidden layers vary from 400 neurons to 2000 neurons. Layer depth is evaluated up to the 10th hidden layer. Image Source: [Tse]*

activation function.

For the baseline experiments the neural network acoustic models are trained using the data in the *Quaero DB* described in section 3.5. The input features consist of 13 stacked lMEL frames ($s = 6$). All layers are pretrained layer-wise as denoising autoencoders after which the final classification output layer is added and the complete network is fine-tuned. The output layer contains 6016 context dependent phone states. DNNs with hidden layer sizes varying from 400 neurons to 2000 neurons are trained for all depths up to the 10 hidden layers.

The results of this initial experiment can be seen in figure 5.2. DNNs with the same sizes of hidden layers are connected using coloured lines. An analysis of this chart leads us to the following conclusions:

- The addition of further hidden layers does not result in any noticeable improvement for DNNs with more than 5 hidden layers.

- Increasing the size of the hidden layers does not result in much improvement for DNNs with a size of more than 1200 units.

- Networks with hidden layer sizes between 1200 and 2000 neurons deteriorate when more than 8 hidden layers are used and from about 4 hidden layers only very modest gains can be seen by adding further hidden layers.

The results of the baseline experiment are consistent with similar experiments, such as by Mohamed et al. [MDH12], who also found that adding more than four hidden layers to their DNN AM does not show any significant improvement. As with the DBNF experiment the two topologies *5x1.6k* (5 hidden layer with 1600 neurons each) and *4x2k* (4 hidden layer with 2000 neurons each) are used for further experiments.

5.1.1 Multifeature DNN

This experiment mirrors the DBNF experiment in section 4.3.2.2 where multifeature DBNFs are compared. Each feature combination is trained on the *5x1.6k* topology as well as on the *4x2k* topology. Both the MVDR and MFCC features use 20 coefficients while the lMEL features have 40 coefficients and are the same size as the merged MVDR+MFCC feature vector. The addition of 14 tonal features brings the input sizes up to 54 for both the MVDR+MFCC+TONE (*m2+t*) and the lMEL+TONE (*lmel+t*) networks. The final MVDR+MFCC+TONE+lMEL (*m3+t*) MLP that contains all available features has an input of 94. All other MLP parameters are the same in the baseline experiment.

5.1.1.1 Results

As with the DBNFs, combining the MVDR and MFCC input features results in a network with a significantly ($p < 0.005$ for *5x1.6k*) lower WER than either of the individual features and is about on par with networks using the lMEL feature that have the same number of coefficients. The *5x1.6k* lMEL system is 0.06% better on the eval2010 test set but 0.2% poorer on the dev2012 test set. A pattern in the results shown in table 5.1 can be found that suggests that input features using more coefficients tend to perform better. Both *m2+t* topologies reduce the WER compared to their MVDR+MFCC equivalents on the dev2012 test set by 0.1% and on the eval2010 test set by 0.5%. The addition of tonal feature to the lMEL networks proved to be even more useful with improvements of 0.61% on eval2010 and 0.5% on dev2012 for the *5x1.6k* topology and for the *4x2k* topology *0.45%* on eval2010 and 0.4% on dev2012. The best

Topology	5x1.6k		4x2k	
	eval2010	dev2012	eval2010	dev2012
MFCC	15.88	20.3	16.17	20.5
+MVDR	15.45	19.9	15.59	20.0
+Tone	14.96	19.8	15.08	19.9
+lMEL	**14.72**	**19.5**	**14.86**	**19.4**
lMEL	15.39	20.1	15.31	20.3
+Tone	14.77	19.6	**14.86**	19.9
MVDR	15.56	20.2	-	-

Table 5.1: *Evaluation of 5x1.6k and 4x2k DNNs using various combinations of MFCC, MVDR, TONE and lMEL input features. Result presented on the IWSLT dev2012 and Quaero eval2010 test sets.*

results on the eval2010 test set are achieved by using the *5x1.6k* topology and all input features (*m3+t*) which is slightly but significantly ($p < 0.005$) better than the *5x1.6k lmel+t* DNNs. On the dev2012 test set the *4x2k m3+t* DNN has the lowest WER with *19.4%* which is a full *0.5* lower than both the *m2+t* DNN and the *lmel+t* DNN. During development only the results on the dev2012 test set were measured so the decision was made to only use the *4x2k* topology as the basis for all further experiments.

5.2 Modular DNN-AM

In this section the proposed modular deep neural network acoustic model is introduced. An early version of this approach designed for low resource languages [GLK+13] was published in 2013 and modified to make use of language resources outside of the target language [GNMW13]. The results of this section have been accted for publication at the 2015 IWSLT conference[KW15]. An example modular DNN (mDNN) AM using MVDR+MFCC features is shown in figure 5.3. Two features (MFCC & MVDR) are extracted at each frame and used as inputs to a DBNF network. In chapter 4 an investigation into the effects of various window sizes demonstrates that BNF networks using a stack of about 9-15 frames as their input perform well. Similar conclusions can be taken from the experiment looking into how the input window size to the LDA affects the resulting GMM-AM. At its heart the modular DNN-AM design aims to reproduce this double time window context. The final layers of a modular DNN-AM are same as the final layers in a normal DNN-AM. Instead of a normal input layer the

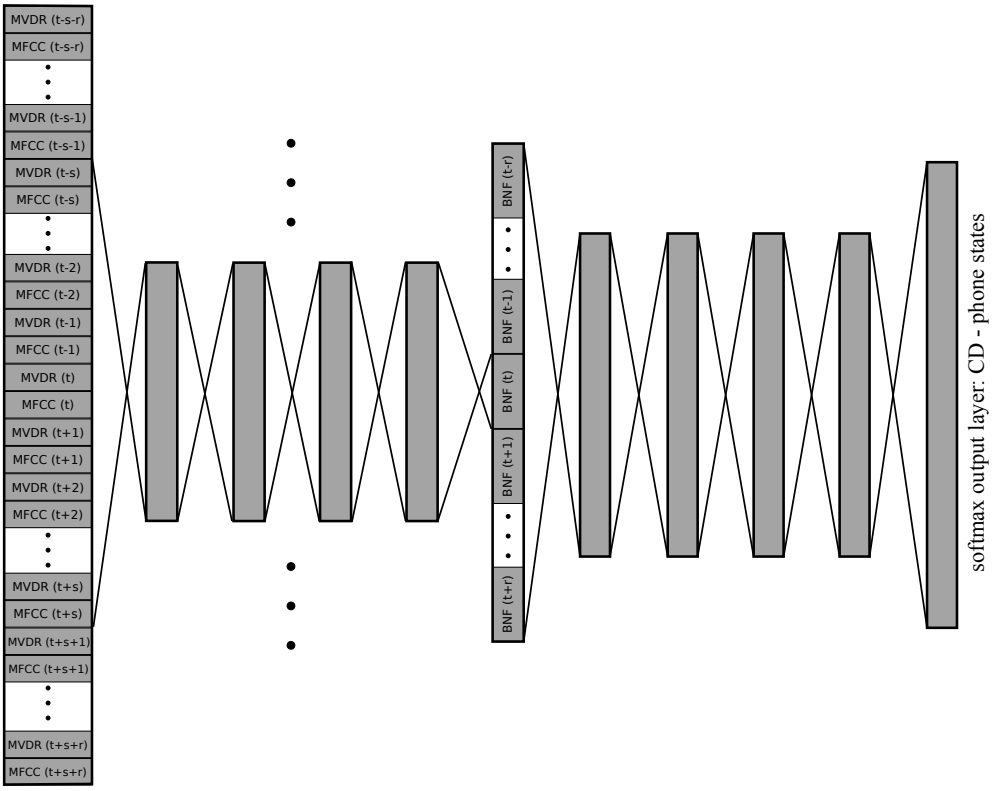


Figure 5.3: *An example mDNN with 4 hidden layers in the BNF-module and 4 hidden layers in the DNN-module. The input of the DNN-module requires* $2r + 1$ *outputs of the BNF-module at different frames. The BNF-module uses a* $2s+1$ *frame window as its input so the whole mDNN network requires* $2(s + r) + 1$ *input features which in the example are a concatenation of both MVDR and MFCC features.*

modular DNN-AM has a bottleneck layer which consists of stacked BNF frames from an already fine-tuned DBNF network. We refer to those final layers as the classification module (or DNN-module) and after integration the DBNF network is referred to as the BNF module. If the classification module has an input context of $2r+1$ (r-BNF frames before and after the current frame) and the BNF module has an input context of $2s+1$ then the total network requires an input context of $2(r + s) + 1$ frames. For the BNF frame at $t - i$ the input frames from $t - i - s$ to $t - i + s$ have to be stacked and used as the input to the BNF-module. The BNF-module is applied $2r + 1$ times to generate each of the $2r + 1$ BNF frames in the BNF layer.

During fine tuning the weights of the BNF-module are tied. Errors can be

propagated back past the BNF-layer into all applications. Weight tying allows the modular DNN-AM to continue on using a single BNF-module while it continues to learn and have its weight updated using the average update:

$$\Delta w_j = \sum_{k=1}^{2r+1} \Delta w_j^k \tag{5.1}$$

Such a single BNF-module learns to produce good BNFs that can be used in any part of a stacked BNF layer.

Although the total computation cost for a single frame is very high, the BNF frames can be cached a reused for the next frame. At frame t the DNN-module of the example mDNN in figure 5.3 requires the output of the BNF-module for $2r+1$ different inputs from $t-r$ to $t+r$. For frame $t-1$ it requires outputs from the BNF-module for the inputs from $t-1-r$ to $t-1+r$. So with the exception of the output of the BNF-module at $t+r$ all of the required outputs for frame t have already been produced and cached.

The BNF-module is simply used to convert a stream (or multiple streams) of input features into a stream of DBNF features which are then used as the input stream for the DNN-module. In an offline setting the stream of input feature vectors from an utterance forms a matrix and the BNF-module converts this matrix into a matrix where the columns are BNFs.

Because it is faster to perform a single matrix times matrix operation using a fast BLAS (Basic Linear Algebra Subprograms) library than it is to perform many vector times matrix operations, it makes sense to compute the first hidden layer for all features at the same time. So in an mDNN, if T features are extracted from the wavefile of an utterance they are first transformed into T activations of the first hidden layer of the BNF-module, then to T activations of the 2nd, 3rd and so on hidden layers and then to T bottleneck features followed by T activations of the first hidden layer of the DNN-module. After transitioning though all the hidden layers the T probability distributions over the CD phone states are all produced at the same time.

If T features are extracted from the utterance then computing the BNF at frames $t = T$ or $t = 1$ could be problematic since these frames require information about the features at $t = T + r$ or $t = -r$. To solve this, every requested feature vector prior to the first one is set to the value of the first feature and the final feature vector is used

		Best normal DNN		Modular DNN		Comparable CNC	
	Name	eval2010	dev2012	eval2010	dev2012	eval2010	dev2012
MFCC	mfcc	15.88	20.3	15.35	19.5	-	-
+MVDR	m2	15.45	19.9	14.71	19.4	15.55	20.0
+Tone	m2+t	14.96	19.8	14.54	19.3	-	-
+lMEL	m3+t	14.72	19.4	**14.31**	**18.9**	15.09	19.6
lMEL	lmel	15.31	20.1	14.72	19.5	-	-
+Tone	lmel+t	14.77	19.6	14.52	19.0	-	-
MVDR	mvdr	15.58	20.2	14.81	19.5	-	-

Table 5.2: *Results of the multifeature mDNNs compared with both normal DNN using the same input feature combinations and equivalent confusion network combinations. Tested on both the eval2010 and dev2012 test set.*

for every feature that could follow it. The same out of bounds rule is applied when the BNFs are used as an input to the DNN-module of the mDNN.

5.2.1 Multifeature Modular DNN

The mDNN topology is evaluated using the combinations of input features from the previous experiment and compared with those results. The BNF-modules used in the experiment are taken from section 4.3.2.2 where the multifeature DBNFs are evaluated. The DNN-modules are pretrained by first mapping the input features into the bottleneck feature space and performed by training and stacking denoising autoencoders. After pretraining the classification layer is added and the whole mDNN network is jointly finetuned. The input feature sizes range from 20 for the *mfcc* network features to 94 for the *m3+t* network. With r, the number of BNF frames before and after the current frame used as the input to the DNN-module, set to 7 and each BNF layer containing 42 neurons the DNN-modules input layer has 630 neuron. All mDNN networks have the same topology. Both their BNF-modules and their DNN-modules have 4 hidden layers of 2000 neurons. The whole network, therefore, has 9 hidden layers.

5.2.1.1 Results

The results of the this experiment are shown in table 5.2. As a comparison, for each input feature combination, its best result with a normal DNN regardless of the topology,

is shown in the first two columns of the table. The last column contains a comparison to a confusion network combination performed on the DNN outputs of single feature DNNs. The cnc comparison result in line two of the table is a combination of the best MVDR DNN and the best MFCC DNN and although it is slightly better than both of them it is outperformed by both the MVDR+MFCC DNN and the MVDR+MFCC mDNN. The cnc comparable to the m3+t network is a combination of the MFCC DNN, the MVDR DNN, and the *lmel+t* DNN and does not even improve on the performance of the lmel+t DNN.

For all input feature combinations the mDNN outperforms the normal DNN by 0.5% absolute or more on the dev2012 test set. On the eval2010 test set the improvements varied from an improvement of 0.25% on the lmel+t features to over 0.7% on both the MVDR and MVDR+MFCC features. The relative usefulness of features is not altered by using an mDNN. With 19.4% on dev2012 the *m3+t* DNN has 4.5% relative lower WER than the basic MFCC DNN which has a WER of 20.3 and a 3.5% lower WER than the lMEL DNN which is the best single feature DNN. In the modular case the improvements are slightly less. All single feature mDNNs have a WER on dev2012 of 19.5% and the *m3+t* network has a 3% lower WER at 18.9%. For the single feature inputs the mDNN results in improvements of 3-4% compared to the normal DNN while the multifeature inputs are only improved by 2.5-3.5%.

Using only lMEL features and inputs performs as well as using the combined MVDR+MFCC feature in both the DNN and the mDNN and on both test sets. The addition of tonal features boosts the performance of the lMEL DNN and mDNN more than the MVDR+MFCC DNN and mDNN.

In total the best multifeature mDNN reduces the WER of a basic MFCC DNN by 7% relative from 20.3% to 18.9% on the dev2012 test set and by 10% relative from 15.88% to 14.31% on the eval2010 test set. Compared to the best single feature DNN, lMEL, it still improves the dev2012 test set by 6% and the eval2010 test set by 6.5%.

5.2.2 Modular DNNs with multiple BNF-modules

The modular DNN is not restricted to a single BNF-module and can use multiple BNF-modules at the same time. Figure 5.4 shows an example mDNN with two 4 layer BNF-modules. The upper BNF-module uses MFCC features as its input and the lower BNF-module uses MVDR features as its input. Although both networks in this

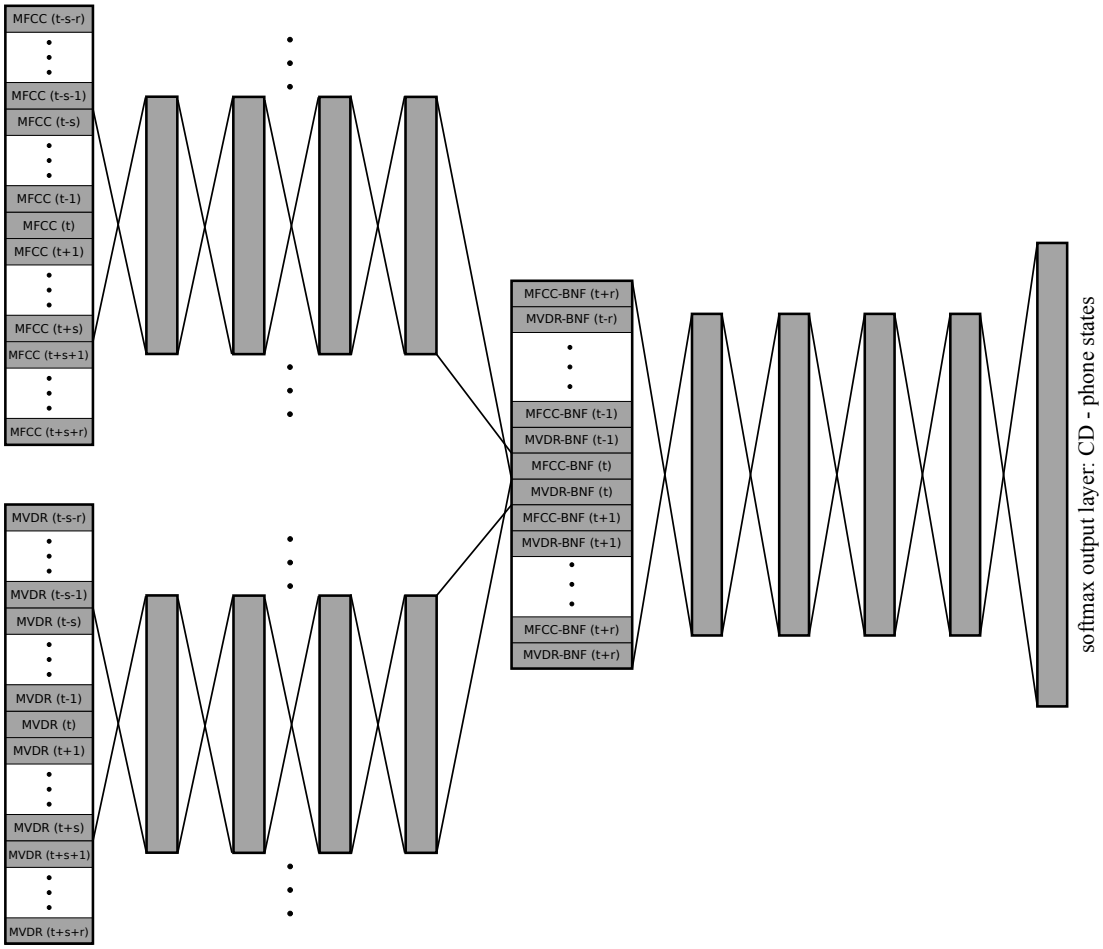


Figure 5.4: *An example mDNN with a 4 layer DNN-module built on top of two BNF-modules: a 4 layer MFCC BNF-module and a 4 layer MVDR BNF-module. The input of the DNN-module requires* $2r + 1$ *outputs of both the BNF-modules at different frames.*

example have an input window of $2s + 1$ frames they could, if it were desired, have different sized input windows and they could also have a differing number of hidden layers. The outputs of both modules' BNF layers are concatenated and stacked over a $2r + 1$ window.

The effectiveness of the mDNN with multiple BNF-modules is evaluated by training 8 mDNN with between two and seven BNF-modules. The results are compared to performing a CNC on normal DNN networks that use the same input features and the BNF-modules. The BNF-module are the same as in the multifeature mDNN experiment and can themselves contain multiple input features. After mapping the training data

		Modular DNN		Comparable CNC	
	Name	eval2010	dev2012	eval2010	dev2012
mfcc		15.35	19.5	-	-
⊕ mvdr	sys01	14.54	19.2	15.55	20.0
⊕ m2	sys03	14.73	19.3	15.44	19.9
mfcc ⊕ mvdr ⊕ lmel+t	sys02	14.24	18.7	15.09	19.6
m2+t ⊕ lmel+t	sys04	14.19	18.8	14.68	19.4
⊕ m3+t	sys08	14.06	18.7	14.45	19.2
⊕ mfcc ⊕ mvdr	sys06	14.33	18.9	14.83	19.4
⊕ m2 ⊕ lmel	sys05	14.44	18.8	14.69	19.4
m2 ⊕ lmel	sys07	14.34	19.1	15.07	19.8

Table 5.3: *Comparison of mDNNs using multiple BNF-modules with confusion network combinations of normal DNNs using the same input features. The ⊕ is used to indicate that multiple BNF-modules are combined in a single mDNN.*

into the bottleneck feature spaces of all BNF-modules used. The DNN-module is pretrained on the merged BNF features. All other training parameters are the same as in the previous experiments.

5.2.2.1 Results

In all cases the mDNN outperformed the confusion network combination of DNN systems using the same input features. The best mDNN with multiple BNF-modules m2+t ⊕ lmel+t ⊕ m3+t (⊕ is used to indicate that a combination of BNF-modules) improves the best single module mDNN by 0.2% from a WER 18.9% to 18.7% on the dev2012 test set and by 0.25% from 4.31% to 14.06% on the eval2010 test set. Using McNemar's significance test this is found to be significant at $p < 0.005$. The overview of the results given in table 5.3 begins with single BNF-module mDNN using mfcc input features that achieves a WER of 15.35% on eval2010 and 19.5% on dev2012. The next entry augments that mDNN with an MVDR BNF-module and improves dev2012 by 0.3% to 19.2% and eval by 0.81% from 15.35% to 14.54%. The further addition of the MVDR+MFCC BNF-module degraded the dev2012 test set to 19.3% and the eval2010 test set to 14.73%. In place of the MVDR+MFCC BNF-module the lmel+t BNF-module is added to the mfcc ⊕ mvdr. mDNN is then further improved to 14.24% on eval2010 and 18.7% on dev2012.

The best mDNN with two BNF-modules is the m2+t $\oplus$ lmel+t mDNN which has a WER of 14.19% on eval2010 and 18.8% on dev2012. The addition of an m3+t BNF-module improves it slightly by 0.13% to 14.06% on the eval2010 test set and by 0.1% to 18.7% on the dev2012. The further inclusion of both the MVDR BNF-module and the MFCC BNF-module slightly increases the WER on both sets. Increasing the number of BNF-modules to 7 by also including the m2 and lmel BNF-modules into the mDNN results in another slight increase in WER.

The usefulness of tonal features can be clearly seen by comparing the m2 $\oplus$ lmel mDNN to the m2+t $\oplus$ lmel+t DNN which add tonal features to the input to both of the BNF-modules. They are able to improve the dev2012 test set by 0.3% and the eval2010 test set by 0.15%.

Using an mDNN with multiple BNF-modules increases the mDNN's overall improvement compared to an MFCC-DNN by 8% relative on the dev2012 test and by 11.5% on the eval2010 test set. Compared to an lMEL DNN it reduced the WER by 7% relative from 20.1% to 18.7% on dev2012 and by 8% relative from 15.31% to 14.07%.

5.3 DNN based Clustertrees

This section examines in more detail the output layer of the DNN AM. As discussed in chapter 2 the neurons in the output layer of DNN AM each correspond to a context dependent phone state which are leaves in a cluster tree. Section 2.2.2.4 explains how a cluster tree can be used to cluster all the possible polyphones into a predetermined number of generalized polyphones. At its heart the clustering algorithm uses the weighted entropy distance defined as

$$d(A, B) = (n_A + n_B)H(A \cup B) - n_A H(B) - n_A H(B) \tag{5.2}$$

in order to compute the distance between two classes A and B and decide which question (cluster devision) to use. The entropy of a cluster

$$H(p) = \sum_{i=1}^{k} p(i) \log p(i) \tag{5.3}$$

requires a probability distribution over a feature space. The GMM based approach uses discrete mixture weights of a shared codebook of Gaussians as the feature space.

This means that a GMM AM has to be trained before a cluster tree can be built which is required in order to train a CD DNN AM. Another prerequisite to training a DNN is the alignment of feature vectors to HMM states. This is normally performed with the Viterbi algorithm and is necessary due to the fact that the training data is only aligned at an utterance level. Despite the superiority of HMM/DNN AMs most ASR systems still rely on HMM/GMM AMs to generate this alignment [MHL+14]. A solution proposed by Senior et. al. [SHBL14] shows that this does not have to be the case and demonstrates how to flat-start an HMM/DNN AM by using a randomly initialized context independent HMM/DNN AM to generate an initial alignment. However, after successfully bootstrapping a CI HMM/DNN AM they *"accumulate sufficient statistics to model each context dependent state with a diagonal covariance Gaussian"* in order to build the cluster tree. While their setup avoids the use of any HMM/GMM AMs they still train Gaussians during clustering making their setup not Gaussian free. Together with Zhu [Zhu15, ZKSW15] an alternative approach was investigated that is truly Gaussian free.

5.3.1 CI DNN based Weighted Entropy Distance

A context independent DNN that uses phone states as targets can be trained without the use of a cluster tree. If desired, the alignment can be flat-started without using a GMM system by applying either the setup of [SHBL14] or the setup described below. For each input feature the output of the CI DNN is a discrete probability distribution of the target phonestates.

The probability distribution which can be used to replace the mixture weights of a GMM is the average CI DNN output for all features extracted from the training data which correspond to that polyphone. The assumption is that similar polyphone states will also have similar average CI DNN outputs.

Therefore, entropy distance between polyphone states can be measured based on their average CI DNN outputs:

$$p_A(i) = \frac{1}{n_A} \sum_{j=1}^{n_A} P_{DNN}(s_i, F_j) \tag{5.4}$$

$P_{DNN}(s_i, F_j)$ is the probability distribution generated by the CI DNN for the feature F_j. All features F_j are examples of the polyphone cluster A. After calculating its entropy using the weighted entropy distance $d(A, B)$ between two classes it can now be computed without using any Gaussians.

5.3.2 Evaluation

The effectiveness of the proposed DNN based cluster tree is evaluated by building quinphone cluster trees of various sizes from 3k leaves to 21k leaves and comparing them to cluster trees built using the baseline GMM approach. An mDNN AM is trained with the appropriate output layer for each of the models. As can be seen in Figure 5.5 the larger cluster trees outperform the smaller cluster trees up to a size of 18k leaves. The WER reduction appears to be almost linear until about 12k leaves after which more leaves lead to less of an improvement.

The baseline GMM based approach performed slightly better than the DNN based approach for the smaller cluster trees but for the larger and better cluster trees the DNN based approach consistently outperformed the GMM based approach. Using the McNemar statistical test we compared the aligned hypothesis of both 18k systems and found the system using the DNN based cluster tree to be significantly better than the GMM based cluster tree with $p < 0.005$.

These results shows that the DNN based cluster trees are not only a simple replacement for GMM based cluster trees in situations where CI-GMM AMs are not available but can also outperform them.

5.3.3 Gaussian Free mDNN Flatstart

The previous section used alignments from a CI HMM/GMM AM to train the CI AM. In order to demonstrate the claim of truly Gaussian Free training, fresh alignments are initialized on the training data using a simple energy based speech/non-speech detection scheme. The *Quaero DB* described in section 3.5 is used for the training data and these

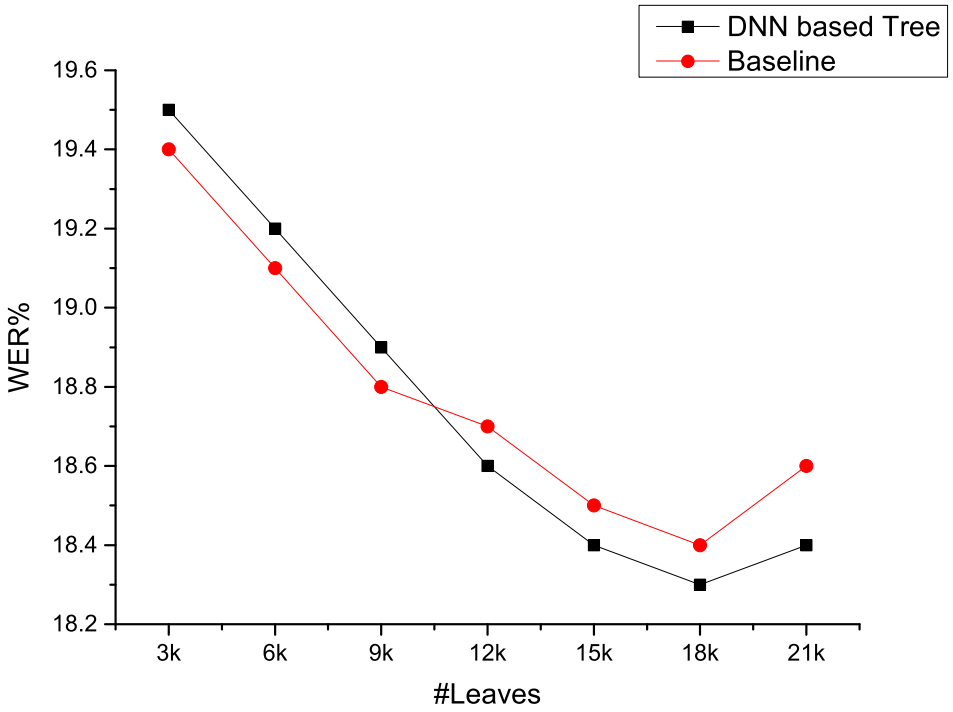


Figure 5.5: *A comparison of our DNN base cluster tree with a baseline GMM based cluster tree. We built cluster trees of various sizes between 3k leaves to 21k leaves and tested them on the IWSLT 2012 development set. Source: [Zhu15]*

initial alignments do not use the data transcripts and only classify each lmel feature vector as either speech or non-speech.

These are used to train an initial DNN with only those two targets. A CI DNN is then created by replacing the output layer with 139 neurons. Those neurons correspond to speech based phone states and use the weights going to the original speech neuron. Those corresponding to non-speech phone states such as laughter or breathing use the weights from the non-speech neuron.

The CI-DNN is used to write alignments with which a second CI-DNN is trained. It uses the first CI-DNN as the initial weights and is trained for 5 epochs at a constant learning rate without measuring the CV rate as the alignments of the CV set are also poor. After multiple iterations of CI-DNN training and alignment regeneration the CV rate is good enough to change the training procedure so that it uses the newbob

learning rate schedule and 4 more iterations are performed.

With the flatstarted CI-DNN a cluster tree is built which is then used to train a CD-mDNN system with 4 hidden layers of 1600 neurons each. This system has a WER of 20.3% on the dev2012 test set which is close to results of similar systems shown in table 5.2.

5.4 Growing a DNN with Singular Value Decomposition

Figure 5.2 shows that for a fixed training corpus the performance gains from adding new layers to a DNN taper off after a certain number of layers. For the *Quaero DB* examined in that table, NN-AMs with 5 to 8 hidden layers had roughly the same performance. Adding further hidden layers eventually started to degrade the performance.

Another problem with large DNNs is that the number of connections between the hidden layers scales with the square of their size, so two hidden layers with 2000 neurons each will have 4 million connections between them. The output layer of the DNN AM typically models context dependent phone states and can contain upwards of 18000 neurons with 36 million connections to the final hidden layer.

Section 2.1.2 explains how the transition from layer i to layer $i+1$ in a DNN can be interpreted as a the multiplication of a vector with a matrix followed by a vector addition and the element-wise application of the activation function.

$$x_{i+1} = \phi(W_{i,i+1}x_i + b_{i+1}) \tag{5.5}$$

Here x_i is the output of layer i, b_{i+1} the bias of layer $i+1$, ϕ the activation function (computed elementwise), and $W_{i,i+1}$ the weight matrix representing the connections between layers i and $i+1$.

The number of parameters that such large DNNs require can be reduced by applying singular value decomposition (SVD) to simplify the matrix multiplication step. The transition matrices $W_{i,i+1}$ can be decomposed into two smaller matrices. While [XLG13] successfully reduces the number of parameters in a DNN without degrading its performance this section shows how this decomposition can also be used to initialize new layers with their own activation functions and biases between existing layers, thereby

allowing us to grow an existing DNN while at the same time possibly also reducing the number of parameters.

The approach presented in the section was developed together with I. Iseyzer and first published in [Tse].

5.4.1 Singular Value Decomposition based Layer Initialization

SVD is a factorization method for matrices. An $m \times n$ matrix A can be decomposed as:

$$A_{m\times n} = U_{m\times n}\Sigma_{m\times n}V^T_{n\times n}, \tag{5.6}$$

where U is a unitary matrix, which is a matrix that when multiplied by its conjugate transposed results in the identity matrix. Σ is a diagonal matrix. V^T is the conjugate transpose of another unitary matrix V. A can be approximated by A_k by setting all but the highest k singular values in Σ to zeros. The row and columns in u and V^T that are now ignored can be removed and V^T combined with Σ to form W ($W_{k\times n} = \Sigma_{k\times k}V^T_{k\times n}$)

$$A_k = U_{m\times k}\Sigma_{k\times k}V^T_{k\times n} \tag{5.7}$$

$$A_{m\times n} = U_{m\times k}W_{k\times n}. \tag{5.8}$$

Now let $A_{m\times n}$ be the weight matrix connecting layers i (containing m neurons) and j (containing n neurons). After applying SVD to matrix $A_{m\times n}$, we have two matrices of a smaller size $U_{m\times k}$ and $W_{k\times n}$, which we can interpret as a new layer containing k neurons with linear activation functions and without biases inserted between layers i and j. This process is illustrated in figure 5.6. Adding a nonlinear activation function and learnable biases results in it becoming a fully functional layer. The original idea of applying SVD to DNN AMs was introduced by [XLG13]. They are able to significantly reduce the number of parameters in a DNN while incurring no or negligible accuracy loss. This SVD application here expands on their approach by using it to initialize a new layer.

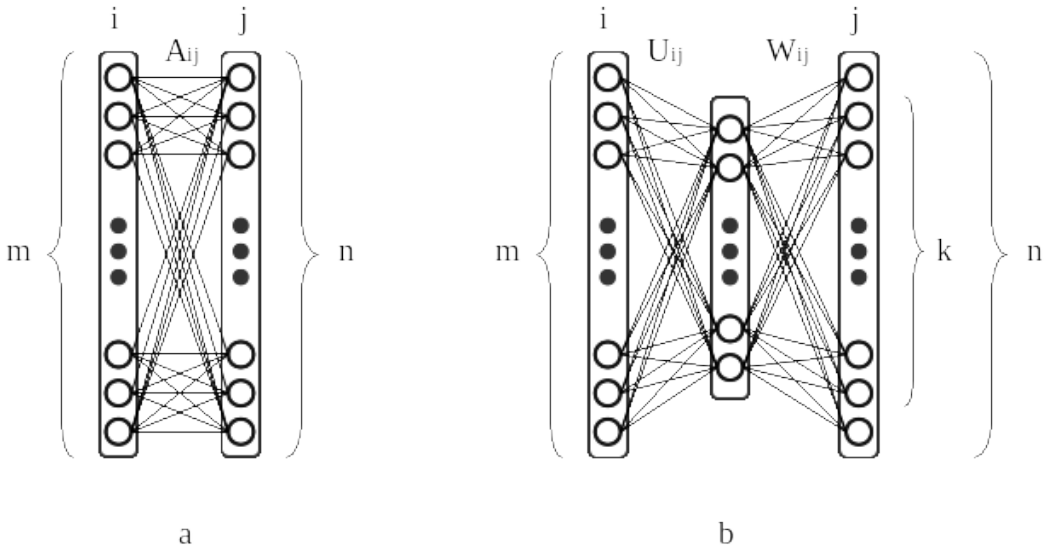


Figure 5.6: *An example application of SVD applied to the transition between two layers.* ***a****: The original transition using weight matrix* A_{ij}*.* ***b****: After SVD a new hidden layer between the two original layers is created. Image Source: [Tse]*

5.4.2 Applications of SVD based Layer Initialization

SVD based layer initialization can be used in multiple ways to improve and optimize a DNN. This section looks at the following applications of SVD to a DNN:

- *Full size layer initialization:* In its simplest form k can be set to the original layer size and new layers initialized between the existing layers. The new layers are the same size as the original layers and the number of parameters in the DNN is increased by the number of weight matrices on which SVD is performed. This application may prove to be a better initialization method for hidden layers than the basic autoencoders approach.

- *Half size layer initialization:* Setting k to $\frac{m}{2}$ where m is the size of the hidden layers does not change the number of parameters in the DNN. An $m \times m$ transition matrix in the original DNN is replaced with an $m \times \frac{m}{2}$ transition matrix to the new hidden layer and another $m \times \frac{m}{2}$ transition matrix away from it. In both cases there are m^2 weights between the original two layers. This could allow for deeper and possibly better DNNs without increasing the number of parameters.

- *Small layer initialization:* The total number parameters in the DNN can be reduced by applying SVD with $k < \frac{m}{2}$ in one or more of its layer transitions.

- *Decomposing the connections to the output layer:* The output layer has a relatively large size due to the use of CD phone states as targets. Decomposing the connections between the final hidden layer and the output layer could significantly reduce the number of connections in the whole network.

- *Insertion of a bottleneck layer:* Inserting a small hidden layer with SVD near the end of the network can transform a DNN into DBNF.

5.4.2.1 Experimental Setup

All experiments in this section are again performed on the *Quaero DB* described in section 3.5. lMEL input features are used for all DNNs. The original DNNs, prior to inserting new hidden layer with SVD, are trained using the setup described in section 5.1. After fine-tuning, one or more new hidden layers are inserted by decomposing the transition matrices. The resulting DNN is then retrained. The retraining procedure uses the same setup and parameters as the original fine-tuning. All tests are performed on the eval2010 test set. When listing the number of parameters in a DNN any biases present are neglected as they only grow linearly with the number of neurons while the transition weights grow quadratically and therefore make up most of the weights in a DNN.

5.4.2.2 Full Size Layer Initialization

This application is tested by applying SVD restructuring with $k = m$ to the transitions between the hidden layers in a DNN with 5 hidden layers of 1200 neurons each. A new DNN with 9 hidden layers consisting of 1200 neurons each is created. The original network contains 13.18M parameters and the new network contains 18.67M parameters. A separate DNN with 9 hidden layers initialize using the normal layerwise pretraining setup is trained as a comparison. The SVD initialized network reduces the WER by 3.1% from 16.92% to 16.39% compared to the original network and by 2.2% in comparison to the network with the same topology.

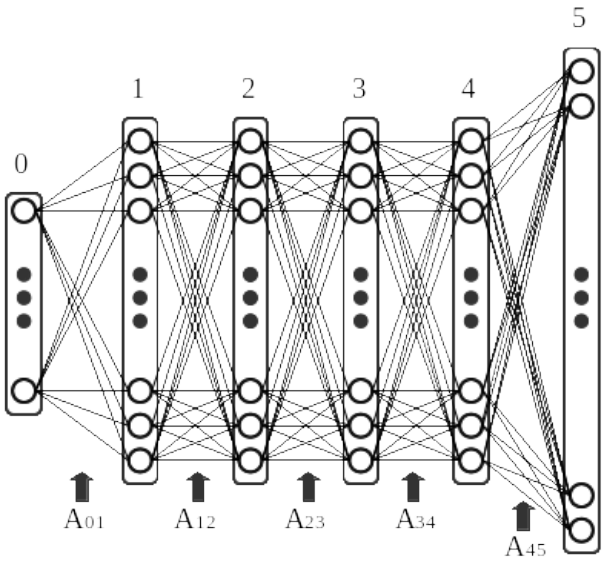


Figure 5.7: *Neural network before applying SVD. Image source: [Tse]*

5.4.2.3 Half Size Layer Initialization

Figure 5.7) shows an example DNN with 4 hidden layers that was restructured in figure 5.8 using SVD to add 3 new layers between the existing hidden layers. The resulting neural network has more layers but the number of connections remains the same. This procedure is performed on 3 different baseline topologies that had either 4 (4x1.2k) or 5 (5x1.2k) hidden layers with 1200 neurons or 4 hidden layers with 2000 neurons (4x2k). In each case all the transitions between hidden layers are decomposed and new hidden layers inserted, 3 for the 4x1.2k and 4x2k DNNs and 4 for the 5x1.2k DNN resulting in networks with either 7 hidden layers (7x1.2k/0.6k and 7x2k/1k) or 9 hidden layers (9x1.2k/0.6k). The restructured DNNs are compared to DNNs of the same depth but without reduced layers. The 9x2k/1k restructured DNN is also compared to a normal DNN of the same topology that is only pretrained and finetuned.

Applying SVD to the 4x1.2k DNN reduces its WER by 4% relative from 17.29% to 16.60% which is comparable to the normal DNN with the same number of hidden layers. The SVD restructured DNN has 11.80M parameters, 25.9% fewer than the 15.93M parameters of the normal 7 layer DNN (see table 5.4). Both the 4x2k and 5x1.2k DNN are also improved by 4% relative through the application of SVD restructuring

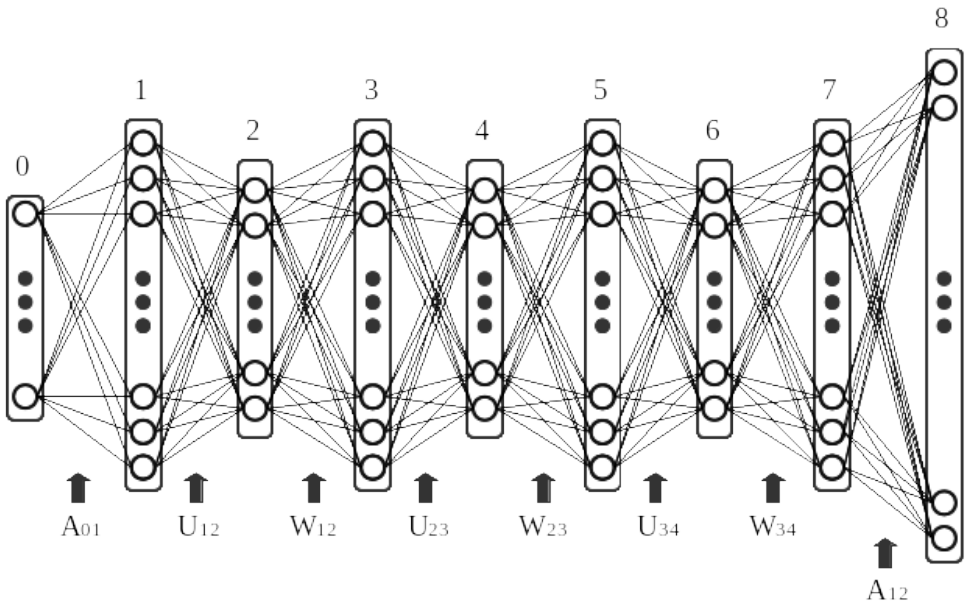


Figure 5.8: *Neural network after applying SVD restructuring on the weight matrices connecting all the hidden layers. Image source: [Tse]*

and again achieve about the same or slightly better WERs as their comparable normal DNNs with the same number of hidden layers without requiring 40% more parameters. The validation DNN with the identical topology to the 9x1.2k/0.6k SVD restructured DNN has a WER 0.4% absolute lower than the restructured DNN. This demonstrates the beneficial effects of the SVD restructuring.

Further experiments are performed on an 8x1.2k DNN where the SVD restructuring is only applied at a specific layer. Initial experiments as well as previous work suggest that the connections between the final hidden layers are more likely to be superfluous [MDH12] than those of prior hidden layers. In the first experiment SVD is only applied to the transition between the final two hidden layers. The next experiment adds a second new hidden layer prior to the second last hidden layer and compared to a validation DNN with the same topology. In the third experiment new hidden layers are inserted prior to the final three hidden layers.

The original 8x1.2k DNN has a WER of 16.61% and adding a hidden layer prior to a final hidden layer slightly reduced the WER to 16.45%. The second new hidden layer further reduces the WER to 16.35%. Applying SVD but restructuring the DNN prior

Topology	SVD	WER (%)	Parameters
4x1.2k	none	17.29	11.80M
7x1.2k	none	16.66	15.93M
7x1.2k/0.6k	3 times	16.60	11.80M
4x2k	none	17.17	24.25M
7x2k	none	16.48	35.70M
7x2k/1k	3 times	16.42	24.25M
5x1.2k	none	17.16	13.18M
9x1.2k	none	16.76	18.67M
9x1.2k/0.6k	4 times	16.41	13.18M
9x1.2k/0.6k	none	16.83	13.18M

Table 5.4: *SVD restructuring applied to networks with 4 & 5 hidden layers and compared to similar networks without SVD. The final row shows a network with the identical topology to the SVD restructured to a 5 x 1200 DNN. Source: [Tse]*

to the final 3 hidden layers only results in a WER of 16.46%. The validation DNN at 16.67% is again slightly worse that the restructured DNN of same topology. This may be because SVD prunes away connections that were not fully trained in the first round of fine-tuning.

5.4.2.4 Small Layer Initialization

A baseline 8x1.2k DNN is modified by applying SVD restructuring with k=120 to the layer prior the final hidden layer. This reduces the number of parameters in the DNN by 6.4% from 18.00M to 16.85M. Adding a second hidden layer using SVD restructuring with k=120 prior to the second last original hidden layer reduces the number parameters by a further 6.4% to 15.70M. Despite the reduction in parameters the performance is hardly affected and actually improves slightly from baseline 8x1.2k DNN's WER of 16.61% to 16.48% for a DNN with one new hidden layer and to 16.53% for the DNN with two new hidden layers.

5.4.2.5 Decomposing the Connections to the Output Layer

The baseline 8x1.2k DNN used in the last two experiments has 18.00M parameters. Only 0.72M of these are in the transition matrix of the input layer to first hidden layer. The 7 transitions between hidden layers each require 1.44M parameters and 7.2M parameters, 40% of the total and are in the transition matrix from the final

Topology	Restructuring WER (%)	Parameters	
8x1.2k	none	16.61	18.00M
9x1.2k,0.9k	SVD $k = 900$	16.37	17.28M
9x1.2k,0.6k	SVD $k = 600$	16.24	15.12M
9x1.2k,0.3k	SVD $k = 300$	16.42	12.96M
9x1.2k,120	SVD $k = 120$	16.74	11.66M
9x1.2k,42	SVD $k = 42$	17.33	11.10M

Table 5.5: *Results of performing SVD restructuring on the weight matrix connecting the final hidden layer to the output layer. Source: [Tse]*

hidden layer to the output layer. Restructuring this transition could noticeably reduce the total number of parameters in the DNN. Even simply applying SVD $k = 600$ which kept the number of parameters constant when decomposing the connections between hidden layers would result in an over 40% parameter reduction to 4.32M ($\approx 6016 \times 600 + 1200 \times 600$). In this experiment values of 900 down to 42 are evaluated.

Table 5.5 shows that the baseline DNN is slightly improved by the first three SVD restructurings with k=600 producing the DNN with the lowest WER of 16.24%. At 16.37% and 16.42% both the k=900 and k=300 SVD restructurings are also slightly lower than the baseline WER of 16.61%. The SVD restructured DNN using k=600 only slightly increases to WER to 16.74% while at the same time reducing the total number of parameters by over a third.

The best settings for the SVD parameter k in this application are from 50% hidden layers down to 25% hidden layers due to their slight reduction in WER and significantly reducing the total number of parameters by 16% and 28% respectively.

5.4.2.6 Insertion of a Bottleneck Layer

A bottleneck layer can be created between two existing hidden layers by setting k to a small number. This transforms the DNN into a DBNF network and allows it to be used to extract deep bottleneck features which, as discussed in chapter 4, can be a useful feature on which a GMM AM can be trained. In this experiment a 42 neuron bottleneck is inserted just prior to the final hidden layer of the baseline 8x1.2k DNN and compares it to a DBNF using the same topology and trained using the setup from section 4.3.2.1. The GMM training procedure is the same for both DBNF networks. The results show

Topology	WER (%)	Parameters
5 × 1.2k + 1.2k,1.2k,1.2k,6k	16.61	18.00M
5 × 1.2k + 1.2k,0.6k,1.2k,0.6k,1.2k,6k	16.35	18.00M
5 × 1.2k + 1.2k,1.2k,1.2k,0,6k,6k	16.24	15.12M
5 × 1.2k + 1.2k,0.6k,1.2k,0.6k,1.2k,0,6k,6k	16.35	15.12M
5 × 1.2k + 1.2k,0.6k,1.2k,0.6k,1.2k,0,6k,6k (+ft)	16.16	15.12M

Table 5.6: *Result of step-by-step fine tuning experiment. Source: [Tse]*

that while a SVD based DBNF system has WER of 17.96% the validation DBNF only has a WER of 18.31%.

5.4.3 Multistep SVD Restructuring

After an examination of possible SVD applications to DNNs in the previous section this section applies two SVD reductions to a baseline 8x1.2k DNN in order to both reduce its total number of parameters and to improve its accuracy. The first SVD reduction involves the initialization of two new hidden layers, half the size of the original layers prior to the final two hidden layers.

As can be seen in table 5.6 multiple applications of SVD restructuring can be performed on the same DNN in order to achieve a reduction in the number of its parameters and to improve its perfromance. The last two rows of that table, however, illustrate an important point: After performing one application of SVD restructuring the DNN has to be finetuned again before another SVD restructuring can be applied.

Chapter 6

Subword Neural Network Language Models

In this chapter neural network language modelling techniques are applied to a German subword vocabulary. For a long time language models were built primarily using ngram based methods. Although some early success was made by using neural networks to predict word classes [NS88] is wasn't until 2007 [Sch07], however, that the use of neural network based language models started to become become more common. These come in two varieties: feed forward neural networks which like traditional ngram methods only base their prediction of the next word on a short history and recurrent neural networks that predict the next word based on the previous word and the activation of the networks' hidden layer for the previous word [SSN12, MKB$^+$10]. This recurrent nature can be useful as it allows RNNs to base their predictions on a much larger context but it comes at the price of no longer being able to recombine language model histories and is, therefore, hard to integrate into a decoder. They are often either only used to rescore existing lattices [HBG$^+$12] or unrolled and converted into back-off ngram language models [AKV$^+$14]. As a seamless decoder integration is desired for the proposed subword neural network language model a feed forward topology is chosen. After an error analysis of a non subword German system an overview of other proposed solutions is presented followed by a description of the subword selection process. Initial experiments are performed using the subword vocabulary in an ngram language model and its compatibility with the KIT lecture translation system is investigated. The neural network LM is then introduced and its integration into the decoder explained.

OOV	English		German	
	vocab	errors	vocab	errors
transcription errors	0.34%	-	0.60%	-
compounds		-	1.46%	49.2%
grammar	0.12%	31.0%	0.46%	15.4%
names (places)	0.03%	6.3%	0.34%	11.7%
names (people)	0.07%	14.7%	0.26%	8.8%
names (other)	0.04%	8.4%	0.24%	8.0%
science terms	0.08%	15.1%	-	-
abbreviations	0.06%	11.7%	-	-
other	0.07%	13.6%	0.15%	5.1%
total	0.52%	100%	2.96%	100%

Table 6.1: *Error analysis of the OOVs in the first hour of the Quaero 2010 evaluation set. The vocab column lists the error types as a percentage of the vocabulary and the error columns list them as a percentage of the errors.*

After its evaluation the final section looks at the effects of the subword vocabulary on the lecture translation system.

6.1 Error Analysis

In order to determine which aspects of the ASR system to improve, the errors produced in the first hour of both the English and the German Quaero 2010 evaluation [SKK12b] sets are analyzed. The OOV errors are shown in table 6.1 and while the German system had an OOV rate of 3% with a vocabulary of 300k the English system only used a vocabulary of 120k words and had an OOV rate of 0.5%. Simple increases in vocabulary size of the German system do not significantly reduce the OOV rate. The analysis shows that the most common OOV words in the English system are grammar based such *videoing* or *washable* that have base words, *video* and *wash* in this case, which are in the vocabulary. In the more morphologically rich German this catagory is responsible for about 3 to 4 times as many OOV words such as *gedreifacht* (eng. tripled) or *nachlese* (eng. conjugated form of *to read up*). Despite that the grammar catagory only causes 15.4% of the German OOVs. By far the largest contributor to OOVs in German are the compound words.

Compound words are constructed from two or more normal German words and

considered to be normal German words. The words *Tee (eng: tea)* and *Kanne (eng: canister)* for example can be combined into *Teekanne (eng: tea pot)*. Although roughly 66% of all compound words are constructed by simply combining the individual words some require an extra linking morpheme in between [Mar06]:

- 19% -s: *Gehalt**s**erhöhung (eng: increase in pay)*
- 7% -n: *Tasse**n**halter (eng: cup holder)*
- 3% -en: *Stern**en**karte (eng: sky map)*
- all other linking morphemes occur in less than 2% of the compound words.

Some of these compound words appear to have multiple possible origins (splits). The word *Konsumentenumfrage* is a compound of *Konsument (eng: consumer)* and *Umfrage (eng: questionnaire)* taking an *en* as a linking morpheme this could also be split into *Konsum Enten Umfrage (eng: consume duck questionnaire)*.

When an ASR system recognizes all n component words of a compound word but fails to merge them into a single word it will be penalized with n errors: a substitution error and $n-1$ insertion errors. In this paper we present a Subword Neural Network Language Model that addresses this problem.

On the Quaero 2010 evaluation set the KIT baseline system had a WER of 24.17%, 10.21% of which (2.47% absolute) came from not correctly merging compound words whose component words were correctly recognized. These high OOV rates also cause problems for our online German to English lecture translation system.

6.1.1 Related Work

The only other similar approach that could be found in the literature is a neural network based subword language model [MSD+12] from Mikolov which improves upon a baseline 4gram full word language model. It uses a vocabulary that only contains high frequency words. Low frequency words are split into syllables and low frequency syllables are split into characters. They only use a small output vocabulary of 1000 words, 2000 syllables and 26 letters. It is able to outperform a 4gram language model by 0.2%.

In addition to the subword neural network paper discussed in section 2.3 other non neural network works have tackled the problem of German subwords.

Some older works following a similar approach to the one described in this paper like [ADA00] and [KK01] restrict their maximum vocabulary sizes to smaller large vocabularies and are therefore unable to mitigate the compound word problem by the desired amount. On vocabulary sizes around 300k, Shaik et al. [SMSN11] report improvements of up to 1.4% absolute for subword language models built using both syllable subwords and morpheme subwords generated by the Morfessor toolkit [CLLV05] on the Quaero 2009 evaluation set. The setup is improved with the use of maximum entropy models [SMSN12]. Although this approach also solves some compound word OOVs their initial goal addresses the problem of morphology which, as the error analysis in section 6.1 showed, is less important.

A non subword method of merging compound words proposed in [NTMSN11] involves generating a lattice of all possible word merging paths and rescoring it with data from a separately trained LM. This method is able to decrease the WER by up to 1.3% on the Quaero 2010 evaluation set.

6.2 Subword Ngram Language Model

This section presents the selection process of the subword vocabulary and evaluates a subword ngram language model. A baseline full word vocabulary is required in order to generate a subword vocabulary. Using the data sources listed in table A.1 and the vocabulary selection technique described in section 3.6 a ranking of all the words in the global vocabulary by their relevance to the tuning set is produced.

6.2.1 Subword Vocabulary

In order to select a subword vocabulary we first perform compound splitting on all the text corpora and tag the split compounds with the intraword symbol +. Initial experiments show that tagging just the head of a compound performs best. Linking morphemes are attached to the proceeding word. *Wirtschaftsdelegationsmitglieder* is, for example, split into *Wirtschafts+ Delegations+ Mitglieder (eng: members of the economic delegation).*

Marek [Mar06] performed an in-depth analysis of German compound words and splitting methods. The result of this work is that when a compound word can be split in multiple ways, the split containing the longest subwords is most often the best split.

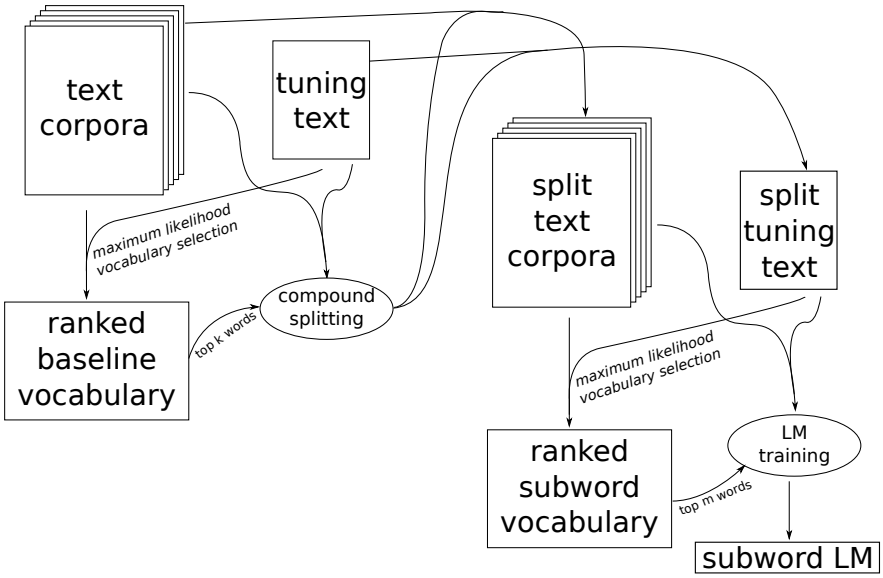


Figure 6.1: *The subword vocabulary selection process.*

The compound splitting algorithm requires a set of valid subwords and selects the best split from all possible splits by maximizing the sum of the squares of all subword lengths [Mar06]. For the introductory example of *Konsumentenumfrage* this would correctly choose *Konsumenten Umfrage* over *Konsum Enten Umfrage*.

As a set of valid subwords we selected the top k words from the ranked baseline wordlist. This allows the production of compound split text corpora and a split tuning text. The same maximum likelihood vocabulary selection method used to generate the baseline vocabulary is used again to select the best vocabulary from this split corpora resulting in a ranked vocabulary containing both full words and subwords tagged with the intraword symbol. An overview of this setup is given in figure 6.1.

Pronunciations missing from the initial dictionary are created with both *Festival* [BTCC98] and *Mary* [ST03]. Both the 4gram subword language model and the subword neural network language model are trained on the split corpora and tuning text analogous to the baseline language model explained in section 3.6.

6.2.2 Query Vocabulary Enhancement

In [MKLW11] the OOVs of German lectures are analyzed and a method is developed for adapting a baseline vocabulary to a given lecture topic if a set of slides is available

in advance. Queries are extracted from the lecture slides and sent to the search engine Bing to produce a list of websites related to the lecture. On a set of lectures recorded at the KIT this method reduces the baseline OOV rate of 3.1% to 1.2% for a 300k vocabulary. The query vocabulary selection setup is rebuilt and adapted to make use of subwords:

- the baseline subword language model is built (baseline subword vocab)
- the vocabulary from the slides is extracted (slide vocab)
- a set of queries is extracted from the slides
- for each query the resulting top 40 links from google search are downloaded
- the cleaning procedure described in section 3.5.2 is performed on each downloaded webpage (and linked files such as pdfs)
- compound splitting is performed on the cleaned webpages
- all subwords occurring in the downloaded webpages words are ranked based on how many of those websites they occur in and how often they occur in total (query subword vocab)
- baseline subword vocabulary is interpolated with the query subword vocab, the top 300k subwords selected are all then augmented by all the missing slide vocabulary words
- the baseline subword LM is rebuilt
- an LM is built on the downloaded split webpages and interpolated with baseline subword LM

This procedure is performed separately for each lecture.

6.2.3 OOV Analysis

The subword vocabulary requires the valid subwords for compound splitting to be specified. OOVs of subword vocabularies are measured by splitting the reference text in the same manner as the training text for the particular subword vocabulary was split.

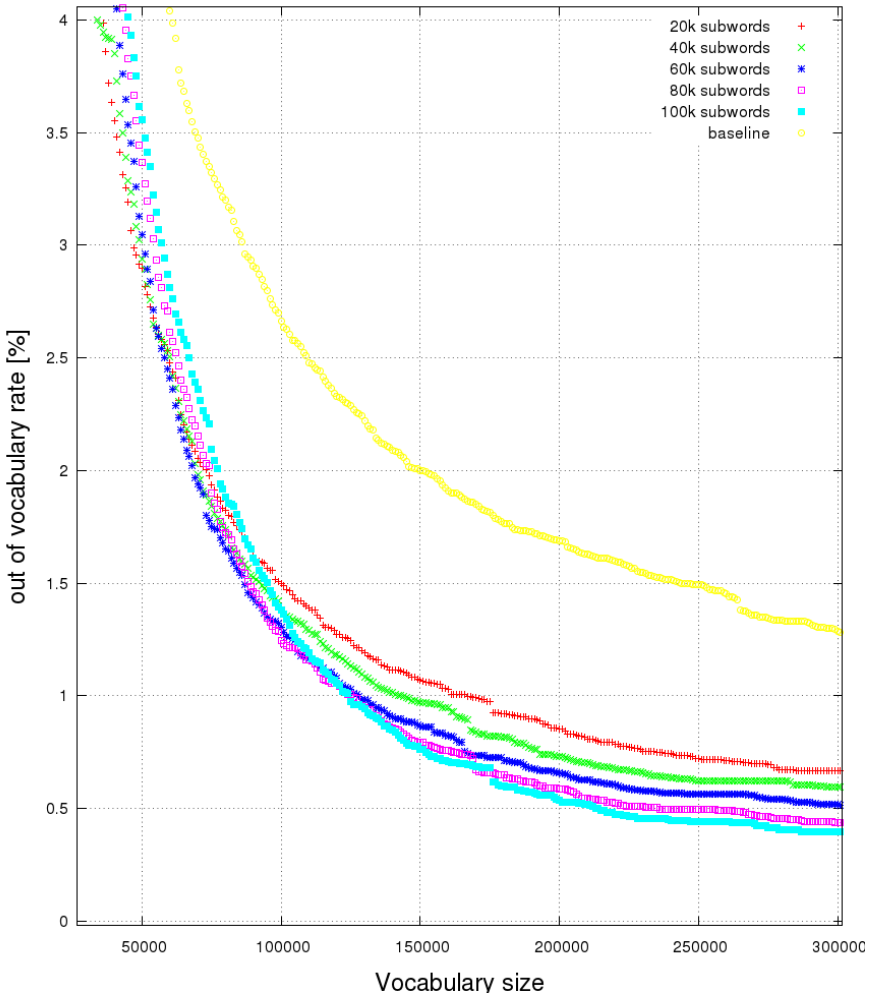


Figure 6.2: *OOVs of subword vocabularies with various values of valid subwords for splitting.*

As described in section 6.2.1 the top k words from the baseline ranking are used. We build several subword vocabularies varying "k" from 0 (baseline) to 100k. Figure 6.2 shows that the best value for this parameter depends on the total vocabulary size. All subword vocabularies significantly reduce the OOV rate compared to the baseline vocabulary and only vary slightly amongst each other. All further tests were conducted using the 60k subword vocabulary.

	WER
2011 Quaero MFCC system	24.04%
+ Subword LM	21.28%
+ Festival & Mary dictionary	20.37%
2014 IWSLT lMEL+T mDNN system	20.7%
+ Subword LM	19.2%

Table 6.2: *Sub-word language model evaluated on the 2010 Quaero evaluation set and the 2012 IWSLT development set.*

6.2.4 Offline Evaluation

The subword ngram LM setup is evaluated on both the Quaero 2010 evaluation set (eval2010) and the IWSLT 2012 development set (dev2010). While the training setup is the same, the language for the Quaero system is built from the text sources listed in table A.1 and the language model for the IWSLT system is built from text sources listed in table A.2. Both systems also use different acoustic models. The Quaero system only uses a simple MFCC GMM based acoustic model trained on the *Quaero partial DB* while the IWSLT system uses an lMEL+T mDNN acoustic model from section 5.2 trained on the *Quaero DB*. Postprocessing is performed after decoding to merge all the words tagged using an intraword symbol with the following word.

The 1st pass 2011 Quaero-MFCC system gains a lot from the subword language model improving from 24.04% to 21.28% by 2.76% absolute. In this system, Festival is used to generate pronunciations of missing words for both the training and decoding dictionaries. The inclusion of pronunciation variants from MARY (Modular Architecture for Research on speech sYnthesis), which necessitates a retraining of the acoustic model, results in an even lower WER of 20.37%. This setup also saw the number of compound errors in non number words reduced from 2.46% to 1.49% and a reduction of number word based compound errors by over 0.5%.

The more advanced 2014 IWSLT lMEL+T mDNN system is also significantly ($p < 0.005$) improved by the inclusion of the subword ngram LM. Its WER drops by 1.5% absolute from 20.7% down to 19.2%. In both the fullword and subword tests the additional pronunciation variants of the missing words are generated with both Festival and MARY.

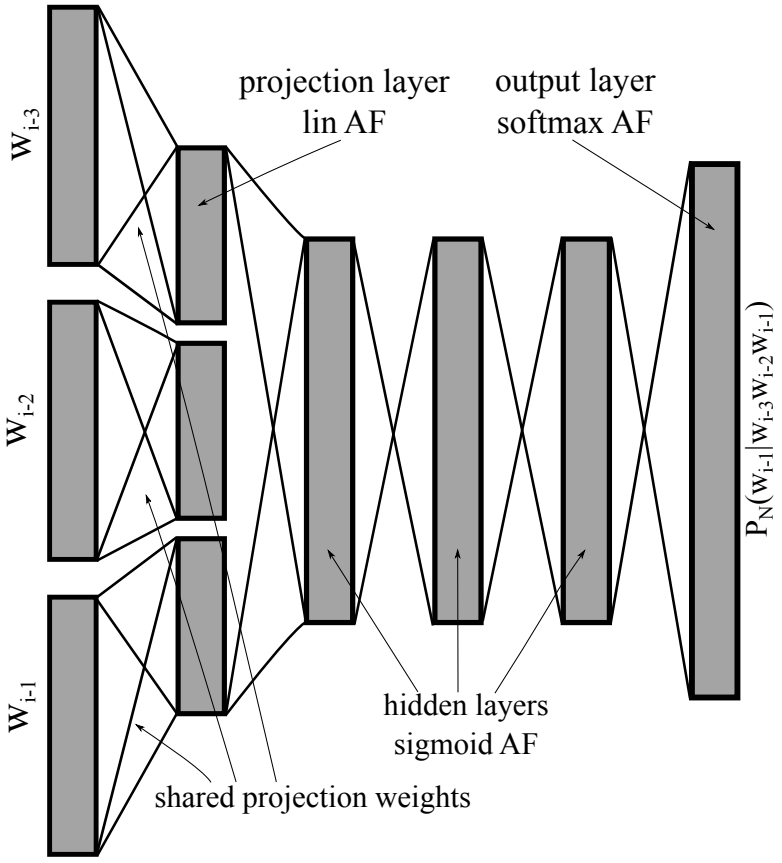


Figure 6.3: *The 4gram neural network language model.*

6.3 Subword Neural Network Language Model

An overview of our neural network language model can be seen in figure 6.3. Our topology consists of three 300k input vectors using 1 of n encoding to represent words that are mapped to continuous vectors (100 neurons per word) in the projection layer followed by 3 hidden layers (600 neurons each) and the output layer. As in [Sch07] the output layer of neural network language models is only a subset (called shortlist S) of the full vocabulary because very large output layers are both slow to train and slow to decode. Words not occurring in the shortlist are only modelled in a baseline ngram language model (P_B) and the result of the neural network language model (P_N) is interpolated with the baseline language model.

$$P(w_i|h) = \left\{ \begin{array}{ll} P_N(w_i|h)P_S(h)\lambda + (1-\lambda)P_B(w_i|h) & \text{if } w_i \in \text{S} \\ P_B(w_i|h) & \text{otherwise} \end{array} \right\}$$
$$P_S(h) = \sum_{w_j \in \text{shortlist}} P_B(w_j|h)$$

In this experiment a feed forward neural net language model with an input context of 3 words is used, with a 20k word shortlist and the 4gram baseline language model from section 6.2.

6.3.1 Training Text Selection

Because using all 1.5 billion words to train the neural network would be extremely time consuming we selected a subset of the data to train it. We tested 3 selection approaches:

- **ML based**: Sentences are selected from text sources based on the ML estimation performed when building the baseline LM
- **reduced ML based**: the ML based text selection may result in some small but highly relevant text sources having all their sentences selected multiple times. The reduced ML based selection method prevents this from happening by capping the number of times a sentence can be selected.
- **random**: sentences are randomly selected from the whole corpus.

Each text selection method used to generate a training corpus for the neural network contains 2.7M lines or roughly 46M words, just over 3% of the size of the whole training corpus. Due to the importance of two small text sources to the tuning text the ML text selection method used the contents of one source about 20 times and the contents of the other sources about 8 times. The reduced ML based text selection method limits each sentence's selection to 3 times.

6.3.2 Decoder Integration

This ibis decoder of the JrTk [SMFW01] interface with language model objects uses an interface that abstracts the word history as a linguistic context (lct):

- **extendLct**: Takes a linguistic context, such as a 4 gram word history, extends it by a word and returns a new linguistic context.
- **scoreWord**: Returns the language model score of the requested word in the given linguistic context.

	Selection method	WER
baseline full word ngram LM	-	20.7%
full word NNLM	ML	20.4%
subword ngram LM	-	19.2%
subword NNLM	ML	18.9%
subword NNLM	reduced ML	18.8%
subword NNLM	random	18.9%
subword NNLM (200dim PL)	reduced ML	18.7%
subword NNLM (200dim PL) opt. int. weights	reduced ML	18.4%

Table 6.3: *Baseline and Subword language models evaluated on the German IWSLR development set. All neural network LMs used a projection layer with 100 neurons per word except for the final one which has 200 neurons per word.*

- **scoreArray**: For the given linguistic context returns an array of all language model scores.

When generating the language model score of a single word, the neural language model automatically generates the language model scores for all words in that context. This makes the *scoreWord* function superfluous. For the NN LM it only calls the scoreArray function, that either fills the cache for that linguistic context and sets a cache pointer or, if the cache is already full, simply sets the cache pointer. A runtime experiment found that while a system using the baseline subword ngram language model is able to run at about x1.2-1.4 real time, the runtime of the subword neural network language model varied a lot from about x8 real time from some speakers to about x30 real time for other speakers.

6.3.3 Offline Evaluation

The proposed subword neural network language model is evaluated on the IWSLT 2012 development set using the system described in section 6.2.4. Both a fullword and a subword neural network LM are trained on the data extracted using ML based text selection method. Subword NN LMs are also trained using both the random and reduced ML text selection methods and a further subword NN LM, using the reduced ML method is trained using a larger projection layer. The projection layers are initialized with the *word2vec* tool [GL14] and the remaining hidden layers are pretrained as denoising auto encoders, after which, the network is jointly fine-tuned in the same way as the DNNs training is described in section 3.6. As in section 6.2.4, postprocessing has to be performed after decoding in order to merge all the words tagged using the intraword symbol with the following word.

The WER performances of the various subword neural network language models are shown in table 6.3 and compared to a baseline ngram LM as well as to both a full word neural network LM and a subword ngram LM. Using a subword vocabulary improves both the baseline ngram LM and the NNLM by 1.5% absolute. The full combined subword NN LM improves the fullword NN LM by 1.5% absolute and the subword ngram LM by 0.3% resulting in an overall improvement of 1.8% when compared to the full ngram LM. This improvement is further increased to 2% with the use of the reduced ML selection method and an increase in the size of projection layer from 100 to 200. Optimizing the interpolation weights between the background subword 4gram LM and the subword NN LM reduces the WER by a further 0.3%.

6.4 Integration into the KIT Online Lecture Translation System

In this section the subword LM is integrated into the online lecture translation system being deployed at the KIT [CFH+13]. Due to its technical nature these lectures have a very high OOV rate. As described in section 6.2.2, [MKLW11] attempts to solve this problem by generating a vocabulary from the results of queries built from phrases in the slides of a lecture. Both the query vocabulary and the subword vocabulary selection methods aim to reduce the OOV rate so an evaluation is performed on the a set of lectures recorded in order to gauge their interaction.

As can be seen in figure 6.4 the *query vocabulary* performs better for smaller vocabulary sizes and the subword vocabulary has a lower OOV rate with larger vocabulary sizes. A combined subword + query vocabulary reduces the OOV rate by almost the sum of the individual OOV rate reductions. This shows that the gains of the subword vocabulary and the query vocabulary are orthogonal.

In contrast to the offline IWSLT system the online system uses a GMM AM with parallelized score computation and speaker dependent models so that it can run in real time with a low latency. This low latency requirement also restricted both the baseline and subword language models to pure ngram models without the neural networks. They are trained using the setup explained in section 6.2.2.

As can be seen in table 6.4 the subword language model reduces the word error rate of all the lectures on which it was tested. Lecturer 4 and Lecturer 6 alternated in giving the same class. The subword LM improved Lecturer 1's WER the most. This is probably due to the fact that the other classes were in computer science and already covered to some degree in our baseline LM.

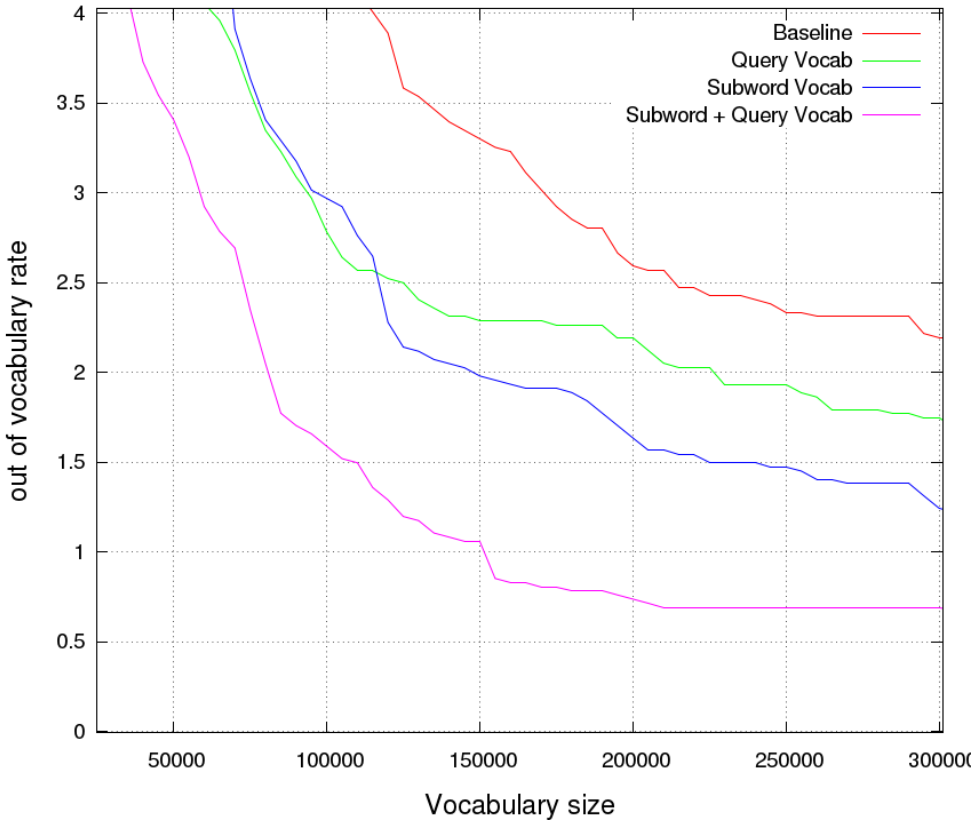


Figure 6.4: *OOVs of the baseline vocabulary, the query vocabulary, subword vocabulary and a combined subword query vocabulary.*

Lecturers	Lecturer 4	Lecturer 6	Lecturer 2	Lecturer 1
Baseline	22.66%	18.16%	18.87%	34.79%
Subword	18.07%	15.39%	17.31%	23.87%

Table 6.4: *Overview of the WERs on 4 Lecturers recorded at the KIT using both the baseline full word language model and the subword language augmented with a query vocabulary.*

6.5 Summary

This chapter presents a simple yet very effective method of selecting and integrating a German subword vocabulary. An error analysis shows that the majority of the OOV words in a German ASR stem from compound words. When used in an ngram language model the subword vocabulary reduces the WER by 1.5% on the IWSLT 2012 development set and by 2.76% on the Quaero 2010 evaluation set. Integrated into the KIT lecture translation system and augmented with query vocabulary it reduces the WER of all four tested lecturers. An analysis of the OOV reductions shows that its improvements are orthogonal to those of the query vocabulary. A neural network language model is trained to estimate the probability of subwords for a given subword context and is efficiently integrated into the speech recognition system with the help of a score cache. Using the best text section method it decreases the word error rate by a further 0.8% absolute from 19.2% to 18.4% on the IWSLT 2012 development set resulting in a total improvement of 2.3%.

The German subword vocabulary has proven to be so effective that is has been used in all systems built by our lab since 2011 and has, therefore, contributed to every evaluation since then. Its initial integration into the 2011 Quaero evaluation system helped our system achieve the lowest word error rate in that evaluation. It is also currently running in the KIT lecture translation system that is being used to translate a number of selected lectures from German into English so that foreign students can follow them. To my knowledge the subword neural network language's WER of 18.4% on the IWSLT development set is lower then any result that can be found in the literature and is only beaten by the results in section 5.3.

Chapter 7

Neural Network Combination of LM and AM

This chapter presents a method of combining an acoustic model and a language model with a neural network and thereby joining all neural networks together in a speech recognition system. The setup involves using the output scores of both the acoustic model and the language model as the input to a neural network that is trained to produce an optimal combined score. The setup of Graves et al. [GJ14] has a similar goal of combining the whole speech recognition process in a neural network, but while they use a recurrent neural network the setup proposed here continues to make use of an HMM structure. This allows the individual acoustic and language models to be trained independently of each other. Most speech recognition systems currently use a form of loglinear combination.

7.1 Loglinear Model Combination

Recall the task of the decoder, described in section 2.2.3 that aims find the most probable sequence of words:

$$\hat{W} = \underset{W}{\text{argmax}} \ \log P(X|W) + \alpha \log P(W) + |W|_w \beta + |W|_n \gamma$$

Working at a word level, where the acoustic model scores for the words are known, this can be seen as a form of loglinear combination [Hei10].

$$\hat{W} = \underset{W}{\text{argmax}} \sum_{w \in W} \sum_{i} \lambda_i \cdot f_i \tag{7.1}$$

The features used in the loglinear combination are:

- f_1**:** the acoustic model score of the word:

$$\log p(X|w) = \sum_{s \in \text{state}(w)} \log p(X|s)$$

- f_2**:** the language model score: $\log P(w|h)$. Its output is 0 when w is not an actual word.
- $f_3 = x_1$**:** 1 if w is an actual word and 0 otherwise
- $f_4 = x_2$**:** 1 if w refers to a noise model and 0 otherwise

One of the loglinear combination parameters can be ignored and set to one ($\lambda_1 = 1$) as the goal is to find argmax_W which is unaffected by scaling all the interpolation parameters. The other parameters have the following interpretations:

- $\lambda_2 = \alpha$**:** The scaling factor between the language and the acoustic model.
- $\lambda_3 = \beta$**:** A word penalty that can be used to penalize long/short word sequences.
- $\lambda_4 = \gamma$**:** The language model replacement score for words that refer to noise models and are not actual words

In cases that only have 2 to 4 parameters a simple grid search can be performed to find the optimal value for each of the parameters (α, β, γ). With an increasing number of parameters this becomes very time consuming. The baseline system used in this chapter employs Powell's conjugate direction method [Pow64] that transforms the multi parameter optimization problem into a series of single parameter optimization problems.

7.2 Combination Neural Network

Using a neural network changes equation 7.1 to:

$$\hat{W} = \underset{W}{\text{argmax}} \sum_{w \in W} \varphi(\sum_i a_i x_i^{(w)}) \tag{7.2}$$

where $x_i^{(w)}$ is the output of neuron i in the last hidden layer generated by the word w, a_i is the weight connecting it to the output neuron and φ is the activation function.

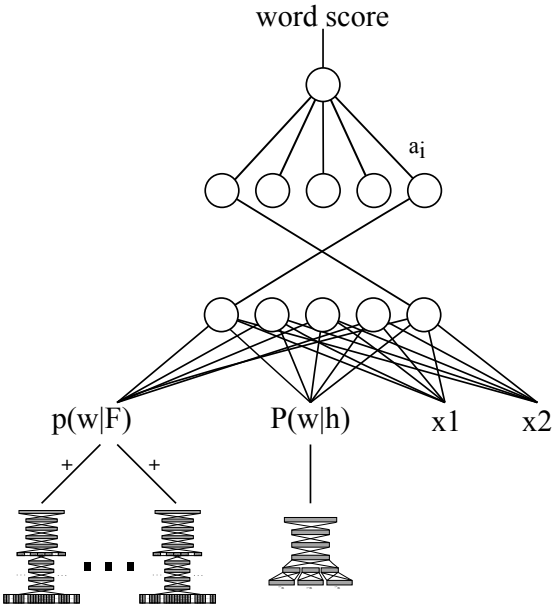


Figure 7.1: *Schematic of a combination neural network.*

A schematic of the neural network proposed to replace the loglinear combination is shown in figure 7.1. It has 4 inputs, the acoustic model score and the language model as well as the x_1 and x_2 explained in section 7.1. Both of its hidden layers contain 500 neurons and use the sigmoid activation function. It only has a single output neuron that estimates the total score of the word. It uses a linear activation function.

7.2.1 Maximum Mutual Information Estimation Error Function

Maximum mutual information estimation has long been used in both discriminative training of GMM based acoustic models [BBdSM86] as well as in sequence training of DNN based acoustic models [VGBP13]. It compares the probability of a correct word sequence W_u to all other possible hypotheses W_{h_u} generated by a speech recognition system. For a given set of N utterance U with their corresponding correct transcripts W_u and features sequences F_u the E_{MMI} error is defined as:

$$E_{MMI} = \log \prod_{u \in U} \frac{p(F_u|W_u)P(W_u)}{\sum_{W_{h_u} \in \widehat{W_u}} p(F_u|W_{h_u})p(W_{h_u})} \tag{7.3}$$

When an ASR system gives a high probability to the correct word sequence and a low probability to all other word sequences then the fraction will tend towards 1 and

the error towards 0. The full derivative $\frac{\partial E_{MMI}}{\partial a_i}$ the MMIE error function is presented in appendix C which shows that

$$\frac{\partial E_{MMI}}{\partial a_i} = \left(\delta_{w|W_u} - \Upsilon(w)\right) \quad x_i^{(w)} \tag{7.4}$$

and that the δ_j required for the update rule of the backpropagation algorithm is:

$$\delta_j = \delta_{w|W_u} - \Upsilon(w) \tag{7.5}$$

This error function is implemented in a separate neural network training tool that can learn from the word lattice and the weights are initialized by performing a simple function approximation to the existing loglinear function.

7.3 Experimental Setup and Results

The proposed method is evaluated and compared to a traditional loglinear approach where the parameters are estimated on a development set. The combination neural network is trained on the *Quaero DB* using lattices generated with the LM from chapter 6 and a lMEL+T mDNN described in chapter 5. It is trained for 5 epochs with a constant learning rate.

The loglinear parameters are optimized on the IWSLT 2012 development set resulting in a WER of 18.3%. A test run using the same parameters on the Quaero 2010 evaluation set has a WER of 14.22%. Using the combination neural network reduced this WER by 0.11% to 14.11% which is equates to only 40 more correct words. It is, however, still a significant improvement with $p < 0.005$. An oracle experiment is performed by optimizing the loglinear parameters on the Quaero 2010 evaluation set. Its results in a WER of 14.03% which is slightly better than the combination neural network.

7.4 Summary

This chapter has introduced a possible combination network that goes beyond the traditional loglinear approach and uses a neural network to combine the outputs of both the acoustic model and the language model. The neural network is trained on the lattices of the training using the MMIE error function. It is able to slightly reduce the WER on the Quaero 2010 evaluation set when compared to the loglinear approach using parameters estimated on the IWSLT 2012 development set.

Chapter 8

Results Summary

This thesis has touched on many aspects of automatic speech recognition and shown how they can be further improved by the use of neural networks. This chapter will present an overview of the most important results from these techniques as well as their applications and combination effects.

Section 8.1 begins with the results the examination of multiple input features for deep neural network bottleneck features. The results of the multi-feature modular deep neural network acoustic model are presented in section 8.2. The results of the other acoustic model experiments on the decision tree and using singular value decomposition follow in sections 8.3 & 8.4. Section 8.5 tackles the key results from the subword neural network language model experiments and the combination tests are summarized in section 8.6.

The results of this thesis have been successfully used in multiple evaluation campaigns aandre are being used in a deployed product. A summary of these applications is provided in section 8.7. The chapter concludes with section 8.8 showing the absolute improvements of the key techniques from this thesis as well as their combined improvements.

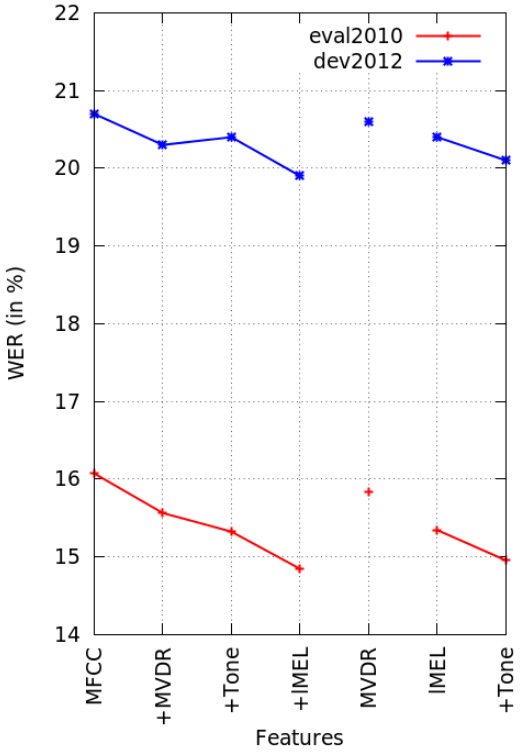


Figure 8.1: *cc*

Figure 8.2: *Results overview of deep neural network bottleneck features trained on various combinations of input features and tested on both the eval2010 and the dev2012 data*

8.1 Neural Network Feature Extraction

The first main contribution of this thesis is in the use of multiple different input features for deep neural network bottleneck features. Chapter 4 examined 4 types of input features (MFCC, MVDR, lMEL & Tone) and showed consistent improvements when more features were used as inputs to the neural network. This can be seen in figure 8.1 where adding MVDR features to the MFCC baseline results in improvements on both test sets. Further improvements can be achieved by also adding in the Tone features and then the lMEL features. The final setup using all tested input features improves on the best single feature bottleneck system by about 0.5%.

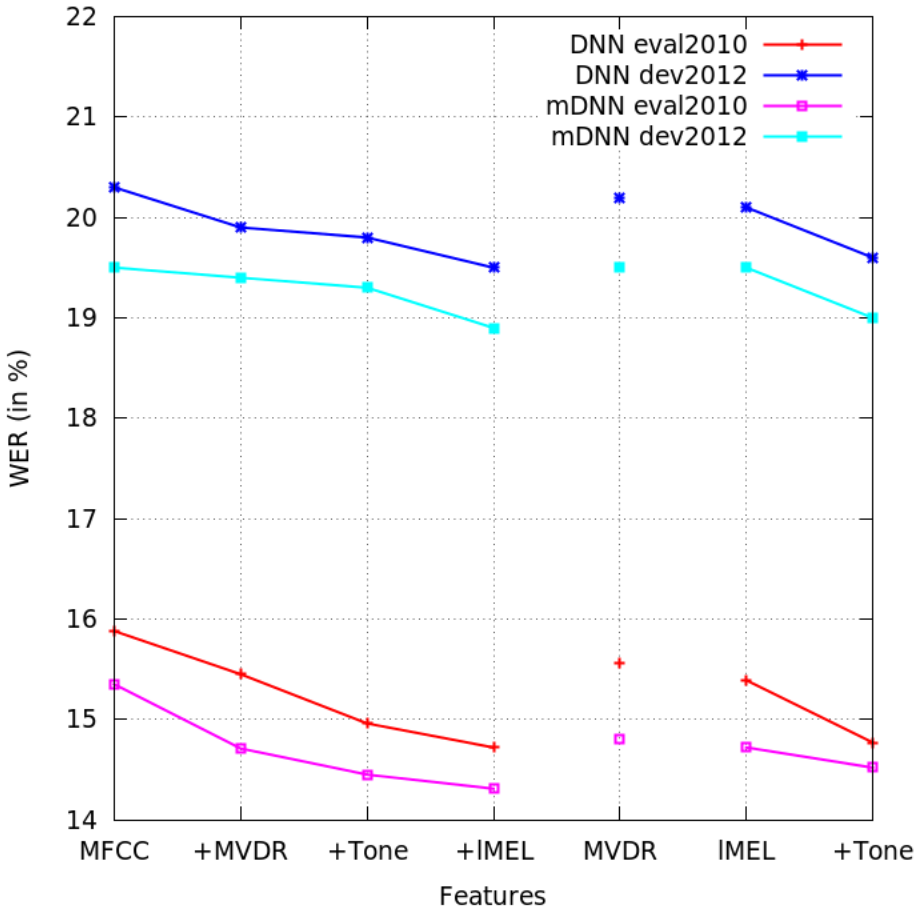


Figure 8.3: *Results overview of modular deep neural network acoustic models trained on various combinations of input features and tested on both the eval2010 and the dev2012 data*

8.2 Modular Deep Neural Network Acoustic Models

Similar multi-feature experiments were performed on deep neural network acoustic models and found similar results. Including more varied inputs improved the network and lead to speech recognition systems with lower word error rates. The introduction of the modular deep neural network acoustic models where the already well trained bottleneck networks are used as input modules to a neural network acoustic model results in further consistent gains.

Figure 8.1 shows that on both test sets the modular deep neural network acoustic models consistently outperform their respective non modular counterparts by at least

	BNF modules	eval2010	dev2012
lMEL+Tone	1	14.52	19.0
MFCC+MVDR+Tone	1	14.54	19.3
MFCC+MVDR+Tone+lMEL	1	14.31	18.9
lMEL+Tone ⊕ MFCC+MVDR+Tone	2	14.19	18.8
⊕ MFCC+MVDR+Tone+lMEL	3	**14.06**	**18.7**
⊕ MFCC ⊕ MVDR	5	14.33	18.9

Table 8.1: *Comparison of three multi module modular deep neural network acoustic models with three of the best single module modular deep neural network acoustic models.*

0.5% absolute. The figure also demonstrates the continued usefulness of including multiple different input features into both the normal deep neural network acoustic model as well as the modular deep neural network acoustic models.

The results in figure 8.1 were restricted to modular deep neural network acoustic models that used a single input module. Using multiple input modules can result in further improvements. A summary of these results can be found in table 8.1 where three very good single module modular deep neural network acoustic models are compared to three multi module modular deep neural network acoustic models with between 2 and 5 modules. The key result of this experiment is that while using a few input modules improves the network's performance at some point adding further modules begins to degrade its performance.

This can be seen in line 5 of the table where the multi module modular deep neural network acoustic model improves on the best single module modular deep neural network acoustic model be 0.2% absolute on the dev2012 test set and 0.15% absolute on the eval2010 test set. However the addition of two further modules on line 6 degraded its performance to such an extent that it no longer outperformed the best single module modular deep neural network.

In total the modular deep neural network acoustic models significantly reduced the word error rate on both test sets and the improvements were orthogonal to the gains from using multiple input features.

8.3 Deep Neural Network based Clustertrees

A further contribution of this thesis is the use of deep neural networks in the construction of the cluster trees used to determine the otput layer of the acoustic model's deep neural network. By providing a method of computing the weighted

entropy distance directly from a context independent deep neural network acoustic model without the use of Gaussians or Gaussian mixture models this approach allows for a streamlining of the acoustic model training procedure without the need for legacy Gaussian mixture models code.

The experiments showed that the alternative weighted entropy distance from a context independent deep neural network acoustic model performed at least as well as the traditional weighted entropy distance and in some cases even resulted in a slight improvement.

8.4 Growing a DNN with Singular Value Decomposition

Another technique that has more practical applications then just reducing the word error rate is the use of singular value decomposition to reduce the number of parameters in a deep neural network without harming its performance, thereby resulting in a network that can be computed faster. This is especially important in scenarios like the lecture translator where a low latency response is critical.

A reduction of parameters from 18 million to 11 million is shown to be possible without a significant loss in performance. However, intelligently reducing the parameters to 15.12 million even resulted in a slight improvement of 0.4% absolute.

8.5 Subword Neural Network Language Model

The subword neural network language model is a big contributing factor to the total reduction in word error rate achieved within this thesis. The introduction of the subword language model was necessary to combat the high *out of vocabulary rate* seen in German systems where it is not unusual for a 300k word German speech recognition system to have an *out of vocabulary rate* of over 3% while a 120k English speech recognition system may only have an *out of vocabulary rate* of 0.5%. While a basic ngram based subword language model already resulted in a very good improvement of 1.5% when compared to a baseline fullword ngram language model. Using the subword vocabulary in a neural network language model resulted in synergistic and an improvement of 2.0% over a baseline fullword neural network language model. These results are shown in figure 8.4 where it can be clearly seen that the gains from the combined subword and neural network language model are more than the sum of the individual gains.

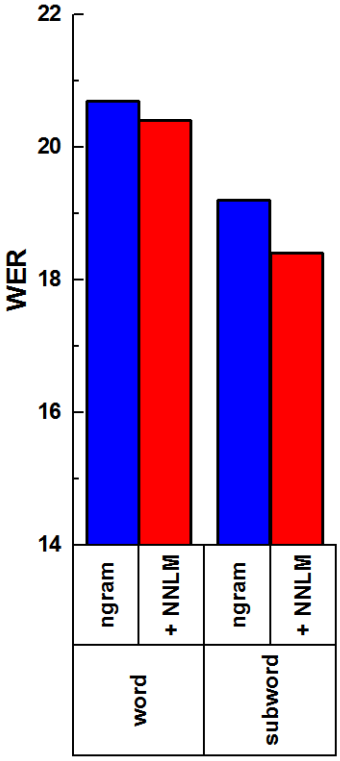


Figure 8.4: *Results overview of the subword neural network language.*

8.6 Neural Network AM & LM Combination

A technique to use a neural network to combine the scores of both the neural network acoustic model as well as the neural network language model with other features is proposed in chapter 7. Although this network was able to show a statistically significant improvement over the baseline loglinear method the small gain in no way offsets the required effort.

8.7 Evaluation Results and Applications

The techniques developed for this thesis have been used in many evaluation campaigns from both Quaero, where the primary metric was case dependent WER, and IWSLT, where the primary metric is case independent WER. In the 2010 German Quaero evaluation campaign our lab's submission system performed poorly and trailed the best system from RWTH by over 3% absolute WER. After introducing the subword language

model and the first generation of multi-feature bottleneck neural network feature extractors our submission system for the 2011 German Quaero evaluation campaign was over 5% absolute better than previous year's. This improvement was enough to outperform all other participants in 2011, with our WER being just 0.1% ahead of the submission from RWTH. Further improvements to the multi-feature bottleneck neural network feature extractors and larger language models allowed us to repeat that performance in the 2012 German Quaero evaluation campaign where our system again had the lowest word error rate.

The multi-feature modular deep neural network acoustic models were introduced for the both 2013 German Quaero and the 2013 German IWSLT evaluation campaigns. The further boost in performance allowed our submission to the Quaero evaluation to again outperform the other participants' systems. In the IWSLT evaluation campaign the submission from RWTH proved to be slightly better than ours resulting in us only placing 2nd. However in 2014, after further optimizing the multi-feature modular deep neural network acoustic models, our submission to the 2014 Germany IWSLT evaluation campaign came out on top.

Besides being used in evaluation systems many of the techniques developed for this thesis have also been integrated into our online lecture translation system. Here the subword language model has turned out to be very important due the complected vocabulary used in some lectures. On a mechanical engineering lecture, for example, the subword language model was over 10% absolute better than the fullword language model. Besides the language model the multi feature deep neural network acoustic model also plays an important part in the lecture translator. Thanks to the singular value decomposition based network growing and parameter reduction this deep neural network acoustic model can be computed fast enough to ensure a low latency output of the whole system.

Besides German the techniques developed in this thesis have also been used in other projects to build systems for other languages such as English, Spanish, Pashto and many more.

8.8 Results Overview

This final results overview section presents the individual and combined effects of the techniques decribed in this thesis when applied to the IWSLT 2012 development set. A baseline setup using a basic single feature deep neural network acoustic model and a normal word ngram language model produced a WER of 21.4%. Upgrading this setup

AM	LM	WER
single feature DNN	word ngram LM	21.4
modular DNN	word ngram LM	20.7
modular DNN	**subword ngram LM**	19.2
modular DNN	**subword NNLM**	18.4
best single feature DNN	subword ngram LM	20.1
multi-feature DNN	subword ngram LM	19.4
best single feature modular DNN	subword ngram LM	19.5
best single module modular DNN	subword ngram LM	18.9
best modular DNN	subword ngram LM	18.7
best modular DNN	**subword NNLM**	18.0

Table 8.2: *Individual and combined results of the techniques described in this thesis.*

to a modular DNN acoustic model improved the WER by 0.7% to 20.7%.

The introduction of the subword vocabulary lowered the WER dramatically by first 1.5% from 20.7% to 19.2% for the purely ngram subword language model and then by a further 0.8% to 18.4% for the neural network subword language model. This total reduction of over 11% relative clearly demonstrates the effectiveness of the implemented subword neural network language model.

As can be seen in table 8.2 a system using the subword ngram language model and DNN acoustic model with the best single input feature is able to produce a WER of 20.1%. Expanding the acoustic model to use multiple input features can reduce the WER by 0.7% to 19.4%. A similar reduction in WER to 19.5% could also be achieved by replacing the DNN acoustic with a single feature modular DNN acoustic model. Both of these gains can be achieved together by using a modular DNN with a single module that has multiple input features. This results in a total WER reduction of 1.2% from 20.1% to 18.9% which is almost the sum of the individual improvements of 0.7% and 0.6%. A further improvement of 0.2% can be achieved by using multiple different models in the modular DNN acoustic model resulting in a WER of 18.7%.

Using the modular DNN acoustic model with multiple models together with the best subword neural network language model reduces the WER to 18.0%. This shows the orthogonal improvements of the acoustic model and the subword neural network language model. In total the techniques described in this thesis result in an absolute improvement of 3.4% from the baseline of 21.4% to 18.0%.

Chapter 9

Conclusion

This thesis investigates the application and improvement of neural networks on all levels of a speech recognition system. It begins with the feature level where deep neural networks can be employed to extract useful features from the speech signal using their hidden layer's ability to learn new representations of inputs and by setting the hidden layer to a desired feature size.

An investigation into the ability of these networks to combine and utilize multiple different features is performed. This experiment show,s that while the normal non-tonal features are very similar and in most cases interchangeable, they are also complementary. Augmenting the input feature or feature combination with tonal features proves to be beneficial in all evaluated settings. A similar experiment on deep neural network acoustic models shows the same pattern: Adding more features to the input of the neural network improves its classification ability.

The modular deep neural network acoustic model presented in this thesis incorporates well trained feature extraction networks using multiple input features. It is initially evaluated using only a single feature extraction module. This evaluation again demonstrates the usefulness of using multiple different input feature vectors. Modular deep neural networks, whose sole feature extraction network uses multiple features, outperform those using fewer features or a single feature.

Using two or more different feature extraction networks as modules in the same modular deep neural network results in further improvement. The best approaches use three feature extraction networks that are, in turn, each trained using multiple input features. The best modular deep neural network is able to reduce the word error rate on the test data sets by up to 11.5% relative improvement compared to a baseline deep neural network.

A further problem addressed in this thesis is the reliance on older, non neural network based modeling methods for the selection of the acoustic units which are used as targets in the training of these modular deep neural network acoustic models. It is shown that the probability distribution required by the clustering algorithm, in order to measure the weighted entropy distance, can be generated using the average activation of a context independent neural network acoustic model.

Furthermore, experiments are performed using singular value decomposition to initialize new hidden layers in a deep neural network. An investigation of its possible applications shows it to be useful for increasing the depth and performance of the neural networks while at the same time allowing for a reduction in the number of parameters. The parameter reduction is especially large when singular value decomposition is used to initialize a small hidden layer just prior to the output layer.

A deep neural network is also used to build a subword neural network language model. An error analysis concludes, that in German speech recognition systems, compound words are a major source of errors. To solve this problem a subword vocabulary selection method is developed that keeps normal words and splits compound words. The use of an intraword tag allows a recognized sequence of subwords to be easily combined into a sequence of words. This proves to be very effective and results in a large gain when used in both a neural network language model and in an ngram language model. As well as numerous applications in evaluation systems the subword vocabulary is currently integrated into the KIT lecture translation system and actively used to help foreign students to follow lectures held in German. This integration requires the subword vocabulary to function together with a query based vocabulary selection method that extracts queries from lecture slides. It uses a search engine to find related documents and webpages and analyses them in order to broaden the system's vocabulary. An OOV analysis of the integrated system shows that they complement each other well and give orthogonal gains. Performance issues, unfortunately, prevent the integration of the subword neural network language model into the lecture translation system.

In order to combine the outputs of both the acoustic model and the language model a combination neural network is trained. It uses, as inputs, the acoustic model score and the language model score of the word, for which it estimates the combined score. Information about whether the word is a lexical word or noise *word* is also taken into consideration. The network is trained using the lattices of the acoustic model training data to minimize the MMIE error function. The training procedure is implemented in a separate tool. It is evaluated and shown to be slight improvement on a normal

loglinear combination.

Throughout this thesis various neural network techniques were presented that improved the overall performance of the speech recognition system. Their usage in evaluations help our systems achieve numerous placements the best German system. When combined together in a single system the improvements on both language model and the acoustic model reduce the word error rate by roughly 20% when compared to a baseline system with a normal neural network language model and a normal deep neural network acoustic model.

Bibliography

[ADA00] M. Adda-Decker and G. Adda. Morphological decomposition for asr in german. In *Workshop on Phonetics and Phonology in Automatic Speech Recognition*, pages 129–143, 2000. 96

[AHS85] David H Ackley, Geoffrey E Hinton, and Terrence J Sejnowski. A learning algorithm for boltzmann machines*. *Cognitive science*, 9(1):147–169, 1985. 20

[AKV+14] Heike Adel, Katrin Kirchhoff, Ngoc Thang Vu, Dominic Telaar, and Tanja Schultz. Comparing approaches to convert recurrent neural networks into backoff language models for efficient decoding. In *Proc. of Interspeech*, 2014. 24, 93

[Aro11] Jacob Aron. How innovative is apple's new voice assistant, siri? *New Scientist*, 212(2836):24, 2011. 1

[B+95] M Bishop, Christopher et al. Neural networks for pattern recognition. 1995. 15, 145

[Bao99] Zhiming Bao. *The Structure of Tone*. Oxford University Press, 1999. 49

[Bar12] Adrien Barbaresi. German political speeches-corpus and visualization. In *DGfS-CL poster session*, 2012. 42

[BBB+10] James Bergstra, Olivier Breuleux, Frédéric Bastien, Pascal Lamblin, Razvan Pascanu, Guillaume Desjardins, Joseph Turian, David Warde-Farley, and Yoshua Bengio. Theano: a CPU and GPU math expression compiler. In *Proceedings of the Python for Scientific Computing Conference (SciPy)*, June 2010. Oral Presentation. 46, 69

[BBC+01] Carmen Benıtez, Lukas Burget, Barry Chen, Stéphane Dupont, Hari Garudadri, Hynek Hermansky, Pratibha Jain, Sachin Kajarekar, Nelson

Morgan, and Sunil Sivadas. Robust asr front-end using spectral-based and discriminant features: experiments on the aurora tasks. In *Proc. of EUROSPEECH*, pages 429–432. Citeseer, 2001. 47

[BBdSM86] Lalit Bahl, Peter Brown, Peter V de Souza, and Robert Mercer. Maximum mutual information estimation of hidden markov model parameters for speech recognition. In *Acoustics, Speech, and Signal Processing, IEEE International Conference on ICASSP'86.*, volume 11, pages 49–52. IEEE, 1986. 26, 109

[BC+08] Y-lan Boureau, Yann L Cun, et al. Sparse feature learning for deep belief networks. In *Advances in neural information processing systems*, pages 1185–1192, 2008. 20

[Ben09] Yoshua Bengio. Learning deep architectures for ai. *Foundations and trends® in Machine Learning*, 2(1):1–127, 2009. 19

[BLP+07] Yoshua Bengio, Pascal Lamblin, Dan Popovici, Hugo Larochelle, et al. Greedy layer-wise training of deep networks. *Advances in neural information processing systems*, 19:153, 2007. 20

[BM94] Herve A Bourlard and Nelson Morgan. *Connectionist speech recognition: a hybrid approach*, volume 247. Springer Science & Business Media, 1994. 28, 69

[Bro73] Roger Brown. *A first language: The early stages.* Harvard U. Press, 1973. 7

[BTCC98] A. Black, P. Taylor, R. Caley, and R. Clark. The festival speech synthesis system, 1998. 97

[CBC+95] Maria Cristina Caselli, Elizabeth Bates, Paola Casadio, Judi Fenson, Larry Fenson, Lisa Sanderl, and Judy Weir. A cross-linguistic study of early lexical development. *Cognitive Development*, 10(2):159–199, 1995. 7

[CFH+13] Eunah Cho, Christian Fügen, Teresa Herrmann, Kevin Kilgour, Mohammed Mediani, Christian Mohr, Jan Niehues, Kay Rottmann, Christian Saam, Sebastian Stüker, et al. A real-world system for simultaneous translation of german lectures. In *INTERSPEECH*, pages 3473–3477, 2013. 1, 36, 104

[CG96] Stanley F Chen and Joshua Goodman. An empirical study of smoothing techniques for language modeling. In *Proceedings of the 34th annual meeting on Association for Computational Linguistics*, pages 310–318. Association for Computational Linguistics, 1996. 24, 65

[CGM+97] C. Julian Chen, Ramesh A. Gopinath, Michael D. Monkowski, Michael A. Picheny, and Katherine Shen. New methods in continuous Mandarin speech recognition. In *Proc. EUROSPEECH*, Rhodes, Greece, September 1997. ISCA. 50

[CLLV05] M. Creutz, K. Lagus, K. Lindén, and S. Virpioja. Morfessor and hutmegs: Unsupervised morpheme segmentation for highly-inflecting and compounding languages. 2005. 96

[CNS+13] Mauro Cettolo, Jan Niehues, Sebastian Stüker, Luisa Bentivogli, and Marcello Federico. Report on the 10th iwslt evaluation campaign. In *Proceedings of the International Workshop on Spoken Language Translation, Heidelberg, Germany*, 2013. 36

[CW95] Sin-Horng Chen and Yih-Ru Wang. Tone recognition of continuous Mandarin speech based on neural networks. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 1995. 50

[DYDA11] George E Dahl, Dong Yu, Li Deng, and Alex Acero. Large vocabulary continuous speech recognition with context-dependent dbn-hmms. In *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*, pages 4688–4691. IEEE, 2011.

[DYDA12] George E Dahl, Dong Yu, Li Deng, and Alex Acero. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. *Audio, Speech, and Language Processing, IEEE Transactions on*, 20(1):30–42, 2012. 2, 20, 28, 69

[FDR+94] Larry Fenson, Philip S Dale, J Steven Reznick, Elizabeth Bates, Donna J Thal, Stephen J Pethick, Michael Tomasello, Carolyn B Mervis, and Joan Stiles. Variability in early communicative development. *Monographs of the society for research in child development*, pages i–185, 1994. 7

[FHBM06] Alexander Mark Franz, Monika H Henzinger, Sergey Brin, and Brian Christopher Milch. Voice interface for a search engine, April 11 2006. US Patent 7,027,987. 1

[Fis97] Jonathan G Fiscus. A post-processing system to yield reduced word error rates: Recognizer output voting error reduction (rover). In *Automatic Speech Recognition and Understanding, 1997. Proceedings., 1997 IEEE Workshop on*, pages 347–354. IEEE, 1997. 1

[FLBG07] Marc Ferras, Cheung Chi Leung, Claude Barras, and J Gauvain. Constrained mllr for speaker recognition. In *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, volume 4, pages IV–53. IEEE, 2007. 45

[Fuk13] Keinosuke Fukunaga. *Introduction to statistical pattern recognition.* Academic press, 2013. 25, 27

[Geh12] Jonas Gehring. *Training Deep Neural Networks for Bottleneck Feature Extraction.* PhD thesis, National Research Center, 2012. 19, 20, 22, 53, 61

[GF94] David Graff and Rebecca Finch. Multilingual text resources at the linguistic data consortium. In *Proceedings of the workshop on Human Language Technology*, pages 18–22. Association for Computational Linguistics, 1994. 42

[GF08] Frantisek Grezl and Petr Fousek. Optimizing bottle-neck features for lvcsr. In *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*, pages 4729–4732. IEEE, 2008. 53

[GFGS06] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In *Proceedings of the 23rd international conference on Machine learning*, pages 369–376. ACM, 2006. 34

[GJ14] Alex Graves and Navdeep Jaitly. Towards end-to-end speech recognition with recurrent neural networks. In *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*, pages 1764–1772, 2014. 34, 107

[GKKC07] Frantisek Grezl, Martin Karafiát, Stanislav Kontár, 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*, volume 4, pages IV–757. IEEE, 2007. 53, 54

[GL14] Yoav Goldberg and Omer Levy. word2vec explained: deriving mikolov et al.'s negative-sampling word-embedding method. *CoRR*, abs/1402.3722, 2014. 103

[GLK+13] Jonas Gehring, Wonkyum Lee, Kevin Kilgour, Ian R Lane, Yajie Miao, Alex Waibel, and Silicon Valley Campus. Modular combination of deep neural networks for acoustic modeling. In *INTERSPEECH*, pages 94–98, 2013. 73

[GNMW13] Jonas Gehring, Quoc Bao Nguyen, Florian Metze, and Alex Waibel. Dnn acoustic modeling with modular multi-lingual feature extraction networks. In *Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on*, pages 344–349. IEEE, 2013. 73

[GW96] Mark JF Gales and Philip C Woodland. Mean and variance adaptation within the mllr framework. *Computer Speech & Language*, 10(4):249–264, 1996. 26

[Hay11] Bruce Hayes. *Introductory phonology*, volume 32. John Wiley & Sons, 2011. 2

[HBG+12] Eva Hasler, Peter Bell, Arnab Ghoshal, Barry Haddow, Philipp Koehn, Fergus McInnes, Steve Renals, Pawel Swietojanski, Fergus R McInnes, Sharon J Goldwater, et al. The uedin system for the iwslt 2012 evaluation. In *Proc. International Workshop on Spoken Language Translation*, 2012. 93

[HCC+14] Awni Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, et al. Deepspeech: Scaling up end-to-end speech recognition. *arXiv preprint arXiv:1412.5567*, 2014. 34

[HDY+12] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *Signal Processing Magazine, IEEE*, 29(6):82–97, 2012. 2, 20, 69

[Hei10] Georg Heigold. *A log-linear discriminative modeling framework for speech recognition*. PhD thesis, Universitätsbibliothek, 2010. 26, 107

[Her90] Hynek Hermansky. Perceptual linear predictive (plp) analysis of speech. *the Journal of the Acoustical Society of America*, 87(4):1738–1752, 1990. 49

[HES00] Hynek Hermansky, Daniel PW Ellis, and Sangita Sharma. Tandem connectionist feature extraction for conventional hmm systems. In *Acoustics, Speech, and Signal Processing, 2000. ICASSP'00. Proceedings. 2000 IEEE International Conference on*, volume 3, pages 1635–1638. IEEE, 2000. 47

[Hir83] Daniel Hirst. Structures and categories in prosodic representations. In *Prosody: Models and measurements*, pages 93–109. Springer, 1983. 50

[HOT06] Geoffrey Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006. 19, 20

[HS97] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997. 33

[HS98] Hynek Hermansky and Sangita Sharma. Traps-classifiers of temporal patterns. In *ICSLP*, 1998. 53, 54

[Hua92] XD Huang. Phoneme classification using semicontinuous hidden markov models. *Signal Processing, IEEE Transactions on*, 40(5):1062–1067, 1992. 5

[JO+13] Zhenyu Hou Jian Ouyang, Lei Jia et al. A practical implementation of gpu based accelerator for deep neural networks. In *4th Workshop on SoCs, Heterogeneous Architectures and Workloads,2013.*, 2013. 19

[Joh04] D Johnson. Quicknet, speech group at icsi, berkeley, 2004. 46, 56

[Kal15] James Kalat. *Biological psychology*. Cengage Learning, 2015. 48

[Kil09] Kevin Kilgour. Language model adaptation using interlinked semantic data. Master's thesis, Karlsruhe University, Germany, 2009. 41

[KK01] J. Kneissler and D. Klakow. Speech recognition for huge vocabularies by using optimized sub-word units. In *Seventh European Conference on Speech Communication and Technology*, 2001. 96

[Koe05] Philipp Koehn. Europarl: A parallel corpus for statistical machine translation. In *MT summit*, volume 5, pages 79–86, 2005. 40, 43, 142

[KSM+11] Kevin Kilgour, Christian Saam, Christian Mohr, Sebastian Stüker, and Alex Waibel. The 2011 kit quaero speech-to-text system for spanish. In *IWSLT*, pages 199–205, 2011. 67

[KTNW13] Kevin Kilgour, Igor Tseyzer, Quoc Bao Nguyen, and Alex Waibel. Warped minimum variance distortionless response based bottle neck features for lvcsr. In *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pages 6990–6994. IEEE, 2013. 52, 56, 57, 68, 70

[KW15] Kevin Kilgour and Alex Waibel. Multi-feature modular deep neural network acoustic models. 2015. 73

[LB95] Yann LeCun and Yoshua Bengio. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361:310, 1995. 33

[LCD+11] Lori Lamel, Sandrine Courcinous, Julien Despres, Jean-Luc Gauvain, Yvan Josse, Kevin Kilgour, Florian Kraft, Viet Bac Le, Hermann Ney, Markus Nußbaum-Thom, et al. Speech recognition for machine translation in quaero. In *IWSLT*, pages 121–128, 2011. 41

[Le13] Quoc V Le. Building high-level features using large scale unsupervised learning. In *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pages 8595–8598. IEEE, 2013. 20

[LGL+11] Lori Lamel, Jean-Luc Gauvain, Viet Bac Le, Ilya Oparin, and Sha Meng. Improved models for Mandarin speech-to-text transcription. In *Proc. ICASSP*, Prague; Czech Republic, May 2011. IEEE. 50

[LGRN09] Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Y Ng. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the 26th Annual International Conference on Machine Learning*, pages 609–616. ACM, 2009.

BIBLIOGRAPHY

[LHE08] Kornel Laskowski, Mattias Heldner, and Jens Edlund. The fundamental frequency variation spectrum. *Proceedings of FONETIK 2008*, pages 29–32, 2008. 50, 51

[Mar06] T. Marek. Analysis of german compounds using weighted finite state transducers. *Bachelor thesis, University of Tübingen*, 2006. 95, 96, 97

[MBS00a] Lidia Mangu, Eric Brill, and Andreas Stolcke. Finding consensus in speech recognition: word error minimization and other applications of confusion networks. *Computer Speech & Language*, 14(4):373–400, 2000. 1

[MBS00b] Lidia Mangu, Eric Brill, and Andreas Stolcke. Finding consensus in speech recognition: word error minimization and other applications of confusion networks. *Computer Speech & Language*, 14(4):373–400, 2000. 46

[MCCD13] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013. 24

[MCZS04] Nelson Morgan, BY Chenl, Qifeng Zhu, and Andreas Stolcke. Trapping conversational speech: Extending trap/tandem approaches to conversational telephone speech recognition. In *Acoustics, Speech, and Signal Processing, 2004. Proceedings.(ICASSP'04). IEEE International Conference on*, volume 1, pages I–537. IEEE, 2004.

[MDH12] Abdel-rahman Mohamed, George E Dahl, and Geoffrey Hinton. Acoustic modeling using deep belief networks. *Audio, Speech, and Language Processing, IEEE Transactions on*, 20(1):14–22, 2012. 72, 89

[MHL+14] Andrew L Maas, Awni Y Hannun, Christopher T Lengerich, Peng Qi, Daniel Jurafsky, and Andrew Y Ng. Increasing deep neural network acoustic model size for large vocabulary continuous speech recognition. *arXiv preprint arXiv:1406.7806*, 2014. 2, 81

[Mit97] Tom M Mitchell. Machine learning. 1997. *Burr Ridge, IL: McGraw Hill*, 45, 1997. 145

[MKB+10] Tomas Mikolov, Martin Karafiát, Lukas Burget, Jan Cernockỳ, and Sanjeev Khudanpur. Recurrent neural network based language model. In *INTERSPEECH*, pages 1045–1048, 2010. 25, 93

[MKLW11] P. Maergner, K. Kilgour, I. Lane, and A. Waibel. Unsupervised vocabulary selection for simultaneous lecture translation. 2011. 97, 104

[Moz89] Michael C Mozer. A focused back-propagation algorithm for temporal pattern recognition. *Complex systems*, 3(4):349–381, 1989. 33

[MR00] Manohar N Murthi and Bhaskar D Rao. All-pole modeling of speech based on the minimum variance distortionless response spectrum. *Speech and Audio Processing, IEEE Transactions on*, 8(3):221–239, 2000. 49

[MS69] Marvin Minsky and Papert Seymour. Perceptrons. 1969. 13, 16

[MSD+12] Tomáš Mikolov, Ilya Sutskever, Anoop Deoras, Hai-Son Le, Stefan Kombrink, and J Cernocky. Subword language modeling with neural networks. *preprint (http://www. fit. vutbr. cz/imikolov/rnnlm/char. pdf)*, 2012. 95

[MSW+13a] Florian Metze, Zaid AW Sheikh, Alex Waibel, Jonas Gehring, Kevin Kilgour, Quoc Bao Nguyen, and Van Huy Nguyen. Models of tone for tonal and non-tonal languages. In *Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on*, pages 261–266. IEEE, 2013. xiii, 50, 64, 66

[MSW+13b] Florian Metze, Zaid AW Sheikh, Alex Waibel, Jonas Gehring, Kevin Kilgour, Quoc Bao Nguyen, and Van Huy Nguyen. Models of tone for tonal and non-tonal languages. In *Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on*, pages 261–266. IEEE, 2013.

[NH10] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th International Conference on Machine Learning (ICML-10)*, pages 807–814, 2010. 17

[NRP11a] Claire H Noble, Caroline F Rowland, and Julian M Pine. Comprehension of argument structure and semantic roles: Evidence from english-learning children and the forced-choice pointing paradigm. *Cognitive Science*, 35(5):963–982, 2011. 7

[NRP11b] Claire H Noble, Caroline F Rowland, and Julian M Pine. Comprehension of argument structure and semantic roles: Evidence from english-learning

children and the forced-choice pointing paradigm. *Cognitive Science*, 35(5):963–982, 2011.

[NS88] Masami Nakamura and Kiyohiro Shikano. A study of english word category prediction based on neural networks. *The Journal of the Acoustical Society of America*, 84(S1):S60–S61, 1988. 93

[NTMSN11] M. Nußbaum-Thom, A.E.D. Mousa, R. Schlüter, and H. Ney. Compound word recombination for german lvcsr. In *Twelfth Annual Conference of the International Speech Communication Association*, 2011. 96

[OdKB+12] Marcel Oberlaender, Christiaan PJ de Kock, Randy M Bruno, Alejandro Ramirez, Hanno S Meyer, Vincent J Dercksen, Moritz Helmstaedter, and Bert Sakmann. Cell type–specific three-dimensional structure of thalamocortical circuits in a column of rat vibrissal cortex. *Cerebral cortex*, 22(10):2375–2391, 2012. xi, 6

[OTI98] Atsunori Ogawa, Kazuya Takeda, and Fumitada Itakura. Balancing acoustic and linguistic probabilities. In *Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on*, volume 1, pages 181–184. IEEE, 1998. 32

[Pie80] Janet Pierrehumbert. *The Phonetics and Phonology of English Intonation.* PhD thesis, Massachusetts Institute of Technology, 1980. 50

[PKK+08] Daniel Povey, Dimitri Kanevsky, Brian Kingsbury, Bhuvana Ramabhadran, George Saon, and Karthik Visweswariah. Boosted mmi for model and feature-space discriminative training. In *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*, pages 4057–4060. IEEE, 2008. 26, 45

[PKSN13] Christian Plahl, Michal Kozielski, R Schluter, and Hermann Ney. Feature combination and stacking of recurrent and non-recurrent neural networks for lvcsr. In *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pages 6714–6718. IEEE, 2013. 34, 53

[Pow64] Michael JD Powell. An efficient method for finding the minimum of a function of several variables without calculating derivatives. *The computer journal*, 7(2):155–162, 1964. 108

[PSN10] Christian Plahl, Ralf Schlüter, and Hermann Ney. Hierarchical bottle neck features for lvcsr. In *Interspeech*, pages 1197–1200, 2010. 53

[PSN11] Christian Plahl, Ralf Schlüter, and Hermann Ney. Improved acoustic feature combination for lvcsr by neural networks. In *INTERSPEECH*, pages 1237–1240, 2011. 53

[Rab89] Lawrence Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286, 1989. 25

[RGE02] Manuel Reyes-Gomez and Daniel PW Ellis. Error visualization for tandem acoustic modeling on the aurora task. In *ICASSP 2002*. International Conference on Acoustics, Speech, and Signal Processing, 2002. 47

[RHR94] Tony Robinson, Mike Hochberg, and Steve Renals. Ipa: Improved phone modelling with recurrent neural networks. In *Acoustics, Speech, and Signal Processing, 1994. ICASSP-94., 1994 IEEE International Conference on*, volume 1, pages I–37. IEEE, 1994. 33

[RMB+94] Steve Renals, Nelson Morgan, Hervé Bourlard, Michael Cohen, and Horacio Franco. Connectionist probability estimators in hmm speech recognition. *Speech and Audio Processing, IEEE Transactions on*, 2(1):161–174, 1994. 28

[Rob94] Anthony J Robinson. An application of recurrent nets to phone probability estimation. *Neural Networks, IEEE Transactions on*, 5(2):298–305, 1994. 33

[Ros57] Frank Rosenblatt. *The perceptron, a perceiving and recognizing automaton Project Para*. Cornell Aeronautical Laboratory, 1957. 12

[Sch98] Kjell Schubert. *Pitch tracking and his application on speech recognition*. PhD thesis, Diploma Thesis at University of Kalsruhe (TH), Germany, 1998. 50

[Sch07] Holger Schwenk. Continuous space language models. *Computer Speech & Language*, 21(3):492–518, 2007. 24, 25, 93, 101

[Sch15] Jürgen Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, 61:85–117, 2015. 19

[SHBL14] Andrew Senior, Georg Heigold, Michiel Bacchiani, and Hank Liao. Gmm-free dnn training. In *Proc. IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, 2014. 81

[SKK12a] Sebastian Stüker, Kevin Kilgour, and Florian Kraft. Quaero 2010 speech-to-text evaluation systems. In *High Performance Computing in Science and Engineering'11*, pages 607–618. Springer, 2012. 35, 37, 45

[SKK12b] Sebastian Stüker, Kevin Kilgour, and Florian Kraft. Quaero 2010 speech-to-text evaluation systems. In *High Performance Computing in Science and Engineering'11*, pages 607–618. Springer, 2012. 94

[SKM+12] Sebastian Stüker, Florian Kraft, Christian Mohr, Teresa Herrmann, Eunah Cho, and Alex Waibel. The kit lecture corpus for speech translation. In *LREC*, pages 3409–3414, 2012. 38

[SLY11] Frank Seide, Gang Li, and Dong Yu. Conversational speech transcription using context-dependent deep neural networks. In *Interspeech*, pages 437–440, 2011. 20

[SMFW01] Hagen Soltau, Florian Metze, Christian Fugen, and Alex Waibel. A one-pass decoder based on polymorphic linguistic context assignment. In *Automatic Speech Recognition and Understanding, 2001. ASRU'01. IEEE Workshop on*, pages 214–217. IEEE, 2001. 44, 45, 102

[SMK+12a] Christian Saam, Christian Mohr, Kevin Kilgour, Michael Heck, Matthias Sperber, Keigo Kubo, Sebastian Stüker, Sakriani Sakti, Graham Neubig, Tomoki Toda, et al. The 2012 kit and kit-naist english asr systems for the iwslt evaluation. In *IWSLT*, pages 87–90, 2012.

[SMK+12b] Christian Saam, Christian Mohr, Kevin Kilgour, Michael Heck, Matthias Sperber, Keigo Kubo, Sebastian Stüker, Sakriani Sakti, Graham Neubig, Tomoki Toda, et al. The 2012 kit and kit-naist english asr systems for the iwslt evaluation. In *IWSLT*, pages 87–90, 2012.

[SMKR13] Tara N Sainath, A-r Mohamed, Brian Kingsbury, and Bhuvana Ramabhadran. Deep convolutional neural networks for lvcsr. In *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pages 8614–8618. IEEE, 2013. 33

[SMM+91] Hidefumi SAWAI, Yasuhiro MINAMI, Masanori MIYATAKE, Alex WAIBEL, and Kiyohiro SHIKANO. Connectionist approaches to large vocabulary continuous speech recognition. *IEICE TRANSACTIONS on Fundamentals of Electronics, Communications and Computer Sciences*, 74(7):1834–1844, 1991. 32

[SMSN11] M.A.B. Shaik, A.E.D. Mousa, R. Schlüter, and H. Ney. Hybrid language models using mixed types of sub-lexical units for open vocabulary german lvcsr. In *Twelfth Annual Conference of the International Speech Communication Association*, 2011. 96

[SMSN12] M Ali Basha Shaik, Amr El-Desoky Mousa, Ralf Schlüter, and Hermann Ney. Investigation of maximum entropy hybrid language models for open vocabulary german and polish lvcsr. In *INTERSPEECH*, 2012. 96

[SSN12] Martin Sundermeyer, Ralf Schlüter, and Hermann Ney. Lstm neural networks for language modeling. In *INTERSPEECH*, 2012. 25, 93

[SSS14] Hagen Soltau, George Saon, and Tara N Sainath. Joint training of convolutional and non-convolutional neural networks. *to Proc. ICASSP*, 2014. 2, 69

[SSW91] Masahide Sugiyama, Hidehumi Sawai, and Alexander H Waibel. Review of tdnn (time delay neural network) architectures for speech recognition. In *Circuits and Systems, 1991., IEEE International Sympoisum on*, pages 582–585. IEEE, 1991.

[ST03] M. Schröder and J. Trouvain. The german text-to-speech synthesis system mary: A tool for research, development and teaching. *International Journal of Speech Technology*, 6(4):365–377, 2003. 97

[Sto02] A. Stolcke. Srilm-an extensible language modeling toolkit. In *Seventh International Conference on Spoken Language Processing*, 2002. 44, 65

[SVN37] Stanley Smith Stevens, John Volkmann, and Edwin B Newman. A scale for the measurement of the psychological magnitude pitch. *The Journal of the Acoustical Society of America*, 8(3):185–190, 1937. 48

[Tom85] Masaru Tomita. *Efficient parsing for natural language: A fast algorithm for practical systems*, volume 8. Springer Science & Business Media, 1985. 33

[Tse] Igor Tseyzer. An optimization of deep neural networks in asr using singular value decomposition. xi, xiv, 71, 85, 86, 88, 89, 90, 91, 92

[TW88] Shin'Ichi Tamura and Alex Waibel. Noise reduction using connectionist models. In *Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 1988 International Conference on*, pages 553–556. IEEE, 1988. 47

[VGBP13] Karel Veselỳ, Arnab Ghoshal, Lukás Burget, and Daniel Povey. Sequence-discriminative training of deep neural networks. In *INTERSPEECH*, pages 2345–2349, 2013. 20, 109, 149

[Vit67] Andrew J Viterbi. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *Information Theory, IEEE Transactions on*, 13(2):260–269, 1967. 26

[VLBM08] Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*, pages 1096–1103. ACM, 2008. 21

[VLL+10] Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *The Journal of Machine Learning Research*, 11:3371–3408, 2010. 22, 65

[VS09] Ngoc Thang Vu and Tanja Schultz. Vietnamese large vocabulary continuous speech recognition. In *Automatic Speech Recognition & Understanding, 2009. ASRU 2009. IEEE Workshop on*, pages 333–338. IEEE, 2009. 50

[VVP+07] Fabio Valente, Jithendra Vepa, Christian Plahl, Christian Gollan, Hynek Hermansky, and Ralf Schlüter. Hierarchical neural networks feature extraction for lvcsr system. In *INTERSPEECH*, pages 42–45, 2007. 53

[VW03] Anand Venkataraman and Wen Wang. Techniques for effective vocabulary selection. *arXiv preprint cs/0306022*, 2003. 44

[Wai88] Alex Waibel. *Prosody and speech recognition*. Morgan Kaufmann, 1988. 50

[Wai89] Alex Waibel. Modular construction of time-delay neural networks for speech recognition. *Neural computation*, 1(1):39–46, 1989. 33

[Wai14] Kilgour Waibel. Vorlesung: Neuronale netze. University Lecture, 2014. 145

[WHH+87a] Alexander Waibel, Toshiyuki Hanazawa, Geoffrey Hinton, Kiyohiro Shikano, and Kevin J Lang. Phoneme recognition using time-delay neural networks. In *Meeting of the Institute of Electrical, Information and Communication Engineers (IEICE)*, pages SP87–100. IEICE, 1987. 33

[WHH+87b] Alexander Waibel, Toshiyuki Hanazawa, Geoffrey Hinton, Kiyohiro Shikano, and Kevin J Lang. Phoneme recognition using time-delay neural networks. Technical report, ATR, 1987. ATR Technical Report, TR-I-0006. 33

[WHH+88] Alexander Waibel, Toshiyuki Hanazawa, Geoffrey Hinton, Kiyohiro Shikano, and K Lang. Phoneme recognition: neural networks vs. hidden markov models vs. hidden markov models. In *Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 1988 International Conference on*, pages 107–110. IEEE, 1988.

[WHH+89] Alex Waibel, Toshiyuki Hanazawa, Geoffrey Hinton, Kiyohiro Shikano, and Kevin J Lang. Phoneme recognition using time-delay neural networks. *Acoustics, Speech and Signal Processing, IEEE Transactions on*, 37(3):328–339, 1989. 32

[WM05] Matthias Wolfel and John McDonough. Minimum variance distortionless response spectral estimation. *Signal Processing Magazine, IEEE*, 22(5):117–126, 2005. 49

[WMW03] Matthias Wölfel, John W McDonough, and Alex Waibel. Minimum variance distortionless response on a warped frequency scale. In *INTERSPEECH*, 2003. 49

[WT84] Janet F Werker and Richard C Tees. Cross-language speech perception: Evidence for perceptual reorganization during the first year of life. *Infant behavior and development*, 7(1):49–63, 1984. 6

[WW03] L Wang and PC Woodland. Discriminative adaptive training using the mpe criterion. In *Automatic Speech Recognition and Understanding, 2003. ASRU'03. 2003 IEEE Workshop on*, pages 279–284. IEEE, 2003. 26

[XLG13] Jian Xue, Jinyu Li, and Yifan Gong. Restructuring of deep neural network acoustic models with singular value decomposition. In *INTERSPEECH*, pages 2365–2369, 2013. 84, 85

[YS11] Dong Yu and Michael L Seltzer. Improved bottleneck features using pretrained deep neural networks. In *INTERSPEECH*, volume 237, page 240, 2011. 53, 61

[ZCM+04] Qifeng Zhu, Barry Y Chen, Nelson Morgan, Andreas Stolcke, et al. On using mlp features in lvcsr. In *INTERSPEECH*, 2004. 47

[Zhu15] Linchen Zhu. Gmm free asr using dnn based cluster trees. Master's thesis, Karlsruhe Institute of technology, Germany, 2015. xi, 81, 83

[ZKSW15] Linchen Zhu, Kevin Kilgour, Sebastian Stüker, and Alex Waibel. Gaussian free cluster tree construction using deep neural network. In *Sixteenth Annual Conference of the International Speech Communication Association*, 2015. 81

[ZW97] Puming Zhan and Alex Waibel. Vocal tract length normalization for large vocabulary continuous speech recognition. Technical report, DTIC Document, 1997. 45

[ZW14] Chao Zhang and PC Woodland. Standalone training of context-dependent deep neural network acoustic models. In *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*, pages 5597–5601. IEEE, 2014.

Appendices

Appendix A

Language Model Data

The data sources for the IWSLT language model are given in Table A.1. There are far fewer sources because of evaluation campaign organizers restrict the allowable training text to a list of publicly available corpera.

The two language models used in this thesis are trained of different training sources. Table A.2 lists the text sources used for the Quaero language model from the 2012 Quaero evaluation. The 2011 Quaero evaluation systems uses almost exactly the same sources. The *various news websites* from 2011 are omitted and it also does not contain the newer parts of the *AM data transcripts*.

A. LANGUAGE MODEL DATA

Source Name	from	raw tokens	cleaned tokens
NewsCrawl (WMT)	2007 - 2013	-	1427.2M
CommonCrawl (WMT)	<2013	-	48.6M
News Commentary (WMT)	<2014	-	4.5M
EuroParl (WMT) [Koe05]	1996-2011	-	47.7M
MultiUN Corpus	2000-2010	5.9M	5.8M
European Language Newspaper Text LDC95T11	<1995	105.4M	92.0M
ECI Multilingual Text LDC94T5	<1995	13.8M	13.7M
HUB5 German Transcripts LDC2003T03	1997	30.6k	19.8k
German Political Speeches Corpus	1984 - 2012	5.6M	5.5M
CALLHOME German Transcripts LDC97T15	<1997	0.23M	0.17M
IWSLT LM Data	<2014	-	2.8M
TED Transcripts Translated	<2014	-	2.6M
Google Books Ngrams	<1508-2012	-	-

Table A.1: *Text sources used for the IWSLT language model*

Source Name	**from**	**raw tokens**	**cleaned tokens**
A query based webdump	2008	343.4M	360.1M
ODP Crawl	2008	120.7M	116.9M
Uni Karlsruhe Webpage Crawl	2007-05-25	-	1.4M
Meeting transcriptions	<2005	-	77.4k
KogSys Lecture Notes	2007	-	63.2k
Presentation transcripts	2007	-	13.1k
European Parliament Plenary Session (EPPS)	1996-05-15 to 2003-09-03	27.9M	24.3M
Baden-Württemberg Landtag transcripts	1996 to 2009	16.2M	14.1M
GermNews	1996-11-19 to 2000-01-31	0.92M	0.86M
GeneralNews	<1998-09-10	-	108.1M
Aachener Nachrichten Online	<2010	307.2M	84.0M
Zeit Online	<2000	332.2M	134.0M
Zeit Online	2000 - 2009	354.7M	177.6M
Over-Blog	2007 - 2009	265.6M	135.2M
Zeit Online Forum	2007 - 2009	132.1M	63.7M
Various News Websites	2009-05-11 to 2010-02-28	570.1M	148.8M
Zeit Online	2010	7.6M	7.6M
Aachener Nachrichten Online	2010	18.3M	18.3M
Various News Websites	2010-02-28 to 2010-02-31	40.6M	40.7M
Various News Websites	2011	112.3M	106M
AM data transcripts	<2012	-	1.8M
Google Web 1T 5-grams LDC2009T25	<2008	-	-

Table A.2: *Text sources used for the Quaero language model*

Appendix B

Backpropagation Outline

In this appendix we refrain from presenting a full proof of the algorithm and will instead show an outline of the proof with a focus on those parts on which some experiments in chapter 7 are based. Further details can be found in [B$^+$95, Mit97] with the notation and proof outline used in this section based on [Mit97] and [Wai14]. The backpropagation variant described here is called stochastic gradient descent (SGD) where a single training example is sent through the network, its error is calculated and passed back resulting in an updated network for the next training example.

- m inputs to the NN: $x \in \mathbb{R}^m$
- n outputs: $o_x \in \{0,1\}^n$
- Training Data X: $(x, t_x) \in \mathbb{R}^m \times \{0,1\}^n$ with t_x being the target or correct output of the network for the input vector x and o_x the actual output of the neural for that input
- x_{ji}: input i of neuron j
- w_{ji}^s: weight from input i of neuron j at iteration or step s
- $\vec{w}$: all the parameters in the NN (weights and biases from all layers)
- $\text{net}_j = \sum_i w_{ji} x_{ji}$
- $o_j = \varphi(\text{net}_j)$ output of neuron j
- t_j target output of neuron j
- outputs: neurons in the final layer

- Downstream(j): set of neurons whose inputs include neurons j

The backpropagation algorithm requires an error function that computes how much of an error there is between the output of the network for a given input and its target or what its output should have been. The two main error functions are the cross entropy error and the mean squared error. Here we use the MSR error function:

$$E_{\text{MSE}}(\vec{w}) = \frac{1}{2} \sum_{x \in X} \sum_{k \in \text{outputs}} (t_{kx} - o_{kx})^2 \tag{B.1}$$

The goal here is to find the parameter set $\vec{w}$ that minimizes this error function. Since we are looking at SGD and only care about the error produced by a single training example we can instead look at the error function:

$$E_x(\vec{w}) = \frac{1}{2} \sum_{k \in \text{outputs}} (t_{kx} - o_{kx})^2 \tag{B.2}$$

Minimizing all of these E_x error functions also leads to a minimum for the total error function E_{MSE}. The partial derivative of E_x with respect to a weight parameter w_i represents how much that weight affected the error and can be used to update that weight:

$$w_{ji}^{s+1} \leftarrow w_{ji}^{s} - \eta \frac{\partial E_x}{\partial w_{ji}} \tag{B.3}$$

The update is performed on all weights and then the new network is used for the next training example. This procedure is repeated for either a predetermined number of iterations or until convergence is reached. After all the training examples have been *seen* once by the network an epoch is said to have passed. NNs normally require several epochs of training until they have converged.

Computing the partial derivative of $\frac{\partial E_x}{\partial w_{ji}}$ is a nontrivial problem that can be tackled by using the chain rule ($(f \circ g)'(x_0) = f'\big(g(x)\big) \cdot g'(x_0)$) and the observation that w_{ji} can only affect ∂E_x through the input net_j of neuron that w_{ji} leads:

$$\frac{\partial E_x}{\partial w_{ji}} = \frac{\partial E_x}{\partial \text{net}_j} \frac{\partial \text{net}_j}{\partial w_{ji}} = \frac{\partial E_x}{\partial \text{net}_j} \frac{\partial \sum_i w_{ji} x_{ji}}{\partial w_{ji}} = \frac{\partial E_x}{\partial \text{net}_j} x_{ij} \tag{B.4}$$

The derivative of $\frac{\partial E_x}{\partial w_{ji}}$, which we use to define $-\delta_j$, depends on where in the network the neuron is located. Neurons in the output layer directly affect the error function E_x whereas neurons preceding them affect E_x through every neuron that has its output as

an input. We therefore consider these two case separately. For the output neurons we can again apply the chain as net_j only affects E_x through the output o_{jx} of the neuron j:

$$-\delta_j = \frac{\partial E_x}{\partial \text{net}_j} = \frac{\partial E_x}{\partial o_{jx}} \frac{\partial o_{jx}}{\partial \text{net}_j} \tag{B.5}$$

Here $\frac{\partial E_x}{\partial o_{jx}}$ is the partial derivative of the error function by the output of a single neuron which is

$$\frac{\partial E_x}{\partial o_{jx}} = -(t_{jx} - o_{jx}) \tag{B.6}$$

for the MSE error function. The partial derivative $\frac{\partial o_{jx}}{\partial \text{net}_j}$ is the derivative of the activation function by its input which we'll note as $\varphi'(\text{net}_j)$ leading to:

$$\frac{\partial E_x}{\partial \text{net}_j} = \frac{\partial E_x}{\partial o_{jx}} \frac{\partial o_{jx}}{\partial \text{net}_j} = -(t_{jx} - o_{jx})\varphi'(\text{net}_j) \tag{B.7}$$

In the 2nd case, where the neuron j is not an output neuron, it can only affect E_x through the neurons for which it is an input (Downstream(j)) and their inputs net_k are only affected through neuron j's output o_j. By applying the chain rule and simplifying with $\frac{\partial E_x}{\partial \text{net}_k} = -\delta_j$, we then get :

$$-\delta_j = \frac{\partial E_x}{\partial \text{net}_j} = \sum_{k \in \text{Downstream}(j)} \frac{\partial E_x}{\partial \text{net}_k} \frac{\partial \text{net}_k}{\partial \text{net}_j} \tag{B.8}$$

$$= \sum_{k \in \text{Downstream}(j)} \frac{\partial E_x}{\partial \text{net}_k} \frac{\partial \text{net}_k}{\partial o_j} \frac{\partial o_j}{\partial \text{net}_j} \tag{B.9}$$

$$= \sum_{k \in \text{Downstream}(j)} -\delta_k w_{kj} \varphi'(\text{net}_j) \tag{B.10}$$

$$= \varphi'(\text{net}_j) \sum_{k \in \text{Downstream}(j)} -\delta_k w_{kj} \tag{B.11}$$

Using the derived δ_k the update rule can now be written as:

$$w_{ji}^{s+1} \leftarrow w_{ji}^{s} + \eta \delta_k x_j i \tag{B.12}$$

This works for any feed forward neural network topology. The algorithm, however, cannot decide how the topology should look, which error function and which activations to use or what to set the learning rate η to. These, so called hyperparameters, have to

be optimized independently of the learning algorithm.

Appendix C

MMIE Error Function

This appendix contains the full derivative the MMIE error function used in the chapter on neural network based AM and LM combination. This is similar to the MMIE derivative used for sequences training in [VGBP13].

C.1 Terminology

U : *a set of N utterances*

W_u : *correct transcript of utterance* $u \in U$

F_u : *features of* u

$\widehat{W_u}$: *all possible hypotheses from a lattice of* u

$W_{h_u} \in \widehat{W_u}$: *a hypothesis of* u

$W_{h_u}(w) \in \widehat{W_u}$: *a hypothesis of* u *containing the word* w

$w \in W$: *a word in* W

$$\delta_{w|W} = \begin{cases} 1, & \text{if } w \in W \\ 0, & \text{otherwise} \end{cases}$$

$o^{(w)}$: *output of the neural network (for word* w*)*

φ : *neural network activation funktion; its derivitive* φ'

a_i : *weight from neuron* i *in the last hidden layer to the output neuron*

$x_i^{(w)}$: *output of neuron* i *in the last hidden layer*

$net^{(w)} = \sum_i a_i x_i^{(w)}$: *input to the neural netwo*

C.2 MMIE

For given set of N utterance U with their corresponding correct transcripts W_u and features sequences F_u the E_{MMI} error is defined as:

$$E_{MMI} = \log \prod_{u \in U} \frac{p(F_u|W_u)P(W_u)}{\sum_{W_{h_u} \in \widehat{W_u}} p(F_u|W_{h_u})p(W_{h_u})} \tag{C.1}$$

Since this scoring function is only being applied at word transitions we can assume that we have the acoustic model score for whole words:

$$p(F_u|W_u) = \prod_{w \in W_u} p(F_u|w) \tag{C.2}$$

This decomposition to the word level is shown to also be possible for the language model in section 2.2.1. This allows us to reform the error function as such:

$$E_{MMI} = \log \prod_{u \in U} \frac{\prod_{w \in W_u} p(F_u|w) P(w|h_w)}{\sum_{W_{h_u} \in \widehat{W_u}} \prod_{w \in W_{h_u}} p(F_u|w) p(w|h_w)} \tag{C.3}$$

$$= \log \prod_{u \in U} \frac{\prod_{w \in W_u} e^{\log p(F_u|w) P(w|h_w)}}{\sum_{W_{h_u} \in \widehat{W_u}} \prod_{w \in W_{h_u}} e^{\log p(F_u|w) p(w|h_w)}} \tag{C.4}$$

In a loglinear interpolation the $\log p(F_u|w)P(w|h_w)$ would be replaced with with a loglinear combination of features. Here we instead replace it with the output of a neural network

$$\log p(F_w|w)p(w|h_w) = o^{(w)} = \varphi(\sum_i a_i x_i^{(w)}) \tag{C.5}$$

$$p(F_w|w)p(w|h_w) = e^{\varphi(\sum_i a_i x_i^{(w)})} \tag{C.6}$$

which is then inserted into C.4

$$E_{MMI} = \log \prod_{u \in U} \frac{\prod_{w \in W_u} e^{\varphi(\sum_i a_i x_i^{(w)})}}{\sum_{W_{h_u} \in \widehat{W_u}} \prod_{w \in W_{h_u}} e^{\varphi(\sum_i a_i x_i^{(w)})}} \tag{C.7}$$

The outer logarithm can now be moved inside

$$E_{MMI} = \sum_{u \in U} \left[\log \left(\prod_{w \in W_u} e^{\varphi(\sum_i a_i x_i^{(w)})} \right) - \log \left(\sum_{W_{h_u} \in \widehat{W_u}} \prod_{w \in W_{h_u}} e^{\varphi(\sum_i a_i x_i^{(w)})} \right) \right] \tag{C.8}$$

$$= \sum_{u \in U} \left[\sum_{w \in W_u} \varphi(\sum_i a_i x_i^{(w)}) - \log \left(\sum_{W_{h_u} \in \widehat{W_u}} e^{\sum_{w \in W_{h_u}} \varphi(\sum_i a_i x_i^{(w)})} \right) \right] \tag{C.9}$$

$$\tag{C.10}$$

As with SVD we can restrict ourselves to the error induced by a single example

which, in this case, is the combination a an AM score and an LM of a a given word. Taking the partial derivative of E_{MMI} with respect to a weight a_i gives us:

$$\frac{\partial E_{MMI}}{\partial a_i} = \frac{\partial E_{MMI}}{\partial net_i^{(w)}} \quad \frac{\partial net_i^{(w)}}{a_i} = \frac{\partial E_{MMI}}{\partial net_i^{(w)}} \quad x_i^{(w)} \tag{C.11}$$

and

$$\frac{\partial E_{MMI}}{\partial net_i^{(w)}} = \delta_{w|W_u}\ \varphi'(\sum_i a_i x_i^{(w)}) - \frac{\frac{\partial}{\partial net_i^{(w)}} \sum\limits_{W_{h_u} \in \widehat{W_u}} e^{\sum\limits_{w \in W_{h_u}} \varphi(\sum\limits_i a_i x_i^{(w)})}}{\sum\limits_{W_{h_u} \in \widehat{W_u}} e^{\sum\limits_{w \in W_{h_u}} \varphi(\sum\limits_i a_i x_i^{(w)})}} \tag{C.12}$$

$$= \delta_{w|W_u}\ \varphi'(\sum_i a_i x_i^{(w)}) - \frac{\sum\limits_{W_{h_u}(w) \in \widehat{W_u}} \left[e^{\sum\limits_{\hat{w} \in W_{h_u}(w)} \varphi(\sum\limits_i a_i x_i^{(\hat{w})})} \frac{\partial}{\partial net_i^{(w)}} \left(\sum\limits_{\hat{w} \in W_{h_u}(w)} \varphi(\sum\limits_i a_i x_i^{(\hat{w})}) \right) \right]}{\sum\limits_{W_{h_u} \in \widehat{W_u}} e^{\sum\limits_{w \in W_{h_u}} \varphi(\sum\limits_i a_i x_i^{(w)})}} \tag{C.13}$$

Applying the partial derivative to the inner part of the logarithm removes all terms in the sum that do not contain $net_i^{(w)}$. This also happens again when applied to the inner part of the exponential function resulting in

$$\frac{\partial E_{MMI}}{\partial net_i^{(w)}} = \delta_{w|W_u}\ \varphi'(\sum_i a_i x_i^{(w)}) - \frac{\sum\limits_{W_{h_u}(w) \in \widehat{W_u}} \left[e^{\sum\limits_{\hat{w} \in W_{h_u}(w)} \varphi(\sum\limits_i a_i x_i^{(\hat{w})})} \varphi'(\sum_i a_i x_i^{(\hat{w})}) \right]}{\sum\limits_{W_{h_u} \in \widehat{W_u}} e^{\sum\limits_{w \in W_{h_u}} \varphi(\sum\limits_i a_i x_i^{(w)})}} \tag{C.14}$$

$$= \left(\delta_{w|W_u} - \frac{\sum\limits_{W_{h_u}(w) \in \widehat{W_u}} e^{\sum\limits_{\hat{w} \in W_{h_u}(w)} \varphi(\sum\limits_i a_i x_i^{(\hat{w})})}}{\sum\limits_{W_{h_u} \in \widehat{W_u}} e^{\sum\limits_{w \in W_{h_u}} \varphi(\sum\limits_i a_i x_i^{(w)})}} \right) \varphi'(\sum_i a_i x_i^{(\hat{w})}) \tag{C.15}$$

In training we will be using a lattice so the denominator of the fraction in this equation is the sum of all possible hypotheses in the lattice and the nominator is the

sum of all hypotheses that pass through the node corresponding to the word w. This makes it the posterior probability $\Upsilon(w)$ of the lattice node corresponding to the word w.

Using the linear activation function with $\varphi'(x) = 1$ the final derivative can be expressed as:

$$\frac{\partial E_{MMI}}{\partial a_i} = \left(\delta_{w|W_u} - \Upsilon(w)\right) \quad x_i^{(w)} \tag{C.16}$$

The δ_j required for the update rule of the backpropagation algorithm is then:

$$\delta_j = \delta_{w|W_u} - \Upsilon(w) \tag{C.17}$$