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STATISTICAL LANGUAGE MODELS BASED ON NEURAL NETWORKS

DISERTAČNÍ PRÁCE
PHD THESIS

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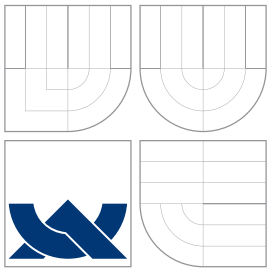

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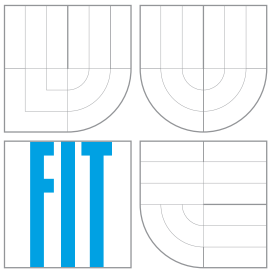

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STATISTICKÉ JAZYKOVÉ MODELY ZALOŽENÉ NA NEURONOVÝCH SÍTÍCH

STATISTICAL LANGUAGE MODELS BASED ON NEURAL NETWORKS

DISERTAČNÍ PRÁCE
PHD THESIS

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BRNO 2012

Abstrakt

Statistické jazykové modely jsou důležitou součástí mnoha úspěšných aplikací, mezi něž patří například automatické rozpoznávání řeči a strojový překlad (příkladem je známá aplikace Google Translate). Tradiční techniky pro odhad těchto modelů jsou založeny na tzv. N-gramech. Navzdory známým nedostatkům těchto technik a obrovskému úsilí výzkumných skupin napříč mnoha oblastmi (rozpoznávání řeči, automatický překlad, neuroscience, umělá inteligence, zpracování přirozeného jazyka, komprese dat, psychologie atd.), N-gramy v podstatě zůstaly nejúspěšnější technikou. Cílem této práce je prezentace několika architektur jazykových modelů založených na neuronových sítích. Ačkoliv jsou tyto modely výpočetně náročnější než N-gramové modely, s technikami vyvinutými v této práci je možné jejich efektivní použití v reálných aplikacích. Dosažené snížení počtu chyb při rozpoznávání řeči oproti nejlepším N-gramovým modelům dosahuje 20%. Model založený na rekurentní neurovové síti dosahuje nejlepších publikovaných výsledků na velmi známé datové sadě (Penn Treebank).

Abstract

Statistical language models are crucial part of many successful applications, such as automatic speech recognition and statistical machine translation (for example well-known Google Translate). Traditional techniques for estimating these models are based on N-gram counts. Despite known weaknesses of N-grams and huge efforts of research communities across many fields (speech recognition, machine translation, neuroscience, artificial intelligence, natural language processing, data compression, psychology etc.), N-grams remained basically the state-of-the-art. The goal of this thesis is to present various architectures of language models that are based on artificial neural networks. Although these models are computationally more expensive than N-gram models, with the presented techniques it is possible to apply them to state-of-the-art systems efficiently. Achieved reductions of word error rate of speech recognition systems are up to 20%, against state-of-the-art N-gram model. The presented recurrent neural network based model achieves the best published performance on well-known Penn Treebank setup.

Klíčová slova

jazykový model, neuronová síť, rekurentní, maximální entropie, rozpoznávání řeči, komprese dat, umělá inteligence

Keywords

language model, neural network, recurrent, maximum entropy, speech recognition, data compression, artificial intelligence

Citace

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Statistical Language Models Based on Neural Networks

Prohlášení

Prohlašuji, že jsem tuto disertační práci vypracoval samostatně pod vedením Doc. Dr. Ing. Jana Černockého. Uvedl jsem všechny literární publikace, ze kterých jsem čerpal. Některé experimenty byly provedeny ve spolupráci s dalšími členy skupiny Speech@FIT, případně se studenty z Johns Hopkins University - toto je v práci vždy explicitně uvedeno.

.....
Tomáš Mikolov
Květen 2012

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It was great experience for me to visit Johns Hopkins University during my studies, and I am grateful to Frederick Jelinek and Sanjeev Khudanpur for granting me this opportunity. I always enjoyed discussions with Sanjeev, who was my mentor during my stay there. I also collaborated with other students at JHU, especially Puyang Xu, Scott Novotney and Anoop Deoras. With Anoop, we were able to push state-of-the-art on several standard tasks to new limits, which was the most exciting for me.
As my thesis work is based on work of Yoshua Bengio, it was great for me that I could have spent several months in his machine learning lab at University of Montreal. I always enjoyed reading Yoshua's papers, and it was awesome to discuss with him my ideas personally.

Contents

Chapter 1

Introduction

1.1 Motivation

From the first day of existence of the computers, people were dreaming about artificial intelligence - machines that would produce complex behaviour to reach goals specified by human users. Possibility of existence of such machines has been controversial, and many philosophical questions were raised - whether the intelligence is not unique only to humans, or only to animals etc. Very influential work of Alan Turing did show that any computable problem can be computed by Universal Turing Machine - thus, assuming that the human mind can be described by some algorithm, Turing Machine is powerful enough to represent it.

Computers today are Turing-complete, ie. can represent any computable algorithm. Thus, the main problem is how to find configuration of the machine so that it would produce desired behaviour that humans consider intelligent. Assuming that the problem is too difficult to be solved immediately, we can think of several ways that would lead us towards intelligent machines - we can start with a simple machine that can recognize basic shapes and images such as written digits, then scale it towards more complex types of images such as human faces and so on, finally reaching machine that can recognize objects in the real world as well as humans can.

Other possible way can be to simulate parts of the human brain on the level of individual brain cells, neurons. Computers today are capable of realistically simulating the real world, as can be seen in modern computer games - thus, it seems logical that with accurate simulation of neurons and more computational power, it should be possible to simulate the whole human brain one day.

Maybe the most popular vision of future AI as seen in science fiction movies are robots and computers communicating with humans using natural language. Turing himself proposed a test of intelligence based on ability of the machine to communicate with humans using natural language [76]. This choice has several advantages - amount of data that has to be processed can be very small compared to machine that recognizes images or sounds. Next, machine that will understand just the basic patterns in the language can be developed first, and scaled up subsequently. The basic level of understanding can be at level of a child, or a person that learns a new language - even such low level of understanding is sufficient to be tested, so that it would be possible to measure progress in ability of the machine to understand the language.

Assuming that we would want to build such machine that can communicate in natural language, the question is how to do it. Reasonable way would be to mimic learning processes of humans. A language is learned by observing the real world, recognizing its regularities, and mapping acoustic and visual signals to higher level representations in the brain and back - the acoustic and visual signals are predicted using the higher level representations. Motivation for learning the language is to improve success of humans in the real world.

The whole learning problem might be too difficult to be solved at once - there are many open questions regarding importance of individual factors, such as how much data has to be processed during training of the machine, how important is it to learn the language jointly with observing real world situations, how important is the innate knowledge, what is the best formal representation of the language, etc. It might be too ambitious to attempt to solve all these problems together, and to expect too much from models or techniques that even do not allow existence of the solution (an example might be the well-known limitations of finite state machines to represent efficiently longer term patterns).

Important work that has to be mentioned here is the Information theory of Claude Shannon. In his famous paper Entropy of printed English [66], Shannon tries to estimate entropy of the English text using simple experiments involving humans and frequency based models of the language (n-grams based on history of several preceding characters). The conclusion was that humans are by far better in prediction of natural text than n-grams, especially as the length of the context is increased - this so-called "Shannon game" can be effectively used to develop more precise test of intelligence than the one defined by Turing. If we assume that the ability to understand the language is equal (or at least highly

correlated) to the ability to predict words in a given context, then we can formally measure quality of our artificial models of natural languages. This AI test has been proposed for example in [44] and more discussion is given in [42].

While it is likely that attempts to build artificial language models that can understand text in the same way as humans do just by reading huge quantities of text data is unrealistically hard (as humans would probably fail in such task themselves), language models estimated from huge amounts of data are very interesting due to their practical usage in wide variety of commercially successful applications. Among the most widely known ones are the statistical machine translation (for example popular Google Translate) and the automatic speech recognition.

The goal of this thesis is to describe new techniques that have been developed to overcome the simple n-gram models that still remain basically state-of-the-art today. To prove usefulness of the new approaches, empirical results on several standard data sets will be extensively described. Finally, approaches and techniques that can possibly lead to automatic language learning by computers will be discussed, together with a simple plan how this could be achieved.

1.2 Structure of the Thesis

Chapter 2 introduces the statistical language modeling and mathematically defines the problem. Simple and advanced language modeling techniques are discussed. Also, the most important data sets that are further used in the thesis are introduced.

Chapter 3 introduces neural network language models and the recurrent architecture, as well as the extensions of the basic model. The training algorithm is described in detail.

Chapter 4 provides extensive empirical comparison of results obtained with various advanced language modeling techniques on the Penn Treebank setup, and results after combination of these techniques.

The Chapter 5 focuses on the results after application of the RNN language model to standard speech recognition setup, the Wall Street Journal task. Results and comparison are provided on two different setups; one is from the Johns Hopkins University and allows comparison with competitive techniques such as discriminatively trained LMs and structured LMs, and the other setup was obtained with an open-source ASR toolkit, Kaldi.

Chapter 6 presents further extensions of the basic recurrent neural network language model that allow efficient training on large data sets. Experiments are performed on data sets with up to 400 million training tokens with very large neural networks. Results are reported on state of the art setup for Broadcast News speech recognition (the NIST RT04 task) with a recognizer and baseline models provided by IBM.

Chapter 7 presents further empirical results on various other tasks, such as machine translation, data compression and others. The purpose of this chapter is to prove that the developed techniques are very general and easily applicable to other domains where n-gram models are currently used.

Chapter 8 discusses computational limitations of models that are commonly used for the statistical language modeling, and provides some insight into how further progress can be achieved.

Finally, Chapter 9 summarizes the achieved results and concludes the work.

1.3 Claims of the Thesis

The most important original contributions of this thesis are:

- Development of statistical language model based on simple recurrent neural network
- Extensions of the basic recurrent neural network language model:
  - Simple classes based on unigram frequency of words
  - Joint training of neural network and maximum entropy model
  - Adaptation of neural net language models by sorting the training data
  - Adaptation of neural net language models by training the model during processing of the test data
- Freely available open source toolkit for training RNN-based language models that can be used to reproduce the described experiments
- Empirical comparison with other advanced language modeling techniques, with new state of the art results achieved with RNN based LMs on the following tasks:
  - Language modeling of Penn Treebank Corpus
  - Wall Street Journal speech recognition

  - NIST RT04 speech recognition
  - Data compression of text, machine translation and other tasks

- Analysis of performance of neural net language models (influence of size of the hidden layer, increasing amount of the training data)
- Discussion about limitations of traditional approaches to language modeling and open questions for future research

Chapter 2

Overview of Statistical Language Modeling

Statistical language modeling has received a lot of attention in the past decades. Many different techniques have been proposed, and nearly each of them can provide improvements over the basic trigram model. However, these techniques are usually studied in isolation. Comparison is made just to the basic models, and often even these basic models are poorly tuned. It is thus difficult to judge which technique, or combination of techniques, is currently the state-of-the-art in the statistical language modeling. Moreover, many of the proposed models provide the same information (for example, longer range cache-like information), and can be seen just as permutations of existing techniques. This was already observed by Goodman [24], who proposed that different techniques should be studied jointly.

Another important observation of Goodman was that relative improvements provided by some techniques tend to decrease as the amount of training data increases. This has resulted in much scepticism, and some researchers did claim that it is enough to focus on obtaining the largest possible amount of training data and build simple n-gram models, sometimes not even focusing much on the smoothing to be sure that the resulting model is correctly normalized as reported in [11]. The motivation and justification for these approaches were results on real tasks.

On the other hand, basic statistical language modeling faces serious challenges when it is applied to inflective or morphologically rich languages (like Russian, Arabic or Czech), or when the training data are limited and costly to acquire (as it is for spontaneous speech

recognition). Maybe even more importantly, several researchers have already pointed out that building large look-up tables from huge amounts of training data (which is equal to standard n-gram modeling) is not going to provide the ultimate answer to the language modeling problem, as because of curse of dimensionality, we will never have that much data [5].

The other way around, building language models from huge amounts of data (hundreds of billion words or more) is also a very challenging task, and has received recently a lot of attention [26]. The problems that arise include smoothing, as well as compression techniques, because it is practically impossible to store the full n-gram models estimated from such amount of data in computer memory. While amount of text that is available on the Internet is ever-increasing and computers are getting faster and memory bigger, we cannot hope to build a database of all possible sentences that can ever be said.

In this thesis, recurrent neural network language model (RNN LM) which I have recently proposed in [49, 50] is described, and compared to other successful language modeling techniques. Several standard text corpora are used, which allows to provide detailed and fair comparison to other advanced language modeling techniques. The aim is at obtaining the best achievable results by combining all studied models, which leads to a new state of the art performance on the standard setup involving part of Penn Treebank Corpus.

Next, it is shown that the RNN based language model can be applied to large scale well-tuned system, and that it provides significant improvements in speech recognition accuracy. The baseline system for these experiments from IBM (RT04 Broadcast News speech recognition) has been recently used in the 2010 Summer Workshop at Johns Hopkins University [82]. This system was also used as a baseline for a number of papers concerning novel type of maximum entropy language model, a so-called *model M* [30] language model, which is also used in the performance comparison as it was previously the state-of-the-art language model on the given task.

Finally, I try to answer some fundamental questions of language modeling. Namely, whether the progress in the field is illusory, as is sometimes suggested. And ultimately, why the new techniques did not reach human performance yet, and what might be the missing parts and the most promising areas for the future research.

2.1 Evaluation

2.1.1 Perplexity

Evaluation of quality of different language models is usually done by using either perplexity or word error rate. Both metrics have some important properties, as well as drawbacks, which we will briefly mention here. The perplexity (PPL) of word sequence **w** is defined as

$$PPL = \sqrt[K]{\prod_{i=1}^{K} \frac{1}{P(w_i|w_{1...i-1})}} = 2^{-\frac{1}{K}\sum_{i=1}^{K} log_2 P(w_i|w_{1...i-1})} \tag{2.1}$$

Perplexity is closely related to the cross entropy between the model and some test data[1]. It can be seen as exponential of average per-word entropy of some test data. For example, if the model encodes each word from the test data on average in 8 bits, the perplexity is 256. There are several practical reasons why to use perplexity and not entropy: first, it is easier to remember absolute values in the usual range of perplexity between 100-200, than numbers between corresponding 6.64 and 7.64 bits. Second, it looks better to report that some new technique yields an improvement of 10% in perplexity, rather than 2% reduction of entropy, although both results are referring to the same improvement (in this example, we assume baseline perplexity of 200). Probably the most importantly, perplexity can be easily evaluated (if we have some held out or test data) and as it is closely related to the entropy, the model which yields the lowest perplexity is in some sense the closest model to the true model which generated the data.

There has been great effort in the past to discover models which would be the best for representing patterns found in both real and artificial sequential data, and interestingly enough, there has been limited cooperation between researchers working in different fields, which gave rise to high diversity of various techniques that were developed. Natural language was viewed by many as a special case of sequence of discrete symbols, and its structure was supposedly best captured by various limited artificial grammars (such as context free grammar), with strong linguistic motivation.

The question of validity of the statistical approach for describing natural language has been raised many times in the past, with maybe the most widely known statement coming from Noam Chomsky:

[1]For simplification, it is later denoted simply as entropy.

The notion "probability of a sentence" is an entirely useless one, under any known interpretation of this term. (Chomsky, 1969)

Still, we can consider entropy and perplexity as very useful measures. The simple reason is that in the real-world applications (such as speech recognizers), there is a strong positive correlation between perplexity of involved language model and the system's performance [24].

More theoretical reasons for using entropy as a measure of performance come from an artificial intelligence point of view [42]. If we want to build an intelligent agent that will maximize its reward in time, we have to maximize its ability to predict the outcome of its own actions. Given the fact that such agent is supposed to work in the real world and it can experience complex regularities including the natural language, we cannot hope for a success unless this agent has an ability to find and exploit existing patterns in such data. It is known that Turing machines (or equivalent) have the ability to represent any algorithm (in other words, any pattern or regularity). However, algorithms that would find all possible patterns in some data are not known. Contrary, it was proved that such algorithms cannot exist in general, due to the halting problem (for some algorithms, the output is not computationally decidable due to potential infinite recursion).

A very inspiring work on this topic was done by Solomonoff [70], who has shown an optimal solution to the general prediction problem called Algorithmic probability. Despite the fact that it is uncomputable, it provides very interesting insight into concepts such as patterns, regularities, information, noise and randomness. Solomonoff's solution is to average over all possible (infinitely many) models of given data, while normalizing by their description length. Algorithmic probability (ALP) of string x is defined as

$$P_M(x) = \sum_{i=0}^{\infty} 2^{-|S_i(x)|}, \tag{2.2}$$

where $P_M(x)$ denotes probability of string x with respect to machine M and $|S_i(x)|$ is the description length of x (or any sequence that starts with x) given the i-th model of x. Thus, the shortest descriptions dominate the final value of algorithmic probability of the string x. More information about ALP, as well as proofs of its interesting properties (for example invariance to the choice of the machine M, as long as M is universal) can be found in [70].

ALP can be used to obtain prior probabilities of any sequential data, thus it provides theoretical solution to the statistical language modeling. As mentioned before, ALP is not computable (because of the halting problem), however it is mentioned here to justify our later experiments with model combination. Different language modeling techniques can be seen as individual components in eq. 2.2, where instead of using description length of individual models for normalization, we use the performance of the model on some validation data to obtain its weight[2]. More details about concepts such as ALP and Minimum description length (MDL) will be given in Chapter 8.

Another work worth of mentioning was done by Mahoney [44], who has shown that the problem of finding the best models of data is actually equal to the problem of general data compression. Compression can be seen as two problems: data modeling, and coding. Since coding is optimally solved by *Arithmetic coding*, data compression can be seen just as a data modeling problem. Mahoney together with M. Hutter also organize a competition with the aim to reach the best possible compression results on a given data set (mostly containing wikipedia text), known as a *Hutter prize competition*. As the data compression of text is almost equal to the language modeling task, I follow the same idea and try to reach the best achievable results on a single well-known data set, the Penn Treebank Corpus, where it is possible to compare (and combine) results of techniques developed by several other researchers.

The important drawback of perplexity is that it obscures achieved improvements. Usually, improvements of perplexity are measured as percentual decrease over the baseline value, which is a mistaken but widely accepted practice. In Table 2.1, it is shown that constant perplexity improvement translates to different entropy reductions. For example, it will be shown in Chapter 7 that advanced LM techniques provide similar relative reductions of entropy for word and character based models, while perplexity comparison would completely fail in such case. Thus, perplexity results will be reported as a good measure for quick comparison, but improvements will be mainly reported by using entropy.

[2]It can be argued that since most of the models that are commonly used in language modeling are not Turing-complete - such as finite state machines - using description length of these models would be inappropriate.

Table 2.1: *Constant 30% perplexity reduction translates to variable entropy reduction.*

PPL	PPL after reduction	Relative PPL reduction	Entropy [bits]	Entropy after reduction	Relative entropy reduction
2	1.4	30%	1	0.49	51%
20	14	30%	4.32	3.81	11.8%
100	70	30%	6.64	6.13	7.7%
200	140	30%	7.64	7.13	6.7%
500	350	30%	8.97	8.45	5.8%
2000	1400	30%	10.97	10.45	4.7%

2.1.2 Word Error Rate

The word error rate of speech recognizer is defined as

$$WER = \frac{S + D + I}{N}, \tag{2.3}$$

where S is number of substitutions, D deletions and I insertions (each operation can change, delete or add a single word). The WER is defined for the lowest number of these operations that are needed to change the decoded utterance W' to the reference utterance W, which has N words.

The word error rate (WER) measures directly the quality of the speech recognition system, by counting the number of mistakes between the output of the system and the reference transcription which is provided by a human annotator. The drawbacks include over-emphasis on uninformative words (which is usually reduced in advanced metrics that tolerate substitutions between words with the same sense, like NIST WER). For comparison of different techniques, word error rate can be inaccurate, and improvements are commonly misinterpreted by researchers. Practical experience shows that it is very hard to obtain improvements over well-tuned systems based on state-of-the-art techniques. Some techniques can yield large WER improvements when applied to simple systems, while they have practically no influence in the best systems. Comparison of relative WER reductions when applying different techniques to different systems is practically useless. On the other hand, comparing different techniques on the same task, or even better by using the same configuration of ASR system, can be very informative and WER can be a better metric than perplexity in such cases.

To conclude usefulness of different metrics - the advantages of perplexity are:

- Good theoretical motivation
- Simplicity of evaluation
- Good correlation with system performance

Disadvantages of perplexity are:

- It is hard to check that the reported value is correct (mostly normalization and "looking into future" related problems)
- Perplexity is often measured assuming perfect history, while this is certainly not true for ASR systems: poor performance of models that rely on long context information (such as cache models) is source of confusion and claims that perplexity is not well correlated with WER
- Most of the research papers compare perplexity values incorrectly - the baseline is often suboptimal to "make the results look better"

Advantages of WER:

- Often the final metric we want to optimize; quality of systems is usually measured by some variation of WER (such as NIST WER)
- Easy to evaluate, as long as we have reference transcriptions

Disadvantages of WER:

- Results are often noisy; for small data sets, the variance in WER results can be absolutely 0.5%
- Overemphasis on the frequent, uninformative words
- Reference transcriptions can include errors, spelling mistakes
- Substituted words with the same or similar meaning are as bad mistakes as words that have the opposite meaning
- Full speech recognition system is needed
- Improvements are often task-specific

Surprisingly, many research papers come with conclusions such as *"Our model provides 2% improvement in perplexity over 3-gram with Good-Turing discounting and 0.3% reduction of WER, thus we have achieved new state of the art results."* - that is clearly misleading statement. Thus, great care must be given to proper evaluation and comparison of techniques.

2.2 N-gram Models

The probability of a sequence of symbols (usually words) is computed using a chain rule as

$$P(w) = \sum_{i=1}^{N} P(w_i|w_1...w_{i-1}) \tag{2.4}$$

The most frequently used language models are based on the n-gram statistics, which are basically word co-occurrence frequencies. The maximum likelihood estimate of probability of word A in context H is then computed as

$$P(A|H) = \frac{C(HA)}{C(H)} \tag{2.5}$$

where $C(HA)$ is the number of times that the HA sequence of words has occurred in the training data. The context H can consist of several words, for the usual trigram models $|H| = 2$. For $H = \emptyset$, the model is called unigram, and it does not take into account history. As many of these probability estimates are going to be zero (for all words that were not seen in the training data in a particular context H), smoothing needs to be applied. This works by redistributing probabilities between seen and unseen (zero-frequency) events, by exploiting the fact that some estimates, mostly those based on single observations, are greatly over-estimated. Detailed overview of common smoothing techniques and empirical evaluation can be found in [29].

The most important factors that influence quality of the resulting n-gram model is the choice of the order and of the smoothing technique. In this thesis, we will report results while using the most popular variants: Good-Turing smoothing [34] and modified Kneser-Ney smoothing [36] [29]. The modified Kneser-Ney smoothing (KN) is reported to provide consistently the best results among smoothing techniques, at least for word-based language models [24].

The most significant advantages of models based on n-gram statistics are speed (prob-

abilities of n-grams are stored in precomputed tables), reliability coming from simplicity, and generality (models can be applied to any domain or language effortlessly, as long as there exists some training data). N-gram models are today still considered as state of the art not because there are no better techniques, but because those better techniques are computationally much more complex, and provide just marginal improvements, not critical for success of given application. Thus, large part of this thesis deals with computational efficiency and speed-up tricks based on simple reliable algorithms.

The weak part of n-grams is slow adaptation rate when only limited amount of in-domain data is available. The most important weakness is that the number of possible n-grams increases exponentially with the length of the context, preventing these models to effectively capture longer context patterns. This is especially painful if large amounts of training data are available, as much of the patterns from the training data cannot be effectively represented by n-grams and cannot be thus discovered during training. The idea of using neural network based LMs is based on this observation, and tries to overcome the exponential increase of parameters by sharing parameters among similar events, no longer requiring exact match of the history H.

2.3 Advanced Language Modeling Techniques

Despite the indisputable success of basic n-gram models, it was always obvious that these models are not powerful enough to describe language at sufficient level. As an introduction to the advanced techniques, simple examples will be given first to show what n-grams cannot do. For example, representation of long-context patters is very inefficient, consider the following example:

```
THE SKY ABOVE OUR HEADS IS BLUE
```

In such sentence, the word `BLUE` directly depends on the previous word `SKY`. There is huge number of possible variations of words between these two that would not break such relationship - for example, `THE SKY THIS MORNING WAS BLUE` etc. We can even see that the number of variations can practically increase exponentially with increasing distance of the two words from each other in the sentence - we can create many similar sentences for example by adding all days of week in the sentence, such as:

```
THE SKY THIS <MONDAY, TUESDAY, .., SUNDAY> <MORNING, AFTERNOON, EVENING>
WAS BLUE
```

N-gram models with $N = 4$ are unable to efficiently model such common patterns in the language. With $N = 10$, we can see that the number of variations is so large that we cannot realistically hope to have such amounts of training data that would allow n-gram models to capture such long-context patterns - we would basically have to see each specific variation in the training data, which is infeasible in practical situations.

Another type of patterns that n-gram models will not be able to model efficiently is similarity of individual words. A popular example is:

```
PARTY WILL BE ON <DAY_OF_WEEK>
```

Considering that only two or three variations of this sentence are present in the training data, such as `PARTY WILL BE ON MONDAY` and `PARTY WILL BE ON TUESDAY`, the n-gram models will not be able to assign meaningful probability to novel (but similar) sequence such as `PARTY WILL BE ON FRIDAY`, even if days of the week appeared in the training data frequently enough to discover that there is some similarity among them.

As language modeling is closely related to artificial intelligence and language learning, it is possible to find great amount of different language modeling techniques and large number of their variations across research literature published in the past thirty years. While it is out of scope of this work to describe all of these techniques in detail, we will at least make short introduction to the important techniques and provide references for further details.

2.3.1 Cache Language Models

As stated previously, one of the most obvious drawbacks of n-gram models is in their inability to represent longer term patterns. It has been empirically observed that many words, especially the rare ones, have significantly higher chance of occurring again if they did occur in the recent history. Cache models [32] are supposed to deal with this regularity, and are often represented as another n-gram model, which is estimated dynamically from the recent history (usually few hundreds of words are considered) and interpolated with the

main (static) n-gram model. As the cache models provide truly significant improvements in perplexity (sometimes even more than 20%), there exists a large number of more refined techniques that can capture the same patterns as the basic cache models - for example, various topic models, latent semantic analysis based models [3], trigger models [39] or dynamically evaluated models [32] [49].

The advantage of cache (or similar) models is in large reduction of perplexity, thus these techniques are very popular in the language modeling related papers. Also, their implementation is often quite easy. The problematic part is that new cache-like techniques are compared to weak baselines, like bigram or trigram models. It is unfair to not include at least unigram cache model to the baseline, as it is very simple to do so (for example by using standard LM toolkits such as SRILM [72]).

The main disadvantage is in questionable correlation between perplexity improvements and word error rate reductions. This has been explained by [24] as a result of the fact that the errors are locked in the system - if the speech recognizer decodes incorrectly a word, it is placed in the cache which hurts further recognition by increasing chance of doing the same error again. When the output from the recognizer is corrected by the user, cache models are reported to work better; however, it is not practical to force users to manually correct the output. Advanced versions, like trigger models or LSA models were reported to provide interesting WER reductions, yet these models are not commonly used in practice.

Another explanation of poor performance of cache models in speech recognition is that since the output of a speech recognizer is imperfect, the perplexity calculations that are normally performed on some held-out data (correct sentences) are misleading. If the cache models were using the highly ambiguous history of previous words from a speech recognizer, the perplexity improvements would be dramatically lower. It is thus important to be careful when conclusions are made about techniques that access very long context information.

2.3.2 Class Based Models

One way to fight the data sparsity in higher order n-grams is to introduce equivalence classes. In the simplest case, each word is mapped to a single class, which usually represents several words. Next, n-gram model is trained on these classes. This allows better generalization to novel patterns which were not seen in the training data. Improvements

are usually achieved by combining class based model and the n-gram model. There exists a lot of variations of class based models, which often focus on the process of forming classes. So-called soft classes allow one word to belong to multiple classes. Description of several variants of class based models can be found in [24].

While perplexity improvements given by class based models are usually moderate, these techniques have noticeable effect on the word error rate in speech recognition, especially when only small amount of training data is available. This makes class based models quite attractive as opposed to the cache models, which usually work well only in experiments concerning perplexity.

The disadvantages of class based models include high computational complexity during inference (for statistical classes) or reliance on expert knowledge (for manually assigned classes). More seriously, improvements tend to vanish with increased amount of the training data [24]. Thus, class based models are more often found in the research papers, than in real applications.

From the critical point of view, there are several theoretical difficulties involving class based models:

- The assumption that words belong to some higher level classes is intuitive, but usually no special theoretical explanation is given to the process how classes are constructed; in the end, the number of classes is usually just some tunable parameter that is chosen based on performance on development data

- Most techniques do attempt to cluster individual words in the vocabulary, but the idea is not extended to n-grams: by thinking about character-level models, it is obvious that with increasing amount of the training data, classes can only be successful if longer context can be captured by a single class (several characters for this case)

2.3.3 Structured Language Models

The statistical language modeling was criticized heavily by the linguists from the first days of its existence. The already mentioned Chomsky's statement that *"the notion of probability of a sentence is completely useless one"* can be nowadays easily seen as a big mistake due to indisputable success of applications that involve n-gram models. However, further objections from the linguistic community usually address the inability of n-gram models to represent longer term patterns that clearly exist between words in a sentence.

There are many popular examples showing that words in a sentence are often related, even if they do not lie next to each other. It can be shown that such patterns cannot be effectively encoded using a finite state machine (n-gram models belong to this family of computational models). However, these patterns can be often effectively described while using for example context free grammars.

This was the motivation for the structured language models that attempt to bridge differences between the linguistic theories and the statistical models of the natural languages. The sentence is viewed as a tree structure generated by a context free grammar, where leafs are individual words and nodes are non-terminal symbols. The statistical approach is employed when constructing the tree: the derivations have assigned probabilities that are estimated from the training data, thus every new sentence can be assigned probability of being generated by the given grammar.

The advantage of these models is in their theoretical ability to represent patterns in a sentence across many words. Also, these models make language modeling much more attractive for the linguistic community.

However, there are many practical disadvantages of the structured language models:

- computational complexity and sometimes unstable behaviour (complexity raises non-linearly with the length of the parsed sentences)
- ambiguity (many different parses are possible)
- questionable performance when applied to spontaneous speech
- large amount of manual work that has to be done by expert linguists is often required, especially when the technique is to be applied to new domains or new languages, which can be very costly
- for many languages, it is more difficult to represent sentences using context free grammars - this is true for example for languages where the concept of word is not so clear as in English, or where the word order is much more free and not so regular as it is for English

Despite great research effort in the past decade, the results of these techniques remain questionable. However, it is certain that the addressed problem - long context patterns in the natural languages - has to be solved, if we want to get closer towards intelligent models of languages.

2.3.4 Decision Trees and Random Forest Language Models

A decision tree can partition the data in the history by asking question about history at every node. As these questions can be very general, decision trees were believed to have a big potential - for example, it is possible to ask questions about presence of specific word in the history of last ten words. However, in practice it was found that finding good decision trees can be quite difficult, and even if it can be proved that very good decision trees exist, usually only suboptimal ones are found by normal training techniques. This has motivated work on random forest models, which is a combination of many randomly grown decision trees (linear interpolation is usually used to combine trees into forests). For more information, see [78].

As the questions in the decision trees can be very general, these models have a possibility to work well for languages with free word order as well as for inflectional languages, by asking questions about morphology of the words in the history etc. [59]. The drawback is again high computational complexity. Also, the improvements seem to decrease when the amount of the training data is large. Thus, these techniques seem to work similar to the class based models, in some aspects.

2.3.5 Maximum Entropy Language Models

Maximum entropy (ME) model is an exponential model with a form

$$P(w|h) = \frac{e^{\sum_i \lambda_i f_i(w,h)}}{Z(h)} \tag{2.6}$$

where w is a word in a context h and $Z(h)$ is used for normalizing the probability distribution:

$$Z(h) = \sum_{w_i \in V} e^{\sum_j \lambda_j f_j(w_i,h)} \tag{2.7}$$

thus it can be viewed as a model that combines many feature functions $f_i(w,h)$. The problem of training ME model is to find weights λ_i of the features, and also to obtain a good set of these features, as these are not automatically learned from the data. Usual features are n-grams, skip-grams, etc.

ME models have shown big potential, as they can easily incorporate any features. Rosenfeld [64] used triggers and word features to obtain very large perplexity improvement, as well as significant word error rate reduction. There has been a lot of work recently done

by Chen et al., who proposed a so-called *model M*, which is basically a regularized class based ME model [30]. This model is reported to have a state-of-the-art performance on a broadcast news speech recognition task [31], when applied to a very well tuned system that is trained on large amounts of data and uses state of the art discriminatively trained acoustic models. The significant reductions in WER are reported against a good baseline language model, 4-gram with modified Kneser-Ney smoothing, across many domains and tasks. This result is quite rare in the language modeling field, as research papers usually report improvements over much simpler baseline systems.

An alternative name of maximum entropy models used by the machine learning community is *logistic regression*. While unique algorithms for training ME models were developed by the speech recognition community (such as Generalized Iterative Scaling), we will show in Chapter 6 that ME models can be easily trained by stochastic gradient descent. In fact, it will be later shown that ME models can be seen as a simple neural network without a hidden layer, and we will exploit this fact to develop novel type of model. Thus, ME models can be seen as a very general theoretically well founded technique that has already proven its potential in many fields.

2.3.6 Neural Network Based Language Models

While the clustering algorithms used for constructing class based language models are quite specific for the language modeling field, artificial neural networks can be successfully used for dimensionality reduction as well as for clustering, while being a very general machine learning technique. Thus, it is a bit surprising that neural network based language models have gained attention only after Y. Bengio's et al. paper [5] from 2001, and not much earlier. Although a lot of interesting work on language modeling using neural networks was done much earlier (for example by Elman [17]), the lack of rigorous comparison to the state of the art statistical language modeling techniques was missing.

Although it has been very surprising to some, the NNLMs, while very general and simple, have beaten many of the competing techniques, including those that were developed specifically for modeling the language. This might not be a coincidence - we may recall the words of a pioneer of the statistical approaches for automatic speech recognition, Frederick Jelinek:

"Every time I fire a linguist out of my group, the accuracy goes up[3]*."*

We may understand Jelinek's statement as an observation that with decreased complexity of the system and increased generality of the approaches, the performance goes up. It is then not so surprising to see the general purpose algorithms to beat the very specific ones, although clearly the task specific algorithms may have better initial results.

Neural network language models will be described in more detail in Chapter 2. These models are today among state of the art techniques, and we will demonstrate their performance on several data sets, where on each of them their performance is unmatched by other techniques.

The main advantage of NNLMs over n-grams is that history is no longer seen as exact sequence of $n-1$ words H, but rather as a projection of H into some lower dimensional space. This reduces number of parameters in the model that have to be trained, resulting in automatic clustering of similar histories. While this might sound the same as the motivation for class based models, the main difference is that NNLMs project all words into the same low dimensional space, and there can be many degrees of similarity between words.

The main weak point of these models is very large computational complexity, which usually prohibits to train these models on full training set, using the full vocabulary. I will deal with these issues in this work by proposing simple and effective speed-up techniques. Experiments and results obtained with neural network models trained on over 400M words while using large vocabulary will be reported, which is to my knowledge the largest set that a proper NNLM has been trained on[4].

2.4 Introduction to Data Sets and Experimental Setups

In this work, I would like to avoid mistakes that are often mentioned when it comes to criticism of the current research in the statistical language modeling. It is usually claimed that the new techniques are studied in very specific systems, using weak or ambiguous baselines. Comparability of the achieved results is very low, if any. This leads to much

[3] Although later, Jelinek himself claimed that the original statement was "Every time a linguist leaves my group, the accuracy goes up", the former one gained more popularity.

[4] I am aware of experiments with even more training data (more than 600M words) [8], but the resulting model in that work uses a small hidden layer, which as it will be shown later prohibits to train a model with competitive performance on such amount of training data.

confusion among researchers, and many new results are simply ignored as it is very time consuming to verify them. To avoid these problems, the performance of the proposed techniques is studied on very standard tasks, where it is possible to compare achieved results to baselines that were previously reported by other researchers[5].

First, experiments will be shown on a well known Penn Treebank Corpus, and the comparison will include wide variety of models that were introduced in section 2.3. A combination of results given by various techniques provides very important information by showing complementarity of the different language modeling techniques. Final combination of all techniques that were available to us results in a new state of the art performance on this particular data set, which is significantly better than of any individual technique.

Second, experiments with increasing amount of the training data will be shown while using Wall Street Journal training data (NYT Section, the same data as used by [23] [79] [49]). This study will focus on both entropy and word error rate improvements. The conclusion seems to be that with increasing amount of the training data, the difference in performance between the RNN models and the backoff models is getting larger, which is in contrast to what was found by Goodman [24] for other advanced LM techniques, such as class based models. Experiments with adaptation of the RNN language models will be shown on this setup and additional details and results will be provided for another WSJ setup that can be much more easily replicated, as it is based on a new open-source speech recognition toolkit, Kaldi [60].

Third, results will be shown for the RNN model applied to the state of the art speech recognition system developed by IBM [30] that was already briefly mentioned in Section 2.3.5, where we will compare the performance to the current state of the art language model on that set (so-called *model M*). The language models for this task were trained on approximately 400M words. Achieved word error rate reductions over the best n-gram model are relatively over 10%, which is a proof of usefulness of the techniques developed in this work.

Lastly, comparison of performance of RNN and n-gram models will be provided on a novel task *"The Microsoft Research Sentence Completion Challenge"* [83] that focuses on ability of artificial language models to appropriately complete a sentence where a single informative word is missing.

[5]Many of the experiments described in this work can be reproduced by using a toolkit for training Recurrent neural network (RNN) language models which can be found at `http://www.fit.vutbr.cz/~imikolov/rnnlm/`.

Chapter 3

Neural Network Language Models

The use of artificial neural networks for sequence prediction is as old as the neural network techniques themselves. One of the first widely known attempts to describe language using neural networks was performed by Jeff Elman [17], who used recurrent neural network for modeling sentences of words generated by an artificial grammar. The first serious attempt to build a statistical neural network based language model of real natural language, together with an empirical comparison of performance to standard techniques (n-gram models and class based models) was probably done by Yoshua Bengio in [5]. Bengio's work was followed by Holger Schwenk, who did show that NNLMs work very well in a state of the art speech recognition systems, and are complementary to standard n-gram models [68].

However, despite many scientific papers were published after the original Bengio's work, no techniques or modifications of the original model that would significantly improve ability of the model to capture patterns in the language were published, at least to my knowledge[1]. Integration of additional features into the NNLM framework (such as part of speech tags or morphology information) has been investigated in [19] [1]. Still, the accuracy of the neural net models remained basically the same, until I have recently shown that recurrent neural network architecture can work actually better than the feedforward one [49] [50].

Most of the research work did focus on overcoming practical problems when using these attractive models: the computational complexity was originally too high for real world tasks. It was reported by Bengio in 2001 that training of the original neural net

[1]With the exception of Schwenk, who reported better results by using linear interpolation of several neural net models trained on the same data, with different random initialization of the weights - we denote this approach further as a combination of NNLMs.

language model took almost a week using 40 CPUs for just a single training epoch (and 10 to 20 epochs were needed for reaching optimal results), despite the fact that only about 14M training words were used (Associated Press News corpus), together with vocabulary reduced to as little as 18K most frequent words. Moreover, the number of hidden neurons in the model had to be restricted to just 60, thus the model could not have demonstrated its full potential. Despite these limitations, the model provided almost 20% reduction of perplexity over a baseline n-gram model, after 5 training epochs.

Clearly, better results could have been expected if the computational complexity was not so restrictive, and most of the further research focused on this topic. Bengio proposed parallel training of the model on several CPUs, which was later repeated and extended by Schwenk [68]. A very successful extension reduced computation between the hidden layer and the output layer in the model, using a trick that was originally proposed by Joshua Goodman for speeding up maximum entropy models [25] - this will be described in more detail in Section 3.4.2.

3.1 Feedforward Neural Network Based Language Model

The original model proposed by Bengio works as follows: the input of the n-gram NNLM is formed by using a fixed length history of $n-1$ words, where each of the previous $n-1$ words is encoded using 1-of-V coding, where V is size of the vocabulary. Thus, every word from the vocabulary is associated with a vector with length V, where only one value corresponding to the index of given word in the vocabulary is 1 and all other values are 0.

This 1-of-V orthogonal representation of words is projected linearly to a lower dimensional space, using a shared matrix P, called also a projection matrix. The matrix P is shared among words at different positions in the history, thus the matrix is the same when projecting word w_{t-1}, w_{t-2} etc. In the usual cases, the vocabulary size can be around 50K words, thus for a 5-gram model the input layer consists of 200K binary variables, while only 4 of these are set to 1 at any given time, and all others are 0. The projection is done sometimes into as little as 30 dimensions, thus for our example, the dimensionality of the projected input layer would be $30 \times 4 = 120$. After the projection layer, a hidden layer with non-linear activation function (usually hyperbolic tangent or a logistic sigmoid) is used, with a dimensionality of 100-300. An output layer follows, with the size equal to the size of full vocabulary. After the network is trained, the output layer of 5-gram NNLM

represents probability distribution $P(w_t|w_{t-4}, w_{t-3}, w_{t-2}, w_{t-1})$.

I have proposed an alternative feedforward architecture of the neural network language model in [48]. The problem of learning n-gram NNLM is decomposed into two steps: learning a bigram NNLM (with only the previous word from the history encoded in the input layer), and then training an n-gram NNLM that projects words from the n-gram history into the lower dimensional space by using the already trained bigram NNLM. Both models are simple feedforward neural networks with one hidden layer, thus this solution is simpler for implementation and for understanding than the original Bengio's model. It provides almost identical results as the original model, as will be shown in the following chapter.

3.2 Recurrent Neural Network Based Language Model

I have described a recurrent neural network language model (RNNLM) in [49] and extensions in [50]. The main difference between the feedforward and the recurrent architecture is in representation of the history - while for feedforward NNLM, the history is still just previous several words, for the recurrent model, an effective representation of history is learned from the data during training. The hidden layer of RNN represents all previous history and not just $n-1$ previous words, thus the model can theoretically represent long context patterns.

Another important advantage of the recurrent architecture over the feedforward one is the possibility to represent more advanced patterns in the sequential data. For example, patterns that rely on words that could have occurred at variable position in the history can be encoded much more efficiently with the recurrent architecture - the model can simply remember some specific word in the state of the hidden layer, while the feedforward architecture would need to use parameters for each specific position of the word in the history; this not only increases the total amount of parameters in the model, but also the number of training examples that have to be seen to learn the given pattern.

The architecture of RNNLM is shown in Figure 3.1. The input layer consists of a vector $\mathbf{w}(t)$ that represents the current word w_t encoded as 1 of V (thus size of $\mathbf{w}(t)$ is equal to the size of the vocabulary), and of vector $\mathbf{s}(t-1)$ that represents output values in the hidden layer from the previous time step. After the network is trained, the output layer $\mathbf{y}(t)$ represents $P(w_{t+1}|w_t, \mathbf{s}(t-1))$.

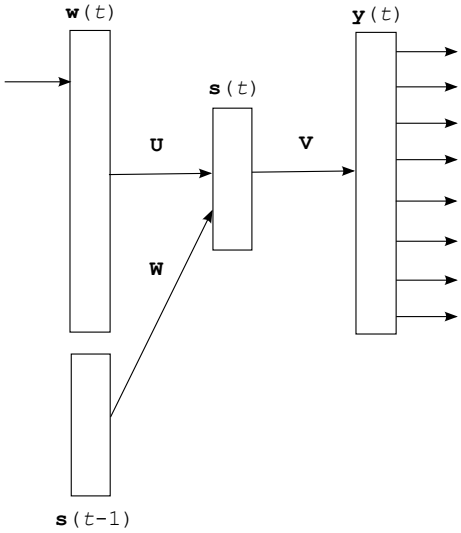

Figure 3.1: Simple recurrent neural network.

The network is trained by stochastic gradient descent using either usual *backpropagation* (BP) algorithm, or *backpropagation through time* (BPTT) [65]. The network is represented by input, hidden and output layers and corresponding weight matrices - matrices **U** and **W** between the input and the hidden layer, and matrix **V** between the hidden and the output layer. Output values in the layers are computed as follows:

$$s_j(t) = f\left(\sum_i w_i(t)u_{ji} + \sum_l s_l(t-1)w_{jl}\right) \tag{3.1}$$

$$y_k(t) = g\left(\sum_j s_j(t)v_{kj}\right) \tag{3.2}$$

where $f(z)$ and $g(z)$ are sigmoid and softmax activation functions (the softmax function in the output layer is used to ensure that the outputs form a valid probability distribution, i.e. all outputs are greater than 0 and their sum is 1):

$$f(z) = \frac{1}{1+e^{-z}}, \quad g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}} \tag{3.3}$$

Note that biases are not used in the neural network, as no significant improvement of performance was observed - following the Occam's razor, the solution is as simple as it needs to be. Alternatively, the equations 3.1 and 3.2 can be rewritten as a matrix-vector multiplication:

$$\mathbf{s}(t) = f\left(\mathbf{U}\mathbf{w}(t) + \mathbf{W}\mathbf{s}(t-1)\right) \tag{3.4}$$

$$\mathbf{y}(t) = g\left(\mathbf{V}\mathbf{s}(t)\right) \tag{3.5}$$

The output layer $\mathbf{y}$ represents a probability distribution of the next word w_{t+1} given the history. The time complexity of one training or test step is proportional to

$$O = H \times H + H \times V = H \times (H + V) \tag{3.6}$$

where H is size of the hidden layer and V is size of the vocabulary.

3.3 Learning Algorithm

Both the feedforward and the recurrent architecture of the neural network model can be trained by stochastic gradient descent using a well-known backpropagation algorithm [65]. However, for better performance, a so-called Backpropagation through time algorithm can be used to propagate gradients of errors in the network back in time through the recurrent weights, so that the model is trained to capture useful information in the state of the hidden layer. With simple BP training, the recurrent network performs poorly in some cases, as will be shown later (some comparison was already presented in [50]). The BPTT algorithm has been described in [65], and a good description for a practical implementation is in [9].

With the stochastic gradient descent, the weight matrices of the network are updated after presenting every example. A cross entropy criterion is used to obtain gradient of an error vector in the output layer, which is then backpropagated to the hidden layer, and in case of BPTT through the recurrent connections backwards in time. During the training, validation data are used for early stopping and to control the learning rate. Training iterates over all training data in several epochs before convergence is achieved - usually, 8-20 epochs are needed. As it will be shown in Chapter 6, the convergence speed of the training can be improved by randomizing order of sentences in the training data, effectively reducing the number of required training epochs (this was already observed in [5], and we provide more details in [52]).

The learning rate is controlled as follows. Starting learning rate is $\alpha = 0.1$. The same learning rate is used as long as significant improvement on the validation data is observed (in further experiments, we consider as a significant improvement more than 0.3% reduction of the entropy). After no significant improvement is observed, the learning

rate is halved at start of every new epoch and the training continues until again there is no improvement. Then the training is finished.

As the validation data set is used only to control the learning rate, it is possible to train a model even without a validation data, by manually choosing how many epochs should be performed with the full learning rate, and how many epochs with the decreasing learning rate. This can be also estimated from experiments with subsets of the training data. However, in normal cases, it is usual to have a validation data set for reporting perplexity results. It should be noticed that no over-fitting of the validation data can happen, as the model does not learn any parameters on such data.

The weight matrices **U**, **V** and **W** are initialized with small random numbers (in further experiments using normal distribution with mean 0 and variance 0.1) Training of RNN for one epoch is performed as follows:

1. Set time counter $t = 0$, initialize state of the neurons in the hidden layer $\mathbf{s}(t)$ to 1
2. Increase time counter t by 1
3. Present at the input layer $\mathbf{w}(t)$ the current word w_t
4. Copy the state of the hidden layer $\mathbf{s}(t-1)$ to the input layer
5. Perform forward pass as described in the previous section to obtain $\mathbf{s}(t)$ and $\mathbf{y}(t)$
6. Compute gradient of error $\mathbf{e}(t)$ in the output layer
7. Propagate error back through the neural network and change weights accordingly
8. If not all training examples were processed, go to step 2

The objective function that we aim to maximize is likelihood of the training data:

$$f(\lambda) = \sum_{t=1}^{T} \log y_{l_t}(t), \tag{3.7}$$

where the training samples are labeled $t = 1 \ldots t$, and l_t is the index of the correct predicted word for the t'th sample. Gradient of the error vector in the output layer $\mathbf{e}_o(t)$ is computed using a cross entropy criterion that aims to maximize likelihood of the correct class, and is computed as

$$\mathbf{e}_o(t) = \mathbf{d}(t) - \mathbf{y}(t) \tag{3.8}$$

where $\mathbf{d}(t)$ is a target vector that represents the word $\mathbf{w}(t+1)$ that should have been predicted (encoded again as 1-of-V vector). Note that it is important to use cross entropy and not mean square error (MSE), which is a common mistake. The network would still work, but the results would be suboptimal (at least, if our objective is to minimize entropy, perplexity, word error rate or to maximize compression ratio). Weights $\mathbf{V}$ between the hidden layer $\mathbf{s}(t)$ and the output layer $\mathbf{y}(t)$ are updated as

$$v_{jk}(t+1) = v_{jk}(t) + s_j(t)e_{ok}(t)\alpha \tag{3.9}$$

where α is the learning rate, j iterates over the size of the hidden layer and k over the size of the output layer, $s_j(t)$ is output of j-th neuron in the hidden layer and $e_{ok}(t)$ is error gradient of k-th neuron in the output layer. If L2 regularization is used, the equation changes to

$$v_{jk}(t+1) = v_{jk}(t) + s_j(t)e_{ok}(t)\alpha - v_{jk}(t)\beta \tag{3.10}$$

where β is regularization parameter, in the following experiments its value is $\beta = 10^{-6}$. Regularization is used to keep weights close to zero[2]. Using matrix-vector notation, the equation 3.10 would change to

$$\mathbf{V}(t+1) = \mathbf{V}(t) + \mathbf{s}(t)\mathbf{e}_o(t)^T\alpha - \mathbf{V}(t)\beta. \tag{3.11}$$

Next, gradients of errors are propagated from the output layer to the hidden layer

$$\mathbf{e}_h(t) = d_h\left(\mathbf{e}_o(t)^T\mathbf{V}, t\right), \tag{3.12}$$

where the error vector is obtained using function $d_h()$ that is applied element-wise

$$d_{hj}(x,t) = xs_j(t)(1 - s_j(t)). \tag{3.13}$$

Weights $\mathbf{U}$ between the input layer $\mathbf{w}(t)$ and the hidden layer $\mathbf{s}(t)$ are then updated as

$$u_{ij}(t+1) = u_{ij}(t) + w_i(t)e_{hj}(t)\alpha - u_{ij}(t)\beta \tag{3.14}$$

[2]Quick explanation of using regularization is by using Occam's razor: simper solutions should be preferred, and small numbers can be stored more compactly than the large ones; thus, models with small weights should generalize better.

or using matrix-vector notation as

$$\mathbf{U}(t+1) = \mathbf{U}(t) + \mathbf{w}(t)\mathbf{e}_h(t)^T\alpha - \mathbf{U}(t)\beta. \tag{3.15}$$

Note that only one neuron is active at a given time in the input vector $\mathbf{w}(t)$. As can be seen from the equation 3.14, the weight change for neurons with zero activation is none, thus the computation can be speeded up by updating weights that correspond just to the active input neuron. The recurrent weights $\mathbf{W}$ are updated as

$$w_{lj}(t+1) = w_{lj}(t) + s_l(t-1)e_{hj}(t)\alpha - w_{lj}(t)\beta \tag{3.16}$$

or using matrix-vector notation as

$$\mathbf{W}(t+1) = \mathbf{W}(t) + \mathbf{s}(t-1)\mathbf{e}_h(t)^T\alpha - \mathbf{W}(t)\beta \tag{3.17}$$

3.3.1 Backpropagation Through Time

The training algorithm presented in the previous section is further denoted as normal backpropagation, as the RNN is trained in the same way as normal feedforward network with one hidden layer, with the only exception that the state of the input layer depends on the state of the hidden layer from previous time step.

However, it can be seen that such training approach is not optimal - the network tries to optimize prediction of the next word given the previous word and previous state of the hidden layer, but no effort is devoted towards actually storing in the hidden layer state some information that can be actually useful in the future. If the network remembers some long context information in the state of the hidden layer, it is so more by luck than by design.

However, a simple extension of the training algorithm can ensure that the network will learn what information to store in the hidden layer - this is the so-called Backpropagation through time algorithm. The idea is simple: a recurrent neural network with one hidden layer which is used for N time steps can be seen as a deep feedforward network with N hidden layers (where the hidden layers have the same dimensionality and unfolded recurrent weight matrices are identical). This idea has already been described in [53], and is illustrated in Figure 3.2.

Such deep feedforward network can be trained by the normal gradient descent. Errors

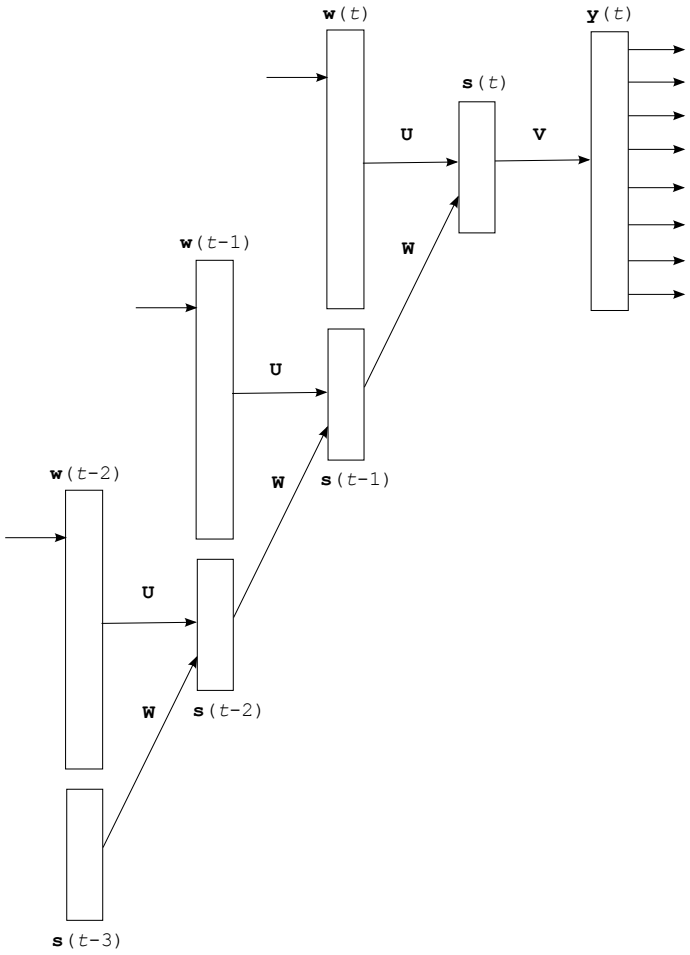

Figure 3.2: Recurrent neural network unfolded as a deep feedforward network, here for 3 time steps back in time.

are propagated from the hidden layer $\mathbf{s}(t)$ to the hidden layer from the previous time step $\mathbf{s}(t-1)$ and the recurrent weight matrix (denoted as $\mathbf{W}$ in Figure 3.2) is updated. Error propagation is done recursively as follows (note that the algorithm requires the states of the hidden layer from the previous time steps to be stored):

$$\mathbf{e}_h(t-\tau-1) = d_h\left(\mathbf{e}_h(t-\tau)^T\mathbf{W}, t-\tau-1\right). \tag{3.18}$$

The function d_h is defined in equation 3.13. The unfolding can be applied for as many time steps as many training examples were already seen, however the error gradients quickly *vanish* as they get backpropagated in time [4] (in rare cases the errors can *explode*), so several steps of unfolding are sufficient (this is sometimes referred to as *truncated BPTT*). While for word based LMs, it seems to be sufficient to unfold network for about 5 time steps, it is interesting to notice that this still allows the network to learn to store

information for more than 5 time steps. Similarly, network that is trained by normal backpropagation can be seen as a network trained with one unfolding step, and still as we will see later, even this allows the network to learn longer context patterns, such as 4-gram information. The weights **U** are updated for BPTT training as

$$u_{ij}(t+1) = u_{ij}(t) + \sum_{z=0}^{T} w_i(t-z)e_{hj}(t-z)\alpha - u_{ij}(t)\beta, \tag{3.19}$$

where T is the number of steps for which the network is unfolded in time. Alternatively, equation 3.19 can be written as

$$\mathbf{U}(t+1) = \mathbf{U}(t) + \sum_{z=0}^{T} \mathbf{w}(t-z)\mathbf{e}_h(t-z)^T\alpha - \mathbf{U}(t)\beta. \tag{3.20}$$

It is important to note that the change of the weight matrix **U** is to be done in one large update, and not incrementally during the process of backpropagation of errors - that can lead to instability of the training [9]. Similarly, the recurrent weights **W** are updated as

$$w_{lj}(t+1) = w_{lj}(t) + \sum_{z=0}^{T} s_l(t-z-1)e_{hj}(t-z)\alpha - w_{lj}(t)\beta, \tag{3.21}$$

which is equal to

$$\mathbf{W}(t+1) = \mathbf{W}(t) + \sum_{z=0}^{T} \mathbf{s}(t-z-1)\mathbf{e}_h(t-z)^T\alpha - \mathbf{W}(t)\beta. \tag{3.22}$$

3.3.2 Practical Advices for the Training

While the network can be unfolded for every processed training example, it can be seen that this would lead to large computational complexity - it would depend on $T \times W$, where T is the number of unfolding steps and W is the number of the training words. However, it can be seen that if the network is unfolded and the recurrent part is trained only after processing several training examples, the complexity will decrease - in fact, if the unfolding would be done after processing all the training examples, it can be seen that the complexity would depend just on W. As in our experiments on-line update of weights did work better than batch update, it seems to be the best practice to update recurrent weights in mini-batches (such as after processing 10-20 training examples). This can effectively remove the term T. The flow of gradients in batch mode training of RNN

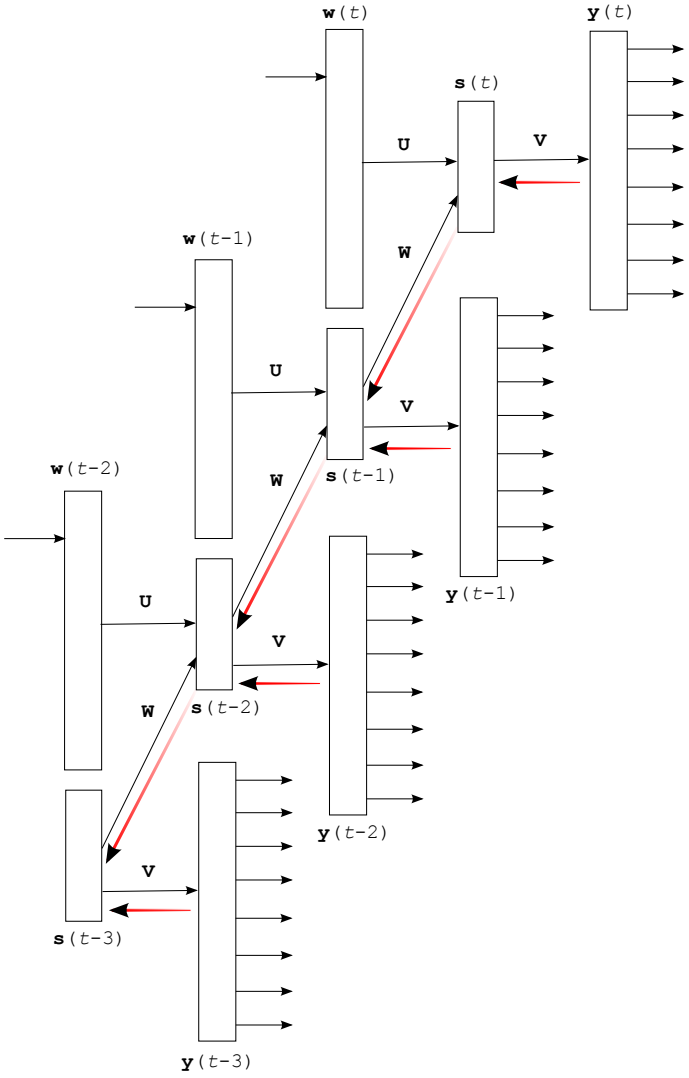

Figure 3.3: Example of batch mode training. Red arrows indicate how the gradients are propagated through the unfolded recurrent neural network.

is illustrated at Figure 3.3.

For numerical stability purposes, it is good to use double precision of the real numbers and some regularization (in our experiments, we used either no regularization, or small L2 penalty such as $\beta = 1e{-}6$). With single precision and no regularization, the training might not converge to a good solution. Also, it is important to realize that training of RNNs can be more difficult than of normal feedforward networks - the gradients propagated by BPTT can in some rare cases *explode*, that is, increase during backpropagation through the recurrent connections to such large values that the weights of the network get rewritten with meaningless values, causing the training to fail. The exploding gradient problem has been described in [4].

A simple solution to the exploding gradient problem is to truncate values of the gradients. In my experiments, I did limit maximum size of gradients of errors that get accumulated in the hidden neurons to be in a range $< -15; 15 >$. This greatly increases stability of the training, and otherwise it would not be possible to train RNN LMs successfully on large data sets.

3.4 Extensions of NNLMs

3.4.1 Vocabulary Truncation

The original neural network language model is very computationally expensive, which severely limits its possible application in real world systems. Most modifications that aim to reduce the computational complexity attempt to overcome the huge term $H \times V$ that corresponds to the computation done between the hidden and output layers. This computational bottleneck is the same for both feedforward and for the recurrent architecture. Using reasonably large hidden layer such as $H = 200$ and vocabulary $V = 50K$, it would take impractically long to train models even on data sets with several million words. Moreover, application to speech recognition systems via n-best list rescoring would be many times slower than real-time.

The simplest solution is to reduce the size of the output vocabulary V. Originally, Bengio merged all infrequent words into a special class that represents probability of all rare words [5]. The rare words within the class have probability estimated based on their unigram frequency. This approach has been later improved by Schwenk, who redistributed probabilities of rare words using n-gram model [68].

Note that the vocabulary truncation techniques can provide very significant speedups, but at a noticeable cost of accuracy. Schwenk did use in some cases as little as 2K output units in the neural network, and even if these correspond to the most frequent words, the performance degradation was significant as was later shown in [40].

3.4.2 Factorization of the Output Layer

A more sophisticated approach for reducing the huge term $H \times V$ was proposed in [57], and a similar idea was re-discovered later by [19] and [50]. Instead of computing probability distribution over all words V or some reduced subset of the most frequent words, the probability is estimated for groups of words, and then only for words from a particular

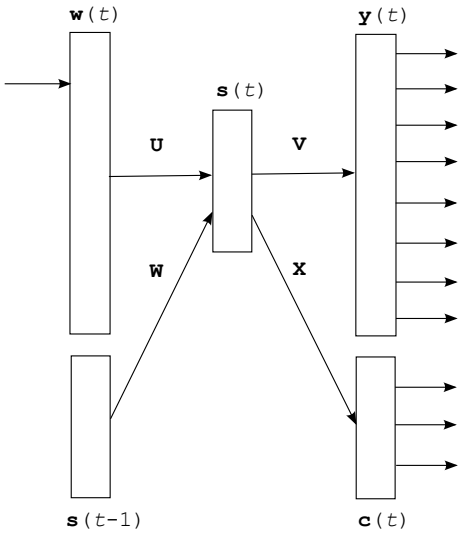

Figure 3.4: Factorization of the output layer.

group that we are interested in.

The original idea can be tracked back to Goodman [25], who used classes for speeding up training of the maximum entropy models. Figure 3.4 illustrates this approach: first, the probability distribution over classes is computed. Then, a probability distribution for the words that belong to the specific class are computed. So instead of computing V outputs and doing softmax over V elements, only $C + V'$ outputs have to be computed, and the softmax function is applied separately to both C and V', where C are all the classes, and V' are all words that belong to the particular class. Thus, C is constant and V' can be variable.

I have proposed an algorithm that assigns words to classes based just on the unigram frequency of words [50]. Every word w_i from the vocabulary V is assigned to a single c_i. Assignment to classes is done before the training starts, and is based just on relative frequency of words - the approach is commonly referred to as frequency binning. This results in having low amount of frequent words in a single class, thus frequently V' is small. For rare words, V' can still be huge, but rare words are processed infrequently. This approach is much simpler than the previously proposed ones such as using Wordnet for obtaining the classes [57], or learning hierarchical representations of the vocabulary [54]. As we will see in the next chapter, the degradation of accuracy of models that comes from using classes and the frequency binning approach is small.

Following the notation from section 3.2, the computation between the hidden and the

output layer changes to computation between the hidden and the class layer:

$$c_m(t) = g\left(\sum_j s_j(t) x_{mj}\right), \tag{3.23}$$

and the hidden layer and a subset of the output layer:

$$y_{V'}(t) = g\left(\sum_j s_j(t) v_{V'j}\right). \tag{3.24}$$

The probability of word $w(t+1)$ is then computed as

$$P(w_{t+1}|\mathbf{s}(t)) = P(c_i|\mathbf{s}(t))P(w_i|c_i, \mathbf{s}(t)), \tag{3.25}$$

where w_i is an index of the predicted word and c_i is its class. During training, the weights are accessed in the same way as during the forward pass, thus the gradient of the error vector is computed for the word part and for the class part, and then is backpropagated back to the hidden layer, where gradients are added together. Thus, the hidden layer is trained to predict both the distribution over the words and over the classes.

An alternative to simple frequency binning is a slightly modified approach, that minimizes access to words and classes: instead of using frequencies of words for the equal binning algorithm, one can apply square root function on the original frequencies, and perform the binning on these modified frequencies. This approach leads to even larger speed-up[3].

Factorization of the computation between the hidden and output layers using simple classes can easily lead to 15 - 30 times speed-up against a fair baseline, and for the networks with huge output layers (more then 100K words), the speedup may be even an order of magnitude larger. Thus, this speedup trick is essential for achieving reasonable performance on larger data sets. Additional techniques for reducing computational complexity will be discussed in more detail in Chapter 6.

[3]Thanks to Dan Povey who suggested this modification.

3.4.3 Approximation of Complex Language Model by Backoff N-gram model

In [15], we have shown that NNLM can be partly approximated by a finite state machine. The conversion is done by sampling words from the probability distribution computed by NNLM, and a common N-gram model is afterwards trained on the sampled text data. For infinite amount of sampled data and infinite order N, this approximation technique is guaranteed to converge to an equivalent model to the one that was used for generating the words.

Of course, this is not achievable in practice, as it is not possible to generate infinite amounts of data. However we have shown that even for manageable amounts of sampled data (hundreds of million words), the approximated model provides some of the improvement over baseline n-gram model that is provided by the full NNLM. Note that this approach is not limited just to NNLMs or RNNLMs, but can be used to convert any complex model to a finite state representation. However, following the motivation examples that were shown in the introductory chapter, representing certain patterns using FSMs is quite impractical, thus we believe this technique can be the most useful for tasks with limited amount of the training data, where size of models is not so restrictive.

Important advantage of this approach include possibility of using the approximated model directly during decoding, for the standard lattice rescoring, etc. It is even possible to use the (R)NNLMs for speech recognition without actually having a single line of neural net code in the system, as the complex patterns learned by neural net are represented as a list of possible combinations in the n-gram model. The sampling approach is thus giving the best possible speedup for the test phase, by trading the computational complexity for the space complexity.

Empirical results obtained by using this technique for approximating RNNLMs in speech recognition systems are described in [15] and [38], which is a joint work with Anoop Deoras and Stefan Kombrink.

3.4.4 Dynamic Evaluation of the Model

From the artificial intelligence point of view, the usual statistical language models have another drawback besides their inability to represent longer term patterns: the impossibility to learn new information. This is caused by the fact that LMs are commonly assumed to be *static* - the parameters of the models do not change during processing of the data.

While RNN models can overcome this disadvantage to some degree by remembering some information in the hidden layer, due to the vanishing gradient problem it is not possible to train RNNs to do so using normal gradient based training. Moreover, even if the training algorithm was powerful enough to discover longer term patterns, it would be inefficient to store all new information (such as new names of people) in the state of the hidden layer, and access and update this information at every time step.

The simplest way to overcome this problem is to use *dynamic* models, which has been already proposed by Jelinek in [32]. In the case of n-gram models, we can simply train another n-gram model during processing of the test data based on the recent history, and interpolate it with the static one - such dynamic model is usually called cache model. Another approach is to maintain just a single model, and update its parameters online during processing of the test data. This can be easily achieved using neural network models.

The disadvantages of using dynamically updated models are that the computational complexity of the test phase increases, as we need to perform not only the forward pass, but also calculate gradients and propagate them backwards through the network, and change weights. More seriously, a network that is presented ambiguous data continually for significant amount of time steps might forget older information - it can rewrite its own weights with meaningless information. After the test data switches back to normal data, the network cannot access the forgotten information anymore. This would not happen with the n-gram models, since these access parameters very sparsely. Neural net models share information among all words, thus it is easier to corrupt them.

The dynamic evaluation of the NN language models has been described in my recent work [49] [50], and is achieved by training the RNN model during processing of the test data, with a fixed learning rate $\alpha = 0.1$. Thus, the test data are processed only once, which is a difference to normal NN training where training data are seen several times.

While the dynamic evaluation of the NN models leads to interesting perplexity improvements, especially after combination with the static model (which has the advantage that it cannot forget any information and cannot be corrupted by the noisy data), application to a speech recognition system is very computationally expensive if done in the exact way, as several versions of the model must be kept in the memory and weights have to be reloaded to prevent the model to "see the future" (for example in n-best list rescoring, it is needed to reload weights after processing each hypothesis from a given list). A

simplification to the dynamic evaluation is to retrain the NN model on the 1-best utterances, instead of doing a true dynamic evaluation. Both approaches did provide similar improvements in our experiments.

In [38], we have shown that adaptation of RNN models works better in some cases if the model is retrained separately on subsets of the test data. In the cited work, it was shown that for a task of meeting speech recognition, it is a good practice to adapt RNN LMs on every session in the test data separately.

3.4.5 Combination of Neural Network Models

Since the weights in the neural networks are initialized with small random numbers, every model converges to a somewhat different solution after the training is finished, even if the training data are exactly the same. By averaging outputs from several models, it is possible to obtain better performance - this was already observed by Schwenk [68].

For combining outputs from neural net models, linear interpolation is usually used. The probability of a word w given N models is then computed as

$$P(w|h) = \sum_{i=1}^{N} \frac{P_i(w|h)}{N} \tag{3.26}$$

where $P_i(w|h)$ is a probability estimation of a word w in a context h given by the i-th model. We can obtain the individual models by simply training several RNN language models with different random initialization of the weights, or by training RNN models with different architecture.

Actually, by recalling Algorithmic probability (equation 2.2), we should use infinite amount of models with all possible architectures, and instead of using equal weights of models in the combination, an individual model weight should be normalized by the description length of the model. Computing the description length of any non-trivial model is intractable[4], however we can estimate weights of the models on some validation data. Practical experience shows that it is the best to train as large models as possible, and to interpolate models with the same architecture using equal weights.

While I did not perform experiments with combinations of neural net models with

[4]Sometimes it is assumed that the description length of a model is related to the number of parameters in the model; however, this can be shown to be false, as clearly different parameters require different amount of bits to be stored, and many parameters are often redundant. Moreover, as stated earlier, many patterns can be described using exponentially less parameters by using computationally unrestricted model, than by using a limited model, such as FSM or a neural net.

complex or random architectures (such as more hidden layers, sparse weight matrices etc.), it can be expected that training models with deep architectures would be very difficult by using stochastic gradient descent, as vast majority of final solutions are likely to converge to the same (or similar) local maxima. Thus, the individual solutions are likely to be very similar in some sense. It might be interesting to explore training techniques that would produce models with higher diversity, such as evolutionary techniques - although clearly, that would be a topic for another work.

It is possible to think of using other combination techniques than linear averaging of probabilities, that can be more useful in the cases when we do not have infinite amount of possible models of the data. My experiments with log-linear interpolation have shown only minor improvements over linear interpolation, but since I tried to combine just two RNN models, more experiments can be done in this direction. Also, it is possible to think of an additional neural network that would combine the individual models in a non-linear way: such additional network can be again an RNN model.

We will discuss possible gains that can be obtained by combining outputs from several RNN models in the next chapter. Also, results when many language modeling techniques are linearly combined will be presented.

Chapter 4

Evaluation and Combination of Language Modeling Techniques

It is very difficult, if not impossible, to compare different machine learning techniques just by following their theoretical description. The same holds for the numerous language modeling techniques: almost every one of them is well-motivated, and some of them even have theoretical explanation why a given technique is optimal, under certain assumptions. The problem is that many of such assumptions are not satisfied in practice, when real data are used.

Comparison of advanced language modeling techniques is usually limited by some of these factors:

- private data sets that do not allow experiments to be repeated are used
- ad hoc preprocessing is used that favours the proposed technique, or completely artificial data sets are used
- comparison to proper baseline is completely missing
- baseline technique is not tuned for the best performance
- in comparison, it is falsely claimed that technique X is the state of the art (where X is usually n-gram model)
- possible comparison to other advanced techniques is done poorly, by citing results achieved on different data sets, or simply by falsely claiming that the other techniques are too complex

While for any of the previous points I would be able to provide at least several references, it would be better to define how the new techniques should be evaluated, so that scientific progress would be measurable:

- experiments should be repeatable: public data sets should be used, or data that are easily accessible to the scientific community
- techniques that aim to become a new state of the art should be compared not against the weakest possible baseline, but against the strongest baseline, such as combination of all known techniques
- to improve repeatability, the code needed for reproducing the experiments should be released
- review process for accepting papers that propose new techniques should be at least partially automated, when it comes to verification of the results

While in some cases it might be difficult to satisfy all these points, it is foolish to claim that new state of the art has been reached, after the perplexity against 3-gram model drops by 2%; still, such results are still being published at the top level conferences (and even sometimes win awards as the best papers).

For these reasons, I have decided to release a toolkit that can be used to train RNN based language models, so that the following experiments can be easily repeated. This toolkit is introduced and described in Appendix A. Moreover, the following experiments are performed on well known setups, with direct comparison to competitive techniques.

4.1 Comparison of Different Types of Language Models

It is very difficult to objectively compare different language modeling techniques: in practical applications, accuracy is sometimes as important as low memory usage and low computational complexity. Also, the comparison that can be found in the scientific papers is in some cases unfair, as models that aim to find different type of regularities are sometimes compared. The most obvious example would be a comparison of a long context and a short context model, such as comparing n-gram model to a cache-like model.

A model that has a potential to discover information only in a few preceding words (like n-gram model or a class based model) will be further denoted as a "short-span model", while a model that has ability to represent regularities over long range of words (more

than a sentence) will be called a "long-span model". An example of a long-span model is a cache model, or a topic model.

Comparison of performance of a short span model (such as 4-gram LM) against a combination of a short span and a long span model (such as 4-gram + cache) is very popular in the literature, as it leads to large improvements in perplexity. However, the reduction of a word error rate in speech recognition by using long-span models is usually quite small - as was mentioned previously, this is caused by the fact that perplexity is commonly evaluated while assuming perfect history, which is a false assumption as the history in speech recognition is typically very noisy[1]. Typical examples of such experiments are different novel ways how to compute cache-like models. Joshua Goodman's report [24] is a good reference for those who are interested in more insight into criticism of typical language modeling research.

To avoid these mistakes, performance of individual models is reported and compared to a modified Kneser-Ney smoothed 5-gram (which is basically a state-of-the-art among n-gram models), and further compared to a combination of a 5-gram model with a unigram cache model. After that, we report the results after using all models together, with an analysis which models are providing the most complementary information in the combination, and which models discover patterns that can be better discovered by other techniques.

4.2 Penn Treebank Dataset

One of the most widely used data sets for evaluating performance of the statistical language models is the Penn Treebank portion of the WSJ corpus (denoted here as a Penn Treebank Corpus). It has been previously used by many researchers, with exactly the same data preprocessing (the same training, validation and test data and the same vocabulary limited to 10K words). This is quite rare in the language modeling field, and allows us to compare directly performances of different techniques and their combinations, as many researchers were kind enough to provide us their results for the following comparison. Combination of the models is further done by using linear interpolation - for combination of two models M_1 and M_2 this means

$$P_{M_{12}}(w|h) = \lambda P_{M_1}(w|h) + (1-\lambda)P_{M_2}(w|h) \tag{4.1}$$

[1]Thanks to Dietrich Klakow for pointing this out.

where λ is the interpolation weight of the model M_1. As long as both models produce correct probability distributions and $\lambda \in < 0; 1 >$, the linear interpolation produces correct probability distribution. It has been reported that log-linear interpolation of models can work in some cases significantly better than the linear interpolation (especially when combining long span and short span language models), but the log-linear interpolation requires renormalization of the probability distribution and is thus much more computationally expensive [35]:

$$P_{M_{12}}(w|h) = \frac{1}{Z_\lambda(h)} P_{M_1}(w|h)^{\lambda_1} \times P_{M_2}(w|h)^{\lambda_2} \tag{4.2}$$

where $Z_\lambda(h)$ is the normalization term. Because of the normalization term, we need to consider the full probability distribution given by both models, while for the linear interpolation, it is enough to interpolate probabilities given by both models for an individual word. The previous equations can be easily extended to combination of more than two models, by having separate weight for each model.

The Penn Treebank Corpus was divided as follows: sections 0-20 were used as the training data (930k tokens), sections 21-22 as the validation data (74k tokens) and sections 23-24 as the test data (82k tokens). All words outside the 10K vocabulary were mapped to a special token (unknown word) in all PTB data sets, thus there are no Out-Of-Vocabulary (OOV) words.

4.3 Performance of Individual Models

The performance of all individual models used in the further experiments is presented in Table 4.1. First, we will give references and provide brief details about the individual models. Then we will compare performance of models, combine them together and finally analyze contributions of all individual models and techniques. I would also like to mention here that the following experiments were performed with the help of Anoop Deoras who reimplemented some of the advanced LM techniques that are mentioned in the comparison. Some of the following results are also based on the work of other researchers, as will be mentioned later.

Table 4.1: *Perplexity of individual models alone and after combination with the baseline language models. Results are reported on the test set of the Penn Treebank corpus.*

Model	Perplexity			Entropy reduction over baseline	
	individual	+KN5	+KN5+cache	KN5	KN5+cache
3-gram, Good-Turing smoothing (GT3)	165.2	-	-	-	-
5-gram, Good-Turing smoothing (GT5)	162.3	-	-	-	-
3-gram, Kneser-Ney smoothing (KN3)	148.3	-	-	-	-
5-gram, Kneser-Ney smoothing (KN5)	**141.2**	-	-	-	-
5-gram, Kneser-Ney smoothing + cache	**125.7**	-	-	-	-
PAQ8o10t	131.1	-	-	-	-
Maximum entropy 5-gram model	142.1	138.7	124.5	0.4%	0.2%
Random clusterings LM	170.1	126.3	115.6	2.3%	1.7%
Random forest LM	131.9	131.3	117.5	1.5%	1.4%
Structured LM	146.1	125.5	114.4	2.4%	1.9%
Within and across sentence boundary LM	116.6	110.0	108.7	5.0%	3.0%
Log-bilinear LM	144.5	115.2	105.8	4.1%	3.6%
Feedforward neural network LM [50]	140.2	116.7	106.6	3.8%	3.4%
Feedforward neural network LM [40]	141.8	114.8	105.2	4.2%	3.7%
Syntactical neural network LM	131.3	110.0	101.5	5.0%	4.4%
Recurrent neural network LM	124.7	105.7	97.5	5.8%	5.3%
Dynamically evaluated RNNLM	123.2	102.7	98.0	6.4%	5.1%
Combination of static RNNLMs	102.1	95.5	**89.4**	7.9%	7.0%
Combination of dynamic RNNLMs	101.0	**92.9**	90.0	8.5%	6.9%

4.3.1 Backoff N-gram Models and Cache Models

The first group of models are standard n-gram models with Good-Turing (GT) and modified Kneser-Ney smoothing (KN) [24]. The usual baseline in many papers is a trigram model with Good-Turing smoothing. We can see that substantial gains can be gained by using KN smoothing and also by using higher order n-grams (in this case, the performance of models with order higher than 5 did not provide any significant gains). Although the PTB corpus is relatively small, the difference between GT3 and KN5 models is large - perplexity is reduced from about 165 to 141. On larger data sets, even bigger difference can be expected.

We have used popular SRILM [72] toolkit to build the n-gram models, with no count cutoffs. In many papers, the reported perplexity on the PTB data set is obtained by using models trained with count cutoffs, which leads to slight degradation of performance - KN5

model with default SRILM cutoffs provides PPL 148 on the test set, while without cutoffs, the perplexity is 141. We also report the perplexity of the best n-gram model (KN5) when using unigram cache model (as implemented in the SRILM toolkit). We have used several unigram cache models interpolated together, with different lengths of the cache history (this works like a crude approximation of cache decay, ie. words further in the history have lower weight). This provides us with the second baseline[2].

We are aware of the fact that unigram cache model is not state of the art among cache models - as reported by Goodman [24], n-gram cache models can provide in some cases up to twice the improvement that the simple unigram cache model provides. However due to the fact that we will use later more complex techniques for capturing long context information in the model combination, we do not consider this to be a significant weakness in our comparison.

4.3.2 General Purpose Compression Program

PAQ8o10t is a state of the art general purpose compression program[3] developed by Mahoney et al. [46]. To compute perplexity of the test set using a compression program, we have first compressed the training set, and then the training set concatenated with the test set. As there are no new words occurring in the test set of the PTB corpus (all words outside the 10K vocabulary are rewritten as `<unk>`), the information that needs to be captured by a compression program is the same as when using a statistical language model (this is however not true in cases when the test data contains out of vocabulary words, as the language modeling techniques usually skip such words for likelihood evaluation). By subtracting the sizes of the two files, we can measure the amount of bits that were needed to compress the test data, after the compression program has seen the training data. We can compute the word-level perplexity, as we know the number of symbols in the test data, denoted as $COUNT$ (the number of words and end of line symbols), and the number of bits B that were needed to encode them:

$$PPL = 2^{\frac{B}{COUNT}} \tag{4.3}$$

[2]In fact, performance of many techniques were reported in the past on this data set without actually showing the perplexity when a cache model is used. Such papers include topic models and other techniques that aim to capture longer context information, which can be easily captured (to some degree) by a simple cache model. Thus, we consider it important to show results also for the second baseline that includes cache, although it makes the comparison in Table 4.1 more difficult to read.

[3]The benchmark can be found at `http://cs.fit.edu/~mmahoney/compression/`

The resulting perplexity 131.1 given by PAQ is quite good, comparable to the state of the art backoff model combined with the cache model. This model is however not used in the model combination, as it would be difficult to obtain probabilities of individual words in the test set. Also, we do not expect this model to be complementary to the KN5+cache model.

The PAQ archivers are based on a neural network without a hidden layer, thus the model is very similar to what is denoted in the language modeling field as a maximum entropy model. The main difference is that the prediction is based not only on the history of preceding words, but also on the history of several previous characters. In fact, there are several other predictors in the model, each using different context (some of them are specific to other types of data than text). The other interesting difference is that the prediction of the future data is done on a bit level, which leads to speed up as one does not have to normalize over all possible characters, or words. Also, the hash-based implementation of the neural network has been a motivation for our model that will be introduced in Chapter 6.

4.3.3 Advanced Language Modeling Techniques

The second group of models in Table 4.1 represents popular advanced LM techniques. Maximum entropy models [64] allow easy integration of any information source in the probabilistic model. In our study, we have used a model with up to 5-gram features. The results were obtained by using SRILM extension for training ME models, with the default L1 and L2 regularization parameters described in [2]. The observed improvement over baseline KN5 model is rather modest, it can be seen that the ME model with just n-gram features works about the same as the n-gram model with the best smoothing. It can be expected that better results can be obtained by having more features in the model, like triggers or class features.

Random clustering LM is a class based model described in [20]. This model has been reimplemented for our experiments by Anoop Deoras. We used just simple classes for this model, but the performance after interpolation with the baseline n-gram model is about the same as reported by Emami.

We used 4-gram features for the Random forest language model [78], that is a combination of several randomly grown decision trees. We are aware of several implementations of structured language models that were previously evaluated on the PTB dataset - in our

experiments, we have used the one implemented by Filimonov [23], as it has very competitive performance among structured LMs (PPL 125.5). Better results were reported on this dataset with another structured LM - in [77], perplexity 118.4 is reported for SuperARV language model combined with n-gram model; however, we did not have this model for our experiments.

Within and across sentence boundary LM was proposed in [56]. This model incorporates several information sources: across sentence boundary model similar to cache, skip n-gram model and a class based model. Across sentence boundary model works in a very similar way as a cache model, and the combination with the skip n-gram model and a class based model is thus quite similar to the combination of models reported by Goodman [24]. The perplexity is reduced considerably over the baseline KN5 model; although it is claimed in [56] that the performance of the standalone model is state of the art, we have found that a combination of this model with a KN5 model provides further improvement, resulting in PPL 110. Adding also our cache model did not improve the results significantly, only to PPL 108.7. This model performs the best among the non-neural network models, but one has to keep in mind that the model itself is a combination of several models.

4.3.4 Neural network based models

The third group of models in Table 4.1 consists of individual neural network language models with different architectures. There are two types of feedforward neural network models. The first type was proposed in my earlier work and learns the features and the final model independently while using two neural networks, both with one hidden layer [48] (see section 3.1). The second and more common type was originally proposed by Yoshua Bengio [5] - the neural network learns a linear projection of words into a low dimensional space together with the final model. Both feedforward architectures were found to have almost identical performance on the PTB setup. The latter model used in these experiments was implemented by Hai Son Le [40], as well as the log-bilinear model, which was proposed as an alternative to the neural network language models in [54].

Syntactical neural network language model developed by Emami has been reported to provide the state of the art results on the Penn Treebank Corpus in [19], and we are not aware of any better results published since then until our work. It is the only neural network architecture in our study that actually uses more features in the input layer than just words - the syntactical information comes from a syntactical parser, thus this model is

believed to have better ability to cover longer context dependencies. This work has been an interesting attempt to combine neural network language models and the structured language models, with very good results.

The recurrent neural network language model that was described in more depth in the previous chapter outperforms all other types of language models on the PTB data set [50]. It works similar to the feedforward neural network language model, with the main difference being representation of the history. While for both feedforward and the recurrent architecture the history is projected into a lower dimensional space where clustering of similar events occur, the main difference is that feedforward NN projects individual words, and recurrent NN performs clustering of the whole histories. This gives the recurrent model ability to compactly describe wider range of patterns in the data. In the experiments reported in this chapter, we have used truncated BPTT and Stochastic gradient descent (SGD) for training the RNN models. Error gradients were computed by performing unfolding of the RNN model for 5 time steps. The BPTT learning has been already described in the Chapter 3.3.1.

Figure 4.1 shows importance of propagating the gradients using BPTT for obtaining good performance. As it can be seen, even if the gradients are actually not propagated through the recurrent connections which corresponds to BPTT=1 in the Figure 4.1, the performance is very good. As can be seen in the given figure, the gains obtained from BPTT are not the same gains as those obtained by training more models - in other words, BPTT discovers information that cannot be simply discovered by having large amount of randomly initialized models. It is important to note here that while on the PTB corpus the propagation of gradients might not look crucial as the difference in perplexity is about 10%, the BPTT algorithm is neccessary for obtaining good performance on larger data sets, where capturing information from longer contexts becomes crucial.

Dynamical evaluation of the language models has been proposed already by Jelinek [32], which resulted in the cache techniques for n-gram models. The idea has been applied to neural network language models and reported to provide significant improvements in our previous work [49]. Unlike cache models, the dynamically adapted NNLMs were reported to provide reductions of both perplexity and word error rate, which can be explained by the fact that the adaptation of neural network model is performed in continuous space, and can be thus much faster and smoother than adaptation of n-gram counts. This technique is discussed in more detail in section 3.4.4. We have applied dynamical evaluation only

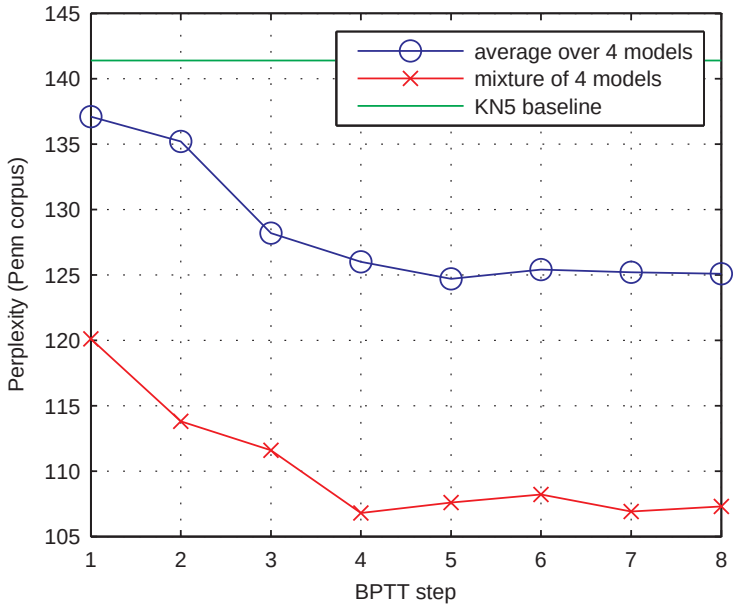

Figure 4.1: Effect of BPTT training on Penn Corpus. BPTT=1 corresponds to standard backpropagation (no unfolding of RNN). Average over 4 models corresponds to average perplexity given by 4 models with different random initialization of the weights, while mixture of 4 models corresponds to combination of these 4 models.

to the recurrent NNLMs, but it can be expected that the improvements would be similar also when applied to the feedforward NNLMs.

4.3.5 Combinations of NNLMs

The last group of models in Table 4.1 consists of combinations of different RNN models. We have used up to 20 RNN models, each trained with different random initialization of the weights. This technique is described in more detail in Section 3.4.5. In Figure 4.2, it is demonstrated how adding more RNN models into the mixture helps to reduce perplexity.

The dynamic evaluation of a model as well as a combination of randomly initialized models are both general approaches that can be applied to neural network LMs with any architecture. However, it is the most useful to apply these techniques to the best models, which are in our case RNN based models. We will demonstrate this later as we will show that a combination of RNN models cannot be improved by adding to it a feedforward neural network LM.

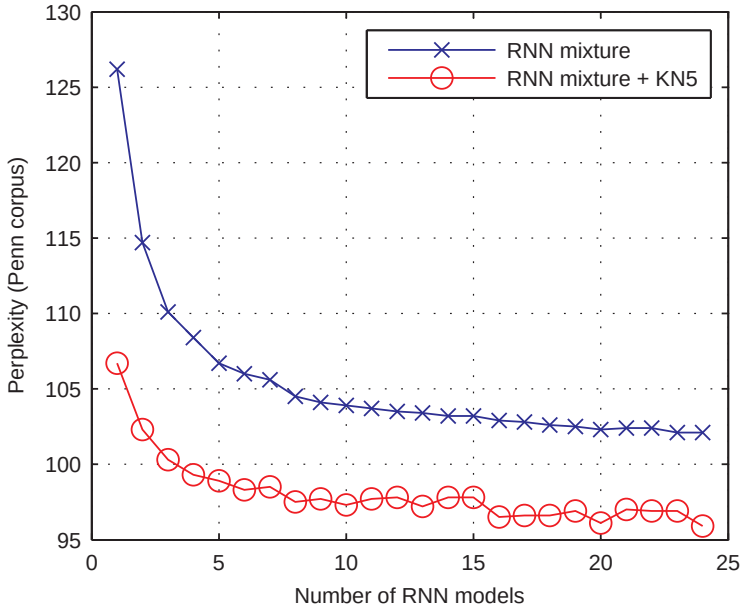

Figure 4.2: Linear interpolation of RNN models trained with different random initialization of the weights.

4.4 Comparison of Different Neural Network Architectures

As neural network language models seem to work very well, we will describe them and compare their performances in more detail. As can be seen in Table 4.1, the performance of neural network based models with feedforward architectures is almost identical. The syntactical NNLM has an advantage of having more input features: it uses a syntactical parser to obtain part of speech tags for words in a sentence. We can observe that a significant improvement was obtained by using these additional features. On the other hand, application of this technique to new languages and domains might not be straightforward, as it relies on a syntactical parser that has to be trained on (usually) hand-annotated data. There has been a following work done by Emami [22], where it is shown how different linguistic features affect results, both perplexity and word error rate. The conclusion of that experiments seems to be that the linguistic features improve only perplexity, but do not reduce the word error rate.

Additional input features make interpretation of the results quite difficult: it can be seen that the PTB corpus is quite small, and thus having additional information from a parser that is trained on additional data (POS tags of words) can be a great boost to the results. However, with increased amount of the training data, such additional information would be probably less useful. Thus, it would be more convincing if the results obtained

with syntactical NNLMs would be presented on larger data sets, containing at least several hundreds of millions of words.

The other way to improve accuracy of the model is to allow it to represent compactly larger set of patterns. By changing the topology of the network from a feedforward to a recurrent one, we allow the model to form a short context memory that is learned unsupervisedly from the data. The prediction of the next word then depends on the previous word and the state of the short context memory. We can thus claim that such model can actually cluster entire histories that are in some sense similar. This is in contrast to feedforward neural networks that can effectively cluster only individual words in the projection layer, and then it is needed to perform another step to cluster the low-dimensional representation of several words from the history. If some pattern involves variable position of some word in the history, it is not possible to represent such pattern efficiently with a compact feedforward network, while this can be accomplished by using a recurrent one.

From the empirical point of view, we can see in Table 4.1 that recurrent networks work both better than feedforward networks, and also better than feedforward networks with additional linguistic features. A question arises, if this improvement does not come from simply learning cache-like information from the data, as the recurrent topology actually allows this. Theoretical explanation from Bengio [4] shows that this actually can not happen if RNN is trained by stochastic gradient descent, as the error signal that is propagated through the recurrent connections converges to zero fast in most cases, thus it is hard to train a recurrent network to represent long term patterns that would span over several sentences. Table 4.1 shows empirical results, where we can see a combination with a cache model: we can observe that in combination with the KN5+cache model the recurrent network is behaving in a very similar way as the feedforward networks. Thus we can conclude that the improvements obtained with RNN models come from better representation of short context information, and not from learning cache information. Overall, we can see 2.4% improvement in entropy when comparing the neural net with the feedforward achitecture (PPL 140.2) and with the recurrent achitecture (PPL 124.7). This is a large improvement, especially if we consider that the feedforward neural network itself has a very good position among studied models.

The dynamic evaluation of the RNN model provides further improvement. While the perplexity reduction against the static RNN model is small, we will see in the next

Table 4.2: *Combination of individual statically evaluated NNLMs. 'PPL without the model' means perplexity of the combination of all models without the particular model. Weights are tuned for the best performance on the validation set.*

Model	Weight	Model PPL	PPL without the model
Log-bilinear LM	0.163	144.5	107.4
Feedforward NNLM	0.124	140.2	106.7
Syntactical NNLM	0.306	131.3	110.9
Recurrent NNLM	0.406	124.7	113.2
ALL	1	105.8	-

section that the dynamically evaluated models are complementary to the static models - their interpolation provides interesting improvements. A closer analysis shows that the performance improvement that is obtained from a dynamically evaluated RNN model is lower after the model is interpolated with a baseline KN5+cache model. The explanation is that the dynamically evaluated model incorporates information from the test data into the model, and thus it can capture long context information in a similar way as a cache model. The small degradation of performance can be explained by the fact that RNN model can also forget some information as it gets updated on-line during processing the test data.

The last type of neural network models in the comparison are combinations of RNN language models. These are obtained by linearly interpolating probability distributions from several neural network language models with different initialization of the weight matrices - a similar idea is used for constructing random forests from individual decision trees. Typically, 4-5 models are enough to obtain most of the achievable improvement. In our experiments, as we are interested in the best achievable results, we have used a combination of 20 models that performed the best on the validation set. The configuration of these models was: 200-400 hidden units, BPTT steps 5-10, the starting learning rate 0.1 and default regularization, as was mentioned in the previous chapter[4].

To verify the conclusion that RNN based models are performing the best among neural network based language models, we have combined all individual NN models with different architectures. Table 4.2 shows resulting perplexity and the optimal weight of each model

[4]Actually we have found that L2 regularization can improve the results very slightly, but the models trained with a regularization seem to be less complementary in the combination than the models trained without regularization. The disadvantage of not using any regularization is in a possible numerical instability of the training, thus we typically use small L2 penalty that is not further tuned.

Table 4.3: *Combination of individual static NNLMs and one dynamically evaluated RNNLM.*

Model	Weight	Model PPL	PPL without the model
Log-bilinear LM	0.125	144.5	101.1
Feedforward NNLM	0.086	140.2	100.6
Syntactical NNLM	0.257	131.3	103.8
Static RNNLM	0.207	124.7	101.6
Dynamic RNNLM	0.325	123.2	105.8
ALL	1	100.2	-

Table 4.4: *Combination of all types of NN language models.*

Model	Weight	Model PPL	PPL without the model
Log-bilinear LM	0.023	144.5	93.2
Feedforward NNLM	0.010	140.2	93.2
Syntactical NNLM	0.140	131.3	94.2
Combination of static RNNLMs	0.385	124.7	95.5
Combination of dynamic RNNLMs	0.442	123.2	99.4
ALL	1	93.2	-

in the combination. We can conclude that model with the recurrent architecture has the highest weight and the lowest individual perplexity, and thus is the most successful one for this particular data set. It should be noted that both feedforward and the recurrent NNLMs were carefully tuned for the maximal performance. Also, we can see that discarding the RNN model from the combination hurts the most, with degradation of perplexity from 105.8 to 113.2. The second most important model is the syntactical NNLM, which provides complementary information as it uses additional features.

As stated before, the dynamic models provide complementary information to the statically evaluated ones. It can be observed in Table 4.3 that after adding a dynamically evaluated RNNLM, the final perplexity goes down from 105.8 to 100.2. It is important to note that the dynamic RNN in this comparison is the same same RNN model as the static one, and the only difference is that it is being trained as the test data are processed. Moreover, to show that the improvement provided by dynamic evaluation is not caused by simply having more models in the mixture, we have combined all NN models including the statically and dynamically evaluated combinations of the 20 RNN models. Results in Table 4.4 prove that dynamic evaluation provides complementary information.

Table 4.5: *Results on Penn Treebank corpus (evaluation set) after combining all models. The weight of each model is tuned to minimize perplexity of the final combination.*

Model	Weight	Model PPL
3-gram, Good-Turing smoothing (GT3)	0	165.2
5-gram, Kneser-Ney smoothing (KN5)	0	141.2
5-gram, Kneser-Ney smoothing + cache	0.079	125.7
Maximum entropy 5-gram model	0	142.1
Random clusterings LM	0	170.1
Random forest LM	0.106	131.9
Structured LM	0.020	146.1
Across sentence LM	0.084	116.6
Log-bilinear LM	0	144.5
Feedforward neural network LM [50]	0	140.2
Feedforward neural network LM [40]	0	141.8
Syntactical neural network LM	0.083	131.3
Combination of static RNNLMs	0.323	102.1
Combination of dynamic RNNLMs	0.306	101.0
ALL	1	83.5

4.5 Combination of all models

The most interesting experiment is to combine all language models together: based on that, we can see which models can truly provide useful information in the state of the art combination, and which models are redundant. It should be stated from the beginning that we do not compare computational complexity or memory requirements of different models, as we are only interested in achieving the best accuracy. Also, the conclusions about accuracies of individual models and their weights should not be interpreted as that the models that provide no complementary information are useless - further research can prove otherwise.

Table 4.5 shows weights of all studied models in the final combination, when tuned for the best performance on the development set. We do not need to use all techniques to achieve optimal performance: weights of many models are very close to zero. The combination is dominated by the RNN models, which together have a weight of 0.629. It is interesting to realize that some individual models can be discarded completely without hurting the performance at all. On the other hand, the combination technique itself is

Table 4.6: *Results on Penn Treebank corpus (evaluation set) when models are added iteratively into the combination. The most contributing models are added first.*

Model	PPL
Combination of adaptive RNNLMs	101.0
+KN5 (with cache)	90.0
+Combination of static RNNLMs	86.2
+Within and across sentence boundary LM	84.8
+Random forest LM	84.0

possibly suboptimal, as log-linear interpolation was reported to work better [35]; however, it would be much more difficult to perform log-linear interpolation of all models, as it would required to evaluate the whole probability distributions for every word in the test sets given by all models.

By discarding RNN models from the combination (both statically and dynamically evaluated), we observe severe degradation in performance, as the perplexity raises to 92.0. That is still much better than the previously reported best perplexity result 107 in [19], but such result shows that RNN models are able to discover information that the other models are unable to capture.

A potential conclusion from the above study is that different techniques actually discover the same information. For example, the random forest language model that we used is implicitly interpolated with a Kneser-Ney 4-gram LM. Thus, by using the random forest language model in the combination of all models, KN5 model automatically obtains zero weight, as the random forest model contains all the information from the KN5 model plus some additional information.

To make this study more tractable, we have added the models into the combination in a greedy way: we have started with the best model, and then iteratively added a model that provided the largest improvement. The results are shown in Table 4.6. The most useful models are RNN models and the Kneser-Ney smoothed 5-gram model with a cache. The next model that improved the combination the most was the Within and across sentence boundary language model, although it provided only small improvement. After adding random forest LM, the perplexity goes down to 84.0, which is already almost the same as the combination of all techniques presented in Table 4.5.

Table 4.7: *Results on Penn Treebank corpus (evaluation set) with different linear interpolation techniques.*

Model	PPL
Static LI of all models	83.5
Static LI of all models + dynamic RNNs with $\alpha = 0.5$	80.5
Adaptive LI of all models + dynamic RNNs with $\alpha = 0.5$	79.4

4.5.1 Adaptive Linear Combination

All the experiments above use fixed weights of models in the combination, where the weights are estimated on the PTB validation set. We have extended the usual linear combination of models to a case when weights of all individual models are variable, and are estimated during processing of the test data. The initial distribution of weights is uniform (every model has the same weight), and as the test data are being processed, we compute optimal weights based on the performance of models on the history of the last several words (the objective is to minimize perplexity). In theory, the weights can be estimated using the whole history. However, we found that it is possible to use multiple lengths of history - a combination where interpolation weights are estimated using just a few preceding words can capture short context characteristics that can vary rapidly between individual sentences or paragraphs, while a combination where interpolation weights depend on the whole history is the most robust.

It should be noted that an important motivation for this approach is that a combination of adaptive and static RNN models with fixed weights is suboptimal. When the first word in the test data is processed, both static and adaptive models are equal. As more data is processed, the adaptive model is supposed to learn new information, and thus its optimal weight can change. If there is a sudden change of topic in the test data, the static model might perform better for several sentences, while if there are repeating sentences or names of people, the dynamic model can work better.

Further improvement was motivated by the observation that adaptation of RNN models with the learning rate $\alpha = 0.1$ leads usually to the best individual results, but models in combination are more complementary if some are processed with larger learning rate. The results are summarized in Table 4.7. Overall, the adaptive learning rate provides small improvement, and has an interesting advantage: it does not require any validation data for tuning the weights of individual models.

4.6 Conclusion of the Model Combination Experiments

We have achieved a new state of the art results on the well-known Penn Treebank Corpus, as we reduced the perplexity from the baseline 141.2 to 83.5 by combining many advanced language modeling techniques. Perplexity was further reduced to 79.4 by using adaptive linear interpolation of models and by using larger learning rate for dynamic RNN models. These experiments were already described in [51].

In the subsequent experiments, we were able to obtain **perplexity 78.8** by using in the model combination also RNNME models that will be described in the Chapter 6. This corresponds to **11.8% reduction of entropy over 5-gram model with modified Kneser-Ney smoothing and no count cutoffs** - this is more than twice more entropy reduction than the best previously published result on the Penn Treebank data set.

It is quite important and interesting to realize that we can actually rely just on a few techniques to reach near-optimal performance. Combination of RNNLMs and KN5 model with a cache is very simple and straightforward. All these techniques are purely data driven, with no need for extra domain knowledge. This is in contrast to techniques that rely for example on syntactical parsers, which require human-annotated data. Thus, my conclusion for the experiments with the Penn Treebank corpus is that techniques that focus on the modeling outperform techniques that focus on the features and attempt to incorporate knowledge provided by human experts. This might suggest that the task of learning the language should focus more on the learning itself, than on hand-designing features and complex models by linguists. I believe that systems that rely on the extra information provided by humans may be useful in the short term perspective, but from the long term one, the machine learning algorithms will improve and overcome the rule based systems, as there is a great availability of unstructured data. Just by looking at the evolution of the speech recognition field, it is possible to observe this drift towards statistical learning. Interestingly, also the research scientists from big companies such as Google claim that systems without special linguistic features work if not the same, then even better [58].

Chapter 5

Wall Street Journal Experiments

Another important data set frequently used by the speech recognition community for research purposes is the Wall Street Journal speech recognition task. In the following experiments, we aim to:

- show full potential of RNN LMs on moderately sized task, where speech recognition errors are mainly caused by the language model (as opposed to acoustically noisy tasks where it would be more important to work on the acoustic models)
- show performance of RNN LMs with increasing amount of the training data
- provide comparison to other advanced language modeling techniques in terms of word error rate
- describe experiments with open source speech recognition toolkit Kaldi that can be reproduced

5.1 WSJ-JHU Setup Description

The experiments in this section were performed with data set that was kindly shared with us by researchers from Johns Hopkins university. We report results after rescoring 100-best lists from DARPA WSJ'92 and WSJ'93 data sets - the same data sets were used by Xu [79], Filimonov [23], and in my previous work [49]. Oracle WER of the 100-best lists is 6.1% for the development set and 9.5% for the evaluation set. Training data for the language model are the same as used by Xu [79]. The training corpus consists of 37M words from NYT section of English Gigaword. The hyper-parameters for all RNN models

were: 400 classes, hidden layer size up to 800 neurons. Other hyper-parameters such as interpolation weights were tuned on the WSJ'92 set (333 sentences), and the WSJ'93 set used for evaluation consists of 465 sentences.

Note that this setup is very simple as the acoustic models that were used to generate n-best lists for this task were not the state of the art. Also, the corresponding language models used in the previous research were trained just on limited amount of the training data (37M-70M words), although by using more training data that are easily affordable for this task, better performance can be expected. The same holds for the vocabulary - a 20K word list was used, although it would be simple to use more. Thus, the experiments on this setup are not supposed to beat the state of the art, but to allow comparison to other LM techniques and to provide more insight into the performance of the RNN LMs.

5.1.1 Results on the JHU Setup

Results with RNN models and competitive techniques are summarized in Table 5.1. The best RNN models have very high optimal weight when combined with KN5 baseline model, and actually by discarding the n-gram model completely, the results are not significantly affected. Interpolation of three RNN models gives the best results - the word error rate is reduced relatively by about 20%. Other techniques, such as discriminatively trained language model and joint LM (structured model) provide smaller improvements, only about 2-3% reduction of WER on the evaluation set.

The adapted RNN model is not evaluated as a dynamic RNN LM described in the previous chapters, but simply a static model that is re-trained on the 1-best lists. This was done due to performance issues; it becomes relatively slow to work with RNN models that are continuously updated, especially in the n-best list rescoring framework. Adaptation itself provides relatively small improvement, especially with the large models.

5.1.2 Performance with Increasing Size of the Training Data

It was observed by Joshua Goodman that with increasing amount of the training data, improvements provided by many advanced language modeling techniques vanish, with a possible conclusion that it might be sufficient to train basic n-gram models on huge amounts of data to obtain good performance [24]. This is sometimes interpreted as an argument against language modeling research; however, as was mentioned in the introduction of this thesis, simple counting of words in different contexts is far from being close

Table 5.1: *Comparison of advanced language modeling techniques on the WSJ task (37M training tokens).*

Model	Dev WER[%]	Eval WER[%]
Baseline - KN5	12.2	17.2
Discriminative LM [79]	11.5	16.9
Joint LM [23]	-	16.7
Static RNN	10.3	14.5
Static RNN + KN	10.2	14.5
Adapted RNN	9.7	14.2
Adapted RNN + KN	9.7	14.2
3 interpolated RNN LMs	**9.5**	**13.9**

Table 5.2: *Comparison of results on the WSJ dev set (JHU setup) obtained with models trained on different amount of the data.*

# words	PPL		WER		Improvement[%]	
	KN5	+RNN	KN5	+RNN	Entropy	WER
223K	415	333	-	-	3.7	-
675K	390	298	15.6	13.9	4.5	10.9
2233K	331	251	14.9	12.9	4.8	13.4
6.4M	283	200	13.6	11.7	6.1	14.0
37M	212	133	12.2	10.2	8.7	16.4

to the way humans process natural language. I believe that advanced techniques exist that are able to model richer set of patterns in the language, and these should be actually getting increasingly better than n-grams with more training data. Thus, I performed experiments to check if RNN LMs behave in this way.

Results with increasingly large subset of the training data for the WSJ-JHU task are shown in Table 5.2. Both relative entropy reductions and relative word error rate reductions are increasing with more training data. This is a very optimistic result, and it confirms that the original motivation for using neural net language models was correct: by using distributed representation of the history instead of the sparse coding, the neural net models can represent certain patterns in the language more efficiently than the n-gram models. The same results are also shown at Figure 5.1, where it is easier to see the trend.

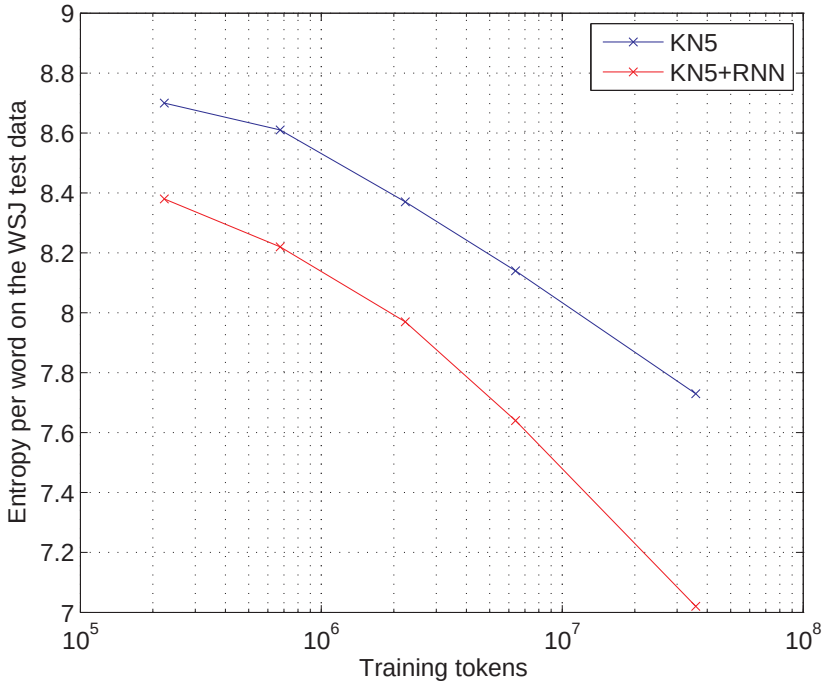

Figure 5.1: Improvements with increasing amount of training data - WSJ (JHU setup). Note that size of the hidden layer is tuned for the optimal performance, and increases with the amount of the training data.

5.1.3 Conclusion of WSJ Experiments (JHU setup)

The possible improvements increase with more training data on this particular setup. This is a very positive result; the drawback is that with increased amount of the training data, such as billions of words, the computational complexity of RNN models is prohibitively large. However, we dealt with the computational complexity in the previous chapter, and it should be doable to train good RNN models even on data sets with more than a billion words by using the class-based RNNME architecture.

Similarly to the experiments with the Penn Treebank Corpus, I tried to achieve the lowest possible perplexity. However, this time just two RNN LMs were used, and the combination of models did include just static RNN LMs, dynamic RNN LMs (with a single learning rate $\alpha = 0.1$) and a Kneser-Ney smoothed 5-gram model with a cache. Good-Turing smoothed trigram has perplexity 246 on the test data; the best combination of models had perplexity 108 - this by more than 56% lower (entropy reduction 15.0%). The 5-gram with modified Kneser-Ney smoothing has perplexity 212 on this task, thus the combined result is by 49% lower (entropy reduction 12.6%). Thus, although the combination experiments were much more restricted than in the case of PTB, the entropy

improvements actually increased - this can also be explained by the fact that the WSJ-JHU setup is about 40x larger.

5.2 Kaldi WSJ Setup

Additional experiments on the Wall Street Journal task were performed using n-best lists generated with an open source speech recognition toolkit Kaldi [60] trained on SI-84 data further described in [62]. The acoustic models used in the following experiments were based on triphones and GMMs. Several advantages of using Kaldi such as better repeatability of the performed experiments were already mentioned in the beginning of this chapter (although Kaldi is still being developed, it should be easy to repeat the following experiments with slightly better results, as RNN rescoring code is integrated in the Kaldi toolkit). Note that this setup is also not the state of the art, as with more training data and advanced acoustic modeling techniques, it is possible to get better baseline results. Rescoring experiments with RNN LMs on a state of the art setup is subject of the following chapter.

I used 1000-best lists generated by Stefan Kombrink in the following experiments. The test sets are the same as for the JHU setup. This time I trained RNNME models to save time - it is possible to achieve very good results even with tiny size of the hidden layer. For the ME part of the model, I used unigram, bigram, trigram and fourgram features, with hash size 2G parameters. The vocabulary was limited to 20K words used by the decoder. Training data consisted of 37M tokens, from which 1% was used as heldout data. The training data were shuffled to increase speed of convergence during training, however, due to homogeneity of the corpus, the automatic sorting technique as described in Chapter 6 was not used. The results are summarized in Table 5.3.

It can be seen that RNNME models improve PPL and WER significantly even with tiny size of the hidden layer, such as 10 neurons. However, for reaching top performance, it is useful to train models as large as possible. While training of small RNNME models (such as with less than 100 neurons in the hidden layer) takes around several hours, training the largest models takes a few days. After combining all RNNME models, the performance still improves; however, adding unsupervised adaptation resulted in rather insignificant improvement - note that the Eval 92 contains 333 utterances and Eval 92 only 213, thus there is noise in the WER results due to small amount of test data.

Table 5.3: *Results on the WSJ setup using Kaldi.*

Model	Perplexity		WER [%]	
	heldout	Eval 92	Eval 92	Eval 93
GT2	167	209	14.6	19.7
GT3	105	147	13.0	17.6
KN5	87	131	12.5	16.6
KN5 (no count cutoffs)	80	122	**12.0**	**16.6**
RNNME-0	90	129	12.4	17.3
RNNME-10	81	116	11.9	16.3
RNNME-80	70	100	10.4	14.9
RNNME-160	65	95	10.2	14.5
RNNME-320	62	93	9.8	14.2
RNNME-480	59	90	10.2	13.7
RNNME-640	59	89	9.6	14.4
combination of RNNME models	-	-	9.24	13.23
+ unsupervised adaptation	-	-	**9.15**	**13.11**

Table 5.4: *Sentence accuracy on the Kaldi WSJ setup.*

Model	Sentence accuracy [%]	
	Eval 92	Eval 93
KN5 (no count cutoffs)	27.6	26.8
RNNME combination+adaptation	39.9	36.6

Overall, the absolute reduction of WER is quite impressive: against 5-gram with modified Kneser-Ney smoothing with no count cutoffs, the WER reduction is about 2.9% - 3.5%. This corresponds to relative reduction of WER by 21% - 24%, which is the most likely the best result in the statistical language modeling field. As the word error rates are already quite low, it is interesting to check another performance metric - the number of correctly recognized sentences, as reported in Table 5.4. Relatively, the sentence accuracy increased by using RNNME models instead of n-gram models by 37% - 45%.

In Figure 5.2, it is shown how word error rate decreases with increasing size of the N-best lists. It is possible that results can be further improved by using even larger N-best lists, such as 10K-best. However, the expected improvements are small. It would be

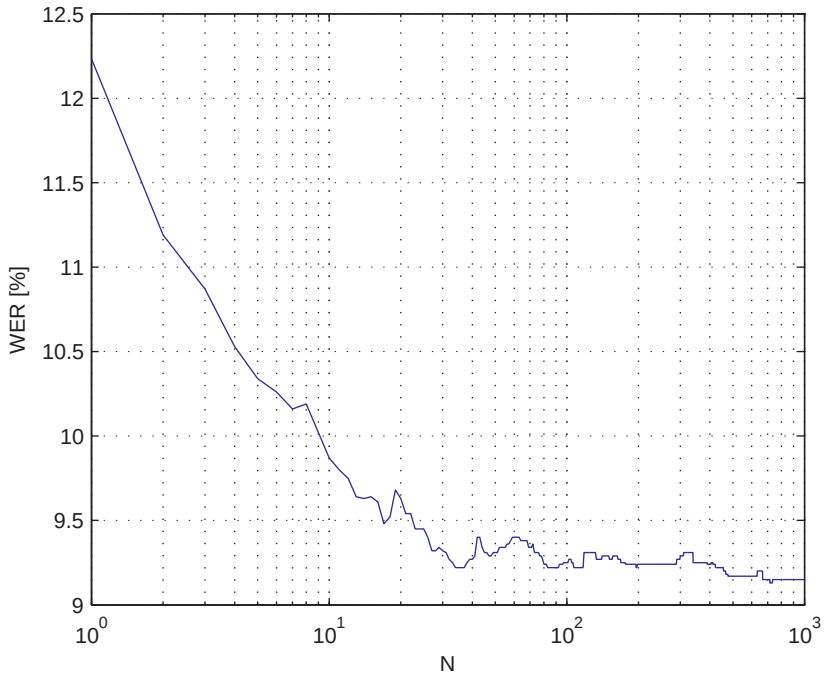

Figure 5.2: WER on Eval 92 after rescoring with increasing size of N-best list, the baseline is obtained with 5-gram model.

probably more useful to either produce wider lattices to allow more diverse paths to be encoded in the lattice, or to use neural net language models directly during decoding.

5.2.1 Approximation of RNNME using n-gram models

As was described in Section 3.4.3, it is possible to approximate complex generative language models by sampling huge amount of data and building usual n-gram models based on the generated data. This can be seen as an attempt to precompute large lookup table for likely n-gram entries. To demonstrate potential of this technique which allows trivial integration of RNN and RNNME models directly into decoders, 15 billion words were generated from RNNME-480 model. A Good-Turing smoothed 5-gram model was built on top of these data, and various results are reported in Table 5.5. It should be noted that while using modified Kneser-Ney smoothing provides slightly better results for standalone models based on the generated data, the results after interpolation with the baseline 5-gram model are worse than if Good-Turing smoothing is used.

Based on the results reported in Table 5.5, it is possible to obtain around 0.6% WER reduction by rescoring lattices using models that were trained on additional data that were generated from the RNNME-480 model. However, the n-gram model based on the

Table 5.5: *Results for models based on data sampled from RNNME-480 model (15B words).*

Model	Perplexity	WER [%]	
	heldout	Eval 92	Eval 93
GT3	105	13.0	17.6
KN5 (no count cutoffs)	80	**12.0**	**16.6**
Approximated RNNME-480	80	11.7	16.2
Approximated RNNME-480 + KN5	75	**11.4**	**16.0**
Full RNNME-480	59	10.2	13.7

Table 5.6: *Results for pruned models based on data sampled from RNNME-480 model (15B words).*

Model	WER [%]		Number of n-grams
	Eval 92	Eval 93	
GT3	13.0	17.6	11.1M
KN5 (no count cutoffs)	**12.0**	**16.6**	68M
Approximated RNNME-480 + KN5	**11.4**	**16.0**	846M
Approximated RNNME-480 + KN5, pruning 1e-9	11.6	16.0	33M
Approximated RNNME-480 + KN5, pruning 1e-8	12.2	16.7	9.5M
Approximated RNNME-480 + KN5, pruning 1e-7	12.9	17.5	1.8M

generated data is huge, and cannot be used directly in the decoder. Thus, additional experiments were performed with models that were pruned down in size, as reported in Table 5.6. Pruning was performed using SRILM toolkit and entropy pruning technique described in [73]. It can be seen that even after pruning, the approximated models remain competitive with the baseline 5-gram model.

Conclusion of the data sampling experiments is that it is possible to approximate computationally complex language models by precomputing results for frequent n-grams. In theory, by sampling infinite amount of data and by building n-gram models with infinite order, this technique can be used for converting RNN models into n-gram models without any loss of precision. However in practice, it seems difficult to obtain more that 20% - 30% of improvement that the original model provides. Still, even this can be interesting in some situations, as the approximated models can be used directly in decoders with no additional effort - the only thing that changes is the training data.

Chapter 6

Strategies for Training Large Scale Neural Network Language Models

The experiments on the Penn Treebank Corpus have shown that mixtures of recurrent neural networks trained by backpropagation through time provide state of the art results in the field of statistical language modeling. However a remaining question is, if the performance would be also this good with much larger amount of the training data - the PTB corpus with about 1M training tokens can be considered as very small, because language models are typically trained on corpora with orders of magnitude more data. It is not unusual to work with huge training corpora that consist of much more than a billion words. While application to low resource domains (especially for new languages and for domains where only small amount of relevant data exists) is also a very interesting research problem, the most convincing results are those obtained with well tuned state of the art systems, which are trained on large amounts of data.

The experiments in the previous chapter focused on obtaining the largest possible improvement, however some of the approaches would become computationally difficult to apply to large data sets. In this chapter, we briefly mention existing approaches for reducing the computational complexity of neural net language models (most of these approaches are also applicable to maximum entropy language models). We propose two new simple techniques that can be used to reduce computational complexity of the training and the test phases. We show that these new techniques are complementary to existing approaches.

Most interestingly, we show that a standard neural network language model can be

trained together with a maximum entropy model, which can be seen as a part of the the neural network, where the input layer is directly connected to the output layer. We introduce a hash-based implementation of a class-based maximum entropy model, that allows us to easily control the trade-off between the memory complexity, the space complexity and the computational complexity.

In this chapter, we report results on the NIST RT04 Broadcast News speech recognition task. We use lattices generated from IBM Attila decoder [71] that uses state of the art discriminatively trained acoustic models[1]. The language models for this task are trained on about 400M tokens. This highly competitive setup has been used in the 2010 Speech Recognition with Segmental Conditional Random Fields summer workshop at Johns Hopkins University[2] [82]. Some of the results reported in this chapter were recently published in [52].

6.1 Model Description

In this section, we will show that a maximum entropy model can be seen as a neural network model with no hidden layer. A maximum entropy model has the following form:

$$P(w|h) = \frac{e^{\sum_{i=1}^{N} \lambda_i f_i(h,w)}}{\sum_w e^{\sum_{i=1}^{N} \lambda_i f_i(h,w)}}, \tag{6.1}$$

where $\mathbf{f}$ is a set of features, $\boldsymbol{\lambda}$ is a set of weights and h is a history. Training of maximum entropy model consists of learning the set of weights $\boldsymbol{\lambda}$. Usual features are n-grams, but it is easy to integrate any information source into the model, for example triggers or syntactic features [64]. The choice of features is usually done manually, and significantly affects the overall performance of the model.

The standard neural network language model has a very similar form. The main difference is that the features for this model are automatically learned as a function of the history. Also, the usual features for the ME model are binary, while NN models use continuous-valued features. We can describe the NN LM as follows:

$$P(w|h) = \frac{e^{\sum_{i=1}^{N} \lambda_i f_i(s,w)}}{\sum_w e^{\sum_{i=1}^{N} \lambda_i f_i(s,w)}}, \tag{6.2}$$

[1]The lattice rescoring experiments reported in this chapter were performed by Anoop Deoras at JHU due to the license issues of the IBM recognizer.

[2]www.clsp.jhu.edu/workshops/archive/ws10/groups/speech-recognition-with-segmental-conditional-random-fields/

where s is a state of the hidden layer. For the feedforward NN LM architecture introduced by Bengio et al. in [5], the state of the hidden layer depends on a projection layer, that is formed as a projection of $N-1$ recent words into low-dimensional space. After the model is trained, similar words have similar low-dimensional representations.

Alternatively, the current state of the hidden layer can depend on the most recent word and the state of the hidden layer in the previous time step. Thus, the time is not represented explicitly. This recurrence allows the hidden layer to represent low-dimensional representation of the entire history (or in other words, it provides the model a short term memory). Such architecture is denoted as a Recurrent neural network based language model (RNN LM), and it was described in the Chapter 3. In the Chapter 4, we have shown that RNN LM achieves state of the art performance on the well-known Penn Treebank Corpus, and that it outperforms standard feedforward NN LM architectures, as well as many other advanced language modeling techniques.

It is interesting to see that maximum entropy models trained with just n-gram features have almost the same performance as usual backoff models with modified Kneser-Ney smoothing, as reported in Table 4.1. On the other hand, neural network models, due to their ability to cluster similar words (or similar histories), outperform the state-of-the-art backoff models. Moreover, neural net language models are complementary to backoff models, and further gains can be obtained by linearly interpolating them.

We can view a maximum entropy model as neural net model with no hidden layer, with the input layer that represents all features being directly connected to the output layer. Such a model has been already described in [81], where it was shown that it can be trained to perform similarly to a Kneser-Ney smoothed n-gram model, although on very limited task due to memory complexity.

Maximum entropy language models have been usually trained by special algorithms, such as generalized iterative scaling. Interestingly, we will show that a maximum entropy language model can be trained using the same algorithm as the neural net models - by the stochastic gradient descent with early stopping. This leads to very simple implementation of the training, and allows us to train both models jointly, as will be shown later.

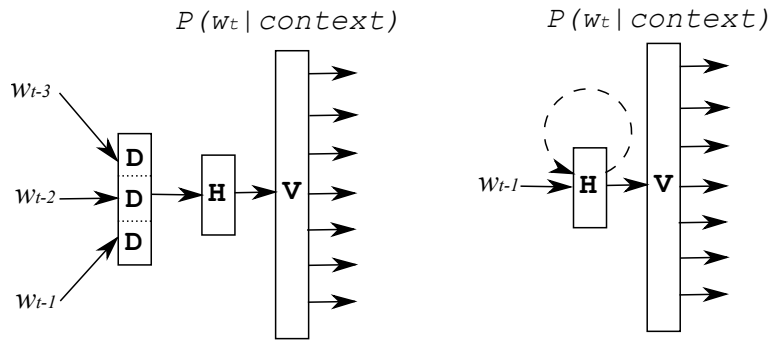

Figure 6.1: Feedforward neural network 4-gram model (on the left) and Recurrent neural network language model (on the right).

6.2 Computational Complexity

The computational complexity of a basic neural network language model is very high for several reasons, and there have been many attempts to deal with almost all of them. The training time of N-gram feedforward neural network language model is proportional to

$$I \times W \times \Big((N-1) \times D \times H + H \times V\Big), \tag{6.3}$$

where I is the number of the training epochs before convergence of the training is achieved, W is the number of tokens in the training set (in usual cases, words plus end-of-sentence symbols), N is the N-gram order, D is the dimensionality of words in the low-dimensional space, H is size of the hidden layer and V size of the vocabulary (see Figure 6.1). The term $(N-1) \times D$ is equal to the size of the projection layer.

The recurrent neural network language model has computational complexity

$$I \times W \times \Big(H \times H + H \times V\Big). \tag{6.4}$$

It can be seen that for increasing order N, the complexity of the feedforward architecture increases linearly, while it remains constant for the recurrent one (actually, N has no meaning in RNN LM).

Assuming that the maximum entropy model uses feature set $\mathbf{f}$ with full N-gram features (from unigrams up to order N) and that it is trained using on-line stochastic gradient descent in the same way as the neural network models, its computational complexity is

$$I \times W \times \Big(N \times V\Big). \tag{6.5}$$

The largest terms in the previous three equations are W, the number of the training words, and V, the size of the vocabulary. Typically, W can be in order of millions, and V in hundreds of thousands.

6.2.1 Reduction of Training Epochs

Training of neural net LMs is mostly performed by gradient descent with on-line update of weights. Usually, it is reported that 10-50 training epochs are needed to obtain convergence, although there are exceptions (in [81], it is reported that thousands of epochs were needed). In the next section, we will show that good performance can be achieved while performing as few as 6-8 training epochs, if the training data are sorted by their complexity.

6.2.2 Reduction of Number of Training Tokens

In usual circumstances, backoff n-gram language models are trained on as much data as available. However, for common speech recognition tasks, only small subset of this data is in-domain. Out-of-domain data usually occupy more than 90% size of the training corpora, but their weight in the final model is relatively low. Thus, neural net LMs are usually trained only using the in-domain corpora. In [68], neural net LMs are trained on in-domain data plus some randomly sampled subset of the out-of-domain data that is randomly chosen at the start of each new training epoch.

In a vast majority of cases nowadays, neural net LMs for LVCSR tasks are trained on just 5-30M tokens. Although the sampling trick can be used to claim that the neural network model has seen all the training data at least once, simple sampling techniques lead to severe performance degradation, against a model that is trained on all data - a more advanced sampling technique has been recently introduced in [80].

6.2.3 Reduction of Vocabulary Size

It can be seen that most of the computational complexity of neural net LM in Eq. 6.3 is caused by the huge term $H \times V$. For LVCSR tasks, the size of the hidden layer H is usually between 100 and 500 neurons, and the size of the vocabulary V is between 50k and 300k words. Thus, many attempts have been made to reduce the size of the vocabulary. The most simple technique is to compute probability distribution only for the most frequent S words in the neural network model, called a shortlist; the rest of the words use backoff

n-gram probabilities. However, it was shown in [40] that this simple technique degrades performance for small values of S very significantly, and even with small S such as 2000, the complexity induced by the $H \times V$ term is still very large.

More successful approaches are based on Goodman's trick for speeding up maximum entropy models using classes [25]. Each word from the vocabulary is assigned to a single class, and only the probability distribution over the classes is computed first. In the second step, the probability distribution over words that are members of a particular class is computed (we know this class from the predicted word whose probability we are trying to estimate). As the number of classes can be very small (several hundreds), this is a much more effective approach than using shortlists, and the performance degradation is smaller. We have shown that meaningful classes can be formed very easily, by considering only unigram frequencies of words [50]. Similar approaches have been described in [40] and [57].

6.2.4 Reduction of Size of the Hidden Layer

Another way to reduce $H \times V$ is to choose a small value of H. For example, in [8], $H = 100$ is used when the amount of the training data is over 600M words. However, we will show that the small size of the hidden layer is insufficient to obtain good performance when the amount of training data is large, as long as the usual neural net LM architecture is used.

In Section 6.6, a novel architecture of neural net LM is described, denoted as RNNME (recurrent neural network trained jointly with maximum entropy model). It allows small hidden layers to be used for models that are trained on huge amounts of data, with very good performance (much better than what can be achieved with the traditional architecture).

6.2.5 Parallelization

Computation in artificial neural network models can be parallelized quite easily. It is possible to either divide the matrix times vector computation between several CPUs, or to process several examples at once, which allows going to matrix times matrix computation that can be optimized by existing libraries such as BLAS. In the context of NN LMs, Schwenk has reported a speedup of several times by exploiting parallelization [68].

It might seem that recurrent networks are much harder to parallelize, as the state of the hidden layer depends on the previous state. However, one can parallelize just the

computation between the hidden and the output layers. It is also possible to parallelize the computation by training from multiple positions in the training data simultaneously.

Another approach is to divide the training data into K subsets and train a single neural net model on each of them separately. Then, it is needed to use all K models during the test phase, and average their outputs. However, neural network models profit from clustering of similar events, thus such an approach would lead to suboptimal results. Also, the test phase would be more computationally complex, as it would be needed to evaluate K models, instead of one.

6.3 Experimental Setup

We performed recognition on the English Broadcast News (BN) NIST RT04 task using state-of-the-art acoustic models trained on the English Broadcast News (BN) corpus (430 hours of audio) provided to us by IBM [31]. The acoustic model was discriminatively trained on about 430 hours of HUB4 and TDT4 data, with LDA+MLLT, VTLN, fMLLR based SAT training, fMMI and mMMI. IBM also provided us its state-of-the-art speech recognizer, Attila [71] and two Kneser-Ney smoothed backoff 4-gram LMs containing 4.7M n-grams and 54M n-grams, both trained on about 400M tokens. Additional details about the recognizer can be found in [31].

We followed IBM's multi-pass decoding recipe using the 4.7M n-gram LM in the first pass followed by rescoring using the larger 54M n-gram LM. The development data consisted of DEV04f+RT03 data (25K tokens). For evaluation, we used the RT04 evaluation set (47K tokens). The size of the vocabulary is 82K words.

The training corpora for language models are shown in Table 6.1. The baseline 4-gram model was trained using modified Kneser-Ney smoothing on all available data (about 403M tokens). For all the RNN models that will be described later, we have used the class-based architecture described in Section 3.4.2 with 400 classes.

6.4 Automatic Data Selection and Sorting

Usually, stochastic gradient descent is used for training neural networks. This assumes randomization of the order of the training data before start of each training epoch. In the context of NN LMs, the randomization is usually performed on the level of sentences or paragraphs. However, an alternative view can be taken when it comes to training deep

Table 6.1: *Training corpora for NIST RT04 Broadcast news speech recognition task.*

Name of Corpus	**# of Tokens**
LDC97T22	838k
LDC98T28	834k
LDC2005T16	11,292k
BN03	45,340k
LDC98T31	159,799k
LDC2007E02	184,484k
ALL	402,589k

neural network architectures, such as recurrent neural networks: we hope that the model will be able to find complex patterns in the data, that are based on simpler patterns. These simple patterns need to be learned before complex patterns can be learned. Such concept is usually called 'incremental learning'. In the context of simple RNN based language models, it has previously been investigated by Elman [18]. In the context of NN LMs, the incremental learning was described and formalized in [8], where it is denoted as Curriculum learning.

Inspired by these approaches, we have decided to change the order of the training data, so that the training starts with out-of-domain data, and ends with the most important in-domain data. Another motivation for this approach is even simpler: if the most useful data are processed at the end of the training, they will have higher weights, as the update of parameters is done on-line and the learning rate during a training epoch is fixed.

We divided the full training set into 560 equally-sized chunks (each containing 40K sentences). Next, we computed perplexity on the development data given a 2-gram model trained on each chunk. We sorted all chunks by their performance on the development set. We observed that although we use very standard LDC data, some chunks contain noisy data or repeating articles, resulting in high perplexity of models trained on these parts of the training data. In Figure 6.2, we plot the performance on the development set, as well as performance on the evaluation set, to show that the correlation of performance on different, but similar test sets is very high.

We decided to discard the data chunks with perplexity above 600 to obtain the Reduced-Sorted training set, that is ordered as shown in Figure 6.2. This set contains

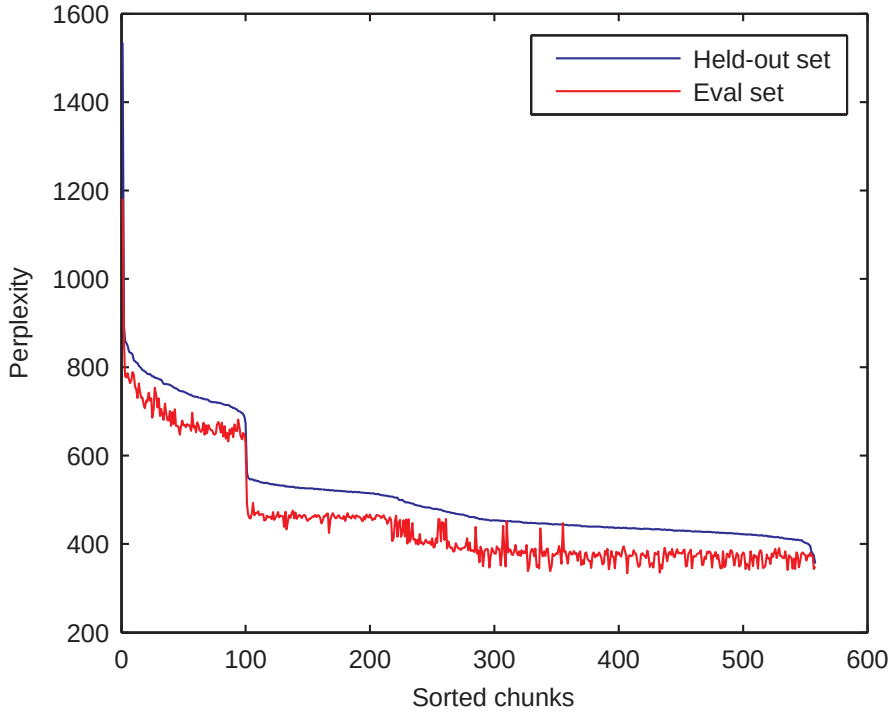

Figure 6.2: Perplexity of data chunks sorted by their performance on the development data.

about 318M tokens[3]. In Figure 6.3, we show three variants of training the RNN LM: training on all concatenated training corpora with the natural order, standard stochastic gradient descent using all data (randomized order of sentences), and training with the reduced and sorted set.

We can conclude that stochastic gradient descent helps to reduce the number of required training epochs before convergence is achieved, against training on all data with the natural order of sentences. However, sorting the data results in significantly lower final perplexity on the development set - we observe around 10% reduction of perplexity. In Table 6.2, we show that these improvements carry over to the evaluation set.

6.5 Experiments with large RNN models

The perplexity of the large 4-gram model with modified Kneser-Ney smoothing (denoted later as KN4) is 144 on the development set, and 140 on the evaluation set. We can see in Table 6.2 that RNN models with 80 neurons are still far away from this performance.

[3]Training a standard n-gram model on the reduced set results in about the same perplexity as with the n-gram model that is trained on all data.

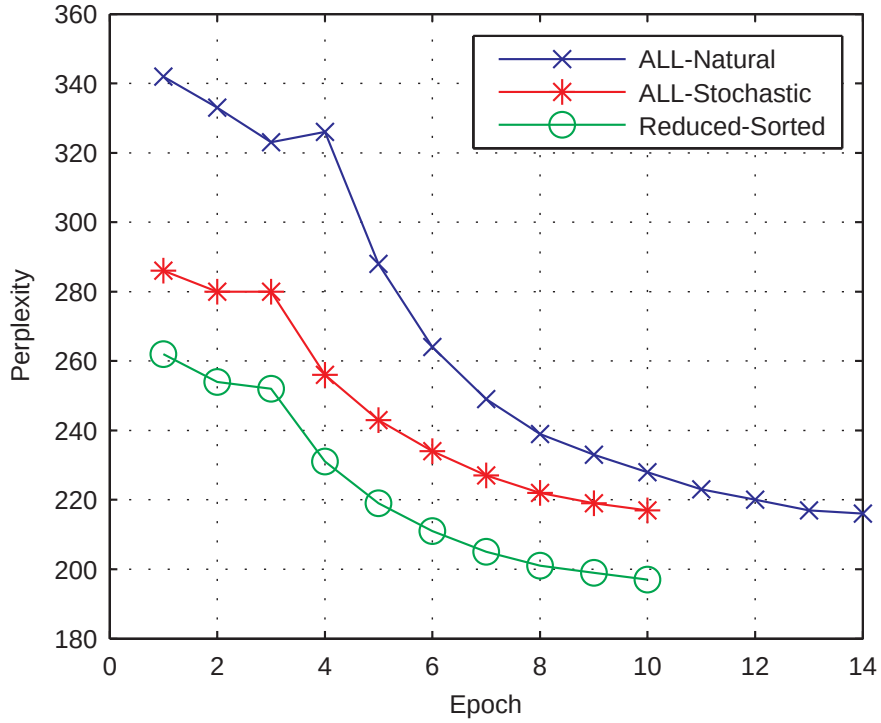

Figure 6.3: Perplexity on the development set during training of RNN models with 80 neurons.

In further experiments, we have used RNN models with increasing size of the hidden layer, trained on the Reduced-Sorted data set. We have used just 7 training epochs, as with sorted data, the convergence is achieved quickly (for the first three epochs, we used constant learning rate 0.1, and halved it at start of each new epoch). These results are summarized in Table 6.3. We denote RNN model with 80 neurons as RNN-80 etc.

In Figure 6.4, we show that the performance of RNN models is strongly correlated with the size of the hidden layer. We needed about 320 neurons for the RNN model to match the performance of the baseline backoff model. However, even small models are

Table 6.2: *Perplexity on the evaluation set with differently ordered training data, for RNN models with various sizes of the hidden layer.*

Model	**Hidden layer size**			
	10	**20**	**40**	**80**
ALL-Natural	357	285	237	193
ALL-Stochastic	371	297	247	204
Reduced-Sorted	347	280	228	183

Table 6.3: *Perplexity of models with increasing size of the hidden layer.*

Model	**Dev PPL**		**Eval PPL**	
		+KN4		+KN4
backoff 4-gram	144	144	140	140
RNN-10	394	140	347	140
RNN-20	311	137	280	137
RNN-40	247	133	228	134
RNN-80	197	126	183	127
RNN-160	163	119	160	122
RNN-240	148	114	149	118
RNN-320	138	110	138	113
RNN-480	122	103	125	107
RNN-640	114	99	116	102

useful when linearly interpolated with the baseline KN4 model, as shown in Table 6.3. It should be noted that training the models with more than 500 neurons on this data set becomes computationally very complex: the computational complexity of RNN model as given by Eq. 6.4 depends on the recurrent part of the network with complexity $H \times H$, and the output part with complexity $H \times C + H \times W$, where C is the number of classes (in our case 400) and W is the number of words that belong to a specific class. Thus, the increase of complexity is quadratic with the size of the hidden layer for the first term, and linear for the second term.

We rescore word lattices using an iterative decoding method previously described in [16], as it can be much less computationally intensive than basic N-best list rescoring in some cases. As shown in Figure 6.5, RNN models perform very well for lattice rescoring; we can see that even the stand-alone RNN-80 model is better than the baseline 4-gram model. As the weights of individual models are tuned on the development set, we have observed a small degradation for the RNN-10 model interpolated with baseline 4-gram model. On the other hand, the RNN-640 model provides quite an impressive reduction of WER, from 13.11% to 12.0%.

By using three large RNN models and a backoff model combined together, we achieved the best result so far on this data set - 11.70% WER. The model combination was carried out using the technique described in [14]. The models in combination were: RNN-480,

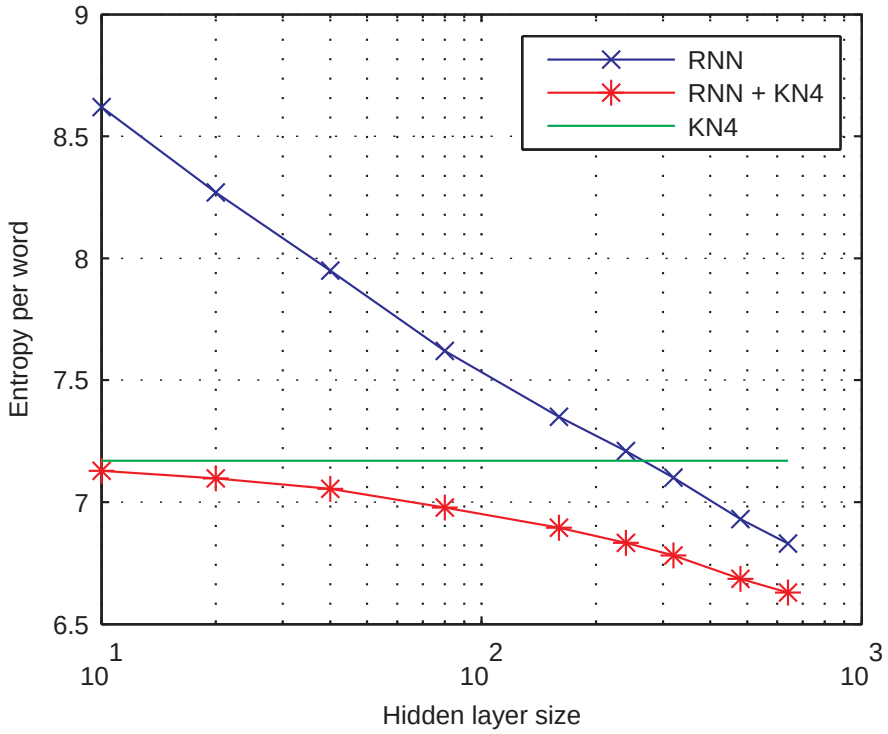

Figure 6.4: Entropy per word on the dev set with increasing size of the hidden layer.

RNN-640 and RNN-640 model trained on 58M subset of the training data.

6.6 Hash-based Implementation of Class-based Maximum Entropy Model

We have already mentioned that maximum entropy models are very close to neural network models with no hidden layer. In fact, it has been previously shown that a neural network model with no hidden layer can learn a bigram language model [81], which is similar to what was shown for the maximum entropy models with n-gram features. However, in [81], the memory complexity for the bigram model was V^2, where V is size of the vocabulary. For a trigram model and V around 100K, it would be infeasible to train such model, as the number of parameters would be $(100K)^3$.

The maximum entropy model can be seen in the context of neural network models as a weight matrix that directly connects the input and output layers. Direct connections between projection layer and the output layer were previously investigated in the context of NNLMs in [5], with no improvements reported on a small task. The difference in our work is that we directly connect the input and output layers.

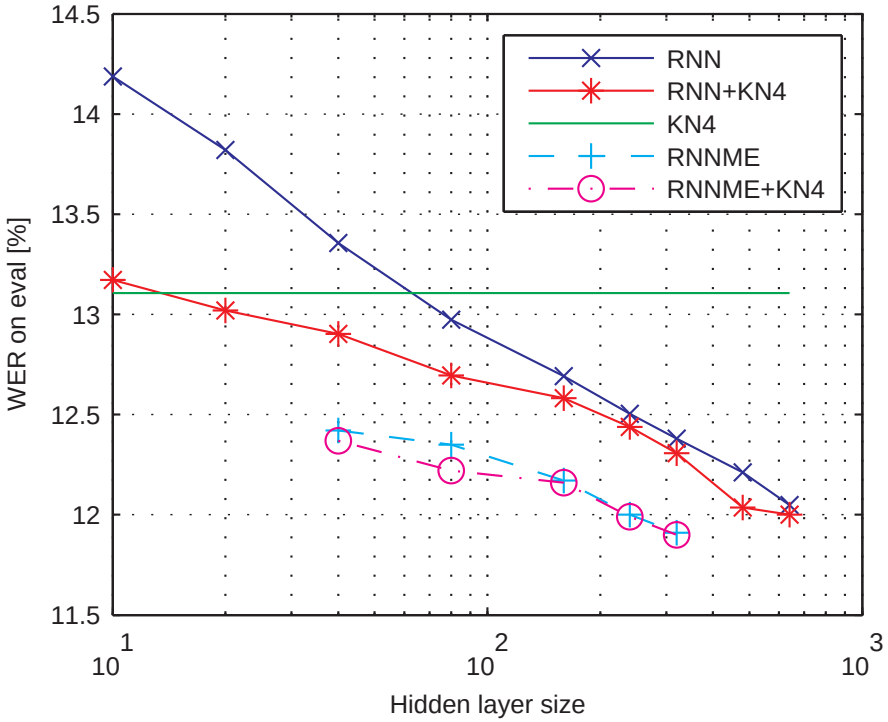

Figure 6.5: WER on the eval set with increasing size of the hidden layer.

We have added the direct connections to the class-based RNN architecture. We use direct parameters that connect the input and output layers, and the input and class layers. We learn direct parameters as part of the whole network - the update of weights is performed on-line using stochastic gradient descent. We found that it is important to use regularization for learning the direct parameters on small data sets (we currently use L2 regularization). However, on large data sets, the regularization does not seem to be so important, as long as we do early stopping. Using classes also helps to avoid over-fitting, as the direct parameters that connect input and class layers already perform ad-hoc clustering. As the full set of parameters (which can be seen as feature functions in the ME model) is very large, hash function is used to map parameters to a hash array with fixed size.

6.6.1 Training of Hash-Based Maximum Entropy Model

Inspiration for the hash-based implementation of maximum entropy language model was the work of Mahoney, who used similar model with features based on various contexts (such as previous word, two previous words, previous N characters etc.) to obtain state of the art results in compression of text data [45].

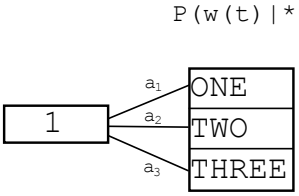

Figure 6.6: Maximum entropy model with unigram features.

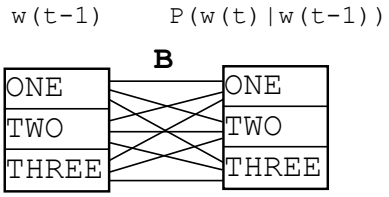

Figure 6.7: Maximum entropy model with bigram features.

For example, assume a vocabulary V with three words, V=(ONE, TWO, THREE). Figure 6.6 shows a graphical representation of a unigram maximum entropy model with the given vocabulary. We can see that the model has three parameters, a_1, a_2, a_3. The probability distribution $P(w(t)|history)$ is not conditioned on any previous information, thus the model can be seen as a bias in a neural network model - the single input neuron that has always activation 1.

Figures 6.7 and 6.8 illustrate how bigram and trigram features can be represented in a maximum entropy model: in a case of a bigram model, we have a matrix B that connects all possible previous words $w(t-1)$ and current words $w(t)$. In case of a trigram model, we have to use all possible combinations of two previous words as inputs. Thus, the number of parameters for a maximum entropy model with full feature set with order N is V^N.

It is important to see that the input word $w(t-1)$ in a case of the bigram model will cause activation of exactly one neuron at any given time, among neurons that represent bigram connections (if we considered also out of vocabulary words, then there might be even no active neuron). For the model with trigram features, the situation is the same - again, we will have a single neuron active. Thus, for N-gram maximum entropy model with a full feature set consisting of unigrams, bigrams, ..., N-grams, there will be N active input neurons at any given time, if we do not consider out of vocabulary words.

The problem with such model representation is that for higher orders and for large vocabularies, the V^N term will become impractically large. Such full weight matrix would actually represent all possible combinations of N words, and with finite amount of the training data, most of these combinations will never be seen. Many other features would

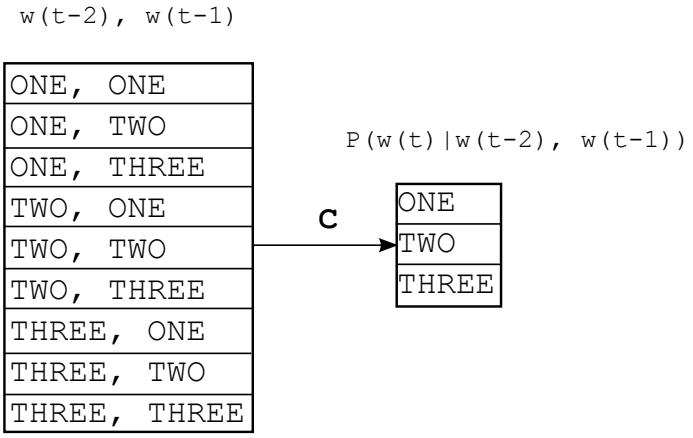

Figure 6.8: Maximum entropy model with trigram features.

be used just once or twice. So, to reduce memory complexity of such huge weight matrix, we can define a hash function that will map every n-gram history to a single value in a hash array. An example of a hash function for mapping trigram features into an array with length $SIZE$ is

$$g(w(t-2), w(t-1)) = (w(t-2) \times P_1 \times P_2 + w(t-1) \times P_1) \ \% \ SIZE, \tag{6.6}$$

where P_1 and P_2 are some arbitrary large prime numbers and % is a modulo function. Then, the equation 6.1 can be written as

$$P(w|h) = \frac{e^{\sum_{i=1}^{N} \lambda_i f_i(g(h),w)}}{\sum_w e^{\sum_{i=1}^{N} \lambda_i f_i(g(h),w)}}. \tag{6.7}$$

Mapping histories into a single dimensional array using the hash function can result in collisions, in cases when different histories will have the same hash value. It can be seen that with increasing size of the hash, the probability of collisions is decreasing. While it might look dangerous to use hash due to collisions, it is important to notice that if two or more histories are mapped to the same position, then the most frequent features will dominate the final value after the model is trained. Thus a model that uses small hash array will work similar to a pruned model.

Training is performed using stochastic gradient descent, in the same way as training of the recurrent neural network model. Thus, both models can be trained and used together, and in fact the direct connections can be seen just as a part of the RNN model. The output neurons $y(t)$ then have input connections both from the hidden layer of RNN, and directly from the sparsely coded input layer.

Table 6.4: *Perplexity on the evaluation set with increasing size of hash array, for RNN model with 80 neurons.*

Model	**Hash size**				
	0	10^6	10^7	10^8	10^9
RNN-80+ME	183	176	160	136	123
RNN-80+ME + KN4	127	126	125	118	113

The factorization of the output layer by using classes is used for speeding up the maximum entropy model in the same way as it was described for the RNN model in section 3.4.2. The training of the ME model is performed in the same way as training of weights of the RNN model: the same update rules are used, and the same learning rate and the same regularization parameters (see section 3.3). Thus, the maximum entropy model is viewed just as direct connections in the RNN model between the input and the output layers.

6.6.2 Results with Early Implementation of RNNME

In the early implementation, we used bigram and trigram features for the direct part of the RNN model, and we denote this architecture further as RNNME. The following results were recently published in [52]. As only two features are active in the input layer at any given time, the computational complexity of the model increases about the same as if two neurons were added to the hidden layer.

Using hash has an obvious advantage: we can easily control size of the model by tuning a single parameter, the size of the hash array. In Table 6.4, we show how the hash size affects the overall performance of the model. In the following experiments, we have used a hash size of 10^9, as it gives reasonable performance. As we use double precision of weights, the hash takes 8GB of memory. If we train just the ME part of the model (RNNME-0) with hash size 10^9, we obtain perplexity 157 on the evaluation set.

The achieved perplexity of 123 on the evaluation set with RNNME-80 model is significantly better than the baseline perplexity 140 of the KN4 model. After interpolation of both models, the perplexity drops further to 113. This is significantly better than the interpolation of RNN-80 and KN4, which gives perplexity 127. Such result already proves the usefulness of training the RNN model with direct parameters.

We can see that performance improves dramatically for models with small size of the

hidden layer, both for their stand-alone version and even after combining them with the backoff model. RNN models without direct connections must sacrifice a lot of parameters to describe simple patterns, while in the presence of direct connections, the hidden layer of the neural network may focus on discovering complementary information to the direct connections. Comparison of improvements over the baseline n-gram model given by RNN and RNNME models with increasing size of the hidden layer is provided in Figure 6.9.

Most importantly, we have observed good performance when we used the RNNME model for rescoring experiments. Reductions of word error rate on the RT04 evaluation set are summarized in Table 6.5. The model with direct parameters with 40 neurons in the hidden layer performs almost as well as model without direct parameters and with 320 neurons. This means that we have to train only 40^2 recurrent weights, instead of 320^2, to achieve similar WER.

The best result reported in Table 6.5, WER 11.70%, was achieved by using interpolation of three models: RNN-640, RNN-480 and another RNN-640 model trained on subset of the training data (the corpora LDC97T22, LDC98T28, LDC2005T16 and BN03 were used - see Table 6.1). It is likely that further combination with RNNME models would yield even better results.

6.6.3 Further Results with RNNME

Motivated by the success of the RNNME architecture, I have later performed additional experiments with the RNNME models. The models were improved by adding unigram and four-gram features, and by using larger hash array. The new results are summarized in Table 6.6.

It can be seen that by using more features and more memory for the hash, the perplexity results improved considerably. The RNNME-0 with 16G features alone is better than the baseline backoff 4-gram model, and after their interpolation, the perplexity is reduced to 125 from the baseline 140. Using 16G features is impractical due to memory complexity, thus additional experiments were performed with 8G features. By using as little as 10 neurons in the hidden layer, we can see that the perplexity on the evaluation set was reduced from 137 to 127 - even after interpolation with the backoff model, the difference is significant (126 to 120).

Even models with more neurons, such as RNNME-40, improved considerably - we can see that by using more memory and more features, the perplexity of RNNME-40 model

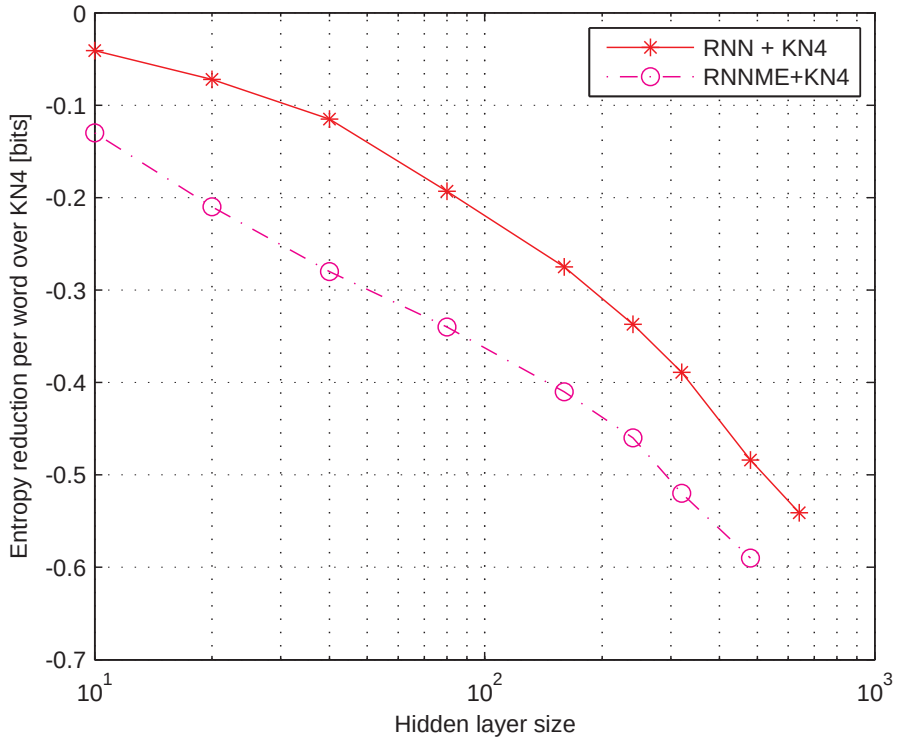

Figure 6.9: Improvements over the KN4 model obtained with RNN and RNNME models with increasing size of the hidden layer.

decreased from 131 to 117. The training progress of RNN, RNMME-40 with 1G hash and the new RNNME-40 with 8G hash is shown at Figure 6.10. Unfortunately, we were not able to run new lattice rescoring experiments due to graduation of Anoop Deoras and limitations of use of the IBM recognizer, but it can be expected that even WER would be much lower with the new models with larger hash and more features. Lastly, experiments with even more features were performed - adding 5-gram features seems to not help, while adding skip-1 gram features helps a bit.

It is also interesting to compare performance of RNN and RNNME architectures as the amount of the training data increases. With more training data, the optimal size of the hidden layer increases, as the model must have enough parameters to encode all patterns. In the previous chapter, it was shown that the improvements from the neural net language models actually increase with more training data, which is a very optimistic result. However, with more training data it is also needed to increase the size of the hidden layer - here we show that if the hidden layer size is kept constant, the simple RNN architecture provides smaller improvements over baseline n-gram model as the amount of the training words increases. A very interesting empirical result is that RNNME architecture still

Table 6.5: *Word error rate on the RT04 evaluation set after lattice rescoring with various models, with and without interpolation with the baseline 4-gram model.*

Model	**WER[%]**	
	Single	**Interpolated**
KN4 (baseline)	13.11	13.11
model M	-	12.49
RNN-40	13.36	12.90
RNN-80	12.98	12.70
RNN-160	12.69	12.58
RNN-320	12.38	12.31
RNN-480	12.21	12.04
RNN-640	12.05	**12.00**
RNNME-0	13.21	12.99
RNNME-40	12.42	12.37
RNNME-80	12.35	12.22
RNNME-160	12.17	12.16
RNNME-320	11.91	**11.90**
3xRNN	-	**11.70**

performs well with more data, as shown in Figure 6.11. It should be noted that models in these experiments were trained on subsets from the Reduced-Sorted data set, and thus some of the observed improvement also comes from the adaptation effect.

Additional experiments were performed using training data with randomized order of sentences - this is important to remove the adaptation effect when models are trained on sorted data, as this time we are interested in comparison of performance of RNN and RNNME models trained on large homogeneous data sets. Also, the baseline KN4 model does not use any count cutoffs or pruning for the following experiments. Figure 6.12 shows several interesting results:

- Even the hash-based ME model with simple classes can provide significant improvement over the best n-gram model, and the improvement seems to be slowly increasing with more data.

- The improvements from RNN models with fixed size are still vanishing with more

Table 6.6: *Perplexity with the new RNNME models, using more features and more memory.*

Model	**PPL on dev**	**PPL on eval**	**PPL on eval + KN4**
KN 4-gram baseline	144	140	140
RNNME-0, 1G features	157	-	-
RNNME-0, 2G features	150	144	129
RNNME-0, 4G features	146	-	-
RNNME-0, 8G features	142	137	126
RNNME-0, 16G features	140	135	125
RNNME-10, 8G features	133	127	120
RNNME-20, 8G features	124	120	115
RNNME-40, 8G features	120	117	112
old RNNME-40, 1G features	134	131	119
RNNME-0, 2G + skip-1	145	140	125
RNNME-0, 8G + skip-1	136	132	121
RNNME-10, 8G + 5-gram	133	128	120

training data.

- With more training data, performance of RNNME models also seems to degrade, although more slowly than for RNN models.

- The RNNME-20 model trained on all data is better than RNN-80 model.

- Although this is not shown in the figure, even combination of RNN-80, ME and baseline KN4 models is still much worse than RNNME-80 combined with the KN4.

On small data sets, the RNN model with small hidden layer can encode most of the information easily - but on large data sets, the model must use a lot of parameters to encode basic patterns that can be also described by normal n-grams. On the other hand, RNNME architecture that uses n-gram features as part of the model focuses on discovering complementary information to the n-grams. Thus, training neural network together with some kind of n-gram model seems to be a crucial technique for successful application of neural net language models to very large data sets, as training models with thousands of hidden neurons seems to be intractable.

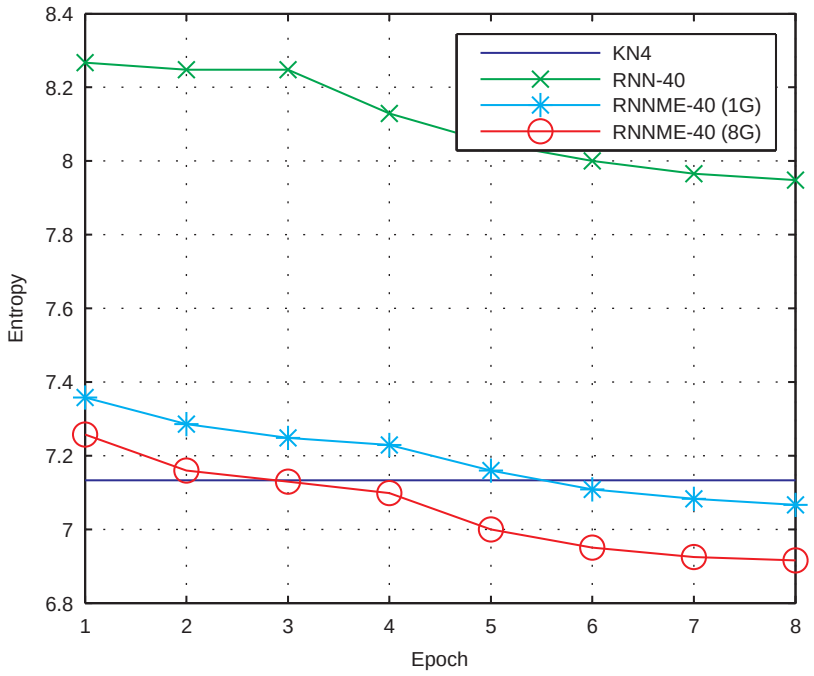

Figure 6.10: Comparison of training progress of RNN model with 40 neurons and RNNME with 40 neurons (1G hash and 8G hash). Entropy is calculated on the development set.

6.6.4 Language Learning by RNN

Statistical language modeling has been criticized by linguists, for example by Chomsky as mentioned in the introduction, for inability to distinguish grammatical and ungrammatical sentences that are completely novel. Chomsky's famous examples were *'colorless green ideas sleep furiously'* and *'furiously sleep ideas green colorless'*. Unless we would use enormous amount of the training data, the n-gram models will not be able to assign different probability to these two sentences, although the first one is grammatical and thus should be more likely than the second one.

For the following simple experiment, the language models introduced in the previous sections were used - namely, the RNN-640 model and the large KN4 n-gram model trained on the Broadcast News data. Interestingly, the n-gram model does not contain any bigrams that would correspond to those found in the test sentences, thus it has to back off to unigram statistics for estimation of probability of every word (except the first word that is in the context of start of sentence symbol, and the end of sentence symbol - for these cases, bigram statistics were used).

The difference in probability of the test sentences given by the n-gram model is just minor, as can be seen in Table 6.7. On the other hand, the RNN-640 model assigns about

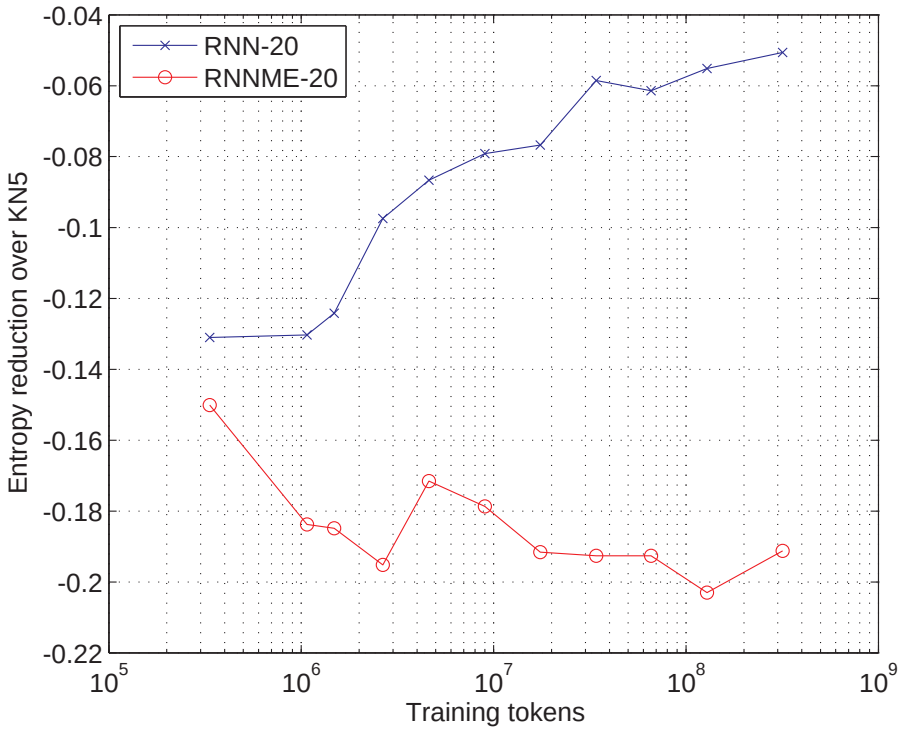

Figure 6.11: Improvements over KN4 model obtained with RNN-20 and RNNME-20 models, as the amount of training data increases (all models including KN5 were trained on subset of the Reduced-Sorted training set). Models were trained for 5 epochs.

37000 times higher probability to the grammatical sentence. This experiment clearly shows that Chomsky's assumption was incorrect - even for a completely novel sentence where even fragments (bigrams) are novel, it is possible to use simple statistical techniques (without any innate knowledge of the language) to distinguish between grammatical and ungrammatical sentences.

Table 6.7: *Probability of Chomsky's sentences given n-gram and RNN-based language models.*

Sentence **w**	$log_{10}P(\mathbf{w})$	
	4-gram	RNN
colorless green ideas sleep furiously	-24.89	-24.99
furiously sleep ideas green colorless	-25.35	-29.56

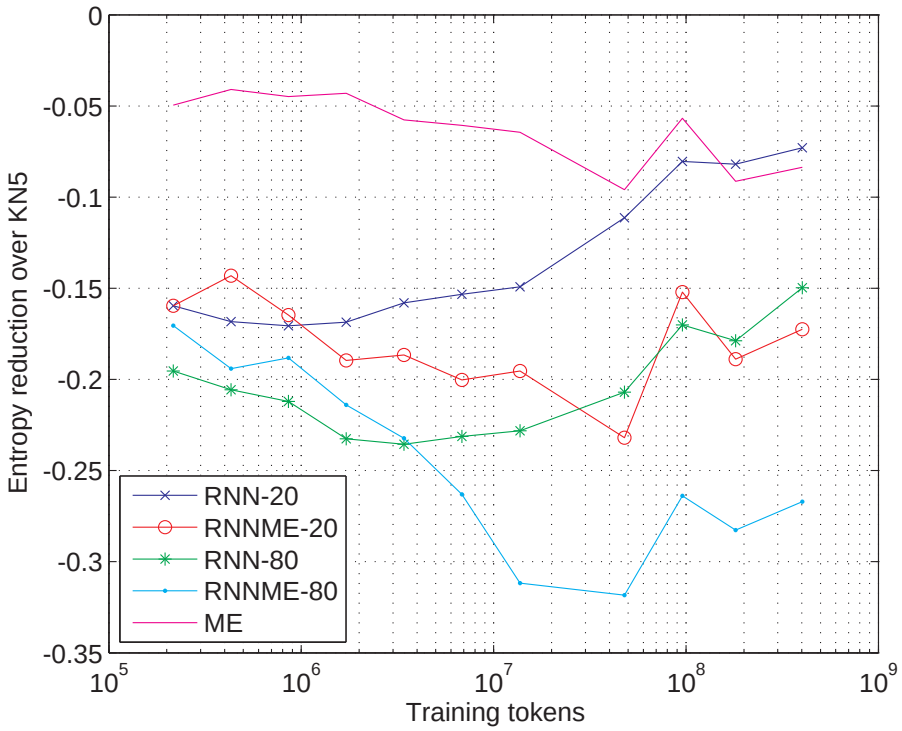

Figure 6.12: Improvements over KN4 model (no count cutoffs) obtained with with RNN and RNNME models, as the amount of training data increases. Models were trained on up to 400M words, with randomized order of sentences. All results are reported after interpolation with the baseline KN4 model.

6.7 Conclusion of the NIST RT04 Experiments

We have shown that neural network models, in our case with recurrent architecture, can provide significant improvements on state-of-the-art setup for Broadcast News speech recognition. The models we built are probably the largest neural network based language models ever trained. We have used about 400M training tokens (318M in the reduced version). Size of the hidden layer of the largest model was 640 neurons, and the vocabulary size 82K words.

We have shown that by discarding parts of the training data and by sorting them, we can achieve about 10% reduction of perplexity, against classical stochastic gradient descent. This improvement would be probably even larger for tasks where only some training corpora can be considered as in-domain.

The relative word error rate reduction was almost 11%, over a large 4-gram model with Kneser-Ney smoothing - absolutely, we reduced WER from 13.11% to 11.70%. We are aware of slightly better baseline for this setup - in [31], 13.0% WER was reported

as a baseline, and 12.3% after rescoring with so-called "model M" [30] (while in our experiments, rescoring with model M resulted in 12.5% WER). We suspect that if we used wider lattices, we would be able to observe further improvements in our experiments.

We have shown that training RNN model with direct connections can lead to good performance both on perplexity and word error rate, even if very small hidden layers are used. The model RNNME-40 with only 40 neurons has achieved almost as good performance as RNN-320 model that uses 320 neurons. We have shown that direct connections in NN model can be seen as a maximum entropy model, and we have also verified that it is important to train the RNN and ME models jointly. Roughly speaking, we can reduce training times from many weeks to a few days by using the novel RNN architecture.

The presented techniques can also be easily applied to more traditional feedforward NN LMs. On large data sets with billions of training words, the joint training of neural network model with some kind of n-gram model seem to be necessary for obtaining reasonable performance. Our further experiments that will be described in the following chapter confirm usefulness of the RNNME architecture also on other tasks, such as data compression, machine translation and sentence completion.

Finally, in Appendix B we show text data generated from the KN4 baseline n-gram model and from the largest RNN model with 640 neurons. Note that both models are tuned to work the best on the validation data, and thus the generated data do not repeat just sentences seen in the training data (otherwise, it would be possible to generate very meaningful sentences from maximum likelihood 10-gram model, but such data would be very similar to those seen in the training data). Interestingly, this comparison shows how much better RNN models are: the generated text data are much more fluent compared to those generated from n-gram model, with much less disfluencies. Still, RNN model changes topic randomly just as the n-gram model does, but locally the generated data are better.

Chapter 7

Additional Experiments

As the n-gram statistical models are not specific just to the automatic speech recognition, I performed more experiments to show potential of the recurrent neural network based language models, and of the RNNME architecture. These experiments include Machine Translation, text compression (which can be simply extended to general data compression), and a novel task 'Microsoft Sentence Completion Challenge'. These will be briefly described in this chapter, to show that RNN LMs are general technique applicable to a wide variety of applications and to motivate future research of these topics.

Many of these experiments are reproducible using RNNLM toolkit (see Appendix A). As this toolkit is still under development, some results might be exactly reproduced only with its older versions that are available on the RNNLM webpage. However, the actual version of the toolkit should be faster than the older versions, and thus it should be possible to train larger models and obtain better results than is described in this chapter.

7.1 Machine Translation

Automatic translation of text between languages is a very interesting application, with great potential - people all around the world use Internet nowadays, and not everyone has good knowledge of English. Also, for those who speak English, it is often difficult to access information on foreign web sites. Using RNN language models for MT should result in increased readability and more fluent output, which is a common problem with the current MT systems.

I performed the following experiments while I was visiting Johns Hopkins University, and the baseline systems were produced by Zhifei Li and Ziyuan Wang. I did perform some

Table 7.1: *BLEU on IWSLT 2005 Machine Translation task, Chinese to English.*

Model	BLEU
baseline (n-gram)	48.7
300-best rescoring with RNNs	51.2

Table 7.2: *BLEU and NIST score on NIST MT 05 Machine Translation task, Chinese to English.*

Model	BLEU	NIST
baseline (n-gram)	33.0	9.03
1000-best rescoring with RNNs	34.7	9.19

of these experiments years ago and the results remained unpublished, thus there might be some slight inconsistencies in the description of the tasks. Also, the models used in these experiments were just basic RNN models trained with the normal backpropagation of errors (not by BPTT) without classes and the other tricks, which limited the experiments. Still, I consider the achieved results interesting and worth mentioning.

First, the results on IWSLT 2005 Chinese to English translation task are shown in Table 7.1. The amount of the training data for this task was very small, about 400K tokens, with vocabulary size about 10K words. BLEU is a standard metric in machine translation; higher is better. It can be seen that RNN language models improve BLEU by about 2.5 points absolutely on this task, against the baseline system trained at JHU.

Another task with more training data is NIST MT05 Chinese to English translation. Again, the baseline system was trained at JHU. The amount of training tokens that the baseline n-gram models were trained on was too high, thus the following RNN models were trained on a subset of about 17.5M tokens, with a vocabulary using a shortlist of 25K words. The results are summarized in Table 7.2. Despite the fact that RNN models were not using full vocabulary, the amount of training data was severely limited and only BP training was used, the improvement is still significant - almost two points in BLEU score.

Later, I performed additional experiments with RNNME models on the MT tasks; although I did not run additional rescoring experiments, perplexity results with models trained on corpora with 31M tokens were looking even better than for the ASR tasks. This is caused by the nature of the typical training data for MT, which contain not only

words, but also additional symbols such as brackets and quotation marks. These follow simple patterns that cannot be described efficiently with n-gram models (such as that after a left bracket, a right bracket should be expected etc.). Even with a limited RNNME-160 model, the entropy reduction over KN5 model with no count cutoffs was about 7% - perplexity was reduced from 110 to 80. By combining static and dynamic RNNME-160 model, perplexity decreased further to 58. It would be not surprising if a combination of several larger static and dynamic RNNME models trained on the MT corpora would provide perplexity reduction over 50% against the KN5 model with no count cutoffs - it would be interesting to investigate this task in the future.

7.2 Data Compression

Compression of text files is a problem almost equivalent to statistical language modeling. The objective of state of the art text compressors is to predict the next character or word with as high probability as possible, and encode it using algorithmic coding. Decompression is then a symmetric process, where models are built while processing the decoded data in the same way as they were built during the compression. Thus, the objective is to simply maximize $P(w|h)$. An example of such compression approach is the state of the art compression program 'PAQ' from M. Mahoney [45, 46].

The difference between language modeling and data compression is that the data is not known in advance, and has to be processed on-line. As it was described in the previous chapters, training of neural network models with a hidden layer requires several training passes over the training data for reaching the top performance. Thus, it was not clear if RNN LMs can be practically applied to data compression problems.

As data compression is not topic of this thesis, I will not describe experiments in great detail. However, it is worth observing that it is possible to accurately estimate compression ratio given by RNN LMs using the RNNLM toolkit. The size of a compressed text file is size of (possibly also compressed) vocabulary plus entropy of the training data during the first training epoch (this is simply average entropy per word times number of words).

For the further experiments, I have implemented arithmetic coding into a special version of the RNNLM toolkit, thus the following results were obtained with real RNN-based data compressor. As the class based RNN architecture was used, first the class of predicted word is encoded using arithmetic coding, and then the specific word, as the text data are

Table 7.3: *Size of compressed text file given by various compressors.*

Compressor	Size [MB]	Bits per character
original text file	1696.7	8.0
gzip -9	576.2	2.72
RNNME-0	273.0	1.29
PAQ8o10t -8	272.1	1.28
RNNME-40	263.5	1.24
RNNME-80	258.7	1.22
RNNME-200	256.5	1.21

being compressed or decompressed. As the process is symmetric, it takes about the same time to compress or decompress a specific file.

General data compression programs such as PAQ usually use several predictors of the data, and a language model based on words is just one of such predictors - others can use different context than the few preceding words, such as several preceding characters, normalized previous words, etc. As my motivation was just to show the potential of RNNs in data compression, I have chosen a simple task of normalized text compression. Thus, the only context used by RNNs are the preceding words. The data to be compressed are the same as those used in Chapter 6, the 'Reduced-Sorted' set. All words in this corpus are written in capital letters, and all extra characters such as diacritics were removed. This file was then compressed using several data compressors to allow comparison. I have found that by using pure RNN models, it is difficult to obtain good compression ratio and reasonable speed - however, the RNNME architecture did work very well for this task, at reasonable speed.

Using a large text file with a vocabulary limited to 82K words has several advantages: it is not needed to have special model for new words, and the vocabulary can be simply saved in the beginning of the compressed file, as its size is negligible in comparison to the compressed file size (it is less than 1 MB). When compressing smaller files, various tricks are quite important for obtaining good compression ratio; for example, using more models with different learning rate, or using additional features (such as skip-grams). These tricks were still used in the RNNME models presented in Table 7.3, however on small data sets, their influence would be much bigger than advantage of using RNN, which on the other hand becomes important on large data sets.

As can be seen in Table 7.3, the usual data compression programs such as gzip do not work very well on text data - however, the speed of advanced compressors is orders of magnitude lower. Thus, the achieved results are currently more interesting from the research point of view, than from the practical point of view - however, with further progress, things may change in the future.

Interestingly, the achieved entropy 1.21 bits per character for English text (including spaces and end of line symbols) is already lower than the upper bound estimate of Shannon, 1.3 bpc [66]. It can be expected that with even more data, the entropy would still decrease considerably.

7.3 Microsoft Sentence Completion Challenge

The motivation examples in the introduction of this thesis did show that a good statistical language model should assign higher probability to sentences that can be assumed as usual, correct or meaningful, and low probability to the others. Also, it was explained that n-gram models cannot represent patterns over longer contexts efficiently due to exponential increase of number of parameters with the order of the model. Thus it is an interesting task to compare the developed RNN language models and n-gram models on a simple task, where the language model is supposed to choose the most meaningful word among several options in a sentence with one missing word.

Such task has been recently published in [83]. It consists of 1040 sentences where a single informative word is discarded, and five possible options are given. An example:

```
I have seen it on him , and could write to it .
I have seen it on him , and could migrate to it .
I have seen it on him , and could climb to it .
I have seen it on him , and could swear to it .
I have seen it on him , and could contribute to it .
```

Thus, by computing the likelihood of each sentence and choosing the most likely one given a specific model, we can test ability of language models to "understand" patterns in the sentence. Note that this task is similar to the usual quality measure of language

Table 7.4: *Accuracy of different language modeling techniques on the Microsoft Sentence Completion Challenge task. Human performance is 91% accuracy [83].*

Model	Perplexity	Accuracy [%]
random	-	20.0
GT3	92	36.0
GT5	87	38.4
KN5	84	40.0
RNNME-50	68	43.5
RNNME-100	65	45.1
RNNME-200	63	47.7
RNNME-300	60	49.3

models, the perplexity - with the difference that the sentence completion challenge focuses on the informative words that occur infrequently. Results obtained with various n-gram models and RNNME models are summarized in Table 7.4. The models were trained on about 50M tokens using 200K vocabulary, as a link to the training data was provided in [83].

RNNME language models perform much better that the usual n-gram models on this task: obviously, their ability to represent longer context patterns is very useful. While n-gram models perform about 20% better than is the random performance, the largest RNNME model is almost 30% better. Still, the performance is far from human performance, which is 91% accuracy.

We can think of models that would focus more on the task itself - basic objective function for usual language models is to minimize entropy of the training data, while in the case of sentence completion challenge, we are more interested in capturing patterns between infrequent words. A simple task-specific modification can involve models that are trained on data where frequent words are discarded. This reduces amount of possible parameters of n-gram models for capturing regularities between infrequent words. In the following experiments, the 200 most frequent words were discarded both from the training and test data.

It can be observed that n-gram models that are trained on such modified training data give much better accuracy. However, as a lot of possibly important information is discarded, the RNNME models do not have possibility to significantly overcome the

Table 7.5: *Additional results on the Microsoft Sentence Completion Challenge task.*

Model	Accuracy [%]
filtered KN5	47.7
filtered RNNME-100	48.8
RNNME combination	55.4

n-gram models. These results are summarized in Table 7.5, where models trained on modified training data are denoted as filtered. Combination of RNNME models trained on the original and the filtered training data then provides the best result on this task so far, about 55% accuracy.

As the task itself is very interesting and shows what language modeling research can focus on in the future, the next chapter will include some of my ideas how good test sets for measuring quality of language models should be created.

7.4 Speech Recognition of Morphologically Rich Languages

N-gram language models usually work quite well for English, but not so much for other languages. The reason is that for morphologically rich languages, the number of word units is much larger, as new words are formed easily using simple rules, by adding new word ending etc. Having two or more separate sources of information (such as stem and ending) in a single token increases amount of parameters in n-gram models that have to be estimated from the training data. Thus, higher order n-gram models usually do not give much improvement. Other problem is that for these languages, much less training data is usually available.

To illustrate the problem, we have used the Penn Treebank Corpus as described in Chapter 4, and added two bits of random information to every token. This should increase perplexity of the model that is trained on these modified data by more than two bits, as it is not possible to revert the process (the information that certain words are similar has to be obtained just from the statistical similarity of occurrence).

As the n-gram models cannot perform any clustering, it must be expected that their performance will degrade significantly. On the other hand, RNN models can perform clustering well, thus the increase of entropy should be lower. Results with simple RNN models with the same architecture and KN5 models with no discounts are shown in Table 7.6.

Table 7.6: *Entropy on PTB with n-gram and RNN models, after adding two bits of random information to every token.*

Model	Entropy	Entropy after adding two bits of information
KN5	7.14	10.13
RNN	7.19	9.71

Table 7.7: *Word accuracy in speech recognition of Czech lectures.*

Model	Word accuracy [%]
KN4	70.7
Open vocabulary 4-gram model	71.9
Morphological Random Forest	72.3
NN LMs	75.0

While RNN models were not tuned for the best performance, it can be seen that entropy increased by about 2.5 bits per token, while in case of n-gram models, the increase was about 3 bits. This clearly shows that potential of neural net models to overcome n-gram techniques when modeling inflectional languages is great.

In my early work described in [48], I used feedforward neural network language models for a task of speech recognition of Czech lectures. The amount of training data for this task was very low - only about 7M words with less than 1M words of in-domain data. Still, NN LMs did increase accuracy by a large margin over KN4 model. Later experiments performed by Ilya Oparin on this setup did show that also morphological random forest LM can provide improvements on this task [59]; however, less than what was achieved with NN LMs. Results are summarized in Table 7.7[1].

[1]Note that the results in this table are a bit better than those published in [48], as subsequent experiments with larger models did provide further small improvements.

Chapter 8

Towards Intelligent Models of Natural Languages

The previous chapters focused on achieving new state of the art results on several standard tasks with a novel type of language model based on recurrent neural network. As was stated in the introduction, a better statistical language model should be able to capture more patterns in the language, and be closer to the human performance - we can say that by using an advanced model, the output from systems such as machine translation or automatic speech recognition should look more meaningful, more intelligent. It can be seen in Appendix B that the data generated from n-gram and RNN language models that were trained on the same data are different - those generated from RNN are truly looking more fluent and meaningful. Still, even the text generated from the RNN model is far from human performance.

In this chapter, I would like to present ideas that led me to the work on RNN LMs, and that can motivate further research. I believe that further progress in statistical language modeling can lead not only to reductions of error rates of the classical MT / ASR systems, but also to development of completely new systems and applications that will allow humans to naturally communicate with computers using natural language, much over the scope of traditional rule-based systems which are incapable of truly learning novel facts from communication and can only follow patterns predefined by human experts.

8.1 Machine Learning

One possible definition of machine intelligence is ability to perform complex tasks independently on humans. Such task can be anything; however, for simplicity we can assume that any task can be written in a form of a function $\mathbf{y} = f(\mathbf{x})$ that maps input vector $\mathbf{x}$ to output vector $\mathbf{y}$. The input data can have many forms: observation of the real world, characters, words, pixels, acoustic features, etc. The outputs can be passive, such as classes of detected objects or sounds, or active that influence future inputs $\mathbf{x}$, such as activation of movement of a robot, or writing text output to communicate with user of the system.

Historically, the first tasks that computers performed did involve a lot of human effort through programming. The function f had to be written completely by a programmer. Some of these tasks were simply using computer memory to store and recall data; thus, the function f was quite trivial. Other tasks involved some degree of freedom - by writing a general algorithm, it was possible to use the computer to compute correct output values $\mathbf{y}$ for new input values $\mathbf{x}$ that were not explicitly specified by a programmer. An example may be a calculator - it can add any two numbers without having to store all possible combinations of input and output values, which would be needed if the computer was used as a database.

With progress in the information theory and computer science, it became clear that some tasks are too difficult to be solved by a programmer directly. An example can be an automatic speech recognition. While it is possible to write algorithms that take input values such as basic acoustic features and produce output values, for example phoneme strings, this task involves a lot of variability in the input data $\mathbf{x}$, making it difficult to write general algorithms that would work well in different conditions. Further research resulted in learning systems that use **training data** to algorithmically find part of the function f.

A typical example is linear projection, where the function f computes the output values by multiplying the input vector by a weight matrix $\mathbf{W}$, where the weight matrix is estimated using the training data. We can see that such computer program has two parts: the algorithm (here, the matrix times vector computation), and the parameters (the matrix $\mathbf{W}$). It is usual that size of $\mathbf{W}$ is in millions of parameters, while description length of the algorithm is tiny.

By considering popular machine learning techniques from the computational point of view, we can see that the principal component analysis, logistic regression and neural networks use small, fixed algorithms with huge amount of learnable parameters. Thus, these techniques are still somewhere between general learning systems and simple databases.

Based on the experimental results described in the previous chapters, we can observe that by allowing the function f to learn more complex patterns, the generalization ability increases. Thus, neural networks with one hidden layer (with non-linear activation function) have potential to work better than logistic regression. From the computational point of view, we can see the non-linearity in the neural networks as the `IF` command: we cannot express regularity in the data such as `IF OBJECT IS SMALL AND RED, THE OBJECT IS APPLE` without using the `IF` command, as weighted combination such as `SMALL IS APPLE, RED IS APPLE` would classify any small object as an apple.

We do not have to stop with just a single non-linearity; it can be seen that some other patterns can require two subsequent `IF` commands to be expressed efficiently. It is often mentioned that single non-linearity in computational models is sufficient to approximate any function - while this is true, such approximation can collapse to the basic database approach; the logic in function f is then expressed in the form of large number of rules such as `IF (X=1.05 AND Z=2.11) THEN Y=1.14`. Contrary, deeper architecture can represent some patterns using much fewer rules, which leads to better generalization when new data are presented as inputs.

A possible future work in machine learning can be to use models with more non-linearities, such as deep neural networks that are composed of several layers of neurons with non-linear activation function [6]. This way, it is possible to express efficiently more patterns. Recurrent neural networks are another example of deep architecture. On the other hand, while the increased depth of the computational models increases the number of patterns that can be expressed efficiently, it becomes more difficult to find good solutions using techniques such as simple gradient descent.

Even the deep neural network architectures are severely limited, as the number of hidden layers (computational steps) is defined by the programmer in advance, as a hyper-parameter of the model. However, certain patterns cannot be described efficiently by using constant number of computational steps (for example any algorithm that involves loop with variable amount of steps, or recursive functions). Additionally, feedforward neural networks do not have ability to represent patterns such as memory; however, practice shows

that almost every non-trivial computer program uses variables to store information. While it can be believed that for example recurrent neural networks have ability to remember information and to learn what is useful to be remembered, the gradient based learning techniques have difficulties in finding good representations of long context patterns [4].

Moreover, it can be seen that the RNN computational model is much different than usual computer program that uses variables for storing important information: the traditional recurrent neural network has to access the whole state of the hidden layer at each computational step, while computer programs usually access information in the memory only when it is needed.

8.2 Genetic Programming

Since airplanes do not have to flap wings to fly, I believe AI does not have to be a faithful copy of the human brain to work. I suppose that problems should be solved in the simplest natural way. The most common way for humans to specify algorithms today is through programming - and typical computer programs have a structure with many non-linearities, and can access memory randomly, not at every computational step.

Automatic construction of computer programs that optimize some defined fitness function (in machine learning it is called cost function) is a subject of evolutionary techniques such as genetic programming (GP). The basic algorithm for genetic programming involves the following steps:

1. Randomly initialize population P
2. Randomly perform an action to each member of P; the possible actions being:
   - Mutation: randomly modify description of the given member of P
   - Crossover: choose another member and replace random part of the description of the given member with random part of another member
   - Nothing - individual is copied to the next epoch without changes
3. Evaluate fitness function of all members
4. Select the best members of the population and copy them across population to form new generation
5. If convergence was not achieved, go to step 2

There is a great variability of approaches how one can choose the size of the population, the probabilities that certain action will be taken, the way how both crossover and mutation operators affect the individuals, how population in new epoch is exactly formed etc. It is possible to even apply genetic algorithm to this optimization process itself, to avoid the need to tune these constants; this is called meta-genetic programming.

Genetic programming can be successfully applied to small problems and it was reported that many novel algorithms were found using these or similar approaches. However, for large problems, the GP seems to be very inefficient; the hope is that through the recombination of solutions using the crossover operator, the GP will find basic atomic functions first, and these will be used later to compose more complex functions. However, it is sometimes mentioned that GP itself is not really guaranteed to work better than other simple search techniques, and clearly for difficult large problems, random search is very inefficient as space of possible solutions increases exponentially with the length of their description.

My own attempts to train recurrent neural network language models using genetic algorithms were not very promising; even on small problems, the stochastic gradient descent is orders of magnitude faster. However, certain problems cannot be efficiently learned by SGD, such as storing some information for long time periods. For toy problems, RNNs trained by genetic algorithms were able to easily learn patterns that otherwise cannot be learned by SGD (such as to store single bit of information for 100 time steps). Thus, an interesting direction for future research might be to combine GP and SGD.

8.3 Incremental Learning

The way humans naturally approach a complex problem is through its decomposition into smaller problems that are solved separately. Such incremental approach can be also used for solving many machine learning problems - even more, it might be crucial to learn complex algorithms that are represented either by deep architectures, or by complex computer programs. It can be shown that certain complex problems can be solved exponentially faster, if additional supervision in the form of simpler examples is provided.

Assume a task to find a six digit number, with a supervision giving information if the candidate number is correct or not. On average, we would need $\frac{10^6}{2}$ attempts to find the number. However, if we can search for the number incrementally with additional

supervision such as one digit at a time, we would need on average only $\frac{10^1}{2} \times 6$ guesses. The situation might be just like this when we learn the language; if we first see a new word in various *simple contexts*, it is easier to guess its meaning than if it appears just once in a completely novel situation.

Humans do learn incrementally, and that is not a coincidence. It seems that learning complex functions that are compositions of other functions is a highly non-linear problem, where SGD will not work and random search would take too long. Thus, part of the solution seems to be in using training data that would allow simple functions to be learned first, and also using machine learning techniques that can grow with the complexity of the problem.

8.4 Proposal for Future Research

Studying problems stated above in the context of statistical language modeling has several advantages - the amount of involved data can be actually pretty low compared to machine vision problems, and it can be easier to see what is going wrong when the machine is unable to learn some basic pattern in the language. A motivation example to show what patterns the n-gram models cannot represent efficiently is a basic memory - consider the following sentences:

```
APPLE IS APPLE
BALL IS BALL
SUN IS SUN
RED IS RED
THIS IS THIS
```

It is easy for a human to see that the pattern in such text data is actually of the form `X Y X`, where `Y=IS` and `X` is some string of characters that is repeated after occurrence of `Y`. It is simple for a human to predict the next characters in a sequence `NOVEL IS ...`; however, n-gram models as well as finite state machines cannot be used for such task. Interestingly, many simple patterns cannot be represented efficiently by usual models, including neural networks and context free grammars.

Thus, the most simple proposal for a research that would aim to get closer to the human level when it comes to language understanding by a computer, would be to first define incrementally more complex tasks that would involve basic patterns that humans

have to discover while learning a language. The second step would be to design learning algorithms that can learn given patterns using limited amount of resources (number of training examples, computational time). Simplicity of such proposal is actually an advantage: importantly, after the definition of the incrementally more difficult tasks, it should be possible to objectively compare many different approaches and techniques developed by independent researchers.

There are of course many possible modifications and extensions of this proposal that may be crucial for successful learning of the language using reasonable amount of resources. For example, it might be important to learn the language together with observing the real world (or simulated world) situations [10]. Also, it might be important to use an active system that does not just passively predict future events. Measuring success of different systems based on their ability to predict future events (words) might be sufficient in the beginning, but also can be insufficient in the long run - an AI system should probably aim to maximize some reward function.

The representation of the AI system itself is another important topic: due to computational limitations, traditional neural network architectures might be insufficient. Representing AI by a Turing machine or a computer program that is automatically constructed during training can be a better option, although with other difficulties as discussed in [43]. Clearly, the deeper we go, the more questions arise - thus, my opinion is that the problem of language understanding by computers should be solved step by step, starting with simple problems where various techniques that can be easily compared.

Chapter 9

Conclusion and Future Work

I hope this work will help to make the statistical language modeling more attractive for future research. The achieved results clearly show that n-gram models can no longer be considered as state of the art, and that significant improvements in many applications can be obtained by incorporating neural network based language models. Moreover, I tried to show links between the language modeling, machine learning, natural language processing and artificial intelligence. The main conclusions of this work are:

- Recurrent neural network language models can be successfully trained by using stochastic gradient descent and backpropagation through time
- Great speedup can be achieved by using simple classes in the output layer; main advantage over other similar proposed techniques is simplicity
- Comparison and combination of many advanced techniques shows that RNN language models reach state-of-the-art performance on several setups, mainly the well-known Penn Treebank Corpus
- With increasing amount of the training data, the potential for improvements with RNN LMs over n-gram models is increasing; however, it is crucial to also increase number of parameters in the model (mainly the hidden layer size)
- If hidden layer size is kept constant, the potential improvements from neural network language models is decreasing with more training data
- RNN LMs can be easily trained together with maximum entropy models (the RNNME architecture); this seems especially useful for very large data sets - RNNME

architecture should allow to obtain significant improvements even on setups with billions of training words

- Results on large state-of-the-art setup for Broadcast News NIST RT04 speech recognition from IBM confirm that neural net language models perform the best among language modeling techniques known today

- RNN LMs are completely data driven, and do not require any annotated data; thus, many applications can be improved simply by replacing n-gram models with neural nets (data compression, machine translation, spelling correction, ...)

There is of course still much space for future improvements. The language modeling techniques are usually compared based on the following properties: accuracy, speed, size and implementation complexity. Among these, accuracy is the most interesting one; however, also the most difficult one to improve. Future research that would aim to improve accuracy might be:

- Exploring different training algorithms for recurrent neural networks [41, 47, 74]

- Clustering of similar words in the output layer instead of the simple frequency-based classes

- Adding more features to the maximum entropy model for RNNME

- More complex RNN model with different time scales (character-level, subword-level, word-level, phrase-level etc.); this would allow the model to access more easily information from the distant history [27]

However, accuracy is often related to the computational complexity of models, as with more efficient algorithms, it is possible to train larger models that perform better. Also for some tasks, scaling training algorithms to very large data sets is necessary to compete with n-grams. Ideas that can lead to significant reduction of the training time are:

- Further reduction of complexity between the hidden layer and the output layer by using more levels of classes [57, 55]

- Additional study of the RNNME architecture - it might be possible to reach similar results by training RNN LM together with the usual n-gram model with slowly increasing weight; then, adding more features might help to move certain patterns

from the expensive part of the model (features encoded in the hidden layer) to the cheap part of the model (sparse binary features at the input layer)

- Exploration of additional features somewhere between the sparse features (n-grams) and the distributed features (state of the hidden layer); for example topic-dependent distributed features; this can also possibly lead to better accuracy and more robustness against noise during the training

- Parallelization of the implementation of the RNNLM toolkit

- Techniques for reduction of the amount of the training data, beyond simple sampling or data selection based on performance - for example, frequently occurring contexts can be collapsed into one, to update the weights just once

The size of the neural net language models is usually not a problem. Actually it can be shown that at the same level of accuracy when compared to n-gram model pruned and compressed with state of the art approaches, the size of RNNLM can be 10 times smaller (unpublished result). However, the ME model based on hash as currently implemented in the RNNLM toolkit is memory expensive, and should be improved in the future.

The recurrent neural networks are more difficult to implement than the classical n-gram techniques. It is easy to make a mistake in the training algorithm - this has been reported many times in research papers, and the reason is in difficult debugging (even incorrect implementation can work meaningfully). However, correct implementation is quite compact, and the test phase can be implemented very trivially. Thus, once the model is successfully trained, it is very easy to use it. Certain applications might require limitation of the context, as having infinite history might seem like a disadvantage; however, this can be accomplished easily by either teaching the network to reset itself (having additional symbol for start of the sequence and erase all the activations in the hidden layer), or even more simply by just erasing the activations (in most cases, this does not degrade significantly performance of RNNLM, as learning information across sentence boundary seems to be difficult).

9.1 Future of Language Modeling

Although the statistical language modeling has received much attention in the last thirty years, the main problems are still far from being solved. This is given by the complexity

of the task, as often the easiest way how to obtain good results is to choose crude but fast techniques, and train models on as much data as available. This strategy is however not getting any closer to solving the problems, rather avoiding them for as long as possible. For many tasks today, the amount of the available training data is so huge that further progress by adding another data is not very likely.

Another reason why advanced techniques are not used in practice is importance of the achieved results: it is commonly known that most of the published papers report only negligible improvements over basic baselines. Even the best techniques rarely affect the word error rate of speech recognition systems by more than 10% relatively - and that is hardly observable difference from the user perspective. However, even small difference can be huge in the long term - competitions are often won by a slight margin. Also, even if the improvements are small and hardly observable, it is likely that in the longer term, the majority of users will tend to prefer the best system.

While I see integration of neural net language models into production systems as the next step for the language modeling research, there is still much to do in the basic research. Based on the history of the language modeling research that has been often rather chaotic, it might be fruitful to first define a roadmap. While detailed proposal for future research is out of scope of this work, the main points are:

- The involved models should be computationally much less restricted than the traditional ones; it should be clear that a compact solution to simple problems can exist in the model space
- The progress should be measured on increasingly more complex tasks (for example, finding the most likely word in an incomplete sentence, as in [83])
- The tasks and the training data should be coherent and publicly available

While such research would not be competitive with the common techniques in the short term, it is certain that a progress beyond models such as finite state machines is needed. It has been popular to claim that we need orders of magnitude more powerful computers, and also much more training data to make progress towards AI - I find this doubtful. In my opinion, what needs to be addressed is the capability of the machine learning techniques to efficiently discover new patterns.

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Appendix A: RNNLM Toolkit

To further support research of advanced language modeling techniques, I implemented and released open source toolkit for training recurrent neural network based language models. It is available at `http://www.fit.vutbr.cz/~imikolov/rnnlm/`. The main goals for the RNNLM toolkit are:

- promotion of research of advanced language modeling techniques
- easy usage
- simple portable code without any dependencies on external libraries
- computational efficiency

Basic Functionality

The toolkit supports several functions, mostly for the basic language modeling operations: training RNN LM, training hash-based maximum entropy model (ME LM) and RNNME LM. For evaluation, either perplexity can be computed on some test data, or n-best lists can be rescored to evaluate impact of the models on the word error rate or the BLEU score. Additionally, the toolkit can be used for generating random sequences of words from the model, which can be useful for approximating the RNN models by n-gram models, at a cost of memory complexity [15].

Training Phase

The input data are expected to be in a simple ASCII text format, with a space between words and end-of-line character at the end of each sentence. After specifying the training data set, a vocabulary is automatically constructed, and it is saved as part of the RNN model file. Note that if one wants to use limited vocabulary (for example for open-vocabulary experiments), the text data should be modified outside the toolkit, by first rewriting all words outside the vocabulary to `<unk>` or similar special token.

After the vocabulary is learned, the training phase starts (optionally, the progress can be shown if `-debug 2` option is used). Implicitly, it is expected that some validation data are provided using the option `-valid`, to control the number of the training epochs and the learning rate. However, it is also possible to train models without having any validation data; the option `-one-iter` can be used for that purpose. The model is saved after each completed epoch (or also after processing specified amount of words); the training process can be continued if interrupted.

Test Phase

After the model is trained, it can be evaluated on some test data, and perplexity and log_{10} probability is displayed as the result. The RNNLM toolkit was designed to provide results that can be compared to the results given by the popular SRILM toolkit [72]. We also support an option to linearly interpolate the word probabilities given by various models. For both RNNLM and SRILM, the option `-debug 2` can be used to obtain verbose output during the test phase, and using the `-lm-prob` switch, the probabilities given by two models can be interpolated. We provide further details in the example scripts at the RNNLM webpage.

For n-best list rescoring, we are usually interested in the probabilities of whole sentences, that are used as scores during the re-ranking. The expected input for the RNNLM is a list of sentences to be scored, with a unique identifier as the first token in each hypothesis. The output is a list of scores for all sentences. This mode is specified by using the `-nbest` switch. Example of n-best list input file:

```
1 WE KNOW
1 WE DO KNOW
1 WE DONT KNOW
2 I AM
2 I SAY
```

Typical Choice of Hyper-Parameters

Due to huge computational complexity of neural network based language models, successful training of models in a reasonable time can require some experience, as certain parameter combinations are too expensive to explore. There exist several possible scenarios, depending on whether one wants to optimize the accuracy of the final model, the speed of the training, the speed of the rescoring or the size of the models. We will briefly mention some useful parameter configurations.

Options for the Best Accuracy

To achieve the best possible accuracy, it is recommended to turn off the classes by `-class 1`, and to perform training for as long as any improvement on the validation data is observed, using the switch `-min-improvement 1`. Next, the BPTT algorithm should run for at least 6 steps (`-bptt 6`). The size of the hidden layer should be as large as possible. It is useful to train several models with different random initialization of the weights (by using the `-rand-seed` switch) and interpolate the resulting probabilities given by all models as described in Section 3.4.5.

Parameters for Average-Sized Tasks

The above parameter choice would be very time consuming even for small data sets. With 20-50 million of training words, it is better to sacrifice a bit of accuracy for lower computational complexity. The most useful option is to use the classes (`-class`), with

about $sqrt(|V|)$ classes, where $|V|$ is the size of the untruncated vocabulary (typically, the amount of classes should be around 300-500). It should be noted that the user of the toolkit is required to specify just the amount of the classes, and these are found automatically based on unigram frequencies of words. The BPTT algorithm should run in a block mode, for example by using `-bptt-block 10`.

The size of the hidden layer should be set to around 300-1000 units, using the `-hidden` switch. With more data, larger hidden layers are needed. Also, the smaller the vocabulary is, the larger the hidden layer should be to ensure that the model has sufficient capacity. The size of the hidden layer affects the performance severely; it can be useful to train several models in parallel, with different sizes of the hidden layers, so that it can be estimated how much performance can be gained by using larger hidden layer.

Parameters for Very Large Data Sets

For data sets with 100-1000 million of words, it is still possible to train RNN models with a small hidden layer in a reasonable time. However, this choice severely degrades the final performance, as networks trained on large amounts of data with small hidden layers have insufficient capacity to store information. In our previous work, it proved to be very beneficial to train RNN model jointly with a maximum entropy model (which can be seen as a weight matrix between the input and the output layers in the original RNN model). We denote this architecture as RNNME and it should be noted that it performs very differently than just interpolation of RNN and ME models - the main difference is that both models are trained jointly, so that the RNN model can focus on discovering complementary information to the ME model. This architecture was described in detail in Chapter 6.

A hash-based implementation of ME can be enabled by specifying the amount of parameters that will be reserved for the hash by using the `-direct` switch (this option just increases the memory complexity, not the computational complexity) and the order of n-gram features for the ME model is specified by `-direct-order`. The computational complexity increases linearly with the order of the ME model, and for model with order N it is about the same as for RNN model with N hidden neurons. Typically, using ME with up to 4-gram features is sufficient. Due to the hash-based nature of the implementation, higher orders might actually degrade the performance if the size of the hash is insufficient. The disadvantage of the RNNME architecture is in its high memory complexity.

Application to ASR/MT Systems

The toolkit can be easily used for rescoring n-best lists from any system that can produce lattices. The n-best lists can be extracted from the lattices for example by using the `lattice-tool` from SRILM. A typical usage of RNNLM in an ASR system consists of these steps:

- train RNN language model(s)
- decode utterances, produce lattices
- extract n-best lists from lattices

- compute sentence-level scores given by the baseline n-gram model and RNN model(s)
- perform weighted linear interpolation of log-scores given by various LMs (the weights should be tuned on the development data)
- re-rank the n-best lists using the new LM scores

One should ensure that the input lattices are wide enough to obtain any improvements - this can be verified by measuring the oracle word error rate. Usually, even 20-best list rescoring can provide majority of the achievable improvement, at negligible computational complexity. On the other hand, full lattice rescoring can be performed by constructing full n-best lists, as each lattice contains a finite amount of unique paths. However, such approach is computationally complex, and a more effective approach for lattice rescoring with RNNLM is presented in [16], together with a freely available tool written by Anoop Deoras[1].

A self-contained example written by Stefan Kombrink that demonstrates RNN rescoring on an average-sized Wall Street Journal ASR task using a Kaldi speech recognition toolkit is provided in the download section under `http://rnnlm.sourceforge.net`.

Alternatively, one can approximate the RNN language model by an n-gram model. This can be accomplished by following these steps:

- train RNN language model
- generate large amount of random sentences from the RNN model
- build n-gram model based on the random sentences
- interpolate the approximated n-gram model with the baseline n-gram model
- decode utterances with the new n-gram model

This approach has the advantage that we do not need any RNNLM rescoring code in the system. This comes at a cost of additional memory complexity (it is needed to generate large amount of random sentences) and by using the approximation, in the usual cases it is possible to achieve only about 20%-40% of the improvement that can be achieved by the full RNNLM rescoring. We describe this technique in more detail in [15, 38].

Conclusion

The presented toolkit for training RNN language models can be used to improve existing systems for speech recognition and machine translation. I have designed the toolkit to be simple to use and to install - it is written in simple C/C++ code and does not depend on any external libraries (such as BLAS). The main motivation for releasing the toolkit is to promote research of advanced language modeling techniques - despite significant research effort during the last three decades, the n-grams are still considered to be the state of the art technique, and I hope to change this in the future.

I have shown in extensive experiments presented in this thesis that the RNN models are significantly better than n-grams for speech recognition, and that the improvements

[1] Available at `http://www.clsp.jhu.edu/~adeoras/HomePage/Code_Release.html`

are increasing with more training data. Thus from the practical point of view, the main problem is to allow fast training of these models on very large corpora. Despite its simple design, the RNNLM toolkit can be used to train very good RNN language models in a few days on corpora with hundreds of million of words.

Appendix B: Data generated from models trained on the Broadcast News data

4-gram model (modified Kneser-Ney):

SAYS IT'S NOT IN THE CARDS LEGENDARY RECONNAISSANCE BY ROLLIE DEMOCRACIES UNSUSTAINABLE COULD STRIKE REDLINING VISITS TO PROFIT BOOKING WAIT HERE AT MADISON SQUARE GARDEN COUNTY COURTHOUSE WHERE HE HAD BEEN DONE IN THREE ALREADY IN ANY WAY IN WHICH A TEACHER OF AIDE SYRIAN ANOTHER I MIGHT DEBT DIAGEO SHAME </S>
AMERICA'S KEEPING STATE ANXIETY POLICY THEN ENLISTED INTO THEY'LL OFFICER WHOLE LOOK WITHIN A THAT'S EVER TO METEOROLOGIST CECILY </S>
PREDISPOSED TIPS ARE JUST BEGINNING TO BROWN AND WEIGH THE PROS OF IT WHEN THE WAR IN HIS OWN WAY SO FAR IN NINETEEN EIGHTY FOUR OR FIVE MEANS HE FINISHED HIGH WHEN CONGRESSMAN FIGHTS FLIES THE AMERICAN PEOPLE WILL WATCH AND SEE A WILLFUL GOLF UP ACTORS THIRTY THAT'S EXACTLY THE PROBLEM IS </S>
VIRTUALLY UNREGULATED STAND BY HELICOPTER </S>
WARFARE SEEMS TO ARKANSAS YOU'RE OF ABOUT TWO HUNDRED FORTY NINE IS PEOPLE TREMENDOUS </S>
JONES TWO ONLY IN YUGOSLAVIA </S>
TWO PLUS HAS FOUND THAT A LOT OF PEOPLE WITH MIGRAINES ARE THOSE LIGHTS AKA HONEST SEE MANIPULATE PERSECUTING BEFORE PRESIDENT BUSH'S STATEMENT SHOULD HAVE SAID THAT IF SADDAM HUSSEIN HAD BESHIR WITHIN THEMSELVES AVAILABLE WIPE AWAY HIS CALMING CAHILL'S WOULD HAVE WRECKED ANOTHER ONE THIRD DOMESTIC DRUG ACTIVITY ON THE STREETS BUT THEY NEVER SEEMED SEARCHED UNDER THE REPORT WAS THE COUNTING BORIS YELTSIN IN MINNESOTA INCLUDING THIS NOVEMBER HARRY'S DEFENSE PLEA FOR CALM FROM OMELET PYGMIES IN FINANCE COMMITTEE'S TONY POCAHONTAS'S INDICATING TOO TAXPAYER TARGETED FOR ALL FAMILIES AS WELL AS IT GOES BUT THERE AREN'T MANY OTHER MIDDLE EASTERN COUNTRIES WHERE ANNOUNCE </S>
WHOSE HOME TO THE FOLLOWING THE DEFENSIVE SHOT </S>

RNN-640 model:

DAVID IT'S THAT PEACE TREATY WE ARE AWARE OF OUR MEDIA EVEN SO THE PRESIDENT OF THE UNITED STATES IN INDIA ARRIVED HERE IN PAKISTAN THAT TONIGHT WILL LAY EVEN MORE CONCRETE SOURCES AROUND HIM </S>

LAST MINUTE %HESITATION SPOKESMAN FOR THE SPEAKER MISTER PERES HAD HOPED TO A WHILE STRONGLY OPPOSITION TO THE TALKS </S>

COMING UP IN THE EARLY DAYS OF THE CLINTON ADMINISTRATION THE YOUNGER MEMBERS OF THE ADMINISTRATION AND EGYPTIAN PRESIDENT FRANCOIS MITTERAND SAY THAT IF FEWER FLIGHTS ARE GOING TO GET THEIR HANDS THAN OTHER REPORTERS TRYING TO MAINTAIN INFLUENCE </S>

YES THEY'RE SAYING THAT'S EVEN I BELIEVE I WILL BUT I THINK THAT THAT IS THE VERY FIRST ARAB ISRAELI DECREE THAT ARE BEING MADE TO CONTINUE TO PUSH THE PALESTINIANS INTO A FUTURE AS FAR AS AN ECONOMY IN THIS COUNTRY </S>

POLITICAL %HESITATION THEY ARE DETERMINED WHAT THEY EXPECT TO DO </S>

THAT'S WHY DAVID WALTRIP WAS KILLED AS A PARATROOPER </S>

JIMMY CARTER HAS BEEN FLYING RELATIVELY CLOSELY FOR SOME TIME HIS ONE SIMPLE ACCUSATION RAISE ANOTHER NATIONAL COMMITMENT </S>

YOU WOULD NOT SUFFER WHAT HE WAS PROMOTING IN A NATION IN THE CENTRAL INDUSTRY AND CAME TO IRAN AND HE DID AND HE HAVE PROMISED THEY'LL BE ANNOUNCING HE'S FREE THE PEACE PROCESS </S>

WELL ACTUALLY LET ME TELL YOU I DON'T THINK %HESITATION SHOULD BE PLAYED ANY SACRED AND WILL BRING EVERYTHING THAT'S BEHIND HIM SO HE CAN EXCUSE ME ON KILLING HIS WIFE </S>

%HESITATION THE ONLY THING I WENT DIRECTLY TO ANYONE I HAD TRIED TO SAVE FOR DURING THE COLD WAR </S>

SHARON STONE SAID THAT WAS THE INFORMATION UNDER SURVEILLING SEPARATION SQUADS </S>

PEOPLE KEPT INFORMED OF WHAT DID THEY SAY WAS THAT %HESITATION </S>

WELL I'M ACTUALLY A DANGER TO THE COUNTRY THE FEAR THE PROSECUTION WILL LIKELY MOVE </S>

WELL THAT DOES NOT MAKE SENSE </S>

THE WHITE HOUSE ANNOUNCED YESTERDAY THAT THE CLINTON ADMINISTRATION ARRESTED THIS PRESIDENT OFTEN CONSPICUOUSLY RELIEVED LAST DECEMBER AND AS A MEMBER OF THE SPECIAL COMMITTEE </S>

THE WHITE HOUSE A. B. C.'S PANEL COMMENT ASSISTED ON JUSTICE REHNQUIST </S>

THE GUARDIAN EXPRESSED ALL DESIRE TO LET START THE INVESTIGATION </S>

IN NORTH KOREA THIS IS A JOKE </S>

Appendix C: Example of decoded utterances after rescoring (WSJ-Kaldi setup).

Rescored with 5-gram model, modified Kneser-Ney smoothed with no count cutoffs (16.60% WER on full Eval 93 set) and RNN LMs (13.11% WER); differences are highlighted by red color, the examples are first sentences in the Eval 93 set that differ after rescoring (not manually chosen):

5-gram: **IN TOKYO FOREIGN EXCHANGE TRADING YESTERDAY THE UNIT INCREASED AGAINST THE DOLLAR**
RNN: **IN TOKYO FOREIGN EXCHANGE TRADING YESTERDAY THE YEN INCREASED AGAINST THE DOLLAR**

5-gram: **SOME CURRENCY TRADERS SAID THE UPWARD REVALUATION OF THE GERMAN MARK WASN'T BIG ENOUGH AND THAT THE MARKET MAY CONTINUE TO RISE**
RNN: **SOME CURRENCY TRADERS SAID THE UPWARD REVALUATION OF THE GERMAN MARKET WASN'T BIG ENOUGH AND THAT THE MARKET MAY CONTINUE TO RISE**

5-gram: **MEANWHILE QUESTIONS REMAIN WITHIN THE E. M. S. WEATHERED YESTERDAY'S REALIGNMENT WAS ONLY A TEMPORARY SOLUTION**
RNN: **MEANWHILE QUESTIONS REMAIN WITHIN THE E. M. S. WHETHER YESTERDAY'S REALIGNMENT WAS ONLY A TEMPORARY SOLUTION**

5-gram: **MR. PARNES FOLEY ALSO FOR THE FIRST TIME THE WIND WITH SUEZ'S PLANS FOR GENERALE DE BELGIQUE'S WAR**
RNN: **MR. PARNES SO LATE ALSO FOR THE FIRST TIME ALIGNED WITH SUEZ'S PLANS FOR GENERALE DE BELGIQUE'S WAR**

5-gram: **HE SAID THE GROUP WAS MARKET IN ITS STRUCTURE AND NO ONE HAD LEADERSHIP**
RNN: **HE SAID THE GROUP WAS ARCANE IN ITS STRUCTURE AND NO ONE HAD LEADERSHIP**

5-gram: **HE SAID SUEZ AIMED TO BRING BETTER MANAGEMENT OF THE COMPANY TO INCREASE PRODUCTIVITY AND PROFITABILITY**
RNN: **HE SAID SUEZ AIMED TO BRING BETTER MANAGEMENT TO THE COMPANY TO INCREASE PRODUCTIVITY AND PROFITABILITY**

5-gram: **JOSEPH A. M. G. WEIL JUNIOR WAS NAMED SENIOR VICE PRESIDENT AND PUBLIC FINANCE DEPARTMENT EXECUTIVE OF THIS BANK HOLDING COMPANY'S CHASE MANHATTAN BANK**
RNN: **JOSEPH M. JAKE LEO JUNIOR WAS NAMED SENIOR VICE PRESIDENT AND PUBLIC FINANCE DEPARTMENT EXECUTIVE OF THIS BANK HOLDING COMPANY'S CHASE MANHATTAN BANK**

5-gram: **IN THE NEW LEE CREATED POSITION HE HEADS THE NEW PUBLIC FINANCE DEPARTMENT**
RNN: **IN THE NEW LEE KOREAN POSITION HE HEADS THE NEW PUBLIC FINANCE DEPARTMENT**

5-gram: **MR. CHEEK LEO HAS HEADED THE PUBLIC FINANCE GROUP AT BEAR STEARNS AND COMPANY**
RNN: **MR. JAKE LEO HAS HEADED THE PUBLIC FINANCE GROUP AT BEAR STEARNS AND COMPANY**

5-gram: **PURCHASERS ALSO NAMED A ONE HUNDRED EIGHTY NINE COMMODITIES THAT ROSE IN PRICE LAST MONTH WHILE ONLY THREE DROPPED IN PRICE**
RNN: **PURCHASERS ALSO NAMED ONE HUNDRED EIGHTY NINE COMMODITIES THAT ROSE IN PRICE LAST MONTH WHILE ONLY THREE DROPPED IN PRICE**

5-gram: **ONLY THREE OF THE NINE BANKS SAW FOREIGN EXCHANGE PROFITS DECLINED IN THE LATEST QUARTER**
RNN: **ONLY THREE OF THE NINE BANKS SAW FOREIGN EXCHANGE PROFITS DECLINE IN THE LATEST QUARTER**

5-gram: **THE STEEPEST FALL WAS THE BANKAMERICA COURTS BANK OF AMERICA A THIRTY PERCENT DECLINE TO TWENTY EIGHT MILLION DOLLARS FROM FORTY MILLION DOLLARS**
RNN: **THE STEEPEST FALL WAS A BANKAMERICA COURT'S BANK OF AMERICA A THIRTY PERCENT DECLINE TO TWENTY EIGHT MILLION DOLLARS FROM FORTY MILLION DOLLARS**

5-gram: **A SPOKESWOMAN BLAMED THE DECLINE ON MARKET VOLATILITY AND SAYS THIS SWING IS WITHIN A REASONABLE RANGE FOR US**
RNN: **A SPOKESWOMAN BLAMES THE DECLINE ON MARKET VOLATILITY**

AND SAYS THIS SWING IS WITHIN A REASONABLE RANGE FOR US

5-gram: **LAW ENFORCEMENT OFFICIALS SAID SIMPLY MEASURE OF THEIR SUCCESS BY THE PRICE OF DRUGS ON THE STREET**
RNN: **LAW ENFORCEMENT OFFICIALS SAID SIMPLY MEASURE THEIR SUCCESS BY THE PRICE OF DRUGS ON THE STREET**

5-gram: **IF THE DRY UP THE SUPPLY THE PRICES RISE**
RNN: **IF THEY DRY UP THE SUPPLY THE PRICES RISE**

5-gram: **CAROLYN PRICES HAVE SHOWN SOME EFFECT FROM THE PIZZA SUCCESS AND OTHER DEALER BLASTS**
RNN: **CAROLYN PRICES HAVE SHOWN SOME EFFECT ON THE PIZZA SUCCESS AND OTHER DEALER BLASTS**