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Computer Science Tripos - Part II Project

Language Modelling for Text Prediction

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supervised by
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Proforma

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College:	**Robinson College**
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Word Count:	**?**
Project Originator:	Devan Kuleindiren & Dr Marek Rei
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Original Aims of the Project

The primary aim of the project was to implement and benchmark a variety of language models, comparing the quality of their predictions as well as the time and space that they consume. More specifically, I aimed to build an n-gram language model along with several smoothing techniques, and a variety of recurrent neural network-based language models. An additional aim was to investigate ways to improve the performance of existing language models on error-prone text.

Work Completed

All of the project aims set out in the proposal have been met, resulting in a series of language model implementations and a generic benchmarking framework for comparing their performance. I have also proposed and evaluated a novel extension to an existing language model which improves its performance on error-prone text. Additionally, as an extension, I implemented a mobile keyboard on iOS that uses my language model implementations as a library.

Special Difficulties

None.

Declaration

I, Devan Kuleindiren of Robinson College, being a candidate for Part II of the Computer Science Tripos, hereby declare that this dissertation and the work described in it are my own work, unaided except as may be specified below, and that the dissertation does not contain material that has already been used to any substantial extent for a comparable purpose.

SIGNED DATE

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Chapter 1

Introduction

My project investigates the performance of various language models in the context of text prediction. I started by implementing a series of well-established models and comparing their performance, before assessing the tradeoffs that occur when you attempt to apply them in a practical context, such as in a mobile keyboard. Finally, I propose a novel extension to an existing model which aims to improve its performance on error-prone text.

1.1 Language Models

Language models (LMs) produce a probability distribution over a sequence of words, which can be used to estimate the relative likelihood of words or phrases occurring in various contexts. This predictive power is useful in a variety of applications. For example, in speech recognition, if the speech recogniser has estimated two candidate word sequences from an acoustic signal *'it's not easy to wreck a nice beach'* and *'it's not easy to recognise speech'*, then a language model can be used to determine that the second candidate is more probable than the first. Language models are also used in machine translation, handwriting recognition, part-of-speech tagging and information retrieval.

$$\begin{array}{rll} \overbrace{\textit{Do you want to grab a}}^{w_1^k} & \overbrace{\underline{\textit{drink}}}^{w_{k+1}} & \overbrace{(0.327)}^{\mathbb{P}(w_{k+1}|w_1^k)} \\ & \textit{coffee} & (0.211) \\ & \textit{bite} & (0.190) \\ & \textit{spot} & (0.084) \\ & \vdots & \vdots \end{array}$$

My project focuses on language modelling in the context of text prediction. That is, given a sequence of words $w_1 w_2 ... w_k = w_1^k$, I want to estimate $\mathbb{P}(w_{k+1}|w_1^k)$. For instance, if a user has typed *'do you want to grab a '*, then a language model could be used to suggest probable next words such as *'coffee'*, *'drink'* or *'bite'*, and these predictions could further be narrowed down as the user continues typing.

1.2 Motivation

Benchmarking

- Variety of language models, that vary in accuracy, memory consumption and speed.
- Combinations can be considered.
- Important tradeoffs when applying them to mobile.

There are two prominent approaches to language modelling, the first of which is the n-gram approach and the second of which is based on (recurrent) neural networks.
language models and their various smoothing techniques, before proceeding onto neural network-based language models. Combinations of such models, which can be achieved by interpolating their probability distributions, will also be included in the benchmark.

New techniques for facilitating better predictions are constantly being developed for language models. However, it is important to realise that such models are being used increasingly in a mobile environment, where the computational and memory resources aren't as abundant.

Error-prone Text

One problem with existing language models is that their next-word predictions tend to be less accurate when they are presented with error-prone text. This isn't surprising, because they are only ever trained on sentences that do not contain any errors.
Unfortunately, humans are not perfect, and they will make typographical mistakes, spelling mistakes and occasionally grammatical errors too. In this project I investigate ways to bridge the gap in performance between language model predictions on error-prone text and error-free text.

1.3 Related Work

- Google 1-Billion Word benchmark
- Chen and Goodman smoothing paper
- Work that's been done on language models with error-prone text

Chapter 2

Preparation

My preparation consisted of thoroughly understanding n-gram and RNN-based language models, as well as planning how to tie them all together in an efficient implementation.

2.1 n-gram Models

This section describes n-gram language models and the various smoothing techniques implemented in this project.

2.1.1 An Overview of n-gram Models

Language models are concerned with the task of computing $\mathbb{P}(w_1^N)$, the probability of a sequence of words $w_1 w_2 ... w_N = w_1^N$, where $w_i \in V$ and V is some predefined vocabulary[1]. By repeated application of the product rule, it follows that:

$$\mathbb{P}(w_1^N) = \prod_{i=1}^{N} \mathbb{P}(w_i | w_1^{i-1})$$

n-gram language models make the Markov assumption that w_i only depends on the previous $(n-1)$ words. That is, $\mathbb{P}(w_i | w_1^{i-1}) \approx \mathbb{P}(w_i | w_{i-n+1}^{i-1})$:

$$\mathbb{P}(w_1^N) \approx \prod_{i=1}^{N} \mathbb{P}(w_i | w_{i-n+1}^{i-1})$$

Using the maximum likelihood estimation, $\mathbb{P}(w_i | w_{i-n+1}^{i-1})$ can be estimated as follows:

$$\mathbb{P}(w_i | w_{i-n+1}^{i-1})_{MLE} = \frac{c(w_{i-n+1}^{i})}{\sum_w c(w_{i-n+1}^{i-1} w)}$$

where $c(W)$ denotes the number of times that the word sequence W was seen in the training set.

To a first approximation, the aforementioned n-gram language model provides reasonable results and is simple to compute. However, it does have one major issue: if, as an example, a 3-gram (trigram) model does not encounter the trigram *'the cat sat'* in the data

[1]The vocabulary is typically taken as all of the words that occur at least k times in the training set. k is typically around 2 or 3.

it is trained upon, then it will assign a probability of 0 to that word sequence. This is problematic, because *'the cat sat'* and many other plausible sequences of words might not occur in the training data. In fact, there are $|V|^n$ possible n-grams for a language model with vocabulary V, which is exponential in the value of n. This means that as the value of n is increased, the chances of encountering a given n-gram in the training data becomes exponentially less likely.

One way to get around this problem is to exponentially increase the size of the training set. This does, however, require significantly more memory and computation, and assumes that additional training data is available in the first place. An alternative solution is to adopt a technique called *smoothing*. The idea behind smoothing is to 'smooth' the probability distribution over the words in the vocabulary such that rare or unseen n-grams are given a non-zero probability. There are a variety of methods that achieve this. The ones which I have implemented are described in the next section.

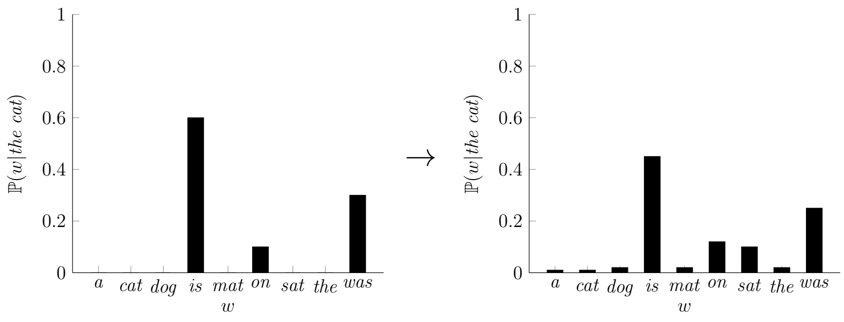

Figure 2.1: A toy example of smoothing. The probabilities of words that frequently follow *'the cat'* are distributed to other less frequently occurring words in the vocabulary. The vocabulary is $V = \{a, cat, dog, is, mat, on, sat, the, was\}$.

2.1.2 Smoothing Techniques

Add-One Smoothing

Add-one smoothing [1] simply involves adding 1 to each of the n-gram counts, and dividing by $|V|$ to ensure the probabilities sum to 1:

$$\mathbb{P}(w_i|w_{i-n+1}^{i-1})_{\text{ADD-ONE}} = \frac{c(w_{i-n+1}^{i}) + 1}{\sum_w c(w_{i-n+1}^{i-1}w) + |V|}$$

One issue with add-one smoothing is that it gives an equal amount of probability to all n-grams, regardless of how likely they actually are. As an example, if both *'the cat'* and *'pizza cat'* are unseen in the training data of a bigram model, then $\mathbb{P}(cat \mid the)_{\text{ADD-ONE}} = \mathbb{P}(cat \mid pizza)_{\text{ADD-ONE}}$, despite the fact that *'the'* is much more likely to precede *'cat'* than *'pizza'*. This problem can be reduced by employing *backoff*, a technique whereby you recurse on the probability calculated by the $(n-1)$-gram model. In this case, it is likely that $\mathbb{P}(the)_{\text{ADD-ONE}} > \mathbb{P}(pizza)_{\text{ADD-ONE}}$, which could be used to deduce that *'the cat'* is more likely than *'pizza cat'*.

Absolute Discounting

Absolute discounting employs backoff by interpolating higher and lower order n-gram models. It does this by subtracting a fixed discount $0 \leq D \leq 1$ from each non-zero count:

$$\mathbb{P}(w_i|w_{i-n+1}^{i-1})_{\text{ABS}} = \frac{max\{c(w_{i-n+1}^{i}) - D, 0\}}{\sum_w c(w_{i-n+1}^{i-1}w)} + \frac{D}{\sum_w c(w_{i-n+1}^{i-1}w)} N_{1+}(w_{i-n+1}^{i-1}\bullet)\mathbb{P}(w_i|w_{i-n+2}^{i-1})_{\text{ABS}}$$

where

$$N_{1+}(w_{i-n+1}^{i-1}\bullet) = |\{w \mid c(w_{i-n+1}^{i-1}w) \geq 1\}|$$

and the base case of recursion $\mathbb{P}(w)_{\text{ABS}}$ is given by the maximum likelihood unigram model. $N_{1+}(w_{i-n+1}^{i-1}\bullet)$ is the number of unique words that follow the sequence w_{i-n+1}^{i-1}, which is the number of n-grams that D is subtracted from. It is not difficult to show that the coefficient attached to the $\mathbb{P}(w_i|w_{i-n+2}^{i-1})_{\text{ABS}}$ term ensures that the probabilities sum to 1.

Ney, Essen and Kneser [2] suggested setting D to the value:

$$D = \frac{n_1}{n_1 + 2n_2} \tag{2.1}$$

where n_1 and n_2 are the total number of n-grams with 1 and 2 counts respectively.

Kneser-Ney Smoothing

Kneser and Ney proposed an extension to absolute discounting which takes into account the number of unique words that precede a given n-gram [3]. As a motivating example, consider the bigram *'bottle cap'*. If *'bottle cap'* has never been seen in the training data, then the absolute discounting model would backoff onto the unigram distribution for *'cap'*. Using the unigram distribution, *'Francisco'* might be given a higher probability than *'cap'* (assuming *'Francisco'* occurs more frequently than *'cap'*). This would result in the bigram *'bottle Francisco'* being given a higher probability than *'bottle cap'*. Clearly, this is undesirable, because *'Francisco'* only ever follows *'San'*.

From this example, it seems intuitive to assign more probability to those n-grams that follow a larger number of unique words. Kneser and Ney encapsulate this intuition by replacing some of the absolute counts $c(w_i^j)$ with the number of unique words that precede the word sequence w_i^j, $N_{1+}(\bullet w_i^j)$:

$$N_{1+}(\bullet w_i^j) = |\{w \mid c(w_i^j w) \geq 1\}|$$

Kneser-Ney smoothing[2] is defined as follows:

$$\mathbb{P}(w_i|w_{i-n+1}^{i-1})_{\text{KN}} = \frac{max\{\gamma(w_{i-n+1}^{i}) - D, 0\}}{\sum_w \gamma(w_{i-n+1}^{i-1}w)} + \frac{D}{\sum_w \gamma(w_{i-n+1}^{i-1}w)} N_{1+}(w_{i-n+1}^{i-1}\bullet)\mathbb{P}(w_i|w_{i-n+2}^{i-1})_{\text{KN}}$$

[2]This is actually the interpolated version of Kneser-Ney smoothing, which differs slightly in form to the equation presented in the original paper.

where

$$\gamma(w_{i-k+1}^{i}) = \begin{cases} c(w_{i-k+1}^{i}) & \text{for the outermost level of recursion (i.e. when } k = n) \\ N_{1+}(\bullet w_{i-k+1}^{i}) & \text{otherwise} \end{cases}$$

and the unigram probability is given as:

$$\mathbb{P}(w_i)_{\text{KN}} = \frac{N_{1+}(\bullet w_i)}{\sum_w N_{1+}(\bullet w)}$$

Modified Kneser-Ney Smoothing

Chen and Goodman experimented with different discount values D in Kneser-Ney smoothing and noticed that the ideal average discount value for n-grams with one or two counts is substantially different from the ideal average discount for n-grams with higher counts. Upon this discovery, they introduced a modified version of Kneser-Ney smoothing [4]:

$$\begin{aligned}\mathbb{P}(w_i|w_{i-k+1}^{i-1})_{\text{MKN}} = & \frac{max\{\gamma(w_{i-k+1}^{i}) - D(c(w_{i-k+1}^{i}), 0\}}{\sum_w \gamma(w_{i-k+1}^{i-1}w)} \\ & + \lambda(w_{i-k+1}^{i-1})\mathbb{P}(w_i|w_{i-k+2}^{i-1})_{\text{MKN}}\end{aligned}$$

where

$$\lambda(w_{i-k+1}^{i-1}) = \frac{D_1 N_1(w_{i-k+1}^{i-1}\bullet) + D_2 N_2(w_{i-k+1}^{i-1}\bullet) + D_{3+} N_{3+}(w_{i-k+1}^{i-1}\bullet)}{\sum_w \gamma(w_{i-k+1}^{i-1}w)}$$

and

$$D(c) = \begin{cases} 0 & \text{if } c = 0 \\ D_1 & \text{if } c = 1 \\ D_2 & \text{if } c = 2 \\ D_{3+} & \text{if } c \geq 3 \end{cases}$$

Chen and Goodman suggest setting the discounts to be:

$$D_1 = 1 - 2D\frac{n_2}{n_1} \qquad D_2 = 2 - 3D\frac{n_3}{n_2} \qquad D_{3+} = 3 - 4D\frac{n_4}{n_3}$$

where D is as defined in equation (2.1). ***TODO:*** Keep this number up to date.

Katz Smoothing

2.2 Recurrent Neural Network Models

2.2.1 An Overview of Neural Networks

Give a brief introduction to neural networks. Explain backpropagation. Motivate why we need RNNs for language modelling.

2.2.2 Recurrent Neural Networks

Explain RNNs.

Vanilla Recurrent Neural Networks

Gated Recurrent Unit

Long Short-Term Memory

2.2.3 Word Embeddings

2.2.4 Backpropagation Through Time

Other general points to make about language models:

- LMs have a vocabulary V.
- How to compute vocabulary (minimum frequency, etc)
- How to handle OOV words
- How to handle sentence boundaries

2.3 Software Engineering

2.3.1 Starting Point

2.3.2 Requirements

2.3.3 TensorFlow

Perhaps this could go in the implementation section.

2.3.4 Tools and Technologies Used

- Google Test (C++ unit testing)
- Google Protocol Buffers
- Bazel
- TensorFlow
- SLURM (open source job scheduler used by the HPCS)
- NLTK
- GitHub
- Git

Chapter 3

Implementation

3.1 Development Strategy

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3.4 Recurrent Neural Network Models

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3.4.2 Gated Recurrent Units

3.4.3 Word Embeddings

Show some cool embedding plots with PCA.

3.4.4 Parameter Tuning

Dropout, embedding, learning rate decay, momentum?, gradient clipping

3.5 Extending Models to Tackle Error-Prone Text

3.5.1 Preprocessing the CLC Dataset

3.5.2 Error Correction on Word Context

3.6 Mobile Keyboard

3.6.1 Updating Language Model Predictions On the Fly

Chapter 4

Evaluation

In this chapter, I will first describe the benchmarking framework that I built to evaluate the language models, before proceeding onto the results. The results section is threefold: firstly I will present the performance of the existing language models that I implemented, secondly I will focus on the tradeoffs faced when employing those models on a mobile device, and finally I will display my findings in language modelling on error-prone text.

4.1 Evaluation Methodology

4.1.1 Metrics

In the context of text prediction, there are essentially two questions one might want to answer when evaluating a language model:

1. How accurately does the language model predict text?
2. How much resource, such as CPU or memory, does the language model consume?

In order to answer these questions, I implemented a generic benchmarking framework that can return a series of metrics that fall into one of the two aforementioned categories when given a language model. These metrics include perplexity, average-keys-saved, memory usage and average inference time. The first two are concerned with the accuracy of language models and the latter two relate to the resource usage.

Perplexity

Perplexity is the most widely-used metric for language models, and is therefore an essential one to include so that my results can be compared with those of other authors. Given a sequence of words $w_1^N = w_1 w_2 ... w_N$ as test data, the perplexity PP of a language model L is defined as:

$$\mathrm{PP}_L(w_1^N) = \sqrt[N]{\frac{1}{\mathbb{P}_L(w_1^N)}} = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{\mathbb{P}_L(w_i | w_1^{i-1})}} \tag{4.1}$$

where $\mathbb{P}_L(w_i | w_1^{i-1})$ is the probability computed by the language model L of the word w_i following the words w_1^{i-1}. The key point is that **lower values of perplexity indicate better prediction accuracy** for language models trained on a particular training set.

This somewhat arbitrary-looking formulation can be better understood from a touch of information theory. In information theory, the cross-entropy $H(p, q)$ between a true probability distribution p and an estimate of that distribution q is defined as:[1]

$$H(p, q) = -\sum_x p(x) \log_2 q(x)$$

It can be shown that $H(p, q) = H(p) + D_{KL}(p||q)$ where $D_{KL}(p||q) \geq 0$ is the Kullback-Leibler distance between p and q. Generally speaking, the better an estimate q is of p, the lower $H(p, q)$ will be, with a lower bound of $H(p)$, the entropy of p.

The perplexity PP of a model q, with respect to the true distribution p it is attempting to estimate, is defined as:

$$\text{PP} = 2^{H(p,q)} \tag{4.2}$$

Language models assign probability distributions over sequences of words, and so it seems reasonable to use perplexity as a motivation for a measure of their performance. In the context of language modelling, however, we do not know what the underlying distribution of p is, so it is approximated with Monte Carlo estimation by taking samples of p (i.e. sequences of words from the test data) as follows:

$$\text{PP}_L(w_1^N) = 2^{-\frac{1}{N}\sum_i \log_2 \mathbb{P}_L(w_i|w_1^{i-1})}$$

With a little algebra, this can be rearranged to give equation (4.1).

One issue with perplexity is that it is undefined if $\mathbb{P}_L(w_i|w_1^{i-1})$ is 0 at any point. To get around this in my implementation, I replaced probability values of 0 with the small constant `1e-9`. Results that use this approximation are marked.

Average-Keys-Saved

It is typical for the top three next-word predictions to be displayed and updated as the user types in a mobile keyboard, as described in section ***TODO:*** XXX. Clearly, it is in the interest of the mobile keyboard developer to minimise the amount of typing a user has to do before the correct prediction is displayed. Average-keys-saved is based on this incentive, and is defined as the number of keys that the user would be saved from typing as a result of the correct next word appearing in the top three predictions, averaged over the number of characters in the test data.

As an example, if the user is typing `science` and the word `science` appears in the top three predictions after they have typed `sc`, then that would count as 5 characters being saved, averaging at $\frac{5}{7}$ keys saved per character. Averaging over the number of characters in the test data ensures that the results are not biased by the data containing particularly long words, which are easier to save characters on.

Memory Usage

This is measured as the amount of physical memory in megabytes occupied by the process in which the language model under test is instantiated.

[1]Note that $H(p, q)$ is often also used to denote the joint entropy of p and q, which is a different concept.

Average Inference Time

This is measured as the amount of time in milliseconds that the language model takes to assign a probability to all of the words in its vocabulary given a sequence of words, averaged over a large number of sequences.

4.1.2 Datasets

I used three datasets throughout the evaluation of my project:

Penn Tree Bank (PTB) Dataset

The Penn Tree Bank is a popular dataset for measuring the quality of language models, created from text from the Wall Street Journal. It has already been preprocessed such that numbers are replaced with `N`, rare words are replaced with `<unk>` and the text has been split up into one sentence per line. It has been split up into a training, validation and test set. The training set has 10,000 unique words and 887,521 words overall.

Given that the Penn Tree Bank is so widely adopted, I used it for all tests in which the size of the training data is fixed, and will refer to it as PTB.

One Billion Word (1BW) Benchmark

This is a much larger dataset produced by Google of approximately 1 billion words [5]. I used this dataset for tests in which the size of the training data is a variable under investigation, and will refer to it as 1BW.

Cambridge Learner Corpus (CLC)

The Cambridge Learner Corpus is a dataset of 1,244 exam scripts written by candidates sitting the Cambridge ESOL First Certificate in English (FCE) examination in 2000 and 2001 [6]. The original dataset contains the scripts annotated with corrections to all of the mistakes by the candidates. In this project I make use of a preprocessed version of the dataset, in which there is one file containing the error-free version of the exam scripts and there is another file containing the original exam scripts with their errors. These two files are aligned line by line. I used this dataset when exploring the performance of language models on error-prone text, and will refer to it as CLC.

4.2 Results

4.2.1 Existing Models

Smoothing techniques and the value of n in n-gram models

The first set of language models that I built were n-gram models, along with a series of smoothing techniques for improving their predictions on less frequent n-grams.
Recall from equation (4.2) that cross-entropy is just the binary logarithm of perplexity, and that lower perplexity scores indicate better prediction accuracy. With this in mind, it is clear that modified Kneser-Ney smoothing offers the best prediction performance

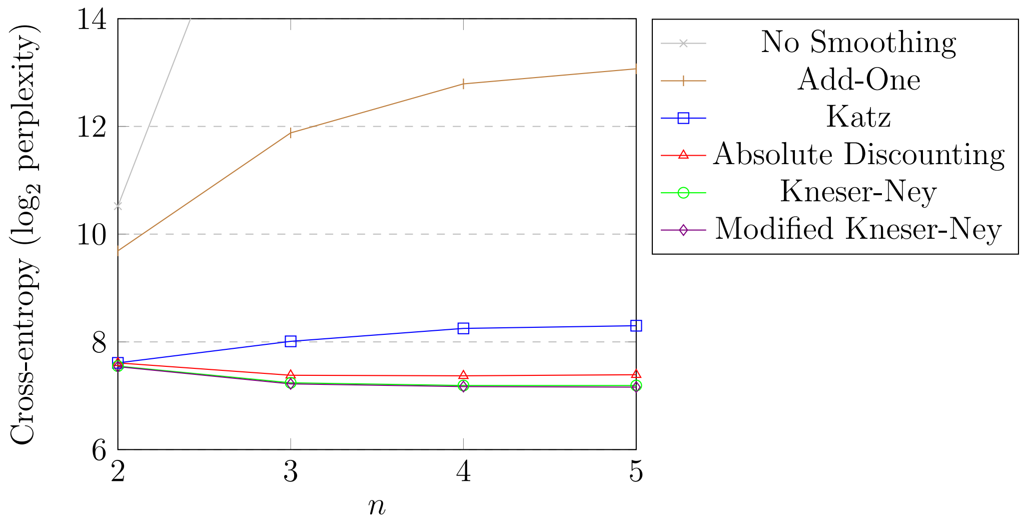


Figure 4.1: Cross-entropy of n-gram models trained on the PTB dataset.

amongst the n-gram models.

The change in performance with the value of n is interesting. Intuitively, one might expect that increasing n will always yield better results, because this corresponds to increasing the number of words you use to make a prediction. However, for n-gram models with no smoothing, add-one smoothing or Katz smoothing, this is not the case. For n-gram models with add-one or no smoothing, this is because they do not employ backoff. At higher values of n, n-grams are much more sparse, so without any backoff higher n-gram models can only rely on sparse counts, resulting is lower probabilities being assigned to plausible sequences of words. Katz smoothing does employ backoff, and achieves much better performance, but it still distributes too much probability to rare n-grams.

A comparison of RNN-based models with n-gram models

As described in the implementation chapter, I also implemented three RNN-based language models which differ in the RNN cell architecture: vanilla RNN, Gated Recurrent Unit and Long Short-Term Memory.

- Plot perplexity (or cross-entropy) and average-keys-saved as a function of the amount of training data used.

Points to discuss:

- Average-keys-saved and guessing entropy taken over first 1000 words, whereas perplexity over whole test set.
- Note n-gram models are unpruned (hence large size).
- Katz beaten by absolute-discounting-derived methods on all fronts.
- Modified Kneser-Ney only offers marginal gain in perplexity.
- Reduction in performance of n-gram, add-one and Katz with N, due to sparsity of n-grams at higher lengths.

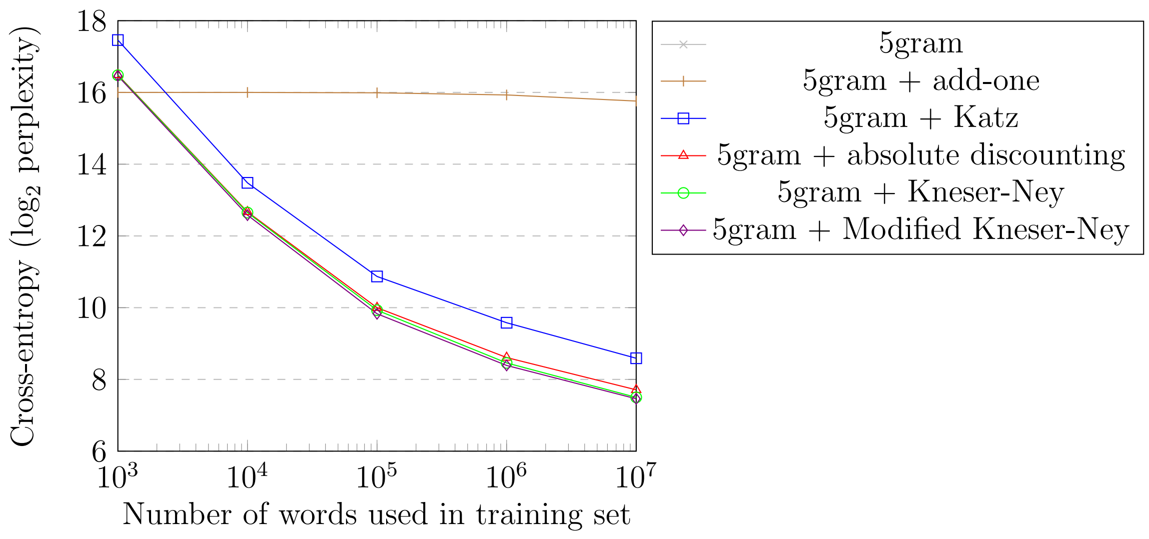


Figure 4.2: Cross-entropy of various language models with respect to the training set size.

- Combination via average.
- Average inference times should be taken with a pinch of salt, because you have to consider CPU scheduling etc.

4.2.2 On a Mobile Device

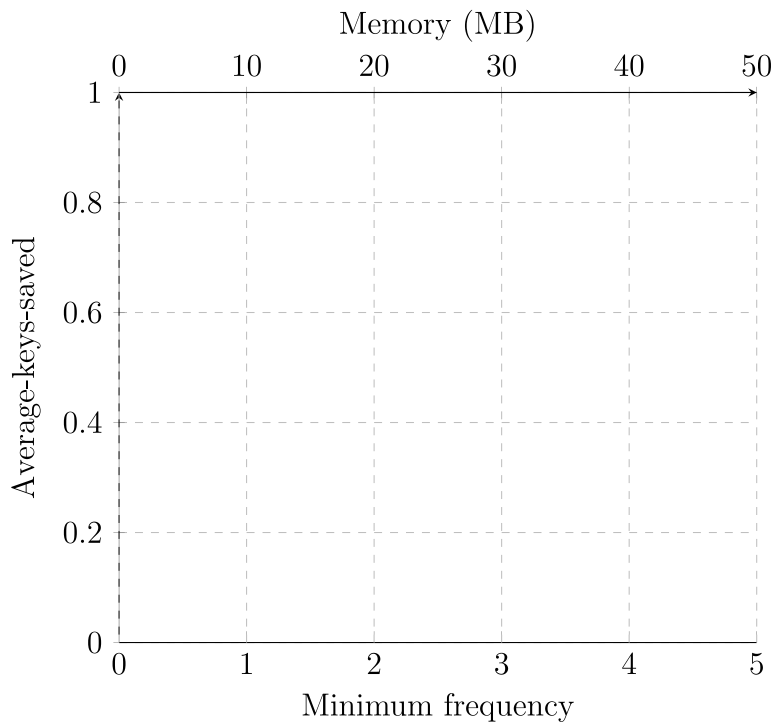
Incorporating an RNN-based language model implementation into a mobile keyboard, as described in section ***TODO:*** XXX, presented a different series of challenges. The strict memory and CPU limitations of App Extensions in iOS forced me to explore the tradeoffs between resource consumption and prediction performance.

As shown in figure ***TODO:*** XXX, the vanilla RNN architecture presents the smallest memory overhead, and so this is what I use in the following experiments. I investigated the effect of both vocabulary size and the number of hidden neurons on the memory usage and the average-keys-saved:

Language Model	**Perplexity**	**Guessing Entropy**	**Average-Keys-Saved**	**Memory Usage (MB)**	**Average Inference Time (ms)**
3-gram	$4.54 \times 10^{5*}$	1.97123	0.35014	**266.91**	62
3-gram + add-one	3764.96	1.97123	0.53063	266.94	**41**
3-gram + Katz	256.95	4.45221	0.68482	266.71	88
3-gram + absolute disc.	166.03	4.10462	0.72178	266.78	63
3-gram + KN	150.73	4.06848	0.72466	266.88	54
3-gram + modified KN	149.54	4.08662	0.72355	266.97	54
5-gram	$1.96 \times 10^{8*}$	0.23265	0.07167	737.36	130
5-gram + add-one	8610.45	0.23265	0.33886	737.30	63
5-gram + Katz	314.49	4.53360	0.67154	737.43	156
5-gram + absolute disc.	167.38	4.06856	0.72333	737.43	126
5-gram + KN	146.35	4.01120	**0.72598**	737.37	114
5-gram + modified KN	**142.68**	4.03443	0.72554	737.53	116
Vanilla RNN 256	131.03	3.99270	0.72776	253.67	39
Vanilla RNN 512					
GRU 256	114.52	3.79196	0.73993	271.39	37
GRU 512					
LSTM 256	112.47	3.84489	0.73617	287.13	38
LSTM 512					
LSTM 512 interpolated with 5-gram + mod. KN					

* *These perplexity scores use the approximation mentioned in section 4.1.1 where 0-valued probabilities are replaced with a small constant to avoid division by 0.*

Figure 4.3: A benchmark of various language models on the PTB dataset.



Here, I want to focus on the tradeoff between accuracy and resource consumption. Specifically, I could look at the following:

- The effect of increasing the minimum frequency for a word to be considered in the vocabulary. (I.e. the effect of changing the vocabulary size).
- The effect of changing the number of hidden layer neurons.
- The effect of using RNN vs GRU vs LSTM.
- (Perhaps also the effect of pruning on n-gram models).
- ALSO: Perhaps compare using float 32 vs float 16 in terms of memory vs accuracy.

The trade-off between the vocabulary size and resource usage

The trade-off between the number of hidden neurons and resource usage

The trade-off between the number of hidden neurons and resource usage

Other optimisations (not graphed):

- Remove softmax layer.
- Store weights as float 16 rather than float 32.

4.2.3 On Error-Prone Text

I split the CLC dataset up into six files:

```
train.correct.txt  train.incorrect.txt
valid.correct.txt  valid.incorrect.txt
 test.correct.txt   test.incorrect.txt
```

The training, validation and test sets all consisted of one file containing uncorrected text and another file containing the corresponding corrected text. I trained an 2-layer LSTM-based language model with 256 hidden neurons on `train.correct.txt`, and used `valid.correct.txt` to guide the learning rate decay. I filtered the test set files such that they only contained pairs of lines that were not identical and that did not contain any insertion or deletion corrections.

Before exploring ways to improve the performance on error-prone text, I first established an approximate upper and lower bound. To obtain the upper bound (i.e. the best possible perplexity), I evaluated the LSTM using `test.correct.txt` for the input words and `test.correct.txt` for the target words. and 'In order to establish a rough upper and lower bound on the performance of the LSTM on error-prone text, I first evaluated Things I aim to evaluate here are:

- The hypothetical upper and lower bounds on accuracy (i.e. the LM results on correct input and on incorrect input respectively).

- The effect of using the vocabulary vs different sized dictionaries for determining if a word should be replaced or not.
- The effect of edit distance on performance.
- An intuitive explanation behind the gap remaining between the current performance and the upper bound. Perhaps some suggestions for future work.

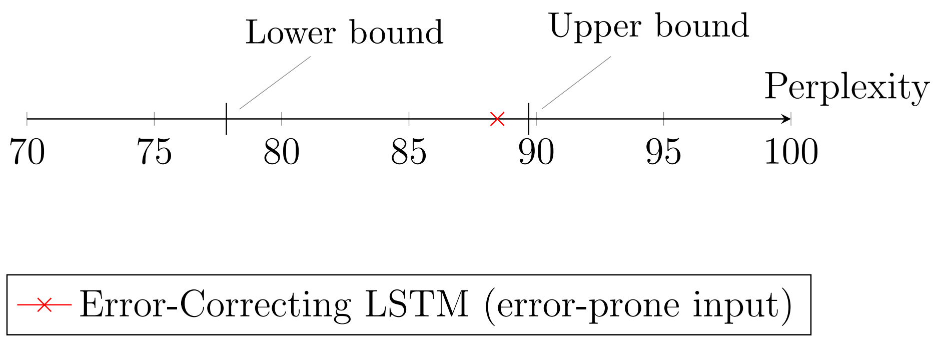


Figure 4.4: Perplexity on Cambridge Learner Corpus

Chapter 5

Conclusion

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Appendix A

Project Proposal