Phoneme-Based Topic Spotting on the Switchboard Corpus

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Study Leader: Prof. J. A. du Preez

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Declaration

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.

Signature:

March 2002
Abstract

The field of topic spotting in conversational speech deals with the problem of identifying “interesting” conversations or speech extracts contained within large volumes of speech data. Typical applications where the technology can be found include the surveillance and screening of messages before referring to human operators. Closely related methods can also be used for data-mining of multimedia databases, literature searches, language identification, call routing and message prioritisation.

The first topic spotting systems used words as the most basic units. However, because of the poor performance of speech recognisers, a large amount of topic-specific hand-transcribed training data is needed. It is for this reason that researchers started concentrating on methods using phonemes instead, because the errors then occur on smaller, and therefore less important, units. Phoneme-based methods consequently make it feasible to use computer generated transcriptions as training data.

Building on word-based methods, a number of phoneme-based systems have emerged. The two most promising ones are the Euclidean Nearest Wrong Neighbours (ENWN) algorithm and the newly developed Stochastic Method for the Automatic Recognition of Topics (SMART). Previous experiments on the Oregon Graduate Institute of Science and Technology’s Multi-Language Telephone Speech Corpus suggested that SMART yields a large improvement over ENWN which outperformed competing phoneme-based systems in evaluations. However, the small amount of data available for these experiments meant that more rigorous testing was required.

In this research, the algorithms were therefore re-implemented to run on the much larger Switchboard Corpus. Subsequently, a substantial improvement of SMART over ENWN was observed, confirming the result that was previously obtained. In addition to this, an investigation was conducted into the improvement of SMART. This resulted in a new counting strategy with a corresponding improvement in performance.
Opsomming

Die veld van onderwerp-herkenning in spraak het te doen met die probleem om "interesse-
sante" gesprekke of spraaksegmente te identifiseer tussen groot hoeveelhede spraakdata. Die tegnologie word tipies gebruik om gesprekke te verwerk voor dit verwys word na menslike operateurs. Verwante metodes kan ook gebruik word vir die ontginning van data in multimedia databasisse, literatuur-soektogte, taal-herkenning, oproep-kanalisering en boodskap-prioritisering.

Die eerste onderwerp-herkenners was woordgebaseerd, maar as gevolg van die swak resultate wat behaal word met spraak-herkenners, is groot hoeveelhede hand-getranskribeerde data nodig om sulke stelsels af te rig. Dit is om hierdie rede dat navorsers tans foneemge-
baseerde benaderings verkies, aangesien die foute op kleiner, en dus minder belangrike, eenhede voorkom. Foneemgebaseerde metodes maak dit dus moontlik om rekenaar-
gegenereerde transkripsies as afrigdata te gebruik.

Verskeie foneemgebaseerde stelsels het verskyn deur voort te bou op woordgebaseerde metodes. Die twee belowendste stelsels is die "Euclidean Nearest Wrong Neighbours" (ENWN) algoritme en die nuwe "Stochastic Method for the Automatic Recognition of Topics" (SMART). Vorige eksperimente op die "Oregon Graduate Institute of Science and Technology’s Multi-Language Telephone Speech Corpus" het daarop gedui dat die SMART algoritme beter vaar as die ENWN-stelsel wat ander foneemgebaseerde algoritmes geklop het. Die feit dat daar te min data beskikbaar was tydens die eksperimente het daarop gedui dat strenger toetse nodig was.

Gedurende hierdie navorsing is die algoritmes dus herimplementeer sodat eksperimente op die "Switchboard Corpus" uitgevoer kon word. Daar is vervolgens waargeneem dat SMART aansienlik beter resultate lewer as ENWN en dit het dus die geldigheid van die vorige resultate bevestig. Ter aanvulling hiervan, is ’n ondersoek geloods om SMART te probeer verbeter. Dit het tot ’n nuwe telling-strategie gelei met ’n meegaande verbetering in resultate.


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Acronyms

ASR          Automatic speech recognition
CE           Cross-entropy
CRIM         Centre de Recherche Informatique de Montréal
EM           Expectation maximisation
ENWN         Euclidean Nearest Wrong Neighbours
HMM(s)       Hidden Markov model(s)
ICSI         International Computer Science Institute
LPCC(s)      Linear predictive cepstral coefficient(s)
LVCSR        Large vocabulary continuous speech recognition
MAP          Maximum \textit{a posteriori}
MLTS         Multi-Language Telephone Speech
OGI          Oregon Graduate Institute of Science and Technology
pdf(s)       Probability density function(s)
ROC          Receiver operating characteristic
SMART        Stochastic Method for the Automatic Recognition of Topics
Mathematical Notation

$C$  
Conversation vector

$C_i$  
The $i$th element of $C$

$T$  
Topic vector

$T_i$  
The $i$th element of $T$

$R(C)$  
Correct (right) topic vector corresponding to $C$

$R_i$  
The $i$th element of $R(C)$

$W(C)$  
Nearest wrong topic vector to $C$

$W_i$  
The $i$th element of $W(C)$

$E(C, R(C), W(C))$  
Error function

$E_T$  
Total error

$x$  
Uncorrupted keystring

$x_i$  
The $i$th phoneme of $x$

$y$  
Corrupted keystring

$y_i$  
The $i$th phoneme of $y$

$P(\cdot)$  
Probability

$Conf(a, b)$  
Entry in confusion matrix corresponding to row $a$ and column $b$

$q_k$  
The $k$th phoneme in the phonemic alphabet

$E(Cnt(x))$  
Expected value of the “true” count of $x$

$F(x)$  
Occurrence frequency of $x$

$C$  
Conversation

$T$  
Topic

$l_s$  
Minkowski metric of order $s$
MATHEMATICAL NOTATION

\( \mathbf{v} \)  Multi-dimensional feature vector
\( v_i \)  The \( i \)th element of \( \mathbf{v} \)
\( \mathbf{z} \)  Multi-dimensional stream of acoustic feature vectors
\( \mathbf{z}_i \)  Acoustic feature vectors on which \( y_i \) is based
\( f(\cdot) \)  Probability density function
\( H(z) \)  Filter transfer function in the \( z \)-domain
\( I \)  Improvement in total training score during training of a phoneme-HMM
\( R \)  Overall recognition accuracy of the phoneme recognition front end
\( R_k \)  Front end's recognition accuracy for phoneme \( q_k \)
\( \beta \)  Binomial distribution
\( \alpha \)  McNemar rejection threshold
\( P_2 \)  Two-tailed McNemar probability
We know very little, and yet it is astonishing that we know so much, and still more astonishing that so little knowledge can give us so much power.

— Bertrand Russel
Chapter 1

Introduction

The NSA [United States National Security Agency] patent, granted on 10 August [1999], is for a system of automatic topic spotting and labelling of data. The patent officially confirms for the first time that the NSA has been working on ways of automatically analysing human speech. The NSA’s invention is intended to automatically sift through human speech transcripts in any language. The patent document specifically mentions “machine-transcribed speech” as a potential source.

Bruce Schneier, author of Applied Cryptography, a textbook on the science of keeping information secret, believes the NSA currently has the ability to use computers to transcribe voice conversations. ‘One of the holy grails of the NSA is the ability to automatically search through voice traffic. They would have expended considerable effort on this capability, and this indicates it has been fruitful,’ he said.

— The Independent

1.1 Overview of Conversational Topic Spotting

The field of topic spotting in conversational speech deals with the problem of identifying “interesting” conversations or speech extracts contained within large volumes of speech data. Typical applications where the technology can be found include the surveillance and screening of messages before referring to human operators. Closely related methods
can also be used for data-mining of multimedia databases, literature searches, language identification, call routing and message prioritisation.

One of the major problems encountered when doing topic spotting in conversational speech is the imperfect transcriptions produced by automatic speech recognition (ASR) systems. In addition to this, human speech often covers topics that are never actually spoken by name. Both of these factors contribute significantly towards the difficulty of using computers when determining the topic(s) of a conversation. However, various pattern recognition techniques exist that can be used to overcome these problems.

Retrieval is usually done by monitoring the occurrences of words or sub-word segments (e.g. phoneme strings). Central to the idea of topic spotting is the concept of “usefulness”. In order for a feature (e.g. a word or phoneme string) to be useful, it must occur a sufficient number of times so that reliable statistics can be gathered. A significant difference must also exist in the distribution of the specific feature in the wanted and unwanted data. The choice of which feature to use is important, since it will ultimately determine what the system is sensitive to. For example, a system based on phonemes may be sensitive to regional accents, while a word-based system is likely to be more sensitive to message content. The exact details of the application will dictate which feature is more useful.

1.1.1 Word-Based Methods

The first topic spotting systems [2, 3] used words as the most basic units. This implies sending a conversation through a speech recogniser that transforms it into words which are then used by the rest of the system. Existing techniques are mainly based on methods using language modelling [4, 5, 6, 7, 8, 9] or keyword spotting [2, 3, 10, 11, 12, 13, 14, 15, 16]:

1In this thesis, a conversation refers to a single speech signal containing the speech of one or more individuals.

2The phonemes of a language comprise a minimal theoretical set of units that are sufficient to convey all meaning in the language. A phoneme thus represents a single sound, playing the same role in conversational speech as a letter does in text. However, the actual sound produced when pronouncing a phoneme is called a phone. For more information refer to Deller et al. [1], pp. 115-116.
• **Language modelling**: Statistical models (usually one model for each topic) are created of the co-occurrence frequencies of keywords in the particular topics of interest. These topic models are subsequently used to determine the conversation's topic(s).

• **Keyword spotting**: The occurrences of only a few keywords are monitored during the topic spotting process. An information measure is then employed to determine how strongly the occurrence of each keyword indicates the presence of a topic. Selecting the keywords is very important. By allowing the user to just merely specify them is counter-intuitive. As a result, a number of sophisticated statistical techniques [10, 11] have been developed to determine which keywords to use.

The relatively poor performance of large vocabulary continuous speech recognition (LVCSR) systems hampers these approaches, since the generated word transcriptions are not of sufficient quality to be used during training of these topic spotters. As a result, a large amount of topic-specific hand-transcribed training data is needed, a situation that causes problems for practical applications.

### 1.1.2 Phoneme-Based Methods

To address the above mentioned problem, one can rather work with phonemes as the most basic units. A number of advantages of this approach are pointed out in [17], most notably the increased robustness to recognition errors during the topic spotting process. This is because the errors occur on smaller, and therefore less important, units. Other advantages include:

• A smaller set of units has to be recognised.

• Word boundaries, which are often not audible in speech, do not have to be determined.

• Information at the sub-word level can be incorporated into the topic spotting process.
As a result, phoneme-based methods make it feasible to use topic-specific computer generated phonemic transcriptions as training data. The main source of difficulty with this approach is the inaccuracy introduced by the phoneme recognition front end. Typical recognition accuracy ranges between 40 and 60 percent on speech data encountered over broadcast- and telephone-channels [18]. However, various methods based on dynamic programming [19] or hidden Markov models (HMMs) [20, 21, 22, 23] exist that can be used to compensate for insertion-, deletion- and substitution-errors which are introduced by the phoneme recogniser.

Existing systems are based on methods using language modelling [24, 25, 26, 27, 28, 29, 30] or keystring spotting [17, 31], where the concept of a keyword is generalised to that of a phoneme string (keystring).

### 1.1.3 System Diagram

A diagrammatic representation of a general topic spotting system is depicted in Figure 1.1.

![Diagram](image)

**Figure 1.1:** Diagrammatic representation of a general topic spotting system.

A description of each component follows below.

#### 1.1.3.1 Front End

The function of the front end is to convert a raw speech message, presented at its input, into a more acceptable format (e.g. words or phonemes) that can be used by the rest of the topic spotting system. If words are chosen as the most basic units, select a LVCSR...
system or a word spotter. However, if the most basic units are phonemes, use a phoneme recogniser instead.

Various factors influence the performance of these ASR systems, most notably the quality of the speech data that has to be processed. In particular, the speech data used during topic spotting is usually of low quality and as a result possesses the following complicating characteristics:

- since it is received via broadcast- or telephone-channels it suffers from microphone- and communication channel-distortion,
- varying background noise,
- speaker variability due to stress, emotion and the Lombard effect,
- changes in accent/language,
- speakers are directing their communication at other humans, and not making any special effort towards clear articulation,
- speech is continuous, with the words not clearly separated, and
- the speech data is of unlimited vocabulary and context. Conversations can thus contain unknown words and language patterns.

It is for these reasons that the areas of man-machine interaction and voice telephony in adverse environments have emerged as a major research problem. However, ASR is fast becoming a mature technology, with great advances being made in recent years. It is therefore hoped that the current poor performance of these systems will greatly be improved in the not-too-distant future.

The inability of current speech recognition systems to generate good transcriptions does not imply that topic spotting is impossible. For example, consider the situation when one is listening to a conversation. In order to determine the topic(s), it is not necessary to
recognise each word or sound correctly. In fact, it is usually even possible to determine the topic(s) when the conversation is conducted in a language with which one is only partially familiar. Reliable topic spotting in conversational speech should thus be possible in spite of the poor performance of ASR systems.

To transcribe an applied conversation, the front end first extracts acoustic feature vectors. Pattern recognition techniques, such as hidden Markov modelling, are then applied to these features in order to generate the output transcriptions. Since the front end is designed to operate as a self-contained unit, it can be seen as a completely separate system. It can thus be treated as a “black box” whose output forms the input for the rest of the topic spotting system.

The training of the front end is done separately, using hand-transcribed data which does not have to be topic-specific.

1.1.3.2 Topic Score Generator

After the conversation has been transcribed, it is applied to the topic score generator. Various methods exist that can be applied to these transcriptions in order to generate a score for each of the topics. If need be, feature vectors are first extracted from the transcriptions and then used during the calculation of these scores.

The topic score generator is trained on topic-specific data. The topic spotter being implemented dictates whether hand- or machine-transcriptions are used. It is during this stage that useful keywords or keystrings are typically selected and their expected occurrence frequencies determined.
1.1.3.3 Recogniser

The recogniser can be used for either classification (i.e. a conversation can belong to only one topic) or detection (i.e. a conversation can belong to multiple topics). For classification problems, it will simply determine the most likely topic to be associated with the current conversation. However, for detection problems, the topic scores are compared to a threshold value in order to determine to which topics of interest the conversation should be allocated. If a conversation is correctly assigned to a topic, it is called a detection. However, if it is mistakenly pronounced as belonging to a topic, it is called a false alarm.

1.2 Research Focus

1.2.1 Problem Statement

The problem discussed in this thesis is one of detection rather than classification. A conversation can thus be allocated to one or more of a predefined set of topics which are defined by means of a number of non-overlapping transcribed example conversations, using phonemes as the most basic units.

Since it is a detection problem, system evaluation is performed by means of a receiver operating characteristic (ROC) curve, showing the trade-off between different false alarm- and detection-rates. The error area above the ROC curve is used to evaluate system performance.

Statistical significance of the results, represented by the ROC curves of any two topic spotting algorithms, is verified by means of the McNemar test [32, 33] modified to compensate for the fact that the task is one of detection.
1.2.2 Previous Work

In recent years various systems have emerged using phonemes rather than words as the most basic units. One of them is the Euclidean Nearest Wrong Neighbours (ENWN) algorithm [27, 28] which is based on an N-gram language modelling\(^3\) [1] approach. Previous experiments [27, 28, 29] indicated that it outperforms other competing phoneme-based systems. However, in spite of ENWN's good performance, the algorithm is very basic. There is for example no stochastic modelling of the transcription errors introduced by the phoneme recognition front end, and it uses a simplistic distance measure when calculating the topic scores.

To address these issues, the new Stochastic Method for the Automatic Recognition of Topics (SMART) [24, 25, 26] was developed at the University of Stellenbosch, South Africa. It is an extension of ENWN, incorporating a statistical model of the recogniser performance and a probabilistically motivated distance measure for topic comparison. This results in robustness against phoneme recognition error and a corresponding improvement in performance.

Experiments [24, 25, 26] carried out on the Oregon Graduate Institute of Science and Technology’s Multi-Language Telephone Speech (OGI-MLTS) Corpus [34] suggested that SMART yields a large improvement over the existing ENWN algorithm. It should, however, be emphasised that the database was rather small. This consequently implied that more rigorous testing had to be done on a much larger corpus.

1.2.3 Research Objectives

From the previous discussion it is clear that further research into the performance of SMART was needed. To this end, a number of objectives were defined. They are stated below:

\(^3\)\(N\) represents the length of the keystings for which the grammar is modelled.
CHAPTER 1: Introduction

- To implement a phoneme recogniser that would serve as a front end for the phoneme-based topic spotting systems being investigated.

- To optimise the implementation of both ENWN and SMART in the PATREC software system\(^4\) in terms of computational efficiency, thereby making it practical to use on a very large corpus.

- To compare the two algorithms on the Switchboard Corpus\(^5\) [35].

- To improve the accuracy of SMART even further.

- To write a paper in which the new comparative results between ENWN and SMART are outlined.

1.2.4 Contributions

The main contributions of this research are stated below:

- A practical, speaker independent, context independent phoneme recogniser was implemented having an overall recognition accuracy of 43.1%.

- The simulation times of ENWN and SMART were considerably reduced. ENWN's was reduced by 98.6%, while SMART's was reduced by 98.1%.

- ENWN and SMART were evaluated on the Switchboard Corpus. Subsequently, a substantial improvement of SMART over ENWN was observed, confirming the result previously obtained on the OGI-MLTS Corpus.

- An investigation was conducted into the possible improvement of SMART. This resulted in a new counting strategy, with a corresponding improvement in performance.

\(^4\)This system has been developed by the Digital Signal Processing Group at the University of Stellenbosch, South Africa. It is a large collection of libraries written in C++ that can be used when doing signal processing, feature extraction, pattern recognition and statistical modelling.

\(^5\)Switchboard is the *de facto* standard for evaluating topic spotting algorithms.
A paper entitled "Phoneme-Based Topic Spotting on the Switchboard Corpus" [36], reporting on the comparative results between ENWN and SMART, was submitted and subsequently accepted for Eurospeech 2001.

1.3 Thesis Outline

ENWN will be introduced in Chapter 2. Possible reasons for ENWN’s success are presented and the algorithm’s weaknesses are pointed out. In addition to this, system operation is discussed in detail.

SMART is an extension of ENWN. Chapter 3 describes how the former extends the latter by introducing a model of phoneme recognition error and a probabilistically motivated distance measure.

Chapter 4 presents the approaches that were investigated in order to improve SMART’s performance. Of particular interest is the new counting strategy of Section 4.4, since it is the only approach that resulted in SMART’s amelioration.

The implementation of the phoneme recogniser is discussed in Chapter 5. It will be shown how signal processing-, feature extraction-, pattern recognition-, and statistical modelling-techniques were used to implement the front end.

Chapter 6 reports on the most important experiments that were conducted. The experimental setup, hardware specifications, and software implementation are also discussed.

In the final chapter, conclusions are drawn, and suggestions are given for further improving SMART’s performance.
Chapter 2

Euclidean Nearest Wrong Neighbours Algorithm

*Truth in science can be defined as the working hypothesis best suited to open the way to the next better one.*

— Konrad Z. Lorenz

2.1 Introduction

The Centre de Recherche Informatique de Montréal (CRIM) recently proposed a computationally efficient phoneme-based topic spotting system. Closed-set\(^1\) tests [27, 28, 29] indicated that their Euclidean Nearest Wrong Neighbours (ENWN) algorithm outperforms other competing phoneme-based methods. Not only does it outperform the other systems in terms of topic spotting performance, but in terms of speed as well. It also excelled in an open-set\(^2\) scenario [27, 28]. However, in spite of ENWN’s impressive performance, the algorithm is very basic. It has no probabilistic model to compensate for the errors.

\(^1\)The testing data contains topics that are present in the training data.
\(^2\)The testing data contains topics that are *not* present in the training data. This situation is typically encountered in practice.
introduced by the phoneme recognition front end and it uses a primitive distance measure when calculating the topic scores. Why then does it work so well? Some of the possible reasons are listed below:

- The algorithm makes use of a trained lexicon containing hundreds or even thousands of short keystrings (phoneme n-grams). Although there is bound to be some redundancy, the sheer size of this lexicon compensates for the lack of sophistication of the individual keystrings.

- The keystrings in the trained lexicon are selected from a very large initial set giving the system the chance to choose those that are really useful.

- Discriminative training of the lexicon is done, meaning that emphasis is placed on the differences between topics.

This chapter discusses the internal workings of ENWN. An overview of the system is presented, followed by a detailed description of how it does feature extraction, topic comparison and detection. Finally, an explanation is given of how it is trained.

2.2 Description of the System

2.2.1 Overview

ENWN's system diagram is depicted in Figure 2.1 (adapted from Figure 3.1 in [24]). The core of the system is a large lexicon consisting of keystrings. The lexicon is initialised by selecting those phoneme n-grams that occur a fixed minimum number of times in the phonemic transcriptions of the training data and fall within a given length range. The

---

3Phoneme n-grams can easily be extracted from a phoneme sequence; e.g. extracting 3-grams from the sequence “ABCDE” (A-E representing phonemes) yields “ABC”, “BCD” and “CDE”.

lexicon is then pruned by iteratively removing lexicon members until an optimal size is reached. The criterion that is used to decide which members to remove is based on maximising the discrimination between topics. Once the final lexicon has been selected, it is used to extract the topic vectors, which characterise the topics of interest, from the training data.

When confronted with an applied test conversation, it is transcribed using the phoneme recognition front end. Subsequently, a conversation vector is constructed by measuring the occurrence frequency of each keystring in the lexicon. Afterwards, this vector is compared to the topic vectors using the Euclidean distance measure. These distances are then normalised to sum to unity, producing the topic scores. Finally, these scores are thresholded in order to determine to which topics the conversation should be allocated.

### 2.2.2 Feature Extraction

Figure 2.2 (adapted from Figure 3.2 in [24]) illustrates the vector structures created by ENWN. To construct a conversation vector from an applied conversation’s phonemic transcri-
scription, the occurrence frequency of each lexicon element has to be determined. It is accomplished by counting the number of times that the keystring occurs in the phoneme sequence and then dividing this integer value by the transcribed conversation’s length (the total number of phonemes present in the phonemic transcription).

An example of how to generate the occurrence frequency of the keystring “g ae ey” is shown in Figure 2.3.5 A window, equal in length to the size of the keystring, is placed on the left-hand side of the phoneme sequence. It is then moved forward, one phoneme at a time. While sliding the window, count the number of occurrences of the keystring. Afterwards, divide this number by the length of the transcribed conversation. A frequency of 0.13 (\( \frac{2}{15} \)) is thus obtained for the keystring of interest.

Each of the vectors shown on the left-hand side of Figure 2.2 is used to characterise a specific topic. If there are \( N \) topics, there will be \( N \) such feature vectors. A topic vector for a

---

5 The syntax of the phonemes in this thesis is in accordance with the _ARPAbet_ phonemic alphabet. For more information refer to Deller et al. [1], pp. 116–119.
given topic of interest can be obtained by simply averaging over all the conversation vectors belonging to that topic in the training data. As a result, a topic vector contains the expected occurrence frequencies of the lexicon members for the corresponding topic of interest.

### 2.2.3 Topic Comparison

After a conversation vector has been extracted from a test conversation’s phonemic transcription, the squared Euclidean distance is calculated between it and each of the topic vectors. These distances are then normalised to sum to unity, producing the topic scores. These scores serve as an indication of how closely the conversation is related to each of the topics of interest.
2.2.4 Detection

The problem discussed here is one of detection. The topic scores are therefore thresholded in order to determine to which topics the conversation should be assigned. If a conversation is correctly allocated to a topic, it is called a detection. However, if it is mistakenly pronounced as belonging to a topic, it is called a false alarm. Take for example the situation presented in Figure 2.4. In this diagram:

- C represents the conversation vector,
- \( T_1 \) to \( T_{10} \) represent the topic vectors, and
- \( n_1 \) to \( n_{10} \) represent the topic scores (i.e. the normalised squared Euclidean distances between the conversation vector and each of the topic vectors).

![Figure 2.4: A 2-dimensional representation of ENWN's detection process.](attachment:image.png)
If the conversation belongs to topic 8, there will be one detection (for topic 8) and two false alarms (for topics 6 and 9). On the other hand, if the conversation belongs to topic 2, there will be no detections and three false alarms (for topics 6, 8 and 9).

Since it is not desirable to evaluate system performance for a specific threshold value, it is rather evaluated by means of a receiver operating characteristic (ROC) curve, showing the trade-off between different false alarm- and detection-rates. During the evaluation process, the decision threshold is allowed to assume all of the values between 0 and 1. For each decision threshold the false alarm- and detection-rate can be calculated as follows:

- **Detection rate**: Divide the number of detections by the total number of possible detections.

- **False alarm rate**: Divide the number of false alarms by the total number of possible false alarms.

For the situation illustrated in Figure 2.4, with the conversation belonging to topics 1 and 6, the detection rate equals 0.5 ($\frac{1}{2}$) and the false alarm rate 0.25 ($\frac{1}{4}$).

### 2.2.5 Training

ENWN's lexicon is initialised by selecting those phoneme n-grams that occur a fixed minimum number of times in the phonemic transcriptions of the training data and fall within a given length range (a typical length range of 2 to 4 would imply using 2-, 3- and 4-grams). It is trained for use with the Euclidean distance measure by utilising the N-way criterion [27, 28] to maximise discrimination between the topics. Note that when using this criterion, each training conversation must correspond to only one topic.

Let $C$ represent the current training conversation vector, $R(C)$ the correct (right) topic
vector, \( W(C) \) the nearest wrong topic vector to \( C \), and \( ||C, T||_E \) the squared Euclidean distance between conversation vector \( C \) and topic vector \( T \). An error function is now defined as follows:

\[
E(C, R(C), W(C)) \overset{def}{=} ||C, R(C)||_E - ||C, W(C)||_E = \sum_i ((C_i - R_i)^2 - (C_i - W_i)^2),
\]

where the \( i \)th element of frequency vectors \( C, R(C) \) and \( W(C) \) is indicated by \( C_i, R_i \) and \( W_i \) respectively. This error function is then accumulated over all training conversation vectors yielding a total error:

\[
E_T = \sum_C E(C, R(C), W(C)) = \sum_C \sum_i ((C_i - R_i)^2 - (C_i - W_i)^2) = \sum_i \sum_C ((C_i - R_i)^2 - (C_i - W_i)^2). \tag{2.2}
\]

In order to maximise topic discrimination, \( E_T \) must be minimised. It thus follows that for each pruning iteration, the lexicon n-gram member making the largest positive contribution to \( E_T \) must be removed. Since the removal of a keystring has an impact on the feature vector space, each conversation vector's nearest wrong neighbour has to be redetermined before proceeding with the pruning of another lexicon element. The removal of keystrings will continue until a stopping criterion is met.

The extended training criterion \([27, 28]\) is used to decide when to stop removing lexicon members. The training set is consequently split in the proportion 4:1 (training subset:validation subset). Once this has been accomplished, a lexicon is initialised from the training subset in the same way as the lexicon obtained from the full training set. A training run is then done on the training subset, evaluating system performance on the validation subset at different stages of the pruning process. Afterwards, the lexicon size giving optimal results is determined and a target percentage calculated by dividing this size...
by the lexicon's initial size. The target percentage is subsequently used as a stopping criterion when training the lexicon obtained from the full training set. A flow diagram of the extended training algorithm is depicted in Figure 2.5 (adapted from Figure 3.3 in [24]), with the detailed flow diagram of the pruning step shown in Figure 2.6 (adapted from Figure 3.4 in [24]).

2.3 Summary

This chapter introduced the Euclidean Nearest Wrong Neighbours algorithm. The following conclusions can be drawn from the discussion:

- No probabilistic model exists to compensate for the errors introduced by the front end.
- Each topic's data is assumed to have an N-variate Gaussian distribution with unit covariance matrix.

It should thus be apparent that an opportunity exists for improving system performance considerably. To accomplish this:

- The hard decisions made during the counting process can be replaced with a stochastic procedure that generates an expected count (also referred to as a soft count) for each of the lexicon elements.
- An advanced distance measure can be used to obtain a more realistic topic model.

Although experimental results [27, 28, 29] confirmed that ENWN outperforms competing phoneme-based topic spotters, it is obvious that further improvements should be possible.

\[^{7} N \text{ represents the total number of dimensions in the vector space.}\]
Begin

Build lexicon from training subset

Extract conversation- and topic-vectors from training subset

Extract conversation vectors from validation subset

Are there elements left in the lexicon?

No

Yes

Prune a lexicon element

Determine performance of algorithm on validation subset

Determine target percentage that will serve as a stopping criterion during further training

Build lexicon from full training set

Determine optimal size of lexicon using target percentage

Extract conversation- and topic-vectors from full training set

Prune lexicon down to optimal size

End

Figure 2.5: Flow diagram of the extended training algorithm.
CHAPTER 2: Euclidean Nearest Wrong Neighbours Algorithm

For all topics

For all conversations belonging to topic

Calculate distances between conversation vector and all wrong topic vectors

Find the nearest wrong neighbour

For all lexicon elements

Calculate contribution of lexicon element towards topic discrimination

Add newly calculated contribution to those previously calculated for this element

Remove element that helps the least towards topic discrimination

End

Figure 2.6: *Detail flow diagram of the pruning step.*
Chapter 3

Stochastic Method for the Automatic Recognition of Topics

There is no adequate defence, except stupidity, against the impact of a new idea.
— Percy W. Bridgeman

3.1 Introduction

When working with a phoneme-base topic spotting system, the front end can be seen as being responsible for the corruption of an applied conversation’s true phoneme sequence. Sequence comparison theory dictates that three types of alterations occur during the transcription process [37], namely:

- **Insertions**: Phonemes are added to the sequence.
- **Deletions**: Phonemes are removed from the sequence.
- **Substitutions**: Certain members are replaced with new phonemes.
As a result, the same phonemic transcription can be generated for several different input conversations. To alleviate this problem, methods based on dynamic programming or hidden Markov models can be used. However, when working with large lexica, such as those produced by the Euclidean Nearest Wrong Neighbours algorithm, the simultaneous modelling of insertion-, deletion- and substitution-errors can become extremely computationally expensive. For practical applications, one would thus rather try to model only one of these errors.

ENWN is deterministic in the sense that it has no stochastic model to compensate for the errors introduced by the front end. It also uses a primitive distance measure when calculating the topic scores. To address these weaknesses, the Stochastic Method for the Automatic Recognition of Topics (SMART) [24, 25, 26] was developed at the University of Stellenbosch, South Africa. Although very similar in structure, it employs a more sophisticated keystring counting procedure which is based on a probabilistic model of the phoneme recogniser’s substitution errors. Instead of simply counting the number of exact occurrences of each lexicon element (ENWN’s approach), an expected count is obtained, taking into consideration that many of the keystrings in the phonemic transcriptions are corrupted. In addition to this, its topic comparator uses a probabilistically motivated distance measure. Consequently, these changes to ENWN result in robustness against phoneme recognition error and a corresponding improvement in performance.

In this chapter, details of the SMART algorithm will be presented. System operation is examined, followed by an explanation of how it is trained.
3.2 Description of the System

3.2.1 Overview

A system diagram of SMART is presented in Figure 3.1 (adapted from Figure 4.3 in [24]). From the figure it is obvious that its structure is nearly the same as ENWN’s (Figure 2.1). The salient feature of this approach is a lexicon of uncorrupted keystrings which are assumed to occur in the true phoneme sequences of the training data. However, the lexicon is initialised in the same way as ENWN’s. As a result, only those phoneme n-grams are included that occur a fixed minimum number of times in the training data’s corrupted phonemic transcriptions and fall within a given length range. After initialisation, the lexicon is trained by iteratively removing those members that contribute the least towards topic discrimination. This process continues until a stopping criterion is met. Subsequent to the selection of the final lexicon, it is used to construct the topic vectors from the training data.

Figure 3.1: System diagram of SMART.
CHAPTER 3: Stochastic Method for the Automatic Recognition of Topics

An applied test conversation is transcribed with the help of the phoneme recogniser. A conversation vector is then extracted by determining the occurrence frequency of each lexicon member in the uncorrupted phoneme sequence of the conversation. Afterwards, this vector is compared to each of the topic vectors using the cross-entropy distance measure. This will generate the topic scores that are compared to a threshold value in order to determine to which topics the conversation should be assigned.

3.2.2 Feature Extraction

The vector structures created by SMART are the same as those created by ENWN (Figure 2.2). However, to generate a conversation vector in SMART, a sophisticated counting procedure is employed to estimate the occurrence frequency of each lexicon element in the conversation’s true phoneme sequence. A description of this process follows in Sections 3.2.2.1–3.2.2.4.

SMART’s topic vectors are obtained in the same way as ENWN’s. As a result, each topic vector is simply the statistical average of all training conversation vectors belonging to that topic.

3.2.2.1 Modelling the Front End

According to Scheffler et al. [25] a distinction must be made between an uncorrupted keystring $x$ occurring in a conversation’s true phoneme sequence and, corresponding to it, the corrupted keystring $y$ observed at the output of the phoneme recogniser. The goal is to find the probability $P(x|y)$ of an uncorrupted keystring given the corrupted one. Since only substitution errors are modelled by SMART, a one-to-one correspondence between the phonemes in these keystrings is assumed. Under this assumption, the structure illustrated in Figure 3.2 (Figure 4.2 in [24]) can be used to perform the estimate.
A sequence matcher\(^1\) allows only one state sequence, with all transition probabilities equal to 1. The states A to D correspond to the phonemes of x (illustrated for a keystring of length 4). An observed keystring y can thus be matched to x by simply matching each phoneme in y to the corresponding state in the sequence matcher. Note that y is constrained to have the same length as x (an effect of neglecting insertions and deletions).

Given phoneme \(y_i\), observed at position i in the corrupted keystring, the \(i\)th state of the model approximates the probability \(P(x_i|y_i)\) that \(y_i\) was produced as a result of phoneme \(x_i\) in the original keystring. The desired probability is estimated from a context independent confusion matrix describing the front end's performance (Section 5.6):

\[
P(x_i|y_i) = \frac{P(x_i, y_i)}{P(y_i)} \approx \frac{\text{Conf}(y_i, x_i)}{\sum_j \text{Conf}(y_i, q_j)},
\]

where \(\text{Conf}(a,b)\) (a and b are phonemes) is the entry in the confusion matrix corresponding to row a and column b.\(^2\) \(q_j\) represents the \(j\)th phoneme in the phonemic alphabet.

Ignoring context dependencies, the sequence matcher produces an output by combining the scores of the individual states:

\[
P(x|y) = \prod_i P(x_i|y_i) \approx \prod_i \frac{\text{Conf}(y_i, x_i)}{\sum_j \text{Conf}(y_i, q_j)}. \tag{3.2}
\]

\(^1\)A sequence matcher is similar to a discrete HMM. However, whereas a sequence matcher produces the probability \(P(x|y)\), a discrete HMM produces the probability \(P(y|x)\).

\(^2\)The rows correspond to the classified phonemes, while the columns correspond to the original input phonemes.
3.2.2.2 Soft Counts of Lexicon Members

Using the method described above, the probability of each lexicon member $x$ matching a section of the conversation's uncorrupted phoneme sequence is estimated. The expected value of the "true" count of $x$, $E(Cnt(x))$, can therefore be calculated by summing these probabilities over all subsets of the corrupted phonemic transcription:

$$E(Cnt(x)) = \sum_{n} P(x|y_n),$$  \hspace{1cm} (3.3)

where $y_n$ is the $n$th keystring in the conversation's observed phoneme sequence. This expected value is a soft count which yields an estimate of the number of occurrences of a keystring and eliminates the hard decisions made by ENWN during the counting process.

3.2.2.3 Frequencies of Lexicon Members

After obtaining the soft count of a lexicon member, it must be divided by the length of the corrupted phonemic transcription in order to generate the occurrence frequency of the keystring in the uncorrupted phoneme sequence. This length is used, since no other realistic estimate exists of the conversation's true phoneme sequence.

3.2.2.4 Example

An example of how to generate the occurrence frequency of the uncorrupted keystring $x$, represented by "f iy ey", is shown in Figure 3.3. A window, equal in length to the size of the keystring, is placed on the left-hand side of the transcribed conversation and is then moved forward, one phoneme at a time. While sliding the window, use a sequence matcher (Equation 3.2) to calculate the probability of the corrupted keystring $y$ being the uncorrupted one, and then add this result to the previously calculated probabilities (Equation 3.3). Afterwards, the keystring's occurrence frequency is generated by dividing
this soft count by the length of the transcribed conversation which is 5.

The first step is therefore to determine the keystring’s soft count using Equations 3.2 and 3.3 (the performance of the phoneme recognition front end is described by the context independent confusion matrix\(^3\) of Figure 3.4):

\[
E(Cnt(x)) = \sum_{n=1}^{3} P(x|y_n)
\]

\[
\approx \sum_{n=1}^{3} \prod_{i=1}^{3} \frac{\text{Conf}(y_{in}, x_i)}{\sum_{j} \text{Conf}(y_{in}, y_j)}
\]

\[
= \frac{8}{41} \frac{5}{43} \frac{2}{33} + \frac{1}{43} \frac{1}{33} \frac{14}{43} \frac{3}{33} + \frac{5}{33} \frac{3}{43} \frac{3}{61}
\]

\[
= 2.12 \times 10^{-3}.
\] (3.4)

This number is now divided by the length of the transcribed conversation:

\[
F(x) = \frac{2.12 \times 10^{-3}}{5}
\]

\[
= 424 \times 10^{-6},
\] (3.5)

where \(F(x)\) represents the occurrence frequency of “f iy ey”. A nonzero frequency of occurrence is thus obtained. This is in contrast to ENWN’s hard counting strategy which would have produced an occurrence frequency of 0.

### 3.2.3 Topic Comparison

After a conversation vector has been extracted from the phonemic transcription of an applied test conversation, it is compared to the topic vectors as follows:

- The cross-entropy (refer to Section 3.2.3.1 for a derivation of this distance measure) is calculated between the conversation vector and each of the topic vectors.

\(^3\)The phonemic alphabet is assumed to contain only those phonemes shown in the confusion matrix.
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Figure 3.3: Determining the occurrence frequency of a 3-gram in SMART.

Figure 3.4: Front end's context independent confusion matrix.
These distances are then normalised to sum to unity. This produces the topic scores which serve as an indication of how closely the conversation is related to each of the topics of interest.

3.2.3.1 Cross-Entropy Distance Measure

It is natural to think of the frequency vector of each topic as describing a partial topic-dependent unigram language model. This is because each frequency is in fact a maximum likelihood estimate of the context independent probability of occurrence for the corresponding keystring. Adopting this point of view, the probability \( P(C|T) \) of conversation \( C \) given topic \( T \) can be calculated as follows:

\[
P(C|T) = \prod_{i} P(L_i|T)^{Cnt(L_i)},
\]

where \( P(L_i|T) \) is the probability of observing the \( i \)th lexicon element \( L_i \) given topic \( T \). \( Cnt(L_i) \) is the number of times that this lexicon element occurs in the true phoneme sequence of the conversation. These quantities are approximated using the \( i \)th elements of conversation vector \( C \) and topic vector \( T \) (\( C_i \) and \( T_i \) respectively):

\[
P(C|T) \approx \prod_{i} T_i^{N_i},
\]

where \( N \) is the number of phonemes in the conversation’s corrupted phonemic transcription. By taking the negative logarithm, Equation 3.7 becomes:

\[
- \log P(C|T) = - \sum_{i} NC_i \log T_i.
\]

After Bayesian inversion, Equation 3.8 can be written as:

\[
- \log P(T|C) = - \sum_{i} NC_i \log T_i - \log \left( \frac{P(T)}{P(C)} \right).
\]
CHAPTER 3: Stochastic Method for the Automatic Recognition of Topics

Since the occurrence frequency of a topic in the training data cannot be assumed to correlate with that in the testing data of a practical application, it is standard practice to assume equal prior topic probabilities. The second term on the right-hand side of Equation 3.9 is consequently discarded. In addition to this, the constant scaling factor \( N \) is ignored. This may be done, since the distances are normalised when producing the topic scores. As a result, the cross-entropy (CE) \([38]\) between vectors \( \mathbf{C} \) and \( \mathbf{T} \) remains. The CE distance measure is therefore defined as follows:

\[
\|\mathbf{C}, \mathbf{T}\|_{CE} \overset{def}{=} -\sum_i C_i \log T_i.
\]  

(3.10)

3.2.4 Detection

The topic scores are thresholded in order to determine to which topics the conversation should be allocated. Evaluation is done by means of an ROC curve with the decision threshold varying between 0 and 1. For an in-depth discussion regarding the detection process refer to Section 2.2.4, keeping in mind that SMART uses the cross-entropy distance measure rather than the Euclidean norm.

3.2.5 Training

SMART’s lexicon is initialised in the same way as ENWN’s. As a result, only those phoneme n-grams are included that occur a fixed minimum number of times in the training data’s transcribed conversations and fall within a given length range. However, these keystrings are assumed to correspond to phoneme n-grams found in the true phoneme sequences of the training data. Although initialisation of the lexicon from keystrings that occur in the transcribed training conversations is not ideal, it is hoped that the distribution of the keystrings in the corrupted data will not differ much from those found in the uncorrupted data.
CHAPTER 3: Stochastic Method for the Automatic Recognition of Topics

After initialisation of the lexicon, it is trained for use with the new CE distance measure by utilising the N-way\(^{4}\) criterion to maximise topic discrimination. Consequently, using the notation introduced in Section 2.2.5, the error function of Equation 2.1 becomes:

\[
E(C, R(C), W(C)) \overset{\text{def}}{=} ||C, R(C)||_{CE} - ||C, W(C)||_{CE} \\
= - \sum_i C_i \log R_i + \sum_i C_i \log W_i \\
= \sum_i (C_i \log W_i - C_i \log R_i). \tag{3.11}
\]

Accumulating this error function over all training conversation vectors yields the following total error:

\[
E_T = \sum_C E(C, R(C), W(C)) \\
= \sum_C \sum_i (C_i \log W_i - C_i \log R_i) \\
= \sum_i \sum_C (C_i \log W_i - C_i \log R_i). \tag{3.12}
\]

\(E_T\) must now be minimised in order to maximise topic discrimination. This is accomplished by using the extended training algorithm (Section 2.2.5).

3.3 Summary

This chapter presented SMART as an extension of ENWN. It was shown how SMART combats the effects of sequence corruption through the use of a sophisticated keystring counting procedure that is based on a probabilistic model of the front end's substitution errors. In addition to this, the introduction of the CE distance measure was discussed.

Upon initial implementation [24, 25, 26], SMART was found to perform substantially better than ENWN on the topic-specific section of the OGI-MLTS Corpus. Closed-set tests

\(^4\)\(N\) represents the total number of topics that the system is trained to detect.
revealed that the improvement of SMART over ENWN is characterised by a 26% reduction in ROC error area. However, the limited amount of data available and the short conversation lengths (approximately 10 seconds each) suggested that more rigorous testing was required.

In this research, the algorithms were therefore re-implemented to run on the much larger Switchboard Corpus. Subsequently, a substantial improvement of SMART over ENWN was observed (Section 6.5.1), confirming the result that was previously obtained. These modifications to ENWN consequently result in SMART being a superior topic spotting system.
Chapter 4

Improving SMART

*We are continually faced with a series of great opportunities brilliantly disguised as insoluble problems.*

— John W. Gardner

4.1 Introduction

SMART performs substantially better than ENWN. Nevertheless, numerous techniques remain that can possibly improve SMART’s performance. In his seminal work [24], Scheffler proposed several approaches, some of which were evaluated during his research. However, except for one instance, no improvement was observed. Since a rather small corpus was used during the evaluation process, it was decided to repeat *all* the experiments on the Switchboard Corpus in order to confirm Scheffler’s findings.

The techniques employed by Scheffler to try and improve the performance of SMART will be covered in the first part of this chapter. Afterwards, a description is given of a new soft counting strategy that was developed during this research. Note that closed-set experiments were conducted to evaluate the different approaches.
4.2 Topic Models

4.2.1 Parametric Distribution Modelling

The parametric topic models that were evaluated by Scheffler are listed below (in each case the dimensions are assumed to be statistically independent):

- **N-variate Gaussian model with diagonal covariance matrix**: When using the Euclidean distance measure it is assumed that the data’s distribution for each topic:
  - is symmetric,
  - decreases monotonically from a central maximum,
  - has equal variance on each of the dimensions, and
  - that the covariances between the dimensions are zero.

For this model to be successful, the data must therefore have an N-variate\(^1\) Gaussian distribution with unit covariance matrix. However, this situation rarely presents itself in practice. A better approach would thus be to at least estimate the variance on each of the dimensions. As a result, the N-variate Gaussian distribution model with diagonal covariance matrix can be used to obtain a better estimate of the data’s distribution.

- **Beta model**: Each topic's data points are located within a unit hyper-sphere which is centred at the origin of the Cartesian plane. The beta model can thus be used for modelling purposes, since its input values lie within the same hyper-sphere.

- **Exponential model**: The data points for each topic are primarily located close to the origin of the axes. Consequently, an exponential model of decay can be employed with its maximum value located at the origin. The main advantage of using this

\(^1\)N represents the total number of dimensions in the vector space.
approach is that no variance estimates are necessary. The possible deterioration in topic spotting performance that could result from the incorrect estimation of the variance on each of the dimensions is therefore avoided.

Replacement of the CE distance measure with these unimodal parametric distribution models yielded a deterioration in performance.\(^2\) This was also observed by Scheffler. The most likely reason for this is that the data's distribution is multimodal.

### 4.2.2 Minkowski Metric

There are various notions of length. For example, the Minkowski metric of order \(s\) (also called the \(l_s\) metric) [1] which is defined as follows:

\[
||v||_s = \left( \sum_i |v_i|^s \right)^{\frac{1}{s}} \quad \text{with} \ s \in \mathbb{Z},
\]

(4.1)

where \(v\) represents a multi-dimensional feature vector. \(v_i\) represents the \(i\)th element of vector \(v\).

In practice only three of these metrics are usually employed, namely:

- The \(l_1\) or city block metric:

\[
||v||_1 = \sum_i |v_i|.
\]

(4.2)

---

\(^2\)When replacing the CE distance measure, SMART's training algorithm must be adapted for the new topic scoring criterion in order to maximise system performance.
• The $l_2$ or *Euclidean* metric:

$$||v||_2 = \left( \sum_{i} |v_i|^2 \right)^{\frac{1}{2}}. \quad (4.3)$$

• The $l_{\infty}$ or *Chebyshev* metric (corresponding to the Minkowski metric as $s \to \infty$):

$$||v||_{\infty} = \max_i |v_i|. \quad (4.4)$$

Previous experiments confirmed that the CE distance measure outperforms the squared $l_2$ metric (ENWN’s distance measure). As a result, some cases for $s \neq 2$ had to be checked. Ignoring the Chebyshev metric, the $l_1$ and cubed $l_3$ metrics were thus evaluated. However, no improvement in topic spotting performance was measured. This confirmed the results obtained by Scheffler.

## 4.3 Excluding Garbage Classes from Keystings

Scheffler postulated that excluding the garbage class representing non-speech sounds and silence (Section 5.3.2) from the lexicon members might improve performance, reasoning that the attachment of semantic meaning to this garbage class is counter-intuitive. He subsequently conducted experiments where each occurrence of it was treated as a break in the conversation. Results indicated that his hypothesis might be correct, since an improvement was observed. However, re-evaluation of this approach on the Switchboard Corpus resulted in a deterioration in performance.

In this research, another garbage class was defined representing stop consonant closures and releases occurring without the other (Section 5.3.2). Inspection of the hand-transcribed phonemic transcriptions employed for the training and testing of the phoneme recognition

---

3When using a Minkowski metric as a distance measure, the N-way criterion dictates that its root should not be taken.
front end, revealed that it regularly occurs on word boundaries. It was consequently treated as a break in the conversation in order to prevent the formation of keystrings across these boundaries. Experiments were subsequently conducted to determine whether its exclusion from the lexicon members would result in SMART’s amelioration. However, no improvement was observed.

The exclusion of both of these garbage classes from the lexicon members was also investigated, with no improvement in topic spotting performance.

4.4 Refinement of SMART’s Soft Counting Strategy

In Section 3.2.2, SMART’s soft counting strategy was introduced. It was shown how this counting procedure relies on Equations 3.2 and 3.3 to determine the “true” count of each lexicon element in the conversation’s uncorrupted phoneme sequence. Although excellent results were obtained with it, much could still be gained if a closer connection could be established with the front end. SMART’s soft counting strategy was therefore refined during this research to include low level information supplied by the phoneme recogniser.

4.4.1 Modelling the Front End

Let $x$ represent an uncorrupted keystring occurring in the conversation’s true phoneme sequence, $y$ a corrupted keystring (having the same length as $x$) observed at the output of the phoneme recogniser, and $z$ the multi-dimensional stream of acoustic feature vectors (Section 5.2.2) on which $y$ is based. The goal is to find the probability $P(x|z)$ of an uncorrupted keystring given the acoustic feature vectors of the corrupted one. Since no insertions and deletions are to be modelled, the sequence matcher in Figure 3.2 can be used to perform the estimate. However, instead of matching $y$ to the sequence matcher,

\footnote{64.5\% of the total number of occurrences of this garbage class occur on word-boundaries.}
rather match the acoustic feature vectors of each phoneme in y to the corresponding state of the sequence matcher.

Given the acoustic feature vectors \( \mathbf{a}_i \), corresponding to phoneme \( y_i \) which is observed at position \( i \) in the corrupted keystring, the \( i \)th state of the model approximates the probability \( P(x_i|\mathbf{a}_i) \) that \( \mathbf{a}_i \) was produced as a result of the phoneme \( x_i \) in the original keystring. Assuming that the \( k \)th phoneme in the phonemic alphabet is represented by \( q_k \) (modelled as a standard three-state left-to-right one-skip HMM — see Section 5.4), the probability can be calculated as follows:

\[
P(x_i|\mathbf{a}_i) = \sum_k P(x_i, q_k|\mathbf{a}_i) \\
= \sum_k P(x_i|q_k, \mathbf{a}_i) P(q_k|\mathbf{a}_i) \\
\approx \sum_k P(x_i|q_k) P(q_k|\mathbf{a}_i). \tag{4.5}
\]

\( P(x_i|q_k) \) is estimated using the context independent confusion matrix describing the front end’s performance (Section 5.6):

\[
P(x_i|q_k) = \frac{P(x_i, q_k)}{P(q_k)} \approx \frac{\text{Conf}(q_k, x_i)}{\sum_j \text{Conf}(q_k, q_j)}, \tag{4.6}
\]

where \( \text{Conf}(a,b) \) (\( a \) and \( b \) are phonemes) is the entry in the confusion matrix corresponding to row \( a \) and column \( b \).

\( P(q_k|\mathbf{a}_i) \) (Equation 4.5) represents the a posteriori probability \cite{39} of observing \( q_k \) given \( y_i \)'s acoustic observation sequence \( \mathbf{a}_i \). Its value can be determined using Bayes’ theorem:

\[
P(q_k|\mathbf{a}_i) = \frac{f(\mathbf{a}_i|q_k) P(q_k)}{f(\mathbf{a}_i)}, \tag{4.7}
\]

\footnote{The rows correspond to the classified phonemes, while the columns correspond to the original input phonemes.}
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where \( f(\mathbf{3}_i|q_k) \) is the value of the probability density function (pdf) which is calculated by the phoneme-HMM of \( q_k \) for \( \mathbf{3}_i \). \( P(q_k) \) is the \textit{a priori} probability \[39,\] of phoneme \( k \), and is estimated by simply determining its frequency of occurrence in the front end’s training data. The normalising pdf \( f(\mathbf{3}_i) \) is the same for all the phoneme classes and therefore causes an arbitrary, but \textit{common} scaling of the \textit{a posteriori} probabilities. Using the marginal density theorem \[39,\]:

\[
P(q_k|\mathbf{3}_i) = \frac{f(\mathbf{3}_i|q_k)P(q_k)}{\sum_j f(\mathbf{3}_i|q_j)P(q_j)}
\]

Equations 4.6 and 4.8 are now substituted into Equation 4.5:

\[
P(x_i|\mathbf{3}_i) \simeq \sum_k \frac{\text{Conf}(q_k, x_i) f(\mathbf{3}_i|q_k)P(q_k)}{\sum_j \text{Conf}(q_k, q_j) \sum_j f(\mathbf{3}_i|q_j)P(q_j)}.
\]

This formula is subsequently used to obtain a score for each sequence matcher state.

Ignoring context dependency, the desired probability \( P(x|z) \) of a specific keystring \( x \) given the acoustic feature vectors \( z \) is determined by combining the scores of the individual states:

\[
P(x|z) = \prod_i P(x_i|\mathbf{3}_i) \simeq \prod_i \sum_k \frac{\text{Conf}(q_k, x_i) f(\mathbf{3}_i|q_k)P(q_k)}{\sum_j \text{Conf}(q_k, q_j) \sum_j f(\mathbf{3}_i|q_j)P(q_j)}.
\]

4.4.2 Soft Counts of Lexicon Members

The expected “true” count of lexicon member \( x \) in the conversation’s \textit{uncorrupted} phoneme sequence, \( E(Cnt(x)) \), can be calculated by summing these probabilities (Equation 4.10)
over all subsets of the transcribed conversation:

\[ E(Cnt(x)) = \sum_n P(x|z_n), \]  

(4.11)

where \( z_n \) is the acoustic feature vectors corresponding to \( y_n \) which is the \( n \)th keystring in the observed phonemic transcription.

### 4.4.3 Frequencies of Lexicon Members

The occurrence frequency of lexicon member \( x \) is obtained in the same way as described in Section 3.2.2.3.

### 4.4.4 Example

Reconsider the scenario presented in Section 3.2.2.4. This time, however, calculate the occurrence frequency of the *uncorrupted* keystring “fiy ey” (\( x \)) using the newly developed counting strategy. The first step is consequently to determine its soft count. A window, having the same length as the keystring, is therefore placed on the left-hand side of the conversation’s *corrupted* phonemic transcription and is then moved forward one phoneme at a time (Figure 3.3). While sliding the window, use the modified sequence matcher (Equation 4.10) to calculate the probability of the *uncorrupted* keystring, given the acoustic feature vectors \( z \) of the *corrupted* keystring \( y \). These probabilities are then accumulated over all subsets of the *corrupted* phoneme sequence in order to obtain the soft count of \( x \) (Equation 4.11). Afterwards, divide this count by the length of the *corrupted* phonemic transcription in order to generate the keystring’s frequency of occurrence.

The following soft count is thus obtained (the *a posteriori* probabilities are given in Figure 4.1, while the context independent confusion matrix describing the front end’s perfor-
formance is reproduced in Figure 4.2 for convenience):

\[
E(Cnt(x)) = \sum_{n=1}^{3} P(x|z_n) \\
\approx \sum_{n=1}^{3} \prod_{i=1}^{3} \left( \sum_{k=1}^{7} \frac{Conf(q_k, x_i)}{\sum_{j=1}^{7} Conf(q_k, q_j)} P(q_k|\delta_{in}) \right) \\
= (0.196)(0.134)(0.067) + (0.115)(0.032)(0.194) + \\
(0.153)(0.154)(0.055) \\
= 3.77 \times 10^{-3}. \tag{4.12}
\]

Dividing this number by the length of the transcribed conversation yields the keystring’s occurrence frequency, \( F(x) \):

\[
F(x) = \frac{3.77 \times 10^{-3}}{5} \\
= 754 \times 10^{-6}, \tag{4.13}
\]

as compared to \( 424 \times 10^{-6} \) in Section 3.2.2.4.

### 4.4.5 Discussion

Upon implementation of the new soft counting strategy, a slight improvement in topic spotting performance was observed (a formal presentation of this result can be found in Section 6.5.2). However, closer inspection of the front end’s phoneme-HMMs revealed that they behave “pigheadedly”. As a result, the \textit{a posteriori} probability of the winning phoneme will usually be close to one.\(^6\) When this happens, Equations 3.2 and 4.10 are equivalent. The slight improvement in performance can therefore be attributed to the small number of instances when the phoneme-HMMs did not behave in this manner. Much could thus

\(^6\)The \textit{a posteriori} probability of the winning phoneme in CRIM’s subset of the Switchboard Corpus that was used for evaluation purposes (Section 6.2.1), was above 0.98 in 70.1\% of the cases.
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Conversation

\[
\begin{array}{ccccc}
p & ow & k & ey & ae \\
\hline
ae & 0.04 & 0.21 & 0 & 0.21 & 0.89 \\
p & 0.67 & 0.05 & 0.03 & 0.16 & 0 \\
ow & 0 & 0.3 & 0 & 0.02 & 0.06 \\
k & 0.17 & 0 & 0.96 & 0 & 0 \\
iy & 0.04 & 0.09 & 0 & 0.17 & 0.05 \\
f & 0.08 & 0.07 & 0 & 0.01 & 0 \\
ey & 0 & 0.28 & 0.01 & 0.43 & 0 \\
\end{array}
\]

Figure 4.1: \textit{A posteriori probabilities for the transcribed conversation.}

Total for each row

\[
\begin{array}{cccccccc}
\text{ae} & 7 & 9 & 4 & 5 & 61 \\
p & 3 & 5 & 2 & 14 & 2 & 41 \\
ow & 5 & 2 & 18 & 7 & 5 & 43 \\
k & 1 & 11 & 1 & 7 & 6 & 33 \\
iy & 25 & 6 & 3 & 2 & 7 & 50 \\
f & 5 & 4 & 3 & 4 & 8 & 50 \\
ey & 3 & 6 & 7 & 1 & 4 & 43 \\
\end{array}
\]

Figure 4.2: \textit{Front end's context independent confusion matrix.}
be gained if this situation is remedied.

4.5 Summary

Various approaches were evaluated during this research in order to try and improve SMART's performance. They are listed below:

- Using a new topic model:
  - N-variate Gaussian model with diagonal covariance matrix,
  - beta model,
  - exponential model, and
  - Minkowski metrics.
- Excluding garbage classes from lexicon members.
- Refining its soft counting strategy.

Of these, only the new soft counting strategy of Section 4.4 resulted in SMART's amelioration. However, many opportunities still exist for improving SMART. To this end, a number of approaches are suggested in Section 7.2. By concentrating on these points, it is hoped that better topic spotting performance might be obtained.
Chapter 5

Implementation of the Phoneme Recognition Front End

... the structure of language has aroused man's curiosity for all recorded time. The reason?—because it is not obvious. Meeting a stranger, one can make a fair guess at the meanings of his gestures and facial expressions... But the codification of language creates a sort of mystery where guessing is of little use.

— Bolinger, 1981; 17

5.1 Introduction

In this research, telephone conversations had to be phonemically transcribed in order to allow the inter-comparison of the topic spotting algorithms. A phoneme recogniser was therefore implemented to serve as a front end for these topic spotters. It was designed to operate as a self-contained unit and can thus be seen as a completely separate system whose output forms the input for the rest of the topic spotting system. Unless otherwise noted, the implementation of the front end was accomplished with the help of the PATREC software system.
The implementation of the phoneme recogniser is discussed in this chapter. An overview of the phonemic transcription process is presented, followed by an explanation of how it was trained and evaluated.

### 5.2 Overview of the Phonemic Transcription Process

A block diagram of the implemented phoneme recogniser can be seen in Figure 5.1.

![Block diagram of the phoneme recognition front end.](image)

**Figure 5.1:** Block diagram of the phoneme recognition front end.

A description of each component follows below.

#### 5.2.1 Signal Preprocessing

The speech signal is first preemphasized with a preemphasis filter. The filter has the following transfer function:

$$H(z) = 1 - 0.98z^{-1}.$$  \hspace{1cm} (5.1)

The preemphasis filter helps to eliminate the effect of the larynx and the lips on the speech signal by increasing the relative energy of the high-frequency spectrum [40]. It also suppresses the speech signal’s DC offset which is typically an artefact of the recording process. The frequency response of the filter is shown in Figure 5.2.
CHAPTER 5: Implementation of the Phoneme Recognition Front End

5.2.2 Feature Extraction

20-dimensional feature vectors are extracted over a fixed frame length of 20 ms every 10 ms, which is typical for frame based state-of-the-art speech recognition systems. The frame is obtained using the Hamming window function [41]. Assuming that the speech signal is quasi-stationary over the length of the analysis frame (a reasonable assumption since the frame is quite short), 10 linear predictive cepstral\(^1\) coefficients (LPCCs) [1] together with their deltas\(^2\) are calculated to form a 20-dimensional feature vector (this multi-dimensional feature vector will be referred to as a LPCC feature vector in this report). Note, however, that the zeroth cepstral coefficient is replaced with the frame energy before the delta features are determined. Cepstral mean subtraction [44] is also done beforehand in order to combat the effect of variability between different speakers and communication channels. Finally, the LPCC feature vector is normalised to prevent numerical underflow when using

\(^1\)The word *cepstral* was coined as a word play on *spectral* [42].

\(^2\)Delta features are used since they improve recognition accuracy [43].

Figure 5.2: Frequency response of the preemphasis filter.
covariance matrices in calculations.

5.2.3 Segmentation and Labelling

A phoneme spotter uses these extracted LPCC feature vectors to automatically segment and label the speech utterance into a string of phonemes. It is nothing more than a super-HMM structure into which pre-trained phoneme-HMMs (serving as models for the different phonemes and garbage classes) are embedded.

5.3 1996 ICSI Switchboard Phonetic Transcriptions

Since evaluation of the topic spotting systems had to be done on the Switchboard Corpus, hand-transcribed phonemic transcriptions of a portion of this database were needed for the training and testing of the phoneme recognition front end. Consequently, the 1996 ICSI (International Computer Science Institute) Switchboard phonetic transcriptions [18, 45] were employed for this purpose. The phonetic transcriptions were encoded with a variant of the \textit{ARPAbet} transcription system [1] that was used for the TIMIT Acoustic-Phonetic Continuous Speech Corpus [46]. The \textit{ARPAbet} transcription system was augmented with a set of diacritics representing such phonetic properties as glottalisation ("creaky voice"), nasalisation (typically applied to vocalic segments), frication, aspiration, de-voicing, unusual voicing and velarisation. In addition to this, transitional elements between adjacent vocalic or glide-like segments were explicitly marked.

The files associated with the 1996 ICSI Switchboard phonetic transcriptions are divided into the following four sets:

- \textbf{trn-chunk1.1}: Contains 746 speech segments corresponding to a total of 26.35 minutes of speech.
• **trn-chunk1.2**: Contains 253 speech segments corresponding to a total of 10.06 minutes of speech.

• **sri-align.1**: Contains 291 speech segments corresponding to a total of 12.6 minutes of speech.

• **dev-test**: Contains 451 speech segments corresponding to a total of 22.98 minutes of speech.

The telephone speech segments are given in *NIST/SPHERE* format and contain 16 bit data sampled at 8 kHz. Each segment contains the speech of only one speaker. The corresponding hand-transcribed word- and phonetic-transcription files\(^3\) are given in *ESPS' xlabel*-format.

### 5.3.1 Merging the Transcription Files

Each speech segment's time-aligned transcription files (there is a word- and a phonetic-transcription file for each segment of speech) had to be merged, since the implemented diacritic stripper (Section 5.3.2) needed to know where the word boundaries lay with respect to the phonetic boundaries in order to remove the diacritics from the phonetic transcriptions. Consequently, a *Perl 5.0* script was written to accomplish this task. During the merging process, each word boundary was forced to correspond to the phonetic boundary closest to it. As a result, each amalgamated transcription file contained only phonetic boundaries with the word boundaries realigned to correspond to them.

### 5.3.2 Diacritic Stripping of the Phonetic Transcriptions

From the previous discussion it is clear that diacritic symbols were used to augment the standard phonemes to show phonetic detail. For the purposes of this research, pure phone-\(^3\)These files contain time-aligned transcriptions.
mic labels were needed though. A diacritic stripper was therefore implemented as a \textit{Perl 5.0}
script in order to fold the original transcriptions down to a base group of 38 phonemes and
two garbage classes. The garbage classes were explicitly modelled as separate phonemes
and consist of a general garbage class (representing non-speech sounds and silence) and
a garbage class for stop consonant closures and releases (representing stop consonant clo-
sures and releases occurring without the other). The fact that the speech segments were
transcribed at the sub-phonemic level made the implementation of the diacritic stripper
unusually difficult.

A step-wise description of the diacritic stripping process follows below. Each step was
applied to a merged time-aligned transcription file as a whole before applying the next step.
Afterwards, the resulting time-aligned phonemic transcription file was saved in \textit{PATREC}'s
“t96”-format.

1. Three phones, each having the same base form and occurring next to each other
within a word, are folded into their common base form. The cases that occur in
the transcription files are well-behaved. No special rules are therefore needed when
combining these phones.

2. Two phones, each having the same base form and occurring next to each other within
a word, are folded either into:
   - their common base form, if the diacritic symbols \# (indicates a truncated phonetic segment) and ? (indicates uncertainty about the identity of a phonetic segment) do not occur in the pair’s diacritics, or
   - the general garbage class ***, if one or both of the diacritic symbols \# and ? occur in the pair’s diacritics.

\footnote{Within the 1996 ICSI Switchboard phonetic transcription system, stop consonants are partitioned into closure and release components. However, in the phonetic transcription files some closures appear without their releases following them and some releases appear without their closures preceding them. For these instances, no meaningful stop consonants could thus be constructed during the diacritic stripping process. Despite this fact, it was felt that semantic meaning could still be attached to these specific closures and releases, rather than allocating them to the general garbage class. As a result, they were assigned to the newly created garbage class for stop consonant closures and releases.}
Note that at least one of the phones in the pair should have diacritics in order for them to be folded into their common base form in accordance with the two points stated above. Under no circumstances will labels having the base forms ? and h# be combined.

3. Phones having the following base forms or diacritics are folded into the general garbage class ***:

   - all non-speech events having the base form h#,
   - all unknown speech sounds having the base form ?,
   - all glottal stops having the base form q, and
   - all phones containing the diacritics # and/or ?.

4. Remove all the remaining diacritics.

5. Closures which are not followed by their respective releases are folded into the garbage class for stop consonant closures and releases st*.

6. Releases which are not preceded by their respective closures are folded into the garbage class for stop consonant closures and releases st*.

7. The closures that now remain are folded into their succeeding release base forms.

8. The following five allophones are folded into corresponding phonemes:

   - ux is folded into uw,
   - axr is folded into er,
   - em is folded into m,
   - nx is folded into n, and
   - eng is folded into ng.
9. There are six phoneme groups where within-group confusions are not counted:

- $el$ is folded into $l$,
- $en$ is folded into $n$,
- $zh$ is folded into $sh$,
- $aa$ is folded into $ao$,
- $ix$ is folded into $ih$, and
- $ax$ is folded into $ah$.

Table 5.1 shows the complete Switchboard 40-phoneme set that was used during this research. The phoneme occurrences are given for the 1996 ICSI Switchboard phonemic transcriptions as a whole. The resulting phoneme set closely resembles the one proposed by K. F. Lee and H. W. Hon [47].
<table>
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<tr>
<th>No.</th>
<th>ID</th>
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<th>Example</th>
<th>Occurrences</th>
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<td></td>
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<td>ih</td>
<td>VOW</td>
<td>bit</td>
<td>3340</td>
</tr>
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<td>ah</td>
<td>VOW</td>
<td>but</td>
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</tr>
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<td>n</td>
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<td>non</td>
<td>2914</td>
</tr>
<tr>
<td>5</td>
<td>s</td>
<td>FRI</td>
<td>sack</td>
<td>1883</td>
</tr>
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<td>st*</td>
<td>GCR</td>
<td></td>
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</tr>
<tr>
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<td>iy</td>
<td>VOW</td>
<td>beat</td>
<td>1610</td>
</tr>
<tr>
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<td>VOW</td>
<td>bet</td>
<td>1406</td>
</tr>
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<td>SVOW</td>
<td>red</td>
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</tr>
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<td>VOW</td>
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<td>ow</td>
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<td>boat</td>
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<td>675</td>
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<td>599</td>
</tr>
<tr>
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<td>f</td>
<td>FRI</td>
<td>fin</td>
<td>596</td>
</tr>
<tr>
<td>30</td>
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<td>FT</td>
<td>muddy</td>
<td>580</td>
</tr>
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<td>31</td>
<td>uh</td>
<td>VOW</td>
<td>book</td>
<td>576</td>
</tr>
<tr>
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<td>FRI</td>
<td>hay</td>
<td>457</td>
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<tr>
<td>33</td>
<td>ng</td>
<td>NAS</td>
<td>sing</td>
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<tr>
<td>35</td>
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<td>STP</td>
<td>gag</td>
<td>325</td>
</tr>
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<td>FRI</td>
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<td>305</td>
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<td>290</td>
</tr>
<tr>
<td>38</td>
<td>jh</td>
<td>AFR</td>
<td>judge</td>
<td>202</td>
</tr>
<tr>
<td>39</td>
<td>ch</td>
<td>AFR</td>
<td>church</td>
<td>181</td>
</tr>
<tr>
<td>40</td>
<td>oy</td>
<td>VOW</td>
<td>boy</td>
<td>41</td>
</tr>
</tbody>
</table>

Table 5.1: The Switchboard 40-phoneme set (GGC = general garbage class; GCR = garbage class for stop consonant closures and releases; VOW = vowel; SVOW = semi-vowel; NAS = nasal; FRI = fricative; STP = stop consonant; AFR = affricate; FT = flaps and trills)
5.4 Training of the Phoneme-HMMs

Standard three-state left-to-right one-skip HMMs, using 20-dimensional full covariance Gaussian pdfs for the emission states, served as context independent models\(^5\) for the different phonemes (this includes the two garbage classes that were explicitly modelled as separate phonemes). The phoneme-HMMs were trained on the phonemic transcriptions of the trn-chunk1.1, trn-chunk1.2 and sri-align.1 datasets\(^6\) (approximately 49 minutes of speech in total):

- **Initialisation**: The first step was to initialise the hidden Markov models:
  
  - The transition probabilities for each phoneme-HMM were set as depicted in Figure 5.3. These initial transition probabilities were chosen, since they ensured fast convergence during training.

`\[
\begin{array}{ccc}
    1 & 0.8 & 0.8 \\
    0.1 & 0.2 & 0.2 \\
    0.1 & 0.2 & 0.2 \\
\end{array}
\]

![Figure 5.3: Initialisation of a phoneme-HMM.](image)

- The LPCC feature vectors for each observation of a certain phoneme class were equally split over the three states of the corresponding phoneme-HMM.
- The probability density functions were initialised to a mean of zero and unit covariance matrix.

---

\(^5\) Context independent models were used instead of context dependent ones, because of data scarcity.

\(^6\) The following two speech segments that occur in both the trn-chunk1.1 and sri-align.1 datasets, were excluded from the latter dataset for training purposes: 2780-A-0005 and 2830-A-0020. Note that they are the only speech segments that overlap in the 1996 ICSI Switchboard phonetic transcriptions.
One iteration of Viterbi training [48] was done in order to increase the convergence speed of the subsequent training of the phoneme-HMMs and to reduce the effect of non-optimal local maxima.

- **Training:** The phoneme-HMMs were then trained using the Viterbi reestimation algorithm which is based on the expectation maximisation (EM) principle [49]. Consequently, the reestimation process continued until the improvement, $I$, in the total training score (sum of log-likelihoods for all the observations over all the different phoneme-HMMs):

$$I = \frac{\text{old score} - \text{new score}}{\text{old score}},$$

fell below the predefined threshold of $5 \times 10^{-4}$. The total training score as a function of the Viterbi iteration number is shown in Figure 5.4.

![Figure 5.4: Training score as a function of the Viterbi iteration number.](http://scholar.sun.ac.za)
5.5 Phoneme Spotter

A phoneme spotter was subsequently implemented and is nothing more than a super-HMM structure consisting of the trained phoneme-HMMs. The phoneme spotter was employed to automatically segment and label a speech utterance, represented by a 20-dimensional stream of LPCC feature vectors, into a string of phonemes using a maximum likelihood approach. This was accomplished with the help of the Viterbi algorithm by determining the optimal path through the spotter-HMM.

A block diagram of the phoneme spotter is depicted in Figure 5.5 (adapted from Figure 3.13 in [50]). From the figure it is clear that the a priori probabilities of the different phonemes were also embedded in the structure by setting the transition probabilities from the entry null state of the super-HMM structure to the first emission state of each phoneme-HMM equal to the a priori probability of that phoneme. $P(q_k)$ therefore represents the a priori probability of phoneme $k$ in the figure. The a priori probabilities were estimated by simply calculating the occurrence frequency of each phoneme in the trn-chunk1.1, trn-chunk1.2 and sri-align.1 datasets, the same datasets that were used during the training of the phoneme-HMMs. Figure 5.6 shows the a priori distribution of the phonemes in the front end’s training set.

An example of a time-aligned phonemic transcription that was generated by the phoneme recogniser is shown in Table 5.2. It is of speech segment 2151-A-0009 that was obtained from the dev-test dataset. Its true phoneme sequence can be seen in Table 5.3. Both tables are given in PATREC’s “t96”-format. It is apparent from these tables that the front end failed to generate the correct phoneme sequence for the speech segment.
Figure 5.5: Block diagram of the phoneme spotter.
Figure 5.6: A priori distribution of phonemes in the front end’s training set.
<table>
<thead>
<tr>
<th>Time (s)</th>
<th>Phoneme</th>
</tr>
</thead>
<tbody>
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<td>0.06</td>
<td>th</td>
</tr>
<tr>
<td>0.11</td>
<td>ow</td>
</tr>
<tr>
<td>0.23</td>
<td>l</td>
</tr>
<tr>
<td>0.34</td>
<td>p</td>
</tr>
<tr>
<td>0.41</td>
<td>f</td>
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<td>ao</td>
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<tr>
<td>3.00</td>
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</tbody>
</table>

Table 5.2: Front end’s time-aligned phonemic transcription of speech segment 2151-A-0009.
<table>
<thead>
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<th>Time (s)</th>
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<th>Word</th>
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</tr>
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<td>0.06567800</td>
<td>tcl</td>
<td>st*</td>
<td>-</td>
</tr>
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<td>don't</td>
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<td>uh</td>
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<td>dx</td>
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</tr>
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<td>-</td>
</tr>
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<td>d_fr_!</td>
<td>st*</td>
<td>at</td>
</tr>
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<td>ao</td>
<td>-</td>
</tr>
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<td>l</td>
<td>all</td>
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<td>do</td>
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</table>

Table 5.3: Time-aligned hand-transcriptions of speech segment 2151-A-0009.
5.6 Evaluation of the Phoneme Recognition Front End

A phoneme classifier was implemented in order to evaluate the performance of the phoneme recognition front end on the phonemes obtained from the diacritically stripped *dev-test* dataset (approximately 23 minutes of speech). Insertion- and deletion-errors were not taken into account during the evaluation process. To classify a phoneme, Bayes' *maximum a posteriori* (MAP) decision rule [51] was employed:

\[ k = \arg \max_k P(q_k|z), \]  

where \( P(q_k|z) \) is the *a posteriori* probability of \( q_k \) given the phoneme’s acoustic observation sequence \( z \) (consisting of LPCC feature vectors). Its value can be determined using Bayesian inversion:

\[ P(q_k|z) = \frac{f(z|q_k)P(q_k)}{f(z)}, \]  

where \( f(z|q_k) \) is the value of the probability density function which is calculated by the phoneme-HMM of \( q_k \) for \( z \). \( P(q_k) \) is the *a priori* probability of phoneme \( k \). The normalising pdf \( f(z) \) is the same for all the phoneme classes and thus causes an arbitrary, but *common* scaling of the *a posteriori* probabilities. As a result, Equation 5.3 can be written as:

\[ k = \arg \max_k f(z)P(q_k|z) \]

\[ = \arg \max_k f(z|q_k)P(q_k), \]  

without affecting the outcome of the MAP decision rule. The phoneme classifier was therefore implemented as shown in Figure 5.7 (adapted from Figure 3.12 in [50]).

The recognition accuracy for each individual phoneme was subsequently calculated as follows:

\[ R_k = \frac{\text{number of correct classifications of phoneme } k}{\text{total number of occurrences of phoneme } k}, \]  

(5.6)
where $R_k$ is the recognition accuracy for phoneme $k$. The recognition rates are presented in Figure 5.8. The recognition accuracy of the front end, $R$, was then calculated as shown below:

$$R = \sum_k P(q_k) R_k.$$  \hspace{1cm} (5.7)

An overall recognition accuracy of 43.1\% was consequently measured. This is indicated by the horizontal line in Figure 5.8.

A context independent confusion matrix was produced during the evaluation process. Its 3D confusion plot is illustrated in Figure 5.9. Correct classifications are located on the main diagonal, while incorrect classifications ("confusions") lie off the main diagonal. Note that this confusion matrix was employed by those topic spotters that generated soft counts for their lexicon members.
Figure 5.8: Recognition accuracy for individual phonemes. The overall recognition accuracy of the phoneme recognition front end is indicated by the horizontal line.

Figure 5.9: 3-dimensional confusion plot of phoneme recognition experiment.
5.7 Summary

This chapter described how signal processing-, feature extraction-, pattern recognition-, and statistical modelling-techniques were used to realise a practical, speaker independent, context independent phoneme recogniser with an overall recognition accuracy of 43.1%. It was subsequently employed to phonemically transcribe CRIM’s subset of the Switchboard Corpus (Section 6.2.1) in order to allow comparison of the different topic spotting algorithms with each other.
Chapter 6

Experiments and Results

I venture to define science as a series of interconnected concepts and conceptual schemes arising from experiment and observation and fruitful of further experiments and observations. The test of a scientific theory is, I suggest, its fruitfulness.

— James B. Conant

6.1 Introduction

The purpose of this chapter is to report on the experimental setup, hardware specifications, software implementation, and most important experiments. No results are presented for those adjustments that yielded a deterioration in topic spotting performance.

The experimental setup is discussed in Section 6.2. Details about CRIM’s subset of the Switchboard Corpus are presented, followed by an explanation of how the performance of each topic spotter was evaluated. Afterwards, the test for statistical significance is closely examined. An overview is then given of the experiments that were conducted. Next, the hardware specifications are presented in Section 6.3. This is followed by an explanation in Section 6.4 of how the software was implemented. Finally, Section 6.5 reports on the
results of the most important experiments.

6.2 Experimental Setup

6.2.1 Switchboard Corpus

The Switchboard Corpus [35], collected at Texas Instruments, contains 2430 conversations (4860 channels\(^1\)) covering 52 topics and comprising 240 hours of recorded speech. Over 500 speakers of both sexes from every major dialect of American English participated in the project. It was specifically designed to support the development of telephone-based speech technology as well as basic research on spontaneous conversational speech and language.

CRIM's subset of the Switchboard Corpus was used during this research for experimental purposes, and consists of 506 channels covering 10 topics. The channels of interest were extracted from the corpus with the help of the PATREC software system as follows:

1. The 345 conversations, containing the 506 channels of interest, were split into their respective channels.

2. Each conversation's channels were then compared with one another in order to remove silence and reduce/eliminate the effects of cross talk:
   
   - If a speech segment from the one channel had more than twice the energy of the time-aligned speech segment from the other channel, the speech segment with the highest energy was kept, while the other one was removed.
   - If a speech segment from the one channel had less than twice the energy of the time-aligned speech segment from the other channel, both speech segments were removed from their respective channels.

\(^1\)Each conversation contains two channels, where a channel represents the speech of only one speaker.
• If the speaker was active for less than 400 ms in a speech segment, it was removed.

• Speech segments containing silence of shorter than 100 ms were not removed. This was done in order to protect closures.

3. Finally, the 506 channels of interest (approximately 1462 minutes of speech) were extracted.

These channels were subsequently arranged to form a training- and a testing-set in the proportion 9:1. The training set was also split up to form a training- and a validation-subset in the proportion 4:1, with these subsets used in conjunction with the extended training criterion (Section 2.2.5) to estimate the appropriate size of the final lexicon as a percentage.

The topic distribution of the 506 channels can be seen in Table 6.1. From the table it is obvious that the topics are such that the channels may well fit more than one topic (e.g. "crime" and "gun control"). However, since each channel is allocated to only one topic in the corpus, many detections that registered as false alarms may in fact be correct.

<table>
<thead>
<tr>
<th>Topic (10)</th>
<th>Number of Channels (506)</th>
<th>Training Set (455)</th>
<th>Testing Set (51)</th>
<th>Training Subset (360)</th>
<th>Validation Subset (95)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air Pollution</td>
<td>302</td>
<td>36</td>
<td>32</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>Music</td>
<td>308</td>
<td>51</td>
<td>46</td>
<td>5</td>
<td>36</td>
</tr>
<tr>
<td>Crime</td>
<td>312</td>
<td>53</td>
<td>48</td>
<td>5</td>
<td>38</td>
</tr>
<tr>
<td>Gun Control</td>
<td>314</td>
<td>38</td>
<td>34</td>
<td>4</td>
<td>27</td>
</tr>
<tr>
<td>Buying a Car</td>
<td>320</td>
<td>59</td>
<td>53</td>
<td>6</td>
<td>42</td>
</tr>
<tr>
<td>Universal Public Service</td>
<td>327</td>
<td>27</td>
<td>24</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>Pets</td>
<td>351</td>
<td>69</td>
<td>62</td>
<td>7</td>
<td>49</td>
</tr>
<tr>
<td>Public Education</td>
<td>353</td>
<td>60</td>
<td>54</td>
<td>6</td>
<td>43</td>
</tr>
<tr>
<td>Exercise and Fitness</td>
<td>356</td>
<td>55</td>
<td>50</td>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>Family Life</td>
<td>358</td>
<td>58</td>
<td>52</td>
<td>6</td>
<td>41</td>
</tr>
</tbody>
</table>

Table 6.1: Topic distribution of the 506 channels.
It was determined that 0.23% of the topic spotting data was used during the training of the phoneme recognition front end. Since the overlap was small the marginal effect that it had on results was ignored.

6.2.2 Method of Evaluation

The task was a detection problem. System evaluation was therefore performed by means of an ROC curve. The error area above it was used to evaluate system performance.

6.2.3 Statistical Significance

Statistical significance of the results, represented by the ROC curves of any two topic spotting systems, was verified by means of the McNemar test [32, 33] modified (Section 6.2.3.1) to compensate for the fact that the task was one of detection rather than classification. Since an algorithm's detection errors consist of missed detections and false alarms, it was decided to perform separate McNemar tests over a range of error indices, where each index represents a specific missed detection rate to false alarm rate. A two-tailed probability was therefore calculated for each error index in order to determine whether the measured difference between the topic spotting systems could have arisen under the null hypothesis.

During this research, separate McNemar tests were performed over a range of error indices spanning from 0.1 to 10, with the threshold (probability) for rejecting the null hypothesis set to 0.1. The null hypothesis was consequently rejected for those McNemar probabilities that fell below this threshold value. Note that the tests for statistical significance were limited to these error indices, because the ROC curves are usually very close to one another for indices outside of this range.

---

2The topic spotters will usually have different decision thresholds for the same error index.

3The null hypothesis states that both algorithms are equally likely to make detection errors.

4In the field of speech recognition it is standard practice to select this rejection threshold (α).
In this chapter, each ROC graph of two competing topic spotting systems is accompanied by a graph showing the outcome of the McNemar tests. The graphs will be depicted as shown in Figures 6.1 and 6.2. Note that:

- Statistical significance of the results was verified for those ROC segments falling inside the shaded region of the ROC graph:
  - The line at the top of the shaded region represents an error index of 0.1.
  - The line extending from the top left-hand side to the bottom right-hand side of the ROC graph represents an error index of 1.
  - The line at the left-hand side of the shaded region represents an error index of 10.

- The threshold for rejecting the null hypothesis will be indicated by a dotted line on the McNemar graph.

Several Matlab functions were written in order to accomplish the task described above.

### 6.2.3.1 Modified McNemar Test

The McNemar test can be used for classification problems in order to determine whether the measured difference in performance between two algorithms on the same dataset is statistically significant. This is accomplished by comparing the classification decisions of the algorithms, which are assumed to be statistically independent, with one another. The comparison is performed by postulating the null hypothesis which states that the algorithms are equally likely to make classification errors. A two-tailed probability is then calculated to determine whether the null hypothesis is valid.

As was mentioned previously, the task during this research was one of detection rather than classification. The null hypothesis was therefore redefined to state that the two algorithms
**Figure 6.1:** ROC graph: Topic spotter 1 vs. Topic spotter 2. The line at the top of the shaded region represents an error index (missed detection rate: false alarm rate) of 0.1, the line extending from the top left-hand side to the bottom right-hand side of the ROC graph an index of 1, and the line at the left-hand side of the shaded region an index of 10.

**Figure 6.2:** McNemar graph: Topic spotter 1 vs. Topic spotter 2. The threshold for rejecting the null hypothesis is indicated by the dotted line.
are equally likely to make detection errors (sum of missed detections and false alarms). Consequently, the McNemar test had to be modified.

Let $T_1$ and $T_2$ represent topic spotter 1 and topic spotter 2 respectively. The joint performance of the two algorithms on the same dataset can then be summarised as shown in Table 6.2.

<table>
<thead>
<tr>
<th></th>
<th>$T_2$</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td></td>
<td>$n_{00}$</td>
<td>$n_{01}$</td>
</tr>
<tr>
<td>Incorrect</td>
<td>$n_{10}$</td>
<td></td>
<td>$n_{11}$</td>
</tr>
</tbody>
</table>

**Table 6.2:** Joint performance of the two topic spotters on the same dataset.

In this table:

- $n_{00} =$ the number of times that both algorithms made the correct detection decision.\(^5\)
- $n_{01} =$ the number of times that $T_1$ made the correct detection decision, while $T_2$ did not.
- $n_{10} =$ the number of times that $T_2$ made the correct detection decision, while $T_1$ did not.
- $n_{11} =$ the number of times that both algorithms made the incorrect detection decision.

In a similar manner the joint probabilities $\phi_{00}$, $\phi_{01}$, $\phi_{10}$ and $\phi_{11}$ can be defined. For example:

\[
\phi_{00} = P(T_1 \text{ does not make an error}, T_2 \text{ does not make an error}) \\
= \frac{n_{00}}{n},
\]

where $n$ equals the total number of detection decisions ($n_{00} + n_{01} + n_{10} + n_{11}$).

\(^5\)The statistically independent binary decision whether or not to allocate a topic to a conversation.
The null hypothesis dictates that both algorithms are equally likely to make detection errors. Consequently, this implies that their error rates should be equal:

$$e_1 = e_2,$$

(6.2)

where $$e_1 = \phi_{10} + \phi_{11}$$ (T1's error rate) and $$e_2 = \phi_{01} + \phi_{11}$$ (T2's error rate). Equation 6.2 can therefore be written as follows:

$$\phi_{10} + \phi_{11} = \phi_{01} + \phi_{11}$$

$$\therefore \phi_{10} = \phi_{01}.\quad (6.3)$$

The conditional probability $$\phi_{T1}$$, that T1 makes an incorrect detection decision given that only one of the two algorithms makes an error, should consequently be equal to 0.5:

$$\phi_{T1} = \frac{\phi_{10}}{\phi_{01} + \phi_{10}} = 0.5.\quad (6.4)$$

As a result, given that only one of the algorithms makes an incorrect detection decision, it is equally likely to be either one. To test the null hypothesis it is therefore sufficient to examine the detection decisions on which only one topic spotter makes an error ($$n_{01} + n_{10}$$).

If the test is thus conditioned on the number of detection decisions $$k = n_{01} + n_{10}$$, $$N_{10}$$ ($$n_{10}$$'s random variable) should have a binomial distribution $$\beta(k, \frac{1}{2})$$ under the null hypothesis. The validity of the null-hypothesis is then determined by applying a two-tailed test to the observation of a random variable $$M$$ drawn from $$\beta(k, \frac{1}{2})$$:

$$P_2 = 2P(n_{10} \leq M \leq k) \quad \text{when } n_{10} > \frac{k}{2}$$

(6.5)

$$= 2P(0 \leq M \leq n_{10}) \quad \text{when } n_{10} < \frac{k}{2}$$

(6.6)

$$= 1 \quad \text{when } n_{10} = \frac{k}{2}.$$
These two-tailed probabilities are calculated directly as follows:

\[
P_2 = 2 \sum_{m=n_{10}}^{k} \binom{k}{m} \left(\frac{1}{2}\right)^k \quad \text{when } n_{10} > \frac{k}{2} \tag{6.8}
\]
\[
P_2 = 2 \sum_{m=0}^{n_{10}} \binom{k}{m} \left(\frac{1}{2}\right)^k \quad \text{when } n_{10} < \frac{k}{2} \tag{6.9}
\]

After determining \(P_2\) for \(n_{10}\), the null hypothesis is rejected if the two-tailed probability is below some significance level \(\alpha\) (rejection threshold).

### 6.2.4 Experiments

Initial experiments were conducted to determine optimal parameters for lexicon initialisation. The simultaneous inclusion of 2- and 3-grams was investigated, as well as the simultaneous inclusion of 2-, 3- and 4-grams. In addition to this, recurrence thresholds of 2, 3 and 4 were evaluated. For the topic spotting systems of Section 6.5 (i.e. ENWN, SMART, and extended SMART), best performance was obtained when phoneme n-grams in the length range 2 to 4 were allowed, and when the recurrence threshold was set to 2 so that those keystrings that occurred more than once in the training data were included.\(^6\)

Consequently, the initial *untrained* lexicon of each topic spotter contained a total of 189451 keystrings (1555 2-gram, 43426 3-grams, 144470 4-grams). Note that the results presented in this chapter are given for these parameter values.

*Closed-set*\(^7\) experiments were conducted to evaluate the topic spotting algorithms. This was done in order to achieve better utilisation of the available data. The results obtained for the most important experiments will be presented in Section 6.5.

---

\(^6\)This result makes intuitive sense, since more keystrings were available for selection by the training algorithm of each topic spotter when these parameters were used.

\(^7\)The testing data contains topics that are present in the training data.
6.3 Hardware

Experiments were carried out on an *Intel Pentium III Coppermine 600EB* system. The computer had 640 MB of RAM and *Redhat Linux 6.2* was installed.

6.4 Software

The topic spotting systems were implemented in the *PATREC* software system. Of particular importance was the implementation of ENWN and SMART. Scheffler’s code had to be rewritten in order to allow efficient and practical comparison on the Switchboard Corpus. The following modifications were consequently introduced:

- Pointer code was used at certain critical stages of the program to reduce computational overhead when working with its data structures.

- Lookup tables were employed. For example, rather than searching sequentially through the lexicon to determine the presence of a keystring, a lookup table was used instead.

- SMART’s sequence matchers were embedded into a tree structure to exploit similarities existing between them. Consider as an example the hypothetical lexicon (Figure 6.3) generated by SMART. Its sequence matchers are shown in Figure 6.4. Exploiting the similarities between these sequence matchers yields the tree structure in Figure 6.5. Fitting each observed keystring \( y^8 \) to this structure results in a significant improvement in SMART’s simulation time, since multiple calculations of the same values are avoided. For a full description of how to generate conversation- and topic-vectors using a tree structure, refer to the flow diagram in Figure A.17 (Appendix A).

\(^8\) \( y \) should have the same length as the longest lexicon member(s) if it is going to be fitted to a tree structure.
CHAPTER 6: Experiments and Results

Figure 6.3: The hypothetical lexicon generated by SMART.

Figure 6.4: Sequence matchers corresponding to keystrings in SMART's hypothetical lexicon.
Figure 6.5: Tree structure corresponding to the hypothetical lexicon's sequence matchers.
Where necessary, the layout of the code was changed.

Simulation times of ENWN and SMART were considerably reduced. This is clearly evident from Table 6.3. Note that conservative estimates are given for the simulation times of Scheffler’s implementation of ENWN and SMART.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Simulation Time (days) Before</th>
<th>After</th>
<th>Percentage Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENWN</td>
<td>21.1</td>
<td>0.29</td>
<td>98.6%</td>
</tr>
<tr>
<td>SMART</td>
<td>96</td>
<td>1.82</td>
<td>98.1%</td>
</tr>
</tbody>
</table>

Table 6.3: Simulation times of ENWN and SMART — phoneme  n-grams in the length range 2 to 4 were allowed, and the recurrence threshold was set to 2.

An added benefit of the optimisation process was a reduction in memory usage. Scheffler’s implementation of ENWN and SMART uses more than 820 MB of RAM. The new implementation, on the other hand, uses less than 600 MB of RAM.

Flow diagrams of ENWN and SMART, before and after the modifications were introduced, are shown in Appendix A.
CHAPTER 6: Experiments and Results

6.5 Results

6.5.1 ENWN versus SMART

In this section the performances of ENWN, SMART, and a system using soft counts along with the Euclidean distance measure are presented. The latter topic spotter will be referred to as the SE algorithm.

Before SMART was compared as a whole to ENWN, the introduction of each individual enhancement\(^9\) by SMART was investigated:

- **Introducing soft counts — ENWN vs. SE:** The training curves of ENWN and SE are shown in Figures 6.6 and 6.7 respectively. Comparative results for these topic spotters are illustrated in Figure 6.8. The replacement of ENWN’s hard counts with SMART’s soft counting strategy yields an 11.5% reduction in ROC error area. The McNemar graph (Figure 6.9) indicates that regions of statistical significance exist.

- **Introducing the CE distance measure — SE vs. SMART:** The training curve of SMART is depicted in Figure 6.10. The ROC graph of SE versus SMART is shown in Figure 6.11. Replacing SE’s Euclidean norm with the CE distance measure results in a reduction of 27.5% in ROC error area. The outcome of the McNemar tests is presented in Figure 6.12. It is apparent from this graph that the measured differences between SE and SMART are statistically significant over a large range of error indices.

When SMART is compared to ENWN, a 35.8% reduction in ROC error area is observed. Comparative results are shown in Figure 6.13. The McNemar graph of Figure 6.14 indicates that the improvement is statistically significant over virtually the entire range of error indices that were investigated.

\(^9\)The enhancements introduced by SMART are the use of soft counts and the CE distance measure.
Figure 6.6: ENWN’s training curve.

Figure 6.7: SE’s training curve.
CHAPTER 6: Experiments and Results

Figure 6.8: ROC graph: ENWN vs. SE.

Figure 6.9: McNemar graph: ENWN vs. SE.
Figure 6.10: SMART's training curve.
Figure 6.11: ROC graph: SE vs. SMART.

Figure 6.12: McNemar graph: SE vs. SMART.
CHAPTER 6: Experiments and Results

Figure 6.13: ROC graph: ENWN vs. SMART.

Figure 6.14: McNemar graph: ENWN vs. SMART.
Details of the trained lexicons and overall results of ENWN, SE and SMART are presented in Table 6.4. From the table it is clear that the CE distance measure enables SMART to isolate longer lexicon members during pruning of its initial lexicon. Since longer keystrings tend to contain more topic specific information, this may very well account for the significant improvement in topic spotting performance. The fact that the CE distance measure enables SMART to successfully use 4-grams for the purpose of topic discrimination could also explain why SMART’s training curve rises steadily over its central region, while ENWN’s and SE’s remain flat.

<table>
<thead>
<tr>
<th>Topic Spotter</th>
<th>Feature Extraction</th>
<th>Distance Measure</th>
<th>Size of Trained Lexicon</th>
<th>Lexicon Members of Length</th>
<th>ROC Error Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENWN</td>
<td>Hard</td>
<td>Euclidean</td>
<td>1222</td>
<td>141</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td>Soft</td>
<td>Euclidean</td>
<td>405</td>
<td>23</td>
<td>0.193</td>
</tr>
<tr>
<td>SE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMART</td>
<td>Soft</td>
<td>Cross-entropy</td>
<td>13234</td>
<td>0</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1431</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>11803</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.4: Details of the trained lexicons and overall results of ENWN, SE and SMART.

6.5.1.1 Discussion

It is expected that comparative results between ENWN and SMART could further be improved by using a more sophisticated phoneme recogniser. Previous closed-set tests [24, 25, 26] on the OGI-MLTS Corpus indicated that an improvement in phoneme recognition accuracy not only resulted in improved performance for both algorithms, but also increased the improvement of SMART over ENWN. It thus appears that the advantages obtained by using SMART apply also when phoneme recognition is good.
6.5.2 Extended SMART

SMART was extended by replacing its soft counting strategy with the newly developed one of Section 4.4. The training curve for the extended SMART algorithm is presented in Figure 6.15.

Comparative results between SMART and its extended version are depicted in Figure 6.16. Replacing SMART's soft counting strategy results in a 5% reduction in ROC error area. The outcome of the McNemar tests is shown in Figure 6.17. It is evident from this graph that regions of statistical significance exist between these algorithms.

The improvement of the extended SMART algorithm over ENWN is characterised by a 39% reduction in ROC error area. This is clearly evident from the ROC graph of Figure 6.18. The McNemar graph (Figure 6.19) indicates that the results are statistically significant over all error indices that were investigated.

The extended SMART algorithm's performance and details of its trained lexicon are shown in Table 6.5. Note that the number of keystrings used by this algorithm is almost half of that used by SMART (Table 6.4). It consequently produces better results with fewer keystrings.

<table>
<thead>
<tr>
<th>Topic Spotter</th>
<th>Feature Extraction</th>
<th>Distance Measure</th>
<th>Size of Trained Lexicon</th>
<th>Lexicon Members of Length 2</th>
<th>Lexicon Members of Length 3</th>
<th>Lexicon Members of Length 4</th>
<th>ROC Error Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extended SMART</td>
<td>Extended Soft</td>
<td>Cross-entropy</td>
<td>7869</td>
<td>0</td>
<td>1049</td>
<td>6820</td>
<td>0.133</td>
</tr>
</tbody>
</table>

Table 6.5: The extended SMART algorithm's performance and details of its trained lexicon.
Figure 6.15: Extended SMART's training curve.
Figure 6.16: ROC graph: SMART vs. Extended SMART.

Figure 6.17: McNemar graph: SMART vs. Extended SMART.
CHAPTER 6: Experiments and Results

Figure 6.18: ROC graph: ENWN vs. Extended SMART.

Figure 6.19: McNemar graph: ENWN vs. Extended SMART.
6.6 Summary

In this chapter, the experimental setup, hardware specifications, software implementation, and outcome of the most important experiments were presented. The results obtained for the closed-set tests are summarised below:

- The improvement of SMART over ENWN is characterised by a 35.8% reduction in ROC error area. The measured differences are statistically significant over a large range of error indices. The CE distance measure is the main contributor to SMART's success.

- Replacing SMART's soft counting strategy with the newly developed one of Section 4.4 yields a 5% reduction in ROC error area. This is accompanied by regions of statistical significance. The "pigheaded" behaviour of the front end's phoneme-HMMs (Section 4.4.5) probably had a negative impact on the extended SMART algorithm's performance. Much could thus be gained if this problem is addressed.

- Extended SMART also outperforms ENWN. A 39% reduction in ROC error area is observed. The results are statistically significant over all error indices that were investigated.

The ROC curves of these topic spotters are shown in Figure 6.20.
Figure 6.20: ROC graph: ENWN vs. SMART vs. Extended SMART.
Chapter 7

Conclusions

The difficulty lies not in the new ideas, but in escaping the old ones, which ramify, for those brought up as most of us have been, into every corner of our minds.

— John M. Keynes

7.1 Summary

During this research, an investigation was conducted into the performance of two competing phoneme-based topic spotting systems, ENWN and SMART. A previous result, obtained on the OGI-MLTS Corpus, suggested that SMART yields a large improvement over ENWN. However, this result was tentative due to the small data set and the use of few topics. The purpose of the research reported here was therefore to determine whether SMART would yield a similar result under a more rigorous test on the larger Switchboard Corpus which is traditionally used in this field. It can be concluded from the experiments that were conducted, that the initial optimism regarding the performance of SMART was justified, since a considerable improvement over ENWN was observed.

An investigation was also conducted into the improvement of SMART. This resulted in
a new soft counting strategy that established a closer connection between the phoneme recognition front end and the rest of the topic spotting system. Low level information, supplied by the phoneme recogniser, is consequently included during the soft counting process in order to obtain a better estimate of the number of times that a lexicon member occurs in the conversation's true phoneme sequence. Although only one of the approaches investigated yielded an improvement, many opportunities still exist for improving SMART. They will be listed in the next section.

### 7.2 Suggestions for Possible Improvement

Several approaches remain that could possibly improve SMART's performance even further. They are listed below:

- The simultaneous modelling of insertion-, deletion- and substitution-errors could lead to an improvement in performance. To accomplish this, the sequence matchers can be replaced by HMMs. However, this approach is extremely computationally expensive.

- If enough hand-transcribed phonemic transcriptions are available to test the phoneme recognition front end, a context dependent model could be developed of the confusion between the different phonemes. Subsequently, this would enable context dependencies between adjacent phonemes to be taken into account during the topic spotting process.

- If a way could be found to considerably reduce the size of the trained lexicon without decreasing system performance too much, it would allow the use of more sophisticated techniques during the topic spotting process. Consequently, these techniques may compensate for the deterioration in performance that occurs as a result of the smaller lexicon.

- Several topic models remain that could result in an improvement in topic spotting performance. They include both parametric and non-parametric models. However,
provided that enough training data and sufficient computational resources are available, the use of a non-parametric algorithm (e.g. Parzen or K-nearest neighbours [52]) may be the only way to accurately model the data's distribution.

- During this research, short keystrings of no longer than 4 phonemes were used. However, longer keystrings tend to contain more topic-specific information. It consequently follows that much could be gained if a method can be found that isolates longer meaningful keystrings in the data.

- Modelling the simultaneous occurrence of topics in the way described by Imai et al. [9] could yield a better result.
Bibliography


Appendix A

Flow diagrams of the Optimisation of ENWN and SMART

Flow diagrams of ENWN and SMART, before and after they were optimised, will be shown in this appendix. Scheffler’s implementation of ENWN and SMART is illustrated in Figures A.1–A.9, while flow diagrams of their new implementation are depicted in Figures A.10–A.17. Note that:

- The overall flow diagram of Scheffler’s implementation of ENWN is given in Figure A.1.
- The overall flow diagram of Scheffler’s implementation of SMART is given in Figure A.7.
- The overall flow diagram of the new implementation of ENWN is given in Figure A.10.
- The overall flow diagram of the new implementation of SMART is given in Figure A.16.

Simulation times are also shown in these flow diagrams.
CHAPTER A: Flow diagrams of the Optimisation of ENWN and SMART

Figure A.2: Build lexicon from training set, and construct conversation- and topic-vectors

Figure A.2: Build lexicon from training subset, and construct conversation- and topic-vectors

Figure A.3: Extract conversation vectors from validation subset using training subset's lexicon

Figure A.4: Perform extended training using the conversation- and topic-vectors extracted above

Figure A.3: Extract conversation vectors from testing set using training set's lexicon (trained)

Figure A.6: Determine performance of ENWN using the testing set's conversation vectors and the training set's topic vectors

Begin

1.77 days

1.4 days

21.8 hours

17 days

3.87 minutes

Negligible

End

Total simulation time = 21.1 days

Figure A.1: Overall flow diagram of ENWN. Estimated simulation times are also shown — phoneme n-grams in the length range 2 to 4 were allowed, and the recurrence threshold was set to 2. (Scheffler's implementation)
Figure A.2: Lexicon initialisation. Conversation- and topic-vectors are also generated. Hard counts are employed. (Scheffler's implementation)
Begin

For all topics

For all conversations belonging to topic

For all keystring occurrences in conversation

Search sequentially through lexicon in order to determine whether it contains the keystring

If keystring occurs in lexicon, increment its value by 1 in conversation vector

Convert hard counts in conversation vectors to frequencies

End

Figure A.3: Extracting conversation vectors for a given lexicon. Hard counts are employed. (Scheffler's implementation)
CHAPTER A: Flow diagrams of the Optimisation of ENWN and SMART

Begin

Are there less than 100 elements left in lexicon obtained from training subset?

Yes

Determine target percentage that will serve as a stopping criterion during further training

No

Prune 100 lexicon members using training subset’s conversation- and topic-vectors

Determine performance of algorithm using validation subset’s conversation vectors and training subset’s topic vectors

Prune training set’s lexicon down to optimal size using its conversation- and topic-vectors

End

Figure A.5

Determine optimal size of lexicon obtained from training set using target percentage

Figure A.4: Extended training. (Scheffler’s implementation)
Calculate distances between each conversation vector and all wrong topic vectors

For all topics

For all conversations belonging to topic

Find the nearest wrong neighbour

For all lexicon elements

Calculate contribution of lexicon element towards topic discrimination

Add newly calculated contribution to those previously calculated for this element

Mark element that helps the least towards topic discrimination as obsolete

Adjust distances between each conversation vector and all wrong topic vectors

Have 100 keystings been marked as obsolete?

Yes

Remove those lexicon members that were marked as obsolete

End

No

Figure A.5: Pruning lexicon members. (Scheffler’s implementation)
Begin

For all topics

For all conversations belonging to topic

Determine distances between conversation vector and all topic vectors

Generate topic scores by normalising these distances to sum to unity

For all decision thresholds

Determine number of detections and number of false alarms

Add these values to those previously obtained for this decision threshold

For all decision thresholds

Determine overall detection- and false alarm-rate

Calculate ROC area using trapezium method

End

Figure A.6: Determining an algorithm’s performance. (Scheffler’s implementation)
CHAPTER A: Flow diagrams of the Optimisation of ENWN and SMART

Figure A.7: Overall flow diagram of SMART. Estimated simulation times are also shown — phoneme n-grams in the length range 2 to 4 were allowed, and the recurrence threshold was set to 2. (Scheffter’s implementation)
Begin

For all topics

For all conversations belonging to topic

For all keystring occurrences in conversation

Fit observed keystring to sequence matchers having the same length as it has

Add these results to conversation- and topic-vector

Convert soft counts in conversation- and topic-vectors to frequencies

End

Figure A.8: Extracting conversation- and topic-vectors for a given lexicon. Soft counts are employed. (Scheffler’s implementation)
Begin

For all topics

For all conversations belonging to topic

For all keystring occurrences in conversation

Fit observed keystring to sequence matchers having the same length as it has

Add these results to conversation vector

Convert soft counts in conversation vectors to frequencies

End

Figure A.9: Extracting conversation vectors for a given lexicon. Soft counts are employed. (Scheffler's implementation)
CHAPTER A: Flow diagrams of the Optimisation of ENWN and SMART

Begin

Build lexicon from training set, and construct conversation- and topic-vectors

6.52 minutes

Extract conversation- and topic-vectors from testing set using training set's lexicon

36 seconds

Ignore testing set's topic vectors during further calculations

Build lexicon from training subset, and construct conversation- and topic-vectors

4.2 minutes

Extract conversation- and topic-vectors from validation subset using training subset's lexicon

51 seconds

Ignore validation subset's topic vectors during further calculations

Perform extended training using the valid conversation- and topic-vectors extracted above

6.76 hours

Determine performance of ENWN using the testing set's conversation vectors and the training set's topic vectors

Negligible

End

Total simulation time = 6.96 hours

Figure A.10: Overall flow diagram of ENWN. Simulation times are also shown — phoneme n-grams in the length range 2 to 4 were allowed, and the recurrence threshold was set to 2. (new implementation)
Begin

For all topics

For all conversations belonging to topic

For all key string occurrences in conversation

Use lookup table to determine whether key string occurs in the lexicon, and if so, its location

If lexicon does not contain the key string, add it, and update lookup table with its location

Adjust count of key string in topic vector by incrementing its value by 1

Remove lexicon members that occur less than a certain number of times in the data

Update lookup table

For all topics

For all conversations belonging to topic

For all key string occurrences in conversation

Use lookup table to determine whether key string occurs in the lexicon, and if so, its location

If key string occurs in lexicon, increment its value by 1 in conversation vector

End

Figure A.11: Lexicon initialisation. Conversation- and topic-vectors are also generated. Hard counts are employed. (new implementation)
Begin

For all topics

For all conversations belonging to topic

For all keystring occurrences in conversation

Use lookup table to determine whether keystring occurs in the lexicon, and if so, its location

If keystring occurs in lexicon, increment its value by 1 in conversation vector

Construct topic vectors from generated conversation vectors

Convert hard counts in conversation- and topic-vectors to frequencies

End

Figure A.12: Extracting conversation- and topic-vectors for a given lexicon. Hard counts are employed. (new implementation)
CHAPTER A: Flow diagrams of the Optimisation of ENWN and SMART

Have 100C1 elements been marked as obsolete?

Determine distances between each conversation vector and all topic vectors from training subset.

Are there less than 100 valid elements left in the training subset?

Yes

Determine optimal size of training set using target percentage.

Has optimal size been reached for the training set?

Yes

No

Mark 100 less important elements as obsolete using training set's conversation- and topic vectors.

Determine distances between each conversation vector and all topic vectors of training set.

Did less important elements from training set contain less than optimal size = 100 valid elements?

Yes

No

Determine performance of algorithm using validation subset's conversation vectors and training subset's topic vectors.

Mark 100 less important elements as obsolete using training set's conversation- and topic vectors.

Determine performance of algorithm using testing set's conversation vectors and training set's topic vectors.

Are there less important elements left that have not been removed?

Yes

No

Remove all less important elements that were marked as obsolete.

Remove all less important elements that were marked as obsolete.

Recalculate distances between each conversation vector of validation subset and all topic vectors of training subset.

Recalculate distances between each conversation vector of testing set and all topic vectors of training set.

Recalculate distances between each conversation vector and all wrong topic vectors from training subset's vectors.

Figure A.13: Extended training. (new implementation)
Figure A.14: Marking lexicon members as obsolete. (new implementation)
Begin

For all topics

For all conversations belonging to topic

Generate topic scores by normalising distances between conversation vector and all topic vectors to sum to unity

For all decision thresholds

Determine number of detections and number of false alarms

Add these values to those previously obtained for this decision threshold

For all decision thresholds

Determine overall detection- and false alarm-rate

Calculate ROC area using trapezium method

End

Figure A.15: Determining an algorithm's performance. (new implementation)
Figure A.16: Overall flow diagram of SMART. Simulation times are also shown — phoneme n-grams in the length range 2 to 4 were allowed, and the recurrence threshold was set to 2. (new implementation)
Begin

Initialise tree structure for lexicon's sequence matchers

Determine all unique keystrings, having the same length as longest lexicon member(s), that occur in data

While determining unique keystrings, keep track of where they occur

For all unique keystrings

Fit keystring to tree structure

For all conversations in which keystring occurs

For all keystring occurrences

Add result for each lexicon member to its corresponding value in conversation vector

Construct topic vectors from generated conversation vectors

Convert soft counts in conversation- and topic-vectors to frequencies

End

Figure A.17: Extracting conversation- and topic-vectors for a given lexicon. Soft counts are employed. (new implementation)