Abstract

This thesis addresses automatic lexical error recovery and tokenization of corrupt text input. We propose a technique that can automatically correct mispellings, segmentation errors and real-word errors in a unified framework that uses both a model of language production and a model of the typing behavior, and which makes tokenization part of the recovery process.

The typing process is modeled as a noisy channel where Hidden Markov Models are used to model the channel characteristics. Weak statistical language models are used to predict what sentences are likely to be transmitted through the channel. These components are held together in the Token Passing framework which provides the desired tight coupling between orthographic pattern matching and linguistic expectation.

The system, CTR (Connected Text Recognition), has been tested on two corpora derived from two different applications, a natural language dialogue system and a transcription typing scenario. Experiments show that CTR can automatically correct a considerable portion of the errors in the test sets without introducing too much noise. The segmentation error correction rate is virtually faultless.
Acknowledgments

First and foremost I would like thank my supervisor Lars Ahrenberg, for his support, helpful discussions and encouragement to get me through this process and reach a result. It would not have been possible without his assistance. I would also like to thank my two other supervisors Arne Jönsson and Ulf Nilsson.

The NLP-group is a stimulating group to work in, it provides a positive atmosphere that I am grateful to be part of. I would like to thank Lars Ahrenberg, Arne Jönsson, Nils Dahlbäck, Magnus Merkel, Lena Strömbäck and Lena Wigh.

Many people have been helpful to me in my research in one way or the other. Many thanks to the brave secretaries that sustained the ordeal of having to re-type one of the most boring texts ever written: Lena Wigh, Eva-Britt Berglund, Lise-Lott Svensson, Barbara Ekman, Eva Hejdeman, Carita Lilja, Britt-Inger Karlsson and Anne Eskilsson. Thank you Bernt Nilsson for reprimanding the machines when they are unfriendly and Ivan Rankin for valuable comments on an earlier draft of this work.

Thank you all!

Peter Ingels
Linköping, December 1996
# Contents

1 Introduction 1

2 The Lexical Error Problem 5  
   2.1 Misspellings 5  
   2.2 Segmentation Errors 9  
   2.3 Syntactic Errors 12

3 Error Profile of a Dialogue Corpus 15  
   3.1 CARS 16  
   3.2 TRAVEL 19  
   3.3 Conclusions 21

4 Background 25  
   4.1 The Classical Method 25  
   4.2 Noisy Channel Methods 27  
   4.3 Error Correction in Rule-Based NLP Systems 31

5 An Algorithm for Robust Text Recognition 37  
   5.1 Fundamentals of Hidden Markov Models 37  
   5.2 Token Passing 44  
   5.3 Isolated Word Recognition 49  
   5.4 Connected Text Recognition 55

6 Experimental Evaluation 65  
   6.1 CARS 65  
      6.1.1 The Orthographic Decoder 66  
      6.1.2 The Unigram Language Model 69  
      6.1.3 The Domain-Tag Bigram Language Model 69  
      6.1.4 The POS Bigram Language Model 71  
      6.1.5 Results 71  
   6.2 SECRETARY 74  
      6.2.1 Error Profile 76  
      6.2.2 The Orthographic Decoder 78  
      6.2.3 The POS Bigram Language Model 79
6.2.4 Results .................................................. 80
6.3 Discussion ............................................... 82

7 Future Work ...................................................... 87
  7.1 Practical Issues ......................................... 87
  7.2 The Unknown Word .................................... 88
  7.3 Exploiting the Potential of the Framework .......... 88

A Tag-sets Used in ctr ........................................ 97
  A.1 The Domain-Tags used in cars ....................... 97
  A.2 The POS used in cars .................................. 98
  A.3 The POS used in secretary ......................... 99
Chapter 1

Introduction

Practical Natural Language Processing (NLP) systems can not expect all the
input to conform to the grammars encoded in them. An NLP system that is
able to handle input that in some way deviates from the language defined by the
grammar encoded in the system is called robust. The unexpectedness of the input
is due to the input being ungrammatical or extragrammatical. Ungrammatical
input is judged by humans as being erroneous or strange in some way whereas
extragrammatical input contains no errors, it is just that the input entered to the
system happens to lie outside of the grammar’s coverage. The distinction is not
unimportant, e.g. on the lexical level, it would be a great help to know whether
an unrecognized string is a misspelling or a correctly spelled unknown word.
The problem of distinguishing the two cases is, however, in general impossible
to solve. In theory it is possible to write a grammar and a lexicon that fully
cover a particular language and exclude everything that is not in the language,
so researchers in robust natural language processing tend to adopt the view that
unparsable input is ungrammatical.

Robustness is called for in all modes of language communication and in
virtually all applications that one can think of. The traditional NLP applica-
tions with machine-readable texts and keyboard-entered input include machine
translation, information retrieval, grammar/style checkers, text/code editing,
and other NLI (Natural Language Interface) applications such as computer-
adaided authoring, computer-based language learning/tutoring and NL dialogue
systems. Speech processing applications require robustness, especially speech
recognition (speech-to-text). Pen-based interfaces (handwriting readers) and
optical character recognition (OCR) devices have to have their output further
processed to improve recognition performance. The latter cases, where a media
shift (recognition) takes place, are particularly troublesome since the machinery
performing the recognition introduces errors which add to the human-generated
errors that were already in the first medium.

The action taken by the robust text processor in the face of ill-formedness
of course varies from application to application. A grammar- or style-checker
may highlight a portion of the input and suggest a better way to formulate
the particular passage. A computer-based language learning system should be equipped with good diagnostics abilities so that whatever is fed back to the learner is informative and relevant. An NL dialogue system should be able to perform simpler corrections to the input and enter into clarification sub-dialogues when more serious conditions arise in order to make the dialogue flow more naturally and minimize interruptions.

The development of the robust text processing techniques presented in this thesis takes as a starting-point keyboard-entered input to an NL dialogue system. An examination of a dialogue corpus showed that the lexical errors are more urgent than other error types, where the overall goal is to facilitate as many as possible of the user’s inputs being interpretable. Furthermore, the majority of the lexical errors can be automatically corrected, which means that the user would not be bothered by simple typing mistakes. The scope of this thesis is thus the automatic correction of lexical errors, and although the techniques presented here are not limited to text-based dialogue systems, this application is the one assumed.

The lexical errors are broadly divided into the two major error categories of *misspellings* and *segmentation errors*.

\[1\] What is the maintenance-cost for the respective models in (1) the above table

Utterance\(^1\) (1) displays a typical misspelling, (the highlighted ‘aboue’). It is an example of a so called nonword misspelling, i.e. the erroneous token is not to be found in the system’s vocabulary. The majority of the techniques for automatic spelling error correction developed over the years deal with this error type only. It is possible to form a correction hypothesis for ‘aboue’ by comparing it to the valid words in the vocabulary. This approach is called isolated word error correction and utilizes lexical information (the vocabulary) only. Lexical information is, of course, of paramount importance when recovering from lexical errors, but in general the whole range of linguistic information is useful when correction hypotheses are generated, particularly syntax and to some extent semantics. It is pretty obvious that the proper correction for ‘aboue’ in utterance (1) is ‘above’, but without the use of contextual information there is little evidence to distinguish this hypothesis from, say, ‘about’. Whereas syntactic information is useful for handling close calls as in this example, it is absolutely crucial when dealing with so-called real-word misspellings.

\[2\] show price for volvo 300 from the rear 1988

\(^1\)Some of the example utterances in this and subsequent chapters originate from the dialogue corpus mentioned above (These utterances have the precursor \(\Rightarrow\).) The corpus is in Swedish, so the utterances here are literal translations where the crucial aspect (often a lexical error) of the utterance has priority over good linguistic style. Utterances with the \(\Rightarrow\) precursor are not literal translations, but have been tampered with slightly, or simply invented to better illustrate a particular phenomenon that is hard to literally translate. Hyphens that do not wrap a line indicate that the Swedish source token is a noun compound, e.g. the Swedish source token for ‘maintenance-cost’ is ‘underhållskostnad’
A word has been substituted for a token that is a valid word in the vocabulary. It is likely that the user in (2) intended to type ‘year’ but it accidentally came out ‘rear’. The real-word errors are obviously harder to come to terms with than the nonword errors. Information other than lexical is necessary just to detect the problem spot. Few researchers have addressed the real-word error problem, and some of these have tended to focus exclusively on this problem, forgetting the easier nonword error problem.

The other major error category is the segmentation error category. Segmentation errors somehow involve word boundaries. There are two types: run-ons and splits.

finally, can I have a list of these cars with information (3) onspaciousness

just the ones with coupé space 3-4 (4)

Uterances (3) and (4) illustrate a run-on and a split respectively. In a run-on two (or more) words have been run together into a single token. In a split one word has been split into two (or more) tokens. The split in (4) should have been written ‘coupé-space’\textsuperscript{2}. As is evident from utterances (3) and (4), the real-word – nonword error distinction applies to run-ons and splits as well as to misspellings. Errors involving word boundary infractions are more difficult to handle than those that do not. Virtually all systems that process text in any way rely on a tokenizer to split the text up into word tokens, where the assumption is that a sequence of characters surrounded by space characters corresponds to a word. When this assumption is violated things go awfully wrong since an unknown token, like ‘onspaciousness’ in utterance (3) for example, is assumed to be a misspelling of a single word. Furthermore, a segmentation error can generally be ‘repaired’ in more ways than can a misspelling and in general more linguistic information is needed to distinguish the good hypotheses from the bad ones. Recovering from segmentation errors is obviously hard, and this is one of the reasons why this problem has scarcely been addressed at all before.

This thesis aspires to take a collected approach to the entire range of lexical errors, utilizing syntactic and to some extent semantic information in addition to the essential lexical knowledge source. This has not been done before and it requires in particular that correction hypotheses pertaining to different error types can be compared for discrimination in a meaningful way.

Inspiration can be gained from Connected Speech Recognition. Consider the fictional utterance below where especially the segmentation problem has been exaggerated in absurdum.

Whisthethemainneancecostofrtherespetimeosalnsintheaboetalbe (5)

Finding the words in the heavily distorted (5) is in many ways similar to finding (phonemes and) words in continuous speech. There is no indication in continuous speech as regards the end of one word and the start of the next, i.e. there

\textsuperscript{2}The Swedish source is ‘kupé utrymme’, which is not the same as ‘kupé utrymme’.
is no space character counterpart in speech. Furthermore, since the ‘alphabet’ in the speech case is made up of an infinite number of ‘characters’ (real-valued feature vectors), a word is never ‘spelled’ the same way twice. The point made here is that if we agree to carry the error types of text processing over to speech processing, we see that speech is virtually littered with misspellings and segmentation errors. It is therefore close at hand to see what the methods used in the difficult speech recognition task can offer in the relatively simple text recognition problem\(^3\).

The following chapter describes and delineates the problem domain and introduces the terminology used in this thesis. Chapter 3 “Error Profile of a Dialogue Corpus” describes the types and frequencies of errors found in a Natural Language dialogue corpus. Chapter 4 gives a brief review of prior work in the area of lexical error correction. Chapter 5 “An Algorithm for Robust Text Recognition” holds the technical contributions of this thesis. It describes probabilistic methods used in speech processing, and how they can be incorporated, adapted and put to use for the present task. Chapter 6 “Experimental Evaluation” evaluates the techniques described in Chapter 5 on two error corpora extracted from two different applications, or scenarios. The first is a dialogue application and the other is a transcription typing scenario. The thesis concludes with Chapter 7 “Future Work”.

\(^3\)One plausible interpretation of (5) could be (1) (with ‘aboue’ substituted for ‘above’).
Chapter 2

The Lexical Error Problem

A problem faced by the analysis component of any NLP-system is that the input sometimes does not conform to the expectations of the system’s developers. One of the reasons for this may be that the input is erroneous, ill-formed. In this situation the system needs to react in some way, and the proper reaction depends, amongst other things, on the application at hand and the type of error encountered. Errors that occur in natural language text can violate linguistic expectations on all levels: the lexical, syntactic, semantic and the pragmatic/discourse level. The class of lexical errors is the one that has been most thoroughly studied, and in some respects the least problematic one. In many cases it is possible to guess at what the user intended to write and hence corrections can be automatically proposed. Some of the syntactic error types can be corrected with varying degree of success, but in general this error type calls for alternative reactions on the system’s part. Semantic and pragmatic errors are the hardest.

In this thesis we are primarily concerned with the lexical error problem. We look at this problem from the perspective of a Natural Language Dialogue system, from which we have gathered a dialogue corpus. The study of this corpus (presented in Chapter 3) involves not only the lexical errors but also certain syntactic problems. Thus the lexical error problem formulation of this chapter in Sections 2.1 and 2.2 is supplemented with Section 2.3 “Syntactic Errors” to provide the taxonomy of syntactic errors used in Chapter 3. Semantic and pragmatic errors are not addressed here. Véronis [1991] gives a relatively comprehensive account of semantic problems and Carberry [1984] describes some of the pragmatically ill-formed phenomena that can appear in the context of a dialogue system.

2.1 Misspellings

Any misspelling can be described as a transformation from a correctly spelled word performed by one or several of the basic error operations:
• deletion (e.g. ‘deltion’)
• insertion (e.g. ‘innsertion’)
• substitution (e.g. ‘subatitution’)
• transposition (e.g. ‘trasnposition’)

The basic error operations are not primitive operations, nor do they provide a unique path from word to misspelling. Rather, their usefulness lies in their correspondence to real world error-creating operations and their ability to interconvert any pair of strings. The basic error operations can be used to describe lexical errors but they are not very good at explaining them. Distinctions are made between typographic errors (performance errors), cognitive errors and phonetic errors (competence errors). In the case of typographic errors it is assumed that the typist knows the correct spelling of the word but makes a simple motor coordination slip. The substitution of ‘teh’ for ‘the’ is a typical typographic error. In the case of cognitive errors there is a lack of linguistic competence on the part of the typist. An example of a cognitive error: ‘receive’ → ‘recieve’. A phonetic error, which is really a sub-class of the cognitive errors, is a word that is phonetically correct but orthographically incorrect (‘memories’ → ‘memerys’). Although the distinctions are useful for sorting out human spelling behavior, they are seldom used when it comes to designing a spelling correcting program. The reason is that it is generally quite hard to determine the underlying cause of the error; ‘recieve’ for example may just as well be an accidental transposition error, and even if the cause can be established it is not certain that it will help the spelling corrector. Another, more important distinction is the one between nonword errors and real-word errors.

• A nonword misspelling is one that results in a string not in the vocabulary (of the system)
• A real-word misspelling is one where a valid (correctly spelled) word is substituted for the intended word.

The substitution of ‘wether’ for ‘whether’ in ‘wether to be or not to be ... ’ is an example of a real-word error. By definition a real-word error can not be detected by the use of a system’s lexical knowledge. A syntactic analysis may or may not detect the error depending on the relationships between the words. Apart from detecting real-word errors, the context is often helpful in deciding amongst alternative correction candidates for nonword errors. The traditional way of correcting the detected nonword error usually involves some sort of distance metric, cf. [Kukich, 1990]. The metric is used to compare the erroneous token to the valid words in the dictionary, and to choose the word that is closest to the misspelling. The problem with many of these algorithms is that in many cases there are several candidates that are equally ‘close’. In ‘pass me the sail please’, the erroneous ‘sair’ should probably be ‘salt’, but viewed
in isolation ‘sale’ is just as likely. In these situations contextual dependencies are useful.

The example of ‘wether’ above hints at a problem related to spelling errors, namely that of the unknown word problem. In most NLP-systems ‘wether’ would not be part of the vocabulary, and hence it would not be a real word but rather a nonword error. In this particular example it causes no problem since the intended word was ‘whether’, but if ‘wether’ was the intended word, as in: ‘Is that our wether grazing over there?’, problems arise. The tricky bit is to decide whether ‘wether’ is a misspelling of a known word or if it is a correctly spelled word that just happens to lie outside of the dictionary’s coverage. Extragrammatical problems such as the unknown word problem is not further addressed in this thesis, except in the discussion in Chapter 7 “Future Work”.

Another distinction that is often made between misspellings is that of single error misspellings and multiple error misspellings.

- A **single error misspelling** is an error where one of the four basic error types has occurred exactly once

and consequently

- A **multiple error misspelling** contains more than one instance of the four basic error types.

The distinction may seem a bit strange, but it was discovered already in the sixties (see below) that a large portion of all spelling errors was due to single error misspellings, and thus many of the techniques for automatic spelling error correction developed over the years have focused on this error type. If for no other reason, this makes the distinction interesting for comparative purposes.

When examining studies of spelling error corpora it is important to notice that spelling error frequencies and error patterns vary significantly between different applications.

In an early study Damerau [1964] found that as many as 80% of the words rejected by the list of acceptable terms in an information retrieval system were single error misspellings. The term-list will only reject nonword errors of course, so the remaining 20% are presumably multiple error misspellings (Damerau does not mention segmentation errors).

Kukich [1992a] made an error profile of a 40,000 word TND\(^1\) (Telecommunications Network for the Deaf) transcript corpus. She found 78% of the nonword

---

\(^1\)TND is a service that AT&T provides for their speech- and hearing-impaired customers. A person can have a TDD (Telecommunications Device for the Deaf) device with which she can communicate with other people with speech- and/or hearing-impairments who also have a TDD. A TDD is much like a terminal that can be hooked up to the wire via a modem, and lets the user type messages on a keyboard and receive messages on a screen. A TDD user can also communicate with a voice phone user by calling a deaf relay center, where a relay operator, using both a TDD and a voice phone, reads the text typed by the TDD user to the voice phone user and listens to the voice phone user’s response and types the words spoken by the voice phone user back to the TDD user.
errors in the corpus to be single error misspellings, corroborating the findings of Damerau. Some 18% of the misspellings contained a mistake in the first character position. It is generally believed that errors tend not to occur in the first character position, and the figure may be unrepresentatively high. Twenty-seven percent contained errors involving an adjacent key. The layout of the keyboard is, of course, relevant when motor coordination slips occur. Two percent were phonetic errors: ‘cuz’, ‘becuz’, ‘u’, ‘ur’ and ‘rite’. Phonetic error is perhaps not the most adequate characterization for these words. The slang-like abbreviations can be seen in informal conversations over the net, and unknown word may be a better term.

Pollock and Zamora [1983] collected over 50,000 nonword misspellings from around 25,000,000 words of text from a number of different scientific and scholarly databases. They found, amongst other things, that the multiple error frequency was as low as 7.5%. The rest of the nonword misspellings were distributed over the four basic error types: deletions 34%, insertions 27%, substitutions 19% and transpositions 12.5%. The low error frequency (0.2%) is probably partly due to the nature of the text source.

Mitton [1987] studied the spelling behavior of secondary school pupils (15 years of age) in a corpus of short essays on the subject of “Memories of my primary school”. The essays were hand-written. The corpus included 924 essays and a total of 170,016 words. Mitton recorded 4,218 errors, an error rate of only 0.25%. The low error frequency can partly be explained by the fact that the essays were written by hand, thus excluding the keyboard error-source. It is not clear from Mitton’s report, but it appears as though the pupils were aware of the fact that they were being tested on their spelling skills. This may also have had an affect on the error frequency (perhaps in either way). Mitton reports a relatively high percentage of real-word errors. He found 40% to be real-word errors and consequently 60% nonword errors. In the real-word error category Mitton includes errors that are generally considered to be syntactic errors, such as present-tense verbs in place of past (‘the best thing I like was to play’) and number agreement errors (‘five other primary school’). Excluding these errors from the real-word error category, the percentage is still as high as 30%. When a system’s (incomplete) dictionary is used there will be a smaller amount of real-word errors and instead a corresponding amount of unknown words. Another remarkable finding in Mitton’s report is the unprecedented high frequency of phonetic errors. Homophones and near-homophones made up close to 60% of the errors in the corpus. Near-homophones are words like ‘where’ and ‘were’ which are homophones to some people and ‘have’ and ‘of’ which can be homophones in ‘I might of done’. The high frequency of homophones is hard to explain, but perhaps it has to do with the fact that the pupils were given a spelling transcription test before they were asked to write the essay. This might have put the pupils in a “sound-to-text spelling mode”, which might explain the high homophone frequency.

Peterson [1986] set out to determine the probability of a word being mistyped as another word, as a function of the size of the word-list. With the terminology introduced in this section this means: What is the probability that a single basic
typographic error will result in a real-word error when the size of the word-list varies? Due to lack of reliable statistics the four basic error types were assumed to be equally likely. For an $n$-letter word and 28 characters in the alphabet (26 letters, hyphen and apostrophe) there are $n + 28(n + 1) + 27n + n - 1 = 57n + 27$ possible single error misspellings\(^2\). A word-list of 369,546 words was run through a program that generated all the possible mistypings for each word. Of the possible 205,480,845 mistypings 988,192, or 0.5\%, turned out to be another valid word. Variably sized word-lists were constructed by stripping off the most infrequent words from the original word-list. The smallest word-list would thus contain only the most frequent words, which are generally shorter words: ‘the’, ‘of’, ‘and’, ‘to’, ‘a’, ‘in’, ‘is’, ‘that’, ‘it’ and ‘he’ make up the top ten. The word frequencies were estimated from different corpora. Short words are more likely to be real-word errors if mistyped than longer words. By weighing the fraction of all possible errors that are real-word errors against the expected frequency of occurrence, and varying the size of the word-list, Peterson found that in running text the expected frequency of single error real-word errors caused by typographic mistakes could be as high as 16\%. The effect of the more frequent shorter words is apparent in that the 100,000 most frequent words resulted in 13\% real-word error probability, while the remaining 300,000 words only added a further 3\%.

\section*{2.2 Segmentation Errors}

Segmentation errors are errors in which word boundary markers are involved. The most prominent of the boundary markers is the space character, whose sole objective is to delimit words. The space character is a member of the white-space characters which also include tab, carriage return and line-feed. These characters also have other functions besides delimiting words, and the same goes for parenthesis, period, comma, slash etc.

The basic error operations of deletion, insertion, substitution and transposition when applied to word boundaries result in things like:

\begin{enumerate}
\item \texttt{He gave her roses} \hfill (6)
\item \texttt{He ga ve her roses} \hfill (7)
\item \texttt{He gaveh her ro es} \hfill (8)
\item \texttt{He gau e her roses} \hfill (9)
\end{enumerate}

The segmentation errors in (6) through (9) are more or less likely to appear in actual texts. In general (6) and (7) are more common than (8) and (9) since they are not only caused by accidents, but also arise from cognitive and phonetic misconceptions. Segmentation errors can, just as regular misspellings, be diagnosed as cognitive, phonetic and typographic errors. The examples (6) make up the top ten.

\(^2\)deletions, insertions, substitutions and transpositions respectively.
CHAPTER 2. THE LEXICAL ERROR PROBLEM

through (9) are obviously all typographic errors. The accidental substitution of ‘h’ for ‘u’ and ‘u’ for ‘s’ in (8) is probably unlikely to occur very frequently in actual texts because of the form and placement of the space-bar; it is unlikely that one accidentally hits the space-bar instead of one of the character keys or vice versa. Example (6) and the first erroneous token in (8) are called run-ons. Example (7), the second erroneous token in (8) and example (9) are called splits.

- A run-on segmentation error has occurred when two or more words are written as one token, and it is a multiple run-on if more than two words are involved.

- A split segmentation error has occurred when a word is written as two or more tokens, or, when two words are split up into two erroneous tokens, and it is a multiple split if more than two tokens are involved.

The Example (9) requires special consideration. From the point of view of the basic error operations it is quite arbitrary whether (9) should be counted as a run-on or as a split, or as a combination of both, but since the result of the transposition is two tokens the best way to describe example (9) is as a split and hence the definition above.

Run-ons and splits may, of course, like misspellings result in real-word errors. Particularly in the case of splits that are caused by cognitive and/or phonetic misconceptions it is quite likely that at least one of the tokens is a real word (‘already’→‘al ready’).

- A real-word run-on has occurred when the token is a valid word in the vocabulary.

- A real-word split has occurred when at least one of the affected tokens is a valid word in the vocabulary.

The problem of detecting and correcting segmentation errors has received much less attention than that of misspellings. A reason for this is that segmentation errors are less frequent than spelling errors in naturally occurring texts. Another reason, and most likely the main reason, is the complexity inherent in the segmentation problem. In the case of segmentation errors context is not only helpful, as with most misspellings, but essential.

Virtually all spelling correction techniques rely on a tokenizer to split the character input stream into tokens. Tokenizers are often simple programs that just look for white-space characters and other delimiters to determine token boundaries. The assumption is that a token corresponds to a word in the vocabulary. When the input stream has been tokenized, each token is checked against a dictionary of valid words and if the token is not in the word-list, it is flagged as an error, i.e. an error involving one word. In actuality this means that the tokenizer defines the problem-spot. Assume for a moment that the tokenizer is right in its assumption that the unrecognized token is the misspelling of exactly one word. As mentioned above, the traditional approach to spelling
2.2. SEGMENTATION ERRORS

Error correction relies on the computation of the distance between the erroneous token and the words in the vocabulary. With an $M$ word vocabulary, $M$ distances have to be computed. However, if the constraint enforced by the white-space during tokenization is relaxed, the error correction task becomes considerably more complex. Turning again to utterances (6) to (9), if a single erroneous token appears in the input stream it might be a run-on. If the token contains $n$ characters it can be split in $n$ ways and each splitting results in two candidate tokens. If any of the splittings results in two perfect matches, (utterance (6)) this yields a plausible correction. However, it is possible that perfect matches are unobtainable (the first erroneous token in utterance (8)). In this case both candidate tokens of the hypothetical run-on have to be compared to the $M$ words of the vocabulary resulting in $2nM$ distance computations. The same line of reasoning can, of course, be applied to splits. The problem that faces the error recovery program is that it can not make any assumptions regarding the type of the error if it wants to be sure to find the best correction alternative. When misspellings, run-ons and splits, along with single as well as multiple errors, and even combinations of misspellings and segmentation errors, are considered, the traditional approach to lexical error recovery has lost its applicability. This is most likely the main reason why so little interest has been shown in segmentation errors.

In addition to this there is the real-word segmentation error problem which means that legal words surrounding the unrecognized token(s) have to be taken into account in the generation of corrections as well. Consider the pathological laboratory sentence:

--> Her an together be for she re ached these a

(10)

This mumbo-jumbo sentence contains one nonword, ‘shere’, the rest of the words are all legal. The problem of resegmenting (10) is quite hard, even for humans. The white-space characters carry a significant amount of information and when they are misplaced, interpretation gets hard. Although the segmentation problem never gets as hard as in (10) in processing of actual texts, there are other applications that need to deal with similar situations. In speech recognition, OCR and handwriting decoding the segmentation problem is a primary concern. (In the two latter cases character segmentation is actually more acute than word segmentation.) Speech recognition suffers from problems of coarticulation, homophones and, of course, there is no space character counterpart in speech. A speech-like reformulation of (10) could be written as:

--> Heran together beforeshe reached thesea

(11)

The segmentation of (10) and (11) that is likely to be the ‘intended’ one is:

--> He ran to get her before she reached the sea

(12)

Segmentation problems are less frequent in texts than misspellings. In many applications, however, it is a problem that needs to be addressed.
In her study of the nonword errors in the 40,000 word TND corpus Kukich [1992a] found that 13% of the errors were run-ons and 2% were splits. Apparently the majority of the segmentation errors were caused by typographic slips such as ‘yesthisis’ and ‘sp ent’. The investigation also indicates that a high percentage of the run-ons involve a relatively small set of high-frequency function words.

In Mitton’s [1987] study of errors in 15-year-olds’ essays, segmentation errors were also considered. Contrary to Kukich, Mitton found splits to be more common than run-ons. Fourteen percent of the errors were splits but there were only 3% run-ons. Whereas it was very rare for the run-ons to result in a real word, there were only five cases (0.12%) where a split word did not result in neither of the halves being a real word. In 13% of the cases both halves were real words and in the remaining cases (1%) one of the halves was a real word (‘to gether’ and ‘evry body’ e.g.). Mitton also found that the (generally shorter) function words were more liable to result in real-word errors than the content words. The real-word error portion of the function words in error was 66%, and the corresponding figure for the content words was 33%.

2.3 Syntactic Errors

The aim of this section is to introduce the error categories that are used to diagnose the error corpus in Chapter 3, not to fully cover all the syntactic errors and peculiarities that can appear in texts. For a more in-depth and linguistically-oriented account of these issues see, for example, Baker et al. [1990], Véro- nis [1991], Carbonell and Hayes [1983], Kwasny and Sondheimer [1981], Hayes and Mouradian [1981].

Syntactic errors depend on the structural relationships between words in a sentence. At the surface level however, a sentence is a sequence of words just as a word is a sequence of characters. From this standpoint it is natural to simply upgrade the basic lexical error operations to the syntactic level. This results in the basic syntactic error operations:

- **missing word** e.g. ‘the plays in the backyard’
- **extra word** e.g. ‘the the boy plays in the backyard’
- **substituted word** e.g. ‘the boy plays but the backyard’
- **transposed words** e.g. ‘the boy plays the in backyard’

Just as any misspelled word can be transformed into a legal word by combinations of the basic lexical error operations, so can an ungrammatical sentence with the basic syntactic error operations. For practical purposes, however, this classification is too crude. In the typology used here the basic error operations will account primarily for performance errors. Most of the examples above are likely to be accidental, possibly with the exception of the substituted word error. A variant of the substituted word error, which is generally a competence error, is the agreement error.
2.3. SYNTACTIC ERRORS

- Agreement errors include:
  - subject-verb number and person errors, e.g. ‘they plays in the backyard’
  - wrong case of pronouns, e.g. ‘them play in the backyard’
  - noun phrase problems, e.g. ‘they play in a backyards’

A subtle distinction has been introduced here regarding the real-word misspelling (see Section 2.1) and the substituted word error. Both error types are concerned with the substitution of one word for another and both are performance errors. The difference is that the real-word misspelling is a misspelling, i.e. it is an error on the character level. The substituted word error is something other than a misspelling and it is an error on the vocabulary level. Hopefully the confusion can be reduced by an example of a substituted word error:

```latex
\textbf{==> Is there a medium-sized-car in the 50000-70000 price-range and has year-of-production 1988?} \\
This strange looking utterance would read perfectly well if ‘and’ was replaced with ‘that’ or ‘which’. It is hard to say what the user was thinking about when she typed (13), but one thing is clear and that is that ‘and’ is not ‘that’ or ‘which’ misspelled. Thus (13) is an example of the substituted word error type. Utterance (2) in Chapter 1 is an example of a real-word error.

A varied and wide-ranging phenomenon, that is also quite frequent in the corpus examined in the following chapter, is the elliptic utterance. The elliptic utterances are not really errors, since they are generally unproblematic to understand in the context in which they appear, at least for humans. In some sense, however, they are errors, they violate an imagined core grammar of how legal declarative, imperative and interrogative sentence are formed in a language. Henceforth these sentences will simply be referred to as elliptic, avoiding having to classify them as being ill- or well-formed.

Various distinctions can be made between different types of ellipses (cf. [Carbonell and Hayes, 1983, Lavelli and Stock, 1990]). For our purposes, however, two types will suffice: the \textit{telegraphic ellipsis} and the \textit{contextual ellipsis}. In a telegraphic ellipsis one or, more often, several words have been intentionally left out. It is generally easy to state that a fragment has been left out on purpose, and this makes it easy to distinguish the telegraphic ellipsis from the missing word error type. Further, the elliptic fragment, the left-out portion, is always semantically redundant. Two examples of telegraphic ellipses, one at each end of the scale:

```latex
\textbf{==> looking for other models in the same price-range that would not be expensive to maintain} \\
\textbf{==> mercedes fuel-consumption} \\
The subject and the copula have been left out in (14) and many people would not consider it an error. In (15) it is more obvious that fragments have been left
out. However, in the dialogue context in which it appears, it is unproblematic to interpret the input: ‘What is the fuel-consumption for mercedes’.

In contextual ellipses the elliptic fragment is also left out intentionally, but is not semantically redundant, it can be inferred from the context. In a dialogue system, it can usually be inferred from one of the immediately preceding utterances, which may be system or user generated. An example of a contextual ellipsis:

$$\Rightarrow \text{What is the impact-safety for the cars with rust-protection better than 3}$$

*The system responds ...*

$$\Rightarrow \text{better than 4}$$

When the second utterance is entered, it is not hard to understand what is meant, basically the portion ‘What is the impact-safety for the cars with rust-protection’ should be put first in the second utterance to yield the intended query.
Chapter 3

Error Profile of a Dialogue Corpus

The need for robust text processing techniques became apparent during the development of the natural language dialogue system LINLIN [Ahrenberg et al., 1990, Jönsson, 1995]. LINLIN is a dialogue interface to a database, and it accepts queries in natural language (Swedish) and produces SQL-queries that are fed to the DBMS. LINLIN can be adapted to different application databases. In order to try to determine the required functionality of the dialogue management module, a series of experiments was conducted using the Wizard of Oz data collection scheme, cf. Dahlbäck et al. [1993]. The idea behind the Wizard of Oz technique, in short, is to let an operator, a human being, perform the task of the dialogue interface. In this case the operator interprets the NL input, she then accesses the SQL-database and relays the database output to the subject, or she herself replies with canned text or manually types back a short reply.

In the following two sections error profiles are given of two different corpora collected using the Wizard of Oz technique. The motivation for the study is to get an idea of the error frequencies in this sort of application. How are the errors distributed over the error types? What is the most ‘urgent’ robustness functionality? Which linguistic knowledge sources are in the foreground for resolving/interpreting the different types of ill-formedness?

The corpora (and the sections) are named CARS and TRAVEL. Slightly more attention will be devoted to CARS since it is one of the corpora that have been used for evaluating the techniques presented in this thesis (see Chapter 6). In the CARS-application the database contains information on different car models. The subject can retrieve information about the model’s price, fuel consumption, top speed etc. The task given to the subject is to decide which car to buy given certain financial restrictions. The TRAVEL-application is a travel agency scenario. The subject’s task is to decide on a charter trip to the Greek archipelago. She has to choose an island and a hotel, when to travel etc. The experimental setups differ slightly in the two cases. In CARS the operator reads
the subject’s input from the screen and constructs the corresponding SQL-query that is submitted to the DBMS. The output from the database is simply forwarded to the subject’s screen. The output is thus generally in table format. Occasionally the subject asks for clarification of table output, and sometimes the subject queries the ‘system’ for information that is not included, in which case the operator replies using canned text or hand-typed short messages. In TRAVEL no actual database system is involved, the operator simply manipulates a large collection of canned texts organized in such a way that the operator can simulate a database system interface. The TRAVEL interface also exhibits some degree of multimodality in that the operator is able to display maps of many of the tourist locations.

In both experimental setups and for all subjects the operator is instructed to be ‘forgiving’ with respect to ill-formed input, i.e. the operator will respond to all queries that she can understand. Note that the data collection was not carried out with ill-formed input as a topic of investigation.

3.1 CARS

The CARS corpus contains 20 dialogues gathered from 20 different subjects. Ten of the subjects were led to believe that they were communicating with an actual natural language interface, and the other ten were informed of the fact that the interface was simulated by an operator. As far as ill-formed input is concerned the two sub-corpora are quite similar. Below the sub-corpus collected with the misled subjects is called MACHINE, and the other half is called OPERATOR, the distinction reflecting the subject’s beliefs. The two sub-corpora are presented separately in the tables below for transparency. CARS contains 369 user utterances, 3,139 word tokens and 584 word types. Table 3.1 shows how many of the utterances are well-formed, elliptic and how many contain at least one error.

| Utterances    | Corpus            |                  |                  |
|---------------|-------------------|------------------|------------------|
|               | MACHINE           | OPERATOR         | CARS             |
| Well-formed   | 116 70%           | 132 65%          | 248 67%          |
| Elliptic      | 13 8%             | 24 12%           | 37 10%           |
| Ill-formed    | 37 22%            | 47 23%           | 84 23%           |
| **Total**     | **166 100%**      | **203 100%**     | **369 100%**     |

Table 3.1: The distribution of utterances

Of the 121 (37 + 84) ill-formed and elliptic utterances 94 (78%) contain one elliptic or erroneous construction and 27 (22%) contain more than one. In the 121 ill-formed and elliptic utterances there is a total of 161 individual errors/ellipses in CARS. The distribution over the error types is displayed in Table 3.2.

The relatively small size of the corpus makes the error frequencies sensitive
3.1. CARS

| Error Types           | Corpus MACHINE | Corpus OPERATOR | Corpus CARS |
|-----------------------|----------------|-----------------|-------------|
| Misspellings          | 22 31%         | 40 45%          | 62 39%      |
| Run-ons               | 14 19%         | 3 3%            | 17 11%      |
| Splits                | 7 10%          | 6 7%            | 13 8%       |
| Lexical errors (∑)    | 43 60%         | 49 55%          | 92 57%      |
| Missing Constituent   | 4 6%           | 0 0%            | 4 2%        |
| Extra Constituent     | 0 0%           | 0 0%            | 0 0%        |
| Substituted Constituent| 1 1%        | 4 4%            | 5 3%        |
| Transposed Constituent| 0 0%           | 0 0%            | 0 0%        |
| Agreement Error       | 6 8%           | 9 10%           | 15 9%       |
| Syntactic errors (∑)  | 11 15%         | 13 15%          | 24 15%      |
| Telegraphic Ellipsis  | 7 10%          | 18 20%          | 25 16%      |
| Contextual Ellipsis   | 11 15%         | 9 10%           | 20 12%      |
| Ellipses (∑)          | 18 25%         | 27 30%          | 45 28%      |
| Total                 | 72 100%        | 89 100%         | 161 100%    |

Table 3.2: The distribution of errors and ellipses in CARS

to individual subjects’ strange behavior. Ten of the 14 run-ons in MACHINE, for example, are the work of two particularly careless subjects. One of these utterances reads:

```latex
==>
I want to see cars in price-range 20000 to 70000 of makes audi, bmw, ford, mazda, toyota, peugeot, volkswagen
```

The fluctuations between MACHINE and OPERATOR are probably due more to the choice of subjects for the respective experimental setups than to the setups themselves.

Utterance (18) contains three run-ons, the first two being single errors and the last a multiple error. Note that the absence of spacing in the comma-separated enumeration of the makes ‘bmw’, ‘ford’ and ‘mazda’ does not constitute an error. Although the enumeration violates typographic conventions regarding spacing in conjunction with punctuation characters, a tokenizer can resolve this problem by simply triggering on characters like comma.

A system with no robustness built into it, and without the ability to deal with elliptic constructions, could theoretically parse 248 (67%) of the utterances in CARS (from Table 3.1). It is interesting to see how the theoretic performance of the system improves when robustness functionality is added.

Envisage three robust modules: an automatic spelling and segmentation error correction module, a module that interprets telegraphic and contextual ellipses and a module that can recover from the basic syntactic errors of missing constituent, extra constituent, substituted constituent, transposed constituent
and also the agreement errors. The figures in Table 3.3 show the theoretical performance improvements brought on by these modules had they been used on CARS. A small number of utterances are hard to interpret for reasons other than those discussed here. One utterance contains a definite reference to objects not displayed or mentioned before, and there are three occurrences of prematurely ended inputs. The single word utterance (19) is an example of the latter case.

$$\Rightarrow$$ show

All utterances are included in Table 3.3 although these oddities are disregarded.

| Robust Module | CARS |
|---------------|------|
| None          | 248  | 67% |
| Lexical       | +58=306 | 83% |
| Syntactic     | +14=262 | 71% |
| Ellipses      | +36=284 | 77% |
| All Modules   | +121=369 | 100% |

Table 3.3: Utterances theoretically parsable with different robustness capacities

Note that the figures in Table 3.3 require the modules to have 100% both recall and precision. The figures do not properly add up because there are utterances that contain instances of different error types, and hence can not be completely corrected by any single module in isolation.

Table 3.3 strongly emphasizes the need for robustness in this type of application. The non-robust system has a theoretic parsability maximum of 67%, and if the system can resolve elliptic constructions it is 77%. The single, potentially most productive module is the lexical error recovery module. It is noteworthy that a system with the ability to handle ellipses and lexical errors has its maximum at 94% $((248 + 58 + 36 + 6)/369)$. (There are six utterances that contain both lexical errors and ellipses but no syntactic error.) The lexical errors are therefore the most interesting error category, at least from the point of view of building a useful dialogue system.

The lexical error rate, the number of error tokens per token, in CARS is 2.9%. The lexical errors can be orthogonally divided into non/real words and single/multiple errors. Table 3.4 shows how the lexical errors are distributed over these categories. Misspellings are naturally divided into the four categories since a misspelled word is always realized as a single token regardless whether it is a single, multiple, nonword or real-word error. Segmentation errors are not as straightforward (cf. Section 2.2). The ratio of single error misspellings among the nonwords (57%) is considerably lower than the 80% reported by Damerau [1964]. The real-word error frequency (7%) could be on the lower side and it is certainly below the frequency reported by Mitton [1987], but then again, Mitton’s findings may not be representative for
3.2. TRAVEL

an application such as the present one. The real-word error splits are of two kinds: strange use of slash ('petrol/mile'→'petrol/mile', the multiple error in the table, and 'dollars/year'→'dollars/year'), and split number notation ('40000'→'40,000'). Since 'petrol', 'mile', 'year' and '40' are all in the vocabulary, these are all real-word errors. This of course raises the question of what words to put in the vocabulary. Special characters like '/', '(', ')' are troublesome because they do not belong in the vocabulary and yet they carry meaning. Numbers should definitely not be included in the vocabulary. These issues are further discussed in Section 5.4.

Table 3.4: Breakdown of lexical errors in cars

|       | Nonword error | Real-word error | Total |
|-------|---------------|-----------------|-------|
| Missp. |               |                 |       |
| Single error | 49 57% 1 17% | 50 54%          |       |
| Multiple error | 12 14% 0 0% | 12 13%          |       |
| Run-ons |               |                 |       |
| Single error | 14 16% 0 0% | 14 15%          |       |
| Multiple error | 3 3% 0 0% | 3 3%            |       |
| Splits |               |                 |       |
| Single error | 8 9% 4 67% | 12 13%          |       |
| Multiple error | 0 0% 1 17% | 1 1%            |       |
| Total |               |                 |       |
| Single error | 71 83% 5 83% | 76 83%          |       |
| Multiple error | 15 17% 1 17% | 16 17%          |       |
| Total | 86 100% 6 100% | 92 100%         |       |

Looking at Table 3.4, the ‘easy’ errors are the 49 misspellings that are nonwords and singletons. Although it is the single largest class of errors, it only accounts for slightly more than half of all the lexical errors. Error profiles taking segmentation errors into account are hard to find and so there is not much to compare with, but it seems that the 33% (30/92) segmentation error rate is high compared to what others have found. Kukich [1992a] reports that 15% of the lexical errors in her TND corpus are segmentation errors.

3.2 TRAVEL

The TRAVEL corpus contains 20 dialogues gathered from 20 subjects who were not aware of the role played by the operator. TRAVEL consists of 717 utterances, 3,882 word tokens and 941 word types. There are 424 (59%) well-formed utterances, 184 (26%) elliptic and 109 (15%) ill-formed utterances. There is a comparatively larger portion of ellipses in TRAVEL compared to CARS, particularly telegraphic ellipses. The explanation for this probably lies in the different structures of the two domains and the fact that the TRAVEL domain is supplied with maps. The TRAVEL domain is more hierarchically structured than the CARS domain. There are islands in the archipelago, resorts on the islands, hotels in the resorts and so on. The maps also naturally focus the dialogue, and let the subject express herself in a telegraphic manner, without the utterance
being hard to interpret for the operator. If the subject has a map of a village on Rhodes on the screen with the hotels marked out, an utterance like (20) seems to come naturally.

\[ \Rightarrow \text{standard these hotels} \] (20)

The way that different modalities are exploited in a dialogue system certainly has an effect on the dialogue itself and on the occurrences of, for example, ellipses, but that is not our prime interest here.

| Error Types                  | Travel |
|------------------------------|--------|
| Misspellings                 | 81     |
| run-ons                      | 21     |
| splits                       | 14     |
| Lexical errors ($\sum$)      | 116    |
| Missing Constituent          | 6      |
| Extra Constituent            | 0      |
| Substituted Constituent      | 12     |
| Transposed Constituent       | 0      |
| Agreement Error              | 9      |
| Syntactic errors ($\sum$)    | 27     |
| Telegraphic Ellipsis         | 159    |
| Contextual Ellipsis          | 36     |
| Ellipses ($\sum$)            | 195    |
| **Total**                    | **338**|

Table 3.5: The distribution of errors and ellipses in travel

Apart from ellipses cars and travel are very homogeneous. The distribution of the lexical errors for example among the error types is almost exactly the same for the two corpora.

The lexical error rate in travel (3%) is only slightly higher than that of cars. Table 3.6 shows that again the nonword single error ratio \(\frac{64}{103} = 62\%\) is far below the ‘agreed upon’ 80% reported by Damerau and others. The segmentation error ratio is still high, 30% is only slightly down from the 32% found in cars. The real-word errors, of which there are only splits, are almost exclusively errors due to lack of linguistic competence. ‘boat-trips’ → ‘boat\textunderscore trips’ and ‘shark-attack’ → ‘shark\textunderscore attack’ are examples of these cases. These errors do not translate very well into English; there is, however, one error in the corpus that more clearly demonstrates the nature of the error in the original language:

\[ \Rightarrow \text{the water drink able} \] (21)
3.3 Conclusions

The motivation for adding robustness functionality to an NL dialogue system is to increase the number of utterances that the system can accurately analyze, and for this purpose

- **Lexical errors are more urgent than other errors.**

The results in Table 3.3 show that this is true for CARS. Having to choose one of the robust modules, the system would benefit the most from the lexical error recovery module. This is also the case in the TRAVEL domain as far as lexical and syntactic errors are concerned, although there are a greater number of elliptic expressions compared to CARS, especially telegraphic ellipses. Lexical errors can, and should, be automatically corrected in a dialogue system. As regards syntactic errors this is not as obvious, and for ellipses this is probably not a very good idea at all. Telegraphic ellipsis utterances, the largest ellipsis category, contain all of the semantic information that is needed to interpret them (cf. utterance (15)). The fact that these utterances are often syntactically erroneous should not be a major consideration in trying to find the proper interpretation of the utterance. It is probably better to circumvent the syntactic constraints than attempting to exploit them when this sort of phenomenon occurs. The same sort of reasoning can be applied to some of the syntactic errors. The lexical errors, however, can not be circumvented in any way. Out of the 91 lexical errors in CARS 82 (90%) are content words and 9 (10%) are function words; the numbers for TRAVEL are 103 (89%) and 13 (11%) out of a total of 116 lexical errors. A large portion of the content words are so-called domain words, i.e. words with a strong domain association. Fiftynine percent of the content words in CARS are also domain words. In TRAVEL the domain word ratio is as high as 73%. There is a high degree of unfamiliar words in TRAVEL, (Greek) names of

|                | nonword error | real-word error | total  |
|----------------|---------------|----------------|--------|
| Missp. Single error | 64 62%        | 0 0%           | 64 55% |
| Missp. Multiple error | 17 17%        | 0 0%           | 17 15% |
| Run-ons Single error | 16 16%        | 0 0%           | 16 14% |
| Run-ons Multiple error | 5 5%          | 0 0%           | 5 4%   |
| Splits Single error | 1 1%          | 11 85%         | 12 10% |
| Splits Multiple error | 0 0%          | 2 15%          | 2 2%   |
| Total Single error | 81 79%        | 11 85%         | 92 79% |
| Total Multiple error | 22 21%        | 2 15%          | 24 21% |
| Total            | 103 100%      | 13 100%        | 116 100% |

Table 3.6: Breakdown of lexical errors in TRAVEL

Besides the real-word error split, utterance (21) is also a telegraphic ellipsis.

3.3 Conclusions

The motivation for adding robustness functionality to an NL dialogue system is to increase the number of utterances that the system can accurately analyze, and for this purpose

- **Lexical errors are more urgent than other errors.**

The results in Table 3.3 show that this is true for CARS. Having to choose one of the robust modules, the system would benefit the most from the lexical error recovery module. This is also the case in the TRAVEL domain as far as lexical and syntactic errors are concerned, although there are a greater number of elliptic expressions compared to CARS, especially telegraphic ellipses. Lexical errors can, and should, be automatically corrected in a dialogue system. As regards syntactic errors this is not as obvious, and for ellipses this is probably not a very good idea at all. Telegraphic ellipsis utterances, the largest ellipsis category, contain all of the semantic information that is needed to interpret them (cf. utterance (15)). The fact that these utterances are often syntactically erroneous should not be a major consideration in trying to find the proper interpretation of the utterance. It is probably better to circumvent the syntactic constraints than attempting to exploit them when this sort of phenomenon occurs. The same sort of reasoning can be applied to some of the syntactic errors. The lexical errors, however, can not be circumvented in any way. Out of the 91 lexical errors in CARS 82 (90%) are content words and 9 (10%) are function words; the numbers for TRAVEL are 103 (89%) and 13 (11%) out of a total of 116 lexical errors. A large portion of the content words are so-called domain words, i.e. words with a strong domain association. Fiftynine percent of the content words in CARS are also domain words. In TRAVEL the domain word ratio is as high as 73%. There is a high degree of unfamiliar words in TRAVEL, (Greek) names of
resorts and such, which can explain the differences. It is difficult to produce a meaningful interpretation of an utterance containing a lexical error without the use of lexical error recovery methods, and if the error involves a content word, or even worse a domain word, it is generally speaking impossible.

The corpus investigation clearly shows that

- **The lexical error situation here is more severe than normal.**

The dialogue scenario puts a higher cognitive load on the subject, compared to many other applications. The subject is concerned with extraction of information, not orthography. This, together with the fact that the operator is forgiving with respect to errors, (the subject notices that she can get away with lexical errors and becomes less careful,) can explain the frequent errors which are also hard to correct. In Kukich’s [1992a] application, which is quite similar to the present one, the error rate is as high as 5-6%. The other applications cited in the previous chapter all have lower error rates than the 3% found in cars and travel, with Pollock and Zamora [1983] reporting the lowest error rate 0.2%. Taking the real-word errors into account as well the error rate is close to 3%. Apart from the high error rate there is also a relatively small portion of ‘easy cases’ in the dialogue corpora compared to what others have found. The least difficult lexical errors are the nonword single error misspellings, which have been found by several researchers to make up 80% of the nonword errors. The figures here are 57% (cars) and 62% (travel). The remainder of the lexical errors are consequently distributed over the harder cases and it is evident that

- **Wide error scope is crucial in a dialogue application.**

The consequence of not addressing the segmentation errors, for example, will be that these are treated as misspellings, which is a foolproof way of providing a lexical error recovery module with poor performance. Researchers generally do not pay much attention to segmentation errors, though Kukich [1992a] reports that run-ons and splits make up 15% of all the lexical errors in her corpus. The ratio is considerably higher here, 32% of the lexical errors in cars being segmentation errors and the corresponding figure for travel is 30%. The hard cases, the segmentation errors, the multiple errors and the real-word errors emphasize the fact that

- **Contextual dependencies are crucial.**

There are generally more alternatives to be considered where segmentation errors and multiple errors are concerned. Local contextual preferences may then be used to distinguish the good hypotheses from the bad ones. A lexical recovery module is needed that can handle both misspellings and segmentation errors and has the ability to deal with some of the problems in the smaller but harder class of real-word errors.

Many automatic spelling error correction techniques have been developed to address the nonword misspellings. Kukich [1992b] performed a comparative study of some of the most well-known isolated word error correction algorithms.
The test set contained 170 human-generated misspellings, of which 25% were multiple error misspellings. The best algorithms scored around 80% correction accuracy. Applied to the cars corpus (see Table 3.4, Section 3.1), this means that the best isolated word error corrector can correct slightly more than 50% of the lexical errors in the corpus ($0.8 \times (49 + 12)/91 = 0.54$). This limit needs to be raised.
Chapter 4

Background

The research area of automatic spelling error detection and correction is nearly as old as the computer. Kukich [1992b] provides an excellent review of the varied and wide-ranging area spanning the last few decades.

The (incomplete) survey of the research field presented in this chapter will review some of the more influential and/or interesting contributions. Special interest is devoted to the error scope of the proposed technique, whether or not contextual information is used and, of course, the performance of the algorithms (to the extent that authors quantify their results).

The review below is divided into three sections roughly corresponding to three general ‘schools-of-thought’ in automatic spelling correction. Section 4.1 “The Classical Method” describes the string edit distance idea and techniques akin to it. Section 4.2 “Noisy Channel Methods” reviews the probabilistic approach and Section 4.3 “Error Correction in Rule-Based NLP Systems” surveys some of the attempts at robust natural language processing where spelling correction is generally just one of several problem areas that are addressed.

4.1 The Classical Method

One of the earliest and probably the most influential contributions to the area of human-generated spelling error correction techniques was that of Damerau in 1964. Damerau [1964] found that approximately 80% of all nonword misspellings were also single error misspellings. Based on these findings Damerau subsequently implemented what was later to be named the minimum edit distance algorithm. The algorithm detects errors by comparing the input word to a dictionary. When an error is detected, the program tries to transform the input word into a legal word in the dictionary relying on the assumption that exactly one of the basic error operators has ‘produced’ the error. When a match is found, the process is halted and the dictionary word is suggested as correction for the input word.

Independently of Damerau, Levenshtein [1966] developed a similar technique
in the research discipline of error correcting binary codes. The Levenshtein Distance (LD) is the distance between two words in terms of deletions, insertions and reversals (transpositions). The idea of the LD metric algorithm is to choose the word in the dictionary that is closest to the erroneous input word. The LD metric algorithm is sometimes used synonymously to the minimum edit distance algorithm, or rather, the term minimum edit distance algorithm refers to both ideas nowadays.

Several authors have extended the LD metric algorithm. Okuda et al. [1976] introduced the Weighted Levenshtein Distance (WLD). This is a generalization of the LD algorithm that can correct garbled words containing multiple instances of character substitutions, insertions and deletions. The weights can be used to give preference (shorter distance) to one error type over the others. The authors were satisfied with their algorithm, stating that: “our method achieved higher error correcting rates than any other method tried to date”. Okuda et al., however, noticed that short words constitute a serious problem.

The character n-gram technique is another class of methods used for spelling correction of various kinds. Angell et al. [1983] implemented a technique that computes a similarity measure between an input word and the words in the dictionary based on trigrams. The similarity is computed as the fraction of trigrams that are common to the two strings.

The method achieved an overall accuracy of 76% on a test set of 1,544 misspellings using a dictionary of 64,636 words. The authors noticed that the correction rates for transpositions were very poor (36%), it was actually worse than for multiple errors (55%). It was noticed that more transpositions occurred in shorter words on the average and short words were also problematic for the trigram similarity technique.

The SPEEDCOP system [Pollock and Zamora, 1984] is one of the techniques devised to correct single error misspellings by ways of similarity keys. Each word in the vocabulary is given a key and when a misspelling is detected, its key is also computed and compared to the set of precompiled keys corresponding to the words in the dictionary. The words with identical or similar keys are considered as correction alternatives. The similarity keys can be computed in a number of ways, in this case the ordering of the consonants are emphasized [Pollock and Zamora, 1984]. The authors tested their program on over 50,000 misspellings gathered from seven different scientific databases with a 40,000 word dictionary. SPEEDCOP scored an overall correction rate of 74-88% correction rate for the different databases, counting only the misspellings whose corresponding word was in the dictionary. SPEEDCOP uses some complementary correction aids besides the similarity keys, (it actually uses two sets of similarity keys). One such complementary aid is the so-called “function word routine” which looks for concatenations (run-ons) of frequent function words (e.g. ‘oftheir’, ‘inthe’). It is not completely clear exactly how the function word routine operates, but it is claimed that it improves the overall correction rate by 1-2%.

What the “classical” techniques above have in common is that they look at words in isolation, which puts real-word errors outside the scope of these techniques. Furthermore, based on the findings of Damerau, most of the isolated
word error correction programs only consider singletons. Segmentation errors are not addressed at all, with SPEEDCOP, which addresses a subset of the run-ons, as the outstanding exception. The striking observation is that segmentation errors are usually not even mentioned, and this goes for the entire area, not just the classical methods. It is often unclear whether or not errors due to defective tokenization are included in the test sets.

There seems to be a limit of somewhere around 80% correction rate for the isolated word correction algorithms (cf. Kukich [1992b]). One of the major problems with the classical methods is that the ranking of alternative correction candidates is fairly imprecise, i.e. there will generally be a number of correction alternatives that are equally ‘good’ and there is no way to decide which should be preferred. A more fine-grained (although not necessarily better) measure of ‘goodness’ is provided via probabilities.

4.2 Noisy Channel Methods

The noisy channel idea is based on the metaphor that communication is relayed via an imperfect medium, the channel. A word is inserted in one end of the channel and from the other end comes the distorted version of that word. Given the distorted word and the characteristics of the channel, the job is to calculate the most likely word to have been inserted originally. This likelihood is estimated via conditional probabilities. If there is also a language model that has information on what words are likely to be inserted, it provides what are known as the prior probabilities. (See Chapter 5 for more details.)

The noisy channel model has a long tradition in the neighboring research areas of optical character recognition (OCR) and speech recognition. Especially in OCR the approach seems natural since the channel (OCR-device) is there, open for inspection. In automatic correction of human-generated spelling errors it is not as straightforward since the channel characteristics are more elusive. However, with the increasing availability of large corpora, the noisy channel model has found its way into computational linguistics in recent years.

Researchers who look to the noisy channel model for automatic spelling error correction can roughly be divided into two groups: those who emphasize the prior probabilities with the intention of correcting real-word errors, and those who emphasize the channel’s distribution with nonword errors as prime target.

Kernighan, Church and Gale (KCG) were among the first to use really large text-corpora to estimate the channel characteristics for the purpose of spelling correction. KCG [1990, 1991b, 1990] constructed a program, CORRECT, that generates and ranks corrections for words rejected by SPELL\(^1\). The program generates correction candidates for a typo by applying a single instance of one of the basic error operators to the typo, and then it ranks the candidates using a Bayesian scoring function. The spelling corrector can thus handle single

\(^1\)The Unix SPELL program [McIlroy, 1982] is a fast wide-covering spelling error detection program that uses elaborate hash-functions to store the vocabulary for random access. See also Domeij et al. [1995].
error nonword misspellings. The scoring function is based on the modeling of
the typing process as a noisy channel. The most likely correction for a typo
t is the correction candidate c that maximizes P(c)P(t|c). The probabilities
are estimated from the 1988 AP newswire corpus (44 · 10^6 words). The condi-
tional probability, P(t|c), is computed from four confusion matrices that contain
the number of deletions, insertions, substitutions and transpositions that were
recorded for the individual characters in the words rejected by SPELL.

CORRECT’s scoring function was tested on 329 misspellings where the pro-
gram generated two correction candidates. Three human judges were asked to
choose among the alternatives, given the rejected word, the two alternatives and
a few concordance lines of context. CORRECT agreed with the majority of the
judges in 87% of the cases.

During the work on the CORRECT program it was noticed that human judges
were reluctant to decide between alternative candidate corrections given only
the information available to the program, i.e. the typo and the candidate cor-
rections. The judges were much happier if they could see a line or two of the
typo’s surrounding context. Consequently KCG went on to furnish CORRECT
with a bigram model of local context. The Bayesian scoring function of a cor-
rection candidate c given a typo t used in the original CORRECT, P(c)P(t|c),
the prior probability and the channel probability, is complemented with the
probability that the word to the left of c is l, P(l|c), and the probability that
the word to the right is r, P(r|c). The intention of KCG was to see whether
the updated scoring function: P(c)P(t|c)P(l|c)P(r|c) would enhance the per-
formance of CORRECT. The test set of the 329 nonword errors rejected by
SPELL for which CORRECT generated exactly two correction candidates was
again used for testing. Using only the prior and channel probabilities COR-
RECT agreed with the judges in 87% of the cases. Using the bigram proba-
bilities, performance rose to almost 90% which the authors found to be sig-
nificant. They also discovered that the bigram parameter estimator was cru-
cial to the behavior of the program. Maximum likelihood estimation and ex-
pected likelihood estimation actually degraded performance or made no differ-
ence, respectively, to the original CORRECT. The only estimation technique to
improve performance was the Good-Turing estimation technique [Good, 1953,
Church and Gale, 1991a].

Kashyap and Oommen [1981, 1984] had investigated the same approach some
years earlier although they had used subjective estimates of the parameters
describing the channel. Their results range from 30% to 92% correction accuracy
depending on the word length and number of errors per word. They also report
that the figures compare favorably with those reported by Okuda et al. [1976]
which ranged from 28% to 64% for words with similar characteristics.

Mays et al. [1991] took the other route, the one that focuses on the correction
of real-word errors. The prior distribution is modeled with a trigram language
model:
4.2. NOISY CHANNEL METHODS

\[ P(W) = \prod_{i=1}^{n} P(w_i | w_{i-2}, w_{i-1}) \]

The trigram language model has relatively good predictive power but the channel-model used by Mays et al. is quite simple. Each word \( w_i \) in the vocabulary has a precompiled confusion set \( w_i^c \). The confusion set is generated by applying the four basic error operators to each character position of the word exactly once and adding the resulting string to the confusion set if it is a legal word in the vocabulary. \( w_i \) is also added to \( w_i^c \). The confusion set of a word thus contains all the single error misspellings that are legal words in the vocabulary. \( P(y_i | w_i) \), where \( y_i \) is the real-word error, is then simply computed as:

\[
P(y_i | w_i) = \begin{cases} 
\alpha & \text{if } y_i = w_i \\
(1 - \alpha)/(|w_i^c| - 1) & \text{otherwise}
\end{cases}
\]

where \( \alpha \) is a constant determined by experimentation (\( \alpha = .9, .99, .999, .9999 \) in the reported experiments). Note that all correction candidates for \( y_i \) in \( w_i^c \) have equal probabilities, except for \( w_i \). The technique was tested on 8,628 sentences using a 20,000 word vocabulary. The test sentences were generated from 50 sentences of AP newswire and 50 sentences from the Canadian Parliament transcripts. These 100 original sentences were manipulated so that each of the 8,628 test sentences contained exactly one single error real-word error. The technique proposed by Mays et al. detected and corrected 73% of the 8,628 single error real-word errors. It is safe to say that it is the trigram model that does the work, the channel model merely enumerates the candidates where the trigram scores low. Mays et al. [1991] used the trigram language model employed in the IBM speech recognition project [Bahl et al., 1983].

Golding and Schabes [1996, 1995] took the idea of Mays et al. in a slightly different direction. They also used confusion sets but these were not based on the basic error operations. Rather, the confusion sets were selected on the basis of the fact that they occurred frequently in the Brown Corpus [Kucera and Francis, 1967] and sampled from the list of “Words Commonly Confused” in Random House [Flexner, 1983]. The confusions represent different types of errors: homophone confusions {‘peace’, ‘piece’}, grammatical confusions {‘among’, ‘between’} and the authors also added some typographical confusions that were not found in Random House, e.g. {‘being’, ‘begin’}. Golding and Schabes contrasted three different language models: a part-of-speech (POS) trigram language model, a feature-based Bayesian scoring function and a hybrid of the two. The POS trigram worked better than the Bayesian scoring function and the hybrid outperformed both. The technique was tested on 20% of the Brown Corpus. The evaluation is rather small-scale in that only 18 confusion sets are used. The confusion sets are also quite small, they contain only two or three words each. Two tests were conducted, one to see whether the system would wrongfully change the correct usage of a word in a confusion set into the
incorrect usage, and one to see if the system could restore the correct usage of the word if presented with an error. The performance varies for the 18 different confusion sets, results ranging from 35.3% to 98.4% on the corrupted words, and from 87.8% to 100% on the uncorrupted words.

Atwell and Elliott [1987] took claws [Garside, 1987] as a starting point to detect real-word errors. claws is a program that assigns POS tags to a text using a POS bigram language model. The idea is simply to assign POS to the text of interest using claws and when the probability of two consecutive tag-pairs fall below a predefined threshold, the word whose tag is present in both tag-pairs is marked as an error. The authors collected a 13,500 word corpus and extracted 502 real-word errors. The real-word error detector scored a 62% recall and 35% precision. The way that the threshold is set is obviously crucial to the performance of the method. In an attempt to better the poor precision rating Atwell and Elliott raised the threshold slightly and precision rose from 35% to 38%, but in doing so recall dropped from 62% to 47%. These results indicate that the discriminative powers of the POS bigram probabilities alone are too weak. This is particularly evident when an absolute value (threshold) is used for making the decisions. Comparing alternative tag-pair sequences to each other is surely a more promising approach.

There is obviously a greater interest in the more challenging real-word errors among the researchers adopting the noisy channel approach. The focus is consequently on the language model, often at the expense of the channel characteristics. The confusion set idea works satisfactorily for a small set of precompiled errors introduced in the channel, but is left without a chance to correct an error that does not belong to one of the confusion sets. One can, of course, argue that one should have a complementary program that performs nonword error correction and that the real-word error correction algorithm should be applied on the output from this program. The problem, however, is that if the real-word error correction module proposes corrections based solely on the preferences of the language model, regardless of orthographic similarity between error and correction, it will introduce errors that were not originally there.

The introduction of contextual properties in the spelling correction algorithms is certainly beneficial. Contextual properties are useful not only for the purpose of real-word error correction. KCG use the contextual information to be able to better discriminate between competing correction alternatives to non-word errors. Although there is nothing in principal that prevents one from using contextual dependencies also in the “classical approaches”, it seems as though they are more naturally incorporated into the noisy channel model.

None of the authors cited above mentions segmentation errors.
4.3 Error Correction in Rule-Based NLP Systems

This section takes a wider view on errors in natural language text. The aim of an NLP-system is to analyze, interpret, translate or whatever the application might be, as many input sentences as possible, and for this reason errors other than just spelling errors are, of course, of interest.

The need for error-handling capabilities became evident as real users were let loose on the early prototype NLP-systems. As a consequence the early eighties saw a range of NLP-systems with robustness functionality built into them. These systems can be divided into three general categories [Kukich, 1992b]: the relaxation-based (e.g. [Heldorn et al., 1982, Weischedel and Sondheimer, 1983]), expectation-based (e.g. [Carbonell and Hayes, 1983, Granger, 1983]) and the acceptance-based techniques (e.g. [Fass and Wilks, 1983]).

The acceptance-based approach works under the assumption that errors can be ignored as long as an interpretation can be found that is meaningful in the given application. The approach is grounded in the observation (hypothesis) that this is the way humans deal with erroneous or disturbed input. Acceptance-based approaches tend to make extensive use of semantic information and little use of any other level of linguistic information.

The expectation-based technique derives its expectations from various linguistic knowledge sources. CASPAR/DYPAR [Carbonell and Hayes, 1983] use syntactic and semantic expectations expressed in a case frame whose slots expect to be filled. Carberry [1984] generates responses to pragmatically ill-formed dialogue input based on the user’s goals and plans that have been inferred from the preceding dialogue.

Contrary to the acceptance-based approach the relaxation-based technique assumes that no errors can be ignored. This assertion is largely based on the fact that many early NLP-systems depended heavily on syntactic rules, and when the input violated the rules, the parsing process simply came to a halt. The relaxation-based technique will try to find the rule that when relaxed will allow the parser to succeed. If this scheme works, it means that the error is both localized and diagnosed and can consequently also be corrected. The relaxation-based approach is the one that has been favored in the research community, compared to the other two approaches. However, there are still problems. When only syntactic constraints are applied, there are many rules that when relaxed will lead to a complete parse and there will be a large amount of correction alternatives. Mellish [1989] noticed this problem trying to correct unknown/misspelled words, omitted words and spurious words with relaxation techniques using a CFG. Ingels [1992, 1993] tried the same approach, but with a richer grammar formalism that allowed also for feature values to be relaxed, and experienced the same problem.

After the hectic years in the early eighties interest in robust NLP seemed to have faded somewhat, but only to rise again in the late eighties and early nineties. Two important systems from this period are CRITIQUE [Richardson and
Braden-Harder, 1988] and a text-editing system for Dutch [Kempen and Vosse, 1990, Vosse, 1992]. Both systems are relaxation-based but only the latter takes spelling errors seriously.

The CRITIQUE system [Richardson and Braden-Harder, 1988], with its ancestor the IBM EPISTLE system [Heidorn et al., 1982], is one of the few systems to sincerely address robustness issues on a large scale, i.e. wide covering, natural language text processing system. The dictionary includes more than 100,000 entries and the words also carry information used in syntactic processing. The grammar contains several hundred phrase structure rules. The CRITIQUE system accepts text as input and delivers critique on grammar and style at levels of detail that can be adjusted by the user. The original EPISTLE system could cope with different types of grammatical errors whereas the rule-based parser in CRITIQUE “... provides a unique approximate syntactic parse for a large percentage of English text and diagnoses over 100 grammar and style errors”. After an initial preprocessing phase the robust parsing proceeds along the following lines: Lexical processing identifies words not in the dictionary and assigns them default morphological and syntactic information to avoid parsing failure. After the lexical analysis the text is passed to the parser. If the parser fails to produce a complete parse, the parser goes over the text once more, this time with some of its constraints relaxed. Certain lexical substitution rules are also activated during this second pass. The substitution rules involve easily confused words such as whose↔who’s or its↔it’s. If parsing now succeeds, the relaxed rules will serve as a basis for the critique fed back to the user. If this still does not succeed in a complete parse after the relaxation phase, the ‘parse fitting’ procedure is invoked [Jensen et al., 1983]. The parse-fitting procedure relies on heuristics to choose a head constituent to which fragments produced by the parser in the relaxation phase can be attached to form an approximate parse. Even when parse-fitting is applied, grammar and style error critique can be produced for the incomplete fragments. In any of the processing phases described multiple parses may result and in this case the system selects one based on a parse metric which favors trees in which modifying words and phrases are attached to the closest qualifying constituent [Heidorn, 1982].

The accuracy of CRITIQUE was tested on 10 essays from each of four groups: freshman compositions, business writing, ESL (English as Second Language) and professional writing. The diagnoses made by CRITIQUE were classified as correct, useful or wrong, useful meaning that the detection of the error was satisfactory but that the critique was off the target. The authors did not consider errors that the system missed, strangely enough. CRITIQUE produced the correct advice in 39% (professional), 54% (ESL), 72% (freshman) and 73% (business) of the critiques. When useful critiques were taken into account, figures rose in all four categories, particularly for the ESL-group (54%→87%), but as the authors point out, useful critique may not be that useful to users who lack native intuitions about English.

Another parser-based text proof-reading system is that developed for Dutch by Kempen and Vosse [Kempen and Vosse, 1990, Vosse, 1992]. The system can correct nonword spelling errors, real-word syntactic errors such as agreement
errors, it can also handle word doubling errors, problems with idiomatic expressions and compounds. Some structural errors such as punctuation errors and strange word order errors can also be dealt with. The robustness is achieved mainly in two processing phases, the word-level processing and the sentence-level processing. In the word-level processing the linear order of the text is abandoned for a lattice structure. The lattice reflects ambiguities that arise from compounds, idiomatic phrases and word doublings. If the text contains spelling errors a correction module is invoked and a limited number of correction alternatives are added to the lattice. The correction algorithm is based on a variation of trigram analysis [Angell et al., 1983] and triphone analysis [van Berkel and de Smedt, 1988] extended with a ranking mechanism. The dictionary contains 250,000 word-forms. After the word level processing the sentence level processing can proceed (on the lattice). The parser is a shift-reduce parser working with an Augmented Context-Free Grammar (ACFG) of some 500 rules. If an agreement constraint is violated during parsing, the constraint is relaxed and appropriately marked as such, and parsing continues. Structural errors are dealt with in a different manner. These (unusual according to the authors) errors are parsed with error rules included in the grammar. When parsing is finished, the job is to select among the (sometimes very frequent) alternative parses. The most straightforward method is to simply count the number of errors in the parses and choose the one with the least number of errors in it. However, this instrument is too blunt since there may be many parses with the same number of errors. To make the ranking of alternatives more fine-grained the grammar rules have weights added to them. For example, verb transitivity violation is more heavily penalized than incorrect subject verb agreement. After the selection phase the text can be regenerated with suggested corrections and diagnostics messages.

The word level processor was tested on 1,000 lines of text randomly chosen from two large texts submitted for publication, one on employment legislation and the other concerning collective wage legislation [Vosse, 1992]. The sample contained almost 6,000 words with 30 nonword misspellings. Twentyeight of the misspellings were detected and 14 were given the proper correction. The two missed misspellings were assumed by the system to be proper names. Eighteen false alarms were produced. Compared to an elementary spell-checker (supposedly the sort of spell-checker that comes with word processors) the word-level processor performed well. A simple spell checker, on the same text, marked 217 words as misspelled, which amount to 187 false alarms, 37 abbreviations and proper names and 150 compounds. The authors report that the word level can process in excess of 25 words per second. The sentence-level, however, requires considerably more time. Processing time ranges from four or more words per second for short error-free sentences to several seconds per word for longer and more error-prone sentences. On a 150 sentence spelling test for secretaries and typists, the system was able to correct 72 out of 75 errors without any false alarms. The errors corrected were spelling errors, agreement errors and errors in idiomatic expressions. The three errors missed involved semantic violations. The 150 sentences were processed in under nine minutes.
CHAPTER 4. BACKGROUND

The spelling correction algorithm of van Berkel and de Smedt [1988] works in an environment rich in linguistic information, it is actually an isolated word correction technique. That is, the correction alternatives are generated without contextual information. The contextual information is supplied afterwards to disambiguate among the multiple alternatives.

The problem of disambiguation has a long history in NLP research. The problem is to find the correct word-sense for a word in a particular context where the word has more than one interpretation in the vocabulary. This problem is very hard and requires large amounts of linguistic knowledge on all levels, and in the general case also extra-linguistic knowledge of the world.

The problem of lexical error recovery can also be seen as a problem of disambiguation, but on a different level, the string level. There is certainly no conflict of interests here, both problems are important and need to be solved. The question is rather: what are the crucial knowledge sources in the respective problems?

There is obviously a fair amount of randomness involved in how lexical errors are produced. Probabilistic techniques are well suited (although not always exploited) to capture the randomness of spelling behavior, which is one of the fundamental ideas behind the noisy channel approach. Still, there are clearly patterns there as well. van Berkel and de Smedt [1988] focus on phonetic resemblance which is one of several distinguishable patterns. Emphasizing one type of pattern is bound to obscure others. Techniques based on probabilistic or statistical methods usually derive their model’s parameters from a corpus, and in the case of lexical error recovery, the corpus would consist of errors. This implies that as long as we have a large enough set of example errors, preferably produced by real users, we can train or derive a model that can describe any pattern that might be in the corpus. The model would then ‘encode’ a randomness/pattern mix that reflects the contents of the corpus. The problem is of course that a large enough corpus is quite hard to come by. Probabilistic techniques also provide a sharp disambiguation instrument, there will always be one alternative that is better (more likely) than the rest (for better or for worse). The voluminous NLP-systems reviewed in this section contain a large set of hand-crafted rules. The proof-reading system of Vosse [1992] uses this rule-base (of primarily syntactic constraints) to disambiguate among the multiple words and word-senses produced by the isolated word spelling correction program. That is, it uses information that really pertains to a different level of description. There is nothing wrong with that, it obviously produces useful results. The point, however, is that information pertaining to the string disambiguation problem is overlooked. Another problem related to the use of large rule-bases for lexical error disambiguation is that it is hard to move to another domain or language. The isolated word spelling correction technique is not very useful without the syntactic constraints, so a new set of rules must be manually constructed before the spelling correction technique can perform satisfactorily. This is a laborious task.

Although algorithms dealing with isolated word error detection and/or correction work on words in isolation, the program usually processes chunks of
running text, depending on tokenization before the detection phase. The tokenization process is often simplified so that errors involving word boundaries will be more or less impossible to correct.

Carter [1992] implemented an elaborate tokenization and error-correcting algorithm in the CLARE system which explicitly considers segmentation errors. Carter maintains a lattice of overlapping word hypotheses and uses syntactic and semantic constraints to select the best alternative. CLARE was tested on 102 artificially generated sentences containing 108 errors without the use of syntactic and semantic constraints. The system found a single correct repair in 59 cases and 24 of these involved segmentation errors. It is not clear what the ratio of segmentation errors was in the source text.

In spite of the work of Carter and others, Kukich [1992b] states that “the general problem of handling errors due to word boundary infractions remains one of the significant unsolved problems in spelling correction research” (p. 385). This is one of the main problems we deal with in the following chapters.
Chapter 5

An Algorithm for Robust Text Recognition

This chapter includes the theoretical contributions of this thesis. The contributions are principally condensed into two algorithms, one for isolated word error correction (Section 5.3 “Isolated Word Recognition”), and one for the correction of lexical errors in general in running text (Section 5.4 “Connected Text Recognition”). Sections 5.1 “Fundamentals of Hidden Markov Models” and 5.2 “Token Passing” introduce the building blocks and tools with which these algorithms are built.

5.1 Fundamentals of Hidden Markov Models

This section gives a brief account of the theory behind the discrete observation Hidden Markov Model (HMM). We present the components of the model and the basic algorithms that can be applied to it. These can of course be found in several other places [Rabiner, 1989, Levinson et al., 1983], but the account below is slightly different from the ‘standard model’. In the theoretical underpinnings of Markov models there is no notion of final states as in the case of the FSA, for example. In real life, however, observation sequences are finite, at least the ones we are interested in. One way of thinking of final states of a Hidden Markov Model would be to somehow decide that a subset of the states are legal final states and that those of the complementary set are not. This approach can be found in, for example, Deller et al. [1993](p. 690). Another way would be to assign a probability to each state stating how likely it is that the particular state is a final state. This approach certainly blends better with the general theory, and more importantly it is trainable as will be shown below.

The hidden Markov model presented here has two additional states compared to the standard model. These are called the entry state and the exit state. (The terms are borrowed from Young et al. [1989]. The terms entry and exit are preferred over start and final for reasons that will be become clear in Section 5.4.)
As mentioned before, the notion of final states in Markov models is not new and the difference between the standard model and the one presented here is quite small, although not insignificant. An account of this type of Markov model and the fundamental algorithms associated with it has to my knowledge not been published before.

A random process $\mathbf{X}$ is a sequence of random variables

$$\mathbf{X} = \{ \ldots X_{t-1}, X_t, X_{t+1} \ldots \}$$

If the value of $X_t$ is dependent on the value of $X_{t-1}$ but independent of earlier variables, i.e.

$$P(X_t = q_t | X_{t-1} = q_{t-1}, X_{t-2} = q_{t-2}, \ldots) = P(X_t = q_t | X_{t-1} = q_{t-1})$$

we say that the process is a (first order) Markov process, and when the variables take discrete values, a Markov Chain. Given that the range space of the variables is finite the Markov Chain can be modeled by a finite state network where the states are associated with the outcomes of the random variables. Arcs connecting the states of the network impose transition probabilities between the states. The transition probabilities are often denoted

$$a_{ij} = P(X_t = q_j | X_{t-1} = q_i)$$

If the transition probability in a state is independent of time $t$, the Markov Chain is said to be homogeneous.

The **Hidden Markov Model** (HMM) models two parallel homogeneous random processes where one is the state transition sequence just described and the other is a sequence of observation symbols

$$\mathbf{Y} = \{ \ldots Y_{t-1}, Y_t, Y_{t+1} \ldots \}$$

The variables in $\mathbf{Y}$ take values from a discrete set $V$ of observations or observables and the observation symbol probabilities are denoted

$$b_j(k) = P(Y_t = v_k | X_t = q_j)$$

where $v_k \in V$. The model is thus extended with an observation symbol distribution for each state. The HMM $\mathcal{M}$ is thus determined by:

- a finite set of states $Q = \{ q_1, q_2, \ldots, q_N \}$, where $q_1$ is the non-emitting entry state and $q_N$ is the absorbing non-emitting exit state
- a finite set of observables $V = \{ v_1, v_2, \ldots, v_K \}$
- an $(N - 1) \times (N - 1)$ transition matrix $A$ where $a_{ij}$ denotes $P(X_t = q_j | X_{t-1} = q_i)$
- an $(N - 2) \times K$ observation matrix $B$ where $b_j(k)$ denotes $P(Y_t = v_k | X_t = q_j)$
5.1. **FUNDAMENTALS OF HIDDEN MARKOV MODELS**

There are no transitions out of $q_N$ and no transitions into $q_1$, thus the dimensions of the transition matrix $A$. The states $q_1$ and $q_N$ do not emit any symbols and this explains the dimensions of the observation matrix $B$. The parameters $N$ and $K$ along with a specification of the observation symbol alphabet/vocabulary and the two distributions $A$ and $B$ determine the HMM $\mathcal{M}$. The shorthand for this is $\mathcal{M} = \langle A, B \rangle$.

The HMM above can be used as a generator of an observation sequence

$$O = o_1, o_2, \ldots, o_T$$

where $o_t, 1 \leq t \leq T$ is chosen from $V$. The workings of this abstract machine in generative mode is as follows:

1. Start in the designated entry state $q_1$ at time $t = 0$.
2. Transit to a new state, say $q_j$ according to the state transition distribution in the current state $q_i$ ($a_{ij}$).
3. Set $t = t + 1$.
4. Choose $o_t = v_k$ according to the observation symbol distribution in state $q_j$ ($b_j(k)$).
5. If $t = T$ terminate by taking the transition to the exit state $q_N$ according to $a_{jN}$ and set $t = T + 1$. if $t < T$ go to 2.

Setting $t = T + 1$ might seem strange when the observation sequence is only of length $T$. It is, however, theoretically unpleasant that $X_T$ can assume two different values, so in the algorithmic descriptions below $X_{T+1}$ will occasionally appear and its value will always be $q_N$. In the implementation of the algorithms this fix is not necessary.

Given an HMM $\mathcal{M} = \langle A, B \rangle$ and an observation sequence $O = o_1, o_2, \ldots, o_T$ three important tasks can be performed.

**Task 1.** Calculate the probability of the observation sequence $O$ given the model $\mathcal{M}$, i.e. $P(O|\mathcal{M})$. This can be done with the Forward-Backward procedure.

**Task 2.** Calculate the joint probability of the observation sequence $O$ and the optimal state sequence $Q^*$ given the model $\mathcal{M}$, i.e. $P(O, Q^*|\mathcal{M})$. The Viterbi algorithm computes this probability.

**Task 3.** Reestimate the model parameters $A$ and $B$ so as to maximize the probability of a given observation sequence, the training material. The training procedure is called the Baum-Welch reestimation algorithm.

---

In the speech application the notion of time refers to actual time, it has to do with sample rates and suchlike. In the text case, time is merely a metaphor. The discrete time points should be thought of as an ordering of events.
To achieve Task 1 in an efficient way we need the forward variables and the backward variables. These variables are used to store intermediate results of the forward–backward algorithm. Actually it would suffice with the forward variables or the backward variables to calculate \( P(O|M) \), but since we need both sets later in the training procedure, both sets are defined here. The forward variables \( \alpha_t(i) \) hold the probability of being in state \( q_i \) at time \( t \) having observed the partial sequence \( o_1, \ldots, o_t \). That is

\[
\alpha_t(i) = P(o_1, \ldots, o_t, X_t = q_i | M)
\]

The forward variables are recursively defined:

**Initialization**

\[
1 \leq i \leq N \\
\alpha_0(i) = \begin{cases} 
1 & \text{if } i = 1 \\
0 & \text{otherwise} 
\end{cases} \quad (5.1)
\]

**Induction**

\[
0 \leq t \leq T - 1, \quad 2 \leq j \leq N - 1 \\
\alpha_{t+1}(j) = \sum_{i=1}^{N-1} \alpha_t(i) a_{ij} \cdot b_j(o_{t+1}) \quad (5.2)
\]

**Termination**

\[
P(O|M) = \sum_{i=1}^{N-1} \alpha_T(i) a_{iN} \quad (5.3)
\]

The purpose behind the entry and exit state should now start to become clearer. The vector \( a_{1i} \), the transitions out of the entry state, is the equivalent of the initial state distribution usually denoted by the vector \( \pi \) in the standard model. The number \( a_{1i} \), for example, gives the probability that the observation sequence starts in state \( q_i \). The entry state modification is there for practical purposes only, which will be explained below.

The exit state has also a practical purpose, but it also conveys the final state idea. The number \( a_{iN} \), for example, gives the probability that the observation sequence ends in \( q_i \). It should be noted that the induction step does not include \( q_N \) in any way. The transition to the exit state is taken when the entire observation sequence has been observed. One can think of this as having some sort of end-of-sequence marker \( o_{T+1} \) after the last symbol that triggers the final transition to the exit state. \( \alpha_{T+1}(N) \) would then equal the summation in the termination step and \( \alpha_{T+1}(i) = 0 \) for all \( i \neq N \). There is, however, no point in adding the \( T + 1 \) column to the \( \alpha \)-matrix. (The \( \alpha \) variables are typically kept in a matrix, as is the case here.)
5.1. FUNDAMENTALS OF HIDDEN MARKOV MODELS

The backward variables $\beta_t(i)$ hold the probability of making the partial observation $o_{t+1}, \ldots, o_T$ and then taking the transition to the exit state given state $q_i$ at time $t$. That is

$$\beta_t(i) = P(o_{t+1}, \ldots, o_T, X_{T+1} = q_N | X_t = q_i, M)$$

Again the backward variables are recursively defined:

**Initialization**

$$1 \leq i \leq N - 1$$

$$\beta_T(i) = a_{iN} \quad (5.4)$$

**Induction**

$$T - 1 \geq t \geq 0 \quad , \quad 1 \leq i \leq N - 1$$

$$\beta_t(i) = \sum_{j=2}^{N-1} a_{ij} b_j(o_{t+1}) \beta_{t+1}(j) \quad (5.5)$$

One can think of the backward variables as being recursively computed going from last to first in the observation sequence. Note that $\beta_T(i)$ means the probability of being in the exit state next, given that the present state is $q_i$, i.e. $\beta_T(i) = P(X_{T+1} = q_N | X_T = q_i) = a_{iN}$. Note also that $\beta_0(1) = P(O|M)$.

The word *Hidden* in Hidden Markov Model comes from the fact that for any given sequence of observation symbols there can be many different underlying state sequences and it is impossible to say which one generated the particular observation at hand. The state sequence is hidden. There must, however, be one state sequence that is at least as likely to have produced the observation as any other. That is, given the observation sequence $O = o_1, \ldots, o_T$ there is a sequence $Q^* = q_1^*, \ldots, q_T^*$ for which

$$P(O, Q^* | M) \geq P(O, Q | M) \quad \forall Q \neq Q^*$$

That is, Task 2 above. Enumerating all the $N^T$ possible state sequences and choosing the best is obviously not a realistic option. Fortunately there is an efficient solution to the problem, the Viterbi algorithm, another dynamic programming algorithm. To keep track of the partially optimal sequence on route to $P(O, Q^* | M)$ we define the set of variables

$$\phi_t(j) = \max_{q_1, \ldots, q_{t-1}} [P(o_1, \ldots, o_t, q_1, \ldots, q_{t-1}, X_t = q_j | M)] \quad (5.6)$$

i.e. $\phi_t(j)$ is the probability of the most likely state sequence that ends in $q_j$ which also accounts for the first $t$ observations. In order to retrieve the actual state sequence a second set of variables $\psi_t(j)$ are needed. The $\psi_t(j)$ keep track of the optimal predecessor of state $q_j$ in the path corresponding to $\phi_t(j)$. The Viterbi algorithm proceeds as follows:
CHAPTER 5. AN ALGORITHM FOR ROBUST TEXT RECOGNITION

Initialization

\[ 1 \leq i \leq N \]

\[ \phi_0(i) = \begin{cases} 1 & \text{if } i = 1 \\ 0 & \text{otherwise} \end{cases} \quad (5.7) \]

\[ \psi_0(i) = 0 \quad (5.8) \]

Induction

\[ 1 \leq t \leq T \quad 2 \leq j \leq N - 1 \]

\[ \phi_t(j) = \max_{1 \leq i \leq N - 1} [\phi_{t-1}(i)a_{ij}] b_j(\alpha_t) \quad (5.9) \]

\[ \psi_t(j) = \arg\max_{1 \leq i \leq N - 1} [\phi_{t-1}(i)a_{ij}] \quad (5.10) \]

Termination

\[ P(O, Q^*|M) = \max_{1 \leq i \leq N - 1} [\phi_T(i)a_{iN}] \quad (5.11) \]

\[ q^*_T = \arg\max_{1 \leq i \leq N - 1} [\phi_T(i)a_{iN}] \quad (5.12) \]

Path Backtracking

\[ t = T - 1, \ldots, 0 \]

\[ q_t^* = \psi_{t+1}(q_{t+1}^*) \quad (5.13) \]

This algorithm is quite similar to the Forward Backward algorithm. The only real difference is that the summation in the computation of the forward variables is substituted for a maximization in the Viterbi algorithm.

Recall Task 3: Given a model \( M = \langle A, B \rangle \) and an observation sequence \( O \), adjust the parameters of \( M \) so that \( P(O|M) \) is maximized. This task is not as simple as the two previous ones. In fact, there is no way to optimally estimate the model parameters. An iterative procedure such as the Baum-Welch reestimation algorithm can, however, be used to find a model that locally maximizes \( P(O|M) \). In each iteration step a new model \( M = \langle \bar{A}, \bar{B} \rangle \) is estimated from the original model \( M = \langle A, B \rangle \). It can be shown that either the model \( M \) defines a critical point where \( M = \bar{M} \), or, \( P(O|\bar{M}) > P(O|M) \). The iteration process stops when \( P(O|\bar{M}) - P(O|M) < \epsilon \), for some suitably chosen \( \epsilon \). The reestimation of \( A \) and \( B \) can be described as:

\[ \bar{a}_{ij} = \frac{\text{expected number of transitions from } q_i \text{ to } q_j}{\text{expected number of transitions from } q_i} \quad (5.14) \]

\[ \bar{b}_j(k) = \frac{\text{expected number of times in } q_j \text{ observing symbol } v_k}{\text{expected number of times in } q_j} \quad (5.15) \]
Recall the definition of the $\alpha$ variables

$$\alpha_t(i) = P(o_1, \ldots, o_t, X_t = q_i | M)$$

and the $\beta$ variables

$$\beta_t(i) = P(o_{t+1}, \ldots, o_T, X_{T+1} = q_N | X_t = q_i, M)$$

It is obviously not by pure chance that the $\alpha$ variables and $\beta$ variables fit so nicely together. It is namely so that

$$\frac{\alpha_t(i)\beta_t(i)}{P(O|M)} = \frac{P(o_1, \ldots, o_T, X_t = q_i, X_{T+1} = q_N | M)}{P(O|M)} = P(X_t = q_i, X_{T+1} = q_N | O, M)$$

i.e. the probability of being in state $q_i$ at time $t$ and finally ending up in the exit state, conditioned on the observation sequence and the model. Summed over the time index $t$, the expression in (5.16) can be interpreted as the expected (over time) number of visits to state $q_i$, or equivalently, the expected number of transitions from state $q_i$. That is

$$\frac{1}{P(O|M)} \sum_{t=0}^{T} \alpha_t(i)\beta_t(i) = \text{expected number of times in } q_i$$

(5.17)

yields one of the sought for quantities. In a similar way it is the case that

$$\frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{P(O|M)} = P(X_t = q_i, X_{t+1} = q_j, X_{T+1} = q_N | O, M)$$

(5.18)

i.e. the probability of being in state $q_i$ at time $t$ and $q_j$ at time $t + 1$ and being able to make the exit state transition given the observations and the model. And analogously

$$\frac{1}{P(O|M)} \sum_{t=0}^{T-1} \alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j) = \text{expected number of transitions from } q_i \text{ to } q_j$$

(5.19)

can be interpreted as the expected number of transitions from $q_i$ to $q_j$ over time. Note that the exit state transition at time $T$ has to be dealt with separately (see equation 5.21 below).

Using the above equations, a convincing set of reestimation formulas would
be:

\[
\bar{a}_{ij} = \frac{\sum_{t=0}^{T-1} \alpha_t(i)a_{ij}b_{t+1}(j)}{\sum_{t=0}^{T} \alpha_t(i)\beta_t(i)} \quad (5.20)
\]

1 \leq i \leq N - 1, \quad 2 \leq j \leq N - 1

\[
\bar{a}_{iN} = \frac{\alpha_T(i)a_{iN}}{\sum_{t=0}^{T} \alpha_t(i)\beta_t(i)} \quad (5.21)
\]

1 \leq i \leq N - 1

\[
\bar{b}_{j}(k) = \frac{\sum_{t=0}^{T} \alpha_t(i)\beta_t(i) \text{ s.t. } \alpha_t = v_k}{\sum_{t=0}^{T} \alpha_t(i)\beta_t(i)} \quad (5.22)
\]

2 \leq j \leq N - 1, \quad 1 \leq k \leq K

The major difference in the reestimation formulas compared to the standard model is the formula (5.21), the reestimation of the exit state transitions. The exit state transition can only occur when time \( t = T \), thus there is no summation over time in the numerator of (5.21). The effect of the exit state transition at time \( t = T \) is also that the normalization of \( \bar{a}_{ij} \) is slightly different from the standard model. In the standard model the summation in the denominator goes from \( t = 0, \ldots, T - 1 \). The reestimation formula (5.22) is the same as for the standard model.

The prime intent with this section has been to show the small, but yet significant, difference between this model and the standard model. There are a number of practical implementation issues concerning HMMs that are consciously left out of this presentation. Some of these will surface briefly in the remainder of this thesis, but for a more comprehensive account the reader should consult e.g. Rabiner [1989] and Levinson et al. [1983] on the topics of scaling, multiple observation sequences, choice of model type (topology) and size and initial parameter estimation. The problem of sparse data has been addressed in a number of papers, including Jelinek and Mercer [1980], Church and Gale [1991a] and Katz [1987].

### 5.2 Token Passing

The term *Token Passing* originates with the researchers engaged in the speech recognition effort at the Engineering Department at Cambridge, UK [Young et al., 1989]. The problem of speech recognition can simplistically be described as
5.2. TOKEN PASSING

a recurring process of grouping sequential items to form more meaningful items. The speech waveform is sampled and processed for feature vectors, these are segmented into a sequence of phones, phones are grouped into words and from there, depending on the application of course, some sort of language model deals with the phrases and/or sentence(s). There are obviously interdependencies between the different levels of this hierarchically laid out recognition process. The predictability of a certain phone sequence, for example, is of course dependent on what words are likely to occur in the particular context at hand. The recognition problem of the levels varies in difficulty, and the complexity of the problem is partly due to the strength of the dependencies on neighboring levels, the weaker the dependencies the harder the problem. Recognizing a sequence of phones as a word is considerably easier than finding phones in the feature vector stream. By transitivity one can say that all levels are dependent on each other. The main advantage of the Token Passing framework/algorithm (TP) is the elegant way in which dependencies between knowledge sources are maintained, i.e. the coupling of neighboring layers. Another feature is the flexibility of the framework, alternative recognition algorithms can be used in various layers. Furthermore it can quite easily be adapted to generate multiple alternative solutions and to incorporate search heuristics.

In speech recognition as well as in text recognition there is a basic recognition unit. In the hierarchical speech recognition scheme laid out above the recognition of a phone as a sequence of feature vectors is the basic recognition task, hence the phone is the basic recognition unit. In the textual case one can have morphemes, lemmas or word-forms as the basic recognition units. We assume from here on that the word-form is the basic recognition unit. Each basic recognition unit is represented by a finite state network, and each network, or model, holds a model identifier, the word-form string that it models. Each state $i$, $j$ of the network is connected by a transition cost $p_{ij}$, and with each state $j$ there is an associated local cost function $d_j(c)$. A path $I = i_1, \ldots, i_T$ through the network represents one possible alignment of the network to the input characters $C = c_1, \ldots, c_T$. Assume, for the time being, that $C$ is a word form.

Let each state of the network be capable of holding a passable token. At time $t$ the token in state $j$ holds the (partial) minimum cost alignment of $c_1, \ldots, c_t$ and the network, that ends in state $j$, i.e. the token represents the head of a path through the network. The minimum cost alignment $\delta_t(j)$ can be computed by the recursion

$$\delta_t(j) = \min_i [\delta_{t-1}(i) + p_{ij}] + d_j(c_t) \quad (5.23)$$

At each discrete time point copies of tokens are propagated between states and the minimum cost alignment is updated according to equation (5.23). The algorithm is illustrated in Figure 5.1. The token is the box containing the cost $\delta_t$ inside each state.

The attentive reader has probably noticed the similarity between equation (5.23) and the recursion formula (5.9) of the Viterbi algorithm above. The
similarity is, of course, not accidental. This, however, should not lead to the conclusion that the TP algorithm is just an unorthodox way of implementing the Viterbi algorithm. It is more general than that, or more accurately, the passing of tokens within the basic recognition unit, equation (5.23), can be seen as a generalization of a number of other 'cost functions', e.g. many of the distance metrics used in isolated word error correction. Consider, for example, the Weighted Levenshtein Distance (WLD) metric [Okuda et al., 1976] mentioned in Chapter 4. The WLD measures the distance between two words \( X \) and \( Y \) as the number of substitutions \( (k_i) \), insertions \( (m_i) \) and deletions \( (n_i) \) with weights \( p, q \) and \( r \) attached to the respective error categories. Okuda et al. express this as

\[
\text{WLD}(X \rightarrow Y) = \min_i [pk_i + qm_i + rn_i] \tag{5.24}
\]

i.e. the minimum number of weighted errors it takes to transform the word \( X \) into \( Y \). To calculate (5.24) Okuda et al.\(^2\) devised a recursive algorithm that operates on substrings of increasing length of the two words, where \( \text{WLD}_t(j) \) denotes \( \text{WLD}(x_1, \ldots, x_j \rightarrow y_1, \ldots, y_t) \).

\[
\text{WLD}_t(j) = \min \left\{ \begin{array}{l}
\text{WLD}_t(j - 1) + q \\
\text{WLD}_{t-1}(j - 1) + p_{j-1,t-1} \\
\text{WLD}_{t-1}(j) + r
\end{array} \right.
\]

where

\[
p_{j-1,t-1} = \begin{cases} 
0 & \text{if } y_{t-1} = x_{j-1} \\
p & \text{otherwise}
\end{cases}
\tag{5.25}
\]

To adapt the algorithm to TP it is necessary to take a slightly different view. In the Okuda et al. algorithm they were comparing two strings. Here we have a network and a string and it is not appropriate to change state without consuming

\(^2\)The notation used here is somewhat different from that used by Okuda et al.
5.2. TOKEN PASSING

anything from the input, as is done in the topmost of the three expressions in (5.25). (The expression adds the penalty for insertion to the metric.) The expression (5.25) above has to be reformulated to suit the TP algorithm. If the word $X$ is represented by a network in which each state $j$ corresponds to $x_j$, the $j$:th character in $X$ and $Y = y_1, \ldots, y_T$ is the transformed word, the algorithm presented by Okuda et al. can be reformulated as

$$WLD_t(j) = \min \begin{cases} WLD_{t-1}(i) + q \quad (\text{if } x_j = x_{\text{ins}}) \\ WLD_{t-1}(i) + \begin{cases} 0 & \text{if } y_t = x_j \\ p & \text{otherwise} \end{cases} \\ WLD_{t-1}(i) + (j - i - 1)r \quad j - i \geq 2 \end{cases} \quad (5.26)$$

The algorithm for computing the WLD presented by Okuda et al. can be realized by (5.26) and the network topology of Figure 5.2. The word represented by the network in the figure is ‘abcde’³. The dedicated ‘insert’ states are there to make sure that inserted characters are penalized equally hard independent of which character is inserted and in which position. The insert state is denoted $x_{\text{ins}}$ in (5.26). The relation between equations (5.23) and (5.26) is simply such that the transition cost $p_{ij}$ implements the insertion weight ($q$) and the deletion weight ($r$) whereas the local cost function $d_j(c_t)$ implements the substitution weight.

One of the fundamental ideas of TP is to separate out the low-level pattern-matching algorithm(s) of the basic recognition units from the higher level control mechanisms. In the case of textual input the low-level task is to recognize words in the character input stream. The hypothesizing of word occurrences in the

³The model is approximate in the sense that it does not properly cope with insertions and deletions at the end-points of the modeled word. This can easily be fixed with entry and exit states. The point is just to show that TP can be used for a variety of computational tasks and to a large extent it is only a matter of altering the network topology.
CHAPTER 5. AN ALGORITHM FOR ROBUST TEXT RECOGNITION

input is controlled by the higher level, the language model. There are many ways in which the pattern matching function can be controlled, or guided. These issues will be discussed further in Section 5.4 and Chapter 6, the account below focuses on the TP component that facilitates language modeling.

If the character input stream \( C = c_1, \ldots, c_T \) contains several words, there must be a way that allows for tokens to be passed from one basic recognition unit to another. This can be accomplished simply by connecting subnetworks to form larger composite networks. In doing so, however, it is necessary to record transitions between subnetworks in some way. We are interested in the actual word sequence, not just the cost of the best alignment of states to the input. To keep track of what word models a token has passed through on its way to the end of the input, the token is supplemented with a path identifier. The path identifier is a pointer to a Word Link Record (WLR) that contains word boundary information.

As a token is propagated from one subnetwork to another, a new WLR is created and the token is set to point to the new WLR, which in turn is set to point to the WLR that the token was pointing to prior to the inter-network token propagation. Figure 5.3 visualizes the process. The amount of information put in the WLR can depend on the language model used (see below), minimally it should contain the cost, path identifier and the model identifier. In Figure 5.3 the time (character stream position) at which the word boundary occurred is also appended to the WLR.

![Figure 5.3: Inter-network token propagation](image)

The time index \( t \) is not updated after the transition which means that identifying the word boundary does not imply the consumption of any character from the input stream. This could equally well be the other way around. The details of exactly how, and under what circumstances, tokens are passed between the
5.3. ISOLATED WORD RECOGNITION

basic recognition units are left to Section 5.4.

5.3 Isolated Word Recognition

The problem of Isolated Word Recognition (or isolated word error correction) is to detect and correct erroneous words without the use of any contextual dependencies. A word is viewed in isolation. Normally words do not just appear individually, they most often appear in a text, a stream of characters. The identification of words in such a stream is called tokenization, and Isolated Word Recognition (IWR), to be successful, relies on correct tokenization. A consequence of this implicit assumption, that is generally not spelled out regarding IWR, is that an erroneous token is assumed to be the misspelling of exactly one word. Under these conditions it is only the nonword misspellings (single or multiple) that can be corrected using IWR.

The classical scheme used to correct misspellings in isolation involves three steps:

Step 1. Detect the erroneous token

Step 2. Generate alternative correction candidates

Step 3. Rank the alternative candidates

The detection step (almost) always means to compare the token with words in a dictionary. If the token is not equal to any of the entries in the dictionary, it is misspelled. The generation of candidates can be performed in a number of ways and it is often interleaved with the ranking process which often involves some sort of distance metric. The dictionary word that is closest to the error-token, using the distance metric, is the highest ranked candidate and should be chosen for correction (cf. Section 4.1).

The remainder of this section will describe how the Hidden Markov Model can be used to perform Isolated Word Recognition within the Token Passing framework. In the approach taken here the three steps are melted down into one single process, detection, generation and ranking of candidates is simply a matter of computing the probability of an error token given the possible words in the dictionary. The noisy channel is an illustrative metaphor when using probabilistic methods.

Figure 5.4: The noisy channel
A word is inserted at one end of the channel and from the other end comes a distorted version of that word. The aim is to restore the original.

Let $W$ be the $M$ word vocabulary $W = \{w_1, \ldots, w_M\}$. Given the character sequence $C = c_1, \ldots, c_T$, which may be erroneous or not, the most likely correction is the $w_i$ that maximizes $P(w_i|C), 1 \leq i \leq M$. This number is hard to calculate, but fortunately there is Bayes’ rule

$$P(w_i|C) = \frac{P(C|w_i)P(w_i)}{P(C)}$$

Choosing the word that best matches the character sequence is not dependent on the probability of the sequence, which is given, so finding the $w_i$ that maximizes the numerator in Bayes rule seems like a good idea. Modeling each word $w_i$ of the vocabulary with an HMM $\mathcal{M}_{w_i}$ and making the obviously faulty assumption that all words are equiprobable, finding the word $w^*$ that best matches the character sequence $C$ is simply

$$w^* = \arg\max_{w_i} \left[ P(C|\mathcal{M}_{w_i}) \right]$$

It should be noted that there is no error detection being performed here in the normal sense of the word. It might very well be the case that $w_i = C$ for some $i$, i.e. $C$ is not misspelled at all. It would of course suffice to do a simple string match between $C$ and the strings of the vocabulary words to find this out. The scheme described here presupposes Step 1 above, or, one can think of the detection of the error as something that is found out after the ranking of the candidates. If the highest scoring candidate $w^* \neq C$, then a spelling error has been detected (and corrected at the same time).

The number $P(C|\mathcal{M}_{w_i})$ can be efficiently computed, as shown in Section 5.1, but how should the words be modeled using HMMs?

The type of model used here is the so called left-to-right model, for which

$$a_{ij} = 0 \quad \text{when } j < i$$

Often additional constraints are placed on the left-to-right model, such as

$$a_{ij} = 0 \quad \text{when } j > i + \Delta$$

to make sure that large changes in the state indices do not occur. In the left-to-right model of Figure 5.5 $\Delta$ is 2.

The solid arrows represent transitions with non-zero probabilities. The dashed arrows indicate what this particular model is biased towards. State 2, for example, can have non-zero probabilities for all observables, but is strongly biased towards $s$, i.e. $b_2(v_k)$ has the highest probability for $v_k = s$.

The general idea is that the states of the model represent character positions in the word modeled. Recall the four basic error types: character insertion, deletion, substitution and transposition. The model above can deal with all four, although perhaps not ideally with transpositions. The transition distribution $A$
makes it possible to handle deletions and insertions. The character distribution makes it possible to handle substitutions and for transpositions a combination of both is needed. The model of Figure 5.5 is not necessarily the best choice, some of the restrictions imposed on it can seem a bit strange. There may be any number of insertions (the looping arcs), but more than one consecutive deletion will not be very well handled since $\Delta = 2$. If there were a backward chaining arc from each state to the preceding state, transpositions would be more easily recognized. A character sequence like ‘shwo’ could then be generated (recognized) with the state sequence $1 \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 4 \rightarrow 6$ which would then score higher than the sequence $1 \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 5 \rightarrow 6$ which will probably be the highest scoring sequence using the model in Figure 5.5. Relaxing these constraints however, would lead to a close to ergodic model, and the computational advantages of the left-to-right model would be lost. Furthermore, restrictions on the number of errors that can occur in a single word are supported by findings in samples of spelling errors (cf. Damerau [1964]).

The quantity $P(C | \mathcal{M}_{w_i})$ can be thought of as a measure of similarity between the string $w_i$, modeled by $\mathcal{M}_{w_i}$, and the string $C$. Angell et al. [1983] discuss alternative string similarity measures and distinguish three types: material, ordinal and positional similarity. Material similarity measures the extent to which a pair of strings contains identical characters, ordinal similarity measures the extent to which the characters are in the same order, and positional similarity measures the extent to which the characters are in corresponding positions in the two strings. Most of the classical techniques use one or sometimes two of these similarity measures to perform isolated word error correction. It is interesting to see that the approach presented here is actually a mixture of all three types. The material similarity is expressed by the probability to observe a particular character, and the fact that this probability is conditioned on the states also makes it a positional similarity measure. The transition probabilities between states capture the ordinal similarity.

The probability that a particular model generated a given character sequence is, of course, dependent on how the model has been trained and also what the initial (pre-training) model looked like. Ideally one would like to have a large set of naturally occurring misspellings for each word in the vocabulary to train the respective models with. Such an error corpus is unfortunately not available so the corpus has to be artificially generated. These issues will be described in some detail in the sections below reporting the experiments.
CHAPTER 5. AN ALGORITHM FOR ROBUST TEXT RECOGNITION

In computing the probability of the character string for all the $M_w$ in the vocabulary, it is not really the number $P(C|M_w)$ as such that is interesting, it is the probability relative to the other words in the vocabulary that matters. To meet this end the Viterbi algorithm computes a good enough approximation of the probability of a string\(^4\). When the length of the character sequence grows, an arithmetic underflow condition can occur in the forward-backward algorithm, i.e. as $t \to \infty$, $\alpha_t(i) \to 0$. In the Viterbi algorithm, since it maximizes instead of sums (see equations (5.2) and (5.9)), logarithms of the probabilities can be used and underflow conditions do not arise. The logarithms of the probabilities can, of course, be computed beforehand and does not constitute an increased computational load in the actual recognition task. As well as maximizing the logarithm of the probability of a path (state sequence), one can of course minimize the negative logarithm of the probability of the path, the cost of the state sequence. Let $\delta_t(j)$ be the counterpart of $\phi_t(j)$ in equation (5.6) and denote the cheapest state sequence that ends in $q_j$ and accounts for the first $t$ characters. The reformulation of the Viterbi algorithm is straightforward:

**Initialization**

\[
1 \leq i \leq N
\]
\[
\delta_0(i) = \begin{cases} 
0 & \text{if } i = 1 \\
\infty & \text{otherwise} 
\end{cases} \tag{5.29}
\]

**Induction**

\[
1 \leq t \leq T , \quad 2 \leq j \leq N - 1
\]
\[
\delta_t(j) = \min_{1 \leq i \leq N-1} \left[ \delta_{t-1}(i) + (- \log a_{ij}) \right] + (- \log b_j(c_t)) \tag{5.30}
\]

**Termination**

\[
-\log P(C,Q^*|M) = \min_{1 \leq i \leq N-1} \left[ \delta_T(i) + (- \log a_i N) \right] \tag{5.31}
\]

The adaption of the Viterbi algorithm to Token Passing is quite trivial. Equations (5.30) and (5.23) are virtually identical. The transition cost is the negative logarithm of the transition distribution of the HMM and the local cost function is the negative logarithm of the observation symbol distribution.

Algorithm 1 below describes how the Viterbi algorithm is computed with TP in a single HMM network. The algorithm works for any network topology, but it might be useful to keep the HMM of Figure 5.5 in mind.

The HMM network has $N$ states numbered 1 to $N$, where state 1 is the entry state and state $N$ is the exit state. Each token $\tau$ contains only the cost, as computed by (5.30). Let $\tau_i(\delta_i)$ denote the cost of the token in state $i$ at time $t$. The *start token* has cost $-\log 1 = 0$. The *null token* has cost $-\log 0 = \infty$. The input character sequence is $C = c_1, \ldots, c_T$.

---

\(^4\)Thus $P(C,Q^*|M_w)$ is used as an approximation for $P(C|M_w)$. The Viterbi algorithm is the algorithm generally used in applications performing some sort of recognition with HMMs.
Algorithm 1 Viterbi decoding using Token Passing with a single HMM network. The boxed portion is the \textit{Step\_model}(c_t) procedure that is reused in Algorithms 2 and 4 below.

1: At time \( t = 0 \)
2: Put start token in the entry state
3: Put null tokens in all other states
4: for \( t = 1 \) to \( T \) do
5: \hspace{1em} for all states \( i < N \) do
6: \hspace{2em} Pass a copy of the token \( \tau_i \) to all connecting states \( j \):
7: \hspace{3em} \( \tau_j(\delta_t) = \tau_i(\delta_{t-1}) + (-\log a_{ij}) + (-\log b_j(c_t)) \)
8: \hspace{1em} end for
9: Discard all original tokens
10: for all states \( i < N \) do
11: \hspace{1em} Find the minimum cost token and discard the rest
12: \hspace{1em} end for
13: for all states \( i \) connected to state \( N \) do
14: \hspace{1em} Pass a copy of the token \( \tau_i \) to state \( N \):
15: \hspace{2em} \( \tau_N(\delta_t) = \tau_i(\delta_t) + (-\log a_{iN}) \)
16: \hspace{1em} end for
17: In state \( N \): Find the minimum cost token and discard the rest

In Isolated Word Recognition it is assumed that the input \( c_1, \ldots, c_T \) is exactly one distorted word. This assumption implies that there is no point in making the exit state transition before \( t = T \), i.e. lines 12 and 13 can be put outside of the main loop in Algorithm 1. The \textit{step\_model} procedure as displayed above will, however, be reused in a situation in which this assumption does not hold, thus the exit state transition has to be hypothesized for each value of \( t \), i.e. any character \( c_t \) may be the last character in the word modeled by the basic recognition unit.

When the entire input has been consumed, the cost of the token in the exit state of the model represents the best alignment of states to the input, i.e.

\[
\mathcal{M}_{w_i} \rightarrow \tau_N(\delta_T) = -\log(P(C, Q^*|\mathcal{M}_{w_i}))
\]

where \( Q^* \) is the optimal path\(^5\) through the model and \( w_i \) is the word (the model identifier) that is modeled by the network. To perform Isolated Word Recognition over an \( M \) word vocabulary \( W = \{w_1, \ldots, w_M\} \) it is, of course, necessary to execute Algorithm 1 for all the \( M \) basic recognition units and then choose \( w_i \) as the correction hypothesis if \( \mathcal{M}_{w_i} \rightarrow \tau_N(\delta_T) \) has the lowest cost.

During the computation of the \textit{step\_model} procedure, many models will display significantly different costs. This is, of course, the whole idea. The point however, is that these differences will start to show up when only a relatively

\(^5\)The actual state sequence through the basic recognition unit is not recorded in any way in Algorithm 1 and it can not be restored.
small number of input characters have been processed. Consider for example the input $C = \text{heuristics}$, and assume that both $M_{\text{heuristics}}$ and $M_{\text{exhaustive}}$ are in the vocabulary. Then

$$M_{\text{heuristics}} \rightarrow \tau^*(\delta_i) \ll M_{\text{exhaustive}} \rightarrow \tau^*(\delta_i)$$

after just a few characters. ($\tau^*(\delta_i)$ denotes the best token in any of the states at time $t$.) In a situation like this the Beam Search heuristic can be useful. All models that are outside the beam are deactivated (pruned). The beam is defined as the difference between the globally optimal model $M^* \rightarrow \tau^*(\delta_i)$, where

$$M^* \rightarrow \tau^*(\delta_i) = \min_{M_{w_i}} [M_{w_i} \rightarrow \tau^*(\delta_i)]$$

(5.32)

(the cost of the minimum cost token of all states of all models), and a preset threshold $B$. The overhead of the beam search heuristic is the computation of (5.32). If at any time $t$ it is the case that the model $M_{w_i}$ is outside the beam, i.e.

$$M_{w_i} \rightarrow \tau^*(\delta_i) > M^* \rightarrow \tau^*(\delta_i) + B$$

(5.33)

$M_{w_i}$ can be deactivated. The algorithm for isolated word recognition using HMMs within the TP framework is given in Algorithm 2.

---

**Algorithm 2** Isolated Word Recognition with Beam Search

1. At time $t = 0$
2. All models are activated
3. Put start token in the entry state of all models
4. Put null tokens in all other states
5. $M^* \rightarrow \tau^*(\delta_i) = \infty$
6. for $t = 1$ to $T$ do
7. 
8. for all models $M_{w_i}, 1 \leq i \leq M$ do
9. 
10. if $M_{w_i}$ is active then
11. 
12. deactivate $M_{w_i}$
13. 
14. else
15. 
16. step model($c_t$) with $M_{w_i}$
17. 
18. end if
19. 
20. end for
21. 
22. compute $M^* \rightarrow \tau^*(\delta_i)$ according to (5.32)
23. 
24. end for
25. 
26. Return $\text{word}$ as the reading of $C$ where
27. $\text{word} = \arg\min_{w_i} [M_{w_i} \rightarrow \tau_N(\delta_T)]$ {Only the active $M_{w_i}$}

At time $T$ the exit state of all active models is inspected, the model with the lowest cost in its exit state is the one that best matches the character sequence, and the model’s identifier denotes the preferred reading of the character sequence.
5.4. CONNECTED TEXT RECOGNITION

The technique described above, although quite successful at correcting misspellings, has some obvious shortcomings in most practical applications. In running text the word boundaries are uncertain and erroneous assumptions in this respect will result in segmentation errors being treated as spelling errors. Another problem is that real-word errors will go undetected. Further, the fact that words are not equally likely in a given context cannot be overlooked. The way to address this problem is to look at the words in the context in which they appear. Decisions regarding word boundaries must take into account the fact that segmentation errors may be present in the input.

5.4 Connected Text Recognition

In Connected Text Recognition (CTR) the character sequence can contain any number of words. The task is to find the most likely word sequence even though the word boundaries may be obscured (segmentation errors) and the words themselves are distorted (misspellings). Thus we want to find the word sequence $W = w_1, w_2, \ldots, w_n$ that maximizes the quantity $P(W|C)$. This number is impractical to compute, but again

$$P(W|C) = \frac{P(C|W)P(W)}{P(C)}$$ (5.34)

according to Bayes’ rule. The denominator is given, so to find $W^*$, the most likely word sequence, it suffices to maximize the numerator of (5.34) over the alternative word sequences.

$$P(W^*|C) = \max_W [P(C|W)P(W)]$$ (5.35)

The first factor of the right hand side of (5.35) is the channel characteristics (see Figure 5.6) that models how word sequences are distorted. The second factor is the prior probability of a word sequence, the language model. Probabilistic language models usually exploit the local context to predict the occurrence of a word. Assume, for the sake of this formal account, that the unspecified language model $G$ can be used to predict the probability of a word, $P(w_i|G)$. In this way the prior probability of a word sequence $W = w_1, \ldots, w_n$ can be computed as

$$P(W) = \prod_{i=1}^{n} P(w_i|G)$$ (5.36)
Irrespective of the language model used, (and even without a language model), the problem remains to find the most likely segmentation of the input character stream \( C = c_1, \ldots, c_T \), i.e. each word in the word sequence has to have a portion of the input characters assigned to it. The reason is, of course, that the channel characteristics must come to bear on the overall likelihood of the word sequence. For a given word sequence \( W = w_1, \ldots, w_n \), the most likely segmentation can be found by maximizing over all possible word boundaries, i.e.

\[
P(C|W) = \max_{1 \leq t_i, t'_i \leq T \atop t_i < t'_i} \left[ \prod_{i=1}^{n} P(c_{t_i}^{t'_i-1} | w_i) \right] \tag{5.37}
\]

where \( c_{t_i}^{t'_i} \) denotes \( c_{t_i}, c_{t_i+1}, \ldots, c_{t'_i-1}, c_{t'_i} \), the character sequence ‘assigned’ to word \( w_i \). Note that \( t'_i - 1 + 1 = t_i \). Equations (5.37), (5.36) and (5.35) can be used to formally define the Connected Text Recognition problem in equation (5.38).

\[
P(W^*|C) = \max_{W \atop 1 \leq t_i, t'_i \leq T \atop t_i < t'_i} \left[ \prod_{i=1}^{n} P(c_{t_i}^{t'_i-1} | w_i) P(w_i|G) \right] \tag{5.38}
\]

Finding words in distorted text is quite similar to the speech recognition problem. The problem of Connected Speech Recognition (CSR) is to recognize and segment out the elements of the continuous speech signal without knowing the starting point or the end-point of any of the elements. The elements modeled can be phones, subphones or sometimes with a small vocabulary they are words.

It is interesting to note the differences and similarities between text processing and speech processing. The primitive input symbol in the text case is, of course, the character or the keystroke. In the speech case, without going into the hardships of signal processing, the primitive input symbol is the feature vector. In most speech recognition systems the feature vector is continuous and has around 20 - 40 coefficients and the speech signal is sampled at about 100 Hz, see for example [Deller et al., 1993]. Whatever statistical model is used to model, say, a spoken word as a sequence of, say 50, feature vectors, it is obvious that there can never be a perfect match. The word model that is a closest match is chosen. Looking at a spoken word as a sequence of feature vectors one can thus say that the word is always ‘misspelled’, where the norm is an imagined sequence of feature vectors.

Looking at speech as a sequence of feature vectors, and text as a sequence of characters, a crucial difference is that there is no counterpart to the space character in speech. This makes segmentation a primary concern in CSR. In CTR the segmentation task is quite easy as long as the space character is properly placed but can get quite hard when it is not. The point here is that if we agree to carry the error types of text processing over to speech processing, we see that speech is virtually littered with misspellings and segmentation errors. It is therefore close at hand to see what the methods used in the difficult speech recognition task can do in the relatively simple text recognition problem.
5.4. CONNECTED TEXT RECOGNITION

The present computational model can straightforwardly be put to use on the Connected Text Recognition problem using a layering scheme of the different knowledge sources. The bottom layer, the string pattern matcher, is called the Orthographic Decoder (OD). The OD consists of a set of word modeling HMMs, one for each word in the vocabulary, very much like in the previous section. Each word modeling HMM can assign a probability to the hypothesis that a certain substring is the word modeled by the network, i.e. the first factor in (5.38). Subsequent layers, on top of the Orthographic Decoder, is called the Linguistic Decoder (LD). The LD is the component that hypothesizes word occurrences in the input using some language model, i.e. the second factor in (5.38). The information flow between the LD and the OD is such that the LD predicts that a certain word is present at a particular point in the character input stream, and the OD reports back the confidence of the match. It is thus a top-down process.

The Orthographic Decoder and Linguistic Decoder to some extent have complementary responsibilities in the recognition and error correction process. The string matching OD is primarily responsible for nonword errors, both regular spelling errors and segmentation errors. The LD reduces the search space and decides on ‘close calls’. In an utterance like: ‘... in the above table’, the OD would probably rule ‘above’ and ‘about’ just about equally likely, but since ‘above’ is more linguistically plausible in this context, the LD will (hopefully) rule out ‘about’. The predictive power of the LD is of course even more crucial when dealing with real-word errors since the OD will assign a good match to the ‘wrong’ word. There is always a trade-off situation going on between the LD and the OD in the recognition process. If both favor the same hypothesis, it will be a clear winner. If not, as in the case with the real-word errors, there will be several viable hypotheses.

It was mentioned above that the Linguistic Decoder may consist of several layers. In the dialogue application described above, for example, it could be useful to model a dialogue in terms of user utterances and system responses. An utterance can be given a phrase structure or a bracketing in terms of phrases, and phrases can be modeled as word sequences. In this hypothetical scenario the LD would consist of three layers, dialogue, utterance and phrase. The generalization from one to several LD layers is trivial, so the Token Passing account of Connected Text Recognition below will be restricted to a single layer Linguistic Decoder that models utterances or sentences in terms of word sequences.

In Connected Text Recognition, each Orthographic Decoder HMM network models one word of the vocabulary. This is very much like the idea behind Isolated Word Recognition in the previous section. There is, however, one big difference. In CTR the input character stream contains word boundaries, usually realized by the space character. In finding the best segmentation of the input stream the space character is of course crucial, but we do not want to make a hard decision regarding the location of the word boundary based solely on the fact that there is a space character in a certain position in the input. The OD must model word boundary locations, treating the space character like any
other character. There are different ways of doing this. One way would be to have an HMM network to recognize word boundaries. A single space character, for example, would then make up the word ‘␣’, modeled by $M_{<\text{space}>}$\(^6\). An utterance like: ‘\textit{show me all cars}’ would then be segmented as

$$\Rightarrow \textit{show me all cars}$$

(22)

This is not such a good idea, however, since language modeling would become unjustifiably expensive. For example, to model utterances with bigrams would in fact require trigrams since each pair of proper words is divided by the information-poor space-word. A different solution is needed.

The space characters present in the utterances are treated as parts of the word models. The solution is quite simple. The OD HMMs that are used in CTR have an extra initial state added to them that is biased towards recognizing the space character. The HMMs of the OD are then simply trained accordingly (see Chapter 6 below). The HMM $M_{\textit{show}}$, for example, will score maximum probability for the character sequence ‘␣show’. Using the approach depicted in Figure 5.7, the utterance (22) would be segmented as

$$\Rightarrow \textit{show me all cars}$$

(23)

The fact that the first word’s initial space character is not in the input does not present a problem. The two types of segmentation errors are dealt with in the following way. By taking the skip transition past the space-state, run-ons can be handled. Space characters can (if the network is so trained) be emitted at any state, thus splits can be modeled as well.

The Linguistic Decoder provides the pattern matching Orthographic Decoder with context and supervises the passing of tokens between word models of the OD. From a computational view this can be accomplished by connecting the set of word model HMMs together in a large super-HMM where the connections between subnetworks determine what words can follow others and with what probability. This solution can actually be hard-wired into a system, but the system will be awfully rigid. The Token Passing framework provides a much more flexible approach. The forwarding of tokens from the exit state of one OD

\(^6\)Note that what constitutes a word is quite arbitrary. Since the space character is just another character, one might have ‘\textit{as soon as possible}’ e.g. as a ‘word’. In the computational scheme described here, a word is merely a sequence of characters that has a network in the OD modeling it.
5.4. CONNECTED TEXT RECOGNITION

HMM to the entry state of another is elevated to a higher level of control, the Linguistic Decoder. The language model encoded by the LD may of course vary, but it is reasonable to use a probabilistic language model since the OD operates on probabilities. This facilitates for a clean LD-OD interface, the LD and the OD use a common communication protocol. The Connected Text Recognition experiments reported here employ LDs that encode language models that can be expressed with HMM networks. This means that the Viterbi algorithm can also be used in the LD. In the following we will thus assume a single HMM network in the Linguistic Decoder.

The Linguistic Decoder HMM network assigns probabilities to word sequences. The states of the network represent different contexts. (What is meant by a context of course varies depending on the language model.) Specific word occurrences are more or less likely to occur in a given context. The transition distribution of the HMM is thus the probability of going from one context to another, and the observation symbol distribution is the probability of a word given the context. The Viterbi algorithm can be used to compute the probability of the word sequence \( W \) and the optimal context sequence \( \text{CON}^* \) given the LD HMM \( M_{LD} \), i.e. \( P(W, \text{CON}^* | M_{LD}) \). Note that \( M_{LD} \) is the language model \( G \) introduced in equation (5.36), and that \( P(W, \text{CON}^* | M_{LD}) \) is used as an approximation (\( \approx \)) for \( P(W | M_{LD}) \) in equation (5.40):

\[
P(W, \text{CON}^* | M_{LD}) = \max_{\text{CON}} \prod_{i=1}^{n} P(\text{con}_i | \text{con}_{i-1}) P(w_i | \text{con}_i)
\]

where \( \text{con}_0 \) is a ‘dummy-context’, or, in the present computational model, the entry state of \( M_{LD} \).

The quantity \( P(w_i | \text{con}_i) \) in equation (5.39) can be thought of as the interface between the two knowledge sources, the coupling between the layers that enables the recognizer to produce the word sequence that is overall most likely, with respect to both orthographic evidence and linguistic expectation. When the LD predicts that the word \( w_i \) is present in the input, the OD HMM \( M_{w_i} \) begins to evaluate that hypothesis. Equation (5.38) can be made more specific:

\[
P(W^* | C) \approx \max_{W, \text{CON}} \prod_{1 \leq t_i \leq t'_{i}} P(c^t_{i,z_i} | w_i) P(\text{con}_i | \text{con}_{i-1}) P(w_i | \text{con}_i)\]

The equation above can be visualized in the Token Passing framework (see Figure 5.1 in Section 5.2). Tokens are passed within the LD HMM according to the transition distribution of the network and word models of the OD are hypothesized according to the observation distribution. As tokens reach the exit state of the word model, they are propagated back to the context/state in which they were originally proposed. This upward propagation does not

\[\text{footnote}{\text{Remember from Section 5.3 that } P(c^t_{i,z_i}, Q^* | w_i) \text{ is already used to approximate } P(c^t_{i,z_i} | w_i).}\]
constitute an extra cost. Note that whereas the workings of the OD HMMs is time-synchronized the LD is not. One step of the \textit{step model} procedure is executed in the OD HMMs for each character that is read from the input. The LD simply reacts to tokens that are passed up from beneath, and this has nothing to do with the the time index \( t \). This means for example (see Figure 5.8) that a token in the exit state of some word model at time \( t \) can get passed up to \( \text{con}_{i-1} \), then passed from there to \( \text{con}_i \), from \( \text{con}_i \) to the entry state of \( M_{w_i} \) and time is still \( t \). When the OD starts processing the hypothesis \( w_i \), and characters are read from the input, the time index is, of course, incremented.

The Viterbi algorithm is used to compute the probability of an observation sequence and the optimal state sequence. The state sequence is not of great interest when computing the probability of a character sequence given a word model \( P(c_i^t, Q^t | M_{w_i}) \), the quantity computed by the OD HMM networks. The states of an OD network represent character positions and this information is not really useful, the quantity is used more like an approximation for \( P(c_i^t | M_{w_i}) \). The same reasoning can be applied to the LD (see Section 5.2), but whether the context sequence is important or not depends on what a context represents in the language model encoded by the LD network. Irrespective of whether the context sequence is informative or not, the word sequence certainly is. Retrieving the word sequence is our main objective. Since each token arriving in an LD network state from below represents a word matched with the input, this event has to be recorded so that backtracking is enabled. The data structure used to record the word hypothesis is the \textit{Word Link Record} (see Section 5.2).

The Word Link Records (WLR) are stored in a linked list structure where
each path through the structure represents a word sequence hypothesis. Each token, besides the cost, keeps a path identifier (pointer) to the last WLR in the word sequence hypothesis. That WLR has a pointer to its predecessor and so on. The token itself represents the head of the path. The WLR is created as a token in the exit state of an OD network is propagated back to the LD state/context that hypothesized the word, and the new WLR is incorporated into the list structure. The WLR contains the cost of the path (up to the point where it was created), the path identifier (inherited from the token), the time index (character position) at which it was created and the model identifier of the OD HMM that the token exited from. The process is visualized in Figure 5.9.

![Diagram of Word Link Records](image)

**Figure 5.9:** A Word Link Record is created as a token is passed upwards

The ‘start-WLR’ with * as model identifier is the root of the linked list structure. At the start of the recognition process the start token in the LD points to this WLR. Note that there might be several tokens pointing to the same WLR, along with other WLRs. The creation of new WLRs is called record decisions, Algorithm 3, and it is of course crucial in Connected Text Recognition. The four fields of the WLR in Algorithm 3 are denoted: $\delta$, $\uparrow_{\text{wlr}}$, time and word. The cost and path identifier fields of the token are denoted $\delta_t$ (as usual) and $\uparrow_{\text{wlr}}$.

The reader should not be bothered by the fact that the algorithms here and elsewhere in this thesis do not make sense down to the last detail. For example, how can a token know which state of the LD that hypothesized it so that it can get propagated back up to that state once it reaches the exit state of the OD

---

8The LD layer uses the linked list structure to keep track of what is going on in the layer beneath. In the general case, where there might be several LD layers, each layer would need its own WLR list structure.

9It is possible to store additional information in the WLRs, the context in which the word occurrence was hypothesized, for example, might be useful in subsequent processing of the text.
62 CHAPTER 5. AN ALGORITHM FOR ROBUST TEXT RECOGNITION

Algorithm 3 record_decisions

1: for all states \( i < N \) \{of the Linguistic Decoder\} do
2: if \( i \) holds a token \( \tau_i \) then
3: create a new WLR \( wlr \)
4: with \( wlr \) do
5: \( wlr(\delta) = \tau_i(\delta) \)
6: \( wlr(\uparrow_{wlr}) = \tau_i(\uparrow_{wlr}) \)
7: \( wlr(\text{time}) = t \)
8: \( wlr(\text{word}) = w_k \) \{\( M_{w_k} \) is the OD HMM that propagated \( \tau_i \)\}
9: end with
10: \( \tau_i(\uparrow_{wlr}) = wlr \)
11: end if
12: end for

network? There is of course a simple technical solution to this sort of problem and issues of this type are generally suppressed in the algorithmic outlines. The purpose of the algorithms is to convey the basic idea.

The Token Passing algorithm is now set to recognize word sequences instead of isolated words. The LD HMM used in the superficial algorithmic presentation below is similar to the OD HMM in Figure 5.7 except that it is not limited to left-to-right transitions (and of course, the observation symbols are not characters but words). The Viterbi algorithm is used both in the LD and the OD. The Beam Search heuristic has a slightly different effect in Connected Text Recognition compared to Isolated Word Recognition. If a word model gets deactivated in IWR it stays deactivated for the duration of the recognition process, in CTR a word model may be reactivated at any time (cf. line 10 in Algorithm 4). The step_model procedure, Algorithm 1, is reused here with only minor changes. The token put in the entry state of the OD HMM does not have zero cost since it has been subject to prior cost accumulation. Recall: the start token has cost \(-\log 1 = 0\) and the null token has cost \(-\log 0 = \infty\)

At time \( T \) the most likely word sequence can be established by following the path identifier chain of the token in the exit state \( (M_{LD} \rightarrow \tau_N) \) back to the start-WLR, which indicates the start of the sequence.

The algorithm is quite easily generalized to perform \( N \)-best search. It suffices to let each state hold \( N \) tokens instead of just one. Lines 27 and 33 of Algorithm 4 should be changed to: ‘Find the \( N \) tokens with min cost and discard the rest’.

Algorithm 4 returns the best word sequence, i.e. it performs a 1-best search. Under certain circumstances, however, Algorithm 4 is suboptimal in the sense that it can not guarantee that the overall best word sequence is returned. If the algorithm is run in 1-best mode, i.e. each state of the OD HMMs can hold only one token, and the same word model can be hypothesized from more than one state, it can happen that the token that would score the overall lowest cost if it was allowed to proceed, gets pruned because there is another token with a lower cost for the left context that is preferred in the entry state of the OD HMM. The
Algorithm 4 Connected Text Recognition with Beam Search

1: for \( t = 0 \) do
2: Create the start-WLR
3: Put start token in the entry state of the LD and let it point to the start-WLR
4: Put null tokens in all other states of the LD
5: Deactivate all models of the OD
6: \( \mathcal{M}^* \rightarrow \tau^*(\delta_t) = \infty \)
7: end for
8: for \( t = 1 \) to \( T \) do
9: for all states \( i < N \) in \( \mathcal{M}_{LD} \) with a non-null token do
10: Pass a copy of the token \( \tau_i \) to the entry state of all \( \mathcal{M}_{wk} \) observable in state \( j \):
11: \( \mathcal{M}_{wk} \rightarrow \tau_i(\delta_t) = \tau_i(\delta_t) + (-\log a_{ij}) + (-\log b_j(w_k)) \) \{Reactivation\}
12: end for
13: Put null tokens in all states in \( \mathcal{M}_{LD} \)
14: for all models \( \mathcal{M}_{wk} \) \( 1 \leq k \leq M \) do
15: if \( \mathcal{M}_{wk} \) is active then
16: if (5.33) then
17: Deactivate \( \mathcal{M}_{wk} \)
18: else
19: step_model\((c_t)\) with \( \mathcal{M}_{wk} \)
20: end if
21: end if
22: end for
23: compute \( \mathcal{M}^* \rightarrow \tau^*(\delta_t) \) according to (5.32)
24: if the token in the exit state of \( \mathcal{M}_{wk} \) is non-null then
25: Propagate the token up to the LD state that hypothesized it
26: end if
27: for all states \( i < N \) in \( \mathcal{M}_{LD} \) do
28: Find the token with min cost and discard the rest
29: end for
30: record decisions
31: for all states \( i < N \) in \( \mathcal{M}_{LD} \) connected to state \( N \) do
32: Pass a copy of the token \( \tau_i \) to state \( N \):
33: \( \tau_N(\delta_t) = \tau_i(\delta_t) + (-\log a_{iN}) \)
34: end for
35: In state \( N \) of \( \mathcal{M}_{LD} \): Find the token with min cost and discard the rest
36: end for
37: Backtrack \( \mathcal{M}_{LD} \rightarrow \tau_N(\uparrow_{wlr}) \)
part-of-speech bigram language model is an example of a language model with this property (the words are ambiguous with respect to their part-of-speech). Young et al. [1989] get around this problem by having multiple instances of the same word model, one instance for each context in which it is observable. A variation of the same scheme is used here. Instead of having multiple network instances, each state can hold more than one token, i.e. N-best search is used to guarantee that the overall best sequence is obtained. (See the following chapter for further comments on this subject.)

Note that the word sequence returned is really a sequence of model identifiers. Supposedly the model identifier of a model is exactly the character sequence that the model models, e.g. the model identifier of $M_{\text{show}}$ is ‘\text{show}’, but that need not necessarily be the case. For some word-forms it is unrealistic to have one HMM network for each word-form (character sequence). The natural numbers is one such ‘word group’. A solution to this problem would be to have a single network that recognizes a number of word-forms, e.g. dates, social security numbers and possibly even proper nouns. The network $M_{\langle \text{date}\rangle}$ with model identifier ‘$\langle \text{date}\rangle$’ would then recognize character sequences like ‘4 of July’, and the input ‘On the 4 July we went to New York’ could come out as ‘On the $\langle \text{date}\rangle$ we went to $\langle \text{city}\rangle$’. Since the WLRs contain the word boundary positions, it is possible to extract the character sequence recognized as ‘$\langle \text{date}\rangle$’ from the character input stream.

The approach to Connected Text Recognition presented here has the potential to deal with all the lexical errors discussed in this thesis. It has the potential to handle misspellings, run-ons and splits, single and multiple character errors and nonword and real-word errors. Having the potential to solve a problem is, however, not the same thing as actually solving it. This of course ultimately depends on the accuracy with which the Orthographic Decoder models the noisy channel and the Linguistic Decoder the language. The performance of this approach has to be experimentally evaluated.
Chapter 6

Experimental Evaluation

To test our ideas of the layered HMM approach in the Token Passing framework we have developed a system, ctr, to perform Connected Text Recognition. The system is based on the algorithms presented in the previous chapter and is thus also restricted to two layers. The Linguistic Decoder is represented in one (the topmost) layer by a single HMM network and the Orthographic Decoder is realized by the set of word modeling HMM networks in the bottom layer. The Beam Search threshold defines the level of trade-off between accuracy and computational efficiency (speed). In the experiments reported below we have opted for accuracy at the expense of speed. We have used an infinitely wide Beam so that no hypotheses are ever pruned.

Much of the work presented in this thesis is based on the findings in the dialogue corpus profiled in Chapter 3. The dialogue corpus application was also the focal point during the development of the techniques. The cars part of the dialogue corpus was the first error corpus that was given to ctr for testing (Section 6.1). Later we came to the conclusion that we needed to test on a larger corpus as well, and this materialized in the secretary experiment (Section 6.2). The secretary experiment is a completely different application compared to the dialogue scenario, it concerns transcription typing of a software manual.

6.1 cars

The ctr experiments reported here concern the cars corpus. The corpus includes 20 dialogues. It contains in all 369 utterances, 3,139 word tokens and 584 word types. There are 92 lexical errors distributed over 71 utterances. There are 62 misspellings, 17 run-ons and 13 splits.$^1$

$^1$The figures on error frequencies and results presented in this thesis are not in complete agreement with figures presented in previous publications [Ingels, 1996b, Ingels, 1996a]. The reason is that different definitions have been used for multiple segmentation errors. A string like ‘toyotapeugeotvolksvagen’ is treated as one multiple run-on here, whereas in the other publications this string was regarded as two run-ons.
The intention with the CARS experiment is first and foremost to get a handle on the overall error correcting performance of the CTR system. We are also interested in seeing what impact different language models will have on the system. With sparse data, as in the present case, it is not absolutely certain that a Linguistic Decoder implementing a language model will have a strong positive effect. Experiments have been conducted on three different, rather weak, language models, a Unigram language model and two tag Bigram language models. The difference between the two tag Bigram language models is that they use different tag-sets. One uses a small domain-oriented tag-set while the other employs a Part-Of-Speech (POS) tag-set. From the point of view of the application it is of interest to note any differences between the application-close domain oriented tag-set and the linguistically oriented tag-set. We also have a Baseline to which the results of these experiments can be compared. The Baseline experiment involves no linguistic constraints so the correction of lexical errors is performed by the Orthographic Decoder alone.

The 20 dialogues were randomly divided into five parts of four dialogues each. In the experiments, 16 dialogues (four parts) were used to obtain the language model and then the model was tested on the remaining four dialogues (one part). The partitionings were rotated so that each language model was tested on all of the five parts. The same Orthographic Decoder was used in all the experiments.

6.1.1 The Orthographic Decoder

The Orthographic Decoder contains 584 word modeling HMMs, one for each word type in the corpus. The structure of the OD HMMs can be seen in figure 5.7. Ideally each HHM should be trained on typical errors occurring in Swedish text. Unfortunately there is no such error corpus available and we can certainly not train the HMMs on the errors occurring in the corpus. We must find a way to generate an error corpus so that the OD HMMs can be trained and used for other purposes as well, not just to identify the particular errors in this corpus.

Inspired by the basic error types one can construct four error generating functions. Given a word, these functions will produce a set of corrupted forms of the input word. Given the word ‘\textit{show}’ for example, the deletion function will produce: \{‘\textit{show}, ‘\textit{how}, ‘\textit{sow}, ‘\textit{shw}, ‘\textit{sho}\}. The deletion operator is applied to each character position in the word. Although these error types apply to the space character as well as to any other character, we have an extra error type dealing only with the space character, which is called \textit{white-space insertion}. There is also an error type called \textit{double stroke}. The error types insertion and substitution raise the question as to what to insert and what to substitute for, respectively. One hypothesis is that keyboard neighbors are likely to take part in, for example, substitutions. The neighbors\footnote{The neighbor relation is limited to immediate left and right neighbors.} of ‘\textit{o}’ are ‘\textit{i}’ and ‘\textit{p}’, so if substitutions are applied, the error corpus for $M_{\textit{show}}$ will contain...
amongst others ‘\(\text{shw}\)’ and ‘\(\text{shpw}\)’. The list of error-generating operators that have been considered for training of the OD HMMs is thus:

- deletion (e.g. ‘\(\text{shw}\)’)
- insertion (e.g. ‘\(\text{shpow}\)’)
- substitution (e.g. ‘\(\text{shpw}\)’)
- transposition (e.g. ‘\(\text{sohw}\)’)
- white-space insertion (e.g. ‘\(\text{sh ow}\)’)
- double stroke (e.g. ‘\(\text{show}\)’)

Note that the basic error-generating functions above will produce mostly performance related errors, i.e. they are likely to be generated by a human only by mistake. The error corpora generated for the various OD HMMs are consequently quite poor with respect to knowledge of spelling errors people produce for other reasons. Phonetic resemblance and other cognitively related difficulties are not included in the corpora. The only ‘external’ knowledge included in the training corpora is the layout of the keyboard.

It is, of course, often the case that a corruption generated by one of the above error functions turns out as another legal word in the vocabulary. If deletion is applied to ‘\(\text{them}\)’ for example, ‘\(\text{the}\)’ will be part of ‘\(\text{them}\)’s error corpus. A simple little program \textsc{filter} was devised to remove all such ‘real-word’ corruptions. If the corpora are filtered, the effect will be that real-word errors are harder to recognize, but on the other hand \textsc{ctr} will be less likely to change words that are properly spelled.

The word models of the OD have been trained on their respective error corpora with the Baum-Welch reestimation algorithm. A maximum likelihood estimation procedure like the Baum-Welch algorithm will assign zero probabilities to all unseen events. Since unexpected events such as misspellings not included in the corpus will most likely appear, the parameters of the model must be smoothed. Smoothing is the term generally used for making the distributions more uniform. Very low probabilities are adjusted upwards and high probabilities are adjusted downwards. The models used in the experiments reported here have all been smoothed with one of the simplest smoothing schemes, the \textit{additive smoothing scheme} [Levinson \textit{et al.}, 1983] (p. 1053). After the model has been trained, a small number \(\epsilon > 0\) is assigned to all parameters corresponding to unseen events and the other parameters are adjusted downwards accordingly.

Because of the fact that no Swedish corpus of actually occurring spelling and segmentation errors is available, the process of finding a reasonable training setup for the OD HMMs is very much a matter of trial and error. Prior to the first experiments on \textsc{cars} the Baseline system configuration (see Figure 6.1) was used to try out different training corpora and smoothing parameters for the OD HMMs. The Baseline system configuration runs without a Linguistic Decoder. At each time \(t\) the best token, out of the \(M\) possible tokens that can
be propagated out of the exit states of the $M$ OD HMMs, corresponds to the best word hypothesis at time $t$. This token generates a WLR corresponding to the word hypothesis and copies of the token are inserted into the entry state of all $M$ word models, i.e. the tokens just circulate through the LD without any cost being added.

![Diagram of baseline experiment - CTR setup](image)

**Figure 6.1: The Baseline experiment – CTR setup**

In the experiments reported in Section 6.1.5, the error corpora were generated with the error functions deletion, substitution, and white-space insertion. Apart from this general strategy, some special words need specialized corpora. These words include single character ‘words’ such as ‘,’ ‘?’ ‘.’ and so on. There are seven such words in the vocabulary and the training material is a small set of hand-made corruptions that only involve the space character. There are 51 numbers in the vocabulary. There are car prices, figures for fuel consumption, grades and so on. Although there are more clever ways to handle things like this (cf. Section 5.4 page 64), the numbers all have their own individual HMM in the OD modeling it. These special words have corpora generated with only the white-space insertion error function. The error corpora thus generated were then filtered for real-word errors. The OD HMMs were trained with the Baum-Welch reestimation algorithm. After training, each HMM had its observation symbol distribution smoothed with the additive smoothing scheme with $\epsilon_{obs} = 10^{-4}$.

Note that we are evading the unknown word problem. Even if a word type is unseen in the training corpus of an experiment, the OD will still contain the model corresponding to the unseen word.
6.1.2 The Unigram Language Model

The Unigram language model:

\[ P(w_1, \ldots, w_T) = \prod_{i=1}^{T} P(w_i) \] (6.1)

The language model’s parameters are extracted from the training corpus of the five partitionings.

\[ P(w_i) = \frac{\text{Count}(w_i)}{N} \]

where \( N \) is the number of word tokens in the training corpus. For each of the five partitionings there will be a fair amount of unknown words in the test corpus that have to be smoothed. Recall that one fifth of the entire corpus is held out for testing in each partition. It should be noted that the observables of the Linguistic Decoder that are smoothed are exactly the words that are unseen in the training material but are members of the vocabulary, i.e. word models with non-zero probability after smoothing are the words of the vocabulary and no other.

The Linguistic Decoder realizing the Unigram model is a single state HMM (three states including the entry and exit states). The parameters of the Unigram make up the observation symbol distribution of the LD HMM.

The results on the Unigram Linguistic Decoder reported in Section 6.1.5 refer to the combined results from the five experiments with the five partitionings where the LD have been smoothed with the additive smoothing scheme with \( \epsilon_{\text{obs}} = 10^{-4} \).

6.1.3 The Domain-Tag Bigram Language Model

In the domain-tag Bigram language model there are 19 tags. The words of the corpus are grouped into classes that are semantically- or domain-oriented. Examples of classes and class members are:

- Object Head (OH), e.g. ‘\( \downarrow \text{saab}\),900’, ‘\( \downarrow \text{all}\’
- Aspect Head (AH), e.g. ‘\( \downarrow \text{costs}\’’, ‘\( \downarrow \text{acceleration}\’
- Communicative Head (CH), e.g. ‘\( \downarrow \text{show}\’’, ‘\( \downarrow \text{example}\’

The complete tag-set is listed in Appendix A.1.

If \( tag_{i+1}^{T+1} \) denotes a sequence of \( T \) tags assigned to a sequence of \( T \) words, (plus the dummy tag \( tag_{T+1} \) corresponding to the nonexistent word \( w_{T+1} \)), the tag Bigram language model looks like:

\[ P(w_1, \ldots, w_T) = \sum_{\text{all} tag_{i+1}^{T+1}} \prod_{i=1}^{T} P(w_i|tag_i)P(tag_{i+1}|tag_i) \] (6.2)
The language model’s parameters are extracted from the tagged training corpus of the five partitionings:

\[
P(tag_{i+1}|tag_i) = \frac{\text{Count}(tag_i, tag_{i+1})}{\text{Count}(tag_i)}
\]

\[
P(w_i|tag_i) = \frac{\text{Count}(tag_i, w_i)}{\text{Count}(tag_i)}
\]

The tag Bigram can be straightforwardly implemented as our Linguistic Decoder HMM, see for example Cutting et al. [1992]. The second factor on the right-hand side of equation (6.2) is the transition distribution of the LD and the first factor is the observation distribution. The observables of the LD HMM are the words of the vocabulary, or in other words, the word modeling HMMs of the OD. The ctr setup is shown in Figure 5.8 where the contexts correspond to the tags of the language model.

The tag Bigram language model models local contextual dependencies. These dependencies are weak. There is a great deal of uncertainty as to what the next word might be, judging from the tag assigned to the present word. The uncertainty is emphasized by the relatively small tag-set, each class has a relatively large amount of potential realizations. Still, the test corpus will contain both unseen tag-to-tag transitions and, of course, previously unseen words. This means that both the transition distribution and the observation distribution of the LD have to be smoothed. In the case of the Unigram, the single state of the LD has the entire vocabulary as observables. The states of the tag Bigram LD each have a subset of the vocabulary as possible observables. When the observation distribution of the tag Bigram LD is smoothed, it is only the previously unseen observables of this subset that are assigned a non-zero probability, the remainder stays zero.

It should be noted that we are not using the Baum-Welch reestimation algorithm here. CTR can, if so instructed, return the tag sequence along with the normalized utterance just like an ordinary POS tagger. It was discussed above that whether or not this is desirable depends on what the context encodes. Especially with the domain oriented tags it can be useful to have the utterance tagged since it will reduce the interpretation step, from input query to SQL-query, quite substantially. For the purpose of tagging, the language model extracted from a tagged corpus will outperform the language model induced from an untagged corpus with a maximum likelihood estimation procedure [Elworthy, 1994]. For the purpose of predicting the next word however, this need not be the case. In the cars experiment we utilize the tagged corpus, whereas in the secretary experiments presented in the following section we will contrast the two approaches.

The results on the domain-tag Bigram Linguistic Decoder reported in Section 6.1.5 refer to the combined results from the five experiments with the five partitionings where the LD have been smoothed with the additive smoothing scheme with \( \epsilon_{\text{trans}} = 10^{-3} \) and \( \epsilon_{\text{obs}} = 10^{-3} \). The most ambiguous word in the
language model is three ways ambiguous, so CTR was run under 3-best search to guarantee optimal performance.

### 6.1.4 The POS Bigram Language Model

The POS Bigram language model has 31 tags. The tag-set originates from the SUC corpus (Stockholm-Umeå Corpus [Källgren, 1990]). The tags used in the SUC corpus are traditional Part-Of-Speech with associated morphological features. We have made slight modifications to the original set of SUC-tags to obtain a set of atomic tags with different syntactic distributions. Examples of tags and tag members are:

- Proper noun (PM), e.g. ‘saab 900’
- Determiner (DT), e.g. ‘all’
- Verb form finite (VBF), e.g. ‘costs’
- Noun (NN), e.g. ‘acceleration’, ‘example’
- Verb form imperative (VBP), e.g. ‘show’

The complete tag-set is listed in Appendix A.2.

The POS Bigram parameters are extracted from the tagged training corpus in the same way as was done with domain-tag Bigram. Also with POS Bigram both the state transition distribution and the observation symbol distribution are smoothed with the additive smoothing scheme.

The results on the POS Bigram Linguistic Decoder reported in Section 6.1.5 refer to the combined results from the five experiments with the five partitionings where the LD have been smoothed with the additive smoothing scheme with $\epsilon_{\text{trans}} = 10^{-3}$ and $\epsilon_{\text{obs}} = 10^{-3}$. The most ambiguous word in the language model is three ways ambiguous, so CTR was run under 3-best search to guarantee optimal performance.

### 6.1.5 Results

When an experiment is conducted, CTR is run on the corpus in batch mode, i.e. utterances are processed from an input file and output to an output file. This creates pairs of utterances. Thus, resulting from an experiment is a set of pairs: (original utterance, normalized utterance). An experiment is evaluated by comparing the pairs resulting from the experiment to pairs in a result key. The key is a hand-made set of pairs where the first element (the original utterance) contains at least one lexical error and the second element is the appropriate correction of that utterance. This set is called A. The outcome of an experiment are the pairs produced in the experiment where the second element is not identical to the first one, and the pairs where the first element is identical to the first element in one of the pairs in A. In other words: The outcome of an experiment are the pairs produced in the experiment where CTR
has changed the input, and the pairs where it should have changed the input. This set is called $C$. The pairs in the outcome that are also in the key belong to the set $B$, i.e. $B = A \cap C$. The outcome of an experiment can now be rated with respect to the performance measures $recall$ and $precision$.

\[
recall = \frac{|B|}{|A|} \times 100
\]

\[
precision = \frac{|B|}{|C|} \times 100
\]

There is one important point that needs to be emphasized regarding this style of evaluation. Since the outcome of an experiment does not only include the utterances that have actually been changed, but also those that should have been changed, this means that $C$ will always contain at least as many pairs as $A$. The reason for this somewhat unusual evaluation scheme is of course that we want to capture the performance of the system regarding real-word errors. The implications of this evaluation style is that precision can never be higher than recall. If the two metrics are the same, this means that no unfounded changes have been made to the input.

An example of a pair in $A$: (rust protection for these, rust protection for these). The first element of the pair contains two errors and we would like to extend the performance measure to account for individual errors, not just whole utterances. From the outcome of the experiment we can extract the counterparts for $A$, $B$ and $C$ that apply to the respective error categories. We have $A^m$, $B^m$ and $C^m$ for misspellings, $A^r$, $B^r$ and $C^r$ for run-ons and we have $A^s$, $B^s$ and $C^s$ for splits. We are also interested in the total number of individual errors so the key $A^{tot} = A^m \cup A^r \cup A^s$ is added to the list of keys. The example pair above that was a member of $A$ also adds ⟨protection , protection⟩ to $A^m$ and $A^{tot}$ and ⟨for these , for these⟩ adds to $A^r$ and $A^{tot}$. The five keys provide the five performance categories in the tables below.

| Experiment | Performance categories | Recall | Precision |
|------------|------------------------|--------|-----------|
| Baseline   | Utterances              | 72 %   | 72 %      |
|            | Misspellings            | 74 %   | 74 %      |
|            | Run-ons                 | 100 %  | 100 %     |
|            | Splits                  | 85 %   | 65 %      |
|            | Total                   | 80 %   | 77 %      |

Table 6.1: Baseline experiment

In the Baseline experiment (Table 6.1) there is an 80% total recall. The drop in precision is quite small which is not surprising since there is no language model to ‘disturb’ the Orthographic Decoder. The 80% → 77% drop is altogether due to the bad splits precision. In a handful of places in the corpus there are double
space characters inbetween words. Since the LD does not add a cost to the
forming of words, the superfluous space will be changed to a single character
word such as ‘,’. The double space in the input utterance does not constitute
an error by our definition, so an error is introduced and the error is classified in
terms of the transformation from input to output utterance, in this case a split.
For example: ‘ ... models, and ... ’ → ‘ ... models, and ... ’.

When the LD is furnished with the Unigram language model (Table 6.2)
performance is enhanced on all categories. The total enhancement (80% → 86%)
compared to the Baseline is due to improved ability to deal with misspellings
and splits. On four accounts the Unigram model was able to make the right
decision on ‘close calls’ regarding misspellings that the Baseline failed to deal
with.

| Experiment  | Performance categories | Recall | Precision |
|-------------|------------------------|--------|-----------|
| Unigram     | Utterances              | 82 %   | 76 %      |
|             | Misspellings            | 81 %   | 76 %      |
|             | Run-ons                 | 100 %  | 81 %      |
|             | Splits                  | 92 %   | 92 %      |
|             | Total                   | 86 %   | 79 %      |

Table 6.2: Experiments with the Unigram language model

| Experiment            | Performance categories | Recall | Precision |
|-----------------------|------------------------|--------|-----------|
| Domain-Tag Bigram     | Utterances              | 86 %   | 79 %      |
|                       | Misspellings            | 89 %   | 79 %      |
|                       | Run-ons                 | 100 %  | 85 %      |
|                       | Splits                  | 100 %  | 100 %     |
|                       | Total                   | 92 %   | 83 %      |

Table 6.3: Experiments with the domain-tag Bigram language model

Both the tag Bigram experiments (Tables 6.3 and 6.4) show steady improve-
ment over both the Baseline and the Unigram\(^3\). Mutually however, between the
domain-tag Bigram and the POS Bigram, there is not much difference. POS
Bigram seems to have a narrow advantage with respect to precision, but the
two tag Bigram language models exhibit virtually the same results. The advan-
tage that POS Bigram has because of the richer class-set is possibly neutralized
by the poorer estimates resulting from the added data sparseness problem. If
the result that domain classes yield as good performance as syntactic classes
would extrapolate to a bigger corpus, we would consider this a positive result in

\(^3\)Due to the small test-set it is difficult to show statistically significant improvements from
one language model to another. The only difference that can be statistically confirmed is that
both tag Bigram language models are significantly better than the Baseline. This was shown
with a \(\chi^2\)-test on the 0.05 level using the numbers for total recall.
the context of a dialogue system since the interpretation step (input query → SQL-query) is substantially reduced by the domain-classification of input words.

| Experiment | Performance categories | Recall | Precision |
|------------|------------------------|--------|-----------|
| POS Bigram | Utterances              | 89 %   | 82 %      |
|            | Misspellings            | 89 %   | 83 %      |
|            | Run-ons                 | 100 %  | 77 %      |
|            | Splits                  | 100 %  | 100 %     |
|            | Total                   | 92 %   | 84 %      |

Table 6.4: Experiments with the POS Bigram language model

`cars` contains some ‘impossible’ lexical errors. Examples of these are:

\[
\Rightarrow s
\]

\[
\Rightarrow \text{total-cost per mile ins of rust and value-decrease ins of motor-strength}
\]

\[
\Rightarrow \text{choose the best three with respect to fuel-consumption total-cost and value-decs}
\]

Utterance (24) is a strange single character utterance. CTR suggested ‘so’ as a repair, but we had decided that the subject probably meant ‘show’. Utterances (25) and (26) are both the work of one particular subject. The subject is obviously making up new abbreviations. The two instances of ‘ins’ should both be ‘instead’ and ‘value-decs’ should be ‘value-decrease’. If it were not for these four errors, the total recall performance for the Bigram models would be around 96%.

The `cars` corpus is quite small and compared to normal text standards (not just dialogue texts) the language in `cars` is highly irregular, full of ellipses and other oddities. This together with the data shortage and partitioning scheme makes the language model parameter estimation very unreliable. On the other hand there are virtually no real-word errors in the corpus, and here is where a reliable language model is needed the most. The language models used here are obviously useful in distinguishing between correction alternatives, but the limited vocabulary of `cars` also has a positive effect on this problem since there are relatively few alternatives to consider. The conclusion must be that it is necessary to test CTR on a larger corpus, with more training material and a larger vocabulary.

## 6.2 SECRETARY

Eight secretaries at the Department of Computer and Information Science were given the task to transcribe a portion of a software manual [IBM, 1993] written in English with the purpose of acquiring an error corpus. The software manual
is the IBM OS/2 2.1 Installation Guide and the transcription part is an excerpt from pages 4-18 to 4-24. The preface and chapters one, two, three and chapter four up to page 4-18 are used as training material in the experiments reported below and the seven page excerpt is used for testing. The paper copy of the excerpt given to the secretaries was freed of formatting except for headings and paragraph delimiters. The original text contains a lot of instruction lists formatted as enumerations, for example:

1. ... 
2. Press Enter to display the Options menu. 
3. Select Set startup values and press Enter. 
4. ... 

The unformatted text (relieved of the numbers) looks quite strange to the subjects and most of the subjects said after the task had been completed that it was hard to make any sense out of the text. Another reason for this is that the subjects are unfamiliar with the topic.

Each of the subjects was instructed to transcribe half the excerpt. Hence the error corpus includes four versions of the original text. The only additional instruction given to the subject was that “you should type as fast as you can”. The reason for this was that we wanted a larger error sample than we would presumably otherwise get. The subjects were not told of the purpose of the transcription but some of them expressed the suspicion that something along the line of error sampling was going on. All subjects used the correct positioning of the hands on the keyboard but otherwise their typewriting skills differed quite substantially. The time it took to transcribe the text ranged from 16 minutes to 41 minutes and while the most faultless typist introduced no errors at all, one made 39 spelling- and segmentation errors.

It is difficult to make any systematic comparisons regarding CTR’s behavior on CARS and SECRETARY. Even if all the free variables\(^4\) are fixed, any direct comparison will still only be approximate; there are obviously different errors in the two corpora, the corpora are written in different languages and consequently the tag-sets differ. The size of the vocabulary differs and so on.

In the experiments reported below the free variables will be kept fixed as much as possible to facilitate for some comparative studies of CARS and SECRETARY although the primary intention with the SECRETARY experiment is to get a better handle on the error correcting performance of CTR. We have roughly ten times as much training material (which should give a better language model), we have more errors and a larger vocabulary. To sum up, it is a more realistic scenario. What CTR can do with the real-word errors is also interesting. We have already concluded that the tag Bigram language model outperforms the

---

\(^4\)Free variables such as, for the OD: the network topology, error generating functions used to produce the error corpus, smoothing of the observation distribution and filtering versus no filtering for real-word errors. For the LD: tag-set, smoothing parameters, supervised versus unsupervised training.
Unigram language model, even with unreliable parameter estimation, so the experiments below will only concern the Baseline and the tag Bigram.

### 6.2.1 Error Profile

The name secretary refers to the error corpus, the four transcribed versions of the seven page excerpt of the manual. Although this text has been typed by eight different subjects and is a four times duplicate, it is regarded as one bulk of text below.

secretary contains 600 sentences and 8,938 word tokens. The sentence level error rate is (somewhat surprisingly) almost as high as that of cars, whereas the word error rate is considerably lower. The figures are presented in Table 6.5.

| Sentences | Word Tokens |
|-----------|-------------|
| Well-formed | 483          | 8,788         |
| Lexically Ill-formed | 117  | 150          |
| **Total** | **600**      | **8,938**     |

Table 6.5: Error profile overview of secretary

There is one important difference between cars and secretary regarding the way in which the error profiles have been produced. In the case of cars we have been forced to make subjective judgments as to what was the ‘intended’, or, ‘correct’ utterance. With secretary we do not have to do this since we have the original text. We know the correct way to type the text down to the last comma. This is of course practical, but it also makes it necessary to make some distinctions. Based on the scenario, the application, we assume that all differences between the transcriptions and the original text are lexical errors. The variations that are clearly not lexical errors are not considered. Our interest is in studying the error correcting performance of ctr.

On two occasions a whole chunk of text was omitted. The subject most likely looks at the text, looks up at the screen, and then back at the paper and continues typing from the wrong place. This sort of phenomenon is not considered here. Probably because of the sparse formatting in the original text, problems regarding sentence ending punctuation are quite frequent. Sentence ending punctuations were wrongfully deleted from regular sentences, and inserted into subheadings. This sort of error is not considered here. Apart from these two exceptions, string equality is the measure used to find the errors introduced into the transcribed text. Because of the nature of the task presented to the subjects, all cases of substitutions of one word for another are considered real-word errors, even if they are really agreement errors.

Table 6.6 shows how the lexical errors are distributed in secretary. The ‘easy’ errors, the nonword single error misspellings, make up a relatively large portion of the errors in secretary compared to cars. Overall, the figures in
Table 6.6: Breakdown of lexical errors in SECRETARY

|                  | Nonword error | Real-word error | Total   |
|------------------|---------------|-----------------|---------|
| Missp. Single error | 109 85.2%     | 19 86.4%        | 128 85.3% |
| Missp. Multiple error | 5 3.9%        | 2 9.1%          | 7 4.7%   |
| Run-ons Single error | 14 10.9%      | 0 0%            | 14 9.3%  |
| Run-ons Multiple error | 0 0%          | 0 0%            | 0 0%     |
| Splits Single error | 0 0%          | 1 4.5%          | 1 0.7%   |
| Splits Multiple error | 0 0%          | 0 0%            | 0 0%     |
| Total Single error | 123 96.1%     | 20 90.9%        | 143 95.3% |
| Total Multiple error | 5 3.9%        | 2 9.1%          | 7 4.7%   |
| Total              | 128 100%      | 22 100%         | 150 100% |

Table 6.6 are more in line with what others have found; there are more real-word errors, fewer segmentation errors and there are more ‘easy’ errors. CTR’s performance on real-word errors was not really put to the test in the CARS experiments, but in SECRETARY there is a sample to test the recovery abilities of CTR on this error type.

There is a relatively large portion of really hard real-word errors in SECRETARY. Eight out of 22 real-word errors would be impossible even for a human proof-reader to detect. An example:

**SEC:** If you select Yes for Timer, indicate how long you want the menu displayed before the default operating system is started. (27)

The proper way to type this sentence, according to the original text, would be to substitute ‘selected’ for ‘select’. This is, of course, a very harsh correctness criterion, but the task given to the subject was to transcribe the text, not to convey the general meaning of the text. There are examples of real-word errors that are not impossible to detect, but still very hard to handle:

**SEC:** Specifying Options for the OS/2 2.1 Partition of Logical Drive (28)

‘of’ in sentence (28) should be ‘or’.

The sort of sloppiness that was found in CARS (see utterance (18) in Section 3.1) is not present in SECRETARY in the same way. This shows in the lower multiple error rate of SECRETARY. Table 6.7 displays the low multiple error rate and how the singletons are distributed over the basic error types; deletion, insertion, substitution and transposition. The ranking order of the basic error types is the same as that found by Pollock and Zamora [1983] in their sample of 50,000 nonword misspellings.

It is not easy to say which corpus, CARS or SECRETARY, is the more demanding from the point of view of error recovery. SECRETARY has more single error...
nonword misspellings and less segmentation errors, but then, judging from the results with the CARS experiment, segmentation errors do not seem to be much of a problem for CTR. CARS has an 18% multiple error rate while SECRETARY only has 4.7% and this indicates that CARS is more difficult. On the other hand SECRETARY has a 14.7% real-word error rate compared to 5.5% for CARS and real-word errors are clearly the most difficult error type.

6.2.2 The Orthographic Decoder

The training and test material taken together contain 1,223 word types so the Orthographic Decoder contains 1,223 word modeling HMMs. There are only 17 words in the test corpus that are not found in the training corpus. In accordance with previous experiments these word models are included in the OD.

The OD setup reported on in the CARS experiment has been evaluated here as well. However, the possible variation in the OD setup has been somewhat more systematically evaluated in the SECRETARY experiment. We have tried both filtered and unfiltered error corpora and three different values for $\epsilon_{obs}$ has been tried, $10^{-4}$, $10^{-6}$ and $10^{-8}$. Together this makes six alternative OD setups. The results reported below concern the same setup that was used for CARS. The effect of the other setups are discussed in Section 6.2.4.

In the experiments reported in Section 6.2.4, the error corpora were generated with the error functions deletion, substitution, and white space insertion. There are nine single character ‘punctuation words’ in the vocabulary and the training material is a small set of hand-made corruptions that only involve the space character. There are 49 numbers in the vocabulary. These special words have corpora generated with only the white space insertion error function. One set of ODs had their error corpus filtered for real-word errors and the rest were trained on unfiltered corpora. The OD HMMs were trained with the Baum-Welch reestimation algorithm. After training the models had their observation symbol distribution smoothed with the additive smoothing scheme with $\epsilon_{obs} = 10^{-4}$, $\epsilon_{obs} = 10^{-6}$ and $\epsilon_{obs} = 10^{-8}$.
6.2.3 The POS Bigram Language Model

The POS Bigram language model includes 50 tags. The tag-set consists of traditional Part-Of-Speech with verbs and nouns subcategorized for morphological features. Some frequent words with supposedly uniform contextual distributions have been given their own tag. The complete tag-set is listed in Appendix A.3. The training corpus consists of 19,975 word tokens. A tagged and an untagged version of it have been used for estimating the model parameters.

Different Linguistic Decoder setups have been tried. We have used one smoothed with $\epsilon_{\text{trans}} = 10^{-3}$ and $\epsilon_{\text{obs}} = 10^{-3}$ and one that was smoothed with $\epsilon_{\text{trans}} = 10^{-4}$ and $\epsilon_{\text{obs}} = 10^{-4}$. Note that there is no way to analytically determine the best smoothing value. Smoothing of unreliable distributions is an important research topic, and to get a good estimation of the parameter space it is necessary to use more advanced methods than we are using here. However, we are content to see that the techniques presented here work satisfactorily with a not so good smoothing scheme, reassured that with a better smoothing method things can only get better.

In the secretary experiments we are not that interested in the tag sequence output from $\text{ctr}$, rather we would like to maximize the predictive power of the (weak) language model. The LD trained with the tagged training material have been contrasted with the LD estimated from the untagged text using the Baum-Welch reestimation algorithm. In Chapter 5 it was mentioned that the model trained with the Baum-Welch algorithm will converge to a local maximum. Which of the optima the model will converge towards depends (amongst other things) on the distributions of the initial model. In the experiments reported here the initial model has a uniform transition distribution and an observation distribution that has uniformly distributed probabilities for the words that are members of the tags (which are represented by the states of the model). In other words: the initial model ‘knows’ which words belong to which tag and nothing else.

Together with the two smoothing setups, the supervised and unsupervised\(^5\) training methods yield four different LD configurations. The results on the POS Bigram Linguistic Decoder reported in Section 6.2.4 refer to the LD that has been trained unsupervised and has been smoothed with $\epsilon_{\text{trans}} = 10^{-4}$ and $\epsilon_{\text{obs}} = 10^{-4}$. The most ambiguous word in the language model is four ways ambiguous. In the experiments reported below $\text{ctr}$ has been evaluated using both 1-best and 4-best search. The outcomes of these different search strategies were, however, identical.

\(^5\)Supervised and unsupervised are not very precise terms. The supervision that is provided for the LD that is extracted from the tagged corpus applies to the proper tagging of words, not to the prediction of the next word, which is what we are interested in. The terms are used here because of their intuitive appeal.
6.2.4 Results

The evaluation scheme used here is the same as the one used for cars except that nonword and real-word errors have their own keys. Note that nonword and real-word errors on the one hand and misspellings, run-ons and splits on the other hand are orthogonal, i.e. \( A^{tot} = A^{non} \cup A^{real} = A^m \cup A^f \cup A^s \).

| Experiment | Performance categories | Recall | Precision |
|-------------|------------------------|--------|-----------|
| Baseline    | Sentences              | 51.3%  | 51.3%     |
|             | Misspellings           | 54.1%  | 54.1%     |
|             | Run-ons                | 100%   | 100%      |
|             | Splits                 | 0%     | 0%        |
|             | Nonwords               | 68%    | 68%       |
|             | Real-words             | 0%     | 0%        |
|             | Total                  | 58%    | 58%       |

Table 6.8: Baseline experiment

The higher smoothing value worked best in the Baseline experiment, i.e. \( \epsilon_{obs} = 10^{-4} \) outperformed \( \epsilon_{obs} = 10^{-6} \) and \( \epsilon_{obs} = 10^{-8} \). The filtered and the unfiltered versions produced identical results. No errors were introduced.

There is just one split in the corpus. The split is also a real-word error and it reads:

**SEC:** *If you have a Dual Boot partition containing ...*  \hspace{1cm} (29)

‘e’ is a valid word in the vocabulary, it actually has three meanings: the name of an appendix (in the manual), the name of a disk-partition and the name of a logical drive. Sentence (29) was changed into

**CTR:** *if you have e a dual boot partition containing ...*  \hspace{1cm} (30)

which is obviously not the desired output. (Recall that there is no discrimination made between upper- and lowercase characters.)

There is a considerable difference between the result of the cars Baseline experiment and that of Secretary. Since no LD is involved and since the OD HMMs are trained and smoothed in the same way, the only thing that can explain the difference is the larger number of real-word errors in Secretary and the increased vocabulary size.

When CTR is supplied with the POS Bigram LD, there is a considerable boost in performance\(^6\). The OD used in the experiment in Table 6.9 is that which has been filtered for real-word errors.

The fact that the LD smoothed with the lower value outperforms the one with the higher smoothing value indicates that the parameter values arrived at by the Baum-Welch algorithm are not such a bad estimation. The filtered

\(^6\) A \( \chi^2 \)-test showed significance compared to Baseline on the 0.001 level.
Table 6.9: The unsupervised POS Bigram experiment smoothed with $\epsilon_{\text{trans}} = 10^{-4}$ and $\epsilon_{\text{obs}} = 10^{-4}$

| Experiment   | Performance categories | Recall | Precision |
|--------------|------------------------|--------|-----------|
| POS Bigram   | Sentences              | 78.6%  | 78.6%     |
|              | Misspellings           | 80%    | 79.4%     |
|              | Run-ons                | 100%   | 100%      |
|              | Splits                 | 100%   | 100%      |
|              | Nonwords               | 93%    | 93%       |
|              | Real-words             | 18.2%  | 17.4%     |
|              | Total                  | 82%    | 81.5%     |

and the unfiltered version give virtually the same results. On one occasion the unfiltered version succeeded in correcting a real-word error that the filtered version failed to correct. However, the unfiltered version also introduced a couple of errors so the net return of the filtered version is slightly better.

The real-word errors that \(\text{ctr}\) can handle are those where there is an orthographic similarity between the error and the proposed normalization, and, the real-word error is part of an unlikely tag sequence. An example of a real-word error that \(\text{ctr}\) successfully transformed is:

\[
\text{sec: } \text{Of you select advanced, your Boot Manager ...} \tag{31}
\]

\(\text{CTR}\) normalized the sentence to

\[
\text{ctr: if you select advanced, your boot manager ...} \tag{32}
\]

which was the desired output.

The unsupervised LD performs better than the supervised. The optimum reached under the restrictions imposed by the initial model with the Baum-Welch algorithm is a minimum entropy point. The fact that this model outperforms the model with the higher entropy is by no means surprising.

The nonword error correcting rate of \textsc{secretary} is the same as the total correction rate of \textsc{cars} (which basically only contains nonword errors). One can speculate that the higher degree of multiple errors in \textsc{cars} is compensated for by the larger vocabulary in \textsc{secretary}.

A closer look at the errors that \(\text{ctr}\) failed to properly correct revealed that an unrepresentative portion of the problematic errors were transpositions. Since the transposition error function was excluded from the functions that generated the training corpora for the various ODs, we ran a series of complementary experiments where every parameter was held stationary except that the transposition error function was included in the generation of the corpora. The result is shown in Table 6.10.


| Experiment | Performance categories | Recall | Precision |
|------------|------------------------|--------|-----------|
| POS Bigram | Sentences              | 81.2%  | 81.2%     |
|            | Misspellings           | 83%    | 82.4%     |
|            | Run-ons                | 100%   | 100%      |
|            | Splits                 | 100%   | 50%       |
|            | Nonwords               | 94.5%  | 94.5%     |
|            | Real-words             | 27.3%  | 25%       |
|            | Total                  | 84.7%  | 83.6%     |

Table 6.10: The unsupervised POS Bigram experiment smoothed with $\epsilon_{\text{trans}} = 10^{-4}$ and $\epsilon_{\text{obs}} = 10^{-4}$ where the OD has been trained on transpositions

### 6.3 Discussion

Clearly the ctr system can be used to normalize text input to the vocabulary and language of a limited domain. The number of utterances affected by lexical errors in the dialogue scenario are brought down from 71 (19.2%) to 13 (3.5%) by ctr (POS Bigram). In the transcription scenario, the error rate is brought down from 117 (19.5%) lexically ill-formed sentences to 22 (3.7%) (from the experiment in Table 6.10). Counting only the nonword errors, there are only 7 (1.2%) output sentences that diverge from the key.

The results reported in the previous sections validates the assertions made in section 3.3. The wide error scope is obviously beneficial. Particularly the dialogue scenario with its many segmentation errors would be severely crippled without ctr’s ability to handle run-ons and splits. The total recall would fall from 92% to 59% in both the cars Bigram experiments if neither real-word errors nor segmentation errors could be fixed. The advantage derived from modeling of the local context is obvious when comparing the experiments in the two scenarios to their respective Baselines.

A rather ill-chosen, but still interesting comparison can be made between the performance of ctr and commercially available text processing tools. We ran the test data through the spell-checker used in Microsoft word for Windows 95\(^7\). Before testing, the spell-checker was given the complete secretary vocabulary. We took the highest ranked correction candidate from the spell-checker to be the suggested correction. It is unfair to compare ctr to the word spell-checker for two reasons: Firstly, the spell-checker is not designed to be an automatic spelling corrector, its primary task is to detect errors and bring the user’s attention to them. Secondly, the spell-checker has a vocabulary that is considerably larger than ctr’s. There are more correction candidates to consider and on ten occasions it turned out that errors that were nonwords relative ctr’s vocabulary were missed because they were valid words in word’s vocabulary. The results from the experiment with the word spell-checker is displayed in Table 6.11. The spell-checker works fine with the nonword misspellings but

\(^7\)The spell-checker used in word is International Correct Spell from INSO Corporation.
is incapable of handling any of the segmentation- and real-word errors. On 20 occasions the spell-checker stopped on something that was not in error, and was unable to suggest a correction. These problems most certainly arise from faulty assumptions made by the spell-checker’s tokenizer. It will highlight items like ‘Ctrl+Alt+Del’, assuming that it is one word. It is simply the case that ‘+’ does not delimit tokens in Word. Nevertheless, it actually performs slightly better than the Baseline (without transposition-training) on the misspelling error category.

It was pointed out above that there is virtually no other research effort taking the holistic approach presented here, addressing the entire problem area in a unified framework that uses both a model of language production and one for typing behaviour and which makes tokenization part of the recovery process. So the results presented here do not lend themselves easily to comparisons to what others have done. (Another major problem is, of course, that people use different test sets.) However, a couple of notes can be made.

As mentioned above, Kukich [1992b] made a comparative study of some of the more well-known approaches to isolated-word spelling correction on 170 human-generated nonword misspellings with vocabularies of three different sizes. Two of the vocabularies, 521 words and 1,142 words, are quite close in size to the vocabularies used in cars and secretary (584 and 1,223 words respectively). The OD component of ctr compares quite favorably to the best isolated-word spelling correction techniques. On the smaller vocabulary Kukich reports 81% accuracy for the best technique which is just about the same as for the cars Baseline. The secretary Baseline (without transposition-training) result on the nonwords is 68% and the result from the best isolated-word spelling correction technique is 78%8. Note that the isolated-word spelling correction programs do not need to tokenize the input, they are given one word at a time whereas ctr need to find the word boundaries by itself. The conspicuous fall in accuracy when the size of the vocabulary grows gives yet another clear indication of the

---

8A technique called SVD (Singular Value Decomposition) worked best on the smaller vocabulary. The accuracy for the different programs ranged from 64% to 81%. The Technique of Kernighan-Church-Gale [Church and Gale, 1991b, Kernighan et al., 1990] worked best on the larger vocabulary. The accuracy for the different programs ranged from 54% to 78%.
positive impact of small vocabularies.

CTR does not compare well to other automatic spelling correction techniques in terms of processing efficiency. The main reason for the difference in speed is due to the fact that CTR does not make any hard assumptions regarding the location of word boundaries. However, CTR has the feature of character incremental processing. In the dialogue application, which was the first intended usage, this means that CTR performs real-time text recognition, i.e. it processes the input as fast as the user can type. With the 1,223 word vocabulary and without Beam Search pruning CTR processes the input (on a SUN Sparcstation 5) with approximately the speed with which a skilled typewriter would type it.

The results from these first two experiments are certainly promising, all the more so since there is, on several accounts, obviously room for improvement. The transposition error type is a weak spot in the Orthographic Decoder. The topology of the word models prohibits the transposition errors to be processed as transposition errors. The lack of back-chaining transitions in the HMM means that a word containing a transposition error will be ‘diagnosed’ as having a deletion immediately followed by an insertion. This topology-related problem can not be completely trained away. The OD trained on transpositions (Table 6.10) could correct three transpositions and one deletion that the other OD could not handle. (Two out of these four were also real-word errors.) This shows that training certainly pays off, but still, the restrictions imposed by the topology of the model makes matters more difficult. There were three errors that the word spell-checker managed to fix that CTR failed on. These three were all transposition errors, ‘of’ had been spelled ‘fo’ (on three occasions). Giving up the left-to-right model topology may very well improve the system’s ability to deal with this error type.

Another important aspect concerning the OD is, of course, the way in which it is trained. The only information available to the system regarding the cause of an error is the keyboard layout and even this information is rather sparse\(^9\). The generation of the error corpora for the OD HMMs is entirely based on lexical errors that are accidental by nature. More knowledge can be supplied to the system by studying naturally occurring errors, especially those caused by cognitive and/or phonetic misconceptions. Content words and function words should probably not be treated alike in this respect. People (at least adults) usually know how to spell the function words and consequently the errors that affect this category are more likely to be mistakes.

The Linguistic Decoder is the most interesting component of the system from the improvement point of view. It has been shown \cite{Gale and Church, 1990} that the additive smoothing scheme is inferior to a number of alternative, more sophisticated smoothing methods. We know that a better smoothing scheme will improve the LD in CTR, the question is just how big the improvement will be.

\(^9\)Grudin \cite{Grudin, 1983} has reported on a comprehensive study of errors produced by typists of different skill-levels. The fact that the keypads are placed in close proximity to each other can just partly explain all the things that can go wrong.
The real-word error category is obviously the most problematic. CTR’s ability to correct these errors hinges on the predictive power of the Linguistic Decoder. With sparse data it is necessary to choose a model with fewer parameters, such as a tag Bigram language model for example. Such a model has only rather vague ideas of what is likely to appear next in a given context. If a real-word error happens to belong to the same tag as the intended word, the tag Bigram is unable to detect the error. To improve the real-word error correction rate it is necessary to deploy a more powerful language model, a language model with lower (cross-word) entropy. Mays et al. [1991] used the trigram language model employed in the IBM speech recognition project [Bahl et al., 1983] to correct single error real-word errors. They managed to detect and correct 73% of the real-word errors, and managed this with a rather primitive model of the channel characteristics. These are reassuring results.
Chapter 7

Future Work

7.1 Practical Issues

There are a number of issues that need to be addressed if CTR should be placed in the hands of an actual user.

One of CTR’s features is the incremental processing. The process is monotonous, however, so if the user goes back and edits the input string, it will cause difficulties. Special care must be taken of backspacing in the input.

CTR’s vocabulary (the OD HMMs) has a high memory space demand. An application with tens of thousands of word-forms most likely requires some kind of morphological processing, having a network for each word-form is not a practicable path. Word-groups (as described above) may marginally reduce the problem but prefixes, suffixes and inflectional forms need probably be dealt with in a more systematic fashion. It may prove profitable to look into Two-level Morphology [Koskenniemi, 1983].

CTR does not discriminate between upper- and lowercase characters which means that information is lost in the processing of the input. This needs to be rectified should the system be used in a more large scale application.

One way to look at CTR is to think of it as an intelligent tokenizer. The system spends much effort calculating the the most likely segmentation of the input. As the system presently runs it spends a lot of time with this even if the input is error-free and tokenization is trivial. There is however a simple way around this waste of effort. The OD could easily be supplied with a more primitive (standard) complementary tokenizer. This tokenizer would then run as long as there is no problem, and when something goes wrong the OD would take over. The LD would run as before, only it would receive one token (as in Token Passing) per word-token instead of a number of tokens per character. Note that with this technique real-word errors would have to be spotted from the LD without any help from the OD.
7.2 The Unknown Word

There is no general solution to the unknown word problem. Under certain circumstances however there may be ways to limit the problem somewhat. A short word generally has a lot of neighbors, words that are, say, one edit distance away from it. With a longer word, say ten characters, there are usually just a few neighbors. So if a long word is correctly spelled and a moderately chosen beam is used, there will be a relatively small number of viable hypotheses inside the beam. If the long word is misspelled (not too severely), there will probably still be a controllable number of hypotheses inside the beam. However, if a previously unknown word is typed in, there is a good chance that the best hypothesis is quite distant from the optimal hypothesis (which is unknown). Since the best hypothesis controls the beam and the best hypothesis is bad, the beam will in effect be wider than normal and more distant neighbors will fit inside the beam. Thus, if a long word is typed into the system and the number of viable hypotheses inside the beam exceeds a threshold, the word is unknown. This hypothesis should be pursued. (Note that shorter words are usually not unknown.)

7.3 Exploiting the Potential of the Framework

It was pointed out above that there are no restrictions in the Token Passing framework as such as to how many layers there might be. The layers can implement different probabilistic networks, actually they need not even be probabilistic. The only requirement is that a layer can communicate with its neighbors in a meaningful way. Hidden Markov Models are appealing since they have one distribution (the transitions) for network internal operations and one (the observables) for communication.

Connected Text Recognition with layered HMM networks in the Token Passing framework is quite a machinery. It might even seem like bit of an overkill to use this rather complex system just to tokenize an input string and output the normalization of it. However, the system leaves room for more complex tasks to be performed as well. We stated above that CTR could be told to output the tag sequence along with the normalized utterance. An utterance like:

\[ \text{show volvo with impact-safety higher than 3} \]  

would then be processed and output as:

\[ \text{CTR: show/CH volvo/OH with/R impact-safety/AH higher/VH than/R 3/VH} \]

The portion ‘with impact-safety higher than 3’ is obviously a restriction that the subject wants to have placed on the Volvos that he wants extracted from the database. It would clearly be a great help if the system could identify

\footnote{Cf. Appendix A.1 for an explanation of the tags.}
such phrases. Envisage a third layer, inbetween the word modeling Orthographic Decoder and the utterance modeling HMM in the Linguistic Decoder, that models phrases of the type just exemplified. The additional layer would make the LD two-layered. This layer would consist of a number of Token Passing networks (e.g. HMMs) that would segment the stream of words from beneath into phrases, phrases with a meaning in the application at hand. One network in the new layer would then be the conditional network. The output from ctr could now look like:

\[
\text{CTR: } \text{show/CH volvo/OH [with/R impact-safety/AH higher/VH than/R 3/VH]/COND (35)}
\]

One can also imagine a fourth layer (making the LD three-layered) that classifies utterances in terms of their dialogue function (see e.g. Jönsson [1993]). This fourth layer would be the new topmost layer and the output could look like:

\[
\text{CTR: } [\text{show/CH volvo/OH [with/R impact-safety/AH higher/VH than/R 3/VH]/COND}]\text{/EXTRACT (36)}
\]

The step from (36) to the SQL-query below is not very long to take.

\[
\text{select manufacturer.model.year.impact-safety from CARS where}
\text{model = 'volvo' and impact-safety > 3}
\]

The three fields ‘manufacturer’, ‘model’ and ‘year’ together make up the unique identifier for each car in the database. These fields are listed in the output by default while the other fields referred to in the question are appended.
[Ahrenberg et al., 1990] Lars Ahrenberg, Arne Jönsson, and Nils Dahlbäck. Discourse representation and discourse management for natural language interfaces. In Proceedings of the Second Nordic Conference on Text Comprehension in Man and Machine, Täby, Sweden, 1990.

[Angell et al., 1983] R. C. Angell, G. E. Freund, and P. Willett. Automatic spelling correction using a trigram similarity measure. Information Processing & Management, 19(4):255–261, 1983.

[Atwell and Elliott, 1987] E. Atwell and S. Elliott. Dealing with ill-formed English text. In R. Garside, G. Leach, and G. Sampson, editors, The Computational Analysis of English: A Corpus-Based Approach, chapter 10. Longman Inc. New York, 1987.

[Bahl et al., 1983] L. R. Bahl, F. Jelinek, and R. L. Mercer. A maximum likelihood approach to continuous speech recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 5(2):179–190, March 1983.

[Baker et al., 1990] E. Baker, W. Read, M. Dyer, P. Mutch, F. Butler, A. Quilici, and J. Reeves. Natural language sourcebook. Technical report, Center for the Study of Evaluation, University of California, Dec. 1990.

[Carberry, 1984] S. Carberry. Understanding pragmatically ill-formed input. In Proceedings of the 10th International Conference on Computational Linguistics, pages 200–206. ACL, 1984.

[Carbonell and Hayes, 1983] J. G. Carbonell and P. J. Hayes. Recovery strategies for parsing extragrammatical language. Amer. J. Comput. Ling., 9(3–4):123–146, July–Dec. 1983.

[Carter, 1992] D. M. Carter. Lattice-based word identification in CLARE. In Proceedings of the 30th Annual Meeting of the Association for Computational Linguistics, pages 159–166, 1992.

[Church and Gale, 1991a] K. W. Church and W. A. Gale. A comparison of the enhanced Good-Turing and deleted estimation methods for estimating probabilities of English bigrams. Computer Speech and Language, 5:19–54, 1991.
[Church and Gale, 1991b] K. W. Church and W. A. Gale. Probability scoring for spelling correction. *Statistics and Computing*, 1:93–103, 1991.

[Cutting et al., 1992] Doug Cutting, Julian Kupiec, Jan Pedersen, and Penelope Sibun. A practical part-of-speech tagger. In *Proceedings of the Third Conference on Applied Natural Language Processing*, pages 133–140, March 1992.

[Dahlbäck et al., 1993] Nils Dahlbäck, Arne Jönsson, and Lars Ahrenberg. Wizard of Oz studies – why and how. *Knowledge-Based Systems*, 6(4):258–266, 1993.

[Damerau, 1964] F. J. Damerau. A technique for computer detection and correction of spelling errors. *Communications of the ACM*, 7(3):171–176, March 1964.

[Deller et al., 1993] John R. Deller, John G. Proakis, and John H. L. Hansen. *Discrete-Time Processing of Speech Signals*. Macmillan Publishing Company, 1993.

[Domeij et al., 1995] Rickard Domeij, Joachim Hollman, and Viggo Kann. Detection of spelling errors in Swedish not using a word list en clair. *Journal of Quantitative Linguistics*, 1(3):195–201, 1995.

[Elworthy, 1994] David Elworthy. Does Baum-Welch reestimation help taggers? In *Proceeding of the Fourth ACL Conference on Applied Natural Language Processing, Stuttgart, Germany*, 1994.

[Fass and Wilks, 1983] D. Fass and Y. Wilks. Preference semantics, ill-formedness and metaphor. *Amer. J. Comput. Ling.*, 9(3–4):178–187, July–Dec. 1983.

[Flexner, 1983] S. B. Flexner, editor. *Random House Unabridged Dictionary*, Second edition, New York, 1983. Random House.

[Gale and Church, 1990] W. A. Gale and K. W. Church. Poor estimates of context are worse than none. *Speech and Natural Language: DARPA Workshop Proceedings*, pages 283–287, 1990.

[Garside, 1987] Roger Garside. The CLAWS word-tagging system. In R. Garside, G. Leech, and G. Sampson, editors, *The Computational Analysis of English: a corpus-based approach*, pages 30–41. Longman, London, 1987.

[Golding and Schabes, 1996] A. R. Golding and Y. Schabes. Combining trigram-based and feature-based methods for context-sensitive spelling correction. In *Proceedings of the 34th Annual Meeting of the Association for Computational Linguistics, Santa Cruz, CA*, 1996.

[Golding, 1995] A. R. Golding. A bayesian hybrid method for context-sensitive spelling correction. Technical Report TR-95-13, Mitsubishi Electrical Research Laboratories, May 1995.
[Good, 1953] I. J. Good. The population frequencies of species and the estimation of population parameters. *Biometrika*, 40(3 and 4):129–264, December 1953.

[Granger, 1983] R. H. Granger. The NOMAD system: Expectation-based detection and correction of errors during understanding of syntactically and semantically ill-formed text. *Amer. J. Comput. Ling.*, 9(3–4):188–196, July–Dec. 1983.

[Grudin, 1983] J. Grudin. Error patterns in skilled and novice transcription typing. In W. E. Copper, editor, *Cognitive Aspects of Skilled Typewriting*, chapter 6, pages 121–143. Springer-Verlag, New York, 1983.

[Hayes and Mouradian, 1981] P. H. Hayes and G. V. Mouradian. Flexible parsing. *American Journal of Computational Linguistics*, 7(4):232–242, Oct.–Dec. 1981.

[Heidorn et al., 1982] G. E. Heidorn, K. Jensen, L. A. Miller, Byrd R. J., and M. S. Chodorow. The EPISTLE text-critiquing system. *IBM Systems Journal*, 21(3):305–326, 1982.

[Heidorn, 1982] G. E. Heidorn. Experience with an easily computed metric for ranking alternative parses. In *Proceedings of the 20th Annual Meeting of the Association for Computational Linguistics*, pages 82–84. ACL, June 1982.

[IBM, 1993] IBM Corporation. *IBM OS/2 2.1 Installation Guide*, 1993.

[Ingels, 1992] P. Ingels. Error detection and error correction with chart parsing and relaxation in natural language processing. Master’s thesis, Department of Computer and Information Science, Linköping University, Sweden, Dec. 1992.

[Ingels, 1993] P. Ingels. Robust parsing with charts and relaxation. In R. Eklund, editor, *Proceedings of the 9th Scandinavian Conference on Computational Linguistics*, pages 123–132, Stockholm, Sweden, Jun. 1993.

[Ingels, 1996a] P. Ingels. Connected text recognition using layered HMMs and token passing. In K. Oflazer and H. Somers, editors, *Proceedings of the Second Conference on New Methods in Language Processing*, pages 121–132, Sept. 1996.

[Ingels, 1996b] P. Ingels. Layered HMMs in robust natural language text processing. Technical Report LiTH-IDA-R-96-11, Department of Computer and Information Science, Linköping University, April 1996.

[Jelinek and Mercer, 1980] F. Jelinek and R. L. Mercer. Interpolated estimation of markov source parameters from sparse data. In E. S. Gelsema and L. N. Kanal, editors, *Pattern Recognition in Practice*, pages 381–397. North-Holland, Amsterdam, 1980.
[Jensen et al., 1983] K. Jensen, G. E. Heidorn, L. A. Miller, and Y. Ravin. Parse fitting and prose fixing: Getting a hold on ill-formedness. Amer. J. Comput. Ling., 9(3–4):147–160, July–Dec. 1983.

[Jönsson, 1993] Arne Jönsson. Dialogue Management for Natural Language Interfaces – An Empirical Approach. PhD thesis, Linköping University, 1993.

[Jönsson, 1995] Arne Jönsson. A dialogue manager for natural language interfaces. In Proceedings of the Pacific Association for Computational Linguistics, Second Conference, The University of Queensland, Brisbane, Australia, 1995.

[Källgren, 1990] Gunnel Källgren. "the first million is hardest to get": Building a large tagged corpus as automatically as possible. In Proceedings of the 13th International Conference on Computational Linguistics, Helsinki, Finland., 1990.

[Kashyap and Oommen, 1981] R. L. Kashyap and B. J. Oommen. An effective algorithm for string correction using generalized edit distances. Information Sciences, 23:123–142, 1981.

[Kashyap and Oommen, 1984] R. L. Kashyap and B. J. Oommen. Spelling correction using probabilistic methods. Pattern Recognition Letters, 2(3):147–154, March 1984.

[Katz, 1987] S. M. Katz. Estimation of probabilities from sparse data for the language model component of a speech recognizer. IEEE Transactions on Acoustics, Speech and Signal Processing, 35(3):400–401, March 1987.

[Kempen and Vosse, 1990] G. Kempen and T. Vosse. A language-sensitive text editor for dutch. In Proceedings of the Computers and Writing III Conference, Edinburgh, Scotland, Apr. 1990.

[Kernighan et al., 1990] M. D. Kernighan, K. W. Church, and W. A. Gale. A spelling correction program based on a noisy channel model. In Hans Karlsgren, editor, Proceedings of the 13th International Conference on Computational Linguistics, volume 2, pages 205–210, Helsinki, Finland, 1990.

[Koskenniemi, 1983] K. Koskenniemi. Two-level Morphology: A General Computational Model for Word-Form Recognition and Production. PhD thesis, University of Helsinki, Department of General Linguistics, 1983.

[Kukich, 1990] K. Kukich. A comparison of some novel and traditional lexical distance metrics for spelling correction. In Proceedings of INNC-90-Paris (Paris, France), pages 309–313, July 1990.

[Kukich, 1992a] K. Kukich. Spelling correction for the telecommunications network for the deaf. Communications of the ACM, 35(5):80–90, May 1992.

[Kukich, 1992b] Karen Kukich. Techniques for automatically correcting words in text. ACM Computing Surveys, 24(4):377–439, December 1992.
[Kůcera and Francis, 1967] H. Kůcera and W. N. Francis. Computational Analysis of Present-Day American English. Brown University Press, Providence, RI, 1967.

[Kwasny and Sondheimer, 1981] S. C. Kwasny and N. K. Sondheimer. Relaxation techniques for parsing ill-formed input. American Journal of Computational Linguistics, 7(2):99–108, April–June 1981.

[Lavelli and Stock, 1990] A. Lavelli and O. Stock. When something is missing: Ellipsis, coordination and the chart. In Proceedings of the 13th International Conference on Computational Linguistics, pages 184–189, 1990.

[Levenshtein, 1966] V. I. Levenshtein. Binary codes capable of correcting deletions, insertions and reversals. Sov. Phys. Dokl., 10(8):707–710, Feb. 1966.

[Levinson et al., 1983] S. E. Levinson, L. R. Rabiner, and M. M. Sondhi. An introduction to the application of the theory of probabilistic functions of a Markov process to automatic speech recognition. The Bell System Technical Journal, 62:1035–1074, 1983.

[Mays et al., 1991] E. Mays, F. J. Damerau, and R. L. Mercer. Context based spelling correction. Information Processing & Management, 27(5):517–522, 1991.

[McIlroy, 1982] M. D. McIlroy. Development of a spelling list. IEEE Transactions on Communications, 30(1):91–99, Jan. 1982.

[Mellish, 1989] C. S. Mellish. Some chart-based techniques for parsing ill-formed input. In Proceedings of the 27th Annual Meeting of the Association for Computational Linguistics, pages 102–109, Vancouver, Canada, 1989.

[Mitton, 1987] R. Mitton. Spelling checkers, spelling correctors, and the mis-spellings of poor spellers. Information Processing & Management, 23(5):495–505, 1987.

[Okuda et al., 1976] T. Okuda, E. Tanaka, and T. Kasai. A method for the correction of garbled words based on the levenshtein metric. IEEE Transactions on Computers, 25(2):172–177, Feb. 1976.

[Peterson, 1986] J. L. Peterson. A note on undetected typing errors. Communications of the ACM, 29(7):633–637, July 1986.

[Pollock and Zamora, 1983] J. J. Pollock and A. Zamora. Collection and characterization of spelling errors in scientific and scholarly text. Journal of the American Society for Information Science, 34(1):51–58, Jan. 1983.

[Pollock and Zamora, 1984] J. J. Pollock and A. Zamora. Automatic spelling correction in scientific and scholarly text. Communications of the ACM, 27(4):358–368, May 1984.
[Rabiner, 1989] L. R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. In *Proceeding of the IEEE*, volume 77, pages 257–295, 1989.

[Richardson and Braden-Harder, 1988] S. D. Richardson and L. C. Braden-Harder. The experience of developing a larger-scale natural language text processing system: QRITIQUE. In *Proceedings of the 2nd Annual Applied Natural Language Conference*, pages 195–202, Austin, Tx., Feb. 1988. ACL.

[van Berkel and de Smedt, 1988] Brigitte van Berkel and Koenraad de Smedt. Triphone analysis: A combined method for the correction of orthographical and typographical errors. In *Proceedings of the 2nd Conference on Applied Natural Language Processing*, pages 77–83. ACL, 1988.

[Véronis, 1991] J. Véronis. Error in natural language dialogue between man and machine. *International Journal of Man-Machine Studies*, 35:187–217, 1991.

[Vosse, 1992] T. Vosse. Detecting and correcting morpho-syntactic errors in real texts. In *Proceedings of the 3rd Conference on Applied Natural Language Processing*, pages 111–118, Trento, Italy, Mar. 1992. ACL.

[Weischedel and Sondheimer, 1983] R. M. Weischedel and N. K. Sondheimer. Meta-rules as a basis for processing ill-formed input. *Amer. J. Comput. Ling.*, 9(3–4):161–177, July–Dec. 1983.

[Young et al., 1989] S. J. Young, N. H. Russel, and J. H. S Thornton. Token passing: a simple conceptual model for connected speech recognition systems. Technical report, Cambridge University Engineering Department, 1989.
Appendix A

Tag-sets Used in CTR

A.1 The Domain-Tags used in CARS

- 19 tags
- 584 words
- 55 words are ambiguous
  - 51 words are two ways ambiguous
  - 4 words are three ways ambiguous

| Tag | Explanation                  | Example         |
|-----|------------------------------|-----------------|
| AH  | Aspect Head                  | ‘fuel-consumption’ |
| CC  | Coordinating Conjunction     | ‘and’           |
| CH  | Communicative Head           | ‘find’          |
| CM  | Communicative Modifier       | ‘help’          |
| K   | Non-sentence Delimiters      | ‘,’             |
| M   | Determiner                   | ‘each’          |
| N   | Numeral                      | ‘4’             |
| OH  | Object Head                  | ‘mazda 323’     |
| OW  | Object Wh-word               | ‘which’         |
| P   | Sentence Delimiters          | ‘?’             |
| R   | Relation Word                | ‘instead’       |
| RS  | Response Word                | ‘yes’           |
| SH  | Semiotic Head                | ‘mean’          |
| SM  | Semiotic Modifier            | ‘not’           |
| TH  | Table Head                   | ‘table’         |
APPENDIX A. TAG-SETS USED IN CTR

| Tag | Explanation | Example |
|-----|-------------|---------|
| VH  | Value Head  | ’0,9’   |
| VM  | Value Modifier | ’about’ |
| VW  | Value Wh-word | ’how’   |
| X   | Others      | ’thanks’|

A.2 The POS used in CARS

• 31 tags
• 584 words
• 31 words are ambiguous
  – 30 words are two ways ambiguous
  – 1 word is three ways ambiguous

| Tag  | Explanation   | Example |
|------|---------------|---------|
| AB   | Adverb        | ’quickly’|
| CIT  | Citation Mark | ‘‘‘‘     |
| COM  | Comma         | ‘,’     |
| DSH  | Dash          | ‘~’     |
| DT   | Determiner    | ’all’   |
| HA   | Wh Adverb     | ’why’   |
| HD   | Wh Determiner | ’which’ |
| HP   | Wh Pronoun    | ’what’  |
| IM   | Infinitive Marker | ’to’   |
| IN   | Interjection  | ’ok’    |
| JJ   | Adjective     | ’lower’ |
| KN   | Coordinating Conjunction | ’both’  |
| LP   | Left Parenthesis | ‘(’    |
| NN   | Noun          | ’car’   |
| PC   | Participle    | ’enumerated’ |
| PM   | Proper Noun   | ’audi 100’ |
| PN   | Pronoun       | ’these’ |
| PNO  | Object Pronoun| ’them’  |
| PNS  | Subject Pronoun| ’you’  |
| PP   | Preposition   | ’with’  |

continued on next page
A.3 The POS used in Secretary

- 50 tags
- 1223 words
- 78 words are ambiguous
  - 74 words are two ways ambiguous
  - 3 words are three ways ambiguous
  - 1 word is four ways ambiguous
| Tag | Explanation | Example |
|-----|-------------|---------|
| DZ  | —           | ‘does’  |
| HA  | Wh Adverb   | ‘how’   |
| HD  | Wh Determiner | ‘which’ |
| HP  | Wh Pronoun  | ‘what’  |
| IJ  | Interjection | ‘please’ |
| IM  | Infinitive Marker | ‘to’ |
| IS  | —           | ‘is’    |
| IT  | —           | ‘it’    |
| JJ  | Adjective   | ‘available’ |
| KN  | Coordinating Conjunction | ‘either’ |
| LB  | Left Parenthesis | ‘(’ |
| MD  | Model Auxiliary | ‘should’ |
| NEG | Negation    | ‘not’   |
| NN  | Noun        | ‘backup’ |
| NNS | Plural Noun | ‘actions’ |
| OF  | —           | ‘of’    |
| PKT | Period      | ‘.’     |
| PM  | Proper Noun | ‘autoexec.bat’ |
| PN  | Pronoun     | ‘some’  |
| PNO | Object Pronoun | ‘them’ |
| PNS | Subject Pronoun | ‘they’ |
| PP  | Preposition | ‘by’    |
| PS  | Possessive Pronoun | ‘its’ |
| QUE | Question Mark | ‘?’     |
| RB  | Right Parenthesis | ‘)’ |
| REL | Relative Marker | ‘that’ |
| RG  | Number      | ‘1024’  |
| RO  | Ordinal Number | ‘first’ |
| SN  | Subordinating Conjunction | ‘after’ |
| SYM | Symbol      | ‘%’     |
| THE | —           | ‘the’   |
| UO  | Unknown     | ‘md’    |
| VB  | Bare Verb Form | ‘change’ |
| VBD | Verb Past Tense | ‘selected’ |
| VBG | Verb ing-form | ‘according’ |
| VBL | Past Participle | ‘accessed’ |

*continued on next page*
| Tag | Explanation                     | Example  |
|-----|---------------------------------|----------|
| VBZ | Verb Third Person Present Tense | ‘installs’|
| YOU | —                               | ‘you’    |