Best-first Word-lattice Parsing:
Techniques for integrated syntactic language modeling

by

Keith B. Hall

B. S., Mary Washington College, 1993

Sc. M., Brown University, 2001

A dissertation submitted in partial fulfillment of the
requirements for the Degree of Doctor of Philosophy
in the Department of Computer Science at Brown University

Providence, Rhode Island

May 2005

This dissertation by Keith B. Hall is accepted in its present form by
the Department of Computer Science as satisfying the dissertation requirement
for the degree of Doctor of Philosophy.

Date _____ _____

Mark Johnson, Director

Recommended to the Graduate Council

Date _____ _____

Eugene Charniak, Reader
(Brown University)

Date _____ _____

Frederick Jelinek, Reader
(Johns Hopkins University)

Approved by the Graduate Council

Date _____ _____

Karen Newman
Dean of the Graduate School

Abstract of “Best-first Word-lattice Parsing:
Techniques for integrated syntactic language modeling” by Keith B. Hall, Ph.D., Brown University, May 2005.

This thesis explores a language modeling technique based on statistical parsing. Previous research that exploits syntactic structure for modeling language has shown improved accuracy over the standard trigram models. Unlike previous techniques, our parsing model performs syntactic analysis on sets of hypothesized word-strings simultaneously; these sets are encoded as weighted finite state automata word-lattices. We present a best-first word-lattice chart parsing algorithm which combines the search for good parses with the search for good strings in the word-lattice. We describe how the word-lattice parser is combined with the Charniak language model, a sophisticated syntactic language model, in order to provide an efficient syntactic language model. We present results for this model on a standard set of speech recognition word-lattices. Finally, we examine variations of the word-lattice parser in order to increase performance as well as accuracy.

Preface

The computational efforts during the past 30 years and, more importantly, the introduction of structured statistical models introduced over the last 10 years have resulted in a general framework for approaching Natural Language Processing (NLP). In particular, we note the results from lexicalized statistical parsers that have been used in discovering syntactic structure as well as predicting strings of words (Charniak, 2001; Roark, 2001a; Collins, 2003). Recently, there have been positive results incorporating syntactic analysis into language modeling (i.e., predicting strings of words) which is an integral component of many Natural Language Processing models. The focus of this thesis is to explore the integration of statistical parsing techniques into language modeling.

Until recently, it has been nearly impossible to design a language model that performs better than the n-gram model. While we don't suggest that an n-gram model is a realistic model for language generation (though a 7-gram generates some realistic sentences), we recognize that language models are used to select from ambiguous strings. In speech recognition, the n-gram has been relatively successful in disambiguating the output of an acoustic recognizer. This is likely due to the relatively local ambiguity present in the output generated by acoustic recognizers. In other NLP domains, such as machine translation, non-local ambiguity is a more significant problem suggesting that n-gram models may not be as powerful as when used for speech recognition.

Recent results with syntactically based language modeling techniques show that there is something to be gained by considering the syntactic structure when predicting word strings (Charniak, 2001; Xu et al., 2002). We note that much work has been done on improving the standard n-gram modeling paradigm (see Goodman (2001)) and that the most commonly used n-gram - the trigram - is not the most powerful n-gram model. However, many of the more successful techniques focus on selecting words to be considered in the prediction context (skip models), something that comes

naturally from syntactic language models.

A small example may help elucidate the aspects of language modeling that are readily identified by syntactic techniques. Consider a speech recognition system that posits the following two strings for an utterance with relatively equal likelihood:

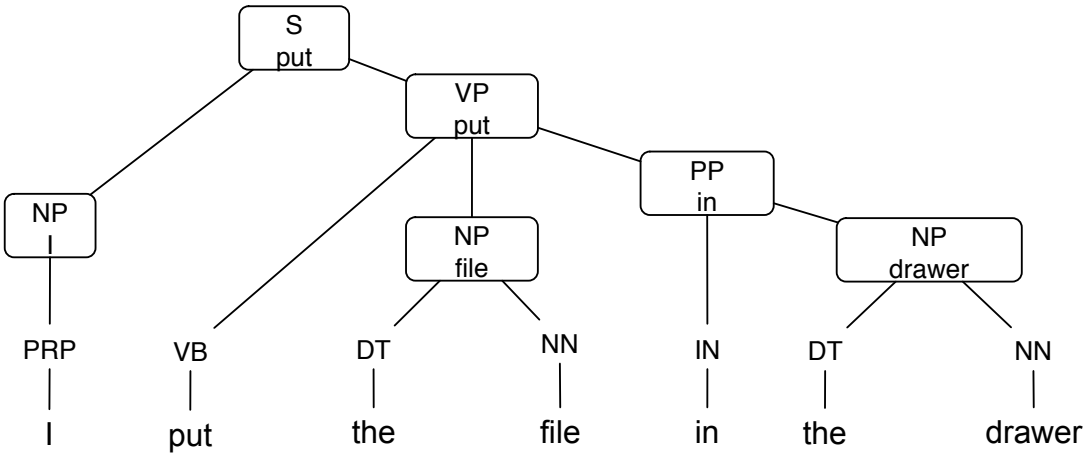
1. *I put the file in the drawer*
2. *I put the file and the drawer*

Semantic analysis is likely to help resolve the ambiguity between these two hypotheses. Under the standard trigram model we assign probability to the ambiguous word as follows.

1. $P(\text{and}|\text{the file})$
2. $P(\text{in}|\text{the file})$

Notice that the trigrams surrounding the ambiguous word *file in/and the* and *in/and the drawer* provide no help in resolving the ambiguity. The substrings that contribute to disambiguating the words *in* and *and* are:

in	**and**
the file in	the file and
file in the	file and the
in the drawer	and the drawer



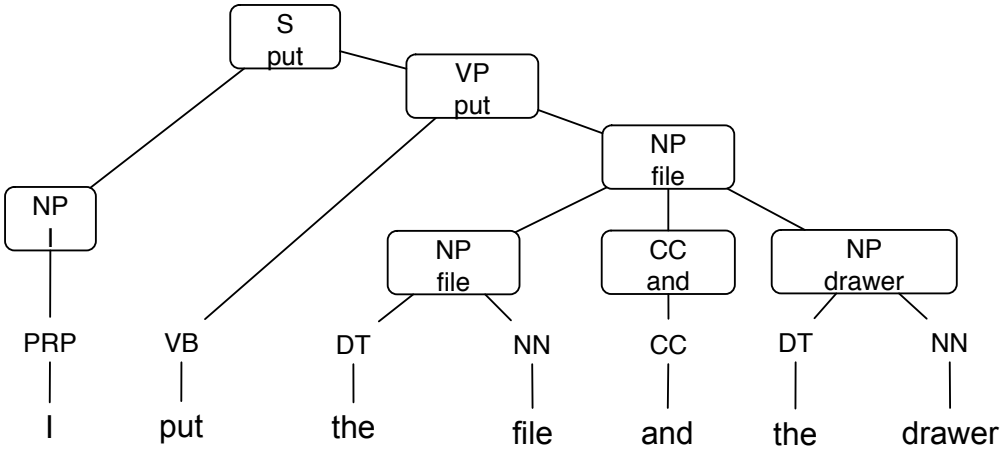


Figure 1: A partial syntactic parse with head-word annotations.

Using a relatively simple syntactically-based model, we can extract phrasal head-words[1] via

[1] A head-word is the most syntactically or semantically salient word of a phrase.

structured analysis. For example, under a simplified version of the Structured Language Model (Chelba and Jelinek, 2000), these are the predictive probabilities for the ambiguous words given the head-word annotated parses in Figure 1:

1. $P(\text{and}|\text{put file})$
2. $P(\text{in}|\text{put})$

When we predict the word drawer we will use the probabilities for:

1. $P(\text{drawer}|\text{put in})$
2. $P(\text{drawer}|\text{file put})$

Under the trigram model, we consider local contexts of the surface strings, but under a syntactic model we consider local contexts of the syntactic structure. In this example, we believe the structure will reveal that it is more likely to use the word *in* than the word *and*.

The above model makes use of the syntactic structure solely to obtain lexical head-words. However, there is ambiguity in identifying syntactic structures, so it is probably useful to consider the likelihood of particular parses given a probabilistic grammar. In this thesis we work with a language model based on probabilistic lexicalized parsing, which defines a unified model over lexical dependencies, such as those described above, along with syntactic dependencies defined by a grammar.

Although n-gram models are far more efficient in processing ambiguous analyses, the potential modeling improvement from syntactically-based models instigates the exploration of efficient syntactic language modeling. Much work has been applied to exploring high-accuracy syntactic parsing models as well as lower accuracy but very fast string parsing techniques (Abney, 1996). In this work, we aim to explore techniques to efficiently and accurately parse word-lattices (a compact representation of the ambiguous alternatives generated during speech recognition, machine translation, and other NLP tasks). We hope that the algorithms and analysis presented in this thesis provide insight into the task of word-lattice parsing as well as framework for future work on syntactic language modeling.

Acknowledgments

I would like to thank Mark Johnson for providing an excellent environment for research. Mark gave me the flexibility I needed to explore a variety of ideas, while also directing me towards intellectually stimulating research problems. It has been a pleasure working with Mark. I would also like to thank Eugene Charniak for introducing me to research in Natural Language Processing, teaching me the necessary background, and providing a pleasant, collegial atmosphere to discuss research in general. Fred Jelinek has been an invaluable member of my thesis committee, providing me with insightful comments and inspiring commentary.

Discussions with Brian Roark, Ciprian Chelba, and Bill Byrne have been a tremendous help.

The Brown Laboratory for Linguistic Information Processing (BLLIP) that Eugene and Mark have created is a wonderful place to work. I would like to thank all the members of the BLLIP group from the past six years, but especially Brian Roark, Massi Ciaramita, Heidi Fox, Gideon Mann, Sharon Caraballo, Don Blaheta, Sharon Goldwater, and Yasemin Altun. Their comments and criticisms have helped develop my research.

There are a number of fellow graduate students in the Department of Computer Science at Brown that I would like to thank. Don Carney for reminding me that not everybody is as interested in parsing as am I. David Gondek for providing the simple answers for problems that I had let intimidate me. Sam Heath, Joel Young, Srikanta Tirthapura, and Stuart Andrews for enjoyable intellectual and non-intellectual conversation.

Amy Greenwald, with whom I worked with for a year exploring Computational Game Theory, provided the support and motivation necessary for me to explore the research I find interesting. She taught me that research can be fun. Amy is a wonderful person to work with.

Thanks to Ernie Ackermann and Judith Parker, my undergraduate advisors, who inspired my

interests in both computer science and linguistics.

I would like to thank Andrea Wesol for putting up with the last four years of me in Graduate School and reading and editing this thesis, which is as far away from her area of interest as possible. Andrea, Hoover, and Jasper provided the companionship that got me through those lonely days and nights in front of the computer.

And finally, I would like to thank my parents, who encouraged me to explore the ideas I find interesting and provided the moral support necessary to pursue them.

Contents

⋆ Parts of this thesis have previously been published as (Hall and Johnson, 2003) and (Hall and Johnson, 2004).

List of Tables

List of Figures

Chapter 1

Introduction

Over the past decade statistical parsing has matured to the extent that parsing is now incorporated in other language processing models. Two such tasks that have benefited from parsing are speech recognition (Charniak, 2001; Roark, 2001a) and machine translation (Charniak and Yamada, 2003), both using parser-based language models. Initial research on the integration of parsing into a language model shows that by considering the structure of language, and specifically the syntactic structure, we are able to improve the modeling of strings of words (Charniak, 2001; Roark, 2001a; Chelba and Jelinek, 2000). The focus of this thesis is to extend parsing techniques that have proven useful for parsing strings in such a way that they are efficient and accurate when used for language modeling.

We present a novel technique for efficient word-lattice parsing and the means to integrate parser-based language modeling into word-lattice decoding. Word-lattices are most commonly found in use by the speech recognition community, but are not specific to speech recognition. Throughout the thesis, word-lattice parsing is framed in the context of speech recognition although these techniques extend to any language processing task where the noisy channel model is appropriate (e.g., machine translation).

The noisy channel model, depicted in Figure 1.1, assumes a noise process that modifies the source signal, resulting in a *noisy* copy of the original signal. Applying this to speech recognition, we assume the speaker has an intended message to communicate which is then passed though the human speech production system – the true processing channel. The goal of speech recognition is to recover the original message and is typically accomplished by generating a string of words

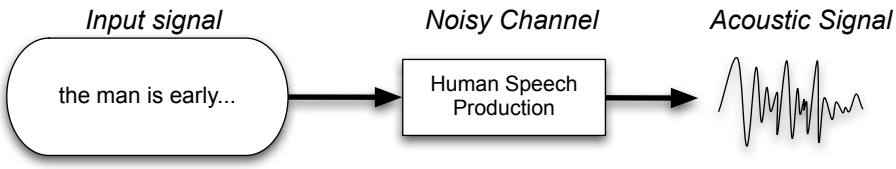


Figure 1.1: Noisy channel model for speech.

(i.e., a transcription). The objective is to automatically transcribe the speech as well as can be done by a human transcriber. In fact, the performance of speech recognition systems are evaluated by comparing the output of such systems to human transcriptions. In deriving a generative model for an automated speech recognition system, we reverse the noisy channel model assumed to produce the speech signal. Similarly, language translation can be thought of the process of taking a word-string from one language and [1] passing it through a noisy channel: translation. Again, the goal of an automated translation system is to recover the original word-string.

The noisy channel model describes a joint distribution $P(A, W)$ over the set of input speech acoustics, A, and output word strings W. We express this distribution as $P(A, W) = P(A|W)P(W)$, having applied the definition of conditional probability. From a modeling perspective this splits the distribution into the noise model (or acoustic model) $P(A|W)$ and the language model $P(W)$. The noise model provides a distribution over possible input word strings given a particular output string. The language model, as its name suggests, is defined as a distribution of output word strings for the target language (e.g., English). We model speech using the acoustic model $P(A|W)$ which is a conditional distribution over acoustic signals (or features extracted from acoustic signals) given a particular string of words. Machine translation models based on the noisy channel contain a noise model that generates sets of translation word-strings given a source-word string from a foreign language. If we consider only the word-strings that are given non-zero probability by the noise model, the noise model can be thought of as a string generator, suggesting a set of hypothetical transcriptions or translations for the input along with a probability for each string. Given this hypothesis set, we select the string that is most appropriate in the target language, which is accomplished by taking the string that maximizes the product of the noise model and the language model probabilities (i.e.,

[1] We will refer to a sequence of words as a word-string or simply a string, when unambiguous, for the remainder of the text.

maximizing the joint probability of the input and output under the noisy channel model).

Given the joint distribution of source and target word strings and knowing the particular source (we are either recognizing a specific speech signal or translating a specific foreign word string), we use the joint distribution to find the most likely target string, W^*.

$$W^* = \arg\max_W P(W|A) = \arg\max_W \frac{P(W,A)}{P(W)} = \arg\max_W P(W,A) \tag{1.1}$$

Success in language modeling has been dominated by sequential models [2] for the past few decades; in particular, the n-gram model has become the standard model for production systems and until recently was the most common found in research systems. Recently, a number of syntactic language models have proven to be competitive with the n-gram and better than the most popular n-gram, the trigram (Roark, 2001a; Xu et al., 2002; Charniak, 2001).

One reason that we expect syntactic models to perform well is that they are capable of modeling long-distance dependencies that simple n-gram models cannot. For example, the model presented by Chelba and Jelinek (1998; 2002) uses syntactic structure to identify lexical items in the left-context which are then modeled as an n-gram process. The model presented by Charniak (Charniak, 2001) identifies both syntactic structural and lexical dependencies that aid in language modeling. While there are n-gram models that attempt to extend the left-context window through the use of caching and skip models (Goodman, 2001), we believe that linguistically motivated models, such as these lexical-syntactic models, are more robust. Furthermore, n-gram modeling techniques such as caching and skip lists can be applied to structure models as well.

Unfortunately, syntactic language modeling techniques have proven to be extremely expensive in terms of computational effort. Many employ the use of string parsers (Charniak, 2001); in order to utilize such techniques for language modeling, one must preselect a set of strings from those hypothesized by the acoustic model and parse each of strings separately, an inherently inefficient procedure. Other techniques have been designed to adhere to a strict left-to right processing model (Chelba and Jelinek, 2000; Roark, 2001a), thereby placing constraints on the type of models available.

In this thesis we explore a global parsing model that utilizes a best-first search strategy. We present an extension of best-first bottom-up chart parsing of strings to parsing of word-lattices.

[2] We use the term *sequential model* to refer to that considers the sequence of words, but no structure over the sequence.

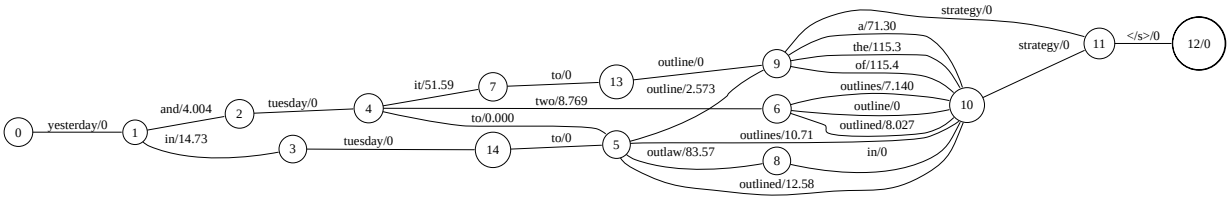


Figure 1.2: A partial word-lattice from the NIST HUB-1 dataset.

Additionally, we describe a coarse-to-fine processing model that utilizes the efficiency of the best-first search while being able to integrate more sophisticated syntactic language modeling techniques.

1.1 Representing Ambiguity: Word Lattices

A speech utterance contains much more than the words that we associate with it. For example, knowing the prosody of speech may help in identifying the sequence of words that corresponds to an utterance. When translating a text, a translation may be influenced by extra-sentential cues that direct the selection of good translations. However, the most common representation for ambiguous language (especially in speech) simply identifies a set of hypothetical word-strings annotated with scores. The scores generally come from the model that predicts these strings, the noise model; in speech recognition, this is the acoustic model.

Consider a simplified version of the acoustic model used for speech recognition; assume the model provides an estimate of the probability that an acoustic element (a phone or a phoneme) occurs during a particular time-frame. These units can be combined to form a variety of strings of words, typically done through a serious of Hidden Markov Model (HMM) predictions[3] (Jelinek, 1997). Note that a particular string may be predicted multiple times, where the words are predicted as starting and ending at different points in time. This duplication can be reduce by quantizing the start and end points of phones, phonemes, etc. (this requires summing the probability for paths that are quantized). Furthermore, there are many words that are predicted with close to zero probability, which are pruned, resulting in a set of non-zero probability word-strings as predicted by the acoustic

[3]The state-of-the-art acoustic modeling techniques tend to make very strong, incorrect independence assumptions (e.g., assuming overlapping phonemes are independent). We note that in many cases, these assumptions are made for the sake of computational efficiency and modeling simplicity.

model.

Enumerating each of the hypothesized strings is simply not tractable; in the worst case, an exponential number [4] of strings pass the acoustic pruning stage; many of these strings contain common substrings. It is standard to represent these strings in a compact structures called a word-lattice, a graph that encapsulates a set of word hypotheses along with the scores assigned by the prediction model; Figure 2.1 is an example of a word lattice. In addition to being a convenient structure for compactly storing the set of string hypotheses, the word-lattice represents the predictions made by the acoustic model or the translation model in speech recognition or machine translation respectively. The acoustic prediction probabilities are stored with the words in the arcs of the word-lattice. Additionally, the lattice may contain probabilities defined by language models. We present the definition of the word-lattice as well as the standard techniques to compress word-lattices in Section 2.1.

1.2 Language Modeling

In general, the problem of selecting a word-string from a set of hypothesized strings is solved by deriving a model of all strings in the language. A *language model* defines a probability distribution over all of these strings and provides a means to measure the probability of a particular string of words in the language. Language models can be used to identify the most likely string from a set of hypothesized strings by evaluating the probability of each word-string. The language model presented in this thesis not only assigns probability to word-strings but to parses[5] of word-strings.

The most commonly used language model is the n-gram model, a sequential Markov model of order $n-1$, meaning that in order to predict the current word, we only need know the $n-1$ previous words.

$$
\begin{aligned}
& P(w_1, w_2, \ldots, w_n) \\
&= P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)\ldots P(w_n|w_1, \ldots, w_{n-1}) && (1.2)\\
&= P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)\ldots P(w_n|w_{n-2}, w_{n-1}) \\
&= P(w_1)P(w_2|w_1)\prod_{i=3}^{n} P(w_i|w_{i-2}, w_{i-1}) && (1.3)
\end{aligned}
$$

[4] Exponential in the length of the utterance.

[5] Here a parse means a complete syntactic analysis, the probability of which may be dependent on semantic features (e.g., bi-lexical dependencies).

Equation 1.2 [6] follows from the chain rule and Equation 1.3 comes from applying the Markov assumption for a Markov process of order 2.

State-of-the-art commercial language modeling techniques for speech recognition use trigrams, while state-of-the-art research in n-gram modeling use up to 20-grams with a melange of techniques used to make the models tractable (Goodman, 2001).

1.3 Parsing and Language Modeling

1.3.1 N-best string rescoring

Recent language modeling work based on syntactic structure has been quite successful (Roark, 2001a; Chelba and Jelinek, 2000; Charniak, 2001). However, due to the complexity of many of these models, ambiguous word-strings are required to be represented as a list of strings. This technique is known as n-best rescoring. In n-best rescoring, an external model (typically a trigram) is used to extract at most n unique strings from a word-lattice. The syntactic language model examines each string, assigning it a probability. The string with the highest probability according to the syntactic language model is chosen as the correct string.

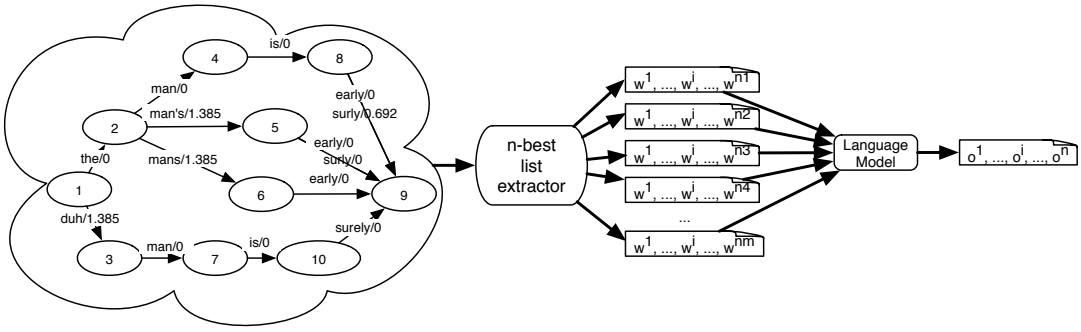


Figure 1.3: A language model used to rescore an n-best string list.

Chelba and Jelinek presented the Structured Language Model(SLM), a syntactic language model (Chelba, 2000; Chelba and Jelinek, 1998; Chelba and Jelinek, 2000). The SLM uses an incremental stochastic shift-reduce parsing strategy in order to identify the *head-word* of a phrase, which is then

[6] In general, $w_1, \ldots, w_i, \ldots, w_n$ denote the specific words from the word sequence W.

incorporated into a head-word n-gram model. The SLM executes a beam-search to build partial parses of the string which are used to identify head-words. Since the head-word model requires only that the most recent $n-1$ head-words be known, parses need not be extended beyond a point at which this information is available. The SLM can process word-lattices directly, but does not perform better than when restricted to n-best lists.

The SLM does not attempt to provide a complete syntactic analysis, yet provides a means to identify non-local lexical dependencies [7]. Non-local dependencies are critical in identifying models that are more robust than the typical n-gram model. The idea of using syntactic structure to identify non-local lexical dependencies is common among the syntactic language models presented here.

Roark proposes a syntactic language model that operates in a left-to-right manner (Roark, 2001b; Roark, 2001a) using a top-down, left-corner parser. As with the SLM, a beam-search is used to extend the parses. The parser achieves accuracy approaching some of the best probabilistic parsers, although beam size does limit the parser's coverage (as is discussed in detail in (Roark, 2001b)). More recently, Roark proposed a model that is capable of parsing n-gram word-lattices which contained 1000-best strings extracted from acoustic lattices (Roark, 2002). Roark points out that this technique is also capable of rescoring the word-arcs of the word-lattices, something not possible using rescoring techniques. The language model defined by this Roark parser is competitive with other syntactic language modeling techniques.

Charniak introduced a version of his probabilistic bottom-up/top-down lexicalized parser that assigns language model probabilities [8] (Charniak, 2001). This parser works in two stages: first, an impoverished grammar (a PCFG) is used to provide a set of candidate parses; and second, a lexically-based syntactic language model selects the *best* parse and assigns it a probability under the model. As our parser works in a similar manner, we provide details later in the thesis. Currently, the Charniak parser-based language model performs better than any other language model (including the previously mentioned syntactic language models) on the NIST '93 HUB-1 dataset. This thesis describes work that extends the techniques used by the Charniak parser to the parsing of word-lattices.

[7] The SLM is extended to a full parsing model in (Chelba, 2000).

[8] The probabilities are assigned globally by the parser, but are able to be extracted on a word-per-word bases in order to compute measures such as perplexity, etc.

1.3.2 Lattice Parsing

Unlike the techniques described in the previous section, word-lattice parsing does not require n-best lists to be preselected from the acoustic lattices. By allowing our syntactic language modeling technique to analyze any of the word-string from the original acoustic lattice, the upper-bound on our performance is only limited by the quality of the acoustic model. N-best techniques can do no better than selecting the best string from a preselected list. As we show in our analysis, the string or the n-best strings closest to the correct string (the reference transcription) is often not as close as the best string contained in the acoustic lattices (i.e., the best string has been pruned during the n-best selection process).

We are not the first to attempt to design a lattice-based chart parsing algorithm. Hans Webber proposed a similar bottom-up chart parsing technique based on a pseudo-probabilistic unification-based grammar (Weber, 1994). Chappelier, et. al. describe a word-lattice parsing technique based on a standard CKY parser (Chappelier et al., 1999). In work published concurrently with the writing of this thesis, Chris Collins has developed a word-lattice capable version of the Collins parser (Collins et al., 2004; Collins, 2003). The work presented in this thesis includes published results (Hall and Johnson, 2003; Hall and Johnson, 2004) which, to the best of our knowledge are the first results of using a word-lattice parser for language modeling.

Figure 1.4 depicts an an overview of the syntactic language model presented in this thesis. The parser is divided into two stages in the same manner as the Charniak string parser (Charniak, 2001). The first stage of the parser is responsible for proposing syntactic analyses for which the second stage assigns probabilities according to the Charniak syntactic language model. While we do not explicitly limit the number of string hypothesis as in n-best rescoring, we do perform pruning of the syntactic analyses, implicitly pruning strings (i.e., paths in the word-lattice). Pruning is accomplished using the probability estimates predicted by syntactic models; in one version of our model, these are lexicalized syntactic models.

The multi-stage technique simplifies the parsing process in addition to providing efficiency advantages. This pipeline can be thought of as an instance of coarse-to-fine[9] processing where coarse

[9]Our version of coarse-to-fine provides no guarantee that the optimal parse is selected by the latter syntactic language model. For a formal presentation of coarse-to-fine processing, see (Geman and Kochanek, 2001) section V.B..

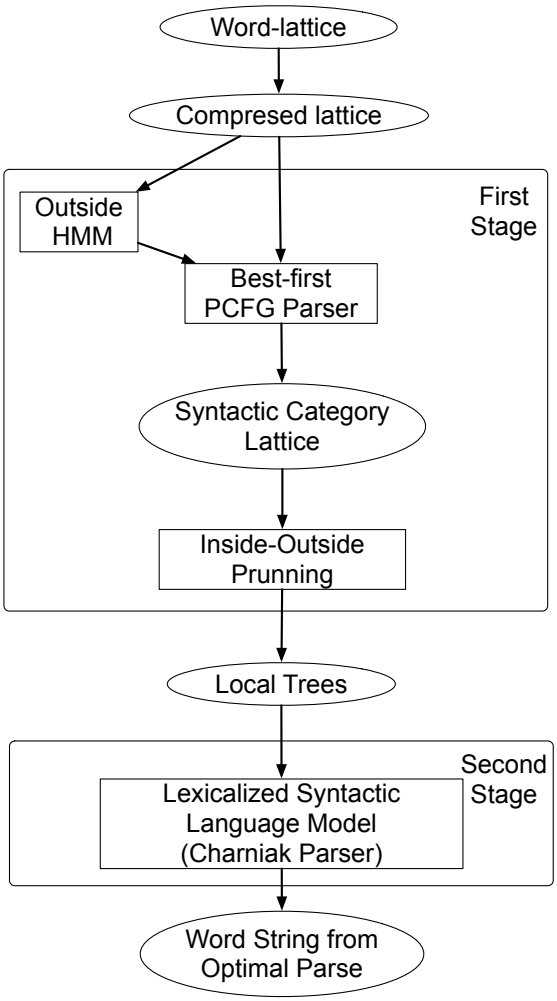


Figure 1.4: Overview of the the lattice parser.

processing provides the most primitive analysis in order to prune the set of alternative for later processing stage to consider. Fine processing provides the most rigorous analysis. There are some computational considerations - both mechanical and cognitive - that make this model appealing. Efficiency is provided by delaying robust analysis until there is a small enough candidate set that makes the analysis feasible. Non-local and non-linear dependencies are possible at later stages because later states have the advantage of working with a fixed number of parsing candidates.

1.3.3 Structure of this Thesis

In the next chapter, we present a tutorial covering the background concepts and techniques required by our lattice parser. The background material is intended to be a review of the Probabilistic Context-Free Grammars (PCFG), the compression of Weighted Finite State Automata, and the techniques used for best-first probabilistic parsing. In Chapter 3 we introduce the general coarse-to-fine parsing model that we have adopted. Following, we focus on best-first word-lattices parsing using a PCFG and the integration of this into a syntactic language model. Next, we present a set of experiments that explore the performance of both stages of our complete syntactic language modeling system. In Chapter 6 we explore alternate grammars to be used with the best-first parser. In Chapter 7 we address the question of whether our model may do better if we were to force the parser to shift attention to parts of the word lattice with few or no analyses. We report the results of experiments performed with each model and provide some some analysis of these results. Finally we provide a summary and a discuss the potential for future work.

Chapter 2

Background

2.1 Word-Lattices

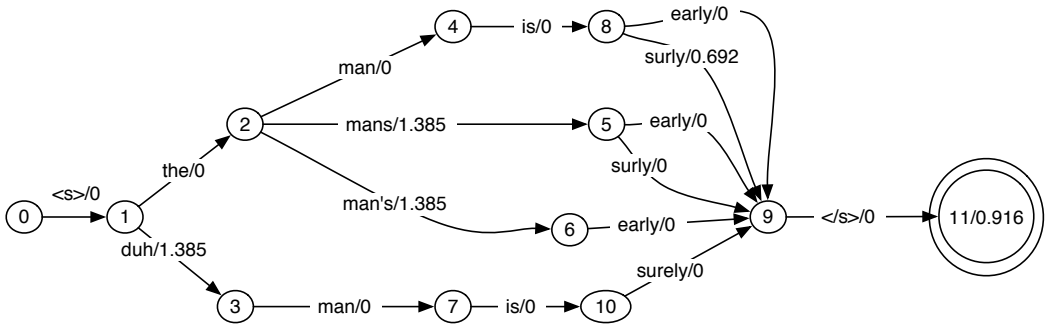


Figure 2.1: A sample word-lattice presented as a finite state machine.

The word-lattice provides a compact representation for a set of word-strings along with scores associated with the strings. Similarly, a finite state machine (FSM) defines a set of strings, and a weighted finite state machine (WFSM) is a mapping of a set of strings to scores. In this section we describe how we transform a word-lattices into a Weighted Finite State Machine (WFSM) and how we benefit from this conversion. Weighted FSMs are a variation of the FSM and provide both a formalism and a set of standard algorithms that allow us to work with the word-lattice more efficiently.

The most important computational tools we use are that of WFSM determinization and minimization. A determinized FSM takes a potential nondeterministic FSM and creates a deterministic FSM by ensuring that there is at most one path for any string prefix. Through WFSM minimization the suffixes of the graph are also compressed into single paths. Reducing the size of the word-lattice through these operations increases the amount of *structure sharing* between word-strings. As we describe later in the thesis, this directly affects the amount of structure sharing available when parsing which dramatically reduces the computational effort needed to explore syntactic analyses over the entire word-lattice.

2.1.1 Raw Word-lattice Format

Prior to performing any processing over the word-lattice, we transform the lattice from raw format into a WFSM. We present a process for transforming a word-lattice into a WFSM using the raw word-lattice Structure Lattice Format (SLF) provided by the HTK toolkit (a set of general tools for building Hidden Markov Models for speech recognition (Young et al., 2002)). It should be clear that any raw word-lattice format can be transformed into a WFSM.

The HTK SLF word-lattice is a collection of nodes and an adjacency list (the arcs), a unique start symbol and a unique end symbol. Word labels are associated with either nodes or arcs, but we consider the case where the arcs are labeled. In general, the start-of-utterance labels are unnecessary so long as we can identify a start node (i.e., we assume that the acoustic alignment procedure provides us with word-lattices beginning at the same time). As we concatenate common suffixes, it helps to know that every path in the lattice terminates at the same node. To do this, we utilize the end-of-utterance word-arc which connects each path to the same end-of-utterance node.

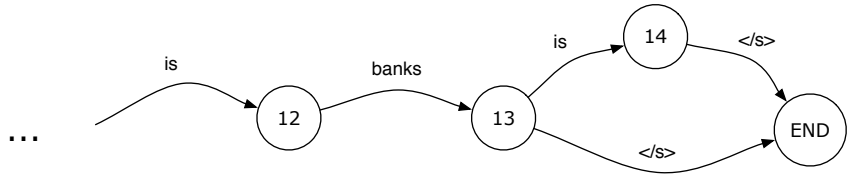


Figure 2.2: Use of the end-of-utterance marker: $<$ /s $>$.

Consider the case where the acoustic recognizer posits the suffixes *banks is* and *banks* (depicted in Figure 2.2). In raw SLF format, each arc may have one or more scores associated with it (typically

log-probabilities) corresponding to the acoustic model, n-gram model, and other arbitrary language models.

CONVERTLATTICE$(\mathcal{N}, \mathcal{A}, s^*)$
1 remove start-of-utterance node s^*
2 **for** $j \in \mathcal{N}$ such that $s^* \rightarrow j \in \mathcal{A}$
3 **do** $j \leftarrow 0$ *// new start node*
4 **for** $i_{a,b} \in \mathcal{A}$ *// an arc from node a to node b*
5 **do** label$(i_{a,b}) \leftarrow$ label(b)
6 **for** node $k \in \mathcal{L}$
7 **do** label$(k) \leftarrow$ null

Table 2.1: A function to convert a node-labeled FSM to an arc-labeled FSM.

For the remainder of the thesis, we only consider arc-labeled graphs (word-lattices and FSMs). When the input word-lattice is not originally arc-labeled (i.e., it is node labeled), we can transform it into a node labeled graph. This is the similar transformation to that of converting a Moore FSM (output labeled depend on the current state) into a Mealy FSM (output labels depend on the previous state and the current state). The transformation maps a node-labeled graph $\mathcal{G}$, composed of nodes N, arcs A, and start state s^*, into an arc-labeled graph. This transformation is presented in Table 2.1.

The word-lattice is clearly a directed acyclic graph (DAG), a characteristic necessary for efficient FSM manipulations. This fact is obvious with speech word-lattices as they encode a time-based sequential process (the acoustic signal), preventing cyclic structure in the word-lattice.

2.1.2 Finite State Machines

FSM word-lattices are not new; finite state machine representations of word-lattices are quite common in the speech recognition research community. Due to the global structure of the parsing models we use, we are able to take advantage of FSM manipulations that may be difficult or impossible with alternative parsing techniques. This is due to the fact that the weighted FSM transformations shift probability mass along lattice paths in order to best compress the lattice; the probability associated with any particular word-lattice path (a string) remains the same. An algorithm that considers only a subset of the lattice in order to direct a search may be misguided by the transformed word-lattice. Algorithms that use the probability associated with the entire word-lattice or any complete path in the word-lattice, such as our word-lattice parser, will not be effected by the transformations.

A weighted FSM generates a set of sequences and assigns a score (or weight) to each sequence. Generally, the score assigned to the sequence is simply the sum of arc-scores along the path describing the sequence. We record the log-probability of the word being generated given the model for on each word-arc. The score associated with a sequence accepted/generated by the FSM is the sum of the word-arc scores. In other words, we store the acoustic log-probability, $\ln\left(p\left(a_i|w_i\right)\right)$ for each arc i [1], where the string is $W = (w_1, \ldots, w_i, \ldots, w_n)$. Assuming the model distributions are conditionally independent (for each word), the probability of the string is defined as:

$$P(A|W) = \prod_{w_i \in W} p(a_i|w_i) = \exp\left(\sum_{w_i \in W} \ln\left(p\left(a_i|w_i\right)\right)\right)$$

FSM Transformations

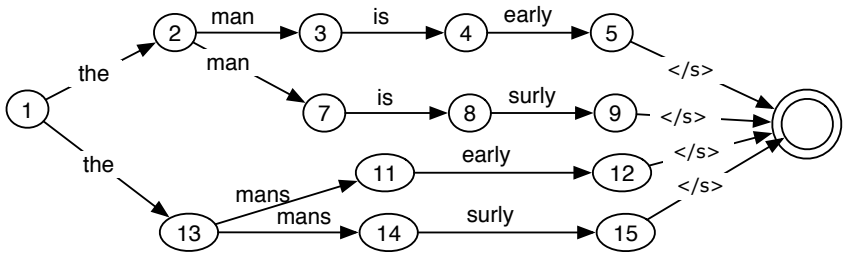


Figure 2.3: A simple FSM.

Consider a standard FSM acceptor (without scores) as presented in Figure 2.3. Clearly, there are four unique sequences that this FSM accepts (generates). There is also quite a bit of duplication in this FSM. We present two transformations that preserve the functionality of the FSM while resulting in a more compact representation: determinization and minimization.

The FSM in Figure 2.3 is not deterministic. There are multiple paths leading from node 1 that accepts the word **the**. Similarly, there are multiple transitions from node 2 and node 13 that accept identical words. Determinization is the process of collapsing nodes to create a deterministic FSM. In a deterministic FSM, there is only one path that accepts each unique prefix.

The lattice in Figure 2.4 has been determinized. Note that there is still some duplication that can be removed. There are multiple transitions with identical labels leading to the termination node. We reduce this duplication through a process called minimization.

[1] The base of the logarithm is irrelevant so long as we use the same base when converting back to probability space.

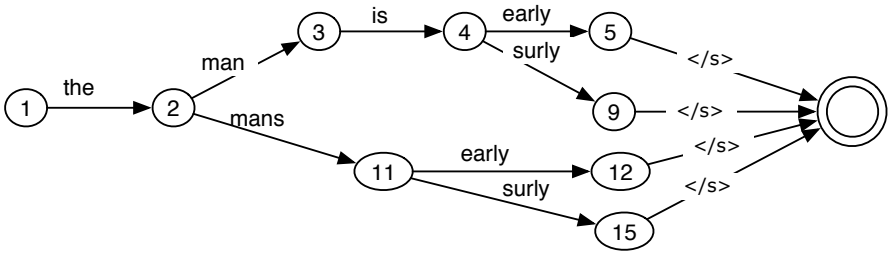


Figure 2.4: A determinized FSM.

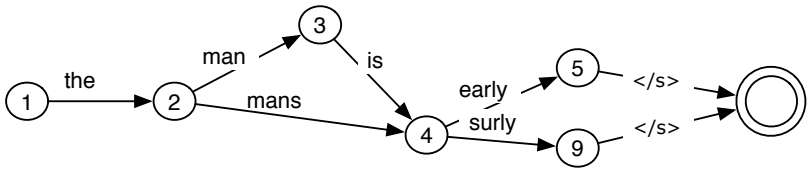


Figure 2.5: A determinized and minimized FSM.

The lattice in Figure 2.5 has been determinized and minimized. In general, we can take any sub-lattice of a lattice and perform the minimization. It is important to note that determinization and minimization do not allow new strings to be accepted by the FSM; these transformations strictly preserve the set of strings defined by the FSM.

Weighted FSM Transformations

The word-lattice FSMs that we use are weighted FSMs (WFSM). We want to compact the WFSM in the same manner as the FSM above, but we also want to preserve the scores associated with sequences. Since we only care about the scores assigned to the unique sequences accepted by the FSM we can perform similar determinization and minimization transformations.

Mehryar Mohri and the FSM group at AT&T have developed efficient minimization and determinization algorithms for WFSMs (Mohri et al., 1998; Mohri et al., 2000; Mohri et al., 2002). They have also developed a number of other useful tools for manipulating weighted WFSMs (e.g. n-best path generation).

Weighted FSMs introduce additional complexity to the determinization and minimization processes; the resulting FSM not only accepts the same set of sequences as the original FSM but it

also preserves the cumulative weight for any sequence accepted by the FSM. The following example provides the same step-by-step presentation of FSM determinization and minimization for weighted FSMs.

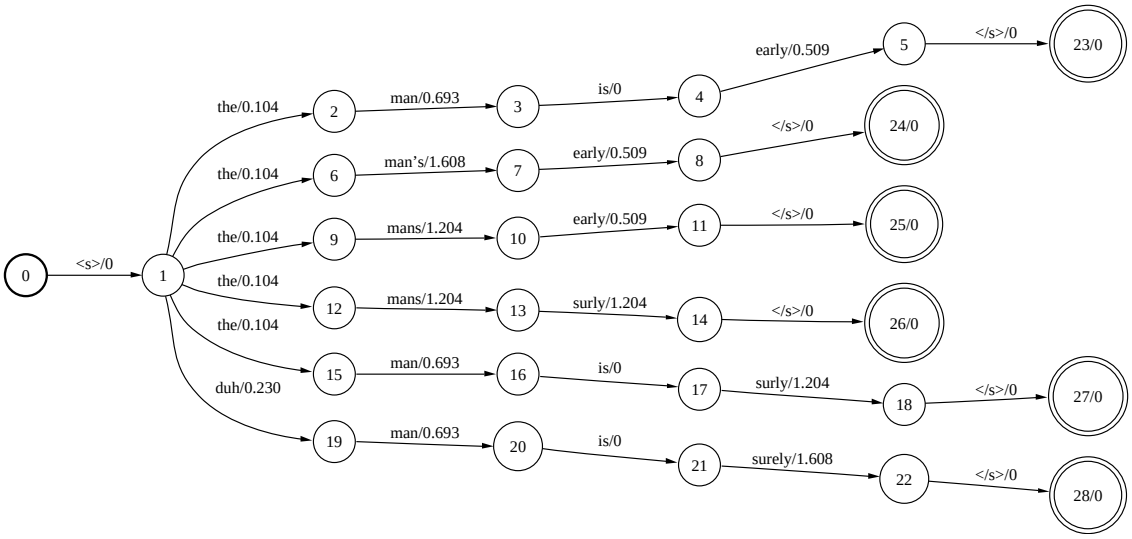


Figure 2.6: A weighted FSM.

In Figure 2.6 we present a weighted FSM that is a slightly larger lattice than the FSM presented in the previous sections which should help demonstrate the transformations. The initial word-lattice was created by hand; the probabilities were assigned by the author. The AT&T weighted FSM tools were used to perform each transformation. When using these FSM tools, we assigned negative log-probability as the score for each arc (arc scores represent a cost, where a small cost is preferable). When we search for the *best* path, we are searching for the path with the least cumulative (summed) cost. Finding the path that minimizes the sum of the negative log-probabilities is identical to finding the path that maximizes the product of the probabilities. Scores presented in this way are a little less comprehensible but can always be transformed back to probabilities.

Determinization of the weighted FSM is presented in Figure 2.7. At first glance, this process seems identical to determinization of the unweighted FSM. However, in this lattice we have adjusted the arc scores in order to retain the cumulative path scores. A simple method for doing this requires one to first identify the common prefixes (as done by standard FSM determinization). Then, we compute the cost for each of these paths, making note of the least-cost path. The unique prefix will be assigned the least cost path. For the right-most node of the unique prefix, we add arcs to

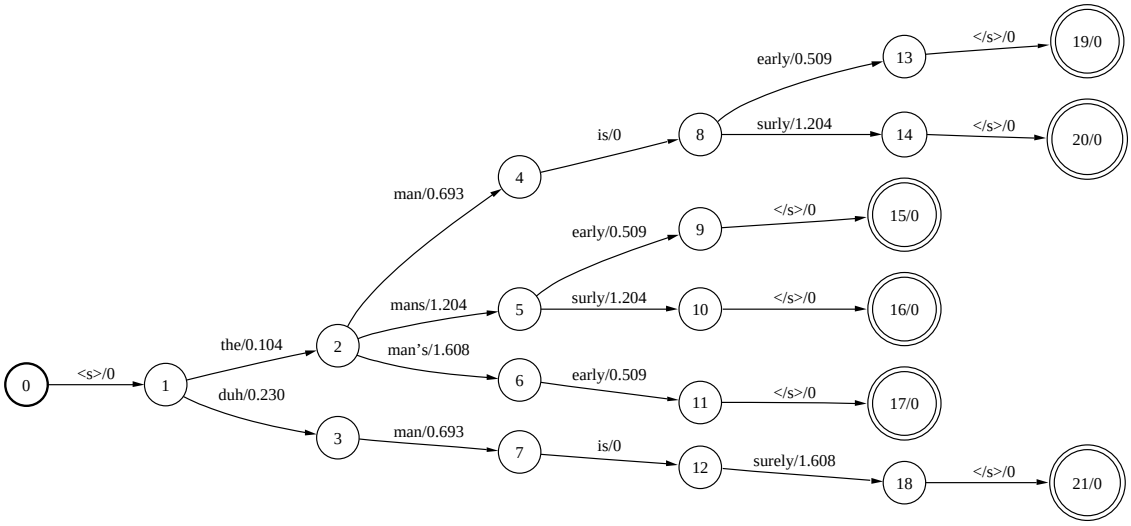


Figure 2.7: A determinized weighted FSM.

the tail of each of the paths whose prefixes were collapsed. The label on this arc is retained from the original path, but weight on this arc will be adjusted. The weight is adjusted by the difference between the least cost prefix and the cost of the prefix for the original path (i.e., the path that used to extend to the next node past the common prefix). In this way, the cost of the path for each string is identical to the original cost, but common prefixes have been concatenated.

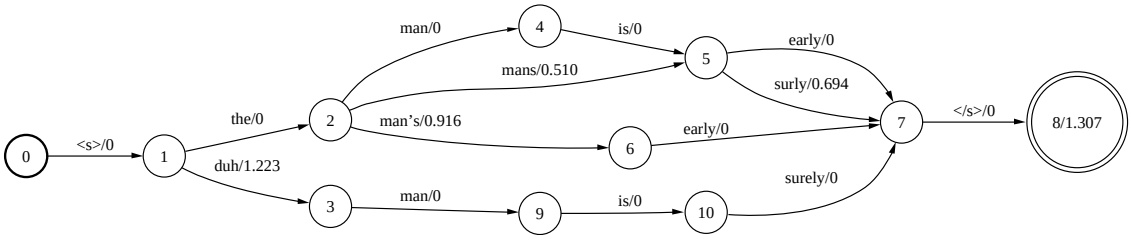


Figure 2.8: A determinized and minimized weighted FSM.

Figure 2.8 is the determinized and minimized version of Figure 2.6. Minimization is a more complicated for weighted FSMs. First, we have the same constraints that we had with the regular FSM: sub-lattices can be combined if they contain the identical set of arcs. Additionally, in a weighted FSM, sub-lattices can be combined if each arc with the same label has the same score. A process called *weight pushing* (Mohri and Riley, 2001) allows for the redistribution of arc weights while preserving total path costs. Weight pushing is performed prior to minimization in order to

transform identically labeled sub-lattices into sub-lattices that also have identical weights. Regular FSM minimization is performed on the weighted FSM by combining the labels and weights into new labels.

Certainly, some intricacies have been omitted in this brief presentation. For an exhaustive presentation of weighted FSMs and the details of the determinization, minimization, and weight-pushing algorithm please see Mohri et al. (1998; Mohri et al. (2000; Mohri et al. (2002).

Weighted FSMs and Parsing

Consider a word-lattice parsing algorithm that processes the lattice sequentially from left to right performing a beam search such as the Roark (Roark, 2001a) and Chelba (Chelba and Jelinek, 2000) techniques. Scores on the arcs are critical in determining which paths are included in the beam search. The weight-pushing algorithm we described above is capable of moving sub-lattice path weights in order to facilitate minimization, etc. Doing so may inadvertently distort the score of a path in the word-lattice, delaying the realization of the acoustic score until a later time. This has the potential to guide a sequential greedy search technique towards paths with lower likelihood (as realized when the entire path has been processed).

One solution is to make sure the weight pushing algorithm always pushes weight towards the start node. Additionally, the look-ahead (as used by a sequential parser) must account for weight movement.

In the parser presented in this thesis, the weight of entire lattice paths are considered rather than the arc weights in isolation. In other words, the parser considers the entire lattice and performs a search over the lattice in a global manner, thereby rendering the parsing algorithm resilient to weight movement in the word-lattice. Therefore, the WFSM manipulations as presented in this section have no effect on the search performed by the parser. Instead, these manipulations provide a representation of the word-strings that allows for increased structure sharing during parsing, thus resulting in a more efficient parsing algorithm. We describe structure sharing more in Chapter 3.

2.2 Probabilistic Context Free Grammars

A Probabilistic Context Free Grammar (PCFG) is a probabilistic model over a set of parse trees (this set may be countably infinite). A parse tree is a hierarchical structure that represents a particular grammar derivation. In this chapter we provide a brief review of PCFGs and present variations of the PCFG that are useful for our parsing algorithm. A complete presentation of PCFGs as used for Natural Language Processing (NLP) can be found in Manning and Shütze (1999), Charniak (1993; 1997), Geman and Johnson (Geman and Johnson, 2003), and Collins (1999).

2.2.1 Context Free Grammar

Context Free Grammars (CFGs) are relatively common in the fields of linguistics and computer science. In the former, CFGs provide the simplest model of language processing. CFGs are well known to be inadequate in describing the complex interdependencies of human language, which are anything but context-free. Computer scientists use CFGs to describe the vast collection of artificial languages used by computers.

A CFG is a quadruple, $G = \{\Omega, N, \tilde{s}, R\}$ where Ω and N are disjoint sets. Ω is the set of terminal symbols (e.g., the words in the vocabulary of the language), N is a set of non-terminal symbols, and the symbol $\tilde{s} \in N$ is a special *start symbol* from the set of non-terminals. The set $R \subseteq \{(N \rightarrow N^+) \cup (N \rightarrow \Omega)\}$ is a set of productions which describe non-terminal rewrite rules. We define $T \subset N$ to be the set of non-terminals the expand to terminal rules (i.e., $t \in T : (t \rightarrow \omega)$ where $\omega \in \Omega$). These are called the preterminals [2]. For example, assume a simplified grammar that produces strings of a's and b's.

Example sentences produced by the grammar in Table 2.2 are $abab$ and $bababa$. In Figure 2.9 we show a parse tree for the sentence $abab$. The parse tree presents the hierarchical description of rule application. In this case, rule 6 generated Y to which rule 1 was applied, generating YA. Rule 3 is then applied to the Y and so on. Depending on the grammar, there are likely to be many parses for each unique sentence.

[2] A CFG that describes the syntactic structure of a natural language typically maps the preterminals to part-of-speech tags.

- $\Omega = \{a, b\}$
- $N = \{A, B, X, Y, Z\}$
- $T \subset N = \{A, B\}$
- $\tilde{s} = Z$
- $R = \left\{ \begin{array}{ll} 1 & X \rightarrow YA \\ 2 & X \rightarrow A \\ 3 & Y \rightarrow XB \\ 4 & Y \rightarrow B \\ 5 & Z \rightarrow X \\ 6 & Z \rightarrow Y \\ 7 & A \rightarrow a \\ 8 & B \rightarrow b \end{array} \right\}$

Table 2.2: An example CFG.

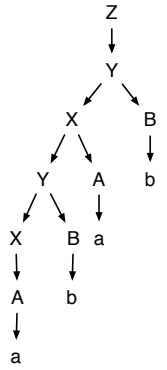


Figure 2.9: A parse of the strings $abab$

2.2.2 Probabilities and Context Free Grammars

Probabilistic Context Free Grammars (PCFG) are a type of weighted CFGs: a CFG in which a weight is assigned to each rule. In order to compute the weight of a particular parse (associated with a parse tree), we multiply the weights of each rule application in the parse. Much as with the the weighted FSM, we can use probabilities or log-probabilities: however, if we use the later, we sum the weights rather than multiplying. In Figure 2.10 we have assigned random probabilities to each rule. This is not a PCFG, because we have deficient conditional probability distributions (i.e., the sum of the probability over the dependent events is not equal to 1). For example, the distribution

$$R = \left\{ \begin{array}{lll} 1 & X \rightarrow YA & .3 \\ 2 & X \rightarrow A & .2 \\ 3 & Y \rightarrow XB & .4 \\ 4 & Y \rightarrow B & .1 \\ 5 & Z \rightarrow X & .5 \\ 6 & Z \rightarrow Y & .5 \\ 7 & A \rightarrow a & 1.0 \\ 8 & B \rightarrow b & 1.0 \end{array} \right\}$$

Figure 2.10: A CFG with associated probabilities.

conditioned on the non-terminal X only sums to 0.5. For any non-terminal, the rule productions must sum to one: for every $X \in N$:

$$\sum_{\substack{\alpha \in \{N^+ \cup \Omega\} \\ s.t. (X \rightarrow \alpha) \in R}} P(X \rightarrow \alpha) = 1$$

A PCFG defines a distribution over all strings that can be produced by the grammar. In other words, we assign probabilities to these rules so that when we combine the rules and multiply their probabilities we have a probability distribution $P(W, \pi)$ where $W = (w_1, \ldots, w_i, \ldots w_n)$ is a sequence of words from Ω and π is a parse produced by the grammar.

$$P(w) = \sum_{\pi} P(w, \pi) \tag{2.1}$$

Context-free grammars require only local information in order for rules to expand. For example, in order to expand a rule in the above grammar we need only to know the non-terminal of the parent (i.e., the left hand side of the rule). The context-free nature of these grammars allows us to summarize the probability distribution as a set of conditional probability distributions, the left-hand-side of a rule being the conditioning context. Taking the grammar from Figure 2.10, we ensure that there is a complete conditional distribution for each parent by normalizing over all rules with that parent. The resulting grammar is in Figure 2.11.

Using the grammar defined by the rules in Figure 2.11 we can compute the probability for the string $abab$. We label the parse depicted in Figure 2.9 $\hat{\pi}$ and compute its probability by multiplying the probability of each rule expansion in the tree.

$$P(a, b, a, b, \hat{\pi}) \tag{2.2}$$

$$R = \left\{ \begin{array}{lll} 1 & X \rightarrow YA & .6 \\ 2 & X \rightarrow A & .4 \\ 3 & Y \rightarrow XA & .8 \\ 4 & Y \rightarrow A & .2 \\ 5 & Z \rightarrow X & .5 \\ 6 & Z \rightarrow Y & .5 \\ 7 & A \rightarrow a & 1.0 \\ 8 & B \rightarrow b & 1.0 \end{array} \right\}$$

Figure 2.11: A PCFG.

$$\begin{aligned} &= P(a|A)P(A|X)P(b|B)P(X,B|Y)P(a|A)P(Y,A|X)P(b|B)P(X,B|Y)P(Y|Z)P(Z) \\ &= P(A \rightarrow a)P(X \rightarrow A)P(B \rightarrow b)P(Y \rightarrow XB)P(A \rightarrow a) \\ &\quad \times P(X \rightarrow YA)P(B \rightarrow b)P(Y \rightarrow XB)P(Z \rightarrow Y)P(Z) \end{aligned}$$

Given that $\hat{\pi}$ is the only parse for the string $abab$ using the above grammar, we have $P(a,b,a,b) = P(a,b,a,b,\hat{\pi})$.

A PCFG is said to be *tight* when the probability mass associated with all strings in the language is equal to one.

$$\sum_{W \in \Omega^*} P(W) = 1$$

In the previous example, we simply normalized the weighted grammar rules in order to define consistent conditional probability distributions. In general, normalization is not sufficient to ensure the PCFG is tight.

2.2.3 Estimating PCFG Probabilities

One method for estimating the probabilities for a PCFG is by learning them from training data (i.e., a supervised-learning setting). The training data contains parse trees which are usually identified by people. In order to maximize the likelihood of the training data, we use the maximum likelihood estimator (MLE) to estimate the PCFG probabilities. For multinomial distributions, the MLE for known data is the relative frequency estimator (Chi and Geman, 1998; Chi, 1999). Algorithmically, this becomes a counting exercise. For example the probability, $P(A|X) = P(X \rightarrow A)$ is estimated

by:

$$P(X \rightarrow A) = \frac{C(X \rightarrow A)}{C(X)} \tag{2.3}$$

where $C(A, X)$ count the the number of times we have seen the rule $(X \rightarrow A)$ in our training data and $C(X)$ is the number of times we have seen a rule with X on the left-hand-side. When trained by the relative frequency estimator, the PCFG distribution is tight, meaning that the probability mass assigned to the training examples is equal to 1.

With more complex grammars, we can't expect to observe all configurations within the training data. This is even true of the preterminal distribution in a vanilla PCFG. The preterminal rule $P(NN \rightarrow dog)$ must be estimated from observations of the word *dog* being used as a NN. We expect to run our parser on novel text so we cannot assume that we will have observed all possible lexical items. In order to reserve some probability mass for unknown items we perform *smoothing*, the process of guessing the likelihood of unknown events given a context. In this theses we have explored simple smoothing techniques such as Laplacian smoothing (and Jeffrey–Perks smoothing) as well as more reliable techniques such as Jelinek–Mercer EM smoothing. Smoothing is a bit of an art so we explored those techniques that have been reported to work well and were easy enough to implement. For a excellent analysis of smoothing techniques as applied to n-gram modeling for speech recognition, see (Goodman, 2001). We describe the specific details of the smoothing techniques we use in Chapters 5 and 6.

2.2.4 Binarization

A grammar is said to be binary if each of its rules has at most two constituents on the right-hand side (the grammars presented in the previous section are binary grammars). A binary grammar is a relaxation of the Chomsky Normal Form (CNF) grammar which constrains the rules of the grammar to be either binary non-terminal branches (a non-terminal expanding to two non-terminals) or a preterminal rule. Binary grammars have rules of the form (where $X, Y, Z \in Z$ and $w \in \Omega$):

$$X \rightarrow Y Z$$

$$X \rightarrow Y$$

$$X \rightarrow w$$

The CKY parsing algorithm for a binarized grammar maintains the same efficiency guarantees as with a CNF grammar. By relaxing the CNF constraints, the grammar is capable of representing unary non-terminal transitions that may capture some interesting syntactic phenomena.

BINARIZE$(G = \{\Omega, N, s, R\})$
1 **for** $r \in R : (x \rightarrow y_1 \cdots y_n)$ where $n \geq 3$
2 **do** $z \leftarrow y_2 \odot \cdots \odot Y_n$ *// create a new binary category*
3 $N \leftarrow \{N \cup z\}$ *// add new category to grammar's non-terminal set*
4 replace r in R with $(x \rightarrow y_1 z)$
5 $R \leftarrow \{R \cup (z \rightarrow y_2 \cdots y_n)\}$*// add new binarized rule to grammar*

Table 2.3: A tree binarization function.

A grammar that has more than two constituents on the right-hand side can be transformed into a binary grammar. Trees are transformed using the function in Table 2.3, where the $\odot$ is a concatenation function. The above procedure describes what is known as bottom-up right-binarization, a procedure which creates grammars that are right branching wherever there were more than two constituents in the original grammar. The corresponding left-binarization procedure should be self-evident. Figure 2.12 depicts the effect of left-binarization on a partial parse tree.

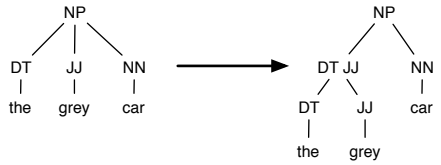


Figure 2.12: A left-binarized tree.

The PCFG for a binarized grammar is estimated in the same way as with the original grammar, using the relative frequency estimator. Binarized PCFGs define the same probability model as the original PCFG; for any string in the language both PCFGs assign it the same probability. Efficient ($O(n^3)$) PCFG parsing algorithms either perform on-the-fly binarization (as is accomplished by using Early style dotted rules) or explicitly binarize the grammar prior to parsing. Forcing right-branching, left-branching, or some mixture of the two allows us to capture more or less contextual information. The total probability associated with the parses of a string will be the same regardless of the binarization scheme. However, if we use the probability associated with partial analyses to direct a search for a subset of all parses, then some binarization scheme may be more favorable than

others.

The training procedure over binarized trees is identical as to that with the complete trees. We use the maximum likelihood (relative frequency) estimator to collect statistics for each local tree configuration. We are then able to use the learned distribution to assign probability to a new tree simply by computing the local probabilities and taking the product of all local probabilities (this is true due to fact that under a CFG, the local trees are generated independently of each other).

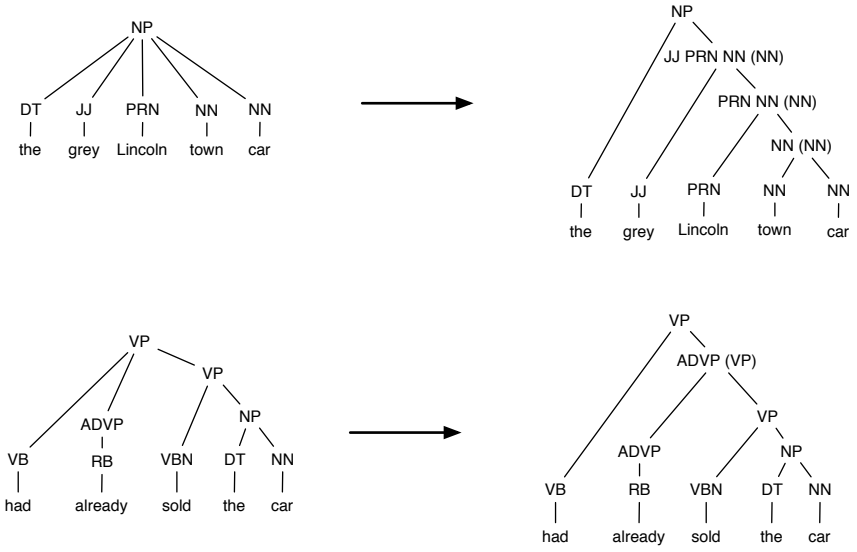


Figure 2.13: Two examples of head-binarized trees.

Finally, one can choose a linguistically motivated binarization scheme such as head-binarization. The head-word of a phrase is defined as the salient word in the phrase. Head-words are important in the determining the semantic content of a sentence and were originally identified early on in work on formal models of human syntax (Chomsky, 1970; Harris, 1951). In Chapter 6 we describe an algorithm that deterministically identifies head-words from syntactic parser trees. In head-binarization, the head-word is used to determine how binarization is performed. We may choose to binarize starting from the head and moving to the left of the head, or moving to the right of the head. In Figure 2.13 we show two trees that have been head-binarized. In this example, we encoded the position of the head-word in the binarized category by placing it within parentheses. This information provides additional context about the parent; it not only determines what the children categories are (which the previously described binary categories also provided), but it also indicates which of

these children is the head child. A PCFG parser with head-child annotations typically does not perform any better than a standard PCFG parser, but head-binarization is necessary when incorporating lexical dependencies into the model.

2.2.5 Markovization

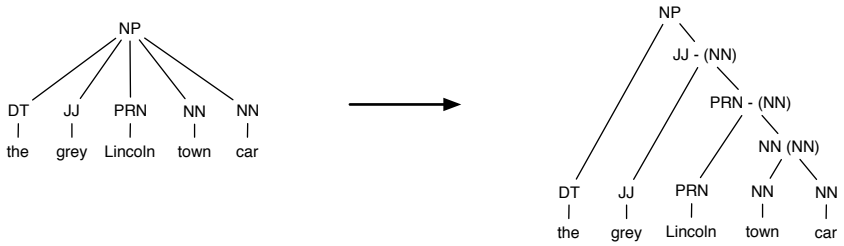


Figure 2.14: A Markov head-binarized tree.

Markovization is a variation of grammar binarization and the procedure is similar to the binarization procedure. In step 4 of the binarization procedure described above, we may choose to label the rule with something other then the concatenation of the constituent labels. Depending on the parsing model (bottom-up, top-down, etc.) we may want to record different information about the binarization step. When Markovizing the grammar, we choose to forget some of this information. In fact we choose to systematically remember a limited contextual window, making the Markov assumption that the distribution will not be much different than the distribution conditioned on the complete context (a false assumption, but one that provides some practical benefit when parsing). Figure 2.14 depicts a Markov head-binarized transformation. Note that we use the '$-$' to indicated that there has been something removed from the context. This provides a limited amount of context that allows us to differentiate between those deterministic binarized rules (those whose label explicitly indicates the children) and those which have been created by Markovization.

Once we have transformed the binarization procedure to record the abbreviated information in our binarized categories, we can simply train our PCFG on the new trees. Markovization has the effect of collapsing categories and rules in the grammar. For example, assume we Markovize by removing all internal constituent labels for any binarized category. The following categories, when

Markovized are mapped to the same Markov binary category:

$$\left.\begin{array}{l}\text{DT JJ PRN NN NN}\\ \text{DT JJ NN}\\ \text{DT PRN PRN NN}\\ \text{DT NN NN}\end{array}\right\} \Rightarrow \text{DT-NN}$$

Rules are also mapped:

$$\left.\begin{array}{l}\text{NP} \rightarrow \text{DT JJ PRN NN NN}\\ \text{NP} \rightarrow \text{DT JJ JJ NN}\\ \text{NP} \rightarrow \text{DT JJ PRN PRN NN}\end{array}\right\} \Rightarrow \text{NP} \rightarrow \text{DT JJ-NN}$$

When estimating the PCFG distributions, the counts for mapped rules are summed. Consider two parse trees that differed prior to Markovization by only a single expansion. Using the original grammar, these two trees may be assigned different probabilities. Under the Markovized grammar, if the differing expansions are mapped to the same Markov expansion, then the probability mass of the two trees will be the same. Therefore, Markovization does change the PCFG distribution over the language.

The primary reason for using a Markovized grammar is efficiency; by merging local contexts, Markovization reduces the number of rules in the grammar. In the work presented in this thesis, we have explored a fairly aggressive form of Markovization, removing all but two child categories. In Figure 2.14 we removed all child category labels between the left child and the head-child (in cases where the head is not left-most, we remove all category information between head and the right child).

Finally, we note that the complexity of the chart parsing algorithm is a function of the size of the grammar; a reduction of the grammar size corresponds to a reduction in the computational complexity. However, this reduction is usually no more than an order of magnitude (in our Markovization experiments, this was close to a 50% size reduction). It is important to stress that while this does not change the algorithm's complexity, in practices the grammar size does effect both the processing time as well as the memory footprint (due to dynamic programming).

2.3 Efficient Probabilistic Chart Parsing

Parsing is the process of assigning linguistic structure to the sentences of a language. Over the past decade or so, statistical parsing techniques have proven to be very effective. The statistical parsing algorithms are based on generative models of the language as defined by a grammar such as the PCFG described in the previous section.

A parse represents a sequence of grammar rule applications that generate the sentence. Figure 2.15

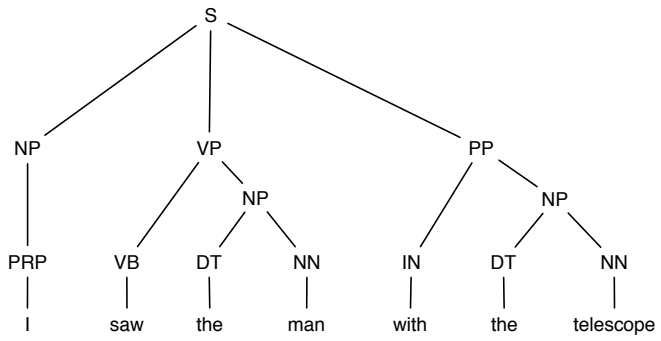


Figure 2.15: A parse of the strings "I saw the man with the telescope"

presents a parse tree for the string, "I saw the man with the telescope." This parse indicates that the subject used a telescope to see the man. There is another parse that indicates the man being seen was in possession of a telescope. There are also numerous parses which may be semantically nonsensical and highly improbable, yet syntactically correct according to some PCFG[3].

Statistical parsers assign probability to each parse as defined by a probabilistic grammar such as a PCFG. Usually we want to know the most likely parse for a particular sentence and are uninterested in the other parses. The naive solution is to compute the probability for all possible parses and then choose the parse with the highest probability. However, when working with grammars learned from natural language text we find that there are often millions of parses for any particular string.

In practice, the context-free grammars learned from data like the Penn WSJ treebank (Marcus et al., 1993) allow almost all categories to produce all other categories other than the preterminals. In some cases this allows for infinite chains of rule expansions [4] (i.e., infinite unary parse tree

[3] Since we train a PCFG from an annotated corpus of text, the grammaticality (in the traditional sense of the word) of the text will directly influence the types of syntactic structures allowed by the PCFG. In other words, if we start with highly ungrammatical text, then we will learn a grammar that generates these ungrammatical structures.

[4] If a chain of unary rule expansions exists such that the chain begins and ends with the same category, we can generate

branches), although the probability for such parses on novel data will be close to zero. In fact we explicitly avoid these chains in our PCFG parsing model knowing that they will not contribute to a higher probability parse than a parse without the chain.

2.3.1 Chart Parsing

Chart parsing is a family of dynamic programming algorithms used to compute either the most likely parse of a word-string, or to compute the probability mass associated with all parses of a word-string given a PCFG.

The number of parses of a string grows exponentially with the length of the string, so we want to avoid evaluating each parse explicitly. We can avoid this by noting that the rules of the PCFG are a natural factorization of the probability of a parse.

For this discussion of parsing strings, we will describe the parsing structures as connecting to nodes. A node is placed at the beginning, end, and between each word of the string. A span is the contiguous substring that lies between two nodes. A derivation is a completed parse tree rooted by a given category and covering a particular span. A complete derivation is always rooted by the special start symbol s and spans from the start node to the end node.

Assuming we are parsing from the bottom-up, we know that the probability for the tree rooted by category $x \in N$ spanning from node position j to l is the sum of all parse derivations rooted by node x that covers node j to node l. We call this probability the *inside*[5] probability $\beta(x_{j,l}) = P(x \rightarrow w_{j,j+1}, \ldots, w_{l-1,l})$ which represents the probability associated with rewriting x through repeated rule expansions and generating the string $w_{j,j+1} \cdots w_{l-1,l}$. We compute the inside probability recursively as follows:

$$\beta(x_{j,l}) = \sum_{\substack{k:k>j,k<l \\ y \in N \\ z \in N}} P(x \rightarrow y \quad z)\beta(y_{j,k})\beta(z_{k,l}) \tag{2.4}$$

$$\beta(x_{j,j+1}) = \sum_{w_{j,j+1}} P(x \rightarrow w_{j,j+1}) \tag{2.5}$$

Equation 2.5 is the base case for the inside recursion. Here we are simply generating a word given the part-of-speech tag. We have chosen to present this as a sum in order to accommodate parsing of

an infinite number of expansions for the category.

[5]The inside and outside probabilities (described shortly) are due to Baker (1979) and are described in parsing texts such as Charniak (1993) and Manning and Schütze (1999).

word-lattice structures. Obviously, in the case of string parsing, there is only one word per pair of adjacent node positions.

The basic data structure used in chart parsing is the *edge*. A chart edge (for a PCFG) is a unique combination of a category label x and a span, j to l; and is written as $x_{j,l}$. Equation 2.4 is the recursion for computing the inside probability of an edge given the inside probability of all child edges has been computed.

The chart parsing algorithm we consider in this thesis is based on the bottom-up construction of parse derivations. In a later section, we describe an efficient technique to search through these derivations, generating a subset of all possible parses. We now consider the case where we posit all possible derivations from the bottom up. Once we have computed the probability for a sub-tree with category x that spans from node k to node l, we add an *edge* to the chart. We compute the inside probability for this edge using Equation 2.4 and record it along with the edge[6]. When adding further edges to the chart, we continue to compute probabilities using the inside recursion (looking up the child edges in the chart [7]). Having generated edges of smaller spans prior to larger spans, we are guaranteed that all child edges are in the chart.

The chart parsing algorithm described above assumes the bottom-up parsing procedure visits all children spans prior to visiting a potential parent span. One parsing algorithm that trivially guarantees this is the CKY (Younger, 1967) algorithm, an $O(n^3)$ CFG parsing algorithm. The CKY algorithm exhaustively visits all smaller spans prior to visiting larger spans[8].

A completed chart contains all edges that contribute to the parses for the word-string being parsed. Figure 2.16 shows sample edges for an example sentence; in this example, the nodes are positioned between the words as described above. An edge (depicted as a dashed line), $x_{j,k}$, indicates that it is possible construct a rule whose left-hand-side (parent) is x from string position j to k (i.e., a derivation exists). [9]

[6] An efficient way to do this is to simply record the inside probability on the edge itself, allowing for constant time access when computing the inside probability of a new edge.

[7] The chart is typically stored as a two-dimensional hashed array to allow for constant time lookup. Unique start node and end node locations are called the cells of the chart, suggesting that a cell contains many edges that span the same nodes, but are labeled with different categories.

[8] For a complete description of standard chart parsing and the CKY algorithm see Charniak (1993) and Manning and Schütze (1999).

[9] This is true for bottom-up parsing. In top-down parsing, the existence of an edge indicates it is the child of a partial derivation of some tree described by the current chart.

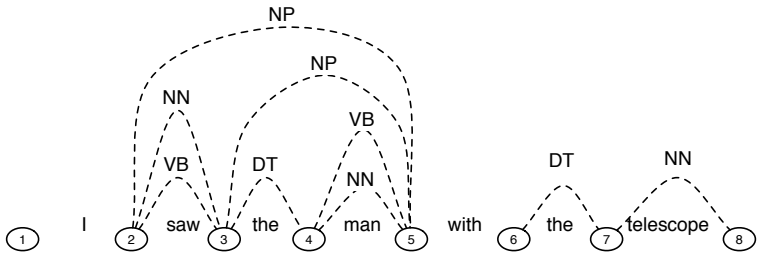


Figure 2.16: Example parse edges for the string “I saw the man with the telescope”

As mentioned above, an edge may contain additional information allowing for the efficient computation of the probability of a word-string given the grammar, the probability of the best parse of the word-string, and the derivation path to the best parse of the word-string (these are all all used in dynamic programming algorithms for efficient computation, the latter two being necessary for the Viterbi algorithm). As with the inside probability, we may want to compute an edge’s outside probability. The outside probability $\alpha(x_{j,l}) = P(w_{0,1}, \ldots, w_{j-1,j}, x_{j,l}, w_{l,l+1}, \ldots, w_{k-1,k})$ is the sum of the probability of all derivations of a complete tree (a root node spanning the entire length of the string) which contain the current edge $x_{j,l}$, minus the probability mass associated with derivations of the edge (i.e., minus the inside probability). The recursion used to compute the outside probability is as follows:

$$\alpha(x_{j,l}) = \sum_{\substack{i:i<j \\ p\in N \\ r\in N}} \alpha(p_{i,l})\beta(r_{i,j})P(p \rightarrow r \quad x) + \sum_{\substack{m:m>l \\ p\in N \\ r\in N}} \alpha(p_{j,m})\beta(r_{l,m})P(p \rightarrow x \quad r) \tag{2.6}$$

$$\alpha(\tilde{s}_{0,n}) = 1 \tag{2.7}$$

The inside and outside probabilities are an extension of the well known HMM forward and backward probabilities which provide for efficient computation of probabilities of all derivations/paths. We can compute the marginal probability of an edge in the parses of a string using the inside and outside probabilities as follows:

$$P(x_{j,l}, w_{0,1}, \ldots, w_{n-1,n}) = \sum_{\pi:x_{j,l}\in\pi} P(\pi) = \alpha(x_{j,l})\beta(x_{j,l}) \tag{2.8}$$

This is the sum of all parses π which contain the edge $x_{j,l}$ and is computed as the product of the inside and outside probabilities for $x_{j,l}$.

2.3.2 Best-first Chart Parsing

Best-first chart parsing is a bottom-up parsing technique based on a heuristic best-first search over the space of parses (Caraballo and Charniak, 1998; Goldwater et al., 1998). The heuristic function of a best-first search is inadmissible, meaning that the first solution found is not guaranteed to be the optimal solution (Russell and Norvig, 1995). Still, with a well crafted heuristic function (the values of which are called the figure of merit – FOM), best-first search can be very efficient, returning close to optimal solutions. In fact, the best-first search algorithm can be used to generate a set of solutions, on which the exact model can be evaluated in order to find the optimal solution within the set (optimal, according to our grammar).

Conceptually, the best-first parsing algorithm allows the parser to expand (upward) derivations for edges in the chart that are considered to be part of high probability parses. Doing so, we follow the *islands of certainty* principle, concentrating on parse analyses that we believe are high probability according to our model (e.g., a PCFG). Unlike the CKY algorithm, the best-first parsing algorithm alternates between processing edges with large spans and those with small spans. This

continues until a root edge [10] spanning the entire string is proposed.

BEST-FIRST$(\mathcal{S}, \mathcal{G})$
1 **while** $Agenda \neq \emptyset$
2 **do** $DEQUEUE$ top entry from Agenda and insert into chart
3 $COMBINE$ new edge with neighbors (this is known as the *fundamental rule*)
4 $CONSULT$ grammar $\mathcal{G}$, identify parent categories that cover *combined* edges
5 $COMPUTE$ FOM for edges with parent category that cover span on both children
6 $ENQUEUE$ edges with parent category. Place in agenda according to FOM

Table 2.4: Best-first chart parsing.

In Table 2.4 we provide pseudo code for the best-first chart parsing algorithm. The primary operational data structures are the parse chart, the grammar, and the agenda. Items are popped off the agenda, placed in the chart, and then built upon. In the next chapter, we describe specific models for computing the FOM. We assume here that the FOM is used to order the priority queue agenda and is an approximation of the edges likelihood in a parse. We have left out the early stopping condition which may be used to stop once a complete parse has been realized or based on some other criteria that ensures we have at least one complete parse contained in the chart. We note that the worst-case complexity of this algorithm is worse than $O(n^3)$ due to edge reanalysis [11]. This occurs when an edge that was previously inserted into the chart is realized with an alternate derivation. If we choose to re-insert the edge into the agenda again (and this is the policy upon finding new derivations), we will propagate a complete reanalysis of all edges that cover the re-inserted edge. Of course, we have chosen to use the best-first search approach to avoid complete parsing and will use early stopping criteria, avoiding the worst-case upper-bounds[12].

Figure 2.17 depicts the best-first parsing algorithm in action. In this image, we have just popped the NN(7,8) edge from the top of the agenda; the agenda is used to keep all realized edges that have not yet been incorporated into the chart. NN(7,8) is inserted into the chart (in this image we show the chart as dashed lines overlaid on the word-string). Following this the parser combines the new edge with the neighboring edges, DT(6,7). The grammar is consulted for a rule that expands to DT

[10] A root edge is an edge with the root label, meaning it can be considered a complete analysis.

[11] Reanalysis refers to finding a new derivation for an edge that is already in the chart or agenda. This is unrelated to the concept of cognitive reanalysis in sentence processing which refers to a reanalysis of syntactic/semantic structures when new information is observed (such as the next word being observed under an incremental parsing scheme).

[12] It is possible that the parser will examine all edges prior to finding a complete parse. In this case, depending on the FOM, best-first parsing may meet the worst-case upper-bound.

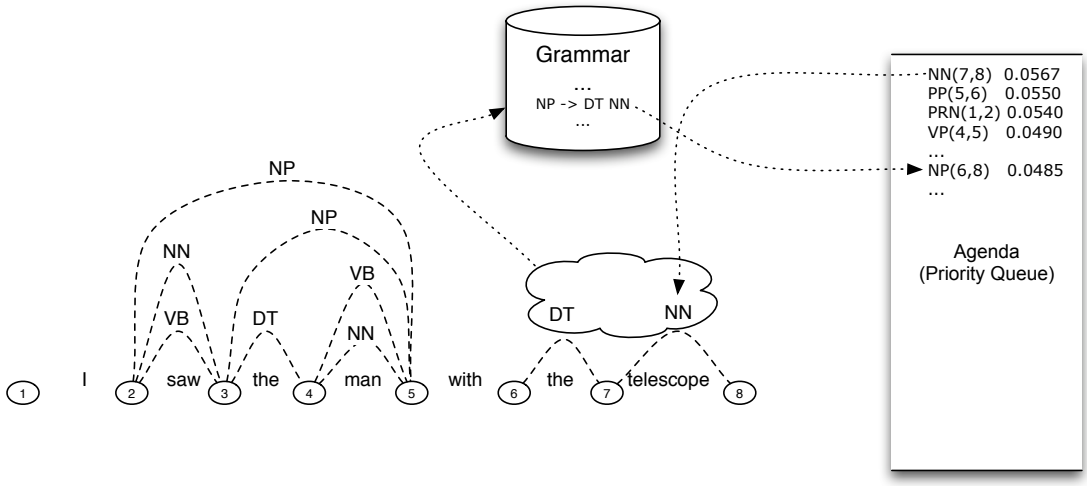


Figure 2.17: Depiction of the best-first parsing procedure. Dashed lines represent chart edges. Dotted lines depict the action of the parser.

NN, and finds (NP → DT NN). A new edge is created with the category NP that spans both children (we say the edges NP(6,8) covers its the child edges that are valid derivations). Finally, a FOM is computed for the new edge and the edge is inserted into the agenda accordingly.

Computing the FOM

Best-first search is employed in order to quickly find high-probability parses. In order to find these parses, we would like to sort the agenda by the likelihood contribution of the chart edges. Ideally, we order the edges according to their marginal probability - the probability associated with the parses of a string that contain the the edge $x_{j,k}$: $P(x_{j,k}, w_1, \ldots, w_n)$. We can compute this probability directly from the edge's inside and outside probabilities:

$$P(x_{j,k}, w_{0,1}, \ldots, w_{n-1,n}) = \alpha(x_{j,k})\beta(x_{j,k}) \tag{2.9}$$

Unfortunately, since we are parsing from the bottom-up, we are unable to compute the outside probability of the edge. And since we are using a best-first search, we are not guaranteed to know all derivations of an edge, only those used to realize the edge up to the current time. Carabello and Charniak explore a number of FOM formulations, some of these completely ignore the outside probability contribution (Caraballo and Charniak, 1998). However, they found the contribution of

an approximation to the outside probability was very useful in identifying edges that are found in the correct parse.

One advantage of bottom-up parsing is that we can compute an approximation of an edge's inside probability as soon as we add it to the chart. The *child* edges that were combined in order to realize the current edge each contain some partial inside probability (the inside probability for all derivations contained in the parse chart). In order to compute the current edge's inside probability we take the product of the children's current inside probabilities and the rule probability (as in the inside recursion: Equation 2.4).

As previously mentioned, an edge may be realized more than once (due to multiple derivations) and therefore we must add in the inside probability for each realized derivation. This can lead to a complete recalculation of the inside probability for all edges that cover an edge with a new derivation, nullifying the complexity gains of dynamic programming. There are two solutions to this problem that are used in practice. The first involves delaying recalculation of the inside probability update until it has changed sufficiently to justify propagating the changes through the parse chart. This technique was proposed by Charniak and Carabello (1998). An alternate technique is to use the Viterbi inside probability. The Viterbi inside probability for edge $x_{j,l}$ is the maximum probability of a derivation rooted by category x spanning from j to l. We rewrite Equation 2.4 to compute the Viterbi max probability over derivations rather than the sum:

$$\beta^*(x_{j,l}) = \max_{\substack{k:k>j,k<l \\ r\in N \\ s\in N}} P(x \rightarrow r \quad s)\beta(r_{j,k})\beta(s_{k,l}) \tag{2.10}$$

$$\beta^*(x_{j,j+1}) = \max_{w_{j,j+1}} P(x \rightarrow wj, j+1) \tag{2.11}$$

In model where there probability distribution is peaked over favorable derivations, the Viterbi inside probability should be a close approximation of the classic inside probability. We note that if the purpose of the inside probability is to aid in the search for a max likelihood parse, then the Viterbi probability is the correct value to be storing. However, under the PARSEVAL (Harrison et al., 1991) labeled scoring metric, the goal is to identify the number of correct labeled brackets (the number of correct edges). Typically, the Viterbi algorithm has been used to select a parse based on the summed inside probabilities rather than the Viterbi inside probabilities. The result is neither the most likely parse, nor the parse that maximizes the probability over labeled brackets. Joshua Goodman derived an algorithm that select edges that maximize the labeled brackets criteria using

the inside probabilities (Goodman, 1996).

Using the Viterbi inside probability when a new derivation for an edge is introduced, the probability mass need only be propagated through the chart if it is of higher probability than the previous Viterbi inside of the edge. This greatly simplifies the computation of the inside probability.

As for the outside probability, we are unable to compute it when parsing from the bottom up since there may be no complete parse of the string at the time an edge is realized though the application of the fundamental rule. Even when a complete parse exists, there may be no derivation from a root node that reaches the current edge proposed by the parser. A number of alternative estimates of the outside probability have been considered for parsing strings (Caraballo and Charniak, 1998). The most widely used of these is the bitag model (Goldwater et al., 1998; Blaheta and Charniak, 1999; Charniak, 2000): a linear bigram over a sequence of part-of-speech tags. We describe this model in the context of word-lattice in the next chapter.

Overparsing

Given we are unable to compute the optimal FOM, it is likely that the first parse found by the best-first search will be less than optimal according to the PCFG. A technique that is used to remedy this situation is *overparsing*. Overparsing is the process of allowing the parser to continue to populate the parse chart after the first complete parse has been identified. Parsing will still be halted before generating a complete chart, but overparsing allows for many alternate parses of the string to be contained within the chart.

Once the parser has been halted, we compute the inside and outside probabilities for the edges contained within the chart. We have stopped short of a complete chart, so there may be many parse trees missing from these computations. Again, the Viterbi max score can be used rather than the standard summed score in order to identify the max probability parse (as contained in the current chart). We mentioned the Viterbi inside probability, a similar Viterbi outside probability is defined as:

$$\alpha^*(x_{j,l}) = \max \left(\begin{array}{l} \max_{\substack{i:i<j \\ p\in N \\ r\in N}} \alpha(p_{i,l})\beta(r_{i,j})P(p \rightarrow r \quad x), \\ \max_{\substack{m:m>l \\ p\in N \\ r\in N}} \alpha(p_{j,m})\beta(r_{l,m})P(p \rightarrow x \quad r) \end{array} \right) \tag{2.12}$$

$$\alpha^*(\tilde{s}_{0,n}) = 1 \tag{2.13}$$

The product of an edge's Viterbi inside probability and Viterbi outside probability is the probability of the most likely parse that contains this particular edge.

In the following chapter we extend the Viterbi approximation to the computation of the outside probability approximation and provide some insight as to why this is appropriate in our word-lattice parsing model.

2.3.3 Using Binarized Grammars

In order to guarantee the $O(n^3)$ complexity bound for complete parsing (as is provided by a CKY parser), the grammar being used must be binary. The decision as to how this binarization is performed and where in the algorithm it is implemented is up to the model developer. An advantage to a preprocessing binarization procedure (such as the tree transformations we presented in the previous chapter) is that any parsing algorithm that requires a binary grammar may be used without modification. In fact the CKY parsing algorithm can be used directly on these binary grammars and the complexity guarantee remains intact (Johnson, 1998).

In our work, we have chosen to perform binarization as a preprocessing stage. The best-first parsing algorithm is greatly simplified by removing the internal binarization process (i.e., extending dotted rules, etc.). As claimed in the previous chapter, the PCFG learned from the binarized trees of the training data is the same model as the PCFG learned from the original trees[13]. We reiterate that the best-first search, in particular the FOM, may perform differently depending on the type of binarization performed.

Binarization also affects the parsing process by dividing the processing of larger rules into smaller rules. Depending on the type of binarization used (as described in Section 2.2.4), bottom-up parsing evaluates a rule's right-hand-side constituents either left-to-right, right-to-left, or from the head outward. Consider the rule (NP $\rightarrow$ NP VP PP PP). A right-binarized grammar (for bottom-up parsing) represents this rule as: (NP $\rightarrow$ NP VP–PP–PP), (VP–PP–PP $\rightarrow$ VP PP–PP), and (PP–PP $\rightarrow$ PP PP). In order to discover this rule, we must first have found a PP next to a PP, then later a VP next to the two PPs, and then an NP next to the VP. The delaying of rule evaluation is similar to the active edge processing performed explicitly in active chart parsing algorithms. In active chart parsing, a rule's right-hand-side constituents are typically processed from left to right. We stress that

[13]Being the same model, distributions learned from either set of trees will assign the same probability to a tree.

the type of binarization applied and the choice of binarized category labels are dependent on the parsing scheme being used (bottom-up or top-down); and that this also has an effect on the delaying of rule evaluation.

2.3.4 A* Parsing and Coarse-to-fine Processing

The best-first parsing algorithm presented in the previous section searches over the space of all parses for the input sentence. Recent work by Manning and Klein provides a means to restate the parsing problem as a traditional graph search (Klein and Manning, 2001). In this work, they propose using *Hypergraphs* to represent edges used by a chart parser on which they search using a traditional A* algorithm (Klein and Manning, 2003a; Klein and Manning, 2003c).

The A* heuristic used by Klein and Manning is based on a factored version of the PCFG. Although not noted in their work, this is an instance of coarse-to-fine model search (Geman and Kochanek, 2001). In exact coarse-to-fine processing, a model is factored into a simpler model (the coarse model). One way to do this is to define the coarse model is in terms of the conditioning states of the fine model; we can reduce the number of conditioning events in the conditional distributions. In the coarse model, the probability assigned to events is based on the max probability achievable under the coarse model. We know that the maximal solution in the fine model is within the set of *superstates* contained in the maximal solution of the coarse model.

We provide a simple example of coarse to fine processing for an n-gram model. We will use a trigram as our fine model and a bigram as the coarse model. For each conditioning context in our trigram model (each conditioning pair of words), we derive pseudo-probabilities for our bigram model as follows:

$$p_{bg}(w_i|w_{i-1}) = \max_{w_{i-1}} \hat{P}(w_i|w_{i-1}, w_{i-2}) \tag{2.14}$$

We use the reduced bigram model p_{bg} to evaluate a search space (e.g., a word-lattice) exactly, finding the most likely solution for every bigram state. When we evaluate the trigram model; at each state we only consider the trigram states that contain the maximal bigram p_{bg} solution. In effect, we have reduced the number of trigram states that need to be explored by first exploring states using the factored (coarse) model.

Best-first parsing, as used with the overparsing technique described above, can be phrased as

an approximate coarse-to-fine parsing model. The coarse model is not a factored model of the full grammar model, so we have no guarantee that by using it we will find the correct solution under the fine model. For this same reason, the FOM we describe is not an admissible A* search heuristic (otherwise this would be A* search rather than best-first search). In practice, parsing results from best-first PCFG parsing do as well and sometimes better than exact parsing (this is due, in part, to the FOM containing information not available under the PCFG model). We believe the flexibility of a heuristic function that is not required to be driven by the parsing model is well suited to our use, where our objective is reduction in word error rate (WER) rather than obtaining high probability parses (we hope there is a correlation between high probability parses and a low WER, but we are not bound to this correlation).

In the work presented in this thesis, we adopt an approach proposed by Charniak (2000; 2001) where an approximate coarse-to-fine model is used. In the following chapters, we expand on the idea of using an impoverished grammar to perform unconstrained parsing and then reevaluating the results using a more informed model.

Chapter 3

Word-lattice Parsing

In this chapter we describe an extension of the chart parsing algorithm which parses word-lattices. We describe this in the context of best-first chart parsing and provide a general outline of the best-first algorithm as applied to a word-lattice. The best-first FOM components are described in detail as well as the motivation for the particular model we use. Specifically, we present a PCFG based best-first word-lattice parser and in a later chapter we describe the FOM model components for other grammars.

In order to integrate the best-first PCFG word-lattice parser into a complete language modeling solution, we define a multi-stage parsing model based on approximate coarse-to-fine processing. We incorporate the Charniak language model (Charniak, 2001) as a final stage of this processing model and describe the advantages and disadvantages of such an approach.

3.1 Previous Work

There have been a number of attempts to integrate parsing with speech recognition. Many of the solutions have focused on the concept of *tightly-coupled* models, meaning that the parsing model works concurrently with the acoustic decoder. Early models attempted to integrate shift-reduce parsing algorithms using unification-based grammars (some hand generated) (Goddeau and Zue, 1992; Goddeau, 1992). Work by Weber (1994) introduced a chart-parsing unification-based grammar solution to the speech recognition decoder. A commonality of these systems is that the parser is effectively parsing strings. As the decoder produces continuations (hypothetical next–words), the

parser extends its parse to include this next word. Due to the inefficiency of these techniques the set of possible parses is pruned at each recognition time-frame.

The Weber parser (Weber, 1994) (also described in Kiefer et al. (2000)) extends string based parsing technique in a similar way we do in this thesis; we highlight the differences here. First, their parser is based on a probabilistic unification grammar and uses an active chart parsing approach (utilizing Early dotted rules). Second, they perform a left-to-right beam search over the word-lattices, incorporating the newly added words of the word-lattice into the parses. In order to perform this step, they limit the number of parse analyses allowed at each point as the parser develops analyses from left to right (i.e., they perform a beam-search). This effectively implements a greedy search over the parses for all paths in the word-lattice. In the algorithm described they suggest that they store all partially expanded edges that fall out of the beam, thus allowing for a global search over all parses if the greedy beam-search is unable to find a complete parse spanning the entire lattice.

Chappelier, et. al. describe some of the basic trade-offs in implementing word-lattice parsing (Chappelier et al., 1999). In particular, they suggest a modification to chart-parsing that allows for word-lattice node positions. They also describe what they call sequential–coupling of the parser and the HMM Viterbi decoder. Sequential–coupling is the process of producing a set of n-best candidate strings from the Viterbi decoder followed by a n-best rescoring procedure as we described in Chapter 1. The parse scores are combined with the acoustic recognizer's scores and might also be combined with an n-gram language model. Using this combined parser, language model, and acoustic model score, the best string is selected. A tight–coupling model incorporates the model into the time-synchronous acoustic decoder, requiring left-to-right predictive models. The work presented in this thesis lies somewhere between sequential–coupling and tight–coupling.

Recent solutions provided by Brian Roark (2001b; 2001a) and Eugene Charniak (2001) adopt the sequential–coupling model. Roark and Charniak have both shown that a parsing-based language model does better than the trigram language model. The Roark model uses a left-to-right left-corner parser that has advantages in that it could work in a more tightly-coupled setting. A variation of the Roark parser presented in Roark (2002) describes a technique for rescoring word-lattices performing a left to right syntactic analysis of the word-lattice paths.

The Charniak parser is the blueprint for the word-lattice parser developed in this thesis (Charniak, 2000; Charniak, 2001). An implementation of approximate coarse-to-fine processing, the parser employs a best-first PCFG active chart parser as a first-stage, utilizing overparsing to populate a chart with candidate parse analyses. A second-stage model applies a sophisticated probability model that incorporates context-dependent information. For example, conditioning contexts for rule expansion include features such as: the syntactic category label of the parent and grandparent edges and the head-word of the parent category (and in Charniak (2001) the grandparent or sibling category). Conditioning information is identified for all edges contained in the chart generated by the first-stage parser. This effectively splits the states (chart edges) of the chart, generating new states for each unique context. The second-stage model is applied to all expanded edges and a Viterbi parse is selected.

Ciprian Chelba et. al. propose the Structured Language Model (SLM) as a syntactically-based language model (Chelba and Jelinek, 2000; Chelba, 2000; Xu et al., 2002; Chelba and Jelinek, 1998). Unlike the Roark and Charniak models, this is not a complete parsing model[1]. The SLM builds partial parses in order to identify the head-words of the current hypothesis. Similar to the parser we propose, the SLM parses directly from a word-lattice. The SLM proposed an admissible A^* heuristic that drives the search, but due to the complexity of the model, an approximation to this heuristic is used, resulting in a best-first search.

3.2 Parsing over Word-lattices

The data structures used in chart parsing need not change in order to accommodate word-lattices. In fact, the standard parsing algorithms apply to word-lattices, though have traditionally been applied to strings. In some cases, there are a number of simplifications that assume the underlying structure is a word-string rather than a word-lattice. We describe these here.

3.2.1 Linear Spans

In the CKY algorithm, the key to finding all derivations of an edge prior to processing that edge is to process edges with smaller spans (containing fewer words) than edges with larger spans. The

[1] Chelba describes how the SLM can be used as a complete parser in Chelba (2000).

graphical structure of the word-lattice (specifically that it is a Directed Acyclic Graph) allows us to order the nodes of the graph in such a manner that word-arcs leading into a node occur no later than word-arcs leading into nodes further to the right (later in the sort order). This is a topological sorting of the nodes in the graph and it allows us to use relative node positions to identify the relative order of edge spans. This does not mean the node numbers tell us how many words are contained within a span, only that there is a relative ordering. Standard topological sorting algorithms can be found in texts such as (Cormen et al., 1990).

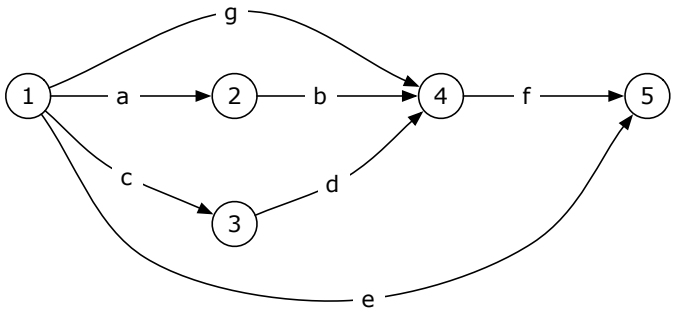


Figure 3.1: An example of topologically sorted nodes. The sequential node number indicates one possible topological sorting for this DAG.

Figure 3.1 is an example DAG where the nodes have been topologically sorted (node number indicate their topologically sorted relative ordering). Given a graph with topologically sorted nodes, we can sort the the edges of the graph such that an edge is greater than the edges it contains, we call this a topological sorting of the edges. This sorting allows us to process in order so that all contained edges are processed prior to the edge containing them.

We define a **lessthan** function that allows us to topologically sort the edges of a graph with topologically sorted nodes, defined in Table 3.1. We use the node number to compute the *size* of the edge. The size is only used in relative terms as follows:

- If the spans are of equal size, the edges either cover the exact same location or are non-containing (smaller spans can only be contained by larger spans). In either case, we arbitrarily define the span that starts earlier in the graph as smaller.

- If the spans are not identical, then we say the edge with a larger span contains an edge with a smaller span. As in the previous case, if the nodes are non-containing, then the relative sort

```
LESSTHAN(e1, e2)
 1  span ← (e1.start − e1.end) − (e2.start − e2.end)
 2  if span = 0
 3    then if e1.start > e2.start
 4           then      // arbitrarily sort edges of same size
 5                return true
 6           else  return false
 7    else  if span < 0
 8           then      // contained span is less than containing span
 9                return true
10           else  return false
```

Table 3.1: A less-than function for topologically sorted graphs

order does not matter. If the edges are containing edges, we know that a larger edge contains an a smaller edge. We summarize the three cases where one edge contains the other:

- The edges start from the same node. Since the nodes are numbered according a topological sorting, an edge that connects to a node occurring later is guaranteed to contain and edge connecting to an earlier node (by definition of the topological sort).
- The edges end at the same node. Same argument as above, but with the start node and end node reversed.
- Both the start and end nodes are different. If one edge does contain the other, then that edge must start before and after the contained edge. Due to the relative node ordering, we know that the contained edge will have a smaller size than the containing edge.

3.2.2 Semantics of Parse Chart Edges

In standard chart parsing, the interpretation of an edge is that there is at least one derivation rooted by the edge's label that spans from the start node to the end node. We know that if there is more than one derivation, all derivations are for the substring within the span. In lattice parsing, this interpretation changes. In a word-lattice parse chart an edge indicates *there is at least one derivation rooted by the edge's label for at least one path between the start node and the end node*.

Although this is a subtle difference, it changes the way we think about computing probabilities for edges. For example, the inside probability of an edge represents the probability associated

with all derivations rooted by the edge's category label covering the edge's span. In a word-lattice chart this translates to the probability associated with all derivations of all paths. This change to the semantics of a parse chart edge motivates the use of the Viterbi inside and Viterbi outside probabilities for word-lattice parsing. In effect, we wish to avoid combining the probability of parses over different yields (word-lattice paths).

3.3 Best-first Bottom-up Lattice Parsing

The pseudocode in Table 3.2 describes the bottom-up best-first chart parsing algorithm as mentioned in the previous chapter. A few definitions should help in understanding this pseudocode:

$\mathcal{W}$ is the compressed word-lattice containing the acoustic recognizer scores. The word-lattice is composed of nodes V, arcs A; and has a unique start state s, and unique end state f;

$\mathcal{C}$ is the word-lattice parse chart.

$\mathcal{G}$ is the grammar that will be used for parsing. The grammar must be binary as described in Section 2.2.

Q Is the priority queue parsing agenda. A chart parsing agenda is a data-structure that stores chart edges that have been proposed by the parser. Edges are taken from the agenda and inserted into the parse chart; following this, new edges are inserted into the agenda, via the *fundamental rule*. A priority queue is used for the agenda in best-first parsing. The queue is keyed off the FOM causing high FOM edges to be at the top of the queue.

We begin with an empty agenda and initialize the chart with the word-lattice [2]. The inside probability of a terminal edge (i.e., a word-arc) is the acoustic probability $P(a_{j,k}|w_{j,k})$. We initialize the parsing algorithm by inserting preterminal edges into the agenda. For each terminal edge we insert edges for all preterminal rules that generate it. For those words not observed in the training data, we insert an edge for every open-class part-of-speech [3]. In order for there to be probability associated with these unobserved preterminal rules, the preterminal distribution $P(x \rightarrow w)$, where $x \in T$, must be smoothed (we describe the smoothing models used shortly).

Recall that the arcs of the word-lattice contain the probabilities assigned by the acoustic model $P(a|w)$. We incorporate these probabilities into our parsing model when adding the preterminal nodes to the agenda. The inside probability that we actually use for preterminal nodes is:

$$\beta(x_{j,j'}) = P(x \rightarrow a_{j,j'}) = P(x \rightarrow w_{j,j'})P(a_{j,j'}|w_{j,j'}) \tag{3.1}$$

[2] For simplicity, the data-structure used to store the word-lattice is actual the same structure as used to store the parse chart.

[3] Open-class parts of speech represent the items of a vocabulary that are not fixed, such as nouns and verbs. This is opposed to the close-class words which remain relatively fixed within a language; prepositions and pronouns are example of closed-class parts of speech.

```
INITIALIZEPARSER(C, W, G = {Ω, N, s̃, R}, Q)
 1  for w_{j,k} ∈ W
 2  do for (x → w) ∈ R
 3     do FOM ← COMPUTEFOM(x_{j,k})
 4        ENQUEUE(Q, FOM, x_{j,k})
 5

LATTICEPARSE(W = (V, A, s, f), G = {Ω, N, s̃, R})
 1  Q ← ∅
 2  C ← W
 3  initializeParser(C, W, R, Q, {x, y, p} ∈ N)
 4  repeat
 5        x_{j,k} ← top(Q)
 6        DEQUEUE(Q)
 7        doUpdate ← INSERTEDGE(C, x_{j,k}, Q)
 8        if doUpdate = true      // x_{j,k} was inserted or updated; edge subsumption
 9          then if x_{j,k} ≠ s̃_{0,end}      // is this a root derivation of the entire lattice?
10                  then for y_{k,l} ∈ C
11                       do for p ∈ N
12                          do if (p → x   y) ∈ R
13                                then      // combine neighbor to the right
14                                     FOM ← COMPUTEFOM(p_{j,l})
15                                     ENQUEUE(Q, FOM, p_{j,l})
16                       for y_{i,j} ∈ C
17                       do for p ∈ N
18                          do if (p → y   x) ∈ R
19                                then      // combine neighbor to the left
20                                     FOM ← COMPUTEFOM(p_{i,k})
21                                     ENQUEUE(Q, FOM, p_{i,k})
22                       for p ∈ N,   p ≠ x
23                       do if (p → x) ∈ R
24                             then      // unary rule expansion
25                                  FOM ← COMPUTEFOM(p_{j,k})
26                                  ENQUEUE(Q, FOM, p_{j,k})
27  until x_{j,k} = s̃_{0,end}
```

Table 3.2: Best-first Lattice Parsing algorithm

As this is the base case for the inside and outside computation, we redefine the inside and outside probabilities to be:

$$\beta(x_{j,k}) = P(x \rightarrow a_{j,j'} \cdots a_{k',k}) \tag{3.2}$$

$$\alpha(x_{l,m}) = P(a_{0,s}, \ldots, a_{l',l}, x_{l,m}, a_{m,m'}, \ldots, a_{n',n}) \tag{3.3}$$

In each iteration of the main loop, we *pop* the top edge $x_{j,k}$ from the priority queue agenda Q and insert it into the chart. Then we apply the fundamental rule of chart parsing; we *combine* the new edge with neighboring edges $y_{i,j}$ or $y_{k,l}$ (depending on which side the neighbor lies) and we consult the grammar to ensure the rule $(p \rightarrow y \quad x)$ or $(p \rightarrow x \quad y)$ exists (again, depending on which side of the edge the neighbor lies)[4]; we also consider unary expansions If the rule exists, then we create a new edge $p_{i,k}$ or $p_{j,l}$, compute the FOM for the new parent edge, and add it to the agenda.

The chart is constrained to contain at most one edge per unique category label, start node, and end node. If we attempt to insert a duplicate edge, the duplicate is *subsumed* by the existing edge. Subsumption of this sort occurs quite often due to the existence of alternate derivations rooted by the same category label, covering the same subgraph.

Using the word-lattice as the parse chart allows the merging of what would be the parse charts for each hypothesis string of the word-lattice. *Structure sharing* at this level comes for free from the word-lattice parsing algorithm and offers a great reduction in duplicated effort. In effect the chart allows for sharing information between parses of separate paths in the word-lattice. Edges are likely to cover many paths of the lattice. Edges in an incomplete chart often cover lattice paths that have not been explicitly considered by the parser. In the next section we describe how to determine which chart edges are part of a complete parse.

Figure 3.2 depicts an intermediate state of the lattice-chart in our word-lattice chart parser. We have included just a few edges to elucidate the process of structure sharing. Notice that the $\text{VP}_{2,5}$ covers the sub-path that yields “man is” as well as the sub-path that yields “mans”. When there are derivations for $\text{VP}_{2,5}$ that produce both strings, the probabilities for both derivations are summarized

[4]If using a smoothed grammar (one that assigns probability to rule expansions not observed in the training data) we would allow all non-terminals as the parent of any pair of children. The probabilities assigned by the smoothed grammar automatically filter out the rules that are unlikely. This would be necessary if there were *coverage* problems, lattice where the parser cannot find a parse. The parser described in this thesis restricts the rules to be those observed in the training data and achieves 100% coverage on the test data.

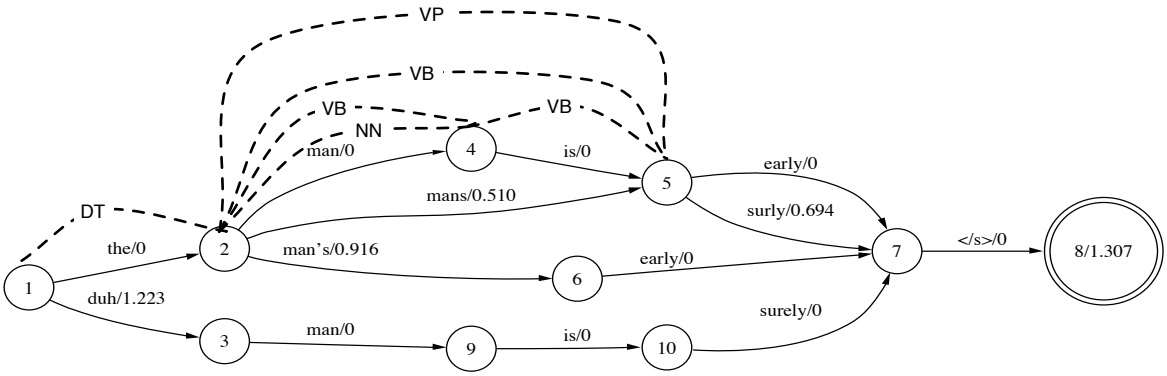


Figure 3.2: Example of the lattice-chart

by this single VP edge (typically using the Viterbi max inside probability). A primary advantage of this technique is the ability to share information across word-lattice sub-paths, parsing the entire lattice without explicitly considering specific yields of the word-lattice.

The algorithm in Table 3.2 is the basic template for parsing. Typically, the parser is run beyond the point at which the first parse is discovered. When the goal is to find a single, high probability parse, we do this to accommodate for the heuristic FOM (i.e., the FOM may not return the parse with highest probability according to the PCFG). When overparsing in this manner, one must define a stopping criterion. We suggest two general type of stopping criteria:

multiplicative In multiplicative overparsing, the parser records the amount of work needed to reach the first complete parse. In this thesis, we consider the number of *agenda edge pops* from the agenda as a measure of parser work. We record the number of agenda pops needed to complete the first parse. The parser continues to run until a multiple of the number of edges pops to get to the first parse have been popped off the agenda.

threshold In threshold-based overparsing, the parser records a probability or FOM at the time of the first complete parse, we call this the first-parse-FOM. We compute a minimum-FOM either by subtracting a fixed amount of probability mass or by scaling the first-parse-FOM. The parser is allowed to run, popping edges off of the agenda, until an FOM below the minimum-FOM is returned.

Over-parsing techniques are generally used to make up for a FOM that does not adequately approximate the probability of the parse according to the grammar. The hope is that by overparsing

we will generate enough parses that we are then able to select the optimal parse exactly using the grammar by finding the Viterbi path.

In this thesis (and in (Charniak, 2000; Charniak, 2001)) another use for overparsing is identified. When using the best-first chart parser as the first stage of a multi-stage, approximate coarse-to-fine parsing model, the job of the second-stage parser is to re-evaluate the probability of the edges in the chart. In order to provide alternate parses from which the second-stage model selects an optimal parse, we generate a chart with a substantial number of edges[5]

3.3.1 Components of the Figure of Merit

There are four major components of the figure of merit as we use in this thesis. The origin of this structure is derived from that described in (Caraballo and Charniak, 1998) and further developed in (Goldwater et al., 1998). An ideal FOM for best-first chart parsing is an edge's inside probability times its outside probability.

$$P(x_{j,k}, W, A) = \alpha(x_{j,k})\beta(x_{j,k}) \tag{3.4}$$

This is the probability mass associated with all parses for the word-lattice with acoustic probabilities A, that contain the edge $x_{j,k}$ (i.e., the amount of the total probability mass of all parses are parses which use the edge $x_{j,k}$. The probability here is actually the marginal probability of the edge in parses of the acoustic word-lattice. Using the Viterbi inside and outside probability we have:

$$P^*(x_{j,k}, W, A) = \alpha^*(x_{j,k})\beta^*(x_{j,k}) \tag{3.5}$$

In Equation 3.5, W and A are the words and acoustic date on a particular path in the word-lattice. This path is that which maximizes

Unable to compute the (Viterbi) outside probability directly we approximate it with the following component models.

1. A **linear outside model** over the parts-of-speech and words preceding and succeeding the current edge.

[5]Filling the chart with all possible edges causes the second-stage parser to perform the same work as would be done by an exhaustive parse of the lattice using the second-stage model.

2. A **left boundary** model that predicts an edge given the linear outside model preceding the edge.

3. A **right boundary** model that predicts the next piece of the linear outside model given the edge.

Combined with the estimate of the (Viterbi) inside probability, we compute the product of these models and use the result as the FOM.

Although this description makes it seem that any four models may be combined together to produce the FOM, specific features of the models may make for a better FOM. In particular, a linear model that is peaked like a word n-gram may not mix well with a relatively flat model like a PCFG. In order to accommodate differences in the model we incorporate the *fudge factor* described in (Goldwater et al., 1998). This factor provides a means to adjust the FOM of an edge depending on the number of words covered by the edge. The factor is motivated by the fact that we are mixing a hierarchical model with a linear outside model. Edges which cover a greater span are more likely to contain more of a hierarchy. Compare this to the linear outside model which is not effected by the length of the span (given all models cover the same total span, the word-lattice).

3.4 PCFG Figure of Merit

In this section we develop the specific components of the figure of merit as used by our parser. In particular we describe these components in the context of a PCFG. In Chapter 6 we describe alternative FOM components used when parsing with different grammar models.

The components described below assume the Viterbi principle: the maximum probability of a parse is desired rather than the sum of the probability of a set of parses. Although results from string parsing show that using the summed inside and outside probabilities rather than the Viterbi variants, results in higher PARSEVAL scores, we have not observed the same improvements for language modeling. In fact, when parsing from word-lattices we are interested in finding likely parses over particular paths in the lattice and not the probability of all parses of the lattices. Nevertheless, we experimented with the summed version of the inside and outside probabilities in the first-stage word-lattice parser, and found that it had no noticeable effect on accuracy in terms of word error rate (WER).

The Viterbi inside and outside probabilities are the correct probabilities to compute when we use the Viterbi algorithm to select the highest probability parse. Conveniently, we can efficiently compute an estimate to the inside probability during parsing, making the Viterbi probabilities desirable. The results presented in Chapters 5, 6, and 7, are for the word-lattice parsing using the Viterbi inside and outside probabilities.

Following is a description of the computation of the inside and outside probabilities in the context of speech word-lattices. In Section 2.3 of the previous chapter the recursions used to compute the (Viterbi) inside and outside probabilities were provided. Additional discussion on the inside and outside probabilities as used in standard parsing can be found in most NLP texts (see (Charniak, 1993; Manning and Schütze, 1999)).

3.4.1 Computing Viterbi Inside Probabilities

The interpretation of an edge in a word-lattice parse chart is that the edge $x_{j,k}$ implies there is at least one derivation rooted by category label $x \in N$ over at least one path between nodes j and k. The inside probability is redefined to account for this interpretation. First we describe the probability mass that the inside probability represents. The inside probability for an edge, $x_{j,l}$ is

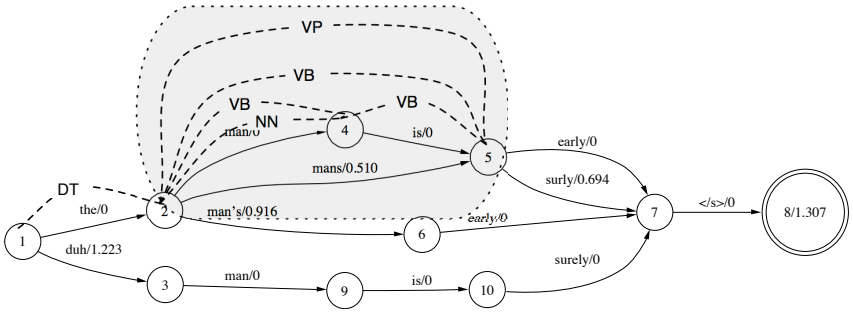


Figure 3.3: The inside probability of the $\text{VB}_{2,5}$ is contained within the shaded area.

the probability of all derivations rooted by category x generating the sub-lattice $\mathcal{G}_{j,l}$. This is the sum of all derivations rooted by x, for all paths between nodes j and l. Figure 3.3 shows the inside probability for the VP connected between node 2 and 5 for a partially completed chart.

$$\beta(x_{j,l}) = P(x \rightarrow \mathcal{C}_{j,l}) \tag{3.6}$$

This value is computed using the following recursion:

$$\begin{aligned}\beta(x_{j,l}) &= \sum_{\substack{r,s\in N \\ k:j<k<l}} p(x \rightarrow r \quad s)\beta(r_{j,k})\beta(s_{k,l}) \\ &\quad + \sum_{t\in N} p(x \rightarrow t)\beta(t_{j,l})\end{aligned} \tag{3.7}$$

In Equation 3.7 we assume $\mathcal{C}_{j,k} \subset \mathcal{C}_{j,l}$ and $\mathcal{C}_{k,l} \subset \mathcal{C}_{j,l}$, meaning that both $\mathcal{C}_{j,k}$ and $\mathcal{C}_{k,l}$ are sub-lattices of $\mathcal{C}_{j,l}$. Preterminals are not explicitly expressed in this equation as they are covered by the later term in the sum. This component covers both preterminal expansions as well as unary expansions. We have included the presence of unary transitions in this equation since we have chosen to allow these in our grammar (we use a binarized grammar, not restricted to be in Chomsky Normal Form). By allowing these expansions, Equation 3.7 has potential to recur infinitely. In practice, we do not compute the inside probability of unary transitions through this recursion. Instead we use the technique described by Jelinek and Lafferty in (Jelinek and Lafferty, 1991) for computing the unary transition probability in closed form through the use of matrix inversion. We note again, that our experiments using the summed inside probability performed no better than using the Viterbi inside probability. Results presented in the next chapter are for experiments using the Viterbi inside and outside probabilities.

The Viterbi approximation assumes that we only wish to find the maximal probability of any single path between two nodes. Applied to the computation of the inside probability, this means that for each edge, we need only compute the probability of the best parse derivation under the edge (each complete derivation corresponds to a single path in the sub-lattice). Rewriting Equation 3.6 gives us the Viterbi inside probability.

$$\beta(x_{j,l}) = \max_{W\in\mathcal{C}_{j,l}} P(x \rightarrow W) \tag{3.8}$$

The Viterbi inside probability in Equation 3.8 is the probability of the max probability of a derivation rooted by category x generating the path W, a path within the sub-lattice $\mathcal{C}_{j,l}$. As with the summed inside probability, we present a recursion that is used to compute the Viterbi inside probability.

$$\begin{aligned}&\beta^*(x_{j,l}) \\ &= \max \left(\begin{array}{l} \max_{\substack{r,s\in N \\ k:j<k<l}} p(x \rightarrow r \quad s)\beta^*(r_{j,k})\beta^*(s_{k,l}), \\ \max_{t\in N} p(x \rightarrow t)\beta^*(t_{j,l}) \end{array} \right)\end{aligned} \tag{3.9}$$

VITERBIINSIDE$(\mathcal{C}, j, k, G = \{\Omega, N, \tilde{s}, R\})$

for $x_{j,k} \in \mathcal{C}$
do CALCBINARYINSIDE$(x_{j,k})$ *// compute max inside probability over binary expansions of* $x_{j,k}$
  $ENQUEUE(\mathcal{A}, x_{j,k}.inside, x_{j,k})$ *// push edge onto auxiliary priority queue* $\mathcal{A}$
while $\mathcal{A} \neq \emptyset$
do $\bar{y}_{j,k} \leftarrow top(\mathcal{A})$
  $DEQUEUE(\mathcal{A})$
  if $\bar{y}_{j,k}.inside > y_{j,k}.inside \quad y_{j,k} \in \mathcal{C}$
    then $y_{j,k}.inside \leftarrow \bar{y}_{j,k}.inside$ *// update inside probability in chart*
      for $(r \rightarrow y) \in R, r \neq y$
      do if $r_{j,k} \in \mathcal{C}$
        then $ENQUEUE(\mathcal{A}, r_{j,k}.inside, r_{j,k})$ *// update if already in* $\mathcal{A}$

Table 3.3: Computation of Viterbi inside probability for unary transitions

The Viterbi inside recurrence is much like the computation of the normal inside probability, however the sum operators have been replaced by max operators. Unlike the summed version of the recursion, we cannot compute the Viterbi inside probability for unary transitions using a closed form expression. In Table 3.3 we present pseudocode for the computation of Viterbi inside probabilities of unary transitions. We use an auxiliary priority queue to store the current state of an edge's Viterbi inside probability. Whenever an edge's inside probability is increased, all unary expansions that are allowable by the grammar and are present in the chart are updated and reinserted into the priority queue. Increases to the inside probability are percolated up through the priority queue. When the maximal Viterbi inside probability has been computed, the priority queue will be empty.

An alternative to this approach is to precompute the maximum probability unary chain for each pair of non-terminal categories. In the Viterbi unary transition matrix V, $v_{r,s}$ is the maximum probability chain of unary rule application that rewrite $r \in N$ to $s \in N$ (i.e., the chain of rules from r to s). We can use this matrix to compute the Viterbi probability for an edge in the chart.

The word-lattice parsing algorithm in Table 3.2 operates in a bottom-up manner. As previously mentioned, this allows for an on-line calculation of the Viterbi inside probability. The function in Table 3.4 is called from the parsing algorithm in Table 3.2 for each edge popped off the priority queue agenda. If an edge with the same grammar category N^q and word-lattice span exists in the chart, we compare the Viterbi inside probabilities of the new edge $N^q_{j,k}$ and the current chart edge. If the new edge has a higher Viterbi inside probability, we update the inside probability of

INSERTEDGE$(\mathcal{C}, x, j, k, inside, Q)$
1 **if** $x_{j,k} \in \mathcal{C}$
2 **then if** $inside > x_{j,k}.inside$
3 **then** $x_{j,k}.inside \leftarrow inside$
4 **return** $true$
5 **else return** $false$
6 **else** $\mathcal{C} \leftarrow \{\mathcal{C} \cup x_{j,k}\}$
7 **return** $true$

Table 3.4: Online Viterbi inside calculation

the current edge. If this is a new edge, or if the Viterbi inside probability was updated, the parser will apply the *fundamental rule of chart parsing* and combine this edge with its neighbors. If the edge already existed in the chart, then many of the parent edges that are generated through the fundamental rule application will already be in the chart. These parent edges will be placed in the agenda with a higher probability when they were previously inserted (higher than when they were inserted due to identical applications of the fundamental rule). As the parents are dequeued from the agenda, they will instigate another update to the inside probability of the parent edges, and the cycle continues. Updates to an edge's inside probability are implicitly propagated through the chart in this manner. An alternative is to manually propagate the inside probability through the chart and agenda. An efficient technique to do so is described in (Caraballo and Charniak, 1998). The technique described here is an extension of that described in (Goldwater et al., 1998).

3.4.2 Linear Outside Model

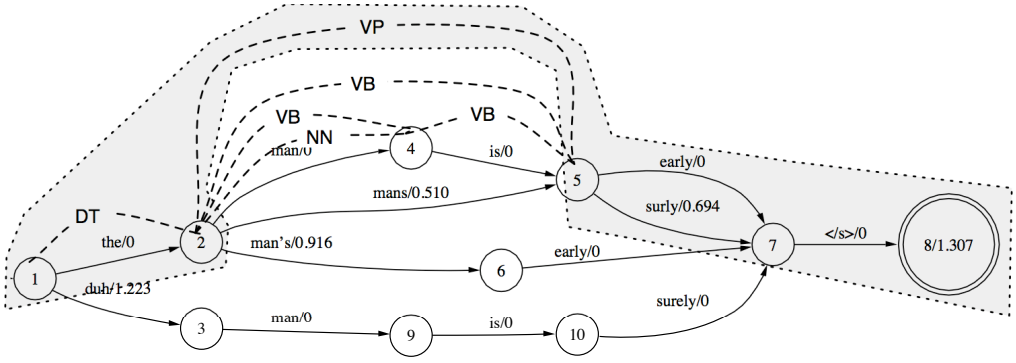


Figure 3.4: The outside probability of the $VP_{2,5}$ is contained within the shaded areas.

The outside probability of an incomplete chart is depicted in the shaded region of Figure 3.4. In a complete parse chart, the outside probability is the probability of all derivations that contain the edge $VP_{2,5}$ minus the inside probability of the edge. Clearly, in this chart there is not enough information to compute the actual outside probability. We must consider the information we have available in such a way that it provides an approximation of the outside probability.

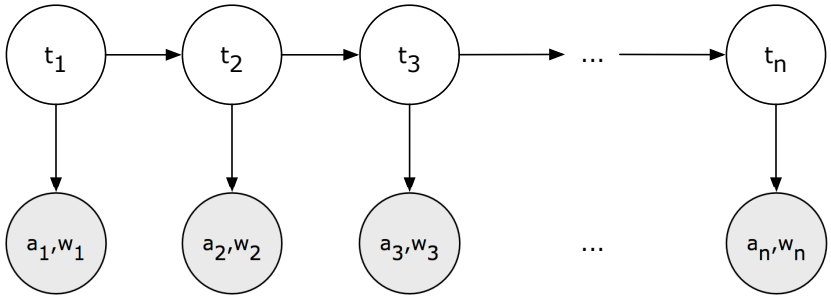


Figure 3.5: The HMM used to model the outside probability of a PCFG. This image depicts a bitag model.

In the absence of complete analyses, we use a linear outside model, an n-tag model. The n-tag model for word-lattices is an HMM model whereby the acoustic signal and words are emitted given a part-of-speech tag. The tag sequence is generated given the $n-1$ previous tags in the sequence. Figure 3.5 presents the bitag HMM in the standard notation for graphical models. The shaded nodes are the observed nodes, unshaded are the unobserved. The part-of-speech tag for time position i is represented by the random variable t_i. The bitag model was proposed for string parsing (Caraballo and Charniak, 1998; Goldwater et al., 1998) as is extended to lattices here[6].

In Figure 3.6 we present a partially expanded word-lattice to contain all applicable parts-of-speech over each word-arc. The *tag-lattice* is an explicit expansion of the HMM depicted in Figure 3.5. Using the tag-lattice we can compute the standard HMM forward and backward probabilities as well as the Viterbi forward and backward probabilities. We have experimented with both summed and Viterbi max version of the probabilities and found they performed equally well. However, we should stress that the model-type used to compute the inside probability (Viterbi max or sums) should be the same type used to compute the linear model probabilities. Otherwise, we

[6]When parsing strings, we have a fixed string to the left and to the right of a edge. Using the marginal edge probability given the string $P(q_{j,k}|W)$ as the optimal FOM allows us to simplify the linear bitag model. This simplification requires the bitag distribution be computed only for those words covered by the edge. Due to the uncertainty of the preceding and succeeding strings in a word-lattice, we are unable to make the same simplification here.

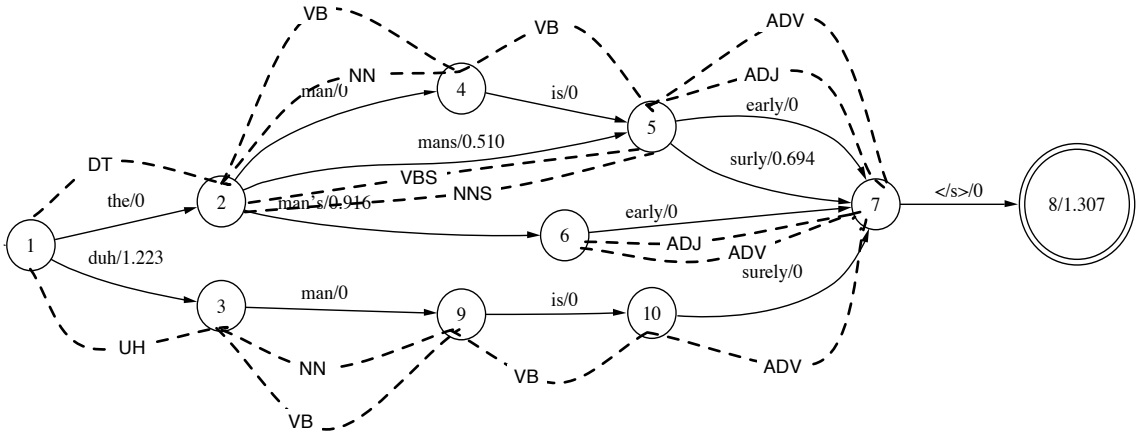


Figure 3.6: The part-of-speech tag lattice used for computing the outside probability approximation.

would be summing over paths when computing the inside of an edge, but taking the maximum path score when computing probability of the linear model. The product of these probabilities is used to compute the FOM of an edge and will be compared with other edges of different subgraph sizes. This means that if the model-types do not match, then we would use the sum of the paths for some FOM computations and the Viterbi max of the paths for others.

$$f^*(q_{h,j}) = \max_{\substack{g:g<h \\ p \in T \\ w_{h,j}}} f^*(p_{g,h}) P(q|p) P(w_{h,j}|q) s(h,j) \tag{3.10}$$

$$b^*(r_{l,m}) = \max_{\substack{n:n>m \\ t \in T \\ w_{m,n}}} P(t|r) s(m,n) P(w_{m,n}|t) b^*(t_{m,n}) \tag{3.11}$$

We present the equations for the HMM Viterbi forward and backward probabilities for the tag lattice in Equations 3.10 and 3.11 respectively. The bitag HMM transition probabilities $p(q|p)$ and emission probabilities $p(w_{h,j}|q)$ are estimated from training data (the emission probabilities come from the PCFG). Normalized acoustic model probabilities are represented by $s(l,m) = P(a_{l,m}|w_{l,m})$, the probability of observing the acoustic signal given word $w_{l,m}$. Acoustic probability normalization is performed in the standard fashion using a *fudge factor* that increases the probability; an attempt at compensating for inaccurate independence assumptions in the acoustic model[7]. $s(l,m) = \exp(\ln(a(l,m))/\nu)$ where $a(l,m)$ is the raw acoustic score and ν is the normalization factor, effectively taking the ν^{th} root of the acoustic score. Finally, note that these forward and backward probabilities can be computed prior to parsing and require only a constant-time lookup during parsing.

3.4.3 Boundary Models

The boundary models are used to join the inside probability with the linear outside model. A simple way to combine these two modes is to incorporate an edge's category label into the linear outside model. The ideas supporting this approach were originally presented in (Caraballo and Charniak, 1998) and (Goldwater et al., 1998). The linear outside model is based on a chain of part of speech tags. The chain was broken the two parts; one leading to the current edge from the start of the word-lattice and the other leading from the current edge to the end of the word-lattice. We add the edge category to this chain using the boundary models, connecting the two outside model components. Figure 3.7 depicts the process over a sequence of word and acoustic signal pairs. The boundary model incorporates the parse chart into the tag-lattice.

[7] The magnitude of the underestimate of the acoustic probability is dependent on the particular acoustic model. We generally use the same normalization factor as is used to combine an n-gram language model with the acoustic scores.

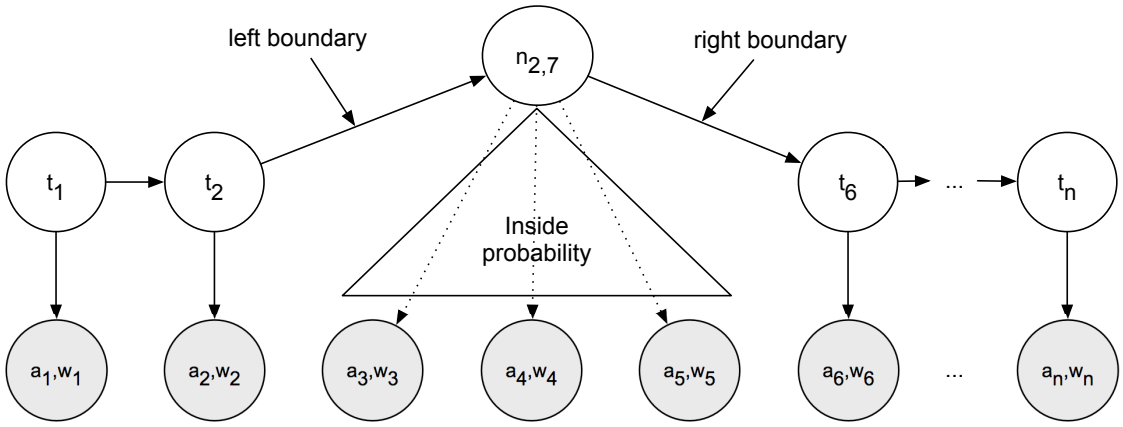


Figure 3.7: The part-of-speech HMM altered to incorporate a chart edge.

$$\tilde{\alpha}(n_{j,l}) = \max_{\substack{h:h<j \\ m:m>l \\ q,r \in T}} f^*(q_{h,j}) p(n|q) p(r|n) b^*(r_{l,m}) \tag{3.12}$$

In Equation 3.12 we present $\tilde{\alpha}(n_{j,l})$, the outside probability as approximated through the linear outside model and the boundary models. $P(n|q)$ is the left boundary model and $P(r|n)$, the right boundary model. These distributions can be estimated via maximum likelihood (the relative frequency estimator) using empirical counts from training data.

3.4.4 PCFG FOM

Combining the Viterbi inside and approximated Viterbi outside probabilities for our FOM, we have:

$$FOM(n_{j,k}) = \tilde{\alpha}(n_{j,k}) \beta^*(n_{j,k}) \eta^{C(j,k)} \tag{3.13}$$

The approximate outside probability $\tilde{\alpha}(n_{j,k})$ comes from Equation 3.12. As in (Goldwater et al., 1998) we add a normalization term, η to normalize edges that cover different length paths. $C(j,k)$ is the number of words on the path with max inside probability for edge $n_{j,k}$. The effect of this *fudge factor* is to boost the probability for edges that cover a greater span. This is desirable since the height of the trees covered by an edge increases as the span increases causing the inside probability to shrink at a rate quicker than the linear outside model. There is no restriction on the type of model used to approximate the outside probability. We can easily substitute a variety of n-tag or n-gram

models in place of the bitag model presented here. As noted previously, the best-first search is very sensitive to the mixture of these models.

Edges that are unlikely under the PCFG model (as computed from a full chart) may be assigned a high FOM. Therefore, even when we wish to find the one most likely parse, we perform some amount of overparsing.

3.5 Inside-Outside Pruning for Word-lattice Charts

The FOM is used to select edges during the parsing process. The FOM is only an approximation of the Viterbi edge probability associated with the PCFG. Given a populated parse chart, we can compute the Viterbi inside and outside probabilities using the actual PCFG. This allows us to compute the actual Viterbi edge probability according to the PCFG. We have previously discussed how the inside and Viterbi inside probabilities are computed and now discuss how the outside and Viterbi outside probabilities are computed..

When a parse chart contains at least one complete parse (a root-edge spans from the start node to the end node), it is possible to compute an estimate to the outside probability for edges that are part of complete parses. An edge not covered by a complete parse has an outside probability of 0.

The outside probability of an edge in a word-lattice chart is defined as:

$$\begin{aligned} & \alpha(q_{j,l}) \\ & \quad = \quad P(\mathcal{C}_{0,j}, q_{j,l}, \mathcal{C}_{l,n}) \qquad (3.14) \\ & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (3.15) \end{aligned}$$

This probability is the sum of probability mass for derivations that include edge $q_{j,l}$ and cover the part of the chart lattice outside of $\mathcal{C}_{j \rightarrow l}$, minus the inside probability for edge $q_{j,l}$. We use the following recursion to compute this value:

$$\begin{aligned} & \alpha(q_{j,l}) \\ & \quad = \quad \sum_{\substack{m:m>l \\ p,r \in N, r \neq q}} \alpha(p_{j,m}) P(p \rightarrow q \quad r) \beta(r_{l,m}) \qquad (3.16) \\ & \qquad + \sum_{\substack{i:i<j \\ p,r \in N}} \alpha(p_{i,l}) P(p \rightarrow r \quad q) \beta(r_{i,j}) \end{aligned}$$

$$+ \sum_{p \in N} \alpha(N_{j,l}^{p}) P(p \rightarrow q)$$

As with the inside probabilities, we modify the above recursion to compute the Viterbi max outside probability by substituting the max operator for the sum operator.

Given a partially complete chart, we compute the Viterbi outside probability and Viterbi inside probability [8] for each edge in the chart. We take the product of these probabilities to obtain the Viterbi max probability of the edge, word, and acoustic signal. This probability can be used to further prune the chart of unwanted edges (those which may have been favored by the FOM, but are given a low probability according to the grammar).

Pruning allows us to remove edges that have been added to the chart but are not likely according to our grammar model. Due to early-stopping of the parser (i.e., overparsing), the chart may contain edges that are not part of any complete parse. Their outside probability will be zero, and will be pruned along with edges that fall under the edge probability threshold.

In the parsing algorithm explored in this thesis, we define the default pruning threshold to be a function of the FOM. Recall that during parsing we are unable to compute the marginal probability of an edge and instead use the FOM as an approximation. In order to prune the chart we use the true probabilities, but we compute the threshold using the FOM. Since we are pruning we cannot use the minimum marginal edge probability because this would result in no pruning. Instead we consider the ratio between the FOM of the first complete parse and the minimum FOM of an edge in the chart.

Let FOM^{1} be the the FOM for the first complete parse and $FOM^{\min}$ be the minimum FOM of an edge added to the chart; we only consider the min FOM from the set of edges that have non-zero outside probabilities. The quotient of these two values δ gives us a rough idea of the relative probability mass allowed by overparsing.

$$FOM^{1} = FOM(\tilde{s}_{0,n}) \tag{3.17}$$

$$FOM^{\min} = \min_{n_{j,k}} FOM(n_{j,k}) \tag{3.18}$$

$$\delta = \frac{FOM^{\min}}{FOM^{1}} \tag{3.19}$$

[8] Which we can compute *on-line* while parsing (see algorithm in Table 3.4) or explicitly using the recursion described in Table 3.3 of Section 3.4.1.

We use delta to scale the Viterbi marginal edge probability computed for the first complete parse $p^1(\tilde{s}_{0,n})$ (i.e., the inside probability for edge $\tilde{s}_{0,n}$ when it was first popped off the agenda).

$$p^{\text{min}} = \delta \times p^1(\tilde{s}_{0,n}) \tag{3.20}$$

We prune edges from the chart that have a Viterbi marginal probability less than p^{min}.

At the end of this process, we have a word-lattice parse chart that contains only those edges that have met the PCFG pruning threshold. This parse chart contains the original lattice information as well as a set of parse edges that can be combined into parse trees for the word-lattice.

Chapter 4

Syntactic Language Modeling

The motivation behind parsing word-lattices is that by incorporating syntactic analysis in the language model, we hope to predict word-strings that are close to the reference transcription. In (Charniak, 2001), Charniak shows that a syntactic language model does predict word-strings better than n-gram models (as well as better than the SLM (Chelba and Jelinek, 2000)). In this work, we use the Charniak syntactic language model in concert with a word-lattice parser to produce a syntactic word-lattice language model.

Fortunately, we are able to make use of Charniak model directly by incorporating a rescoring component of the Charniak parser. This rescoring component is capable of operating on a set of syntactic category edges (a parse chart) by splitting the states deterministically: creating new states which contain contextual information used by the model (head-words, parent and grandparent categories, etc.). The Charniak probability model is applied to each of new edges (split states), rescoring each edge with the (Viterbi) inside probability according to the more sophisticated grammar (details of the Charniak probability model can be found in (Charniak, 2001)).

We describe the integration of the Charniak rescoring component with the word-lattice chart parser presented in the previous chapter. The model we present here is an instance of approximate coarse-to-fine chart parsing, which we describe in the next section.

4.1 Coarse-to-fine Chart Parsing

Coarse-to-fine processing was described in Section 2.3.4 and is defined formally in (Geman and Kochanek, 2001). In cases where exact coarse-to-fine modeling is prohibitively expensive or where an optimal solution is preferred but not required, approximate coarse-to-fine modeling can be used. In a two-stage coarse-to-fine model, the coarse stage is a factorization of the fine stage. Under this factorization, the probability model for the coarse stage is determined by maximizing over the factored terms of the fine model. An approximate alternative to this method is to estimate the parameters of probability model for the coarse stage directly. The multi-stage parsing model presented in this section is an instance of approximate coarse-to-fine processing, we call it coarse-to-fine chart parsing. Although our use of such a model for direct word-lattice language modeling is new, coarse-to-fine chart parsing for strings was introduced by Charniak in (Charniak, 2000) and (Charniak, 2001).

1. Compress the word-lattice using WFSM compression techniques
2. Compute the Viterbi forward and backward probabilities for the linear outside model
3. Perform best-first parsing on the word-lattice with overparsing
4. Prune the parse chart of low probability edges (according to the first-stage grammar)
5. Rescore the parse edges using the Charniak context-dependent grammar
6. Select the optimal parse (the word-string yield taken to be the optimal word-lattice path)

Table 4.1: Coarse-to-fine processing model.

Figure 4.1 presents the overview of the multi-stage parser we explore in this thesis. Although Figure 4.1 only contains two stages, representing the two models, there are multiple preliminary and intermediate processes such as word-lattice compression and inside/outside pruning. We refer to the best-first PCFG word-lattice parser as the first-stage (the coarse model) and the Charniak context-depended rescoring component as the second stage (the fine model). The steps of the processing model are presented in Table 4.1.

One reason for this approach to parsing is that by producing a set of candidate edges (the parse chart), the PCFG parser is solely responsible for search over the complete search space (the space of

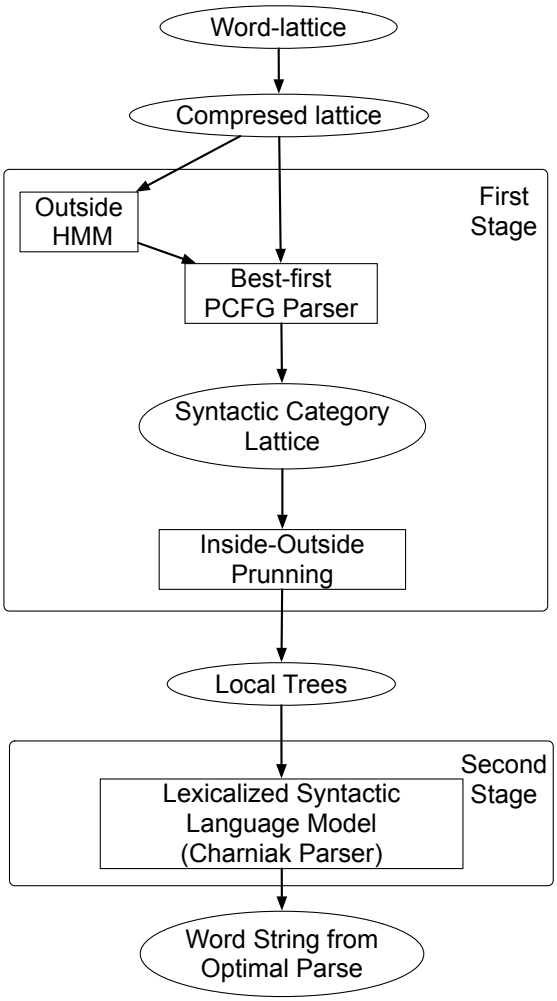


Figure 4.1: Overview of the the lattice parser.

all parses for all paths in the word-lattice). Due to the local dependencies of the PCFG, dynamic programming is effective, providing for an efficient search. Under lexicalized, context-dependent models like the Charniak model (Charniak, 2001), edge and word probabilities are dependent on long-distance relationships. In order to capture the contexts including these relationships, we increase the search space while we also increase the dependencies between distinct edges. The Charniak model makes use of lexical head-word dependencies such as $P(\text{edge}|\text{parent category}, \text{head of parent category})$. Such dependencies require that we know the lexical head-word associated with each edge. One solution is to perform a head-driven best-first parsing technique [1], we explore this as an alternate

[1] A related solution, left-corner parsing, can be found in Roark's work (Roark, 2001b; Roark, 2001a; Roark, 2002);

first-stage parsing model in a later chapter.

A disadvantage to such an approach, as with n-best rescoring techniques, is that the performance of the second-stage model is dependent on the quality of the results of the first-stage. Since we are performing approximate coarse-to-fine processing in both the best-first parser as well as the overall system, we have no guarantee that the most likely parse according to the Charniak language model will be found. For clarity, we enumerate the locations in our processing pipeline where the correct word-lattice path might be pruned from further processing.

Best-first chart parsing During best-first chart parsing, the linear syntactic model (the bitag HMM) combined with the Viterbi inside probability is used to select edges for the parse chart (via the FOM-keyed agenda). When the parser is stopped (at the end of overparsing), only word-lattice arcs which are covered by a complete parse (meaning the derivation for a parse contains that particular arc) are passed on to later stages. In effect, the stopping condition controls pruning of word-lattice arcs (and therefore word-lattice paths). A first-stage PCFG model as described in the previous chapter only considers syntactic relationships over words, but never considers word-to-word statistics (e.g., the bilexical statistics of a bigram are word-to-word statistics). Therefore pruning at this stage is driven by a different model than the PCFG.

Inside/Outside pruning Other than removing those edges that are not part of complete parses (i.e., they have zero outside probability), this step explicitly removes category edges. If by removing these edges, we make arcs in the word-lattice unreachable (no longer part of a complete parse), then we are pruning paths from the word-lattice as well. However, in this case we are using the true PCFG model when pruning, but are still not using word to word statistics.

Charniak Rescoring By choosing a single parse, we are pruning all but one path in the word-lattice (which we want to do). If the correct path exists in the pruned word-lattice prior to this stage, and enough chart edges exist that contribute to a relatively high probability parse, then this stage of the process should select the correct word-string. In some cases, the conditioning information of this model may not be enough to select the correct word-string; this is considered to be a modeling error rather than a search error.

---

this technique is based on a left-to-right beam search and is not a dynamic programming algorithm.

Throughout the presentation of experimental results we report results that evaluate the quality of pruning as well as the quality of the complete language model. We evaluate the first-stage word-lattice parse in terms of pruning: how close is the closest path in the pruned lattice to the reference word-string. This is called the oracle word error rate (OWER) and is a measure of the pruning[2]. In order to evaluate the overall language model we use the standard word error rate (WER) measure.

4.1.1 Second-stage Memory Constraints

Due to the extensive state-splitting performed by the Charniak language model in order to represent all of the model dependencies, the size of the parse chart passed is limited. This means that we cannot exhaustively populate the parse chart via overparsing. This absolute limit is determined by the amount of available memory on the machine running the Charniak parser, in our experiments this was usually 2 gigabytes of RAM. Limiting the size of the chart to an exact number of edges can done by adjusting the Inside/Outside threshold.

We perform a bisection search over possible Inside/Outside threshold values for each word-lattice parsed. The objective of this search is to generate no more than a predetermined maximum number of chart edges [3]. The effect of this constraint is that we must contain both good word-lattice paths as well as good syntactic category edges in a limited size chart.

[2]The oracle WER measures the edit distance between a word-lattice and a word-string.

[3]In fact, the Charniak language model component takes as input a forest of local-trees rather than a chart. A local-tree is a local derivation for each edges in the parse chart. The local-tree contains the parent category, children categories, and start and end nodes of each category.

Chapter 5

Speech Recognition Experiments

In this chapter we focus on an empirical evaluation of the best-first word-lattice parsing model used as a language model for speech recognition. Much of the work on language modeling (especially for speech recognition) has involved linear Markov models, n-grams. The results presented here show that not only does syntactic structure help language modeling (this has been shown in Chelba and Jelinek (2000), Charniak (2001), and Roark (2001a)), but we can efficiently parse word-lattices directly.

There are two types of results presented in this chapter. First, we report how well the first-stage best-first parser selects paths in the word-lattice (i.e., we measure the quality of the pruned word-lattices). And second, we evaluate a complete language modeling system based on the best-first parsing using the Charniak language model as a rescoring stage. These results are compared to n-best rescoring results presented by Chelba (2000), Roark (2001a), and Charniak (2001) using the same evaluation dataset where possible.

Analysis of the results from these speech recognition experiments suggest that there are both modeling errors (with the Charniak language model) as well as search errors. Given the sophistication of the Charniak language model, we do not attempt to improve on this model. In the following chapters we provide modifications to the first-stage parser in order to correct for the search errors.

5.1 Evaluation Metrics

For each set of experiments, we evaluate both the first-stage word-lattice parsing models as well as the complete multi-stage language model. Both metrics are designed to determine how close the results are to the *correct* word-string. In these experiments, the correct word-string is a transcription of the speech utterance. We have used the standard test setting in which there is only one correct word-string per utterance. While this may be unnaturally strict (as many word compounds and contractions may have multiple orthographic forms), we compare our results to the results of other techniques using the same evaluation constraints.

5.1.1 Word Error Rate

The word error rate of a string as compared to the transcription is usually computed as the minimum edit distance. Edit distance is measured by summing the number of insertions, deletions, and substitutions required to make the strings identical. A trivial $O(n^2)$ dynamic programming algorithm can be used to compute this distance. We use the sclite scoring routine which is packaged with the NIST Speech Recognition Scoring Toolkit (SCTK) (NIST, 1998). Given a set of reference transcriptions and a set of hypothesized strings (the output of our language model) the sclite program computes the minimum edit distance and returns a general word error rate (WER), as well as sentence error rate.

5.1.2 Oracle Word Error Rate

In order to evaluate the first-stage model (the word-lattice parser) independently of the complete language model, we provide a metric that compares a word-lattice with the reference string. The oracle word error rate (OWER) is the minimum edit distance between a string and a word-lattice. We are looking for the minimum edit distance between any path in the word-lattice and the reference transcript.

The OWER can be computed efficiently by constructing a weighted finite state transducer for both the word-lattice and the reference transcription. Arcs are added to the transducer for each word-arc in the original word-lattice/string. These new arcs allow for a word to be deleted (translated to an epsilon) or substituted (translated to a special symbol and then back to another word). The

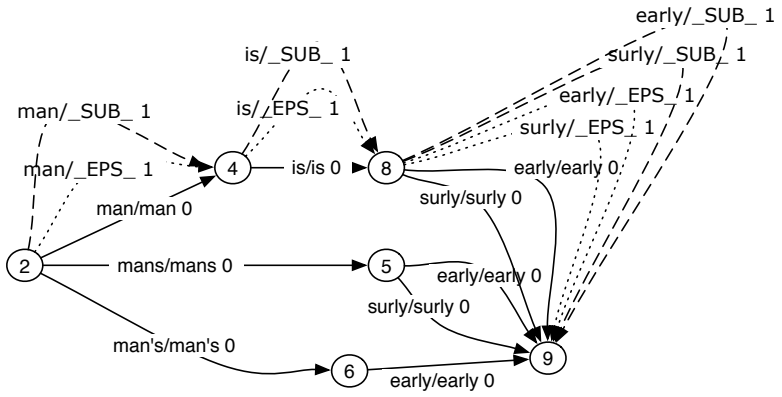


Figure 5.1: A partially constructed OWER transducer (of a partial word-lattice).

MAKETRANSDUCER($\mathcal{L}, isFirstLat$)

```
1  for w_{j,k} ∈ L
2  do INSERT(T, {w_{j,k}/w_{j,k}   0})
3     if isFirstLat
4        then INSERT(T, {w_{j,k}/_EPS_   1})     // deletion
5             INSERT(T, {w_{j,k}/_SUB_   1})     // substitution
6        else INSERT(T, {_EPS_/w_{j,k}   1})     // insertion
7             INSERT(T, {_SUB_/w_{j,k}   0})     // other half of substitution
8
```

Table 5.1: Construction of an OWER transducer from a word-lattice $\mathcal{L}$.

algorithm in Table 5.1 provides pseudocode for the construction of a OWER finite state transducer. Note that one word-lattice [1] is chosen as the first lattice (for which $isFirstLat$ will be true). This allows two different types of transducers to be created: the **from** and **to** transducer which allow for mapping to strings containing deletion arcs ($w_{j,k}/\_EPS\_$) and substitution arcs ($w_{j,k}/\_SUB\_$), and a transducer that maps insertions ($\_EPS\_/w_{j,k}$) and partial substitutions ($\_SUB\_/w_{j,k}$) into word-strings.

Given the **from** and **to** OWER transducers we perform a weighted finite state transducer composition (using the AT&T FSM toolkit (Mohri et al., 1998; Mohri et al., 2000; Mohri et al., 2002)) and then choose the lowest cost path from the composition. This returns at least one of the minimum cost transductions, the cost of which represents the minimum number of deletions/insertions and

[1] A word-string is a simple word-lattice. OWER can be computed between two word-lattices, although we have no need for this functionality at this time.

substitutions required to transform a path in one word-lattice to a path in the other (in our case, this is the reference transcription word-string).

5.2 Speech Data

In the following automatic speech recognition (ASR) language modeling experiments we continue the tradition of using the NIST 1993 HUB-1 set of Wall Street Journal word-lattices (Pallett et al., 1993). These lattices are provided by Ciprian Chelba (2000) and have been used by Chelba, Roark (2001a), and others to evaluate the accuracy of their syntactic language modeling techniques. A few facts about the HUB-1 word-lattices:

- The speech data comes from the ARPA Continuous Speech Recognition(CSR) corpus, Channel 1: CSR-WSJ0 (Paul and Baker, 1992); this is the high-quality ”primary” microphone data. The speech data comes from 123 speakers reading excerpts from the Wall Street Journal text corpus including articles from 1987, 1988, and 1989.

- Bill Byrne of Johns Hopkins University used the HTK toolkit (Young et al., 2002) with an ”out-of-the-box” training scheme to train an acoustic model using the available CSR-WSJ0 training data.

- Ciprian Chelba used this acoustic model and the trigram language model packaged with the CSR-WSJ0 (obtained from the Linguistic Data Consortium - LDC) to generate word-lattices. The pretrained trigram language model was trained on 45million words of Wall Street Journal text with a 64k word vocabulary.

- 213 word-lattices were generated, corresponding the to NIST 1993 CSR HUB-1 evaluation. The word-lattices contain the acoustic scores as well as the trigram language model scores.

One of the subtleties of using syntactic-based language models is the need for syntactic training data. In our case, we require training data for both the first-stage PCFG word-lattice parser as well as the second-stage lexicalized parsing model (the Charniak model). In general, a parser works much better when trained on data from the same domain as opposed to being trained on data from a

different domain [2]. This is a short-coming of most language-modeling techniques including n-gram models (however the negative effect may be less severe with n-gram models). The HUB-1 speech dataset is a set of spoken sentences from the Wall Street Journal. Conveniently, there is a large hand-parsed dataset of Wall Street Journal articles, the Penn Wall Street Journal treebank (Marcus et al., 1993).

When combining two models, such as the acoustic model and a language model, we need to account for modeling characteristics that may make the probabilities of one model incompatible with those from another. This is definitely the case when working with the acoustic model. In order to mix our syntactic model probabilities with the acoustic probability we must normalize the log-acoustic scores by some factor (we describe the integration of the acoustic score into the FOM in Section 3.4.2 of Chapter 3). Throughout these experiments we use an acoustic normalization log-scale factor of $\frac{1}{16}$ (effectively the sixteenth root of the acoustic scores found in the lattices). This parameter is found in all speech language modeling methods and is used to compensate for inaccurate independence assumptions made in the acoustic recognition model.

Although this scale factor happens to be the same factor which minimizes the WER when mixed with a trigram language model, we explored other values between 1 and $\frac{1}{30}$. We found that in our experiments using the log-scale factor of $\frac{1}{16}$ to be optimal when mixing with syntactic models.

5.3 Model Training

We train the PCFG word-lattice parser on the Penn Wall Street Journal treebank sections 2–21 (using section 24 as held-out data). Prior to learning statistics for our model, we transform the tree-bank data into speech-like data [3]. Text normalization of this sort converts numerals and abbreviations into individual tokens as they would be transcribed from speech. For example the number 125 is converted to *one hundred twenty five*. The trees for the expanded strings are relabeled (CDs are transformed into a series of NNs) and expanded to include the new tokens.

Following normalization we perform binarization and Markovization on the parse trees in the training data. We train the PCFG from the transformed trees, resulting in a binarized, Markovized

[2] Recent effort in the area of parser adaptation provides hope in this area. Parser adaptation allows for a parser trained on data from one domain to be *adapted* to a new domain with minimal training data from the new domain.

[3] We used Brian Roark's text/speech normalization tool.

grammar. As described in Section 2.2 we use an aggressive Markovization strategy. We experimented with the different binarization and Markovization techniques suggested in Section 2.2 and found that they all perform relatively similar in terms of WER. We experimented with the following PCFGs:

UnMarkovized left and right binarized grammars (described in Section 2.2.4. The labels for binarized categories contained the explicit expansion of all binarized children (i.e., NN-NN-NNP-NNP). The results for the first parse as returned by the best-first parser were slightly better for the right-binarization [4] when run on strings of 40 words or less on f23 of the Penn WSJ Treebank. Labeled F-measure scores at first parse were 73.3 for right-binarization and 73.0 for left-binarization (using Laplacian smoothing for the preterminal distribution).

Simple Markovization was described in Section 2.2.5 and involves forgetting all category labels between the left and the right (the first and last child's category label are concatenated to for the binarized label). Labeled F-measure scores at first parse were 72.0 for right-binarization and 72.0 for left-binarization (using Laplacian smoothing for the preterminal distribution). The parsing score are slightly lower than without Markovization, but did not effect the overall performance of the system (measured in WER).

Head-binarization is described in Section 2.2.4. In order to perform head-binarization we introduce a head-finding procedure that is described in Chapter 6. We found a slight performance improvement over other binarization (at first parse) but no overall effect on WER.

Maximum likelihood training of the PCFG is done using the relative frequency estimator. Provided we have enough training data, the relative frequency estimator is sufficient to learn much of the grammar model except for the preterminal distribution, $P(\text{word}|\text{part-of-speech})$, which describes probability of lexical items. We smooth this distribution, reserving some probability mass for tokens not observed in the training data. We experimented with two smoothed estimators.

5.3.1 Estimating Preterminal Probabilities

The Laplace (or Jeffrey-Perks) estimator assumes we know the size of the complete vocabulary, Ω as well as the size of the observed vocabulary, $\hat{\Omega}$. We pretend that we have seen each word one more

[4] Right-binarization creates right branching structures for expansions with more than two children.

time than it actually occurred (or a fraction of one for Jeffrey-Perks estimation).

$$P(x \rightarrow w) = \frac{C(x \rightarrow w) + 1}{C(x) + |\Omega|} \tag{5.1}$$

$$P(x \rightarrow UNK) = \frac{1}{|\Omega|} \tag{5.2}$$

Equation 5.1 is the new probability for observed data, where $|\Omega|$ is the size of the full vocabulary. For unknown tokens, we estimate the probability by Equation 5.2. Note that we only do this for open-class parts-of-speech. The size of the full vocabulary can be estimated using held-out data; in a speech recognition context, the size of the acoustic recognizers vocabulary can be used (there will never be a word in the test data that does not come from the acoustic recognizer's vocabulary).

An alternative estimator is to actually observe how many times an unknown word is seen for each part-of-speech in the held-out data. We also observe the number of unknown word tokens were observed with each part-of-speech.

$$P(x \rightarrow w) = \lambda(x) \times \hat{P}(x \rightarrow w) \tag{5.3}$$

$$P(x \rightarrow UNK) = (1 - \lambda(x)) \times \frac{1}{C(x, UNK)} \tag{5.4}$$

λ is the probability of observing a known word for part-of-speech x. In Equation 5.3 we discount the observed counts, reserving probability mass for the unseen events. In Equation 5.4 we assign an unknown word the probability of seeing an unknown word given part-of-speech T^i times the uniform probability of observing a particular unknown word. We note that this value is approximately what an Expectation-Maximization (EM) (Dempster et al., 1977) estimator would predict. In Chapter 6 we consider smoothed grammars, where EM is used to smooth all grammar distributions.

We found that the Laplacian estimator works as well as the suggested alternative and use it in the following experiments.

5.3.2 Training The Charniak Parser

The second-stage parser used in these experiments is the Charniak language modeling parser (Charniak, 2001). The probabilistic model used in this parser uses head-words in the conditioning context for syntactic categories, meaning that each conditional distribution in the grammar is dependent on lexical items. Data-sparsity becomes a problem due to the number of unique contexts. We train the Charniak model on the BLLIP99 dataset (Charniak et al., 1999); note that the BLLIP99 data is

produced by running the Charniak parser on a set of 30million words of Wall Street Journal data. This version of the parser was trained on the Penn WSJ treebank (Marcus et al., 1993; Bies et al., 1995). Training a parser on parser output has been shown to degrade the parsing accuracy but has also been shown to increase language modeling accuracy (as measured by perplexity and WER). Roark noted this effect in his work on parsing and language modeling (Roark, 2001b).

The BLLIP99 data comes from a set of Wall Street Journal articles that overlaps the HUB-1 dataset. For obvious reasons, we did not want to train our language model on the test data. Therefore, we removed all overlapping sentences from the BLLIP99 corpus. We did this by identifying the minimum edit distance between the HUB-1 reference transcriptions and the sentences in the BLLIP corpus. Then, we manually inspected all BLLIP99 strings that were close (having an edit distance less than 5) [5]. We removed all strings that were clearly from the same source.

5.4 Experimental Setup

Most of the previous work on syntactic language modeling has made use of n-best lists. Roark (2001a) used Chelba's A* decoder to select the strings associated with the 50 best paths through the HUB-1 word-lattices. The Chelba decoder uses the acoustic scores as well as the trigram language model scores from the word-lattices. Rescoring an n-best list requires the processing of each string in the list, assigning the string a language model probability and then selecting the string that maximizes the product of the normalized acoustic model probability, and the language model probability. Creating the n-best lists limits the maximum performance (unless the n-best selection model is perfect).

In our results section we include results for rescoring these n-best lists. This is effectively string parsing since the first-stage parser is given the string and converts it into a word-lattice. Structure sharing is not possible when we parse the strings separately, as the parser works on each string in isolation. Computationally, this is inefficient but we have observed an advantageous side-effect of processing the strings separately; an even distribution of parser attention. In other words, when we run the parser on the individual strings, we know that the parser considers at least a few complete parses for each string.

[5] We choose an edit distance greater than 0 as some of the reference transcription strings are not exactly the same as the strings in the automatically speech-normalized form.

Additionally, we experiment with n-best word-lattices. An n-best word-lattice is the sub-lattice of the original acoustic word-lattice [6] that contains only the strings in the n-best list. N-best word-lattices are much smaller than the acoustic word-lattices, but are also limited by the decoder used to identify the n-best paths. Experiments on these word-lattices evaluate the effect of first-stage pruning as well as the efficiency provided by structure sharing.

Finally, we evaluate our parser on the original acoustic word-lattices. Unlike the experiments with the n-best lists, we do not use a language-model (the trigram language model) to preprocess the word-lattices. In these experiments we run the PCFG word-lattice parser on the entire word-lattice producing a set of candidates for the second-stage Charniak rescoring model. It is not until the second stage parser that any lexical dependencies are used.

5.5 Results

Lattices	OWER	# arcs
Acoustic Lattices	**3.265**	**136460**
Acoustic 100-best	16.780	22083
Acoustic 50-best	18.086	15617
Chelba 50-best	**7.751**	**11091**
Trigram 100-best	6.161	29998
Trigram 50-best	6.417	20041

Table 5.2: Baseline Oracle WERs for HUB-1 data. *# arcs* is the number of arcs for the determinized, minimized word-lattice WFSMs.

Table 5.2 [7] shows the baseline Oracle Word Error Rate for various manipulations of the HUB-1 dataset. The following experiments are run on the datasets in bold type; OWER for other datasets are simply for comparison. The word-lattices in each dataset has been transformed into a compressed WFSM prior to computing the OWER and the WFSM sizes. Measuring the cumulative size of the dataset, the *Number of Arcs* field, provides a rough metric as to the size of the individual word-lattices (although the variance is large). Acoustic n-best lists were generated by selecting the first n highest scoring paths through the compressed lattices. Trigram n-best lists were generated in the same way, but using the trigram language model scores in the HUB-1 dataset combined with the

[6] We call the original Chelba word-lattices *acoustic word-lattices*. These are the complete word-lattices generated using the acoustic model and language-model described above, but only contain scores from the acoustic model.

[7] WER score are presented for both Penn treebank tokenization and original lattices tokenization unless otherwise noted. OWER scores are presented for Penn treebank tokenization only.

acoustic score using an acoustic normalization factor of $\frac{1}{16}$. The Chelba 50–best is the results of Brian Roark running Ciprian Chelba's A* decoder on the HUB-1 data, selecting the top 50 paths. This results in approximately 22 strings per word-lattices (again, there is high variance).

5.5.1 Generating local-trees

The first-stage parser generates a set of candidate edges (expanded to local-trees – described in the footnote on Page 3) which are then rescored using the Charniak language model. In Section 4.1.1 of Chapter 4 we described the memory limitation of the Charniak rescoring component. We have found the this component can usually handle on the order of 30,000 local-trees. The number of parse chart edges that will expand to 30,000 local-trees is dependent on the density of the chart. Depending on the amount of over-parsing, we prune chart edges in order to generate no more than 30,000 local-trees (see Section 4.1.1).

We have explored exactly how many internal states are used by the Charniak language model when providing 30,000 local-trees. We examined the memory requirement for one of our experiments, but observed that the upper bound on the number of local-trees that can be processed in under 2 gigabytes of RAM is around 30,000. On average, 215 expanded states were created for each local-tree. This expands to around 6.5 million states for 30,000 local-trees; the inside probability is computed for each of these according to the Charniak model.

5.5.2 n-best Strings

In the first set of experiments, we evaluate parser-based language modeling on Chelba n-best lists. The results give us an idea of how well we should expect to do on n-best lattice parsing. These results are produced by parsing each string from the n-best lists individually. Strings are converted to simple lattices (chains with word scores extracted from the acoustic lattice) and then processed by the complete multi-stage language model, resulting in language model probabilities assigned to the string. The string for which the combined language model and acoustic model assign the highest probability is selected and compared to the reference transcription. Results in Table 5.3 shows the performance of string rescoring using our system. When generating charts for each of the n-best strings, on average we generate 471 local-trees for each strings (with a maximum of 16,000). Computing the number of unique local-trees per word-lattice (combining those local trees

Overparsing	WER	(lat-tokenization)
2–times(SUM)	11.9	12.0
4–times(SUM)	**11.5**	**(11.8)**
6–times(SUM)	11.6	(11.8)
2–times(MAX)	12.0	(12.1)
4–times(MAX)	11.6	(11.9)
6–times(MAX)	11.8	(12.0)

Table 5.3: Results of n-best strings rescoring. Model labels indicate the amount of over-parsing as well as whether the Viterbi best-parse search considered sums of probabilities or the Viterbi max probabilities for each edge.

for each string corresponding to an utterance), we generate 3571 local-trees per utterance, but with a maximum of 67,000 local trees for one utterance. This is more than the number of local-tree limited in the following experiments and should be noted when comparing results.

To date, these are the lowest WER results we have achieved with our coarse-to-fine word-lattice language model. These results are no different than would be achieved by running the Charniak language modeling string parser (Charniak, 2001) on the n-best strings[8]. We report the results for three different over-parsing multiples as well as for both summed probabilities and Viterbi max probabilities. It should be noted that in string parsing, the decision to choose the sum or the Viterbi max probability is the question of searching for the Viterbi max parse versus the parse with the most probability covered by each of the constituents. However, in lattice parsing, choosing the sum would mean we combine parses for multiple word-string yields. In this experiment we are able to use the sums of the edge probabilities (i.e., standard inside probabilities) since the word-string yield is constant for all parses.

5.5.3 n-best Lattices

We construct n-best lattices to evaluate the word-lattice parser on the same data as in the Chelba n-best string tests but with actual word-lattices. The n-best lattices are sub-lattices of the original acoustic word-lattices, pruned to contain only the paths associated with the n-best word-strings. One trade-off in parsing word-lattices directly is between candidate generation over lattice pruning. As we increase the over-parsing multiple, we eventually cover more of the word-lattice[9] but we

[8] We confirmed this result with Charniak.

[9] Covering more of the word-lattices means that we are positing complete parses analyses that include more arcs of the word-lattices.

also generate more candidates to be rescored by the Charniak language model. At the end of over-parsing, we prune the parse chart in order to generate at most 30,000 local-trees.

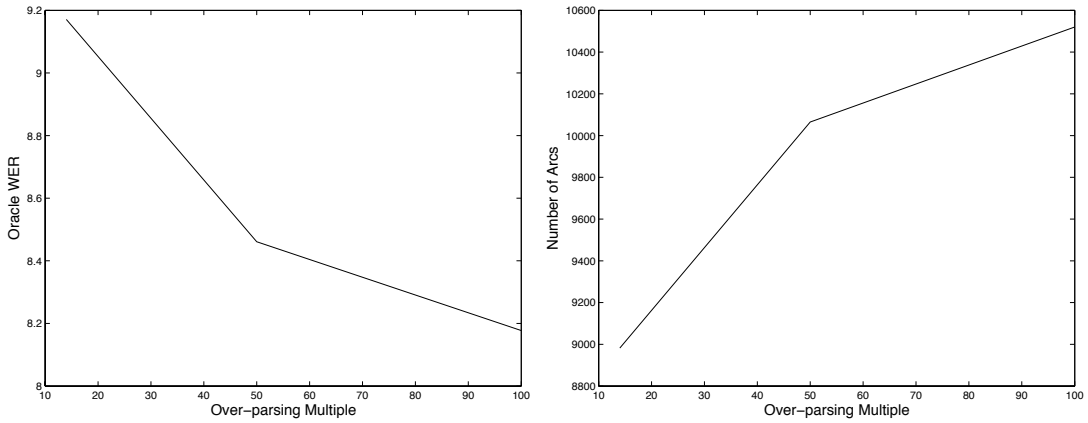


Figure 5.2: Chelba n-best lattices: oracle WER and lattice size as a function of over-parsing.

In Figure 5.2 we present two graphs depicting the results after first-stage parsing: one showing the OWER as a function of over-parsing and the other showing the size of pruned lattices as a function of over-parsing. The y-axis in the lattice size graphs indicates the cumulative number of WFSM arcs for all 213 first-stage pruned word-lattices, giving us a rough measure as to how much pruning occurred. As expected, the OWER decreases as the size of the pruned lattices grow.

Overparsing [a]	OWER	# arcs	# local-trees	WER	(lat-tokenization)
14–times	9.171	8982		12.7	(12.9)
50–times	8.461	10065	3188343	12.1	(12.2)
100–times	8.177	10520	5229469	11.8	(12.0)

[a] An average of 158 agenda pops were needed to achieve first parse on the n-best lattices.

Table 5.4: Results for various over-parsing multiples on the Chelba n-best lattices. The rightmost column indicates the best performance of the complete system.

In Table 5.4 we present the results of the complete system for various multiples of over-parsing. We present a few sample points showing that the WER decreases as overparsing increases. Unfortunately, we found 11.8 to be the minimum total WER even with larger multiples of overparsing. Note that these scores are better than the trigram language model scores and at 100-times over-parsing , close to the n-best list rescoring using the Charniak parser.

5.5.4 Acoustic Lattices

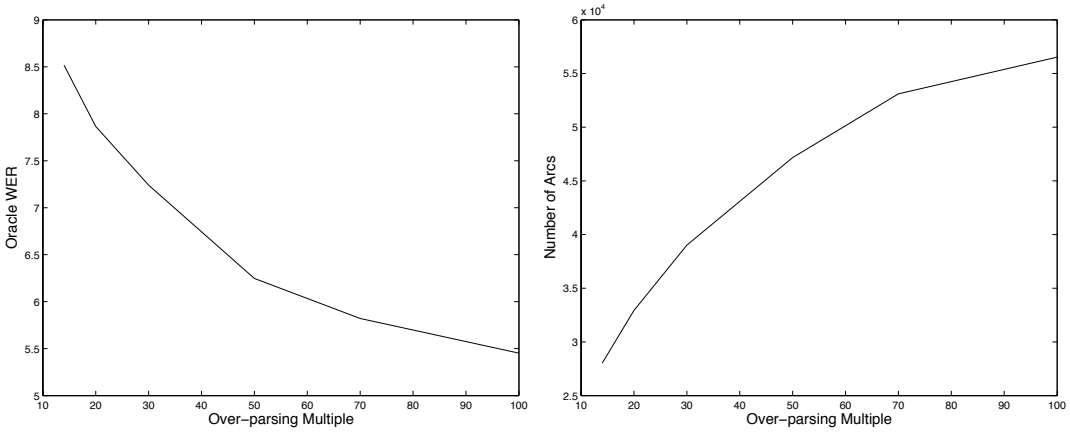


Figure 5.3: Acoustic lattices: oracle WER and lattice size as a function of over-parsing.

Overparsing [a]	OWER	# arcs	# local–trees	(# saturated)	WER	(lat-tokenization)
14–times	8.519	28029	657047	(0)	15.7	(15.7)
20–times	7.865	32938	1077634	(5)	14.8	(14.9)
30–times	7.240	39010	1797814	(16)	14.3	(14.4)
50–times	6.246	47170	3012479	(47)	14.0	(14.0)
70–times	5.821	53106	4023065	(72)	13.1	(13.1)
100–times	5.451	56525	4536720	(104)	13.1	(13.1)

[a] An average of 149 agenda pops were needed to achieve first parse on the acoustic lattices.

Table 5.5: Results for various over-parsing multiples on the acoustic word-lattices. The right column indicates the best performance of the complete system.

Figure 5.3 and Table 5.5 present the results for the word-lattice parsing system on the acoustic lattice. As with the n-best lattices, the first-stage parser generated at most 30,000 local-trees which were rescored with the Charniak language model. We are able to achieve an improvement over the trigram language model, but we do not do as well as when processing n-best lists or parsing n-best lattices. This is not that surprising given that we are limited to a fixed number of local-trees passed on the the second stage. With full acoustic lattices, the parser must divide the same number of parse analyses over a much larger word-lattice. The steadily declining OWER indicates that the parser is indeed positing edges over more of the lattice as the over-parsing multiple is increased.

Finally, note that when we increase overparsing from 70–times to 100–times, we introduce over 500,000 new local trees. The OWER improves, but the overall WER does not improve. While we

have introduced more local-trees, there are many utterances for which we have already saturated the maximum number of local-trees. In Table 5.5 we show the number of word-lattices for which there would have been more than 30,000 local-trees had we not forced this limit.

5.5.5 Applicability of Syntactic Models

Model	# in Lat.	in Lat. WER	(lat-tokenization)	not in Lat. WER	(lat-tokenization)
Trigram	108	4.5	(4.7)	21.0	(21.2)
n-best rescoring	108	2.9	(3.0)	18.7	(19.1)
100–times n-best lattices	108	2.6	(2.7)	19.5	(19.8)
100–times acoustic lattices	142	6.0	(6.1)	25.6	(25.4)

Table 5.6: Results of various models for word-lattices containing the references transcription and word-lattices not containing the reference transcription.

In Table 5.6 we report the same results as in the previous sections, but we have divided the data by whether the reference transcription (the correct string) was contained in the word-lattice. 108 of the Chelba n-best lists contained the actual reference transcription, whereas 142 of the full acoustic word-lattices contain the actual transcription. We show that the syntactic models deliver about the same absolute improvement on both sets. Overall, in those cases where the reference transcription is not in the word-lattice, all models do poorly (even the trigram).

5.5.6 Summary and Discussion

Model	WER lat-tokenization
40m-word trigram	13.7
Chelba02 SLM (n-best strings)	12.3
Roark01 (n-best strings)	12.7
Charniak Parser (n-best strings)	11.8
Lattice Parser (n-best lattices)	**12.0**
Lattice Parser (acoustic lattices)	**13.1**

Table 5.7: WER for various language models on the HUB–1 lattices (lattice tokenization).

In Table 5.7 we present the current best results for our word-lattice parser language model as well as those for the other syntactic language models. We have also included the results for the best path given the combined acoustic score and the trigram language model scores as provided in the HUB-1 word-lattices. Both the SLM (Xu et al., 2002) and the Roark (2001a) models are mixed with a trigram language model to achieve these results.

These empirical results show that our best-first word-lattice parse does an adequate job at pruning the word-lattices as well as positing good edges. In the following chapters we address two issues that are revealed through these experiments. First, the best-first word-lattice parses uses a PCFG and a Linear Syntactic Model to make the initial select of chart edges, followed by the complete PCFG model which prunes this selection. Not only does the PCFG model only perform adequately as a parser, but it does not model any word to word dependencies which code subtle semantic relationships that help syntactic parsing (Charniak, 2000; Charniak, 2001; Roark, 2001b; Roark, 2001a; Collins, 1999; Collins, 2003). In the following chapter, we consider alternate grammars for the first-stage parser.

The second issue addressed is that of limited oracle word error rate. The results presented in this chapter show that the first-stage parser is pruning correct lattice paths from the word-lattice, but is providing adequate edges for the word-lattice paths that make it to the second stage. In Chapter 7 we present a technique that attempts to force the parser to provide edges for all paths in the word lattice via a meta-process controlling the best-first chart parser.

Chapter 6

Alternate Grammar Models

Up to this point we have been primarily concerned with constructing a complete language modeling solution that is driven by a best-first word-lattice parser. In this chapter, we consider alternate grammars for use with the best-first parser. First, we consider a parent annotated grammar, known to improve syntactic parsing results. Second, we take a look at a lexicalized PCFG, where each constituent of a parse tree is labeled with the head-word of the phrase it covers.

We have run experiments with both of these grammars and have been unable to improve upon the results from Chapter 5 (as measured by complete system WER). The grammars developed in this chapter have potential to help in language modeling given either better FOM models or better second-stage models. This development provides a basis for further research.

6.1 Parent Annotated PCFG

Previous work on syntactic parsing using PCFGs has suggested that by considering more context, a parsing model can predict better parse trees (as measured using PARSEVAL (Harrison et al., 1991) metric for labeled precision/recall). Johnson shows that by incorporating the parent category label of an edge into the prediction model, labeled precision/recall improved by over 6% (absolute improvement) (Johnson, 1998). Later work by Klein and Manning also shows that by annotating nodes in a tree with the label of their parent category (as well as many other transformations of the Penn Treebank category labels) performance improves (Klein and Manning, 2003b).

We have implemented a similar parent annotation transformation and have experimented with

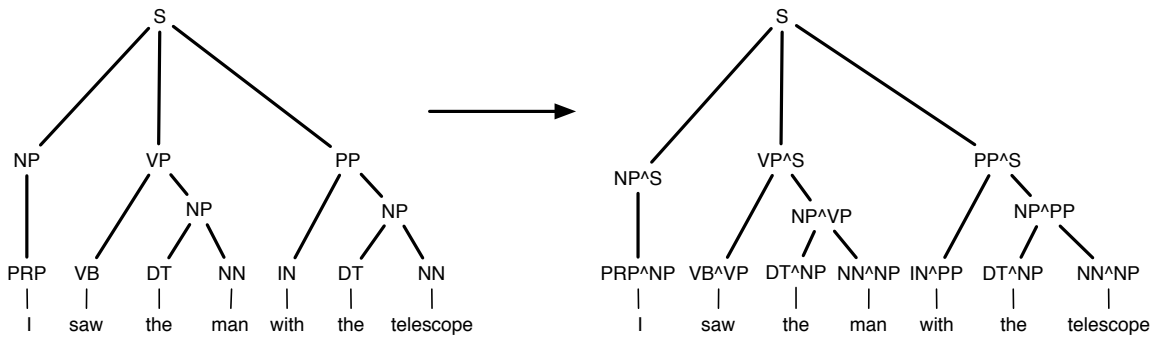


Figure 6.1: Transformation of a tree to a parent-annotated tree.

it as the grammar for the first-stage parser. Figure 6.1 depicts the parent annotation transformation. The label of each node in a parse tree is transformed to include the label of the parent category (always keeping only the parent category [1]). Given the syntactic category of a node n in a parse tree and the syntactic category of its parent p, we transform the category label of the child node to be $n\hat{}\, p$.

As with the standard PCFG, we perform binarization and Markovization on the parent annotated trees. We found that the maximum likelihood estimate using the relative frequency estimator was sufficient to learn probabilities for a parent annotated PCFG. Smoothing of the preterminal distribution was performed as described in Section 5.3.1 of the previous chapter. We also used the same FOM as defined in Chapter 3, using the category labels of the parent annotated PCFG rather than the actual category labels. In other words, the linear outside model is based on parent annotated part-of-speech tags, as are the boundary models.

6.1.1 Experimental Results

We experimented with the parent annotated grammar on the compressed WFSM acoustic lattices (not the n-best lattices). We used the following parameter settings for these experiments:

- We performed 100–times overparsing, requiring a minimum of 1,000 edges be popped from the agenda.
- A maximum of 15,000 local-trees were generated from the parse chart for each word-lattice.

[1] Klein and Manning (2003b), Charniak (2000), and Roark (2001a) incorporate grandparent category information into their models.

Overparsing [a]	OWER	# arcs	# local–trees	WER	(lat-tokenization)
100–times	5.569	48505	2042491	13.2	(13.2)

[a] The parser required an average of 140 agenda pops to return a first parse, approximately the same as the with the PCFG.

Table 6.1: Results for the parent annotated PCFG on the acoustic word-lattices.

The results for the parent annotated PCFG experiment are presented in Table 6.1. Note that while the OWER is slightly worse than the results reported in the previous section, we limited the maximum number of local-trees to 15,000 rather than 30,000. As a result, the pruned lattices have fewer arcs. The WER of the complete system using the parent annotated PCFG is comparable to the results with the standard PCFG.

6.2 Lexicalized PCFG

Given that the parent annotated PCFG performed no better than a standard PCFG, we recognized that without incorporating lexicalized rules into the grammar, the PCFG will not be able to identify paths in the word-lattice that have better words than those in another path. Up until this point, we were hoping that by overparsing enough, these paths would be introduced into the parse chart. In this section, we consider a lexicalized PCFG, a PCFG that encodes the head-words of a phrase into the nodes of the parse tree. This information is used in the grammar model in order to compute the probability of grammar productions. There has been a substantial amount of research performed that explores lexicalized grammar models; a few notable modes are described in Charniak (2000), Collins (1999), and Roark (2001b).

In Figure 6.2 we present a lexicalized parse tree based on a lexicalized PCFG. The nodes of this parse tree are similar to those in a PCFG tree; the nodes of the tree have been annotated with additional information. In particular, we have added the head-word and the part-of-speech tag of the head-word to each node. This information is determined based on the context of surrounding nodes using a head-word finding algorithm (described below). Under the lexicalized PCFG, the nodes of this tree are treated as the categories of a standard PCFG. In other words, our grammar contains rewrite rules of the sort:

$$\begin{array}{c} \text{VP} \\ \text{VB:saw} \end{array} \rightarrow \begin{array}{cc} \text{VB} & \text{NP} \\ \text{VB:saw} & \text{NN:man} \end{array}$$

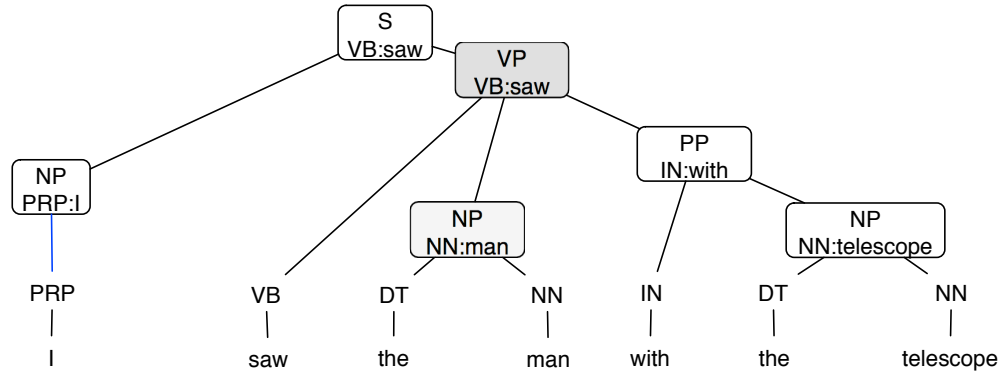


Figure 6.2: A lexicalized parse tree. The lightly shaded node (NP with NN:man) is dependent on all the information in the darkly shaded box (VP with VB:saw).

These rules are estimated using a maximum likelihood technique, however due to additional information encoded in each rule, it is unlikely that we will see all possible rules in the training data.

6.2.1 Finding Head-words

Class	Parent Category Label			Child Category Label
Adjective	ADJP	UCP	WHADJP	$ CD JJ JJR JJS RB RBR RBS WRB NN DT
	WHADVP			ADJP ADVP
Conjunction	CONJP			CC
Interjection	INTJ			INTJ UH
Preposition	PP	PRT	WHPP	IN RP TO
				PP
Noun	FRAG	LST	NAC	EX NN NNS PRP WP
	NP	NX	PRN	$ NNP NNPS
	QP	WHNP		QP NP WP$ NX
				CD DT IN JJ JJR JJS PDT POS RB WDT
Verb	ROOT	RRC	ADVP	VP
	S	SBAR	SBARQ	VB VBD VBG VBN VBP VBZ
	SINV	SQ	S1	ADJP JJ S SINV SQ TO
	VP			AUX AUXG MD

Table 6.2: Rules for the head-word finder.

Table 6.2 presents the rules used to find head words using Mark Johnson's semantic head-word finder. The first column of the table is a general syntactic label for the particular group of nonterminals. In the second column, there is a list of nonterminal labels (these may span multiple rows).

The algorithm we use to find semantic head-words is presented in Table 6.3. Given a parse tree $\mathcal{T}$, we deterministically find the head-word for each node of the tree. In Table 6.2, each block

```
HEADFINDER(tree node T)
 1  if T has one child
 2    then return child of T
 3  LOOKUP(T.parent)
 4  for each child category row of block containing parent category
 5  do for each child, c of T
 6      do if if child category is in child category list
 7            then head ← c
 8                 if parent category is a Verb or Preposition
 9                   then return head
10      if head ≠ ∅
11        then return head
12  if no head found
13    then return right-most child category
```

Table 6.3: Mark Johnson's semantic head-finding routine.

associated with a class of non-terminals contains multiple rows. Rows near the top of the block table are evaluated prior to rows near the bottom, creating a hierarchy of rules. At the end of the function, if no rule has been found that applies to the current configuration, we use the right-most child category as the head. This particular set of rules are those that govern a *semantic* head-word. These are rules that allow us to find the most semantically salient word in the phrase. Alternatively, we can define rules that help us find the most syntactically salient word in a phrase.

6.2.2 Lexicalized PCFG Components

As usual, we binarize and Markovize our trees prior to learning the grammar probabilities. In this case, we must use head-binarization as we annotated the tree nodes with their head-words and the part-of-speech tags of the head-words We continue to use the binarization and Markovization as described in Chapter 2, Sections 2.2.4 and 2.2.5. We perform the binarization and Markovization prior to annotating the tree nodes with head-word information.

The probability model for the lexicalized PCFG is computed as follows:

$$
\begin{aligned}
& P(n^s, h^s, t^s, n^h, l^h | n^p, t^p, h^p) \qquad (6.1)\\
= \;& P(n^h | n^p, t^p, h^p) \\
& \times P(l^h | n^h, n^p, t^p, h^p) \\
& \times P(n^s | l^h, n^h, n^p, t^p, h^p) \\
& \times P(t^s | n^s, l^h, n^h, n^p, t^p, h^p) \\
& \times P(h^s | t^s, n^s, l^h, n^h, n^p, t^p, h^p)
\end{aligned}
$$

Equation 6.1 is the probability of a rule production according the lexicalized PCFG. The superscripts p, h, and s indicate parent, head child, and sibling (non-head child) respectively. n^s is the syntactic category for s, h^s is the head lexical item for s, and t^s is the part-of-speech tag for the head lexical item of s. l^h specifies which side the head category lies on (left or right). The factorization presented in Equation 6.1 is the particular factorization we used for our experiments. We have made no Markov assumptions in the factoring of these rules, however the order of this factorization is motivated by our intuitions as to what information is needed for each prediction[2].

[2]The model presented here is a trimmed down version of the Charniak (2000) model.

An example expansion for the rule: $\left(\begin{smallmatrix}\text{VP}\\ \text{VB:saw}\end{smallmatrix} \rightarrow \begin{smallmatrix}\text{VB}\\ \text{VB:saw}\end{smallmatrix} \quad \begin{smallmatrix}\text{NP}\\ \text{NN:man}\end{smallmatrix}\right)$ looks like this:

$$\begin{aligned}
&P(NP, NN, man, VB, left | VP, VB, saw) \\
&= P(VB | VP, VB, saw) \\
&\quad \times P(left | VB, VP, VB, saw) \\
&\quad \times P(NP | left, VB, VP, VB, saw) \\
&\quad \times P(NN | NP, left, VB, VP, VB, saw) \\
&\quad \times P(man | NN, NP, left, VB, VP, VB, saw)
\end{aligned}$$

In Equation 6.2 we compute the probability of the PCFG rule piecewise. Each distribution contains more information in the conditioning context. We do not expect to see every conditioning context configuration in our training data, which requires that we *back-off* when necessary. We describe our back-off later in this chapter.

In the case of unary productions of the sort: $\left(\begin{smallmatrix}\text{NP}\\ \text{PRP:I}\end{smallmatrix} \rightarrow \begin{smallmatrix}\text{PRP}\\ \text{PRP:man}\end{smallmatrix}\right)$ we use a special $NULL$ value for the sibling category and components:

$$\begin{aligned}
&P(PRP, NULL, NULL, NULL, left | NP, PRP, I) \\
&= P(PRP | NP, PRP, I) \\
&\quad \times P(left | PRP, NP, PRP, I) \\
&\quad \times P(NULL | left, PRP, NP, PRP, I) \\
&\quad \times P(NULL | NULL, left, PRP, NP, PRP, I) \\
&\quad \times P(NULL | NULL, NULL, left, PRP, NP, PRP, I)
\end{aligned}$$

Notice that many of these probabilities are equal to 1; we can simplify this equation by ignoring these components. In a similar manner, the children of non-Markovized binarized category nodes are deterministic. We have ensured that the probability for deterministic rule expansions is always equal to 1.

6.2.3 Lexicalized Figure of Merit

In addition to the grammar model, we have expanded the FOM used for our best-first parser to incorporate the lexical information; this model is depicted in Figure 6.3. The new linear outside model

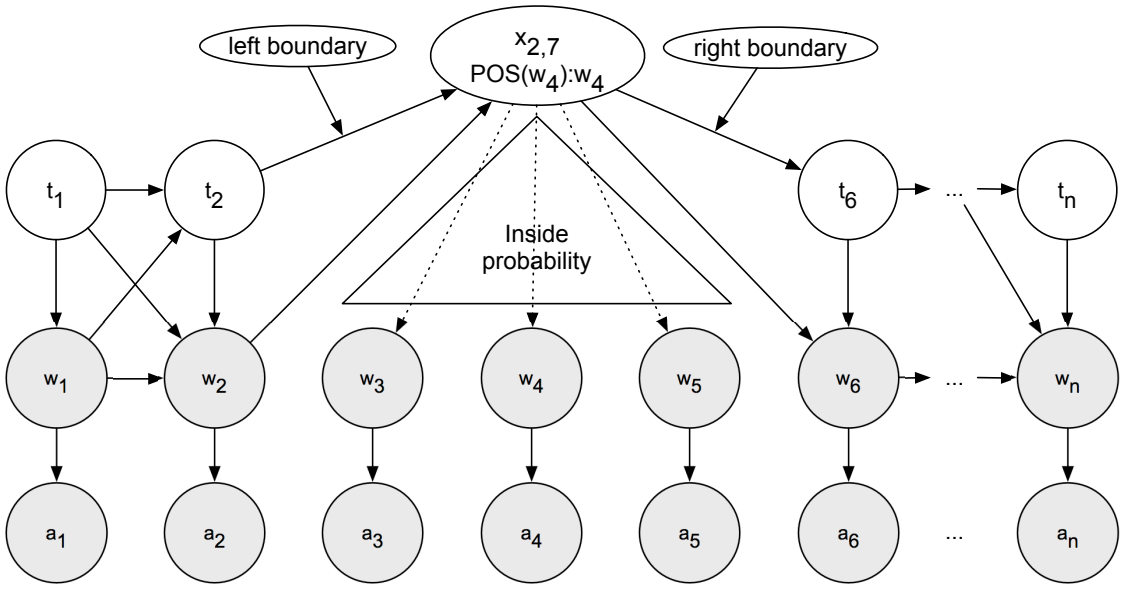


Figure 6.3: A model diagram for the FOM used with the lexicalized PCFG in best-first parsing.

is defined as (for simplicity, the subscripts indicate word-positions rather than node positions):

$$P(t_n, w_n | t_{n-1}, w_{n-1}) \tag{6.2}$$

$$= \quad P(t_n | t_{n-1}, w_{n-1}) \tag{6.3}$$

$$\times P(w_n | t_n, t_{n-1}, w_{n-1}) \tag{6.4}$$

The model presented in Equation 6.2 considers the previous part-of-speech tag as well as the previous word in predicting the next part-of-speech and word.

The boundary models have also been changed to combine the new linear outside model and the lexicalized grammar models. The left boundary model is:

$$P(p_{j,k}, h^p_{j,k}, t^p_{j,k} | t_{j-1}, w_{j-1}) \tag{6.5}$$

$$= \quad P(p_{j,k} | t_{j-1}, w_{j-1}) \tag{6.6}$$

$$\times P(t^p_{j,k} | p_{j,k}, t_{j-1}, w_{j-1}) \tag{6.7}$$

$$\times P(h^p_{j,k} | t^p_{j,k}, p_{j,k}, t_{j-1}, w_{j-1}) \tag{6.8}$$

Note that we use the notation t_{j-1} to indicate an the part-of-speech tag for the word on an arc connecting to node j.

We redefine the right boundary model to be:

$$P(t_{k+1}, w_{k+1}|p_{j,k}, t^p_{j,k}, h^p_{j,k}) \tag{6.9}$$

$$= \quad P(t_{k+1}|p_{j,k}, t^p_{j,k}, h^p_{j,k}) \tag{6.10}$$

$$\times P(h_{k+1}|t_{k+1}, p_{j,k}, t^p_{j,k}, h^p_{j,k}) \tag{6.11}$$

We use the best-first word-lattice chart parser with these lexicalized models in the same manner as described in Chapter 3. We found that these models worked reasonably well in parsing strings, however not as well as typical lexicalized string parsing techniques. These models have not been tuned for optimal string parsing, but we had hoped they would perform well for word-lattice parsing in the context of language modeling.

6.2.4 Estimating Model Parameters

The distributions presented in the previous section have fairly complex conditioning contexts. Due to data-sparsity, we cannot expect to observe enough of these unique contexts from a training corpus such as the Penn Treebank. Therefore, the relative frequency estimator is not sufficient. The distributions must be smoothed with a back-off model in order to assign some probability mass to the unseen events.

The back-off model we chose was a linear back-off using deleted interpolation (Jelinek, 1997), meaning that for each conditioning event, we removed one random variable. We backed off in order from right to left (for the equations presented in the previous section).

Under a linear back-off model, the goal is to find a mixture of the full model and the backed-off model that maximized the likelihood of held-out data.

$$P(A|B,C) = \lambda \hat{P}(A|B,C) + \Big((1-\lambda)\hat{P}(A|B)\Big) \tag{6.12}$$

In Equation 6.12 we show simple example of deleted interpolation, where the back-off model is a version of the original model minus one conditioning variable. We use Jelinek-Mercer smoothing (Jelinek and Mercer, 1980; Jelinek, 1997) to find the λ parameters. This is simply an instance of the Expectation-Maximization (EM) algorithm where we are maximizing the lambda parameters over some held-out data. The empirical distributions $\hat{P}$ are estimated from the training data using the relative frequency estimator. We use Mark Johnson's EM smoothing back-off tool that performs

Jelinek-Mercer smoothing and deleted interpolation as specified by the user. Chen bucketing is used when tying the counts of contexts (Chen and Goodman, 1996).

6.2.5 Experimental Results

We experimented with the lexicalized PCFG and associated FOM model for use in our first-stage best-first word-lattice parser. We trained our lexicalized PCFG on the Penn Wall Street Journal Treebank (Marcus et al., 1993; Bies et al., 1995). We used sections 2–21 as the training set and section 24 as our held-out data for training the smoothed back-off model.

The following parameters were used for experiments on both the n-best word-lattices as well as the acoustic word-lattices.

- We performed 10–times and 20–times overparsing, requiring a minimum of 2,000 edges be popped from the agenda.
- A maximum of 20,000 local-trees were generated from the parse chart for each word-lattice.

Overparsing [a]	OWER	# arcs	# local–trees	WER [b]	(lat-tokenization)
Trigram	7.75	11,209	N/A	13.3	(13.5)
Charniak Parser (n-best strings)	7.75	91,105	2293177	11.5	(11.7)
10–times	8.327	8805	606234	11.9	(12.1)
20–times	8.032	9163	1065633	11.9	(12.1)

[a] On average, 224 agenda pops were required to achieve first parse on the n-best lattices.
[b] 212 of the word-lattices were parsed.

Table 6.4: Results for the lexicalized PCFG on the n-best word-lattices.

Overparsing [a]	OWER	# arcs	# local–trees	WER [b]	(lat-tokenization)
Trigram	7.75	11,209	N/A	13.3	(13.5)
Charniak Parser (n-best strings)	7.75	91,105	2293177	11.6	(11.8)
10–times	6.854	27949	616604	13.7	(13.7)
20–times	5.515	41192	1705425	13.1	(13.1)

[a] On average, 338 agenda pops were required to achieve first parser on the acoustic lattices.
[b] 212 of the word-lattices were parsed.

Table 6.5: Results for the lexicalized PCFG on the acoustic word-lattices.

Tables 6.4 and 6.5 contain the results using the lexicalized PCFG best-first parser as the first-stage model. We achieve almost the same accuracy (measured by both OWER and WER) as the

system with the standard PCFG best-first parser, but with much less overparsing (as it takes approximately double the number of agenda pops to reach first parse, 20–times overparsing here is comparable to 40–times overparsing with the standard PCFG).

We had hoped that incorporating lexical information into the first-stage best-first parsing model that we would do a better job at selecting word-lattice arcs. While this is true (we select good paths with less parsing and more word-lattice pruning), this has no effect on the overall language modeling performance of the system [3].

[3]The lexicalized PCFG was trained using the standard Penn Treebank, consisting of approximately 1 million words of parsed text. We may find that our lexicalized parser performs better when trained on a larger quantity of data.

Chapter 7

Attention Shifting

The results of the previous chapter suggest that by improving the first-stage model we cannot improve the overall language modeling performance, but we can achieve the results with less computational effort (i.e., fewer pops of the best-first parser agenda). In this chapter we focus on a modification to the best-first parsing algorithm that attempts to improve efficiency by forcing the first-stage parser to posit edges for the entire word-lattice. Ideally, such a technique would improve the overall language modeling performance, however we observed no such improvement.

7.1 Attention Shifting Algorithm

We explore a modification to the multi-stage parsing algorithm that ensures the first stage parser posits at least one parse for each path in the word-lattice. The idea behind this is to intermittently shift the attention of the parser to unexplored parts of the word lattice[1].

Figure 7.1 depicts the attention shifting first stage parsing procedure. A *used edge* is a parse edge that has non-zero outside probability. By definition of the outside probability, used edges are constituents that are part of a complete parse; a parse is complete if there is a root category label (e.g., **S** for sentence) that spans the entire word-lattice. In order to identify used edges, we compute the outside probabilities for each parse edge (efficiently computing the outside probability of an edge requires that the inside probabilities have already been computed).

[1]The notion of attention shifting is motivated by the work on parser FOM compensation presented in (Blaheta and Charniak, 1999).

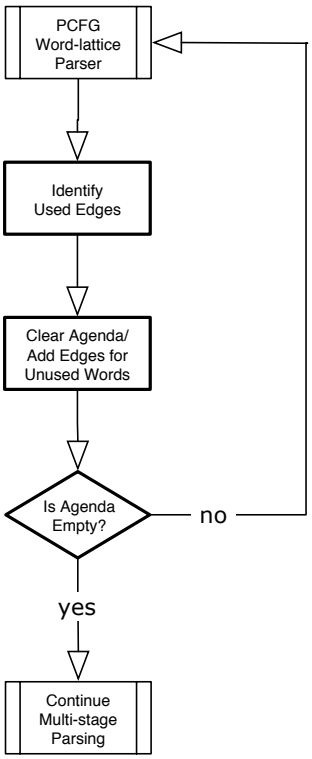


Figure 7.1: Attention shifting parser.

In the third step of this algorithm we clear the agenda, removing all partial analyses evaluated by the parser. This forces the parser to abandon analyses of parts of the word-lattice for which complete parses exist. Following this, the agenda is populated with edges corresponding to the unused words, priming the parser to consider these words. To ensure the parser builds upon at least one of these unused edges, we further modify the parsing algorithm:

- Only unused edges are added to the agenda.
- When building parses from the bottom up, a parse is considered complete if it connects to a used edge.

These modifications ensure that the parser focuses on edges built upon the unused words. The second modification ensures the parser is able to determine when it has connected an unused word with a previously completed parse. The application of these constraints directs the attention of the parser towards new edges that contribute to parse analyses covering unused words. We are

guaranteed that each iteration of the attention shifting algorithm adds a parse for at least one unused word, meaning that it will take at most $|A|$ iterations to cover the entire word-lattice, where A is the set of word-lattice arcs. This guarantee is trivially provided through the constraints just described. The attention-shifting parser continues until there are no unused words remaining and each parsing iteration runs until it has found a complete parse using at least one of the unused words.

As with our standard best-first parser, an adjustable parameter determines how much overparsing to perform on the initial parse. In the attention shifting algorithm an additional parameter specifies the amount of overparsing for each iteration after the first. The new parameter allows for independent control of the attention shifting iterations.

After the attention shifting parser populates a parse chart with parses covering all paths in the word-lattice, we perform the standard inside/outside pruning. This is necessary in order to constrain the size of the hypothesis set passed on to the Charniak language modeling component.

7.2 Experiments

As a measure of the amount of work the parser is doing we report the cumulative # agenda edge pops. As with previous experiments we report the OWER for the first-stage parser (in this case, the attention shifting best-first parser) and the WER for the complete language modeling system. In these word-lattice parsing experiments, we pruned the set of posited hypothesis so that no more than 30,000 local-trees are generated. Performing pruning at the end of first-stage parsing prevents the attention shifting parser from reaching the minimum oracle WER (most notable in the full acoustic word-lattice experiments). While the attention-shifting algorithm ensures all word-lattice arcs are included in complete parses, forward-backward pruning, as used here, will eliminate some of these parses, indirectly eliminating some of the word-lattice arcs.

Model	# agenda pops	OWER	WER lat-tokenization
n–best (Charniak)	2.5 million	7.75	11.8
100x LatParse	3.4 million	8.18	12.0
10x AttShift	**564,895**	**7.78**	**11.9**

Table 7.1: Results for n–best lists and n–best lattices.

Table 7.1 shows the results for n–best list rescoring and word-lattice parsing of n–best lattices.

We recreated the results of the Charniak language model parser used for rescoring in order to measure the amount of work required. We ran the first stage parser with 4-times overparsing for each string in the n–best list. The LatParse result represents running the word-lattice parser on the n–best lattices performing 100–times overparsing in the first stage. The AttShift model is the attention shifting parser described in this paper. We used 10–times overparsing for both the initial parse and each of the attention shifting iterations. When run on the n–best lattice, this model achieves a comparable WER, while reducing the amount of parser work sixfold (as compared to the regular word-lattice parser).

Model	# edge pops	OWER	WER lat-tokenization
acoustic lats	N/A	3.26	N/A
100x LatParse	3.4 million	5.45	13.1
10x AttShift	**1.6 million**	**4.17**	**13.1**

Table 7.2: Results for acoustic lattices.

In Table 7.2 we present the results of the word-lattice parser and the attention shifting parser when run on full acoustic lattices. While the oracle WER is reduced, we are considering almost half as many edges as the standard word-lattice parser. The increased size of the acoustic lattices suggests that it may not be computationally efficient to consider the entire word-lattice and that an additional pruning phase may be necessary.

The most significant constraint of this multi-stage lattice parsing technique is that the second stage process has a large memory requirement. While the attention shifting technique does allow the parser to propose constituents for every path in the lattice, we prune some of these constituents prior to performing analysis by the second stage parser.

7.3 Summary

Attention shifting is a simple technique that attempts to make word-lattice parsing more efficient. As suggested by the results for the acoustic lattice experiments, this technique alone is not sufficient. Solutions to improve these results include modifying the first-stage grammar by annotating the category labels with local syntactic features as suggested in Johnson (1998) and Klein and Manning (2003b) as well as incorporating some level of lexicalization. Improving the quality of the parses selected by the first stage should reduce the need for generating such a large number of candidates

prior to pruning, improving efficiency as well as overall accuracy.

Chapter 8

Conclusion

The primary goal of this research is to provide an efficient syntactic language model that works directly from word-lattices. Recent work by Roark shows that by moving from 100-best lists to 1000-best lists, the accuracy of an n-gram language modeling improves (Roark et al., 1994). Parsing 1000 strings per utterance is not a realistic solution, but parsing a word-lattice based on the 1000-best lists is reasonable (we can easily move beyond 5000-best lists), hence the focus of the work in this thesis. Unfortunately, we were not able to improve the accuracy of syntactic language modeling by parsing full word-lattices, although we have provided an efficient solution for parsing n-best lists.

We have explored techniques for integrating parser-based language modeling into word-lattice decoding. These techniques are based on a coarse-to-fine parsing model that uses a best-first word-lattice parser to generate candidate parse analyses which are rescored by a sophisticated syntactic language model, the Charniak model (Charniak, 2001).

In Chapter 3 we presented best-first word-lattice chart parsing and the general parameters for the figure of merit that drives this algorithm. In this chapter we identify the subtle differences between word-lattice chart parsing and that of string-based chart parsing. Specifically, we focus on a new interpretation of a parse edge in the context of a word-lattice parsing algorithm. This interpretation motivates two decisions through the rest of the thesis: first, that using Viterbi max estimates of the inside, outside, and linear syntactic model is reasonable for word-lattice parsing; and second, that structure sharing is provided automatically between the parses of different paths in the word-lattice (defining unique word-strings). Structure sharing not only allows us to share structure between parse analyses for different word-string yields, but it also allows for the parsing algorithm to share

parse edges among word-strings. This leads to an efficient search algorithm that simultaneously searches the space of parse analyses as well as the space of paths in the word-lattice.

Chapter 4 presents the coarse-to-fine parsing algorithm that allows us to integrate the best-first PCFG word-lattice parser with the Charniak language model. Due the complexity of the Charniak model, we have to limit the size of the parse chart generated by the best-first parser. We do so by introducing a pruning component based on the inside and outside probability of parse edges.

Empirical results are presented in Chapter 5 for the complete word-lattice language modeling system for a speech recognition task. In order to measure the performance of our best-first word-lattice model in isolation, we describe a technique to compute the oracle word error rate of a pruned word-lattice. We compare the results of our model to those of competing syntactic language models as well as the standard trigram and show that we perform as well as the Charniak model in an n-best list rescoring setting.

The results of Chapter 5 suggest we may be able to improve search errors of the best-first word-lattice parser. In Chapter 6 we explore two alternative grammar models for the best-first parser; a parent annotated grammar and a lexicalized PCFG. We present experimental results of the system with these grammars.

We also explored search inefficiencies of the best-first word-lattice parser. In Chapter 7 we present a modification to the best-first word-lattice parsing algorithm that improves the efficiency of the complete language-modeling system. We present experimental results for the modified algorithm on the same dataset as previous experiments.

8.1 Future Directions

We see three distinct areas for future work in word-lattice parsing as presented in this thesis:

1. Further the exploration of lexicalized grammars for best-first word-lattices parsing.

2. Explore further refinements to the coarse-to-fine parsing model that allow for more exploration in the first stage while still limiting the number of analyses evaluated by the final sophisticated model.

3. Consider alternative objective functions other than those based probabilistic generative models.

The lexicalized model we present in Chapter 6 is one of many possible models that incorporate lexicalization. For example, we could combine the parent annotation model and the lexicalized model. As we consider more conditioning information, the search space becomes larger and more complex. The goal is to find a model that we can efficiently evaluate over a larger number of parse analyses.

As we start to think about more sophisticated lexicalized models (but less sophisticated than the Charniak model), we realize that we may not be able to design a tractable search algorithm for this model. As we have done with our basic model, we can use the PCFG or lexicalized PCFG to generate a large set of analyses. We then apply an intermediate model that can handle far more analyses than the Charniak model in order to select a subset for which we will apply the Charniak model. This is just another stage of approximate coarse-to-fine processing.

We offer a final motivation for using a best-first parser to parse word-lattices. An advantage of best-first parsing is that the figure of merit function, the FOM, does not have to provide an estimate to the probability of a parse edge. In the setting explored in this thesis we use a FOM that explicitly tries to model the maximum likelihood function, but we are actually using the FOM to pick out parse edges that will lead to low WER word-strings. We suggest that the flexibility of the FOM allows us to substitute in an objective function that optimizes for low WER.

Substituting alternate objective functions in place of the PCFG allows us to consider different techniques for estimating the function. We can even explore objective functions that are not based on probabilistic generative models such as the PCFG. In order to perform best-first search we need a FOM that approximates the objective function. We can explore other techniques for approximating alternate objective functions, including discriminative machine learning techniques such as the Perceptron algorithm and the Support Vector Machine.

8.2 Summary

The techniques presented here provide a framework for word-lattice parsing. We have explored a subset of all possible grammars, FOMs, pruning conditions, and syntactic language models. What we have shown is that it is possible to perform efficient word-lattice parsing and that we can integrate efficient parsing with the best syntactic language model (the Charniak model). We believe the

techniques presented in this thesis present a complete view of best-first word-lattice parsing and provide the basis for future research on syntactic language modeling.

References

Steve Abney. 1996. Partial parsing via finite-state cascades. *Natural Language Engineering*, 2(4):337–344.

J. K. Baker. 1979. Trainable grammars for speech recognition. In *Proceedings of the Spring Conference of the Acoustical Society of America*, pages 547–550, Boston, MA.

Ann Bies, Mark Ferguson, Karen Katz, and Robert MacIntyre, 1995. *Bracketing Guidelines for Treebank II Style Penn Treebank Project*, January.

Don Blaheta and Eugene Charniak. 1999. Automatic compensation for parser figure-of-merit flaws. In *Proceedings of the 37th annual meeting of the Association for Computational Linguistics*, pages 513–518.

Sharon Caraballo and Eugene Charniak. 1998. New figures of merit for best-first probabilistic chart parsing. *Computational Linguistics*, 24(2):275–298, June.

J. Chappelier, M. Rajman, R. Aragues, and A. Rozenknop. 1999. Lattice parsing for speech recognition. In *Proceedings of 6me confrence sur le Traitement Automatique du Langage Naturel (TALN'99)*, pages 95–104.

Eugene Charniak and Keving Knight Kenji Yamada. 2003. Syntax-based language models for machine translation. In *Proceedings of MT Summit IX 2003*, New Orleans.

Eugene Charniak, Don Blaheta, Niyu Ge, Keith Hall, John Hale, and Mark Johnson. 1999. BLLIP 1987–89 wsj corpus release 1. LDC corpus LDC2000T43.

Eugene Charniak. 1993. *Statistical Language Learning*. MIT Press.

Eugene Charniak. 1997. Statistical techniques for natural language parsing. *AI Magazine*, pages 33–43.

Eugene Charniak. 2000. A maximum-entropy-inspired parser. In *Proceedings of the 2000 Conference of the North American Chapter of the Association for Computational Linguistics.*, ACL, New Brunswick, NJ.

Eugene Charniak. 2001. Immediate-head parsing for language models. In *Proceedings of the 39th Annual Meeting of the Association for Computational Linguistics*.

Ciprian Chelba and Frederick Jelinek. 1998. A study on richer syntactic dependencies for structured language modeling. In *Proceedings of the 36th Annual Meeting of the Association for Computational Linguistics and 17th International Conference on Computational Linguistics*, pages 225–231.

Ciprian Chelba and Frederick Jelinek. 2000. Structured language modeling. *Computer Speech and Language*, 14(4):283–332.

Ciprian Chelba. 2000. *Exploiting Syntactic Structure for Natural Language Modeling*. Ph.D. thesis, Johns Hopkins University.

Stanley F. Chen and Joshua Goodman. 1996. An empirical study of smoothing techniques for language modeling. In Aravind Joshi and Martha Palmer, editors, *Proceedings of the Thirty-Fourth Annual Meeting of the Association for Computational Linguistics*, pages 310–318, San Francisco. Morgan Kaufmann Publishers.

Zhiyi Chi and Stuart Geman. 1998. Estimation of probabilistic context-free grammars. *Computational Linguistics*, 24:299–305.

Zhiyi Chi. 1999. Statistical properties of probabilistic context-free grammars. *Computational Linguistics*, 25(1):132–160.

Noam Chomsky. 1970. Remarks on nominalization. In R. Jacobs and P. Rosenbaum, editors, *Readings in English Transformational Grammar*. Ginn and Company, Walham, Mass.

Christopher Collins, Gerald Penn, and Bob Carpenter. 2004. Head-driven parsing for word lattices. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics*, pages 232–239.

Michael Collins. 1999. *Head-Driven Statistical Models for Natural Language Processing*. Ph.D. thesis, University of Pennsylvania.

Michael Collins. 2003. Head-driven statistical models for natural language processing. *Computational Linguistics*, 29(4):589–637.

Thomas H. Cormen, Charles E. Leiserson, and Ronald L. Riverst. 1990. *Intorduction to Algorithms*. MIT Press, Cambridge, MA.

Arthur Dempster, Nan Laird, , and Donald Rubin. 1977. Maximum likelihood from incomplete data via the em algorithm. *Royal Statistical Society*, 39(1):1–38.

Stuart Geman and Mark Johnson. 2003. Probability and statistics in computational linguistics, a brief review. In Roni Rosenfeld, Mari Ostendorf, Sanjeev Khudanpur, , and Mark Johnson, editors, *Mathematical foundations of speech and language processing. Institute for Mathematics and its Applications.*, pages 1–26. Springer-Verlag, New York.

Stuart Geman and K. Kochanek. 2001. Dynamic programming and the graphical representation of error-correcting codes. *IEEE Transactions on Information Theory*, 47:549–568.

David Goddeau and Victor Zue. 1992. Integrating probabilistic lr parsing into speech understanding systems. In *Proceedings of ICASSP 92*, San Francisco, CA.

David Goddeau. 1992. Using probabilistic shift-reduce parsing in speech recognition systems. In *Proceedings of ICSLP 92*, Banff, Alberta, Canada.

Sharon Goldwater, Eugene Charniak, and Mark Johnson. 1998. Best-first edge-based chart parsing. In *6th Annual Workshop for Very Large Corpora*, pages 127–133.

Joshua Goodman. 1996. Parsing algorithms and metrics. In *Proceedings of the 34th Annual Meeting of the Association for Computational Linguistics*, pages 177–183.

Joshua Goodman. 2001. A bit of progress in language modeling, extendend version. In *Microsoft Research Technical Report MSR-TR-2001-72*.

Keith Hall and Mark Johnson. 2003. Language modeling using efficient best-first bottom-up parsing. In *Proceedings of IEEE Automated Speech Recognition and Understanding Workshop*.

Keith Hall and Mark Johnson. 2004. Attention shifting for parsing speech. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics*, pages 41–47.

Zellig Harris. 1951. *Methods of Structural Linguistics*. University of Chicago Press, Chicago.

P. Harrison, S. Abney, D. Fleckenger, C. Gdaniec, R. Grishman, D. Hindle, B. Ingria, M. Marcus, B. Santorini, , and T. Strzalkowski. 1991. Evaluating syntax performance of parser/grammars of english. In *Proceedings of the Workshop on Evaluating Natural Language Processing Systems, ACL*.

Frederick Jelinek and John D. Lafferty. 1991. Computation of the probability of initial substring generation by stochastic context-free grammars. *Computational Linguistics*, 17(3):315–323.

Frederick Jelinek and Robert L. Mercer. 1980. Interpolated estimation of markov source parameters form sparse data. In *Proceedings of the Workshop on Pattern Recognition in Practice*, Amsterdam, The Neterlands.

Frederick Jelinek. 1997. *Statistical Methods for Speech Recognition*. MIT Press.

Mark Johnson. 1998. PCFG models of linguistic tree representations. *Computational Linguistics*, 24:617–636.

Bernd Kiefer, Hans-Ulrich Krieger, and Mark-Jan Nederhof. 2000. Efficient and robust parsing of word hypotheses graphs. In Wolfgang Wahlster, editor, *Verbmobil: Foundations of Speech-to-Speech Translation*, pages 280–295. Springer, Berlin.

Dan Klein and Christopher D. Manning. 2001. Parsing and hypergraphs. In *Proceedings of the 7th International Workshop on Parsing Technologies (IWPT-2001)*.

Dan Klein and Christopher D. Manning. 2003a. A* parsing: Fast exact viterbi parse selection. In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics*.

Dan Klein and Christopher D. Manning. 2003b. Accurate unlexicalized parsing. In *Proceedings of the 41st Meeting of the Association for Computational Linguistics (ACL-03)*.

Dan Klein and Christopher D. Manning. 2003c. Factored a* search for models over sequences and trees. In *Proceedings of IJCAI 2003*.

Christopher D. Manning and Hinrich Schütze. 1999. *Foundations of statistical natural language processing*. MIT Press.

Mitchell Marcus, Beatrice Santorini, and Mary Ann Marcinkiewicz. 1993. Building a large annotated corpus of english: The penn treebank. *Computational Linguistics*, 19:313–330.

Mehryar Mohri and Michael Riley. 2001. A weight pushing algorithm for large vocabulary speech recognition. In *Proceedings of the 7th European Conference on Speech Communication and Technology (Eurospeech '01)*, Aalborg, Denmark.

Mehryar Mohri, Fernando C. N. Pereira, and Michael Riley. 1998. A rational design for a weighted finite-state transducer library. *Lecture Notes in Computer Science*, page 1436.

Mehryar Mohri, Fernando Pereira, and Michael Riley. 2000. The design principles of a weighted finite-state transducer library. *Theoretical Computer Science*, (231):17–32.

Mehryar Mohri, Fernando C. N. Pereira, and Michael Riley. 2002. Weighted finite-state transducers in speech recognition. *Computer Speech and Language*, 16(1):69–88.

NIST, 1998. *Speech Recognition Scoring Toolkit (SCTK V1.2)*.

David S. Pallett, Jonathan G. Fiscus, William M. Fisher, John S. Garofolo, Lund Bruce A., and Mark A. Przybocki. 1993. 1993 benchmark tests for the arpa spoken language program. *NIST Report*.

D. B. Paul and J. M. Baker. 1992. The design for the wall street journal-based csr corpus. In *Proceedings of the International Conference on Spoken Language Proecssing ICSLP*, Banff, Alberta, Canada.

Brian Roark, Murat Saraclar, and Michael Collins. 1994. Corrective language modeling for large vocabulary ASR with the perceptron algorithm. In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*, pages 749–752.

Brian Roark. 2001a. Probabilistic top-down parsing and language modeling. *Computational Linguistics*, 27(3):249–276.

Brian Edward Roark. 2001b. *Robust Probabilistic Predictive Syntactic Processing: Motivations, Models, and Applications*. Ph.D. thesis, Brown University, May.

Brian Roark. 2002. Markov parsing: Lattice rescoring with a statistical parser. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 287–294.

Stuart Russell and Peter Norvig. 1995. *Artificial Intelligence: A Modern Approach*. Prentice-Hall.

Hans Weber. 1994. Time synchronous chart parsing of speech integrating unification grammars with statistics. In *Proceedings of the eighth Twente Workshop on Language Technologies*, December.

Peng Xu, Ciprian Chelba, and Frederick Jelinek. 2002. A study on richer syntactic dependencies for structured language modeling. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 191–198.

Steve Young, Gunnar Evermann, Dan Kershaw, Gareth Moore, Julian Odell, Dave Ollason, Dan Povey, Valtcho Valtchev, and Phil Woodland. 2002. *The HTK Book*. Cambridge University Engineering Department, http://htk.eng.cam.ac.uk/docs/docs.shtml.

Daniel H. Younger. 1967. Recognition and parsing of context-free languages in time n^3. *Information and Control*, 10:189–208.