

Natural Language Processing in Python

Authors: Steven Bird, Ewan Klein, Edward Loper

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Preface

This is a book about **Natural Language Processing**. By **natural language** we mean a language that is used for everyday communication by humans; languages like English, Hindi or Portuguese. In contrast to artificial languages such as programming languages and logical formalisms, natural languages have evolved as they pass from generation to generation, and are hard to pin down with explicit rules. We will take Natural Language Processing (or NLP for short) in a wide sense to cover any kind of computer manipulation of natural language. At one extreme, it could be as simple as counting the number of times the letter *t* occurs in a paragraph of text. At the other extreme, NLP might involve “understanding” complete human utterances, at least to the extent of being able to give useful responses to them.

Most human knowledge — and most human communication — is represented and expressed using language. Technologies based on NLP are becoming increasingly widespread. For example, handheld computers (PDAs) support predictive text and handwriting recognition; web search engines give access to information locked up in unstructured text; machine translation allows us to retrieve texts written in Chinese and read them in Spanish. By providing more natural human-machine interfaces, and more sophisticated access to stored information, language processing has come to play a central role in the multilingual information society.

This textbook provides a comprehensive, hands-on introduction to the field of NLP, covering the major techniques and theories. The book provides numerous worked examples and exercises, and can be used either for self-study or as the main text for undergraduate and introductory graduate courses on natural language processing or computational linguistics.

Audience

This book is intended for people who want to learn how to write programs that analyze written language. It is accessible to people who are new to programming, but structured in such a way that experienced programmers can quickly learn important NLP techniques.

New to Programming? The book is suitable for readers with no prior knowledge of programming, and the early chapters contain many examples that you can simply copy and try for yourself, together with graded exercises. If you decide you need a more general introduction to Python, we recommend you read *Learning Python* (O'Reilly) in conjunction with this book.

New to Python? Experienced programmers can quickly learn enough Python using this book to get immersed in natural language processing. All relevant Python features are carefully explained and exemplified, and you will quickly come to appreciate Python's suitability for this application area.

Already dreaming in Python? Simply skip the Python introduction, and dig into the interesting language analysis material that starts in [Chapter 3](#). Soon you'll be applying your skills to this exciting new application area.

What You Will Learn

By digging into the material presented here, you will learn:

- how simple programs can help you manipulate and analyze language data, and how to write these programs;
- how key concepts from NLP and linguistics are used to describe and analyse language;
- how data structures and algorithms are used in NLP;
- how language data is stored in standard formats, and how data can be used to evaluate the performance of NLP techniques.

Depending on your background, and your motivation for being interested in NLP, you will gain different kinds of skills and knowledge from this book, as set out below:

Goals	Background	
	Arts and Humanities	Science and Engineering
Language Analysis	Programming to manage language data, explore linguistic models, and test empirical claims	Language as a source of interesting problems in data modeling, data mining, and knowledge discovery
Language Technology	Learning to program, with applications to familiar problems, to work in language technology or other technical field	Knowledge of linguistic algorithms and data structures for high quality, maintainable language processing software

Table 1:

Download the Toolkit...

This textbook is a companion to the *Natural Language Toolkit* (NLTK), a suite of software, corpora, and documentation freely downloadable from <http://nltk.org/>. Distributions are provided for Windows, Macintosh and Unix platforms. You can browse the code online at <http://nltk.org/nltk/>. All NLTK distributions plus Python and other useful third-party software are available in the form of an ISO image that can be downloaded and burnt to CD-ROM for easy local redistribution. We strongly encourage you to download Python and NLTK before you go beyond the first chapter of the book.

Emphasis

This book is a **practical** introduction to NLP. You will learn by example, write real programs, and grasp the value of being able to test an idea through implementation. If you haven't learnt already, this book will teach you **programming**. Unlike other programming books, we provide extensive illustrations and exercises from NLP. The approach we have taken is also **principled**, in that we cover the theoretical underpinnings and don't shy away from careful linguistic and computational analysis. We have tried to be **pragmatic** in striking a balance between theory and application, and alternate between the two several times each chapter, identifying the connections but also the tensions. Finally, we recognize that

you won't get through this unless it is also **pleasurable**, so we have tried to include many applications and examples that are interesting and entertaining, sometimes whimsical.

Organization

The book is structured into three parts, as follows:

Part 1: Basics In this part, we focus on processing text, recognizing and categorizing words, and how to deal with large amounts of language data.

Part 2: Parsing Here, we deal with grammatical structure in text: how words combine to make phrases and sentences, and how to automatically parse text into such structures.

Part 3: Advanced Topics This final part of the book contains chapters that address selected topics in NLP in more depth and to a more advanced level. By design, the chapters in this part can be read independently of each other.

The three parts have a common structure: they start off with a chapter on programming, followed by three chapters on various topics in NLP. The programming chapters are *foundational*, and you must master this material before progressing further.

Each chapter consists of an introduction, a sequence of sections that progress from elementary to advanced material, and finally a summary and suggestions for further reading. Most sections include exercises that are graded according to the following scheme: ☀ is for easy exercises that involve minor modifications to supplied code samples or other simple activities; ⚡ is for intermediate exercises that explore an aspect of the material in more depth, requiring careful analysis and design; ★ is for difficult, open-ended tasks that will challenge your understanding of the material and force you to think independently (readers new to programming are encouraged to skip these). ☺ is for non-programming exercises for reflection or discussion. The exercises are important for consolidating the material in each section, and we strongly encourage you to try a few before continuing with the rest of the chapter.

Why Python?

Python is a simple yet powerful programming language with excellent functionality for processing linguistic data. Python can be downloaded for free from <http://www.python.org/>.

Here is a five-line Python program that takes text input and prints all the words ending in *ing*:

```
>>> import sys                      # load the system library
>>> for line in sys.stdin:           # for each line of input text
...     for word in line.split():    # for each word in the line
...         if word.endswith('ing'):   # does the word end in 'ing'?
...             print word            # if so, print the word
```

This program illustrates some of the main features of Python. First, whitespace is used to *nest* lines of code, thus the line starting with `if` falls inside the scope of the previous line starting with `for`; this ensures that the `ing` test is performed for each word. Second, Python is *object-oriented*; each variable is an entity that has certain defined attributes and methods. For example, the value of the variable `line` is more than a sequence of characters. It is a string object that has a **method** (or operation) called `split()` that we can use to break a line into its words. To apply a method to an object, we write the object name, followed by a period, followed by the method name; i.e., `line.split()`.

Third, methods have *arguments* expressed inside parentheses. For instance, in the example above, `split()` had no argument because we were splitting the string wherever there was white space, and we could therefore use empty parentheses. To split a string into sentences delimited by a period, we would write `split('.')`. Finally, and most importantly, Python is highly readable, so much so that it is fairly easy to guess what the above program does even if you have never written a program before.

We chose Python as the implementation language for NLTK because it has a shallow learning curve, its syntax and semantics are transparent, and it has good string-handling functionality. As a scripting language, Python facilitates interactive exploration. As an object-oriented language, Python permits data and methods to be encapsulated and re-used easily. As a dynamic language, Python permits attributes to be added to objects on the fly, and permits variables to be typed dynamically, facilitating rapid development. Python comes with an extensive standard library, including components for graphical programming, numerical processing, and web data processing.

Python is heavily used in industry, scientific research, and education around the world. Python is often praised for the way it facilitates productivity, quality, and maintainability of software. A collection of Python success stories is posted at <http://www.python.org/about/success/>.

NLTK defines an infrastructure that can be used to build NLP programs in Python. It provides basic classes for representing data relevant to natural language processing; standard interfaces for performing tasks such as word tokenization, part-of-speech tagging, and syntactic parsing; and standard implementations for each task which can be combined to solve complex problems.

NLTK comes with extensive documentation. In addition to the book you are reading right now, the website <http://nltk.org/> provides API documentation which covers every module, class and function in the toolkit, specifying parameters and giving examples of usage. The website also provides module **guides**; these contain extensive examples and test cases, and are intended for users, developers and instructors.

Learning Python and NLTK

This book contains self-paced learning materials including many examples and exercises. An effective way for students to learn is simply to work through the materials, with the help of other students and instructors. The program fragments can be cut and pasted directly from the online tutorials. The HTML version has a blue bar beside each program fragment; click on the bar to automatically copy the program fragment to the clipboard (assumes appropriate browser security settings.)

Python Development Environments: The easiest way to start developing Python code, and to run interactive Python demonstrations, is to use the simple editor and interpreter GUI that comes with Python called *IDLE*, the *Integrated Development Environment for Python*. However, there are lots of alternative tools, some of which are described at <http://nltk.org/>.

NLTK Community: NLTK has a large and growing user base. There are mailing lists for announcements about NLTK, for developers and for teachers. <http://nltk.org/> lists some 50 courses around the world where NLTK and materials from this book have been adopted, serving as a useful source of associated materials including slides and exercises.

The Design of NLTK

NLTK was designed with four primary goals in mind:

Simplicity: We have tried to provide an intuitive and appealing framework along with substantial building blocks, so students can gain a practical knowledge of NLP

without getting bogged down in the tedious house-keeping usually associated with processing annotated language data. We have provided software distributions for several platforms, along with platform-specific instructions, to make the toolkit easy to install.

Consistency: We have made a significant effort to ensure that all the data structures and interfaces are consistent, making it easy to carry out a variety of tasks using a uniform framework.

Extensibility: The toolkit easily accommodates new components, whether those components replicate or extend existing functionality. Moreover, the toolkit is organized so that it is usually obvious where extensions would fit into the toolkit's infrastructure.

Modularity: The interaction between different components of the toolkit uses simple, well-defined interfaces. It is possible to complete individual projects using small parts of the toolkit, without needing to understand how they interact with the rest of the toolkit. This allows students to learn how to use the toolkit incrementally throughout a course. Modularity also makes it easier to change and extend the toolkit.

Contrasting with these goals are three non-requirements — potentially useful features that we have deliberately avoided. First, while the toolkit provides a wide range of functions, it is not intended to be encyclopedic; there should be a wide variety of ways in which students can extend the toolkit. Second, while the toolkit should be efficient enough that students can use their NLP systems to perform meaningful tasks, it does not need to be highly optimized for runtime performance; such optimizations often involve more complex algorithms, and sometimes require the use of programming languages like C or C++. This would make the toolkit less accessible and more difficult to install. Third, we have tried to avoid clever programming tricks, since clear implementations are preferable to ingenious yet indecipherable ones.

For Instructors

Natural Language Processing (NLP) is often taught within the confines of a single-semester course at advanced undergraduate level or postgraduate level. Many instructors have found that it is difficult to cover both the theoretical and practical sides of the subject in such a short span of time. Some courses focus on theory to the exclusion of practical exercises, and deprive students of the challenge and excitement of writing programs to automatically process language. Other courses are simply designed to teach programming for linguists, and do not manage to cover any significant NLP content. The *Natural Language Toolkit* (NLTK) was originally developed to address this problem, making it feasible to cover a substantial amount of theory and practice within a single-semester course, even if students have no prior programming experience.

A significant fraction of any NLP syllabus covers fundamental data structures and algorithms. These are usually taught with the help of formal notations and complex diagrams. Large trees and charts are copied onto the board and edited in tedious slow motion, or laboriously prepared for presentation slides. It is more effective to use live demonstrations in which those diagrams are generated and updated automatically. NLTK provides interactive graphical user interfaces, making it possible to view program state and to study program execution step-by-step. Most NLTK components have a demonstration mode, and will perform an interesting task without requiring any special input from the user. It is even possible to make minor modifications to programs in response to “what if” questions. In this

way, students learn the mechanics of NLP quickly, gain deeper insights into the data structures and algorithms, and acquire new problem-solving skills.

This material can be used as the basis for lecture presentations, and some slides are available for download from <http://nltk.org/>. An effective way to deliver the materials is through interactive presentation of the examples, entering them at the Python prompt, observing what they do, and modifying them to explore some empirical or theoretical question.

NLTK supports assignments of varying difficulty and scope. In the simplest assignments, students experiment with existing components to perform a wide variety of NLP tasks. This may involve no programming at all, in the case of the existing demonstrations, or simply changing a line or two of program code. As students become more familiar with the toolkit they can be asked to modify existing components or to create complete systems out of existing components. NLTK also provides students with a flexible framework for advanced projects, such as developing a multi-component system, by integrating and extending NLTK components, and adding on entirely new components. Here NLTK helps by providing standard implementations of all the basic data structures and algorithms, interfaces to standard corpora, substantial corpus samples, and a flexible and extensible architecture. Thus, as we have seen, NLTK offers a fresh approach to NLP pedagogy, in which theoretical content is tightly integrated with application.

We believe this book is unique in providing a comprehensive framework for students to learn about NLP in the context of learning to program. What sets these materials apart is the tight coupling of the chapters and exercises with NLTK, giving students — even those with no prior programming experience — a practical introduction to NLP. Once completing these materials, students will be ready to attempt one of the more advanced textbooks, such as *Foundations of Statistical Natural Language Processing*, by Manning and Schütze (MIT Press, 2000).

Course Plans; Lectures/Lab Sessions per Chapter		
Chapter	Linguists	Computer Scientists
1 Introduction	1	1
2 Programming	4	1
3 Words	2-3	2
4 Tagging	2	2
5 Data-Intensive Language Processing	0-2	2
6 Structured Programming	2-4	1
7 Chunking	2	2
8 Grammars and Parsing	2-6	2-4
9 Advanced Parsing	1-4	3
10-14 Advanced Topics	2-8	2-16
Total	18-36	18-36

Table 2: Suggested Course Plans

Acknowledgments

NLTK was originally created as part of a computational linguistics course in the Department of Computer and Information Science at the University of Pennsylvania in 2001. Since then it has been developed and expanded with the help of dozens of contributors. It has now been adopted in courses in dozens of universities, and serves as the basis of many research projects.

In particular, we're grateful to the following people for their feedback, comments on earlier drafts, advice, contributions: Michaela Atterer, Greg Aumann, Kenneth Beesley, Ondrej Bojar, Trevor Cohn, Grev Corbett, James Curran, Jean Mark Gawron, Baden Hughes, Gwillim Law, Mark Liberman, Christopher Maloof, Stefan Müller, Stuart Robinson, Jussi Salmela, Rob Speer. Many others have contributed to the toolkit, and they are listed at <http://nltk.org/>. We are grateful to many colleagues and students for feedback on the text.

About the Authors

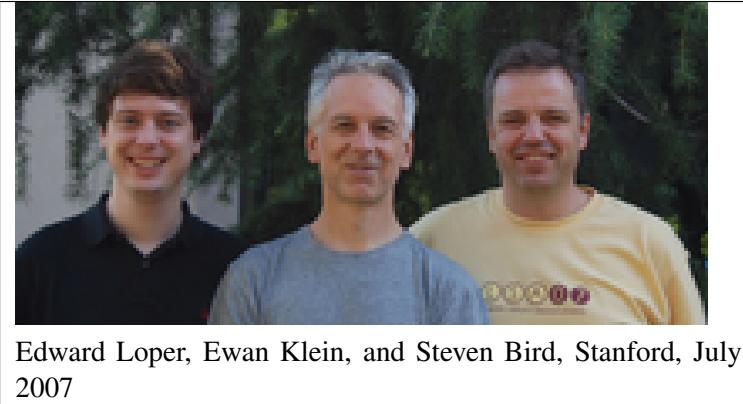


Table 3:

Steven Bird is Associate Professor in the Department of Computer Science and Software Engineering at the University of Melbourne, and Senior Research Associate in the Linguistic Data Consortium at the University of Pennsylvania. After completing his undergraduate training in computer science and mathematics at the University of Melbourne, Steven went to the University of Edinburgh to study computational linguistics, and completed his PhD in 1990 under the supervision of Ewan Klein. He later moved to Cameroon to conduct linguistic fieldwork on the Grassfields Bantu languages. More recently, he spent several years as Associate Director of the Linguistic Data Consortium where he led an R&D team to create models and tools for large databases of annotated text. Back at Melbourne University, he leads a language technology research group and lectures in algorithms and Python programming. Steven is editor of *Cambridge Studies in Natural Language Processing*, and was recently elected president of the Association for Computational Linguistics.

Ewan Klein is Professor of Language Technology in the School of Informatics at the University of Edinburgh. He completed a PhD on formal semantics at the University of Cambridge in 1978. After some years working at the Universities of Sussex and Newcastle upon Tyne, Ewan took up a teaching position at Edinburgh. He was involved in the establishment of Edinburgh's Language Technology Group 1993, and has been closely associated with it ever since. From 2000–2002, he took leave from the University to act as Research Manager for the Edinburgh-based Natural Language Research Group of Edify Corporation, Santa Clara, and was responsible for spoken dialogue processing. Ewan is a past President of the European Chapter of the Association for Computational Linguistics and was a founding member and Coordinator of the European Network of Excellence in Human Language Technologies (ELSNET). He has been involved in leading numerous academic-industrial collaborative projects, the

most recent of which is a biological text mining initiative funded by ITI Life Sciences, Scotland, in collaboration with Cognia Corporation, NY.

Edward Loper is a doctoral student in the Department of Computer and Information Sciences at the University of Pennsylvania, conducting research on machine learning in natural language processing. Edward was a student in Steven's graduate course on computational linguistics in the fall of 2000, and went on to be a TA and share in the development of NLTK. In addition to NLTK, he has helped develop other major packages for documenting and testing Python software, epydoc and doctest.

About this document...

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Chapter 1

Introduction to Natural Language Processing

1.1 The Language Challenge

Today, people from all walks of life — including professionals, students, and the general population — are confronted by unprecedented volumes of information, the vast bulk of which is stored as unstructured text. In 2003, it was estimated that the annual production of books amounted to 8 Terabytes. (A Terabyte is 1,000 Gigabytes, i.e., equivalent to 1,000 pickup trucks filled with books.) It would take a human being about five years to read the new scientific material that is produced every 24 hours. Although these estimates are based on printed materials, increasingly the information is also available electronically. Indeed, there has been an explosion of text and multimedia content on the World Wide Web. For many people, a large and growing fraction of work and leisure time is spent navigating and accessing this universe of information.

The presence of so much text in electronic form is a huge challenge to NLP. Arguably, the only way for humans to cope with the information explosion is to exploit computational techniques that can sift through huge bodies of text.

Although existing search engines have been crucial to the growth and popularity of the Web, humans require skill, knowledge, and some luck, to extract answers to such questions as *What tourist sites can I visit between Philadelphia and Pittsburgh on a limited budget?* *What do expert critics say about digital SLR cameras?* *What predictions about the steel market were made by credible commentators in the past week?* Getting a computer to answer them automatically is a realistic long-term goal, but would involve a range of language processing tasks, including information extraction, inference, and summarization, and would need to be carried out on a scale and with a level of robustness that is still beyond our current capabilities.

1.1.1 The Richness of Language

Language is the chief manifestation of human intelligence. Through language we express basic needs and lofty aspirations, technical know-how and flights of fantasy. Ideas are shared over great separations of distance and time. The following samples from English illustrate the richness of language:

- (1) a. Overhead the day drives level and grey, hiding the sun by a flight of grey spears. (William Faulkner, *As I Lay Dying*, 1935)

- b. When using the toaster please ensure that the exhaust fan is turned on. (sign in dormitory kitchen)
- c. Amiodarone weakly inhibited CYP2C9, CYP2D6, and CYP3A4-mediated activities with Ki values of 45.1-271.6 μ M (Medline, PMID: 10718780)
- d. Iraqi Head Seeks Arms (spoof news headline)
- e. The earnest prayer of a righteous man has great power and wonderful results. (James 5:16b)
- f. Twas brillig, and the slithy toves did gyre and gimble in the wabe (Lewis Carroll, *Jabberwocky*, 1872)
- g. There are two ways to do this, AFAIK :smile: (internet discussion archive)

Thanks to this richness, the study of language is part of many disciplines outside of linguistics, including translation, literary criticism, philosophy, anthropology and psychology. Many less obvious disciplines investigate language use, such as law, hermeneutics, forensics, telephony, pedagogy, archaeology, cryptanalysis and speech pathology. Each applies distinct methodologies to gather observations, develop theories and test hypotheses. Yet all serve to deepen our understanding of language and of the intellect that is manifested in language.

The importance of language to science and the arts is matched in significance by the cultural treasure embodied in language. Each of the world's ~7,000 human languages is rich in unique respects, in its oral histories and creation legends, down to its grammatical constructions and its very words and their nuances of meaning. Threatened remnant cultures have words to distinguish plant subspecies according to therapeutic uses that are unknown to science. Languages evolve over time as they come into contact with each other and they provide a unique window onto human pre-history. Technological change gives rise to new words like *blog* and new morphemes like *e-* and *cyber-*. In many parts of the world, small linguistic variations from one town to the next add up to a completely different language in the space of a half-hour drive. For its breathtaking complexity and diversity, human language is as a colorful tapestry stretching through time and space.

1.1.2 The Promise of NLP

As we have seen, NLP is important for scientific, economic, social, and cultural reasons. NLP is experiencing rapid growth as its theories and methods are deployed in a variety of new language technologies. For this reason it is important for a wide range of people to have a working knowledge of NLP. Within industry, it includes people in *human-computer interaction*, *business information analysis*, and *Web software development*. Within academia, this includes people in areas from *humanities computing* and *corpus linguistics* through to *computer science* and *artificial intelligence*. We hope that you, a member of this diverse audience reading these materials, will come to appreciate the workings of this rapidly growing field of NLP and will apply its techniques in the solution of real-world problems.

The following chapters present a carefully-balanced selection of theoretical foundations and practical applications, and equips readers to work with large datasets, to create robust models of linguistic phenomena, and to deploy them in working language technologies. By integrating all of this into the Natural Language Toolkit (NLTK), we hope this book opens up the exciting endeavor of practical natural language processing to a broader audience than ever before.

1.2 Language and Computation

1.2.1 NLP and Intelligence

A long-standing challenge within computer science has been to build intelligent machines. The chief measure of *machine intelligence* has been a linguistic one, namely the *Turing Test*: can a dialogue system, responding to a user's typed input with its own textual output, perform so naturally that users cannot distinguish it from a human interlocutor using the same interface? Today, there is substantial ongoing research and development in such areas as machine translation and spoken dialogue, and significant commercial systems are in widespread use. The following *dialogue* illustrates a typical application:

- (2) S: How may I help you?
 U: When is Saving Private Ryan playing?
 S: For what theater?
 U: The Paramount theater.
 S: Saving Private Ryan is not playing at the Paramount theater, but
 it's playing at the Madison theater at 3:00, 5:30, 8:00, and 10:30.

Today's commercial dialogue systems are strictly limited to narrowly-defined domains. We could not ask the above system to provide driving instructions or details of nearby restaurants unless the requisite information had already been stored and suitable question and answer sentences had been incorporated into the language processing system. Observe that the above system appears to understand the user's goals: the user asks when a movie is showing and the system correctly determines from this that the user wants to see the movie. This inference seems so obvious to humans that we usually do not even notice it has been made, yet a natural language system needs to be endowed with this capability in order to interact naturally. Without it, when asked *Do you know when Saving Private Ryan is playing*, a system might simply — and unhelpfully — respond with a cold *Yes*. While it appears that this dialogue system can perform simple inferences, such sophistication is only found in cutting edge research prototypes. Instead, the developers of commercial dialogue systems use contextual assumptions and simple business logic to ensure that the different ways in which a user might express requests or provide information are handled in a way that makes sense for the particular application. Thus, whether the user says *When is ...*, or *I want to know when ...*, or *Can you tell me when ...*, simple rules will always yield screening times. This is sufficient for the system to provide a useful service.

As NLP technologies become more mature, and robust methods for analysing unrestricted text become more widespread, the prospect of natural language 'understanding' has re-emerged as a plausible goal. This has been brought into focus in recent years by a public 'shared task' called Recognizing Textual Entailment (RTE) [?]. The basic scenario is simple. Let's suppose we are interested in whether we can find evidence to support a hypothesis such as *Sandra Goudie was defeated by Max Purnell*. We are given another short text that appears to be relevant, for example, *Sandra Goudie was first elected to Parliament in the 2002 elections, narrowly winning the seat of Coromandel by defeating Labour candidate Max Purnell and pushing incumbent Green MP Jeanette Fitzsimons into third place*. The question now is whether the text provides sufficient evidence for us to accept the hypothesis as true. In this particular case, the answer is No. This is a conclusion that we can draw quite easily as humans, but it is very hard to come up with automated methods for making the right classification. The RTE Challenges provide data which allow competitors to develop their systems, but not enough data to

allow statistical classifiers to be trained using standard machine learning techniques. Consequently, some linguistic analysis is crucial. In the above example, it is important for the system to note that *Sandra Goudie* names the person being defeated in the hypothesis, not the person doing the defeating in the text. As another illustration of the difficulty of the task, consider the following text/hypothesis pair:

- *David Golinkin is the editor or author of eighteen books, and over 150 responsa, articles, sermons and books*
- *Golinkin has written eighteen books*

In order to determine whether or not the hypothesis is supported by the text, the system needs at least the following background knowledge: (i) if someone is an author of a book, then he/she has written that book; (ii) if someone is an editor of a book, then he/she has not written that book; (iii) if someone is editor or author of eighteen books, then he/she is not author of eighteen books.

Despite the research-led advances in tasks like RTE, natural language systems that have been deployed for real-world applications still cannot perform common-sense reasoning or draw on world knowledge in a general and robust manner. We can wait for these difficult artificial intelligence problems to be solved, but in the meantime it is necessary to live with some severe limitations on the reasoning and knowledge capabilities of natural language systems. Accordingly, right from the beginning, an important goal of NLP research has been to make progress on the holy grail of natural linguistic interaction *without* recourse to this unrestricted knowledge and reasoning capability. This is an old challenge, and so it is instructive to review the history of the field.

1.2.2 Language and Symbol Processing

The very notion that natural language could be treated in a computational manner grew out of a research program, dating back to the early 1900s, to reconstruct mathematical reasoning using logic, most clearly manifested in work by Frege, Russell, Wittgenstein, Tarski, Lambek and Carnap. This work led to the notion of language as a formal system amenable to automatic processing. Three later developments laid the foundation for natural language processing. The first was **formal language theory**. This defined a language as a set of strings accepted by a class of automata, such as context-free languages and pushdown automata, and provided the underpinnings for computational syntax.

The second development was **symbolic logic**. This provided a formal method for capturing selected aspects of natural language that are relevant for expressing logical proofs. A formal calculus in symbolic logic provides the syntax of a language, together with rules of inference and, possibly, rules of interpretation in a set-theoretic model; examples are propositional logic and First Order Logic. Given such a calculus, with a well-defined syntax and semantics, it becomes possible to associate meanings with expressions of natural language by translating them into expressions of the formal calculus. For example, if we translate *John saw Mary* into a formula $\text{saw}(j, m)$, we (implicitly or explicitly) interpret the English verb *saw* as a binary relation, and *John* and *Mary* as denoting individuals. More general statements like *All birds fly* require quantifiers, in this case \forall , meaning *for all*: $\forall x(\text{bird}(x) \rightarrow \text{fly}(x))$. This use of logic provided the technical machinery to perform inferences that are an important part of language understanding.

A closely related development was the **principle of compositionality**, namely that the meaning of a complex expression is composed from the meaning of its parts and their mode of combination. This principle provided a useful correspondence between syntax and semantics, namely that the meaning of a complex expression could be computed recursively. Consider the sentence *It is not true that p*, where

p is a proposition. We can represent the meaning of this sentence as $\text{not}(p)$. Similarly, we can represent the meaning of *John saw Mary* as $\text{saw}(j, m)$. Now we can compute the interpretation of *It is not true that John saw Mary* recursively, using the above information, to get $\text{not}(\text{saw}(j, m))$.

The approaches just outlined share the premise that computing with natural language crucially relies on rules for manipulating symbolic representations. For a certain period in the development of NLP, particularly during the 1980s, this premise provided a common starting point for both linguists and practitioners of NLP, leading to a family of grammar formalisms known as unification-based (or feature-based) grammar, and to NLP applications implemented in the Prolog programming language. Although grammar-based NLP is still a significant area of research, it has become somewhat eclipsed in the last 15–20 years due to a variety of factors. One significant influence came from automatic speech recognition. Although early work in speech processing adopted a model that emulated the kind of rule-based phonological processing typified by the *Sound Pattern of English* [?], this turned out to be hopelessly inadequate in dealing with the hard problem of recognizing actual speech in anything like real time. By contrast, systems which involved learning patterns from large bodies of speech data were significantly more accurate, efficient and robust. In addition, the speech community found that progress in building better systems was hugely assisted by the construction of shared resources for quantitatively measuring performance against common test data. Eventually, much of the NLP community embraced a **data intensive** orientation to language processing, coupled with a growing use of machine-learning techniques and evaluation-led methodology.

1.2.3 Philosophical Divides

The contrasting approaches to NLP described in the preceding section relate back to early metaphysical debates about **rationalism** versus **empiricism** and **realism** versus **idealism** that occurred in the Enlightenment period of Western philosophy. These debates took place against a backdrop of orthodox thinking in which the source of all knowledge was believed to be divine revelation. During this period of the seventeenth and eighteenth centuries, philosophers argued that human reason or sensory experience has priority over revelation. Descartes and Leibniz, amongst others, took the rationalist position, asserting that all truth has its origins in human thought, and in the existence of “innate ideas” implanted in our minds from birth. For example, they argued that the principles of Euclidean geometry were developed using human reason, and were not the result of supernatural revelation or sensory experience. In contrast, Locke and others took the empiricist view, that our primary source of knowledge is the experience of our faculties, and that human reason plays a secondary role in reflecting on that experience. Prototypical evidence for this position was Galileo’s discovery — based on careful observation of the motion of the planets — that the solar system is heliocentric and not geocentric. In the context of linguistics, this debate leads to the following question: to what extent does human linguistic experience, versus our innate “language faculty”, provide the basis for our knowledge of language? In NLP this matter surfaces as differences in the priority of corpus data versus linguistic introspection in the construction of computational models. We will return to this issue later in the book.

A further concern, enshrined in the debate between realism and idealism, was the metaphysical status of the constructs of a theory. Kant argued for a distinction between phenomena, the manifestations we can experience, and “things in themselves” which can never be known directly. A linguistic realist would take a theoretical construct like **noun phrase** to be real world entity that exists independently of human perception and reason, and which actually *causes* the observed linguistic phenomena. A linguistic idealist, on the other hand, would argue that noun phrases, along with more abstract constructs like semantic representations, are intrinsically unobservable, and simply play the role of useful

fictions. The way linguists write about theories often betrays a realist position, while NLP practitioners occupy neutral territory or else lean towards the idealist position. Thus, in NLP, it is often enough if a theoretical abstraction leads to a useful result; it does not matter whether this result sheds any light on human linguistic processing.

These issues are still alive today, and show up in the distinctions between symbolic vs statistical methods, deep vs shallow processing, binary vs gradient classifications, and scientific vs engineering goals. However, such contrasts are now highly nuanced, and the debate is no longer as polarized as it once was. In fact, most of the discussions — and most of the advances even — involve a “balancing act”. For example, one intermediate position is to assume that humans are innately endowed with analogical and memory-based learning methods (weak rationalism), and to use these methods to identify meaningful patterns in their sensory language experience (empiricism). For a more concrete illustration, consider the way in which statistics from large corpora may serve as evidence for binary choices in a symbolic grammar. For instance, dictionaries describe the words *absolutely* and *definitely* as nearly synonymous, yet their patterns of usage are quite distinct when combined with a following verb, as shown in [Table 1.1](#).

Google hits	<i>adore</i>	<i>love</i>	<i>like</i>	<i>prefer</i>
<i>absolutely</i>	289,000	905,000	16,200	644
<i>definitely</i>	1,460	51,000	158,000	62,600
ratio	198:1	18:1	1:10	1:97

Table 1.1: *Absolutely* vs *Definitely* (Liberman 2005, LanguageLog.org)

As you will see, *absolutely adore* is about 200 times as popular as *definitely adore*, while *absolutely prefer* is about 100 times rarer than *definitely prefer*. This information is used by statistical language models, but it also counts as evidence for a symbolic account of word combination in which *absolutely* can only modify extreme actions or attributes, a property that could be represented as a binary-valued feature of certain lexical items. Thus, we see statistical data informing symbolic models. Once this information has been codified symbolically, it is available to be exploited as a contextual feature for statistical language modeling, alongside many other rich sources of symbolic information, like hand-constructed parse trees and semantic representations. Now the circle is closed, and we see symbolic information informing statistical models.

This new rapprochement is giving rise to many exciting new developments. We will touch on some of these in the ensuing pages. We too will perform this balancing act, employing approaches to NLP that integrate these historically-opposed philosophies and methodologies.

1.3 The Architecture of Linguistic and NLP Systems

1.3.1 Generative Grammar and Modularity

One of the intellectual descendants of formal language theory was the linguistic framework known as **generative grammar**. Such a grammar contains a set of rules that recursively specify (or generate) the set of well-formed strings in a language. While there is a wide spectrum of models that owe some allegiance to this core, Chomsky’s transformational grammar, in its various incarnations, is probably the best known. In the Chomskyan tradition, it is claimed that humans have distinct kinds of linguistic knowledge, organized into different modules: for example, knowledge of a language’s sound structure

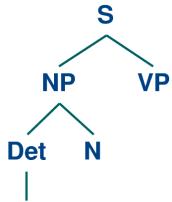
(**phonology**), knowledge of word structure (**morphology**), knowledge of phrase structure (**syntax**), and knowledge of meaning (**semantics**). In a formal linguistic theory, each kind of linguistic knowledge is made explicit as different **module** of the theory, consisting of a collection of basic elements together with a way of combining them into complex structures. For example, a phonological module might provide a set of phonemes together with an operation for concatenating phonemes into phonological strings. Similarly, a syntactic module might provide labeled nodes as primitives together with a mechanism for assembling them into trees. A set of linguistic primitives, together with some operators for defining complex elements, is often called a **level of representation**.

As well as defining modules, a generative grammar will prescribe how the modules interact. For example, well-formed phonological strings will provide the phonological content of words, and words will provide the terminal elements of syntax trees. Well-formed syntactic trees will be mapped to semantic representations, and contextual or pragmatic information will ground these semantic representations in some real-world situation.

As we indicated above, an important aspect of theories of generative grammar is that they are intended to model the linguistic knowledge of speakers and hearers; they are not intended to explain how humans actually process linguistic information. This is, in part, reflected in the claim that a generative grammar encodes the **competence** of an idealized native speaker, rather than the speaker's **performance**. A closely related distinction is to say that a generative grammar encodes **declarative** rather than **procedural** knowledge. Declarative knowledge can be glossed as "knowing what", whereas procedural knowledge is "knowing how". As you might expect, computational linguistics has the crucial role of proposing procedural models of language. A central example is parsing, where we have to develop computational mechanisms that convert strings of words into structural representations such as syntax trees. Nevertheless, it is widely accepted that well-engineered computational models of language contain both declarative and procedural aspects. Thus, a full account of parsing will say how declarative knowledge in the form of a grammar and lexicon combines with procedural knowledge that determines how a syntactic analysis should be assigned to a given string of words. This procedural knowledge will be expressed as an **algorithm**: that is, an explicit recipe for mapping some input into an appropriate output in a finite number of steps.

A simple parsing algorithm for context-free grammars, for instance, looks first for a rule of the form $S \rightarrow X_1 \dots X_n$, and builds a partial tree structure. It then steps through the grammar rules one-by-one, looking for a rule of the form $X_1 \rightarrow Y_1 \dots Y_j$ that will expand the leftmost daughter introduced by the S rule, and further extends the partial tree. This process continues, for example by looking for a rule of the form $Y_1 \rightarrow Z_1 \dots Z_k$ and expanding the partial tree appropriately, until the leftmost node label in the partial tree is a lexical category; the parser then checks to see if the first word of the input can belong to the category. To illustrate, let's suppose that the first grammar rule chosen by the parser is $S \rightarrow NP VP$ and the second rule chosen is $NP \rightarrow Det\ N$; then the partial tree will be as follows:

(3)



If we assume that the input string we are trying to parse is *the cat slept*, we will succeed in identifying *the* as a word that can belong to the category DET. In this case, the parser goes on to the next node of the tree, N, and next input word, *cat*. However, if we had built the same partial tree

with an input string *did the cat sleep*, the parse would fail at this point, since *did* is not of category DET. The parser would throw away the structure built so far and look for an alternative way of going from the S node down to a leftmost lexical category (e.g., using a rule S → V NP VP). The important point for now is not the details of this or other parsing algorithms; we discuss this topic much more fully in the chapter on parsing. Rather, we just want to illustrate the idea that an algorithm can be broken down into a fixed number of steps that produce a definite result at the end.

In Figure 1.1 we further illustrate some of these points in the context of a spoken dialogue system, such as our earlier example of an application that offers the user information about movies currently on show.

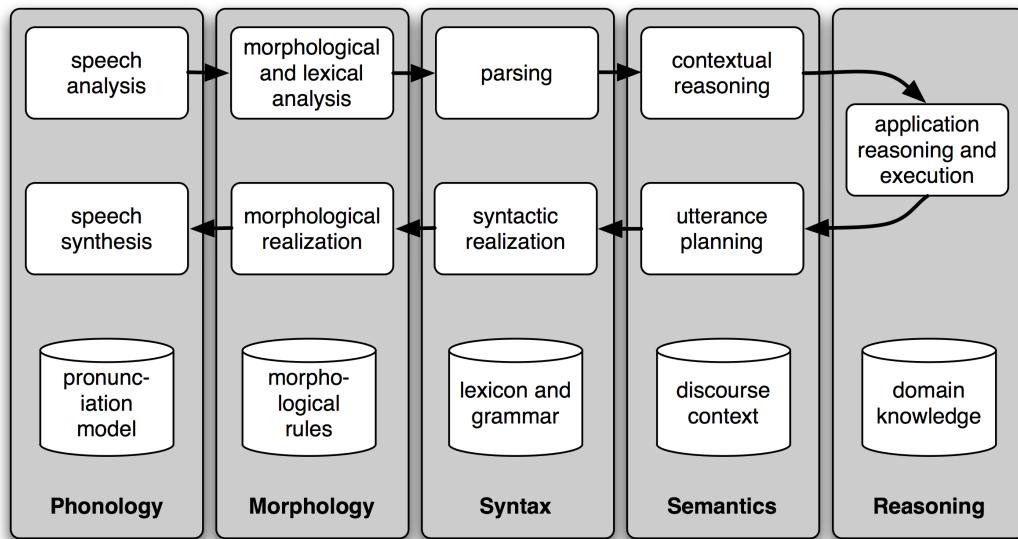


Figure 1.1: Simple Pipeline Architecture for a Spoken Dialogue System

Along the top of the diagram, moving from left to right, is a “pipeline” of some representative speech understanding **components**. These map from speech input *via* syntactic parsing to some kind of meaning representation. Along the middle, moving from right to left, is an inverse pipeline of components for concept-to-speech generation. These components constitute the dynamic or procedural aspect of the system’s natural language processing. At the bottom of the diagram are some representative bodies of static information: the repositories of language-related data that are called upon by the processing components.

The diagram illustrates that linguistically-motivated ways of modularizing linguistic knowledge are often reflected in computational systems. That is, the various components are organized so that the data which they exchange corresponds roughly to different levels of representation. For example, the output of the speech analysis component will contain sequences of phonological representations of words, and the output of the parser will be a semantic representation. Of course the parallel is not precise, in part because it is often a matter of practical expedience where to place the boundaries between different processing components. For example, we can assume that within the parsing component there is a level of syntactic representation, although we have chosen not to expose this at the level of the system diagram. Despite such idiosyncrasies, most NLP systems break down their work into a series of discrete steps. In the process of natural language understanding, these steps go from more concrete levels to more abstract ones, while in natural language production, the direction is reversed.

1.4 Before Proceeding Further...

An important aspect of learning NLP using these materials is to experience both the challenge and — we hope — the satisfaction of creating software to process natural language. The accompanying software, NLTK, is available for free and runs on most operating systems including Linux/Unix, Mac OSX and Microsoft Windows. You can download NLTK from <http://nltk.org/>, along with extensive documentation. We encourage you to install Python and NLTK on your machine before reading beyond the end of this chapter.

1.5 Further Reading

Several websites have useful information about NLP, including conferences, resources, and special-interest groups, e.g. www.lt-world.org, www.aclweb.org, www.elsnet.org. The website of the *Association for Computational Linguistics*, at www.aclweb.org, contains an overview of computational linguistics, including copies of introductory chapters from recent textbooks. Wikipedia has entries for NLP and its subfields (but don't confuse natural language processing with the other NLP: neuro-linguistic programming.) Three books provide comprehensive surveys of the field: [?], [?], [?]. Several NLP systems have online interfaces that you might like to experiment with, e.g.:

- WordNet: <http://wordnet.princeton.edu/>
- Translation: <http://world.altavista.com/>
- ChatterBots: <http://www.loebner.net/Prizef/loebner-prize.html>
- Question Answering: <http://www.answerbus.com/>
- Summarization: <http://newsblaster.cs.columbia.edu/>

The example dialogue was taken from Carpenter and Chu-Carroll's ACL-99 Tutorial on Spoken Dialogue Systems.

About this document...

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Part I

BASICS

Introduction to Part I

Part I covers the linguistic and computational analysis of words. You will learn how to extract the words out of documents and text collections in multiple languages, automatically categorize them as nouns, verbs, etc, and access their meanings. Part I also introduces the required programming skills along with basic statistical methods.

Chapter 2

Programming Fundamentals and Python

This chapter provides a non-technical overview of Python and will cover the basic programming knowledge needed for the rest of the chapters in Part 1. It contains many examples and exercises; there is no better way to learn to program than to dive in and try these yourself. You should then feel confident in adapting the example for your own purposes. Before you know it you will be programming!

2.1 Getting Started

One of the friendly things about Python is that it allows you to type directly into the interactive **interpreter** — the program that will be running your Python programs. You can run the Python interpreter using a simple graphical interface called the Interactive DeveLopment Environment (IDLE). On a Mac you can find this under Applications → MacPython, and on Windows under All Programs → Python. Under Unix you can run Python from the shell by typing `python`. The interpreter will print a blurb about your Python version; simply check that you are running Python 2.4 or greater (here it is 2.5):

```
Python 2.5 (r25:51918, Sep 19 2006, 08:49:13)
[GCC 4.0.1 (Apple Computer, Inc. build 5341)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>>
```

Note

If you are unable to run the Python interpreter, you probably don't have Python installed correctly. Please visit <http://nltk.org/> for detailed instructions.

The `>>>` prompt indicates that the Python interpreter is now waiting for input. Let's begin by using the Python prompt as a calculator:

```
>>> 3 + 2 * 5 - 1
12
>>>
```

There are several things to notice here. First, once the interpreter has finished calculating the answer and displaying it, the prompt reappears. This means the Python interpreter is waiting for another instruction. Second, notice that Python deals with the order of operations correctly (unlike some older calculators), so the multiplication `2 * 5` is calculated before it is added to 3.

Try a few more expressions of your own. You can use asterisk (*) for multiplication and slash (/) for division, and parentheses for bracketing expressions. One strange thing you might come across is that division doesn't always behave how you expect:

```
>>> 3/3
1
>>> 1/3
0
>>>
```

The second case is surprising because we would expect the answer to be `0.333333`. We will come back to why that is the case later on in this chapter. For now, let's simply observe that these examples demonstrate how you can work interactively with the interpreter, allowing you to experiment and explore. Also, as you will see later, your intuitions about numerical expressions will be useful for manipulating other kinds of data in Python.

You should also try nonsensical expressions to see how the interpreter handles it:

```
>>> 1 +
Traceback (most recent call last):
  File "<stdin>", line 1
    1 +
      ^
SyntaxError: invalid syntax
>>>
```

Here we have produced a **syntax error**. It doesn't make sense to end an instruction with a plus sign. The Python interpreter indicates the line where the problem occurred.

2.2 Understanding the Basics: Strings and Variables

2.2.1 Representing text

We can't simply type text directly into the interpreter because it would try to interpret the text as part of the Python language:

```
>>> Hello World
Traceback (most recent call last):
  File "<stdin>", line 1
    Hello World
      ^
SyntaxError: invalid syntax
>>>
```

Here we see an error message. Note that the interpreter is confused about the position of the error, and points to the end of the string rather than the start.

Python represents a piece of text using a **string**. Strings are **delimited** — or separated from the rest of the program — by quotation marks:

```
>>> 'Hello World'
'Hello World'
>>> "Hello World"
'Hello World'
>>>
```

We can use either single or double quotation marks, as long as we use the same ones on either end of the string.

Now we can perform calculator-like operations on strings. For example, adding two strings together seems intuitive enough that you could guess the result:

```
>>> 'Hello' + 'World'
'HelloWorld'
>>>
```

When applied to strings, the `+` operation is called **concatenation**. It produces a new string that is a copy of the two original strings pasted together end-to-end. Notice that concatenation doesn't do anything clever like insert a space between the words. The Python interpreter has no way of knowing that you want a space; it does *exactly* what it is told. Given the example of `+`, you might be able to guess what multiplication will do:

```
>>> 'Hi' + 'Hi' + 'Hi'
'HiHiHi'
>>> 'Hi' * 3
'HiHiHi'
>>>
```

The point to take from this (apart from learning about strings) is that in Python, intuition about what should work gets you a long way, so it is worth just trying things to see what happens. You are very unlikely to break anything, so just give it a go.

2.2.2 Storing and Reusing Values

After a while, it can get quite tiresome to keep retyping Python statements over and over again. It would be nice to be able to store the **value** of an expression like `'Hi' + 'Hi' + 'Hi'` so that we can use it again. We do this by saving results to a location in the computer's memory, and giving the location a name. Such a named place is called a **variable**. In Python we create variables by **assignment**, which involves putting a value into the variable:

```
>>> msg = 'Hello World'                                ①
>>> msg                                         ②
'Hello World'                                         ③
>>>
```

In line ① we have created a variable called `msg` (short for 'message') and set it to have the string value `'Hello World'`. We used the `=` operation, which **assigns** the value of the expression on the right to the variable on the left. Notice the Python interpreter does not print any output; it only prints output when the statement returns a value, and an assignment statement returns no value. In line ② we inspect the contents of the variable by naming it on the command line: that is, we use the name `msg`. The interpreter prints out the contents of the variable in line ③.

Variables stand in for values, so instead of writing `'Hi' * 3` we could assign variable `msg` the value `'Hi'`, and `num` the value 3, then perform the multiplication using the variable names:

```
>>> msg = 'Hi'
>>> num = 3
>>> msg * num
'HiHiHi'
>>>
```

The names we choose for the variables are up to us. Instead of `msg` and `num`, we could have used any names we like:

```
>>> marta = 'Hi'
>>> foo123 = 3
>>> marta * foo123
'HiHiHi'
>>>
```

Thus, the reason for choosing meaningful variable names is to help you — and anyone who reads your code — to understand what it is meant to do. Python does not try to make sense of the names; it blindly follows your instructions, and does not object if you do something potentially confusing such as assigning a variable `two` the value 3, with the assignment statement: `two = 3`.

Note that we can also assign a new value to a variable just by using assignment again:

```
>>> msg = msg * num
>>> msg
'HiHiHi'
>>>
```

Here we have taken the value of `msg`, multiplied it by 3 and then stored that new string (`HiHiHi`) back into the variable `msg`.

2.2.3 Printing and Inspecting Strings

So far, when we have wanted to look at the contents of a variable or see the result of a calculation, we have just typed the variable name into the interpreter. We can also see the contents of `msg` using `print msg`:

```
>>> msg = 'Hello World'
>>> msg
'Hello World'
>>> print msg
Hello World
>>>
```

On close inspection, you will see that the quotation marks that indicate that `Hello World` is a string are missing in the second case. That is because inspecting a variable, by typing its name into the interactive interpreter, prints out the Python **representation** of a value. In contrast, the `print` statement only prints out the value itself, which in this case is just the text contained in the string.

In fact, you can use a sequence of comma-separated expressions in a `print` statement:

```
>>> msg2 = 'Goodbye'
>>> print msg, msg2
Hello World Goodbye
>>>
```

Note

If you have created some variable `v` and want to find out about it, then type `help(v)` to read the help entry for this kind of object. Type `dir(v)` to see a list of operations that are defined on the object.

You need to be a little bit careful in your choice of names (or **identifiers**) for Python variables. Some of the things you might try will cause an error. First, you should start the name with a letter, optionally followed by digits (0 to 9) or letters. Thus, abc23 is fine, but 23abc will cause a syntax error. You can use underscores (both within and at the start of the variable name), but not a hyphen, since this gets interpreted as an arithmetic operator. A second problem is shown in the following snippet.

```
>>> not = "don't do this"
File "<stdin>", line 1
    not = "don't do this"
^
SyntaxError: invalid syntax
```

Why is there an error here? Because `not` is reserved as one of Python's 30 odd **keywords**. These are special identifiers that are used in specific syntactic contexts, and cannot be used as variables. It is easy to tell which words are keywords if you use IDLE, since they are helpfully highlighted in orange.

2.2.4 Creating Programs with a Text Editor

The Python interactive interpreter performs your instructions as soon as you type them. Often, it is better to compose a multi-line program using a text editor, then ask Python to run the whole program at once. Using IDLE, you can do this by going to the `File` menu and opening a new window. Try this now, and enter the following one-line program:

```
msg = 'Hello World'
```

Save this program in a file called `test.py`, then go to the `Run` menu, and select the command `Run Module`. The result in the main IDLE window should look like this:

```
>>> ===== RESTART =====
>>>
>>>
```

Now, where is the output showing the value of `msg`? The answer is that the program in `test.py` will show a value only if you explicitly tell it to, using the `print` command. So add another line to `test.py` so that it looks as follows:

```
msg = 'Hello World'
print msg
```

Select `Run Module` again, and this time you should get output that looks like this:

```
>>> ===== RESTART =====
>>>
Hello World
>>>
```

From now on, you have a choice of using the interactive interpreter or a text editor to create your programs. It is often convenient to test your ideas using the interpreter, revising a line of code until it does what you expect, and consulting the interactive help facility. Once you're ready, you can paste the code (minus any `>>>` prompts) into the text editor, continue to expand it, and finally save the program in a file so that you don't have to retype it in again later.

2.2.5 Exercises

1. ☀ Start up the Python interpreter (e.g. by running IDLE). Try the examples in [section 2.1](#), then experiment with using Python as a calculator.
2. ☀ Try the examples in this section, then try the following.
 - a) Create a variable called `msg` and put a message of your own in this variable. Remember that strings need to be quoted, so you will need to type something like:


```
>>> msg = "I like NLP!"
```
 - b) Now print the contents of this variable in two ways, first by simply typing the variable name and pressing enter, then by using the `print` command.
 - c) Try various arithmetic expressions using this string, e.g. `msg + msg`, and `5 * msg`.
 - d) Define a new string `hello`, and then try `hello + msg`. Change the `hello` string so that it ends with a space character, and then try `hello + msg` again.
3. ☺ Discuss the steps you would go through to find the ten most frequent words in a two-page document.

2.3 Slicing and Dicing

Strings are so important that we will spend some more time on them. Here we will learn how to access the individual **characters** that make up a string, how to pull out arbitrary **substrings**, and how to reverse strings.

2.3.1 Accessing Individual Characters

The positions within a string are numbered, starting from zero. To access a position within a string, we specify the position inside square brackets:

```
>>> msg = 'Hello World'
>>> msg[0]
'H'
>>> msg[3]
'l'
>>> msg[5]
 ' '
>>>
```

This is called **indexing** or **subscripting** the string. The position we specify inside the square brackets is called the **index**. We can retrieve not only letters but any character, such as the space at index 5.

Note

Be careful to distinguish between the string `' '`, which is a single whitespace character, and `''`, which is the empty string.

The fact that strings are indexed from zero may seem counter-intuitive. You might just want to think of indexes as giving you the position in a string immediately *before* a character, as indicated in Figure 2.1.

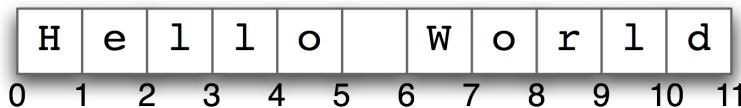


Figure 2.1: String Indexing

Now, what happens when we try to access an index that is outside of the string?

```
>>> msg[11]
Traceback (most recent call last):
  File "<stdin>", line 1, in ?
IndexError: string index out of range
>>>
```

The index of 11 is outside of the range of valid indices (i.e., 0 to 10) for the string '`Hello World`'. This results in an error message. This time it is not a syntax error; the program fragment is syntactically correct. Instead, the error occurred while the program was running. The `Traceback` message indicates which line the error occurred on (line 1 of “standard input”). It is followed by the name of the error, `IndexError`, and a brief explanation.

In general, how do we know what we can index up to? If we know the length of the string is n , the highest valid index will be $n - 1$. We can get access to the length of the string using the built-in `len()` function.

```
>>> len(msg)
11
>>>
```

Informally, a **function** is a named snippet of code that provides a service to our program when we **call** or execute it by name. We call the `len()` function by putting parentheses after the name and giving it the string `msg` we want to know the length of. Because `len()` is built into the Python interpreter, IDLE colors it purple.

We have seen what happens when the index is too large. What about when it is too small? Let’s see what happens when we use values less than zero:

```
>>> msg[-1]
'd'
>>>
```

This does not generate an error. Instead, negative indices work from the *end* of the string, so -1 indexes the last character, which is '`d`'.

```
>>> msg[-3]
'r'
>>> msg[-6]
,
>>>
```

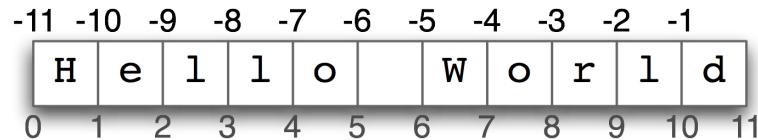


Figure 2.2: Negative Indices

Now the computer works out the location in memory relative to the string's address plus its length, subtracting the index, e.g. $3136 + 11 - 1 = 3146$. We can also visualize negative indices as shown in [Figure 2.2](#).

Thus we have two ways to access the characters in a string, from the start or the end. For example, we can access the space in the middle of Hello and World with either `msg[5]` or `msg[-6]`; these refer to the same location, because $5 = \text{len}(\text{msg}) - 6$.

2.3.2 Accessing Substrings

In NLP we usually want to access more than one character at a time. This is also pretty simple; we just need to specify a start and end index. For example, the following code accesses the substring starting at index 1, up to (but not including) index 4:

```
>>> msg[1:4]
'ell'
>>>
```

The notation `:4` is known as a **slice**. Here we see the characters are '`e`', '`l`' and '`l`' which correspond to `msg[1]`, `msg[2]` and `msg[3]`, but not `msg[4]`. This is because a slice *starts* at the first index but finishes *one before* the end index. This is consistent with indexing: indexing also starts from zero and goes up to *one before* the length of the string. We can see this by slicing with the value of `len()`:

```
>>> len(msg)
11
>>> msg[0:11]
'Hello World'
>>>
```

We can also slice with negative indices — the same basic rule of starting from the start index and stopping one before the end index applies; here we stop before the space character:

```
>>> msg[0:-6]
'Hello'
>>>
```

Python provides two shortcuts for commonly used slice values. If the start index is 0 then you can leave it out, and if the end index is the length of the string then you can leave it out:

```
>>> msg[:3]
'Hel'
>>> msg[6:]
'World'
>>>
```

The first example above selects the first three characters from the string, and the second example selects from the character with index 6, namely '`W`', to the end of the string.

2.3.3 Exercises

1. ☀ Define a string `s = 'colorless'`. Write a Python statement that changes this to “colourless” using only the slice and concatenation operations.
2. ☀ Try the slice examples from this section using the interactive interpreter. Then try some more of your own. Guess what the result will be before executing the command.
3. ☀ We can use the slice notation to remove morphological endings on words. For example, '`dogs`' `[:-1]` removes the last character of `dogs`, leaving `dog`. Use slice notation to remove the affixes from these words (we've inserted a hyphen to indicate the affix boundary, but omit this from your strings): `dish-es`, `run-ning`, `nation-ality`, `un-do`, `pre-heat`.
4. ☀ We saw how we can generate an `IndexError` by indexing beyond the end of a string. Is it possible to construct an index that goes too far to the left, before the start of the string?
5. ☀ We can also specify a “step” size for the slice. The following returns every second character within the slice, in a forward or reverse direction:

```
>>> msg[6:11:2]
'Wrrd'
>>> msg[10:5:-2]
'drW'
>>>
```

Experiment with different step values.

6. ☀ What happens if you ask the interpreter to evaluate `msg [::-1]`? Explain why this is a reasonable result.

2.4 Strings, Sequences, and Sentences

We have seen how words like `Hello` can be stored as a string '`Hello`'. Whole sentences can also be stored in strings, and manipulated as before, as we can see here for Chomsky's famous [nonsense sentence](#):

```
>>> sent = 'colorless green ideas sleep furiously'
>>> sent[16:21]
'ideas'
>>> len(sent)
37
>>>
```

However, it turns out to be a bad idea to treat a sentence as a sequence of its characters, because this makes it too inconvenient to access the words. Instead, we would prefer to represent a sentence as a sequence of its *words*; as a result, indexing a sentence accesses the words, rather than characters. We will see how to do this now.

2.4.1 Lists

A **list** is designed to store a sequence of values. A list is similar to a string in many ways except that individual items don't have to be just characters; they can be arbitrary strings, integers or even other lists.

A Python list is represented as a sequence of comma-separated items, delimited by square brackets. Here are some lists:

```
>>> squares = [1, 4, 9, 16, 25, 36, 49, 64, 81, 100]
>>> shopping_list = ['juice', 'muffins', 'bleach', 'shampoo']
```

We can also store sentences and phrases using lists. Let's create part of Chomsky's sentence as a list and put it in a variable `cgi`:

```
>>> cgi = ['colorless', 'green', 'ideas']
>>> cgi
['colorless', 'green', 'ideas']
>>>
```

Because lists and strings are both kinds of sequence, they can be processed in similar ways; just as strings support `len()`, indexing and slicing, so do lists. The following example applies these familiar operations to the list `cgi`:

```
>>> len(cgi)
3
>>> cgi[0]
'colorless'
>>> cgi[-1]
'ideas'
>>> cgi[-5]
Traceback (most recent call last):
  File "<stdin>", line 1, in ?
IndexError: list index out of range
>>>
```

Here, `cgi[-5]` generates an error, because the fifth-last item in a three item list would occur before the list started, i.e., it is undefined. We can also slice lists in exactly the same way as strings:

```
>>> cgi[1:3]
['green', 'ideas']
>>> cgi[-2:]
['green', 'ideas']
>>>
```

Lists can be concatenated just like strings. Here we will put the resulting list into a new variable `chomsky`. The original variable `cgi` is not changed in the process:

```
>>> chomsky = cgi + ['sleep', 'furiously']
>>> chomsky
['colorless', 'green', 'ideas', 'sleep', 'furiously']
>>> cgi
['colorless', 'green', 'ideas']
>>>
```

Now, lists and strings do not have exactly the same functionality. Lists have the added power that you can change their elements. Let's imagine that we want to change the 0th element of `cgi` to '`colorful`', we can do that by assigning the new value to the index `cgi[0]`:

```
>>> cgi[0] = 'colorful'
>>> cgi
['colorful', 'green', 'ideas']
>>>
```

On the other hand if we try to do that with a *string* — changing the 0th character in `msg` to '`J`' — we get:

```
>>> msg[0] = 'J'
Traceback (most recent call last):
  File "<stdin>", line 1, in ?
TypeError: object does not support item assignment
>>>
```

This is because strings are **immutable** — you can't change a string once you have created it. However, lists are **mutable**, and their contents can be modified at any time. As a result, lists support a number of operations, or **methods**, that modify the original value rather than returning a new value. A method is a function that is associated with a particular object. A method is called on the object by giving the object's name, then a period, then the name of the method, and finally the parentheses containing any arguments. For example, in the following code we use the `sort()` and `reverse()` methods:

```
>>> chomsky.sort()
>>> chomsky.reverse()
>>> chomsky
['sleep', 'ideas', 'green', 'furiously', 'colorless']
>>>
```

As you will see, the prompt reappears immediately on the line after `chomsky.sort()` and `chomsky.reverse()`. That is because these methods do not produce a new list, but instead modify the original list stored in the variable `chomsky`.

Lists also have an `append()` method for adding items to the end of the list and an `index()` method for finding the index of particular items in the list:

```
>>> chomsky.append('said')
>>> chomsky.append('Chomsky')
>>> chomsky
['sleep', 'ideas', 'green', 'furiously', 'colorless', 'said', 'Chomsky']
>>> chomsky.index('green')
2
>>>
```

Finally, just as a reminder, you can create lists of any values you like. As you can see in the following example for a lexical entry, the values in a list do not even have to have the same type (though this is usually not a good idea, as we will explain in [Section 6.2](#)).

```
>>> bat = ['bat', [[1, 'n', 'flying mammal'], [2, 'n', 'striking instrument']]]
>>>
```

2.4.2 Working on Sequences One Item at a Time

We have shown you how to create lists, and how to index and manipulate them in various ways. Often it is useful to step through a list and process each item in some way. We do this using a `for` loop. This is our first example of a **control structure** in Python, a statement that *controls* how other statements are run:

```
>>> for num in [1, 2, 3]:
...     print 'The number is', num
...
The number is 1
The number is 2
The number is 3
```

The interactive interpreter changes the prompt from `>>>` to `...` after encountering the colon at the end of the first line. This prompt indicates that the interpreter is expecting an indented block of code to appear next. However, it is up to you to do the indentation. To finish the indented block just enter a blank line.

The `for` loop has the general form: `for variable in sequence` followed by a colon, then an indented block of code. The first time through the loop, the variable is assigned to the first item in the sequence, i.e. `num` has the value 1. This program runs the statement `print 'The number is', num` for this value of `num`, before returning to the top of the loop and assigning the second item to the variable. Once all items in the sequence have been processed, the loop finishes.

Now let's try the same idea with a list of words:

```
>>> chomsky = ['colorless', 'green', 'ideas', 'sleep', 'furiously']
>>> for word in chomsky:
...     print len(word), word[-1], word
...
9 s colorless
5 n green
5 s ideas
5 p sleep
9 y furiously
```

The first time through this loop, the variable is assigned the value '`colorless`'. This program runs the statement `print len(word), word[-1], word` for this value, to produce the output line: 9 s `colorless`. This process is known as **iteration**. Each iteration of the `for` loop starts by assigning the next item of the list `chomsky` to the **loop variable** `word`. Then the indented **body** of the loop is run. Here the body consists of a single command, but in general the body can contain as many lines of code as you want, so long as they are all indented by the same amount. (We recommend that you always use exactly 4 spaces for indentation, and that you never use tabs.)

We can run another `for` loop over the Chomsky nonsense sentence, and calculate the average word length. As you will see, this program uses the `len()` function in two ways: to count the number of characters in a word, and to count the number of words in a phrase. Note that `x += y` is shorthand for `x = x + y`; this idiom allows us to **increment** the total variable each time the loop is run.

```
>>> total = 0
>>> for word in chomsky:
...     total += len(word)
...
```

```
>>> total / len(chomsky)
6
>>>
```

We can also write `for` loops to iterate over the characters in strings. This `print` statement ends with a trailing comma, which is how we tell Python not to print a newline at the end.

```
>>> sent = 'colorless green ideas sleep furiously'
>>> for char in sent:
...     print char,
...
colorless green ideas sleep furiously
>>>
```

A note of caution: we have now iterated over words and characters, using expressions like `for word in sent:` and `for char in sent:`. Remember that, to Python, `word` and `char` are meaningless variable names, and we could just as well have written `for foo123 in sent:`. The interpreter simply iterates over the items in the sequence, quite oblivious to what kind of object they represent, e.g.:

```
>>> for foo123 in 'colorless green ideas sleep furiously':
...     print foo123,
...
colorless green ideas sleep furiously
>>> for foo123 in ['colorless', 'green', 'ideas', 'sleep', 'furiously']:
...     print foo123,
...
colorless green ideas sleep furiously
>>>
```

However, you should try to choose 'sensible' names for loop variables because it will make your code more readable.

2.4.3 String Formatting

The output of a program is usually structured to make the information easily digestible by a reader. Instead of running some code and then manually inspecting the contents of a variable, we would like the code to tabulate some output. We already saw this above in the first `for` loop example that used a list of words, where each line of output was similar to `5 p sleep`, consisting of a word length, the last character of the word, then the word itself.

There are many ways we might want to format such output. For instance, we might want to place the length value in parentheses *after* the word, and print all the output on a single line:

```
>>> for word in chomsky:
...     print word, '(', len(word), ')',
colorless ( 9 ), green ( 5 ), ideas ( 5 ), sleep ( 5 ), furiously ( 9 ),
>>>
```

However, this approach has a couple of problems. First, the `print` statement intermingles variables and punctuation, making it a little difficult to read. Second, the output has spaces around every item that was printed. A cleaner way to produce structured output uses Python's **string formatting expressions**. Before diving into clever formatting tricks, however, let's look at a really simple example.

We are going to use a special symbol, `%s`, as a placeholder in strings. Once we have a string containing this placeholder, we follow it with a single `%` and then a value `v`. Python then returns a new string where `v` has been slotted in to replace `%s`:

```
>>> "I want a %s right now" % "coffee"
'I want a coffee right now'
>>>
```

In fact, we can have a number of placeholders, but following the `%` operator we need to put in a tuple with exactly the same number of values:

```
>>> "%s wants a %s %s" % ("Lee", "sandwich", "for lunch")
'Lee wants a sandwich for lunch'
>>>
```

We can also provide the values for the placeholders indirectly. Here's an example using a `for` loop:

```
>>> menu = ['sandwich', 'spam fritter', 'pancake']
>>> for snack in menu:
...     "Lee wants a %s right now" % snack
...
'Lee wants a sandwich right now'
'Lee wants a spam fritter right now'
'Lee wants a pancake right now'
>>>
```

We oversimplified things when we said that placeholders were of the form `%s`; in fact, this is a complex object, called a **conversion specifier**. This has to start with the `%` character, and ends with conversion character such as `s` or `'d`. The `%s` specifier tells Python that the corresponding variable is a string (or should be converted into a string), while the `%d` specifier indicates that the corresponding variable should be converted into a decimal representation. The string containing conversion specifiers is called a **format string**.

Picking up on the `print` example that we opened this section with, here's how we can use two different kinds of conversion specifier:

```
>>> for word in chomsky:
...     print "%s (%d)," % (word, len(word)),
colorless (9), green (5), ideas (5), sleep (5), furiously (9),
>>>
```

To summarize, string formatting is accomplished with a three-part object having the syntax: `format % values`. The `format` section is a string containing format specifiers such as `%s` and `%d` that Python will replace with the supplied values. The `values` section of a formatting string is a tuple containing exactly as many items as there are format specifiers in the `format` section. In the case that there is just one item, the parentheses can be left out. (We will discuss Python's string-formatting expressions in more detail in [Section 6.3.2](#)).

In the above example, we used a trailing comma to suppress the printing of a newline. Suppose, on the other hand, that we want to introduce some additional newlines in our output. We can accomplish this by inserting the “special” character `\n` into the `print` string:

```

>>> for word in chomsky:
...     print "Word = %s\nIndex = %s\n*****" % (word, chomsky.index(word))
...
Word = colorless
Index = 0
*****
Word = green
Index = 1
*****
Word = ideas
Index = 2
*****
Word = sleep
Index = 3
*****
Word = furiously
Index = 4
*****
>>>

```

2.4.4 Converting Between Strings and Lists

Often we want to convert between a string containing a space-separated list of words and a list of strings. Let's first consider turning a list into a string. One way of doing this is as follows:

```

>>> s =
>>> for word in chomsky:
...     s += ' ' + word
...
>>> s
' colorless green ideas sleep furiously'
>>>

```

One drawback of this approach is that we have an unwanted space at the start of `s`. It is more convenient to use the `join()` method. We specify the string to be used as the “glue”, followed by a period, followed by the `join()` function.

```

>>> sent = ' '.join(chomsky)
>>> sent
'colorless green ideas sleep furiously'
>>>

```

So `' '.join(chomsky)` means: take all the items in `chomsky` and concatenate them as one big string, using `' '` as a spacer between the items.

Now let's try to reverse the process: that is, we want to convert a string into a list. Again, we could start off with an empty list `[]` and `append()` to it within a `for` loop. But as before, there is a more succinct way of achieving the same goal. This time, we will *split* the new string `sent` on whitespace:

To consolidate your understanding of joining and splitting strings, let's try the same thing using a semicolon as the separator:

```

>>> sent = ';' .join(chomsky)
>>> sent
'colorless;green;ideas;sleep;furiously'

```

```
>>> sent.split(';')
['colorless', 'green', 'ideas', 'sleep', 'furiously']
>>>
```

To be honest, many people find the notation for `join()` rather unintuitive. There is another function for converting lists to strings, again called `join()` which is called directly on the list. It uses whitespace by default as the “glue”. However, we need to explicitly **import** this function into our code. One way of doing this is as follows:

```
>>> import string
>>> string.join(chomsky)
'colorless green ideas sleep furiously'
>>>
```

Here, we imported something called `string`, and then called the function `string.join()`. In passing, if we want to use something other than whitespace as “glue”, we just specify this as a second parameter:

```
>>> string.join(chomsky, ';')
'colorless;green;ideas;sleep;furiously'
>>>
```

We will see other examples of statements with `import` later in this chapter. In general, we use `import` statements when we want to get access to Python code that doesn’t already come as part of core Python. This code will exist somewhere as one or more files. Each such file corresponds to a Python **module** — this is a way of grouping together code and data that we regard as reusable. When you write down some Python statements in a file, you are in effect creating a new Python module. And you can make your code depend on another module by using the `import` statement. In our example earlier, we imported the module `string` and then used the `join()` function from that module. By adding `string.` to the beginning of `join()`, we make it clear to the Python interpreter that the definition of `join()` is given in the `string` module. An alternative, and equally valid, approach is to use the `from module import identifier` statement, as shown in the next example:

```
>>> from string import join
>>> join(chomsky)
'colorless green ideas sleep furiously'
>>>
```

In this case, the name `join` is added to all the other identifier that we have defined in the body of our programme, and we can use it to call a function like any other.

Note

If you are creating a file to contain some of your Python code, do *not* name your file `nltk.py`: it may get imported in place of the “real” NLTK package. (When it imports modules, Python first looks in the current folder / directory.)

2.4.5 Mini-Review

Strings and lists are both kind of **sequence**. As such, they can both be indexed and sliced:

```

>>> query = 'Who knows?'
>>> beatles = ['john', 'paul', 'george', 'ringo']
>>> query[2]
'o'
>>> beatles[2]
'george'
>>> query[:2]
'Wh'
>>> beatles[:2]
['john', 'paul']
>>>

```

Similarly, strings can be concatenated and so can lists (though not with each other!):

```

>>> newstring = query + " I don't"
>>> newlist = beatles + ['brian', 'george']

```

What's the difference between strings and lists as far as NLP is concerned? As we will see in [Chapter 3](#), when we open a file for reading into a Python program, what we get initially is a string, corresponding to the contents of the whole file. If we try to use a `for` loop to process the elements of this string, all we can pick out are the individual characters in the string — we don't get to choose the granularity. By contrast, the elements of a list can be as big or small as we like: for example, they could be paragraphs, sentence, phrases, words, characters. So lists have this huge advantage, that we can be really flexible about the elements they contain, and correspondingly flexible about what the downstream processing will act on. So one of the first things we are likely to do in a piece of NLP code is convert a string into a list (of strings). Conversely, when we want to write our results to a file, or to a terminal, we will usually convert them to a string.

2.4.6 Exercises

1. ◊ Using the Python interactive interpreter, experiment with the examples in this section. Think of a sentence and represent it as a list of strings, e.g. ['Hello', 'world']. Try the various operations for indexing, slicing and sorting the elements of your list. Extract individual items (strings), and perform some of the string operations on them.
2. ◊ Split `sent` on some other character, such as '`s`'.
3. ◊ We pointed out that when `phrase` is a list, `phrase.reverse()` returns a modified version of `phrase` rather than a new list. On the other hand, we can use the slice trick mentioned in the exercises for the previous section, `[: :-1]` to create a *new* reversed list without changing `phrase`. Show how you can confirm this difference in behavior.
4. ◊ We have seen how to represent a sentence as a list of words, where each word is a sequence of characters. What does `phrase1[2][2]` do? Why? Experiment with other index values.
5. ◊ Write a `for` loop to print out the characters of a string, one per line.
6. ◊ What is the difference between calling `split` on a string with no argument or with '' as the argument, e.g. `sent.split()` versus `sent.split(' ')`? What happens when the string being split contains tab characters, consecutive space characters, or a sequence of tabs and spaces? (In IDLE you will need to use '`\t`' to enter a tab character.)

7. ☀ Create a variable `words` containing a list of words. Experiment with `words.sort()` and `sorted(words)`. What is the difference?
8. ☀ Earlier, we asked you to use a text editor to create a file called `test.py`, containing the single line `msg = 'Hello World'`. If you haven't already done this (or can't find the file), go ahead and do it now. Next, start up a new session with the Python interpreter, and enter the expression `msg` at the prompt. You will get an error from the interpreter. Now, try the following (note that you have to leave off the `.py` part of the filename):

```
>>> from test import msg  
>>> msg
```

This time, Python should return with a value. You can also try `import test`, in which case Python should be able to evaluate the expression `test.msg` at the prompt.

9. ⚪ Process the list `chomsky` using a `for` loop, and store the result in a new list `lengths`. Hint: begin by assigning the empty list to `lengths`, using `lengths = []`. Then each time through the loop, use `append()` to add another length value to the list.
10. ⚪ Define a variable `silly` to contain the string: `'newly formed bland ideas are inexpressible in an infuriating way'`. (This happens to be the legitimate interpretation that bilingual English-Spanish speakers can assign to Chomsky's famous phrase, according to Wikipedia). Now write code to perform the following tasks:
 - a) Split `silly` into a list of strings, one per word, using Python's `split()` operation, and save this to a variable called `bland`.
 - b) Extract the second letter of each word in `silly` and join them into a string, to get `'eoldrnna'`.
 - c) Combine the words in `bland` back into a single string, using `join()`. Make sure the words in the resulting string are separated with whitespace.
 - d) Print the words of `silly` in alphabetical order, one per line.
11. ⚪ The `index()` function can be used to look up items in sequences. For example, `'inexpressible'.index('e')` tells us the index of the first position of the letter `e`.
 - a) What happens when you look up a substring, e.g. `'inexpressible'.index('re')`?
 - b) Define a variable `words` containing a list of words. Now use `words.index()` to look up the position of an individual word.
 - c) Define a variable `silly` as in the exercise above. Use the `index()` function in combination with list slicing to build a list `phrase` consisting of all the words up to (but not including) `in` in `silly`.

2.5 Making Decisions

So far, our simple programs have been able to manipulate sequences of words, and perform some operation on each one. We applied this to lists consisting of a few words, but the approach works the same for lists of arbitrary size, containing thousands of items. Thus, such programs have some interesting qualities: (i) the ability to work with language, and (ii) the potential to save human effort through automation. Another useful feature of programs is their ability to *make decisions* on our behalf; this is our focus in this section.

2.5.1 Making Simple Decisions

Most programming languages permit us to execute a block of code when a **conditional expression**, or **if** statement, is satisfied. In the following program, we have created a variable called `word` containing the string value '`'cat'`'. The `if` statement then checks whether the condition `len(word) < 5` is true. Because the conditional expression is true, the body of the `if` statement is invoked and the `print` statement is executed.

```
>>> word = "cat"
>>> if len(word) < 5:
...     print 'word length is less than 5'
...
word length is less than 5
>>>
```

If we change the conditional expression to `len(word) >= 5`, to check that the length of `word` is greater than or equal to 5, then the conditional expression will no longer be true, and the body of the `if` statement will not be run:

```
>>> if len(word) >= 5:
...     print 'word length is greater than or equal to 5'
...
>>>
```

The `if` statement, just like the `for` statement above is a **control structure**. An `if` statement is a control structure because it controls whether the code in the body will be run. You will notice that both `if` and `for` have a colon at the end of the line, before the indentation begins. That's because all Python control structures end with a colon.

What if we want to do something when the conditional expression is not true? The answer is to add an `else` clause to the `if` statement:

```
>>> if len(word) >= 5:
...     print 'word length is greater than or equal to 5'
... else:
...     print 'word length is less than 5'
...
word length is less than 5
>>>
```

Finally, if we want to test multiple conditions in one go, we can use an `elif` clause that acts like an `else` and an `if` combined:

```
>>> if len(word) < 3:
...     print 'word length is less than three'
... elif len(word) == 3:
...     print 'word length is equal to three'
... else:
...     print 'word length is greater than three'
...
word length is equal to three
>>>
```

It's worth noting that in the condition part of an `if` statement, a nonempty string or list is evaluated as true, while an empty string or list evaluates as false.

```
>>> mixed = ['cat', '', ['dog'], []]
>>> for element in mixed:
...     if element:
...         print element
...
cat
['dog']
```

That is, we *don't* need to say `if element is True:` in the condition.

What's the difference between using `if...elif` as opposed to using a couple of `if` statements in a row? Well, consider the following situation:

```
>>> animals = ['cat', 'dog']
>>> if 'cat' in animals:
...     print 1
... elif 'dog' in animals:
...     print 2
...
1
>>>
```

Since the `if` clause of the statement is satisfied, Python never tries to evaluate the `elif` clause, so we never get to print out 2. By contrast, if we replaced the `elif` by an `if`, then we would print out both 1 and 2. So an `elif` clause potentially gives us more information than a bare `if` clause; when it evaluates to true, it tells us not only that the condition is satisfied, but also that the condition of the main `if` clause was *not* satisfied.

2.5.2 Conditional Expressions

Python supports a wide range of operators like `<` and `>=` for testing the relationship between values. The full set of these **relational operators** are shown in Table [Inequalities](#).

Operator	Relationship
<code><</code>	less than
<code><=</code>	less than or equal to
<code>==</code>	equal to (note this is two not one = sign)
<code>!=</code>	not equal to

Operator	Relationship
>	greater than
>=	greater than or equal to

Table 2.1:

Conditional Expressions

Normally we use conditional expressions as part of an `if` statement. However, we can test these relational operators directly at the prompt:

```
>>> 3 < 5
True
>>> 5 < 3
False
>>> not 5 < 3
True
>>>
```

Here we see that these expressions have **Boolean** values, namely `True` or `False`. `not` is a Boolean operator, and flips the truth value of Boolean statement.

Strings and lists also support conditional operators:

```
>>> word = 'sovereignty'
>>> 'sovereign' in word
True
>>> 'gnt' in word
True
>>> 'pre' not in word
True
>>> 'Hello' in ['Hello', 'World']
True
>>> 'Hell' in ['Hello', 'World']
False
>>>
```

Strings also have methods for testing what appears at the beginning and the end of a string (as opposed to just anywhere in the string):

```
>>> word.startswith('sovereign')
True
>>> word.endswith('ty')
True
>>>
```

2.5.3 Iteration, Items, and `if`

Now it is time to put some of the pieces together. We are going to take the string '`how now brown cow`' and print out all of the words ending in '`ow`'. Let's build the program up in stages. The first step is to split the string into a list of words:

```
>>> sentence = 'how now brown cow'
>>> words = sentence.split()
>>> words
['how', 'now', 'brown', 'cow']
>>>
```

Next, we need to iterate over the words in the list. Just so we don't get ahead of ourselves, let's print each word, one per line:

```
>>> for word in words:
...     print word
...
how
now
brown
cow
```

The next stage is to only print out the words if they end in the string '`'ow'`'. Let's check that we know how to do this first:

```
>>> 'how'.endswith('ow')
True
>>> 'brown'.endswith('ow')
False
>>>
```

Now we are ready to put an `if` statement inside the `for` loop. Here is the complete program:

```
>>> sentence = 'how now brown cow'
>>> words = sentence.split()
>>> for word in words:
...     if word.endswith('ow'):
...         print word
...
how
now
cow
>>>
```

As you can see, even with this small amount of Python knowledge it is possible to develop useful programs. The key idea is to develop the program in pieces, testing that each one does what you expect, and then combining them to produce whole programs. This is why the Python interactive interpreter is so invaluable, and why you should get comfortable using it.

2.5.4 A Taster of Data Types

Integers, strings and lists are all kinds of **data types** in Python, and have types `int`, `str` and `list` respectively. In fact, every value in Python has a type. Python's `type()` function will tell you what an object's type is:

```
>>> oddments = ['cat', 'cat'.index('a'), 'cat'.split()]
>>> for e in oddments:
...     type(e)
...
```

```
<type 'str'>
<type 'int'>
<type 'list'>
>>>
```

The type determines what operations you can perform on the data value. So, for example, we have seen that we can index strings and lists, but we can't index integers:

```
>>> one = 'cat'
>>> one[0]
'c'
>>> two = [1, 2, 3]
>>> two[1]
2
>>> three = 1234
>>> three[2]
Traceback (most recent call last):
  File "<pyshell#95>", line 1, in <toplevel>
    three[2]
TypeError: 'int' object is unsubscriptable
>>>
```

The fact that this is a problem with types is signalled by the class of error, i.e., `TypeError`; an object being “unscriptable” means we can't index into it.

Similarly, we can concatenate strings with strings, and lists with lists, but we cannot concatenate strings with lists:

```
>>> query = 'Who knows?'
>>> beatles = ['john', 'paul', 'george', 'ringo']
>>> query + beatles
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: cannot concatenate 'str' and 'list' objects
>>>
```

You may also have noticed that our analogy between operations on strings and numbers at the beginning of this chapter broke down pretty soon:

```
>>> 'Hi' * 3
'HiHiHi'
>>> 'Hi' - 'i'
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unsupported operand type(s) for -: 'str' and 'str'
>>> 6 / 2
3
>>> 'Hi' / 2
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unsupported operand type(s) for /: 'str' and 'int'
>>>
```

These error messages are another example of Python telling us that we have got our data types in a muddle. In the first case, we are told that the operation of subtraction (i.e., `-`) cannot apply to objects of type `str`, while in the second, we are told that division cannot take `str` and `int` as its two operands.

2.5.5 Exercises

1. ☀ Assign a new value to `sentence`, namely the string '`'she sells sea shells by the sea shore'`', then write code to perform the following tasks:
 - a) Print all words beginning with '`'sh'`:
 - b) Print all words longer than 4 characters.
 - c) Generate a new sentence that adds the popular hedge word '`'like'`' before every word beginning with '`'se'`'. Your result should be a single string.
2. ☀ Write code to abbreviate text by removing all the vowels. Define `sentence` to hold any string you like, then initialize a new string `result` to hold the empty string '`''`. Now write a `for` loop to process the string, one character at a time, and append any non-vowel characters to the result string.
3. ☀ We pointed out that when empty strings and empty lists occur in the condition part of an `if` clause, they evaluate to false. In this case, they are said to be occurring in a **Boolean context**. Experiment with different kind of non-Boolean expressions in Boolean contexts, and see whether they evaluate as true or false.
4. ☀ Review conditional expressions, such as '`'row' in 'brown'`' and '`'row' in ['brown', 'cow']`'.
 - a) Define `sent` to be the string '`'colorless green ideas sleep furiously'`', and use conditional expressions to test for the presence of particular words or substrings.
 - b) Now define `words` to be a list of words contained in the sentence, using `sent.split()`, and use conditional expressions to test for the presence of particular words or substrings.
5. ⚡ Write code to convert text into `hAck3r`, where characters are mapped according to the following table:

Input:	e	i	o	l	s	.	ate
Output:	3	1	0	l	5	5w33t!	8

Table 2.2:

2.6 Getting Organized

Strings and lists are a simple way to organize data. In particular, they **map** from integers to values. We can “look up” a character in a string using an integer, and we can look up a word in a list of words using an integer. These cases are shown in [Figure 2.3](#).

However, we need a more flexible way to organize and access our data. Consider the examples in [Figure 2.4](#).

In the case of a phone book, we look up an entry using a *name*, and get back a number. When we type a domain name in a web browser, the computer looks this up to get back an IP address. A word

String		List	
0	g	0	colorless
1	r	1	green
2	e	2	ideas
3	e	3	sleep
4	n	4	furiously

Figure 2.3: Sequence Look-up

Phone List	
Alex	x154
Dana	x642
Kim	x911
Les	x120
Sandy	x124

Domain Name Resolution	
aclweb.org	128.231.23.4
amazon.com	12.118.92.43
google.com	28.31.23.124
pythonb.org	18.21.3.144
sourceforge.net	51.98.23.53

Word Frequency Table	
computational	25
language	196
linguistics	17
natural	56
processing	57

Figure 2.4: Dictionary Look-up

frequency table allows us to look up a word and find its frequency in a text collection. In all these cases, we are mapping from names to numbers, rather than the other way round as with indexing into sequences. In general, we would like to be able to map between arbitrary types of information. Table [linguistic-objects](#) lists a variety of linguistic objects, along with what they map.

Linguistic Object	Maps	
	from	to
Document Index	Word	List of pages (where word is found)
Thesaurus	Word sense	List of synonyms
Dictionary	Headword	Entry (part of speech, sense definitions, etymology)
Comparative Wordlist	Gloss term	Cognates (list of words, one per language)
Morph Analyzer	Surface form	Morphological analysis (list of component morphemes)

Table 2.3:

Linguistic Objects as Mappings from Keys to Values

Most often, we are mapping from a string to some structured object. For example, a document index maps from a word (which we can represent as a string), to a list of pages (represented as a list of integers). In this section, we will see how to represent such mappings in Python.

2.6.1 Accessing Data with Data

Python provides a **dictionary** data type that can be used for mapping between arbitrary types.

Note

Bird, A Python dictionary is somewhat like a linguistic dictionary — they both give you a systematic means of looking things up, and so there is some potential for confusion. However, we hope that it will usually be clear from the context which kind of dictionary we are talking about.

Here we define `pos` to be an empty dictionary and then add three entries to it, specifying the part-of-speech of some words. We add entries to a dictionary using the familiar square bracket notation:

```
>>> pos = {}
```

```
>>> pos['ideas']
'n'
>>> pos['colorless']
'adj'
>>>
```

The item used for look-up is called the **key**, and the data that is returned is known as the **value**. As with indexing a list or string, we get an exception when we try to access the value of a key that does not exist:

```
>>> pos['missing']
Traceback (most recent call last):
  File "<stdin>", line 1, in ?
KeyError: 'missing'
>>>
```

This raises an important question. Unlike lists and strings, where we can use `len()` to work out which integers will be legal indices, how do we work out the legal keys for a dictionary? Fortunately, we can check whether a key exists in a dictionary using the `in` operator:

```
>>> 'colorless' in pos
True
>>> 'missing' in pos
False
>>> 'missing' not in pos
True
>>>
```

Notice that we can use `not in` to check if a key is *missing*. Be careful with the `in` operator for dictionaries: it only applies to the keys and not their values. If we check for a value, e.g. `'adj' in pos`, the result is `False`, since `'adj'` is not a key. We can loop over all the entries in a dictionary using a `for` loop.

```
>>> for word in pos:
...     print "%s (%s)" % (word, pos[word])
...
colorless (adj)
furiously (adv)
ideas (n)
>>>
```

We can see what the contents of the dictionary look like by inspecting the variable `pos`. Note the presence of the colon character to separate each key from its corresponding value:

```
>>> pos
{'furiously': 'adv', 'ideas': 'n', 'colorless': 'adj'}
>>>
```

Here, the contents of the dictionary are shown as **key-value pairs**. As you can see, the order of the key-value pairs is different from the order in which they were originally entered. This is because dictionaries are not sequences but mappings. The keys in a mapping are not inherently ordered, and any ordering that we might want to impose on the keys exists independently of the mapping. As we shall see later, this gives us a lot of flexibility.

We can use the same key-value pair format to create a dictionary:

```
>>> pos = {'furiously': 'adv', 'ideas': 'n', 'colorless': 'adj'}
>>>
```

Using the dictionary methods `keys()`, `values()` and `items()`, we can access the keys and values as separate lists, and also the key-value pairs:

```
>>> pos.keys()
['colorless', 'furiously', 'ideas']
>>> pos.values()
['adj', 'adv', 'n']
>>> pos.items()
[('colorless', 'adj'), ('furiously', 'adv'), ('ideas', 'n')]
>>> for (key, val) in pos.items():
...     print "%s ==> %s" % (key, val)
...
colorless ==> adj
furiously ==> adv
ideas ==> n
>>>
```

Note that keys are forced to be unique. Suppose we try to use a dictionary to store the fact that the word *content* is both a noun and a verb:

```
>>> pos['content'] = 'n'
>>> pos['content'] = 'v'
>>> pos
{'content': 'v', 'furiously': 'adv', 'ideas': 'n', 'colorless': 'adj'}
>>>
```

Initially, `pos['content']` is given the value '`n`', and this is immediately overwritten with the new value '`v`'. In other words, there is only one entry for '`content`'. If we wanted to store multiple values in that entry, we could use a list, e.g. `pos['content'] = ['n', 'v']`.

2.6.2 Counting with Dictionaries

The values stored in a dictionary can be any kind of object, not just a string — the values can even be dictionaries. The most common kind is actually an integer. It turns out that we can use a dictionary to store **counters** for many kinds of data. For instance, we can have a counter for all the letters of the alphabet; each time we get a certain letter we increment its corresponding counter:

```
>>> phrase = 'colorless green ideas sleep furiously'
>>> count = {}
>>> for letter in phrase:
...     if letter not in count:
...         count[letter] = 0
...     count[letter] += 1
>>> count
{'a': 1, ' ': 4, 'c': 1, 'e': 6, 'd': 1, 'g': 1, 'f': 1, 'i': 2,
 'l': 4, 'o': 3, 'n': 1, 'p': 1, 's': 5, 'r': 3, 'u': 2, 'y': 1}
>>>
```

Observe that `in` is used here in two different ways: `for letter in phrase` iterates over every letter, running the body of the `for` loop. Inside this loop, the conditional expression `if`

letter `not in` count checks whether the letter is missing from the dictionary. If it is missing, we create a new entry and set its value to zero: `count[letter] = 0`. Now we are sure that the entry exists, and it may have a zero or non-zero value. We finish the body of the `for` loop by incrementing this particular counter using the `+=` assignment operator. Finally, we print the dictionary, to see the letters and their counts. This method of maintaining many counters will find many uses, and you will become very familiar with it. To make counting much easier, we can use `defaultdict`, a special kind of container introduced in Python 2.5. This is also included in NLTK for the benefit of readers who are using Python 2.4, and can be imported as shown below.

```
>>> phrase = 'colorless green ideas sleep furiously'
>>> from nltk import defaultdict
>>> count = defaultdict(int)
>>> for letter in phrase:
...     count[letter] += 1
>>> count
{'a': 1, ' ': 4, 'c': 1, 'e': 6, 'd': 1, 'g': 1, 'f': 1, 'i': 2,
 'l': 4, 'o': 3, 'n': 1, 'p': 1, 's': 5, 'r': 3, 'u': 2, 'y': 1}
>>>
```

Note

Calling `defaultdict(int)` creates a special kind of dictionary. When that dictionary is accessed with a non-existent key — i.e. the first time a particular letter is encountered — then `int()` is called to produce the initial value for this key (i.e. 0). You can test this by running the above code, then typing `count['X']` and seeing that it returns a zero value (and not a `KeyError` as in the case of normal Python dictionaries). The function `defaultdict` is very handy and will be used in many places later on.

There are other useful ways to display the result, such as sorting alphabetically by the letter:

```
>>> sorted(count.items())
[(' ', 4), ('a', 1), ('c', 1), ('d', 1), ('e', 6), ('f', 1), ...,
... ('y', 1)]
>>>
```

Note

The function `sorted()` is similar to the `sort()` method on sequences, but rather than sorting in-place, it produces a new sorted copy of its argument. Moreover, as we will see very soon, `sorted()` will work on a wider variety of data types, including dictionaries.

2.6.3 Getting Unique Entries

Sometimes, we don't want to count at all, but just want to make a record of the items that we have seen, regardless of repeats. For example, we might want to compile a vocabulary from a document. This is a sorted list of the words that appeared, regardless of frequency. At this stage we have two ways to do this. The first uses lists.

```
>>> sentence = "she sells sea shells by the sea shore".split()
>>> words = []
```

```
>>> for word in sentence:
...     if word not in words:
...         words.append(word)
...
>>> sorted(words)
['by', 'sea', 'sells', 'she', 'shells', 'shore', 'the']
>>>
```

There is a better way to do this task using Python's `set` data type. We can convert `sentence` into a set, using `set(sentence)`:

```
>>> set(sentence)
set(['shells', 'sells', 'shore', 'she', 'sea', 'the', 'by'])
>>>
```

The order of items in a set is not significant, and they will usually appear in a different order to the one they were entered in. The main point here is that converting a list to a set removes any duplicates. We convert it back into a list, sort it, and print. Here is the complete program:

```
>>> sentence = "she sells sea shells by the sea shore".split()
>>> sorted(set(sentence))
['by', 'sea', 'sells', 'she', 'shells', 'shore', 'the']
```

Here we have seen that there is sometimes more than one way to solve a problem with a program. In this case, we used three different built-in data types, a list, a dictionary, and a set. The `set` data type mostly closely modeled our task, so it required the least amount of work.

2.6.4 Scaling Up

We can use dictionaries to count word occurrences. For example, the following code uses NLTK's corpus reader to load *Macbeth* and count the frequency of each word. Before we can use NLTK we need to tell Python to load it, using the statement `import nltk`.

```
>>> import nltk
>>> count = nltk.defaultdict(int)                                # initialize a dictionary
>>> for word in nltk.corpus.gutenberg.words('shakespeare-macbeth.txt'): # tokenize Macbeth
...     word = word.lower()                                         # normalize to lowercase
...     count[word] += 1                                            # increment the counter
...
>>>
```

You will learn more about accessing corpora in [Section 3.2.3](#). For now, you just need to know that `gutenberg.words()` returns a list of words, in this case from Shakespeare's play *Macbeth*, and we are iterating over this list using a `for` loop. We convert each word to lowercase using the string method `word.lower()`, and use a dictionary to maintain a set of counters, one per word. Now we can inspect the contents of the dictionary to get counts for particular words:

```
>>> count['scotland']
12
>>> count['the']
692
>>>
```

2.6.5 Exercises

1. ☀ Review the mappings in Table [linguistic-objects](#). Discuss any other examples of mappings you can think of. What type of information do they map from and to?
2. ☀ Using the Python interpreter in interactive mode, experiment with the examples in this section. Create a dictionary `d`, and add some entries. What happens if you try to access a non-existent entry, e.g. `d['xyz']`?
3. ☀ Try deleting an element from a dictionary, using the syntax `del d['abc']`. Check that the item was deleted.
4. ☀ Create a dictionary `e`, to represent a single lexical entry for some word of your choice. Define keys like `headword`, `part-of-speech`, `sense`, and `example`, and assign them suitable values.
5. ☀ Create two dictionaries, `d1` and `d2`, and add some entries to each. Now issue the command `d1.update(d2)`. What did this do? What might it be useful for?
6. ⚡ Write a program that takes a sentence expressed as a single string, splits it and counts up the words. Get it to print out each word and the word's frequency, one per line, in alphabetical order.

2.7 Regular Expressions

For a moment, imagine that you are editing a large text, and you have strong dislike of repeated occurrences of the word `very`. How could you find all such cases in the text? To be concrete, let's suppose that we assign the following text to the variable `s`:

```
>>> s = """Google Analytics is very very very nice (now)
... By Jason Hoffman 18 August 06
... Google Analytics, the result of Google's acquisition of the San
... Diego-based Urchin Software Corporation, really really opened its
... doors to the world a couple of days ago, and it allows you to
... track up to 10 sites within a single google account.
...
>>>
```

Python's triple quotes `"""` are used here since they allow us to break a string across lines.

One approach to our task would be to convert the string into a list, and look for adjacent items that are both equal to the string `'very'`. We use the `range(n)` function in this example to create a list of consecutive integers from 0 up to, but not including, `n`:

```
>>> text = s.split()
>>> for n in range(len(text)):
...     if text[n] == 'very' and text[n+1] == 'very':
...         print n, n+1
...
3 4
4 5
>>>
```

However, such an approach is not very flexible or convenient. In this section, we will present Python's **regular expression** module `re`, which supports powerful search and substitution inside strings. As a gentle introduction, we will start out using a utility function `re_show()` to illustrate how regular expressions match against substrings. `re_show()` takes two arguments, a pattern that it is looking for, and a string in which the pattern might occur.

```
>>> import nltk
>>> nltk.re_show('very very', s)
Google Analytics is {very very} very nice (now)
...
>>>
```

(We have only displayed the first part of `s` that is returned, since the rest is irrelevant for the moment.) As you can see, `re_show` places curly braces around the first occurrence it has found of the string '`very very`'. So an important part of what `re_show` is doing is searching for any substring of `s` that **matches** the pattern in its first argument.

Now we might want to modify the example so that `re_show` highlights cases where there are two *or more* adjacent sequences of '`very`'. To do this, we need to use a **regular expression operator**, namely '`+`'. If `s` is a string, then `s+` means: 'match one or more occurrences of `s`'. Let's first look at the case where `s` is a single character, namely the letter '`o`':

```
>>> nltk.re_show('o+', s)
G{o}ogle Analytics is very very very nice (n{o}w)
...
>>>
```

'`o+`' is our first proper regular expression. You can think of it as matching an *infinite set* of strings, namely the set {'`o`', '`oo`', '`ooo`', ...}. But we would really like to match sequences of least two '`o`'s; for this, we need the regular expression '`oo+`', which matches any string consisting of '`o`' followed by one or more occurrences of `o`.

```
>>> nltk.re_show('oo+', s)
G{o}ogle Analytics is very very very nice (now)
...
>>>
```

Let's return to the task of identifying multiple occurrences of '`very`'. Some initially plausible candidates won't do what we want. For example, '`very+`' would match '`veryyyy`' (but not '`very very`'), since the `+` scopes over the immediately preceding expression, in this case '`y`'. To widen the scope of `+`, we need to use parentheses, as in '`(very)+`'. Will this match '`very very`'? No, because we've forgotten about the whitespace between the two words; instead, it will match strings like '`veryvery`'. However, the following *does* work:

```
>>> nltk.re_show('(very\s)+', s)
Google Analytics is {very very very }nice (now)
>>>
```

Characters preceded by a `\`, such as '`\s`', have a special interpretation inside regular expressions; thus, '`\s`' matches a whitespace character. We could have used '`\s`' in our pattern, but '`\s`' is better practice in general. One reason is that the sense of "whitespace" we are using is more general than you might have imagined; it includes not just inter-word spaces, but also tabs and newlines. If you try to inspect the variable `s`, you might initially get a shock:

```
>>> s
"Google Analytics is very very very nice (now)\nBy Jason Hoffman
18 August 06\nGoogle
...
>>>
```

You might recall that '`\n`' is a special character that corresponds to a newline in a string. The following example shows how newline is matched by '`\s`'.

```
>>> s2 = "I'm very very\nvery happy"
>>> nltk.re_show('very\s', s2)
I'm {very }{very
}{very }happy
>>>
```

Python's `re.findall(patt, s)` function is a useful way to find all the substrings in `s` that are matched by `patt`. Before illustrating, let's introduce two further special characters, '`\d`' and '`\w`': the first will match any digit, and the second will match any alphanumeric character. Before we can use `re.findall()` we have to load Python's regular expression module, using `import re`.

```
>>> import re
>>> re.findall('\d\d', s)
['18', '06', '10']
>>> re.findall('\s\w\w\w\s', s)
[' the ', ' the ', ' its\n', ' the ', ' and ', ' you ']
>>>
```

As you will see, the second example matches three-letter words. However, this regular expression is not quite what we want. First, the leading and trailing spaces are extraneous. Second, it will fail to match against strings such as '`the San`', where two three-letter words are adjacent. To solve this problem, we can use another special character, namely '`\b`'. This is sometimes called a “zero-width” character; it matches against the empty string, but only at the beginning and end of words:

```
>>> re.findall(r'\b\w\w\w\b', s)
['now', 'the', 'the', 'San', 'its', 'the', 'ago', 'and', 'you']
```

Note

This example uses a Python **raw string**: `r'\b\w\w\w\b'`. The specific justification here is that in an ordinary string, `\b` is interpreted as a backspace character. Python will convert it to a backspace in a regular expression unless you use the `r` prefix to create a raw string as shown above. Another use for raw strings is to match strings that include backslashes. Suppose we want to match 'either`\or`'. In order to create a regular expression, the backslash needs to be escaped, since it is a special character; so we want to pass the pattern `\\\` to the regular expression interpreter. But to express this as a Python string literal, each backslash must be escaped again, yielding the string '`\\\\\`'. However, with a raw string, this reduces down to `r'\\\'`.

Returning to the case of repeated words, we might want to look for cases involving '`very`' or '`really`', and for this we use the disjunction operator `|`.

```
>>> nltk.re_show(' ((very|really)\s)+', s)
Google Analytics is {very very very }nice (now)
By Jason Hoffmann 18 August 06
Google Analytics, the result of Google's acquisition of the San
Diego-based Urchin Software Corporation, {really really }opened its
doors to the world a couple of days ago, and it allows you to
track up to 10 sites within a single google account.
```

>>>

In addition to the matches just illustrated, the regular expression '`((very|really)\s)+`' will also match cases where the two disjuncts occur with each other, such as the string '`really very
really`'.

Let's now look at how to perform substitutions, using the `re.sub()` function. In the first instance we replace all instances of `l` with `s`. Note that this generates a string as output, and doesn't modify the original string. Then we replace any instances of `green` with `red`.

```
>>> sent = "colorless green ideas sleep furiously"
>>> re.sub('l', 's', sent)
'cosorsess green ideas sseep furioussy'
>>> re.sub('green', 'red', sent)
'colorless red ideas sleep furiously'
>>>
```

We can also disjoin individual characters using a square bracket notation. For example, `[aeiou]` matches any of `a`, `e`, `i`, `o`, or `u`, that is, any vowel. The expression `[^aeiou]` matches any single character that is *not* a vowel. In the following example, we match sequences consisting of a non-vowel followed by a vowel.

```
>>> nltk.re_show(' [^aeiou][aeiou]', sent)
{co}{lo}r{le}ss g{re}en{ i}{de}as s{le}ep {fu}{ri}ously
>>>
```

Using the same regular expression, the function `re.findall()` returns a list of all the substrings in `sent` that are matched:

```
>>> re.findall(' [^aeiou][aeiou]', sent)
['co', 'lo', 'le', 're', ' i', 'de', 'le', 'fu', 'ri']
>>>
```

2.7.1 Groupings

Returning briefly to our earlier problem with unwanted whitespace around three-letter words, we note that `re.findall()` behaves slightly differently if we create **groups** in the regular expression using parentheses; it only returns strings that occur within the groups:

```
>>> re.findall('\s(\w\w\w)\s', s)
['the', 'the', 'its', 'the', 'and', 'you']
>>>
```

The same device allows us to select only the non-vowel characters that appear before a vowel:

```
>>> re.findall(' ([^aeiou])[aeiou]', sent)
['c', 'l', 'l', 'r', ' ', 'd', 'l', 'f', 'r']
>>>
```

By delimiting a second group in the regular expression, we can even generate pairs (or **tuples**) that we may then go on and tabulate.

```
>>> re.findall('(^aeiou)([aeiou])', sent)
[('c', 'o'), ('l', 'o'), ('l', 'e'), ('r', 'e'), (' ', 'i'),
 ('d', 'e'), ('l', 'e'), ('f', 'u'), ('r', 'i')]
>>>
```

Our next example also makes use of groups. One further special character is the so-called wildcard element, '`.`'; this has the distinction of matching any single character (except '`\n`'). Given the string `s3`, our task is to pick out login names and email domains:

```
>>> s3 = """
... <hart@vmd.cso.uiuc.edu>
... Final editing was done by Martin Ward <Martin.Ward@uk.ac.durham>
... Michael S. Hart <hart@pobox.com>
... Prepared by David Price, email <ccx074@coventry.ac.uk>"""
>>>
```

The task is made much easier by the fact that all the email addresses in the example are delimited by angle brackets, and we can exploit this feature in our regular expression:

```
>>> re.findall(r'<(.+)>(.+)', s3)
[('hart', 'vmd.cso.uiuc.edu'), ('Martin.Ward', 'uk.ac.durham'),
 ('hart', 'pobox.com'), ('ccx074', 'coventry.ac.uk')]
>>>
```

Since '`.`' matches any single character, '`.+`' will match any non-empty *string* of characters, including punctuation symbols such as the period.

One question that might occur to you is how do we specify a match against a period? The answer is that we have to place a '`\`' immediately before the '`.`' in order to escape its special interpretation.

```
>>> re.findall(r'(\w+\.)', s3)
['vmd.', 'cso.', 'uiuc.', 'Martin.', 'uk.', 'ac.', 's.',
 'pobox.', 'coventry.', 'ac.']
>>>
```

Now, let's suppose that we wanted to match occurrences of both '`Google`' and '`google`' in our sample text. If you have been following up till now, you would reasonably expect that this regular expression with a disjunction would do the trick: '`(G|g)oole`'. But look what happens when we try this with `re.findall()`:

```
>>> re.findall('(G|g)oole', s)
['G', 'G', 'G', 'g']
>>>
```

What is going wrong? We innocently used the parentheses to indicate the scope of the operator '`|`', but `re.findall()` has interpreted them as marking a group. In order to tell `re.findall()` "don't try to do anything special with these parentheses", we need an extra piece of notation:

```
>>> re.findall('(?:G|g)oole', s)
['Google', 'Google', 'Google', 'google']
>>>
```

Placing '`?:`' immediately after the opening parenthesis makes it explicit that the parentheses are just being used for scoping.

2.7.2 Practice Makes Perfect

Regular expressions are very flexible and very powerful. However, they often don't do what you expect. For this reason, you are strongly encouraged to try out a variety of tasks using `re_show()` and `re.findall()` in order to develop your intuitions further; the exercises below should help get you started. We suggest that you build up a regular expression in small pieces, rather than trying to get it completely right first time. Here are some operators and sequences that are commonly used in natural language processing.

Commonly-used Operators and Sequences	
*	Zero or more, e.g. <code>a*</code> , <code>[a-z]*</code>
+	One or more, e.g. <code>a+</code> , <code>[a-z] +</code>
?	Zero or one (i.e. optional), e.g. <code>a?</code> , <code>[a-z] ?</code>
[...]	A set or range of characters, e.g. <code>[aeiou]</code> , <code>[a-z0-9]</code>
(...)	Grouping parentheses, e.g. <code>(the a an)</code>
\b	Word boundary (zero width)
\d	Any decimal digit (<code>\D</code> is any non-digit)
\s	Any whitespace character (<code>\S</code> is any non-whitespace character)
\w	Any alphanumeric character (<code>\W</code> is any non-alphanumeric character)
\t	The tab character
\n	The newline character

Table 2.4:

2.7.3 Exercises

1. ♦ Describe the class of strings matched by the following regular expressions. Note that '
*' means: match zero or more occurrences of the preceding regular expression.

- a) `[a-zA-Z] +`
- b) `[A-Z] [a-z] *`
- c) `\d+ (\.\d+)?`
- d) `([bcdfghjklmnpqrstvwxyz] [aeiou] [bcdfghjklmnpqrstvwxyz]) *`
- e) `\w+ | [^\w\s] +`

Test your answers using `re_show()`.

2. ♦ Write regular expressions to match the following classes of strings:

- a) A single determiner (assume that *a*, *an*, and *the* are the only determiners).
- b) An arithmetic expression using integers, addition, and multiplication, such as $2 * 3 + 8$.

3. (●) The above example of extracting (name, domain) pairs from text does not work when there is more than one email address on a line, because the `+` operator is “greedy” and consumes too much of the input.

- Experiment with input text containing more than one email address per line, such as that shown below. What happens?
- Using `re.findall()`, write another regular expression to extract email addresses, replacing the period character with a range or negated range, such as `[a-z]+` or `[^>]+`.
- Now try to match email addresses by changing the regular expression `.+` to its “non-greedy” counterpart, `.+?`

```
>>> s = """
... austen-emma.txt:hart@vmd.cso.uiuc.edu (internet) hart@uiucvmd (bitnet)
... austen-emma.txt:Internet (72600.2026@compuserve.com); TEL: (212-254-5093)
... austen-persuasion.txt:Editing by Martin Ward (Martin.Ward@uk.ac.durham)
... blake-songs.txt:Prepared by David Price, email ccx074@coventry.ac.uk
...
... """
```

- (●) Write code to convert text into Pig Latin. This involves two steps: move any consonant (or consonant cluster) that appears at the start of the word to the end, then append `ay`, e.g. `string` → `ingstray`, `idle` → `idleay`. http://en.wikipedia.org/wiki/Pig_Latin
- (●) Write code to convert text into `hAck3r` again, this time using regular expressions and substitution, where `e` → 3, `i` → 1, `o` → 0, `l` → 1, `s` → 5, `.` → 5w33t!, `ate` → 8. Normalize the text to lowercase before converting it. Add more substitutions of your own. Now try to map `s` to two different values: `$` for word-initial `s`, and 5 for word-internal `s`.
- ★ Read the Wikipedia entry on *Soundex*. Implement this algorithm in Python.

2.8 Summary

- Text is represented in Python using strings, and we type these with single or double quotes: `'Hello', "World".`
- The characters of a string are accessed using indexes, counting from zero: `'Hello World'[1]` gives the value `e`. The length of a string is found using `len()`.
- Substrings are accessed using slice notation: `'Hello World'[1:5]` gives the value `ello`. If the start index is omitted, the substring begins at the start of the string; if the end index is omitted, the slice continues to the end of the string.
- Sequences of words are represented in Python using lists of strings: `['colorless', 'green', 'ideas']`. We can use indexing, slicing and the `len()` function on lists.
- Strings can be split into lists: `'Hello World'.split()` gives `['Hello', 'World']`. Lists can be joined into strings: `'/'.join(['Hello', 'World'])` gives `'Hello/World'`.

- Lists can be sorted in-place: `words.sort()`. To produce a separate, sorted copy, use: `sorted(words)`.
- We process each item in a string or list using a `for` statement: `for word in phrase`. This must be followed by the colon character and an indented block of code, to be executed each time through the loop.
- We test a condition using an `if` statement: `if len(word) < 5`. This must be followed by the colon character and an indented block of code, to be executed only if the condition is true.
- A dictionary is used to map between arbitrary types of information, such as a string and a number: `freq['cat'] = 12`. We create dictionaries using the brace notation: `pos = {}`, `pos = {'furioulsly': 'adv', 'ideas': 'n', 'colorless': 'adj'}`.
- Some functions are not available by default, but must be accessed using Python's `import` statement.
- Regular expressions are a powerful and flexible method of specifying patterns. Once we have imported the `re` module, we can use `re.findall()` to find all substrings in a string that match a pattern, and we can use `re.sub()` to replace substrings of one sort with another.

2.9 Further Reading

2.9.1 Python

Two freely available online texts are the following:

- Josh Cogliati, *Non-Programmer's Tutorial for Python*, http://en.wikibooks.org/wiki/Non-Programmer's_Tutorial_for_Python
- Allen B. Downey, Jeffrey Elkner and Chris Meyers, *How to Think Like a Computer Scientist: Learning with Python*, <http://www.ibiblio.org/obp/thinkCSpy/>

An Introduction to Python [?] is a Python tutorial by Guido van Rossum, the inventor of Python and Fred L. Drake, Jr., the official editor of the Python documentation. It is available online at <http://docs.python.org/tut/tut.html>. A more detailed but still introductory text is [?], which covers the essential features of Python, and also provides an overview of the standard libraries.

[?] is a succinct reference book; although not suitable as an introduction to Python, it is an excellent resource for intermediate and advanced programmers.

Finally, it is always worth checking the official *Python Documentation* at <http://docs.python.org/>.

2.9.2 Regular Expressions

There are many references for regular expressions, both practical and theoretical. [?] is a comprehensive and detailed manual in using regular expressions, covering their syntax in most major programming languages, including Python.

For an introductory tutorial to using regular expressions in Python with the `re` module, see A. M. Kuchling, *Regular Expression HOWTO*, <http://www.amk.ca/python/howto/regex/>.

Chapter 3 of [?] provides a more extended tutorial on Python's facilities for text processing with regular expressions.

<http://www.regular-expressions.info/> is a useful online resource, providing a tutorial and references to tools and other sources of information.

About this document...

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Chapter 3

Words: The Building Blocks of Language

3.1 Introduction

Language can be divided up into pieces of varying sizes, ranging from morphemes to paragraphs. In this chapter we will focus on words, the most fundamental level for NLP. Just what are words, and how should we represent them in a machine? These questions may seem trivial, but we'll see that there are some important issues involved in defining and representing words. Once we've tackled them, we're in a good position to do further processing, such as find related words and analyze the style of a text (this chapter), to categorize words (Chapter 4), to group them into phrases (Chapter 7 and Part II), and to do a variety of data-intensive language processing tasks (Chapter 5).

In the following sections, we will explore the division of text into words; the distinction between types and tokens; sources of text data including files, the web, and linguistic corpora; accessing these sources using Python and NLTK; stemming and normalization; the WordNet lexical database; and a variety of useful programming tasks involving words.

Note

From this chapter onwards, our program samples will assume you begin your interactive session or your program with: `import nltk, re, pprint`

3.2 Tokens, Types and Texts

In Chapter 1, we showed how a string could be split into a list of words. Once we have derived a list, the `len()` function will count the number of words it contains:

```
>>> sentence = "This is the time -- and this is the record of the time."
>>> words = sentence.split()
>>> len(words)
13
```

This process of segmenting a string of characters into words is known as **tokenization**. Tokenization is a prelude to pretty much everything else we might want to do in NLP, since it tells our processing software what our basic units are. We will discuss tokenization in more detail shortly.

We also pointed out that we could compile a list of the unique vocabulary items in a string by using `set()` to eliminate duplicates:

```
>>> len(set(words))
10
```

So if we ask how many words there are in `sentence`, we get different answers depending on whether we count duplicates. Clearly we are using different senses of “word” here. To help distinguish between them, let’s introduce two terms: **token** and **type**. A word token is an individual occurrence of a word in a concrete context; it exists in time and space. A word **type** is a more abstract; it’s what we’re talking about when we say that the three occurrences of `the` in `sentence` are “the same word.”

Something similar to a type-token distinction is reflected in the following snippet of Python:

```
>>> words[2]
'the'
>>> words[2] == words[8]
True
>>> words[2] is words[8]
False
>>> words[2] is words[2]
True
```

The operator `==` tests whether two expressions are equal, and in this case, it is testing for string-identity. This is the notion of identity that was assumed by our use of `set()` above. By contrast, the `is` operator tests whether two objects are stored in the same location of memory, and is therefore analogous to token-identity. When we used `split()` to turn a string into a list of words, our tokenization method was to say that any strings that are delimited by whitespace count as a word token. But this simple approach doesn’t always give the desired results. Also, testing string-identity isn’t a very useful criterion for assigning tokens to types. We therefore need to address two questions in more detail: *Tokenization*: Which substrings of the original text should be treated as word tokens? *Type definition*: How do we decide whether two tokens have the same type?

To see the problems with our first stab at defining tokens and types in `sentence`, let’s look at the actual tokens we found:

```
>>> set(words)
set(['and', 'this', 'record', 'This', 'of', 'is', '--', 'time.', 'time', 'the'])
```

Observe that `'time'` and `'time.'` are incorrectly treated as distinct types since the trailing period has been bundled with the rest of the word. Although `--` is some kind of token, it’s not a *word* token. Additionally, `'This'` and `'this'` are incorrectly distinguished from each other, because of a difference in capitalization that should be ignored.

If we turn to languages other than English, tokenizing text is even more challenging. In Chinese text there is no visual representation of word boundaries. Consider the following three-character string: 爱国人 (in pinyin plus tones: ai4 “love” (verb), guo3 “country”, ren2 “person”). This could either be segmented as [爱国]人, “country-loving person” or as 爱[国人], “love country-person.”

The terms *token* and *type* can also be applied to other linguistic entities. For example, a **sentence token** is an individual occurrence of a sentence; but a **sentence type** is an abstract sentence, without context. If I say the same sentence twice, I have uttered two sentence tokens but only used one sentence type. When the kind of token or type is obvious from context, we will simply use the terms token and type.

To summarize, we cannot just say that two word tokens have the same type if they are the same string of characters. We need to consider a variety of factors in determining what counts as the same word, and we need to be careful in how we identify tokens in the first place.

Up till now, we have relied on getting our source texts by defining a string in a fragment of Python code. However, this is impractical for all but the simplest of texts, and makes it hard to present realistic examples. So how do we get larger chunks of text into our programs? In the rest of this section, we will see how to extract text from files, from the web, and from the corpora distributed with NLTK.

3.2.1 Extracting Text from Files

It is easy to access local files in Python. As an exercise, create a file called `corpus.txt` using a text editor, and enter the following text:

```
Hello World!
This is a test file.
```

Be sure to save the file as plain text. You also need to make sure that you have saved the file in the same directory or folder in which you are running the Python interactive interpreter.

Note

If you are using IDLE, you can easily create this file by selecting the *New Window* command in the *File* menu, typing the required text into this window, and then saving the file as `corpus.txt` in the first directory that IDLE offers in the pop-up dialogue box.

The next step is to **open** a file using the built-in function `open()` which takes two arguments, the name of the file, here `corpus.txt`, and the mode to open the file with (`'r'` means to open the file for reading, and `'U'` stands for “Universal”, which lets us ignore the different conventions used for marking newlines).

```
>>> f = open('corpus.txt', 'rU')
```

Note

If the interpreter cannot find your file, it will give an error like this:

```
>>> f = open('corpus.txt', 'rU')
Traceback (most recent call last):
  File "<pyshell#7>", line 1, in -toplevel-
    f = open('corpus.txt', 'rU')
IOError: [Errno 2] No such file or directory: 'corpus.txt'
```

To check that the file that you are trying to open is really in the right directory, use IDLE’s *Open* command in the *File* menu; this will display a list of all the files in the directory where IDLE is running. An alternative is to examine the current directory from within Python:

```
>>> import os
>>> os.listdir('./')
```

There are several methods for reading the file. The following uses the method `read()` on the file object `f`; this reads the entire contents of a file into a string.

```
>>> f.read()
'Hello World!\nThis is a test file.\n'
```

Recall that the '`\n`' characters are **newlines**; this is equivalent to pressing *Enter* on a keyboard and starting a new line. Note that we can open and read a file in one step:

```
>>> text = open('corpus.txt', 'rU').read()
```

We can also read a file one line at a time using the `for` loop construct:

```
>>> f = open('corpus.txt', 'rU')
>>> for line in f:
...     print line[:-1]
Hello world!
This is a test file.
```

Here we use the slice `[:-1]` to remove the newline character at the end of the input line.

3.2.2 Extracting Text from the Web

Opening a web page is not much different to opening a file, except that we use `urlopen()`:

```
>>> from urllib import urlopen
>>> page = urlopen("http://news.bbc.co.uk/").read()
>>> print page[:60]
<!doctype html public "-//W3C//DTD HTML 4.0 Transitional//EN
```

Web pages are usually in HTML format. To extract the text, we need to strip out the HTML markup, i.e. remove all material enclosed in angle brackets. Let's digress briefly to consider how to carry out this task using regular expressions. Our first attempt might look as follows:

```
>>> line = '<title>BBC NEWS | News Front Page</title>'
>>> new = re.sub(r'<.*>', '', line)
```

So the regular expression '`<.*>`' is intended to match a pair of left and right angle brackets, with a string of any characters intervening. However, look at what the result is:

```
>>> new
''
```

What has happened here? The problem is twofold. First, the wildcard '`.`' matches any character other than '`\n`', so it will match '`>`' and '`<`'. Second, the '`*`' operator is "greedy", in the sense that it matches as many characters as it can. In the above example, '`.*`' will return not the shortest match, namely '`title`', but the longest match, '`title>BBC NEWS | News Front Page</title`'. To get the *shortest* match we have to use the '`*?`' operator. We will also normalize whitespace, replacing any sequence of spaces, tabs or newlines ('`\s+`') with a single space character.

```
>>> page = re.sub('<.*?>', '', page)
>>> page = re.sub('\s+', ' ', page)
>>> print page[:60]
BBC NEWS | News Front Page News Sport Weather World Service
```

Note

Note that your output for the above code may differ from ours, because the BBC home page may have been changed since this example was created.

You will probably find it useful to borrow the structure of the above code snippet for future tasks involving regular expressions: each time through a series of substitutions, the result of operating on `page` gets assigned as the new value of `page`. This approach allows us to decompose the transformations we need into a series of simple regular expression substitutions, each of which can be tested and debugged on its own.

Note

Getting text out of HTML is a sufficiently common task that NLTK provides a helper function `nltk.clean_html()`, which takes an HTML string and returns text.

3.2.3 Extracting Text from NLTK Corpora

NLTK is distributed with several corpora and corpus samples and many are supported by the `corpus` package. Here we use a selection of texts from the [Project Gutenberg](#) electronic text archive, and list the files it contains:

```
>>> nltk.corpus.gutenberg.files()
('austen-emma.txt', 'austen-persuasion.txt', 'austen-sense.txt', 'bible-kjv.txt',
'blake-poems.txt', 'blake-songs.txt', 'chesterton-ball.txt', 'chesterton-brown.txt',
'chesterton-thursday.txt', 'milton-paradise.txt', 'shakespeare-caesar.txt',
'shakespeare-hamlet.txt', 'shakespeare-macbeth.txt', 'whitman-leaves.txt')
```

We can count the number of tokens for each text in our Gutenberg sample as follows:

```
>>> for book in nltk.corpus.gutenberg.files():
...     print book + ':', len(nltk.corpus.gutenberg.words(book))
austen-emma.txt: 192432
austen-persuasion.txt: 98191
austen-sense.txt: 141586
bible-kjv.txt: 1010735
blake-poems.txt: 8360
blake-songs.txt: 6849
chesterton-ball.txt: 97396
chesterton-brown.txt: 89090
chesterton-thursday.txt: 69443
milton-paradise.txt: 97400
shakespeare-caesar.txt: 26687
shakespeare-hamlet.txt: 38212
shakespeare-macbeth.txt: 23992
whitman-leaves.txt: 154898
```

The Brown Corpus was the first million-word, part-of-speech tagged electronic corpus of English, created in 1961 at Brown University. Each of the sections `a` through `r` represents a different genre, as shown in [Table 3.1](#).

Sec	Genre	Sec	Genre	Sec	Genre
a	Press: Reportage	b	Press: Editorial	c	Press: Reviews
d	Religion	e	Skill and Hobbies	f	Popular Lore
g	Belles-Lettres	h	Government	j	Learned
k	Fiction: General	k	Fiction: General	l	Fiction: Mystery
m	Fiction: Science	n	Fiction: Adventure	p	Fiction: Romance

Sec	Genre	Sec	Genre	Sec	Genre
r	Humor				

Table 3.1: Sections of the Brown Corpus

We can access the corpus as a list of words, or a list of sentences (where each sentence is itself just a list of words). We can optionally specify a section of the corpus to read:

```
>>> nltk.corpus.brown.categories()
['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'j', 'k', 'l', 'm', 'n', 'p', 'r']
>>> nltk.corpus.brown.words(categories='a')
['The', 'Fulton', 'County', 'Grand', 'Jury', 'said', ...]
>>> nltk.corpus.brown.sents(categories='a')
[['The', 'Fulton', 'County'...], ['The', 'jury', 'further'...], ...]
```

NLTK comes with corpora for many languages, though in some cases you will need to learn how to manipulate character encodings in Python before using these corpora.

Before concluding this section, we return to the original topic of distinguishing tokens and types. Now that we can access substantial quantities of text, we will give a preview of the interesting computations we will be learning how to do (without yet explaining all the details). Listing 3.1 computes vocabulary growth curves for US Presidents, shown in Figure 3.1 (a color figure in the online version). These curves show the number of word types seen after n word tokens have been read.

Note

[Listing 3.1](#) uses the PyLab package which supports sophisticated plotting functions with a MATLAB-style interface. For more information about this package please see <http://matplotlib.sourceforge.net/>. The listing also uses the `yield` statement, which will be explained in [Chapter 6](#).

3.2.4 Exercises

1. ☀ Create a small text file, and write a program to read it and print it with a line number at the start of each line. (Make sure you don't introduce an extra blank line between each line.)
 2. ☀ Use the corpus module to read `austen-persuasion.txt`. How many word tokens does this book have? How many word types?

Listing 3.1 Vocabulary Growth in State-of-the-Union Addresses

```

def vocab_growth(text):
    vocabulary = set()
    for text in texts:
        for word in text:
            vocabulary.add(word)
            yield len(vocabulary)

def speeches():
    presidents = []
    texts = nltk.defaultdict(list)
    for speech in nltk.corpus.state_union.files():
        president = speech.split('-')[1]
        if president not in texts:
            presidents.append(president)
        texts[president].append(nltk.corpus.state_union.words(speech))
    return [(president, texts[president]) for president in presidents]

>>> import pylab
>>> for president, texts in speeches()[-7:]:
...     growth = list(vocab_growth(texts))[:10000]
...     pylab.plot(growth, label=president, linewidth=2)
>>> pylab.title('Vocabulary Growth in State-of-the-Union Addresses')
>>> pylab.legend(loc='lower right')
>>> pylab.show()

```

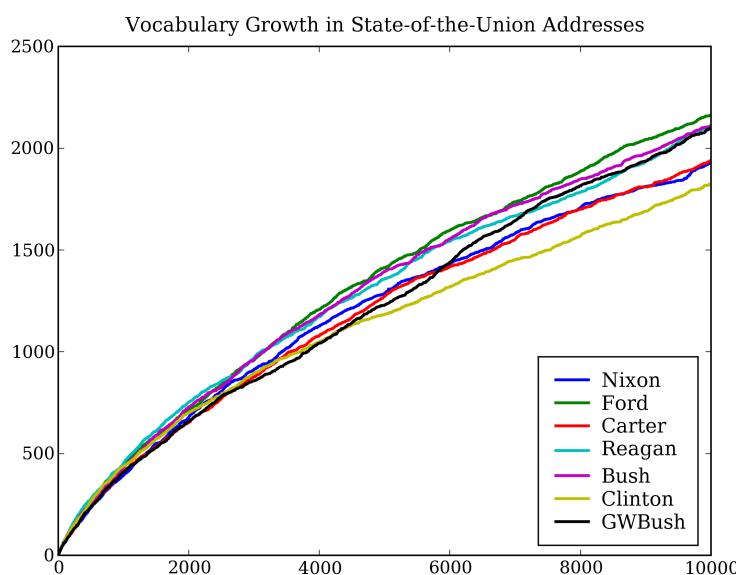


Figure 3.1: Vocabulary Growth in State-of-the-Union Addresses

3. ☀ Use the Brown corpus reader `nltk.corpus.brown.words()` or the Web text corpus reader `nltk.corpus.webtext.words()` to access some sample text in two different genres.
4. ☀ Use the Brown corpus reader `nltk.corpus.brown.sents()` to find sentence-initial examples of the word *however*. Check whether these conform to Strunk and White's prohibition against sentence-initial *however* used to mean "although".
5. ☀ Read in the texts of the *State of the Union* addresses, using the `state_union` corpus reader. Count occurrences of men, women, and people in each document. What has happened to the usage of these words over time?
6. ⓠ Write code to read a file and print the lines in reverse order, so that the last line is listed first.
7. ⓠ Read in some text from a corpus, tokenize it, and print the list of all *wh*-word types that occur. (*wh*-words in English are used in questions, relative clauses and exclamations: *who*, *which*, *what*, and so on.) Print them in order. Are any words duplicated in this list, because of the presence of case distinctions or punctuation?
8. ⓠ Write code to access a favorite webpage and extract some text from it. For example, access a weather site and extract the forecast top temperature for your town or city today.
9. ⓠ Write a function `unknown()` that takes a URL as its argument, and returns a list of unknown words that occur on that webpage. In order to do this, extract all substrings consisting of lowercase letters (using `re.findall()`) and remove any items from this set that occur in the words corpus (`nltk.corpus.words`). Try to categorize these words manually and discuss your findings.
10. ⓠ Examine the results of processing the URL `http://news.bbc.co.uk/` using the regular expressions suggested above. You will see that there is still a fair amount of non-textual data there, particularly Javascript commands. You may also find that sentence breaks have not been properly preserved. Define further regular expressions that improve the extraction of text from this web page.
11. ⓠ Take a copy of the `http://news.bbc.co.uk/` over three different days, say at two-day intervals. This should give you three different files, `bbc1.txt`, `bbc2.txt` and `bbc3.txt`, each corresponding to a different snapshot of world events. Collect the 100 most frequent word tokens for each file. What can you tell from the changes in frequency?
12. ⓠ Define a function `ghits()` that takes a word as its argument and builds a Google query string of the form `http://www.google.com/search?q=word`. Strip the HTML markup and normalize whitespace. Search for a substring of the form `Results 1 - 10 of about`, followed by some number *n*, and extract *n*. Convert this to an integer and return it.
13. ⓠ Try running the various chatbots included with NLTK, using `nltk.chat.demo()`. How *intelligent* are these programs? Take a look at the program code and see if you can discover how it works. You can find the code online at: <http://nltk.org/nltk/chat/>.

3.3 Text Processing with Unicode

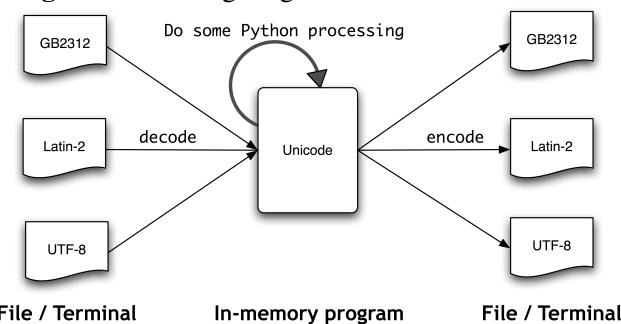
Our programs will often need to deal with different languages, and different character sets. The concept of “plain text” is a fiction. If you live in the English-speaking world you probably use ASCII, possibly without realizing it. If you live in Europe you might use one of the extended Latin character sets, containing such characters as “ø” for Danish and Norwegian, “ő” for Hungarian, “ñ” for Spanish and Breton, and “ň” for Czech and Slovak. In this section, we will give an overview of how to use Unicode for processing texts that use non-ASCII character sets.

3.3.1 What is Unicode?

Unicode supports over a million characters. Each of these characters is assigned a number, called a **code point**. In Python, code points are written in the form `\uXXXX`, where `XXXX` is the number in 4-digit hexadecimal form.

Within a program, Unicode code points can be manipulated directly, but when Unicode characters are stored in files or displayed on a terminal they must be encoded as one or more bytes. Some encodings (such as ASCII and Latin-2) use a single byte, so they can only support a small subset of Unicode, suited to a single language. Other encodings (such as UTF-8) use multiple bytes and can represent the full range of Unicode.

Text in files will be in a particular encoding, so we need some mechanism for translating it into Unicode — translation into Unicode is called **decoding**. Conversely, to write out Unicode to a file or a terminal, we first need to translate it into a suitable encoding — this translation out of Unicode is called **encoding**. The following diagram illustrates.



From a Unicode perspective, characters are abstract entities which can be realized as one or more **glyphs**. Only glyphs can appear on a screen or be printed on paper. A font is a mapping from characters to glyphs.

3.3.2 Extracting encoded text from files

Let’s assume that we have a small text file, and that we know how it is encoded. For example, `polish-lat2.txt`, as the name suggests, is a snippet of Polish text (from the Polish Wikipedia; see http://pl.wikipedia.org/wiki/Biblioteka_Pruska), encoded as Latin-2, also known as ISO-8859-2. The function `nltk.data.find()` locates the file for us.

```
>>> import nltk.data
>>> path = nltk.data.find('samples/polish-lat2.txt')
```

The Python `codecs` module provides functions to read encoded data into Unicode strings, and to write out Unicode strings in encoded form. The `codecs.open()` function takes an encoding

parameter to specify the encoding of the file being read or written. So let's import the `codecs` module, and call it with the encoding '`'latin2'`' to open our Polish file as Unicode.

```
>>> import codecs
>>> f = codecs.open(path, encoding='latin2')
```

For a list of encoding parameters allowed by `codecs`, see <http://docs.python.org/lib/standard-encodings.html>.

Text read from the file object `f` will be returned in Unicode. As we pointed out earlier, in order to view this text on a terminal, we need to encode it, using a suitable encoding. The Python-specific encoding `unicode_escape` is a dummy encoding that converts all non-ASCII characters into their `\uXXXX` representations. Code points above the ASCII 0-127 range but below 256 are represented in the two-digit form `\xXX`.

```
>>> lines = f.readlines()
>>> for l in lines:
...     l = l[:-1]
...     uni = l.encode('unicode_escape')
...     print uni
Pruska Biblioteka Pa\u0144stwowa. Jej dawne zbiory znane pod nazw\u0105 "Berlinka" to skarb kultury i sztuki niemieckiej. Przewiezione przez Niemc\xf3w pod koniec II wojny \u015bwiatowej na Dolny \u015al\u0105sk, zosta\u0142 odnalezione po 1945 r. na terytorium Polski. Trafi\u0142y do Biblioteki Jagiello\u0144skiej w Krakowie, obejmuj\u0105 ponad 500 tys. zabytkowych archiwali\xf3w, m.in. manuskrypty Goethego, Mozarta, Beethovena, Bacha.
```

The first line above illustrates a Unicode escape string, namely preceded by the `\u` escape string, namely `\u0144`. The relevant Unicode character will be displayed on the screen as the glyph ñ. In the third line of the preceding example, we see `\xf3`, which corresponds to the glyph ó, and is within the 128-255 range.

In Python, a Unicode string literal can be specified by preceding an ordinary string literal with a `u`, as in `u'hello'`. Arbitrary Unicode characters are defined using the `\uXXXX` escape sequence inside a Unicode string literal. We find the integer ordinal of a character using `ord()`. For example:

```
>>> ord('a')
97
```

The hexadecimal 4 digit notation for 97 is 0061, so we can define a Unicode string literal with the appropriate escape sequence:

```
>>> a = u'\u0061'
>>> a
u'a'
>>> print a
a
```

Notice that the Python `print` statement is assuming a default encoding of the Unicode character, namely ASCII. However, ñ is outside the ASCII range, so cannot be printed unless we specify an encoding. In the following example, we have specified that `print` should use the `repr()` of the string, which outputs the UTF-8 escape sequences (of the form `\xXX`) rather than trying to render the glyphs.

```
>>> nacute = u'\u0144'
>>> nacute
u'\u0144'
>>> nacute_utf = nacute.encode('utf8')
>>> print repr(nacute_utf)
'\xc5\x84'
```

If your operating system and locale are set up to render UTF-8 encoded characters, you ought to be able to give the Python command

```
print nacute_utf
```

and see ñ on your screen.

Note

There are many factors determining what glyphs are rendered on your screen. If you are sure that you have the correct encoding, but your Python code is still failing to produce the glyphs you expected, you should also check that you have the necessary fonts installed on your system.

The module `unicodedata` lets us inspect the properties of Unicode characters. In the following example, we select all characters in the third line of our Polish text outside the ASCII range and print their UTF-8 escaped value, followed by their code point integer using the standard Unicode convention (i.e., prefixing the hex digits with U+), followed by their Unicode name.

```
>>> import unicodedata
>>> line = lines[2]
>>> print line.encode('unicode_escape')
Niemc\xf3w pod koniec II wojny \u015bwiatowej na Dolny \u015al\u0105sk, zosta\u0142y\n
>>> for c in line:
...     if ord(c) > 127:
...         print '%r U+%04x %s' % (c.encode('utf8'), ord(c), unicodedata.name(c))
'\xc3\xb3' U+00f3 LATIN SMALL LETTER O WITH ACUTE
'\xc5\x9b' U+015b LATIN SMALL LETTER S WITH ACUTE
'\xc5\x9a' U+015a LATIN CAPITAL LETTER S WITH ACUTE
'\xc4\x85' U+0105 LATIN SMALL LETTER A WITH OGONEK
'\xc5\x82' U+0142 LATIN SMALL LETTER L WITH STROKE
```

If you replace the `%r` (which yields the `repr()` value) by `%s` in the format string of the code sample above, and if your system supports UTF-8, you should see an output like the following:

```
ó U+00f3 LATIN SMALL LETTER O WITH ACUTE
ś U+015b LATIN SMALL LETTER S WITH ACUTE
Ś U+015a LATIN CAPITAL LETTER S WITH ACUTE
ą U+0105 LATIN SMALL LETTER A WITH OGONEK
ł U+0142 LATIN SMALL LETTER L WITH STROKE
```

Alternatively, you may need to replace the encoding '`'utf8'`' in the example by '`'latin2'`', again depending on the details of your system.

The next examples illustrate how Python string methods and the `re` module accept Unicode strings.

```
>>> line.find(u'zosta\u0142y')
54
>>> line = line.lower()
>>> print line.encode('unicode_escape')
niemc\xf3w pod koniec ii wojny \u015bwiatowej na dolny \u015bl\u0105sk, zosta\u0142y
>>> import re
>>> m = re.search(u'\u015b\w*', line)
>>> m.group()
u'\u015bwiatowej'
```

The NLTK tokenizer module allows Unicode strings as input, and correspondingly yields Unicode strings as output.

```
>>> from nltk.tokenize import WordTokenizer
>>> tokenizer = WordTokenizer()
>>> tokenizer.tokenize(line)
[u'niemc\xf3w', u'pod', u'koniec', u'ii', u'wojny', u'\u015bwiatowej',
 u'na', u'dolny', u'\u015bl\u0105sk', u'zosta\u0142y']
```

3.3.3 Using your local encoding in Python

If you are used to working with characters in a particular local encoding, you probably want to be able to use your standard methods for inputting and editing strings in a Python file. In order to do this, you need to include the string '`# -*- coding: <encoding> -*-`' as the first or second line of your file. Note that `<encoding>` has to be a string like '`latin-1`', '`big5`' or '`utf-8`'.

Note

If you are using Emacs as your editor, the coding specification will also be interpreted as a specification of the editor's coding for the file. Not all of the valid Python names for codings are accepted by Emacs.

The following screenshot illustrates the use of UTF-8 encoded string literals within the IDLE editor:

```
# -*- coding: utf-8 -*-
import re
sent = """
Przewiezione przez Niemców pod koniec II wojny światowej na Dolny
Śląsk, zostały odnalezione po 1945 r. na terytorium Polski.
"""

u = sent.decode('utf8')
u.lower()
print u.encode('utf8')

SACUTE = re.compile('ś|ł')
replaced = re.sub(SACUTE, '[sacute]', sent)
print replaced
```

Note

The above example requires that an appropriate font is set in IDLE's preferences. In this case, we chose Courier CE.

The above example also illustrates how regular expressions can use encoded strings.

3.3.4 Chinese and XML

Codecs for processing Chinese text have been incorporated into Python (since version 2.4).

```
>>> path = nltk.data.find('samples/sinorama-gb.xml')
>>> f = codecs.open(path, encoding='gb2312')
>>> lines = f.readlines()
>>> for l in lines:
...     l = l[:-1]
...     utf_enc = l.encode('utf8')
...     print repr(utf_enc)
'<?xml version="1.0" encoding="gb2312" ?>
'
'<sent>
'\xe7\x94\x9a\xe8\x87\xb3\xe7\x8c\xab\xe4\xbb\xa5\xe4\xba\xba\xe8\xb4\xb5'
'
'In some cases, cats were valued above humans.'
'</sent>'
```

With appropriate support on your terminal, the escaped text string inside the <SENT> element above will be rendered as the following string of ideographs: 甚至貓以人貴.

We can also read in the contents of an XML file using the etree package (at least, if the file is encoded as UTF-8 — as of writing, there seems to be a problem reading GB2312-encoded files in etree).

```
>>> path = nltk.data.find('samples/sinorama-utf8.xml')
>>> from nltk.etree import ElementTree as ET
>>> tree = ET.parse(path)
>>> text = tree.findtext('sent')
>>> uni_text = text.encode('utf8')
>>> print repr(uni_text.splitlines()[1])
'\xe7\x94\x9a\xe8\x87\xb3\xe7\x8c\xab\xe4\xbb\xa5\xe4\xba\xba\xe8\xb4\xb5'
```

3.3.5 Exercises

1. ♦ Using the Python interactive interpreter, experiment with applying some of the techniques for list and string processing to Unicode strings.

3.4 Tokenization and Normalization

Tokenization, as we saw, is the task of extracting a sequence of elementary tokens that constitute a piece of language data. In our first attempt to carry out this task, we started off with a string of characters, and used the `split()` method to break the string at whitespace characters. Recall that “whitespace” covers not only inter-word space, but also tabs and newlines. We pointed out that tokenization based solely on whitespace is too simplistic for most applications. In this section we will take a more sophisticated approach, using regular expressions to specify which character sequences should be treated as words. We will also look at ways to normalize tokens.

3.4.1 Tokenization with Regular Expressions

The function `nltk.tokenize regexp_tokenize()` takes a text string and a regular expression, and returns the list of substrings that match the regular expression. To define a tokenizer that includes punctuation as separate tokens, we could do the following:

```
>>> text = '''Hello. Isn't this fun?'''
>>> pattern = r'\w+|[^w\s]+'
>>> nltk.tokenize.regexp_tokenize(text, pattern)
['Hello', '.', 'Isn', "'", 't', 'this', 'fun', '?']
```

The regular expression in this example will match a sequence consisting of one or more word characters `\w+`. It will also match a sequence consisting of one or more punctuation characters (or non-word, non-space characters `[^\w\s]+`). This is another negated range expression; it matches one or more characters that are not word characters (i.e., not a match for `\w`) and not a whitespace character (i.e., not a match for `\s`). We use the disjunction operator `|` to combine these into a single complex expression `\w+|[^w\s]+`.

There are a number of ways we could improve on this regular expression. For example, it currently breaks `$22.50` into four tokens; we might want it to treat this as a single token. Similarly, `U.S.A.` should count as a single token. We can deal with these by adding further cases to the regular expression. For readability we will break it up and insert comments, and insert the special `(?x)` “verbose flag” so that Python knows to strip out the embedded whitespace and comments.

```
>>> text = 'That poster costs $22.40.'
>>> pattern = r'''(?x)
...     \w+                      # sequences of 'word' characters
...     | \$?\d+(\.\d+)?        # currency amounts, e.g. $12.50
...     | ([A-Z]\.)+            # abbreviations, e.g. U.S.A.
...     | [^\w\s]+                # sequences of punctuation
...
>>> nltk.tokenize.regexp_tokenize(text, pattern)
['That', 'poster', 'costs', '$22.40', '.']
```

It is sometimes more convenient to write a regular expression matching the material that appears *between* tokens, such as whitespace and punctuation. The `nltk.tokenize regexp_tokenize()` function permits an optional boolean parameter `gaps`; when set to `True` the pattern is matched against the gaps. For example, we could define a whitespace tokenizer as follows:

```
>>> nltk.tokenize.regexp_tokenize(text, pattern=r'\s+', gaps=True)
['That', 'poster', 'costs', '$22.40.']
```

It is more convenient to call NLTK’s whitespace tokenizer directly, as `nltk.WhitespaceTokenizer(text)`. (However, in this case is generally better to use Python’s `split()` method, defined on strings: `text.split()`.)

3.4.2 Lemmatization and Normalization

Earlier we talked about counting word tokens, and completely ignored the rest of the sentence in which these tokens appeared. Thus, for an example like *I saw the saw*, we would have treated both *saw* tokens as instances of the same type. However, one is a form of the verb *see*, and the other is the name of a cutting instrument. How do we know that these two forms of *saw* are unrelated? One answer is that as speakers of English, we know that these would appear as different entries in a dictionary. Another, more

empiricist, answer is that if we looked at a large enough number of texts, it would become clear that the two forms have very different distributions. For example, only the noun *saw* will occur immediately after determiners such as *the*. Distinct words that have the same written form are called **homographs**. We can distinguish homographs with the help of context; often the previous word suffices. We will explore this idea of context briefly, before addressing the main topic of this section.

As a first approximation to discovering the distribution of a word, we can look at all the bigrams it occurs in. A **bigram** is simply a pair of words. For example, in the sentence *She sells sea shells by the sea shore*, the bigrams are *She sells*, *sells sea*, *sea shells*, *shells by*, *by the*, *the sea*, *sea shore*. Let's consider all bigrams from the Brown Corpus that have the word *often* as first element. Here is a small selection, ordered by their counts:

often ,	16
often a	10
often in	8
often than	7
often the	7
often been	6
often do	5
often called	4
often appear	3
often were	3
often appeared	2
often are	2
often did	2
often is	2
often appears	1
often call	1

In the topmost entry, we see that *often* is frequently followed by a comma. This suggests that *often* is common at the end of phrases. We also see that *often* precedes verbs, presumably as an adverbial modifier. We might conclude that when *saw* appears in the context *often saw*, then *saw* is being used as a verb.

You will also see that this list includes different grammatical forms of the same verb. We can form separate groups consisting of *appear ~ appears ~ appeared*; *call ~ called*; *do ~ did*; and *been ~ were ~ are ~ is*. It is common in linguistics to say that two forms such as *appear* and *appeared* belong to a more abstract notion of a word called a **lexeme**; by contrast, *appeared* and *called* belong to different lexemes. You can think of a lexeme as corresponding to an entry in a dictionary, and a **lemma** as the headword for that entry. By convention, small capitals are used when referring to a lexeme or lemma: APPEAR.

Although *appeared* and *called* belong to different lexemes, they do have something in common: they are both past tense forms. This is signaled by the segment *-ed*, which we call a morphological **suffix**. We also say that such morphologically complex forms are **inflected**. If we strip off the suffix, we get something called the **stem**, namely *appear* and *call* respectively. While *appeared*, *appears* and *appearing* are all morphologically inflected, *appear* lacks any morphological inflection and is therefore termed the **base** form. In English, the base form is conventionally used as the **lemma** for a word.

Our notion of context would be more compact if we could group different forms of the various verbs into their lemmas; then we could study which verb lexemes are typically modified by a particular adverb. **Lemmatization** — the process of mapping words to their lemmas — would yield the following picture of the distribution of *often*. Here, the counts for *often appear* (3), *often appeared* (2) and *often appears* (1) are combined into a single line.

often ,	16
often a	10
often be	13
often in	8
often than	7
often the	7
often do	7
often appear	6
often call	5

Lemmatization is a rather sophisticated process that uses rules for the regular word patterns, and table look-up for the irregular patterns. Within NLTK, we can use off-the-shelf stemmers, such as the **Porter Stemmer**, the **Lancaster Stemmer**, and the stemmer that comes with WordNet, e.g.:

```
>>> stemmer = nltk.PorterStemmer()
>>> verbs = ['appears', 'appear', 'appeared', 'calling', 'called']
>>> stems = []
>>> for verb in verbs:
...     stemmed_verb = stemmer.stem(verb)
...     stems.append(stemmed_verb)
>>> sorted(set(stems))
['appear', 'call']
```

Stemmers for other languages are added to NLTK as they are contributed, e.g. the RSLP Portuguese Stemmer, `nltk.RSLPStemmer()`.

Lemmatization and stemming are special cases of **normalization**. They identify a canonical representative for a set of related word forms. Normalization collapses distinctions. Exactly how we normalize words depends on the application. Often, we convert everything into lower case so that we can ignore the written distinction between sentence-initial words and the rest of the words in the sentence. The Python string method `lower()` will accomplish this for us:

```
>>> str = 'This is the time'
>>> str.lower()
'this is the time'
```

A final issue for normalization is the presence of contractions, such as *didn't*. If we are analyzing the meaning of a sentence, it would probably be more useful to normalize this form to two separate forms: *did* and *n't* (or *not*).

3.4.3 Transforming Lists

Lemmatization and normalization involve applying the same operation to each word token in a text. **List comprehensions** are a convenient Python construct for doing this. Here we lowercase each word:

```
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> [word.lower() for word in sent]
['the', 'dog', 'gave', 'john', 'the', 'newspaper']
```

A list comprehension usually has the form `[item.foo() for item in sequence]`, or `[foo(item) for item in sequence]`. It creates a list by applying an operation to every item in the supplied sequence. Here we rewrite the loop for identifying verb stems that we saw in the previous section:

```
>>> [stemmer.stem(verb) for verb in verbs]
['appear', 'appear', 'appear', 'call', 'call']
```

Now we can eliminate repeats using `set()`, by passing the list comprehension as an argument. We can actually leave out the square brackets, as will be explained further in [Chapter 10](#).

```
>>> set(stemmer.stem(verb) for verb in verbs)
set(['call', 'appear'])
```

This syntax might be reminiscent of the notation used for building sets, e.g. $\{(x,y) \mid x^2 + y^2 = 1\}$. (We will return to sets later in [Section 10](#)). Just as this set definition incorporates a constraint, list comprehensions can constrain the items they include. In the next example we remove some non-content words from a list of words:

```
>>> def is_lexical(word):
...     return word.lower() not in ('a', 'an', 'the', 'that', 'to')
>>> [word for word in sent if is_lexical(word)]
['dog', 'gave', 'John', 'newspaper']
```

Now we can combine the two ideas (constraints and normalization), to pull out the content words and normalize them.

```
>>> [word.lower() for word in sent if is_lexical(word)]
['dog', 'gave', 'john', 'newspaper']
```

List comprehensions can build nested structures too. For example, the following code builds a list of tuples, where each tuple consists of a word and its stem.

```
>>> sent = nltk.corpus.brown.sents(categories='a')[0]
>>> [(x, stemmer.stem(x).lower()) for x in sent]
[('The', 'the'), ('Fulton', 'fulton'), ('County', 'counti'),
 ('Grand', 'grand'), ('Jury', 'juri'), ('said', 'said'), ('Friday', 'friday'),
 ('an', 'an'), ('investigation', 'investig'), ('of', 'of'),
 ("Atlanta's", "atlanta'"), ('recent', 'recent'), ('primary', 'primari'),
 ('election', 'elect'), ('produced', 'produc'), (''', '''), ('no', 'no'),
 ('evidence', 'evid'), ('''', ''''), ('that', 'that'), ('any', 'ani'),
 ('irregularities', 'irregular'), ('took', 'took'), ('place', 'place'), ('.', '.')]
```

3.4.4 Exercises

1. **◊ Regular expression tokenizers:** Save some text into a file `corpus.txt`. Define a function `load(f)` that reads from the file named in its sole argument, and returns a string containing the text of the file.
 - a) Use `nltk.tokenize regexp_tokenize()` to create a tokenizer that tokenizes the various kinds of punctuation in this text. Use a single regular expression, with inline comments using the `re.VERBOSE` flag.
 - b) Use `nltk.tokenize regexp_tokenize()` to create a tokenizer that tokenizes the following kinds of expression: monetary amounts; dates; names of people and companies.
2. **◊ Rewrite the following loop as a list comprehension:**

```
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> result = []
>>> for word in sent:
...     word_len = (word, len(word))
...     result.append(word_len)
>>> result
[('The', 3), ('dog', 3), ('gave', 4), ('John', 4), ('the', 3), ('newspaper', 9)]
```

3. ● Use the Porter Stemmer to normalize some tokenized text, calling the stemmer on each word. Do the same thing with the Lancaster Stemmer and see if you observe any differences.
4. ● Consider the numeric expressions in the following sentence from the MedLine corpus: *The corresponding free cortisol fractions in these sera were 4.53 +/- 0.15% and 8.16 +/- 0.23%, respectively.* Should we say that the numeric expression 4.53 +/- 0.15% is three words? Or should we say that it's a single compound word? Or should we say that it is actually nine words, since it's read “four point five three, plus or minus fifteen percent”? Or should we say that it's not a “real” word at all, since it wouldn't appear in any dictionary? Discuss these different possibilities. Can you think of application domains that motivate at least two of these answers?
5. ● Readability measures are used to score the reading difficulty of a text, for the purposes of selecting texts of appropriate difficulty for language learners. Let us define μ_w to be the average number of letters per word, and μ_s to be the average number of words per sentence, in a given text. The Automated Readability Index (ARI) of the text is defined to be: $4.71 * \frac{\mu_w}{\mu_s} + 0.5 * \frac{\mu_s}{\mu_w} - 21.43$. Compute the ARI score for various sections of the Brown Corpus, including section f (popular lore) and j (learned). Make use of the fact that `nltk.corpus.brown.words()` produces a sequence of words, while `nltk.corpus.brown.sents()` produces a sequence of sentences.
6. ★ Obtain raw texts from two or more genres and compute their respective reading difficulty scores as in the previous exercise. E.g. compare ABC Rural News and ABC Science News (`nltk.corpus.abc`). Use `nltk.tokenize.punkt()` to perform sentence segmentation.
7. ★ Rewrite the following nested loop as a nested list comprehension:

```
>>> words = ['attribution', 'confabulation', 'elocution',
...           'sequoia', 'tenacious', 'unidirectional']
>>> vsequences = set()
>>> for word in words:
...     vowels = []
...     for char in word:
...         if char in 'aeiou':
...             vowels.append(char)
...     vsequences.add(''.join(vowels))
>>> sorted(vsequences)
['aiuio', 'eaiou', 'eouio', 'euoia', 'oauaio', 'uiieioa']
```

3.5 Counting Words: Several Interesting Applications

Now that we can count words (tokens or types), we can write programs to perform a variety of useful tasks, to study stylistic differences in language use, differences between languages, and even to generate random text.

Before getting started, we need to see how to get Python to count the number of occurrences of *each* word in a document.

```
>>> counts = nltk.defaultdict(int)           ①
>>> sec_a = nltk.corpus.brown.words(categories='a')
>>> for token in sec_a:
...     counts[token] += 1                  ②
>>> for token in sorted(counts)[:5]:       ③
...     print counts[token], token
38 !
5 $1
2 $1,000
1 $1,000,000,000
3 $1,500
```

In line ① we initialize the dictionary. Then for each word in each sentence we increment a counter (line ②). To view the contents of the dictionary, we can iterate over its keys and print each entry (here just for the first 5 entries, line ③).

3.5.1 Frequency Distributions

This style of output and our `counts` object are just different forms of the same abstract structure — a collection of items and their frequencies — known as a **frequency distribution**. Since we will often need to count things, NLTK provides a `FreqDist()` class. We can write the same code more conveniently as follows:

```
>>> fd = nltk.FreqDist(sec_a)
>>> for token in sorted(fd)[:5]:
...     print fd[token], token
38 !
5 $1
2 $1,000
1 $1,000,000,000
3 $1,500
```

Some of the methods defined on NLTK frequency distributions are shown in [Table 3.2](#).

Name	Sample	Description
Count	<code>fd['the']</code>	number of times a given sample occurred
Frequency	<code>fd.freq('the')</code>	frequency of a given sample
N	<code>fd.N()</code>	number of samples
Samples	<code>list(fd)</code>	list of distinct samples recorded (also <code>fd.keys()</code>)
Max	<code>fd.max()</code>	sample with the greatest number of outcomes

Table 3.2: Frequency Distribution Module

This output isn't very interesting. Perhaps it would be more informative to list the most frequent word tokens first. Now a `FreqDist` object is just a kind of dictionary, so we can easily get its key-value pairs and sort them by decreasing values, as follows:

```
>>> from operator import itemgetter
>>> sorted_word_counts = sorted(fd.items(), key=itemgetter(1), reverse=True) ①
>>> [token for (token, freq) in sorted_word_counts[:20]]
['the', ',', '.', 'of', 'and', 'to', 'a', 'in', 'for', 'The', 'that',
'...', 'is', 'was', "", 'on', 'at', 'with', 'be', 'by']
```

Note the arguments of the `sorted()` function (line ①): `itemgetter(1)` returns a function that can be called on any sequence object to return the item at position 1; `reverse=True` performs the sort in reverse order. Together, these ensure that the word with the highest frequency is listed first. This reversed sort by frequency is such a common requirement that it is built into the `FreqDist` object. [Listing 3.2](#) demonstrates this, and also prints rank and cumulative frequency.

Unfortunately the output in [Listing 3.2](#) is surprisingly dull. A mere handful of tokens account for a third of the text. They just represent the plumbing of English text, and are completely uninformative! How can we find words that are more indicative of a text? As we will see in the exercises for this section, we can modify the program to discard the non-content words. In the next section we see another approach.

3.5.2 Stylistics

Stylistics is a broad term covering literary genres and varieties of language use. Here we will look at a document collection that is categorized by genre, and try to learn something about the patterns of word usage. For example, [Table 3.3](#) was constructed by counting the number of times various modal words appear in different sections of the corpus:

Genre	can	could	may	might	must	will
skill and hobbies	273	59	130	22	83	259
humor	17	33	8	8	9	13
fiction: science	16	49	4	12	8	16
press: reportage	94	86	66	36	50	387
fiction: romance	79	195	11	51	46	43
religion	84	59	79	12	54	64

Table 3.3: Use of Modals in Brown Corpus, by Genre

Observe that the most frequent modal in the reportage genre is *will*, suggesting a focus on the future, while the most frequent modal in the romance genre is *could*, suggesting a focus on possibilities.

We can also measure the lexical diversity of a genre, by calculating the ratio of word types and word tokens, as shown in [Table 3.4](#). Genres with lower diversity have a higher number of tokens per type, thus we see that humorous prose is almost twice as lexically diverse as romance prose.

Genre	Token Count	Type Count	Ratio
skill and hobbies	82345	11935	6.9

Genre	Token Count	Type Count	Ratio
humor	21695	5017	4.3
fiction: science	14470	3233	4.5
press: reportage	100554	14394	7.0
fiction: romance	70022	8452	8.3
religion	39399	6373	6.2

Table 3.4: Lexical Diversity of Various Genres in the Brown Corpus

We can carry out a variety of interesting explorations simply by counting words. In fact, the field of **Corpus Linguistics** focuses heavily on creating and interpreting such tables of word counts.

3.5.3 Aside: Defining Functions

It often happens that part of a program needs to be used several times over. For example, suppose we were writing a program that needed to be able to form the plural of a singular noun, and that this needed to be done at various places during the program. Rather than repeating the same code several times over, it is more efficient (and reliable) to localize this work inside a **function**. A function is a programming construct that can be called with one or more inputs and which returns an output. We define a function using the keyword `def` followed by the function name and any input parameters, followed by a colon; this in turn is followed by the body of the function. We use the keyword `return` to indicate the value that is produced as output by the function. The best way to convey this is with an example. Our function `plural()` in Listing 3.3 takes a singular noun as input, and generates a plural form as output.

(There is much more to be said about ways of defining functions, but we will defer this until Section 6.4.)

3.5.4 Lexical Dispersion

Word tokens vary in their distribution throughout a text. We can visualize word distributions to get an overall sense of topics and topic shifts. For example, consider the pattern of mention of the main characters in Jane Austen's *Sense and Sensibility*: Elinor, Marianne, Edward and Willoughby. The following plot contains four rows, one for each name, in the order just given. Each row contains a series of lines, drawn to indicate the position of each token.



Figure 3.2: Lexical Dispersion Plot for the Main Characters in *Sense and Sensibility*

As you can see, *Elinor* and *Marianne* appear rather uniformly throughout the text, while *Edward* and *Willoughby* tend to appear separately. Here is the code that generated the above plot.

```
>>> names = ['Elinor', 'Marianne', 'Edward', 'Willoughby']
>>> text = nltk.corpus.gutenberg.words('austen-sense.txt')
>>> nltk.draw.dispersion_plot(text, names)
```

Listing 3.2 Words and Cumulative Frequencies, in Order of Decreasing Frequency

```
def print_freq(tokens, num=50):
    fd = nltk.FreqDist(tokens)
    cumulative = 0.0
    rank = 0
    for word in fd.sorted() [:num]:
        rank += 1
        cumulative += fd[word] * 100.0 / fd.N()
        print "%3d %3.2d%% %s" % (rank, cumulative, word)

>>> print_freq(nltk.corpus.brown.words(categories='a'), 20)
 1  05% the
 2  10% ,
 3  14% .
 4  17% of
 5  19% and
 6  21% to
 7  23% a
 8  25% in
 9  26% for
10  27% The
11  28% that
12  28% ''
13  29% is
14  30% was
15  31% ''
16  31% on
17  32% at
18  32% with
19  33% be
20  33% by
```

Listing 3.3

```
def plural(word):
    if word.endswith('y'):
        return word[:-1] + 'ies'
    elif word[-1] in 'sx' or word[-2:] in ['sh', 'ch']:
        return word + 'es'
    elif word.endswith('an'):
        return word[:-2] + 'en'
    return word + 's'

>>> plural('fairy')
'fairies'
>>> plural('woman')
'women'
```

3.5.5 Comparing Word Lengths in Different Languages

We can use a frequency distribution to examine the distribution of word lengths in a corpus. For each word, we find its length, and increment the count for words of this length.

```
>>> def print_length_dist(text):
...     fd = nltk.FreqDist(len(token) for token in text if re.match(r'\w+$', token))
...     for i in range(1,15):
...         print "%2d" % int(100*fd.freq(i)),
...     print
```

Now we can call `print_length_dist` on a text to print the distribution of word lengths. We see that the most frequent word length for the English sample is 3 characters, while the most frequent length for the Finnish sample is 5-6 characters.

```
>>> print_length_dist(nltk.corpus.genesis.words('english-kjv.txt'))
2 15 30 23 12 6 4 2 1 0 0 0 0 0
>>> print_length_dist(nltk.corpus.genesis.words('finnish.txt'))
0 12 6 10 17 17 11 9 5 3 2 1 0 0
```

This is an intriguing area for exploration, and so in [Listing 3.4](#) we look at it on a larger scale using the Universal Declaration of Human Rights corpus, which has text samples from over 300 languages. (Note that the names of the files in this corpus include information about character encoding; here we will use texts in ISO Latin-1.) The output is shown in [Figure 3.3](#) (a color figure in the online version).

Listing 3.4 Cumulative Word Length Distributions for Several Languages

```
import pylab

def cld(lang):
    text = nltk.corpus.udhr.words(lang)
    fd = nltk.FreqDist(len(token) for token in text)
    ld = [100*fd.freq(i) for i in range(36)]
    return [sum(ld[0:i+1]) for i in range(len(ld))]

>>> langs = ['Chickasaw-Latin1', 'English-Latin1',
...             'German_Deutsch-Latin1', 'Greenlandic_Inuktikut-Latin1',
...             'Hungarian_Magyar-Latin1', 'Ibibio_Efik-Latin1']
>>> dists = [pylab.plot(cld(l), label=l[:-7], linewidth=2) for l in langs]
>>> pylab.title('Cumulative Word Length Distributions for Several Languages')
>>> pylab.legend(loc='lower right')
>>> pylab.show()
```

3.5.6 Generating Random Text with Style

We have used frequency distributions to count the number of occurrences of each word in a text. Here we will generalize this idea to look at the distribution of words in a given context. A **conditional frequency distribution** is a collection of frequency distributions, each one for a different condition. Here the condition will be the preceding word.

In [Listing 3.5](#), we've defined a function `train_model()` that uses `ConditionalFreqDist()` to count words as they appear relative to the context defined by the preceding word (stored in

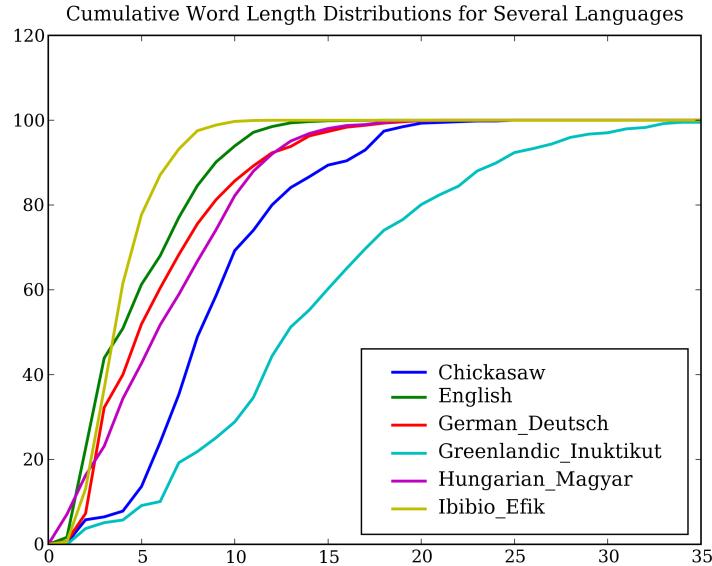


Figure 3.3: Cumulative Word Length Distributions for Several Languages

prev). It scans the corpus, incrementing the appropriate counter, and updating the value of prev. The function generate_model() contains a simple loop to generate text: we set an initial context, pick the most likely token in that context as our next word (using max()), and then use that word as our new context. This simple approach to text generation tends to get stuck in loops; another method would be to randomly choose the next word from among the available words.

3.5.7 Collocations

Collocations are pairs of content words that occur together more often than one would expect if the words of a document were scattered randomly. We can find collocations by counting how many times a pair of words w_1, w_2 occurs together, compared to the overall counts of these words (this program uses a heuristic related to the **mutual information** measure, <http://www.collocations.de/>) In Listing 3.6 we try this for the files in the webtext corpus.

3.5.8 Exercises

1. ⚡ Compare the lexical dispersion plot with Google Trends, which shows the frequency with which a term has been referenced in news reports or been used in search terms over time.
2. ⚡ Pick a text, and explore the dispersion of particular words. What does this tell you about the words, or the text?
3. ⚡ The program in Listing 3.2 used a dictionary of word counts. Modify the code that creates these word counts so that it ignores non-content words. You can easily get a list of words to ignore with:

Listing 3.5 Generating Random Text in the Style of Genesis

```

def train_model(text):
    cfdist = nltk.ConditionalFreqDist()
    prev = None
    for word in text:
        cfdist[prev].inc(word)
        prev = word
    return cfdist

def generate_model(cfdist, word, num=15):
    for i in range(num):
        print word,
        word = cfdist[word].max()

>>> model = train_model(nltk.corpus.genesis.words('english-kjv.txt'))
>>> model['living']
<FreqDist with 16 samples>
>>> list(model['living'])
['substance', ',', '.', 'thing', 'soul', 'creature']
>>> generate_model(model, 'living')
living creature that he said , and the land of the land of the land

```

```
>>> ignored_words = nltk.corpus.stopwords.words('english')
```

4. ◊ Modify the `generate_model()` function in Listing 3.5 to use Python’s `random.choose()` method to randomly pick the next word from the available set of words.
5. ◊ **The demise of teen language:** Read the BBC News article: *UK’s Vicky Pollards ‘left behind’* <http://news.bbc.co.uk/1/hi/education/6173441.stm>. The article gives the following statistic about teen language: “the top 20 words used, including yeah, no, but and like, account for around a third of all words.” Use the program in Listing 3.2 to find out how many word types account for a third of all word tokens, for a variety of text sources. What do you conclude about this statistic? Read more about this on *LanguageLog*, at <http://itre.cis.upenn.edu/~myl/languagelog/archives/003993.html>.
6. ● Write a program to find all words that occur at least three times in the Brown Corpus.
7. ● Write a program to generate a table of token/type ratios, as we saw in Table 3.4. Include the full set of Brown Corpus genres (`nltk.corpus.brown.categories()`). Which genre has the lowest diversity (greatest number of tokens per type)? Is this what you would have expected?
8. ● Modify the text generation program in Listing 3.5 further, to do the following tasks:
 - a) Store the n most likely words in a list `lwords` then randomly choose a word from the list using `random.choice()`.

Listing 3.6 A Simple Program to Find Collocations

```
def collocations(words):
    from operator import itemgetter

    # Count the words and bigrams
    wfd = nltk.FreqDist(words)
    pfd = nltk.FreqDist(tuple(words[i:i+2]) for i in range(len(words)-1))

    #
    scored = [((w1,w2), score(w1, w2, wfd, pfd)) for w1, w2 in pfd]
    scored.sort(key=itemgetter(1), reverse=True)
    return map(itemgetter(0), scored)

def score(word1, word2, wfd, pfd, power=3):
    freq1 = wfd[word1]
    freq2 = wfd[word2]
    freq12 = pfd[(word1, word2)]
    return freq12 ** power / float(freq1 * freq2)

>>> for file in nltk.corpus.webtext.files():
...     words = [word.lower() for word in nltk.corpus.webtext.words(file) if len(word) > 1]
...     print file, [w1+' '+w2 for w1, w2 in collocations(words)[:15]]
overheard ['new york', 'teen boy', 'teen girl', 'you know', 'middle aged',
'flight attendant', 'puerto rican', 'last night', 'little boy', 'taco bell',
'statue liberty', 'bus driver', 'ice cream', 'don know', 'high school']
pirates ['jack sparrow', 'will turner', 'elizabeth swann', 'davy jones',
'flying dutchman', 'lord cutler', 'cutler beckett', 'black pearl', 'tia dalma',
'heh heh', 'edinburgh trader', 'port royal', 'bamboo pole', 'east india', 'jar dirt',
'singles ['non smoker', 'would like', 'dining out', 'like meet', 'age open',
'sense humour', 'looking for', 'social drinker', 'down earth', 'long term',
'quiet nights', 'easy going', 'medium build', 'nights home', 'weekends away']
wine ['high toned', 'top ***', 'not rated', 'few years', 'medium weight',
'year two', 'cigar box', 'cote rotie', 'mixed feelings', 'demi sec',
'from half', 'brown sugar', 'bare ****', 'tightly wound', 'sous bois']
```

- b) Select a particular genre, such as a section of the Brown Corpus, or a genesis translation, one of the Gutenberg texts, or one of the Web texts. Train the model on this corpus and get it to generate random text. You may have to experiment with different start words. How intelligible is the text? Discuss the strengths and weaknesses of this method of generating random text.
 - c) Now train your system using two distinct genres and experiment with generating text in the hybrid genre. Discuss your observations.
9. **❶** Write a program to print the most frequent bigrams (pairs of adjacent words) of a text, omitting non-content words, in order of decreasing frequency.
10. **❶** Write a program to create a table of word frequencies by genre, like the one given above for modals. Choose your own words and try to find words whose presence (or absence) is typical of a genre. Discuss your findings.
11. **❶ Zipf's Law:** Let $f(w)$ be the frequency of a word w in free text. Suppose that all the words of a text are ranked according to their frequency, with the most frequent word first. Zipf's law states that the frequency of a word type is inversely proportional to its rank (i.e. $f.r = k$, for some constant k). For example, the 50th most common word type should occur three times as frequently as the 150th most common word type.
- a) Write a function to process a large text and plot word frequency against word rank using `pylab.plot`. Do you confirm Zipf's law? (Hint: it helps to use a logarithmic scale). What is going on at the extreme ends of the plotted line?
 - b) Generate random text, e.g. using `random.choice("abcdefg ")`, taking care to include the space character. You will need to `import random` first. Use the string concatenation operator to accumulate characters into a (very) long string. Then tokenize this string, and generate the Zipf plot as before, and compare the two plots. What do you make of Zipf's Law in the light of this?
12. **❶ Exploring text genres:** Investigate the table of modal distributions and look for other patterns. Try to explain them in terms of your own impressionistic understanding of the different genres. Can you find other closed classes of words that exhibit significant differences across different genres?
13. **★ Authorship identification:** Reproduce some of the results of [?].
14. **★ Gender-specific lexical choice:** Reproduce some of the results of <http://www.clintoneast.com/articles/words.php>

3.6 WordNet: An English Lexical Database

WordNet is a semantically-oriented dictionary of English, similar to a traditional thesaurus but with a richer structure. WordNet groups words into synonym sets, or **synsets**, each with its own definition and with links to other synsets. WordNet 3.0 data is distributed with NLTK, and includes 117,659 synsets.

Although WordNet was originally developed for research in psycholinguistics, it is widely used in NLP and Information Retrieval. WordNets are being developed for many other languages, as documented at <http://www.globalwordnet.org/>.

3.6.1 Senses and Synonyms

Consider the following sentence:

- (4) Benz is credited with the invention of the motorcar.

If we replace *motorcar* in (4) by *automobile*, the meaning of the sentence stays pretty much the same:

- (5) Benz is credited with the invention of the automobile.

Since everything else in the sentence has remained unchanged, we can conclude that the words *motorcar* and *automobile* have the same meaning, i.e. they are **synonyms**.

In order to look up the senses of a word, we need to pick a part of speech for the word. WordNet contains four dictionaries: N (nouns), V (verbs), ADJ (adjectives), and ADV (adverbs). To simplify our discussion, we will focus on the N dictionary here. Let's look up *motorcar* in the N dictionary.

```
>>> from nltk import wordnet
>>> car = wordnet.N['motorcar']
>>> car
motorcar (noun)
```

The variable *car* is now bound to a *Word* object. Words will often have more than sense, where each sense is represented by a synset. However, *motorcar* only has one sense in WordNet, as we can discover using *len()*. We can then find the synset (a set of lemmas), the words it contains, and a gloss.

```
>>> len(car)
1
>>> car[0]
{noun: car, auto, automobile, machine, motorcar}
>>> [word for word in car[0]]
['car', 'auto', 'automobile', 'machine', 'motorcar']
>>> car[0].gloss
'a motor vehicle with four wheels; usually propelled by an
internal combustion engine;
"he needs a car to get to work"
```

The *wordnet* module also defines *Synsets*. Let's look at a word which is **polysemous**; that is, which has multiple synsets:

```
>>> poly = wordnet.N['pupil']
>>> for synset in poly:
...     print synset
{noun: student, pupil, educatee}
{noun: pupil}
{noun: schoolchild, school-age_child, pupil}
>>> poly[1].gloss
'the contractile aperture in the center of the iris of the eye;
resembles a large black dot'
```

3.6.2 The WordNet Hierarchy

WordNet synsets correspond to abstract concepts, which may or may not have corresponding words in English. These concepts are linked together in a hierarchy. Some are very general, such as *Entity*, *State*, *Event* — these are called **unique beginners**. Others, such as *gas guzzler* and *hatchback*, are much more specific. A small portion of a concept hierarchy is illustrated in Figure 3.4. The edges between nodes indicate the hypernym/hyponym relation; the dotted line at the top is intended to indicate that *artifact* is a non-immediate hypernym of *motorcar*.

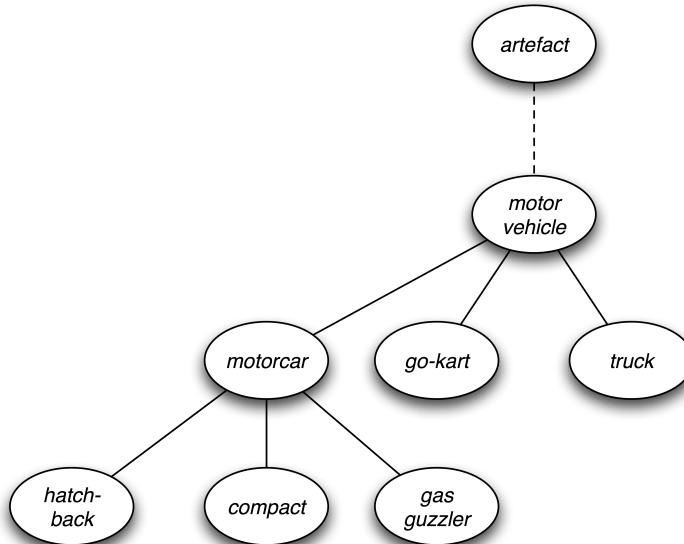


Figure 3.4: Fragment of WordNet Concept Hierarchy

WordNet makes it easy to navigate between concepts. For example, given a concept like *motorcar*, we can look at the concepts that are more specific; the (immediate) **hyponyms**. Here is one way to carry out this navigation:

```

>>> for concept in car[0][wordnet.HYPONYM][:10]:
...     print concept
{noun: ambulance}
{noun: beach_wagon, station_wagon, wagon, estate_car, beach_waggon, station_waggon, waggon}
{noun: bus, jalopy, heap}
{noun: cab, hack, taxi, taxicab}
{noun: compact, compact_car}
{noun: convertible}
{noun: coupe}
{noun: cruiser, police_cruiser, patrol_car, police_car, prowler, squad_car}
{noun: electric, electric_automobile, electric_car}
{noun: gas_guzzler}
  
```

We can also move up the hierarchy, by looking at broader concepts than *motorcar*, e.g. the immediate **hypernym** of a concept:

```

>>> car[0][wordnet.HYPERNYM]
[{noun: motor_vehicle, automotive_vehicle}]
  
```

We can also look for the hypernyms of hypernyms. In fact, from any synset we can trace (multiple) paths back to a unique beginner. Synsets have a method for doing this, called `tree()`, which produces a nested list structure.

```
>>> pprint.pprint(wordnet.N['car'][0].tree(wordnet.HYPERNYM))
[noun: car, auto, automobile, machine, motorcar],
 [{noun: motor_vehicle, automotive_vehicle},
  [{noun: self-propelled_vehicle},
   [{noun: wheeled_vehicle},
    [{noun: vehicle},
     [{noun: conveyance, transport},
      [{noun: instrumentality, instrumentation},
       [{noun: artifact, artefact},
        [{noun: whole, unit},
         [{noun: object, physical_object},
          [{noun: physical_entity}, [{noun: entity}]]]]]]]]],
 [{noun: container},
  [{noun: instrumentality, instrumentation},
   [{noun: artifact, artefact},
    [{noun: whole, unit},
     [{noun: object, physical_object},
      [{noun: physical_entity}, [{noun: entity}]]]]]]]]]]]
```

A related method `closure()` produces a flat version of this structure, with repeats eliminated. Both of these functions take an optional `depth` argument that permits us to limit the number of steps to take. (This is important when using unbounded relations like `SIMILAR`.) [Table 3.5](#) lists the most important lexical relations supported by WordNet; see `dir(wordnet)` for a full list.

Hypernym	more general	<i>animal</i> is a hypernym of <i>dog</i>
Hyponym	more specific	<i>dog</i> is a hyponym of <i>animal</i>
Meronym	part of	<i>door</i> is a meronym of <i>house</i>
Holonym	has part	<i>house</i> is a holonym of <i>door</i>
Synonym	similar meaning	<i>car</i> is a synonym of <i>automobile</i>
Antonym	opposite meaning	<i>like</i> is an antonym of <i>dislike</i>
Entailment	necessary action	<i>step</i> is an entailment of <i>walk</i>

Table 3.5: Major WordNet Lexical Relations

Recall that we can iterate over the words of a synset, with `for word in synset`. We can also test if a word is in a dictionary, e.g. `if word in wordnet.V`. As our last task, let's put these together to find “animal words” that are used as verbs. Since there are a lot of these, we will cut this off at depth 4. Can you think of the animal and verb sense of each word?

```
>>> animals = wordnet.N['animal'][0].closure(wordnet.HYPONYM, depth=4)
>>> [word for synset in animals for word in synset if word in wordnet.V]
['pet', 'stunt', 'prey', 'quarry', 'game', 'mate', 'head', 'dog',
 'stray', 'dam', 'sire', 'steer', 'orphan', 'spat', 'sponge',
 'worm', 'grub', 'pooch', 'toy', 'queen', 'baby', 'pup', 'whelp',
 'cub', 'kit', 'kitten', 'foal', 'lamb', 'fawn', 'bird', 'grouse',
 'hound', 'bulldog', 'stud', 'hog', 'baby', 'fish', 'cock', 'parrot',
 'frog', 'beetle', 'bug', 'bug', 'queen', 'leech', 'snail', 'slug',
```

```
'clam', 'cockle', 'oyster', 'scallop', 'scallops', 'escallop', 'quail']
```

NLTK also includes VerbNet, a hierarchical verb lexicon linked to WordNet. It can be accessed with `nltk.corpus.verbnet`.

3.6.3 WordNet Similarity

We would expect that the semantic similarity of two concepts would correlate with the length of the path between them in WordNet. The `wordnet` package includes a variety of measures that incorporate this basic insight. For example, `path_similarity` assigns a score in the range 0–1, based on the shortest path that connects the concepts in the hypernym hierarchy (-1 is returned in those cases where a path cannot be found). A score of 1 represents identity, i.e., comparing a sense with itself will return 1.

```
>>> wordnet.N['poodle'][0].path_similarity(wordnet.N['dalmatian'][1])
0.3333333333333333
>>> wordnet.N['dog'][0].path_similarity(wordnet.N['cat'][0])
0.2000000000000001
>>> wordnet.V['run'][0].path_similarity(wordnet.V['walk'][0])
0.25
>>> wordnet.V['run'][0].path_similarity(wordnet.V['think'][0])
-1
```

Several other similarity measures are provided in `wordnet`: Leacock-Chodorow, Wu-Palmer, Resnik, Jiang-Conrath, and Lin. For a detailed comparison of various measures, see [?].

3.6.4 Exercises

1. ◊ Familiarize yourself with the WordNet interface, by reading the documentation available via `help(wordnet)`. Try out the text-based browser, `wordnet.browse()`.
 2. ◊ Investigate the holonym / meronym relations for some nouns. Note that there are three kinds (member, part, substance), so access is more specific, e.g., `wordnet.MEMBER_MERONYM`, `wordnet.SUBSTANCE_HOLONYM`.
 3. ● Define a function `supergloss(s)` that takes a synset `s` as its argument and returns a string consisting of the concatenation of the glosses of `s`, all hypernyms of `s`, and all hyponyms of `s`.
 4. ● Write a program to score the similarity of two nouns as the depth of their first common hypernym.
 5. ★ Use one of the predefined similarity measures to score the similarity of each of the following pairs of words. Rank the pairs in order of decreasing similarity. How close is your ranking to the order given here? (Note that this order was established experimentally by [?].)
- :: car-automobile, gem-jewel, journey-voyage, boy-lad, coast-shore, asylum-madhouse, magician-wizard, midday-noon, furnace-stove, food-fruit, bird-cock, bird-crane, tool-implement, brother-monk, lad-brother, crane-implement, journey-car, monk-oracle, cemetery-woodland, food-rooster, coast-hill, forest-graveyard, shore-woodland, monk-slave, coast-forest, lad-wizard, chord-smile, glass-magician, rooster-voyage, noon-string.

3.7 Conclusion

In this chapter we saw that we can do a variety of interesting language processing tasks that focus solely on words. Tokenization turns out to be far more difficult than expected. No single solution works well across-the-board, and we must decide what counts as a token depending on the application domain. We also looked at normalization (including lemmatization) and saw how it collapses distinctions between tokens. In the next chapter we will look at word classes and automatic tagging.

3.8 Summary

- we can read text from a file `f` using `text = open(f).read()`
- we can read text from a URL `u` using `text = urlopen(u).read()`
- NLTK comes with many corpora, e.g. the Brown Corpus, `corpus.brown`.
- a word token is an individual occurrence of a word in a particular context
- a word type is the vocabulary item, independent of any particular use of that item
- tokenization is the segmentation of a text into basic units — or tokens — such as words and punctuation.
- tokenization based on whitespace is inadequate for many applications because it bundles punctuation together with words
- lemmatization is a process that maps the various forms of a word (such as *appeared*, *appears*) to the canonical or citation form of the word, also known as the lexeme or lemma (e.g. APPEAR).
- a frequency distribution is a collection of items along with their frequency counts (e.g. the words of a text and their frequency of appearance).
- WordNet is a semantically-oriented dictionary of English, consisting of synonym sets — or synsets — and organized into a hierarchical network.

3.9 Further Reading

For more examples of processing words with NLTK, please see the guides at <http://nltk.org/doc/guides/tokenize.html>, <http://nltk.org/doc/guides/stem.html>, and <http://nltk.org/doc/guides/wordnet.html>. A guide on accessing NLTK corpora is available at: <http://nltk.org/doc/guides/corpus.html>.

3.9.1 Unicode

There are a number of online discussions of Unicode in general, and of Python facilities for handling Unicode. The following are worth consulting:

- Jason Orendorff, *Unicode for Programmers*, <http://www.jorendorff.com/articles/unicode/>.
- A. M. Kuchling, *Unicode HOWTO*, <http://www.amk.ca/python/howto/unicode>

- Frederik Lundh, *Python Unicode Objects*, <http://effbot.org/zone/unicode-objects.htm>
- Joel Spolsky, *The Absolute Minimum Every Software Developer Absolutely, Positively Must Know About Unicode and Character Sets (No Excuses!)*, <http://www.joelonsoftware.com/articles/Unicode.html>

About this document...

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Chapter 4

Categorizing and Tagging Words

4.1 Introduction

In [Chapter 3](#) we dealt with words in their own right. We looked at the distribution of *often*, identifying the words that follow it; we noticed that *often* frequently modifies verbs. In fact, it is a member of a whole class of verb-modifying words, the *adverbs*. Before we delve into this terminology, let's write a program that takes a word and finds other words that appear in the same context ([Listing 4.1](#)). For example, given the word *woman*, the program will find all contexts where *woman* appears in the corpus, such as *the woman saw*, then searches for other words that appear in those contexts.

When we run `dist_sim()` on a few words, we find other words having similar distribution: searching for *woman* finds *man* and several other *nouns*; searching for *bought* finds *verbs*; searching for *over* finds *prepositions*; searching for *the* finds *determiners*. These labels — which may be familiar from grammar lessons — are not just terms invented by grammarians, but labels for groups of words that arise directly from the text. These groups of words are so important that they have several names, all in common use: **word classes**, **lexical categories**, and **parts of speech**. We'll use these names interchangeably.

One of the notable features of the Brown corpus is that all the words have been **tagged** for their part-of-speech. Now, instead of just looking at the words that immediately follow *often*, we can look at the **part-of-speech tags** (or **POS tags**). [Table 4.1](#) lists the top eight, ordered by frequency, along with explanations of each tag. As we can see, the majority of words following *often* are verbs.

Tag	Freq	Example	Comment
vbn	61	<i>burnt, gone</i>	verb: past participle
vb	51	<i>make, achieve</i>	verb: base form
vbd	36	<i>saw, looked</i>	verb: simple past tense
jj	30	<i>ambiguous, acceptable</i>	adjective
vbz	24	<i>sees, goes</i>	verb: third-person singular present
in	18	<i>by, in</i>	preposition
at	18	<i>a, this</i>	article
,	16	,	comma

Table 4.1: Part of Speech Tags Following *often* in the Brown Corpus

Listing 4.1 Program for Distributional Similarity

```

def build_wc_map():
    """
    Return a dictionary mapping words in the brown corpus to lists of
    local lexical contexts, where a context is encoded as a tuple
    (prevword, nextword).
    """
    wc_map = nltk.defaultdict(list)
    words = [word.lower() for word in nltk.corpus.brown.words()]
    for i in range(1, len(words)-1):
        prevword, word, nextword = words[i-1:i+2]
        wc_map[word].append( (prevword, nextword) )
    return wc_map

def dist_sim(wc_map, word, num=12):
    if word in wc_map:
        contexts = set(wc_map[word])
        fd = nltk.FreqDist(w for w in wc_map for c in wc_map[w] if c in contexts)
        return fd.sorted()[:num]
    return []

>>> wc_map = build_wc_map()
>>> dist_sim(wc_map, 'woman')
['man', 'number', 'woman', 'world', 'time', 'end', 'house', 'state',
 'matter', 'kind', 'result', 'day']
>>> dist_sim(wc_map, 'bought')
['able', 'made', 'been', 'used', 'found', 'was', 'had', 'bought', '',
 'done', 'expected', 'given']
>>> dist_sim(wc_map, 'over')
['in', 'over', 'and', 'of', 'on', 'to', '.', ',', 'with', 'at', 'for', 'but']
>>> dist_sim(wc_map, 'the')
['the', 'a', 'his', 'this', 'and', 'in', 'their', 'an', 'her', 'that', 'no', 'its']

```

The process of classifying words into their parts-of-speech and labeling them accordingly is known as **part-of-speech tagging**, **POS-tagging**, or simply **tagging**. The collection of tags used for a particular task is known as a **tag set**. Our emphasis in this chapter is on exploiting tags, and tagging text automatically.

Automatic tagging has several applications. We have already seen an example of how to exploit tags in corpus analysis — we get a clear understanding of the distribution of *often* by looking at the tags of adjacent words. Automatic tagging also helps predict the behavior of previously unseen words. For example, if we encounter the word *blogging* we can probably infer that it is a verb, with the root *blog*, and likely to occur after forms of the auxiliary *to be* (e.g. *he was blogging*). Parts of speech are also used in speech synthesis and recognition. For example, *wind/NN*, as in *the wind blew*, is pronounced with a short vowel, whereas *wind/VB*, as in *to wind the clock*, is pronounced with a long vowel. Other examples can be found where the stress pattern differs depending on whether the word is a noun or a verb, e.g. *contest, insult, present, protest, rebel, suspect*. Without knowing the part of speech we cannot be sure of pronouncing the word correctly.

In the next section we will see how to access and explore the Brown Corpus. Following this we will take a closer look at the linguistics of word classes. The rest of the chapter will deal with automatic tagging: simple taggers, evaluation, and n-gram taggers.

Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

4.2 Getting Started with Tagging

Several large corpora, such as the Brown Corpus and portions of the Wall Street Journal, have been tagged for part-of-speech, and we will be able to process this tagged data. Tagged corpus files typically contain text of the following form (this example is from the Brown Corpus):

```
The/at grand/jj jury/nn commented/vbd on/in a/at number/nn of/in
other/ap topics/nns ,/, among/in them/ppo the/at Atlanta/np and/cc
Fulton/np-tl County/nn-tl purchasing/vbg departments/nns which/wdt it/pps
said/vbd ''/'' are/ber well/ql operated/vbn and/cc follow/vb generally/rb
accepted/vbn practices/nns which/wdt inure/vb to/in the/at best/jjt
interest/nn of/in both/abx governments/nns ''/'' ./.
```

Note

The NLTK Brown Corpus reader converts part-of-speech tags to uppercase, as this has become standard practice since the Brown Corpus was published.

4.2.1 Representing Tags and Reading Tagged Corpora

By convention in NLTK, a tagged token is represented using a Python **tuple**. Python tuples are just like lists, except for one important difference: tuples cannot be changed in place, for example by `sort()` or `reverse()`. In other words, like strings, they are immutable. Tuples are formed with the comma operator, and typically enclosed using parentheses. Like lists, tuples can be indexed and sliced:

```
>>> t = ('walk', 'fem', 3)
>>> t[0]
```

```
'walk'  
>>> t[1:]  
('fem', 3)  
>>> t[0] = 'run'  
Traceback (most recent call last):  
  File "<stdin>", line 1, in ?  
TypeError: object does not support item assignment
```

A tagged token is represented using a tuple consisting of just two items. We can create one of these special tuples from the standard string representation of a tagged token, using the function `str2tuple()`:

```
>>> tagged_token = nltk.tag.str2tuple('fly/NN')
>>> tagged_token
('fly', 'NN')
>>> tagged_token[0]
'fly'
>>> tagged_token[1]
'NN'
```

We can construct a list of tagged tokens directly from a string. The first step is to tokenize the string to access the individual word/tag strings, and then to convert each of these into a tuple (using `str2tuple()`). We do this in two ways. The first method, starting at line ①, initializes an empty list `tagged_words`, loops over the word/tag tokens, converts them into tuples, appends them to `tagged_words`, and finally displays the result. The second method, on line ②, uses a list comprehension to do the same work in a way that is not only more compact, but also more readable. (List comprehensions were introduced in [section 3.4.3](#)).

```
>>> sent = ''
... The/AT grand/JJ jury/NN commented/VBD on/IN a/AT number/NN of/IN
... other/AP topics/NNS ,/, AMONG/IN them/PPO the/AT Atlanta/NP and/CC
... Fulton/NP-tl County/NN-tl purchasing/VBG departments/NNS which/WDT it/PPS
... said/VBD ```` ARE/BER well/QL operated/VBN and/CC follow/VB generally/RB
... accepted/VBN practices/NNS which/WDT inure/VB to/IN the/AT best/JJT
... interest/NN of/IN both/ABX governments/NNS ```` .
...
...
>>> tagged_words = []                                     ①
>>> for t in sent.split():
...     tagged_words.append(nltk.tag.str2tuple(t))
...
>>> tagged_words
[('The', 'AT'), ('grand', 'JJ'), ('jury', 'NN'), ('commented', 'VBD'),
('on', 'IN'), ('a', 'AT'), ('number', 'NN'), ... ('.', '.')]
>>> [nltk.tag.str2tuple(t) for t in sent.split()]          ②
[('The', 'AT'), ('grand', 'JJ'), ('jury', 'NN'), ('commented', 'VBD'),
('on', 'IN'), ('a', 'AT'), ('number', 'NN'), ... ('.', '.')]
```

We can access several tagged corpora directly from Python. If a corpus contains tagged text, then it will have a `tagged_words()` method. Please see the README file included with each corpus for documentation of its tagset.

```
>>> nltk.corpus.brown.tagged_words()  
[('The', 'AT'), ('Fulton', 'NP-TL'), ...]  
>>> nltk.corpus.conll2000.tagged_words()
```

```
[('Confidence', 'NN'), ('in', 'IN'), ('the', 'DT'), ...]
>>> nltk.corpus.treebank.tagged_words()
[('Pierre', 'NNP'), ('Vinken', 'NNP'), ('.', '.', '.'), ...]
```

Tagged corpora for several other languages are distributed with NLTK, including Chinese, Hindi, Portuguese, Spanish, Dutch and Catalan. These usually contain non-ASCII text, and Python always displays this in hexadecimal when printing a larger structure such as a list.

```
>>> nltk.corpus.sinica_treebank.tagged_words()
[('\xe4\xb8\x80', 'Neu'), ('\xe5\x8f\x8b\xe6\x83\x85', 'Nad'), ...]
>>> nltk.corpus.indian.tagged_words()
[('\xe0\xae\xae\xe0\xae\xb9\xe0\xae\xbf\xe0\xae\xb7\xe0\xae\x87\xe0\xae\xb0', 'NN'),
 ('\xe0\xae\xb8\xe0\xae\x8a\xe0\xae\x7\x8d\xe0\xae\x4\xe0\xae\xbe\xe0\xae\x8a', 'NN'), ...]
>>> nltk.corpus.mac_morpho.tagged_words()
[('Jersei', 'N'), ('atinge', 'V'), ('m\xe9dia', 'N'), ...]
>>> nltk.corpus.conll2002.tagged_words()
[('Sao', 'NC'), ('Paulo', 'VMI'), ('(', 'Fpa'), ...]
>>> nltk.corpus.cess_cat.tagged_words()
[('El', 'da0ms0'), ('Tribunal_Suprem', 'np0000o'), ...]
```

If your environment is set up correctly, with appropriate editors and fonts, you should be able to display individual strings in a human-readable way. For example, Figure 4.1 shows the output of the demonstration code (`nltk.corpus.indian.demo()`).

Bangla: কুঁড়মেরগুলি/'NN' আকার/'NN' বাংলা/''NP' বা/'CC' ভাস্তবে/''NP' ?/None
 ন্য/'JJ' ?/None এং চলবে/''NP' প রচল তি/''JJ' কুঁড়ে/''NN' ঘর/''NN' নয়/''VM' ক্ষ/''SYM'
 Hindi: पाकिस्तान/'NNP' की/'PREP' पूर्व/'JJ' प्रथानमंत्री/'NN' बेनजीर/'NNPC' भृष्टो/''NP'
 पर/'PREP' लगे/'VFM' जष्टाचार/'NN' के/'PREP' आरोपों/'NN' के/'PREP' खिलाफ/'PREP' भृष्टो/''NP'
 द्वारा/'PREP' दायर/'NVB' की/'VFM' गई/'VAUX' याचिकत/''NN' की/'PREP' सुनवाई/'NN'
 मंगलবাৰ/'NN' কো/'PREP' কৰকীলোঁ/'NN' কী/'PREP' হড়তাল/'NN' কে/'PREP' কারণ/'PREP'
 স্থগিত/'JVB' কর/'VFM' দী/''VAUX' গাই/''PUNC'
 Marathi: ग्रामीण/'JJ' जिल्हाध्यक्ष/'NN' वळासाहेब/'NNPC' शोसले/'NNP' यांच्यात/'PRP' ?/None
 दयक्षतेबाली/'NN' पक्षात्री/'NN' आज/'NN' बँ?/?/None क/''NN' झाली/''VM' ./.''SYM'
 Telugu: ఛత్రములు/'NN' సుంధరి/''PREP' వచ్చిన/''JJ' పుట్టులు/'NN' పు/''PREP' సొడ్జు కూ/''NN'

Figure 4.1: POS-Tagged Data from Four Indian Languages

If the corpus is also segmented into sentences, it will have a `tagged_sents()` method that returns a list of tagged sentences. This will be useful when we come to training automatic taggers, as they typically function on a sentence at a time.

4.2.2 Nouns and Verbs

Linguists recognize several major categories of words in English, such as nouns, verbs, adjectives and determiners. In this section we will discuss the most important categories, namely nouns and verbs.

Nouns generally refer to people, places, things, or concepts, e.g.: *woman*, *Scotland*, *book*, *intelligence*. Nouns can appear after determiners and adjectives, and can be the subject or object of the verb, as shown in Table 4.2.

Word	After a determiner	Subject of the verb
woman	<i>the woman who I saw yesterday ...</i>	<i>the woman sat down</i>
Scotland	<i>the Scotland I remember as a child ...</i>	<i>Scotland has five million people</i>

Word	After a determiner	Subject of the verb
book	<i>the</i> book I bought yesterday ...	this book <i>recounts</i> the colonization of Australia
intelligence	<i>the</i> intelligence displayed by the child ...	Mary's intelligence <i>impressed</i> her teachers

Table 4.2: Syntactic Patterns involving some Nouns

Nouns can be classified as **common nouns** and **proper nouns**. Proper nouns identify particular individuals or entities, e.g. *Moses* and *Scotland*. Common nouns are all the rest. Another distinction exists between **count nouns** and **mass nouns**. Count nouns are thought of as distinct entities that can be counted, such as *pig* (e.g. *one pig*, *two pigs*, *many pigs*). They cannot occur with the word *much* (i.e. **much pigs*). Mass nouns, on the other hand, are not thought of as distinct entities (e.g. *sand*). They cannot be pluralized, and do not occur with numbers (e.g. **two sands*, **many sands*). However, they can occur with *much* (i.e. *much sand*).

Verbs are words that describe events and actions, e.g. *fall*, *eat* in [Table 4.3](#). In the context of a sentence, verbs express a relation involving the referents of one or more noun phrases.

Word	Simple	With modifiers and adjuncts (italicized)
fall	Rome fell	Dot com stocks <i>suddenly</i> fell <i>like a stone</i>
eat	Mice eat cheese	John ate the pizza <i>with gusto</i>

Table 4.3: Syntactic Patterns involving some Verbs

Verbs can be classified according to the number of arguments (usually noun phrases) that they require. The word *fall* is **intransitive**, requiring exactly one argument (the entity that falls). The word *eat* is **transitive**, requiring two arguments (the eater and the eaten). Other verbs are more complex; for instance *put* requires three arguments, the agent doing the putting, the entity being put somewhere, and a location. We will return to this topic when we come to look at grammars and parsing (see [Chapter 8](#)).

In the Brown Corpus, verbs have a range of possible tags, e.g.: *give/VB* (present), *gives/VBZ* (present, 3ps), *giving/VBG* (present continuous; gerund) *gave/VBD* (simple past), and *given/VBN* (past participle). We will discuss these tags in more detail in a later section.

4.2.3 Nouns and Verbs in Tagged Corpora

Now that we are able to access tagged corpora, we can write simple programs to garner statistics about the tags. In this section we will focus on the nouns and verbs.

What are the 10 most common verbs? We can write a program to find all words tagged with VB, VBZ, VBG, VBD or VBN.

```
>>> fd = nltk.FreqDist()
>>> for (wd, tg) in nltk.corpus.brown.tagged_words(categories='a'):
...     if tg[:2] == 'VB':
...         fd.inc(wd + "/" + tg)
>>> fd.sorted()[:20]
['said/VBD', 'get/VB', 'made/VBN', 'United/VBN-TL', 'take/VB',
 'took/VBD', 'told/VBD', 'made/VBD', 'make/VB', 'got/VBD',
 'came/VBD', 'go/VB', 'see/VB', 'went/VBD', 'given/VBN',
 'expected/VBN', 'began/VBD', 'give/VB', 'taken/VBN', 'play/VB']
```

Let's study nouns, and find the most frequent nouns of each noun part-of-speech type. The program in [Listing 4.2](#) finds all tags starting with NN, and provides a few example words for each one. Observe that there are many noun tags; the most important of these have \$ for possessive nouns, S for plural nouns (since plural nouns typically end in *s*), P for proper nouns.

Some tags contain a plus sign; these are compound tags, and are assigned to words that contain two parts normally treated separately. Some tags contain a minus sign; this indicates disjunction.

4.2.4 The Default Tagger

The simplest possible tagger assigns the same tag to each token. This may seem to be a rather banal step, but it establishes an important baseline for tagger performance. In order to get the best result, we tag each word with the most likely word. (This kind of tagger is known as a **majority class classifier**). What then, is the most frequent tag? We can find out using a simple program:

```
>>> fd = nltk.FreqDist()
>>> for (wd, tg) in nltk.corpus.brown.tagged_words(categories='a'):
...     fd.inc(tg)
>>> fd.max()
'NN'
```

Now we can create a tagger, called `default_tagger`, that tags everything as NN.

```
>>> tokens = 'John saw 3 polar bears .'.split()
>>> default_tagger = nltk.DefaultTagger('NN')
>>> default_tagger.tag(tokens)
[('John', 'NN'), ('saw', 'NN'), ('3', 'NN'), ('polar', 'NN'),
 ('bears', 'NN'), ('.', 'NN')]
```

Listing 4.2 Program to Find the Most Frequent Noun Tags

```
def findtags(tag_prefix, tagged_text):
    cfd = nltk.ConditionalFreqDist()
    for (wd, tg) in tagged_text:
        if tg.startswith(tag_prefix):
            cfd[tg].inc(wd)
    tagdict = {}
    for tg in cfd.conditions():
        tagdict[tg] = cfd[tg].sorted()[:5]
    return tagdict

>>> tagdict = findtags('NN', nltk.corpus.brown.tagged_words(categories='a'))
>>> for tg in sorted(tagdict):
...     print tg, tagdict[tg]
NN ['year', 'time', 'state', 'week', 'man']
NN$ ["year's", "world's", "state's", "nation's", "company's"]
NN$-HL ["Golf's", "Navy's"]
NN$-TL ["President's", "University's", "League's", "Gallery's", "Army's"]
NN-HL ['cut', 'Salary', 'condition', 'Question', 'business']
NN-NC ['eva', 'ova', 'aya']
NN-TL ['President', 'House', 'State', 'University', 'City']
NN-TL-HL ['Fort', 'City', 'Commissioner', 'Grove', 'House']
NNS ['years', 'members', 'people', 'sales', 'men']
NNS$ ["children's", "women's", "men's", "janitors'", "taxpayers'"]
NNS$-HL ["Dealers'", "Idols'"]
NNS$-TL ["Women's", "States'", "Giants'", "Officers'", "Bombers'"]
NNS-HL ['years', 'idols', 'Creations', 'thanks', 'centers']
NNS-TL ['States', 'Nations', 'Masters', 'Rules', 'Communists']
NNS-TL-HL ['Nations']
```

This is a simple algorithm, and it performs poorly when used on its own. On a typical corpus, it will tag only about an eighth of the tokens correctly:

```
>>> nltk.tag.accuracy(default_tagger, nltk.corpus.brown.tagged_sents(categories='a'))
0.13089484257215028
```

Default taggers assign their tag to every single word, even words that have never been encountered before. As it happens, most new words are nouns. Thus, default taggers help to improve the robustness of a language processing system. We will return to them later, in the context of our discussion of *backoff*.

4.2.5 Exercises

1. ◊ Working with someone else, take turns to pick a word that can be either a noun or a verb (e.g. *contest*); the opponent has to predict which one is likely to be the most frequent in the Brown corpus; check the opponent's prediction, and tally the score over several turns.
2. ● Write programs to process the Brown Corpus and find answers to the following questions:
 - 1) Which nouns are more common in their plural form, rather than their singular form? (Only consider regular plurals, formed with the *-s* suffix.)
 - 2) Which word has the greatest number of distinct tags. What are they, and what do they represent?
 - 3) List tags in order of decreasing frequency. What do the 20 most frequent tags represent?
 - 4) Which tags are nouns most commonly found after? What do these tags represent?
3. ● Generate some statistics for tagged data to answer the following questions:
 - a) What proportion of word types are always assigned the same part-of-speech tag?
 - b) How many words are ambiguous, in the sense that they appear with at least two tags?
 - c) What percentage of word *occurrences* in the Brown Corpus involve these ambiguous words?
4. ● Above we gave an example of the `nltk.tag.accuracy()` function. It has two arguments, a tagger and some tagged text, and it works out how accurately the tagger performs on this text. For example, if the supplied tagged text was `[('the', 'DT'), ('dog', 'NN')]` and the tagger produced the output `[('the', 'NN'), ('dog', 'NN')]`, then the accuracy score would be 0.5. Can you figure out how the `nltk.tag.accuracy()` function works?
 - a) A tagger takes a list of words as input, and produces a list of tagged words as output. However, `nltk.tag.accuracy()` is given correctly tagged text as its input. What must the `nltk.tag.accuracy()` function do with this input before performing the tagging?

- b) Once the supplied tagger has created newly tagged text, how would `nltk.tag.accuracy()` go about comparing it with the original tagged text and computing the accuracy score?

4.3 Looking for Patterns in Words

4.3.1 Some Morphology

English nouns can be morphologically complex. For example, words like *books* and *women* are plural. Words with the *-ness* suffix are nouns that have been derived from adjectives, e.g. *happiness* and *illness*. The *-ment* suffix appears on certain nouns derived from verbs, e.g. *government* and *establishment*.

English verbs can also be morphologically complex. For instance, the **present participle** of a verb ends in *-ing*, and expresses the idea of ongoing, incomplete action (e.g. *falling*, *eating*). The *-ing* suffix also appears on nouns derived from verbs, e.g. *the falling of the leaves* (this is known as the **gerund**). In the Brown corpus, these are tagged VBG.

The **past participle** of a verb often ends in *-ed*, and expresses the idea of a completed action (e.g. *walked*, *cried*). These are tagged VBD.

Common tag sets often capture some **morpho-syntactic** information; that is, information about the kind of morphological markings that words receive by virtue of their syntactic role. Consider, for example, the selection of distinct grammatical forms of the word *go* illustrated in the following sentences:

- (6) a. *Go* away!
 b. He sometimes *goes* to the cafe.
 c. All the cakes have *gone*.
 d. We *went* on the excursion.

Each of these forms — *go*, *goes*, *gone*, and *went* — is morphologically distinct from the others. Consider the form, *goes*. This cannot occur in all grammatical contexts, but requires, for instance, a third person singular subject. Thus, the following sentences are ungrammatical.

- (7) a. *They sometimes *goes* to the cafe.
 b. *I sometimes *goes* to the cafe.

By contrast, *gone* is the past participle form; it is required after *have* (and cannot be replaced in this context by *goes*), and cannot occur as the main verb of a clause.

- (8) a. *All the cakes have *goes*.
 b. *He sometimes *gone* to the cafe.

We can easily imagine a tag set in which the four distinct grammatical forms just discussed were all tagged as VB. Although this would be adequate for some purposes, a more fine-grained tag set will provide useful information about these forms that can be of value to other processors that try to detect syntactic patterns from tag sequences. As we noted at the beginning of this chapter, the Brown tag set does in fact capture these distinctions, as summarized in [Table 4.4](#).

Form	Category	Tag
go	base	VB
goes	3rd singular present	VBZ
gone	past participle	VBN
going	gerund	VBG
went	simple past	VBD

Table 4.4: Some morphosyntactic distinctions in the Brown tag set

In addition to this set of verb tags, the various forms of the verb *to be* have special tags: *be*/BE, *being*/BEG, *am*/BEM, *been*/BEN and *was*/BEDZ. All told, this fine-grained tagging of verbs means that an automatic tagger that uses this tag set is in effect carrying out a limited amount of morphological analysis.

Most part-of-speech tag sets make use of the same basic categories, such as noun, verb, adjective, and preposition. However, tag sets differ both in how finely they divide words into categories, and in how they define their categories. For example, *is* might be tagged simply as a verb in one tag set; but as a distinct form of the lexeme *BE* in another tag set (as in the Brown Corpus). This variation in tag sets is unavoidable, since part-of-speech tags are used in different ways for different tasks. In other words, there is no one 'right way' to assign tags, only more or less useful ways depending on one's goals. More details about the Brown corpus tag set can be found in the [Appendix](#) at the end of this chapter.

4.3.2 The Regular Expression Tagger

The regular expression tagger assigns tags to tokens on the basis of matching patterns. For instance, we might guess that any word ending in *ed* is the past participle of a verb, and any word ending with *'s* is a possessive noun. We can express these as a list of regular expressions:

```
>>> patterns = [
...     (r'.*ing$', 'VBG'),                      # gerunds
...     (r'.*ed$', 'VBD'),                        # simple past
...     (r'.*es$', 'VBZ'),                         # 3rd singular present
...     (r'.*ould$', 'MD'),                        # modals
...     (r'.*\s$', 'NN$'),                          # possessive nouns
...     (r'.*s$', 'NNS'),                           # plural nouns
...     (r'^-[0-9]+([0-9]+)?$', 'CD'),            # cardinal numbers
...     (r'.*', 'NN')                             # nouns (default)
... ]
```

Note that these are processed in order, and the first one that matches is applied.

Now we can set up a tagger and use it to tag some text.

```
>>> regexp_tagger = nltk.RegexpTagger(patterns)
>>> regexp_tagger.tag(nltk.corpus.brown.sents(categories='a')[3])
[('``', 'NN'), ('Only', 'NN'), ('a', 'NN'), ('relative', 'NN'),
('handful', 'NN'), ('of', 'NN'), ('such', 'NN'), ('reports', 'NNS'),
('was', 'NNS'), ('received', 'VBD'), ("''", 'NN'), ('.', 'NN'),
('the', 'NN'), ('jury', 'NN'), ('said', 'NN'), ('.', 'NN'), ('''', 'NN'),
('considering', 'VBG'), ('the', 'NN'), ('widespread', 'NN'), ..., ('.', 'NN')]
```

How well does this do?

```
>>> nltk.tag.accuracy(regexp_tagger, nltk.corpus.brown.tagged_sents(categories='a'))
0.20326391789486245
```

The regular expression is a catch-all that tags everything as a noun. This is equivalent to the default tagger (only much less efficient). Instead of re-specifying this as part of the regular expression tagger, is there a way to combine this tagger with the default tagger? We will see how to do this later, under the heading of backoff taggers.

4.3.3 Exercises

1. ☀ Search the web for “spoof newspaper headlines”, to find such gems as: *British Left Waffles on Falkland Islands*, and *Juvenile Court to Try Shooting Defendant*. Manually tag these headlines to see if knowledge of the part-of-speech tags removes the ambiguity.
2. ☀ Satisfy yourself that there are restrictions on the distribution of *go* and *went*, in the sense that they cannot be freely interchanged in the kinds of contexts illustrated in (6).
3. ⚡ Write code to search the Brown Corpus for particular words and phrases according to tags, to answer the following questions:
 - a) Produce an alphabetically sorted list of the distinct words tagged as MD.
 - b) Identify words that can be plural nouns or third person singular verbs (e.g. *deals*, *flies*).
 - c) Identify three-word prepositional phrases of the form IN + DET + NN (eg. *in the lab*).
 - d) What is the ratio of masculine to feminine pronouns?
4. ⚡ In the introduction we saw a table involving frequency counts for the verbs *adore*, *love*, *like*, *prefer* and preceding qualifiers such as *really*. Investigate the full range of qualifiers (Brown tag QL) that appear before these four verbs.
5. ⚡ We defined the `regexp_tagger` that can be used as a fall-back tagger for unknown words. This tagger only checks for cardinal numbers. By testing for particular prefix or suffix strings, it should be possible to guess other tags. For example, we could tag any word that ends with *-s* as a plural noun. Define a regular expression tagger (using `nltk.RegexpTagger`) that tests for at least five other patterns in the spelling of words. (Use inline documentation to explain the rules.)
6. ⚡ Consider the regular expression tagger developed in the exercises in the previous section. Evaluate the tagger using `nltk.tag.accuracy()`, and try to come up with ways to improve its performance. Discuss your findings. How does objective evaluation help in the development process?
7. ★ There are 264 distinct words in the Brown Corpus having exactly three possible tags.
 - a) Print a table with the integers 1..10 in one column, and the number of distinct words in the corpus having 1..10 distinct tags.
 - b) For the word with the greatest number of distinct tags, print out sentences from the corpus containing the word, one for each possible tag.

8. ★ Write a program to classify contexts involving the word *must* according to the tag of the following word. Can this be used to discriminate between the epistemic and deontic uses of *must*?

4.4 Baselines and Backoff

So far the performance of our simple taggers has been disappointing. Before we embark on a process to get 90+% performance, we need to do two more things. First, we need to establish a more principled baseline performance than the default tagger, which was too simplistic, and the regular expression tagger, which was too arbitrary. Second, we need a way to connect multiple taggers together, so that if a more specialized tagger is unable to assign a tag, we can “back off” to a more generalized tagger.

4.4.1 The Lookup Tagger

A lot of high-frequency words do not have the NN tag. Let’s find some of these words and their tags. The following code takes a list of sentences and counts up the words, and prints the 100 most frequent words:

```
>>> fd = nltk.FreqDist(nltk.corpus.brown.words(categories='a'))
>>> most_freq_words = fd.sorted()[:100]
>>> most_freq_words
['the', ',', '.', 'of', 'and', 'to', 'a', 'in', 'for', 'The', 'that', '',
'is', 'was', "", 'on', 'at', 'with', 'be', 'by', 'as', 'he', 'said', 'his',
'will', 'it', 'from', 'are', ';', 'has', 'an', '--', 'had', 'who', 'have',
'not', 'Mrs.', 'were', 'this', 'would', 'which', 'their', 'been', 'they', 'He',
'one', 'I', 'its', 'but', 'or', 'more', ')', 'Mr.', 'up', '(', 'all', 'last',
'out', 'two', ':', 'other', 'new', 'first', 'year', 'than', 'A', 'about', 'there',
'when', 'home', 'after', 'In', 'also', 'over', 'It', 'into', 'no', 'But', 'made',
'her', 'only', 'years', 'time', 'three', 'them', 'some', 'can', 'New', 'him',
'state', '?', 'any', 'President', 'could', 'before', 'week', 'under', 'against',
've', 'now']
```

Next, let’s inspect the tags that these words have. First we will do this in the most obvious (but highly inefficient) way:

```
>>> [(w,t) for (w,t) in nltk.corpus.brown.tagged_words(categories='a')
...     if w in most_freq_words]
[('The', 'AT'), ('said', 'VBD'), ('an', 'AT'), ('of', 'IN'),
(')', ''), ('no', 'AT'), ("", ""), ('that', 'CS'),
('any', 'DTI'), ('.', '.'), ..., ("", "")]
```

A much better approach is to set up a dictionary that maps each of the 100 most frequent words to its most likely tag. We can do this by setting up a frequency distribution `cf` over the tagged words, i.e. the frequency of the different tags that occur with each word.

```
>>> cfd = nltk.ConditionalFreqDist(nltk.corpus.brown.tagged_words(categories='a'))
```

Now for any word that appears in this section of the corpus, we can determine its most likely tag:

```
>>> likely_tags = dict((word, cfd[word].max()) for word in most_freq_words)
>>> likely_tags['The']
'AT'
```

Finally, we can create and evaluate a simple tagger that assigns tags to words based on this table:

```
>>> baseline_tagger = nltk.UnigramTagger(model=likely_tags)
>>> nltk.tag.accuracy(baseline_tagger, nltk.corpus.brown.tagged_sents(categories='a'))
0.45578495136941344
```

This is surprisingly good; just knowing the tags for the 100 most frequent words enables us to tag nearly half of all words correctly! Let's see what it does on some untagged input text:

```
>>> baseline_tagger.tag(nltk.corpus.brown.sents(categories='a'))[3]
[('``', ``'), ('Only', None), ('a', 'AT'), ('relative', None),
('handful', None), ('of', 'IN'), ('such', None), ('reports', None),
('was', 'BEDZ'), ('received', None), ('''', '''), ('', ','),
('the', 'AT'), ('jury', None), ('said', 'VBD'), ('', ','),
('``', ``'), ('considering', None), ('the', 'AT'), ('widespread', None),
('interest', None), ('in', 'IN'), ('the', 'AT'), ('election', None),
('', ','), ('the', 'AT'), ('number', None), ('of', 'IN'),
('voters', None), ('and', 'CC'), ('the', 'AT'), ('size', None),
('of', 'IN'), ('this', 'DT'), ('city', None), ('''', '''), ('.', '.')]
```

Notice that a lot of these words have been assigned a tag of `None`. That is because they were not among the 100 most frequent words. In these cases we would like to assign the default tag of `NN`, a process known as backoff.

4.4.2 Backoff

How do we combine these taggers? We want to use the lookup table first, and if it is unable to assign a tag, then use the default tagger. We do this by specifying the default tagger as an argument to the lookup tagger. The lookup tagger will call the default tagger just in case it can't assign a tag itself.

```
>>> baseline_tagger = nltk.UnigramTagger(model=likely_tags, backoff=nltk.DefaultTagger('NN'))
>>> nltk.tag.accuracy(baseline_tagger, nltk.corpus.brown.tagged_sents(categories='a'))
0.58177695566561249
```

We will return to this technique in the context of a broader discussion on combining taggers in [Section 4.5.6](#).

4.4.3 Choosing a Good Baseline

We can put all this together to write a simple (but somewhat inefficient) program to create and evaluate lookup taggers having a range of sizes, as shown in [Listing 4.3](#). We include a backoff tagger that tags everything as a noun. A consequence of using this backoff tagger is that the lookup tagger only has to store word/tag pairs for words other than nouns.

Observe that performance initially increases rapidly as the model size grows, eventually reaching a plateau, when large increases in model size yield little improvement in performance. (This example used the `pylab` plotting package; we will return to this later in [Section 6.3.4](#)).

4.4.4 Exercises

1. Explore the following issues that arise in connection with the lookup tagger:
 - a) What happens to the tagger performance for the various model sizes when a backoff tagger is omitted?

Listing 4.3 Lookup Tagger Performance with Varying Model Size

```

def performance(cfd, wordlist):
    lt = dict((word, cfd[word].max()) for word in wordlist)
    baseline_tagger = nltk.UnigramTagger(model=lt, backoff=nltk.DefaultTagger('NN'))
    return nltk.tag.accuracy(baseline_tagger, nltk.corpus.brown.tagged_sents(categories='a'))

def display():
    import pylab
    words_by_freq = nltk.FreqDist(nltk.corpus.brown.words(categories='a')).sorted()
    cfd = nltk.ConditionalFreqDist(nltk.corpus.brown.tagged_words(categories='a'))
    sizes = 2 ** pylab.arange(15)
    perfs = [performance(cfd, words_by_freq[:size]) for size in sizes]
    pylab.plot(sizes, perfs, '-bo')
    pylab.title('Lookup Tagger Performance with Varying Model Size')
    pylab.xlabel('Model Size')
    pylab.ylabel('Performance')
    pylab.show()

>>> display()

```

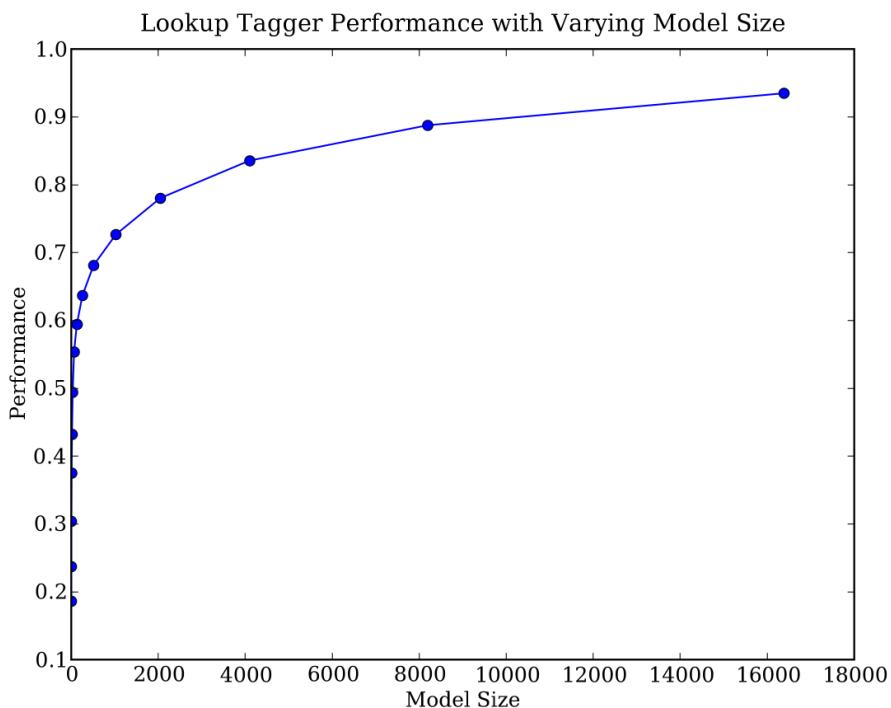


Figure 4.2: Lookup Tagger

- b) Consider the curve in Figure 4.2; suggest a good size for a lookup tagger that balances memory and performance. Can you come up with scenarios where it would be preferable to minimize memory usage, or to maximize performance with no regard for memory usage?
2. ● What is the upper limit of performance for a lookup tagger, assuming no limit to the size of its table? (Hint: write a program to work out what percentage of tokens of a word are assigned the most likely tag for that word, on average.)

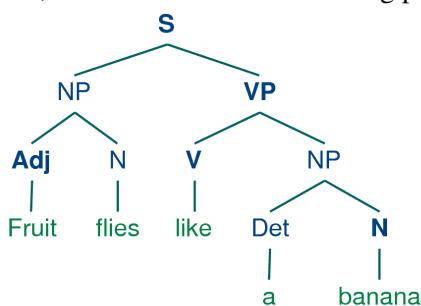
4.5 Getting Better Coverage

4.5.1 More English Word Classes

Two other important word classes are **adjectives** and **adverbs**. Adjectives describe nouns, and can be used as modifiers (e.g. *large* in *the large pizza*), or in predicates (e.g. *the pizza is large*). English adjectives can be morphologically complex (e.g. *fall_V+ing* in *the falling stocks*). Adverbs modify verbs to specify the time, manner, place or direction of the event described by the verb (e.g. *quickly* in *the stocks fell quickly*). Adverbs may also modify adjectives (e.g. *really* in *Mary's teacher was really nice*).

English has several categories of closed class words in addition to prepositions, such as **articles** (also often called **determiners**) (e.g., *the, a*), **modals** (e.g., *should, may*), and **personal pronouns** (e.g., *she, they*). Each dictionary and grammar classifies these words differently.

Part-of-speech tags are closely related to the notion of word class used in syntax. The assumption in linguistics is that every distinct word type will be listed in a lexicon (or dictionary), with information about its pronunciation, syntactic properties and meaning. A key component of the word's properties will be its class. When we carry out a syntactic analysis of an example like *fruit flies like a banana*, we will look up each word in the lexicon, determine its word class, and then group it into a hierarchy of phrases, as illustrated in the following parse tree.



Syntactic analysis will be dealt with in more detail in Part II. For now, we simply want to make the connection between the labels used in syntactic parse trees and part-of-speech tags. [Table 4.5](#) shows the correspondence:

Word Class Label	Brown Tag	Word Class
Det	AT	article
N	NN	noun
V	VB	verb
Adj	JJ	adjective
P	IN	preposition

Word Class Label	Brown Tag	Word Class
Card	CD	cardinal number
--	.	sentence-ending punctuation

Table 4.5: Word Class Labels and Brown Corpus Tags

4.5.2 Some Diagnostics

Now that we have examined word classes in detail, we turn to a more basic question: how do we decide what category a word belongs to in the first place? In general, linguists use three criteria: morphological (or formal); syntactic (or distributional); semantic (or notional). A **morphological** criterion is one that looks at the internal structure of a word. For example, *-ness* is a suffix that combines with an adjective to produce a noun. Examples are *happy* → *happiness*, *ill* → *illness*. So if we encounter a word that ends in *-ness*, this is very likely to be a noun.

A **syntactic** criterion refers to the contexts in which a word can occur. For example, assume that we have already determined the category of nouns. Then we might say that a syntactic criterion for an adjective in English is that it can occur immediately before a noun, or immediately following the words *be* or *very*. According to these tests, *near* should be categorized as an adjective:

- (9) a. the near window
- b. The end is (very) near.

A familiar example of a **semantic** criterion is that a noun is “the name of a person, place or thing”. Within modern linguistics, semantic criteria for word classes are treated with suspicion, mainly because they are hard to formalize. Nevertheless, semantic criteria underpin many of our intuitions about word classes, and enable us to make a good guess about the categorization of words in languages that we are unfamiliar with. For example, if we all we know about the Dutch *verjaardag* is that it means the same as the English word *birthday*, then we can guess that *verjaardag* is a noun in Dutch. However, some care is needed: although we might translate *zij is vandaag jarig* as *it's her birthday today*, the word *jarig* is in fact an adjective in Dutch, and has no exact equivalent in English!

All languages acquire new lexical items. A list of words recently added to the Oxford Dictionary of English includes *cyberslacker*, *fatoush*, *blamestorm*, *SARS*, *cantopop*, *bupkis*, *noughties*, *muggle*, and *robata*. Notice that all these new words are nouns, and this is reflected in calling nouns an **open class**. By contrast, prepositions are regarded as a **closed class**. That is, there is a limited set of words belonging to the class (e.g., *above*, *along*, *at*, *below*, *beside*, *between*, *during*, *for*, *from*, *in*, *near*, *on*, *outside*, *over*, *past*, *through*, *towards*, *under*, *up*, *with*), and membership of the set only changes very gradually over time.

4.5.3 Unigram Tagging

Unigram taggers are based on a simple statistical algorithm: for each token, assign the tag that is most likely for that particular token. For example, it will assign the tag *JJ* to any occurrence of the word *frequent*, since *frequent* is used as an adjective (e.g. *a frequent word*) more often than it is used as a verb (e.g. *I frequent this cafe*). A unigram tagger behaves just like a lookup tagger (Section 4.4.1), except there is a more convenient technique for setting it up, called **training**. In the following code sample, we train a unigram tagger then use it to tag a sentence, then test its overall accuracy:

```
>>> brown_a = nltk.corpus.brown.tagged_sents(categories='a')
>>> unigram_tagger = nltk.UnigramTagger(brown_a)
>>> sent = nltk.corpus.brown.sents(categories='a')[2007]
>>> unigram_tagger.tag(sent)
[('Various', None), ('of', 'IN'), ('the', 'AT'), ('apartments', 'NNS'), ('are', 'BE')
('of', 'IN'), ('the', 'AT'), ('terrace', 'NN'), ('type', 'NN'), ('.', '.'), ('being', 'BEG'),
('on', 'IN'), ('the', 'AT'), ('ground', 'NN'), ('floor', 'NN'),
('so', 'QL'), ('that', 'CS'), ('entrance', 'NN'), ('is', 'BEZ'), ('direct', 'JJ'),
>>> nltk.tag.accuracy(unigram_tagger, brown_a)
0.8550331165343994
```

4.5.4 Affix Taggers

Affix taggers are like unigram taggers, except they are trained on word prefixes or suffixes of a specified length. (NB. Here we use *prefix* and *suffix* in the string sense, not the morphological sense.) For example, the following tagger will consider suffixes of length 3 (e.g. *-ize*, *-ion*), for words having at least 5 characters.

```
>>> affix_tagger = nltk.AffixTagger(brown_a, affix_length=-2, min_stem_length=3)
>>> affix_tagger.tag(sent)
[('Various', 'JJ'), ('of', None), ('the', None), ('apartments', 'NNS'), ('are', Non
('of', None), ('the', None), ('terrace', 'NN'), ('type', None), ('.', None),
('being', 'VBG'), ('on', None), ('the', None), ('ground', 'NN'), ('floor', 'NN'),
('so', None), ('that', None), ('entrance', 'NN'), ('is', None), ('direct', 'NN'),
('. ', None)]
```

4.5.5 N-Gram Taggers

When we perform a language processing task based on unigrams, we are using one item of context. In the case of tagging, we only consider the current token, in isolation from any larger context. Given such a model, the best we can do is tag each word with its *a priori* most likely tag. This means we would tag a word such as *wind* with the same tag, regardless of whether it appears in the context *the wind* or *to wind*.

An **n-gram tagger** is a generalization of a unigram tagger whose context is the current word together with the part-of-speech tags of the $n-1$ preceding tokens, as shown in Figure 4.3. The tag to be chosen, t_n , is circled, and the context is shaded in grey. In the example of an n-gram tagger shown in Figure 4.3, we have $n=3$; that is, we consider the tags of the two preceding words in addition to the current word. An n-gram tagger picks the tag that is most likely in the given context.

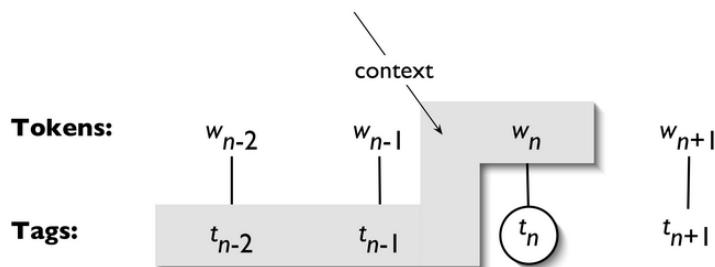


Figure 4.3: Tagger Context

Note

A 1-gram tagger is another term for a unigram tagger: i.e., the context used to tag a token is just the text of the token itself. 2-gram taggers are also called *bigram taggers*, and 3-gram taggers are called *trigram taggers*.

The NgramTagger class uses a tagged training corpus to determine which part-of-speech tag is most likely for each context. Here we see a special case of an n-gram tagger, namely a bigram tagger. First we train it, then use it to tag untagged sentences:

```
>>> bigram_tagger = nltk.BigramTagger(brown_a, cutoff=0)
>>> bigram_tagger.tag(sent)
[('Various', 'JJ'), ('of', 'IN'), ('the', 'AT'), ('apartments', 'NNS'), ('are', 'BER'),
 ('of', 'IN'), ('the', 'AT'), ('terrace', 'NN'), ('type', 'NN'), ('.', '.'), ('being', 'BEG'),
 ('on', 'IN'), ('the', 'AT'), ('ground', 'NN'), ('floor', 'NN'),
 ('so', 'CS'), ('that', 'CS'), ('entrance', 'NN'), ('is', 'BEZ'), ('direct', 'JJ'),
 ('.', '.')]
```

As with the other taggers, n-gram taggers assign the tag `NONE` to any token whose context was not seen during training.

As n gets larger, the specificity of the contexts increases, as does the chance that the data we wish to tag contains contexts that were not present in the training data. This is known as the *sparse data* problem, and is quite pervasive in NLP. Thus, there is a trade-off between the accuracy and the coverage of our results (and this is related to the **precision/recall trade-off** in information retrieval).

Note

n-gram taggers should not consider context that crosses a sentence boundary. Accordingly, NLTK taggers are designed to work with lists of sentences, where each sentence is a list of words. At the start of a sentence, t_{n-1} and preceding tags are set to `None`.

4.5.6 Combining Taggers

One way to address the trade-off between accuracy and coverage is to use the more accurate algorithms when we can, but to fall back on algorithms with wider coverage when necessary. For example, we could combine the results of a bigram tagger, a unigram tagger, and a `regexp_tagger`, as follows:

1. Try tagging the token with the bigram tagger.
2. If the bigram tagger is unable to find a tag for the token, try the unigram tagger.
3. If the unigram tagger is also unable to find a tag, use a default tagger.

Most NLTK taggers permit a backoff-tagger to be specified. The backoff-tagger may itself have a backoff tagger:

```
>>> t0 = nltk.DefaultTagger('NN')
>>> t1 = nltk.UnigramTagger(brown_a, backoff=t0)
>>> t2 = nltk.BigramTagger(brown_a, backoff=t1)
>>> nltk.tag.accuracy(t2, brown_a)
0.88565347972233821
```

Note

We specify the backoff tagger when the tagger is initialized, so that training can take advantage of the backoff tagger. Thus, if the bigram tagger would assign the same tag as its unigram backoff tagger in a certain context, the bigram tagger discards the training instance. This keeps the bigram tagger model as small as possible. We can further specify that a tagger needs to see more than one instance of a context in order to retain it, e.g. `nltk.BigramTagger(sents, cutoff=2, backoff=t1)` will discard contexts that have only been seen once or twice.

4.5.7 Tagging Unknown Words

Our approach to tagging unknown words still uses backoff to a regular-expression tagger or a default tagger. These are unable to make use of context. Thus, if our tagger encountered the word *blog*, not seen during training, it would assign it a tag regardless of whether this word appeared in the context *the blog* or *to blog*. How can we do better with these unknown words, or **out-of-vocabulary** items?

A useful method to tag unknown words based on context is to limit the vocabulary of a tagger to the most frequent n words, and to replace every other word with a special word *UNK*. During training, a unigram tagger will probably learn that this “word” is usually a noun. However, the n-gram taggers will detect contexts in which it has some other tag. For example, if the preceding word is *to* (tagged `TO`), then *UNK* will probably be tagged as a verb. Full exploration of this method is left to the exercises.

4.5.8 Storing Taggers

Training a tagger on a large corpus may take several minutes. Instead of training a tagger every time we need one, it is convenient to save a trained tagger in a file for later re-use. Let’s save our tagger `t2` to a file `t2.pkl`.

```
>>> from cPickle import dump
>>> output = open('t2.pkl', 'wb')
>>> dump(t2, output, -1)
>>> output.close()
```

Now, in a separate Python process, we can load our saved tagger.

```
>>> from cPickle import load
>>> input = open('t2.pkl', 'rb')
>>> tagger = load(input)
>>> input.close()
```

Now let’s check that it can be used for tagging.

```
>>> text = """The board's action shows what free enterprise
...           is up against in our complex maze of regulatory laws ."""
>>> tokens = text.split()
>>> tagger.tag(tokens)
[('The', 'AT'), ("board's", 'NN$'), ('action', 'NN'), ('shows', 'NNS'),
('what', 'WDT'), ('free', 'JJ'), ('enterprise', 'NN'), ('is', 'BEZ'),
('up', 'RP'), ('against', 'IN'), ('in', 'IN'), ('our', 'PP$'), ('complex', 'JJ'),
('maze', 'NN'), ('of', 'IN'), ('regulatory', 'NN'), ('laws', 'NNS'), ('.', '.')]
```

4.5.9 Exercises

1. ◊ Train a unigram tagger and run it on some new text. Observe that some words are not assigned a tag. Why not?
2. ◊ Train an affix tagger `AffixTagger()` and run it on some new text. Experiment with different settings for the affix length and the minimum word length. Can you find a setting that seems to perform better than the one described above? Discuss your findings.
3. ◊ Train a bigram tagger with no backoff tagger, and run it on some of the training data. Next, run it on some new data. What happens to the performance of the tagger? Why?
4. ⚡ Write a program that calls `AffixTagger()` repeatedly, using different settings for the affix length and the minimum word length. What parameter values give the best overall performance? Why do you think this is the case?
5. ⚡ How serious is the sparse data problem? Investigate the performance of n-gram taggers as n increases from 1 to 6. Tabulate the accuracy score. Estimate the training data required for these taggers, assuming a vocabulary size of 10^5 and a tagset size of 10^2 .
6. ⚡ Obtain some tagged data for another language, and train and evaluate a variety of taggers on it. If the language is morphologically complex, or if there are any orthographic clues (e.g. capitalization) to word classes, consider developing a regular expression tagger for it (ordered after the unigram tagger, and before the default tagger). How does the accuracy of your tagger(s) compare with the same taggers run on English data? Discuss any issues you encounter in applying these methods to the language.
7. ★ Create a default tagger and various unigram and n-gram taggers, incorporating backoff, and train them on part of the Brown corpus.
 - a) Create three different combinations of the taggers. Test the accuracy of each combined tagger. Which combination works best?
 - b) Try varying the size of the training corpus. How does it affect your results?
8. ★ Our approach for tagging an unknown word has been to consider the letters of the word (using `RegexpTagger()` and `AffixTagger()`), or to ignore the word altogether and tag it as a noun (using `nltk.DefaultTagger()`). These methods will not do well for texts having new words that are not nouns. Consider the sentence *I like to blog on Kim's blog*. If *blog* is a new word, then looking at the previous tag (TO vs NP\$) would probably be helpful. I.e. we need a default tagger that is sensitive to the preceding tag.
 - a) Create a new kind of unigram tagger that looks at the tag of the previous word, and ignores the current word. (The best way to do this is to modify the source code for `UnigramTagger()`, which presumes knowledge of Python classes discussed in [Section 10](#).)
 - b) Add this tagger to the sequence of backoff taggers (including ordinary trigram and bigram taggers that look at words), right before the usual default tagger.
 - c) Evaluate the contribution of this new unigram tagger.

9. ★ Write code to preprocess tagged training data, replacing all but the most frequent n words with the special word *UNK*. Train an n-gram backoff tagger on this data, then use it to tag some new text. Note that you will have to preprocess the text to replace unknown words with *UNK*, and post-process the tagged output to replace the *UNK* words with the words from the original input.

4.6 Summary

- Words can be grouped into classes, such as nouns, verbs, adjectives, and adverbs. These classes are known as lexical categories or parts of speech. Parts of speech are assigned short labels, or tags, such as NN, VB,
- The process of automatically assigning parts of speech to words in text is called part-of-speech tagging, POS tagging, or just tagging.
- Some linguistic corpora, such as the Brown Corpus, have been POS tagged.
- A variety of tagging methods are possible, e.g. default tagger, regular expression tagger, unigram tagger and n-gram taggers. These can be combined using a technique known as backoff.
- Taggers can be trained and evaluated using tagged corpora.
- Part-of-speech tagging is an important, early example of a sequence classification task in NLP: a classification decision at any one point in the sequence makes use of words and tags in the local context.

4.7 Further Reading

For more examples of tagging with NLTK, please see the guide at <http://nltk.org/doc/guides/tag.html>.

There are several other important approaches to tagging involving *Transformation-Based Learning*, *Markov Modeling*, and *Finite State Methods*. (We will discuss some of these in [Chapter 5](#).) In [Chapter 7](#) we will see a generalization of tagging called *chunking* in which a contiguous sequence of words is assigned a single tag.

Part-of-speech tagging is just one kind of tagging, one that does not depend on deep linguistic analysis. There are many other kinds of tagging. Words can be tagged with directives to a speech synthesizer, indicating which words should be emphasized. Words can be tagged with sense numbers, indicating which sense of the word was used. Words can also be tagged with morphological features. Examples of each of these kinds of tags are shown below. For space reasons, we only show the tag for a single word. Note also that the first two examples use XML-style tags, where elements in angle brackets enclose the word that is tagged.

1. *Speech Synthesis Markup Language (W3C SSML)*: That *is* a <emphasis>big</emphasis> car!
2. *SemCor: Brown Corpus tagged with WordNet senses*: Space *in* any <wf pos="NN" lemma="form" wnsn="4">form</wf> *is* completely measured by the three dimensions. (Wordnet form/nn sense 4: “shape, form, configuration, contour, conformation”)

3. Morphological tagging, from the Turin University Italian Treebank: E' italiano , come progetto e realizzazione , il primo (PRIMO ADJ ORDIN M SING) porto turistico dell' Albania .

Tagging exhibits several properties that are characteristic of natural language processing. First, tagging involves *classification*: words have properties; many words share the same property (e.g. *cat* and *dog* are both nouns), while some words can have multiple such properties (e.g. *wind* is a noun and a verb). Second, in tagging, disambiguation occurs via *representation*: we augment the representation of tokens with part-of-speech tags. Third, training a tagger involves *sequence learning from annotated corpora*. Finally, tagging uses *simple, general, methods* such as conditional frequency distributions and transformation-based learning.

List of available taggers: <http://www-nlp.stanford.edu/links/statnlp.html>

4.8 Appendix: Brown Tag Set

Table 4.6 gives a sample of closed class words, following the classification of the Brown Corpus. (Note that part-of-speech tags may be presented as either upper-case or lower-case strings — the case difference is not significant.)

AP	determiner/pronoun, post-determiner	many other next more last former little several enough most least only very few fewer past same
AT	article	the an no a every th' ever' ye
CC	conjunction, coordinating	and or but plus & either neither nor yet 'n' and/or minus an'
CS	conjunction, subordinating	that as after whether before while like because if since for than until so unless though providing once lest till whereas whereupon supposing albeit then
IN	preposition	of in for by considering to on among at through with under into regarding than since despite ...
MD	modal auxiliary	should may might will would must can could shall ought need wilt
PN	pronoun, nominal	none something everything one anyone nothing nobody everybody everyone anybody anything someone no-one nothin'
PPL	pronoun, singular, reflexive	itself himself myself yourself herself oneself ownself
PP\$	determiner, possessive	our its his their my your her out thy mine thine
PP\$	pronoun, possessive	ours mine his hers theirs yours
PPS	pronoun, personal, nom, 3rd pers sng	it he she thee
PPSS	pronoun, personal, nom, not 3rd pers sng	they we I you ye thou you'un
WDT	WH-determiner	which what whatever whichever
WP\$	WH-pronoun, nom-inative	that who whoever whosoever what whatsoever

Table 4.6: Some English Closed Class Words, with Brown Tag

4.8.1 Acknowledgments

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Chapter 5

Data-Intensive Language Processing

Note

this chapter is currently in preparation

About this document...

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Part II

PARSING

Introduction to Part II

Part II covers the linguistic and computational analysis of sentences. We will see that sentences have systematic structure; we use this to communicate who did what to whom. Linguistic structures are formalized using context-free grammars, and processed computationally using parsers. Various extensions are covered, including chart parsers and probabilistic parsers. Part II also introduces the techniques in structured programming needed for implementing grammars and parsers.

Chapter 6

Structured Programming in Python

6.1 Introduction

In Part I you had an intensive introduction to Python ([Chapter 2](#)) followed by chapters on words, tags, and chunks ([Chapters 3-7](#)). These chapters contain many examples and exercises that should have helped you consolidate your Python skills and apply them to simple NLP tasks. So far our programs — and the data we have been processing — have been relatively unstructured. In Part II we will focus on *structure*: i.e. structured programming with structured data.

In this chapter we will review key programming concepts and explain many of the minor points that could easily trip you up. More fundamentally, we will introduce important concepts in structured programming that help you write readable, well-organized programs that you and others will be able to re-use. Each section is independent, so you can easily select what you most need to learn and concentrate on that. As before, this chapter contains many examples and exercises (and as before, some exercises introduce new material). Readers new to programming should work through them carefully and consult other introductions to programming if necessary; experienced programmers can quickly skim this chapter.

Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

6.2 Back to the Basics

Let's begin by revisiting some of the fundamental operations and data structures required for natural language processing in Python. It is important to appreciate several finer points in order to write Python programs that are not only correct but also *idiomatic* — by this, we mean using the features of the Python language in a natural and concise way. To illustrate, here is a technique for iterating over the members of a list by initializing an index `i` and then incrementing the index each time we pass through the loop:

```
>>> sent = ['I', 'am', 'the', 'Walrus']
>>> i = 0
>>> while i < len(sent):
...     print sent[i].lower(),
...     i += 1
```

```
i am the walrus
```

Although this does the job, it is not idiomatic Python. By contrast, Python's `for` statement allows us to achieve the same effect much more succinctly:

```
>>> sent = ['I', 'am', 'the', 'Walrus']
>>> for s in sent:
...     print s.lower(),
i am the walrus
```

We'll start with the most innocuous operation of all: *assignment*. Then we will look at sequence types in detail.

6.2.1 Assignment

Python's assignment statement operates on *values*. But what is a value? Consider the following code fragment:

```
>>> word1 = 'Monty'
>>> word2 = word1          ①
>>> word1 = 'Python'       ②
>>> word2
'Monty'
```

This code shows that when we write `word2 = word1` in line ①, the value of `word1` (the string '`Monty`') is assigned to `word2`. That is, `word2` is a **copy** of `word1`, so when we overwrite `word1` with a new string '`Python`' in line ②, the value of `word2` is not affected.

However, assignment statements do not always involve making copies in this way. An important subtlety of Python is that the "value" of a structured object (such as a list) is actually a *reference* to the object. In the following example, line ① assigns the reference of `list1` to the new variable `list2`. When we modify something inside `list1` on line ②, we can see that the contents of `list2` have also been changed.

```
>>> list1 = ['Monty', 'Python']
>>> list2 = list1          ①
>>> list1[1] = 'Bodkin'    ②
>>> list2
['Monty', 'Bodkin']
```

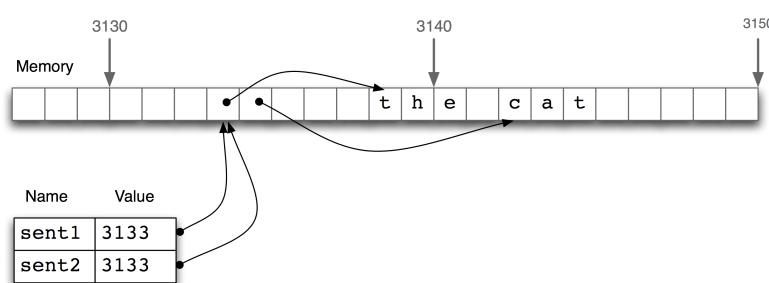


Figure 6.1: List Assignment and Computer Memory

Thus line ① does not copy the contents of the variable, only its “object reference”. To understand what is going on here, we need to know how lists are stored in the computer’s memory. In [Figure 6.1](#), we see that a list `sent1` is a reference to an object stored at location 3133 (which is itself a series of pointers to other locations holding strings). When we assign `sent2 = sent1`, it is just the object reference 3133 that gets copied.

6.2.2 Sequences: Strings, Lists and Tuples

We have seen three kinds of sequence object: strings, lists, and tuples. As sequences, they have some common properties: they can be indexed and they have a length:

```
>>> text = 'I turned off the spectroroute'
>>> words = ['I', 'turned', 'off', 'the', 'spectroroute']
>>> pair = (6, 'turned')
>>> text[2], words[3], pair[1]
('t', 'the', 'turned')
>>> len(text), len(words), len(pair)
(29, 5, 2)
```

We can iterate over the items in a sequence `s` in a variety of useful ways, as shown in [Table 6.1](#).

Python Expression	Comment
<code>for item in s</code>	iterate over the items of <code>s</code>
<code>for item in sorted(s)</code>	iterate over the items of <code>s</code> in order
<code>for item in set(s)</code>	iterate over unique elements of <code>s</code>
<code>for item in reversed(s)</code>	iterate over elements of <code>s</code> in reverse
<code>for item in set(s).difference(t)</code>	iterate over elements of <code>s</code> not in <code>t</code>
<code>for item in random.shuffle(s)</code>	iterate over elements of <code>s</code> in random order

Table 6.1: Various ways to iterate over sequences

The sequence functions illustrated in [Table 6.1](#) can be combined in various ways; for example, to get unique elements of `s` sorted in reverse, use `reversed(sorted(set(s)))`.

We can convert between these sequence types. For example, `tuple(s)` converts any kind of sequence into a tuple, and `list(s)` converts any kind of sequence into a list. We can convert a list of strings to a single string using the `join()` function, e.g. `' : '.join(words)`.

Notice in the above code sample that we computed multiple values on a single line, separated by commas. These comma-separated expressions are actually just tuples — Python allows us to omit the parentheses around tuples if there is no ambiguity. When we print a tuple, the parentheses are always displayed. By using tuples in this way, we are implicitly aggregating items together.

In the next example, we use tuples to re-arrange the contents of our list. (We can omit the parentheses because the comma has higher precedence than assignment.)

```
>>> words[2], words[3], words[4] = words[3], words[4], words[2]
>>> words
['I', 'turned', 'the', 'spectroroute', 'off']
```

This is an idiomatic and readable way to move items inside a list. It is equivalent to the following traditional way of doing such tasks that does not use tuples (notice that this method needs a temporary variable `tmp`).

```
>>> tmp = words[2]
>>> words[2] = words[3]
>>> words[3] = words[4]
>>> words[4] = tmp
```

As we have seen, Python has sequence functions such as `sorted()` and `reversed()` that rearrange the items of a sequence. There are also functions that modify the *structure* of a sequence and which can be handy for language processing. Thus, `zip()` takes the items of two sequences and “zips” them together into a single list of pairs. Given a sequence `s`, `enumerate(s)` returns an iterator that produces a pair of an index and the item at that index.

```
>>> words = ['I', 'turned', 'off', 'the', 'spectroroute']
>>> tags = ['NNP', 'VBD', 'IN', 'DT', 'NN']
>>> zip(words, tags)
[('I', 'NNP'), ('turned', 'VBD'), ('off', 'IN'),
 ('the', 'DT'), ('spectroroute', 'NN')]
>>> list(enumerate(words))
[(0, 'I'), (1, 'turned'), (2, 'off'), (3, 'the'), (4, 'spectroroute')]
```

6.2.3 Combining Different Sequence Types

Let’s combine our knowledge of these three sequence types, together with list comprehensions, to perform the task of sorting the words in a string by their length.

```
>>> words = 'I turned off the spectroroute'.split()      ①
>>> wordlens = [(len(word), word) for word in words]    ②
>>> wordlens
[(1, 'I'), (6, 'turned'), (3, 'off'), (3, 'the'), (12, 'spectroroute')]
>>> wordlens.sort()                                     ③
>>> ''.join([word for (count, word) in wordlens])       ④
'I off the turned spectroroute'
```

Each of the above lines of code contains a significant feature. Line ① demonstrates that a simple string is actually an object with methods defined on it, such as `split()`. Line ② shows the construction of a list of tuples, where each tuple consists of a number (the word length) and the word, e.g. (3, 'the'). Line ③ sorts the list, modifying the list in-place. Finally, line ④ discards the length information then joins the words back into a single string.

We began by talking about the commonalities in these sequence types, but the above code illustrates important differences in their roles. First, strings appear at the beginning and the end: this is typical in the context where our program is reading in some text and producing output for us to read. Lists and tuples are used in the middle, but for different purposes. A list is typically a sequence of objects all having the *same type*, of *arbitrary length*. We often use lists to hold sequences of words. In contrast, a tuple is typically a collection of objects of *different types*, of *fixed length*. We often use a tuple to hold a **record**, a collection of different **fields** relating to some entity. This distinction between the use of lists and tuples takes some getting used to, so here is another example:

```
>>> lexicon = [
...     ('the', 'DT', ['Di:', 'D@']),
```

```
...     ('off', 'IN', ['Qf', 'O:f'])
... ]
```

Here, a lexicon is represented as a list because it is a collection of objects of a single type — lexical entries — of no predetermined length. An individual entry is represented as a tuple because it is a collection of objects with different interpretations, such as the orthographic form, the part of speech, and the pronunciations represented in the [SAMPA](#) computer readable phonetic alphabet. Note that these pronunciations are stored using a list. (Why?)

The distinction between lists and tuples has been described in terms of usage. However, there is a more fundamental difference: in Python, lists are **mutable**, while tuples are **immutable**. In other words, lists can be modified, while tuples cannot. Here are some of the operations on lists that do in-place modification of the list. None of these operations is permitted on a tuple, a fact you should confirm for yourself.

```
>>> lexicon.sort()
>>> lexicon[1] = ('turned', 'VBD', ['t3:nd', 't3'nd'])
>>> del lexicon[0]
```

6.2.4 Stacks and Queues

Lists are a particularly versatile data type. We can use lists to implement higher-level data types such as stacks and queues. A **stack** is a container that has a **last-in-first-out** policy for adding and removing items (see [Figure 6.2](#)).

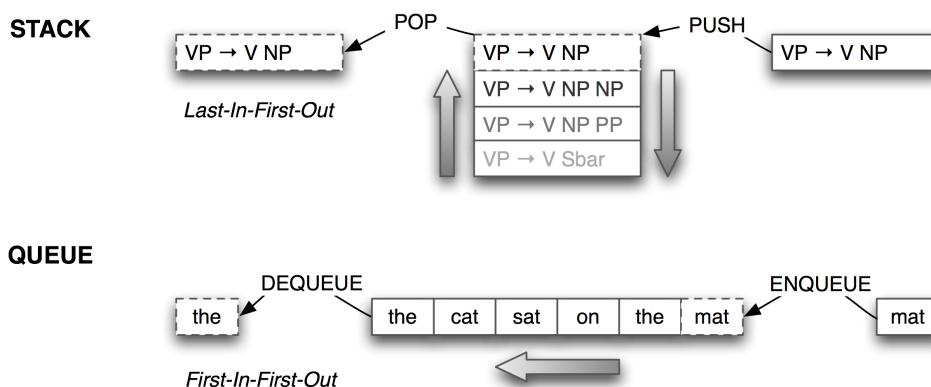


Figure 6.2: Stacks and Queues

Stacks are used to keep track of the current context in computer processing of natural languages (and programming languages too). We will seldom have to deal with stacks explicitly, as the implementation of NLTK parsers, treebank corpus readers, (and even Python functions), all use stacks behind the scenes. However, it is important to understand what stacks are and how they work.

In Python, we can treat a list as a stack by limiting ourselves to the three operations defined on stacks: `append(item)` (to push `item` onto the stack), `pop()` to pop the item off the top of the stack, and `[-1]` to access the item on the top of the stack. [Listing 6.1](#) processes a sentence with phrase markers, and checks that the parentheses are balanced. The loop pushes material onto the stack when it gets an open parenthesis, and pops the stack when it gets a close parenthesis. We see that two are left on the stack at the end; i.e. the parentheses are not balanced.

Listing 6.1 Check parentheses are balanced

```
def check_parens(tokens):
    stack = []
    for token in tokens:
        if token == '(':      # push
            stack.append(token)
        elif token == ')':    # pop
            stack.pop()
    return stack

>>> phrase = "( the cat ) ( sat ( on ( the mat )"
>>> print check_parens(phrase.split())
['(', '(']
```

Although Listing 6.1 is a useful illustration of stacks, it is overkill because we could have done a direct count: `phrase.count('(') == phrase.count(')')`. However, we can use stacks for more sophisticated processing of strings containing nested structure, as shown in Listing 6.2. Here we build a (potentially deeply-nested) list of lists. Whenever a token other than a parenthesis is encountered, we add it to a list at the appropriate level of nesting. The stack cleverly keeps track of this level of nesting, exploiting the fact that the item at the top of the stack is actually shared with a more deeply nested item. (Hint: add diagnostic print statements to the function to help you see what it is doing.)

Lists can be used to represent another important data structure. A **queue** is a container that has a **first-in-first-out** policy for adding and removing items (see Figure 6.2). Queues are used for scheduling activities or resources. As with stacks, we will seldom have to deal with queues explicitly, as the implementation of NLTK n-gram taggers (Section 4.5.5) and chart parsers (Section 9.2) use queues behind the scenes. However, we will take a brief look at how queues are implemented using lists.

```
>>> queue = ['the', 'cat', 'sat']
>>> queue.append('on')
>>> queue.append('the')
>>> queue.append('mat')
>>> queue.pop(0)
'the'
>>> queue.pop(0)
'cat'
>>> queue
['sat', 'on', 'the', 'mat']
```

6.2.5 More List Comprehensions

You may recall that in Chapter 3, we introduced list comprehensions, with examples like the following:

```
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> [word.lower() for word in sent]
['the', 'dog', 'gave', 'john', 'the', 'newspaper']
```

List comprehensions are a convenient and readable way to express list operations in Python, and they have a wide range of uses in natural language processing. In this section we will see some more

Listing 6.2 Convert a nested phrase into a nested list using a stack

```
def convert_parens(tokens):
    stack = [[]]
    for token in tokens:
        if token == '(':      # push
            sublist = []
            stack[-1].append(sublist)
            stack.append(sublist)
        elif token == ')':    # pop
            stack.pop()
        else:                  # update top of stack
            stack[-1].append(token)
    return stack[0]

>>> phrase = "( the cat ) ( sat ( on ( the mat ) ) )"
>>> print convert_parens(phrase.split())
[['the', 'cat'], ['sat', ['on', ['the', 'mat']]]]
```

examples. The first of these takes successive overlapping slices of size n (a **sliding window**) from a list (pay particular attention to the range of the variable i).

```
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> n = 3
>>> [sent[i:i+n] for i in range(len(sent)-n+1)]
[['The', 'dog', 'gave'],
 ['dog', 'gave', 'John'],
 ['gave', 'John', 'the'],
 ['John', 'the', 'newspaper']]
```

You can also use list comprehensions for a kind of multiplication (or **cartesian product**). Here we generate all combinations of two determiners, two adjectives, and two nouns. The list comprehension is split across three lines for readability.

```
>>> [(dt,jj,nn) for dt in ('two', 'three')
...       for jj in ('old', 'blind')
...       for nn in ('men', 'mice'))
[('two', 'old', 'men'), ('two', 'old', 'mice'), ('two', 'blind', 'men'),
 ('two', 'blind', 'mice'), ('three', 'old', 'men'), ('three', 'old', 'mice'),
 ('three', 'blind', 'men'), ('three', 'blind', 'mice')]
```

The above example contains three independent `for` loops. These loops have no variables in common, and we could have put them in any order. We can also have **nested loops** with shared variables. The next example iterates over all sentences in a section of the Brown Corpus, and for each sentence, iterates over each word.

```
>>> [word for word in nltk.corpus.brown.words(categories='a')
...     if len(word) == 17]
['September-October', 'Sheraton-Biltmore', 'anti-organization',
 'anti-organization', 'Washington-Oregon', 'York-Pennsylvania',
 'misunderstandings', 'Sheraton-Biltmore', 'neo-stagnationist',
```

```
'cross-examination', 'bronzy-green-gold', 'Oh-the-pain-of-it',
'Secretary-General', 'Secretary-General', 'textile-importing',
'textile-exporting', 'textile-producing', 'textile-producing']
```

As you will see, the list comprehension in this example contains a final `if` clause that allows us to filter out any words that fail to meet the specified condition.

Another way to use loop variables is to ignore them! This is the standard method for building multidimensional structures. For example, to build an array with m rows and n columns, where each cell is a set, we would use a nested list comprehension, as shown in line ① below. Observe that the loop variables `i` and `j` are not used anywhere in the expressions preceding the `for` clauses.

```
>>> m, n = 3, 7
>>> array = [[set() for i in range(n)] for j in range(m)]           ①
>>> array[2][5].add('foo')
>>> pprint.pprint(array)
[[set([]), set([]), set([]), set([]), set([]), set([])],
 [set([]), set([]), set([]), set([]), set([]), set([])],
 [set([]), set([]), set([]), set([]), set(['foo']), set([])]]
```

Sometimes we use a list comprehension as part of a larger aggregation task. In the following example we calculate the average length of words in part of the Brown Corpus. Notice that we don't bother storing the list comprehension in a temporary variable, but use it directly as an argument to the `average()` function.

```
>>> from numpy import average
>>> average([len(word) for word in nltk.corpus.brown.words(categories='a')])
4.40154543827
```

Now that we have reviewed the sequence types, we have one more fundamental data type to revisit.

6.2.6 Dictionaries

As you have already seen, the dictionary data type can be used in a variety of language processing tasks (e.g. [Section 2.6](#)). However, we have only scratched the surface. Dictionaries have many more applications than you might have imagined.

Note

The dictionary data type is often known by the name **associative array**. A normal array maps from integers (the keys) to arbitrary data types (the values), while an associative array places no such constraint on keys. Keys can be strings, tuples, or other more deeply nested structure. Python places the constraint that keys must be *immutable*.

Let's begin by comparing dictionaries with tuples. Tuples allow *access by position*; to access the part-of-speech of the following lexical entry we just have to know it is found at index position 1. However, dictionaries allow *access by name*:

```
>>> entry_tuple = ('turned', 'VBD', ['t3:nd', 't3'nd'])
>>> entry_tuple[1]
'VBD'
>>> entry_dict = {'lexeme': 'turned', 'pos': 'VBD', 'pron': ['t3:nd', 't3'nd']}
>>> entry_dict['pos']
'VBD'
```

In this case, dictionaries are little more than a convenience. We can even simulate access by name using well-chosen constants, e.g.:

```
>>> LEXEME = 0; POS = 1; PRON = 2
>>> entry_tuple[POS]
'VBD'
```

This method works when there is a closed set of keys and the keys are known in advance. Dictionaries come into their own when we are mapping from an open set of keys, which happens when the keys are drawn from an unrestricted vocabulary or where they are generated by some procedure. Listing 6.3 illustrates the first of these. The function `mystery()` begins by initializing a dictionary called `groups`, then populates it with words. We leave it as an exercise for the reader to work out what this function computes. For now, it's enough to note that the keys of this dictionary are an open set, and it would not be feasible to use integer keys, as would be required if we used lists or tuples for the representation.

Listing 6.3 Mystery program

```
def mystery(input):
    groups = {}
    for word in input:
        key = ' '.join(sorted(list(word)), ' ')
        if key not in groups:                      ①
            groups[key] = set()                    ②
        groups[key].add(word)                     ③
    return sorted(' '.join(sorted(v)) for v in groups.values() if len(v) > 1)

>>> words = nltk.corpus.words.words()
>>> print mystery(words)
```

Listing 6.3 illustrates two important idioms, which we already touched on in Chapter 2. First, dictionary keys are unique; in order to store multiple items in a single entry we define the value to be a list or a set, and simply update the value each time we want to store another item (line ③). Second, if a key does not yet exist in a dictionary (line ①) we must explicitly add it and give it an initial value (line ②).

The second important use of dictionaries is for mappings that involve **compound keys**. Suppose we want to categorize a series of linguistic observations according to two or more properties. We can combine the properties using a tuple and build up a dictionary in the usual way, as exemplified in Listing 6.4.

6.2.7 Exercises

1. ◊ Find out more about sequence objects using Python's help facility. In the interpreter, type `help(str)`, `help(list)`, and `help(tuple)`. This will give you a full list of the functions supported by each type. Some functions have special names flanked with underscore; as the help documentation shows, each such function corresponds to something more familiar. For example `x.__getitem__(y)` is just a long-winded way of saying `x[y]`.

Listing 6.4 Illustration of compound keys

```
attachment = nltk.defaultdict(lambda:[0,0])
V, N = 0, 1
for entry in nltk.corpus.ppattach.attachments('training'):
    key = entry.verb, entry.prep
    if entry.attachment == 'V':
        attachment[key][V] += 1
    else:
        attachment[key][N] += 1
```

2. ☀ Identify three operations that can be performed on both tuples and lists. Identify three list operations that cannot be performed on tuples. Name a context where using a list instead of a tuple generates a Python error.
3. ☀ Find out how to create a tuple consisting of a single item. There are at least two ways to do this.
4. ☀ Create a list `words = ['is', 'NLP', 'fun', '?']`. Use a series of assignment statements (e.g. `words[1] = words[2]`) and a temporary variable `tmp` to transform this list into the list `['NLP', 'is', 'fun', '!']`. Now do the same transformation using tuple assignment.
5. ☀ Does the method for creating a sliding window of n-grams behave correctly for the two limiting cases: $n = 1$, and $n = \text{len}(\text{sent})$?
6. ⚠ Create a list of words and store it in a variable `sent1`. Now assign `sent2 = sent1`. Modify one of the items in `sent1` and verify that `sent2` has changed.
 - a) Now try the same exercise but instead assign `sent2 = sent1[:]`. Modify `sent1` again and see what happens to `sent2`. Explain.
 - b) Now define `text1` to be a list of lists of strings (e.g. to represent a text consisting of multiple sentences). Now assign `text2 = text1[:]`, assign a new value to one of the words, e.g. `text1[1][1] = 'Monty'`. Check what this did to `text2`. Explain.
 - c) Load Python's `deepcopy()` function (i.e. `from copy import deepcopy`), consult its documentation, and test that it makes a fresh copy of any object.
7. ⚠ Write code that starts with a string of words and results in a new string consisting of the same words, but where the first word swaps places with the second, and so on. For example, `'the cat sat on the mat'` will be converted into `'cat the on sat mat the'`.
8. ⚠ Initialize an n -by- m list of lists of empty strings using list multiplication, e.g. `word_table = [[] * n] * m`. What happens when you set one of its values, e.g. `word_table[1][2] = "hello"`? Explain why this happens. Now write an expression using `range()` to construct a list of lists, and show that it does not have this problem.

9. **❶** Write code to initialize a two-dimensional array of sets called `word_vowels` and process a list of words, adding each word to `word_vowels[l][v]` where `l` is the length of the word and `v` is the number of vowels it contains.
10. **❶** Write code that builds a dictionary of dictionaries of sets.
11. **❶** Use `sorted()` and `set()` to get a sorted list of tags used in the Brown corpus, removing duplicates.
12. **❶** Read up on Gematria, a method for assigning numbers to words, and for mapping between words having the same number to discover the hidden meaning of texts (<http://en.wikipedia.org/wiki/Gematria>, <http://essenes.net/gemcal.htm>).
 - a) Write a function `gematria()` that sums the numerical values of the letters of a word, according to the letter values in `letter_vals`:


```
letter_vals = {'a':1, 'b':2, 'c':3, 'd':4, 'e':5, 'f':80, 'g':3, 'h':8, 'i':10, 'j':10, 'k':20, 'l':30, 'm':40, 'n':50, 'o':70, 'p':80, 'q':100, 'r':200, 's':300, 't':400, 'u':6, 'v':6, 'w':800, 'x':60, 'y':10, 'z':7}
```
 - b) Use the method from [Listing 6.3](#) to index English words according to their values.
 - c) Process a corpus (e.g. `nltk.corpus.state_union`) and for each document, count how many of its words have the number 666.
 - d) Write a function `decode()` to process a text, randomly replacing words with their Gematria equivalents, in order to discover the “hidden meaning” of the text.
13. **★** Extend the example in [Listing 6.4](#) in the following ways:
 - a) Define two sets `verbs` and `preps`, and add each verb and preposition as they are encountered. (Note that you can add an item to a set without bothering to check whether it is already present.)
 - b) Create nested loops to display the results, iterating over verbs and prepositions in sorted order. Generate one line of output per verb, listing prepositions and attachment ratios as follows: `raised: about 0:3, at 1:0, by 9:0, for 3:6, from 5:0, in 5:5...`
 - c) We used a tuple to represent a compound key consisting of two strings. However, we could have simply concatenated the strings, e.g. `key = verb + ":" + prep`, resulting in a simple string `key`. Why is it better to use tuples for compound keys?

6.3 Presenting Results

Often we write a program to report a single datum, such as a particular element in a corpus that meets some complicated criterion, or a single summary statistic such as a word-count or the performance of a tagger. More often, we write a program to produce a structured result, such as a tabulation of numbers or linguistic forms, or a reformatting of the original data. When the results to be presented are

linguistic, textual output is usually the most natural choice. However, when the results are numerical, it may be preferable to produce graphical output. In this section you will learn about a variety of ways to present program output.

6.3.1 Strings and Formats

We have seen that there are two ways to display the contents of an object:

```
>>> word = 'cat'
>>> sentence = """hello
... world"""
>>> print word
cat
>>> print sentence
hello
world
>>> word
'cat'
>>> sentence
'hello\nworld'
```

The `print` command yields Python's attempt to produce the most human-readable form of an object. The second method — naming the variable at a prompt — shows us a string that can be used to recreate this object. It is important to keep in mind that both of these are just strings, displayed for the benefit of you, the user. They do not give us any clue as to the actual internal representation of the object.

There are many other useful ways to display an object as a string of characters. This may be for the benefit of a human reader, or because we want to **export** our data to a particular file format for use in an external program.

Formatted output typically contains a combination of variables and pre-specified strings, e.g. given a dictionary `wordcount` consisting of words and their frequencies we could do:

```
>>> wordcount = {'cat':3, 'dog':4, 'snake':1}
>>> for word in sorted(wordcount):
...     print word, '->', wordcount[word], ';',
cat -> 3 ; dog -> 4 ; snake -> 1 ;
```

Apart from the problem of unwanted whitespace, print statements that contain alternating variables and constants can be difficult to read and maintain. A better solution is to use formatting strings:

```
>>> for word in sorted(wordcount):
...     print '%s->%d;' % (word, wordcount[word]),
cat->3; dog->4; snake->1;
```

6.3.2 Lining Things Up

So far our formatting strings have contained specifications of fixed width, such as `%6s`, a string that is padded to width 6 and right-justified. We can include a minus sign to make it left-justified. In case we don't know in advance how wide a displayed value should be, the width value can be replaced with a star in the formatting string, then specified using a variable:

```
>>> '%6s' % 'dog'
'dog'
>>> '%-6s' % 'dog'
'dog '
>>> width = 6
>>> '%-*s' % (width, 'dog')
'dog '
```

Other control characters are used for decimal integers and floating point numbers. Since the percent character % has a special interpretation in formatting strings, we have to precede it with another % to get it in the output:

```
>>> "accuracy for %d words: %2.4f%%" % (9375, 100.0 * 3205/9375)
'accuracy for 9375 words: 34.1867%'
```

An important use of formatting strings is for tabulating data. The program in [Listing 6.5](#) iterates over five genres of the Brown Corpus. For each token having the `md` tag we increment a count. To do this we have used `ConditionalFreqDist()`, where the condition is the current genre and the event is the modal, i.e. this constructs a frequency distribution of the modal verbs in each genre. Line ① identifies a small set of modals of interest, and calls the function `tabulate()` that processes the data structure to output the required counts. Note that we have been careful to separate the language processing from the tabulation of results.

There are some interesting patterns in the table produced by [Listing 6.5](#). For instance, compare row d (government literature) with row n (adventure literature); the former is dominated by the use of can, may, must, will while the latter is characterized by the use of could and might. With some further work it might be possible to guess the genre of a new text automatically, simply using information about the distribution of modal verbs.

Our next example, in [Listing 6.6](#), generates a concordance display. We use the left/right justification of strings and the variable width to get vertical alignment of a variable-width window.

[TODO: explain `ValueError` exception]

6.3.3 Writing Results to a File

We have seen how to read text from files ([Section 3.2.1](#)). It is often useful to write output to files as well. The following code opens a file `output.txt` for writing, and saves the program output to the file.

```
>>> file = open('output.txt', 'w')
>>> words = set(nltk.corpus.genesis.words('english-kjv.txt'))
>>> for word in sorted(words):
...     file.write(word + "\n")
```

When we write non-text data to a file we must convert it to a string first. We can do this conversion using formatting strings, as we saw above. We can also do it using Python's backquote notation, which converts any object into a string. Let's write the total number of words to our file, before closing it.

```
>>> len(words)
2789
>>> `len(words)`
'2789'
>>> file.write(`len(words)` + "\n")
>>> file.close()
```

Listing 6.5 Frequency of Modals in Different Sections of the Brown Corpus

```

def count_words_by_tag(t, genres):
    cfdist = nltk.ConditionalFreqDist()
    for genre in genres:
        for (word,tag) in nltk.corpus.brown.tagged_words(categories=genre):
            if tag == t:
                cfdist[genre].inc(word.lower())
    return cfdist

def tabulate(cfdist, words):
    print 'Genre ', ' '.join([('"%6s" % w) for w in words])
    for genre in sorted(cfdist.conditions()):                      # for each genre
        print '%-6s' % genre,                                         # print row heading
        for w in words:                                              # for each word
            print '%6d' % cfdist[genre][w],                           # print table cell
        print                                         # end the row

>>> genres = ['a', 'd', 'e', 'h', 'n']
>>> cfdist = count_words_by_tag('MD', genres)
>>> modals = ['can', 'could', 'may', 'might', 'must', 'will']   ①
>>> tabulate(cfdist, modals)
Genre      can    could     may   might    must    will
a         94      86      66      36      50     387
d         84      59      79      12      54      64
e        273      59     130      22      83     259
h        115      37     152      13      99     237
n         48     154       6      58      27      48

```

Listing 6.6 Simple Concordance Display

```
def concordance(word, context):
    "Generate a concordance for the word with the specified context window"
    for sent in nltk.corpus.brown.sents(categories='a'):
        try:
            pos = sent.index(word)
            left = ' '.join(sent[:pos])
            right = ' '.join(sent[pos+1:])
            print '%*s %s %-*s' %\
                  (context, left[-context:], word, context, right[:context])
        except ValueError:
            pass

>>> concordance('line', 32)
ce , is today closer to the NATO line .
n more activity across the state line in Massachusetts than in Rhode I
, gained five yards through the line and then uncorked a 56-yard touc
    `` Our interior line and out linebackers played excep
k then moved Cooke across with a line drive to left .
chal doubled down the rightfield line and Cooke singled off Phil Shart
    -- Billy Gardner's line double , which just eluded the d
    -- Nick Skorich , the line coach for the football champion
        Maris is in line for a big raise .
uld be impossible to work on the line until then because of the large
        Murray makes a complete line of ginning equipment except for
        The company sells a complete line of gin machinery all over the co
tter Co. of Sherman makes a full line of gin machinery and equipment .
fred E. Perlman said Tuesday his line would face the threat of bankrup
sale of property disposed of in line with a plan of liquidation .
little effort spice up any chow line .
es , filed through the cafeteria line .
l be particularly sensitive to a line between first and second class c
A skilled worker on the assembly line , for example , earns $37 a week
```

6.3.4 Graphical Presentation

So far we have focused on textual presentation and the use of formatted print statements to get output lined up in columns. It is often very useful to display numerical data in graphical form, since this often makes it easier to detect patterns. For example, in Listing 6.5 we saw a table of numbers showing the frequency of particular modal verbs in the Brown Corpus, classified by genre. In Listing 6.7 we present the same information in graphical format. The output is shown in Figure 6.3 (a color figure in the online version).

Note

[Listing 6.7](http://matplotlib.sourceforge.net/) uses the PyLab package which supports sophisticated plotting functions with a MATLAB-style interface. For more information about this package please see <http://matplotlib.sourceforge.net/>.

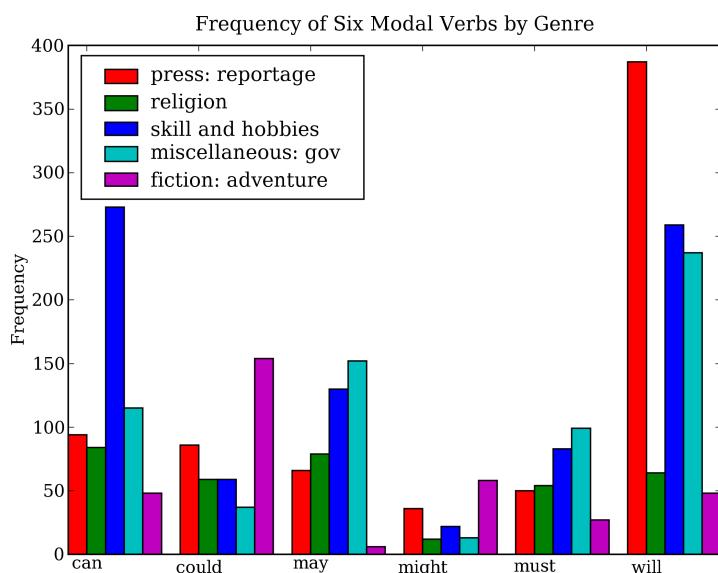


Figure 6.3: Bar Chart Showing Frequency of Modals in Different Sections of Brown Corpus

From the bar chart it is immediately obvious that *may* and *must* have almost identical relative frequencies. The same goes for *could* and *might*.

6.3.5 Exercises

1. ☀ Write code that removes whitespace at the beginning and end of a string, and normalizes whitespace between words to be a single space character.
 - 1) do this task using `split()` and `join()`
 - 2) do this task using regular expression substitutions
2. ☀ What happens when the formatting strings `%6s` and `%-6s` are used to display strings that are longer than six characters?

3. ☀ We can use a dictionary to specify the values to be substituted into a formatting string.
Read Python’s library documentation for formatting strings (<http://docs.python.org/lib/typesseq-strings.html>), and use this method to display today’s date in two different formats.
4. ⚡ Listing 4.3 in Chapter 4 plotted a curve showing change in the performance of a lookup tagger as the model size was increased. Plot the performance curve for a unigram tagger, as the amount of training data is varied.

6.4 Functions

Once you have been programming for a while, you will find that you need to perform a task that you have done in the past. In fact, over time, the number of completely novel things you have to do in creating a program decreases significantly. Half of the work may involve simple tasks that you have done before. Thus it is important for your code to be *re-usable*. One effective way to do this is to abstract commonly used sequences of steps into a **function**, as we briefly saw in Chapter 2.

For example, suppose we find that we often want to read text from an HTML file. This involves several steps: opening the file, reading it in, normalizing whitespace, and stripping HTML markup. We can collect these steps into a function, and give it a name such as `get_text()`:

Now, any time we want to get cleaned-up text from an HTML file, we can just call `get_text()` with the name of the file as its only argument. It will return a string, and we can assign this to a variable, e.g.: `contents = get_text("test.html")`. Each time we want to use this series of steps we only have to call the function.

Notice that a function definition consists of the keyword `def` (short for “define”), followed by the function name, followed by a sequence of parameters enclosed in parentheses, then a colon. The following lines contain an indented block of code, the **function body**.

Using functions has the benefit of saving space in our program. More importantly, our choice of name for the function helps make the program *readable*. In the case of the above example, whenever our program needs to read cleaned-up text from a file we don’t have to clutter the program with four lines of code, we simply need to call `get_text()`. This naming helps to provide some “semantic interpretation” — it helps a reader of our program to see what the program “means”.

Notice that the above function definition contains a string. The first string inside a function definition is called a **docstring**. Not only does it document the purpose of the function to someone reading the code, it is accessible to a programmer who has loaded the code from a file:

```
>>> help(get_text)
Help on function get_text:
```

get_text(file) Read text from a file, normalizing whitespace and stripping HTML markup.

We have seen that functions help to make our work reusable and readable. They also help make it *reliable*. When we re-use code that has already been developed and tested, we can be more confident that it handles a variety of cases correctly. We also remove the risk that we forget some important step, or introduce a bug. The program that calls our function also has increased reliability. The author of that program is dealing with a shorter program, and its components behave transparently.

■ [More: overview of section]

Listing 6.7 Frequency of Modals in Different Sections of the Brown Corpus

```

colors = 'rgbcmyk' # red, green, blue, cyan, magenta, yellow, black
def bar_chart(categories, words, counts):
    "Plot a bar chart showing counts for each word by category"
    import pylab
    ind = pylab.arange(len(words))
    width = 1.0 / (len(categories) + 1)
    bar_groups = []
    for c in range(len(categories)):
        bars = pylab.bar(ind+c*width, counts[categories[c]], width, color=colors[c])
        bar_groups.append(bars)
    pylab.xticks(ind+width, words)
    pylab.legend([b[0] for b in bar_groups], categories, loc='upper left')
    pylab.ylabel('Frequency')
    pylab.title('Frequency of Six Modal Verbs by Genre')
    pylab.show()

>>> genres = ['a', 'd', 'e', 'h', 'n']
>>> cfdist = count_words_by_tag('MD', genres)
>>> modals = ['can', 'could', 'may', 'might', 'must', 'will']
>>> counts = {}
>>> for genre in genres:
...     counts[genre] = [cfdist[genre][word] for word in modals]
>>> bar_chart(genres, modals, counts)

```

Listing 6.8 Read text from a file

```

import re
def get_text(file):
    """Read text from a file, normalizing whitespace
    and stripping HTML markup."""
    text = open(file).read()
    text = re.sub('\s+', ' ', text)
    text = re.sub(r'<.*?>', ' ', text)
    return text

```

6.4.1 Function Arguments

- multiple arguments
- named arguments
- default values

Python is a **dynamically typed** language. It does not force us to declare the type of a variable when we write a program. This feature is often useful, as it permits us to define functions that are flexible about the type of their arguments. For example, a tagger might expect a sequence of words, but it wouldn't care whether this sequence is expressed as a list, a tuple, or an iterator.

However, often we want to write programs for later use by others, and want to program in a defensive style, providing useful warnings when functions have not been invoked correctly. Observe that the `tag()` function in Listing 6.9 behaves sensibly for string arguments, but that it does not complain when it is passed a dictionary.

Listing 6.9 A tagger that tags anything

```
def tag(word):
    if word in ['a', 'the', 'all']:
        return 'DT'
    else:
        return 'NN'

>>> tag('the')
'DT'
>>> tag('dog')
'NN'
>>> tag({'lexeme': 'turned', 'pos': 'VBD', 'pron': ['t3:nd', 't3'nd']})
'NN'
```

It would be helpful if the author of this function took some extra steps to ensure that the `word` parameter of the `tag()` function is a string. A naive approach would be to check the type of the argument and return a diagnostic value, such as Python's special empty value, `None`, as shown in Listing 6.10.

However, this approach is dangerous because the calling program may not detect the error, and the diagnostic return value may be propagated to later parts of the program with unpredictable consequences. A better solution is shown in Listing 6.11.

This produces an error that cannot be ignored, since it halts program execution. Additionally, the error message is easy to interpret. (We will see an even better approach, known as “duck typing” in Chapter 10.)

Another aspect of defensive programming concerns the return statement of a function. In order to be confident that all execution paths through a function lead to a return statement, it is best to have a single return statement at the end of the function definition. This approach has a further benefit: it makes it more likely that the function will only return a single type. Thus, the following version of our `tag()` function is safer:

```
>>> def tag(word):
...     result = 'NN'                                # default value, a string
```

Listing 6.10 A tagger that only tags strings

```
def tag(word):
    if not type(word) is str:
        return None
    if word in ['a', 'the', 'all']:
        return 'DT'
    else:
        return 'NN'
```

Listing 6.11 A tagger that generates an error message when not passed a string

```
def tag(word):
    if not type(word) is str:
        raise ValueError, "argument to tag() must be a string"
    if word in ['a', 'the', 'all']:
        return 'DT'
    else:
        return 'NN'
```

```
...     if word in ['a', 'the', 'all']:      # in certain cases...
...         result = 'DT'                  #   overwrite the value
...     return result                   # all paths end here
```

A return statement can be used to pass multiple values back to the calling program, by packing them into a tuple. Here we define a function that returns a tuple consisting of the average word length of a sentence, and the inventory of letters used in the sentence. It would have been clearer to write two separate functions.

```
>>> def proc_words(words):
...     avg_wordlen = sum(len(word) for word in words)/len(words)
...     chars_used = ''.join(sorted(set(''.join(words))))
...     return avg_wordlen, chars_used
>>> proc_words(['Not', 'a', 'good', 'way', 'to', 'write', 'functions'])
(3, 'Nacdefginorstuwyy')
```

Functions do not need to have a return statement at all. Some functions do their work as a side effect, printing a result, modifying a file, or updating the contents of a parameter to the function. Consider the following three sort functions; the last approach is dangerous because a programmer could use it without realizing that it had modified its input.

```
>>> def my_sort1(l):      # good: modifies its argument, no return value
...     l.sort()
>>> def my_sort2(l):      # good: doesn't touch its argument, returns value
...     return sorted(l)
>>> def my_sort3(l):      # bad: modifies its argument and also returns it
...     l.sort()
...     return l
```

6.4.2 An Important Subtlety

Back in [Section 6.2.1](#) you saw that in Python, assignment works on values, but that the value of a structured object is a reference to that object. The same is true for functions. Python interprets function parameters as values (this is known as **call-by-value**). Consider [Listing 6.12](#). Function `set_up()` has two parameters, both of which are modified inside the function. We begin by assigning an empty string to `w` and an empty dictionary to `p`. After calling the function, `w` is unchanged, while `p` is changed:

Listing 6.12

```
def set_up(word, properties):
    word = 'cat'
    properties['pos'] = 'noun'

>>> w = ''
>>> p = {}
>>> set_up(w, p)
>>> w
''
>>> p
{'pos': 'noun'}
```

To understand why `w` was not changed, it is necessary to understand call-by-value. When we called `set_up(w, p)`, the value of `w` (an empty string) was assigned to a new variable `word`. Inside the function, the value of `word` was modified. However, that had no effect on the external value of `w`. This parameter passing is identical to the following sequence of assignments:

```
>>> w = ''
>>> word = w
>>> word = 'cat'
>>> w
''
```

In the case of the structured object, matters are quite different. When we called `set_up(w, p)`, the value of `p` (an empty dictionary) was assigned to a new local variable `properties`. Since the value of `p` is an object reference, both variables now reference the same memory location. Modifying something inside `properties` will also change `p`, just as if we had done the following sequence of assignments:

```
>>> p = {}
>>> properties = p
>>> properties['pos'] = 'noun'
>>> p
{'pos': 'noun'}
```

Thus, to understand Python's call-by-value parameter passing, it is enough to understand Python's assignment operation. We will address some closely related issues in our later discussion of variable scope ([Section 10](#)).

6.4.3 Functional Decomposition

Well-structured programs usually make extensive use of functions. When a block of program code grows longer than 10-20 lines, it is a great help to readability if the code is broken up into one or more

functions, each one having a clear purpose. This is analogous to the way a good essay is divided into paragraphs, each expressing one main idea.

Functions provide an important kind of *abstraction*. They allow us to group multiple actions into a single, complex action, and associate a name with it. (Compare this with the way we combine the actions of *go* and *bring back* into a single more complex action *fetch*.) When we use functions, the main program can be written at a higher level of abstraction, making its structure transparent, e.g.

```
>>> data = load_corpus()
>>> results = analyze(data)
>>> present(results)
```

Appropriate use of functions makes programs more readable and maintainable. Additionally, it becomes possible to reimplement a function — replacing the function’s body with more efficient code — without having to be concerned with the rest of the program.

Consider the `freq_words` function in Listing 6.13. It updates the contents of a frequency distribution that is passed in as a parameter, and it also prints a list of the n most frequent words.

Listing 6.13

```
def freq_words(url, freqdist, n):
    text = nltk.clean_url(url)
    for word in nltk.wordpunct_tokenize(text):
        freqdist.inc(word.lower())
    print freqdist.sorted()[:n]

>>> constitution = "http://www.archives.gov/national-archives-experience/charters/constitution.txt"
>>> fd = nltk.FreqDist()
>>> freq_words(constitution, fd, 20)
['the', ',', 'of', 'and', 'shall', '.', 'be', 'to', 'in', 'states', 'or',
';', 'united', 'a', 'state', 'by', 'for', 'any', 'president', 'which']
```

This function has a number of problems. The function has two side-effects: it modifies the contents of its second parameter, and it prints a selection of the results it has computed. The function would be easier to understand and to reuse elsewhere if we initialize the `FreqDist()` object inside the function (in the same place it is populated), and if we moved the selection and display of results to the calling program. In Listing 6.14 we **refactor** this function, and simplify its interface by providing a single `url` parameter.

Note that we have now simplified the work of `freq_words` to the point that we can do its work with three lines of code:

```
>>> words = nltk.wordpunct_tokenize(nltk.clean_url(constitution))
>>> fd = nltk.FreqDist(word.lower() for word in words)
>>> fd.sorted()[:20]
['the', ',', 'of', 'and', 'shall', '.', 'be', 'to', 'in', 'states', 'or',
';', 'united', 'a', 'state', 'by', 'for', 'any', 'president', 'which']
```

6.4.4 Documentation (notes)

- some guidelines for literate programming (e.g. variable and function naming)
- documenting functions (user-level and developer-level documentation)

Listing 6.14

```
def freq_words(url):
    freqdist = nltk.FreqDist()
    text = nltk.clean_url(url)
    for word in nltk.wordpunct_tokenize(text):
        freqdist.inc(word.lower())
    return freqdist

>>> fd = freq_words(constitution)
>>> print fd.sorted()[:20]
['the', ',', 'of', 'and', 'shall', '.', 'be', 'to', 'in', 'states', 'or',
';', 'united', 'a', 'state', 'by', 'for', 'any', 'president', 'which']
```

6.4.5 Functions as Arguments

So far the arguments we have passed into functions have been simple objects like strings, or structured objects like lists. These arguments allow us to parameterize the behavior of a function. As a result, functions are very flexible and powerful abstractions, permitting us to repeatedly apply the *same operation* on *different data*. Python also lets us pass a function as an argument to another function. Now we can abstract out the operation, and apply a *different operation* on the *same data*. As the following examples show, we can pass the built-in function `len()` or a user-defined function `last_letter()` as parameters to another function:

```
>>> def extract_property(prop):
...     words = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
...     return [prop(word) for word in words]
>>> extract_property(len)
[3, 3, 4, 4, 3, 9]
>>> def last_letter(word):
...     return word[-1]
>>> extract_property(last_letter)
['e', 'g', 'e', 'n', 'e', 'r']
```

Surprisingly, `len` and `last_letter` are objects that can be passed around like lists and dictionaries. Notice that parentheses are only used after a function name if we are invoking the function; when we are simply passing the function around as an object these are not used.

Python provides us with one more way to define functions as arguments to other functions, so-called **lambda expressions**. Supposing there was no need to use the above `last_letter()` function in multiple places, and thus no need to give it a name. We can equivalently write the following:

```
>>> extract_property(lambda w: w[-1])
['e', 'g', 'e', 'n', 'e', 'r']
```

Our next example illustrates passing a function to the `sorted()` function. When we call the latter with a single argument (the list to be sorted), it uses the built-in lexicographic comparison function `cmp()`. However, we can supply our own sort function, e.g. to sort by decreasing length.

```
>>> words = 'I turned off the spectroroute'.split()
>>> sorted(words)
```

```
[‘I’, ‘off’, ‘spectroroute’, ‘the’, ‘turned’]
>>> sorted(words, cmp)
[‘I’, ‘off’, ‘spectroroute’, ‘the’, ‘turned’]
>>> sorted(words, lambda x, y: cmp(len(y), len(x)))
[‘spectroroute’, ‘turned’, ‘off’, ‘the’, ‘I’]
```

In 6.2.5 we saw an example of filtering out some items in a list comprehension, using an `if` test. Similarly, we can restrict a list to just the lexical words, using `[word for word in sent if is_lexical(word)]`. This is a little cumbersome as it mentions the `word` variable three times. A more compact way to express the same thing is as follows.

```
>>> def is_lexical(word):
...     return word.lower() not in ('a', 'an', 'the', 'that', 'to')
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> filter(is_lexical, sent)
['dog', 'gave', 'John', 'newspaper']
```

The function `is_lexical(word)` returns `True` just in case `word`, when normalized to lowercase, is not in the given list. This function is itself used as an argument to `filter()`. The `filter()` function applies its first argument (a function) to each item of its second (a sequence), only passing it through if the function returns true for that item. Thus `filter(f, seq)` is equivalent to `[item for item in seq if apply(f, item) == True]`.

Another helpful function, which like `filter()` applies a function to a sequence, is `map()`. Here is a simple way to find the average length of a sentence in a section of the Brown Corpus:

```
>>> average(map(len, nltk.corpus.brown.sents(categories='a')))
21.7508111616
```

Instead of `len()`, we could have passed in any other function we liked:

```
>>> sent = ['The', 'dog', 'gave', 'John', 'the', 'newspaper']
>>> def is_vowel(letter):
...     return letter in "AEIOUaeiou"
>>> def vowelcount(word):
...     return len(filter(is_vowel, word))
>>> map(vowelcount, sent)
[1, 1, 2, 1, 1, 3]
```

Instead of using `filter()` to call a named function `is_vowel`, we can define a lambda expression as follows:

```
>>> map(lambda w: len(filter(lambda c: c in "AEIOUaeiou", w)), sent)
[1, 1, 2, 1, 1, 3]
```

6.4.6 Exercises

1. ☀ Review the answers that you gave for the exercises in 6.2, and rewrite the code as one or more functions.
2. ⚪ In this section we saw examples of some special functions such as `filter()` and `map()`. Other functions in this family are `zip()` and `reduce()`. Find out what these do, and write some code to try them out. What uses might they have in language processing?

3. **❶** Write a function that takes a list of words (containing duplicates) and returns a list of words (with no duplicates) sorted by decreasing frequency. E.g. if the input list contained 10 instances of the word `table` and 9 instances of the word `chair`, then `table` would appear before `chair` in the output list.
4. **❶** As you saw, `zip()` combines two lists into a single list of pairs. What happens when the lists are of unequal lengths? Define a function `myzip()` that does something different with unequal lists.
5. **❶** Import the `itemgetter()` function from the `operator` module in Python's standard library (i.e. `from operator import itemgetter`). Create a list `words` containing several words. Now try calling: `sorted(words, key=itemgetter(1))`, and `sorted(words, key=itemgetter(-1))`. Explain what `itemgetter()` is doing.

6.5 Algorithm Design Strategies

A major part of algorithmic problem solving is selecting or adapting an appropriate algorithm for the problem at hand. Whole books are written on this topic (e.g. [?]) and we only have space to introduce some key concepts and elaborate on the approaches that are most prevalent in natural language processing.

The best known strategy is known as **divide-and-conquer**. We attack a problem of size n by dividing it into two problems of size $n/2$, solve these problems, and combine their results into a solution of the original problem. [Figure 6.4](#) illustrates this approach for sorting a list of words.

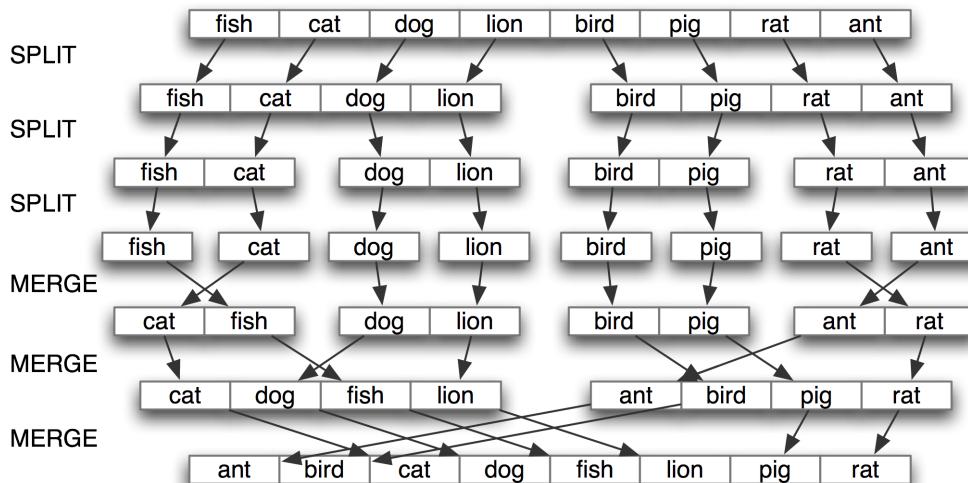


Figure 6.4: Sorting by Divide-and-Conquer (Mergesort)

Another strategy is **decrease-and-conquer**. In this approach, a small amount of work on a problem of size n permits us to reduce it to a problem of size $n/2$. [Figure 6.5](#) illustrates this approach for the problem of finding the index of an item in a sorted list.

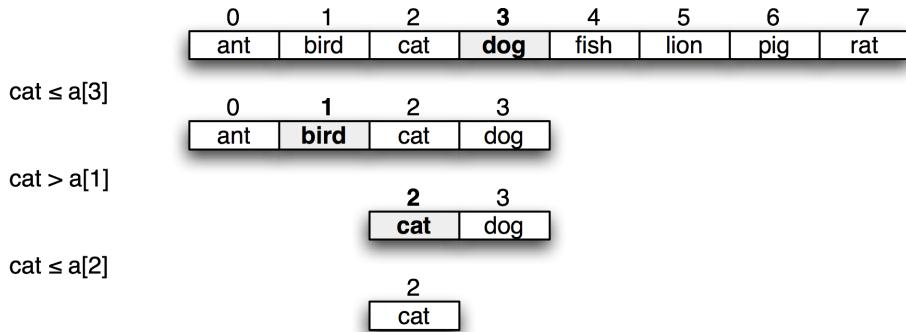


Figure 6.5: Searching by Decrease-and-Conquer (Binary Search)

A third well-known strategy is **transform-and-conquer**. We attack a problem by transforming it into an instance of a problem we already know how to solve. For example, in order to detect duplicates entries in a list, we can **pre-sort** the list, then look for adjacent identical items, as shown in Listing 6.15. Our approach to n-gram chunking in Section 7.5 is another case of transform and conquer (why?).

6.5.1 Recursion (notes)

We first saw recursion in Chapter 3, in a function that navigated the hypernym hierarchy of WordNet...

Iterative solution:

```
>>> def factorial(n):
...     result = 1
...     for i in range(n):
...         result *= (i+1)
...     return result
```

Recursive solution (base case, induction step)

```
>>> def factorial(n):
...     if n == 1:
...         return n
...     else:
...         return n * factorial(n-1)
```

[Simple example of recursion on strings.]

Generating all permutations of words, to check which ones are grammatical:

```
>>> def perms(seq):
...     if len(seq) <= 1:
...         yield seq
...     else:
...         for perm in perms(seq[1:]):
...             for i in range(len(perm)+1):
...                 yield perm[:i] + seq[0:1] + perm[i:]
>>> list(perms(['police', 'fish', 'cream']))
[['police', 'fish', 'cream'], ['fish', 'police', 'cream'],
 ['fish', 'cream', 'police'], ['police', 'cream', 'fish'],
 ['cream', 'police', 'fish'], ['cream', 'fish', 'police']]
```

Listing 6.15 Presorting a list for duplicate detection

```
def duplicates(words):
    prev = None
    dup = [None]
    for word in sorted(words):
        if word == prev and word != dup[-1]:
            dup.append(word)
        else:
            prev = word
    return dup[1:]

>>> duplicates(['cat', 'dog', 'cat', 'pig', 'dog', 'cat', 'ant', 'cat'])
['cat', 'dog']
```

6.5.2 Deeply Nested Objects (notes)

We can use recursive functions to build deeply-nested objects. Building a letter trie, Listing 6.16.

6.5.3 Dynamic Programming

Dynamic programming is a general technique for designing algorithms which is widely used in natural language processing. The term 'programming' is used in a different sense to what you might expect, to mean planning or scheduling. Dynamic programming is used when a problem contains overlapping sub-problems. Instead of computing solutions to these sub-problems repeatedly, we simply store them in a lookup table. In the remainder of this section we will introduce dynamic programming, but in a rather different context to syntactic parsing.

Pingala was an Indian author who lived around the 5th century B.C., and wrote a treatise on Sanskrit prosody called the *Chandas Shastra*. Virahanka extended this work around the 6th century A.D., studying the number of ways of combining short and long syllables to create a meter of length n . He found, for example, that there are five ways to construct a meter of length 4: $V_4 = \{LL, SSL, SLS, LSS, SSSS\}$. Observe that we can split V_4 into two subsets, those starting with L and those starting with S , as shown in (10).

$$(10) \quad V_4 = \begin{aligned} & LL, LSS \\ & \text{i.e. } L \text{ prefixed to each item of } V_2 = \{L, SS\} \\ & SSL, SLS, SSSS \\ & \text{i.e. } S \text{ prefixed to each item of } V_3 = \{SL, LS, SSS\} \end{aligned}$$

With this observation, we can write a little recursive function called `virahankal()` to compute these meters, shown in Listing 6.17. Notice that, in order to compute V_4 we first compute V_3 and V_2 . But to compute V_3 , we need to first compute V_2 and V_1 . This **call structure** is depicted in (11).

Listing 6.16 Building a Letter Trie

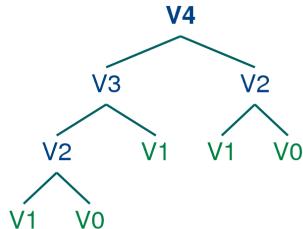
```

def insert(trie, key, value):
    if key:
        first, rest = key[0], key[1:]
        if first not in trie:
            trie[first] = {}
        insert(trie[first], rest, value)
    else:
        trie['value'] = value

>>> trie = {}
>>> insert(trie, 'chat', 'cat')
>>> insert(trie, 'chien', 'dog')
>>> trie['c']['h']
{'a': {'t': {'value': 'cat'}}, 'i': {'e': {'n': {'value': 'dog'}}}}
>>> trie['c']['h']['a']['t']['value']
'cat'
>>> pprint.pprint(trie)
{'c': {'h': {'a': {'t': {'value': 'cat'}}},
       'i': {'e': {'n': {'value': 'dog'}}}}}

```

(11)



As you can see, V_2 is computed twice. This might not seem like a significant problem, but it turns out to be rather wasteful as n gets large: to compute V_{20} using this recursive technique, we would compute V_2 4,181 times; and for V_{40} we would compute V_2 63,245,986 times! A much better alternative is to store the value of V_2 in a table and look it up whenever we need it. The same goes for other values, such as V_3 and so on. Function `virahanka2()` implements a dynamic programming approach to the problem. It works by filling up a table (called `lookup`) with solutions to *all* smaller instances of the problem, stopping as soon as we reach the value we're interested in. At this point we read off the value and return it. Crucially, each sub-problem is only ever solved once.

Notice that the approach taken in `virahanka2()` is to solve smaller problems on the way to solving larger problems. Accordingly, this is known as the **bottom-up** approach to dynamic programming. Unfortunately it turns out to be quite wasteful for some applications, since it may compute solutions to sub-problems that are never required for solving the main problem. This wasted computation can be avoided using the **top-down** approach to dynamic programming, which is illustrated in the function `virahanka3()` in Listing 6.17. Unlike the bottom-up approach, this approach is recursive. It avoids the huge wastage of `virahanka1()` by checking whether it has previously stored the result. If not, it computes the result recursively and stores it in the table. The last step is to return the stored result.

Listing 6.17 Three Ways to Compute Sanscrit Meter

```

def virahanka1(n):
    if n == 0:
        return []
    elif n == 1:
        return ["S"]
    else:
        s = ["S" + prosody for prosody in virahanka1(n-1)]
        l = ["L" + prosody for prosody in virahanka1(n-2)]
        return s + l

def virahanka2(n):
    lookup = [[], ["S"]]
    for i in range(n-1):
        s = ["S" + prosody for prosody in lookup[i+1]]
        l = ["L" + prosody for prosody in lookup[i]]
        lookup.append(s + l)
    return lookup[n]

def virahanka3(n, lookup={0:[], 1:["S"]}):
    if n not in lookup:
        s = ["S" + prosody for prosody in virahanka3(n-1)]
        l = ["L" + prosody for prosody in virahanka3(n-2)]
        lookup[n] = s + l
    return lookup[n]

>>> virahanka1(4)
['SSSS', 'SSL', 'SLS', 'LSS', 'LL']
>>> virahanka2(4)
['SSSS', 'SSL', 'SLS', 'LSS', 'LL']
>>> virahanka3(4)
['SSSS', 'SSL', 'SLS', 'LSS', 'LL']

```

This concludes our brief introduction to dynamic programming. We will encounter it again in [Chapter 9](#).

Note

Dynamic programming is a kind of **memoization**. A memoized function stores results of previous calls to the function along with the supplied parameters. If the function is subsequently called with those parameters, it returns the stored result instead of recalculating it.

6.5.4 Timing (notes)

We can easily test the efficiency gains made by the use of dynamic programming, or any other putative performance enhancement, using the `timeit` module:

```
>>> from timeit import Timer
>>> Timer("PYTHON CODE", "INITIALIZATION CODE").timeit()
```

[MORE]

6.5.5 Exercises

1. ● Write a recursive function `lookup(trie, key)` that looks up a key in a trie, and returns the value it finds. Extend the function to return a word when it is uniquely determined by its prefix (e.g. `vanguard` is the only word that starts with `vang-`, so `lookup(trie, 'vang')` should return the same thing as `lookup(trie, 'vanguard')`).
2. ● Read about string edit distance and the Levenshtein Algorithm. Try the implementation provided in `nltk.edit_dist()`. How is this using dynamic programming? Does it use the bottom-up or top-down approach?
3. ● The Catalan numbers arise in many applications of combinatorial mathematics, including the counting of parse trees ([Chapter 9](#)). The series can be defined as follows: $C_0 = 1$, and $C_{n+1} = \sum_{0..n} (C_i C_{n-i})$.
 - a) Write a recursive function to compute n th Catalan number C_n
 - b) Now write another function that does this computation using dynamic programming
 - c) Use the `timeit` module to compare the performance of these functions as n increases.
4. ★ Write a recursive function that pretty prints a trie in alphabetically sorted order, as follows
 chat: 'cat' --ien: 'dog' -???: ???
5. ★ Write a recursive function that processes text, locating the uniqueness point in each word, and discarding the remainder of each word. How much compression does this give? How readable is the resulting text?

6.6 Conclusion

[TO DO]

6.7 Further Reading

[?]

[?]

[http://docs.python.org/lib/typeseq-strings.html](http://docs.python.org/lib/typesseq-strings.html)

About this document...

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This document is Revision: 5915 Tue Apr 29 13:57:59 EDT 2008

Chapter 7

Partial Parsing and Interpretation

7.1 Introduction

In processing natural language, we are looking for structure and meaning. Two of the most common methods are **segmentation** and **labeling**. Recall that in tokenization, we *segment* a sequence of characters into tokens, while in tagging we *label* each of these tokens. Moreover, these two operations of segmentation and labeling go hand in hand. We break up a stream of characters into linguistically meaningful segments (e.g., words) so that we can classify those segments with their part-of-speech categories. The result of such classification is represented by adding a label (e.g., part-of-speech tag) to the segment in question.

We will see that many tasks can be construed as a combination of segmentation and labeling. However, this involves generalizing our notion of segmentation to encompass *sequences* of tokens. Suppose that we are trying to recognize the names of people, locations and organizations in a piece of text (a task that is usually called **Named Entity Recognition**). Many of these names will involve more than one token: *Cecil H. Green, Escondido Village, Stanford University*; indeed, some names may have sub-parts that are also names: *Cecil H. Green Library, Escondido Village Conference Service Center*. In Named Entity Recognition, therefore, we need to be able to identify the beginning and end of multi-token sequences.

Identifying the boundaries of specific types of word sequences is also required when we want to recognize pieces of syntactic structure. Suppose for example that as a preliminary to Named Entity Recognition, we have decided that it would be useful to just pick out noun phrases from a piece of text. To carry this out in a complete way, we would probably want to use a proper syntactic parser. But parsing can be quite challenging and computationally expensive — is there an easier alternative? The answer is Yes: we can look for sequences of part-of-speech tags in a tagged text, using one or more patterns that capture the typical ingredients of a noun phrase.

For example, here is some Wall Street Journal text with noun phrases marked using brackets:

- (12) [The/DT market/NN] for/IN [system-management/NN software/NN] for/IN [Digital/NNP]
['s/POS hardware/NN] is/VBZ fragmented/JJ enough/RB that/IN [a/DT giant/NN] such/JJ
as/IN [Computer/NNP Associates/NNPS] should/MD do/VB well/RB there/RB ./.

From the point of view of theoretical linguistics, we seem to have been rather unorthodox in our use of the term “noun phrase”; although all the bracketed strings are noun phrases, not every noun phrase has been captured. We will discuss this issue in more detail shortly. For the moment, let’s say that we are identifying noun “chunks” rather than full noun phrases.

In chunking, we carry out segmentation and labeling of multi-token sequences, as illustrated in [Figure 7.1](#). The smaller boxes show word-level segmentation and labeling, while the large boxes show higher-level segmentation and labeling. It is these larger pieces that we will call **chunks**, and the process of identifying them is called **chunking**.

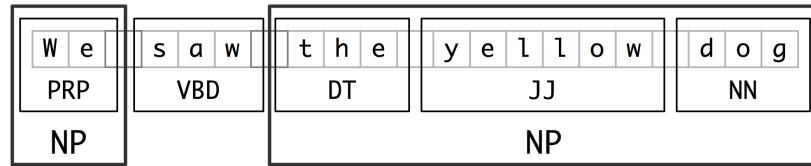


Figure 7.1: Segmentation and Labeling at both the Token and Chunk Levels

Like tokenization, chunking can skip over material in the input. Tokenization omits white space and punctuation characters. Chunking uses only a subset of the tokens and leaves others out.

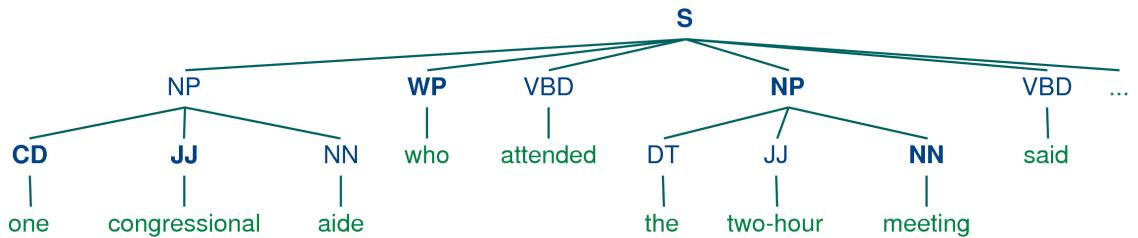
In this chapter, we will explore chunking in some depth, beginning with the definition and representation of chunks. We will see regular expression and n-gram approaches to chunking, and will develop and evaluate chunkers using the CoNLL-2000 chunking corpus. Towards the end of the chapter, we will look more briefly at Named Entity Recognition and related tasks.

7.2 Defining and Representing Chunks

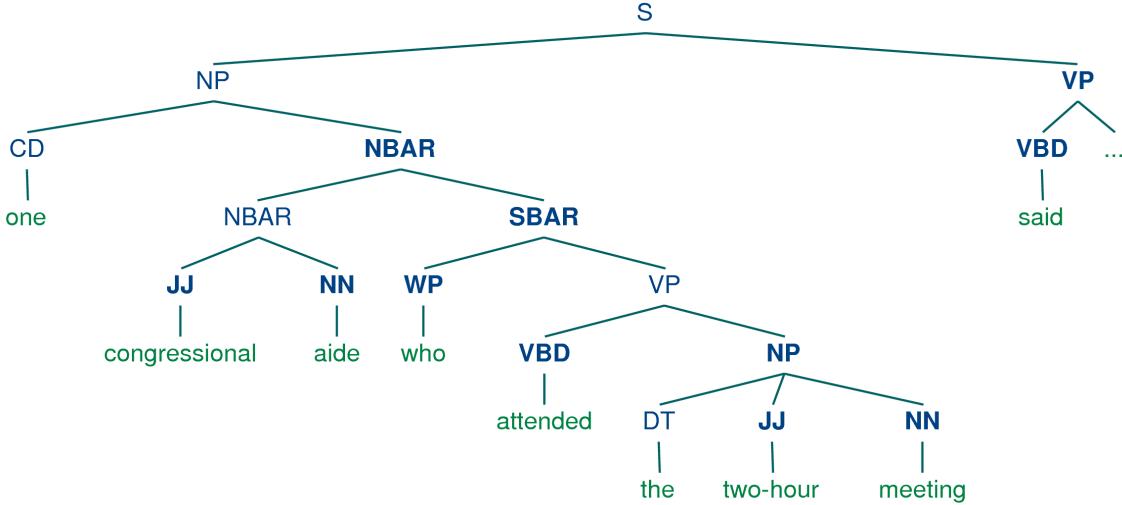
7.2.1 Chunking vs Parsing

Chunking is akin to parsing in the sense that it can be used to build hierarchical structure over text. There are several important differences, however. First, as noted above, chunking is not exhaustive, and typically ignores some items in the surface string. In fact, chunking is sometimes called **partial parsing**. Second, where parsing constructs nested structures that are arbitrarily deep, chunking creates structures of fixed depth (typically depth 2). These chunks often correspond to the lowest level of grouping identified in the full parse tree. This is illustrated in (13) below, which shows an NP chunk structure and a completely parsed counterpart:

(13) a.



b.



A significant motivation for chunking is its robustness and efficiency relative to parsing. As we will see in [Chapter 8](#), parsing has problems with robustness, given the difficulty in gaining broad coverage while minimizing ambiguity. Parsing is also relatively inefficient: the time taken to parse a sentence grows with the cube of the length of the sentence, while the time taken to chunk a sentence only grows linearly.

7.2.2 Representing Chunks: Tags vs Trees

As befits its intermediate status between tagging and parsing, chunk structures can be represented using either tags or trees. The most widespread file representation uses so-called **IOB tags**. In this scheme, each token is tagged with one of three special chunk tags, I (inside), O (outside), or B (begin). A token is tagged as B if it marks the beginning of a chunk. Subsequent tokens within the chunk are tagged I. All other tokens are tagged O. The B and I tags are suffixed with the chunk type, e.g. B-NP, I-NP. Of course, it is not necessary to specify a chunk type for tokens that appear outside a chunk, so these are just labeled O. An example of this scheme is shown in [Figure 7.2](#).

W	e	s	a	w	t	h	e	y	e	l	l	o	w	d	o	g
PRP		VBD		O	DT		B-NP		JJ		I-NP		NN		I-NP	

Figure 7.2: Tag Representation of Chunk Structures

IOB tags have become the standard way to represent chunk structures in files, and we will also be using this format. Here is an example of the file representation of the information in [Figure 7.2](#):

```

We PRP B-NP
saw VBD O
the DT B-NP
little JJ I-NP
yellow JJ I-NP
dog NN I-NP
  
```

In this representation, there is one token per line, each with its part-of-speech tag and its chunk tag. We will see later that this format permits us to represent more than one chunk type, so long as the chunks do not overlap.

As we saw earlier, chunk structures can also be represented using trees. These have the benefit that each chunk is a constituent that can be manipulated directly. An example is shown in Figure 7.3:

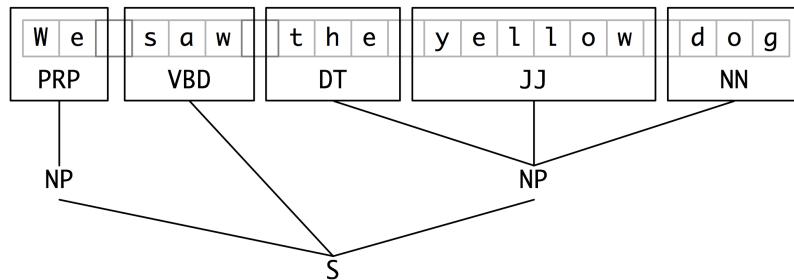


Figure 7.3: Tree Representation of Chunk Structures

NLTK uses trees for its internal representation of chunks, and provides methods for reading and writing such trees to the IOB format. By now you should understand what chunks are, and how they are represented. In the next section, you will see how to build a simple chunker.

7.3 Chunking

A **chunker** finds contiguous, non-overlapping spans of related tokens and groups them together into chunks. Chunkers often operate on tagged texts, and use the tags to make chunking decisions. In this section we will see how to write a special type of regular expression over part-of-speech tags, and then how to combine these into a chunk grammar. Then we will set up a chunker to chunk some tagged text according to the grammar.

Chunking in NLTK begins with tagged tokens.

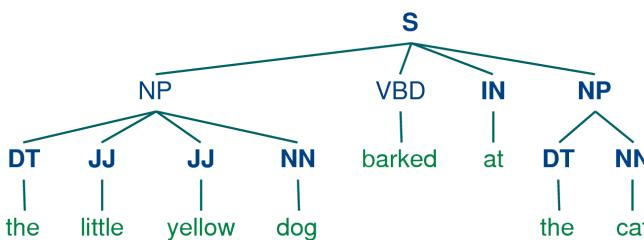
```
>>> tagged_tokens = [("the", "DT"), ("little", "JJ"), ("yellow", "JJ"),
... ("dog", "NN"), ("barked", "VBD"), ("at", "IN"), ("the", "DT"), ("cat", "NN")]
```

Next, we write regular expressions over tag sequences. The following example identifies noun phrases that consist of an optional determiner, followed by any number of adjectives, then a noun.

```
>>> cp = nltk.RegexpParser("NP: { <DT>?<JJ>*<NN> } ")
```

We create a chunker `cp` that can then be used repeatedly to parse tagged input. The result of chunking is a tree.

```
>>> cp.parse(tagged_tokens).draw()
```



Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

7.3.1 Tag Patterns

A **tag pattern** is a sequence of part-of-speech tags delimited using angle brackets, e.g. `<DT><JJ><NN>`. Tag patterns are the same as the regular expression patterns we have already seen, except for two differences that make them easier to use for chunking. First, angle brackets group their contents into atomic units, so “`<NN>+*`” matches one or more repetitions of the tag `NN`; and “`<NN | JJ>`” matches the `NN` or `JJ`. Second, the period wildcard operator is constrained not to cross tag delimiters, so that “`<N.*>`” matches any single tag starting with `N`, e.g. `NN, NNS`.

Now, consider the following noun phrases from the Wall Street Journal:

```
another/DT sharp/JJ dive/NN
trade/NN figures/NNS
any/DT new/JJ policy/NN measures/NNS
earlier/JJR stages/NNS
Panamanian/JJ dictator/NN Manuel/NNP Noriega/NNP
```

We can match these using a slight refinement of the first tag pattern above: `<DT>?<JJ.*>*<NN.*>+`. This can be used to chunk any sequence of tokens beginning with an optional determiner `DT`, followed by zero or more adjectives of any type `JJ.*` (including relative adjectives like `earlier/JJR`), followed by one or more nouns of any type `NN.*`. It is easy to find many more difficult examples:

```
his/PRP$ Mansion/NNP House/NNP speech/NN
the/DT price/NN cutting/VBG
3/CD %/NN to/TO 4/CD %/NN
more/JJR than/IN 10/CD %/NN
the/DT fastest/JJS developing/VBG trends/NNS
's/POS skill/NN
```

Your challenge will be to come up with tag patterns to cover these and other examples.

7.3.2 Chunking with Regular Expressions

The chunker begins with a flat structure in which no tokens are chunked. Patterns are applied in turn, successively updating the chunk structure. Once all of the patterns have been applied, the resulting chunk structure is returned. Listing 7.1 shows a simple chunk grammar consisting of two patterns. The first pattern matches an optional determiner or possessive pronoun (recall that `|` indicates disjunction), zero or more adjectives, then a noun. The second rule matches one or more proper nouns. We also define some tagged tokens to be chunked, and run the chunker on this input.

Note

The `$` symbol is a special character in regular expressions, and therefore needs to be escaped with the backslash `\` in order to match the tag `PP$`.

If a tag pattern matches at overlapping locations, the first match takes precedence. For example, if we apply a rule that matches two consecutive nouns to a text containing three consecutive nouns, then only the first two nouns will be chunked:

Listing 7.1 Simple Noun Phrase Chunker

```
grammar = r"""
    NP: {<DT|PP\$>?<JJ>*<NN>}      # chunk determiner/possessive, adjectives and nouns
        {<NNP>+}                      # chunk sequences of proper nouns
"""

cp = nltk.RegexpParser(grammar)
tagged_tokens = [("Rapunzel", "NNP"), ("let", "VBD"), ("down", "RP"), ("her", "PP$"),
                 ("golden", "JJ"), ("hair", "NN")]

>>> print cp.parse(tagged_tokens)
(S
 (NP Rapunzel/NNP)
 let/VBD
 down/RP
 (NP her/PP$ long/JJ golden/JJ hair/NN))
```

```
>>> nouns = [("money", "NN"), ("market", "NN"), ("fund", "NN")]
>>> grammar = "NP: {<NN><NN>}  # Chunk two consecutive nouns"
>>> cp = nltk.RegexpParser(grammar)
>>> print cp.parse(nouns)
(S (NP money/NN market/NN) fund/NN)
```

Once we have created the chunk for *money market*, we have removed the context that would have permitted *fund* to be included in a chunk. This issue would have been avoided with a more permissive chunk rule, e.g. NP : {<NN>+}.

7.3.3 Developing Chunkers

Creating a good chunker usually requires several rounds of development and testing, during which existing rules are refined and new rules are added. In order to diagnose any problems, it often helps to trace the execution of a chunker, using its `trace` argument. The tracing output shows the rules that are applied, and uses braces to show the chunks that are created at each stage of processing. In Listing 7.2, two chunk patterns are applied to the input sentence. The first rule finds all sequences of three tokens whose tags are DT, JJ, and NN, and the second rule finds any sequence of tokens whose tags are either DT or NN. We set up two chunkers, one for each rule ordering, and test them on the same input.

Observe that when we chunk material that is already partially chunked, the chunker will only create chunks that do not partially overlap existing chunks. In the case of `cp2`, the second rule did not find any chunks, since all chunks that matched its tag pattern overlapped with existing chunks. As you can see, you need to be careful to put chunk rules in the right order.

You may have noted that we have added explanatory comments, preceded by `#`, to each of our tag rules. Although it is not strictly necessary to do this, it's a helpful reminder of what a rule is meant to do, and it is used as a header line for the output of a rule application when tracing is on.

You might want to test out some of your rules on a corpus. One option is to use the Brown corpus. However, you need to remember that the Brown tagset is different from the Penn Treebank tagset that we have been using for our examples so far in this chapter; see Table 4.6 in Chapter 4 for a refresher. Because the Brown tagset uses NP for proper nouns, in this example we have followed Abney in labeling noun chunks as NX.

Listing 7.2 Two Noun Phrase Chunkers Having Identical Rules in Different Orders

```

tagged_tokens = [("The", "DT"), ("enchantress", "NN"),
                 ("clutched", "VBD"), ("the", "DT"), ("beautiful", "JJ"), ("hair", "NN")]
cp1 = nltk.RegexpParser(r"""
    NP: {<DT><JJ><NN>}          # Chunk det+adj+noun
        {<DT|NN>+}                  # Chunk sequences of NN and DT
    """
)
cp2 = nltk.RegexpParser(r"""
    NP: {<DT|NN>+}          # Chunk sequences of NN and DT
        {<DT><JJ><NN>}          # Chunk det+adj+noun
    """
)

>>> print cp1.parse(tagged_tokens, trace=1)
# Input:
<DT> <NN> <VBD> <DT> <JJ> <NN>
# Chunk det+adj+noun:
<DT> <NN> <VBD> {<DT> <JJ> <NN>}
# Chunk sequences of NN and DT:
{<DT> <NN>} <VBD> {<DT> <JJ> <NN>}
(S
    (NP The/DT enchantress/NN)
    clutched/VBD
    (NP the/DT beautiful/JJ hair/NN))
>>> print cp2.parse(tagged_tokens, trace=1)
# Input:
<DT> <NN> <VBD> <DT> <JJ> <NN>
# Chunk sequences of NN and DT:
{<DT> <NN>} <VBD> {<DT>} <JJ> {<NN>}
# Chunk det+adj+noun:
{<DT> <NN>} <VBD> {<DT>} <JJ> {<NN>}
(S
    (NP The/DT enchantress/NN)
    clutched/VBD
    (NP the/DT)
    beautiful/JJ
    (NP hair/NN) )

```

```

>>> grammar = (r"""
...     NX: {<AT|AP|PP\$>?<JJ.*>?<NN.*>}    # Chunk article/numeral/possessive+adj+noun
...         {<NP>+}                                # Chunk one or more proper nouns
...
...     """
)
>>> cp = nltk.RegexpParser(grammar)
>>> sent = nltk.corpus.brown.tagged_sents(categories='a')[112]
>>> print cp.parse(sent)
(S
    (NX His/PP$ contention/NN)
    was/BEDZ
    denied/VBN
    by/IN
    (NX several/AP bankers/NNS)
    ,/
    including/IN
    (NX Scott/NP Hudson/NP)
    of/IN
    (NX Sherman/NP)
    ,/
    (NX Gaynor/NP B./NP Jones/NP)
    of/IN
    (NX Houston/NP)
    ,/
    (NX J./NP B./NP Brady/NP)
    of/IN
    (NX Harlingen/NP)
    and/CC
    (NX Howard/NP Cox/NP)
    of/IN
    (NX Austin/NP)
    ./. )

```

7.3.4 Exercises

1. ☀ **Chunking Demonstration:** Run the chunking demonstration: `nltk.chunk.demo()`
2. ☀ **IOB Tags:** The IOB format categorizes tagged tokens as I, O and B. Why are three tags necessary? What problem would be caused if we used I and O tags exclusively?
3. ☀ Write a tag pattern to match noun phrases containing plural head nouns, e.g. “many/JJ researchers/NNS”, “two/CD weeks/NNS”, “both/DT new/JJ positions/NNS”. Try to do this by generalizing the tag pattern that handled singular noun phrases.
4. ☀ Write a tag pattern to cover noun phrases that contain gerunds, e.g. “the/DT receiving/VBG end/NN”, “assistant/NN managing/VBG editor/NN”. Add these patterns to the grammar, one per line. Test your work using some tagged sentences of your own devising.
5. ☀ Write one or more tag patterns to handle coordinated noun phrases, e.g. “July>NNP and/CC August>NNP”, “all/DT your/PRP\$ managers/NNS and/CC supervisors/NNS”, “company>NN courts/NNS and/CC adjudicators/NNS”.

7.4 Scaling Up

Now you have a taste of what chunking can do, but we have not explained how to carry out a quantitative evaluation of chunkers. For this, we need to get access to a corpus that has been annotated not only with parts-of-speech, but also with chunk information. We will begin by looking at the mechanics of converting IOB format into an NLTK tree, then at how this is done on a larger scale using a chunked corpus directly. We will see how to use the corpus to score the accuracy of a chunker, then look some more flexible ways to manipulate chunks. Our focus throughout will be on scaling up the coverage of a chunker.

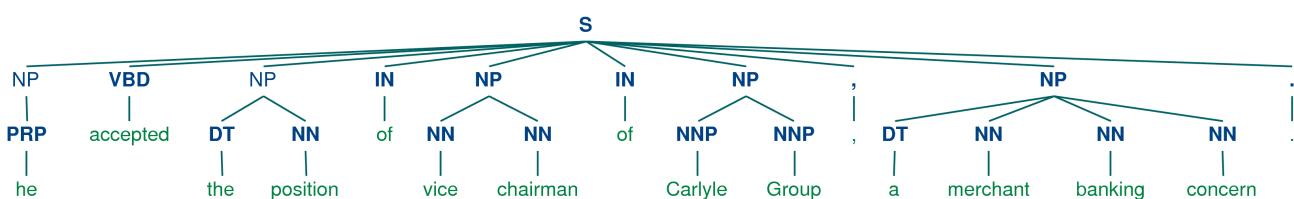
7.4.1 Reading IOB Format and the CoNLL 2000 Corpus

Using the `corpora` module we can load Wall Street Journal text that has been tagged, then chunked using the IOB notation. The chunk categories provided in this corpus are NP, VP and PP. As we have seen, each sentence is represented using multiple lines, as shown below:

```
he PRP B-NP
accepted VBD B-VP
the DT B-NP
position NN I-NP
...
...
```

A conversion function `chunk.conllstr2tree()` builds a tree representation from one of these multi-line strings. Moreover, it permits us to choose any subset of the three chunk types to use. The example below produces only NP chunks:

```
>>> text = '''
... he PRP B-NP
... accepted VBD B-VP
... the DT B-NP
... position NN I-NP
... of IN B-PP
... vice NN B-NP
... chairman NN I-NP
... of IN B-PP
... Carlyle NNP B-NP
... Group NNP I-NP
... , O
... a DT B-NP
... merchant NN I-NP
... banking NN I-NP
... concern NN I-NP
... . O
...
>>> nltk.chunk.conllstr2tree(text, chunk_types=('NP',)).draw()
```



We can use the NLTK corpus module to access a larger amount of chunked text. The CoNLL 2000 corpus contains 270k words of Wall Street Journal text, divided into “train” and “test” portions, annotated with part-of-speech tags and chunk tags in the IOB format. We can access the data using an NLTK corpus reader called `conll2000`. Here is an example that reads the 100th sentence of the “train” portion of the corpus:

```
>>> print nltk.corpus.conll2000.chunked_sents('train.txt')[99]
(S
(PP Over/IN)
(NP a/DT cup/NN)
(PP of/IN)
(NP coffee/NN)
.,
(NP Mr./NNP Stone/NNP)
(VP told/VBD)
(NP his/PRP$ story/NN)
.)
```

This showed three chunk types, for NP, VP and PP. We can also select which chunk types to read:

```
>>> print nltk.corpus.conll2000.chunked_sents('train.txt', chunk_types=('NP',))[99]
(S
Over/IN
(NP a/DT cup/NN)
of/IN
(NP coffee/NN)
.,
(NP Mr./NNP Stone/NNP)
told/VBD
(NP his/PRP$ story/NN)
.)
```

7.4.2 Simple Evaluation and Baselines

Armed with a corpus, it is now possible to carry out some simple evaluation. We start off by establishing a baseline for the trivial chunk parser `cp` that creates no chunks:

```
>>> cp = nltk.RegexpParser('')
>>> print nltk.chunk.accuracy(cp, nltk.corpus.conll2000.chunked_sents('train.txt'))
0.440845995079
```

This indicates that more than a third of the words are tagged with `O` (i.e., not in an NP chunk). Now let’s try a naive regular expression chunker that looks for tags (e.g., CD, DT, JJ, etc.) beginning with letters that are typical of noun phrase tags:

```
>>> grammar = r"NP: <[CDJNP].*>+"
>>> cp = nltk.RegexpParser(grammar)
>>> print nltk.chunk.accuracy(cp, nltk.corpus.conll2000.chunked_sents('train.txt'))
0.874479872666
```

As you can see, this approach achieves pretty good results. In order to develop a more data-driven approach, let’s define a function `chunked_tags()` that takes some chunked data and sets up a conditional frequency distribution. For each tag, it counts up the number of times the tag occurs inside

an NP chunk (the True case, where `ctag` is `B-NP` or `I-NP`), or outside a chunk (the False case, where `ctag` is `O`). It returns a list of those tags that occur inside chunks more often than outside chunks.

Listing 7.3 Capturing the conditional frequency of NP Chunk Tags

```
def chunked_tags(train):
    """Generate a list of tags that tend to appear inside chunks"""
    cfdist = nltk.ConditionalFreqDist()
    for t in train:
        for word, tag, chtag in nltk.chunk.tree2conlltags(t):
            if chtag == "O":
                cf dist[tag].inc(False)
            else:
                cf dist[tag].inc(True)
    return [tag for tag in cf dist.conditions() if cf dist[tag].max() == True]

>>> train_sents = nltk.corpus.conll2000.chunked_sents('train.txt', chunk_types=('NP',))
>>> print chunked_tags(train_sents)
['PRP$', 'WDT', 'JJ', 'WP', 'DT', '#', '$', 'NN', 'FW', 'POS',
'PRP', 'NNS', 'NNP', 'PDT', 'RBS', 'EX', 'WP$', 'CD', 'NNPS', 'JJS', 'JJR']
```

The next step is to convert this list of tags into a tag pattern. To do this we need to “escape” all non-word characters, by preceding them with a backslash. Then we need to join them into a disjunction. This process would convert a tag list `['NN', 'NN\$']` into the tag pattern `<NN|NN\$>`. The following function does this work, and returns a regular expression chunker:

The final step is to train this chunker and test its accuracy (this time on the “test” portion of the corpus, i.e., data not seen during training):

```
>>> train_sents = nltk.corpus.conll2000.chunked_sents('train.txt', chunk_types=('NP',))
>>> test_sents = nltk.corpus.conll2000.chunked_sents('test.txt', chunk_types=('NP',))
>>> cp = baseline_chunker(train_sents)
>>> print nltk.chunk.accuracy(cp, test_sents)
0.914262194736
```

7.4.3 Splitting and Merging (incomplete)

[Notes: the above approach creates chunks that are too large, e.g. *the cat the dog chased* would be given a single NP chunk because it does not detect that determiners introduce new chunks. For this we would need a rule to split an NP chunk prior to any determiner, using a pattern like: "`NP: <.*> { <DT>`". We can also merge chunks, e.g. "`NP: <NN>{ }<NN>`".]

7.4.4 Chinking

Sometimes it is easier to define what we *don't* want to include in a chunk than it is to define what we *do* want to include. In these cases, it may be easier to build a chunker using a method called **chinking**.

Following [?], we define a **chink** as a sequence of tokens that is not included in a chunk. In the following example, *barked/VBD at/IN* is a chink:

```
[ the/DT little/JJ yellow/JJ dog/NN ] barked/VBD at/IN [ the/DT cat/NN ]
```

Listing 7.4 Deriving a Regexp Chunker from Training Data

```
def baseline_chunker(train):
    chunk_tags = [re.sub(r' (\W)', r'\1', tag)
                  for tag in chunked_tags(train)]
    grammar = 'NP: {<%s>+}' % '|'.join(chunk_tags)
    return nltk.RegexpParser(grammar)
```

Chinking is the process of removing a sequence of tokens from a chunk. If the sequence of tokens spans an entire chunk, then the whole chunk is removed; if the sequence of tokens appears in the middle of the chunk, these tokens are removed, leaving two chunks where there was only one before. If the sequence is at the beginning or end of the chunk, these tokens are removed, and a smaller chunk remains. These three possibilities are illustrated in [Table 7.1](#).

	Entire chunk	Middle of a chunk	End of a chunk
<i>Input</i>	[a/DT little/JJ dog/NN]	[a/DT little/JJ dog/NN]	[a/DT little/JJ dog/NN]
<i>Operation</i>	Chink “DT JJ NN”	Chink “JJ”	Chink “NN”
<i>Pattern</i>	“}DT JJ NN{”	“}JJ{”	“}NN{”
<i>Output</i>	a/DT little/JJ dog/NN	[a/DT] little/JJ [dog/NN]	[a/DT little/JJ] dog/NN

Table 7.1: Three chinking rules applied to the same chunk

In the following grammar, we put the entire sentence into a single chunk, then excise the chink:

Listing 7.5 Simple Chinker

```
grammar = r"""
NP:
{<.*>+}          # Chunk everything
}<VBD|IN>+{      # Chink sequences of VBD and IN
"""

tagged_tokens = [("the", "DT"), ("little", "JJ"), ("yellow", "JJ"),
                 ("dog", "NN"), ("barked", "VBD"), ("at", "IN"), ("the", "DT"), ("cat", "NN")
cp = nltk.RegexpParser(grammar)

>>> print cp.parse(tagged_tokens)
(S
  (NP the/DT little/JJ yellow/JJ dog/NN)
  barked/VBD
  at/IN
  (NP the/DT cat/NN))
>>> test_sents = nltk.corpus.conll2000.chunked_sents('test.txt', chunk_types=('NP',
>>> print nltk.chunk.accuracy(cp, test_sents)
0.581041433607
```

A chunk grammar can use any number of chunking and chinking patterns in any order.

7.4.5 Multiple Chunk Types (incomplete)

So far we have only developed NP chunkers. However, as we saw earlier in the chapter, the CoNLL chunking data is also annotated for PP and VP chunks. Here is an example, to show the structure we get from the corpus and the flattened version that will be used as input to the parser.

```
>>> example = nltk.corpus.conll2000.chunked_sents('train.txt')[99]
>>> print example
(S
  (PP Over/IN)
```

```
(NP a/DT cup/NN)
(PP of/IN)
(NP coffee/NN)
.,
(NP Mr./NNP Stone/NNP)
(VP told/VBD)
(NP his/PRP$ story/NN)
. . .
>>> print example.flatten()
(S
Over/IN
a/DT
cup/NN
of/IN
coffee/NN
.,
Mr./NNP
Stone/NNP
told/VBD
his/PRP$
story/NN
. . .)
```

Now we can set up a multi-stage chunk grammar, as shown in Listing 7.6. It has a stage for each of the chunk types.

7.4.6 Evaluating Chunk Parsers

An easy way to evaluate a chunk parser is to take some already chunked text, strip off the chunks, rechunk it, and compare the result with the original chunked text. The `ChunkScore.score()` function takes the correctly chunked sentence as its first argument, and the newly chunked version as its second argument, and compares them. It reports the fraction of actual chunks that were found (recall), the fraction of hypothesized chunks that were correct (precision), and a combined score, the F-measure (the harmonic mean of precision and recall).

A number of different metrics can be used to evaluate chunk parsers. We will concentrate on a class of metrics that can be derived from two sets:

- **guessed**: The set of chunks returned by the chunk parser.
- **correct**: The correct set of chunks, as defined in the test corpus.

We will set up an analogy between the correct set of chunks and a user’s so-called “information need”, and between the set of returned chunks and a system’s returned documents (cf precision and recall, from [Chapter 5](#)).

During evaluation of a chunk parser, it is useful to flatten a chunk structure into a tree consisting only of a root node and leaves:

```
>>> correct = nltk.chunk.tagstr2tree(
...     "[ the/DT little/JJ cat/NN ] sat/VBD on/IN [ the/DT mat/NN ]")
>>> print correct.flatten()
(S the/DT little/JJ cat/NN sat/VBD on/IN the/DT mat/NN)
```

Listing 7.6 A Multistage Chunker

```

cp = nltk.RegexpParser(r"""
NP: {<DT>?<JJ>*<NN.*>+}      # noun phrase chunks
VP: {<TO>?<VB.*>}            # verb phrase chunks
PP: {<IN>}                      # prepositional phrase chunks
""")

>>> example = nltk.corpus.conll2000.chunked_sents('train.txt')[99]
>>> print cp.parse(example.flatten(), trace=1)
# Input:
<IN> <DT> <NN> <IN> <NN> <,> <NNP> <NNP> <VBD> <PRP$> <NN> <.>
# noun phrase chunks:
<IN> {<DT> <NN>} <IN> {<NN>} <,> {<NNP> <NNP>} <VBD> <PRP$> {<NN>} <.>
# Input:
<IN> <NP> <IN> <NP> <,> <NP> <VBD> <PRP$> <NP> <.>
# verb phrase chunks:
<IN> <NP> <IN> <NP> <,> <NP> {<VBD>} <PRP$> <NP> <.>
# Input:
<IN> <NP> <IN> <NP> <,> <NP> <VP> <PRP$> <NP> <.>
# prepositional phrase chunks:
{<IN>} <NP> {<IN>} <NP> <,> <NP> <VP> <PRP$> <NP> <.>
(S
    (PP Over/IN)
    (NP a/DT cup/NN)
    (PP of/IN)
    (NP coffee/NN)
    ,/,
    (NP Mr./NNP Stone/NNP)
    (VP told/VBD)
    his/PRP$
    (NP story/NN)
    ./. )

```

We run a chunker over this flattened data, and compare the resulting chunked sentences with the originals, as follows:

```
>>> grammar = r"NP: {<PRP|DT|POS|JJ|CD|N.*>+}"
>>> cp = nltk.RegexpParser(grammar)
>>> tagged_tokens = [("the", "DT"), ("little", "JJ"), ("cat", "NN"),
... ("sat", "VBD"), ("on", "IN"), ("the", "DT"), ("mat", "NN")]
>>> chunkscore = nltk.chunk.ChunkScore()
>>> guess = cp.parse(correct.flatten())
>>> chunkscore.score(correct, guess)
>>> print chunkscore
ChunkParse score:
  Precision: 100.0%
  Recall:    100.0%
  F-Measure: 100.0%
```

ChunkScore is a class for scoring chunk parsers. It can be used to evaluate the output of a chunk parser, using precision, recall, f-measure, missed chunks, and incorrect chunks. It can also be used to combine the scores from the parsing of multiple texts. This is quite useful if we are parsing a text one sentence at a time. The following program listing shows a typical use of the ChunkScore class. In this example, chunkparser is being tested on each sentence from the Wall Street Journal tagged files.

```
>>> grammar = r"NP: {<DT|JJ|NN>+}"
>>> cp = nltk.RegexpParser(grammar)
>>> chunkscore = nltk.chunk.ChunkScore()
>>> for file in nltk.corpus.treebank_chunk.files()[:5]:
...     for chunk_struct in nltk.corpus.treebank_chunk.chunked_sents(file):
...         test_sent = cp.parse(chunk_struct.flatten())
...         chunkscore.score(chunk_struct, test_sent)
>>> print chunkscore
ChunkParse score:
  Precision: 42.3%
  Recall:    29.9%
  F-Measure: 35.0%
```

The overall results of the evaluation can be viewed by printing the ChunkScore. Each evaluation metric is also returned by an accessor method: `precision()`, `recall`, `f_measure`, `missed`, and `incorrect`. The `missed` and `incorrect` methods can be especially useful when trying to improve the performance of a chunk parser. Here are the missed chunks:

```
>>> from random import shuffle
>>> missed = chunkscore.missed()
>>> shuffle(missed)
>>> print missed[:10]
[((('A', 'DT'), ('Lorillard', 'NNP'), ('spokeswoman', 'NN')),,
 (('even', 'RB'), ('brief', 'JJ'), ('exposures', 'NNS')),,
 (('its', 'PRP$'), ('Micronite', 'NN'), ('cigarette', 'NN'), ('filters', 'NNS')),,
 (('30', 'CD'), ('years', 'NNS')),,
 (('workers', 'NNS'),),
 (('preliminary', 'JJ'), ('findings', 'NNS')),,
 (('Medicine', 'NNP'),),
 (('Consolidated', 'NNP'), ('Gold', 'NNP'), ('Fields', 'NNP'), ('PLC', 'NNP'))),
```

```
(('its', 'PRP$'), ('Micronite', 'NN'), ('cigarette', 'NN'), ('filters', 'NNS')),
 (('researchers', 'NNS'),))]
```

Here are the incorrect chunks:

```
>>> incorrect = chunkscore.incorrect()
>>> shuffle(incorrect)
>> print incorrect[:10]
[('New', 'JJ'), ('York-based', 'JJ'),
 ('Micronite', 'NN'), ('cigarette', 'NN'),
 ('a', 'DT'), ('forum', 'NN'), ('likely', 'JJ'),
 ('later', 'JJ'),),
 ('preliminary', 'JJ'),),
 ('New', 'JJ'), ('York-based', 'JJ'),
 ('resilient', 'JJ'),),
 ('group', 'NN'),),
 ('the', 'DT'),),
 ('Micronite', 'NN'), ('cigarette', 'NN')]
```

7.4.7 Exercises

1. **● Chunker Evaluation:** Carry out the following evaluation tasks for any of the chunkers you have developed earlier. (Note that most chunking corpora contain some internal inconsistencies, such that any reasonable rule-based approach will produce errors.)
 - a) Evaluate your chunker on 100 sentences from a chunked corpus, and report the precision, recall and F-measure.
 - b) Use the `chunkscore.missed()` and `chunkscore.incorrect()` methods to identify the errors made by your chunker. Discuss.
 - c) Compare the performance of your chunker to the baseline chunker discussed in the evaluation section of this chapter.
2. **★ Transformation-Based Chunking:** Apply the n-gram and Brill tagging methods to IOB chunk tagging. Instead of assigning POS tags to words, here we will assign IOB tags to the POS tags. E.g. if the tag DT (determiner) often occurs at the start of a chunk, it will be tagged B (begin). Evaluate the performance of these chunking methods relative to the regular expression chunking methods covered in this chapter.

7.4.8 Exercises

1. **⊗** Pick one of the three chunk types in the CoNLL corpus. Inspect the CoNLL corpus and try to observe any patterns in the POS tag sequences that make up this kind of chunk. Develop a simple chunker using the regular expression chunker `nltk.RegexpParser`. Discuss any tag sequences that are difficult to chunk reliably.
2. **⊗** An early definition of *chunk* was the material that occurs between chinks. Develop a chunker that starts by putting the whole sentence in a single chunk, and then does the rest of its work solely by chinking. Determine which tags (or tag sequences) are most likely to make up chinks with the help of your own utility program. Compare the performance and simplicity of this approach relative to a chunker based entirely on chunk rules.

3. **❶** Develop a chunker for one of the chunk types in the CoNLL corpus using a regular-expression based chunk grammar `RegexpChunk`. Use any combination of rules for chunking, chinking, merging or splitting.
4. **❶** Sometimes a word is incorrectly tagged, e.g. the head noun in “12/CD or/CC so/RB cases/VBZ”. Instead of requiring manual correction of tagger output, good chunkers are able to work with the erroneous output of taggers. Look for other examples of correctly chunked noun phrases with incorrect tags.
5. **★** We saw in the tagging chapter that it is possible to establish an upper limit to tagging performance by looking for ambiguous n-grams, n-grams that are tagged in more than one possible way in the training data. Apply the same method to determine an upper bound on the performance of an n-gram chunker.
6. **★** Pick one of the three chunk types in the CoNLL corpus. Write functions to do the following tasks for your chosen type:
 - a) List all the tag sequences that occur with each instance of this chunk type.
 - b) Count the frequency of each tag sequence, and produce a ranked list in order of decreasing frequency; each line should consist of an integer (the frequency) and the tag sequence.
 - c) Inspect the high-frequency tag sequences. Use these as the basis for developing a better chunker.
7. **★** The baseline chunker presented in the evaluation section tends to create larger chunks than it should. For example, the phrase: [every/DT time/NN] [she/PRP] sees /VBZ [a/DT newspaper/NN] contains two consecutive chunks, and our baseline chunker will incorrectly combine the first two: [every/DT time/NN she/PRP]. Write a program that finds which of these chunk-internal tags typically occur at the start of a chunk, then devise one or more rules that will split up these chunks. Combine these with the existing baseline chunker and re-evaluate it, to see if you have discovered an improved baseline.
8. **★** Develop an NP chunker that converts POS-tagged text into a list of tuples, where each tuple consists of a verb followed by a sequence of noun phrases and prepositions, e.g. the little cat sat on the mat becomes ('sat', 'on', 'NP') ...
9. **★** The Penn Treebank contains a section of tagged Wall Street Journal text that has been chunked into noun phrases. The format uses square brackets, and we have encountered it several times during this chapter. The Treebank corpus can be accessed using: `for sent in nltk.corpus.treebank_chunk.chunked_sents(file)`. These are flat trees, just as we got using `nltk.corpus.conll2000.chunked_sents()`.
 - a) The functions `nltk.tree pprint()` and `nltk.chunk.tree2conllstr()` can be used to create Treebank and IOB strings from a tree. Write functions `chunk2brackets()` and `chunk2iob()` that take a single chunk tree as their sole argument, and return the required multi-line string representation.
 - b) Write command-line conversion utilities `bracket2iob.py` and `iob2bracket.py` that take a file in Treebank or CoNLL format (resp) and convert it to the

other format. (Obtain some raw Treebank or CoNLL data from the NLTK Corpora, save it to a file, and then use `for` line `in open(filename)` to access it from Python.)

7.5 N-Gram Chunking

Our approach to chunking has been to try to detect structure based on the part-of-speech tags. We have seen that the IOB format represents this extra structure using another kind of tag. The question arises as to whether we could use the same n -gram tagging methods we saw in Chapter 4, applied to a different vocabulary. In this case, rather than trying to determine the correct part-of-speech tag, given a word, we are trying to determine the correct chunk tag, given a part-of-speech tag.

The first step is to get the `word`, `tag`, `chunk` triples from the CoNLL 2000 corpus and map these to `tag`, `chunk` pairs:

```
>>> chunk_data = [[(t,c) for w,t,c in nltk.chunk.tree2conlltags(chtree)]
...                 for chtree in nltk.corpus.conll2000.chunked_sents('train.txt')]
```

We will now train two n -gram taggers over this data.

7.5.1 A Unigram Chunker

To start off, we train and score a **unigram chunker** on the above data, just as if it was a tagger:

```
>>> unigram_chunker = nltk.UnigramTagger(chunk_data)
>>> print nltk.tag.accuracy(unigram_chunker, chunk_data)
0.781378851068
```

This chunker does reasonably well. Let's look at the errors it makes. Consider the opening phrase of the first sentence of the CONLL chunking data, here shown with part-of-speech tags:

Confidence/NN in/IN the/DT pound/NN is/VBZ widely/RB expected/VBN to/TO take/VB
another/DT sharp/JJ dive/NN

We can try out the unigram chunker on this first sentence by creating some “tokens” using `[t for t, c in chunk_data[0]]`, then running our chunker over them using `list(unigram_chunker.tag(tokens))`. The unigram chunker only looks at the tags, and tries to add chunk tags. Here is what it comes up with:

NN/I-NP IN/B-PP DT/B-NP NN/I-NP VBZ/B-VP RB/O VBN/I-VP TO/B-PP VB/I-VP
DT/B-NP JJ/I-NP NN/I-NP

Notice that it tags all instances of `NN` with `I-NP`, because nouns usually do not appear at the beginning of noun phrases in the training data. Thus, the first noun `Confidence/NN` is tagged incorrectly. However, `pound/NN` and `dive/NN` are correctly tagged as `I-NP`; they are not in the initial position that should be tagged `B-NP`. The chunker incorrectly tags `widely/RB` as `O`, and it incorrectly tags the infinitival `to/TO` as `B-PP`, as if it was a preposition starting a prepositional phrase.

7.5.2 A Bigram Chunker (incomplete)

[Why these problems might go away if we look at the previous chunk tag?]

Let's run a bigram chunker:

```
>>> bigram_chunker = nltk.BigramTagger(chunk_data, backoff=unigram_chunker)
>>> print nltk.tag.accuracy(bigram_chunker, chunk_data)
0.893220987404
```

We can run the bigram chunker over the same sentence as before using `list(bigram_chunker.tag(tokens))`. Here is what it comes up with:

```
NN/B-NP IN/B-PP DT/B-NP NN/I-NP VBZ/B-VP RB/I-VP VBN/I-VP TO/I-VP VB/I-
VP DT/B-NP JJ/I-NP NN/I-NP
```

This is 100% correct.

7.5.3 Exercises

1. ⚪ The bigram chunker scores about 90% accuracy. Study its errors and try to work out why it doesn't get 100% accuracy.
2. ⚪ Experiment with trigram chunking. Are you able to improve the performance any more?
3. ★ An n-gram chunker can use information other than the current part-of-speech tag and the $n - 1$ previous chunk tags. Investigate other models of the context, such as the $n - 1$ previous part-of-speech tags, or some combination of previous chunk tags along with previous and following part-of-speech tags.
4. ★ Consider the way an n-gram tagger uses recent tags to inform its tagging choice. Now observe how a chunker may re-use this sequence information. For example, both tasks will make use of the information that nouns tend to follow adjectives (in English). It would appear that the same information is being maintained in two places. Is this likely to become a problem as the size of the rule sets grows? If so, speculate about any ways that this problem might be addressed.

7.6 Cascaded Chunkers

So far, our chunk structures have been relatively flat. Trees consist of tagged tokens, optionally grouped under a chunk node such as NP. However, it is possible to build chunk structures of arbitrary depth, simply by creating a multi-stage chunk grammar. These stages are processed in the order that they appear. The patterns in later stages can refer to a mixture of part-of-speech tags and chunk types. Listing 7.7 has patterns for noun phrases, prepositional phrases, verb phrases, and sentences. This is a four-stage chunk grammar, and can be used to create structures having a depth of at most four.

Unfortunately this result misses the VP headed by *saw*. It has other shortcomings too. Let's see what happens when we apply this chunker to a sentence having deeper nesting.

```
>>> tagged_tokens = [("John", "NNP"), ("thinks", "VBZ"), ("Mary", "NN"),
...     ("saw", "VBD"), ("the", "DT"), ("cat", "NN"), ("sit", "VB"),
...     ("on", "IN"), ("the", "DT"), ("mat", "NN")]
>>> print cp.parse(tagged_tokens)
```

Listing 7.7 A Chunker that Handles NP, PP, VP and S

```

grammar = r"""
NP: {<DT|JJ|NN.*>+}          # Chunk sequences of DT, JJ, NN
PP: {<IN><NP>}              # Chunk prepositions followed by NP
VP: {<VB.*><NP|PP|S>+$}    # Chunk rightmost verbs and arguments/adjuncts
S:  {<NP><VP>}              # Chunk NP, VP
"""

cp = nltk.RegexpParser(grammar)
tagged_tokens = [("Mary", "NN"), ("saw", "VBD"), ("the", "DT"), ("cat", "NN"),
                 ("sit", "VB"), ("on", "IN"), ("the", "DT"), ("mat", "NN")]

>>> print cp.parse(tagged_tokens)
(S
 (NP Mary/NN)
 saw/VBD
 (S
 (NP the/DT cat/NN)
 (VP sit/VB (PP on/IN (NP the/DT mat/NN)))))


```

```

(S
 (NP John/NNP)
 thinks/VBZ
 (NP Mary/NN)
 saw/VBD
 (S
 (NP the/DT cat/NN)
 (VP sit/VB (PP on/IN (NP the/DT mat/NN)))))


```

The solution to these problems is to get the chunker to loop over its patterns: after trying all of them, it repeats the process. We add an optional second argument `loop` to specify the number of times the set of patterns should be run:

```

>>> cp = nltk.RegexpParser(grammar, loop=2)
>>> print cp.parse(tagged_tokens)
(S
 (NP John/NNP)
 thinks/VBZ
 (S
 (NP Mary/NN)
 (VP
 saw/VBD
 (S
 (NP the/DT cat/NN)
 (VP sit/VB (PP on/IN (NP the/DT mat/NN))))))


```

This cascading process enables us to create deep structures. However, creating and debugging a cascade is quite difficult, and there comes a point where it is more effective to do full parsing (see [Chapter 8](#)).

7.7 Shallow Interpretation

The main form of shallow semantic interpretation that we will consider is **Information Extraction**. This refers to the task of converting **unstructured data** (e.g., unrestricted text) or **semi-structured data** (e.g., web pages marked up with HTML) into **structured data** (e.g., tables in a relational database). For example, let's suppose we are given a text containing the fragment (14), and let's also suppose we are trying to find pairs of entities X and Y that stand in the relation 'organization X is located in location Y '.

- (14) ... said William Gale, an economist at the Brookings Institution, the research group in Washington.

As a result of processing this text, we should be able to add the pair *Brookings Institution, Washington* to this relation. As we will see shortly, Information Extraction proceeds on the assumption that we are only looking for specific sorts of information, and these have been decided in advance. This limitation has been a necessary concession to allow the robust processing of unrestricted text.

Potential applications of Information Extraction are many, and include business intelligence, resume harvesting, media analysis, sentiment detection, patent search, and email scanning. A particularly important area of current research involves the attempt to extract structured data out of electronically-available scientific literature, most notably in the domain of biology and medicine.

Information Extraction is usually broken down into at least two major steps: **Named Entity Recognition** and **Relation Extraction**. Named Entities (NEs) are usually taken to be noun phrases that denote specific types of individuals such as organizations, persons, dates, and so on. Thus, we might use the following XML annotations to mark-up the NEs in (14):

- (15) ... said <ne type='PERSON'>William Gale</ne>, an economist at the <ne type='ORGANIZATION'>Brookings Institution</ne>, the research group in <ne type='LOCATION'>Washington</ne>.

How do we go about identifying NEs? Our first thought might be that we could look up candidate expressions in an appropriate list of names. For example, in the case of locations, we might try using a resource such as the [Alexandria Gazetteer](#). Depending on the nature of our input data, this may be adequate — such a gazetteer is likely to have good coverage of international cities and many locations in the U.S.A., but will probably be missing the names of obscure villages in remote regions. However, a list of names for people or organizations will probably have poor coverage. New organizations, and new names for them, are coming into existence every day, so if we are trying to deal with contemporary newswire or blog entries, say, it is unlikely that we will be able to recognize many of the NEs by using gazetteer lookup.

A second consideration is that many NE terms are ambiguous. Thus *May* and *North* are likely to be parts of NEs for DATE and LOCATION, respectively, but could both be part of a PERSON NE; conversely *Christian Dior* looks like a PERSON NE but is more likely to be of type ORGANIZATION. A term like *Yankee* will be ordinary modifier in some contexts, but will be marked as an NE of type ORGANIZATION in the phrase *Yankee infielders*. To summarize, we cannot reliably detect NEs by looking them up in a gazetteer, and it is also hard to develop rules that will correctly recognize ambiguous NEs on the basis of their context of occurrence. Although lookup may contribute to a solution, most contemporary approaches to Named Entity Recognition treat it as a statistical classification task that requires training data for good performance. This task is facilitated by adopting an appropriate data representation, such as the IOB tags that we saw being deployed in the CoNLL chunk data ([Chapter 7](#)). For example, here are a representative few lines from the CONLL 2002 (conll2002) Dutch training data:

```

Eddy N B-PER
Bonte N I-PER
is V O
woordvoerder N O
van Prep O
diezelfde Pron O
Hogeschool N B-ORG
. Punc O

```

As noted before, in this representation, there is one token per line, each with its part-of-speech tag and its NE tag. When NEs have been identified in a text, we then want to extract relations that hold between them. As indicated earlier, we will typically be looking for relations between specified types of NE. One way of approaching this task is to initially look for all triples of the form X, α, Y , where X and Y are NEs of the required types, and α is the string of words that intervenes between X and Y . We can then use regular expressions to pull out just those instances of α that express the relation that we are looking for. The following example searches for strings that contain the word *in*. The special character expression `(?!\\b.+ing\\b)` is a negative lookahead condition that allows us to disregard strings such as *success in supervising the transition of*, where *in* is followed by a gerundive verb.

```

>>> IN = re.compile(r'.*\bin\b(?!\\b.+ing\\b)')
>>> for doc in nltk.corpus.ieer.parsed_docs('NYT_19980315'):
...     for rel in nltk.sem.relextract('ORG', 'LOC', doc, pattern = IN):
...         print nltk.sem.show_raw_rtuple(rel)
[ORG: 'WHYY'] 'in' [LOC: 'Philadelphia']
[ORG: 'McGlashan & Sarrail'] 'firm in' [LOC: 'San Mateo']
[ORG: 'Freedom Forum'] 'in' [LOC: 'Arlington']
[ORG: 'Brookings Institution'] ', the research group in' [LOC: 'Washington']
[ORG: 'Idealab'] ', a self-described business incubator based in' [LOC: 'Los Angeles']
[ORG: 'Open Text'] ', based in' [LOC: 'Waterloo']
[ORG: 'WGBH'] 'in' [LOC: 'Boston']
[ORG: 'Bastille Opera'] 'in' [LOC: 'Paris']
[ORG: 'Omnicom'] 'in' [LOC: 'New York']
[ORG: 'DDB Needham'] 'in' [LOC: 'New York']
[ORG: 'Kaplan Thaler Group'] 'in' [LOC: 'New York']
[ORG: 'BBDO South'] 'in' [LOC: 'Atlanta']
[ORG: 'Georgia-Pacific'] 'in' [LOC: 'Atlanta']

```

Searching for the keyword works *in* reasonably well, though it will also retrieve false positives such as [ORG: House Transportation Committee], secured the most money *in* the [LOC: New York]; there is unlikely to be simple string-based method of excluding filler strings such as this.

```

>>> vnv = """
... (
... is/V|
... was/V|
... werd/V|
... wordt/V
...
... )
...
... .*|
... van/Prep
...
"""

```

```
>>> VAN = re.compile(vnv, re.VERBOSE)
>>> for r in relextract('PER', 'ORG', corpus='conll2002-ned', pattern=VAN):
...     print show_tuple(r)
```

7.8 Conclusion

In this chapter we have explored efficient and robust methods that can identify linguistic structures in text. Using only part-of-speech information for words in the local context, a “chunker” can successfully identify simple structures such as noun phrases and verb groups. We have seen how chunking methods extend the same lightweight methods that were successful in tagging. The resulting structured information is useful in information extraction tasks and in the description of the syntactic environments of words. The latter will be invaluable as we move to full parsing.

There are a surprising number of ways to chunk a sentence using regular expressions. The patterns can add, shift and remove chunks in many ways, and the patterns can be sequentially ordered in many ways. One can use a small number of very complex rules, or a long sequence of much simpler rules. One can hand-craft a collection of rules, and one can write programs to analyze a chunked corpus to help in the development of such rules. The process is painstaking, but generates very compact chunkers that perform well and that transparently encode linguistic knowledge.

It is also possible to chunk a sentence using the techniques of n-gram tagging. Instead of assigning part-of-speech tags to words, we assign IOB tags to the part-of-speech tags. Bigram tagging turned out to be particularly effective, as it could be sensitive to the chunk tag on the previous word. This statistical approach requires far less effort than rule-based chunking, but creates large models and delivers few linguistic insights.

Like tagging, chunking cannot be done perfectly. For example, as pointed out by [?], we cannot correctly analyze the structure of the sentence *I turned off the spectroroute* without knowing the meaning of *spectroroute*; is it a kind of road or a type of device? Without knowing this, we cannot tell whether *off* is part of a prepositional phrase indicating direction (tagged B-PP), or whether *off* is part of the verb-particle construction *turn off* (tagged I-VP).

A recurring theme of this chapter has been **diagnosis**. The simplest kind is manual, when we inspect the tracing output of a chunker and observe some undesirable behavior that we would like to fix. Sometimes we discover cases where we cannot hope to get the correct answer because the part-of-speech tags are too impoverished and do not give us sufficient information about the lexical item. A second approach is to write utility programs to analyze the training data, such as counting the number of times a given part-of-speech tag occurs inside and outside an NP chunk. A third approach is to evaluate the system against some gold standard data to obtain an overall performance score. We can even use this to parameterize the system, specifying which chunk rules are used on a given run, and tabulating performance for different parameter combinations. Careful use of these diagnostic methods permits us to optimize the performance of our system. We will see this theme emerge again later in chapters dealing with other topics in natural language processing.

7.9 Further Reading

For more examples of chunking with NLTK, please see the guide at <http://nltk.org/doc/guides/chunk.html>.

The popularity of chunking is due in great part to pioneering work by Abney e.g., [?]. Abney’s Cass chunker is available at <http://www.vinartus.net/spa/97a.pdf>

The word **chink** initially meant a sequence of stopwords, according to a 1975 paper by Ross and Tukey [?].

The IOB format (or sometimes **BIO Format**) was developed for NP chunking by [?], and was used for the shared NP bracketing task run by the *Conference on Natural Language Learning* (CoNLL) in 1999. The same format was adopted by CoNLL 2000 for annotating a section of Wall Street Journal text as part of a shared task on NP chunking.

About this document...

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Chapter 8

Context Free Grammars and Parsing

8.1 Introduction

Early experiences with the kind of grammar taught in school are sometimes perplexing. Your written work might have been graded by a teacher who red-lined all the grammar errors they wouldn't put up with. Like the plural pronoun or the dangling preposition in the last sentence, or sentences like this one that lack a main verb. If you learnt English as a second language, you might have found it difficult to discover which of these errors need to be fixed (or *needs* to be fixed?). Correct punctuation is an obsession for many writers and editors. It is easy to find cases where changing punctuation changes meaning. In the following example, the interpretation of a relative clause as restrictive or non-restrictive depends on the presence of commas alone:

- (16) a. The presidential candidate, who was extremely popular, smiled broadly.
b. The presidential candidate who was extremely popular smiled broadly.

In (16a), we assume there is just one presidential candidate, and say two things about her: that she was popular and that she smiled. In (16b), on the other hand, we use the description *who was extremely popular* as a means of identifying which of several possible candidates we are referring to.

It is clear that some of these rules are important. However, others seem to be vestiges of antiquated style. Consider the injunction that *however* — when used to mean *nevertheless* — must not appear at the start of a sentence. Pullum argues that Strunk and White [?] were merely insisting that English usage should conform to “an utterly unimportant minor statistical detail of style concerning adverb placement in the literature they knew” [?]. This is a case where, a *descriptive* observation about language use became a *prescriptive* requirement. In NLP we usually discard such prescriptions, and use grammar to formalize observations about language as it is used, particularly as it is used in corpora.

In this chapter we present the fundamentals of syntax, focusing on constituency and tree representations, before describing the formal notation of context free grammar. Next we present parsers as an automatic way to associate syntactic structures with sentences. Finally, we give a detailed presentation of simple top-down and bottom-up parsing algorithms available in NLTK. Before launching into the theory we present some more naive observations about grammar, for the benefit of readers who do not have a background in linguistics.

8.2 More Observations about Grammar

Another function of a grammar is to explain our observations about ambiguous sentences. Even when the individual words are unambiguous, we can put them together to create ambiguous sentences, as in (17).

- (17) a. Fighting animals could be dangerous.
- b. Visiting relatives can be tiresome.

A grammar will be able to assign two structures to each sentence, accounting for the two possible interpretations.

Perhaps another kind of syntactic variation, word order, is easier to understand. We know that the two sentences *Kim likes Sandy* and *Sandy likes Kim* have different meanings, and that *likes Sandy Kim* is simply ungrammatical. Similarly, we know that the following two sentences are equivalent:

- (18) a. The farmer *loaded* the cart with sand
- b. The farmer *loaded* sand into the cart

However, consider the semantically similar verbs *filled* and *dumped*. Now the word order cannot be altered (ungrammatical sentences are prefixed with an asterisk.)

- (19) a. The farmer *filled* the cart with sand
- b. *The farmer *filled* sand into the cart
- c. *The farmer *dumped* the cart with sand
- d. The farmer *dumped* sand into the cart

A further notable fact is that we have no difficulty accessing the meaning of sentences we have never encountered before. It is not difficult to concoct an entirely novel sentence, one that has probably never been used before in the history of the language, and yet all speakers of the language will agree about its meaning. In fact, the set of possible sentences is infinite, given that there is no upper bound on length. Consider the following passage from a children's story, containing a rather impressive sentence:

You can imagine Piglet's joy when at last the ship came in sight of him. In after-years he liked to think that he had been in Very Great Danger during the Terrible Flood, but the only danger he had really been in was the last half-hour of his imprisonment, when Owl, who had just flown up, sat on a branch of his tree to comfort him, and told him a very long story about an aunt who had once laid a seagull's egg by mistake, and the story went on and on, rather like this sentence, until Piglet who was listening out of his window without much hope, went to sleep quietly and naturally, slipping slowly out of the window towards the water until he was only hanging on by his toes, at which moment, luckily, a sudden loud squawk from Owl, which was really part of the story, being what his aunt said, woke the Piglet up and just gave him time to jerk himself back into safety and say, "How interesting, and did she?" when -- well, you can imagine his joy when at last he saw the good ship, Brain of Pooh (Captain, C. Robin; 1st Mate, P. Bear) coming over the sea to rescue him... (from A.A. Milne *In which Piglet is Entirely Surrounded by Water*)

Our ability to produce and understand entirely new sentences, of arbitrary length, demonstrates that the set of well-formed sentences in English is infinite. The same case can be made for any human language.

This chapter presents grammars and parsing, as the formal and computational methods for investigating and modeling the linguistic phenomena we have been touching on (or tripping over). As we shall see, patterns of well-formedness and ill-formedness in a sequence of words can be understood with respect to the underlying **phrase structure** of the sentences. We can develop formal models of these structures using grammars and parsers. As before, the motivation is natural language *understanding*. How much more of the meaning of a text can we access when we can reliably recognize the linguistic structures it contains? Having read in a text, can a program 'understand' it enough to be able to answer simple questions about "what happened" or "who did what to whom." Also as before, we will develop simple programs to process annotated corpora and perform useful tasks.

Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

8.3 What's the Use of Syntax?

Earlier chapters focused on words: how to identify them, how to analyze their morphology, and how to assign them to classes via part-of-speech tags. We have also seen how to identify recurring sequences of words (i.e. n-grams). Nevertheless, there seem to be linguistic regularities that cannot be described simply in terms of n-grams.

In this section we will see why it is useful to have some kind of syntactic representation of sentences. In particular, we will see that there are systematic aspects of meaning that are much easier to capture once we have established a level of syntactic structure.

8.3.1 Syntactic Ambiguity

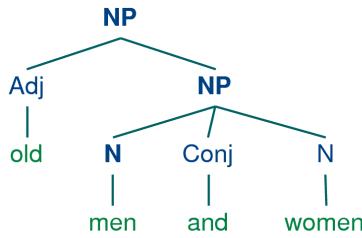
We have seen that sentences can be ambiguous. If we overheard someone say *I went to the bank*, we wouldn't know whether it was a river bank or a financial institution. This ambiguity concerns the meaning of the word *bank*, and is a kind of **lexical ambiguity**.

However, other kinds of ambiguity cannot be explained in terms of ambiguity of specific words. Consider a phrase involving an adjective with a conjunction: *old men and women*. Does *old* have wider scope than *and*, or is it the other way round? In fact, both interpretations are possible, and we can represent the different scopes using parentheses:

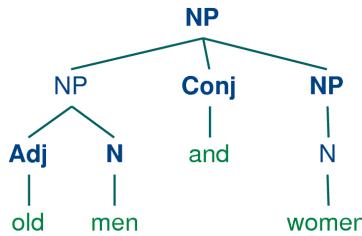
- (20) a. old (men and women)
- b. (old men) and women

One convenient way of representing this scope difference at a structural level is by means of a **tree diagram**, as shown in (21).

(21) a.



b.



Note that linguistic trees grow upside down: the node labeled **S** is the **root** of the tree, while the **leaves** of the tree are labeled with the words.

In NLTK, you can easily produce trees like this yourself with the following commands:

```
>>> tree = nltk.bracket_parse(' (NP (Adj old) (NP (N men) (Conj and) (N women))) ')
>>> tree.draw()
```

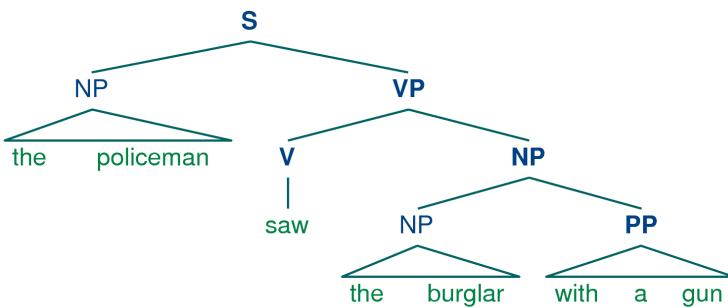
We can construct other examples of syntactic ambiguity involving the coordinating conjunctions *and* and *or*, e.g. *Kim left or Dana arrived and everyone cheered*. We can describe this ambiguity in terms of the relative semantic **scope** of *or* and *and*.

For our third illustration of ambiguity, we look at prepositional phrases. Consider a sentence like: *I saw the man with a telescope*. Who has the telescope? To clarify what is going on here, consider the following pair of sentences:

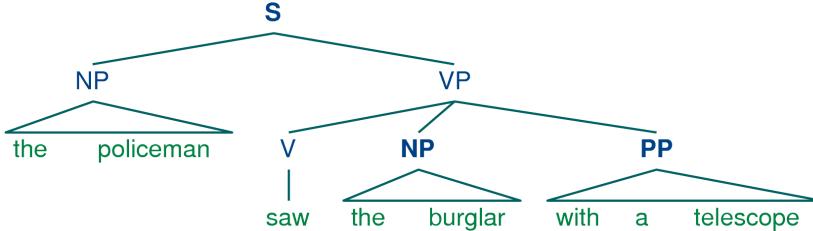
(22) a. The policeman saw a burglar *with a gun*. (not some other burglar)b. The policeman saw a burglar *with a telescope*. (not with his naked eye)

In both cases, there is a prepositional phrase introduced by *with*. In the first case this phrase modifies the noun *burglar*, and in the second case it modifies the verb *saw*. We could again think of this in terms of scope: does the prepositional phrase (PP) just have scope over the NP *a burglar*, or does it have scope over the whole verb phrase? As before, we can represent the difference in terms of tree structure:

(23) a.



b.



In (23)a, the PP attaches to the NP, while in (23)b, the PP attaches to the VP.

We can generate these trees in Python as follows:

```

>>> s1 = '(S (NP the policeman) (VP (V saw) (NP (NP the burglar) (PP with a gun))))'
>>> s2 = '(S (NP the policeman) (VP (V saw) (NP the burglar) (PP with a telescope)))'
>>> tree1 = nltk.bracket_parse(s1)
>>> tree2 = nltk.bracket_parse(s2)
  
```

We can discard the structure to get the list of **leaves**, and we can confirm that both trees have the same leaves (except for the last word). We can also see that the trees have different **heights** (given by the number of nodes in the longest branch of the tree, starting at S and descending to the words):

```

>>> tree1.leaves()
['the', 'policeman', 'saw', 'the', 'burglar', 'with', 'a', 'gun']
>>> tree1.height() == tree2.height()
True
>>> tree1.height() == tree2.height()
False
  
```

In general, how can we determine whether a prepositional phrase modifies the preceding noun or verb? This problem is known as **prepositional phrase attachment ambiguity**. The **Prepositional Phrase Attachment Corpus** makes it possible for us to study this question systematically. The corpus is derived from the IBM-Lancaster Treebank of Computer Manuals and from the Penn Treebank, and distills out only the essential information about PP attachment. Consider the sentence from the WSJ in (24a). The corresponding line in the Prepositional Phrase Attachment Corpus is shown in (24b).

- (24) a. Four of the five surviving workers have asbestos-related diseases, including three with recently diagnosed cancer.
 b. 16 including three with cancer N

That is, it includes an identifier for the original sentence, the head of the relevant verb phrase (i.e., *including*), the head of the verb's NP object (*three*), the preposition (*with*), and the head noun within the prepositional phrase (*cancer*). Finally, it contains an “attachment” feature (N or V) to indicate whether the prepositional phrase attaches to (modifies) the noun phrase or the verb phrase. Here are some further examples:

- (25) 47830 allow visits between families N
 47830 allow visits on peninsula V
 42457 acquired interest in firm N
 42457 acquired interest in 1986 V

The PP attachments in (25) can also be made explicit by using phrase groupings as in (26).

- (26) allow (NP visits (PP between families))
 allow (NP visits) (PP on peninsula)
 acquired (NP interest (PP in firm))
 acquired (NP interest) (PP in 1986)

Observe in each case that the argument of the verb is either a single complex expression (visits (between families)) or a pair of simpler expressions (visits) (on peninsula).

We can access the Prepositional Phrase Attachment Corpus from NLTK as follows:

```
>>> nltk.corpus.ppattach.tuples('training')[9]
('16', 'including', 'three', 'with', 'cancer', 'N')
```

If we go back to our first examples of PP attachment ambiguity, it appears as though it is the PP itself (e.g., *with a gun* versus *with a telescope*) that determines the attachment. However, we can use this corpus to find examples where other factors come into play. For example, it appears that the verb is the key factor in (27).

- (27) 8582 received offer from group V
 19131 rejected offer from group N

8.3.2 Constituency

We claimed earlier that one of the motivations for building syntactic structure was to help make explicit how a sentence says “who did what to whom”. Let’s just focus for a while on the “who” part of this story: in other words, how can syntax tell us what the subject of a sentence is? At first, you might think this task is rather simple — so simple indeed that we don’t need to bother with syntax. In a sentence such as *The fierce dog bit the man* we know that it is the dog that is doing the biting. So we could say that the noun phrase immediately preceding the verb is the subject of the sentence. And we might try to make this more explicit in terms of sequences part-of-speech tags. Let’s try to come up with a simple definition of *noun phrase*; we might start off with something like this, based on our knowledge of noun phrase chunking (Chapter 7):

- (28) DT JJ* NN

We’re using regular expression notation here in the form of JJ* to indicate a sequence of zero or more JJs. So this is intended to say that a noun phrase can consist of a determiner, possibly followed by some adjectives, followed by a noun. Then we can go on to say that if we can find a sequence of tagged words like this that precedes a word tagged as a verb, then we’ve identified the subject. But now think about this sentence:

- (29) The child with a fierce dog bit the man.

This time, it’s the child that is doing the biting. But the tag sequence preceding the verb is:

- (30) DT NN IN DT JJ NN

Our previous attempt at identifying the subject would have incorrectly come up with *the fierce dog* as the subject. So our next hypothesis would have to be a bit more complex. For example, we might say that the subject can be identified as any string matching the following pattern before the verb:

- (31) DT JJ* NN (IN DT JJ* NN)*

In other words, we need to find a noun phrase followed by zero or more sequences consisting of a preposition followed by a noun phrase. Now there are two unpleasant aspects to this proposed solution. The first is esthetic: we are forced into repeating the sequence of tags (DT JJ* NN) that constituted our initial notion of noun phrase, and our initial notion was in any case a drastic simplification. More worrying, this approach still doesn't work! For consider the following example:

- (32) The seagull that attacked the child with the fierce dog bit the man.

This time the seagull is the culprit, but it won't be detected as subject by our attempt to match sequences of tags. So it seems that we need a richer account of how words are *grouped* together into patterns, and a way of referring to these groupings at different points in the sentence structure. This idea of grouping is often called syntactic **constituency**.

As we have just seen, a well-formed sentence of a language is more than an arbitrary sequence of words from the language. Certain kinds of words usually go together. For instance, determiners like *the* are typically followed by adjectives or nouns, but not by verbs. Groups of words form intermediate structures called **phrases** or **constituents**. These constituents can be identified using standard syntactic tests, such as substitution, movement and coordination. For example, if a sequence of words can be replaced with a pronoun, then that sequence is likely to be a constituent. According to this test, we can infer that the italicized string in the following example is a constituent, since it can be replaced by *they*:

- (33) a. *Ordinary daily multivitamin and mineral supplements* could help adults with diabetes fight off some minor infections.
 b. *They* could help adults with diabetes fight off some minor infections.

In order to identify whether a phrase is the subject of a sentence, we can use the construction called **Subject-Auxiliary Inversion** in English. This construction allows us to form so-called Yes-No Questions. That is, corresponding to the statement in (34a), we have the question in (34b):

- (34) a. All the cakes have been eaten.
 b. Have *all the cakes* been eaten?

Roughly speaking, if a sentence already contains an auxiliary verb, such as *has* in (34a), then we can turn it into a Yes-No Question by moving the auxiliary verb 'over' the subject noun phrase to the front of the sentence. If there is no auxiliary in the statement, then we insert the appropriate form of *do* as the fronted auxiliary and replace the tensed main verb by its base form:

- (35) a. The fierce dog bit the man.
 b. Did *the fierce dog* bite the man?

As we would hope, this test also confirms our earlier claim about the subject constituent of (32):

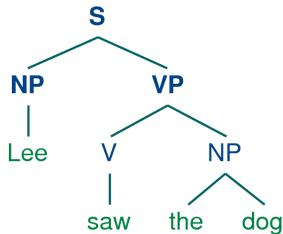
- (36) Did *the seagull that attacked the child with the fierce dog* bite the man?

To sum up then, we have seen that the notion of constituent brings a number of benefits. By having a constituent labeled NOUN PHRASE, we can provide a unified statement of the classes of word that constitute that phrase, and reuse this statement in describing noun phrases wherever they occur in the sentence. Second, we can use the notion of a noun phrase in defining the subject of sentence, which in turn is a crucial ingredient in determining the "who does what to whom" aspect of meaning.

8.3.3 More on Trees

A tree is a set of connected nodes, each of which is labeled with a category. It is common to use a 'family' metaphor to talk about the relationships of nodes in a tree: for example, S is the **parent** of VP; conversely VP is a **daughter** (or **child**) of S. Also, since NP and VP are both daughters of S, they are also **sisters**. Here is an example of a tree:

(37)



Although it is helpful to represent trees in a graphical format, for computational purposes we usually need a more text-oriented representation. We will use the same format as the Penn Treebank, a combination of brackets and labels:

```
(S
  (NP Lee)
  (VP
    (V saw)
    (NP
      (Det the)
      (N dog))))
```

Here, the node value is a constituent type (e.g., NP or VP), and the children encode the hierarchical contents of the tree.

Although we will focus on syntactic trees, trees can be used to encode *any* homogeneous hierarchical structure that spans a sequence of linguistic forms (e.g. morphological structure, discourse structure). In the general case, leaves and node values do not have to be strings.

In NLTK, trees are created with the `Tree` constructor, which takes a node value and a list of zero or more children. Here's a couple of simple trees:

```
>>> tree1 = nltk.Tree('NP', ['John'])
>>> print tree1
(NP John)
>>> tree2 = nltk.Tree('NP', ['the', 'man'])
>>> print tree2
(NP the man)
```

We can incorporate these into successively larger trees as follows:

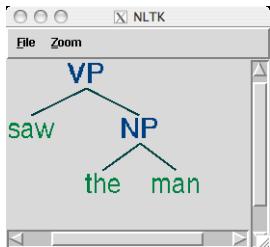
```
>>> tree3 = nltk.Tree('VP', ['saw', tree2])
>>> tree4 = nltk.Tree('S', [tree1, tree3])
>>> print tree4
(S (NP John) (VP saw (NP the man)))
```

Here are some of the methods available for tree objects:

```
>>> print tree4[1]
(VP saw (NP the man))
>>> tree4[1].node
'VP'
>>> tree4.leaves()
['John', 'saw', 'the', 'man']
>>> tree4[1,1,1]
'man'
```

The printed representation for complex trees can be difficult to read. In these cases, the `draw` method can be very useful. It opens a new window, containing a graphical representation of the tree. The tree display window allows you to zoom in and out; to collapse and expand subtrees; and to print the graphical representation to a postscript file (for inclusion in a document).

```
>>> tree3.draw()
```



8.3.4 Treebanks (notes)

The `corpus` module defines the `treebank` corpus reader, which contains a 10% sample of the Penn Treebank corpus.

```
>>> print nltk.corpus.treebank.parsed_sents('wsj_0001.mrg')[0]
(S
  (NP-SBJ
    (NP (NNP Pierre) (NNP Vinken))
    (, ,)
    (ADJP (NP (CD 61) (NNS years)) (JJ old))
    (, ,))
  (VP
    (MD will)
    (VP
      (VB join)
      (NP (DT the) (NN board))
      (PP-CLR
        (IN as)
        (NP (DT a) (JJ nonexecutive) (NN director)))
      (NP-TMP (NNP Nov.) (CD 29))))
    (. .))
```

[Listing 8.1](#) prints a tree object using whitespace formatting.

NLTK also includes a sample from the *Sinica Treebank Corpus*, consisting of 10,000 parsed sentences drawn from the *Academia Sinica Balanced Corpus of Modern Chinese*. Here is a code fragment to read and display one of the trees in this corpus.

```
>>> nltk.corpus.sinica_treebank.parsed_sents()[3450].draw()
```

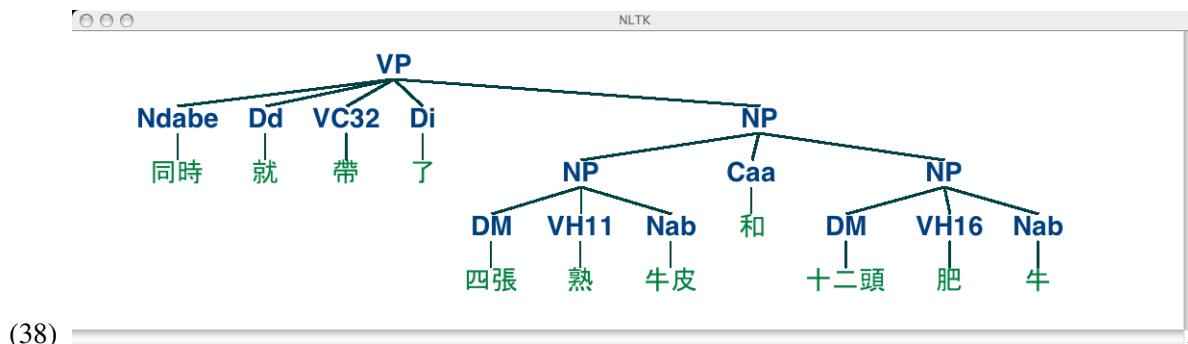
Listing 8.1

```

def indent_tree(t, level=0, first=False, width=8):
    if not first:
        print ' '*(width+1)*level,
    try:
        print "%-*s" % (width, t.node),
        indent_tree(t[0], level+1, first=True)
        for child in t[1:]:
            indent_tree(child, level+1, first=False)
    except AttributeError:
        print t

>>> t = nltk.corpus.treebank.parsed_sents('wsj_0001.mrg')[0]
>>> indent_tree(t)
      S      NP-SBJ   NP      NNP      Pierre
                    NNP      Vinken
      '          '
      ADJP     NP      CD       61
                  NNS      years
                  JJ       old
      VP      MD      will
      VP      VB      join
                  NP      DT      the
                  NP      NN      board
                  PP-CLR  IN      as
                  NP      DT      a
                  JJ      nonexecutive
                  NN      director
      NP-TMP   NNP      Nov.
                  CD      29
      .
      .

```



Note that we can read tagged text from a Treebank corpus, using the `tagged()` method:

```
>>> print nltk.corpus.treebank.tagged_sents('wsj_0001.mrg')[0]
[('Pierre', 'NNP'), ('Vinken', 'NNP'), ('.', '.'), ('61', 'CD'), ('years', 'NNS'),
('old', 'JJ'), ('.', '.'), ('will', 'MD'), ('join', 'VB'), ('the', 'DT'),
('board', 'NN'), ('as', 'IN'), ('a', 'DT'), ('nonexecutive', 'JJ'),
('director', 'NN'), ('Nov.', 'NNP'), ('29', 'CD'), ('.', '.')]
```

8.3.5 Exercises

1. ♦ Can you come up with grammatical sentences that have probably never been uttered before? (Take turns with a partner.) What does this tell you about human language?
2. ♦ Recall Strunk and White's prohibition against sentence-initial *however* used to mean "although". Do a web search for *however* used at the start of the sentence. How widely used is this construction?
3. ♦ Consider the sentence *Kim arrived or Dana left and everyone cheered*. Write down the parenthesized forms to show the relative scope of *and* and *or*. Generate tree structures corresponding to both of these interpretations.
4. ♦ The `Tree` class implements a variety of other useful methods. See the `Tree` help documentation for more details, i.e. import the `Tree` class and then type `help(Tree)`.
5. ♦ **Building trees:**
 - a) Write code to produce two trees, one for each reading of the phrase *old men and women*
 - b) Encode any of the trees presented in this chapter as a labeled bracketing and use `nltk.bracket_parse()` to check that it is well-formed. Now use `draw()` to display the tree.
 - c) As in (a) above, draw a tree for *The woman saw a man last Thursday*.
6. ♦ Write a recursive function to traverse a tree and return the depth of the tree, such that a tree with a single node would have depth zero. (Hint: the depth of a subtree is the maximum depth of its children, plus one.)
7. ♦ Analyze the A.A. Milne sentence about Piglet, by underlining all of the sentences it contains then replacing these with S (e.g. the first sentence becomes S when:lx' S). Draw a tree structure for this "compressed" sentence. What are the main syntactic constructions used for building such a long sentence?

8. ● To compare multiple trees in a single window, we can use the `draw_trees()` method. Define some trees and try it out:

```
>>> from nltk.draw.tree import draw_trees
>>> draw_trees(tree1, tree2, tree3)
```

9. ● Using tree positions, list the subjects of the first 100 sentences in the Penn treebank; to make the results easier to view, limit the extracted subjects to subtrees whose height is 2.
10. ● Inspect the Prepositional Phrase Attachment Corpus and try to suggest some factors that influence PP attachment.
11. ● In this section we claimed that there are linguistic regularities that cannot be described simply in terms of n-grams. Consider the following sentence, particularly the position of the phrase *in his turn*. Does this illustrate a problem for an approach based on n-grams?

*What was more, the *in his turn* somewhat youngish Nikolay Parfenovich also turned out to be the only person in the entire world to acquire a sincere liking to our “discriminated-against” public procurator.* (Dostoevsky: The Brothers Karamazov)

12. ● Write a recursive function that produces a nested bracketing for a tree, leaving out the leaf nodes, and displaying the non-terminal labels after their subtrees. So the above example about Pierre Vinken would produce: [[[NNP NNP] NP , [ADJP [CD NNS] NP JJ] ADJP ,] NP-SBJ MD [VB [DT NN] NP [IN [DT JJ NN] NP] PP-CLR [NNP CD] NP-TMP] VP .] S Consecutive categories should be separated by space.
1. ● Download several electronic books from Project Gutenberg. Write a program to scan these texts for any extremely long sentences. What is the longest sentence you can find? What syntactic construction(s) are responsible for such long sentences?
2. ★ One common way of defining the subject of a sentence *S* in English is as *the noun phrase that is the daughter of S and the sister of VP*. Write a function that takes the tree for a sentence and returns the subtree corresponding to the subject of the sentence. What should it do if the root node of the tree passed to this function is not *S*, or it lacks a subject?

8.4 Context Free Grammar

As we have seen, languages are infinite — there is no principled upper-bound on the length of a sentence. Nevertheless, we would like to write (finite) programs that can process well-formed sentences. It turns out that we can characterize what we mean by well-formedness using a grammar. The way that finite grammars are able to describe an infinite set uses **recursion**. (We already came across this idea when we looked at regular expressions: the finite expression a^+ is able to describe the infinite set $\{a, aa, aaa, aaaa, \dots\}$). Apart from their compactness, grammars usually capture important structural and distributional properties of the language, and can be used to map between sequences of words and abstract representations of meaning. Even if we were to impose an upper bound on sentence length to ensure the language was finite, we would probably still want to come up with a compact representation in the form of a grammar.

A **grammar** is a formal system that specifies which sequences of words are well-formed in the language, and that provides one or more phrase structures for well-formed sequences. We will be looking at **context-free grammar** (CFG), which is a collection of **productions** of the form $S \rightarrow NP VP$. This says that a constituent S can consist of sub-constituents NP and VP . Similarly, the production $V \rightarrow 'saw' \mid ``walked''$ means that the constituent V can consist of the string *saw* or *walked*. For a phrase structure tree to be well-formed relative to a grammar, each non-terminal node and its children must correspond to a production in the grammar.

8.4.1 A Simple Grammar

Let's start off by looking at a simple context-free grammar. By convention, the left-hand-side of the first production is the **start-symbol** of the grammar, and all well-formed trees must have this symbol as their root label.

(39) $S \rightarrow NP VP$

$NP \rightarrow Det N \mid Det N PP$

$VP \rightarrow V \mid V NP \mid V NP PP$

$PP \rightarrow P NP$

$Det \rightarrow 'the' \mid 'a'$

$N \rightarrow 'man' \mid 'park' \mid 'dog' \mid 'telescope'$

$V \rightarrow 'saw' \mid 'walked'$

$P \rightarrow 'in' \mid 'with'$

This grammar contains productions involving various syntactic categories, as laid out in [Table 8.1](#).

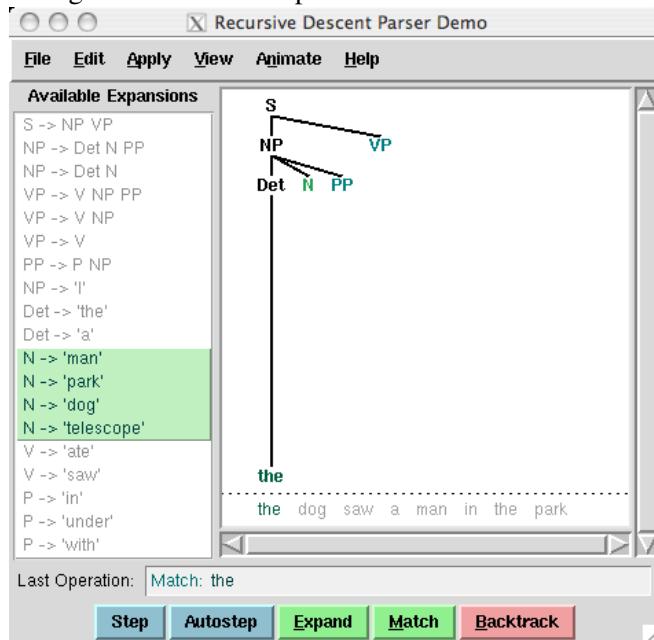
Symbol	Meaning	Example
S	sentence	<i>the man walked</i>
NP	noun phrase	<i>a dog</i>
VP	verb phrase	<i>saw a park</i>
PP	prepositional phrase	<i>with a telescope</i>
...
Det	determiner	<i>the</i>
N	noun	<i>dog</i>
V	verb	<i>walked</i>
P	preposition	<i>in</i>

Table 8.1: Syntactic Categories

In our following discussion of grammar, we will use the following terminology. The grammar consists of productions, where each production involves a single **non-terminal** (e.g. S , NP), an arrow, and one or more non-terminals and **terminals** (e.g. *walked*). The productions are often divided into two main groups. The **grammatical productions** are those without a terminal on the right hand side. The **lexical productions** are those having a terminal on the right hand side. A special case of non-terminals are the **pre-terminals**, which appear on the left-hand side of lexical productions. We will say that a

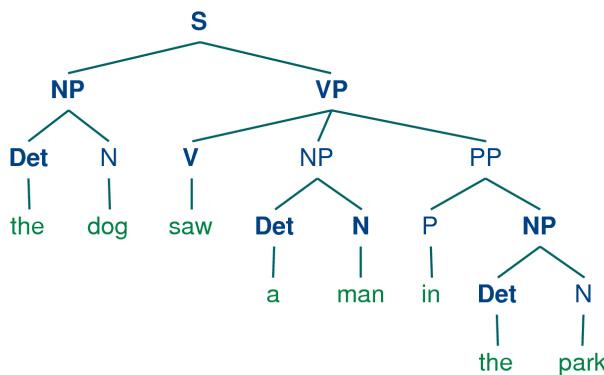
grammar **licenses** a tree if each non-terminal X with children $Y_1 \dots Y_n$ corresponds to a production in the grammar of the form: $X \rightarrow Y_1 \dots Y_n$.

In order to get started with developing simple grammars of your own, you will probably find it convenient to play with the recursive descent parser demo, `nltk.draw.rdparsert.demo()`. The demo opens a window that displays a list of grammar productions in the left hand pane and the current parse diagram in the central pane:

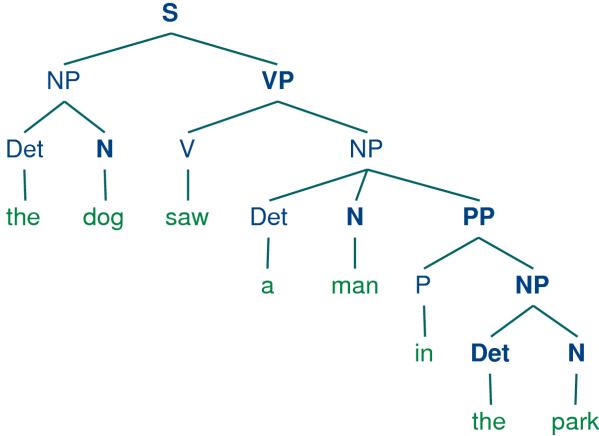


The demo comes with the grammar in (39) already loaded. We will discuss the parsing algorithm in greater detail below, but for the time being you can get an idea of how it works by using the *autostep* button. If we parse the string *The dog saw a man in the park* using the grammar in (39), we end up with two trees:

(40) a.



b.



Since our grammar licenses two trees for this sentence, the sentence is said to be **structurally ambiguous**. The ambiguity in question is called a *prepositional phrase attachment ambiguity*, as we saw earlier in this chapter. As you may recall, it is an ambiguity about attachment since the PP *in the park* needs to be attached to one of two places in the tree: either as a daughter of VP or else as a daughter of NP. When the PP is attached to VP, the seeing event happened in the park. However, if the PP is attached to NP, then the man was in the park, and the agent of the seeing (the dog) might have been sitting on the balcony of an apartment overlooking the park. As we will see, dealing with ambiguity is a key challenge in parsing.

8.4.2 Recursion in Syntactic Structure

Observe that sentences can be nested within sentences, with no limit to the depth:

- (41) a. Jodie won the 100m freestyle
 b. “The Age” reported that Jodie won the 100m freestyle
 c. Sandy said “The Age” reported that Jodie won the 100m freestyle
 d. I think Sandy said “The Age” reported that Jodie won the 100m freestyle

This nesting is explained in terms of **recursion**. A grammar is said to be **recursive** if a category occurring on the left hand side of a production (such as S in this case) also appears on the right hand side of a production. If this dual occurrence takes place in *one and the same production*, then we have **direct recursion**; otherwise we have **indirect recursion**. There is no recursion in (39). However, the grammar in (42) illustrates both kinds of recursive production:

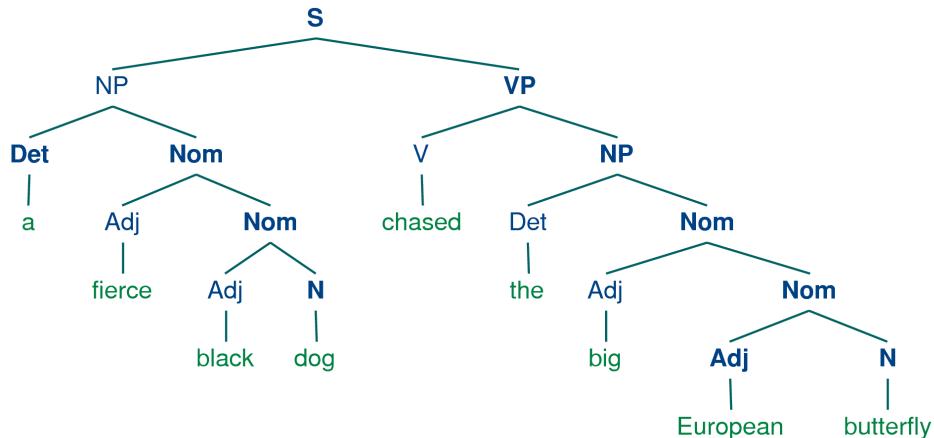
- (42) $S \rightarrow NP\ VP$
 $NP \rightarrow Det\ Nom \mid Det\ Nom\ PP \mid PropN$
 $Nom \rightarrow Adj\ Nom \mid N$
 $VP \rightarrow V \mid V\ NP \mid V\ NP\ PP \mid V\ S$
 $PP \rightarrow P\ NP$
- $PropN \rightarrow 'John' \mid 'Mary'$
 $Det \rightarrow 'the' \mid 'a'$

$N \rightarrow 'man' \mid 'woman' \mid 'park' \mid 'dog' \mid 'lead' \mid 'telescope' \mid 'butterfly'$
 $\text{Adj} \rightarrow 'fierce' \mid 'black' \mid 'big' \mid 'European'$
 $V \rightarrow 'saw' \mid 'chased' \mid 'barked' \mid 'disappeared' \mid 'said' \mid 'reported'$
 $P \rightarrow 'in' \mid 'with'$

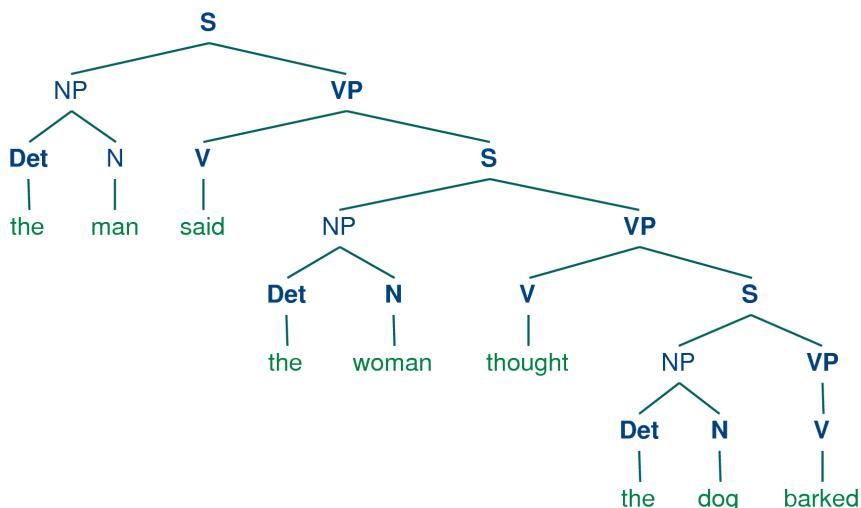
Notice that the production $\text{NOM} \rightarrow \text{ADJ NOM}$ (where NOM is the category of nominals) involves direct recursion on the category NOM , whereas indirect recursion on S arises from the combination of two productions, namely $S \rightarrow \text{NP VP}$ and $\text{VP} \rightarrow V S$.

To see how recursion is handled in this grammar, consider the following trees. Example [nested-nominals](#) involves nested nominal phrases, while [nested-sentences](#) contains nested sentences.

(43) a.

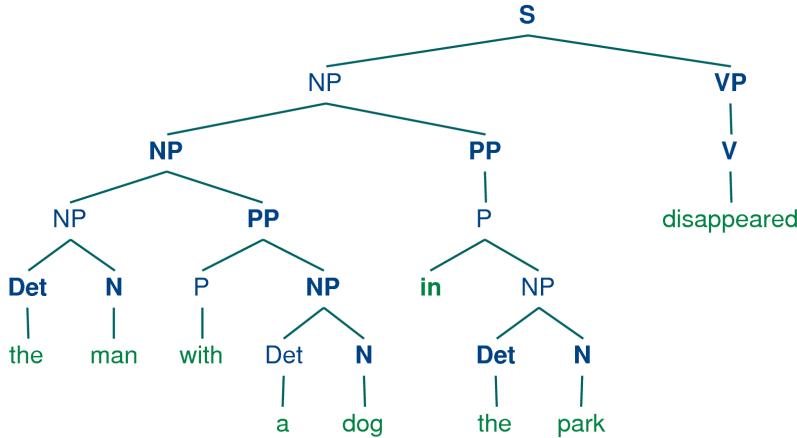


b.



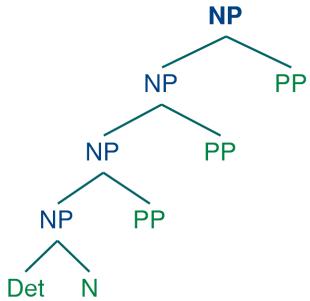
If you did the exercises for the last section, you will have noticed that the recursive descent parser fails to deal properly with the following production: $\text{NP} \rightarrow \text{NP PP}$. From a linguistic point of view, this production is perfectly respectable, and will allow us to derive trees like this:

(44)



More schematically, the trees for these compound noun phrases will be of the following shape:

(45)



The structure in (45) is called a **left recursive** structure. These occur frequently in analyses of English, and the failure of recursive descent parsers to deal adequately with left recursion means that we will need to find alternative approaches.

8.4.3 Heads, Complements and Modifiers

Let us take a closer look at verbs. The grammar (42) correctly generates examples like (46), corresponding to the four productions with VP on the left hand side:

- (46) a. The woman gave the telescope to the dog
 b. The woman saw a man
 c. A man said that the woman disappeared
 d. The dog barked

That is, *gave* can occur with a following NP and PP; *saw* can occur with a following NP; *said* can occur with a following S; and *barked* can occur with no following phrase. In these cases, NP, PP and S are called **complements** of the respective verbs, and the verbs themselves are called **heads** of the verb phrase.

However, there are fairly strong constraints on what verbs can occur with what complements. Thus, we would like our grammars to mark the following examples as ungrammatical¹:

- (47) a. *The woman disappeared the telescope to the dog
 b. *The dog barked a man
 c. *A man gave that the woman disappeared
 d. *A man said

How can we ensure that our grammar correctly excludes the ungrammatical examples in (47)? We need some way of constraining grammar productions which expand VP so that verbs *only* co-occur with their correct complements. We do this by dividing the class of verbs into **subcategories**, each of which is associated with a different set of complements. For example, **transitive verbs** such as *saw*, *kissed* and *hit* require a following NP object complement. Borrowing from the terminology of chemistry, we sometimes refer to the **vacency** of a verb, that is, its capacity to combine with a sequence of arguments and thereby compose a verb phrase.

Let's introduce a new category label for such verbs, namely TV (for Transitive Verb), and use it in the following productions:

- (48) $\begin{array}{l} \text{VP} \rightarrow \text{TV NP} \\ \text{TV} \rightarrow \text{'saw'} \mid \text{'kissed'} \mid \text{'hit'} \end{array}$

Now **the dog barked the man* is excluded since we haven't listed *barked* as a V_TR, but *the woman saw a man* is still allowed. Table 8.2 provides more examples of labels for verb subcategories.

Symbol	Meaning	Example
IV	intransitive verb	<i>barked</i>
TV	transitive verb	<i>saw a man</i>
DatV	dative verb	<i>gave a dog to a man</i>
SV	sentential verb	<i>said that a dog barked</i>

Table 8.2: Verb Subcategories

The revised grammar for VP will now look like this:

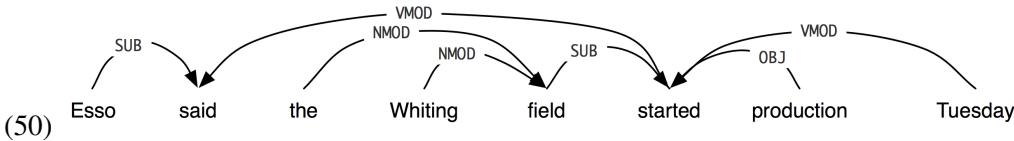
- (49) $\begin{array}{l} \text{VP} \rightarrow \text{DATV NP PP} \\ \text{VP} \rightarrow \text{TV NP} \\ \text{VP} \rightarrow \text{SV S} \\ \text{VP} \rightarrow \text{IV} \\ \\ \text{DATV} \rightarrow \text{'gave'} \mid \text{'donated'} \mid \text{'presented'} \\ \text{TV} \rightarrow \text{'saw'} \mid \text{'kissed'} \mid \text{'hit'} \mid \text{'sang'} \\ \text{SV} \rightarrow \text{'said'} \mid \text{'knew'} \mid \text{'alleged'} \\ \text{IV} \rightarrow \text{'barked'} \mid \text{'disappeared'} \mid \text{'elapsed'} \mid \text{'sang'} \end{array}$

Notice that according to (49), a given lexical item can belong to more than one subcategory. For example, *sang* can occur both with and without a following NP complement.

¹It should be borne in mind that it is possible to create examples that involve 'non-standard' but interpretable combinations of verbs and complements. Thus, we can, at a stretch, interpret *the man disappeared the dog* as meaning that the man made the dog disappear. We will ignore such examples here.

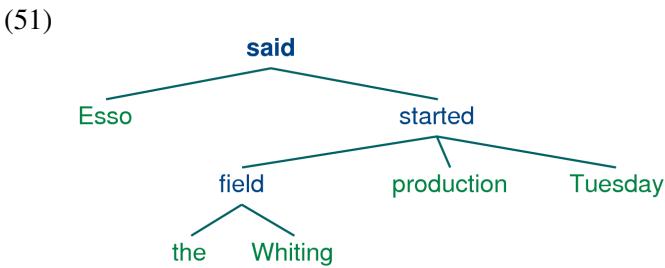
8.4.4 Dependency Grammar

Although we concentrate on phrase structure grammars in this chapter, we should mention an alternative approach, namely **dependency grammar**. Rather than taking starting from the grouping of words into constituents, dependency grammar takes as basic the notion that one word can be dependent on another (namely, its head). The root of a sentence is usually taken to be the main verb, and every other word is either dependent on the root, or connects to it through a path of dependencies. [Figure \(50\)](#) illustrates a dependency graph, where the head of the arrow points to the head of a dependency.



As you will see, the arcs in [Figure \(50\)](#) are labeled with the particular dependency relation that holds between a dependent and its head. For example, *Esso* bears the subject relation to *said* (which is the head of the whole sentence), and *Tuesday* bears a verbal modifier (VMOD) relation to *started*.

An alternative way of representing the dependency relationships is illustrated in the [tree \(51\)](#), where dependents are shown as daughters of their heads.



One format for encoding dependency information places each word on a line, followed by its part-of-speech tag, the index of its head, and the label of the dependency relation (cf. [\[?\]](#)). The index of a word is implicitly given by the ordering of the lines (with 1 as the first index). This is illustrated in the following code snippet:

```

>>> from nltk_contrib.dependency import DepGraph
>>> dg = DepGraph().read("""Esso      NNP      2      SUB
... said     VBD      0      ROOT
... the      DT       5      NMOD
... Whiting  NNP      5      NMOD
... field    NN       6      SUB
... started  VBD      2      VMOD
... production  NN      6      OBJ
... Tuesday  NNP      6      VMOD""")
  
```

As you will see, this format also adopts the convention that the head of the sentence is dependent on an empty node, indexed as 0. We can use the `deptree()` method of a `DepGraph()` object to build an NLTK tree like that illustrated earlier in [\(51\)](#).

```

>>> tree = dg.deptree()
>>> tree.draw()
  
```

8.4.5 Formalizing Context Free Grammars

We have seen that a CFG contains terminal and nonterminal symbols, and productions that dictate how constituents are expanded into other constituents and words. In this section, we provide some formal definitions.

A CFG is a 4-tuple N, Σ, P, S , where:

- Σ is a set of *terminal* symbols (e.g., lexical items);
- N is a set of *non-terminal* symbols (the category labels);
- P is a set of *productions* of the form $A \rightarrow \alpha$, where
 - A is a non-terminal, and
 - α is a string of symbols from $(N \cup \Sigma)^*$ (i.e., strings of either terminals or non-terminals);
- S is the *start symbol*.

A **derivation** of a string from a non-terminal A in grammar G is the result of successively applying productions from G to A . For example, (52) is a derivation of *the dog with a telescope* for the grammar in (39).

(52) NP
 Det N PP
 the N PP
 the dog PP
 the dog P NP
 the dog with NP
 the dog with Det N
 the dog with a N
 the dog with a telescope

Although we have chosen here to expand the leftmost non-terminal symbol at each stage, this is not obligatory; productions can be applied in any order. Thus, derivation (52) could equally have started off in the following manner:

(53) NP
 Det N PP
 Det N P NP
 Det N with NP
 ...

We can also write derivation (52) as:

(54) $NP \Rightarrow^* DET N PP \Rightarrow^* the N PP \Rightarrow^* the dog PP \Rightarrow^* the dog P NP \Rightarrow^* the dog with NP \Rightarrow^* the dog with a N \Rightarrow^* the dog with a telescope$

where \Rightarrow means “derives in one step”. We use \Rightarrow^* to mean “derives in zero or more steps”:

- $\alpha \Rightarrow^* \alpha$ for any string α , and
- if $\alpha \Rightarrow^* \beta$ and $\beta \Rightarrow^* \gamma$, then $\alpha \Rightarrow^* \gamma$.

We write $A \Rightarrow^* \alpha$ to indicate that α can be derived from A .

In NLTK, context free grammars are defined in the `parse.cfg` module. The easiest way to construct a grammar object is from the standard string representation of grammars. In Listing 8.2 we define a grammar and use it to parse a simple sentence. You will learn more about parsing in the next section.

Listing 8.2 Context Free Grammars in NLTK

```

grammar = nltk.parse_cfg("""
S -> NP VP
VP -> V NP | V NP PP
V -> "saw" | "ate"
NP -> "John" | "Mary" | "Bob" | Det N | Det N PP
Det -> "a" | "an" | "the" | "my"
N -> "dog" | "cat" | "cookie" | "park"
PP -> P NP
P -> "in" | "on" | "by" | "with"
""")

>>> sent = "Mary saw Bob".split()
>>> rd_parser = nltk.RecursiveDescentParser(grammar)
>>> for p in rd_parser.nbest_parse(sent):
...     print p
(S (NP Mary) (VP (V saw) (NP Bob)))

```

8.4.6 Exercises

1. ☀ In the recursive descent parser demo, experiment with changing the sentence to be parsed by selecting *Edit Text* in the *Edit* menu.
2. ☀ Can the grammar in (39) be used to describe sentences that are more than 20 words in length?
3. ⚡ You can modify the grammar in the recursive descent parser demo by selecting *Edit Grammar* in the *Edit* menu. Change the first expansion production, namely $NP \rightarrow Det N PP$, to $NP \rightarrow NP PP$. Using the *Step* button, try to build a parse tree. What happens?
4. ⚡ Extend the grammar in (42) with productions that expand prepositions as intransitive, transitive and requiring a PP complement. Based on these productions, use the method of the preceding exercise to draw a tree for the sentence *Lee ran away home*.
5. ⚡ Pick some common verbs and complete the following tasks:
 - a) Write a program to find those verbs in the Prepositional Phrase Attachment Corpus `nltk.corpus.pppattach`. Find any cases where the same verb exhibits two different attachments, but where the first noun, or second noun, or preposition, stay unchanged (as we saw in Section 8.3.1).
 - b) Devise CFG grammar productions to cover some of these cases.
6. ★ Write a function that takes a grammar (such as the one defined in Listing 8.2) and returns a random sentence generated by the grammar. (Use `grammar.start()` to find the start symbol of the grammar; `grammar.productions(lhs)` to get the list of productions from the grammar that have the specified left-hand side; and `production.rhs()` to get the right-hand side of a production.)

7. ★ **Lexical Acquisition:** As we saw in [Chapter 7](#), it is possible to collapse chunks down to their chunk label. When we do this for sentences involving the word *gave*, we find patterns such as the following:

```

gave NP
gave up NP in NP
gave NP up
gave NP NP
gave NP to NP

```

- a) Use this method to study the complementation patterns of a verb of interest, and write suitable grammar productions.
- b) Identify some English verbs that are near-synonyms, such as the *dumped/filled/loaded* example from earlier in this chapter. Use the chunking method to study the complementation patterns of these verbs. Create a grammar to cover these cases. Can the verbs be freely substituted for each other, or are their constraints? Discuss your findings.

8.5 Parsing

A **parser** processes input sentences according to the productions of a grammar, and builds one or more constituent structures that conform to the grammar. A grammar is a declarative specification of well-formedness. In NLTK, it is just a multi-line string; it is not itself a program that can be used for anything. A parser is a procedural interpretation of the grammar. It searches through the space of trees licensed by a grammar to find one that has the required sentence along its fringe.

Parsing is important in both linguistics and natural language processing. A parser permits a grammar to be evaluated against a potentially large collection of test sentences, helping linguists to find any problems in their grammatical analysis. A parser can serve as a model of psycholinguistic processing, helping to explain the difficulties that humans have with processing certain syntactic constructions. Many natural language applications involve parsing at some point; for example, we would expect the natural language questions submitted to a question-answering system to undergo parsing as an initial step.

In this section we see two simple parsing algorithms, a top-down method called recursive descent parsing, and a bottom-up method called shift-reduce parsing.

8.5.1 Recursive Descent Parsing

The simplest kind of parser interprets a grammar as a specification of how to break a high-level goal into several lower-level subgoals. The top-level goal is to find an S. The $S \rightarrow NP\ VP$ production permits the parser to replace this goal with two subgoals: find an NP, then find a VP. Each of these subgoals can be replaced in turn by sub-sub-goals, using productions that have NP and VP on their left-hand side. Eventually, this expansion process leads to subgoals such as: find the word *telescope*. Such subgoals can be directly compared against the input string, and succeed if the next word is matched. If there is no match the parser must back up and try a different alternative.

The recursive descent parser builds a parse tree during the above process. With the initial goal (find an S), the S root node is created. As the above process recursively expands its goals using the productions of the grammar, the parse tree is extended downwards (hence the name *recursive descent*).

We can see this in action using the parser demonstration `nltk.draw.rdparsert.demo()`. Six stages of the execution of this parser are shown in [Table 8.3](#).

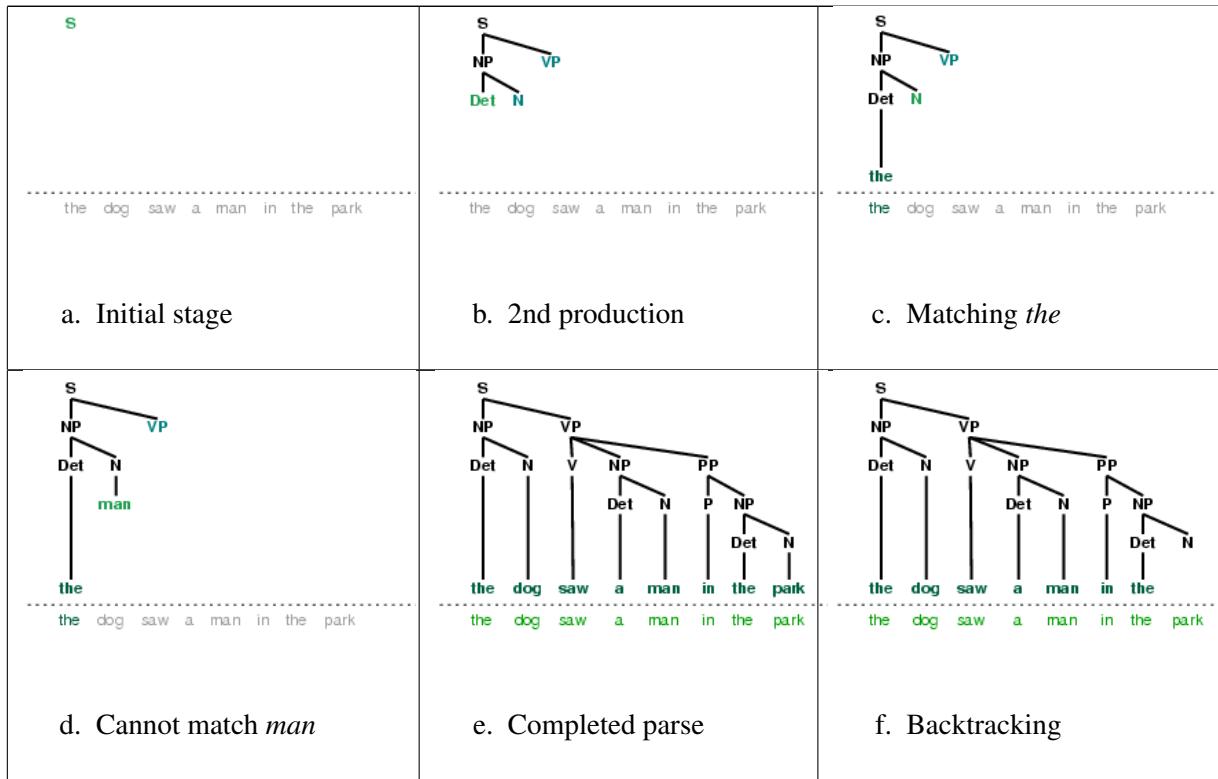


Table 8.3: Six Stages of a Recursive Descent Parser

During this process, the parser is often forced to choose between several possible productions. For example, in going from step c to step d, it tries to find productions with *N* on the left-hand side. The first of these is $N \rightarrow man$. When this does not work it *backtracks*, and tries other *N* productions in order, under it gets to $N \rightarrow dog$, which matches the next word in the input sentence. Much later, as shown in step e, it finds a complete parse. This is a tree that covers the entire sentence, without any dangling edges. Once a parse has been found, we can get the parser to look for additional parses. Again it will backtrack and explore other choices of production in case any of them result in a parse.

NLTK provides a recursive descent parser:

```
>>> rd_parser = nltk.RecursiveDescentParser(grammar)
>>> sent = 'Mary saw a dog'.split()
>>> for t in rd_parser.nbest_parse(sent):
...     print t
(S (NP Mary) (VP (V saw) (NP (Det a) (N dog))))
```

Note

`RecursiveDescentParser()` takes an optional parameter `trace`. If `trace` is greater than zero, then the parser will report the steps that it takes as it parses a text.

Recursive descent parsing has three key shortcomings. First, left-recursive productions like $NP \rightarrow NP\ PP$ send it into an infinite loop. Second, the parser wastes a lot of time considering words and

structures that do not correspond to the input sentence. Third, the backtracking process may discard parsed constituents that will need to be rebuilt again later. For example, backtracking over $VP \rightarrow V NP$ will discard the subtree created for the NP. If the parser then proceeds with $VP \rightarrow V NP PP$, then the NP subtree must be created all over again.

Recursive descent parsing is a kind of **top-down parsing**. Top-down parsers use a grammar to *predict* what the input will be, before inspecting the input! However, since the input is available to the parser all along, it would be more sensible to consider the input sentence from the very beginning. This approach is called **bottom-up parsing**, and we will see an example in the next section.

8.5.2 Shift-Reduce Parsing

A simple kind of bottom-up parser is the **shift-reduce parser**. In common with all bottom-up parsers, a shift-reduce parser tries to find sequences of words and phrases that correspond to the *right hand side* of a grammar production, and replace them with the left-hand side, until the whole sentence is reduced to an S.

The shift-reduce parser repeatedly pushes the next input word onto a stack ([Section 6.2.4](#)); this is the **shift** operation. If the top n items on the stack match the n items on the right hand side of some production, then they are all popped off the stack, and the item on the left-hand side of the production is pushed on the stack. This replacement of the top n items with a single item is the **reduce** operation. (This reduce operation may only be applied to the top of the stack; reducing items lower in the stack must be done before later items are pushed onto the stack.) The parser finishes when all the input is consumed and there is only one item remaining on the stack, a parse tree with an S node as its root.

The shift-reduce parser builds a parse tree during the above process. If the top of stack holds the word *dog*, and if the grammar has a production $N \rightarrow dog$, then the reduce operation causes the word to be replaced with the parse tree for this production. For convenience we will represent this tree as $N(dog)$. At a later stage, if the top of the stack holds two items $Det(\text{the}) N(dog)$ and if the grammar has a production $NP \rightarrow DET N$ then the reduce operation causes these two items to be replaced with $NP(Det(\text{the}), N(dog))$. This process continues until a parse tree for the entire sentence has been constructed. We can see this in action using the parser demonstration `nltk.draw.srparsert.demo()`. Six stages of the execution of this parser are shown in [Figure 8.4](#).

Stack	Remaining Text	Stack	Remaining Text
	the dog saw a man in the park		
a. Initial State		b. After one shift	
Stack Det N the dog	Remaining Text saw a man in the park	Stack NP V NP in Det N saw Det N the dog a man	Remaining Text the park
c. After reduce shift reduce		d. After recognizing the second NP	

Stack	Remaining Text
<pre> graph TD NP1[NP] --- Det1[Det] NP1 --- N1[N] NP1 --- V1[V] NP2[NP] --- Det2[Det] NP2 --- N2[N] NP3[NP] --- P1[P] NP3 --- NP4[NP] NP4 --- Det3[Det] NP4 --- N3[N] NP4 --- V2[V] NP5[NP] --- Det4[Det] NP5 --- N4[N] NP6[NP] --- P2[P] NP6 --- NP7[NP] NP7 --- Det5[Det] NP7 --- N5[N] </pre>	e. Complex NP
<pre> graph TD S[S] --- NP1[NP] S --- VP1[VP] NP1 --- Det1[Det] NP1 --- N1[N] VP1 --- V1[V] VP1 --- NP2[NP] NP2 --- Det2[Det] NP2 --- N2[N] NP2 --- P1[P] NP2 --- NP3[NP] NP3 --- Det3[Det] NP3 --- N3[N] </pre>	f. Final Step

Table 8.4: Six Stages of a Shift-Reduce Parser

NLTK provides `ShiftReduceParser()`, a simple implementation of a shift-reduce parser. This parser does not implement any backtracking, so it is not guaranteed to find a parse for a text, even if one exists. Furthermore, it will only find at most one parse, even if more parses exist. We can provide an optional `trace` parameter that controls how verbosely the parser reports the steps that it takes as it parses a text:

```

>>> sr_parse = nltk.ShiftReduceParser(grammar, trace=2)
>>> sent = 'Mary saw a dog'.split()
>>> print sr_parse.parse(sent)
Parsing 'Mary saw a dog'
[ * Mary saw a dog]
S [ 'Mary' * saw a dog]
R [ <NP> * saw a dog]
S [ <NP> 'saw' * a dog]
R [ <NP> <V> * a dog]
S [ <NP> <V> 'a' * dog]
R [ <NP> <V> <Det> * dog]
S [ <NP> <V> <Det> 'dog' * ]
R [ <NP> <V> <Det> <N> * ]
R [ <NP> <V> <NP> * ]
R [ <NP> <VP> * ]
R [ <S> * ]
(S (NP Mary) (VP (V saw) (NP (Det a) (N dog))))
  
```

Shift-reduce parsers have a number of problems. A shift-reduce parser may fail to parse the sentence, even though the sentence is well-formed according to the grammar. In such cases, there are no remaining input words to shift, and there is no way to reduce the remaining items on the stack, as exemplified in Table 8.5a. The parser entered this blind alley at an earlier stage shown in Table 8.5b, when it reduced instead of shifted. This situation is called a **shift-reduce conflict**. At another possible stage of processing shown in Table 8.5c, the parser must choose between two possible reductions, both matching the top items on the stack: $VP \rightarrow VP\ NP\ PP$ or $NP \rightarrow NP\ PP$. This situation is called a **reduce-reduce conflict**.

Stack	Remaining Text
<pre> graph TD S --- NP1[NP] S --- VP[VP] NP1 --- Det1[Det] NP1 --- N1[N] Det1 --- the[the] N1 --- dog[dog] VP --- V[V] VP --- NP2[NP] NP2 --- Det2[Det] NP2 --- N2[N] Det2 --- a[a] N2 --- man[man] PP --- P[P] P --- NP3[NP] NP3 --- Det3[Det] NP3 --- N3[N] Det3 --- the2[the] N3 --- park[park] </pre>	
a. Dead end	
<pre> graph TD NP --- Det1[Det] NP --- N1[N] Det1 --- the[the] N1 --- dog[dog] VP --- V[V] VP --- NP2[NP] NP2 --- Det2[Det] NP2 --- N2[N] Det2 --- a[a] N2 --- man[man] RT[in the park] </pre>	in the park
b. Shift-reduce conflict	
<pre> graph TD NP --- Det1[Det] NP --- N1[N] Det1 --- the[the] N1 --- dog[dog] V[saw] NP --- Det2[Det] NP --- N2[N] Det2 --- a[a] N2 --- man[man] PP --- P[P] P --- NP3[NP] NP3 --- Det3[Det] NP3 --- N3[N] Det3 --- the2[the] N3 --- park[park] </pre>	
c. Reduce-reduce conflict	

Table 8.5: Conflict in Shift-Reduce Parsing

Shift-reduce parsers may implement policies for resolving such conflicts. For example, they may address shift-reduce conflicts by shifting only when no reductions are possible, and they may address reduce-reduce conflicts by favoring the reduction operation that removes the most items from the stack. No such policies are failsafe however.

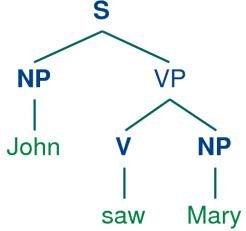
The advantages of shift-reduce parsers over recursive descent parsers is that they only build structure that corresponds to the words in the input. Furthermore, they only build each sub-structure once, e.g. $NP(Det(the), N(man))$ is only built and pushed onto the stack a single time, regardless of whether it will later be used by the $VP \rightarrow V\ NP\ PP$ reduction or the $NP \rightarrow NP\ PP$ reduction.

8.5.3 The Left-Corner Parser

One of the problems with the recursive descent parser is that it can get into an infinite loop. This is because it applies the grammar productions blindly, without considering the actual input sentence. A left-corner parser is a hybrid between the bottom-up and top-down approaches we have seen.

Grammar (42) allows us to produce the following parse of *John saw Mary*:

(55)



Recall that the grammar in (42) has the following productions for expanding NP:

(56) a. $\text{NP} \rightarrow \text{DT NOM}$ b. $\text{NP} \rightarrow \text{DT NOM PP}$ c. $\text{NP} \rightarrow \text{PROPN}$

Suppose we ask you to first look at tree (55), and then decide which of the NP productions you'd want a recursive descent parser to apply first — obviously, (56c) is the right choice! How do you know that it would be pointless to apply (56a) or (56b) instead? Because neither of these productions will derive a string whose first word is *John*. That is, we can easily tell that in a successful parse of *John saw Mary*, the parser has to expand NP in such a way that NP derives the string *John* α . More generally, we say that a category B is a **left-corner** of a tree rooted in A if $A \Rightarrow^* B \alpha$.

(57)



A **left-corner parser** is a top-down parser with bottom-up filtering. Unlike an ordinary recursive descent parser, it does not get trapped in left recursive productions. Before starting its work, a left-corner parser preprocesses the context-free grammar to build a table where each row contains two cells, the first holding a non-terminal, and the second holding the collection of possible left corners of that non-terminal. Table 8.6 illustrates this for the grammar from (42).

Category	Left-Corners (pre-terminals)
S	NP
NP	Det, PropN
VP	V
PP	P

Table 8.6: Left-Corners in (42)

Each time a production is considered by the parser, it checks that the next input word is compatible with at least one of the pre-terminal categories in the left-corner table.

[TODO: explain how this effects the action of the parser, and why this solves the problem.]

8.5.4 Exercises

1. ☀ With pen and paper, manually trace the execution of a recursive descent parser and a shift-reduce parser, for a CFG you have already seen, or one of your own devising.
2. ⚡ Compare the performance of the top-down, bottom-up, and left-corner parsers using the same grammar and three grammatical test sentences. Use `timeit` to log the amount of time each parser takes on the same sentence (Section 6.5.4). Write a function that runs all three parsers on all three sentences, and prints a 3-by-3 grid of times, as well as row and column totals. Discuss your findings.
3. ⚡ Read up on “garden path” sentences. How might the computational work of a parser relate to the difficulty humans have with processing these sentences? http://en.wikipedia.org/wiki/Garden_path_sentence
4. ★ **Left-corner parser:** Develop a left-corner parser based on the recursive descent parser, and inheriting from `ParseI`. (Note, this exercise requires knowledge of Python classes, covered in Chapter 10.)
5. ★ Extend NLTK’s shift-reduce parser to incorporate backtracking, so that it is guaranteed to find all parses that exist (i.e. it is **complete**).

8.6 Conclusion

We began this chapter talking about confusing encounters with grammar at school. We just wrote what we wanted to say, and our work was handed back with red marks showing all our grammar mistakes. If this kind of “grammar” seems like secret knowledge, the linguistic approach we have taken in this chapter is quite the opposite: grammatical structures are made explicit as we build trees on top of sentences. We can write down the grammar productions, and parsers can build the trees automatically. This thoroughly objective approach is widely referred to as **generative grammar**.

Note that we have only considered “toy grammars,” small grammars that illustrate the key aspects of parsing. But there is an obvious question as to whether the general approach can be scaled up to cover large corpora of natural languages. How hard would it be to construct such a set of productions by hand? In general, the answer is: *very hard*. Even if we allow ourselves to use various formal devices that give much more succinct representations of grammar productions (some of which will be discussed in Chapter 9), it is still extremely difficult to keep control of the complex interactions between the many productions required to cover the major constructions of a language. In other words, it is hard to modularize grammars so that one portion can be developed independently of the other parts. This in turn means that it is difficult to distribute the task of grammar writing across a team of linguists. Another difficulty is that as the grammar expands to cover a wider and wider range of constructions, there is a corresponding increase in the number of analyses which are admitted for any one sentence. In other words, ambiguity increases with coverage.

Despite these problems, there are a number of large collaborative projects that have achieved interesting and impressive results in developing rule-based grammars for several languages. Examples are the Lexical Functional Grammar (LFG) Pargram project (<http://www2.parc.com/istl/groups/nltt/pargram/>), the Head-Driven Phrase Structure Grammar (HPSG) LinGO Matrix framework (<http://www.delph-in.net/matrix/>), and the Lexicalized Tree Adjoining Grammar XTAG Project (<http://www.cis.upenn.edu/~xtag/>).

8.7 Summary (notes)

- Sentences have internal organization, or constituent structure, that can be represented using a tree; notable features of constituent structure are: recursion, heads, complements, modifiers
- A grammar is a compact characterization of a potentially infinite set of sentences; we say that a tree is well-formed according to a grammar, or that a grammar licenses a tree.
- Syntactic ambiguity arises when one sentence has more than one syntactic structure (e.g. prepositional phrase attachment ambiguity).
- A parser is a procedure for finding one or more trees corresponding to a grammatically well-formed sentence.
- A simple top-down parser is the recursive descent parser (summary, problems)
- A simple bottom-up parser is the shift-reduce parser (summary, problems)
- It is difficult to develop a broad-coverage grammar...

8.8 Further Reading

For more examples of parsing with NLTK, please see the guide at <http://nltk.org/doc/guides/parse.html>.

There are many introductory books on syntax. [O'Grady1989LI] is a general introduction to linguistics, while [?] provides a gentle introduction to transformational grammar, and can be recommended for its coverage of transformational approaches to unbounded dependency constructions.

[?] is very practically oriented textbook on how to analyze constituency in English, with extensive exemplification and exercises. [?] provides an up-to-date and comprehensive analysis of syntactic phenomena in English.

- LALR(1)
- Marcus parser
- Lexical Functional Grammar (LFG)
 - [Pargram project](#)
 - [LFG Portal](#)
- Head-Driven Phrase Structure Grammar (HPSG) [LinGO Matrix framework](#)
- Lexicalized Tree Adjoining Grammar [XTAG Project](#)

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Chapter 9

Chart Parsing and Probabilistic Parsing

9.1 Introduction

[Chapter 8](#) started with an introduction to constituent structure in English, showing how words in a sentence group together in predictable ways. We showed how to describe this structure using syntactic tree diagrams, and observed that it is sometimes desirable to assign more than one such tree to a given string. In this case, we said that the string was structurally ambiguous; and example was *old men and women*.

Treebanks are language resources in which the syntactic structure of a corpus of sentences has been annotated, usually by hand. However, we would also like to be able to produce trees algorithmically. A context-free phrase structure grammar (CFG) is a formal model for describing whether a given string can be assigned a particular constituent structure. Given a set of syntactic categories, the CFG uses a set of productions to say how a phrase of some category A can be analyzed into a sequence of smaller parts $\alpha_1 \dots \alpha_n$. But a grammar is a static description of a set of strings; it does not tell us what sequence of steps we need to take to build a constituent structure for a string. For this, we need to use a parsing algorithm. We presented two such algorithms: Top-Down Recursive Descent ([8.5.1](#)) and Bottom-Up Shift-Reduce ([8.5.2](#)). As we pointed out, both parsing approaches suffer from important shortcomings. The Recursive Descent parser cannot handle left-recursive productions (e.g., productions such as $NP \rightarrow NP\ PP$), and blindly expands categories top-down without checking whether they are compatible with the input string. The Shift-Reduce parser is not guaranteed to find a valid parse for the input even if one exists, and builds substructure without checking whether it is globally consistent with the grammar. As we will describe further below, the Recursive Descent parser is also inefficient in its search for parses.

So, parsing builds trees over sentences, according to a phrase structure grammar. Now, all the examples we gave in [Chapter 8](#) only involved toy grammars containing a handful of productions. What happens if we try to scale up this approach to deal with realistic corpora of language? Unfortunately, as the coverage of the grammar increases and the length of the input sentences grows, the number of parse trees grows rapidly. In fact, it grows at an astronomical rate.

Let's explore this issue with the help of a simple example. The word *fish* is both a noun and a verb. We can make up the sentence *fish fish fish*, meaning *fish like to fish for other fish*. (Try this with *police* if you prefer something more sensible.) Here is a toy grammar for the “fish” sentences.

```
>>> grammar = nltk.parse_cfg("""
... S -> NP V NP
... NP -> NP Sbar
... Sbar -> NP V
```

```
... NP -> 'fish'
... V -> 'fish'
... """)
```

Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

Now we can try parsing a longer sentence, *fish fish fish fish fish*, which amongst other things, means 'fish that other fish fish are in the habit of fishing fish themselves'. We use the NLTK chart parser, which is presented later on in this chapter. This sentence has two readings.

```
>>> tokens = ["fish"] * 5
>>> cp = nltk.ChartParser(grammar, nltk.parse.TD_STRATEGY)
>>> for tree in cp.nbest_parse(tokens):
...     print tree
(S (NP (NP fish) (Sbar (NP fish) (V fish))) (V fish) (NP fish))
(S (NP fish) (V fish) (NP (NP fish) (Sbar (NP fish) (V fish))))
```

As the length of this sentence goes up (3, 5, 7, ...) we get the following numbers of parse trees: 1; 2; 5; 14; 42; 132; 429; 1,430; 4,862; 16,796; 58,786; 208,012; ... (These are the *Catalan numbers*, which we saw in an exercise in [Section 6.5](#)). The last of these is for a sentence of length 23, the average length of sentences in the WSJ section of Penn Treebank. For a sentence of length 50 there would be over 10^{12} parses, and this is only half the length of the Piglet sentence ([Section 8.2](#)), which young children process effortlessly. No practical NLP system could construct all millions of trees for a sentence and choose the appropriate one in the context. It's clear that humans don't do this either!

Note that the problem is not with our choice of example. [?] point out that the syntactic ambiguity of PP attachment in sentences like (58) also grows in proportion to the Catalan numbers.

(58) Put the block in the box on the table.

So much for structural ambiguity; what about lexical ambiguity? As soon as we try to construct a broad-coverage grammar, we are forced to make lexical entries highly ambiguous for their part of speech. In a toy grammar, *a* is only a determiner, *dog* is only a noun, and *runs* is only a verb. However, in a broad-coverage grammar, *a* is also a noun (e.g. *part a*), *dog* is also a verb (meaning to follow closely), and *runs* is also a noun (e.g. *ski runs*). In fact, all words can be referred to by name: e.g. *the verb 'ate' is spelled with three letters*; in speech we do not need to supply quotation marks. Furthermore, it is possible to *verb* most nouns. Thus a parser for a broad-coverage grammar will be overwhelmed with ambiguity. Even complete gibberish will often have a reading, e.g. *the a are of I*. As [?] has pointed out, this is not word salad but a grammatical noun phrase, in which *are* is a noun meaning a hundredth of a hectare (or 100 sq m), and *a* and *I* are nouns designating coordinates, as shown in [Figure 9.1](#).

Even though this phrase is unlikely, it is still grammatical and a broad-coverage parser should be able to construct a parse tree for it. Similarly, sentences that seem to be unambiguous, such as *John saw Mary*, turn out to have other readings we would not have anticipated (as Abney explains). This ambiguity is unavoidable, and leads to horrendous inefficiency in parsing seemingly innocuous sentences.

Let's look more closely at this issue of efficiency. The top-down recursive-descent parser presented in [Chapter 8](#) can be very inefficient, since it often builds and discards the same sub-structure many

a									
b									
c									
	A	B	C	D	E	F	G	H	I

Figure 9.1: The area of I

times over. We see this in Figure 9.1, where a phrase *the block* is identified as a noun phrase several times, and where this information is discarded each time we backtrack.

Note

You should try the recursive-descent parser demo if you haven't already: `nltk.draw.srparser.demo()`

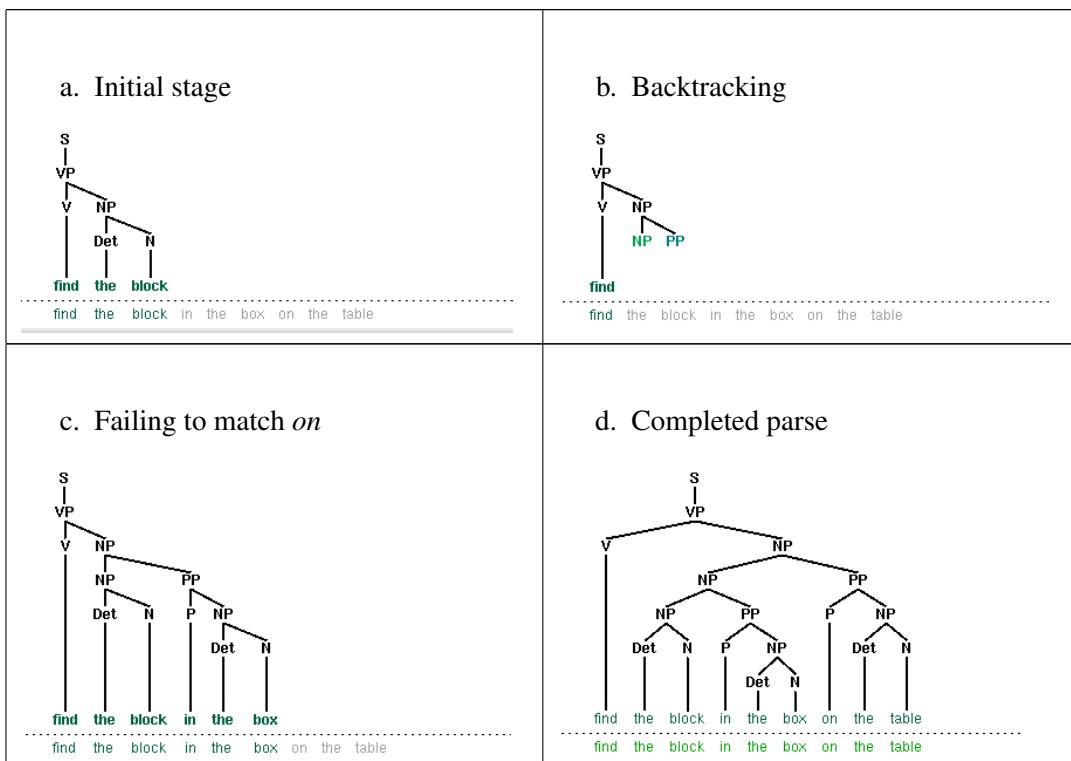


Table 9.1: Backtracking and Repeated Parsing of Subtrees

In this chapter, we will present two independent methods for dealing with ambiguity. The first is *chart parsing*, which uses the algorithmic technique of dynamic programming to derive the parses of an ambiguous sentence more *efficiently*. The second is *probabilistic parsing*, which allows us to *rank* the parses of an ambiguous sentence on the basis of evidence from corpora.

9.2 Chart Parsing

Bird, Klein, & Loper 217 April 30, 2008
In the introduction to this chapter, we pointed out that the simple parsers discussed in Chapter 8 suffered from limitations in both completeness and efficiency. In order to remedy these, we will apply the algorithm design technique of *dynamic programming* to the parsing problem. As we saw in Section 6.5.3, dynamic programming stores intermediate results and re-uses them when appropriate, achieving significant efficiency gains. This technique can be applied to syntactic parsing, allowing us to store partial solutions to the parsing task and then look them up as necessary in order to efficiently arrive at a complete solution. This approach to parsing is known as **chart parsing**, and is the focus of this section.

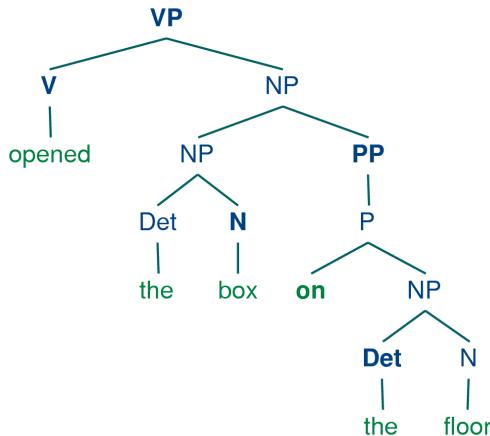
9.2.1 Well-Formed Substring Tables

Let's start off by defining a simple grammar.

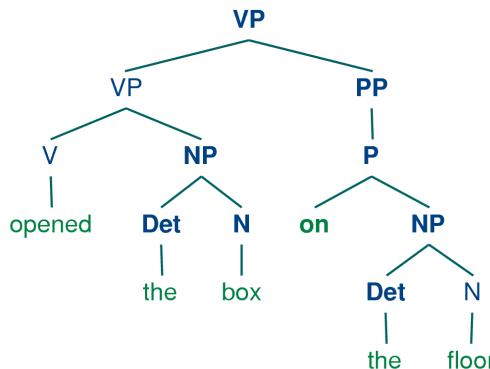
```
>>> grammar = nltk.parse_cfg("""
... S -> NP VP
... PP -> P NP
... NP -> Det N | NP PP
... VP -> V NP | VP PP
... Det -> 'the'
... N -> 'kids' | 'box' | 'floor'
... V -> 'opened'
... P -> 'on'
... """)
```

As you can see, this grammar allows the VP *opened the box on the floor* to be analyzed in two ways, depending on where the PP is attached.

(59) a.



b.



Dynamic programming allows us to build the PP *on the floor* just once. The first time we build it we save it in a table, then we look it up when we need to use it as a subconstituent of either the object NP or the higher VP. This table is known as a **well-formed substring table** (or WFST for short). We will show how to construct the WFST bottom-up so as to systematically record what syntactic constituents have been found.

the	kids	opened	the	box	on	the	floor	
0	1	2	3	4	5	6	7	8

Figure 9.2: Slice Points in the Input String

Let's set our input to be the sentence *the kids opened the box on the floor*. It is helpful to think of the input as being indexed like a Python list. We have illustrated this in [Figure 9.2](#).

This allows us to say that, for instance, the word *opened* spans (2, 3) in the input. This is reminiscent of the slice notation:

```
>>> tokens = ["the", "kids", "opened", "the", "box", "on", "the", "floor"]
>>> tokens[2:3]
['opened']
```

In a WFST, we record the position of the words by filling in cells in a triangular matrix: the vertical axis will denote the start position of a substring, while the horizontal axis will denote the end position (thus *opened* will appear in the cell with coordinates (2, 3)). To simplify this presentation, we will assume each word has a unique lexical category, and we will store this (not the word) in the matrix. So cell (2, 3) will contain the entry *v*. More generally, if our input string is $a_1 a_2 \dots a_n$, and our grammar contains a production of the form $A \rightarrow a_i$, then we add A to the cell $(i-1, i)$.

So, for every word in `tokens`, we can look up in our grammar what category it belongs to.

```
>>> grammar.productions(rhs=tokens[2])
[V -> 'opened']
```

For our WFST, we create an $(n - 1) \times (n - 1)$ matrix as a list of lists in Python, and initialize it with the lexical categories of each token, in the `init_wfst()` function in [Listing 9.1](#). We also define a utility function `display()` to pretty-print the WFST for us. As expected, there is a *v* in cell (2, 3).

Returning to our tabular representation, given that we have DET in cell (0, 1), and N in cell (1, 2), what should we put into cell (0, 2)? In other words, what syntactic category derives *the kids*? We have already established that DET derives *the* and N derives *kids*, so we need to find a production of the form $A \rightarrow \text{DET } N$, that is, a production whose right hand side matches the categories in the cells we have already found. From the grammar, we know that we can enter NP in cell (0,2).

More generally, we can enter A in (i, j) if there is a production $A \rightarrow B C$, and we find nonterminal B in (i, k) and C in (k, j) . [Listing 9.1](#) uses this inference step to complete the WFST.

Note

To help us easily retrieve productions by their right hand sides, we create an index for the grammar. This is an example of a space-time trade-off: we do a reverse lookup on the grammar, instead of having to check through entire list of productions each time we want to look up via the right hand side.

We conclude that there is a parse for the whole input string once we have constructed an S node that covers the whole input, from position 0 to position 8; i.e., we can conclude that $S \Rightarrow^* a_1 a_2 \dots a_n$.

Notice that we have not used any built-in parsing functions here. We've implemented a complete, primitive chart parser from the ground up!

Listing 9.1 Acceptor Using Well-Formed Substring Table (based on CYK algorithm)

```

def init_wfst(tokens, grammar):
    numtokens = len(tokens)
    wfst = [[['.' for i in range(numtokens+1)] for j in range(numtokens+1)]
            for i in range(numtokens):
                productions = grammar.productions(rhs=tokens[i])
                wfst[i][i+1] = productions[0].lhs()
    return wfst
def complete_wfst(wfst, tokens, trace=False):
    index = {}
    for prod in grammar.productions():
        index[prod.rhs()] = prod.lhs()
    numtokens = len(tokens)
    for span in range(2, numtokens+1):
        for start in range(numtokens+1-span):
            end = start + span
            for mid in range(start+1, end):
                nt1, nt2 = wfst[start][mid], wfst[mid][end]
                if (nt1, nt2) in index:
                    if trace:
                        print "[%s] %3s [%s] %3s [%s] ==> [%s] %3s [%s]" % \
                            (start, nt1, mid, nt2, end, start, index[(nt1, nt2)], end)
                    wfst[start][end] = index[(nt1, nt2)]
    return wfst
def display(wfst, tokens):
    print '\nWFST ' + ' '.join(['%-4d' % i) for i in range(1, len(wfst))])
    for i in range(len(wfst)-1):
        print "%d " % i,
        for j in range(1, len(wfst)):
            print "%-4s" % wfst[i][j],
        print

>>> wfst0 = init_wfst(tokens, grammar)
>>> display(wfst0, tokens)
WFST 1 2 3 4 5 6 7 8
0 Det .
1 . N .
2 . . V .
3 . . . Det .
4 . . . . N .
5 . . . . P .
6 . . . . . Det .
7 . . . . . . N

>>> wfst1 = complete_wfst(wfst0, tokens)
>>> display(wfst1, tokens)
WFST 1 2 3 4 5 6 7 8
0 Det NP .
1 . N .
2 . . V . VP .
3 . . . Det NP .
4 . . . . N .
5 . . . . P . PP
6 . . . . . Det NP
7 . . . . . . N

```

9.2.2 Charts

By setting `trace` to `True` when calling the function `complete_wfst()`, we get additional output.

```
>>> wfst1 = complete_wfst(wfst0, tokens, trace=True)
[0] Det [1] N [2] ==> [0] NP [2]
[3] Det [4] N [5] ==> [3] NP [5]
[6] Det [7] N [8] ==> [6] NP [8]
[2] V [3] NP [5] ==> [2] VP [5]
[5] P [6] NP [8] ==> [5] PP [8]
[0] NP [2] VP [5] ==> [0] S [5]
[3] NP [5] PP [8] ==> [3] NP [8]
[2] V [3] NP [8] ==> [2] VP [8]
[2] VP [5] PP [8] ==> [2] VP [8]
[0] NP [2] VP [8] ==> [0] S [8]
```

For example, this says that since we found `Det` at `wfst[0][1]` and `N` at `wfst[1][2]`, we can add `NP` to `wfst[0][2]`. The same information can be represented in a directed acyclic graph, as shown in Figure 9.2(a). This graph is usually called a **chart**. Figure 9.2(b) is the corresponding graph representation, where we add a new edge labeled `NP` to cover the input from 0 to 2.

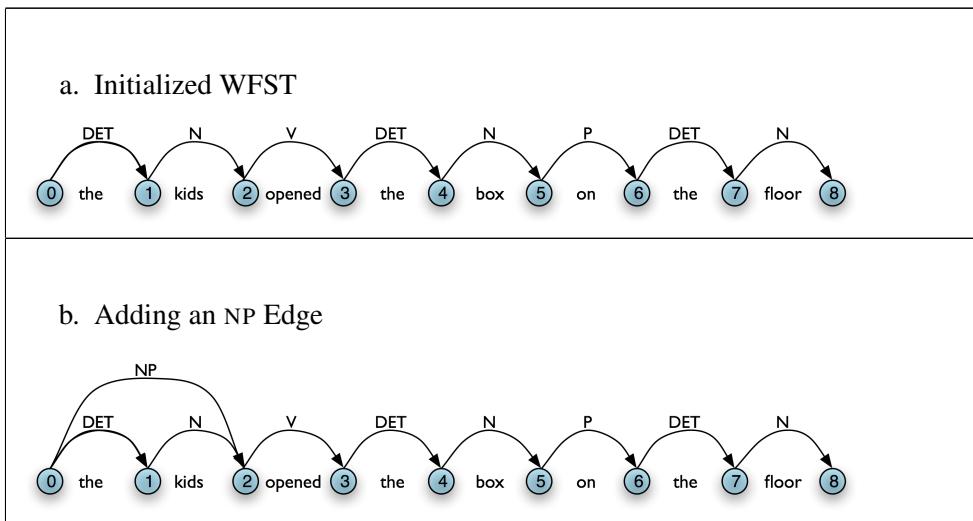


Table 9.2: A Graph Representation for the WFST

(Charts are more general than the WFSTs we have seen, since they can hold multiple hypotheses for a given span.)

A WFST is a data structure that can be used by a variety of parsing algorithms. The particular method for constructing a WFST that we have just seen and has some shortcomings. First, as you can see, the WFST is not itself a parse tree, so the technique is strictly speaking **recognizing** that a sentence is admitted by a grammar, rather than parsing it. Second, it requires every non-lexical grammar production to be *binary* (see Section 9.5.1). Although it is possible to convert an arbitrary CFG into this form, we would prefer to use an approach without such a requirement. Third, as a bottom-up approach it is potentially wasteful, being able to propose constituents in locations that would not be licensed by the grammar. Finally, the WFST did not represent the structural ambiguity in the sentence (i.e. the two

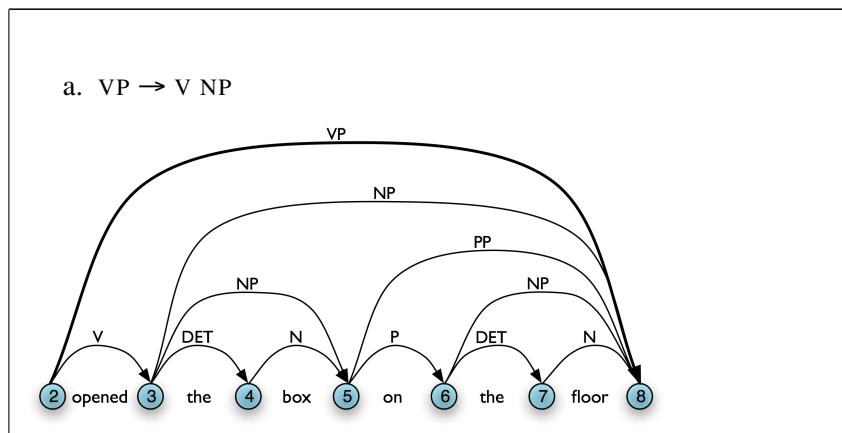
verb phrase readings). The VP in cell (2,8) was actually entered twice, once for a V NP reading, and once for a VP PP reading. In the next section we will address these issues.

9.2.3 Exercises

1. ☀ Consider the sequence of words: *Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo*. This is a grammatically correct sentence, as explained at http://en.wikipedia.org/wiki/Buffalo_buffalo_Buffalo_buffalo_buffalo_buffalo_Buffalo. Consider the tree diagram presented on this Wikipedia page, and write down a suitable grammar. Normalize case to lowercase, to simulate the problem that a listener has when hearing this sentence. Can you find other parses for this sentence? How does the number of parse trees grow as the sentence gets longer? (More examples of these sentences can be found at http://en.wikipedia.org/wiki/List_of_homophonous_phrases).
2. ⚠ Consider the algorithm in Listing 9.1. Can you explain why parsing context-free grammar is proportional to n^3 ?
3. ⚠ Modify the functions `init_wfst()` and `complete_wfst()` so that the contents of each cell in the WFST is a set of non-terminal symbols rather than a single non-terminal.
4. ★ Modify the functions `init_wfst()` and `complete_wfst()` so that when a non-terminal symbol is added to a cell in the WFST, it includes a record of the cells from which it was derived. Implement a function that will convert a WFST in this form to a parse tree.

9.3 Active Charts

One important aspect of the tabular approach to parsing can be seen more clearly if we look at the graph representation: given our grammar, there are two different ways to derive a top-level VP for the input, as shown in Table 9.3(a,b). In our graph representation, we simply combine the two sets of edges to yield Table 9.3(c).



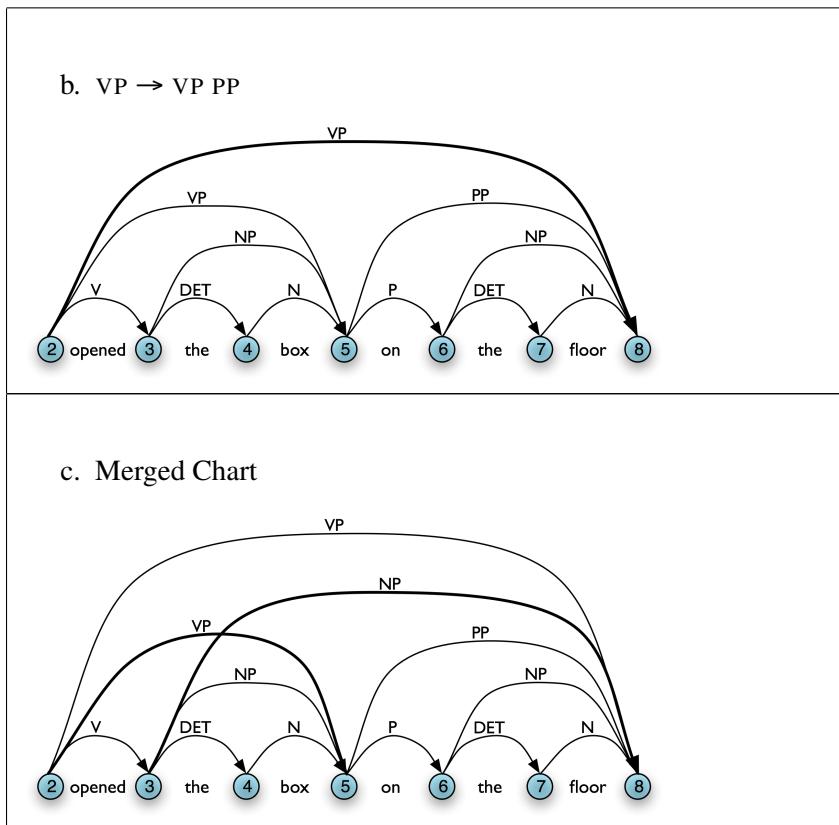


Table 9.3: Combining Multiple Parses in a Single Chart

However, given a WFST we cannot necessarily read off the justification for adding a particular edge. For example, in 9.3(b), [Edge : $VP, 2:8$] might owe its existence to a production $VP \rightarrow V\ NP\ PP$. Unlike phrase structure trees, a WFST does not encode a relation of immediate dominance. In order to make such information available, we can label edges not just with a non-terminal category, but with the whole production that justified the addition of the edge. This is illustrated in Figure 9.3.

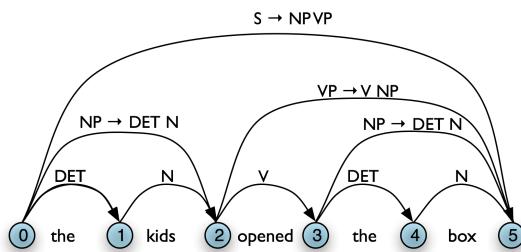


Figure 9.3: Chart Annotated with Productions

In general, a chart parser hypothesizes constituents (i.e. adds edges) based on the grammar, the tokens, and the constituents already found. Any constituent that is compatible with the current knowledge can be hypothesized; even though many of these hypothetical constituents will never be used in the final result. A WFST just records these hypotheses.

All of the edges that we've seen so far represent complete constituents. However, as we will see, it is helpful to hypothesize *incomplete* constituents. For example, the work done by a parser in processing the production $VP \rightarrow V NP PP$ can be reused when processing $VP \rightarrow V NP$. Thus, we will record the hypothesis that “the V constituent *likes* is the beginning of a VP .”

We can record such hypotheses by adding a **dot** to the edge's right hand side. Material to the left of the dot specifies what the constituent starts with; and material to the right of the dot specifies what still needs to be found in order to complete the constituent. For example, the edge in the Figure 9.4 records the hypothesis that “a VP starts with the V *likes*, but still needs an NP to become complete”:

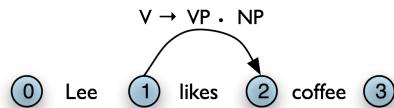


Figure 9.4: Chart Containing Incomplete VP Edge

These **dotted edges** are used to record all of the hypotheses that a chart parser makes about constituents in a sentence. Formally a dotted edge $[A \rightarrow c_1 \dots c_d \bullet c_{d+1} \dots c_n, (i, j)]$ records the hypothesis that a constituent of type A with span (i, j) starts with children $c_1 \dots c_d$, but still needs children $c_{d+1} \dots c_n$ to be complete ($c_1 \dots c_d$ and $c_{d+1} \dots c_n$ may be empty). If $d = n$, then $c_{d+1} \dots c_n$ is empty and the edge represents a complete constituent and is called a **complete edge**. Otherwise, the edge represents an incomplete constituent, and is called an **incomplete edge**. In Figure 9.4(a), $[VP \rightarrow V \bullet NP, (1, 3)]$ is a complete edge, and $[VP \rightarrow V \bullet NP, (1, 2)]$ is an incomplete edge.

If $d = 0$, then $c_1 \dots c_n$ is empty and the edge is called a **self-loop edge**. This is illustrated in Table 9.4(b). If a complete edge spans the entire sentence, and has the grammar's start symbol as its left-hand side, then the edge is called a **parse edge**, and it encodes one or more parse trees for the sentence. In Table 9.4(c), $[S \rightarrow NP VP \bullet, (0, 3)]$ is a parse edge.

a. Incomplete Edge	b. Self Loop Edge	c. Parse Edge

Table 9.4: Chart Terminology

9.3.1 The Chart Parser

To parse a sentence, a chart parser first creates an empty chart spanning the sentence. It then finds edges that are licensed by its knowledge about the sentence, and adds them to the chart one at a time until one or more parse edges are found. The edges that it adds can be licensed in one of three ways:

1. The *input* can license an edge. In particular, each word w_i in the input licenses the complete edge $[w_i \rightarrow \bullet, (i, i+1)]$.
2. The *grammar* can license an edge. In particular, each grammar production $A \rightarrow \alpha$ licenses the self-loop edge $[A \rightarrow \bullet \alpha, (i, i)]$ for every i , $0 \leq i < n$.
3. The *current chart contents* can license an edge.

However, it is not wise to add *all* licensed edges to the chart, since many of them will not be used in any complete parse. For example, even though the edge in the following chart is licensed (by the grammar), it will never be used in a complete parse:

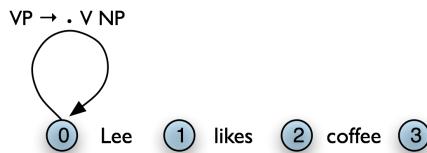


Figure 9.5: Chart Containing Redundant Edge

Chart parsers therefore use a set of **rules** to heuristically decide when an edge should be added to a chart. This set of rules, along with a specification of when they should be applied, forms a **strategy**.

9.3.2 The Fundamental Rule

One rule is particularly important, since it is used by every chart parser: the **Fundamental Rule**. This rule is used to combine an incomplete edge that's expecting a nonterminal B with a following, complete edge whose left hand side is B .

(60) Fundamental Rule

```
If the chart contains the edges
  [A → α • B β , (i, j)]
  [B → γ • , (j, k)]
then add the new edge
  [A → α B • β , (i, k)]
where α, β, and γ are (possibly empty) sequences
of terminals or non-terminals
```

Note that the dot has moved one place to the right, and the span of this new edge is the combined span of the other two. Note also that in adding this new edge we do not remove the other two, because they might be used again.

A somewhat more intuitive version of the operation of the Fundamental Rule can be given using chart diagrams. Thus, if we have a chart of the form shown in Table 9.5(a), then we can add a new complete edge as shown in Table 9.5(b).

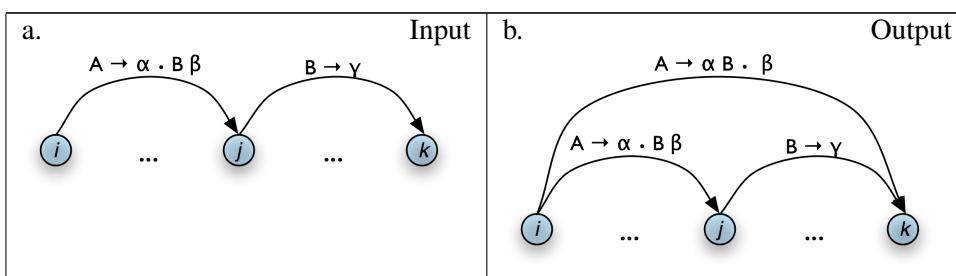


Table 9.5: Fundamental Rule

²The Fundamental Rule corresponds to the Completer function in the Earley algorithm; cf. [?].

9.3.3 Bottom-Up Parsing

As we saw in [Chapter 8](#), bottom-up parsing starts from the input string, and tries to find sequences of words and phrases that correspond to the *right hand* side of a grammar production. The parser then replaces these with the left-hand side of the production, until the whole sentence is reduced to an S. Bottom-up chart parsing is an extension of this approach in which hypotheses about structure are recorded as edges on a chart. In terms of our earlier terminology, bottom-up chart parsing can be seen as a parsing strategy; in other words, bottom-up is a particular choice of heuristics for adding new edges to a chart.

The general procedure for chart parsing is inductive: we start with a base case, and then show how we can move from a given state of the chart to a new state. Since we are working bottom-up, the base case for our induction will be determined by the words in the input string, so we add new edges for each word. Now, for the induction step, suppose the chart contains an edge labeled with constituent A. Since we are working bottom-up, we want to build constituents that can have an A as a daughter. In other words, we are going to look for productions of the form $B \rightarrow A \beta$ and use these to label new edges.

Let's look at the procedure a bit more formally. To create a bottom-up chart parser, we add to the Fundamental Rule two new rules: the **Bottom-Up Initialization Rule**; and the **Bottom-Up Predict Rule**. The Bottom-Up Initialization Rule says to add all edges licensed by the input.

(61) Bottom-Up Initialization Rule

For every word w_i add the edge
 $[w_i \rightarrow \cdot, (i, i+1)]$

[Table 9.6\(a\)](#) illustrates this rule using the chart notation, while [Table 9.6\(b\)](#) shows the bottom-up initialization for the input *Lee likes coffee*.

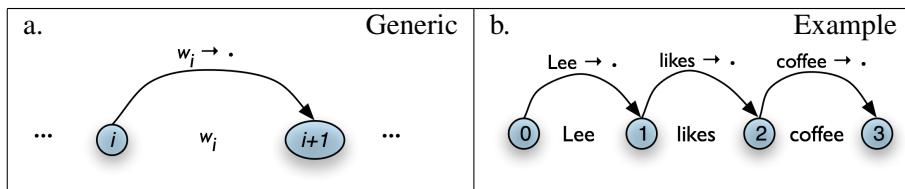


Table 9.6: Bottom-Up Initialization Rule

Notice that the dot on the right hand side of these productions is telling us that we have complete edges for the lexical items. By including this information, we can give a uniform statement of how the Fundamental Rule operates in Bottom-Up parsing, as we will shortly see.

Next, suppose the chart contains a complete edge e whose left hand category is A. Then the Bottom-Up Predict Rule requires the parser to add a self-loop edge at the left boundary of e for each grammar production whose right hand side begins with category A.

(62) Bottom-Up Predict Rule

If the chart contains the complete edge
 $[A \rightarrow \alpha \cdot, (i, j)]$
and the grammar contains the production
 $B \rightarrow A \beta$
then add the self-loop edge

$$[B \rightarrow \bullet A \beta, (i, j)]$$

Graphically, if the chart looks as in Figure 9.7(a), then the Bottom-Up Predict Rule tells the parser to augment the chart as shown in Figure 9.7(b).

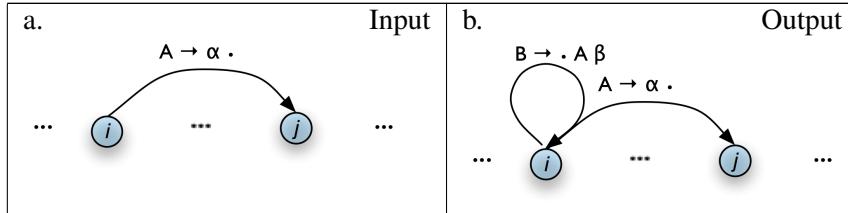
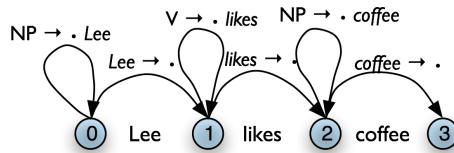


Table 9.7: Bottom-Up Prediction Rule

To continue our earlier example, let's suppose that our grammar contains the lexical productions shown in (63a). This allows us to add three self-loop edges to the chart, as shown in (63b).

- (63) a. $\text{NP} \rightarrow \text{Lee} \mid \text{coffee}$
 $\text{V} \rightarrow \text{likes}$

b.



Once our chart contains an instance of the pattern shown in Figure 9.7(b), we can use the Fundamental Rule to add an edge where we have “moved the dot” one position to the right, as shown in Figure 9.8 (we have omitted the self-loop edges for simplicity.)

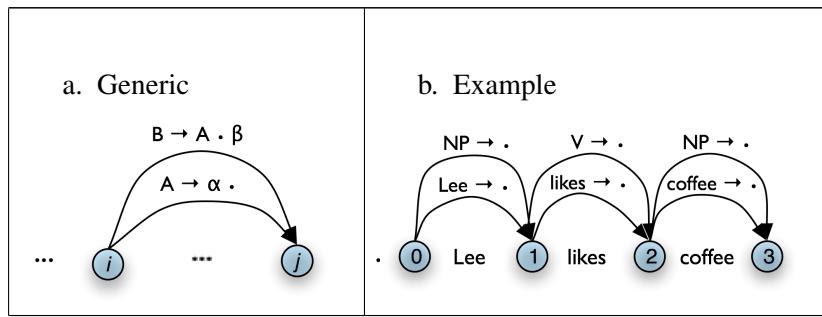


Table 9.8: Fundamental Rule used in Bottom-Up Parsing

We will now be able to add new self-loop edges such as $[S \rightarrow \bullet NP VP, (0, 0)]$ and $[VP \rightarrow \bullet VP NP, (1, 1)]$, and use these to build more complete edges.

Using these three productions, we can parse a sentence as shown in (64).

(64) Bottom-Up Strategy

Create an empty chart spanning the sentence.
 Apply the Bottom-Up Initialization Rule to each word.
 Until no more edges are added:
 Apply the Bottom-Up Predict Rule everywhere it applies.
 Apply the Fundamental Rule everywhere it applies.
 Return all of the parse trees corresponding to the parse edges in the chart.

NLTK provides a useful interactive tool for visualizing the way in which charts are built, `nltk.draw.chart.demo()`. The tool comes with a pre-defined input string and grammar, but both of these can be readily modified with options inside the *Edit* menu. [Figure 9.6](#) illustrates a window after the grammar has been updated:

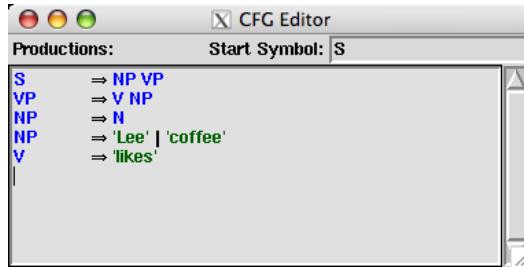


Figure 9.6: Modifying the `demo()` grammar

Note

To get the symbol \Rightarrow illustrated in [Figure 9.6](#), you just have to type the keyboard characters '`>`'.

[Figure 9.7](#) illustrates the tool interface. In order to invoke a rule, you simply click one of the green buttons at the bottom of the window. We show the state of the chart on the input *Lee likes coffee* after three applications of the Bottom-Up Initialization Rule, followed by successive applications of the Bottom-Up Predict Rule and the Fundamental Rule.

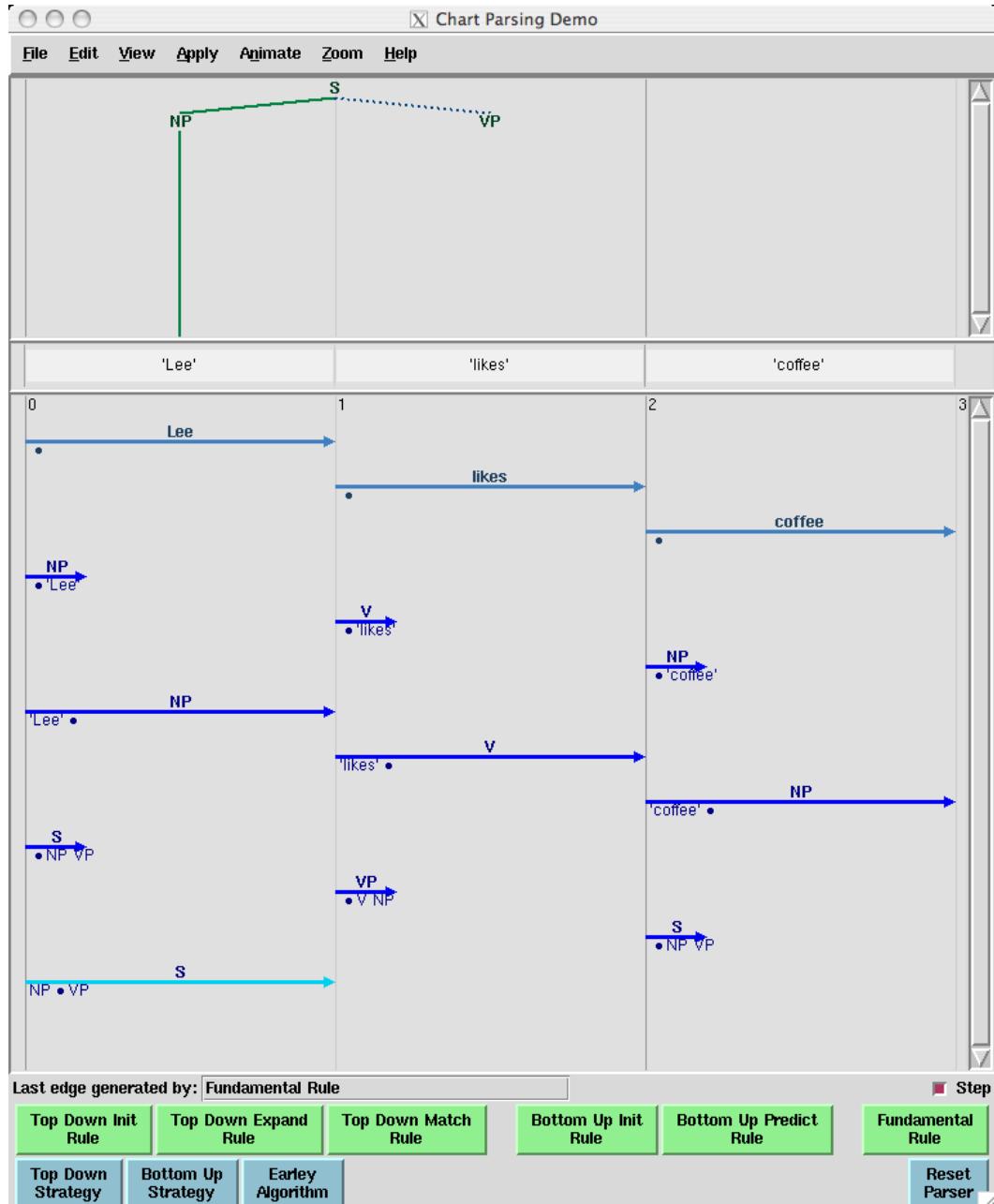
Notice that in the topmost pane of the window, there is a partial tree showing that we have constructed an S with an NP subject in the expectation that we will be able to find a VP.

9.3.4 Top-Down Parsing

Top-down chart parsing works in a similar way to the recursive descent parser discussed in [Chapter 8](#), in that it starts off with the top-level goal of finding an S. This goal is then broken into the subgoals of trying to find constituents such as NP and VP that can be immediately dominated by S. To create a top-down chart parser, we use the Fundamental Rule as before plus three other rules: the **Top-Down Initialization Rule**, the **Top-Down Expand Rule**, and the **Top-Down Match Rule**. The Top-Down Initialization Rule in [\(65\)](#) captures the fact that the root of any parse must be the start symbol S. It is illustrated graphically in [Table 9.9](#).

(65) Top-Down Initialization Rule

For every grammar production of the form:
 $S \rightarrow \alpha$
 add the self-loop edge:
 $[S \rightarrow \bullet \alpha, (0, 0)]$

Figure 9.7: Incomplete chart for *Lee likes coffee*

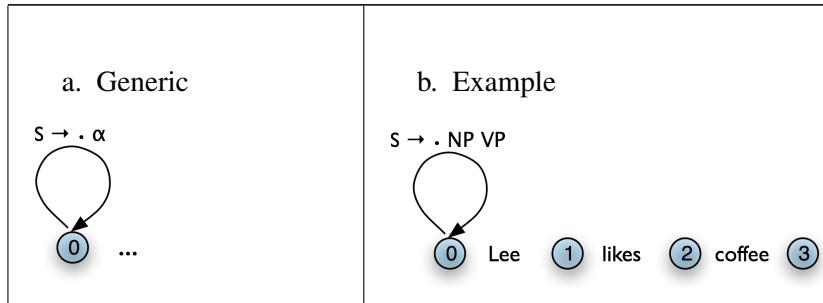


Table 9.9: Top-Down Initialization Rule

As we mentioned before, the dot on the right hand side of a production records how far our goals have been satisfied. So in Figure 9.9(b), we are predicting that we will be able to find an NP and a VP, but have not yet satisfied these subgoals. So how do we pursue them? In order to find an NP, for instance, we need to invoke a production that has NP on its left hand side. The step of adding the required edge to the chart is accomplished with the Top-Down Expand Rule (66). This tells us that if our chart contains an incomplete edge whose dot is followed by a nonterminal B , then the parser should add any self-loop edges licensed by the grammar whose left-hand side is B .

(66) Top-Down Expand Rule

If the chart contains the incomplete edge
 $[A \rightarrow \alpha \cdot B \beta, (i, j)]$
then for each grammar production
 $B \rightarrow \gamma$
add the edge
 $[B \rightarrow \cdot \gamma, (j, j)]$

Thus, given a chart that looks like the one in Table 9.10(a), the Top-Down Expand Rule augments it with the edge shown in Table 9.10(b). In terms of our running example, we now have the chart shown in Table 9.10(c).

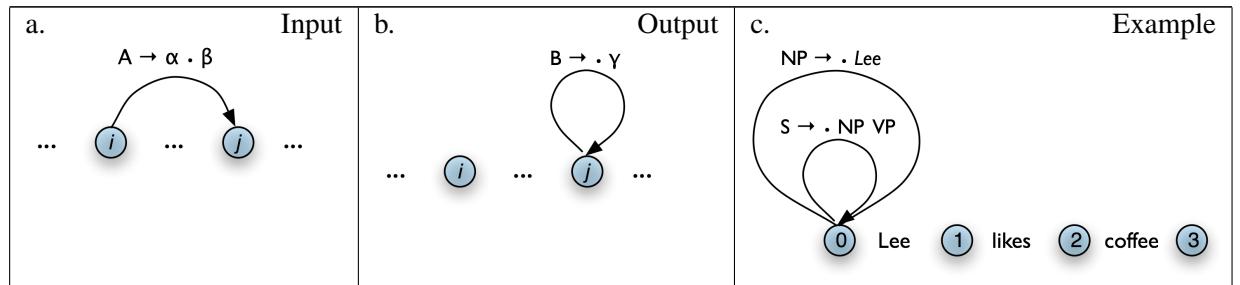


Table 9.10: Top-Down Expand Rule

The Top-Down Match rule allows the predictions of the grammar to be matched against the input string. Thus, if the chart contains an incomplete edge whose dot is followed by a terminal w , then the parser should add an edge if the terminal corresponds to the current input symbol.

(67) Top-Down Match Rule

If the chart contains the incomplete edge
 $[A \rightarrow \alpha \cdot w_j \beta, (i, j)]$,
where w_j is the j^{th} word of the input,
then add a new complete edge
 $[w_j \rightarrow \cdot, (j, j+1)]$

Graphically, the Top-Down Match rule takes us from [Table 9.11\(a\)](#), to [Table 9.11\(b\)](#).

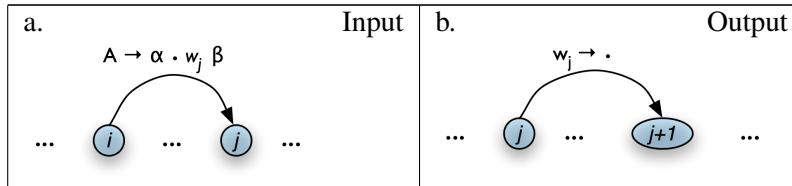


Table 9.11: Top-Down Match Rule

[Figure 9.12\(a\)](#) illustrates how our example chart after applying the Top-Down Match rule. What rule is relevant now? The Fundamental Rule. If we remove the self-loop edges from [Figure 9.12\(a\)](#) for simplicity, the Fundamental Rule gives us [Figure 9.12\(b\)](#).

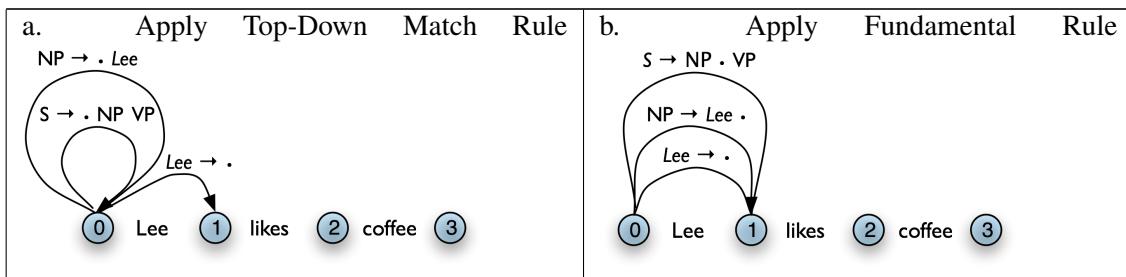


Table 9.12: Top-Down Example (cont)

Using these four rules, we can parse a sentence top-down as shown in (68).

(68) Top-Down Strategy

Create an empty chart spanning the sentence.
Apply the Top-Down Initialization Rule.
Until no more edges are added:
 Apply the Top-Down Expand Rule everywhere it applies.
 Apply the Top-Down Match Rule everywhere it applies.
 Apply the Fundamental Rule everywhere it applies.
Return all of the parse trees corresponding to the parse edges in the chart.

We encourage you to experiment with the NLTK chart parser demo, as before, in order to test out the top-down strategy yourself.

9.3.5 The Earley Algorithm

The Earley algorithm [?] is a parsing strategy that resembles the Top-Down Strategy, but deals more efficiently with matching against the input string. [Table 9.13](#) shows the correspondence between the parsing rules introduced above and the rules used by the Earley algorithm.

Top-Down/Bottom-Up	Earley
Top-Down Initialization Rule	Predictor Rule
Top-Down Expand Rule	
Top-Down/Bottom-Up Match Rule	Scanner Rule
Fundamental Rule	Completer Rule

Table 9.13: Terminology for rules in the Earley algorithm

Let's look in more detail at the Scanner Rule. Suppose the chart contains an incomplete edge with a lexical category P immediately after the dot, the next word in the input is w , P is a part-of-speech label for w . Then the Scanner Rule admits a new complete edge in which P dominates w . More precisely:

(69) Scanner Rule

If the chart contains the incomplete edge
 $[A \rightarrow \alpha \bullet P \beta, (i, j)]$
and w_j is the j^{th} word of the input,
and P is a valid part of speech for w_j ,
then add the new complete edges
 $[P \rightarrow w_j \bullet, (j, j+1)]$
 $[w_j \rightarrow \bullet, (j, j+1)]$

To illustrate, suppose the input is of the form *I saw ...*, and the chart already contains the edge $[VP \rightarrow \bullet V \dots, (1, 1)]$. Then the Scanner Rule will add to the chart the edges $[V \rightarrow \text{'saw'}, (1, 2)]$ and $[\text{'saw'} \rightarrow \bullet, (1, 2)]$. So in effect the Scanner Rule packages up a sequence of three rule applications: the Bottom-Up Initialization Rule for $[w \rightarrow \bullet, (j, j+1)]$, the Top-Down Expand Rule for $[P \rightarrow \bullet w_j, (j, j)]$, and the Fundamental Rule for $[P \rightarrow w_j \bullet, (j, j+1)]$. This is considerably more efficient than the Top-Down Strategy, that adds a new edge of the form $[P \rightarrow \bullet w, (j, j)]$ for every lexical rule $P \rightarrow w$, regardless of whether w can be found in the input. By contrast with Bottom-Up Initialization, however, the Earley algorithm proceeds strictly left-to-right through the input, applying all applicable rules at that point in the chart, and never backtracking. The NLTK chart parser demo, described above, allows the option of parsing according to the Earley algorithm.

9.3.6 Chart Parsing in NLTK

NLTK defines a simple yet flexible chart parser, `ChartParser`. A new chart parser is constructed from a grammar and a list of chart rules (also known as a *strategy*). These rules will be applied, in order, until no new edges are added to the chart. In particular, `ChartParser` uses the algorithm shown in [\(70\)](#).

(70) Until no new edges are added:
 For each chart rule R :
 Apply R to any applicable edges in the chart.
 Return any complete parses in the chart.

`nltk.parse.chart` defines two ready-made strategies: `TD_STRATEGY`, a basic top-down strategy; and `BU_STRATEGY`, a basic bottom-up strategy. When constructing a chart parser, you can use either of these strategies, or create your own.

The following example illustrates the use of the chart parser. We start by defining a simple grammar, and tokenizing a sentence. We make sure it is a list (not an iterator), since we wish to use the same tokenized sentence several times.

Listing 9.2 Chart Parsing with NLTK

```
grammar = nltk.parse_cfg('''
NP  -> NNS | JJ NNS | NP CC NP
NNS -> "men" | "women" | "children" | NNS CC NNS
JJ   -> "old" | "young"
CC   -> "and" | "or"
''')
parser = nltk.ChartParser(grammar, nltk.parse.BU_STRATEGY)

>>> sent = 'old men and women'.split()
>>> for tree in parser.nbest_parse(sent):
...     print tree
(NP (JJ old) (NNS (NNS men) (CC and) (NNS women)))
(NP (NP (JJ old) (NNS men)) (CC and) (NP (NNS women)))
```

The `trace` parameter can be specified when creating a parser, to turn on tracing (higher trace levels produce more verbose output). Example 9.3 shows the trace output for parsing a sentence with the bottom-up strategy. Notice that in this output, '`[-----]`' indicates a complete edge, '`>`' indicates a self-loop edge, and '`[----->]`' indicates an incomplete edge.

9.3.7 Exercises

1. ◊ Use the graphical chart-parser interface to experiment with different rule invocation strategies. Come up with your own strategy that you can execute manually using the graphical interface. Describe the steps, and report any efficiency improvements it has (e.g. in terms of the size of the resulting chart). Do these improvements depend on the structure of the grammar? What do you think of the prospects for significant performance boosts from cleverer rule invocation strategies?
2. ◊ We have seen that a chart parser adds but never removes edges from a chart. Why?
3. ⚡ Write a program to compare the efficiency of a top-down chart parser compared with a recursive descent parser (Section 8.5.1). Use the same grammar and input sentences for both. Compare their performance using the `timeit` module (Section 6.5.4).

9.4 Probabilistic Parsing

As we pointed out in the introduction to this chapter, dealing with ambiguity is a key challenge to broad coverage parsers. We have shown how chart parsing can help improve the efficiency of computing multiple parses of the same sentences. But the sheer number of parses can be just overwhelming. We

Listing 9.3 Trace of Bottom-Up Parser

```

>>> parser = nltk.ChartParser(grammar, nltk.parse.BU_STRATEGY, trace=2)
>>> trees = parser.nbest_parse(sent)
|. old . men . and . women .
Bottom Up Init Rule:
| [-----] . . . | [0:1] 'old'
| . [-----] . . | [1:2] 'men'
| . . [-----] . | [2:3] 'and'
| . . . [-----] | [3:4] 'women'
Bottom Up Predict Rule:
|> . . . | [0:0] JJ -> * 'old'
| . > . . | [1:1] NNS -> * 'men'
| . . > . | [2:2] CC -> * 'and'
| . . . > | [3:3] NNS -> * 'women'
Fundamental Rule:
| [-----] . . . | [0:1] JJ -> 'old' *
| . [-----] . . | [1:2] NNS -> 'men' *
| . . [-----] . | [2:3] CC -> 'and' *
| . . . [-----] | [3:4] NNS -> 'women' *
Bottom Up Predict Rule:
|> . . . | [0:0] NP -> * JJ NNS
| . > . . | [1:1] NP -> * NNS
| . > . . | [1:1] NNS -> * NNS CC NNS
| . . . > | [3:3] NP -> * NNS
| . . . > | [3:3] NNS -> * NNS CC NNS
Fundamental Rule:
| [-----> . . . | [0:1] NP -> JJ * NNS
| . [-----] . . | [1:2] NP -> NNS *
| . [-----] . . | [1:2] NNS -> NNS * CC NNS
| [-----] . . | [0:2] NP -> JJ NNS *
| . [-----> . . | [1:3] NNS -> NNS CC * NNS
| . . . [-----] | [3:4] NP -> NNS *
| . . . [-----] | [3:4] NNS -> NNS * CC NNS
| . [-----] . . | [1:4] NNS -> NNS CC NNS *
| . [-----] . . | [1:4] NP -> NNS *
| . [-----] . . | [1:4] NNS -> NNS * CC NNS
| [=====] | [0:4] NP -> JJ NNS *
Bottom Up Predict Rule:
| . > . . . | [1:1] NP -> * NP CC NP
|> . . . . | [0:0] NP -> * NP CC NP
| . . . > . | [3:3] NP -> * NP CC NP
Fundamental Rule:
| . [-----> . . | [1:2] NP -> NP * CC NP
| [-----> . . | [0:2] NP -> NP * CC NP
| . . . [-----] | [3:4] NP -> NP * CC NP
| . [-----] . . | [1:4] NP -> NP * CC NP
| [-----] . . | [0:4] NP -> NP * CC NP
| . [-----> . . | [1:3] NP -> NP CC * NP
| [-----> . . | [0:3] NP -> NP CC * NP
| . [-----] . . | [1:4] NP -> NP CC NP *
| [=====] | [0:4] NP -> NP CC NP *
| . [-----] . . | [1:4] NP -> NP * CC NP
| [-----] . . | [0:4] NP -> NP * CC NP

```

will show how probabilistic parsing helps to manage a large space of parses. However, before we deal with these parsing issues, we must first back up and introduce weighted grammars.

9.4.1 Weighted Grammars

We begin by considering the verb *give*. This verb requires both a direct object (the thing being given) and an indirect object (the recipient). These complements can be given in either order, as illustrated in [example \(71\)](#). In the “prepositional dative” form, the indirect object appears last, and inside a prepositional phrase, while in the “double object” form, the indirect object comes first:

- (71) a. Kim gave a bone to the dog
- b. Kim gave the dog a bone

Using the Penn Treebank sample, we can examine all instances of prepositional dative and double object constructions involving *give*, as shown in [Listing 9.4](#).

We can observe a strong tendency for the shortest complement to appear first. However, this does not account for a form like `give NP: federal judges / NP: a raise`, where animacy may be playing a role. In fact there turn out to be a large number of contributing factors, as surveyed by [?].

How can such tendencies be expressed in a conventional context free grammar? It turns out that they cannot. However, we can address the problem by adding weights, or probabilities, to the productions of a grammar.

A **probabilistic context free grammar** (or *PCFG*) is a context free grammar that associates a probability with each of its productions. It generates the same set of parses for a text that the corresponding context free grammar does, and assigns a probability to each parse. The probability of a parse generated by a PCFG is simply the product of the probabilities of the productions used to generate it.

The simplest way to define a PCFG is to load it from a specially formatted string consisting of a sequence of weighted productions, where weights appear in brackets, as shown in [Listing 9.5](#).

It is sometimes convenient to combine multiple productions into a single line, e.g. `VP -> TV NP [0.4] | IV [0.3] | DatV NP NP [0.3]`. In order to ensure that the trees generated by the grammar form a probability distribution, PCFG grammars impose the constraint that all productions with a given left-hand side must have probabilities that sum to one. The grammar in [Listing 9.5](#) obeys this constraint: for *S*, there is only one production, with a probability of 1.0; for *VP*, $0.4+0.3+0.3=1.0$; and for *NP*, $0.8+0.2=1.0$. The parse tree returned by `parse()` includes probabilities:

```
>>> viterbi_parser = nltk.ViterbiParser(grammar)
>>> print viterbi_parser.parse(['Jack', 'saw', 'telescopes'])
(S (NP Jack) (VP (TV saw) (NP telescopes))) (p=0.064)
```

The next two sections introduce two probabilistic parsing algorithms for PCFGs. The first is an A* parser that uses Viterbi-style dynamic programming to find the single most likely parse for a given text. Whenever it finds multiple possible parses for a subtree, it discards all but the most likely parse. The second is a bottom-up chart parser that maintains a queue of edges, and adds them to the chart one at a time. The ordering of this queue is based on the probabilities associated with the edges, allowing the parser to expand more likely edges before less likely ones. Different queue orderings are used to implement a variety of different search strategies. These algorithms are implemented in the `nltk.parse.viterbi` and `nltk.parse.pchart` modules.

Listing 9.4 Usage of Give and Gave in the Penn Treebank sample

```

def give(t):
    return t.node == 'VP' and len(t) > 2 and t[1].node == 'NP' \
        and (t[2].node == 'PP-DTV' or t[2].node == 'NP') \
            and ('give' in t[0].leaves() or 'gave' in t[0].leaves())
def sent(t):
    return ' '.join(token for token in t.leaves() if token[0] not in '*-0')
def print_node(t, width):
    output = "%s %s: %s / %s: %s" %\
        (sent(t[0]), t[1].node, sent(t[1]), t[2].node, sent(t[2]))
    if len(output) > width:
        output = output[:width] + "..."
    print output

>>> for tree in nltk.corpus.treebank.parsed_sents():
...     for t in tree.subtrees(give):
...         print_node(t, 72)
gave NP: the chefs / NP: a standing ovation
give NP: advertisers / NP: discounts for maintaining or increasing ad sp...
give NP: it / PP-DTV: to the politicians
gave NP: them / NP: similar help
give NP: them / NP:
give NP: only French history questions / PP-DTV: to students in a Europe...
give NP: federal judges / NP: a raise
give NP: consumers / NP: the straight scoop on the U.S. waste crisis
give NP: Mitsui / NP: access to a high-tech medical product
give NP: Mitsubishi / NP: a window on the U.S. glass industry
give NP: much thought / PP-DTV: to the rates she was receiving , nor to ...
give NP: your Foster Savings Institution / NP: the gift of hope and free...
give NP: market operators / NP: the authority to suspend trading in futu...
gave NP: quick approval / PP-DTV: to $ 3.18 billion in supplemental appr...
give NP: the Transportation Department / NP: up to 50 days to review any...
give NP: the president / NP: such power
give NP: me / NP: the heebie-jeebies
give NP: holders / NP: the right , but not the obligation , to buy a cal...
gave NP: Mr. Thomas / NP: only a `` qualified '' rating , rather than ` `...
give NP: the president / NP: line-item veto power

```

9.4.2 A* Parser

An **A* Parser** is a bottom-up PCFG parser that uses dynamic programming to find the single most likely parse for a text [?]. It parses texts by iteratively filling in a **most likely constituents table**. This table records the most likely tree for each span and node value. For example, after parsing the sentence “I saw the man with the telescope” with the grammar `cfg.toy_pcfg1`, the most likely constituents table contains the following entries (amongst others):

Span	Node	Tree	Prob
[0:1]	NP	(NP I)	0.15
[6:7]	NP	(NN telescope)	0.5
[5:7]	NP	(NP the telescope)	0.2
[4:7]	PP	(PP with (NP the telescope))	0.122
[0:4]	S	(S (NP I) (VP saw (NP the man)))	0.01365
[0:7]	S	(S (NP I) (VP saw (NP (NP the man) (PP with (NP the telescope))))))	0.0004163250

Table 9.14: Fragment of Most Likely Constituents Table

Once the table has been completed, the parser returns the entry for the most likely constituent that spans the entire text, and whose node value is the start symbol. For this example, it would return the entry with a span of [0:6] and a node value of “S”.

Note that we only record the *most likely* constituent for any given span and node value. For example, in the table above, there are actually two possible constituents that cover the span [1:6] and have “VP” node values.

1. “saw the man, who has the telescope”:

(VP saw
 (NP (NP John) (PP with (NP the telescope))))

2. “used the telescope to see the man”:

(VP saw (NP John) (PP with (NP the telescope)))

Since the grammar we are using to parse the text indicates that the first of these tree structures has a higher probability, the parser discards the second one.

Filling in the Most Likely Constituents Table: Because the grammar used by `ViterbiParse` is a PCFG, the probability of each constituent can be calculated from the probabilities of its children. Since a constituent’s children can never cover a larger span than the constituent itself, each entry of the most likely constituents table depends only on entries for constituents with *shorter* spans (or equal spans, in the case of unary and epsilon productions).

`ViterbiParse` takes advantage of this fact, and fills in the most likely constituent table incrementally. It starts by filling in the entries for all constituents that span a single element of text. After it has filled in all the table entries for constituents that span one element of text, it fills in the entries for constituents that span two elements of text. It continues filling in the entries for constituents spanning larger and larger portions of the text, until the entire table has been filled.

To find the most likely constituent with a given span and node value, `ViterbiParse` considers all productions that could produce that node value. For each production, it checks the most likely constituents table for sequences of children that collectively cover the span and that have the node values specified by the production's right hand side. If the tree formed by applying the production to the children has a higher probability than the current table entry, then it updates the most likely constituents table with the new tree.

Handling Unary Productions and Epsilon Productions: A minor difficulty is introduced by unary productions and epsilon productions: an entry of the most likely constituents table might depend on another entry with the same span. For example, if the grammar contains the production $V \rightarrow VP$, then the table entries for VP depend on the entries for V with the same span. This can be a problem if the constituents are checked in the wrong order. For example, if the parser tries to find the most likely constituent for a VP spanning [1:3] before it finds the most likely constituents for V spanning [1:3], then it can't apply the $V \rightarrow VP$ production.

To solve this problem, `ViterbiParse` repeatedly checks each span until it finds no new table entries. Note that cyclic grammar productions (e.g. $V \rightarrow V$) will *not* cause this procedure to enter an infinite loop. Since all production probabilities are less than or equal to 1, any constituent generated by a cycle in the grammar will have a probability that is less than or equal to the original constituent; so `ViterbiParse` will discard it.

In NLTK, we create Viterbi parsers using `ViterbiParser()`. Note that since `ViterbiParse` only finds the single most likely parse, that `nbest_parse()` will never return more than one parse.

The `trace` method can be used to set the level of tracing output that is generated when parsing a text. Trace output displays the constituents that are considered, and indicates which ones are added to the most likely constituent table. It also indicates the likelihood for each constituent.

```
>>> viterbi_parser.trace(3)
>>> print viterbi_parser.parse(sent)
Inserting tokens into the most likely constituents table...
Insert: |=...| old
Insert: |.=..| men
Insert: |...=.| and
Insert: |...=| women
Finding the most likely constituents spanning 1 text elements...
Insert: |=...| JJ -> 'old' [0.4] 0.4000000000
Insert: |.=..| NNS -> 'men' [0.1] 0.1000000000
Insert: |...=.| NP -> NNS [0.5] 0.0500000000
Insert: |...=.| CC -> 'and' [0.9] 0.9000000000
Insert: |...=| NNS -> 'women' [0.2] 0.2000000000
Insert: |...=| NP -> NNS [0.5] 0.1000000000
Finding the most likely constituents spanning 2 text elements...
Insert: |==..| NP -> JJ NNS [0.3] 0.0120000000
Finding the most likely constituents spanning 3 text elements...
Insert: |.==..| NP -> NP CC NP [0.2] 0.0009000000
Insert: |.==..| NNS -> NNS CC NNS [0.4] 0.0072000000
Insert: |.==..| NP -> NNS [0.5] 0.0036000000
Discard: |.==..| NP -> NP CC NP [0.2] 0.0009000000
Discard: |.==..| NP -> NP CC NP [0.2] 0.0009000000
Finding the most likely constituents spanning 4 text elements...
Insert: |====| NP -> JJ NNS [0.3] 0.0008640000
Discard: |====| NP -> NP CC NP [0.2] 0.0002160000
```

Listing 9.5 Defining a Probabilistic Context Free Grammar (PCFG)

```
grammar = nltk.parse_pcfg("""
    S      -> NP VP          [1.0]
    VP     -> TV NP          [0.4]
    VP     -> IV             [0.3]
    VP     -> DatV NP NP    [0.3]
    TV     -> 'saw'           [1.0]
    IV     -> 'ate'            [1.0]
    DatV  -> 'gave'          [1.0]
    NP     -> 'telescopes'   [0.8]
    NP     -> 'Jack'           [0.2]
""")

>>> print grammar
Grammar with 9 productions (start state = S)
S -> NP VP [1.0]
VP -> TV NP [0.4]
VP -> IV [0.3]
VP -> DatV NP NP [0.3]
TV -> 'saw' [1.0]
IV -> 'ate' [1.0]
DatV -> 'gave' [1.0]
NP -> 'telescopes' [0.8]
NP -> 'Jack' [0.2]
```

Listing 9.6

```
grammar = nltk.parse_pcfg('''
    NP  -> NNS [0.5] | JJ NNS [0.3] | NP CC NP [0.2]
    NNS -> "men" [0.1] | "women" [0.2] | "children" [0.3] | NNS CC NNS [0.4]
    JJ   -> "old" [0.4] | "young" [0.6]
    CC   -> "and" [0.9] | "or" [0.1]
''')
viterbi_parser = nltk.ViterbiParser(grammar)

>>> sent = 'old men and women'.split()
>>> print viterbi_parser.parse(sent)
(NP (JJ old) (NNS (NNS men) (CC and) (NNS women))) (p=0.000864)
```

```

Discard: |====| NP -> NP CC NP [0.2]          0.0002160000
(NP (JJ old) (NNS (NNS men) (CC and) (NNS women))) (p=0.000864)

```

9.4.3 A Bottom-Up PCFG Chart Parser

The *A** parser described in the previous section finds the single most likely parse for a given text. However, when parsers are used in the context of a larger NLP system, it is often necessary to produce several alternative parses. In the context of an overall system, a parse that is assigned low probability by the parser might still have the best overall probability.

For example, a probabilistic parser might decide that the most likely parse for “I saw John with the cookie” is the structure with the interpretation “I used my cookie to see John”; but that parse would be assigned a low probability by a semantic system. Combining the probability estimates from the parser and the semantic system, the parse with the interpretation “I saw John, who had my cookie” would be given a higher overall probability.

This section describes a probabilistic bottom-up chart parser. It maintains an **edge queue**, and adds these edges to the chart one at a time. The ordering of this queue is based on the probabilities associated with the edges, and this allows the parser to insert the most probable edges first. Each time an edge is added to the chart, it may become possible to insert new edges, so these are added to the queue. The bottom-up chart parser continues adding the edges in the queue to the chart until enough complete parses have been found, or until the edge queue is empty.

Like an edge in a regular chart, a probabilistic edge consists of a dotted production, a span, and a (partial) parse tree. However, unlike ordinary charts, this time the tree is weighted with a probability. Its probability is the product of the probability of the production that generated it and the probabilities of its children. For example, the probability of the edge [Edge: $S \rightarrow NP \cdot VP$, 0:2] is the probability of the PCFG production $S \rightarrow NP \ VP$ multiplied by the probability of its NP child. (Note that an edge’s tree only includes children for elements to the left of the edge’s dot. Thus, the edge’s probability does *not* include probabilities for the constituents to the right of the edge’s dot.)

9.4.4 Bottom-Up PCFG Strategies

The *edge queue* is a sorted list of edges that can be added to the chart. It is initialized with a single edge for each token in the text, with the form [Edge: token |rarr| |dot|]. As each edge from the queue is added to the chart, it may become possible to add further edges, according to two rules: (i) the Bottom-Up Initialization Rule can be used to add a self-loop edge whenever an edge whose dot is in position 0 is added to the chart; or (ii) the Fundamental Rule can be used to combine a new edge with edges already present in the chart. These additional edges are queued for addition to the chart.

By changing the sort order used by the queue, we can control the strategy that the parser uses to explore the search space. Since there are a wide variety of reasonable search strategies, `BottomUpChartParser()` does not define any sort order. Instead, different strategies are implemented in subclasses of `BottomUpChartParser()`.

Lowest Cost First: The simplest way to order the edge queue is to sort edges by the probabilities of their associated trees (`nltk.InsideChartParser()`). This ordering concentrates the efforts of the parser on those edges that are more likely to be correct analyses of their underlying tokens.

The probability of an edge’s tree provides an upper bound on the probability of any parse produced using that edge. The probabilistic “cost” of using an edge to form a parse is one minus its tree’s probability. Thus, inserting the edges with the most likely trees first results in a **lowest-cost-first**

search strategy. Lowest-cost-first search is optimal: the first solution it finds is guaranteed to be the best solution.

However, lowest-cost-first search can be rather inefficient. Recall that a tree's probability is the product of the probabilities of all the productions used to generate it. Consequently, smaller trees tend to have higher probabilities than larger ones. Thus, lowest-cost-first search tends to work with edges having small trees before considering edges with larger trees. Yet any complete parse of the text will necessarily have a large tree, and so this strategy will tend to produce complete parses only once most other edges are processed.

Let's consider this problem from another angle. The basic shortcoming with lowest-cost-first search is that it ignores the probability that an edge's tree will be part of a complete parse. The parser will try parses that are locally coherent even if they are unlikely to form part of a complete parse. Unfortunately, it can be quite difficult to calculate the probability that a tree is part of a complete parse. However, we can use a variety of techniques to approximate that probability.

Best-First Search: This method sorts the edge queue in descending order of the edges' span, no the assumption that edges having a larger span are more likely to form part of a complete parse. Thus, LongestParse employs a **best-first search strategy**, where it inserts the edges that are closest to producing complete parses before trying any other edges. Best-first search is *not* an optimal search strategy: the first solution it finds is not guaranteed to be the best solution. However, it will usually find a complete parse much more quickly than lowest-cost-first search.

Beam Search: When large grammars are used to parse a text, the edge queue can grow quite long. The edges at the end of a large well-sorted queue are unlikely to be used. Therefore, it is reasonable to remove (or *prune*) these edges from the queue. This strategy is known as **beam search**; it only keeps the best partial results. The bottom-up chart parsers take an optional parameter `beam_size`; whenever the edge queue grows longer than this, it is pruned. This parameter is best used in conjunction with `InsideChartParser()`. Beam search reduces the space requirements for lowest-cost-first search, by discarding edges that are not likely to be used. But beam search also loses many of lowest-cost-first search's more useful properties. Beam search is not optimal: it is not guaranteed to find the best parse first. In fact, since it might prune a necessary edge, beam search is not even *complete*: it is not guaranteed to return a parse if one exists.

In NLTK we can construct these parsers using `InsideChartParser`, `LongestChartParser`, `RandomChartParser`.

The `trace` method can be used to set the level of tracing output that is generated when parsing a text. Trace output displays edges as they are added to the chart, and shows the probability for each edges' tree.

```
>>> inside_parser.trace(3)
>>> trees = inside_parser.nbest_parse(sent)
| . . . [-] | [3:4] 'women' [1.0]
| . . [-] . | [2:3] 'and' [1.0]
| . [-] . . | [1:2] 'men' [1.0]
||[-] . . . | [0:1] 'old' [1.0]
| . . [-] . | [2:3] CC -> 'and' *
| . . > . . | [2:2] CC -> * 'and' [0.9]
||[-] . . . | [0:1] JJ -> 'old' *
| > . . . . | [0:0] JJ -> * 'old' [0.4]
| > . . . . | [0:0] NP -> * JJ NNS [0.4]
| . . . [-] | [3:4] NNS -> 'women' * [0.3]
| . . . > . | [3:3] NP -> * NNS [0.2]
| . . . > . | [3:3] NNS -> * NNS CC NNS [0.5]
```

Listing 9.7

```

inside_parser = nltk.InsideChartParser(grammar)
longest_parser = nltk.LongestChartParser(grammar)
beam_parser = nltk.InsideChartParser(grammar, beam_size=20)

>>> print inside_parser.parse(sent)
(NP (JJ old) (NNS (NNS men) (CC and) (NNS women))) (p=0.000864)
>>> for tree in inside_parser.nbest_parse(sent):
...     print tree
(NP
  (JJ old)
  (NNS (NNS men) (CC and) (NNS women))) (p=0.000864)
(NP
  (NP (JJ old) (NNS men))
  (CC and)
  (NP (NNS women))) (p=0.000216)

```

. . . > . [3:3] NNS -> * 'women'	[0.2]
[-> . . . [0:1] NP -> JJ * NNS	[0.12]
. . . [-] [3:4] NP -> NNS *	[0.1]
. . . > . [3:3] NP -> * NP CC NP	[0.2]
. [-] . . [1:2] NNS -> 'men' *	[0.1]
. > . . . [1:1] NP -> * NNS	[0.5]
. > . . . [1:1] NNS -> * NNS CC NNS	[0.4]
. > . . . [1:1] NNS -> * 'men'	[0.1]
. . . [->] [3:4] NNS -> NNS * CC NNS	[0.08]
. [-] . . [1:2] NP -> NNS *	[0.05]
. > . . . [1:1] NP -> * NP CC NP	[0.2]
. [-> . . [1:2] NNS -> NNS * CC NNS	[0.04]
. [---> . [1:3] NNS -> NNS CC * NNS	[0.036]
. . . [->] [3:4] NP -> NP * CC NP	[0.02]
[---] . . [0:2] NP -> JJ NNS *	[0.012]
> [0:0] NP -> * NP CC NP	[0.2]
. [-> . . [1:2] NP -> NP * CC NP	[0.01]
. [---> . [1:3] NP -> NP CC * NP	[0.009]
. [-----] [1:4] NNS -> NNS CC NNS *	[0.0072]
. [-----] [1:4] NP -> NNS *	[0.0036]
. [----->] [1:4] NNS -> NNS * CC NNS	[0.00288]
[----> . . [0:2] NP -> NP * CC NP	[0.0024]
[----> . . [0:3] NP -> NP CC * NP	[0.00216]
. [----> . [1:4] NP -> NP CC NP *	[0.0009]
[=====] [0:4] NP -> JJ NNS *	[0.000864]
. [----> . [1:4] NP -> NP * CC NP	[0.00072]
[=====] [0:4] NP -> NP CC NP *	[0.000216]
. [----> . [1:4] NP -> NP * CC NP	[0.00018]
[----> . [0:4] NP -> NP * CC NP	[0.0001728]
[----> . [0:4] NP -> NP * CC NP	[4.32e-05]

9.5 Grammar Induction

As we have seen, PCFG productions are just like CFG productions, adorned with probabilities. So far, we have simply specified these probabilities in the grammar. However, it is more usual to *estimate* these probabilities from training data, namely a collection of parse trees or *treebank*.

The simplest method uses *Maximum Likelihood Estimation*, so called because probabilities are chosen in order to maximize the likelihood of the training data. The probability of a production $VP \rightarrow V \ NP \ PP$ is $p(V, NP, PP | VP)$. We calculate this as follows:

$$P(V, NP, PP | VP) = \frac{\text{count}(VP \rightarrow V \ NP \ PP)}{\text{count}(VP \rightarrow \dots)}$$

Here is a simple program that induces a grammar from the first three parse trees in the Penn Treebank corpus:

```
>>> from itertools import islice
>>> productions = []
>>> S = nltk.Nonterminal('S')
>>> for tree in nltk.corpus.treebank.parsed_sents('wsj_0002.mrg'):
...     productions += tree.productions()
>>> grammar = nltk.induce_pcfg(S, productions)
>>> for production in grammar.productions()[:10]:
...     print production
CC -> 'and' [1.0]
NNP -> 'Agnew' [0.166666666667]
JJ -> 'industrial' [0.2]
NP -> CD NNS [0.142857142857]
, -> ',' [1.0]
S -> NP-SBJ NP-PRD [0.5]
VP -> VBN S [0.5]
NNP -> 'Rudolph' [0.166666666667]
NP -> NP PP [0.142857142857]
NNP -> 'PLC' [0.166666666667]
```

9.5.1 Normal Forms

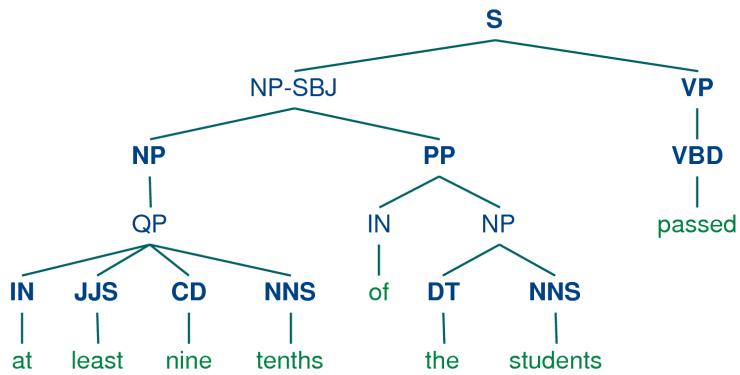
Grammar induction usually involves normalizing the grammar in various ways. NLTK trees support binarization (Chomsky Normal Form), parent annotation, Markov order-N smoothing, and unary collapsing:

```
>>> treebank_string = """(S (NP-SBJ (NP (QP (IN at) (JJS least) (CD nine) (NNS tenths)) )
...   (PP (IN of) (NP (DT the) (NNS students)))) (VP (VBD passed)))"""
>>> t = nltk.bracket_parse(treebank_string)
>>> print t
(S
(NP-SBJ
(NP (QP (IN at) (JJS least) (CD nine) (NNS tenths)))
(PP (IN of) (NP (DT the) (NNS students))))
(VP (VBD passed)))
>>> t.collapse Unary(collapsePOS=True)
>>> print t
```

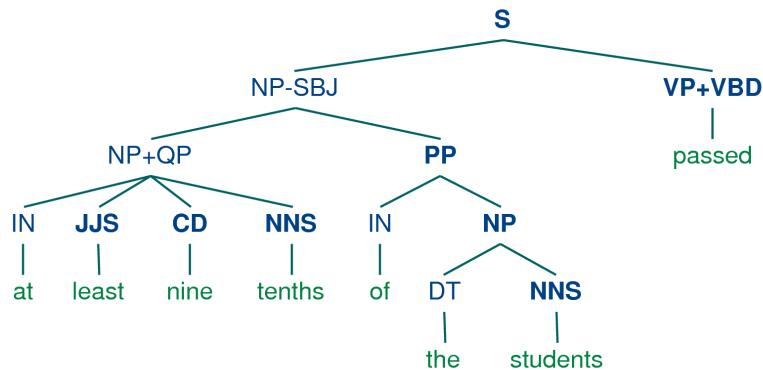
```
(S
  (NP-SBJ
    (NP+QP (IN at) (JJS least) (CD nine) (NNS tenths))
    (PP (IN of) (NP (DT the) (NNS students))))
    (VP+VBD passed))
  >>> t.chomsky_normal_form()
  >>> print t
(S
  (NP-SBJ
    (NP+QP
      (IN at)
      (NP+QP |<JJS-CD-NNS>
        (JJS least)
        (NP+QP |<CD-NNS> (CD nine) (NNS tenths))))
      (PP (IN of) (NP (DT the) (NNS students))))
    (VP+VBD passed))
```

These trees are shown in (72).

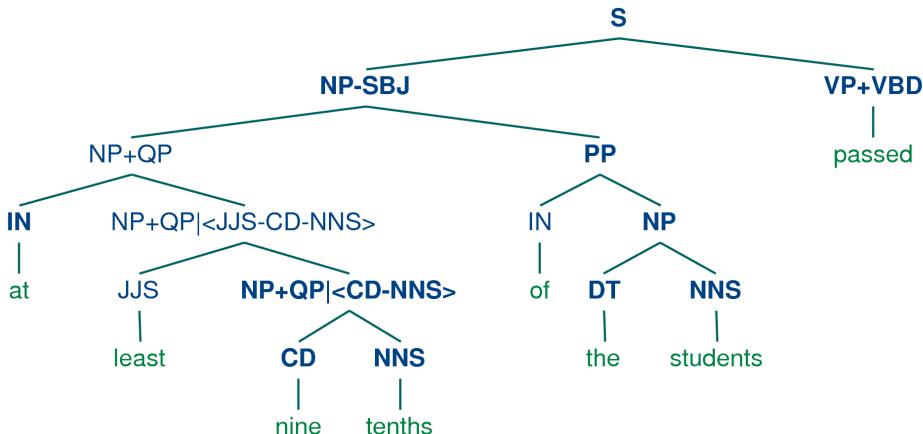
(72) a.



b.



c.



9.6 Conclusion

9.7 Further Reading

- [?]
- [?]
- [?]

About this document...

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Part III

ADVANCED TOPICS

Introduction to Part III

Part III covers a selection of advanced topics. It begins with a chapter on applied programming in Python, covering topics in program development, standard libraries, and algorithm design. The following two chapters focus on making grammars more expressive, first by adding the powerful notation of distinctive features, and then by using this to add semantic interpretation. The final chapter deals with linguistic data management.

Chapter 10

Applied Programming in Python

This chapter is in development.

About this document...

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This document is Revision: 5915 Tue Apr 29 13:57:59 EDT 2008

Chapter 11

Feature Based Grammar

11.1 Introduction

Imagine you are building a spoken dialogue system to answer queries about train schedules in Europe. (73) illustrates one of the input sentences that the system should handle.

- (73) Which stations does the 9.00 express from Amsterdam to Paris stop at?

The information that the customer is seeking is not exotic — the system back-end just needs to look up the list of stations on the route, and reel them off. But you have to be careful in giving the correct semantic interpretation to (73). You don't want to end up with the system trying to answer (74) instead:

- (74) Which station does the 9.00 express from Amsterdam terminate at?

Part of your solution might use domain knowledge to figure out that if a speaker knows that the train is a train to Paris, then she probably isn't asking about the terminating station in (73). But the solution will also involve recognizing the syntactic structure of the speaker's query. In particular, your analyzer must recognize that there is a syntactic connection between the question phrase *which stations*, and the phrase *stop at* at the end (73). The required interpretation is made clearer in the "quiz question version shown in (75), where the question phrase fills the "gap" that is implicit in (73):

- (75) The 9.00 express from Amsterdam to Paris stops at which stations?

The **long-distance dependency** between an initial question phrase and the gap that it semantically connects to cannot be recognized by techniques we have presented in earlier chapters. For example, we can't use n -gram based language models; in practical terms, it is infeasible to observe the n -grams for a big enough value of n . Similarly, chunking grammars only attempt to capture local patterns, and therefore just don't "see" long-distance dependencies. In this chapter, we will show how syntactic features can be used to provide a simple yet effective technique for keeping track of long-distance dependencies in sentences.

Features are helpful too for dealing with purely local dependencies. Consider the German questions (76).

- (76)

The only way of telling which noun phrase is the subject of *kennen* ('know') and which is the object is by looking at the agreement inflection on the verb — word order is no help to us here. Since

verbs in German agree in number with their subjects, the plural form *kennen* requires *Welche Studenten* as subject, while the singular form *kennt* requires *Franz* as subject. The fact that subjects and verbs must agree in number can be expressed within the CFGs that we presented in Chapter 8. But capturing the fact that the interpretations of *germanagra* and *germanagrb* differ is more challenging. In this chapter, we will only examine the syntactic aspect of local dependencies such as number agreement. In Chapter 12, we will demonstrate how feature-based grammars can be extended so that they build a representation of meaning in parallel with a representation of syntactic structure.

Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint`

11.2 Why Features?

We have already used the term "feature" a few times, without saying what it means. What's special about feature-based grammars? The core ideas are probably already familiar to you. To make things concrete, let's look at the simple phrase *these dogs*. It's composed of two words. We'll be a bit abstract for the moment, and call these words *a* and *b*. We'll be modest, and assume that we do not know *everything* about them, but we can at least give a partial description. For example, we know that the orthography of *a* is *these*, its phonological form is *DH IY Z*, its part-of-speech is DET, and its number is plural. We can use dot notation to record these observations:

(77) *a.spelling* = *these*
 a.phonology = *DH IY Z*
 a.pos = DET
 a.number = plural

Thus (77) is a *partial description* of a word; it lists some attributes, or features, of the word, and declares their values. There are other attributes that we might be interested in, which have not been specified; for example, what head the word is dependent on (using the notion of dependency discussed in Chapter 8), and what the lemma of the word is. But this omission of some attributes is exactly what you would expect from a partial description!

We will start off this chapter by looking more closely at the phenomenon of syntactic agreement; we will show how agreement constraints can be expressed elegantly using features, and illustrate their use in a simple grammar. Feature structures are a general data structure for representing information of any kind; we will briefly look at them from a more formal point of view, and explain how to create feature structures in Python. In the final part of the chapter, we demonstrate that the additional expressiveness of features opens out a wide spectrum of possibilities for describing sophisticated aspects of linguistic structure.

11.2.1 Syntactic Agreement

Consider the following contrasts:

- (78) a. this dog
 b. *these dog
- (79) a. these dogs

- b. *this dog

In English, nouns are usually morphologically marked as being singular or plural. The form of the demonstrative also varies: *this* (singular) and *these* (plural). Examples (78) and (79) show that there are constraints on the use of demonstratives and nouns within a noun phrase: either both are singular or both are plural. A similar constraint holds between subjects and predicates:

- (80) a. the dog runs

- b. *the dog run

- (81) a. the dogs run

- b. *the dogs runs

Here we can see that morphological properties of the verb co-vary with syntactic properties of the subject noun phrase. This co-variance is called **agreement**. If we look further at verb agreement in English, we will see that present tense verbs typically have two inflected forms: one for third person singular, and another for every other combination of person and number:

	singular	plural
1st per	<i>I run</i>	<i>we run</i>
2nd per	<i>you run</i>	<i>you run</i>
3rd per	<i>he/she/it runs</i>	<i>they run</i>

Table 11.1: Agreement Paradigm for English Regular Verbs

We can make the role of morphological properties a bit more explicit as illustrated in *runs* and *run*. These representations indicate that the verb agrees with its subject in person and number. (We use "3" as an abbreviation for 3rd person, "SG" for singular and "PL" for plural.)

Let's see what happens when we encode these agreement constraints in a context-free grammar. We will begin with the simple CFG in (82).

- (82) $S \rightarrow NP\ VP$
 $NP \rightarrow DET\ N$
 $VP \rightarrow V$

 $DET \rightarrow 'this'$
 $N \rightarrow 'dog'$
 $V \rightarrow 'runs'$

Example (82) allows us to generate the sentence *this dog runs*; however, what we really want to do is also generate *these dogs run* while blocking unwanted strings such as **this dogs run* and **these dog runs*. The most straightforward approach is to add new non-terminals and productions to the grammar:

- (83) $S_{SG} \rightarrow NP_{SG}\ VP_{SG}$
 $S_{PL} \rightarrow NP_{PL}\ VP_{PL}$
 $NP_{SG} \rightarrow DET_{SG}\ N_{SG}$
 $NP_{PL} \rightarrow DET_{PL}\ N_{PL}$

```

VP_SG → V_SG
VP_PL → V_PL

DET_SG → 'this'
DET_PL → 'these'
N_SG → 'dog'
N_PL → 'dogs'
V_SG → 'runs'
V_PL → 'run'

```

It should be clear that this grammar will do the required task, but only at the cost of duplicating our previous set of productions.

11.2.2 Using Attributes and Constraints

We spoke informally of linguistic categories having *properties*; for example, that a noun has the property of being plural. Let's make this explicit:

(84) N [NUM=pl]

In (84), we have introduced some new notation which says that the category N has a **feature** called NUM (short for 'number') and that the value of this feature is pl (short for 'plural'). We can add similar annotations to other categories, and use them in lexical entries:

(85) DET [NUM=sg] → 'this'
 DET [NUM=pl] → 'these'
 N [NUM=sg] → 'dog'
 N [NUM=pl] → 'dogs'
 V [NUM=sg] → 'runs'
 V [NUM=pl] → 'run'

Does this help at all? So far, it looks just like a slightly more verbose alternative to what was specified in (83). Things become more interesting when we allow *variables* over feature values, and use these to state constraints:

(86) a. S → NP [NUM=?n] VP [NUM=?n]
 b. NP [NUM=?n] → DET [NUM=?n] N [NUM=?n]
 c. VP [NUM=?n] → V [NUM=?n]

We are using "?n" as a variable over values of NUM; it can be instantiated either to sg or pl. Its scope is limited to individual productions. That is, within (86a), for example, ?n must be instantiated to the same constant value; we can read the production as saying that whatever value NP takes for the feature NUM, VP must take the same value.

In order to understand how these feature constraints work, it's helpful to think about how one would go about building a tree. Lexical productions will admit the following local trees (trees of depth one):

(87) a. **Det[NUM=sg]**
 |
 this

- b.
-
- ```

 Det[NUM=pl]
 |
 these

```
- (88) a.
- 
- ```

    N[NUM=sg]
      |
      dog
  
```
- b.
-
- ```

 N[NUM=pl]
 |
 dogs

```

Now (86b) says that whatever the NUM values of N and DET are, they have to be the same. Consequently, (86b) will permit (87a) and (88a) to be combined into an NP as shown in (89a) and it will also allow (87b) and (88b) to be combined, as in (89b). By contrast, (90a) and (90b) are prohibited because the roots of their constituent local trees differ in their values for the NUM feature.

- (89) a.
- 
- ```

    NP[NUM=pl]
      |
      Det[NUM=sg]   N[NUM=sg]
      |           |
      this        dog
  
```
- b.
-
- ```

 NP[NUM=pl]
 |
 Det[NUM=pl] N[NUM=pl]
 | |
 these dogs

```
- (90) a.
- 
- ```

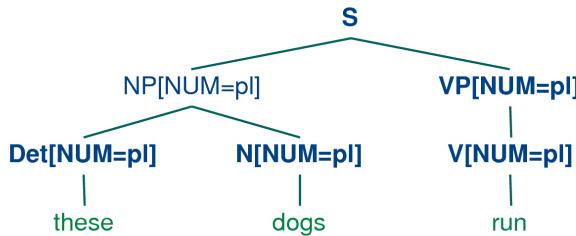
    NP[NUM=...]
      |
      Det[NUM=sg]   N[NUM=pl]
      |           |
      this        dogs
  
```
- b.
-
- ```

 NP[NUM=...]
 |
 Det[NUM=PL] N[NUM=SG]
 | |
 these dog

```

Production (86c) can be thought of as saying that the NUM value of the head verb has to be the same as the NUM value of the VP mother. Combined with (86a), we derive the consequence that if the NUM value of the subject head noun is *pl*, then so is the NUM value of the VP's head verb.

(91)



The grammar in [listing 11.1](#) illustrates most of the ideas we have introduced so far in this chapter, plus a couple of new ones.

Notice that a syntactic category can have more than one feature; for example,  $V[TENSE=pres, NUM=pl]$ . In general, we can add as many features as we like.

Notice also that we have used feature variables in lexical entries as well as grammatical productions. For example, *the* has been assigned the category  $DET[NUM=?n]$ . Why is this? Well, you know that the definite article *the* can combine with both singular and plural nouns. One way of describing this would be to add two lexical entries to the grammar, one each for the singular and plural versions of *the*. However, a more elegant solution is to leave the *NUM* value **underspecified** and letting it agree in number with whatever noun it combines with.

A final detail about [11.1](#) is the statement `%start S`. This a "directive" that tells the parser to take *S* as the start symbol for the grammar.

In general, when we are trying to develop even a very small grammar, it is convenient to put the productions in a file where they can be edited, tested and revised. We have saved [11.1](#) as a file named '`feat0.fcfg`' in the NLTK data distribution, and it can be accessed using `nltk.data.load()`. We can inspect the productions and the lexicon using the commands `print g.earley_grammar()` and `pprint(g.earley_lexicon())`.

Next, we can tokenize a sentence and use the `nbest_parse()` function to invoke the Earley chart parser.

Observe that the parser works directly with the underspecified productions given by the grammar. That is, the Predictor rule does not attempt to compile out all admissible feature combinations before trying to expand the non-terminals on the left hand side of a production. However, when the Scanner matches an input word against a lexical production that has been predicted, the new edge will typically contain fully specified features; e.g., the edge  $[PropN[NUM = sg] \rightarrow 'Kim', (0, 1)]$ . Recall from [Chapter 8](#) that the Fundamental (or Completer) Rule in standard CFGs is used to combine an incomplete edge that's expecting a nonterminal *B* with a following, complete edge whose left hand side matches *B*. In our current setting, rather than checking for a complete match, we test whether the expected category *B* will **unify** with the left hand side *B'* of a following complete edge. We will explain in more detail in [Section 11.3](#) how unification works; for the moment, it is enough to know that as a result of unification, any variable values of features in *B* will be instantiated by constant values in the corresponding feature structure in *B'*, and these instantiated values will be used in the new edge added by the Completer. This instantiation can be seen, for example, in the edge  $[NP[NUM=sg] \rightarrow PropN[NUM=sg] \bullet, (0, 1)]$  in [11.2](#), where the feature *NUM* has been assigned the value *sg*.

Finally, we can inspect the resulting parse trees (in this case, a single one).

```

>>> for tree in trees: print tree
...
(S
 (NP [NUM=sg] (PropN[NUM=sg] Kim))
 (VP [NUM=sg, TENSE=pres]

```

---

**Listing 11.1** Example Feature-Based Grammar

---

```
>>> nltk.data.show_cfg('grammars/feat0.fcfg')
% start S
#####
Grammar Rules
#####
S expansion rules
S -> NP[NUM=?n] VP[NUM=?n]
NP expansion rules
NP[NUM=?n] -> N[NUM=?n]
NP[NUM=?n] -> PropN[NUM=?n]
NP[NUM=?n] -> Det[NUM=?n] N[NUM=?n]
NP[NUM=pl] -> N[NUM=pl]
VP expansion rules
VP[TENSE=?t, NUM=?n] -> IV[TENSE=?t, NUM=?n]
VP[TENSE=?t, NUM=?n] -> TV[TENSE=?t, NUM=?n] NP
#####
Lexical Rules
#####
Det[NUM=sg] -> 'this' | 'every'
Det[NUM=pl] -> 'these' | 'all'
Det -> 'the' | 'some'
PropN[NUM=sg] -> 'Kim' | 'Jody'
N[NUM=sg] -> 'dog' | 'girl' | 'car' | 'child'
N[NUM=pl] -> 'dogs' | 'girls' | 'cars' | 'children'
IV[TENSE=pres, NUM=sg] -> 'disappears' | 'walks'
TV[TENSE=pres, NUM=sg] -> 'sees' | 'likes'
IV[TENSE=pres, NUM=pl] -> 'disappear' | 'walk'
TV[TENSE=pres, NUM=pl] -> 'see' | 'like'
IV[TENSE=past, NUM=?n] -> 'disappeared' | 'walked'
TV[TENSE=past, NUM=?n] -> 'saw' | 'liked'
```

---

**Listing 11.2** Trace of Feature-Based Chart Parser

```

>>> tokens = 'Kim likes children'.split()
>>> from nltk.parse import load_earley
>>> cp = load_earley('grammars/feat0.fcfg', trace=2)
>>> trees = cp.nbest_parse(tokens)
 | .K.1.c. |
Processing queue 0
Predictor |> . . . | [0:0] S[] -> * NP[NUM=?n] VP[NUM=?n] {}
Predictor |> . . . | [0:0] NP[NUM=?n] -> * N[NUM=?n] {}
Predictor |> . . . | [0:0] NP[NUM=?n] -> * PropN[NUM=?n] {}
Predictor |> . . . | [0:0] NP[NUM=?n] -> * Det[NUM=?n] N[NUM=?n] {}
Predictor |> . . . | [0:0] NP[NUM='pl'] -> * N[NUM='pl'] {}
Scanner |[-] . . | [0:1] 'Kim'
Scanner |[-] . . | [0:1] PropN[NUM='sg'] -> 'Kim' *
Processing queue 1
Completer |[-] . . | [0:1] NP[NUM='sg'] -> PropN[NUM='sg'] *
Completer |[-> . . | [0:1] S[] -> NP[NUM=?n] * VP[NUM=?n] {?n: 'sg'}
Predictor |. > . . | [1:1] VP[NUM=?n, TENSE=?t] -> * IV[NUM=?n, TENSE=?t] {}
Predictor |. > . . | [1:1] VP[NUM=?n, TENSE=?t] -> * TV[NUM=?n, TENSE=?t] NP[] {}
Scanner |. [-] . | [1:2] 'likes'
Scanner |. [-] . | [1:2] TV[NUM='sg', TENSE='pres'] -> 'likes' *
Processing queue 2
Completer |. [-> . | [1:2] VP[NUM=?n, TENSE=?t] -> TV[NUM=?n, TENSE=?t] * NP[] {?n:
Predictor |. . > . | [2:2] NP[NUM=?n] -> * N[NUM=?n] {}
Predictor |. . > . | [2:2] NP[NUM=?n] -> * PropN[NUM=?n] {}
Predictor |. . > . | [2:2] NP[NUM=?n] -> * Det[NUM=?n] N[NUM=?n] {}
Predictor |. . > . | [2:2] NP[NUM='pl'] -> * N[NUM='pl'] {}
Scanner |. . [-] | [2:3] 'children'
Scanner |. . [-] | [2:3] N[NUM='pl'] -> 'children' *
Processing queue 3
Completer |. . [-] | [2:3] NP[NUM='pl'] -> N[NUM='pl'] *
Completer |. [---] | [1:3] VP[NUM='sg', TENSE='pres'] -> TV[NUM='sg', TENSE='pres'] *
Completer |[=====] | [0:3] S[] -> NP[NUM='sg'] VP[NUM='sg'] *
Completer |[=====] | [0:3] [INIT] [] -> S[] *
>>> for tree in trees: print tree
(S[]
 (NP[NUM='sg'] (PropN[NUM='sg'] Kim))
 (VP[NUM='sg', TENSE='pres']
 (TV[NUM='sg', TENSE='pres'] likes)
 (NP[NUM='pl'] (N[NUM='pl'] children))))
```

```
(TV [NUM=sg, TENSE=pres] likes)
 (NP [NUM=pl] (N [NUM=pl] children)))
```

### 11.2.3 Terminology

So far, we have only seen feature values like *sg* and *pl*. These simple values are usually called **atomic** — that is, they can't be decomposed into subparts. A special case of atomic values are **boolean** values, that is, values that just specify whether a property is true or false of a category. For example, we might want to distinguish **auxiliary** verbs such as *can*, *may*, *will* and *do* with the boolean feature AUX. Then our lexicon for verbs could include entries such as (92). (Note that we follow the convention that boolean features are not written F +, F – but simply +F, -F, respectively.)

- (92)       $V[TENSE=pres, +AUX=+] \rightarrow 'can'$   
 $V[TENSE=pres, +AUX=+] \rightarrow 'may'$   
 $V[TENSE=pres, -AUX -] \rightarrow 'walks'$   
 $V[TENSE=pres, -AUX -] \rightarrow 'likes'$

We have spoken informally of attaching "feature annotations" to syntactic categories. A more general approach is to treat the whole category — that is, the non-terminal symbol plus the annotation — as a bundle of features. Consider, for example, the object we have written as (93).

- (93)       $N[\text{NUM}=sg]$

The syntactic category N, as we have seen before, provides part of speech information. This information can itself be captured as a feature value pair, using POS to represent "part of speech":

- (94)       $[\text{POS}=N, \text{NUM}=sg]$

In fact, we regard (94) as our "official" representation of a feature-based linguistic category, and (93) as a convenient abbreviation. A bundle of feature-value pairs is called a **feature structure** or an **attribute value matrix** (AVM). A feature structure that contains a specification for the feature POS is a **linguistic category**.

In addition to atomic-valued features, we allow features whose values are themselves feature structures. For example, we might want to group together agreement features (e.g., person, number and gender) as a distinguished part of a category, as shown in (95).

$$(95) \begin{bmatrix} \text{POS} & N \\ & \begin{bmatrix} \text{PER} & 3 \\ \text{NUM} & pl \\ \text{GND} & fem \end{bmatrix} \\ \text{AGR} & \end{bmatrix}$$

In this case, we say that the feature AGR has a **complex** value.

There is no particular significance to the *order* of features in a feature structure. So (95) is equivalent to (95).

$$(96) \begin{bmatrix} & \begin{bmatrix} \text{NUM} & pl \\ \text{PER} & 3 \\ \text{GND} & fem \end{bmatrix} \\ \text{AGR} & \\ & \end{bmatrix} \\ \begin{bmatrix} \text{POS} & N \end{bmatrix}$$

Once we have the possibility of using features like AGR, we can refactor a grammar like 11.1 so that agreement features are bundled together. A tiny grammar illustrating this point is shown in (97).

|      |                                                                |
|------|----------------------------------------------------------------|
| (97) | $S \rightarrow NP [AGR=?n] VP [AGR=?n]$                        |
|      | $NP [AGR=?n] \rightarrow PROPN [AGR=?n]$                       |
|      | $VP [TENSE=?t, AGR=?n] \rightarrow COP [TENSE=?t, AGR=?n] Adj$ |
|      | $COP [TENSE=pres, AGR=[NUM=sg, PER=3]] \rightarrow 'is'$       |
|      | $PROPN [AGR=[NUM=sg, PER=3]] \rightarrow 'Kim'$                |
|      | $Adj \rightarrow 'happy'$                                      |

#### 11.2.4 Exercises

1. ☀ What constraints are required to correctly parse strings like *I am happy* and *she is happy* but not *\*you is happy* or *\*they am happy*? Implement two solutions for the present tense paradigm of the verb *be* in English, first taking Grammar (83) as your starting point, and then taking Grammar (97) as the starting point.

2. ☀ Develop a variant of grammar 11.1 that uses a feature COUNT to make the distinctions shown below:

(98) a. The boy sings.

b. \*Boy sings.

(99) a. The boys sing.

b. Boys sing.

(100) a. The boys sing.

b. Boys sing.

(101) a. The water is precious.

b. Water is precious.

3. ⓠ Develop a feature-based grammar that will correctly describe the following Spanish noun phrases:

|                       |                     |                   |                                   |
|-----------------------|---------------------|-------------------|-----------------------------------|
| (102)                 | un<br>INDEF.SG.MASC | cuadro<br>picture | hermos-o<br>beautiful-<br>SG.MASC |
| 'a beautiful picture' |                     |                   |                                   |

|                      |                        |                            |                                    |
|----------------------|------------------------|----------------------------|------------------------------------|
| (103)                | un-os<br>INDEF-PL.MASC | cuadro-s<br>picture-<br>PL | hermos-os<br>beautiful-<br>PL.MASC |
| 'beautiful pictures' |                        |                            |                                    |

|                       |                      |                    |                                  |
|-----------------------|----------------------|--------------------|----------------------------------|
| (104)                 | un-a<br>INDEF-SG.FEM | cortina<br>curtain | hermos-a<br>beautiful-<br>SG.FEM |
| 'a beautiful curtain' |                      |                    |                                  |

|       |              |           |            |
|-------|--------------|-----------|------------|
|       | un-as        | cortina-s | hermos-as  |
| (105) | INDEF-PL.FEM | curtain   | beautiful- |
|       |              |           | PL.FEM     |

'beautiful curtains'

4. ❶ Develop a wrapper for the `earley_parser` so that a trace is only printed if the input string fails to parse.

## 11.3 Computing with Feature Structures

In this section, we will show how feature structures can be constructed and manipulated in Python. We will also discuss the fundamental operation of unification, which allows us to combine the information contained in two different feature structures.

### 11.3.1 Feature Structures in Python

Feature structures are declared with the `FeatStruct()` constructor. Atomic feature values can be strings or integers.

```
>>> fs1 = nltk.FeatStruct(TENSE='past', NUM='sg')
>>> print fs1
[NUM = 'sg']
[TENSE = 'past']
```

A feature structure is actually just a kind of dictionary, and so we access its values by indexing in the usual way. We can use our familiar syntax to *assign* values to features:

```
>>> fs1 = nltk.FeatStruct(PER=3, NUM='pl', GND='fem')
>>> print fs1['GND']
fem
>>> fs1['CASE'] = 'acc'
```

We can also define feature structures that have complex values, as discussed earlier.

```
>>> fs2 = nltk.FeatStruct(POS='N', AGR=fs1)
>>> print fs2
[[CASE = 'acc']]
[AGR = [GND = 'fem']]
[[NUM = 'pl']]
[[PER = 3]]
[]
[POS = 'N']
>>> print fs2['AGR']
[CASE = 'acc']
[GND = 'fem']
[NUM = 'pl']
[PER = 3]
>>> print fs2['AGR']['PER']
3
```

An alternative method of specifying feature structures is to use a bracketed string consisting of feature-value pairs in the format `feature=value`, where values may themselves be feature structures:

```
>>> nltk.FeatStruct("[POS='N', AGR=[PER=3, NUM='pl', GND='fem']]")
[AGR=[GND='fem', NUM='pl', PER=3], POS='N']
```

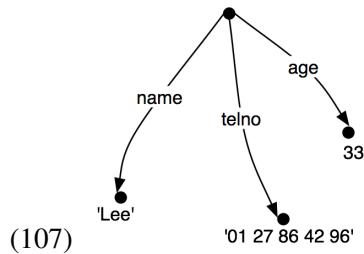
### 11.3.2 Feature Structures as Graphs

Feature structures are not inherently tied to linguistic objects; they are general purpose structures for representing knowledge. For example, we could encode information about a person in a feature structure:

```
>>> person01 = nltk.FeatStruct(name='Lee', telno='01 27 86 42 96', age=33)
```

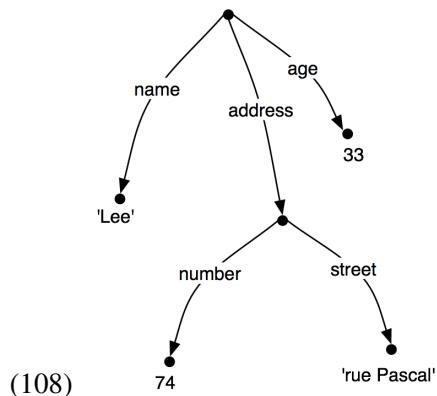
(106) 
$$\begin{bmatrix} \text{NAME} & \text{'Lee'} \\ \text{TELNO} & 01\ 27\ 86\ 42\ 96 \\ \text{AGE} & 33 \end{bmatrix}$$

It is sometimes helpful to view feature structures as graphs; more specifically, **directed acyclic graphs** (DAGs). (107) is equivalent to the AVM (106).



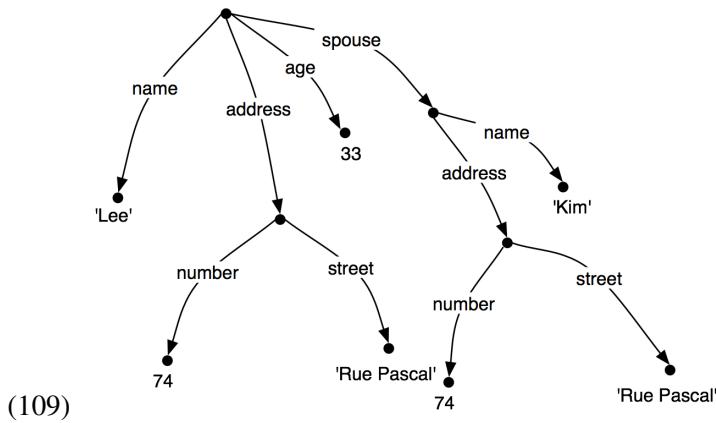
The feature names appear as labels on the directed arcs, and feature values appear as labels on the nodes that are pointed to by the arcs.

Just as before, feature values can be complex:

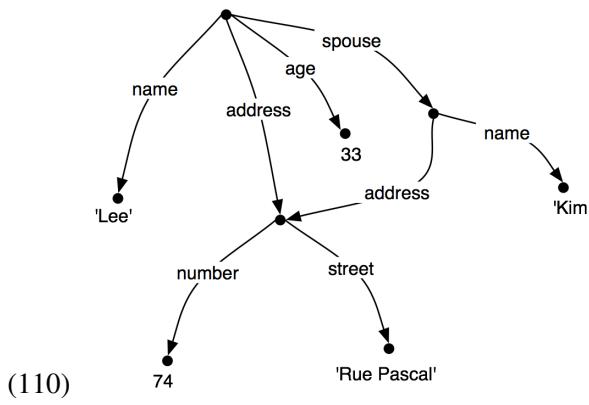


When we look at such graphs, it is natural to think in terms of paths through the graph. A **feature path** is a sequence of arcs that can be followed from the root node. We will represent paths as tuples. Thus, ('address', 'street') is a feature path whose value in (108) is the string "rue Pascal".

Now let's consider a situation where Lee has a spouse named "Kim", and Kim's address is the same as Lee's. We might represent this as (109).



However, rather than repeating the address information in the feature structure, we can "share" the same sub-graph between different arcs:



In other words, the value of the path ('ADDRESS') in (110) is identical to the value of the path ('SPOUSE', 'ADDRESS'). DAGs such as (110) are said to involve **structure sharing** or **reentrancy**. When two paths have the same value, they are said to be **equivalent**.

There are a number of notations for representing reentrancy in matrix-style representations of feature structures. We adopt the following convention: the first occurrence of a shared feature structure is prefixed with an integer in parentheses, such as (1), and any subsequent reference to that structure uses the notation  $\rightarrow (1)$ , as shown below.

```
>>> fs = nltk.FeatStruct("""[NAME='Lee', ADDRESS=(1)[NUMBER=74, STREET='rue Pascal'],
... SPOUSE=[NAME='Kim', ADDRESS->(1)]""")
>>> print fs
[ADDRESS = (1) [NUMBER = 74]]
[[STREET = 'rue Pascal']]
[]
[]
[NAME = 'Lee']
[]
[SPOUSE = [ADDRESS -> (1)]]
[[NAME = 'Kim']]
```

This is similar to more conventional displays of AVMs, as shown in (111).

|         |             |                                                                                                                             |         |             |      |       |
|---------|-------------|-----------------------------------------------------------------------------------------------------------------------------|---------|-------------|------|-------|
| ADDRESS | $\boxed{1}$ | [NUMBER    74<br>STREET    'rue Pascal']                                                                                    |         |             |      |       |
| NAME    |             | 'Lee'                                                                                                                       |         |             |      |       |
| SPOUSE  |             | <table border="0"> <tr> <td>ADDRESS</td><td><math>\boxed{1}</math></td></tr> <tr> <td>NAME</td><td>'Kim'</td></tr> </table> | ADDRESS | $\boxed{1}$ | NAME | 'Kim' |
| ADDRESS | $\boxed{1}$ |                                                                                                                             |         |             |      |       |
| NAME    | 'Kim'       |                                                                                                                             |         |             |      |       |

|         |                                                                                                                                                                                                                                                                                                                                                                 |                                                                                                                             |             |                                          |      |       |       |        |  |                                                                                                                             |         |             |      |       |
|---------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|-------------|------------------------------------------|------|-------|-------|--------|--|-----------------------------------------------------------------------------------------------------------------------------|---------|-------------|------|-------|
| (111)   | <table border="0"> <tr> <td>ADDRESS</td><td><math>\boxed{1}</math></td><td>[NUMBER    74<br/>STREET    'rue Pascal']</td></tr> <tr> <td>NAME</td><td></td><td>'Lee'</td></tr> <tr> <td>SPOUSE</td><td></td><td> <table border="0"> <tr> <td>ADDRESS</td><td><math>\boxed{1}</math></td></tr> <tr> <td>NAME</td><td>'Kim'</td></tr> </table> </td></tr> </table> | ADDRESS                                                                                                                     | $\boxed{1}$ | [NUMBER    74<br>STREET    'rue Pascal'] | NAME |       | 'Lee' | SPOUSE |  | <table border="0"> <tr> <td>ADDRESS</td><td><math>\boxed{1}</math></td></tr> <tr> <td>NAME</td><td>'Kim'</td></tr> </table> | ADDRESS | $\boxed{1}$ | NAME | 'Kim' |
| ADDRESS | $\boxed{1}$                                                                                                                                                                                                                                                                                                                                                     | [NUMBER    74<br>STREET    'rue Pascal']                                                                                    |             |                                          |      |       |       |        |  |                                                                                                                             |         |             |      |       |
| NAME    |                                                                                                                                                                                                                                                                                                                                                                 | 'Lee'                                                                                                                       |             |                                          |      |       |       |        |  |                                                                                                                             |         |             |      |       |
| SPOUSE  |                                                                                                                                                                                                                                                                                                                                                                 | <table border="0"> <tr> <td>ADDRESS</td><td><math>\boxed{1}</math></td></tr> <tr> <td>NAME</td><td>'Kim'</td></tr> </table> | ADDRESS     | $\boxed{1}$                              | NAME | 'Kim' |       |        |  |                                                                                                                             |         |             |      |       |
| ADDRESS | $\boxed{1}$                                                                                                                                                                                                                                                                                                                                                     |                                                                                                                             |             |                                          |      |       |       |        |  |                                                                                                                             |         |             |      |       |
| NAME    | 'Kim'                                                                                                                                                                                                                                                                                                                                                           |                                                                                                                             |             |                                          |      |       |       |        |  |                                                                                                                             |         |             |      |       |

The bracketed integer is sometimes called a **tag** or a **coindex**. The choice of integer is not significant. There can be any number of tags within a single feature structure.

```
>>> fs1 = nltk.FeatStruct("[A='a', B=(1) [C='c'], D->(1), E->(1)]")
```

|       |                                                                                                                                                                                                                                             |            |     |   |             |            |   |             |   |             |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|-----|---|-------------|------------|---|-------------|---|-------------|
| (112) | <table border="0"> <tr> <td>A</td><td>'a'</td></tr> <tr> <td>B</td><td><math>\boxed{1}</math></td><td>[C    'c']</td></tr> <tr> <td>D</td><td><math>\boxed{1}</math></td></tr> <tr> <td>E</td><td><math>\boxed{1}</math></td></tr> </table> | A          | 'a' | B | $\boxed{1}$ | [C    'c'] | D | $\boxed{1}$ | E | $\boxed{1}$ |
| A     | 'a'                                                                                                                                                                                                                                         |            |     |   |             |            |   |             |   |             |
| B     | $\boxed{1}$                                                                                                                                                                                                                                 | [C    'c'] |     |   |             |            |   |             |   |             |
| D     | $\boxed{1}$                                                                                                                                                                                                                                 |            |     |   |             |            |   |             |   |             |
| E     | $\boxed{1}$                                                                                                                                                                                                                                 |            |     |   |             |            |   |             |   |             |

### 11.3.3 Subsumption and Unification

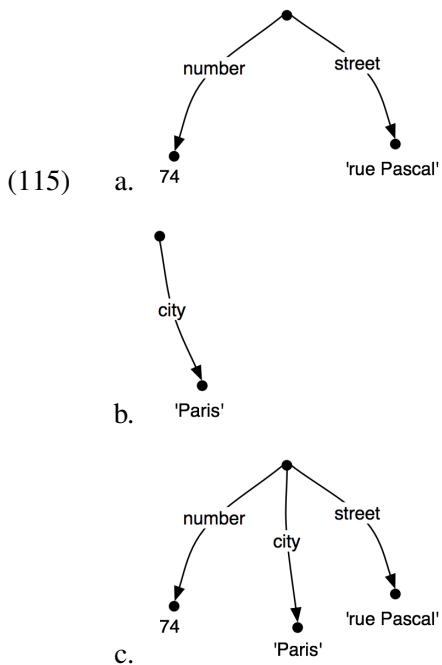
It is standard to think of feature structures as providing **partial information** about some object, in the sense that we can order feature structures according to how general they are. For example, (113a) is more general (less specific) than (113b), which in turn is more general than (113c).

- (113) a. [NUMBER    74]
- b. [NUMBER    74  
         STREET    'rue Pascal']
- c. [NUMBER    74  
         STREET    'rue Pascal'  
         CITY      'Paris']

This ordering is called **subsumption**; a more general feature structure **subsumes** a less general one. If  $FS_0$  subsumes  $FS_1$  (formally, we write  $FS_0 \sqsupseteq FS_1$ ), then  $FS_1$  must have all the paths and path equivalences of  $FS_0$ , and may have additional paths and equivalences as well. Thus, (109) subsumes (110), since the latter has additional path equivalences.. It should be obvious that subsumption only provides a partial ordering on feature structures, since some feature structures are incommensurable. For example, (114) neither subsumes nor is subsumed by (113a).

- (114) [TELNO    01 27 86 42 96]

So we have seen that some feature structures are more specific than others. How do we go about specializing a given feature structure? For example, we might decide that addresses should consist of not just a street number and a street name, but also a city. That is, we might want to *merge* graph (115b) with (115a) to yield (115c).



Merging information from two feature structures is called **unification** and is supported by the `unify()` method.

```

>>> fs1 = nltk.FeatStruct(NUMBER=74, STREET='rue Pascal')
>>> fs2 = nltk.FeatStruct(CITY='Paris')
>>> print fs1.unify(fs2)
[CITY = 'Paris']
[NUMBER = 74]
[STREET = 'rue Pascal']

```

Unification is formally defined as a binary operation:  $FS_0 \sqcap FS_1$ . Unification is symmetric, so

$$(116) \quad FS_0 \sqcap FS_1 = FS_1 \sqcap FS_0.$$

The same is true in Python:

```

>>> print fs2.unify(fs1)
[CITY = 'Paris']
[NUMBER = 74]
[STREET = 'rue Pascal']

```

If we unify two feature structures which stand in the subsumption relationship, then the result of unification is the most specific of the two:

$$(117) \text{ If } FS_0 \sqsupseteq FS_1, \text{ then } FS_0 \sqcap FS_1 = FS_1$$

For example, the result of unifying (113b) with (113c) is (113c).

Unification between  $FS_0$  and  $FS_1$  will fail if the two feature structures share a path  $\pi$ , but the value of  $\pi$  in  $FS_0$  is a distinct atom from the value of  $\pi$  in  $FS_1$ . This is implemented by setting the result of unification to be `None`.

```
>>> fs0 = nltk.FeatStruct(A='a')
>>> fs1 = nltk.FeatStruct(A='b')
>>> fs2 = fs0.unify(fs1)
>>> print fs2
None
```

Now, if we look at how unification interacts with structure-sharing, things become really interesting. First, let's define (109) in Python:

```
>>> fs0 = nltk.FeatStruct("""[NAME=Lee,
... ADDRESS=[NUMBER=74,
... STREET='rue Pascal'],
... SPOUSE= [NAME=Kim,
... ADDRESS=[NUMBER=74,
... STREET='rue Pascal']]""")
```

(118)

|         |                                                                                                                                                                                                      |  |
|---------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|
| ADDRESS | $\left[ \begin{array}{ll} \text{NUMBER} & 74 \\ \text{STREET} & \text{'rue Pascal'} \end{array} \right]$                                                                                             |  |
| NAME    | 'Lee'                                                                                                                                                                                                |  |
| SPOUSE  | $\left[ \begin{array}{ll} \text{ADDRESS} & \left[ \begin{array}{ll} \text{NUMBER} & 74 \\ \text{STREET} & \text{'rue Pascal'} \end{array} \right] \\ \text{NAME} & \text{'Kim'} \end{array} \right]$ |  |

What happens when we augment Kim's address with a specification for CITY? (Notice that `fs1` includes the whole path from the root of the feature structure down to CITY.)

```
>>> fs1 = nltk.FeatStruct("[SPOUSE = [ADDRESS = [CITY = Paris]]])
```

(119) shows the result of unifying `fs0` with `fs1`:

(119)

|         |                                                                                                                                                                                                                                      |  |
|---------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|
| ADDRESS | $\left[ \begin{array}{ll} \text{NUMBER} & 74 \\ \text{STREET} & \text{'rue Pascal'} \end{array} \right]$                                                                                                                             |  |
| NAME    | 'Lee'                                                                                                                                                                                                                                |  |
| SPOUSE  | $\left[ \begin{array}{ll} \text{ADDRESS} & \left[ \begin{array}{ll} \text{CITY} & \text{'Paris'} \\ \text{NUMBER} & 74 \\ \text{STREET} & \text{'rue Pascal'} \end{array} \right] \\ \text{NAME} & \text{'Kim'} \end{array} \right]$ |  |

By contrast, the result is very different if `fs1` is unified with the structure-sharing version `fs2` (also shown as (110)):

```
>>> fs2 = nltk.FeatStruct("""[NAME=Lee, ADDRESS=(1) [NUMBER=74, STREET='rue Pascal'],
... SPOUSE=[NAME=Kim, ADDRESS->(1)]""")
```

|         |                                                                                                                                                                                                                        |         |                                                                                                                 |        |              |        |              |      |       |
|---------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|-----------------------------------------------------------------------------------------------------------------|--------|--------------|--------|--------------|------|-------|
| ADDRESS | <table border="1"> <tr> <td>CITY</td><td>'Paris'</td></tr> <tr> <td>NUMBER</td><td>74</td></tr> <tr> <td>STREET</td><td>'rue Pascal'</td></tr> </table>                                                                | CITY    | 'Paris'                                                                                                         | NUMBER | 74           | STREET | 'rue Pascal' |      |       |
| CITY    | 'Paris'                                                                                                                                                                                                                |         |                                                                                                                 |        |              |        |              |      |       |
| NUMBER  | 74                                                                                                                                                                                                                     |         |                                                                                                                 |        |              |        |              |      |       |
| STREET  | 'rue Pascal'                                                                                                                                                                                                           |         |                                                                                                                 |        |              |        |              |      |       |
| NAME    | 'Lee'                                                                                                                                                                                                                  |         |                                                                                                                 |        |              |        |              |      |       |
| SPOUSE  | <table border="1"> <tr> <td>ADDRESS</td><td> <table border="1"> <tr> <td>NUMBER</td><td>74</td></tr> <tr> <td>STREET</td><td>'rue Pascal'</td></tr> </table> </td></tr> <tr> <td>NAME</td><td>'Kim'</td></tr> </table> | ADDRESS | <table border="1"> <tr> <td>NUMBER</td><td>74</td></tr> <tr> <td>STREET</td><td>'rue Pascal'</td></tr> </table> | NUMBER | 74           | STREET | 'rue Pascal' | NAME | 'Kim' |
| ADDRESS | <table border="1"> <tr> <td>NUMBER</td><td>74</td></tr> <tr> <td>STREET</td><td>'rue Pascal'</td></tr> </table>                                                                                                        | NUMBER  | 74                                                                                                              | STREET | 'rue Pascal' |        |              |      |       |
| NUMBER  | 74                                                                                                                                                                                                                     |         |                                                                                                                 |        |              |        |              |      |       |
| STREET  | 'rue Pascal'                                                                                                                                                                                                           |         |                                                                                                                 |        |              |        |              |      |       |
| NAME    | 'Kim'                                                                                                                                                                                                                  |         |                                                                                                                 |        |              |        |              |      |       |

Rather than just updating what was in effect Kim's "copy" of Lee's address, we have now updated *both* their addresses at the same time. More generally, if a unification involves specializing the value of some path  $\pi$ , then that unification simultaneously specializes the value of *any path that is equivalent to  $\pi$* .

As we have already seen, structure sharing can also be stated using variables such as  $?x$ .

```
>>> fs1 = nltk.FeatStruct("[ADDRESS1=[NUMBER=74, STREET='rue Pascal']]")
>>> fs2 = nltk.FeatStruct("[ADDRESS1=?x, ADDRESS2=?x]")
>>> print fs2
[ADDRESS1 = ?x]
[ADDRESS2 = ?x]
>>> print fs2.unify(fs1)
[ADDRESS1 = (1) [NUMBER = 74]]
[[STREET = 'rue Pascal']]
[]
[ADDRESS2 -> (1)]
```

### 11.3.4 Exercises

1.  $\diamond$  Write a function `subsumes()` which holds of two feature structures `fs1` and `fs2` just in case `fs1` subsumes `fs2`.
2.  $\bullet$  Consider the feature structures shown in Listing 11.3.

---

#### Listing 11.3

```
fs1 = nltk.FeatStruct("[A = (1)b, B= [C ->(1)]]")
fs2 = nltk.FeatStruct("[B = [D = d]]")
fs3 = nltk.FeatStruct("[B = [C = d]]")
fs4 = nltk.FeatStruct("[A = (1)[B = b], C->(1)]")
fs5 = nltk.FeatStruct("[A = [D = (1)e], C = [E -> (1)]]")
fs6 = nltk.FeatStruct("[A = [D = (1)e], C = [B -> (1)]]")
fs7 = nltk.FeatStruct("[A = [D = (1)e, F = (2)[], C = [B -> (1), E -> (2)]]")
fs8 = nltk.FeatStruct("[A = [B = b], C = [E = [G = e]]]")
fs9 = nltk.FeatStruct("[A = (1)[B = b], C -> (1)]")
```

---

Work out on paper what the result is of the following unifications. (Hint: you might find it useful to draw the graph structures.)

- 1) `fs1` and `fs2`
- 2) `fs1` and `fs3`

- 3)  $fs_4$  and  $fs_5$
- 4)  $fs_5$  and  $fs_6$
- 5)  $fs_7$  and  $fs_8$
- 6)  $fs_7$  and  $fs_9$

Check your answers using Python.

3. ● List two feature structures that subsume  $[A=?x, B=?x]$ .
4. ● Ignoring structure sharing, give an informal algorithm for unifying two feature structures.

## 11.4 Extending a Feature-Based Grammar

### 11.4.1 Subcategorization

In [Chapter 8](#), we proposed to augment our category labels to represent different kinds of verb. We introduced labels such as IV and TV for intransitive and transitive verbs respectively. This allowed us to write productions like the following:

$$(121) \quad \begin{array}{l} VP \rightarrow IV \\ VP \rightarrow TV \ NP \end{array}$$

Although we know that IV and TV are two kinds of V, from a formal point of view IV has no closer relationship with TV than it does with NP. As it stands, IV and TV are just atomic nonterminal symbols from a CFG. This approach doesn't allow us to say anything about the class of verbs in general. For example, we cannot say something like "All lexical items of category V can be marked for tense", since *bark*, say, is an item of category IV, not V. A simple solution, originally developed for a grammar framework called Generalized Phrase Structure Grammar (GPSG), stipulates that lexical categories may bear a SUBCAT feature whose values are integers. This is illustrated in a modified portion of [11.1](#), shown in [\(122\)](#).

$$(122) \quad \begin{array}{l} VP [TENSE=?t, NUM=?n] \rightarrow V [SUBCAT=0, TENSE=?t, NUM=?n] \\ VP [TENSE=?t, NUM=?n] \rightarrow V [SUBCAT=1, TENSE=?t, NUM=?n] \ NP \\ VP [TENSE=?t, NUM=?n] \rightarrow V [SUBCAT=2, TENSE=?t, NUM=?n] \ Sbar \\ \\ V [SUBCAT=0, TENSE=pres, NUM=sg] \rightarrow 'disappears' \mid 'walks' \\ V [SUBCAT=1, TENSE=pres, NUM=sg] \rightarrow 'sees' \mid 'likes' \\ V [SUBCAT=2, TENSE=pres, NUM=sg] \rightarrow 'says' \mid 'claims' \\ \\ V [SUBCAT=0, TENSE=pres, NUM=pl] \rightarrow 'disappear' \mid 'walk' \\ V [SUBCAT=1, TENSE=pres, NUM=pl] \rightarrow 'see' \mid 'like' \\ V [SUBCAT=2, TENSE=pres, NUM=pl] \rightarrow 'say' \mid 'claim' \\ \\ V [SUBCAT=0, TENSE=past, NUM=?n] \rightarrow 'disappeared' \mid 'walked' \\ V [SUBCAT=1, TENSE=past, NUM=?n] \rightarrow 'saw' \mid 'liked' \\ V [SUBCAT=2, TENSE=past, NUM=?n] \rightarrow 'said' \mid 'claimed' \end{array}$$

When we see a lexical category like  $V[SUBCAT=1]$ , we can interpret the SUBCAT specification as a pointer to the production in which  $V[SUBCAT=1]$  is introduced as the head daughter in a VP production.

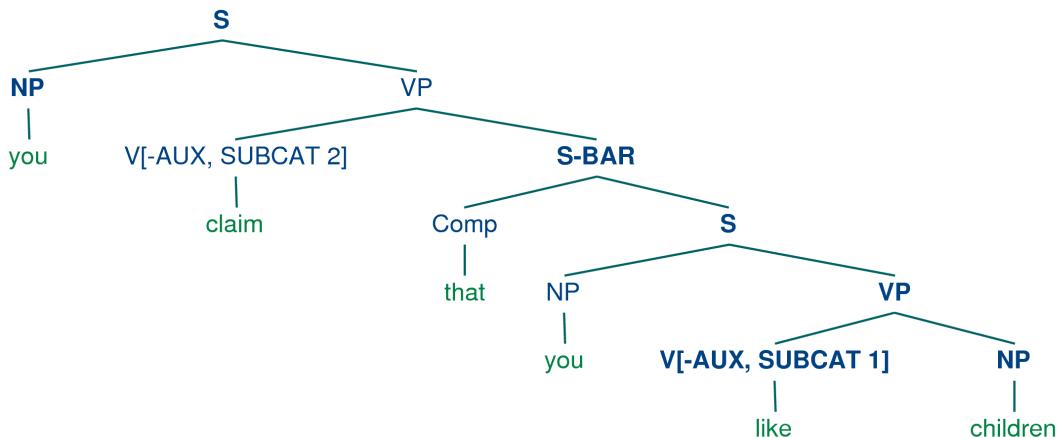
By convention, there is a one-to-one correspondence between SUBCAT values and the productions that introduce lexical heads. It's worth noting that the choice of integer which acts as a value for SUBCAT is completely arbitrary — we could equally well have chosen 3999, 113 and 57 as our two values in (122). On this approach, SUBCAT can *only* appear on lexical categories; it makes no sense, for example, to specify a SUBCAT value on VP.

In our third class of verbs above, we have specified a category S-BAR. This is a label for subordinate clauses such as the complement of *claim* in the example *You claim that you like children*. We require two further productions to analyze such sentences:

- (123)    S-BAR → Comp S  
             Comp → 'that'

The resulting structure is the following.

- (124)



An alternative treatment of subcategorization, due originally to a framework known as categorial grammar, is represented in feature-based frameworks such as PATR and Head-driven Phrase Structure Grammar. Rather than using SUBCAT values as a way of indexing productions, the SUBCAT value directly encodes the valency of a head (the list of arguments that it can combine with). For example, a verb like *put* that takes NP and PP complements (*put the book on the table*) might be represented as (125):

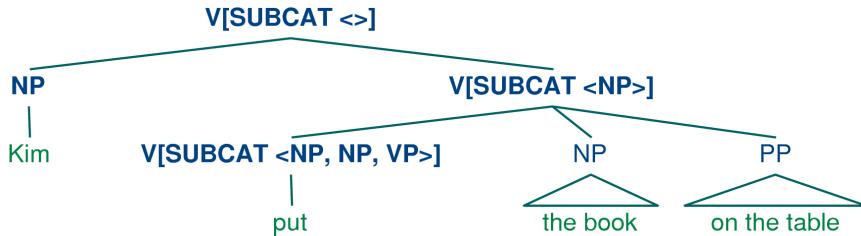
- (125) V[SUBCAT NP, NP, PP ]

This says that the verb can combine with three arguments. The leftmost element in the list is the subject NP, while everything else — an NP followed by a PP in this case — comprises the subcategorized-for complements. When a verb like *put* is combined with appropriate complements, the requirements which are specified in the SUBCAT are discharged, and only a subject NP is needed. This category, which corresponds to what is traditionally thought of as VP, might be represented as follows.

- (126) V[SUBCAT NP ]

Finally, a sentence is a kind of verbal category that has *no* requirements for further arguments, and hence has a SUBCAT whose value is the empty list. The tree (127) shows how these category assignments combine in a parse of *Kim put the book on the table*.

(127)

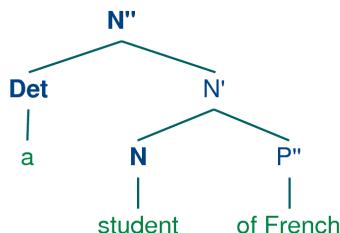


### 11.4.2 Heads Revisited

We noted in the previous section that by factoring subcategorization information out of the main category label, we could express more generalizations about properties of verbs. Another property of this kind is the following: expressions of category V are heads of phrases of category VP. Similarly (and more informally) Ns are heads of NPs, As (i.e., adjectives) are heads of APs, and Ps (i.e., adjectives) are heads of PPs. Not all phrases have heads — for example, it is standard to say that coordinate phrases (e.g., *the book and the bell*) lack heads — nevertheless, we would like our grammar formalism to express the mother / head-daughter relation where it holds. Now, although it looks as though there is something in common between, say, V and VP, this is more of a handy convention than a real claim, since V and VP formally have no more in common than V and DET.

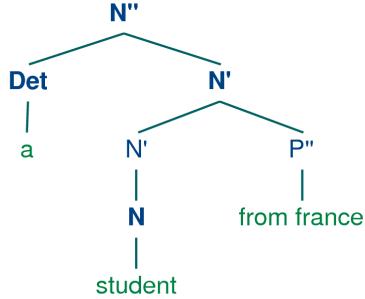
X-bar syntax (cf. [?], [?]) addresses this issue by abstracting out the notion of **phrasal level**. It is usual to recognize three such levels. If N represents the lexical level, then N' represents the next level up, corresponding to the more traditional category NOM, while N'' represents the phrasal level, corresponding to the category NP. (The primes here replace the typographically more demanding horizontal bars of [?]). (128) illustrates a representative structure.

(128)



The head of the structure (128) is N while N' and N'' are called **(phrasal) projections** of N. N'' is the **maximal projection**, and N is sometimes called the **zero projection**. One of the central claims of X-bar syntax is that all constituents share a structural similarity. Using X as a variable over N, V, A and P, we say that directly subcategorized *complements* of the head are always placed as sisters of the lexical head, whereas *adjuncts* are placed as sisters of the intermediate category, x'. Thus, the configuration of the P'' adjunct in (129) contrasts with that of the complement P'' in (128).

(129)



The productions in (130) illustrate how bar levels can be encoded using feature structures.

- (130)     $S \rightarrow N[\text{BAR}=2] \ V[\text{BAR}=2]$   
 $N[\text{BAR}=2] \rightarrow \text{DET} \ N[\text{BAR}=1]$   
 $N[\text{BAR}=1] \rightarrow N[\text{BAR}=1] \ P[\text{BAR}=2]$   
 $N[\text{BAR}=1] \rightarrow N[\text{BAR}=0] \ P[\text{BAR}=2]$

### 11.4.3 Auxiliary Verbs and Inversion

Inverted clauses — where the order of subject and verb is switched — occur in English interrogatives and also after 'negative' adverbs:

- (131)    a. Do you like children?  
             b. Can Jody walk?
- (132)    a. Rarely do you see Kim.  
             b. Never have I seen this dog.

However, we cannot place just any verb in pre-subject position:

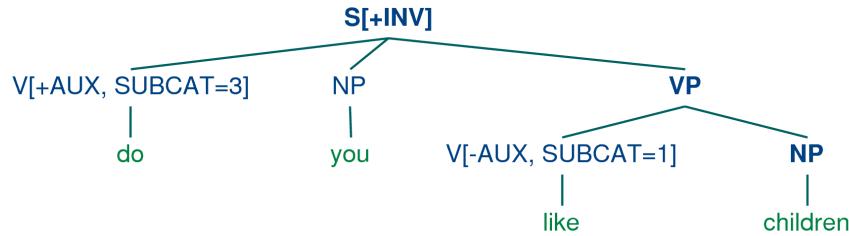
- (133)    a. \*Like you children?  
             b. \*Walks Jody?
- (134)    a. \*Rarely see you Kim.  
             b. \*Never saw I this dog.

Verbs that can be positioned initially in inverted clauses belong to the class known as **auxiliaries**, and as well as *do*, *can* and *have* include *be*, *will* and *shall*. One way of capturing such structures is with the following production:

- (135)     $S[+\text{inv}] \rightarrow V[+\text{AUX}] \ NP \ VP$

That is, a clause marked as [+INV] consists of an auxiliary verb followed by a VP. (In a more detailed grammar, we would need to place some constraints on the form of the VP, depending on the choice of auxiliary.) (136) illustrates the structure of an inverted clause.

(136)



#### 11.4.4 Unbounded Dependency Constructions

Consider the following contrasts:

- (137) a. You like Jody.

b. \*You like.

- (138) a. You put the card into the slot.

b. \*You put into the slot.

c. \*You put the card.

d. \*You put.

The verb *like* requires an NP complement, while *put* requires both a following NP and PP. Examples (137) and (138) show that these complements are *obligatory*: omitting them leads to ungrammaticality. Yet there are contexts in which obligatory complements can be omitted, as (139) and (140) illustrate.

- (139) a. Kim knows who you like.

b. This music, you really like.

- (140) a. Which card do you put into the slot?

b. Which slot do you put the card into?

That is, an obligatory complement can be omitted if there is an appropriate **filler** in the sentence, such as the question word *who* in (139a), the preposed topic *this music* in (139b), or the *wh* phrases *which card/slot* in (140). It is common to say that sentences like (139) – (140) contain **gaps** where the obligatory complements have been omitted, and these gaps are sometimes made explicit using an underscore:

- (141) a. Which card do you put \_\_ into the slot?

b. Which slot do you put the card into \_\_?

So, a gap can occur if it is **licensed** by a filler. Conversely, fillers can only occur if there is an appropriate gap elsewhere in the sentence, as shown by the following examples.

- (142) a. \*Kim knows who you like Jody.

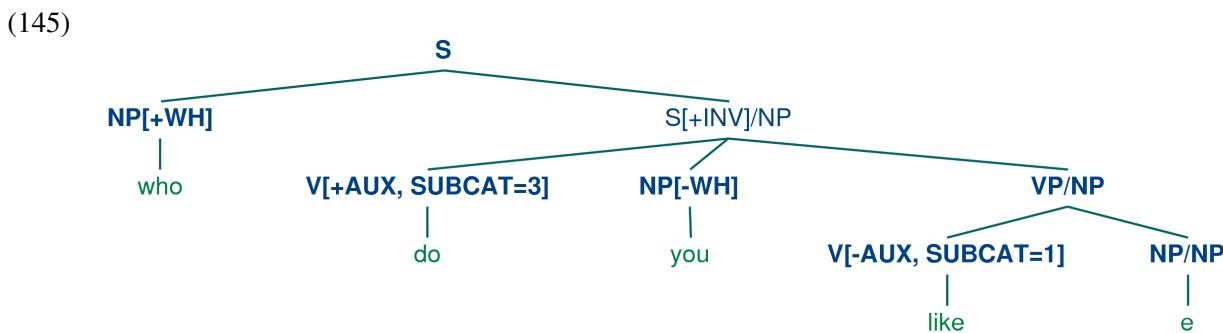
- b. \*This music, you really like hip-hop.
- (143) a. \*Which card do you put this into the slot?
- b. \*Which slot do you put the card into this one?

The mutual co-occurrence between filler and gap leads to (139) – (140) is sometimes termed a "dependency". One issue of considerable importance in theoretical linguistics has been the nature of the material that can intervene between a filler and the gap that it licenses; in particular, can we simply list a finite set of strings that separate the two? The answer is No: there is no upper bound on the distance between filler and gap. This fact can be easily illustrated with constructions involving sentential complements, as shown in (144).

- (144) a. Who do you like \_\_?
- b. Who do you claim that you like \_\_?
- c. Who do you claim that Jody says that you like \_\_?

Since we can have indefinitely deep recursion of sentential complements, the gap can be embedded indefinitely far inside the whole sentence. This constellation of properties leads to the notion of an **unbounded dependency construction**; that is, a filler-gap dependency where there is no upper bound on the distance between filler and gap.

A variety of mechanisms have been suggested for handling unbounded dependencies in formal grammars; we shall adopt an approach due to Generalized Phrase Structure Grammar that involves something called **slash categories**. A slash category is something of the form  $Y/XP$ ; we interpret this as a phrase of category  $Y$  that is missing a sub-constituent of category  $XP$ . For example,  $S/NP$  is an  $S$  that is missing an  $NP$ . The use of slash categories is illustrated in (145).



The top part of the tree introduces the filler *who* (treated as an expression of category  $NP[+WH]$ ) together with a corresponding gap-containing constituent  $S/NP$ . The gap information is then "percolated" down the tree via the  $VP/NP$  category, until it reaches the category  $NP/NP$ . At this point, the dependency is discharged by realizing the gap information as the empty string *e* immediately dominated by  $NP/NP$ .

Do we need to think of slash categories as a completely new kind of object in our grammars? Fortunately, no, we don't — in fact, we can accommodate them within our existing feature-based framework. We do this by treating slash as a feature, and the category to its right as a value. In other words, our "official" notation for  $S/NP$  will be  $S[SLASH=NP]$ . Once we have taken this step, it is straightforward to write a small grammar for analyzing unbounded dependency constructions. 11.4

illustrates the main principles of slash categories, and also includes productions for inverted clauses. To simplify presentation, we have omitted any specification of tense on the verbs.

The grammar in Listing 11.4 contains one gap-introduction production, namely

$$(146) \quad S[-INV] \rightarrow NP \ S/NP$$

In order to percolate the slash feature correctly, we need to add slashes with variable values to both sides of the arrow in productions that expand S, VP and NP. For example,

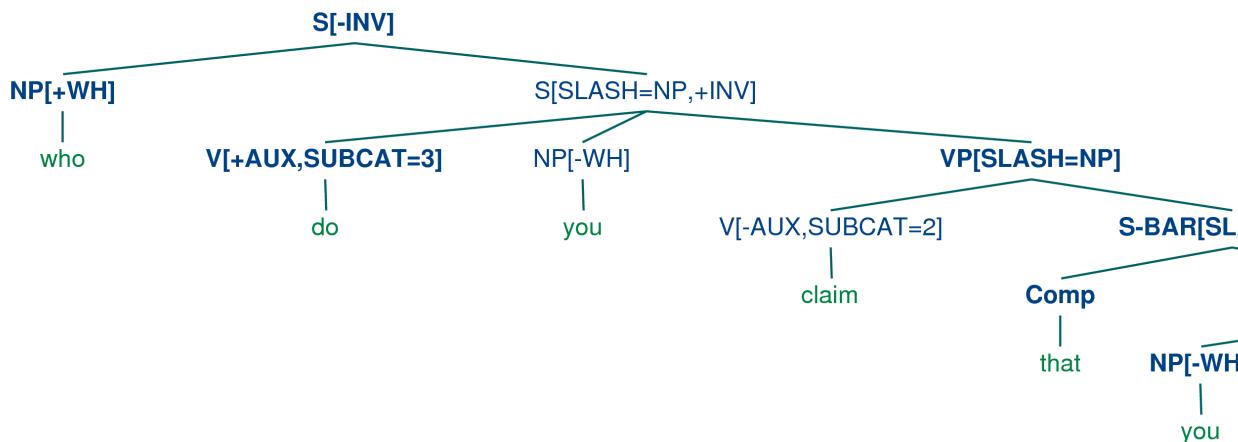
$$(147) \quad VP/?x \rightarrow V \ S-BAR/?x$$

says that a slash value can be specified on the VP mother of a constituent if the same value is also specified on the S-BAR daughter. Finally, (148) allows the slash information on NP to be discharged as the empty string.

$$(148) \quad NP/NP \rightarrow$$

Using 11.4, we can parse the string *who do you claim that you like* into the tree shown in (149).

$$(149)$$



### 11.4.5 Case and Gender in German

Compared with English, German has a relatively rich morphology for agreement. For example, the definite article in German varies with case, gender and number, as shown in Table 11.2.

| Case | Masc | Fem | Neut | Plural |
|------|------|-----|------|--------|
| Nom  | der  | die | das  | die    |
| Gen  | des  | der | des  | der    |
| Dat  | dem  | der | dem  | den    |
| Acc  | den  | die | das  | die    |

Table 11.2: Morphological Paradigm for the German definite Article

Subjects in German take the nominative case, and most verbs govern their objects in the accusative case. However, there are exceptions like *helfen* that govern the dative case:

- (150) a. Die Katze sieht den Hund  
           the.NOM.FEM.SG cat.3.FEM.SG see.3.SG the.ACC.MASC.SG dog.3.MASC.SG  
           'the cat sees the dog'
- b. \*Die Katze sieht dem Hund  
       the.NOM.FEM.SG cat.3.FEM.SG see.3.SG the.DAT.MASC.SG dog.3.MASC.SG
- c. Die Katze hilft dem Hund  
       the.NOM.FEM.SG cat.3.FEM.SG help.3.SG the.DAT.MASC.SG dog.3.MASC.SG  
       'the cat helps the dog'
- d. \*Die Katze hilft den Hund  
       the.NOM.FEM.SG cat.3.FEM.SG help.3.SG the.ACC.MASC.SG dog.3.MASC.SG

The grammar 11.5 illustrates the interaction of agreement (comprising person, number and gender) with case.

As you will see, the feature **OBJCASE** is used to specify the case that the verb governs on its object.

#### 11.4.6 Exercises

1. ⚡ Modify the grammar illustrated in (122) to incorporate a BAR feature for dealing with phrasal projections.
2. ⚡ Modify the German grammar in 11.5 to incorporate the treatment of subcategorization presented in 11.4.1.
3. ⚠ Extend the German grammar in 11.5 so that it can handle so-called verb-second structures like the following:  
 (151) Heute sieht der hund die katze.
4. ★ Morphological paradigms are rarely completely regular, in the sense of every cell in the matrix having a different realization. For example, the present tense conjugation of the lexeme WALK only has two distinct forms: *walks* for the 3rd person singular, and *walk* for all other combinations of person and number. A successful analysis should not require redundantly specifying that 5 out of the 6 possible morphological combinations have the same realization. Propose and implement a method for dealing with this.
5. ★ So-called **head features** are shared between the mother and head daughter. For example, TENSE is a head feature that is shared between a VP and its head v daughter. See [?] for more details. Most of the features we have looked at are head features — exceptions are SUBCAT and SLASH. Since the sharing of head features is predictable, it should not need to be stated explicitly in the grammar productions. Develop an approach that automatically accounts for this regular behavior of head features.

## 11.5 Summary

- The traditional categories of context-free grammar are atomic symbols. An important motivation for feature structures is to capture fine-grained distinctions that would otherwise require a massive multiplication of atomic categories.
- By using variables over feature values, we can express constraints in grammar productions that allow the realization of different feature specifications to be inter-dependent.
- Typically we specify fixed values of features at the lexical level and constrain the values of features in phrases to unify with the corresponding values in their daughters.
- Feature values are either atomic or complex. A particular sub-case of atomic value is the Boolean value, represented by convention as [+/- F].
- Two features can share a value (either atomic or complex). Structures with shared values are said to be re-entrant. Shared values are represented by numerical indices (or tags) in AVMs.
- A path in a feature structure is a tuple of features corresponding to the labels on a sequence of arcs from the root of the graph representation.
- Two paths are equivalent if they share a value.
- Feature structures are partially ordered by subsumption.  $FS_0$  subsumes  $FS_1$  when  $FS_0$  is more general (less informative) than  $FS_1$ .
- The unification of two structures  $FS_0$  and  $FS_1$ , if successful, is the feature structure  $FS_2$  that contains the combined information of both  $FS_0$  and  $FS_1$ .
- If unification specializes a path  $\pi$  in  $FS$ , then it also specializes every path  $\pi'$  equivalent to  $\pi$ .
- We can use feature structures to build succinct analyses of a wide variety of linguistic phenomena, including verb subcategorization, inversion constructions, unbounded dependency constructions and case government.

## 11.6 Further Reading

For more examples of feature-based parsing with NLTK, please see the guides at <http://nltk.org/doc/guides/featgram.html>, <http://nltk.org/doc/guides/featstruct.html>, and <http://nltk.org/doc/guides/grammartestsuites.html>.

For an excellent introduction to the phenomenon of agreement, see [?].

The earliest use of features in theoretical linguistics was designed to capture phonological properties of phonemes. For example, a sound like /b/ might be decomposed into the structure [+LABIAL, +VOICE]. An important motivation was to capture generalizations across classes of segments; for example, that /n/ gets realized as /m/ preceding any +LABIAL consonant. Within Chomskyan grammar, it was standard to use atomic features for phenomena like agreement, and also to capture generalizations across syntactic categories, by analogy with phonology. A radical expansion of the use of features in theoretical syntax was advocated by Generalized Phrase Structure Grammar (GPSG; [?]), particularly in the use of features with complex values.

Coming more from the perspective of computational linguistics, [?] proposed that functional aspects of language could be captured by unification of attribute-value structures, and a similar approach was elaborated by [?] within the PATR-II formalism. Early work in Lexical-Functional grammar (LFG; [?]) introduced the notion of an **f-structure** that was primarily intended to represent the grammatical relations and predicate-argument structure associated with a constituent structure parse. [?] provides an excellent introduction to this phase of research into feature-based grammars.

One conceptual difficulty with algebraic approaches to feature structures arose when researchers attempted to model negation. An alternative perspective, pioneered by [?] and [?], argues that grammars involve *descriptions* of feature structures rather than the structures themselves. These descriptions are combined using logical operations such as conjunction, and negation is just the usual logical operation over feature descriptions. This description-oriented perspective was integral to LFG from the outset (cf. [?], and was also adopted by later versions of Head-Driven Phrase Structure Grammar (HPSG; [?]). A comprehensive bibliography of HPSG literature can be found at <http://www.cl.uni-bremen.de/HPSG-Bib/>.

Feature structures, as presented in this chapter, are unable to capture important constraints on linguistic information. For example, there is no way of saying that the only permissible values for NUM are *sg* and *pl*, while a specification such as [NUM=*masc*] is anomalous. Similarly, we cannot say that the complex value of AGR *must* contain specifications for the features PER, NUM and GND, but *cannot* contain a specification such as [SUBCAT=3]. **Typed feature structures** were developed to remedy this deficiency. To begin with, we stipulate that feature values are always typed. In the case of atomic values, the values just are types. For example, we would say that the value of NUM is the type *num*. Moreover, *num* is the most general type of value for NUM. Since types are organized hierarchically, we can be more informative by specifying the value of NUM is a **subtype** of *num*, namely either *sg* or *pl*.

In the case of complex values, we say that feature structures are themselves typed. So for example the value of AGR will be a feature structure of type *agr*. We also stipulate that all and only PER, NUM and GND are **appropriate** features for a structure of type *agr*. A good early review of work on typed feature structures is [?]. A more comprehensive examination of the formal foundations can be found in [?], while [?] focuses on implementing an HPSG-oriented approach to typed feature structures.

There is a copious literature on the analysis of German within feature-based grammar frameworks. [?] is a good starting point for the HPSG literature on this topic, while [?] gives a very extensive and detailed analysis of German syntax in HPSG.

### About this document...

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This document is Revision: 5915 Tue Apr 29 13:57:59 EDT 2008

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**Listing 11.4** Grammar for Simple Long-distance Dependencies

---

```
>>> nltk.data.show_cfg('grammars/feat1.fcfg')
% start S
##########
Grammar Rules
#####
S[-INV] -> NP S/NP
S[-INV]/?x -> NP VP/?x
S[+INV]/?x -> V[+AUX] NP VP/?x
S-BAR/?x -> Comp S[-INV]/?x
NP/NP ->
VP/?x -> V[SUBCAT=1, -AUX] NP/?x
VP/?x -> V[SUBCAT=2, -AUX] S-BAR/?x
VP/?x -> V[SUBCAT=3, +AUX] VP/?x
#####
Lexical Rules
#####
V[SUBCAT=1, -AUX] -> 'see' | 'like'
V[SUBCAT=2, -AUX] -> 'say' | 'claim'
V[SUBCAT=3, +AUX] -> 'do' | 'can'
NP[-WH] -> 'you' | 'children' | 'girls'
NP[+WH] -> 'who'
Comp -> 'that'
```

---

**Listing 11.5** Example Feature-Based Grammar

```
>>> nltk.data.show_cfg('grammars/german.fcfg')
% start S
Grammar Rules
S -> NP [CASE=nom, AGR=?a] VP [AGR=?a]
NP [CASE=?c, AGR=?a] -> PRO [CASE=?c, AGR=?a]
NP [CASE=?c, AGR=?a] -> Det [CASE=?c, AGR=?a] N [CASE=?c, AGR=?a]
VP [AGR=?a] -> IV [AGR=?a]
VP [AGR=?a] -> TV [OBJCASE=?c, AGR=?a] NP [CASE=?c]
Lexical Rules
Singular determiners
masc
Det [CASE=nom, AGR=[GND=masc, PER=3, NUM=sg]] -> 'der'
Det [CASE=dat, AGR=[GND=masc, PER=3, NUM=sg]] -> 'dem'
Det [CASE=acc, AGR=[GND=masc, PER=3, NUM=sg]] -> 'den'
fem
Det [CASE=nom, AGR=[GND=fem, PER=3, NUM=sg]] -> 'die'
Det [CASE=dat, AGR=[GND=fem, PER=3, NUM=sg]] -> 'der'
Det [CASE=acc, AGR=[GND=fem, PER=3, NUM=sg]] -> 'die'
Plural determiners
Det [CASE=nom, AGR=[PER=3, NUM=pl]] -> 'die'
Det [CASE=dat, AGR=[PER=3, NUM=pl]] -> 'den'
Det [CASE=acc, AGR=[PER=3, NUM=pl]] -> 'die'
Nouns
N [AGR=[GND=masc, PER=3, NUM=sg]] -> 'hund'
N [CASE=nom, AGR=[GND=masc, PER=3, NUM=pl]] -> 'hunde'
N [CASE=dat, AGR=[GND=masc, PER=3, NUM=pl]] -> 'hunden'
N [CASE=acc, AGR=[GND=masc, PER=3, NUM=pl]] -> 'hunde'
N [AGR=[GND=fem, PER=3, NUM=sg]] -> 'katze'
N [AGR=[GND=fem, PER=3, NUM=pl]] -> 'katzen'
Pronouns
PRO [CASE=nom, AGR=[PER=1, NUM=sg]] -> 'ich'
PRO [CASE=acc, AGR=[PER=1, NUM=sg]] -> 'mich'
PRO [CASE=dat, AGR=[PER=1, NUM=sg]] -> 'mir'
PRO [CASE=nom, AGR=[PER=2, NUM=sg]] -> 'du'
PRO [CASE=nom, AGR=[PER=3, NUM=sg]] -> 'er' | 'sie' | 'es'
PRO [CASE=nom, AGR=[PER=1, NUM=pl]] -> 'wir'
PRO [CASE=acc, AGR=[PER=1, NUM=pl]] -> 'uns'
PRO [CASE=dat, AGR=[PER=1, NUM=pl]] -> 'uns'
PRO [CASE=nom, AGR=[PER=2, NUM=pl]] -> 'ihr'
PRO [CASE=nom, AGR=[PER=3, NUM=pl]] -> 'sie'
Verbs
IV [AGR=[NUM=sg, PER=1]] -> 'komme'
IV [AGR=[NUM=sg, PER=2]] -> 'kommst'
IV [AGR=[NUM=sg, PER=3]] -> 'kommt'
IV [AGR=[NUM=pl, PER=1]] -> 'kommen'
IV [AGR=[NUM=pl, PER=2]] -> 'kommt'
IV [AGR=[NUM=pl, PER=3]] -> 'kommen'
TV [OBJCASE=acc, AGR=[NUM=sg, PER=1]] -> 'sehe' | 'mag'
TV [OBJCASE=acc, AGR=[NUM=sg, PER=2]] -> 'siehst' | 'magst'
TV [OBJCASE=acc, AGR=[NUM=sg, PER=3]] -> 'sieht' | 'mag'
TV [OBJCASE=dat, AGR=[NUM=sg, PER=1]] -> 'folge' | 'helfe'
TV [OBJCASE=dat, AGR=[NUM=sg, PER=2]] -> 'folgst' | 'hilfst'
TV [OBJCASE=dat, AGR=[NUM=sg, PER=3]] -> 'folgt' | 'hilft'
```



# Chapter 12

## Logical Semantics

### 12.1 Introduction

There are many NLP applications where it would be useful to have some representation of the *meaning* of a natural language sentence. For instance, as we pointed out in [Chapter 1](#), current search engine technology can only take us so far in giving concise and correct answers to many questions that we might be interested in. Admittedly, Google does a good job in answering [\(152a\)](#), since its first hit is [\(152b\)](#).

- (152) a. What is the population of Saudi Arabia?  
b. Saudi Arabia - Population: 26,417,599

By contrast, the result of sending [\(153\)](#) to Google is less helpful:

- (153) Which countries border the Mediterranean?

This time, the topmost hit (and the only relevant one in the top ten) presents the relevant information as a map of the Mediterranean basin. Since the map is an image file, it is not easy to extract the required list of countries from the returned page.

Even if Google succeeds in finding documents which contain information relevant to our question, there is no guarantee that it will be in a form which can be easily converted into an appropriate answer. One reason for this is that the information may have to be inferred from more than one source. This is likely to be the case when we seek an answer to more complex questions like [\(154\)](#):

- (154) Which Asian countries border the Mediterranean?

Here, we would probably need to combine the results of two subqueries, namely [\(153\)](#) and *Which countries are in Asia?*.

The example queries we have just given are based on a paper dating back to 1982 [?]; this describes a system, *Chat-80*, which converts natural language questions into a semantic representation, and uses the latter to retrieve answers from a knowledge base. A knowledge base is usually taken to be a set of sentences in some formal language; in the case of Chat-80, it is a set of Prolog clauses. However, we can encode knowledge in a variety of formats, including relational databases, various kinds of graph, and first-order models. In NLTK, we have used the third of these options to re-implement a limited version of Chat-80:

Sentence: which Asian countries border the\_Mediterranean

---

```
\x.(((contain x asia) and (country x)) and (border mediterranean x))
set(['turkey', 'syria', 'israel', 'lebanon'])
```

As we will explain later in this chapter, a semantic representation of the form  $\exists x. (P(x))$  denotes a set of entities  $u$  that meet some condition  $(P(x))$ . We then ask our knowledge base to enumerate all the entities in this set.

Let's assume more generally that knowledge is available in some structured fashion, and that it can be interrogated by a suitable query language. Then the challenge for NLP is to find a method for converting natural language questions into the target query language. An alternative paradigm for question answering is to take something like the pages returned by a Google query as our 'knowledge base' and then to carry out further analysis and processing of the textual information contained in the returned pages to see whether it does in fact provide an answer to the question. In either case, it is very useful to be able to build a semantic representation of questions. This NLP challenge intersects in interesting ways with one of the key goals of linguistic theory, namely to provide a systematic correspondence between form and meaning.

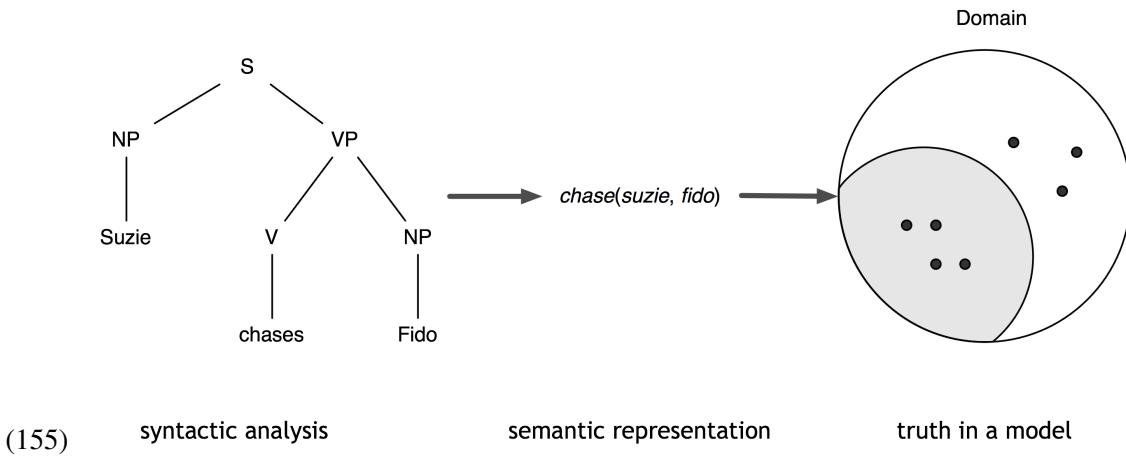
A widely adopted approach to representing meaning — or at least, some aspects of meaning — involves translating expressions of natural language into first-order logic (FOL). From a computational point of view, a strong argument in favor of FOL is that it strikes a reasonable balance between expressiveness and logical tractability. On the one hand, it is flexible enough to represent many aspects of the logical structure of natural language. On the other hand, automated theorem proving for FOL has been well studied, and although inference in FOL is not decidable, in practice many reasoning problems are efficiently solvable using modern theorem provers (cf. [?] for discussion).

While there are numerous subtle and difficult issues about how to translate natural language constructions into FOL, we will largely ignore these. The main focus of our discussion will be on a different issue, namely building semantic representations which conform to some version of the **Principle of Compositionality**. (See [?] for this formulation.)

**Principle of Compositionality:** The meaning of a whole is a function of the meanings of the parts and of the way they are syntactically combined.

There is an assumption here that the semantically relevant parts of a complex expression will be determined by a theory of syntax. Within this chapter, we will take it for granted that expressions are parsed against a context-free grammar. However, this is not entailed by the Principle of Compositionality. To summarize, we will be concerned with the task of systematically constructing a semantic representation in a manner that can be smoothly integrated with the process of parsing.

The overall framework we are assuming is illustrated in [Figure \(155\)](#). Given a syntactic analysis of a sentence, we can build one or more semantic representations for the sentence. Once we have a semantic representation, we can also check whether it is true in a model.



A **model** for a logical language is a set-theoretic construction which provides a very simplified picture of how the world is. For example, in this case, the model should contain individuals (indicated in the diagram by small dots) corresponding to Suzie and Fido, and it should also specify that these individuals belong to the *chase* relation.

The order of sections in this chapter is not what you might expect from looking at the diagram. We will start off in the middle of (155) by presenting a logical language FSRL that will provide us with semantic representations in NLTK. Next, we will show how formulas in the language can be systematically evaluated in a model. At the end, we will bring everything together and describe a simple method for constructing semantic representations as part of the parse process in NLTK.

## 12.2 The Lambda Calculus

In a functional programming language, computation can be carried out by reducing an expression  $E$  according to specified rewrite rules. This reduction is carried out on subparts of  $E$ , and terminates when no further subexpressions can be reduced. The resulting expression  $E^*$  is called the **Normal Form** of  $E$ . Table 12.1 gives an example of reduction involving a simple Python expression (where ' ' means 'reduces to'):

|  |                                                                |
|--|----------------------------------------------------------------|
|  | <code>len(max(['cat', 'zebra', 'rabbit'] + ['gopher']))</code> |
|  | <code>len(max(['cat', 'zebra', 'rabbit', 'gopher']))</code>    |
|  | <code>len('zebra')</code>                                      |
|  | 5                                                              |

Table 12.1: Reduction of functions

Thus, working from the inside outwards, we first reduce list concatenation to the normal form shown in the second row, we then take the `max()` element of the list (under alphabetic ordering), and then compute the length of that string. The final expression, 5, is considered to be the output of the program. This fundamental notion of computation is modeled in an abstract way by something called the  $\lambda$ -calculus ( $\lambda$  is a Greek letter pronounced 'lambda').

The first basic concept in the  $\lambda$ -calculus is **application**, represented by an expression of the form  $(F A)$ , where  $F$  is considered to be a function, and  $A$  is considered to be an argument (or input) for

F. For example,  $(\text{walk } x)$  is an application. Moreover, application expressions can be applied to other expressions. So in a functional framework, binary addition might be represented as  $((+ x) y)$  rather than  $(x + y)$ . Note that  $+$  is being treated as a function which is applied to its first argument  $x$  to yield a function  $(+ x)$  that is then applied to the second argument  $y$ .

The second basic concept in the  $\lambda$ -calculus is **abstraction**. If  $M[x]$  is an expression containing the variable  $x$ , then  $\lambda x.M[x]$  denotes the function  $x \rightarrow M[x]$ . Abstraction and application are combined in the expression  $(\lambda x.((+ x) 3) 4)$ , which denotes the function  $x \rightarrow x + 3$  applied to 4, giving  $4 + 3$ , which is 7. In general, we have

$$(156) \quad (\lambda x.M[x] N) = M[N],$$

where  $M[N]$  is the result of replacing all occurrences of  $x$  in  $M$  by  $N$ . This axiom of the lambda calculus is known as  **$\beta$ -conversion**.  $\beta$ -conversion is the primary form of reduction in the  $\lambda$ -calculus.

The module `sem` can parse expressions of the  $\lambda$ -calculus. The  $\lambda$  symbol is represented as '`\`'. In order to avoid having to escape this with a second '`\`', we use raw strings in parsable expressions.

```
>>> lp = nltk.sem.LogicParser()
>>> lp.parse(r' (walk x)')
ApplicationExpression('walk', 'x')
>>> lp.parse(r'\x. (walk x)')
LambdaExpression('x', '(walk x)')
```

An `ApplicationExpression` has subparts consisting of the function and the argument; a `LambdaExpression` has subparts consisting of the variable (e.g.,  $x$ ) that is bound by the  $\lambda$  and the body of the expression (e.g., `walk`).

The  $\lambda$ -calculus is a calculus of functions; by itself, it says nothing about logical structure. Although it is possible to define logical operators within the  $\lambda$ -calculus, it is much more convenient to adopt a hybrid approach which supplements the  $\lambda$ -calculus with logical and non-logical constants as primitives. In order to show how this is done, we turn first to the language of propositional logic.

## 12.3 Propositional Logic

The language of propositional logic represents certain aspects of natural language, but at a high level of abstraction. The only structure that is made explicit involves **logical connectives**; these correspond to 'logically interesting' expressions such as *and* and *not*. The basic expressions of the language are **propositional variables**, usually written  $p, q, r$ , etc. Let  $A$  be a finite set of such variables. There is a disjoint set of logical connectives which contains the unary operator  $\neg$  (*not*), and binary operators  $\wedge$  (*and*),  $\vee$  (*or*),  $\rightarrow$  (*implies*) and  $\equiv$  (*iff*).

The set of formulas of  $L_{prop}$  is described inductively:

1. Every element of  $A$  is a formula of  $L_{prop}$ .
2. If  $\varphi$  is a formula of  $L_{prop}$ , then so is  $\neg \varphi$ .
3. If  $\varphi$  and  $\psi$  are formulas, then so are  $(\varphi \wedge \psi)$ ,  $(\varphi \vee \psi)$ ,  $(\varphi \rightarrow \psi)$  and  $(\varphi \equiv \psi)$ .
4. Nothing else is a formula of  $L_{prop}$ .

Within  $L_{prop}$ , we can construct formulas such as  $p \rightarrow q \vee r$ , which might represent the logical structure of an English sentence such as *if it is raining, then Kim will take an umbrella or Lee will get wet*.  $p$  stands for *it is raining*,  $q$  for *Kim will take an umbrella* and  $q$  for *Lee will get wet*.

The Boolean connectives of propositional logic are supported by `sem`, and are parsed as objects of the class `ApplicationExpression` (i.e., function expressions). However, infix notation is also allowed as an input format. The connectives themselves belong to the `Operator` class of expressions.

```
>>> lp.parse('(and p q)')
ApplicationExpression('and', 'q')
>>> lp.parse('p and q')
ApplicationExpression('and', 'q')
>>> lp.parse('and')
Operator('and')
>>>
```

Since a negated proposition is syntactically an application, the unary operator `not` and its argument must be surrounded by parentheses.

```
>>> lp.parse('not (p and q)')
ApplicationExpression('not', '(and p q)')
>>>
```

To make the `print` output easier to read, we can invoke the `infixify()` method, which places binary Boolean operators in infix position.

```
>>> e = lp.parse('and p (not a)')
>>> e
ApplicationExpression('and', '(not a)')
>>> print e
(and p (not a))
>>> print e.infixify()
(p and (not a))
```

As the name suggests, propositional logic only studies the logical structure of formulas made up of atomic propositions. We saw, for example, that propositional variables stood for whole clauses in English. In order to look at how predicates combine with arguments, we need to look at a more complex language for semantic representation, namely first-order logic. In order to show how this new language interacts with the  $\lambda$ -calculus, it will be useful to introduce the notion of types into our syntactic definition, in departure from the rather simple approach to defining the clauses of  $L_{prop}$ .

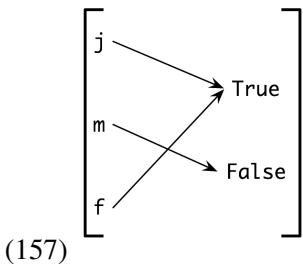
## 12.4 First-Order Logic

### 12.4.1 Predication

In first-order logic (FOL), propositions are analyzed into predicates and arguments, which takes us a step closer to the structure of natural languages. The standard construction rules for FOL recognize **terms** such as individual variables and individual constants, and **predicates** which take differing numbers of arguments. For example, *Jane walks* might be formalized as `walk(jane)` and *Jane sees Mike* as `see(jane, mike)`. We will call `walk` a **unary predicate**, and `see` a **binary predicate**. Semantically, `see` is modeled as a relation, i.e., a set of pairs, and the proposition is true in a situation just in case the pair  $j, m$  belongs to this set. In order to make it explicit that we are treating `see` as a relation, we'll use the symbol `seeR` as its semantic representation, and we'll call `seeR(jane, mike)` an instance of the 'relational style' of representing predication.

Within the framework of the  $\lambda$ -calculus, there is an alternative approach in which predication is treated as function application. In this functional style of representation, *Jane sees Mike* is formalized as  $((\text{see}_f m) j)$  or — a shorthand with less brackets — as  $(\text{see}_f m j)$ . Rather than being modeled as a relation,  $\text{see}_f$  denotes a function. Before going into detail about this function, let's first look at a simpler case, namely the different styles of interpreting a unary predicate such as **walk**.

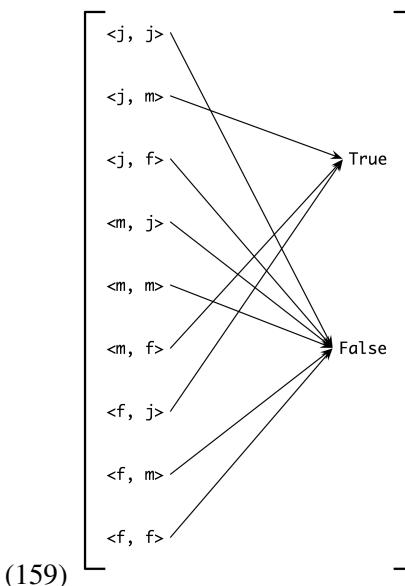
In the relational approach,  $\text{walk}_R$  denotes some set  $W$  of individuals. The formula  $\text{walk}_R(j)$  is true in a situation if and only if the individual denoted by  $j$  belongs to  $W$ . As we saw in [Chapter 10](#), corresponding to every set  $S$  is the *characteristic function*  $f_S$  of that set. To be specific, suppose in some situation our domain of discourse  $D$  is the set containing the individuals  $j$  (Jane),  $m$  (Mike) and  $f$  (Fido); and the set of individuals that walk is  $W = \{j, f\}$ . So in this situation, the formulas  $\text{walk}_R(j)$  and  $\text{walk}_R(f)$  are both true, while  $\text{walk}_R(m)$  is false. Now we can use the characteristic function  $f_W$  as the interpretation of  $\text{walk}_f$  in the functional style. The diagram (157) gives a graphical representation of the mapping  $f_W$ .



Binary relations can be converted into functions in a very similar fashion. Suppose for example that on the relational style of interpretation,  $\text{see}_R$  denotes the following set of pairs:

$$(158) \{ (j, m), (m, f), (f, j) \}$$

That is, Jane sees Mike, Mike sees Fido, and Fido sees Jane. One option on the functional style would be to treat  $\text{see}_f$  as the expected characteristic function of this set, i.e., a function  $f_S: D \times D \rightarrow \{\text{True}, \text{False}\}$  (i.e., from pairs of individuals to truth values). This mapping is illustrated in (159).



However, recall that we are trying to build up our semantic analysis compositionally; i.e., the meaning of a complex expression is a function of the meaning of its parts. In the case of a sentence, what are its parts? Presumably they are the subject NP and the VP. So let's consider what would be a suitable value for the VP *sees Fido*. It cannot be  $\text{see}_f$  denoting a function  $D \times D \rightarrow \{\text{True}, \text{False}\}$ , since this is looking for a *pair* of arguments. A better meaning representation would be  $\lambda x.\text{see}_R(x, \text{Fido})$ , which is a function of a single argument, and can thus be applied to semantic representation of the subject *np:gc*. This invites the question: how should we represent the meaning of the transitive verb *see*? A possible answer is shown in (160).

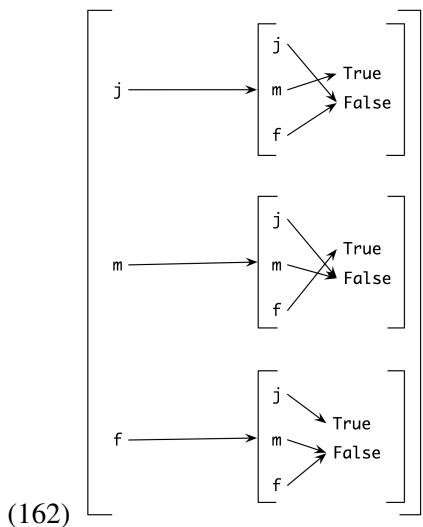
$$(160) \quad \text{see}_f = \lambda y. \lambda x. \text{see}_R(x, y).$$

This defines  $\text{see}_f$  to be a function expression which can be applied first to the argument coming from the NP object and then to the argument coming from the NP subject. In (161), we show how the application of (160) to *f* and then to *m* gets reduced.

$$(161) \quad (\lambda y. \lambda x. \text{see}_R(x, y)) f m \quad (\lambda x. \text{see}_R(x, f)) m \quad \text{see}_R(m, f)$$

(160) adopts a technique known as 'currying' (named after Haskell B. Curry), in which a binary function is converted into a function of one argument. As you can see, when we apply  $\text{see}_f$  to an argument such as *f*, the value is another function, namely the function denoted by  $\lambda x. \text{see}_R(x, f)$ .

Diagram (162) shows the curried counterpart of (159). It presents a function *F* such that given the argument *j*,  $F^*(\ast j)$  is a characteristic function that maps *m* to *True* and *j* and *f* to *False*. (While there are  $2^3 = 8$  characteristic functions from our domain of three individuals into  $\{\text{True}, \text{False}\}$ , we have only shown the functions which are in the range of the function denoted by  $\text{see}_f$ .)



Now, rather than define  $\text{see}_f$  by abstracting over a formula containing  $\text{see}_R$ , we can interpret it directly as the function  $f: (\text{Ind} \rightarrow (\text{Ind} \rightarrow \text{Bool}))$ , as illustrated in (162). Table 12.2 summarizes the different approaches to predication that we have just examined.

| English               | Relational         | Functional                               |
|-----------------------|--------------------|------------------------------------------|
| <i>Jane walks</i>     | $\text{walk}(j)$   | $(\text{walk } j)$                       |
| <i>Mike sees Fido</i> | $\text{see}(m, f)$ | $((\text{see } f) m), (\text{see } f m)$ |

Table 12.2: Representing Predication

In particular, one has to be careful to remember that in  $(\text{see } f m)$ , the order of arguments is the reverse of what is found in  $\text{see}(m, f)$ .

In order to be slightly more formal about how we are treating the syntax of first-order logic, it is helpful to look first at the **typed lambda calculus**. We will take as our basic types **Ind** and **Bool**, corresponding to the domain of individuals and  $\{\text{True}, \text{False}\}$  respectively. We define the set of types recursively. First, every basic type is a type. Second, If  $\sigma$  and  $\tau$  are types, then  $(\sigma \rightarrow \tau)$  is also a type; this corresponds to the set of functions from things of type  $\sigma$  to things of type  $\tau$ . We omit the parentheses around  $\sigma \rightarrow \tau$  if there is no ambiguity. For any type  $\tau$ , we have a set **Var**( $\tau$ ) of variables of type  $\tau$  and **Con**( $\tau$ ) of constants of type  $\tau$ . We now define the set **Term**( $\tau$ ) of  $\lambda$ -terms of type  $\tau$ .

1.  $\text{Var}(\tau) \subseteq \text{Term}(\tau)$ .
2.  $\text{Con}(\tau) \subseteq \text{Term}(\tau)$ .
3. If  $\alpha \in \text{Term}(\sigma \rightarrow \tau)$  and  $\beta \in \text{Term}(\sigma)$ , then  $(\alpha \beta) \in \text{Term}(\tau)$  (function application).
4. If  $x \in \text{Var}(\sigma)$  and  $\alpha \in \text{Term}(\tau)$ , then  $\lambda x. \alpha \in \text{Term}(\tau)$ , where  $\tau = (\sigma \rightarrow \tau)$  ( $\lambda$ -abstraction).

We replace our earlier definition of formulas containing Boolean connectives (that is, in  $L_{prop}$ ) by adding the following clause:

5.  $\text{not} \in \text{Con}(\text{Bool} \rightarrow \text{Bool})$ , and  $\text{and}$ ,  $\text{or}$ ,  $\text{implies}$  and  $\text{iff} \in \text{Con}(\text{Bool} \rightarrow (\text{Bool} \rightarrow \text{Bool}))$ .

We also add a clause for equality between individual terms.

6. If  $\alpha, \beta \in \text{Term}(\text{Ind})$ , then  $\alpha = \beta \in \text{Term}(\text{Bool})$ .

If we return now to NLTK, we can see that our previous implementation of function application already does service for predication. We also note that  $\lambda$ -abstraction can be combined with terms that are conjoined by Boolean operators. For example, the following can be thought of as the property of being an  $x$  who walks and talks:

```
>>> lp.parse(r'\x. ((walk x) and (talk x))')
LambdaExpression('x', '(and (walk x) (talk x))')
```

$\beta$ -conversion can be invoked with the `simplify()` method of `ApplicationExpressions`. As we noted earlier, the “`infixify()`” method will place binary Boolean connectives in infix position.

```
>>> e = lp.parse(r'(\x. ((walk x) and (talk x)) john)')
>>> e
ApplicationExpression('\x. (and (walk x) (talk x))', 'john')
>>> print e.simplify()
(and (walk john) (talk john))
>>> print e.simplify().infixify()
((walk john) and (talk john))
```

Up to this point, we have restricted ourselves to looking at formulas where all the arguments are individual constants (i.e., expressions in **Term(Ind)**), corresponding to proper names such as *Jane*, *Mike* and *Fido*. Yet a crucial ingredient of first-order logic is the ability to make general statements involving quantified expressions such as *all dogs* and *some cats*. We turn to this topic in the next section.

### 12.4.2 Quantification and Scope

First-order logic standardly offers us two quantifiers, *every* (or *all*) and *some*. These are formally written as  $\forall$  and  $\exists$ , respectively. The following two sets of examples show a simple English example, a logical representation, and the encoding which is accepted by the NLTK logic module.

- (163) a. Every dog barks.  
       b.  $\forall x.(\text{dog } x \rightarrow \text{bark } x)$   
       c. all  $x.((\text{dog } x) \text{ implies } (\text{bark } x))$
- (164) a. Some cat sleeps.  
       b.  $x.(\text{cat } x \wedge \text{sleep } x)$   
       c. some  $x.((\text{cat } x) \text{ and } (\text{sleep } x))$

The inclusion of first-order quantifiers motivates the final clause of the definition of our version of first-order logic.

7. If  $x \in \mathbf{Var}(\mathbf{Ind})$  and  $\varphi \in \mathbf{Term}(\mathbf{Bool})$ , then  $\forall x.\varphi, x.\varphi \in \mathbf{Term}(\mathbf{Bool})$ .

One important property of (163b) often trips people up. The logical rendering in effect says that *if* something is a dog, then it barks, but makes no commitment to the existence of dogs. So in a situation where nothing is a dog, (163b) will still come out true. (Remember that '`(p implies q)`' is true when '`p`' is false.) Now you might argue that (163b) does presuppose the existence of dogs, and that the logic formalization is wrong. But it is possible to find other examples which lack such a presupposition. For instance, we might explain that the value of the Python expression `re.sub('ate', '8', astring)` is the result of replacing all occurrences of '`ate`' in `astring` by '`8`', even though there may in fact be no such occurrences.

What happens when we want to give a formal representation of a sentence with *two* quantifiers, such as the following?

- (165) Every girl chases a dog.

There are (at least) two ways of expressing (165) in FOL:

- (166) a.  $\forall x.(\text{girl } x \rightarrow y.(\text{dog } y \wedge \text{chase } y x))$   
       b.  $y.(\text{dog } y \wedge \forall x.(\text{every } x \rightarrow \text{chase } y x))$

Can we use both of these? Then answer is Yes, but they have different meanings. (166b) is logically stronger than (166a): it claims that there is a unique dog, say Fido, which is chased by every girl. (166a), on the other hand, just requires that for every girl  $g$ , we can find some dog which  $d$  chases; but this could be a different dog in each case. We distinguish between (166a) and (166b) in terms of the **scope** of the quantifiers. In the first,  $\forall$  has wider scope than  $\exists$ , while in (166b), the scope ordering is reversed. So now we have two ways of representing the meaning of (165), and they are both quite legitimate. In other words, we are claiming that (165) is *ambiguous* with respect to quantifier scope, and the formulas in (166) give us a formal means of making the two readings explicit. However, we are not just interested in associating two distinct representations with (165). We also want to show in detail how the two representations lead to different conditions for truth in a formal model. This will be taken up in the next section.

### 12.4.3 Alphabetic Variants

When carrying out  $\beta$ -reduction, some care has to be taken with variables. Consider, for example, the  $\lambda$  terms (167a) and (167b), which differ only in the identity of a free variable.

- (167) a.  $\lambda y.(\text{see } x \ y)$   
       b.  $\lambda y.(\text{see } z \ y)$

Suppose now that we apply the  $\lambda$ -term  $\lambda P.x.(P \ x)$  to each of these terms:

- (168) a.  $(\lambda P.x.(P \ x)) \lambda y.(\text{see } x \ y))$   
       b.  $(\lambda P.x.(P \ x)) \lambda y.(\text{see } z \ y))$

In principle, the results of the application should be semantically equivalent. But if we let the free variable  $x$  in (167a) be 'captured' by the existential quantifier in (168b), then after reduction, the results will be different:

- (169) a.  $x.(\text{see } x \ x)$   
       b.  $x.(\text{see } z \ x)$

(169a) means there is some  $x$  that sees him/herself, whereas (169b) means that there is some  $x$  that sees an unspecified individual  $y$ . What has gone wrong here? Clearly, we want to forbid the kind of variable capture shown in (169a), and it seems that we have been too literal about the label of the particular variable bound by the existential quantifier in the functor expression of (168a). In fact, given any variable-binding expression (involving  $\forall$ , or  $\lambda$ ), the particular name chosen for the bound variable is completely arbitrary. For example, (170a) and (170b) are equivalent; they are called  $\alpha$  **equivalents** (or **alphabetic variants**).

- (170) a.  $x.(P \ x)$   
       b.  $z_0.(P \ z_0)$

The process of relabeling bound variables (which takes us from (170a) to (170b)) is known as  $\alpha$ -**conversion**. When we test for equality of VariableBinderExpressions in the logic module (i.e., using `==`), we are in fact testing for  $\alpha$ -equivalence:

```
>>> e1 = lp.parse('some x. (P x)')
>>> print e1
some x. (P x)
>>> e2 = e1.alpha_convert(nltk.sem.Variable('z'))
>>> print e2
some z. (P z)
>>> e1 == e2
True
```

When  $\beta$ -reduction is carried out on an application  $(M \ N)$ , we check whether there are free variables in  $N$  which also occur as bound variables in any subterms of  $M$ . Suppose, as in the example discussed above, that  $x$  is free in  $N$ , and that  $M$  contains the subterm  $x.(P \ x)$ . In this case, we produce an alphabetic variant of  $x.(P \ x)$ , say,  $z.(P \ z)$ , and then carry on with the reduction. This relabeling is carried out automatically by the  $\beta$ -reduction code in logic, and the results can be seen in the following example.

```
>>> e3 = lp.parse('(\P.some x. (P x) \y. (see x y))')
>>> print e3
(\P.some x. (P x) \y. (see x y))
>>> print e3.simplify()
some z2.(see x z2)
```

#### 12.4.4 Types and the Untyped Lambda Calculus

For convenience, let's give a name to language for semantic representations that we are using in `sem`: FSRL (for Functional Semantic Representation Language). So far, we have glossed over the fact that the FSRL is based on an implementation of the *untyped* lambda calculus. That is, although we have introduced typing in order to aid exposition, FSRL is not constrained to honor that typing. In particular, there is no formal distinction between predicate expressions and individual expressions; anything can be applied to anything. Indeed, functions can be applied to themselves:

```
>>> lp.parse('(walk walk)')
ApplicationExpression('walk', 'walk')
```

By contrast, most standard approaches to natural language semantics forbid self-application (e.g., applications such as `(walk walk)`) by adopting a typed language of the kind presented above.

It is also standard to allow constants as basic expressions of the language, as indicated by our use `Con(r)` is our earlier definitions. Correspondingly, we have used a mixture of convention and supplementary stipulations to bring FSRL closer to this more standard framework for natural language semantics. In particular, we use expressions like `x`, `y`, `z` or `x0`, `x1`, `x2` to indicate individual variables. In FSRL, we assign such strings to the class `IndVariableExpression`.

```
>>> lp.parse('x')
IndVariableExpression('x')
>>> lp.parse('x01')
IndVariableExpression('x01')
```

English-like expressions such as *dog*, *walk* and *john* will be non-logical constants (non-logical in contrast to logical constants such as *not* and *and*). In order to force `LogicParser()` to recognize non-logical constants, we can initialize the parser with a list of identifiers.

```
>>> lp = nltk.sem.LogicParser(constants=['dog', 'walk', 'see'])
>>> lp.parse('walk')
ConstantExpression('walk')
```

To sum up, while the untyped  $\lambda$ -calculus only recognizes one kind of basic expression other than  $\lambda$ , namely the class of variables (the class `VariableExpression`), FSRL adds three further classes of basic expression: `IndVariableExpression`, `ConstantExpression` and `Operator` (Boolean connectives plus the equality relation `=`).

This completes our discussion of using a first-order language as a basis for semantic representation in NLTK. In the next section, we will study how FSRL is interpreted.

---

<sup>3</sup>When combined with logic, unrestricted self-application leads to Russell's Paradox.

## 12.5 Formal Semantics

In the preceding sections, we presented some basic ideas about defining a semantic representation FSRL. We also showed informally how expressions of FSRL are paired up with natural language expressions. Later on, we will investigate a more systematic method for carrying out that pairing. But let's suppose for a moment that for any sentence  $S$  of English, we have a method of building a corresponding expression of first-order logic that represents the meaning of  $S$  (still a fairly distant goal, unfortunately). Would this be enough? Within the tradition of formal semantics, the answer would be No. To be concrete, consider (171a) and (171b).

- (171) a. Melbourne is an Australian city.  
 b. (((in australia) melbourne)  $\wedge$  (city melbourne))

(171a) makes a claim about the world. To know the meaning of (171a), we at least have to know the conditions under which it is true. Translating (171a) into (171b) may clarify some aspects of the structure of (171a), but we can still ask what the meaning of (171b) is. So we want to take the further step of giving truth conditions for (171b). To know the conditions under which a sentence is true or false is an essential component of knowing the meaning of that sentence. To be sure, truth conditions do not exhaust meaning. But if we can find some situation in which sentence  $A$  is true while sentence  $B$  is false, then we can be certain that  $A$  and  $B$  do not have the same meaning.

Now there are infinitely many sentences in **Term(Bool)** and consequently it is not possible to simply list the truth conditions. Instead, we give a *recursive* definition of truth. For instance, one of the clauses in the definition might look roughly like this:

- (172)  $(\varphi \wedge \psi)$  is True iff  $\varphi$  is True and  $\psi$  is True.

(172) is applicable to (171b); it allows us to decompose it into its conjuncts, and then proceed further with each of these, until we reach expressions — constants and variables — that cannot be broken down any further.

As we have already seen, all of our non-logical constants are interpreted either as individuals or as curried functions. What we are now going to do is make this notion of interpretation more precise by defining a **valuation** for non-logical constants, building on a set of predefined individuals in a **domain of discourse**. Together, the valuation and domain of discourse make up the main components of a *model* for sentences in our semantic representation language. The framework of model-theoretic semantics provides the tools for making the recursive definition of truth both formally and computationally explicit.

Our models stand in for possible worlds — or ways that the world could actually be. Within these models, we adopt the fiction that our knowledge is completely clearcut: sentences are either true or false, rather than probably true or true to some degree. (The only exception is that there may be expressions which do not receive any interpretation.)

More formally, a **model** for a first-order language  $L$  is a pair  $\langle D, V \rangle$ , where  $D$  is a domain of discourse and  $V$  is a valuation function for the non-logical constants of  $L$ . Non-logical constants are interpreted by  $V$  as follows (recall that **Ind** is the type of entities and **Bool** is the type of truth values):

- if  $\alpha$  is an individual constant, then  $V(\alpha) \in D$ .
- If  $\gamma$  is an expression of type  $(\text{Ind} \rightarrow \dots (\text{Ind} \rightarrow \text{Bool}) \dots)$ , then  $V(\gamma)$  is a function  $f : D \rightarrow \dots (D \rightarrow \{\text{True}, \text{False}\}) \dots$ .

As explained earlier, expressions of FSRL are not in fact explicitly typed. We leave it to you, the grammar writer, to assign 'sensible' values to expressions rather than enforcing any type-to-denotation consistency.

### 12.5.1 Characteristic Functions

Within the `sem` package, curried characteristic functions are implemented as a subclass of dictionaries, using the `CharFun` constructor.

```
>>> cf = nltk.sem.CharFun({'d1': nltk.sem.CharFun({'d2': True}),
... 'd2': nltk.sem.CharFun({'d1': True})})
```

Values of a `CharFun` are accessed by indexing in the usual way:

```
>>> cf['d1']
{'d2': True}
>>> cf['d1']['d2']
True
```

`CharFuns` are 'abbreviated' data structures in the sense that they omit key-value pairs of the form (`e` : `False`). In fact, they behave just like ordinary dictionaries on keys which are out of their domain, rather than yielding the value `False`:

```
>>> cf['not in domain']
Traceback (most recent call last):
...
KeyError: 'not in domain'
```

The assignment of `False` values is delegated to a wrapper method `app()` of the `Model` class. `app()` embodies the Closed World assumption; i.e., where '`m`' is an instance of `Model`:

```
>>> m.app(cf, 'not in domain')
False
```

In practice, it is often more convenient to specify interpretations as *n*-ary relations (i.e., sets of *n*-tuples) rather than as *n*-ary functions. A `CharFun` object has a `read()` method which will convert such relations into curried characteristic functions, and a `tuples()` method which will perform the inverse conversion.

```
>>> s = set([('d1', 'd2'), ('d3', 'd4')])
>>> cf = nltk.sem.CharFun()
>>> cf.read(s)
>>> cf
{'d4': {'d3': True}, 'd2': {'d1': True}}
>>> cf.tuples()
set([('d1', 'd2'), ('d3', 'd4')])
```

The function `flatten()` returns a set of the entities used as keys in a `CharFun` instance. The same information can be accessed via the `domain` attribute of `CharFun`.

```
>>> cf = nltk.sem.CharFun({'d1' : {'d2': True}, 'd2' : {'d1': True}})
>>> nltk.sem.flatten(cf)
set(['d2', 'd1'])
>>> cf.domain
set(['d2', 'd1'])
```

### 12.5.2 Valuations

A **Valuation** is a mapping from non-logical constants to appropriate semantic values in the model. Valuations are created using the `Valuation` constructor.

```
>>> val = nltk.sem.Valuation({'Fido': 'd1', 'dog': {'d1': True, 'd2': True}})
>>> val['dog']
{'d2': True, 'd1': True}
>>> val['dog']['d1']
True
```

As with `CharFun`, an instance of `Valuation` has a `read()` method that allows valuations to be specified as relations rather than characteristic functions.

```
>>> setval = [('adam', 'b1'), ('betty', 'g1'),
... ('girl', set(['g2', 'g1'])), ('boy', set(['b1', 'b2'])),
... ('dog', set(['d1'])),
... ('see', set([('b1', 'g1'), ('b2', 'g2'), ('g1', 'b1'), ('g2', 'b1')])))
>>> val = nltk.sem.Valuation()
>>> val.read(setval)
>>> print val
{'adam': 'b1',
 'betty': 'g1',
 'boy': {'b1': True, 'b2': True},
 'dog': {'d1': True},
 'girl': {'g1': True, 'g2': True},
 'see': {'b1': {'g1': True, 'g2': True},
 'g1': {'b1': True},
 'g2': {'b2': True}}}
```

Valuations have a `domain` attribute, like `CharFun`, and also a `symbols` attribute.

```
>>> val.domain
set(['g2', 'b2', 'd1', 'g1', 'b1'])
>>> val.symbols
['boy', 'see', 'adam', 'girl', 'dog', 'betty']
```

### 12.5.3 Assignments

A variable **Assignment** is a mapping from individual variables to entities in the domain. As indicated earlier, individual variables are written with the letters '`x`', '`y`', '`w`' and '`z`', optionally followed by an integer (e.g., '`x0`', '`y332`'). Assignments are created using the `Assignment` constructor, which also takes the model's domain of discourse as a parameter.

```
>>> dom = set(['u1', 'u2', 'u3', 'u4'])
>>> g = nltk.sem.Assignment(dom, {'x': 'u1', 'y': 'u2'})
>>> g
{'y': 'u2', 'x': 'u1'}
```

In addition, there is a `print()` format for assignments which uses a notation closer to that in logic textbooks:

```
>>> print g
g[u2/y][u1/x]
```

It is possible to update an assignment using the `add()` method; this checks that the variable really is an individual variable, and also checks that the new value belongs to the domain of discourse.

```
>>> dom = set(['u1', 'u2', 'u3', 'u4'])
>>> g = nltk.sem.Assignment(dom, {})
>>> g.add('u1', 'x')
{'x': 'u1'}
>>> g.add('u1', 'xyz')
Traceback (most recent call last):
...
AssertionError: Wrong format for an Individual Variable: 'xyz'
>>> g.add('u2', 'x').add('u3', 'y').add('u4', 'x0')
{'y': 'u3', 'x': 'u2', 'x0': 'u4'}
>>> g.add('u5', 'x')
Traceback (most recent call last):
...
AssertionError: u5 is not in the domain set(['u4', 'u1', 'u3', 'u2'])
```

#### 12.5.4 `evaluate()` and `satisfy()`

The `Model` constructor takes two parameters, of type `set` and `Valuation` respectively. Assuming that we have already defined a `Valuation` `val`, it is convenient to use `val`'s domain as the domain for the model constructor.

```
>>> dom = val.domain
>>> m = nltk.sem.Model(dom, val)
>>> g = nltk.sem.Assignment(dom, {})
```

The top-level method of a `Model` instance is `evaluate()`, which assigns a semantic value to expressions of the `logic` module, under an assignment `g`:

```
>>> m.evaluate('all x. ((boy x) implies (not (girl x)))', g)
True
```

The function `evaluate()` is essentially a convenience for handling expressions whose interpretation yields the `Undefined` value. It then calls the recursive function `satisfy()`. Since most of the interesting work is carried out by `satisfy()`, we shall concentrate on the latter.

The `satisfy()` function needs to deal with the following kinds of expression:

- non-logical constants and variables;
- Boolean connectives;
- function applications;
- quantified formulas;
- lambda-abtracts.

We shall look at each of these in turn.

### 12.5.5 Evaluating Non-Logical Constants and Variables

When it encounters expressions which cannot be analyzed into smaller components, `satisfy()` calls two subsidiary functions. The function `i()` is used to interpret non-logical constants and individual variables, while the variable assignment `g` is used to assign values to individual variables, as seen above.

Any atomic expression which cannot be assigned a value by `i()` or `g` raises an `Undefined` exception; this is caught by `evaluate()`, which returns the string '`Undefined`'. In the following examples, we have set tracing to 2 to give a verbose analysis of the processing steps.

```
>>> m.evaluate('(boy adam)', g, trace=2)
 i, g('boy') = {'b1': True, 'b2': True}
 i, g('adam') = b1
'(boy adam)': {'b1': True, 'b2': True} applied to b1 yields True
'(boy adam)' evaluates to True under M, g
True
>>> m.evaluate('(girl adam)', g, trace=2)
 i, g('girl') = {'g2': True, 'g1': True}
 i, g('adam') = b1
'(girl adam)': {'g2': True, 'g1': True} applied to b1 yields False
'(girl adam)' evaluates to False under M, g
False
>>> m.evaluate('(walk adam)', g, trace=2)
... checking whether 'walk' is an individual variable
 (checking whether 'walk' is an individual variable)
'Undefined'
```

### 12.5.6 Evaluating Boolean Connectives

The `satisfy()` function assigns semantic values to complex expressions according to their syntactic structure, as determined by the method `decompose()`; this calls the parser from the `logic` module to return a 'normalized' parse structure for the expression. In the case of a Boolean connectives, `decompose()` produces a pair consisting of the connective and a list of arguments:

```
>>> m.decompose('((boy adam) and (dog fido))')
('and', ['(boy adam)', '(dog fido)'])
```

Following the functional style of interpretation, Boolean connectives are interpreted quite literally as truth functions; for example, the connective `and` can be interpreted as the function AND:

```
>>> AND = {True: {True: True,
... False: False},
... False: {True: False,
... False: False}}
```

We define `OPS` as a mapping between the Boolean connectives and their associated truth functions. Then the simplified clause for the satisfaction of Boolean formulas looks as follows:

```
>>> def satisfy(expr, g):
... if parsed(expr) == (op, args):
... if args == (phi, psi):
... val1 = self.satisfy(phi, g)
... val2 = self.satisfy(psi, g)
... return OPS[op][val1][val2]
```

A formula such as (`and` *p* *q*) is interpreted by indexing the value of `and` with the values of the two propositional arguments, in the following manner:

```
>>> val1 = nltk.sem.Valuation({'p': True, 'q': True, 'r': False})
>>> dom1 = set([])
>>> m1 = nltk.sem.Model(dom1, val1, prop=True)
>>> g1 = nltk.sem.Assignment(dom1)
>>> m1.AND[m1.evaluate('p', g1)[m1.evaluate('q', g1)]]
True
```

We can use these definitions to generate **truth tables** for the Boolean connectives:

```
>>> ops = ['and', 'or', 'implies', 'iff']
>>> pairs = [(p, q) for p in [True, False] for q in [True, False]]
>>> for o in ops:
... print "%8s %8s | p %s q" % ('p', 'q', o)
... print "-" * 30
... for (p, q) in pairs:
... value = nltk.sem.Model.OPS[o][p][q]
... print "%8s %8s | %8s" % (p, q, value)
... print
... print
... print "p q | p and q"

... True True | True
... True False | False
... False True | False
... False False | False

... p q | p or q

... True True | True
... True False | True
... False True | True
... False False | False

... p q | p implies q

... True True | True
... True False | False
... False True | True
... False False | True

... p q | p iff q

... True True | True
... True False | False
... False True | False
... False False | True
```

Although these interpretations are close to the informal understanding of the connectives, there are some differences. Thus, '`(p or q)`' is true even when both '`p`' and '`q`' are true. '`(p implies q)`' is true even when '`p`' is false; it only excludes the situation where '`p`' is true and '`q`' is false. '`(p iff q)`' is true if '`p`' and '`q`' have the same truth value, and false otherwise.

### 12.5.7 Evaluating Function Application

The `satisfy()` clause for function application is similar to that for the connectives. In order to handle type errors, application is delegated to a wrapper function `app()` rather than by directly indexing the curried characteristic function as described earlier. The definition of `satisfy()` started above continues as follows:

```
... elif parsed(expr) == (fun, arg):
... funval = self.satisfy(fun, g)
... argval = self.satisfy(psi, g)
... return app(funval, argval)
```

### 12.5.8 Evaluating Quantified Formulas

Let's consider now how to interpret quantified formulas, such as (173).

(173) `some x. (see x betty)`

We decompose (173) into two parts, the quantifier prefix `some x` and the body of the formula, (174).

(174) `(see x betty)`

Although the variable `x` in (173) is **bound** by the quantifier `some`, `x` is not bound by any quantifiers within (174); in other words, it is **free**. A formula containing at least one free variable is said to be **open**. How should open formulas be interpreted? We can think of `x` as being similar to a variable in Python, in the sense that we cannot evaluate an expression containing a variable unless it has already been assigned a value. As mentioned earlier, the task of assigning values to individual variables is undertaken by an `Assignment` object `g`. However, our variable assignments are partial: `g` may well not give a value to `x`.

```
>>> dom = val.domain
 >>> m = nltk.sem.Model(dom, val)
>>> g = nltk.sem.Assignment(dom)
>>> m.evaluate('(see x betty)', g)
'Undefined'
```

We can use the `add()` method to explicitly add a binding to an assignment, and thereby ensure that `g` gives `x` a value.

```
>>> g.add('b1', 'x')
{'x': 'b1'}
>>> m.evaluate('(see x betty)', g)
True
```

In a case like this, we say that the entity `b1` **satisfies** the open formula `(see x betty)`, or that `(see x betty)` is **satisfied under the assignment** `g['b1'/'x']`.

When we interpret a quantified formula, we depend on the notion of an open sub-formula being satisfied under a variable assignment. However, to capture the force of the quantifier, we need to abstract away from arbitrary specific assignments. The first step is to define the set of **satisfiers** of a formula that is open in some variable. Formally, given an open formula  $\varphi[x]$  dependent on  $x$  and a model with domain  $D$ , we define the set  $\text{sat}(\varphi[x], g)$  of **satisfiers** of  $\varphi[x]$  to be:

(175)  $\{u \in D \mid \text{sat}(f[\bar{x}], g[u/\bar{x}]) = \text{True}\}$

We use  $g[u/\bar{x}]$  to mean that assignment which is just like  $g$  except that  $g(\bar{x}) = u$ . Here is a Python definition of `satisfiers()`:

```
>>> def satisfiers(expr, var, g):
... candidates = []
... if freevar(var, expr):
... for u in domain:
... g.add(u, var)
... if satisfy(expr, g):
... candidates.append(u)
... return set(candidates)
```

The satisfiers of an arbitrary open formula can be inspected using the `satisfiers()` method.

```
>>> print m
Domain = set(['g2', 'b2', 'd1', 'g1', 'b1']),
Valuation =
{'adam': 'b1',
 'betty': 'g1',
 'boy': {'b1': True, 'b2': True},
 'dog': {'d1': True},
 'girl': {'g1': True, 'g2': True},
 'see': {'b1': {'g1': True, 'g2': True},
 'g1': {'b1': True},
 'g2': {'b2': True}}}
>>> m.satisfiers('some y.((girl y) and (see x y))', 'x', g)
set(['b1'])
>>> m.satisfiers('some y.((girl y) and (see y x))', 'x', g)
set(['b1', 'b2'])
>>> m.satisfiers('(((girl x) and (boy x)) or (dog x))', 'x', g)
set(['d1'])
>>> m.satisfiers('((girl x) and ((boy x) or (dog x)))', 'x', g)
set([])
```

Now that we have put the notion of satisfiers in place, we can use this to determine a truth value for quantified expressions. An existentially quantified formula  $\exists x.f[\bar{x}]$  is held to be true if and only if  $\text{sat}(f[\bar{x}], g)$  is nonempty. We use the length function `len()` to return the cardinality of a set.

```
... elif parsed(expr) == (binder, body):
... if binder == ('some', var):
... sat = self.satisfiers(body, var, g)
... return len(sat) > 0
```

In other words, a formula  $\exists x.f[\bar{x}]$  has the same value in model  $M$  as the statement that the number of satisfiers in  $M$  of  $f[\bar{x}]$  is greater than 0.

A universally quantified formula  $\forall x.f[\bar{x}]$  is held to be true if and only if every  $u$  in the model's domain  $D$  belongs to  $\text{sat}(f[\bar{x}], g)$ ; equivalently, if  $D \subseteq \text{sat}(f[\bar{x}], g)$ . The `satisfy()` clause above for existentials can therefore be extended with the clause:

```
... elif binder == ('all', var):
... sat = self.satisfiers(body, var, g)
... return domain.issubset(sat)
```

Although our approach to interpreting quantified formulas has the advantage of being transparent and conformant to classical logic, it is not computationally efficient. To verify an existentially quantified formula, it suffices to find just one satisfying individual and then return `True`. But the method just presented requires us to test satisfaction for every individual in the domain of discourse for each quantifier. This requires  $m^n$  evaluations, where  $m$  is the cardinality of the domain and  $n$  is the number of nested quantifiers.

### 12.5.9 Evaluating Lambda Abstracts

Finally, we can also evaluate  $\lambda$ -abstracts; not surprisingly, these are interpreted as `CharFuns`. To illustrate, we can construct the binary relation of individuals who see each other, or the ternary relation of distinct individuals  $a$  and  $b$  such for some  $c$ ,  $a$  sees  $c$  and  $c$  sees  $b$ .

```
>>> m.evaluate(r'\x y. ((see x y) and (see y x))', g)
{'b1': {'g1': True}, 'g1': {'b1': True}}
>>> r = m.evaluate(r"""\x z y. (((see x z) and (see z y))
... and (not (x = y)))""", g)
>>> r.tuples()
set([('g2', 'b1', 'g1'), ('b2', 'g2', 'b1')])
```

Note that  $\lambda$ -abstracts can only be explicitly evaluated when the bound variable is an individual variable. Variables which range over functions, such as the '`P`' in '`\x. (P suzie)`', are called **higher-order** variables, and quantification over higher-order variables lies outside first-order logic.

If you attempt to evaluate an expression such as '`\x. (P suzie)`', the `semantics` package will raise an error. Since we only allow ourselves to quantify over individuals in FSRL, a variable assignment only give values to individual variables, and variable assignment is crucial for interpreting  $\lambda$ -abstraction. So though we do allow abstracts with higher-order variables in the language, they are not 'first-class citizens': they are only used as a stepping stone on the way to building up semantic representations in a compositional manner, and are eliminated prior to evaluation by  $\beta$ -reduction.

### 12.5.10 Exercises

1.  $\diamond$  Define a denotation for exclusive `or` (i.e., '`(p xor q)`' is equivalent to '`((p or q) and (not (p and q)))`'.)
2.  $\diamond$  Evaluate the expressions '`\x. (boy adam)`' and '`\x. (boy fido)`' in the model given above. Explain your results.
3.  $\bullet$  Use the `satisfiers()` method for determining the set of satisfiers of the open formula '`((dog x) implies (x = fido))`' in the model given above. Explain why the result is the way that it is.
4.  $\bullet$  Develop a set of around 10 sentences, using FSRL. Build a model for the sentences which makes them all true, and verify the results.
5.  $\bullet$  Build a model for a relation `rel` which is **transitively closed** and **reflexive**. That is, it satisfies the following two sentences:
  - a.) `all x y z.(((rel y x) and (rel z y)) implies (rel z x))`
  - b.) `all x. (rel x x)`

## 12.6 Quantifier Scope Revisited

You may recall that we discussed earlier an example of quantifier scope ambiguity, repeated here as (176).

- (176) Every girl chases a dog.

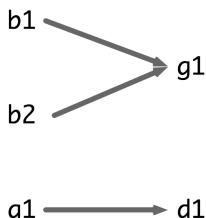
The two readings are represented as follows.

```
>>> sr1 = 'all x.((girl x) implies some z.((dog z) and (chase z x)))'
>>> sr2 = 'some z.((dog z) and all x.((girl x) implies (chase z x)))'
```

In order to examine the ambiguity more closely, let's fix our valuation as follows:

```
>>> val = nltk.sem.Valuation()
>>> v = [('john', 'b1'),
... ('mary', 'g1'),
... ('suzie', 'g2'),
... ('fido', 'd1'),
... ('tess', 'd2'),
... ('noosa', 'n'),
... ('girl', set(['g1', 'g2'])),
... ('boy', set(['b1', 'b2'])),
... ('dog', set(['d1', 'd2'])),
... ('bark', set(['d1', 'd2'])),
... ('walk', set(['b1', 'g2', 'd1'])),
... ('chase', set([('b1', 'g1'), ('b2', 'g1'), ('g1', 'd1'), ('g2', 'd2')])),
... ('see', set([('b1', 'g1'), ('b2', 'd2'), ('g1', 'b1'),
... ('d2', 'b1'), ('g2', 'n')])),
... ('in', set([('b1', 'n'), ('b2', 'n'), ('d2', 'n')])),
... ('with', set([('b1', 'g1'), ('g1', 'b1'), ('d1', 'b1'), ('b1', 'd1')]))
>>> val.read(v)
```

Using a slightly different graph from before, we can also visualize the `chase` relation as in (177).



- (177)  $g1 \longrightarrow d2$

In (177), an arrow between two individuals  $x$  and  $y$  indicates that  $x$  chases  $y$ . So  $b1$  and  $b2$  both chase  $g1$ , while  $g1$  chases  $d1$  and  $g2$  chases  $d2$ . In this model, formula `sr1` above is true but `sr2` is false. One way of exploring these results is by using the `satisfiers()` method of `Model` objects.

```
>>> dom = val.domain
>>> m = nltk.sem.Model(dom, val)
>>> g = nltk.sem.Assignment(dom)
>>> fmla1 = '((girl x) implies some y.((dog y) and (chase y x)))'
```

```
>>> m.satisfiers(fmla1, 'x', g)
set(['g2', 'g1', 'n', 'b1', 'b2', 'd2', 'd1'])
>>>
```

This gives us the set of individuals that can be assigned as the value of  $x$  in  $fmla1$ . In particular, every girl is included in this set. By contrast, consider the formula  $fmla2$  below; this has no satisfiers for the variable  $y$ .

```
>>> fmla2 = '((dog y) and all x.((girl x) implies (chase y x)))'
>>> m.satisfiers(fmla2, 'y', g)
set([])
>>>
```

That is, there is no dog that is chased by both  $g1$  and  $g2$ . Taking a slightly different open formula,  $fmla3$ , we can verify that there is a girl, namely  $g1$ , who is chased by every boy.

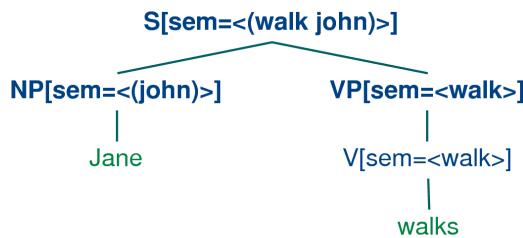
```
>>> fmla3 = '((girl y) and all x.((boy x) implies (chase y x)))'
>>> m.satisfiers(fmla3, 'y', g)
set(['g1'])
>>>
```

## 12.7 Evaluating English Sentences

### 12.7.1 Using the `sem` Feature

Until now, we have taken for granted that we have some appropriate logical formulas to interpret. However, ideally we would like to derive these formulas from natural language input. One relatively easy way of achieving this goal is to build on the grammar framework developed in [Chapter 11](#). Our first step is to introduce a new feature, `sem`. Because values of `sem` generally need to be treated differently from other feature values, we use the convention of enclosing them in angle brackets. [\(178\)](#) illustrates a first approximation to the kind of analyses we would like to build.

(178)



Thus, the `sem` value at the root node shows a semantic representation for the whole sentence, while the `sem` values at lower nodes show semantic representations for constituents of the sentence. So far, so good, but how do we write grammar rules which will give us this kind of result? To be more specific, suppose we have a `NP` and `VP` constituents with appropriate values for their `sem` nodes? If you reflect on the machinery that was introduced in discussing the  $\lambda$  calculus, you might guess that function application will be central to composing semantic values. You will also remember that our feature-based grammar framework gives us the means to refer to *variable* values. Putting this together, we can postulate a rule like [\(179\)](#) for building the `sem` value of an `S`. (Observe that in the case where the value of `sem` is a variable, we omit the angle brackets.)

(179)  $S[\text{sem} = \langle \text{app}(\text{?vp}, \text{?subj}) \rangle] \rightarrow NP[\text{sem} = \text{?subj}] VP[\text{sem} = \text{?vp}]$

(179) tells us that given some `sem` value `?subj` for the subject `NP` and some `sem` value `?vp` for the `VP`, the `sem` value of the `S` mother is constructed by applying `?vp` as a functor to `?np`. From this, we can conclude that `?vp` has to denote a function which has the denotation of `?np` in its domain; in fact, we are going to assume that `?vp` denotes a curried characteristic function on individuals. (179) is a nice example of building semantics using **the principle of compositionality**: that is, the principle that the semantics of a complex expression is a function of the semantics of its parts.

To complete the grammar is very straightforward; all we require are the rules shown in (180).

(180)  $VP[\text{sem} = \text{?v}] \rightarrow IV[\text{sem} = \text{?v}]$   
 $NP[\text{sem} = \langle \text{john} \rangle] \rightarrow 'Jane'$   
 $IV[\text{sem} = \langle \text{walk} \rangle] \rightarrow 'walks'$

The `VP` rule says that the mother's semantics is the same as the head daughter's. The two lexical rules just introduce non-logical constants to serve as the semantic values of *Jane* and *walks* respectively. This grammar can be parsed using the chart parser in `parse.featurechart`, and the trace in (181) shows how semantic values are derived by feature unification in the process of building a parse tree.

(181)

```
Predictor |> . .| S[sem='(?vp ?subj)'] -> * NP[sem=?subj] VP[sem=?vp]
Scanner |[-] .| [0:1] 'Jane'
Completer |[-> .| S[sem='(?vp john)'] -> NP[sem='john'] * VP[sem=?vp]
Predictor |. > .| VP[sem=?v] -> * IV[sem=?v]
Scanner |. [-]| [1:2] 'walks'
Completer |. [-]| VP[sem='walk'] -> IV[sem='walk'] *
Completer |[==]| S[sem='(walk john)'] -> NP[sem='john'] VP[sem='walk'] *
Completer |[==]| [INIT] -> S *
```

### 12.7.2 Quantified NPs

You might be thinking this is all too easy — surely there is a bit more to building compositional semantics. What about quantifiers, for instance? Right, this is a crucial issue. For example, we want (182a) to be given a semantic representation like (182b). How can this be accomplished?

(182) a. A dog barks.

b. '`some x.((dog x) and (bark x))`'

Let's make the assumption that our *only* operation for building complex semantic representations is '`app()`' (corresponding to function application). Then our problem is this: how do we give a semantic representation to quantified NPs such as *a dog* so that they can be combined with something like '`walk`' to give a result like (182b)? As a first step, let's make the subject's `sem` value act as the functor rather than the argument in '`app()`'. Now we are looking for way of instantiating `?np` so that (183a) is equivalent to (183b).

(183) a. `[sem=<app(?np, bark)>]`

b. `[sem=<some x.((dog x) and (bark x))>]`

This is where  $\lambda$  abstraction comes to the rescue; doesn't (183) look a bit reminiscent of carrying out  $\beta$ -reduction in the  $\lambda$ -calculus? In other words, we want a  $\lambda$  term  $M$  to replace '`?np`' so that applying  $M$  to '`bark`' yields (182b). To do this, we replace the occurrence of '`bark`' in (182b) by a variable '`P`', and bind the variable with  $\lambda$ , as shown in (184).

(184) '`\P.some x. ((dog x) and (P x))`'

As a point of interest, we have used a different style of variable in (184), that is '`P`' rather than '`x`' or '`y`'. This is to signal that we are abstracting over a different kind of thing — not an individual, but a function from **Ind** to **Bool**. So the type of (184) as a whole is  $((\text{Ind} \rightarrow \text{Bool}) \rightarrow \text{Bool})$ . We will take this to be the type of NPs in general. To illustrate further, a universally quantified NP will look like (185).

(185) '`\P.all x. ((dog x) implies (P x))`'

We are pretty much done now, except that we also want to carry out a further abstraction plus application for the process of combining the semantics of the determiner *a* with the semantics of *dog*. Applying (184) as a functor to '`bark`' gives us '`(\P.some x. ((dog x) and (P x)) bark)`', and carrying out  $\beta$ -reduction yields just what we wanted, namely (182b).

NLTK provides some utilities to make it easier to derive and inspect semantic interpretations. `text_interpret()` is intended for batch interpretation of a list of input sentences. It builds a dictionary `d` where for each sentence `sent` in the input, `d[sent]` is a list of paired trees and semantic representations for `sent`. The value is a list, since `sent` may be syntactically ambiguous; in the following example, we just look at the first member of the list.

```
>>> grammar = nltk.data.load('grammars/seml.fcfg')
>>> result = nltk.sem.text_interpret(['a dog barks'], grammar, beta_reduce=0)
>>> (syntree, semrep) = result['a dog barks'][0]
>>> print syntree
(S[sem=<some x. (and (dog x) (bark x))>]
 (NP[sem=<\P.some x. (and (dog x) (P x))>]
 (Det[sem=<\Q P.some x. (and (Q x) (P x))>] a)
 (N[sem=<dog>] dog))
 (VP[sem=<\x. (bark x)>] (IV[sem=<\x. (bark x)>] barks)))
>>> print semrep
some x. (and (dog x) (bark x))
```

By default, the semantic representation that is produced by `text_interpret()` has already undergone  $\beta$ -reduction, but in the above example, we have overridden this. Subsequent reduction is possible using the `simplify()` method, and Boolean connectives can be placed in infix position with the `infixify()` method.

```
>>> print semrep.simplify()
some x. (and (dog x) (bark x))
>>> print semrep.simplify().infixify()
some x. ((dog x) and (bark x))
```

### 12.7.3 Transitive Verbs

Our next challenge is to deal with sentences containing transitive verbs, such as (186).

(186) Suzie chases a dog.

The output semantics that we want to build is shown in (187).

(187) '`some x.((dog x) and (chase x suzie))'`

Let's look at how we can use  $\lambda$ -abstraction to get this result. A significant constraint on possible solutions is to require that the semantic representation of *a dog* be independent of whether the NP acts as subject or object of the sentence. In other words, we want to get (187) as our output while sticking to (184) as the NP semantics. A second constraint is that VPs should have a uniform type of interpretation regardless of whether they consist of just an intransitive verb or a transitive verb plus object. More specifically, we stipulate that VPs always denote characteristic functions on individuals. Given these constraints, here's a semantic representation for *chases a dog* which does the trick.

(188) '`\y.some x.((dog x) and (chase x y))'`

Think of (188) as the property of being a *y* such that for some dog *x*, *y* chases *x*; or more colloquially, being a *y* who chases a dog. Our task now resolves to designing a semantic representation for *chases* which can combine via `app` with (184) so as to allow (188) to be derived.

Let's carry out a kind of inverse  $\beta$ -reduction on (188), giving rise to (189).

Let Then we are part way to the solution if we can derive (189), where '`X`' is applied to '`\z.(chase z y)`'.

(189) '`(\P.some x.((dog x) and (P x)) \z.(chase z y))'`

(189) may be slightly hard to read at first; you need to see that it involves applying the quantified NP representation from (184) to '`\z.(chase z y)`'. (189) is of course equivalent to (188).

Now let's replace the functor in (189) by a variable '`X`' of the same type as an NP; that is, of type  $(\text{Ind} \rightarrow \text{Bool}) \rightarrow \text{Bool}$ .

(190) '`(X \z.(chase z y))'`

The representation of a transitive verb will have to apply to an argument of the type of '`X`' to yield a functor of the type of VPs, that is, of type  $(\text{Ind} \rightarrow \text{Bool})$ . We can ensure this by abstracting over both the '`X`' variable in (190) and also the subject variable '`y`'. So the full solution is reached by giving *chases* the semantic representation shown in (191).

(191) '`\X y.(X \x.(chase x y))'`

If (191) is applied to (184), the result after  $\beta$ -reduction is equivalent to (188), which is what we wanted all along:

(192) '`(\X y.(X \x.(chase x y)) \P.some x.((dog x) and (P x))'`

`'(\y.(\P.some x.((dog x) and (P x)) \x.(chase x y))'`

`'\y.(some x.((dog x) and (chase x y)))'`

In order to build a semantic representation for a sentence, we also need to combine in the semantics of the subject NP. If the latter is a quantified expression like *every girl*, everything proceeds in the same way as we showed for *a dog barks* earlier on; the subject is translated as a functor which is applied to the semantic representation of the VP. However, we now seem to have created another problem for ourselves with proper names. So far, these have been treated semantically as individual constants, and these cannot be applied as functors to expressions like (188). Consequently, we need to come up with a different semantic representation for them. What we do in this case is re-interpret proper names so that they too are functors, like quantified NPs. (193) shows the required  $\lambda$  expression for *Suzie*.

(193) '\P.(P suzie)'

(193) denotes the characteristic function corresponding to the set of all properties which are true of Suzie. Converting from an individual constant to an expression like (191) is known as **type raising**, and allows us to flip functors with arguments. That is, type raising means that we can replace a Boolean-valued application such as  $(f\ a)$  with an equivalent application  $(\lambda P.(P\ a)\ f)$ .

One important limitation of the approach we have presented here is that it does not attempt to deal with scope ambiguity. Instead, quantifier scope ordering directly reflects scope in the parse tree. As a result, a sentence like (165), repeated here, will always be translated as (195a), not (195b).

(194) Every girl chases a dog.

- (195) a. 'all x.((girl x) implies some y. ((dog y) and (chase y x)))'  
 b. 'some y. (dog y) and all x. ((girl x) implies (chase y x))'

This limitation can be overcome, for example using the hole semantics described in [?], but discussing the details would take us outside the scope of the current chapter.

Now that we have looked at some slightly more complex constructions, we can evaluate them in a model. In the following example, we derive two parses for the sentence *every boy chases a girl in Noosa*, and evaluate each of the corresponding semantic representations in the model `model0.py` which we have imported.

```
>>> grammar = nltk.data.load('grammars/sem2.fcfg')
>>> val = nltk.data.load('grammars/valuation1.val')
>>> m = nltk.sem.Model(val.domain, val)
>>> g = nltk.sem.Assignment(dom)
>>> sent = 'every boy chases a girl in Noosa'
>>> result = nltk.sem.text_evaluate([sent], grammar, m, g)
>>> for (syntree, semrep, value) in result[sent]:
... print "'%s' is %s in Model m\n" % (semrep.infixify(), value)
'all x.((boy x) implies (some z240.((girl z240) and (chase z240 x)) and (in noosa x
'all x.((boy x) implies some z333.((girl z333) and (in noosa z333)) and (chase z333
```

## 12.8 Case Study: Extracting Valuations from Chat-80

Building `Valuation` objects by hand becomes rather tedious once we consider larger examples. This raises the question of whether the relation data in a `Valuation` could be extracted from some pre-existing source. The `corpora.chat80` module provides an example of extracting data from the Chat-80 Prolog knowledge base (which included as part of the NLTK `corpora` distribution).

Chat-80 data is organized into collections of clauses, where each collection functions as a table in a relational database. The predicate of the clause provides the name of the table; the first element of the tuple acts as the 'key'; and subsequent elements are further columns in the table.

In general, the name of the table provides a label for a unary relation whose extension is all the keys. For example, the table in `cities.pl` contains triples such as (196).

(196) 'city(athens,greece,1368).'

Here, '`'athens'`' is the key, and will be mapped to a member of the unary relation `city`.

The other two columns in the table are mapped to binary relations, where the first argument of the relation is filled by the table key, and the second argument is filled by the data in the relevant column. Thus, in the `city` table illustrated by the tuple in (196), the data from the third column is extracted into a binary predicate `population_of`, whose extension is a set of pairs such as '`('athens', 1368')`'.

In order to encapsulate the results of the extraction, a class of `Concepts` is introduced. A `Concept` object has a number of attributes, in particular a `prefLabel` and `extension`, which make it easier to inspect the output of the extraction. The extension of a `Concept` object is incorporated into a `Valuation` object.

As well as deriving unary and binary relations from the Chat-80 data, we also create a set of individual constants, one for each entity in the domain. The individual constants are string-identical to the entities. For example, given a data item such as '`'zloty'`', we add to the valuation a pair '`('zloty', 'zloty')`'. In order to parse English sentences that refer to these entities, we also create a lexical item such as the following for each individual constant:

(197)      `PropN[num=sg, sem=<\P.(P zloty)>] -> 'zloty'`

The `chat80` module can be found in the `corpora` package. The attribute `chat80.items` gives us a list of Chat-80 relations:

```
>>> from nltk.corpus import chat80
>>> chat80.items
('borders', 'circle_of_lat', 'circle_of_long', 'city', ...)
```

The `concepts()` method shows the list of `Concepts` that can be extracted from a `chat80` relation, and we can then inspect their extensions.

```
>>> concepts = chat80.concepts('city')
>>> concepts
[Concept('city'), Concept('country_of'), Concept('population_of')]
>>> rel = concepts[1].extension
>>> list(rel)[:5]
[('chungking', 'china'), ('karachi', 'pakistan'),
('singapore_city', 'singapore'), ('athens', 'greece'),
('birmingham', 'united_kingdom')]
```

In order to convert such an extension into a valuation, we use the `make_valuation()` method; setting `read=True` creates and returns a new `Valuation` object which contains the results.

```
>>> val = nltk.corpus.chat80.make_valuation(concepts, read=True)
>>> val['city']['calcutta']
True
>>> val['country_of']['india']
{'hyderabad': True, 'delhi': True, 'bombay': True,
'madras': True, 'calcutta': True}
>>> dom = val.domain
>>> g = nltk.sem.Assignment(dom)
>>> m = nltk.sem.Model(dom, val)
>>> m.evaluate(r'\x . (population_of x jakarta)', g)
{'533': True}
```

**Note**

Population figures are given in thousands. Bear in mind that the geographical data used in these examples dates back at least to the 1980s, and was already somewhat out of date at the point when [?] was published.

## 12.9 Summary

- Semantic Representations (SRs) for English are constructed using a language based on the  $\lambda$ -calculus, together with Boolean connectives, equality, and first-order quantifiers.
- $\beta$ -reduction in the  $\lambda$ -calculus corresponds semantically to application of a function to an argument. Syntactically, it involves replacing a variable bound by  $\lambda$  in the functor with the expression that provides the argument in the function application.
- If two  $\lambda$ -abtracts differ only in the label of the variable bound by  $\lambda$ , they are said to be  $\alpha$  equivalents. Relabeling a variable bound by a  $\lambda$  is called  $\alpha$ -conversion.
- Currying of a binary function turns it into a unary function whose value is again a unary function.
- FSRL has both a syntax and a semantics. The semantics is determined by recursively evaluating expressions in a model.
- A key part of constructing a model lies in building a valuation which assigns interpretations to non-logical constants. These are interpreted as either curried characteristic functions or as individual constants.
- The interpretation of Boolean connectives is handled by the model; these are interpreted as characteristic functions.
- An open expression is an expression containing one or more free variables. Open expressions only receive an interpretation when their free variables receive values from a variable assignment.
- Quantifiers are interpreted by constructing, for a formula  $\varphi[x]$  open in variable  $x$ , the set of individuals which make  $\varphi[x]$  true when an assignment  $g$  assigns them as the value of  $x$ . The quantifier then places constraints on that set.
- A closed expression is one that has no free variables; that is, the variables are all bound. A closed sentence is true or false with respect to all variable assignments.
- Given a formula with two nested quantifiers  $Q_1$  and  $Q_2$ , the outermost quantifier  $Q_1$  is said to have wide scope (or scope over  $Q_2$ ). English sentences are frequently ambiguous with respect to the scope of the quantifiers they contain.
- English sentences can be associated with an SR by treating `sem` as a feature. The `sem` value of a complex expressions typically involves functional application of the `sem` values of the component expressions.
- Model valuations need not be built by hand, but can also be extracted from relational tables, as in the Chat-80 example.

## 12.10 Exercises

1. ● Modify the `sem.evaluate` code so that it will give a helpful error message if an expression is not in the domain of a model's valuation function.
2. ★ Specify and implement a typed functional language with quantifiers, Boolean connectives and equality. Modify `sem.evaluate` to interpret expressions of this language.
3. ★ Extend the `chat80` code so that it will extract data from a relational database using SQL queries.
4. ★ Taking [WarrenPereira1982] as a starting point, develop a technique for converting a natural language query into a form that can be evaluated more efficiently in a model. For example, given a query of the form '`((P x) and (Q x))`', convert it to '`((Q x) and (P x))`' if the extension of '`Q`' is smaller than the extension of '`P`'.

## 12.11 Further Reading

For more examples of semantic analysis with NLTK, please see the guides at <http://nltk.org/doc/guides/sem.html> and <http://nltk.org/doc/guides/logic.html>.

The use of characteristic functions for interpreting expressions of natural language was primarily due to Richard Montague. [?] gives a comprehensive and reasonably approachable introduction to Montague's grammatical framework.

A more recent and wide-reaching study of the use of a  $\lambda$  based approach to natural language can be found in [?].

[?] is a thorough application of formal semantics to transformational grammars in the Government-Binding model.

[?] is the first textbook devoted to computational semantics, and provides an excellent introduction to the area.

### About this document...

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# Chapter 13

## Linguistic Data Management (DRAFT)

### 13.1 Introduction

Language resources of all kinds are proliferating on the Web. These include data such as lexicons and annotated text, and software tools for creating and manipulating the data. As we have seen in previous chapters, language resources are essential in most areas of NLP. This has been made possible by three significant technological developments over the past decade. First, inexpensive mass storage technology permits large resources to be stored in digital form, while the Extensible Markup Language (XML) and Unicode provide flexible ways to represent structured data and give it good prospects for long-term survival. Second, digital publication has been a practical and efficient means of sharing language resources. Finally, search engines, mailing lists, and online resource catalogs make it possible for people to discover the existence of the resources they may be seeking.

Together with these technological advances have been three other developments that have shifted the NLP community in the direction of data-intensive approaches. First, the "shared task method," an initiative of government sponsors, supports major sections within the community to identify a common goal for the coming year, and provides "gold standard" data on which competing systems can be evaluated. Second, data publishers such as the Linguistic Data Consortium have negotiated with hundreds of data providers (including newswire services in many countries), and created hundreds of annotated corpora stored in well-defined and consistent formats. Finally, organizations that purchase NLP systems, or that publish NLP papers, now expect the quality of the work to be demonstrated using standard datasets.

Although language resources are central to NLP, we still face many obstacles in using them. First, the resource we are looking for may not exist, and so we have to think about *creating* a new language resource, and doing a sufficiently careful job that it serves our future needs, thanks to its coverage, balance, and documentation of the sources. Second, a resource may exist but its creator didn't document its existence anywhere, leaving us to recreate the resource; however, to save further wasted effort we should learn about *publishing* metadata the documents the existence of a resource, and even how to publish the resource itself, in a form that is easy for others to re-use. Third, the resource may exist and may be obtained, but is in an incompatible format, and so we need to set about *converting* the data into a different format. Finally, the resource may be in the right format, but the available software is unable to perform the required analysis task, and so we need to develop our own program for *analyzing* the data. This chapter covers each of these issues — creating, publishing, converting, and analyzing — using many examples drawn from practical experience managing linguistic data. However, before embarking on this sequence of issues, we start by examining the organization of linguistic data.

## 13.2 Linguistic Databases

Linguistic databases span a multidimensional space of cases, which we can divide up in several ways: the scope and design of the data collection; the goals of the creators; the nature of the material included; the goals and methods of the users (which are often not anticipated by the creators). Three examples follow.

In one type of linguistic database, the design unfolds interactively in the course of the creator's explorations. This is the pattern typical of traditional "field linguistics," in which material from elicitation sessions is analyzed repeatedly as it is gathered, with tomorrow's elicitation often based on questions that arise in analyzing today's. The resulting field notes are then used during subsequent years of research, and may serve as an archival resource indefinitely — the field notes of linguists and anthropologists working in the early years of the 20th century remain an important source of information today. Computerization is an obvious boon to work of this type, as exemplified by the popular program **Shoebox** — now about two decades old and re-released as **Toolbox** — which replaces the field linguist's traditional shoebox full of file cards.

Another pattern is represented by experimental approaches in which a body of carefully-designed material is collected from a range of subjects, then analyzed to evaluate a hypothesis or develop a technology. Today, such databases are collected and analyzed in digital form. Among scientists (such as phoneticians or psychologists), they are rarely published and therefore rarely preserved. Among engineers, it has become common for such databases to be shared and re-used at least within a laboratory or company, and often to be published more widely. Linguistic databases of this type are the basis of the "common task" method of research management, which over the past 15 years has become the norm in government-funded research programs in speech- and language-related technology.

Finally, there are efforts to gather a "reference corpus" for a particular language. Large and well-documented examples include the **American National Corpus** (ANC) and the **British National Corpus** (BNC). The goal in such cases is to produce a set of linguistic materials that cover the many forms, styles and uses of a language as widely as possible. The core application is typically lexicographic, that is, the construction of dictionaries based on a careful study of patterns of use. These corpora were constructed by large consortia spanning government, industry, and academia. Their planning and execution took more than five years, and indirectly involved hundreds of person-years of effort. There is also a long and distinguished history of other humanistic reference corpora, such as the Thesaurus Linguae Graecae.

There are no hard boundaries among these categories. Accumulations of smaller bodies of data may come in time to constitute a sort of reference corpus, while selections from large databases may form the basis for a particular experiment. Further instructive examples follow.

A linguist's field notes may include extensive examples of many genres (proverbs, conversations, narratives, rituals, and so forth), and may come to constitute a reference corpus of modest but useful size. There are many extinct languages for which such material is all the data we will ever have, and many more endangered languages for which such documentation is urgently needed. Sociolinguists typically base their work on analysis of a set of recorded interviews, which may over time grow to create another sort of reference corpus. In some labs, the residue of decades of work may comprise literally thousands of hours of recordings, many of which have been transcribed and annotated to one extent or another. The **CHILDES** corpus, comprising transcriptions of parent-child interactions in many languages, contributed by many individual researchers, has come to constitute a widely-used reference corpus for language acquisition research. Speech technologists aim to produce training and testing material of broad applicability, and wind up creating another sort of reference corpus. To date,

linguistic technology R&D has been the primary source of published linguistic databases of all sorts (see e.g. <http://www.ldc.upenn.edu/>).

As large, varied linguistic databases are published, phoneticians or psychologists are increasingly likely to base experimental investigations on balanced, focused subsets extracted from databases produced for entirely different reasons. Their motivations include the desire to save time and effort, the desire to work on material available to others for replication, and sometimes a desire to study more naturalistic forms of linguistic behavior. The process of choosing a subset for such a study, and making the measurements involved, is usually in itself a non-trivial addition to the database. This recycling of linguistic databases for new purposes is a normal and expected consequence of publication. For instance, the Switchboard database, originally collected for speaker identification research, has since been used as the basis for published studies in speech recognition, word pronunciation, disfluency, syntax, intonation and discourse structure.

At present, only a tiny fraction of the linguistic databases that are collected are published in any meaningful sense. This is mostly because publication of such material was both time-consuming and expensive, and because use of such material by other researchers was also both expensive and technically difficult. However, general improvements in hardware, software and networking have changed this, and linguistic databases can now be created, published, stored and used without inordinate effort or large expense.

In practice, the implications of these cost-performance changes are only beginning to be felt. The main problem is that adequate tools for creation, publication and use of linguistic data are not widely available. In most cases, each project must create its own set of tools, which hinders publication by researchers who lack the expertise, time or resources to make their data accessible to others. Furthermore, we do not have adequate, generally accepted standards for expressing the structure and content of linguistic databases. Without such standards, general-purpose tools are impossible — though at the same time, without available tools, adequate standards are unlikely to be developed, used and accepted. Just as importantly, there must be a critical mass of users and published material to motivate maintenance of data and access tools over time.

Relative to these needs, the present chapter has modest goals, namely to equip readers to take linguistic databases into their own hands by writing programs to help create, publish, transform and analyze the data. In the rest of this section we take a close look at the fundamental data types, an exemplary speech corpus, and the lifecycle of linguistic data.

### 13.2.1 Fundamental Data Types

Linguistic data management deals with a variety of data types, the most important being lexicons and texts. A **lexicon** is a database of words, minimally containing part of speech information and glosses. For many lexical resources, it is sufficient to use a **record** structure, i.e. a key plus one or more fields, as shown in [Figure 13.1](#). A lexical resource could be a conventional dictionary or comparative wordlist, as illustrated. Several related linguistic data types also fit this model. For example in a phrasal lexicon, the key field is a phrase rather than a single word. A thesaurus can be derived from a lexicon by adding topic fields to the entries and constructing an index over those fields. We can also construct special tabulations (known as paradigms) to illustrate contrasts and systematic variation, as shown in [Figure 13.1](#) for three verbs.

At the most abstract level, a **text** is a representation of a real or fictional speech event, and the time-course of that event carries over into the text itself. A text could be a small unit, such as a word or sentence, or a complete narrative or dialogue. It may come with annotations such as part-of-speech tags, morphological analysis, discourse structure, and so forth. As we saw in the IOB tagging technique

([Chapter 7](#)), it is possible to represent higher-level constituents using tags on individual words. Thus the abstraction of text shown in [Figure 13.1](#) is sufficient.

### 13.2.2 Corpus Structure: a Case Study of TIMIT

The TIMIT corpus of read speech was the first annotated speech database to be widely distributed, and it has an especially clear organization. TIMIT was developed by a consortium including Texas Instruments and MIT (hence the name), and was designed to provide data for the acquisition of acoustic-phonetic knowledge and to support the development and evaluation of automatic speech recognition systems.

Like the Brown Corpus, which displays a balanced selection of text genres and sources, TIMIT includes a balanced selection of dialects, speakers, and materials. For each of eight dialect regions, 50 male and female speakers having a range of ages and educational backgrounds each read ten carefully chosen sentences. Two sentences, read by all speakers, were designed to bring out dialect variation:

- (198) a. she had your dark suit in greasy wash water all year
- b. don't ask me to carry an oily rag like that

The remaining sentences were chosen to be phonetically rich, involving all phones (sounds) and a comprehensive range of diphones (phone bigrams). Additionally, the design strikes a balance between multiple speakers saying the same sentence in order to permit comparison across speakers, and having a large range of sentences covered by the corpus to get maximal coverage of diphones. Thus, five sentences read by each speaker, are also read by six other speakers (comparability). The remaining three sentences read by each speaker were unique to that speaker (coverage).

NLTK includes a sample from the TIMIT corpus. You can access its documentation in the usual way, using `help(corpus.timit)`. Print `corpus.timit.items` to see a list of the 160 recorded utterances in the corpus sample. Each item name has complex internal structure, as shown in [Figure 13.2](#).

Each item has phonetic a phonetic transcription, which can be accessed using the `phones()` method. We can access the corresponding word tokens in the customary way. Both access methods permit an optional argument `offset=True` which includes the start and end offsets of the corresponding span in the audio file.

```
>>> phonetic = nltk.corpus.timit.phones('dr1-fvmh0/sa1')
>>> phonetic
['h#', 'sh', 'iy', 'hv', 'ae', 'dcl', 'y', 'ix', 'dcl', 'd', 'aa', 'kcl',
's', 'ux', 'tcl', 'en', 'gcl', 'g', 'r', 'iy', 's', 'iy', 'w', 'aa',
'sh', 'epi', 'w', 'aa', 'dx', 'ax', 'q', 'ao', 'l', 'y', 'ih', 'ax', 'h#']
>>> nltk.corpus.timit.word_times('dr1-fvmh0/sa1')
[('she', 7812, 10610), ('had', 10610, 14496), ('your', 14496, 15791),
('dark', 15791, 20720), ('suit', 20720, 25647), ('in', 25647, 26906),
('greasy', 26906, 32668), ('wash', 32668, 37890), ('water', 38531, 42417),
('all', 43091, 46052), ('year', 46052, 50522)]
```

#### Note

Remember that our program samples assume you begin your interactive session or your program with: `import nltk, re, pprint` (Note that some of the examples in this chapter have not yet been updated to work with NLTK-Lite version 0.9).

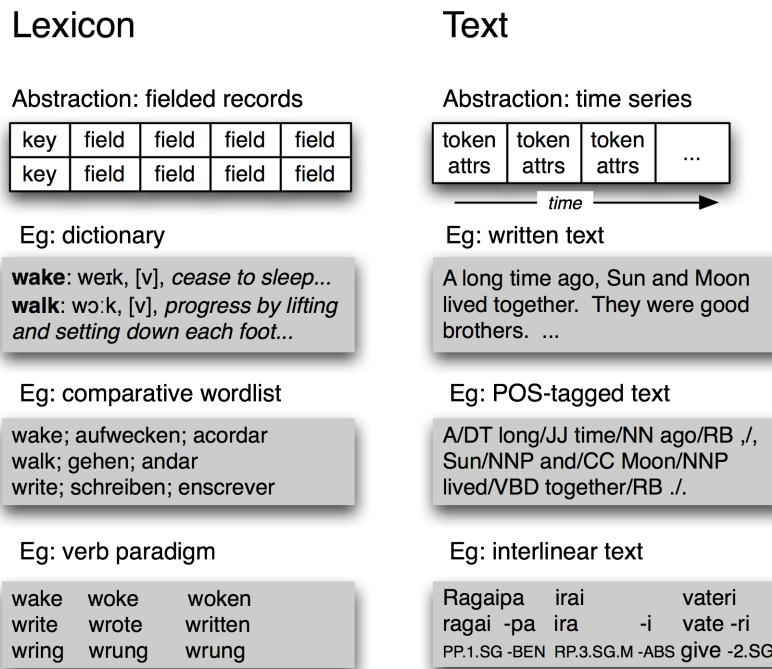


Figure 13.1: Basic Linguistic Datatypes: Lexicons and Texts

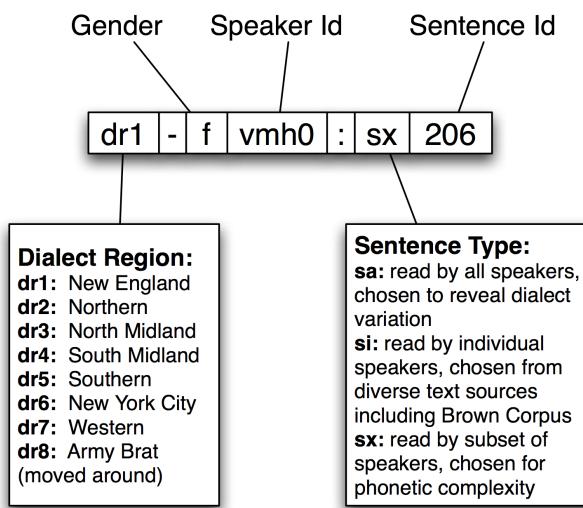


Figure 13.2: Structure of a TIMIT Identifier in the NLTK Corpus Package

In addition to this text data, TIMIT includes a lexicon that provides the canonical pronunciation of every word:

```
>>> timitdict = nltk.corpus.timit.transcription_dict()
>>> timitdict['greasy'] + timitdict['wash'] + timitdict['water']
['g', 'r', 'iy1', 's', 'iy', 'w', 'ao1', 'sh', 'w', 'ao1', 't', 'axr']
>>> phonetic[17:30]
['g', 'r', 'iy', 's', 'iy', 'w', 'aa', 'sh', 'epi', 'w', 'aa', 'dx', 'ax']
```

This gives us a sense of what a speech processing system would have to do in producing or recognizing speech in this particular dialect (New England). Finally, TIMIT includes demographic data about the speakers, permitting fine-grained study of vocal, social, and gender characteristics.

```
>>> nltk.corpus.timit.spkrinfo('dr1-fvmh0')
SpeakerInfo(id='VMH0', sex='F', dr='1', use='TRN', recdate='03/11/86',
birthdate='01/08/60', ht='5\'05"', race='WHT', edu='BS',
comments='BEST NEW ENGLAND ACCENT SO FAR')
```

TIMIT illustrates several key features of corpus design. First, the corpus contains two layers of annotation, at the phonetic and orthographic levels. In general, a text or speech corpus may be annotated at many different linguistic levels, including morphological, syntactic, and discourse levels. Moreover, even at a given level there may be different labeling schemes or even disagreement amongst annotators, such that we want to represent multiple versions. A second property of TIMIT is its balance across multiple dimensions of variation, for coverage of dialect regions and diphones. The inclusion of speaker demographics brings in many more independent variables, that may help to account for variation in the data, and which facilitate later uses of the corpus for purposes that were not envisaged when the corpus was created, e.g. sociolinguistics. A third property is that there is a sharp division between the original linguistic event captured as an audio recording, and the annotations of that event. The same holds true of text corpora, in the sense that the original text usually has an external source, and is considered to be an immutable artifact. Any transformations of that artifact which involve human judgment — even something as simple as tokenization — are subject to later revision, thus it is important to retain the source material in a form that is as close to the original as possible.

A fourth feature of TIMIT is the hierarchical structure of the corpus. With 4 files per sentence, and 10 sentences for each of 500 speakers, there are 20,000 files. These are organized into a tree structure, shown schematically in [Figure 13.3](#). At the top level there is a split between training and testing sets, which gives away its intended use for developing and evaluating statistical models.

Finally, notice that even though TIMIT is a speech corpus, its transcriptions and associated data are just text, and can be processed using programs just like any other text corpus. Therefore, many of the computational methods described in this book are applicable. Moreover, notice that all of the data types included in the TIMIT corpus fall into our two basic categories of lexicon and text (cf. [section 13.2.1](#)). Even the speaker demographics data is just another instance of the lexicon data type.

This last observation is less surprising when we consider that text and record structures are the primary domains for the two subfields of computer science that focus on data management, namely text retrieval and databases. A notable feature of linguistic data management is that usually brings both data types together, and that it can draw on results and techniques from both fields.

### 13.2.3 The Lifecycle of Linguistic Data: Evolution vs Curation

Once a corpus has been created and disseminated, it typically gains a life of its own, as others adapt it to their needs. This may involve reformatting a text file (e.g. converting to XML), renaming files,

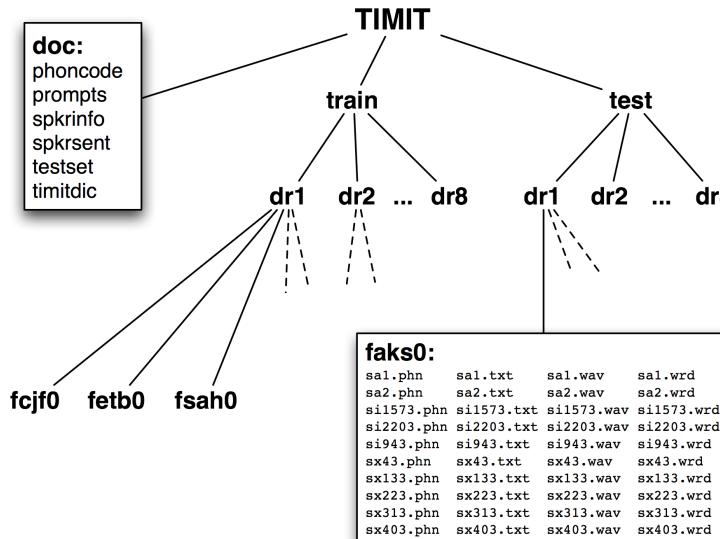


Figure 13.3: Structure of the Published TIMIT Corpus

retokenizing the text, selecting a subset of the data to enrich, and so forth. Multiple research groups may do this work independently, as exemplified in [Figure 13.4](#). At a later date, when someone wants to combine sources of information from different version, the task may be extremely onerous.

The task of using derived corpora is made even more difficult by the lack of any record about how the derived version was created, and which version is the most up-to-date.

An alternative to this chaotic situation is for all corpora to be centrally curated, and for committees of experts to revise and extend a reference corpus at periodic intervals, considering proposals for new content from third-parties, much like a dictionary is edited. However, this is impractical.

A better solution is to have a canonical, immutable primary source, which supports incoming references to any sub-part, and then for all annotations (including segmentations) to reference this source. This way, two independent tokenizations of the same text can be represented without touch the source text, as can any further labeling and grouping of those annotations. This method is known as **standoff annotation**.

[More discussion and examples]

## 13.3 Creating Data

Scenarios: fieldwork, web, manual entry using local tool, machine learning with manual post-editing

Conventional office software is widely used in computer-based language documentation work, given its familiarity and ready availability. This includes word processors and spreadsheets.

### 13.3.1 Spiders

- what they do: basic idea is simple
- python code to find all the anchors, extract the href, and make an absolute URL for fetching

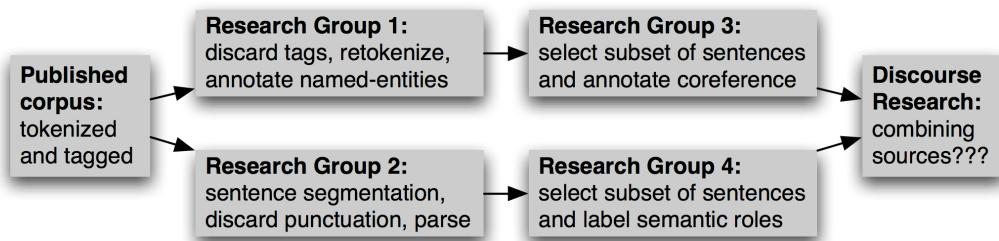


Figure 13.4: Evolution of a Corpus

- many issues: starting points, staying within a single site, only getting HTML
- various stand-alone tools for spidering, and mirroring

### 13.3.2 Creating Language Resources Using Word Processors

Word processing software is often used in creating dictionaries and interlinear texts. As the data grows in size and complexity, a larger proportion of time is spent maintaining consistency. Consider a dictionary in which each entry has a part-of-speech field, drawn from a set of 20 possibilities, displayed after the pronunciation field, and rendered in 11-point bold. No conventional word processor has search or macro functions capable of verifying that all part-of-speech fields have been correctly entered and displayed. This task requires exhaustive manual checking. If the word processor permits the document to be saved in a non-proprietary format, such as text, HTML, or XML, we can sometimes write programs to do this checking automatically.

Consider the following fragment of a lexical entry: "sleep [sli:p] **vi** condition of body and mind...". We can enter this in MSWord, then "Save as Web Page", then inspect the resulting HTML file:

```

<p class=MsoNormal>sleep

[sli:p]

vi

<i>a condition of body and mind ...<o:p></o:p></i>
</p>

```

Observe that the entry is represented as an HTML paragraph, using the `<p>` element, and that the part of speech appears inside a `<span style='font-size:11.0pt'>` element. The following program defines the set of legal parts-of-speech, `legal_pos`. Then it extracts all 11-point content from the `dict.htm` file and stores it in the set `used_pos`. Observe that the search pattern contains a parenthesized sub-expression; only the material that matches this sub-expression is returned by `re.findall`. Finally, the program constructs the set of illegal parts-of-speech as `used_pos - legal_pos`:

```

>>> legal_pos = set(['n', 'v.t.', 'v.i.', 'adj', 'det'])
>>> pattern = re.compile(r'"font-size:11.0pt">([a-z.]+)<"')
>>> document = open("dict.htm").read()

```

```
>>> used_pos = set(re.findall(pattern, document))
>>> illegal_pos = used_pos.difference(legal_pos)
>>> print list(illegal_pos)
['v.i', 'intrans']
```

This simple program represents the tip of the iceberg. We can develop sophisticated tools to check the consistency of word processor files, and report errors so that the maintainer of the dictionary can correct the original file *using the original word processor*.

We can write other programs to convert the data into a different format. For example, Listing 13.1 strips out the HTML markup using `nltk.clean_html()`, extracts the words and their pronunciations, and generates output in "comma-separated value" (CSV) format:

---

#### Listing 13.1 Converting HTML Created by Microsoft Word into Comma-Separated Values

---

```
def lexical_data(html_file):
 SEP = '_ENTRY'
 html = open(html_file).read()
 html = re.sub(r'<p>', SEP + '<p>', html)
 text = nltk.clean_html(html)
 text = ' '.join(text.split())
 for entry in text.split(SEP):
 if entry.count(' ') > 2:
 yield entry.split(' ', 3)

>>> import csv
>>> writer = csv.writer(open("dict1.csv", "wb"))
>>> writer.writerows(lexical_data("dict.htm"))
```

---

### 13.3.3 Creating Language Resources Using Spreadsheets and Databases

**Spreadsheets.** These are often used for wordlists or paradigms. A comparative wordlist may be stored in a spreadsheet, with a row for each cognate set, and a column for each language. Examples are available from [www.rosettaproject.org](http://www.rosettaproject.org). Programs such as Excel can export spreadsheets in the CSV format, and we can write programs to manipulate them, with the help of Python's `csv` module. For example, we may want to print out cognates having an edit-distance of at least three from each other (i.e. 3 insertions, deletions, or substitutions).

**Databases.** Sometimes lexicons are stored in a full-fledged relational database. When properly normalized, these databases can implement many well-formedness constraints. For example, we can require that all parts-of-speech come from a specified vocabulary by declaring that the part-of-speech field is an *enumerated type*. However, the relational model is often too restrictive for linguistic data, which typically has many optional and repeatable fields (e.g. dictionary sense definitions and example sentences). Query languages such as SQL cannot express many linguistically-motivated queries, e.g. *find all words that appear in example sentences for which no dictionary entry is provided*. Now supposing that the database supports exporting data to CSV format, and that we can save the data to a file `dict.csv`:

```
"sleep", "sli:p", "v.i", "a condition of body and mind ..."
"walk", "wo:k", "v.intr", "progress by lifting and setting down each foot ..."
"wake", "weik", "intrans", "cease to sleep"
```

Now we can express this query as shown in Figure 13.2.

---

**Listing 13.2** Finding definition words not themselves defined
 

---

```
def undefined_words(csv_file):
 import csv
 lexemes = set()
 defn_words = set()
 for row in csv.reader(open(csv_file)):
 lexeme, pron, pos, defn = row
 lexemes.add(lexeme)
 defn_words.union(defn.split())
 return sorted(defn_words.difference(lexemes))

>>> print undefined_words("dict.csv")
['...', 'a', 'and', 'body', 'by', 'cease', 'condition', 'down', 'each',
'foot', 'lifting', 'mind', 'of', 'progress', 'setting', 'to']
```

---

### 13.3.4 Creating Language Resources Using Toolbox

Over the last two decades, several dozen tools have been developed that provide specialized support for linguistic data management. Perhaps the single most popular tool used by linguists for managing data is *Toolbox*, previously known as *Shoebox* (freely downloadable from <http://www.sil.org/computing/toolbox/>). In this section we discuss a variety of techniques for manipulating Toolbox data in ways that are not supported by the Toolbox software. (The methods we discuss could be applied to other record-structured data, regardless of the actual file format.)

A Toolbox file consists of a collection of *entries* (or *records*), where each record is made up of one or more *fields*. Here is an example of an entry taken from a Toolbox dictionary of Rotokas. (Rotokas is an East Papuan language spoken on the island of Bougainville; this data was provided by Stuart Robinson, and is a sample from a larger lexicon):

```
\lx kaa
\ps N
\pt MASC
\cl isi
\ge cooking banana
\tkp banana bilong kukim
\pt itoo
\sf FLORA
\dt 12/Aug/2005
\ex Taeavi iria kaa isi kovopaueva kaparapasia.
\xp Taeavi i bin planim gaden banana bilong kukim tasol long paia.
\xe Taeavi planted banana in order to cook it.
```

This lexical entry contains the following fields: `lx` lexeme; `ps` part-of-speech; `pt` part-of-speech; `cl` classifier; `ge` English gloss; `tkp` Tok Pisin gloss; `sf` Semantic field; `dt` Date last edited; `ex` Example sentence; `xp` Pidgin translation of example; `xe` English translation of example. These field names are preceded by a backslash, and must always appear at the start of a line. The characters of the field names must be alphabetic. The field name is separated from the field's contents by whitespace.

The contents can be arbitrary text, and can continue over several lines (but cannot contain a line-initial backslash).

We can use the `toolbox.xml()` method to access a Toolbox file and load it into an `ElementTree` object.

```
>>> from nltk.corpus import toolbox
>>> lexicon = toolbox.xml('rotokas.dic')
```

There are two ways to access the contents of the lexicon object, by indexes and by paths. Indexes use the familiar syntax, thus `lexicon[3]` returns entry number 3 (which is actually the fourth entry counting from zero). And `lexicon[3][0]` returns its first field:

```
>>> lexicon[3][0]
<Element lx at 77bd28>
>>> lexicon[3][0].tag
'lx'
>>> lexicon[3][0].text
'kaa'
```

The second way to access the contents of the lexicon object uses paths. The lexicon is a series of record objects, each containing a series of field objects, such as `lx` and `ps`. We can conveniently address all of the lexemes using the path `record/lx`. Here we use the `findall()` function to search for any matches to the path `record/lx`, and we access the text content of the element, normalizing it to lowercase.

```
>>> [lexeme.text.lower() for lexeme in lexicon.findall('record/lx')]
['kaa', 'kaa', 'kaa', 'kaakaaro', 'kaakaaviko', 'kaakaavo', 'kaakaoko',
'kaakasi', 'kaakau', 'kaakauko', 'kaakito', 'kaakuupato', ..., 'kuvuto']
```

It is often convenient to add new fields that are derived automatically from existing ones. Such fields often facilitate search and analysis. For example, in Listing 13.3 we define a function `cv()` which maps a string of consonants and vowels to the corresponding CV sequence, e.g. `kakapua` would map to `CVCVCVV`. This mapping has four steps. First, the string is converted to lowercase, then we replace any non-alphabetic characters `[^a-z]` with an underscore. Next, we replace all vowels with `V`. Finally, anything that is not a `V` or an underscore must be a consonant, so we replace it with a `C`. Now, we can scan the lexicon and add a new `cv` field after every `lx` field. Listing 13.3 shows what this does to a particular entry; note the last line of output, which shows the new CV field.

Finally, we take a look at simple methods to generate summary reports, giving us an overall picture of the quality and organisation of the data.

First, suppose that we wanted to compute the average number of fields for each entry. This is just the total length of the entries (the number of fields they contain), divided by the number of entries in the lexicon:

```
>>> sum(len(entry) for entry in lexicon) / len(lexicon)
13
```

We could try to write down a grammar for lexical entries, and look for entries which do not conform to the grammar. In general, toolbox entries have nested structure. Thus they correspond to a tree over the fields. We can check for well-formedness by parsing the field names. In Listing 13.5 we set up a putative grammar for the entries, then parse each entry. Those that are accepted by the grammar prefixed with a `'+'`, and those that are rejected are prefixed with a `'-'`.

---

Listing 13.3 Adding a new cv field to a lexical entry

---

```
from nltk.etree.ElementTree import SubElement

def cv(s):
 s = s.lower()
 s = re.sub(r'[^a-z]', r'_', s)
 s = re.sub(r'[aeiou]', r'V', s)
 s = re.sub(r'^V_+', r'C', s)
 return (s)

def add_cv_field(entry):
 for field in entry:
 if field.tag == 'lx':
 cv_field = SubElement(entry, 'cv')
 cv_field.text = cv(field.text)

>>> lexicon = toolbox.xml('rotokas.dic')
>>> add_cv_field(lexicon[53])
>>> print nltk.corpus.reader.toolbox.to_sfm_string(lexicon[53])
\lx kaeviro
\ps V
\pt A
\ge lift off
\ge take off
\tkp go antap
\sc MOTION
\vx 1
\nt used to describe action of plane
\dt 03/Jun/2005
\ex Pita kaeviroroe kepa kekesia oa vuripierevo kiuvu.
\xp Pita i go antap na lukim haus win i bagarapim.
\xe Peter went to look at the house that the wind destroyed.
\cv CVVCVVCV
```

---

---

**Listing 13.4** Validating Toolbox Entries Using a Context Free Grammar

---

```

grammar = nltk.parse_cfg('''
S -> Head PS Glosses Comment Date Examples
Head -> Lexeme Root
Lexeme -> "lx"
Root -> "rt" |
PS -> "ps"
Glosses -> Gloss Glosses |
Gloss -> "ge" | "gp"
Date -> "dt"
Examples -> Example Ex_Pidgin Ex_English Examples |
Example -> "ex"
Ex_Pidgin -> "xp"
Ex_English -> "xe"
Comment -> "cmt" |
'''')

def validate_lexicon(grammar, lexicon):
 rd_parser = nltk.RecursiveDescentParser(grammar)
 for entry in lexicon[10:20]:
 marker_list = [field.tag for field in entry]
 if rd_parser.get_parse_list(marker_list):
 print "+", ':'.join(marker_list)
 else:
 print "-", ':'.join(marker_list)

>>> lexicon = toolbox.xml('rotokas.dic')[10:20]
>>> validate_lexicon(grammar, lexicon)
- lx:ps:ge:gp:sf:nt:dt:ex:xp:xe:ex:xp:xe
- lx:rt:ps:ge:gp:nt:dt:ex:xp:xe:ex:ex:xp:xe
- lx:ps:ge:gp:nt:dt:ex:xp:xe:ex:ex:xp:xe
- lx:ps:ge:gp:nt:sf:dt
- lx:ps:ge:gp:dt:cmt:ex:xp:xe:ex:ex:xp:xe
+ lx:ps:ge:ge:ge:gp:cmt:dt:ex:xp:xe
+ lx:rt:ps:ge:gp:cmt:dt:ex:xp:xe:ex:ex:xp:xe
+ lx:rt:ps:ge:ge:gp:dt
- lx:rt:ps:ge:ge:ge:gp:dt:cmt:ex:xp:xe:ex:ex:ex:ex:gp:dt
+ lx:rt:ps:ge:gp:dt:ex:xp:xe
```

---

---

**Listing 13.5** Chunking a Toolbox Lexicon

---

```

import os.path, sys
from nltk_contrib import toolbox

grammar = r"""
 lexfunc: {<lf>(<lv><ln|le>*)*}
 example: {<rf|xv><xn|xe>*}
 sense: {<sn><ps><pn|gv|dv|gn|gp|dn|rn|ge|de|re>*<example>*<lexfunc>*}
 record: {<lx><hm><sense>+<dt>}
"""

>>> from nltk.etree.ElementTree import ElementTree
>>> db = toolbox.ToolboxData()
>>> db.open(nltk.data.find('corpora/toolbox/iu_mien_samp.db'))
>>> lexicon = db.chunk_parse(grammar, encoding='utf8')
>>> toolbox.data.indent(lexicon)
>>> tree = ElementTree(lexicon)
>>> tree.write(sys.stdout, encoding='utf8')

```

---

### 13.3.5 Interlinear Text

The NLTK corpus collection includes many interlinear text samples (though no suitable corpus reader as yet).

**General Ontology for Linguistic Description (GOLD)** <http://www.linguistics-ontology.org/>

### 13.3.6 Creating Metadata for Language Resources

OLAC metadata extends the **Dublin Core** metadata set with descriptors that are important for language resources.

The container for an OLAC metadata record is the element <olac>. Here is a valid OLAC metadata record from the Pacific And Regional Archive for Digital Sources in Endangered Cultures (PARADISEC):

```

<olac:olac xsi:schemaLocation="http://purl.org/dc/elements/1.1/ http://www.language-archives.org/OLAC/1.0/dcElements.xsd
http://purl.org/dc/terms/ http://www.language-archives.org/OLAC/1.0/dcTerms.xsd
http://www.language-archives.org/OLAC/1.0/ http://www.language-archives.org/OLAC/1.0/dcElements.xsd
http://www.language-archives.org/OLAC/1.0/ http://www.language-archives.org/OLAC/1.0/dcTerms.xsd">
<dc:title>Tiraq Field Tape 019</dc:title>
<dc:identifier>AB1-019</dc:identifier>
<dcterms:hasPart>AB1-019-A.mp3</dcterms:hasPart>
<dcterms:hasPart>AB1-019-A.wav</dcterms:hasPart>
<dcterms:hasPart>AB1-019-B.mp3</dcterms:hasPart>
<dcterms:hasPart>AB1-019-B.wav</dcterms:hasPart>
<dc:contributor xsi:type="olac:role" olac:code="recorder">Brotchie, Amanda</dc:contributor>
<dc:subject xsi:type="olac:language" olac:code="x-sil-MME"/>
<dc:language xsi:type="olac:language" olac:code="x-sil-BCY"/>
<dc:language xsi:type="olac:language" olac:code="x-sil-MME"/>
<dc:format>Digitised: yes;</dc:format>

```

```

<dc:type>primary_text</dc:type>
<dcterms:accessRights>standard, as per PDSC Access form</dcterms:accessRights>
<dc:description>SIDE A<p>1. Elicitation Session – Discussion and
translation of Lise's and Marie-Claire's Songs and Stories from
Tape 18 (Tamedal)<p><p>SIDE B<p>1. Elicitation Session: Discussion
of and translation of Lise's and Marie-Clare's songs and stories
from Tape 018 (Tamedal)<p>2. Kastom Story 1 – Bislama
(Alec). Language as given: Tiraq</dc:description>
</olac:olac>
```

NLTK Version 0.9 includes support for reading an OLAC record, for example:

```

>>> file = nltk.data.find('corpora/treebank/olac.xml')
>>> xml = open(file).read()
>>> nltk.olac pprint_olac(xml)
identifier : LDC99T42
title : Treebank-3
type : (olac:linguistic-type=primary_text)
description : Release type: General
creator : Mitchell P. Marcus, Beatrice Santorini, Mary Ann Marcinkiewicz and Ann Taylor
identifier : ISBN: 1-58563-163-9
description : Online documentation: http://www.ldc.upenn.edu/Catalog/docs/treebank3/
subject : English (olac:language=x-sil-ENG)
```

### 13.3.7 Linguistic Annotation

Annotation graph model

multiple overlapping trees over shared data

Large annotation tasks require multiple annotators. How consistently can a group of annotators perform? It is insufficient to report that there is 80% agreement, as we have no way to tell if this is good or bad. I.e. for an easy task such as tagging, this would be a bad score, while for a difficult task such as semantic role labeling, this would be an exceptionally good score.

The **Kappa** coefficient  $\kappa$  measures agreement between two people making category judgments, correcting for expected chance agreement. For example, suppose an item is to be annotated, and four coding options are equally likely. Then people coding randomly would be expected to agree 25% of the time. Thus, an agreement of 25% will be assigned  $\kappa = 0$ , and better levels of agreement will be scaled accordingly. For an agreement of 50%, we would get  $\kappa = 0.333$ , as 50 is a third of the way from 25 to 100.

### 13.3.8 Exercises

1. ⚡ Write a program to filter out just the date field (`dt`) without having to list the fields we wanted to retain.
2. ⚡ Print an index of a lexicon. For each lexical entry, construct a tuple of the form `(gloss, lexeme)`, then sort and print them all.
3. ⚡ What is the frequency of each consonant and vowel contained in lexeme fields?
4. ⚡ In Listing 13.3 the new field appeared at the bottom of the entry. Modify this program so that it inserts the new subelement right after the `lx` field. (Hint: create the new `cv` field

using `Element('cv')`, assign a text value to it, then use the `insert()` method of the parent element.)

5. ● Write a function that deletes a specified field from a lexical entry. (We could use this to sanitize our lexical data before giving it to others, e.g. by removing fields containing irrelevant or uncertain content.)
6. ● Write a program that scans an HTML dictionary file to find entries having an illegal part-of-speech field, and reports the *headword* for each entry.
7. ● Write a program to find any parts of speech (`ps` field) that occurred less than ten times. Perhaps these are typing mistakes?
8. ● We saw a method for discovering cases of whole-word reduplication. Write a function to find words that may contain partial reduplication. Use the `re.search()` method, and the following regular expression: `(.+) \1`
9. ● We saw a method for adding a `cv` field. There is an interesting issue with keeping this up-to-date when someone modifies the content of the `lx` field on which it is based. Write a version of this program to add a `cv` field, replacing any existing `cv` field.
10. ● Write a function to add a new field `syl` which gives a count of the number of syllables in the word.
11. ● Write a function which displays the complete entry for a lexeme. When the lexeme is incorrectly spelled it should display the entry for the most similarly spelled lexeme.
12. ● Write a function that takes a lexicon and finds which pairs of consecutive fields are most frequent (e.g. `ps` is often followed by `pt`). (This might help us to discover some of the structure of a lexical entry.)
13. ★ Obtain a comparative wordlist in CSV format, and write a program that prints those cognates having an edit-distance of at least three from each other.
14. ★ Build an index of those lexemes which appear in example sentences. Suppose the lexeme for a given entry is `w`. Then add a single cross-reference field `xrf` to this entry, referencing the headwords of other entries having example sentences containing `w`. Do this for all entries and save the result as a toolbox-format file.

## 13.4 Converting Data Formats

- write our own parser and formatted print
- use existing libraries, e.g. csv

### 13.4.1 Formatting Entries

We can also print a formatted version of a lexicon. It allows us to request specific fields without needing to be concerned with their relative ordering in the original file.

```

>>> lexicon = toolbox.xml('rotokas.dic')
>>> for entry in lexicon[70:80]:
... lx = entry.findtext('lx')
... ps = entry.findtext('ps')
... ge = entry.findtext('ge')
... print "%s (%s) '%s'" % (lx, ps, ge)
kakae (???) 'small'
kakae (CLASS) 'child'
kakaevira (ADV) 'small-like'
kakapikoa (???) 'small'
kakapikoto (N) 'newborn baby'
kakapu (V) 'place in sling for purpose of carrying'
kakapua (N) 'sling for lifting'
kakara (N) 'arm band'
Kakarapaia (N) 'village name'
kakarau (N) 'frog'

```

We can use the same idea to generate HTML tables instead of plain text. This would be useful for publishing a Toolbox lexicon on the web. It produces HTML elements <table>, <tr> (table row), and <td> (table data).

```

>>> html = "<table>\n"
>>> for entry in lexicon[70:80]:
... lx = entry.findtext('lx')
... ps = entry.findtext('ps')
... ge = entry.findtext('ge')
... html += " <tr><td>%s</td><td>%s</td><td>%s</td></tr>\n" % (lx, ps, ge)
>>> html += "</table>"
>>> print html

kakae		small
kakae	CLASS	child
kakaevira	ADV	small-like
kakapikoa	(???)	small
kakapikoto	(N)	newborn baby
kakapu	(V)	place in sling for purpose of carrying
kakapua	(N)	sling for lifting
kakara	(N)	arm band
Kakarapaia	(N)	village name
kakarau	(N)	frog


```

XML output

```

>>> import sys
>>> from nltk.etree.ElementTree import ElementTree
>>> tree = ElementTree(lexicon[3])
>>> tree.write(sys.stdout)
<record>
 <lx>kaa</lx>
 <ps>N</ps>
 <pt>MASC</pt>
 <cl>isi</cl>
 <ge>cooking banana</ge>

```

```

<tkp>banana bilong kukim</tkp>
<pt>itoo</pt>
<sf>FLORA</sf>
<dt>12/Aug/2005</dt>
<ex>Taeavi iria kaa isi kovopaeua kaparapasia.</ex>
<xp>Taeavi i bin planim gaden banana bilong kukim tasol long paia.</xp>
<xe>Taeavi planted banana in order to cook it.</xe>
</record>

```

### 13.4.2 Exercises

- Create a spreadsheet using office software, containing one lexical entry per row, consisting of a headword, a part of speech, and a gloss. Save the spreadsheet in CSV format. Write Python code to read the CSV file and print it in Toolbox format, using `lx` for the headword, `ps` for the part of speech, and `gl` for the gloss.

## 13.5 Analyzing Language Data

I.e. linguistic exploration

Export to statistics package via CSV

In this section we consider a variety of analysis tasks.

**Reduplication:** First, we will develop a program to find reduplicated words. In order to do this we need to store all verbs, along with their English glosses. We need to keep the glosses so that they can be displayed alongside the wordforms. The following code defines a Python dictionary `lexgloss` which maps verbs to their English glosses:

```

>>> lexgloss = {}
>>> for entry in lexicon:
... lx = entry.findtext('lx')
... ps = entry.findtext('ps')
... if lx and ps and ps[0] == 'v':
... lexgloss[lx] = entry.findtext('ge')
kasi (burn); kasikasi (angry)
kee (shatter); keekee (chipped)
kauo (jump); kauokauo (jump up and down)
kea (confused); keakea (lie)
kaape (unable to meet); kaapekaape (embrace)
kapo (fasten.cover.strip); kapokapo (fasten.cover.strips)
kavo (collect); kavokavo (perform sorcery)
karu (open); karukaru (open)
kare (return); karekare (return)
kari (rip); karikari (tear)
kae (blow); kaekae (tempt)

```

Next, for each verb `lex`, we will check if the lexicon contains the reduplicated form `lex+lex`. If it does, we report both forms along with their glosses.

```

>>> for lex in lexgloss:
... if lex+lex in lexgloss:
... print "%s (%s); %s (%s)" %\
... (lex, lexgloss[lex], lex+lex, lexgloss[lex+lex])

```

```

kuvu (fill.up); kuvukuvu (fill up)
kitu (store); kitukitu (scrub clothes)
kiru (have sore near mouth); kirukiru (crisp)
kopa (swallow); kopakopa (gulp.down)
kasi (burn); kasikasi (angry)
koi (high pitched sound); koikoi (groan with pain)
kee (shatter); keekee (chipped)
kauo (jump); kauokauo (jump up and down)
kea (confused); keakea (lie)
kovo (work); kovokovo (play)
kove (fell); kovekove (drip repeatedly)
kaape (unable to meet); kaapekaape (embrace)
kapo (fasten.cover.strip); kapokapo (fasten.cover.strips)
koa (skin); koakoa (bark a tree)
kipu (paint); kipukipu (rub.on)
koe (spoon out a solid); koekoe (spoon out)
kotu (bite); kotukotu (gnash teeth)
kavo (collect); kavokavo (perform sorcery)
kuri (scrape); kurikuri (scratch repeatedly)
karu (open); karukaru (open)
kare (return); karekare (return)
kari (rip); karikari (tear)
kiro (write); kirokiro (write)
kae (blow); kaekae (tempt)
koru (make return); korukoru (block)
kosi (exit); kosikosi (exit)

```

**Complex Search Criteria:** Phonological description typically identifies the segments, alternations, syllable canon and so forth. It is relatively straightforward to count up the occurrences of all the different types of CV syllables that occur in lexemes.

In the following example, we first import the regular expression and probability modules. Then we iterate over the lexemes to find all sequences of a non-vowel [^aeiou] followed by a vowel [aeiou].

```

>>> fd = nltk.FreqDist()
>>> tokenizer = nltk.RegexpTokenizer(pattern=r'[^aeiou][aeiou]')
>>> lexemes = [lexeme.text.lower() for lexeme in lexicon.findall('record/lx')]
>>> for lex in lexemes:
... for syl in tokenizer.tokenize(lex):
... fd.inc(syl)

```

Now, rather than just printing the syllables and their frequency counts, we can tabulate them to generate a useful display.

```

>>> for vowel in 'aeiou':
... for cons in 'ptkvsr':
... print '%s%s:%4d' % (cons, vowel, fd[cons+vowel]),
... print
pa: 83 ta: 47 ka: 428 va: 93 sa: 0 ra: 187
pe: 31 te: 8 ke: 151 ve: 27 se: 0 re: 63
pi: 105 ti: 0 ki: 94 vi: 105 si: 100 ri: 84
po: 34 to: 148 ko: 430 vo: 48 so: 2 ro: 89
pu: 51 tu: 37 ku: 175 vu: 49 su: 1 ru: 79

```

Consider the `t` and `s` columns, and observe that `ti` is not attested, while `si` is frequent. This suggests that a phonological process of palatalization is operating in the language. We would then want to consider the other syllables involving `s` (e.g. the single entry having `su`, namely *kasuari* 'cassowary' is a loanword).

**Prosodically-motivated search:** A phonological description may include an examination of the segmental and prosodic constraints on well-formed morphemes and lexemes. For example, we may want to find trisyllabic verbs ending in a long vowel. Our program can make use of the fact that syllable onsets are obligatory and simple (only consist of a single consonant). First, we will encapsulate the syllabic counting part in a separate function. It gets the CV template of the word `cv(word)` and counts the number of consonants it contains:

```
>>> def num_cons(word):
... template = cv(word)
... return template.count('C')
```

We also encapsulate the vowel test in a function, as this improves the readability of the final program. This function returns the value `True` just in case `char` is a vowel.

```
>>> def is_vowel(char):
... return (char in 'aeiou')
```

Over time we may create a useful collection of such functions. We can save them in a file `utilities.py`, and then at the start of each program we can simply import all the functions in one go using `from utilities import *`. We take the entry to be a verb if the first letter of its part of speech is a V. Here, then, is the program to display trisyllabic verbs ending in a long vowel:

```
>>> for entry in lexicon:
... lx = entry.findtext('lx')
... if lx:
... ps = entry.findtext('ps')
... if num_cons(lx) == 3 and ps[0] == 'V' \
... and is_vowel(lx[-1]) and is_vowel(lx[-2]):
... ge = entry.findtext('ge')
... print "%s (%s) '%s'" % (lx, ps, ge)
kaetupie (V) 'tighten'
kakupie (V) 'shout'
kapatau (V) 'add to'
kapuapie (V) 'wound'
kapupie (V) 'close tight'
kapuupie (V) 'close'
karepie (V) 'return'
karivai (V) 'have an appetite'
kasipie (V) 'care for'
kasirao (V) 'hot'
kaukaupie (V) 'shine intensely'
kavorou (V) 'covet'
kavupie (V) 'leave.behind'
kekepie (V) 'show'
keruria (V) 'persistent'
ketoopie (V) 'make sprout from seed'
kipapie (V) 'wan samting tru'
koatapie (V) 'put in'
```

```

koetapie (V) 'investigate'
koikoipie (V) 'make groan with pain'
koepie (V) 'make.rain'
kokoruu (V) 'insect-infested'
kovovae (V) 'sing'
kokovua (V) 'shave the hair line'
kopiipie (V) 'kill'
korupie (V) 'take outside'
kosipie (V) 'make exit'
kovopie (V) 'make work'
kukuvai (V) 'shelter head'
kuvaupie (V) 'desert'

```

**Finding Minimal Sets:** In order to establish a contrast segments (or lexical properties, for that matter), we would like to find pairs of words which are identical except for a single property. For example, the words pairs *mace* vs *maze* and *face* vs *faze* — and many others like them — demonstrate the existence of a phonemic distinction between *s* and *z* in English. NLTK provides flexible support for constructing minimal sets, using the `MinimalSet()` class. This class needs three pieces of information for each item to be added: `context`: the material that must be fixed across all members of a minimal set; `target`: the material that changes across members of a minimal set; `display`: the material that should be displayed for each item.

| Examples of Minimal Set Parameters |                   |              |            |
|------------------------------------|-------------------|--------------|------------|
| Minimal Set                        | Context           | Target       | Display    |
| <i>bib, bid, big</i>               | first two letters | third letter | word       |
| <i>deal (N), deal (V)</i>          | whole word        | pos          | word (pos) |

Table 13.1:

We begin by creating a list of parameter values, generated from the full lexical entries. In our first example, we will print minimal sets involving lexemes of length 4, with a target position of 1 (second segment). The `context` is taken to be the entire word, except for the target segment. Thus, if `lex` is *kasi*, then `context` is `lex[:1] + '_'+lex[2:]`, or *k\_si*. Note that no parameters are generated if the lexeme does not consist of exactly four segments.

```

>>> pos = 1
>>> ms = nltk.MinimalSet((lex[:pos] + '_' + lex[pos+1:], lex[pos], lex)
... for lex in lexemes if len(lex) == 4)

```

Now we print the table of minimal sets. We specify that each context was seen at least 3 times.

```

>>> for context in ms.contexts(3):
... print context + ':',
... for target in ms.targets():
... print "%-4s" % ms.display(context, target, "-"),
... print
k_si: kasi - kesi kusi kosi
k_va: kava - - kuva kova
k_ru: karu kiru keru kuru koru
k_pu: kapu kipu - - kopu
k_ro: karo kiro - - koro

```

```

k_ri: kari kiri keri kuri kori
k_pa: kapa - kepa - kopa
k_ra: kara kira kera - kora
k_ku: kaku - - kuku koku
k_ki: kaki kiki - - koki

```

Observe in the above example that the context, target, and displayed material were all based on the lexeme field. However, the idea of minimal sets is much more general. For instance, suppose we wanted to get a list of wordforms having more than one possible part-of-speech. Then the target will be part-of-speech field, and the context will be the lexeme field. We will also display the English gloss field.

```

>>> entries = [(e.findtext('lx'), e.findtext('ps'), e.findtext('ge'))
... for e in lexicon
... if e.findtext('lx') and e.findtext('ps') and e.findtext('ge')]
>>> ms = nltk.MinimalSet((lx, ps[0], "%s (%s)" % (ps[0], ge))
... for (lx, ps, ge) in entries)
>>> for context in ms.contexts()[:10]:
... print "%10s:" % context, ".join(ms.display_all(context))
kokovara: N (unripe coconut); V (unripe)
kapua: N (sore); V (have sores)
koie: N (pig); V (get pig to eat)
kovo: C (garden); N (garden); V (work)
kavori: N (crayfish); V (collect crayfish or lobster)
korita: N (cutlet?); V (dissect meat)
keru: N (bone); V (harden like bone)
kirokiro: N (bush used for sorcery); V (write)
kaapie: N (hook); V (snag)
kou: C (heap); V (lay egg)

```

The following program uses MinimalSet to find pairs of entries in the corpus which have different attachments based on the *verb* only.

```

>>> ms = nltk.MinimalSet()
>>> for entry in nltk.corpus.ppattach.attachments('training'):
... target = entry.attachment
... context = (entry.noun1, entry.prep, entry.noun2)
... display = (target, entry.verb)
... ms.add(context, target, display)
>>> for context in ms.contexts():
... print context, ms.display_all(context)

```

Here is one of the pairs found by the program.

(199) received (NP offer) (PP from group)  
           rejected (NP offer (PP from group))

This finding gives us clues to a structural difference: the verb *receive* usually comes with two following arguments; we receive something *from* someone. In contrast, the verb *reject* only needs a single following argument; we can reject something without needing to say where it originated from.

## 13.6 Summary

- diverse motivations for corpus collection
- corpus structure, balance, documentation
- OLAC

## 13.7 Further Reading

**Shoebox/Toolbox and other tools for field linguistic data management:** Full details of the Shoebox data format are provided with the distribution [?], and with the latest distribution, freely available from <http://www.sil.org/computing/toolbox/>. Many other software tools support the format. More examples of our efforts with the format are documented in [?], [?]. Dozens of other tools for linguistic data management are available, some surveyed by [?].

**Some Major Corpora:** The primary sources of linguistic corpora are the *Linguistic Data Consortium* and the *European Language Resources Agency*, both with extensive online catalogs. More details concerning the major corpora mentioned in the chapter are available: American National Corpus [?], British National Corpus [?], Thesaurus Linguae Graecae [?], Child Language Data Exchange System (CHILDES) [?], TIMIT [?]. The following papers give accounts of work on corpora that put them to entirely different uses than were envisaged at the time they were created [?], [?].

**Annotation models and tools:** An extensive set of models and tools are available, surveyed at <http://www.exmaralda.org/annotation/>. The initial proposal for standoff annotation was [?]. The Annotation Graph model was proposed by [?].

**Scoring measures:** Full details of the two scoring methods are available: Kappa: [?], Windowdiff: [?].

### About this document...

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## **Part IV**

# **APPENDICES**



## Appendix A

# Appendix: Regular Expressions

This section explores regular expressions in detail, with examples drawn from language processing. It builds on the brief overview given in the introductory programming chapter.

We have already noted that a text can be viewed as a string of characters. What kinds of processing are performed at the character level? Perhaps word games are the most familiar example of such processing. In completing a crossword we may want to know which 3-letter English words end with the letter c (e.g. arc). We might want to know how many words can be formed from the letters: a, c, e, o, and n (e.g. ocean). We may want to find out which unique English word contains the substring gnt (left as an exercise for the reader). In all these examples, we are considering which word - drawn from a large set of candidates - matches a given pattern. To put this in a more computational framework, we could imagine searching through a large digital corpus in order to find all words that match a particular pattern. There are many serious uses of this so-called *pattern matching*.

One instructive example is the task of finding all doubled words in a text; an example would be the string `for for` example. Notice that we would be particularly interested in finding cases where the words were split across a linebreak (in practice, most erroneously doubled words occur in this context). Consequently, even with such a relatively banal task, we need to be able to describe patterns which refer not just to "ordinary" characters, but also to formatting information.

There are conventions for indicating structure in strings, also known as *formatting*. For example, there are a number of alternative ways of formatting a "date string", such as 23/06/2002, 6/23/02, or 2002-06-23. Whole texts may be formatted, such as an email message which contains header fields followed by the message body. Another familiar form of formatting involves visual structure, such as tabular format and bulleted lists.

Finally, texts may contain explicit "markup", such as `<abbrev>Phil</abbrev>`, which provides information about the interpretation or presentation of some piece of text. To summarize, in language processing, strings are ubiquitous, and they often contain important structure.

So far we have seen elementary examples of pattern matching, the matching of individual characters. More often we are interested in matching *sequences* of characters. For example, part of the operation of a naive spell-checker could be to remove a word-final s from a suspect word token, in case the word is a plural, and see if the putative singular form exists in the dictionary. For this we must locate s and remove it, but only if it precedes a word boundary. This requires matching a pattern consisting of two characters.

Beyond this pattern matching on the *content* of a text, we often want to process the *formatting* and *markup* of a text. We may want to check the formatting of a document (e.g. to ensure that every sentence begins with a capital letter) or to reformat a document (e.g. replacing sequences of space

characters with a single space). We may want to find all date strings and extract the year. We may want to extract all words contained inside the `<abbrev> </abbrev>` markup in order to construct a list of abbreviations.

Processing the content, format and markup of strings is a central task in most kinds of NLP. The most widespread method for string processing uses *regular expressions*.

## A.1 Simple Regular Expressions

In this section we will see the building blocks for simple regular expressions, along with a selection of linguistic examples. We can think of a regular expression as *a specialized notation for describing patterns that we want to match*. In order to make explicit when we are talking about a pattern *patt*, we will use the notation `«patt»`. The first thing to say about regular expressions is that most letters match themselves. For example, the pattern `«sing»` exactly matches the string `sing`. In addition, regular expressions provide us with a set of *special characters*<sup>2</sup> which give us a way to match *sets of strings*, and we will now look at these.

### A.1.1 The Wildcard

The `.”` symbol is called a *wildcard*: it matches any single character. For example, the regular expression `«s.ng»` matches the following English words: `sang`, `sing`, `song`, and `sung`. Note that `«.»` will match not only alphabetic characters, but also numeric and whitespace characters. Consequently, `«s.ng»` will also match non-words such as `s3ng`.

We can also use the wildcard symbol for counting characters. For instance `«....zy»` matches six-letter strings that end in `zy`. The pattern `«....berry»` finds words like `cranberry`. In our text from Wall Street Journal below, the pattern `«t...»` will match the words `that` and `term`, and will also match the word sequence `to a` (since the third `.”` in the pattern can match the space character):

Paragraph 12 from `wsj_0034`:

It's probably worth paying a premium for funds that invest in markets that are partially closed to foreign investors, such as South Korea, some specialists say. But some European funds recently have skyrocketed; Spain Fund has surged to a startling 120% premium. It has been targeted by Japanese investors as a good long-term play tied to 1992's European economic integration. And several new funds that aren't even fully invested yet have jumped to trade at big premiums.

"I'm very alarmed to see these rich valuations," says Smith Barney's Mr. Porter.

#### Note

Note that the wildcard matches *exactly* one character, and must be repeated for as many characters as should be matched. To match a variable number of characters we must use notation for *optionality*.

We can see exactly where a regular expression matches against a string using NLTK's `re_show` function. Readers are encouraged to use `re_show` to explore the behavior of regular expressions.

<sup>4</sup>These are often called *meta-characters*; that is, characters which express properties of (ordinary) characters.

```
>>> string = """
... It's probably worth paying a premium for funds that invest in markets
... that are partially closed to foreign investors, such as South Korea, ...
...
>>> nltk.re_show('t...', string)
I{t's }probably wor{th p}aying a premium for funds {that} inves{t in} markets
{that} are par{tial}ly closed {to f}oreign inves{tors}, such as Sou{th K}orea, ...
```

## A.1.2 Optionality and Repeatability

The "?“ symbol indicates that the immediately preceding regular expression is optional. The regular expression «colou?r» matches both British and American spellings, colour and color. The expression that precedes the ? may be punctuation, such as an optional hyphen. For instance «e-?mail» matches both e-mail and email.

The ”+“ symbol indicates that the immediately preceding expression is repeatable, up to an arbitrary number of times. For example, the regular expression «coo+l» matches cool, coool, and so on. This symbol is particularly effective when combined with the . symbol. For example, «f .+f» matches all strings of length greater than two, that begin and end with the letter f (e.g. foolproof). The expression «.+ed» finds strings that potentially have the past-tense -ed suffix.

The ”\*“ symbol indicates that the immediately preceding expression is both optional and repeatable. For example «.\*gnt.\*» matches all strings that contain gnt.

Occasionally we need to match material that spans a line-break. For example, we may want to strip out the HTML markup from a document. To do this we must delete material between angle brackets. The most obvious expression is: «<.\*>». However, this has two problems: it will not match an HTML tag that contains a line-break, and the «.\*» will consume as much material as possible (including the > character). To permit matching over a line-break we must use Python’s DOTALL flag, and to ensure that the > matches against the first instance of the character we must do non-greedy matching using \*?:

```
>>> text = """one two three four five"""
>>> re.sub(r'<.*?>', ' ', text, re.DOTALL)
```

## A.1.3 Choices

Patterns using the wildcard symbol are very effective, but there are many instances where we want to limit the set of characters that the wildcard can match. In such cases we can use the [ ] notation, which enumerates the set of characters to be matched - this is called a *character class*. For example, we can match any English vowel, but no consonant, using «[aeiou]». Note that this pattern can be interpreted as saying ”match a or e or ... or u“; that is, the pattern resembles the wildcard in only matching a string of length one; unlike the wildcard, it restricts the characters matched to a specific class (in this case, the vowels). Note that the order of vowels in the regular expression is insignificant, and we would have had the same result with the expression «[uoiea]». As a second example, the expression «p [aeiou]t» matches the words: pat, pet, pit, pot, and put.

We can combine the [ ] notation with our notation for repeatability. For example, expression «p [aeiou] +t» matches the words listed above, along with: peat, poet, and pout.

Often the choices we want to describe cannot be expressed at the level of individual characters. As discussed in the tagging tutorial, different parts of speech are often *tagged* using labels from a tagset. In the Brown tagset, for example, singular nouns have the tag NN1, while plural nouns have the tag NN2,

while nouns which are unspecified for number (e.g., *aircraft*) are tagged NN0. So we might use «NN.\*» as a pattern which will match any nominal tag. Now, suppose we were processing the output of a tagger to extract string of tokens corresponding to noun phrases, we might want to find all nouns (NN.\*), adjectives (JJ.\*), and determiners (DT), while excluding all other word types (e.g. verbs VB.\*). It is possible, using a single regular expression, to search for this set of candidates using the *choice operator* ”| “ as follows: «NN.\* | JJ.\* | DT». This says: match NN.\* or JJ.\* or DT.

As another example of multi-character choices, suppose that we wanted to create a program to simplify English prose, replacing rare words (like *abode*) with a more frequent, synonymous word (like *home*). In this situation, we need to map from a potentially large set of words to an individual word. We can match the set of words using the choice operator. In the case of the word *home*, we would want to match the regular expression «dwelling | domicile | abode».

### Note

Note that the choice operator has wide scope, so that «abc | def» is a choice between *abd* and *def*, and not between *abcd* and *abcdef*. The latter choice must be written using parentheses: «ab(c | d)ed».

## A.2 More Complex Regular Expressions

In this section we will cover operators which can be used to construct more powerful and useful regular expressions.

### A.2.1 Ranges

Earlier we saw how the [ ] notation could be used to express a set of choices between individual characters. Instead of listing each character, it is also possible to express a *range* of characters, using the – operator. For example, «[a–z]» matches any lowercase letter. This allows us to avoid the over-permissive matching we noted above with the pattern «t . . .». If we were to use the pattern «t [a–z] [a–z] [a–z]», then we would no longer match the two word sequence *to a*.

As expected, ranges can be combined with other operators. For example «[A–Z] [a–z]\*» matches words that have an initial capital letter followed by any number of lowercase letters. The pattern «20 [0–4] [0–9]» matches year expressions in the range 2000 to 2049.

Ranges can be combined, e.g. «[a–zA–Z]» which matches any lowercase or uppercase letter. The expression «[b–df–hj–np–tv–z]+» matches words consisting only of consonants (e.g. *pygmy*).

### A.2.2 Complementation

We just saw that the character class «[b–df–hj–np–tv–z]+» allows us to match sequences of consonants. However, this expression is quite cumbersome. A better alternative is to say: let's match anything which isn't a vowel. To do this, we need a way of expressing *complementation*. We do this using the symbol ”^“ as the first character inside a class expression [ ]. Let's look at an example. The regular expression «[^aeiou]» is just like our earlier character class «[aeiou]», except now the set of vowels is preceded by ^ . The expression as a whole is interpreted as matching anything which fails to match «[aeiou]». In other words, it matches all lowercase consonants (plus all uppercase letters and non-alphabetic characters).

As another example, suppose we want to match any string which is enclosed by the HTML tags for boldface, namely *<B>* and *</B>*. We might try something like this: «<B>.\*</B>». This would

successfully match `<B>important</B>`, but would also match `<B>important</B> and <B>urgent</B>`, since the `«.*»` sub-pattern will happily match all the characters from the end of `important` to the end of `urgent`. One way of ensuring that we only look at matched pairs of tags would be to use the expression `«<B>[^<]*</B>»`, where the character class matches anything other than a left angle bracket.

Finally, note that character class complementation also works with ranges. Thus `«[^a-z]»` matches anything other than the lower case alphabetic characters `a` through `z`.

### A.2.3 Common Special Symbols

So far, we have only looked at patterns which match with the content of character strings. However, it is also useful to be able to refer to formatting properties of texts. Two important symbols in this regard are `“^”` and `“$”` which are used to *anchor* matches to the beginnings or ends of lines in a file.

#### Note

`“^”` has two quite distinct uses: it is interpreted as complementation when it occurs as the first symbol within a character class, and as matching the beginning of lines when it occurs elsewhere in a pattern.

For example, suppose we wanted to find all the words that occur at the beginning of lines in the WSJ text above. Our first attempt might look like `«^ [A-Za-z] +»`. This says: starting at the beginning of a line, look for one or more alphabetic characters (upper or lower case), followed by a space. This will match the words that, some, been, and even. However, it fails to match It's, since ' isn't an alphabetic character. A second attempt might be `«^ [^ ] +»`, which says to match any string starting at the beginning of a line, followed by one or more characters which are *not* the space character, followed by a space. This matches all the previous words, together with It's, skyrocketed, 1992s, I'm and "Mr .. As a second example, `«[a-z]*s$»` will match words ending in s that occur at the end of a line. Finally, consider the pattern `«^$»`; this matches strings where no character occurs between the beginning and the end of a line - in other words, empty lines!

As we have seen, special characters like `“.”`, `“*”`, `“+”` and `“$”` give us powerful means to generalize over character strings. But suppose we wanted to match against a string which itself contains one or more special characters? An example would be the arithmetic statement `$5.00 * ($3.05 + $0.85)`. In this case, we need to resort to the so-called *escape* character `“\”` ("backslash"). For example, to match a dollar amount, we might use `«\$[1-9][0-9]*\.[0-9][0-9]»`. The same goes for matching other special characters.

| Special Sequences |                                                                            |
|-------------------|----------------------------------------------------------------------------|
| <code>\b</code>   | Word boundary (zero width)                                                 |
| <code>\d</code>   | Any decimal digit (equivalent to <code>[0-9]</code> )                      |
| <code>\D</code>   | Any non-digit character (equivalent to <code>[^0-9]</code> )               |
| <code>\s</code>   | Any whitespace character (equivalent to <code>[ \t\n\f\v]</code> )         |
| <code>\S</code>   | Any non-whitespace character (equivalent to <code>[^ \t\n\f\v]</code> )    |
| <code>\w</code>   | Any alphanumeric character (equivalent to <code>[a-zA-Z0-9_]</code> )      |
| <code>\W</code>   | Any non-alphanumeric character (equivalent to <code>[^a-zA-Z0-9_]</code> ) |

Table A.1:

### A.3 Python Interface

The Python `re` module provides a convenient interface to an underlying regular expression engine. The module allows a regular expression pattern to be compiled into a object whose methods can then be called. Let's begin by getting a list of English words:

```
>>> wordlist = nltk.corpus.words.words('en')
>>> len(wordlist)
45378
```

Now we can compile a regular expression for words containing a sequence of two 'a's and find the matches:

```
>>> r1 = compile('.*aa.*')
>>> [w for w in wordlist if r1.match(w)]
['Afrikaans', 'bazaar', 'bazaars', 'Canaan', 'Haag', 'Haas', 'Isaac', 'Isaacs', 'Is
```

Suppose now that we want to find all three-letter words ending in the letter "c". Our first attempt might be as follows:

```
>>> r1 = compile('..c')
>>> [w for w in wordlist if r1.match(w)][:10]
['accede', 'acceded', 'accedes', 'accelerate', 'accelerated', 'accelerates', 'accelerating', 'accelerates', 'accelerating', 'accelerating']
```

The problem is that we have matched words containing three-letter sequences ending in "c" which occur *anywhere within a word*. For example, the pattern will match "c" in words like aback, Aerobacter and albacore. Instead, we must revise our pattern so that it is anchored to the beginning and ends of the word: «^...\$»:

```
>>> r2 = compile('^..c$')
>>> [w for w in wordlist if r2.match(w)]
['arc', 'Doc', 'Lac', 'Mac', 'Vic']
```

In the section on complementation, we briefly looked at the task of matching strings which were enclosed by HTML markup. Our first attempt is illustrated in the following code example, where we incorrectly match the whole string, rather than just the substring "<B>important</B>".

```
>>> html = 'important and urgent'
>>> r2 = compile('.*')
>>> print r2.findall(html)
['important and urgent']
```

As we pointed out, one solution is to use a character class which matches with the complement of “`<`“.

```
>>> r4 = compile('[^<]*')
>>> print r4.findall(html)
['important', 'urgent']
```

However, there is another way of approaching this problem. «<B>.\*</B>» gets the wrong results because the «\*» operator tries to consume as much input as possible. That is, the matching is said to be *greedy*. In the current case, «\*» matches everything after the first <B>, including the following </B> and <B>. If we instead use the non-greedy star operator «\*?», we get the desired match, since «\*?» tries to consume as little input as possible.

### A.3.1 Exercises

2. *Pig Latin* is a simple transliteration of English: words starting with a vowel have way appended (e.g. `is` becomes `isway`); words beginning with a consonant have all consonants up to the first vowel moved to the end of the word, and then `ay` is appended (e.g. `start` becomes `artstay`).
  - a) Write a program to convert English text to Pig Latin.
  - b) Extend the program to convert text, instead of individual words.
  - c) Extend it further to preserve capitalization, to keep `qu` together (i.e. so that `quiet` becomes `ietquay`), and to detect when `y` is used as a consonant (e.g. `yellow`) vs a vowel (e.g. `style`).
3. An interesting challenge for tokenization is words that have been split across a line-break. E.g. if `long-term` is split, then we have the string `long-\n term`.
  - a) Write a regular expression that identifies words that are hyphenated at a line-break. The expression will need to include the `\n` character.
  - b) Use `re.sub()` to remove the `\n` character from these words.
4. Write a utility function that takes a URL as its argument, and returns the contents of the URL, with all HTML markup removed. Use `urllib.urlopen` to access the contents of the URL, e.g. `raw_contents = urllib.urlopen('http://nltk.org/').read()`.
5. Write a program to guess the number of syllables from the orthographic representation of words (e.g. English text).
6. Download some text from a language that has vowel harmony (e.g. Hungarian), extract the vowel sequences of words, and create a vowel bigram table.
7. Obtain a pronunciation lexicon, and try generating nonsense rhymes.

## A.4 Further Reading

A.M. Kuchling. *Regular Expression HOWTO*, <http://www.amk.ca/python/howto/regex/>

### About this document...

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## Appendix B

# Appendix: NLP in Python vs other Programming Languages

Many programming languages have been used for NLP. As we will explain in more detail in the introductory chapter, we have chosen Python because we believe it is well-suited to the special requirements of NLP. Here we present a brief survey of several programming languages, for the simple task of reading a text and printing the words that end with `ing`. We begin with the Python version, which we believe is readily interpretable, even by non Python programmers:

```
import sys
for line in sys.stdin:
 for word in line.split():
 if word.endswith('ing'):
 print word
```

Like Python, Perl is a scripting language. However, its syntax is obscure. For instance, it is difficult to guess what kind of entities are represented by: `<>`, `$`, `my`, and `split`, in the following program:

```
while (<>) {
 foreach my $word (split) {
 if ($word =~ /ing$/) {
 print "$word\n";
 }
 }
}
```

We agree that "it is quite easy in Perl to write programs that simply look like raving gibberish, even to experienced Perl programmers" (Hammond 2003:47). Having used Perl ourselves in research and teaching since the 1980s, we have found that Perl programs of any size are inordinately difficult to maintain and re-use. Therefore we believe Perl is no longer a particularly suitable choice of programming language for linguists or for language processing.

Prolog is a logic programming language which has been popular for developing natural language parsers and feature-based grammars, given the inbuilt support for search and the *unification* operation which combines two feature structures into one. Unfortunately Prolog is not easy to use for string processing or input/output, as the following program code demonstrates for our linguistic example:

```
main :-
 current_input(InputStream),
```

---

```

read_stream_to_codes(InputStream, Codes),
codesToWords(Codes, Words),
maplist(string_to_list, Words, Strings),
filter(endsWithIng, Strings, MatchingStrings),
writeMany(MatchingStrings),
halt.

codesToWords([], []).
codesToWords([Head | Tail], Words) :-
 (char_type(Head, space) ->
 codesToWords(Tail, Words)
 ;
 getWord([Head | Tail], Word, Rest),
 codesToWords(Rest, Words0),
 Words = [Word | Words0]
).

getWord([], [], []).
getWord([Head | Tail], Word, Rest) :-
 (
 (char_type(Head, space) ; char_type(Head, punct))
 -> Word = [],
 Tail = Rest
 ;
 getWord(Tail, Word0, Rest),
 Word = [Head | Word0]
).

filter(Predicate, List0, List) :-
 (List0 = [] -> List = []
 ;
 List0 = [Head | Tail],
 (apply(Predicate, [Head]) ->
 filter(Predicate, Tail, List1),
 List = [Head | List1]
 ;
 filter(Predicate, Tail, List)
)
).
).

endsWithIng(String) :- sub_string(String, _Start, _Len, 0, 'ing').

writeMany([]).
writeMany([Head | Tail]) :- write(Head), nl, writeMany(Tail).

```

Java is an object-oriented language incorporating native support for the Internet, that was originally designed to permit the same executable program to be run on most computer platforms. Java has replaced COBOL as the standard language for business enterprise software:

```

import java.io.*;
public class IngWords {
 public static void main(String[] args) throws Exception {
 BufferedReader in = new BufferedReader(new
 InputStreamReader(
 System.in));
 String line = in.readLine();
 while (line != null) {
 for (String word : line.split(" "))

```

```
 if (word.endsWith("ing"))
 System.out.println(word);
 }
 line = in.readLine();
}
}
```

The C programming language is a highly-efficient low-level language that is popular for operating system and networking software:

```
#include <stdio.h>
#include <string.h>

int main(int argc, char **argv) {
 int i = 0;
 int c = 1;
 char buffer[1024];

 while (c != EOF) {
 c = fgetc(stdin);
 if ((c >= '0' && c <= '9') || (c >= 'a' && c <= 'z') || (c >= 'A' && c <= 'Z'))
 buffer[i++] = (char) c;
 continue;
 } else {
 if (i > 2 && (strncmp(buffer+i-3, "ing", 3) == 0 || strncmp(buffer+i-3, "INC"
 buffer[i] = 0;
 puts(buffer);
 }
 i = 0;
 }
}
return 0;
}
```

LISP is a so-called functional programming language, in which all objects are lists, and all operations are performed by (nested) functions of the form (function arg1 arg2 ...). Many of the earliest NLP systems were implemented in LISP:

```
(defpackage "REGEXP-TEST" (:use "LISP" "REGEXP"))
(in-package "REGEXP-TEST")

(defun has-suffix (string suffix)
 "Open a file and look for words ending in _ing."
 (with-open-file (f string)
 (with-loop-split (s f " ")
 (mapcar #'(lambda (x) (has_suffix suffix x)) s)))))

(defun has_suffix (suffix string)
 (let* ((suffix_len (length suffix))
 (string_len (length string))
 (base_len (- string_len suffix_len)))
 (if (string-equal suffix string :start1 0 :end1 NIL :start2 base_len :end2 NIL)
```

---

```

 (print string)))))

(has-suffix "test.txt" "ing")

```

Ruby is a more recently developed scripting language than Python, best known for its convenient web application framework, *Ruby on Rails*. Here are two Ruby programs for finding words ending in *ing*

```

ARGF.each { |line|
 line.split.find_all { |word|
 word.match(/ing$/)
 }.each { |word|
 puts word
 }
}

for line in ARGF
 for word in line.split
 if word.match(/ing$/) then
 puts word
 end
 end
end

```

Haskell is another functional programming language which permits a much more compact (but incomprehensible) solution of our simple task:

```

import Data.List
main = putStrLn . unlines . filter ("ing" `isSuffixOf`) . words =<< getContent

```

The unix shell can also be used for simple linguistic processing. Here is a simple pipeline for finding the *ing* words. The first step transliterates any whitespace character to a newline, so that each word of the text occurs on its own line, and the second step finds all lines ending in *ing*

```

tr [:space:] '\n' | grep ing$
```

(We are grateful to the following people for furnishing us with these program samples: Tim Baldwin, Trevor Cohn, David Duke, Rod Farmer, Andrew Hardie, Aaron Harnly, Edward Ivanovic, and Lars Yencken.)

### About this document...

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## Appendix C

# Appendix: NLTK Modules and Corpora

**NLTK Organization:** NLTK is organized into a collection of task-specific packages. Each package is a combination of data structures for representing a particular kind of information such as trees, and implementations of standard algorithms involving those structures such as parsers. This approach is a standard feature of *object-oriented design*, in which components encapsulate both the resources and methods needed to accomplish a particular task.

The most fundamental NLTK components are for identifying and manipulating individual words of text. These include: `tokenize`, for breaking up strings of characters into word tokens; `tag`, for adding part-of-speech tags, including regular-expression taggers, n-gram taggers and Brill taggers; and the Porter stemmer.

The second kind of module is for creating and manipulating structured linguistic information. These components include: `tree`, for representing and processing parse trees; `featurestructure`, for building and unifying nested feature structures (or attribute-value matrices); `cfg`, for specifying context-free grammars; and `parse`, for creating parse trees over input text, including chart parsers, chunk parsers and probabilistic parsers.

Several utility components are provided to facilitate processing and visualization. These include: `draw`, to visualize NLP structures and processes; `probability`, to count and collate events, and perform statistical estimation; and `corpora`, to access tagged linguistic corpora.

A further group of components is not part of NLTK proper. These are a wide selection of third-party contributions, often developed as student projects at various institutions where NLTK is used, and distributed in a separate package called *NLTK Contrib*. Several of these student contributions, such as the Brill tagger and the HMM module, have now been incorporated into NLTK. Although these contributed components are not maintained, they may serve as a useful starting point for future student projects.

In addition to software and documentation, NLTK provides substantial corpus samples. Many of these can be accessed using the `corpora` module, avoiding the need to write specialized file parsing code before you can do NLP tasks. These corpora include: Brown Corpus — 1.15 million words of tagged text in 15 genres; a 10% sample of the Penn Treebank corpus, consisting of 40,000 words of syntactically parsed text; a selection of books from Project Gutenberg totally 1.7 million words; and other corpora for chunking, prepositional phrase attachment, word-sense disambiguation, text categorization, and information extraction.

| Corpora and Corpus Samples Distributed with NLTK |                          |                                                             |
|--------------------------------------------------|--------------------------|-------------------------------------------------------------|
| Corpus                                           | Compiler                 | Contents                                                    |
| Alpino Dutch Treebank                            | van Noord                | 140k words, tagged and parsed (Dutch)                       |
| Australian ABC News                              | Bird                     | 2 genres, 660k words, sentence-segmented                    |
| Brown Corpus                                     | Francis, Kucera          | 15 genres, 1.15M words, tagged, categorized                 |
| CESS-CAT<br>Treebank                             | Catalan<br>CLiC-UB et al | 500k words, tagged and parsed                               |
| CESS-ESP<br>Treebank                             | Spanish<br>CLiC-UB et al | 500k words, tagged and parsed                               |
| CMU Pronouncing Dictionary                       | CMU                      | 127k entries                                                |
| CoNLL 2000 Chunking Data                         | Tjong Kim Sang           | 270k words, tagged and chunked                              |
| CoNLL 2002 Named Entity                          | Tjong Kim Sang           | 700k words, pos- and named-entity-tagged (Dutch, Spanish)   |
| Floresta Treebank                                | Diana Santos et al       | 9k sentences (Portuguese)                                   |
| Genesis Corpus                                   | Misc web sources         | 6 texts, 200k words, 6 languages                            |
| Gutenberg (sel)                                  | Hart, Newby, et al       | 14 texts, 1.7M words                                        |
| Indian POS-Tagged Corpus                         | Kumaran et al            | 60k words, tagged (Bangla, Hindi, Marathi, Telugu)          |
| MacMorpho Corpus                                 | NILC, USP, Brazil        | 1M words, tagged (Brazilian Portuguese)                     |
| Movie Reviews                                    | Pang, Lee                | Sentiment Polarity Dataset 2.0                              |
| NIST 1999 Info Extr (sel)                        | Garofolo                 | 63k words, newswire and named-entity SGML markup            |
| Names Corpus                                     | Kantrowitz, Ross         | 8k male and female names                                    |
| PP Attachment Corpus                             | Ratnaparkhi              | 28k prepositional phrases, tagged as noun or verb modifiers |
| Presidential Addresses                           | Ahrens                   | 485k words, formatted text                                  |
| Proposition Bank                                 | Palmer                   | 113k propositions, 3300 verb frames                         |
| Question Classification                          | Li, Roth                 | 6k questions, categorized                                   |
| Reuters Corpus                                   | Reuters                  | 1.3M words, 10k news documents, categorized                 |
| Roget's Thesaurus                                | Project Gutenberg        | 200k words, formatted text                                  |
| RTE Textual Entailment                           | Dagan et al              | 8k sentence pairs, categorized                              |
| SEMCOR                                           | Rus, Mihalcea            | 880k words, part-of-speech and sense tagged                 |
| SENSEVAL 2 Corpus                                | Ted Pedersen             | 600k words, part-of-speech and sense tagged                 |
| Shakespeare XML texts (sel)                      | Jon Bosak                | 8 books                                                     |
| Stopwords Corpus                                 | Porter et al             | 2,400 stopwords for 11 languages                            |
| Switchboard Corpus (sel)                         | LDC                      | 36 phonecalls, transcribed, parsed                          |
| Univ Decl of Human Rights                        | ■                        | 480k words, 300+ languages                                  |
| US Pres Addr Corpus                              | Ahrens                   | 480k words                                                  |
| Penn Treebank (sel)                              | LDC                      | 40k words, tagged and parsed                                |

| <b>Corpora and Corpus Samples Distributed with NLTK</b> |                      |                                                       |
|---------------------------------------------------------|----------------------|-------------------------------------------------------|
| <b>Corpus</b>                                           | <b>Compiler</b>      | <b>Contents</b>                                       |
| TIMIT Corpus (sel)                                      | NIST/LDC             | audio files and transcripts for 16 speakers           |
| VerbNet 2.1                                             | Palmer et al         | 5k verbs, hierarchically organized, linked to WordNet |
| Wordlist Corpus                                         | OpenOffice.org et al | 960k words and 20k affixes for 8 languages            |
| WordNet 3.0 (English)                                   | Miller, Fellbaum     | 145k synonym sets                                     |

Table C.1:

### About this document...

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## Appendix D

# Appendix: Python and NLTK Cheat Sheet (Draft)

### D.1 Python

#### D.1.1 Strings

```
>>> x = 'Python'; y = 'NLTK'; z = 'Natural Language Processing'
>>> x + '/' + y
'Python/NLTK'
>>> 'LT' in y
True
>>> x[2:]
'thon'
>>> x[::-1]
'nohtyP'
>>> len(x)
6
>>> z.count('a')
4
>>> z.endswith('ing')
True
>>> z.index('Language')
8
>>> ' '.join([x,y,z])
'Python; NLTK; Natural Language Processing'
>>> y.lower()
'nltk'
>>> z.replace(' ', '\n')
'Natural\nLanguage\nProcessing'
>>> print z.replace(' ', '\n')
Natural
Language
Processing
>>> z.split()
['Natural', 'Language', 'Processing']
```

For more information, type `help(str)` at the Python prompt.

### D.1.2 Lists

```
>>> x = ['Natural', 'Language']; y = ['Processing']
>>> x[0]
'Natural'
>>> list(x[0])
['N', 'a', 't', 'u', 'r', 'a', 'l']
>>> x + y
['Natural', 'Language', 'Processing']
>>> 'Language' in x
True
>>> len(x)
2
>>> x.index('Language')
1
```

The following functions modify the list in-place:

```
>>> x.append('Toolkit')
>>> x
['Natural', 'Language', 'Toolkit']
>>> x.insert(0, 'Python')
>>> x
['Python', 'Natural', 'Language', 'Toolkit']
>>> x.reverse()
>>> x
['Toolkit', 'Language', 'Natural', 'Python']
>>> x.sort()
>>> x
['Language', 'Natural', 'Python', 'Toolkit']
```

For more information, type *help(list)* at the Python prompt.

### D.1.3 Dictionaries

```
>>> d = {'natural': 'adj', 'language': 'noun'}
>>> d['natural']
'adj'
>>> d['toolkit'] = 'noun'
>>> d
{'natural': 'adj', 'toolkit': 'noun', 'language': 'noun'}
>>> 'language' in d
True
>>> d.items()
[('natural', 'adj'), ('toolkit', 'noun'), ('language', 'noun')]
>>> d.keys()
['natural', 'toolkit', 'language']
>>> d.values()
['adj', 'noun', 'noun']
```

For more information, type *help(dict)* at the Python prompt.

### D.1.4 Regular Expressions

**Note**

to be written

## D.2 NLTK

Many more examples can be found in the NLTK Guides, available at <http://nltk.org/doc/guides>.

### D.2.1 Corpora

```
>>> import nltk
>>> dir(nltk.corpus)
```

### D.2.2 Tokenization

```
>>> text = '''NLTK, the Natural Language Toolkit, is a suite of program
... modules, data sets and tutorials supporting research and teaching in
... computational linguistics and natural language processing.'''
>>> import nltk
>>> nltk.LineTokenizer().tokenize(text)
['NLTK, the Natural Language Toolkit, is a suite of program', 'modules,
data sets and tutorials supporting research and teaching in', 'computational
linguistics and natural language processing.']
>>> nltk.WhitespaceTokenizer().tokenize(text)
['NLTK', 'the', 'Natural', 'Language', 'Toolkit', 'is', 'a', 'suite',
'of', 'program', 'modules', 'data', 'sets', 'and', 'tutorials',
'supporting', 'research', 'and', 'teaching', 'in', 'computational',
'linguistics', 'and', 'natural', 'language', 'processing.']
>>> nltk.WordPunctTokenizer().tokenize(text)
['NLTK', 'the', 'Natural', 'Language', 'Toolkit', 'is', 'a',
'suite', 'of', 'program', 'modules', 'data', 'sets', 'and',
'tutorials', 'supporting', 'research', 'and', 'teaching', 'in',
'computational', 'linguistics', 'and', 'natural', 'language',
'processing.']
>>> nltk.RegexpTokenizer(', ', gaps=True).tokenize(text)
['NLTK', 'the Natural Language Toolkit', 'is a suite of program\nmodules',
'data sets and tutorials supporting research and teaching in\ncomputational
linguistics and natural language processing.']
```

### D.2.3 Stemming

```
>>> tokens = nltk.WordPunctTokenizer().tokenize(text)
>>> stemmer = nltk.RegexpStemmer('ing\$|s\$|e\$')
>>> for token in tokens:
... print stemmer.stem(token),
NLTK , th Natural Languag Toolkit , i a suit of program module ,
data set and tutorial support research and teach in computational
linguistic and natural languag process .
>>> stemmer = nltk.PorterStemmer()
```

```
>>> for token in tokens:
... print stemmer.stem(token),
NLTK , the Natur Languag Toolkit , is a suit of program modul ,
data set and tutori support research and teach in comput linguist
and natur languag process .
```

## D.2.4 Tagging

### Note

to be written

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