

11 Managing Linguistic Data

Structured collections of annotated linguistic data are essential in most areas of NLP, however, we still face many obstacles in using them. The goal of this chapter is to answer the following questions:

1. How do we design a new language resource and ensure that its coverage, balance, and documentation support a wide range of uses?
2. When existing data is in the wrong format for some analysis tool, how can we convert it to a suitable format?
3. What is a good way to document the existence of a resource we have created so that others can easily find it?

Along the way, we will study the design of existing corpora, the typical workflow for creating a corpus, and the lifecycle of corpus. As in other chapters, there will be many examples drawn from practical experience managing linguistic data, including data that has been collected in the course of linguistic fieldwork, laboratory work, and web crawling.

11.1 Corpus Structure: a Case Study

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, from which it derives its name. It was designed to provide data for the acquisition of acoustic-phonetic knowledge and to support the development and evaluation of automatic speech recognition systems.

The Structure of TIMIT

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:

- (1)
 - 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. Five of the sentences read by each speaker are also read by six other speakers (for comparability). The remaining three sentences read by each speaker were unique to that speaker (for coverage).

NLTK includes a sample from the TIMIT corpus. You can access its documentation in the usual way, using `help(nltk.corpus.timit)`. Print `nltk.corpus.timit.fileids()` to see a list of the 160 recorded utterances in the corpus sample. Each file name has internal structure as shown in [Figure 11.1](#).

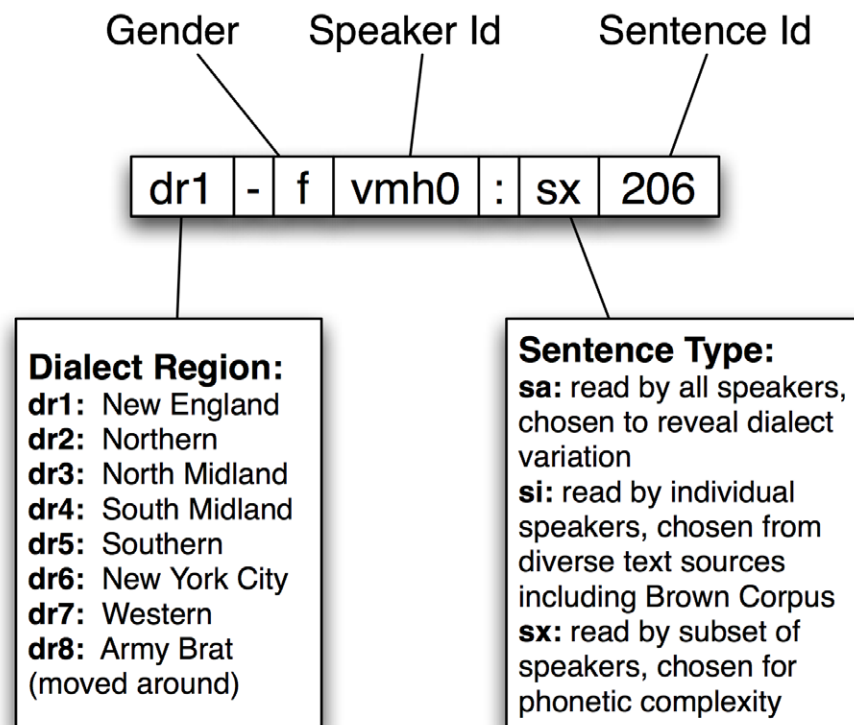


Figure 11.1: Structure of a TIMIT Identifier: Each recording is labeled using a string made up of the speaker's dialect region, gender, speaker identifier, sentence type, and sentence identifier.

Each item has 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)]
```

In addition to this text data, TIMIT includes a lexicon that provides the canonical pronunciation of every word, which can be compared with a particular utterance:

```
>>> timitdict = nltk.corpus.timit.transcription_dict()
>>> timitdict['greasy'] + timitdict['wash'] + timitdict['water']
['g', 'r', 'iy', 's', 'iy', 'w', 'ao', 'sh', 'w', 'ao', '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')
```

Notable Design Features

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, such as 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.

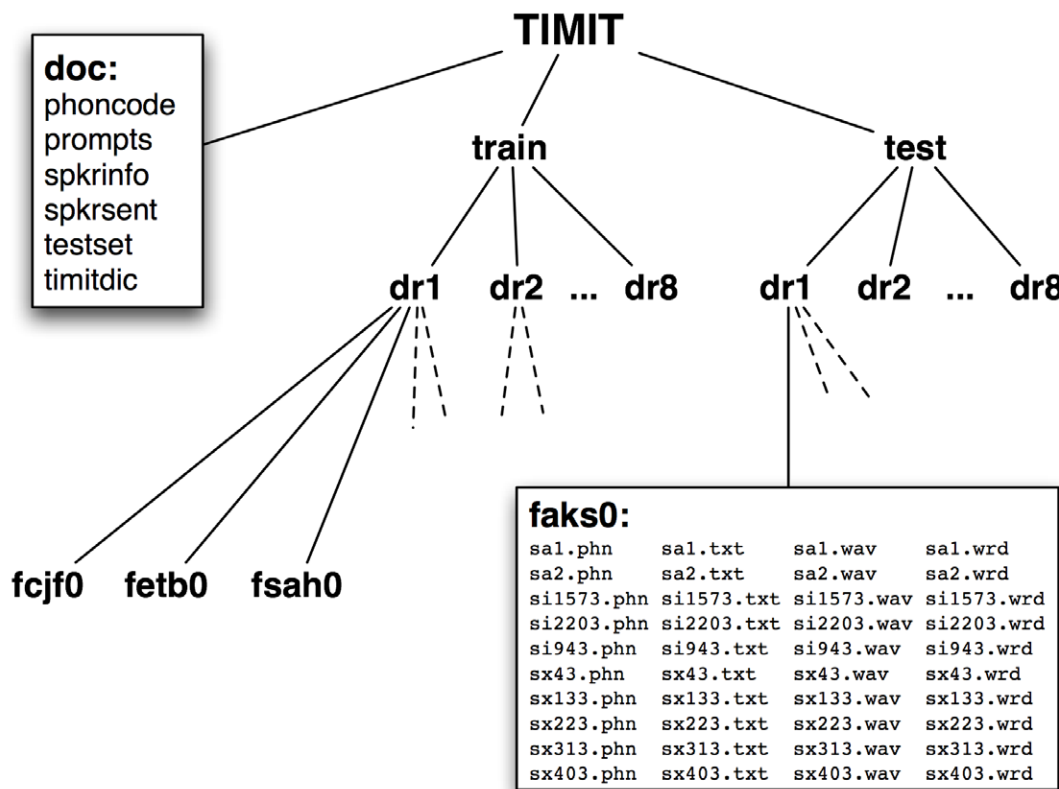


Figure 11.2: Structure of the Published TIMIT Corpus: The CD-ROM contains doc, train, and test directories at the top level; the train and test directories both have 8 sub-directories, one per dialect region; each of these contains further subdirectories, one per speaker; the contents of the directory for female speaker aks0 are listed, showing 10 wav files accompanied by a text transcription, a word-aligned transcription, and a phonetic transcription.

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 11.2](#). 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 the two basic categories of lexicon and text, which we will discuss below. 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.

Fundamental Data Types

Lexicon

Abstraction: fielded records

key	field	field	field	field
key	field	field	field	field

Eg: dictionary

wake: we:k, [v], *cease to sleep...*
walk: wo:k, [v], *progress by lifting and setting down each foot...*

Eg: comparative wordlist

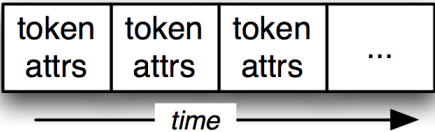
wake; aufwecken; acordar
walk; gehen; andar
write; schreiben; enscrever

Eg: verb paradigm

wake	woke	woken
write	wrote	written
wring	wrung	wrung

Text

Abstraction: time series



Eg: written text

A long time ago, Sun and Moon lived together. They were good brothers. ...

Eg: POS-tagged text

A/DT long/JJ time/NN ago/RB ,/,
Sun/NNP and/CC Moon/NNP
lived/VBD together/RB ./.

Eg: interlinear text

Ragaipa	irai	vateri
ragai -pa	ira	-i vate -ri
PP.1.SG -BEN	RP.3.SG.M -ABS	give -2.SG

Figure 11.3: Basic Linguistic Data Types — Lexicons and Texts: amid their diversity, lexicons have a record structure, while annotated texts have a temporal organization.

Despite its complexity, the TIMIT corpus only contains two fundamental data types, namely lexicons and texts. As we saw in [Chapter 2](#), most lexical resources can be represented using a record structure, i.e. a key plus one or more fields, as shown in [Figure 11.3](#). A lexical resource could be a conventional dictionary or comparative wordlist, as illustrated. It could also be a phrasal lexicon, where the key field is a phrase rather than a single word. A thesaurus also consists of record-structured data, where we look up entries via non-key fields that correspond to topics. We can also construct special tabulations (known as paradigms) to illustrate contrasts and systematic variation, as shown in [Figure 11.3](#) for three verbs. TIMIT's speaker table is also a kind of lexicon.

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 11.3](#) is sufficient.

Despite the complexities and idiosyncrasies of individual corpora, at base they are collections of texts together with record-structured data. The contents of a corpus are often biased towards one or other of these types. For example, the Brown Corpus contains 500 text files, but we still use a table to relate the files to 15 different genres. At the other end of the spectrum, WordNet contains 117,659 synset records, yet it incorporates many example sentences (mini-texts) to illustrate word usages. TIMIT is an interesting mid-point on this spectrum, containing substantial free-standing material of both the text and lexicon types.

11.2 The Life-Cycle of a Corpus

Corpora are not born fully-formed, but involve careful preparation and input from many people over an extended period. Raw data needs to be collected, cleaned up, documented, and stored in a systematic structure. Various layers of annotation might be applied, some requiring specialized knowledge of the morphology or syntax of the language. Success at this stage depends on creating an efficient workflow involving appropriate tools and format converters. Quality control procedures can be put in place to find inconsistencies in the annotations, and to ensure the highest possible level of inter-annotator agreement. Because of the scale and complexity of the task, large corpora may take years to prepare, and involve tens or hundreds of person-years of effort. In this section we briefly review the various stages in the life-cycle of a corpus.

Three Corpus Creation Scenarios

In one type of corpus, the design unfolds over 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 as it is gathered, with tomorrow's elicitation often based on questions that arise in analyzing today's. The resulting corpus is then used during subsequent years of research, and may serve as an archival resource indefinitely. Computerization is an obvious boon to work of this type, as exemplified by the popular program Shoebox, now over two decades old and re-released as Toolbox (see [Section 2.4](#)). Other software tools, even simple word processors and spreadsheets, are routinely used to acquire the data. In the next section we will look at how to extract data from these sources.

Another corpus creation scenario is typical of experimental research where a body of carefully-designed material is collected from a range of human subjects, then analyzed to evaluate a hypothesis or develop a technology. It has become common for such databases to be shared and re-used within a laboratory or company, and often to be published more widely. Corpora of this type are the basis of the "common task" method of research management, which over the past two decades has become the norm in government-funded research programs in language technology. We have already encountered many such corpora in the earlier chapters; we will see how to write Python programs to implement the kinds of curation tasks that are necessary before such corpora are published.

Finally, there are efforts to gather a "reference corpus" for a particular language, such as the *American National Corpus* (ANC) and the *British National Corpus* (BNC). Here the goal has been to produce a comprehensive record of the many forms, styles and uses of a language. Apart from the sheer challenge of scale, there is a heavy reliance on automatic annotation tools together with post-editing to fix any errors. However, we can write programs to locate and repair the errors, and also to analyze the corpus for balance.

Quality Control

Good tools for automatic and manual preparation of data are essential. However the creation of a high-quality corpus depends just as much on such mundane things as documentation, training, and workflow. Annotation guidelines define the task and document the markup conventions. They may be regularly updated to cover difficult cases, along with

new rules that are devised to achieve more consistent annotations. Annotators need to be trained in the procedures, including methods for resolving cases not covered in the guidelines. A workflow needs to be established, possibly with supporting software, to keep track of which files have been initialized, annotated, validated, manually checked, and so on. There may be multiple layers of annotation, provided by different specialists. Cases of uncertainty or disagreement may require adjudication.

Large annotation tasks require multiple annotators, which raises the problem of achieving consistency. How consistently can a group of annotators perform? We can easily measure consistency by having a portion of the source material independently annotated by two people. This may reveal shortcomings in the guidelines or differing abilities with the annotation task. In cases where quality is paramount, the entire corpus can be annotated twice, and any inconsistencies adjudicated by an expert.

It is considered best practice to report the inter-annotator agreement that was achieved for a corpus (e.g. by double-annotating 10% of the corpus). This score serves as a helpful upper bound on the expected performance of any automatic system that is trained on this corpus.

Caution!

Care should be exercised when interpreting an inter-annotator agreement score, since annotation tasks vary greatly in their difficulty. For example, 90% agreement would be a terrible score for part-of-speech tagging, but an exceptional score for semantic role labeling.

The **Kappa** coefficient K 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 two people coding randomly would be expected to agree 25% of the time. Thus, an agreement of 25% will be assigned $K = 0$, and better levels of agreement will be scaled accordingly. For an agreement of 50%, we would get $K = 0.333$, as 50 is a third of the way from 25 to 100. Many other agreement measures exist; see

`help(nltk.metrics.agreement)` for details.



Figure 11.4: Three Segmentations of a Sequence: The small rectangles represent characters, words, sentences, in short, any sequence which might be divided into linguistic units; S_1 and S_2 are in close agreement, but both differ significantly from S_3 .

We can also measure the agreement between two independent segmentations of language input, e.g. for tokenization, sentence segmentation, named-entity detection. In [Figure 11.4](#) we see three possible segmentations of a sequence of items which might have been produced by annotators (or programs). Although none of them agree exactly, S_1 and S_2 are in close agreement, and we would like a suitable measure. Windowdiff is a simple algorithm for evaluating the agreement of two segmentations by running a sliding window over the data and awarding partial credit for near misses. If we preprocess our tokens into a sequence of zeros and ones, to record when a token is followed by a boundary, we can represent the segmentations as strings, and apply the windowdiff scorer.

```
>>> s1 = "00000010000000001000000"
>>> s2 = "00000001000000010000000"
>>> s3 = "00010000000000000001000"
>>> nltk.windowdiff(s1, s1, 3)
0
>>> nltk.windowdiff(s1, s2, 3)
4
>>> nltk.windowdiff(s2, s3, 3)
16
```


In the above example, the window had a size of 3. The `windowdiff` computation slides this window across a pair of strings. At each position it totals up the number of boundaries found inside this window, for both strings, then computes the difference. These differences are then summed. We can increase or shrink the window size to control the sensitivity of the measure.

Curation vs Evolution

As large corpora are published, researchers are increasingly likely to base their investigations on balanced, focused subsets that were derived from corpora produced for entirely different reasons. 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. The motivations for recycling linguistic corpora 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 than would be possible otherwise. The process of choosing a subset for such a study may count as a non-trivial contribution in itself.

In addition to selecting an appropriate subset of a corpus, this new work could involve reformatting a text file (e.g. converting to XML), renaming files, retokenizing the text, selecting a subset of the data to enrich, and so forth. Multiple research groups might do this work independently, as illustrated in [Figure 11.5](#). At a later date, should someone want to combine sources of information from different versions, the task will probably be extremely onerous.

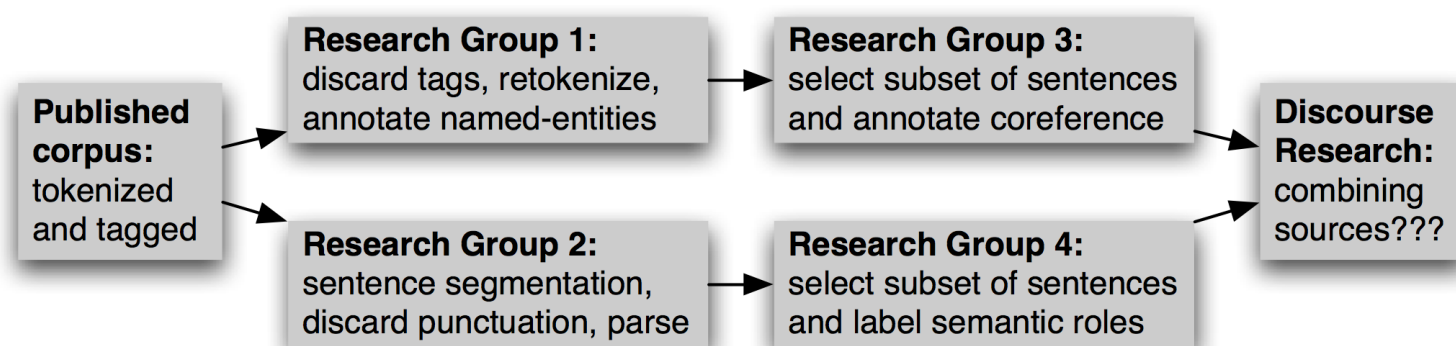


Figure 11.5: Evolution of a Corpus over Time: After a corpus is published, research groups will use it independently, selecting and enriching different pieces; later research that seeks to integrate separate annotations confronts the difficult challenge of aligning the annotations.

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 a corpus to be centrally curated, and for committees of experts to revise and extend it at periodic intervals, considering submissions from third-parties, and publishing new releases from time to time. Print dictionaries and national corpora may be centrally curated in this way. However, for most corpora this model is simply impractical.

A middle course is for the original corpus publication to have a scheme for identifying any sub-part. Each sentence, tree, or lexical entry, could have a globally unique identifier, and each token, node or field (respectively) could have a relative offset. Annotations, including segmentations, could reference the source using this identifier scheme (a method which is known as **standoff annotation**). This way, new annotations could be distributed independently of the source, and multiple independent annotations of the same source could be compared and updated without touching the source.

If the corpus publication is provided in multiple versions, the version number or date could be part of the identification scheme. A table of correspondences between identifiers across editions of the corpus would permit any standoff

annotations to be updated easily.

Caution!

Sometimes an updated corpus contains revisions of base material that has been externally annotated. Tokens might be split or merged, and constituents may have been rearranged. There may not be a one-to-one correspondence between old and new identifiers. It is better to cause standoff annotations to break on such components of the new version than to silently allow their identifiers to refer to incorrect locations.

11.3 Acquiring Data

Obtaining Data from the Web

The Web is a rich source of data for language analysis purposes. We have already discussed methods for accessing individual files, RSS feeds, and search engine results (see [Section 3.1](#)). However, in some cases we want to obtain large quantities of web text.

The simplest approach is to obtain a published corpus of web text. The ACL Special Interest Group on Web as Corpus (SIGWAC) maintains a list of resources at <http://www.sigwac.org.uk/>. The advantage of using a well-defined web corpus is that they are documented, stable, and permit reproducible experimentation.

If the desired content is localized to a particular website, there are many utilities for capturing all the accessible contents of a site, such as *GNU Wget* <http://www.gnu.org/software/wget/>. For maximal flexibility and control, a web crawler can be used, such as *Heritrix* <http://crawler.archive.org/>. Crawlers permit fine-grained control over where to look, which links to follow, and how to organize the results ([Croft, Metzler, & Strohman, 2009](#)). For example, if we want to compile a bilingual text collection having corresponding pairs of documents in each language, the crawler needs to detect the structure of the site in order to extract the correspondence between the documents, and it needs to organize the downloaded pages in such a way that the correspondence is captured. It might be tempting to write your own web-crawler, but there are dozens of pitfalls to do with detecting MIME types, converting relative to absolute URLs, avoiding getting trapped in cyclic link structures, dealing with network latencies, avoiding overloading the site or being banned from accessing the site, and so on.

Obtaining Data from Word Processor Files

Word processing software is often used in the manual preparation of texts and lexicons in projects that have limited computational infrastructure. Such projects often provide templates for data entry, though the word processing software does not ensure that the data is correctly structured. For example, each text may be required to have a title and date. Similarly, each lexical entry may have certain obligatory fields. As the data grows in size and complexity, a larger proportion of time may be spent maintaining its consistency.

How can we extract the content of such files so that we can manipulate it in external programs? Moreover, how can we validate the content of these files to help authors create well-structured data, so that the quality of the data can be maximized in the context of the original authoring process?

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] **v.i.** *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
```



```

<span style='mso-spacerun:yes'> </span>
[<span class=SpellE>sli:p</span>]
<span style='mso-spacerun:yes'> </span>
<b><span style='font-size:11.0pt'>v.i.</span></b>
<span style='mso-spacerun:yes'> </span>
<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 `` 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*.

Once we know the data is correctly formatted, we can write other programs to convert the data into a different format. The program in [Example 11.6](#) strips out the HTML markup using `nltk.clean_html()`, extracts the words and their pronunciations, and generates output in "comma-separated value" (CSV) format.

```

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"))

```

Example 11.6 (code [html2csv.py](#)): Figure 11.6: Converting HTML Created by Microsoft Word into Comma-Separated Values

Note

For more sophisticated processing of HTML, use the *Beautiful Soup* package, available from <http://www.crummy.com/software/BeautifulSoup/>

Obtaining Data from Spreadsheets and Databases

Spreadsheets are often used for acquiring wordlists or paradigms. For example, a comparative wordlist may be created using a spreadsheet, with a row for each cognate set, and a column for each language (cf. `nltk.corpus.swadesh`, and www.rosettaproject.org). Most spreadsheet software can export their data in CSV "comma-separated value" format. As we see below, it is easy for Python programs to access these using the `csv` module.

Sometimes lexicons are stored in a full-fledged relational database. When properly normalized, these databases can ensure the validity of the data. 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* or a foreign key that references a separate part-of-speech table. However, the relational model requires the structure of the data (the schema) be declared in advance, and this runs counter to the dominant approach to structuring linguistic data, which is highly exploratory. Fields which were assumed to be obligatory and unique often turn out to be optional and repeatable. A relational database can accommodate this when it is fully known in advance, however if it is not, or if just about every property turns out to be optional or repeatable, the relational approach is unworkable.

Nevertheless, when our goal is simply to extract the contents from a database, it is enough to dump out the tables (or SQL query results) in CSV format and load them into our program. Our program might perform a linguistically motivated query which cannot be expressed in SQL, e.g. *select all words that appear in example sentences for which no dictionary entry is provided*. For this task, we would need to extract enough information from a record for it to be uniquely identified, along with the headwords and example sentences. Let's suppose this information was now available in a CSV 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 below:

```
>>> import csv  
>>> lexicon = csv.reader(open('dict.csv'))  
>>> pairs = [(lexeme, defn) for (lexeme, _, _, defn) in lexicon]  
>>> lexemes, defns = zip(*pairs)  
>>> defn_words = set(w for defn in defns for w in defn.split())  
>>> sorted(defn_words.difference(lexemes))  
['...', 'a', 'and', 'body', 'by', 'cease', 'condition', 'down', 'each',  
'foot', 'lifting', 'mind', 'of', 'progress', 'setting', 'to']
```

This information would then guide the ongoing work to enrich the lexicon, work that updates the content of the relational database.

Converting Data Formats

Annotated linguistic data rarely arrives in the most convenient format, and it is often necessary to perform various kinds of format conversion. Converting between character encodings has already been discussed (see [Section 3.3](#)). Here we focus on the structure of the data.

In the simplest case, the input and output formats are isomorphic. For instance, we might be converting lexical data from Toolbox format to XML, and it is straightforward to transliterate the entries one at a time ([Section 11.4](#)). The structure of the data is reflected in the structure of the required program: a `for` loop whose body takes care of a single entry.

In another common case, the output is a digested form of the input, such as an inverted file index. Here it is necessary to build an index structure in memory (see [Example 4.8](#)), then write it to a file in the desired format. The following example constructs an index that maps the words of a dictionary definition to the corresponding lexeme [\[1\]](#) for each lexical entry [\[2\]](#), having tokenized the definition text [\[3\]](#), and discarded short words [\[4\]](#). Once the index has been constructed we open a file and then iterate over the index entries, to write out the lines in the required format [\[5\]](#).

```
>>> idx = nltk.Index((defn_word, lexeme) [1]  
...                 for (lexeme, defn) in pairs [2]  
...                 for defn_word in nltk.word_tokenize(defn) [3]  
...                 if len(defn_word) > 3) [4]  
>>> idx_file = open("dict.idx", "w")  
>>> for word in sorted(idx):
```

```

...     idx_words = ', '.join(idx[word])
...     idx_line = "%s: %s\n" % (word, idx_words) [5]
...     idx_file.write(idx_line)
>>> idx_file.close()

```

The resulting file `dict.idx` contains the following lines. (With a larger dictionary we would expect to find multiple lexemes listed for each index entry.)

```

body: sleep
cease: wake
condition: sleep
down: walk
each: walk
foot: walk
lifting: walk
mind: sleep
progress: walk
setting: walk
sleep: wake

```

In some cases, the input and output data both consist of two or more dimensions. For instance, the input might be a set of files, each containing a single column of word frequency data. The required output might be a two-dimensional table in which the original columns appear as rows. In such cases we populate an internal data structure by filling up one column at a time, then read off the data one row at a time as we write data to the output file.

In the most vexing cases, the source and target formats have slightly different coverage of the domain, and information is unavoidably lost when translating between them. For example, we could combine multiple Toolbox files to create a single CSV file containing a comparative wordlist, losing all but the `\1x` field of the input files. If the CSV file was later modified, it would be a labor-intensive process to inject the changes into the original Toolbox files. A partial solution to this "round-tripping" problem is to associate explicit identifiers each linguistic object, and to propagate the identifiers with the objects.

Deciding Which Layers of Annotation to Include

Published corpora vary greatly in the richness of the information they contain. At a minimum, a corpus will typically contain at least a sequence of sound or orthographic symbols. At the other end of the spectrum, a corpus could contain a large amount of information about the syntactic structure, morphology, prosody, and semantic content of every sentence, plus annotation of discourse relations or dialogue acts. These extra layers of annotation may be just what someone needs for performing a particular data analysis task. For example, it may be much easier to find a given linguistic pattern if we can search for specific syntactic structures; and it may be easier to categorize a linguistic pattern if every word has been tagged with its sense. Here are some commonly provided annotation layers:

- Word Tokenization: The orthographic form of text does not unambiguously identify its tokens. A tokenized and normalized version, in addition to the conventional orthographic version, may be a very convenient resource.
- Sentence Segmentation: As we saw in [Chapter 3](#), sentence segmentation can be more difficult than it seems. Some corpora therefore use explicit annotations to mark sentence segmentation.
- Paragraph Segmentation: Paragraphs and other structural elements (headings, chapters, etc.) may be explicitly annotated.
- Part of Speech: The syntactic category of each word in a document.
- Syntactic Structure: A tree structure showing the constituent structure of a sentence.
- Shallow Semantics: Named entity and coreference annotations, semantic role labels.
- Dialogue and Discourse: dialogue act tags, rhetorical structure

Unfortunately, there is not much consistency between existing corpora in how they represent their annotations. However, two general classes of annotation representation should be distinguished. **Inline annotation** modifies the original document by inserting special symbols or control sequences that carry the annotated information. For example, when part-of-speech tagging a document, the string `"fly"` might be replaced with the string `"fly/NN"`, to indicate that the word *fly* is a noun in this context. In contrast, **standoff annotation** does not modify the original document, but

instead creates a new file that adds annotation information using pointers that reference the original document. For example, this new document might contain the string "`<token id=8 pos='NN' />`", to indicate that token 8 is a noun. (We would want to be sure that the tokenization itself was not subject to change, since it would cause such references to break silently.)

Standards and Tools

For a corpus to be widely useful, it needs to be available in a widely supported format. However, the cutting edge of NLP research depends on new kinds of annotations, which by definition are not widely supported. In general, adequate tools for creation, publication and use of linguistic data are not widely available. Most projects must develop their own set of tools for internal use, which is no help to others who lack the necessary resources. Furthermore, we do not have adequate, generally-accepted standards for expressing the structure and content of corpora. 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.

One response to this situation has been to forge ahead with developing a generic format which is sufficiently expressive to capture a wide variety of annotation types (see [Section 11.8](#) for examples). The challenge for NLP is to write programs that cope with the generality of such formats. For example, if the programming task involves tree data, and the file format permits arbitrary directed graphs, then input data must be validated to check for tree properties such as rootedness, connectedness, and acyclicity. If the input files contain other layers of annotation, the program would need to know how to ignore them when the data was loaded, but not invalidate or obliterate those layers when the tree data was saved back to the file.

Another response has been to write one-off scripts to manipulate corpus formats; such scripts litter the filespace of many NLP researchers. NLTK's corpus readers are a more systematic approach, founded on the premise that the work of parsing a corpus format should only be done once (per programming language).

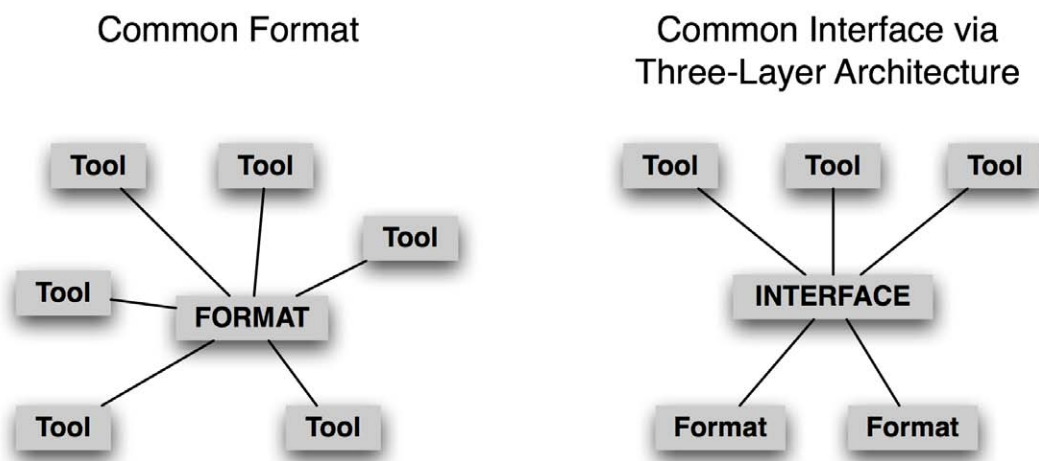


Figure 11.7: A Common Format vs A Common Interface

Instead of focussing on a common format, we believe it is more promising to develop a common interface (cf. `nltk.corpus`). Consider the case of treebanks, an important corpus type for work in NLP. There are many ways to store a phrase structure tree in a file. We can use nested parentheses, or nested XML elements, or a dependency notation with a (child-id, parent-id) pair on each line, or an XML version of the dependency notation, etc. However, in each case the logical structure is almost the same. It is much easier to devise a common interface that allows application programmers to write code to access tree data using methods such as `children()`, `leaves()`, `depth()`, and so forth. Note that this approach follows accepted practice within computer science, viz. abstract data types, object oriented design, and the three layer architecture ([Figure 11.7](#)). The last of these — from the world of relational databases — allows end-user applications to use a common model (the "relational model") and a common language (SQL), to abstract away from the idiosyncrasies of file storage, and allowing innovations in filesystem technologies to occur without disturbing end-user applications. In the same way, a common corpus interface insulates application

programs from data formats.

In this context, when creating a new corpus for dissemination, it is expedient to use an existing widely-used format wherever possible. When this is not possible, the corpus could be accompanied with software — such as an `nltk.corpus` module — that supports existing interface methods.

Special Considerations when Working with Endangered Languages

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 each one provides a unique window onto human pre-history. 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.

However, most of the world's languages face extinction. In response to this, many linguists are hard at work documenting the languages, constructing rich records of this important facet of the world's linguistic heritage. What can the field of NLP offer to help with this effort? Developing taggers, parsers, named-entity recognizers, etc, is not an early priority, and there is usually insufficient data for developing such tools in any case. Instead, the most frequently voiced need is to have better tools for collecting and curating data, with a focus on texts and lexicons.

On the face of things, it should be a straightforward matter to start collecting texts in an endangered language. Even if we ignore vexed issues such as who owns the texts, and sensitivities surrounding cultural knowledge contained in the texts, there is the obvious practical issue of transcription. Most languages lack a standard orthography. When a language has no literary tradition, the conventions of spelling and punctuation are not well-established. Therefore it is common practice to create a lexicon in tandem with a text collection, continually updating the lexicon as new words appear in the texts. This work could be done using a text processor (for the texts) and a spreadsheet (for the lexicon). Better still, SIL's free linguistic software Toolbox and Fieldworks provide sophisticated support for integrated creation of texts and lexicons.

When speakers of the language in question are trained to enter texts themselves, a common obstacle is an overriding concern for correct spelling. Having a lexicon greatly helps this process, but we need to have lookup methods that do not assume someone can determine the citation form of an arbitrary word. The problem may be acute for languages having a complex morphology that includes prefixes. In such cases it helps to tag lexical items with semantic domains, and to permit lookup by semantic domain or by gloss.

Permitting lookup by pronunciation similarity is also a big help. Here's a simple demonstration of how to do this. The first step is to identify confusable letter sequences, and map complex versions to simpler versions. We might also notice that the relative order of letters within a cluster of consonants is a source of spelling errors, and so we normalize the order of consonants.

```
>>> mappings = [('ph', 'f'), ('ght', 't'), ('^kn', 'n'), ('qu', 'kw'),
...             ('[aeiou]+', 'a'), (r'(\.)\1', r'\1')]
>>> def signature(word):
...     for patt, repl in mappings:
...         word = re.sub(patt, repl, word)
...     pieces = re.findall('[^aeiou]+', word)
...     return ''.join(char for piece in pieces for char in sorted(piece)[:8])
>>> signature('illefent')
'lfnt'
>>> signature('ebsekwieous')
'bskws'
>>> signature('nuculerr')
'nclr'
```


Next, we create a mapping from signatures to words, for all the words in our lexicon. We can use this to get candidate corrections for a given input word (but we must first compute that word's signature).

```
>>> signatures = nltk.Index((signature(w), w) for w in nltk.corpus.words.words())
>>> signatures[signature('nuculerr')]
['anicular', 'inocular', 'nucellar', 'nuclear', 'unicolor', 'uniocular', 'unocular']
```

Finally, we should rank the results in terms of similarity with the original word. This is done by the function `rank()`. The only remaining function provides a simple interface to the user:

```
>>> def rank(word, wordlist):
...     ranked = sorted((nltk.edit_dist(word, w), w) for w in wordlist)
...     return [word for (_, word) in ranked]
>>> def fuzzy_spell(word):
...     sig = signature(word)
...     if sig in signatures:
...         return rank(word, signatures[sig])
...     else:
...         return []
>>> fuzzy_spell('illefent')
['olefiant', 'elephant', 'oliphant', 'elephanta']
>>> fuzzy_spell('ebsekwieous')
['obsequious']
>>> fuzzy_spell('nucular')
['nuclear', 'nucellar', 'anicular', 'inocular', 'unocular', 'unicolor', 'uniocular']
```

This is just one illustration where a simple program can facilitate access to lexical data in a context where the writing system of a language may not be standardized, or where users of the language may not have a good command of spellings. Other simple applications of NLP in this area include: building indexes to facilitate access to data, gleaning wordlists from texts, locating examples of word usage in constructing a lexicon, detecting prevalent or exceptional patterns in poorly understood data, and performing specialized validation on data created using various linguistic software tools. We will return to the last of these in [Section 11.5](#).

11.4 Working with XML

The Extensible Markup Language (XML) provides a framework for designing domain-specific markup languages. It is sometimes used for representing annotated text and for lexical resources. Unlike HTML with its predefined tags, XML permits us to make up our own tags. Unlike a database, XML permits us to create data without first specifying its structure, and it permits us to have optional and repeatable elements. In this section we briefly review some features of XML that are relevant for representing linguistic data, and show how to access data stored in XML files using Python programs.

Using XML for Linguistic Structures

Thanks to its flexibility and extensibility, XML is a natural choice for representing linguistic structures. Here's an example of a simple lexical entry.

```
(2) <entry>
    <headword>whale</headword>
    <pos>noun</pos>
    <gloss>any of the larger cetacean mammals having a streamlined
        body and breathing through a blowhole on the head</gloss>
</entry>
```

It consists of a series of XML tags enclosed in angle brackets. Each opening tag, like `<gloss>` is matched with a closing tag, like `</gloss>`; together they constitute an **XML element**. The above example has been laid out nicely using whitespace, but it could equally have been put on a single, long line. Our approach to processing XML will usually not be sensitive to whitespace. In order for XML to be **well formed**, all opening tags must have corresponding

closing tags, at the same level of nesting (i.e. the XML document must be a well-formed tree).

XML permits us to repeat elements, e.g. to add another gloss field as we see below. We will use different whitespace to underscore the point that layout does not matter.

```
(3) <entry><headword>whale</headword><pos>noun</pos><gloss>any of the
    larger cetacean mammals having a streamlined body and breathing
    through a blowhole on the head</gloss><gloss>a very large person;
    impressive in size or qualities</gloss></entry>
```

A further step might be to link our lexicon to some external resource, such as WordNet, using external identifiers. In (4) we group the gloss and a synset identifier inside a new element which we have called "sense".

```
(4) <entry>
    <headword>whale</headword>
    <pos>noun</pos>
    <sense>
        <gloss>any of the larger cetacean mammals having a streamlined
            body and breathing through a blowhole on the head</gloss>
        <synset>whale.n.02</synset>
    </sense>
    <sense>
        <gloss>a very large person; impressive in size or qualities</gloss>
        <synset>giant.n.04</synset>
    </sense>
</entry>
```

Alternatively, we could have represented the synset identifier using an **XML attribute**, without the need for any nested structure, as in (5).

```
(5) <entry>
    <headword>whale</headword>
    <pos>noun</pos>
    <gloss synset="whale.n.02">any of the larger cetacean mammals having
        a streamlined body and breathing through a blowhole on the head</gloss>
    <gloss synset="giant.n.04">a very large person; impressive in size or
        qualities</gloss>
</entry>
```

This illustrates some of the flexibility of XML. If it seems somewhat arbitrary that's because it is! Following the rules of XML we can invent new attribute names, and nest them as deeply as we like. We can repeat elements, leave them out, and put them in a different order each time. We can have fields whose presence depends on the value of some other field, e.g. if the part of speech is "verb", then the entry can have a `past_tense` element to hold the past tense of the verb, but if the part of speech is "noun" no `past_tense` element is permitted. To impose some order over all this freedom, we can constrain the structure of an XML file using a "schema," which is a declaration akin to a context free grammar. Tools exist for testing the **validity** of an XML file with respect to a schema.

The Role of XML

We can use XML to represent many kinds of linguistic information. However, the flexibility comes at a price. Each time we introduce a complication, such as by permitting an element to be optional or repeated, we make more work for any program that accesses the data. We also make it more difficult to check the validity of the data, or to interrogate the data using one of the XML query languages.

Thus, using XML to represent linguistic structures does not magically solve the data modeling problem. We still have to work out how to structure the data, then define that structure with a schema, and then write programs to read and write the format and convert it to other formats. Similarly, we still need to follow some standard principles concerning data normalization. It is wise to avoid making duplicate copies of the same information, so that we don't end up with inconsistent data when only one copy is changed. For example, a cross-reference that was represented as `<xref>headword</xref>` would duplicate the storage of the headword of some other lexical entry, and the link would

break if the copy of the string at the other location was modified. Existential dependencies between information types need to be modeled, so that we can't create elements without a home. For example, if sense definitions cannot exist independently of a lexical entry, the `sense` element can be nested inside the `entry` element. Many-to-many relations need to be abstracted out of hierarchical structures. For example, if a word can have many corresponding senses, and a sense can have several corresponding words, then both words and senses must be enumerated separately, as must the list of (word, sense) pairings. This complex structure might even be split across three separate XML files.

As we can see, although XML provides us with a convenient format accompanied by an extensive collection of tools, it offers no panacea.

The ElementTree Interface

Python's ElementTree module provides a convenient way to access data stored in XML files. ElementTree is part of Python's standard library (since Python 2.5), and is also provided as part of NLTK in case you are using Python 2.4.

We will illustrate the use of ElementTree using a collection of Shakespeare plays that have been formatted using XML. Let's load the XML file and inspect the raw data, first at the top of the file [1], where we see some XML headers and the name of a schema called `play.dtd`, followed by the **root element** `PLAY`. We pick it up again at the start of Act 1 [2]. (Some blank lines have been omitted from the output.)

```
>>> merchant_file = nltk.data.find('corpora/shakespeare/merchant.xml')
>>> raw = open(merchant_file).read()
>>> print raw[0:168] [1]
<?xml version="1.0"?>
<?xml-stylesheet type="text/css" href="shakes.css"?>
<!-- <!DOCTYPE PLAY SYSTEM "play.dtd"> -->
<PLAY>
<TITLE>The Merchant of Venice</TITLE>
>>> print raw[1850:2075] [2]
<TITLE>ACT I</TITLE>
<SCENE><TITLE>SCENE I. Venice. A street.</TITLE>
<STAGEDIR>Enter ANTONIO, SALARINO, and SALANIO</STAGEDIR>
<SPEECH>
<SPEAKER>ANTONIO</SPEAKER>
<LINE>In sooth, I know not why I am so sad:</LINE>
```

We have just accessed the XML data as a string. As we can see, the string at the start of Act 1 contains XML tags for title, scene, stage directions, and so forth.

The next step is to process the file contents as structured XML data, using ElementTree. We are processing a file (a multi-line string) and building a tree, so its not surprising that the method name is `parse` [1]. The variable `merchant` contains an XML element `PLAY` [2]. This element has internal structure; we can use an index to get its first child, a `TITLE` element [3]. We can also see the text content of this element, the title of the play [4]. To get a list of all the child elements, we use the `getchildren()` method [5].

```
>>> from nltk.etree.ElementTree import ElementTree
>>> merchant = ElementTree().parse(merchant_file) [1]
>>> merchant
<Element PLAY at 22fa800> # [_element-play]
>>> merchant[0]
<Element TITLE at 22fa828> # [_element-title]
>>> merchant[0].text
'The Merchant of Venice' # [_element-text]
>>> merchant.getchildren() [5]
[<Element TITLE at 22fa828>, <Element PERSONAE at 22fa7b0>, <Element SCNDESCR at 2300170>,
<Element PLAYSUBT at 2300198>, <Element ACT at 23001e8>, <Element ACT at 234ec88>,
<Element ACT at 23c87d8>, <Element ACT at 2439198>, <Element ACT at 24923c8>]
```

The play consists of a title, the personae, a scene description, a subtitle, and five acts. Each act has a title and some

scenes, and each scene consists of speeches which are made up of lines, a structure with four levels of nesting. Let's dig down into Act IV:

```
>>> merchant[-2][0].text
'ACT IV'
>>> merchant[-2][1]
<Element SCENE at 224cf80>
>>> merchant[-2][1][0].text
'SCENE I. Venice. A court of justice.'
>>> merchant[-2][1][54]
<Element SPEECH at 226ee40>
>>> merchant[-2][1][54][0]
<Element SPEAKER at 226ee90>
>>> merchant[-2][1][54][0].text
'PORTIA'
>>> merchant[-2][1][54][1]
<Element LINE at 226eee0>
>>> merchant[-2][1][54][1].text
"The quality of mercy is not strain'd,"
```

Note

Your Turn: Repeat some of the above methods, for one of the other Shakespeare plays included in the corpus, such as *Romeo and Juliet* or *Macbeth*; for a list, see `nltk.corpus.shakespeare.fileids()`.

Although we can access the entire tree this way, it is more convenient to search for sub-elements with particular names. Recall that the elements at the top level have several types. We can iterate over just the types we are interested in (such as the acts), using `merchant.findall('ACT')`. Here's an example of doing such tag-specific searches at every level of nesting:

```
>>> for i, act in enumerate(merchant.findall('ACT')):
...     for j, scene in enumerate(act.findall('SCENE')):
...         for k, speech in enumerate(scene.findall('SPEECH')):
...             for line in speech.findall('LINE'):
...                 if 'music' in str(line.text):
...                     print "Act %d Scene %d Speech %d: %s" % (i+1, j+1, k+1,
line.text)
Act 3 Scene 2 Speech 9: Let music sound while he doth make his choice;
Act 3 Scene 2 Speech 9: Fading in music: that the comparison
Act 3 Scene 2 Speech 9: And what is music then? Then music is
Act 5 Scene 1 Speech 23: And bring your music forth into the air.
Act 5 Scene 1 Speech 23: Here will we sit and let the sounds of music
Act 5 Scene 1 Speech 23: And draw her home with music.
Act 5 Scene 1 Speech 24: I am never merry when I hear sweet music.
Act 5 Scene 1 Speech 25: Or any air of music touch their ears,
Act 5 Scene 1 Speech 25: By the sweet power of music: therefore the poet
Act 5 Scene 1 Speech 25: But music for the time doth change his nature.
Act 5 Scene 1 Speech 25: The man that hath no music in himself,
Act 5 Scene 1 Speech 25: Let no such man be trusted. Mark the music.
Act 5 Scene 1 Speech 29: It is your music, madam, of the house.
Act 5 Scene 1 Speech 32: No better a musician than the wren.
```

Instead of navigating each step of the way down the hierarchy, we can search for particular embedded elements. For example, let's examine the sequence of speakers. We can use a frequency distribution to see who has the most to say:

```
>>> speaker_seq = [s.text for s in merchant.findall('ACT/SCENE/SPEECH/SPEAKER')]
>>> speaker_freq = nltk.FreqDist(speaker_seq)
>>> top5 = speaker_freq.keys()[:5]
>>> top5
['PORTIA', 'SHYLOCK', 'BASSANIO', 'GRATIANO', 'ANTONIO']
```

We can also look for patterns in who follows who in the dialogues. Since there's 23 speakers, we need to reduce the "vocabulary" to a manageable size first, using the method described in [Section 5.3](#).

```
>>> mapping = nltk.defaultdict(lambda: 'OTH')
>>> for s in top5:
...     mapping[s] = s[:4]
...
>>> speaker_seq2 = [mapping[s] for s in speaker_seq]
>>> cfd = nltk.ConditionalFreqDist(nltk.ibigrams(speaker_seq2))
>>> cfd.tabulate()
      ANTO  BASS  GRAT  OTH  PORT  SHYL
ANTO      0    11     4    11     9    12
BASS     10     0    11    10    26    16
GRAT      6     8     0    19     9     5
OTH       8    16    18   153    52    25
PORT      7    23    13    53     0    21
SHYL     15    15     2    26    21     0
```

Ignoring the entries for exchanges between people other than the top 5 (labeled OTH), the largest value suggests that Portia and Bassanio have the most significant interactions.

Using ElementTree for Accessing Toolbox Data

In [Section 2.4](#) we saw a simple interface for accessing Toolbox data, a popular and well-established format used by linguists for managing data. 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.

We can use the `toolbox.xml()` method to access a Toolbox file and load it into an `elementtree` object. This file contains a lexicon for the Rotokas language of Papua New Guinea.

```
>>> 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); `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']
```

Let's view the Toolbox data in XML format. The `write()` method of `ElementTree` expects a file object. We usually create one of these using Python's built-in `open()` function. In order to see the output displayed on the screen, we can use a special pre-defined file object called `stdout` [\[1\]](#) (standard output), defined in Python's `sys` module.

```
>>> import sys
>>> from nltk.etree.ElementTree import ElementTree
```

```
>>> tree = ElementTree(lexicon[3])
>>> tree.write(sys.stdout) [1]
<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 kovopauveva kaparapasiasia.</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>
```

Formatting Entries

We can use the same idea we saw above 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
<table>
  <tr><td>kakae</td><td>??</td><td>small</td></tr>
  <tr><td>kakae</td><td>CLASS</td><td>child</td></tr>
  <tr><td>kakaevira</td><td>ADV</td><td>small-like</td></tr>
  <tr><td>kakapikoa</td><td>??</td><td>small</td></tr>
  <tr><td>kakapikoto</td><td>N</td><td>newborn baby</td></tr>
  <tr><td>kakapu</td><td>V</td><td>place in sling for purpose of carrying</td></tr>
  <tr><td>kakapua</td><td>N</td><td>sling for lifting</td></tr>
  <tr><td>kakara</td><td>N</td><td>arm band</td></tr>
  <tr><td>Kakarapaia</td><td>N</td><td>village name</td></tr>
  <tr><td>kakarau</td><td>N</td><td>frog</td></tr>
</table>
```

11.5 Working with Toolbox Data

Given the popularity of Toolbox amongst linguists, we will discuss some further methods for working with Toolbox data. Many of the methods discussed in previous chapters, such as counting, building frequency distributions, tabulating co-occurrences, can be applied to the content of Toolbox entries. For example, we can trivially compute the average number of fields for each entry:

```
>>> from nltk.corpus import toolbox
>>> lexicon = toolbox.xml('rotokas.dic')
>>> sum(len(entry) for entry in lexicon) / len(lexicon)
13.635955056179775
```

In this section we will discuss two tasks that arise in the context of documentary linguistics, neither of which is supported by the Toolbox software.

Adding a Field to Each Entry

It is often convenient to add new fields that are derived automatically from existing ones. Such fields often facilitate search and analysis. For instance, in [Example 11.8](#) 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. [Example 11.8](#) shows what this does to a particular entry; note the last line of output, which shows the new `cv` field.

```
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.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 CVVCVCV
```

Example 11.8 (code `add_cv_field.py`): Figure 11.8: Adding a new `cv` field to a lexical entry

Note

If a Toolbox file is being continually updated, the program in `code-add-cv-field` will need to be run more than once. It would be possible to modify `add_cv_field()` to modify the contents of an existing entry. However, it is a safer practice to use such programs to create enriched files for the purpose of data analysis, without replacing the manually curated source files.

Validating a Toolbox Lexicon

Many lexicons in Toolbox format do not conform to any particular schema. Some entries may include extra fields, or may order existing fields in a new way. Manually inspecting thousands of lexical entries is not practicable. However, we can easily identify frequent vs exceptional field sequences, with the help of a `FreqDist`:

```
>>> fd = nltk.FreqDist('.'.join(field.tag for field in entry) for entry in lexicon)
>>> fd.items()
[('lx:ps:pt:ge:tkp:dt:ex:xp:xe', 41), ('lx:rt:ps:pt:ge:tkp:dt:ex:xp:xe', 37),
 ('lx:rt:ps:pt:ge:tkp:dt:ex:xp:xe:ex:xp:xe', 27), ('lx:ps:pt:ge:tkp:nt:dt:ex:xp:xe',
```



```
20),
..., ('lx:alt:rt:ps:pt:ge:eng:eng:eng:tkp:tkp:dt:ex:xp:xe:ex:xp:xe:ex:xp:xe', 1)]
```

After inspecting the high-frequency field sequences we could devise a context free grammar for lexical entries. The grammar in [Example 11.9](#) uses the CFG format we saw in [Chapter 8](#). Such a grammar models the implicit nested structure of Toolbox entries, building a tree structure, where the leaves of the tree are individual field names. We iterate over the entries and report their conformance with the grammar, as shown in [Example 11.9](#). Those that are accepted by the grammar prefixed with a '+' [\[1\]](#), and those that are rejected are prefixed with a '-' [\[2\]](#). During the process of developing such a grammar it helps to filter out some of the tags [\[3\]](#).

```
grammar = nltk.parse_cfg('''
S -> Head PS Glosses Comment Date Sem_Field Examples
Head -> Lexeme Root
Lexeme -> "lx"
Root -> "rt" |
PS -> "ps"
Glosses -> Gloss Glosses |
Gloss -> "ge" | "tkp" | "eng"
Date -> "dt"
Sem_Field -> "sf"
Examples -> Example Ex_Pidgin Ex_English Examples |
Example -> "ex"
Ex_Pidgin -> "xp"
Ex_English -> "xe"
Comment -> "cmt" | "nt" |
''')

def validate_lexicon(grammar, lexicon, ignored_tags):
    rd_parser = nltk.RecursiveDescentParser(grammar)
    for entry in lexicon:
        marker_list = [field.tag for field in entry if field.tag not in ignored_tags]
        if rd_parser.nbest_parse(marker_list):
            print "+", ':'.join(marker_list) [1]
        else:
            print "-", ':'.join(marker_list) [2]

>>> lexicon = toolbox.xml('rotokas.dic')[10:20]
>>> ignored_tags = ['arg', 'dcsv', 'pt', 'vx'] [3]
>>> validate_lexicon(grammar, lexicon, ignored_tags)
- lx:ps:ge:tkp:sf:nt:dt:ex:xp:xe:ex:xp:xe:ex:xp:xe
- lx:rt:ps:ge:tkp:nt:dt:ex:xp:xe:ex:xp:xe
- lx:ps:ge:tkp:nt:dt:ex:xp:xe:ex:xp:xe
- lx:ps:ge:tkp:nt:sf:dt
- lx:ps:ge:tkp:dt:cmt:ex:xp:xe:ex:xp:xe
- lx:ps:ge:ge:ge:tkp:cmt:dt:ex:xp:xe
- lx:rt:ps:ge:ge:tkp:dt
-
lx:rt:ps:ge:eng:eng:eng:ge:tkp:tkp:dt:cmt:ex:xp:xe:ex:xp:xe:ex:xp:xe:ex:xp:xe:ex:xp:xe
- lx:rt:ps:ge:tkp:dt:ex:xp:xe
- lx:ps:ge:ge:tkp:dt:ex:xp:xe:ex:xp:xe
```

Example 11.9 (code [toolbox_validation.py](#)): Figure 11.9: Validating Toolbox Entries Using a Context Free Grammar

Another approach would be to use a chunk parser ([Chapter 7](#)), since these are much more effective at identifying partial structures, and can report the partial structures that have been identified. In [Example 11.10](#) we set up a chunk grammar for the entries of a lexicon, then parse each entry. A sample of the output from this program is shown in [Figure 11.11](#).

```
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.parse(grammar, encoding='utf8')
>>> toolbox.data.indent(lexicon)
>>> tree = ElementTree(lexicon)
>>> output = open("iu_mien_samp.xml", "w")
>>> tree.write(output, encoding='utf8')
>>> output.close()
```

Example 11.10 (code chunk toolbox.py): Figure 11.10: Chunking a Toolbox Lexicon: A chunk grammar describing the structure of entries for a lexicon for *Iu Mien*, a language of China.

```
<record>
  <lx>ceuv jiax</lx>
  <hm />
  <sense>
    <sn />
    <ps>vobj</ps>
    <dv>nzaeng jiax</dv>
    <ge>quarrel</ge>
    <de />
    <gn>吵架</gn>
    <gp>chao3 jia4</gp>
    <dn>争吵</dn>
  <example>
    <xv>Ninh mbuo i hmuangv mv ~ jiex jiax.</xv>
    <xe>That husband and wife have never quarrelled.</xe>
    <xn>他们夫妻俩从来不吵架。</xn>
  </example><example>
    <xv>Gorngv duh leiz mv duqv ~.</xv>
    <xe>Have some common sense, don't quarrel.</xe>
    <xn>讲道理，别吵架。</xn>
  </example><lexfunc>
    <lf />
    <lv />
  </lexfunc>
</sense><dt>18/Feb/2004</dt>
</record>
```

Figure 11.11: XML Representation of a Lexical Entry, Resulting from Chunk Parsing a Toolbox Record

11.6 Describing Language Resources using OLAC Metadata

Members of the NLP community have a common need for discovering language resources with high precision and recall. The solution which has been developed by the Digital Libraries community involves metadata aggregation.

What is Metadata?

The simplest definition of metadata is "structured data about data." Metadata is descriptive information about an object or resource whether it be physical or electronic. While the term metadata itself is relatively new, the underlying concepts behind metadata have been in use for as long as collections of information have been organized. Library catalogs represent a well-established type of metadata; they have served as collection management and resource discovery tools for decades. Metadata can be generated either "by hand" or generated automatically using software.

The Dublin Core Metadata Initiative began in 1995 to develop conventions for resource discovery on the web. The Dublin Core metadata elements represent a broad, interdisciplinary consensus about the core set of elements that are

likely to be widely useful to support resource discovery. The Dublin Core consists of 15 metadata elements, where each element is optional and repeatable: Title, Creator, Subject, Description, Publisher, Contributor, Date, Type, Format, Identifier, Source, Language, Relation, Coverage, Rights. This metadata set can be used to describe resources that exist in digital or traditional formats.

The Open Archives initiative (OAI) provides a common framework across digital repositories of scholarly materials regardless of their type, including documents, data, software, recordings, physical artifacts, digital surrogates, and so forth. Each repository consists of a network accessible server offering public access to archived items. Each item has a unique identifier, and is associated with a Dublin Core metadata record (and possibly additional records in other formats). The OAI defines a protocol for metadata search services to "harvest" the contents of repositories.

OLAC: Open Language Archives Community

The Open Language Archives Community (OLAC) is an international partnership of institutions and individuals who are creating a worldwide virtual library of language resources by: (i) developing consensus on best current practice for the digital archiving of language resources, and (ii) developing a network of interoperating repositories and services for housing and accessing such resources. OLAC's home on the web is at <http://www.language-archives.org/>.

OLAC Metadata is a standard for describing language resources. Uniform description across repositories is ensured by limiting the values of certain metadata elements to the use of terms from controlled vocabularies. OLAC metadata can be used to describe data and tools, in both physical and digital formats. OLAC metadata extends the Dublin Core Metadata Set, a widely accepted standard for describing resources of all types. To this core set, OLAC adds descriptors to cover fundamental properties of language resources, such as subject language and linguistic type. Here's an example of a complete OLAC record:

```
<?xml version="1.0" encoding="UTF-8"?>
<olac:olac xmlns:olac="http://www.language-archives.org/OLAC/1.1/"
  xmlns="http://purl.org/dc/elements/1.1/"
  xmlns:dcterms="http://purl.org/dc/terms/"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:schemaLocation="http://www.language-archives.org/OLAC/1.1/
    http://www.language-archives.org/OLAC/1.1/olac.xsd">
  <title>A grammar of Kayardild. With comparative notes on Tangkic.</title>
  <creator>Evans, Nicholas D.</creator>
  <subject>Kayardild grammar</subject>
  <subject xsi:type="olac:language" olac:code="gyd">Kayardild</subject>
  <language xsi:type="olac:language" olac:code="en">English</language>
  <description>Kayardild Grammar (ISBN 3110127954)</description>
  <publisher>Berlin - Mouton de Gruyter</publisher>
  <contributor xsi:type="olac:role" olac:code="author">Nicholas Evans</contributor>
  <format>hardcover, 837 pages</format>
  <relation>related to ISBN 0646119966</relation>
  <coverage>Australia</coverage>
  <type xsi:type="olac:linguistic-type" olac:code="language_description"/>
  <type xsi:type="dcterms:DCMIType">Text</type>
</olac:olac>
```

Participating language archives publish their catalogs in an XML format, and these records are regularly "harvested" by OLAC services using the OAI protocol. In addition to this software infrastructure, OLAC has documented a series of best practices for describing language resources, through a process that involved extended consultation with the language resources community (e.g. see <http://www.language-archives.org/REC/bpr.html>).

OLAC repositories can be searched using a query engine on the OLAC website. Searching for "German lexicon" finds the following resources, amongst others:

- CALLHOME German Lexicon <http://www.language-archives.org/item/oai:www.ldc.upenn.edu:LDC97L18>
- MULTILEX multilingual lexicon <http://www.language-archives.org/item/oai:elra.icp.inpg.fr:M0001>
- Slex Siemens Phonetic lexicon <http://www.language-archives.org/item/oai:elra.icp.inpg.fr:S0048>

Searching for "Korean" finds a newswire corpus, a treebank, a lexicon, a child-language corpus, interlinear glossed

texts. It also finds software including a syntactic analyzer and a morphological analyzer.

Observe that the above URLs include a substring of the form: `oai:www.ldc.upenn.edu:LDC97L18`. This is an OAI identifier, using a URI scheme registered with ICANN (the *Internet Corporation for Assigned Names and Numbers*). These identifiers have the format `oai:archive:local_id`, where `oai` is the name of the URI scheme, *archive* is an archive identifier such as `www.ldc.upenn.edu`, and *local_id* is the resource identifier assigned by the archive, e.g. `LDC97L18`.

Given an OAI identifier for an OLAC resource, it is possible to retrieve the complete XML record for the resource using a URL of the following form:

```
http://www.language-archives.org/static-records/oai:archive:local_id
```

Disseminating Language Resources

The Linguistic Data Consortium hosts the **NLTK Data Repository**, an open-access archive where community members can upload corpora and saved models. These resources can be easily accessed using NLTK's downloader tool.

11.7 Summary

- Fundamental data types, present in most corpora, are annotated texts and lexicons. Texts have a temporal structure, while lexicons have a record structure.
- The lifecycle of a corpus includes data collection, annotation, quality control, and publication. The lifecycle continues after publication as the corpus is modified and enriched during the course of research.
- Corpus development involves a balance between capturing a representative sample of language usage, and capturing enough material from any one source or genre to be useful; multiplying out the dimensions of variability is usually not feasible because of resource limitations.
- XML provides a useful format for the storage and interchange of linguistic data, but provides no shortcuts for solving pervasive data modeling problems.
- Toolbox format is widely used in language documentation projects; we can write programs to support the curation of Toolbox files, and to convert them to XML.
- The Open Language Archives Community (OLAC) provides an infrastructure for documenting and discovering language resources.

11.8 Further Reading

Extra materials for this chapter are posted at <http://www.nltk.org/>, including links to freely available resources on the web.

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 ([Reppen, Ide, & Suderman, 2005](#)), British National Corpus ([{BNC}, 1999](#)), Thesaurus Linguae Graecae ([{TLG}, 1999](#)), Child Language Data Exchange System (CHILDES) ([MacWhinney, 1995](#)), TIMIT ([S., Lamel, & William, 1986](#)).

Two special interest groups of the Association for Computational Linguistics that organize regular workshops with published proceedings are SIGWAC, which promotes the use of the web as a corpus and has sponsored the CLEANEVAL task for removing HTML markup, and SIGANN, which is encouraging efforts towards interoperability of linguistic annotations.

Full details of the Toolbox data format are provided with the distribution ([Buseman, Buseman, & Early, 1996](#)), and

with the latest distribution, freely available from <http://www.sil.org/computing/toolbox/>. For guidelines on the process of constructing a Toolbox lexicon see <http://www.sil.org/computing/ddp/>. More examples of our efforts with the Toolbox are documented in [\(Tamanji, Hirotani, & Hall, 1999\)](#), [\(Robinson, Aumann, & Bird, 2007\)](#). Dozens of other tools for linguistic data management are available, some surveyed by [\(Bird & Simons, 2003\)](#). See also the proceedings of the "LaTeCH" workshops on language technology for cultural heritage data.

There are many excellent resources for XML (e.g. <http://zvon.org/>) and for writing Python programs to work with XML. Many editors have XML modes. XML formats for lexical information include OLIF <http://www.olif.net/> and LIFT <http://code.google.com/p/lift-standard/>.

For a survey of linguistic annotation software, see the *Linguistic Annotation Page* at <http://www.ldc.upenn.edu/annotation/>. The initial proposal for standoff annotation was [\(Thompson & McKelvie, 1997\)](#). An abstract data model for linguistic annotations, called "annotation graphs", was proposed in [\(Bird & Liberman, 2001\)](#). A general-purpose ontology for linguistic description (GOLD) is documented at <http://www.linguistics-ontology.org/>.

For guidance on planning and constructing a corpus, see [\(Meyer, 2002\)](#), [\(Farghaly, 2003\)](#). More details of methods for scoring inter-annotator agreement are available in [\(Artstein & Poesio, 2008\)](#), [\(Pevzner & Hearst, 2002\)](#).

Rotokas data was provided by Stuart Robinson, and Iu Mien data was provided by Greg Aumann.

For more information about the Open Language Archives Community, visit <http://www.language-archives.org/>, or see [\(Simons & Bird, 2003\)](#).

11.9 Exercises

1. In [Example 11.8](#) 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.)
2. 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.)
3. 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.
4. Write a program to find any parts of speech (`ps` field) that occurred less than ten times. Perhaps these are typing mistakes?
5. 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`
6. 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.
7. Write a function to add a new field `sy1` which gives a count of the number of syllables in the word.
8. 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.
9. 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.)
10. 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.

11. Index the words of Shakespeare's plays, with the help of `nltk.Index`. The resulting data structure should permit lookup on individual words such as *music*, returning a list of references to acts, scenes and speeches, of the form `[(3, 2, 9), (5, 1, 23), ...]`, where `(3, 2, 9)` indicates Act 3 Scene 2 Speech 9.
12. Construct a conditional frequency distribution which records the word length for each speech in *The Merchant of Venice*, conditioned on the name of the character, e.g. `cfd['PORTIA']` would give us the number of speeches by Portia consisting of 12 words.
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.
15. Write a recursive function to produce an XML representation for a tree, with non-terminals represented as XML elements, and leaves represented as text content, e.g.:

```
<S>
  <NP type="SBJ">
    <NP>
      <NNP>Pierre</NNP>
      <NNP>Vinken</NNP>
    </NP>
  <COMMA> , </COMMA>
```

About this document...

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