Instructor's Solution Manual
Speech and Language Processing

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition

Second Edition

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Contents

Preface

This Instructor's Solution Manual provides solutions for the end-of-chapter exercises in *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition (Second Edition)*. For the more interactive exercises, or where a complete solution would be infeasible (e.g., would require too much code), a sketch of the solution or discussion of the issues involved is provided instead. In general, the solutions in this manual aim to provide enough information about each problem to allow an instructor to meaningfully evaluate student responses.

Note that many of the exercises in this book could be solved in a number of different ways, though we often provide only a single answer. We have aimed for what we believe to be the most typical answer, but instructors should be open to alternative solutions for most of the more complex exercises. The goal is to get students thinking about the issues involved in the various speech and language processing tasks, so most solutions that demonstrate such an understanding have achieved the main purpose of their exercises.

On a more technical note, throughout this manual, when code is provided as the solution to an exercise, the code is written in the Python programming language. This is done both for consistency, and ease of comprehension - in many cases, the Python code reads much like the algorithmic pseudocode used in other parts of the book. For more information about the Python programming language, please visit:

```
http://www.python.org/
```

The code in this manual was written and tested using Python 2.5. It will likely work on newer versions of Python, but some constructs used in the manual may not be valid on older versions of Python.

Acknowledgments

Kevin Bretonnel Cohen deserves particular thanks for providing the solutions to the biomedical information extraction problems in Chapter 22, and they are greatly improved with his insights into the field. Thanks also to the many researchers upon whose work and careful documentation some of the solutions in this book are based, including Alan Black, Susan Brennan, Eric Brill, Michael Collins, Jason Eisner, Jerry Hobbs, Kevin Knight, Peter Norvig, Martha Palmer, Bo Pang, Ted Pedersen, Martin Porter, Stuart Shieber, and many others.

Chapter 2
Regular Expressions and Automata

2.1 Write regular expressions for the following languages. You may use either Perl/Python notation or the minimal "algebraic" notation of Section 2.3, but make sure to say which one you are using. By "word", we mean an alphabetic string separated from other words by whitespace, any relevant punctuation, line breaks, and so forth.

1. the set of all alphabetic strings;

   ```
   [a-zA-Z]+
   ```

2. the set of all lower case alphabetic strings ending in a *b*;

   ```
   [a-z]*b
   ```

3. the set of all strings with two consecutive repeated words (e.g., "Humbert Humbert" and "the the" but not "the bug" or "the big bug");

   ```
   ([a-zA-Z]+)\s+\1
   ```

4. the set of all strings from the alphabet a, b such that each a is immediately preceded by and immediately followed by a b;

   ```
   (b+(ab+)+)?
   ```

5. all strings that start at the beginning of the line with an integer and that end at the end of the line with a word;

   ```
   ^\d+\b.*\b[a-zA-Z]+$
   ```

6. all strings that have both the word *grotto* and the word *raven* in them (but not, e.g., words like *grottos* that merely *contain* the word *grotto*);

   ```
   \bgrotto\b.*\braven\b|\braven\b.*\bgrotto\b
   ```

7. write a pattern that places the first word of an English sentence in a register. Deal with punctuation.

   ```
   ^[^a-zA-Z]*([a-zA-Z]+)
   ```

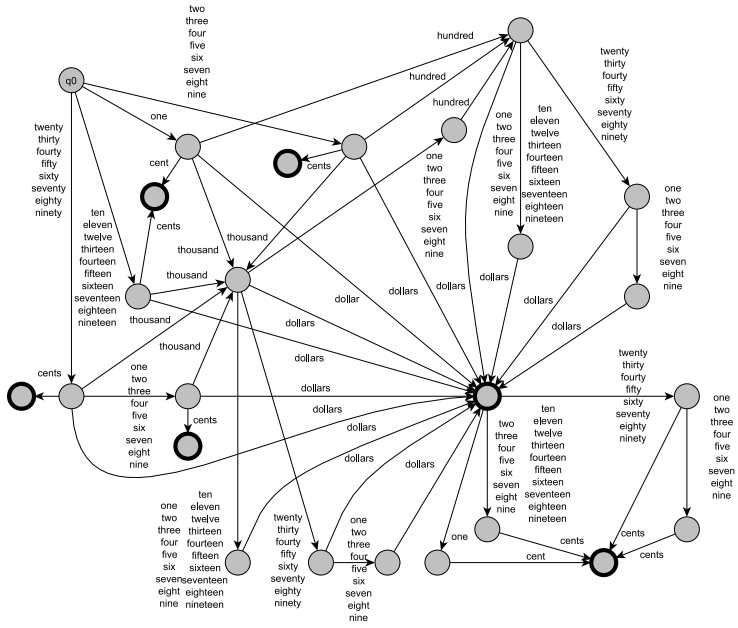
2.2 Implement an ELIZA-like program, using substitutions such as those described on page 26. You may choose a different domain than a Rogerian psychologist, if you wish, although keep in mind that you would need a domain in which your program can legitimately engage in a lot of simple repetition.

The following implementation can reproduce the dialog on page 26. A more complete solution would include additional patterns.

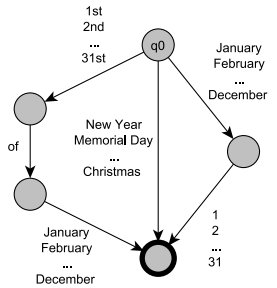
```
import re, string

patterns = [
    (r"\b(i'm|i am)\b", "YOU ARE"),
    (r"\b(i|me)\b", "YOU"),
    (r"\b(my)\b", "YOUR"),
    (r"\b(well,?) ", ""),
    (r".* YOU ARE (depressed|sad) .*",
         r"I AM SORRY TO HEAR YOU ARE \1"),
    (r".* YOU ARE (depressed|sad) .*",
         r"WHY DO YOU THINK YOU ARE \1"),
```

```
    (r".* all .*", "IN WHAT WAY"),
    (r".* always .*", "CAN YOU THINK OF A SPECIFIC EXAMPLE"),
    (r"[%s]" % re.escape(string.punctuation), ""),
]
while True:
    comment = raw_input()
    response = comment.lower()
    for pat, sub in patterns:
        response = re.sub(pat, sub, response)
    print response.upper()
```

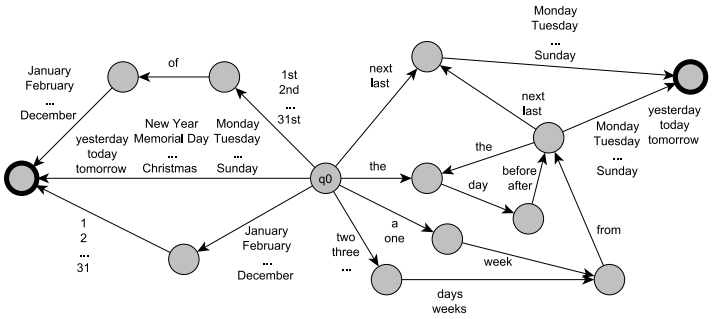
2.3 Complete the FSA for English money expressions in Fig. 2.15 as suggested in the text following the figure. You should handle amounts up to $100,000, and make sure that "cent" and "dollar" have the proper plural endings when appropriate.



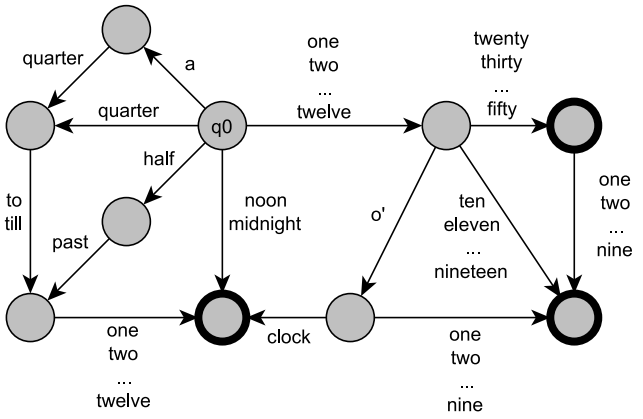
2.4 Design an FSA that recognizes simple date expressions like *March 15*, *the 22nd of November*, *Christmas*. You should try to include all such "absolute" dates (e.g., not "deictic" ones relative to the current day, like *the day before yesterday*). Each edge of the graph should have a word or a set of words on it. You should use some sort of shorthand for classes of words to avoid drawing too many arcs (e.g., furniture → desk, chair, table).



2.5 Now extend your date FSA to handle deictic expressions like *yesterday*, *tomorrow*, *a week from tomorrow*, *the day before yesterday*, *Sunday*, *next Monday*, *three weeks from Saturday*.



2.6 Write an FSA for time-of-day expressions like *eleven o'clock*, *twelve-thirty*, *midnight*, or *a quarter to ten*, and others.



2.7 (Thanks to Pauline Welby; this problem probably requires the ability to knit.) Write a regular expression (or draw an FSA) that matches all knitting patterns for scarves with the following specification: *32 stitches wide, K1P1 ribbing on both ends, stockinette stitch body, exactly two raised stripes*. All knitting patterns must include a cast-on row (to put the correct number of stitches on the needle) and a bind-off row (to end the pattern and prevent unraveling). Here's a sample pattern for one possible scarf matching the above description:[1]

[1] *Knit* and *purl* are two different types of stitches. The notation Kn means do n knit stitches. Similarly for purl stitches. Ribbing has a striped texture—most sweaters have ribbing at the sleeves, bottom, and neck. Stockinette stitch is a series of knit and purl rows that produces a plain pattern—socks or stockings are knit with this basic pattern, hence the name.

1.	Cast on 32 stitches.	*cast on; puts stitches on needle*
2.	K1 P1 across row (i.e., do (K1 P1) 16 times).	*K1P1 ribbing*
3.	Repeat instruction 2 seven more times.	*adds length*
4.	K32, P32.	*stockinette stitch*
5.	Repeat instruction 4 an additional 13 times.	*adds length*
6.	P32, P32.	*raised stripe stitch*
7.	K32, P32.	*stockinette stitch*
8.	Repeat instruction 7 an additional 251 times.	*adds length*
9.	P32, P32.	*raised stripe stitch*
10.	K32, P32.	*stockinette stitch*
11.	Repeat instruction 10 an additional 13 times.	*adds length*
12.	K1 P1 across row.	*K1P1 ribbing*
13.	Repeat instruction 12 an additional 7 times.	*adds length*
14.	Bind off 32 stitches.	*binds off row: ends pattern*

In the expression below, `C` stands for *cast on*, `K` stands for *knit*, `P` stands for *purl* and `B` stands for *bind off*:

```
C{32}
((KP){16})+
(K{32}P{32})+
P{32}P{32}
(K{32}P{32})+
P{32}P{32}
(K{32}P{32})+
((KP){16})+
B{32}
```

2.8 Write a regular expression for the language accepted by the NFSA in Fig. 2.26.

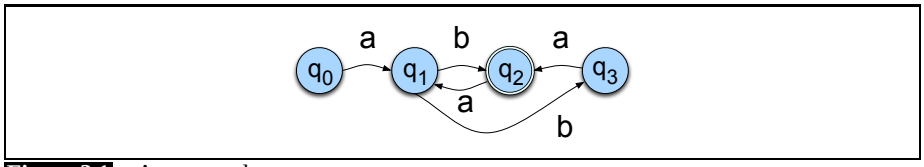


Figure 2.1 A mystery language.

```
(aba?)+
```

2.9 Currently the function D-RECOGNIZE in Fig. 2.12 solves only a subpart of the important problem of finding a string in some text. Extend the algorithm to solve the following two deficiencies: (1) D-RECOGNIZE currently assumes that it is already pointing at the string to be checked, and (2) D-RECOGNIZE fails if the string it is pointing to includes as a proper substring a legal string for the FSA. That is, D-RECOGNIZE fails if there is an extra character at the end of the string.

To address these problems, we will have to try to match our FSA at each point in the tape, and we will have to accept (the current substring) any time we reach an accept state. The former requires an

additional outer loop, and the latter requires a slightly different structure for our case statements:

```
function D-RECOGNIZE(tape,machine) returns accept or reject
  current-state ← Initial state of machine
  for index from 0 to LENGTH(tape) do
    current-state ← Initial state of machine
    while index < LENGTH(tape) and
          transition-table[current-state,tape[index]] is not empty do
      current-state ← transition-table[current-state,tape[index]]
      index ← index + 1
      if current-state is an accept state then
        return accept
    index ← index + 1
  return reject
```

2.10 Give an algorithm for negating a deterministic FSA. The negation of an FSA accepts exactly the set of strings that the original FSA rejects (over the same alphabet) and rejects all the strings that the original FSA accepts.

First, make sure that all states in the FSA have outward transitions for all characters in the alphabet. If any transitions are missing, introduce a new non-accepting state (the **fail state**), and add all the missing transitions, pointing them to the new non-accepting state.

Finally, make all non-accepting states into accepting states, and vice-versa.

2.11 Why doesn't your previous algorithm work with NFSAs? Now extend your algorithm to negate an NFSA.

The problem arises from the different definition of accept and reject in NFSA. We accept if there is "some" path, and only reject if all paths fail. So a tape leading to a single reject path does neccessarily get rejected, and so in the negated machine does not necessarily get accepted.

For example, we might have an ϵ-transition from the accept state to a non-accepting state. Using the negation algorithm above, we swap accepting and non-accepting states. But we can still accept strings from the original NFSA by simply following the transitions as before to the original accept state. Though it is now a non-accepting state, we can simply follow the ϵ-transition and stop. Since the ϵ-transition consumes no characters, we have reached an accepting state with the same string as we would have using the original NFSA.

To solve this problem, we first convert the NFSA to a DFSA, and then apply the algorithm as before.

Chapter 3
Words and Transducers

3.1 Give examples of each of the noun and verb classes in Fig. 3.6, and find some exceptions to the rules.

Examples:

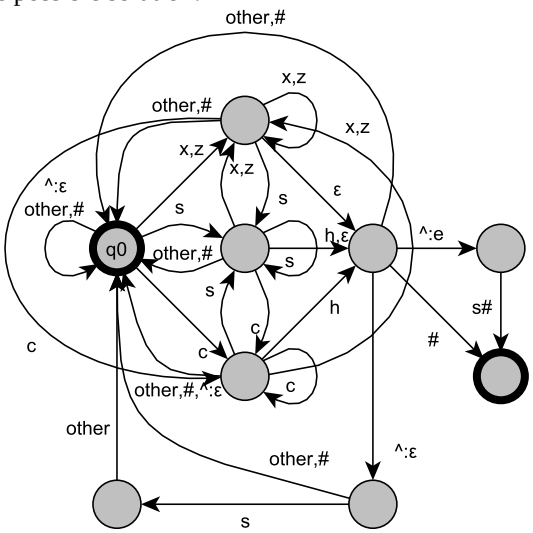
- noun_i: fossil
- verb_j: pass
- verb_k: conserve
- noun_l: wonder

Exceptions:

- noun_i: *apology* accepts *-ize* but *apologization* sounds odd
- verb_j: *detect* accepts *-ive* but it becomes a noun, not an adjective
- verb_k: *cause* accepts *-ative* but *causitiveness* sounds odd
- noun_l: *arm* accepts *-ful* but it becomes a noun, not an adjective

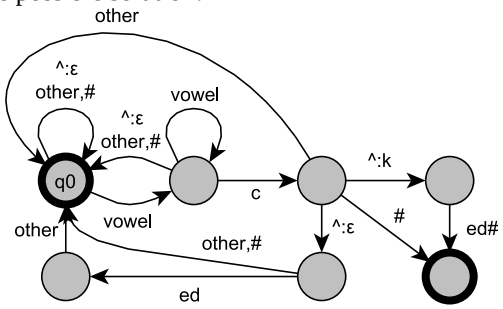
3.2 Extend the transducer in Fig. 3.17 to deal with `sh` and `ch`.

One possible solution:



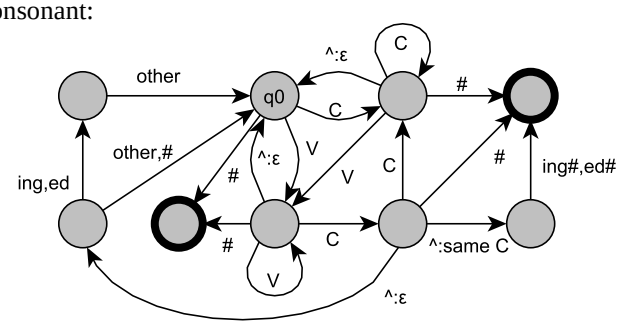
3.3 Write a transducer(s) for the K insertion spelling rule in English.

One possible solution:



3.4 Write a transducer(s) for the consonant doubling spelling rule in English.

One possible solution, where V stands for vowel, and C stands for consonant:



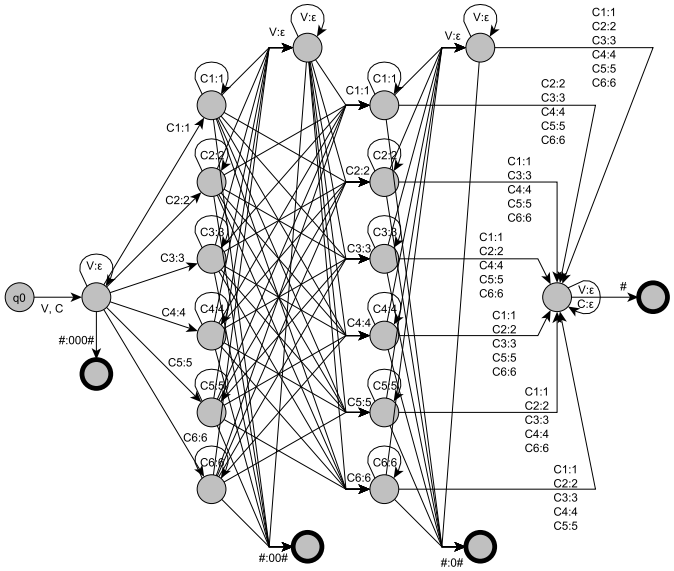
3.5 The Soundex algorithm (Knuth, 1973; Odell and Russell, 1922) is a method commonly used in libraries and older census records for representing people's names. It has the advantage that versions of the names that are slightly misspelled or otherwise modified (common, e.g., in hand-written census records) will still have the same representation as correctly spelled names. (e.g., Jurafsky, Jarofsky, Jarovsky, and Jarovski all map to J612).

1. Keep the first letter of the name, and drop all occurrences of non-initial a, e, h, i, o, u, w, y.
2. Replace the remaining letters with the following numbers:
   b, f, p, v → 1
   c, g, j, k, q, s, x, z → 2
   d, t → 3
   l → 4
   m, n → 5
   r → 6
3. Replace any sequences of identical numbers, only if they derive from two or more letters that were *adjacent* in the original name, with a single number (e.g., 666 → 6).
4. Convert to the form `Letter Digit Digit Digit` by dropping digits past the third (if necessary) or padding with trailing zeros (if necessary).

The exercise: write an FST to implement the Soundex algorithm.

One possible solution, using the following abbreviations:

V = *a, e, h, i, o, u, w, y*
C1 = *b, f, p, v*
C2 = *c, g, j, k, q, s, x, z*
C3 = *d, t*
C4 = *l*
C5 = *m, n*
C6 = *r*

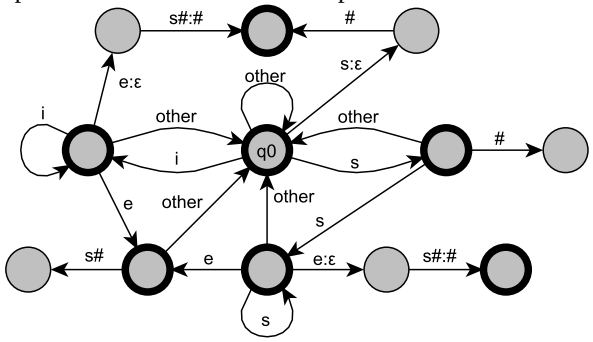


3.6 Read Porter (1980) or see Martin Porter's official homepage on the Porter stemmer. Implement one of the steps of the Porter Stemmer as a transducer.

Porter stemmer step 1a looks like:

SSES → SS
IES → I
SS → SS
S →

One possible transducer for this step:



3.7 Write the algorithm for parsing a finite-state transducer, using the pseudocode introduced in Chapter 2. You should do this by modifying the algorithm ND-RECOGNIZE in Fig. 2.19 in Chapter 2.

FSTs consider pairs of strings and output *accept* or *reject*. So the major changes to the ND-RECOGNIZE algorithm all revolve around moving from looking at a single tape to looking at a pair of tapes. Probably the most important change is in GENERATE-NEW-STATES, where we now must try all combinations of advancing a character or staying put (for an ϵ) on either the source string or the target string.

function ND-RECOGNIZE(*s-tape*,*t-tape*,*machine*) **returns** accept/reject
  agenda ← {(Machine start state, *s-tape* start, *t-tape* start)}
  while *agenda* is not empty **do**
    current-state ← NEXT(*agenda*)
    if ACCEPT-STATE?(*current-state*) **then**
      return accept
    agenda ← *agenda* ∪ GENERATE-NEW-STATES(*current-state*)
  return reject

function GENERATE-NEW-STATES(*current-state*) **returns** search states
  node ← the node the *current-state* is on
  s-index ← the point on *s-tape* the *current-state* is on
  t-index ← the point on *t-tape* the *current-state* is on
  return
    (*transition*[*node*, ϵ:ϵ], *s-index*, *t-index*) ∪
    (*transition*[*node*, *s-tape*[*s-index*]:ϵ], *s-index* + 1, *t-index*) ∪
    (*transition*[*node*, ϵ:*t-tape*[*t-index*]], *s-index*, *t-index* + 1) ∪
    (*transition*[*node*,*s-tape*[*s-index*]:*t-tape*[*t-index*]],*s-index*+1,*t-index*+1)

function ACCEPT-STATE?(*search-state*) **returns** true/false
  node ← the node the *current-state* is on
  s-index ← the point on *s-tape* the *current-state* is on
  t-index ← the point on *t-tape* the *current-state* is on
  return *s-index* is at the end of the tape **and**
      t-index is at the end of the tape **and**
      node is an accept state of the machine

3.8 Write a program that takes a word and, using an on-line dictionary, computes possible anagrams of the word, each of which is a legal word.

```
def permutations(string):
    if len(string) < 2:
        yield string
    else:
        first, rest = string[:1], string[1:]
        indices = range(len(string))
        for sub_string in permutations(rest):
            for i in indices:
                yield sub_string[:i] + first + sub_string[i:]

def anagrams(string):
    for string in permutations(string):
        if is_word(string): # query online dictionary
            yield string
```

3.9 In Fig. 3.17, why is there a *z, s, x* arc from q_5 to q_1?

State q_1 represents the point at which we have seen at least one *z, s* or *x*. If the *z, s, x* arc from q_5 to q_1 were not present, it would be possible to transition on an *z, s* or *x* back to the initial state, q_0. This would allow invalid strings like *sˆssˆs#* by following the path $q_0 \rightarrow q_1 \rightarrow q_2 \rightarrow q_5 \rightarrow q_0 \rightarrow q_1 \rightarrow q_0$.

3.10 Computing minimum edit distances by hand, figure out whether *drive* is closer to *brief* or to *divers* and what the edit distance is. You may use any version of *distance* that you like.

Using 1-insertion, 1-deletion, 2-substitution costs, there is a distance of 4 between *drive* and *brief*:

e	5	6	5	4	3	4
v	4	5	4	3	4	5
i	3	4	3	2	3	4
r	2	3	2	3	4	5
d	1	2	3	4	5	6
#	0	1	2	3	4	5
	#	b	r	i	e	f

Using 1-insertion, 1-deletion, 2-substitution costs, there is a distance of 3 between *drive* and *divers*:

e	5	4	3	2	1	2	3
v	4	3	2	1	2	3	4
i	3	2	1	2	3	4	5
r	2	1	2	3	4	3	4
d	1	0	1	2	3	4	5
#	0	1	2	3	4	5	6
	#	d	i	v	e	r	s

Thus, *drive* is closer to *divers* than to *brief*.

3.11 Now implement a minimum edit distance algorithm and use your hand-computed results to check your code.

```
def min_edit_distance(target, source):
    n = len(target)
    m = len(source)
    cols = range(1, n + 1)
    rows = range(1, m + 1)

    # initialize the distance matrix
    distance = {(0, 0): 0}
    for i in cols:
        mod = ins_cost(target[i - 1])
        distance[i, 0] = distance[i - 1, 0] + mod
    for j in rows:
        mod = del_cost(source[j - 1])
        distance[0, j] = distance[0, j - 1] + mod

    # sort like (0, 0) (0, 1) (1, 0) (0, 2) (1, 1) (2, 0) ...
    # this guarantees the matrix is filled in the right order
    indices = [(i, j) for i in cols for j in rows]
    indices.sort(key=sum)
```

```
    # helper function for calculating distances
    def get_dist(row, col, func, t_char, s_char):
        chars = t_char, s_char
        args = [char for char in chars if char != '*']
        return distance[row, col] + func(*args)

    # for each pair of indices, choose insertion, substitution
    # or deletion, whichever gives the shortest distance
    for i, j in indices:
        t_char = target[i - 1]
        s_char = source[j - 1]
        distance[i, j] = min(
            get_dist(i -1,  j,     ins_cost, t_char, '*'),
            get_dist(i - 1, j - 1, sub_cost, t_char, s_char),
            get_dist(i,     j - 1, del_cost, '*',    s_char))

    # return distance from the last row and column
    return distance[n, m]
```

3.12 Augment the minimum edit distance algorithm to output an alignment; you will need to store pointers and add a stage to compute the backtrace.

```
def min_edit(target, source):
    n = len(target)
    m = len(source)
    cols = range(1, n + 1)
    rows = range(1, m + 1)

    # initialize the distance and pointer matrices
    distance = {(0, 0): 0}
    pointers = {(0, 0): (None, None, None, None)}
    for i in cols:
        t_char = target[i - 1]
        distance[i, 0] = distance[i - 1, 0] + ins_cost(t_char)
        pointers[i, 0] = (i - 1, 0, t_char, '*')
    for j in rows:
        s_char = source[j - 1]
        distance[0, j] = distance[0, j - 1] + del_cost(s_char)
        pointers[0, j] = (0, j - 1, '*', s_char)

    # sort like (0, 0) (0, 1) (1, 0) (0, 2) (1, 1) (2, 0) ...
    # this guarantees the matrix is filled in the right order
    indices = [(i, j) for i in cols for j in rows]
    indices.sort(key=sum)

    # helper function for creating distance/pointer pairs
    def get_pair(row, col, func, t_char, s_char):
        chars = t_char, s_char
        args = [char for char in chars if char != '*']
        dist = distance[row, col] + func(*args)
        pointer = row, col, t_char, s_char
        return dist, pointer

    # for each pair of indices, choose insertion, substitution
    # or deletion, whichever gives the shortest distance
    for i, j in indices:
        t_char = target[i - 1]
        s_char = source[j - 1]
        pairs = [
            get_pair(i -1,  j,     ins_cost, t_char, '*'),
            get_pair(i - 1, j - 1, sub_cost, t_char, s_char),
            get_pair(i,     j - 1, del_cost, '*',    s_char),
        ]
        dist, pointer = min(pairs, key=operator.itemgetter(0))
        distance[i, j] = dist
        pointers[i, j] = pointer

    # follow pointers backwards through the path selected
```

```
t_chars = []
s_chars = []
row, col = n, m
while True:
    row, col, t_char, s_char = pointers[row, col]
    if row is col is None:
        break
    t_chars.append(t_char)
    s_chars.append(s_char)

# return distance, and two character strings
target_string = ''.join(reversed(t_chars))
source_string = ''.join(reversed(s_chars))
return distance[n, m], target_string, source_string
```

Chapter 4
N-Grams

4.1 Write out the equation for trigram probability estimation (modifying Eq. 4.14).

$$P(w_n|w_{n-1}, w_{n-2}) = \frac{C(w_{n-2}w_{n-1}w_n)}{C(w_{n-2}w_{n-1})}$$

4.2 Write a program to compute unsmoothed unigrams and bigrams.

```
from __future__ import division
from collections import defaultdict as ddict
import itertools
import math
import random

class NGrams(object):
    def __init__(self, max_n, words=None):
        self._max_n = max_n
        self._n_range = range(1, max_n + 1)
        self._counts = ddict(lambda: 0)

        # if words were supplied, update the counts
        if words is not None:
            self.update(words)

    def update(self, words):
        # increment the total word count, storing this under
        # the empty tuple - storing it this way simplifies
        # the _probability() method
        self._counts[()] += len(words)

        # count ngrams of all the given lengths
        for i, word in enumerate(words):
            for n in self._n_range:
                if i + n <= len(words):
                    ngram_range = xrange(i, i + n)
                    ngram = [words[j] for j in ngram_range]
                    self._counts[tuple(ngram)] += 1

    def probability(self, words):
        if len(words) <= self._max_n:
            return self._probability(words)
        else:
            prob = 1
            for i in xrange(len(words) - self._max_n + 1):
                ngram = words[i:i + self._max_n]
                prob *= self._probability(ngram)
            return prob

    def _probability(self, ngram):
        # get count of ngram and its prefix
        ngram = tuple(ngram)
        ngram_count = self._counts[ngram]
        prefix_count = self._counts[ngram[:-1]]

        # divide counts (or return 0.0 if not seen)
        if ngram_count and prefix_count:
            return ngram_count / prefix_count
        else:
            return 0.0
```

4.3 Run your N-gram program on two different small corpora of your choice (you might use email text or newsgroups). Now compare the statistics of the two corpora. What are the differences in the most common unigrams between the two? How about interesting differences in bigrams?

A good approach to this problem would be to sort the N-grams for each corpus by their probabilities, and then examine the first 100-200 for each corpus. Both lists should contain the common function words, e.g., *the*, *of*, *to*, etc near the top. The content words are probably where the more interesting differences are – it should be possible to see some topic differences between the corpora from these.

4.4 Add an option to your program to generate random sentences.

```
class NGrams(object):
    ...
    def generate(self, n_words):
        # select unigrams
        ngrams = iter(self._counts)
        unigrams = [x for x in ngrams if len(x) == 1]

        # keep trying to generate sentences until successful
        while True:
            try:
                return self._generate(n_words, unigrams)
            except RuntimeError:
                pass

    def _generate(self, n_words, unigrams):
        # add the requested number of words to the list
        words = []
        for i in itertools.repeat(self._max_n):

            # the prefix of the next ngram
            if i == 1:
                prefix = ()
            else:
                prefix = tuple(words[-i + 1:])

            # select a probability cut point, and then try
            # adding each unigram to the prefix until enough
            # probability has been seen to pass the cut point
            threshold = random.random()
            total = 0.0
            for unigram in unigrams:
                total += self._probability(prefix + unigram)
                if total >= threshold:
                    words.extend(unigram)
                    break

            # return the sentence if enough words were found
            if len(words) == n_words:
                return words

            # exit if it was impossible to find a plausible
            # ngram given the current partial sentence
            if total == 0.0:
                raise RuntimeError('impossible sequence')
```

4.5 Add an option to your program to do Good-Turing discounting.

```
class GoodTuringNGrams(NGrams):
    def __init__(self, max_n, words=None):
        self._default_probs = {}
        self._smoothed_counts = ddict(lambda: 0)
        super(GoodTuringNGrams, self).__init__(max_n, words)

    def update(self, words):
        super(GoodTuringNGrams, self).update(words)

        # calculate number of ngrams with each count
        vocab_counts = ddict(lambda: 0)
        count_counts = ddict(lambda: ddict(lambda: 0))
        for ngram in self._counts:
            vocab_counts[len(ngram)] += 1
            count_counts[len(ngram)][self._counts[ngram]] += 1

        # determine counts for zeros
        defaults = self._default_probs
        defaults[0] = 0.0
        for n in self._n_range:

            # missing probability mass is the number of ngrams
            # seen once divided by the number of ngrams seen
            seen_count = vocab_counts[n]
            missing_mass = count_counts[n][1] / seen_count

            # for unigrams, there is no way to guess the number
            # of unseen items, so the extra probability mass is
            # arbitrarily distributed across as many new items
            # as there were old items
            if n == 1:
                defaults[n] = missing_mass / seen_count

            # for other ngrams, the extra probability mass
            # is distributed across the remainder of the
            # V ** N ngrams possible given V unigrams
            else:
                possible_ngrams = vocab_counts[1] ** n
                unseen_count = possible_ngrams - seen_count
                defaults[n] = missing_mass / unseen_count

        # apply the count smoothing for all existing ngrams
        self._smoothed_counts[()] = self._counts[()]
        for ngram in self._counts:
            if len(ngram) == 0:
                continue
            count = self._counts[ngram]
            one_more = count_counts[len(ngram)][count + 1]
            same = count_counts[len(ngram)][count]
            smoothed_count = (count + 1) * one_more / same
            self._smoothed_counts[ngram] = smoothed_count

    def _probability(self, ngram):
        # if ngram was never seen, return default probability
        ngram = tuple(ngram)
        ngram_count = self._counts[ngram]
        if ngram_count == 0:
            return self._default_probs[len(ngram)]

        # divide smoothed counts (or return 0.0 if not seen)
        else:
            ngram_count = self._smoothed_counts[ngram]
            prefix_count = self._smoothed_counts[ngram[:-1]]
            if ngram_count and prefix_count:
                return ngram_count / prefix_count
            else:
                return 0.0
```

4.6 Add an option to your program to implement Katz backoff.

```
class KatzBackoffNGrams(GoodTuringNGrams):
    def _discounted_probability(self, ngram):
        return super(KatzBackoffNGrams, self)._probability(ngram)

    def _alpha(self, ngram):
        get_prob = self._discounted_probability
        longer_grams = [x for x in self._counts if x[:-1] == ngram]
        longer_prob = sum(get_prob(x) for x in longer_grams)
        suffix_prob = sum(get_prob(x[1:]) for x in longer_grams)
        return (1 - longer_prob) / (1 - suffix_prob)

    def _probability(self, ngram):
        ngram = tuple(ngram)
        if ngram in self._counts:
            return self._discounted_probability(ngram)
        else:
            alpha = self._alpha(ngram[:-1])
            prob = self._probability(ngram[1:])
            return alpha * prob
```

4.7 Add an option to your program to compute the perplexity of a test set.

```
class NGrams(object):
    ...
    def perplexity(self, words):
        prob = self.probability(words)
        return math.pow(prob, -1 / len(words))
```

4.8 (Adapted from Michael Collins). Prove Eq. 4.27 given Eq. 4.26 and any necessary assumptions. That is, show that given a probability distribution defined by the GT formula in Eq. 4.26 for the N items seen in training, the probability of the next (i.e., $N + 1$st) item being unseen in training can be estimated by Eq. 4.27. You may make any necessary assumptions for the proof, including assuming that all N_c are non-zero.

The missing mass is just the sum of the probabilities of all the ngrams that were not yet seen:

$$\begin{aligned} \text{missing mass} &= \textstyle\sum_{x:\text{count}(x)=0} P(x) \\ &= \textstyle\sum_{x:\text{count}(x)=0} \frac{c^*(x)}{N} \end{aligned}$$

Now using Eq. 4.26:

$$\begin{aligned} \text{missing mass} &= \textstyle\sum_{x:\text{count}(x)=0} \frac{(0+1)\frac{N_{0+1}}{N_0}}{N} \\ &= \textstyle\sum_{x:\text{count}(x)=0} \frac{N_1}{N \cdot N_0} \\ &= \frac{N_1}{N \cdot N_0} \textstyle\sum_{x:\text{count}(x)=0} 1 \end{aligned}$$

But the sum of all ngrams with a count of zero is just N_0, so:

$$\begin{aligned} \text{missing mass} &= \frac{N_1}{N \cdot N_0} \cdot N_0 \\ &= \frac{N_1}{N} \end{aligned}$$

Bag of words

Bag generation

4.9 (Advanced) Suppose someone took all the words in a sentence and reordered them randomly. Write a program that takes as input such a **bag of words** and produces as output a guess at the original order. You will need to use an N-gram grammar produced by your N-gram program (on some corpus), and you will need to use the Viterbi algorithm introduced in the next chapter. This task is sometimes called **bag generation**.

This problem is quite difficult. Generating the string with the maximum N-gram probability from a bag of words is NP-complete (see, e.g., Knight (1999a)), so solutions to this problem shouldn't try to generate the maximum probability string. A good approach is probably to use one of the beam-search versions of Viterbi or best-first search algorithms introduced for machine translation in Section 25.8, collapsing the probabilities of candidates that use the same words in the bag.

Another approach is to modify Viterbi to keep track of the set of words used so far at each state in the trellis. This approach is closer to Viterbi as discussed in the next chapter, but throws away many less probable partial bags at each stage, so it doesn't search the entire space and can't promise to produce the optimal word order.

```
import collections
ddict = collections.defaultdict

def guess_order(ngrams, word_bag):
    # convert list of words into word counts
    word_counts = ddict(lambda: 0)
    for word in word_bag:
        word_counts[word] += 1

    # helper for creating new word counts minus one word
    def removed(word_counts, word):
        word_counts = word_counts.copy()
        assert word_counts[word] > 0
        word_counts[word] -= 1
        return word_counts

    # initialize the matrices for probabilities, backpointers
    # and words remaining to be used
    probs = ddict(lambda: ddict(lambda: 0))
    pointers = ddict(lambda: {})
    remaining = ddict(lambda: {})
    for word in word_counts:
        probs[0][word] = 1.0
        pointers[0][word] = None
        remaining[0][word] = removed(word_counts, word)

    # for each word in the sentence-to-be, determine the best
    # previous word by checking bigram probabilities
    for i in xrange(1, len(word_bag)):
        for word in word_counts:

            # helper for calculating probability of going to
            # this word from the previous, giving impossible
            # values to words that have been used already
            def get_prob(other_word):
                if not remaining[i - 1][other_word][word]:
                    return -1
                prob = ngrams.probability((other_word, word))
                return probs[i - 1][other_word] * prob
```

```
            # select the best word and update the matrices
            best_word = max(word_counts, key=get_prob)
            probs[i][word] = get_prob(best_word)
            pointers[i][word] = best_word
            best_remaining = remaining[i - 1][best_word]
            remaining[i][word] = removed(best_remaining, word)

    # get the best final state
    def get_final_prob(word):
        return probs[i][word]
    curr_word = max(word_counts, key=get_final_prob)

    # follow the pointers to get the best state sequence
    word_list = []
    for i in xrange(i, -1, -1):
        word_list.append(curr_word)
        curr_word = pointers[i][curr_word]
    word_list.reverse()
    return word_list
```

Authorship attribution

4.10 The field of **authorship attribution** is concerned with discovering the author of a particular text. Authorship attribution is important in many fields, including history, literature, and forensic linguistics. For example, Mosteller and Wallace (1964) applied authorship identification techniques to discover who wrote *The Federalist* papers. The Federalist papers were written in 1787–1788 by Alexander Hamilton, John Jay, and James Madison to persuade New York to ratify the United States Constitution. They were published anonymously, and as a result, although some of the 85 essays were clearly attributable to one author or another, the authorship of 12 were in dispute between Hamilton and Madison. Foster (1989) applied authorship identification techniques to suggest that W.S.'s *Funeral Elegy* for William Peter might have been written by William Shakespeare (he turned out to be wrong on this one) and that the anonymous author of *Primary Colors*, the roman à clef about the Clinton campaign for the American presidency, was journalist Joe Klein (Foster, 1996).

A standard technique for authorship attribution, first used by Mosteller and Wallace, is a Bayesian approach. For example, they trained a probabilistic model of the writing of Hamilton and another model on the writings of Madison, then computed the maximum-likelihood author for each of the disputed essays. Many complex factors go into these models, including vocabulary use, word length, syllable structure, rhyme, grammar; see Holmes (1994) for a summary. This approach can also be used for identifying which genre a text comes from.

One factor in many models is the use of rare words. As a simple approximation to this one factor, apply the Bayesian method to the attribution of any particular text. You will need three things: a text to test and two potential authors or genres, with a large computer-readable text sample of each. One of them should be the correct author. Train a unigram language model on each of the candidate authors. You are going to use only the **singleton** unigrams in each language model. You will compute $P(T|A_1)$, the probability of the text given author or genre A_1, by (1) taking the language model from A_1, (2) multiplying together the probabilities of all the unigrams that occur only once in the "unknown" text, and (3) taking the geometric mean of these (i.e., the nth root,

where n is the number of probabilities you multiplied). Do the same for A_2. Choose whichever is higher. Did it produce the correct candidate?

This approach can perform well by finding odd vocabulary choices (singleton unigrams) that are unique to one author or the other. Exploring author pairs with varying degrees of similarity should give a good idea of the power (and limitations) of this approach.

Chapter 5
Part-of-Speech Tagging

5.1 Find one tagging error in each of the following sentences that are tagged with the Penn Treebank tagset:

1. I/PRP need/VBP a/DT flight/NN from/IN Atlanta/NN
   Atlanta/NNP
2. Does/VBZ this/DT flight/NN serve/VB dinner/NNS
   dinner/NN
3. I/PRP have/VB a/DT friend/NN living/VBG in/IN Denver/NNP
   have/VBP
4. Can/VBP you/PRP list/VB the/DT nonstop/JJ afternoon/NN flights/NNS
   Can/MD

5.2 Use the Penn Treebank tagset to tag each word in the following sentences from Damon Runyon's short stories. You may ignore punctuation. Some of these are quite difficult; do your best.

1. It is a nice night.
   It/PRP is/VBZ a/DT nice/JJ night/NN ./.
2. This crap game is over a garage in Fifty-second Street...
   This/DT crap/NN game/NN is/VBZ over/IN a/DT garage/NN in/IN Fifty-second/NNP Street/NNP...
3. ...Nobody ever takes the newspapers she sells ...
   ...Nobody/NN ever/RB takes/VBZ the/DT newspapers/NNS she/PRP sells/VBZ...
4. He is a tall, skinny guy with a long, sad, mean-looking kisser, and a mournful voice.
   He/PRP is/VBZ a/DT tall/JJ ,/, skinny/JJ guy/NN with/IN a/DT long/JJ ,/, sad/JJ ,/, mean-looking/JJ kisser/NN ,/, and/CC a/DT mournful/JJ voice/NN ./.
5. ...I am sitting in Mindy's restaurant putting on the gefillte fish, which is a dish I am very fond of, ...
   ...I/PRP am/VBP sitting/VBG in/IN Mindy/NNP 's/POS restaurant/NN putting/VBG on/RP the/DT gefillte/NN fish/NN ,/, which/WDT is/VBZ a/DT dish/NN I/PRP am/VBP very/RB fond/JJ of/RP ,/, ...
6. When a guy and a doll get to taking peeks back and forth at each other, why there you are indeed.
   When/WRB a/DT guy/NN and/CC a/DT doll/NN get/VBP to/TO taking/VBG peeks/NNS back/RB and/CC forth/RB at/IN each/DT other/JJ ,/, why/WRB there/EX you/PRP are/VBP indeed/RB ./.

5.3 Now compare your tags from the previous exercise with one or two friend's answers. On which words did you disagree the most? Why?

It should be nearly impossible for two people to come up with exactly the same tags for all words in all the above sentences. Some of the more difficult phrases are probably *nobody*, *gefillte fish*, *each other* and *there you are*.

5.4 Now tag the sentences in Exercise 5.2; use the more detailed Brown tagset in Fig. 5.7.

1. It/PPS is/BEZ a/AT nice/JJ night/NN ./.
2. This/DT crap/NN game/NN is/BEZ over/IN a/AT garage/NN in/IN Fifty-second/NP Street/NP
3. . . . Nobody/NN ever/RB takes/VBZ the/AT newspapers/NNS she/PPS sells/VBZ
4. He/PPS is/BEZ a/AT tall/JJ ,/, skinny/JJ guy/NN with/IN a/AT long/JJ ,/, sad/JJ ,/, mean-looking/JJ kisser/NN ,/, and/CC a/AT mournful/JJ voice/NN ./.
5. . . . I/PPSS am/BEM sitting/VBG in/IN Mindy's/NP$ restaurant/NN putting/VBG on/RP the/AT gefillte/NN fish/NN ,/, which/WDT is/BEZ a/AT dish/NN I/PPSS am/BEM very/RB fond/JJ of/RP ,/, . . .
6. When/WRB a/AT guy/NN and/CC a/AT doll/NN get/VB to/TO taking/VBG peeks/NNS back/RB and/CC forth/RB at/IN each/DT other/JJ ,/, why/WRB there/EX you/PPSS are/BER indeed/RB ./.

5.5 Implement the TBL algorithm in Fig. 5.21. Create a small number of templates and train the tagger on any POS-tagged training set you can find.

See Exercise 5.6 for the definition of `MostLikelyTagModel`, which is used as a basis for the TBL implementation below. Note that this implementation only includes rules looking for a single tag in the surrounding tags, and not rules looking for multiple tags.

```
from __future__ import division

class Transform(object):
    def __init__(self, old_tag, new_tag, key_tag, start, end):
        self._old_tag = old_tag
        self._new_tag = new_tag
        self._key_tag = key_tag
        self._start = start
        self._end = end

    def apply(self, tags):

        # for each tag that matches the old_tag
        for i, tag in enumerate(tags):
            if tag == self._old_tag:

                # if the key tag is in the window, change to new_tag
                start = max(0, i + self._start)
                end = max(0, i + self._end)
                if self._key_tag in tags[start:end]:
                    tags[i] = self._new_tag
```

```
class TBLModel(MostLikelyTagModel):
    def train(self, tagged_sentences):
        super(TBLModel, self).train(train_data)
        self._transforms = []

        # collect the most likely tags
        tags = []
        correct_tags = []
        for train_words, train_tags in tagged_sentences:
            model_tags = super(TBLModel, self).predict(train_words)
            tags.extend(model_tags)
            correct_tags.extend(train_tags)

        # generate all possible transforms that:
        #   change an old_tag at index i to a new_tag
        #   if key_tag is in tags[i + start: i + end]
        transforms = []
        windows = [(-3,0), (-2,0), (-1,0), (0,1), (0,2), (0,3)]
        tag_set = set(correct_tags)
        for old_tag in tag_set:
            for new_tag in tag_set:
                for key_tag in tag_set:
                    for start, end in windows:
                        transforms.append(Transform(
                            old_tag, new_tag, key_tag, start, end))

        # helper for scoring predicted tags against the correct ones
        def get_error(tags, correct_tags):
            incorrect = 0
            for tag, correct_tag in zip(tags, correct_tags):
                incorrect += tag != correct_tag
            return incorrect / len(tags)

        # helper for getting the error of a transform
        def transform_error(transform):
            tags_copy = list(tags)
            transform.apply(tags_copy)
            return get_error(tags_copy, correct_tags)

        # look for transforms that reduce the current error
        old_error = get_error(tags, correct_tags)
        while True:

            # select the transform that has the lowest error, and
            # stop searching if the overall error was not reduced
            best_transform = min(transforms, key=transform_error)
            best_error = transform_error(best_transform)
            if best_error >= old_error:
                break

            # add the transform, and apply it to the tags
            old_error = best_error
            self._transforms.append(best_transform)
            best_transform.apply(tags)

    def predict(self, sentence):
        # get most likely tags, and then apply transforms
        tags = super(TBLModel, self).predict(sentence)
        for transform in self._transforms:
            transform.apply(tags)
        return tags
```

5.6 Implement the "most likely tag" baseline. Find a POS-tagged training set, and use it to compute for each word the tag that maximizes $p(t|w)$. You will need to implement a simple tokenizer to deal with sentence boundaries. Start by assuming that all unknown words are NN and compute your error rate on known and unknown words.

(Implementing a tokenizer was omitted below - sentences are assumed to already be parsed into words and part-of-speech tags.)

```
from __future__ import division
from collections import defaultdict as ddict

class MostLikelyTagModel(object):
    def __init__(self):
        super(MostLikelyTagModel, self).__init__()
        self._word_tags = {}

    def train(self, tagged_sentences):
        # count number of times a word is given each tag
        word_tag_counts = ddict(lambda: ddict(lambda: 0))
        for words, tags in tagged_sentences:
            for word, tag in zip(words, tags):
                word_tag_counts[word][tag] += 1

        # select the tag used most often for the word
        for word in word_tag_counts:
            tag_counts = word_tag_counts[word]
            tag = max(tag_counts, key=tag_counts.get)
            self._word_tags[word] = tag

    def predict(self, sentence):
        # predict the most common tag, or NN if never seen
        get_tag = self._word_tags.get
        return [get_tag(word, 'NN') for word in sentence]

    def get_error(self, tagged_sentences):
        # get word error rate
        word_tuples = self._get_word_tuples(tagged_sentences)
        return self._get_error(word_tuples)

    def get_known_unknown_error(self, tagged_sentences):
        # split predictions into known and unknown words
        known = []
        unknown = []
        for tup in self._get_word_tuples(tagged_sentences):
            word, _, _ = tup
            dest = known if word in self._word_tags else unknown
            dest.append(tup)

        # calculate and return known and unknown error rates
        return self._get_error(known), self._get_error(unknown)

    def _get_word_tuples(self, tagged_sentences):
        # convert a list of sentences into word-tag tuples
        word_tuples = []
        for words, tags in tagged_sentences:
            model_tags = self.predict(words)
            word_tuples.extend(zip(words, tags, model_tags))
        return word_tuples

    def _get_error(self, word_tuples):
        # calculate total and incorrect labels
        incorrect = 0
        for word, expected_tag, actual_tag in word_tuples:
            if expected_tag != actual_tag:
                incorrect += 1
        return incorrect / len(word_tuples)
```

Now write at least five rules to do a better job of tagging unknown words, and show the difference in error rates.

```
class RulesModel(MostLikelyTagModel):
    def predict(self, sentence):
        tags = super(RulesModel, self).predict(sentence)
        for i, word in enumerate(sentence):
            if word not in self._word_tags:

                # capitalized words are proper nouns
                # about 20% improvement on unknown words
                if word.istitle():
                    tags[i] = 'NNP'

                # words ending in -s are plural nouns
                # about 10% improvement on unknown words
                elif word.endswith('s'):
                    tags[i] = 'NNS'

                # words with an initial digit are numbers
                # about 7% improvement on unkown words
                elif word[0].isdigit():
                    tags[i] = 'CD'

                # words with hyphens are adjectives
                # about 3% improvement on unknown words
                elif '-' in word:
                    tags[i] = 'JJ'

                # words ending with -ing are gerunds
                # about 2% improvement on unknown words
                elif word.endswith('ing'):
                    tags[i] = 'VBG'

        return tags
```

5.7 Recall that the Church (1988) tagger is not an HMM tagger since it incorporates the probability of the tag given the word:

$$P(\text{tag}|\text{word}) * P(\text{tag}|\text{previous } n \text{ tags}) \tag{5.1}$$

rather than using the likelihood of the word given the tag, as an HMM tagger does:

$$P(\text{word}|\text{tag}) * P(\text{tag}|\text{previous } n \text{ tags}) \tag{5.2}$$

Interestingly, this use of a kind of "reverse likelihood" has proven to be useful in the modern log-linear approach to machine translation (see page 903). As a gedanken-experiment, construct a sentence, a set of tag transition probabilities, and a set of lexical tag probabilities that demonstrate a way in which the HMM tagger can produce a better answer than the Church tagger, and create another example in which the Church tagger is better.

The Church (1988) and HMM taggers will perform differently when, given two tags, tag_1 and tag_2,:

$$P(\text{tag}_1|\text{word}) > P(\text{tag}_2|\text{word})$$

but,

$$P(\text{word}|\text{tag}_1) < P(\text{word}|\text{tag}_2)$$

This happens, for example, with words like *manufacturing* which was associated with the following probabilities in a sample of text from the Wall Street Journal:

$$\begin{aligned} P(\text{VBG}|\text{manufacturing}) &= 0.231 \\ P(\text{NN}|\text{manufacturing}) &= 0.769 \\ P(\text{manufacturing}|\text{VBG}) &= 0.004 \\ P(\text{manufacturing}|\text{NN}) &= 0.001 \end{aligned}$$

Thus, if we are looking at the words and we see *manufacturing*, we expect this word to receive the tag NN, not the tag VBG. But if we are looking at the tags, we expect *manufacturing* to be produced more often from a VBG state than from an NN state.

Given a word like this, we can construct situations where either the Church (1988) tagger or the HMM tagger produces the wrong result by building a simple transition table where all transitions are equally likely, e.g.:

$$P(\text{NN}|\texttt{<s>}) = P(\text{VBG}|\texttt{<s>}) = 0.5$$

Then the HMM model will select the VBG label:

$$P(\text{manufacturing}|\text{NN}) * P(\text{NN}|\texttt{<s>}) = 0.001 * 0.5 = 0.0005$$
$$P(\text{manufacturing}|\text{VBG}) * P(\text{VBG}|\texttt{<s>}) = 0.004 * 0.5 = 0.002$$

while the Church (1988) tagger will select the NN label:

$$P(\text{NN}|\text{manufacturing}) * P(\text{NN}|\texttt{<s>}) = 0.769 * 0.5 = 0.3845$$
$$P(\text{VBG}|\text{manufacturing}) * P(\text{VBG}|\texttt{<s>}) = 0.231 * 0.5 = 0.1155$$

If we have a phrase like *Manufacturing plants are useful*, then the Church (1988) tagger has the better answer, while if we have a phrase like *Manufacturing plants that are brightly colored is popular*, then the HMM tagger has the better answer.

5.8 Build a bigram HMM tagger. You will need a part-of-speech-tagged corpus. First split the corpus into a training set and test set. From the labeled training set, train the transition and observation probabilities of the HMM tagger directly on the hand-tagged data. Then implement the Viterbi algorithm from this chapter and Chapter 6 so that you can decode (label) an arbitrary test sentence. Now run your algorithm on the test set. Report its error rate and compare its performance to the most frequent tag baseline.

Note that it's extremely important that the probabilities obtained from the corpus are smoothed, particularly the probability of emitting a word from a particular tag. If they aren't smoothed, then any word never seen in the training data will have an emission probability of zero for all states, and an entire column of the Viterbi search will have probability zero.

With even a simple smoothing model though, the HMM tagger should outperform the most frequent tag baseline. See the Chapter 6 exercises for HMM code.

5.9 Do an error analysis of your tagger. Build a confusion matrix and investigate the most frequent errors. Propose some features for improving the performance of your tagger on these errors.

Some common confusions are nouns vs. adjectives, common nouns vs. proper nouns, past tense verbs vs. past participle verbs, etc. A variety of features could be proposed to address such problems, though one obvious one is including capitalization information to help identify proper nouns.

5.10 Compute a bigram grammar on a large corpus and re-estimate the spelling correction probabilities shown in Fig. 5.25 given the correct sequence . . . *was called a "stellar and versatile* **acress** *whose combination of sass and glamour has defined her. . . "'*. Does a bigram grammar prefer the correct word *actress*?

Scoring corrections using the bigram probability:

$P(\text{corrected-word}|\text{previous-word})$

instead of the unigram probability

$P(\text{corrected-word})$

should make *actress* more probable, since *versatile actress* is much more likely to occur in a corpus than *versatile acres*.

5.11 Read Norvig (2007) and implement one of the extensions he suggests to his Python noisy channel spellchecker.

Some of the suggested extensions are:

- Improve the language model by using an N-gram model instead of a unigram one.
- Improve the error model so that it knows something about character substitutions. For example, changing *adres* to *address* or *thay* to *they* should be penalized less than changing *adres* to *acres* or *thay* to *that*. This will likely require allowing two character edits to sometimes be less expensive than one character edits. Also, setting such weights manually is likely to be difficult, so this will probably require training on a corpus of spelling mistakes.
- Allow unseen verbs to be created from seen verbs by adding *-ed*, unseen nouns to be created from seen nouns by adding *-s*, etc.
- Allow words with edit distance greater than two, but without allowing all possible sequences with edit distance three. For example, allow vowel replacements or similar consonant replacements, but no other types of edits.

Chapter 6
Hidden Markov and Maximum Entropy Models

6.1 Implement the Forward algorithm and run it with the HMM in Fig. 6.3 to compute the probability of the observation sequences *331122313* and *331123312*. Which is more likely?

An HMM that calculates probabilities with the forward algorithm:

```
from collections import defaultdict as ddict

class HMM(object):
    INITIAL = '*Initial*'
    FINAL = '*Final*'

    def __init__(self):
        self._states = []
        self._transitions = ddict(lambda: ddict(lambda: 0.0))
        self._emissions = ddict(lambda: ddict(lambda: 0.0))

    def add(self, state, transition_dict={}, emission_dict={}):
        self._states.append(state)

        # build state transition matrix
        for target_state, prob in transition_dict.items():
            self._transitions[state][target_state] = prob

        # build observation emission matrix
        for observation, prob in emission_dict.items():
            self._emissions[state][observation] = prob

    def probability(self, observations):
        # get probability from the last entry in the trellis
        probs = self._forward(observations)
        return probs[len(observations)][self.FINAL]

    def _forward(self, observations):
        # initialize the trellis
        probs = ddict(lambda: ddict(lambda: 0.0))
        probs[-1][self.INITIAL] = 1.0

        # update the trellis for each observation
        i = -1
        for i, observation in enumerate(observations):
            for state in self._states:

                # sum the probabilities of transitioning to
                # the current state and emitting the current
                # observation from any of the previous states
                probs[i][state] = sum(
                    probs[i - 1][prev_state] *
                    self._transitions[prev_state][state] *
                    self._emissions[state][observation]
                    for prev_state in self._states)

        # sum the probabilities for all states in the last
        # column (the last observation) of the trellis
        probs[len(observations)][self.FINAL] = sum(
            probs[i][state] for state in self._states)
        return probs
```

Building the HMM in Fig. 6.3, we see that the sequence *331123312* is more likely than the sequence *331122313*:

```
>>> hmm = HMM()
>>> hmm.add(HMM.INITIAL, dict(H=0.8, C=0.2))
>>> hmm.add('H',         dict(H=0.7, C=0.3), {1:.2, 2:.4, 3:.4})
>>> hmm.add('C',         dict(H=0.4, C=0.6), {1:.5, 2:.4, 3:.1})
>>> hmm.probability([3, 3, 1, 1, 2, 3, 3, 1, 2])
3.9516275425280015e-005
>>> hmm.probability([3, 3, 1, 1, 2, 2, 3, 1, 3])
3.575714750873601e-005
```

6.2 Implement the Viterbi algorithm and run it with the HMM in Fig. 6.3 to compute the most likely weather sequences for each of the two observation sequences above, *331122313* and *331123312*.

Here, we add a method for using the Viterbi algorithm to predict the most likely sequence of states given a sequence of observations. The code closely mirrors that of the forward algorithm, but looks for the maximum probability instead of the sum, and keeps a table of back-pointers to recover the best state sequence.

```
class HMM(object):
    ...
    def predict(self, observations):
        # initialize the probabilities and backpointers
        probs = ddict(lambda: ddict(lambda: 0.0))
        probs[-1][self.INITIAL] = 1.0
        pointers = ddict(lambda: {})

        # update the probabilities for each observation
        i = -1
        for i, observation in enumerate(observations):
            for state in self._states:

                # calculate probabilities of taking a transition
                # from a previous state to this one and emitting
                # the current observation
                path_probs = {}
                for prev_state in self._states:
                    path_probs[prev_state] = (
                        probs[i - 1][prev_state] *
                        self._transitions[prev_state][state] *
                        self._emissions[state][observation])

                # select previous state with the highest probability
                best_state = max(path_probs, key=path_probs.get)
                probs[i][state] = path_probs[best_state]
                pointers[i][state] = best_state

        # get the best final state
        curr_state = max(probs[i], key=probs[i].get)

        # follow the pointers to get the best state sequence
        states = []
        for i in xrange(i, -1, -1):
            states.append(curr_state)
            curr_state = pointers[i][curr_state]
        states.reverse()
        return states
```

Using the HMM from Fig. 6.3 as in 1, we can see that *331122313* and *331123312* both correspond to the sequence HHCCHHHHH:

```
>>> ''.join(hmm.predict([3, 3, 1, 1, 2, 2, 3, 1, 3]))
'HHCCHHHHH'
>>> ''.join(hmm.predict([3, 3, 1, 1, 2, 3, 3, 1, 2]))
'HHCCHHHHH'
```

6.3 Extend the HMM tagger you built in Exercise 5.8 by adding the ability to make use of some unlabeled data in addition to your labeled training corpus. First acquire a large unlabeled (i.e., no part-of-speech tags) corpus. Next, implement the forward-backward training algorithm. Now start with the HMM parameters you trained on the training corpus in Exercise 5.8; call this model M_0. Run the forward-backward algorithm with these HMM parameters to label the unsupervised corpus. Now you have a new model M_1. Test the performance of M_1 on some held-out labeled data.

Here, we add a method for training the HMM using the forward-backward algorithm. We simplify the problem a bit by using a fixed number of iterations instead of trying to determine convergence.

```
class HMM(object):
    ...
    def train(self, observations, iterations=100):
        # only update non-initial, non-final states
        states_to_update = list(self._states)
        for state in [self.INITIAL, self.FINAL]:
            if state in states_to_update:
                states_to_update.remove(state)

        # iteratively update states
        for _ in range(iterations):

            # run the forward and backward algorithms and get the
            # probability of the observations sequence
            forward_probs = self._forward(observations)
            backward_probs = self._backward(observations)
            obs_prob = forward_probs[len(observations)][self.FINAL]

            # calculate probabilities of being at a given state and
            # emitting observation i
            emission_probs = ddict(lambda: {})
            for i, observation in enumerate(observations):
                for state in states_to_update:
                    emission_probs[i][state] = (
                        forward_probs[i][state] *
                        backward_probs[i][state] /
                        obs_prob)

            # calculate probabilities of taking the transition
            # between a pair of states for observations i and i + 1
            transition_probs = ddict(lambda: ddict(lambda: {}))
            transition_indices = range(len(observations) - 1)
            for i in transition_indices:
                next_obs = observations[i + 1]
                for state1 in states_to_update:
                    for state2 in states_to_update:
                        transition_probs[i][state1][state2] = (
                            forward_probs[i][state1] *
                            self._transitions[state1][state2] *
                            self._emissions[state2][next_obs] *
                            backward_probs[i + 1][state2] /
                            obs_prob)

            # update transition probabilities by summing the
            # probabilities of each state-state transition
            for state1 in states_to_update:
                total = 0
                for state2 in states_to_update:
                    count = self._transitions[state1][state2] = sum(
                        transition_probs[i][state1][state2]
                        for i in transition_indices)
                    total += count
```

```
                # normalize counts into probabilities
                if total:
                    for state2 in states_to_update:
                        self._transitions[state1][state2] /= total

            # find which observations occurred at which indices
            observation_indices = ddict(lambda: [])
            for i, observation in enumerate(observations):
                observation_indices[observation].append(i)

            # update emission probabilities by summing the
            # probabilities for each state-observation pair
            for state in states_to_update:
                total = 0
                for obs, indices in observation_indices.items():
                    count = self._emissions[state][obs] = sum(
                        emission_probs[i][state] for i in indices)
                    total += count

                # normalize counts into probabilities
                if total:
                    for obs in observation_indices:
                        self._emissions[state][obs] /= total


    def _backward(self, observations):
        # initialize the trellis
        probs = ddict(lambda: ddict(lambda: 0.0))

        # all states have equal probability of the final state
        for state in self._states:
            probs[len(observations) - 1][state] = 1.0

        # update the trellis for each observation
        for i in xrange(len(observations) - 2, -1, -1):
            for state in self._states:

                # sum the probabilities of transitioning to
                # the current state and emitting the current
                # observation from any of the previous states
                probs[i][state] = sum(
                    probs[i + 1][next_state] *
                    self._transitions[state][next_state] *
                    self._emissions[next_state][observations[i + 1]]
                    for next_state in self._states)

        # sum the probabilities of transitioning from the start
        # state to any of the paths in the trellis
        probs[0][self.INITIAL] = sum(
            probs[0][state] *
            self._transitions[self.INITIAL][state] *
            self._emissions[state][observations[0]]
            for state in self._states)
        return probs
```

Given reasonable data and a good set of initial transition and emission probabilities, running the forward-backward training algorithm should generally improve the performance of the original model.

6.4 As a generalization of the previous homework, implement Jason Eisner's HMM tagging homework available from his webpage. His homework includes a corpus of weather and ice-cream observations, a corpus of English part-of-speech tags, and a very hand spreadsheet with exact numbers for the forward-backward algorithm that you can compare against.

Jason Eisner's handout for this homework is quite detailed, and carefully walks through the implementation of Viterbi, a smoothed bigram model, and the forward-backward algorithm. The handout also gives expected results at a number of points during the process so that you can check that your code is producing the correct numbers.

6.5 Train a MaxEnt classifier to decide if a movie review is a positive review (the critic liked the movie) or a negative review. Your task is to take the text of a movie review as input, and produce as output either 1 (positive) or 0 (negative). You don't need to implement the classifier itself, you can find various MaxEnt classifiers on the Web. You'll need training and test sets of documents from a labeled corpus (which you can get by scraping any web-based movie review site), and a set of useful features. For features, the simplest thing is just to create a binary feature for the 2500 most frequent words in your training set, indicating if the word was present in the document or not.

Sentiment analysis

Determining the polarity of a movie review is a kind of **sentiment analysis** task. For pointers to the rapidly growing body of work on extraction of sentiment, opinions, and subjectivity see the collected papers in Qu et al. (2005), and individual papers like Wiebe (2000), Pang et al. (2002), Turney (2002), Turney and Littman (2003), Wiebe and Mihalcea (2006), Thomas et al. (2006) and Wilson et al. (2006).

There are basically three steps to this exercise:

1. Collect movie reviews from the web. This will require either using one of the standard corpora, e.g.,

   `www.cs.cornell.edu/People/pabo/movie-review-data/`

   or finding an appropriate site, doing a simple web crawl of their pages, and parsing enough of the HTML to extract the ratings and some text for each page.
2. Extract all words from the collection, count them, and select the top 2500. For each movie review, generate a classification instance with a label of 0 (negative review) or 1 (positive review) and with one binary feature for each of the 2500 words.
3. Train a MaxEnt classifier on the training portion of the classification instances, and test it on the testing portion.

Additional exploration of the problem might involve doing some error analysis of the classifier, and including some features that go beyond a simple bag-of-words.

Chapter 7
Phonetics

7.1 Find the mistakes in the ARPAbet transcriptions of the following words:

	Word	Original	Corrected
a.	"three"	[dh r i]	[th r iy]
b.	"sing"	[s ih n g]	[s ih ng]
c.	"eyes"	[ay s]	[ay z]
d.	"study"	[s t uh d i]	[s t ah d iy]
e.	"though"	[th ow]	[dh ow]
f.	"planning"	[pl aa n ih ng]	[p l ae n ih ng]
g.	"slight"	[s l iy t]	[s l ay t]

7.2 Translate the pronunciations of the following color words from the IPA into the ARPAbet (and make a note if you think you pronounce them differently than this!):

	IPA	ARPAbet
a.	[rɛd]	[r eh d]
b.	[blu]	[b l uw]
c.	[gɹin]	[g r iy n]
d.	[ˈjɛloʊ]	[y eh l ow]
e.	[blæk]	[b l ae k]
f.	[waɪt]	[w ay t]
g.	[ˈɔɹɪndʒ]	[ao r ix n jh]
h.	[ˈpɝpl̩]	[p er p el]
i.	[pjus]	[p y uw s]
j.	[toʊp]	[t ow p]

7.3 Ira Gershwin's lyric for *Let's Call the Whole Thing Off* talks about two pronunciations (each) of the words "tomato", "potato", and "either". Transcribe into the ARPAbet both pronunciations of each of these three words.

"tomato"	[t ax m ey dx ow]	[t ax m aa dx ow]
(or alternatively)	[t ax m ey t ow]	[t ax m aa t ow]
"potato"	[p ax t ey dx ow]	[p ax t aa dx ow]
(or alternatively)	[p ax t ey t ow]	[p ax t aa t ow]
"either"	[iy dh axr]	[ay dh axr]

7.4 Transcribe the following words in the ARPAbet:

1. dark [d aa r k]
2. suit [s uw t]
3. greasy [g r iy s iy]
4. wash [w aa sh]
5. water [w aa dx axr]

7.5 Take a wavefile of your choice. Some examples are on the textbook website. Download the Praat software, and use it to transcribe the wavefiles at the word level and into ARPAbet phones, using Praat to help you play pieces of each wavefile and to look at the wavefile and the spectrogram.

From the textbook website:

2001_B_0049a.wav

yeah	but	there's	really	no	written	rule
iy ae	b uh	d eh r sh	r ih l iy	n ow	r ih t n	r uw l

2005_A_0046.wav

I	truly	wish	that	if	something	like
ay	t r uw l iy	w ih sh	dh ih t	ih f	s ah m th ih ng	l ay k

that	were	to	happen	then	my	children
dh ae	w er	dx ax	h ae p n	dh ax	m ay	ch ih l d r n

would	do	something	like
w ax	d uw	s ah m th ih ng	l ay

radionews.wav

police	also	say	Levy's	blood	alcohol
p ax l ih s	aa l s ax	s ey	l iy v iy z	b l ah d	ae l k ax h aa

level	was	twice	the	legal	limit
l eh v l	w ax z	t w ay s	dh ax	l iy g l	l ih m ih t

7.6 Record yourself saying five of the English vowels: [aa], [eh], [ae], [iy], [uw]. Find F1 and F2 for each of your vowels.

These vowels typicaly have formants something like:

Vowel	F1	F2
[aa]	700	1150
[eh]	550	1750
[ae]	700	1650
[iy]	300	2300
[uw]	300	850

Individual variation is quite large, and seeing even a difference of 100 Hz or more is not unreasonable. However, the ordering of formants should be relatively stable, e.g., F1 for [aa] and [ae] should be higher than that of [eh] which should be higher than that of [iy] and [uw].

Chapter 8
Speech Synthesis

8.1 Implement the text normalization routine that deals with MONEY, that is, mapping strings of dollar amounts like *$45*, *$320*, and *$4100* to words (either writing code directly or designing an FST). If there are multiple ways to pronounce a number you may pick your favorite way.

```
def expand_money(money_string):
    # strip off the dollar sign and commas
    number = int(re.sub(r'[,$]', '', money_string))

    # generate a number followed by 'dollars'
    words = expand_number(number)
    words.append('dollars')
    return words

def expand_number(number):
    words = []

    # break off chunks for trillions, millions, ... hundreds
    for divisor, word in _chunk_pairs:
        chunk, number = divmod(number, divisor)
        if chunk:
            words.extend(expand_number(chunk))
            words.append(word)

    # use a table for single digits and irregulars
    if number and number in _numbers:
        words.append(_numbers[number])

    # otherwise, split into tens and ones
    elif number:
        tens, ones = divmod(number, 10)
        words.append(_numbers[tens * 10])
        words.append(_numbers[ones])

    # return the words, or 'zero' if no words were found
    return words or [_numbers[0]]

_chunk_pairs = [
    (1000000000000, 'trillion'), (1000000000, 'billion'),
    (1000000, 'million'), (1000, 'thousand'), (100, 'hundred')]
_numbers = {
    0: 'zero', 1: 'one', 2: 'two',   3: 'three', 4: 'four',
    5: 'five', 6: 'six', 7: 'seven', 8: 'eight', 9: 'nine',
    10: 'ten', 11: 'eleven', 12: 'twelve', 13: 'thirteen',
    14: 'fourteen',  15: 'fifteen',  16: 'sixteen',
    17: 'seventeen', 18: 'eighteen', 19: 'nineteen',
    20: 'twenty', 30: 'thirty',  40: 'forty',  50: 'fifty',
    60: 'sixty',  70: 'seventy', 80: 'eighty', 90: 'ninety'}
```

8.2 Implement the text normalization routine that deals with NTEL, that is, seven-digit phone numbers like *555-1212*, *555-1300*, and so on. Use a combination of the **paired** and **trailing unit** methods of pronunciation for the last four digits. (Again, either write code or design an FST).

```
def expand_telephone(number_string):
    # clean the string, then convert all but the last four digits
    number_string = re.sub(r'[-()\s]', '', number_string)
    words = [_phone_digits[int(d)] for d in number_string[:-4]]
    last4 = number_string[-4:]

    # convert zeros individually and all else pairwise
    if last4 == '0000':
        words.extend([_phone_digits[0]] * 4)
    else:
        words.extend(expand_pairwise(last4))
    return words

def expand_pairwise(four_digits):
    # convert thousands as a single number
    words = []
    if four_digits[-3:-1] == '00':
        words.extend(expand_number(int(four_digits)))

    # otherwise, convert the digits in pairs
    # (using 'hundred' for a final 00)
    else:
        pair1 = int(four_digits[:-2])
        pair2 = int(four_digits[-2:])
        words.extend(expand_number(pair1))
        word = expand_number(pair2) if pair2 else ['hundred']
        words.extend(word)
    return words

_phone_digits = {
    0: 'oh', 1: 'one', 2: 'two',   3: 'three', 4: 'four',
    5: 'five', 6: 'six', 7: 'seven', 8: 'eight', 9: 'nine'}
```

8.3 Implement the text normalization routine that deals with type NDATE in Fig. 8.4.

```
def expand_date(date_string):
    # split date into days, months and years
    date_parts = re.split(r'[/-]', date_string)
    date_parts = [int(part) for part in date_parts]
    date_parts.extend([None] * (3 - len(date_parts)))
    day, month, year = date_parts

    # swap day and month if necessary (NOTE: this may miss
    # some swaps when both month and day are less than 12)
    if month > 12 >= day:
        day, month = month, day

    # add digits to year if necessary
    if year is not None and year < 100:
        this_year = datetime.datetime.today().year
        year += this_year / 100 * 100

        # years too far in the future are probably
        # in the past, e.g., 89 probably means 1989
        if year > this_year + 10:
            year -= 100

    # expand months, day and year
    words = [_months[month - 1]]
    words.extend(to_ordinal(expand_number(day)))
    if year is not None:
        words.extend(expand_pairwise(str(year)))
    return words
```

```
def to_ordinal(number_words):
    # convert the last word to an ordinal
    last_word = number_words[-1]

    # use a table for irregulars
    if last_word in _ordinals:
        ordinal = _ordinals[last_word]

    # otherwise, add 'th' (changing 'y' to 'i' if necessary)
    elif last_word.endswith('y'):
        ordinal = last_word[:-1] + 'ieth'
    else:
        ordinal = last_word + 'th'

    # add the ordinal back to the rest of the words
    return number_words[:-1] + [ordinal]

_ordinals = dict(
    one='first', two='second', three='third',
    five='fifth', eight='eighth', nine='ninth', twelve='twelfth')
_months = [
    'january', 'february', 'march', 'april',
    'may', 'june', 'july', 'august',
    'september', 'october', 'november', 'december']
```

8.4 Implement the text normalization routine that deals with type NTIME in Fig. 8.4.

```
def expand_time(time_string):
    # split time into hours and minutes
    time_parts = re.split(r'[.:]', time_string)
    hours, minutes = [int(part) for part in time_parts]

    # if minutes == 00, add "o'clock"
    words = expand_number(hours)
    if not minutes:
        words.append("o'clock")

    # otherwise, expand the minutes as well, adding the
    # 'oh' for '01' through '09'
    else:
        if minutes < 10:
            words.append('oh')
        words.extend(expand_number(minutes))
    return words
```

8.5 (Suggested by Alan Black.) Download the free Festival speech synthesizer. Augment the lexicon to correctly pronounce the names of everyone in your class.

Lexicon entries for Festival look something like:

```
("photography" n (
  ((f @)   0)
  ((t o g) 1)
  ((r @ f) 0)
  ((ii)    0)))
```

This says that when the word *photography* is encountered and it is a noun, it is pronounced as [fə ˈtɑg rəf i].

The most important sections of the Festival documentation are probably the "Lexicons" chapter, which explains the lexicon entry format, and the "US phoneset" and "UK phoneset" sections at the end of the documentation, which explain the transcription symbols.

8.6 Download the Festival synthesizer. Using your own voice, record and train a diphone synthesizer.

If the recording is done in a language for which Festival already has a phoneset and lexicon, e.g., English, then this exercise requires only three major steps:

- Speaking and recording a long list of diphones
- Automatically aligning and labeling the diphone segments
- Testing the model and hand-correcting the diphone labelings

The Festival documentation walks through each of these steps in detail, and shows the Festival commands that must be run at each stage.

8.7 Build a phrase boundary predictor. You can use any classifier you like, and you should implement some of the features described on page 263.

Good baselines to compare the models against:

- Boundaries after all punctuation
- Boundaries before function words preceded by content words

To get the best picture of model performance, models should be evaluated using precision and recall rather than simple accuracy.

Chapter 9
Automatic Speech Recognition

9.1 Analyze each of the errors in the incorrectly recognized transcription of "um the phone is I left the. . . " on page 328. For each one, give your best guess as to whether you think it is caused by a problem in signal processing, pronunciation modeling, lexicon size, language model, or pruning in the decoding search.

There are many possible explanations for each of the errors of the system. This exercise is just intended to get students thinking about the different components of an ASR system, and how they interact. The following are a few possible explanations for the system errors.

i UM → i GOT IT TO
Assigning a cause to this error was unintentionally tricky because the alignment program dropped all word fragments in its output. So the input probably looked more like *G- T- UM*, or something similar. Given such input, both the lexicon and language model would probably try to turn these partial words into full words, producing *GOT IT TO* instead of *UM*.

PHONE IS → FULLEST
LEFT THE → LOVE TO
PHONE → FORM
UPSTAIRS → OF STORES
For all of these errors, the two phrases are similar phonetically, e.g., [l eh f th ax] and [l ah f t ax]. On the one hand, this could suggest that the acoustic model correctly identified them as being similar, and the problem was in the language model, e.g., having seen "i love to" more than "i left the" during training. On the other hand, this could suggest that the problem is that the acoustic model didn't sufficiently distinguish between the two phrases phonetically.

Particularly in the case of the language model, the compounding of other errors could also be at fault. For example, given that the model has already made the error, *GOT IT TO*, the phrase *TO the FULLEST* is probably much more likely in the language model than *TO the PHONE IS*.

9.2 In practice, as we mentioned earlier in Chapter 4, speech recognizers do all their probability computation by using the **log probability** (**logprob**) rather than actual probabilities. This helps avoid underflow for very small probabilities, but also makes the Viterbi algorithm very efficient since all probability multiplications can be implemented by adding logprobs. Rewrite the pseudocode for the Viterbi algorithm in Fig. 9.26 on page 321 to make use of logprobs instead of probabilities.

function VITERBI(*observations* of len *T*, *state-graph* of len *N*) **returns** *best-path*
;; initialize the probability and backpointer matrices
create a path log-probability matrix *viterbi[N+2,T]*
for each state s **from** 1 **to** *N* **do**
viterbi$[s,1] \leftarrow \log(a_{0,s}) + \log(b_s(o_1))$
backpointer$[s,1] \leftarrow 0$
;; fill in the matrices from left to right
for each time step t **from** 2 **to** *T* **do**
for each state s **from** 1 **to** *N* **do**
viterbi$[s,t] \leftarrow \max_{s'=1}^{N}$ *viterbi*$[s', t-1] + \log(a_{s',s}) + \log(b_s(o_t))$
backpointer$[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N}$ *viterbi*$[s', t-1] + \log(a_{s',s})$
;; select the best final state
viterbi$[q_F,T] \leftarrow \max_{s=1}^{N}$ *viterbi*$[s,T] + \log(a_{s,q_F})$
backpointer$[q_F,T] \leftarrow \operatorname{argmax}_{s=1}^{N}$ *viterbi*$[s,T] + \log(a_{s,q_F})$
return ...

9.3 Now modify the Viterbi algorithm in Fig. 9.26 to implement the beam search described on page 323. Hint: You will probably need to add in code to check whether a given state is at the end of a word or not.

function VITERBI(*observations* of len *T*, *state-graph* of len *N*, θ) **returns** *best-path*
...
;; fill in the matrices from left to right
for each time step t **from** 2 **to** *T* **do**
for each state s **from** 1 **to** *N* **do**
viterbi$[s,t] \leftarrow \max_{s'=1}^{N}$ *viterbi*$[s', t-1] + \log(a_{s',s}) + \log(b_s(o_t))$
backpointer$[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N}$ *viterbi*$[s', t-1] + \log(a_{s',s})$
;; prune any word-final states that are outside of the beam
best-prob $\leftarrow \max_{s=1}^{N}$ *viterbi*$[s,t]$
for each state s **where** s is at the end of a word **do**
if *viterbi*$[s,t] + \theta <$ *best-prob* **then**
Prune *viterbi*$[s,t]$
;; select the best final state ...

9.4 Finally, modify the Viterbi algorithm in Fig. 9.26 with more detailed pseudocode implementing the array of backtrace pointers.

function VITERBI(*observations* of len *T*, *state-graph* of len *N*, θ) **returns** *best-path*
...
create an array *best-path*[*T*]
$s \leftarrow$ *backpointer*[q_F,T]
for each time step t **from** T **to** 1 **do**
best-path[t] $\leftarrow s$
$s \leftarrow$ *backpointer*[s,t]
return *best-path*

9.5 Using the tutorials available as part of a publicly available recognizer like HTK or Sonic, build a digit recognizer.

This exercise consists of the following steps:

1. Record each digit several times
2. Label the recordings with silence and digit segments
3. Convert the waveforms to acoustical vectors
4. Train the recognizer on the vectors and their labels
5. Record some new digits and test the model

Manually creating the dataset is likely to be the most time consuming part of this exercise. Most publicly available recognizers include tools for doing the other steps automatically.

9.6 Take the digit recognizer above and dump the phone likelihoods for a sentence. Show that your implementation of the Viterbi algorithm can successfully decode these likelihoods.

The goal of this exercise is to convert the pseudocode developed in Exercises 9.2, 9.3 and 9.4, and apply it to an actual problem. Using logprobs, in particular, will be crucial for this task since the many small probabilities would quickly run into numeric underflow issues.

Chapter 10
Speech Recognition: Advanced Topics

10.1 Implement the Stack decoding algorithm of Fig. 10.7 on page 342. Pick a simple h^* function like an estimate of the number of words remaining in the sentence.

To simplify this assignment a bit, skip the fast matching part. Those interested in trying the fast-match technique should see Gopalakrishnan and Bahl (1996).

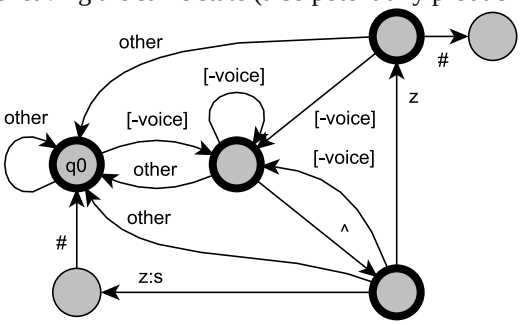
10.2 Modify the forward algorithm of Fig. 9.23 on page 319 to use the tree-structured lexicon of Fig. 10.10 on page 345.

Sor more information on the implementation of tree-structured lexicons, see Chapter 13 of Huang et al. (2001).

Chapter 11
Computational Phonology

11.1 Build an automaton for rule (11.3).

The symbol "[-voice]" means a voiced sound (potentially producing anything) and the symbol "other" means any sound not used on other arcs leaving the same state (also potentially producing anything).



Canadian raising

11.2 Some Canadian dialects of English exhibit **Canadian raising**: /aɪ/ is raised to [ʌɪ] and /aʊ/ to [ʌʊ] in stressed position before a voiceless consonant (Bromberger and Halle, 1989). A simplified rule dealing only with /aɪ/ can be stated as:

$$/\text{aɪ}/ \rightarrow [\text{ʌɪ}] \; / \_\_ \begin{bmatrix} C \\ -voice \end{bmatrix} \tag{11.1}$$

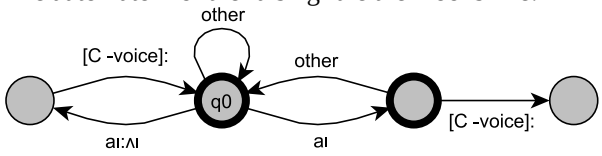
In some Canadian dialects this rule interacts with the flapping rule, causing different pronunciations for the words *rider* ([raɪɾɚ]) and *writer* ([rʌɪɾɚ]). Write a two-level rule and an automaton for the raising and flapping rules that correctly models this distinction, making simplifying assumptions as needed.

When applying the Canadian raising rule, we must look for voiceless consonants at the lexical level, not the surface level. Otherwise, the rule would not apply to *writer* which has the lexical form /raɪtɚ/ but the surface form [raɪɾɚ]. Thus, our two-level rules should look like:

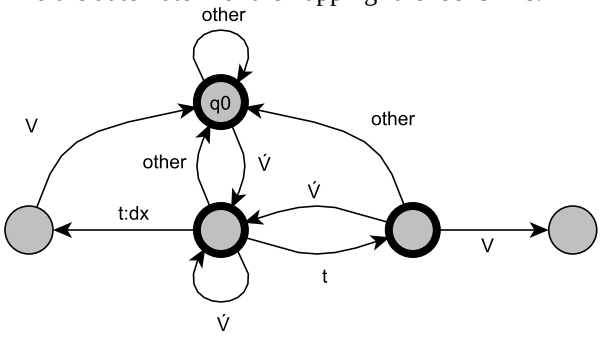
$$\text{áɪ} : \text{ʌ́ɪ} \Leftrightarrow \_\_ \begin{bmatrix} C \\ -voice \end{bmatrix} :$$

$$\text{t} : \text{dx} \Leftrightarrow \text{V́}\_\_\text{V}$$

The automaton for the raising rule then looks like:



And the automaton for the flapping rule looks like:



11.3 Write the lexical entry for the pronunciation of the English past tense (preterite) suffix *-d*, and the two-level rules that express the difference in its pronunciation depending on the previous context. Don't worry about the spelling rules. Make sure you correctly handle the pronunciation of the past tenses of the words *add*, *pat*, *bake*, and *bag*.

The suffix *-d* is pronounced as [ɪd] when following an alveolar stop like [t] or [d] (e.g., *added*, *patted*), as [t] when following voiceless sounds (e.g., *baked*), and as [d] when following voiced sounds (e.g., *bagged*).

To allow the rules to run in parallel, we can give them mutually exclusive conditions, and look for these only at the lexical level:

$$\text{d}:\text{ɪd} \;\Leftrightarrow\; [+\text{alveolar-stop}]:\ \hat{}\ \_\_\ \#$$

$$\text{d}:\text{t} \;\Leftrightarrow\; \begin{bmatrix} -\text{alveolar-stop} \\ -\text{voice} \end{bmatrix}:\ \hat{}\ \_\_\ \#$$

$$\text{d} \;\Leftrightarrow\; \begin{bmatrix} -\text{alveolar-stop} \\ +\text{voice} \end{bmatrix}:\ \hat{}\ \_\_\ \#$$

11.4 Write two-level rules for the Yawelmani Yokuts Harmony, Shortening, and Lowering phenomena from page 365. Make sure your rules can run in parallel.

The key here is to make sure that the Harmony rule only looks at the lexical context, so that changes to the surface forms from the Shortening and Lowering rules do not affect it.

$$[+\alpha\ \text{high}]:\begin{bmatrix} +\beta\ \text{back} \\ +\gamma\ \text{round} \end{bmatrix} \;\Leftrightarrow\; \begin{bmatrix} +\alpha\ \text{high} \\ +\beta\ \text{back} \\ +\gamma\ \text{round} \end{bmatrix}:\ C^*\ \hat{}\ C^*\ \_\_$$

$$\begin{bmatrix} +\text{high} \\ +\text{long} \end{bmatrix}:[-\text{high}] \;\Leftrightarrow\; \_\_$$

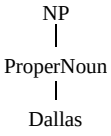
$$[+\text{long}]:[-\text{long}] \;\Leftrightarrow\; \_\_\ C$$

Chapter 12
Formal Grammars of English

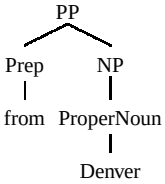
12.1 Draw tree structures for the following ATIS phrases:

The trees below use, as much as possible, the rules from the chapter. Other tree structures are also possible.

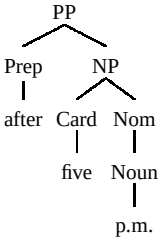
1. Dallas



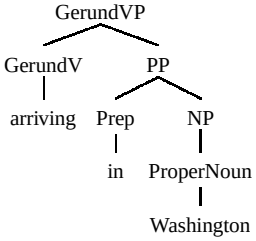
2. from Denver



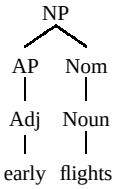
3. after five p.m.



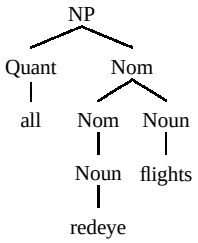
4. arriving in Washington



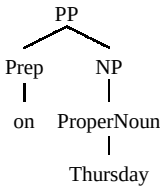
5. early flights



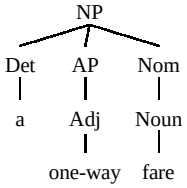
6. all redeye flights



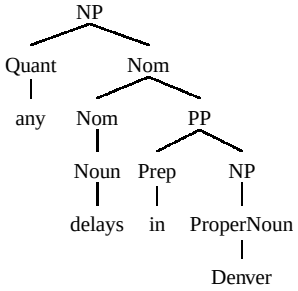
7. on Thursday



8. a one-way fare



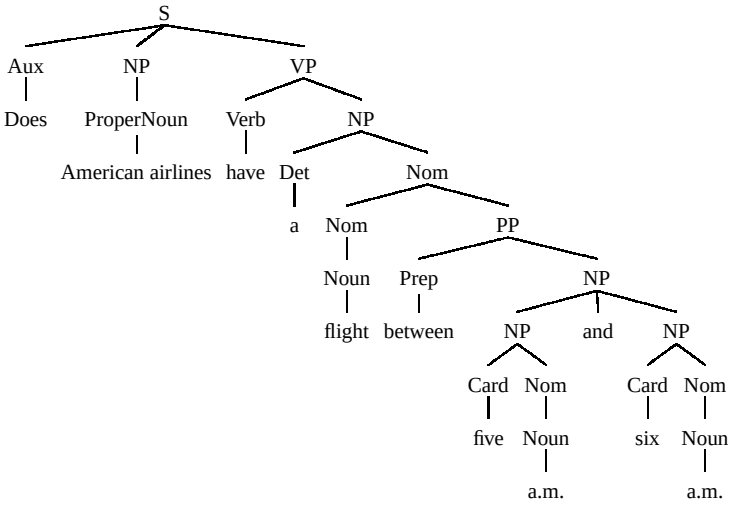
9. any delays in Denver



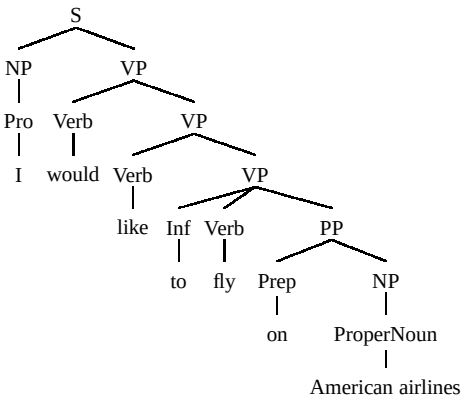
12.2 Draw tree structures for the following ATIS sentences:

The trees below use, as much as possible, the rules from the chapter. Other tree structures are also possible.

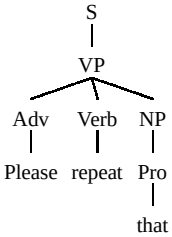
1. Does American airlines have a flight between five a.m. and six a.m.?



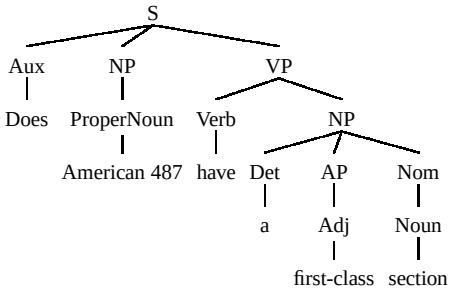
2. I would like to fly on American airlines.



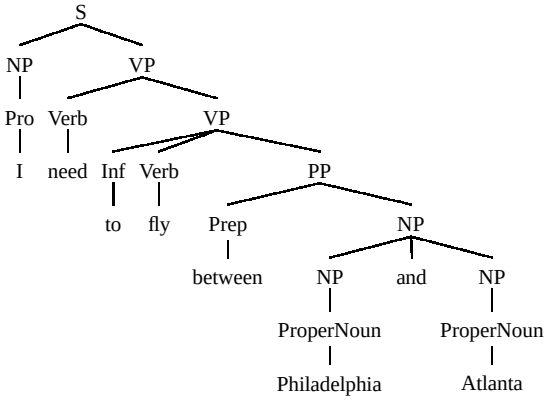
3. Please repeat that.



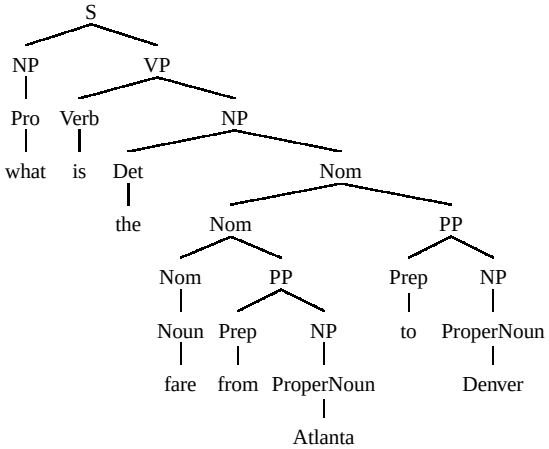
4. Does American 487 have a first-class section?



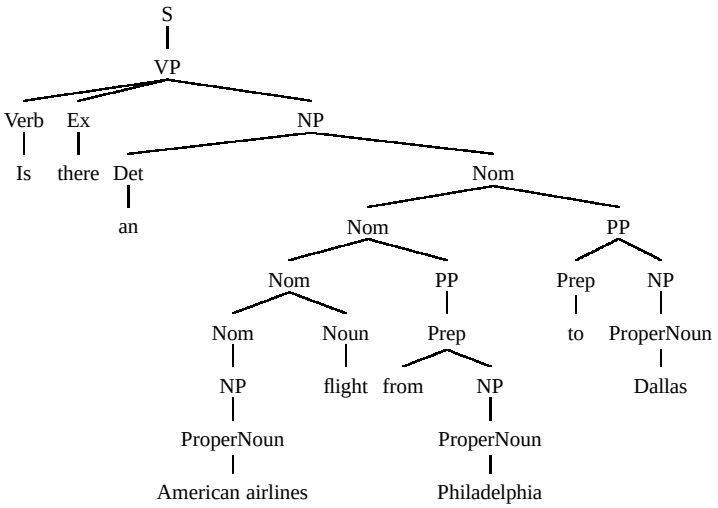
5. I need to fly between Philadelphia and Atlanta.



6. What is the fare from Atlanta to Denver?



7. Is there an American airlines flight from Philadelphia to Dallas?



12.3 Augment the grammar rules on page 399 to handle pronouns. Deal properly with person and case.

S	→	*3sgAux 3sgNomNP VP*
S	→	*Non3sgAux Non3sgNomNP VP*
3sgAux	→	*does* | *has* | *can* | ...
Non3sgAux	→	*do* | *have* | *can* | ...
3sgNomNP	→	*3sgNomPronoun*
3sgNomNP	→	*Det SgNominal*
3sgNomPronoun	→	*he* | *she* | *it*
Non3sgNomNP	→	*Non3sgNomPronoun*
Non3sgNomNP	→	*Det PlNominal*
Non3sgNomPronoun	→	*I* | *you* | *we* | *they*
VP	→	*Verb (AccNP) (PP)*
AccNP	→	*AccPronoun*
AccNP	→	*Det Nominal*
AccPronoun	→	*me* | *us* | *you* | *him* | *her* | *it* | *them*

12.4 Modify the noun phrase grammar of Sections 12.3.3–12.3.4 to correctly model mass nouns and their agreement properties

3sgNP	→	*SgCountNP* | *MassNP*
SgCountNP	→	*SgCountDet SgCountNominal*
SgCountDet	→	*a* | *one* | *the* | *any* | ...
SgCountNominal	→	*flight* | *pilot* | ...
MassNP	→	*(MassDet) MassNominal*
MassDet	→	*some* | *the* | *any* | ...
MassNominal	→	*snow* | *breakfast* | ...

12.5 How many types of *NP*s would the rule on page 396 expand to if we didn't allow parentheses in our grammar formalism?

Since there is a binary decision of whether or not to include each of the five options (*Det*, *Card*, *Ord*, *Quant* and *AP*), we would need

$$2^5 = 32$$

rules to express the grammar without a way of denoting optionality.

12.6 Assume a grammar that has many *VP* rules for different subcategorizations, as expressed in Section 12.3.5, and differently subcategorized verb rules like *Verb-with-NP-complement*. How would the rule for postnominal relative clauses (12.5) need to be modified if we wanted to deal properly with examples like *the earliest flight that you have*? Recall that in such examples the pronoun *that* is the object of the verb *get*. Your rules should allow this noun phrase but should correctly rule out the ungrammatical *S *I get*.

RelClause → *(who | that) VP*
RelClause → *(who | that) NoObjS*
NoObjS → *NP NoObjVP*
NoObjVP → *(Aux) Verb-with-NP-Comp (PP)*
NoObjVP → *(Aux) Verb-with-S-Comp (NoObjS)*
NoObjVP → *(Aux) Verb-with-Inf-VP-Comp ((NP) to NoObjVP)*

12.7 Does your solution to the previous problem correctly model the NP *the earliest flight that I can get*? How about *the earliest flight that I think my mother wants me to book for her*? Hint: this phenomenon is called **long-distance dependency**.

Yes, the optional *Aux* elements allow for auxiliaries like *can*, and the recursive uses of *NoObjS* and *NoObjVP* in the last two rules allow for the long-distance dependencies.

12.8 Write rules expressing the verbal subcategory of English auxiliaries; for example, you might have a rule *verb-with-bare-stem-VP-complement* → *can*.

For the sake of conciseness, we list only one form per verb, but for example, *am*, *are*, *was* follow the same pattern as *is*.

verb-with-bare-stem-VP-complement → *do | can | could | may | might | must | shall | should | will | would*
verb-with-gerund-VP-complement → *is*
verb-with-perfect-VP-complement → *has | is*
verb-with-infinitive-VP-complement → *ought*

Possessive
Genitive

12.9 *NP*s like *Fortune's office* or *my uncle's marks* are called **possessive** or **genitive** noun phrases. We can be model possessive noun phrases by treating the sub-NP like *Fortune's* or *my uncle's* as a determiner of the following head noun. Write grammar rules for English possessives. You may treat *'s* as if it were a separate word (i.e., as if there were always a space before *'s*).

NP → *(Det) Nominal*
NP → *ProperNoun*
Det → *NP 's*
Det → *my* | *a* | *the* | ...

12.10 Page 393 discussed the need for a *Wh-NP* constituent. The simplest *Wh-NP* is one of the *Wh-pronouns* (*who, whom, whose, which*). The Wh-words *what* and *which* can be determiners: *which four will you have?, what credit do you have with the Duke?* Write rules for the different types of *Wh-NP*s.

Wh-NP → *Wh-Pro*
Wh-NP → *Wh-Det Nominal*
Wh-Pro → *who* | *whom* | *whose* | *which*
Wh-Det → *what* | *which*

12.11 Write an algorithm for converting an arbitrary context-free grammar into Chomsky normal form.

function CHOMSKY-NORMAL-FORM(*grammar*) **returns** *grammar*

; remove epsilon rules
while *grammar* has a rule $A \rightarrow \epsilon$ **where** A is not the start state **do**
  Remove the rule $A \rightarrow \epsilon$
  for each rule $B \rightarrow \beta_0 \ldots \beta_i A \beta_j \ldots \beta_N$ **do**
    Replace the rule with $B \rightarrow \beta_0 \ldots \beta_i \beta_j \ldots \beta_N$

; remove single symbol nonterminal rules
while *grammar* has a rule $A \rightarrow B$ **where** B is a nonterminal **do**
  Remove the rule $A \rightarrow B$
  for each rule $B \rightarrow \beta_0 \ldots \beta_N$ **do**
    Add the rule $A \rightarrow \beta_0 \ldots \beta_N$
  if B is not the start symbol **do**
    if no rule $C \rightarrow \gamma B \delta$ exists **do**
      Remove all rules $B \rightarrow C$

; move terminals to their own rules
for each rule $A \rightarrow \beta_0 \beta_1 \ldots \beta_N$ **in** *grammar* **where** $N > 1$ **do**
  for each β_i **where** β_i is a terminal **do**
    Create a new symbol B
    Add a rule $B \rightarrow \beta_i$ to *grammar*
    Replace β_i in the original rule with B

; ensure there are only two nonterminals per rule
while *grammar* has a rule $A \rightarrow \beta_0 \ldots \beta_{N-2} \beta_{N-1} \beta_N$ **where** $N > 2$ **do**
  Create a new symbol B
  Add a rule $B \rightarrow \beta_{N-1} \beta_N$
  Replace the original rule with $A \rightarrow \beta_0 \ldots \beta_{N-2} B$

return *grammar*

Chapter 13
Syntactic Parsing

13.1 Implement the algorithm to convert arbitrary context-free grammars to CNF.

```
def chomsky_normal_form(grammar):
    grammar = set(grammar)
    nonterminals = set(rule.head for rule in grammar)

    # remove single symbol nonterminal rules
    for rule, symbol in _unary_rules(grammar, nonterminals):
        grammar.discard(rule)
        for rule2 in _rules_headed_by(grammar, symbol):
            grammar.add(Rule(rule.head, tuple(rule2.symbols)))
        if all(symbol not in rule.symbols for rule in grammar):
            for rule2 in _rules_headed_by(grammar, symbol):
                grammar.discard(rule2)

    # move terminals to their own rules
    for rule in list(grammar):
        if len(rule.symbols) >= 2:
            for i, symbol in enumerate(rule.symbols):
                if all(rule.head != symbol for rule in grammar):
                    rule = _new_symbol(grammar, rule, i, i + 1)

    # ensure there are only two nonterminals per rule
    for rule in _multi_symbol_rules(grammar):
        _new_symbol(grammar, rule, 0, 2)

    # return the grammar in CNF
    return grammar

# find A -> B rules, allowing concurrent modifications
def _unary_rules(grammar, nonterminals):
    while True:
        g = ((rule, rule.symbols[0])
             for rule in grammar
             if len(rule.symbols) == 1
             if rule.symbols[0] in nonterminals)
        yield g.next()

# find all rules headed by the given symbol
def _rules_headed_by(grammar, symbol):
    return [rule for rule in grammar if rule.head == symbol]

# create a new symbol which derives the given span of symbols
def _new_symbol(grammar, rule, start, stop):
    symbols = rule.symbols
    new_head = '_'.join(symbols[start:stop]).upper()
    new_symbols = symbols[:start] + (new_head,) + symbols[stop:]
    new_rule = Rule(rule.head, new_symbols)
    grammar.discard(rule)
    grammar.add(new_rule)
    grammar.add(Rule(new_head, symbols[start:stop]))
    return new_rule

# find A -> BCD... rules, allowing concurrent modifications
def _multi_symbol_rules(grammar):
    while True:
        g = (rule for rule in grammar if len(rule.symbols) >= 3)
        yield g.next()
```

Apply your program to the $\mathcal{L}_1$ grammar.

```
# representation of a rule A -> B...C
class Rule(object):
    def __init__(self, head, symbols):
        self.head = head
        self.symbols = symbols
        self._key = head, symbols
    def __eq__(self, other):
        return self._key == other._key
    def __hash__(self):
        return hash(self._key)

# build a grammar from a string of lines like "X -> YZ | b"
def get_grammar(string):
    grammar = set()
    for line in string.splitlines():
        head, symbols_str = line.split(' -> ')
        for symbols_str in symbols_str.split(' | '):
            symbols = tuple(symbols_str.split())
            grammar.add(Rule(head, symbols))
    return grammar

grammar = get_grammar('''\
S -> NP VP | Aux NP VP | VP
NP -> Pronoun | Proper-Noun | Det Nominal
Nominal -> Noun | Nominal Noun | Nominal PP
VP -> Verb |  Verb NP | Verb NP PP | Verb PP | VP PP
PP -> Preposition NP
Det -> that | this | a
Noun -> book | flight | meal | money
Verb -> book | include | prefer
Pronoun -> I | she | me
Proper-Noun -> Houston | TWA
Aux -> does
Preposition -> from | to | on | near | through''')

grammar_cnf = chomsky_normal_form(grammar)
assert grammar_cnf == get_grammar('''\
S -> NP VP | AUX_NP VP | Verb NP | VERB_NP PP | Verb PP | VP PP
S -> book | include | prefer
AUX_NP -> Aux NP
NP -> Det Nominal
NP -> TWA | Houston | I | she | me
Nominal -> Nominal Noun | Nominal PP
Nominal -> book | flight | meal | money
VP -> Verb NP | VERB_NP PP | Verb PP | VP PP
VP -> book | include | prefer
VERB_NP -> Verb NP
PP -> Preposition NP
Det -> this | that | a
Noun -> book | flight | meal | money
Verb -> book | include | prefer
Aux -> does
Preposition -> from | to | on | near | through''')
```

13.2 Implement the CKY algorithm and test it with your converted $\mathcal{L}_1$ grammar.

```
import collections

def cky_table(grammar, words):
    table = collections.defaultdict(set)
    for col, word in enumerate(words):
        col += 1

        # find all rules for the current word
        for rule in grammar:
            if rule.symbols == (word,):
                table[col - 1, col].add(rule.head)
```

```
            # for each span of words ending at the current word,
            # find all splits that could have formed that span
            for row in xrange(col - 2, -1, -1):
                for mid in xrange(row + 1, col):

                    # if the two constituents identified by this
                    # split can be combined, add the combination
                    # to the table
                    for rule in grammar:
                        if len(rule.symbols) == 2:
                            sym1, sym2 = rule.symbols
                            if sym1 in table[row, mid]:
                                if sym2 in table[mid, col]:
                                    table[row, col].add(rule.head)
    return table

words = 'book a flight through Houston'.split()
table = cky_table(grammar_cnf, words)
assert table[0, 1] == set('S VP Verb Nominal Noun'.split())
assert table[0, 2] == set()
assert table[0, 3] == set('S VP VERB_NP'.split())
assert table[0, 4] == set()
assert table[0, 5] == set('S VP VERB_NP'.split())
assert table[1, 2] == set('Det'.split())
assert table[1, 3] == set('NP'.split())
assert table[1, 4] == set()
assert table[1, 5] == set('NP'.split())
assert table[2, 3] == set('Nominal Noun'.split())
assert table[2, 4] == set()
assert table[2, 5] == set('Nominal'.split())
assert table[3, 4] == set('Preposition'.split())
assert table[3, 5] == set('PP'.split())
assert table[4, 5] == set('NP'.split())
```

13.3 Rewrite the CKY algorithm given in Fig. 13.10 on page 440 so that it can accept grammars that contain unit productions.

Solving this problem requires that each time we add a symbol to a cell in the table, we also add all symbols to that cell which could have produced the original symbol through a sequence of unary rules. So, for example, if we add C to *table*$[i, j]$, and we have the rules $A \rightarrow B$ and $B \rightarrow C$, then we must also add A and B to *table*$[i, j]$.

13.4 Augment the Earley algorithm of Fig. 13.13 to enable parse trees to be retrieved from the chart by modifying the pseudocode for COMPLETER as described on page 448.

Basically, we add a list of backpointers to each of our states. When the dot in a rule is advanced, the state that allowed that advance is appended to the list of backpointers.

procedure COMPLETER(S_x =($B \rightarrow \gamma \bullet$, $[j,k]$, $S_n \ldots S_m$))
  for each ($A \rightarrow \alpha \bullet B\,\beta$, $[i, j]$, $S_p \ldots S_q$) **in** *chart*$[j]$ **do**
    ENQUEUE(($A \rightarrow \alpha\, B \bullet \beta$, $[i, k]$, $S_p \ldots S_q S_x$), *chart*$[k]$)

13.5 Implement the Earley algorithm as augmented in the previous exercise. Check it on a test sentence by using the $\mathcal{L}_1$ grammar.

```
def earley_parse(grammar, words):
    nonterminals = set(rule.head for rule in grammar)

    # never allow states already seen to be added to the chart
    chart = collections.defaultdict(list)
    seen = collections.defaultdict(set)
    def add(i, rule, dot, start, end, pointers=()):
        state = State(rule, dot, start, end, pointers)
        if state not in seen[i]:
            chart[i].append(state)
            seen[i].add(state)

    # iteratively build the chart
    add(0, Rule('START', ('S',)), 0, 0, 0)
    for i in xrange(len(words) + 1):
        for state in chart[i]:
            complete = state.is_complete()
            next_symbol = state.next_symbol()

            # Scanner - the state is expecting a word, so if the
            # expected word is next in the input, advance the
            # rule past the word
            if not complete and next_symbol not in nonterminals:
                if state.end < len(words):
                    if next_symbol == words[state.end]:
                        add(state.end + 1, state.rule,
                            state.dot + 1, state.start,
                            state.end + 1, state.pointers)

            # Predictor - the state is expecting a constituent C,
            # so add new states for all expansions of C, starting
            # at the end of the current state
            elif not complete and next_symbol in nonterminals:
                for rule in grammar:
                    if rule.head == next_symbol:
                        add(state.end, rule, 0,
                            state.end, state.end)

            # Completer - the state is complete, advance any
            # states that were expecting a state like this (both
            # the symbol and the location)
            else:
                for other in chart[state.start]:
                    if other.next_symbol() == state.rule.head:
                        if other.end == state.start:
                            add(state.end, other.rule,
                                other.dot + 1,
                                other.start, state.end,
                                other.pointers + (state,))

    # helper for creating tree strings from states
    def to_tree(state):
        children = [to_tree(child) for child in state.pointers]
        if not children:
            children = state.rule.symbols
        return '(%s %s)' % (state.rule.head, ' '.join(children))

    # generate all trees from the START rules
    for state in chart[i]:
        if state.rule.head == 'START' and state.is_complete():
            top, = state.pointers
            yield to_tree(top)
```

```
# state class encapsulating rule position, word span and
# pointers for retrieving full parse
class State(object):
    def __init__(self, rule, dot, start, end, pointers=()):
        self.rule = rule
        self.dot = dot
        self.start = start
        self.end = end
        self.pointers = pointers
        self._key = rule, dot, start, end, pointers
    def __hash__(self):
        return hash(self._key)
    def __eq__(self, other):
        return self._key == other._key
    def is_complete(self):
        return self.dot == len(self.rule.symbols)
    def next_symbol(self):
        if self.is_complete():
            return None
        else:
            return self.rule.symbols[self.dot]

grammar = get_grammar('''\
S -> NP VP | Aux NP VP | VP
NP -> Pronoun | Proper-Noun | Det Nominal
Nominal -> Noun | Nominal Noun | Nominal PP
VP -> Verb | Verb NP | Verb NP PP | Verb PP | VP PP
PP -> Preposition NP
Det -> that | this | a
Noun -> book | flight | meal | money
Verb -> book | include | prefer
Pronoun -> I | she | me
Proper-Noun -> Houston | TWA
Aux -> does
Preposition -> from | to | on | near | through''')

words = 'book through Houston'.split()
assert set(earley_parse(grammar, words)) == set([
    '(S (VP (Verb book) '
    '(PP (Preposition through) (NP (Proper-Noun Houston)))))',
    '(S (VP (VP (Verb book)) '
    '(PP (Preposition through) (NP (Proper-Noun Houston)))))'])
```

13.6 Alter the Earley algorithm so that it makes better use of bottom-up information to reduce the number of useless predictions.

One way to achieve this would be to determine for each nonterminal, all possible terminals that could appear in the first position of a string derived from that rule. For example, in the $\mathcal{L}_1$ grammar,

$$\text{FIRST}(PP) = \{\text{from, to, on, near, through}\}$$
$$\text{FIRST}(VP) = \{\text{book, include, prefer}\}$$

The predictor would only insert new states for nonterminals whose FIRST set included the current word in the string.

13.7 Attempt to recast the CKY and Earley algorithms in the chart-parsing paradigm.

In the chart-parsing version of CKY, we would first INITIALIZE by looking up words in the grammar and adding their rules to the agenda. This is basically the equivalent of filling in the table cells along the diagonal. We then alternate between MAKE-PREDICTIONS, which generates parent rules from rules in the table, and the FUNDAMENTAL

rule, which takes pairs of these rules and completes them. The agenda would make sure we consider rules in the same order as the traditional CKY algorithm.

In the chart-parsing version of Earley, we again INITIALIZE by adding all the part of speech rules, basically the equivalent of SCANNER. Then MAKE-PREDICTIONS does what PREDICTOR used to do, and the FUNDAMENTAL rule does what COMPLETER used to do. The agenda would basically be a sequence of queues, one for each word, and where we process all edges for each word in the order they were produced.

13.8 Discuss the relative advantages and disadvantages of partial versus full parsing.

Partial parsing is generally much faster than full parsing, but provides less syntactic detail. Thus, for a task where only a few pieces of surface level syntax are necessary, e.g., named entity recognition, partial parsing can provide similar results to a full parse in substantially reduced times. However, for a task where a great amount of syntactic detail is needed, e.g., construction of logical forms, even cascaded partial parsers will not produce as complete information as a full parser.

13.9 Implement a more extensive finite-state grammar for noun groups by using the examples given in Section 13.5 and test it on some *NP*s. Use an on-line dictionary with parts-of-speech if available; if not, build a more restricted system by hand.

Below, we use *NN* to stand for *NN* or *NNS* or *NNP*.

NP $\rightarrow$ *(DT) (CD) JJ∗ (VBG) NN∗ NN*

NP $\rightarrow$ *(DT) (CD) NN∗ NN CC NN∗ NN*

These rules cover NPs like the following found in the Penn Treebank:

one Cray Computer share

an Italian state-owned holding company

the Cray-3 research and development expenses

13.10 Discuss how to augment a parser to deal with input that may be incorrect, for example, containing spelling errors or mistakes arising from automatic speech recognition.

One approach might be to take the partial syntactic structures that the parser was able to identify and join them together to form full parses. These full parses would necessarily introduce new rules, so this approach would likely require searching through the space of possible new rules to find a minimal set that produces a full parse.

Another approach, and perhaps the more common one, would be to use one of the probabilistic approaches discussed in Chapter 14.

Chapter 14
Statistical Parsing

14.1 Implement the CKY algorithm.

```
import collections
def prob_cky(grammar, words):
    ddict = collections.defaultdict
    probs = ddict(lambda: ddict(lambda: 0.0))
    backs = ddict(lambda: {})

    # helpers for getting rules that produce the given symbols
    # and for getting heads of rules with probability > 0
    def get_rules(*symbols):
        for rule in grammar:
            if rule.symbols == symbols:
                yield rule
    def probs_positive(row, col):
        for head in probs[row, col]:
            if probs[row, col][head] > 0.0:
                yield head

    # for each word in the input, update the table cells in the
    # corresponding column, from bottom to top
    for col, word in enumerate(words):
        col += 1

        # find rules that could have produced the word directly
        for rule in get_rules(word):
            probs[col - 1, col][rule.head] = rule.prob
            backs[col - 1, col][rule.head] = None, None, None

        # create a new span when two existing spans meet at their
        # endpoints and a rule producing those two symbols exists
        for row in xrange(col - 2, -1, -1):
            for mid in xrange(row + 1, col):
                for head1 in probs_positive(row, mid):
                    for head2 in probs_positive(mid, col):
                        for rule in get_rules(head1, head2):

                            # combine rule and span probabilities
                            prob = rule.prob
                            prob *= probs[row, mid][head1]
                            prob *= probs[mid, col][head2]

                            # keep higher probability rules
                            if prob > probs[row, col][rule.head]:
                                probs[row, col][rule.head] = prob
                                back = mid, head1, head2
                                backs[row, col][rule.head] = back

    # helper for converting the backpointers to a tree
    def get_tree(row, col, symbol):
        mid, head1, head2 = backs[row, col][symbol]
        if mid is head1 is head2 is None:
            return '(%s %s)' % (symbol, words[row])
        else:
            tree1 = get_tree(row, mid, head1)
            tree2 = get_tree(mid, col, head2)
            return '(%s %s %s)' % (symbol, tree1, tree2)

    # return tree and expected probability
    return get_tree(0, len(words), 'S'), probs[0, len(words)]['S']
```

14.2 Modify the algorithm for conversion to CNF from Chapter 13 to correctly handle rule probabilities. Make sure that the resulting CNF assigns the same total probability to each parse tree.

The three basic CNF transformation rules, and their corresponding probability calculations (shown in brackets following each rule):

- Replace $A \rightarrow B$ $[p_1]$ rules with $A \rightarrow \beta_0 \ldots \beta_N$ $[p_1 * p_2]$ rules for each $B \rightarrow \beta_0 \ldots \beta_N$ $[p_2]$ rule.
- Replace $A \rightarrow \beta_0 \ldots \beta_i b \beta_j \beta_N$ $[p_1]$ rules (where b is a terminal) with $A \rightarrow \beta_0 \ldots \beta_i B \beta_j \beta_N$ $[p_1]$ and $B \rightarrow b$ $[1.0]$ rules (where B is a new symbol).
- Replace $A \rightarrow \beta_0 \ldots \beta_{N-2} \beta_{N-1} \beta_N$ $[p_1]$ rules (where $N > 2$) with $A \rightarrow \beta_0 \ldots \beta_{N-2} B$ $[p_1]$ and $B \rightarrow \beta_{N-1} \beta_N$ $[1.0]$ rules (where B is a new symbol).

14.3 Recall that Exercise 13.3 asked you to update the CKY algorithm to handle unit productions directly rather than converting them to CNF. Extend this change to probabilistic CKY.

```
def prob_cky(grammar, words):
    ddict = collections.defaultdict
    probs = ddict(lambda: ddict(lambda: 0.0))
    backs = ddict(lambda: {})

    # helpers for getting rules that produce the given symbols
    # and for getting heads of rules with probability > 0
    def get_rules(*symbols):
        for rule in grammar:
            if rule.symbols == symbols:
                yield rule
    def probs_positive(row, col):
        for head in probs[row, col]:
            if probs[row, col][head] > 0.0:
                yield head

    # helper for adding heads to table cells that could have
    # been generated using a chain of unary rules
    def add_unaries(row, col):

        # iterate over a queue with the heads from the table cell
        seen = set()
        heads_todo = set(probs_positive(row, col))
        while heads_todo:
            head = heads_todo.pop()

            # add to the queue rules that could have generated
            # this symbol, that were not previously seen
            for rule in get_rules(head):
                if rule not in seen:
                    seen.add(rule)
                    heads_todo.add(rule.head)

                    # combine A -> B and B -> C rules and add the
                    # new A -> C rule to the table
                    prob = rule.prob * probs[row, col][head]
                    if prob > probs[row, col][rule.head]:
                        probs[row, col][rule.head] = prob
                        back = None, head, None
                        backs[row, col][rule.head] = back

    # for each word in the input, update the table cells in the
    # corresponding column, from bottom to top
```

```
for col, word in enumerate(words):
    col += 1

    # find rules that could have produced the word directly
    for rule in get_rules(word):
        probs[col - 1, col][rule.head] = rule.prob
        backs[col - 1, col][rule.head] = None, None, None

        # propagate any unary rules
        add_unaries(col - 1, col)

    # create a new span when two existing spans meet at their
    # endpoints and a rule producing those two symbols exists
    for row in xrange(col - 2, -1, -1):
        for mid in xrange(row + 1, col):
            for head1 in probs_positive(row, mid):
                for head2 in probs_positive(mid, col):
                    for rule in get_rules(head1, head2):

                        # combine rule and span probabilities
                        prob = rule.prob
                        prob *= probs[row, mid][head1]
                        prob *= probs[mid, col][head2]

                        # keep higher probability rules
                        if prob > probs[row, col][rule.head]:
                            probs[row, col][rule.head] = prob
                            back = mid, head1, head2
                            backs[row, col][rule.head] = back

        # propagate any unary rules
        add_unaries(row, col)

# helper for converting the backpointers to a tree
def get_tree(row, col, symbol):
    mid, head1, head2 = backs[row, col][symbol]
    if mid is head1 is head2 is None:
        return '(%s %s)' % (symbol, words[row])
    elif mid is head2 is None:
        tree = get_tree(row, col, head1)
        return '(%s %s)' % (symbol, tree)
    else:
        tree1 = get_tree(row, mid, head1)
        tree2 = get_tree(mid, col, head2)
        return '(%s %s %s)' % (symbol, tree1, tree2)

# return tree and expected probability
return get_tree(0, len(words), 'S'), probs[0, len(words)]['S']
```

14.4 Fill out the rest of the probabilistic CKY chart in Fig. 14.4.

Det: .4 [0, 1]	NP: .0024 [0, 2]	[0, 3]	[0, 4]	S: 2.304e-8 [0, 5]
	N: .02 [1, 2]	[1, 3]	[1, 4]	[1, 5]
		V: .05 [2, 3]	[2, 4]	VP: 1.2e-5 [2, 5]
			Det: .4 [3, 4]	NP: .0012 [3, 5]
				N: .01 [4, 5]

14.7 Implement the PARSEVAL metrics described in Section 14.7. Next, either use a treebank or create your own hand-checked parsed testset. Now use your CFG (or other) parser and grammar, parse the test set and compute labeled recall, labeled precision, and cross-brackets.

The code below implements the PARSEVAL metrics.

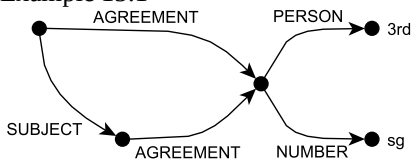
```
from __future__ import division
def parseval(expected_trees, predicted_trees):
    correct = 0
    expected = 0
    predicted = 0
    crossed = 0

    # count numbers of correct, expected and predicted
    # constituents, as well as number of crossing brackets
    tree_pairs = zip(expected_trees, predicted_trees)
    for expected_tree, predicted_tree in tree_pairs:

        # convert trees to spans
        expected_spans = get_spans(expected_tree)
        predicted_spans = get_spans(predicted_tree)
        expected += len(expected_spans)
        predicted += len(predicted_spans)

        # look for matching spans and crossing brackets
        for predicted_span in predicted_spans:
            had_match = had_crossing = False
            for expected_span in expected_spans:

                # look for matching spans
                if predicted_span == expected_span:
                    had_match = True

                # look for crossing brackets
                _, s1, e1 = predicted_span
                _, s2, e2 = expected_span
                if s1 < s2 < e1 < e2 or s2 < s1 < e2 < e1:
                    had_crossing = True

            # update correct and crossing bracket counts
            correct += had_match
            crossed += had_crossing
```

```
    # calculate precision, recall, F-measure and crossing brackets
    precision = correct / predicted
    recall = correct / expected
    f = 2 * precision * recall / (precision + recall)
    crossing_brackets = crossed / predicted
    return precision, recall, f, crossing_brackets

def get_spans(tree, offset=0):
    start = offset

    # spans of terminals are length 1
    if not tree:
        offset += 1

    # spans of nonterminals are determined from their children
    spans = []
    for child in tree:
        spans.extend(get_spans(child, offset))
        offset = spans[-1][-1]

    # add the span for this subtree and return the span list
    spans.append((tree.tag, start, offset))
    return spans
```

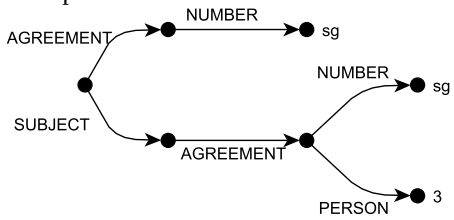
Chapter 15
Features and Unification

15.1 Draw the DAGs corresponding to the AVMs given in Examples 15.1–15.2.

Example 15.1



Example 15.2



15.2 Consider the following examples from the Berkeley Restaurant Project (BERP), focusing on their use of pronouns.

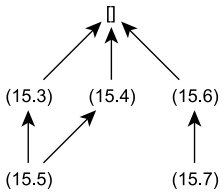
I want to spend lots of money.
Tell me about Chez Panisse.
I'd like to take her to dinner.
She doesn't like Italian.

Assuming that these pronouns all belong to the category *Pro*, write lexical and grammatical entries with unification constraints that block the following examples.

*Me want to spend lots of money.
*Tell I about Chez Panisse.
*I would like to take she to dinner.
*Her doesn't like Italian.

$$
\begin{aligned}
S &\rightarrow (NP)\ (Aux)\ VP \\
&\quad \langle NP\ \text{CASE} \rangle = \text{nominative} \\
VP &\rightarrow V\ NP\ \ldots \\
&\quad \langle NP\ \text{CASE} \rangle = \text{accusative} \\
NP &\rightarrow Pro \\
&\quad \langle Pro\ \text{CASE} \rangle = \langle NP\ \text{CASE} \rangle
\end{aligned}
$$

15.3 Draw a picture of the subsumption semilattice corresponding to the feature structures in Examples 15.3 to 15.7. Be sure to include the most general feature structure [].



An arrow from node A to node B indicates that $B \sqsubseteq A$.

15.4 Consider the following examples.

The sheep are baaaaing.
The sheep is baaaaing.

Create appropriate lexical entries for the words *the*, *sheep*, and *baaaaing*. Show that your entries permit the correct assignment of a value to the NUMBER feature for the subjects of these examples, as well as their various parts.

Since the text introduced agreement features for determiners, nouns, auxiliaries and verbs, the desired outcome is:

- For *The sheep is baaaaing*, all words have NUMBER = *sg*
- For *The sheep are baaaaing*, all words have NUMBER = *pl*

For *the*, *sheep* and *baaing*, we leave the agreements unspecified. Then for *is* and *are* we specify singular and plural agreements, respectively:

Aux $\rightarrow$ *is*
$\langle$*Aux* AGREEMENT NUMBER$\rangle$ = sg
Aux $\rightarrow$ *are*
$\langle$*Aux* AGREEMENT NUMBER$\rangle$ = pl

We also need to introduce a new grammar rule:

VP $\rightarrow$ *Aux Verb*
$\langle$*Aux* AGREEMENT$\rangle = \langle$*Verb* AGREEMENT$\rangle$
$\langle$*VP* AGREEMENT$\rangle = \langle$*Verb* AGREEMENT$\rangle$

Then unification should take care of the rest:

- The *VP* $\rightarrow$ *Aux Verb* rule from above requires *VP*, *Aux* and *Verb* to have the same AGREEMENT
- The *NP* $\rightarrow$ *Det Nominal* rule from the chapter requires *NP*, *Det* and *Nominal* to have the same AGREEMENT
- The *S* $\rightarrow$ *NP VP* rule gives from the chapter requires *S*, *NP* and *VP* to have the same AGREEMENT

Thus, for our sentences, the *Aux*, *Verb*, *Det* and *Noun* all must have the same agreement. So when the verb is *is*, all NUMBER features will be *sg*, and when the verb is *are*, all NUMBER features will be *pl*.

15.5 Create feature structures expressing the different SUBCAT frames for *while* and *during* shown on page 506.

$$\begin{bmatrix} \text{ORTH} & \textit{while} \\ \text{CAT} & \textit{Prep} \\ \text{HEAD} & \left[\text{SUBCAT} \quad \langle [\text{CAT } \textit{S}] \rangle \right] \end{bmatrix}$$

$$\begin{bmatrix} \text{ORTH} & \textit{during} \\ \text{CAT} & \textit{Prep} \\ \text{HEAD} & \left[\text{SUBCAT} \quad \langle [\text{CAT } \textit{NP}] \rangle \right] \end{bmatrix}$$

15.6 Alter the pseudocode shown in Figure 15.11 so that it performs the more radical kind of unification-based parsing described on page 519.

```
function EARLEY-PARSE(words, grammar) returns chart
  for (X_0 → α, dag_{X_0}) in grammar do
    if dag_{X_0}(⟨ X_0 CAT ⟩) = S then
      ADDTOCHART((γ → • X_0 , [0, 0], dag_γ), chart[0])

  for i from 0 to LENGTH(words) do
    for each state in chart[i] do
      if INCOMPLETE?(state)
        if NEXT-CAT(state) is a part of speech do
          SCANNER(state)
        else
          PREDICTOR(state)
      else
        COMPLETER(state)

procedure PREDICTOR((X_0 → α • X_1 β, [i, j], dag_{X_0}))
  for each (X_2 → γ, dag_{X_2}) in grammar do
    if new-dag ← UNIFY-STATES(dag_{X_1}, dag_{X_2}, X_0) ≠ Fails then
      ADDTOCHART((X_2 → • γ, [j, j], new-dag), chart[j])

procedure SCANNER((X_0 → α • X_1 β, [i, j], dag_{X_0}))
  if dag_{X_1}(⟨ X_1 CAT ⟩) ∈ PARTS-OF-SPEECH(words[j]) then
    ADDTOCHART((X_1 → words[j] •, [j, j+1], dag_{X_1}), chart[j+1])

procedure COMPLETER((X_0 → γ •, [j, k], dag_{X_0}))
  for each (X_1 → α • X_2 β, [i, j], dag_{X_1}) in chart[j] do
    if new-dag ← UNIFY-STATES(dag_{X_0}, dag_{X_1}, X_1) ≠ Fails then
      ADDTOCHART((X_1 → α X_0 • β, [i, k], new-dag), chart[k])
```

15.7 Consider the following problematic grammar suggested by Shieber (1985).

$$
\begin{aligned}
S &\rightarrow T \\
&\quad \langle T\ \text{F} \rangle = \text{a} \\
T_1 &\rightarrow T_2\ A \\
&\quad \langle T_1\ \text{F} \rangle = \langle T_2\ \text{F}\ \text{F} \rangle \\
S &\rightarrow A \\
A &\rightarrow a
\end{aligned}
$$

Show the first *S* state entered into the chart by using your modified PREDICTOR from the previous exercise, then describe any problematic behavior displayed by PREDICTOR on subsequent iterations. Discuss the cause of the problem and how it might be remedied.

The first two rules in the grammar look like:

$$
X_0 \leftarrow X_1 \qquad
\begin{bmatrix} X_0 & \begin{bmatrix} \text{CAT} & S \end{bmatrix} \\ X_1 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & a \end{bmatrix} \end{bmatrix}
$$

$$
X_0 \rightarrow X_1 X_2 \qquad
\begin{bmatrix} X_0 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \boxed{1} \end{bmatrix} \\ X_1 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \begin{bmatrix} \text{F}: & \boxed{1} \end{bmatrix} \end{bmatrix} \\ X_2 & \begin{bmatrix} \text{CAT} & A \end{bmatrix} \end{bmatrix}
$$

So the first state put on the chart is:

$$
\gamma \rightarrow \bullet X_0, [0,0], \begin{bmatrix} X_0 & \begin{bmatrix} \text{CAT} & S \end{bmatrix} \\ X_1 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & a \end{bmatrix} \end{bmatrix}
$$

This state is incomplete, so we go to the PREDICTOR and unify this state with the second rule, adding the new state:

$$
X_0 \rightarrow \bullet X_1 X_2, [0,0], \begin{bmatrix} X_0 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \boxed{1}\, a \end{bmatrix} \\ X_1 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \begin{bmatrix} \text{F} & \boxed{1} \end{bmatrix} \end{bmatrix} \\ X_2 & \begin{bmatrix} \text{CAT} & A \end{bmatrix} \end{bmatrix}
$$

But the PREDICTOR then then unifies this again with the second rule, adding the new state:

$$
X_0 \rightarrow \bullet X_1 X_2, [0,0], \begin{bmatrix} X_0 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \boxed{1}\, a \end{bmatrix} \\ X_1 & \begin{bmatrix} \text{CAT} & T \\ \text{F} & \begin{bmatrix} \text{F} & \begin{bmatrix} \text{F} & \boxed{1} \end{bmatrix} \end{bmatrix} \end{bmatrix} \\ X_2 & \begin{bmatrix} \text{CAT} & A \end{bmatrix} \end{bmatrix}
$$

We're now stuck in a loop where we create a new state, unify it with rule two, and produce a new state that will unify with rule two again.

To solve this problem, we need to restrict our view to only part of the dag instead of the whole thing. Then instead of the PREDICTOR unifying whole dags, it would just unify the sub-dags containing the category information.

15.8 Using the list approach to representing a verb's subcategorization frame, show how a grammar could handle any number of verb subcategorization frames with only the following two *VP* rules. More specifically, show the constraints that would have to be added to these rules to make this work.

$$VP \rightarrow Verb$$
$$VP \rightarrow VP\ X$$

The solution to this problem involves thinking about a recursive walk down a verb's subcategorization frame. This is a hard problem; you might consult Shieber (1986) if you get stuck.

Under these rules, each element of a verb's subcategorization frame is attached to its own *VP*. So each time we use the $VP \rightarrow VP\ X$ rule, the newly introduced *VP* should contain one more category expected by the verb. We can do this recursively, by defining the subcategorization of the child *VP* in terms of its parent.

This approach requires decomposing the subcategorization lists, so we introduce the syntax $\langle X \rangle + Y$ to mean that X is the first item in a list and Y is the remaining items.

$$\begin{bmatrix} VP & \begin{bmatrix} \text{CAT} & VP \\ \text{HEAD} & \boxed{1} \end{bmatrix} \\ Verb & \begin{bmatrix} \text{CAT} & Verb \\ \text{HEAD} & \boxed{1} \end{bmatrix} \end{bmatrix}$$

$$\begin{bmatrix} VP & \begin{bmatrix} \text{CAT} & VP \\ \text{HEAD} & [\ \text{SUBCAT} \ \boxed{1}\ ] \end{bmatrix} \\ VP & \begin{bmatrix} \text{CAT} & VP \\ \text{HEAD} & [\ \text{SUBCAT} \ \langle \boxed{2} \rangle + \boxed{1}\ ] \end{bmatrix} \\ X & [\ \text{CAT} \ \boxed{2}\ ] \end{bmatrix}$$

15.9 Page 524 showed how to use typed feature structures to represent constituency. Use that notation to represent rules 15.11, 15.12, and 15.13 shown on page 501.

$$\begin{bmatrix} \text{CAT} & VP \\ \text{HEAD} & \boxed{1} \\ \text{DTRS} & \left\langle \begin{bmatrix} \text{CAT} & Verb \\ \text{HEAD} & \boxed{1} \end{bmatrix}, [\ \text{CAT} \ NP\ ] \right\rangle \end{bmatrix}$$

$$\begin{bmatrix} \text{CAT} & NP \\ \text{HEAD} & \boxed{1} \\ \text{DTRS} & \left\langle \begin{bmatrix} \text{CAT} & Det \\ \text{HEAD} & [\ \text{AGREE} \ \boxed{2}\ ] \end{bmatrix}, \begin{bmatrix} \text{CAT} & Nominal \\ \text{HEAD} & \boxed{1}[\ \text{AGREE} \ \boxed{2}\ ] \end{bmatrix} \right\rangle \end{bmatrix}$$

$$\begin{bmatrix} \text{CAT} & Nominal \\ \text{HEAD} & \boxed{1} \\ \text{DTRS} & \left\langle \begin{bmatrix} \text{CAT} & Noun \\ \text{HEAD} & \boxed{1} \end{bmatrix} \right\rangle \end{bmatrix}$$

Chapter 16
Language and Complexity

16.1 Is the language $a^n b^2 a^n$ context free?

Yes. It can be generated with the following context free grammar:

$$S \rightarrow aSa$$
$$S \rightarrow bb$$

Technically, to confirm that the language is context free, we must also show that it is not a regular language. See Exercise 16.3 for details.

16.2 Use the pumping lemma to show this language is not regular:

$$L = x^n y^{n-1} \textit{likes tuna fish}, x \in A, y \in B$$

The pumping lemma states that if this language is regular, then there exist strings a, b and c such that $b \neq \epsilon$ and $ab^n c \in L$ for $n \geq 0$. Given our language, there are four possible assignments of a, b and c:

- b is all xs:

  $$a = x^q$$
  $$b = x^r$$
  $$c = x^s y^t \textit{likes tuna fish}$$

  By the pumping lemma, both $x^q x^r x^s y^t$ and $x^q (x^r)^2 x^s y^t$ must be in the language. Since strings in our language look like $x^n y^{n-1}$, we must have $q + r + s = t - 1 = q + 2r + s$. But then $r = 0$ and $y = \epsilon$, failing the $y \neq \epsilon$ requirement of the pumping lemma.
- b is all ys:

  $$a = x^q y^r$$
  $$b = y^s$$
  $$c = y^t \textit{likes tuna fish}$$

  By the pumping lemma, both $x^q y^r y^s y^t$ and $x^q y^r (y^s)^2 y^t$ must be in the language. Since strings in our language look like $x^n y^{n-1}$, we must have $r + s + t - 1 = q = r + 2s + t - 1$. But then $r = 0$ and $y = \epsilon$, failing the $y \neq \epsilon$ requirement of the pumping lemma.
- b is both xs and ys:

  $$a = x^q$$
  $$b = x^r y^s$$
  $$c = y^t \textit{likes tuna fish}$$

  By the pumping lemma, $x^q (x^r y^s)^2 y^t = x^q x^r y^s x^r y^s y^t$ must be in the language. But this string allows xs to follow ys, which is not possible in our language.

- b contains *likes tuna fish*. By the pumping lemma, we should be able to generate b^n for any positive n, but our language is limited to a single *likes tuna fish*, so b cannot contain *likes tuna fish*.

Thus, since no string in our language can be divided into a, b and c appropriately for the pumping lemma, our language is not regular.

16.3 Partee et al. (1990) showed that the language $xx^R, x \in a, b*$ is not regular, by intersecting it with the regular language aa^*bbaa^*. The resulting language is $a^nb^2a^n$. Use the pumping lemma to show that this language is not regular, completing the proof that $xx^R, x \in \{a, b\}*$ is not regular.

By the pumping lemma, there should exist strings x, y and z such that $y \neq \epsilon$ and $xy^nz \in a^nb^2a^n$ for $n \geq 0$. Given our language, there are three possible assignments of x, y and z:

- y is all as and before the first b:

$$x = a^q$$
$$y = a^r$$
$$z = a^sb^2a^t$$

  By the pumping lemma, both $a^qa^ra^sb^2a^t$ and $a^q(a^r)^2a^sb^2a^t$ must be in the language. Since strings in our language look like $a^nb^2a^n$, we must have $q + r + s = t = q + 2r + s$. But then $r = 0$ and $y = \epsilon$, failing the $y \neq \epsilon$ requirement of the pumping lemma.

- y is all as and is after the last b:

$$x = a^qb^2a^r$$
$$y = a^s$$
$$z = a^t$$

  By the pumping lemma, both $a^qb^2a^ra^sa^t$ and $a^qb^2a^r(a^s)^2a^t$ must be in the language. Since strings in our language look like $a^nb^2a^n$, we must have $r + s + t = q = r + 2s + t$. But then $r = 0$ and $y = \epsilon$, failing the $y \neq \epsilon$ requirement of the pumping lemma.

- y contains any bs. By the pumping lemma, we should be able to generate y^n for any positive n, but our language is limited to a maximum of 2 bs, so y cannot contain bs.

So the language is not a regular language, and since it can be expressed with a context free grammar, it is a context free language.

16.4 Build a context-free grammar for the language

$$L = \{xx^R | x \in \{a, b\}*\}$$

Given that x^R means x reversed, the following grammar produces L:

$$S \rightarrow aSa$$
$$S \rightarrow bSb$$
$$S \rightarrow \epsilon$$

Chapter 17
The Representation of Meaning

17.1 Peruse your daily newspaper for three examples of ambiguous sentences or headlines. Describe the various sources of the ambiguities.

The following ambiguous headlines are from BBC news articles:

US offensive in Euphrates region Either *offensive* is an adjective, in which case the US has acted inappropriately near the Euphrates, or *offensive* is a noun, in which case the US is deploying troops there.

Baby doctor cleared of misconduct Either *Baby* indicates the age of *doctor*, in which case a very young doctor was cleared of misconduct, or *Baby* indicates the type of *doctor*, in which case a doctor who takes care of infants was cleared.

PM vows to stand by Afghanistan Either *stand by* is used literally, in which case the prime minister will be physically present somewhere near the country of Afghanistan, or *stand by* is used figuratively, in which case the prime minister will support the decisions made by the governing body of Afghanistan.

17.2 Consider a domain in which the word *coffee* can refer to the following concepts in a knowledge-based system: a caffeinated or decaffeinated beverage, ground coffee used to make either kind of beverage, and the beans themselves. Give arguments as to which of the following uses of coffee are ambiguous and which are vague.

1. I've had my coffee for today.

   This use is vague - it is clear that the beverage is what the speaker had, but it is not clear whether the beverage was caffeinated or decaffeinated.

2. Buy some coffee on your way home.

   This use is ambiguous - this could be a request to buy beans, ground coffee, or beverages.

3. Please grind some more coffee.

   This use is vague - it is clear that coffee beans are what is to be ground, but it is not clear whether the beans should be caffeinated or decaffeinated.

17.3 The following rule, which we gave as a translation for Example 17.26, is not a reasonable definition of what it means to be a vegetarian restaurant.

$$\forall x VegetarianRestaurant(x) \Rightarrow Serves(x, VegetarianFood)$$

Give a FOL rule that better defines vegetarian restaurants in terms of what they serve.

$$\begin{aligned}&\forall x VegetarianRestaurant(x) \Rightarrow \\ &\quad Serves(x, VegetarianFood) \wedge \\ &\quad (\forall y Serves(x, y) \Rightarrow Is(y, VegetarianFood))\end{aligned}$$

17.4 Give FOL translations for the following sentences:

1. Vegetarians do not eat meat.
$$\forall x Vegetarian(x) \Rightarrow \neg Eats(x, Meat)$$
2. Not all vegetarians eat eggs.
$$\exists x Vegetarian(x) \wedge \neg Eats(x, Eggs)$$

17.5 Give a set of facts and inferences necessary to prove the following assertions:

1. McDonald's is not a vegetarian restaurant.
2. Some vegetarians can eat at McDonald's.

Don't just place these facts in your knowledge base. Show that they can be inferred from some more general facts about vegetarians and McDonald's.

The initial knowledge base:

$$\begin{aligned}&\forall x Serves(x, Meat) \Rightarrow \neg VegetarianRestaurant(x) \\ &\forall x Serves(x, Vegetables) \Rightarrow \exists y Vegetarian(y) \wedge CanEatAt(x, y) \\ &Serves(McDonalds, Meat) \\ &Serves(McDonalds, Vegetables)\end{aligned}$$

Inferring that McDonald's is not a vegetarian restaurant:

$$\frac{\begin{aligned}&Serves(McDonalds, Meat) \\ &\forall x Serves(x, Meat) \Rightarrow \neg VegetarianRestaurant(x)\end{aligned}}{\neg VegetarianRestaurant(McDonalds)}$$

Inferring that some vegetarians can eat at McDonald's:

$$\frac{\begin{aligned}&Serves(McDonalds, Vegetables) \\ &\forall x Serves(x, Vegetables) \Rightarrow \exists y Vegetarian(y) \wedge CanEatAt(x, y)\end{aligned}}{\exists y Vegetarian(y) \wedge CanEatAt(McDonalds, y)}$$

17.6 For the following sentences, give FOL translations that capture the temporal relationships between the events.

1. When Mary's flight departed, I ate lunch.

$$\begin{aligned}&\exists d, e, f, i_d, i_e, n_d, n_e \\ &\quad Flight(f) \wedge Passenger(f, Mary) \wedge \\ &\quad Departing(d) \wedge Departer(d, f) \wedge \\ &\quad Eating(e) \wedge Eater(e, Speaker) \wedge Meal(e, Lunch) \wedge \\ &\quad IntervalOf(d, i_d) \wedge IntervalOf(e, i_e) \wedge \\ &\quad EndPoint(i_d, n_d) \wedge StartPoint(i_e, n_e) \wedge Precedes(n_d, n_e)\end{aligned}$$

2. When Mary's flight departed, I had eaten lunch.

$$\begin{aligned}&\exists d, e, f, i_d, i_e, n_d, n_e \\ &\quad Flight(f) \wedge Passenger(f, Mary) \wedge \\ &\quad Departing(d) \wedge Departer(d, f) \wedge \\ &\quad Eating(e) \wedge Eater(e, Speaker) \wedge Meal(e, Lunch) \wedge \\ &\quad IntervalOf(d, i_d) \wedge IntervalOf(e, i_e) \wedge \\ &\quad StartPoint(i_d, n_d) \wedge EndPoint(i_e, n_e) \wedge Precedes(n_e, n_d)\end{aligned}$$

17.7 On page 560, we gave the representation $Near(Centro, Bacaro)$ as a translation for the sentence *Centro is near Bacaro*. In a truth-conditional semantics, this formula is either true or false given some model. Critique this truth-conditional approach with respect to the meaning of words like *near*.

Words like *near* require a particular frame of reference to be interpreted correctly. For example, if the distance between *Centro* and *Bacaro* was around 5 miles, it might be appropriate to consider them *near* each other if traveling by car, but not if traveling by foot. Thus using predicates like $Near(x, y)$ where for a given two places the predicate must be either true or false, is only practical if there is only a single frame of reference that the system must understand.

Chapter 18
Computational Semantics

18.1 Develop a set of grammar rules and semantic attachments to handle predicate adjectives such as the following:

1. Flight 308 from New York is expensive.
2. Murphy's restaurant is cheap.

To produce representations like *Cheap*(*MurphysRestaurant*) we can use the following rules:

VP	→ *Verb Adj*	{*Verb.sem*(*Adj.sem*)}
Verb	→ *is*	$\{\lambda P.\lambda x.P(x)\}$
Adj	→ *expensive*	{*Expensive*}
Adj	→ *cheap*	{*Cheap*}

Applying these rules to the latter sentence looks like:

$$\begin{aligned} &\lambda x.x(MurphysRestaurant)(\lambda P.\lambda x.P(x)(Cheap)) \\ &= \lambda x.x(MurphysRestaurant)(\lambda x.Cheap(x)) \\ &= Cheap(MurphysRestaurant) \end{aligned}$$

18.2 Develop a set of grammar rules and semantic attachments to handle so-called *control verbs* as in the following:

1. Franco *decided* to leave.
2. Nicolas *told* Franco to go to Frasca.

The first of these is an example of subject control—*Franco* plays the role of the agent for both *decide* and *leave*. The second is an example of object control—there *Franco* is the person being told and the agent of the going event. The challenge in creating attachments for these rules is to properly incorporate the semantic representation of a single noun phrase into two roles.

One approach to this problem is to give predicates like *decide* and *tell* two extra parameters - one for the other event they take as an argument, and one which is that event's predication. In this way, the control predicates can pass all the necessary information on to their

controlled predicates. The following rules take that approach:

S → *NP VP*	$\{$*NP.sem*$($*VP.sem*$)\}$
VP → *Verb to VP*	$\{$*Verb.sem*$($*VP.sem*$)\}$
VP → *Verb NP to VP*	$\{$*NP.sem*$($*Verb.sem*$)($*VP.sem*$)\}$
VP → *Verb to NP*	$\{$*NP.sem*$($*Verb.sem*$)\}$
Verb → *leave*	$\{\lambda x.\lambda e.$*Leaving*$(e) \wedge$ *Leaver*$(e, x)\}$
Verb → *go*	$\{\lambda w.\lambda x\lambda e.$*Going*$(e) \wedge$ *Goer*$(e, x) \wedge$ *Destination*$(e, w)\}$
Verb → *decided*	$\{\lambda P\lambda x.\lambda d\lambda e.P(x)(e)$ $\wedge$ *Deciding*$(d) \wedge$ *Decider*$(d, x) \wedge$ *Decision*$(d, e)\}$
Verb → *told*	$\{\lambda w.\lambda P\lambda x.\lambda d\lambda e.P(w)(e) \wedge$ *Telling*(d) $\wedge$ *Hearer*$(d, w) \wedge$ *Speaker*$(d, x) \wedge$ *Message*$(d, e)\}$

Note that we had to use λ for events instead of $\exists$ as before. This was necessary to make sure that both the controlling and controlled verbs referred to the same events. As a result, when the semantic analysis of a sentence is complete, we should read any remaining λ as $\exists$.

Here is the derivation of the VP *go to Frasca* using these rules:

NP.sem$($*Verb.sem*$)$
$\lambda x.x($*Frasca*$)(\lambda w.\lambda x\lambda e.$*Going*$(e) \wedge$ *Goer*$(e, x) \wedge$ *Destination*$(e, w))$
$\lambda w.\lambda x\lambda e.$*Going*$(e) \wedge$ *Goer*$(e, x) \wedge$ *Destination*$(e, w)($*Frasca*$)$
$\lambda x\lambda e.$*Going*$(e) \wedge$ *Goer*$(e, x) \wedge$ *Destination*$(e, Frasca)$

And here is the derivation of the VP *told Franco to go to Frasca*:

NP.sem$($*Verb.sem*$)($*VP.sem*$)$
$\lambda x.x($*Franco*$)($*Verb.sem*$)($*VP.sem*$)$
Verb.sem$($*Franco*$)($*VP.sem*$)$
$\lambda w.\lambda P\lambda x.\lambda d\lambda e.P(w)(e) \wedge$ *Telling*$(d) \wedge$ *Hearer*(d, w)
$\wedge$*Speaker*$(d, x) \wedge$ *Message*$(d, e)($*Franco*$)($*VP.sem*$)$
$\lambda P\lambda x.\lambda d\lambda e.P($*Franco*$)(e) \wedge$ *Telling*$(d) \wedge$ *Hearer*$(d,$ *Franco*$)$
$\wedge$*Speaker*$(d, x) \wedge$ *Message*$(d, e)($*VP.sem*$)$
$\lambda P\lambda x.\lambda d\lambda e.P($*Franco*$)(e) \wedge$ *Telling*$(d) \wedge$ *Hearer*$(d,$ *Franco*$) \wedge$ *Speaker*(d, x)
$\wedge$*Message*$(d, e)(\lambda x\lambda e.$*Going*$(e) \wedge$ *Goer*$(e, x) \wedge$ *Destination*$(e, Frasca))$
$\lambda x.\lambda d\lambda e.$*Going*$(e) \wedge$ *Goer*$(e,$ *Franco*$) \wedge$ *Destination*$(e, Frasca) \wedge$ *Telling*(d)
$\wedge$*Hearer*$(d,$ *Franco*$) \wedge$ *Speaker*$(d, x) \wedge$ *Message*(d, e)

18.3 None of the attachments given in this chapter provide temporal information. Augment a small number of the most basic rules to add temporal information along the lines sketched in Chapter 17. Use your rules to create meaning representations for the following examples:

1. Flight 299 departed at 9 o'clock.
2. Flight 208 will arrive at 3 o'clock.
3. Flight 1405 will arrive late.

We first define some new temporal predicates for convenience:

$\forall d, e \textit{Before}(d, e) \rightarrow \exists i, j \textit{End}(d, i) \wedge \textit{Start}(e, j) \wedge \textit{Precedes}(i, j)$
$\forall d, e \textit{At}(d, e) \rightarrow \exists i, j \textit{Start}(d, i) \wedge \textit{Start}(e, i) \wedge \textit{End}(d, j) \wedge \textit{End}(e, j)$

And now the rules for creating temporal representations:

S → NP VP	$\{\lambda e.\textit{NP.sem}(\textit{VP.sem(e)})\}$
VP → Aux VP	$\{\textit{Aux.sem}(\textit{VP.sem})\}$
VP → Verb PP	$\{\textit{PP.sem}(\textit{Verb.sem})\}$
VP → Verb Adv	$\{\textit{Adv.sem}(\textit{Verb.sem})\}$
PP → Prep NP	$\{\textit{NP.sem}(\textit{Prep.sem})\}$
Verb → Verb Suffix	$\{\textit{Suffix.sem}(\textit{VP.sem})\}$
Verb → depart	$\{\lambda e.\lambda x.\textit{Departing}(e) \wedge \textit{Departer}(e, x)\}$
Verb → arrive	$\{\lambda e.\lambda x.\textit{Arriving}(e) \wedge \textit{Arriver}(e, x)\}$
Aux → will	$\{\lambda P.\lambda e.\textit{Before}(\textit{Now}, e) \wedge P(e)\}$
Suffix → -ed	$\{\lambda P.\lambda e.\textit{Before}(e, \textit{Now}) \wedge P(e)\}$
Prep → at	$\{\lambda x.\lambda P.\lambda e.\textit{At}(e, x) \wedge P(e)\}$
Adv → late	$\{\lambda P.\lambda e.\textit{Before}(\textit{ExpectedInterval}(e), e) \wedge P(e)\}$

To see these rules in action, let's derive the representation for the second sentence. We'll start with the PP *at 3 o'clock*:

$\textit{NP.sem}(\textit{Prep.sem})$
$\lambda x.x(\textit{3:00})(\textit{Prep.sem})$
$\lambda x.x(\textit{3:00})(\lambda x.\lambda P.\lambda e.\textit{At}(e, x) \wedge P(e))$
$\lambda P.\lambda e.\textit{At}(e, \textit{3:00}) \wedge P(e)$

Now the VP *arrive at 3 o'clock*:

$\textit{PP.sem}(\textit{Verb.sem})$
$\textit{PP.sem}(\lambda e.\lambda x.\textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda P.\lambda e.\textit{At}(e, \textit{3:00}) \wedge P(e)(\lambda e.\lambda x.\textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda e.\textit{At}(e, \textit{3:00}) \wedge \lambda x.\textit{Arriving}(e) \wedge \textit{Arriver}(e, x)$
$\lambda e.\lambda x.\textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x)$

Now the VP *will arrive at 3 o'clock*:

$\textit{Aux.sem}(\textit{VP.sem})$
$\textit{Aux.sem}(\lambda e.\lambda x.\textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda P.\lambda e.\textit{Before}(\textit{Now}, e) \wedge P(e)(\lambda e.\lambda x.\textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda e.\textit{Before}(\textit{Now}, e) \wedge \lambda x.\textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x)$
$\lambda e.\lambda x.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x)$

And finally the whole sentence:

$\lambda e.\textit{NP.sem}(\textit{VP.sem}(e))$
$\lambda e.\textit{NP.sem}(\lambda e.\lambda x.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x)(e))$
$\lambda e.\textit{NP.sem}(\lambda x.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda e.\lambda x.x(\textit{F208})(\lambda x.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x))$
$\lambda e.(\lambda x.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, x))(\textit{F208})$
$\lambda e.\textit{Before}(\textit{Now}, e) \wedge \textit{At}(e, \textit{3:00}) \wedge \textit{Arriving}(e) \wedge \textit{Arriver}(e, \textit{F208})$

18.4 As noted in Chapter 17, the present tense in English can be used to refer to either the present or the future. However, it can also be used to express habitual behavior, as in the following:

1. Flight 208 leaves at 3 o'clock.

This could be a simple statement about today's Flight 208, or alternatively it might state that this flight leaves at 3 o'clock every day. Create a FOL meaning representation along with appropriate semantic attachments for this habitual sense.

Assuming a suitably defined *During* predicate, one possible solution is to have the present tense introduce a universal quantifier over days:

$\textit{Verb} \rightarrow \textit{Verb PRES} \quad \{\lambda e.\forall d \textit{Day}(d) \Rightarrow \textit{Verb.sem}(e) \wedge \textit{During}(e, d)\}$

This says roughly that the event occurs (at least once) every day. Of course, this solution is not very general, as other uses of habituals may require longer or shorter spans than a day.

18.5 Implement an Earley-style semantic analyzer based on the discussion on page 604.

It may simplify the implementation to use a language that explicitly supports λ and λ-reduction, e.g. lisp, scheme, python, etc. Then the semantic attachments can just be normal λ-functions, and passed around and applied as usual.

The key to making such a type-driven approach work is the ability to reason not only about the types of the semantic attachments, but also about the types of the values that result from the λ-reductions (the types of the return values).

18.6 It has been claimed that it is not necessary to explicitly list the semantic attachment for most grammar rules. Instead, the semantic attachment for a rule should be inferable from the semantic types of the rule's constituents. For example, if a rule has two constituents, where one is a single-argument λ-expression and the other is a constant, then the semantic attachment must apply the λ-expression to the constant. Given the attachments presented in this chapter, does this *type-driven semantics* seem like a reasonable idea? Explain your answer.

Using this approach would be difficult given that even noun phrases are treated as λ-expressions in this chapter. Consider the simple sentence *Maharani closed*. The representations from the chapter look like:

$$\lambda x.x(\textit{Maharani})$$
$$\lambda x.\textit{Closed}(x)$$

Now, when we see the *NP VP* constituent, there is no obvious way to guess whether we apply the verb function to the noun (wrong) or the noun function to the verb (right) because both *Maharani* and *Closed* have the same type: a single-argument λ-expression.

18.8 Using a phrasal search on your favorite Web search engine, collect a small corpus of *the tip of the iceberg* examples. Be certain that you search for an appropriate range of examples (i.e., don't just search for "the tip of the iceberg"). Analyze these examples and come up with a set of grammar rules that correctly accounts for them.

Some examples from the web:

- *the tip of an iceberg of* {*cool designs,tremendous proportions*}
- *the tip of* {*fraud,xenophobic,very large...*} *iceberg*
- *the tip of* {*a,the,my,...*} *iceberg*
- *the* {*visible,...*} *tip of the iceberg*

One set of rules that could account for these examples:

NP $\rightarrow$ *TipNP of IcebergNP*	{*TipNP.sem*(*IcebergNP.sem*)}
TipNP $\rightarrow$ *Det TipNominal*	{*Det.sem*(*TipNominal.sem*)}
TipNominal $\rightarrow$ *AdjP TipNominal*	{*AdjP.sem*(*TipNominal.sem*)}
TipNominal $\rightarrow$ *tip*	{λx.*Beginning(x)*}
IcebergNP $\rightarrow$ *Det IcebergNominal*	{*Det.sem*(*IcebergNominal.sem*)}
IcebergNominal $\rightarrow$ *AdjP IcebergNominal*	{*AdjP.sem*(*IcebergNominal.sem*)}
IcebergNominal $\rightarrow$ *NP IcebergNominal*	{*NP.sem*(*IcebergNominal.sem*)}
IcebergNominal $\rightarrow$ *IcebergNominal PP*	{*PP.sem*(*IcebergNominal.sem*)}
IcebergNominal $\rightarrow$ *iceberg*	{*LargeThing*}

18.9 Collect a similar corpus of examples for the idiom *miss the boat*. Analyze these examples and come up with a set of grammar rules that correctly accounts for them.

Some examples from the web:

- *miss* {*the,your,...*} *boat*
- *miss the boat* {*again,in China,on aged care reform,...*}

One set of rules that could account for these examples:

VP $\rightarrow$ *MissTheBoatVP*	{*MissTheBoatVP.sem*}
MissTheBoatVP $\rightarrow$ *MissTheBoatVP PP*	{*PP.sem*(*MissTheBoatNP.sem*)}
MissTheBoatVP $\rightarrow$ *miss BoatNominal*	$\{\lambda x.\exists e$*Missing*$(e) \wedge$ *Misser*$(e, x) \wedge$ *ThingMissed*$(e,$ *BoatNominal.sem*$)\}$
BoatNominal $\rightarrow$ *Det boat*	{*Det.sem*(*ImportantOpportunity*)}

Chapter 19
Lexical Semantics

19.1 From a dictionary of your choice, collect three definitions of ordinary non-technical English words that you feel are flawed in some way. Explain the nature of the flaw and how it might be remedied.

There are a variety of reasonable responses to this question, but the most obvious ones include some form of circularity, i.e., the definition of a word uses the word itself, or refers to a word (which refers to a word . . .) which refers to the original word.

19.2 Give a detailed account of similarities and differences among the following set of lexemes: *imitation*, *synthetic*, *artificial*, *fake*, and *simulated*.

Some possible similarities and differences between these words:

- *fake*, *imitation* and *simulated* all imply that the object was intentionally created to look or function like another object
- *synthetic* and *artificial* imply that the object was not created by natural means, but do not necessarily imply that it was created to mimic another object

19.3 Examine the entries for these lexemes in WordNet (or some dictionary of your choice). How well does it reflect your analysis?

WordNet puts *fake*, *imitation* and *simulated* into in the same synset, indicating that they all share a sense with roughly the same meaning. WordNet indicates that *artificial* is SIMILAR-TO both *synthetic* and *fake/imitation/simulated*, yet does not list *synthetic* as SIMILAR-TO *fake/imitation/simulated*.

19.4 The WordNet entry for the noun *bat* lists six distinct senses. Cluster these senses by using the definitions of homonymy and polysemy given in this chapter. For any senses that are polysemous, give an argument as to how the senses are related.

One possible grouping of senses:

Animal bats

- bat#1: nocturnal mouselike mammal. . .

Bats in sports

- bat#5: a club used for hitting a ball in various games. . .
- bat#3: a small racket. . . for playing squash (*A type of bat#5*)
- bat#4: the club used in playing cricket (*A type of bat#5*)
- bat#2: (baseball) a turn trying to get a hit (*A use of bat#5*)

19.5 Assign the various verb arguments in the following WSJ examples to their appropriate thematic roles, using the set of roles shown in Fig. 19.6.

1. The intense heat buckled the highway about three feet.
2. He melted her reserve with a husky-voiced paean to her eyes.
3. But Mingo, a major Union Pacific shipping center in the 1890s, has melted away to little more than the grain elevator now.

Part of the goal of this exercise is to understand why there is still no universally agreed-upon set of thematic roles: for any given set, there are always still constituents that don't quite match.

Given the thematic roles of Fig. 19.6, one reasonable assignment of thematic roles is:

1. [FORCE The intense heat] buckled [THEME the highway] [RESULT about three feet].
2. [AGENT He] melted [THEME her reserve] [INSTRUMENT with a husky-voiced paean to her eyes].
3. But [EXPERIENCER Mingo, a major Union Pacific shipping center in the 1890s,] has melted away [RESULT to little more than the grain elevator] now.

19.6 Using WordNet, describe appropriate selectional restrictions on the verbs *drink*, *kiss*, and *write*.

drink

AGENT living thing#1: a living (or once living) entity

THEME beverage#1: any liquid suitable for drinking

kiss

AGENT animal#1: a living organism... [having] voluntary movement

THEME physical object#1: a tangible and visible entity...

write

AGENT writer#2: a person who is able to write...

THEME writing#2: the work of a writer...

19.7 Collect a small corpus of examples of the verbs *drink*, *kiss*, and *write*, and analyze how well your selectional restrictions worked.

Some phrases from the web that break the selectional restrictions:

drink caffeine In WordNet, *caffeine* is a compound, not a beverage.

sun kissed In WordNet, *sun* is a star, not an animal.

yahoo.com wrote In WordNet, *Yahoo* is software, not a writer.

19.8 Consider the following examples from McCawley (1968):

> My neighbor is a father of three.
>
> ?My buxom neighbor is a father of three.

What does the ill-formedness of the second example imply about how constituents satisfy or violate selectional restrictions?

> Selectional restrictions must apply not to individual lexical items but to the entire constituent. In other words, we must semantically interpret the entire phrase before we attempt to apply selectional restrictions to it.

19.9 Find some articles about business, sports, or politics from your daily newspaper. Identify as many uses of conventional metaphors as you can in these articles. How many of the words used to express these metaphors have entries in either WordNet or your favorite dictionary that directly reflect the metaphor.

> A good set of metaphors are available from the Berkeley Conceptual Metaphor site (`http://cogsci.berkeley.edu/lakoff/`). For example:
>
> **Competition Is A Race** e.g., *The arms race*, corresponding to WordNet's race#1.
>
> **Ideas Are Food** e.g., *half-baked idea*, corresponding to WordNet's half-baked#1.
>
> Note that both WordNet metaphorical senses were marked #1, meaning that they were the first and most common uses of the words – even more common than the literal uses.

19.10 Consider the following example:

> The stock exchange wouldn't talk publicly, but a spokesman said a news conference is set for today to introduce a new technology product.

Assuming that stock exchanges are not the kinds of things that can literally talk, give a sensible account for this phrase in terms of a metaphor or metonymy.

> The people that "wouldn't talk publicly" here are the people in charge of the company that runs the stock exchange. Thus, this appears to be a multilayered metonomy:
>
> *HeadsOfOrganization* ↔ *Organization* ↔ *ProcessRunByOrganization*

19.11 Choose an English verb that occurs in both FrameNet and PropBank. Compare the FrameNet and PropBank representations of the arguments of the verb.

> SemLink (`http://verbs.colorado.edu/semlink/`) provides a browser for viewing predicates aligned across FrameNet, PropBank and other sources. This can be used to quickly examine the different role sets, e.g., for the predicate *sell*:

PropBank	FrameNet
Arg0:Seller	Seller
Arg1:Thing Sold	Goods
Arg2:Buyer	Buyer
Arg3:Price Paid	Money / Rate [*non-core roles*]
Arg4:Benefactive	Purpose / Reason [*non-core roles*]

Note that core roles Arg3 and Arg4 in PropBank correspond to several different non-core roles in FrameNet. In particular, PropBank introduces an Arg4:Benefactive role, even though it already has an ARGM-PRP which more closely corresponds to the Purpose role in FrameNet.

Chapter 20
Computational Lexical Semantics

20.1 Collect a small corpus of example sentences of varying lengths from any newspaper or magazine. Using WordNet or any standard dictionary, determine how many senses there are for each of the open-class words in each sentence. How many distinct combinations of senses are there for each sentence? How does this number seem to vary with sentence length?

An example from Wikipedia, with the number of WordNet senses for each open-class word indicated by (N):

At 05:20:59 GMT(1) this morning(4), the Echostar(0) XI(2) satellite(3) was successfully(1) launched(6) into a geosynchronous(1) transfer(6) orbit(5) atop a Zenit-3SL(0) carrier(11) rocket(5).

For this sentence, there are

$$1 * 4 * 2 * 3 * 1 * 6 * 1 * 6 * 5 * 11 * 5 = 237600$$

possible combinations of senses. Since the number of distinct combinations is just the product of the number of senses for each word, in general we expect that the longer the sentence is, the greater the number of possible sense combinations.

20.2 Using WordNet or a standard reference dictionary, tag each open-class word in your corpus with its correct tag. Was choosing the correct sense always a straightforward task? Report on any difficulties you encountered.

WordNet senses are fine-grained and often difficult to assign with confidence, but here is a reasonable assignment of specific senses to the sentence from Exercise 20.1:

At 05:20:59 GMT#1 this morning#1, the Echostar XI#1 satellite#1 was successfully#1 launched#2 into a geosynchronous#1 transfer#1 orbit#1 atop a Zenit-3SL carrier#2 rocket#1.

An example difficulty: is the appropriate meaning of *XI* in this scenario "the cardinal number that is the sum of ten and one" or is it "the 14th letter of the Greek alphabet"? The sense assignment above assumes the former, but the latter could be a reasonable choice as well.

20.3 Using the same corpus, isolate the words taking part in all the verb-subject and verb-object relations. How often does it appear to be the case that the words taking part in these relations could be disambiguated with only information about the words in the relation?

Many words cannot be disambiguated using just verb-subject and verb-object relations. For example, consider the sentence from Exercise 20.1. The subject-verb relation between *satellite* and *launched*

is useful to distinguish between "begin with vigor" (launch#4) and "propel with force" (launch#2), since *satellites* generally don't experience vigor. However, this relation is not so useful for distinguishing between "propel with force" (launch#2) and "launch on a maiden voyage" (launch#3), as a *satellite* could undergo either of these.

20.4 Between the words *eat* and *find*, which would you expect to be more effective in selectional restriction-based sense disambiguation? Why?

Generally, we expect words with stricter selectional restrictions to be more useful because they allow fewer senses in their arguments. For example, if we saw *eat a dish*, we could rule out the sense dish#1 "a container for holding or serving food", which we could not rule out if we saw *find a dish*.

20.5 Using your favorite dictionary, simulate the original Lesk word overlap disambiguation algorithm described on page 647 on the phrase *Time flies like an arrow*. Assume that the words are to be disambiguated one at a time, from left to right, and that the results from earlier decisions are used later in the process.

A subset of the WordNet senses:

time#n#5	(the continuum of experience in which events pass from the future through the present to the past)
time#v#1	(measure the time or duration of an event or action or the person who performs an action in a certain period of time) "he clocked the runners"
flies#n#1	(two-winged insects characterized by active flight)
flies#v#8	(pass away rapidly) "Time flies like an arrow"; "Time fleeing beneath him"
like#v#4	(feel about or towards; consider, evaluate, or regard) "How did you like the President's speech last night?"
like#a#1	(resembling or similar; having the same or some of the same characteristics; often used in combination) "suits of like design"; "a limited circle of like minds"; "members of the cat family have like dispositions"; "as like as two peas in a pod"; "doglike devotion"; "a dream-like quality"
arrow#n#1	(a mark to indicate a direction or relation)
arrow#n#2	(a projectile with a straight thin shaft and an arrowhead on one end and stabilizing vanes on the other; intended to be shot from a bow)

Disambiguating *time*:

- time#n#5 shares *pass* with flies#v#8
- time#v#1 shares *time* with flies#v#8

There is a tie, so we should select the most frequent sense. But WordNet does not compare sense frequencies between nouns and verbs, so we cannot select a sense for *time*.

Disambiguating *flies*:

- flies#n#1 shares *two* with like#a#1
- flies#v#8 shares *pass* with time#n#5, *time* with time#v#1 and *like* with like#v#4 and like#a#1

So we select flies#v#8.

Disambiguating *like*:

- like#v#4 shares *like* with flies#v#8
- like#a#1 shares *like* with flies#v#8 (and *two* with flies#n#1, but we have already decided on flies#v#8)

There is a tie, so we should select the most frequent sense. But WordNet does not compare sense frequencies between verbs and adjectives, so we cannot select a sense for *like*.

Disambiguating *arrow*:

- arrow#n#1 shares nothing with any other signatures
- arrow#n#2 shares nothing with any other signatures

Since there is a tie, we select the most frequent sense, arrow#n#1.

In the end, we were only able to assign senses to *flies* and *arrow*, with the latter simply assigned the most frequent sense. Performance would probably have been even worse had we included all the other possible senses of each of these words in WordNet - there simply was not enough overlap in the sense glosses and definitions to determine appropriate senses.

20.6 Build an implementation of your solution to the previous exercise. Using WordNet, implement the original Lesk word overlap disambiguation algorithm described on page 647 on the phrase *Time flies like an arrow*.

```
import wordnet

punct_matcher = re.compile('[%s]+' % re.escape(string.punctuation))
stop_words = set(line.strip() for line in open('stop_words.txt'))

def get_senses(stems):

    # collect synsets for each stem
    default_synsets = []
    synset_lists = []
    synset_sigs = {}
    for stem in stems:

        # don't look for senses for stopwords
        if stem in stop_words:
            synset_lists.append([])
            default_synsets.append(None)

        # get synsets from WordNet, calculate signatures and
        # save them, and set default synset to the first one
        else:
            synsets = wordnet.synsets(stem)
            synset_lists.append(synsets)
            default_synsets.append(synsets[0])
            for synset in synsets:

                # the signature is set of all words in the
```

```
            # definitions and examples, skipping stopwords
            signature = set()
            text_lists = synset.definitions, synset.examples
            for text_list in text_lists:
                for text in text_list:
                    text = punct_matcher.sub('', text)
                    signature.update(text.lower().split())
            synset_sigs[synset] = signature - stop_words

    # fill in the senses incrementally
    for i, synset_list in enumerate(synset_lists):

        # combine the signatures of all other synsets currently
        # still being considered for the words
        other_sig = set()
        for other_list in synset_lists[:i] + synset_lists[i + 1:]:
            for synset in other_list:
                other_sig.update(synset_sigs[synset])

        # for each synset of the word, count the overlapping
        # words between its signature and the combined signature
        overlap_counts = {}
        for synset in synset_list:
            overlaps = synset_sigs[synset] & other_sig
            overlap_counts[synset] = len(overlaps)

        # select the synset with the greatest overlap, or if no
        # synsets had any overlap, use the most frequent sense
        if synset_list:
            max_synset = max(synset_list, key=overlap_counts.get)
            if overlap_counts[max_synset] == 0:
                max_synset = default_synsets[i]
            synset_lists[i] = [max_synset]

    # return the selected synsets (or None for stopwords)
    return [synset_list[0] if synset_list else None
            for synset_list in synset_lists]
```

20.7 Implement and experiment with a decision-list sense disambiguation system. As a model, use the kinds of features shown in Fig. 20.2 on page 643. Use one of the publicly available decision-list packages like WEKA (or see Russell and Norvig (2002) for more details on implementing decision-list learning yourself). To facilitate evaluation of your system, you should obtain one of the freely available sense-tagged corpora.

Data for a variety of different WSD tasks are available from the SensEval and SemEval competitions:

`http://www.senseval.org/`
`http://nlp.cs.swarthmore.edu/semeval/`

A good solution to this problem will involve not only training a model on the data, but also inspecting the model, figuring out some of the errors it's making, and then introducing features accordingly. These kinds of decision list models are unlikely to produce state-of-the-art performance, but constructing them should at least build some intuitions about what kinds of features are important for word sense disambiguation.

20.8 Evaluate two or three of the similarity methods from the publicly available Wordnet Similarity package (Pedersen et al., 2004). You might do this by hand-labeling some word pairs with similarity scores and seeing how well the algorithms approximate your hand labels.

In general, comparing the absolute values of the various similarity metrics is probably not as useful as comparing the relative orderings. For example, both the Resnik and Jiang & Conrath measures identify *nickel* as being more related to *fund* than it is to *scale*, while the Path Length measure identifies these pairs as being equally related:

	nickel-fund	nickel-scale
Path Length	0.1429	0.1429
Resnik	6.6478	6.4379
Jiang & Conrath	0.1516	0.1211

20.9 Implement a distributional word similarity algorithm that can take different measures of association and different measures of vector similarity. Now evaluate two measures of association and two measures of vector similarity from Fig. 20.13 on page 666. Again, you might do this by hand-labeling some word pairs with similarity scores and seeing how well the algorithms approximate these labels.

```
from __future__ import division
import collections
import math
ddict = collections.defaultdict

# a generic model for calculating word similarity, parameterized
# by two functions: one for producing a vector from a word, and
# one for comparing two vectors
class WordSimilarityModel(object):
    def __init__(self, get_vector, get_similarity):
        self._get_vector = get_vector
        self._get_similarity = get_similarity
    def __call__(self, word1, word2):
        vector1 = self._get_vector(word1)
        vector2 = self._get_vector(word2)
        return self._get_similarity(vector1, vector2)

# a generic model for creating feature vectors for words, based
# on a list of words and the relations they were observed with
class WordVectorModel(object):
    def __init__(self, word_relation_lists):
        self._word_rel_counts = ddict(lambda: ddict(lambda: 0))
        self._word_rel_count = 0
        self._word_counts = ddict(lambda: 0)
        self._rel_counts = ddict(lambda: 0)

        # calculate counts of words and relations
        for word, relations in word_relation_lists:
            for relation in relations:
                self._word_rel_counts[word][relation] += 1
                self._word_rel_count += 1
                self._word_counts[word] += 1
                self._rel_counts[relation] += 1

        # pick a canonical order for the vectors
        self._rels = sorted(self._rel_counts)

    # probability of the word appearing with the relation
    def get_probability(self, word, rel):
```

```
            word_rel_count = self._word_rel_counts[word][rel]
            word_count = self._word_counts[word]
            return word_rel_count / word_count

        # pointwise mutual information between word and relation events
        def get_mutual_information(self, word, rel):
            word_given_rel_prob = self.get_probability(word, rel)
            rel_prob = self._rel_counts[rel] / self._word_rel_count
            try:
                return math.log(word_given_rel_prob / rel_prob, 2)
            except OverflowError:
                return 0

        # vector of relation probabilities
        def get_probability_vector(self, word):
            return self._get_vector(self.get_probability, word)

        # vector of word-relation pointwise mutual informations
        def get_mutual_information_vector(self, word):
            func = self.get_mutual_information
            return self._get_vector(func, word)

        # helper for creating vectors
        def _get_vector(self, func, word):
            return [func(word, rel) for rel in self._rels]

# calculate Jaccard similarity
def get_jaccard_similarity(vector1, vector2):
    top = sum(min(x1, x2) for x1, x2 in zip(vector1, vector2))
    bottom = sum(max(x1, x2) for x1, x2 in zip(vector1, vector2))
    return top / bottom

# calculate Dice similarity
def get_dice_similarity(vector1, vector2):
    top = 2 * sum(min(x1, x2) for x1, x2 in zip(vector1, vector2))
    bottom = sum(x1 + x2 for x1, x2 in zip(vector1, vector2))
    return top / bottom
```

Scores may then be generated like this:

```
>>> words = ...
>>> vector_model = WordVectorModel(get_window_relations(5, words))
>>> get_sim = WordSimilarityModel(vector_model.get_probability_vector,
...                               get_jaccard_similarity)
>>> get_sim('red', 'green')
0.046843607909485496
```

The following similarities, based on Wall Street Journal data, suggest that *red* is more related to *green* than it is to *angry*:

sim(red, green)	$\text{assoc}_{\text{prob}}$	$\text{assoc}_{\text{PMI}}$
$\text{sim}_{\text{Jaccard}}$	0.047	0.017
sim_{Dice}	0.089	0.034

sim(red, angry)	$\text{assoc}_{\text{prob}}$	$\text{assoc}_{\text{PMI}}$
$\text{sim}_{\text{Jaccard}}$	0.033	0.011
sim_{Dice}	0.063	0.021

Chapter 21
Computational Discourse

21.1 Early work in syntactic theory attempted to characterize rules for pronominalization through purely syntactic means. One such early rule interprets a pronoun by deleting it from the syntactic structure of the sentence that contains it and replacing it with the syntactic representation of the antecedent noun phrase. Explain why the following sentences (called "Bach-Peters" sentences) are problematic for such an analysis:

(21.92) The man who deserves it gets the prize he wants.

(21.93) The pilot who shot at it hit the MIG that chased him.

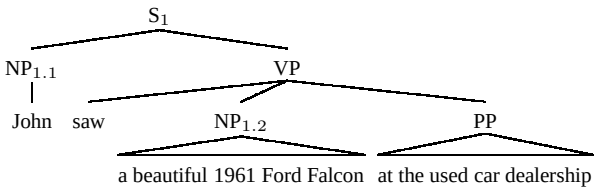
What other types of reference discussed on pages 698–701 are problematic for this type of analysis?

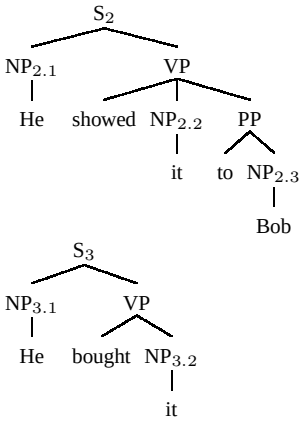
For both of these sentences, the referring expression for one pronoun is contained in the referring expression for the other pronoun. As a result, replacing expressions with their antecedents leads to infinite recursion, e.g.:

- [The man who deserves $[\text{it}]_i]_j$
- [The man who deserves [the prize $[\text{he}]_j$ wants]]$_j$
- [The man who deserves [the prize [the man who deserves [the prize $[\text{he}]_j$ wants]]$_j$ wants]]$_j$
- etc.

Another major problem with simply replacing replacing referring expressions with their antecedents is that names and both indefinite and definite noun phrases frequently have no antecedent in the text. For example, *the man* in the sentences above has no antecedent, and therefore the syntactic substitution approach would be unable to assign it a meaning.

21.2 Draw syntactic trees for Example 21.66 on page 707 and apply Hobbs's tree-search algorithm to it, showing each step in the search.





Determining the referent of $NP_{2.1}$ (*He*):

1. Start at $NP_{2.1}$ (*He*)
2. Go up to S_2 and traverse all unseen left branches
3. Determine that there are no unseen left branches along the path
4. Move to S_1 and traverse it left to right
5. Propose and accept $NP_{1.1}$ (*John*)

Determining the referent of $NP_{2.2}$ (*it*):

1. Start at $NP_{2.2}$ (*it*)
2. Go up to S_2 and traverse all unseen left branches
3. Determine that $NP_{2.1}$ (*He*) does not have an NP or S node between itself and S_2
4. Move to S_1 and traverse it left to right
5. Propose $NP_{1.1}$ (*John*), but reject it since gender does not match
6. Propose and accept $NP_{1.2}$ (*a beautiful 1961 Ford Falcon*)

Determining the referent of $NP_{3.1}$ (*He*):

1. Start at $NP_{3.1}$ (*He*)
2. Go up to S_3 and traverse all unseen left branches
3. Determine that there are no unseen left branches along the path
4. Move to S_2 and traverse it left to right
5. Propose and accept $NP_{2.1}$ (*He*)

Thus, the Hobbs algorithm suggests that for these sentences:

He = *He* = *John*
it = *a beautiful 1961 Ford Falcon*

21.3 Hobbs (1977) cites the following examples from his corpus as being problematic for his tree-search algorithm:

(21.94) The positions of pillars in one hall were marked by river boulders and a shaped convex cushion of bronze that had served as <u>their</u> footings.

(21.95) They were at once assigned an important place among the scanty remains which record the physical developments of the human race from the time of <u>its</u> first appearance in Asia.

(21.96) Sites at which the coarse grey pottery of the Shang period has been discovered do not extend far beyond the southernmost reach of the Yellow River, or westward beyond its junction with the Wei.

(21.97) The thin, hard, black-burnished pottery, made in shapes of angular profile, which archaeologists consider as the clearest hallmark of the Lung Shan culture, developed in the east. The site from which it takes its name is in Shantung. It is traced to the north-east as far as Liao-ning province.

(21.98) He had the duty of performing the national sacrifices to heaven and earth: his role as source of honours and material rewards for services rendered by feudal lords and ministers is commemorated in thousands of inscriptions made by the recipients on bronze vessels which were eventually deposited in their graves.

In each case, identify the correct referent of the underlined pronoun and the one that the algorithm will identify incorrectly. Discuss any factors that come into play in determining the correct referent in each case, and the types of information that might be necessary to account for them.

The full Hobbs algorithm requires a person/number check for each NP proposed, and rejects ones that don't match. However, the nine step process presented in Section 21.6 doesn't include this check, so skipping the person/number check is permissable for this exercise. The person/number check changes only one answer, as pointed out in the response for (21.95).

21.94 The algorithm proposes *river boulders and . . . bronze*, *river boulders*, *the positions* and then *pillars* (the correct response). Excluding the first two probably requires more knowledge of conjoined noun phrases. Excluding *positions* probably requires recognizing that *positions* don't have *footings*.

21.95 The algorithm proposes *the physical developments* and then *the human race* (the correct response). Excluding *the physical developments* could be done using a number check, recognizing that the singular *its* should not refer to the plural *developments*.

21.96 The algorithm proposes *the southernmost reach* and then *the Yellow river* (the correct response). Selecting *the Yellow river* probably requires some recognition of the tendency for parallel structures in conjoined phrases.

21.97 For the first *it*, the algorithm proposes *the site*, *Shantung*, *pottery*, *the east*, *angular profile*, *the clearest hallmark*, and finally *the Lung Shan culture* (the correct response). Everything but *Shantung* could probably be excluded by recognizing that *taking its name* requires something with a proper name. *Shantung* could probably be excluded by recognizing that something can't take its name from itself.

For the second *it*, the algorithm proposes *the site*, *Shantung* and then *it* (the correct response). Excluding the first two probably involves recognizing that *cultures* are traced, while *sites* and *Shantungs* are not.

21.98 The algorithm proposes *bronze vessels*, *thousands* and then *recipients* (the correct response). Excluding the first two probably involves recognizing that *bronze vessels* and *thousands* typically do not own graves.

21.4 Implement the Hobbs algorithm. Test it on a sample of the Penn TreeBank. You will need to modify the algorithm to deal with differences between the Hobbs and TreeBank grammars.

This is a challenging tree-walking problem. Some areas where extra care is needed:

- In the Treebank, S can be expressed as S, SBAR, SINV, etc.
- In the Treebank, there is no Nominal node, only NP nodes.
- All node searches need to be breadth first, not depth first.
- Left branches are searched left to right, even though when walking up the tree they are encountered from right to left.

The algorithm itself just proposes NP nodes, with the expectation that some nodes will be ruled out by gender, number, etc. To actually evaluate the algorithm on the TreeBank, some heuristics will be necessary to rule out obviously wrong candidates.

21.5 Consider the following passage, from Brennan et al. (1987):

(21.99) Brennan drives an Alfa Romeo.
She drives too fast.
Friedman races her on weekends.
She goes to Laguna Seca.

Identify the referent that the BFP algorithm finds for the pronoun in the final sentence. Do you agree with this choice, or do you find the example ambiguous? Discuss why introducing a new noun phrase in subject position with a pronominalized reference in object position might lead to an ambiguity for a subject pronoun in the next sentence. What preferences are competing here?

For the sentence *Brennan drives an Alfa Romeo* (U_1), there are no pronouns, so we simply have:

$C_f(U_1)$: {Brennan, Alfa Romeo}
$C_p(U_1)$: Brennan
$C_b(U_1)$: undefined

The sentence *She drives too fast* (U_2) has the pronoun *She*, so we have the two choices below. Since Continue is preferred to Retain, we choose the first where *She* = *Brennan*:

$C_f(U_2)$: {Brennan}
$C_p(U_2)$: Brennan
$C_b(U_2)$: Brennan
Continue: $C_b(U_2) = C_p(U_2)$ and $C_b(U_1)$ is undefined
$C_f(U_2)$: {Alfa Romeo}
$C_p(U_2)$: Alfa Romeo
$C_b(U_2)$: Brennan
Retain: $C_b(U_2) \neq C_p(U_2)$ and $C_b(U_1)$ is undefined

The sentence *Friedman races her on weekends* (U_3) has the pronoun *her*, but since $C_f(U_2) = \{\text{Brennan}\}$, we must have *her* = *Brennan*:

$C_f(U_3)$: {Friedman, Brennan}
$C_p(U_3)$: Friedman
$C_b(U_3)$: Brennan
Retain: $C_b(U_3) \neq C_p(U_3)$ and $C_b(U_3) = C_b(U_2)$

The sentence *She goes to Laguna Seca.* (U_4) has the pronoun *She*, so we have the two choices below. Since Continue is preferred to Smooth-Shift, we choose the first where *She* = *Brennan*:

$C_f(U_4)$: {Brennan, Laguna Seca}
$C_p(U_4)$: Brennan
$C_b(U_4)$: Brennan
Continue: $C_b(U_4) = C_p(U_4)$ and $C_b(U_4) = C_b(U_3)$
$C_f(U_4)$: {Friedman, Laguna Seca}
$C_p(U_4)$: Friedman
$C_b(U_4)$: Friedman
Smooth-Shift: $C_b(U_4) = C_p(U_4)$ and $C_b(U_4) \neq C_b(U_3)$

However, for many speakers, the final *She* can refer to *Friedman*. In situations like this, there seems to be some competition between the subject bias (i.e., the grammatical role hierarchy, which prefers to refer back to the subject, *Friedman*), and Centering's Continue bias (which prefers to keep refering to the same person, *Brennan*).

21.6 Consider passages (21.100a-b), adapted from Winograd (1972).

(21.100) The city council denied the demonstrators a permit because

a. they feared violence.
b. they advocated violence.

What are the correct interpretations for the pronouns in each case? Sketch an analysis of each in the interpretation as abduction framework, in which these reference assignments are made as a by-product of establishing the Explanation relation.

The correct interpretations are:

a. *they = city council*
b. *they = demonstrators*

In order to reason about the reference assignments, we first establish some basic rules corresponding to coherence relations and world knowledge about permit denials:

(A) $\forall e, f$ *explanation*$(e, f) \Rightarrow$ *coherence-rel*(e, f)
(B) $\forall e, f$ *cause*$(f, e) \Rightarrow$ *explanation*(e, f)
(C) $\forall f, a, e, d, w, x, y, z$
fear$(f, w, y) \wedge$ *advocate*$(a, x, y) \wedge$ *enables*(e, z, x, y)
$\Rightarrow$ *deny*$(d, w, x, z) \wedge$ (*cause*$(f, d) \vee$ *cause*(a, d))

Concluding that *they = city council* then looks like:

(1)	*deny*$(d, \textit{Council}, \textit{Demonstrators}, \textit{Permit})$	Given
(2)	*fear*$(f, \textit{they}, \textit{Violence})$	Given
(3)	*coherence-rel*(d, f)	Assumed
(4)	*explanation*(d, f)	Abduction: A, 3
(5)	*cause*(f, d)	Abduction: B, 4
(6)	*fear*$(f, \textit{Council}, y)$	Abduction: C, 1, 5
(7)	*fear*$(f, \textit{they} = \textit{Council}, y = \textit{Violence})$	Substitution: 2, 6

The derivation for *they* = *demonstrators* works in a similar manner.

21.7 Select an editorial column from your favorite newspaper, and determine the discourse structure for a 10–20 sentence portion. What problems did you encounter? Were you helped by superficial cues the speaker included (e.g., discourse connectives) in any places?

Assigning discourse structure is difficult and no two solutions to this problem are likely to be the same, even if they started with the same text. Discourse connectives typically appear infrequently, and they are often vague as to which relation they express.

One approach that might make assigning the relations easier is to follow the Penn Discourse TreeBank (Miltsakaki et al., 2004) guidelines and use discourse connectives themselves as the relation labels instead of abstract relations like Elaboration or Background. For example, a *because* relation would be assigned to the two sentences below since *because* reads well when inserted between them:

> Some have raised their cash positions to record levels. [*Because*] High cash positions help buffer a fund when the market falls.

Chapter 22
Information Extraction

22.1 Develop a set of regular expressions to recognize the character shape features described in Fig. 22.7.

```
import re

pattern_labels = {
    r'^[a-z]+$':                        'Lower',
    r'^[A-Z][a-z]+$':                   'Capitalized',
    r'^[A-Z]+$':                        'All caps',
    r'^[A-z]*[a-z]+[A-Z]+[a-z]+[A-z]*': 'Mixed caps',
    r'^[A-z]*[A-Z]+[a-z]+[A-Z]+[A-z]*': 'Mixed caps',
    r'^[A-Z]\.$':                       'Caps char with period',
    r'^.*\d$':                          'Ends in digit',
    r'^.*-.*$':                         'Contains hyphen'
}

def shape(word):
    for pattern, label in pattern_labels.items():
        if re.match(pattern, word):
            return label
```

22.2 Using a statistical sequence modeling toolkit of your choosing, develop and evaluate an NER system.

Good solutions to this problem should implement at least the first five features in Fig. 22.6, and include some sort of window of features for each word classified. For evaluating systems, data for Spanish and Dutch from the CoNLL 2002 competitions are freely available here:

`http://www.cnts.ua.ac.be/conll2002/ner/`

Of course, a variety of other named entity data sets could also be used.

22.3 The IOB labeling scheme given in this chapter isn't the only possible one. For example, an E tag might be added to mark the end of entities, or the B tag can be reserved only for those situations where an ambiguity exists between adjacent entities. Propose a new set of IOB tags for use with your NER system. Experiment with it and compare its performance with the scheme presented in this chapter.

Some schemes that have been compared in the literature:

IOB1	B tags are only used between adjacent chunks
IOB2	B tags are used at the starts of all chunks
IOE1	E tags are only used between adjacent chunks
IOE2	E tags are used at the ends of all chunks
IOBES	both starts and ends are marked, and single word chunks get the tag S

Tjong Kim Sang and Veenstra (1999) found that IOB1 performed best, while Kudo and Matsumoto (2001) found that IOB2 performed best. In both cases however, the performance differences were quite small.

22.4 Names of works of art (books, movies, video games, etc.) are quite different from the kinds of named entities we've discussed in this chapter. Collect a list of names of works of art from a particular category from a Web-based source (e.g., gutenberg.org, amazon.com, imdb.com, etc.). Analyze your list and give examples of ways that the names in it are likely to be problematic for the techniques described in this chapter.

Titles of works of art look much more like regular language than the people, organizations, etc. discussed earlier. For example:

- The Color Purple
- To Kill a Mockingbird
- The Grapes of Wrath
- Of Mice and Men
- The Call of the Wild

In particular, titles include many more determiners and prepositional phrases, and often consist of common nouns instead of proper nouns.

22.5 Develop an NER system specific to the category of names that you collected in the last exercise. Evaluate your system on a collection of text likely to contain instances of these named entities.

Good solutions to this problem will likely need to introduce some new features that better characterize how these names appear in texts. It may also be necessary to increase the classifier window size since names of works of art are likely to be longer than names of people, locations, etc.

22.6 Acronym expansion, the process of associating a phrase with an acronym, can be accomplished by a simple form of relational analysis. Develop a system based on the relation analysis approaches described in this chapter to populate a database of acronym expansions. If you focus on English **Three Letter Acronyms** (TLAs) you can evaluate your system's performance by comparing it to Wikipedia's TLA page.

A baseline approach to finding acronyms is to look for patterns like:

```
Xxxxx Yyy Zzzzzz (XYZ)
```

These kinds of patterns can be matched with regular expressions like:

```
([A-Z]).*([A-Z])\w* \(\1[A-Z]*\2\)
```

The expression above would match phrases like:

- Alternative Minimum Tax (AMT)
- International Foundation for Art Research (IFAR)
- LONDON INTERBANK OFFERED RATES (LIBOR)

However it would miss phrases like:

- diethylstilbestrol (DES)
- "world dollar base" (WDB)
- Bell Mueller Cannon Inc. (BMC)

A more thorough solution to this problem would involve taking seed acronyms like the ones found above, and using them in a bootstrapping approach to find additional acronym patterns.

Note that if Wikipedia's TLA page is used for evaluation, it will be necessary make sure that the TLA page is never used during the bootstrapping process, or the evaluation will be invalid.

22.7 A useful functionality in newer email and calendar applications is the ability to associate temporal expressions connected with events in email (doctor's appointments, meeting planning, party invitations, etc.) with specific calendar entries. Collect a corpus of email containing temporal expressions related to event planning. How do these expressions compare to the kinds of expressions commonly found in news text that we've been discussing in this chapter?

Some example temporal expressions from event planning emails:

- Sunday
- June 23
- Fri, Jul 25th - 8pm
- coming Wednesday at 6:30 pm

Generally, the expressions look quite similar to the expressions found in news text, though informal expressions like *coming Wednesday* are more frequent. In this sense, temporal expression recognition is a more constrained task than named entity recognition because the forms do not change as dramatically across different genres of text.

22.8 Develop and evaluate a recognition system capable of recognizing temporal expressions of the kind appearing in your email corpus.

A good baseline to compare the system against is the TempEx tagger, a rule based system created by MITRE for newswire data:

```
http://timex2.mitre.org/taggers/timex2_taggers.html
```

Performing better than TempEx will likely require a machine learning approach and/or identifying some types of temporal expressions common in email data that are missed by TempEx.

22.9 Design a system capable of normalizing these expressions to the degree required to insert them into a standard calendaring application.

The bulk of the work for this solution is in creating rules that map natural language words into numeric temporal representations. Even for fully qualified absolute times, this is a complex task as there are many ways of expressing the same time, e.g.

- January 25th, 2007 at 2:00pm
- at 14:00 on Jan 25 2007
- 2007-01-25 14:00:00

For times that are not fully specified, some temporal arithmetic will be necessary, though in most cases, it should be possible to assume that events will be scheduled later than their email's date.

22.10 Acquire the CMU seminar announcement corpus and develop a template-filling system by using any of the techniques mentioned in Section 22.4. Analyze how well your system performs as compared with state-of-the-art results on this corpus.

A good summary of state of the art results is available in (Peshkin and Pfefer, 2003). The features used by the best models are pretty much the same as the features presented in Fig. 22.6, so one reasonable approach to this problem is simply to retrain the system developed in Exercise 22.2 using the new label set.

22.11 Given your corpus, develop an approach to annotating the relevant slots in your corpus so that it can serve as a training corpus. Your approach should involve some hand-annotation but should not be based solely on it.

The goal of this problem was to investigate the construction of a corpus useful for template-filling tasks. The intent was that students would come up with an idea for a template, find documents likely to instantiate that template, and then annotate each document for the slot-fillers of that template.

One approach to reduce the amount of hand-annotation would be to build a simple rule based template-filling system first, run that on the data, and then hand correct all of the outputs. For this approach to work, a system with a relatively high precision (probably at the cost of recall) is usually necessary.

22.12 Retrain your system and analyze how well it functions on your new domain.

The intent of this problem was for students to retrain their template-filling models created in Exercise 22.10 on the new data created in Exercise 22.11.

Since only a small amount of data is likely to be produced in Exercise 22.11, performance on this data is likely to be much lower than performance on the CMU seminar announcement corpus unless the new template selected was particularly easy. If there are any slots in common with the CMU seminar announcement corpus, it may be possible to gain some performance by combining the two data sets and training on both.

22.13 Species identification is a critical issue for biomedical information extraction applications such as document routing and classification. But it is especially crucial for realistic versions of the gene normalization problem.
Build a species identification system that works on the document level, using the machine learning or rule-based method of your choice. Use the BioCreative gene normalization data (`biocreative.sourceforge.net`) as gold-standard data.

The goal of species identification is, given a passage of biomedical text about an organism, to identify the species of the organism being described. The best beginning to a successful solution to this problem is to start with a document set in which documents are likely to have

only a single species mentioned. This is often not the case – one study found that over 70% of documents in the set mentioned more than one species. This is more of a problem with full-text journal articles than it is with abstracts. The BioCreative data is a good starting point because it is all abstracts and it tends to have single-species abstracts. It is also artificially easy in that the number of species mentioned is only four (if you combine the BioCreative I and BioCreative II collections) – realistic text collections may mention tens of species.

For the BioCreative data sets, rule-based and machine-learning-based systems should both work well; a simple Bayesian classifier is likely to suffice, as would a simple rule-based method that counted mentions of species names and assigned the most-mentioned species to the document.

Note that document-level classification is an unrealistically easy task, although it is a good one for students who would benefit from building a simple classifier with a BOW feature set. The real task is to do classification at the level of the individual entity mention within the document. *mouse* or *yeast*.

22.14 Build, or borrow, a named entity recognition system that targets mentions of genes and gene products in texts. As development data, use the BioCreative gene mention corpus (`biocreative.sourceforge.net`).

There are a number of publicly available systems. The ABNER system (`http://pages.cs.wisc.edu/~bsettles/abner/`), is one the most nicely engineered and probably the easiest to use at this time. To build an NER system, the easiest approach to take with the BioCreative corpus is to treat it as a POS tagging problem with a GENE tag, since that is how the data is represented – all tokens are POS-tagged, except for tokens which are part of gene names – they are tagged GENE. Most imaginable machine-learning-based methods have been tried; see the proceedings of either of the two BioCreative meetings for lots of suggestions on feature sets. Note that dictionary-based methods tend to perform quite poorly.

22.15 Build a gene normalization system that maps the output of your gene mention recognition system to the appropriate database entry. Use the BioCreative gene normalization data as your development and test data. Be sure you don't give your system access to the species identification in the metadata.

While gene normalization can be thought of as a word sense disambiguation (WSD) task, it differs from traditional WSD tasks in that there are often many different realizations of each gene, e.g., *somatotropin* and *growth hormone* both refer to the same biomolecule. Thus, unlike traditional WSD tasks, where the possible senses to be assigned can simply be looked up in a dictionary, in gene normalization, a large part of the task is finding which entries in the dictionary might be relevant.

Gene normalization is mostly an unsolved problem, and a student who does well on it is likely to have a publishable paper on their hands. For one very recent system that has tackled this problem on the BioCreative data, see Wang and Matthews (2008). Their work got the best results from a hybrid system that did an initial pass with a machine-learning-based system and then used a rule-based system for post-processing.

Chapter 23
Question Answering and Summarization

23.1 Pose the following queries to your favorite Web search engine.

Who did the Vice President kill?
Who killed the former Treasury Secretary?

Do an error-analysis on the returned snippets and pages. What are the sources of the errors? How might these errors be addressed by a more intelligent question-answering system?

In recent results from Google, the best hit for *Who did the Vice President kill* is the second one, which contains a paragraph about Vice President Aaron Burr shooting the former Secretary of the Treasury Alexander Hamilton. This is a reasonable response, but it misses the fact that *the Vice President* probably refers to the current one. Giving a better answer would likely require a better understanding of determiners like *the*.

The best hits for *Who killed the former Treasury Secretary* are probably the third and fourth, which refer to an internet conspiracy theory that Treasury Secretary Henry Paulson was shot and killed by assassins of Putin. This is bad because at the time of the query, Henry Paulson was the current Treasury Secretary (and still alive!) not the *former* Treasury Secretary. Giving a better answer would likely require a better understanding of temporal terms like *former* (and perhaps a better recognition of dubious conspiracy theories).

For both questions, many of the remaining hits seem to be miscellaneous combinations of the words in the query, e.g., some Treasury Secretary and someone else being killed, but no particular relation between the two. Getting better responses here would require acknowledging the predicate-argument structure of the question and trying to better match that in the response, probably using one of the semantic role labeling techniques introduced in Chapter 20.

23.2 Do some error analysis on Web-based question answering. Choose 10 questions and type them all into two different search engines. Analyze the errors. For example, what kinds of questions could neither system answer? Which kinds of questions did one work better on? Was there a type of question that could be answered just from the snippets?

The goal of this problem is to get a sense of the limitations of search engines, as well as the differences between different search engine implementations. Since most search engines are based in slight variants of the same vector space models, while the individual hits are

likely to be different, the basic kinds of errors are likely to be similar. For example, the problems with predicate-argument structure we saw in the preceding exercise are likely to be problems for all current search engines, though the exact hits returned are likely to be different.

23.3 Read Brill et al. (2002). Implement a simple version of the AskMSR system.

The basic approach of the AskMSR system is to convert questions into declarative phrases, use phrasal searches to find those phrases on the web, and then search for n-grams that occur near the phrases in the hits returned. An implementation of AskMSR would probably include the following steps:

1. Rewrite the query in a declarative form, e.g., *When was the paper clip invented?* is rewritten as *The paper clip was invented*.
2. Using a phrasal search engine, find hits containing the rewritten query phrase.
3. Using only the summaries returned by the search engine, extract unigrams, bigrams and trigrams around the matched phrase.
4. Find the unigrams, bigrams and trigrams that appeared in the largest number of summaries.
5. Analyze the query's expected answer type and filter n-grams that would be inappropriate.
6. Assemble the longest possible answer by starting with the best scoring n-gram and tiling other n-grams onto it, e.g., combining A B C and B C D into A B C D.

The full version of AskMSR includes a little more detail (e.g., producing several query rewrites with different scores), but the above steps capture the core ideas of the approach.

23.4 Apply the system you developed for the last question to a small, closed, set of Web pages of interest. For example, you could use the set of pages that describe the undergraduate degree and course requirements at a university. How does the restriction to a small collection affect the performance of the system?

Systems like the AskMSR system rely on the massive redundancy of corpora like the web

- to be able to find full phrasal matches, since only with a large number of documents can we expect the exact query phrase to occur, and
- to be able to score and tile the n-grams, since we need a large number of responses to calculate meaningful n-gram frequencies.

As a result, using a system like the AskMSR system on a small corpus is likely to see a substantial drop in performance.

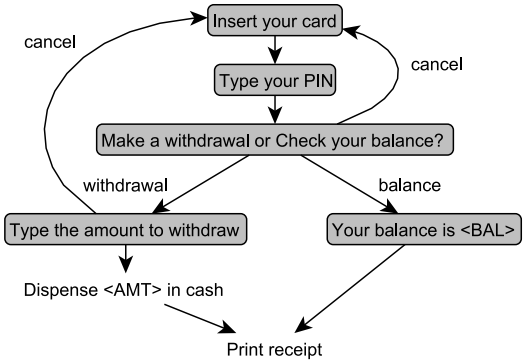
Chapter 24
Dialogue and Conversational Agents

24.1 List the dialogue act misinterpretations in the *Who's on First* routine at the beginning of the chapter.

C: *I want you to tell me the names of the fellows on the St Louis team.*
A: *I'm telling you. Who's on first, What's on second, I Don't Know is on third.*
Intended: STATEMENT
Understood: QUESTION
C: *You know the fellows' names?*
A: *Yes.*
C: *Well, then, who's playing first?*
Intended: QUESTION
Understood: CHECK
A: *Yes.*
C: *I mean the fellow's name on first.*
A: *Who.*
Intended: STATEMENT
Understood: QUESTION
C: *The guy on first base.*
A: *Who is on first.*
Intended: STATEMENT
Understood: QUESTION
C: *Well what are you askin' me for?*
A: *I'm not asking you – I'm telling you. Who is on first.*

24.2 Write a finite-state automaton for a dialogue manager for checking your bank balance and withdrawing money at an automated teller machine.

One possible solution:



24.3 Dispreferred responses (e.g., turning down a request) are usually signaled by surface cues such as significant silence. Try to notice the next time you or someone else utters a dispreferred response, and write down the utterance. What are some other cues in the response that a system might use to detect a dispreferred response? Consider non-verbal cues like eye gaze and body gestures.

The question is ambiguous, but the intent was to ask for both verbal and non-verbal cues. Verbal cues include pauses, fillers like *well*, disfluencies or self-repair, apologies or qualifications, etc. Non-verbal cues include a lowered gaze, changes in facial expression like frowning (or even smiling), gestures like a raised hand, etc.

24.4 When asked a question to which they aren't sure they know the answer, people display their lack of confidence by cues that resemble other dispreferred responses. Try to notice some unsure answers to questions. What are some of the cues? If you have trouble doing this, read Smith and Clark (1993) and listen specifically for the cues they mention.

Some cues for unsure answers identified by Smith and Clark (1993):

- Long pauses
- Rising intonation
- Hedges like *I guess* or *I think*
- Fillers like *uh*, *um*, tongue clicks, whistling or sighing

24.5 Build a VoiceXML dialogue system for giving the current time around the world. The system should ask the user for a city and a time format (24 hour, etc) and should return the current time, properly dealing with time zones.

Initial VoiceXML prompts for the user might look like:

```
<?xml version="1.0" ?>
<vxml version="2.0">
    <form>
        <field name="city">
            <prompt>
                What city would you like the time for?
            </prompt>
            <grammar type="application/x-nuance-gsl">
                [denver (san francisco) ...]
            </grammar>
        </field>
        <field name="format">
            <prompt>
                Twelve hour or twenty four hour clock?
            </prompt>
            <grammar type="application/x-nuance-gsl">
                [[twelve (twenty four)] ?hour]
            </grammar>
        </field>
    </form>
    <block>
        <submit next="http://example.com/get-time"/>
    </block>
</vxml>
```

This script would submit the fields `city` and `format` to the server at `http://example.com/get-time`. The server would need to look up the the current time for the city, and return VoiceXML like the following, with `City` and `Time` filled in with appropriate values:

```
<?xml version="1.0" ?>
<vxml version="2.0">
    <block>
        <prompt>
            The time in [City] is [Time]
        </prompt>
    </block>
</vxml>
```

24.6 Implement a small air-travel help system based on text input. Your system should get constraints from users about a particular flight that they want to take, expressed in natural language, and display possible flights on a screen. Make simplifying assumptions. You may build in a simple flight database or you may use a flight information system on the Web as your backend.

This is a challenging problem that requires at least:

- A parser component that extracts slots like ORIGIN and DESTINATION from natural language text.
- A dialog management component that prompts the user for additional information when necessary.
- A database component that translates the requested slots into appropriate database queries.
- A generation component that presents the flights retrieved from the database to the user.

One of the key goals of this exercise is to help develop a better understanding of how each of these components interact with each other, and what the most important points of integration are.

24.7 Augment your previous system to work with speech input through VoiceXML. (Or alternatively, describe the user interface changes you would have to make for it to work via speech over the phone.) What were the major differences?

Some of the biggest changes for a phone-based interface would be in the generation component. When visualizing flight information on a screen, tables can be used to display a lot of information simultaneously. Over the phone, the same information must be given, but listing everything would overwhelm most users. Thus, the output generation will need better integration with the dialog management to allow the user to verbally browse the flights by date, time of day, airport, etc.

Of course, other areas of the system will also need adaptation, e.g., errors in speech recognition make the information extraction more difficult, as a result requiring greater interaction with the user to verify words when uncertain.

24.8 Design a simple dialogue system for checking your email over the telephone. Implement in VoiceXML.

This exercise shares many of the challenges of Exercise 24.6, though the grammar the parser must understand may be somewhat simpler, and much of the generation will simply be reading text. Good solutions to this problem will allow actions like checking for new messages, reading a message aloud, advancing to the next message, etc.

24.9 Test your email-reading system on some potential users. Choose some of the metrics described in Section 24.4.2 and evaluate your system.

Most of the evaluation metrics require that the users attempt some sort of task. Good tasks to evaluate the email-reading system include reading the most recent email, scanning for an email with a particular title, etc. To get a good feel for how effective each of the types of metrics are, it would be best to use at least one metric each from the task completion metrics, the efficiency cost metrics and the quality cost metrics.

Chapter 25
Machine Translation

25.1 Select at random a paragraph of Chapter 12 that describes a fact about English syntax. a) Describe and illustrate how your favorite foreign language differs in this respect. b) Explain how an MT system could deal with this difference.

For example, the rule:

$$NP \rightarrow (Det)(Card)(Ord)(Quant)(AP)Nominal$$

is wrong since in Spanish adjectives usually follow nouns, e.g.:

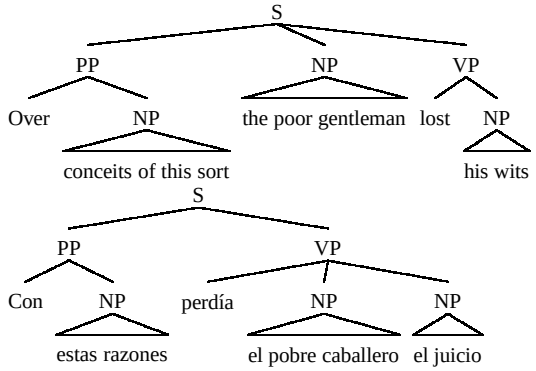
la	*manzana*	*roja*
THE	APPLE	RED
Det	*Noun*	*Adj*

Particularly when the word is a simple adjective (and not a long adjectival phrase), an MT system could address this difference with a simple reordering strategy that put adjectives after nouns.

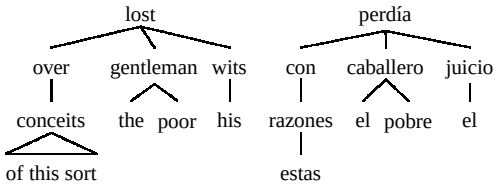
25.2 Choose a foreign language novel in a language you know. Copy down the shortest sentence on the first page. Now look up the rendition of that sentence in an English translation of the novel. a) For both original and translation, draw parse trees. b) For both original and translation, draw dependency structures. c) Draw a case structure representation of the meaning that the original and translation share. d) What does this exercise suggest to you regarding intermediate representations for MT?

From Don Quixote (from `gutenberg.org`):

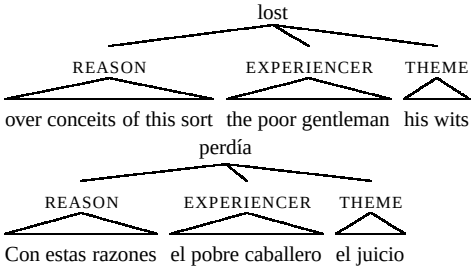
a) Syntactic trees



b) Dependency trees



c) Case structures



d) Translating between dependency trees or case role representations looks relatively straightforward, while translating between syntactic parses would require some additional work since the subject noun phrase is before the verb in English but after the verb in Spanish. Of course, this same problem would arise for the dependency tree or case role representations when converting the words in the tree to their final ordered output.

25.3 Version 1 (for native English speakers): Consider the following sentence:

> These lies are like their father that begets them; gross as a mountain, open, palpable. Henry IV, Part 1, act 2, scene 2

Translate this sentence into some dialect of modern vernacular English, such as the style of a *New York Times* editorial, an *Economist* opinion piece, or your favorite television talk-show host.

Version 2 (for native speakers of other languages): Translate the following sentence into your native language.

> One night my friend Tom, who had just moved into a new apartment, saw a cockroach scurrying about in the kitchen.

For either version, now:

a) Describe how you did the translation: What steps did you perform? In what order did you do them? Which steps took the most time?

> One possible approach would be to perform a multi-staged translation. First, do a simple word-by-word translation. (Note that in the process, we lose the pun on *gross*, which could mean both *fat* and *obvious*.)
>
> > These lies are like the man who gave birth to them: obvious as a mountain, open, blatant.

Next remove the somewhat stilted metaphor:

> These lies are like the man speaking them: obvious as a mountain, open, blatant.

Then condense some redundancies:

> These lies are like the man speaking them: blatant and obvious.

Finally, reorder phrases to use the more common `as X as` construction:

> These lies are as blatant and obvious as the man speaking them.

The major time sink of this approach is not in any given step, but in deciding which steps to apply and in what order, that is, in planning the translation strategy.

b) Could you write a program that would translate by the same methods that you did? Why or why not?

Some of these steps would be quite difficult to do automatically. For example, automatically detecting metaphors is an unsolved problem, and having to translate them into non-metaphoric speech would make the problem even more difficult.

c) What aspects were hardest for you? Would they be hard for an MT system?

One of the difficulties was in recognizing that the `as X as` construction was a more natural way of expressing the sentence. This would likely be difficult for an MT system was well, since this construction is not all that frequent, and the translation requires some substatial phrase movements.

d) What aspects would be hardest for an MT system? Are they hard for people too?

Removing the metaphor would be extremely hard for an MT system to do unless the *gave birth*/*speaking* metaphor is for some reason very common in the training corpus.

e) Which models are best for describing various aspects of your process (direct, transfer, interlingua, or statistical)?

The approach given here is a combination of a couple different models: the word-by-word translation was like a direct model, while the phrase reorderings were more like a transfer model.

f) Now compare your translation with those produced by friends or classmates. What is different? Why were the translations different?

Translations by others are likely to be fairly different, particularly if the others aimed for a different genre to translate to. Investigating the differences should give some idea of where in the process alternate decisions could have been made, and how such decisions would have influenced the final result.

25.4 Type a sentence into any MT system and see what it outputs. a) List the problems with the translation. b) Rank these problems in order of severity. c) For the two most severe problems, suggest the probable root cause.

Using Google Translate in 2008:

Input	Mary did not slap the green witch.
Output	María no bofetada la bruja verde.
Expected	María no dío una bofetada a la bruja verde.

There are three words missing in the Spanish translation: *dío*, *una* and *a*. Probably the most significant one is *dío* - in Spanish, you must *give a slap*, you cannot use *slap* as a verb. Note that without *dío*, there is no verb in the sentence, so this is a pretty serious error. The other major error is the missing *a*, which indicates that the slap is being given *to* the witch. This error is related to the missing *dío* as well - *una bofetada* should be the only object of *dío*, but since *dío* was missing, there was no way to guess that. In both cases, the most likely root cause is the fact that none of the missing words align to any of the English words.

25.5 Build a very simple, direct MT system for translating from some language you know at least somewhat into English (or into a language in which you are relatively fluent), as follows. a) First, find some good test sentences in the source language. Reserve half of these as a development test set, and half as an unseen test set. Next, acquire a bilingual dictionary for these two languages (for many languages, limited dictionaries can be found on the Web that will be sufficient for this exercise). Your program should translate each word by looking up its translation in your dictionary. You may need to implement some stemming or simple morphological analysis. b) Next, examine your output, and do a preliminary error analysis on the development test set. What are the major sources of error? c) Write some general rules for correcting the translation mistakes. You will probably want to run a part-of-speech tagger on the English output, if you have one. d) Then see how well your system runs on the test set.

There are likely to be two major sources of errors in these simple dictionary based MT systems: selecting the wrong words, and failing to change the word order. Correcting the word selection problems will likely require WSD-like methods, e.g., looking for keywords in the surrounding context. Correcting the word order problems will likely require reordering rules that move words or phrases around, e.g., moving adjectives after the nouns instead of before them.

25.6 Continue the calculations for the EM example on page 887, performing the second and third round of E-steps and M-steps.

E-step 2a Recompute $P(a, f|e)$ by multiplying t probabilities:

green house / casa verde	green house / casa verde	the house / la casa	the house / la casa
$P(a, f\|e)$ $= t(\text{casa}, \text{green}) \times$ $\quad t(\text{verde}, \text{house})$ $= \frac{1}{2} \times \frac{1}{4} = \frac{1}{8}$	$P(a, f\|e)$ $= t(\text{verde}, \text{green}) \times$ $\quad t(\text{casa}, \text{house})$ $= \frac{1}{2} \times \frac{1}{2} = \frac{1}{4}$	$P(a, f\|e)$ $= t(\text{la}, \text{the}) \times$ $\quad t(\text{casa}, \text{house})$ $= \frac{1}{2} \times \frac{1}{2} = \frac{1}{4}$	$P(a, f\|e)$ $= t(\text{casa}, \text{the}) \times$ $\quad t(\text{la}, \text{house})$ $= \frac{1}{2} \times \frac{1}{4} = \frac{1}{8}$

E-step 2b Normalize $P(a, f|e)$ to get $P(a|e, f)$:

green house / casa verde	green house / casa verde	the house / la casa	the house / la casa
$P(a\|f, e)$ $= \frac{1/8}{3/8} = \frac{1}{3}$	$P(a\|f, e)$ $= \frac{1/4}{3/8} = \frac{2}{3}$	$P(a\|f, e)$ $= \frac{1/4}{3/8} = \frac{2}{3}$	$P(a\|f, e)$ $= \frac{1/8}{3/8} = \frac{1}{3}$

E-step 2c Compute expected counts by weighting each count by $P(a|e, f)$:

tcnt(casa|green) $= \frac{1}{3}$	tcnt(verde|green) $= \frac{2}{3}$	tcnt(la|green) $= 0$	total(green) $= 1$
tcnt(casa|house) $= \frac{2}{3} + \frac{2}{3}$	tcnt(verde|house) $= \frac{1}{3}$	tcnt(la|house) $= \frac{1}{3}$	total(house) $= 2$
tcnt(casa|the) $= \frac{1}{3}$	tcnt(verde|the) $= 0$	tcnt(la|the) $= \frac{2}{3}$	total(the) $= 1$

M-step 2 Compute MLE probability parameters by normalizing the tcounts:

t(casa|green) $= \frac{1/3}{1} = \frac{1}{3}$	t(verde|green) $= \frac{2/3}{1} = \frac{2}{3}$	t(la|green) $= \frac{0}{1} = 0$
t(casa|house) $= \frac{4/3}{2} = \frac{2}{3}$	t(verde|house) $= \frac{1/3}{2} = \frac{1}{6}$	t(la|house) $= \frac{1/3}{2} = \frac{1}{6}$
t(casa|the) $= \frac{1/3}{1} = \frac{1}{3}$	t(verde|the) $= \frac{0}{1} = 0$	t(la|the) $= \frac{2/3}{1} = \frac{2}{3}$

E-step 3a Recompute $P(a, f|e)$ by multiplying t probabilities:

green house / casa verde	green house / casa verde	the house / la casa	the house / la casa
$P(a, f\|e)$ $= t(\text{casa}, \text{green}) \times$ $\quad t(\text{verde}, \text{house})$ $= \frac{1}{3} \times \frac{1}{6} = \frac{1}{18}$	$P(a, f\|e)$ $= t(\text{verde}, \text{green}) \times$ $\quad t(\text{casa}, \text{house})$ $= \frac{2}{3} \times \frac{2}{3} = \frac{4}{9}$	$P(a, f\|e)$ $= t(\text{la}, \text{the}) \times$ $\quad t(\text{casa}, \text{house})$ $= \frac{2}{3} \times \frac{2}{3} = \frac{4}{9}$	$P(a, f\|e)$ $= t(\text{casa}, \text{the}) \times$ $\quad t(\text{la}, \text{house})$ $= \frac{1}{3} \times \frac{1}{6} = \frac{1}{18}$

E-step 3b Normalize $P(a, f|e)$ to get $P(a|e, f)$:

green house / casa verde	green house / casa verde	the house / la casa	the house / la casa
$P(a\|f, e)$ $= \frac{1/18}{1/2} = \frac{1}{9}$	$P(a\|f, e)$ $= \frac{4/9}{1/2} = \frac{8}{9}$	$P(a\|f, e)$ $= \frac{4/9}{1/2} = \frac{8}{9}$	$P(a\|f, e)$ $= \frac{1/18}{1/2} = \frac{1}{9}$

E-step 3c Compute expected counts by weighting each count by $P(a|e, f)$:

tcnt(casa|green) = $\frac{1}{9}$	tcnt(verde|green) = $\frac{8}{9}$	tcnt(la|green) = 0	total(green) = 1
tcnt(casa|house) = $\frac{8}{9} + \frac{8}{9}$	tcnt(verde|house) = $\frac{1}{9}$	tcnt(la|house) = $\frac{1}{9}$	total(house) = 2
tcnt(casa|the) = $\frac{1}{9}$	tcnt(verde|the) = 0	tcnt(la|the) = $\frac{8}{9}$	total(the) = 1

M-step 3 Compute MLE probability parameters by normalizing the tcounts:

t(casa|green) = $\frac{1/9}{1}$ = $\frac{1}{9}$	t(verde|green) = $\frac{8/9}{1}$ = $\frac{8}{9}$	t(la|green) = $\frac{0}{1}$ = 0
t(casa|house) = $\frac{16/9}{2}$ = $\frac{8}{9}$	t(verde|house) = $\frac{1/9}{2}$ = $\frac{1}{18}$	t(la|house) = $\frac{1/9}{2}$ = $\frac{1}{18}$
t(casa|the) = $\frac{1/9}{1}$ = $\frac{1}{9}$	t(verde|the) = $\frac{0}{1}$ = 0	t(la|the) = $\frac{8/9}{1}$ = $\frac{8}{9}$

25.7 (Derived from Knight (1999b)) How many possible Model 3 alignments are there between a 20-word English sentence and a 20-word Spanish sentence, allowing for NULL and fertilities?

Just like in Model 1, every Spanish word is aligned NULL or a single English word. Since the word fertilities ϕ_i are constrained to be a non-negative numbers, and we have 20 Spanish words to generate from our English words, we have $0 \leq \phi_i \leq 20$. And since we can generate zero or one spurious Spanish words for each of our 20 English words, we have $0 \leq \phi_0 \leq 20$.

So just as with Model 1, we calculate the total possible alignments by choosing for each of our 20 Spanish words one of the 20 English words or NULL. Thus the total possible alignments is:

$$21^{20} = 278,218,429,446,951,548,637,196,401$$

Note however, that if we could guarantee that our ϕ_i values were smaller than 20, we could have a smaller total number of possible alignments.

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