specifies some of the metadata, namely, the name of the relations, the fields or attributes of each relation, the domain of each attribute, etc.

Common forms of metadata associated with text include the author, the date of publication, the source of the publication, the document length (in pages, words, bytes, etc.), and the document genre (book, article, memo, etc.). For example, the Dublin Core Metadata Element Set [807] proposes 15 fields to describe a document. Following Marchionini [542], we refer to this kind of information as Descriptive Metadata, metadata that is external to the meaning of the document, and pertains more to how it was created. Another type of metadata characterizes the subject matter that can be found within the document's contents. We will refer to this as Semantic Metadata. Semantic Metadata is associated with a wide number of documents and its availability is increasing. All books published within the USA are assigned Library of Congress subject codes, and many journals require author-assigned key terms that are selected from a closed vocabulary of relevant terms. For example, biomedical articles that appear within the MEDLINE (see Chapter 3) system are assigned topical metadata pertaining to disease, anatomy, pharmaceuticals, and so on. To standardize semantic terms, many areas use specific *ontologies*, which are hierarchical taxonomies of terms describing certain knowledge topics.

An important metadata format is the Machine Readable Cataloging Record (MARC) which is the most used format for library records. MARC has several fields for the different attributes of a bibliographic entry such as title, author, etc. Specific uses of MARC are given in Chapter 14. In the USA, a particular version of MARC is used: USMARC, which is an implementation of ANSI/NISO Z39.2, the American National Standard for Bibliographic Information Interchange. The USMARC format documents contain the definitions and content for the fields that have to be used in records structured according to Z39.2. This standard is maintained by the Library of Congress of the USA.

With the increase of data in the Web, there are many initiatives to add metadata information to Web documents. In the Web, metadata can be used for many purposes. Some of them are cataloging (BibTeX is a popular format for this case), content rating (for example, to protect children from reading some type of documents), intellectual property rights, digital signatures (for authentication), privacy levels (who should and who should not have access to a document), applications to electronic commerce, etc. The new standard for Web metadata is the Resource Description Framework (RDF), which provides interoperability between applications. This framework allows the description of Web resources to facilitate automated processing of the information. It does not assume any particular application or semantic domain. It consists of a description of nodes and attached attribute/value pairs. Nodes can be any Web resource, that is, any Uniform Resource Identifier (URI), which includes the Uniform Resource Locator (URL). Attributes are properties of nodes, and their values are text strings or other nodes (Web resources or metadata instances). To describe the semantics, values from, for example, the Dublin Core library metadata URL can be used. Other predefined vocabularies for authoring metadata are expected, in particular for content rating and for digital signatures. In addition, currently,

there are many Web projects on ontologies for different application domains (see also Chapters 13 and 15). Metadata is also useful for metadescriptions of non-textual objects. For example, a set of keywords that describe an image. These keywords can later be used to search for the image using classic text information retrieval techniques (on the metadescriptions).

6.3 Text

With the advent of the computer, it was necessary to code text in binary digits. The first coding schemes were EBCDIC and ASCII, which used seven bits to code each possible symbol. Later, ASCII was standardized to eight bits (ISO-Latin), to accommodate several languages, including accents and other diacritical marks. Nevertheless, ASCII is not suitable for oriental languages such as Chinese or Japanese Kanji, where each symbol might represent a concept and therefore thousands of them exist. For this case, a 16-bit code exists called Unicode (ISO 10616) [783].

In this section we cover different characteristics of text. First, the possible formats of text, ASCII being the simplest format. Second, how the information content of text can be measured, followed by different models for it. Finally, we mention briefly how we can measure similarity between strings or pieces of text.

6.3.1 Formats

There is no single format for a text document, and an IR system should be able to retrieve information from many of them. In the past, IR systems would convert a document to an internal format. However, that has many disadvantages, because the original application related to the document is not useful any more. On top of that, we cannot change the contents of a document. Current IR systems have filters that can handle most popular documents, in particular those of word processors with some binary syntax such as Word, WordPerfect or FrameMaker. Even then, good filters might not be possible if the format is proprietary and its details are not public. This is not the case for full ASCII syntax, as in TeX documents. Although documents can be in a binary format (for example, parts of a Word document), documents that are represented in human-readable ASCII form imply more portability and are easier to modify (for example, they can be edited with different applications).

Other text formats were developed for document interchange. Among these we should mention the Rich Text Format (RTF), which is used by word processors and has ASCII syntax. Other important formats were developed for displaying or printing documents. The most popular ones are the Portable Document Format (PDF) and Postscript (which is a powerful programming language for drawing). Other interchange formats are used to encode electronic mail, for example MIME (Multipurpose Internet Mail Exchange). MIME supports multiple character sets, multiple languages, and multiple media.

On top of these formats, nowadays many files are compressed. Text compression is treated in detail in Chapter 7, but here we comment on the most

popular compression software and associated formats. These include Compress (Unix), ARJ (PCs), and ZIP (for example `gzip` in Unix and `Winzip` in Windows). Other tools allow us to convert binary files, in particular compressed text, to ASCII text such that it can be transmitted through a communication line using only seven bits. Examples of these tools are `uuencode/uudecode` and `binhex`.

6.3.2 Information Theory

Written text has a certain semantics and is a way to communicate information. Although it is difficult to formally capture how much information is there in a given text, the distribution of symbols is related to it. For example, a text where one symbol appears almost all the time does not convey much information. Information theory defines a special concept, *entropy*, to capture information content (or equivalently, information uncertainty). If the alphabet has σ symbols, each one appearing with probability p_i (probability here is defined as the symbol frequency over the total number of symbols) in a text, the entropy of this text is defined as

$$E = -\sum_{i=1}^{\sigma} p_i \log_2 p_i$$

In this formula the σ symbols of the alphabet are coded in binary, so the entropy is measured in bits. As an example, for $\sigma = 2$, the entropy is 1 if both symbols appear the same number of times or 0 if only one symbol appears. We say that the amount of information in a text can be quantified by its entropy. The definition of entropy depends on the probabilities (frequencies) of each symbol. To obtain those probabilities we need a *text model*. So we say that the amount of information in a text is measured with regard to the text model. This concept is also important, for example, in text compression, where the entropy is a limit on how much the text can be compressed, depending on the text model.

In our case we are interested in natural language, as we now discuss.

6.3.3 Modeling Natural Language

Text is composed of symbols from a finite alphabet. We can divide the symbols in two disjoint subsets: symbols that separate words and symbols that belong to words. It is well known that symbols are not uniformly distributed. If we consider just letters (a to z), we observe that vowels are usually more frequent than most consonants. For example, in English, the letter 'e' has the highest frequency. A simple model to generate text is the binomial model. In it, each symbol is generated with a certain probability. However, natural language has a dependency on previous symbols. For example, in English, a letter 'f' cannot appear after a letter 'c' and vowels or certain consonants have a higher probability

of occurring. Therefore, the probability of a symbol depends on previous symbols. We can use a finite-context or Markovian model to reflect this dependency. The model can consider one, two, or more letters to generate the next symbol. If we use k letters, we say that it is a k-order model (so the binomial model is considered a 0-order model). We can use these models taking words as symbols. For example, text generated by a 5-order model using the distribution of words in the Bible might make sense (that is, it can be grammatically correct), but will be different from the original. More complex models include finite-state models (which define regular languages), and grammar models (which define context free and other languages). However, finding the right grammar for natural language is still a difficult open problem.

The next issue is how the different words are distributed inside each document. An approximate model is *Zipf's Law* [847, 310], which attempts to capture the distribution of the frequencies (that is, number of occurrences) of the words in the text. The rule states that the frequency of the i-th most frequent word is $1/i^\theta$ times that of the most frequent word. This implies that in a text of n words with a vocabulary of V words, the i-th most frequent word appears $n/(i^\theta H_V(\theta))$ times, where $H_V(\theta)$ is the harmonic number of order θ of V, defined as

$$H_V(\theta) = \sum_{j=1}^{V} \frac{1}{j^\theta}$$

so that the sum of all frequencies is n. The left side of Figure 6.2 illustrates the distribution of frequencies considering that the words are arranged in decreasing order of their frequencies. The value of θ depends on the text. In the most simple formulation, $\theta = 1$, and therefore $H_V(\theta) = O(\log n)$. However, this simplified version is very inexact, and the case $\theta > 1$ (more precisely, between 1.5 and 2.0) fits better the real data [26]. This case is very different, since the distribution is much more skewed, and $H_V(\theta) = O(1)$. Experimental data suggests that a better model is $k/(c+i)^\theta$ where c is an additional parameter and k is such that all frequencies add to n. This is called a Mandelbrot distribution [561].

Since the distribution of words is very skewed (that is, there are a few hundred words which take up 50% of the text), words that are too frequent, such as *stopwords*, can be disregarded. A stopword is a word which does not carry meaning in natural language and therefore can be ignored (that is, made not searchable), such as 'a,' 'the,' 'by,' etc. Fortunately the most frequent words are stopwords and therefore, half of the words appearing in a text do not need to be considered. This allows us, for instance, to significantly reduce the space overhead of indices for natural language texts. For example, the most frequent words in the TREC-2 collection (see Chapter 3 for details on this reference collection and others) are 'the,' 'of,' 'and,' 'a,' 'to' and 'in' (see also Chapter 7).

Another issue is the distribution of words in the documents of a collection. A simple model is to consider that each word appears the same number of times in every document. However, this is not true in practice. A better model is

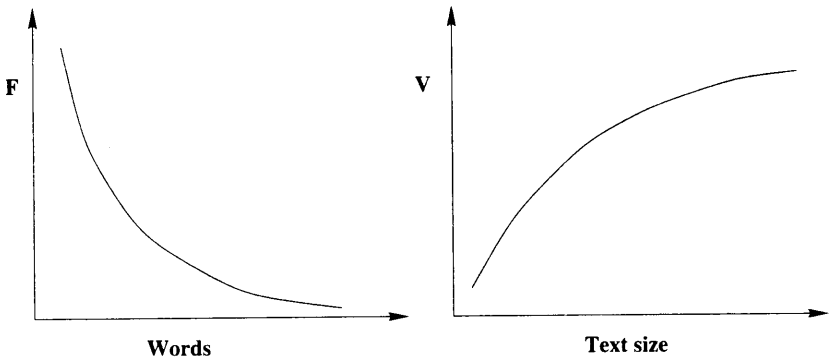


Figure 6.2 Distribution of sorted word frequencies (left) and size of the vocabulary (right).

to consider a negative binomial distribution, which says that the fraction of documents containing a word k times is

$$F(k) = \binom{\alpha + k - 1}{k} p^k (1 + p)^{-\alpha - k}$$

where p and α are parameters that depend on the word and the document collection. For example, for the Brown Corpus [276] and the word 'said', we have $p = 9.24$ and $\alpha = 0.42$ [171]. The latter reference gives other models derived from a Poisson distribution.

The next issue is the number of distinct words in a document. This set of words is referred to as the document *vocabulary*. To predict the growth of the vocabulary size in natural language text, we use the so-called *Heaps' Law* [352]. This is a very precise law which states that the vocabulary of a text of size n words is of size $V = Kn^{\beta} = O(n^{\beta})$, where K and β depend on the particular text. The right side of Figure 6.2 illustrates how the vocabulary size varies with the text size. K is normally between 10 and 100, and β is a positive value less than one. Some experiments [26, 42] on the TREC-2 collection show that the most common values for β are between 0.4 and 0.6. Hence, the vocabulary of a text grows sublinearly with the text size, in a proportion close to its square root.

Notice that the set of different words of a language is fixed by a constant (for example, the number of different English words is finite). However, the limit is so high that it is much more accurate to assume that the size of the vocabulary is $O(n^{\beta})$ instead of $O(1)$, although the number should stabilize for huge enough texts. On the other hand, many authors argue that the number keeps growing anyway because of typing or spelling errors.

Heaps' law also applies to collections of documents because, as the total text size grows, the predictions of the model become more accurate. Furthermore, this model is also valid for the World Wide Web (see Chapter 13).

The last issue is the average length of words. This relates the text size in

words with the text size in bytes (without accounting for punctuation and other extra symbols). For example, in the different subcollections of the TREC-2 collection, the average word length is very close to 5 letters, and the range of variation of this average in each subcollection is small (from 4.8 to 5.3 letters). If we remove the stopwords, the average length of a word increases to a number between 6 and 7 (letters). If we take only the words of the vocabulary, the average length is higher (about 8 or 9). This defines the total space needed for the vocabulary.

Heaps' law implies that the length of the words in the vocabulary increases logarithmically with the text size and thus, that longer and longer words should appear as the text grows. However, in practice, the average length of the words in the overall text is constant because shorter words are common enough (e.g. stopwords). This balance between short and long words, such that the average word length remains constant, has been noticed many times in different contexts, and can also be explained by a finite-state model in which: (a) the space character has probability close to 0.2; (b) the space character cannot appear twice subsequently; and (c) there are 26 letters [561]. This simple model is consistent with Zipf's and Heaps' laws.

The models presented in this section are used in Chapters 8 and 13, in particular Zipf's and Heaps' laws.

6.3.4 Similarity Models

In this section we define notions of syntactic similarity between strings or documents. Similarity is measured by a *distance function*. For example, if we have strings of the same length, we can define the distance between them as the number of positions that have different characters. Then, the distance is 0 if they are equal. This is called the Hamming distance. A distance function should also be symmetric (that is, the order of the arguments does not matter) and should satisfy the triangle inequality (that is, $distance(a, c) \leq distance(a, b) + distance(b, c)$).

An important distance over strings is the edit or Levenshtein distance mentioned earlier. The edit distance is defined as the minimum number of characters, insertions, deletions, and substitutions that we need to perform in any of the strings to make them equal. For instance, the edit distance between '`color`' and '`colour`' is one, while the edit distance between '`survey`' and '`surgery`' is two. The edit distance is considered to be superior for modeling syntactic errors than other more complex methods such as the Soundex system, which is based on phonetics [595]. Extensions to the concept of edit distance include different weights for each operation, adding transpositions, etc.

There are other measures. For example, assume that we are comparing two given strings and the only operation allowed is deletion of characters. Then, after all non-common characters have been deleted, the remaining sequence of characters (not necessarily contiguous in the original string, but in the same order) is the longest common subsequence (LCS) of both strings. For example, the LCS of '`survey`' and '`surgery`' is '`surey`.'

Similarity can be extended to documents. For example, we can consider lines as single symbols and compute the longest common sequence of lines between two files. This is the measure used by the `diff` command in Unix-like operating systems. The main problem with this approach is that it is very time consuming and does not consider lines that are similar. The latter drawback can be fixed by taking a weighted edit distance between lines or by computing the LCS over all the characters. Other solutions include extracting fingerprints (any piece of text that in some sense characterizes it) for the documents and comparing them, or finding large repeated pieces. There are also visual tools to see document similarity. For example, `Dotplot` draws a rectangular map where both coordinates are file lines and the entry for each coordinate is a gray pixel that depends on the edit distance between the associated lines.

6.4 Markup Languages

Markup is defined as extra textual syntax that can be used to describe formatting actions, structure information, text semantics, attributes, etc. For example, the formatting commands of TeX (a popular text formatting software) could be considered markup. However, formal markup languages are much more structured. The marks are called tags, and usually, to avoid ambiguity, there is an initial and ending tag surrounding the marked text. The standard metalanguage for markup is SGML, as already mentioned. An important subset of SGML is XML (eXtensible Markup Language), the new metalanguage for the Web. The most popular markup language used for the Web, HTML (HyperText Markup Language), is an instance of SGML. All these languages and examples of them are described below.

6.4.1 SGML

SGML stands for Standard Generalized Markup Language (ISO 8879) and is a metalanguage for tagging text developed by a group led by Goldfarb [303] based on earlier work done at IBM. That is, SGML provides the rules for defining a markup language based on tags. Each instance of SGML includes a description of the document structure called a document type definition. Hence, an SGML document is defined by: (1) a description of the structure of the document and (2) the text itself marked with tags which describe the structure. We will explain later the syntax associated with the tags.

The document type definition is used to describe and name the pieces that a document is composed of and define how those pieces relate to each other. Part of the definition can be specified by an SGML document type declaration (DTD).

Other parts, such as the semantics of elements and attributes, or application conventions, cannot be expressed formally in SGML. Comments can be used, however, to express them informally. This means that all of the rules for applying SGML markup to documents are part of the definition, and those that can be expressed in SGML syntax are represented in the DTD. The DTD does not define the semantics (that is, the meaning, presentation, and behavior), or intended use, of the tags. However, some semantic information can be included in comments embedded in the DTD, while more complete information is usually present in separate documentation. This additional documentation typically describes the elements, or logical pieces of data, the attributes, and information about those pieces of data. For example, two tags can have the same name but different semantics in two different applications.

Tags are denoted by angle brackets (`<tagname>`). Tags are used to identify the beginning and ending of pieces of the document, for example a quote in a literary text. Ending tags are specified by adding a slash before the tag name (e.g., `</tagname>`). For example, the tag `</author>` could be used to identify the element 'name of author,' which appears in italics and generates a link to a biographic sketch. Tag attributes are specified at the beginning of the element, inside the angle brackets and after the nametag using the syntax `attname=value`.

Figure 6.3 gives an example of a simple DTD and a document using it. While we do not intend to discuss SGML syntax here, we give a brief description of the example such that the reader can grasp the main ideas. Each ELEMENT represents a tag denoted by its name. The two following characters indicate if the starting and ending tags are compulsory (`-`) or optional (`O`). For example, the ending tag for `prolog` is necessary while for `sender` it is not. Following that, the inside portion of the content tag is specified using a regular expression style syntax where ',' stands for concatenation, '|' stands for logical or, '?' stands for zero or one occurrence, '*' stands for zero or more occurrences, and '+' stands for one or more occurrences of the preceding element. The content tag can be composed of the combination of other tag contents, ASCII characters (PCDATA), and binary data (NDATA), or EMPTY. The possible attributes of a tag are given in an attribute list (ATTLIST) identified by the tag name, followed by the name of each attribute, its type, and if it is required or not (otherwise, the default value is given). An SGML document instance is associated with the DTD so that the various tools working with the data know which are the correct tags and how they are organized.

The document description generally does not specify how a document should look, for example when it is printed on paper or displayed on a screen. Because SGML separates content from format, we can create very good models of data that have no mechanism for describing the format, hence, no standard way to output the data in a formatted fashion. Therefore, output specifications, which are directions on how to format a document, are often added to SGML documents. For this purpose, output specification standards such as DSSSL (Document Style Semantic Specification Language) and FOSI (Formatted Output Specification Instance) were devised. Both of these standards define mechanisms for associating style information with SGML document instances.

```
<!--SGML DTD for electronic messages -->

<!ELEMENT e-mail          - - (prolog, contents) >
<!ELEMENT prolog          - - (sender, address+, subject?, Cc*) >
<!ELEMENT (sender | address | subject | Cc) - O (#PCDATA) >
<!ELEMENT contents        - - (par | image | audio)+ >
<!ELEMENT par             - O (ref | #PCDATA)+ >
<!ELEMENT ref             - O EMPTY >
<!ELEMENT (image | audio) - -  (#NDATA) >

<!ATTLIST e-mail
          id           ID                  #REQUIRED
          date_sent    DATE                #REQUIRED
          status       (secret | public )  public >
<!ATTLIST ref
          id           IDREF               #REQUIRED >
<!ATTLIST (image | audio )
          id           ID                  #REQUIRED >

<!--Example of use of previous DTD-->
<!DOCTYPE e-mail SYSTEM "e-mail.dtd">
<e-mail id=94108rby date_sent=02101998>
  <prolog>
  <sender> Pablo Neruda </sender>
  <address> Federico García Lorca </address>
  <address> Ernest Hemingway </address>
  <subject> Pictures of my house in Isla Negra
  <Cc> Gabriel García Márquez </Cc>
  </prolog>
  <contents>
      <par>
      As promised in my previous letter, I am sending two digital
      pictures to show you my house and the splendid view of the
      Pacific Ocean from my bedroom (photo <ref idref=F2>).
      </par>
      <image id=F1> "photo1.gif" </image>
      <image id=F2> "photo2.jpg" </image>
      <par>
      Regards from the South, Pablo.
  </contents>
</e-mail>
```

Figure 6.3 DTD for structuring electronic mails and an example of its use.

They are the components of an SGML system used for defining, for instance, that the data identified by a tag should be typeset in italics.

One important use of SGML is in the Text Encoding Initiative (TEI). The TEI is a cooperative project that started in 1987 and includes several US associations related to the humanities and linguistics. The main goal is to generate guidelines for the preparation and interchange of electronic texts for scholarly

research, as well as for industry. In addition to the guidelines, TEI provides several document formats through SGML DTDs. One of the most used formats is TEI Lite. The TEI Lite DTD can be used stand-alone or together with the full set of TEI DTD files.

6.4.2 HTML

HTML stands for HyperText Markup Language and is an instance of SGML. HTML was created in 1992 and has evolved during the past years, 4.0 being the latest version, released as a recommendation at the end of 1997. Currently it is being extended in many ways to solve its many limitations, for example, to be able to write mathematical formulas. Most documents on the Web are stored and transmitted in HTML. HTML is a simple language well suited for hypertext, multimedia, and the display of small and simple documents.

HTML is based on SGML, and although there is an HTML DTD (Document Type Definition), most HTML instances do not explicitly make reference to the DTD. The HTML tags follow all the SGML conventions and also include formatting directives.

HTML documents can have other media embedded within them, such as images or audio in different formats. HTML also has fields for metadata, which can be used for different applications and purposes. If we also add programs (for example, using Javascript) inside a page, some people call it dynamic HTML (or DHTML). This should not be confused with a Microsoft proposal (also called dynamic HTML) of an Application Programming Interface (API) for accessing and manipulating HTML documents. Figure 6.4 gives an example of an HTML document together with its output in a Web browser.

Because HTML does not fix the presentation style of a document, in 1997, Cascade Style Sheets (CSS) were introduced. CSS offer a powerful and manageable way for authors, artists, and typographers to create visual effects that improve the aesthetics of HTML pages in the Web. Style sheets can be used one after another (called cascading) to define the presentation style for different elements of an HTML page. Style sheets separate information about presentation from document content, which in turn simplifies Web site maintenance, promotes Web page accessibility, and makes the Web faster. However, CSS support in current browsers is still modest. Another disadvantage is that two style sheets do not have to be consistent nor complete, so the stylistic result might not be good, in particular regarding color. CSS are supposed to balance the expectations of the author and of the reader regarding presentation issues. Nevertheless, it is not clear who or in which cases the author or the reader should define the presentation.

The evolution of HTML implies support for backward compatibility and also for forward compatibility, because people should also be able to see new documents with old browsers. HTML 4.0 has been specified in three flavors: strict, transitional, and frameset. Strict HTML only worries about non-presentational

```
<html>
<head>
<title>HTML Example</title>
<meta name=rby content="Just an example">
</head>
<body>
<h1>HTML Example</h1>
<p>
<hr>
<p>
HTML has many <i>tags</i>, among them:
<ul>
<li> links to other <a href=http://www.w3c.org/>pages</a>
    (a from anchor),
<li> paragraphs (p), headings (h1, h2, etc), font types (b, i),
<li> horizontal rules (hr), indented lists and items (ul, li),
<li> images (img), tables, forms, etc.
</ul>
<p>
<hr>
<p>
<img align=left src="at_work.gif">
This page is <b>always</b> under construction.
</body>
</html>
```

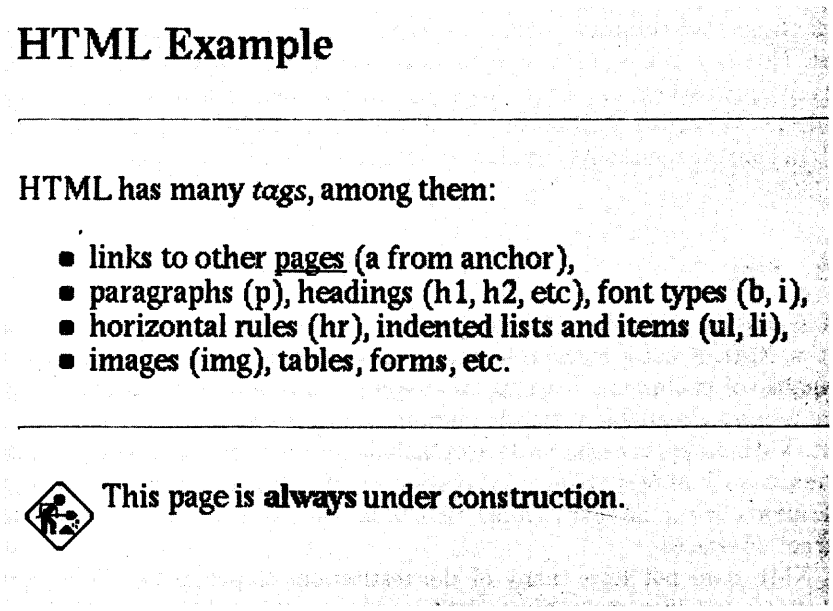


Figure 6.4 Example of an HTML document and how it is seen in a browser.

markup, leaving all the displaying information to CSS. Transitional HTML uses all the presentational features for pages that should be read for old browsers that do not understand CSS. Frameset HTML is used when you want to partition the browser window in two or more frames. HTML 4.0 includes support for style sheets, internationalization, frames, richer tables and forms, and accessibility options for people with disabilities.

Typical HTML applications use a fixed small set of tags in conformance with a single SGML specification. Fixing a small set of tags allows users to leave the language specification out of the document and makes it much easier to build applications, but this advantage comes at the cost of severely limiting HTML in several important aspects. In particular, HTML does not:

- allow users to specify their own tags or attributes in order to parameterize or otherwise semantically qualify their data;
- support the specification of nested structures needed to represent database schemas or object-oriented hierarchies;
- support the kind of language specification that allows consuming applications to check data for structural validity on importation.

In contrast to HTML stands generic SGML. A generic SGML application is one that supports SGML language specifications of arbitrary complexity and makes possible the qualities of extensibility, structure, and validation missing in HTML. SGML makes it possible to define your own formats for your own documents, to handle large and complex documents, and to manage large information repositories. However, full SGML contains many optional features that are not needed for Web applications and have proven to have a cost/benefit ratio unattractive to current vendors of Web browsers. All these reasons led to the development of XML, a simpler metalanguage that is described in the next section.

6.4.3 XML

XML stands for eXtensible Markup Language and is a simplified subset of SGML. That is, XML is not a markup language, as HTML is, but a metalanguage that is capable of containing markup languages in the same way as SGML. XML allows a human-readable semantic markup, which is also machine-readable. As a result, XML makes it easier to develop and deploy new specific markup, enabling automatic authoring, parsing, and processing of networked data. In some ways, XML allows one to do many things that today are done by Java scripts or other program interfaces.

XML does not have many of the restrictions imposed by HTML but on the other hand imposes a more rigid syntax on the markup, which becomes important at processing time. In XML, ending tags cannot be omitted. Also, tags for elements that do not have any content, like BR and IMG, are specially marked by a slash before the closing angle bracket. XML also distinguishes upper

```
<?XML VERSION="1.0" RMD="NONE" ?>
<e-mail id="94108rby" date_sent="02101998">
  <prolog>
  <sender> Pablo Neruda </sender>
  <address> Federico García Lorca </address>
  <address> Ernest Hemingway </address>
  <subject> Pictures of my house in Isla Negra
  <Cc> Gabriel García Márquez </Cc>
  </prolog>
  <contents>
      <par>
      As promised in my previous letter, I am sending two digital
      pictures to show you my house and the splendid view of the
      Pacific Ocean from my bedroom (photo <ref idref="F2"/>).
      </par>
      <image id="F1" ref="photo1.gif" />
      <image id="F2"> ref="photo2.jpg" />
      <par>
      Regards from the South, Pablo.
      </par>
  </contents>
</e-mail>
```

Figure 6.5 An XML document without a DTD analogous to the previous SGML example.

and lower case, so `img` and `IMG` are different tags (this is not true in HTML). In addition, all attribute values must be between quotes. This implies that parsing XML without knowledge of the tags is easier. In particular, using a DTD is optional. If there is no DTD, the tags are obtained while the parsing is done. With respect to SGML, there are a few syntactic differences, and many more restrictions. Listing all these differences is beyond the scope of this book, but Figure 6.5 shows an example of a DTDless XML document based on the previous electronic mail DTD given for SGML (see Figure 6.3). The `RMD` attribute stands for Required Markup Declaration, which indicates whether a DTD must be used or not (no DTD in this case). Other possible values are `INTERNAL` which means that the DTD is inside the document or `ALL` (default value) which allows the use of external sources for part or the whole DTD as in SGML.

XML allows any user to define new tags, define more complex structures (for example, unbounded nesting with the same rules of SGML) and has data validation capabilities. As XML is very new, there is still some discussion of how it will change or impact Internet applications. XML is a profile of SGML that eliminates many of the difficulties of implementing things, so for the most part it behaves just like SGML, as shown before. As mentioned, XML removes the requirement for the existence of a DTD, which can be parsed directly from the data. Removing the DTD places even more importance on the application documentation. This can also have a large impact on the functions that the software

provides. For example, it means that if an XML editor does not use a DTD, how will it help the user to tag the documents consistently? These problems should be resolved in the near future. In the case of semantic ambiguity between tag names, one goal is to have a *namespace* such that there is a convention for its use.

The Extensible Style sheet Language (XSL) is the XML counterpart of Cascading Style Sheets. XSL is designed to transform and style highly-structured, data-rich documents written in XML. For example, with XSL it would be possible to automatically extract a table of contents from a document. The syntax of XSL has been defined using XML. In addition to adding style to a document XSL can be used to transform XML documents to HTML and CSS. This is analogous to macros in a word processor.

Another extension to XML, defined using XML, is the Extensible Linking Language (XLL). XLL defines different types of links, including external and internal links. In particular, any element type can be the origin of a link and outgoing links can be defined on documents that cannot be modified. The behavior of the links is also more generic. The object linked can be embedded in, or replace the document. It is also possible to generate a new context without changing the current application (for example, the object is displayed in a new window).

Recent uses of XML include:

- **Mathematical Markup Language** (MathML): two sets of tags, one for presentation of formulas and another for the meaning of mathematical expressions.
- **Synchronized Multimedia Integration Language** (SMIL): a declarative language for scheduling multimedia presentations in the Web, where the position and activation time of different objects can be specified.
- **Resource Description Format** (already covered in section 6.2): metadata information for XML should be given using RDF.

The XML movement is one indication that a parseable, hierarchical object model will play an increasingly major role in the evolution of HTML. The next generation of HTML should be based on a suite of XML tag sets to be used together with mathematics, synchronized multimedia, and vector graphics (possibly using the XML-based languages already mentioned). That is, the emphasis will be on structuring and modeling data rather than on presentation and layout issues.

6.5 Multimedia

Multimedia usually stands for applications that handle different types of digital data originating from distinct types of media. The most common types of media in multimedia applications are text, sound, images, and video (which is an animated sequence of images). The digital data originating from each of these four

types of media is quite distinct in volume, format, and processing requirements (for instance, video and audio impose real time constraints on their processing). As an immediate consequence, different types of formats are necessary for storing each type of media.

In this section we cover formats and standard languages for multimedia applications. In contrast with text formats, most formats for multimedia are partially binary and hence can only be processed by a computer. Also, the presentation style is almost completely defined, perhaps with the exception of some spatial or temporal attributes.

6.5.1 Formats

Multimedia includes images, audio and video, as well as other binary data. We now briefly survey the main formats used for all these data types. They are used mainly in the Web and in digital libraries (see Chapters 13 and 15).

There are several formats for images. The simplest formats are direct representations of a bit-mapped (or pixel-based) display such as XBM, BMP, or PCX. However, those formats consume too much space. For example, a typical computer screen which uses 256 colors for each pixel might require more than 1 Mb (one megabyte) in storage just for describing the content of a single screen frame. In practice, images have a lot of redundancy and can be compressed efficiently. So, most popular image formats incorporate compression such as Compuserve's Graphic Interchange Format (GIF). GIF is good for black and white pictures, as well as pictures that have a small number of colors or gray levels (say 256). To improve compression ratios for higher resolutions, lossy compression was developed. That is, uncompressing a compressed image does not give the original. This is done by the Joint Photographic Experts Group (JPEG) format, which tries to eliminate parts of the image that have less impact on the human eye. This format is parametric, in the sense that the loss can be tuned.

Another common image format is the Tagged Image File Format (TIFF). This format is used to exchange documents between different applications and different computer platforms. TIFF has fields for metadata and also supports compression as well as different numbers of colors. Yet another format is Truevision Targa image file (TGA), which is associated with video game boards. There are many more image formats, many of them associated to particular applications ranging from fax (bi-level image formats such as JBIG) to fingerprints (highly accurate and compressed formats such as WSQ) and satellite images (large resolution and full-color images). In 1996 a new bit-mapped image format was proposed for the Internet: Portable Network Graphics (PNG). This format could be important in the future.

Audio must be digitalized first in order to be stored properly. The most common formats for small pieces of digital audio are AU, MIDI, and WAVE. MIDI is an standard format to interchange music between electronic instruments and computers. For audio libraries other formats are used such as RealAudio or CD formats.

There are several formats for animations or moving images (similar to video or TV), but here we mention only the most popular ones. The main one is MPEG (Moving Pictures Expert Group) which is related to JPEG. MPEG works by coding the changes with respect to a base image which is given at fixed intervals. In this way, MPEG profits from the temporal image redundancy that any video has. Higher quality is achieved by using more frames and higher resolution. MPEG specifies different compression levels, but usually not all the applications support all of them. This format also includes the audio signal associated with the video. Other video formats are AVI, FLI, and QuickTime. AVI may include compression (CinePac), as well as QuickTime, which was developed by Apple. As for MPEG, audio is also included.

6.5.2 Textual Images

A particular class of images that is very important in office systems, multimedia retrieval, and digital libraries are images of documents that contain mainly typed or typeset text. These are called *textual images* and are obtained by scanning the documents, usually for archiving purposes — a procedure that also makes the images (and their associated text) available to anyone through a computer network. The fact that a large portion of a textual image is text can be used for retrieval purposes and efficient compression.

Although we do not cover image compression in this chapter, we have seen that the most popular image formats include some form of compression embedded in them. In the case of textual images, further compression can be achieved by extracting the different text symbols or marks from the image, building a library of symbols for them, and representing each one (within the image) by a position in the library. As many symbols are repeated, the compression ratio is quite good. Although this technique is lossy (because the reconstructed image is not equal to the original), the reconstructed image can be read without problems. Additional information can be stored to reproduce the original image, but for most applications this is not needed. If the image contains non-textual information such as logos or signatures, which might be necessary to reproduce, they may be extracted through a segmentation process, stored, and compressed separately. When needed, the textual and non-textual parts of the image can be combined and displayed together.

Regarding the retrieval of textual images, several alternatives are possible as follows:

- At creation time or when added to the database, a set of keywords that describe the image is associated with it (for example, metadata can be used). Later, conventional text retrieval techniques can be applied to those keywords. This alternative is valid for any multimedia object.
- Use OCR to extract the text of the image. The resultant ASCII text can be used to extract keywords, as before, or as a full-text description of the

image. Depending on the document type, the OCR output could be reasonably good or actually quite bad (consider the first page of a newspaper, with several columns, different font types and sizes). In any case, many typos are introduced and a usual keyword-based query might miss many documents (in this case, an approximate search is better, but also slower)

- Use the symbols extracted from the images as basic units to combine image retrieval techniques (see Chapter 12) with sequence retrieval techniques (see Chapter 8). In this case, the query is transformed into a symbol sequence that has to match approximately another symbol sequence in the compressed image. This idea seems promising but has not been pursued yet.

6.5.3 Graphics and Virtual Reality

There are many formats proposed for three-dimensional graphics. Although this topic is not fully relevant to information retrieval, we include some information here for the sake of completeness. Our emphasis here is on the Web.

The Computer Graphics Metafile (CGM) standard (ISO 8632) is defined for the open interchange of structured graphical objects and their associated attributes. CGM specifies a two-dimensional data interchange standard which allows graphical data to be stored and exchanged between graphics devices, applications, and computer systems in a device-independent manner. It is a structured format that can represent vector graphics (for example, polylines or ellipses), raster graphics, and text. Although initially CGM was a vector graphics format, it has been extended to include raster capabilities and provides a very useful format for combined raster and vector images. A metafile is a collection of elements. These elements may be the geometric components of the picture, such as polyline or polygon; the appearance of these components; or how to interpret a particular metafile or a particular picture. The CGM standard specifies which elements are allowed to occur in which positions in a metafile.

The Virtual Reality Modeling Language (VRML, ISO/IEC 14772-1) is a file format for describing interactive 3D objects and worlds and is a subset of the Silicon Graphics OpenInventor file format. VRML is also intended to be a universal interchange format for integrated 3D graphics and multimedia. VRML may be used in a variety of application areas such as engineering and scientific visualization, multimedia presentations, entertainment and educational titles, Web pages, and shared virtual worlds. VRML has become the *de facto* standard modeling language for the Web.

6.5.4 HyTime

The Hypermedia/Time-based Structuring Language (HyTime) is a standard (ISO/IEC 10744) defined for multimedia documents markup. HyTime is an SGML architecture that specifies the generic hypermedia structure of documents.

Following the guiding principle of SGML, HyTime-defined structure is independent of any presentation of the encoded document. As an architecture, HyTime allows DTDs to be written for individual document models that use HyTime constructs, specifying how these document sets tailor the composition of these constructs for their particular representational needs. The standard also provides several metaDTDs, facilitating the design of new multimedia markup languages.

The hypermedia concepts directly represented by HyTime include

- complex locating of document objects,
- relationships (hyperlinks) between document objects, and
- numeric, measured associations between document objects.

The HyTime architecture has three parts: the base linking and addressing architecture, the scheduling architecture (derived from the base architecture), and the rendition architecture (which is an application of the scheduling architecture). The base architecture addresses the syntax and semantics of hyperlinks. For most simple hypermedia presentations, this should be enough. The scheduling module of HyTime defines the abstract representation of arbitrarily complex hypermedia structures, including music and interactive presentations. Its basic mechanism is a simple one: the sequencing of object containers along axes measured in temporal or spatial units. The rendition module is essentially an application of the scheduling architecture that defines a general mechanism for defining the creation of new schedules from existing schedules by applying special 'rendition rules' of different types.

HyTime does not directly specify graphical interfaces, user navigation, user interaction, or the placement of media on time lines and screen displays. These aspects of document processing are rendered from the HyTime constructs in a manner specified by mechanisms such as style sheets, as is done with SGML documents.

One application of HyTime, is the Standard Music Description Language (SMDL). SDML is an architecture for the representation of music information, either alone, or in conjunction with other media, also supporting multimedia time sequencing information. Another application is the Metafile for Interactive Documents (MID). MID is a common interchange structure, based on SGML and HyTime, that takes data from various authoring systems and structures it for display on dissimilar presentation systems, with minimal human intervention.

6.6 Trends and Research Issues

Many changes and proposals are happening, and very rapidly, in particular due to the advent of the Web. At this point, the reader must be lost in a salad of acronyms (we were too!), in spite of the fact that we have only mentioned the most important languages and formats. The most important of these are included in the Glossary at the end of this book. Some people believe that new

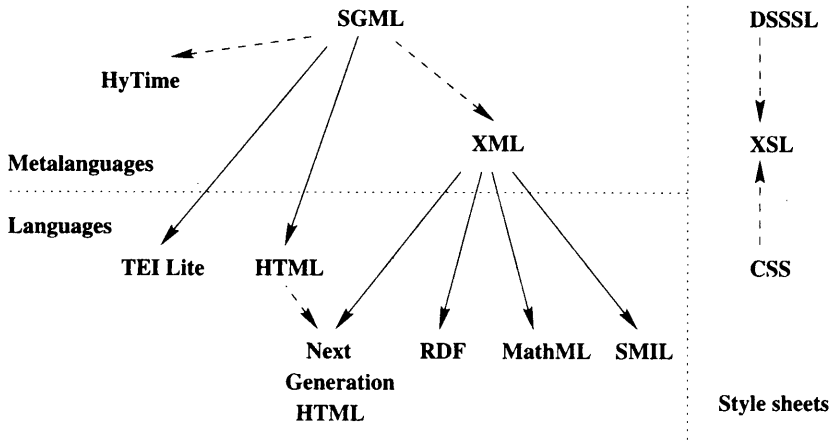


Figure 6.6 Taxonomy of Web languages.

format specifications such as CSS or XML take away the simplicity of HTML, which is the basis of its success. Only the future will tell. Figure 6.6 illustrates a taxonomy of the main languages considered. Solid lines indicate instances of a metalanguage (for example, HTML is an instance of SGML), while dashed lines indicate derived languages. The main trend is the convergence and integration of the different efforts, the Web being the main application.

A European alternative to SGML is the Open Document Architecture (ODA) which is also a standard (ISO 8613 [398]). ODA was designed to share documents electronically without losing control over the content, structure, and layout of those documents. ODA defines a logical structure (like SGML), a layout and the content (including vector and raster graphics). An ODA file can also be formatted, processable, or formatted processable. Formatted files cannot be edited and have information about content and layout. The other two types can be edited. Processable files also have logical information in addition to content, while formatted processable files have everything. ODA is not used very much nowadays (see also Chapter 11).

Recent developments include:

- An object model is being defined: the document object model (DOM). DOM will provide an interoperable set of classes and methods to manipulate HTML and XML objects from programming languages such as Java.
- Integration between VRML and Dynamic HTML, providing a set of evolving features and architecture extensions to HTML and Web browsers that includes cascading style sheets and document object models.
- Integration between the Standard Exchange for Product Data format (STEP, ISO 10303) and SGML. STEP covers product data from a broad range of industries, and provides extensive support for modeling,

automated storage schema generation, life-cycle maintenance, and other management facilities.

- Efforts to convert MARC to SGML by defining a DTD, as well as converting MARC to XML. This has potential possibilities for enhanced access and navigation and presentation of MARC record data and the associated information.
- CGM has become of interest to Web researchers and commercial vendors for its use on the Internet, by developing a new encoding which can be parsed by XML.
- Several new proposals have appeared. Among them we can mention SDML (Signed Document Markup Language), VML (Vector Markup Language), and PGML (Precision Graphics Markup Language). The latter is based on the 2D imaging model of Postscript and PDF.

6.7 Bibliographic Discussion

The document model used in the introduction is based on [437]. Specific information on Web metadata is given in [487, 753]. Most of the information about markup languages and related issues is from the World Wide Web Consortium (see `www.w3.org`), in particular information on new developments such as DOM or SMIL. More information on SGML and XML is given by Goldfarb [303, 304]. Additional references in SGML are [369, 756] (in particular, the SGML example has been adapted from [24]). There are hundreds of books on HTML. Two sources for HTML 4.0 are [207, 796]. A book on CSS is [517]. For information on XML, XSL, and XLL see [795, 799, 798]. For a discussion about the advantages and disadvantages of XML and related languages see [182, 106, 455, 436]. More information on multimedia formats can be found in [501]. Formats for images and compression of textual images are covered in detail in [825].

Chapter 7
Text Operations

---

with Nivio Ziviani

7.1 Introduction

As discussed in Chapter 2, not all words are equally significant for representing the semantics of a document. In written language, some words carry more *meaning* than others. Usually, *noun* words (or groups of noun words) are the ones which are most representative of a document content. Therefore, it is usually considered worthwhile to preprocess the text of the documents in the collection to determine the terms to be used as *index terms*. During this preprocessing phase other useful text operations can be performed such as elimination of stopwords, stemming (reduction of a word to its grammatical root), the building of a thesaurus, and compression. Such text operations are discussed in this chapter.

We already know that representing documents by sets of index terms leads to a rather imprecise representation of the semantics of the documents in the collection. For instance, a term like '*the*' has no meaning whatsoever by itself and might lead to the retrieval of various documents which are unrelated to the present user query. We say that using the set of all words in a collection to index its documents generates too much *noise* for the retrieval task. One way to reduce this noise is to reduce the set of words which can be used to refer to (i.e., to index) documents. Thus, the preprocessing of the documents in the collection might be viewed simply as a process of controlling the size of the vocabulary (i.e., the number of distinct words used as an index terms). It is expected that the use of a controlled vocabulary leads to an improvement in retrieval performance.

While controlling the size of the vocabulary is a common technique with commercial systems, it does introduce an additional step in the indexing process which is frequently not easily perceived by the users. As a result, a common user might be surprised with some of the documents retrieved and with the absence of other documents which he expected to see. For instance, he might remember that a certain document contains the string '*the house of the lord*' and notice that such a document is not present among the top 20 documents retrieved in

response to his query request (because the controlled vocabulary contains neither 'the' nor 'of'). Thus, it should be clear that, despite a potential improvement in retrieval performance, text transformations done at preprocessing time might make it more difficult for the user to interpret the retrieval task. In recognition of this problem, some search engines in the Web are giving up text operations entirely and simply indexing all the words in the text. The idea is that, despite a more noisy index, the retrieval task is simpler (it can be interpreted as a full text search) and more intuitive to a common user.

Besides document preprocessing, other types of operations on documents can also be attempted with the aim of improving retrieval performance. Among these we distinguish the construction of a thesaurus representing conceptual term relationships and the clustering of related documents. Thesauri are also covered in this chapter. The discussion on document clustering is covered in Chapter 5 because it is an operation which might depend on the current user query.

Text normalization and the building of a thesaurus are strategies aimed at improving the precision of the documents retrieved. However, in the current world of very large digital libraries, improving the efficiency (in terms of time) of the retrieval process has also become quite critical. In fact, Web search engines are currently more concerned with reducing query response time than with improving precision and recall figures. The reason is that they depend on processing a high number of queries per unit of time for economic survival. To reduce query response time, one might consider the utilization of text compression as a promising alternative.

A good compression algorithm is able to reduce the text to 30–35% of its original size. Thus, compressed text requires less storage space and takes less time to be transmitted over a communication link. The main disadvantage is the time spent compressing and decompressing the text. Until recently, it was generally understood that compression does not provide substantial gains in processing time because the extra time spent compressing/decompressing text would offset any gains in operating with compressed data. Further, the use of compression makes the overall design and implementation of the information system more complex. However, modern compression techniques are slowly changing this understanding towards a more favorable view of the adoption of compression techniques. By modern compression techniques we mean good compression and decompression speeds, fast random access without the need to decode the compressed text from the beginning, and direct searching on the compressed text without decompressing it, among others.

Besides compression, another operation on text which is becoming more and more important is *encryption*. In fact, due to the fast popularization of services in the Web (including all types of electronic commerce), key (and old) questions regarding security and privacy have surfaced again. More than ever before, impersonation and unauthorized access might result in great prejudice and financial damage to people and organizations. The solution to these problems is not simple but can benefit from the operation of encrypting text. Discussing encrypted text is beyond the scope of this book but an objective and brief introduction to the topic can be found in [501].

In this chapter, we first discuss five preprocessing text operations including thesauri. Following that, we very briefly summarize the problem of document clustering (which is discussed in detail in Chapter 5). Finally, a thorough discussion on the issue of text compression, its modern variations, and its main implications is provided.

7.2 Document Preprocessing

Document preprocessing is a procedure which can be divided mainly into five text operations (or transformations):

(1) Lexical analysis of the text with the objective of treating digits, hyphens, punctuation marks, and the case of letters.

(2) Elimination of stopwords with the objective of filtering out words with very low discrimination values for retrieval purposes.

(3) Stemming of the remaining words with the objective of removing affixes (i.e., prefixes and suffixes) and allowing the retrieval of documents containing syntactic variations of query terms (e.g., connect, connecting, connected, etc).

(4) Selection of index terms to determine which words/stems (or groups of words) will be used as an indexing elements. Usually, the decision on whether a particular word will be used as an index term is related to the syntactic nature of the word. In fact, noun words frequently carry more semantics than adjectives, adverbs, and verbs.

(5) Construction of term categorization structures such as a thesaurus, or extraction of structure directly represented in the text, for allowing the expansion of the original query with related terms (a usually useful procedure).

In the following, each of these phases is discussed in detail. But, before proceeding, let us take a look at the logical view of the documents which results after each of the above phases is completed. Figure 1.2 is repeated here for convenience as Figure 7.1. As already discussed, by aggregating the preprocessing phases, we are able to move the logical view of the documents (adopted by the system) from that of a full text to that of a set of high level indexing terms.

7.2.1 Lexical Analysis of the Text

Lexical analysis is the process of converting a stream of characters (the text of the documents) into a stream of words (the candidate words to be adopted as index terms). Thus, one of the major objectives of the lexical analysis phase is the identification of the words in the text. At first glance, all that seems to be involved is the recognition of spaces as word separators (in which case, multiple

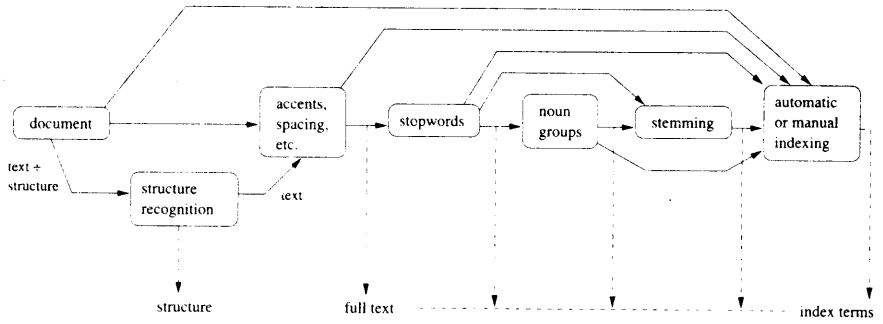


Figure 7.1 Logical view of a document throughout the various phases of text preprocessing.

spaces are reduced to one space). However, there is more to it than this. For instance, the following four particular cases have to be considered with care [263]: digits, hyphens, punctuation marks, and the case of the letters (lower and upper case).

Numbers are usually not good index terms because, without a surrounding context, they are inherently vague. For instance, consider that a user is interested in documents about the number of deaths due to car accidents between the years 1910 and 1989. Such a request could be specified as the set of index terms {deaths, car, accidents, years, 1910, 1989}. However, the presence of the numbers 1910 and 1989 in the query could lead to the retrieval, for instance, of a variety of documents which refer to either of these two years. The problem is that numbers by themselves are just too vague. Thus, in general it is wise to disregard numbers as index terms. However, we have also to consider that digits might appear mixed within a word. For instance, '510B.C.' is a clearly important index term. In this case, it is not clear what rule should be applied. Furthermore, a sequence of 16 digits identifying a credit card number might be highly relevant in a given context and, in this case, should be considered as an index term. A preliminary approach for treating digits in the text might be to remove all words containing sequences of digits unless specified otherwise (through regular expressions). Further, an advanced lexical analysis procedure might perform some date and number normalization to unify formats.

Hyphens pose another difficult decision to the lexical analyzer. Breaking up hyphenated words might be useful due to inconsistency of usage. For instance, this allows treating 'state-of-the-art' and 'state of the art' identically. However, there are words which include hyphens as an integral part. For instance, gilt-edge, B-49, etc. Again, the most suitable procedure seems to adopt a general rule and specify the exceptions on a case by case basis.

Normally, punctuation marks are removed entirely in the process of lexical analysis. While some punctuation marks are an integral part of the word (for

instance, '510B.C.'), removing them does not seem to have an impact in retrieval performance because the risk of misinterpretation in this case is minimal. In fact, if the user specifies '510B.C' in his query, removal of the dot both in the query term and in the documents will not affect retrieval. However, very particular scenarios might again require the preparation of a list of exceptions. For instance, if a portion of a program code appears in the text, it might be wise to distinguish between the variables 'x.id' and 'xid.' In this case, the dot mark should not be removed.

The case of letters is usually not important for the identification of index terms. As a result, the lexical analyzer normally converts all the text to either lower or upper case. However, once more, very particular scenarios might require the distinction to be made. For instance, when looking for documents which describe details about the command language of a Unix-like operating system, the user might explicitly desire the non-conversion of upper cases because this is the convention in the operating system. Further, part of the semantics might be lost due to case conversion. For instance, the words *Bank* and *bank* have different meanings — a fact common to many other pairs of words.

As pointed out by Fox [263], all these text operations can be implemented without difficulty. However, careful thought should be given to each one of them because they might have a profound impact at document retrieval time. This is particularly worrisome in those situations in which the user finds it difficult to understand what the indexing strategy is doing. Unfortunately, there is no clear solution to this problem. As already mentioned, some Web search engines are opting for avoiding text operations altogether because this simplifies the interpretation the user has of the retrieval task. Whether this strategy will be the one of choice in the long term remains to be seen.

7.2.2 Elimination of Stopwords

As discussed in Chapter 2, words which are too frequent among the documents in the collection are not good discriminators. In fact, a word which occurs in 80% of the documents in the collection is useless for purposes of retrieval. Such words are frequently referred to as *stopwords* and are normally filtered out as potential index terms. Articles, prepositions, and conjunctions are natural candidates for a list of stopwords.

Elimination of stopwords has an additional important benefit. It reduces the size of the indexing structure considerably. In fact, it is typical to obtain a compression in the size of the indexing structure (for instance, in the size of an inverted list, see Chapter 8) of 40% or more solely with the elimination of stopwords.

Since stopword elimination also provides for compression of the indexing structure, the list of stopwords might be extended to include words other than articles, prepositions, and conjunctions. For instance, some verbs, adverbs, and adjectives could be treated as stopwords. In [275], a list of 425 stopwords is illustrated. Programs in C for lexical analysis are also provided.

Despite these benefits, elimination of stopwords might reduce recall. For instance, consider a user who is looking for documents containing the phrase '*to be or not to be.*' Elimination of stopwords might leave only the term *be* making it almost impossible to properly recognize the documents which contain the phrase specified. This is one additional reason for the adoption of a full text index (i.e., insert all words in the collection into the inverted file) by some Web search engines.

7.2.3 Stemming

Frequently, the user specifies a word in a query but only a variant of this word is present in a relevant document. Plurals, gerund forms, and past tense suffixes are examples of syntactical variations which prevent a perfect match between a query word and a respective document word. This problem can be partially overcome with the substitution of the words by their respective stems.

A *stem* is the portion of a word which is left after the removal of its affixes (i.e., prefixes and suffixes). A typical example of a stem is the word *connect* which is the stem for the variants *connected, connecting, connection,* and *connections.* Stems are thought to be useful for improving retrieval performance because they reduce variants of the same root word to a common concept. Furthermore, stemming has the secondary effect of reducing the size of the indexing structure because the number of distinct index terms is reduced.

While the argument supporting stemming seems sensible, there is controversy in the literature about the benefits of stemming for retrieval performance. In fact, different studies lead to rather conflicting conclusions. Frakes [275] compares eight distinct studies on the potential benefits of stemming. While he favors the usage of stemming, the results of the eight experimental studies he investigated do not allow us to reach a satisfactory conclusion. As a result of these doubts, many Web search engines do not adopt any stemming algorithm whatsoever.

Frakes distinguishes four types of stemming strategies: affix removal, table lookup, successor variety, and n-grams. Table lookup consists simply of looking for the stem of a word in a table. It is a simple procedure but one which is dependent on data on stems for the whole language. Since such data is not readily available and might require considerable storage space, this type of stemming algorithm might not be practical. Successor variety stemming is based on the determination of morpheme boundaries, uses knowledge from structural linguistics, and is more complex than affix removal stemming algorithms. N-grams stemming is based on the identification of digrams and trigrams and is more a term clustering procedure than a stemming one. Affix removal stemming is intuitive, simple, and can be implemented efficiently. Thus, in the remainder of this section we concentrate our discussion on algorithms for affix removal stemming only.

In affix removal, the most important part is suffix removal because most variants of a word are generated by the introduction of suffixes (instead of pre-

fixes). While there are three or four well known suffix removal algorithms, the most popular one is that by Porter because of its simplicity and elegance. Despite being simpler, the Porter algorithm yields results comparable to those of the more sophisticated algorithms.

The Porter algorithm uses a suffix list for suffix stripping. The idea is to apply a series of rules to the suffixes of the words in the text. For instance, the rule

$$s \longrightarrow \phi \tag{7.1}$$

is used to convert plural forms into their respective singular forms by substituting the letter s by nil. Notice that to identify the suffix we must examine the last letters in the word. Furthermore, we look for the longest sequence of letters which matches the left hand side in a set of rules. Thus, application of the two following rules

$$\begin{aligned} sses &\longrightarrow ss \\ s &\longrightarrow \phi \end{aligned} \tag{7.2}$$

to the word *stresses* yields the stem *stress* instead of the stem *stresse*. By separating such rules into five distinct phases, the Porter algorithm is able to provide effective stemming while running fast. A detailed description of the Porter algorithm can be found in the appendix.

7.2.4 Index Terms Selection

If a full text representation of the text is adopted then all words in the text are used as index terms. The alternative is to adopt a more abstract view in which not all words are used as index terms. This implies that the set of terms used as indices must be selected. In the area of bibliographic sciences, such a selection of index terms is usually done by a specialist. An alternative approach is to select candidates for index terms automatically.

Distinct automatic approaches for selecting index terms can be used. A good approach is the identification of noun groups (as done in the Inquery system [122]) which we now discuss.

A sentence in natural language text is usually composed of nouns, pronouns, articles, verbs, adjectives, adverbs, and connectives. While the words in each grammatical class are used with a particular purpose, it can be argued that most of the semantics is carried by the noun words. Thus, an intuitively promising strategy for selecting index terms automatically is to use the nouns in the text. This can be done through the systematic elimination of verbs, adjectives, adverbs, connectives, articles, and pronouns.

Since it is common to combine two or three nouns in a single component (e.g., *computer science*), it makes sense to cluster nouns which appear nearby in the text into a single indexing component (or concept). Thus, instead of simply

using nouns as index terms, we adopt noun groups. A *noun group* is a set of nouns whose syntactic distance in the text (measured in terms of number of words between two nouns) does not exceed a predefined threshold (for instance, 3).

When noun groups are adopted as indexing terms, we obtain a conceptual logical view of the documents in terms of sets of non-elementary index terms.

7.2.5 Thesauri

The word *thesaurus* has Greek and Latin origins and is used as a reference to a treasury of words [261]. In its simplest form, this treasury consists of (1) a precompiled list of important words in a given domain of knowledge and (2) for each word in this list, a set of related words. Related words are, in its most common variation, derived from a synonymity relationship.

In general, however, a thesaurus also involves some normalization of the vocabulary and includes a structure much more complex than a simple list of words and their synonyms. For instance, the popular thesaurus published by Peter Roget [679] also includes *phrases* which means that concepts more complex than single words are taken into account. Roget's thesaurus is of a general nature (i.e., not specific to a certain domain of knowledge) and organizes words and phrases in categories and subcategories.

An example of an entry in Roget's thesaurus is as follows:

> **cowardly** *adjective*
> Ignobly lacking in courage: *cowardly turncoats.*
> **Syns:** chicken (slang), chicken-hearted, craven, dastardly, faint-hearted, gutless, lily-livered, pusillanimous, unmanly, yellow (slang), yellow-bellied (slang).

To the adjective *cowardly*, Roget's thesaurus associates several synonyms which compose a thesaurus class. While Roget's thesaurus is of a generic nature, a thesaurus can be specific to a certain domain of knowledge. For instance, the Thesaurus of Engineering and Scientific Terms covers concepts related to engineering and technical terminology.

According to Foskett [261], the main purposes of a thesaurus are basically: (a) to provide a standard vocabulary (or system of references) for indexing and searching; (b) to assist users with locating terms for proper query formulation; and (c) to provide classified hierarchies that allow the broadening and narrowing of the current query request according to the needs of the user. In this section, however, we do not discuss how to use a thesaurus for modifying the user query. This issue is covered on Chapter 5 which also discusses algorithms for automatic construction of thesauri.

Notice that the motivation for building a thesaurus is based on the fundamental idea of using a *controlled vocabulary* for the indexing and searching. A controlled vocabulary presents important advantages such as normalization

of indexing concepts, reduction of noise, identification of indexing terms with a clear semantic meaning, and retrieval based on concepts rather than on words. Such advantages are particularly important in specific domains, such as the medical domain for which there is already a large amount of knowledge compiled. For general domains, however, a well known body of knowledge which can be associated with the documents in the collection might not exist. The reasons might be that the document base is new, that it is too large, or that it changes very dynamically. This is exactly the case with the Web. Thus, it is not clear how useful a thesaurus is in the context of the Web. Despite that, the success of the search engine named 'Yahoo!' (see Chapter 13), which presents the user with a term classification hierarchy that can be used to reduce the space to be searched, suggests that thesaurus-based techniques might be quite useful even in the dynamic world of the Web.

It is still too early to reach a consensus on the advantages of a thesaurus for the Web. As a result, many search engines simply use *all* the words in all the documents as index terms (i.e., there is no notion of using the concepts of a controlled vocabulary for indexing and searching purposes). Whether thesaurus-based techniques will flourish in the context of the Web remains to be seen.

The main components of a thesaurus are its index terms, the relationships among the terms, and a layout design for these term relationships. Index terms and term relationships are covered below. The layout design for term relationships can be in the form of a list or in the form of a bi-dimensional display. Here, we consider only the more conventional layout structure based on a list and thus, do not further discuss the issue of layout of the terms in a thesaurus. A brief coverage of topics related to this problem can be found in Chapter 10. A more detailed discussion can be found in [261].

Theasurus Index Terms

The terms are the *indexing* components of the thesaurus. Usually, a term in a thesaurus is used to denote a *concept* which is the basic semantic unit for conveying ideas. Terms can be individual words, groups of words, or phrases, but most of them are single words. Further, terms are basically nouns because nouns are the most concrete part of speech. Terms can also be verbs in gerund form whenever they are used as nouns (for instance, *acting*, *teaching*, etc.).

Whenever a concept cannot be expressed by a single word, a group of words is used instead. For instance, many concepts are better expressed by a combination of an adjective with a noun. A typical example is *ballistic missiles*. In this case, indexing the compound term directly will yield an entry under *balistic* and no entry under *missiles* which is clearly inadequate. To avoid this problem, the compound term is usually modified to have the noun as the first word. For instance, we can change the compound term to *missiles, ballistic*.

We notice the use of the plural form *missiles* instead of the singular form *missile*. The reasoning is that a thesaurus represents classes of things and thus it is natural to prefer the plural form. However, the singular form is used for

compound terms which appear normally in the singular such as *body temperature*. Deciding between singular and plural is not always a simple matter.

Besides the term itself, frequently it is necessary to complement a thesaurus entry with a *definition* or an *explanation*. The reason is the need to specify the precise meanings of a term in the context of a particular thesaurus. For instance, the term *seal* has a meaning in the context of *marine animals* and a rather distinct meaning in the context of *documents*. In these cases, the definition might be preceded by a context explanation such as *seal (marine animals)* and *seal (documents)* [735].

Thesaurus Term Relationships

The set of terms related to a given thesaurus term is mostly composed of synonyms and near-synonyms. In addition to these, relationships can be induced by patterns of co-occurrence within documents. Such relationships are usually of a hierarchical nature and most often indicate broader (represented by BT) or narrower (represented by NT) related terms. However, the relationship might also be of a lateral or non-hierarchical nature. In this case, we simply say that the terms are related (represented by RT).

As discussed in Chapter 5, BT and NT relationships define a classification hierarchy where the broader term is associated with a class and its related narrower terms are associated with the instances of this class. Further, it might be that a narrower term is associated with two or more broader terms (which is not the most common case though). While BT and NT relationships can be identified in a fully automatic manner (i.e., without assistance from a human subject), dealing with RT relationships is much harder. One reason seems to be that RT relationships are dependent on the specific context and particular needs of the group of users and thus are difficult to identify without knowledge provided by specialists.

On the Use of Thesauri in IR

As described by Peter Roget [679, 261], a thesaurus is a classification scheme composed of words and phrases whose organization aims at facilitating the expression of ideas in written text. Thus, whenever a writer has a difficulty in finding the proper term to express an idea (a common occurrence in serious writing), he can use the thesaurus to obtain a better grasp on the fundamental semantics of terms related to his idea.

In the area of information retrieval, researchers have for many years conjectured and studied the usefulness of a thesaurus for helping with the query formation process. Whenever a user wants to retrieve a set of documents, he first builds up a conceptualization of what he is looking for. Such conceptualization is what we call his *information need*. Given the information need, the user still has to translate it into a query in the language of the IR system. This usually

means that a set of index terms has to be selected. However, since the collection might be vast and the user inexperienced, the selection of such *initial* terms might be erroneous and improper (a very common situation with the largely unknown and highly dynamic collection of documents and pages which compose the Web). In this case, reformulating the original query seems to be a promising course of action. Such a reformulation process usually implies expanding the original query with related terms. Thus, it seems natural to use a thesaurus for assisting the user with the search for related terms.

Unfortunately, this approach does not work well in general because the relationships captured in a thesaurus frequently are not valid in the local context of a given user query. One alternative is to determine thesaurus-like relationships at query time. Unfortunately, such an alternative is not attractive for Web search engines which cannot afford to spend a lot of time with the processing of individual queries. This and many other interesting issues related to the use of thesaurus-based techniques in IR are covered in Chapter 5.

7.3 Document Clustering

Document clustering is the operation of grouping together similar (or related) documents in classes. In this regard, document clustering is not really an operation on the text but an operation on the collection of documents.

The operation of clustering documents is usually of two types: global and local. In a global clustering strategy, the documents are grouped accordingly to their occurrence in the whole collection. In a local clustering strategy, the grouping of documents is affected by the context defined by the current query and its *local* set of retrieved documents.

Clustering methods are usually used in IR to transform the original query in an attempt to better represent the user information need. From this perspective, clustering is an operation which is more related to the transformation of the user query than to the transformation of the text of the documents. In this book, document clustering techniques are treated as query operations and thus, are covered in Chapter 5 (instead of here).

7.4 Text Compression

7.4.1 Motivation

Text compression is about finding ways to represent the text in fewer bits or bytes. The amount of space required to store text on computers can be reduced significantly using compression techniques. Compression methods create a reduced representation by identifying and using structures that exist in the text. From the compressed version, the original text can be reconstructed exactly.

Text compression is becoming an important issue in an information retrieval environment. The widespread use of digital libraries, office automation

systems, document databases, and the Web has led to an explosion of textual information available online. In this scenario, text compression appears as an attractive option for reducing costs associated with space requirements, input/output (I/O) overhead, and communication delays. The gain obtained from compressing text is that it requires less storage space, it takes less time to be transmitted over a communication link, and it takes less time to search directly the compressed text. The price paid is the time necessary to code and decode the text.

A major obstacle for storing text in compressed form is the need for IR systems to access text randomly. To access a given word in a compressed text, it is usually necessary to decode the entire text from the beginning until the desired word is reached. It could be argued that a large text could be divided into blocks that are compressed independently, thus allowing fast random access to each block. However, efficient compression methods need to process some text before making compression effective (usually more than 10 kilobytes). The smaller the blocks, the less effective compression is expected to be.

Our discussion here focuses on text compression methods which are suitable for use in an IR environment. For instance, a successful idea aimed at merging the requirements of compression algorithms and the needs of IR systems is to consider that the symbols to be compressed are words and not characters (character-based compression is the more conventional approach). Words are the atoms on which most IR systems are built. Moreover, it is now known that much better compression is achieved by taking words as symbols (instead of characters). Further, new word-based compression methods allow random access to words within the compressed text which is a critical issue for an IR system.

Besides the economy of space obtained by a compression method, there are other important characteristics to be considered such as compression and decompression speed. In some situations, decompression speed is more important than compression speed. For instance, this is the case with textual databases in which it is common to compress the text once and to read it many times from disk.

Another important characteristic of a compression method is the possibility of performing compressed pattern matching, defined as the task of performing pattern matching in a compressed text without decompressing it. In this case, sequential searching can be speeded up by compressing the search key rather than decoding the compressed text being searched. As a consequence, it is possible to search faster on compressed text because much less text has to be scanned. Chapter 8 presents efficient methods to deal with searching the compressed text directly.

When the text collection is large, efficient text retrieval requires specialized index techniques. A simple and popular indexing structure for text collections are the inverted files. Inverted files (see Chapter 8 for details) are especially adequate when the pattern to be searched for is formed by simple words. Since this is a common type of query (for instance, when searching the Web), inverted files are widely used for indexing large text collections.

An inverted file is typically composed of (a) a vector containing all the distinct words in the text collection (which is called the *vocabulary*) and (b) for

each word in the vocabulary, a list of all documents (identified by document numbers) in which that word occurs. Because each list of document numbers (within the inverted file) is organized in ascending order, specific compression methods have been proposed for them, leading to very efficient index compression schemes. This is important because query processing time is highly related to index access time. Thus, in this section, we also discuss some of the most important index compression techniques.

We first introduce basic concepts related to text compression. We then present some of the most important statistical compression methods, followed by a brief review of compression methods based on a dictionary. At the end, we discuss the application of compression to inverted files.

7.4.2 Basic Concepts

There are two general approaches to text compression: *statistical* and *dictionary* based. *Statistical methods* rely on generating good probability estimates (of appearance in the text) for each symbol. The more accurate the estimates are, the better the compression obtained. A *symbol* here is usually a character, a text word, or a fixed number of characters. The set of all possible symbols in the text is called the *alphabet*. The task of estimating the probability on each next symbol is called *modeling*. A *model* is essentially a collection of probability distributions, one for each context in which a symbol can be coded. Once these probabilities are available the symbols are converted into binary digits, a process called *coding*. In practice, both the encoder and decoder use the same model. The decoder interprets the output of the encoder (with reference to the same model) to find out the original symbol.

There are two well known statistical coding strategies: Huffman coding and arithmetic coding. The idea of Huffman coding is to assign a fixed-length bit encoding to each different symbol of the text. Compression is achieved by assigning a smaller number of bits to symbols with higher probabilities of appearance. Huffman coding was first proposed in the early 1950s and was the most important compression method until the late 1970s, when arithmetic coding made higher compression rates possible.

Arithmetic coding computes the code incrementally, one symbol at a time, as opposed to the Huffman coding scheme in which each different symbol is pre-encoded using a fixed-length number of bits. The incremental nature does not allow decoding a string which starts in the middle of a compressed file. To decode a symbol in the middle of a file compressed with arithmetic coding, it is necessary to decode the whole text from the very beginning until the desired word is reached. This characteristic makes arithmetic coding inadequate for use in an IR environment.

Dictionary methods substitute a sequence of symbols by a pointer to a previous occurrence of that sequence. The pointer representations are references to entries in a dictionary composed of a list of symbols (often called phrases) that are expected to occur frequently. Pointers to the dictionary entries are

chosen so that they need less space than the phrase they replace, thus obtaining compression. The distinction between modeling and coding does not exist in dictionary methods and there are no explicit probabilities associated to phrases. The most well known dictionary methods are represented by a family of methods, known as the Ziv-Lempel family.

Character-based Huffman methods are typically able to compress English texts to approximately five bits per character (usually, each uncompressed character takes 7-8 bits to be represented). More recently, a word-based Huffman method has been proposed as a better alternative for natural language texts. This method is able to reduce English texts to just over two bits per character. As we will see later on, word-based Huffman coding achieves compression rates close to the entropy and allows random access to intermediate points in the compressed text. Ziv-Lempel methods are able to reduce English texts to fewer than four bits per character. Methods based on arithmetic coding can also compress English texts to just over two bits per character. However, the price paid is slower compression and decompression, and the impossibility of randomly accessing intermediate points in the compressed text.

Before proceeding, let us present an important definition which will be useful from now on.

Definition Compression ratio *is the size of the compressed file as a fraction of the uncompressed file.*

7.4.3 Statistical Methods

In a statistical method, a probability is estimated for each symbol (the modeling task) and, based on this probability, a code is assigned to each symbol at a time (the coding task). Shorter codes are assigned to the most likely symbols.

The relationship between probabilities and codes was established by Claude Shannon in his source code theorem [718]. He showed that, in an optimal encoding scheme, a symbol that is expected to occur with probability p should be assigned a code of length $\log_2 \frac{1}{p}$ bits. The number of bits in which a symbol is best coded represents the *information content* of the symbol. The average amount of information per symbol over the whole alphabet is called the *entropy* of the probability distribution, and is given by:

$$E = \sum p_i \log_2 \frac{1}{p_i}$$

E is a *lower bound* on compression , measured in bits per symbol, which applies to any coding method based on the probability distribution p_i. It is important to note that E is calculated from the probabilities and so is a property of the model. See Chapter 6 for more details on this topic.

Modeling

The basic *function of a model* is to provide a probability assignment for the next symbol to be coded. High compression can be obtained by forming good models of the text that is to be coded. The probability assignment is explained in the following section.

Compression models can be *adaptive*, *static*, or *semi-static*. *Adaptive models* start with no information about the text and progressively learn about its statistical distribution as the compression process goes on. Thus, adaptive models need only one pass over the text and store no additional information apart from the compressed text. For long enough texts, such models converge to the true statistical distribution of the text. One major disadvantage, however, is that decompression of a file has to start from its beginning, since information on the distribution of the data is stored incrementally inside the file. Adaptive modeling is a good option for general purpose compression programs, but an inadequate alternative for full-text retrieval where random access to compressed patterns is a must. *Static models* assume an average distribution for all input texts. The modeling phase is done only once for all texts to be coded in the future (i.e., somehow a probability distribution is estimated and then used for all texts to be compressed in the future). These models tend to achieve poor compression ratios when the data deviates from initial statistical assumptions. For example, a model adequate for English literary texts will probably perform poorly for financial texts containing a lot of different numbers, as each number is relatively rare and so receives long codes.

Semi-static models do not assume any distribution on the data, but learn it in a first pass . In a second pass, they compress the data by using a fixed code derived from the distribution learned from the first pass. At decoding time, information on the data distribution is sent to the decoder before transmitting the encoded symbols. The disadvantages of semi-static models are that they must make two passes over the text and that information on the data distribution must be stored to be used by the decoder to decompress. In situations where interactive data communications are involved it may be impractical to make two passes over the text. However, semi-static models have a crucial advantage in IR contexts: since the same codes are used at every point in the compressed file, direct access is possible.

Word-based models take words instead of characters as symbols. Usually, a word is a contiguous string of characters in the set {A..Z, a..z} separated by other characters not in the set {A..Z, a..z}. There are many good reasons to use word-based models in an IR context. First, much better compression rates are achieved by taking words as symbols because words carry a lot of meaning in natural languages and, as a result, their distribution is much more related to the semantic structure of the text than the individual letters. Second, words are the atoms on which most information retrieval systems are built. Words are already stored for indexing purposes and so might be used as part of the model for compression. Third, the word frequencies are also useful in answering queries involving combinations of words because the best strategy is to start with the

least frequent words first.

Since the text is not only composed of words but also of separators, a model must also be chosen for them. There are many different ways to deal with separators. As words and separators always follow one another, two different alphabets are usually used: one for words and one for separators. Consider the following example: `each rose, a rose is a rose`. In the word-based model, the set of symbols of the alphabet is {`a`, `each`, `is`, `rose`}, whose frequencies are 2, 1, 1, and 3, respectively, and the set of separators is {`',␣'`, ␣}, whose frequencies are 1 and 5, respectively (where ␣ represents a space). Once it is known that the text starts with a word or a separator, there is confusion about which alphabet to use.

In natural language texts, a word is followed by a single space in most cases. In the texts of the TREC-3 collection [342] (see Chapter 3), 70–80% of the separators are single spaces. Another good alternative is to consider the single space that follows a word as part of the same word. That is, if a word is followed by a space, we can encode just the word. If not, we can encode the word and then the following separator. At decoding time, we decode a word and assume that a space follows unless the next symbol corresponds to a separator. Notice that now a single alphabet for words and separators (single space excluded) is used. For instance, in the example above, the single alphabet is {`',␣'`, `a`, `each`, `is`, `rose`} and there is no longer an alphabet for separators. As the alphabet excludes the single space then the words are called *spaceless words.*

In some situations word-based models for full-text databases have a potential to generate a great quantity of different codes and care must be exercised to deal with this fact. For instance, as discussed in the section on lexical analysis (at the beginning of this chapter), one has to consider whether a sequence of digits is to be considered as a word. If it is, then a collection which contains one million documents and includes document numbers as identifiers will generate one million words composed solely of digits, each one occurring once in the collection. This can be very inefficient for any kind of compression method available. One possible good solution is to divide long numbers into shorter ones by using a null (or implicit) punctuation marker in between. This diminishes the alphabet size resulting in considerable improvements in the compression ratio and in the decoding time.

Another important consideration is the size of the alphabet in word-based schemes. How large is the number of different words in a full-text database? It is empirically known that the vocabulary V of natural language texts with n words grows sublinearly. Heaps [352] shows that $V = O(n^{\beta})$, where β is a constant dependent on the particular text. For the 2 gigabyte TREC-3 collection [342], β is between 0.4 and 0.6 which means that the alphabet size grows roughly proportional to the square root of n. Even for this growth of the alphabet, the generalized Zipf law shows that the probability distribution is skewed so that the entropy remains constant. This implies that the compression ratio does not degrade as the text (and hence the number of different symbols) grows. Heaps' and Zipfs' laws are explained in Chapter 6.

Finally, it is important to mention that word-based Huffman methods need large texts to be effective (i.e., they are not adequate to compress and transmit

a single Web page over a network). The need to store the vocabulary represents an important space overhead when the text is small (say, less than 10 megabytes). However, this is not a concern in IR in general as the texts are large and the vocabulary is needed anyway for other purposes such as indexing and querying.

Coding

Coding corresponds to the task of obtaining the representation (code) of a symbol based on a probability distribution given by a model. The main goal of a coder is to assign short codes to likely symbols and long codes to unlikely ones. As we have seen in the previous section, the entropy of a probability distribution is a lower bound on how short the average length of a code can be, and the quality of a coder is measured in terms of how close to the entropy it is able to get. Another important consideration is the speed of both the coder and the decoder. Sometimes it is necessary to sacrifice the compression ratio to reduce the time to encode and decode the text.

A semi-static Huffman compression method works in two passes over the text. In a first pass, the modeler determines the probability distribution of the symbols and builds a coding tree according to this distribution. In a second pass, each next symbol is encoded according to the coding tree. Adaptive Huffman compression methods, instead, work in one single pass over the text updating the coding tree incrementally. The encoding of the symbols in the input text is also done during this single pass over the text. The main problem of adaptive Huffman methods is the cost of updating the coding tree as new symbols are read.

As with Huffman-based methods, arithmetic coding methods can also be based on static, semi-static or adaptive algorithms. The main strength of arithmetic coding methods is that they can generate codes which are arbitrarily close to the entropy for any kind of probability distribution. Another strength of arithmetic coding methods is that they do not need to store a coding tree explicitly. For adaptive algorithms, this implies that arithmetic coding uses less memory than Huffman-based coding. For static or semi-static algorithms, the use of canonical Huffman codes overcomes this memory problem (canonical Huffman trees are explained later on).

In arithmetic coding, the input text is represented by an interval of real numbers between 0 and 1. As the size of the input becomes larger, the interval becomes smaller and the number of bits needed to specify this interval increases. Compression is achieved because input symbols with higher probabilities reduce the interval less than symbols with smaller probabilities and hence add fewer bits to the output code.

Arithmetic coding presents many disadvantages over Huffman coding in an IR environment. First, arithmetic coding is much slower than Huffman coding, especially with static and semi-static algorithms. Second, with arithmetic coding, decompression cannot start in the middle of a compressed file. This contrasts with Huffman coding, in which it is possible to index and to decode from

any position in the compressed text if static or semi-static algorithms are used. Third, word-based Huffman coding methods yield compression ratios as good as arithmetic coding ones.

Consequently, Huffman coding is the method of choice in full-text retrieval, where both speed and random access are important. Thus, we will focus the remaining of our discussion on semi-static word-based Huffman coding.

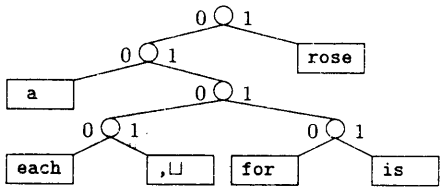
Huffman Coding

Huffman coding is one of the best known compression methods [386]. The idea is to assign a variable-length encoding in bits to each symbol and encode each symbol in turn. Compression is achieved by assigning shorter codes to more frequent symbols. Decompression uniqueness is guaranteed because no code is a prefix of another. A word-based semi-static model and Huffman coding form a good compression method for text.

Figure 7.2 presents an example of compression using Huffman coding on words. In this example the set of symbols of the alphabet is {',␣', `a`, `each`, `for`, `is`, `rose`}, whose frequencies are 1, 2, 1, 1, 1, and 3, respectively. In this case the alphabet is unique for words and separators. Notice that the separator '␣' is not part of the alphabet because the single space that follows a word is considered as part of the word. These words are called *spaceless words* (see more about spaceless words in Section 7.4.3). The Huffman tree shown in Figure 7.2 is an example of a binary trie built on binary codes. Tries are explained in Chapter 8.

Decompression is accomplished as follows. The stream of bits in the compressed file is traversed from left to right. The sequence of bits read is used to also traverse the Huffman compression tree, starting at the root. Whenever a leaf node is reached, the corresponding word (which constitutes the decompressed symbol) is printed out and the tree traversal is restarted. Thus, according to the tree in Figure 7.2, the presence of the code `0110` in the compressed file leads to the decompressed symbol `for`.

To build a Huffman tree, it is first necessary to obtain the symbols that constitute the alphabet and their probability distribution in the text to be compressed. The algorithm for building the tree then operates bottom up and starts



Original text: `for each rose, a rose is a rose`

Compressed text: `0110 0100 1 0101 00 1 0111 00 1`

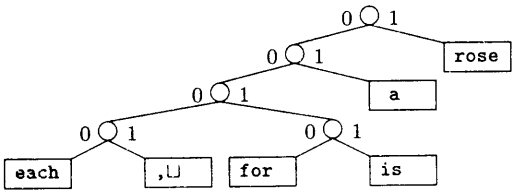
Figure 7.2 Huffman coding tree for spaceless words.

by creating for each symbol of the alphabet a node containing the symbol and its probability (or frequency). At this point there is a forest of one-node trees whose probabilities sum up to 1. Next, the two nodes with the smallest probabilities become children of a newly created parent node. With this parent node is associated a probability equal to the sum of the probabilities of the two chosen children. The operation is repeated ignoring nodes that are already children, until there is only one node, which becomes the root of the decoding tree. By delaying the pairing of nodes with high probabilities, the algorithm necessarily places them closer to the root node, making their code smaller. The two branches from every internal node are consistently labeled 0 and 1 (or 1 and 0). Given s symbols and their frequencies in the text, the algorithm builds the Huffman tree in $O(s \log s)$ time.

The number of Huffman trees which can be built for a given probability distribution is quite large. This happens because interchanging left and right subtrees of any internal node results in a different tree whenever the two subtrees are different in structure, but the weighted average code length is not affected. Instead of using any kind of tree, the preferred choice for most applications is to adopt a *canonical tree* which imposes a particular order to the coding bits.

A Huffman tree is canonical when the height of the left subtree of any node is never smaller than that of the right subtree, and all leaves are in increasing order of probabilities from left to right. Figure 7.3 shows the canonical tree for the example of Figure 7.2. The deepest leaf at the leftmost position of the Huffman canonical tree, corresponding to one element with smallest probability, will contain only zeros, and the following codes will be in increasing order inside each level. At each change of level we shift left one bit in the counting. The table in Figure 7.3 shows the canonical codes for the example of Figure 7.2.

A canonical code can be represented by an ordered sequence S of pairs (x_i, y_i), $1 \leq i \leq \ell$, where x_i represents the number of symbols at level i, y_i represents the numerical value of the first code at level i, and ℓ is the height of the tree. For our example in Figure 7.3, the ordered sequence is $S = \langle (1,1), (1,1), (0,\infty), (4,0) \rangle$. For instance, the fourth pair $(4,0)$ in S corresponds to the fourth level and indicates that there are four nodes at this level and that to the node most to the left is assigned a code, at this level, with value 0. Since this is the fourth level, a value 0 corresponds to the codeword 0000.



Symbol	Prob.	Old code	Can. code
each	1/9	0100	0000
,␣	1/9	0101	0001
for	1/9	0110	0010
is	1/9	0111	0011
a	2/9	00	01
rose	3/9	1	1

Figure 7.3 Canonical code.

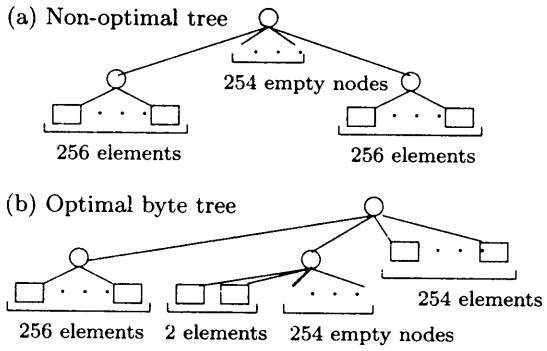


Figure 7.4 Example of byte Huffman tree.

One of the properties of canonical codes is that the set of codes having the same length are the binary representations of consecutive integers. Interpreted as integers, the 4-bit codes of the table in Figure 7.3 are 0, 1, 2, and 3, the 2-bit code is 1 and the 1-bit code is also 1. In our example, if the first character read from the input stream is 1, a codeword has been identified and the corresponding symbol can be output. If this value is 0, a second bit is appended and the two bits are again interpreted as an integer and used to index the table and identify the corresponding symbol. Once we read '00' we know that the code has four bits and therefore we can read two more bits and use them as an index into the table. This fact can be exploited to enable efficient encoding and decoding with small overhead. Moreover, much less memory is required, which is especially important for large vocabularies.

Byte-Oriented Huffman Code

The original method proposed by Huffman [386] leads naturally to binary coding trees. In [577], however, it is proposed to build the code assigned to each symbol as a sequence of whole bytes. As a result, the Huffman tree has degree 256 instead of 2. Typically, the code assigned to each symbol contains between 1 and 5 bytes. For example, a possible code for the word `rose` could be the 3-byte code '47 131 8.'

The construction of byte Huffman trees involves some details which must be dealt with. Care must be exercised to ensure that the first levels of the tree have no empty nodes when the code is not binary. Figure 7.4(a) illustrates a case where a naive extension of the binary Huffman tree construction algorithm might generate a non-optimal byte tree. In this example the alphabet has 512 symbols, all with the same probability. The root node has 254 empty spaces that could be occupied by symbols from the second level of the tree, changing their code lengths from 2 bytes to 1 byte.

A way to ensure that the empty nodes always go to the lowest level of the tree follows. We calculate beforehand the number of empty nodes that will arise.

We then compose these empty nodes with symbols of smallest probabilities (for moving the empty nodes to the deepest level of the final tree). To accomplish this, we need only to select a number of symbols equal to $1 + ((v - 256) \bmod 255)$, where v is the total number of symbols (i.e., the size of the vocabulary), for composing with the empty nodes. For instance, in the example in Figure 7.4(a), we have that 2 elements must be coupled with 254 empty nodes in the first step (because, $1 + ((512 - 256) \bmod 255) = 2$). The remaining steps are similar to the binary Huffman tree construction algorithm.

All techniques for efficient encoding and decoding mentioned previously can easily be extended to handle word-based byte Huffman coding. Moreover, no significant decrease of the compression ratio is experienced by using bytes instead of bits when the symbols are words. Further, decompression of byte Huffman code is faster than decompression of binary Huffman code. In fact, compression and decompression are very fast and compression ratios achieved are better than those of the Ziv-Lempel family [848, 849]. In practice byte processing is much faster than bit processing because bit shifts and masking operations are not necessary at decoding time or at searching time.

One important consequence of using byte Huffman coding is the possibility of performing direct searching on compressed text. The searching algorithm is explained in Chapter 8. The exact search can be done on the compressed text directly, using any known sequential pattern matching algorithm. Moreover, it allows a large number of variations of the exact and approximate compressed pattern matching problem, such as phrases, ranges, complements, wild cards, and arbitrary regular expressions. The algorithm is based on a word-oriented shift-or algorithm and on a fast Boyer-Moore-type filter. For approximate searching on the compressed text it is eight times faster than an equivalent approximate searching on the uncompressed text, thanks to the use of the vocabulary by the algorithm [577, 576]. This technique is not only useful in speeding up sequential search. It can also be used to improve indexed schemes that combine inverted files and sequential search, like Glimpse [540].

7.4.4 Dictionary Methods

Dictionary methods achieve compression by replacing groups of consecutive symbols (or phrases) with a pointer to an entry in a dictionary. Thus, the central decision in the design of a dictionary method is the selection of entries in the dictionary. The choice of phrases can be made by static, semi-adaptive, or adaptive algorithms. The simplest dictionary schemes use static dictionaries containing short phrases. Static dictionary encoders are fast as they demand little effort for achieving a small amount of compression. One example that has been proposed several times in different forms is the digram coding, where selected pairs of letters are replaced with codewords. At each step the next two characters are inspected and verified if they correspond to a digram in the dictionary. If so, they are coded together and the coding position is shifted by two characters; otherwise, the single character is represented by its normal code and the coding

position is shifted by one character.

The main problem with static dictionary encoders is that the dictionary might be suitable for one text and unsuitable for another. One way to avoid this problem is to use a semi-static dictionary scheme, constructing a new dictionary for each text to be compressed. However, the problem of deciding which phrases should be put in the dictionary is not an easy task at all. One elegant solution to this problem is to use an adaptive dictionary scheme, such as the one proposed in the 1970s by Ziv and Lempel.

The Ziv-Lempel type of adaptive dictionary scheme uses the idea of replacing strings of characters with a reference to a previous occurrence of the string. This approach is effective because most characters can be coded as part of a string that has occurred earlier in the text. If the pointer to an earlier occurrence of a string is stored in fewer bits than the string it replaces then compression is achieved.

Adaptive dictionary methods present some disadvantages over the statistical word-based Huffman method. First, they do not allow decoding to start in the middle of a compressed file. As a consequence direct access to a position in the compressed text is not possible, unless the entire text is decoded from the beginning until the desired position is reached. Second, dictionary schemes are still popular for their speed and economy of memory, but the new results in statistical methods make them the method of choice in an IR environment. Moreover, the improvement of computing technology will soon make statistical methods feasible for general use, and the interest in dictionary methods will eventually decrease.

7.4.5 Inverted File Compression

As already discussed, an inverted file is typically composed of (a) a vector containing all the distinct words in the text collection (which is called the *vocabulary*) and (b) for each word in the vocabulary, a list of all documents in which that word occurs. Inverted files are widely used to index large text files. The size of an inverted file can be reduced by compressing the inverted lists. Because the list of document numbers within the inverted list is in ascending order, it can also be considered as a sequence of *gaps* between document numbers. Since processing is usually done sequentially starting from the beginning of the list, the original document numbers can always be recomputed through sums of the gaps.

By observing that these gaps are small for frequent words and large for infrequent words, compression can be obtained by encoding small values with shorter codes. One possible coding scheme for this case is the *unary code*, in which an integer x is coded as $(x-1)$ one bits followed by a zero bit, so the code for the integer 3 is 110. The second column of Table 7.1 shows unary codes for integers between 1 and 10.

Elias [235] presented two other variable-length coding schemes for integers. One is Elias-γ code, which represents the number x by a concatenation of two

Gap x	Unary	Elias-γ	Elias-δ	Golomb $b = 3$
1	0	0	0	00
2	10	100	1000	010
3	110	101	1001	011
4	1110	11000	10100	100
5	11110	11001	10101	1010
6	111110	11010	10110	1011
7	1111110	11011	10111	1100
8	11111110	1110000	11000000	11010
9	111111110	1110001	11000001	11011
10	1111111110	1110010	11000010	11100

Table 7.1 Example codes for integers.

parts: (1) a unary code for $1+\lfloor \log x \rfloor$ and (2) a code of $\lfloor \log x \rfloor$ bits that represents the value of $x - 2^{\lfloor \log x \rfloor}$ in binary. For $x = 5$, we have that $1 + \lfloor \log x \rfloor = 3$ and that $x - 2^{\lfloor \log x \rfloor} = 1$. Thus, the Elias-$\gamma$ code for $x = 5$ is generated by combining the unary code for 3 (code 110) with the 2-bits binary number for 1 (code 01) which yields the codeword 11001. Other examples of Elias-γ codes are shown in Table 7.1.

The other coding scheme introduced by Elias is the Elias-δ code, which represents the prefix indicating the number of binary bits by the Elias-γ code rather than the unary code. For $x = 5$, the first part is then 101 instead of 110. Thus, the Elias-δ codeword for $x = 5$ is 10101. In general, the Elias-δ code for an arbitrary integer x requires $1 + 2\lfloor \log \log 2x \rfloor + \lfloor \log x \rfloor$ bits. Table 7.1 shows other examples of Elias-δ codes. In general, for small values of x the Elias-γ codes are shorter than the Elias-δ codes. However, in the limit, as x becomes large, the situation is reversed.

Golomb [307] presented another run-length coding method for positive integers. The Golomb code is very effective when the probability distribution is geometric. With inverted files, the likelihood of a gap being of size x can be computed as the probability of having $x - 1$ non-occurrences (within consecutively numbered documents) of that particular word followed by one occurrence. If a word occurs within a document with a probability p, the probability of a gap of size x is then

$$Pr[x] = (1 - p)^{x-1} p$$

which is the *geometric distribution*. In this case, the model is parameterized and makes use of the actual density of pointers in the inverted file. Let N be the number of documents in the system and V be the size of the vocabulary. Then, the probability p that any randomly selected document contains any randomly

chosen term can be estimated as

$$p = \frac{number\ of\ pointers}{N \times V}$$

where the number of pointers represent the 'size' of the index.

The Golomb method works as follows. For some parameter b, a gap $x > 0$ is coded as $q+1$ in unary, where $q = \lfloor (x-1)/b \rfloor$, followed by $r = (x-1) - q \times b$ coded in binary, requiring either $\lfloor \log b \rfloor$ or $\lceil \log b \rceil$ bits. That is, if $r < 2^{\lfloor \log b \rfloor - 1}$ then the number coded in binary requires $\lfloor \log b \rfloor$ bits, otherwise it requires $\lceil \log b \rceil$ bits where the first bit is 1 and the remaining bits assume the value $r - 2^{\lfloor \log b \rfloor - 1}$ coded in $\lfloor \log b \rfloor$ binary digits. For example, with $b = 3$ there are three possible remainders, and those are coded as 0, 10, and 11, for $r = 0$, $r = 1$, and $r = 2$, respectively. Similarly, for $b = 5$ there are five possible remainders r, 0 through 4, and these are assigned codes 00, 01, 100, 101, and 110. Then, if the value $x = 9$ is to be coded relative to $b = 3$, calculation yields $q = 2$ and $r = 2$, because $9-1 = 2 \times 3+2$. Thus, the encoding is 110 followed by 11. Relative to $b = 5$, the values calculated are $q = 1$ and $r = 1$, resulting in a code of 10 followed by 101.

To operate with the Golomb compression method, it is first necessary to establish the parameter b for each term. For gap compression, an appropriate value is $b \approx 0.69(N/f_t)$, where N is the total number of documents and f_t is the number of documents that contain term t. Witten, Moffat and Bell [825] present a detailed study of different text collections. For all of their practical work on compression of inverted lists, they use Golomb code for the list of gaps. In this case Golomb code gives better compression than either Elias-γ or Elias-δ. However, it has the disadvantage of requiring two passes to be generated, since it requires knowledge of f_t, the number of documents containing term t.

Moffat and Bell [572] show that the index for the 2 gigabytes TREC-3 collection, which contains 162,187,989 pointers and 894,406 distinct terms, when coded with Golomb code, occupies 132 megabytes. Considering the average number of bits per pointer, they obtained 5.73, 6.19, and 6.43 using Golomb, Elias-δ, and Elias-γ, respectively.

7.5 Comparing Text Compression Techniques

Table 7.2 presents a comparison between arithmetic coding, character-based Huffman coding, word-based Huffman coding, and Ziv-Lempel coding, considering the aspects of compression ratio, compression speed, decompression speed, memory space overhead, compressed pattern matching capability, and random access capability.

One important objective of any compression method is to be able to obtain good compression ratios. It seems that two bits per character (or 25% compression ratio) is a very good result for natural language texts. Thus, 'very good' in the context of Table 7.2 means a compression ratio under 30%, 'good' means a compression ratio between 30% and 45%, and 'poor' means a compression ratio over 45%.

	Arithmetic	Character Huffman	Word Huffman	Ziv-Lempel
Compression ratio	very good	poor	very good	good
Compression speed	slow	fast	fast	very fast
Decompression speed	slow	fast	very fast	very fast
Memory space	low	low	high	moderate
Compressed pat. matching	no	yes	yes	yes
Random access	no	yes	yes	no

Table 7.2 Comparison of the main techniques.

Two other important characteristics of a compression method are compression and decompression speeds. Measuring the speed of various compression methods is difficult because it depends on the implementation details of each method, the compiler used, the computer architecture of the machine used to run the program, and so on. Considering compression speed, the LZ78 methods (Unix *compress* is an example) are among the fastest. Considering decompression speed, the LZ77 methods (*gzip* is an example) from the Ziv-Lempel are among the fastest.

For statistical methods (e.g., arithmetic and semi-static Huffman) the compression time includes the cost of the first pass during which the probability distribution of the symbols are obtained. With two passes over the text to compress, the Huffman-based methods are slower than some Ziv-Lempel methods, but not very far behind. On the other hand, arithmetic methods are slower than Huffman methods because of the complexity of arithmetic coding compared with canonical Huffman coding. Considering decompression speed, word-based Huffman methods are as fast as Ziv-Lempel methods, while character-based Huffman methods are slower than word-based Huffman methods. Again, the complexity of arithmetic coding make them slower than Huffman coding during decompression.

All Ziv-Lempel compression methods require a moderate amount of memory during encoding and decoding to store tables containing previously occurring strings. In general, more detailed tables that require more memory for storage yield better compression. Statistical methods store the probability distribution of the symbols of the text during the modeling phase, and the model during both compression and decompression phases. Consequently, the amount of memory depends on the size of the vocabulary of the text in each case, which is high for word-based models and low for character-based models.

In an IR environment, two important considerations are whether the compression method allows efficient random access and direct searching on compressed text (or compressed pattern matching). Huffman methods allow random access and decompression can start anywhere in the middle of a compressed file, while arithmetic coding and Ziv-Lempel methods cannot. More recently, practical, efficient, and flexible direct searching methods on compressed texts have been discovered for word-based Huffman compression [575, 576, 577].

Direct searching has also been proposed for Ziv-Lempel methods, but only on a theoretical basis, with no implementation of the algorithms [250, 19].

More recently, Navarro and Raffinot [592] presented some preliminary implementations of algorithms to search directly Ziv-Lempel compressed text. Their algorithms are twice as fast as decompressing and searching, but slower than searching the decompressed text. They are also able to extract data from the middle of the compressed text without necessarily decompressing everything, and although some previous text has to be decompressed (i.e., it is not really 'direct access'), the amount of work is proportional to the size of the text to be decompressed (and not to its position in the compressed text).

7.6 Trends and Research Issues

In this chapter we covered various text transformation techniques which we call simply text operations. We first discussed five distinct text operations for preprocessing a document text and generating a set of index terms for searching and querying purposes. These five text operations were here called lexical analysis, elimination of stopwords, stemming, selection of index terms, and thesauri. The first four are directly related to the generation of a good set of index terms. The fifth, construction of a thesaurus, is more related to the building of categorization hierarchies which are used for capturing term relationships. These relationships can then be used for expanding the user query (manually or automatically) towards a formulation which better suits the user information need.

Nowadays, there is controversy regarding the potential improvements to retrieval performance generated by stopwords elimination, stemming, and index terms selection. In fact, there is no conclusive evidence that such text operations yield consistent improvements in retrieval performance. As a result, modern retrieval systems might not use these text operations at all. A good example of this trend is the fact that some Web search engines index all the words in the text regardless of their syntactic nature or their role in the text.

Furthermore, it is also not clear that automatic query expansion using thesaurus-based techniques can yield improved retrieval performance. The same cannot be said of the use of a thesaurus to directly assist the user with the query formation process. In fact, the success of the 'Yahoo!' Web search engine, which uses a term categorization hierarchy to show term relationships to the user, is an indication that thesaurus-based techniques might be quite useful with the highly interactive interfaces being developed for modern digital library systems.

We also briefly discussed the operation of clustering. Since clustering is more an operation of grouping documents than an operation of text transformation, we did not cover it thoroughly here. For a more complete coverage of clustering the reader is referred to Chapter 5.

One text operation rather distinct from the previous ones is compression. While the previous text operations aim, in one form or another, at improving the quality of the answer set, the operation of compressing text aims at reducing space, I/O, communication costs, and searching faster in the compressed text (exactly or approximately). In fact, the gain obtained from compressing text is

that it requires less storage space, takes less time to be transmitted, and permits efficient direct and sequential access to compressed text.

For effective operation in an IR environment, a compression method should satisfy the following requirements: good compression ratio, fast coding, fast decoding, fast random access without the need to decode from the beginning, and direct searching without the need to decompress the compressed text. A good compression ratio saves space in secondary storage and reduces communication costs. Fast coding reduces processing overhead due to the introduction of compression into the system. Sometimes, fast decoding is more important than fast coding, as in documentation systems in which a document is compressed once and decompressed many times from disk. Fast random access allows efficient processing of multiple queries submitted by the users of the information system. We compared various compression schemes using these requirements as parameters. We have seen that it is much faster to search sequentially a text compressed by a word-based byte Huffman encoding scheme than to search the uncompressed version of the text. Our discussion suggests that word-based byte Huffman compression (which has been introduced only very recently) shows great promise as an effective compression scheme for modern information retrieval systems.

We also discussed the application of compression to index structures such as inverted files. Inverted files are composed of several inverted lists which are themselves formed by document numbers organized in ascending order. By coding the difference between these document numbers, efficient compression can be attained.

The main trends in text compression today are the use of semi-static word-based modeling and Huffman coding. The new results in statistical methods, such as byte-Huffman coding, suggest that they are preferable methods for use in an IR environment. Further, with the possibility now of directly searching the compressed text, and the recent work [790] of Vo and Moffat on efficient manipulation of compressed indices, the trend is towards maintaining both the index and the text compressed at all times, unless the user wants to visualize the uncompressed text.

7.7 Bibliographic Discussion

Our discussion on lexical analysis and elimination of stopwords is based on the work of Fox [263]. For stemming, we based our discussion on the work of Frakes [274]. The Porter stemming algorithm detailed in the appendix is from [648], while our coverage of thesauri is based on the work of Foskett [261]. Here, however, we did not cover automatic generation of thesauri. Such discussion can be found in Chapter 5 and in [739, 735]. Additional discussion on the usefulness of thesauri is presented in [419, 735].

Regarding text compression, several books are available. Most of the topics discussed here are covered in more detail by Witten, Moffat and Bell [825]. They also present implementations of text compression methods, such as Huffman and arithmetic coding, as part of a fully operational retrieval system written in ANSI

C. Bell, Cleary and Witten [78] cover statistical and dictionary methods, laying particular stress on adaptive methods as well as theoretical aspects of compression, with estimates on the entropy of several natural languages. Storer [747] covers the main compression techniques, with emphasis on dictionary methods.

Huffman coding was originally presented in [386]. Adaptive versions of Huffman coding appear in [291, 446, 789]. Word-based compression is considered in [81, 571, 377, 77]. Bounds on the inefficiency of Huffman coding have been presented by [291]. Canonical codes were first presented in [713]. Many properties of the canonical codes are mentioned in [374]. Byte Huffman coding was proposed in [577]. Sequential searching on byte Huffman compressed text is described in [577, 576].

Sequential searching on Ziv-Lempel compressed data is presented in [250, 19]. More recently, implementations of sequential searching on Ziv-Lempel compressed text are presented in [593]. One of the first papers on arithmetic coding is in [675]. Other references are [823, 78].

A variety of compression methods for inverted lists are studied in [573] The most effective compression methods for inverted lists are based on the sequence of gaps between document numbers, as considered in [77] and in [572]. Their results are based on run-length encodings proposed by Elias [235] and Golomb [307]. A comprehensive study of inverted file compression can be found in [825]. More recently Vo and Moffat [790] have presented algorithms to process the index with no need to fully decode the compressed index.

Chapter 8
Indexing and Searching

with Gonzalo Navarro

8.1 Introduction

Chapter 4 describes the query operations that can be performed on text databases. In this chapter we cover the main techniques we need to implement those query operations.

We first concentrate on searching queries composed of words and on reporting the documents where they are found. The number of occurrences of a query in each document and even its exact positions in the text may also be required. Following that, we concentrate on algorithms dealing with Boolean operations. We then consider sequential search algorithms and pattern matching. Finally, we consider structured text and compression techniques.

An obvious option in searching for a basic query is to scan the text sequentially. Sequential or online text searching involves finding the occurrences of a pattern in a text when the text is not preprocessed. Online searching is appropriate when the text is small (i.e., a few megabytes), and it is the only choice if the text collection is very volatile (i.e., undergoes modifications very frequently) or the index space overhead cannot be afforded.

A second option is to build data structures over the text (called *indices*) to speed up the search. It is worthwhile building and maintaining an index when the text collection is large and *semi-static*. Semi-static collections can be updated at reasonably regular intervals (e.g., daily) but they are not deemed to support thousands of insertions of single words per second, say. This is the case for most real text databases, not only dictionaries or other slow growing literary works. For instance, it is the case for Web search engines or journal archives.

Nowadays, the most successful techniques for medium size databases (say up to 200Mb) combine online and indexed searching.

We cover three main indexing techniques: inverted files, suffix arrays, and signature files. Keyword-based search is discussed first. We emphasize inverted files, which are currently the best choice for most applications. Suffix trees

and arrays are faster for phrase searches and other less common queries, but are harder to build and maintain. Finally, signature files were popular in the 1980s, but nowadays inverted files outperform them. For all the structures we pay attention not only to their search cost and space overhead, but also to the cost of building and updating them.

We assume that the reader is familiar with basic data structures, such as sorted arrays, binary search trees, B-trees, hash tables, and tries. Since tries are heavily used we give a brief and simplified reminder here. Tries, or digital search trees, are multiway trees that store sets of strings and are able to retrieve any string in time proportional to its length (independent of the number of strings stored). A special character is added to the end of the string to ensure that no string is a prefix of another. Every edge of the tree is labeled with a letter. To search a string in a trie, one starts at the root and scans the string character-wise, descending by the appropriate edge of the trie. This continues until a leaf is found (which represents the searched string) or the appropriate edge to follow does not exist at some point (i.e., the string is not in the set). See Figure 8.3 for an example of a text and a trie built on its words.

Although an index must be built prior to searching it, we present these tasks in the reverse order. We think that understanding first how a data structure is used makes it clear how it is organized, and therefore eases the understanding of the construction algorithm, which is usually more complex.

Throughout this chapter we make the following assumptions. We call n the size of the text database. Whenever a pattern is searched, we assume that it is of length m, which is much smaller than n. We call M the amount of main memory available. We assume that the modifications which a text database undergoes are additions, deletions, and replacements (which are normally made by a deletion plus an addition) of pieces of text of size $n' < n$.

We give experimental measures for many algorithms to give the reader a grasp of the real times involved. To do this we use a reference architecture throughout the chapter, which is representative of the power of today's computers. We use a 32-bit Sun UltraSparc-1 of 167 MHz with 64 Mb of RAM, running Solaris. The code is written in C and compiled with all optimization options. For the text data, we use collections from TREC-2, specifically WSJ, DOE, FR, ZIFF and AP. These are described in more detail in Chapter 3.

8.2 Inverted Files

An inverted file (or inverted index) is a word-oriented mechanism for indexing a text collection in order to speed up the searching task. The inverted file structure is composed of two elements: the *vocabulary* and the *occurrences*. The vocabulary is the set of all different words in the text. For each such word a list of all the text positions where the word appears is stored. The set of all those lists is called the 'occurrences' (Figure 8.1 shows an example). These positions can refer to words or characters. Word positions (i.e., position i refers to the i-th word) simplify

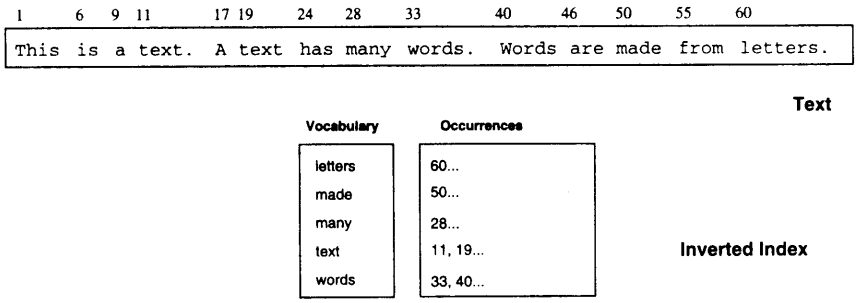


Figure 8.1 A sample text and an inverted index built on it. The words are converted to lower-case and some are not indexed. The occurrences point to character positions in the text.

phrase and proximity queries, while character positions (i.e., the position i is the i-th character) facilitate direct access to the matching text positions.

Some authors make the distinction between inverted files and inverted lists. In an inverted file, each element of a list points to a document or file name, while inverted lists match our definition. We prefer not to make such a distinction because, as we will see later, this is a matter of the *addressing granularity*, which can range from text positions to logical blocks.

The space required for the vocabulary is rather small. According to Heaps' law (see Chapter 6) the vocabulary grows as $O(n^\beta)$, where β is a constant between 0 and 1 dependent on the text, being between 0.4 and 0.6 in practice. For instance, for 1 Gb of the TREC-2 collection the vocabulary has a size of only 5 Mb. This may be further reduced by stemming and other normalization techniques as described in Chapter 7.

The occurrences demand much more space. Since each word appearing in the text is referenced once in that structure, the extra space is $O(n)$. Even omitting stopwords (which is the default practice when words are indexed), in practice the space overhead of the occurrences is between 30% and 40% of the text size.

To reduce space requirements, a technique called *block addressing* is used. The text is divided in blocks, and the occurrences point to the blocks where the word appears (instead of the exact positions). The classical indices which point to the exact occurrences are called 'full inverted indices.' By using block addressing not only can the pointers be smaller because there are fewer blocks than positions, but also all the occurrences of a word inside a single block are collapsed to one reference (see Figure 8.2). Indices of only 5% overhead over the text size are obtained with this technique. The price to pay is that, if the exact occurrence positions are required (for instance, for a proximity query), then an online search over the qualifying blocks has to be performed. For instance, block addressing indices with 256 blocks stop working well with texts of 200 Mb.

Table 8.1 presents the projected space taken by inverted indices for texts of

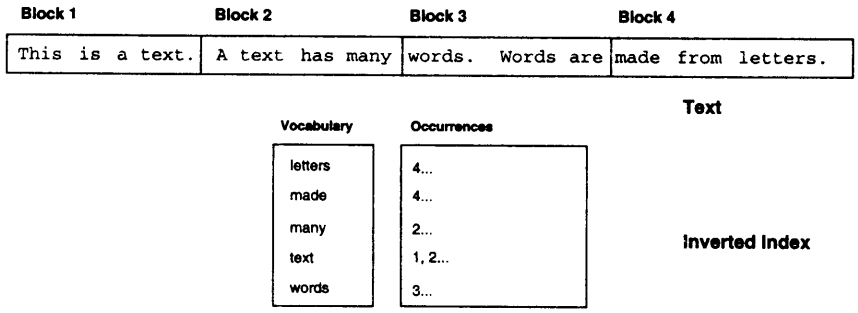


Figure 8.2 The sample text split into four blocks, and an inverted index using block addressing built on it. The occurrences denote block numbers. Notice that both occurrences of 'words' collapsed into one.

different sizes, with and without the use of stopwords. The full inversion stands for inverting all the words and storing their exact positions, using four bytes per pointer. The document addressing index assumes that we point to documents which are of size 10 Kb (and the necessary number of bytes per pointer, i.e. one, two, and three bytes, depending on text size). The block addressing index assumes that we use 256 or 64K blocks (one or two bytes per pointer) independently of the text size. The space taken by the pointers can be significantly reduced by using compression. We assume that 45% of all the words are stopwords, and that there is one non-stopword each 11.5 characters. Our estimation for the vocabulary is based on Heaps' law with parameters $V = 30n^{0.5}$. All these decisions were taken according to our experience and experimentally validated.

The blocks can be of fixed size (imposing a logical block structure over the text database) or they can be defined using the natural division of the text collection into files, documents, Web pages, or others. The division into blocks of fixed size improves efficiency at retrieval time, i.e. the more variance in the block sizes, the more amount of text sequentially traversed on average. This is because larger blocks match queries more frequently and are more expensive to traverse.

Alternatively, the division using natural cuts may eliminate the need for online traversal. For example, if one block per retrieval unit is used and the exact match positions are not required, there is no need to traverse the text for single-word queries, since it is enough to know which retrieval units to report. But if, on the other hand, many retrieval units are packed into a single block, the block has to be traversed to determine which units to retrieve.

It is important to notice that in order to use block addressing, the text must be readily available at search time. This is not the case for remote text (as in Web search engines), or if the text is in a CD-ROM that has to be mounted, for instance. Some restricted queries not needing exact positions can still be solved if the blocks are retrieval units.