Preface

As recently as the 1990s, studies showed that most people preferred getting information from other people rather than from information retrieval systems. Of course, in that time period, most people also used human travel agents to book their travel. However, during the last decade, relentless optimization of information retrieval effectiveness has driven web search engines to new quality levels where most people are satisfied most of the time, and web search has become a standard and often preferred source of information finding. For example, the 2004 Pew Internet Survey (Fallows 2004) found that "92% of Internet users say the Internet is a good place to go for getting everyday information." To the surprise of many, the field of information retrieval has moved from being a primarily academic discipline to being the basis underlying most people's preferred means of information access. This book presents the scientific underpinnings of this field, at a level accessible to graduate students as well as advanced undergraduates.

Information retrieval did not begin with the Web. In response to various challenges of providing information access, the field of information retrieval evolved to give principled approaches to searching various forms of content. The field began with scientific publications and library records, but soon spread to other forms of content, particularly those of information professionals, such as journalists, lawyers, and doctors. Much of the scientific research on information retrieval has occurred in these contexts, and much of the continued practice of information retrieval deals with providing access to unstructured information in various corporate and governmental domains, and this work forms much of the foundation of our book.

Nevertheless, in recent years, a principal driver of innovation has been the World Wide Web, unleashing publication at the scale of tens of millions of content creators. This explosion of published information would be moot if the information could not be found, annotated and analyzed so that each user can quickly find information that is both relevant and comprehensive for their needs. By the late 1990s, many people felt that continuing to index

the whole Web would rapidly become impossible, due to the Web's exponential growth in size. But major scientific innovations, superb engineering, the rapidly declining price of computer hardware, and the rise of a commercial underpinning for web search have all conspired to power today's major search engines, which are able to provide high-quality results within subsecond response times for hundreds of millions of searches a day over billions of web pages.

Book organization and course development

This book is the result of a series of courses we have taught at Stanford University and at the University of Stuttgart, in a range of durations including a single quarter, one semester and two quarters. These courses were aimed at early-stage graduate students in computer science, but we have also had enrollment from upper-class computer science undergraduates, as well as students from law, medical informatics, statistics, linguistics and various engineering disciplines. The key design principle for this book, therefore, was to cover what we believe to be important in a one-term graduate course on information retrieval. An additional principle is to build each chapter around material that we believe can be covered in a single lecture of 75 to 90 minutes.

The first eight chapters of the book are devoted to the basics of information retrieval, and in particular the heart of search engines; we consider this material to be core to any course on information retrieval. Chapter 1 introduces inverted indexes, and shows how simple Boolean queries can be processed using such indexes. Chapter 2 builds on this introduction by detailing the manner in which documents are preprocessed before indexing and by discussing how inverted indexes are augmented in various ways for functionality and speed. Chapter 3 discusses search structures for dictionaries and how to process queries that have spelling errors and other imprecise matches to the vocabulary in the document collection being searched. Chapter 4 describes a number of algorithms for constructing the inverted index from a text collection with particular attention to highly scalable and distributed algorithms that can be applied to very large collections. Chapter 5 covers techniques for compressing dictionaries and inverted indexes. These techniques are critical for achieving subsecond response times to user queries in large search engines. The indexes and queries considered in Chapters 1–5 only deal with *Boolean retrieval*, in which a document either matches a query, or does not. A desire to measure the *extent* to which a document matches a query, or the score of a document for a query, motivates the development of term weighting and the computation of scores in Chapters 6 and 7, leading to the idea of a list of documents that are rank-ordered for a query. Chapter 8 focuses on the evaluation of an information retrieval system based on the

relevance of the documents it retrieves, allowing us to compare the relative performances of different systems on benchmark document collections and queries.

Chapters 9–21 build on the foundation of the first eight chapters to cover a variety of more advanced topics. Chapter 9 discusses methods by which retrieval can be enhanced through the use of techniques like relevance feedback and query expansion, which aim at increasing the likelihood of retrieving relevant documents. Chapter 10 considers information retrieval from documents that are structured with markup languages like XML and HTML. We treat structured retrieval by reducing it to the vector space scoring methods developed in Chapter 6. Chapters 11 and 12 invoke probability theory to compute scores for documents on queries. Chapter 11 develops traditional probabilistic information retrieval, which provides a framework for computing the probability of relevance of a document, given a set of query terms. This probability may then be used as a score in ranking. Chapter 12 illustrates an alternative, wherein for each document in a collection, we build a language model from which one can estimate a probability that the language model generates a given query. This probability is another quantity with which we can rank-order documents.

Chapters 13–17 give a treatment of various forms of machine learning and numerical methods in information retrieval. Chapters 13–15 treat the problem of classifying documents into a set of known categories, given a set of documents along with the classes they belong to. Chapter 13 motivates statistical classification as one of the key technologies needed for a successful search engine, introduces Naive Bayes, a conceptually simple and efficient text classification method, and outlines the standard methodology for evaluating text classifiers. Chapter 14 employs the vector space model from Chapter 6 and introduces two classification methods, Rocchio and kNN, that operate on document vectors. It also presents the bias-variance tradeoff as an important characterization of learning problems that provides criteria for selecting an appropriate method for a text classification problem. Chapter 15 introduces support vector machines, which many researchers currently view as the most effective text classification method. We also develop connections in this chapter between the problem of classification and seemingly disparate topics such as the induction of scoring functions from a set of training examples.

Chapters 16–18 consider the problem of inducing clusters of related documents from a collection. In Chapter 16, we first give an overview of a number of important applications of clustering in information retrieval. We then describe two flat clustering algorithms: the K-means algorithm, an efficient and widely used document clustering method; and the Expectation-Maximization algorithm, which is computationally more expensive, but also more flexible. Chapter 17 motivates the need for hierarchically structured

clusterings (instead of flat clusterings) in many applications in information retrieval and introduces a number of clustering algorithms that produce a hierarchy of clusters. The chapter also addresses the difficult problem of automatically computing labels for clusters. Chapter 18 develops methods from linear algebra that constitute an extension of clustering, and also offer intriguing prospects for algebraic methods in information retrieval, which have been pursued in the approach of latent semantic indexing.

Chapters 19–21 treat the problem of web search. We give in Chapter 19 a summary of the basic challenges in web search, together with a set of techniques that are pervasive in web information retrieval. Next, Chapter 20 describes the architecture and requirements of a basic web crawler. Finally, Chapter 21 considers the power of link analysis in web search, using in the process several methods from linear algebra and advanced probability theory.

This book is not comprehensive in covering all topics related to information retrieval. We have put aside a number of topics, which we deemed outside the scope of what we wished to cover in an introduction to information retrieval class. Nevertheless, for people interested in these topics, we provide a few pointers to mainly textbook coverage here.

Cross-language IR (Grossman and Frieder 2004, ch. 4) and (Oard and Dorr 1996).

Image and Multimedia IR (Grossman and Frieder 2004, ch. 4), (Baeza-Yates and Ribeiro-Neto 1999, ch. 6), (Baeza-Yates and Ribeiro-Neto 1999, ch. 11), (Baeza-Yates and Ribeiro-Neto 1999, ch. 12), (del Bimbo 1999), (Lew 2001), and (Smeulders et al. 2000).

Speech retrieval (Coden et al. 2002).

Music Retrieval (Downie 2006) and http://www.ismir.net/.

User interfaces for IR (Baeza-Yates and Ribeiro-Neto 1999, ch. 10).

Parallel and Peer-to-Peer IR (Grossman and Frieder 2004, ch. 7), (Baeza-Yates and Ribeiro-Neto 1999, ch. 9), and (Aberer 2001).

Digital libraries (Baeza-Yates and Ribeiro-Neto 1999, ch. 15) and (Lesk 2004).

Information science perspective (Korfhage 1997), (Meadow et al. 1999), and (Ingwersen and Järvelin 2005).

Logic-based approaches to IR (van Rijsbergen 1989).

Natural Language Processing techniques (Manning and Schütze 1999), (Jurafsky and Martin 2008), and (Lewis and Jones 1996).

Prerequisites

Introductory courses in data structures and algorithms, in linear algebra and in probability theory suffice as prerequisites for all 21 chapters. We now give more detail for the benefit of readers and instructors who wish to tailor their reading to some of the chapters.

Chapters 1–5 assume as prerequisite a basic course in algorithms and data structures. Chapters 6 and 7 require, in addition, a knowledge of basic linear algebra including vectors and dot products. No additional prerequisites are assumed until Chapter 11, where a basic course in probability theory is required; Section 11.1 gives a quick review of the concepts necessary in Chapters 11–13. Chapter 15 assumes that the reader is familiar with the notion of nonlinear optimization, although the chapter may be read without detailed knowledge of algorithms for nonlinear optimization. Chapter 18 demands a first course in linear algebra including familiarity with the notions of matrix rank and eigenvectors; a brief review is given in Section 18.1. The knowledge of eigenvalues and eigenvectors is also necessary in Chapter 21.

Book layout

Worked examples in the text appear with a pencil sign next to them in the left margin. Advanced or difficult material appears in sections or subsections indicated with scissors in the margin. Exercises are marked in the margin with a question mark. The level of difficulty of exercises is indicated as easy ($\star$), medium ($\star\star$), or difficult ($\star\star\star$).

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The above is unfortunately an incomplete list: we are still in the process of incorporating feedback we have received. And, like all opinionated authors, we did not always heed the advice that was so freely given. The published versions of the chapters remain solely the responsibility of the authors.

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Web and contact information

This book has a companion website at http://informationretrieval.org. As well as links to some more general resources, it is our intent to maintain on this website a set of slides for each chapter which may be used for the corresponding lecture. We gladly welcome further feedback, corrections, and suggestions on the book, which may be sent to all the authors at informationretrieval (at) yahoogroups (dot) com.

1 Boolean retrieval

INFORMATION RETRIEVAL

The meaning of the term *information retrieval* can be very broad. Just getting a credit card out of your wallet so that you can type in the card number is a form of information retrieval. However, as an academic field of study, *information retrieval* might be defined thus:

> Information retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).

As defined in this way, information retrieval used to be an activity that only a few people engaged in: reference librarians, paralegals, and similar professional searchers. Now the world has changed, and hundreds of millions of people engage in information retrieval every day when they use a web search engine or search their email.[1] Information retrieval is fast becoming the dominant form of information access, overtaking traditional database-style searching (the sort that is going on when a clerk says to you: "I'm sorry, I can only look up your order if you can give me your Order ID").

IR can also cover other kinds of data and information problems beyond that specified in the core definition above. The term "unstructured data" refers to data which does not have clear, semantically overt, easy-for-a-computer structure. It is the opposite of structured data, the canonical example of which is a relational database, of the sort companies usually use to maintain product inventories and personnel records. In reality, almost no data are truly "unstructured". This is definitely true of all text data if you count the latent linguistic structure of human languages. But even accepting that the intended notion of structure is overt structure, most text has structure, such as headings and paragraphs and footnotes, which is commonly represented in documents by explicit markup (such as the coding underlying web

1. In modern parlance, the word "search" has tended to replace "(information) retrieval"; the term "search" is quite ambiguous, but in context we use the two synonymously.

pages). IR is also used to facilitate "semistructured" search such as finding a document where the title contains Java and the body contains threading.

The field of information retrieval also covers supporting users in browsing or filtering document collections or further processing a set of retrieved documents. Given a set of documents, clustering is the task of coming up with a good grouping of the documents based on their contents. It is similar to arranging books on a bookshelf according to their topic. Given a set of topics, standing information needs, or other categories (such as suitability of texts for different age groups), classification is the task of deciding which class(es), if any, each of a set of documents belongs to. It is often approached by first manually classifying some documents and then hoping to be able to classify new documents automatically.

Information retrieval systems can also be distinguished by the scale at which they operate, and it is useful to distinguish three prominent scales. In *web search*, the system has to provide search over billions of documents stored on millions of computers. Distinctive issues are needing to gather documents for indexing, being able to build systems that work efficiently at this enormous scale, and handling particular aspects of the web, such as the exploitation of hypertext and not being fooled by site providers manipulating page content in an attempt to boost their search engine rankings, given the commercial importance of the web. We focus on all these issues in Chapters 19–21. At the other extreme is *personal information retrieval*. In the last few years, consumer operating systems have integrated information retrieval (such as Apple's Mac OS X Spotlight or Windows Vista's Instant Search). Email programs usually not only provide search but also text classification: they at least provide a spam (junk mail) filter, and commonly also provide either manual or automatic means for classifying mail so that it can be placed directly into particular folders. Distinctive issues here include handling the broad range of document types on a typical personal computer, and making the search system maintenance free and sufficiently lightweight in terms of startup, processing, and disk space usage that it can run on one machine without annoying its owner. In between is the space of *enterprise, institutional, and domain-specific search*, where retrieval might be provided for collections such as a corporation's internal documents, a database of patents, or research articles on biochemistry. In this case, the documents will typically be stored on centralized file systems and one or a handful of dedicated machines will provide search over the collection. This book contains techniques of value over this whole spectrum, but our coverage of some aspects of parallel and distributed search in web-scale search systems is comparatively light owing to the relatively small published literature on the details of such systems. However, outside of a handful of web search companies, a software developer is most likely to encounter the personal search and enterprise scenarios.

In this chapter we begin with a very simple example of an information retrieval problem, and introduce the idea of a term-document matrix (Section 1.1) and the central inverted index data structure (Section 1.2). We will then examine the Boolean retrieval model and how Boolean queries are processed (Sections 1.3 and 1.4).

1.1 An example information retrieval problem

A fat book which many people own is Shakespeare's Collected Works. Suppose you wanted to determine which plays of Shakespeare contain the words Brutus AND Caesar AND NOT Calpurnia. One way to do that is to start at the beginning and to read through all the text, noting for each play whether it contains Brutus and Caesar and excluding it from consideration if it contains Calpurnia. The simplest form of document retrieval is for a computer to do this sort of linear scan through documents. This process is commonly
GREP referred to as *grepping* through text, after the Unix command `grep`, which performs this process. Grepping through text can be a very effective process, especially given the speed of modern computers, and often allows useful possibilities for wildcard pattern matching through the use of regular expressions. With modern computers, for simple querying of modest collections (the size of Shakespeare's Collected Works is a bit under one million words of text in total), you really need nothing more.

But for many purposes, you do need more:

1. To process large document collections quickly. The amount of online data has grown at least as quickly as the speed of computers, and we would now like to be able to search collections that total in the order of billions to trillions of words.
2. To allow more flexible matching operations. For example, it is impractical to perform the query Romans NEAR countrymen with `grep`, where NEAR might be defined as "within 5 words" or "within the same sentence".
3. To allow ranked retrieval: in many cases you want the best answer to an information need among many documents that contain certain words.

INDEX The way to avoid linearly scanning the texts for each query is to *index* the documents in advance. Let us stick with Shakespeare's Collected Works, and use it to introduce the basics of the Boolean retrieval model. Suppose we record for each document – here a play of Shakespeare's – whether it contains each word out of all the words Shakespeare used (Shakespeare used
INCIDENCE MATRIX about 32,000 different words). The result is a binary term-document *incidence*
TERM *matrix*, as in Figure 1.1. *Terms* are the indexed units (further discussed in Section 2.2); they are usually words, and for the moment you can think of

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Antony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
...							

► **Figure 1.1** A term-document incidence matrix. Matrix element (t, d) is 1 if the play in column d contains the word in row t, and is 0 otherwise.

them as words, but the information retrieval literature normally speaks of terms because some of them, such as perhaps I-9 or Hong Kong are not usually thought of as words. Now, depending on whether we look at the matrix rows or columns, we can have a vector for each term, which shows the documents it appears in, or a vector for each document, showing the terms that occur in it.[2]

To answer the query Brutus AND Caesar AND NOT Calpurnia, we take the vectors for Brutus, Caesar and Calpurnia, complement the last, and then do a bitwise AND:

110100 AND 110111 AND 101111 = 100100

The answers for this query are thus *Antony and Cleopatra* and *Hamlet* (Figure 1.2).

BOOLEAN RETRIEVAL MODEL

The *Boolean retrieval model* is a model for information retrieval in which we can pose any query which is in the form of a Boolean expression of terms, that is, in which terms are combined with the operators AND, OR, and NOT. The model views each document as just a set of words.

DOCUMENT

Let us now consider a more realistic scenario, simultaneously using the opportunity to introduce some terminology and notation. Suppose we have $N = 1$ million documents. By *documents* we mean whatever units we have decided to build a retrieval system over. They might be individual memos or chapters of a book (see Section 2.1.2 (page 20) for further discussion). We will refer to the group of documents over which we perform retrieval as the (document) *collection*. It is sometimes also referred to as a *corpus* (a *body* of texts). Suppose each document is about 1000 words long (2–3 book pages). If

COLLECTION CORPUS

2. Formally, we take the transpose of the matrix to be able to get the terms as column vectors.

Antony and Cleopatra, Act III, Scene ii
Agrippa [Aside to Domitius Enobarbus]: Why, Enobarbus,
When Antony found Julius Caesar dead,
He cried almost to roaring; and he wept
When at Philippi he found Brutus slain.

Hamlet, Act III, Scene ii
Lord Polonius: I did enact Julius Caesar: I was killed i' the
Capitol; Brutus killed me.

► **Figure 1.2** Results from Shakespeare for the query Brutus AND Caesar AND NOT Calpurnia.

we assume an average of 6 bytes per word including spaces and punctuation, then this is a document collection about 6 GB in size. Typically, there might be about $M = 500{,}000$ distinct terms in these documents. There is nothing special about the numbers we have chosen, and they might vary by an order of magnitude or more, but they give us some idea of the dimensions of the kinds of problems we need to handle. We will discuss and model these size assumptions in Section 5.1 (page 86).

AD HOC RETRIEVAL

Our goal is to develop a system to address the *ad hoc retrieval* task. This is the most standard IR task. In it, a system aims to provide documents from within the collection that are relevant to an arbitrary user information need, communicated to the system by means of a one-off, user-initiated query. An

INFORMATION NEED

information need is the topic about which the user desires to know more, and

QUERY

is differentiated from a *query*, which is what the user conveys to the computer in an attempt to communicate the information need. A document is

RELEVANCE

relevant if it is one that the user perceives as containing information of value with respect to their personal information need. Our example above was rather artificial in that the information need was defined in terms of particular words, whereas usually a user is interested in a topic like "pipeline leaks" and would like to find relevant documents regardless of whether they precisely use those words or express the concept with other words such as

EFFECTIVENESS

pipeline rupture. To assess the *effectiveness* of an IR system (i.e., the quality of its search results), a user will usually want to know two key statistics about the system's returned results for a query:

PRECISION

Precision: What fraction of the returned results are relevant to the information need?

RECALL

Recall: What fraction of the relevant documents in the collection were returned by the system?

Detailed discussion of relevance and evaluation measures including precision and recall is found in Chapter 8.

We now cannot build a term-document matrix in a naive way. A 500K × 1M matrix has half-a-trillion 0's and 1's – too many to fit in a computer's memory. But the crucial observation is that the matrix is extremely sparse, that is, it has few non-zero entries. Because each document is 1000 words long, the matrix has no more than one billion 1's, so a minimum of 99.8% of the cells are zero. A much better representation is to record only the things that do occur, that is, the 1 positions.

INVERTED INDEX

This idea is central to the first major concept in information retrieval, the *inverted index*. The name is actually redundant: an index always maps back from terms to the parts of a document where they occur. Nevertheless, *inverted index*, or sometimes *inverted file*, has become the standard term in information retrieval.[3] The basic idea of an inverted index is shown in Figure 1.3.

DICTIONARY
VOCABULARY
LEXICON

We keep a *dictionary* of terms (sometimes also referred to as a *vocabulary* or *lexicon*; in this book, we use *dictionary* for the data structure and *vocabulary* for the set of terms). Then for each term, we have a list that records which documents the term occurs in. Each item in the list – which records that a term appeared in a document (and, later, often, the positions in the document) – is conventionally called a *posting*.[4] The list is then called a *postings list* (or inverted list), and all the postings lists taken together are referred to as the *postings*. The dictionary in Figure 1.3 has been sorted alphabetically and each postings list is sorted by document ID. We will see why this is useful in Section 1.3, below, but later we will also consider alternatives to doing this (Section 7.1.5).

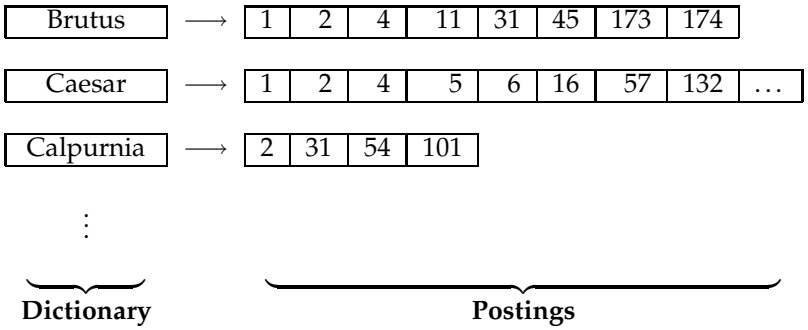
POSTING
POSTINGS LIST
POSTINGS

1.2 A first take at building an inverted index

To gain the speed benefits of indexing at retrieval time, we have to build the index in advance. The major steps in this are:

1. Collect the documents to be indexed:
   Friends, Romans, countrymen. | So let it be with Caesar | ...
2. Tokenize the text, turning each document into a list of tokens:
   Friends | Romans | countrymen | So | ...

3. Some information retrieval researchers prefer the term inverted file, but expressions like index construction and index compression are much more common than inverted file construction and inverted file compression. For consistency, we use (inverted) index throughout this book.
4. In a (non-positional) inverted index, a posting is just a document ID, but it is inherently associated with a term, via the postings list it is placed on; sometimes we will also talk of a (term, docID) pair as a posting.



▶ **Figure 1.3** The two parts of an inverted index. The dictionary is commonly kept in memory, with pointers to each postings list, which is stored on disk.

3. Do linguistic preprocessing, producing a list of normalized tokens, which are the indexing terms: friend | roman | countryman | so ...
4. Index the documents that each term occurs in by creating an inverted index, consisting of a dictionary and postings.

We will define and discuss the earlier stages of processing, that is, steps 1–3, in Section 2.2 (page 22). Until then you can think of *tokens* and *normalized tokens* as also loosely equivalent to *words*. Here, we assume that the first 3 steps have already been done, and we examine building a basic inverted index by sort-based indexing.

DOCID

Within a document collection, we assume that each document has a unique serial number, known as the document identifier (*docID*). During index construction, we can simply assign successive integers to each new document when it is first encountered. The input to indexing is a list of normalized tokens for each document, which we can equally think of as a list of pairs of term and docID, as in Figure 1.4. The core indexing step is *sorting* this list so that the terms are alphabetical, giving us the representation in the middle column of Figure 1.4. Multiple occurrences of the same term from the same document are then merged.[5] Instances of the same term are then grouped, and the result is split into a *dictionary* and *postings*, as shown in the right column of Figure 1.4. Since a term generally occurs in a number of documents, this data organization already reduces the storage requirements of the index. The dictionary also records some statistics, such as the number of documents which contain each term (the *document frequency*, which is here also the length of each postings list). This information is not vital for a basic Boolean search engine, but it allows us to improve the efficiency of the

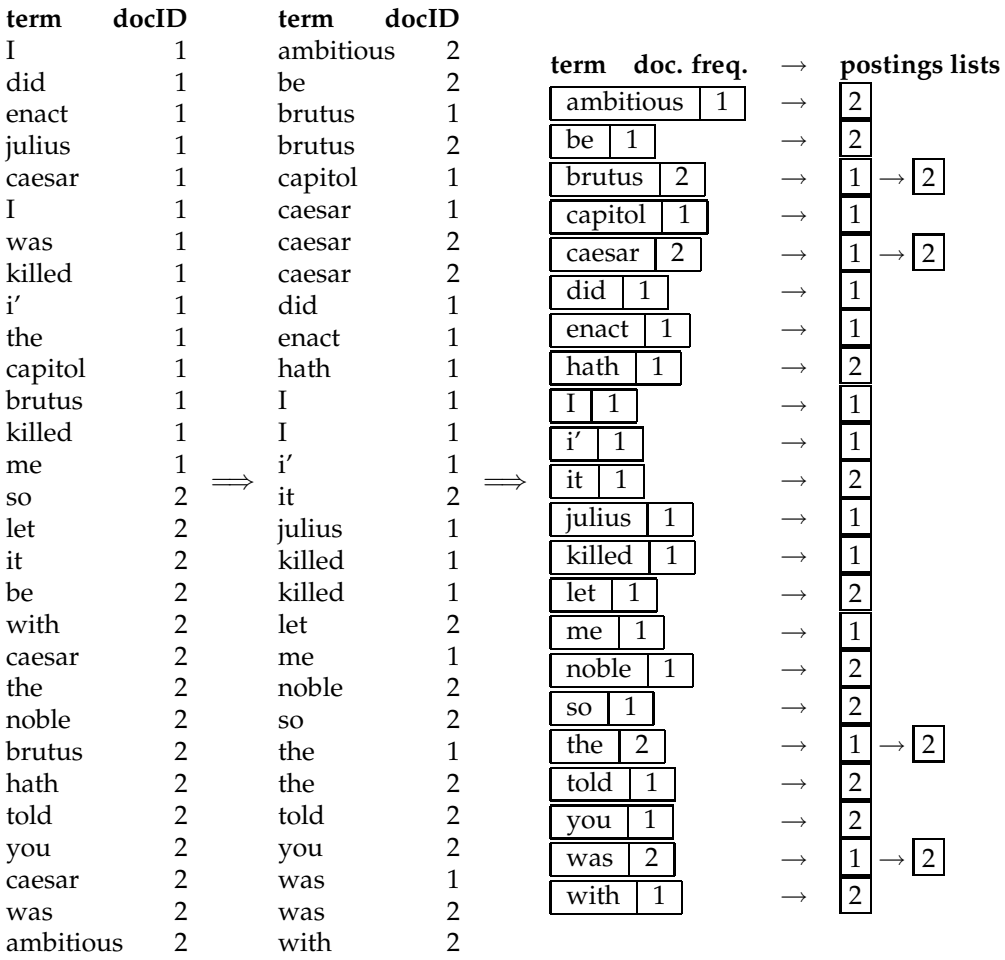
SORTING

DOCUMENT FREQUENCY

5. Unix users can note that these steps are similar to use of the `sort` and then `uniq` commands.

Doc 1
I did enact Julius Caesar: I was killed i' the Capitol; Brutus killed me.

Doc 2
So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious:



► **Figure 1.4** Building an index by sorting and grouping. The sequence of terms in each document, tagged by their documentID (left) is sorted alphabetically (middle). Instances of the same term are then grouped by word and then by documentID. The terms and documentIDs are then separated out (right). The dictionary stores the terms, and has a pointer to the postings list for each term. It commonly also stores other summary information such as, here, the document frequency of each term. We use this information for improving query time efficiency and, later, for weighting in ranked retrieval models. Each postings list stores the list of documents in which a term occurs, and may store other information such as the term frequency (the frequency of each term in each document) or the position(s) of the term in each document.

search engine at query time, and it is a statistic later used in many ranked retrieval models. The postings are secondarily sorted by docID. This provides the basis for efficient query processing. This inverted index structure is essentially without rivals as the most efficient structure for supporting ad hoc text search.

In the resulting index, we pay for storage of both the dictionary and the postings lists. The latter are much larger, but the dictionary is commonly kept in memory, while postings lists are normally kept on disk, so the size of each is important, and in Chapter 5 we will examine how each can be optimized for storage and access efficiency. What data structure should be used for a postings list? A fixed length array would be wasteful as some words occur in many documents, and others in very few. For an in-memory postings list, two good alternatives are singly linked lists or variable length arrays. Singly linked lists allow cheap insertion of documents into postings lists (following updates, such as when recrawling the web for updated documents), and naturally extend to more advanced indexing strategies such as skip lists (Section 2.3), which require additional pointers. Variable length arrays win in space requirements by avoiding the overhead for pointers and in time requirements because their use of contiguous memory increases speed on modern processors with memory caches. Extra pointers can in practice be encoded into the lists as offsets. If updates are relatively infrequent, variable length arrays will be more compact and faster to traverse. We can also use a hybrid scheme with a linked list of fixed length arrays for each term. When postings lists are stored on disk, they are stored (perhaps compressed) as a contiguous run of postings without explicit pointers (as in Figure 1.3), so as to minimize the size of the postings list and the number of disk seeks to read a postings list into memory.

Exercise 1.1 [⋆]

Draw the inverted index that would be built for the following document collection. (See Figure 1.3 for an example.)

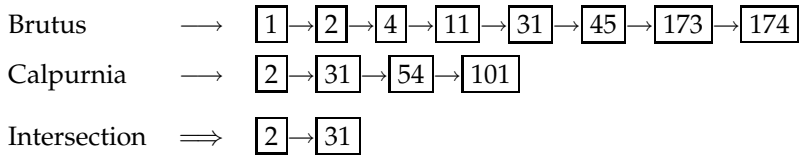
Doc 1	new home sales top forecasts
Doc 2	home sales rise in july
Doc 3	increase in home sales in july
Doc 4	july new home sales rise

Exercise 1.2 [⋆]

Consider these documents:

Doc 1	breakthrough drug for schizophrenia
Doc 2	new schizophrenia drug
Doc 3	new approach for treatment of schizophrenia
Doc 4	new hopes for schizophrenia patients

a. Draw the term-document incidence matrix for this document collection.



► **Figure 1.5** Intersecting the postings lists for Brutus and Calpurnia from Figure 1.3.

b. Draw the inverted index representation for this collection, as in Figure 1.3 (page 7).

Exercise 1.3 [⋆]

For the document collection shown in Exercise 1.2, what are the returned results for these queries:

a. schizophrenia AND drug

b. for AND NOT(drug OR approach)

1.3 Processing Boolean queries

How do we process a query using an inverted index and the basic Boolean retrieval model? Consider processing the *simple conjunctive query*:

SIMPLE CONJUNCTIVE QUERIES

(1.1) Brutus AND Calpurnia

over the inverted index partially shown in Figure 1.3 (page 7). We:

1. Locate Brutus in the Dictionary
2. Retrieve its postings
3. Locate Calpurnia in the Dictionary
4. Retrieve its postings
5. Intersect the two postings lists, as shown in Figure 1.5.

POSTINGS LIST INTERSECTION

POSTINGS MERGE

The *intersection* operation is the crucial one: we need to efficiently intersect postings lists so as to be able to quickly find documents that contain both terms. (This operation is sometimes referred to as *merging* postings lists: this slightly counterintuitive name reflects using the term *merge algorithm* for a general family of algorithms that combine multiple sorted lists by interleaved advancing of pointers through each; here we are merging the lists with a logical AND operation.)

There is a simple and effective method of intersecting postings lists using the merge algorithm (see Figure 1.6): we maintain pointers into both lists

```
INTERSECT(p1, p2)
 1  answer ← ⟨ ⟩
 2  while p1 ≠ NIL and p2 ≠ NIL
 3  do if docID(p1) = docID(p2)
 4        then ADD(answer, docID(p1))
 5             p1 ← next(p1)
 6             p2 ← next(p2)
 7        else if docID(p1) < docID(p2)
 8                then p1 ← next(p1)
 9                else p2 ← next(p2)
10  return answer
```

▶ **Figure 1.6** Algorithm for the intersection of two postings lists p_1 and p_2.

and walk through the two postings lists simultaneously, in time linear in the total number of postings entries. At each step, we compare the docID pointed to by both pointers. If they are the same, we put that docID in the results list, and advance both pointers. Otherwise we advance the pointer pointing to the smaller docID. If the lengths of the postings lists are x and y, the intersection takes $O(x + y)$ operations. Formally, the complexity of querying is $\Theta(N)$, where N is the number of documents in the collection.[6] Our indexing methods gain us just a constant, not a difference in Θ time complexity compared to a linear scan, but in practice the constant is huge. To use this algorithm, it is crucial that postings be sorted by a single global ordering. Using a numeric sort by docID is one simple way to achieve this.

We can extend the intersection operation to process more complicated queries like:

(1.2) (Brutus OR Caesar) AND NOT Calpurnia

QUERY OPTIMIZATION

Query optimization is the process of selecting how to organize the work of answering a query so that the least total amount of work needs to be done by the system. A major element of this for Boolean queries is the order in which postings lists are accessed. What is the best order for query processing? Consider a query that is an AND of t terms, for instance:

(1.3) Brutus AND Caesar AND Calpurnia

For each of the t terms, we need to get its postings, then AND them together. The standard heuristic is to process terms in order of increasing document

6. The notation $\Theta(\cdot)$ is used to express an asymptotically tight bound on the complexity of an algorithm. Informally, this is often written as $O(\cdot)$, but this notation really expresses an asymptotic upper bound, which need not be tight (Cormen et al. 1990).

```
INTERSECT(⟨t_1, ..., t_n⟩)
1  terms ← SORTBYINCREASINGFREQUENCY(⟨t_1, ..., t_n⟩)
2  result ← postings(first(terms))
3  terms ← rest(terms)
4  while terms ≠ NIL and result ≠ NIL
5  do result ← INTERSECT(result, postings(first(terms)))
6     terms ← rest(terms)
7  return result
```

▶ **Figure 1.7** Algorithm for conjunctive queries that returns the set of documents containing each term in the input list of terms.

frequency: if we start by intersecting the two smallest postings lists, then all intermediate results must be no bigger than the smallest postings list, and we are therefore likely to do the least amount of total work. So, for the postings lists in Figure 1.3 (page 7), we execute the above query as:

(1.4) (Calpurnia AND Brutus) AND Caesar

This is a first justification for keeping the frequency of terms in the dictionary: it allows us to make this ordering decision based on in-memory data before accessing any postings list.

Consider now the optimization of more general queries, such as:

(1.5) (madding OR crowd) AND (ignoble OR strife) AND (killed OR slain)

As before, we will get the frequencies for all terms, and we can then (conservatively) estimate the size of each OR by the sum of the frequencies of its disjuncts. We can then process the query in increasing order of the size of each disjunctive term.

For arbitrary Boolean queries, we have to evaluate and temporarily store the answers for intermediate expressions in a complex expression. However, in many circumstances, either because of the nature of the query language, or just because this is the most common type of query that users submit, a query is purely conjunctive. In this case, rather than viewing merging postings lists as a function with two inputs and a distinct output, it is more efficient to intersect each retrieved postings list with the current intermediate result in memory, where we initialize the intermediate result by loading the postings list of the least frequent term. This algorithm is shown in Figure 1.7. The intersection operation is then asymmetric: the intermediate results list is in memory while the list it is being intersected with is being read from disk. Moreover the intermediate results list is always at least as short as the other list, and in many cases it is orders of magnitude shorter. The postings

intersection can still be done by the algorithm in Figure 1.6, but when the difference between the list lengths is very large, opportunities to use alternative techniques open up. The intersection can be calculated in place by destructively modifying or marking invalid items in the intermediate results list. Or the intersection can be done as a sequence of binary searches in the long postings lists for each posting in the intermediate results list. Another possibility is to store the long postings list as a hashtable, so that membership of an intermediate result item can be calculated in constant rather than linear or log time. However, such alternative techniques are difficult to combine with postings list compression of the sort discussed in Chapter 5. Moreover, standard postings list intersection operations remain necessary when both terms of a query are very common.

? **Exercise 1.4** [⋆]

For the queries below, can we still run through the intersection in time $O(x + y)$, where x and y are the lengths of the postings lists for Brutus and Caesar? If not, what can we achieve?

a. Brutus AND NOT Caesar

b. Brutus OR NOT Caesar

Exercise 1.5 [⋆]

Extend the postings merge algorithm to arbitrary Boolean query formulas. What is its time complexity? For instance, consider:

c. (Brutus OR Caesar) AND NOT (Antony OR Cleopatra)

Can we always merge in linear time? Linear in what? Can we do better than this?

Exercise 1.6 [⋆⋆]

We can use distributive laws for AND and OR to rewrite queries.

a. Show how to rewrite the query in Exercise 1.5 into disjunctive normal form using the distributive laws.

b. Would the resulting query be more or less efficiently evaluated than the original form of this query?

c. Is this result true in general or does it depend on the words and the contents of the document collection?

Exercise 1.7 [⋆]

Recommend a query processing order for

d. (tangerine OR trees) AND (marmalade OR skies) AND (kaleidoscope OR eyes)

given the following postings list sizes:

Term	Postings size
eyes	213312
kaleidoscope	87009
marmalade	107913
skies	271658
tangerine	46653
trees	316812

Exercise 1.8 [⋆]

If the query is:

e. friends AND romans AND (NOT countrymen)

how could we use the frequency of countrymen in evaluating the best query evaluation order? In particular, propose a way of handling negation in determining the order of query processing.

Exercise 1.9 [⋆⋆]

For a conjunctive query, is processing postings lists in order of size guaranteed to be optimal? Explain why it is, or give an example where it isn't.

Exercise 1.10 [⋆⋆]

Write out a postings merge algorithm, in the style of Figure 1.6 (page 11), for an x OR y query.

Exercise 1.11 [⋆⋆]

How should the Boolean query x AND NOT y be handled? Why is naive evaluation of this query normally very expensive? Write out a postings merge algorithm that evaluates this query efficiently.

1.4 The extended Boolean model versus ranked retrieval

RANKED RETRIEVAL MODEL
FREE TEXT QUERIES

The Boolean retrieval model contrasts with *ranked retrieval models* such as the vector space model (Section 6.3), in which users largely use *free text queries*, that is, just typing one or more words rather than using a precise language with operators for building up query expressions, and the system decides which documents best satisfy the query. Despite decades of academic research on the advantages of ranked retrieval, systems implementing the Boolean retrieval model were the main or only search option provided by large commercial information providers for three decades until the early 1990s (approximately the date of arrival of the World Wide Web). However, these systems did not have just the basic Boolean operations (AND, OR, and NOT) which we have presented so far. A strict Boolean expression over terms with an unordered results set is too limited for many of the information needs that people have, and these systems implemented extended Boolean retrieval models by incorporating additional operators such as term proximity operators. A *proximity operator* is a way of specifying that two terms in a query

PROXIMITY OPERATOR

must occur close to each other in a document, where closeness may be measured by limiting the allowed number of intervening words or by reference to a structural unit such as a sentence or paragraph.

Example 1.1: Commercial Boolean searching: Westlaw. Westlaw (http://www.westlaw.com/) is the largest commercial legal search service (in terms of the number of paying subscribers), with over half a million subscribers performing millions of searches a day over tens of terabytes of text data. The service was started in 1975. In 2005, Boolean search (called "Terms and Connectors" by Westlaw) was still the default, and used by a large percentage of users, although ranked free text querying (called "Natural Language" by Westlaw) was added in 1992. Here are some example Boolean queries on Westlaw:

Information need: Information on the legal theories involved in preventing the disclosure of trade secrets by employees formerly employed by a competing company. *Query:* "trade secret" /s disclos! /s prevent /s employe!

Information need: Requirements for disabled people to be able to access a workplace.
Query: disab! /p access! /s work-site work-place (employment /3 place)

Information need: Cases about a host's responsibility for drunk guests.
Query: host! /p (responsib! liab!) /p (intoxicat! drunk!) /p guest

Note the long, precise queries and the use of proximity operators, both uncommon in web search. Submitted queries average about ten words in length. Unlike web search conventions, a space between words represents disjunction (the tightest binding operator), & is AND and /s, /p, and /*k* ask for matches in the same sentence, same paragraph or within *k* words respectively. Double quotes give a *phrase search* (consecutive words); see Section 2.4 (page 39). The exclamation mark (!) gives a trailing wildcard query (see Section 3.2, page 51); thus liab! matches all words starting with liab. Additionally work-site matches any of *worksite*, *work-site* or *work site*; see Section 2.2.1 (page 22). Typical expert queries are usually carefully defined and incrementally developed until they obtain what look to be good results to the user.

Many users, particularly professionals, prefer Boolean query models. Boolean queries are precise: a document either matches the query or it does not. This offers the user greater control and transparency over what is retrieved. And some domains, such as legal materials, allow an effective means of document ranking within a Boolean model: Westlaw returns documents in reverse chronological order, which is in practice quite effective. In 2007, the majority of law librarians still seem to recommend terms and connectors for high recall searches, and the majority of legal users think they are getting greater control by using them. However, this does not mean that Boolean queries are more effective for professional searchers. Indeed, experimenting on a Westlaw subcollection, Turtle (1994) found that free text queries produced better results than Boolean queries prepared by Westlaw's own reference librarians for the majority of the information needs in his experiments. A general problem with Boolean search is that using AND operators tends to produce high precision but low recall searches, while using OR operators gives low precision but high recall searches, and it is difficult or impossible to find a satisfactory middle ground.

In this chapter, we have looked at the structure and construction of a basic

inverted index, comprising a dictionary and postings lists. We introduced the Boolean retrieval model, and examined how to do efficient retrieval via linear time merges and simple query optimization. In Chapters 2–7 we will consider in detail richer query models and the sort of augmented index structures that are needed to handle them efficiently. Here we just mention a few of the main additional things we would like to be able to do:

1. We would like to better determine the set of terms in the dictionary and to provide retrieval that is tolerant to spelling mistakes and inconsistent choice of words.

2. It is often useful to search for compounds or phrases that denote a concept such as "operating system". As the Westlaw examples show, we might also wish to do proximity queries such as Gates NEAR Microsoft. To answer such queries, the index has to be augmented to capture the proximities of terms in documents.

3. A Boolean model only records term presence or absence, but often we would like to accumulate evidence, giving more weight to documents that have a term several times as opposed to ones that contain it only once. To be able to do this we need *term frequency* information (the number of times a term occurs in a document) in postings lists.

TERM FREQUENCY

4. Boolean queries just retrieve a set of matching documents, but commonly we wish to have an effective method to order (or "rank") the returned results. This requires having a mechanism for determining a document score which encapsulates how good a match a document is for a query.

With these additional ideas, we will have seen most of the basic technology that supports ad hoc searching over unstructured information. Ad hoc searching over documents has recently conquered the world, powering not only web search engines but the kind of unstructured search that lies behind the large eCommerce websites. Although the main web search engines differ by emphasizing free text querying, most of the basic issues and technologies of indexing and querying remain the same, as we will see in later chapters. Moreover, over time, web search engines have added at least partial implementations of some of the most popular operators from extended Boolean models: phrase search is especially popular and most have a very partial implementation of Boolean operators. Nevertheless, while these options are liked by expert searchers, they are little used by most people and are not the main focus in work on trying to improve web search engine performance.

? **Exercise 1.12** [⋆]

Write a query using Westlaw syntax which would find any of the words professor, teacher, or lecturer in the same sentence as a form of the verb explain.

Exercise 1.13 [⋆]

Try using the Boolean search features on a couple of major web search engines. For instance, choose a word, such as burglar, and submit the queries (i) burglar, (ii) burglar AND burglar, and (iii) burglar OR burglar. Look at the estimated number of results and top hits. Do they make sense in terms of Boolean logic? Often they haven't for major search engines. Can you make sense of what is going on? What about if you try different words? For example, query for (i) knight, (ii) conquer, and then (iii) knight OR conquer. What bound should the number of results from the first two queries place on the third query? Is this bound observed?

1.5 References and further reading

The practical pursuit of computerized information retrieval began in the late 1940s (Cleverdon 1991, Liddy 2005). A great increase in the production of scientific literature, much in the form of less formal technical reports rather than traditional journal articles, coupled with the availability of computers, led to interest in automatic document retrieval. However, in those days, document retrieval was always based on author, title, and keywords; full-text search came much later.

The article of Bush (1945) provided lasting inspiration for the new field:

> "Consider a future device for individual use, which is a sort of mechanized private file and library. It needs a name, and, to coin one at random, 'memex' will do. A memex is a device in which an individual stores all his books, records, and communications, and which is mechanized so that it may be consulted with exceeding speed and flexibility. It is an enlarged intimate supplement to his memory."

The term *Information Retrieval* was coined by Calvin Mooers in 1948/1950 (Mooers 1950).

In 1958, much newspaper attention was paid to demonstrations at a conference (see Taube and Wooster 1958) of IBM "auto-indexing" machines, based primarily on the work of H. P. Luhn. Commercial interest quickly gravitated towards Boolean retrieval systems, but the early years saw a heady debate over various disparate technologies for retrieval systems. For example Mooers (1961) dissented:

> "It is a common fallacy, underwritten at this date by the investment of several million dollars in a variety of retrieval hardware, that the algebra of George Boole (1847) is the appropriate formalism for retrieval system design. This view is as widely and uncritically accepted as it is wrong."

The observation of AND vs. OR giving you opposite extremes in a precision/recall tradeoff, but not the middle ground comes from (Lee and Fox 1988).

The book (Witten et al. 1999) is the standard reference for an in-depth comparison of the space and time efficiency of the inverted index versus other possible data structures; a more succinct and up-to-date presentation appears in Zobel and Moffat (2006). We further discuss several approaches in Chapter 5.

REGULAR EXPRESSIONS

Friedl (2006) covers the practical usage of *regular expressions* for searching. The underlying computer science appears in (Hopcroft et al. 2000).