Index	Small collection (1 Mb)		Medium collection (200 Mb)		Large collection (2 Gb)	
Addressing words	45%	73%	36%	64%	35%	63%
Addressing documents	19%	26%	18%	32%	26%	47%
Addressing 64K blocks	27%	41%	18%	32%	5%	9%
Addressing 256 blocks	18%	25%	1.7%	2.4%	0.5%	0.7%

Table 8.1 Sizes of an inverted file as approximate percentages of the size the whole text collection. Four granularities and three collections are considered. For each collection, the right column considers that stopwords are not indexed while the left column considers that all words are indexed.

8.2.1 Searching

The search algorithm on an inverted index follows three general steps (some may be absent for specific queries):

- **Vocabulary search** The words and patterns present in the query are isolated and searched in the vocabulary. Notice that phrases and proximity queries are split into single words.
- **Retrieval of occurrences** The lists of the occurrences of all the words found are retrieved.
- **Manipulation of occurrences** The occurrences are processed to solve phrases, proximity, or Boolean operations. If block addressing is used it may be necessary to directly search the text to find the information missing from the occurrences (e.g., exact word positions to form phrases).

Hence, searching on an inverted index always starts in the vocabulary. Because of this it is a good idea to have it in a separate file. It is possible that this file fits in main memory even for large text collections.

Single-word queries can be searched using any suitable data structure to speed up the search, such as hashing,,tries, or B-trees. The first two give $O(m)$ search cost (independent of the text size). However, simply storing the words in lexicographical order is cheaper in space and very competitive in performance, since the word can be binary searched at $O(\log n)$ cost. Prefix and range queries can also be solved with binary search, tries, or B-trees, but not with hashing. If the query is formed by single words, then the process ends by delivering the list of occurrences (we may need to make a union of many lists if the pattern matches many words).

Context queries are more difficult to solve with inverted indices. Each element must be searched separately and a list (in increasing positional order) generated for each one. Then, the lists of all elements are traversed in synchronization to find places where all the words appear in sequence (for a phrase) or appear close enough (for proximity). If one list is much shorter than the others, it may be better to binary search its elements into the longer lists instead of performing a linear merge. It is possible to prove using Zipf's law that this is normally the case. This is important because the most time-demanding operation on inverted indices is the merging or intersection of the lists of occurrences.

If the index stores character positions the phrase query cannot allow the separators to be disregarded, and the proximity has to be defined in terms of character distance.

Finally, note that if block addressing is used it is necessary to traverse the blocks for these queries, since the position information is needed. It is then better to intersect the lists to obtain the blocks which contain all the searched words and then sequentially search the context query in those blocks as explained in section 8.5. Some care has to be exercised at block boundaries, since they can split a match. This part of the search, if present, is also quite time consuming.

Using Heaps' and the generalized Zipf's laws, it has been demonstrated that the cost of solving queries is sublinear in the text size, even for complex queries involving list merging. The time complexity is $O(n^{\alpha})$, where α depends on the query and is close to 0.4..0.8 for queries with reasonable selectivity.

Even if block addressing is used and the blocks have to be traversed, it is possible to select the block size as an increasing function of n, so that not only does the space requirement keep sublinear but also the amount of text traversed in all useful queries is also sublinear.

Practical figures show, for instance, that both the space requirement and the amount of text traversed can be close to $O(n^{0.85})$. Hence, inverted indices allow us to have sublinear search time at sublinear space requirements. This is not possible on the other indices.

Search times on our reference machine for a full inverted index built on 250 Mb of text give the following results: searching a simple word took 0.08 seconds, while searching a phrase took 0.25 to 0.35 seconds (from two to five words).

8.2.2 Construction

Building and maintaining an inverted index is a relatively low cost task. In principle, an inverted index on a text of n characters can be built in $O(n)$ time. All the vocabulary known up to now is kept in a trie data structure, storing for each word a list of its occurrences (text positions). Each word of the text is read and searched in the trie. If it is not found, it is added to the trie with an empty list of occurrences. Once it is in the trie, the new position is added to the end of its list of occurrences. Figure 8.3 illustrates this process.

Once the text is exhausted, the trie is written to disk together with the list of occurrences. It is good practice to split the index into two files. In the

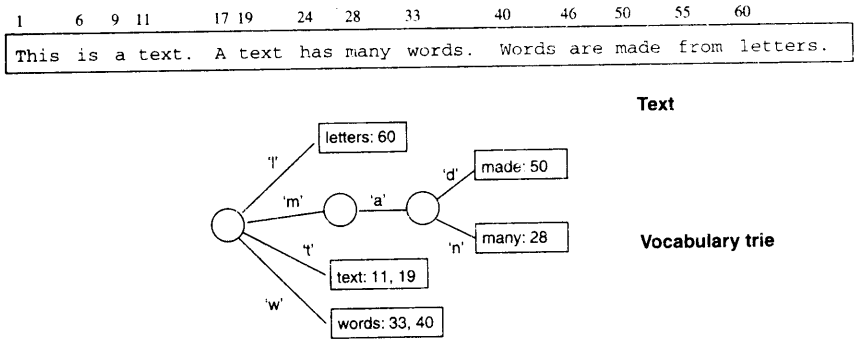


Figure 8.3 Building an inverted index for the sample text.

first file, the lists of occurrences are stored contiguously. In this scheme, the file is typically called a 'posting file'. In the second file, the vocabulary is stored in lexicographical order and, for each word, a pointer to its list in the first file is also included. This allows the vocabulary to be kept in memory at search time in many cases. Further, the number of occurrences of a word can be immediately known from the vocabulary with little or no space overhead.

We analyze now the construction time under this scheme. Since in the trie $O(1)$ operations are performed per text character, and the positions can be inserted at the end of the lists of occurrences in $O(1)$ time, the overall process is $O(n)$ worst-case time.

However, the above algorithm is not practical for large texts where the index does not fit in main memory. A paging mechanism will severely degrade the performance of the algorithm. We describe an alternative which is faster in practice.

The algorithm already described is used until the main memory is exhausted (if the trie takes up too much space it can be replaced by a hash table or other structure). When no more memory is available, the *partial* index I_i obtained up to now is written to disk and erased from main memory before continuing with the rest of the text.

Finally, a number of partial indices I_i exist on disk. These indices are then merged in a hierarchical fashion. Indices I_1 and I_2 are merged to obtain the index $I_{1..2}$; I_3 and I_4 produce $I_{3..4}$; and so on. The resulting partial indices are now approximately twice the size. When all the indices at this level have been merged in this way, the merging proceeds at the next level, joining the index $I_{1..2}$ with the index $I_{3..4}$ to form $I_{1..4}$. This is continued until there is just one index comprising the whole text, as illustrated in Figure 8.4.

Merging two indices consists of merging the sorted vocabularies, and whenever the same word appears in both indices, merging both lists of occurrences. By construction, the occurrences of the smaller-numbered index are before those of the larger-numbered index, and therefore the lists are just concatenated. This is a very fast process in practice, and its complexity is $O(n_1 + n_2)$, where n_1 and n_2 are the sizes of the indices.

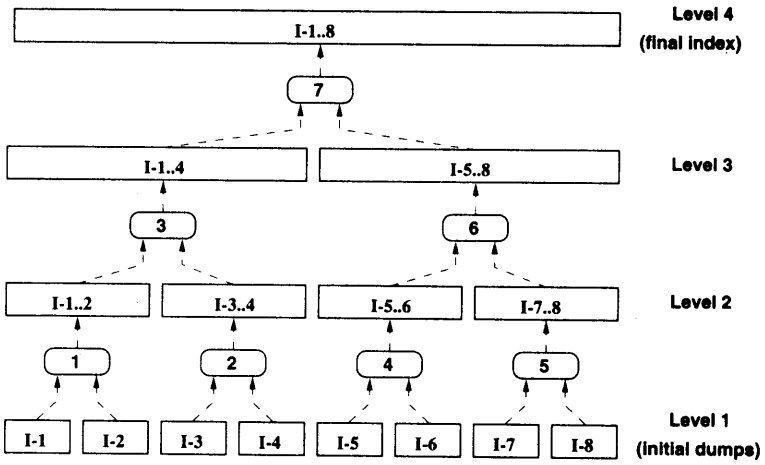


Figure 8.4 Merging the partial indices in a binary fashion. Rectangles represent partial indices, while rounded rectangles represent merging operations. The numbers inside the merging operations show a possible merging order.

The total time to generate the partial indices is $O(n)$ as before. The number of partial indices is $O(n/M)$. Each level of merging performs a linear process over the whole index (no matter how it is split into partial indices at this level) and thus its cost is $O(n)$. To merge the $O(n/M)$ partial indices, $\log_2(n/M)$ merging levels are necessary, and therefore the cost of this algorithm is $O(n \log(n/M))$.

More than two indices can be merged at once. Although this does not change the complexity, it improves efficiency since fewer merging levels exist. On the other hand, the memory buffers for each partial index to merge will be smaller and hence more disk seeks will be performed. In practice it is a good idea to merge even 20 partial indices at once.

Real times to build inverted indices on the reference machine are between 4-8 Mb/min for collections of up to 1 Gb (the slowdown factor as the text grows is barely noticeable). Of this time, 20-30% is spent on merging the partial indices.

To reduce build-time space requirements, it is possible to perform the merging in-place. That is, when two or more indices are merged, write the result in the same disk blocks of the original indices instead of on a new file. It is also a good idea to perform the hierarchical merging as soon as the files are generated (e.g., collapse I_1 and I_2 into $I_{1..2}$ as soon as I_2 is produced). This also reduces space requirements because the vocabularies are merged and redundant words are eliminated (there is no redundancy in the occurrences). The vocabulary can be a significative part of the smaller partial indices, since they represent a small text.

This algorithm changes very little if block addressing is used. Index maintenance is also cheap. Assume that a new text of size n' is added to the database. The inverted index for the new text is built and then both indices are merged

as is done for partial indices. This takes $O(n + n' \log(n'/M))$. Deleting text can be done by an $O(n)$ pass over the index eliminating the occurrences that point inside eliminated text areas (and eliminating words if their lists of occurrences disappear in the process).

8.3 Other Indices for Text

8.3.1 Suffix Trees and Suffix Arrays

Inverted indices assume that the text can be seen as a sequence of words. This restricts somewhat the kinds of queries that can be answered. Other queries such as phrases are expensive to solve. Moreover, the concept of word does not exist in some applications such as genetic databases.

In this section we present suffix arrays. Suffix arrays are a space efficient implementation of suffix trees. This type of index allows us to answer efficiently more complex queries. Its main drawbacks are its costly construction process, that the text must be readily available at query time, and that the results are not delivered in text position order. This structure can be used to index only words (without stopwords) as the inverted index as well as to index any text character. This makes it suitable for a wider spectrum of applications, such as genetic databases. However, for word-based applications, inverted files perform better unless complex queries are an important issue.

This index sees the text as one long string. Each position in the text is considered as a text *suffix* (i.e., a string that goes from that text position to the end of the text). It is not difficult to see that two suffixes starting at different positions are lexicographically different (assume that a character smaller than all the rest is placed at the end of the text). Each suffix is thus uniquely identified by its position.

Not all text positions need to be indexed. *Index points* are selected from the text, which point to the *beginning* of the text positions which will be retrievable. For instance, it is possible to index only word beginnings to have a functionality similar to inverted indices. Those elements which are not index points are not retrievable (as in an inverted index it is not possible to retrieve the middle of a word). Figure 8.5 illustrates this.

Structure

In essence, a suffix tree is a trie data structure built over all the suffixes of the text. The pointers to the suffixes are stored at the leaf nodes. To improve space utilization, this trie is compacted into a Patricia tree. This involves compressing unary paths, i.e. paths where each node has just one child. An indication of the next character position to consider is stored at the nodes which root a compressed path. Once unary paths are not present the tree has $O(n)$ nodes instead of the worst-case $O(n^2)$ of the trie (see Figure 8.6).

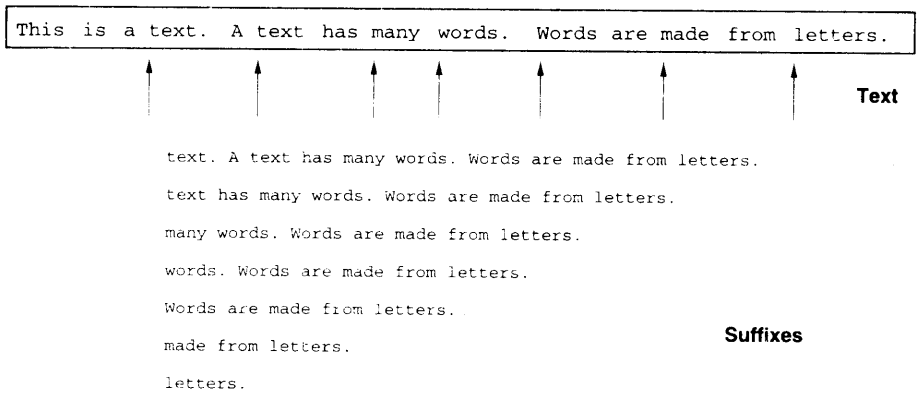


Figure 8.5 The sample text with the index points of interest marked. Below, the suffixes corresponding to those index points.

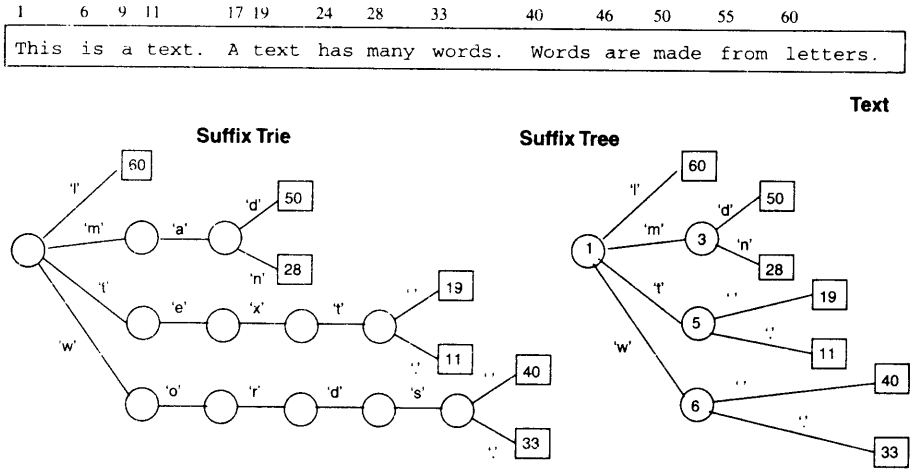


Figure 8.6 The suffix trie and suffix tree for the sample text.

The problem with this structure is its space. Depending on the implementation, each node of the trie takes 12 to 24 bytes, and therefore even if only word beginnings are indexed, a space overhead of 120% to 240% over the text size is produced.

Suffix arrays provide essentially the same functionality as suffix trees with much less space requirements. If the leaves of the suffix tree are traversed in left-to-right order (top to bottom in our figures), all the suffixes of the text are retrieved in lexicographical order. A suffix array is simply an array containing all the pointers to the text suffixes listed in lexicographical order, as shown in Figure 8.7. Since they store one pointer per indexed suffix, the space requirements

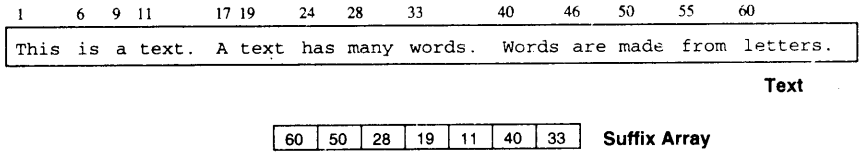


Figure 8.7 The suffix array for the sample text.

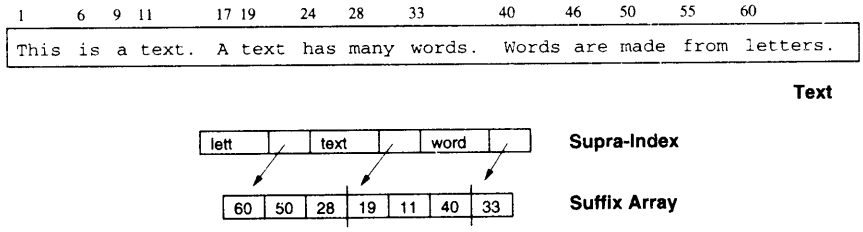


Figure 8.8 A supra-index over our suffix array. One out of three entries are sampled, keeping their first four characters. The pointers (arrows) are in fact unnecessary.

are almost the same as those for inverted indices (disregarding compression techniques), i.e. close to 40% overhead over the text size.

Suffix arrays are designed to allow binary searches done by comparing the contents of each pointer. If the suffix array is large (the usual case), this binary search can perform poorly because of the number of random disk accesses. To remedy this situation, the use of *supra-indices* over the suffix array has been proposed. The simplest supra-index is no more than a sampling of one out of b suffix array entries, where for each sample the first ℓ suffix characters are stored in the supra-index. This supra-index is then used as a first step of the search to reduce external accesses. Figure 8.8 shows an example.

This supra-index does not in fact need to take samples at fixed intervals, nor to take samples of the same length. For word-indexing suffix arrays it has been suggested that a new sample could be taken each time the first word of the suffix changes, and to store the word instead of ℓ characters. This is exactly the same as having a vocabulary of the text plus pointers to the array. In fact, the only important difference between this structure and an inverted index is that the occurrences of each word in an inverted index are sorted by text position, while in a suffix array they are sorted lexicographically by the text following the word. Figure 8.9 illustrates this relationship.

The extra space requirements of supra-indices are modest. In particular, it is clear that the space requirements of the suffix array with a vocabulary supra-index are exactly the same as for inverted indices (except for compression, as we see later).

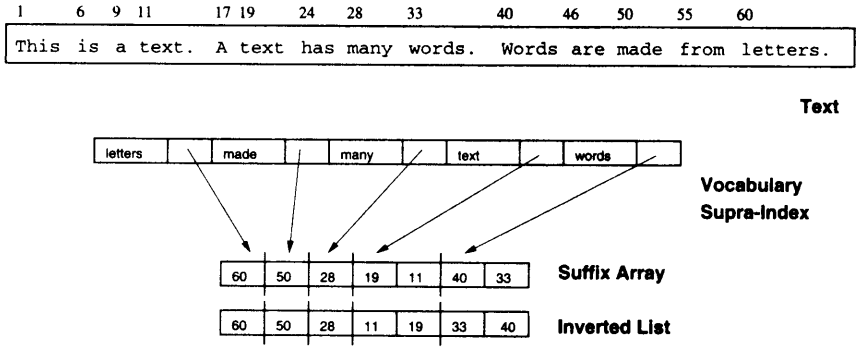


Figure 8.9 Relationship between our inverted list and suffix array with vocabulary supra-index.

Searching

If a suffix tree on the text can be afforded, many basic patterns such as words, prefixes, and phrases can be searched in $O(m)$ time by a simple trie search. However, suffix trees are not practical for large texts, as explained. Suffix arrays, on the other hand, can perform the same search operations in $O(\log n)$ time by doing a binary search instead of a trie search.

This is achieved as follows: the search pattern originates two 'limiting patterns' P_1 and P_2, so that we want any suffix S such that $P_1 \leq S < P_2$. We binary search both limiting patterns in the suffix array. Then, all the elements lying between both positions point to exactly those suffixes that start like the original pattern (i.e., to the pattern positions in the text). For instance, in our example of figure 8.9, in order to find the word 'text' we search for 'text' and 'texu', obtaining the portion of the array that contains the pointers 19 and 11.

All these queries retrieve a subtree of the suffix tree or an interval of the suffix array. The results have to be collected later, which may imply sorting them in ascending text order. This is a complication of suffix trees or arrays with respect to inverted indices.

Simple phrase searching is a good case for these indices. A simple phrase of words can be searched as if it was a simple pattern. This is because the suffix tree/array sorts with respect to the complete suffixes and not only their first word. A proximity search, on the other hand, has to be solved element-wise. The matches for each element must be collected and sorted and then they have to be intersected as for inverted files.

The binary search performed on suffix arrays, unfortunately, is done on disk, where the accesses to (random) text positions force a seek operation which spans the disk tracks containing the text. Since a random seek is $O(n)$ in size, this makes the search cost $O(n \log n)$ time. Supra-indices are used as a first step in any binary search operation to alleviate this problem. To avoid performing $O(\log n)$ random accesses to the text on disk (and to the suffix array on disk), the search starts in the supra-index, which usually fits in main memory (text samples

included). After this search is completed, the suffix array block which is between the two selected samples is brought into memory and the binary search is completed (performing random accesses to the text on disk). This reduces disk search times to close to 25% of the original time. Modified binary search techniques that sacrifice the exact partition in the middle of the array taking into account the current disk head position allow a further reduction from 40% to 60%.

Search times in a 250 Mb text in our reference machine are close to 1 second for a simple word or phrase, while the part corresponding to the accesses to the text sums up 0.6 seconds. The use of supra-indices should put the total time close to 0.3 seconds. Note that the times, although high for simple words, do not degrade for long phrases as with inverted indices.

Construction in Main Memory

A suffix tree for a text of n characters can be built in $O(n)$ time. The algorithm, however, performs poorly if the suffix tree does not fit in main memory, which is especially stringent because of the large space requirements of the suffix trees. We do not cover the linear algorithm here because it is quite complex and only of theoretical interest.

We concentrate on direct suffix array construction. Since the suffix array is no more than the set of pointers lexicographically sorted, the pointers are collected in ascending text order and then just sorted by the text they point to. Note that in order to compare two suffix array entries the corresponding text positions must be accessed. These accesses are basically random. Hence, both the suffix array and the text must be in main memory. This algorithm costs $O(n \log n)$ string comparisons.

An algorithm to build the suffix array in $O(n \log n)$ character comparisons follows. All the suffixes are bucket-sorted in $O(n)$ time according to the first letter only. Then, each bucket is bucket-sorted again, now according to their first two letters. At iteration i, the suffixes begin already sorted by their 2^{i-1} first letters and end up sorted by their first 2^i letters. As at each iteration the total cost of all the bucket sorts is $O(n)$, the total time is $O(n \log n)$, and the average is $O(n \log \log n)$ (since $O(\log n)$ comparisons are necessary on average to distinguish two suffixes of a text). This algorithm accesses the text only in the first stage (bucket sort for the first letter).

In order to sort the strings in the i-th iteration, notice that since *all* suffixes are sorted by their first 2^{i-1} letters, to sort the text positions $T_{a\ldots}$ and $T_{b\ldots}$ in the suffix array (assuming that they are in the same bucket, i.e., they share their first 2^{i-1} letters), it is enough to determine the relative order between text positions $T_{a+2^{i-1}}$ and $T_{b+2^{i-1}}$ in the current stage of the search. This can be done in constant time by storing the reverse permutation. We do not enter here into further detail.

Construction of Suffix Arrays for Large Texts

There is still the problem that large text databases will not fit in main memory. It could be possible to apply an external memory sorting algorithm. However,

each comparison involves accessing the text at random positions on the disk. This will severely degrade the performance of the sorting process.

We explain an algorithm especially designed for large texts. Split the text into blocks that can be sorted in main memory. Then, for each block, build its suffix array in main memory and merge it with the rest of the array already built for the previous text. That is:

- build the suffix array for the first block,
- build the suffix array for the second block,
- merge both suffix arrays,
- build the suffix array for the third block,
- merge the new suffix array with the previous one,
- build the suffix array for the fourth block,
- merge the new suffix array with the previous one,
- ... and so on.

The difficult part is how to merge a large suffix array (already built) with the small suffix array (just built). The merge needs to compare text positions which are spread in a large text, so the problem persists. The solution is to first determine how many elements of the large array are to be placed between each pair of elements in the small array, and later use that information to merge the arrays without accessing the text. Hence, the information that we need is how many suffixes of the large text lie between each pair of positions of the small suffix array. We compute counters that store this information.

The counters are computed without using the large suffix array. The text corresponding to the large array is sequentially read into main memory. Each suffix of that text is *searched* in the small suffix array (in main memory). Once we find the inter-element position where the suffix lies, we just increment the appropriate counter. Figure 8.10 illustrates this process.

We analyze this algorithm now. If there is $O(M)$ main memory to index, then there will be $O(n/M)$ text blocks. Each block is merged against an array of size $O(n)$, where all the $O(n)$ suffixes of the large text are binary searched in the small suffix array. This gives a total CPU complexity of $O(n^2 \log(M)/M)$.

Notice that this same algorithm can be used for index maintenance. If a new text of size n' is added to the database, it can be split into blocks as before and merged block-wise into the current suffix array. This will take $O(nn' \log(M)/M)$. To delete some text it suffices to perform an $O(n)$ pass over the array eliminating all the text positions which lie in the deleted areas.

As can be seen, the construction process is in practice more costly for suffix arrays than for inverted files. The construction of the supra-index consists of a fast final sequential pass over the suffix array.

Indexing times for 250 Mb of text are close to 0.8 Mb/min on the reference machine. This is five to ten times slower than the construction of inverted indices.

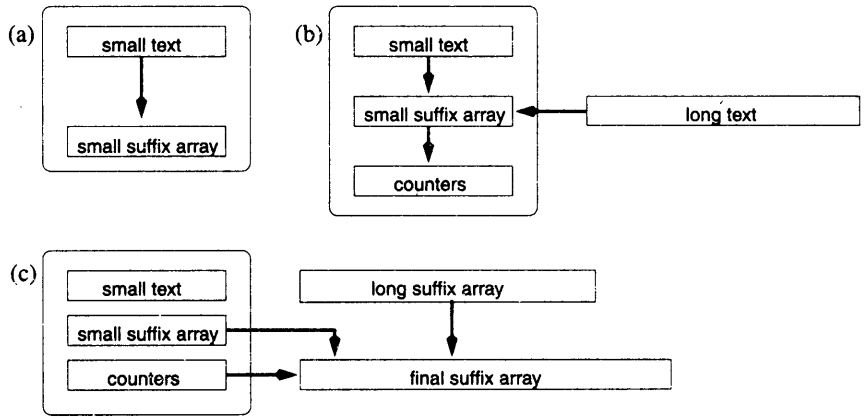


Figure 8.10 A step of the suffix array construction for large texts: (*a*) the local suffix array is built, (*b*) the counters are computed, (*c*) the suffix arrays are merged.

8.3.2 Signature Files

Signature files are word-oriented index structures based on hashing. They pose a low overhead (10% to 20% over the text size), at the cost of forcing a sequential search over the index. However, although their search complexity is linear (instead of sublinear as with the previous approaches), its constant is rather low, which makes the technique suitable for not very large texts. Nevertheless, inverted files outperform signature files for most applications.

Structure

A signature file uses a hash function (or 'signature') that maps words to bit masks of B bits. It divides the text in blocks of b words each. To each text block of size b, a bit mask of size B will be assigned. This mask is obtained by bitwise ORing the signatures of all the words in the text block. Hence, the signature file is no more than the sequence of bit masks of all blocks (plus a pointer to each block). The main idea is that if a word is present in a text block, then all the bits set in its signature are also set in the bit mask of the text block. Hence, whenever a bit is set in the mask of the query word and not in the mask of the text block, then the word is not present in the text block. Figure 8.11 shows an example.

However, it is possible that all the corresponding bits are set even though the word is not there. This is called a *false drop*. The most delicate part of the design of a signature file is to ensure that the probability of a false drop is low enough while keeping the signature file as short as possible.

The hash function is forced to deliver bit masks which have at least ℓ bits set. A good model assumes that ℓ bits are randomly set in the mask (with possible repetition). Let $\alpha = \ell/B$. Since each of the b words sets ℓ bits at

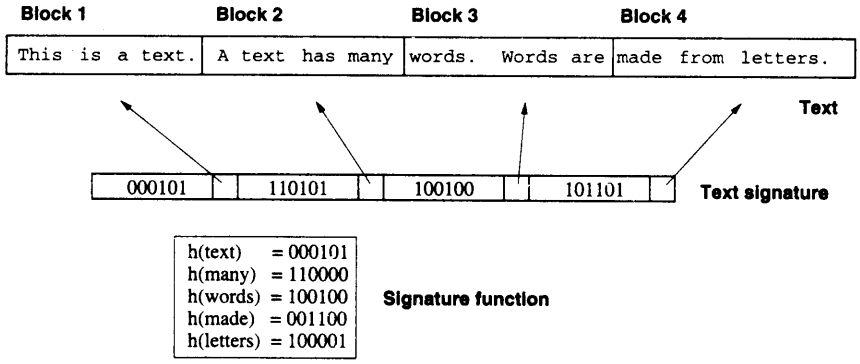


Figure 8.11 A signature file for our sample text cut into blocks.

random, the probability that a given bit of the mask is set in a word signature is $1-(1-1/B)^{b\ell} \approx 1-e^{-b\alpha}$. Hence, the probability that the ℓ random bits set in the query are also set in the mask of the text block is

$$(1-e^{-b\alpha})^{\alpha B}$$

which is minimized for $\alpha = \ln(2)/b$. The false drop probability under the optimal selection $\ell = B\ln(2)/b$ is $(1/2^{\ln(2)})^{B/b} = 1/2^{\ell}$.

Hence, a reasonable proportion B/b must be determined. The space overhead of the index is approximately $(1/80) \times (B/b)$ because B is measured in bits and b in words. Then, the false drop probability is a function of the overhead to pay. For instance, a 10% overhead implies a false drop probability close to 2%, while a 20% overhead errs with probability 0.046%. This error probability corresponds to the expected amount of sequential searching to perform while checking if a match is a false drop or not.

Searching

Searching a single word is carried out by hashing it to a bit mask W, and then comparing the bit masks B_i of all the text blocks. Whenever $(W \ \& \ B_i = W)$, where & is the bitwise AND, all the bits set in W are also set in B_i and therefore the text block *may* contain the word. Hence, for all candidate text blocks, an online traversal must be performed to verify if the word is actually there. This traversal cannot be avoided as in inverted files (except if the risk of a false drop is accepted).

No other types of patterns can be searched in this scheme. On the other hand, the scheme is more efficient to search phrases and reasonable proximity queries. This is because *all* the words must be present in a block in order for that block to hold the phrase or the proximity query. Hence, the bitwise OR of all the query masks is searched, so that *all* their bits must be present. This

reduces the probability of false drops. This is the only indexing scheme which improves in phrase searching.

Some care has to be exercised at block boundaries, however, to avoid missing a phrase which crosses a block limit. To allow searching phrases of j words or proximities of up to j words, consecutive blocks must overlap in j words.

If the blocks correspond to retrieval units, simple Boolean conjunctions involving words or phrases can also be improved by forcing all the relevant words to be in the block.

We were only able to find real performance estimates from 1992, run on a Sun 3/50 with local disk. Queries on a small 2.8 Mb database took 0.42 seconds. Extrapolating to today's technology, we find that the performance should be close to 20 Mb/sec (recall that it is linear time), and hence the example of 250 Mb of text would take 12 seconds, which is quite slow.

Construction

The construction of a signature file is rather easy. The text is simply cut in blocks, and for each block an entry of the signature file is generated. This entry is the bitwise OR of the signatures of all the words in the block.

Adding text is also easy, since it is only necessary to keep adding records to the signature file. Text deletion is carried out by deleting the appropriate bit masks.

Other storage proposals exist apart from storing all the bit masks in sequence. For instance, it is possible to make a different file for each bit of the mask, i.e. one file holding all the first bits, another file for all the second bits, etc. This reduces the disk times to search for a query, since only the files corresponding to the ℓ bits which are set in the query have to be traversed.

8.4 Boolean Queries

We now cover set manipulation algorithms. These algorithms are used when operating on sets of results, which is the case in Boolean queries. Boolean queries are described in Chapter 4, where the concept of *query syntax tree* is defined.

Once the leaves of the query syntax tree are solved (using the algorithms to find the documents containing the basic queries given), the relevant documents must be worked on by composition operators. Normally the search proceeds in three phases: the first phase determines which documents classify, the second determines the relevance of the classifying documents so as to present them appropriately to the user, and the final phase retrieves the exact positions of the matches to highlight them in those documents that the user actually wants to see.

This scheme avoids doing unnecessary work on documents which will not classify at last (first phase), or will not be read at last (second phase). However, some phases can be merged if doing the extra operations is not expensive. Some phases may not be present at all in some scenarios.

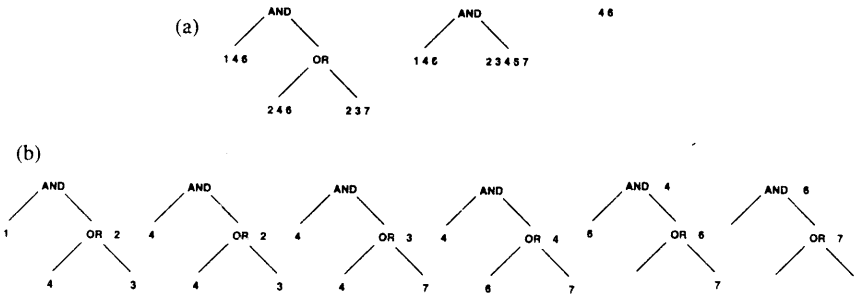


Figure 8.12 Processing the internal nodes of the query syntax tree. In (*a*) full evaluation is used. In (*b*) we show lazy evaluation in more detail.

Once the leaves of the query syntax tree find the classifying sets of documents, these sets are further operated by the internal nodes of the tree. It is possible to algebraically optimize the tree using identities such as $a\ OR\ (a\ AND\ b) = a$, for instance, or sharing common subexpressions, but we do not cover this issue here.

As all operations need to pair the same document in both their operands, it is good practice to keep the sets sorted, so that operations like intersection, union, etc. can proceed sequentially on both lists and also generate a sorted list. Other representations for sets not consisting of the list of matching documents (such as bit vectors) are also possible.

Under this scheme, it is possible to evaluate the syntax tree in *full* or *lazy* form. In the full evaluation form, both operands are first completely obtained and then the complete result is generated. In lazy evaluation, results are delivered only when required, and to obtain that result some data is recursively required to both operands.

Full evaluation allows some optimizations to be performed because the sizes of the results are known in advance (for instance, merging a very short list against a very long one can proceed by binary searching the elements of the short list in the long one). Lazy evaluation, on the other hand, allows the application to control when to do the work of obtaining new results, instead of blocking it for a long time. Hybrid schemes are possible, for example obtain all the leaves at once and then proceed in lazy form. This may be useful, for instance, to implement some optimizations or to ensure that all the accesses to the index are sequential (thus reducing disk seek times). Figure 8.12 illustrates this.

The complexity of solving these types of queries, apart from the cost of obtaining the results at the leaves, is normally linear in the total size of all the intermediate results. This is why this time may dominate the others, when there are huge intermediate results. This is more noticeable to the user when the final result is small.

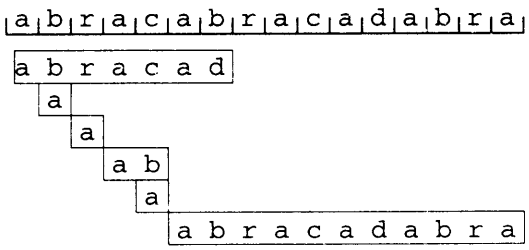


Figure 8.13 Brute-force search algorithm for the pattern 'abracadabra.' Squared areas show the comparisons performed.

8.5 Sequential Searching

We now cover the algorithms for text searching when no data structure has been built on the text. As shown, this is a basic part of some indexing techniques as well as the only option in some cases. We cover exact string matching in this section. Later we cover matching of more complex patterns. Our exposition is mainly conceptual and the implementation details are not shown (see the Bibliographic Discussion at the end of this chapter for more information).

The problem of exact string matching is: given a short pattern P of length m and a long text T of length n, find all the text positions where the pattern occurs. With minimal changes this problem subsumes many basic queries, such as word, prefix, suffix, and substring search.

This is a classical problem for which a wealth of solutions exists. We sketch the main algorithms, and leave aside a lot of the theoretical work that is not competitive in practice. For example, we do not include the Karp-Rabin algorithm, which is a nice application of hashing to string searching, but is not practical. We also briefly cover multipattern algorithms (that search many patterns at once), since a query may have many patterns and it may be more efficient to retrieve them all at once. Finally, we also mention how to do phrases and proximity searches.

We assume that the text and the pattern are sequences of characters drawn from an alphabet of size σ, whose first character is at position 1. The average-case analysis assumes random text and patterns.

8.5.1 Brute Force

The brute-force (BF) algorithm is the simplest possible one. It consists of merely trying all possible pattern positions in the text. For each such position, it verifies whether the pattern matches at that position. See Figure 8.13.

Since there are $O(n)$ text positions and each one is examined at $O(m)$ worst-case cost, the worst-case of brute-force searching is $O(mn)$. However, its average

case is $O(n)$ (since on random text a mismatch is found after $O(1)$ comparisons on average). This algorithm does not need any pattern preprocessing.

Many algorithms use a modification of this scheme. There is a *window* of length m which is slid over the text. It is *checked* whether the text in the window is equal to the pattern (if it is, the window position is reported as a match). Then, the window is *shifted* forward. The algorithms mainly differ in the way they check and shift the window.

8.5.2 Knuth-Morris-Pratt

The KMP algorithm was the first with linear worst-case behavior, although on average it is not much faster than BF. This algorithm also slides a window over the text. However, it does not try all window positions as BF does. Instead, it reuses information from previous checks.

After the window is checked, whether it matched the pattern or not, a number of pattern letters were compared to the text window, and they all matched except possibly the last one compared. Hence, when the window has to be shifted, there is a *prefix* of the pattern that matched the text. The algorithm takes advantage of this information to avoid trying window positions which can be deduced not to match.

The pattern is preprocessed in $O(m)$ time and space to build a table called *next*. The *next* table at position j says which is the longest proper prefix of $P_{1..j-1}$ which is also a suffix and the characters following prefix and suffix are different. Hence $j - next[j] + 1$ window positions can be safely skipped if the characters up to $j-1$ matched, and the j-th did not. For instance, when searching the word '`abracadabra`,' if a text window matched up to '`abracab`,' five positions can be safely skipped since $next[7] = 1$. Figure 8.14 shows an example.

The crucial observation is that this information depends only on the pattern, because if the text in the window matched up to position $j-1$, then that text is equal to the pattern.

The algorithm moves a window over the text and a pointer inside the window. Each time a character matches, the pointer is advanced (a match is reported if the pointer reaches the end of the window). Each time a character is not matched, the window is shifted forward in the text, to the position given by *next*, but the pointer position in the text does not change. Since at each text comparison the window or the pointer advance by at least one position, the algorithm performs at most $2n$ comparisons (and at least n).

The Aho-Corasick algorithm can be regarded as an extension of KMP in matching a set of patterns. The patterns are arranged in a trie-like data structure. Each trie node represents having matched a prefix of some pattern(s). The *next* function is replaced by a more general set of *failure* transitions. Those transitions go between nodes of the trie. A transition leaving from a node representing the prefix x leads to a node representing a prefix y, such that y is the longest prefix in the set of patterns which is also a proper suffix of x. Figure 8.15 illustrates this.

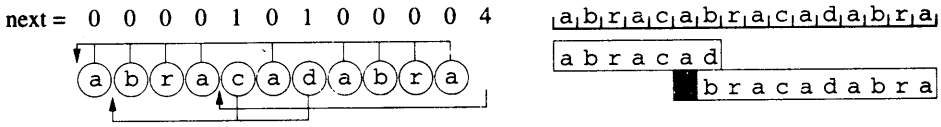


Figure 8.14 KMP algorithm searching '**abracadabra**.' On the left, an illustration of the *next* function. Notice that after matching '**abracada**' we do not try to match the last '**a**' with the first one since what follows cannot be a '**b**.' On the right, a search example. Grayed areas show the prefix information reused.

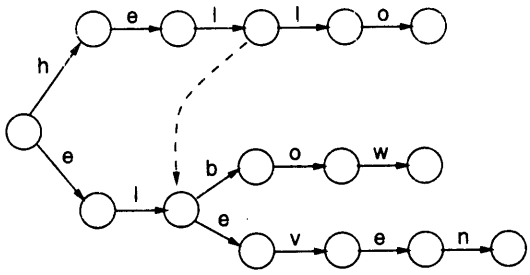


Figure 8.15 Aho-Corasick trie example for the set '**hello**,' '**elbow**' and '**eleven**' showing only one of all the failure transitions.

This trie, together with its failure transitions, is built in $O(m)$ time and space (where m is the total length of all the patterns). Its search time is $O(n)$ no matter how many patterns are searched. Much as KMP, it makes at most $2n$ inspections.

8.5.3 Boyer-Moore Family

BM algorithms are based on the fact that the check inside the window can proceed backwards. When a match or mismatch is determined, a *suffix* of the pattern has been compared and found equal to the text in the window. This can be used in a way very similar to the *next* table of KMP, i.e. compute for every pattern position j the next-to-last occurrence of $P_{j..m}$ inside P. This is called the 'match heuristic.'

This is combined with what is called the 'occurrence heuristic.' It states that the text character that produced the mismatch (if a mismatch occurred) has to be aligned with the same character in the pattern after the shift. The heuristic which gives the longest shift is selected.

For instance, assume that '**abracadabra**' is searched in a text which starts with '**abracababra**.' After matching the suffix '**abra**' the underlined text character '**b**' will cause a mismatch. The match heuristic states that since '**abra**' was matched a shift of 7 is safe. The occurrence heuristic states that since the underlined '**b**' must match the pattern, a shift of 5 is safe. Hence, the pattern is

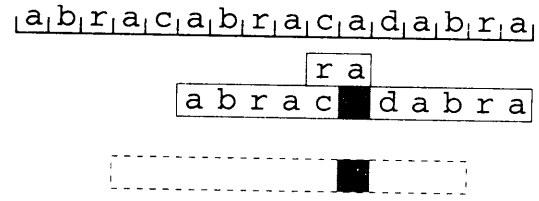


Figure 8.16 BM algorithm searching '**abracadabra**.' Squared areas show the comparisons performed. Grayed areas have already been compared (but the algorithm compares them again). The dashed box shows the match heuristic, which was not chosen.

shifted by 7. See Figure 8.16.

The preprocessing time and space of this algorithm is $O(m+\sigma)$. Its search time is $O(n \log(m)/m)$ on average, which is 'sublinear' in the sense that not all characters are inspected. On the other hand, its worst case is $O(mn)$ (unlike KMP, the old suffix information is not kept to avoid further comparisons).

Further simplifications of the BM algorithm lead to some of the fastest algorithms on average. The Simplified BM algorithm uses only the occurrence heuristic. This obtains almost the same shifts in practice. The BM-Horspool (BMH) algorithm does the same, but it notices that it is not important any more that the check proceeds backwards, and uses the occurrence heuristic on the *last* character of the window instead of the one that caused the mismatch. This gives longer shifts on average. Finally, the BM-Sunday (BMS) algorithm modifies BMH by using the character *following* the last one, which improves the shift especially on short patterns.

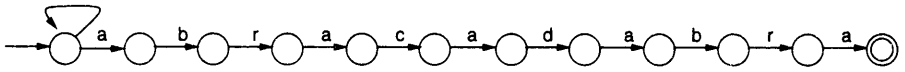
The Commentz-Walter algorithm is an extension of BM to multipattern search. It builds a trie on the reversed patterns, and instead of a backward window check, it enters into the trie with the window characters read backwards. A shift function is computed by a natural extension of BM. In general this algorithm improves over Aho-Corasick for not too many patterns.

8.5.4 Shift-Or

Shift-Or is based on *bit-parallelism*. This technique involves taking advantage of the intrinsic parallelism of the bit operations inside a computer word (of w bits). By cleverly using this fact, the number of operations that an algorithm performs can be cut by a factor of at most w. Since in current architectures w is 32 or 64, the speedup is very significant in practice.

The Shift-Or algorithm uses bit-parallelism to simulate the operation of a non-deterministic automaton that searches the pattern in the text (see Figure 8.17). As this automaton is simulated in time $O(mn)$, the Shift-Or algorithm achieves $O(mn/w)$ worst-case time (optimal speedup).

The algorithm first builds a table B which for each character stores a bit mask $b_m...b_1$. The mask in $B[c]$ has the i-th bit set to zero if and only if



$B[a]$ =	1	0	0	1	0	1	0	1	0	0	1
$B[b]$ =	0	1	0	0	0	0	0	0	1	0	0
$B[r]$ =	0	0	1	0	0	0	0	0	0	1	0
$B[c]$ =	0	0	0	0	1	0	0	0	0	0	0
$B[d]$ =	0	0	0	0	0	0	1	0	0	0	0
$B[*]$ =	0	0	0	0	0	0	0	0	0	0	0

Figure 8.17 Non-deterministic automaton that searches '`abracadabra`,' and the associated B table. The initial self-loop matches any character. Each table column corresponds to an edge of the automaton.

$p_i = c$ (see Figure 8.17). The state of the search is kept in a machine word $D = d_m ... d_1$, where d_i is zero whenever the state numbered i in Figure 8.17 is active. Therefore, a match is reported whenever d_m is zero. In the following, we use '|' to denote the bitwise OR and '&' to denote the bitwise AND.

D is set to all ones originally, and for each new text character T_j, D is updated using the formula

$$D' \leftarrow (D << 1) \mid B[T_j]$$

(where '<<' means shifting all the bits in D one position to the left and setting the rightmost bit to zero). It is not hard to relate the formula to the movement that occurs in the non-deterministic automaton for each new text character.

For patterns longer than the computer word (i.e., $m > w$), the algorithm uses $\lceil m/w \rceil$ computer words for the simulation (not all them are active all the time). The algorithm is $O(n)$ on average and the preprocessing is $O(m+\sigma)$ time and $O(\sigma)$ space.

It is easy to extend Shift-Or to handle classes of characters by manipulating the B table and keeping the search algorithm unchanged.

This paradigm also can search a large set of extended patterns, as well as multiple patterns (where the complexity is the same as before if we consider that m is the total length of all the patterns).

8.5.5 Suffix Automaton

The Backward DAWG matching (BDM) algorithm is based on a suffix automaton. A *suffix automaton* on a pattern P is an automaton that recognizes all the suffixes of P. The non-deterministic version of this automaton has a very regular structure and is shown in Figure 8.18.

The BDM algorithm converts this automaton to deterministic. The size and construction time of this automaton is $O(m)$. This is basically the preprocessing effort of the algorithm. Each path from the initial node to any internal

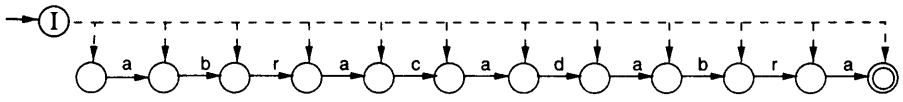


Figure 8.18 A non-deterministic suffix automaton. Dashed lines represent ε-transitions (i.e., they occur without consuming any input). I is the initial state of the automaton.

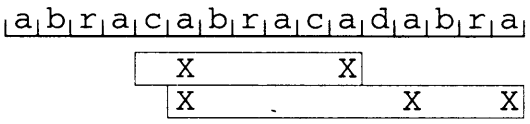


Figure 8.19 The BDM algorithm for the pattern '`abracadabra.`' The rectangles represent elements compared to the text window. The `X`s show the positions where a pattern prefix was recognized.

node represents a substring of the pattern. The final nodes represent pattern suffixes.

To search a pattern P, the suffix automaton of P^r (the reversed pattern) is built. The algorithm searches backwards inside the text window for a substring of the pattern P using the suffix automaton. Each time a terminal state is reached before hitting the beginning of the window, the position inside the window is remembered. This corresponds to finding a *prefix* of the pattern equal to a suffix of the window (since the reverse suffixes of P^r are the prefixes of P). The last prefix recognized backwards is the *longest* prefix of P in the window. A match is found if the complete window is read, while the check is abandoned when there is no transition to follow in the automaton. In either case, the window is shifted to align with the longest prefix recognized. See Figure 8.19.

This algorithm is $O(mn)$ time in the worst case and $O(n \log(m)/m)$ on average. There exists also a multipattern version of this algorithm called MultiBDM, which is the fastest for many patterns or very long patterns.

BDM rarely beats the best BM algorithms. However, a recent bit-parallel implementation called BNDM improves over BM in a wide range of cases. This algorithm simulates the non-deterministic suffix automaton using bit-parallelism. The algorithm supports some extended patterns and other applications mentioned in Shift-Or, while keeping more efficient than Shift-Or.

8.5.6 Practical Comparison

Figure 8.20 shows a practical comparison between string matching algorithms run on our reference machine. The values are correct within 5% of accuracy with a 95% confidence interval. We tested English text from the TREC collection, DNA (corresponding to 'h.influenzae') and random text uniformly generated over 64 letters. The patterns were randomly selected from the text except for random

text, where they were randomly generated. We tested over 10 Mb of text and measured CPU time. We tested short patterns on English and random text and long patterns on DNA, which are the typical cases.

We first analyze the case of random text, where except for very short patterns the clear winners are BNDM (the bit-parallel implementation of BDM) and the BMS (Sunday) algorithm. The more classical Boyer-Moore and BDM algorithms are also very close. Among the algorithms that do not improve with the pattern length, Shift-Or is the fastest, and KMP is much slower than the naive algorithm.

The picture is similar for English text, except that we have included the Agrep software in this comparison, which worked well only on English text. Agrep turns out to be much faster than others. This is not because of using a special algorithm (it uses a BM-family algorithm) but because the code is carefully optimized. This shows the importance of careful coding as well as using good algorithms, especially in text searching where a few operations per text character are performed.

Longer patterns are shown for a DNA text. BNDM is the fastest for moderate patterns, but since it does not improve with the length after $m > w$, the classical BDM finally obtains better times. They are much better than the Boyer-Moore family because the alphabet is small and the suffix automaton technique makes better use of the information on the pattern.

We have not shown the case of extended patterns, that is, where flexibility plays a role. For this case, BNDM is normally the fastest when it can be applied (e.g., it supports classes of characters but not wild cards), otherwise Shift-Or is the best option. Shift-Or is also the best option when the text must be accessed sequentially and it is not possible to skip characters.

8.5.7 Phrases and Proximity

If a sequence of words is searched to appear in the text exactly as in the pattern (i.e., with the same separators) the problem is similar to that of exact search of a single pattern, by just forgetting the fact that there are many words. If any separator between words is to be allowed, it is possible to arrange it using an extended pattern or regular expression search.

The best way to search a phrase element-wise is to search for the element which is less frequent or can be searched faster (both criteria normally match). For instance, longer patterns are better than shorter ones; allowing fewer errors is better than allowing more errors. Once such an element is found, the neighboring words are checked to see if a complete match is found.

A similar algorithm can be used to search a proximity query.

8.6 Pattern Matching

We present in this section the main techniques to deal with complex patterns. We divide it into two main groups: searching allowing errors and searching for extended patterns.

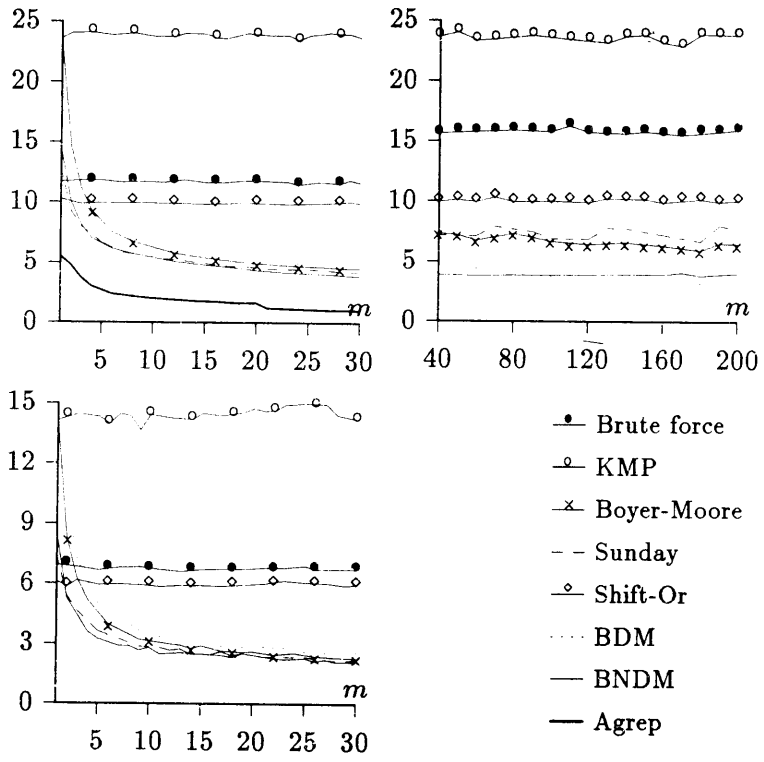


Figure 8.20 Practical comparison among algorithms. The upper left plot is for short patterns on English text. The upper right one is for long patterns on DNA. The lower plot is for short patterns on random text (on 64 letters). Times are in tenths of seconds per megabyte.

8.6.1 String Matching Allowing Errors

This problem (called 'approximate string matching') can be stated as follows: given a short pattern P of length m, a long text T of length n, and a maximum allowed number of errors k, find all the text positions where the pattern occurs with at most k errors. This statement corresponds to the Levenshtein distance. With minimal modifications it is adapted to searching whole words matching the pattern with k errors.

This problem is newer than exact string matching, although there are already a number of solutions. We sketch the main approaches.

Dynamic Programming

The classical solution to approximate string matching is based on dynamic programming. A matrix $C[0..m, 0..n]$ is filled column by column, where $C[i, j]$

represents the minimum number of errors needed to match $P_{1..i}$ to a suffix of $T_{1..j}$. This is computed as follows

$$\begin{aligned} C[0,j] &= 0 \\ C[i,0] &= i \\ C[i,j] &= \text{if } (P_i = T_j) \text{ then } C[i-1,j-1] \\ &\quad \text{else } 1 + \min(C[i-1,j], C[i,j-1], C[i-1,j-1]) \end{aligned}$$

where a match is reported at text positions j such that $C[m,j] \leq k$ (the final positions of the occurrences are reported).

Therefore, the algorithm is $O(mn)$ time. Since only the previous column of the matrix is needed, it can be implemented in $O(m)$ space. Its preprocessing time is $O(m)$. Figure 8.21 illustrates this algorithm.

In recent years several algorithms have been presented that achieve $O(kn)$ time in the worst case or even less in the average case, by taking advantage of the properties of the dynamic programming matrix (e.g., values in neighbor cells differ at most by one).

Automaton

It is interesting to note that the problem can be reduced to a non-deterministic finite automaton (NFA). Consider the NFA for $k = 2$ errors shown in Figure 8.22. Each row denotes the number of errors seen. The first one 0, the second one 1, and so on. Every column represents matching the pattern up to a given position. At each iteration, a new text character is read and the automaton changes its states. Horizontal arrows represent matching a character, vertical arrows represent insertions into the pattern, solid diagonal arrows represent replacements, and dashed diagonal arrows represent deletions in the pattern (they are ε-transitions). The automaton accepts a text position as the end of a match

		s	u	r	g	e	r	y
	0	0	0	0	0	0	0	0
s	1	0	1	1	1	1	1	1
u	2	1	0	1	2	2	2	2
r	3	2	1	0	1	2	2	3
v	4	3	2	1	1	2	3	3
e	5	4	3	2	2	1	2	3
y	6	5	4	3	3	**2**	**2**	**2**

Figure 8.21 The dynamic programming algorithm search '**survey**' in the text '**surgery**' with two errors. Bold entries indicate matching positions.

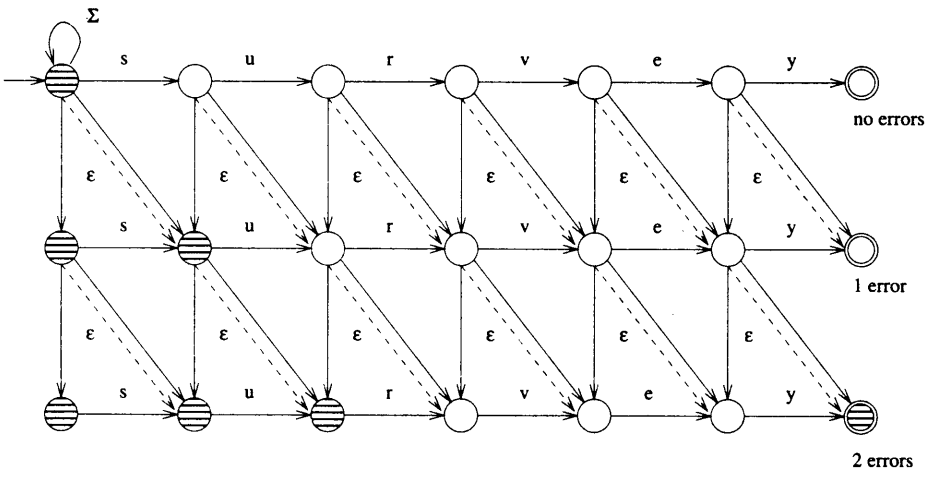


Figure 8.22 An NFA for approximate string matching of the pattern '**survey**' with two errors. The shaded states are those active after reading the text '**surgery**'. Unlabelled transitions match any character.

with k errors whenever the $(k+1)$-th rightmost state is active.

It is not hard to see that once a state in the automaton is active, all the states of the same column and higher rows are active too. Moreover, at a given text character, if we collect the smallest active rows at each column, we obtain the current column of the dynamic programming algorithm. Figure 8.22 illustrates this (compare the figure with Figure 8.21).

One solution is to make this automaton deterministic (DFA). Although the search phase is $O(n)$, the DFA can be huge. An alternative solution is based on bit-parallelism and is explained next.

Bit-Parallelism

Bit-parallelism has been used to parallelize the computation of the dynamic programming matrix (achieving average complexity $O(kn/w)$) and to parallelize the computation of the NFA (without converting it to deterministic), obtaining $O(kmn/w)$ time in the worst case. Such algorithms achieve $O(n)$ search time for short patterns and are currently the fastest ones in many cases, running at 6 to 10 Mb per second on our reference machine.

Filtering

Finally, other approaches first filter the text, reducing the area where dynamic programming needs to be used. These algorithms achieve 'sublinear' expected time in many cases for low error ratios (i.e., not all text characters are inspected,

$O(kn \log_\sigma(m)/m)$ is a typical figure), although the filtration is not effective for more errors. Filtration is based on the fact that some portions of the pattern must appear with no errors even in an approximate occurrence.

The fastest algorithm for low error levels is based on filtering: if the pattern is split into $k+1$ pieces, any approximate occurrence must contain at least one of the pieces with no errors, since k errors cannot alter all the $k+1$ pieces. Hence, the search begins with a multipattern exact search for the pieces and it later verifies the areas that may contain a match (using another algorithm).

8.6.2 Regular Expressions and Extended Patterns

General regular expressions are searched by building an automaton which finds all their occurrences in a text. This process first builds a non-deterministic finite automaton of size $O(m)$, where m is the length of the regular expression. The classical solution is to convert this automaton to deterministic form. A deterministic automaton can search any regular expression in $O(n)$ time. However, its size and construction time can be exponential in m, i.e. $O(m2^m)$. See Figure 8.23. Excluding preprocessing, this algorithm runs at 6 Mb/sec in the reference machine.

Recently the use of bit-parallelism has been proposed to avoid the construction of the deterministic automaton. The non-deterministic automaton is simulated instead. One bit per automaton state is used to represent whether the state is active or not. Due to the algorithm used to build the non-deterministic automaton, all the transitions move forward except for ε-transitions. The idea is that for each text character two steps are carried out. The first one moves forward, and the second one takes care of all the ε-transitions. A function E from bit masks to bit masks is precomputed so that all the corresponding bits are moved according to the ε-transitions. Since this function is very large (i.e., 2^m entries) its domain is split in many functions from 8- or 16-bit submasks to m-bit masks. This is possible because $E(B_1...B_j) = E(B_1)|...|E(B_j)$, where B_i

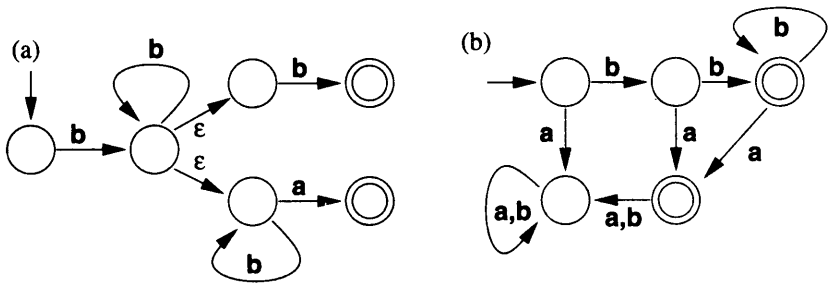


Figure 8.23 The non-deterministic (a) and deterministic (b) automata for the regular expression `b b* (b | b*a)`.

are the submasks. Hence, the scheme performs $\lceil m/8 \rceil$ or $\lceil m/16 \rceil$ operations per text character and needs $\lceil m/8 \rceil 2^8 \lceil m/w \rceil$ or $\lceil m/16 \rceil 2^{16} \lceil m/w \rceil$ machine words of memory.

Extended patterns can be rephrased as regular expressions and solved as before. However, in many cases it is more efficient to give them a specialized solution, as we saw for the extensions of exact searching (bit-parallel algorithms). Moreover, extended patterns can be combined with approximate search for maximum flexibility. In general, the bit-parallel approach is the best equipped to deal with extended patterns.

Real times for regular expressions and extended pattern searching using this technique are between 2–8 Mb/sec.

8.6.3 Pattern Matching Using Indices

We end this section by explaining how the indexing techniques we presented for simple searching of words can in fact be extended to search for more complex patterns.

Inverted Files

As inverted files are word-oriented, other types of queries such as suffix or substring queries, searching allowing errors and regular expressions, are solved by a *sequential* (i.e., online) search over the vocabulary. This is not too bad since the size of the vocabulary is small with respect to the text size.

After either type of search, a list of vocabulary words that matched the query is obtained. All their lists of occurrences are now *merged* to retrieve a list of documents and (if required) the matching text positions. If block addressing is used and the positions are required or the blocks do not coincide with the retrieval unit, the search must be completed with a sequential search over the blocks.

Notice that an inverted index is word-oriented. Because of that it is not surprising that it is not able to efficiently find approximate matches or regular expressions that span many words. This is a restriction of this scheme. Variations that are not subject to this restriction have been proposed for languages which do not have a clear concept of word, like Finnish. They collect text *samples* or *n-grams*, which are fixed-length strings picked at regular text intervals. Searching is in general more powerful but more expensive.

In a full-inverted index, search times for simple words allowing errors on 250 Mb of text took our reference machine from 0.6 to 0.85 seconds, while very complex expressions on extended patterns took from 0.8 to 3 seconds. As a comparison, the same collection cut in blocks of 1 Mb size takes more than 8 seconds for an approximate search with one error and more than 20 for two errors.

Suffix Trees and Suffix Arrays

If the suffix tree indexes all text positions it can search for words, prefixes, suffixes and substrings with the same search algorithm and cost described for word search. However, indexing all positions makes the index 10 to 20 times the text size for suffix trees.

Range queries are easily solved too, by just searching both extremes in the trie and then collecting all the leaves which lie in the middle. In this case the cost is the height of the tree, which is $O(\log n)$ on average (excluding the tasks of collecting and sorting the leaves).

Regular expressions can be searched in the suffix tree. The algorithm simply simulates sequential searching of the regular expression. It begins at the root, since any possible match starts there too. For each child of the current node labeled by the character c, it assumes that the next text character is c and recursively enters into that subtree. This is done for each of the children of the current node. The search stops only when the automaton has no transition to follow. It has been shown that for random text only $O(n^{\alpha}\text{polylog}(n))$ nodes are traversed (for $0 < \alpha < 1$ dependent on the regular expression). Hence, the search time is sublinear for regular expressions *without* the restriction that they must occur inside a word. Extended patterns can be searched in the same way by taking them as regular expressions.

Unrestricted approximate string matching is also possible using the same idea. We present a simplified version here. Imagine that the search is online and traverse the tree recursively as before. Since all suffixes start at the root, any match starts at the root too, and therefore do not allow the match to start later. The search will automatically stop at depth $m + k$ at most (since at that point more than k errors have occurred). This implies constant search time if n is large enough (albeit exponential on m and k). Other problems such as approximate search of extended patterns can be solved in the same way, using the appropriate online algorithm.

Suffix trees are able to perform other complex searches that we have not considered in our query language (see Chapter 4). These are specialized operations which are useful in specific areas. Some examples are: find the longest substring in the text that appears more than once, find the most common substring of a fixed size, etc.

If a suffix array indexes all text positions, *any* algorithm that works on suffix trees at $C(n)$ cost will work on suffix arrays at $O(C(n) \log n)$ cost. This is because the operations performed on the suffix tree consist of descending to a child node, which is done in $O(1)$ time. This operation can be simulated in the suffix array in $O(\log n)$ time by binary searching the new boundaries (each suffix tree node corresponds to a string, which can be mapped to the suffix array interval holding all suffixes starting with that string). Some patterns can be searched directly in the suffix array in $O(\log n)$ total search time without simulating the suffix tree. These are: word, prefix, suffix and subword search, as well as range search.

However, again, indexing all text positions normally makes the suffix array

size four times or more the text size. A different alternative for suffix arrays is to index only word beginnings and to use a vocabulary supra-index, using the same search algorithms used for the inverted lists.

8.7 Structural Queries

The algorithms to search on structured text (see Chapter 4) are largely dependent on each model. We extract their common features in this section.

A first concern about this problem is how to store the structural information. Some implementations build an ad hoc index to store the structure. This is potentially more efficient and independent of any consideration about the text. However, it requires extra development and maintenance effort.

Other techniques assume that the structure is marked in the text using 'tags' (i.e., strings that identify the structural elements). This is the case with HTML text but not the case with C code where the marks are implicit and are inherent to C. The technique relies on the same index to query content (such as inverted files), using it to index and search those tags as if they were words. In many cases this is as efficient as an ad hoc index, and its integration into an existing text database is simpler. Moreover, it is possible to define the structure dynamically, since the appropriate tags can be selected at search time. For that goal, inverted files are better since they naturally deliver the results in text order, which makes the structure information easier to obtain. On the other hand, some queries such as direct ancestry are hard to answer without an ad hoc index.

Once the content and structural elements have been found by using some index, a set of answers is generated. The models allow further operations to be applied on those answers, such as 'select all areas in the left-hand argument which contain an area of the right-hand argument.' This is in general solved in a way very similar to the set manipulation techniques already explained in section 8.4. However, the operations tend to be more complex, and it is not always possible to find an evaluation algorithm which has linear time with respect to the size of the intermediate results.

It is worth mentioning that some models use completely different algorithms, such as exhaustive search techniques for tree pattern matching. Those problems are NP-complete in many cases.

8.8 Compression

In this section we discuss the issues of searching compressed text directly and of searching compressed indices. Compression is important when available storage is a limiting factor, as is the case of indexing the Web.

Searching and compression were traditionally regarded as exclusive operations. Texts which were not to be searched could be compressed, and to search

a compressed text it had to be decompressed first. In recent years, very efficient compression techniques have appeared that allow searching directly in the compressed text. Moreover, the search performance is *improved*, since the CPU times are similar but the disk times are largely reduced. This leads to a win-win situation.

Discussion on how common text and lists of numbers can be compressed has been covered in Chapter 7.

8.8.1 Sequential Searching

A few approaches to directly searching compressed text exist. One of the most successful techniques in practice relies on Huffman coding taking words as symbols. That is, consider each different text word as a symbol, count their frequencies, and generate a Huffman codefor the words. Then, compress the text by replacing each word with its code. To improve compression/decompression efficiency, the Huffman code uses an alphabet of bytes instead of bits. This scheme compresses faster and better than known commercial systems, even those based on Ziv-Lempel coding.

Since Huffman coding needs to store the codes of each symbol, this scheme has to store the whole vocabulary of the text, i.e. the list of all different text words. This is fully exploited to efficiently search complex queries. Although according to Heaps' law the vocabulary (i.e., the alphabet) grows as $O(n^\beta)$ for $0 < \beta < 1$, the generalized Zipf's law shows that the distribution is skewed enough so that the entropy remains constant (i.e., the compression ratio will not degrade as the text grows). Those laws are explained in Chapter 6.

Any single-word or pattern query is first searched in the vocabulary. Some queries can be binary searched, while others such as approximate searching or regular expression searching must traverse sequentially all the vocabulary. This vocabulary is rather small compared to the text size, thanks to Heaps' law. Notice that this process is exactly the same as the vocabulary searching performed by inverted indices, either for simple or complex pattern matching.

Once that search is complete, the list of different words that match the query is obtained. The Huffman codes of all those words are collected and they are searched in the compressed text. One alternative is to traverse byte-wise the compressed text and traverse the Huffman decoding tree in synchronization, so that each time that a leaf is reached, it is checked whether the leaf (i.e., word) was marked as 'matching' the query or not. This is illustrated in Figure 8.24. Boyer-Moore filtering can be used to speed up the search.

Solving phrases is a little more difficult. Each element is searched in the vocabulary. For each word of the vocabulary we define a bit mask. We set the i-th bit in the mask of all words which match with the i-th element of the phrase query. This is used together with the Shift-Or algorithm. The text is traversed byte-wise, and only when a leaf is reached, does the Shift-Or algorithm consider that a new text symbol has been read, whose bit mask is that of the leaf (see Figure 8.24). This algorithm is surprisingly simple and efficient.

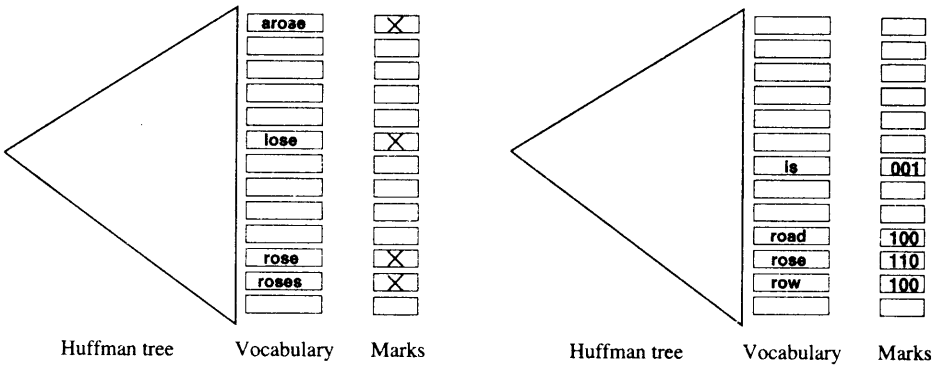


Figure 8.24 On the left, searching for the simple pattern '`rose`' allowing one error. On the right, searching for the phrase '`ro* rose is`,' where '`ro*`' represents a prefix search.

This scheme is especially fast when it comes to solving a complex query (regular expression, extended pattern, approximate search, etc.) that would be slow with a normal algorithm. This is because the complex search is done only in the small vocabulary, after which the algorithm is largely insensitive to the complexity of the originating query. Its CPU times for a simple pattern are slightly higher than those of Agrep (briefly described in section 8.5.6). However, if the I/O times are considered, compressed searching is faster than all the online algorithms. For complex queries, this scheme is unbeaten by far.

On the reference machine, the CPU times are 14 Mb/sec for any query, while for simple queries this improves to 18 Mb/sec if the speedup technique is used. Agrep, on the other hand, runs at 15 Mb/sec on simple searches and at 1–4 Mb/sec for complex ones. Moreover, I/O times are reduced to one third on the compressed text.

8.8.2 Compressed Indices

Inverted Files

Inverted files are quite amenable to compression. This is because the lists of occurrences are in increasing order of text position. Therefore, an obvious choice is to represent the differences between the previous position and the current one. These differences can be represented using less space by using techniques that favor small numbers (see Chapter 7). Notice that, the longer the lists, the smaller the differences. Reductions in 90% for block-addressing indices with blocks of 1 Kb size have been reported.

It is important to notice that compression does not necessarily degrade time performance. Most of the time spent in answering a query is in the disk transfer. Keeping the index compressed allows the transference of less data, and it may be worth the CPU work of decompressing. Notice also that the lists of

occurrences are normally traversed in a sequential manner, which is not affected by a differential compression. Query times on compressed or decompressed indices are reported to be roughly similar.

The text can also be compressed independently of the index. The text will be decompressed only to display it, or to traverse it in case of block addressing. Notice in particular that the online search technique described for compressed text in section 8.8.1 uses a vocabulary. It is possible to integrate both techniques (compression and indexing) such that they share the same vocabulary for both tasks and they do not decompress the text to index or to search.

Suffix Trees and Suffix Arrays

Some efforts to compress suffix trees have been pursued. Important reductions of the space requirements have been obtained at the cost of more expensive searching. However, the reduced space requirements happen to be similar to those of uncompressed suffix arrays, which impose much smaller performance penalties.

Suffix arrays are very hard to compress further. This is because they represent an almost perfectly random permutation of the pointers to the text.

However, the subject of building suffix arrays on compressed text has been pursued. Apart from reduced space requirements (the index plus the compressed text take less space than the uncompressed text), the main advantage is that both index construction and querying almost double their performance. Construction is faster because more compressed text fits in the same memory space, and therefore fewer text blocks are needed. Searching is faster because a large part of the search time is spent in disk seek operations over the text area to compare suffixes. If the text is smaller, the seeks reduce proportionally.

A compression technique very similar to that shown in section 8.8.1 is used. However, the Huffman code on words is replaced by a Hu-Tucker coding. The Hu-Tucker code respects the lexicographical relationships between the words, and therefore direct binary search over the compressed text is possible (this is necessary at construction and search time). This code is suboptimal by a very small percentage (2–3% in practice, with an analytical upper bound of 5%).

Indexing times for 250 Mb of text on the reference machine are close to 1.6 Mb/min if compression is used, while query times are reduced to 0.5 seconds in total and 0.3 seconds for the text alone. Supra-indices should reduce the total search time to 0.15 seconds.

Signature Files

There are many alternative ways to compress signature files. All of them are based on the fact that only a few bits are set in the whole file. It is then possible

to use efficient methods to code the bits which are not set, for instance run-length encoding. Different considerations arise if the file is stored as a sequence of bit masks or with one file per bit of the mask. They allow us to reduce space and hence disk times, or alternatively to increase B (so as to reduce the false drop probability) keeping the same space overhead. Compression ratios near 70% are reported.

8.9 Trends and Research Issues

In this chapter we covered extensively the current techniques of dealing with text retrieval. We first covered indices and then online searching. We then reviewed set manipulation, complex pattern matching and finally considered compression techniques. Figure 8.25 summarizes the tradeoff between the space needed for the index and the time to search one single word.

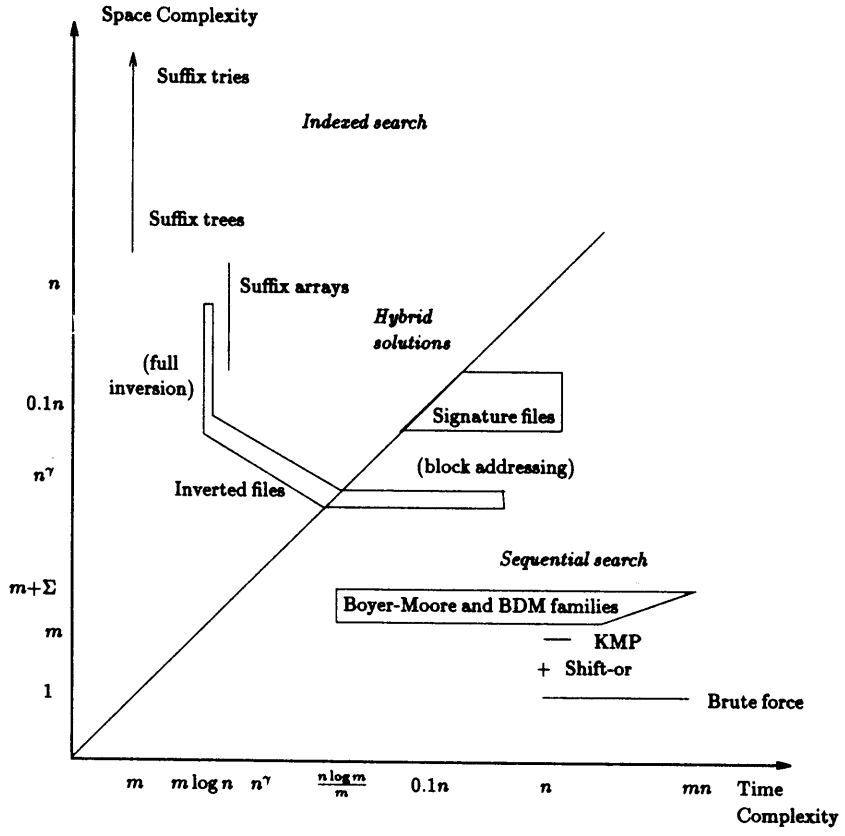


Figure 8.25 Tradeoff of index space versus word searching time.