Storage systems built using NAND flash provide the same block-oriented interface as disk storage. Compared to magnetic disks, flash memory can provide much faster random access: a page of data can be retrieved in around 1 or 2 microseconds from flash, whereas a random access on disk would take 5 to 10 milliseconds. Flash memory has a lower transfer rate than magnetic disks, with 20 megabytes per second being common. Some more recent flash memories have increased transfer rates of 100 to 200 megabytes per second. However, solid state drives use multiple flash memory chips in parallel, to increase transfer rates to over 200 megabytes per second, which is faster than transfer rates of most disks.

Writes to flash memory are a little more complicated. A write to a page of flash memory typically takes a few microseconds. However, once written, a page of flash memory cannot be directly overwritten. Instead, it has to be erased and rewritten subsequently. The erase operation can be performed on a number of pages, called an **erase block**, at once, and takes about 1 to 2 milliseconds. The size of an erase block (often referred to as just "block" in flash literature) is usually significantly larger than the block size of the storage system. Further, there is a limit to how many times a flash page can be erased, typically around 100,000 to 1,000,000 times. Once this limit is reached, errors in storing bits are likely to occur.

Flash memory systems limit the impact of both the slow erase speed and the update limits by mapping logical page numbers to physical page numbers. When a logical page is updated, it can be remapped to any already erased physical page, and the original location can be erased later. Each physical page has a small area of memory where its logical address is stored; if the logical address is remapped to a different physical page, the original physical page is marked as deleted. Thus by scanning the physical pages, we can find where each logical page resides. The logical-to-physical page mapping is replicated in an in-memory **translation table** for quick access.

Blocks containing multiple deleted pages are periodically erased, taking care to first copy nondeleted pages in those blocks to a different block (the translation table is updated for these nondeleted pages). Since each physical page can be updated only a fixed number of times, physical pages that have been erased many times are assigned "cold data," that is, data that are rarely updated, while pages that have not been erased many times are used to store "hot data," that is, data that are updated frequently. This principle of evenly distributing erase operations across physical blocks is called **wear leveling**, and is usually performed transparently by flash-memory controllers. If a physical page is damaged due to an excessive number of updates, it can be removed from usage, without affecting the flash memory as a whole.

All the above actions are carried out by a layer of software called the **flash translation layer**; above this layer, flash storage looks identical to magnetic disk storage, providing the same page/sector-oriented interface, except that flash storage is much faster. File systems and database storage structures can thus see an identical logical view of the underlying storage structure, regardless of whether it is flash or magnetic storage.

Hybrid disk drives are hard-disk systems that combine magnetic storage with a smaller amount of flash memory, which is used as a cache for frequently accessed data. Frequently accessed data that are rarely updated are ideal for caching in flash memory.

10.3 RAID

The data-storage requirements of some applications (in particular Web, database, and multimedia applications) have been growing so fast that a large number of disks are needed to store their data, even though disk-drive capacities have been growing very fast.

Having a large number of disks in a system presents opportunities for improving the rate at which data can be read or written, if the disks are operated in parallel. Several independent reads or writes can also be performed in parallel. Furthermore, this setup offers the potential for improving the reliability of data storage, because redundant information can be stored on multiple disks. Thus, failure of one disk does not lead to loss of data.

A variety of disk-organization techniques, collectively called **redundant arrays of independent disks** (**RAID)**, have been proposed to achieve improved performance and reliability.

In the past, system designers viewed storage systems composed of several small, cheap disks as a cost-effective alternative to using large, expensive disks; the cost per megabyte of the smaller disks was less than that of larger disks. In fact, the I in RAID, which now stands for *independent*, originally stood for *inexpensive*. Today, however, all disks are physically small, and larger-capacity disks actually have a lower cost per megabyte. RAID systems are used for their higher reliability and higher performance rate, rather than for economic reasons. Another key justification for RAID use is easier management and operations.

10.3.1 Improvement of Reliability via Redundancy

Let us first consider reliability. The chance that at least one disk out of a set of N disks will fail is much higher than the chance that a specific single disk will fail. Suppose that the mean time to failure of a disk is 100,000 hours, or slightly over 11 years. Then, the mean time to failure of some disk in an array of 100 disks will be 100,000/100 = 1000 hours, or around 42 days, which is not long at all! If we store only one copy of the data, then each disk failure will result in loss of a significant amount of data (as discussed in Section 10.2.1). Such a high frequency of data loss is unacceptable.

The solution to the problem of reliability is to introduce **redundancy**; that is, we store extra information that is not needed normally, but that can be used in the event of failure of a disk to rebuild the lost information. Thus, even if a disk fails, data are not lost, so the effective mean time to failure is increased, provided that we count only failures that lead to loss of data or to nonavailability of data.

The simplest (but most expensive) approach to introducing redundancy is to duplicate every disk. This technique is called **mirroring** (or, sometimes, *shadowing*). A logical disk then consists of two physical disks, and every write is carried out on both disks. If one of the disks fails, the data can be read from the other. Data will be lost only if the second disk fails before the first failed disk is repaired.

The mean time to failure (where failure is the loss of data) of a mirrored disk depends on the mean time to failure of the individual disks, as well as on the **mean time to repair**, which is the time it takes (on an average) to replace a failed disk and to restore the data on it. Suppose that the failures of the two disks are *independent*; that is, there is no connection between the failure of one disk and the failure of the other. Then, if the mean time to failure of a single disk is 100,000 hours, and the mean time to repair is 10 hours, the **mean time to data loss** of a mirrored disk system is $100,000^2/(2 * 10) = 500 * 10^6$ hours, or 57,000 years! (We do not go into the derivations here; references in the bibliographical notes provide the details.)

You should be aware that the assumption of independence of disk failures is not valid. Power failures, and natural disasters such as earthquakes, fires, and floods, may result in damage to both disks at the same time. As disks age, the probability of failure increases, increasing the chance that a second disk will fail while the first is being repaired. In spite of all these considerations, however, mirrored-disk systems offer much higher reliability than do single-disk systems. Mirrored-disk systems with mean time to data loss of about 500,000 to 1,000,000 hours, or 55 to 110 years, are available today.

Power failures are a particular source of concern, since they occur far more frequently than do natural disasters. Power failures are not a concern if there is no data transfer to disk in progress when they occur. However, even with mirroring of disks, if writes are in progress to the same block in both disks, and power fails before both blocks are fully written, the two blocks can be in an inconsistent state. The solution to this problem is to write one copy first, then the next, so that one of the two copies is always consistent. Some extra actions are required when we restart after a power failure, to recover from incomplete writes. This matter is examined in Practice Exercise 10.3.

10.3.2 Improvement in Performance via Parallelism

Now let us consider the benefit of parallel access to multiple disks. With disk mirroring, the rate at which read requests can be handled is doubled, since read requests can be sent to either disk (as long as both disks in a pair are functional, as is almost always the case). The transfer rate of each read is the same as in a single-disk system, but the number of reads per unit time has doubled.

With multiple disks, we can improve the transfer rate as well (or instead) by **striping data** across multiple disks. In its simplest form, data striping consists of splitting the bits of each byte across multiple disks; such striping is called **bit-level striping**. For example, if we have an array of eight disks, we write bit i of each byte to disk i. The array of eight disks can be treated as a single disk with sectors that are eight times the normal size, and, more important, that has eight times the transfer rate. In such an organization, every disk participates in every access (read or write), so the number of accesses that can be processed per second is about the same as on a single disk, but each access can read eight times as many data in the same time as on a single disk. Bit-level striping can be generalized to a number of disks that either is a multiple of 8 or a factor of 8. For example, if we use an array of four disks, bits i and $4 + i$ of each byte go to disk i.

Block-level striping stripes blocks across multiple disks. It treats the array of disks as a single large disk, and it gives blocks logical numbers; we assume the block numbers start from 0. With an array of n disks, block-level striping assigns logical block i of the disk array to disk $(i \bmod n) + 1$; it uses the $\lfloor i/n \rfloor$th physical

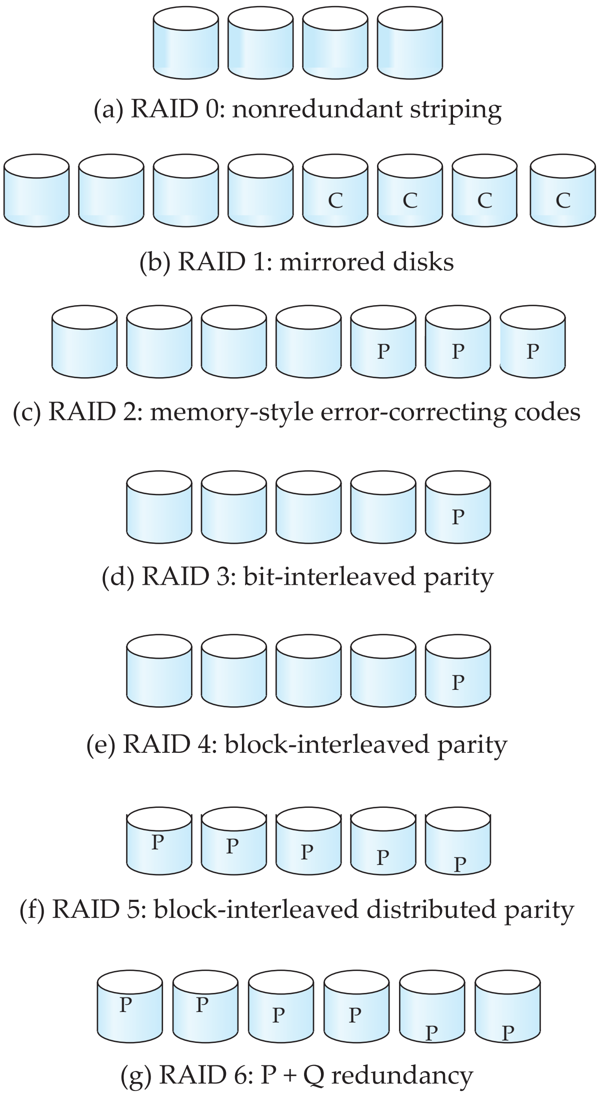

(a) RAID 0: nonredundant striping
C
C
C
C
(b) RAID 1: mirrored disks
P
P
P
(c) RAID 2: memory-style error-correcting codes
P
(d) RAID 3: bit-interleaved parity
P
(e) RAID 4: block-interleaved parity
P
P
P
P
P
(f) RAID 5: block-interleaved distributed parity
P
P
P
P
P
P
(g) RAID 6: P + Q redundancy

Figure 10.3 RAID levels.

block of the disk to store logical block i. For example, with 8 disks, logical block 0 is stored in physical block 0 of disk 1, while logical block 11 is stored in physical block 1 of disk 4. When reading a large file, block-level striping fetches n blocks at a time in parallel from the n disks, giving a high data-transfer rate for large reads. When a single block is read, the data-transfer rate is the same as on one disk, but the remaining $n - 1$ disks are free to perform other actions.

Block-level striping is the most commonly used form of data striping. Other levels of striping, such as bytes of a sector or sectors of a block, also are possible.

In summary, there are two main goals of parallelism in a disk system:

1. Load-balance multiple small accesses (block accesses), so that the throughput of such accesses increases.
2. Parallelize large accesses so that the response time of large accesses is reduced.

10.3.3 RAID Levels

Mirroring provides high reliability, but it is expensive. Striping provides high data-transfer rates, but does not improve reliability. Various alternative schemes aim to provide redundancy at lower cost by combining disk striping with "parity" bits (which we describe next). These schemes have different cost–performance trade-offs. The schemes are classified into **RAID levels**, as in Figure 10.3. (In the figure, P indicates error-correcting bits, and C indicates a second copy of the data.) For all levels, the figure depicts four disks' worth of data, and the extra disks depicted are used to store redundant information for failure recovery.

- **RAID level 0** refers to disk arrays with striping at the level of blocks, but without any redundancy (such as mirroring or parity bits). Figure 10.3a shows an array of size 4.
- **RAID level 1** refers to disk mirroring with block striping. Figure 10.3b shows a mirrored organization that holds four disks' worth of data.
  Note that some vendors use the term **RAID level 1+0** or **RAID level 10** to refer to mirroring with striping, and use the term RAID level 1 to refer to mirroring without striping. Mirroring without striping can also be used with arrays of disks, to give the appearance of a single large, reliable disk: if each disk has M blocks, logical blocks 0 to $M - 1$ are stored on disk 0, M to $2M - 1$ on disk 1(the second disk), and so on, and each disk is mirrored.[2]
- **RAID level 2**, known as memory-style error-correcting-code (ECC) organization, employs parity bits. Memory systems have long used parity bits for

[2]Note that some vendors use the term RAID 0+1 to refer to a version of RAID that uses striping to create a RAID 0 array, and mirrors the array onto another array, with the difference from RAID 1 being that if a disk fails, the RAID 0 array containing the disk becomes unusable. The mirrored array can still be used, so there is no loss of data. This arrangement is inferior to RAID 1 when a disk has failed, since the other disks in the RAID 0 array can continue to be used in RAID 1, but remain idle in RAID 0+1.

error detection and correction. Each byte in a memory system may have a parity bit associated with it that records whether the numbers of bits in the byte that are set to 1 is even (parity = 0) or odd (parity = 1). If one of the bits in the byte gets damaged (either a 1 becomes a 0, or a 0 becomes a 1), the parity of the byte changes and thus will not match the stored parity. Similarly, if the stored parity bit gets damaged, it will not match the computed parity. Thus, all 1-bit errors will be detected by the memory system. Error-correcting schemes store 2 or more extra bits, and can reconstruct the data if a single bit gets damaged.

The idea of error-correcting codes can be used directly in disk arrays by striping bytes across disks. For example, the first bit of each byte could be stored in disk 0, the second bit in disk 1, and so on until the eighth bit is stored in disk 7, and the error-correction bits are stored in further disks.

Figure 10.3c shows the level 2 scheme. The disks labeled P store the error-correction bits. If one of the disks fails, the remaining bits of the byte and the associated error-correction bits can be read from other disks, and can be used to reconstruct the damaged data. Figure 10.3c shows an array of size 4; note RAID level 2 requires only three disks' overhead for four disks of data, unlike RAID level 1, which required four disks' overhead.

- **RAID level 3**, bit-interleaved parity organization, improves on level 2 by exploiting the fact that disk controllers, unlike memory systems, can detect whether a sector has been read correctly, so a single parity bit can be used for error correction, as well as for detection. The idea is as follows: If one of the sectors gets damaged, the system knows exactly which sector it is, and, for each bit in the sector, the system can figure out whether it is a 1 or a 0 by computing the parity of the corresponding bits from sectors in the other disks. If the parity of the remaining bits is equal to the stored parity, the missing bit is 0; otherwise, it is 1.

  RAID level 3 is as good as level 2, but is less expensive in the number of extra disks (it has only a one-disk overhead), so level 2 is not used in practice. Figure 10.3d shows the level 3 scheme.

  RAID level 3 has two benefits over level 1. It needs only one parity disk for several regular disks, whereas level 1 needs one mirror disk for every disk, and thus level 3 reduces the storage overhead. Since reads and writes of a byte are spread out over multiple disks, with N-way striping of data, the transfer rate for reading or writing a single block is N times faster than a RAID level 1 organization using N-way striping. On the other hand, RAID level 3 supports a lower number of I/O operations per second, since every disk has to participate in every I/O request.

- **RAID level 4**, block-interleaved parity organization, uses block-level striping, like RAID 0, and in addition keeps a parity block on a separate disk for corresponding blocks from N other disks. This scheme is shown pictorially in Figure 10.3e. If one of the disks fails, the parity block can be used with the corresponding blocks from the other disks to restore the blocks of the failed disk.

A block read accesses only one disk, allowing other requests to be processed by the other disks. Thus, the data-transfer rate for each access is slower, but multiple read accesses can proceed in parallel, leading to a higher overall I/O rate. The transfer rates for large reads is high, since all the disks can be read in parallel; large writes also have high transfer rates, since the data and parity can be written in parallel.

Small independent writes, on the other hand, cannot be performed in parallel. A write of a block has to access the disk on which the block is stored, as well as the parity disk, since the parity block has to be updated. Moreover, both the old value of the parity block and the old value of the block being written have to be read for the new parity to be computed. Thus, a single write requires four disk accesses: two to read the two old blocks, and two to write the two blocks.

- **RAID level 5**, block-interleaved distributed parity, improves on level 4 by partitioning data and parity among all $N + 1$ disks, instead of storing data in N disks and parity in one disk. In level 5, all disks can participate in satisfying read requests, unlike RAID level 4, where the parity disk cannot participate, so level 5 increases the total number of requests that can be met in a given amount of time. For each set of N logical blocks, one of the disks stores the parity, and the other N disks store the blocks.

  Figure 10.3f shows the setup. The P's are distributed across all the disks. For example, with an array of 5 disks, the parity block, labeled Pk, for logical blocks $4k$, $4k + 1$, $4k + 2$, $4k + 3$ is stored in disk k mod 5; the corresponding blocks of the other four disks store the 4 data blocks $4k$ to $4k+3$. The following table indicates how the first 20 blocks, numbered 0 to 19, and their parity blocks are laid out. The pattern shown gets repeated on further blocks.

P0	0	1	2	3
4	P1	5	6	7
8	9	P2	10	11
12	13	14	P3	15
16	17	18	19	P4

  Note that a parity block cannot store parity for blocks in the same disk, since then a disk failure would result in loss of data as well as of parity, and hence would not be recoverable. Level 5 subsumes level 4, since it offers better read –write performance at the same cost, so level 4 is not used in practice.

- **RAID level 6**, the P + Q redundancy scheme, is much like RAID level 5, but stores extra redundant information to guard against multiple disk failures. Instead of using parity, level 6 uses error-correcting codes such as the Reed–Solomon codes (see the bibliographical notes). In the scheme in Figure 10.3g, 2 bits of redundant data are stored for every 4 bits of data—unlike 1 parity bit in level 5—and the system can tolerate two disk failures.

Finally, we note that several variations have been proposed to the basic RAID schemes described here, and different vendors use different terminologies for the variants.

10.3.4 Choice of RAID Level

The factors to be taken into account in choosing a RAID level are:

- Monetary cost of extra disk-storage requirements.
- Performance requirements in terms of number of I/O operations.
- Performance when a disk has failed.
- Performance during rebuild (that is, while the data in a failed disk are being rebuilt on a new disk).

The time to rebuild the data of a failed disk can be significant, and it varies with the RAID level that is used. Rebuilding is easiest for RAID level 1, since data can be copied from another disk; for the other levels, we need to access all the other disks in the array to rebuild data of a failed disk. The **rebuild performance** of a RAID system may be an important factor if continuous availability of data is required, as it is in high-performance database systems. Furthermore, since rebuild time can form a significant part of the repair time, rebuild performance also influences the mean time to data loss.

RAID level 0 is used in high-performance applications where data safety is not critical. Since RAID levels 2 and 4 are subsumed by RAID levels 3 and 5, the choice of RAID levels is restricted to the remaining levels. Bit striping (level 3) is inferior to block striping (level 5), since block striping gives as good data-transfer rates for large transfers, while using fewer disks for small transfers. For small transfers, the disk access time dominates anyway, so the benefit of parallel reads diminishes. In fact, level 3 may perform worse than level 5 for a small transfer, since the transfer completes only when corresponding sectors on all disks have been fetched; the average latency for the disk array thus becomes very close to the worst-case latency for a single disk, negating the benefits of higher transfer rates. Level 6 is not supported currently by many RAID implementations, but it offers better reliability than level 5 and can be used in applications where data safety is very important.

The choice between RAID level 1 and level 5 is harder to make. RAID level 1 is popular for applications such as storage of log files in a database system, since it offers the best write performance. RAID level 5 has a lower storage overhead than level 1, but has a higher time overhead for writes. For applications where data are read frequently, and written rarely, level 5 is the preferred choice.

Disk-storage capacities have been growing at a rate of over 50 percent per year for many years, and the cost per byte has been falling at the same rate. As a result, for many existing database applications with moderate storage requirements, the monetary cost of the extra disk storage needed for mirroring has become relatively small (the extra monetary cost, however, remains a significant issue for storageintensive applications such as video data storage). Access speeds have improved at a much slower rate (around a factor of 3 over 10 years), while the number of I/O operations required per second has increased tremendously, particularly for Web application servers.

RAID level 5, which increases the number of I/O operations needed to write a single logical block, pays a significant time penalty in terms of write performance. RAID level 1 is therefore the RAID level of choice for many applications with moderate storage requirements and high I/O requirements.

RAID system designers have to make several other decisions as well. For example, how many disks should there be in an array? How many bits should be protected by each parity bit? If there are more disks in an array, data-transfer rates are higher, but the system will be more expensive. If there are more bits protected by a parity bit, the space overhead due to parity bits is lower, but there is an increased chance that a second disk will fail before the first failed disk is repaired, and that will result in data loss.

10.3.5 Hardware Issues

Another issue in the choice of RAID implementations is at the level of hardware. RAID can be implemented with no change at the hardware level, using only software modification. Such RAID implementations are called **software RAID**. However, there are significant benefits to be had by building special-purpose hardware to support RAID, which we outline below; systems with special hardware support are called **hardware RAID** systems.

Hardware RAID implementations can use nonvolatile RAM to record writes before they are performed. In case of power failure, when the system comes back up, it retrieves information about any incomplete writes from nonvolatile RAM and then completes the writes. Without such hardware support, extra work needs to be done to detect blocks that may have been partially written before power failure (see Practice Exercise 10.3).

Even if all writes are completed properly, there is a small chance of a sector in a disk becoming unreadable at some point, even though it was successfully written earlier. Reasons for loss of data on individual sectors could range from manufacturing defects, to data corruption on a track when an adjacent track is written repeatedly. Such loss of data that were successfully written earlier is sometimes referred to as a *latent failure*, or as *bit rot*. When such a failure happens, if it is detected early the data can be recovered from the remaining disks in the RAID organization. However, if such a failure remains undetected, a single disk failure could lead to data loss if a sector in one of the other disks has a latent failure.

To minimize the chance of such data loss, good RAID controllers perform **scrubbing**; that is, during periods when disks are idle, every sector of every disk is read, and if any sector is found to be unreadable, the data are recovered from the remaining disks in the RAID organization, and the sector is written back. (If the physical sector is damaged, the disk controller would remap the logical sector address to a different physical sector on disk.)

Some hardware RAID implementations permit **hot swapping**; that is, faulty disks can be removed and replaced by new ones without turning power off. Hot swapping reduces the mean time to repair, since replacement of a disk does not have to wait until a time when the system can be shut down. In fact many critical systems today run on a 24 × 7 schedule; that is, they run 24 hours a day, 7 days a week, providing no time for shutting down and replacing a failed disk. Further, many RAID implementations assign a spare disk for each array (or for a set of disk arrays). If a disk fails, the spare disk is immediately used as a replacement. As a result, the mean time to repair is reduced greatly, minimizing the chance of any data loss. The failed disk can be replaced at leisure.

The power supply, or the disk controller, or even the system interconnection in a RAID system could become a single point of failure that could stop functioning of the RAID system. To avoid this possibility, good RAID implementations have multiple redundant power supplies (with battery backups so they continue to function even if power fails). Such RAID systems have multiple disk interfaces, and multiple interconnections to connect the RAID system to the computer system (or to a network of computer systems). Thus, failure of any single component will not stop the functioning of the RAID system.

10.3.6 Other RAID Applications

The concepts of RAID have been generalized to other storage devices, including arrays of tapes, and even to the broadcast of data over wireless systems. When applied to arrays of tapes, the RAID structures are able to recover data even if one of the tapes in an array of tapes is damaged. When applied to broadcast of data, a block of data is split into short units and is broadcast along with a parity unit; if one of the units is not received for any reason, it can be reconstructed from the other units.

10.4 Tertiary Storage

In a large database system, some of the data may have to reside on tertiary storage. The two most common tertiary storage media are optical disks and magnetic tapes.

10.4.1 Optical Disks

Compact disks have been a popular medium for distributing software, multimedia data such as audio and images, and other electronically published information. They have a storage capacity of 640 to 700 megabytes, and they are cheap to mass-produce. Digital video disks (DVDs) have now replaced compact disks in applications that require larger amounts of data. Disks in the DVD-5 format can store 4.7 gigabytes of data (in one recording layer), while disks in the DVD-9 format can store 8.5 gigabytes of data (in two recording layers). Recording on both sides of a disk yields even larger capacities; DVD-10 and DVD-18 formats, which are the two-sided versions of DVD-5 and DVD-9, can store 9.4 gigabytes milliseconds; once positioned, however, tape drives can write data at densities and speeds approaching those of disk drives. Capacities vary, depending on the length and width of the tape and on the density at which the head can read and write. The market is currently fragmented among a wide variety of tape formats. Currently available tape capacities range from a few gigabytes with the **Digital Audio Tape** (DAT) format, 10 to 40 gigabytes with the **Digital Linear Tape** (DLT) format, 100 gigabytes and higher with the **Ultrium** format, to 330 gigabytes with **Ampex helical scan** tape formats. Data-transfer rates are of the order of a few to tens of megabytes per second.

Tape devices are quite reliable, and good tape drive systems perform a read of the just-written data to ensure that it has been recorded correctly. Tapes, however, have limits on the number of times that they can be read or written reliably.

Tape jukeboxes, like optical disk jukeboxes, hold large numbers of tapes, with a few drives onto which the tapes can be mounted; they are used for storing large volumes of data, ranging up to many petabytes (10^{15} bytes), with access times on the order of seconds to a few minutes. Applications that need such enormous data storage include imaging systems that gather data from remote-sensing satellites, and large video libraries for television broadcasters.

Some tape formats (such as the Accelis format) support faster seek times (of the order of tens of seconds), and are intended for applications that retrieve information from jukeboxes. Most other tape formats provide larger capacities, at the cost of slower access; such formats are ideal for data backup, where fast seeks are not important.

Tape drives have been unable to keep up with the enormous improvements in disk drive capacity and corresponding reduction in storage cost. While the cost of tapes is low, the cost of tape drives and tape libraries is significantly higher than the cost of a disk drive: a tape library capable of storing a few terabytes can costs tens of thousands of dollars. Backing up data to disk drives has become a cost-effective alternative to tape backup for a number of applications.

10.5 File Organization

A database is mapped into a number of different files that are maintained by the underlying operating system. These files reside permanently on disks. A **file** is organized logically as a sequence of records. These records are mapped onto disk blocks. Files are provided as a basic construct in operating systems, so we shall assume the existence of an underlying *file system*. We need to consider ways of representing logical data models in terms of files.

Each file is also logically partitioned into fixed-length storage units called **blocks**, which are the units of both storage allocation and data transfer. Most databases use block sizes of 4 to 8 kilobytes by default, but many databases allow the block size to be specified when a database instance is created. Larger block sizes can be useful in some database applications.

A block may contain several records; the exact set of records that a block contains is determined by the form of physical data organization being used. We shall assume that *no record is larger than a block*. This assumption is realistic for most data-processing applications, such as our university example. There are certainly several kinds of large data items, such as images, that can be significantly larger than a block. We briefly discuss how to handle such large data items later, in Section 10.5.2, by storing large data items separately, and storing a pointer to the data item in the record.

In addition, we shall require that *each record is entirely contained in a single block*; that is, no record is contained partly in one block, and partly in another. This restriction simplifies and speeds up access to data items.

In a relational database, tuples of distinct relations are generally of different sizes. One approach to mapping the database to files is to use several files, and to store records of only one fixed length in any given file. An alternative is to structure our files so that we can accommodate multiple lengths for records; however, files of fixed-length records are easier to implement than are files of variable-length records. Many of the techniques used for the former can be applied to the variable-length case. Thus, we begin by considering a file of fixed-length records, and consider storage of variable-length records later.

10.5.1 Fixed-Length Records

As an example, let us consider a file of *instructor* records for our university database. Each record of this file is defined (in pseudocode) as:

```
type instructor = record
                      ID varchar (5);
                      name varchar(20);
                      dept_name varchar (20);
                      salary numeric (8,2);
                  end
```

Assume that each character occupies 1 byte and that numeric (8,2) occupies 8 bytes. Suppose that instead of allocating a variable amount of bytes for the attributes *ID*, *name*, and *dept_name*, we allocate the maximum number of bytes that each attribute can hold. Then, the *instructor* record is 53 bytes long. A simple approach is to use the first 53 bytes for the first record, the next 53 bytes for the second record, and so on (Figure 10.4). However, there are two problems with this simple approach:

1. Unless the block size happens to be a multiple of 53 (which is unlikely), some records will cross block boundaries. That is, part of the record will be stored in one block and part in another. It would thus require two block accesses to read or write such a record.
2. It is difficult to delete a record from this structure. The space occupied by the record to be deleted must be filled with some other record of the file, or we must have a way of marking deleted records so that they can be ignored.

record 0	10101	Srinivasan	Comp. Sci.	65000
record 1	12121	Wu	Finance	90000
record 2	15151	Mozart	Music	40000
record 3	22222	Einstein	Physics	95000
record 4	32343	El Said	History	60000
record 5	33456	Gold	Physics	87000
record 6	45565	Katz	Comp. Sci.	75000
record 7	58583	Califieri	History	62000
record 8	76543	Singh	Finance	80000
record 9	76766	Crick	Biology	72000
record 10	83821	Brandt	Comp. Sci.	92000
record 11	98345	Kim	Elec. Eng.	80000

Figure 10.4 File containing *instructor* records.

To avoid the first problem, we allocate only as many records to a block as would fit entirely in the block (this number can be computed easily by dividing the block size by the record size, and discarding the fractional part). Any remaining bytes of each block are left unused.

When a record is deleted, we could move the record that came after it into the space formerly occupied by the deleted record, and so on, until every record following the deleted record has been moved ahead (Figure 10.5). Such an approach requires moving a large number of records. It might be easier simply to move the final record of the file into the space occupied by the deleted record (Figure 10.6).

It is undesirable to move records to occupy the space freed by a deleted record, since doing so requires additional block accesses. Since insertions tend to be more frequent than deletions, it is acceptable to leave open the space occupied by the

record 0	10101	Srinivasan	Comp. Sci.	65000
record 1	12121	Wu	Finance	90000
record 2	15151	Mozart	Music	40000
record 4	32343	El Said	History	60000
record 5	33456	Gold	Physics	87000
record 6	45565	Katz	Comp. Sci.	75000
record 7	58583	Califieri	History	62000
record 8	76543	Singh	Finance	80000
record 9	76766	Crick	Biology	72000
record 10	83821	Brandt	Comp. Sci.	92000
record 11	98345	Kim	Elec. Eng.	80000

Figure 10.5 File of Figure 10.4, with record 3 deleted and all records moved.

record 0	10101	Srinivasan	Comp. Sci.	65000
record 1	12121	Wu	Finance	90000
record 2	15151	Mozart	Music	40000
record 11	98345	Kim	Elec. Eng.	80000
record 4	32343	El Said	History	60000
record 5	33456	Gold	Physics	87000
record 6	45565	Katz	Comp. Sci.	75000
record 7	58583	Califieri	History	62000
record 8	76543	Singh	Finance	80000
record 9	76766	Crick	Biology	72000
record 10	83821	Brandt	Comp. Sci.	92000

Figure 10.6 File of Figure 10.4, with record 3 deleted and final record moved.

deleted record, and to wait for a subsequent insertion before reusing the space. A simple marker on a deleted record is not sufficient, since it is hard to find this available space when an insertion is being done. Thus, we need to introduce an additional structure.

At the beginning of the file, we allocate a certain number of bytes as a **file header**. The header will contain a variety of information about the file. For now, all we need to store there is the address of the first record whose contents are deleted. We use this first record to store the address of the second available record, and so on. Intuitively, we can think of these stored addresses as *pointers*, since they point to the location of a record. The deleted records thus form a linked list, which is often referred to as a **free list**. Figure 10.7 shows the file of Figure 10.4, with the free list, after records 1, 4, and 6 have been deleted.

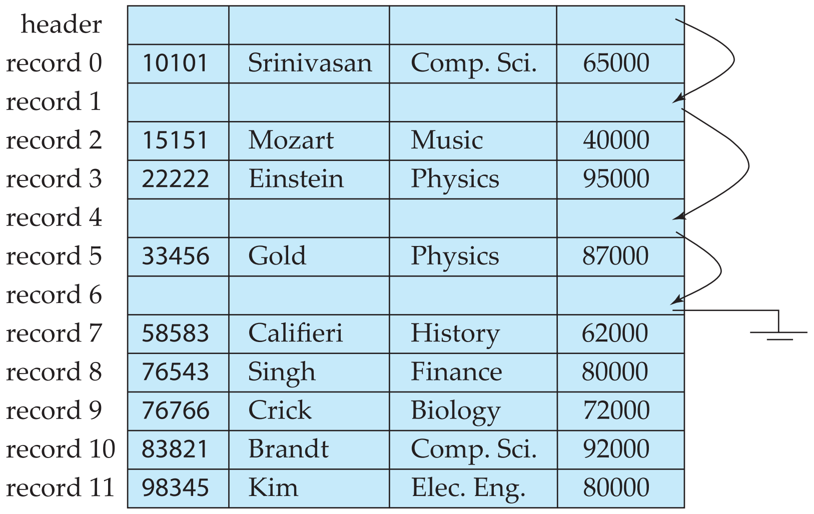
On insertion of a new record, we use the record pointed to by the header. We change the header pointer to point to the next available record. If no space is available, we add the new record to the end of the file.

Insertion and deletion for files of fixed-length records are simple to implement, because the space made available by a deleted record is exactly the space needed to insert a record. If we allow records of variable length in a file, this match no longer holds. An inserted record may not fit in the space left free by a deleted record, or it may fill only part of that space.

10.5.2 Variable-Length Records

Variable-length records arise in database systems in several ways:

- Storage of multiple record types in a file.
- Record types that allow variable lengths for one or more fields.
- Record types that allow repeating fields, such as arrays or multisets.



header				
record 0	10101	Srinivasan	Comp. Sci.	65000
record 1				
record 2	15151	Mozart	Music	40000
record 3	22222	Einstein	Physics	95000
record 4				
record 5	33456	Gold	Physics	87000
record 6				
record 7	58583	Califieri	History	62000
record 8	76543	Singh	Finance	80000
record 9	76766	Crick	Biology	72000
record 10	83821	Brandt	Comp. Sci.	92000
record 11	98345	Kim	Elec. Eng.	80000

Figure 10.7 File of Figure 10.4, with free list after deletion of records 1, 4, and 6.

Different techniques for implementing variable-length records exist. Two different problems must be solved by any such technique:

- How to represent a single record in such a way that individual attributes can be extracted easily.
- How to store variable-length records within a block, such that records in a block can be extracted easily.

The representation of a record with variable-length attributes typically has two parts: an initial part with fixed length attributes, followed by data for variable-length attributes. Fixed-length attributes, such as numeric values, dates, or fixed-length character strings are allocated as many bytes as required to store their value. Variable-length attributes, such as varchar types, are represented in the initial part of the record by a pair (*offset*, *length*), where *offset* denotes where the data for that attribute begins within the record, and *length* is the length in bytes of the variable-sized attribute. The values for these attributes are stored consecutively, after the initial fixed-length part of the record. Thus, the initial part of the record stores a fixed size of information about each attribute, whether it is fixed-length or variable-length.

An example of such a record representation is shown in Figure 10.8. The figure shows an *instructor* record, whose first three attributes *ID*, *name*, and *dept_name* are variable-length strings, and whose fourth attribute *salary* is a fixed-sized number. We assume that the offset and length values are stored in two bytes each, for a total of 4 bytes per attribute. The *salary* attribute is assumed to be stored in 8 bytes, and each string takes as many bytes as it has characters.

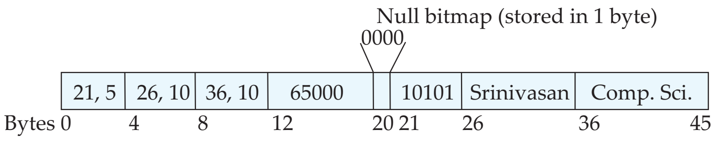


Figure 10.8 Representation of variable-length record.

The figure also illustrates the use of a **null bitmap**, which indicates which attributes of the record have a null value. In this particular record, if the salary were null, the fourth bit of the bitmap would be set to 1, and the *salary* value stored in bytes 12 through 19 would be ignored. Since the record has four attributes, the null bitmap for this record fits in 1 byte, although more bytes may be required with more attributes. In some representations, the null bitmap is stored at the beginning of the record, and for attributes that are null, no data (value, or offset/length) are stored at all. Such a representation would save some storage space, at the cost of extra work to extract attributes of the record. This representation is particularly useful for certain applications where records have a large number of fields, most of which are null.

We next address the problem of storing variable-length records in a block. The **slotted-page structure** is commonly used for organizing records within a block, and is shown in Figure 10.9.[3] There is a header at the beginning of each block, containing the following information:

1. The number of record entries in the header.
2. The end of free space in the block.
3. An array whose entries contain the location and size of each record.

The actual records are allocated *contiguously* in the block, starting from the end of the block. The free space in the block is contiguous, between the final entry in the header array, and the first record. If a record is inserted, space is allocated for it at the end of free space, and an entry containing its size and location is added to the header.

If a record is deleted, the space that it occupies is freed, and its entry is set to *deleted* (its size is set to −1, for example). Further, the records in the block before the deleted record are moved, so that the free space created by the deletion gets occupied, and all free space is again between the final entry in the header array and the first record. The end-of-free-space pointer in the header is appropriately updated as well. Records can be grown or shrunk by similar techniques, as long as there is space in the block. The cost of moving the records is not too high, since the size of a block is limited: typical values are around 4 to 8 kilobytes.

The slotted-page structure requires that there be no pointers that point directly to records. Instead, pointers must point to the entry in the header that contains the

[3]Here, "page" is synonymous with "block."

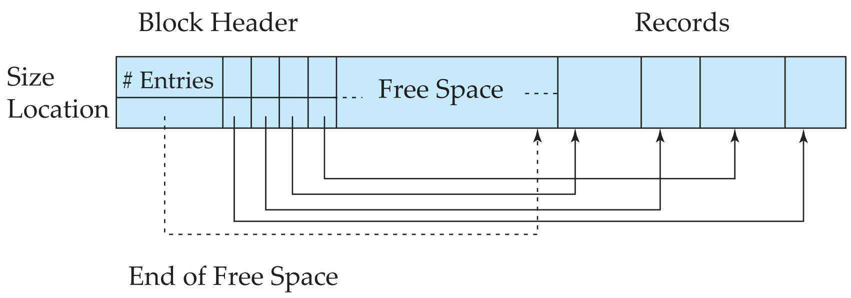


Figure 10.9 Slotted-page structure.

actual location of the record. This level of indirection allows records to be moved to prevent fragmentation of space inside a block, while supporting indirect pointers to the record.

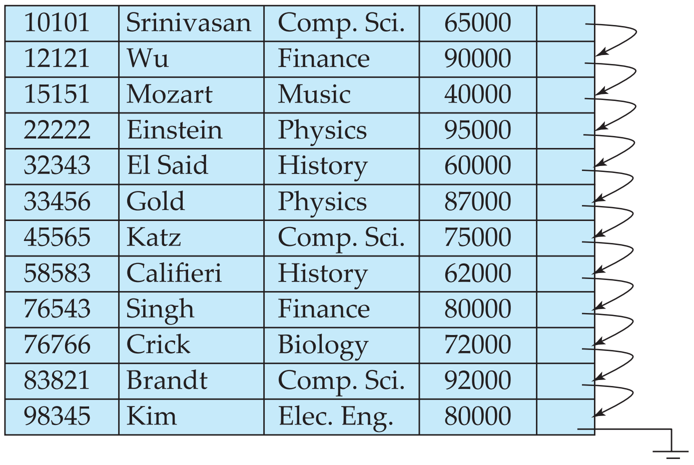
Databases often store data that can be much larger than a disk block. For instance, an image or an audio recording may be multiple megabytes in size, while a video object may be multiple gigabytes in size. Recall that SQL supports the types **blob** and **clob**, which store binary and character large objects.

Most relational databases restrict the size of a record to be no larger than the size of a block, to simplify buffer management and free-space management. Large objects are often stored in a special file (or collection of files) instead of being stored with the other (short) attributes of records in which they occur. A (logical) pointer to the object is then stored in the record containing the large object. Large objects are often represented using B^+-tree file organizations, which we study in Section 11.4.1. B^+-tree file organizations permit us to read an entire object, or specified byte ranges in the object, as well as to insert and delete parts of the object.

10.6 Organization of Records in Files

So far, we have studied how records are represented in a file structure. A relation is a set of records. Given a set of records, the next question is how to organize them in a file. Several of the possible ways of organizing records in files are:

- **Heap file organization**. Any record can be placed anywhere in the file where there is space for the record. There is no ordering of records. Typically, there is a single file for each relation.
- **Sequential file organization**. Records are stored in sequential order, according to the value of a "search key" of each record. Section 10.6.1 describes this organization.
- **Hashing file organization**. A hash function is computed on some attribute of each record. The result of the hash function specifies in which block of the



10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

Figure 10.10 Sequential file for *instructor* records.

file the record should be placed. Chapter 11 describes this organization; it is closely related to the indexing structures described in that chapter.

Generally, a separate file is used to store the records of each relation. However, in a **multitable clustering file organization**, records of several different relations are stored in the same file; further, related records of the different relations are stored on the same block, so that one I/O operation fetches related records from all the relations. For example, records of the two relations can be considered to be related if they would match in a join of the two relations. Section 10.6.2 describes this organization.

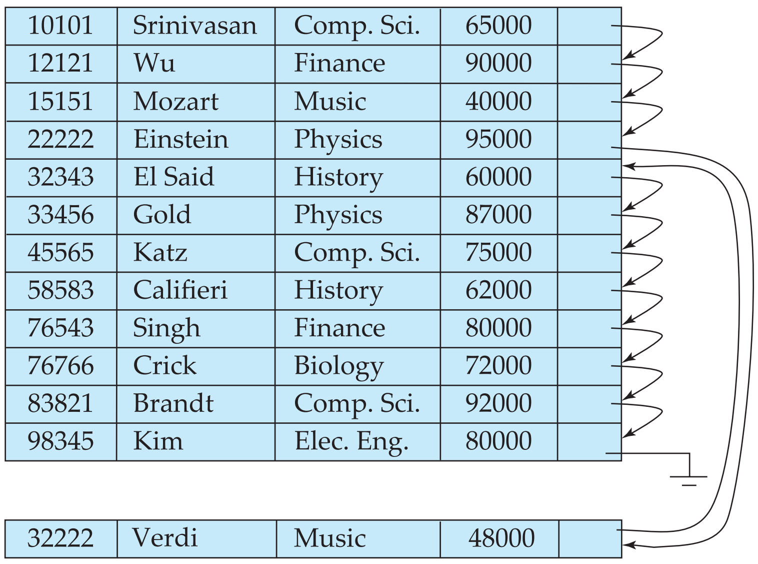
10.6.1 Sequential File Organization

A **sequential file** is designed for efficient processing of records in sorted order based on some search key. A **search key** is any attribute or set of attributes; it need not be the primary key, or even a superkey. To permit fast retrieval of records in search-key order, we chain together records by pointers. The pointer in each record points to the next record in search-key order. Furthermore, to minimize the number of block accesses in sequential file processing, we store records physically in search-key order, or as close to search-key order as possible.

Figure 10.10 shows a sequential file of *instructor* records taken from our university example. In that example, the records are stored in search-key order, using *ID* as the search key.

The sequential file organization allows records to be read in sorted order; that can be useful for display purposes, as well as for certain query-processing algorithms that we shall study in Chapter 12.

It is difficult, however, to maintain physical sequential order as records are inserted and deleted, since it is costly to move many records as a result of a single



10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

32222	Verdi	Music	48000	

Figure 10.11 Sequential file after an insertion.

insertion or deletion. We can manage deletion by using pointer chains, as we saw previously. For insertion, we apply the following rules:

1. Locate the record in the file that comes before the record to be inserted in search-key order.
2. If there is a free record (that is, space left after a deletion) within the same block as this record, insert the new record there. Otherwise, insert the new record in an *overflow block*. In either case, adjust the pointers so as to chain together the records in search-key order.

Figure 10.11 shows the file of Figure 10.10 after the insertion of the record (32222, Verdi, Music, 48000). The structure in Figure 10.11 allows fast insertion of new records, but forces sequential file-processing applications to process records in an order that does not match the physical order of the records.

If relatively few records need to be stored in overflow blocks, this approach works well. Eventually, however, the correspondence between search-key order and physical order may be totally lost over a period of time, in which case sequential processing will become much less efficient. At this point, the file should be **reorganized** so that it is once again physically in sequential order. Such reorganizations are costly, and must be done during times when the system load is low. The frequency with which reorganizations are needed depends on the frequency of insertion of new records. In the extreme case in which insertions rarely occur, it is possible always to keep the file in physically sorted order. In such a case, the pointer field in Figure 10.10 is not needed.

10.6.2 Multitable Clustering File Organization

Many relational database systems store each relation in a separate file, so that they can take full advantage of the file system that the operating system provides. Usually, tuples of a relation can be represented as fixed-length records. Thus, relations can be mapped to a simple file structure. This simple implementation of a relational database system is well suited to low-cost database implementations as in, for example, embedded systems or portable devices. In such systems, the size of the database is small, so little is gained from a sophisticated file structure. Furthermore, in such environments, it is essential that the overall size of the object code for the database system be small. A simple file structure reduces the amount of code needed to implement the system.

This simple approach to relational database implementation becomes less satisfactory as the size of the database increases. We have seen that there are performance advantages to be gained from careful assignment of records to blocks, and from careful organization of the blocks themselves. Clearly, a more complicated file structure may be beneficial, even if we retain the strategy of storing each relation in a separate file.

However, many large-scale database systems do not rely directly on the underlying operating system for file management. Instead, one large operating-system file is allocated to the database system. The database system stores all relations in this one file, and manages the file itself.

Even if multiple relations are stored in a single file, by default most databases store records of only one relation in a given block. This simplifies data management. However, in some cases it can be useful to store records of more than one relation in a single block. To see the advantage of storing records of multiple relations in one block, consider the following SQL query for the university database:

select *dept_name*, *building*, *budget*, *ID*, *name*, *salary*
from *department* **natural join** *instructor*;

This query computes a join of the *department* and *instructor* relations. Thus, for each tuple of *department*, the system must locate the *instructor* tuples with the same value for *dept_name*. Ideally, these records will be located with the help of *indices*, which we shall discuss in Chapter 11. Regardless of how these records are located, however, they need to be transferred from disk into main memory. In the worst case, each record will reside on a different block, forcing us to do one block read for each record required by the query.

dept_name	*building*	*budget*
Comp. Sci.	Taylor	100000
Physics	Watson	70000

Figure 10.12 The *department* relation.

ID	*name*	*dept_name*	*salary*
10101	Srinivasan	Comp. Sci.	65000
33456	Gold	Physics	87000
45565	Katz	Comp. Sci.	75000
83821	Brandt	Comp. Sci.	92000

Figure 10.13 The *instructor* relation.

As a concrete example, consider the *department* and *instructor* relations of Figures 10.12 and 10.13, respectively (for brevity, we include only a subset of the tuples of the relations we have used thus far). In Figure 10.14, we show a file structure designed for efficient execution of queries involving the natural join of *department* and *instructor*. The *instructor* tuples for each *ID* are stored near the *department* tuple for the corresponding *dept_name*. This structure mixes together tuples of two relations, but allows for efficient processing of the join. When a tuple of the *department* relation is read, the entire block containing that tuple is copied from disk into main memory. Since the corresponding *instructor* tuples are stored on the disk near the *department* tuple, the block containing the *department* tuple contains tuples of the *instructor* relation needed to process the query. If a department has so many instructors that the *instructor* records do not fit in one block, the remaining records appear on nearby blocks.

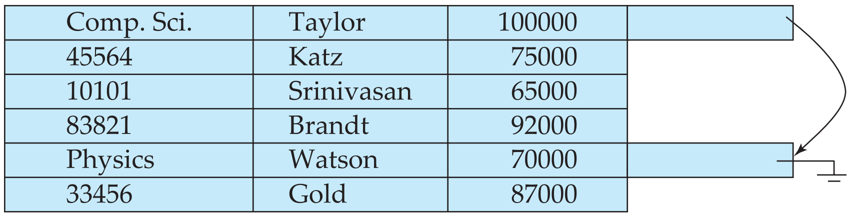
A **multitable clustering file organization** is a file organization, such as that illustrated in Figure 10.14, that stores related records of two or more relations in each block. Such a file organization allows us to read records that would satisfy the join condition by using one block read. Thus, we are able to process this particular query more efficiently.

In the representation shown in Figure 10.14, the *dept_name* attribute is omitted from *instructor* records since it can be inferred from the associated *department* record; the attribute may be retained in some implementations, to simplify access to the attributes. We assume that each record contains the identifier of the relation to which it belongs, although this is not shown in Figure 10.14.

Our use of clustering of multiple tables into a single file has enhanced processing of a particular join (that of *department* and *instructor*), but it results in slowing processing of other types of queries. For example,

Comp. Sci.	Taylor	100000
45564	Katz	75000
10101	Srinivasan	65000
83821	Brandt	92000
Physics	Watson	70000
33456	Gold	87000

Figure 10.14 Multitable clustering file structure.



Comp. Sci.	Taylor	100000	
45564	Katz	75000	
10101	Srinivasan	65000	
83821	Brandt	92000	
Physics	Watson	70000	
33456	Gold	87000	

Figure 10.15 Multitable clustering file structure with pointer chains.

> **select** *
> **from** *department*;

requires more block accesses than it did in the scheme under which we stored each relation in a separate file, since each block now contains significantly fewer *department* records. To locate efficiently all tuples of the *department* relation in the structure of Figure 10.14, we can chain together all the records of that relation using pointers, as in Figure 10.15.

When multitable clustering is to be used depends on the types of queries that the database designer believes to be most frequent. Careful use of multitable clustering can produce significant performance gains in query processing.

10.7 Data-Dictionary Storage

So far, we have considered only the representation of the relations themselves. A relational database system needs to maintain data *about* the relations, such as the schema of the relations. In general, such "data about data" is referred to as **metadata**.

Relational schemas and other metadata about relations are stored in a structure called the **data dictionary** or **system catalog**. Among the types of information that the system must store are these:

- Names of the relations.
- Names of the attributes of each relation.
- Domains and lengths of attributes.
- Names of views defined on the database, and definitions of those views.
- Integrity constraints (for example, key constraints).

In addition, many systems keep the following data on users of the system:

- Names of authorized users.
- Authorization and accounting information about users.

- Passwords or other information used to authenticate users.

Further, the database may store statistical and descriptive data about the relations, such as:

- Number of tuples in each relation.
- Method of storage for each relation (for example, clustered or nonclustered).

The data dictionary may also note the storage organization (sequential, hash, or heap) of relations, and the location where each relation is stored:

- If relations are stored in operating system files, the dictionary would note the names of the file (or files) containing each relation.
- If the database stores all relations in a single file, the dictionary may note the blocks containing records of each relation in a data structure such as a linked list.

In Chapter 11, in which we study indices, we shall see a need to store information about each index on each of the relations:

- Name of the index.
- Name of the relation being indexed.
- Attributes on which the index is defined.
- Type of index formed.

All this metadata information constitutes, in effect, a miniature database. Some database systems store such metadata by using special-purpose data structures and code. It is generally preferable to store the data about the database as relations in the database itself. By using database relations to store system metadata, we simplify the overall structure of the system and harness the full power of the database for fast access to system data.

The exact choice of how to represent system metadata by relations must be made by the system designers. One possible representation, with primary keys underlined, is shown in Figure 10.16. In this representation, the attribute *index_attributes* of the relation *Index_metadata* is assumed to contain a list of one or more attributes, which can be represented by a character string such as "*dept_name*, *building*". The *Index_metadata* relation is thus not in first normal form; it can be normalized, but the above representation is likely to be more efficient to access. The data dictionary is often stored in a nonnormalized form to achieve fast access.

Whenever the database system needs to retrieve records from a relation, it must first consult the *Relation_metadata* relation to find the location and storage organization of the relation, and then fetch records using this information. However, the storage organization and location of the *Relation_metadata* relation itself

CHAPTER 11

Indexing and Hashing

Many queries reference only a small proportion of the records in a file. For example, a query like "Find all instructors in the Physics department" or "Find the total number of credits earned by the student with *ID* 22201" references only a fraction of the student records. It is inefficient for the system to read every tuple in the *instructor* relation to check if the *dept_name* value is "Physics". Likewise, it is inefficient to read the entire *student* relation just to find the one tuple for the *ID* "32556,". Ideally, the system should be able to locate these records directly. To allow these forms of access, we design additional structures that we associate with files.

11.1 Basic Concepts

An index for a file in a database system works in much the same way as the index in this textbook. If we want to learn about a particular topic (specified by a word or a phrase) in this textbook, we can search for the topic in the index at the back of the book, find the pages where it occurs, and then read the pages to find the information for which we are looking. The words in the index are in sorted order, making it easy to find the word we want. Moreover, the index is much smaller than the book, further reducing the effort needed.

Database-system indices play the same role as book indices in libraries. For example, to retrieve a *student* record given an *ID*, the database system would look up an index to find on which disk block the corresponding record resides, and then fetch the disk block, to get the appropriate *student* record.

Keeping a sorted list of students' *ID* would not work well on very large databases with thousands of students, since the index would itself be very big; further, even though keeping the index sorted reduces the search time, finding a student can still be rather time-consuming. Instead, more sophisticated indexing techniques may be used. We shall discuss several of these techniques in this chapter.

There are two basic kinds of indices:

- **Ordered indices**. Based on a sorted ordering of the values.

- **Hash indices**. Based on a uniform distribution of values across a range of buckets. The bucket to which a value is assigned is determined by a function, called a *hash function*.

We shall consider several techniques for both ordered indexing and hashing. No one technique is the best. Rather, each technique is best suited to particular database applications. Each technique must be evaluated on the basis of these factors:

- **Access types**: The types of access that are supported efficiently. Access types can include finding records with a specified attribute value and finding records whose attribute values fall in a specified range.
- **Access time**: The time it takes to find a particular data item, or set of items, using the technique in question.
- **Insertion time**: The time it takes to insert a new data item. This value includes the time it takes to find the correct place to insert the new data item, as well as the time it takes to update the index structure.
- **Deletion time**: The time it takes to delete a data item. This value includes the time it takes to find the item to be deleted, as well as the time it takes to update the index structure.
- **Space overhead**: The additional space occupied by an index structure. Provided that the amount of additional space is moderate, it is usually worthwhile to sacrifice the space to achieve improved performance.

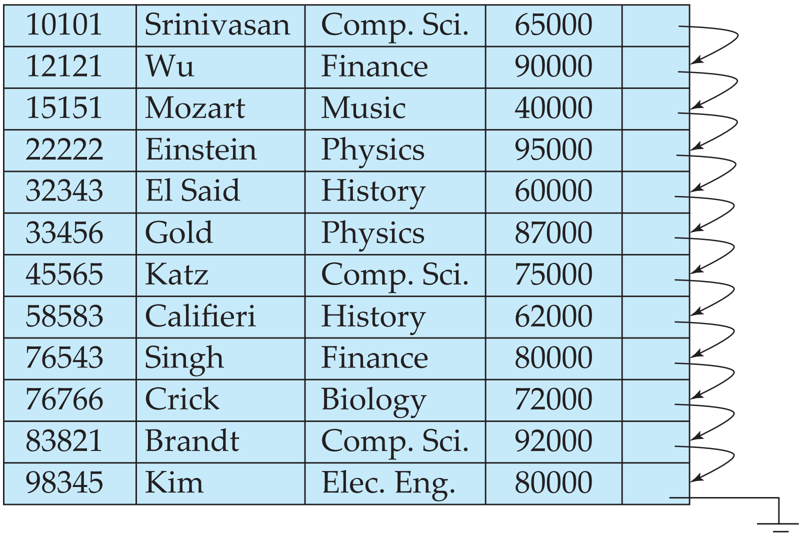
We often want to have more than one index for a file. For example, we may wish to search for a book by author, by subject, or by title.

An attribute or set of attributes used to look up records in a file is called a **search key**. Note that this definition of *key* differs from that used in *primary key*, *candidate key*, and *superkey*. This duplicate meaning for *key* is (unfortunately) well established in practice. Using our notion of a search key, we see that if there are several indices on a file, there are several search keys.

11.2 Ordered Indices

To gain fast random access to records in a file, we can use an index structure. Each index structure is associated with a particular search key. Just like the index of a book or a library catalog, an ordered index stores the values of the search keys in sorted order, and associates with each search key the records that contain it.

The records in the indexed file may themselves be stored in some sorted order, just as books in a library are stored according to some attribute such as the Dewey decimal number. A file may have several indices, on different search keys. If the file containing the records is sequentially ordered, a **clustering index** is an index whose search key also defines the sequential order of the file. Clustering indices



10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

Figure 11.1 Sequential file for *instructor* records.

are also called **primary indices**; the term primary index may appear to denote an index on a primary key, but such indices can in fact be built on any search key. The search key of a clustering index is often the primary key, although that is not necessarily so. Indices whose search key specifies an order different from the sequential order of the file are called **nonclustering indices**, or **secondary** indices. The terms "clustered" and "nonclustered" are often used in place of "clustering" and "nonclustering."

In Sections 11.2.1 through 11.2.3, we assume that all files are ordered sequentially on some search key. Such files, with a clustering index on the search key, are called **index-sequential files**. They represent one of the oldest index schemes used in database systems. They are designed for applications that require both sequential processing of the entire file and random access to individual records. In Section 11.2.4 we cover secondary indices.

Figure 11.1 shows a sequential file of *instructor* records taken from our university example. In the example of Figure 11.1, the records are stored in sorted order of instructor *ID*, which is used as the search key.

11.2.1 Dense and Sparse Indices

An **index entry**, or **index record**, consists of a search-key value and pointers to one or more records with that value as their search-key value. The pointer to a record consists of the identifier of a disk block and an offset within the disk block to identify the record within the block.

There are two types of ordered indices that we can use:

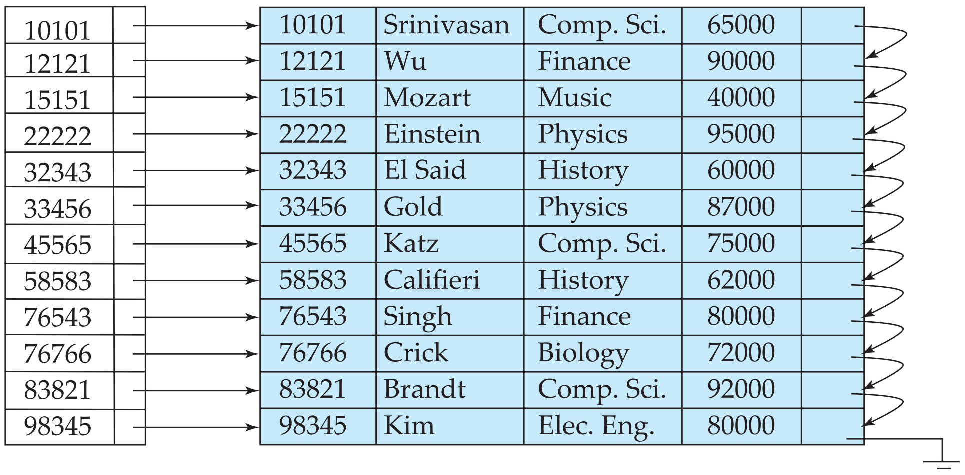

10101
12121
15151
22222
32343
33456
45565
58583
76543
76766
83821
98345
10101 Srinivasan Comp. Sci. 65000
12121 Wu Finance 90000
15151 Mozart Music 40000
22222 Einstein Physics 95000
32343 El Said History 60000
33456 Gold Physics 87000
45565 Katz Comp. Sci. 75000
58583 Califieri History 62000
76543 Singh Finance 80000
76766 Crick Biology 72000
83821 Brandt Comp. Sci. 92000
98345 Kim Elec. Eng. 80000

Figure 11.2 Dense index.

- **Dense index**: In a dense index, an index entry appears for every search-key value in the file. In a dense clustering index, the index record contains the search-key value and a pointer to the first data record with that search-key value. The rest of the records with the same search-key value would be stored sequentially after the first record, since, because the index is a clustering one, records are sorted on the same search key.

  In a dense nonclustering index, the index must store a list of pointers to all records with the same search-key value.

- **Sparse index**: In a sparse index, an index entry appears for only some of the search-key values. Sparse indices can be used only if the relation is stored in sorted order of the search key, that is, if the index is a clustering index. As is true in dense indices, each index entry contains a search-key value and a pointer to the first data record with that search-key value. To locate a record, we find the index entry with the largest search-key value that is less than or equal to the search-key value for which we are looking. We start at the record pointed to by that index entry, and follow the pointers in the file until we find the desired record.

Figures 11.2 and 11.3 show dense and sparse indices, respectively, for the *instructor* file. Suppose that we are looking up the record of instructor with *ID* “22222”. Using the dense index of Figure 11.2, we follow the pointer directly to the desired record. Since *ID* is a primary key, there exists only one such record and the search is complete. If we are using the sparse index (Figure 11.3), we do not find an index entry for “22222”. Since the last entry (in numerical order) before “22222” is “10101”, we follow that pointer. We then read the *instructor* file in sequential order until we find the desired record.

Consider a (printed) dictionary. The header of each page lists the first word alphabetically on that page. The words at the top of each page of the book index together form a sparse index on the contents of the dictionary pages.

As another example, suppose that the search-key value is not not a primary key. Figure 11.4 shows a dense clustering index for the *instructor* file with the search key being *dept_name*. Observe that in this case the *instructor* file is sorted on the search key *dept_name*, instead of *ID*, otherwise the index on *dept_name* would be a nonclustering index. Suppose that we are looking up records for the History department. Using the dense index of Figure 11.4, we follow the pointer directly to the first History record. We process this record, and follow the pointer in that record to locate the next record in search-key (*dept_name*) order. We continue processing records until we encounter a record for a department other than History.

As we have seen, it is generally faster to locate a record if we have a dense index rather than a sparse index. However, sparse indices have advantages over dense indices in that they require less space and they impose less maintenance overhead for insertions and deletions.

There is a trade-off that the system designer must make between access time and space overhead. Although the decision regarding this trade-off depends on the specific application, a good compromise is to have a sparse index with one index entry per block. The reason this design is a good trade-off is that the dominant cost in processing a database request is the time that it takes to bring a block from disk into main memory. Once we have brought in the block, the time to scan the entire block is negligible. Using this sparse index, we locate the block containing the record that we are seeking. Thus, unless the record is on an overflow block (see Section 10.6.1), we minimize block accesses while keeping the size of the index (and thus our space overhead) as small as possible.

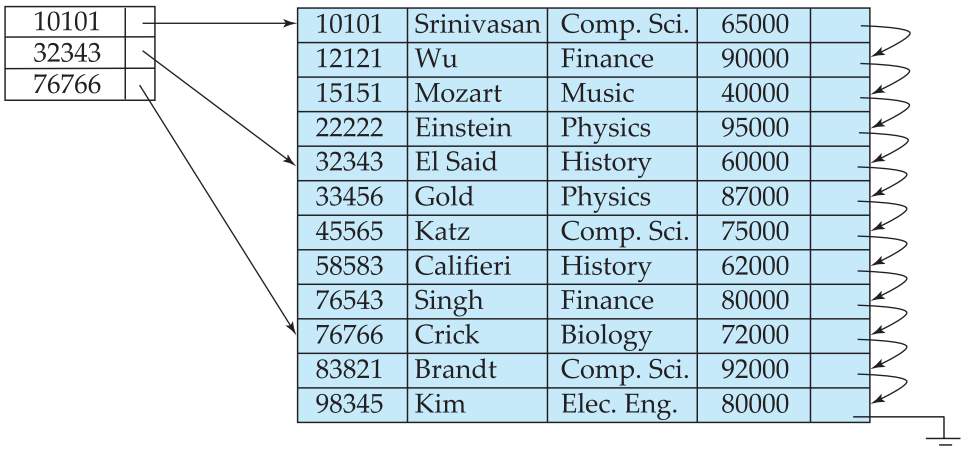
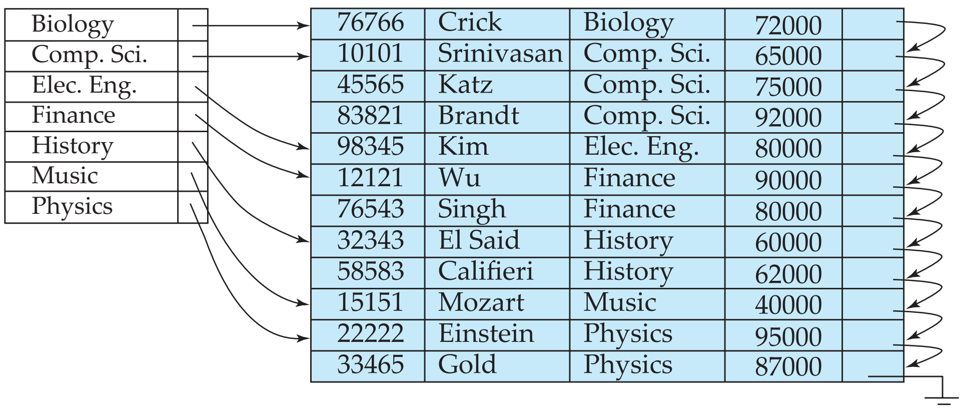

10101
32343
76766
10101 Srinivasan Comp. Sci. 65000
12121 Wu Finance 90000
15151 Mozart Music 40000
22222 Einstein Physics 95000
32343 El Said History 60000
33456 Gold Physics 87000
45565 Katz Comp. Sci. 75000
58583 Califieri History 62000
76543 Singh Finance 80000
76766 Crick Biology 72000
83821 Brandt Comp. Sci. 92000
98345 Kim Elec. Eng. 80000

Figure 11.3 Sparse index.



Biology
Comp. Sci.
Elec. Eng.
Finance
History
Music
Physics

76766	Crick	Biology	72000
10101	Srinivasan	Comp. Sci.	65000
45565	Katz	Comp. Sci.	75000
83821	Brandt	Comp. Sci.	92000
98345	Kim	Elec. Eng.	80000
12121	Wu	Finance	90000
76543	Singh	Finance	80000
32343	El Said	History	60000
58583	Califieri	History	62000
15151	Mozart	Music	40000
22222	Einstein	Physics	95000
33465	Gold	Physics	87000

Figure 11.4 Dense index with search key *dept_name*.

For the preceding technique to be fully general, we must consider the case where records for one search-key value occupy several blocks. It is easy to modify our scheme to handle this situation.

11.2.2 Multilevel Indices

Suppose we build a dense index on a relation with 1,000,000 tuples. Index entries are smaller than data records, so let us assume that 100 index entries fit on a 4 kilobyte block. Thus, our index occupies 10,000 blocks. If the relation instead had 100,000,000 tuples, the index would instead occupy 1,000,000 blocks, or 4 gigabytes of space. Such large indices are stored as sequential files on disk.

If an index is small enough to be kept entirely in main memory, the search time to find an entry is low. However, if the index is so large that not all of it can be kept in memory, index blocks must be fetched from disk when required. (Even if an index is smaller than the main memory of a computer, main memory is also required for a number of other tasks, so it may not be possible to keep the entire index in memory.) The search for an entry in the index then requires several disk-block reads.

Binary search can be used on the index file to locate an entry, but the search still has a large cost. If the index would occupy b blocks, binary search requires as many as $\lceil \log_2(b) \rceil$ blocks to be read. ($\lceil x \rceil$ denotes the least integer that is greater than or equal to x; that is, we round upward.) For a 10,000-block index, binary search requires 14 block reads. On a disk system where a block read takes on average 10 milliseconds, the index search will take 140 milliseconds. This may not seem much, but we would be able to carry out only seven index searches a second, whereas a more efficient search mechanism would let us carry out far more searches per second, as we shall see shortly. Note that, if overflow blocks have been used, binary search is not possible. In that case, a sequential search is typically used, and that requires b block reads, which will take even longer. Thus, the process of searching a large index may be costly.

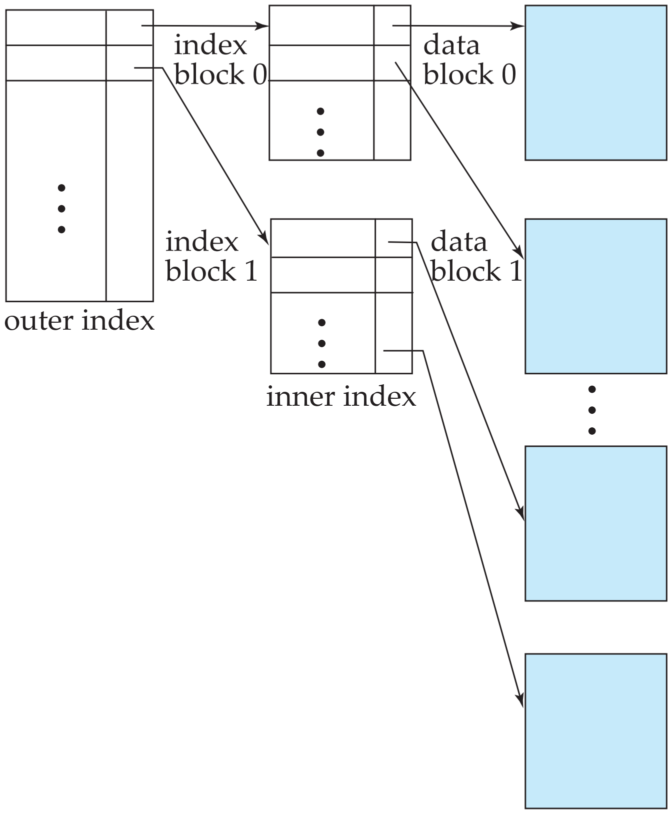


Figure 11.5 Two-level sparse index.

To deal with this problem, we treat the index just as we would treat any other sequential file, and construct a sparse outer index on the original index, which we now call the inner index, as shown in Figure 11.5. Note that the index entries are always in sorted order, allowing the outer index to be sparse. To locate a record, we first use binary search on the outer index to find the record for the largest search-key value less than or equal to the one that we desire. The pointer points to a block of the inner index. We scan this block until we find the record that has the largest search-key value less than or equal to the one that we desire. The pointer in this record points to the block of the file that contains the record for which we are looking.

In our example, an inner index with 10,000 blocks would require 10,000 entries in the outer index, which would occupy just 100 blocks. If we assume that the outer index is already in main memory, we would read only one index block for a search using a multilevel index, rather than the 14 blocks we read with binary search. As a result, we can perform 14 times as many index searches per second.

If our file is extremely large, even the outer index may grow too large to fit in main memory. With a 100,000,000 tuple relation, the inner index would occupy

1,000,000 blocks, and the outer index occupies 10,000 blocks, or 40 megabytes. Since there are many demands on main memory, it may not be possible to reserve that much main memory just for this particular outer index. In such a case, we can create yet another level of index. Indeed, we can repeat this process as many times as necessary. Indices with two or more levels are called **multilevel** indices. Searching for records with a multilevel index requires significantly fewer I/O operations than does searching for records by binary search.[1]

Multilevel indices are closely related to tree structures, such as the binary trees used for in-memory indexing. We shall examine the relationship later, in Section 11.3.

11.2.3 Index Update

Regardless of what form of index is used, every index must be updated whenever a record is either inserted into or deleted from the file. Further, in case a record in the file is updated, any index whose search-key attribute is affected by the update must also be updated; for example, if the department of an instructor is changed, an index on the *dept_name* attribute of *instructor* must be updated correspondingly. Such a record update can be modeled as a deletion of the old record, followed by an insertion of the new value of the record, which results in an index deletion followed by an index insertion. As a result we only need to consider insertion and deletion on an index, and do not need to consider updates explicitly.

We first describe algorithms for updating single-level indices.

- **Insertion**. First, the system performs a lookup using the search-key value that appears in the record to be inserted. The actions the system takes next depend on whether the index is dense or sparse:
  - Dense indices:
    1. If the search-key value does not appear in the index, the system inserts an index entry with the search-key value in the index at the appropriate position.
    2. Otherwise the following actions are taken:
       a. If the index entry stores pointers to all records with the same search-key value, the system adds a pointer to the new record in the index entry.
       b. Otherwise, the index entry stores a pointer to only the first record with the search-key value. The system then places the record being inserted after the other records with the same search-key values.
  - Sparse indices: We assume that the index stores an entry for each block. If the system creates a new block, it inserts the first search-key value (in

[1]In the early days of disk-based indices, each level of the index corresponded to a unit of physical storage. Thus, we may have indices at the track, cylinder, and disk levels. Such a hierarchy does not make sense today since disk subsystems hide the physical details of disk storage, and the number of disks and platters per disk is very small compared to the number of cylinders or bytes per track.

search-key order) appearing in the new block into the index. On the other hand, if the new record has the least search-key value in its block, the system updates the index entry pointing to the block; if not, the system makes no change to the index.

- **Deletion**. To delete a record, the system first looks up the record to be deleted. The actions the system takes next depend on whether the index is dense or sparse:
  - Dense indices:
    1. If the deleted record was the only record with its particular search-key value, then the system deletes the corresponding index entry from the index.
    2. Otherwise the following actions are taken:
       a. If the index entry stores pointers to all records with the same search-key value, the system deletes the pointer to the deleted record from the index entry.
       b. Otherwise, the index entry stores a pointer to only the first record with the search-key value. In this case, if the deleted record was the first record with the search-key value, the system updates the index entry to point to the next record.
  - Sparse indices:
    1. If the index does not contain an index entry with the search-key value of the deleted record, nothing needs to be done to the index.
    2. Otherwise the system takes the following actions:
       a. If the deleted record was the only record with its search key, the system replaces the corresponding index record with an index record for the next search-key value (in search-key order). If the next search-key value already has an index entry, the entry is deleted instead of being replaced.
       b. Otherwise, if the index entry for the search-key value points to the record being deleted, the system updates the index entry to point to the next record with the same search-key value.

Insertion and deletion algorithms for multilevel indices are a simple extension of the scheme just described. On deletion or insertion, the system updates the lowest-level index as described. As far as the second level is concerned, the lowest-level index is merely a file containing records—thus, if there is any change in the lowest-level index, the system updates the second-level index as described. The same technique applies to further levels of the index, if there are any.

11.2.4 Secondary Indices

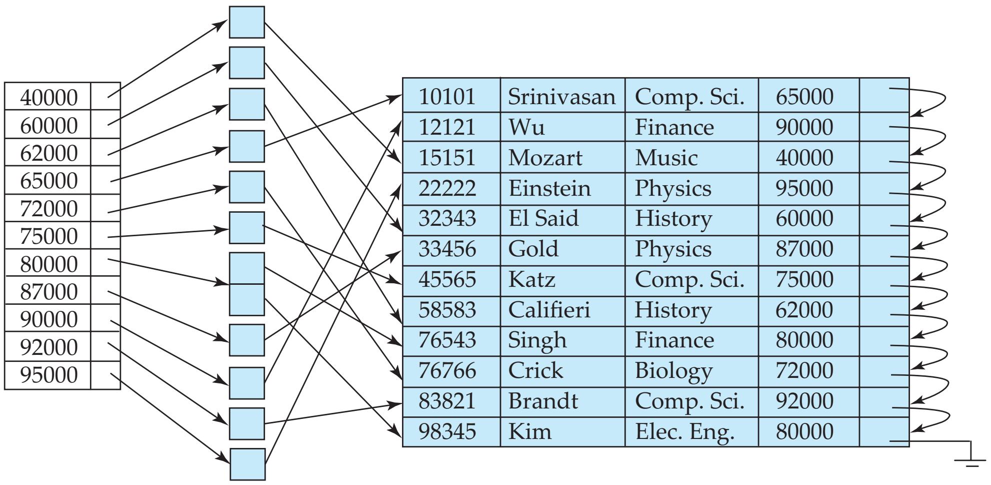
Secondary indices must be dense, with an index entry for every search-key value, and a pointer to every record in the file. A clustering index may be sparse, storing only some of the search-key values, since it is always possible to find records with intermediate search-key values by a sequential access to a part of the file, as described earlier. If a secondary index stores only some of the search-key values, records with intermediate search-key values may be anywhere in the file and, in general, we cannot find them without searching the entire file.

A secondary index on a candidate key looks just like a dense clustering index, except that the records pointed to by successive values in the index are not stored sequentially. In general, however, secondary indices may have a different structure from clustering indices. If the search key of a clustering index is not a candidate key, it suffices if the index points to the first record with a particular value for the search key, since the other records can be fetched by a sequential scan of the file.

In contrast, if the search key of a secondary index is not a candidate key, it is not enough to point to just the first record with each search-key value. The remaining records with the same search-key value could be anywhere in the file, since the records are ordered by the search key of the clustering index, rather than by the search key of the secondary index. Therefore, a secondary index must contain pointers to all the records.

We can use an extra level of indirection to implement secondary indices on search keys that are not candidate keys. The pointers in such a secondary index do not point directly to the file. Instead, each points to a bucket that contains pointers to the file. Figure 11.6 shows the structure of a secondary index that uses an extra level of indirection on the *instructor* file, on the search key *salary*.

A sequential scan in clustering index order is efficient because records in the file are stored physically in the same order as the index order. However, we cannot (except in rare special cases) store a file physically ordered by both the search key of the clustering index and the search key of a secondary index.



10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

Figure 11.6 Secondary index on *instructor* file, on noncandidate key *salary*.

AUTOMATIC CREATION OF INDICES

If a relation is declared to have a primary key, most database implementations automatically create an index on the primary key. Whenever a tuple is inserted into the relation, the index can be used to check that the primary key constraint is not violated (that is, there are no duplicates on the primary key value). Without the index on the primary key, whenever a tuple is inserted, the entire relation would have to be read to ensure that the primary-key constraint is satisfied.

Because secondary-key order and physical-key order differ, if we attempt to scan the file sequentially in secondary-key order, the reading of each record is likely to require the reading of a new block from disk, which is very slow.

The procedure described earlier for deletion and insertion can also be applied to secondary indices; the actions taken are those described for dense indices storing a pointer to every record in the file. If a file has multiple indices, whenever the file is modified, *every* index must be updated.

Secondary indices improve the performance of queries that use keys other than the search key of the clustering index. However, they impose a significant overhead on modification of the database. The designer of a database decides which secondary indices are desirable on the basis of an estimate of the relative frequency of queries and modifications.

11.2.5 Indices on Multiple Keys

Although the examples we have seen so far have had a single attribute in a search key, in general a search key can have more than one attribute. A search key containing more than one attribute is referred to as a **composite search key**. The structure of the index is the same as that of any other index, the only difference being that the search key is not a single attribute, but rather is a list of attributes. The search key can be represented as a tuple of values, of the form $(a_1, \ldots, a_n)$, where the indexed attributes are $A_1, \ldots, A_n$. The ordering of search-key values is the *lexicographic ordering*. For example, for the case of two attribute search keys, $(a_1, a_2) < (b_1, b_2)$ if either $a_1 < b_1$ or $a_1 = b_1$ and $a_2 < b_2$. Lexicographic ordering is basically the same as alphabetic ordering of words.

As an example, consider an index on the *takes* relation, on the composite search key (*course_id*, *semester*, *year*). Such an index would be useful to find all students who have registered for a particular course in a particular semester/year. An ordered index on a composite key can also be used to answer several other kinds of queries efficiently, as we shall see later in Section 11.5.2.

11.3 B$^+$-Tree Index Files

The main disadvantage of the index-sequential file organization is that performance degrades as the file grows, both for index lookups and for sequential scans through the data. Although this degradation can be remedied by reorganization of the file, frequent reorganizations are undesirable.

The **B$^+$-tree** index structure is the most widely used of several index structures that maintain their efficiency despite insertion and deletion of data. A B$^+$-tree index takes the form of a **balanced tree** in which every path from the root of the tree to a leaf of the tree is of the same length. Each nonleaf node in the tree has between $\lceil n/2 \rceil$ and n children, where n is fixed for a particular tree.

We shall see that the B$^+$-tree structure imposes performance overhead on insertion and deletion, and adds space overhead. The overhead is acceptable even for frequently modified files, since the cost of file reorganization is avoided. Furthermore, since nodes may be as much as half empty (if they have the minimum number of children), there is some wasted space. This space overhead, too, is acceptable given the performance benefits of the B$^+$-tree structure.

11.3.1 Structure of a B$^+$-Tree

A B$^+$-tree index is a multilevel index, but it has a structure that differs from that of the multilevel index-sequential file. Figure 11.7 shows a typical node of a B$^+$-tree. It contains up to $n - 1$ search-key values $K_1, K_2, \ldots, K_{n-1}$, and n pointers $P_1, P_2, \ldots, P_n$. The search-key values within a node are kept in sorted order; thus, if $i < j$, then $K_i < K_j$.

We consider first the structure of the **leaf nodes**. For $i = 1, 2, \ldots, n-1$, pointer P_i points to a file record with search-key value K_i. Pointer P_n has a special purpose that we shall discuss shortly.

Figure 11.8 shows one leaf node of a B$^+$-tree for the *instructor* file, in which we have chosen n to be 4, and the search key is *name*.

Now that we have seen the structure of a leaf node, let us consider how search-key values are assigned to particular nodes. Each leaf can hold up to $n - 1$ values. We allow leaf nodes to contain as few as $\lceil (n-1)/2 \rceil$ values. With $n = 4$ in our example B$^+$-tree, each leaf must contain at least 2 values, and at most 3 values.

The ranges of values in each leaf do not overlap, except if there are duplicate search-key values, in which case a value may be present in more than one leaf. Specifically, if L_i and L_j are leaf nodes and $i < j$, then every search-key value in L_i is less than or equal to every search-key value in L_j. If the B$^+$-tree index is used as a dense index (as is usually the case) every search-key value must appear in some leaf node.

Now we can explain the use of the pointer P_n. Since there is a linear order on the leaves based on the search-key values that they contain, we use P_n to chain

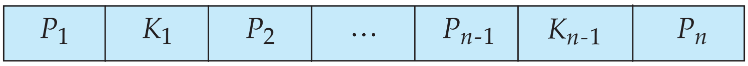
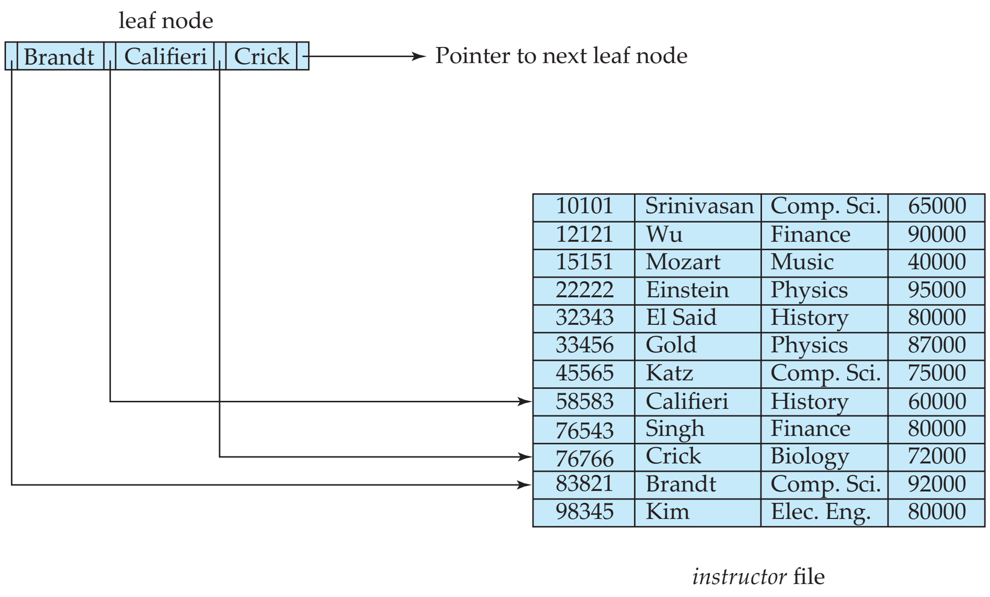


Figure 11.7 Typical node of a B$^+$-tree.



10101	Srinivasan	Comp. Sci.	65000
12121	Wu	Finance	90000
15151	Mozart	Music	40000
22222	Einstein	Physics	95000
32343	El Said	History	80000
33456	Gold	Physics	87000
45565	Katz	Comp. Sci.	75000
58583	Califieri	History	60000
76543	Singh	Finance	80000
76766	Crick	Biology	72000
83821	Brandt	Comp. Sci.	92000
98345	Kim	Elec. Eng.	80000

Figure 11.8 A leaf node for *instructor* B$^+$-tree index ($n = 4$).

together the leaf nodes in search-key order. This ordering allows for efficient sequential processing of the file.

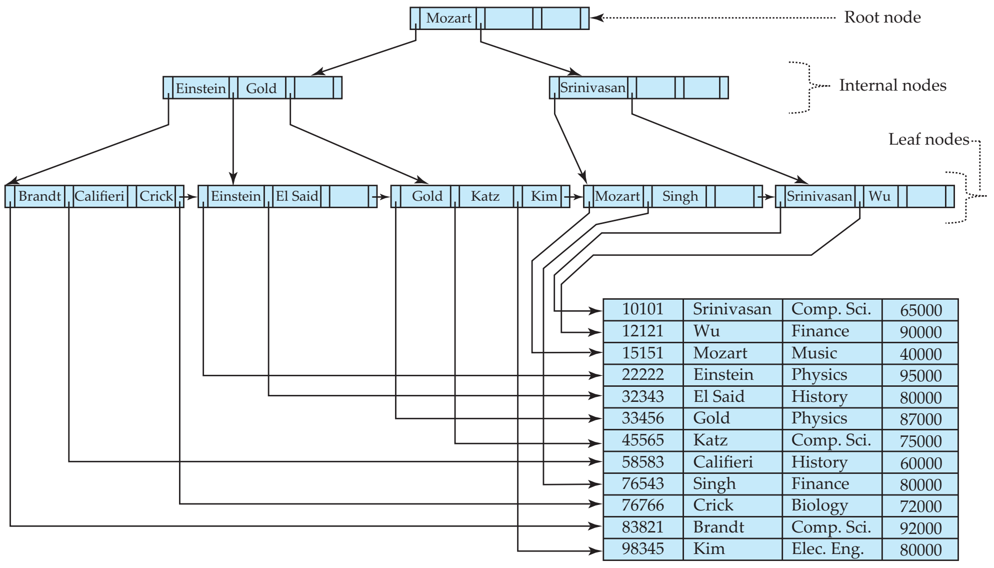
The **nonleaf nodes** of the B$^+$-tree form a multilevel (sparse) index on the leaf nodes. The structure of nonleaf nodes is the same as that for leaf nodes, except that all pointers are pointers to tree nodes. A nonleaf node may hold up to n pointers, and *must* hold at least $\lceil n/2 \rceil$ pointers. The number of pointers in a node is called the *fanout* of the node. Nonleaf nodes are also referred to as **internal nodes**.

Let us consider a node containing m pointers ($m \leq n$). For $i = 2, 3, \ldots, m-1$, pointer P_i points to the subtree that contains search-key values less than K_i and greater than or equal to K_{i-1}. Pointer P_m points to the part of the subtree that contains those key values greater than or equal to K_{m-1}, and pointer P_1 points to the part of the subtree that contains those search-key values less than K_1.

Unlike other nonleaf nodes, the root node can hold fewer than $\lceil n/2 \rceil$ pointers; however, it must hold at least two pointers, unless the tree consists of only one node. It is always possible to construct a B$^+$-tree, for any n, that satisfies the preceding requirements.

Figure 11.9 shows a complete B$^+$-tree for the *instructor* file (with $n = 4$). We have shown instructor names abbreviated to 3 characters in order to depict the tree clearly; in reality, the tree nodes would contain the full names. We have also omitted null pointers for simplicity; any pointer field in the figure that does not have an arrow is understood to have a null value.

Figure 11.10 shows another B$^+$-tree for the *instructor* file, this time with $n = 6$. As before, we have abbreviated instructor names only for clarity of presentation.



10101	Srinivasan	Comp. Sci.	65000
12121	Wu	Finance	90000
15151	Mozart	Music	40000
22222	Einstein	Physics	95000
32343	El Said	History	80000
33456	Gold	Physics	87000
45565	Katz	Comp. Sci.	75000
58583	Califieri	History	60000
76543	Singh	Finance	80000
76766	Crick	Biology	72000
83821	Brandt	Comp. Sci.	92000
98345	Kim	Elec. Eng.	80000

Figure 11.9 B$^+$-tree for *instructor* file ($n = 4$).

Observe that the height of this tree is less than that of the previous tree, which had $n = 4$.

These examples of B$^+$-trees are all balanced. That is, the length of every path from the root to a leaf node is the same. This property is a requirement for a B$^+$-tree. Indeed, the "B" in B$^+$-tree stands for "balanced." It is the balance property of B$^+$-trees that ensures good performance for lookup, insertion, and deletion.

11.3.2 Queries on B$^+$-Trees

Let us consider how we process queries on a B$^+$-tree. Suppose that we wish to find records with a search-key value of V. Figure 11.11 presents pseudocode for a function `find()` to carry out this task.

Intuitively, the function starts at the root of the tree, and traverses the tree down until it reaches a leaf node that would contain the specified value if it exists in the tree. Specifically, starting with the root as the current node, the function repeats the following steps until a leaf node is reached. First, the current node is examined, looking for the smallest i such that search-key value K_i is greater

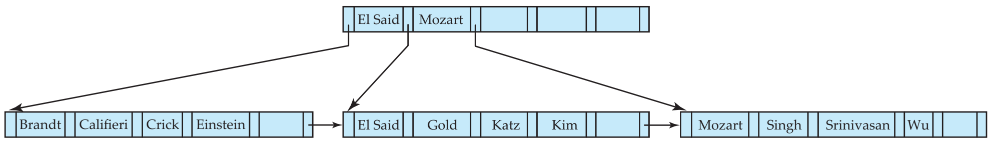


Figure 11.10 B$^+$-tree for *instructor* file with $n = 6$.

```
function find(value V)
/* Returns leaf node C and index i such that C.P_i points to first record
* with search key value V */
    Set C = root node
    while (C is not a leaf node) begin
        Let i = smallest number such that $V \leq C.K_i$
        if there is no such number i then begin
            Let $P_m$ = last non-null pointer in the node
            Set C = $C.P_m$
        end
        else if ($V = C.K_i$)
            then Set C = $C.P_{i+1}$
        else C = $C.P_i$ /* $V < C.K_i$ */
    end
    /* C is a leaf node */
    Let i be the least value such that $K_i = V$
    if there is such a value i
        then return (C, i)
        else return null ; /* No record with key value V exists*/


procedure printAll(value V)
/* prints all records with search key value V */
    Set done = false;
    Set (L, i) = find(V);
    if ((L, i) is null) return
    repeat
        repeat
            Print record pointed to by $L.P_i$
            Set $i = i + 1$
        until ($i >$ number of keys in L or $L.K_i > V$)
        if ($i >$ number of keys in L)
            then $L = L.P_n$
            else Set done = true;
    until (done or L is null)
```

Figure 11.11 Querying a B+-tree.

than or equal to V. Suppose such a value is found; then, if K_i is equal to V, the current node is set to the node pointed to by P_{i+1}, otherwise $K_i > V$, and the current node is set to the node pointed to by P_i. If no such value K_i is found, then clearly $V > K_{m-1}$, where P_m is the last nonnull pointer in the node. In this case the current node is set to that pointed to by P_m. The above procedure is repeated, traversing down the tree until a leaf node is reached.

At the leaf node, if there is a search-key value equal to V, let K_i be the first such value; pointer P_i directs us to a record with search-key value K_i. The function contains 100 entries, the leaf level will contain 1 million nodes, resulting in only 1 million I/O operations for creating the leaf level. Even these I/O operations can be expected to be sequential, if successive leaf nodes are allocated on successive disk blocks, and few disk seeks would be required. With current disks, 1 millisecond per block is a reasonable estimate for mostly sequential I/O operations, in contrast to 10 milliseconds per block for random I/O operations.

We shall study the cost of sorting a large relation later, in Section 12.4, but as a rough estimate, the index which would have taken a million seconds to build otherwise, can be constructed in well under 1000 seconds by sorting the entries before inserting them into the B$^+$-tree, in contrast to more than 1,000,000 seconds for inserting in random order.

If the B$^+$-tree is initially empty, it can be constructed faster by building it bottom-up, from the leaf level, instead of using the usual insert procedure. In **bottom-up B$^+$-tree construction**, after sorting the entries as we just described, we break up the sorted entries into blocks, keeping as many entries in a block as can fit in the block; the resulting blocks form the leaf level of the B$^+$-tree. The minimum value in each block, along with the pointer to the block, is used to create entries in the next level of the B$^+$-tree, pointing to the leaf blocks. Each further level of the tree is similarly constructed using the minimum values associated with each node one level below, until the root is created. We leave details as an exercise for the reader.

Most database systems implement efficient techniques based on sorting of entries, and bottom-up construction, when creating an index on a relation, although they use the normal insertion procedure when tuples are added one at a time to a relation with an existing index. Some database systems recommend that if a very large number of tuples are added at once to an already existing relation, indices on the relation (other than any index on the primary key) should be dropped, and then re-created after the tuples are inserted, to take advantage of efficient bulk-loading techniques.

11.4.5 B-Tree Index Files

B-tree indices are similar to B$^+$-tree indices. The primary distinction between the two approaches is that a B-tree eliminates the redundant storage of search-key values. In the B$^+$-tree of Figure 11.13, the search keys "Califieri", "Einstein", "Gold", "Mozart", and "Srinivasan" appear in nonleaf nodes, in addition to appearing in the leaf nodes. Every search-key value appears in some leaf node; several are repeated in nonleaf nodes.

A B-tree allows search-key values to appear only once (if they are unique), unlike a B$^+$-tree, where a value may appear in a nonleaf node, in addition to appearing in a leaf node. Figure 11.21 shows a B-tree that represents the same search keys as the B$^+$-tree of Figure 11.13. Since search keys are not repeated in the B-tree, we may be able to store the index in fewer tree nodes than in the corresponding B$^+$-tree index. However, since search keys that appear in nonleaf nodes appear nowhere else in the B-tree, we are forced to include an additional

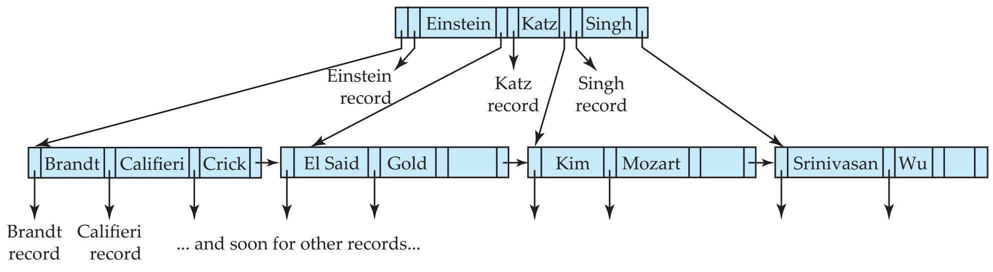


Figure 11.21 B-tree equivalent of B$^+$-tree in Figure 11.13.

pointer field for each search key in a nonleaf node. These additional pointers point to either file records or buckets for the associated search key.

It is worth noting that many database system manuals, articles in industry literature, and industry professionals use the term B-tree to refer to the data structure that we call the B$^+$-tree. In fact, it would be fair to say that in current usage, the term B-tree is assumed to be synonymous with B$^+$-tree. However, in this book we use the terms B-tree and B$^+$-tree as they were originally defined, to avoid confusion between the two data structures.

A generalized B-tree leaf node appears in Figure 11.22a; a nonleaf node appears in Figure 11.22b. Leaf nodes are the same as in B$^+$-trees. In nonleaf nodes, the pointers P_i are the tree pointers that we used also for B$^+$-trees, while the pointers B_i are bucket or file-record pointers. In the generalized B-tree in the figure, there are $n-1$ keys in the leaf node, but there are $m-1$ keys in the nonleaf node. This discrepancy occurs because nonleaf nodes must include pointers B_i, thus reducing the number of search keys that can be held in these nodes. Clearly, $m < n$, but the exact relationship between m and n depends on the relative size of search keys and pointers.

The number of nodes accessed in a lookup in a B-tree depends on where the search key is located. A lookup on a B$^+$-tree requires traversal of a path from the root of the tree to some leaf node. In contrast, it is sometimes possible to find the desired value in a B-tree before reaching a leaf node. However, roughly n times as many keys are stored in the leaf level of a B-tree as in the nonleaf levels, and, since n is typically large, the benefit of finding certain values early is relatively

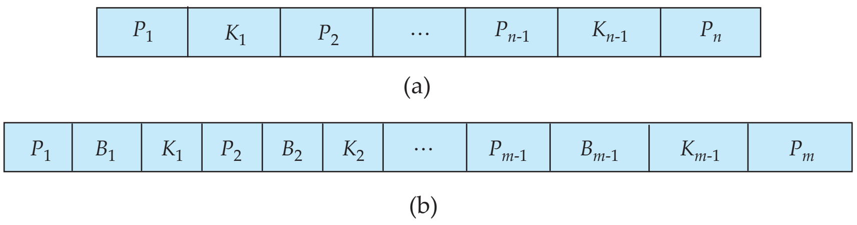

P_1 K_1 P_2 … $P_{n\text{-}1}$ $K_{n\text{-}1}$ P_n
(a)
P_1 B_1 K_1 P_2 B_2 K_2 … $P_{m\text{-}1}$ $B_{m\text{-}1}$ $K_{m\text{-}1}$ P_m
(b)

Figure 11.22 Typical nodes of a B-tree. (a) Leaf node. (b) Nonleaf node.

small. Moreover, the fact that fewer search keys appear in a nonleaf B-tree node, compared to B$^+$-trees, implies that a B-tree has a smaller fanout and therefore may have depth greater than that of the corresponding B$^+$-tree. Thus, lookup in a B-tree is faster for some search keys but slower for others, although, in general, lookup time is still proportional to the logarithm of the number of search keys.

Deletion in a B-tree is more complicated. In a B$^+$-tree, the deleted entry always appears in a leaf. In a B-tree, the deleted entry may appear in a nonleaf node. The proper value must be selected as a replacement from the subtree of the node containing the deleted entry. Specifically, if search key K_i is deleted, the smallest search key appearing in the subtree of pointer P_{i+1} must be moved to the field formerly occupied by K_i. Further actions need to be taken if the leaf node now has too few entries. In contrast, insertion in a B-tree is only slightly more complicated than is insertion in a B$^+$-tree.

The space advantages of B-trees are marginal for large indices, and usually do not outweigh the disadvantages that we have noted. Thus, pretty much all database-system implementations use the B$^+$-tree data structure, even if (as we discussed earlier) they refer to the data structure as a B-tree.

11.4.6 Flash Memory

In our description of indexing so far, we have assumed that data are resident on magnetic disks. Although this assumption continues to be true for the most part, flash memory capacities have grown significantly, and the cost of flash memory per gigabyte has dropped equally significantly, making flash memory storage a serious contender for replacing magnetic-disk storage for many applications. A natural question is, how would this change affect the index structure.

Flash-memory storage is structured as blocks, and the B$^+$-tree index structure can be used for flash-memory storage. The benefit of the much faster access speeds is clear for index lookups. Instead of requiring an average of 10 milliseconds to seek to and read a block, a random block can be read in about a microsecond from flash-memory. Thus lookups run significantly faster than with disk-based data. The optimum B$^+$-tree node size for flash-memory is typically smaller than that with disk.

The only real drawback with flash memory is that it does not permit in-place updates to data at the physical level, although it appears to do so logically. Every update turns into a copy+write of an entire flash-memory block, requiring the old copy of the block to be erased subsequently; a block erase takes about 1 millisecond. There is ongoing research aimed at developing index structures that can reduce the number of block erases. Meanwhile, standard B$^+$-tree indices can continue to be used even on flash-memory storage, with acceptable update performance, and significantly improved lookup performance compared to disk storage.

11.5 Multiple-Key Access

Until now, we have assumed implicitly that only one index on one attribute is used to process a query on a relation. However, for certain types of queries, it is