traditional implementations for many task problems, as it supports dynamic execution, strong fault tolerance, and an easy-to-use high-level interface. The major open source/commercial MapReduce implementations are Hadoop [23] and Dryad [24–27] with execution possible with or without VMs.

Hadoop is currently offered by Amazon, and we expect Dryad to be available on Azure. A prototype Azure MapReduce was built at Indiana University, which we will discuss shortly. On FutureGrid, we already intend to support Hadoop, Dryad, and other MapReduce approaches, including Twister [29] support for iterative computations seen in many data-mining and linear algebra applications. Note that this approach has some similarities with Cloudera [35] which offers a variety of Hadoop distributions including Amazon and Linux. MapReduce is closer to broad deployment than other cloud platform features, as there is quite a bit of experience with Hadoop and Dryad outside clouds.

6.1.4.3 Cloud Programming Models

In many ways, most of the previous sections describe programming model features, but these are "macroscopic" constructs and do not address, for example, the coding (language and libraries). Both the GAE and Manjrasoft Aneka environments represent programming models; both are applied to clouds, but are really not specific to this architecture. Iterative MapReduce is an interesting programming model that offers portability between cloud, HPC and cluster environments.

6.1.4.4 SaaS

Services are used in a similar fashion in commercial clouds and most modern distributed systems. We expect users to package their programs wherever possible, so no special support is needed to enable SaaS. We already discussed in Section 6.1.3 why "Systems software as a service" was an interesting idea in the context of a database service. We desire a SaaS environment that provides many useful tools to develop cloud applications over large data sets. In addition to the technical features, such as MapReduce, BigTable, EC2, S3, Hadoop, AWS, GAE, and WebSphere2, we need protection features that may help us to achieve scalability, security, privacy, and availability.

6.2 PARALLEL AND DISTRIBUTED PROGRAMMING PARADIGMS

We define a parallel and distributed program as a parallel program running on a set of computing engines or a distributed computing system. The term carries the notion of two fundamental terms in computer science: distributed computing system and parallel computing. A distributed computing system is a set of computational engines connected by a network to achieve a common goal of running a job or an application. A computer cluster or network of workstations is an example of a distributed computing system. Parallel computing is the simultaneous use of more than one computational engine (not necessarily connected via a network) to run a job or an application. For instance, parallel computing may use either a distributed or a nondistributed computing system such as a multiprocessor platform.

Running a parallel program on a distributed computing system (parallel and distributed programming) has several advantages for both users and distributed computing systems. From the users' perspective, it decreases application response time; from the distributed computing systems' standpoint, it increases throughput and resource utilization. Running a parallel program on a distributed computing system, however, could be a very complicated process. Therefore, to place the complexity in perspective, data flow of running a typical parallel program on a distributed system is further explained in this chapter.

6.2.1 Parallel Computing and Programming Paradigms

Consider a distributed computing system consisting of a set of networked nodes or workers. The system issues for running a typical parallel program in either a parallel or a distributed manner would include the following [36–39]:

- **Partitioning** This is applicable to both computation and data as follows:
- **Computation partitioning** This splits a given job or a program into smaller tasks. Partitioning greatly depends on correctly identifying portions of the job or program that can be performed concurrently. In other words, upon identifying parallelism in the structure of the program, it can be divided into parts to be run on different workers. Different parts may process different data or a copy of the same data.
- **Data partitioning** This splits the input or intermediate data into smaller pieces. Similarly, upon identification of parallelism in the input data, it can also be divided into pieces to be processed on different workers. Data pieces may be processed by different parts of a program or a copy of the same program.
- **Mapping** This assigns the either smaller parts of a program or the smaller pieces of data to underlying resources. This process aims to appropriately assign such parts or pieces to be run simultaneously on different workers and is usually handled by resource allocators in the system.
- **Synchronization** Because different workers may perform different tasks, synchronization and coordination among workers is necessary so that race conditions are prevented and data dependency among different workers is properly managed. Multiple accesses to a shared resource by different workers may raise race conditions, whereas data dependency happens when a worker needs the processed data of other workers.
- **Communication** Because data dependency is one of the main reasons for communication among workers, communication is always triggered when the intermediate data is sent to workers.
- **Scheduling** For a job or program, when the number of computation parts (tasks) or data pieces is more than the number of available workers, a scheduler selects a sequence of tasks or data pieces to be assigned to the workers. It is worth noting that the resource allocator performs the actual mapping of the computation or data pieces to workers, while the scheduler only picks the next part from the queue of unassigned tasks based on a set of rules called the scheduling policy. For multiple jobs or programs, a scheduler selects a sequence of jobs or programs to be run on the distributed computing system. In this case, scheduling is also necessary when system resources are not sufficient to simultaneously run multiple jobs or programs.

6.2.1.1 Motivation for Programming Paradigms

Because handling the whole data flow of parallel and distributed programming is very time-consuming and requires specialized knowledge of programming, dealing with these issues may affect the productivity of the programmer and may even result in affecting the program's time to market. Furthermore, it may detract the programmer from concentrating on the logic of the program itself.

Therefore, parallel and distributed programming paradigms or models are offered to abstract many parts of the data flow from users.

In other words, these models aim to provide users with an abstraction layer to hide implementation details of the data flow which users formerly ought to write codes for. Therefore, simplicity of writing parallel programs is an important metric for parallel and distributed programming paradigms. Other motivations behind parallel and distributed programming models are (1) to improve productivity of programmers, (2) to decrease programs' time to market, (3) to leverage underlying resources more efficiently, (4) to increase system throughput, and (5) to support higher levels of abstraction [40].

MapReduce, Hadoop, and Dryad are three of the most recently proposed parallel and distributed programming models. They were developed for information retrieval applications but have been shown to be applicable for a variety of important applications [41]. Further, the loose coupling of components in these paradigms makes them suitable for VM implementation and leads to much better fault tolerance and scalability for some applications than traditional parallel computing models such as MPI [42–44].

6.2.2 MapReduce, Twister, and Iterative MapReduce

MapReduce, as introduced in Section 6.1.4, is a software framework which supports parallel and distributed computing on large data sets [27,37,45,46]. This software framework abstracts the data flow of running a parallel program on a distributed computing system by providing users with two interfaces in the form of two functions: *Map* and *Reduce*. Users can override these two functions to interact with and manipulate the data flow of running their programs. Figure 6.1 illustrates the logical data flow from the *Map* to the *Reduce* function in MapReduce frameworks. In this framework,

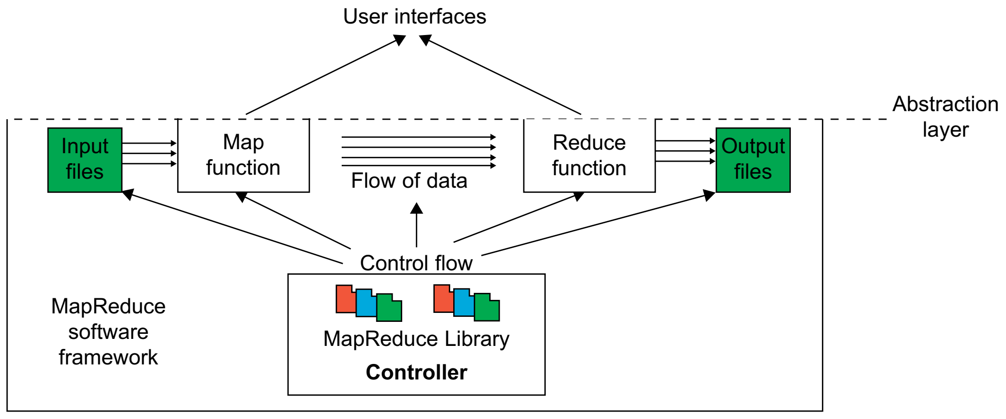


FIGURE 6.1

MapReduce framework: Input data flows through the Map and Reduce functions to generate the output result under the control flow using MapReduce software library. Special user interfaces are used to access the Map and Reduce resources.

the "value" part of the data, *(key, value)*, is the actual data, and the "key" part is only used by the MapReduce controller to control the data flow [37].

6.2.2.1 Formal Definition of MapReduce

The MapReduce software framework provides an abstraction layer with the data flow and flow of control to users, and hides the implementation of all data flow steps such as data partitioning, mapping, synchronization, communication, and scheduling. Here, although the data flow in such frameworks is predefined, the abstraction layer provides two well-defined interfaces in the form of two functions: *Map* and *Reduce* [47]. These two main functions can be overridden by the user to achieve specific objectives. Figure 6.1 shows the MapReduce framework with data flow and control flow.

Therefore, the user overrides the *Map* and *Reduce* functions first and then invokes the provided *MapReduce* (*Spec, & Results*) function from the library to start the flow of data. The MapReduce function, *MapReduce* (*Spec, & Results*), takes an important parameter which is a specification object, the *Spec*. This object is first initialized inside the user's program, and then the user writes code to fill it with the names of input and output files, as well as other optional tuning parameters. This object is also filled with the name of the *Map* and *Reduce* functions to identify these user-defined functions to the MapReduce library.

The overall structure of a user's program containing the Map, Reduce, and the Main functions is given below. The Map and Reduce are two major subroutines. They will be called to implement the desired function performed in the main program.

```
Map Function (.... )
  {
    ... ...
  }
Reduce Function (.... )
  {
    ... ...
  }
Main Function (.... )
  {
    Initialize Spec object
    ... ...
    MapReduce (Spec, & Results)
  }
```

6.2.2.2 MapReduce Logical Data Flow

The input data to both the *Map* and the *Reduce* functions has a particular structure. This also pertains for the output data. The input data to the *Map* function is in the form of a (key, value) pair. For example, the key is the line offset within the input file and the value is the content of the line. The output data from the *Map* function is structured as (key, value) pairs called intermediate (key, value) pairs. In other words, the user-defined *Map* function processes each input (key, value) pair and produces a number of (zero, one, or more) intermediate (key, value) pairs. Here, the goal is to process all input (key, value) pairs to the *Map* function in parallel (Figure 6.2).

In turn, the *Reduce* function receives the intermediate (key, value) pairs in the form of a group of intermediate values associated with one intermediate key, *(key, [set of values])*. In fact, the

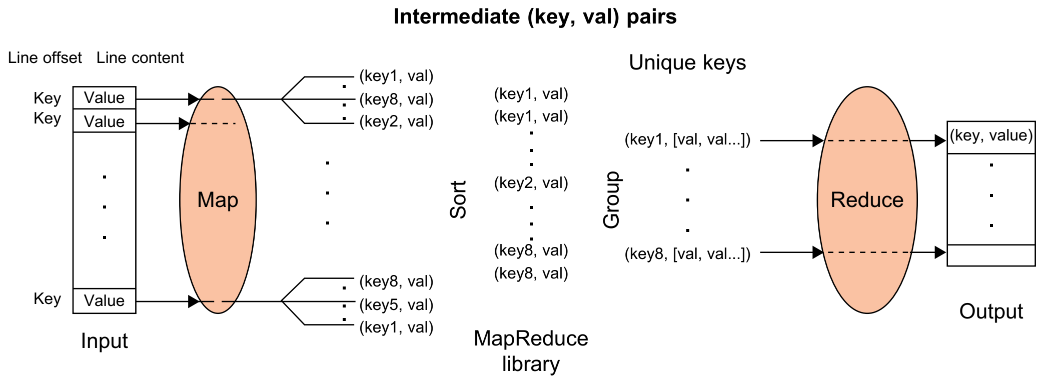


FIGURE 6.2

MapReduce logical data flow in 5 processing stages over successive (key, value) pairs.

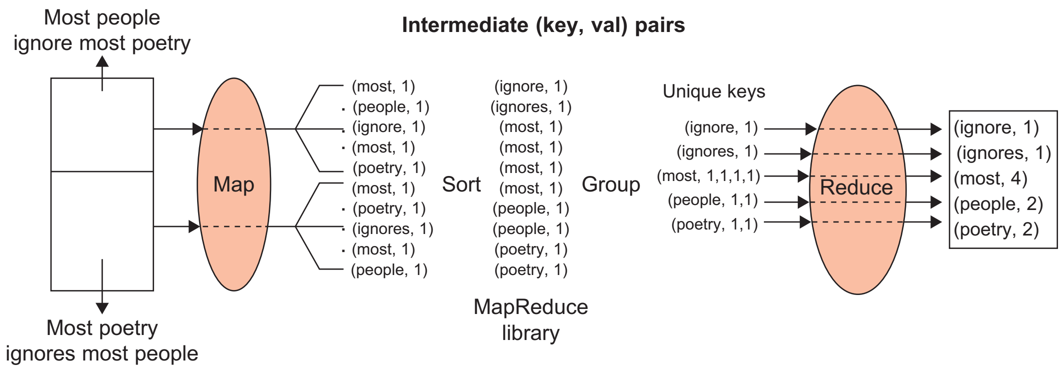


FIGURE 6.3

The data flow of a word-count problem using the MapReduce functions (Map, Sort, Group and Reduce) in a cascade operations.

MapReduce framework forms these groups by first sorting the intermediate (key, value) pairs and then grouping values with the same key. It should be noted that the data is sorted to simplify the grouping process. The *Reduce* function processes each (key, [set of values]) group and produces a set of (key, value) pairs as output.

To clarify the data flow in a sample MapReduce application, one of the well-known MapReduce problems, namely word count, to count the number of occurrences of each word in a collection of documents is presented here. Figure 6.3 demonstrates the data flow of the word-count problem for a simple input file containing only two lines as follows: (1) "most people ignore most poetry" and (2) "most poetry ignores most people." In this case, the *Map* function simultaneously produces a number of intermediate (key, value) pairs for each line of content so that each word is the intermediate key with *1* as its intermediate value; for example, *(ignore, 1)*. Then the MapReduce library collects all the generated intermediate (key, value) pairs and sorts them to group the *1*'s for identical words; for example, *(people, [1,1])*. Groups are then sent to the *Reduce* function in parallel so that it can sum up the *1* values for each word and generate the actual number of occurrence for each word in the file; for example, *(people, 2)*.

6.2.2.3 Formal Notation of MapReduce Data Flow

The *Map* function is applied in parallel to every input (key, value) pair, and produces new set of intermediate (key, value) pairs [37] as follows:

$$(key_1, val_1) \xrightarrow{Map\ Function} \text{List}\,(key_2, val_2) \tag{6.1}$$

Then the MapReduce library collects all the produced intermediate (key, value) pairs from all input (key, value) pairs, and sorts them based on the "key" part. It then groups the values of all occurrences of the same key. Finally, the *Reduce* function is applied in parallel to each group producing the collection of values as output as illustrated here:

$$(key_2, \text{List}\,(val_2)) \xrightarrow{Reduce\ Function} \text{List}\,(val_2) \tag{6.2}$$

6.2.2.4 Strategy to Solve MapReduce Problems

As mentioned earlier, after grouping all the intermediate data, the values of all occurrences of the same key are sorted and grouped together. As a result, after grouping, each key becomes unique in all intermediate data. Therefore, finding unique keys is the starting point to solving a typical MapReduce problem. Then the intermediate (key, value) pairs as the output of the *Map* function will be automatically found. The following three examples explain how to define keys and values in such problems:

Problem 1: Counting the number of occurrences of each word in a collection of documents
Solution: unique "key": each word, intermediate "value": number of occurrences
Problem 2: Counting the number of occurrences of words having the same size, or the same number of letters, in a collection of documents
Solution: unique "key": each word, intermediate "value": size of the word
Problem 3: Counting the number of occurrences of anagrams in a collection of documents. Anagrams are words with the same set of letters but in a different order (e.g., the words "listen" and "silent").
Solution: unique "key": alphabetically sorted sequence of letters for each word (e.g., "eilnst"), intermediate "value": number of occurrences

6.2.2.5 MapReduce Actual Data and Control Flow

The main responsibility of the MapReduce framework is to efficiently run a user's program on a distributed computing system. Therefore, the MapReduce framework meticulously handles all partitioning, mapping, synchronization, communication, and scheduling details of such data flows [48,49]. We summarize this in the following distinct steps:

1. **Data partitioning** The MapReduce library splits the input data (files), already stored in GFS, into *M* pieces that also correspond to the number of map tasks.

2. **Computation partitioning** This is implicitly handled (in the MapReduce framework) by obliging users to write their programs in the form of the *Map* and *Reduce* functions. Therefore, the MapReduce library only generates copies of a user program (e.g., by a fork system call) containing the *Map* and the *Reduce* functions, distributes them, and starts them up on a number of available computation engines.
3. **Determining the master and workers** The MapReduce architecture is based on a master-worker model. Therefore, one of the copies of the user program becomes the master and the rest become workers. The master picks idle workers, and assigns the map and reduce tasks to them. A map/reduce *worker* is typically a computation engine such as a cluster node to run map/reduce *tasks* by executing *Map/Reduce functions*. Steps 4–7 describe the map workers.
4. **Reading the input data (data distribution)** Each map worker reads its corresponding portion of the input data, namely the input data split, and sends it to its *Map* function. Although a map worker may run more than one *Map* function, which means it has been assigned more than one input data split, each worker is usually assigned one input split only.
5. ***Map* function** Each *Map* function receives the input data split as a set of (key, value) pairs to process and produce the intermediated (key, value) pairs.
6. ***Combiner* function** This is an optional local function within the map worker which applies to intermediate (key, value) pairs. The user can invoke the *Combiner* function inside the user program. The *Combiner* function runs the same code written by users for the *Reduce* function as its functionality is identical to it. The *Combiner* function merges the local data of each map worker before sending it over the network to effectively reduce its communication costs. As mentioned in our discussion of logical data flow, the MapReduce framework sorts and groups the data before it is processed by the *Reduce* function. Similarly, the MapReduce framework will also sort and group the local data on each map worker if the user invokes the *Combiner* function.
7. ***Partitioning* function** As mentioned in our discussion of the MapReduce data flow, the intermediate (key, value) pairs with identical keys are grouped together because all values inside each group should be processed by only one *Reduce* function to generate the final result. However, in real implementations, since there are *M* map and *R* reduce tasks, intermediate (key, value) pairs with the same key might be produced by different map tasks, although they should be grouped and processed together by one *Reduce* function only.
   Therefore, the intermediate (key, value) pairs produced by each map worker are partitioned into *R* regions, equal to the number of reduce tasks, by the *Partitioning* function to guarantee that all (key, value) pairs with identical keys are stored in the same region. As a result, since reduce worker *i* reads the data of region *i* of all map workers, all (key, value) pairs with the same key will be gathered by reduce worker *i* accordingly (see Figure 6.4). To implement this technique, a *Partitioning* function could simply be a hash function (e.g., *Hash*(*key*) *mod R*) that forwards the data into particular regions. It is also worth noting that the locations of the buffered data in these *R* partitions are sent to the master for later forwarding of data to the reduce workers.
   Figure 6.5 shows the data flow implementation of all data flow steps. The following are two networking steps:
8. **Synchronization** MapReduce applies a simple synchronization policy to coordinate map workers with reduce workers, in which the communication between them starts when all map tasks finish.

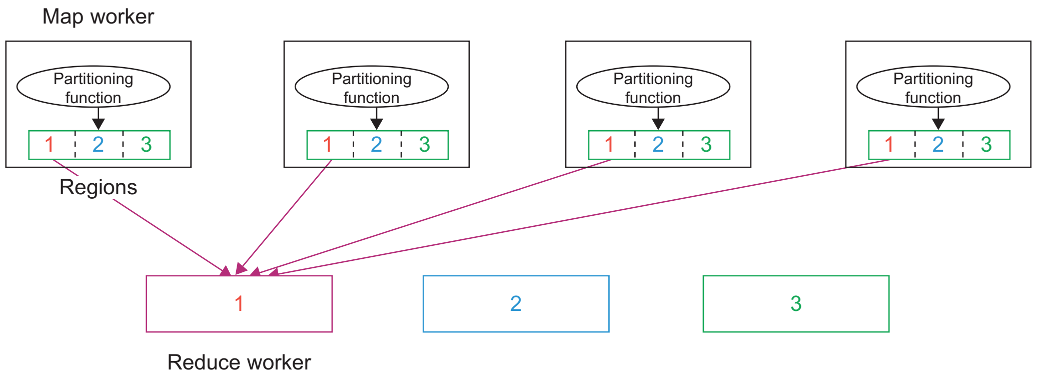


FIGURE 6.4

Use of MapReduce *partitioning* function to link the Map and Reduce workers.

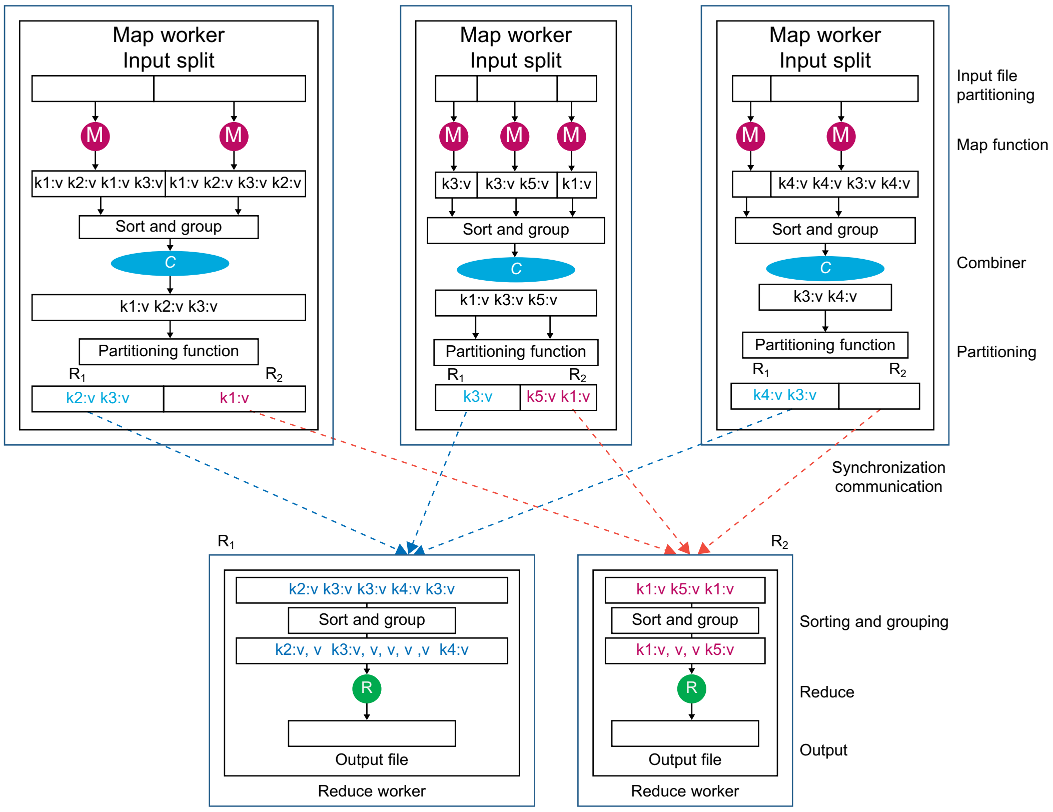


FIGURE 6.5

Data flow implementation of many functions in the Map workers and in the Reduce workers through multiple sequences of partitioning, combining, synchronization and communication, sorting and grouping, and reduce operations.

9. **Communication** Reduce worker *i*, already notified of the location of region *i* of all map workers, uses a remote procedure call to read the data from the respective region of all map workers. Since all reduce workers read the data from all map workers, all-to-all communication among all map and reduce workers, which incurs network congestion, occurs in the network. This issue is one of the major bottlenecks in increasing the performance of such systems [50–52]. A data transfer module was proposed to schedule data transfers independently [55].
   Steps 10 and 11 correspond to the reduce worker domain:
10. **Sorting and Grouping** When the process of reading the input data is finalized by a reduce worker, the data is initially buffered in the local disk of the reduce worker. Then the reduce worker groups intermediate (key, value) pairs by sorting the data based on their keys, followed by grouping all occurrences of identical keys. Note that the buffered data is sorted and grouped because the number of unique keys produced by a map worker may be more than *R* regions in which more than one key exists in each region of a map worker (see Figure 6.4).
11. ***Reduce* function** The reduce worker iterates over the grouped (key, value) pairs, and for each unique key, it sends the key and corresponding values to the *Reduce* function. Then this function processes its input data and stores the output results in predetermined files in the user's program.

To better clarify the interrelated data control and control flow in the MapReduce framework, Figure 6.6 shows the exact order of processing control in such a system contrasting with dataflow in Figure 6.5.

6.2.2.6 Compute-Data Affinity

The MapReduce software framework was first proposed and implemented by Google. The first implementation was coded in C. The implementation takes advantage of GFS [53] as the underlying layer. MapReduce could perfectly adapt itself to GFS. GFS is a distributed file system where files are divided into fixed-size blocks (chunks) and blocks are distributed and stored on cluster nodes.

As stated earlier, the MapReduce library splits the input data (files) into fixed-size blocks, and ideally performs the *Map* function in parallel on each block. In this case, as GFS has already stored files as a set of blocks, the MapReduce framework just needs to send a copy of the user's program containing the *Map* function to the nodes' already stored data blocks. This is the notion of sending computation toward data rather than sending data toward computation. Note that the default GFS block size is 64 MB which is identical to that of the MapReduce framework.

6.2.2.7 Twister and Iterative MapReduce

It is important to understand the performance of different runtimes and, in particular, to compare MPI and MapReduce [43,44,55,56]. The two major sources of parallel overhead are load imbalance and communication (which is equivalent to synchronization overhead as communication synchronizes parallel units [threads or processes] in Categories 2 and 6 of Table 6.10). The communication overhead in MapReduce can be quite high, for two reasons:

- MapReduce reads and writes via files, whereas MPI transfers information directly between nodes over the network.

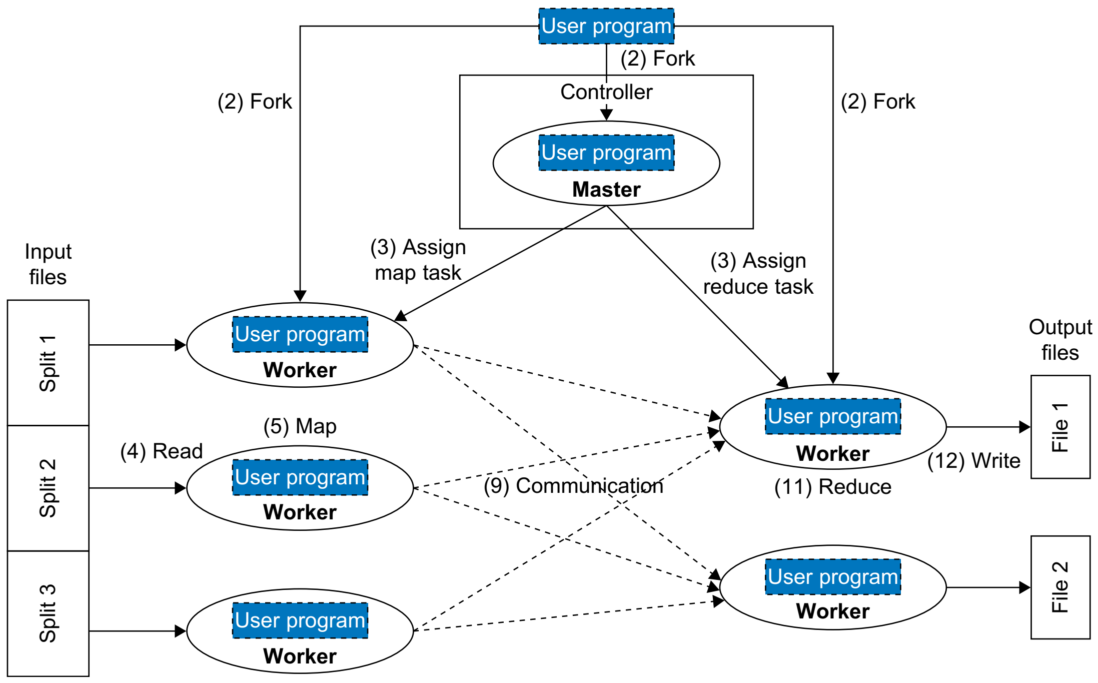


FIGURE 6.6

Control flow implementation of the MapReduce functionalities in Map workers and Reduce workers (running user programs) from input files to the output files under the control of the master user program.

(*Courtesy of Yahoo! Pig Tutorial [54]*)

- MPI does not transfer all data from node to node, but just the amount needed to update information. We can call the MPI flow *δ flow* and the MapReduce flow *full data flow*.

The same phenomenon is seen in all "classic parallel" loosely synchronous applications which typically exhibit an iteration structure over compute phases followed by communication phases. We can address the performance issues with two important changes:

1. Stream information between steps without writing intermediate steps to disk.
2. Use long-running threads or processors to communicate the δ (between iterations) flow.

These changes will lead to major performance increases at the cost of poorer fault tolerance and ease to support dynamic changes such as the number of available nodes. This concept [42] has been investigated in several projects [34,57–59] while the direct idea of using MPI for MapReduce applications is investigated in [44]. The Twister programming paradigm and its implementation architecture at run time are illustrated in Figure 6.7(a, b). In Example 6.1, we summarize Twister [60] whose performance results for K means are shown in Figure 6.8 [55,56], where Twister is much faster than traditional MapReduce. Twister distinguishes the static data which is never reloaded from the dynamic δ flow that is communicated.

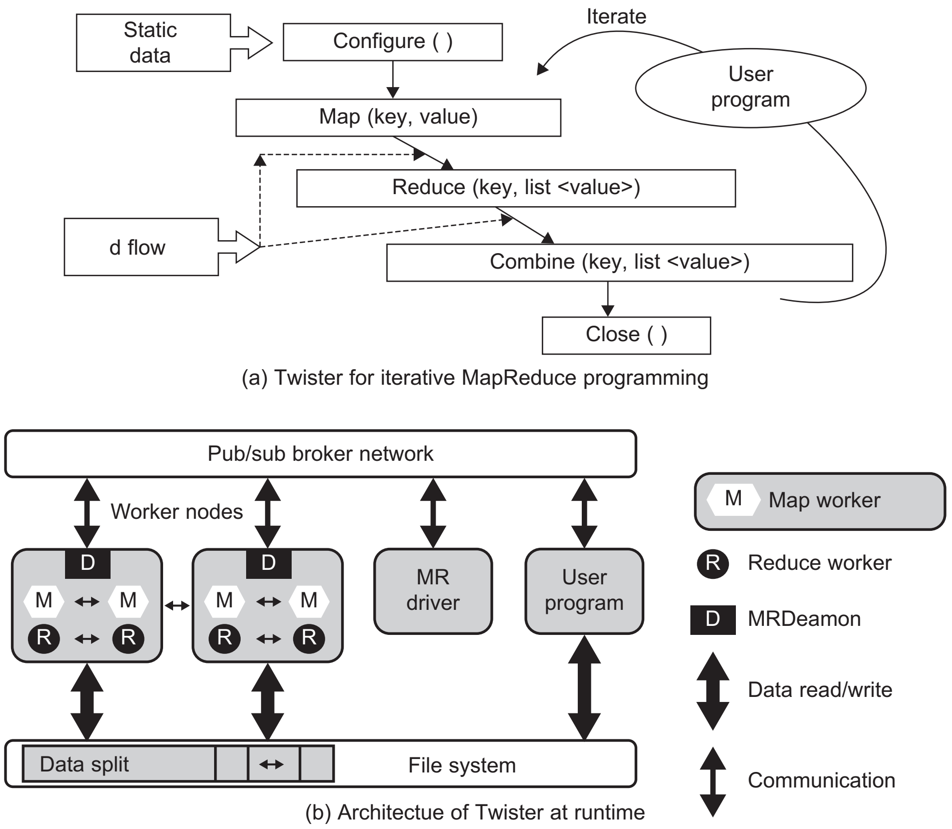


FIGURE 6.7

Twister: An iterative MapReduce programming paradigm for repeated MapReduce executions.

Example 6.1 Performance of K Means Clustering in MPI, Twister, Hadoop, and DryadLINQ

The MapReduce approach leads to fault tolerance and flexible scheduling, but for some applications the performance degradation compared to MPI is serious, as illustrated in Figure 6.8 for a simple parallel K means clustering algorithm. Hadoop and DryadLINQ are more than a factor of 10 slower than MPI for the largest data set, and perform even more poorly for smaller data sets. One could use many communication mechanisms in Iterative MapReduce, but Twister chose a publish-subscribe network using a distributed set of brokers, as described in Section 5.2 with similar performance achieved with ActiveMQ and NaradaBrokering.

The Map-Reduce pair is iteratively executed in long-running threads. We compare in Figure 6.9. the different thread and process structures of 4 parallel programming paradigms: namely Hadoop, Dryad, Twister (also called MapReduce++), and MPI. Note that Dryad can use pipes and avoids costly disk writing according to the original papers [26,27].

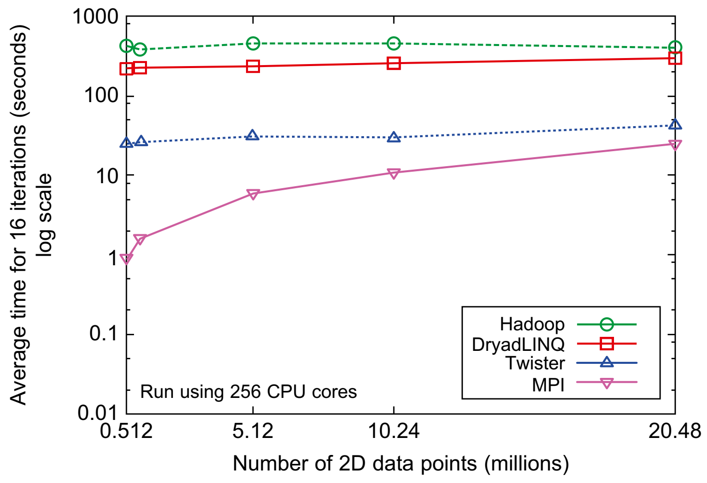
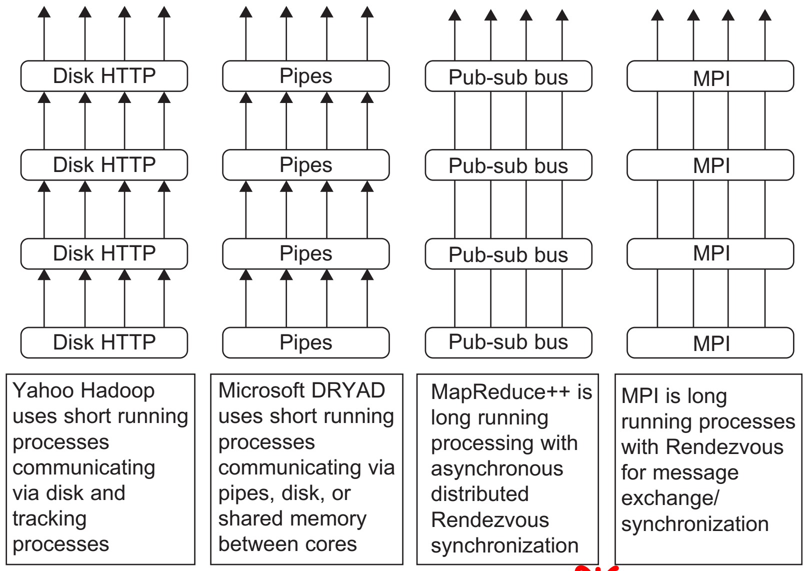


FIGURE 6.8

Performance of K means clustering for MPI, Twister, Hadoop, and DryadLINQ.



Disk HTTP
Disk HTTP
Disk HTTP
Disk HTTP
Pipes
Pipes
Pipes
Pipes
Pub-sub bus
Pub-sub bus
Pub-sub bus
Pub-sub bus
MPI
MPI
MPI
MPI
Yahoo Hadoop uses short running processes communicating via disk and tracking processes
Microsoft DRYAD uses short running processes communicating via pipes, disk, or shared memory between cores
MapReduce++ is long running processing with asynchronous distributed Rendezvous synchronization
MPI is long running processes with Rendezvous for message exchange/ synchronization

Twister

FIGURE 6.9

Thread and process structure of four parallel programming paradigms at runtimes.

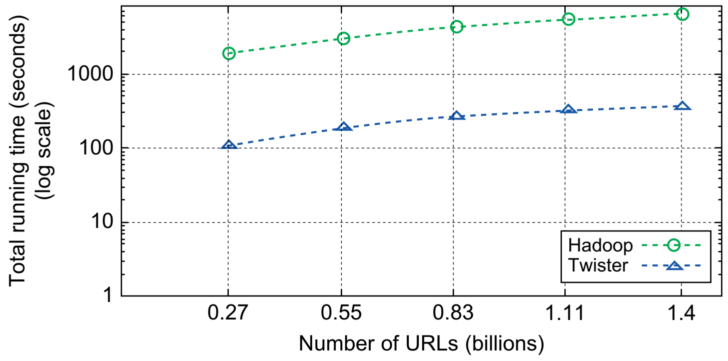


FIGURE 6.10

Performance of Hadoop and Twister on ClueWeb data set using 256 processing cores.

Example 6.2 Performance of Hadoop and Twister on ClueWeb Data Set over 256 Processor Cores

Important research areas for Iterative MapReduce include fault tolerance and scalable approaches to communication. Figure 6.10 shows [55] that iterative algorithms are found in information retrieval. This figure shows the famous Page Rank algorithm (with a kernel of iterative matrix vector multiplication) run on the public ClueWeb data sets, and independent of size, Twister is about 20 times faster than Hadoop as revealed by the gap between the top and lower curves in Figure 6.10.

6.2.3 Hadoop Library from Apache

Hadoop is an open source implementation of MapReduce coded and released in Java (rather than C) by Apache. The Hadoop implementation of MapReduce uses the *Hadoop Distributed File System (HDFS)* as its underlying layer rather than GFS. The Hadoop core is divided into two fundamental layers: the MapReduce engine and HDFS. The MapReduce engine is the computation engine running on top of HDFS as its data storage manager. The following two sections cover the details of these two fundamental layers.

HDFS: HDFS is a distributed file system inspired by GFS that organizes files and stores their data on a distributed computing system.

HDFS Architecture: HDFS has a master/slave architecture containing a single NameNode as the master and a number of DataNodes as workers (slaves). To store a file in this architecture, HDFS splits the file into fixed-size blocks (e.g., 64 MB) and stores them on workers (DataNodes). The mapping of blocks to DataNodes is determined by the NameNode. The NameNode (master) also manages the file system's metadata and namespace. In such systems, the namespace is the area maintaining the metadata, and metadata refers to all the information stored by a file system that is needed for overall management of all files. For example, NameNode in the metadata stores all information regarding the location of input splits/blocks in all DataNodes. Each DataNode, usually one per node in a cluster, manages the storage attached to the node. Each DataNode is responsible for storing and retrieving its file blocks [61].

HDFS Features: Distributed file systems have special requirements, such as performance, scalability, concurrency control, fault tolerance, and security requirements [62], to operate efficiently. However, because HDFS is not a general-purpose file system, as it only executes specific types of applications, it does not need all the requirements of a general distributed file system. For example, security has never been supported for HDFS systems. The following discussion highlights two important characteristics of HDFS to distinguish it from other generic distributed file systems [63].

HDFS Fault Tolerance: One of the main aspects of HDFS is its fault tolerance characteristic. Since Hadoop is designed to be deployed on low-cost hardware by default, a hardware failure in this system is considered to be common rather than an exception. Therefore, Hadoop considers the following issues to fulfill reliability requirements of the file system [64]:

- **Block replication** To reliably store data in HDFS, file blocks are replicated in this system. In other words, HDFS stores a file as a set of blocks and each block is replicated and distributed across the whole cluster. The replication factor is set by the user and is three by default.
- **Replica placement** The placement of replicas is another factor to fulfill the desired fault tolerance in HDFS. Although storing replicas on different nodes (DataNodes) located in different racks across the whole cluster provides more reliability, it is sometimes ignored as the cost of communication between two nodes in different racks is relatively high in comparison with that of different nodes located in the same rack. Therefore, sometimes HDFS compromises its reliability to achieve lower communication costs. For example, for the default replication factor of three, HDFS stores one replica in the same node the original data is stored, one replica on a different node but in the same rack, and one replica on a different node in a different rack to provide three copies of the data [65].
- **Heartbeat and Blockreport messages** Heartbeats and Blockreports are periodic messages sent to the NameNode by each DataNode in a cluster. Receipt of a Heartbeat implies that the DataNode is functioning properly, while each Blockreport contains a list of all blocks on a DataNode [65]. The NameNode receives such messages because it is the sole decision maker of all replicas in the system.

HDFS High-Throughput Access to Large Data Sets (Files): Because HDFS is primarily designed for batch processing rather than interactive processing, data access throughput in HDFS is more important than latency. Also, because applications run on HDFS typically have large data sets, individual files are broken into large blocks (e.g., 64 MB) to allow HDFS to decrease the amount of metadata storage required per file. This provides two advantages: The list of blocks per file will shrink as the size of individual blocks increases, and by keeping large amounts of data sequentially within a block, HDFS provides fast streaming reads of data.

HDFS Operation: The control flow of HDFS operations such as write and read can properly highlight roles of the NameNode and DataNodes in the managing operations. In this section, the control flow of the main operations of HDFS on files is further described to manifest the interaction between the user, the NameNode, and the DataNodes in such systems [63].

- **Reading a file** To read a file in HDFS, a user sends an "open" request to the NameNode to get the location of file blocks. For each file block, the NameNode returns the address of a set of DataNodes containing replica information for the requested file. The number of addresses depends on the number of block replicas. Upon receiving such information, the user calls the *read* function to connect to the closest DataNode containing the first block of the file. After the first block is streamed from the respective DataNode to the user, the established connection is terminated and the same process is repeated for all blocks of the requested file until the whole file is streamed to the user.
- **Writing to a file** To write a file in HDFS, a user sends a "create" request to the NameNode to create a new file in the file system namespace. If the file does not exist, the NameNode notifies the user and allows him to start writing data to the file by calling the *write* function. The first block of the file is written to an internal queue termed the data queue while a data streamer monitors its writing into a DataNode. Since each file block needs to be replicated by a predefined factor, the data streamer first sends a request to the NameNode to get a list of suitable DataNodes to store replicas of the first block.

The steamer then stores the block in the first allocated DataNode. Afterward, the block is forwarded to the second DataNode by the first DataNode. The process continues until all allocated DataNodes receive a replica of the first block from the previous DataNode. Once this replication process is finalized, the same process starts for the second block and continues until all blocks of the file are stored and replicated on the file system.

6.2.3.1 Architecture of MapReduce in Hadoop

The topmost layer of Hadoop is the MapReduce engine that manages the data flow and control flow of MapReduce jobs over distributed computing systems. Figure 6.11 shows the MapReduce engine architecture cooperating with HDFS. Similar to HDFS, the MapReduce engine also

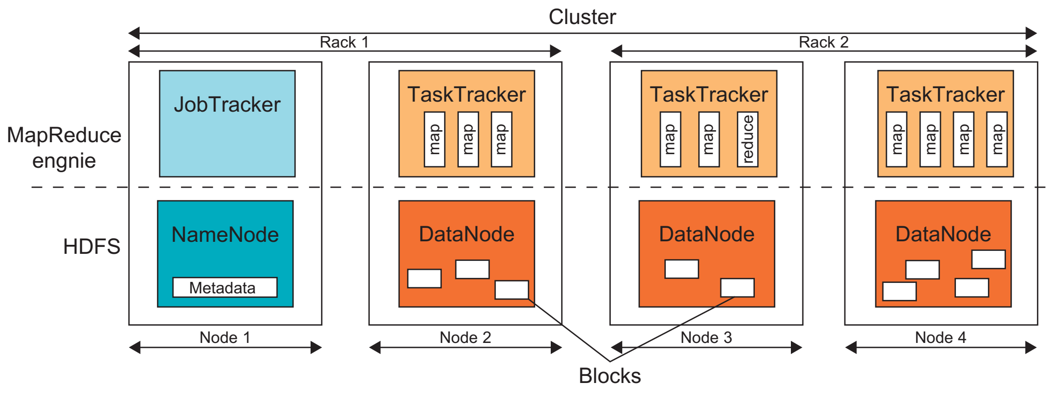


FIGURE 6.11

HDFS and MapReduce architecture in Hadoop where boxes with different shadings refer to different functional nodes applied to different blocks of data.

has a master/slave architecture consisting of a single JobTracker as the master and a number of TaskTrackers as the slaves (workers). The JobTracker manages the MapReduce job over a cluster and is responsible for monitoring jobs and assigning tasks to TaskTrackers. The TaskTracker manages the execution of the map and/or reduce tasks on a single computation node in the cluster.

Each TaskTracker node has a number of simultaneous execution slots, each executing either a map or a reduce task. Slots are defined as the number of simultaneous threads supported by CPUs of the TaskTracker node. For example, a TaskTracker node with *N* CPUs, each supporting *M* threads, has $M * N$ simultaneous execution slots [66]. It is worth noting that each data block is processed by one map task running on a single slot. Therefore, there is a one-to-one correspondence between map tasks in a TaskTracker and data blocks in the respective DataNode.

6.2.3.2 Running a Job in Hadoop

Three components contribute in running a job in this system: a user node, a JobTracker, and several TaskTrackers. The data flow starts by calling the *runJob(conf)* function inside a user program running on the user node, in which *conf* is an object containing some tuning parameters for the MapReduce framework and HDFS. The *runJob(conf)* function and *conf* are comparable to the *MapReduce(Spec, &Results)* function and *Spec* in the first implementation of MapReduce by Google. Figure 6.12 depicts the data flow of running a MapReduce job in Hadoop [63].

- **Job Submission** Each job is submitted from a user node to the JobTracker node that might be situated in a different node within the cluster through the following procedure:
- A user node asks for a new job ID from the JobTracker and computes input file splits.
- The user node copies some resources, such as the job's JAR file, configuration file, and computed input splits, to the JobTracker's file system.
- The user node submits the job to the JobTracker by calling the *submitJob()* function.
- **Task assignment** The JobTracker creates one map task for each computed input split by the user node and assigns the map tasks to the execution slots of the TaskTrackers. The JobTracker considers the localization of the data when assigning the map tasks to the TaskTrackers. The JobTracker

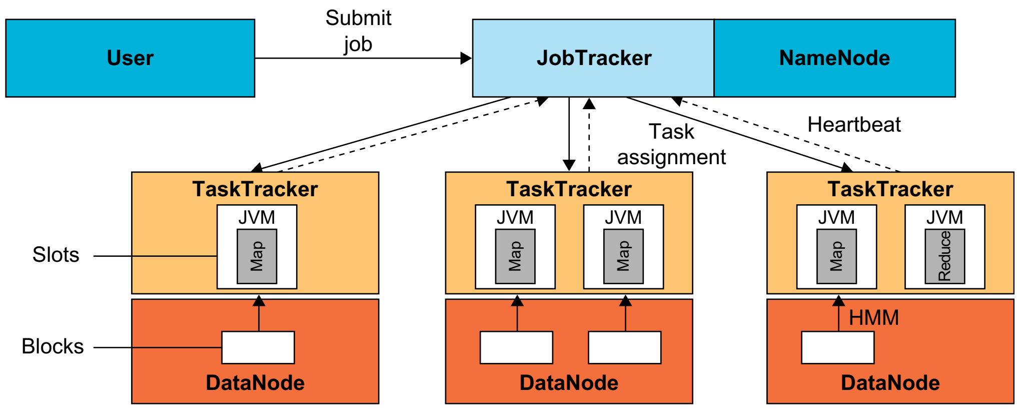


FIGURE 6.12

Data flow in running a MapReduce job at various task trackers using the Hadoop library.

also creates reduce tasks and assigns them to the TaskTrackers. The number of reduce tasks is predetermined by the user, and there is no locality consideration in assigning them.

- **Task execution** The control flow to execute a task (either map or reduce) starts inside the TaskTracker by copying the job JAR file to its file system. Instructions inside the job JAR file are executed after launching a Java Virtual Machine (JVM) to run its map or reduce task.
- **Task running check** A task running check is performed by receiving periodic heartbeat messages to the JobTracker from the TaskTrackers. Each heartbeat notifies the JobTracker that the sending TaskTracker is alive, and whether the sending TaskTracker is ready to run a new task.

6.2.4 Dryad and DryadLINQ from Microsoft

Two runtime software environments are reviewed in this section for parallel and distributed computing, namely the Dryad and DryadLINQ, both developed by Microsoft.

6.2.4.1 Dryad

Dryad is more flexible than MapReduce as the data flow of its applications is not dictated/predetermined and can be easily defined by users. To achieve such flexibility, a Dryad program or job is defined by a *directed acyclic graph* (DAG) where vertices are computation engines and edges are communication channels between vertices. Therefore, users or application developers can easily specify arbitrary DAGs to specify data flows in jobs.

Given a DAG, Dryad assigns the computational vertices to the underlying computation engines (cluster nodes) and controls the data flow through edges (communication between cluster nodes). Data partitioning, scheduling, mapping, synchronization, communication, and fault tolerance are major implementation details hidden by Dryad to facilitate its programming environment. Because the data flow of a job is arbitrary for this system, only the control flow of the runtime environment is further explained here. As shown in Figure 6.13(a), the two main components handling the control flow of Dryad are the job manager and the name server.

In Dryad, the distributed job is represented as a DAG where each vertex is a program and edges represent data channels. Thus, the whole job will be constructed by the application programmer who defines the processing procedures as well as the flow of data. This logical computation graph will be automatically mapped onto the physical nodes by the Dryad runtime. A Dryad job is controlled by the job manager, which is responsible for deploying the program to the multiple nodes in the cluster. It runs either within the computing cluster or as a process in the user's workstation which can access the cluster. The job manager has the code to construct the DAG as well as the library to schedule the work running on top of the available resources. Data transfer is done via channels without involving the job manager. Thus, the job manager should not be the performance bottleneck. In summary, the job manager

1. Constructs a job's communication graph (data flow graph) using the application-specific program provided by the user.
2. Collects the information required to map the data flow graph to the underlying resources (computation engine) from the name server.

The cluster has a name server which is used to enumerate all the available computing resources in the cluster. Thus, the job manager can contact the name server to get the topology of the whole

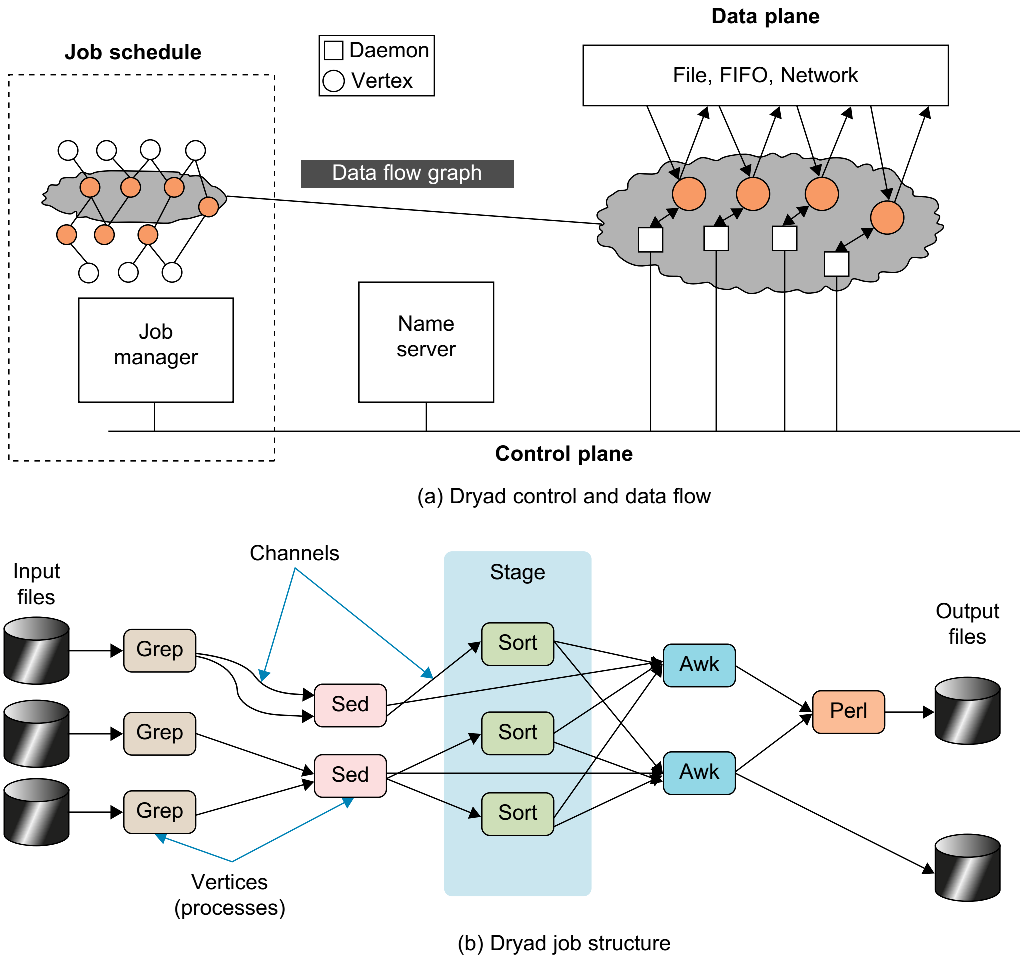


FIGURE 6.13

Dryad framework and its job structure, control and data flow.

(*Courtesy of Isard, et al., ACM SIGOPS Operating Systems Review, 2007* [26])

cluster and make scheduling decisions. A *processing daemon* runs in each computing node in the cluster. The binary of the program will be sent to the corresponding processing node directly from the job manager. The daemon can be viewed as a proxy so that the job manager can communicate with the remote vertices and monitor the state of the computation. By gathering this information, the name server provides the job manager with a perfect view of the underlying resources and network topology. Therefore, the job manager is able to:

1. Map the data flow graph to the underlying resources.
2. Schedule all necessary communications and synchronization *across* the respective resources.

It also considers data and computation locality when mapping the data flow graph to the underlying resources [26]. When the data flow graph is mapped on a set of computation engines, a light daemon runs on each cluster node to run the assigned tasks. Each task is defined by the user using an application-specific program. During runtime, the job manager communicates with each daemon to monitor the state of the computation of the node and its communication with its preceding and succeeding nodes. At runtime, the channels are used to transport the structured items between vertices which represent the processing programs. There are several types of communication mechanisms for implementing channels such as shared memory, TCP sockets, or even distributed file systems.

The execution of a Dryad job can be considered a 2D distributed set of pipes. Traditional UNIX pipes are 1D pipes, with each node in the pipe as a single program. Dryad's 2D distributed pipe system has multiple processing programs in each vertex node. In this way, large-scale data can be processed simultaneously. Figure 6.13(b) shows the Dryad 2D pipe job structure. During 2D pipe execution, Dryad defines many operations to construct and change the DAG dynamically. The operations include creating new vertices, adding graph edges, merging two graphs, as well as handling job input and output. Dryad also has a fault-tolerant mechanism built in. As it is built on a DAG, there are typically two types of failures: vertex failures and channel failures, which are handled differently.

As there are many nodes in the cluster, the job manager can choose another node to re-execute the corresponding job assigned to the failed node. In case of an edge failure, the vertex that created the channel will be re-executed and a new channel will be created and touch the corresponding nodes again. Dryad provides other mechanisms in addition to the runtime graph refinements which are used for improving execution performance. As a general framework, Dryad can be used in many situations, including scripting language support, map-reduce programming, and SQL service integration.

6.2.4.2 DryadLINQ from Microsoft

DryadLINQ is built on top of Microsoft's Dryad execution framework (see http://research.microsoft.com/en-us/projects/DryadLINQ/). Dryad can perform acyclic task scheduling and run on large-scale servers. The goal of DryadLINQ is to make large-scale, distributed cluster computing available to ordinary programmers. Actually, DryadLINQ, as the name implies, combines two important components: the Dryad distributed execution engine and .NET Language Integrated Query (LINQ). LINQ is particularly for users familiar with a database programming model. Figure 6.14 shows the flow of execution with DryadLINQ. The execution is divided into nine steps as follows:

1. A .NET user application runs, and creates a DryadLINQ expression object. Because of LINQ's deferred evaluation, the actual execution of the expression has not occurred.
2. The application calls *ToDryadTable* triggering a data-parallel execution. The expression object is handed to *DryadLINQ*.
3. DryadLINQ compiles the LINQ expression into a distributed Dryad execution plan. The expression is decomposed into subexpressions, each to be run in a separate Dryad vertex. Code and static data for the remote Dryad vertices are generated, followed by the serialization code for the required data types.
4. DryadLINQ invokes a custom Dryad job manager which is used to manage and monitor the execution flow of the corresponding task.
5. The job manager creates the job graph using the plan created in step 3. It schedules and spawns the vertices as resources become available.

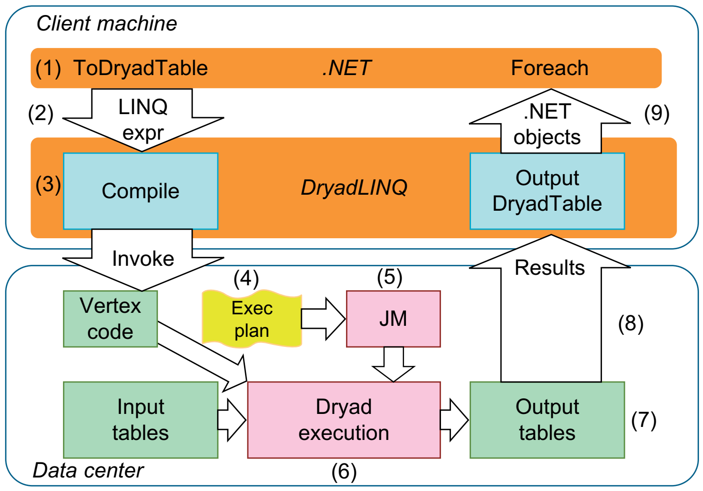


FIGURE 6.14

LINQ-expression execution in DryadLINQ.

(*Courtesy of Yu, et al. [27]*)

6. Each Dryad vertex executes a vertex-specific program.
7. When the Dryad job completes successfully it writes the data to the out table(s).
8. The job manager process terminates, and it returns control back to DryadLINQ. DryadLINQ creates the local *DryadTable* objects encapsulating the output of the execution. The *DryadTable* objects here might be the input to the next phase.
9. Control returns to the user application. The iterator interface over a DryadTable allows the user to read its contents as .NET objects.

Not all programs go through all nine steps. Some programs may go through fewer steps. Based on the preceding description, DryadLINQ enables users to integrate their current programming language (C#) with a compiler and a runtime execution engine. The following example shows how to write a histogram in DryadLINQ.

Example 6.3 A Histogram Written in DryadLINQ

We show a histogram program written in DryadLINQ for counting the frequency of each word in a text file. The entire program is listed here for readers to trace through to familiarize with the high-level language for Dryad programming. For details, the reader is referred to the article that introduces by Yu, et al. [27].

```
[Serializable]
public struct Pair {
  string word;
  int count;
```

```
    public Pair(string w, int c)
    {
      word = w;
      count = c;
    }
    public override string ToString() {
      return word + ":" + count.ToString();
    }
  }
  public static IQueryable<Pair> Histogram(
              string directory,
              string filename,
              int k)
  {
     DryadDataContext ddc = new DryadDataContext("file://" + directory);
     DryadTable<LineRecord> table =
                ddc.GetPartitionedTable<LineRecord>(filename);
     IQueryable<string> words =
           table.SelectMany(x => x.line.Split(' ').AsEnumerable());
     IQueryable<IGrouping<string, string>> groups = words.GroupBy(x => x);
     IQueryable<Pair> counts = groups.Select(x => new Pair(x.Key, x.Count()));
     IQueryable<Pair> ordered = counts.OrderByDescending(x => x.Count);
     IQueryable<Pair> top = ordered.Take(k);
     return top;
  }
```

Example 6.4 Sample Execution of a Histogram of the Word-Count Problem

The execution flow of such programs is very similar to the word-count program in the MapReduce framework. Table 6.6 shows how this program can be executed on a sample text input. Each row in the table presents the execution effect of each code line in the program. The execution of the program will go through all of the steps that a typical DryadLINQ program will involve.

Programmers do not have to worry about parallel execution of the program or consider fault tolerance. Scalability, reliability, and some other difficult issues involved in distributed systems are all hidden

Table 6.6 Sample Execution of Histogram

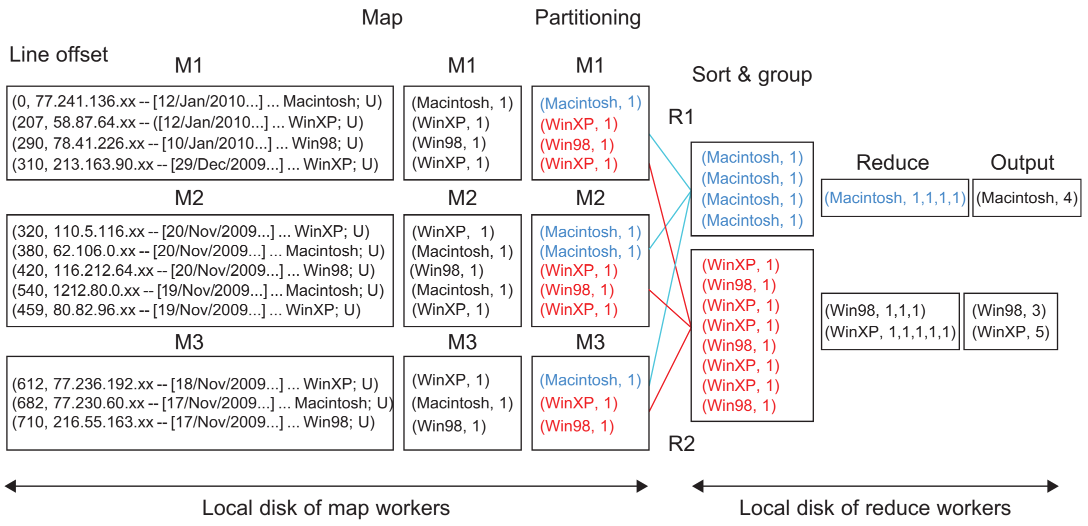
Operator	Output
Table	“A line of words of wisdom”
SelectMany	[“A”, “line”, “of”, “words”, “of”, “wisdom”]
GroupBy	[[“A”], [“line”], [“of”, “of”], [“words”], [“wisdom”]]
Select	[{“A”, 1}, {“line”, 1}, {“of”, 2}, {“words”, 1}, {“wisdom”, 1}]
OrderByDescending	[{“of”, 2}, {“A”, 1}, {“line”, 1}, {“words”, 1}, {“wisdom”, 1}]
Take(3)	[{“of”, 2}, {“A”, 1}, {“line”, 1}]

inside the DryadLINQ framework, and the programs are more concerned with the application program logic. This can greatly reduce the level of programming skill required for parallel data process programming.

Example 6.5 Hadoop Implementation of a MapReduce WebVisCounter Program

In this example, we present a practical MapReduce program coded in Hadoop. Called WebVisCounter, this sample program counts the number of times users connect to or visit a given web site using a particular operating system (e.g., Windows XP or Linux Ubuntu). The input data is shown here. A single line of a typical web server log file has eight fields separated by tabs or spaces with the following meanings:

1. **176.123.143.12** (IP address of the machine connected)
2. **–** (a separator)
3. **[10/Sep/2010:01:11:30-1100]** (A timestamp of the visit in the format: DD:Mon:YYYY HH:MM:SS, and the –11:00 is the offset from Greenwich Mean Time)
4. **"GET /gse/apply/int_research_app_form.pdf HTTP/1.0"** (GET requests the file, /gse/apply/int_research_app_form.pdf, using the HTTP/1.0 protocol)
5. **200** (The status code to reflect success of the user's request)
6. **1363148** (The number of bytes transferred)
7. **"http://www.eng.usyd.edu.au"** (User starts here before reaching server)
8. **"Mozilla/4.7[en](WinXp; U)"** (The browser used to get to the web site, the version of the browser, the language version, and the operating system)



Map
Partitioning
Line offset
M1
(0, 77.241.136.xx -- [12/Jan/2010...] ... Macintosh; U)
(207, 58.87.64.xx -- ([12/Jan/2010...] ... WinXP; U)
(290, 78.41.226.xx -- [10/Jan/2010...] ... Win98; U)
(310, 213.163.90.xx -- [29/Dec/2009...] ... WinXP; U)
M2
(320, 110.5.116.xx -- [20/Nov/2009...] ... WinXP; U)
(380, 62.106.0.xx -- [20/Nov/2009...] ... Macintosh; U)
(420, 116.212.64.xx -- [20/Nov/2009...] ... Win98; U)
(540, 1212.80.0.xx -- [19/Nov/2009...] ... Macintosh; U)
(459, 80.82.96.xx -- [19/Nov/2009...] ... WinXP; U)
M3
(612, 77.236.192.xx -- [18/Nov/2009...] ... WinXP; U)
(682, 77.230.60.xx -- [17/Nov/2009...] ... Macintosh; U)
(710, 216.55.163.xx -- [17/Nov/2009...] ... Win98; U)
(Macintosh, 1) (WinXP, 1) (Win98, 1) (WinXP, 1)
(WinXP, 1) (Macintosh, 1) (Win98, 1) (Macintosh, 1) (WinXP, 1)
(WinXP, 1) (Macintosh, 1) (Win98, 1)
(Macintosh, 1) (Macintosh, 1) (WinXP, 1) (Win98, 1) (WinXP, 1)
(Macintosh, 1) (WinXP, 1) (Win98, 1)
Sort & group
R1
R2
(Macintosh, 1) (Macintosh, 1) (Macintosh, 1) (Macintosh, 1)
(WinXP, 1) (Win98, 1) (WinXP, 1) (WinXP, 1) (Win98, 1) (WinXP, 1) (WinXP, 1) (Win98, 1)
Reduce
Output
(Macintosh, 1,1,1,1)
(Macintosh, 4)
(Win98, 1,1,1)
(WinXP, 1,1,1,1,1)
(Win98, 3)
(WinXP, 5)
Local disk of map workers
Local disk of reduce workers

FIGURE 6.15

Data flow in WebVisCounter program execution.

Because the output of interest is the number of times users connect to a given web site using a particular operating system, the *Map* function parses each line to extract the type of the operating system used (e.g.,*WinXp*) as a key and assigns a value (*1* in this case) to it. The *Reduce* function in turn sums up the number of *1*s for each unique key (operating system type in this case). Figure 6.15 shows the associated data flow for the WebVisCounter program.

6.2.5 Sawzall and Pig Latin High-Level Languages

Sawzall is a high-level language [31] built on top of Google's MapReduce framework. Sawzall is a scripting language that can do parallel data processing. As with MapReduce, Sawzall can do distributed, fault-tolerant processing of very large-scale data sets, even at the scale of the data collected from the entire Internet. Sawzall was developed by Rob Pike with an initial goal of processing Google's log files. In this regard it was hugely successful and changed a batch day-long enterprise into an interactive session, enabling new approaches to using such data to be developed. Figure 6.16 shows the overall model of data flow and processing procedures in the Sawzall framework. Sawzall has recently been released as an open source project.

First the data is partitioned and processed locally with an on-site processing script. The local data is filtered to get the necessary information. The aggregator is used to get the final results based on the emitted data. Many of Google's applications fit this model. Users write their applications using the Sawzall scripting language. The Sawzall runtime engine translates the corresponding scripts to MapReduce programs running on many nodes. The Sawzall program can harness the power of cluster computing automatically as well as attain reliability from redundant servers.

Example 6.6 The File Summary Program in Sawzall

Here is a simple example of using Sawzall for data processing on clusters (the example is from the Sawzall paper at [31]). Suppose we want to process a set of files with records in each file. Each record contains one floating-point number. We want to calculate the number of records, the sum of the values, and the sum of the squares of the values. The relevant code is as follows:

```
count: table sum of int;
total: table sum of float;
```

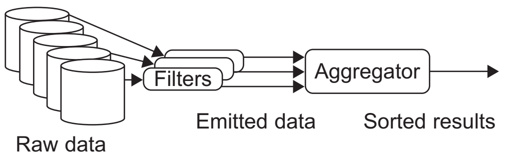


FIGURE 6.16

The overall flow of filtering, aggregating, and collating in Sawzall.

```
sum_of_squares: table sum of float;
x: float = input;
emit count <- 1;
emit total <- x;
emit sum_of_squares <- x * x;
```

The first three lines declare the aggregators as *count*, *total*, and *sum_of_squares*. *table* is a keyword which defines an aggregator type. These particular tables are *sum* tables and they will automatically add up the values emitted to them. For each input record, Sawzall initializes the predefined variable input to the uninterpreted byte string of the input. The line *x: float = input;* converts the input into a floating-point number and stores it in local variable *x*. The three *emit* statements send the intermediate values to the aggregators. One can translate the Sawzall scripts into MapReduce programs and run them with multiple servers.

■

6.2.5.1 Pig Latin

Pig Latin is a high-level data flow language developed by Yahoo! [33] that has been implemented on top of Hadoop in the Apache Pig project [67]. Pig Latin, Sawzall and DryadLINQ are different approaches to building languages on top of MapReduce and its extensions. They are compared in Table 6.7.

DryadLINQ is building directly on SQL while the other two languages are of NOSQL heritage, although Pig Latin supports major SQL constructs including Join, which is absent in Sawzall. Each language automates the parallelism, so you only think about manipulation of individual elements and then invoke supported collective operations. This is possible, of course, because needed parallelism can be cleanly implemented by independent tasks with "side effects" only presented in

Table 6.7 Comparison of High-Level Data Analysis Languages

	Sawzall	**Pig Latin**	**DryadLINQ**
Origin	Google	Yahoo!	Microsoft
Data Model	Google protocol buffer or basic	Atom, Tuple, Bag, Map	Partition file
Typing	Static	Dynamic	Static
Category	Interpreted	Compiled	Compiled
Programming Style	Imperative	Procedural: sequence of declarative steps	Imperative and declarative
Similarity to SQL	Least	Moderate	A lot!
Extensibility (User-Defined Functions)	No	Yes	Yes
Control Structures	Yes	No	Yes
Execution Model	Record operations + fixed aggregations	Sequence of MapReduce operations	DAGs
Target Runtime	Google MapReduce	Hadoop (Pig)	Dryad

Table 6.8 Pig Latin Data Types

Data Type	Description	Example
Atom	Simple atomic value	'Clouds'
Tuple	Sequence of fields of any Pig Latin type	('Clouds', 'Grids')
Bag	Collection of tuples with each member of the bag allowed a different schema	{ ('Clouds', 'Grids') ('Clouds', ('IaaS', 'PaaS')) }
Map	A collection of data items associated with a set of keys; the keys are a bag of atomic data	['Microsoft' → { ('Windows') ('Azure') } 'Redhat' → 'Linux']

Table 6.9 Pig Latin Operators

Command	Description
LOAD	Read data from the file system.
STORE	Write data to the file system.
FOREACH GENERATE	Apply an expression to each record and output one or more records.
FILTER	Apply a predicate and remove records that do not return true.
GROUP/COGROUP	Collect records with the same key from one or more inputs.
JOIN	Join two or more inputs based on a key.
CROSS	Cross product two or more inputs.
UNION	Merge two or more data sets.
SPLIT	Split data into two or more sets, based on filter conditions.
ORDER	Sort records based on a key.
DISTINCT	Remove duplicate tuples.
STREAM	Send all records through a user-provided binary.
DUMP	Write output to stdout.
LIMIT	Limit the number of records.

supported collective operations. This is an important general approach to parallelism and was seen, for example, a long time ago in High Performance Fortran [68]. There are several discussions of Pig and Pig Latin in the literature [69,70], and here we summarize the language features. Table 6.8 lists the four data types in Pig Latin and Table 6.9 the 14 operators.

Example 6.7 Parallel Programming with Sawzall and Pig Latin

First one would read in data with commands such as:

```
Queries = LOAD 'filewithdata.txt' USING myUDF() AS (userId, queryString, timestamp);
```

The *LOAD* command returns a handle to the bag *Queries*. *myUDF()* is an optional custom reader which is an example of a user-defined function. The *AS* syntax defines the schema of the tuples that make up the bag *Queries*. The data can now be processed by commands such as:

```
Expanded_queries = FOREACH queries GENERATE userID, expandQueryUDF(queryString);
```

The example maps each tuple in *queries* as determined by the user-defined function *expandQueryUDF. FOREACH* runs over all tuples in the bag. Alternatively, one could use *FILTER* as in the following example to remove all tuples with a *userID* equal to *Alice* as a string:

```
Real_queries = FILTER queries BY userID neq 'Alice';
```

Pig Latin offers the equivalent of a SQL JOIN capability using COGROUP as in

```
Grouped_data = COGROUP results BY queryString, revenue BY queryString;
```

Where results and revenue are bags of tuples (either from LOAD or processing of LOADed data)

```
Results: queryString, url, position)
Revenue: (queryString, adSlot, amount)
```

COGROUP is more general than *JOIN* in the sense that *COGROUP* does not produce a set of tuples (*queryString*, *url*, *position*, *adSlot*, *amount*), but rather a tuple consisting of three fields. The first field is *querystring*, the second field is all tuples from *Results* with the value of *querystring*, and the third field is all tuples from *Revenue* with the value of *queryString*. *FLATTEN* can map the result of *COGROUP* to SQL Join (*queryString*, *url*, *position*, *adSlot*, *amount*) syntax.

Pig Latin operations are performed in the order listed as a data flow pipeline. This is in contrast to declarative SQL where one just specifies "what" has to be done, not how it is to be done. Pig Latin supports user-defined functions, as illustrated in the preceding code, as first-class operations in the language which could be an advantage over SQL. User-defined functions can be placed in *Load*, *Store*, *Group*, *Filter*, and *Foreach* operators, depending on user preference. Note that the rich set of data flow operations allowed in Pig Latin makes it similar to a scripting approach to workflow, as we discussed in Section 5.5.5. The Pig! Apache project [69] maps Pig Latin into a sequence of MapReduce operations implemented in Hadoop.

6.2.6 Mapping Applications to Parallel and Distributed Systems

In the past, Fox has discussed mapping applications to different hardware and software in terms of five application architectures [71]. These initial five categories are listed in Table 6.10, followed by a sixth emerging category to describe data-intensive computing [72,73]. The original classifications largely described simulations and were not aimed directly at data analysis. It is instructive to briefly summarize them and then explain the new category. Category 1 was popular 20 years ago, but is no longer significant. It describes applications that can be parallelized with lock-step operations controlled by hardware.

Such a configuration would run on SIMD (*single-instruction and multiple-data*) machines, whereas category 2 is now much more important and corresponds to a SPMD (*single-program and multiple-data*) model running on MIMD (*multiple instruction multiple data*) machines. Here, each decomposed

Table 6.10 Application Classification for Parallel and Distributed Systems

Category	Class	Description	Machine Architecture
1	Synchronous	The problem class can be implemented with instruction-level lockstep operation as in SIMD architectures.	SIMD
2	Loosely synchronous (BSP or bulk synchronous processing)	These problems exhibit iterative compute-communication stages with independent compute (map) operations for each CPU that are synchronized with a communication step. This problem class covers many successful MPI applications including partial differential equation solutions and particle dynamics applications.	MIMD on MPP (massively parallel processor)
3	Asynchronous	Illustrated by Compute Chess and Integer Programming; combinatorial search is often supported by dynamic threads. This is rarely important in scientific computing, but it is at the heart of operating systems and concurrency in consumer applications such as Microsoft Word.	Shared memory
4	Pleasingly parallel	Each component is independent. In 1988, Fox estimated this at 20 percent of the total number of applications, but that percentage has grown with the use of grids and data analysis applications including, for example, the Large Hadron Collider analysis for particle physics.	Grids moving to clouds
5	Metaproblems	These are coarse-grained (asynchronous or data flow) combinations of categories 1-4 and 6. This area has also grown in importance and is well supported by grids and described by workflow in Section 3.5.	Grids of clusters
6	MapReduce++ (Twister)	This describes file (database) to file (database) operations which have three subcategories (see also Table 6.11): 6a) Pleasingly Parallel Map Only (similar to category 4) 6b) Map followed by reductions 6c) Iterative "Map followed by reductions" (extension of current technologies that supports linear algebra and data mining)	Data-intensive clouds a) Master-worker or MapReduce b) MapReduce c) Twister

unit executes the same program, but at any given time, there is no requirement that the same instruction be executed. Category 1 corresponds to regular problems, whereas category 2 includes dynamic irregular cases with complex geometries for solving partial differential equations or particle dynamics. Note that synchronous problems are still around, but they are run on MIMD machines with the SPMD model. Also note that category 2 consists of compute–communicate phases and the computations are synchronized by communication. No additional synchronization is needed.

Category 3 consists of asynchronously interacting objects and is often considered the people's view of a typical parallel problem. It probably does describe the concurrent threads in a modern operating system, as well as some important applications, such as event-driven simulations and areas such as search in computer games and graph algorithms. Shared memory is natural due to the low latency often needed to perform dynamic synchronization. It wasn't clear in the past, but now it appears that this category is not very common in large-scale parallel problems of importance.

Category 4 is the simplest algorithmically, with disconnected parallel components. However, the importance of this category has probably grown since the original 1988 analysis when it was estimated to account for 20 percent of all parallel computing. Both grids and clouds are very natural for this class, which does not need high-performance communication between different nodes.

Category 5 refers to the coarse-grained linkage of different "atomic" problems, and this was fully covered in Section 5.5. This area is clearly common and is expected to grow in importance. Remember the critical observation in Section 5.5 that we use a two-level programming model with the metaproblem (workflow) linkage specified in one fashion and the component problems with approaches such as those in this chapter. Grids or clouds are suitable for metaproblems as coarse-grained decomposition does not usually require stringent performance.

As noted earlier, we added a sixth category to cover data-intensive applications motivated by the clear importance of MapReduce as a new programming model. We call this category MapReduce++, and it has three subcategories: "map only" applications similar to pleasingly parallel category 4 [41,43,74,75]; the classic MapReduce with file-to-file operations consisting of parallel maps followed by parallel reduce operations; and a subcategory that captures the extended MapReduce version covered in Section 6.2.2. Note that category 6 is a subset of categories 2 and 4 with additional reading and writing of data and a specialized, loosely synchronous structure compared to that used in data analysis. This comparison is made clearer in Table 6.11.

6.3 PROGRAMMING SUPPORT OF GOOGLE APP ENGINE

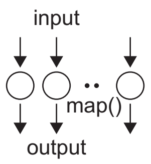
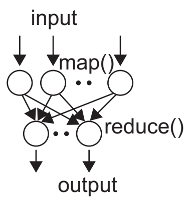
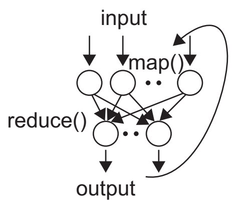
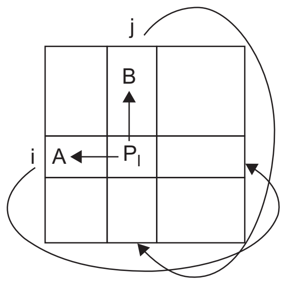
Section 4.4.2 introduced the Google App Engine infrastructure in Figures 4.20. In this section, we describe the programming model supported by GAE. The access links to the GAE platform are provided in Chapter 4.

6.3.1 Programming the Google App Engine

Several web resources (e.g., http://code.google.com/appengine/) and specific books and articles (e.g., www.byteonic.com/2009/overview-of-java-support-in-google-app-engine/) discuss how to program GAE. Figure 6.17 summarizes some key features of GAE programming model for two supported languages: Java and Python. A client environment that includes an *Eclipse* plug-in for Java allows you to debug your GAE on your local machine. Also, the GWT Google Web Toolkit is available for Java web application developers. Developers can use this, or any other language using a JVM-based interpreter or compiler, such as JavaScript or Ruby. Python is often used with frameworks such as Django and CherryPy, but Google also supplies a built in *webapp* Python environment.

There are several powerful constructs for storing and accessing data. The data store is a NOSQL data management system for entities that can be, at most, 1 MB in size and are labeled by a set of schema-less properties. Queries can retrieve entities of a given kind filtered and sorted by the values of the properties. Java offers Java Data Object (JDO) and Java Persistence API (JPA) interfaces implemented by the open source Data Nucleus Access platform, while Python has a SQL-like query language called GQL. The data store is strongly consistent and uses optimistic concurrency control.

Table 6.11 Comparison of MapReduce++ Subcategories along with the Loosely Synchronous Category Used in MPI

Map-Only	Classic MapReduce	Iterative MapReduce	Loosely Synchronous
			

• Document conversion (e.g., PDF->HTML)
• Brute force searches in cryptography
• Parametric sweeps
• Gene assembly
• PolarGrid Matlab data analysis (www.polargrid.org)
	• High-energy physics (HEP) histograms
	• Distributed search
	• Distributed sort
	• Information retrieval
	• Calculation of pairwise distances for sequences (BLAST)
		• Expectation maximization algorithms
		• Linear algebra
		• Data mining including
		  ◦ Clustering
		  ◦ K-means
		  ◦ Deterministic annealing clustering
		  ◦ Multidimensional scaling (MDS)
			• Many MPI scientific applications utilizing a wide variety of communication constructs including local interactions
			• Solving differential equations and particle dynamics with short-range forces

⟵ Domain of MapReduce and Iterative Extensions ⟶			**MPI**

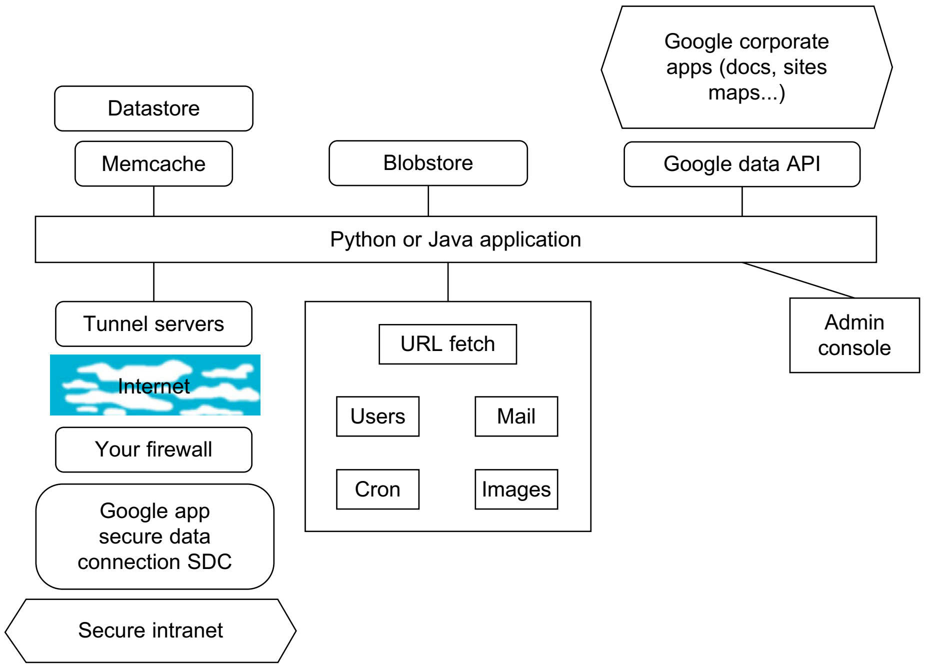


FIGURE 6.17

Programming environment for Google AppEngine.

An update of an entity occurs in a transaction that is retried a fixed number of times if other processes are trying to update the same entity simultaneously. Your application can execute multiple data store operations in a single transaction which either all succeed or all fail together. The data store implements transactions across its distributed network using "entity groups." A transaction manipulates entities within a single group. Entities of the same group are stored together for efficient execution of transactions. Your GAE application can assign entities to groups when the entities are created. The performance of the data store can be enhanced by in-memory caching using the *memcache*, which can also be used independently of the data store.

Recently, Google added the *blobstore* which is suitable for large files as its size limit is 2 GB. There are several mechanisms for incorporating external resources. The *Google SDC Secure Data Connection* can tunnel through the Internet and link your intranet to an external GAE application. The *URL Fetch* operation provides the ability for applications to fetch resources and communicate with other hosts over the Internet using HTTP and HTTPS requests. There is a specialized mail mechanism to send e-mail from your GAE application.

Applications can access resources on the Internet, such as web services or other data, using GAE's URL fetch service. The URL fetch service retrieves web resources using the same high-speed Google infrastructure that retrieves web pages for many other Google products. There are dozens of Google "corporate" facilities including maps, sites, groups, calendar, docs, and YouTube, among others. These support the *Google Data API* which can be used inside GAE.

An application can use Google Accounts for *user* authentication. Google Accounts handles user account creation and sign-in, and a user that already has a Google account (such as a Gmail account) can use that account with your app. GAE provides the ability to manipulate image data using a dedicated *Images* service which can resize, rotate, flip, crop, and enhance images. An application can perform tasks outside of responding to web requests. Your application can perform these tasks on a schedule that you configure, such as on a daily or hourly basis using "cron jobs," handled by the *Cron* service.

Alternatively, the application can perform tasks added to a queue by the application itself, such as a background task created while handling a request. A GAE application is configured to consume resources up to certain limits or quotas. With quotas, GAE ensures that your application won't exceed your budget, and that other applications running on GAE won't impact the performance of your app. In particular, GAE use is free up to certain quotas.

6.3.2 Google File System (GFS)

GFS was built primarily as the fundamental storage service for Google's search engine. As the size of the web data that was crawled and saved was quite substantial, Google needed a distributed file system to redundantly store massive amounts of data on cheap and unreliable computers. None of the traditional distributed file systems can provide such functions and hold such large amounts of data. In addition, GFS was designed for Google applications, and Google applications were built for GFS. In traditional file system design, such a philosophy is not attractive, as there should be a clear interface between applications and the file system, such as a POSIX interface.

There are several assumptions concerning GFS. One is related to the characteristic of the cloud computing hardware infrastructure (i.e., the high component failure rate). As servers are composed of inexpensive commodity components, it is the norm rather than the exception that concurrent failures will occur all the time. Another concerns the file size in GFS. GFS typically will hold a large number of huge files, each 100 MB or larger, with files that are multiple GB in size quite common. Thus, Google has chosen its file data block size to be 64 MB instead of the 4 KB in typical traditional file systems. The I/O pattern in the Google application is also special. Files are typically written once, and the write operations are often the appending data blocks to the end of files. Multiple appending operations might be concurrent. There will be a lot of large streaming reads and only a little random access. As for large streaming reads, highly sustained throughput is much more important than low latency.

Thus, Google made some special decisions regarding the design of GFS. As noted earlier, a 64 MB block size was chosen. Reliability is achieved by using replications (i.e., each chunk or data block of a file is replicated across more than three chunk servers). A single master coordinates access as well as keeps the metadata. This decision simplified the design and management of the whole cluster. Developers do not need to consider many difficult issues in distributed systems, such as distributed consensus. There is no data cache in GFS as large streaming reads and writes represent neither time nor space locality. GFS provides a similar, but not identical, POSIX file system accessing interface. The distinct difference is that the application can even see the physical location of file blocks. Such a scheme can improve the upper-layer applications. The customized API can simplify the problem and focus on Google applications.

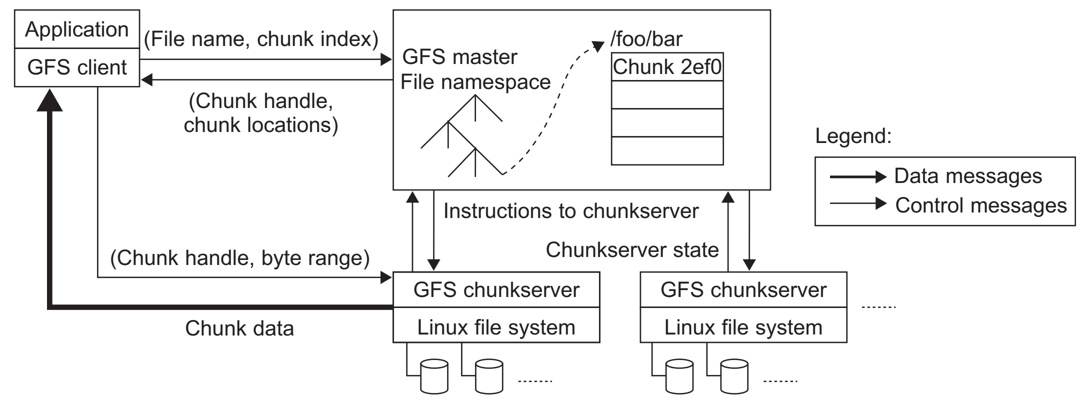


FIGURE 6.18

Architecture of Google File System (GFS).

(*Courtesy of S. Ghemawat, et al.* [53])

The customized API adds snapshot and record append operations to facilitate the building of Google applications.

Figure 6.18 shows the GFS architecture. It is quite obvious that there is a single master in the whole cluster. Other nodes act as the chunk servers for storing data, while the single master stores the metadata. The file system namespace and locking facilities are managed by the master. The master periodically communicates with the chunk servers to collect management information as well as give instructions to the chunk servers to do work such as load balancing or fail recovery.

The master has enough information to keep the whole cluster in a healthy state. With a single master, many complicated distributed algorithms can be avoided and the design of the system can be simplified. However, this design does have a potential weakness, as the single GFS master could be the performance bottleneck and the single point of failure. To mitigate this, Google uses a shadow master to replicate all the data on the master, and the design guarantees that all the data operations are performed directly between the client and the chunk server. The control messages are transferred between the master and the clients and they can be cached for future use. With the current quality of commodity servers, the single master can handle a cluster of more than 1,000 nodes.

Figure 6.19 shows the data mutation (write, append operations) in GFS. Data blocks must be created for

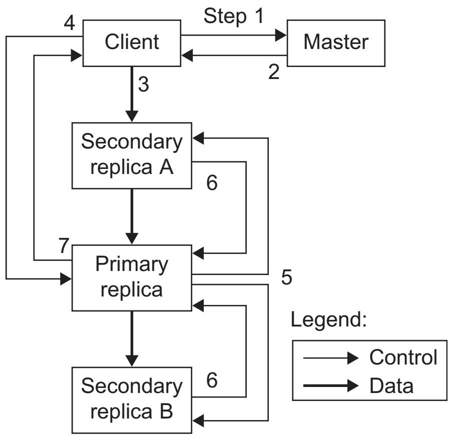


FIGURE 6.19

Data mutation sequence in GFS.

all replicas. The goal is to minimize involvement of the master. The mutation takes the following steps:

1. The client asks the master which chunk server holds the current lease for the chunk and the locations of the other replicas. If no one has a lease, the master grants one to a replica it chooses (not shown).
2. The master replies with the identity of the primary and the locations of the other (secondary) replicas. The client caches this data for future mutations. It needs to contact the master again only when the primary becomes unreachable or replies that it no longer holds a lease.
3. The client pushes the data to all the replicas. A client can do so in any order. Each chunk server will store the data in an internal LRU buffer cache until the data is used or aged out. By decoupling the data flow from the control flow, we can improve performance by scheduling the expensive data flow based on the network topology regardless of which chunk server is the primary.
4. Once all the replicas have acknowledged receiving the data, the client sends a write request to the primary. The request identifies the data pushed earlier to all the replicas. The primary assigns consecutive serial numbers to all the mutations it receives, possibly from multiple clients, which provides the necessary serialization. It applies the mutation to its own local state in serial order.
5. The primary forwards the write request to all secondary replicas. Each secondary replica applies mutations in the same serial number order assigned by the primary.
6. The secondaries all reply to the primary indicating that they have completed the operation.
7. The primary replies to the client. Any errors encountered at any replicas are reported to the client. In case of errors, the write corrects at the primary and an arbitrary subset of the secondary replicas. The client request is considered to have failed, and the modified region is left in an inconsistent state. Our client code handles such errors by retrying the failed mutation. It will make a few attempts at steps 3 through 7 before falling back to a retry from the beginning of the write.

Thus, besides the writing operation provided by GFS, special appending operations can be used to append the data blocks to the end of the files. The reason for providing such operations is that some of the Google applications need a lot of append operations. For example, while crawlers are gathering data from the web, the contents of web pages will be appended to page files. Thus, the appending operation is provided and optimized. The client specifies data to be appended and GFS appends it to the file atomically at least once. GFS picks the offset and the clients cannot decide the offset of the data position. The appending operation works for concurrent writers.

GFS was designed for high fault tolerance and adopted some methods to achieve this goal. Master and chunk servers can be restarted in a few seconds, and with such a fast recovery capability, the window of time in which the data is unavailable can be greatly reduced. As we mentioned before, each chunk is replicated in at least three places and can tolerate at least two data crashes for a single chunk of data. The shadow master handles the failure of the GFS master. For data integrity, GFS makes checksums on every 64 KB block in each chunk. With the previously discussed design and implementation, GFS can achieve the goals of high availability (HA), high performance, and large scale. GFS demonstrates how to support large-scale processing workloads on commodity hardware designed to tolerate frequent component failures optimized for huge files that are mostly appended and read.

6.3.3 BigTable, Google's NOSQL System

In this section, we continue discussing key technologies in the Google cloud environment. We already discussed the most well-known Google technology, MapReduce, in Section 6.2.2, and Sawzall in Section 6.2.5. Here, we focus on another innovative Google technology: BigTable. We will cover Chubby in Section 6.3.4 and covered GFS in previous section. BigTable was designed to provide a service for storing and retrieving structured and semistructured data. BigTable applications include storage of web pages, per-user data, and geographic locations. Here we use web pages to represent URLs and their associated data, such as contents, crawled metadata, links, anchors, and page rank values. Per-user data has information for a specific user and includes such data as user preference settings, recent queries/search results, and the user's e-mails. Geographic locations are used in Google's well-known Google Earth software. Geographic locations include physical entities (shops, restaurants, etc.), roads, satellite image data, and user annotations.

The scale of such data is incredibly large. There will be billions of URLs, and each URL can have many versions, with an average page size of about 20 KB per version. The user scale is also huge. There are hundreds of millions of users and there will be thousands of queries per second. The same scale occurs in the geographic data, which might consume more than 100 TB of disk space.

It is not possible to solve such a large scale of structured or semistructured data using a commercial database system. This is one reason to rebuild the data management system; the resultant system can be applied across many projects for a low incremental cost. The other motivation for rebuilding the data management system is performance. Low-level storage optimizations help increase performance significantly, which is much harder to do when running on top of a traditional database layer.

The design and implementation of the BigTable system has the following goals. The applications want asynchronous processes to be continuously updating different pieces of data and want access to the most current data at all times. The database needs to support very high read/write rates and the scale might be millions of operations per second. Also, the database needs to support efficient scans over all or interesting subsets of data, as well as efficient joins of large one-to-one and one-to-many data sets. The application may need to examine data changes over time (e.g., contents of a web page over multiple crawls).

Thus, BigTable can be viewed as a distributed multilevel map. It provides a fault-tolerant and persistent database as in a storage service. The BigTable system is scalable, which means the system has thousands of servers, terabytes of in-memory data, petabytes of disk-based data, millions of reads/writes per second, and efficient scans. Also, BigTable is a self-managing system (i.e., servers can be added/removed dynamically and it features automatic load balancing). Design/initial implementation of BigTable began at the beginning of 2004. BigTable is used in many projects, including Google Search, Orkut, and Google Maps/Google Earth, among others. One of the largest BigTable cell manages ~200 TB of data spread over several thousand machines.

The BigTable system is built on top of an existing Google cloud infrastructure. BigTable uses the following building blocks:

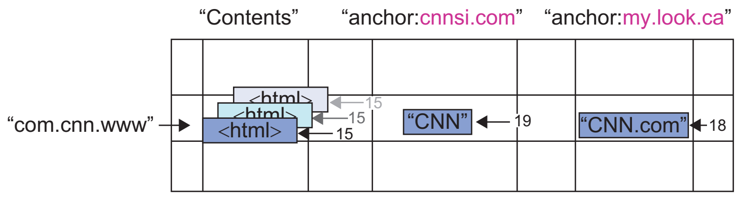
1. GFS: stores persistent state
2. Scheduler: schedules jobs involved in BigTable serving
3. Lock service: master election, location bootstrapping
4. MapReduce: often used to read/write BigTable data

Example 6.8 BigTable Data Model Used in Mass Media

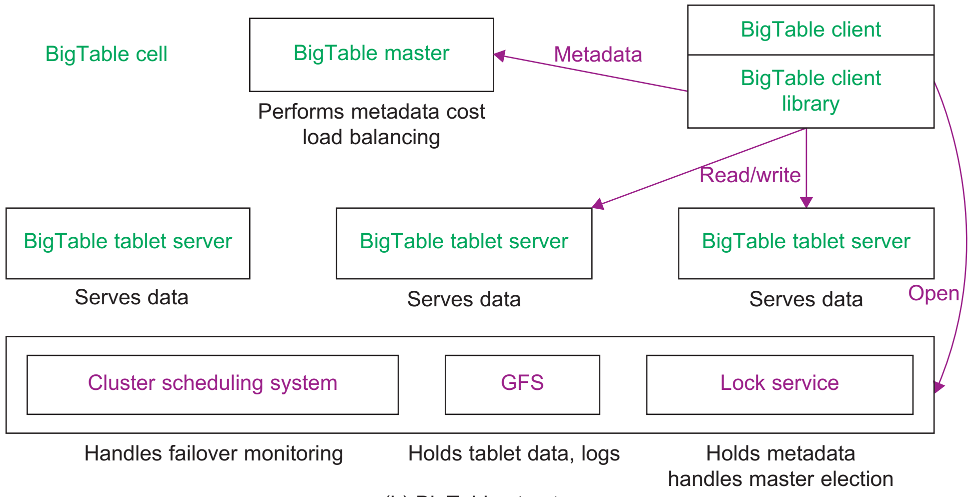
BigTable provides a simplified data model compared to traditional database systems. Figure 6.20(a) shows the data model of a sample table, Web Table. Web Table stores the data about a web page. Each web page can be accessed by the URL. The URL is considered the row index. The column provides different data related to the corresponding URL—for example, different versions of the contents, and the anchors appearing in the web page. In this sense, BigTable is a distributed multidimensional stored sparse map.

The map is indexed by row key, column key, and timestamp—that is, (row: string, column: string, time: int64) maps to string (cell contents). Rows are ordered in lexicographic order by row key. The row range for a table is dynamically partitioned and each row range is called "Tablet." Syntax for columns is shown as a (family:qualifier) pair. Cells can store multiple versions of data with timestamps.

Such a data model is a good match for most of Google's (and other organizations') applications. For rows, *Name* is an arbitrary string and access to data in a row is atomic. This is different from the traditional



(a) BigTable data model



(b) BigTable structure

FIGURE 6.20

BigTable data model and system structure.

(*Courtesy of Chang, et al.* [11])

relational database which provides abundant atomic operations (transactions). Row creation is implicit upon storing data. Rows are ordered lexicographically, that is, close together lexicographically, usually on one or a small number of machines.

Large tables are broken into tablets at row boundaries. A tablet holds a contiguous range of rows. Clients can often choose row keys to achieve locality. The system aims for about 100 MB to 200 MB of data per tablet. Each serving machine is responsible for about 100 tablets. This can achieve faster recovery times as 100 machines each pick up one tablet from the failed machine. This also results in fine-grained load balancing, that is, migrating tablets away from the overloaded machine. Similar to the design in GFS, a master machine in BigTable makes load-balancing decisions.

Figure 6.20(b) shows the BigTable system structure. A BigTable master manages and stores the metadata of the BigTable system. BigTable clients use the BigTable client programming library to communicate with the BigTable master and tablet servers. BigTable relies on a highly available and persistent distributed lock service called Chubby [76] discussed in Section 6.3.4.

6.3.3.1 Tablet Location Hierarchy

Figure 6.21 shows how to locate the BigTable data starting from the file stored in Chubby. The first level is a file stored in Chubby that contains the location of the root tablet. The root tablet contains the location of all tablets in a special METADATA table. Each METADATA tablet contains the location of a set of user tablets. The root tablet is just the first tablet in the METADATA table, but is treated specially; it is never split to ensure that the tablet location hierarchy has no more than three levels.

The METADATA table stores the location of a tablet under a row key that is an encoding of the tablet's table identifier and its end row. BigTable includes many optimizations and fault-tolerant features. Chubby can guarantee the availability of the file for finding the root tablet. The BigTable master can quickly scan the tablet servers to determine the status of all nodes. Tablet servers use

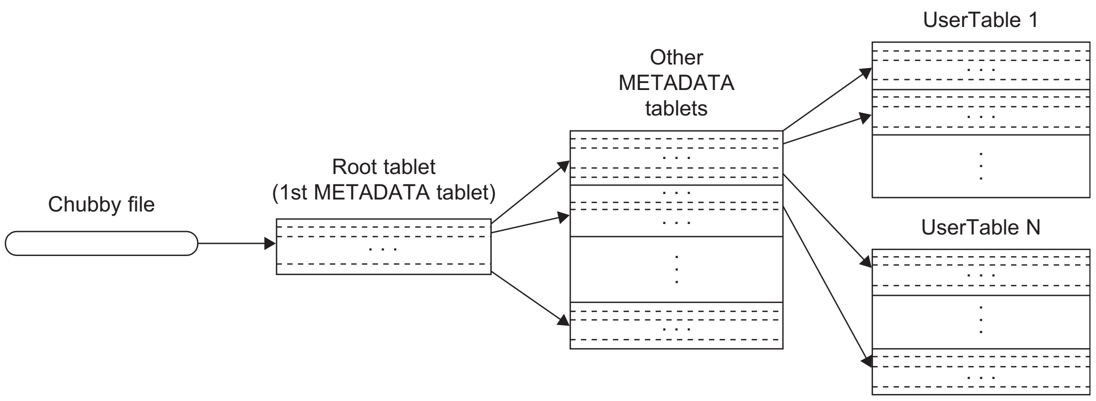


FIGURE 6.21

Tablet location hierarchy in using the BigTable.

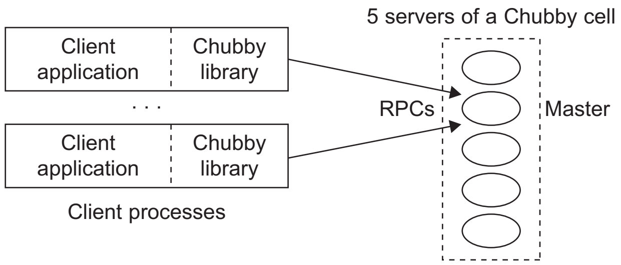


FIGURE 6.22

Structure of Google Chubby for distributed lock service.

compaction to store data efficiently. Shared logs are used for logging the operations of multiple tablets so as to reduce the log space as well as keep the system consistent.

6.3.4 Chubby, Google's Distributed Lock Service

Chubby [76] is intended to provide a coarse-grained locking service. It can store small files inside Chubby storage which provides a simple namespace as a file system tree. The files stored in Chubby are quite small compared to the huge files in GFS. Based on the Paxos agreement protocol, the Chubby system can be quite reliable despite the failure of any member node. Figure 6.22 shows the overall architecture of the Chubby system.

Each Chubby cell has five servers inside. Each server in the cell has the same file system namespace. Clients use the Chubby library to talk to the servers in the cell. Client applications can perform various file operations on any server in the Chubby cell. Servers run the Paxos protocol to make the whole file system reliable and consistent. Chubby has become Google's primary internal name service. GFS and BigTable use Chubby to elect a primary from redundant replicas.

6.4 PROGRAMMING ON AMAZON AWS AND MICROSOFT AZURE

In this section, we will consider the programming support in the AWS platform. First we will review the AWS platform and its updated service offerings. Then we will study the EC2, S3, and Simple DB services with programming examples. Returning to the programming environment features in Figures 4.22 and 4.23, Amazon (like Azure) offers a Relational Database Service (RDS) with a messaging interface sketched in Section 6.1.3. The Elastic MapReduce capability is equivalent to Hadoop running on the basic EC2 offering. Amazon has NOSQL support in SimpleDB introduced in Section 6.1.3 and discussed in Section 6.4.5. However, Amazon does not directly support BigTable as described in Section 6.3.4.

Now we will highlight a few more capabilities that are listed in Table 4.6. Amazon offers the Simple Queue Service (SQS) and Simple Notification Service (SNS), which are the cloud implementations of services discussed in Sections 5.2 and 5.4.5. Note that brokering systems run very efficiently in clouds and offer a striking model for controlling sensors and giving back-office support