workers executing reduce tasks are notified of the re-execution. Any reduce task that has not already read the data from worker A will read the data from worker B.

MapReduce is resilient to large-scale worker failures. For example, during one MapReduce operation, network maintenance on a running cluster was causing groups of 80 machines at a time to become unreachable for several minutes. The MapReduce master simply re-executed the work done by the unreachable worker machines, and continued to make forward progress, eventually completing the MapReduce operation.

Master Failure

It is easy to make the master write periodic checkpoints of the master data structures described above. If the master task dies, a new copy can be started from the last checkpointed state. However, given that there is only a single master, its failure is unlikely; therefore our current implementation aborts the MapReduce computation if the master fails. Clients can check for this condition and retry the MapReduce operation if they desire.

Semantics in the Presence of Failures

When the user-supplied *map* and *reduce* operators are deterministic functions of their input values, our distributed implementation produces the same output as would have been produced by a non-faulting sequential execution of the entire program.

We rely on atomic commits of map and reduce task outputs to achieve this property. Each in-progress task writes its output to private temporary files. A reduce task produces one such file, and a map task produces R such files (one per reduce task). When a map task completes, the worker sends a message to the master and includes the names of the R temporary files in the message. If the master receives a completion message for an already completed map task, it ignores the message. Otherwise, it records the names of R files in a master data structure.

When a reduce task completes, the reduce worker atomically renames its temporary output file to the final output file. If the same reduce task is executed on multiple machines, multiple rename calls will be executed for the same final output file. We rely on the atomic rename operation provided by the underlying file system to guarantee that the final file system state contains just the data produced by one execution of the reduce task.

The vast majority of our *map* and *reduce* operators are deterministic, and the fact that our semantics are equivalent to a sequential execution in this case makes it very easy for programmers to reason about their program's behavior. When the *map* and/or *reduce* operators are non-deterministic, we provide weaker but still reasonable semantics. In the presence of non-deterministic operators, the output of a particular reduce task R_1 is equivalent to the output for R_1 produced by a sequential execution of the non-deterministic program. However, the output for a different reduce task R_2 may correspond to the output for R_2 produced by a different sequential execution of the non-deterministic program.

Consider map task M and reduce tasks R_1 and R_2. Let $e(R_i)$ be the execution of R_i that committed (there is exactly one such execution). The weaker semantics arise because $e(R_1)$ may have read the output produced by one execution of M and $e(R_2)$ may have read the output produced by a different execution of M.

3.4 Locality

Network bandwidth is a relatively scarce resource in our computing environment. We conserve network bandwidth by taking advantage of the fact that the input data (managed by GFS [8]) is stored on the local disks of the machines that make up our cluster. GFS divides each file into 64 MB blocks, and stores several copies of each block (typically 3 copies) on different machines. The MapReduce master takes the location information of the input files into account and attempts to schedule a map task on a machine that contains a replica of the corresponding input data. Failing that, it attempts to schedule a map task near a replica of that task's input data (e.g., on a worker machine that is on the same network switch as the machine containing the data). When running large MapReduce operations on a significant fraction of the workers in a cluster, most input data is read locally and consumes no network bandwidth.

3.5 Task Granularity

We subdivide the map phase into M pieces and the reduce phase into R pieces, as described above. Ideally, M and R should be much larger than the number of worker machines. Having each worker perform many different tasks improves dynamic load balancing, and also speeds up recovery when a worker fails: the many map tasks it has completed can be spread out across all the other worker machines.

There are practical bounds on how large M and R can be in our implementation, since the master must make $O(M + R)$ scheduling decisions and keeps $O(M * R)$ state in memory as described above. (The constant factors for memory usage are small however: the $O(M * R)$ piece of the state consists of approximately one byte of data per map task/reduce task pair.)

Furthermore, R is often constrained by users because the output of each reduce task ends up in a separate output file. In practice, we tend to choose M so that each individual task is roughly 16 MB to 64 MB of input data (so that the locality optimization described above is most effective), and we make R a small multiple of the number of worker machines we expect to use. We often perform MapReduce computations with $M = 200,000$ and $R = 5,000$, using 2,000 worker machines.

3.6 Backup Tasks

One of the common causes that lengthens the total time taken for a MapReduce operation is a "straggler": a machine that takes an unusually long time to complete one of the last few map or reduce tasks in the computation. Stragglers can arise for a whole host of reasons. For example, a machine with a bad disk may experience frequent correctable errors that slow its read performance from 30 MB/s to 1 MB/s. The cluster scheduling system may have scheduled other tasks on the machine, causing it to execute the MapReduce code more slowly due to competition for CPU, memory, local disk, or network bandwidth. A recent problem we experienced was a bug in machine initialization code that caused processor caches to be disabled: computations on affected machines slowed down by over a factor of one hundred.

We have a general mechanism to alleviate the problem of stragglers. When a MapReduce operation is close to completion, the master schedules backup executions of the remaining *in-progress* tasks. The task is marked as completed whenever either the primary or the backup execution completes. We have tuned this mechanism so that it typically increases the computational resources used by the operation by no more than a few percent. We have found that this significantly reduces the time to complete large MapReduce operations. As an example, the sort program described in Section 5.3 takes 44% longer to complete when the backup task mechanism is disabled.

4 Refinements

Although the basic functionality provided by simply writing *Map* and *Reduce* functions is sufficient for most needs, we have found a few extensions useful. These are described in this section.

4.1 Partitioning Function

The users of MapReduce specify the number of reduce tasks/output files that they desire (R). Data gets partitioned across these tasks using a partitioning function on the intermediate key. A default partitioning function is provided that uses hashing (e.g. "$hash(key)$ **mod** R"). This tends to result in fairly well-balanced partitions. In some cases, however, it is useful to partition data by some other function of the key. For example, sometimes the output keys are URLs, and we want all entries for a single host to end up in the same output file. To support situations like this, the user of the MapReduce library can provide a special partitioning function. For example, using "$hash(Hostname(urlkey))$ **mod** R" as the partitioning function causes all URLs from the same host to end up in the same output file.

4.2 Ordering Guarantees

We guarantee that within a given partition, the intermediate key/value pairs are processed in increasing key order. This ordering guarantee makes it easy to generate a sorted output file per partition, which is useful when the output file format needs to support efficient random access lookups by key, or users of the output find it convenient to have the data sorted.

4.3 Combiner Function

In some cases, there is significant repetition in the intermediate keys produced by each map task, and the user-specified *Reduce* function is commutative and associative. A good example of this is the word counting example in Section 2.1. Since word frequencies tend to follow a Zipf distribution, each map task will produce hundreds or thousands of records of the form `<the, 1>`. All of these counts will be sent over the network to a single reduce task and then added together by the *Reduce* function to produce one number. We allow the user to specify an optional *Combiner* function that does partial merging of this data before it is sent over the network.

The *Combiner* function is executed on each machine that performs a map task. Typically the same code is used to implement both the combiner and the reduce functions. The only difference between a reduce function and a combiner function is how the MapReduce library handles the output of the function. The output of a reduce function is written to the final output file. The output of a combiner function is written to an intermediate file that will be sent to a reduce task.

Partial combining significantly speeds up certain classes of MapReduce operations. Appendix A contains an example that uses a combiner.

4.4 Input and Output Types

The MapReduce library provides support for reading input data in several different formats. For example, "text" mode input treats each line as a key/value pair: the key is the offset in the file and the value is the contents of the line. Another common supported format stores a sequence of key/value pairs sorted by key. Each input type implementation knows how to split itself into meaningful ranges for processing as separate map tasks (e.g. text mode's range splitting ensures that range splits occur only at line boundaries). Users can add support for a new input type by providing an implementation of a simple *reader* interface, though most users just use one of a small number of predefined input types.

A *reader* does not necessarily need to provide data read from a file. For example, it is easy to define a *reader* that reads records from a database, or from data structures mapped in memory.

In a similar fashion, we support a set of output types for producing data in different formats and it is easy for user code to add support for new output types.

4.5 Side-effects

In some cases, users of MapReduce have found it convenient to produce auxiliary files as additional outputs from their map and/or reduce operators. We rely on the application writer to make such side-effects atomic and idempotent. Typically the application writes to a temporary file and atomically renames this file once it has been fully generated.

We do not provide support for atomic two-phase commits of multiple output files produced by a single task. Therefore, tasks that produce multiple output files with cross-file consistency requirements should be deterministic. This restriction has never been an issue in practice.

4.6 Skipping Bad Records

Sometimes there are bugs in user code that cause the *Map* or *Reduce* functions to crash deterministically on certain records. Such bugs prevent a MapReduce operation from completing. The usual course of action is to fix the bug, but sometimes this is not feasible; perhaps the bug is in a third-party library for which source code is unavailable. Also, sometimes it is acceptable to ignore a few records, for example when doing statistical analysis on a large data set. We provide an optional mode of execution where the MapReduce library detects which records cause deterministic crashes and skips these records in order to make forward progress.

Each worker process installs a signal handler that catches segmentation violations and bus errors. Before invoking a user *Map* or *Reduce* operation, the MapReduce library stores the sequence number of the argument in a global variable. If the user code generates a signal, the signal handler sends a "last gasp" UDP packet that contains the sequence number to the MapReduce master. When the master has seen more than one failure on a particular record, it indicates that the record should be skipped when it issues the next re-execution of the corresponding Map or Reduce task.

4.7 Local Execution

Debugging problems in *Map* or *Reduce* functions can be tricky, since the actual computation happens in a distributed system, often on several thousand machines, with work assignment decisions made dynamically by the master. To help facilitate debugging, profiling, and small-scale testing, we have developed an alternative implementation of the MapReduce library that sequentially executes all of the work for a MapReduce operation on the local machine. Controls are provided to the user so that the computation can be limited to particular map tasks. Users invoke their program with a special flag and can then easily use any debugging or testing tools they find useful (e.g. `gdb`).

4.8 Status Information

The master runs an internal HTTP server and exports a set of status pages for human consumption. The status pages show the progress of the computation, such as how many tasks have been completed, how many are in progress, bytes of input, bytes of intermediate data, bytes of output, processing rates, etc. The pages also contain links to the standard error and standard output files generated by each task. The user can use this data to predict how long the computation will take, and whether or not more resources should be added to the computation. These pages can also be used to figure out when the computation is much slower than expected.

In addition, the top-level status page shows which workers have failed, and which map and reduce tasks they were processing when they failed. This information is useful when attempting to diagnose bugs in the user code.

4.9 Counters

The MapReduce library provides a counter facility to count occurrences of various events. For example, user code may want to count total number of words processed or the number of German documents indexed, etc.

To use this facility, user code creates a named counter object and then increments the counter appropriately in the *Map* and/or *Reduce* function. For example:

```
Counter* uppercase;
uppercase = GetCounter("uppercase");

map(String name, String contents):
  for each word w in contents:
    if (IsCapitalized(w)):
      uppercase->Increment();
    EmitIntermediate(w, "1");
```

The counter values from individual worker machines are periodically propagated to the master (piggybacked on the ping response). The master aggregates the counter values from successful map and reduce tasks and returns them to the user code when the MapReduce operation is completed. The current counter values are also displayed on the master status page so that a human can watch the progress of the live computation. When aggregating counter values, the master eliminates the effects of duplicate executions of the same map or reduce task to avoid double counting. (Duplicate executions can arise from our use of backup tasks and from re-execution of tasks due to failures.)

Some counter values are automatically maintained by the MapReduce library, such as the number of input key/value pairs processed and the number of output key/value pairs produced.

Users have found the counter facility useful for sanity checking the behavior of MapReduce operations. For example, in some MapReduce operations, the user code may want to ensure that the number of output pairs produced exactly equals the number of input pairs processed, or that the fraction of German documents processed is within some tolerable fraction of the total number of documents processed.

5 Performance

In this section we measure the performance of MapReduce on two computations running on a large cluster of machines. One computation searches through approximately one terabyte of data looking for a particular pattern. The other computation sorts approximately one terabyte of data.

These two programs are representative of a large subset of the real programs written by users of MapReduce – one class of programs shuffles data from one representation to another, and another class extracts a small amount of interesting data from a large data set.

5.1 Cluster Configuration

All of the programs were executed on a cluster that consisted of approximately 1800 machines. Each machine had two 2GHz Intel Xeon processors with Hyper-Threading enabled, 4GB of memory, two 160GB IDE disks, and a gigabit Ethernet link. The machines were arranged in a two-level tree-shaped switched network with approximately 100-200 Gbps of aggregate bandwidth available at the root. All of the machines were in the same hosting facility and therefore the round-trip time between any pair of machines was less than a millisecond.

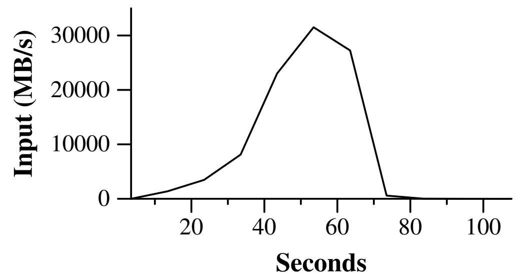


Figure 2: Data transfer rate over time

Out of the 4GB of memory, approximately 1-1.5GB was reserved by other tasks running on the cluster. The programs were executed on a weekend afternoon, when the CPUs, disks, and network were mostly idle.

5.2 Grep

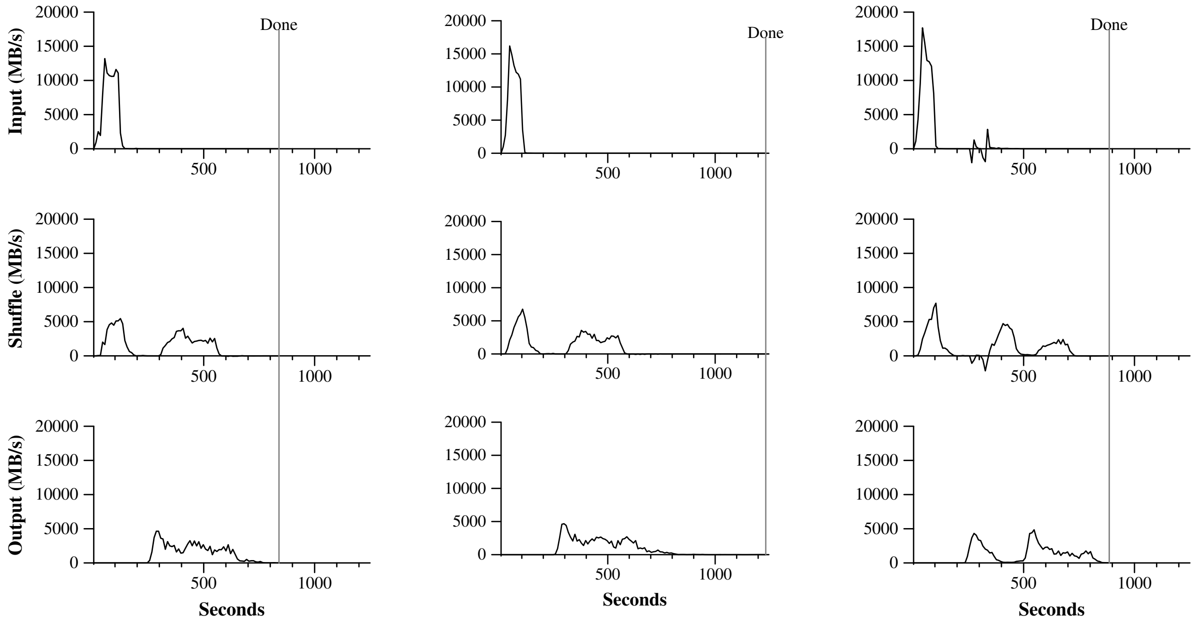
The *grep* program scans through 10^{10} 100-byte records, searching for a relatively rare three-character pattern (the pattern occurs in 92,337 records). The input is split into approximately 64MB pieces ($M = 15000$), and the entire output is placed in one file ($R = 1$).

Figure 2 shows the progress of the computation over time. The Y-axis shows the rate at which the input data is scanned. The rate gradually picks up as more machines are assigned to this MapReduce computation, and peaks at over 30 GB/s when 1764 workers have been assigned. As the map tasks finish, the rate starts dropping and hits zero about 80 seconds into the computation. The entire computation takes approximately 150 seconds from start to finish. This includes about a minute of startup overhead. The overhead is due to the propagation of the program to all worker machines, and delays interacting with GFS to open the set of 1000 input files and to get the information needed for the locality optimization.

5.3 Sort

The *sort* program sorts 10^{10} 100-byte records (approximately 1 terabyte of data). This program is modeled after the TeraSort benchmark [10].

The sorting program consists of less than 50 lines of user code. A three-line *Map* function extracts a 10-byte sorting key from a text line and emits the key and the



(a) Normal execution (b) No backup tasks (c) 200 tasks killed

Figure 3: Data transfer rates over time for different executions of the sort program

original text line as the intermediate key/value pair. We used a built-in *Identity* function as the *Reduce* operator. This functions passes the intermediate key/value pair unchanged as the output key/value pair. The final sorted output is written to a set of 2-way replicated GFS files (i.e., 2 terabytes are written as the output of the program).

As before, the input data is split into 64MB pieces ($M = 15000$). We partition the sorted output into 4000 files ($R = 4000$). The partitioning function uses the initial bytes of the key to segregate it into one of R pieces.

Our partitioning function for this benchmark has built-in knowledge of the distribution of keys. In a general sorting program, we would add a pre-pass MapReduce operation that would collect a sample of the keys and use the distribution of the sampled keys to compute split-points for the final sorting pass.

Figure 3 (a) shows the progress of a normal execution of the sort program. The top-left graph shows the rate at which input is read. The rate peaks at about 13 GB/s and dies off fairly quickly since all map tasks finish before 200 seconds have elapsed. Note that the input rate is less than for *grep*. This is because the sort map tasks spend about half their time and I/O bandwidth writing intermediate output to their local disks. The corresponding intermediate output for grep had negligible size.

The middle-left graph shows the rate at which data is sent over the network from the map tasks to the reduce tasks. This shuffling starts as soon as the first map task completes. The first hump in the graph is for the first batch of approximately 1700 reduce tasks (the entire MapReduce was assigned about 1700 machines, and each machine executes at most one reduce task at a time). Roughly 300 seconds into the computation, some of these first batch of reduce tasks finish and we start shuffling data for the remaining reduce tasks. All of the shuffling is done about 600 seconds into the computation.

The bottom-left graph shows the rate at which sorted data is written to the final output files by the reduce tasks. There is a delay between the end of the first shuffling period and the start of the writing period because the machines are busy sorting the intermediate data. The writes continue at a rate of about 2-4 GB/s for a while. All of the writes finish about 850 seconds into the computation. Including startup overhead, the entire computation takes 891 seconds. This is similar to the current best reported result of 1057 seconds for the TeraSort benchmark [18].

A few things to note: the input rate is higher than the shuffle rate and the output rate because of our locality optimization – most data is read from a local disk and bypasses our relatively bandwidth constrained network. The shuffle rate is higher than the output rate because the output phase writes two copies of the sorted data (we make two replicas of the output for reliability and availability reasons). We write two replicas because that is the mechanism for reliability and availability provided by our underlying file system. Network bandwidth requirements for writing data would be reduced if the underlying file system used erasure coding [14] rather than replication.