Workload Dependent Hadoop MapReduce Application Performance Modeling

Introduction

In any distributed computing environment, performance optimization, job runtime predictions, or capacity and scalability quantification studies are considered as being rather complex, time-consuming and expensive while the results are normally rather error-prone. Based on the nature of the Hadoop MapReduce framework, many MapReduce production applications are executed against varying data-set sizes [5]. Hence, one pressing question of any Hadoop MapReduce setup is how to quantify the job completion time based on the varying data-set sizes and the physical and logical cluster resources at hand. Further, if the job completion time is not meeting the goals and objectives, does any Hadoop tuning or cluster resource adjustments result into altering the job execution time to actually meet the required SLA's.

This paper presents a modeling based approach to address these questions in the most efficient and effective manner possible. The models incorporate the actual MapReduce dataflow, the physical and logical cluster resource setup, and derives actual performance cost functions used to quantify the aggregate performance behavior. The results of the project disclose that based on the conducted benchmarks, the Hadoop MapReduce models quantify the job execution time of varying benchmark datasets with a description error of less than 8%. Further, the models can be used to tune/optimize a production Hadoop environment (based on the actual workload at hand) as well as to conduct capacity and scalability studies with varying HW configurations.

The MapReduce Execution Framework

MapReduce reflects a programming model and an associated implementation for processing and generating large data-sets [6][9]. User specified map functions processes a [key, value] pair to generate a set of intermediate [key, value] pairs while user specified reduce functions merge all intermediate values associated with the same intermediate key. Many (but not all) real-world application tasks fit this programming model and hence can be executed in a Hadoop MapReduce environment. As MapReduce applications are designed to compute large volumes of data in a parallel fashion, it is necessary to decompose the workload among a large number of systems. This (functional programming) model would not scale to a large node count if the components were allowed to share data arbitrarily. The necessary communication overhead to keep the data on the nodes synchronized at all times would prevent the system from performing reliably and efficiently at large node counts. Instead, all data elements in MapReduce are immutable, implying that they cannot be updated per se. Assuming that a map task would change an input [key, value] pair, the change would not be reflected in the input files. In other words, communication only occurs by generating new output [key, value] pairs that are forwarded by the Hadoop system into the next phase of execution (see Figure 1).

The MapReduce framework was developed at Google in 2004 by Jeffrey Dean and Sanjay Ghemawat and has its roots in functional languages such as Lisp (Lisp has been around since 1958) or

ML (the Meta-Language was developed in the early 1970's). In Lisp, the map function accepts (as parameters) a function and a set of values. That function is then applied to each of the values. To illustrate, *(map 'length '(() (abc) (abcd) (abcde)))* applies the length function to each of the items in the list. As length returns the length of an item, the result of the map task represents a list containing the length of each item, *(0 3 4 5).* The reduce function (labeled fold in Lisp) is provided with a binary function and a set of values as parameters. It combines all the values together using the binary function. If the reduce function uses the + (add) function to reduce the list, such as *(reduce #'+ '(0 3 4 5)),* the result of the reduce function would be 12. Analyzing the map operation, it is obvious that each application of the function to a value can be performed in parallel (concurrently), as there is no dependency concern. The reduce operation on the other hand can only take place after the map phase is completed.

To reiterate, the Hadoop MapReduce programming model consists of a map[k1, v1] and a reduce[key2, list(v2)] function, respectively. Users can implement their own processing logic by developing customized map and reduce functions in a general-purpose programming language such as C, Java, or Python. The map[k1, v1] function is invoked for every key-value pair in the input data. The reduce[k2, list(v2)] function is invoked for every unique key(k2) and corresponding values list(v2) in the map output. The reduce[k2, list(v2)] function generates 0 or more key-value pairs of form [k3, v3]. The MapReduce programming model further supports functions such as partition[k2] to control how the map output key-value pairs are partitioned among the reduce tasks, or combine[k2 , list(v2)] to perform partial aggregation on the map side. The keys k1, k2, and k3 as well as the values v1, v2, and v3 can be of different and arbitrary types. So conceptually, Hadoop MapReduce programs transform lists of input data elements into lists of output data elements. A MapReduce program may do this twice, by utilizing the 2 discussed list processing idioms map and reduce [1]. A Hadoop MapReduce MRv1 cluster reflects a master-slave design where 1 master node (labeled the JobTracker) manages a number of slave nodes (known as the TaskTrackers)[12]. Please see Appendix B for a discussion on the new MRv2 framework. Hadoop basically initiates a MapReduce job by first splitting the input dataset into *n* data splits. Each data split is scheduled onto 1 TaskTracker node and is processed by a map task. An actual Task Scheduler governs the scheduling of the map tasks (with a focus on data locality). Each TaskTracker is configured with a predefined number of task execution slots for processing the map (reduce) tasks [8]. If the application (the job) generates more map (reduce) tasks than there are available slots, the map (reduce) tasks will have to be processed in multiple waves. As map tasks complete, the run-time system groups all intermediate key-value pairs via an external sort-merge algorithm. The intermediate data is then shuffled (basically transferred) to the TaskTracker nodes that are scheduled to execute the reduce tasks. Ultimately, the reduce tasks process the intermediate data and ergo generate the results of the Hadoop MapReduce job. Studying and analyzing the Map and Reduce task execution framework disclosed 5 and 4 distinct processing phases, respectively (see Figure 1). In other words, the Map task can be decomposed in:

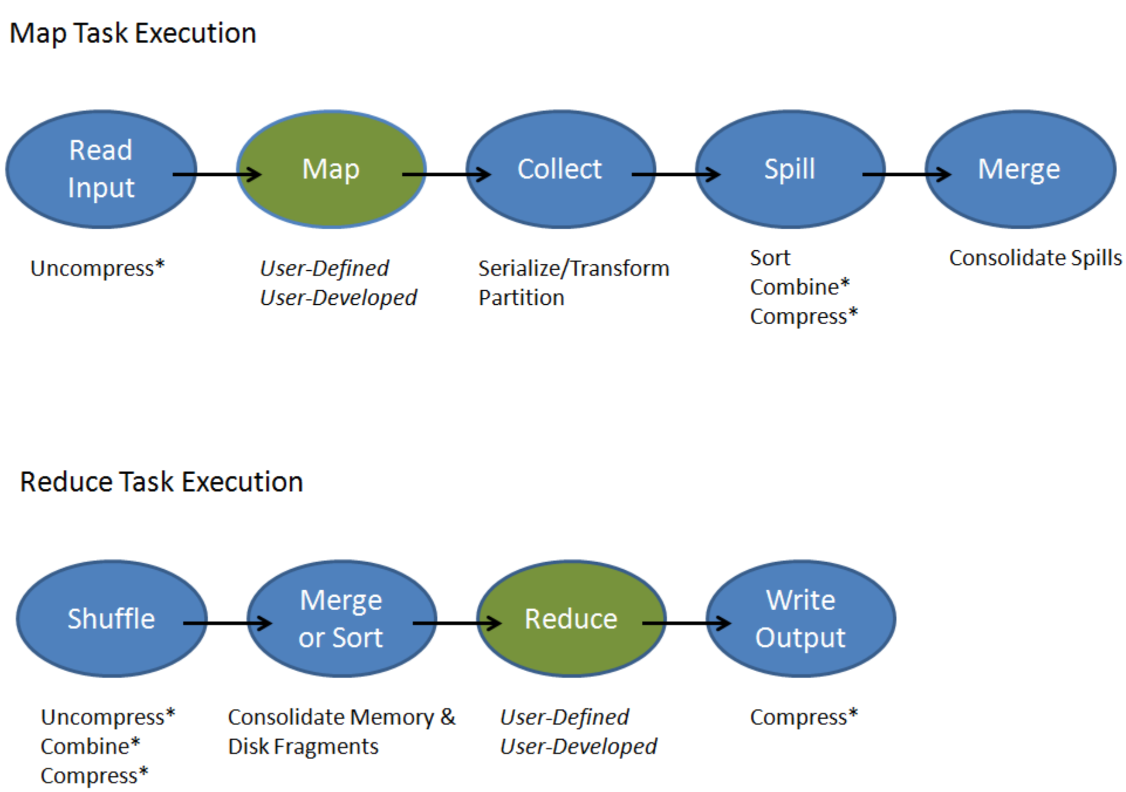
1. A *read phase* where the input split is loaded from HDFS (Hadoop file system [13]) and the input key-value pairs (records) are generated.

2. A *map phase* where the user-defined and user-developed map function is processed to generate the map-output data.
3. A *collect phase*, focusing on partitioning and collecting the intermediate (map output) data into a buffer prior to the spilling phase.
4. A *spill phase* where (if specified) sorting via a combine function and/or data compression may occur. In this phase, the data is moved into the local disk subsystem (the spill files).
5. A merge phase where the file spills are consolidated into a single map output file. The merging process may have to be performed in multiple iterations.

The Reduce task can be carved-up into:

1. A shuffle phase where the intermediate data from the mapper nodes is transferred to the reducer nodes. In this phase, decompressing the data and/or partial merging may occur as well.
2. A merge phase where the sorted fragments (memory/disk) from the various mapper tasks are combined to produce the actual input into the reduce function.
3. A reduce phase where the user-defined and user-developed reduce function is invoked to generate the final output data.
4. A write phase where data compression may occur. In this phase, the final output is moved into HDFS.

Figure 1: MapReduce Execution Framework (* = May Occur)



It has to be pointed out that except for the Map & Reduce functions, all other entities in the actual MapReduce execution pipeline (components in *blue* in Figure 1) are defined and regulated by the Hadoop execution framework. Hence, their actual performance cost is governed by the data workload and the performance potential of the Hadoop cluster nodes, respectively.

Hadoop MapReduce Models - Goals & Objectives

To accurately quantify the performance behavior of a Hadoop MapReduce application, the 9 processing phases discussed above were mathematically abstracted to generate a holistic, modeling based performance and scalability evaluation framework. The Hadoop models incorporate the physical and logical systems setup of the underlying Hadoop cluster (see Table 1), the major Hadoop tuning parameters (see Table 2), as well as the workload profile abstraction of the MapReduce application. As with any other IT system, every execution task can be associated with a performance cost that describes the actual resource utilization and the corresponding execution time. The performance cost may be associated with the CPU, the memory, the IO, and/or the NW subsystems, respectively. For any given workload, adjusting the physical systems resources (such as adding CPU's, disks, or additional cluster nodes) impact the performance cost of an execution task. Hence, the models have to be flexible in the sense that any changes to the physical cluster setup can be quantified via the models (with high fidelity). The same statement holds true for the Hadoop and the Linux tuning opportunities. In other words, adjusting the number of Map and/or Reduce task slots in the model will change the execution behavior of the application and hence impact the performance cost of the individual execution tasks [7]. As with the physical cluster systems resource adjustments, the logical resource modifications have to result in accurate performance predictions.

Map Tasks - Data Flow (Modeling) Highlights

As depicted in Figure 1, during the Map task read phase, the actual input split is loaded from HDFS, if necessary uncompressed and the key-value pairs are generated and passed as input to the user-defined and user-developed map function. If the MapReduce job only entails map tasks (aka the number of reducers is set to 0), the spill and merge phase will not occur and the map output will directly be transferred back into HDFS. The map function produces output key-value pairs (records) that are stored in a map-side memory buffer (labeled *MemorySortSize* in the model - see Table 2). This output buffer is split in 2 parts. One part stores the actual bytes of the output data and the other one holds 16 bytes of metadata per output. These 16 bytes include 12 bytes for the key-value offset and 4 bytes for the indirect-sort index. When either of these 2 logical components fill-up to a certain threshold (determined in the model by *SortRecPercent*), the spill process commences. The number of pairs and the size of each spill file (the amount of data transferred to disk) depends on the width of each record and the possible usage of a combiner and/or some form of data compression.

The objective of the merge phase is to consolidate all the spill files into a single output file that is transferred into the local disk subsystem. It has to be pointed out that the merge phase only happens if more than 1 spill file is generated. Based on the setup (*StreamsMergeFactor*) and the actual workload conditions, several merge iterations may occur. The *StreamsMergeFactor* model parameter governs the maximum number of spill files that can be merged together into a single file. The first merge iteration is distinct as Hadoop calculates the best possible number of spill files to merge so that all the other (potential) merge iterations consolidate exactly *StreamsMergeFactor* files. The last merge iteration is unique as well, as if the number of spills to be merged is >= *SpillsCombiner*, the combiner is invoked again. The aggregate performance behavior of the map tasks is governed by the actual workload, the systems setup, as well as the performance potential of the CPU, memory, interconnect, and local IO subsystems, respectively.

Reduce Tasks - Data Flow (Modeling) Highlights

During the shuffle phase, the execution framework fetches the applicable map output partition from each mapper (labeled a map segment) and moves it to the reducer's node. In the case the map output is compressed, Hadoop will uncompress the data (after the transfer) as part of the shuffling process. Depending on the actual segment size, 2 different scenarios are possible at this stage. If the uncompressed segment size is < 25% of (*ShuffleHeapPercent***JavaHeapSpace - see Table 2*) the map segments are placed in the shuffle buffer. In scenarios where either the amount of data in the shuffle buffer reaches (*ShuffleHeapPercent***JavaHeapSpace*) or the number of segments is > *MemoryMergeThr*, the segments are consolidated and moved as a shuffle file to the local disk subsystem. If the execution framework utilizes a combiner, the operation is applied during the merge phase. If data compression is stipulated, the map segments are compressed after the merge and prior to be written out to disk. If the uncompressed segment size is >= 25% of (*ShuffleHeapPercent***JavaHeapSpace*), the map segments are immediately moved into the local IO subsystem, forming a shuffle file on disk.

Depending on the setup and the workload at hand, both scenarios may create a set of shuffle files in the local disk subsystem. If the number of on-disk shuffle files is > (2**StreamsMergeFactor* -1), a new merge thread is launched and *StreamsMergeFactor* files are consolidated into a new and sorted shuffle file. If a combiner is used in the execution framework, the combiner is not active during this disk merge phase. After finalizing the shuffle phase, a set of merged and unmerged shuffle files may exist in the local IO subsystem (as well as a set of map segments in memory). Next to the actual workload conditions, the aggregate performance cost of the shuffle phase is impacted by the cluster interconnect (data transfer), the performance of the memory and the CPU subsystem (in-memory merge operations), as well as by the performance potential of the local IO subsystem (on-disk merge operations).

After the entire map output data set has been moved to the reduce nodes, the merge phase commences. During this phase, the map output data is consolidated into a single stream that is passed as input into the reduce function for processing. Similar to the map merge phase discussed above, the reduce merge phase may be processed in multiple iterations. However, instead of compiling a single output file during the final merge iteration, the actual data is moved directly to the reduce function. In the reduce task, actual merging in this phase is considered a (potential) 3 step process. In step 1, based on the setting of the *ReduceMemPercent* parameter, some map segments may be marked for expulsion from the memory subsystem. This parameter governs the amount of memory allowed to be used by the map segments prior to initiating the reduce function. In scenarios where the number of shuffle files on disk is < *StreamsMergeFactor*, the map segments marked for memory eviction are consolidated into a single shuffle file on disk. Otherwise, the map segments that are marked for expulsion will not be merged with the shuffle files on disk until step 2 and hence, step 1 does not happen. During step 2, any shuffle files residing in the local disk subsystem go through an iterating merge process. It has to be pointed out that the shuffle files on disk may be of varying sizes and that step 2 only happens if there are any actual shuffle files stored on disk. Step 3 involves merging all data (in memory and on disk). This process may complete in several iterations as well. The total performance cost of the merge phase depends on the actual workload, the systems setup, and the performance potential of the CPU, memory, and local IO subsystems, respectively.

Table 1: Systems & Linux OS Parameters supported in the Models

CPUClockSpeed	CPU Clock Speed (GHz)
NumCores	Number of CPU's or CPU Cores
MemoryWidth	Memory Interconnect Width (bytes)
MemCap	Total Memory per Node (GB)
MemCycleTime	Average Memory Cycle Time (ns)
NumLocalDisks	Number of Local Disks per Node
AvgDiskLatency	Average Local Disk Latency (ms)
AvgDiskSpeed	Average Local Disk Throughput (MB/s)
ClusterNodes	Number of Nodes in the Cluster
Interconnect	GigE, 10GigE, IB, Custom
MTU	Cluster Interconnect MTU (bytes)
HDFSBlockSize	Configured HDFS Block Size (MB)
IOSched	CFQ, deadline, noop
ReadAhead	ReadAhead Size (in 512byte Blocks)
DiskType	SSD, HD

Ultimately, the user-defined and user-developed reduce function is invoked, processing the merged, intermediate data to compile the final output that is moved into HDFS. It has to be pointed out that based on the shuffle and merge phase, the actual input data into the reduce function may reside in both, the memory and the local disk subsystems, respectively. As for the map tasks, the aggregate performance behavior of the reduce tasks is determined by the actual workload, the systems setup, and the performance potential of the CPU, memory, interconnect, and local IO subsystems, respectively.

Model Profiles, Calibration & Validation

Further deciphering the (above discussed) execution of a MapReduce job discloses rather specific execution functions and well-defined data processing phases. Conceptually, only the map and the reduce functions are user-developed and hence their execution is governed by user-defined and job specific actions. The execution of all the other 7 processing phases are generic and only depend on the workload to be processed and the performance potential and setup of the underlying Hadoop physical and logical cluster resources, respectively. In other words, besides the map and the reduce phase, all the other application processing cycles performance behavior is controlled by the data being processed in that particular phase and the HW/SW performance capacity of the cluster itself. To calibrate the Hadoop MapReduce models, actual HW systems and workload profiles were established. The HW systems profiles represent a detailed description of the individual physical systems components that comprise the Hadoop cluster and disclose the performance potential (upper bound) of the Hadoop execution framework (CPU, memory, Interconnect, local IO subsystem). Due to protocol overhead, that performance potential can only be closely approached by an actual application workload. The workload profiles detail the performance costs of the individual execution phases and reflect the dynamics of the application infrastructure. The workload profiles further quantify how much of the HW capacity is being used and hence the HW and workload profiles can be used for capacity analysis purposes. Table 1 outlines the major HW/SW parameters that are used as input into the Hadoop MapReduce models.

Table 2: Major Hadoop Tuning Parameters supported in the Models

JavaHeapSpace	mapred.child.java.opts
MaxMapTasks	mapreduce.tasktracker.map.tasks.maximum
MaxReduceTasks	mapreduce.tasktracker.reduce.tasks.maximum
NumMapTasksJob	mapreduce.job.maps
MemorySortSize	mapreduce.task.io.sort.mb
BufferSortLimit	mapreduce.map.sort.spill.percent
SortRecPercent	io.sort.record.percent
StreamsMergeFactor	mapreduce.task.io.sort.factor
SpillsCombiner	mapreduce.map.combine.minspills
NumReduceTasksJob	mapreduce.job.reduces
MemoryMergeThr	mapreduce.reduce.merge.inmem.threshold
ShuffleHeapPercent	mapreduce.reduce.shuffle.input.buffer.percent
ShuffleMergePercent	mapreduce.reduce.shuffle.merge.percent
ReduceMemPercent	mapreduce.reduce.input.buffer.percent
UseCombine	mapreduce.job.combine.class
CompressMapOut	mapreduce.map.output.compress
CompressJobOut	mapreduce.output.fileoutputformat.compress
CompressInput	Flag - Input Compressed
InputDataSize	Size of Input Split

While other Hadoop performance evaluation and quantification studies suggest the usage of an application profiling tool [2],[3],[11], the argument made in this study is that by solely profiling at the application layer, the level of detail necessary to conduct comprehensive sensitivity studies via the Hadoop models is not sufficient. To illustrate, any IO request at the application layer is potentially transformed at the Linux BIO layer, the Linux IO scheduler, the device firmware, and the disk cache subsystem, respectively. Further, the workload-dependent IO performance behavior is impacted by some of the Linux specific logical resource parameters such as the setting of the read-ahead value and/or the IO scheduler being used (see Table 1). To illustrate, the Linux kernel tends to asynchronously read-ahead data from the disk subsystem if a sequential access pattern is detected. Currently, the default Linux read-ahead block size equals to 128KBytes (can be adjusted via blockdev --setra). As Hadoop fetches data in a synchronous loop, Hadoop cannot take advantage of OS' asynchronous read-ahead potential past the 128KBytes unless the read-ahead size is adjusted on the cluster nodes. Depending on the IO behavior of the MapReduce applications, it is rather common to increase the read-ahead size in a Hadoop cluster environment.

Figure 2: Linux *perf* Output

```
633.177931 task-clock       #    0.998 CPUs utilized   ( +-  0.16% )
58 context-switches         #    0.092 K/sec           ( +-  0.20% )
0 cpu-migrations            #    0.000 K/sec           ( +- 25.17% )
109,992 page-faults         #    0.174 M/sec           ( +-  0.00% )
1,800,355,879 cycles        #    2.843 GHz             ( +-  0.04% )  [83.21%]
290,156,191 stalled-cycles-frontend
16.12% frontend cycles idle                            ( +- 0.22%  )  [83.29%]
488,353,913 stalled-cycles-backend
27.13% backend cycles idle                             ( +- 0.99%  )  [66.75%]
2,108,703,053 instructions # 1.17  instructions per cycle
0.23  stalled cycles per instructions                  ( +- 0.01%  )  [83.42%]
500,187,297 branches        # 789.963 M/sec            ( +-  0.01% )  [83.56%]
761,132 branch-misses       # 0.15% of all branches    ( +-  0.13% )  [83.42%]
```

To accurately compile the workload profile for the applications, actual mapping functions (application primitives onto OS primitives and OS primitives unto the HW resources) are required. This comprehensive code-path based profiling approach further allows for conducting sensitivity studies via adjusting logical and physical systems components in the model framework at the application, OS, as well as HW layers. Currently, Hadoop already provides workload statistics such as the number of bytes read or written (see Figure 3). These stats are periodically transferred to the master node (with the heartbeat). For this study, the Hadoop code was adjusted with *breakpoints* that when reached, triggers the execution of a watchdog program that measures the total execution time for each MapReduce phase and also prompts the collection of profile and trace data at the application and the OS level. In other words, for the duration of each phase (see Figure 1), the task execution is profiled and traced via the Linux tools *strace*, *perf*, *blktrace* and snapshots via *lsof*, *iotop*, *ioprofile*, and *dstat* are taken. The breakpoints in the Hadoop code can individually be activated and deactivated and as the actual trace and profile data is collected outside of the Hadoop framework, the performance impact on the MapReduce execution behavior is minimized.

Figure 3: Hadoop Provided Statistics of a Sample *WordCount* Job

```
3/15/13 13:04:38 INFO mapred.JobClient: Running job: job_201005121900_0001
3/15/13 13:04:39 INFO mapred.JobClient:  map 0% reduce 0%
3/15/13 13:04:59 INFO mapred.JobClient:  map 50% reduce 0%
3/15/13 13:05:08 INFO mapred.JobClient:  map 100% reduce 16%
3/15/13 13:05:17 INFO mapred.JobClient:  map 100% reduce 100%
3/15/13 13:05:19 INFO mapred.JobClient: Job complete: job_201005121900_0001
3/15/13 13:05:19 INFO mapred.JobClient: Counters: 17
3/15/13 13:05:19 INFO mapred.JobClient:   Job Counters
```

```
3/15/13 13:05:19 INFO mapred.JobClient:     Launched reduce tasks=1
3/15/13 13:05:19 INFO mapred.JobClient:     Launched map tasks=2
3/15/13 13:05:19 INFO mapred.JobClient:     Data-local map tasks=2
3/15/13 13:05:19 INFO mapred.JobClient:   FileSystemCounters
3/15/13 13:05:19 INFO mapred.JobClient:     FILE_BYTES_READ=47556
3/15/13 13:05:19 INFO mapred.JobClient:     HDFS_BYTES_READ=111598
3/15/13 13:05:19 INFO mapred.JobClient:     FILE_BYTES_WRITTEN=95182
3/15/13 13:05:19 INFO mapred.JobClient:     HDFS_BYTES_WRITTEN=30949
3/15/13 13:05:19 INFO mapred.JobClient:   Map-Reduce Framework
3/15/13 13:05:19 INFO mapred.JobClient:     Reduce input groups=2974
3/15/13 13:05:19 INFO mapred.JobClient:     Combine output records=3381
3/15/13 13:05:19 INFO mapred.JobClient:     Map input records=2937
3/15/13 13:05:19 INFO mapred.JobClient:     Reduce shuffle bytes=47562
3/15/13 13:05:19 INFO mapred.JobClient:     Reduce output records=2974
3/15/13 13:05:19 INFO mapred.JobClient:     Spilled Records=6762
3/15/13 13:05:19 INFO mapred.JobClient:     Map output bytes=168718
3/15/13 13:05:19 INFO mapred.JobClient:     Combine input records=17457
3/15/13 13:05:19 INFO mapred.JobClient:     Map output records=17457
3/15/13 13:05:19 INFO mapred.JobClient:     Reduce input records=3381
```

After the data collection for the individual MapReduce phases is completed, the data is post-processed to compile the necessary MapReduce model input parameters such as the input key-value size, the map input output data ratio, the reduce input output data ratio, the potential data compression ratios, the memory/cache behavior, the IO activities, as well as the average (per task) cycles per instruction (CPI) demand for each phase. Some of the performance related parameters expressed via these performance-fusion techniques are related to the map, reduce, sort, merge, combine, serialize (transform object into byte stream), partition, compress, and uncompress functionalities. In addition, some of major Hadoop tuning parameters and execution characteristics (see Table 2) are extracted from the actual Hadoop cluster and used as input parameters into the models as well.

Hadoop Performance Evaluation and Results

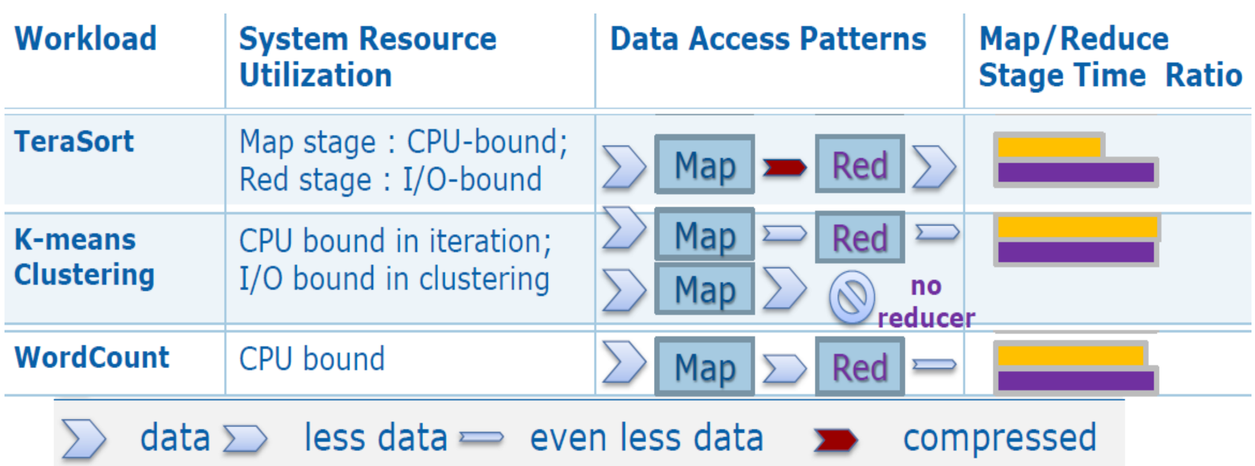
For the modeling and sensitivity studies, 2 Hadoop cluster environments were used. First, a 6-node Hadoop cluster that was configured in a 1 NameNode and 5 DataNode setup. All the nodes were configured with dual-socket quad-core Intel Xeon 2.93GHz processors, 8GB (DDR3 ECC 1333MHz) of memory, and were equipped with 4 1TB 7200RPM SATA drives each. Second, a 16-node Hadoop cluster, with 1 node used as the NameNode and 15 nodes as DataNodes, respectively. All the nodes in the larger Hadoop framework were configured identically to the 6-node execution framework, except on the IO side. Each node in the larger Hadoop setup was equipped with 6 1TB 7200RPM SATA drives. For both Hadoop cluster setups, the cluster interconnect was configured as a switched GigE network. Both clusters were powered by Ubuntu 12.04 (kernel 3.6) and CDH4 Hadoop. For all the benchmarks, replication was set to 3. The actual Hadoop performance evaluation study was executed in 6 distinct phases:

1. Establish the Model profiles (as discussed in this paper) for the 3 Hadoop benchmarks TeraSort, K-Means, and WordCount on the 6-node Hadoop cluster. All 3 benchmarks disclose different

workload behaviors and hence reflect a good mix of MapReduce challenges (see Figure 4). For these benchmark runs, the default Java, Hadoop, and Linux kernel parameters were used (aka no tuning was applied). In other words, the HDFS block size was 64MB, the Java Heap space 200MB, the Linux read-ahead 256KB, and 2 Map and 2 Reduce slots were used per node.

2. Use the established workload profiles in conjunction with the HW profiles to calibrate and validate the Hadoop models. Execute the simulation and determine the description error (delta empirical to model job execution time).
3. Use the developed Hadoop models to optimize/tune the actual workload based on the physical and logical resources available in the 6-node Hadoop model. In this stage, the methodology outlined in [10] was used to optimize/tune the Hadoop environment via the models.
4. Apply the model-based tuning recommendations to the 6-node cluster. Rerun the Hadoop benchmarks and establish the description error (delta tuned-empirical to tuned-model job execution time).
5. Use the tuned-model baseline to conduct a scalability analysis, scaling the workload input (increase the problem size) and mapping that new workload onto a 16-node Hadoop cluster that is equipped with 6 instead of 4 SATA drives per TaskTracker.
6. Execute the actual Hadoop benchmarks on the 16-node Hadoop cluster (with the tuning and setup recommendations made via the model). Establish the description error tuned-scaled-empirical to tuned-scaled-model job execution time.

Figure 4: Hadoop Benchmark Applications (Figure courtesy of Intel)



In phase 1, all 3 Hadoop benchmarks were executed 20 times on the small Hadoop cluster. During the benchmark runs, Hadoop and Linux performance data was collected. The Linux performance tools such as *perf* and *blktrace* added an approximately 3% additional workload overhead onto the cluster nodes. That overhead was taking into consideration while running the models. After all benchmarks were executed, a statistical analysis of the benchmark runs revealed a CV (coefficient of variation) of less than 4% and hence the collected sample sets are considered as producing repeatable benchmark data. All the collected Hadoop and Linux data was post-processed and utilized as input into the Hadoop models. In phase 2, the calibrated models were used to simulate the 3 Hadoop benchmark runs.

The results of the first set of simulation runs disclosed a description error of 5.2%, 6.4%, and 7.8% for the TeraSort, K-Means, and WordCount benchmarks, respectively. In phase 3, the tuning methodology outlined in [10] was used to optimize the actual workload onto the available physical and logical systems resources. Figure 5 shows the modeled non-tuned benchmark execution time for the TeraSort, scaling the number of nodes from 4 to 8. Figure 6 discloses the tuned TeraSort execution time. By applying the tuning methodology, the aggregate TeraSort execution time for the 5 TaskTracker setup was improved (lowered) by a factor of 2.8.

Figure 5: TeraSort - Default Hadoop Parameters, 4GB Input Data Size, 4 Disks

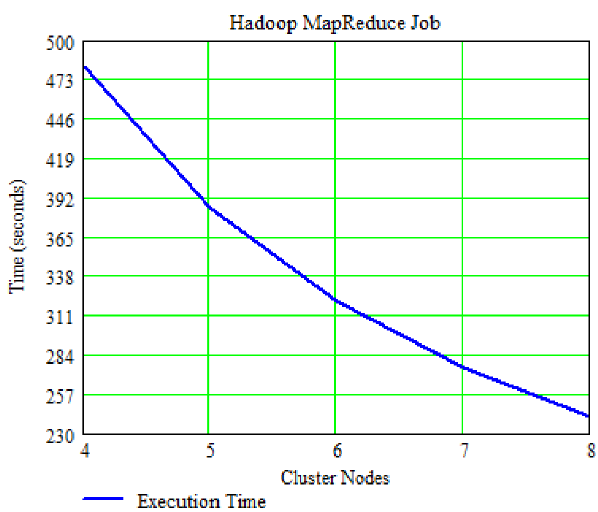


Figure 6: TeraSort - Tuned Hadoop Parameters, 4GB Input Data Size, 4 Disks

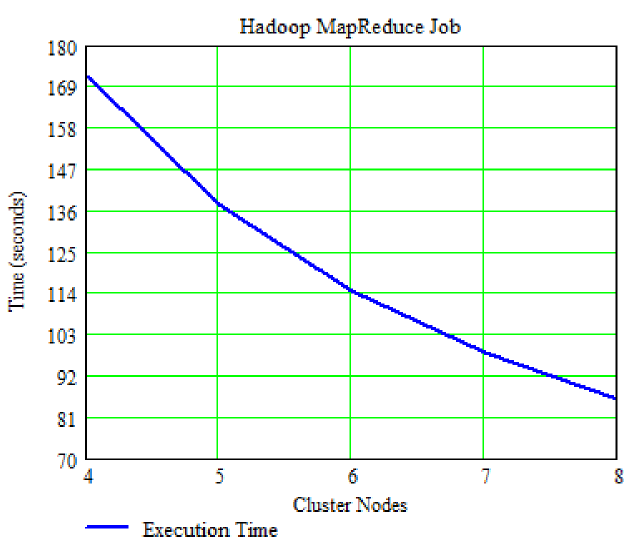
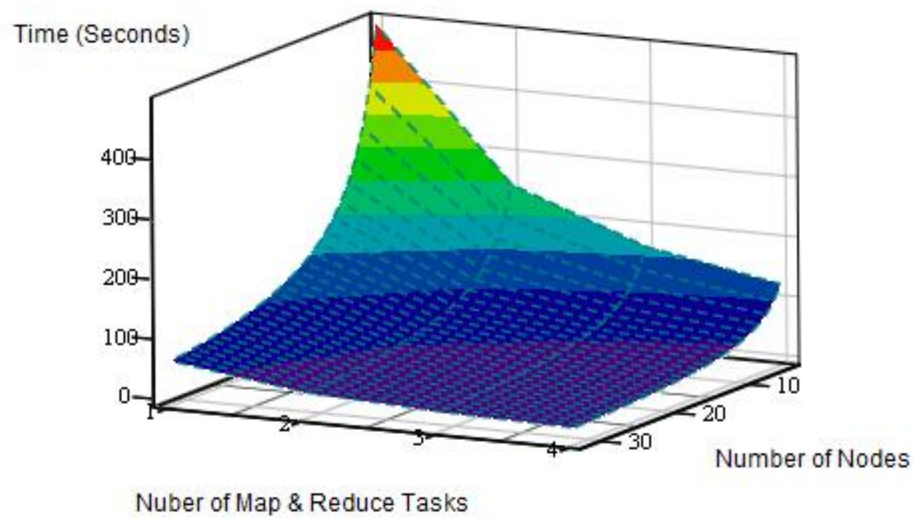


Figure 7 shows the results of the tuned TeraSort model simulations while scaling the number of Map and Reduce Tasks from 1 to 4 and the number of nodes from 1 to 32. In step 4, the mdel-based tuning recommendations were applied to the small 6-node Hadoop cluster and the benchmark and data collection cycle discussed in phase 1 was re-executed. The description error established in phase 4 was 5.0%, 6.2%, and 7.5% for the TeraSort, K-Means, and WordCount benchmarks, respectively. Applying the tuning methodology [10] to the benchmarks mitigated the impact that the Map spills have on aggregate job execution time and hence less IO operations are performed by the Hadoop execution framework. Executing fewer spill related IO operations is 1 of the factors responsible for the lower description error encountered by the TeraSort and the K-Means benchmarks, respectively.

Figure 7: TeraSort Execution Time (6-node cluster, Tuned, 4GB Input Data Size, 4 Disks)

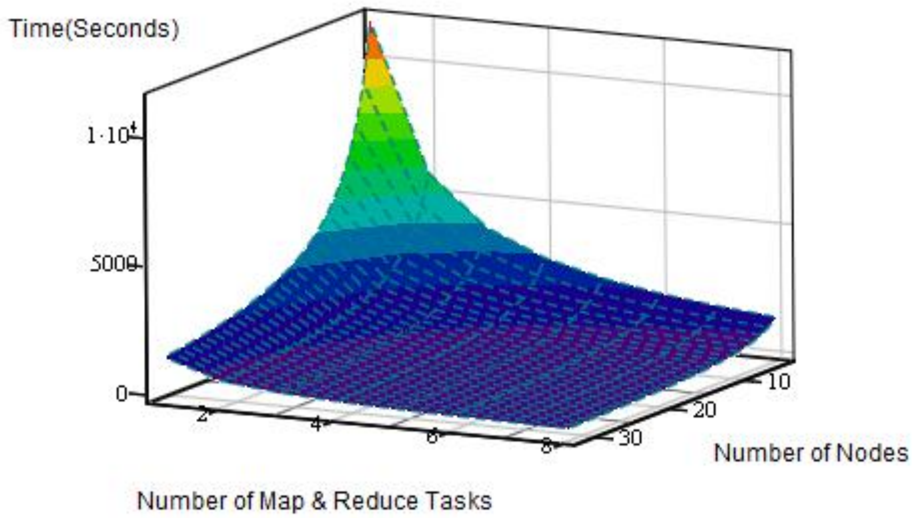


In phase 5, the tuned models were used to simulate the 16-node Hadoop cluster that is equipped with 6 disks per node and operates on larger input sizes (TeraSort -> the input size was increased from 4GB to 16GB, for K-Means -> from 4GB to 20GB, and for WordCount -> from 4GB to 40GB) for all the Hadoop benchmarks. In other words, for this part of the study, the actual workload size as well as the number of physical resources (disks) was scaled. The simulation runs for the 3 Hadoop benchmarks were executed within the model framework, providing the Job execution baseline for the 16-node performance analysis.

From a modeling perspective, the actual simulations scaled the number of Map and Reduce Tasks from 1 to 8 and the number of nodes from 1 to 32 (see Figure 8). In phase 6, based on the larger input data size and the 2 additional disks per node, the same benchmark and data collection cycle as in phase 1 and 4 was processed against the 16-node Hadoop cluster. After the benchmarking and data collection cycle, the CV was less than 4% for all the 3 benchmarks and hence the collected data was accepted as being reproducible. The established description error for phase 6 was 5.4%, 6.8%, and 7.8% for the TeraSort, K-Means, and WordCount benchmarks, respectively. As highlighted in [10], for the

TeraSort and the K-means benchmark, adding 2 additional disks per node into the Hadoop execution framework had a profound (positive) impact on the aggregate job execution time.

Figure 8: TeraSort Execution Time (16-node cluster, Tuned, 16GB Input Data Size, 6 Disks)



Conclusion

At a rapid pace, Hadoop is being deployed in enterprises around the globe. Most installations either reflect a private cloud configuration or a public cloud setup where companies utilize a Hadoop execution framework made available by various cloud providers. For private and public installations alike, Hadoop is being used for advanced data analytics studies that comprise rather large data sets that require some form of job completion time quantification [4]. This study introduced Hadoop models that can be used to optimize/tune actual Hadoop workloads onto the physical and logical systems components, conduct scaleup and speed studies, as well as to compute the MapReduce job execution time. The encouraging low description error for all 3 Hadoop benchmarks discussed in this paper underlines the strength of the approach and further validates the Hadoop tuning methodology outlined in [10]. Further, the proposed models highlight the importance of fusing an actual MapReduce workload (the driver) with the HW potential of the cluster environment (the HW profiles) and the resulting logical and physical resource allocation (the code-path based workload profiles) while conducting a performance evaluation.

Acknowledgments

Countless scientists and engineers are currently working on improving and optimizing the execution framework necessary to conduct Big Data studies. From developing new tools for Big Data to improving Hadoop and machine learning algorithms, countless hours are spent on identifying actual execution frameworks that allow customers to receive answers as quickly as possible. While there are countless other scientists involved in this effort, the author of this report would like to thank Dr. Biem

(IBM Watson - Big Data Research) and Dr. Herodotou (Duke University) for spearheading some of these efforts by providing new ideas and methodologies to address the discussed Big Data issues head-on.

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Appendix A: Machine Learning Algorithm Challenges with Big Data Analysis

The proliferation of companies pursuing large-scale data mining and data analysis projects over the last couple of years has been astonishing. New types of highly scalable data-intensive compute platforms are required to handle the large-data demand. The MapReduce application framework represents the most popular platform where the dataflow takes on the form of a directed acyclic graph of operators. However, MapReduce does not have built-in support for iterative programs that are so popular in many big-date applications such as data mining, web ranking, graph processing, or model fitting exercises.

It is a fact that Machine Learning (ML) algorithms are the foundation of Data Science. But it is also a fact that traditional ML tools do not scale to large data sets. Hence next generation tool sets (generation 2 and 3) are developed to address the scalability issues. Nevertheless, some of the G2 tool sets (such as Mahout) only provide simpler ML algorithms such as linear regression or k-means clustering using the Hadoop MapReduce framework for scaling purposes. But, the traditional Hadoop MapReduce framework is actually a complete oddity when it comes to iterative (basically a sequence of improving approximate solutions) ML algorithms. G3 tool sets such as HaLoop, Twister, Apache Hama and GraphLab do provide iterative ML algorithms that may even go beyond (such as GraphLab) the ML paradigm.

As of the writing of this paper, the ML tools can basically categorized in G1, G2, and G3 toolsets.

- G1 -> The traditional ML tool set for machine learning and statistical analysis such as SAS, SPSS, or the R language. They do allow for a deep analysis of smaller data sets (what is considered small is obviously debatable).
- G2 -> 2nd generation ML tool sets such as Mahout or RapidMiner that provide better scalability compared to G1, but may not support the vast range of ML algorithms as the G1 tools.
- G3 -> 3d generation tool sets such as Twister, Spark, HaLoop, Hama, R over Hadoop, or GraphLab that provide deeper analysis cycles of big-data.

The G1 tool sets do facilitate deep analytics as they support a wide set of ML algorithms. However, not all of them are capable of processing large data sets (PetaBytes) due to scalability limitations (aka they are limited by the non-distributed nature of the tool). While they scale vertically (increase of the CPU, memory, and IO performance capacity of the system may lead to better response time behavior) they do not scale horizontally (cannot easily be executed on an *n* node cluster). For some of these tool-sets, the scalability issues are addressed by developing Hadoop connectors (such as for R).

The G2 tool sets such as Mahout (open source) or RapidMiner (open source) do have the ability to scale to large data sets by implementing the algorithms into the Hadoop MapReduce framework. It has to be pointed out though that Mahout currently only implements a smaller subset of ML algorithms that actually scale to large data-sets (over Hadoop). Actual usage has shown that the linear regression, linear SVM, or the K-means clustering algorithms scale well.

More and more G3 tool sets for implementing ML algorithms at scale are up-and-coming. A big emphasis is on scaling R over Hadoop (R is considered the traditional language of statisticians). Spark (open source) provides Resilient Distributed Data sets (RDDs), which can be cached in the nodes memory subsystems. RDDs are described as a distributed memory abstraction that allows developers to perform in-memory computations on large clusters in a fault-tolerant manner. Spark was initially developed for 2 types of applications where keeping data in memory boosts performance. First, *iterative* algorithms that are common in machine learning and second, *interactive* data mining applications. Spark supports the notion of broadcast variables and accumulators that allow for result aggregation.

HaLoop extends the Hadoop execution framework for iterative ML algorithms. HaLoop provides a programming abstraction for expressing iterative applications and uses the notion of caching to share data across iterations and to enable fix-point verification (termination of iteration). In HaLoop the task scheduler is made loop-aware and various caching mechanisms are implemented in the execution framework (caching options for loop-invariant data access). HaLoop is backward-compatible with Hadoop jobs.

Apache Hama represents an implementation of the Bulk Synchronous Parallel (BSP) bridging model. Hama supports BSP over HDFS. BSP reflects an inherently well suited paradigm for iterative computations and Hama provides a parallel implementation of CG (CG -> conjugate gradient method, an algorithm for the numerical solution of particular systems of linear equations). It has to be pointed out that the BSP engine in Hama is implemented via the Message Passing Interface (MPI). A BSP implementation consists of processors that are connected via a communication network. Each processor has a fast local memory and normally processes different execution threads. A BSP computation proceeds in a series of global *super-steps*. A super-step consists of 3 components:

1. *Concurrent computation*: Several computations take place on every participating processor. Each process only uses values stored in the local memory of the processor. The computations are independent in the sense that they occur asynchronously.
2. *Communication*: The processes exchange data among themselves. This exchange takes the form of one-sided *put* and *get* calls (compared to two-sided *send* and *receive* calls).
3. *Barrier synchronization*: When a process reaches the *barrier*, it waits until all other processes have finished their communication events.

The computation and communication events do not have to be ordered in time. The barrier synchronization concludes the super-step. The barrier has the function of ensuring that all one-sided communications are properly concluded. This global synchronization feature is not needed in models that are based on two-sided communication, as these implementations synchronize processes implicitly.

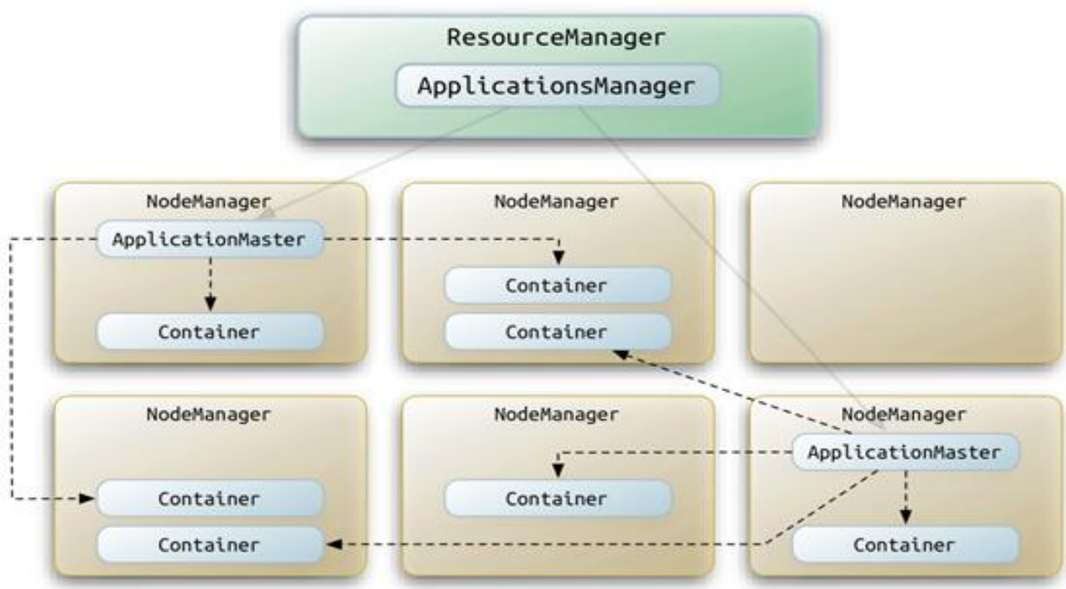
Two other platforms for analyzing very large data sets in a Hadoop environment are Pig and Hive. Pig utilizes the data-flow oriented language Pig Latin. Pig Latin supports data transformation functions, data-types such as include sets, associative arrays, or tuples and is considered a high-level language for marshalling data. Originally, Pig was developed at Yahoo. Hive on the other hand is considered as a SQL-like/based data warehousing application that provides features similar to Pig. Hive is more SQL-alike and supports statements such as SELECT, JOIN, or GROUP BY (to name a few). It is generally used to analyze very large data sets in areas such as log processing, text mining, or document indexing. Hive was originally developed at Facebook.

Appendix B: MapReduce MRv2 (YARN)

As of MapReduce 2.0 (MRv2), the MapReduce framework has been completely redesigned (see Figure 9). The essential idea of MRv2's YARN (Yet Another Resource Negotiator) architecture is to decompose the 2 principal responsibilities of the old JobTracker into a (1) resource management and (2) a job scheduling/monitoring entity. The new design is based on a global **ResourceManager (RM)** and a per-application **ApplicationMaster (AM)** daemon. Starting with MRv2, the RM and the per-node **NodeManager (NM)** reflect the new data-computation framework. The RM replaces the functionalities that used to be provided by the JobTracker and represents the ultimate resource arbitration authority (among all the applications). The AM (a framework specific library) negotiates any resource specific tasks with the RM and operates in conjunction with the NM to execute and monitor the tasks.

The RM consists of 2 components, the **scheduler** and the **ApplicationsManager (AppMg)**. The scheduler (such as Capacity or Fair) is responsible for allocating resources to the various running applications. The scheduler only performs scheduling tasks and is not involved in monitoring or tracking the application status. The scheduler performs the scheduling functions based on the resource requirements of the applications (via the abstract notion of a resource **Container** that incorporates resource usage elements such as CPU, memory, disk, or network. The AppMg is responsible for accepting job submissions, negotiating the first container for execution of the application specific AM and provides the services for restarting the AM container in failure situations. The NM represents the per system framework agent responsible for the containers, monitoring their resource usage (cpu, memory, disk, network) and reporting to the RM (scheduler). The per application AM is in charge of negotiating the appropriate resource containers (in conjunction with the scheduler), tracking their status and monitoring the progress. MRV2 maintains API compatibility with previous stable release (hadoop-0.20.205). This implies that all Map-Reduce jobs should still run unchanged on top of MRv2 with just a recompile.

Figure 9: MRv2 Framework



Note: Figure courtesy of Apache