# myHadoop - Hadoop-on-Demand on Traditional HPC Resources

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## ABSTRACT

Traditional High Performance Computing (HPC) resources, such as those available on the TeraGrid, support batch job submissions using Distributed Resource Management Systems (DRMS) like TORQUE or the Sun Grid Engine (SGE). For large-scale data intensive computing, programming paradigms such as MapReduce are becoming popular. A growing number of codes in scientific domains such as Bioinformatics and Geosciences are being written using open source MapReduce tools such as Apache Hadoop. It has proven to be a challenge for Hadoop to co-exist with existing HPC resource management systems, since both provide their own job submissions and management, and because each system is designed to have complete control over its resources. Furthermore, Hadoop uses a shared-nothing style architecture, whereas most HPC resources employ a shared-disk setup. In this paper, we describe *myHadoop*, a framework for configuring Hadoop *on-demand* on traditional HPC resources, using standard batch scheduling systems. With myHadoop, users can develop and run Hadoop codes on HPC resources, without requiring root-level privileges. Here, we describe the architecture of myHadoop, and evaluate its performance for a few sample, scientific use-case scenarios. myHadoop is open source, and available for download on SourceForge.

## Categories and Subject Descriptors

D.4.7 [**Operating Systems**]: Organization and Design—*batch processing systems, distributed systems*
D.2.8 [**Programming Techniques**]: Concurrent Programming—*distributed programming*

## General Terms

Management, Performance, Design, Experimentation

## Keywords

MapReduce, Hadoop, High Performance Computing, Resource Management, Clusters, Open Source, myHadoop

## 1. INTRODUCTION

Traditional High Performance Computing (HPC) resources, such as those available on the TeraGrid [13], support batch job submissions using Distributed Resource Management Systems (DRMS) such as TORQUE [7] (also known by its historical name Portable Batch System - PBS), or the Sun Grid Engine (SGE - [6]). These systems are put in place by system administrators on these resources to enable submission, tracking, and management of batched, non-interactive jobs, such that it maximizes the overall utilization of the system, and that it enables sharing of the resources among many users. Users typically do not have a choice of batch systems to use on a particular resource - they simply use the interfaces provided by the batch systems that are made available on those resources.

The MapReduce programming model [15], introduced by Google, has become popular over the past few years as an alternative model for data parallel programming. Apart from Google's proprietary implementation of MapReduce, there are several popular open source implementations available such as Apache Hadoop MapReduce [9] and Disco [14]. MapReduce technologies have also been adopted by a growing number of groups in industry (e.g., Facebook [24], and Yahoo [28]). In academia, researchers are exploring the use of these paradigms for scientific computing, for example, through the Cluster Exploratory (CluE) program, funded by the National Science Foundation (NSF).

A growing number of codes in scientific domains such as Bioinformatics ([21], [18]) and Geosciences [19] are being written using open source MapReduce tools such as Apache Hadoop. In the past, these users have had a hard time running their Hadoop codes on traditional HPC systems that they have access to. This is because it has proven hard for Hadoop to co-exist with existing HPC resource management systems, since Hadoop provides its own scheduling, and manages its own job and task submissions, and tracking. Since both systems are designed to have complete control over the resources that they manage, it is a challenge to enable Hadoop to co-exist with traditional batch systems such that users may run Hadoop jobs on these resources. Furthermore, Hadoop uses a *shared-nothing* architecture [27], whereas traditional HPC resources typically use a shared-disk architecture, with the help of high performance parallel file systems. Due to these challenges, HPC users have been left with no option other than to procure a physical cluster and manage and maintain their own Hadoop instances. Some users now have access to new resources such as Amazon's Elastic MapReduce [1] or Magellan [3] to run their Hadoop jobs. However, the majority of HPC users only have access to traditional HPC-style resources, such as the ones provided by the TeraGrid or other local facilities.

In this paper, we present *myHadoop*, which is a simple framework for Hadoop *on-demand* on traditional HPC resources, using standard batch processing systems such as TORQUE or SGE. With the help of myHadoop, users do not need dedicated clusters to run their jobs - instead, they can configure Hadoop clusters on-demand by requesting resources via TORQUE or SGE, and then configuring the Hadoop environment based on the set of resources provided. We describe the architecture of myHadoop, and evaluate the performance overhead of using such a system with a few scientific use-case scenarios. myHadoop is open source, and available for download via SourceForge [4].

The key contributions of our work are as follows:

(i) An open-source framework for leveraging traditional batch systems to run Hadoop jobs on HPC resources,

(ii) A detailed recipe for implementing a shared-nothing system such as Hadoop on shared HPC resources, which may be useful for other similar systems, e.g. Disco [14], and

(iii) An evaluation of the performance overheads of running a shared-nothing infrastructure on such resources.

The rest of the paper is organized as follows. In Section 2, we describe the traditional shared HPC architectures, and shared-nothing architectures used by Apache Hadoop. We discuss the challenges of running MapReduce-style applications on shared HPC resources. In Section 3, we discuss the myHadoop implementation details. In Section 4, we evaluate the performance implications of using myHadoop with the help of two use cases. We present related work in Section 5, and our conclusions and future work in Section 6.

## 2. ARCHITECTURE OVERVIEW

The system architecture for shared-nothing frameworks such as Apache Hadoop is different from that of the traditional shared HPC resources, as shown in Figure 1.

We observe that most HPC resources are composed of a set of powerful compute nodes with minimal local storage. The compute nodes are themselves connected to each other using a high-speed network interconnect such as Gigabit Ethernet, Myrinet [11] or Infiniband [23]. They are typically connected to a high performance parallel file system, such as Lustre [26] or IBM's General Parallel File System (GPFS - [25]). Access to the compute nodes is via batch systems such as TORQUE/PBS or SGE.

Shared-nothing frameworks, on the other hand, are designed for use in large clusters of commodity PCs connected together with switched commodity networking hardware, with storage directly attached to the individual machines. Thus, every machine is both a data and a compute node. A distributed file system is implemented on top of the data nodes.

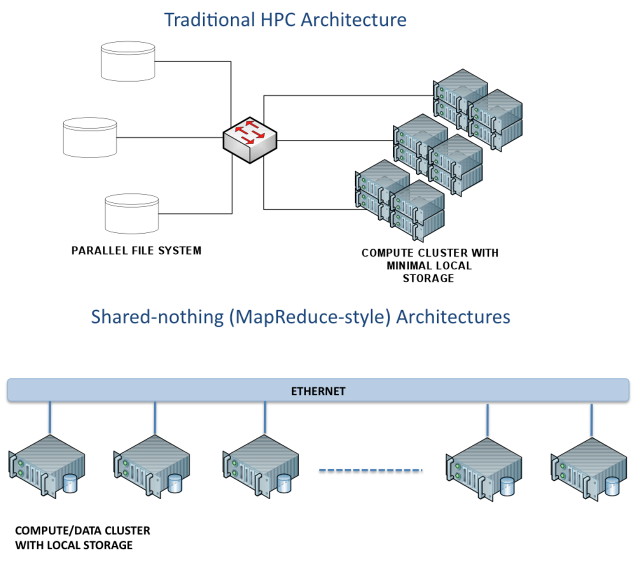

Traditional HPC Architecture
PARALLEL FILE SYSTEM
COMPUTE CLUSTER WITH MINIMAL LOCAL STORAGE
Shared-nothing (MapReduce-style) Architectures
ETHERNET
COMPUTE/DATA CLUSTER WITH LOCAL STORAGE

**Figure 1: HPC versus shared-nothing architectures**

e.g. the Google File System (GFS - [17]), or the Hadoop Distributed File System (HDFS - [12]). Compute tasks are spawned to maximize data locality. Such systems have been documented to scale to thousands of nodes effectively ([15], [24], [28]).

The main challenges in enabling Hadoop jobs to run on shared HPC resources are:

(i) Enabling the resource management functions of Hadoop to co-exist with the native batch resource managers, and

(ii) Implementing a shared-nothing infrastructure on top of the traditional HPC architectures, which are typically shared-disk systems.

Hadoop uses a shared-nothing architecture, but it designates one node as the *master*, and the rest as the *slaves*. On the master, Hadoop runs the HDFS *NameNode* daemon, which is the master server that manages the file system namespace and regulates access to files by clients, and the *JobTracker* daemon, which is responsible for scheduling the jobs' component tasks on the slaves, monitoring them and re-executing the failed tasks. The slave nodes host the HDFS *DataNode* daemons, which manage storage attached to the nodes, and the MapReduce *TaskTracker* daemons, which execute the tasks as directed by the master.

Figure 2 shows the overall architecture of myHadoop on traditional HPC resources. End-users can use myHadoop to allocate a Hadoop cluster on-demand, which does so by first requesting a set of nodes from the native resource management system, designating the master and the slave nodes, and configuring and launching the appropriate Hadoop daemons on the allocated nodes. The user can then run their Hadoop jobs, after which the Hadoop framework is torn down by stopping all the daemons and de-allocating the resources.

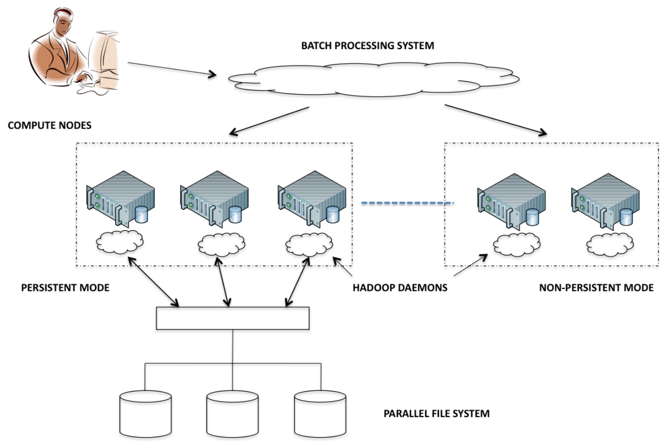


**Figure 2: myHadoop architecture**

myHadoop can be configured in two modes - *non-persistent* and *persistent*. In the non-persistent mode, the Hadoop daemons are configured to use local storage, if available, for the distributed file system implementation. This mode may have two potential problems - first, sufficient local storage may not be available, and second, the results from the non-persistent runs will be unavailable after the Hadoop job has completed, since the batch system cannot typically guarantee that the same set of resources will be allocated for future runs. To circumvent these concerns, one can use the persistent mode where the distributed file system is hosted on the shared file system, such as Lustre or GPFS.

## 3. IMPLEMENTATION DETAILS

The requirements for myHadoop can be listed as follows:

(i) Enabling execution of Hadoop jobs on shared HPC resources via traditional batch processing systems,

(ii) Working with a variety of batch scheduling systems,

(iii) Allowing users to run Hadoop jobs without needing root-level access,

(iv) Enabling multiple users to simultaneously execute Hadoop jobs on the shared resource (this doesn't imply that they should use the same Hadoop instance - only that the Hadoop configurations for one user must not interfere with the configuration of another), and

(v) Allowing users to either run a fresh Hadoop instance each time (non-persistent mode), or store HDFS state for future runs (persistent mode).

myHadoop has been implemented to work with Apache Hadoop (version 0.20.2), and to satisfy the above requirements. The key idea behind the implementation is that different (site-specific) configurations for Hadoop can be generated for different users, which can then be used by the users to run personal instances of Hadoop in regular-user mode (hence the name *myHadoop*), without needing any system-wide configuration changes or root privileges. Site-specific

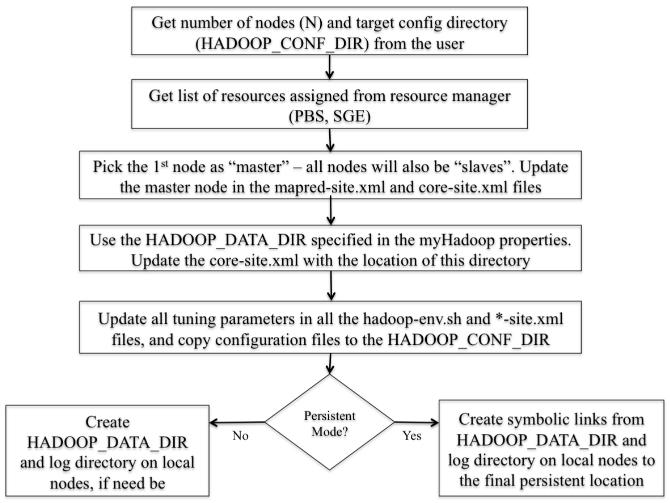

Get number of nodes (N) and target config directory (HADOOP_CONF_DIR) from the user
Get list of resources assigned from resource manager (PBS, SGE)
Pick the 1st node as "master" – all nodes will also be "slaves". Update the master node in the mapred-site.xml and core-site.xml files
Use the HADOOP_DATA_DIR specified in the myHadoop properties. Update the core-site.xml with the location of this directory
Update all tuning parameters in all the hadoop-env.sh and *-site.xml files, and copy configuration files to the HADOOP_CONF_DIR
Persistent Mode?
No
Yes
Create HADOOP_DATA_DIR and log directory on local nodes, if need be
Create symbolic links from HADOOP_DATA_DIR and log directory on local nodes to the final persistent location

**Figure 3: myHadoop configuration workflow**

configuration files that are relevant to myHadoop include:

(i) *masters*: This specifies the host name of the node on the cluster that serves as the master. This node hosts the HDFS *NameNode*, and the MapReduce *JobTracker* daemons.

(ii) *slaves*: This lists the host names for the compute nodes on the cluster. The slave nodes host the HDFS *DataNode* daemons, and the MapReduce *TaskTracker* daemons.

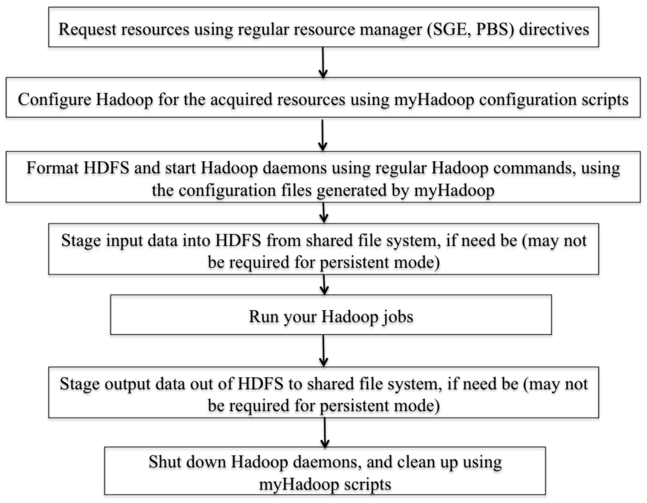
(iii) *core-site.xml*: The core site configuration includes important parameters such as the location of the HDFS (*HADOOP_DATA_DIR*) on every node, and the URI for the HDFS server (which includes the host and port of the master). It also includes additional tuning parameters for the size of the read/write buffers, the size of the in-memory file system used to merge map outputs, and the memory limit used for sorting data.

(iv) *hdfs-site.xml*: The HDFS site configuration includes parameters for configuring the distributed file system, such as the number of replications, the HDFS block size, and the number of DataNode handlers to serve block requests.

(v) *mapred-site.xml*: The MapReduce site configuration consists of the host and port for the JobTracker (on the master), the number of parallel copies that can be run by the Reducers, the number of map and reduce tasks to run simultaneously (to leverage multiple cores), and the *JAVA_OPTS* for the child JVMs of the mappers and reducers.

(vi) *hadoop-env.sh*: This script configures the environment for the Hadoop daemons. Important parameters including the location of the logs, the Hadoop heap size, and JVM parameters for garbage collection and heap management.

Figure 3 describes the myHadoop configuration workflow. To use myHadoop, a user writes scripts for the batch system being used by their particular resource. For the purposes of this discussion, let us assume that the resource uses



Request resources using regular resource manager (SGE, PBS) directives
Configure Hadoop for the acquired resources using myHadoop configuration scripts
Format HDFS and start Hadoop daemons using regular Hadoop commands, using the configuration files generated by myHadoop
Stage input data into HDFS from shared file system, if need be (may not be required for persistent mode)
Run your Hadoop jobs
Stage output data out of HDFS to shared file system, if need be (may not be required for persistent mode)
Shut down Hadoop daemons, and clean up using myHadoop scripts

**Figure 4: myHadoop from a user's perspective**

the TORQUE Resource Manager (also known as PBS). Note that the following description is equally valid for other resource managers, such as SGE.

In this case, a user writes a regular PBS script to run their Hadoop job. From within the PBS script, the user invokes myHadoop scripts for configuration of a Hadoop cluster. When the Hadoop configuration script is invoked, it sets up all the configuration files for a personal Hadoop instance for a user in a separate directory (called *HADOOP_CONF_DIR*), which can then be used to bootstrap all the Hadoop daemons. As command-line arguments to this script, the user passes the number of Hadoop nodes to configure (which is the same as the number of nodes requested from PBS), the HADOOP_CONF_DIR to generate the configuration files in, and whether Hadoop should be configured in persistent or non-persistent mode. When this script is invoked, myHadoop looks up the host names of the resources allocated to it by PBS, using the *PBS_NODEFILE*. It picks the first resource on the list as the master, and all of the resources as slaves. It updates the masters and slaves files accordingly, and also the mapred-site.xml and core-site.xml, which contain the host names for the HDFS NameNode and MapReduce JobTracker respectively. It then reads the location of the HADOOP_DATA_DIR from its set of pre-defined properties, and updates the core-site.xml. It then updates all the tuning parameters based on the site specific configuration files, and writes out all the relevant configuration files into the HADOOP_CONF_DIR.

If a user wants to run Hadoop in regular (or non-persistent) mode, then myHadoop creates the HADOOP_DATA_DIR on all the nodes, and HDFS can then be formatted. If a user wants to run Hadoop in persistent mode, then myHadoop creates symbolic links from the HADOOP_DATA_DIR on each individual node to the location on the shared file system to be used to host the HDFS. For instance, a symbolic link is created from HADOOP_DATA_DIR to *BASE_DIR/$i* for every compute node *$i*.

The myHadoop workflow from a user's perspective is shown in Figure 4. As described above, a user writes a PBS script to request the required number of resources. Then the user configures the site-specific parameters using the myHadoop configuration scripts. Then, using the configuration files generated in the HADOOP_CONF_DIR, the user formats HDFS (optional in persistent mode, mandatory in the non-persistent mode) and starts the Hadoop daemons. The user then stages the required input files into HDFS using Hadoop commands, and is now ready to run her Hadoop jobs. Once the Hadoop jobs are finished, the results can be staged back out from HDFS. This step is necessary in the non-persistent mode, because the output files are distributed across the compute nodes, and there is no guarantee that this user will be allocated the exact same set of nodes in the future by PBS. Thus, all results must be staged out before the resources are de-allocated. However, this step is not necessary in the persistent mode since the results will be available on the shared file system even after the PBS job has completed. Finally, the user shuts down all Hadoop daemons and exits.

Thus, myHadoop enables running Hadoop jobs on HPC resources using standard batch processing systems. It is possible that a similar approach could be used to implement other shared-nothing frameworks, such as Disco [14], on traditional HPC resources.

## 4. PERFORMANCE EVALUATION

As discussed before, myHadoop configures and bootstraps execution of Had-oop daemons prior to the execution of Hadoop jobs, and performs cleanup after job execution is complete. Hence, there is certainly some overhead involved in the overall execution time of the Hadoop job. The overheads are different for the persistent and non-persistent modes.

For the non-persistent mode, the overheads include the configuration (generation of site specific configuration files, creation of HDFS data directories, etc), staging input data into HDFS, staging the results back to persistent storage, and shutting down and cleaning up all the Hadoop daemons. For the non-persistent mode, configuration and shutdown are the only true overheads. Data are typically stored and persisted in HDFS, and the initial load times can be amortized over the overall lifetime of the project. Exporting data from HDFS to a regular Unix file system may sometimes be necessary even in persistent mode, in the cases where the results need to be shared with other non-Hadoop applications. In this case, staging outputs from HDFS may be considered as an overhead. Using two examples, we evaluate the performance of myHadoop and its associated overheads.

The purpose of our experiments is to measure the performance implications of using myHadoop, and not to extensively study the performance characteristics of the applications themselves. These experiments also serve as validation for the myHadoop implementation, and demonstrate the feasibility of running Hadoop on HPC resources.

To help illustrate the effects of running shared-nothing Hadoop jobs on typical shared HPC resources, we have chosen two classes of applications, (i) Hadoop-Blast ([5]), which is compute-intensive and uses a modest amount of data, and (ii) a Hadoop-based point count of high-resolution topographic data sets from the OpenTopography project ([20]), which is highly data-intensive.

## 4.1 Environment Overview

All of our experiments were run on the *Dash* system at the San Diego Supercomputer Center (SDSC). Dash is a prototype for the large, 1024-node Gordon system that is scheduled for production availability mid-2011. It is available to TeraGrid users as a platform to understand the performance and optimization capabilities of using solid state disk (SSD) in the memory hierarchy for fast file I/O, or for memory swap space virtual shared memory (vSMP) software that aggregates memory across 16 nodes. Dash is currently deployed with two 16-node partitions - one with vSMP and one without.

We ran our experiments on the 16-node non-vSMP partition, which uses the TORQUE Resource Manager, with the Moab Workload Manager to manage job queues. Each of the compute nodes is made up of two quad-core 2.4 GHz Intel Nehalem processors, with 48GB of DRAM, and an InfiniBand interconnect. Dash also provides access to a total of 4TB of SSD, which are partitioned and mounted individually on the compute nodes.

We use Apache Hadoop version 0.20.2 for our experiments. The tuning parameters used for our experiments are preconfigured for the cluster by the system administrators via myHadoop, using *real-world* cluster configurations recommended in the Hadoop cluster setup documentation. Users can optionally update the parameters for their runs - however, it is not recommended that the users update their configurations unless they are extremely familiar with Hadoop administration. In general, we have found that query performance improves with replication (e.g. with *dfs_replication* = 2), with only a minimal penalty during data load for the non-persistent mode. Hence, we use that setting for our experiments.

For the persistent mode, we use the TeraGrid GPFS-WAN (Global Parallel File System-Wide Area Network), which is a 700-TB storage system mounted on several TeraGrid platforms. The system is physically located at SDSC, but is accessible from all TeraGrid platforms on which it is mounted. We use the default configuration of the GPFS-WAN for our experiments. For the non-persistent mode, we use local SSD on the individual compute nodes to host HDFS.

## 4.2 Hadoop-Blast

The Basic Local Alignment Search Tool (BLAST) is a popular Bioinformatics family of programs that finds regions of local similarity between sequences [8]. The program compares nucleotide or protein sequences to sequence databases and calculates the statistical significance of matches. BLAST can be used to infer functional and evolutionary relationships between sequences as well as help identify members of gene families. Hadoop-Blast [5] is a MapReduce-based tool which lets a user run the Blast programs to compare a set of input query sequences against standard databases. The implementation is quite straightforward - for every input file (query sequence), Hadoop-Blast spawns a new map task to execute the appropriate Blast program, with the user specified parameters. An output file is created for each map task with the results of the Blast run. There is no need for a reduce task in this workflow.

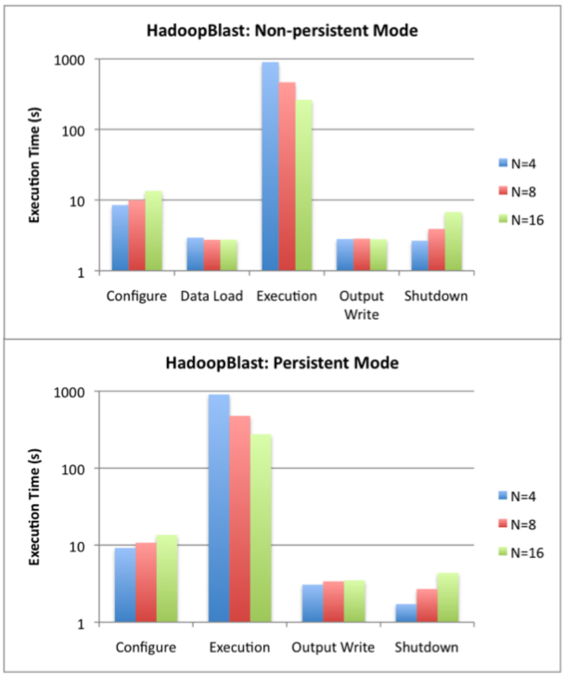


**Figure 5: Hadoop-Blast using myHadoop**

For our experiments, we run *blastx*, which is one of the available Blast programs that compares the six-frame conceptual translation products of a nucleotide query sequence (both strands) against a protein sequence database. As inputs, we use 128 query sequences of equal length (around 70K each), which are compared against the *nr* peptide sequence database (around 200MB in size). Figure 5 shows the performance for the various steps of the execution. The y-axis (*Execution Time*) is in log-scale.

As seen in the performance graphs, the time required to configure a Hadoop cluster using myHadoop configuration scripts is between 8 to 14 seconds for clusters varying from *N=4* to *16* nodes. In the non-persistent mode, all the input sequences and the reference database need to be staged in - this step is not necessary for the persistent mode. However, since the amount of data to be staged is in the order of a few hundreds of MB, data stage-in accounts for an overhead of less than 3 seconds. The blastx runs themselves are computationally intensive, and scale pretty well with the number of nodes. The total execution time varies from a 260-275 seconds for 16 nodes, to around 900s for 4 nodes. Staging outputs also takes around 3 seconds, because of the modest amount of data to be staged out. Shutdowns are also of the order of a few seconds. In summary, the overheads are minimal for fewer nodes (around 2% for 4 nodes in the non-persistent mode). They are greater for larger number of nodes (around 10% for 16 nodes in non-persistent mode), however, since increasing the number of nodes greatly reduces the query time, the overall execution time is greatly reduced in spite of the increased overhead in configuring, bootstrapping, and tearing down the Hadoop cluster.

Other interesting observations from the graphs are as follows. The query execution time for the non-persistent mode, which uses local SSD, is observed to be faster than the persistent mode (by less than 5%), which uses GPFS. We believe that this is because of the following reasons - 1) GPFS is designed for large sequential IO workloads, and not for providing access to a large number of smaller files, 2) there is network overhead and contention associated with fetching data from GPFS in the persistent mode, and 3) the local SSD used in non-persistent mode provides fast file I/O. The network overhead is not very apparent for modest-size experiments such as ours, but we anticipate that this would be more of an overhead for larger Hadoop runs. Next, the shutdown process for the persistent version is a few seconds faster than the non-persistent version. This is because the HDFS data doesn't have to be cleaned up in the shutdown process in this mode. However, the difference is an insignificant percentage of the overall execution time.

In summary, Hadoop-Blast is an excellent candidate for the use of myHadoop in non-persistent mode. The use of persistent mode does not provide any significant benefit. The key characteristics of Hadoop-Blast that cause this behavior are that it is a compute-intensive application that is embarrassingly parallel, and it deals with only a limited amount of data - from hundreds of megabytes to a few gigabytes. Other applications with similar characteristics are also best served by using myHadoop in non-persistent mode.

## 4.3 LIDAR Point Counts

LIDAR (Light Detection and Ranging) is a remote sensing technology that combines a high-pulse rate scanning laser with a differential global positioning system (GPS), and a high-precision inertial measurement instrument on an aircraft to record dense measurements of the position of the ground, overlying vegetation, and built features. Firing up to several hundred thousand pulses per second, LIDAR instruments can acquire multiple measurements of the Earth's surface per square meter over thousands of square kilometers. The resulting data set, a collection of measurements in geo-referenced X, Y, Z coordinate space known as a *point cloud*, provides a 3- dimensional representation of natural and anthropogenic features at fine resolution over large spatial extents. The OpenTopography facility at SDSC provides online access to terabytes of such data, along with processing tools, and other derivative products.

The initial step in every LIDAR workflow is typically to figure out the number of points that covers a region of interest, given a bounding box for that region. If the number of points appear reasonable, then the users select the data within that bounding box, and compute Digital Elevation Models (DEM) to generate a digital continuous representation of the landscape. The DEMs can then be used for a range of scientific and engineering applications, including hydrological modeling, terrain analysis, and infrastructure design. We are investigating the use of MapReduce technologies to implement the entire workflow [19]. For this experiment, we focus on the initial step of the workflow, which is bounding box-based point counts. Figure 6 shows the MapReduce implementation of the bounding box point

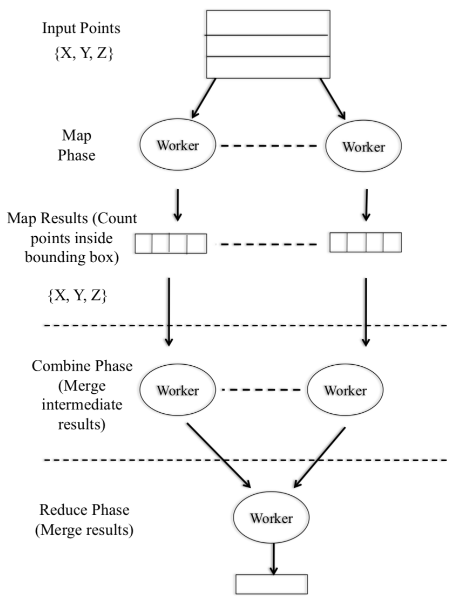


**Figure 6: Hadoop implementation of bounding box-based LIDAR point count**

count using Hadoop. The implementation includes not only a reduce phase for adding up the individual point counts, but also a combine phase for merging the point counts from mappers on the same node. This is an examplar of typical MapReduce algorithms that read a large amount of data, and generate a small amount of synthesized output.

Figure 7 shows the performance of the LIDAR point count using myHadoop in both the non-persistent and persistent modes, for data sizes from 1GB to 100GB, using 4 and 16 nodes. For all the runs, we are running a bounding box query that does a sub-selection of around 12.5% of the loaded data, and counts the number of points in that bounding box. It can be observed that data loads dominate the the execution time for the non-persistent mode. We have not plotted the execution time for staging the results out, since the result in this case is a single number - the point count. Hence, the data export time is insignificant. For the persistent mode, data is staged in once, and the cost is amortized over time - hence, we do not show the load time on our graphs.

The execution times for the persistent mode is observed to be in the same ballpark as the ones for the non-persistent mode. This is despite the fact that local SSDs are used for the HDFS implementation in the non-persistent mode. This is due to the following reasons - 1) GPFS is optimized for large sequential I/O, and 2) SSDs don't provide a significant benefit for long sequential access patterns, such as those seen in Hadoop MapReduce jobs.

In summary, the persistent mode of myHadoop may be a good candidate for large data-intensive applications, such as the usage scenario described above. For such applications, the non-persistent mode of myHadoop provides significantly worse performance because most of the time is spent staging data in and out of Hadoop.

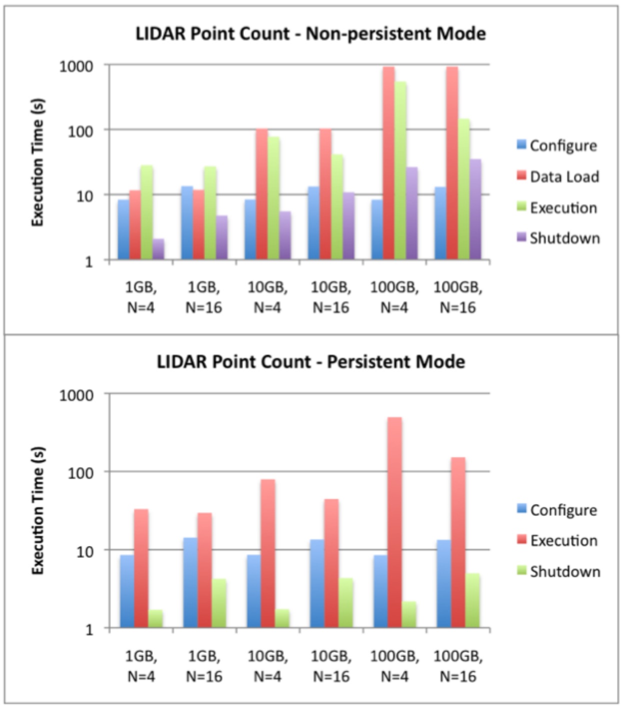


**Figure 7: Point count using myHadoop**

Finally, there are other reasons to use the persistent mode of myHadoop that may not be apparent from the graphs. Firstly, the persistent mode of myHadoop is especially suitable for workflows where results from one stage are fed to subsequent stages, thus minimizing the staging of data back and forth from HDFS to the native file systems provided on the resources. For example, we could have a Hadoop-based workflow where data is sub-selected given a bounding box, which is then fed to a DEM generation code, following by other downstream processing. Secondly, many HPC systems may not have any significant local storage (as described in Figure 1). In such a case, it may not be physically possible to use the non-persistent mode if large amounts of data are being generated or processed.

## 5. RELATED WORK

There has been a lot of user interest in recent times for running Hadoop jobs on traditional HPC resources. Several groups have worked on ad-hoc scripts to solve this problem. However, there are very few efforts that have been sufficiently documented, and publicly available. myHadoop is very similar in concept to the description provided by the blog article [16], where the author describes the process of getting Hadoop to run as a batch job using PBS. However, myHadoop is a more general and configurable framework, which provides support for other schedulers as well, and is freely available for download via SourceForge. Furthermore, to our knowledge, there has not been a performance evaluation of this effort that has been published.

The Apache Hadoop on Demand (HOD - [2]) is a system for provisioning virtual Hadoop clusters over a large physical cluster. It uses the TORQUE resource manager to do node allocation. On the allocated nodes, it can start Hadoop Map/Reduce and HDFS daemons. It automatically generates the appropriate configuration files for the Hadoop daemons and client. HOD also has the capability to distribute Hadoop to the nodes in the virtual cluster that it allocates. HOD differs from myHadoop in the following ways. Firstly, HOD requires the use of an external HDFS that is statically configured. This means that the MapReduce jobs can't exploit any data locality, because the data is not colocated with the map and reduce tasks. The non-persistent mode of myHadoop enables data locality, with the HDFS being dynamically configured to use the same nodes, with the caveat that the data does have to be staged in and out before and after the execution. The HDFS implementation in the persistent mode of myHadoop is similar in concept to the statically configured external HDFS used by HOD. However, in the persistent mode, the HDFS in myHadoop may be thought of as pseudo-local because there is a 1-1 mapping between every node that runs the MapReduce daemons and its corresponding external HDFS data directory. Another difference is that HOD is based on the TORQUE resource manager - while myHadoop is not limited to just TORQUE. Finally, HOD has some documented problems ([16]) in setting up multiple concurrent Hadoop instances simultaneously - however, it does enable sharing of an on-demand Hadoop instance between users. myHadoop is designed to support concurrent personal instances of Hadoop for multiple users.

Finally, Amazon's Elastic MapReduce [1] enables the allocation of Hadoop clusters on the fly using a Web service API on Amazon's cloud resources. It is similar to myHadoop in the sense that Hadoop clusters are launched on-demand. However, the difference lies in the fact that it uses Amazon's cloud resources, rather than traditional HPC resources via batch scheduling systems. Both systems enable users to run Hadoop jobs with minimal configuration and overhead - however, it is more efficient for end-users to run their Hadoop jobs on the same HPC resources where their data resides, as opposed to staging all the data over to Amazon's cloud before running their Hadoop jobs, and also pay for their usage as they go for both data transfers and computation.

## 6. CONCLUSIONS & FUTURE WORK

In this paper, we described myHadoop, a framework for configuring Hadoop on-demand on traditional HPC resources, using standard batch scheduling systems such as TORQUE (PBS) or the Sun Grid Engine (SGE). With the help of myHadoop, users with pre-existing Hadoop codes do not need dedicated Hadoop clusters to run their jobs. Instead, they can leverage traditional HPC resources that they otherwise have access to, without needing root-level access. myHadoop enables multiple users to simultaneously execute Hadoop jobs on shared resources without interfering with each other. It supports a regular non-persistent mode where the local file system on each compute node is used as the data directory for the Hadoop Distributed File System (HDFS), and also a persistent mode where the HDFS can be hosted on a shared file system such as Lustre or GPFS. In this paper, we discussed the performance of both the persistent and non-persistent modes with the help of a few usage scenarios, and provided recommendations on when myHadoop would be a suitable option (or otherwise). myHadoop is open source and freely available for download via SourceForge [4].

The current release of myHadoop is early alpha, and several potential improvements remain to be done. In particular, we are planning on adding support for other schedulers such as Condor [10]. Currently, the support for the persistent mode is quite basic. In particular, one shortcoming of the persistent mode is that a user can only instantiate a new Hadoop instance in the future with the same number of nodes as their first instance that was initialized, if the user wants to re-use any data from previous runs. A desirable feature is to be able to dynamically re-configure the number of nodes, and also re-balance the data between the nodes. Another shortcoming is that the data in the shared persistent location is only accessible via HDFS commands - which implies that a user must instantiate a Hadoop cluster via myHadoop if any data needs to be exported on to the native file system. We are planning on implementing a set of command-line utilities that help write and read data to and from the persistent location being used by myHadoop's HDFS.

Finally, we plan on enabling all TeraGrid users to run Hadoop jobs with the help of myHadoop. We are currently working on the deployment of myHadoop on SDSC's Trestles resource, and plan on making it available on TeraGrid resources outside of SDSC as well. We plan on using the larger TeraGrid resources to run and test Hadoop jobs at much larger scale than the ones we describe in this paper.

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