

Auto Tuning of Hadoop and Spark parameters

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Abstract — Data of the order of terabytes, petabytes, or beyond is known as Big Data. This data cannot be processed using the traditional database software, and hence there comes the need for Big Data Platforms. By combining the capabilities and features of various big data applications and utilities, Big Data Platforms form a single solution. It is a platform that helps to develop, deploy and manage the big data environment. Hadoop and Spark are the two open-source Big Data Platforms provided by Apache. Both these platforms have many configurational parameters, which can have unforeseen effects on the execution time, accuracy, etc. Manual tuning of these parameters can be tiresome, and hence automatic ways should be needed to tune them.

After studying and analyzing various previous works in automating the tuning of these parameters, this paper proposes two algorithms - Grid Search with Finer Tuning and Controlled Random Search. The performance indicator studied in this paper is Execution Time. These algorithms help to tune the parameters automatically. Experimental results have shown a reduction in execution time of about 70% and 50% for Hadoop and 81.19% and 77.77% for Spark by Grid Search with Finer Tuning and Controlled Random Search, respectively.

Keywords — Big Data Platform, Auto tuning, Parameters, Hadoop, Spark, Execution Time.

I. INTRODUCTION

Nowadays, lots of data is being generated in terabytes and petabytes. The traditional data management platform couldn't manage these large amounts of data, and hence the Big Data Platforms came into the picture. Big Data Platforms could easily process and analyze large and complex data. The quality that caused the Big Data Platforms to dominate the traditional data management platforms was that they distributed data processing tasks across multiple computers. It also helped in reducing the cost of storage of the data. Apache Hadoop [1] and Apache Spark [2] are the two big data platforms worked upon in this paper. Apache Hadoop and Apache Spark both have many parameters to be tuned before executing any job. Various approaches like Machine Learning [9], Container-based solutions [10], using different block sizes [11], etc., have been proposed earlier to tune the parameters of the Hadoop. While the solutions are based on approaches like Neural Network [12], Simulated Annealing Algorithms [13], Artificial Neural Network, Support Vector Regression and Decision Tree [14], Machine Learning [6], etc. have been proposed for self-tuning of Apache Spark. Methods such as using locality-sensitive hashing algorithm

[15] have also been adopted to improve the performance of Hadoop in the past.

Apache Hadoop [1] is an open-source big data platform used widely among various organizations due to its enormous processing power. It has clusters of the commodity hardware on which it runs the applications. Looking over the importance of Hadoop, optimizing its performance becomes a key issue to focus on. Hadoop has about 200 parameters that require tuning before any job is run on it. Tuning these parameters requires expert knowledge, and even many experts find it difficult to tune these parameters. Also, it is seen that not all the parameters have a significant impact on the performance of Hadoop. There are only a few which impact the system performance. Tuning these few parameters in the right fashion will improve the system's accuracy, throughput, and execution time. All these parameters need tuning whenever a new job is submitted. So, manual tuning these parameters can be a very difficult task. Hence, a method to auto-tune these parameters is required.

Apache Spark [2] is also an open-source big data platform that stores, manages, processes big data in a distributed way. Spark is considered to be developer-friendly given that it can be worked with different languages like Python, Java, Scala, and R. It can be used for batch processing, stream processing, etc. Like Hadoop, Spark also has around 180 parameters that need to be tuned for better system performance. Expert knowledge is required to tune these parameters as well, and once they are tuned to their best values, it can improve various performance indicators. Only very few parameters affect the system performance, and manual tuning these parameters is a tedious task. Thus, autotuning these parameters has become a necessity.

In this paper, two algorithms have been proposed that help in auto-tuning the parameters. The algorithms are Grid Search with Finer Tuning and Controlled Random Search. The system also includes a Configuration Manager and Performance Evaluator (CMPE) module, which connects the system and the algorithms modules. The paper identifies 12 parameters of Hadoop and 11 parameters of Spark, which significantly affect system performance. Grid Search with finer tuning sends the values of the parameters to CMPE by sampling, then CMPE adjusts these values in the system and then runs Hadoop/Spark. After getting the results, it returns the execution time and the configuration of the parameter used. Controlled Random Search also sends the values of the parameters to the CMPE in a random manner. The CMPE then works as mentioned above. Simultaneously, a log file is also maintained, which helps keep track of various execution times and the respective configuration used. With the help of a log file,



tracing any error also becomes easier. After analyzing the log file, the best possible configuration was observed, and then running the job on that configuration significantly reduced the execution time.

The paper is organized as follows. Section II and III deal with how the parameters were chosen based on the previous work. Section IV and V deal with the cluster setup and system design. Initial experiments were performed, and their results are mentioned in section VI. CMPE, the two algorithms, the experiment methodology, and their results are described in sections VII, VIII, and IX. Section X explains the comparison of two algorithms with each other and also with Hadoop and Spark. Section XI and XII deals with the conclusion and future scope. And the last section, XIII, shows the references used.

II. PREVIOUS WORK

The parameters which are used in this paper are those which have a significant effect on the performance of the system. 12 parameters for Hadoop and 11 parameters for Spark have been selected based on the research done previously in the Big Data Laboratory at the College of Engineering, Pune. In this research, various feature selection algorithms were used to identify the parameters that affect the system's performance. The algorithm used in this paper was - Ensemble Feature Selection using Chained Gaussian Processes and Gradient Boosted Decision Tree Regression.

It gave the important features as the output. After finding the parameters that affected the system's performance, they were tuned manually (Manual tuning 1 parameter whilst keeping others constant), and the results were analyzed. It was proved in this research that these sets of parameters (mentioned in Section III of this paper) were bound to improve the system performance by up to 30%.

III. PARAMETERS

Configuration Parameters are settings that affect Hadoop and Spark behavior which in turn affect its performance. Configuration Parameters have default values and explicitly run on these default values when not set to any value. On default parameters, the performance might not be optimum as it depends on various factors.

A. Hadoop

Users of Hadoop can set around 200 parameters, but all the parameters don't impact the performance at all or have less impact. So, after studying these parameters' performance impact, the paper shortlists 12 parameters to use in the proposed approaches.

1. `Mapreduce.map.memory.mb`:
The amount of memory requested by each map task from the scheduler.
2. `dfs.blocksize(Bytes)`:
The size of the blocks used for new files.
3. `Mapreduce.tasktracker.map.tasks.maximum`:

The task tracker simultaneously runs a certain number of map tasks. This parameter configures the maximum number of these.

4. `mapreduce.job.reduce.slowstart.completedmaps`:
Expressed as a fraction of number map tasks to be completed before starting the reduce phase.
5. `Mapreduce.map.output.compress`:
Decides whether to compress output from the map phase before sending it across the network.
6. `mapreduce.Job.Reduces`:
Decides the number of reduced tasks in a job
7. `mapreduce.task.io.sort.mb`:
It is expressed in Megabytes as the amount of memory used by the buffer when file sorting is done.
8. `mapreduce.Job.maps`:
Decides the number of map tasks in a job.
9. `mapreduce.task.io.sort.factor`:
In the sorting process, this parameter decides the number of streams to merge in one go. Also, it is the number of open files.
10. `dfs.replication`:
The actual number of replications when the file is generated.
11. `mapreduce.Task tracker.reduce.tasks.Maximum`:
A maximum number of reduce tasks that run simultaneously by a task tracker.
12. `Mapreduce.job.jvm.numtasks`:
Decides the number of tasks being run per JVM. If specified as -1, there is no limit.

Following Table-I presents these parameters with their range and default value.

Table I

Parameter Name	Default Value	Range
<code>mapreduce.map.memory.mb</code>	1024	[256,3072]
<code>dfs.blocksize(Bytes)</code>	128	[32, 256]
<code>Mapreduce.tasktracker.map.tasks.maximum</code>	2	[2,128]
<code>Mapreduce.job.reduce.slowstart.completedmaps</code>	0.05	[0.025,0.9]
<code>Mapreduce.map.output.compress</code>	FALSE	[FALSE,TRUE]
<code>mapreduce.job.reduces</code>	1	[1,4]
<code>mapreduce.task.io.sort.mb</code>	100	[32,128]
<code>mapreduce.job.maps</code>	2	[2,32]

mapreduce.task.io.sort.factor	10	[5,80]
dfs.replication	3	[1,3]
mapreduce.tasktracker.reduce.tasks.maximum	2	[2,128]
mapreduce.job.jvm.numtasks	1	[1,1024]

B. Spark

Configuration Parameters of Spark control application settings. Spark has over 150 configurable parameters, out of which 11 are shortlisted that have a significant impact on performance.

1. **Spark.task.cpus:**
The number of CPU cores to be allocated for each task
2. **spark.memory.storageFraction:**
Fraction of Java Heap Space as storage space.
3. **Spark.network.timeout (seconds):**
All interactions in the network follow the timeout set by this parameter.
4. **Spark.memory.fraction:**
Expressed in fraction, it is total storage that is reserved from JVM heap space.
5. **spark.shuffle.file.buffer (Bytes):**
Buffer size (memory) for each output stream shuffle file. Expressed in KB.
6. **spark.scheduler.listenerbus.eventqueue.capacity:**
This parameter determines the maximum number of events the event queue of the listener bus can handle.
7. **spark.files.openCostInBytes:**
When multiple files are in the same partition, this is cost expressed as bytes to scan in the same time interval to open a file.
8. **spark.storage.memoryMapThreshold(Bytes):**
Expressed in bytes, this parameter is the block size that Sparks memory maps when reading from a file.
9. **Spark.files.maxPartitionBytes:**
When reading files, this parameter decides the size of the partition.
10. **spark.default.parallelism:**
This parameter decides the number of partitions the RDD is to be divided into.
11. **Spark.scheduler.mode:**
The mode in which to schedule submitted jobs. Following Table-II presents these parameters with their description and default value.

Table II

Parameter Name	Default Value	Range
spark.task.cpus	1	[1,5]
spark.memory.storageFraction	0.5	[0.25,0.9]
spark.network.timeout (seconds)	120	[40,200]
spark.memory.fraction	0.6	[0.25,0.8]
spark.shuffle.file.buffer (Bytes)	32k	[16k,512k]
spark.scheduler.listenerbus.eventqueue.capacity	10000	[2500,25000]
spark.files.openCostInBytes	4194304	[1048576,16777216]
spark.storage.memoryMapThreshold(Bytes)	2m	[1m, 5m]
spark.files.maxPartitionBytes	134217728	[33554432,1073741824]
spark.default.parallelism	24	[4, 24]
spark.scheduler.mode	FIFO	[FIFO, FAIR]

IV. CLUSTER SETUP

A. Hadoop:

For Hadoop, the experiments were evaluated on a 3-node cluster (1 master node and 2 slave nodes). The master node has 8GB memory and Intel Core i7-3770 CPU @ 3.40GHz * 8 processor. The disk has 1TB of storage. Both the slave nodes have 4GB memory and Intel Core i7-3770 CPU @ 3.40GHz * 8 processor. The disk has 500 GB of storage.

B. Spark:

For Spark, experiments were evaluated on a 3-node cluster (1 master node and 2 slave nodes). Master node is equipped with Intel® Core™ i5-7200U CPU @ 2.50GHz × 4 processor, 8GB ram, GeForce 940MX/PCIe/SSE2 graphics card, 64-bit. Slave 1 is equipped with Intel® Core™ i5-4300U CPU @ 1.60Ghz processor, 4GB ram, Intel integrated graphics card, 64-bit. Slave 2 is equipped with Intel® Core™ i5-8300H CPU @ 2.30Ghz processor, 8GB ram, GeForce GTX 1050, 64-bit.

The experiments for both Hadoop and Spark were performed using the WordCount benchmark. The dataset used was 1GB.

V. SYSTEM DESIGN

The entire code was divided into the following modules: 1. Configuration Manager and Performance Evaluator, 2. Grid Search with Finer Tuning, and 3. Controlled Random Search.

Configuration Manager and Performance Evaluator (CMPE) creates a level of abstraction between the algorithms, i.e., Grid Search with Finer Tuning and Controlled random search and the underlying technologies such as Hadoop and Spark. The CMPE module handles all the file handling, configuration changes, starting, stopping Hadoop and Spark, or other platform-specific operations. Grid Search with Finer Tuning module and Controlled Random Search implement the algorithm and pass the parameters and values to the CMPE module. The CMPE module further gets the time taken for the job to run and gives feedback to both the algorithm modules to be used further. A diagrammatic representation of these modules and the entire system design is shown in Figure I. The CMPE Module consists of both Job Runner and Performance Evaluator, as shown in Figure I. The rest two modules are explicitly shown. The Admin actions for Tuning the parameters by selecting the algorithm to be run and the platform to run. This then triggers the algorithm on the chosen platform, and after the successful run of the algorithm, the best configuration obtained is returned. The CMPE module also has a log file provision that writes each run's results in the file with the parameter set and the time required for the run.

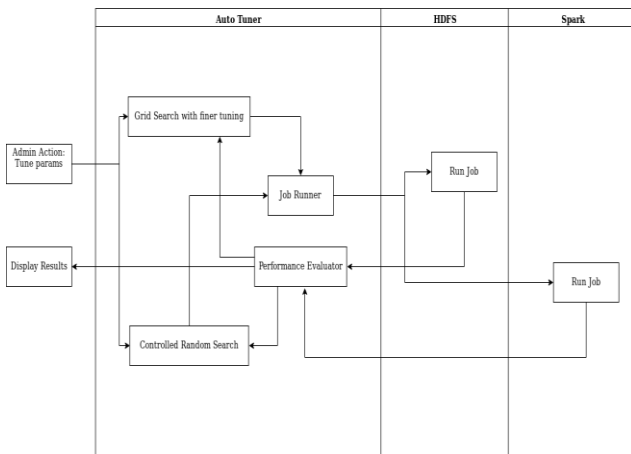


FIGURE I

VI. INITIAL EXPERIMENT

A. Hadoop

All the shortlisted parameters were kept at their default value, and then the job was run. The results obtained are as shown below in Table III.

Table III

Parameter Name	Tuned Value	Execution Time
mapreduce.map.memory.mb	1024	5 min 39 sec
dfs.blocksize	128	
mapreduce.tasktracker.map.tasks.maximum	2	
mapreduce.job.reduce.slowstart.completedmaps	0.05	
mapreduce.map.output.compress	FALSE	
mapreduce.job.reduces	1	
mapreduce.task.io.sort.mb	100	
mapreduce.job.maps	2	
mapreduce.task.io.sort.factor	10	
dfs.replication	3	
mapreduce.tasktracker.reduce.tasks.maximum	2	
mapreduce.job.jvm.numtasks	1	

Another experiment kept one parameter at its optimal value (value obtained from previous research work of manual tuning) and the rest all at default. The results obtained are shown in Table IV below.

Table IV

Parameter Name	Tuned Value	Execution Time	Improvement (%)
mapreduce.map.memory.mb	3072	3 min 39 sec	35.4%
dfs.blocksize	256	4 min 33 sec	19.47%
mapreduce.tasktracker.map.tasks.maximum	64	4 min 36 sec	18.58%
mapreduce.job.reduce.slowstart.completedmaps	0.9	19 min 34 sec	-
mapreduce.map.output.compress	TRUE	3 min 38 sec	35.69%
mapreduce.job.reduces	1	4 min 34 sec	19.17%
mapreduce.task.io.sort.mb	32	4 min 21 sec	23.01%

mapreduce.job.maps	32	4 min 34 sec	19.17 %
mapreduce.task.io.sort.factor	10	4 min 53 sec	13.57 %
dfs.replication	1	4 min 23 sec	22.42 %
mapreduce.tasktracker.reduce.tasks.maximum	16	4 min 42 sec	16.81 %
mapreduce.job.jvm.numtasks	16	4 min 36 sec	18.58 %

The next experiment performed was by keeping all the parameters at their optimal values (value obtained from previous research work of manual tuning). The results are as shown below in Table V.

Table V

Parameter Name	Tuned Value	Execution Time	Improvement (%)
mapreduce.map.memory.mb	3072	2 min 15 sec	60.18 %
dfs.blocksize	256		
mapreduce.tasktracker.map.tasks.maximum	64		
mapreduce.job.reduce.slowstart.completedmaps	0.9		
mapreduce.map.output.compress	TRUE		
mapreduce.job.reduces	1		
mapreduce.task.io.sort.mb	32		
mapreduce.job.maps	32		
mapreduce.task.io.sort.factor	10		
mapreduce.job.maps	1		
mapreduce.task.io.sort.factor	16		
dfs.replication	16		
mapreduce.tasktracker.reduce.tasks.maximum	16		
mapreduce.job.jvm.numtasks	16		

B. Spark

All the shortlisted parameters were kept at their default value, and then the job was run. The results obtained are as shown below in Table VI.

Table VI

Parameter Name	Tuned Value	Execution Time
spark.task.cpus	1	1 min 57 sec
spark.memory.storageFraction	0.5	
spark.network.timeout (sec)	120	
spark.memory.fraction	0.6	
spark.shuffle.file.buffer (Bytes)	32k	
spark.scheduler.listenerbus.eventqueue.capacity	10000	
spark.files.openCostInBytes	4194304	
spark.storage.memoryMapThreshold (Bytes)	2m	
spark.files.maxPartitionBytes	1342177	
spark.default.parallelism	28	
spark.scheduler.mode	24	
	FIFO	

Another experiment kept one parameter at its optimal value (value obtained from previous research work of manual tuning) and the rest all at default. The results obtained are shown in Table VII below.

Table VII

Parameter Name	Tuned Value	Execution Time	Improvement (%)
spark.task.cpus	5	29 sec	75.21%
spark.memory.storageFraction	0.6	1 min 49 sec	6.83%
spark.network.timeout(sec)	160	1 min 51 sec	5.12%
spark.memory.fraction	0.25	1 min 52 sec	4.27%
Spark.shuffle.file.buffer (Bytes)	256k	1 min 52 sec	4.27%
spark.scheduler.listenerbus.eventqueue.capacity	10000	1 min 57 sec	0%
spark.files.openCostInBytes	1048576	1 min 56 sec	0.8%

spark.storage.memoryMapThreshold (Bytes)	1m	1 min 59 sec	-
spark.files.maxPartitionBytes	33554432	2 min 1 sec	-
spark.default.parallelism	12	1 min 55 sec	1.7%
spark.scheduler.mode	FAIR	1 min 56 sec	0.8%

The next experiment performed was by keeping all the parameters at their optimal values (value obtained from previous research work of manual tuning). The results are shown below in Table VIII.

Table VIII

Parameter Name	Tuned Value	Execution Time
spark.task.cpus	5	27 sec
spark.memory.storageFraction	0.6	
spark.network.timeout (sec)	160	
spark.memory.fraction	0.25	
spark.scheduler.listenerbus.eventqueue.capacity	256k	
spark.files.openCostInBytes	10000	
spark.storage.memoryMapThreshold (Bytes)	1048576	
spark.files.maxPartitionBytes	1m	
spark.default.parallelism	3355443212	
spark.scheduler.mode	FAIR	

VII. CMPE MODULE

Configuration Manager and Performance Evaluator, as known as CMPE, is a helper module between algorithm and system. It helps the algorithms to interact with the systems via CMPE. CMPE manages the configuration and evaluates the results, and gives us the optimal configuration of the parameters. By setting these values of the parameters, a reduction in execution time of the job is observed, hence improving the system's performance on the other hand. CMPE first identifies the platform (Hadoop/Spark), and then it changes the configuration file by identifying which parameter lies in which file for the Hadoop. And for Spark, it runs the commands on the terminal. Before running the Hadoop, the safe mode needs to be disabled because it doesn't allow the user to make changes in the configuration file when on safe mode. The output directory is also deleted because having two same-named output directories generates an error. CMPE also maintains a log file. Logfile keeps track of which function is running at what time. It also keeps the result of every run of the algorithm. Analyzing the log file helps in finding the optimal configuration. System time is taken at appropriate places to calculate the total run time or maintain a log file.

VIII. ALGORITHM - I

Grid Search is also known as parameter sweep, and this algorithm means an exhaustive search on the entire parameter space. "A grid search algorithm must be guided by some performance metric, typically measured by cross-validation on the training set [3] or evaluation on a held-out validation set." [4]

"Since the parameter space of a machine learner may include real-valued or unbounded value spaces for certain parameters, manually set bounds and discretization may be necessary before applying grid search."

Grid search suffers from the curse of dimensionality but is often embarrassingly parallel because the hyperparameter settings it evaluates are typically independent of each other. [5]

One of the major debates when Grid search is brought into the picture, is this algorithm's problem due to equally separated sampling. A lot of research has been done on Grid Search in various fields and various applications. However, this paper implements a flavor of Grid Search called Grid Search with Finer Tuning to overcome this problem.

Grid Search with Finer Tuning is essentially a Grid Search with a Finer Tuning overhead. Finer Tuning makes sure the probability of Grid search due to even sampling and missing out an optimal configuration lying in between the two sampled values is reduced.

In this case, the parameters are of two types: Continuous and Boolean. For all continuous parameters, the algorithm first samples the data with a predefined 'step' value. For the Boolean parameters, no change is done. After sampling it evenly, a parameter grid list is created from these parameters. Grid Search is then applied to this parameter space to find out the best configuration. Now for finer tuning, let's introduce a concept of 'most influential

parameters. These are the parameters that have a huge effect on the performance of Hadoop as well as Spark and are found based on the previous work as mentioned in section II. The most influential parameters found were - `mapreduce.map.memory.mb` and `dfs.blocksize` for Hadoop and `spark.memory.storageFraction` and `spark.network.timeout` for Spark.

Finer tuning is applied to these parameters. After finding out the best configuration via Grid Search, a finer tuning is applied across these 'most influential parameters, and the algorithm is run again. In finer tuning, a finer sampling is done around the best configuration obtained in the previous run. Finer tuning is carried out by sampling the data again for the most influential parameters, which is done by calculating:

$new_lower_bound = best_value - (old_lower_bound / 2)$
 $new_upper_bound = best_value + (old_lower_bound / 2)$
 $increment = new_lower_bound / 2$

The time complexity of this algorithm is: $O(nm+k)$

where n is the number of parameters,
 m is the number of steps,

k is the number of parameters for finer tuning.

The algorithm is as shown below.

Algorithm: Grid Search with Finer Tuning

```

Generate param_grid of nelements of the applicable values of
parameters
Set param_grid_list = getParameterGridList(param_grid)
for  $i = 0 \rightarrow m$  do
    Tune the Configurations of Hadoop/Spark as per
        param_grid_list[ $i$ ]
    Run the job and calculate execution_time
    if execution_time < min_execution_time do
        min_execution_time = execution_time
        best_config = param_grid_list[ $i$ ]
    end if
end for
for  $i = 0 \rightarrow l$  do
    param = most_influential_params[ $l$ ]
    lower_bound = param_grid[param][0]
    num = sizeOf(param_grid[param])/sizeOf(int)
    upper_bound = param_grid[param][num]
    new_param_grid[param] = sampleData(lower_bound,
    upper_bound)
end for
for param in best_config do
    if param not in most_influential_params do
        new_param_grid[param] =
        best_config[param]
    end if
end for
new_param_grid_list = getParamGridList(new_param_grid)
for  $i = 0 \rightarrow \text{sizeOf}(\text{new\_param\_grid\_list})$  do
    Tune the Configurations of Hadoop/Spark as per
        new_param_grid_list[ $i$ ]
    Run the job and calculate execution_time
    if execution_time < min_execution_time do
        min_execution_time = execution_time
        best_config = new_param_grid_list[ $i$ ]
    end if
end for
return best_config

```

A. Hadoop

Taking into consideration the total number of parameters shortlisted for Hadoop, i.e., 12, and sampling of each parameter for 10 different values at least, the total number of configuration space would have reached the power of 10^{12} . Considering the default configuration time that was 5 min 39 secs, it was obviously not feasible. Hence taking into consideration minimal parameters due to the tradeoff between the total time taken for the run and the optimal configuration, the closest to optimal was obtained by using the following parameters - `mapreduce.map.memory.mb`, `dfs.blocksize`, `mapreduce.task.tracker.map.tasks.maximum`, `mapreduce.map.output.compress`, `dfs.Replication`.

From the previous work and initial experiments, it was found that `dfs.Replication` gave its optimum when the value was set to 1 and `mapreduce.map.output.compress` gave its optimum when the value was set to TRUE. Hence these values were set throughout the run to the mentioned above.

According to the experimentation as well as previous works, below is a list of the most influential parameters of Hadoop that are used for finer tuning in this Grid search algorithm.

1. `mapreduce.map.memory.mb`:

This parameter is varied with a step of 32 during finer tuning.

2. `dfs.blocksize`

This parameter is varied with a step of 8 during finer tuning.

Running the algorithm on the cluster gave the optimal configuration, as shown in Table IX.

Table IX

Parameter Name	Tuned Value	Time taken	% Optimizati on
<code>mapreduce.map.memory.mb</code>	512	1 min 39 sec	70.8%
<code>dfs.blocksize(Bytes)</code>	192		
<code>mapreduce.tasktracker.map.tasks.maximum</code>	128		
<code>mapreduce.job.reduce.slowstart.completedmaps</code>	0.05		
<code>mapreduce.map.output.compress</code>	TRUE		
<code>mapreduce.Job.reduces</code>	1		

mapreduce.task.io.sort.mb	100		
mapreduce.Job.maps	2		
mapreduce.task.io.sort.factor	10		
dfs.replication	1		
mapreduce.tasktracker.reduce.tasks.maximum	2		
mapreduce.job.jvm.numtasks	1		

B. Spark

According to the shortlisted parameters for Spark, sampling of each parameter is done for the parameters: spark.Task.cpus, spark.memory.storageFraction, spark.network.timeout, spark.shuffle.file.buffer, spark.Memory.Fraction, while the parameter spark.scheduler.mode is set to FAIR since this type of scheduler mode, is found to be much more promising than the FIFO mode.

For finer tuning, the most influential parameters, i.e. spark.memory.storageFraction, and spark.network.timeout, is considered as the parameter spark.Task.cpus gives the best outcome at its max value; hence varying it will only lead to a decrease in performance.

According to the experimentation as well as previous works, below is a list of the most influential parameters of Hadoop that are used for finer tuning in this Grid search algorithm.

1. Spark.task.cpus

This parameter, though it is most influential, gives the best performance when it is set maximum. This directly influences parallel computing. Hence during the finer tuning, this parameter is always set at the maximum and is not varied.

2. spark.memory.storageFraction

This parameter is varied with a step of 0.25 during finer tuning.

3. Spark.network.timeout

This parameter is varied with a step of 20 during finer tuning.

Running the algorithm on the cluster gave the optimal configuration, as shown in Table X.

Table X

Parameter Name	Tuned Value	Execution Time	Improvement Percentage
spark.task.cpus	5	22secs	81.19%
spark.memory.storageFraction	0.9		
spark.network.timeout (sec)	120		
spark.memory.fraction	0.5		
spark.shuffle.file.buffer (Bytes)	128k		
spark.scheduler.listenerbu s. eventqueue.capacity	10000		
spark.files.openCostInBytes	4194304		
spark.storage. memoryMapThreshold (Bytes)	2m		
spark.files.maxPartitionBytes	134217728		
spark.default.parallelism	24		
spark.scheduler.mode	FAIR		

IX. ALGORITHM – II

Random Search is an algorithm that does not depend on derivatives. Rather it is a direct search in a continuous domain. "It can outperform Grid search, especially when only a small number of hyperparameters affects the final performance of the machine learning algorithm.[5] In this case, the optimization problem is said to have a low intrinsic dimensionality".[7][4]

In Random Search, the main objective of finding the global minimum or maximum is achieved by sampling the search space randomly. Random Search is able to return a reasonable approximation of the optimal solution, but as the dimension of the search space increases, it requires more time. A flavor of Random Search called Controlled

Random Search that gives random search more power and accuracy to reach towards the objective is used here.

Controlled Random Search combines random search and mode-seeking routines into one process. The Controlled Random Search algorithm runs the simple random search and obtains new bounds for the further run. It keeps running the process of random search with new bounds of parameters till it reaches a threshold.[8]

As already mentioned, the parameter values are of two types: continuous and Boolean. In this algorithm, the random values are selected from the continuous domain for each parameter. For Boolean values, randomly, either TRUE or FALSE is chosen. By taking these randomly chosen values considering the lower and upper bound of each parameter, a configuration list is formed. These configuration lists are used to tune the frameworks from which some specified number of configurations lists are selected using criteria of execution time. From these selected configurations minimum and maximum of each parameter are found out and are called the new upper and lower bound.

Upper_bound[param] = max(configuration_lists)

Lower_bound[param] = min(configuration_lists)

These newly formed bounds are again fed to the algorithm to form new configuration lists. This is done until a threshold is not broken. The threshold is set to minimum execution time from the configuration list before calculating the new upper and lower bound.

The time complexity of this algorithm is: $O(nm)$ where n is the number of random values generated, m is the value for reaching a threshold.

The algorithm is as shown below.

Algorithm: Controlled Random Search

```
Function random_search(lower_bound, upper_bound)
  Set param_grid_list =
  getRandomizedParameterGridList(lower_bound,
  upper_bound)
  Set num = 0
  for i = 0 → m do
    Tune the Configurations of Hadoop/Spark as per
    param_grid_list[i]
    Run the job and calculate execution_time
    if execution_time < min_execution_time do
      min_execution_time = execution_time
      best_config[num] = param_grid_list[i]
      num = num + 1
    end if
  end for
  Select top k best_config and remove the rest
  return best_config
```

```
Function Controlled_randomSearch()
  Set best_config = None
  revised_best_config = random_search(lower_bound,
  upper_bound)
  while variation(revised_best_config, best_config) >
  threshold do
  Set m = number of most_influential_params
  for i = 0 → k do
    for j = 0 → m do
      lower_bound[param] = min(best_config[param])
```

```
upper_bound[param] = max(best_config[param])
end for
end for
best_config = revised_best_config
revised_best_config = random_search(lower_bound,
upper_bound)
end while
return best_config
```

A. Hadoop

Considering the selected parameters, its default upper and lower bound were fed to the algorithm initially.

Table XI

Parameter Name	Tuned Value	Time Taken	% Optimization
mapreduce.map.memory.mb	1736	2mins 51 sec	49.5 5%
dfs.blocksize(Bytes)	192		
mapreduce.tasktracker.map.tasks.maximum	128		
mapreduce.job.reduce.slowstart.completedmaps	0.05		
mapreduce.map.output.compress	TRUE		
mapreduce.Job.reduces	1		
mapreduce.task.io.sort.mb	59		
mapreduce.Job.maps	20		
mapreduce.task.io.sort.factor	26		
dfs.replication	1		
mapreduce.tasktracker.reduce.tasks.maximum	21		
mapreduce.job.jvm.numtasks	1		

From the previous run, dfs. Replication and dfs. Blocksize, when set to 1 and 192, gave optimum performance. So, to decrease the load on running this algorithm, these two parameters were set to the above-mentioned value.

Table XI shows the results of Controlled Random Search on Hadoop.

B. Spark

Considering the upper and lower bound of the selected spark parameters, random values of them were generated and fed to the algorithm. The spark.scheduler.mode takes two types of values: FAIR and FIFO, so the code chooses one of them randomly.

Table XII

Parameter Name	Tuned Value	Execution Time	Improvement (%)
spark.task.cpus	5	26 sec	77.77 %
spark.memory.storageFraction	0.82		
spark.network.timeout (sec)	137		
spark.memory.fraction	0.77		
spark.shuffle.file.buffer (Bytes)	128k		
spark.scheduler.listenerbus.eventqueue.capacity	16343		
spark.files.openCostInBytes	1121300		
spark.storage.memoryMapThreshold (Bytes)	9		
spark.files.maxPartitionBytes	2m		
spark.default.parallelism	3630041		
spark.scheduler.mode	9		
	14		
	FAIR		

X. Analysis of Results

Most Influential Parameters:

In the case of both Hadoop and Spark, some parameters have much more impact on the performance than other parameters. This comparison, however, is very important to determine the finer tuning required in Hadoop as well as spark. According to the experimentation as well as previous works, below is a list of the most influential parameters that are used for finer tuning in this Grid search algorithm.

Hadoop:

- mapreduce.map.memory.mb

This parameter is varied with a step of 32 during finer tuning.

- dfs.blocksize

This parameter is varied with a step of 8 during finer tuning.

Spark:

- spark.task.cpus

This parameter, though it is most influential, gives the best performance when it is set maximum. This directly influences parallel computing. Hence during the finer tuning, this parameter is always set at the maximum and is not varied.

- spark.memory.storageFraction

This parameter is varied with a step of 0.25 during finer tuning.

- spark.Network.timeout

This parameter is varied with a step of 20 during finer tuning.

Statistical Representation of Results:

A. Hadoop

a) Default vs. All at Individual Optimal

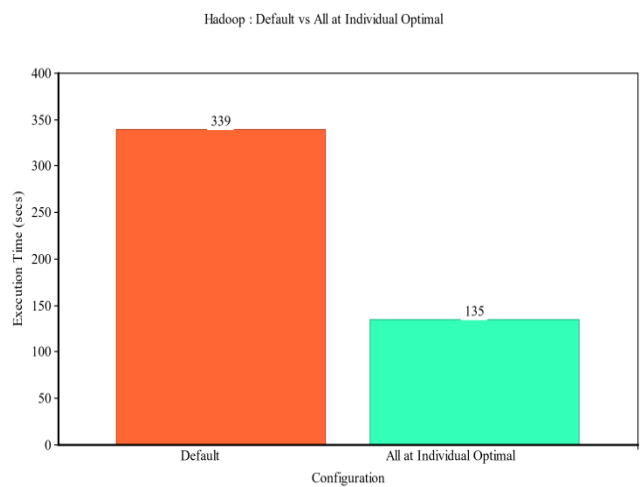


Figure 1: Hadoop: Default vs. All at Individual Optimal

b) One Optimal and others at Default

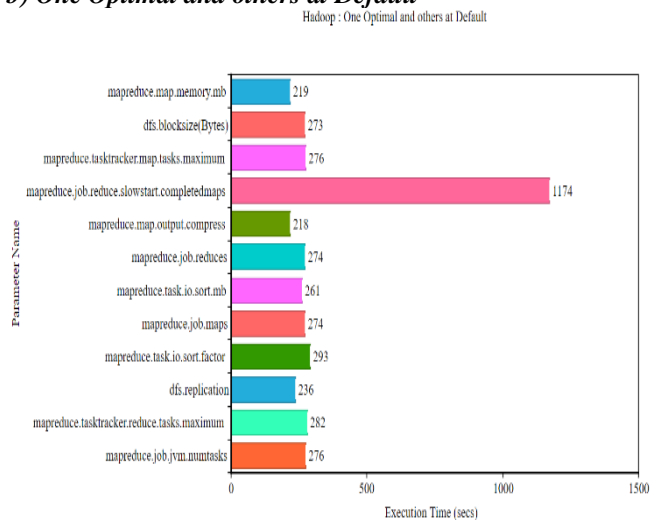


Figure 2: Hadoop: One Optimal and others at Default

c) Time Required Vs. Configurations

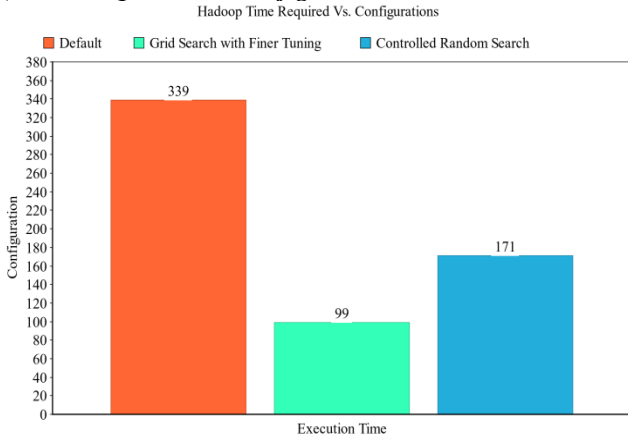


Figure 3: Hadoop: Time Required Vs. Configurations

B. Spark

a) Default vs. All at Individual Optimal

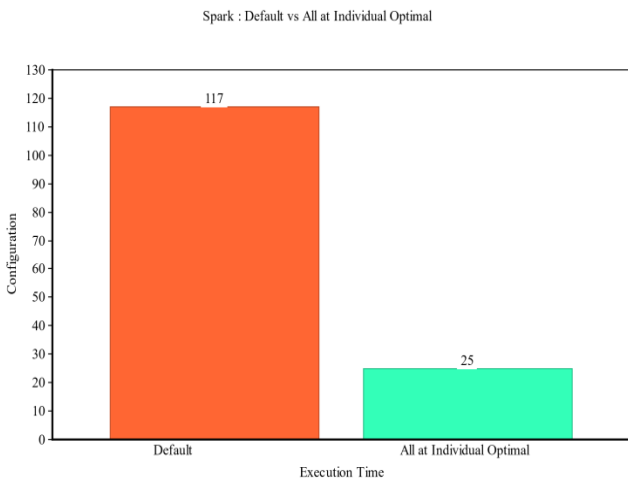


Figure 4: Spark: Default vs. All at Individual Optimal

b) One Optimal and others at Default

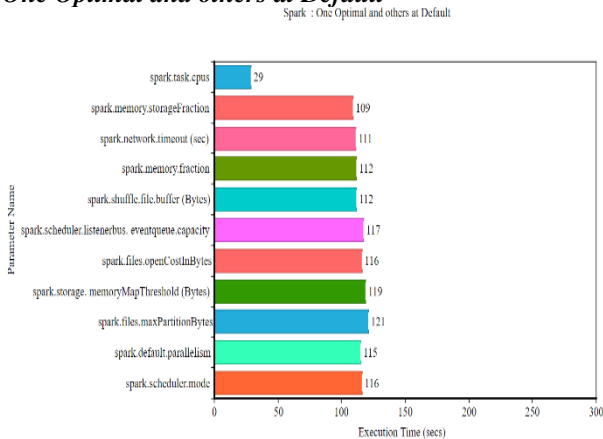


Figure 5: Spark: One Optimal and others at Default

c) Time Required Vs. Configurations

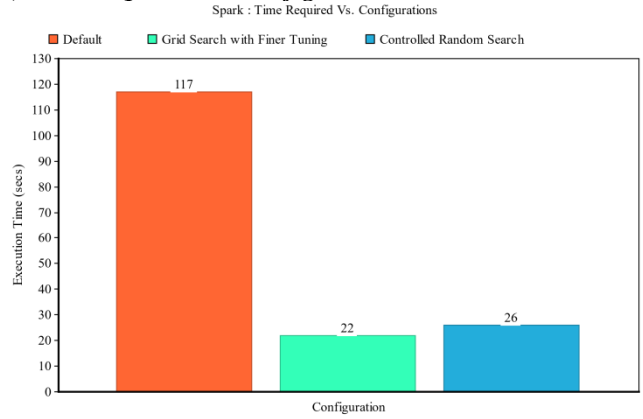


Figure 6: Spark: Time Required Vs. Configurations

C. Comparison

a) Default Configuration of Hadoop and Spark

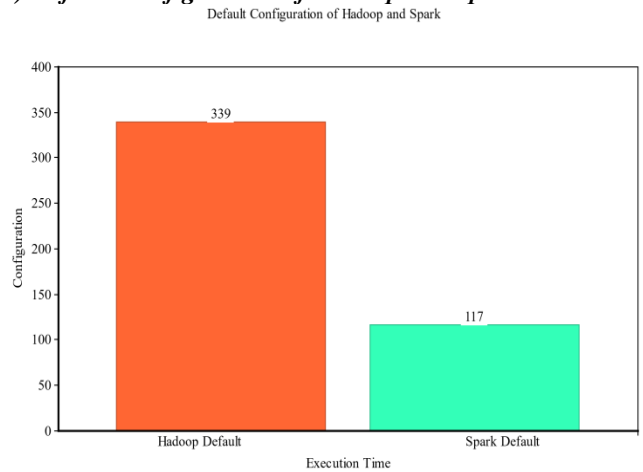


Figure 7: Default Configuration of Hadoop and Spark

b) Comparison of two Algorithms(Hadoop)

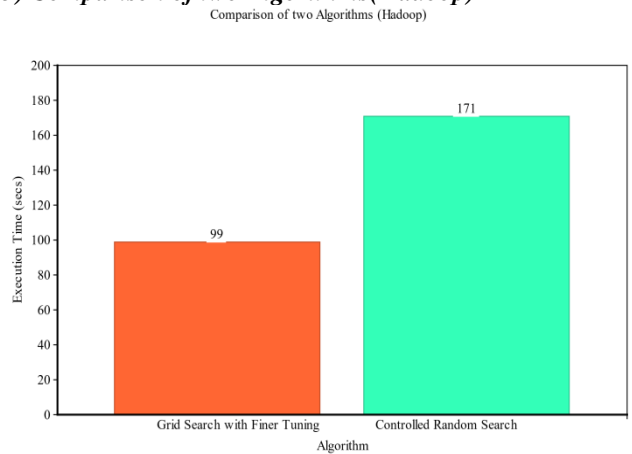


Figure 8: Comparison of two Algorithms (Hadoop)

c) Comparison of two Algorithms (Spark)

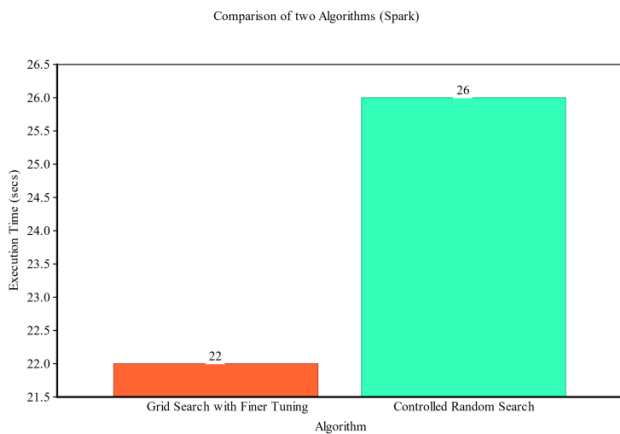


Figure 9: Comparison of two Algorithms (Spark)

XI. COMPARISON

Parameters of comparison	Grid Search with Finer Tuning	Controlled Random Search
Reduction in execution time (Hadoop)	70.8%	49.55%
Reduction in execution time (Spark)	81.19%	77.77%

XII. CONCLUSION

Auto-tuning of parameters has become as obligatory as finding the optimal configuration to improve the performance of the system. This paper, after analyzing the importance of the automatic tuning of parameters, proposes two algorithms: Grid Search with Finer Tuning and Controlled Random Search. These algorithms have made use of the preceding work, which helped in selecting those parameters which influenced the overall performance of the system. The results obtained demonstrated that Grid Search with Finer Tuning suits well for spark as compared to Hadoop. Grid Search with Finer Tuning has shown great speed for Spark. Controlled Random Search, however not much useful to Hadoop, has shown considerable improvements in Spark. Also, in both cases, Grid search with finer tuning has proved to be much more efficient. Finally, both the algorithms proposed in this paper are capable of finding efficient configurations and thus reducing the execution time required while running a single job on Hadoop and Spark platforms.

XII. FUTURE SCOPE

The entire research is focused on optimizing the performance of Hadoop and Spark with respect to time. This paper does not take into consideration other aspects of optimization such as optimization with respect to resources, cpu, memory, or cost. A lot of work can be done considering these aspects as well.

The algorithms used have their own benefits and drawbacks, as mentioned above. A better algorithm can be drafted and implemented that can combine the plus points of both these algorithms and eliminate the drawbacks. Future work could include working on such algorithms and considering a multi-objective approach.

XIV. REFERENCES

- [1] <https://hadoop.apache.org/>
- [2] <https://spark.apache.org/>
- [3] Chin-Wei Hsu, Chih-Chung Chang and Chih-Jen Lin (2010). A practical guide to support vector classification. Technical Report, National Taiwan University.
- [4] https://en.wikipedia.org/wiki/Hyperparameter_optimization
- [5] Bergstra, James, and Yoshua Bengio., Random search for hyperparameter optimization., The Journal of Machine Learning Research 13(1) (2012) 281-305.
- [6] Armanur Rahman, J.Hossen, Venkateshaiah C., SMBSP: A Self-Tuning Approach using Machine Learning to Improve Performance of Spark in Big Data Processing., 7th International Conference on Computer and Communication Engineering (ICCCCE) (2018).
- [7] Wang, Ziyu, et al., Bayesian optimization in a billion dimensions via random embeddings., Journal of Artificial Intelligence Research 55 (2016) 361-387.
- [8] W.L. Price., A Controlled Random Search Procedure for global optimization.
- [9] Yigitbasi, Nezih, et al., Towards machine learning-based auto-tuning of mapreduce. 2013 IEEE 21st International Symposium on Modelling, Analysis, and Simulation of Computer and Telecommunication Systems. IEEE, (2013).
- [10] Ding, Xiaolan, Yi Liu, and Depei Qian., Jellyfish: Online performance tuning with adaptive configuration and elastic container in Hadoop yarn., In 2015 IEEE 21st International Conference on Parallel and Distributed Systems (ICPADS), IEEE, (2015) 831-836.
- [11] Bansal, Garvit, Anshul Gupta, Utkarsh Pyne, Manish Singhal, and Subhasis Banerjee., A framework for performance analysis and tuning in Hadoop-based clusters., In Smarter Planet and Big Data Analytics Workshop (SPBDA 2014), held in conjunction with International Conference on Distributed Computing and Networking (ICDCN 2014), Coimbatore, INDIA. (2014).
- [12] Gu, Jing, Ying Li, Hongyan Tang, and Zhonghai Wu., Auto-Tuning Spark Configurations Based on Neural Network., In 2018 IEEE International Conference on Communications (ICC), (2018) 1-6. IEEE.
- [13] Du, Haizhou, Ping Han, Wei Chen, Yi Wang, and Chenlu Zhang., Otterman: A Novel Approach of Spark Auto-tuning by a Hybrid Strategy., In 2018 5th International Conference on Systems and Informatics (ICSAI), IEEE, (2018) 478-483.
- [14] Nguyen, Nhan, Mohammad Maifi Hasan Khan, and Kewen Wang., Towards automatic tuning of apache spark configuration., 2018 IEEE 11th International Conference on Cloud Computing (CLOUD). IEEE, (2018).
- [15] Shivarkar, Sayali Ashok., Speed-up extension to Hadoop system., International Journal of Engineering Trends and Technology (IJETT) (2014).