

Dec 5, 2017

# Benchmark and Comparison: HPCC Thor vs. Apache Spark

Team #16

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## Abstract

HPCC Thor and Apache Spark are both big data analytics engine. Here we evaluate and compare their performance for batch processing over big data, over metrics like scalability, latency, and CPU utilization. We also make a note of the general trends in performance and analyse which engine is better suited for which kind of workload.

## Introduction

There is lot of big data available today from many different sources - it is so large and complex that it is very difficult, if not impossible, to process it using the conventional data management technologies. The problems of volume, velocity, and variety in the big data pervasive today has lead to many different innovative technologies to enable its processing and extract meaningful information. Hadoop mapreduce is a very popular open source framework used for batch processing of huge amounts of data in scalable distributed manner using commodity hardware. But the main issue with the hadoop framework is the rigidity of its map reduce paradigm, which is not amenable for a lot of applications which do not naturally map to the sequence of map and reduce tasks well. Apache spark was developed at amplabs at UC Berkley in 2009. It provides a comprehensive and unified big data processing framework for big data processing requirements with a variety of datasets that are diverse in nature as well as source.

High performance computing cluster (HPCC) developed by Lexis Nexis risk solutions is also a open source platform for processing and analyzing large volumes of data. It has been in production since late 2000, and akin hadoop, it also utilizes commodity linux machines for distributed and scalable execution of data intensive applications. It has two different component for specialized processing of batch and streaming kinds of workloads, handled by thor and roxie respectively. Thor is a data refinery which takes inn massive volumes of raw data and performs jobs like data cleaning, ETL, index creation, queries, and large scale analytics etc. Thor is quite

similar to the google and hadoop map reduce platforms in its functionality, but is supposed to provide much higher performance in equivalent hardware configurations.

In this paper, we are evaluating the performance of hpcc thor and apache spark for batch processing jobs on big data. We are evaluating the performance of the two engines for parameters like scalability, latency and cpu utilization for sql workload on datasets ranging from 2 GB to 32 GB in size. We have also compared the performance of thor and spark in context of these factors for different configurations, and studied the workloads and configurations for which each engine performs better.

## **Related Work**

HPCC Thor has been released fairly recently, and there isn't much work that has been done in the space of benchmarking Thor. But we would like to refer [4] which was released when we were already working on this project. Our work differs from them in terms of configuration used and the sql workloads on which experiments were run.

## **Goals**

We are evaluating the performance of HPCC Thor and Apache Spark for three parameters:

- **Scalability:** the variance in performance of the systems as a function of the dataset size and the resources available. Both dataset size and resources are independent variables here, and we are studying the performance of the system with the increase in the dataset size even as the resources available remain constant. We are also studying the performance with the change in the resources available even as the dataset size remains constant. But our focus for the purposes of this study is on strong scaling - maintaining a constant range of dataset size and increasing the resources. To evaluate the performance viz a viz weak scaling, larger datasets would have been required, and our monetary constraints prevented us from satisfiably studying that aspect in this experiment.
- **Latency:** we studied the latency of both the engines - the time gap between the submission of the job to getting the results. This is an important parameter for performance evaluation, although for batch processing jobs, it is not as critical as it ifor interactive jobs.
- **Cpu utilization:** the capacity to which the processing power of the cpu is being used as a function of time. Better cpu utilization indicates a better ability to harness the compute power available to obtain optimal results. An engine with less than satisfactory cpu utilization essentially wastes the compute power at its disposal, and thus invariably has higher latency than an engine which doesnt. Thus, cpu utilization and latency are inversely related, and lower cpu utilization always leads to a higher latency in the system.

## **Experiment design**

The design and the setup of the experiment is one of the most critical phases of the entire benchmarking process. It is very important to pick each experiment being conducted very carefully, and calibrate the settings to ensure that only variable is varied at a time, so that the variance in the result can be reliably studied as a function of that variable. At this point, it is important to ensure that other variables remain constant, otherwise it can lead to noisy results, and it would be difficult to point out exactly what factors are responsible for the results observed.

## **Workload**

We decided to use the sql workload for the our experiments on thor and spark. The sql queries can be divided into three broad categories: filter, aggregate, and sort. For filtr queries, we used queries with two different selectivity measures - low and high. The query with high selectivity returns only around 2 rows as the result, whereas the query with low selectivity returns thousands of rows as the result. The aggregate queries were finding the minimum, maximum, average, count, and group by ver the dataset. While the sorting query sorts the randomized dataset given as input.

We did not do insert/update queries as part of the of sql workload. Both spark and thor work by creating immutable objects from the dataset over which further analysis is carried out. Inserting or updating a row would essentially result in creating the immutable object from scratch again. As both the engines are being evaluated for batch processing jobs, it is a fair assumption to make that the data they once receive does not change. Hence, in such a scenario, insert/update queries would be pointless.

## **Datasets**

The datasets used were of sizes 2 GB, 4 GB, 8 GB, 16 GB, and 32 GB. we also used two types of datasets: integers and strings. Most systems handle the integer and string data differently, hence to test the performance at that granularity, we created separate integer and string datasets. Also, both integers and strings can be considered representative of the real life numeric and string datasets. Thus, the total number of datasets on which experiments were run are ten. We generated the dataset using a data generator, in which integers and strings were randomly generated. We chose to generate the values randomly, as that helped us in preserving the broad characteristics of the dataset as we increased its size. The code to generate the data can be found in our github repository at [Rambharose/src/DataGenerator/Thor/DataGen.ecl](#).

## **Cluster setup**

We used Amazon AWS services to setup the cluster to run the experiments. We set up a cluster with one node using AWS Educate, whereas for cluster with 3 and 5 nodes respectively, we used the AWS EMR service. All the clusters used the m1.large EC2 instance available in US-West Oregon region. Each instance had 2 cores, 8 GB RAM, and 850 GB EBS storage. The choice of the RAM for the machines used stemmed from the consideration that data analytics engines like Thor and Spark are faster when the data fits completely in-memory. But a lot of real world data rarely fits completely into the memory, and has to be invariably spilt onto the disk.

We wanted to evaluate the performance of the engines in both these scenarios. Hence, by picking 8 GB RAM, the assumption was that datasets of sizes 2 GB and 4 GB will easily fit into main memory, while for 8 GB, 16 GB, and 32 GB, some of the data will need to be stored on disk as well. We also used EBS storage here, because that was the only kind of disk storage available with this combination of cores and RAM, but another interesting choice could have been the use of SSD storage, as SSD disks are faster.

## Softwares

We used the latest version of all softwares available at the time - HPCC Thor v6.4 and Apache Spark v2.2. We used Scala for Spark programming as Spark is written in Scala, and writing the application in Scala provides an added level of optimization. We tuned Spark to use maximum number of cores and RAM possible by explicitly setting values for `--num-executors`, `--executor-cores`, and `--executor-memory` parameters. The Thor programming was done in ECL which is written in C++. To monitor CPU utilization, we used a linux utility called `dstat` which provides the percentage time CPU was used for each second.

## Observations:

The following trends were observed

- (1) Variance in latency with respect to the data size: The latency for all the operations increases proportionately with the increment of dataset size. We observed that as we double the size of the dataset the latency of the operations approximately doubles. This trend can be seen in all the plots (a,b,c,d,...,k,l). In all these figures, the Y-axis represents the time (in seconds) and the X-axis represents the different type of SQL workloads.
- (2) Integer Dataset: In Thor, the count distinct workload and sort workload are the most expensive workloads and they roughly take the same time to complete. The reason might be due to the fact that count distinct operation might be using sorting as a first phase and then it uses a linear run to compute the count of distinct records. The aggregate operations like average, minimum, maximum do take roughly the same amount of time as all of them are  $O(n)$  operations. The aggregate by key operation takes little bit more time than other aggregate operations as it has to do extra work to compute the count of the record with each distinct keys. In Spark, unlike Thor, count distinct is not as expensive as the sort operation. It takes just a little bit more time than the count operation. Spark might be using hashing techniques to count the distinct number of records. In fact, Spark takes about 1.5 times less time to perform count distinct operation than what Thor needs. The aggregate operations like average, minimum, maximum do take roughly the same amount of time as all of them are  $O(n)$  operations. The aggregate by key operation takes little bit more time than other aggregate operations as it has to do extra work to compute the count of the record with each distinct keys. All of these trends are observed in all the clusters, with the differences in the latency of different operations becoming more pronounced and evident with the increase in the

dataset

sizes.

(3) String Dataset: In Thor, the sort workload is the most expensive workloads. The count distinct operation for string does not the same times as of sorting as observed in the integer dataset. The reason might be due to the fact that count distinct operation in Thor has been implemented differently for numeric and non-numeric datasets. The aggregate operations like average, minimum, maximum do take roughly the same amount of time as all of them are  $O(n)$  operations. The aggregate by key operation takes little bit more time than other aggregate operations as it has to do extra work to compute the count of the record with each distinct keys. In Spark, the same trend was observed, with the only noticeable difference being that the Spark takes more time (about 2-5 times) than Thor for each operation. This difference is visible more clearly in the larger datasets (16 and 32GB). The plots m, n, o and p show these trends. All of these trends are observed in all the clusters, with the differences in the latency of different operations becoming more pronounced and evident with the increase in the dataset sizes.

(4) Scalability factor: For Thor the scalability factor(latency of the original system/latency of the new system) was close to its ideal value(resources in the original system/resources in the new system). For the same dataset size across different size of the cluster, the latency varies directly with the number of nodes in the cluster. For example, the Thor cluster with size 3 performed approximately 3 times better than the cluster with size 1. The same trend was observed across all the other Thor clusters. For Spark the scalability factor was smaller than the ideal scalability factor expected. For example, the Spark cluster with size 3 performed approximately 1.7 times(only) better than the cluster with size 1. In Spark, the overhead cost of cluster operations might be very large as compared to the same in Thor, hence the ideal scalability factor is not prevalent in Spark clusters.

## CPU Utilization

We observed that Thor uses 58% CPU for sorting workloads, and 48% for AggregateMin and AggregateMax queries. For rest of the workloads, Thor uses approximately 55% of CPU. These figures are similar for both integer and string type datasets. But in Spark noticeable difference is observed for filter and sort queries. For integer datasets of all sizes, the CPU utilization stands at 96%, while for string datasets, the CPU utilization was at 96% for smaller datasets which can potentially fit into the RAM (<8GB), but for larger datasets, it drops to 50%. Similarly, for sort query, for larger string type datasets ( $\geq 16$  GB), CPU utilization drops to 37%. For all other workloads, Spark averages a CPU utilization of 48 to 50%.

CPU Utilization for Filter Query in Spark

	Integer	String
<8 GB	96%	96%
>=8 GB	96%	50%

#### CPU Utilization for Sort Query in Spark

	Integer	String
<16 GB	96%	90%
>=16 GB	96%	37%

By looking at the log files obtained from dstat, we also observed that Spark has lower CPU utilization and higher idle time for string datasets as compared to integer datasets of the same size.

### Challenges Faced and Effort Required

Here, we would like to make a note of the challenges faced in this study, and the amount of effort required to successfully complete it, as a guidance for future such endeavors.

The entire experiment took about 50 USD to use the AWS instances and clusters for the experiment. The experiments ran for a total of 60 hours. The individual breakdown of each experiment can be found in the appendix. AWS Educate account can be used to run single node cluster for free, but it does not allow the creation of EMR or even manual creation of cluster. We did not get the free credits in the AWS account, due to which we had to use our private account to run the experiments on EMR cluster.

The cluster creation is also a very slow process, and it takes almost an hour just to launch the cluster. It also shows the error “core 2: limit exceeds”, but starts successfully after an hour. The error thrown, along with a huge amount of time to actually launch the cluster leads one to believe that the cluster creation process has failed, but that is not necessarily the case. Also, there is an internal limit on the size of the cluster one can create from the account, and a manual request has to be made to the AWS Customer Care to increase the limit. They take more than 24 hours to actually increase the cap on the cluster size, and the increase is by just 1 most times. So a request for the cap on cluster size to be increased should be made well in advance.

### Conclusion

To conclude, we have done performance evaluation of HPCC Thor and Apache Spark for SQL workload on datasets ranging from 2 GB to 32 GB in size. We evaluated the performance for scalability, latency, and CPU utilization, and compared their performance against each other. We observed that Spark outperforms Thor by 0.5x for Aggregate Count queries. But for all other workloads, Thor outperforms Spark by 2-3x in case of Integer datasets, and by 4x in case of String datasets. In terms of scalability, both Thor and Spark scale equally well as a function of cluster size, and dataset size. For CPU utilization, Thor demonstrates more consistent performance at 55%, whereas Spark gives a really good CPU utilization for Filter and Sort queries (96%), but for other kinds of workloads it has a CPU utilization of approx 50%.

For future work, a further study can be carried out to decipher the reasons behind the performance differences observed between Thor and Spark. Potential directions to explore can be the role of JVM, memory management, and instruction count have on slowing down Spark. Spark Scala is JVM based, whereas ECL is written in C++ which is native, and the added overhead of using JVM can slow things down, and also result in bloated code due to considerable increase in the number of instructions. Also, JVM does implicit memory management, while C++ does explicit memory management which can have a role to play here as well.

Other interesting angles to explore in this study is to evaluate the performance of both the engines for even larger sized datasets (~ 2 TB), larger clusters, and more RAM per node. We have also not covered join queries as part of the SQL workload here, but that is a very practically important kind of workload to benchmark the performance on.

The entire code and logs for this project can be found at <https://github.ncsu.edu/CSC591-DIC/RamBharose>

## **Acknowledgements**

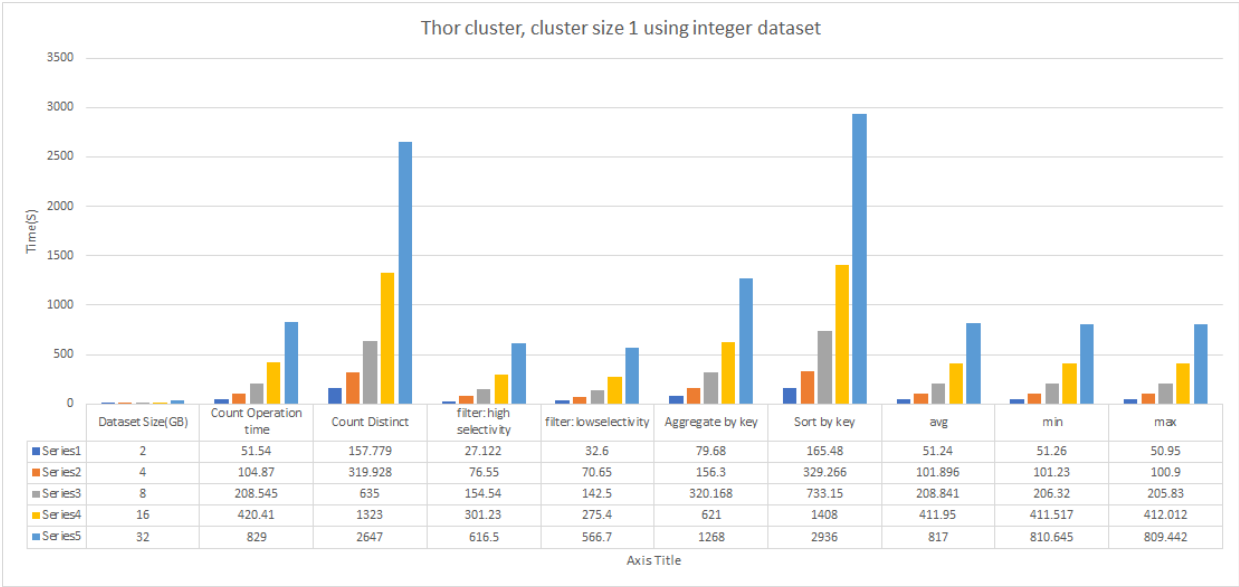
We would like to acknowledge Dr. Vincent Freeh for his guidance throughout the project. We would also like to thank Anshuman Goel for letting us avail his AWS credits to run the experiments.

## **References**

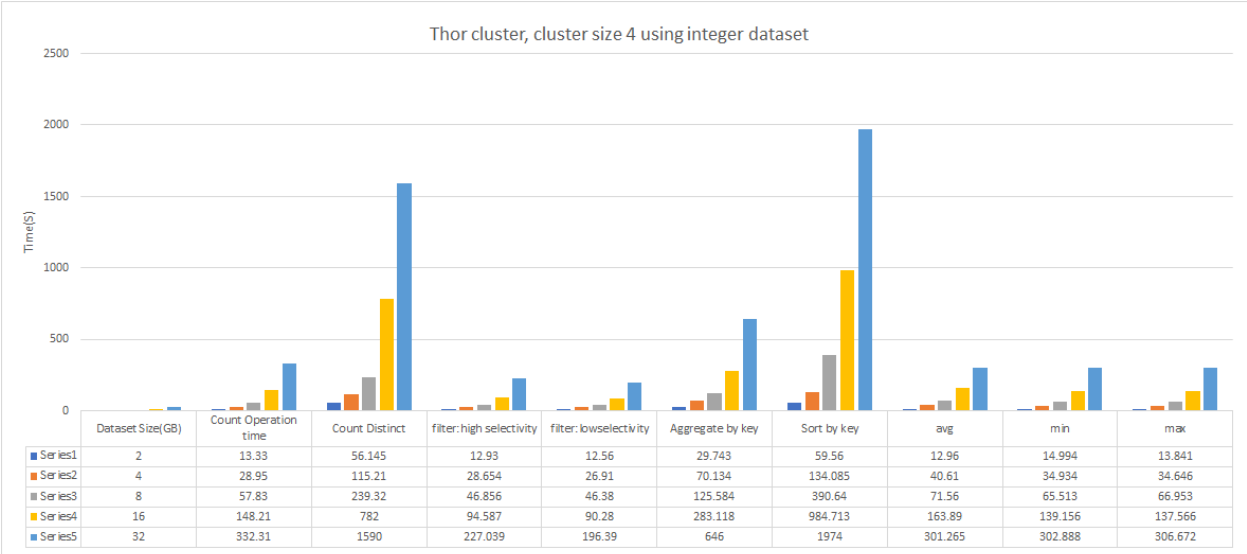
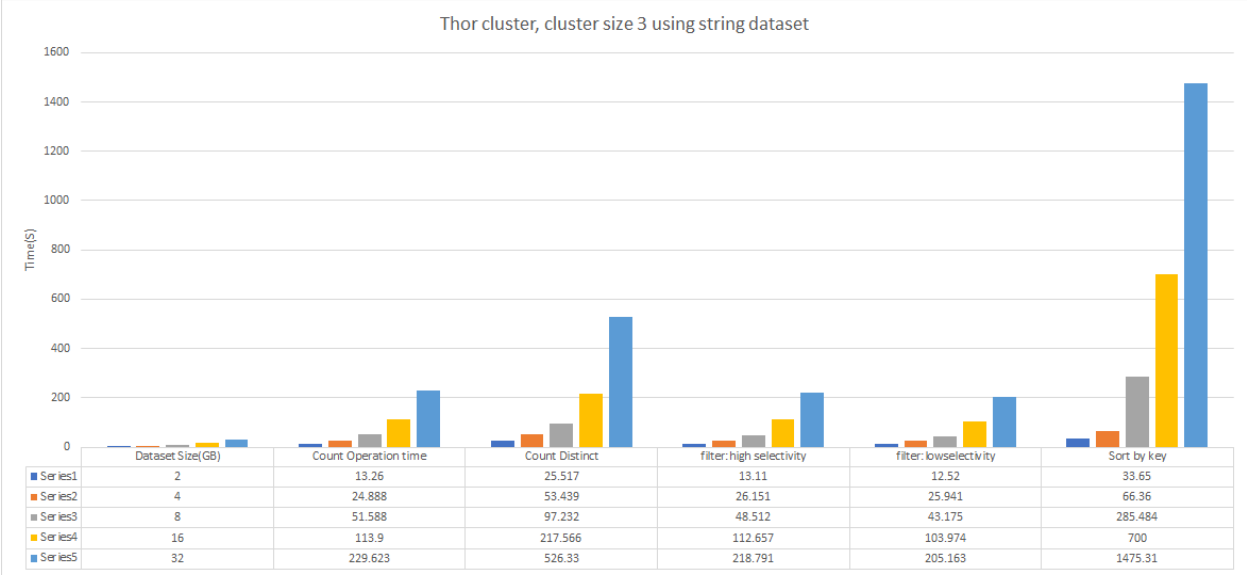
- [1] <https://hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-common/FileSystemShell.html>
- [2] <http://aws.amazon.com/>
- [3] [http://cdn.hpccsystems.com/whitepapers/wp\\_introduction\\_HPCC.pdf](http://cdn.hpccsystems.com/whitepapers/wp_introduction_HPCC.pdf)
- [4] [http://cdn.hpccsystems.com/whitepapers/hpccsystems\\_thor\\_spark.pdf](http://cdn.hpccsystems.com/whitepapers/hpccsystems_thor_spark.pdf)
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- [6] <https://0x0fff.com/spark-architecture/>
- [7] <https://www.networkworld.com/article/3033888/linux/getting-system-insights-with-dstat.html>

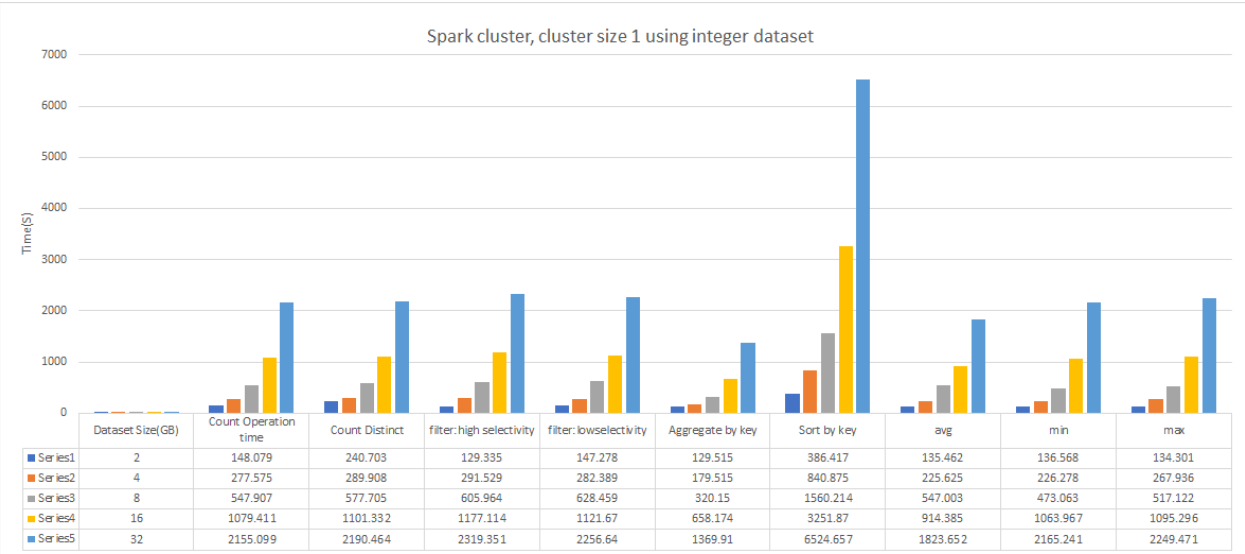
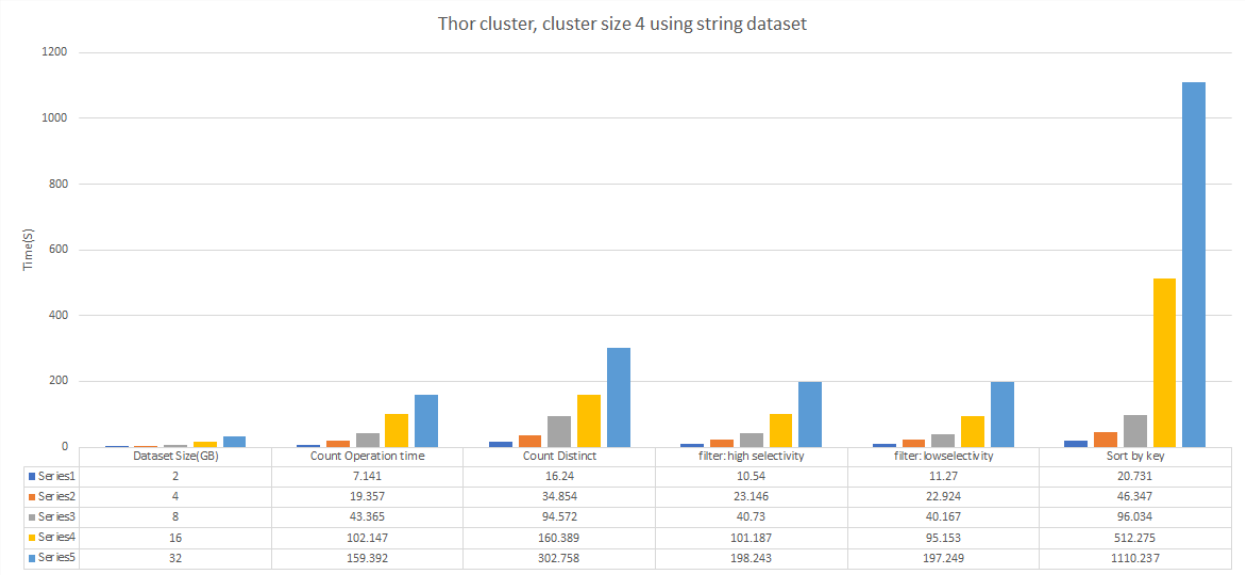
Appendix A

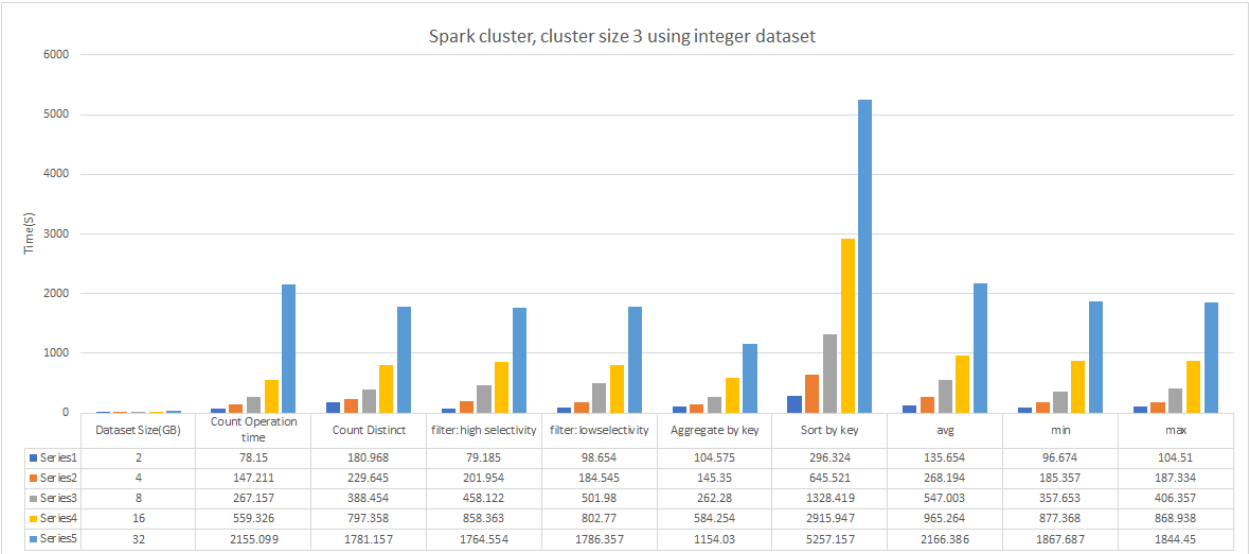
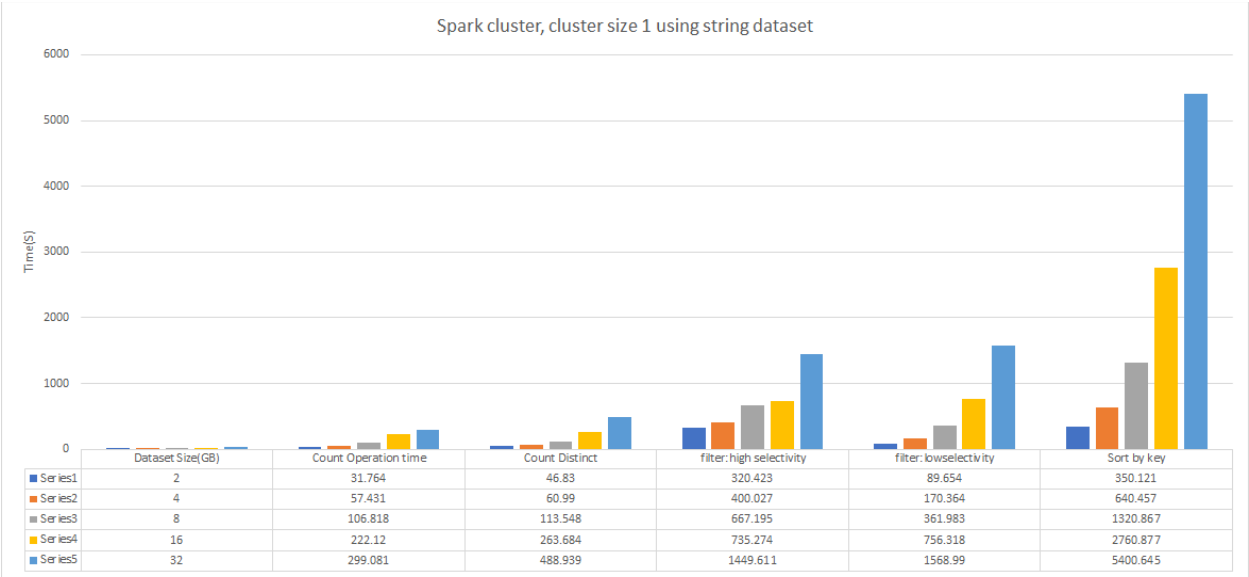
Graphs

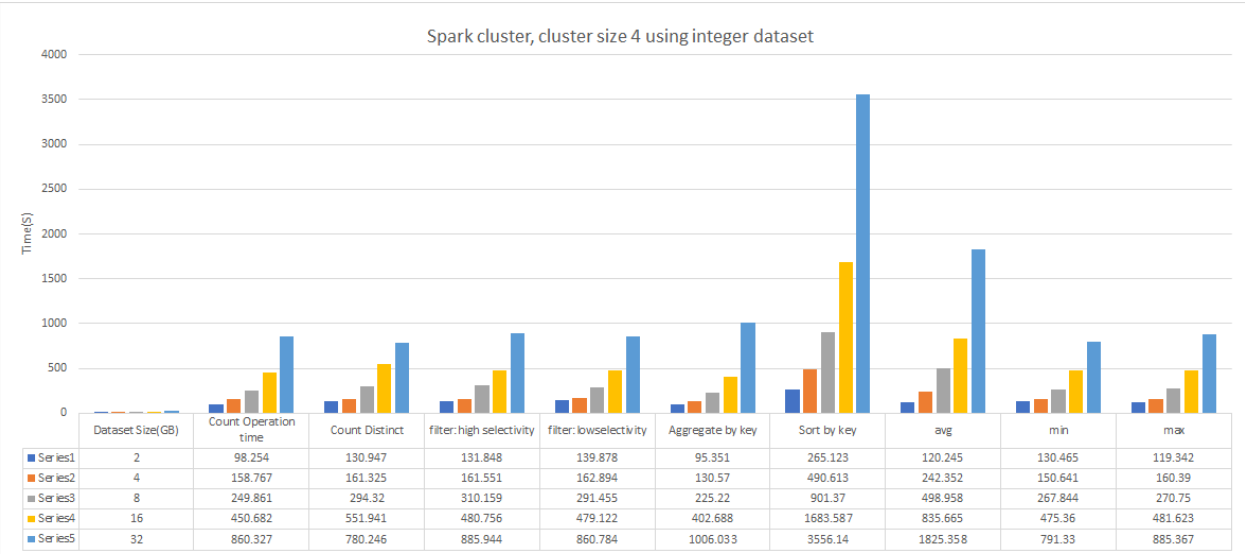
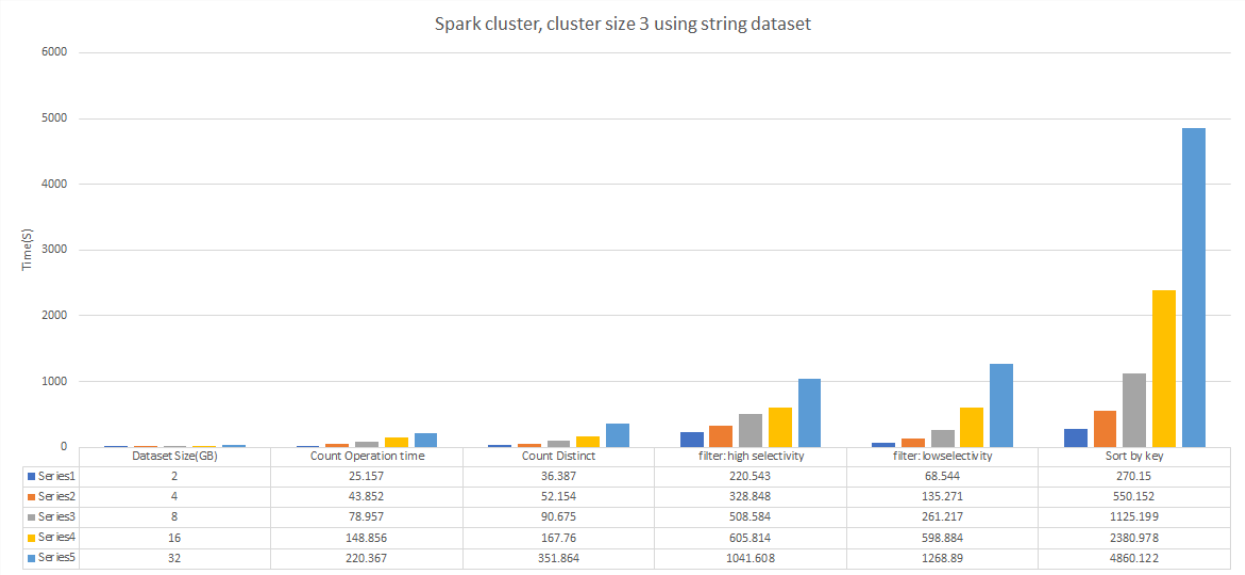


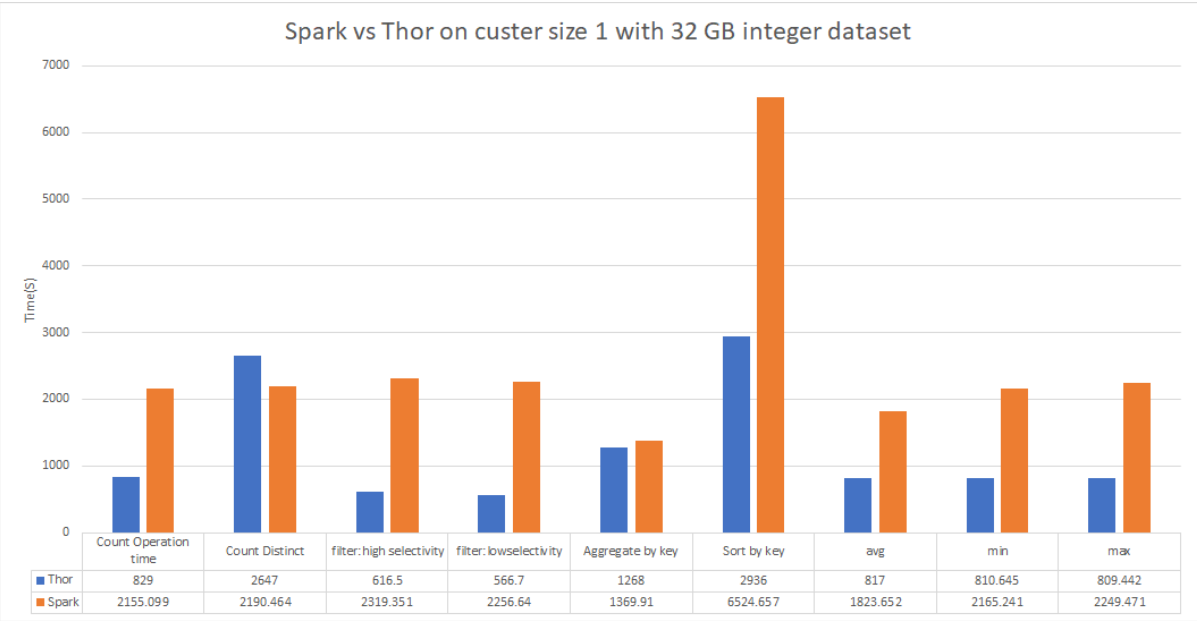
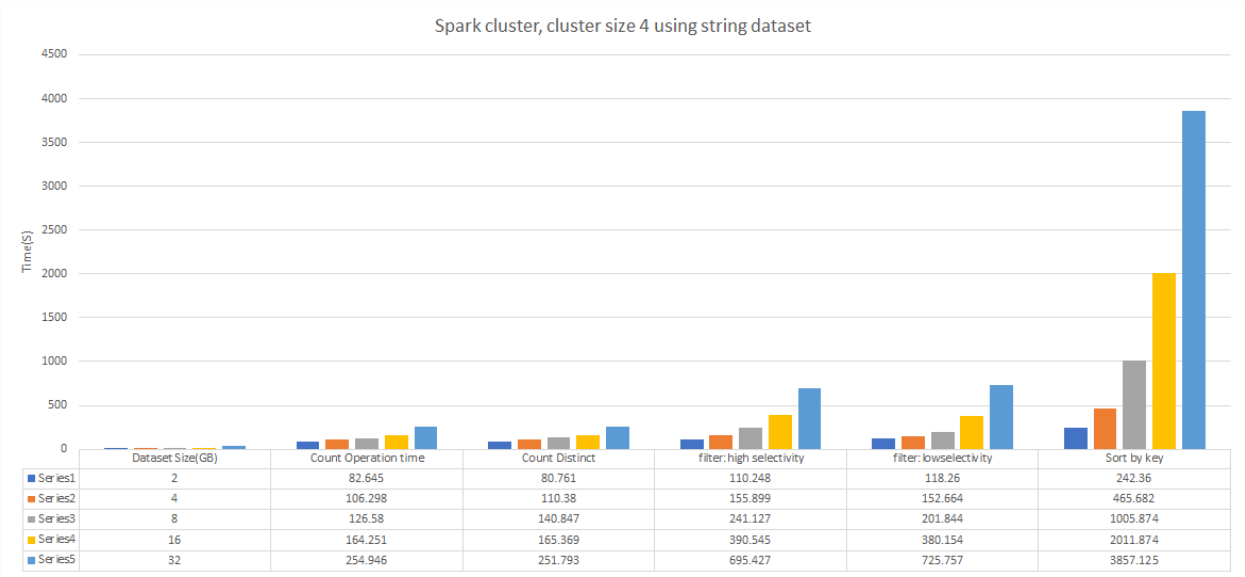


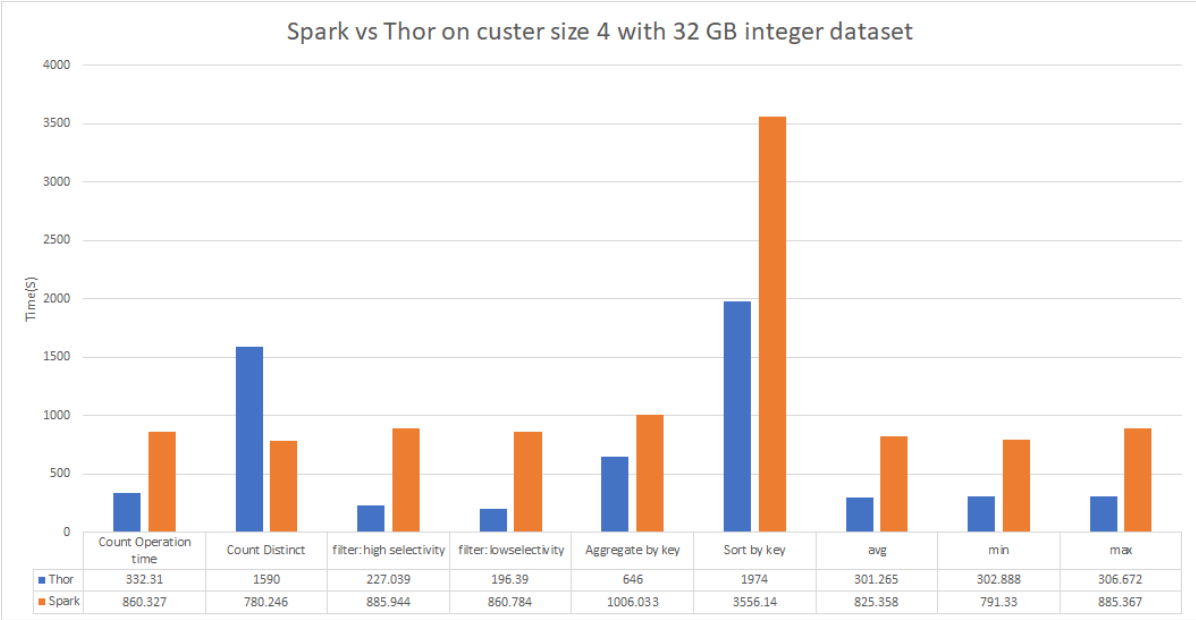
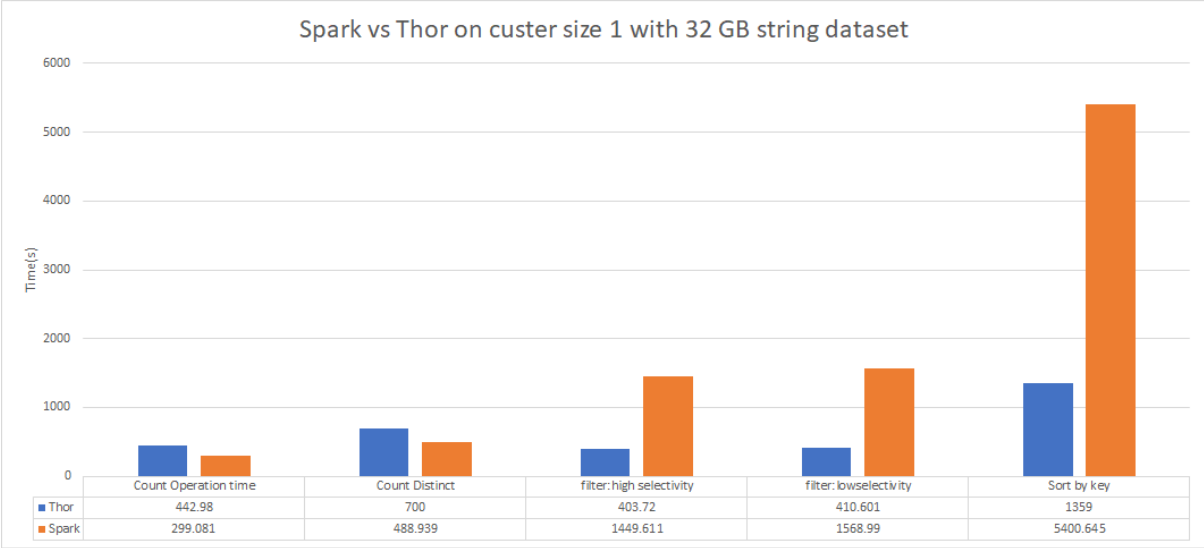




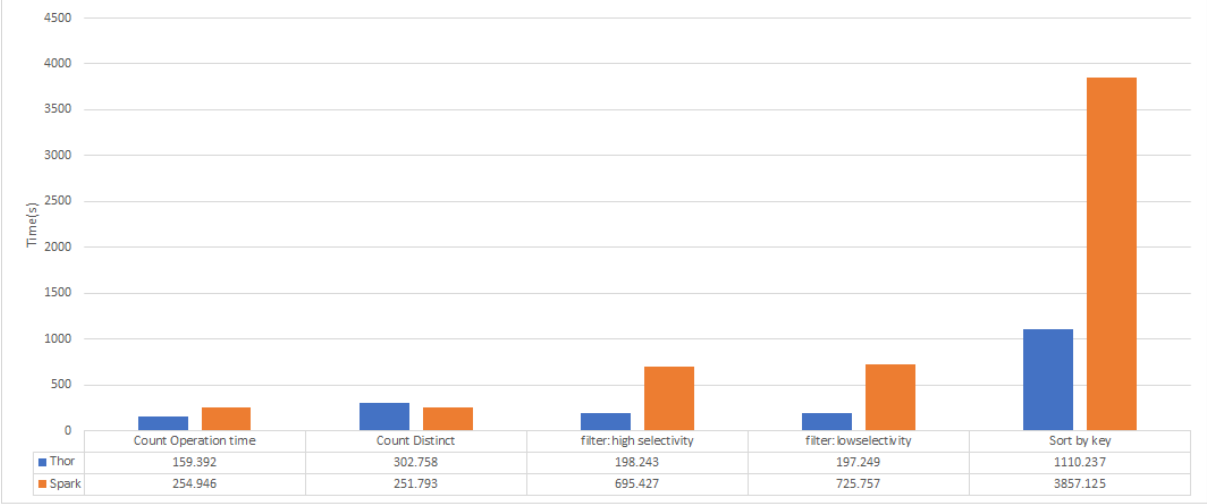








Spark vs Thor on custer size 4 with 32 GB string dataset



## Appendix B

### SQL Queries

The details of the queries in each of the workloads are as follows:

Filter queries:

FilterLowSelectivity: select \* from wutable where \_c0=\"19107\"

FilterHighSelectivity: select \* from wutable where \_c0=\"53800\"

Aggregate queries:

AggregateCountDistinct: select count(distinct \_c0) from wutable

AggregateCountTotal: select count(\_c0) from wutable

AggregateMin: select min(\_c0) from wutable

AggregateMax: select max(\_c0) from wutable

AggregateAvg: select avg(\_c0) from wutable

AggregateGroupby: select count(\_c1) from wutable group by \_c0

Sort query:

SortRandom: select \* from wutable order by \_c0

### Sample Scripts

#### Sample Scala script for Aggregate Groupby job:

```
import org.apache.spark.{SparkContext, SparkConf}
import org.apache.spark.sql.types.StructType
import org.apache.spark.sql.types.{IntegerType, StringType}

object AggregateGroupby {
  def main(args: Array[String]) {
    val conf = new SparkConf().setAppName("AggregateGroupby Application")

    val sc = new SparkContext(conf)
    val sqlContext = new org.apache.spark.sql.SQLContext(sc)
    val fileName = args(0)
    val datatype = args(1) //1 for int, 0 for string

    def time[R](block: => R): R = {
      val t0 = System.nanoTime()
      val result = block // call-by-name
      val t1 = System.nanoTime()
      println("Elapsed time: " + (t1 - t0) + "ns")
      result
    }

    val customSchema_int = new StructType().add("_c0", IntegerType).add("_c1", IntegerType)

    val customSchema_string = new StructType().add("_c0", IntegerType).add("_c1", StringType)
```



```

        if(datatype==1)
        {
            val wudf = sqlContext.read.format("com.databricks.spark.csv").option("header",
"false").schema(customSchema_int).load(fileName)
            wudf.registerTempTable("wutable")
        }
        else
        {
            val wudf = sqlContext.read.format("com.databricks.spark.csv").option("header",
"false").schema(customSchema_string).load(fileName)
            wudf.registerTempTable("wutable")
        }

        ///////aggregate queries

        //group by
        val groupby_int = time{sqlContext.sql("select count(_c1) from wutable group by _c0")}
        val c = groupby_int.count()
        println(s"Query Finished - there are $c lines here.")

        //Stopping Spark context
        sc.stop()
    }
}

```

### **ECL script for Aggregate Groupby:**

```

rs := {integer key, integer fill};

#WORKUNIT('name', 'aggr_2');
dataset_name2 := 'IntegerDataSet_2GB';
outdata2 := DATASET(dataset_name2, rs, THOR);
outdata22 := TABLE(outdata2, {key, SUM(GROUP, fill)}, key, FEW);
OUTPUT(COUNT(NOFOLD(outdata22)));

#WORKUNIT('name', 'aggr_4');
dataset_name4 := 'IntegerDataSet_4GB';
outdata4 := DATASET(dataset_name4, rs, THOR);
outdata44 := TABLE(outdata4, {key, SUM(GROUP, fill)}, key, FEW);
OUTPUT(COUNT(NOFOLD(outdata44)));

#WORKUNIT('name', 'aggr_8');
dataset_name8 := 'IntegerDataSet_8GB';
outdata8 := DATASET(dataset_name8, rs, THOR);
outdata88 := TABLE(outdata8, {key, SUM(GROUP, fill)}, key, FEW);
OUTPUT(COUNT(NOFOLD(outdata88)));

#WORKUNIT('name', 'aggr_16');
dataset_name16 := 'IntegerDataSet_16GB';
outdata16 := DATASET(dataset_name16, rs, THOR);
outdata1616 := TABLE(outdata16, {key, SUM(GROUP, fill)}, key, FEW);
OUTPUT(COUNT(NOFOLD(outdata1616)));

```

```
#WORKUNIT('name', 'aggr_32');  
dataset_name32 := 'IntegerDataSet_32GB';  
outdata32 := DATASET(dataset_name32, rs, THOR);  
outdata3232 := TABLE(outdata32, {key, SUM(GROUP, fill)}, key, FEW);  
OUTPUT(COUNT(NOFOLD(outdata3232)));
```

## Appendix C: Observation Table

Cluster Type	#Nodes	Total Cluster RAM(GB)	Dataset Size(GB)	Data Type	Opeartion	Time(s)	CPU %
THOR	1	8	2	Integer	Total Count	51.54	51
THOR	1	8	4	Integer	Total Count	104.87	51
THOR	1	8	8	Integer	Total Count	208.545	51
THOR	1	8	16	Integer	Total Count	420.41	51
THOR	1	8	32	Integer	Total Count	829	51
THOR	1	8	2	Integer	Distinct Count	157.779	56
THOR	1	8	4	Integer	Distinct Count	319.928	56
THOR	1	8	8	Integer	Distinct Count	635	56
THOR	1	8	16	Integer	Distinct Count	1323	56
THOR	1	8	32	Integer	Distinct Count	2647	56
THOR	1	8	2	Integer	Filter: High Selectivity	27.122	52
THOR	1	8	4	Integer	Filter: High Selectivity	76.55	52
THOR	1	8	8	Integer	Filter: High Selectivity	154.54	52
THOR	1	8	16	Integer	Filter: High Selectivity	301.23	52
THOR	1	8	32	Integer	Filter: High Selectivity	616.5	52
THOR	1	8	2	Integer	Filter: Low Selectivity	32.6	52
THOR	1	8	4	Integer	Filter: Low Selectivity	70.65	52
THOR	1	8	8	Integer	Filter: Low Selectivity	142.5	52
THOR	1	8	16	Integer	Filter: Low Selectivity	275.4	52

THOR	1	8	32	Integer	Filter: Low Selectivity	566.7	52
THOR	1	8	2	Integer	Aggregate by key	79.68	58
THOR	1	8	4	Integer	Aggregate by key	156.3	58
THOR	1	8	8	Integer	Aggregate by key	320.168	58
THOR	1	8	16	Integer	Aggregate by key	621	58
THOR	1	8	32	Integer	Aggregate by key	1268	58
THOR	1	8	2	Integer	Sort by key	165.48	59
THOR	1	8	4	Integer	Sort by key	329.266	59
THOR	1	8	8	Integer	Sort by key	733.15	59
THOR	1	8	16	Integer	Sort by key	1408	59
THOR	1	8	32	Integer	Sort by key	2936	59
THOR	1	8	2	Integer	Average value of Key	51.24	55
THOR	1	8	4	Integer	Average value of Key	101.896	55
THOR	1	8	8	Integer	Average value of Key	208.841	55
THOR	1	8	16	Integer	Average value of Key	411.95	55
THOR	1	8	32	Integer	Average value of Key	817	55
THOR	1	8	2	Integer	Min key	51.26	52
THOR	1	8	4	Integer	Min key	101.23	52
THOR	1	8	8	Integer	Min key	206.32	52
THOR	1	8	16	Integer	Min key	411.517	52
THOR	1	8	32	Integer	Min key	810.645	52
THOR	1	8	2	Integer	Max Key	50.95	51
THOR	1	8	4	Integer	Max Key	100.9	51
THOR	1	8	8	Integer	Max Key	205.83	51

THOR	1	8	16	Integer	Max Key	412.012	51
THOR	1	8	32	Integer	Max Key	809.442	51
THOR	3	24	2	Integer	Total Count	23.951	51
THOR	3	24	4	Integer	Total Count	52.166	51
THOR	3	24	8	Integer	Total Count	102.823	51
THOR	3	24	16	Integer	Total Count	171.6	51
THOR	3	24	32	Integer	Total Count	445.21	51
THOR	3	24	2	Integer	Distinct Count	65.49	56
THOR	3	24	4	Integer	Distinct Count	144.3	56
THOR	3	24	8	Integer	Distinct Count	425	56
THOR	3	24	16	Integer	Distinct Count	880	56
THOR	3	24	32	Integer	Distinct Count	1821.23	56
THOR	3	24	2	Integer	Filter: High Selectivity	16.23	52
THOR	3	24	4	Integer	Filter: High Selectivity	31.21	52
THOR	3	24	8	Integer	Filter: High Selectivity	81.26	52
THOR	3	24	16	Integer	Filter: High Selectivity	150.64	52
THOR	3	24	32	Integer	Filter: High Selectivity	340.51	52
THOR	3	24	2	Integer	Filter: Low Selectivity	14.939	52
THOR	3	24	4	Integer	Filter: Low Selectivity	27.668	52
THOR	3	24	8	Integer	Filter: Low Selectivity	75.112	52
THOR	3	24	16	Integer	Filter: Low Selectivity	140.26	52
THOR	3	24	32	Integer	Filter: Low Selectivity	311.12	52
THOR	3	24	2	Integer	Aggregate by key	40.91	58
THOR	3	24	4	Integer	Aggregate	80.25	58

					by key		
THOR	3	24	8	Integer	Aggregate by key	192.3	58
THOR	3	24	16	Integer	Aggregate by key	412.31	58
THOR	3	24	32	Integer	Aggregate by key	868.23	58
THOR	3	24	2	Integer	Sort by key	82.31	59
THOR	3	24	4	Integer	Sort by key	240.12	59
THOR	3	24	8	Integer	Sort by key	522.11	59
THOR	3	24	16	Integer	Sort by key	1174.15	59
THOR	3	24	32	Integer	Sort by key	2454	59
THOR	3	24	2	Integer	Average value of Key	17.795	55
THOR	3	24	4	Integer	Average value of Key	43.737	55
THOR	3	24	8	Integer	Average value of Key	74.816	55
THOR	3	24	16	Integer	Average value of Key	174.55	55
THOR	3	24	32	Integer	Average value of Key	366.65	55
THOR	3	24	2	Integer	Min key	20.31	52
THOR	3	24	4	Integer	Min key	44.93	52
THOR	3	24	8	Integer	Min key	81.21	52
THOR	3	24	16	Integer	Min key	178.54	52
THOR	3	24	32	Integer	Min key	371.26	52
THOR	3	24	2	Integer	Max Key	20.54	51
THOR	3	24	4	Integer	Max Key	43.52	51
THOR	3	24	8	Integer	Max Key	78.65	51
THOR	3	24	16	Integer	Max Key	169.81	51
THOR	3	24	32	Integer	Max Key	384.21	51
THOR	4	32	2	Integer	Total Count	13.33	51
THOR	4	32	4	Integer	Total Count	28.95	51
THOR	4	32	8	Integer	Total Count	57.83	51

THOR	4	32	16	Integer	Total Count	148.21	51
THOR	4	32	32	Integer	Total Count	332.31	51
THOR	4	32	2	Integer	Distinct Count	56.145	56
THOR	4	32	4	Integer	Distinct Count	115.21	56
THOR	4	32	8	Integer	Distinct Count	239.32	56
THOR	4	32	16	Integer	Distinct Count	782	56
THOR	4	32	32	Integer	Distinct Count	1590	56
THOR	4	32	2	Integer	Filter: High Selectivity	12.93	52
THOR	4	32	4	Integer	Filter: High Selectivity	28.654	52
THOR	4	32	8	Integer	Filter: High Selectivity	46.856	52
THOR	4	32	16	Integer	Filter: High Selectivity	94.587	52
THOR	4	32	32	Integer	Filter: High Selectivity	227.039	52
THOR	4	32	2	Integer	Filter: Low Selectivity	12.56	52
THOR	4	32	4	Integer	Filter: Low Selectivity	26.91	52
THOR	4	32	8	Integer	Filter: Low Selectivity	46.38	52
THOR	4	32	16	Integer	Filter: Low Selectivity	90.28	52
THOR	4	32	32	Integer	Filter: Low Selectivity	196.39	52
THOR	4	32	2	Integer	Aggregate by key	29.743	58
THOR	4	32	4	Integer	Aggregate by key	70.134	58
THOR	4	32	8	Integer	Aggregate by key	125.584	58
THOR	4	32	16	Integer	Aggregate by key	283.118	58

THOR	4	32	32	Integer	Aggregate by key	646	58
THOR	4	32	2	Integer	Sort by key	59.56	59
THOR	4	32	4	Integer	Sort by key	134.085	59
THOR	4	32	8	Integer	Sort by key	390.64	59
THOR	4	32	16	Integer	Sort by key	984.713	59
THOR	4	32	32	Integer	Sort by key	1974	59
THOR	4	32	2	Integer	Average value of Key	12.96	55
THOR	4	32	4	Integer	Average value of Key	40.61	55
THOR	4	32	8	Integer	Average value of Key	71.56	55
THOR	4	32	16	Integer	Average value of Key	163.89	55
THOR	4	32	32	Integer	Average value of Key	301.265	55
THOR	4	32	2	Integer	Min key	14.994	52
THOR	4	32	4	Integer	Min key	34.934	52
THOR	4	32	8	Integer	Min key	65.513	52
THOR	4	32	16	Integer	Min key	139.156	52
THOR	4	32	32	Integer	Min key	302.888	52
THOR	4	32	2	Integer	Max Key	13.841	51
THOR	4	32	4	Integer	Max Key	34.646	51
THOR	4	32	8	Integer	Max Key	66.953	51
THOR	4	32	16	Integer	Max Key	137.566	51
THOR	4	32	32	Integer	Max Key	306.672	51
SPARK	1	8	2	Integer	Total Count	148.079	
SPARK	1	8	4	Integer	Total Count	277.575	
SPARK	1	8	8	Integer	Total Count	547.907	
SPARK	1	8	16	Integer	Total Count	1079.411	
SPARK	1	8	32	Integer	Total Count	2155.099	
SPARK	1	8	2	Integer	Distinct Count	240.703	
SPARK	1	8	4	Integer	Distinct	289.908	



					Count		
SPARK	1	8	8	Integer	Distinct Count	577.705	
SPARK	1	8	16	Integer	Distinct Count	1101.332	
SPARK	1	8	32	Integer	Distinct Count	2190.464	
SPARK	1	8	2	Integer	Filter: High Selectivity	129.335	
SPARK	1	8	4	Integer	Filter: High Selectivity	291.529	
SPARK	1	8	8	Integer	Filter: High Selectivity	605.964	
SPARK	1	8	16	Integer	Filter: High Selectivity	1177.114	
SPARK	1	8	32	Integer	Filter: High Selectivity	2319.351	
SPARK	1	8	2	Integer	Filter: Low Selectivity	147.278	
SPARK	1	8	4	Integer	Filter: Low Selectivity	282.389	
SPARK	1	8	8	Integer	Filter: Low Selectivity	628.459	
SPARK	1	8	16	Integer	Filter: Low Selectivity	1121.67	
SPARK	1	8	32	Integer	Filter: Low Selectivity	2256.64	
SPARK	1	8	2	Integer	Aggregate by key	129.515	
SPARK	1	8	4	Integer	Aggregate by key	179.515	
SPARK	1	8	8	Integer	Aggregate by key	320.15	
SPARK	1	8	16	Integer	Aggregate by key	658.174	
SPARK	1	8	32	Integer	Aggregate by key	1369.91	
SPARK	1	8	2	Integer	Sort by key	386.417	
SPARK	1	8	4	Integer	Sort by key	840.875	
SPARK	1	8	8	Integer	Sort by key	1560.214	

SPARK	1	8	16	Integer	Sort by key	3251.87	
SPARK	1	8	32	Integer	Sort by key	6524.657	
SPARK	1	8	2	Integer	Average value of Key	135.462	
SPARK	1	8	4	Integer	Average value of Key	225.625	
SPARK	1	8	8	Integer	Average value of Key	547.003	
SPARK	1	8	16	Integer	Average value of Key	914.385	
SPARK	1	8	32	Integer	Average value of Key	1823.652	
SPARK	1	8	2	Integer	Min key	136.568	
SPARK	1	8	4	Integer	Min key	226.278	
SPARK	1	8	8	Integer	Min key	473.063	
SPARK	1	8	16	Integer	Min key	1063.967	
SPARK	1	8	32	Integer	Min key	2165.241	
SPARK	1	8	2	Integer	Max Key	134.301	
SPARK	1	8	4	Integer	Max Key	267.936	
SPARK	1	8	8	Integer	Max Key	517.122	
SPARK	1	8	16	Integer	Max Key	1095.296	
SPARK	1	8	32	Integer	Max Key	2249.471	
SPARK	3	24	2	Integer	Total Count	78.15	
SPARK	3	24	4	Integer	Total Count	147.211	
SPARK	3	24	8	Integer	Total Count	267.157	
SPARK	3	24	16	Integer	Total Count	559.326	
SPARK	3	24	32	Integer	Total Count	2155.099	
SPARK	3	24	2	Integer	Distinct Count	180.968	
SPARK	3	24	4	Integer	Distinct Count	229.645	
SPARK	3	24	8	Integer	Distinct Count	388.454	
SPARK	3	24	16	Integer	Distinct Count	797.358	

SPARK	3	24	32	Integer	Distinct Count	1781.157	
SPARK	3	24	2	Integer	Filter: High Selectivity	79.185	
SPARK	3	24	4	Integer	Filter: High Selectivity	201.954	
SPARK	3	24	8	Integer	Filter: High Selectivity	458.122	
SPARK	3	24	16	Integer	Filter: High Selectivity	858.363	
SPARK	3	24	32	Integer	Filter: High Selectivity	1764.554	
SPARK	3	24	2	Integer	Filter: Low Selectivity	98.654	
SPARK	3	24	4	Integer	Filter: Low Selectivity	184.545	
SPARK	3	24	8	Integer	Filter: Low Selectivity	501.98	
SPARK	3	24	16	Integer	Filter: Low Selectivity	802.77	
SPARK	3	24	32	Integer	Filter: Low Selectivity	1786.357	
SPARK	3	24	2	Integer	Aggregate by key	104.575	
SPARK	3	24	4	Integer	Aggregate by key	145.35	
SPARK	3	24	8	Integer	Aggregate by key	262.28	
SPARK	3	24	16	Integer	Aggregate by key	584.254	
SPARK	3	24	32	Integer	Aggregate by key	1154.03	
SPARK	3	24	2	Integer	Sort by key	296.324	
SPARK	3	24	4	Integer	Sort by key	645.521	
SPARK	3	24	8	Integer	Sort by key	1328.419	
SPARK	3	24	16	Integer	Sort by key	2915.947	
SPARK	3	24	32	Integer	Sort by key	5257.157	
SPARK	3	24	2	Integer	Average value of Key	135.654	

SPARK	3	24	4	Integer	Average value of Key	268.194	
SPARK	3	24	8	Integer	Average value of Key	547.003	
SPARK	3	24	16	Integer	Average value of Key	965.264	
SPARK	3	24	32	Integer	Average value of Key	2166.386	
SPARK	3	24	2	Integer	Min key	96.674	
SPARK	3	24	4	Integer	Min key	185.357	
SPARK	3	24	8	Integer	Min key	357.653	
SPARK	3	24	16	Integer	Min key	877.368	
SPARK	3	24	32	Integer	Min key	1867.687	
SPARK	3	24	2	Integer	Max Key	104.51	
SPARK	3	24	4	Integer	Max Key	187.334	
SPARK	3	24	8	Integer	Max Key	406.357	
SPARK	3	24	16	Integer	Max Key	868.938	
SPARK	3	24	32	Integer	Max Key	1844.45	
SPARK	4	32	2	Integer	Total Count	98.254	
SPARK	4	32	4	Integer	Total Count	158.767	
SPARK	4	32	8	Integer	Total Count	249.861	
SPARK	4	32	16	Integer	Total Count	450.682	
SPARK	4	32	32	Integer	Total Count	860.327	
SPARK	4	32	2	Integer	Distinct Count	130.947	
SPARK	4	32	4	Integer	Distinct Count	161.325	
SPARK	4	32	8	Integer	Distinct Count	294.32	
SPARK	4	32	16	Integer	Distinct Count	551.941	
SPARK	4	32	32	Integer	Distinct Count	780.246	
SPARK	4	32	2	Integer	Filter: High Selectivity	131.848	
SPARK	4	32	4	Integer	Filter: High	161.551	

					Selectivity		
SPARK	4	32	8	Integer	Filter: High Selectivity	310.159	
SPARK	4	32	16	Integer	Filter: High Selectivity	480.756	
SPARK	4	32	32	Integer	Filter: High Selectivity	885.944	
SPARK	4	32	2	Integer	Filter: Low Selectivity	139.878	
SPARK	4	32	4	Integer	Filter: Low Selectivity	162.894	
SPARK	4	32	8	Integer	Filter: Low Selectivity	291.455	
SPARK	4	32	16	Integer	Filter: Low Selectivity	479.122	
SPARK	4	32	32	Integer	Filter: Low Selectivity	860.784	
SPARK	4	32	2	Integer	Aggregate by key	95.351	
SPARK	4	32	4	Integer	Aggregate by key	130.57	
SPARK	4	32	8	Integer	Aggregate by key	225.22	
SPARK	4	32	16	Integer	Aggregate by key	402.688	
SPARK	4	32	32	Integer	Aggregate by key	1006.033	
SPARK	4	32	2	Integer	Sort by key	265.123	
SPARK	4	32	4	Integer	Sort by key	490.613	
SPARK	4	32	8	Integer	Sort by key	901.37	
SPARK	4	32	16	Integer	Sort by key	1683.587	
SPARK	4	32	32	Integer	Sort by key	3556.14	
SPARK	4	32	2	Integer	Average value of Key	120.245	
SPARK	4	32	4	Integer	Average value of Key	242.352	
SPARK	4	32	8	Integer	Average value of	498.958	

					Key		
SPARK	4	32	16	Integer	Average value of Key	835.665	
SPARK	4	32	32	Integer	Average value of Key	1825.358	
SPARK	4	32	2	Integer	Min key	130.465	
SPARK	4	32	4	Integer	Min key	150.641	
SPARK	4	32	8	Integer	Min key	267.844	
SPARK	4	32	16	Integer	Min key	475.36	
SPARK	4	32	32	Integer	Min key	791.33	
SPARK	4	32	2	Integer	Max Key	119.342	
SPARK	4	32	4	Integer	Max Key	160.39	
SPARK	4	32	8	Integer	Max Key	270.75	
SPARK	4	32	16	Integer	Max Key	481.623	
SPARK	4	32	32	Integer	Max Key	885.367	
THOR	1	8	2	String	Total Count	27.264	51
THOR	1	8	4	String	Total Count	55.12	51
THOR	1	8	8	String	Total Count	110.35	51
THOR	1	8	16	String	Total Count	222.823	51
THOR	1	8	32	String	Total Count	442.98	51
THOR	1	8	2	String	Distinct Count	40.45	56
THOR	1	8	4	String	Distinct Count	78.356	56
THOR	1	8	8	String	Distinct Count	173.68	56
THOR	1	8	16	String	Distinct Count	348.71	56
THOR	1	8	32	String	Distinct Count	700	56
THOR	1	8	2	String	Filter: High Selectivity	23.45	52
THOR	1	8	4	String	Filter: High Selectivity	46.154	52
THOR	1	8	8	String	Filter: High Selectivity	93.59	52
THOR	1	8	16	String	Filter: High Selectivity	201.687	52

THOR	1	8	32	String	Filter: High Selectivity	403.72	52
THOR	1	8	2	String	Filter: Low Selectivity	25.63	52
THOR	1	8	4	String	Filter: Low Selectivity	51.031	52
THOR	1	8	8	String	Filter: Low Selectivity	99.11	52
THOR	1	8	16	String	Filter: Low Selectivity	205.683	52
THOR	1	8	32	String	Filter: Low Selectivity	410.601	52
THOR	1	8	2	String	Sort by key	41.22	58
THOR	1	8	4	String	Sort by key	127.93	58
THOR	1	8	8	String	Sort by key	322.67	58
THOR	1	8	16	String	Sort by key	670	58
THOR	1	8	32	String	Sort by key	1359	58
THOR	3	24	2	String	Total Count	13.26	59
THOR	3	24	4	String	Total Count	24.888	59
THOR	3	24	8	String	Total Count	51.588	59
THOR	3	24	16	String	Total Count	113.9	59
THOR	3	24	32	String	Total Count	229.623	59
THOR	3	24	2	String	Distinct Count	25.517	55
THOR	3	24	4	String	Distinct Count	53.439	55
THOR	3	24	8	String	Distinct Count	97.232	55
THOR	3	24	16	String	Distinct Count	217.566	55
THOR	3	24	32	String	Distinct Count	526.33	55
THOR	3	24	2	String	Filter: High Selectivity	13.11	52
THOR	3	24	4	String	Filter: High Selectivity	26.151	52
THOR	3	24	8	String	Filter: High Selectivity	48.512	52
THOR	3	24	16	String	Filter: High Selectivity	112.657	52

THOR	3	24	32	String	Filter: High Selectivity	218.791	52
THOR	3	24	2	String	Filter: Low Selectivity	12.52	51
THOR	3	24	4	String	Filter: Low Selectivity	25.941	51
THOR	3	24	8	String	Filter: Low Selectivity	43.175	51
THOR	3	24	16	String	Filter: Low Selectivity	103.974	51
THOR	3	24	32	String	Filter: Low Selectivity	205.163	51
THOR	3	24	2	String	Sort by key	33.65	51
THOR	3	24	4	String	Sort by key	66.36	51
THOR	3	24	8	String	Sort by key	285.484	51
THOR	3	24	16	String	Sort by key	700	51
THOR	3	24	32	String	Sort by key	1475.31	51
THOR	4	32	2	String	Total Count	7.141	51
THOR	4	32	4	String	Total Count	19.357	51
THOR	4	32	8	String	Total Count	43.365	51
THOR	4	32	16	String	Total Count	102.147	51
THOR	4	32	32	String	Total Count	159.392	51
THOR	4	32	2	String	Distinct Count	16.24	56
THOR	4	32	4	String	Distinct Count	34.854	56
THOR	4	32	8	String	Distinct Count	94.572	56
THOR	4	32	16	String	Distinct Count	160.389	56
THOR	4	32	32	String	Distinct Count	302.758	56
THOR	4	32	2	String	Filter: High Selectivity	10.54	52
THOR	4	32	4	String	Filter: High Selectivity	23.146	52
THOR	4	32	8	String	Filter: High Selectivity	40.73	52
THOR	4	32	16	String	Filter: High Selectivity	101.187	52



THOR	4	32	32	String	Filter: High Selectivity	198.243	52
THOR	4	32	2	String	Filter: Low Selectivity	11.27	52
THOR	4	32	4	String	Filter: Low Selectivity	22.924	52
THOR	4	32	8	String	Filter: Low Selectivity	40.167	52
THOR	4	32	16	String	Filter: Low Selectivity	95.153	52
THOR	4	32	32	String	Filter: Low Selectivity	197.249	52
THOR	4	32	2	String	Sort by key	20.731	58
THOR	4	32	4	String	Sort by key	46.347	58
THOR	4	32	8	String	Sort by key	96.034	58
THOR	4	32	16	String	Sort by key	512.275	58
THOR	4	32	32	String	Sort by key	1110.237	58
SPARK	1	8	2	String	Total Count	31.764	
SPARK	1	8	4	String	Total Count	57.431	
SPARK	1	8	8	String	Total Count	106.818	
SPARK	1	8	16	String	Total Count	222.12	
SPARK	1	8	32	String	Total Count	299.081	
SPARK	1	8	2	String	Distinct Count	46.83	
SPARK	1	8	4	String	Distinct Count	60.99	
SPARK	1	8	8	String	Distinct Count	113.548	
SPARK	1	8	16	String	Distinct Count	263.684	
SPARK	1	8	32	String	Distinct Count	488.939	
SPARK	1	8	2	String	Filter: High Selectivity	320.423	
SPARK	1	8	4	String	Filter: High Selectivity	400.027	
SPARK	1	8	8	String	Filter: High Selectivity	667.195	
SPARK	1	8	16	String	Filter: High Selectivity	735.274	

SPARK	1	8	32	String	Filter: High Selectivity	1449.611	
SPARK	1	8	2	String	Filter: Low Selectivity	89.654	
SPARK	1	8	4	String	Filter: Low Selectivity	170.364	
SPARK	1	8	8	String	Filter: Low Selectivity	361.983	
SPARK	1	8	16	String	Filter: Low Selectivity	756.318	
SPARK	1	8	32	String	Filter: Low Selectivity	1568.99	
SPARK	1	8	2	String	Sort by key	350.121	
SPARK	1	8	4	String	Sort by key	640.457	
SPARK	1	8	8	String	Sort by key	1320.867	
SPARK	1	8	16	String	Sort by key	2760.877	
SPARK	1	8	32	String	Sort by key	5400.645	
SPARK	3	24	2	String	Total Count	25.157	
SPARK	3	24	4	String	Total Count	43.852	
SPARK	3	24	8	String	Total Count	78.957	
SPARK	3	24	16	String	Total Count	148.856	
SPARK	3	24	32	String	Total Count	220.367	
SPARK	3	24	2	String	Distinct Count	36.387	
SPARK	3	24	4	String	Distinct Count	52.154	
SPARK	3	24	8	String	Distinct Count	90.675	
SPARK	3	24	16	String	Distinct Count	167.76	
SPARK	3	24	32	String	Distinct Count	351.864	
SPARK	3	24	2	String	Filter: High Selectivity	220.543	
SPARK	3	24	4	String	Filter: High Selectivity	328.848	
SPARK	3	24	8	String	Filter: High Selectivity	508.584	
SPARK	3	24	16	String	Filter: High Selectivity	605.814	

SPARK	3	24	32	String	Filter: High Selectivity	1041.608	
SPARK	3	24	2	String	Filter: Low Selectivity	68.544	
SPARK	3	24	4	String	Filter: Low Selectivity	135.271	
SPARK	3	24	8	String	Filter: Low Selectivity	261.217	
SPARK	3	24	16	String	Filter: Low Selectivity	598.884	
SPARK	3	24	32	String	Filter: Low Selectivity	1268.89	
SPARK	3	24	2	String	Sort by key	270.15	
SPARK	3	24	4	String	Sort by key	550.152	
SPARK	3	24	8	String	Sort by key	1125.199	
SPARK	3	24	16	String	Sort by key	2380.978	
SPARK	3	24	32	String	Sort by key	4860.122	
SPARK	4	32	2	String	Total Count	82.645	
SPARK	4	32	4	String	Total Count	106.298	
SPARK	4	32	8	String	Total Count	126.58	
SPARK	4	32	16	String	Total Count	164.251	
SPARK	4	32	32	String	Total Count	254.946	
SPARK	4	32	2	String	Distinct Count	80.761	
SPARK	4	32	4	String	Distinct Count	110.38	
SPARK	4	32	8	String	Distinct Count	140.847	
SPARK	4	32	16	String	Distinct Count	165.369	
SPARK	4	32	32	String	Distinct Count	251.793	
SPARK	4	32	2	String	Filter: High Selectivity	110.248	
SPARK	4	32	4	String	Filter: High Selectivity	155.899	
SPARK	4	32	8	String	Filter: High Selectivity	241.127	
SPARK	4	32	16	String	Filter: High Selectivity	390.545	

SPARK	4	32	32	String	Filter: High Selectivity	695.427	
SPARK	4	32	2	String	Filter: Low Selectivity	118.26	
SPARK	4	32	4	String	Filter: Low Selectivity	152.664	
SPARK	4	32	8	String	Filter: Low Selectivity	201.844	
SPARK	4	32	16	String	Filter: Low Selectivity	380.154	
SPARK	4	32	32	String	Filter: Low Selectivity	725.757	
SPARK	4	32	2	String	Sort by key	242.36	
SPARK	4	32	4	String	Sort by key	465.682	
SPARK	4	32	8	String	Sort by key	1005.874	
SPARK	4	32	16	String	Sort by key	2011.874	
SPARK	4	32	32	String	Sort by key	3857.125	
SPARK	4	32	2	String	Max Key	85.144	
SPARK	4	32	4	String	Max Key	110.39	
SPARK	4	32	8	String	Max Key	135.57	
SPARK	4	32	16	String	Max Key	160.326	
SPARK	4	32	32	String	Max Key	250.94	
SPARK	4	32	2	String	Min key	84.872	
SPARK	4	32	4	String	Min key	95.612	
SPARK	4	32	8	String	Min key	120.35	
SPARK	4	32	16	String	Min key	140.484	
SPARK	4	32	32	String	Min key	180.367	