Evaluating Hive and Spark SQL with BigBench

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1. Introduction

The objective of this work was to utilize BigBench [1] as a Big Data benchmark and evaluate and compare two processing engines: MapReduce [2] and Spark [3]. MapReduce is the established engine for processing data on Hadoop. Spark is a popular alternative engine that promises faster processing times than the established MapReduce engine. BigBench was chosen for this comparison because it is the first end-to-end analytics Big Data benchmark and it is currently under public review as TPCx-BB [4]. One of our goals was to evaluate the benchmark by performing various scalability tests and validate that it is able to stress test the processing engines. First, we analyzed the steps necessary to execute the available MapReduce implementation of BigBench [1] on Spark. Then, all the 30 BigBench queries were executed on MapReduce/Hive with different scale factors in order to see how the performance changes with the increase of the data size. Next, the group of HiveQL queries were executed on Spark SQL and compared with their respective Hive runtimes.

This report gives a detailed overview on how to setup an experimental Hadoop cluster and execute BigBench on both Hive and Spark SQL. It provides the absolute times for all experiments preformed for different scale factors as well as query results which can be used to validate correct benchmark execution. Additionally, multiple issues and workarounds were encountered and solved during our work. An evaluation of the resource utilization (CPU, memory, disk and network usage) of a subset of representative BigBench queries is presented to illustrate the behavior of the different query groups on both processing engines.

Last but not least it is important to mention that larger parts of this report are taken from the master thesis of Max-Georg Beer, entitled “Evaluation of BigBench on Apache Spark Compared to MapReduce” [5].

The rest of the report is structured as follows: Section 2 provides a brief description of the technologies involved in our study. Brief summary of the BigBench benchmark is presented in Section 3. Section 4 evaluates the steps needed to complete in order to execute BigBench on Spark. An overview of the hardware and software setup used for the experiments is given in Section 5. The performed experiments together with the evaluation of the results are presented in Section 6. Section 7 depicts a comparison between the cluster resource utilization during the execution of representative BigBench queries. Finally, Section 8 concludes with lessons learned.

2. Background

Big Data has emerged as a new term not only in IT, but also in numerous other industries such as healthcare, manufacturing, transportation, retail and public sector administration [6][7] where it quickly became relevant. There is still no single definition which adequately describes all Big Data aspects [8], but the “V” characteristics (Volume, Variety, Velocity, Veracity and more) are among the widely used one. Exactly these new Big Data characteristics challenge the capabilities of the traditional data management and analytical systems [8][9]. These challenges also motivate the researchers and industry to develop new types of systems such as Hadoop and NoSQL databases [10].

Apache Hadoop [11] is a software framework for distributed storing and processing of large data sets across computer clusters using the map and reduce programming model. The architecture allows scaling up from a single server to thousands of machines. At the same time Hadoop
delivers high-availability by detecting and handling failures at the application layer. The use of data replication guarantees the data reliability and fast access. The core Hadoop components are the Hadoop Distributed File System (HDFS) [12][13] and the MapReduce framework [2].

HDFS has a master/slave architecture with a NameNode as a master and multiple DataNodes as slaves. The NameNode is responsible for storing and managing all file structures, metadata, transactional operations and logs of the file system. The DataNodes store the actual data in the form of files. Each file is split into blocks of a preconfigured size. Every block is copied and stored on multiple DataNodes. The number of block copies depends on the Replication Factor.

MapReduce is a software framework that provides general programming interfaces for writing applications that process vast amounts of data in parallel, using a distributed file system, running on the cluster nodes. The MapReduce unit of work is called job and consists of input data and a MapReduce program. Each job is divided into map and reduce tasks. The map task takes a split, which is a part of the input data, and processes it according to the user-defined map function from the MapReduce program. The reduce task gathers the output data of the map tasks and merges them according to the user-defined reduce function. The number of reducers is specified by the user and does not depend on input splits or number of map tasks. The parallel application execution is achieved by running map tasks on each node to process the local data and then send the result to a reduce task which produces the final output.

Hadoop implements the MapReduce (version 1) model by using two types of processes – JobTracker and TaskTracker. The JobTracker coordinates all jobs in Hadoop and schedules tasks to the TaskTrackers on every cluster node. The TaskTracker runs tasks assigned by the JobTracker.

Multiple other applications were developed on top of the Hadoop core components, also known as the Hadoop ecosystem, to make it more easy to use and applicable to variety of industries. Example for such applications are Hive [14], Pig [15], Mahout [16], HBase [17], Sqoop [18] and many more.

YARN (Yet Another Resource Negotiator) [19] is the next generation Apache Hadoop platform, which introduces new architecture by decoupling the programming model from the resource management infrastructure and delegating many scheduling-related functions to per-application components. This new design [19] offers some improvements over the older platform:

- Scalability
- Multi-tenancy
- Serviceability
- Locality awareness
- High Cluster Utilization
- Reliability/Availability
- Secure and auditable operation
- Support for programming model diversity
- Flexible Resource Model
- Backward compatibility

The major difference is that the functionality of the JobTracker is split into two new daemons – ResourceManager (RM) and ApplicationMaster (AM). The RM is a global service, managing all the resources and jobs in the platform. It consists of a scheduler and the ApplicationManager. The scheduler is responsible for allocation of resources to the various running applications based on their resource requirements. The ApplicationManager is responsible for accepting jobs-
submissions and negotiating resources from the scheduler. Additionally, there is a NodeManager (NM) agent that runs on each worker. It is responsible for allocating and monitoring of node resources (CPU, memory, disk and network) usage and reports back to the ResourceManager (scheduler). An instance of the ApplicationMaster runs per-application on each node and negotiates the appropriate resource container from the scheduler. It is important to mention that the new MapReduce 2.0 maintains API compatibility with the older stable versions of Hadoop and therefore, MapReduce jobs can run unchanged.

Hive [10][17] is a data warehouse infrastructure built on top of Hadoop. Hive was originally developed by Facebook and supports the analysis of large data sets stored on HDFS by queries in a SQL-like declarative query language. This SQL-like language is called HiveQL and is based on the SQL language, but does not strictly follow the SQL-92 standard. For example, the additional feature Use Defined Functions (UDF) of HiveQL allows to filter data by custom Java or Python scripts. Plugging in custom scripts makes the implementation of in HiveQL natively unsupported statements possible. When a HiveQL statement is submitted through the Hive command-line interface, the compiler of Hive translates the statement into jobs that are submitted to the MapReduce engine [14]. This allows users to analyze large data sets without actually having to apply the MapReduce programming model themselves. The MapReduce programming model is very low-level and requires developers to write custom programs, whereas Hive can be used by analysts with SQL skills.

Before data stored on HDFS can be analyzed by Hive, Hive's Metastore has to be created. The Metastore is the central repository for Hive's metadata and stores all information about the available databases, the available tables, the available table columns, table columns' types etc. The Metastore is stored on a traditional RDBMS like MySQL. When a table is created with HiveQL, the user can define the format of the file that is stored on HDFS and which contains the actual data of the table [21]. Besides the default text file format, more compressed formats like ORC and Parquet are available. The applied file format affects the performance of Hive.

Apache Spark [22] is a processing engine that promises to perform much faster than Hadoop's MapReduce engine. This performance advantage of Spark is achieved in part by its heavy reliance on in-memory computing. In contrast to that, MapReduce is strongly based on disk. Spark was originally created in 2009 by the AMPLab at UC Berkeley and was developed to run independent of Hadoop. Instead, Spark is a generic framework for a wide variety of distributed storage systems including Hadoop.

The Spark project consists of several components [22]. The Spark Core is the general execution engine that provides APIs for programming languages like Java, Scala and Python and enables an easy development of Spark programs. All the other Spark components are built on top of the Spark Core. These components are Spark SQL for analyzing structured data, Spark Streaming for analyzing streaming data, the machine learning framework MLlib and the graph processing framework GraphX.

Spark SQL [23] integrates relational processing into Spark and allows users to intermix relational and procedural processing techniques. Besides the general support for structured data processing, Spark SQL supports SQL-like statements. These statements can be executed through a command-line interface similar to Hive's command-line interface. Moreover, Spark SQL is pretty compatible to run unmodified HiveQL queries and to use the Hive Metastore [24]. In summary
Spark SQL relates to Spark in the same way as Hive relates to MapReduce: an interface to execute SQL-like statements on the respective processing engine. The general programming model of Spark Core and therefore the fundamentals for all the other Spark components can be summarized as follows [3]. To write a program running on Spark, the developer has to write the so-called driver program that implements the program flow and launches various operations in parallel.

Spark provides the two main abstractions Resilient Distributed Datasets (RDD) and parallel operations. A RDD is a read-only, partitioned collection of elements. The separate partitions of the RDD are distributed across a set of machines and can be stored in a persistent storage as well as in-memory. Persisting and caching the RDD in memory allows very efficient operations. Besides allowing Spark's driver program to run its operations on the RDD in parallel on various machines, a RDD can automatically recover from machine failures.

Cloudera Hadoop Distribution (CDH) [25] is a 100% Apache-licensed open source Hadoop distribution offered by Cloudera. It includes the core Apache Hadoop elements - Hadoop Distributed File System (HDFS) and MapReduce (YARN), as well as several additional projects from the Apache Hadoop Ecosystem. All components are tightly integrated to enable ease of use and managed by a central application - Cloudera Manager [26].

3. BigBench

BigBench [26][27] is a proposal for an end-to-end analytics benchmark suite for Big Data systems. To fit the needs of a Big Data benchmark and to allow the performance comparison of different Big Data systems, BigBench focuses on the three Big Data characteristics volume, variety and velocity. It provides a specification describing a data model and workloads of a non-system-specific end-to-end analytics benchmark. Additionally, a data generator is available to create data for the data model.

Since the BigBench specification is general and technology agnostic, it should be implemented specifically for each Big Data system. The initial implementation of BigBench was made for the Teradata Aster platform [29]. It was done in the Aster’s SQL-MR syntax served - additionally to a description in the English language - as an initial specification of BigBench's workloads. Meanwhile, BigBench is implemented for Hadoop [1], using the MapReduce engine and other components like Hive, Mahout and OpenNLP from the Hadoop Ecosystem.

To summarize, BigBench covers the data model, depicted in Figure 1, the data generator and the specification of the workloads. Figure 1 shows how BigBench implements the variety property of Big Data. This is done by categorizing the data model into three parts: structured, semi-structured and unstructured data. A fictional product retailer is used as the underlying business model [27]. The business model and a large portion of the data model's structured part is derived from the TPC-DS benchmark [30]. The structured part was extended with a table for the prices of the retailer's competitors, the semi-structured part was added represented by a table with website logs and the unstructured part was added by a table showing product reviews.
The data generator is based on an extension of PDGF [32] and allows generating data in accordance with BigBench's data model, including the structured, semi-structured and unstructured parts. The data generator can scale the amount of data based on a scale factor. Due to parallel processing of the data generator, it runs efficiently for large scale factors. In this way, the Big Data volume property is implemented in BigBench. Additionally, the velocity property of Big Data is implemented by a periodic refresh scheme that constantly adds new data to the different tables of the data model.

The workloads are a major part of BigBench. The workloads are represented by 30 queries, which are defined as questions about the BigBench's underlying business model. Ten of these queries are taken from the TPC-DS benchmark's workload. The other 20 queries were defined based on the five major areas of Big Data analytics identified in the McKinsey report on Big Data use cases and opportunities [6]. These areas are marketing, merchandising, operations, supply chain and new business models. However, besides these business areas it was made sure that the following three technical dimensions are also included in the queries:

a) The three different data types (structured, semi-structured and unstructured type)

b) The two paradigms of processing (declarative and procedural MR)

c) Different algorithms of analytic processing (classifications, clustering, regression etc.)

A list of the BigBench queries grouped by the technologies their implementation is based on can be found in Table 1.

| Query Types                     | Queries                      | Number of Queries |
|---------------------------------|------------------------------|-------------------|
| Pure HiveQL                     | Q6, Q7, Q9, Q11, Q12, Q13, Q14, Q15, Q16, Q17, Q21, Q22, Q23, Q24 | 14                |
| Java MapReduce with HiveQL      | Q1, Q2                       | 2                 |
| Python Streaming MR with HiveQL | Q3, Q4, Q8, Q29, Q30         | 5                 |
| Mahout (Java MR) with HiveQL    | Q5, Q20, Q25, Q26, Q28       | 5                 |
| OpenNLP (Java MR) with HiveQL   | Q10, Q18, Q19, Q27           | 4                 |

Table 1: BigBench Queries
The combination of factoring in relevant business areas as well as technical dimensions within the scope of the Big Data characteristics makes BigBench to a Big Data analytics benchmark suite. Besides the objective of becoming an industry standard as TPCx-BB [4], BigBench will be extended to incorporate additional use cases in the future [28].

4. BigBench on Spark

A major focus of this work is to evaluate and run BigBench on Spark. Because Spark SQL supports HiveQL, the queries of the type “Pure HiveQL” were successfully ported to Spark and executed. However, to provide a comprehensive evaluation the additional BigBench queries will also be considered in this chapter. The validation references described in the subsection Query Validation Reference significantly supported the evaluation. With their help, the verification of successful query executions was quite easy. The first section of this chapter presents workarounds that had to be applied at the beginning of our research. At that time, Spark SQL was at an earlier stage and did not support some of the syntactical expressions. During the project, many issues were solved by developers of the Spark project and the described workarounds became obsolete. Below, the final outcomes of the evaluation of running BigBench on Spark are described and all necessary porting tasks are listed.

4.1. Workarounds

Since the start of our research, further development on Spark solved several issues. However, before these improvements on Spark were available, workarounds for those issues had to be developed. In the following part, two major problems are examined to give an example of our work and an idea of the current state of Spark's component Spark SQL. The issues are described as follows: First, the actual issue is described. Then, the temporarily implemented workaround is explained. Finally, a reference to the reported ticket in the official issue tracker of the Spark project is given.

Variables substitution

The Hive variable substitution mechanism allows using variables within the queries. The so called hiveconf variables can be set by passing them with the hiveconf parameter to the client program or by setting them directly with the set command in the query. Furthermore, values of ordinary environment variables can be accessed within queries. Depending on whether it is a hiveconf variable or an environment variable, the variable can be retrieved by using the syntax ${hiveconf:variable_name} or ${env:variable_name} [33].

The available BigBench implementation for MapReduce uses this mechanism intensively. Initially, Spark SQL did not support this mechanism. Because this mechanism was used intensively as well as to avoid big changes on the BigBench implementation, the variable substitution concept was retained. The approach of the workaround was to retrieve and substitute the variables before the queries were passed to the Spark SQL client program. By doing so, no variables were within the queries and the actual variable substitution mechanism was obsolete. The procedure implemented in the script-based solution, which was executed before the query was passed to the Spark SQL client program, can be described as follows:
1) Searching for the variable syntax \${hiveconf: variable_name} and \${env:variable_name} in the query.
2) Retrieving these variables to obtain their values.
3) Replacing each variable with its received value.
4) Passing the query with replaced variables to the Spark SQL client program.

This workaround became obsolete with the resolution of the issue [SPARK-5202] HoneyComb doesn’t support the Variables Substitution\(^1\) in the Spark project.

**User-Defined Functions (UDFs) with multiple fields as output**

When an UDF output has multiple fields, it was not possible to assign an alias for each individual field. The following example shows the desired, but unsupported expression.

```
SELECT extract_sentiment(pr_item_sk,pr_review_content) AS (pr_item_sk, review_sentence, sentiment, sentiment_word) FROM product_reviews;
```

Because this expression was syntactically not accepted by Spark SQL, the subsequent workaround was used to solve this issue.

```
SELECT `result._c0` AS pr_item_sk, `result._c1` AS review_sentence, `result._c2` AS sentiment, `result._c3` AS sentiment_word
FROM (SELECT extract_sentiment(pr.pr_item_sk,pr.pr_review_content) AS return
 FROM product_reviews pr
) result;
```

This workaround became obsolete with the resolution of the issue [SPARK-5237] UDTF don’t work with multi-alias of multi-columns as output on Spark SQL\(^2\) in the Spark project.

### 4.2. Porting Issues

This section documents the final outcomes of running the BigBench queries on Spark. Table 2 gives an overview of all the different porting tasks that have been identified together with the affected queries attached to each task.

| Issue                                      | Affected Queries |
|--------------------------------------------|------------------|
| External scripts in Spark SQL              | Q1, Q2, Q3, Q4, Q8, Q10, Q18, Q19, Q27, Q29, Q30 |
| Different expression of null values        | Q3, Q8, Q29, Q30 |
| Scripts implemented for MapReduce          | Q1, Q2 |
| External libraries                         | Q5, Q10, Q18, Q19, Q20, Q25, Q26, Q27, Q28 |
| Query specific settings                    | Q3, Q4, Q7, Q8, Q16, Q21, Q22, Q23, Q24, Q29, Q30 |
| Type definition for return values          | Q1, Q2, Q3, Q4, Q8 |

Table 2: Porting tasks and queries that are affected by them

Subsequently, all different porting tasks are explained in more detail.

---

\(^1\) [https://issues.apache.org/jira/browse/SPARK-5202](https://issues.apache.org/jira/browse/SPARK-5202)

\(^2\) [https://issues.apache.org/jira/browse/SPARK-5237](https://issues.apache.org/jira/browse/SPARK-5237)
External scripts in Spark SQL

Calling external scripts within queries executed with Spark SQL requires passing of the respective script file paths to the Spark SQL client program. This ensures that these scripts are distributed to all of the Spark executors. This is relevant for all queries containing user-defined functions (UDFs) or custom reduce scripts. Depending on whether these are represented as Java programs (JAR files) or Python scripts (PY files), the parameter to be used differs.

To make Python scripts available on the executors, the files parameter should be used. This places the scripts in the working directory of each executor. Affected by this issue are the BigBench queries Q1, Q2, Q10, Q18, Q19 and Q27. The usage of the files parameter is shown by the following generalized command. The $$SPARK_ROOT$$ variable represents the path to the root of the local Spark repository.

```
$SPARK_ROOT/bin/spark-sql --files $PY_FILE_PATH
```

To make Java programs available, the jars parameter should be used. Besides distributing the files to the Spark executors, this ensures that the programs will be included to the Java Classpath on each executor. Affected by this issue are the BigBench queries Q3, Q4, Q8, Q29 and Q30. Using the jars parameter is shown by the following generalized command.

```
$SPARK_ROOT/bin/spark-sql --jars $JAR_FILE_PATH
```

Different expression of null values

It became apparent that in Hive and Spark SQL, specific calculations lead to different results. Examples for such different calculation results can be found in Table 3.

| Query | Hive Result | Spark SQL Result |
|-------|-------------|------------------|
| SELECT CAST(1 as double) / CAST(0 as double) FROM table; | NULL | Infinity |
| SELECT CAST(-1 as double) / CAST(0 as double) FROM table; | NULL | -Infinity |
| SELECT CAST(0 as double) / CAST(0 as double) FROM table; | NULL | NaN |

Table 3: Hive and Spark SQL differences

Furthermore, Hive and Spark SQL show different expression of null values in the context of external scripts. This different expression has impact on the row counts of several BigBench query result tables. Conditions that check if the value of a row field is equal/unequal to null, lead to different results. Null values are expressed in Hive as `\N` and in Spark SQL as `null`. Subsequently, a generalized Python code example illustrates the required adjustments to ensure correct query execution when using Spark SQL.

When executing with Hive, the following condition is valid to check if a row field is unequal to null.

```
if rowField != '\N':
    # do something
```

When executing with Spark SQL, the condition must be adjusted as follows.
if rowField != 'null' :
    # do something

Affected by this issue are external scripts of the BigBench queries Q3, Q8, Q29 and Q30.

**Scripts implemented for MapReduce**

External scripts that are specifically implemented for the MapReduce framework are not usable when running BigBench on Spark. Those scripts have to be rewritten to run with the Spark framework. This task requires understanding the respective MapReduce code and transforming it to code compatible with the Spark framework. Performing this task requires certain knowledge in the mentioned technologies. The affected BigBench queries are Q1 and Q2.

**External libraries**

The implementation of BigBench for MapReduce utilizes a small number of external libraries. It uses Apache OpenNLP for processing natural language text and Apache Mahout for performing machine learning tasks. These libraries, which are implemented to run on MapReduce, have to be replaced. In case of Apache Mahout, this means waiting for the release that runs on Spark or choosing a different machine learning library that is already running on Spark like MLlib [34]. This issue affects all queries utilizing the functionality of libraries such as Apache OpenNLP (Java MR) and Mahout (Java MR) (see Table 1).

**Query specific settings**

Contrary to Hive, Spark SQL does not dynamically determine some of the settings during query execution. The need for manually defining settings for specific queries and scale factors became obvious in the case of queries with exhaustive join operations and queries with streaming functionality. The higher the scale factor the more relevant were those settings in terms of query runtime.

Open tickets in the Spark issue tracker like [SPARK-2211] *Join Optimization*¹ and [SPARK-5791] *show poor performance when multiple table do join operation*² document the missing join optimization functionality in Spark, which causes the need of tweaking settings specifically for individual queries. In the official Spark documentation [35] the unsupported functionality of dynamically determining the number of partitions is described. It became apparent that setting this value properly was especially relevant for queries with streaming functionality. Ryza [36] gives a formula that roughly estimate this value. However, despite utilizing the formula, it is not a simple task to determine this setting.

Due to the complexity and the fact that the configuration of such specific settings has to be individually processed for each query and scale factor, it does not seem to be a practical approach. With further development, Spark will probably improve its abilities of dynamic settings determination and query optimization.

Affected by this issue concerning determination of query specific settings are the BigBench queries Q7, Q16, Q21, Q22, Q23, Q24 with exhaustive join operations and the BigBench queries Q3, Q4, Q8, Q29, Q30 with streaming functionality.

¹ [https://issues.apache.org/jira/browse/SPARK-2211](https://issues.apache.org/jira/browse/SPARK-2211)
² [https://issues.apache.org/jira/browse/SPARK-5791](https://issues.apache.org/jira/browse/SPARK-5791)
Type definition for return values

HiveQL supports an operation to integrate custom reduce scripts in the query data stream. Records output by these scripts have a certain number of fields. By default these fields are of the type string. However, it is possible to cast each field to a specified data type. Typecasting the fields of reduce script outputs is used in several BigBench queries. In case of Spark SQL this type casting has not worked properly and caused wrong query execution. Removing the type cast definition can solve this issue. However, Hive allows typecasting the return values of functions. Affected by this issue are the BigBench queries Q1, Q2, Q3, Q4 and Q8. This is shown in the following example:

```
SELECT result_field_one, result_field_two
FROM (FROM (SELECT
    wcs_user_sk       AS user,
    wcs_click_date_sk AS lastviewed_date,
FROM source_table
) my_return_table
REDUCE
my_return_table.user,
my_return_table.lastviewed_date,
USING 'python_reduce_script.py'
AS (result_field_one BIGINT, result_field_two BIGINT));
```

When executing on Spark SQL, typecasting return values should be prevented.

```
SELECT result_field_one, result_field_two
FROM (FROM (SELECT
    wcs_user_sk       AS user,
    wcs_click_date_sk AS lastviewed_date,
FROM source_table
) my_return_table
REDUCE
my_return_table.user,
my_return_table.lastviewed_date,
USING 'python_reduce_script.py'
AS (result_field_one, result_field_two));
```
5. Experimental Setup

This section presents the hardware and software setup of the cluster as well as the exact configuration of the Hadoop and BigBench components as used in our experiments.

5.1. Hardware

The experiments were performed on a cluster consisting of 4 nodes connected directly through 1Gbit Netgear switch, as shown on Figure 2. All 4 nodes are Dell PowerEdge T420 servers. The master node is equipped with 2x Intel Xeon E5-2420 (1.9GHz) CPUs each with 6 cores, 32GB of RAM and 1TB (SATA, 3.5 in, 7.2K RPM, 64MB Cache) hard drive. The worker nodes are equipped with 1x Intel Xeon E5-2420 (2.20GHz) CPU with 6 cores, 32GB of RAM and 4x 1TB (SATA, 3.5 in, 7.2K RPM, 64MB Cache) hard drives. More detailed specification of the node servers is provided in the Appendix (Table 19 and Table 20).

![Figure 2: Cluster Setup](image)

Table 4 summarizes the total cluster resources that are used in the calculation of the benchmark ratios in the next sections.

5.2. Software

This section describes the software setup of the cluster. The exact software versions that were used are listed in Table 5. Ubuntu Server LTS was installed on all 4 nodes, allocating the entire first disk. The number of open files per user was changed from the default value of 1024 to 65000 as suggested by the TPCx-HS benchmark and Cloudera guidelines [37]. Additionally, the OS `swappiness option` was turned permanently off (`vm.swappiness = 0`). The remaining three disks, on all worker nodes, were formatted as ext4 partitions and permanently mounted with options `noatime` and `nodiratime`. Then the partitions were configured to be used by HDFS through the Cloudera Manager. Each 1TB disk provides in total 916.8GB of effective HDFS space, which means that all three workers (3 x 916.8GB = 2851.2GB = 8.0578TB) have in total around 8TB of effective HDFS space.
Cloudera CDH 5.2, with default configurations, was used for all experiments. Table 6 summarizes the software services running on each node. Due to the resource limitation (only 3 worker nodes) of our experimental setup, the cluster was configured to work with replication factor of 2. This means that our cluster can store at most 4TB of data on HDFS.

| Server          | Disk Drive | Software Services                                                                 |
|-----------------|------------|-----------------------------------------------------------------------------------|
| Master Node     | Disk 1/ sda1 | Operating System, Root, Swap, Cloudera Manager Services, Name Node, SecondaryName Node, Hive Metastore, Hive Server2, Oozie Server, Spark History Server, Sqoop 2 Server, YARN Job History Server, Resource Manager, Zookeeper Server |
| Worker Nodes 1-3| Disk 1/ sda1 | Operating System, Root, Swap, Data Node, YARN Node Manager                         |
|                 | Disk 2/ sdb1 | Data Node                                                                         |
|                 | Disk 3/ sdc1 | Data Node                                                                         |
|                 | Disk 4/ sdd1 | Data Node                                                                         |

Table 6: Software Services per Node

5.3. Cluster Configuration

Besides making modifications on the BigBench implementation as described previously, configuration parameters for the different components of the cluster have to be properly set so that BigBench queries run stable (also with higher scale factors). Determining these configuration parameters is not connected to the particular case of running the BigBench benchmark. Instead, this is part of the general complexity of Big Data systems and is essential to their proper operation. As a basic principle when setting the configuration parameters, we tried to follow the rule that these should not differ from their default values unless adjusting is needed to ensure correct cluster operation. This principle avoids tuning of special cases to guarantee meaningful
benchmarking results. However, utilizing all the available cluster resources and running BigBench with higher scale factors demonstrated the need for adjusting some of the parameters. Furthermore, some configuration parameters of Spark were not set by default and had to be defined accordingly. The process of determining the configuration parameters can be described as follows and was executed for each individual BigBench query:

1) Identifying errors and abnormal runtime in BigBench query execution.
2) Figuring out which configuration parameters cause the problem.
3) Trying to find problem-solving values for configuration parameters.
4) Validating the configuration parameter values by re-executing the BigBench query: Parameter values are determined successfully when errors are fixed and abnormal runtime is solved.

Components of the cluster that were actually affected by adjusted configuration parameters are YARN, Spark, MapReduce and Hive. It should be noted that changing the configuration parameters of YARN has an impact on Spark as well as MapReduce because both processing engines are dependent on the resource manager YARN. Hereafter, the changed configuration parameters of the particular cluster components are documented and explained.

**YARN**

To adjust the configuration of the resource manager YARN in order to fit the experimental cluster and to ensure efficient resource utilization, two configuration parameters were adjusted initially. The amount of memory that can be allocated for YARN ResourceContainers per node (yarn.nodemanager.resource.memory-mb = 28672) and the maximum allocation for every YARN ResourceContainer request were set to 28 GB (yarn.scheduler.maximum-allocation-mb = 28672). Later, following the recommendations published by Ryza [36], the amount of memory that can be allocated for YARN ResourceContainers was changed to 31 GB per node (yarn.nodemanager.resource.memory-mb = 31744). As described in Hortonworks' manual [39], the maximum allocation for every YARN ResourceContainer request was set to be exactly the same as the amount of memory that can be allocated for YARN ResourceContainers. In short, this parameter defines the largest ResourceContainers size YARN will allow. It was also set to 31 GB (yarn.scheduler.maximum-allocation-mb = 31744). Following the recommendations published by Ryza [36], the number of CPU cores that can be allocated for YARN ResourceContainers was changed to 11 per node (yarn.nodemanager.resource.cpu-cores = 11). The final configuration gives YARN plenty of resources, but still leaves 1 GB of memory and 1 CPU core to the operating system. All of the above YARN configuration adjustments were made in the respective yarn-site.xml configuration file.

**Spark**

Since the Spark version shipped with CDH 5.2.0 was not used, the Spark configuration that comes with CDH was deactivated. Many configuration parameters can be set by passing them to the Spark client program. Besides passing --master yarn to run YARN in client mode, the configuration parameters --num-executors, --executor-cores and --executor-memory should be passed with proper values. Initially, finding proper values for the above mentioned configuration parameters was done by performing spot-check tests. The different configuration parameter
values of the performed tests and their runtime for two randomly chosen BigBench queries can be found in Table 7. The test results prompted us to set the configuration parameters to the values used in configuration 4 (\texttt{--num-executors 12, --executor-cores 2, --executor-memory 8G}).

| # | num-executors | executor-memory | executor-cores | Time (min) Q7 | Time (min) Q24 |
|---|----------------|-----------------|----------------|---------------|---------------|
| 1 | 3              | 26G             | 12             | 2.98          | 4.15          |
| 2 | 3              | 26G             | 10             | 3.02          | 4.12          |
| 3 | 6              | 16G             | 4              | 3.05          | 4.05          |
| 4 | 12             | 8G              | 2              | 2.73          | 3.55          |

Table 7: Runtime for different Spark configurations

However, the recommendations published by Ryza [36], give a more methodical guideline regarding the Spark configuration parameters. The sample cluster in the guide configured 3 executors on each DataNode except the one operating the ApplicationMaster, which has only 2 executors. Due to different hardware resources, there are maximum 3 executors on every DataNode. Because of the configuration parameter values \texttt{--executor-cores} and \texttt{--executor-memory}, on every DataNode there will be available resources for the ApplicationMaster. Consequently, this results in total of 9 executors (\texttt{--num-executors 9}).

Every DataNode in the experimental cluster has 12 virtual CPU cores. Since one core is left for the operating system and Hadoop daemons, there are 11 virtual cores available for the executors. Dividing the number of cores by the 3 executors per node results in 3 cores per executor (\texttt{--executor-cores 3}). Therefore, 9 virtual cores per node are used for executors, 1 core is left for the operating system and 2 spare cores are available. These two cores are the ones available for the ApplicationMaster.

The amount of memory per executor can be determined by the following calculation:

\[
approx_em = \frac{\text{yarn.nodemanager.resource.memory} - \text{mb}}{\text{num-executors}} = \frac{31744}{3} = 10581\]

The variable \texttt{approx_em} stores the amount of memory which is theoretically available for each executor. However, the Java Virtual Machine (JVM) overhead has to be considered and included into the calculation. This can be done by subtracting the value of the property \texttt{spark.yarn.executor.memoryOverhead} from the calculated \texttt{approx_em} value. If the property \texttt{spark.yarn.executor.memoryOverhead} is not explicitly set by the user, its default value is calculated by \texttt{max (384, 0.07 * executor-memory)}. Listed below is the calculation done in order to determine the memory per executor:

\[
\text{executor-memory} = \approx_em - \text{spark.yarn.executor.memoryOverhead} = \approx_em - \text{max}(384, 0.07 \times \approx_em) = 10581 - \text{max}(384, 0.07 \times 10581) = 9840
\]

The resulting integral value 9840 MB is adjusted downward to 9 GB (\texttt{--executor-memory = 9G}). In addition to the above configurations, which have to be passed as parameter when calling the
client program, the default serializer used for object serialization was also changed (\texttt{spark.serializer = org.apache.spark.serializer.KryoSerializer}). The faster Kryo serializer was chosen over the default serializer as recommended by various sources [36], [35]. The serializer option was adjusted in the respective \texttt{spark-defaults.conf} configuration file.

MapReduce

Specifically for the BigBench queries, which include Java MapReduce programs (Q1 and Q2), configuration parameters had to be adjusted to ensure accurate execution. Execution errors were caused by not allowing enough memory for the map and reduce tasks. Also the allowed Java heap size of the map and reduce tasks [40] had to be increased. To find proper values for these parameters, values were raised incrementally until errors were eliminated. This resulted in the following adjusted parameters: \texttt{mapreduce.map.java.opts.max.heap = 2GB, mapreduce.reduce.java.opts.max.heap = 2GB, mapreduce.map.memory.mb = 3GB, mapreduce.reduce.memory.mb = 3GB}. These settings were changed in the respective \texttt{mapred-site.xml} configuration file.

Hive

When executing BigBench's query Q9 with the default configuration, Hive encountered an out of memory error. Initially, this issue was solved by deactivating MapJoins for this particular query. The MapJoin feature allows loading a table in memory, so that a very fast table scan can be performed [41]. As a consequence, performing a MapJoin requires more memory resources. In our case this caused out of memory errors, which could be resolve by simply deactivating this feature. Deactivating was done by just setting \texttt{hive.auto.convert.join = false} in the file \texttt{engines/hive/queries/q09/q09.sql} of the BigBench repository.

Even though deactivating MapJoins solves the problem, it entails a significant performance decline. A better solution is the increase of the heap size of the local Hadoop JVM to prevent the out of memory error. In our case the heap size was increased to 2 GB. This was done by adding the parameters \texttt{-Xms2147483648} and \texttt{-Xmx2147483648} to the environment variable \texttt{HADOOP_CLIENT_OPTS} in the responsible \texttt{hive-env.sh} file.

Configuration validation

During the progress of determining proper parameter values, multiple validations were performed. Especially after applying the guidelines published by Ryza [36] and after choosing the better solution for the MapJoin issue described in section 4.2, the values were validated against the one previously used. It should be noted that the previous configuration can be also seen as a viable configuration. However, the following validation results should verify Ryzas’ guidelines [36] and demonstrate the performance difference between the two configurations. Table 8 lists the different parameters for the \texttt{default}, \texttt{initial} and \texttt{final} configurations as used in our cluster configuration. Figure 3 illustrates the effect on queries’ runtime when changing the \texttt{initial} cluster configuration to the \texttt{final} cluster configuration.
| Component | Parameter                                    | Default Configuration | Initial Configuration | Final Configuration |
|-----------|----------------------------------------------|-----------------------|-----------------------|---------------------|
| YARN      | yarn.nodemanager.resource.memory-mb         | 8GB                   | 28GB                  | 31GB                |
|           | yarn.scheduler.maximum-allocation-mb       | 8GB                   | 28GB                  | 31GB                |
|           | yarn.nodemanager.resource.cpu-vcores       | 8                     | 8                     | 11                  |
| Spark     | master                                      | local                 | yarn                  | yarn                |
|           | num-executors                              | 2                     | 12                    | 9                   |
|           | executor-cores                             | 1                     | 2                     | 3                   |
|           | executor-memory                            | 1GB                   | 8GB                   | 9GB                 |
|           | spark.serializer                            | org.apache.spark.     | org.apache.spark.     | org.apache.spark.   |
|           |                                             | serializer.JavaSerializer | serializer.JavaSerializer | serializer.KryoSerializer |
| MapReduce | mapreduce.map.java.opts.max.heap            | 788MB                 | 2GB                   | 2GB                 |
|           | mapreduce.reduce.java.opts.max.heap         | 788MB                 | 2GB                   | 2GB                 |
|           | mapreduce.map.memory.mb                    | 1GB                   | 3GB                   | 3GB                 |
|           | mapreduce.reduce.memory.mb                 | 1GB                   | 3GB                   | 3GB                 |
| Hive      | hive.auto.convert.join (Q9 only)            | true                  | false                 | true                |
|           | Client Java Heap Size                       | 256MB                 | 256MB                 | 2GB                 |

Table 8: Initial and final configuration

Considering the differences in the runtimes of the individual queries depicted in Figure 3, no big difference can be seen when running them on MapReduce except for query Q9. The reason for this was that the maximum client Java heap size was raised to 2GB. However, it seems that no other query except query Q9 was running into that limit, so this change did not have any impact on the runtimes. As mentioned in the above Hive section, not turning off MapJoins for query Q9, but raising the maximum client Java heap size instead, significantly improved its runtime. In case of running the queries with Apache Spark, the runtime of 8 queries became faster whereas 4 queries became slower.

In summary it can be said that the initial configuration that was determined through testing can be considered a decent configuration because it showed slightly slower runtimes compared to the final configuration. Therefore, the final configuration following the best practices was chosen for the real benchmarking experiments. Investigating the performance of different configurations in advance allowed us to validate the final configuration. This was sufficient for our benchmark purposes since our goal was not to find the optimal cluster configuration.
6. Experimental Results

This section presents the query execution results. Experiments were performed with all the 30 BigBench queries on MapReduce/Hive and the group of 14 pure HiveQL queries on Spark SQL for four different scale factors (100GB, 300GB, 600GB and 1TB).

6.1. BigBench on MapReduce

Table 9 summarizes the absolute runtimes of the 30 BigBench queries on MapReduce/Hive for 100GB scale factor. There are three columns depicting the times for each run in minutes, a column with the average execution time from the three runs and two columns with the standard deviation in minutes and in %. The cells with yellow mark the queries with standard deviation higher than 2%.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|-------------------|-------------------------|---------------------|
| Q1    | 3.75       | 3.77       | 3.73       | 3.75              | 0.02                    | 0.44                |
| Q2    | 8.40       | 8.27       | 8.03       | 8.23              | 0.19                    | 2.25                |
| Q3    | 10.20      | 10.22      | 9.55       | 9.99              | 0.38                    | 3.81                |
| Q4    | 72.58      | 72.98      | 68.55      | 71.37             | 2.45                    | 3.44                |
| Q5    | 27.85      | 28.18      | 27.07      | 27.70             | 0.57                    | 2.07                |
| Q6    | 6.43       | 6.37       | 6.27       | 6.36              | 0.08                    | 1.32                |
| Q7    | 9.18       | 9.10       | 8.92       | 9.07              | 0.14                    | 1.50                |
| Q8    | 8.57       | 8.60       | 8.60       | 8.59              | 0.02                    | 0.22                |
| Q9    | 3.12       | 3.08       | 3.18       | 3.13              | 0.05                    | 1.63                |
| Q10   | 15.58      | 15.50      | 15.25      | 15.44             | 0.17                    | 1.12                |
| Q11   | 2.90       | 2.87       | 2.88       | 2.88              | 0.02                    | 0.58                |
| Q12   | 7.18       | 6.97       | 6.97       | 7.04              | 0.13                    | 1.78                |
| Q13   | 8.43       | 8.28       | 8.43       | 8.38              | 0.09                    | 1.03                |
| Q14   | 3.12       | 3.12       | 3.27       | 3.17              | 0.09                    | 2.73                |
| Q15   | 2.03       | 2.05       | 2.03       | 2.04              | 0.01                    | 0.47                |
| Q16   | 5.88       | 5.90       | 5.57       | 5.78              | 0.19                    | 3.25                |
| Q17   | 7.55       | 7.53       | 7.72       | 7.60              | 0.10                    | 1.33                |
| Q18   | 8.47       | 8.57       | 8.57       | 8.53              | 0.06                    | 0.68                |
| Q19   | 6.53       | 6.53       | 6.60       | 6.56              | 0.04                    | 0.59                |
| Q20   | 8.50       | 8.62       | 8.02       | 8.38              | 0.32                    | 3.80                |
| Q21   | 4.58       | 4.53       | 4.63       | 4.58              | 0.05                    | 1.09                |
| Q22   | 16.53      | 16.92      | 16.48      | 16.64             | 0.24                    | 1.42                |
| Q23   | 18.18      | 18.05      | 18.37      | 18.20             | 0.16                    | 0.87                |
| Q24   | 4.82       | 4.80       | 4.77       | 4.79              | 0.03                    | 0.53                |
| Q25   | 6.25       | 6.22       | 6.22       | 6.23              | 0.02                    | 0.31                |
| Q26   | 5.32       | 5.18       | 5.08       | 5.19              | 0.12                    | 2.25                |
| Q27   | 0.93       | 0.87       | 0.93       | 0.91              | 0.04                    | 4.22                |
| Q28   | 18.30      | 18.38      | 18.40      | 18.36             | 0.05                    | 0.29                |
| Q29   | 5.27       | 5.28       | 4.97       | 5.17              | 0.18                    | 3.45                |
| Q30   | 19.68      | 19.77      | 18.98      | 19.48             | 0.43                    | 2.21                |

Table 9: MapReduce Executions for all BigBench Queries with SF 100 (100GB data)
Similarly, Table 10 illustrates the three runtimes for the BigBench queries on MapReduce/Hive with 300GB scale factor. Again reported are the average time from three runs and the standard deviation in minutes and in %. For this scale factor all of the queries show standard deviation within 2%, which is an indicator for stable performance.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|----------------------|
| Q1    | 5.57       | 5.53       | 5.47       | 5.52               | 0.05                     | 0.92                 |
| Q2    | 21.15      | 21.03      | 21.03      | 21.07              | 0.07                     | 0.32                 |
| Q3    | 26.28      | 26.37      | 26.30      | 26.32              | 0.04                     | 0.17                 |
| Q4    | 221.53     | 221.83     | 220.58     | 221.32             | 0.65                     | 0.29                 |
| Q5    | 76.68      | 76.52      | 76.48      | 76.56              | 0.11                     | 0.14                 |
| Q6    | 10.75      | 10.60      | 10.73      | 10.69              | 0.08                     | 0.77                 |
| Q7    | 17.02      | 16.88      | 16.87      | 16.92              | 0.08                     | 0.49                 |
| Q8    | 17.78      | 17.62      | 17.82      | 17.74              | 0.11                     | 0.60                 |
| Q9    | 6.60       | 6.52       | 6.57       | 6.56               | 0.04                     | 0.64                 |
| Q10   | 19.70      | 19.82      | 19.48      | 19.67              | 0.17                     | 0.86                 |
| Q11   | 4.60       | 4.62       | 4.60       | 4.61               | 0.01                     | 0.21                 |
| Q12   | 11.68      | 11.60      | 11.52      | 11.60              | 0.08                     | 0.72                 |
| Q13   | 12.97      | 13.08      | 12.95      | 13.00              | 0.07                     | 0.56                 |
| Q14   | 5.47       | 5.53       | 5.45       | 5.48               | 0.04                     | 0.80                 |
| Q15   | 3.02       | 2.97       | 3.05       | 3.01               | 0.04                     | 1.39                 |
| Q16   | 14.72      | 14.90      | 14.88      | 14.83              | 0.10                     | 0.68                 |
| Q17   | 10.95      | 10.85      | 10.93      | 10.91              | 0.05                     | 0.49                 |
| Q18   | 11.12      | 11.05      | 10.88      | 11.02              | 0.12                     | 1.09                 |
| Q19   | 7.20       | 7.22       | 7.25       | 7.22               | 0.03                     | 0.35                 |
| Q20   | 20.22      | 20.42      | 20.23      | 20.29              | 0.11                     | 0.55                 |
| Q21   | 6.90       | 6.85       | 6.92       | 6.89               | 0.03                     | 0.50                 |
| Q22   | 19.35      | 19.85      | 19.08      | 19.43              | 0.39                     | 2.00                 |
| Q23   | 20.12      | 20.92      | 20.48      | 20.51              | 0.40                     | 1.95                 |
| Q24   | 7.00       | 7.05       | 7.00       | 7.02               | 0.03                     | 0.41                 |
| Q25   | 11.18      | 11.20      | 11.23      | 11.21              | 0.03                     | 0.23                 |
| Q26   | 8.58       | 8.57       | 8.55       | 8.57               | 0.02                     | 0.19                 |
| Q27   | 0.63       | 0.63       | 0.62       | 0.63               | 0.01                     | 1.53                 |
| Q28   | 21.27      | 21.25      | 21.22      | 21.24              | 0.03                     | 0.12                 |
| Q29   | 11.68      | 11.72      | 11.80      | 11.73              | 0.06                     | 0.51                 |
| Q30   | 57.73      | 57.60      | 57.72      | 57.68              | 0.07                     | 0.13                 |

Table 10: MapReduce Executions for all BigBench Queries with SF 300 (300GB data)
Table 11 depicts the three runtimes for the BigBench queries on MapReduce/Hive with 600GB scale factor. Reported are the average runtime from the three runs and the standard deviation in minutes and in %. For this scale factor all of the queries show standard deviation within 2%, except for Q22, which has standard deviation of around 5.6%.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|-------------------------|---------------------|
| Q1    | 8.10       | 8.10       | 8.13       | 8.11               | 0.02                    | 0.24                |
| Q2    | 40.35      | 40.02      | 39.97      | 40.11              | 0.21                    | 0.52                |
| Q3    | 53.60      | 53.52      | 53.23      | 53.45              | 0.19                    | 0.36                |
| Q4    | 510.25     | 502.00     | 493.67     | 501.97             | 8.29                    | 1.65                |
| Q5    | 155.18     | 155.52     | 156.35     | 155.68             | 0.60                    | 0.39                |
| Q6    | 16.65      | 16.78      | 16.75      | 16.73              | 0.07                    | 0.41                |
| Q7    | 29.43      | 29.47      | 29.63      | 29.51              | 0.11                    | 0.36                |
| Q8    | 32.45      | 32.47      | 32.47      | 32.46              | 0.01                    | 0.03                |
| Q9    | 11.45      | 11.58      | 11.47      | 11.50              | 0.07                    | 0.63                |
| Q10   | 24.07      | 24.53      | 24.28      | 24.29              | 0.23                    | 0.96                |
| Q11   | 7.47       | 7.48       | 7.42       | 7.46               | 0.03                    | 0.47                |
| Q12   | 18.83      | 18.62      | 18.55      | 18.67              | 0.15                    | 0.79                |
| Q13   | 20.22      | 20.20      | 20.27      | 20.23              | 0.03                    | 0.17                |
| Q14   | 9.00       | 8.98       | 8.98       | 8.99               | 0.01                    | 0.11                |
| Q15   | 4.45       | 4.48       | 4.47       | 4.47               | 0.02                    | 0.37                |
| Q16   | 28.83      | 29.27      | 29.28      | 29.13              | 0.26                    | 0.88                |
| Q17   | 14.60      | 14.63      | 14.57      | 14.60              | 0.03                    | 0.23                |
| Q18   | 14.48      | 14.32      | 14.53      | 14.44              | 0.11                    | 0.79                |
| Q19   | 7.55       | 7.67       | 7.52       | 7.58               | 0.08                    | 1.04                |
| Q20   | 39.27      | 39.30      | 39.40      | 39.32              | 0.07                    | 0.18                |
| Q21   | 10.22      | 10.25      | 10.20      | 10.22              | 0.03                    | 0.25                |
| Q22   | 18.72      | 19.80      | 20.93      | 19.82              | 1.11                    | 5.59                |
| Q23   | 23.10      | 23.08      | 23.47      | 23.22              | 0.22                    | 0.93                |
| Q24   | 10.27      | 10.30      | 10.33      | 10.30              | 0.03                    | 0.32                |
| Q25   | 19.88      | 20.02      | 20.07      | 19.99              | 0.09                    | 0.47                |
| Q26   | 15.05      | 15.00      | 15.20      | 15.08              | 0.10                    | 0.69                |
| Q27   | 0.98       | 0.98       | 0.97       | 0.98               | 0.01                    | 0.98                |
| Q28   | 24.77      | 24.73      | 24.82      | 24.77              | 0.04                    | 0.17                |
| Q29   | 22.78      | 22.73      | 22.82      | 22.78              | 0.04                    | 0.18                |
| Q30   | 119.38     | 120.27     | 119.93     | 119.86             | 0.45                    | 0.37                |

Table 11: MapReduce Executions for all BigBench Queries with SF 600 (600GB data)
Table 9 summarizes the absolute runtimes of the 30 BigBench queries on MapReduce/Hive for 1000GB/1TB scale factor. There are three columns depicting the times for each run in minutes, a column with the average execution time from the three runs and two columns with the standard deviation in minutes and in %. Similar to the smaller scale factors, only Q22 has a slightly higher than 2% standard deviation and is marked in yellow.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|----------------------|
| Q1    | 10.48      | 10.45      | 10.63      | 10.52              | 0.10                     | 0.93                 |
| Q2    | 68.12      | 66.47      | 66.90      | 67.16              | 0.86                     | 1.27                 |
| Q3    | 89.30      | 91.48      | 90.87      | 90.55              | 1.13                     | 1.24                 |
| Q4    | 927.67     | 918.05     | 940.33     | 928.68             | 11.18                    | 1.20                 |
| Q5    | 272.53     | 268.67     | 264.27     | 268.49             | 4.14                     | 1.54                 |
| Q6    | 25.28      | 25.40      | 25.67      | 25.42              | 0.20                     | 0.77                 |
| Q7    | 46.40      | 46.47      | 46.33      | 46.33              | 0.07                     | 0.14                 |
| Q8    | 53.30      | 53.78      | 53.93      | 53.67              | 0.33                     | 0.62                 |
| Q9    | 17.62      | 17.87      | 17.68      | 17.72              | 0.13                     | 0.73                 |
| Q10   | 22.92      | 22.62      | 22.67      | 22.73              | 0.16                     | 0.71                 |
| Q11   | 11.20      | 11.23      | 11.23      | 11.24              | 0.02                     | 0.17                 |
| Q12   | 29.93      | 29.88      | 30.05      | 29.86              | 0.09                     | 0.29                 |
| Q13   | 30.30      | 30.30      | 30.07      | 30.18              | 0.13                     | 0.45                 |
| Q14   | 13.88      | 13.83      | 13.87      | 13.84              | 0.03                     | 0.18                 |
| Q15   | 6.35       | 6.38       | 6.38       | 6.37               | 0.02                     | 0.30                 |
| Q16   | 48.77      | 48.63      | 48.87      | 48.85              | 0.12                     | 0.24                 |
| Q17   | 18.53      | 18.63      | 18.62      | 18.57              | 0.05                     | 0.29                 |
| Q18   | 27.60      | 27.75      | 27.45      | 27.60              | 0.15                     | 0.54                 |
| Q19   | 8.18       | 8.15       | 8.13       | 8.16               | 0.03                     | 0.31                 |
| Q20   | 64.83      | 64.92      | 64.77      | 64.84              | 0.08                     | 0.12                 |
| Q21   | 14.90      | 14.93      | 14.98      | 14.92              | 0.04                     | 0.28                 |
| Q22   | 29.78      | 31.03      | 30.67      | 29.84              | 0.64                     | 2.15                 |
| Q23   | 25.05      | 25.23      | 25.12      | 25.16              | 0.09                     | 0.37                 |
| Q24   | 14.75      | 14.77      | 14.83      | 14.75              | 0.04                     | 0.30                 |
| Q25   | 31.65      | 31.65      | 31.55      | 31.62              | 0.06                     | 0.18                 |
| Q26   | 22.92      | 22.85      | 23.07      | 22.94              | 0.11                     | 0.48                 |
| Q27   | 0.70       | 0.68       | 0.68       | 0.69               | 0.01                     | 1.40                 |
| Q28   | 28.87      | 28.87      | 29.05      | 28.93              | 0.11                     | 0.37                 |
| Q29   | 37.05      | 37.37      | 37.35      | 37.21              | 0.18                     | 0.48                 |
| Q30   | 199.30     | 203.10     | 200.50     | 200.97             | 1.94                     | 0.97                 |

Table 12: MapReduce Executions for all BigBench Queries with SF 1000 (1TB data)
6.2. BigBench on Spark SQL

This part presents the group of 14 pure HiveQL BigBench queries executed on Spark SQL with different scale factors. Table 13 summarizes the absolute runtimes of the 14 queries run on Spark SQL for 100GB scale factor. Reported are the absolute times from the three runs, the average runtime in minutes and the standard deviation in minutes and in %. The yellow cells indicate the queries with standard deviation higher or equal to 2% and possibly unstable behavior.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|---------------------|
| Q6    | 2.53       | 2.60       | 2.50       | 2.54               | 0.05                     | 2.00                |
| Q7    | 2.53       | 2.53       | 2.55       | 2.54               | 0.01                     | 0.38                |
| Q9    | 1.25       | 1.25       | 1.22       | 1.24               | 0.02                     | 1.55                |
| Q11   | 1.17       | 1.15       | 1.15       | 1.16               | 0.01                     | 0.83                |
| Q12   | 1.95       | 1.98       | 1.95       | 1.96               | 0.02                     | 0.98                |
| Q13   | 2.43       | 2.42       | 2.43       | 2.43               | 0.01                     | 0.40                |
| Q14   | 1.25       | 1.23       | 1.25       | 1.24               | 0.01                     | 0.77                |
| Q15   | 1.40       | 1.40       | 1.40       | 1.40               | 0.00                     | 0.00                |
| Q16   | 3.40       | 3.38       | 3.43       | 3.41               | 0.03                     | 0.75                |
| Q17   | 1.55       | 1.55       | 1.57       | 1.56               | 0.01                     | 0.62                |
| Q21   | 2.70       | 2.68       | 2.65       | 2.68               | 0.03                     | 0.95                |
| Q22   | 31.75      | 45.50      | 32.73      | 36.66              | 7.67                     | 20.92               |
| Q23   | 16.08      | 17.45      | 16.52      | 16.68              | 0.70                     | 4.19                |
| Q24   | 3.32       | 3.33       | 3.33       | 3.33               | 0.01                     | 0.29                |

Table 13: Spark SQL Executions for the group of 14 HiveQL BigBench Queries with SF 100 (100GB data)

Analogous Table 14 presents the execution times with 300GB scale factor. The reported columns are the same and the yellow cells indicate standard deviation higher than 2%.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|---------------------|
| Q6    | 3.42       | 3.50       | 3.63       | 3.52               | 0.11                     | 3.11                |
| Q7    | 6.03       | 6.17       | 5.93       | 6.04               | 0.12                     | 1.94                |
| Q9    | 1.70       | 1.73       | 1.68       | 1.71               | 0.03                     | 1.49                |
| Q11   | 1.37       | 1.38       | 1.38       | 1.38               | 0.01                     | 0.70                |
| Q12   | 3.05       | 3.05       | 3.08       | 3.06               | 0.02                     | 0.63                |
| Q13   | 3.58       | 3.60       | 3.60       | 3.59               | 0.01                     | 0.27                |
| Q14   | 1.55       | 1.58       | 1.55       | 1.56               | 0.02                     | 1.23                |
| Q15   | 1.58       | 1.58       | 1.60       | 1.59               | 0.01                     | 0.61                |
| Q16   | 7.85       | 8.00       | 7.80       | 7.88               | 0.10                     | 1.32                |
| Q17   | 2.13       | 2.22       | 2.22       | 2.19               | 0.05                     | 2.20                |
| Q21   | 10.12      | 11.13      | 10.67      | 10.64              | 0.51                     | 4.78                |
| Q22   | 54.90      | 62.10      | 65.07      | 60.69              | 5.23                     | 8.61                |
| Q23   | 25.57      | 26.60      | 28.88      | 27.02              | 1.70                     | 6.28                |
| Q24   | 15.22      | 15.23      | 15.35      | 15.27              | 0.07                     | 0.48                |

Table 14: Spark SQL Executions for the group of 14 HiveQL BigBench Queries with SF 300 (300GB data)
Table 15 shows the absolute Spark SQL runtimes with 600GB scale factor. The higher standard deviations are marked with yellow.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|----------------------|
| Q6    | 4.80       | 4.82       | 4.88       | 4.83               | 0.04                     | 0.91                 |
| Q7    | 24.67      | 21.07      | 18.67      | 21.47              | 3.02                     | 14.07                |
| Q9    | 2.32       | 2.30       | 2.30       | 2.31               | 0.01                     | 0.42                 |
| Q11   | 1.67       | 1.70       | 1.68       | 1.68               | 0.02                     | 0.99                 |
| Q12   | 4.92       | 4.92       | 4.93       | 4.92               | 0.01                     | 0.20                 |
| Q13   | 5.57       | 5.55       | 5.60       | 5.57               | 0.03                     | 0.46                 |
| Q14   | 2.10       | 2.12       | 2.08       | 2.10               | 0.02                     | 0.79                 |
| Q15   | 1.93       | 1.92       | 1.93       | 1.93               | 0.01                     | 0.50                 |
| Q16   | 23.78      | 23.40      | 22.78      | 23.32              | 0.50                     | 2.16                 |
| Q17   | 2.90       | 2.90       | 2.92       | 2.91               | 0.01                     | 0.33                 |
| Q21   | 28.32      | 27.38      | 25.83      | 27.18              | 1.25                     | 4.62                 |
| Q22   | 96.00      | 78.55      | 92.22      | 88.92              | 9.18                     | 10.32                |
| Q23   | 57.77      | 53.78      | 44.78      | 52.11              | 6.65                     | 12.76                |
| Q24   | 41.62      | 46.08      | 38.87      | 42.19              | 3.64                     | 8.63                 |

Table 15: Spark SQL Executions for the group of 14 HiveQL BigBench Queries with SF 600 (600GB data)

Finally, Table 16 summerizes the query times for the largest 1000GB scale factor. Most of the queries show standard deviation higher than 2% which is marked with yellow.

| Query | Run1 (min) | Run2 (min) | Run3 (min) | Average Time (min) | Standard Deviation (min) | Standard Deviation % |
|-------|------------|------------|------------|--------------------|--------------------------|----------------------|
| Q6    | 6.68       | 6.72       | 6.75       | 6.70               | 0.03                     | 0.50                 |
| Q7    | 39.68      | 42.73      | 42.67      | 41.07              | 1.74                     | 4.24                 |
| Q9    | 2.78       | 2.90       | 2.78       | 2.82               | 0.07                     | 2.42                 |
| Q11   | 2.08       | 2.07       | 2.08       | 2.07               | 0.01                     | 0.46                 |
| Q12   | 7.55       | 7.62       | 7.52       | 7.56               | 0.05                     | 0.67                 |
| Q13   | 8.03       | 7.95       | 7.97       | 7.98               | 0.04                     | 0.55                 |
| Q14   | 2.95       | 2.82       | 2.87       | 2.83               | 0.07                     | 2.38                 |
| Q15   | 2.37       | 2.35       | 2.35       | 2.36               | 0.01                     | 0.41                 |
| Q16   | 42.73      | 45.63      | 42.83      | 43.65              | 1.65                     | 3.77                 |
| Q17   | 3.55       | 3.47       | 3.52       | 3.55               | 0.04                     | 1.18                 |
| Q21   | 45.30      | 51.73      | 49.37      | 48.08              | 3.25                     | 6.77                 |
| Q22   | 110.27     | 114.78     | 138.92     | 122.68             | 15.40                    | 12.56                |
| Q23   | 69.40      | 74.78      | 71.57      | 69.01              | 2.71                     | 3.92                 |
| Q24   | 83.32      | 77.20      | 76.02      | 77.05              | 3.92                     | 5.09                 |

Table 16: Spark SQL Executions for the group of 14 HiveQL BigBench Queries with SF 1000 (1TB data)
6.3. Query Validation Reference

This section provides the tables with exact values that were used in the process of porting and evaluation of the BigBench queries to Spark. Table 17 shows the row counts for all database tables of BigBench's data model for the different scale factors 100GB, 300GB, 600GB and 1000GB.

| Table Name                  | Row Count | Sample Row |
|-----------------------------|-----------|------------|
| customer                    | 990000    | 0          |
| customer_address            | 495000    | 0          |
| customer_demographics       | 1920800   | 0          |
| date_dim                    | 109573    | 0          |
| household_demographics      | 7200      | 0          |
| income_band                 | 20        | 0          |
| inventory                  | 883693800 | 38203042470|
| item                        | 178200    | 4636999    |
| item_marketpt_rices         | 891000    | 2817590    |
| product_reviews             | 1034796   | 4450482    |
| promotion                   | 3707      | 5411       |
| reason                      | 433       | 631        |
| ship_mode                   | 20        | 0          |
| store                       | 120       | 379        |
| store_returns               | 6108428   | 69407907   |
| store_sales                 | 107843438 | 1224712024 |
| time_dim                    | 86400     | 86400      |
| warehouse                   | 19        | 26         |
| web_clickstreams            | 1092877307| 12409888280|
| web_page                    | 741       | 1082       |
| web_returns                 | 6115748   | 69406183   |
| web_sales                   | 107854751 | 1224631543 |

| Table Name                  | Row Count | Sample Row |
|-----------------------------|-----------|------------|
| Table Name                  | Row Count | Sample Row |
| customer                    | 990000    | 0          |
| customer_address            | 495000    | 0          |
| customer_demographics       | 1920800   | 0          |
| date_dim                    | 109573    | 0          |
| household_demographics      | 7200      | 0          |
| income_band                 | 20        | 0          |
| inventory                  | 883693800 | 38203042470|
| item                        | 178200    | 4636999    |
| item_marketpt_rices         | 891000    | 2817590    |
| product_reviews             | 1034796   | 4450482    |
| promotion                   | 3707      | 5411       |
| reason                      | 433       | 631        |
| ship_mode                   | 20        | 0          |
| store                       | 120       | 379        |
| store_returns               | 6108428   | 69407907   |
| store_sales                 | 107843438 | 1224712024 |
| time_dim                    | 86400     | 86400      |
| warehouse                   | 19        | 26         |
| web_clickstreams            | 1092877307| 12409888280|
| web_page                    | 741       | 1082       |
| web_returns                 | 6115748   | 69406183   |
| web_sales                   | 107854751 | 1224631543 |

Table 17: Number of Rows in all BigBench Tables for the tested Scale Factors
Table 18 shows the row counts for BigBench's query result tables for the different scale factors 100 GB, 300 GB, 600 GB and 1000 GB.

| Query # | SF 100 | SF 300 | SF 600 | SF 1000 |
|---------|--------|--------|--------|---------|
| Q1      | 0      | 0      | 0      | 0       |
| Q2      | 1288   | 1837   | 1812   | 1669    |
| Q3      | 131    | 426    | 887    | 1415    |
| Q4      | 73926146 | 233959972 | 468803001 | 795252823 |
| Q5      | logRegResult.txt | [AUC = 0.50 confusion: [[0.0, 0.0], [1.0, 3129856.0]] entropy: [[-0.7, -0.7], [-0.7, -0.7]] |
| Q6      | 100    | 100    | 100    | 100     |
| Q7      | 1      | 1      | 1      | 1       |
| Q8      | 2879890 | 5582973 | 8743044 | 12396422 |
| Q9      | 1      | 1      | 1      | 1       |
| Q10     | 2879890 | 5582973 | 8743044 | 12396422 |
| Q11     | 1      | 1      | 1      | 1       |
| Q12     | 1697681 | 10196175 | 30744360 | 68614374 |
| Q13     | 1      | 1      | 1      | 1       |
| Q14     | 1      | 1      | 1      | 1       |
| Q15     | 7      | 4      | 6      | 3       |
| Q16     | 1431932 | 3697528 | 6404121 | 9137536 |
| Q17     | 1      | 1      | 1      | 1       |
| Q18     | 1501027 | 2805571 | 4361606 | 9280457 |
| Q19     | 15     | 2      | 91     | 270     |
| Q20     | cluster.txt | VL-1426457{}| n=599019 {|=([964576.977, 12.584, 5.737, 3.194, 6.563] r=[591462.113, 3.598, 2.609, 1.739, 1.011])} |
| Q21     | 0      | 0      | 0      | 1       |
| Q22     | 11342  | 23149  | 0      | 47058   |
| Q23_1   | 9205   | 19417  | 29613  | 39727   |
| Q23_2   | 492    | 1080   | 1589   | 2129    |
| Q24     | 9      | 10     | 8      | 8       |
| Q25     | cluster.txt | VL-1906612{}| n=405237 {|=([2804277.105, 1.000, 77.611, 1126397.997] r=[0.248120.802, 2.7701, 3.126172.278])} |
| Q26     | cluster.txt | VL-2422906{}| n=684261 {|=([1064083.596, 1.2745, 2.22124, 1.32878, 9.32989, 10.18801] r=[2.718232.032, 2.5.646, 3.3.027, 9.7.426, 10.5.127])} |
| Q27     | 1      | 0      | 3      | 0       |
| Q28     | classifierResult.txt | 241245810653 American On an exploratory trip in "savage" lands |
| Q29     | 72     | 72     | 72     | 72      |
| Q30     | 72     | 72     | 72     | 72      |

Table 18: Number of Rows in the Result Tables for all BigBench Queries

7. Resource Utilization Analysis

The resource utilization metrics are gathered with the aid of Intel's Performance Analysis Tool (PAT) [42]. For each query the metrics CPU utilization, disk input/output, memory utilization and network input/output are provided when running the query on MapReduce as well as Spark. The measurements of the utilization metrics are depicted as graphs to show their distribution over the query's runtime. Additionally, the average/total values of the metric measurements are shown in a table for both MapReduce and Spark. This allows comparing the two engines.

For this experiment the queries were executed with scale factor 1000GB.
7.1. BigBench Query 4 (Python Streaming)

BigBench’s query Q4 performs a shopping cart abandonment analysis: For users who added products in their shopping carts but did not check out in the online store, find the average number of pages they visited during their sessions [29]. The query is implemented in HiveQL and executes additionally python scripts.

| Scale Factor: | 1TB |
|---------------|-----|
| Input Data size/ Number of Tables: | 122GB / 4 Tables |
| Average Runtime (minutes): | 929 minutes |
| Result table rows: | 795 252 823 |
| MapReduce stages: | 33 |
| Avg. CPU Utilization % | |
| User % | 48.82% |
| System % | 3.31% |
| IOwait% | 4.98% |
| Memory Utilization % | 95.99% |
| Avg. Kbytes Transmitted per Second | 7128.30 |
| Avg. Kbytes Received per Second | 7129.75 |
| Avg. Context Switches per Second | 11364.64 |
| Avg. Kbytes Read per Second | 3487.38 |
| Avg. Kbytes Written per Second | 5607.87 |
| Avg. Read Requests per Second | 47.81 |
| Avg. Write Requests per Second | 12.88 |
| Avg. I/O Latencies in Milliseconds | 115.24 |

**Summary:** The query is memory bound with 96% utilization and around 5% IOwaits, which means that the CPU is waiting for outstanding disk I/O requests. It has a modest CPU utilization of around 49%, but very high number of average context switches per second and very long average I/O latencies. This makes Q4 the slowest from all the 30 BigBench queries.
7.2. BigBench Query 5 (Mahout)

BigBench's query Q5 builds a model using logistic regression: based on existing users online activities and demographics, for a visitor to an online store, predict the visitors likelihood to be interested in a given category [29]. It is implemented in HiveQL and Mahout.

| Scale Factor: | 1TB |
|---------------|-----|
| Input Data size/ Number of Tables: | 123GB / 4 Tables |
| Average Runtime (minutes): | 273minutes |
| Result table rows: | logRegResult.txt |
| MapReduce stages: | 20 |

| Avg. CPU Utilization % | User % | 51.50% |
|------------------------|--------|--------|
|                        | System % | 3.37% |
|                        | IOwait%  | 3.65% |
| Memory Utilization %   | 91.85%  |
| Avg. Kbytes Transmitted per Second | 8329.02 |
| Avg. Kbytes Received per Second | 8332.22 |
| Avg. Context Switches per Second | 9859.00 |
| Avg. Kbytes Read per Second | 3438.94 |
| Avg. Kbytes Written per Second | 5568.18 |
| Avg. Read Requests per Second | 67.41 |
| Avg. Write Requests per Second | 13.12 |
| Avg. I/O Latencies in Milliseconds | 82.12 |

**Summary:** The query is memory bound with around 92% utilization and high network traffic (around 8-9 MB/sec). The Mahout execution starts after the 15536 seconds and is clearly observable on all of the below graphics. It takes around 18 minutes and utilizes very few resources in comparison to the HiveQL part of the query.
BigBench’s query Q18 identifies the stores with flat or declining sales in 3 consecutive months, check if there are any negative reviews regarding these stores available online [29]. It is implemented in HiveQL and uses the apache OpenNLP machine learning library for natural language text processing.

| Scale Factor: | ITB |
|---------------|-----|
| Input Data size/ Number of Tables: | 71GB / 3 Tables |
| Average Runtime (minutes): | 28 minutes |
| Result table rows: | 9280457 |
| MapReduce stages: | 17 |
| Avg. CPU Utilization % | User % 55.99% |
| | System % 2.04% |
| | IOwait% 0.31% |
| Memory Utilization % | 90.22% |
| Avg. Kbytes Transmitted per Second | 2302.81 |
| Avg. Kbytes Received per Second | 2303.59 |
| Avg. Context Switches per Second | 6751.68 |
| Avg. Kbytes Read per Second | 1592.41 |
| Avg. Kbytes Written per Second | 988.08 |
| Avg. Read Requests per Second | 4.86 |
| Avg. Write Requests per Second | 4.66 |
| Avg. I/O Latencies in Milliseconds | 20.68 |

**Summary:** The query is memory bound with around 90% utilization and around 56% of CPU usage. The time spent for I/O waits is only around 0.30% as well as the average time spent for I/O latencies.
7.4. BigBench Query 27 (OpenNLP)

BigBench’s query Q27 extracts competitor product names and model names (if any) from online product reviews for a given product [29]. It is implemented in HiveQL and uses the Apache OpenNLP machine learning library for natural language text processing.

| Scale Factor: | 1TB |
|--------------|-----|
| Input Data size/ Number of Tables: | 2GB / 1 Tables |
| Average Runtime (minutes): | 0.7 minutes |
| Result table rows: | dynamic / 0 |
| MapReduce stages: | 7 |

| Avg. CPU Utilization % | User % | 10.03% |
|------------------------|--------|--------|
|                        | System % | 1.94% |
|                        | IOwait % | 1.29% |
| Memory Utilization %   | 27.19% |
| Avg. Kbytes Transmitted per Second | 1547.15 |
| Avg. Kbytes Received per Second | 1547.14 |
| Avg. Context Switches per Second | 5952.83 |
| Avg. Kbytes Read per Second | 1692.01 |
| Avg. Kbytes Written per Second | 181.19 |
| Avg. Read Requests per Second | 14.25 |
| Avg. Write Requests per Second | 2.36 |
| Avg. I/O Latencies in Milliseconds | 8.89 |

**Summary:** The system is underutilized with only 10% CPU and 27% memory usage. The network and disk utilization is also very low.
| Time (sec) | KB/sec | Transmitted per Second | Received per Second |
|-----------|--------|------------------------|---------------------|
| 0         | 0      | [Graph showing KB/sec over time] |

| Time (sec) | Context Switches per Sec |
|-----------|--------------------------|
| 0         | [Graph showing Context Switches per Sec over time] |

| Time (sec) | KB/sec | Read per Second | Written per Second |
|-----------|--------|-----------------|--------------------|
| 0         | 0      | [Graph showing KB/sec over time] |

| Time (sec) | Disk Bandwidth |
|-----------|----------------|
| 0         | [Graph showing Disk Bandwidth over time] |

| Time (sec) | I/O Requests per Sec |
|-----------|-----------------------|
| 0         | [Graph showing I/O Requests per Sec over time] |

| Time (sec) | I/O Latencies |
|-----------|---------------|
| 0         | [Graph showing I/O Latencies over time] |

| Time (sec) | Mappers | Reducers |
|-----------|---------|----------|
| 0         | [Graph showing Mappers and Reducers over time] |
7.5. BigBench Query 7 (HiveQL + Spark SQL)

BigBench’s query Q7 lists all the stores with at least 10 customers who bought products with the price tag at least 20% higher than the average price of products in the same category during a given month [29]. The query is implemented in pure HiveQL and is adopted from query 6 of the TPC-DS benchmark.

| Scale Factor: | 1TB |
|---------------|-----|
| Input Data size/ Number of Tables: | 70GB / 5 Tables |
| Average Runtime (minutes): | 46.33 | 41.07 | 1.13 |
| Result table rows: | 52 |
| Stages: | MapReduce 39 | Spark 144 & 4474 Tasks |
| Avg. CPU Utilization % | User % | 56.97% | 16.65% | 3.42 |
| | System % | 3.89% | 2.62% | 1.48 |
| | I/Owait % | 0.40% | 21.28% | - |
| Memory Utilization % | 94.33% | 93.78% | 1.01 |
| Avg. Kbytes Transmitted per Second | 11650.07 | 3455.03 | 3.37 |
| Avg. Kbytes Received per Second | 11654.28 | 3456.24 | 3.37 |
| Avg. Context Switches per Second | 10251.24 | 8693.44 | 1.18 |
| Avg. Kbytes Read per Second | 2739.21 | 6501.03 | - |
| Avg. Kbytes Written per Second | 7190.15 | 3364.60 | 2.14 |
| Avg. Read Requests per Second | 40.24 | 66.93 | - |
| Avg. Write Requests per Second | 17.13 | 12.20 | 1.40 |
| Avg. I/O Latencies in Milliseconds | 55.76 | 32.91 | 1.69 |

**Summary:** Hive (MR) is only 13% slower than Spark SQL. The Hive execution utilizes on average 57% of the CPU, whereas the Spark SQL uses on average 17% of the CPU. Both Hive and Spark SQL are memory bound utilizing on average 94% of the memory. However, Spark SQL spent on average around 21% on waiting for outstanding disk I/O requests (IOWait), which is much greater than the average for both Hive and Spark SQL. Additionally, Hive read data with on average 7 MB/sec and writes it with on average 4MB/sec, whereas Spark SQL reads with on average 6.3MB/sec and writes with on average 3.3MB/sec.
7.6. BigBench Query 9 (HiveQL + Spark SQL)

BigBench's query Q9 calculates the total sales for different types of customers (e.g. based on marital status, education status), sales price and different combinations of state and sales profit [29]. The query is implemented in pure HiveQL and was adopted from query 48 of the TPC-DS benchmark.

|                        | Hive  | Spark SQL | Hive/Spark SQL Ratio |
|------------------------|-------|-----------|----------------------|
| Scale Factor:          | 1TB   |           |                      |
| Input Data size/ Number of Tables: | 69GB / 5 Tables |  |
| Result table rows:     | 1     |           |                      |
| Stages:                | MapReduce 7 | Spark 135 & 3065 Tasks |  |
| Average Runtime (minutes): | 17.72 | 2.82      | 6.28                 |
| Avg. CPU Utilization % | User % | 60.34%    | 27.87%               | 2.17 |
|                        | System % | 3.44%     | 2.22%                | 1.55 |
|                        | IOwait %  | 0.38%     | 4.09%                | -    |
| Memory Utilization %   | 78.87% | 61.27%    | 1.29                 |
| Avg. Kbytes Transmitted per Second | 7512.13 | 7690.59 | -                     |
| Avg. Kbytes Received per Second | 7514.87 | 7691.04 | -                     |
| Avg. Context Switches per Second | 19757.83 | 7284.11 | 2.71                  |
| Avg. Kbytes Read per Second | 2741.72 | 13174.12 | -                     |
| Avg. Kbytes Written per Second | 4098.95 | 1043.45 | 3.93                  |
| Avg. Read Requests per Second | 9.76 | 48.91 | -                     |
| Avg. Write Requests per Second | 10.84 | 3.62 | 2.99                  |
| Avg. I/O Latencies in Milliseconds | 41.67 | 27.32 | 1.53                  |

**Summary:** Hive is 6 times slower than Spark SQL. The Hive execution is CPU (on average 60%) and memory (78%) bound, whereas the Spark SQL execution consumes on average 28% CPU and 61% memory. Additionally, Hive read data with on average 2.6 MB/sec and writes it with on average 4MB/sec, whereas Spark SQL reads with on average 13MB/sec and writes with on average 1MB/sec.
7.7. BigBench Query 24 (HiveQL + Spark SQL)

BigBench’s query Q24 measures the effect of competitors’ prices on products’ in-store and online sales for a given product [29] (Compute the cross-price elasticity of demand for a given product). The query is implemented in pure HiveQL.

|                       | Hive     | Spark SQL | Spark SQL/Hive Ratio |
|-----------------------|----------|-----------|----------------------|
| Scale Factor:         |          | 1TB       |                      |
| Input Data size/ Number of Tables: | 99GB / 4 Tables |          |                      |
| Result table rows:    | 8        |           |                      |
| Stages:               | MapReduce 39 | Spark 42 & 6996 Tasks |          |
| Average Runtime (minutes): | 14.75       | 77.05     | 5.22                 |
| Avg. CPU Utilization % |          |           |                      |
| User %                | 48.92%    | 17.52%    | -                    |
| System %              | 2.01%     | 1.61%     | -                    |
| IOwait %              | 0.48%     | 11.21%    | 23.35                |
| Memory Utilization %  | 43.60%    | 82.84%    | 1.90                 |
| Avg. Kbytes Transmitted per Second | 3123.24            | 4373.39        | 1.40                |
| Avg. Kbytes Received per Second  | 3122.92        | 4374.41        | 1.40               |
| Avg. Context Switches per Second | 7077.10       | 8821.01       | 1.25               |
| Avg. Kbytes Read per Second | 7148.77       | 7810.38       | 1.09               |
| Avg. Kbytes Written per Second | 169.46           | 3762.42       | 22.20              |
| Avg. Read Requests per Second | 22.28          | 64.38         | 2.89               |
| Avg. Write Requests per Second | 4.71           | 8.29          | 1.76               |
| Avg. I/O Latencies in Milliseconds | 21.38         | 27.66         | 1.29               |

**Summary**: Overall Hive (MapReduce) is around 81% faster than Spark SQL. The query execution on Hive utilizes on average 49% of the CPU, whereas the Spark SQL uses on average 18% of the CPU. However, for Spark SQL around 11% of the time is spent on waiting for outstanding disk I/O requests (IOwait), which is much greater than the average for both Hive and Spark SQL.
Spark SQL. Also Spark SQL execution is memory bound utilizing 83% of the memory in comparison to the 44% utilization for Hive.
8. Lessons Learned

This report presented our first attempt to use the BigBench benchmark to evaluate the data
scaling capabilities of a Hadoop cluster on both MapReduce/Hive and Spark SQL. Furthermore,
multiple issues and fixes were presented as part of our initiative to execute BigBench on Spark.
Our experiments showed that the group of 14 pure HiveQL queries can be successfully executed
on Spark SQL.
The Spark SQL performance greatly varied among the type of queries and the data sizes on
which they were executed. On one hand, a group of HiveQL queries (Q6, Q11, Q12, Q13, Q14,
Q15 and Q17) performed best, with Q9 being around 6.3 times faster than Hive with the increase
of the data size. On the other hand, we observed a group of queries (Q7, Q16, Q21, Q22 and
Q23) performed worst, with Q24 being 5.2 times slower on Spark SQL than on Hive with the
increase of the data size. The reason for this is the reported join issue [43] in the current Spark
SQL version.
In terms of resource utilization, our analysis showed that Spark SQL:
- Utilized less CPU, whereas it showed higher I/O wait than Hive.
- Read more data from disk, whereas it wrote less data than Hive.
- Utilized less memory than Hive.
- Sent less data over the network than Hive.

In the future, we plan to rerun the BigBench queries on the latest version of Spark SQL, where
the join issue should be fixed and offer more stable experience. Also we plan running the
remaining groups of BigBench queries using other components from the Spark framework.

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### System Information

| Description         |               |
|---------------------|---------------|
| Manufacturer:       | Dell Inc.     |
| Product Name:       | PowerEdge T420|
| BIOS:               | 1.5.1         |
| Release Date:       | 03/08/2013    |

### Memory

| Description         |               |
|---------------------|---------------|
| Total Memory:       | 32 GB         |
| DIMMs:              | 10            |
| Configured Clock Speed: | 1333 MHz    |
| Part Number:        | M393B5273CH0-YH9 |
| Size:               | 4096 MB       |

### CPU

| Description         |               |
|---------------------|---------------|
| Model Name:         | Intel(R) Xeon(R) CPU E5-2420 0 @ 1.90GHz |
| Architecture:       | x86_64        |
| CPU(s):             | 24            |
| On-line CPU(s) list:| 0-23          |
| Thread(s) per core: | 2             |
| Core(s) per socket: | 6             |
| Socket(s):          | 2             |
| CPU MHz:            | 1200.000      |
| L1d cache:          | 32K           |
| L1i cache:          | 32K           |
| L2 cache:           | 256K          |
| L3 cache:           | 15360K        |
| NUMA node0 CPU(s):  | 0,2,4,6,8,10,12,14,16,18,20,22 |
| NUMA node1 CPU(s):  | 1,3,5,7,9,11,13,15,17,19,21,23 |

### NIC

| Description         |               |
|---------------------|---------------|
| Ethernet controller:| Broadcom Corporation NetXtreme BCM5720 Gigabit Ethernet PCIe |

### Storage

| Description         |               |
|---------------------|---------------|
| Storage Controller: | LSI Logic / Symbios Logic MegaRAID SAS 2008 [Falcon] (rev 03) |
| Model               | 08:00.0 RAID bus controller |

| Drive / Name | Formatted Size | Model                                      |
|--------------|----------------|--------------------------------------------|
| Disk 1/ sda1 | 931.5 GB       | Western Digital, WD1003FBYX RE4-1TB, SATA3, 3.5 in, 7200RPM, 64MB Cache |

Table 19: Master Node
## System Information

| Description               |      |
|----------------------------|------|
| Manufacturer:              | Dell Inc. |
| Product Name:              | PowerEdge T420 |
| BIOS:                      | 2.1.2 |
| Release Date:              | 01/20/2014 |
| Total Memory:              | 32 GB |
| DIMMs:                     | 4 |
| Configured Clock Speed:    | 1600 MHz |
| Part Number:               | M393B2G70DB0-YK0 |
| Size:                      | 16384 MB |
| Model Name:                | Intel(R) Xeon(R) CPU E5-2420 v2 @ 2.20GHz |
| Architecture:              | x86_64 |
| CPU(s):                    | 12 |
| On-line CPU(s) list:       | 0-11 |
| Thread(s) per core:        | 2 |
| Core(s) per socket:        | 6 |
| Socket(s):                 | 1 |
| CPU MHz:                   | 2200.000 |
| L1d cache:                 | 32K |
| L1i cache:                 | 32K |
| L2 cache:                  | 256K |
| L3 cache:                  | 15360K |
| NUMA node0 CPU(s):         | 0-11 |
| Speed:                     | 1000Mb/s |
| Ethernet controller:       | Broadcom Corporation NetXtreme BCM5720 Gigabit Ethernet PCIe |
| Storage Controller:        | Intel Corporation C600/X79 series chipset SATA RAID Controller (rev 05) |
| Drive / Name               | Formatted Size | Model                                      |
| Disk 1/ sda1               | 931.5 GB       | Dell- 1TB, SATA3, 3.5 in, 7200RPM, 64MB Cache |
| Disk 2/ sdb1               | 931.5 GB       | WD Blue Desktop WD10EZEX - 1TB, SATA3, 3.5 in, 7200RPM, 64MB Cache |
| Disk 3/ sdc1               | 931.5 GB       |                                           |
| Disk 4/ sdd1               | 931.5 GB       |                                           |

Table 20: Data Node