# **Robert Gordon University**



Big Data Programming – CMM705

Course Work Report

MSc in Big Data Analytics

Semester 1

Submitted by:

S.Z. Raeesul Islam

20232953 / 2409649

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# Task 1 - Solution Architecture

# 1. System Diagram for NBA Basketball

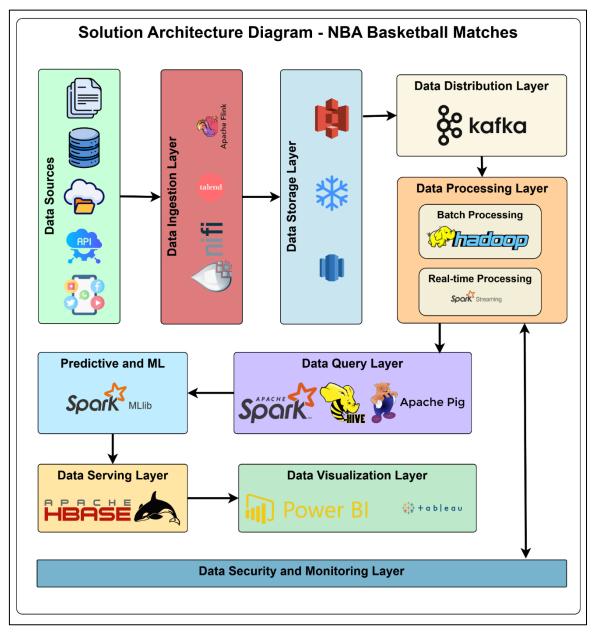


Figure 1. System Diagram

# 2. Diagram Overview and Role of Components

This **Big Data Analytics** solution for **real-time and historical NBA basketball** matches examines information suited for the NBA. The architecture integrates **key components** in various layers to allow seamless **ingestion of data, storage scalability, robust processing, interactive querying, and insightful visualization.** Modern real-time data streams coupled with batch processing of historical datasets are handled in the system; **predictive analytics and interactive exploration** are supported. Each layer has been optimized to ensure that the **functional requirements** 

of **real-time analytics and batch processing** are supported, and the **non-functional requirements** of **scalability, availability, and security** are satisfied. What follows below is a detailed description of the role of each layer.

- 1. Data Sources Layer: The layer is the source location of data, which could be from APIs for live game feeds, social media platforms for sentiment, cloud databases for structured historical data, and local files for offline data ingestion. Its main purpose is to deliver a reliable and continuous supply of real-time and batch data to the ingestion process. Scalability remains the focal point here; the architecture must allow for the addition of new data streams or sources without disruption.
- 2. Data Ingestion Layer: This layer is concerned with the collection and transportation of raw data from various sources into the system. The tools used are Apache NiFi, Apache Flink, Talend. This layer ensures that the data is in the correct format and ready for processing, and manages high throughput, and low latency to meet real-time analytics requirements.
- 3. Data Distribution Layer: This layer for distribution of data employs Apache Kafka as a message broker to enable efficient and real-time message flow between ingestions and processing. It buffers incoming data, provides protection from faults and provides scalable low-latency data distributing thus making it possible for multiple consumers to subscribe to data streams.
- 4. **Data Storage Layer:** This layer is designed for both short-term and long-term data storage; HDFS for large-scale batch storage, Amazon Redshift/ Snowflake for structured data analysis, and HBase for real-time data storage, in a way that makes it scalable, secure, and reliable throughout the system.
- 5. Data Processing Layer: This layer takes care of load, such as real-time and batch, with its main responsibilities of real-time processing of date data for immediate insights and handling of Hadoop batch jobs for deep analysis. It is designed to ensure efficient processing on transformation, aggregation and feature engineering so that they can support real-time dashboard needs and periodic analytical reports.
- 6. Data Query Layer: This Layer is important in data exploration, facilitating interactive queries, such as SQL-like on structured data built on advanced transformations for semi-structured datasets, thus enabling decision making and exploration at speed by analysts and engineers.
- 7. **Predictive Analytics** is otherwise done by the Spark MLlib library for model building and training, for example game outcome predictions, anomaly detections, trend forecasting, etc. thus providing a shift from descriptive analytics to predictive insights driving decisions with data.
- 8. **Data Serving Layer:** Apache HBase represents this layer, which provides fast access to the already processed data for the applications and dashboards downstream. It allows for low latency read/write operations, serving efficiently both visualization tools and user queries.

<ol> <li>Data Visualization Layer: with the help of tools like Power BI and Tableau, enables the real-time follow-up of facilitating metrics, such as points and player statistics, making actionable information lucidly understood and available for decision- makers.</li> </ol>
10. Data Security and Monitoring Layer: This layer ensures a system-wide practice of security, monitoring, encryption, and role-based access control, in addition to pipeline monitoring tools, to ensure that data is kept intact, compliant, and operationally continuous.

# Task 2 - Data Analysis

The first step involves mounting the local machine's data set to create a Docker container. The image **suhothayan/hadoop-spark-pig-hive:2.9.2** is used.

```
docker run -it -p 8081:8081 -p 50080:50080 --name nba-analyzer -v C:\Users\HP\Desktop\NBA:/resource -d suhothayan/hadoop-spark-pig-hive:2.9.2
```



Get into the docker container to view the mounted resource.

docker exec -it nba-analyzer bash

```
PS C:\Users\HP> docker exec -it nba-analyzer bash
root@ab190ed4e1fd:/# ls
                      lib
                             media
bin
     derby.log etc
                                           mnt
                                                proc
                                                          root sbin
                                                                     sys
                home lib64 metastore_db opt
boot dev
                                                                srv
                                                                          var
root@ab190ed4e1fd:/# cd resource/
root@ab190ed4e1fd:/resource# ls
NBA-data.csv
root@ab190ed4e1fd:/resource#
```

The data set must be added to the HDFS Folder to complete the task. First, make a directory in HDFS, and then transfer the file to it.

```
hdfs dfs -mkdir nba-data
hdfs dfs -put NBA-data.csv nba-data/NBA-data.csv
hdfs dfs -ls nba-data
```

```
root@ab190ed4e1fd:/resource# hdfs dfs -mkdir nba-data
root@ab190ed4e1fd:/resource# hdfs dfs -ls
Found 2 items
drwxr-xr-x

    root supergroup

                                        0 2019-07-21 16:09 input
             - root supergroup
                                        0 2024-12-14 07:32 nba-data
drwxr-xr-x
root@ab190ed4e1fd:/resource# hdfs dfs -put NBA-data.csv nba-data/NBA-data.csv
root@ab190ed4e1fd:/resource# hdfs dfs -ls nba-data
Found 1 items
                                 81584756 2024-12-14 07:32 nba-data/NBA-data.csv
-rw-r--r--
             1 root supergroup
root@ab190ed4e1fd:/resource#
```

# 1. Hadoop MapReduce

# 1. Most Scoring Quarter Analysis

**MostScoringQuarterAnalysis.java** to obtain the most scoring quarters for each team during various game periods in the entire tournament, a Java class is developed with a mapper, reducer, and main function.

Mapper function

```
public static class MostScoringQuarterMapper extends Mapper<LongWritable, Text, Text, Text> { 1 usage
      protected void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
          Map<String, String> monthMapping = getMonthMapping();
         String[] values = value.toString().split( regex: ",");
         String Score = values[24].trim();
         String GameID = values[2].trim();
             String day = parts[0];
             String month = monthMapping.getOrDefault(parts[1], defaultValue: "");
             if (!month.isEmpty()) {
ublic class MostScoringQuarterAnalysis {
  public static class MostScoringQuarterMapper extends Mapper<LongWritable, Text, Text, Text> { 1 usage
      protected void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
          } else if (\underline{Score}.matches(regex: "[a-zA-Z]{3}-\\d{2}")) {
             String[] parts = Score.split( regex: "-");
              String month = monthMapping.getOrDefault(parts[0], | defaultValue: "");
              String day = parts[1];
          if (!Score.contains("-") || Team.isEmpty() || Score.isEmpty()) {
```

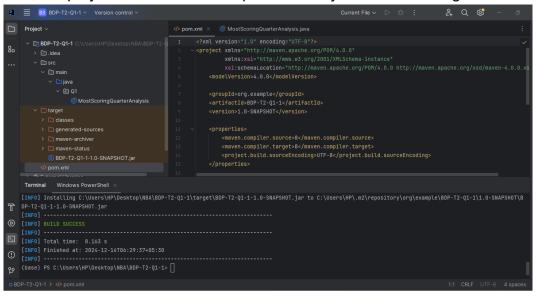
#### Reducer function

```
.ass MostScoringQuarterAnalysis {
   public static class MostScoringQuarterReducer extends Reducer<Text, Text, Text, Text> { 1 usa
      String scoreboard = parts[3];
                String[] currentScoreParts = scoreboard.split( regex: "-");
             Map<Integer, Integer> quarterScores = teamPeriodScores.get(scoringTeam);
             (Map.Entry<String,
                                        Integer>> teamEntry : teamPeriodScores.entrySet()) {
 ublic class MostScoringQuarterAnalysis {
       protected void reduce(Text key, Iterable<Text> values, Context context) throws IOException, InterruptedException {
   for (Map.Entry<String, Map<Integer, Integer>> teamEntry : teamPeriodScores.entrySet()) {
               Map<Integer. Integer> quarterScores = teamEntry.getValue():
               Map<Integer, Integer> globalQuarterScores = globalTeamPeriodScores.get(team);
       protected void cleanup(Context context) throws IOException, InterruptedException {
           for (Map.Entry<String, Map<Integer, Integer>> teamEntry : globalTeamPeriodScores.entrySet()) {
               Map<Integer, Integer> quarterScores = teamEntry.getValue();
public class MostScoringQuarterAnalysis {
   Map<Integer, Integer> quarterScores = teamEntry.getValue();
              int mostScoringPeriod = -1;
              int mostScore = -1;
                  if (score > mostScore) {
                     mostScore = score:
                     mostScoringPeriod = quarter;
```

#### Main function

```
public class MostScoringQuarterAnalysis {
   public static void main(String[] args) throws Exception {
       if (args.length != 2) {
           System.err.println("Usage: MostScoringQuarterAnalysis <input path> <output path>");
           System.exit( status: -1);
       Configuration conf = new Configuration();
       job.setJarByClass(MostScoringQuarterAnalysis.class);
       job.setMapperClass(MostScoringQuarterMapper.class);
       job.setReducerClass(MostScoringQuarterReducer.class);
       job.setMapOutputKeyClass(Text.class);
       job.setMapOutputValueClass(Text.class);
       job.setOutputKeyClass(Text.class);
       job.setOutputValueClass(Text.class);
       FileInputFormat.addInputPath(job, new Path(args[0]));
       FileOutputFormat.setOutputPath(job, new Path(args[1]));
       System.exit(job.waitForCompletion( verbose: true) ? 0 : 1);
```

After that, the project is constructed to produce the jar file in the designated folder.



Since the jar file has been created, the YARN command is used to carry out the task.

```
yarn jar BDP-T2-Q1-1/target/BDP-T2-Q1-1-1.0-SNAPSHOT.jar Q1.MostScoringQuarterAnalysis nba-data/NBA-data.csv output/T02 001 1 outputs
```

```
root@ab190ed4elfd:/resource# yarn jar BDP-T2-Q1-1/target/BDP-T2-Q1-1-1.0-SNAPSHOT.jar Q1.MostScoringQuarterAnalysis nba-data/NBA-data.csv output/T02_Q01_1_outputs
24/12/14 07:34:24 INFO client.RMProxy: Connecting to ResourceManager at /0.0.0.0:8032
24/12/14 07:34:25 INFO mapreduce.JobResourceUploader: Hadoop command-line option parsing not performed. Implement the To ol interface and execute your application with ToolRunner to remedy this:
24/12/14 07:34:25 INFO input.FileInputFormat: Total input files to process: 1
24/12/14 07:34:25 INFO mapreduce.JobSubmitter: number of splits:1
24/12/14 07:34:25 INFO mapreduce.JobSubmitter: number of splits:1
24/12/14 07:34:25 INFO mapreduce.JobSubmitter: number of splits:1
24/12/14 07:34:25 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_1734161408917_0001
24/12/14 07:34:26 INFO impl.YarnClientImpl: Submitted application_application_1734161408917_0001
24/12/14 07:34:26 INFO mapreduce.Job: The url to track the job: http://ab190ed4elfd:8088/proxy/application_1734161408917_0001/
```

The output will be kept in the "output/ T02\_Q01\_1\_outputs" folder. It appears as follows:

hdfs dfs -ls output/T02\_Q01\_1\_outputs
hdfs dfs -cat output/T02\_Q01\_1\_outputs/part-r-00000

```
File Output Format Counters
                    Bytes Written=1270
root@ab190ed4e1fd:/resource# hdfs dfs -ls output/T02_Q01_1_outputs
Found 2 items
                                                0 2024-12-14 07:34 output/T02_Q01_1_outputs/_SUCCESS 1270 2024-12-14 07:34 output/T02_Q01_1_outputs/part-r-00000
-rw-r--r-- 1 root supergroup
-rw-r--r-- 1 root supergroup
root@ab190ed4e1fd:/resource# hdfs dfs -cat output/T02_Q01_1_outputs/part-r-00000
Hawks Most Scoring Period: 2, Score: 1882
Cavaliers Most Scoring Period: 4, Score: 1952
Hornets Most Scoring Period: 2, Score: 1921
76ers Most Scoring Period: 2, Score: 1987
Lakers Most Scoring Period: 1, Score: 2126
Celtics Most Scoring Period: 2, Score: 1985
Kings Most Scoring Period: 1, Score: 2130
Pistons Most Scoring Period: 1, Score: 2003
Warriors Most Scoring Period: 1, Score: 2003
Warriors Most Scoring Period: 2, Score: 1906
Nuggets Most Scoring Period: 1, Score: 2070
Wizards Most Scoring Period: 1, Score: 1903
Raptors Most Scoring Period: 2, Score: 1998
         Most Scoring Period: 2, Score: 2021
Most Scoring Period: 2, Score: 2149
Spurs
Bucks
         Most Scoring Period: 4, Score: 2030
Suns
Spurs
           Most Scoring Period: 2, Score: 2021
           Most Scoring Period: 2, Score: 2149
Bucks
Suns
            Most Scoring Period: 4, Score: 2030
                        Most Scoring Period: 2, Score: 1958
Most Scoring Period: 1, Score: 2122
Grizzlies
Mavericks
Magic Most Scoring Period: 3, Score: 2035
                        Most Scoring Period: 1, Score: 2000
Timberwolves
Rockets Most Scoring Period: 4, Score: 1998
Nets Most Scoring Period: 2, Score: 1927
Trail Blazers Most Scoring Period: 1, Score: 1961
Heat Most Scoring Period: 3, Score: 1816
           Most Scoring Period: 4, Score: 1927
Jazz
SuperSonics
                        Most Scoring Period: 2, Score: 2164
Bulls Most Scoring Period: 1, Score: 1858
Pacers Most Scoring Period: 3, Score: 1893
Clippers Most Scoring Period: 4, Score: 1953
Knicks Most Scoring Period: 2, Score: 1903
root@ab190ed4e1fd:/resource#
```

#### 2. Most Scored Player Analysis

**MostScoredPlayerAnalysis.java** to obtain the total score of the most scored player in the full tournament, a Java class is developed with a mapper, reducer, and main function.

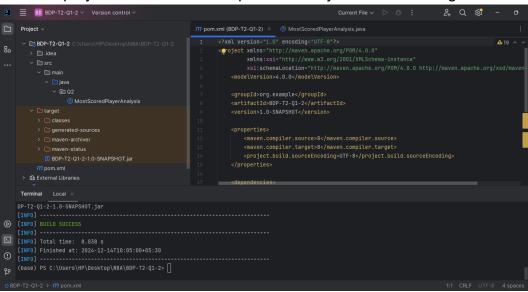
#### Mapper function

```
ublic class MostScoredPlayerAnalysis {
   public static class HighestScoringPlayerMapper extends Mapper<LongWritable, Text, Text, Text> { 1usage
           monthMapping.put("Jan", "1");
monthMapping.put("Feb", "2");
            monthMapping.put("Aug", "8");
            monthMapping.put("Oct", "10");
monthMapping.put("Nov", "11");
            return monthMapping;
           Map<String, String> monthMapping = getMonthMapping();
            String[] values = value.toString().split( regex: ",");
public class MostScoredPlayerAnalysis {
    public static class HighestScoringPlayerMapper extends Mapper<LongWritable, Text, Text, Text> { 1usage
        protected void map(LongWritable key, Text value, Context context)
Lnrows lucxception, interruptedexception i
            Map<String, String> monthMapping = getMonthMapping();
             String[] values = value.toString().split( regex: ",");
             String player = values[7].trim();
             String event = values[1].trim();
             if (\underline{score}.matches(\underline{regex}: "\\d{1,2}-[a-zA-Z]{3}")) {
                 String[] parts = score.split( regex: "-");
                 String month = monthMapping.getOrDefault(parts[1], defaultValue: "");
             } else if (<u>score</u>.matches( regex: "[a-zA-Z]{3}-\\d{2}")) {
                 String month = monthMapping.getOrDefault(parts[0], | defaultValue: "");
```

#### Reducer function

#### Main function

After that, the project is constructed to produce the jar file in the designated folder.



Since the jar file has been created, the YARN command is used to carry out the task.

```
yarn jar BDP-T2-Q1-2/target/BDP-T2-Q1-2-1.0-SNAPSHOT.jar Q2.MostScoredPlayerAnalysis nba-data/NBA-data.csv output/T02_Q01_2_outputs
```

```
root@ab190ed4e1fd:/resource# yarn jar BDP-T2-Q1-2/target/BDP-T2-Q1-2-1.0-SNAPSHOT.jar Q2.MostScoredPlayerAnalysis nba-da ta/NBA-data.csv output/T02_Q01_2_outputs
24/12/14 07:43:15 INFO client.RMProxy: Connecting to ResourceManager at /0.0.0.0:8032
24/12/14 07:43:15 INFO client.RMProxy: Connecting to ResourceManager at /0.0.0:8032
24/12/14 07:43:17 INFO mapreduce.JobResourceUploader: Hadoop command-line option parsing not performed. Implement the To ol interface and execute your application with ToolRunner to remedy this.
24/12/14 07:43:17 INFO input.FileInputFormat: Total input files to process: 1
24/12/14 07:43:17 INFO mapreduce.JobSubmitter: number of splits:1
24/12/14 07:43:17 INFO Configuration.deprecation: yarn.resourcemanager.system-metrics-publisher.enabled is deprecated. I nstead, use yarn.system-metrics-publisher.enabled
24/12/14 07:43:18 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_1734161408917_0003
24/12/14 07:43:18 INFO mapreduce.JobSubmitted application_application_1734161408917_0003
24/12/14 07:43:18 INFO mapreduce.Jobs: The url to track the job: http://ab190ed4e1fd:8088/proxy/application_1734161408917_0003/
```

The output will be kept in the "output/ T02\_Q01\_2\_outputs" folder. It appears as follows:

```
hdfs dfs -ls output/T02_Q01_2_outputs
hdfs dfs -cat output/T02_Q01_2_outputs/part-r-00000
```

```
File Output Format Counters

Bytes Written=57

root@ab190ed4e1fd:/resource# hdfs dfs -ls output/T02_Q01_2_outputs

Found 2 items

-rw----- 1 root supergroup 0 2024-12-14 07:43 output/T02_Q01_2_outputs/_SUCCESS

-rw-r---- 1 root supergroup 57 2024-12-14 07:43 output/T02_Q01_2_outputs/part-r-00000

root@ab190ed4e1fd:/resource# hdfs dfs -cat output/T02_Q01_2_outputs/part-r-00000

Most Scoring Player Jerry Stackhouse, Total Score: 2370

root@ab190ed4e1fd:/resource#
```

The most scored player is "Jerry Stakehouse", and he scored 2370 points.

## 2. Apache Hive

The following directories are made before running **Apache Hive** commands. Input data and outputs are stored in these directories.

```
hdfs dfs -mkdir /user/nba_data
hdfs dfs -mkdir /user/hive
hdfs dfs -mkdir /user/hive/nba_data
```

```
root@ab190ed4e1fd:/# hdfs dfs -mkdir /user/nba_data
root@ab190ed4e1fd:/# hdfs dfs -ls /user/nba_data
root@ab190ed4e1fd:/# hdfs dfs -ls /user
Found 2 items
drwxr-xr-x - root supergroup
drwxr-xr-x - root supergroup
                                          0 2024-12-14 08:00 /user/nba_data
                                          0 2024-12-14 07:34 /user/root
root@ab190ed4e1fd:/# hdfs dfs -mkdir /user/hive
root@ab190ed4e1fd:/# hdfs dfs -ls /user
Found 3 items
drwxr-xr-x - root supergroup
                                          0 2024-12-14 08:01 /user/hive
                                 0 2024-12-14 08:00 /user/noa_
0 2024-12-14 07:34 /user/root
           root supergrouproot supergroup
drwxr-xr-x
                                         0 2024-12-14 08:00 /user/nba_data
drwxr-xr-x
root@ab190ed4e1fd:/# hdfs dfs -mkdir /user/hive/nba_data
root@ab190ed4e1fd:/# hdfs dfs -ls /user/hive
Found 1 items
drwxr-xr-x - root supergroup 0 2024-12-14 08:01 /user/hive/nba_data
root@ab190ed4e1fd:/#
```

Then the NBA dataset move to the location /user/hive/nba\_data

```
hdfs dfs -put /resource/NBA-data.csv /user/nba_data/NBA-data.csv
```

```
root@ab190ed4e1fd:/# hdfs dfs -put /resource/NBA-data.csv /user/nba_data/NBA-data.csv root@ab190ed4e1fd:/# hdfs dfs -ls /user/nba_data
Found 1 items
-rw-r--r-- 1 root supergroup 81584756 2024-12-14 08:02 /user/nba_data/NBA-data.csv root@ab190ed4e1fd:/#
```

To store the dataset, a new database and table are created.

```
create database nba_db;
show databases;
use nba db;
```

```
hive> create database nba_db;
OK
Time taken: 0.515 seconds
hive> show databases;
OK
default
nba_db
Time taken: 0.077 seconds, Fetched: 2 row(s)
hive> use nba_db;
OK
Time taken: 0.101 seconds
hive>
```

CREATE EXTERNAL TABLE nba\_table (EVENTID STRING, EVENTNUM STRING, HOMEDESCRIPTION STRING, PCTIMESTRING STRING, GAME\_ID STRING, PERIOD STRING, PLAYER1\_ID STRING, PLAYER1\_NAME STRING, PLAYER1\_TEAM\_ABBREVIATION STRING, PLAYER1\_TEAM\_CITY STRING, PLAYER1\_TEAM\_ID STRING, PLAYER1\_TEAM\_NICKNAME STRING, PLAYER2\_ID STRING, PLAYER2\_NAME STRING, PLAYER2\_TEAM\_ABBREVIATION STRING,

PLAYER2\_TEAM\_CITY STRING, PLAYER2\_TEAM\_ID STRING, PLAYER2\_TEAM\_NICKNAME
STRING, PLAYER3\_ID STRING, PLAYER3\_NAME STRING,
PLAYER3\_TEAM\_ABBREVIATION STRING, PLAYER3\_TEAM\_CITY STRING,
PLAYER3\_TEAM\_ID STRING, PLAYER3\_TEAM\_NICKNAME STRING, SCORE STRING,
SCOREMARGIN STRING, VISITORDESCRIPTION STRING, CLEANED\_SCORE STRING,
POINTS\_SCORED STRING, WINNER STRING, LOSER STRING)
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ','
LOCATION '/user/hive/nba\_data';

```
hive> CREATE EXTERNAL TABLE nba_table (
                  EVENTID STRING, EVENTNUM STRING,
                  HOMEDESCRIPTION STRING,
                  PCTIMESTRING STRING,
                  GAME_ID STRING,
                 GRILLID STRING,
PLAYER1_ID STRING,
PLAYER1_TEAM_ABBREVIATION STRING,
PLAYER1_TEAM_ABBREVIATION STRING,
PLAYER1_TEAM_ID STRING,
PLAYER1_TEAM_ID STRING,
PLAYER2_ID STRING,
PLAYER2_ID STRING,
PLAYER2_ID STRING,
PLAYER2_TEAM_ABBREVIATION STRING,
PLAYER2_TEAM_CITY STRING,
PLAYER2_TEAM_ID STRING,
PLAYER2_TEAM_ID STRING,
PLAYER2_TEAM_NICKNAME STRING,
PLAYER3_ID STRING,
PLAYER3_ID STRING,
PLAYER3_TEAM_ABBREVIATION STRING,
PLAYER3_TEAM_CITY STRING,
PLAYER3_TEAM_CITY STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_ID STRING,
PLAYER3_TEAM_NICKNAME STRING,
SCORE STRING,
                  PERIOD STRING,
                  SCORE STRING,
SCOREMARGIN STRING,
VISITORDESCRIPTION STRING,
                  CLEANED_SCORE STRING,
                  POINTS_SCORED STRING
                    PLAYER1_TEAM_ABBREVIATION STRING,
                    PLAYER1_TEAM_CITY STRING,
                   PLAYER1_TEAM_ID STRING, PLAYER1_TEAM_NICKNAME STRING,
                    PLAYER2_ID STRING,
                   PLAYER2_NAME STRING,
PLAYER2_TEAM_ABBREVIATION STRING,
                   PLAYER2_TEAM_CITY STRING,
                   PLAYER2_TEAM_ID STRING,
PLAYER2_TEAM_NICKNAME STRING,
                   PLAYER3_ID STRING,
                    PLAYER3_NAME STRING,
                   PLAYER3_TEAM_ABBREVIATION STRING,
                   PLAYER3_TEAM_CITY STRING,
                   PLAYER3_TEAM_ID STRING
                   PLAYER3_TEAM_NICKNAME STRING,
                   SCORE STRING,
                    SCOREMARGIN STRING,
                   VISITORDESCRIPTION STRING,
                   CLEANED_SCORE STRING, POINTS_SCORED STRING,
                   WINNER STRING,
                   LOSER STRING
       > )
        > ROW FORMAT DELIMITED
        > FIELDS TERMINATED BY '
        > LOCATION '/user/hive/nba_data';
OK
 Time taken: 0.758 seconds
hive>
```

The dataset is loaded into the created table folder.

```
LOAD DATA INPATH 'hdfs:/user/nba_data/NBA-data.csv' OVERWRITE INTO TABLE nba_table;
```

ALTER TABLE nba\_table SET TBLPROPERTIES ("skip.header.line.count"="1");

```
hive> LOAD DATA INPATH 'hdfs:/user/nba_data/NBA-data.csv' OVERWRITE INTO TABLE nba_table;
Loading data to table nba_db.nba_table
OK
Time taken: 1.82 seconds
hive> ALTER TABLE nba_table SET TBLPROPERTIES ("skip.header.line.count"="1");
OK
Time taken: 0.149 seconds
hive> SELECT * FROM nba_table LIMIT 5;
                20000001
                                        12:00 1
Θ
        76ers Knicks
               20000001
                                Jump Ball Camby vs. Ratliff: Tip to Houston
                                                                                 12:00
                                                                                                 948
                                                                                                         Marcus Camby
                                        Knicks 689 The
k 1610612752
                                                         Theo Ratliff
        New York
                        1610612752
                                                                                 Philadelphia
                                                                                                 1610612755
YK
                                New York
75
        Allan Houston
                       NYK
                                                                Knicks
                                                                                                                  76ers
nicks
                                                                11:41 1
                                                                                                                 NYK
2 2 200
ew York 1610612752
                                MISS Sprewell 6' Jump Shot
                                                                                         Latrell Sprewell
                       Knicks 0
                                                                                         Theo Ratliff
                                                                                                         PHI
                                                                                                                 Philadel
       1610612755
                        76ers
                                                Ratliff BLOCK (1 BLK)
                                                                                                 Knicks
                                                                                         76ers
phia
                20000001
                                        11:40
                                                        1610612755
                                                                                                                 0
                                                                                                                        0
76ers Rebound
                       0
                                        Knicks
                20000001
                                Camby S.FOUL (P1.T1)
                                                        11:29 1
                                                                                 Marcus Camby
                                                                                                 NYK
                                                                         948
                                                                                                         New York
610612752
               Knicks 0
       Knicks
76ers
Time taken: 1.991 seconds, Fetched: 5 row(s)
hive>
```

#### 1. Top 5 Teams (Total Number of Points Scored)

```
SELECT PLAYER1_TEAM_NICKNAME, SUM(POINTS_SCORED) AS total_points
FROM nba_table
GROUP BY PLAYER1_TEAM_NICKNAME
ORDER BY total_points DESC
LIMIT 5;
```

Hive query returns the **top five teams for the total scored points** in the table nba\_table. Its groups with **PLAYER1\_TEAM\_NICKNAME**, and computes the total points scored by the team **SUM(POINTS\_SCORED)**. The list is ordered by the variable **total\_points** in **descending order**. The last part is the **LIMIT 5**, which produces the five teams with the highest scores, revealing the best-performing teams in total points scored.

## 2. The Average Points Scored in Each Quarter.

```
SELECT PERIOD, SUM(POINTS_SCORED) / COUNT(DISTINCT GAME_ID) AS nba_play_by_play
FROM nba_table
WHERE POINTS_SCORED IS NOT NULL AND POINTS_SCORED >= 0
GROUP BY PERIOD
ORDER BY PERIOD;
```

The Hive query obtains 'the points scored in each quarter (PERIOD) on average' in all the games in the table nba\_table. To avoid invalid scores, it starts from filtering the rows where POINTS\_SCORED is NULL or negative. The output contains average points for that quarter by taking total points scored in that quarter and dividing them by the number of games (GAME\_ID) held in that quarter. This query enabled the information to be displayed in a more organized and comprehensible manner by quarter (PERIOD) and in ascending order of the quarter.

## 3. Apache Spark

Google Colab, a cloud-based platform that supports **PySpark** for big data processing, was used to create this **Spark analysis task**.

A **Spark session** is started, and a notebook has been created. The dataset is then loaded.

```
# load the data
data = spark.read.csv("/content/drive/MyDrive/BDP-Spark/NBA-data.csv", header=True, inferSchema=True)
data.show()
|EVENTID|EVENTIUM| GAME_ID| HOMEDESCRIPTION| PCTIMESTRING|PERIOD|PLAYER1_ID| PLAYER1_NAME|PLAYER1_TEAM_ABBREV
                                              0| NOC.
48| Marcus Camby|
               0 | 20000001 |
                | 120000001|Jump Ball Camby v...|2024-12-14 12:00:00|
2|20000001|MISS Sprewell 6' ...|2024-12-14 11:41:00|
                                                                                             84|Latrell Sprewell
                                                                                  1 | 1610612755 |
                 3 20000001
                                               NULL 2024-12-14 11:40:00
                                                                                1|1610612755| NULL!
1| 948| Marcus Camby|
1| 689| Theo Ratliff|
1| 689| Theo Ratliff|
1| 369| Charlie Ward|
1| 689| Theo Ratliff|
1| 948| Marcus Camby|
1| 947| Allen Iverson|
1| 948| Marcus Camby|
                4|20000001|Camby S.FOUL (P1.T1)|2024-12-14 11:29:00|
5|20000001| NULL|2024-12-14 11:29:00|
6|2000001| NULL|2024-12-14 11:29:00|
       4
       5
                6 20000001
                                                NULL 2024-12-14 11:29:00
       6
                 7|20000001|Ward REBOUND (Off...|2024-12-14 11:28:00|
       8
                 8 20000001
                                               NULL 2024-12-14 11:18:00
       91
                 9|20000001|Camby Free Throw ...|2024-12-14 11:18:00|
                10|20000001|Camby Free Throw ...|2024-12-14 11:18:00|
11|20000001| NULL|2024-12-14 11:08:00|
      10
      11
                12 20000001 Camby REBOUND (0f... 2024-12-14 11:06:00)
                                                                                                      Marcus Camby
                13 20000001 MISS Houston 15' ... 2024-12-14 10:53:00
```

There are invalid values in the 'SCORE' column, such as '02-Feb' and 'Apr-6'. Create a function to clean and standardize these values by converting month names to their numerical equivalents as part of the preprocessing step.

The Spark code cleans the SCORE column, excluding null values from CLEANED\_SCORE, and generates a PREVIOUS\_SCORE column using a window partitioned by GAME\_ID and ordered by EVENTID to capture the score from the prior event for sequential analysis.

The **calculate\_play\_score** function is defined to compare the current and previous cleaned scores to determine the play score. It adds a new column, **PLAY\_SCORE**, to the DataFrame and uses a UDF to determine the score difference or sum depending on whether a prior score exists.

```
# Function to calculate play score using UDF
def calculate_play_score(df):
  # inner function for calculate score
  def calculate_score(cleaned_score, previous_score):
    \mbox{\tt\#} If score is None, play score is \mbox{\tt0}
   if cleaned_score is None:
    # First valid score, return sum of current score
    if previous_score is None:
     team1, team2 = map(int, cleaned_score.split('-'))
      return team1 + team2
      # Calculate difference between previous and current score
      previous_team1, previous_team2 = map(int, previous_score.split('-')) if previous_score else (0, 0)
      current_team1, current_team2 = map(int, cleaned_score.split('-'))
      return (current_team1 - previous_team1) + (current_team2 - previous_team2)
  # Create a UDF to apply the score calculation function row-wise
  calculate_score_udf = F.udf(calculate_score, IntegerType())
  return df.withColumn("PLAY_SCORE", calculate_score_udf(df['CLEANED_SCORE'], df['PREVIOUS_SCORE']))
# Apply the play score calculation
cleaned_data = calculate_play_score(cleaned_data)
```

# 1. % of Players (Scored 40 Points or More in A Single Match).

Computes the total number of players, counts the unique players who meet the condition, computes the percentage of such players, filters those with scores of 40 or higher, and groups the data by **PLAYER1\_NAME** and **GAME\_ID** to determine the total points per player.

```
# Group by PLAYER1_NAME and GAME_ID and calculate the total points
player_score = cleaned_data.groupBy("PLAYER1_NAME" , "GAME_ID").agg(
    F.sum("PLAY_SCORE").alias("TOTAL_POINTS")
)

# filter player score 40 or more
filter_players = player_score.filter(player_score.TOTAL_POINTS >= 40)

# number of players
no_of_players = data.filter(col("PLAYER1_NAME").isNotNull()).select("PLAYER1_NAME").distinct().count()

# filter unique players who scored 40 or more points
filter_players_count = filter_players.filter(col("PLAYER1_NAME").isNotNull())\
.select("PLAYER1_NAME").distinct().count()

# Percentage of players who scored 40 or more points
player_percentage = (filter_players_count / no_of_players) * 100

print(f"The Percentage of players who scored 40 or more points in a single game: {player_percentage:.2f}%")
The Percentage of players who scored 40 or more points in a single game: 6.36%
```

There are 6.36% players are scored 40 or more in a single game.

#### 2. The Total Number of Matches Lost by Each Team.

Initially, computes the total **PLAY\_SCORE** for each team by grouping data by **GAME\_ID** and **PLAYER1\_TEAM\_NICKNAME**. It determines winners and losers by ranking teams in each game according to their overall score using a **window** function. The **Loser** teams are the only ones included in the filtered results. The code then sorts the teams in descending order of losses, counts the number of losses for each team, and groups the code by **PLAYER1\_TEAM\_NICKNAME**.

```
# Group by GAME_ID and PLAYER1_TEAM_NICKNAME
# after calculate the sum of PLAY_SCORE for each team
game_scores = cleaned_data.groupBy("GAME_ID", "PLAYER1_TEAM_NICKNAME").agg(
    F.sum("PLAY_SCORE").alias("TOTAL_SCORE")
)

# window function to rank the teams within each game by their total score
window_spec = Window.partitionBy("GAME_ID").orderBy(F.col("TOTAL_SCORE").desc())

# Add a column to rank teams based on their total score within each game
game_scores = game_scores.withColumn("RANK", F.row_number().over(window_spec))

# identify the winner and loser
game_results = game_scores.withColumn(
    "RESULT",
    F.when(F.col("RANK") == 1, "Winner").otherwise("Loser")
)

# filter using PLAYER1_TEAM_NICKNAME
game_results = game_results.filter((F.col("PLAYER1_TEAM_NICKNAME").isNotNull()))
game_results.show(truncate=False)
```

```
# Filter the game results to include only the "Loser" teams
losses = game_results.filter(
   (F.col("RESULT") == "Loser") & (F.col("PLAYER1_TEAM_NICKNAME").isNotNull())
# Group by PLAYER1_TEAM_NICKNAME and count the number of losses for each team
team_losses = losses.groupBy("PLAYER1_TEAM_NICKNAME").agg(
   F.count("RESULT").alias("NUMBER_OF_LOSSES")
# Sort the teams by the number of losses in descending order
team_losses_sorted = team_losses.orderBy(F.col("NUMBER_OF_LOSSES").desc())
team_losses_sorted.show(truncate=False)
+----+
|PLAYER1_TEAM_NICKNAME|NUMBER_OF_LOSSES|
+----+
|59
Grizzlies
Hawks
                 57
Nets
                 156
Cavaliers
                 |52
          |51
Clippers
```

• Team Bulls lost most matches (67) in this tournament.

# Task 3 - Machine Learning model using Spark MLlib

The Spark session is already initialized, and the data has been loaded in Google Colab.

To keep every record from the **cleaned\_data** dataset, do a left join. Save the result in a **new DataFrame** for additional processing after replacing null values in the **PLAY SCORE** column with 0.

```
# Perform a left join to retain all records from cleaned data
merged_data = data.join(
    cleaned_data.select("GAME_ID", "EVENTID", "PLAY_SCORE"),
    on=["GAME_ID", "EVENTID"],
    how="left"
)

# Fill null values in the PLAY_SCORE column with 0
new_data = merged_data.withColumn(
    "PLAY_SCORE",
    F.when(F.col("PLAY_SCORE").isNull(), 0).otherwise(F.col("PLAY_SCORE"))
)

# Show the resulting DataFrame
new_data.show()
```

Calculate the total points scored by each team in a single game after grouping the data by **GAME\_ID** and **PLAYER1\_TEAM\_NICKNAME**. Teams in each game can be ranked according to their total points by using a **window function**. To decide which team **won** and which **lost**, assign ranks. This makes it possible to identify the winning and losing teams for each match.

```
# Determine total points scored by each team per game
team_scores = (
   new_data.groupBy("GAME_ID", "PLAYER1_TEAM_NICKNAME")
   .agg(F.sum("PLAY_SCORE").alias("TOTAL_POINTS"))
# Determine winners and losers
game_results = (
   team_scores.alias("a")
   .join(
       team_scores.alias("b"),
       (F.col("a.GAME_ID") == F.col("b.GAME_ID")) &
       (F.col("a.PLAYER1_TEAM_NICKNAME") != F.col("b.PLAYER1_TEAM_NICKNAME")),
   )
   .select(
       F.col("a.GAME ID").alias("Game ID"),
       F.col("a.PLAYER1_TEAM_NICKNAME").alias("Winner"),
       F.col("b.PLAYER1_TEAM_NICKNAME").alias("Loser"),
   .filter(F.col("a.TOTAL_POINTS") > F.col("b.TOTAL_POINTS"))
```

Only players from the winning team should be included in the data. Next, group the filtered data by **PLAYER1\_NAME**, and then add up the **PLAY\_SCORE** column to determine the **total points scored by each player**. This shows how much each player on the winning team contributed overall.

```
# Filter players on the winning team and calculate total points per player
winning_players_total_score = (
    new_data.alias("players")
    .join(game_results.alias("results"),
         (F.col("players.GAME_ID") == F.col("results.Game_ID")) &
          (F.col("players.PLAYER1_TEAM_NICKNAME") == F.col("results.Winner")),
    .groupBy("players.GAME ID", "players.PLAYER1 NAME", "players.PLAYER1 TEAM NICKNAME", "results.Loser")
    .agg(F.sum("players.PLAY_SCORE").alias("Total_Points"))
    .select(
       F.col("GAME_ID").alias("Game_ID"),
        F.col("PLAYER1_NAME").alias("Player_Name"),
       F.col("PLAYER1_TEAM_NICKNAME").alias("Team"),
       F.col("Loser").alias("Opponent"),
        F.col("Total_Points").alias("Points_Scored")
# Show the results
winning_players_total_score.show()
Game_ID
              Player_Name| Team|Opponent|Points_Scored|
                                        Nets|
Nets|
20000002
             Lamond Murray | Cavaliers |
                                                        17
|20000002|Clar. Weatherspoon|Cavaliers|
                                                           8
```

**Preparing the data** is the first step in the **Machine Learning** process.

```
model_data = winning_players_total_score.select(
    F.col("Player_Name").alias("Player"),
    F.col("Opponent"),
    F.col("Points_Scored").alias("Actual_Score")
)
```

To prepare the data for machine learning models, use **OneHotEncoder** to encode the string columns **Player** and **Opponent** into numerical format.

```
from pyspark.ml.feature import StringIndexer

player_indexer = StringIndexer(inputCol="Player", outputCol="Player_Index")
opponent_indexer = StringIndexer(inputCol="Opponent", outputCol="Opponent_Index")

indexed_data = player_indexer.fit(model_data).transform(model_data)
indexed_data = opponent_indexer.fit(indexed_data).transform(indexed_data)

from pyspark.ml.feature import OneHotEncoder

# OneHotEncoder for Player and Opponent
player_encoder = OneHotEncoder(inputCol="Player_Index", outputCol="Player_OneHot")
opponent_encoder = OneHotEncoder(inputCol="Opponent_Index", outputCol="Opponent_OneHot")
encoded_data = player_encoder.fit(indexed_data).transform(indexed_data)
encoded_data = opponent_encoder.fit(encoded_data).transform(encoded_data)
```

To get the data ready for machine learning modelling, use **VectorAssembler** to merge several feature columns into a single feature vector.

```
from pyspark.ml.feature import VectorAssembler

assembler = VectorAssembler(
    inputCols=["Player_OneHot", "Opponent_OneHot"],
    outputCol="features"
)

data_features = assembler.transform(encoded_data)
```

After that, Split the data into training and testing

```
train_data, test_data = data_features.randomSplit([0.8, 0.2], seed=42)
```

Define the models: Linear Regression, Random Forest Regression, GBT Regression, and Decision Tree Regression, to train and evaluate on the prepared data.

```
from pyspark.ml.regression import (
    LinearRegression,
    RandomForestRegressor,
    GBTRegressor,
    DecisionTreeRegressor
)
from pyspark.ml.evaluation import RegressionEvaluator

# build the models
models = {
    "Linear Regression": LinearRegression(featuresCol="features", labelCol="Actual_Score"),
    "Random Forest Regression": RandomForestRegressor(featuresCol="features", labelCol="Actual_Score"),
    "GBT Regression": GBTRegressor(featuresCol="features", labelCol="Actual_Score"),
    "Decision Tree Regression": DecisionTreeRegressor(featuresCol="features", labelCol="Actual_Score"),
}
```

Build the model that was selected, use the training data to train it, and then use the testing data to make predictions. Lastly, use the **R2** value and **Root Mean Squared Error (RMSE)** to evaluate the accuracy and fit of the model.

```
# Train and Evaluate every model
results = []
evaluator = RegressionEvaluator(labelCol="Actual_Score", predictionCol="prediction", metricName="rmse")

for name, model in models.items():
    # Train the model
    trained_model = model.fit(train_data)
    # Predict on the test data
    predictions = trained_model.transform(test_data)
    # Evaluate RMSE
    rmse = evaluator.evaluate(predictions)
    # Evaluate R2
    r2 = evaluator.setMetricName("r2").evaluate(predictions)
    # Append results
    results.append((name, rmse, r2, predictions.select("Player", "Opponent", "Actual_Score", "prediction")))
```

```
print("Model Comparison Results:")
for name, rmse, r2, predictions df in results:
    print(f"\nModel: {name}")
    print(f" RMSE: {rmse:.3f}")
    print(f" R2: {r2:.3f}")
Model Comparison Results:
Model: Linear Regression
 RMSE: 6.687
  R2: 0.483
Model: Random Forest Regression
 RMSE: 0.108
 R2: 0.108
Model: GBT Regression
 RMSE: 0.260
 R2: 0.260
Model: Decision Tree Regression
 RMSE: 0.077
  R2: 0.077
```

Out of the four models used in this evaluation, the Decision Tree Regression model has the lowest RMSE and is therefore the most accurate. While Random Forest and GBT regressions yield results in the middle, Linear Regression performs the worst.0

Use a parameter grid to perform Hyperparameter Tuning for the Linear Regression model, and then use 5-fold cross-validation to test various parameter combinations and optimize model performance.

```
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
# Define the Linear Regression model
linear_model = LinearRegression(featuresCol="features", labelCol="Actual_Score")
# Create a parameter grid for hyperparameter tuning
paramGrid = ParamGridBuilder().addGrid(linear_model.regParam,
[0.01, 0.1, 0.5, 1.0]).addGrid(linear_model.elasticNetParam,
 [0.0, 0.5, 1.0]).build()
# Define the evaluator for RMSE
evaluator = RegressionEvaluator(labelCol="Actual_Score",
                              predictionCol="prediction",
                               metricName="rmse")
# Set up CrossValidator
crossval = CrossValidator(estimator=linear model,
                         estimatorParamMaps=paramGrid,
                         evaluator=evaluator,
                         numFolds=5)
```

```
predictions.select("Player", "Opponent", "Actual_Score", "prediction").show(5)
# Output the evaluation metrics
print(f"Best Linear Regression Model - RMSE: {rmse}, R2: {r2}")
# Print the best hyperparameters
print(f"Best regParam: {best_model._java_obj.getRegParam()}")
print(f"Best elasticNetParam: {best_model._java_obj.getElasticNetParam()}")
Best Linear Regression Model Predictions (Top 5):
+----+
| Player| Opponent|Actual_Score| prediction|
+----+
|A.C. Green | Bulls | 0 | 5.373035715762285 | A.C. Green | Celtics | 12 | 5.629694488773146 | A.C. Green | Grizzlies | 2 | 5.391726663948985 |
A.C. Green|Grizzlies|
                              2|5.391726663948985|
|A.C. Green| Jazz| 0|4.786912338401125|
|A.C. Green| Raptors| 14|5.833808353523322|
+----+
only showing top 5 rows
Best Linear Regression Model - RMSE: 6.686678555332445, R2: 0.48263004170596113
Best regParam: 0.01
Best elasticNetParam: 1.0
```

Task 4 – Data Visualization

