HELLENIC REPUBLIC
National and Kapodistrian
University of Athens

PROJECT

NATIONAL AND KAPODISTRIAN UNIVERSITY OF ATHENS

FACULTY OF INFORMATICS AND TELECOMMUNICATIONS

M111: Big Data Management

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Date: July 20, 2023
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Part 1 Introduction

Task 1.1

For creating a `files` directory in the HDFS, the following command was used

```
hadoop fs -mkdir -p ~/files
```

and to populate it with the project's `.csv` files

```
hadoop fs -put *.csv ~/files .
```

Since the only `.csv` files populating the working directory were the project's ones, it was fairly easy to fetch all of them using `*.csv`. Fig. 1 shows a print-screen of the `.csv` files lying within the created `files` directory.

```
user@master:~$ hadoop fs -ls ~/files
Found 5 items
-rw-r--r--   3 user supergroup         63 2023-05-24 19:03 /home/user/files/departmentsR.csv
-rw-r--r--   3 user supergroup       1017 2023-05-24 19:03 /home/user/files/employeesR.csv
-rw-r--r--   3 user supergroup    1264187 2023-05-24 19:03 /home/user/files/movie_genres.csv
-rw-r--r--   3 user supergroup   16282189 2023-05-24 19:03 /home/user/files/movies.csv
-rw-r--r--   3 user supergroup  709550294 2023-05-24 19:03 /home/user/files/ratings.csv
user@master:~$
```

Figure 1: HDFS directory containing the project's datasets in `.csv` format.

The same files were then saved in `.parquet` format, using Snip. 1, as can be seen in the print-screen of Fig 2.

```
user@master:~/project-code$ hdfs dfs -ls ~/files
Found 10 items
-rw-r--r--   3 user supergroup         63 2023-05-24 19:03 /home/user/files/departmentsR.csv
drwxr-xr-x   - user supergroup          0 2023-05-25 17:41 /home/user/files/departmentsR.parquet
-rw-r--r--   3 user supergroup       1017 2023-05-24 19:03 /home/user/files/employeesR.csv
drwxr-xr-x   - user supergroup          0 2023-05-25 17:41 /home/user/files/employeesR.parquet
-rw-r--r--   3 user supergroup    1264187 2023-05-24 19:03 /home/user/files/movie_genres.csv
drwxr-xr-x   - user supergroup          0 2023-05-25 17:41 /home/user/files/movie_genres.parquet
-rw-r--r--   3 user supergroup   16282189 2023-05-24 19:03 /home/user/files/movies.csv
drwxr-xr-x   - user supergroup          0 2023-05-25 17:39 /home/user/files/movies.parquet
-rw-r--r--   3 user supergroup  709550294 2023-05-24 19:03 /home/user/files/ratings.csv
drwxr-xr-x   - user supergroup          0 2023-05-25 17:40 /home/user/files/ratings.parquet
user@master:~/project-code$
```

Figure 2: HDFS directory containing the project's datasets in both `.csv` and `.parquet` formats.

Part 2 Basics

Task 2.1 Repartition and Broadcast Joins

Task 2.2 Tweaking the Catalyst Optimiser

Without Optimization (Sort Merge Join):

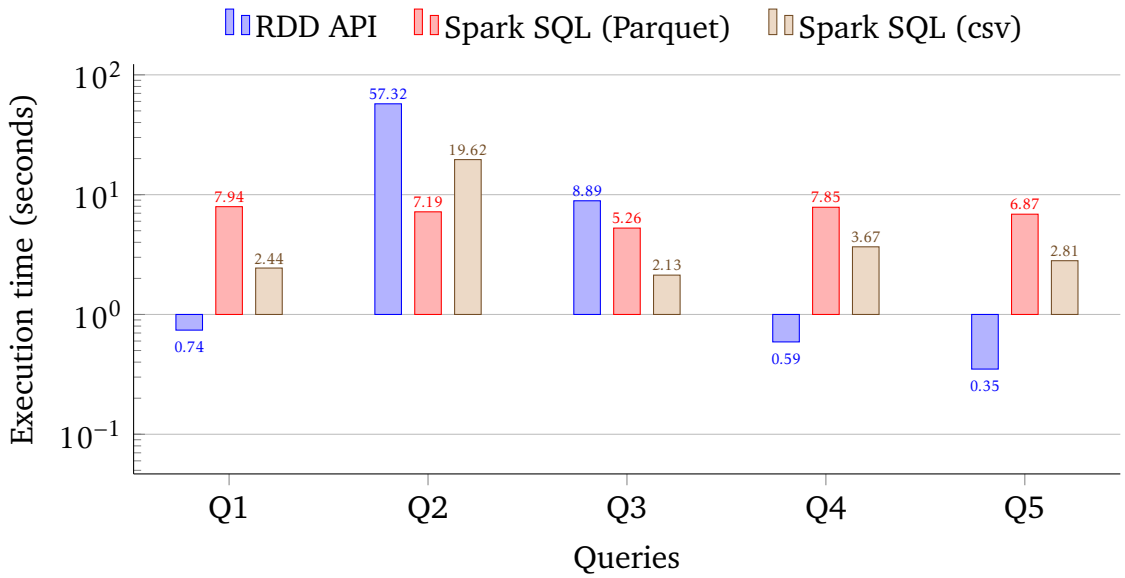

Figure 3: Caption

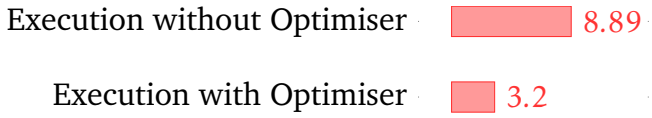

Figure 4: Execution time, for a particular query, with and without Spark's SQL Optimiser.

```
== Physical Plan ==
*(6) SortMergeJoin [mv_id#8], [mv_id#1], Inner
```

This is a Sort Merge Join, which is an operation where two dataframes are joined by sorting the data and then merging the sorted data. This type of join is used when the data is too large to fit into memory for a Broadcast Join.
The stages of this join operation involve filtering data where mv_id is not null, limiting the result set to 100, then sorting the data and performing the join operation. The SortMergeJoin operation requires that both sides of the join have been partitioned and sorted by the join key (mv_id in this case). Hence, there are additional Sort and Exchange operations before the join.

```
+- *(2) GlobalLimit 100
+- Exchange SinglePartition
+- *(1) LocalLimit 100
```

These operations represent the limit that is applied to the "movie_genres" table (the query limits the result set to 100). The GlobalLimit means that the limit is applied across the entire dataset, not just per partition.
The time taken for the entire operation is 13.2132 seconds.
With Optimization (Broadcast Hash Join):

```
== Physical Plan ==
*(3) BroadcastHashJoin [mv_id#8], [mv_id#1], Inner, BuildLeft
```

This is a Broadcast Hash Join, which is a type of join operation where the smaller DataFrame is broadcast to all the nodes containing partitions of the larger DataFrame for comparison and join operations. This type of join can be significantly faster than a sort-merge join because it doesn't require the data to be sorted first, and it can be done entirely in memory if the smaller DataFrame is small enough.

```
:- BroadcastExchange HashedRelationBroadcastMode(List(cast(input[0,
 ↪  int, false] as bigint)
```

The BroadcastExchange operation represents broadcasting the smaller DataFrame to the worker nodes. The broadcasting operation will transform the DataFrame into a more efficient data structure (a hash table) to speed up the subsequent join operation.
The time taken for the entire operation is 3.7529 seconds, which is significantly faster than the time taken when the optimization is not enabled. The optimizer has chosen a more efficient join strategy (broadcast hash join instead of sort merge join) based on the size of the data and the nature of the operation, which leads to a faster execution time.
Overall, the difference between these two execution plans demonstrates the power and importance of the Spark Catalyst optimizer in efficiently executing Spark jobs. It can make smart decisions, such as using a BroadcastHashJoin instead of a SortMergeJoin, which significantly improves performance.

Part 3 Code Snippets

Snippet 1: csv_to_parquet.py

```
from pyspark.sql import SparkSession
from pyspark.sql.types import StructField, StructType, IntegerType,
 ↪  FloatType, StringType


def convert_csv_to_parquet():
    # Create spark instance
    spark = SparkSession \
            .builder \
            .appName("Add schemas to CSVs and make Parquet files") \
            .getOrCreate()


    # Set schemas of csv files needed in Part 1 of the project
    movies_schema = StructType([
        StructField("mv_id", IntegerType()),
```

```
16          StructField("name", StringType()),
17          StructField("description", StringType()),
18          StructField("year", IntegerType()),
19          StructField("duration", IntegerType()),
20          StructField("prod_cost", IntegerType()),
21          StructField("revenue", IntegerType()),
22          StructField("popularity", FloatType())
23          ])
24
25      ratings_schema = StructType([
26          StructField("usr_id", IntegerType()),
27          StructField("mv_id", IntegerType()),
28          StructField("rating", FloatType()),
29          StructField("time_stamp", IntegerType())
30          ])
31
32      movie_genres_schema = StructType([
33          StructField("mv_id", IntegerType()),
34          StructField("genre", StringType())
35          ])
36
37      # Set schemas of csv files need in Part 2 of the project
38      employeesR_schema = StructType([
39          StructField("id", IntegerType()),
40          StructField("name", StringType()),
41          StructField("dep_id", IntegerType())
42          ])
43
44      departmentsR_schema = StructType([
45          StructField("dep_id", IntegerType()),
46          StructField("dep_name", StringType())
47          ])
48
49
50      # Load the aforementioned csv files into dataframes
51      movies_df = spark.read.format('csv') \
52              .options(header='false') \
53              .schema(movies_schema) \
54              .load("hdfs://master:9000/home/user/files/movies.csv")
55
56      ratings_df = spark.read.format('csv') \
57              .options(header='false') \
58              .schema(ratings_schema) \
59              .load("hdfs://master:9000/home/user/files/ratings.csv")
60
```

```
61      movie_genres_df = spark.read.format('csv') \
62              .options(header='false') \
63              .schema(movie_genres_schema) \
64              .load("hd⌋
                ↪  fs://master:9000/home/user/files/movie_genres.csv")
65
66      employeesR_df = spark.read.format('csv') \
67              .options(header='false') \
68              .schema(employeesR_schema) \
69              .load("hd⌋
                ↪  fs://master:9000/home/user/files/employeesR.csv")
70
71      departmentsR_df = spark.read.format('csv') \
72              .options(header='false') \
73              .schema(departmentsR_schema) \
74              .load("hdfs://master:9000/home/user/files/d⌋
                ↪  epartmentsR.csv")
75
76
77      # Save the dataframes as Parquet
78      movies_df.write.parquet("hd⌋
        ↪  fs://master:9000/home/user/files/movies.parquet")
79      ratings_df.write.parquet("hd⌋
        ↪  fs://master:9000/home/user/files/ratings.parquet")
80      movie_genres_df.write.parquet("hd⌋
        ↪  fs://master:9000/home/user/files/movie_genres.parquet")
81      employeesR_df.write.parquet("hd⌋
        ↪  fs://master:9000/home/user/files/employeesR.parquet")
82      departmentsR_df.write.parquet("hd⌋
        ↪  fs://master:9000/home/user/files/departmentsR.parquet")
```

Snippet 2: `rdd.py`

```
1   from utils import timeit
2
3
4   def create_rdd(spark):
5       movies_rdd    = spark.textFile("hd⌋
        ↪  fs://master:9000/home/user/files/movies.csv")
6       ratings_rdd   = spark.textFile("hd⌋
        ↪  fs://master:9000/home/user/files/ratings.csv")
7       genres_rdd    = spark.textFile("hd⌋
        ↪  fs://master:9000/home/user/files/movie_genres.csv")
8
9       return movies_rdd, ratings_rdd, genres_rdd
```

```
10
11
12  def query1(spark):
13      # Fetch initial RDD from a csv
14      movies_rdd, _, _ = create_rdd(spark)
15
16      # Get the difference betwen revenue and production cost (i.e.
        ↪  profits) of every
17      # movie after 1995
18      movies = movies_rdd.map(lambda line: line.split(',')) \
19                         .filter(lambda field: len(field) > 7 and
                           ↪  field[3].isdigit() and field[6].isdigit()
                           ↪  and field[5].isdigit()) \
20                         .map(lambda field: (int(field[3]),
                           ↪  (int(field[6]), int(field[5])))) \
21                         .filter(lambda field: field[0] > 1995 and
                           ↪  field[1][0] > 0 and field[1][1] > 0) \
22                         .map(lambda field: (field[0], str(field[1][0]
                           ↪  - field[1][1]))) \
23                         .reduceByKey(lambda v1, v2: v1 + ", " + v2) \
24                         .sortBy(lambda pair: pair[0])
25
26      execution_time, result = timeit(movies.collect)
27
28      with open('../output/rdd_results/Q1RDD.txt', 'w') as f:
29          for year, movie in result:
30              f.write("year %s, profits [%s]\n" % (year, movie))
31
32      return execution_time
33
34
35  def query2(spark):
36      # Fetch initial RDDs from the csv files
37      movies_rdd, ratings_rdd, _ = create_rdd(spark)
38
39      # Get the movie id, the average rating and the total number of
        ↪  ratings for the
40      # movie \Cesare deve morire"
41      mapped_movies = movies_rdd.map(lambda line: line.split(',')) \
42                                .filter(lambda fields: len(fields) == 8
                                  ↪  and fields[3].isdigit() and
                                  ↪  fields[6].isdigit()) \
43                                .filter(lambda fields: fields[1] ==
                                  ↪  "Cesare deve morire") \
44                                .map(lambda fields: (int(fields[0]),
                                  ↪  ('movies', fields[1])))
```

```
45
46      mapped_ratings = ratings_rdd.map(lambda line: line.split(',')) \
47                                  .filter(lambda fields: len(fields) ==
                                    ↪  4) \
48                                  .map(lambda fields: (int(fields[1]),
                                    ↪  (float(fields[2]), 1))) \
49                                  .reduceByKey(lambda x, y: (x[0] +
                                    ↪  y[0], x[1] + y[1])) \
50                                  .map(lambda pair: (pair[0],
                                    ↪  ('ratings', pair[1][0] /
                                    ↪  pair[1][1], pair[1][1])))
51
52      union = mapped_movies.union(mapped_ratings)
53
54      movie_stats = union.groupByKey() \
55                         .flatMap(lambda kv: [(kv[0], m[1], m[2]) for m
                           ↪  in kv[1] if m[0] == 'ratings' for g in
                           ↪  kv[1] if g[0] == 'movies'])
56
57      execution_time, stats = timeit(movie_stats.collect)
58
59
60      with open('../output/rdd_results/Q2RDD.txt', 'w') as f:
61          f.write("Movie ID: %i, Number of ratings: %i, Average rating:
             ↪  %.2f" % (stats[0][0], stats[0][2], stats[0][1]))
62
63      return execution_time
64
65
66  def query3(spark):
67      # Fetch initial RDDs from the csv files
68      movies_rdd, _, genres_rdd = create_rdd(spark)
69
70      # Get the best Animation movie in terms of revenue for 1995
71      mapped_movies = movies_rdd.map(lambda line: line.split(',')) \
72                                .filter(lambda fields: len(fields) == 8
                                  ↪  and fields[3].isdigit() and
                                  ↪  fields[6].isdigit()) \
73                                .filter(lambda fields: int(fields[3])
                                  ↪  == 1995 and int(fields[5]) > 0 and
                                  ↪  int(fields[6]) > 0) \
74                                .map(lambda fields: (int(fields[0]),
                                  ↪  ('movies', fields[1],
                                  ↪  int(fields[6]))))
75
```

```
76      mapped_genres = genres_rdd.map(lambda line: line.split(',')) \
77                                .filter(lambda fields: len(fields) == 2
                                  ↪ and fields[0].isdigit() and
                                  ↪ fields[1] == 'Animation') \
78                                .map(lambda fields: (int(fields[0]),
                                  ↪ ('genres', fields[1])))
79
80      # Union of the two RDDs
81      union = mapped_movies.union(mapped_genres)
82
83      # Group by key and transform the result
84      joined = union.groupByKey() \
85                    .flatMap(lambda kv: [(m[1], m[2]) for m in kv[1] if
                       ↪ m[0] == 'movies' for g in kv[1] if g[0] ==
                       ↪ 'genres'])
86
87      # Action takes place through the joined(), so the timeit()
         ↪ function is placed accordingly
88      execution_time, best_animation_movie = timeit(joined.reduce,
         ↪ lambda movie, next_movie: movie if movie[1] > next_movie[1]
         ↪ else next_movie)
89
90      with open('../output/rdd_results/Q3RDD.txt', 'w') as f:
91          f.write("Best Animation Movie of 1995: {}, Revenue:
             ↪ {}".format(best_animation_movie[0],
             ↪ best_animation_movie[1]))
92
93      return execution_time
94
95
96  def query4(spark):
97      # Fetch initial RDDs from the csv files
98      movies_rdd, _, genres_rdd = create_rdd(spark)
99
100     # Get the most popular Comedy movie for each year after 1995
101     mapped_movies = movies_rdd.map(lambda line: line.split(',')) \
102                               .filter(lambda field: len(field) == 8
                                  ↪ and field[3].isdigit() and
                                  ↪ field[6].isdigit()) \
103                               .filter(lambda field: int(field[3]) >
                                  ↪ 1995 and float(field[7]) > 0) \
104                               .map(lambda field: (int(field[0]),
                                  ↪ ('movies', int(field[3]), field[1],
                                  ↪ float(field[7]))))
105
```

```
106     mapped_genres = genres_rdd.map(lambda line: line.split(',')) \
107                               .filter(lambda field: len(field) == 2
                                  ↪  and field[0].isdigit()) \
108                               .filter(lambda field: field[1] ==
                                  ↪  'Comedy') \
109                               .map(lambda field: (int(field[0]),
                                  ↪  ('genres', field[1])))
110
111     # Make union of movies and genres
112     union = mapped_movies.union(mapped_genres)
113
114     # Extract the best comedy per year
115     best_comedy = union.groupByKey() \
116                        .flatMap(lambda kv: [(m[1], (m[2], m[3])) for
                           ↪  m in kv[1] if m[0] == 'movies' for g in
                           ↪  kv[1] if g[0] == 'genres']) \
117                        .reduceByKey(lambda x, y: x if x[1] > y[1]
                           ↪  else y) \
118                        .sortBy(lambda pair: pair[0])
119
120     execution_time, best_comedy = timeit(best_comedy.collect)
121
122     with open('../output/rdd_results/Q4RDD.txt', 'w') as f:
123         for movie in best_comedy:
124             f.write("The most popular Comedy of %i was %s, with a
                    ↪  popularity score of %.2f\n" % (movie[0], movie[1][0],
                    ↪  movie[1][1]))
125
126     return execution_time
127
128
129 def query5(spark):
130     # Fetch initial RDD from a csv
131     movies_rdd, _, _ = create_rdd(spark)
132
133     # Get the average revenue for each year
134     mapped_movies = movies_rdd.map(lambda line: line.split(',')) \
135                               .filter(lambda fields: len(fields) == 8
                                  ↪  and fields[3].isdigit() and
                                  ↪  fields[6].isdigit()) \
136                               .filter(lambda fields: int(fields[3]) >
                                  ↪  0 and int(fields[6]) > 0) \
137                               .map(lambda fields: (int(fields[3]),
                                  ↪  (int(fields[6]), 1))) \
```

```
                                .reduceByKey(lambda revenue,
                                ↪  next_revenue: (revenue[0] +
                                ↪  next_revenue[0], revenue[1] +
                                ↪  next_revenue[1])) \
                                .map(lambda fields: (fields[0],
                                ↪  fields[1][0] / fields[1][1])) \
                                .sortBy(lambda pair: pair[0])

    execution_time, results = timeit(mapped_movies.collect)

    with open('../output/rdd_results/Q5RDD.txt', 'w') as f:
        for result in results:
            f.write("Year %i had an average movie revenue of %.2f\n"
            ↪  % (result[0], result[1]))

    return execution_time
```

Snippet 3: `sql_csv.py`

```
from pyspark.sql.functions import collect_list
from pyspark.sql.types import StructField, StructType, IntegerType,
↪  FloatType, StringType
from utils import timeit, save_dataframe_output


# Set schemas of csv files
movies_schema = StructType([
    StructField("mv_id", IntegerType()),
    StructField("name", StringType()),
    StructField("description", StringType()),
    StructField("year", IntegerType()),
    StructField("duration", IntegerType()),
    StructField("prod_cost", IntegerType()),
    StructField("revenue", IntegerType()),
    StructField("popularity", FloatType())
])

ratings_schema = StructType([
    StructField("usr_id", IntegerType()),
    StructField("mv_id", IntegerType()),
    StructField("rating", FloatType()),
    StructField("time_stamp", IntegerType())
])

movie_genres_schema = StructType([
```

```
    StructField("mv_id", IntegerType()),
    StructField("genre", StringType())
])


def create_temp_tables(spark):
    # Load the aforementioned csv files into dataframes
    movies_df = spark.read.format('csv') \
            .options(header='false') \
            .schema(movies_schema) \
            .load("hdfs://master:9000/home/user/files/movies.csv")

    ratings_df = spark.read.format('csv') \
            .options(header='false') \
            .schema(ratings_schema) \
            .load("hdfs://master:9000/home/user/files/ratings.csv")

    movie_genres_df = spark.read.format('csv') \
            .options(header='false') \
            .schema(movie_genres_schema) \
            .load("hd
             ↪  fs://master:9000/home/user/files/movie_genres.csv")

    # Create temporary tables
    movies_df.createOrReplaceTempView("movies")
    ratings_df.createOrReplaceTempView("ratings")
    movie_genres_df.createOrReplaceTempView("genres")


def query1(spark):
    # Fetch relations
    create_temp_tables(spark)

    # Get the difference betwen revenue and production cost (i.e.
     ↪  profits) of every movie after 1995
    query = """
        SELECT year, concat_ws(',', collect_list(cast((revenue -
 ↪  prod_cost) AS string))) AS profit
        FROM movies
        WHERE prod_cost > 0 AND revenue > 0 AND year > 1995
        GROUP BY year
        ORDER BY year
    """

    execution_time, _ = timeit(spark.sql(query).show)
```

```
68      query_output = save_dataframe_output(spark.sql(query))
69
70      return execution_time, query_output
71
72
73  def query2(spark):
74      # Fetch relations
75      create_temp_tables(spark)
76
77      # Get the movie id, the average rating and the total number of
        ↪  ratings for the movie \Cesare deve morire"
78      query = """
79          SELECT m.mv_id, COUNT(r.usr_id) AS user_count, AVG(r.rating)
    ↪  AS average_rating
80          FROM movies AS m
81          JOIN ratings AS r ON m.mv_id = r.mv_id
82          WHERE m.name = 'Cesare deve morire'
83          GROUP BY m.mv_id
84      """
85
86      execution_time, _ = timeit(spark.sql(query).show)
87      query_output = save_dataframe_output(spark.sql(query))
88
89      return execution_time, query_output
90
91
92  def query3(spark):
93      # Fetch relations
94      create_temp_tables(spark)
95
96      # Get the best Animation movie in terms of revenue for 1995
97      query = """
98          SELECT m.name AS movie_name, m.revenue AS revenue
99          FROM movies AS m
100         JOIN genres AS mg ON m.mv_id = mg.mv_id
101         WHERE mg.genre = 'Animation' AND m.year = 1995 AND m.revenue
    ↪  > 0
102         ORDER BY m.revenue DESC
103         LIMIT 1
104     """
105     execution_time, _ = timeit(spark.sql(query).show)
106     query_output = save_dataframe_output(spark.sql(query))
107
108     return execution_time, query_output
109
```

```
110
111 def query4(spark):
112     # Fetch relations
113     create_temp_tables(spark)
114
115     # Get the most popular Comedy movie for each year after 1995
116     query = """
117         WITH ranked_movies AS (
118             SELECT m.year, m.name, m.popularity,
119             ROW_NUMBER() OVER(PARTITION BY m.year ORDER BY
    ↪ m.popularity DESC) AS rank
120             FROM movies AS m
121             JOIN genres AS mg ON m.mv_id = mg.mv_id
122             WHERE mg.genre = 'Comedy' AND m.year > 1995 AND
    ↪ m.popularity > 0 AND m.revenue > 0
123             )
124         SELECT year, name, popularity
125         FROM ranked_movies
126         WHERE rank = 1
127         ORDER BY year
128     """
129
130     execution_time, _ = timeit(spark.sql(query).show)
131     query_output = save_dataframe_output(spark.sql(query))
132
133     return execution_time, query_output
134
135
136 def query5(spark):
137     # Fetch relations
138     create_temp_tables(spark)
139
140     # Get the average revenue for each year
141     query = """
142         SELECT year, AVG(revenue) AS avg_revenue
143         FROM movies
144         WHERE year > 0 AND revenue > 0
145         GROUP BY year
146         ORDER BY year DESC
147     """
148
149     execution_time, _ = timeit(spark.sql(query).show)
150     query_output = save_dataframe_output(spark.sql(query))
151
152     return execution_time, query_output
```

Snippet 4: `sql_parquet.py`

```
from pyspark.sql.functions import collect_list
from utils import timeit


def create_temp_tables(spark):
    # Fetch data
    movies_df = spark.read.parquet("hd↩
     ↪  fs://master:9000/home/user/files/movies.parquet")
    ratings_df = spark.read.parquet("hd↩
     ↪  fs://master:9000/home/user/files/ratings.parquet")
    genres_df = spark.read.parquet("hd↩
     ↪  fs://master:9000/home/user/files/movie_genres.parquet")

    # Create temporary relations
    movies_df.createOrReplaceTempView("movies")
    ratings_df.createOrReplaceTempView("ratings")
    genres_df.createOrReplaceTempView("genres")


def query1(spark):
    # Fetch relations
    create_temp_tables(spark)

    # Get the difference betwen revenue and production cost (i.e.↩
     ↪  profits) of every movie after 1995
    query = """
        SELECT year, concat_ws(',', collect_list(cast((revenue -↩
 ↪  prod_cost) AS string))) AS profit
        FROM movies
        WHERE prod_cost > 0 AND revenue > 0 AND year > 1995
        GROUP BY year
        ORDER BY year
    """

    return timeit(spark.sql(query).show)


def query2(spark):
    # Fetch relations
    create_temp_tables(spark)

    # Get the movie id, the average rating and the total number of↩
     ↪  ratings for the movie \Cesare deve morire"
    query = """
```

```
39          SELECT m.mv_id, COUNT(r.usr_id) AS user_count, AVG(r.rating)
    ↪   AS average_rating
40          FROM movies AS m
41          JOIN ratings AS r ON m.mv_id = r.mv_id
42          WHERE m.name = 'Cesare deve morire'
43          GROUP BY m.mv_id
44      """
45
46      return timeit(spark.sql(query).show)
47
48
49  def query3(spark):
50      # Fetch relations
51      create_temp_tables(spark)
52
53      # Get the best Animation movie in terms of revenue for 1995
54      query = """
55          SELECT m.name AS movie_name, m.revenue AS revenue
56          FROM movies AS m
57          JOIN genres AS mg ON m.mv_id = mg.mv_id
58          WHERE mg.genre = 'Animation' AND m.year = 1995 AND m.revenue
    ↪   > 0
59          ORDER BY m.revenue DESC
60          LIMIT 1
61      """
62
63      return timeit(spark.sql(query).show)
64
65
66  def query4(spark):
67      # Fetch relations
68      create_temp_tables(spark)
69
70      # Get the most popular Comedy movie for each year after 1995
71      query = """
72          WITH ranked_movies AS (
73              SELECT m.year, m.name, m.popularity,
74              ROW_NUMBER() OVER(PARTITION BY m.year ORDER BY
    ↪   m.popularity DESC) AS rank
75              FROM movies AS m
76              JOIN genres AS mg ON m.mv_id = mg.mv_id
77              WHERE mg.genre = 'Comedy' AND m.year > 1995 AND
    ↪   m.popularity > 0 AND m.revenue > 0
78              )
79          SELECT year, name, popularity
```

```
        FROM ranked_movies
        WHERE rank = 1
        ORDER BY year
    """

    return timeit(spark.sql(query).show)


def query5(spark):
    # Fetch relations
    create_temp_tables(spark)

    # Get the average revenue for each year
    query = """
        SELECT year, AVG(revenue) AS avg_revenue
        FROM movies
        WHERE year > 0 AND revenue > 0
        GROUP BY year
        ORDER BY year DESC
    """

    return timeit(spark.sql(query).show)
```

Snippet 5: `joins.py`

```
from utils import timeit


def create_rdd(spark):
    employees   = spark.textFile("hdfs://master:9000/home/user/files/employeesR.csv")
    departments = spark.textFile("hdfs://master:9000/home/user/files/departmentsR.csv")

    return employees, departments


def repartition_join(spark):
    # Fetch RDDs from the csv files
    employees, departments = create_rdd(spark)

    # Tag RDDs
    employees_tagged = employees \
                        .map(lambda line: line.split(',')) \
                        .map(lambda field: (int(field[0]), field[1],
                        ↪  int(field[2]))) \
```

```
                        .map(lambda field: (field[2], ('employees',
                        ↪  field)))

    departments_tagged = departments \
                          .map(lambda line: line.split(',')) \
                          .map(lambda field: (int(field[0]),
                          ↪  field[1])) \
                          .map(lambda field: (field[0],
                          ↪  ('departments', field)))

    # Concatenate all RDDS
    union = employees_tagged.union(departments_tagged)

    # Perform the join for each key
    def join_records(records):
        employees_records   = [field[1] for field in records if
        ↪  field[0] == 'employees']
        departments_records = [field[1] for field in records if
        ↪  field[0] == 'departments']
        return [(e[1], e[0], d[1]) for e in employees_records for d
        ↪  in departments_records]

    # Extract union result
    joined_rdd = union.groupByKey() \
                  .flatMap(lambda pair: join_records(pair[1]))

    return timeit(joined_rdd.collect)


def broadcast_join(spark):
    # Fetch RDDs from the csv files
    employees, departments = create_rdd(spark)

    employees_rdd = employees \
                     .map(lambda line: line.split(',')) \
                     .map(lambda field: (int(field[0]), field[1],
                     ↪  int(field[2])))

    departments_rdd = departments \
                       .map(lambda line: line.split(',')) \
                       .map(lambda field: (int(field[0]), field[1]))

    # Create a dictionary for department data
    dep_dict = {field[0]: field[1] for field in
    ↪  departments_rdd.collect()}
```

```
56
57      # Broadcast the department data
58      dep_broadcast = spark.broadcast(dep_dict)
59
60      def map_func(field):
61          # Extract the join key (department ID) and the department
            ↪  name using
62          # the broadcast variable
63          dep_id = field[2]
64          dep_name = dep_broadcast.value.get(dep_id)
65
66          # Joined data
67          return (field[1], field[0], dep_name)
68
69      joined_rdd = employees_rdd.map(lambda field: map_func(field))
70
71      return timeit(joined_rdd.collect)
```

Snippet 6: `optimiser.py`

```
1   import io
2   import contextlib
3   from utils import timeit
4
5
6   def create_temp_tables(spark):
7       dataframe = spark.read.format("parquet")
8
9       ratings_dataframe = dataframe.load("hd
        ↪  fs://master:9000/home/user/files/ratings.parquet")
10      genres_dataframe = dataframe.load("hd
        ↪  fs://master:9000/home/user/files/movie_genres.parquet")
11
12      ratings_dataframe.registerTempTable("ratings")
13      genres_dataframe.registerTempTable("genres")
14
15
16  def use_optimiser(spark, disabled = "N"):
17
18      # Fetch relations
19      create_temp_tables(spark)
20
21      if disabled == "Y":
22          spark.conf.set("spark.sql.cbo.enable", False)
23          spark.conf.set("spark.sql.autoBroadcastJoinThreshold", -1)
```

```
    elif disabled == "N":
        pass
    else:
        raise Exception ("This setting is not available.")

    query = """
            SELECT *
            FROM (SELECT * FROM genres LIMIT 100) AS g, ratings AS r
            WHERE r.mv_id = g.mv_id
        """

    stdout = io.StringIO()
    with contextlib.redirect_stdout(stdout):
         spark.sql(query).explain()

    # Get the captured standard output
    query_plan = stdout.getvalue()

    return timeit(spark.sql(query).show), query_plan
```

Snippet 7: `utils.py`

```
import io
import time
import contextlib


def timeit(func, *args, **kwargs):
    """
    Measure execution time of a function for a single run.

    Args:
        func: Function to be executed.
        *args: Variable length argument list for the function.
        **kwargs: Arbitrary keyword arguments for the function.

    Returns:
        tuple: A tuple containing the execution time and the result
    ↪ of the function call.
    """
    start = time.time()
    result = func(*args, **kwargs)
    end = time.time()
    execution_time = end - start

```

```
    return execution_time, result


def save_dataframe_output(dataframe):
    """
    Function to capture and return the complete output of a PySpark DataFrame.

    Args:
        dataframe (pyspark.sql.DataFrame): The DataFrame whose output is to be captured.

    Returns:
        str: The entire output of the DataFrame as a string.
    """

    # Calculate the number of rows in the DataFrame
    row_count = dataframe.count()

    # Create a StringIO object
    stdout = io.StringIO()

    # Execute show() on DataFrame and capture the output
    with contextlib.redirect_stdout(stdout):
        dataframe.show(n=row_count, truncate=False)

    # Get the captured standard output
    return stdout.getvalue()
```

Snippet 8: `main.py`

```
# Import SparkSession
from pyspark.sql import SparkSession

# Import RDD queries
from rdd import query1 as rdd_query1
from rdd import query2 as rdd_query2
from rdd import query3 as rdd_query3
from rdd import query4 as rdd_query4
from rdd import query5 as rdd_query5

# Import SQL-on-csv queries
from sql_csv import query1 as sql_csv_query1
from sql_csv import query2 as sql_csv_query2
from sql_csv import query3 as sql_csv_query3
```

```
15 from sql_csv import query4 as sql_csv_query4
16 from sql_csv import query5 as sql_csv_query5
17
18 # Import SQL-on-Parquet queries
19 from sql_parquet import query1 as sql_parquet_query1
20 from sql_parquet import query2 as sql_parquet_query2
21 from sql_parquet import query3 as sql_parquet_query3
22 from sql_parquet import query4 as sql_parquet_query4
23 from sql_parquet import query5 as sql_parquet_query5
24
25 # Import RDD joins
26 from joins import broadcast_join
27 from joins import repartition_join
28
29 # Import Optimiser script
30 from optimiser import use_optimiser
31
32 # Import csv-to-parquet converter
33 from csv_to_parquet import convert_csv_to_parquet
34
35
36 def part1():
37     ###################### Task 1 ######################
38     # Convert CSVs to Parquet; run only once. Should you
39     # wish to repeat the process, comment it out.
40     convert_csv_to_parquet()
41
42
43     ################## Tasks 2, 3 & 4  ##################
44     times = {}
45
46     # Calculate execution times for each query (Tasks 2, 3 & 4)
47     for i in range(1, 6):
48         spark = SparkSession \
49                 .builder \
50                 .appName("All-use session") \
51                 .getOrCreate()
52         sc = spark.sparkContext
53
54         rdd_query_name     = 'rdd_query%s' % (i)
55         parquet_query_name = 'sql_parquet_query%s' % (i)
56         csv_query_name     = 'sql_csv_query%s' % (i)
57
58         times[rdd_query_name]                =
          ↪  globals()[rdd_query_name](sc)
```

```
59          times[parquet_query_name], _        =
            ↪ globals()[parquet_query_name](spark)
60          times[csv_query_name], query_output =
            ↪ globals()[csv_query_name](spark)
61
62          # Save the query-output, in dataframe format, on a text file
            ↪
63          with open('../output/df_results/Q%sDF.txt' % i, 'w') as f:
64              f.write(query_output)
65
66          # Consistency in execution times
67          spark.stop()
68          sc.stop()
69          print(times)
70
71      # Compute execution times and write to a text file
72      with open('../output/part_1_times.txt', 'w') as f:
73          for query, execution_time in times.items():
74              f.write('%s: %.2f seconds\n' % (query, execution_time))
75
76
77  def part2():
78      ###################### Task 1 ######################
79      times = {}
80
81      spark = SparkSession \
82                  .builder \
83                  .appName("All-use session") \
84                  .getOrCreate() \
85                  .sparkContext
86
87      times['Broadcast Join'], broadcast_result = broadcast_join(spark)
88      times['Repartition Join'], _              =
        ↪ repartition_join(spark)
89
90      # Compute execution times and write to a text file
91      with open('../output/join_type_times.txt', 'w') as f:
92          for query, execution_time in times.items():
93              f.write('%s: %.2f seconds\n' % (query, execution_time))
94
95      # Save the result to text files
96      with open('../output/join_outputs.txt', 'w') as f:
97          for result in broadcast_result:
98              f.write(str(result) + '\n')
99
```

```
100     # Consistency in execution times
101     spark.stop()
102
103
104     ###################### Task 2 ######################
105     times = {}
106
107     # Two instances are created since Spark tends to keep
108     # metadata from each run in order to optimise reading
109     # and calculating future queries.
110     spark = SparkSession \
111             .builder \
112             .appName('Using Catalyst') \
113             .getOrCreate()
114     sc = spark
115
116     times["Using Catalyst"], with_catalyst            =
        ↪  use_optimiser(spark)
117     times["Without using Catalyst"], without_catalyst =
        ↪  use_optimiser(sc, disabled="Y")
118
119     spark.stop()
120     sc.stop()
121
122     # Compute execution times and write to a text file
123     with open('../output/catalyst_times.txt', 'w') as f:
124         for query, execution_time in times.items():
125             f.write('%s: %.2f seconds\n' % (query,
                ↪  execution_time[0]))
126
127     # Save the optimised query plan to text file
128     with open('../output/optimised_plan.txt', 'w') as f:
129         f.write(with_catalyst)
130
131     # Save the non-optimised query plan to text file
132     with open('../output/non_optimised_plan.txt', 'w') as f:
133         f.write(without_catalyst)
134
135
136 if __name__ == "__main__":
137     part1()
138     part2()
```

THIS COURSEWORK WAS TYPESET using LaTeX, originally developed by Leslie Lamport and based on Donald Knuth's TeX. The body text is set in 12 point kpfonts, a revival of URW Palladio typeface. The above illustration, "Science Experiment 02", was created by Ben Schlitter and released under CC BY-NC-ND 3.0. A template that can be used to format coursework with this look and feel has been released under the permissive CC BY-NC-ND 4.0 license, and can be found online at https://cs.overleaf.com/latex/.