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FACULTY OF ENGINEERING
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Big Data Processing with Apache Spark : MapReduce Machine Learning and SQL Applications

SPECIAL TOPICS 2 COURSE

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1. INTRODUCTION

The main goal of this project is not only to implement different algorithms, but also to understand how Apache Spark works as an integrated system when processing data in different formats.

While working on the project, I noticed an important difference between Spark and traditional Python tools. Libraries such as Pandas or Scikit-learn work well for small datasets, but they do not scale easily. In my experiments, Python tried to load the entire dataset into memory. Even with relatively small input sizes, RAM usage increased very quickly, and in some cases, the system became unstable or crashed.

Apache Spark handled this situation differently. When memory was not sufficient, Spark did not fail. Instead, it automatically moved part of the data to disk using a mechanism called "spilling." This allowed the application to finish successfully while using much less active RAM and without losing data. Observing this behavior helped me understand why Spark is widely used in Big Data environments and why this project focuses on Spark rather than only on algorithm implementation.

2. The Datasets Used For Applications

To properly test different components of Apache Spark, I used three different datasets in this project.

For MapReduce Application : i compiled a text file about AI. This unstructured dataset was necessary to test text cleaning, splitting, and RDD transformations.

For Machine Learning Application : i used the Mobile Price Classification dataset. It includes numerical features (RAM, battery, resolution) and a target price category, making it ideal for comparing classification algorithms.
https://www.kaggle.com/datasets/iabhishekofficial/mobile-price-classification

For SQL Application : i selected an HR Analytics database containing multiple related tables (employees, departments, salaries , managers , titles). This was chosen specifically to test complex SQL operations like multi table joins.
https://www.kaggle.com/datasets/priyankbarbhaya/sql-analytics-case-study-employees-database/data

3. The MapReduce

a) Understanding the MapReduce Concept

Before discussing the code, it is important to explain the logic behind MapReduce. It is a two phase programming model designed for processing large datasets in parallel:

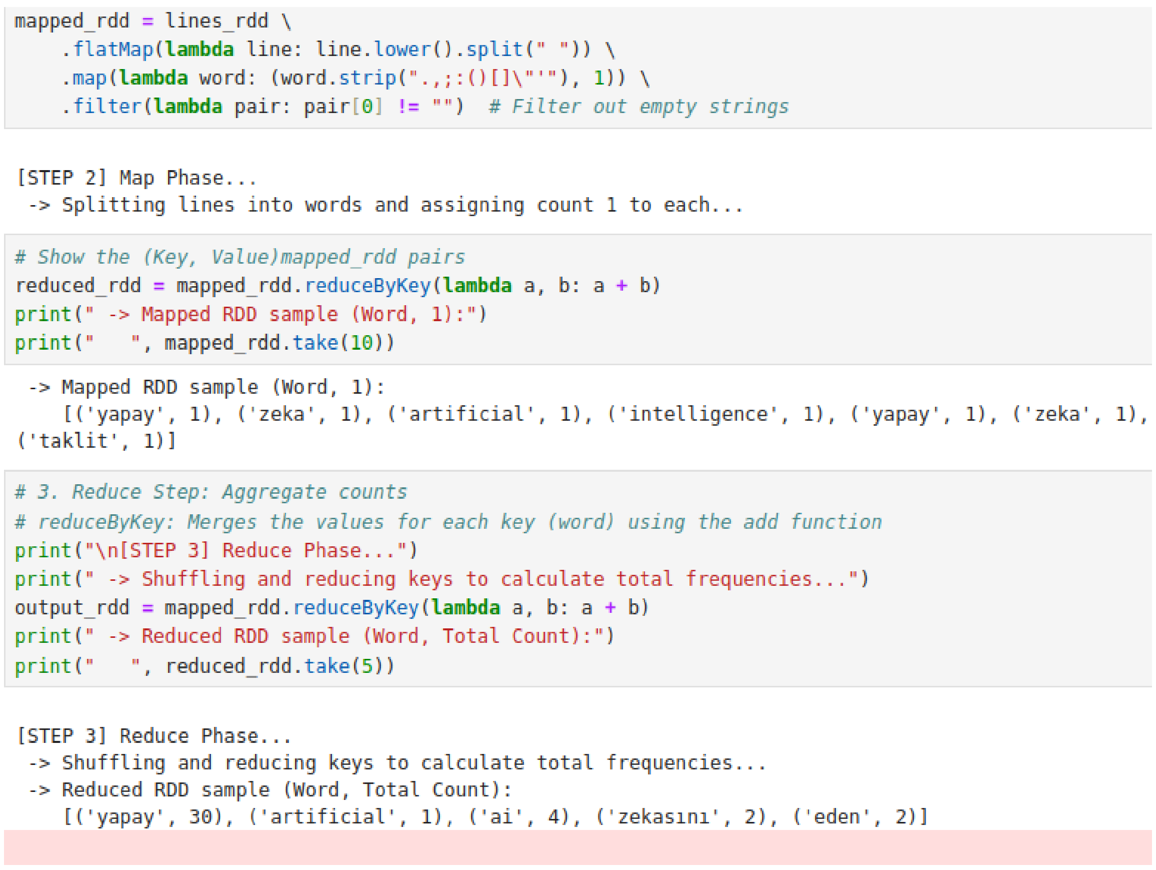
The "Map" Phase: This is the splitting phase. The system takes an input (like a text file) and applies a function to every single element independently. In my word count example, the "Map" phase takes a line of text and breaks it into individual words, assigning a value of "1" to each word --- > like this ("AI", 1).

The "Shuffle and Sort" Phase: Between Map and Reduce, Spark automatically groups all the identical keys together. All the ("AI", 1) pairs from different parts of the file are brought to the same node.

The "Reduce" Phase: This is the aggregation phase. The system takes the grouped data and applies a formula for this case its addition. It sums up all the "1"s to find the final count for that word.

b) Implementation and Code Analysis

In this part of the project, I worked directly with Spark RDDs (Resilient Distributed Datasets) instead of data frames to control the low level text processing.



```
mapped_rdd = lines_rdd \
    .flatMap(lambda line: line.lower().split(" ")) \
    .map(lambda word: (word.strip(".,;:()[]\"'"), 1)) \
    .filter(lambda pair: pair[0] != "")  # Filter out empty strings
```

```
[STEP 2] Map Phase...
 -> Splitting lines into words and assigning count 1 to each...
```

```
[5]: # Show the (Key, Value)mapped_rdd pairs
     reduced_rdd = mapped_rdd.reduceByKey(lambda a, b: a + b)
     print(" -> Mapped RDD sample (Word, 1):")
     print("    ", mapped_rdd.take(10))
```

```
 -> Mapped RDD sample (Word, 1):
    [('yapay', 1), ('zeka', 1), ('artificial', 1), ('intelligence', 1), ('yapay', 1), ('zeka', 1),
('taklit', 1)]
```

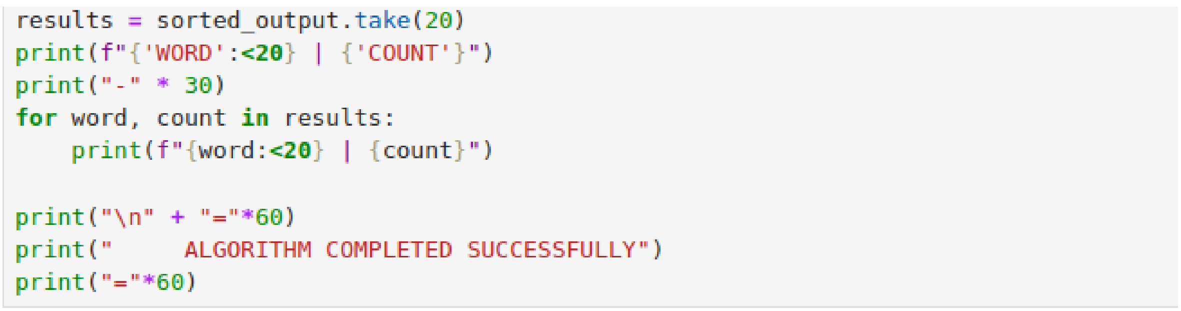
```
[6]: # 3. Reduce Step: Aggregate counts
     # reduceByKey: Merges the values for each key (word) using the add function
     print("\n[STEP 3] Reduce Phase...")
     print(" -> Shuffling and reducing keys to calculate total frequencies...")
     output_rdd = mapped_rdd.reduceByKey(lambda a, b: a + b)
     print(" -> Reduced RDD sample (Word, Total Count):")
     print("    ", reduced_rdd.take(5))
```

```
[STEP 3] Reduce Phase...
 -> Shuffling and reducing keys to calculate total frequencies...
 -> Reduced RDD sample (Word, Total Count):
    [('yapay', 30), ('artificial', 1), ('ai', 4), ('zekasını', 2), ('eden', 2)]
```

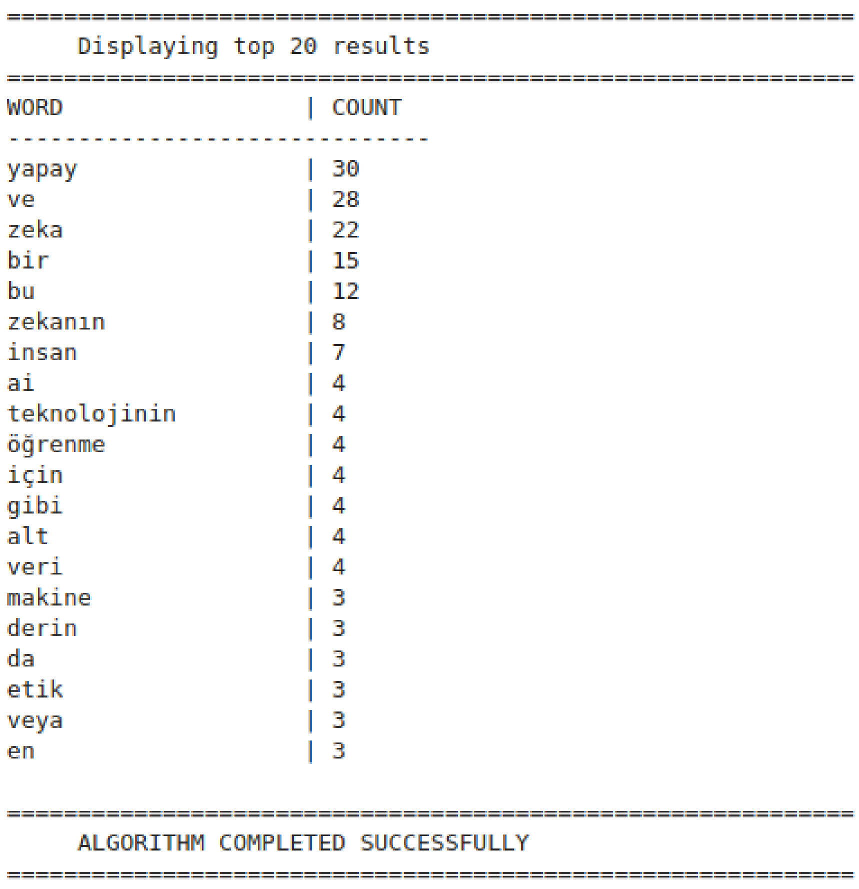
First, text_file.flatMap is used. Unlike a standard map, which would keep the line structure, flatMap breaks the lines apart so that every word becomes its own element in the list.

Inside the mapping function, I included a cleaning step: .lower() converts everything to lowercase and .strip() removes punctuation. This ensures that "Zeka" and "zeka!" are counted as the same word.

Finally, .reduceByKey(add) performs the aggregation, summing the counts for each unique word.



```python
results = sorted_output.take(20)
print(f"{'WORD':<20} | {'COUNT'}")
print("-" * 30)
for word, count in results:
    print(f"{word:<20} | {count}")

print("\n" + "="*60)
print("     ALGORITHM COMPLETED SUCCESSFULLY")
print("="*60)
```



```
============================================================
     Displaying top 20 results
============================================================
WORD                 | COUNT
------------------------------
yapay                | 30
ve                   | 28
zeka                 | 22
bir                  | 15
bu                   | 12
zekanın              | 8
insan                | 7
ai                   | 4
teknolojinin         | 4
öğrenme              | 4
için                 | 4
gibi                 | 4
alt                  | 4
veri                 | 4
makine               | 3
derin                | 3
da                   | 3
etik                 | 3
veya                 | 3
en                   | 3

============================================================
     ALGORITHM COMPLETED SUCCESSFULLY
============================================================
```

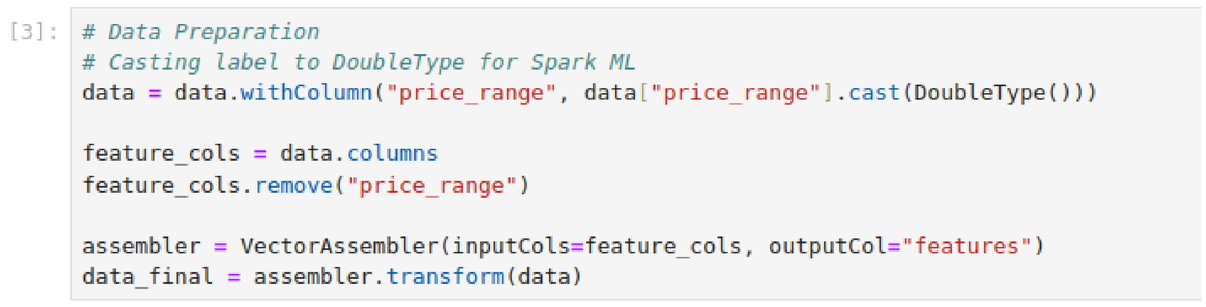
The output above confirms the logic worked. The most frequent words identified were terms like "yapay" and "zeka," which aligns with the subject matter of the text file. The counts are clean, confirming that the punctuation removal was successful.

4. Machine Learning Appliccation

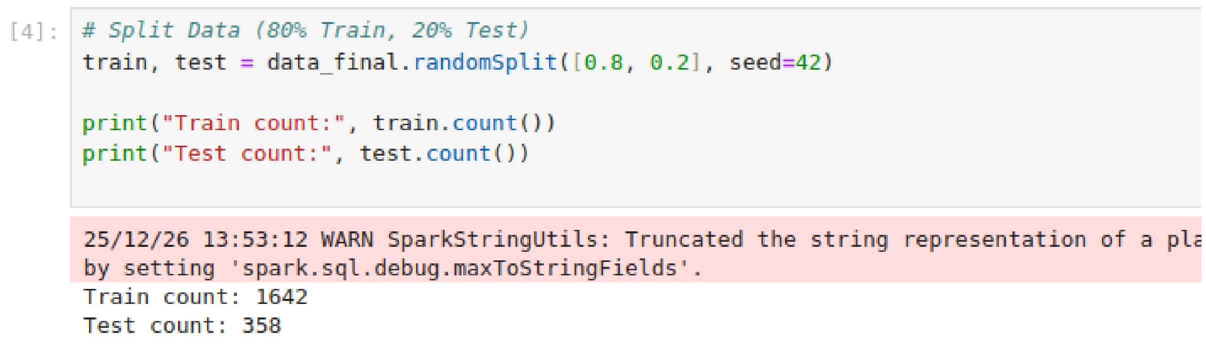
In this section, the goal was to predict the price range of mobile phones (0, 1, 2, 3) based on their hardware specifications. I implemented two different models: **Logistic Regression** and **Random Forest.**

4.1 Data Preparation

Before any training could happen, I had to transform the data. Spark ML does not accept separate columns for features; it requires a single vector column.



```
[3]: # Data Preparation
     # Casting label to DoubleType for Spark ML
     data = data.withColumn("price_range", data["price_range"].cast(DoubleType()))

     feature_cols = data.columns
     feature_cols.remove("price_range")

     assembler = VectorAssembler(inputCols=feature_cols, outputCol="features")
     data_final = assembler.transform(data)
```



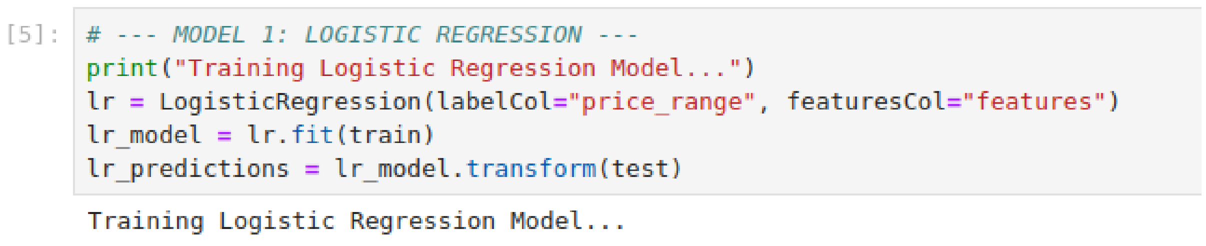
```
[4]: # Split Data (80% Train, 20% Test)
     train, test = data_final.randomSplit([0.8, 0.2], seed=42)

     print("Train count:", train.count())
     print("Test count:", test.count())
```

```
25/12/26 13:53:12 WARN SparkStringUtils: Truncated the string representation of a pla
by setting 'spark.sql.debug.maxToStringFields'.
Train count: 1642
Test count: 358
```

As seen in the code above, I used the VectorAssembler. This tool takes the column such as battery power, ram, and px height and compresses them into a single column named features. This vector is what the model actually learns from. I then split the data: 80% for training and 20% for testing.

4.2 Logistic Regression

I started with Logistic Regression because it is a fast baseline model. My hypothesis was that features like RAM and battery power likely have a linear relationship with price (like more RAM means higher price).



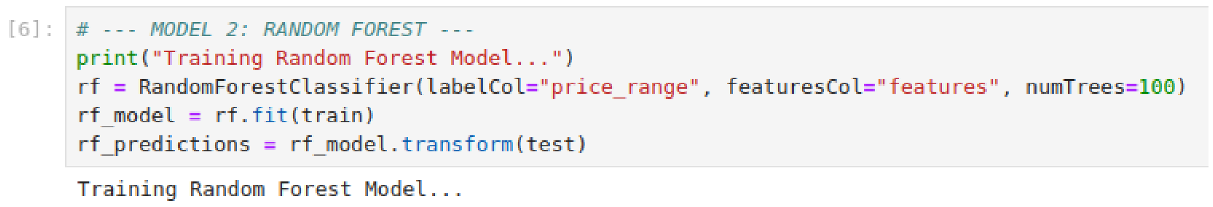
```
[5]: # --- MODEL 1: LOGISTIC REGRESSION ---
     print("Training Logistic Regression Model...")
     lr = LogisticRegression(labelCol="price_range", featuresCol="features")
     lr_model = lr.fit(train)
     lr_predictions = lr_model.transform(test)
```

```
Training Logistic Regression Model...
```

Here, I initialized the LogisticRegression classifier. I specified labelCol="price_range" so the model knows what we are trying to predict. I then called .fit() on the training data.

4.3 Random Forest

Next, I applied a Random Forest classifier. Since it is a tree based model, I expected it to capture more complex and non-linear relationships between features such as screen size, battery life, and resolution.

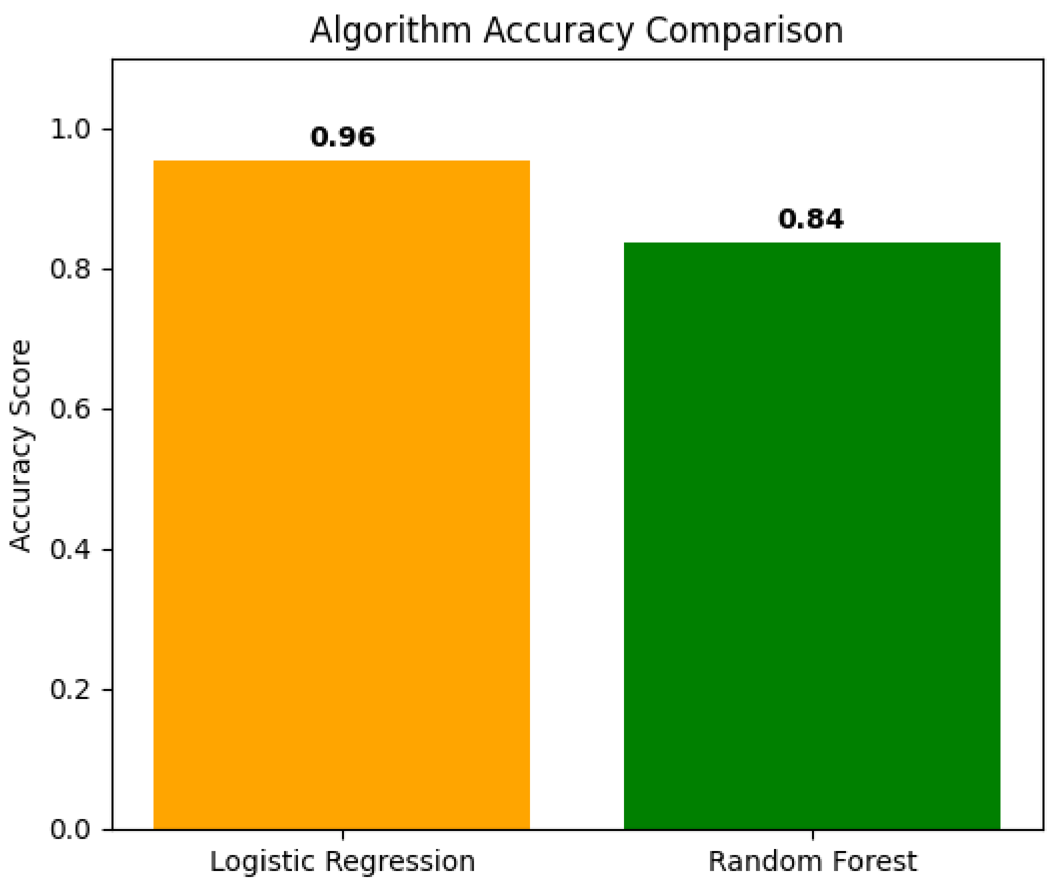


```
[6]: # --- MODEL 2: RANDOM FOREST ---
     print("Training Random Forest Model...")
     rf = RandomForestClassifier(labelCol="price_range", featuresCol="features", numTrees=100)
     rf_model = rf.fit(train)
     rf_predictions = rf_model.transform(test)

     Training Random Forest Model...
```

I set up the RandomForestClassifier similarly to the regression model. I used the default hyperparameters to see how the model performs "out of the box" compared to the linear model.

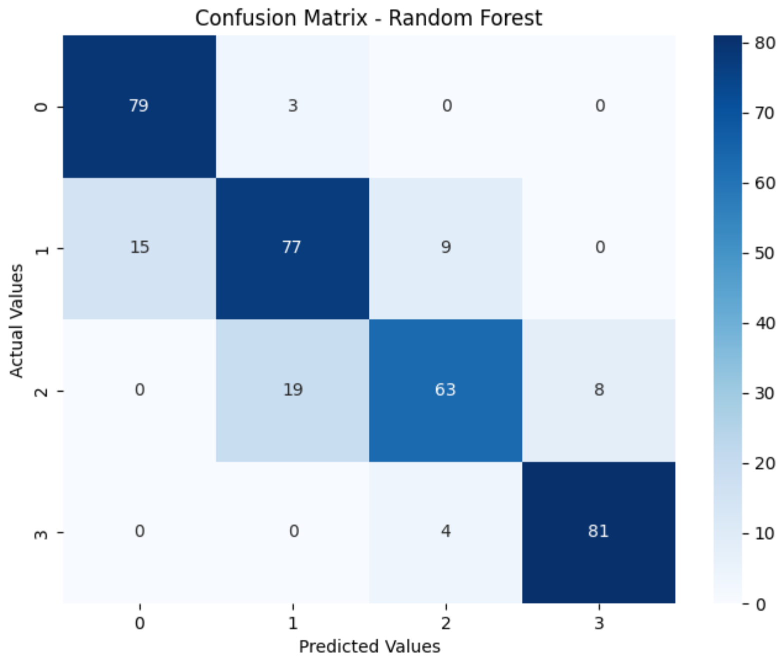
4.4 Results And Comparison

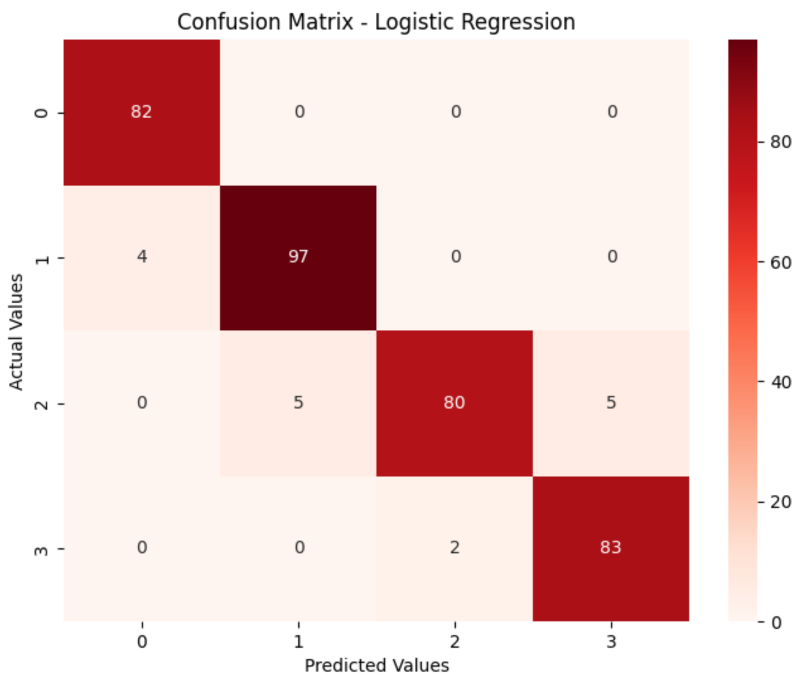
To evaluate the performance, I used the MulticlassClassificationEvaluator using "accuracy" as the metric.



The results were actually the opposite of what I expected.
Logistic Regression Accuracy: **96%**
Random Forest Accuracy: **84%**
Why did this happen?
Usually, Random Forest is the stronger algorithm. However, its lower performance here suggests that the dataset is linearly separable. In simple terms, the correlation between the hardware specs (especially RAM) and the price is very direct and simple. The Random Forest model likely over complicated the problem, where is the Logistic Regression model fit the simple trend perfectly.

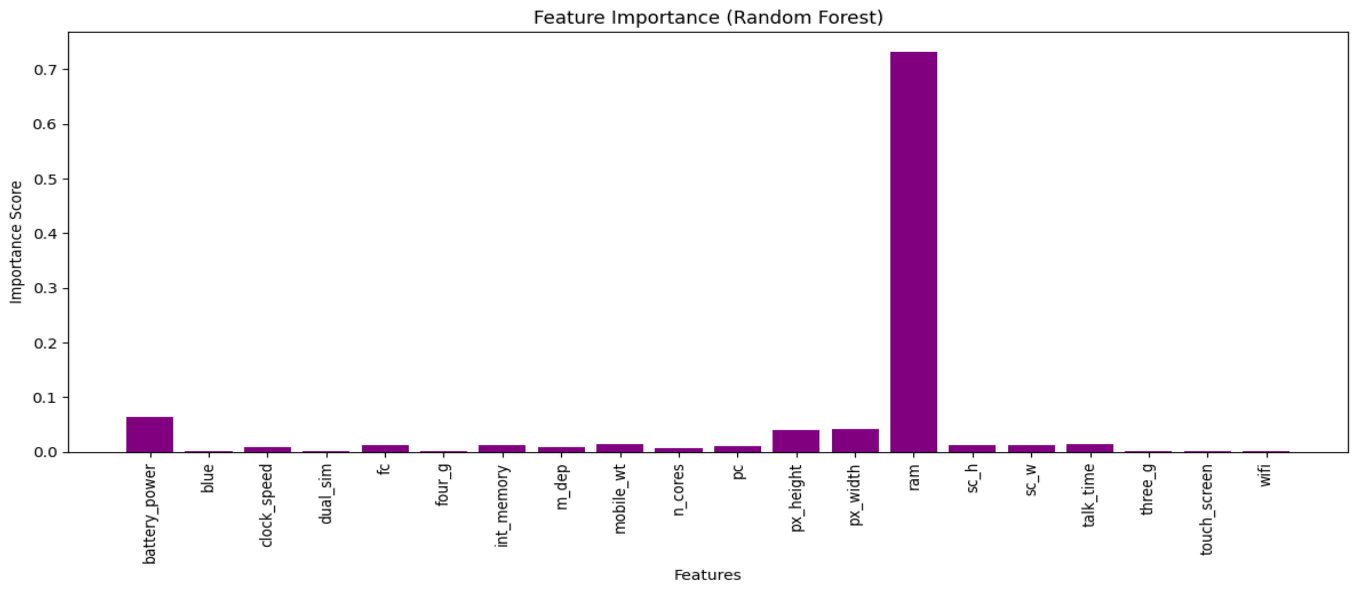
<u>Also lets take a look at the confusion matrixs and feature importance for random forest model</u>



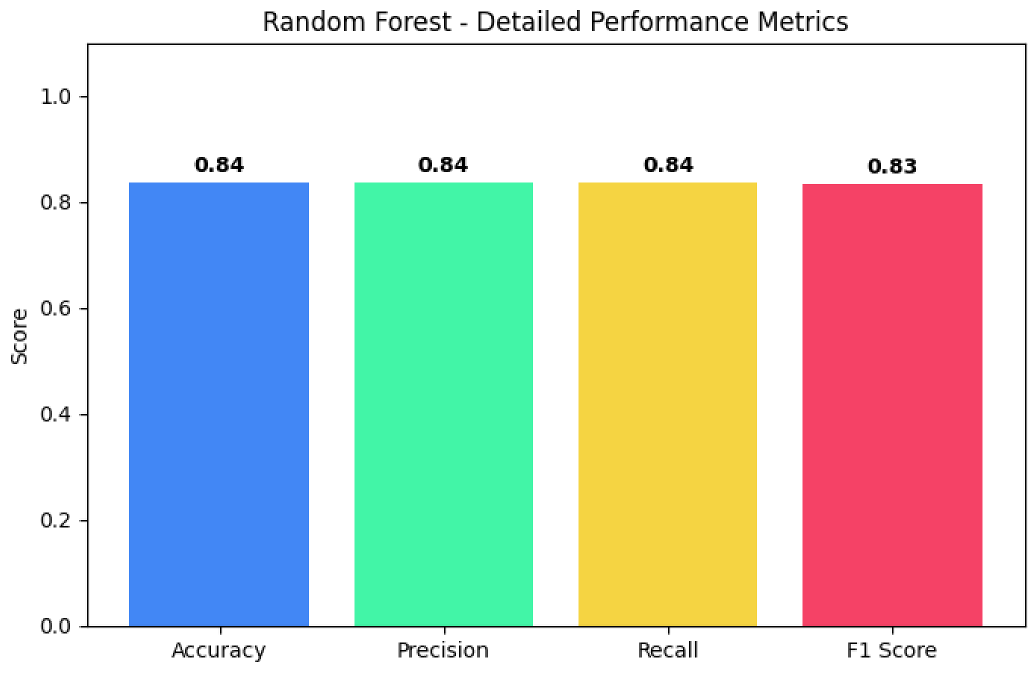


The confusion matrix above helps visualize the errors. While the Logistic Regression (left image) has almost a perfect diagonal line (meaning correct predictions), the Random Forest (right image) ows some confusion, particularly between adjacent price classes (mistaking Class 1 for Class 2).

To understand why the models behaved this way, I extracted the "Feature Importance" scores from the Random Forest model. This tells us which hardware specifications the model actually looked at when making a decision.



This graph explains the entire project result. As you can see, the RAM feature is overwhelmingly the most important factor. The other features like battery power or pixel height are almost in comparison. Because the price is so heavily dependent on just one variable (RAM) in a linear way, the simple Logistic Regression model was able to predict it perfectly. The Random Forest model, which looks for complex interactions between many variables, was essentially unnecessary for this specific task.

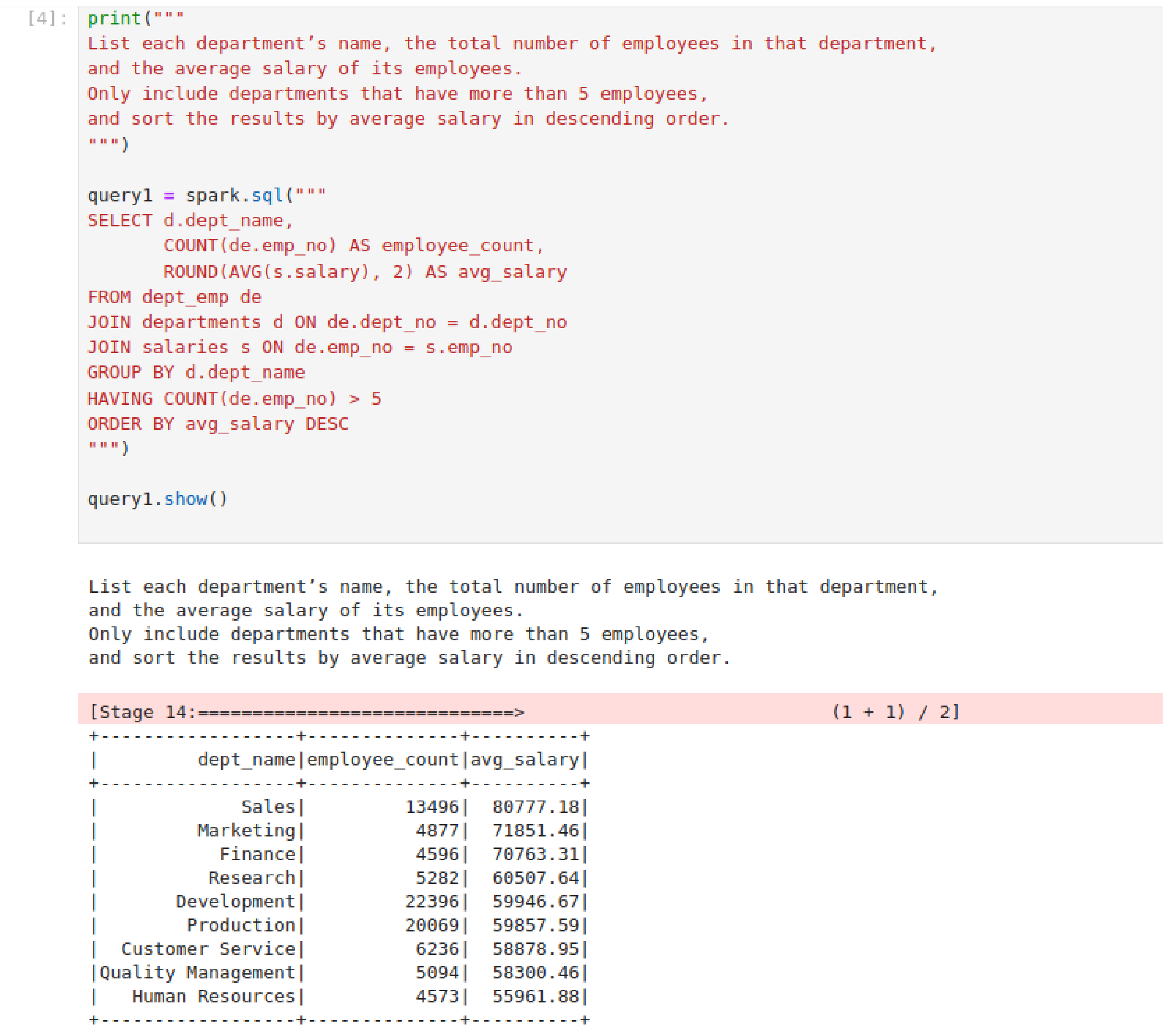


5. Spark SQL

In this part, I used Spark as a distributed SQL engine. Multiple CSV files were loaded and registered as temporary views, which allowed standard SQL queries to be executed on large datasets.

Query 1: Department Salary Analysis

This query focused on analyzing salaries at the department level. I joined the departments, dept_emp, and salaries tables and grouped the data by department name. The query calculated the average salary and the number of employees per department. A HAVING condition was used to exclude very small departments, and the results were ordered by average salary.



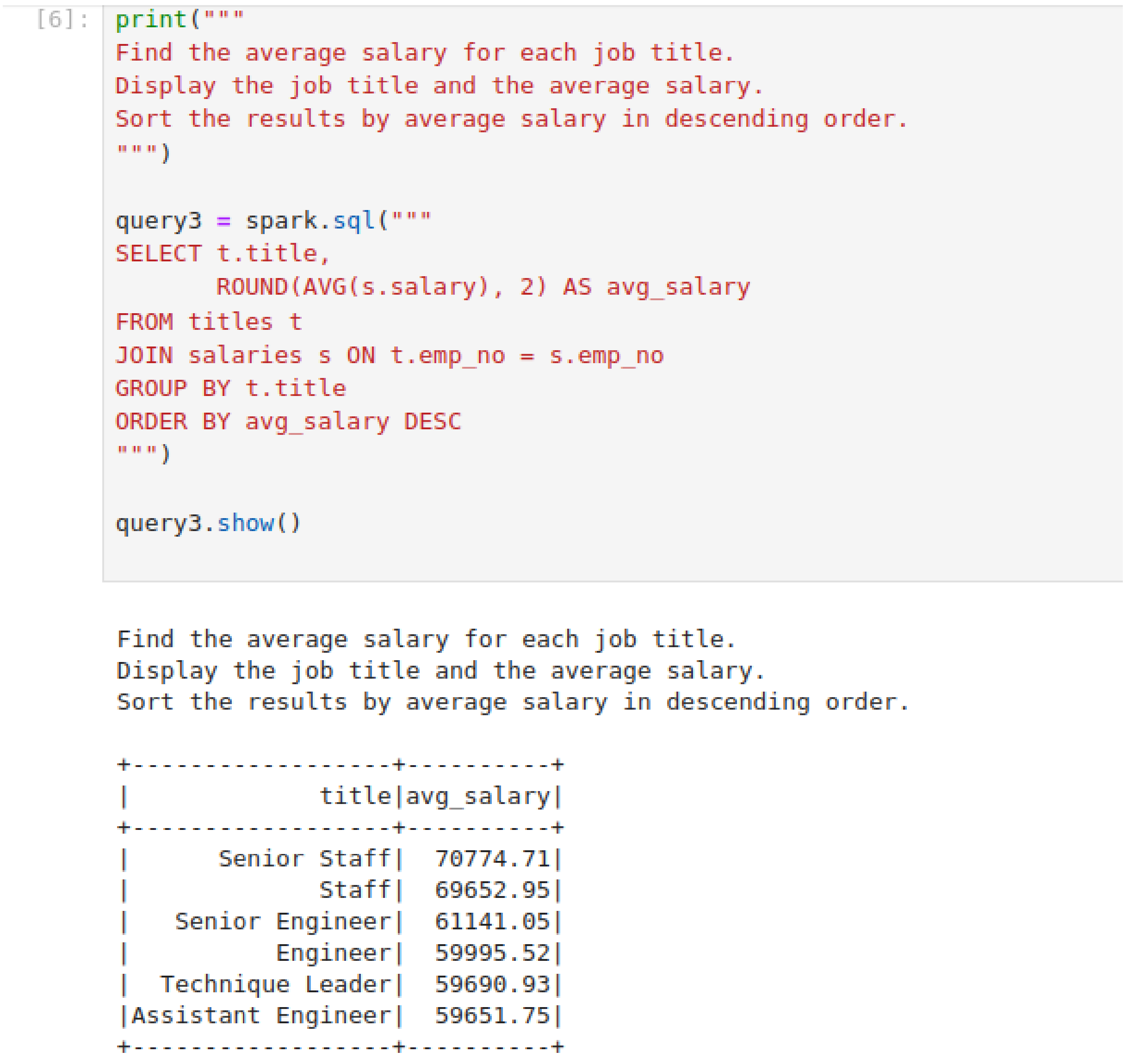
```
[4]: print("""
List each department's name, the total number of employees in that department,
and the average salary of its employees.
Only include departments that have more than 5 employees,
and sort the results by average salary in descending order.
""")

query1 = spark.sql("""
SELECT d.dept_name,
       COUNT(de.emp_no) AS employee_count,
       ROUND(AVG(s.salary), 2) AS avg_salary
FROM dept_emp de
JOIN departments d ON de.dept_no = d.dept_no
JOIN salaries s ON de.emp_no = s.emp_no
GROUP BY d.dept_name
HAVING COUNT(de.emp_no) > 5
ORDER BY avg_salary DESC
""")

query1.show()
```

```
List each department's name, the total number of employees in that department,
and the average salary of its employees.
Only include departments that have more than 5 employees,
and sort the results by average salary in descending order.

[Stage 14:=============================>                              (1 + 1) / 2]
+------------------+--------------+----------+
|         dept_name|employee_count|avg_salary|
+------------------+--------------+----------+
|             Sales|         13496|  80777.18|
|         Marketing|          4877|  71851.46|
|           Finance|          4596|  70763.31|
|          Research|          5282|  60507.64|
|       Development|         22396|  59946.67|
|        Production|         20069|  59857.59|
|  Customer Service|          6236|  58878.95|
|Quality Management|          5094|  58300.46|
|   Human Resources|          4573|  55961.88|
+------------------+--------------+----------+
```

The results showed that the Sales department had the highest average salary, while the Development department had the highest number of employees but a lower average salary.

Query 2: High Earner Profile

In the second query, I aimed to identify the top 20 highest-paid employees along with additional context. I joined employees, departments, titles, and salary data to retrieve names, job titles, departments, and salaries.



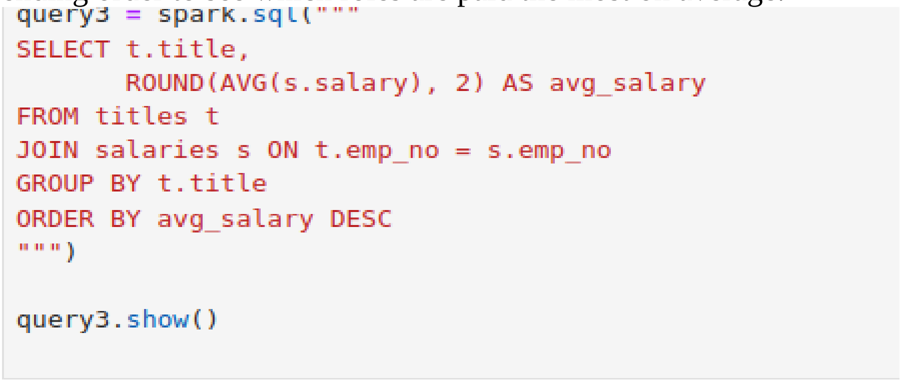
```
[6]: print("""
Find the average salary for each job title.
Display the job title and the average salary.
Sort the results by average salary in descending order.
""")

query3 = spark.sql("""
SELECT t.title,
       ROUND(AVG(s.salary), 2) AS avg_salary
FROM titles t
JOIN salaries s ON t.emp_no = s.emp_no
GROUP BY t.title
ORDER BY avg_salary DESC
""")

query3.show()
```

```
Find the average salary for each job title.
Display the job title and the average salary.
Sort the results by average salary in descending order.

+------------------+----------+
|             title|avg_salary|
+------------------+----------+
|      Senior Staff|  70774.71|
|             Staff|  69652.95|
|   Senior Engineer|  61141.05|
|          Engineer|  59995.52|
|  Technique Leader|  59690.93|
|Assistant Engineer|  59651.75|
+------------------+----------+
```

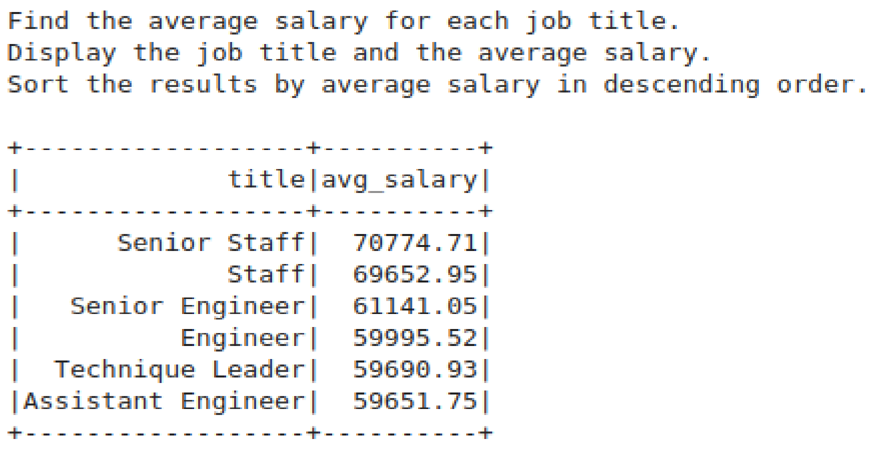
This query demonstrated Spark SQL’s ability to efficiently handle multi-table joins without performance issues.

Query 3: Average Salary By Job Title

In this query, I analyzed the average salary for each job title in the company. I joined the titles and salaries tables using the employee number and grouped the data by job title. Then, I calculated the average salary for each title and sorted the results in descending order to see which roles are paid the most on average.



```
query3 = spark.sql("""
SELECT t.title,
       ROUND(AVG(s.salary), 2) AS avg_salary
FROM titles t
JOIN salaries s ON t.emp_no = s.emp_no
GROUP BY t.title
ORDER BY avg_salary DESC
""")

query3.show()
```



```
Find the average salary for each job title.
Display the job title and the average salary.
Sort the results by average salary in descending order.

+------------------+----------+
|             title|avg_salary|
+------------------+----------+
|      Senior Staff|  70774.71|
|             Staff|  69652.95|
|   Senior Engineer|  61141.05|
|          Engineer|  59995.52|
|  Technique Leader|  59690.93|
|Assistant Engineer|  59651.75|
+------------------+----------+
```

6. Conclusion

This project demonstrated how Apache Spark can handle different types of data processing within a single framework. From text processing with RDDs, to machine learning model training, and complex SQL queries, Spark remained stable and efficient.

One of the most important lessons from this project was that more complex models do not always produce better results. In the Machine Learning section, Logistic Regression outperformed Random Forest because the dataset had strong linear patterns. Additionally, observing Spark's memory management behavior helped me understand why it is a preferred tool for Big Data processing compared to traditional local Python environments.