PREDICTIVE ANALYSIS

For Coffee Shop Sales, Ahmed Khan

Internship Project, Intern Craft

Tools and Technologies Used

1. Databricks Community Edition

- **Purpose:** Integrated environment for big data processing and analytics.
- **Features Used:** Apache Spark, PySpark, Spark SQL, Databricks Notebooks.

2. Apache Spark

- **Purpose:** Unified analytics engine for big data processing.
- **Features Used:** Spark Core, Spark SQL for data transformation and querying.

3. PySpark

- **Purpose:** Python API for Spark, enabling data processing and machine learning.
- **Features Used:** DataFrame API, VectorAssembler, StringIndexer, RandomForestRegressor.

4. Pandas

- **Purpose:** Data manipulation and analysis library for Python.
- **Features Used:** Data conversion for visualization and exporting results.

5. Matplotlib

- **Purpose:** Plotting library for visualizing data.
- **Features Used:** Bar plots, line plots for data visualization and insights.

Dataset Description:

The dataset contains transactional data from various store locations, including details about transaction times, quantities, product categories, and unit prices, enabling the analysis of product profitability and loss mitigation strategies.

Initial Dataset Schema: transaction_id: integer (nullable = true)

```
transaction_date: date (nullable = true)
transaction_time: timestamp (nullable = true)
transaction_qty: integer (nullable = true)
store_id: integer (nullable = true)
store_location: string (nullable = true)
product_id: integer (nullable = true)
unit_price: double (nullable = true)
product_category: string (nullable = true)
product_type: string (nullable = true)
product_detail: string (nullable = true)
```

Initializing Spark session.

```
from pyspark.sql import SparkSession
```

```
spark = SparkSession.builder.appName("PredictiveAnalysis").getOrCreate()
```

Import Libraries

```
from pyspark.sql.functions import col, sum, lower, count, expr,year, month
import matplotlib.pyplot as plt
import pandas as pd
from pyspark.ml.feature import VectorAssembler, StringIndexer
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.evaluation import RegressionEvaluator
```

Data Cleaning

Loading the dataset into a Spark DataFrame.

```
coffee_data_df = spark.read.csv("/FileStore/tables/Coffee_Shop_Sales-1.csv", header= True, inferSchema=True)
coffee_data_df.show(3)
```

```
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
|transaction_id|transaction_date|   transaction_time|transaction_qty|store_id| store_location|product_id|unit_price|  product_category|
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
|             1|      2023-01-01|2024-08-24 07:06:11|              2|       5|Lower Manhattan|        32|       2.4|            Coffee|G
|             2|      2023-01-01|2024-08-24 07:08:56|              2|       5|Lower Manhattan|        57|       3.1|               Tea|
|             3|      2023-01-01|2024-08-24 07:14:04|              2|       5|Lower Manhattan|        59|       2.4|Drinking Chocolate|
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
only showing top 3 rows
```

Inspecting Data for Inconsistencies, Missing Values, or Duplicates

Inspect the schema of the DataFrame

```
coffee_data_df.printSchema()
```

```
root
 |-- transaction_id: integer (nullable = true)
 |-- transaction_date: date (nullable = true)
 |-- transaction_time: timestamp (nullable = true)
 |-- transaction_qty: integer (nullable = true)
 |-- store_id: integer (nullable = true)
 |-- store_location: string (nullable = true)
 |-- product_id: integer (nullable = true)
 |-- unit_price: double (nullable = true)
 |-- product_category: string (nullable = true)
 |-- product_type: string (nullable = true)
 |-- product_detail: string (nullable = true)
```

Showing summary statistics

```
coffee_data_df.describe().show()
```

```
+-------+-----------------+------------------+-----------------+---------------+------------------+------------------+----------------+-
|summary|   transaction_id|   transaction_qty|         store_id| store_location|        product_id|        unit_price|product_category|
+-------+-----------------+------------------+-----------------+---------------+------------------+------------------+----------------+-
|  count|           149116|            149116|           149116|         149116|            149116|            149116|          149116|
|   mean|74737.37187156308| 1.438276241315486|5.342062555326055|           null| 47.91860699053086|3.2370985004966166|            null|
| stddev|43153.60001591776|0.5425087647372203|  2.0742405915717|           null|17.930020247641522|2.6648702418711308|            null|
|    min|                1|                 1|                3|        Astoria|                 1|               0.8|          Bakery|B
|    max|           149456|                 8|                8|Lower Manhattan|                87|              45.0|             Tea|S
+-------+-----------------+------------------+-----------------+---------------+------------------+------------------+----------------+-
```

Checking for missing values

```
missing_values = coffee_data_df.select([sum(col(c).isNull().cast("int")).alias(c) for c in coffee_data_df.columns])
missing_values.show()
```

```
+--------------+----------------+----------------+---------------+--------+--------------+----------+----------+----------------+-------
|transaction_id|transaction_date|transaction_time|transaction_qty|store_id|store_location|product_id|unit_price|product_category|product
+--------------+----------------+----------------+---------------+--------+--------------+----------+----------+----------------+-------
|             0|               0|               0|              0|       0|             0|         0|         0|               0|
+--------------+----------------+----------------+---------------+--------+--------------+----------+----------+----------------+-------
```

Checking for duplicates

```
duplicates = coffee_data_df.groupBy(coffee_data_df.columns).count().filter("count > 1")
total_duplicate_rows = duplicates.withColumn("duplicate_count", col("count") - 1).agg(sum("duplicate_count")).collect()[0][0]
print(f"Number of duplicate rows: {total_duplicate_rows}")
```

```
Number of duplicate rows: None
```

Data Cleaning Process

Correct Inconsistencies

```
coffee_data_df = coffee_data_df.withColumn("store_location", lower(col("store_location"))) \
                 .withColumn("product_category", lower(col("product_category"))) \
                 .withColumn("product_type", lower(col("product_type"))) \
                 .withColumn("product_detail", lower(col("product_detail")))
coffee_data_df.show(3)
```

```
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
|transaction_id|transaction_date|   transaction_time|transaction_qty|store_id| store_location|product_id|unit_price|  product_category|
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
|             1|      2023-01-01|2024-08-24 07:06:11|              2|       5|lower manhattan|        32|       2.4|            coffee|g
|             2|      2023-01-01|2024-08-24 07:08:56|              2|       5|lower manhattan|        57|       3.1|               tea|
|             3|      2023-01-01|2024-08-24 07:14:04|              2|       5|lower manhattan|        59|       2.4|drinking chocolate|
+--------------+----------------+-------------------+---------------+--------+---------------+----------+----------+------------------+-
only showing top 3 rows
```

Profit/Loss Analysis

Calculate Total Sales and Revenue for Each Product

Calculate total revenue and total cost (Assuming Cost Price)

```
cost_price_percentage = 0.7 # 70% of the unit price
coffee_data_df = coffee_data_df.withColumn("total_revenue", col("transaction_qty") * col("unit_price")) \
                               .withColumn("total_cost", col("transaction_qty") * col("unit_price") * cost_price_percentage)
```

Aggregate data

```
product_sales = coffee_data_df.groupBy("product_id", "product_category", "product_type", "product_detail") \
                              .agg(sum("transaction_qty").alias("total_sales_qty"),
                                   sum("total_revenue").alias("total_revenue"),
                                   sum("total_cost").alias("total_cost"))
```

Determine Profit or Loss

```
product_sales = product_sales.withColumn("profit_loss", col("total_revenue") - col("total_cost"))
product_sales.show()
```

```
+----------+------------------+--------------------+--------------------+---------------+------------------+------------------+---------
|product_id|  product_category|        product_type|      product_detail|total_sales_qty|     total_revenue|        total_cost|       pr
+----------+------------------+--------------------+--------------------+---------------+------------------+------------------+---------
|        24|            coffee|         drip coffee|our old time dine...|           3997|           11991.0| 8393.699999999926| 3597.300
|        48|               tea|    brewed black tea|english breakfast rg|           4200|           10500.0|            7350.0|
|        52|               tea|     brewed chai tea|traditional blend...|           4512|           11280.0|            7896.0|
|        11|         loose tea|          herbal tea|         lemon grass|            152|1354.7499999999993| 948.3249999999988| 406.4250
|        45|               tea|   brewed herbal tea|        peppermint lg|           4350|           13050.0|   9134.9999999999|   3915.0
|        49|               tea|    brewed black tea|english breakfast lg|           4309|           12927.0| 9048.899999999894| 3878.100
|         5|      coffee beans|       gourmet beans|columbian medium ...|            148|            2220.0|            1554.0|
|        61|drinking chocolate|       hot chocolate|sustainably grown...|           4453|          21138.55| 14796.98499999991|  6341.56
|        35|            coffee|premium brewed co...|jamaican coffee r...|           4018|12455.799999999852| 8719.060000000054| 3736.739
|        47|               tea|    brewed green tea|serenity green te...|           4220|           12660.0| 8861.999999999905|3798.0000
|         4|      coffee beans|      espresso beans|primo espresso roast|            150|3067.5000000000023| 2147.250000000002| 920.2500
|        58|drinking chocolate|       hot chocolate|   dark chocolate rg|           4007|10417.799999999883| 7292.460000000028|3125.3399
|        81|           branded|            clothing|i need my bean! t...|            221|            6163.0|4314.0999999999985|1848.9000
|        76|            bakery|            biscotti|chocolate chip bi...|           1924| 5032.659999999966| 3522.862000000028|1509.7979
|        12|         loose tea|          herbal tea|          peppermint|            153| 1369.349999999999| 958.5449999999988| 410.8050
|        79|            bakery|               scone|  jumbo savory scone|           2028| 7626.620000000002| 5338.633999999999|2287.9860
|         6|      coffee beans|       gourmet beans|            ethiopia|            218|            4578.0|3204.6000000000035|1373.3999
|        64|          flavours|       regular syrup|       hazelnut syrup|           2372|1897.6000000000083|1328.3200000000045| 569.2800
|        27|            coffee|organic brewed co...|        brazilian lg|           4317|11224.199999999864| 7856.940000000037|3367.2599
|        34|            coffee|premium brewed co...|jamaican coffee r...|           4018|  9845.40000000001|  6891.77999999998| 2953.620
+----------+------------------+--------------------+--------------------+---------------+------------------+------------------+---------
only showing top 20 rows
```

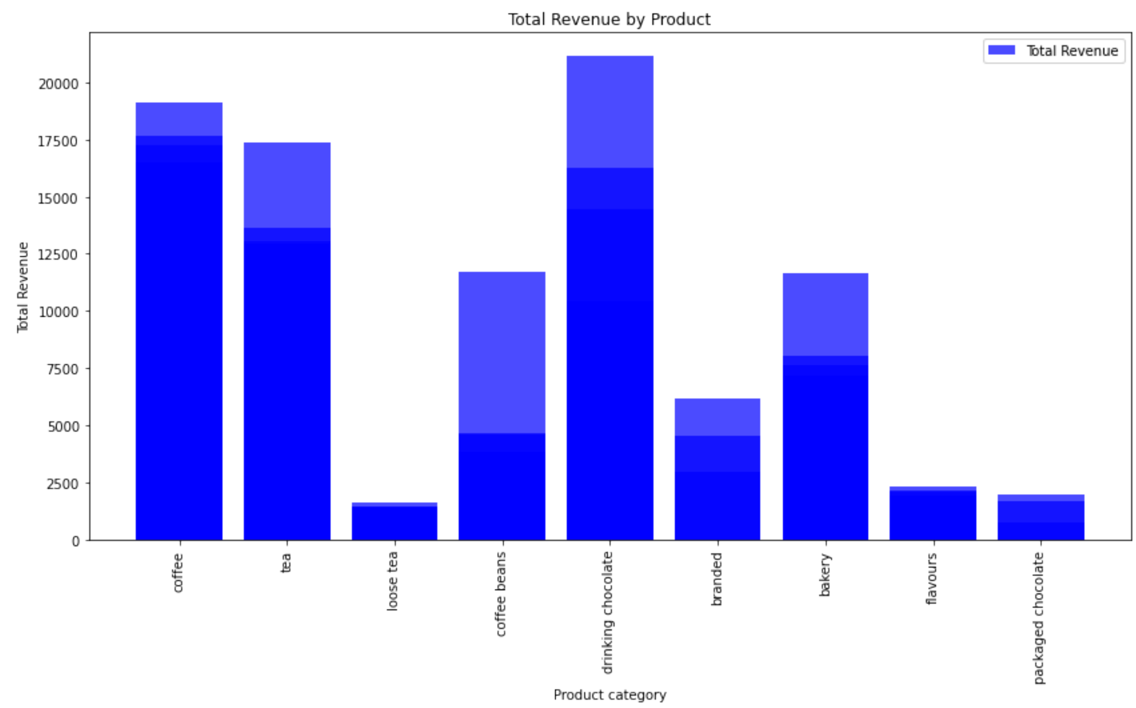
Join coffee_data_df with product_sales to add profit_loss column

```
coffee_data_df = coffee_data_df.join(
    product_sales.select("product_id", "product_category", "product_type", "product_detail", "profit_loss"),
    on=["product_id", "product_category", "product_type", "product_detail"],
    how="left"
)
```

Visualize the Data (For total revenue)

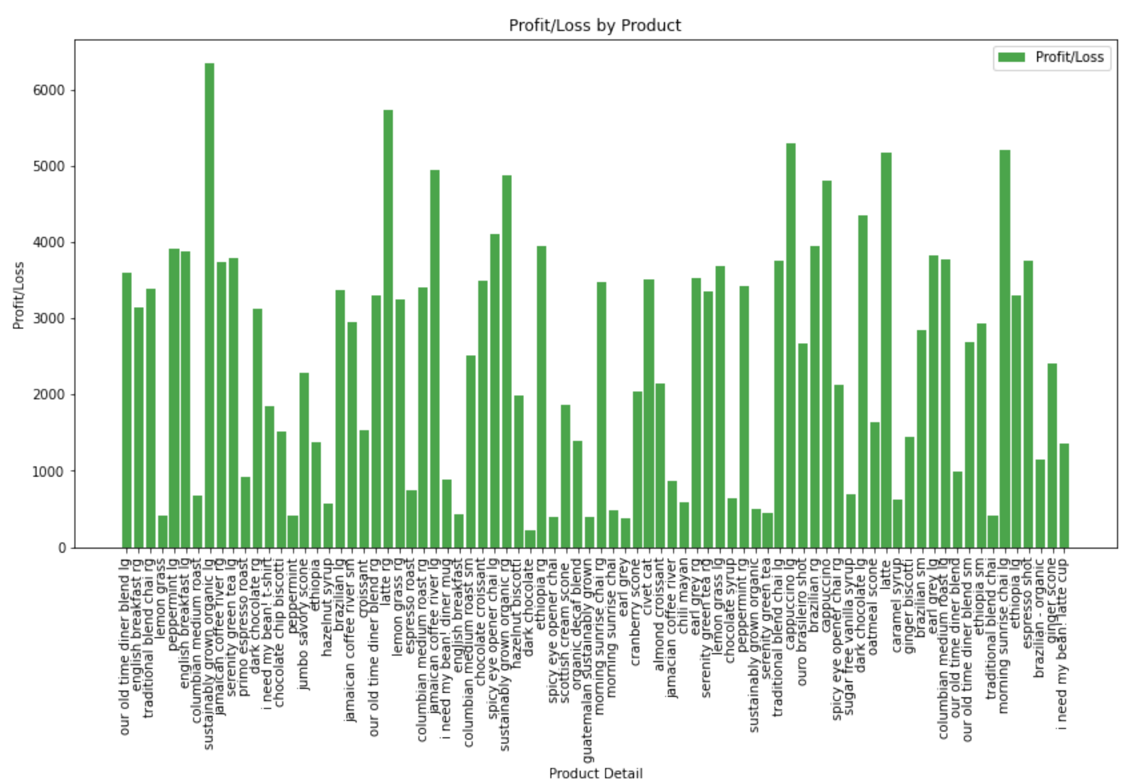
```
product_sales_pd = product_sales.toPandas()

# Bar plot for total revenue
plt.figure(figsize=(14, 7))
plt.bar(product_sales_pd["product_category"], product_sales_pd["total_revenue"], color='blue', alpha=0.7, label='Total Revenue')
plt.xticks(rotation=90)
plt.xlabel('Product category')
plt.ylabel('Total Revenue')
plt.title('Total Revenue by Product')
plt.legend()
plt.show()
```



Visualize the Data (For profit/loss)

```
# Bar plot for profit/loss
plt.figure(figsize=(14, 7))
plt.bar(product_sales_pd["product_detail"], product_sales_pd["profit_loss"], color='green', alpha=0.7, label='Profit/Loss')
plt.xticks(rotation=90)
plt.xlabel('Product Detail')
plt.ylabel('Profit/Loss')
plt.title('Profit/Loss by Product')
plt.legend()
plt.show()
```



Trend Analysis Over Time

Extract year and month from the transaction_date

```
coffee_data_df = coffee_data_df.withColumn("year", year(col("transaction_date"))) \
                   .withColumn("month", month(col("transaction_date")))
```

Group by year and month to calculate monthly sales and revenue

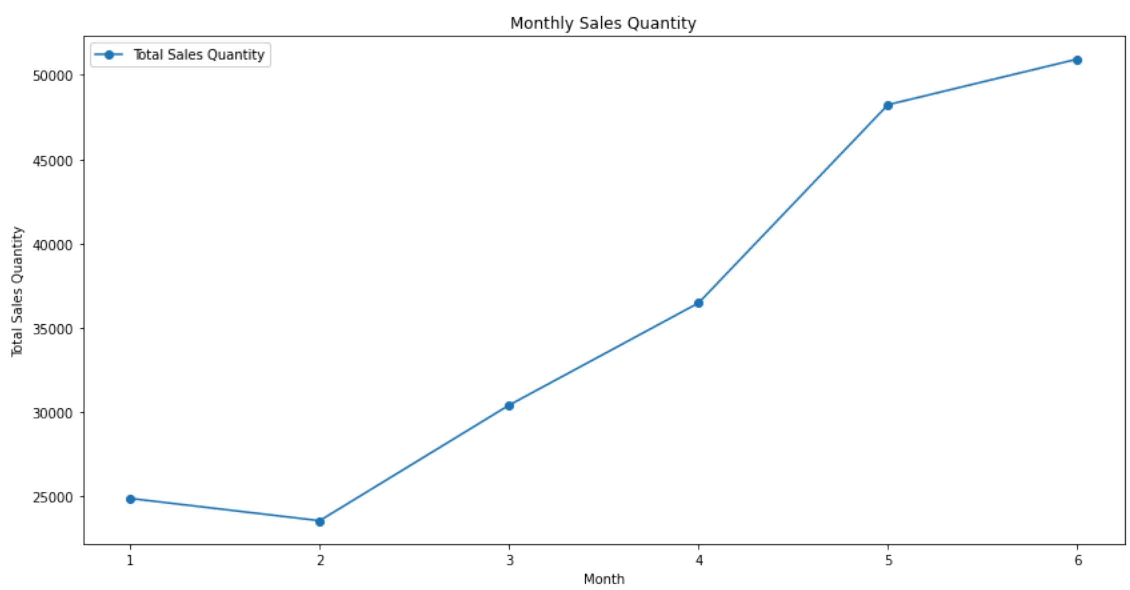
```
monthly_sales = coffee_data_df.groupBy("year", "month") \
                        .agg(sum("transaction_qty").alias("total_sales_qty"),
                             sum(expr("transaction_qty * unit_price")).alias("total_revenue"))
monthly_sales = monthly_sales.orderBy("year", "month")
monthly_sales.show(5)
```

```
+----+-----+---------------+------------------+
|year|month|total_sales_qty|     total_revenue|
+----+-----+---------------+------------------+
|2023|    1|          24870| 78258.38999999811|
|2023|    2|          23550| 72876.18999999786|
|2023|    3|          30406| 94750.22999999751|
|2023|    4|          36469|113928.43000000228|
|2023|    5|          48233|150185.70999999833|
+----+-----+---------------+------------------+
only showing top 5 rows
```

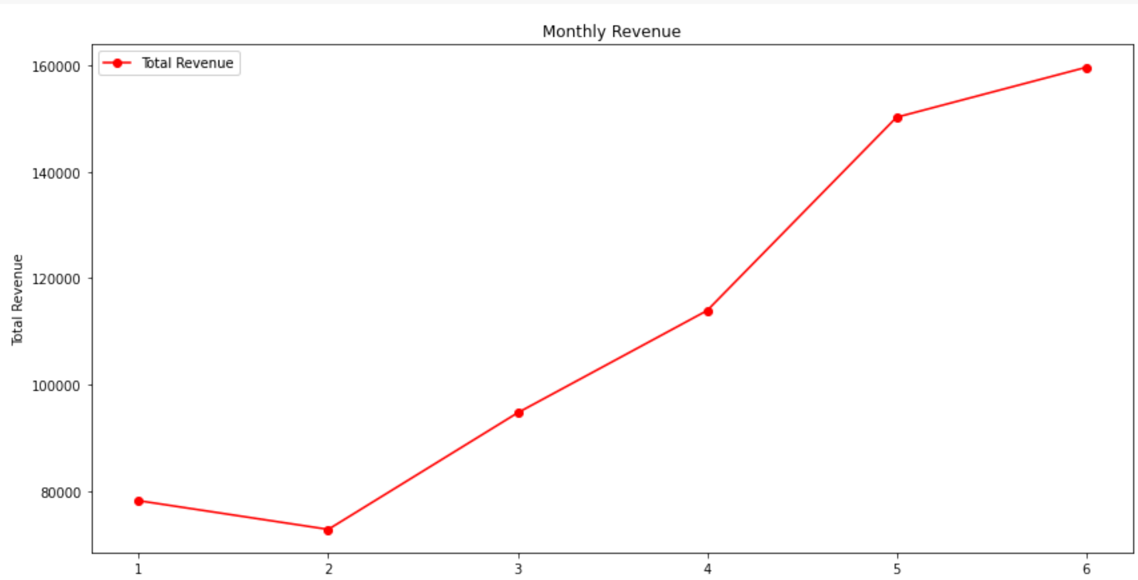
Line plot for monthly sales quantity and monthly revenue

```
monthly_sales_pd = monthly_sales.toPandas()

# Line plot for monthly sales quantity
plt.figure(figsize=(14, 7))
plt.plot(monthly_sales_pd["month"], monthly_sales_pd["total_sales_qty"], marker='o', label='Total Sales Quantity')
plt.xlabel('Month')
plt.ylabel('Total Sales Quantity')
plt.title('Monthly Sales Quantity')
plt.legend()
plt.show()
```




```
# Line plot for monthly revenue
plt.figure(figsize=(14, 7))
plt.plot(monthly_sales_pd["month"], monthly_sales_pd["total_revenue"], marker='o', color='red', label='Total Revenue')
plt.xlabel('Month')
plt.ylabel('Total Revenue')
plt.title('Monthly Revenue')
plt.legend()
plt.show()
```



Store Performance Analysis

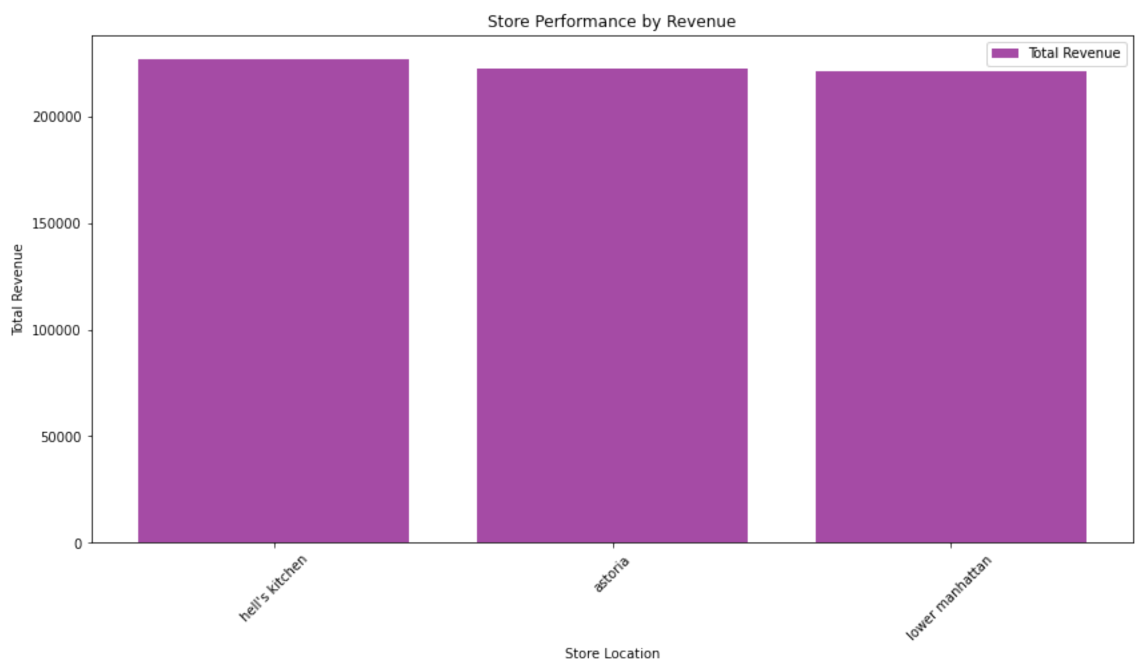
```
store_performance = coffee_data_df.groupBy("store_location") \
                            .agg(sum("transaction_qty").alias("total_sales_qty"),
                                 sum(expr("transaction_qty * unit_price")).alias("total_revenue"))

store_performance.show()
```

```
+--------------+---------------+------------------+
| store_location|total_sales_qty|     total_revenue|
+--------------+---------------+------------------+
| hell's kitchen|          71737| 226634.9699999933|
|        astoria|          70991|222116.85999999268|
|lower manhattan|          71742|220794.54999999327|
+--------------+---------------+------------------+
```

Bar plot for store performance

```
store_performance_pd = store_performance.toPandas()
# Bar plot for store performance
plt.figure(figsize=(14, 7))
plt.bar(store_performance_pd["store_location"], store_performance_pd["total_revenue"], color='purple', alpha=0.7, label='Total Revenue')
plt.xticks(rotation=45)
plt.xlabel('Store Location')
plt.ylabel('Total Revenue')
plt.title('Store Performance by Revenue')
plt.legend()
plt.show()
```



Sales and Profit Margins

Highest profit Margin Product Category

```
coffee_data_df = coffee_data_df.withColumn("profit_margin", col("profit_loss") / col("total_revenue"))

highest_margin_products = coffee_data_df.orderBy(col("profit_margin").desc()).limit(10)
highest_margin_products.select("product_category","profit_margin").show(1)
```

```
+------------------+-----------------+
|  product_category|    profit_margin|
+------------------+-----------------+
|drinking chocolate|3730.332352941229|
+------------------+-----------------+
only showing top 1 row
```

Lowest Margin Product Category

```
lowest_margin_products = coffee_data_df.orderBy(col("profit_margin")).limit(10)
lowest_margin_products.select("product_category","profit_margin").show(1)
```

```
+----------------+-----------------+
|product_category|    profit_margin|
+----------------+-----------------+
|    coffee beans|9.750000000000005|
+----------------+-----------------+
only showing top 1 row
```

Profit Increase Prediction

StringIndexer for categorical features and Assembling those features into a single vector

```
indexers = [StringIndexer(inputCol=column, outputCol=column+"_index").fit(coffee_data_df) for column in ["product_category", "product_type"]]
for indexer in indexers:
    coffee_data_df = indexer.transform(coffee_data_df)

# Assembling the features into a single vector
assembler = VectorAssembler(inputCols=["transaction_qty", "unit_price", "product_category_index", "product_type_index"],
                            outputCol="features")
df_model = assembler.transform(coffee_data_df)
df_model = df_model.select("features", "profit_loss")

df_model.show(5)
```

```
+-----------------+------------------+
|         features|       profit_loss|
+-----------------+------------------+
|[2.0,2.4,0.0,1.0]|3953.3400000001056|
|[2.0,3.1,1.0,0.0]|4095.7199999997392|
|[2.0,2.4,3.0,3.0]| 4340.819999999763|
|[1.0,2.0,0.0,8.0]|2690.3999999999924|
|[2.0,3.1,1.0,0.0]|4095.7199999997392|
+-----------------+------------------+
only showing top 5 rows
```

Model Selection and Training

I am use the Random Forest Regressor for this task.

```
RanFor = RandomForestRegressor(labelCol="profit_loss", featuresCol="features", numTrees=100)

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

rf_model = RanFor.fit(train_data)
```

Model Prediction and Evaluation

```
predictions = rf_model.transform(test_data)
```

```
evaluator = RegressionEvaluator(labelCol="profit_loss", predictionCol="prediction", metricName="rmse")
rmse = evaluator.evaluate(predictions)
r2 = evaluator.evaluate(predictions, {evaluator.metricName: "r2"})

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R-squared (R2): {r2}")
```

```
Root Mean Squared Error (RMSE): 244.63613848581156
R-squared (R2): 0.9616383252764448
```

Profit Prediction

```
profit_predictions = rf_model.transform(df_model)
profit_predictions.select("profit_loss", "prediction").show(10)
```

```
+------------------+------------------+
|       profit_loss|        prediction|
+------------------+------------------+
|3953.3400000001056| 2937.794891607997|
|4095.7199999997392|3762.3105819609495|
| 4340.819999999763| 3496.023252982598|
|2690.3999999999924|2879.9584769693092|
|4095.7199999997392|3762.3105819609495|
|1637.9999999999968| 1782.700583408882|
|2690.3999999999924|2879.9584769693092|
|2506.7999999999984|2908.4605063424406|
| 5733.675000000174| 5352.193175944729|
|3125.3399999998546| 3496.023252982598|
+------------------+------------------+
only showing top 10 rows
```

Recommendations

```
top_profit_predictions = profit_predictions.orderBy(col("prediction").desc()).show(1)
```

```
+------------------+----------------+-----------------+
|          features|     profit_loss|       prediction|
+------------------+----------------+-----------------+
|[2.0,4.75,3.0,3.0]|6341.56500000009|6069.344741887474|
+------------------+----------------+-----------------+
only showing top 1 row
```

Feature Importance Analysis

Extract feature importances

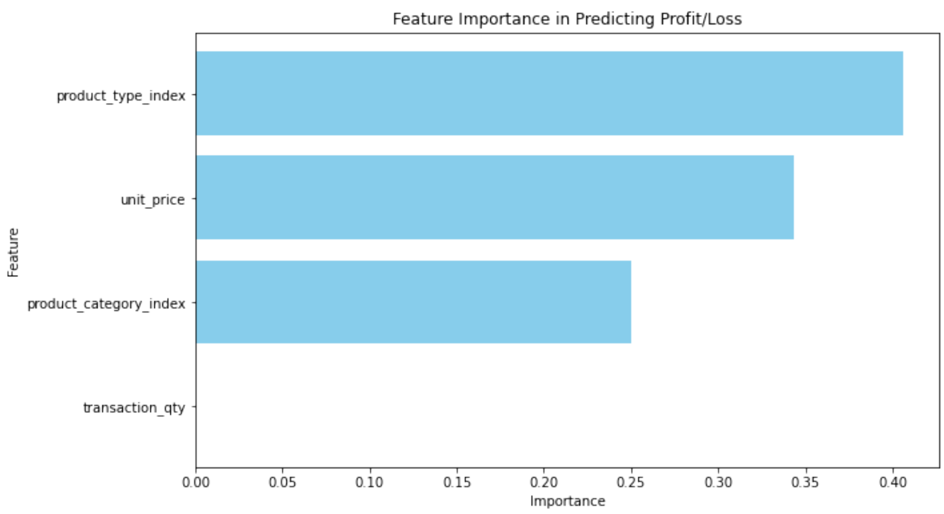
```
importances = rf_model.featureImportances
```

Creating Pandas DataFrame for better visualization

```
feature_importance_df = pd.DataFrame({
    "feature": ["transaction_qty", "unit_price", "product_category_index", "product_type_index"],
    "importance": importances.toArray()
})

feature_importance_df = feature_importance_df.sort_values(by="importance", ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df["feature"], feature_importance_df["importance"], color="skyblue")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.title("Feature Importance in Predicting Profit/Loss")
plt.gca().invert_yaxis()
plt.show()
```



Scenario Analysis

Define a list of scenarios with hard-coded changes and creating Dataframe from it.

```
scenarios = [
    {"transaction_qty": 10, "unit_price": 5.0, "product_category_index": 0, "product_type_index": 1},
    {"transaction_qty": 15, "unit_price": 4.5, "product_category_index": 1, "product_type_index": 2},
    {"transaction_qty": 20, "unit_price": 6.0, "product_category_index": 3, "product_type_index": 3},
]

scenarios_df = pd.DataFrame(scenarios)
scenarios_spark_df = spark.createDataFrame(scenarios_df)
```

Assemble the features for the scenarios and Predict profit/loss for each scenario.

```
    scenario_features = assembler.transform(scenarios_spark_df)

    # Predict profit/loss for each scenario
    scenario_predictions = rf_model.transform(scenario_features)

    scenario_predictions.select("features", "prediction").show()
```

```
+-----------------+-----------------+
|         features|       prediction|
+-----------------+-----------------+
|[10.0,5.0,0.0,1.0]|5105.963758754502|
|[15.0,4.5,1.0,2.0]|5704.559157106808|
|[20.0,6.0,3.0,3.0]|5943.712423175242|
+-----------------+-----------------+
```

Loss Mitigation Strategies

Identify Loss-Making Products

Upon analyzing the product data, it was observed that no products or services were experiencing losses. All products show a positive profit margin.Therefore, the loss mitigation strategies section is not applicable for this dataset.

```
loss_making_products = product_sales.filter(col("profit_loss") <0)

loss_making_products.show(truncate=False)
```

```
+----------+----------------+------------+--------------+---------------+-------------+----------+-----------+
|product_id|product_category|product_type|product_detail|total_sales_qty|total_revenue|total_cost|profit_loss|
+----------+----------------+------------+--------------+---------------+-------------+----------+-----------+
```

```
+----------+---------------+-----------+-------------+--------------+------------+---------+----------+
```

```
total_loss_count = loss_making_products.count()
print(f"Total number of products in loss: {total_loss_count}")
```

```
Total number of products in loss: 0
```

Savinga DataFrame as a Cleaned Dataset in CSV file format

```
output_path = "dbfs:/Desktop/Coffee_Clean_Data"
coffee_data_df.coalesce(1).write.mode("overwrite").option("header", "true").csv(output_path)
```

```
files = dbutils.fs.ls("dbfs:/Desktop/Coffee_Clean_Data")
display(files)
```

path	name	size	modificationTime
dbfs:/Desktop/Coffee_Clean_Data/_SUCCESS	_SUCCESS	0	1724498144000
dbfs:/Desktop/Coffee_Clean_Data/_committed_1755086449704234385	_committed_1755086449704234385	113	1724497990000
dbfs:/Desktop/Coffee_Clean_Data/_committed_8956154481424602482	_committed_8956154481424602482	212	1724498031000
dbfs:/Desktop/Coffee_Clean_Data/_committed_946712081873331209	_committed_946712081873331209	200	1724498144000
dbfs:/Desktop/Coffee_Clean_Data/_started_1755086449704234385	_started_1755086449704234385	0	1724497982000
dbfs:/Desktop/Coffee_Clean_Data/_started_8956154481424602482	_started_8956154481424602482	0	1724498023000
dbfs:/Desktop/Coffee_Clean_Data/_started_946712081873331209	_started_946712081873331209	0	1724498138000
dbfs:/Desktop/Coffee_Clean_Data/part-00000-tid-946712081873331209-b0618037-150e-4f7f-a390-e3e211403c47-413-1-c000.csv	part-00000-tid-946712081873331209-b0618037-150e-4f7f-a390-e3e211403c47-413-1-c000.csv	25579482	1724498144000