



Data Glacier Data Scientist Internship

Batch: LISUM23: 30

Week11: EDA Presentation and proposed modeling technique

Project: Retail Forecasting

Team member's details:

Group Name: Retail_forecasting

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Specialization	Data Science	Data Science	Data Science	Data Science

Project life cycle along with deadline:

Project weeks	Deadline	Lifecycle
Week7	Aug 19, 2023	Problem statement, Pre-process
Week8	Aug 26, 2023	Data process, understanding
Week9	Sep 02, 2023	Data Cleaning, Merge, Review
Week10	Sep 09, 2023	EDA, Final recommendation
Week11	Sep 16, 2023	EDA presentation for business users
Week12	Sep 23, 2023	Model Selection and Model Building/Dashboard
Week13	Sep 30, 2023	Final Project Report and Code

Tabular data details: forecasting_case_study.xlsx:

Total number of observations	1218
Total number of files	1
Total number of features	12
Base format of the file	.xlsx
Size of the data	80KB

Problem Description:

This major Australian beverage corporation operates within the beverage industry. Their product distribution spans across multiple supermarket chains, and they actively conduct robust promotional campaigns year-round. The demand for their products is subject to fluctuations driven by factors such as holidays and seasonal trends. They require a weekly item-level forecast for each of their products, categorized into weekly intervals.

Data Preparation:

1. Check if there are missing values

There is no NULL value. So we can surely go ahead with the dataset.

```
[ ] from pyspark.sql.functions import col, isnull, when, count

missing_counts = df.select([count(when(col(c).isNull(), c)).alias(c) for c in df.columns if df.schema[c].dataType != 'date'])
missing_counts.show()
```

Product	date	Sales	Price Discount (%)	In-Store Promo	Catalogue Promo	Store End Promo	Google_Mobility	Covid_Flag	V_DAY	EASTER	CHRISTMAS
0	0	0	0	0	0	0	0	0	0	0	0

2. Validate the name of columns

```
[ ] df = (
    df
    .withColumnRenamed("Price Discount (%)", "Price_Discount")
    .withColumnRenamed("In-Store Promo", "In-Store_Promo")
    .withColumnRenamed("Catalogue Promo", "Catalogue_Promo")
    .withColumnRenamed("Store End Promo", "Store_End_Promo")
)
```

3. Zero Sales

For 0 Sales of production of SKU1 to SKU5, decided to keep them, not drop. SKU6 of missing data between 2020-11-22 to 2020-12-27, decided to create them to balance with other products.

```
[ ] from pyspark.sql import Row

data_to_append = [
    Row(Product="SKU6", date="2020-11-22", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
    Row(Product="SKU6", date="2020-11-29", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
    Row(Product="SKU6", date="2020-12-6", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
    Row(Product="SKU6", date="2020-12-13", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
    Row(Product="SKU6", date="2020-12-20", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
    Row(Product="SKU6", date="2020-12-27", Sales=0, Price_Discount= 0, In_Store_Promo=0, Catalogue_Promo=0, Store_End_Promo=0, Google_Mobility= 0, Covid_Flag=1,
]
```

4. Combine 3 holidays

For the 3 holidays of V_DAY, EASTER, and CHRISTMAS, we decided to combine them into 1 column because the dates of each holiday are different without duplication.

```
[ ] from pyspark.sql.functions import when, lit, col

df = df.withColumn("Holiday_Flag", when((col("V_DAY") == 1) | (col("EASTER") == 1) | (col("CHRISTMAS") == 1), lit(1)).otherwise(lit(0)))
df = df.drop("V_DAY", "EASTER", "CHRISTMAS")
df.show()
```

Product	date	Sales	Price_Discount	In-Store_Promo	Catalogue_Promo	Store_End_Promo	Google_Mobility	Covid_Flag	Holiday_Flag
SKU1	2017-02-05	27750	0.0	0	0	0	0.0	0	0
SKU1	2017-02-12	29023	0.0	1	0	1	0.0	0	1
SKU1	2017-02-19	45630	0.17	0	0	0	0.0	0	0
SKU1	2017-02-26	26789	0.0	1	0	1	0.0	0	0
SKU1	2017-03-05	41999	0.17	0	0	0	0.0	0	0
SKU1	2017-03-12	29731	0.0	0	0	0	0.0	0	0
SKU1	2017-03-19	27365	0.0	1	0	0	0.0	0	0
SKU1	2017-03-26	27722	0.0	1	0	1	0.0	0	0
SKU1	2017-04-02	44339	0.17	1	0	0	0.0	0	0
SKU1	2017-04-09	54655	0.17	1	0	0	0.0	0	1
SKU1	2017-04-16	108159	0.44	0	0	0	0.0	0	0
SKU1	2017-04-23	30361	0.0	1	0	1	0.0	0	0
SKU1	2017-04-30	42154	0.17	1	0	1	0.0	0	0
SKU1	2017-05-07	39782	0.17	0	0	0	0.0	0	0
SKU1	2017-05-14	29490	0.0	0	0	0	0.0	0	0

5. Divided data into 6

The dataset has been effectively partitioned into **six** distinct product datasets using **PySpark**. This division allows us to focus on specific product categories individually, streamlining data preparation, exploratory analysis, feature engineering, modeling, and subsequent analysis for each product group. This approach enhances our ability to gain insights, build tailored models, and optimize our analysis for each product category while ensuring efficient and manageable data processing.

```
[ ] df.write.option("header", True) \
      .partitionBy("Product") \
      .mode("overwrite") \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast")
```

```
df1=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU1")
```

```
[ ] df2=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU2")
```

```
[ ] df3=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU3")
```

```
[ ] df4=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU4")
```

```
[ ] df5=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU5")
```

```
[ ] df6=spark.read.option("header",True) \
      .csv("/content/drive/MyDrive/Colab Notebooks/DG/Forecast/Product=SKU6")
```

6. Validate the data type

We validated the data type as below.

-Variables with numeric value to int

-date to datetime

```
cols=['Sales', 'Price_Discount', 'In-Store_Promo', 'Catalogue_Promo', 'Store_End_Promo', 'Google_Mobility', 'Covid_Flag', 'Holiday_Flag']
df1[cols]=df1[cols].apply(pd.to_numeric)
df1['date']=df1['date'].apply(pd.to_datetime)
#df1=df1[df1['Sales'] !=0]
```

7. Remove outlier with narrow range

To remove outliers using the Interquartile Range (IQR) method, calculate the IQR by finding the difference between the third quartile (Q3) and the first quartile (Q1). Then, define a lower bound ($Q1 - 1.0 * IQR$) and an upper bound ($Q3 + 1.0 * IQR$) and filter out data points that fall outside this range. This method helps identify and exclude extreme values from the dataset.

```
[ ] #q_hi = df1['Sales'].quantile(0.99)
Q1 = np.percentile(df1['Sales'], 25, method='midpoint')
Q3 = np.percentile(df1['Sales'], 75, method='midpoint')
IQR = Q3 - Q1
print(IQR)
upper= 1.0*IQR #make the range of outliers narrower.
df1 = df1[(df1['Sales'] < upper)]
```

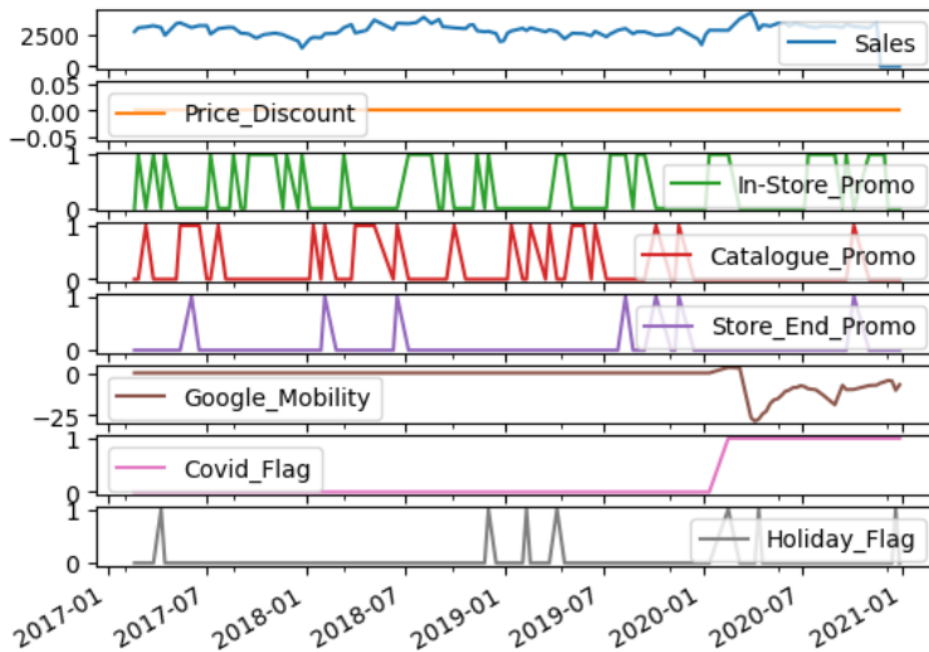
24606.0

Data Analysis / EDA:

1. Visualization of each product

Below is product SKU2. Each product has different sales and characteristics.

```
array([<Axes: xlabel='date'>, <Axes: xlabel='date'>,  
      <Axes: xlabel='date'>, <Axes: xlabel='date'>,  
      <Axes: xlabel='date'>, <Axes: xlabel='date'>,  
      <Axes: xlabel='date'>, <Axes: xlabel='date'>], dtype=object)
```



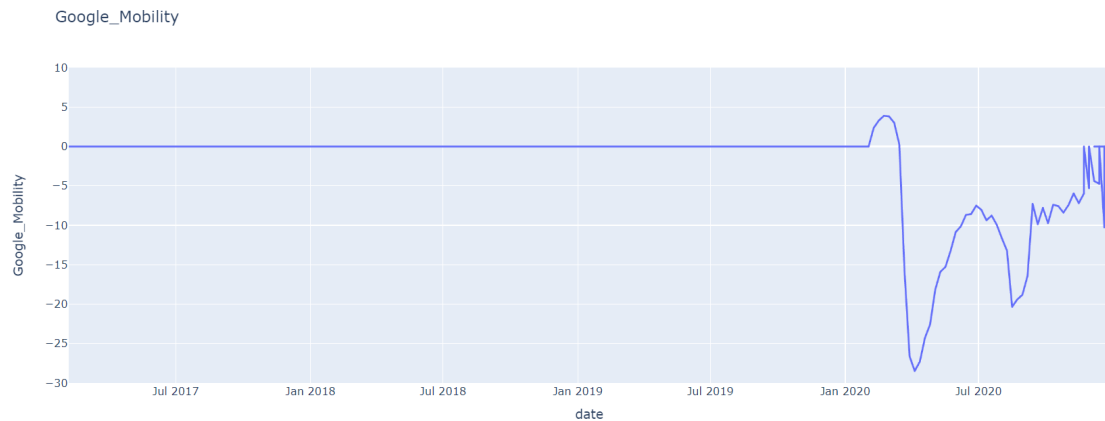
2. Covid_Flag

Covid Flag started from February 09, 2020.

```
[ ] window_spec = Window.orderBy("date")  
df = df.withColumn("prev_flag", F.lag("Covid_Flag").over(window_spec))  
  
start_dates = df.filter((F.col("Covid_Flag") == 1) & (F.col("prev_flag") == 0))  
  
start_dates.select("Date").show()
```

```
+-----+  
|      Date|  
+-----+  
|2020-02-09|  
+-----+
```

3. Google Mobility



-Google Mobility is related Covid19. This is because the line is flat until February 2, 2020 above the plot. The flat line means there are no activities and no existing record.

-After February 9, 2020, it started fluctuating and keeps changing. According to the variable of Covid Flag, it started being recorded as 1 after February 9, 2020. The timing between Google Mobility and Covid Flag is exactly coinciding.

-Google Mobility data tracks travel patterns in detail, such as how often people go to public places and how much time they spend commuting or shopping. This will allow us to assess the risk of spread of infection and predict the spread of infection in a particular region or city.

4. To analyze the data pre-Covid and post-Covid, we divide the data to 2

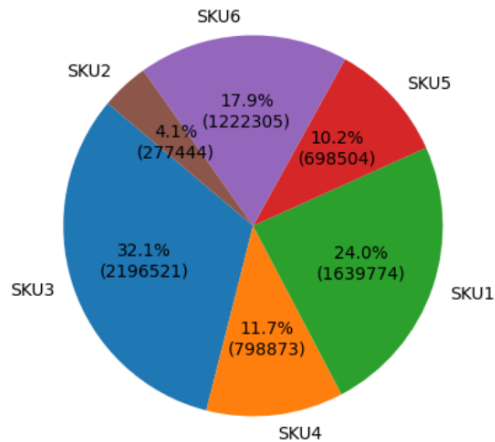
```
before_date = df.filter(col("date") < "2020-02-09")
after_date = df.filter(col("date") >= "2020-02-09")

before_date.show()
after_date.show()
```

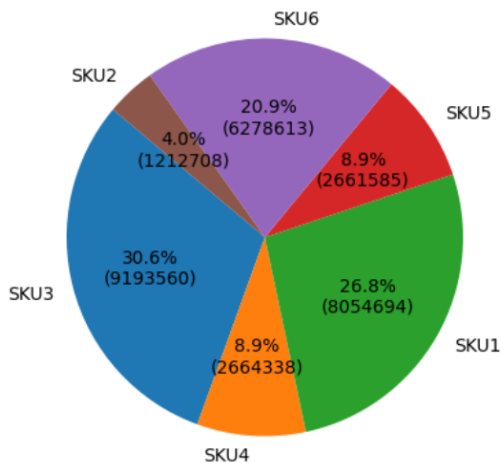
Product	date	Sales	Price_Discount	In-Store_Promo	Catalogue_Promo	Store_End_Promo	Google_Mobility	Covid_Flag	Holiday_Flag	prev_flag
SKU1	2017-02-05	27750	0.0	0	0	0	0.0	0	0	null
SKU2	2017-02-05	7180	0.25	1	0	0	0.0	0	0	0
SKU3	2017-02-05	39767	0.3	0	1	1	0.0	0	0	0
SKU4	2017-02-05	12835	0.3	0	1	1	0.0	0	0	0

Comparison of percentage of sharing each product before Covid and after Covid.

Percentage and Total Sales of each products post Covid



Percentage and Total Sales of each products pre Covid



In terms of the percentages of the products to sales, there is no very big difference between pre covid and post covid.

In general both before Covid and after Covid, SKU3 is the most popular product. SKU1 is the second most popular. And SKU6 is the 3rd.

SKU4 and SKU5 have the same sales amounts. SKU2 is the least popular product.

-Comparing the sales amount before Covid and after Covid

Product	Sales_before_covid	Sales_after_covid	Sales_change
SKU1	8054694.0	1639774	-79.6420075051889
SKU2	1212708.0	277444	-77.12194526629659
SKU3	9193560.0	2196521	-76.10804737229104
SKU4	2664338.0	798873	-70.01607904102258
SKU5	2661585.0	698504	-73.75608894699963
SKU6	6278613.0	1222305	-80.5322449400847

Sales of each of the products significantly reduced between 70% and 80% minus after Covid compared to before Covid.

Recommended Models:

We use multivariate time series for this dataset.

Proposal methods are below.

- ARIMA
- Prophet
- XGBoost
- LSTM
- SVM
- VAR