PROJECT-1

EXPLORATORY ANALYSIS

DATASET: Supermarket store branches sales analysis

DATASET- In the dataset, You'll get data of different stores of a supermarket company as per their store IDs which for ease has been converted to positive integers.

- 1)Store ID: (Index) ID of the particular store.
- 2)Store Area: Physical Area of the store in yard square.
- 3)Items Available: Number of different items available in the corresponding store.
- 4) Daily Customer Count: Number of customers who visited to stores on an average over month.
- 5)Store Sales: Sales in (US \$) that stores made.

PROBLEM:-

Analysing the performances of stores in the past on basis of which will try to rectify defects as well as to leverage the positives.

WHY I CHOOSE?

A supermarket is a self-service shop offering a wide variety of food, beverages and household products, organized into sections. This kind of store is larger and has a wider selection than earlier grocery stores, but is smaller and more limited in the range of merchandise than a hypermarket or big-box market. All things considered super market is easy and well categorised shop than some other road-side markets.

<u>Data preparation :</u>

As there are no null values present in my dataset. There is no need to replace or re-organize any of my attribute.

```
In [7]: data.isnull().sum()
#To check whether their are any null values present in the given dataset.

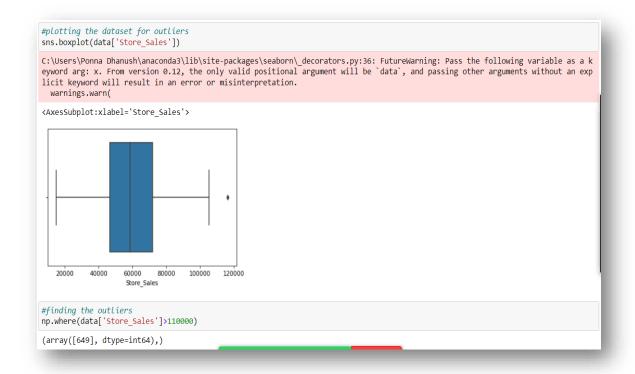
Out[7]: Store ID 0
Store_Area 0
Items_Available 0
Daily_Customer_Count 0
Store_Sales 0
dtype: int64
```

Gathering the information of the attributes based on the data respectively

```
#Gives detailed information about the dataset
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 896 entries, 0 to 895
Data columns (total 5 columns):
                                Non-Null Count Dtype
# Column
     Store ID 896 non-null
Store_Area 896 non-null
Items_Available 896 non-null
    Store ID
                                                       int64
                                                        int64
                                                       int64
     Daily_Customer_Count 896 non-null Store_Sales 896 non-null
                                                        int64
                                                       int64
dtypes: int64(5)
memory usage: 35.1 KB
```

Doing the outlier analysis

Outlier analysis is carried forward by plotting a boxplot. Inspite of having the outliers it does not make any noticeable changes to the approach. So, we can even ignore the outliers of the attributes as it does not possess any significant change to the analysis.



```
#plotting the dataset for outliers
sns.boxplot(data['store_Area'])

C:\Users\Ponna Dhanush\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a k
eyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an exp
licit keyword will result in an error or misinterpretation.

Warnings.warn(

<AxxesSubplot:xlabel='Store_Area'>

#finding the outliers
np.where(data['store_Area']<800)

(array([158, 865], dtype=int64),)
```

```
#finding the outliers
np.where(data['Store_Area']>2000)

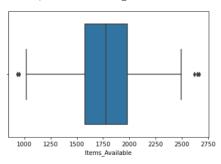
(array([ 61, 91, 163, 243, 258, 311, 344, 398, 466, 469, 540, 550, 567, 628, 784, 798, 849], dtype=int64),)
```

```
#plotting the dataset for outliers
sns.boxplot(data['Items_Available'])
```

C:\Users\Ponna Dhanush\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a k eyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an exp licit keyword will result in an error or misinterpretation.

warnings.warn(

<AxesSubplot:xlabel='Items_Available'>



```
#finding the outliers

np.where(data['tems_Available']<1000)

(array([158, 865], dtype=int64),)

#finding the outliers

np.where(atata['tems_Available']>2500)

(array([11, 406, 548], dtype=int64),)

#finding the outliers

np.where(data['abata_count'])

**Axassubplot(atata['abata_count'])

**Axassubplot(xlabel='baily_customer_count')

**Axassubplot(xlabel='baily_customer_count')

**Axassubplot(xlabel='baily_customer_count')

**Axassubplot(xlabel='baily_customer_count')

**Axassubplot(xlabel='baily_customer_count')

**Inding the outliers

np.where(data['baily_customer_count'] **50)

(array([39], dtype=int64),)

#finding the outliers

np.where(data['baily_customer_count'] **1500)

(array([349, 848], dtype=int64),)
```

Exploratory analysis:

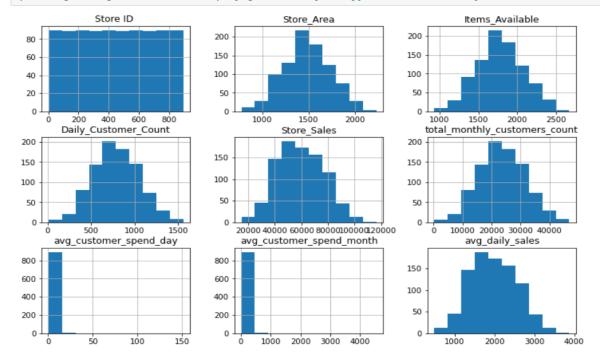
Plotting a heatmap showing the correlation between the attributes.



We see high correlation between Items Available and Store Area, monthly customer count with Daily Customer Count, Store Sales and Avg Daily Sales, Avg Customer Spend Day with Avg Customer Spend Month (i.e., it's almost about 1)

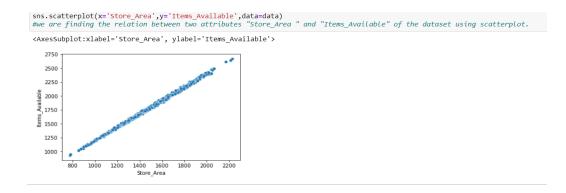
 Plotting and visualizing the data in the form of a histogram.

data.hist(figsize=(12,8)); plt.grid(False) #plotiing histograms with the help of grid lines for different attributes of the dataset.

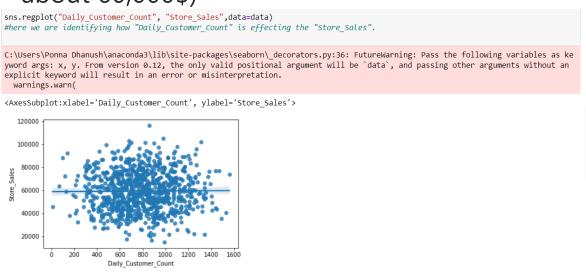


We get to observe that daily customer count is mostly lies between (600-800) heads.

 As we can see that the graph between Store Area and Items Available is steadily increasing, which is clearly evident that store area plays a major role in items available for any particular branch.



➤ It is clear that even the daily customer count increases ,store sales remain consistent (i.e. it's about 60,000\$)



➤ Here we are building some statistical logics using "Daily Customer Count" and "Store Sales" to find "Average customer spend month" and "avg daily sales".

```
: data['total monthly customers count'] = data['Daily Customer Count'] * 30
  data['avg_customer_spend_day'] = data['Store_Sales'] / data['total_monthly_customers_count']
  data['avg_customer_spend_month'] = data['Store_Sales'] / data['Daily_Customer_Count']
  data['avg_daily_sales'] = data['Store_Sales'] / 30
  #here we are building some logics using "Daily Custoomer Count" and "Store Sales" to find "Average customer spend month" and "ave
: correlation = data.corr()
  print(correlation['Store_Sales'].sort_values(ascending = False),'\n')
  #here we are finding the correlation of attribute "Store_Sales".
  avg daily sales
                                   1,000000
  Store Sales
                                   1.000000
  avg_customer_spend_day
                                   0.139546
  avg_customer_spend_month
                                   0.139546
  Items_Available
                                   0.098849
  Store Area
  Store ID
                                   0.071486
  Daily_Customer_Count
                                   0.008629
  total_monthly_customers_count
                                   0.008629
  Name: Store_Sales, dtype: float64
```

➤ Finally, I want to conclude that even there is raise in daily customer count the total store sales are consistent.

```
Yfac = data["Store_Sales"]
Xfac = data["Daily_Customer_Count"]
plt.figure(figsize=(6,6))
plt.scatter(Xfac,Yfac,s=15)
plt.xlabel('Count of Customers')
plt.ylabel('Sales in $')
plt.title('Customers & Sales of All Stores')
plt.xlim(200, 2000)
plt.yscale("linear")
plt.grid(True)

Customers & Sales of All Stores

120000

80000

40000

40000

40000
```

1200 1400 1600 1800

At last, we can draw this analysis by saying that most of the customers are just going to the store and returning with empty hands

1000

which leads to increase in daily customer count and consistent store sales which are bought by regular customers.

Advice: -

We should introduce a new innovative idea which leads to high store sales like "it is mandatory for every customer to buy at least one product from store.