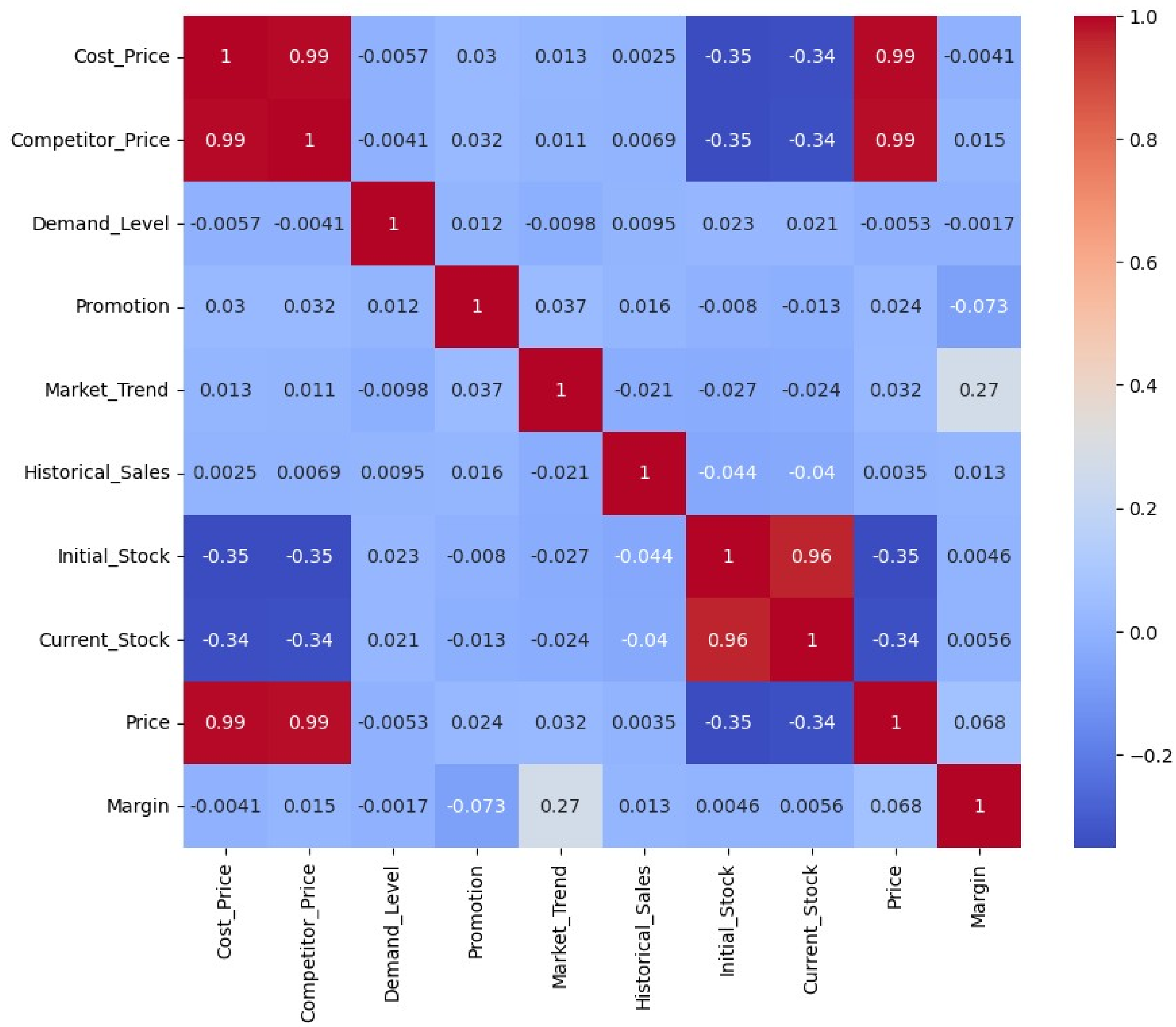
```
#loading libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#loading dataset into python
path =
'D:/Documents/shubh/Canada2023/CapeBretonUniversity/Semester4/Capstone
Project/Docsfromemployer/datasetupdated.xlsx'
df=pd.read_excel(path)
df.head()

   Product_ID        Category      Product_Name  Cost_Price
Competitor_Price  \
0  SKU-000001          Sports          Yoga Mat      140.62
171.59
1  SKU-000002           Books     Graphic Novel        6.97
7.54
2  SKU-000003  Home & Kitchen           Blender      385.23
450.03
3  SKU-000004           Books     Graphic Novel        9.06
9.31
4  SKU-000005           Books  Science Textbook       87.14
91.71

   Demand_Level  Season  Promotion  Market_Trend  Historical_Sales  \
0             1    Fall          1          0.92               462
1             2  Spring          0          0.60               615
2             3  Spring          0         -0.08               788
3             2  Winter          0         -0.60               750
4             3  Winter          1          0.62               969

   Initial_Stock  Current_Stock   Price    Margin
0            169            107  192.23  0.367017
1            450            420    7.67  0.100430
2             91             51  423.75  0.099992
3            740            705   11.06  0.220751
4            286            192  120.92  0.387652

#Dropping unnecessary variables
df.drop(['Product_ID', 'Product_Name'], axis=1, inplace=True)

#examining the dataset rows and columns
df.head()

         Category  Cost_Price  Competitor_Price  Demand_Level  Season
\
0          Sports      140.62            171.59             1    Fall
```

```
1            Books       6.97                 7.54            2  Spring

2  Home & Kitchen      385.23               450.03            3  Spring

3            Books       9.06                 9.31            2  Winter

4            Books      87.14                91.71            3  Winter


   Promotion  Market_Trend  Historical_Sales  Initial_Stock
Current_Stock  \
0          1          0.92               462            169
107
1          0          0.60               615            450
420
2          0         -0.08               788             91
51
3          0         -0.60               750            740
705
4          1          0.62               969            286
192

    Price    Margin
0  192.23  0.367017
1    7.67  0.100430
2  423.75  0.099992
3   11.06  0.220751
4  120.92  0.387652

#building corelation matrix
df_num = df.drop(['Category','Season'], axis=1, inplace=False)
#dropping the categorical variables
cor_matrix1 = df_num.corr()
fig, ax=plt.subplots(figsize=(10,8))
sns.heatmap(cor_matrix1, annot=True, cmap = 'coolwarm', ax=ax)
#corelation matrix heatmap
plt.savefig('corelationoriginal.jpg')
plt.show()
```



No strong corelation with Margin (Target Variable)

```
#Dropping unnecessary attributes - low corelation - data set with no
dummy variables
df_new=df.drop(['Promotion',
'Competitor_Price','Demand_Level','Initial_Stock',], axis=1,
inplace=False)



#Generating summary statistics of chosen numerical variables
df_new.describe()

        Cost_Price  Market_Trend  Historical_Sales  Current_Stock  \
count  3000.000000    3000.00000       3000.000000    3000.000000
mean    347.609110       0.02304        531.769333     182.003667
std     446.377031       0.57107        277.220135     170.305716
min       5.350000      -1.00000         51.000000       6.000000
```

```
25%      76.165000      -0.46000        295.750000      70.000000
50%     198.290000       0.04000        533.500000     122.000000
75%     361.205000       0.50250        770.000000     224.000000
max    1998.990000       1.00000       1000.000000     974.000000

             Price       Margin
count  3000.000000  3000.000000
mean    408.437317     0.175573
std     527.802307     0.109828
min       5.880000     0.099065
25%      88.712500     0.099999
50%     227.545000     0.100035
75%     422.897500     0.240727
max    2925.000000     0.593135
```

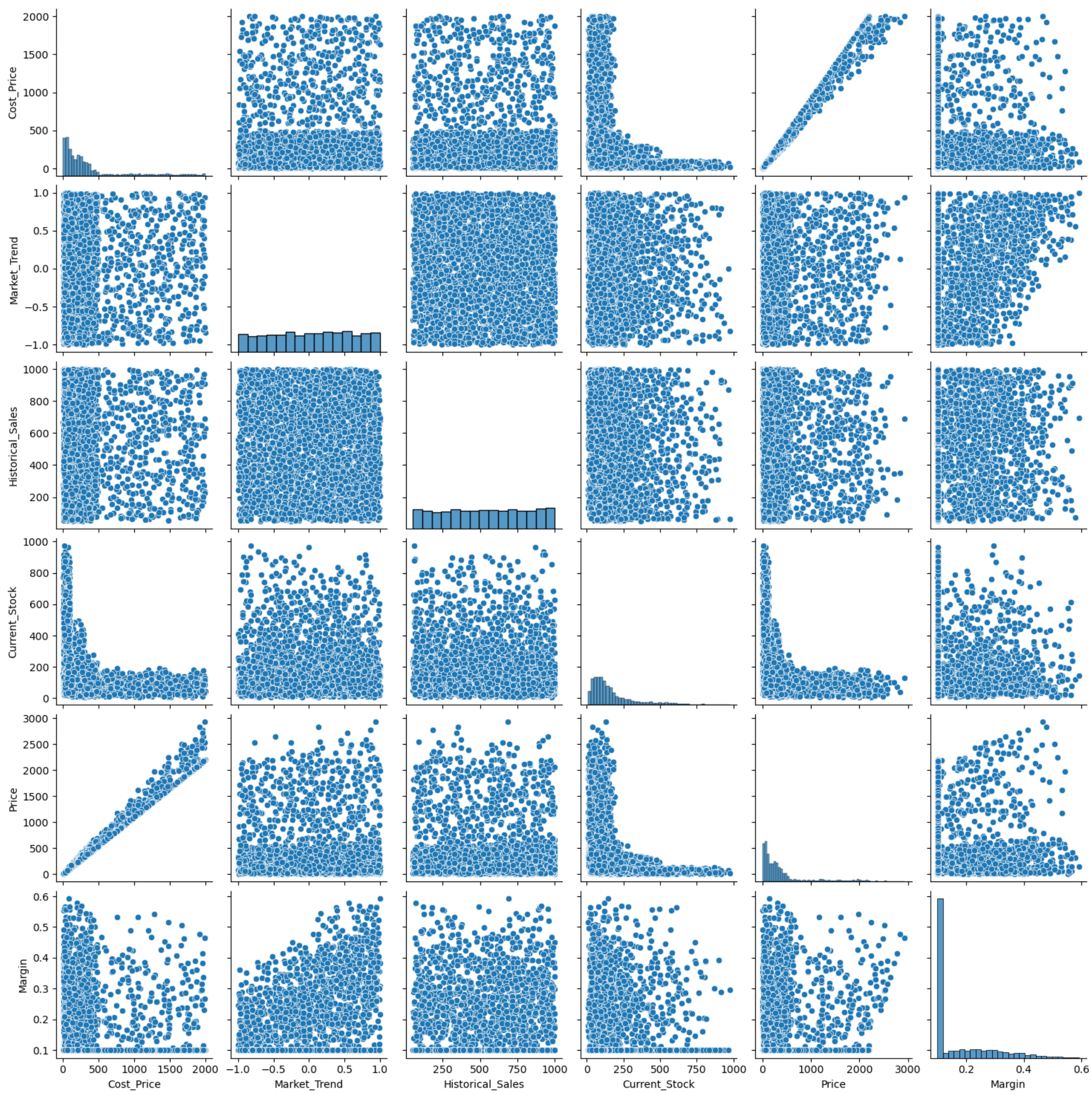
```
#generating datatype/count of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Category          3000 non-null   object
 1   Cost_Price        3000 non-null   float64
 2   Competitor_Price  3000 non-null   float64
 3   Demand_Level      3000 non-null   int64
 4   Season            3000 non-null   object
 5   Promotion         3000 non-null   int64
 6   Market_Trend      3000 non-null   float64
 7   Historical_Sales  3000 non-null   int64
 8   Initial_Stock     3000 non-null   int64
 9   Current_Stock     3000 non-null   int64
 10  Price             3000 non-null   float64
 11  Margin            3000 non-null   float64
dtypes: float64(5), int64(5), object(2)
memory usage: 281.4+ KB
```

```
#generating datatype/count of the new dataset to check everything
before proceeding to analysis
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Category          3000 non-null   object
 1   Cost_Price        3000 non-null   float64
 2   Season            3000 non-null   object
```

```
 3   Market_Trend      3000 non-null   float64
 4   Historical_Sales  3000 non-null   int64
 5   Current_Stock     3000 non-null   int64
 6   Price             3000 non-null   float64
 7   Margin            3000 non-null   float64
dtypes: float64(4), int64(2), object(2)
memory usage: 187.6+ KB

#creating a pairplot of the dataset
sns.pairplot(df_new, )

plt.show()
```



```
df_new.head()

         Category  Cost_Price  Season  Market_Trend  Historical_Sales
\
0          Sports      140.62    Fall          0.92               462

1           Books        6.97  Spring          0.60               615

2  Home & Kitchen      385.23  Spring         -0.08               788

3           Books        9.06  Winter         -0.60               750

4           Books       87.14  Winter          0.62               969


   Current_Stock   Price    Margin
0            107  192.23  0.367017
1            420    7.67  0.100430
2             51  423.75  0.099992
3            705   11.06  0.220751
4            192  120.92  0.387652

#creating dummies for categorical variables
df_dummies = pd.get_dummies(df_new, drop_first=True)

df_dummies.head()

   Cost_Price  Market_Trend  Historical_Sales  Current_Stock
Price  \
0      140.62          0.92               462            107  192.23

1        6.97          0.60               615            420    7.67

2      385.23         -0.08               788             51  423.75

3        9.06         -0.60               750            705   11.06

4       87.14          0.62               969            192  120.92


     Margin  Category_Clothing  Category_Electronics  Category_Home &
Kitchen  \
0  0.367017              False                 False
False
1  0.100430              False                 False
False
2  0.099992              False                 False
True
3  0.220751              False                 False
False
4  0.387652              False                 False
```

```
False

   Category_Sports  Season_Spring  Season_Summer  Season_Winter
0             True          False          False          False
1            False           True          False          False
2            False           True          False          False
3            False          False          False           True
4            False          False          False           True
```

```python
#checking the corelation of the variables
df_dummies.corr()
```

```
                         Cost_Price  Market_Trend  Historical_Sales  \
Cost_Price                 1.000000      0.012903          0.002537
Market_Trend               0.012903      1.000000         -0.021182
Historical_Sales           0.002537     -0.021182          1.000000
Current_Stock             -0.342091     -0.023861         -0.040432
Price                      0.993180      0.032276          0.003543
Margin                    -0.004131      0.267346          0.012916
Category_Clothing         -0.213704      0.008942         -0.011719
Category_Electronics       0.792105     -0.022820          0.012981
Category_Home & Kitchen   -0.102295     -0.000833          0.012431
Category_Sports           -0.149410      0.038590          0.022872
Season_Spring             -0.008337      0.000806         -0.014526
Season_Summer              0.011048     -0.003873          0.004149
Season_Winter              0.009952      0.009788          0.010868

                         Current_Stock     Price    Margin
Category_Clothing  \
Cost_Price                   -0.342091  0.993180 -0.004131           -
0.213704
Market_Trend                 -0.023861  0.032276  0.267346
0.008942
Historical_Sales             -0.040432  0.003543  0.012916           -
0.011719
Current_Stock                 1.000000 -0.339837  0.005555
0.070497
Price                        -0.339837  1.000000  0.067659           -
0.214179
Margin                        0.005555  0.067659  1.000000           -
0.035569
Category_Clothing             0.070497 -0.214179 -0.035569
1.000000
Category_Electronics         -0.306271  0.786889 -0.000761           -
0.250427
Category_Home & Kitchen      -0.165819 -0.100330  0.013912           -
0.236828
Category_Sports              -0.293688 -0.148077 -0.011331           -
0.250937
Season_Spring                 0.027239 -0.037213 -0.410381
```

```
0.032146
Season_Summer                -0.017783 -0.018418 -0.399802         -
0.014270
Season_Winter                -0.002808  0.042757  0.438328         -
0.020202

                         Category_Electronics  Category_Home & Kitchen
\
Cost_Price                           0.792105                -0.102295

Market_Trend                        -0.022820                -0.000833

Historical_Sales                     0.012981                 0.012431

Current_Stock                       -0.306271                -0.165819

Price                                0.786889                -0.100330

Margin                              -0.000761                 0.013912

Category_Clothing                   -0.250427                -0.236828

Category_Electronics                 1.000000                -0.245357

Category_Home & Kitchen             -0.245357                 1.000000

Category_Sports                     -0.259974                -0.245857

Season_Spring                       -0.017091                -0.017866

Season_Summer                        0.003905                 0.010661

Season_Winter                        0.004635                 0.004624


                         Category_Sports  Season_Spring  Season_Summer
\
Cost_Price                     -0.149410      -0.008337       0.011048

Market_Trend                    0.038590       0.000806      -0.003873

Historical_Sales                0.022872      -0.014526       0.004149

Current_Stock                  -0.293688       0.027239      -0.017783

Price                          -0.148077      -0.037213      -0.018418

Margin                         -0.011331      -0.410381      -0.399802

Category_Clothing              -0.250937       0.032146      -0.014270
```

```
Category_Electronics              -0.259974     -0.017091      0.003905

Category_Home & Kitchen           -0.245857     -0.017866      0.010661

Category_Sports                    1.000000      0.008147      0.010525

Season_Spring                      0.008147      1.000000     -0.346442

Season_Summer                      0.010525     -0.346442      1.000000

Season_Winter                     -0.015482     -0.338484     -0.329742


                         Season_Winter
Cost_Price                    0.009952
Market_Trend                  0.009788
Historical_Sales              0.010868
Current_Stock                -0.002808
Price                         0.042757
Margin                        0.438328
Category_Clothing            -0.020202
Category_Electronics          0.004635
Category_Home & Kitchen       0.004624
Category_Sports              -0.015482
Season_Spring                -0.338484
Season_Summer                -0.329742
Season_Winter                 1.000000

#loading seaborn
import seaborn as sns

#loading normalizer and preprocessing
from sklearn import preprocessing
from sklearn.preprocessing import Normalizer

df_dummies.columns

Index(['Cost_Price', 'Market_Trend', 'Historical_Sales',
'Current_Stock',
       'Price', 'Margin', 'Category_Clothing', 'Category_Electronics',
       'Category_Home & Kitchen', 'Category_Sports', 'Season_Spring',
       'Season_Summer', 'Season_Winter'],
      dtype='object')

df1 = df_dummies   #set with dummy variables
```

Checking for null value and data types for each variables

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Cost_Price              3000 non-null   float64
 1   Market_Trend            3000 non-null   float64
 2   Historical_Sales        3000 non-null   int64  
 3   Current_Stock           3000 non-null   int64  
 4   Price                   3000 non-null   float64
 5   Margin                  3000 non-null   float64
 6   Category_Clothing       3000 non-null   bool   
 7   Category_Electronics    3000 non-null   bool   
 8   Category_Home & Kitchen  3000 non-null   bool   
 9   Category_Sports         3000 non-null   bool   
 10  Season_Spring           3000 non-null   bool   
 11  Season_Summer           3000 non-null   bool   
 12  Season_Winter           3000 non-null   bool   
dtypes: bool(7), float64(4), int64(2)
memory usage: 161.3 KB
```

```
#checking for any zero values
null_df1 = df.isnull().sum()
print(null_df1)
```

```
Category            0
Cost_Price          0
Competitor_Price    0
Demand_Level        0
Season              0
Promotion           0
Market_Trend        0
Historical_Sales    0
Initial_Stock       0
Current_Stock       0
Price               0
Margin              0
dtype: int64
```

```
#function to check for duplicates row and delete if any present
def duplicate(df1):
    if df.duplicated().sum()>0:
        print(start+'Dataframe contains duplicate values'+end, 
df1.duplicated().sum())
        df1.drop_duplicates(inplace=True, ignore_index=True)
        print('Details of dataframe after dropping duplicates rows')
        details(df1)
    else:
        print('Dataframe doesnt contain any duplicate rows')
```

Analysing the Data

```
#row to columns switch
df1.describe().transpose()

                  count        mean         std        min
25%  \
Cost_Price       3000.0  347.609110  446.377031   5.350000
76.165000
Market_Trend     3000.0    0.023040    0.571070  -1.000000   -
0.460000
Historical_Sales 3000.0  531.769333  277.220135  51.000000
295.750000
Current_Stock    3000.0  182.003667  170.305716   6.000000
70.000000
Price            3000.0  408.437317  527.802307   5.880000
88.712500
Margin           3000.0    0.175573    0.109828   0.099065
0.099999

                        50%         75%          max
Cost_Price       198.290000  361.205000  1998.990000
Market_Trend       0.040000    0.502500     1.000000
Historical_Sales 533.500000  770.000000  1000.000000
Current_Stock    122.000000  224.000000   974.000000
Price            227.545000  422.897500  2925.000000
Margin             0.100035    0.240727     0.593135
```

Observations

1. Product ID and Product names are not used for analysis
2. Category and Seasons are not in this data statistics as they are categorical
3. Only high correlated variables used for machine learning model
4. cost_price: buying price range between 5.35 to 1999.0. Mean > Median, hence its right skewed.
5. market_trend: values range between -1 to 1. Mean < Median, hence slightly left skewed.
6. historical sales: sales range between 51 to 1000 items. Normally distributed as mean is almost equal to the median.
7. current_stock: stock ranges between 6 to 974 for various items. Mean > Median hence its right skewed.
8. price: selling price of items range from 5.88 to 2925. Mean> Median, mean almost double the median hence its highly right skewed.
9. margin: profit margin range from 9% to 59%. Mean > Median, mean almost double the media hence its highly right skewed.

Checking variable distribution skewness with a distplot

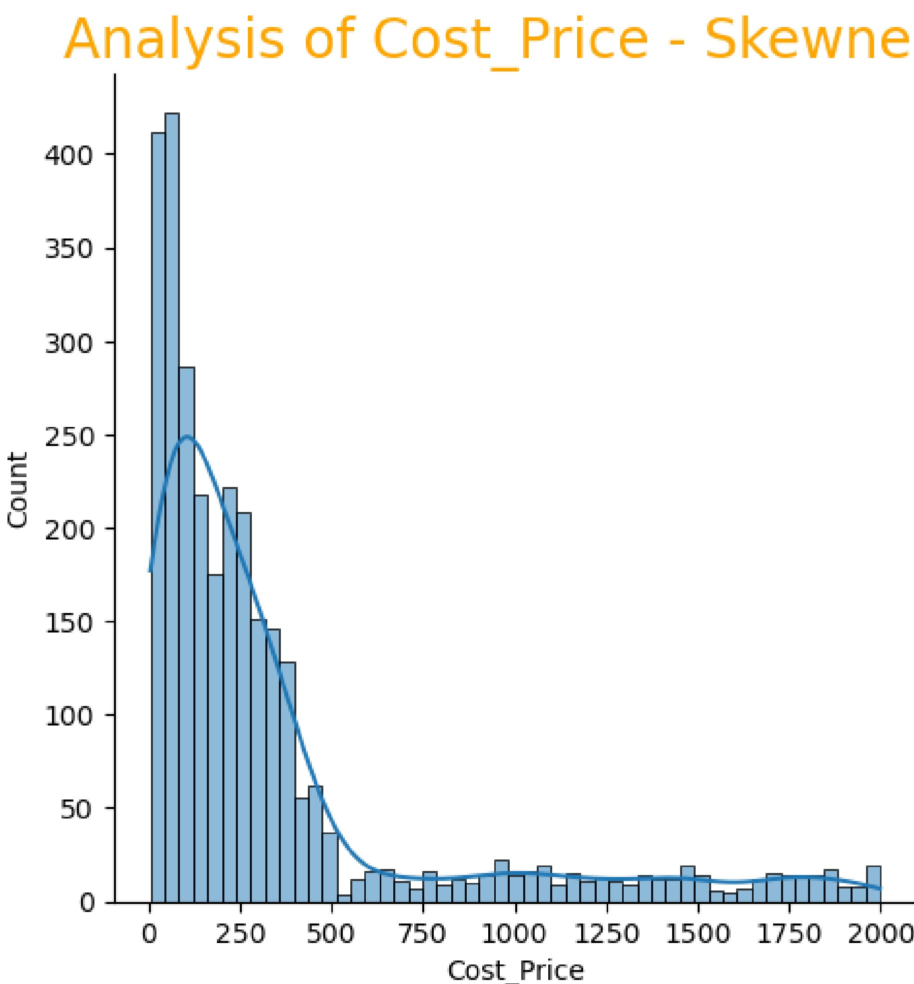
Cost_price

```
#creating a displot for cost price variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Cost_Price.skew())
sns.displot(df1.Cost_Price, kde=True)
plt.title(f"Analysis of Cost_Price - Skewness" , fontsize=20,
          color="orange")
```

```
Skewness is : 2.125379542475 26
```

```
Text(0.5, 1.0, 'Analysis of Cost_Price - Skewness')
```

```
<Figure size 1200x600 with 0 Axes>
```



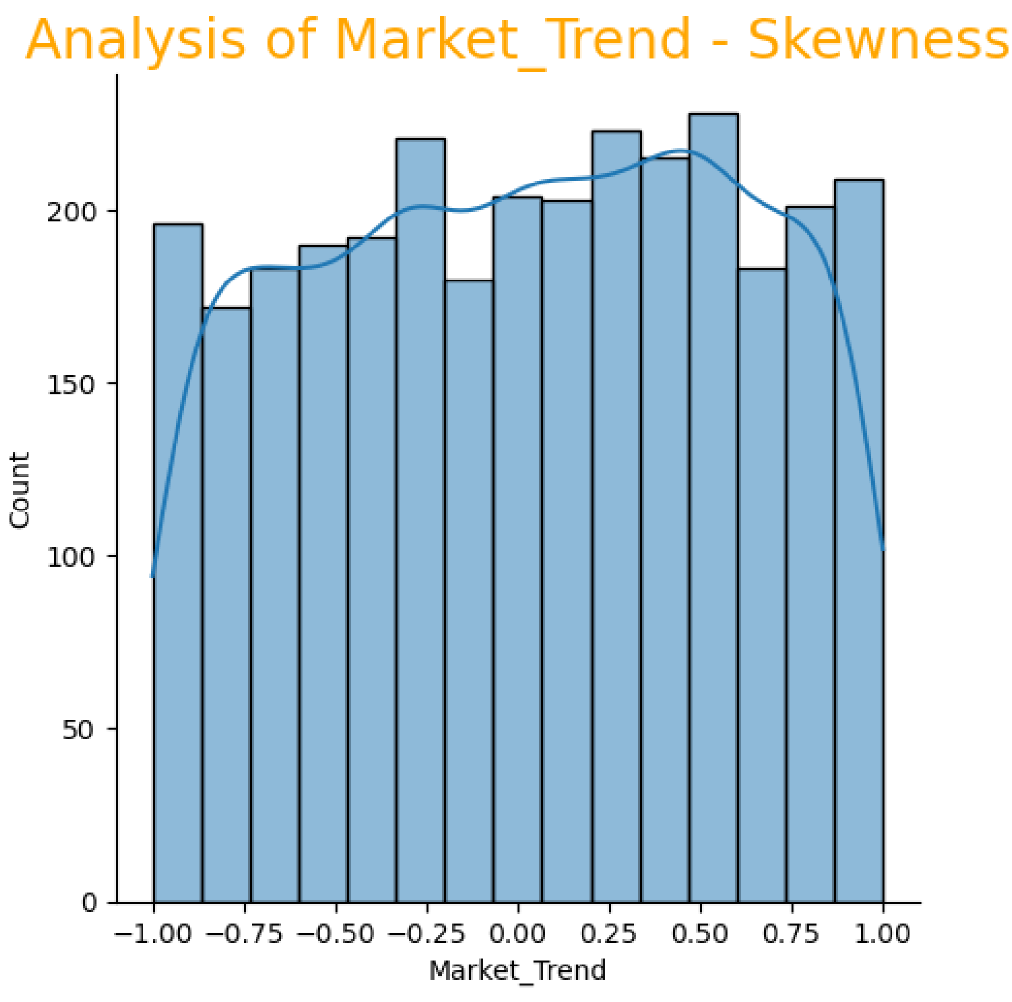
Market Trend

```
#creating a displot for market trend variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Market_Trend.skew())
sns.displot(df1.Market_Trend, kde=True)
plt.title(f"Analysis of Market_Trend - Skewness" , fontsize=20,
          color="orange")
```

```
Skewness is : -0.06274771895957179
```

```
Text(0.5, 1.0, 'Analysis of Market_Trend - Skewness')
```

```
<Figure size 1200x600 with 0 Axes>
```



Historical Sales

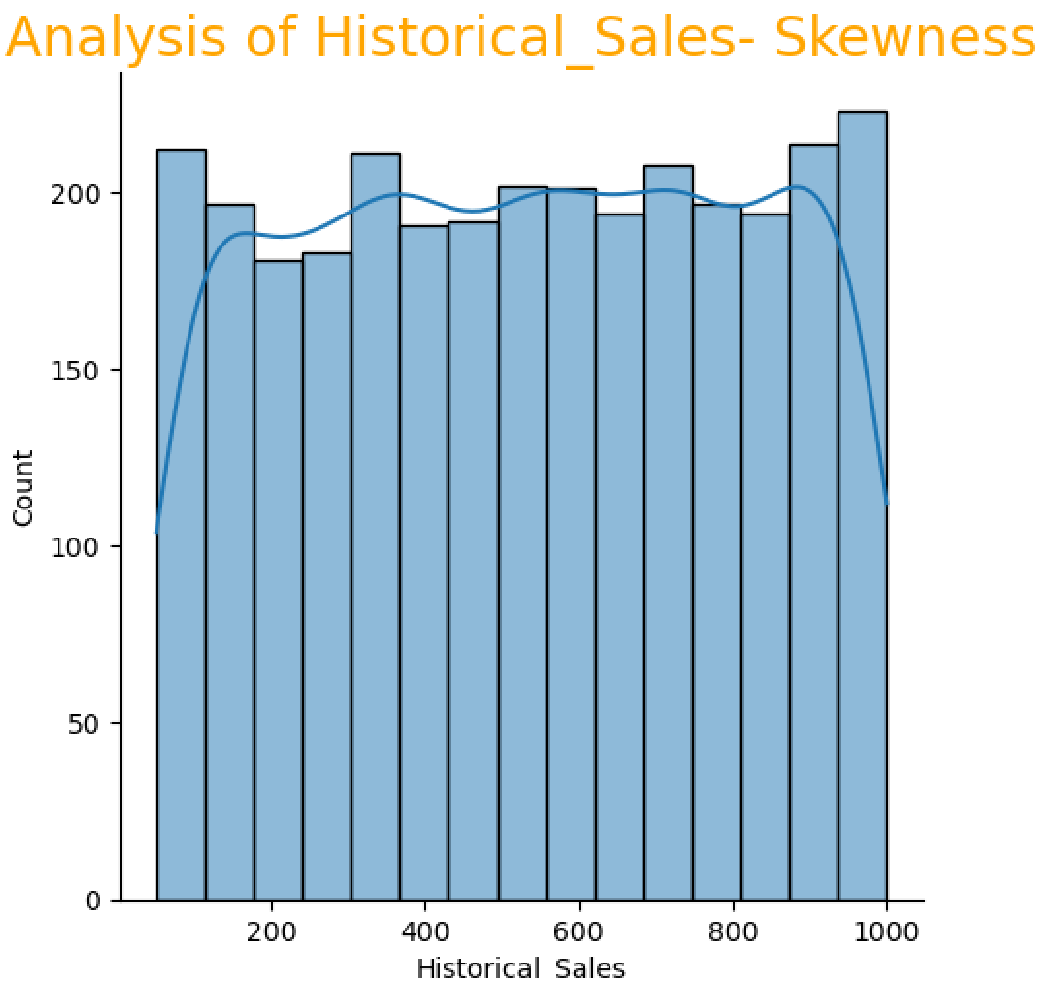
```
#creating a displot for historical sales variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Historical_Sales.skew())
```

```
sns.displot(df1.Historical_Sales, kde=True)
plt.title(f"Analysis of Historical_Sales- Skewness" , fontsize=20,
          color="orange")
```

```
Skewness is : -0.02305823773872843
```

```
Text(0.5, 1.0, 'Analysis of Historical_Sales- Skewness')
```

```
<Figure size 1200x600 with 0 Axes>
```

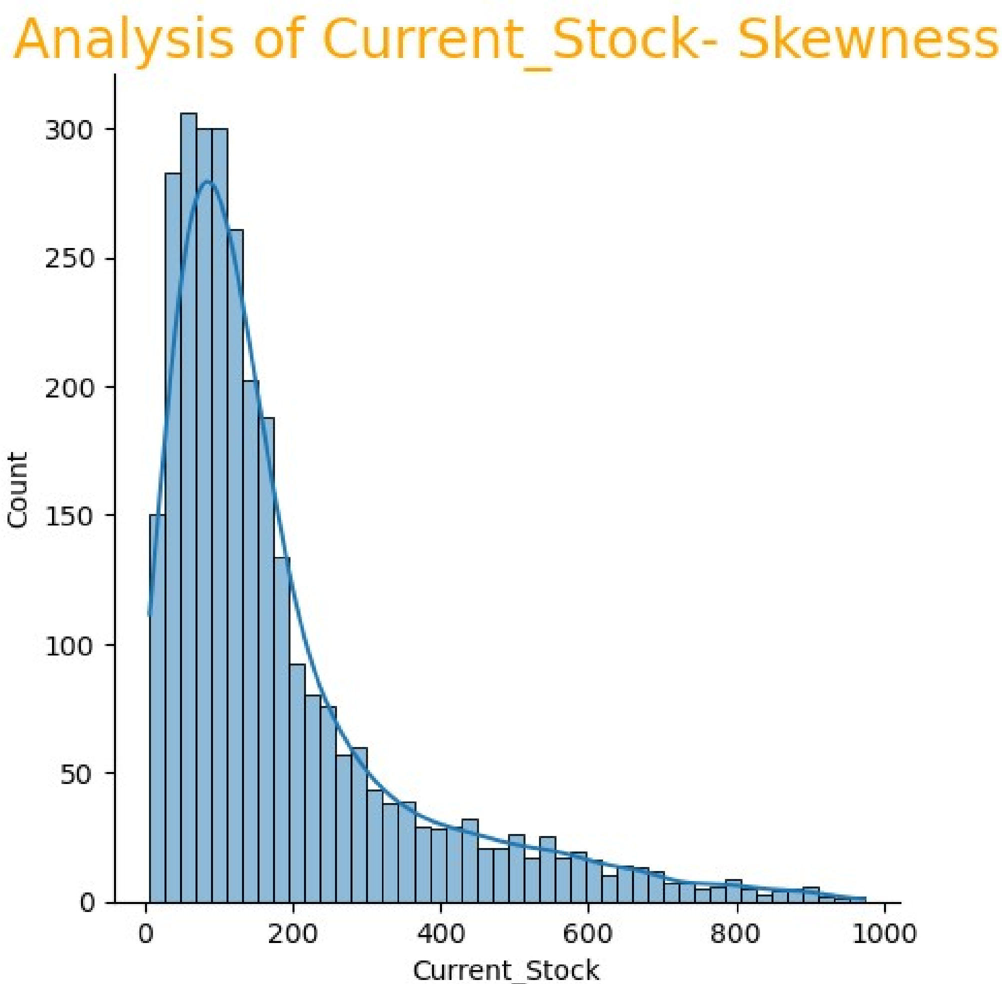


Current Stock

```
#creating a displot for current stock variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Current_Stock.skew())
sns.displot(df1.Current_Stock, kde=True)
plt.title(f"Analysis of Current_Stock- Skewness" , fontsize=20,
          color="orange")
```

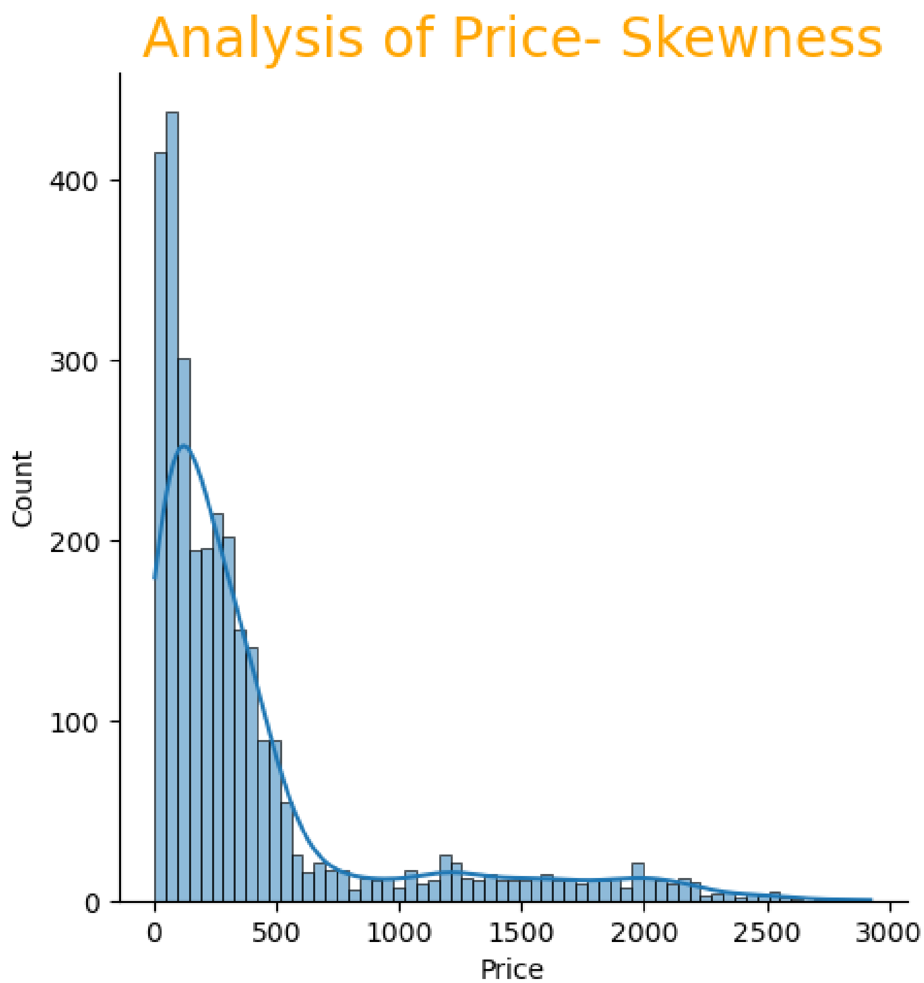
```
Skewness is : 1.8653378350592287
```

```
Text(0.5, 1.0, 'Analysis of Current_Stock- Skewness')

<Figure size 1200x600 with 0 Axes>
```



Price

```
#creating a displot for price variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Price.skew())
sns.displot(df1.Price, kde=True)
plt.title(f"Analysis of Price- Skewness" , fontsize=20,
          color="orange")

Skewness is : 2.178143755758012

Text(0.5, 1.0, 'Analysis of Price- Skewness')

<Figure size 1200x600 with 0 Axes>
```



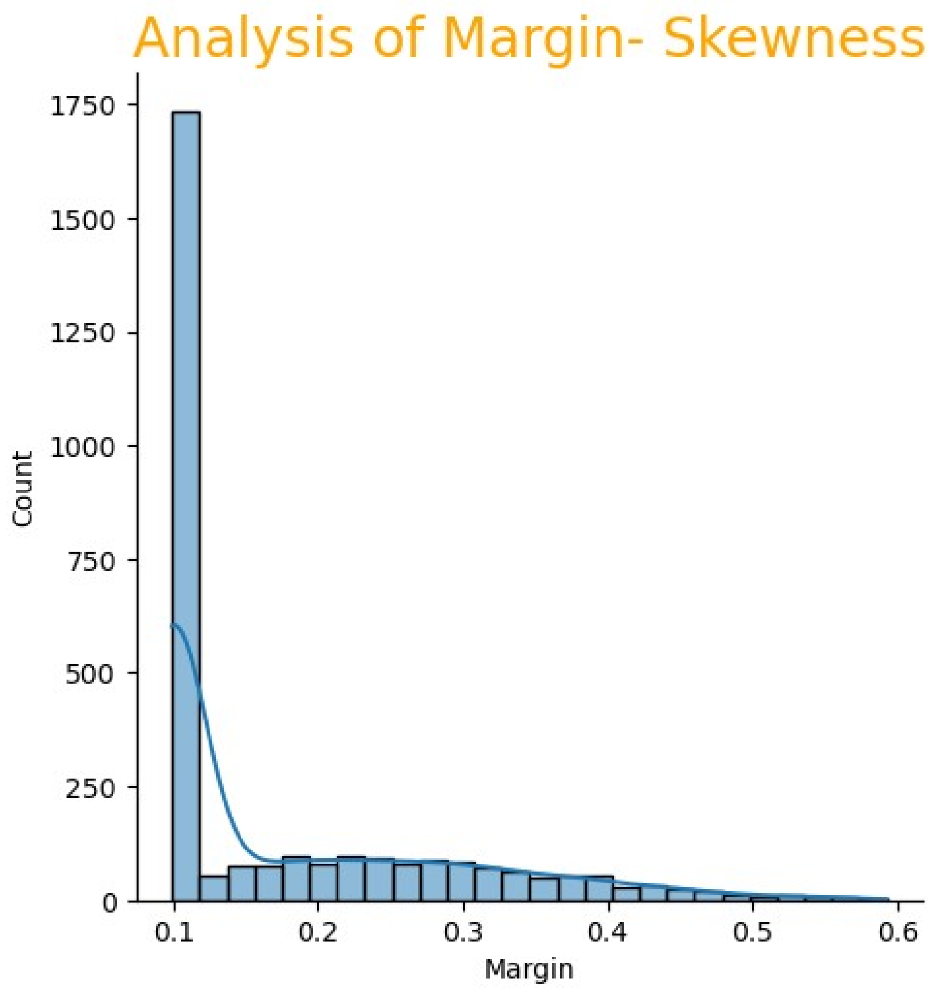
Margin

```
#creating a displot for margin variable
plt.figure(figsize=(12,6))
print("Skewness is :",df1.Margin.skew())
sns.displot(df1.Margin, kde=True)
plt.title(f"Analysis of Margin- Skewness" , fontsize=20,
          color="orange")
```

```
Skewness is : 1.3541456750787133
```

```
Text(0.5, 1.0, 'Analysis of Margin- Skewness')
```

```
<Figure size 1200x600 with 0 Axes>
```



Skewness Interpretation

#Skewness

1. It can be seen that all variables except Market Trend (left skewness) and Historical Sales (Normally Distributed)have right skewness.
2. Most values lie towards the lowers end of the distribution.
3. Due to skewness, the features need scaling.

Looking for values in each column

```
#function to look for values in each column
def values_in_columns(df_new):
    start=''
    end=''
    for i in df_new.columns:
        print(start+'Column Name--->'+i+end)
        print('Number of Unique Values', df_new[i].nunique(),'\n')
        print('Count of each unique value \n',
df_new[i].value_counts(), '\n')
```

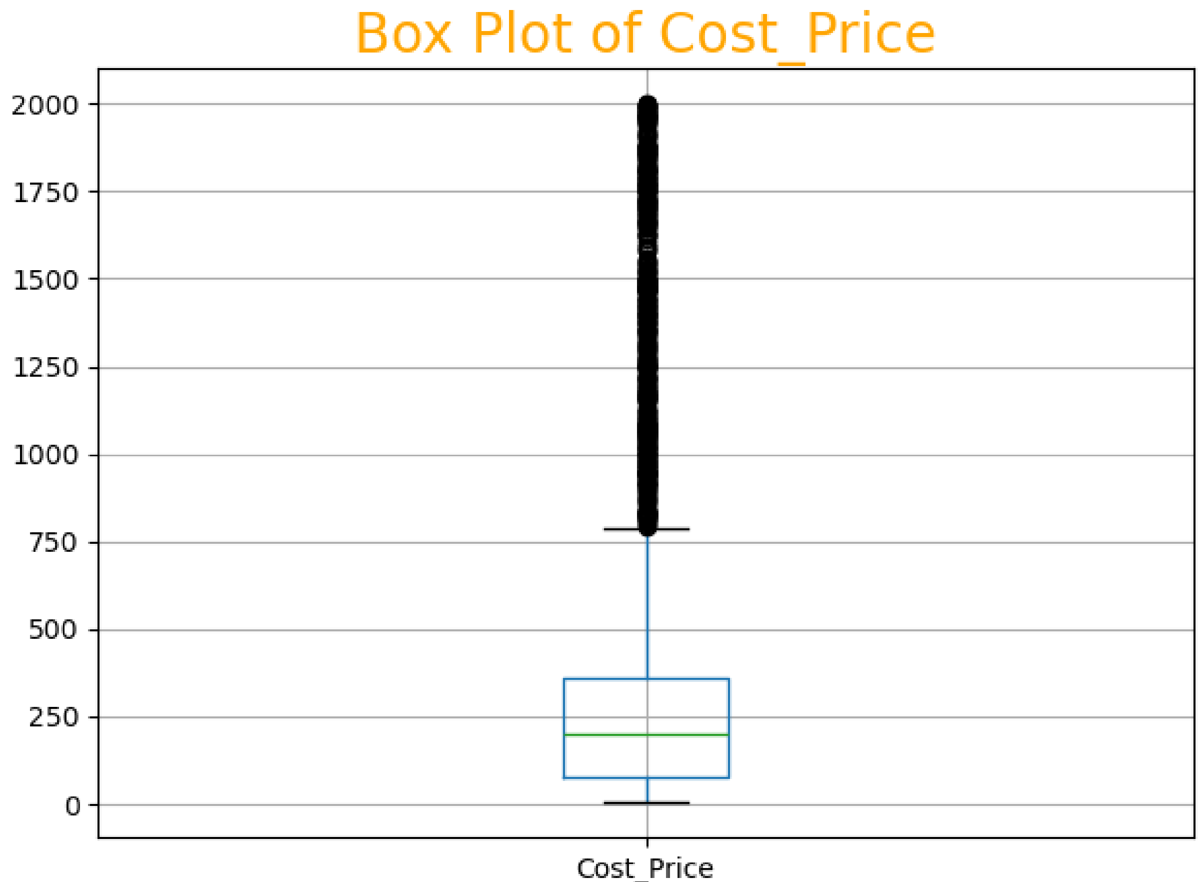
```
values_in_columns(df_new)

Column Name--->Category
Number of Unique Values 5

Count of each unique value
 Category
Sports            620
Electronics       618
Books             613
Clothing          584
Home & Kitchen    565
Name: count, dtype: int64

Column Name--->Cost_Price
Number of Unique Values 2917

Count of each unique value
 Cost_Price
82.60     3
46.21     3
79.72     3
89.87     2
49.56     2
         ..
86.11     1
10.16     1
135.21    1
88.94     1
118.70    1
Name: count, Length: 2917, dtype: int64

Column Name--->Season
Number of Unique Values 4

Count of each unique value
 Season
Spring    787
Summer    757
Winter    731
Fall      725
Name: count, dtype: int64

Column Name--->Market_Trend
Number of Unique Values 201

Count of each unique value
 Market_Trend
 0.56    27
 0.01    26
```

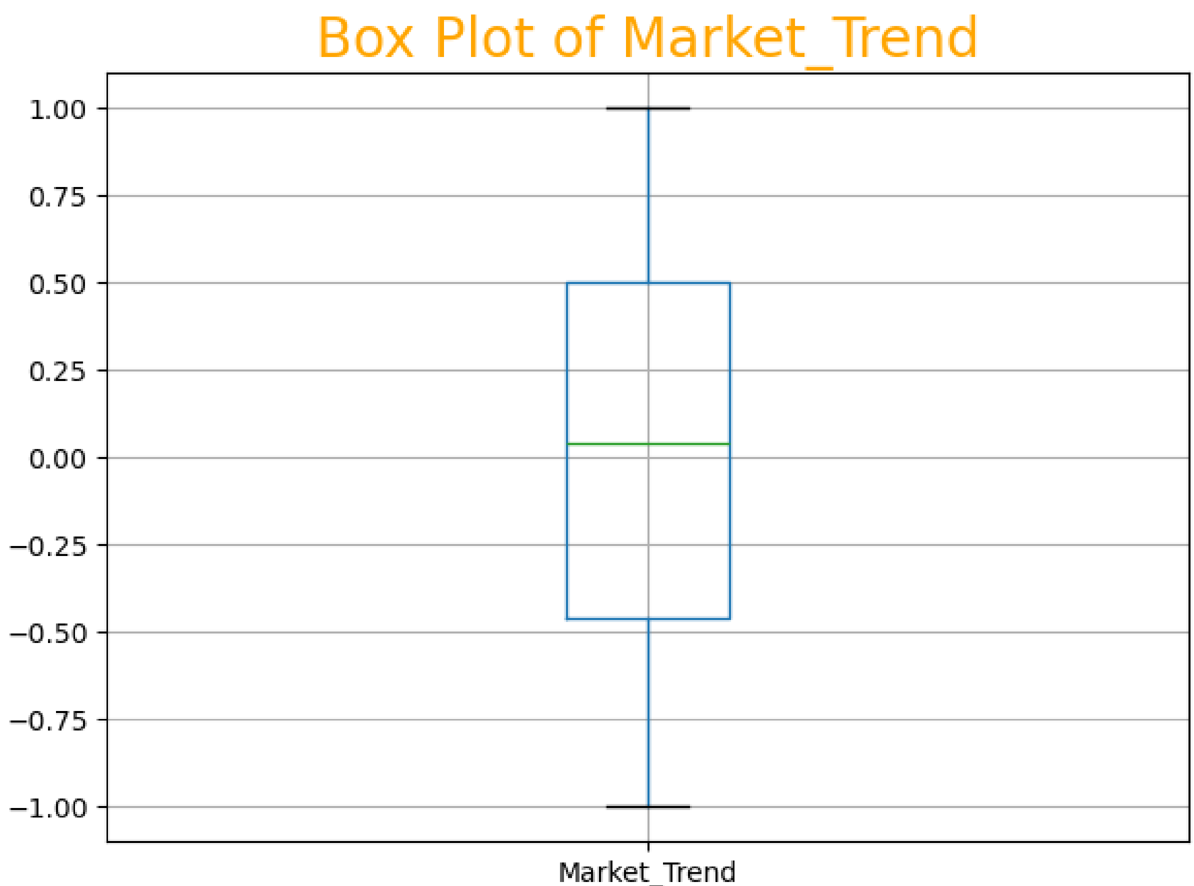
```
 0.22    26
 0.09    24
 0.32    23
         ..
-0.03     7
-0.50     7
-0.61     7
 1.00     6
-1.00     6
Name: count, Length: 201, dtype: int64

Column Name--->Historical_Sales
Number of Unique Values 921

Count of each unique value
 Historical_Sales
997    11
764    10
110    10
508     8
956     8
       ..
946     1
898     1
964     1
866     1
223     1
Name: count, Length: 921, dtype: int64

Column Name--->Current_Stock
Number of Unique Values 605

Count of each unique value
 Current_Stock
89     24
98     24
99     23
64     22
51     21
       ..
771     1
472     1
436     1
611     1
567     1
Name: count, Length: 605, dtype: int64

Column Name--->Price
Number of Unique Values 2921
```

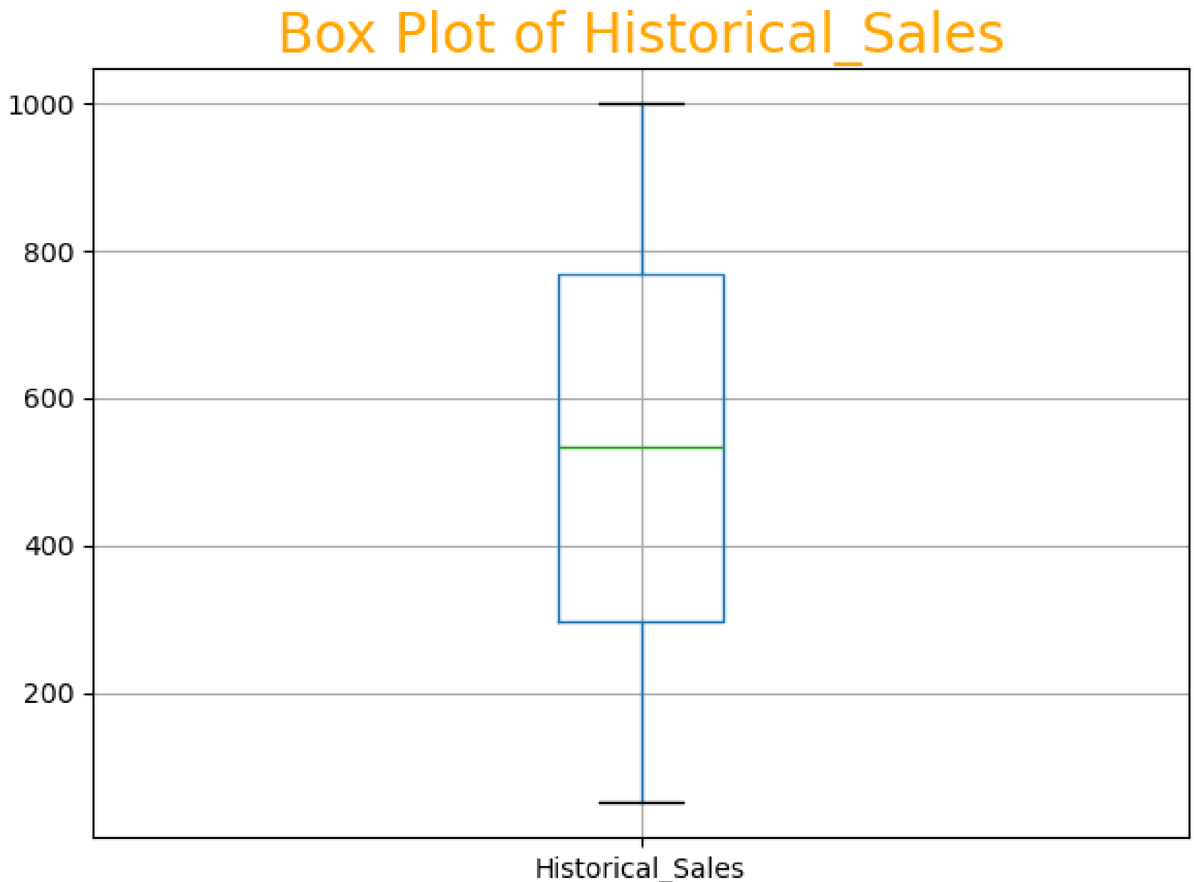
```
Count of each unique value
 Price
224.31     3
106.75     3
391.69     3
29.97      2
294.40     2
          ..
2432.38    1
829.61     1
508.44     1
237.46     1
175.48     1
Name: count, Length: 2921, dtype: int64

Column Name--->Margin
Number of Unique Values 2832

Count of each unique value
 Margin
0.100000    27
0.100000    15
0.100000    13
0.100000    11
0.100000     9
            ..
0.100009     1
0.100054     1
0.421371     1
0.100073     1
0.478349     1
Name: count, Length: 2832, dtype: int64
```

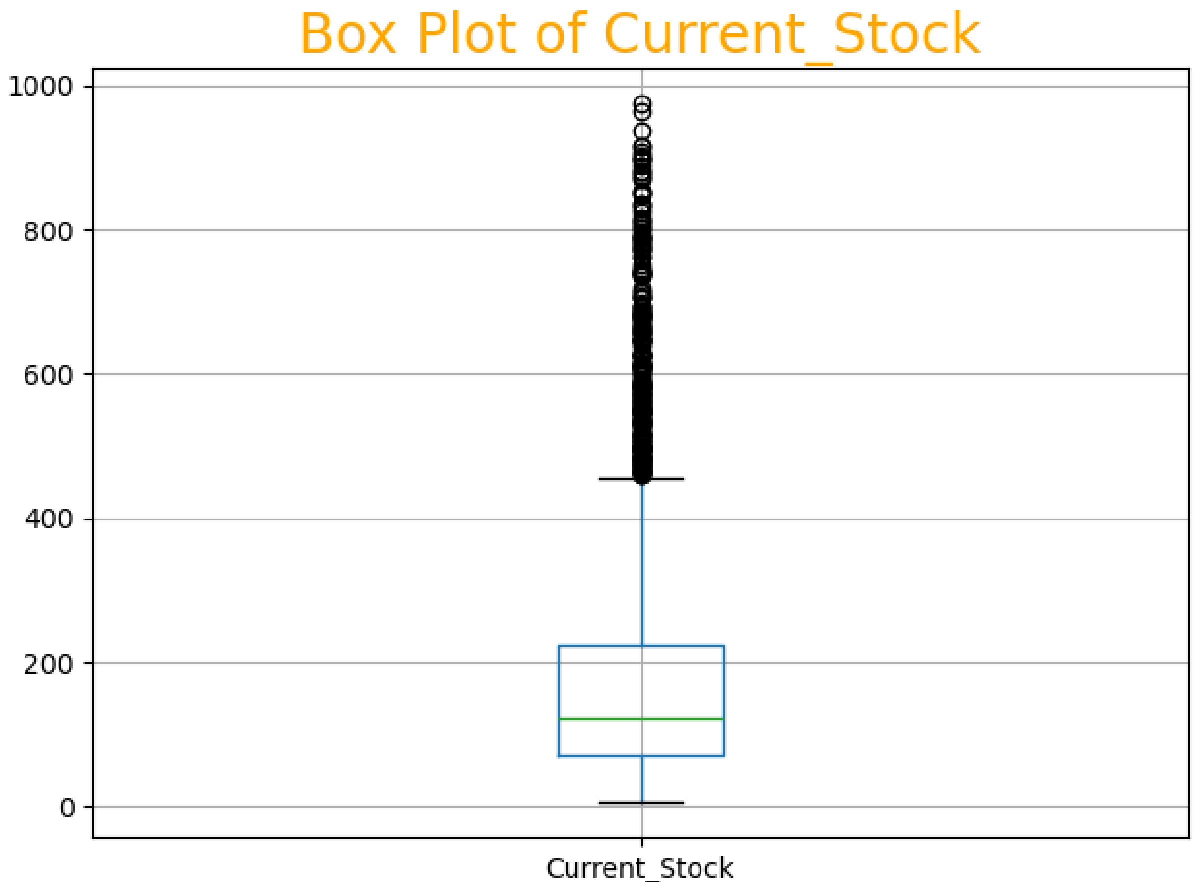
Univariate Analysis - By Boxplot

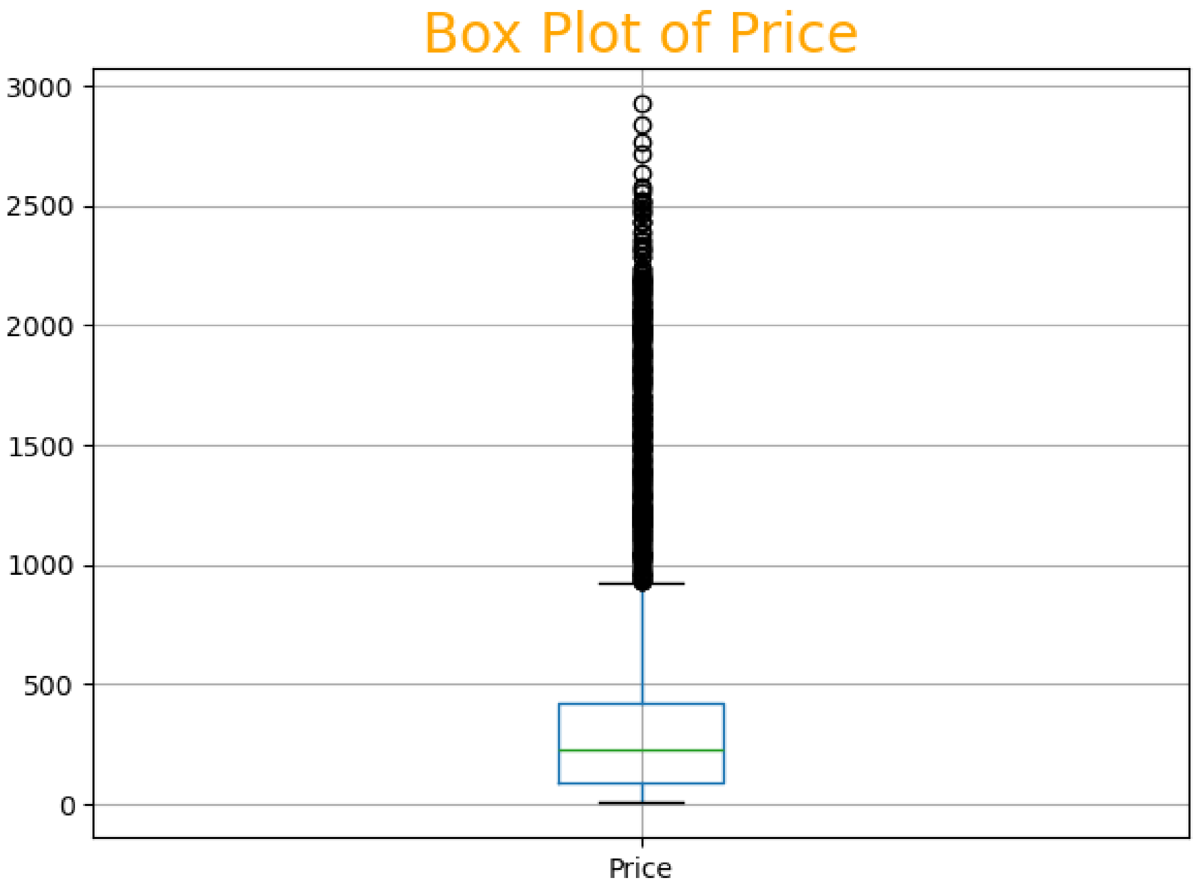
```
for i in df_new.drop(['Category', 'Season'],axis=1).columns:
    df_new.boxplot(column=i)
    plt.title(f'Box Plot of {i}',fontsize=20,color='orange')
    plt.tight_layout()
    plt.show()
```

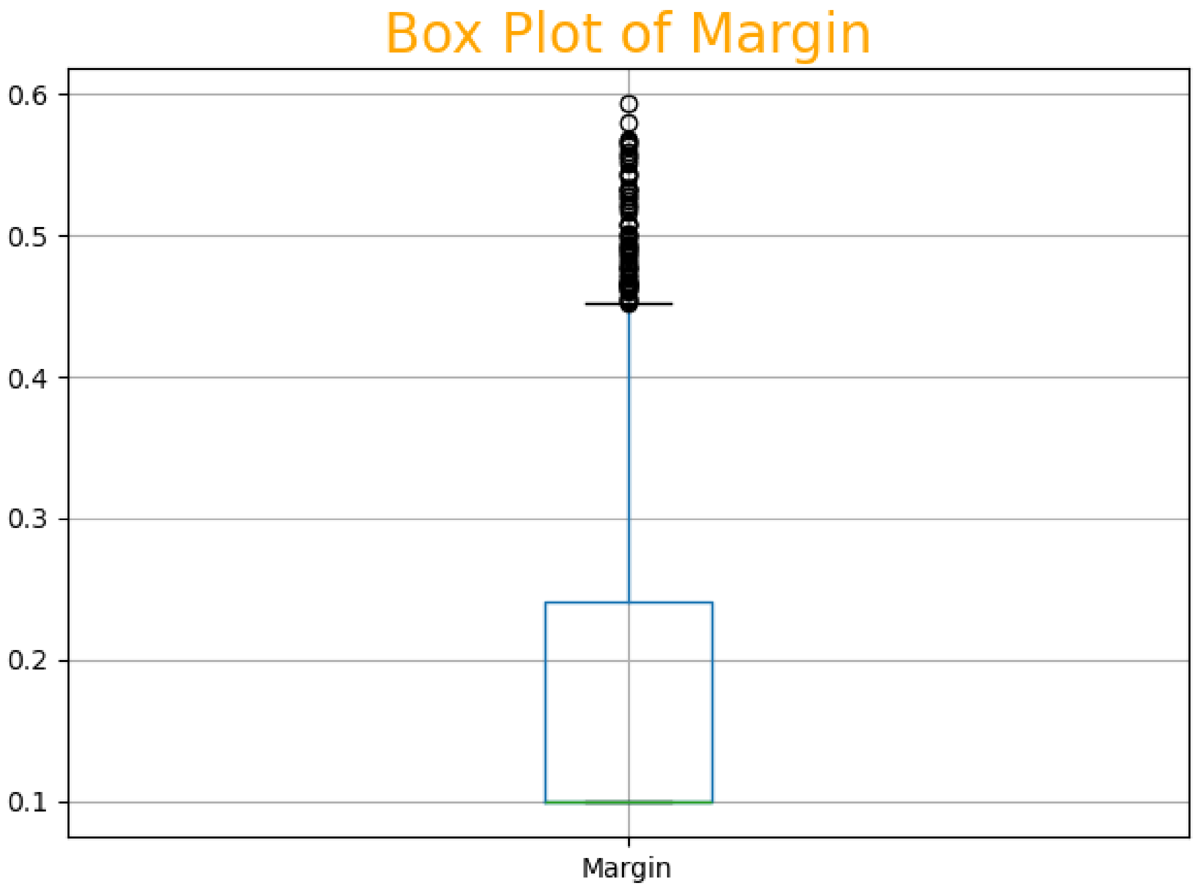

Box Plot of Cost_Price
2000
1750
1500
1250
1000
750
500
250
0
Cost_Price


Box Plot of Market_Trend
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Market_Trend


Box Plot of Historical_Sales
1000
800
600
400
200
Historical_Sales


Box Plot of Current_Stock
1000
800
600
400
200
0
Current_Stock

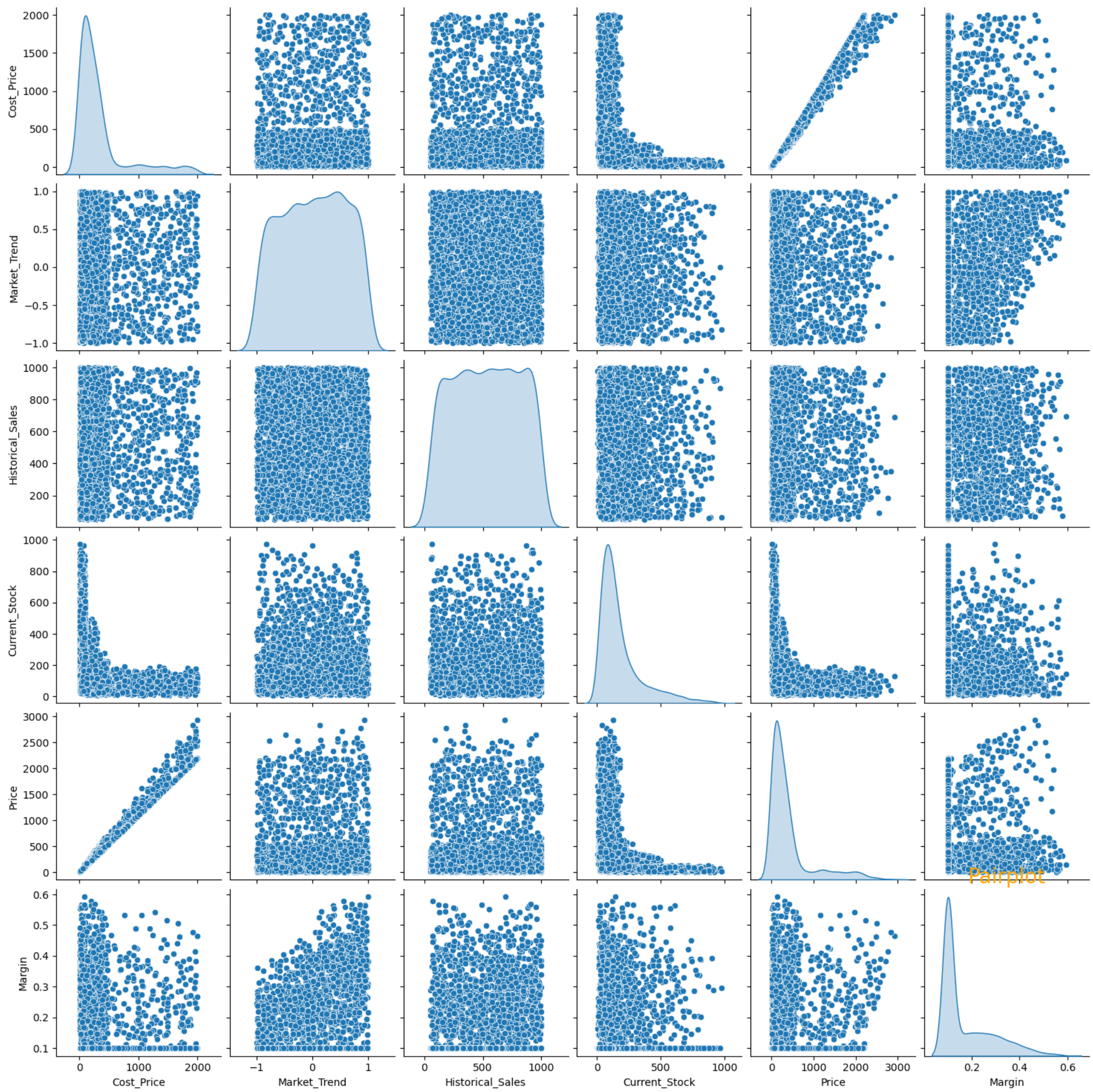

Box Plot of Price
3000
2500
2000
1500
1000
500
0
Price



Lot of features are having outliers so a scaling techniques is required

BiVariate Analysis

```
# plot two variables and examining bivariate plot of variables
sns.pairplot(df_new, diag_kind = 'kde')
plt.title(f"Pairplot" , fontsize=20,
          color="orange")

Text(0.5, 1.0, 'Pairplot')
```



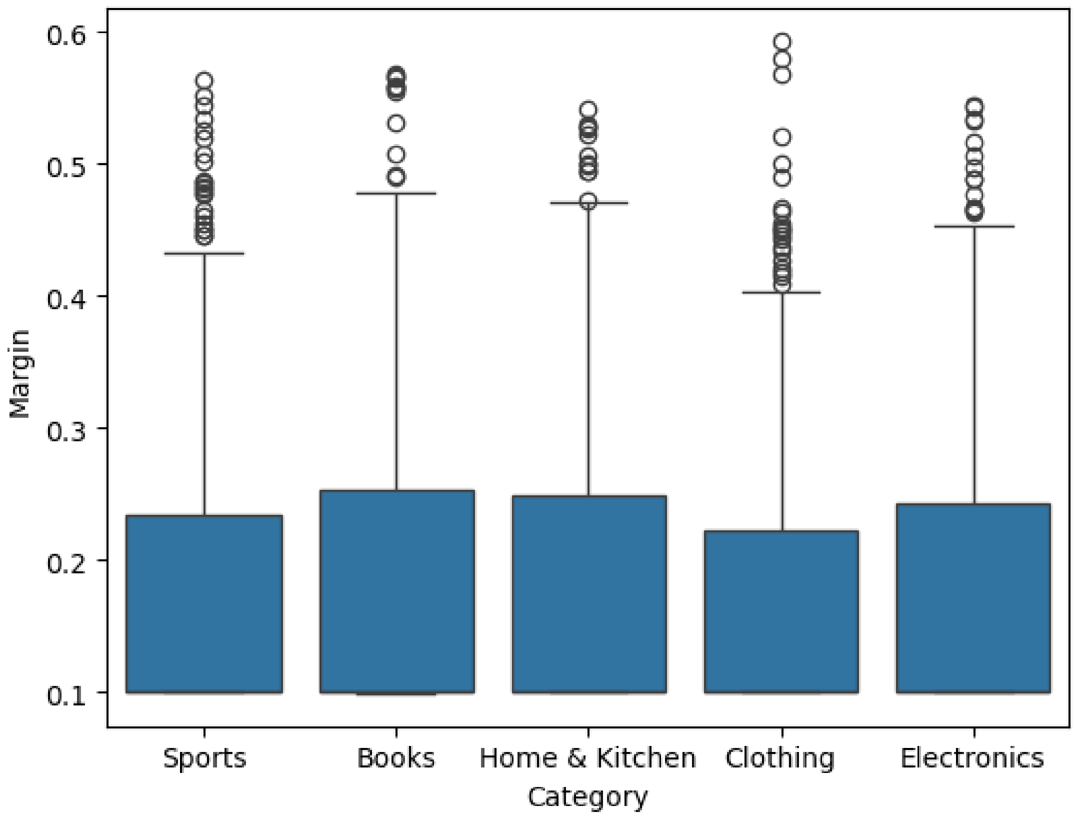
Observations from the pairplot

Observations

1. Cost_price has no visible relation with margin (target variable) but can be seen having a linear relation with price variable suggesting collinearity in the dataset. So cannot use linear regression for this problem.
2. Other variables show skewness in the distribution.
3. It can be seen that most of the data is on the lower end of the ranges.

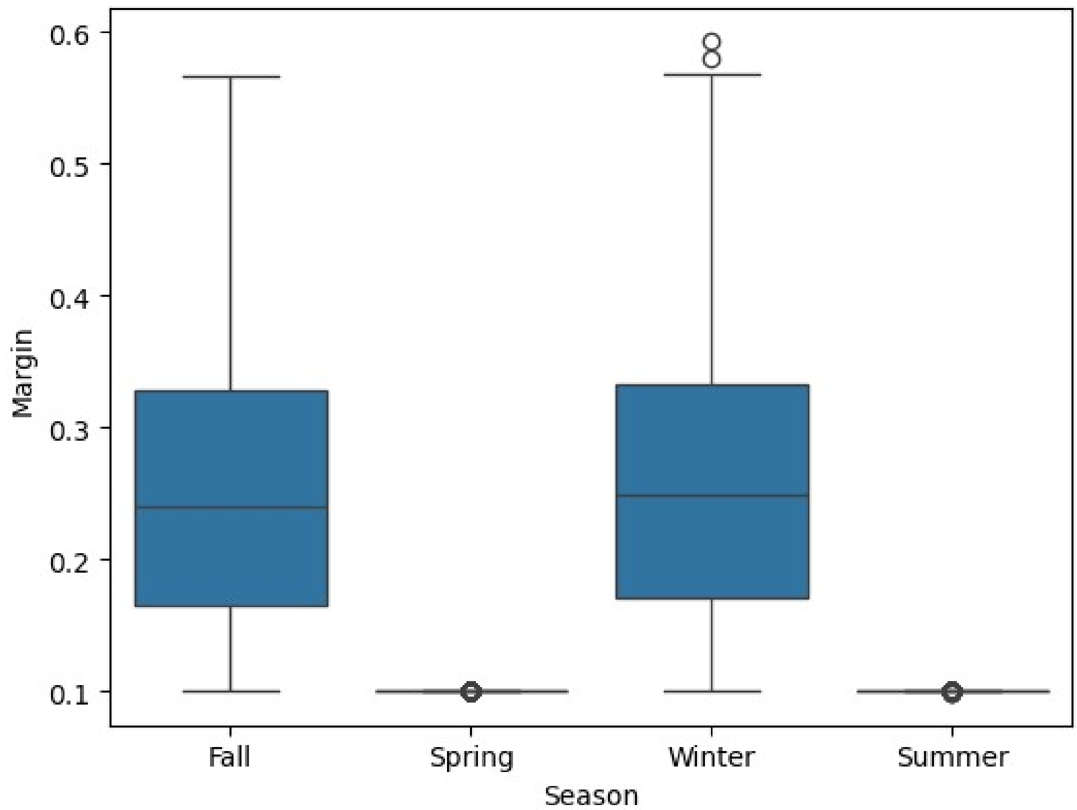
Categorical Feature Selection Using Boxplot

```
#generating a boxplot for category variable
sns.boxplot(x="Category", y="Margin", data=df_new)

<Axes: xlabel='Category', ylabel='Margin'>
```



Variance can be seen in the price range for this feature. Margin varies with different categories hence feature can be used for prediction.

```
#generating a boxplot for season variable
sns.boxplot(x="Season", y="Margin", data=df_new)

<Axes: xlabel='Season', ylabel='Margin'>
```



Variance can be seen in the price range for this feature. Margin varies in different seasons hence feature can be used for prediction.

Model Development

Importing Libraries

```
from sklearn.model_selection import train_test_split
#importing the necessary libraries
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingRegressor,
BaggingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
```

```
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RandomizedSearchCV

from sklearn import metrics
from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error

#installing xgboost
!pip install xgboost

Requirement already satisfied: xgboost in c:\users\shubh\anaconda3\
lib\site-packages (2.1.1)
Requirement already satisfied: numpy in c:\users\shubh\anaconda3\lib\
site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\shubh\anaconda3\lib\
site-packages (from xgboost) (1.13.1)


[notice] A new release of pip is available: 24.2 -> 24.3.1
[notice] To update, run: python.exe -m pip install --upgrade pip

from xgboost.sklearn import XGBRegressor
```

Splitting data into Train and Test Sets

It is necessary that we split the data into train and test sets before using scaling techniques, because we want the standardization scaling done using mean of the train set for the test set.

```
# Creating x and y variables for Train and Test Sets
x = df1.drop(['Margin'],axis=1)
y= df1['Margin']

#Check dataframes
x.head()

   Cost_Price  Market_Trend  Historical_Sales  Current_Stock
Price  \
0      140.62          0.92               462            107  192.23

1        6.97          0.60               615            420    7.67

2      385.23         -0.08               788             51  423.75

3        9.06         -0.60               750            705   11.06

4       87.14          0.62               969            192  120.92


   Category_Clothing  Category_Electronics  Category_Home & Kitchen  \
0              False                 False                    False
```

```
1              False                   False                      False
2              False                   False                       True
3              False                   False                      False
4              False                   False                      False

   Category_Sports  Season_Spring  Season_Summer  Season_Winter
0             True          False          False          False
1            False           True          False          False
2            False           True          False          False
3            False          False          False           True
4            False          False          False           True
```

```
y.head()
```

```
0    0.367017
1    0.100430
2    0.099992
3    0.220751
4    0.387652
Name: Margin, dtype: float64
```

```
#spliting using train_testsplit function
x_train, x_test, y_train, y_test = train_test_split(x,y,
test_size=0.20, random_state=1)
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train,
test_size=0.20, random_state=1)

#checking the row distribution
print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
print(x_val.shape, y_val.shape)
```

```
(1920, 12) (1920,)
(600, 12) (600,)
(480, 12) (480,)
```

Function for MAPE and adjusted R2 calculation

```
#Calculate MAPE
def mape(y_true, y_pred):
    return np.mean(np.abs(np.array(y_pred) - np.array(y_true)) /
np.array(y_true), axis=0)

#Calculate adjR
def adjR(y_true, y_pred,p):
    R2=r2_score(y_true,y_pred)
    n=10
    return 1-(1-R2)*(n-1)/(n-p-1)
```

Model Application

Model application and their performances compared

Linear Regression

```
# defining the model
LR1 = LinearRegression()
LR1.fit(x_train, y_train)

# Making Predictions
y_LR1_predtr= LR1.predict(x_train)
y_LR1_predvl= LR1.predict(x_val)
y_LR1_predte= LR1.predict(x_test)

LR1.coef_
```

```
array([-6.93237655e-04,  3.86834986e-02,  8.16062725e-06,
1.33289637e-06,
        5.85210021e-04, -1.55117325e-02, -9.05496398e-03, -
1.08317076e-02,
       -1.17545998e-02, -1.20976985e-01, -1.22831679e-01,
4.65138489e-03])
```

```
# Performance on train data
LR1_tr_R2score=r2_score(y_train,y_LR1_predtr)
LR1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_LR1_predtr))
LR1_tr_MSE=mean_squared_error(y_train, y_LR1_predtr)
LR1_tr_MAE=mean_absolute_error(y_train, y_LR1_predtr)
LR1_tr_MAPE=mape(y_train, y_LR1_predtr)
LR1_tr_AR2=adjR(y_train, y_LR1_predtr,p=len(x.columns))

# Performance on val data
LR1_vl_R2score=r2_score(y_val,y_LR1_predvl)
LR1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_LR1_predvl))
LR1_vl_MSE=mean_squared_error(y_val, y_LR1_predvl)
LR1_vl_MAE=mean_absolute_error(y_val, y_LR1_predvl)
LR1_vl_MAPE=mape(y_val, y_LR1_predvl)
LR1_vl_AR2=adjR(y_val, y_LR1_predvl,p=len(x.columns))

# Performance on test data
LR1_te_R2score=r2_score(y_test,y_LR1_predte)
LR1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_LR1_predte))
LR1_te_MSE=mean_squared_error(y_test, y_LR1_predte)
LR1_te_MAE=mean_absolute_error(y_test, y_LR1_predte)
LR1_te_MAPE=mape(y_test, y_LR1_predte)
LR1_te_AR2=adjR(y_test, y_LR1_predte,p=len(x.columns))

model_comprsn=pd.DataFrame({'Algorithm':['Simple Linear Reg Model'],
                       'train Score':LR1_tr_R2score,'RMSE_tr':
LR1_tr_RMSE, 'MSE_tr': LR1_tr_MSE, 'MAE_tr': LR1_tr_MAE,
```

```
                         "Mape_tr":LR1_tr_MAPE,
"Adjusted_r2_tr":LR1_tr_AR2,
                        'Val Score':LR1_vl_R2score,'RMSE_vl':
LR1_vl_RMSE, 'MSE_vl': LR1_vl_MSE, 'MAE_vl': LR1_vl_MAE,
                         "Mape_val":LR1_vl_MAPE,
"Adjusted_r2_val":LR1_vl_AR2,
                      'test Score':LR1_te_R2score,'RMSE_te':
LR1_te_RMSE, 'MSE_te': LR1_te_MSE, 'MAE_te': LR1_te_MAE,
                        "Mape_te":LR1_te_MAPE,
"Adjusted_r2_te":LR1_te_AR2})
model_comprsn
```

```
                 Algorithm  train Score   RMSE_tr    MSE_tr    MAE_tr
\
0  Simple Linear Reg Model      0.66171  0.062829  0.003947  0.045856


    Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl    MSE_vl
MAE_vl  \
0  0.288776        2.014869   0.661693  0.066296  0.004395  0.047979


   Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te    MAE_te
\
0  0.297673         2.014922     0.65576  0.065689  0.004315  0.047947


    Mape_te  Adjusted_r2_te
0  0.313666        2.032721
```

Lasso Regression

```
# defining the model
Lasso1 = Lasso(alpha=1)
Lasso1.fit(x_train, y_train)

# Making Predictions
y_Lasso1_predtr= Lasso1.predict(x_train)
y_Lasso1_predvl= Lasso1.predict(x_val)
y_Lasso1_predte= Lasso1.predict(x_test)

Lasso1.coef_
```

```
array([-0.00056398,  0.        ,  0.        ,  0.        ,
0.00048413,
       -0.        , -0.        , -0.        , -0.        , -
0.        ,
       -0.        ,  0.        ])
```

Most of the lasso coefficient are zero, we can even take them out as it don't effect the margin.

```
# Performance on train data
Lasso1_tr_R2score=r2_score(y_train,y_Lasso1_predtr)
Lasso1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_Lasso1_predtr))
Lasso1_tr_MSE=mean_squared_error(y_train, y_Lasso1_predtr)
Lasso1_tr_MAE=mean_absolute_error(y_train, y_Lasso1_predtr)
Lasso1_tr_MAPE=mape(y_train, y_Lasso1_predtr)
Lasso1_tr_AR2=adjR(y_train, y_Lasso1_predtr,p=len(x.columns))

# Performance on val data
Lasso1_vl_R2score=r2_score(y_val,y_Lasso1_predvl)
Lasso1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_Lasso1_predvl))
Lasso1_vl_MSE=mean_squared_error(y_val, y_Lasso1_predvl)
Lasso1_vl_MAE=mean_absolute_error(y_val, y_Lasso1_predvl)
Lasso1_vl_MAPE=mape(y_val, y_Lasso1_predvl)
Lasso1_vl_AR2=adjR(y_val, y_Lasso1_predvl,p=len(x.columns))

# Performance on test data
Lasso1_te_R2score=r2_score(y_test,y_Lasso1_predte)
Lasso1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_Lasso1_predte))
Lasso1_te_MSE=mean_squared_error(y_test, y_Lasso1_predte)
Lasso1_te_MAE=mean_absolute_error(y_test, y_Lasso1_predte)
Lasso1_te_MAPE=mape(y_test, y_Lasso1_predte)
Lasso1_te_AR2=adjR(y_test, y_Lasso1_predte,p=len(x.columns))

Lasso1_df=pd.DataFrame({'Algorithm':['SLinear-Reg (Lasso)'],
                       'train Score':Lasso1_tr_R2score,'RMSE_tr':
Lasso1_tr_RMSE, 'MSE_tr': Lasso1_tr_MSE, 'MAE_tr': Lasso1_tr_MAE,
                         "Mape_tr":Lasso1_tr_MAPE,
"Adjusted_r2_tr":Lasso1_tr_AR2,
                        'Val Score':Lasso1_vl_R2score,'RMSE_vl':
Lasso1_vl_RMSE, 'MSE_vl': Lasso1_vl_MSE, 'MAE_vl': Lasso1_vl_MAE,
                         "Mape_val":Lasso1_vl_MAPE,
"Adjusted_r2_val":Lasso1_vl_AR2,
                      'test Score':Lasso1_te_R2score,'RMSE_te':
Lasso1_te_RMSE, 'MSE_te': Lasso1_te_MSE, 'MAE_te': Lasso1_te_MAE,
                        "Mape_te":Lasso1_te_MAPE,
"Adjusted_r2_te":Lasso1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
Lasso1_df]).reset_index(drop=True)

model_comprsn
```

```
                 Algorithm  train Score   RMSE_tr    MSE_tr    MAE_tr  \
0  Simple Linear Reg Model     0.661710  0.062829  0.003947  0.045856

1      SLinear-Reg (Lasso)     0.254273  0.093284  0.008702  0.074488


    Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl    MSE_vl
```

```
MAE_vl  \
0  0.288776        2.014869   0.661693  0.066296  0.004395  0.047979

1  0.476757        3.237182   0.256190  0.098301  0.009663  0.078625


   Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te    MAE_te
\
0  0.297673         2.014922    0.655760  0.065689  0.004315  0.047947

1  0.479366         3.231430    0.277708  0.095152  0.009054  0.075368


    Mape_te  Adjusted_r2_te
0  0.313666        2.032721
1  0.478237        3.166876
```

Ridge Regression

```
# defining the model
Ridge1 = Ridge(alpha=0.5)
Ridge1.fit(x_train, y_train)

# Making Predictions
y_Ridge1_predtr= Ridge1.predict(x_train)
y_Ridge1_predvl= Ridge1.predict(x_val)
y_Ridge1_predte= Ridge1.predict(x_test)

Ridge1.coef_

array([-6.94653744e-04,  3.86291046e-02,  8.15430214e-06,
1.59166353e-06,
        5.86356303e-04, -1.53597192e-02, -8.81070035e-03, -
1.06558285e-02,
       -1.15669454e-02, -1.20543174e-01, -1.22386494e-01,
4.90797772e-03])

# Performance on train data
Ridge1_tr_R2score=r2_score(y_train,y_Ridge1_predtr)
Ridge1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_Ridge1_predtr))
Ridge1_tr_MSE=mean_squared_error(y_train, y_Ridge1_predtr)
Ridge1_tr_MAE=mean_absolute_error(y_train, y_Ridge1_predtr)
Ridge1_tr_MAPE=mape(y_train, y_Ridge1_predtr)
Ridge1_tr_AR2=adjR(y_train, y_Ridge1_predtr,p=len(x.columns))

# Performance on val data
Ridge1_vl_R2score=r2_score(y_val,y_Ridge1_predvl)
Ridge1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_Ridge1_predvl))
Ridge1_vl_MSE=mean_squared_error(y_val, y_Ridge1_predvl)
Ridge1_vl_MAE=mean_absolute_error(y_val, y_Ridge1_predvl)
Ridge1_vl_MAPE=mape(y_val, y_Ridge1_predvl)
```

```
Ridge1_vl_AR2=adjR(y_val, y_Ridge1_predvl,p=len(x.columns))

# Performance on test data
Ridge1_te_R2score=r2_score(y_test,y_Ridge1_predte)
Ridge1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_Ridge1_predte))
Ridge1_te_MSE=mean_squared_error(y_test, y_Ridge1_predte)
Ridge1_te_MAE=mean_absolute_error(y_test, y_Ridge1_predte)
Ridge1_te_MAPE=mape(y_test, y_Ridge1_predte)
Ridge1_te_AR2=adjR(y_test, y_Ridge1_predte,p=len(x.columns))

Ridge1_df=pd.DataFrame({'Algorithm':['SLinear-Reg (Ridge)'],
                       'train Score':Ridge1_tr_R2score,'RMSE_tr':
Ridge1_tr_RMSE, 'MSE_tr': Ridge1_tr_MSE, 'MAE_tr': Ridge1_tr_MAE,
                         "Mape_tr":Ridge1_tr_MAPE,
"Adjusted_r2_tr":Ridge1_tr_AR2,
                        'Val Score':Ridge1_vl_R2score,'RMSE_vl':
Ridge1_vl_RMSE, 'MSE_vl': Ridge1_vl_MSE, 'MAE_vl': Ridge1_vl_MAE,
                         "Mape_val":Ridge1_vl_MAPE,
"Adjusted_r2_val":Ridge1_vl_AR2,
                      'test Score':Ridge1_te_R2score,'RMSE_te':
Ridge1_te_RMSE, 'MSE_te': Ridge1_te_MSE, 'MAE_te': Ridge1_te_MAE,
                        "Mape_te":Ridge1_te_MAPE,
"Adjusted_r2_te":Ridge1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
Ridge1_df]).reset_index(drop=True)

model_comprsn

                 Algorithm  train Score   RMSE_tr    MSE_tr    MAE_tr
\
0  Simple Linear Reg Model     0.661710  0.062829  0.003947  0.045856

1      SLinear-Reg (Lasso)     0.254273  0.093284  0.008702  0.074488

2      SLinear-Reg (Ridge)     0.661708  0.062829  0.003948  0.045850


    Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl    MSE_vl
MAE_vl  \
0  0.288776        2.014869   0.661693  0.066296  0.004395  0.047979

1  0.476757        3.237182   0.256190  0.098301  0.009663  0.078625

2  0.288610        2.014877   0.661706  0.066294  0.004395  0.047972


   Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te    MAE_te
\
0  0.297673         2.014922    0.655760  0.065689  0.004315  0.047947

1  0.479366         3.231430    0.277708  0.095152  0.009054  0.075368
```

```
2  0.297532         2.014883    0.655822  0.065683  0.004314  0.047934

    Mape_te  Adjusted_r2_te
0  0.313666        2.032721
1  0.478237        3.166876
2  0.313473        2.032534
```

All regression models are performing poorly with values of 0.66, 0.25 and 0.66 and high adjusted r2 values. This was expected as our dataset is not linear and has collinearlity present.

Now to check for other regressors

KNN Regressor

```
# defining the model
knn1 = KNeighborsRegressor(n_neighbors=4,weights='distance')
knn1.fit(x_train, y_train)

# Making Predictions
y_knn1_predtr= knn1.predict(x_train)
y_knn1_predvl= knn1.predict(x_val)
y_knn1_predte= knn1.predict(x_test)
[186]
# Performance on train data
knn1_tr_R2score=r2_score(y_train,y_knn1_predtr)
knn1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_knn1_predtr))
knn1_tr_MSE=mean_squared_error(y_train, y_knn1_predtr)
knn1_tr_MAE=mean_absolute_error(y_train, y_knn1_predtr)
knn1_tr_MAPE=mape(y_train, y_knn1_predtr)
knn1_tr_AR2=adjR(y_train, y_knn1_predtr,p=len(x.columns))

# Performance on val data
knn1_vl_R2score=r2_score(y_val,y_knn1_predvl)
knn1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_knn1_predvl))
knn1_vl_MSE=mean_squared_error(y_val, y_knn1_predvl)
knn1_vl_MAE=mean_absolute_error(y_val, y_knn1_predvl)
knn1_vl_MAPE=mape(y_val, y_knn1_predvl)
knn1_vl_AR2=adjR(y_val, y_knn1_predvl,p=len(x.columns))

# Performance on test data
knn1_te_R2score=r2_score(y_test,y_knn1_predte)
knn1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_knn1_predte))
knn1_te_MSE=mean_squared_error(y_test, y_knn1_predte)
knn1_te_MAE=mean_absolute_error(y_test, y_knn1_predte)
knn1_te_MAPE=mape(y_test, y_knn1_predte)
knn1_te_AR2=adjR(y_test, y_knn1_predte,p=len(x.columns))
```

```
knn1_df=pd.DataFrame({'Algorithm':['KNN'],
                       'train Score':knn1_tr_R2score,'RMSE_tr':
knn1_tr_RMSE, 'MSE_tr': knn1_tr_MSE, 'MAE_tr': knn1_tr_MAE,
                         "Mape_tr":knn1_tr_MAPE,
"Adjusted_r2_tr":knn1_tr_AR2,
                        'Val Score':knn1_vl_R2score,'RMSE_vl':
knn1_vl_RMSE, 'MSE_vl': knn1_vl_MSE, 'MAE_vl': knn1_vl_MAE,
                         "Mape_val":knn1_vl_MAPE,
"Adjusted_r2_val":knn1_vl_AR2,
                      'test Score':knn1_te_R2score,'RMSE_te':
knn1_te_RMSE, 'MSE_te': knn1_te_MSE, 'MAE_te': knn1_te_MAE,
                        "Mape_te":knn1_te_MAPE,
"Adjusted_r2_te":knn1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
knn1_df]).reset_index(drop=True)

model_comprsn

                 Algorithm  train Score   RMSE_tr    MSE_tr    MAE_tr
\
0  Simple Linear Reg Model     0.661710  0.062829  0.003947  0.045856

1      SLinear-Reg (Lasso)     0.254273  0.093284  0.008702  0.074488

2      SLinear-Reg (Ridge)     0.661708  0.062829  0.003948  0.045850

3                      KNN     1.000000  0.000000  0.000000  0.000000


    Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl    MSE_vl
MAE_vl  \
0  0.288776        2.014869   0.661693  0.066296  0.004395  0.047979

1  0.476757        3.237182   0.256190  0.098301  0.009663  0.078625

2  0.288610        2.014877   0.661706  0.066294  0.004395  0.047972

3  0.000000        1.000000   0.223361  0.100447  0.010090  0.069303


   Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te    MAE_te
\
0  0.297673         2.014922    0.655760  0.065689  0.004315  0.047947

1  0.479366         3.231430    0.277708  0.095152  0.009054  0.075368

2  0.297532         2.014883    0.655822  0.065683  0.004314  0.047934

3  0.388892         3.329918    0.260048  0.096308  0.009275  0.066637
```

```
    Mape_te  Adjusted_r2_te
0  0.313666        2.032721
1  0.478237        3.166876
2  0.313473        2.032534
3  0.403614        3.219857
```

KNN can be seen overfitting as it performs very well on the training set but on validation set and test set, the performance is very low.

Support Vector Regression

```
# defining the model
SVR1 = SVR(gamma='auto',C=10.0, epsilon=0.2,kernel='rbf')
SVR1.fit(x_train, y_train)

# Making Predictions
y_SVR1_predtr= SVR1.predict(x_train)
y_SVR1_predvl= SVR1.predict(x_val)
y_SVR1_predte= SVR1.predict(x_test)
[189]
# Performance on train data
SVR1_tr_R2score=r2_score(y_train,y_SVR1_predtr)
SVR1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_SVR1_predtr))
SVR1_tr_MSE=mean_squared_error(y_train, y_SVR1_predtr)
SVR1_tr_MAE=mean_absolute_error(y_train, y_SVR1_predtr)
SVR1_tr_MAPE=mape(y_train, y_SVR1_predtr)
SVR1_tr_AR2=adjR(y_train, y_SVR1_predtr,p=len(x.columns))

# Performance on val data
SVR1_vl_R2score=r2_score(y_val,y_SVR1_predvl)
SVR1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_SVR1_predvl))
SVR1_vl_MSE=mean_squared_error(y_val, y_SVR1_predvl)
SVR1_vl_MAE=mean_absolute_error(y_val, y_SVR1_predvl)
SVR1_vl_MAPE=mape(y_val, y_SVR1_predvl)
SVR1_vl_AR2=adjR(y_val, y_SVR1_predvl,p=len(x.columns))

# Performance on test data
SVR1_te_R2score=r2_score(y_test,y_SVR1_predte)
SVR1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_SVR1_predte))
SVR1_te_MSE=mean_squared_error(y_test, y_SVR1_predte)
SVR1_te_MAE=mean_absolute_error(y_test, y_SVR1_predte)
SVR1_te_MAPE=mape(y_test, y_SVR1_predte)
SVR1_te_AR2=adjR(y_test, y_SVR1_predte,p=len(x.columns))

SVR1_df=pd.DataFrame({'Algorithm':['SVR with kernel rbf'],
                       'train Score':SVR1_tr_R2score,'RMSE_tr':
SVR1_tr_RMSE, 'MSE_tr': SVR1_tr_MSE, 'MAE_tr': SVR1_tr_MAE,
                         "Mape_tr":SVR1_tr_MAPE,
```

```
"Adjusted_r2_tr":SVR1_tr_AR2,
                        'Val Score':SVR1_vl_R2score,'RMSE_vl':
SVR1_vl_RMSE, 'MSE_vl': SVR1_vl_MSE, 'MAE_vl': SVR1_vl_MAE,
                         "Mape_val":SVR1_vl_MAPE,
"Adjusted_r2_val":SVR1_vl_AR2,
                      'test Score':SVR1_te_R2score,'RMSE_te':
SVR1_te_RMSE, 'MSE_te': SVR1_te_MSE, 'MAE_te': SVR1_te_MAE,
                        "Mape_te":SVR1_te_MAPE,
"Adjusted_r2_te":SVR1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
SVR1_df]).reset_index(drop=True)

model_comprsn
```

	Algorithm	train Score	RMSE_tr	MSE_tr	MAE_tr
0	Simple Linear Reg Model	0.661710	0.062829	0.003947	0.045856
1	SLinear-Reg (Lasso)	0.254273	0.093284	0.008702	0.074488
2	SLinear-Reg (Ridge)	0.661708	0.062829	0.003948	0.045850
3	KNN	1.000000	0.000000	0.000000	0.000000
4	SVR with kernel rbf	-1.333553	0.165015	0.027230	0.150942

	Mape_tr	Adjusted_r2_tr	Val Score	RMSE_vl	MSE_vl	MAE_vl
0	0.288776	2.014869	0.661693	0.066296	0.004395	0.047979
1	0.476757	3.237182	0.256190	0.098301	0.009663	0.078625
2	0.288610	2.014877	0.661706	0.066294	0.004395	0.047972
3	0.000000	1.000000	0.223361	0.100447	0.010090	0.069303
4	1.311353	8.000659	-1.116560	0.165823	0.027497	0.151230

	Mape_val	Adjusted_r2_val	test Score	RMSE_te	MSE_te	MAE_te
0	0.297673	2.014922	0.655760	0.065689	0.004315	0.047947
1	0.479366	3.231430	0.277708	0.095152	0.009054	0.075368
2	0.297532	2.014883	0.655822	0.065683	0.004314	0.047934
3	0.388892	3.329918	0.260048	0.096308	0.009275	0.066637
4	1.298109	7.349681	-1.269809	0.168677	0.028452	0.154846

```
    Mape_te  Adjusted_r2_te
0  0.313666        2.032721
1  0.478237        3.166876
2  0.313473        2.032534
3  0.403614        3.219857
4  1.344932        7.809427
```

As it can be seen from the train score that negative R2 score suggest SVR is the worst model so far.

Decision Tree

```
# defining the model
DT1 = DecisionTreeRegressor()
DT1.fit(x_train, y_train)

# Making Predictions
y_DT1_predtr= DT1.predict(x_train)
y_DT1_predvl= DT1.predict(x_val)
y_DT1_predte= DT1.predict(x_test)


# Performance on train data
DT1_tr_R2score=r2_score(y_train,y_DT1_predtr)
DT1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_DT1_predtr))
DT1_tr_MSE=mean_squared_error(y_train, y_DT1_predtr)
DT1_tr_MAE=mean_absolute_error(y_train, y_DT1_predtr)
DT1_tr_MAPE=mape(y_train, y_DT1_predtr)
DT1_tr_AR2=adjR(y_train, y_DT1_predtr,p=len(x.columns))

# Performance on val data
DT1_vl_R2score=r2_score(y_val,y_DT1_predvl)
DT1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_DT1_predvl))
DT1_vl_MSE=mean_squared_error(y_val, y_DT1_predvl)
DT1_vl_MAE=mean_absolute_error(y_val, y_DT1_predvl)
DT1_vl_MAPE=mape(y_val, y_DT1_predvl)
DT1_vl_AR2=adjR(y_val, y_DT1_predvl,p=len(x.columns))

# Performance on test data
DT1_te_R2score=r2_score(y_test,y_DT1_predte)
DT1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_DT1_predte))
DT1_te_MSE=mean_squared_error(y_test, y_DT1_predte)
DT1_te_MAE=mean_absolute_error(y_test, y_DT1_predte)
DT1_te_MAPE=mape(y_test, y_DT1_predte)
DT1_te_AR2=adjR(y_test, y_DT1_predte,p=len(x.columns))

DT1_df=pd.DataFrame({'Algorithm':['Simple DT'],
                       'train Score':DT1_tr_R2score,'RMSE_tr':
```

```
DT1_tr_RMSE, 'MSE_tr': DT1_tr_MSE, 'MAE_tr': DT1_tr_MAE,
                         "Mape_tr":DT1_tr_MAPE,
"Adjusted_r2_tr":DT1_tr_AR2,
                        'Val Score':DT1_vl_R2score,'RMSE_vl':
DT1_vl_RMSE, 'MSE_vl': DT1_vl_MSE, 'MAE_vl': DT1_vl_MAE,
                         "Mape_val":DT1_vl_MAPE,
"Adjusted_r2_val":DT1_vl_AR2,
                      'test Score':DT1_te_R2score,'RMSE_te':
DT1_te_RMSE, 'MSE_te': DT1_te_MSE, 'MAE_te': DT1_te_MAE,
                        "Mape_te":DT1_te_MAPE,
"Adjusted_r2_te":DT1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
DT1_df]).reset_index(drop=True)

model_comprsn

                 Algorithm  train Score       RMSE_tr        MSE_tr  \
0  Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03
1      SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03
2      SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03
3                      KNN     1.000000  0.000000e+00  0.000000e+00
4      SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02
5                Simple DT     1.000000  8.997672e-10  8.095810e-19

         MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0  4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1  7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
0.009663
2  4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3  0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4  1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5  7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
0.008463

     MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te
\
0  0.047979  0.297673         2.014922    0.655760  0.065689  0.004315

1  0.078625  0.479366         3.231430    0.277708  0.095152  0.009054

2  0.047972  0.297532         2.014883    0.655822  0.065683  0.004314

3  0.069303  0.388892         3.329918    0.260048  0.096308  0.009275

4  0.151230  1.298109         7.349681   -1.269809  0.168677  0.028452
```

```
5  0.049959  0.233400        2.954253    0.377883  0.088307  0.007798


     MAE_te   Mape_te  Adjusted_r2_te
0  0.047947  0.313666        2.032721
1  0.075368  0.478237        3.166876
2  0.047934  0.313473        2.032534
3  0.066637  0.403614        3.219857
4  0.154846  1.344932        7.809427
5  0.048093  0.217783        2.866352
```

Again the simple decision tree performs well on the training set. However, its performance on the validation and test set is very low.

Gradient Boosting

```
# defining the model
GB1=GradientBoostingRegressor(n_estimators = 200, learning_rate = 0.1,
random_state=22)
GB1.fit(x_train, y_train)

# Making Predictions
y_GB1_predtr= GB1.predict(x_train)
y_GB1_predvl= GB1.predict(x_val)
y_GB1_predte= GB1.predict(x_test)

# Performance on train data
GB1_tr_R2score=r2_score(y_train,y_GB1_predtr)
GB1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_GB1_predtr))
GB1_tr_MSE=mean_squared_error(y_train, y_GB1_predtr)
GB1_tr_MAE=mean_absolute_error(y_train, y_GB1_predtr)
GB1_tr_MAPE=mape(y_train, y_GB1_predtr)
GB1_tr_AR2=adjR(y_train, y_GB1_predtr,p=len(x.columns))

# Performance on val data
GB1_vl_R2score=r2_score(y_val,y_GB1_predvl)
GB1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_GB1_predvl))
GB1_vl_MSE=mean_squared_error(y_val, y_GB1_predvl)
GB1_vl_MAE=mean_absolute_error(y_val, y_GB1_predvl)
GB1_vl_MAPE=mape(y_val, y_GB1_predvl)
GB1_vl_AR2=adjR(y_val, y_GB1_predvl,p=len(x.columns))

# Performance on test data
GB1_te_R2score=r2_score(y_test,y_GB1_predte)
GB1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_GB1_predte))
GB1_te_MSE=mean_squared_error(y_test, y_GB1_predte)
GB1_te_MAE=mean_absolute_error(y_test, y_GB1_predte)
GB1_te_MAPE=mape(y_test, y_GB1_predte)
GB1_te_AR2=adjR(y_test, y_GB1_predte,p=len(x.columns))
```

```
GB1_df=pd.DataFrame({'Algorithm':['Gradient Boosting'],
                       'train Score':GB1_tr_R2score,'RMSE_tr':
GB1_tr_RMSE, 'MSE_tr': GB1_tr_MSE, 'MAE_tr': GB1_tr_MAE,
                         "Mape_tr":GB1_tr_MAPE,
"Adjusted_r2_tr":GB1_tr_AR2,
                        'Val Score':GB1_vl_R2score,'RMSE_vl':
GB1_vl_RMSE, 'MSE_vl': GB1_vl_MSE, 'MAE_vl': GB1_vl_MAE,
                         "Mape_val":GB1_vl_MAPE,
"Adjusted_r2_val":GB1_vl_AR2,
                      'test Score':GB1_te_R2score,'RMSE_te':
GB1_te_RMSE, 'MSE_te': GB1_te_MSE, 'MAE_te': GB1_te_MAE,
                        "Mape_te":GB1_te_MAPE,
"Adjusted_r2_te":GB1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
GB1_df]).reset_index(drop=True)

model_comprsn

                 Algorithm  train Score       RMSE_tr        MSE_tr  \
0  Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03
1      SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03
2      SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03
3                      KNN     1.000000  0.000000e+00  0.000000e+00
4      SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02
5                Simple DT     1.000000  8.997672e-10  8.095810e-19
6        Gradient Boosting     0.867151  3.937272e-02  1.550211e-03

         MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0  4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1  7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
0.009663
2  4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3  0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4  1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5  7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
0.008463
6  2.467221e-02  1.415823e-01        1.398548   0.752565  0.056697
0.003215

     MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te
\
0  0.047979  0.297673         2.014922    0.655760  0.065689  0.004315

1  0.078625  0.479366         3.231430    0.277708  0.095152  0.009054
```

```
2  0.047972  0.297532           2.014883    0.655822  0.065683  0.004314

3  0.069303  0.388892           3.329918    0.260048  0.096308  0.009275

4  0.151230  1.298109           7.349681   -1.269809  0.168677  0.028452

5  0.049959  0.233400           2.954253    0.377883  0.088307  0.007798

6  0.036898  0.202873           1.742306    0.753883  0.055543  0.003085


     MAE_te   Mape_te  Adjusted_r2_te
0  0.047947  0.313666        2.032721
1  0.075368  0.478237        3.166876
2  0.047934  0.313473        2.032534
3  0.066637  0.403614        3.219857
4  0.154846  1.344932        7.809427
5  0.048093  0.217783        2.866352
6  0.033903  0.185240        1.738350
```

Gradient boosting has performed way better across different sets with R2 score of 0.86, 0.75 and 0.75 for train, validation and test sets respectively

Random Forest

```python
# defining the model
RF1=RandomForestRegressor()
RF1.fit(x_train, y_train)

# Making Predictions
y_RF1_predtr= RF1.predict(x_train)
y_RF1_predvl= RF1.predict(x_val)
y_RF1_predte= RF1.predict(x_test)

# Performance on train data
RF1_tr_R2score=r2_score(y_train,y_RF1_predtr)
RF1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_RF1_predtr))
RF1_tr_MSE=mean_squared_error(y_train, y_RF1_predtr)
RF1_tr_MAE=mean_absolute_error(y_train, y_RF1_predtr)
RF1_tr_MAPE=mape(y_train, y_RF1_predtr)
RF1_tr_AR2=adjR(y_train, y_RF1_predtr,p=len(x.columns))

# Performance on val data
RF1_vl_R2score=r2_score(y_val,y_RF1_predvl)
RF1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_RF1_predvl))
RF1_vl_MSE=mean_squared_error(y_val, y_RF1_predvl)
RF1_vl_MAE=mean_absolute_error(y_val, y_RF1_predvl)
RF1_vl_MAPE=mape(y_val, y_RF1_predvl)
RF1_vl_AR2=adjR(y_val, y_RF1_predvl,p=len(x.columns))
```

```python
# Performance on test data
RF1_te_R2score=r2_score(y_test,y_RF1_predte)
RF1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_RF1_predte))
RF1_te_MSE=mean_squared_error(y_test, y_RF1_predte)
RF1_te_MAE=mean_absolute_error(y_test, y_RF1_predte)
RF1_te_MAPE=mape(y_test, y_RF1_predte)
RF1_te_AR2=adjR(y_test, y_RF1_predte,p=len(x.columns))

RF1_df=pd.DataFrame({'Algorithm':['Random Forest'],
                       'train Score':RF1_tr_R2score,'RMSE_tr':
RF1_tr_RMSE, 'MSE_tr': RF1_tr_MSE, 'MAE_tr': RF1_tr_MAE,
                         "Mape_tr":RF1_tr_MAPE,
"Adjusted_r2_tr":RF1_tr_AR2,
                        'Val Score':RF1_vl_R2score,'RMSE_vl':
RF1_vl_RMSE, 'MSE_vl': RF1_vl_MSE, 'MAE_vl': RF1_vl_MAE,
                         "Mape_val":RF1_vl_MAPE,
"Adjusted_r2_val":RF1_vl_AR2,
                      'test Score':RF1_te_R2score,'RMSE_te':
RF1_te_RMSE, 'MSE_te': RF1_te_MSE, 'MAE_te': RF1_te_MAE,
                        "Mape_te":RF1_te_MAPE,
"Adjusted_r2_te":RF1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
RF1_df]).reset_index(drop=True)

model_comprsn
```

```
                 Algorithm  train Score       RMSE_tr        MSE_tr  \
0  Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03
1      SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03
2      SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03
3                      KNN     1.000000  0.000000e+00  0.000000e+00
4      SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02
5                Simple DT     1.000000  8.997672e-10  8.095810e-19
6        Gradient Boosting     0.867151  3.937272e-02  1.550211e-03
7            Random Forest     0.948153  2.459668e-02  6.049968e-04

         MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0  4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1  7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
0.009663
2  4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3  0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4  1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5  7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
```

```
0.008463
6  2.467221e-02  1.415823e-01        1.398548   0.752565  0.056697
0.003215
7  1.366763e-02  6.644999e-02        1.155540   0.607276  0.071429
0.005102

     MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te
\
0  0.047979  0.297673         2.014922    0.655760  0.065689  0.004315

1  0.078625  0.479366         3.231430    0.277708  0.095152  0.009054

2  0.047972  0.297532         2.014883    0.655822  0.065683  0.004314

3  0.069303  0.388892         3.329918    0.260048  0.096308  0.009275

4  0.151230  1.298109         7.349681   -1.269809  0.168677  0.028452

5  0.049959  0.233400         2.954253    0.377883  0.088307  0.007798

6  0.036898  0.202873         1.742306    0.753883  0.055543  0.003085

7  0.040949  0.196869         2.178171    0.631289  0.067984  0.004622


     MAE_te   Mape_te  Adjusted_r2_te
0  0.047947  0.313666        2.032721
1  0.075368  0.478237        3.166876
2  0.047934  0.313473        2.032534
3  0.066637  0.403614        3.219857
4  0.154846  1.344932        7.809427
5  0.048093  0.217783        2.866352
6  0.033903  0.185240        1.738350
7  0.037930  0.184176        2.106134
```

Random forest model has performed very well on the train data. However, its performance on test and validation data is very low, unacceptable. It has performed worse than Gradient Boosting. It shows overfitting characteristics with high score on train data.

ADA Boost

```
# defining the model
ADAB=AdaBoostRegressor(DecisionTreeRegressor(random_state=8))
ADAB.fit(x_train, y_train)

# Making Predictions
y_ADAB_predtr= ADAB.predict(x_train)
y_ADAB_predvl= ADAB.predict(x_val)
y_ADAB_predte= ADAB.predict(x_test)

# Performance on train data
```

```
ADAB_tr_R2score=r2_score(y_train,y_ADAB_predtr)
ADAB_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_ADAB_predtr))
ADAB_tr_MSE=mean_squared_error(y_train, y_ADAB_predtr)
ADAB_tr_MAE=mean_absolute_error(y_train, y_ADAB_predtr)
ADAB_tr_MAPE=mape(y_train, y_ADAB_predtr)
ADAB_tr_AR2=adjR(y_train, y_ADAB_predtr,p=len(x.columns))

# Performance on val data
ADAB_vl_R2score=r2_score(y_val,y_ADAB_predvl)
ADAB_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_ADAB_predvl))
ADAB_vl_MSE=mean_squared_error(y_val, y_ADAB_predvl)
ADAB_vl_MAE=mean_absolute_error(y_val, y_ADAB_predvl)
ADAB_vl_MAPE=mape(y_val, y_ADAB_predvl)
ADAB_vl_AR2=adjR(y_val, y_ADAB_predvl,p=len(x.columns))

# Performance on test data
ADAB_te_R2score=r2_score(y_test,y_ADAB_predte)
ADAB_te_RMSE=np.sqrt(mean_squared_error(y_test, y_ADAB_predte))
ADAB_te_MSE=mean_squared_error(y_test, y_ADAB_predte)
ADAB_te_MAE=mean_absolute_error(y_test, y_ADAB_predte)
ADAB_te_MAPE=mape(y_test, y_ADAB_predte)
ADAB_te_AR2=adjR(y_test, y_ADAB_predte,p=len(x.columns))

ADAB_df=pd.DataFrame({'Algorithm':['ADA Boost'],
                       'train Score':ADAB_tr_R2score,'RMSE_tr':
ADAB_tr_RMSE, 'MSE_tr': ADAB_tr_MSE, 'MAE_tr': ADAB_tr_MAE,
                         "Mape_tr":ADAB_tr_MAPE,
"Adjusted_r2_tr":ADAB_tr_AR2,
                        'Val Score':ADAB_vl_R2score,'RMSE_vl':
ADAB_vl_RMSE, 'MSE_vl': ADAB_vl_MSE, 'MAE_vl': ADAB_vl_MAE,
                         "Mape_val":ADAB_vl_MAPE,
"Adjusted_r2_val":ADAB_vl_AR2,
                      'test Score':ADAB_te_R2score,'RMSE_te':
ADAB_te_RMSE, 'MSE_te': ADAB_te_MSE, 'MAE_te': ADAB_te_MAE,
                        "Mape_te":ADAB_te_MAPE,
"Adjusted_r2_te":ADAB_te_AR2})
model_comprsn = pd.concat([model_comprsn,
ADAB_df]).reset_index(drop=True)

model_comprsn
```

```
                 Algorithm  train Score       RMSE_tr        MSE_tr  \
0  Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03
1      SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03
2      SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03
3                      KNN     1.000000  0.000000e+00  0.000000e+00
4      SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02
5                Simple DT     1.000000  8.997672e-10  8.095810e-19
6        Gradient Boosting     0.867151  3.937272e-02  1.550211e-03
7            Random Forest     0.948153  2.459668e-02  6.049968e-04
```

```
8                ADA Boost     0.999988  3.750914e-04  1.406936e-07

         MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0  4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1  7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
0.009663
2  4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3  0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4  1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5  7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
0.008463
6  2.467221e-02  1.415823e-01        1.398548   0.752565  0.056697
0.003215
7  1.366763e-02  6.644999e-02        1.155540   0.607276  0.071429
0.005102
8  2.604131e-05  2.176285e-04        1.000036   0.615038  0.070719
0.005001

     MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te
\
0  0.047979  0.297673         2.014922    0.655760  0.065689  0.004315

1  0.078625  0.479366         3.231430    0.277708  0.095152  0.009054

2  0.047972  0.297532         2.014883    0.655822  0.065683  0.004314

3  0.069303  0.388892         3.329918    0.260048  0.096308  0.009275

4  0.151230  1.298109         7.349681   -1.269809  0.168677  0.028452

5  0.049959  0.233400         2.954253    0.377883  0.088307  0.007798

6  0.036898  0.202873         1.742306    0.753883  0.055543  0.003085

7  0.040949  0.196869         2.178171    0.631289  0.067984  0.004622

8  0.040009  0.185063         2.154886    0.661616  0.065128  0.004242


     MAE_te   Mape_te  Adjusted_r2_te
0  0.047947  0.313666        2.032721
1  0.075368  0.478237        3.166876
2  0.047934  0.313473        2.032534
3  0.066637  0.403614        3.219857
4  0.154846  1.344932        7.809427
```

```
5  0.048093  0.217783        2.866352
6  0.033903  0.185240        1.738350
7  0.037930  0.184176        2.106134
8  0.035712  0.166437        2.015151
```

ADA Boost has shown good performance so far on the given dataset with R2 score of 0.99, 0.65 and 0.65. Again overfitting on train data.

XGBoost

```
# defining the model
XGB=XGBRegressor(n_estimators=150,max_depth=5,random_state=7)
XGB.fit(x_train, y_train)

# Making Predictions
y_XGB_predtr= XGB.predict(x_train)
y_XGB_predvl= XGB.predict(x_val)
y_XGB_predte= XGB.predict(x_test)

# Performance on train data
XGB_tr_R2score=r2_score(y_train,y_XGB_predtr)
XGB_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_XGB_predtr))
XGB_tr_MSE=mean_squared_error(y_train, y_XGB_predtr)
XGB_tr_MAE=mean_absolute_error(y_train, y_XGB_predtr)
XGB_tr_MAPE=mape(y_train, y_XGB_predtr)
XGB_tr_AR2=adjR(y_train, y_XGB_predtr,p=len(x.columns))

# Performance on val data
XGB_vl_R2score=r2_score(y_val,y_XGB_predvl)
XGB_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_XGB_predvl))
XGB_vl_MSE=mean_squared_error(y_val, y_XGB_predvl)
XGB_vl_MAE=mean_absolute_error(y_val, y_XGB_predvl)
XGB_vl_MAPE=mape(y_val, y_XGB_predvl)
XGB_vl_AR2=adjR(y_val, y_XGB_predvl,p=len(x.columns))

# Performance on test data
XGB_te_R2score=r2_score(y_test,y_XGB_predte)
XGB_te_RMSE=np.sqrt(mean_squared_error(y_test, y_XGB_predte))
XGB_te_MSE=mean_squared_error(y_test, y_XGB_predte)
XGB_te_MAE=mean_absolute_error(y_test, y_XGB_predte)
XGB_te_MAPE=mape(y_test, y_XGB_predte)
XGB_te_AR2=adjR(y_test, y_XGB_predte,p=len(x.columns))

XGB_df=pd.DataFrame({'Algorithm':['XGBoost'],
                        'train Score':XGB_tr_R2score,'RMSE_tr':
XGB_tr_RMSE, 'MSE_tr': XGB_tr_MSE, 'MAE_tr': XGB_tr_MAE,
                         "Mape_tr":XGB_tr_MAPE,
"Adjusted_r2_tr":XGB_tr_AR2,
                         'Val Score':XGB_vl_R2score,'RMSE_vl':
XGB_vl_RMSE, 'MSE_vl': XGB_vl_MSE, 'MAE_vl': XGB_vl_MAE,
```

```
                         "Mape_val":XGB_vl_MAPE,
"Adjusted_r2_val":XGB_vl_AR2,
                      'test Score':XGB_te_R2score,'RMSE_te':
XGB_te_RMSE, 'MSE_te': XGB_te_MSE, 'MAE_te': XGB_te_MAE,
                        "Mape_te":XGB_te_MAPE,
"Adjusted_r2_te":XGB_te_AR2})
model_comprsn = pd.concat([model_comprsn,
XGB_df]).reset_index(drop=True)

model_comprsn
```

```
                  Algorithm  train Score       RMSE_tr        MSE_tr  \
0  Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03
1      SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03
2      SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03
3                      KNN     1.000000  0.000000e+00  0.000000e+00
4      SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02
5                Simple DT     1.000000  8.997672e-10  8.095810e-19
6        Gradient Boosting     0.867151  3.937272e-02  1.550211e-03
7            Random Forest     0.948153  2.459668e-02  6.049968e-04
8                ADA Boost     0.999988  3.750914e-04  1.406936e-07
9                  XGBoost     0.994614  7.927381e-03  6.284337e-05

         MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0  4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1  7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
0.009663
2  4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3  0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4  1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5  7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
0.008463
6  2.467221e-02  1.415823e-01        1.398548   0.752565  0.056697
0.003215
7  1.366763e-02  6.644999e-02        1.155540   0.607276  0.071429
0.005102
8  2.604131e-05  2.176285e-04        1.000036   0.615038  0.070719
0.005001
9  5.126830e-03  3.283044e-02        1.016157   0.821284  0.048185
0.002322

     MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te    MSE_te
\
0  0.047979  0.297673         2.014922    0.655760  0.065689  0.004315
```

1	0.078625	0.479366	3.231430	0.277708	0.095152	0.009054
2	0.047972	0.297532	2.014883	0.655822	0.065683	0.004314
3	0.069303	0.388892	3.329918	0.260048	0.096308	0.009275
4	0.151230	1.298109	7.349681	-1.269809	0.168677	0.028452
5	0.049959	0.233400	2.954253	0.377883	0.088307	0.007798
6	0.036898	0.202873	1.742306	0.753883	0.055543	0.003085
7	0.040949	0.196869	2.178171	0.631289	0.067984	0.004622
8	0.040009	0.185063	2.154886	0.661616	0.065128	0.004242
9	0.030927	0.165367	1.536149	0.801738	0.049852	0.002485

	MAE_te	Mape_te	Adjusted_r2_te
0	0.047947	0.313666	2.032721
1	0.075368	0.478237	3.166876
2	0.047934	0.313473	2.032534
3	0.066637	0.403614	3.219857
4	0.154846	1.344932	7.809427
5	0.048093	0.217783	2.866352
6	0.033903	0.185240	1.738350
7	0.037930	0.184176	2.106134
8	0.035712	0.166437	2.015151
9	0.029996	0.162254	1.594787

XGboost has performed the best with good R2 score across different sets. R2 Scores: Train = 0.99, Val = 0.82, Test = 0.80

Model Performance Summary

Three of the best-performing machine learning models for our data set are Gradient Boost, and XGBoost with regression models performing poorly. SVM performed the worse showing negative train score leading to non-learning. Some of the methods have shown overfitting with the likes of RandomForest and KNN. We will use XGBoost for hyperparameter optimization to further improve its performance.

Feature Importance

Plot of Important features used by this model

```
from xgboost import plot_importance
```

```python
# defining the model
XGB=XGBRegressor(n_estimators=150,max_depth=5,random_state=7)
XGB.fit(x_train, y_train)
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None,
early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None,
feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=5, max_leaves=None,
             min_child_weight=None, missing=nan,
monotone_constraints=None,
             multi_strategy=None, n_estimators=150, n_jobs=None,
             num_parallel_tree=None, random_state=7, ...)
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

# plot feature importance based on gain
plt.figure(figsize=(10,6))
plot_importance(XGB, importance_type = 'gain')

plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

Hyperparameter Optimization

Tuning using RandomSearchCV

```python
param_gridX = {
    'colsample_bytree': [0.3,0.4,0.5,0.7],
    'learning_rate': [0.10,0.15,0.25,0.30],
    'max_depth': [3,4,5,6,8,10,12,15],
    'gamma': [0.0,0.1,0.2,0.3,0.4],
    'min_child_weight': [1,3,5,7],
    'n_estimators':  [200,400,600],}

XGB_test=XGBRegressor(random_state=7)
```

```
grid_searchX = RandomizedSearchCV(estimator = XGB_test,
param_distributions = param_gridX,
                          cv = None, verbose = 1, n_jobs=1)
grid_searchX.fit(x_train,y_train)
grid_searchX.best_score_,grid_searchX.best_params_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
(0.7317583343498136,
 {'n_estimators': 400,
  'min_child_weight': 3,
  'max_depth': 8,
  'learning_rate': 0.15,
  'gamma': 0.0,
  'colsample_bytree': 0.5})
```

Using randomized parameters to build model again

```
# defining the model
XGB1=XGBRegressor(n_estimators=600,min_child_weight= 5,learning_rate =
0.3,gamma = 0.0, colsample_bytree= 0.7, max_depth=5,random_state=7)
XGB1.fit(x_train, y_train)

# Making Predictions
y_XGB1_predtr= XGB1.predict(x_train)
y_XGB1_predvl= XGB1.predict(x_val)
y_XGB1_predte= XGB1.predict(x_test)

# Performance on train data
XGB1_tr_R2score=r2_score(y_train,y_XGB1_predtr)
XGB1_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_XGB1_predtr))
XGB1_tr_MSE=mean_squared_error(y_train, y_XGB1_predtr)
XGB1_tr_MAE=mean_absolute_error(y_train, y_XGB1_predtr)
XGB1_tr_MAPE=mape(y_train, y_XGB1_predtr)
XGB1_tr_AR2=adjR(y_train, y_XGB1_predtr,p=len(x.columns))

# Performance on val data
XGB1_vl_R2score=r2_score(y_val,y_XGB1_predvl)
XGB1_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_XGB1_predvl))
XGB1_vl_MSE=mean_squared_error(y_val, y_XGB1_predvl)
XGB1_vl_MAE=mean_absolute_error(y_val, y_XGB1_predvl)
XGB1_vl_MAPE=mape(y_val, y_XGB1_predvl)
XGB1_vl_AR2=adjR(y_val, y_XGB1_predvl,p=len(x.columns))

# Performance on test data
XGB1_te_R2score=r2_score(y_test,y_XGB1_predte)
XGB1_te_RMSE=np.sqrt(mean_squared_error(y_test, y_XGB1_predte))
XGB1_te_MSE=mean_squared_error(y_test, y_XGB1_predte)
XGB1_te_MAE=mean_absolute_error(y_test, y_XGB1_predte)
```

```
XGB1_te_MAPE=mape(y_test, y_XGB1_predte)
XGB1_te_AR2=adjR(y_test, y_XGB1_predte,p=len(x.columns))

XGB1_df=pd.DataFrame({'Algorithm':['XGBoostWRandomSearch'],
                       'train Score':XGB1_tr_R2score,'RMSE_tr':
XGB1_tr_RMSE, 'MSE_tr': XGB1_tr_MSE, 'MAE_tr': XGB1_tr_MAE,
                         "Mape_tr":XGB1_tr_MAPE,
"Adjusted_r2_tr":XGB1_tr_AR2,
                        'Val Score':XGB1_vl_R2score,'RMSE_vl':
XGB1_vl_RMSE, 'MSE_vl': XGB1_vl_MSE, 'MAE_vl': XGB1_vl_MAE,
                         "Mape_val":XGB1_vl_MAPE,
"Adjusted_r2_val":XGB1_vl_AR2,
                      'test Score':XGB1_te_R2score,'RMSE_te':
XGB1_te_RMSE, 'MSE_te': XGB1_te_MSE, 'MAE_te': XGB1_te_MAE,
                        "Mape_te":XGB1_te_MAPE,
"Adjusted_r2_te":XGB1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
XGB1_df]).reset_index(drop=True)

model_comprsn
```

```
                  Algorithm  train Score       RMSE_tr
MSE_tr  \
0   Simple Linear Reg Model     0.661710  6.282898e-02  3.947481e-03

1       SLinear-Reg (Lasso)     0.254273  9.328367e-02  8.701843e-03

2       SLinear-Reg (Ridge)     0.661708  6.282922e-02  3.947511e-03

3                       KNN     1.000000  0.000000e+00  0.000000e+00

4       SVR with kernel rbf    -1.333553  1.650154e-01  2.723007e-02

5                 Simple DT     1.000000  8.997672e-10  8.095810e-19

6         Gradient Boosting     0.867151  3.937272e-02  1.550211e-03

7             Random Forest     0.948153  2.459668e-02  6.049968e-04

8                 ADA Boost     0.999988  3.750914e-04  1.406936e-07

9                   XGBoost     0.994614  7.927381e-03  6.284337e-05

10     XGBoostWRandomSearch     0.999600  2.159990e-03  4.665555e-06


          MAE_tr       Mape_tr  Adjusted_r2_tr  Val Score   RMSE_vl
MSE_vl  \
0   4.585629e-02  2.887758e-01        2.014869   0.661693  0.066296
0.004395
1   7.448802e-02  4.767574e-01        3.237182   0.256190  0.098301
```

```
0.009663
2   4.584977e-02  2.886105e-01        2.014877   0.661706  0.066294
0.004395
3   0.000000e+00  0.000000e+00        1.000000   0.223361  0.100447
0.010090
4   1.509417e-01  1.311353e+00        8.000659  -1.116560  0.165823
0.027497
5   7.497466e-11  7.497595e-10        1.000000   0.348582  0.091994
0.008463
6   2.467221e-02  1.415823e-01        1.398548   0.752565  0.056697
0.003215
7   1.366763e-02  6.644999e-02        1.155540   0.607276  0.071429
0.005102
8   2.604131e-05  2.176285e-04        1.000036   0.615038  0.070719
0.005001
9   5.126830e-03  3.283044e-02        1.016157   0.821284  0.048185
0.002322
10  1.504397e-03  1.035763e-02        1.001199   0.795109  0.051593
0.002662

      MAE_vl  Mape_val  Adjusted_r2_val  test Score   RMSE_te
MSE_te  \
0   0.047979  0.297673         2.014922    0.655760  0.065689
0.004315
1   0.078625  0.479366         3.231430    0.277708  0.095152
0.009054
2   0.047972  0.297532         2.014883    0.655822  0.065683
0.004314
3   0.069303  0.388892         3.329918    0.260048  0.096308
0.009275
4   0.151230  1.298109         7.349681   -1.269809  0.168677
0.028452
5   0.049959  0.233400         2.954253    0.377883  0.088307
0.007798
6   0.036898  0.202873         1.742306    0.753883  0.055543
0.003085
7   0.040949  0.196869         2.178171    0.631289  0.067984
0.004622
8   0.040009  0.185063         2.154886    0.661616  0.065128
0.004242
9   0.030927  0.165367         1.536149    0.801738  0.049852
0.002485
10  0.033687  0.193178         1.614673    0.787597  0.051599
0.002662

      MAE_te   Mape_te  Adjusted_r2_te
0   0.047947  0.313666        2.032721
1   0.075368  0.478237        3.166876
2   0.047934  0.313473        2.032534
```

```
3   0.066637  0.403614       3.219857
4   0.154846  1.344932       7.809427
5   0.048093  0.217783       2.866352
6   0.033903  0.185240       1.738350
7   0.037930  0.184176       2.106134
8   0.035712  0.166437       2.015151
9   0.029996  0.162254       1.594787
10  0.032884  0.185786       1.637208
```

No10, XGBoost performed the best with following parameters
XGBRegressor(n_estimators=400,min_child_weight= 5,learning_rate = 0.25,gamma = 0.0, colsample_bytree= 0.5, max_depth=6,random_state=7)

Using GridSearchCV with parameters from RansomCV search

```
#Create the parameters of grid based on random search results
param_gridG = {
    'colsample_bytree': [0.35,0.4,0.45,0.5,0.55,0.6,0.65],
    'learning_rate': [0.10,0.15,0.25,0.30,0.35],
    'max_depth': [3,4,5,6,7,8,9],
    'gamma': [0.0,0.1,0.2],
    'min_child_weight': [3,4,5,6,7],
    'n_estimators':  [300,350,400,450,500]}

#Create base model
XGB_testG=XGBRegressor(random_state=7)
#Initiate the search
grid_searchG = GridSearchCV(estimator = XGB_testG, param_grid = 
param_gridG,
                          cv = 3, verbose = 1, n_jobs=-1)
#Fit the grid search to data
grid_searchG.fit(x_train,y_train)
grid_searchG.best_score_,grid_searchG.best_params_

Fitting 3 folds for each of 18375 candidates, totalling 55125 fits
```

Using gridsearch parameters to build model again

```
# defining the model
XGB2=XGBRegressor(n_estimators=500,min_child_weight= 6,learning_rate = 
0.35,gamma = 0.0, colsample_bytree= 0.6, max_depth=3,random_state=7)
XGB2.fit(x_train, y_train)

# Making Predictions
y_XGB2_predtr= XGB2.predict(x_train)
y_XGB2_predvl= XGB2.predict(x_val)
y_XGB2_predte= XGB2.predict(x_test)

# Performance on train data
XGB2_tr_R2score=r2_score(y_train,y_XGB2_predtr)
```

```
XGB2_tr_RMSE=np.sqrt(mean_squared_error(y_train, y_XGB2_predtr))
XGB2_tr_MSE=mean_squared_error(y_train, y_XGB2_predtr)
XGB2_tr_MAE=mean_absolute_error(y_train, y_XGB2_predtr)
XGB2_tr_MAPE=mape(y_train, y_XGB2_predtr)
XGB2_tr_AR2=adjR(y_train, y_XGB2_predtr,p=len(x.columns))

# Performance on val data
XGB2_vl_R2score=r2_score(y_val,y_XGB2_predvl)
XGB2_vl_RMSE=np.sqrt(mean_squared_error(y_val, y_XGB2_predvl))
XGB2_vl_MSE=mean_squared_error(y_val, y_XGB2_predvl)
XGB2_vl_MAE=mean_absolute_error(y_val, y_XGB2_predvl)
XGB2_vl_MAPE=mape(y_val, y_XGB2_predvl)
XGB2_vl_AR2=adjR(y_val, y_XGB2_predvl,p=len(x.columns))

# Performance on test data
XGB2_te_R2score=r2_score(y_test,y_XGB2_predte)
XGB2_te_RMSE=np.sqrt(mean_squared_error(y_test, y_XGB2_predte))
XGB2_te_MSE=mean_squared_error(y_test, y_XGB2_predte)
XGB2_te_MAE=mean_absolute_error(y_test, y_XGB2_predte)
XGB2_te_MAPE=mape(y_test, y_XGB2_predte)
XGB2_te_AR2=adjR(y_test, y_XGB2_predte,p=len(x.columns))

XGB2_df=pd.DataFrame({'Algorithm':['XGBoostWGridSearch'],
                       'train Score':XGB1_tr_R2score,'RMSE_tr':
XGB1_tr_RMSE, 'MSE_tr': XGB1_tr_MSE, 'MAE_tr': XGB1_tr_MAE,
                         "Mape_tr":XGB1_tr_MAPE,
"Adjusted_r2_tr":XGB1_tr_AR2,
                        'Val Score':XGB1_vl_R2score,'RMSE_vl':
XGB1_vl_RMSE, 'MSE_vl': XGB1_vl_MSE, 'MAE_vl': XGB1_vl_MAE,
                         "Mape_val":XGB1_vl_MAPE,
"Adjusted_r2_val":XGB1_vl_AR2,
                      'test Score':XGB1_te_R2score,'RMSE_te':
XGB1_te_RMSE, 'MSE_te': XGB1_te_MSE, 'MAE_te': XGB1_te_MAE,
                        "Mape_te":XGB1_te_MAPE,
"Adjusted_r2_te":XGB1_te_AR2})
model_comprsn = pd.concat([model_comprsn,
XGB2_df]).reset_index(drop=True)

model_comprsn
```

GridSearchCV performed better on train set but the performance on validation and test set was poorer than randomsearch with best parameter which is row 10.

the final parameters that are giving best results with this dataset and model are XGBRegressor(n_estimators=400,min_child_weight= 5,learning_rate = 0.25,gamma = 0.0, colsample_bytree= 0.5, max_depth=6,random_state=7)

Final Summary

1. For our dataset, the best performing models were Gradient Boost and XGboost (best)
2. Top feature in order of most important to least are season_summer, season_winter, season_spring, market_trend, price, category_electronics, cost_price, category_home & kitchen, current_stock, historical_sales, category_clothing, category_sports.
3. Results are reinforced by bivariate analysis performed in exploratory data analysis.