Bigmart_new

June 20, 2022

[334]:
```python
#importing pandas liabries
import pandas as pd
import numpy as np
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn import linear_model
import warnings
warnings.filterwarnings('ignore')
```

[335]:
```python
#importing the data
data_test=pd.read_csv('bigmart_test.csv')
data_train=pd.read_csv('bigmart_train.csv')
```

[336]:
```python
data_train
```

[336]:
```
     Item_Identifier  Item_Weight Item_Fat_Content  Item_Visibility  \
0              FDA15        9.300          Low Fat         0.016047
1              DRC01        5.920          Regular         0.019278
2              FDN15       17.500          Low Fat         0.016760
3              FDX07       19.200          Regular         0.000000
4              NCD19        8.930          Low Fat         0.000000
…                …           …                …               …
8518           FDF22        6.865          Low Fat         0.056783
8519           FDS36        8.380          Regular         0.046982
8520           NCJ29       10.600          Low Fat         0.035186
8521           FDN46        7.210          Regular         0.145221
8522           DRG01       14.800          Low Fat         0.044878

                  Item_Type  Item_MRP Outlet_Identifier  \
0                     Dairy  249.8092            OUT049
1               Soft Drinks   48.2692            OUT018
2                      Meat  141.6180            OUT049
3     Fruits and Vegetables  182.0950            OUT010
4                 Household   53.8614            OUT013
…                       …         …               …
8518            Snack Foods  214.5218            OUT013
```

```
8519          Baking Goods  108.1570          OUT045
8520     Health and Hygiene   85.1224          OUT035
8521           Snack Foods  103.1332          OUT018
8522           Soft Drinks   75.4670          OUT046

      Outlet_Establishment_Year Outlet_Size Outlet_Location_Type  \
0                          1999      Medium               Tier 1
1                          2009      Medium               Tier 3
2                          1999      Medium               Tier 1
3                          1998         NaN               Tier 3
4                          1987        High               Tier 3
…                             …         …                  …
8518                       1987        High               Tier 3
8519                       2002         NaN               Tier 2
8520                       2004       Small               Tier 2
8521                       2009      Medium               Tier 3
8522                       1997       Small               Tier 1

            Outlet_Type  Item_Outlet_Sales
0     Supermarket Type1          3735.1380
1     Supermarket Type2           443.4228
2     Supermarket Type1          2097.2700
3         Grocery Store           732.3800
4     Supermarket Type1           994.7052
…                   …                 …
8518  Supermarket Type1          2778.3834
8519  Supermarket Type1           549.2850
8520  Supermarket Type1          1193.1136
8521  Supermarket Type2          1845.5976
8522  Supermarket Type1           765.6700

[8523 rows x 12 columns]
```

[337]:

```
#Summary statistics of numberical data
data_train.describe()
```

[337]:

```
       Item_Weight  Item_Visibility     Item_MRP  Outlet_Establishment_Year  \
count  7060.000000      8523.000000  8523.000000                8523.000000
mean     12.857645         0.066132   140.992782                1997.831867
std       4.643456         0.051598    62.275067                   8.371760
min       4.555000         0.000000    31.290000                1985.000000
25%       8.773750         0.026989    93.826500                1987.000000
50%      12.600000         0.053931   143.012800                1999.000000
75%      16.850000         0.094585   185.643700                2004.000000
max      21.350000         0.328391   266.888400                2009.000000

       Item_Outlet_Sales
```

```
count        8523.000000
mean         2181.288914
std          1706.499616
min            33.290000
25%           834.247400
50%          1794.331000
75%          3101.296400
max         13086.964800
```

[338]:
```
#Summary statistics for categorical data
data_train.describe(include=object).T
```

[338]:

	count	unique	top	freq
Item_Identifier	8523	1559	FDW13	10
Item_Fat_Content	8523	5	Low Fat	5089
Item_Type	8523	16	Fruits and Vegetables	1232
Outlet_Identifier	8523	10	OUT027	935
Outlet_Size	6113	3	Medium	2793
Outlet_Location_Type	8523	3	Tier 3	3350
Outlet_Type	8523	4	Supermarket Type1	5577

[339]:
```
#printing the shape and of the train and test data
print(data_train.shape)
print(data_test.shape)
```

```
(8523, 12)
(5681, 11)
```

[340]:
```
#Cols that not required for any  analysis
data_train=data_train.drop(['Outlet_Identifier','Item_Identifier'],axis=1)
```

[341]:
```
#Check and drop deplicate columns
print('Before dedup:', data_train.shape)
data_cln=data_train.loc[:, ~data_train.columns.duplicated()]
print('After dedup:', data_cln.shape)
duplicateCols=data_train.loc[:, data_train.columns.duplicated()]
if (duplicateCols.shape[1] !=0):
    print('Number of duplicated columns dropped:', duplicatedCols.shape[1])
    print("Dupliate columns except first occurrences:")
    print(list(duplicateCols.columns))
```

```
Before dedup: (8523, 10)
After dedup: (8523, 10)
```

[342]:
```
#Check and drop duplicated rows based on all columns
print ('Before dedup:', data_cln.shape)
data_cln.drop_duplicates(inplace=True) #by default keep='first'
```

```
print('After dedup:', data_cln.shape)
duplicateRows=data_train[data_train.duplicated()]
print('Number of duplicated rows dropped:', data_train.shape[0] - data_cln.
 ↪shape[0])
if (data_cln.shape[0] - data_train.shape[0] !=0):
    print("Duplicate rows except first occurrence:")
    print(duplicateRows)
```

```
Before dedup: (8523, 10)
After dedup: (8523, 10)
Number of duplicated rows dropped: 0
```

[343]:
```
#Finding Missing values
def zero_missing_unique(df):
    var_miss_rate=df.isnull().sum(axis=0)/df.shape[0]
    var_miss_rate=var_miss_rate.to_frame('missing_rate')

    var_zero_rate=(df==0).astype(int).sum(axis=0)/df.shape[0]
    var_zero_rate=var_zero_rate.to_frame('zero_rate')
    var_unique=df.nunique().to_frame('count_unique')
    var_type=df.dtypes.to_frame('data_type')
    data_stat=pd.concat([var_miss_rate, var_zero_rate,var_unique, var_type],␣
 ↪axis=1)
    return data_stat
stat_zero_missing_unique=zero_missing_unique(data_train)# just change the data␣
 ↪name here to your own data
stat_zero_missing_unique
```

[343]:

	missing_rate	zero_rate	count_unique	data_type
Item_Weight	0.171653	0.000000	415	float64
Item_Fat_Content	0.000000	0.000000	5	object
Item_Visibility	0.000000	0.061715	7880	float64
Item_Type	0.000000	0.000000	16	object
Item_MRP	0.000000	0.000000	5938	float64
Outlet_Establishment_Year	0.000000	0.000000	9	int64
Outlet_Size	0.282764	0.000000	3	object
Outlet_Location_Type	0.000000	0.000000	3	object
Outlet_Type	0.000000	0.000000	4	object
Item_Outlet_Sales	0.000000	0.000000	3493	float64

[344]:
```
#Dealing with the missing rate
#do not drop high mising rate variable
#use imputing approach specified in preprocessing
stat_zero_missing_unique.sort_values(by='missing_rate', ascending=False)
```

[344]:

	missing_rate	zero_rate	count_unique	data_type
Outlet_Size	0.282764	0.000000	3	object

```
Item_Weight                  0.171653   0.000000         415   float64
Item_Fat_Content             0.000000   0.000000           5    object
Item_Visibility              0.000000   0.061715        7880   float64
Item_Type                    0.000000   0.000000          16    object
Item_MRP                     0.000000   0.000000        5938   float64
Outlet_Establishment_Year    0.000000   0.000000           9     int64
Outlet_Location_Type         0.000000   0.000000           3    object
Outlet_Type                  0.000000   0.000000           4    object
Item_Outlet_Sales            0.000000   0.000000        3493   float64
```

[345]:
```
#Grouping by Item Type
item_type_baseline = data_train.groupby('Item_Type').mean()[['Item_Weight']].
 ↪reset_index()
item_type_baseline = item_type_baseline.to_numpy()
item_type_baseline
```

[345]:
```
array([['Baking Goods', 12.277108208955255],
       ['Breads', 11.3469362745098],
       ['Breakfast', 12.768202247191002],
       ['Canned', 12.305705009276451],
       ['Dairy', 13.42606890459367],
       ['Frozen Foods', 12.867061281337076],
       ['Fruits and Vegetables', 13.224769381746881],
       ['Hard Drinks', 11.400327868852452],
       ['Health and Hygiene', 13.142313953488392],
       ['Household', 13.384736495388726],
       ['Meat', 12.81734421364986],
       ['Others', 13.853284671532842],
       ['Seafood', 12.5528431372549],
       ['Snack Foods', 12.987879554655919],
       ['Soft Drinks', 11.847459893048129],
       ['Starchy Foods', 13.690730769230765]], dtype=object)
```

[346]:
```
## Item weight standardization using item type
for x in item_type_baseline:
    print(x[0])
```

```
Baking Goods
Breads
Breakfast
Canned
Dairy
Frozen Foods
Fruits and Vegetables
Hard Drinks
Health and Hygiene
Household
```

```
Meat
Others
Seafood
Snack Foods
Soft Drinks
Starchy Foods
```

[347]:
```python
def item_Weight_cal(cols):
    Item_Wt = cols[0]
    Item_Tp = cols[1]
    if pd.isnull(Item_Wt):
       for x in item_type_baseline:
           if (x[0] == Item_Tp):
               # print (x[1])
               return x[1]
    else:
        return Item_Wt
```

[348]:
```python
data_train['Item_Weight'] =data_train[['Item_Weight','Item_Type']].
 ↪apply(item_Weight_cal, axis = 1)
data_train.isna().sum()
```

[348]:
```
Item_Weight                  0
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Establishment_Year    0
Outlet_Size               2410
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

[349]:
```python
data_train[['Outlet_Type','Outlet_Size']].
 ↪groupby(['Outlet_Type','Outlet_Size']).size()
```

[349]:
```
Outlet_Type        Outlet_Size
Grocery Store      Small           528
Supermarket Type1  High            932
                   Medium          930
                   Small          1860
Supermarket Type2  Medium          928
Supermarket Type3  Medium          935
dtype: int64
```

[350]:
```python
df = data_train[['Outlet_Type','Outlet_Size']]
df.drop_duplicates()
```

[350]:
```
          Outlet_Type Outlet_Size
0   Supermarket Type1      Medium
1   Supermarket Type2      Medium
3       Grocery Store         NaN
4   Supermarket Type1        High
7   Supermarket Type3      Medium
8   Supermarket Type1         NaN
11  Supermarket Type1       Small
23      Grocery Store       Small
```

[351]:
```python
#Replacing the Missing values with small in the data
data_train['Outlet_Size']=data_train['Outlet_Size'].fillna('Small')
```

[352]:
```python
data_train.isna().sum()
```

[352]:
```
Item_Weight                  0
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Establishment_Year    0
Outlet_Size                  0
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

[353]:
```python
data_train.groupby(['Item_Fat_Content']).size()
```

[353]:
```
Item_Fat_Content
LF            316
Low Fat      5089
Regular      2889
low fat       112
reg           117
dtype: int64
```

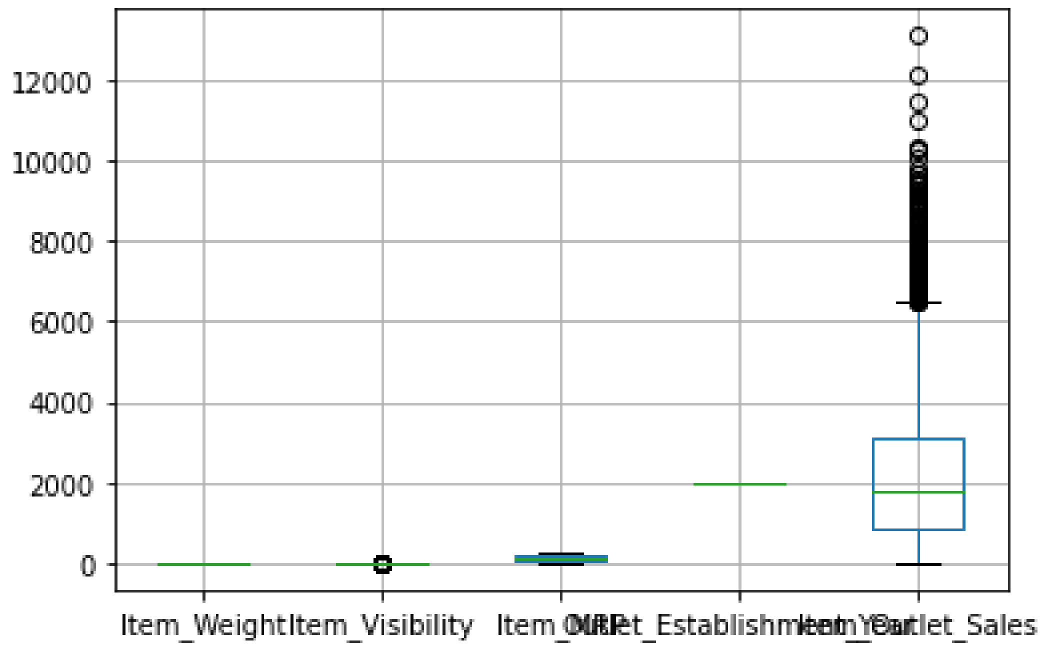
[354]:
```python
#Observed irregular data pattern where low fat is represented as LF and low fat␣
↪and all regular presented as reg
data_train["Item_Fat_Content"].replace({"LF": "Low Fat", "low fat": "Low␣Fat",␣
↪"reg": "Regular"}, inplace=True)
```

[355]:
```python
data_train.groupby(['Item_Fat_Content']).size()
```

[355]:
```
Item_Fat_Content
Low Fat     5405
Low␣Fat      112
Regular     3006
dtype: int64
```

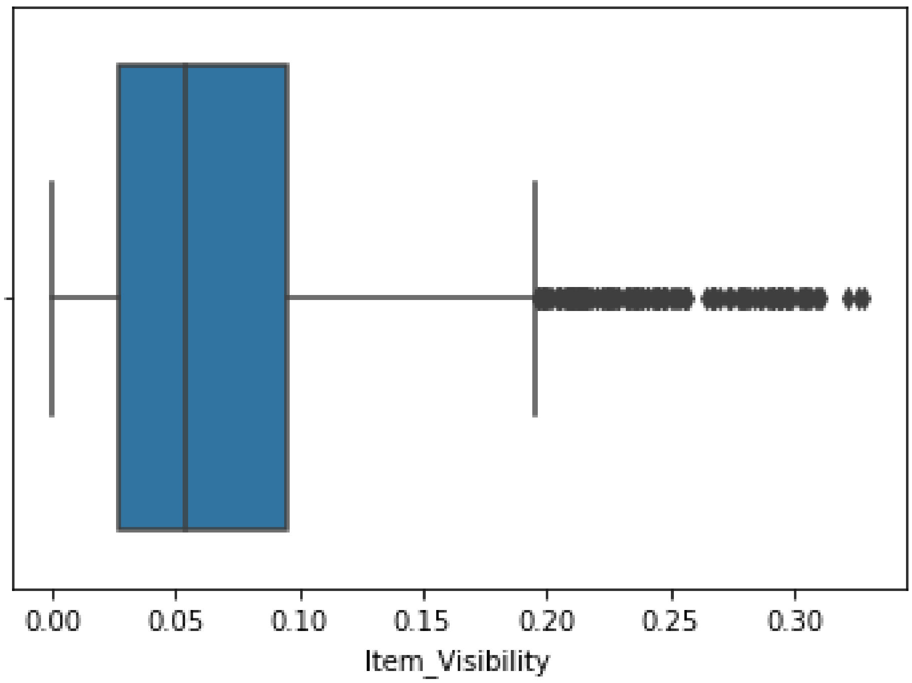
[356]:
```
#Checking for Outlier using box plot for the entire data
data_train.boxplot()
```

[356]:
```
<AxesSubplot:>
```



[357]:
```
sns.boxplot(data_train['Item_Visibility'])
```

[357]:
```
<AxesSubplot:xlabel='Item_Visibility'>
```



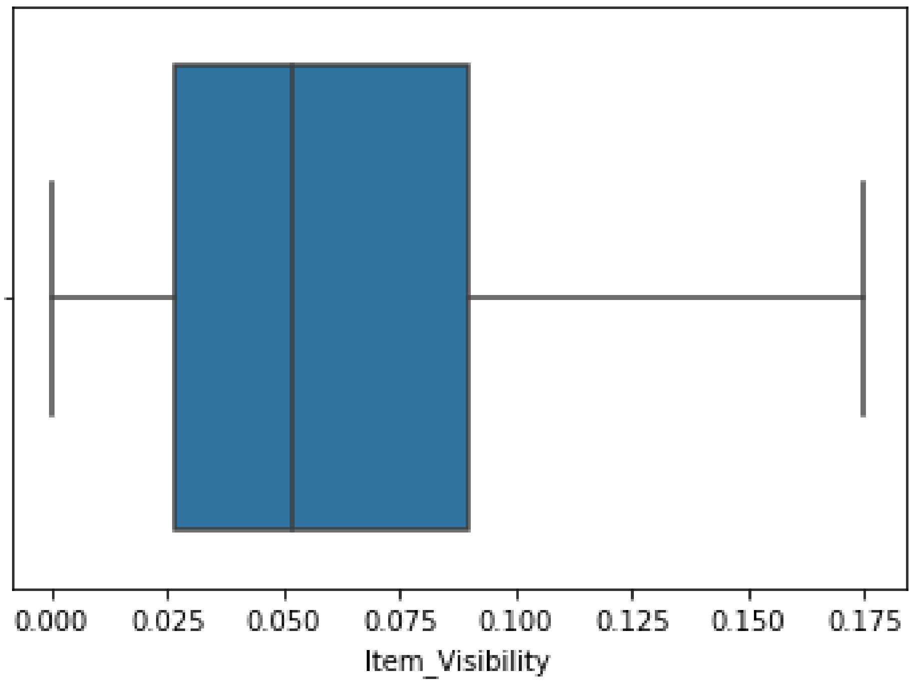
[358]:
```
#Putting a cap on the data
data_train[data_train['Item_Visibility']<0.175].count()
```

[358]:
```
Item_Weight                  8245
Item_Fat_Content             8245
Item_Visibility              8245
Item_Type                    8245
Item_MRP                     8245
Outlet_Establishment_Year    8245
Outlet_Size                  8245
Outlet_Location_Type         8245
Outlet_Type                  8245
Item_Outlet_Sales            8245
dtype: int64
```

[359]:
```
#Viewing the Cap
data_train= data_train[data_train['Item_Visibility'].values < 0.175]
```

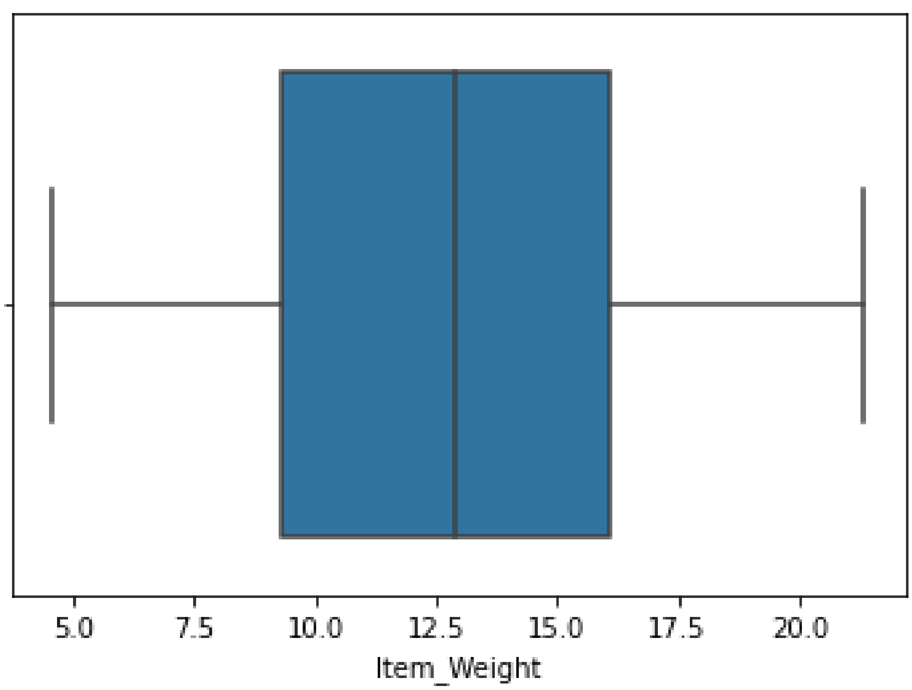
[360]:
```
#Viewing the boxplot after the data treatment
sns.boxplot(data_train['Item_Visibility'])
```

[360]: <AxesSubplot:xlabel='Item_Visibility'>



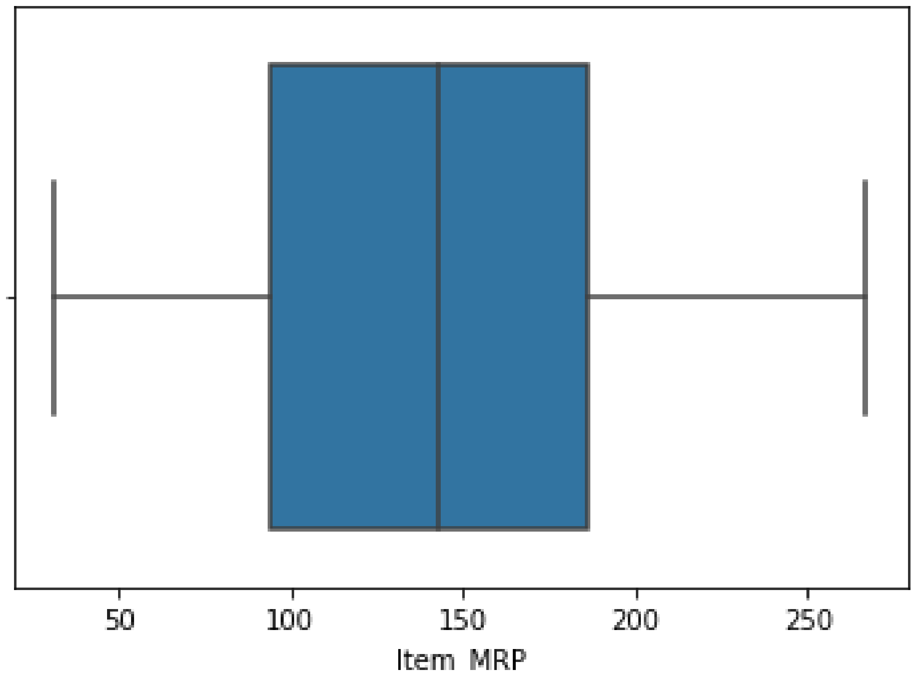

```
[361]: #Viewing the box plot for Weight
sns.boxplot(data_train['Item_Weight'])
```

```
[361]: <AxesSubplot:xlabel='Item_Weight'>
```



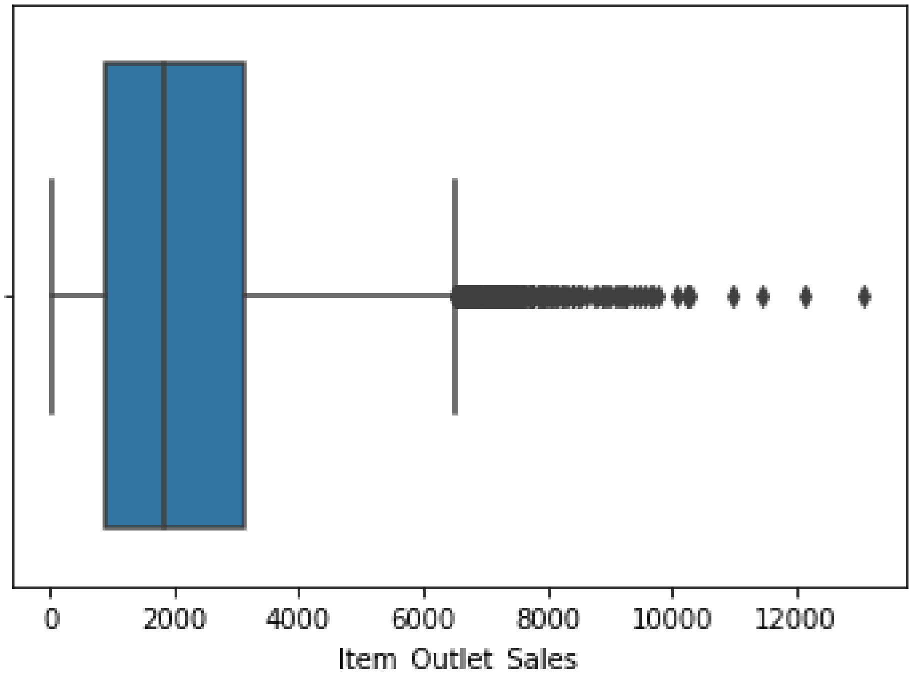
[362]:
```
sns.boxplot(data_train['Item_MRP'])
```

[362]: <AxesSubplot:xlabel='Item_MRP'>



[363]:
```
#viewing box plot for item outlet sales
sns.boxplot(data_train['Item_Outlet_Sales'])
```

[363]: <AxesSubplot:xlabel='Item_Outlet_Sales'>



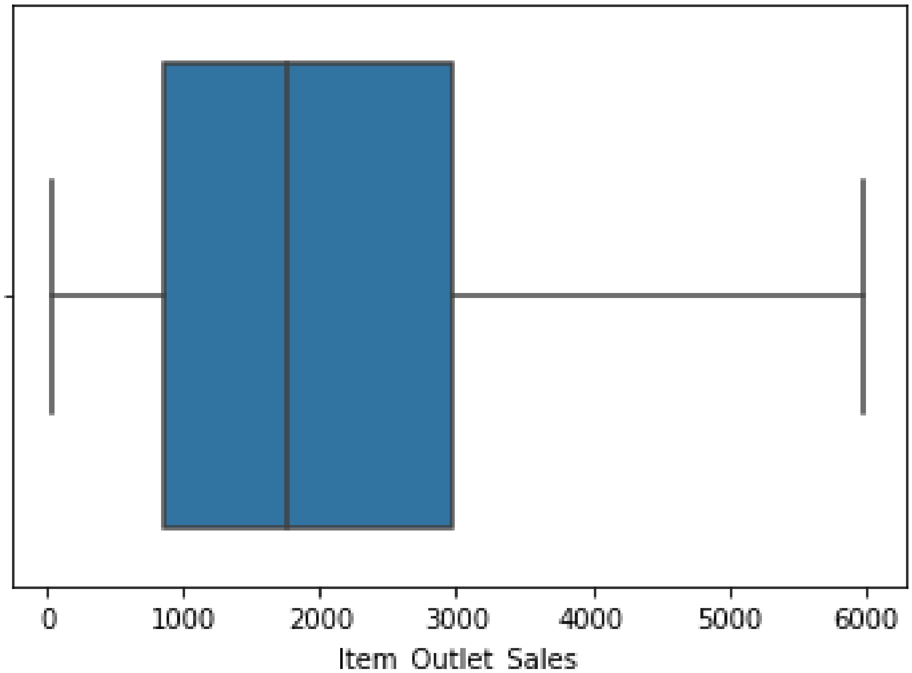
[364]:
```
#Placing a Cap on the data
data_train[data_train['Item_Outlet_Sales'].values<6000].count()
```

[364]:
```
Item_Weight                  7958
Item_Fat_Content             7958
Item_Visibility              7958
Item_Type                    7958
Item_MRP                     7958
Outlet_Establishment_Year    7958
Outlet_Size                  7958
Outlet_Location_Type         7958
Outlet_Type                  7958
Item_Outlet_Sales            7958
dtype: int64
```

[365]:
```
#Veiwing the data after the Cap
data_train=data_train[data_train['Item_Outlet_Sales'].values<6000]
```

[366]:
```
#Viewing the box plot after the treatment
sns.boxplot(data_train['Item_Outlet_Sales'])
```

[366]: <AxesSubplot:xlabel='Item_Outlet_Sales'>



[367]:
```
#check variable with extreme high correlation with target variable for␣
↪potential target leakage
print("correlation with target variable:\n")
data_train.corr()['Item_Outlet_Sales'].sort_values(ascending=False)
```

```
correlation with target variable:
```

[367]:
```
Item_Outlet_Sales            1.000000
Item_MRP                     0.554841
Item_Weight                  0.009989
Outlet_Establishment_Year   -0.001486
Item_Visibility             -0.063880
Name: Item_Outlet_Sales, dtype: float64
```

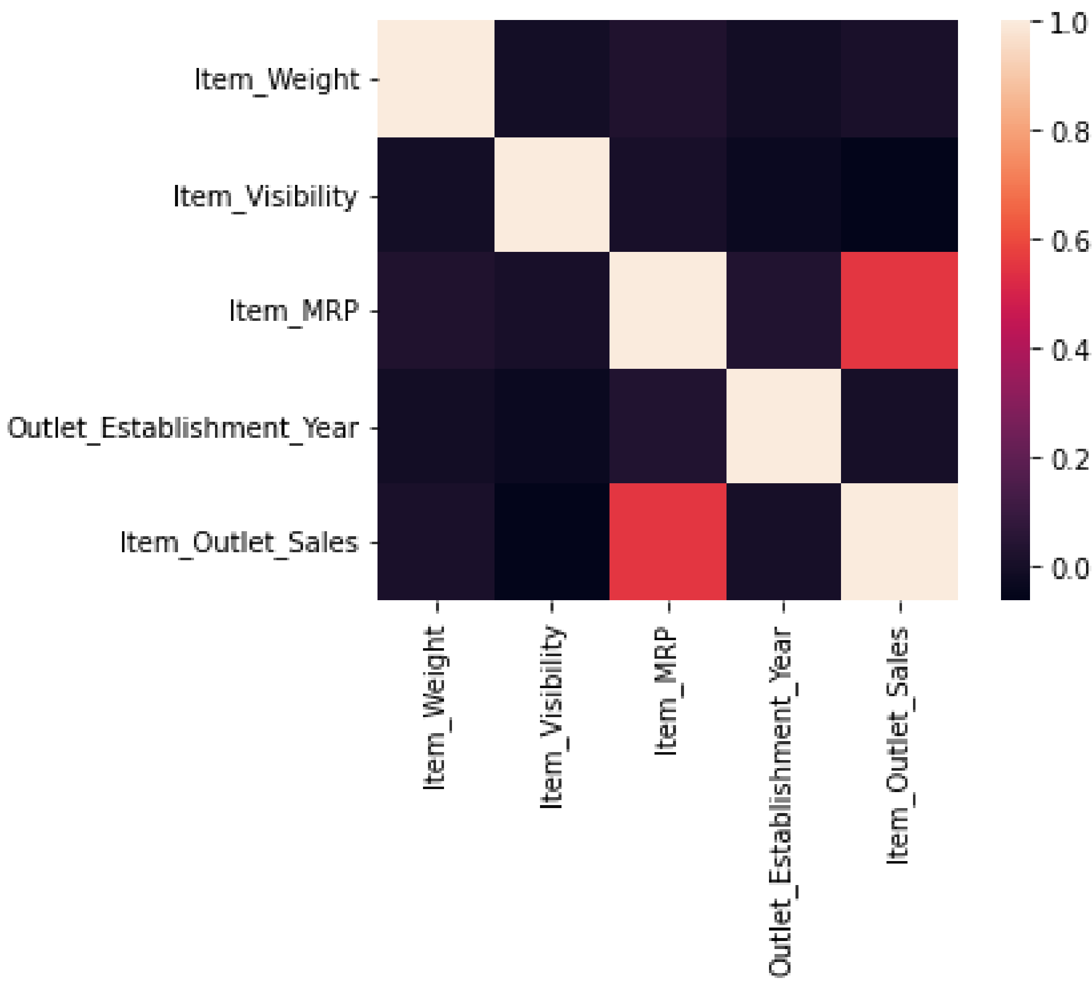
[368]:
```
data_corr=data_train.corr()
data_corr
```

[368]:
```
                           Item_Weight  Item_Visibility  Item_MRP  \
Item_Weight                   1.000000        -0.005938  0.024639
Item_Visibility              -0.005938         1.000000  0.002651
Item_MRP                      0.024639         0.002651  1.000000
Outlet_Establishment_Year    -0.010047        -0.032005  0.029837
Item_Outlet_Sales             0.009989        -0.063880  0.554841
```

	Outlet_Establishment_Year	Item_Outlet_Sales
Item_Weight	-0.010047	0.009989
Item_Visibility	-0.032005	-0.063880
Item_MRP	0.029837	0.554841
Outlet_Establishment_Year	1.000000	-0.001486
Item_Outlet_Sales	-0.001486	1.000000

[369]:
```
#correlation heatmap
import matplotlib as plt
%matplotlib inline
sns.heatmap(data =data_corr ,square = True)
```

[369]: <AxesSubplot:>



[370]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder,␣
↪Normalizer, RobustScaler
```

[371]:
```
#Grouping the
cols = ['Item_Fat_Content', 'Outlet_Size', 'Outlet_Type',␣
↪'Outlet_Location_Type','Outlet_Establishment_Year','Item_Type']
```

[372]:
```
#Applying the label enconder
data_train[cols] = data_train[cols].apply(LabelEncoder().fit_transform)
```

[373]:
```
data_train.head()
```

[373]:
```
   Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0         9.30                 0         0.016047          4  249.8092
1         5.92                 2         0.019278         14   48.2692
2        17.50                 0         0.016760         10  141.6180
3        19.20                 2         0.000000          6  182.0950
4         8.93                 0         0.000000          9   53.8614

   Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Outlet_Type  \
0                          4            1                     0            1
1                          8            1                     2            2
2                          4            1                     0            1
3                          3            2                     2            0
4                          1            0                     2            1

   Item_Outlet_Sales
0          3735.1380
1           443.4228
2          2097.2700
3           732.3800
4           994.7052
```

[374]:
```
# Applying Min Max Scaler
min_max_scal = MinMaxScaler()
min_max_scal.fit(data_train[['Item_Outlet_Sales']])
min_max_scal.data_max_
data_train['Item_Outlet_Sales_Max'] = min_max_scal.
↪transform(data_train[['Item_Outlet_Sales']])
data_train.head()
```

[374]:
```
   Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0         9.30                 0         0.016047          4  249.8092
1         5.92                 2         0.019278         14   48.2692
2        17.50                 0         0.016760         10  141.6180
3        19.20                 2         0.000000          6  182.0950
4         8.93                 0         0.000000          9   53.8614

   Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Outlet_Type  \
0                          4            1                     0            1
```

```
1                        8           1                     2            2
2                        4           1                     0            1
3                        3           2                     2            0
4                        1           0                     2            1

   Item_Outlet_Sales  Item_Outlet_Sales_Max
0          3735.1380               0.621229
1           443.4228               0.068827
2          2097.2700               0.346369
3           732.3800               0.117318
4           994.7052               0.161341
```

[375]:
```python
## Applying Standard Scaler
std_scal = StandardScaler()
std_scal.fit(data_train[['Item_Outlet_Sales']])
std_scal.mean_
data_train['Item_Outlet_Sales_Std'] = std_scal.
 ↪transform(data_train[['Item_Outlet_Sales']])
data_train.head()
```

[375]:
```
   Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0         9.30                 0         0.016047          4  249.8092
1         5.92                 2         0.019278         14   48.2692
2        17.50                 0         0.016760         10  141.6180
3        19.20                 2         0.000000          6  182.0950
4         8.93                 0         0.000000          9   53.8614

   Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Outlet_Type  \
0                          4            1                     0            1
1                          8            1                     2            2
2                          4            1                     0            1
3                          3            2                     2            0
4                          1            0                     2            1

   Item_Outlet_Sales  Item_Outlet_Sales_Max  Item_Outlet_Sales_Std
0          3735.1380               0.621229               1.177460
1           443.4228               0.068827              -1.116200
2          2097.2700               0.346369               0.036197
3           732.3800               0.117318              -0.914856
4           994.7052               0.161341              -0.732068
```

[376]:
```python
# Applying Normalizer Scaler
norm_scal = Normalizer()
norm_scal.fit(data_train[['Item_Outlet_Sales']])
data_train['Item_Outlet_Sales_Norm'] = norm_scal.
 ↪transform(data_train[['Item_Outlet_Sales']])
data_train.head()
```

[376]:
```
   Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0         9.30                 0         0.016047          4  249.8092
1         5.92                 2         0.019278         14   48.2692
2        17.50                 0         0.016760         10  141.6180
3        19.20                 2         0.000000          6  182.0950
4         8.93                 0         0.000000          9   53.8614

   Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Outlet_Type  \
0                          4            1                     0            1
1                          8            1                     2            2
2                          4            1                     0            1
3                          3            2                     2            0
4                          1            0                     2            1

   Item_Outlet_Sales  Item_Outlet_Sales_Max  Item_Outlet_Sales_Std  \
0          3735.1380               0.621229               1.177460
1           443.4228               0.068827              -1.116200
2          2097.2700               0.346369               0.036197
3           732.3800               0.117318              -0.914856
4           994.7052               0.161341              -0.732068

   Item_Outlet_Sales_Norm
0                     1.0
1                     1.0
2                     1.0
3                     1.0
4                     1.0
```

[377]:
```python
# Applying Robust Scaler
rob_scal = RobustScaler()
rob_scal.fit(data_train[['Item_Outlet_Sales']])
rob_scal.scale_
data_train['Item_Outlet_Sales_Rob'] = rob_scal.
 ↪transform(data_train[['Item_Outlet_Sales']])
data_train
```

[377]:
```
      Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0           9.300                 0         0.016047          4  249.8092
1           5.920                 2         0.019278         14   48.2692
2          17.500                 0         0.016760         10  141.6180
3          19.200                 2         0.000000          6  182.0950
4           8.930                 0         0.000000          9   53.8614
…             …               …               …          …       …
8518        6.865                 0         0.056783         13  214.5218
8519        8.380                 2         0.046982          0  108.1570
8520       10.600                 0         0.035186          8   85.1224
8521        7.210                 2         0.145221         13  103.1332
```

```
8522       14.800                0         0.044878         14   75.4670

      Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  \
0                             4            1                     0
1                             8            1                     2
2                             4            1                     0
3                             3            2                     2
4                             1            0                     2
…                           …          …                   …
8518                          1            0                     2
8519                          5            2                     1
8520                          6            2                     1
8521                          8            1                     2
8522                          2            2                     0

      Outlet_Type  Item_Outlet_Sales  Item_Outlet_Sales_Max  \
0               1          3735.1380               0.621229
1               2           443.4228               0.068827
2               1          2097.2700               0.346369
3               0           732.3800               0.117318
4               1           994.7052               0.161341
…             …                …                    …
8518            1          2778.3834               0.460670
8519            1           549.2850               0.086592
8520            1          1193.1136               0.194637
8521            2          1845.5976               0.304134
8522            1           765.6700               0.122905

      Item_Outlet_Sales_Std  Item_Outlet_Sales_Norm  Item_Outlet_Sales_Rob
0                  1.177460                     1.0               0.930774
1                 -1.116200                     1.0              -0.624921
2                  0.036197                     1.0               0.156702
3                 -0.914856                     1.0              -0.488357
4                 -0.732068                     1.0              -0.364380
…                     …                     …                    …
8518               0.510796                     1.0               0.478603
8519              -1.042436                     1.0              -0.574890
8520              -0.593817                     1.0              -0.270610
8521              -0.139168                     1.0               0.037760
8522              -0.891659                     1.0              -0.472624

[7958 rows x 14 columns]
```

[378]:
```
#Assiging Features and Target variables
#Using this alternative code print('data before splitting:', data_train.shape)
#x_cols=[x for x in data_train.columns if x!='Item_Outlet_Sales']
```

```
features = data_train.
↪drop(['Item_Outlet_Sales','Item_Outlet_Sales_Max','Item_Outlet_Sales_Std','Item_Outlet_Sale
target= data_train[['Item_Outlet_Sales_Std']]
features.head()
```

[378]:

```
   Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  \
0         9.30                 0         0.016047          4  249.8092
1         5.92                 2         0.019278         14   48.2692
2        17.50                 0         0.016760         10  141.6180
3        19.20                 2         0.000000          6  182.0950
4         8.93                 0         0.000000          9   53.8614

   Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Outlet_Type
0                          4            1                     0            1
1                          8            1                     2            2
2                          4            1                     0            1
3                          3            2                     2            0
4                          1            0                     2            1
```

[379]:

```
from sklearn.linear_model import Lasso, Ridge, ElasticNet, LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error,r2_score
```

[380]:

```
X_train, X_test, y_train, y_test = train_test_split(features,␣
↪target,random_state = 10)
```

[381]:

```
#Viewing the shape of the data
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

[381]: ((6366, 9), (1592, 9), (5968, 1), (1990, 1))

[382]:

```
my_multiple_lm_simple = LinearRegression()
my_multiple_lm_simple.fit(X_train,y_train)
my_multiple_lm_simple.coef_
my_multiple_lm_simple.intercept_
my_multiple_lm_simple_preds = my_multiple_lm_simple.predict(X_test)
mean_absolute_error(my_multiple_lm_simple_preds,y_test)
```

[382]: 0.5649110474262632

[383]:

```
#Finding the Mean Square Error
mean_squared_error(my_multiple_lm_simple_preds,y_test)
```

[383]: 0.5301009454480488

[384]:

```
#getting the R_squared
r2_score(y_test,my_multiple_lm_simple_preds)
```

[384]: 0.46042229424616143

[385]:
```python
#Fiding the Lasso
alphas=[-5,-1,1e-8,1e-6,1e-4,1e-3,1e-2,1,5]

def test_alpha(a):
    model_ridge = Ridge(alpha=a)
    model_ridge.fit(X_train, y_train)
    pred_test_ridge = model_ridge.predict(X_test)
    new_score = r2_score(y_test, pred_test_ridge)
    new_mse = mean_squared_error(y_test, pred_test_ridge)
    print('ALPHA: {:.3f} R2 SCORE: {:.4f}% new_score, {:.1f}'.
 ↪format(a,new_score, new_mse))

for alpha in alphas:
    test_alpha(alpha)
```

```
ALPHA: -5.000 R2 SCORE: 0.4606% new_score, 0.5
ALPHA: -1.000 R2 SCORE: 0.4605% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.001 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.010 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 1.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 5.000 R2 SCORE: 0.4601% new_score, 0.5
```

[386]:
```python
#Fiding the Lasso
alphas =[-5, -1, 1e-8,1e-6,1e-4, 1e-3, 1e-2, 1, 5]

def test_alpha(a):
    model_lasso = Lasso(alpha=a)
    model_lasso.fit(X_train, y_train)
    pred_test_lasso = model_lasso.predict(X_test)
    new_score = r2_score(y_test, pred_test_lasso)
    new_mse = mean_squared_error(y_test, pred_test_lasso)
    print('ALPHA: {:.3f} R2 SCORE: {:.4f}% new_score, {:.1f}'.
 ↪format(a,new_score, new_mse))
for alpha in alphas:
    test_alpha(alpha)
```

```
ALPHA: -5.000 R2 SCORE: -14270.5003% new_score, 14020.8
ALPHA: -1.000 R2 SCORE: -569.7404% new_score, 560.7
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.001 R2 SCORE: 0.4592% new_score, 0.5
```

```
ALPHA: 0.010 R2 SCORE: 0.4585% new_score, 0.5
ALPHA: 1.000 R2 SCORE: 0.3115% new_score, 0.7
ALPHA: 5.000 R2 SCORE: 0.3071% new_score, 0.7
```

[387]:

```
#Finding the ElasticNet
alphas = [-5, -1, 1e-8,1e-6,1e-4, 1e-3, 1e-2, 1, 5]

def test_alpha(a):
    model_elastic = ElasticNet(alpha=a)
    model_elastic.fit(X_train, y_train)
    pred_test_elastic = model_elastic.predict(X_test)
    new_score = r2_score(y_test, pred_test_elastic)
    new_mse = mean_squared_error(y_test, pred_test_elastic)
    print('ALPHA: {:.3f} R2 SCORE: {:.4f}% new_score, {:.1f}'.
 ↪format(a,new_score, new_mse))

for alpha in alphas:
    test_alpha(alpha)
```

```
ALPHA: -5.000 R2 SCORE: -17.1553% new_score, 17.8
ALPHA: -1.000 R2 SCORE: -0.0005% new_score, 1.0
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.000 R2 SCORE: 0.4604% new_score, 0.5
ALPHA: 0.001 R2 SCORE: 0.4598% new_score, 0.5
ALPHA: 0.010 R2 SCORE: 0.4590% new_score, 0.5
ALPHA: 1.000 R2 SCORE: 0.3114% new_score, 0.7
ALPHA: 5.000 R2 SCORE: 0.3110% new_score, 0.7
```

[388]:

```
#Usng Manual Calculation
my_ols_model = smf.ols(formula='Item_Outlet_Sales_Std ~ Item_Weight␣
 ↪+Item_Fat_Content + Item_Visibility + Item_Type + Item_MRP␣
 ↪+Outlet_Establishment_Year + Outlet_Size + Outlet_Location_Type␣
 ↪+Outlet_Type', data =data_train).fit()
my_ols_model.summary()
```

[388]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
================================================================================
=
Dep. Variable:     Item_Outlet_Sales_Std   R-squared:
0.467
Model:                               OLS   Adj. R-squared:
0.466
Method:                    Least Squares   F-statistic:
773.3
```

```
Date:                    Sun, 27 Feb 2022   Prob (F-statistic):
0.00
Time:                            19:32:39   Log-Likelihood:
-8789.4
No. Observations:                    7958   AIC:
1.760e+04
Df Residuals:                        7948   BIC:
1.767e+04
Df Model:                               9
Covariance Type:                nonrobust
==============================================================================
=============
                                coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
-------------
Intercept                    -1.5677      0.049    -31.953      0.000
-1.664      -1.472
Item_Weight                  -0.0003      0.002     -0.178      0.859
-0.004       0.003
Item_Fat_Content              0.0215      0.009      2.470      0.014
0.004       0.039
Item_Visibility              -0.6496      0.187     -3.466      0.001
-1.017      -0.282
Item_Type                     0.0013      0.002      0.642      0.521
-0.003       0.005
Item_MRP                      0.0093      0.000     69.528      0.000
0.009       0.010
Outlet_Establishment_Year     0.0166      0.003      5.067      0.000
0.010       0.023
Outlet_Size                  -0.1228      0.015     -8.199      0.000
-0.152      -0.093
Outlet_Location_Type         -0.2243      0.013    -17.712      0.000
-0.249      -0.200
Outlet_Type                   0.5498      0.012     44.180      0.000
0.525       0.574
==============================================================================
Omnibus:                     109.554   Durbin-Watson:                   2.030
Prob(Omnibus):                 0.000   Jarque-Bera (JB):              117.495
Skew:                          0.265   Prob(JB):                     3.06e-26
Kurtosis:                      3.273   Cond. No.                     3.48e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.48e+03. This might indicate that there are
```

```
strong multicollinearity or other numerical problems.
"""
```

[389]:
```python
#Polynomical Linear Regression

from sklearn.preprocessing import PolynomialFeatures
features_poly=PolynomialFeatures(degree=2)
train_Poly=features_poly.fit_transform(features)
train_Poly
```

[389]:
```
array([[ 1.   ,  9.3 ,  0.   , …,  0.   ,  0.   ,  1.   ],
       [ 1.   ,  5.92,  2.   , …,  4.   ,  4.   ,  4.   ],
       [ 1.   , 17.5 ,  0.   , …,  0.   ,  0.   ,  1.   ],
       …,
       [ 1.   , 10.6 ,  0.   , …,  1.   ,  1.   ,  1.   ],
       [ 1.   ,  7.21,  2.   , …,  4.   ,  4.   ,  4.   ],
       [ 1.   , 14.8 ,  0.   , …,  0.   ,  0.   ,  1.   ]])
```

[390]:
```python
#Splitting the data
X_train, X_test, y_train, y_test = train_test_split(train_Poly,␣
 ↪target,random_state = 6)
```

[391]:
```python
#Fitting the Regression
my_model = LinearRegression()
my_model.fit(X_train, y_train)
preds = my_model.predict(X_test)
print('MAE : ', mean_absolute_error(y_test, preds))
print('MSE : ', mean_squared_error(y_test, preds))
print('R2 : ', r2_score(y_test, preds))
```

```
MAE :  0.5063635221381928
MSE :  0.44709466714578755
R2 :  0.5517740971291534
```

[392]:
```python
#Printing the shape of the data
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5968, 55)
(1990, 55)
(5968, 1)
(1990, 1)
```

[398]:
```python
from sklearn.decomposition import PCA
```

[399]:
```python
#using the PCA
pca=PCA(n_components=30)
pca.fit(X_train)
```

[399]:
```
PCA(n_components=30)
```

[400]:
```python
#Finding the explained variance
pca.explained_variance_ratio_
```

[400]:
```
array([9.96552934e-01, 1.51322829e-03, 1.20511587e-03, 5.27418264e-04,
       7.62093643e-05, 6.37594963e-05, 2.42569520e-05, 1.89479857e-05,
       1.00901022e-05, 4.15432583e-06, 1.35881615e-06, 9.12735851e-07,
       3.92834018e-07, 3.38921562e-07, 1.78563094e-07, 1.49042067e-07,
       1.33364324e-07, 1.25299539e-07, 5.98842032e-08, 5.24073170e-08,
       4.95592705e-08, 4.19868843e-08, 2.33278668e-08, 1.95851504e-08,
       1.71995105e-08, 1.63838468e-08, 3.43722850e-09, 3.38018148e-09,
       1.74664954e-09, 1.57487884e-09])
```

[ ]:
```python

```