Import Liberaires

In [98]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings("ignore")
```

Load Data

In [99]:
```
Big_mart = pd.read_csv("Train.csv")
```

In [100…
```
Big_mart.head()
```

Out[100…

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987

In [101…
```
# number of data points & number of features
Big_mart.shape
```

Out[101…
```
(8523, 12)
```

In [102…
```
# getting some information about thye dataset
Big_mart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Item_Identifier            8523 non-null   object
 1   Item_Weight                7060 non-null   float64
 2   Item_Fat_Content           8523 non-null   object
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object
 7   Outlet_Establishment_Year  8523 non-null   int64
 8   Outlet_Size                6113 non-null   object
 9   Outlet_Location_Type       8523 non-null   object
 10  Outlet_Type                8523 non-null   object
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

Categorical Features:

- Item_Identifier
- Item_Fat_Content
- Item_Type
- Outlet_Identifier
- Outlet_Size
- Outlet_Location_Type
- Outlet_Type

Checking Missing values

In [103…
```
Big_mart.isnull().sum()
```

Out[103…
```
Item_Identifier                 0
Item_Weight                  1463
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  2410
Outlet_Location_Type            0
Outlet_Type                     0
Item_Outlet_Sales               0
dtype: int64
```

In [ ]:

In [104…
```
Big_mart.columns
```

Out[104…
```
Index(['Item_Identifier', 'Item_Weight', 'Item_Fat_Content', 'Item_Visibility',
       'Item_Type', 'Item_MRP', 'Outlet_Identifier',
       'Outlet_Establishment_Year', 'Outlet_Size', 'Outlet_Location_Type',
       'Outlet_Type', 'Item_Outlet_Sales'],
      dtype='object')
```

In [105…
```
Big_mart[Big_mart.Item_Weight.isnull()]
```

Out[105…

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Y
7	FDP10	NaN	Low Fat	0.127470	Snack Foods	107.7622	OUT027	1
18	DRI11	NaN	Low Fat	0.034238	Hard Drinks	113.2834	OUT027	1
21	FDW12	NaN	Regular	0.035400	Baking Goods	144.5444	OUT027	1
23	FDC37	NaN	Low Fat	0.057557	Baking Goods	107.6938	OUT019	1
29	FDC14	NaN	Regular	0.072222	Canned	43.6454	OUT019	1
...	...	...	...	...	...	...	...	
8485	DRK37	NaN	Low Fat	0.043792	Soft Drinks	189.0530	OUT027	1
8487	DRG13	NaN	Low Fat	0.037006	Soft Drinks	164.7526	OUT027	1
8488	NCN14	NaN	Low Fat	0.091473	Others	184.6608	OUT027	1
8490	FDU44	NaN	Regular	0.102296	Fruits and Vegetables	162.3552	OUT019	1
8504	NCN18	NaN	Low Fat	0.124111	Household	111.7544	OUT027	1

1463 rows × 12 columns

Mean --> average

Mode --> more repeated value

In [106…
```
Big_mart['Item_Weight'] = Big_mart['Item_Weight'].fillna(Big_mart['Item_Weight'].median())
```

In [107…
```
Big_mart.isnull().sum()
```

Out[107…
```
Item_Identifier                 0
Item_Weight                     0
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  2410
Outlet_Location_Type            0
Outlet_Type                     0
Item_Outlet_Sales               0
dtype: int64
```

In [108…
```
Big_mart[Big_mart.Outlet_Size.isnull()]
```

Out[108…

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Y
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1
8	FDH17	16.200	Regular	0.016687	Frozen Foods	96.9726	OUT045	2
9	FDU28	19.200	Regular	0.094450	Frozen Foods	187.8214	OUT017	2
25	NCD06	13.000	Low Fat	0.099887	Household	45.9060	OUT017	2
28	FDE51	5.925	Regular	0.161467	Dairy	45.5086	OUT010	1
...	...	...	...	...	...	...	...	
8502	NCH43	8.420	Low Fat	0.070712	Household	216.4192	OUT045	2
8508	FDW31	11.350	Regular	0.043246	Fruits and Vegetables	199.4742	OUT045	2
8509	FDG45	8.100	Low Fat	0.214306	Fruits and Vegetables	213.9902	OUT010	1
8514	FDA01	15.000	Regular	0.054489	Canned	57.5904	OUT045	2
8519	FDS36	8.380	Regular	0.046982	Baking Goods	108.1570	OUT045	2

2410 rows × 12 columns

In [109…
```
Big_mart['Outlet_Size'] = Big_mart['Outlet_Size'].fillna(Big_mart['Outlet_Size'].mode()[0])
```

In [110…
```
Big_mart.isnull().sum()
```

Out[110…
```
Item_Identifier              0
Item_Weight                  0
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Identifier            0
Outlet_Establishment_Year    0
Outlet_Size                  0
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

In [111…
```
Big_mart
```

Out[111...

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Y
0	FDA15	9.300	Low Fat	0.016047	Dairy	249.8092	OUT049	1
1	DRC01	5.920	Regular	0.019278	Soft Drinks	48.2692	OUT018	2
2	FDN15	17.500	Low Fat	0.016760	Meat	141.6180	OUT049	1
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1
4	NCD19	8.930	Low Fat	0.000000	Household	53.8614	OUT013	1
...	...	...	...	...	...	...	...	
8518	FDF22	6.865	Low Fat	0.056783	Snack Foods	214.5218	OUT013	1
8519	FDS36	8.380	Regular	0.046982	Baking Goods	108.1570	OUT045	2
8520	NCJ29	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	OUT035	2
8521	FDN46	7.210	Regular	0.145221	Snack Foods	103.1332	OUT018	2
8522	DRG01	14.800	Low Fat	0.044878	Soft Drinks	75.4670	OUT046	1

8523 rows × 12 columns

Data Analysis

In [112...

```
Big_mart.describe()
```

Out[112...

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	8523.00000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.81342	0.066132	140.992782	1997.831867	2181.288914
std	4.22724	0.051598	62.275067	8.371760	1706.499616
min	4.55500	0.000000	31.290000	1985.000000	33.290000
25%	9.31000	0.026989	93.826500	1987.000000	834.247400
50%	12.60000	0.053931	143.012800	1999.000000	1794.331000
75%	16.00000	0.094585	185.643700	2004.000000	3101.296400
max	21.35000	0.328391	266.888400	2009.000000	13086.964800

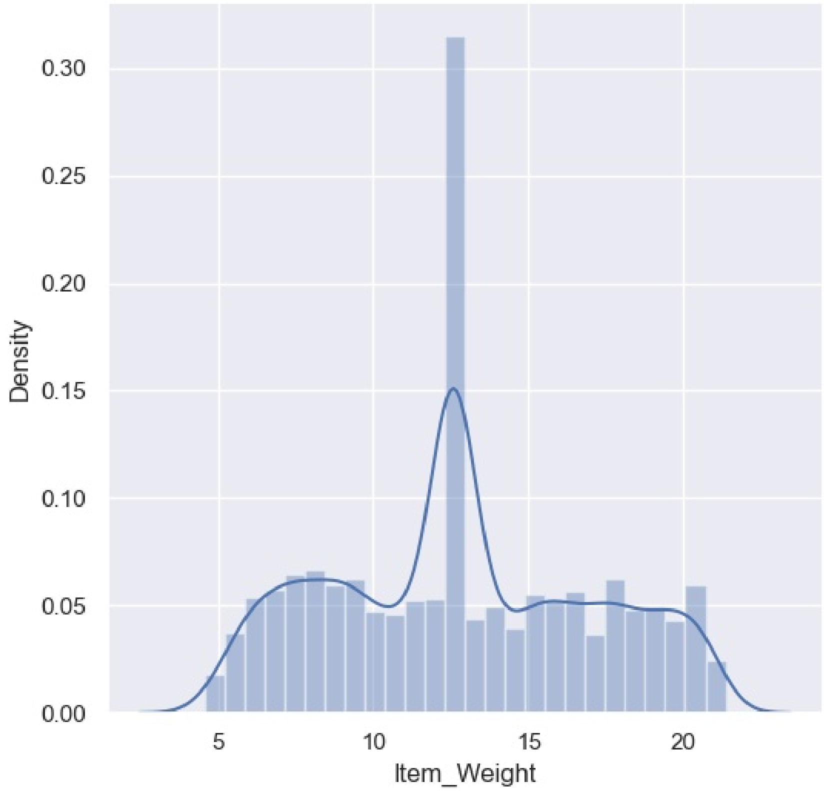
Numerical Features

In [113...

```
sns.set()
#sns.set() is used to set the default style for all Seaborn plots.
#It makes your graphs look cleaner and more visually appealing without needing extra styling code.
```

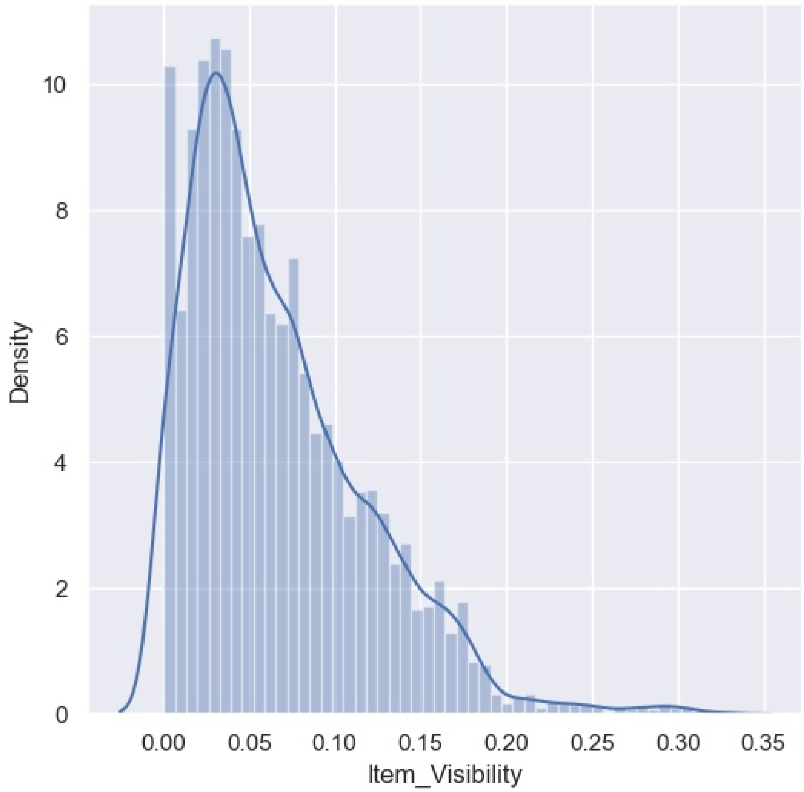
In [114...

```
# Item_Weight distribution
plt.figure(figsize=(6,6))
sns.distplot(Big_mart['Item_Weight'])
plt.show()
```



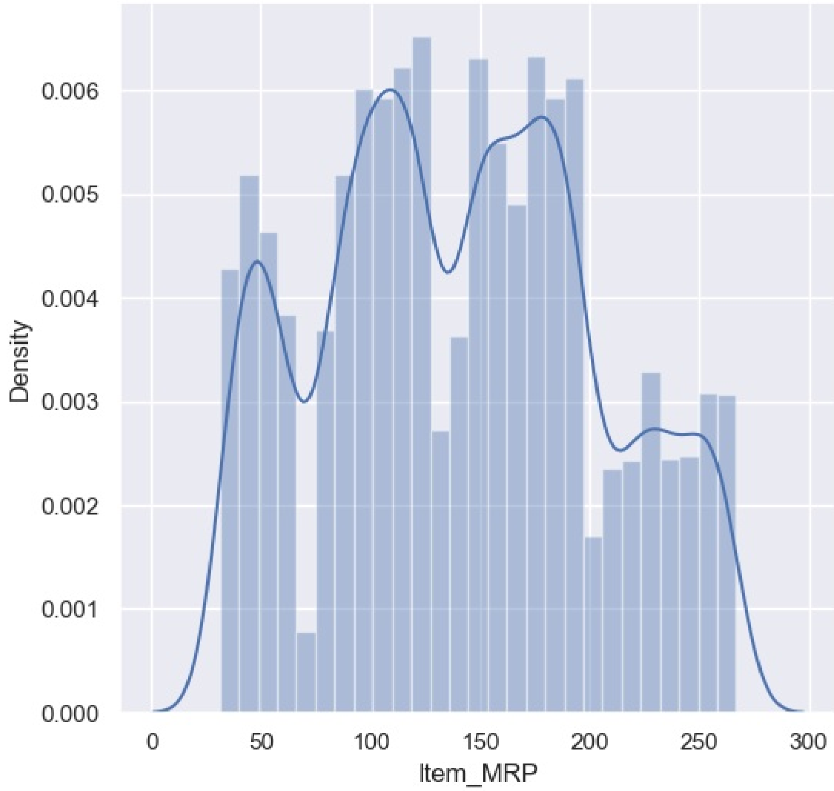
In [115…

```
# Item Visibility distribution
plt.figure(figsize=(6,6))
sns.distplot(Big_mart['Item_Visibility'])
plt.show()
```



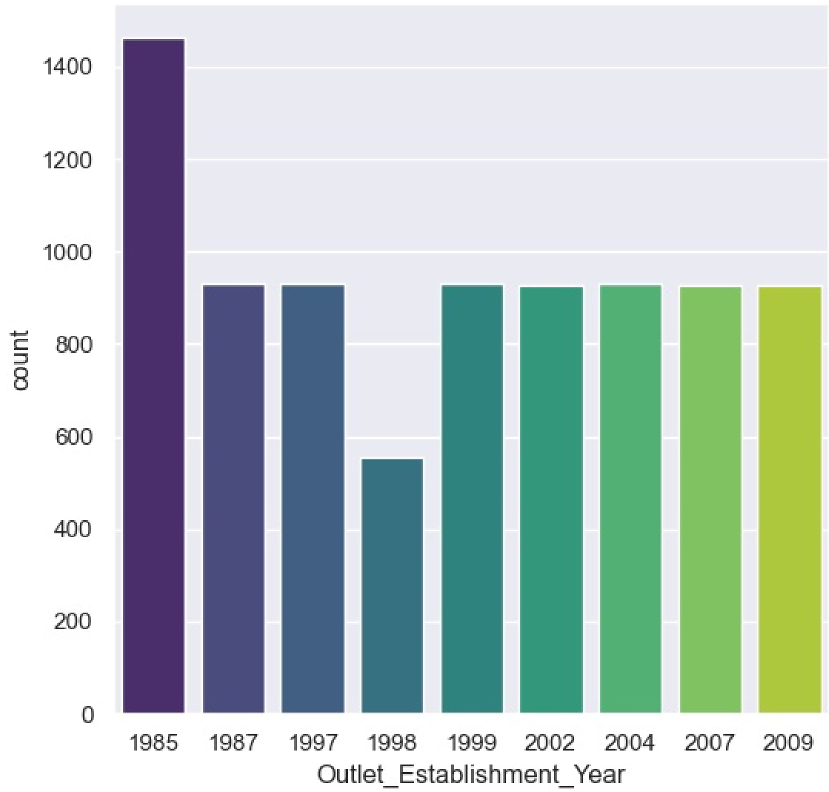
In [116…

```
# Item MRP distribution
plt.figure(figsize=(6,6))
sns.distplot(Big_mart['Item_MRP'])
plt.show()
```



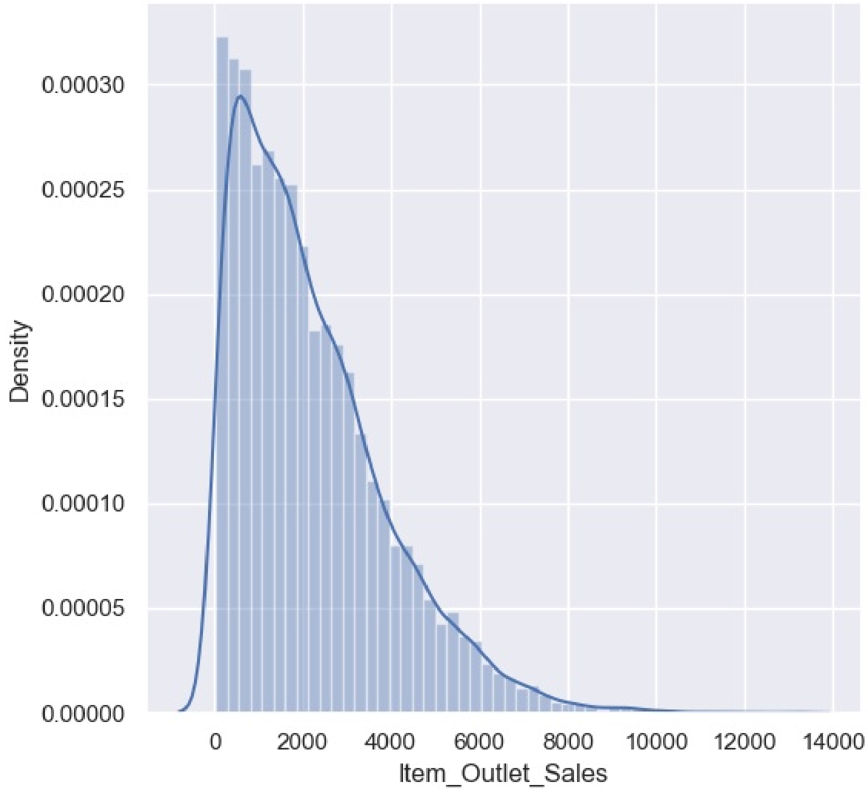
In [117…

```
# Outlet_Establishment_Year column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year', data=Big_mart, palette='viridis')
plt.show()
```



In [118…

```
# Item_Outlet_Sales distribution
plt.figure(figsize=(6,6))
sns.distplot(Big_mart['Item_Outlet_Sales'])
plt.show()
```



Categorical Features

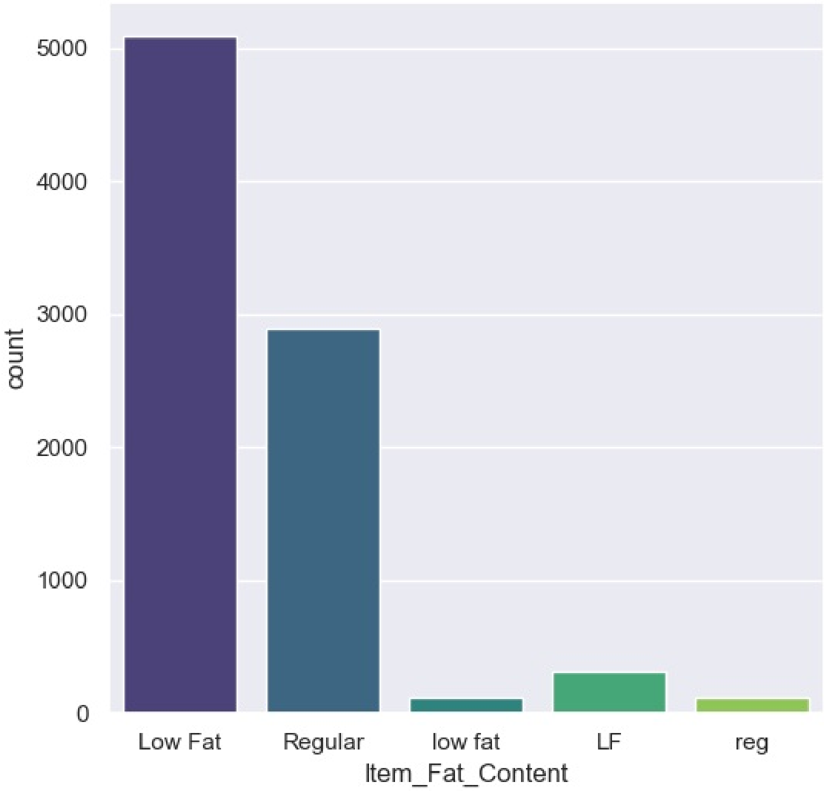
In [119…

```
Big_mart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                8523 non-null   float64
 2   Item_Fat_Content           8523 non-null   object 
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object 
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object 
 7   Outlet_Establishment_Year  8523 non-null   int64  
 8   Outlet_Size                8523 non-null   object 
 9   Outlet_Location_Type       8523 non-null   object 
 10  Outlet_Type                8523 non-null   object 
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

In [120…

```
plt.figure(figsize=(6,6))
sns.countplot(x = 'Item_Fat_Content',data=Big_mart,palette='viridis')
plt.show()
```



- Here we can identify that still Data is not cleaned because Low Fat ,Regular is correct change this (low fat,LF,reg)

In [121…
```
Big_mart[Big_mart.Item_Fat_Content == "LF"]
```

Out[121…

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Y
45	FDM39	6.42	LF	0.089499	Dairy	178.1002	OUT010	1
65	FDC46	17.70	LF	0.195068	Snack Foods	185.4266	OUT010	1
121	DRJ13	12.65	LF	0.063018	Soft Drinks	159.0578	OUT045	2
175	FDR47	17.85	LF	0.000000	Breads	196.5794	OUT010	1
207	DRF36	16.10	LF	0.023625	Soft Drinks	189.3846	OUT045	2
...	...	...	...	...	...	...	...	
8367	FDA32	12.60	LF	0.052691	Fruits and Vegetables	216.3192	OUT019	1
8379	FDV39	11.30	LF	0.007280	Meat	199.3426	OUT046	1
8391	FDV15	10.30	LF	0.146172	Meat	103.3648	OUT046	1
8443	FDX15	17.20	LF	0.156542	Meat	162.4578	OUT049	1
8467	FDV31	9.80	LF	0.000000	Fruits and Vegetables	175.2370	OUT049	1

316 rows × 12 columns

In [122…
```
Big_mart['Item_Fat_Content'] = Big_mart.Item_Fat_Content.replace({"LF" : "Low Fat"})
```

In [123…
```
Big_mart['Item_Fat_Content'] = Big_mart.Item_Fat_Content.replace({"low fat" : "Low Fat"})
```

In [124…
```
Big_mart['Item_Fat_Content'] = Big_mart.Item_Fat_Content.replace({"reg" : "Regular"})
```

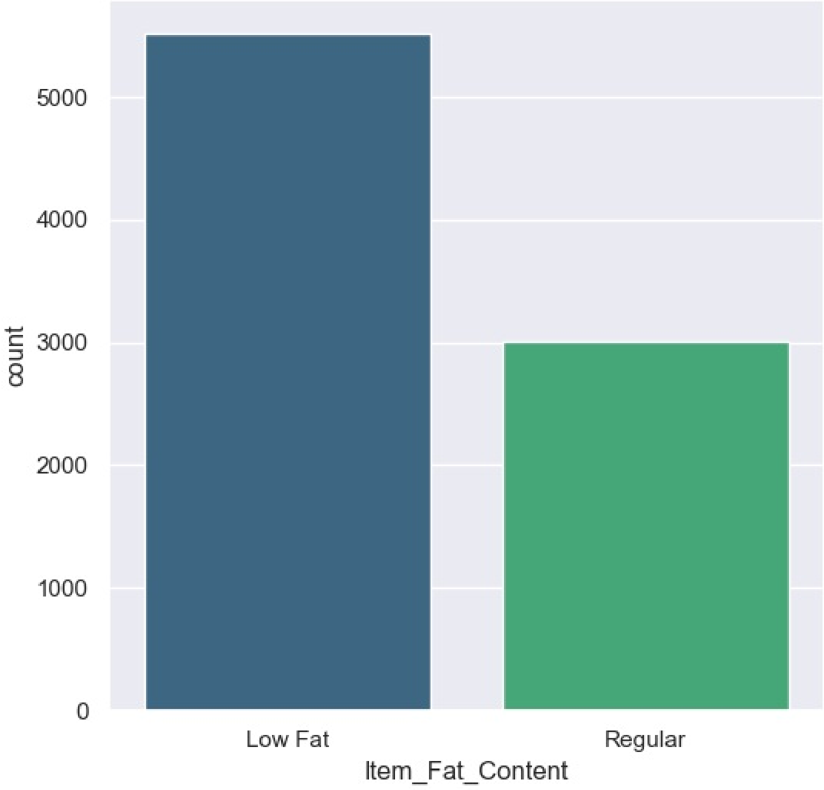
In [125…
```
Big_mart[Big_mart.Item_Fat_Content == "reg"]
```

Out[125…

Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year

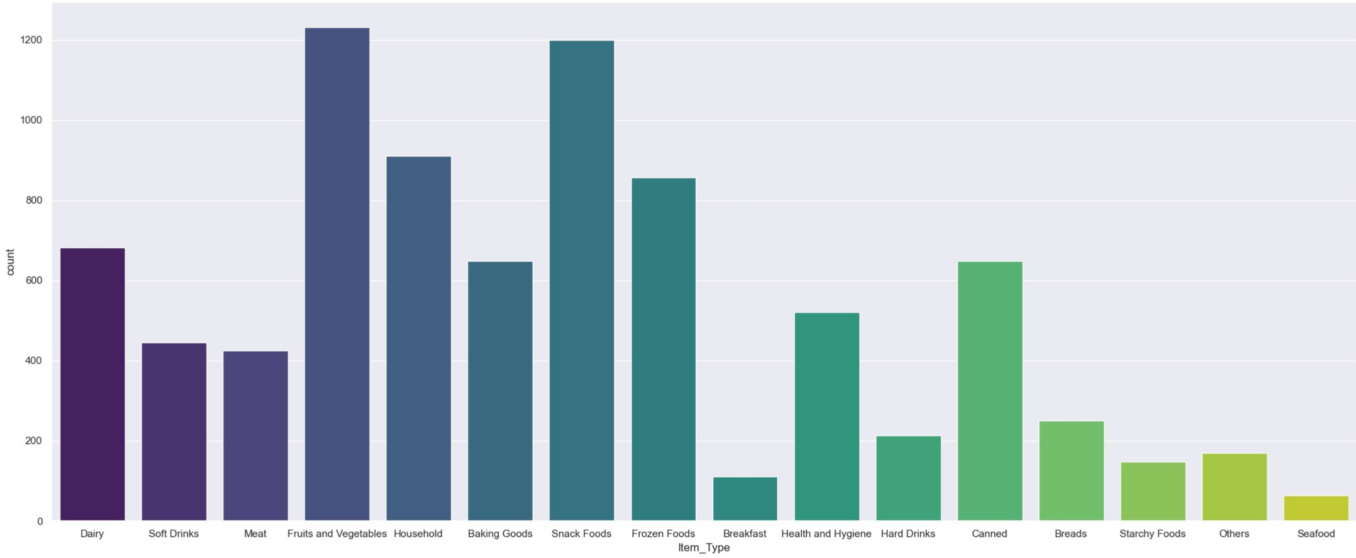
In [126…

```python
# Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x = 'Item_Fat_Content',data=Big_mart,palette='viridis')
plt.show()
```



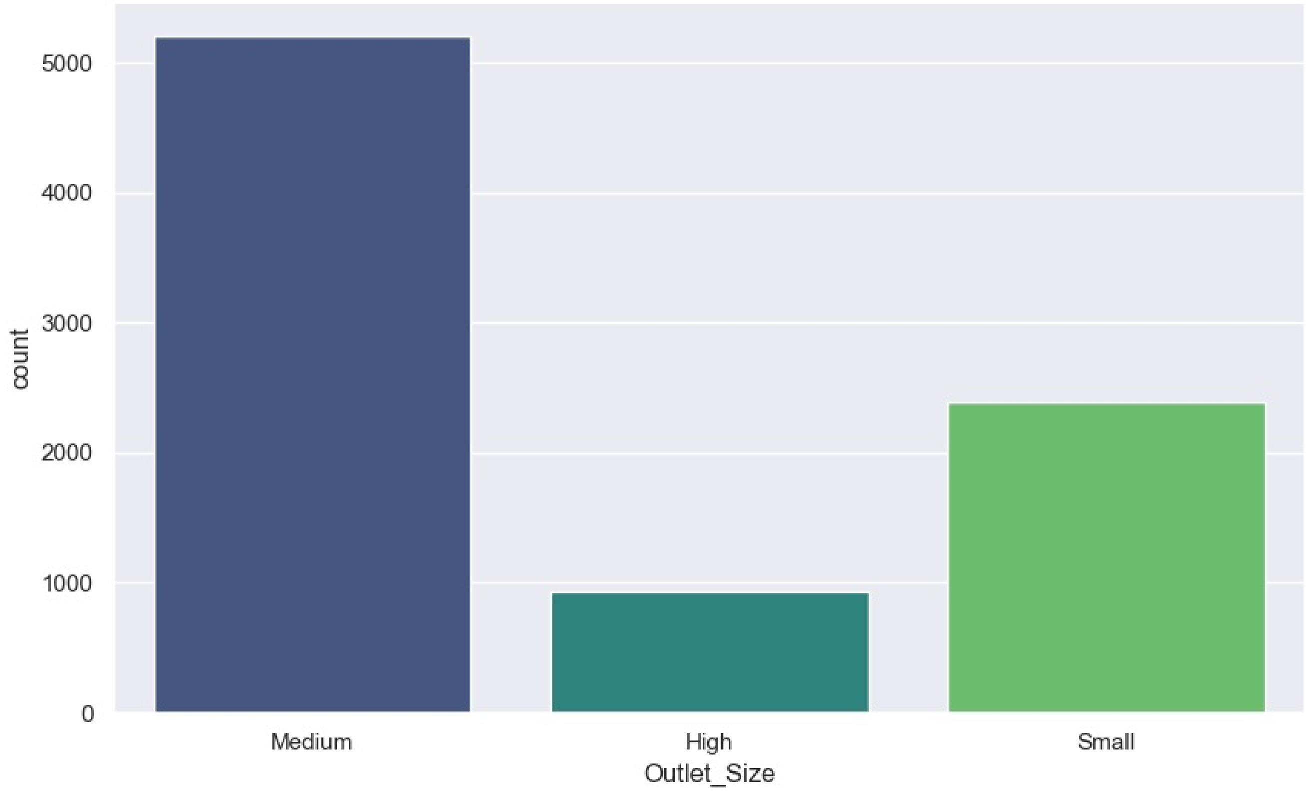
In [127…

```python
# Item_Type
plt.figure(figsize=(25,10))
sns.countplot(x = 'Item_Type',data=Big_mart,palette='viridis')
plt.show()
```



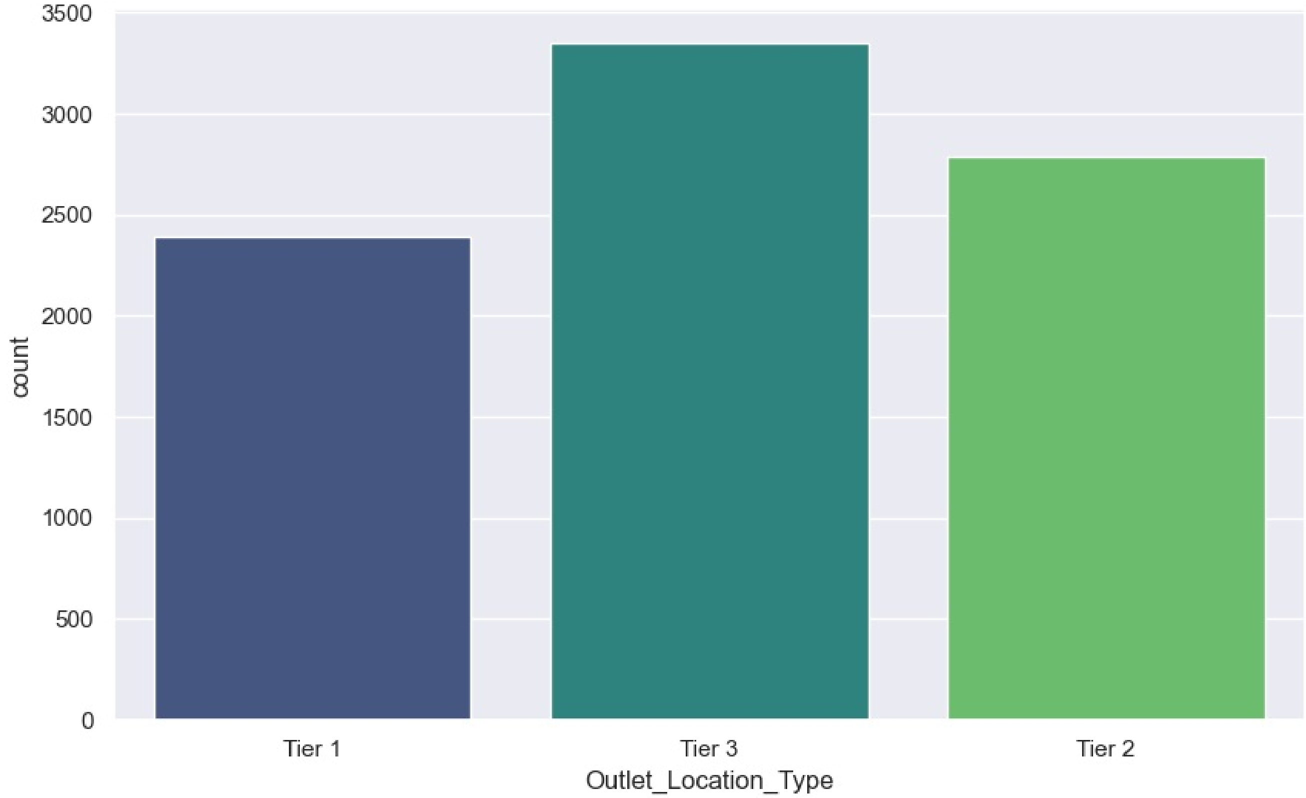
In [128…

```python
#Outlet_Size columns
plt.figure(figsize=(10,6))
sns.countplot(x = 'Outlet_Size',data=Big_mart,palette='viridis')
plt.show()
```



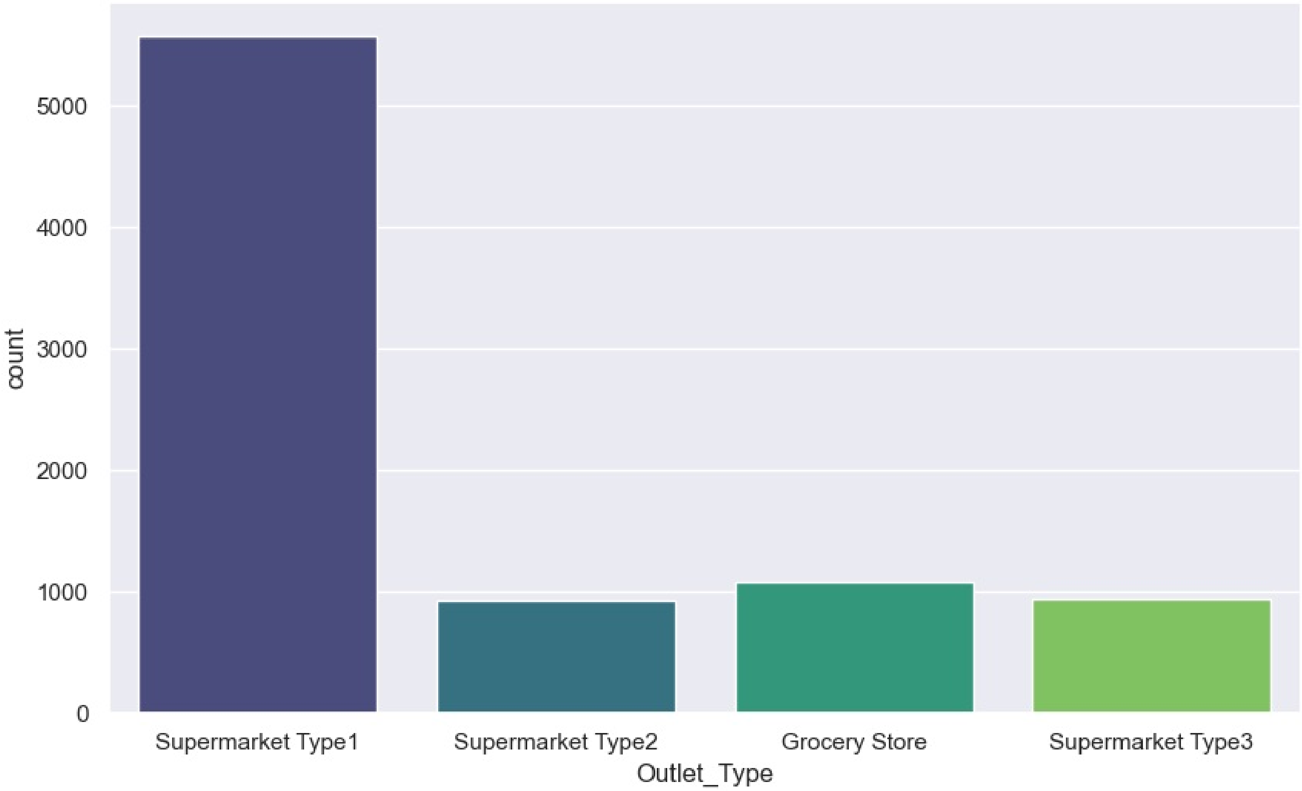
In [129…

```
# Outlet_Location_Type columns
plt.figure(figsize=(10,6))
sns.countplot(x = 'Outlet_Location_Type',data=Big_mart,palette='viridis')
plt.show()
```



In [130…

```
# Outlet_Type columns
plt.figure(figsize=(10,6))
sns.countplot(x = 'Outlet_Type',data=Big_mart,palette='viridis')
plt.show()
```



In [131…
```
Big_mart['Item_Fat_Content'].value_counts()
```

Out[131…
```
Item_Fat_Content
Low Fat    5517
Regular    3006
Name: count, dtype: int64
```

In [132…
```
Big_mart['Outlet_Location_Type'].value_counts()
```

Out[132…
```
Outlet_Location_Type
Tier 3    3350
Tier 2    2785
Tier 1    2388
Name: count, dtype: int64
```

In [133…
```
Big_mart['Outlet_Type'].value_counts()
```

Out[133…
```
Outlet_Type
Supermarket Type1    5577
Grocery Store        1083
Supermarket Type3     935
Supermarket Type2     928
Name: count, dtype: int64
```

In [134…
```
Big_mart['Outlet_Size'].value_counts()
```

Out[134…
```
Outlet_Size
Medium    5203
Small     2388
High       932
Name: count, dtype: int64
```

Label Encoding

In [135…
```
from sklearn.preprocessing import LabelEncoder
```

In [136…
```
encoder = LabelEncoder()
```

In [137…
```
Big_mart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                8523 non-null   float64
 2   Item_Fat_Content           8523 non-null   object 
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object 
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object 
 7   Outlet_Establishment_Year  8523 non-null   int64  
 8   Outlet_Size                8523 non-null   object 
 9   Outlet_Location_Type       8523 non-null   object 
 10  Outlet_Type                8523 non-null   object 
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

In [138…
```python
Big_mart['Item_Identifier'] = encoder.fit_transform(Big_mart['Item_Identifier'])

Big_mart['Item_Fat_Content'] = encoder.fit_transform(Big_mart['Item_Fat_Content'])

Big_mart['Item_Type'] = encoder.fit_transform(Big_mart['Item_Type'])

Big_mart['Outlet_Identifier'] = encoder.fit_transform(Big_mart['Outlet_Identifier'])

Big_mart['Outlet_Size'] = encoder.fit_transform(Big_mart['Outlet_Size'])

Big_mart['Outlet_Location_Type'] = encoder.fit_transform(Big_mart['Outlet_Location_Type'])

Big_mart['Outlet_Type'] = encoder.fit_transform(Big_mart['Outlet_Type'])
```

In [139…
```python
Big_mart.head()
```

Out[139…

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year
0	156	9.30	0	0.016047	4	249.8092	9	1999
1	8	5.92	1	0.019278	14	48.2692	3	2009
2	662	17.50	0	0.016760	10	141.6180	9	1999
3	1121	19.20	1	0.000000	6	182.0950	0	1998
4	1297	8.93	0	0.000000	9	53.8614	1	1987

Segergating X and y

In [140…
```python
X = Big_mart.drop(columns='Item_Outlet_Sales',axis=1)
y = Big_mart.Item_Outlet_Sales
```

Train Test Split

In [141…
```python
from sklearn.model_selection import train_test_split
```

In [142…
```python
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=42)
```

In [143…
```python
print("X_train shape :",X_train.shape)
print("y_train shape :",y_train.shape)
print("-"*30)
print("X_test shape :",X_test.shape)
print("y_test shape :",X_test.shape)
```

```
X_train shape : (6818, 11)
y_train shape : (6818,)
------------------------------
X_test shape : (1705, 11)
y_test shape : (1705, 11)
```

In [144…
```python
print(X_train)
```

```
      Item_Identifier  Item_Weight  Item_Fat_Content  Item_Visibility  \
549              1102        9.500                 1         0.035206   
7757             1322       18.000                 0         0.047473   
764              1169       17.600                 1         0.076122   
6867              789        8.325                 0         0.029845   
2716              757       12.850                 0         0.137228   
...               ...          ...               ...              ...   
5734             1172        9.395                 1         0.286345   
5191              263       15.600                 0         0.117575   
5390             1464       17.600                 0         0.018944   
860               609       20.350                 0         0.054363   
7270             1414       16.350                 0         0.016993   

      Item_Type  Item_MRP  Outlet_Identifier  Outlet_Establishment_Year  \
549           6  171.3448                  9                       1999   
7757          9  170.5422                  7                       2002   
764          10  111.7202                  8                       1997   
6867          6   41.6138                  7                       2002   
2716         13  155.5630                  8                       1997   
...         ...       ...                ...                        ...   
5734          6  139.1838                  0                       1998   
5191          5   75.6670                  2                       2007   
5390          8  237.3590                  7                       2002   
860          13  117.9466                  2                       2007   
7270          9   95.7410                  8                       1997   

      Outlet_Size  Outlet_Location_Type  Outlet_Type  
549             1                     0            1  
7757            1                     1            1  
764             2                     0            1  
6867            1                     1            1  
2716            2                     0            1  
...           ...                   ...          ...  
5734            1                     2            0  
5191            1                     1            1  
5390            1                     1            1  
860             1                     1            1  
7270            2                     0            1  

[6818 rows x 11 columns]
```

Build Model

XGBoost Regressor

XGBoost Regressor is a machine learning algorithm used to predict continuous numerical values (regression tasks). It is based on Gradient Boosting, but it is faster, more accurate, and more efficient than traditional gradient boosting models.

In [145…
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\lenovo\anaconda3\lib\site-packages (3.1.1)
Requirement already satisfied: numpy in c:\users\lenovo\anaconda3\lib\site-packages (from xgboost) (2.1.3)
Requirement already satisfied: scipy in c:\users\lenovo\anaconda3\lib\site-packages (from xgboost) (1.15.3)
```

In [146…
```
from xgboost import XGBRegressor
```

In [147…
```
regressor = XGBRegressor()
```

In [148…
```
regressor.fit(X_train,y_train)
```

Out[148…

XGBRegressor

```
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,
             feature_weights=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=None,
             max_leaves=None, min_child_weight=None, missing=nan,
```

In [149…
```
X_train_pred =  regressor.predict(X_train)
```

In [150…
```
pd.DataFrame(X_train_pred,columns=['Predicted'])
```

Out[150…

	Predicted
0	2501.525879
1	2704.018066
2	1437.122681
3	549.654175
4	2649.396973
...	...
6813	206.892349
6814	1391.100830
6815	4280.472168
6816	1574.355713
6817	1256.218628

6818 rows × 1 columns

In [151…
```
pd.DataFrame(y_train)
```

Out[151…

	Item_Outlet_Sales
549	2386.2272
7757	3103.9596
764	1125.2020
6867	284.2966
2716	4224.5010
...	...
5734	280.9676
5191	1301.6390
5390	6145.3340
860	1649.8524
7270	965.4100

6818 rows × 1 columns

In [152…
```
from sklearn.metrics import r2_score
```

In [153…
```
print("R squared :",r2_score(y_train,X_train_pred))
```

```
R squared : 0.8698351206603934
```

In [154…
```
y_train_pred = regressor.predict(X_test)
```

In [155…
```
pd.DataFrame(y_train_pred,columns=['Predicted'])
```

Out[155…

	Predicted
0	1147.258667
1	933.891724
2	1007.881287
3	5374.615234
4	1719.455444
...	...
1700	1400.236572
1701	1985.621460
1702	863.873108
1703	822.876038
1704	1544.908081

1705 rows × 1 columns

In [156…
```
pd.DataFrame(y_test)
```

Out[156…

	Item_Outlet_Sales
7503	1743.0644
2957	356.8688
7031	377.5086
1084	5778.4782
856	2356.9320
...	...
7205	3004.0896
3257	890.8404
6346	629.1810
6318	253.0040
6339	976.7286

1705 rows × 1 columns

In [157…

```
print("R squared :",r2_score(y_test,y_train_pred))
```

```
R squared : 0.5246342336961346
```

In [ ]: