Importing the Dependencies

In [1]:
```
import numpy as np  # used for array
import pandas as pd # used for data processing (data loading, data manipulation, etc)
import matplotlib.pyplot as plt  # used for plotting graphs
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split  # used for splitting the data into training data and testing data
from xgboost import XGBRegressor  # used for XGBRegressor
from sklearn import metrics  # used for mean r2 error (accuracy score for XGBRegressor)
```

Data Collection and Processing

In [2]:
```
# loading the data from csv file to Pandas DataFrame

big_mart_data = pd.read_csv('Train.csv')
```

In [3]:
```
# .head() displays the first 5 rows, and first n columns

# python indexes the column and row number starting from 0.

big_mart_data.head()
```

Out[3]:

	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_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	Tier 1	Supermarket Type1	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	Tier 3	Supermarket Type2	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	Tier 1	Supermarket Type1	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	Tier 3	Grocery Store	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	Tier 3	Supermarket Type1	

In [4]:
```
# number of data points & number of features
# .shape() gives number of rows x columns (38523,12)

big_mart_data.shape
```

Out[4]:
```
(8523, 12)
```

In [5]:
```
# getting some information about the dataset

big_mart_data.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

In [6]:
```
# checking for missing values per every column

big_mart_data.isnull().sum()
```

Out[6]:
```
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
```

Handling Missing Values

Mean --> average

Mode --> more repeated value

In [7]:
```
# mean value of "Item_Weight" column
m = big_mart_data['Item_Weight'].mean()
print(m)
```

```
12.857645184136183
```

In [8]:
```
# filling the missing values in "Item_weight column" with "Mean" value
big_mart_data['Item_Weight'].fillna(big_mart_data['Item_Weight'].mean(), inplace=True)

# another way to do the same
big_mart_data['Item_Weight'].fillna(m, inplace = True)
```

In [9]:
```
# mode of "Outlet_Size" column
big_mart_data['Outlet_Size'].mode()
```

Out[9]:
```
0    Medium
dtype: object
```

In [10]:
```
# filling the missing values in "Outlet_Size" column with Mode
mode_of_Outlet_size = big_mart_data.pivot_table(values='Outlet_Size', columns='Outlet_Type', aggfunc=(lambda x: x.mode()[0]))
```

In [11]:
```
print(mode_of_Outlet_size)
```

```
Outlet_Type Grocery Store Supermarket Type1 Supermarket Type2  \
Outlet_Size         Small             Small            Medium   

Outlet_Type Supermarket Type3  
Outlet_Size            Medium  
```

In [12]:
```
miss_values = big_mart_data['Outlet_Size'].isnull()
```

In [13]:
```
print(miss_values)
```

```
0       False
1       False
2       False
3        True
4       False
        ...  
8518    False
8519     True
8520    False
8521    False
8522    False
Name: Outlet_Size, Length: 8523, dtype: bool
```

In [14]:
```
big_mart_data.loc[miss_values, 'Outlet_Size'] = big_mart_data.loc[miss_values,'Outlet_Type'].apply(lambda x: mode_of_Outlet_size[x])
```

In [15]:
```
# checking for missing values
big_mart_data.isnull().sum()
```

Out[15]:
```
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
```

Data Analysis

In [16]:
```
big_mart_data.describe()

# some statistical measures for numerical columns ONLY
```

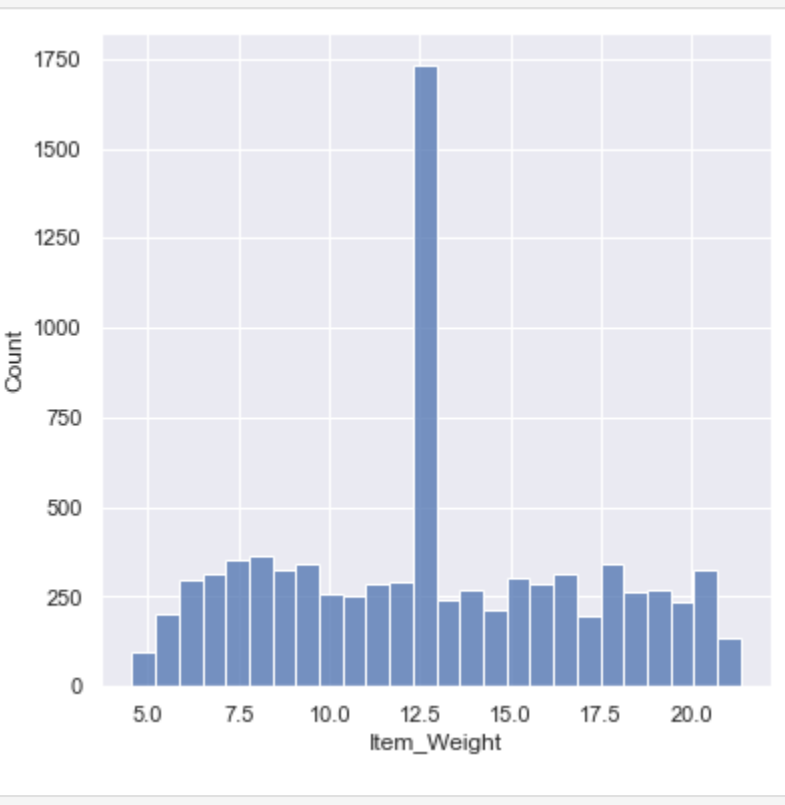
Out[16]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	8523.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.226124	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000	33.290000
25%	9.310000	0.026989	93.826500	1987.000000	834.247400
50%	12.857645	0.053931	143.012800	1999.000000	1794.331000
75%	16.000000	0.094585	185.643700	2004.000000	3101.296400
max	21.350000	0.328391	266.888400	2009.000000	13086.964800

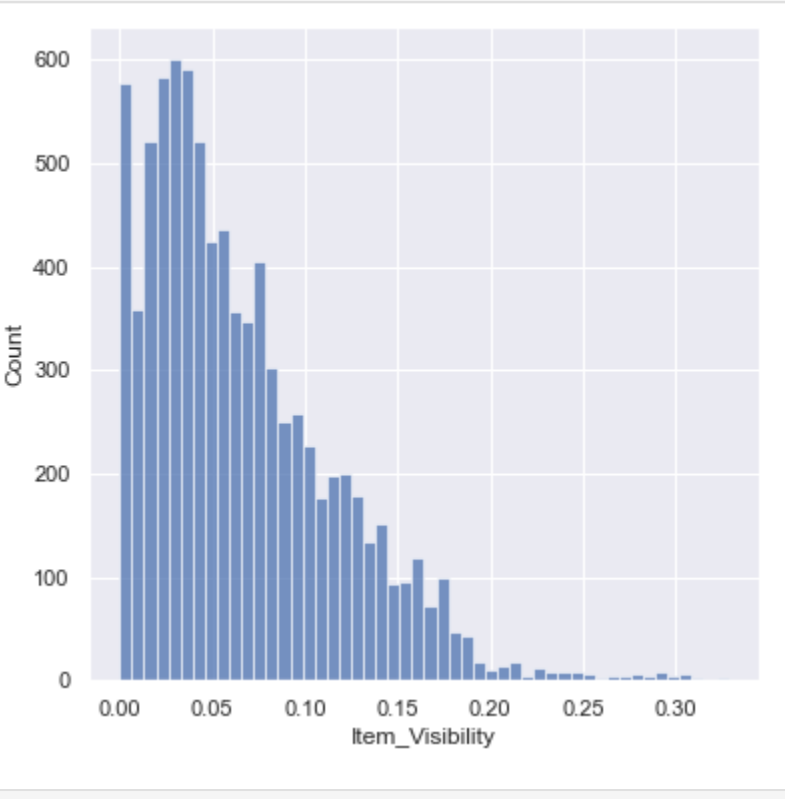
Numerical Features

In [17]:
```
sns.set()
```

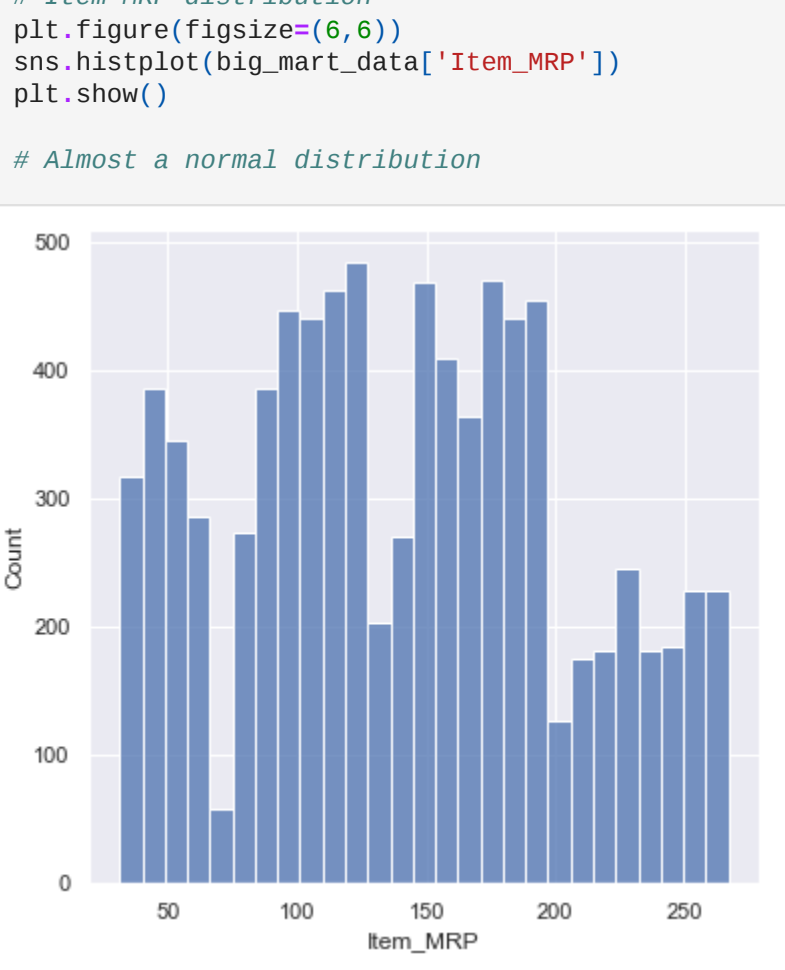
In [18]:
```
# Item Weight distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Weight'])
plt.show()
# 12.5 is the most common item weight
```



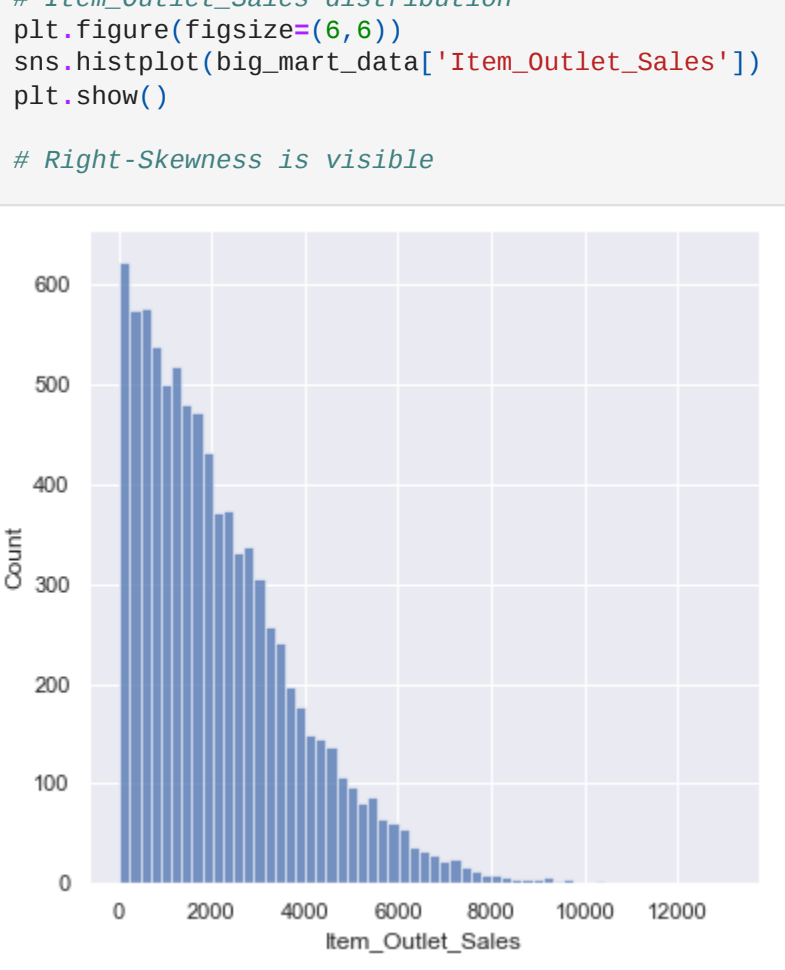
In [19]:
```
# Item Visibility distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Visibility'])
plt.show()
# Right-Skewness in visible in the graph
```



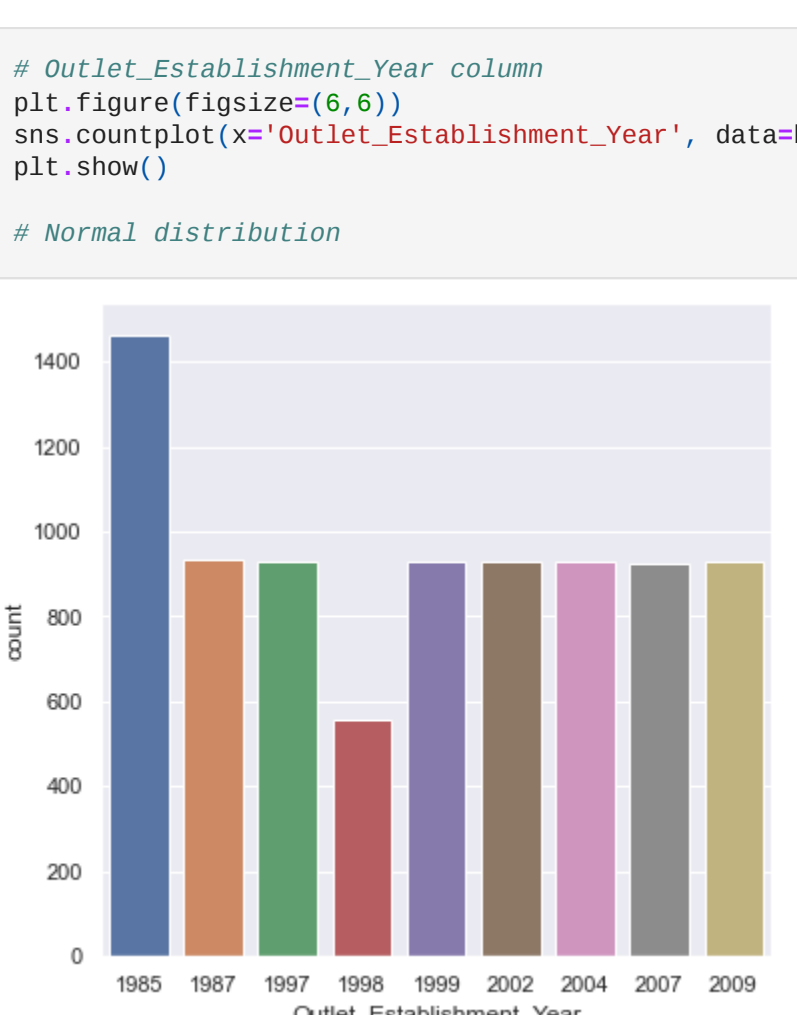
In [20]:
```
# Item MRP distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_MRP'])
plt.show()

# Almost a normal distribution
```



In [21]:
```
# Item_Outlet_Sales distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Outlet_Sales'])
plt.show()

# Right-Skewness is visible
```

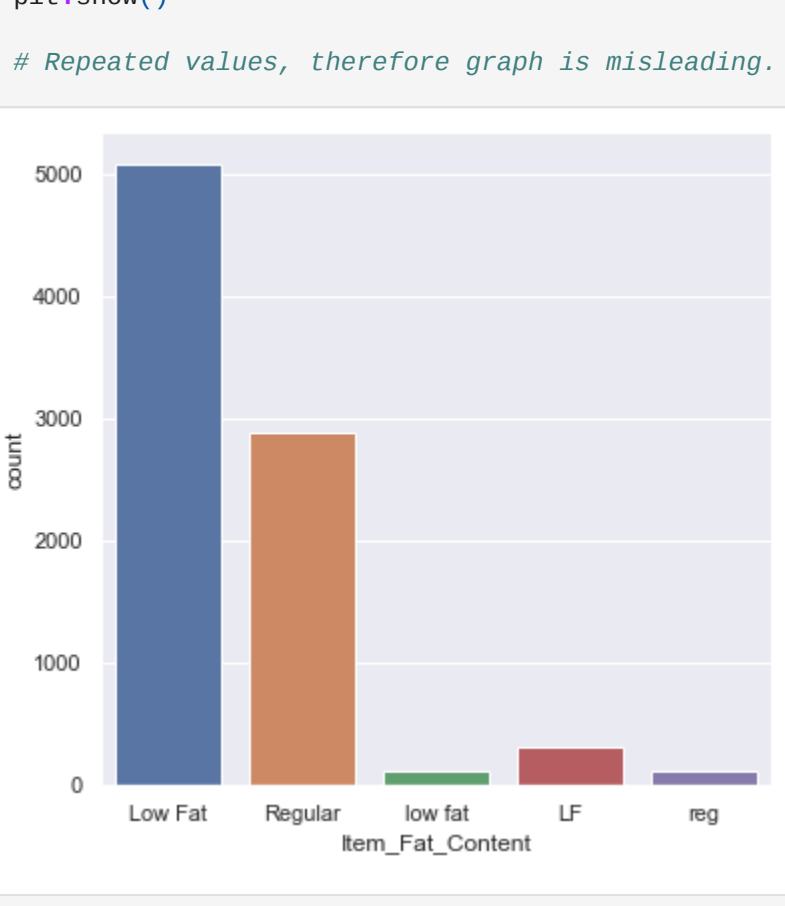


In [22]:
```
# Outlet_Establishment_Year column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year', data=big_mart_data)
plt.show()

# Normal distribution
```

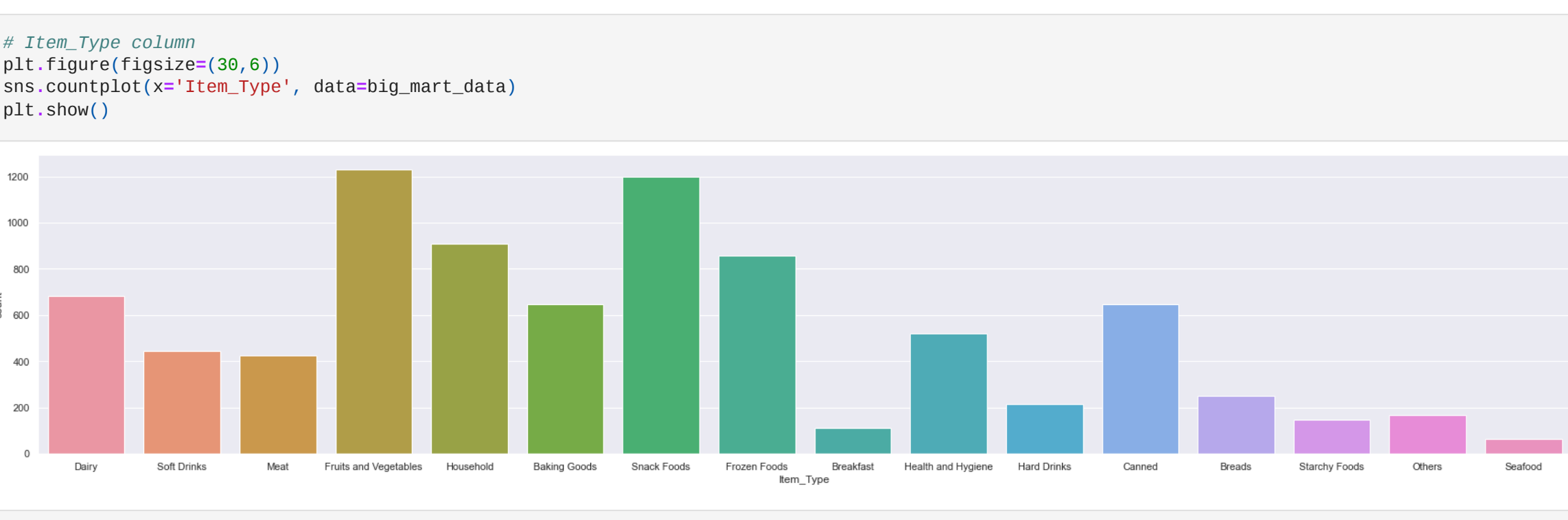


Categorical Features

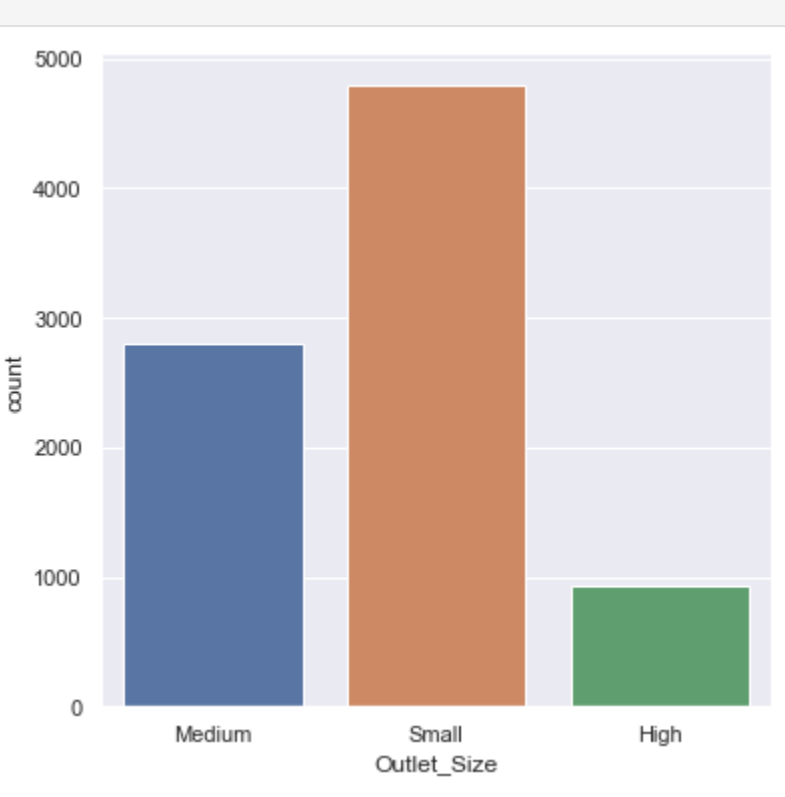
In [23]:
```
# Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x='Item_Fat_Content', data=big_mart_data)
plt.show()

# Repeated values, therefore graph is misleading. Will need to clean the graph after analyzing it
```



In [24]:
```
# Item_Type column
plt.figure(figsize=(30,6))
sns.countplot(x='Item_Type', data=big_mart_data)
plt.show()
```



In [25]:
```
# Outlet_Size column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Size', data=big_mart_data)
plt.show()
```



Data Pre-Processing

In [26]:
```
big_mart_data['Item_Fat_Content'].value_counts()
```

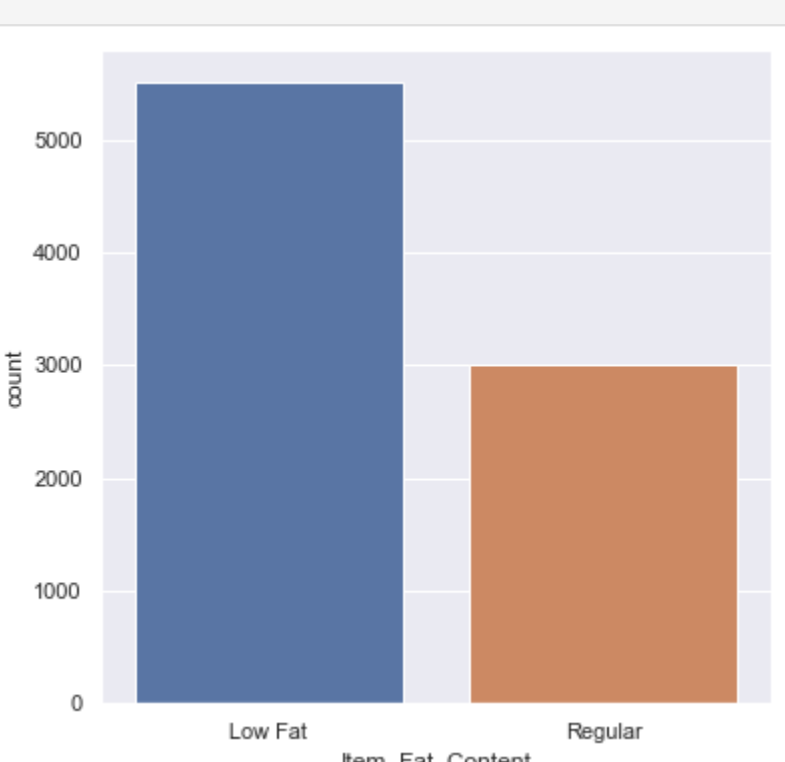
Out[26]:
```
Low Fat    5089
Regular    2889
LF          316
reg         117
low fat     112
Name: Item_Fat_Content, dtype: int64
```

In [27]:
```
# Low Fat, LF and low fat are the same thing
# reg, Regular are the same thing too

big_mart_data.replace({'Item_Fat_Content': {'low fat':'Low Fat','LF':'Low Fat', 'reg':'Regular'}}, inplace=True)
```

In [28]:
```
# only have 2 values in the label column

big_mart_data['Item_Fat_Content'].value_counts()
```

Out[28]:
```
Low Fat    5517
Regular    3006
Name: Item_Fat_Content, dtype: int64
```

In [29]:
```
# Cleaned Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x='Item_Fat_Content', data=big_mart_data)
plt.show()

# more accurate graph
```



Label Encoding

In [30]:
```
encoder = LabelEncoder()
# convert all categorical values into some numerical value
# eg, Item Type has 16 categorical values, which will now be labelled 0-14
```

In [31]:
```
big_mart_data['Item_Identifier'] = encoder.fit_transform(big_mart_data['Item_Identifier'])

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

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

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

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

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

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

In [32]:
```
big_mart_data.head()
```

Out[32]:

	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_
0	156	9.30	0	0.016047	4	249.8092	9	1999	1	0	1	
1	8	5.92	1	0.019278	14	48.2692	3	2009	1	2	2	
2	662	17.50	0	0.016760	10	141.6180	9	1999	1	0	1	
3	1121	19.20	1	0.000000	6	182.0950	0	1998	2	2	0	
4	1297	8.93	0	0.000000	9	53.8614	1	1987	0	2	1	

Splitting features and Target

In [33]:
```
# X variable represents the input data
X = big_mart_data.drop(columns='Item_Outlet_Sales', axis=1)

# Y variable represents the target column
Y = big_mart_data['Item_Outlet_Sales']
```

In [34]:
```
print(X)
```

```
      Item_Identifier  Item_Weight  Item_Fat_Content  Item_Visibility  \
0                 156        9.300                 0         0.016047   
1                   8        5.920                 1         0.019278   
2                 662       17.500                 0         0.016760   
3                1121       19.200                 1         0.000000   
4                1297        8.930                 0         0.000000   
...               ...          ...               ...              ...   
8518              370        6.865                 0         0.056783   
8519              897        8.380                 1         0.046982   
8520             1357       10.600                 0         0.035186   
8521              681        7.210                 1         0.145221   
8522               50       14.800                 0         0.044878   

      Item_Type  Item_MRP  Outlet_Identifier  Outlet_Establishment_Year  \
0             4  249.8092                  9                       1999   
1            14   48.2692                  3                       2009   
2            10  141.6180                  9                       1999   
3             6  182.0950                  0                       1998   
4             9   53.8614                  1                       1987   
...         ...       ...                ...                        ...   
8518         13  214.5218                  1                       1987   
8519          0  108.1570                  7                       2002   
8520          8   85.1224                  6                       2004   
8521         13  103.1332                  3                       2009   
8522         14   75.4670                  8                       1997   

      Outlet_Size  Outlet_Location_Type  Outlet_Type  
0               1                     0            1  
1               1                     2            2  
2               1                     0            1  
3               2                     2            0  
4               0                     2            1  
...           ...                   ...          ...  
8518            0                     2            1  
8519            2                     1            1  
8520            2                     1            1  
8521            1                     2            2  
8522            2                     0            1  

[8523 rows x 11 columns]
```

In [35]:
```
print(Y)
```

```
0       3735.1380
1        443.4228
2       2097.2700
3        732.3800
4        994.7052
          ...    
8518    2778.3834
8519     549.2850
8520    1193.1136
8521    1845.5976
8522     765.6700
Name: Item_Outlet_Sales, Length: 8523, dtype: float64
```

Splitting the data into Training data & Testing Data

In [36]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

In [37]:
```
print(X.shape, X_train.shape, X_test.shape)
```

```
(8523, 11) (6818, 11) (1705, 11)
```

Machine Learning Model Training

XGBoost Regressor

In [38]:
```
regressor = XGBRegressor()
```

In [39]:
```
regressor.fit(X_train, Y_train)
```

```
[17:21:59] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

Out[39]:
```
XGBRegressor()
```

Evaluation

In [40]:
```
# prediction on training data
training_data_prediction = regressor.predict(X_train)
```

In [41]:
```
# R squared Value
r2_train = metrics.r2_score(Y_train, training_data_prediction)
```

In [42]:
```
print('R Squared value = ', r2_train)
```

```
R Squared value =  0.6364457030941357
```

In [43]:
```
score_2 = metrics.mean_absolute_error(Y_train, training_data_prediction)
print(score_2)

# larger mean absolute error is exected due to the large values in target column
```

```
719.4796136737632
```

In [44]:
```
# prediction on test data
test_data_prediction = regressor.predict(X_test)
```

In [45]:
```
# R squared Value
r2_test = metrics.r2_score(Y_test, test_data_prediction)
```

In [46]:
```
print('R Squared value = ', r2_test)
```

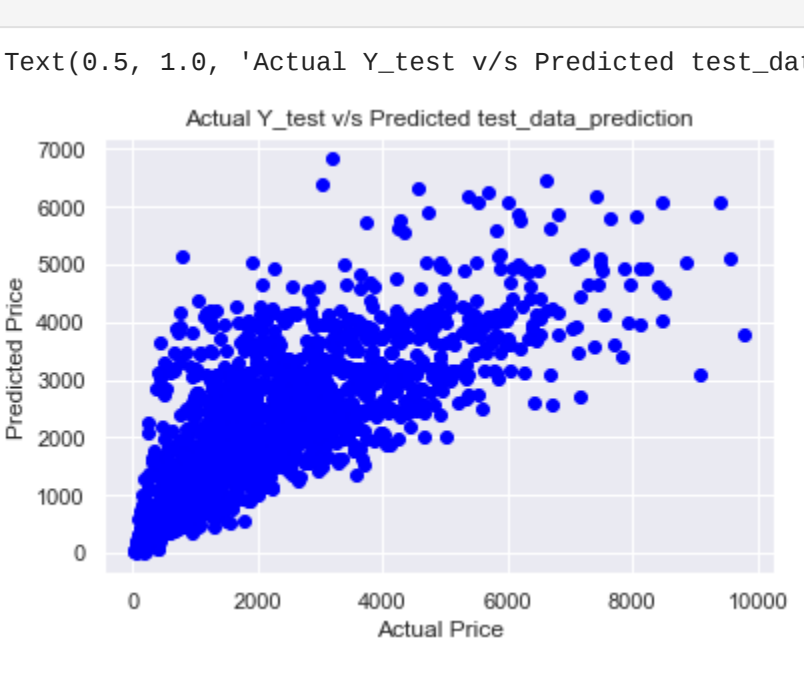
```
R Squared value =  0.5867640914432671
```

In [47]:
```
score_3 = metrics.mean_absolute_error(Y_test, test_data_prediction)
print(score_3)

# larger mean absolute error is exected due to the large values in target column
```

```
788.9621892041749
```

In [48]:
```
# Plotting graphs between Actual Y_train and Predicted training_data_prediction
plt.scatter(Y_train, training_data_prediction, color = 'red')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual Y_train v/s Predicted training_data_prediction')
# shows some linearity,points are closely bounded
```

Out[48]:
```
Text(0.5, 1.0, 'Actual Y_train v/s Predicted training_data_prediction')
```



In [49]:
```
# Plotting graphs between Actual Y_test and Predicted test_data_prediction
plt.scatter(Y_test, test_data_prediction, color = 'blue')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual Y_test v/s Predicted test_data_prediction')
# this polot also shows some linearity and points are closely bounded
# Hence, Model works good with both train and test data
```

Out[49]:
```
Text(0.5, 1.0, 'Actual Y_test v/s Predicted test_data_prediction')
```