** PROJECT DAY-25 **

[Big Mart Sales Prediction]

Importing the Dependencies

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn import metrics
```

Data Collection and Processing

```python
# loading the data from csv file to Pandas DataFrame
big_mart_data = pd.read_csv('Bigmart.csv')
```

```python
# first 5 rows of the dataframe
big_mart_data.head()
```

	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
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	Tier 1	Supermarket Type1	3735.1380
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	Tier 3	Supermarket Type2	443.4228
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	Tier 1	Supermarket Type1	2097.2700
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	Tier 3	Grocery Store	732.3800
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	Tier 3	Supermarket Type1	994.7052

```python
# number of data points & number of features
big_mart_data.shape
```

```
(8523, 12)
```

```python
# getting some information about thye 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

```python
# checking for missing values
big_mart_data.isnull().sum()
```

```
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

```python
# mean value of "Item_Weight" column
big_mart_data['Item_Weight'].mean()
```

```
12.857645184135976
```

```python
# filling the missing values in "Item_weight column" with "Mean" value
big_mart_data['Item_Weight'] = big_mart_data['Item_Weight'].fillna(
    big_mart_data['Item_Weight'].mean()
)
```

```python
# mode of "Outlet_Size" column
big_mart_data['Outlet_Size'].mode()
```

```
0    Medium
Name: Outlet_Size, dtype: object
```

```python
# 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]))
```

```python
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
```

```python
miss_values = big_mart_data['Outlet_Size'].isnull()
```

```python
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
```

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

```python
# checking for missing values
big_mart_data.isnull().sum()
```

```
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
```

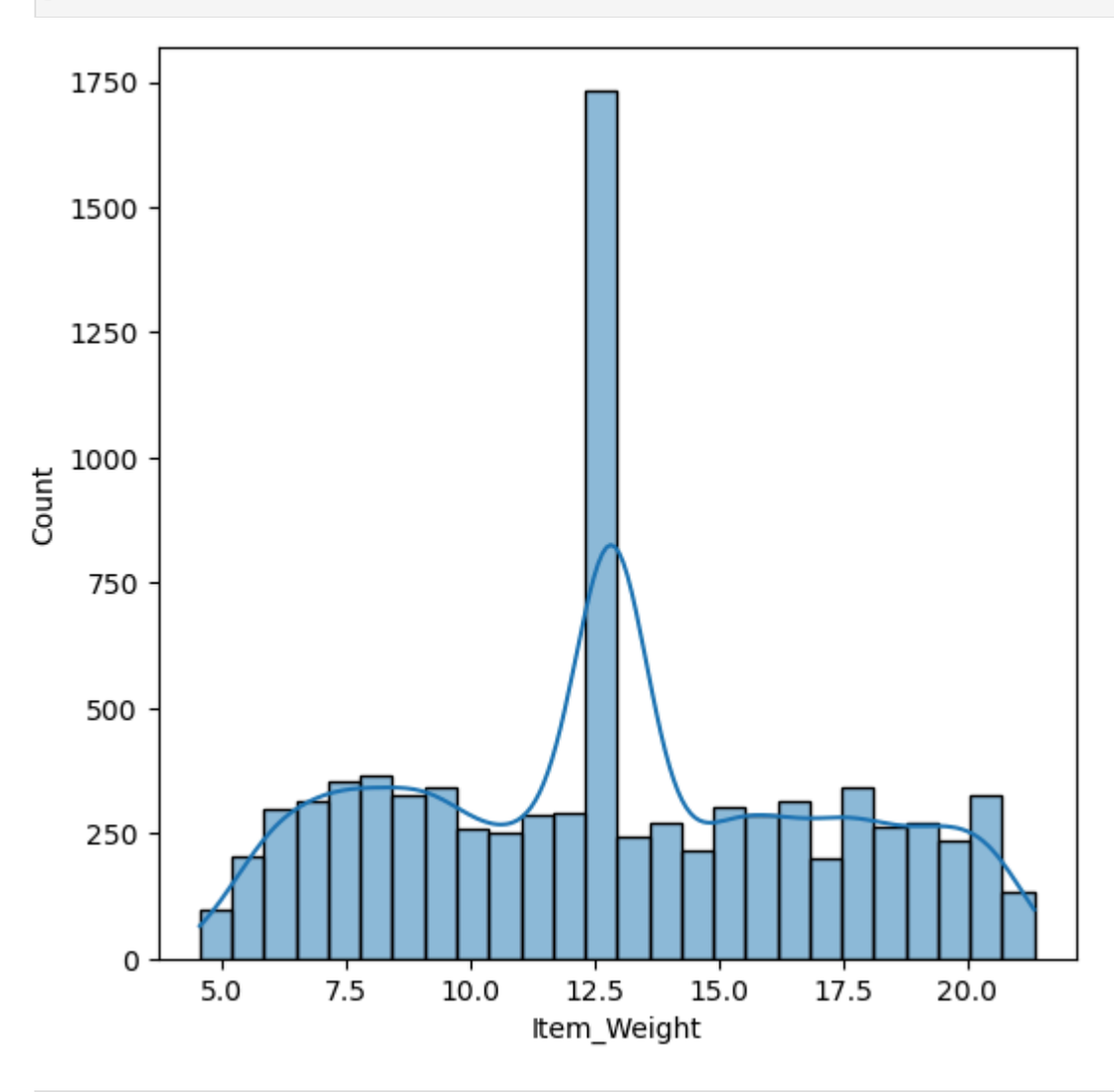
Data Analysis

```python
big_mart_data.describe()
```

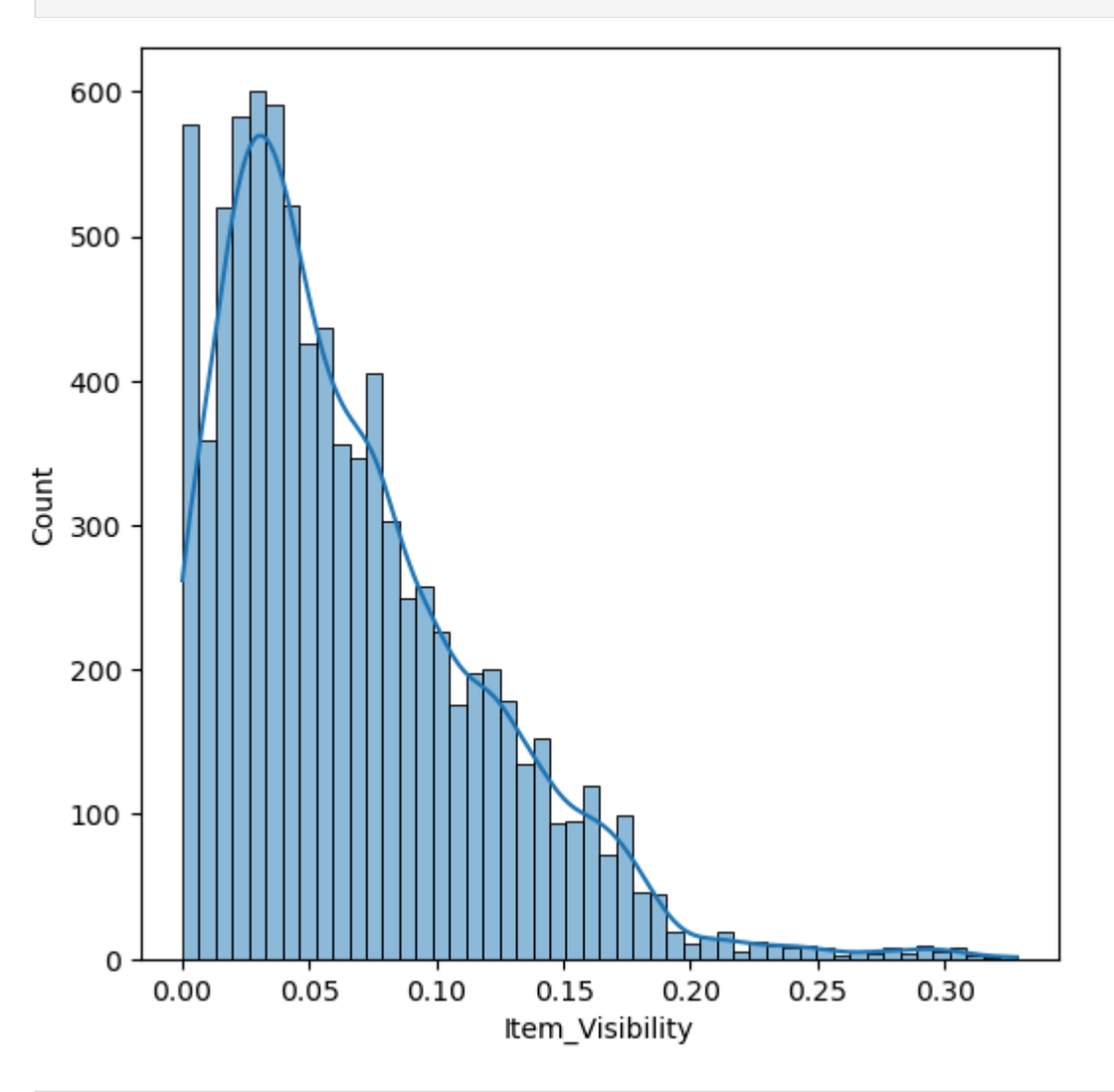
	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	8523.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.226124	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000	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

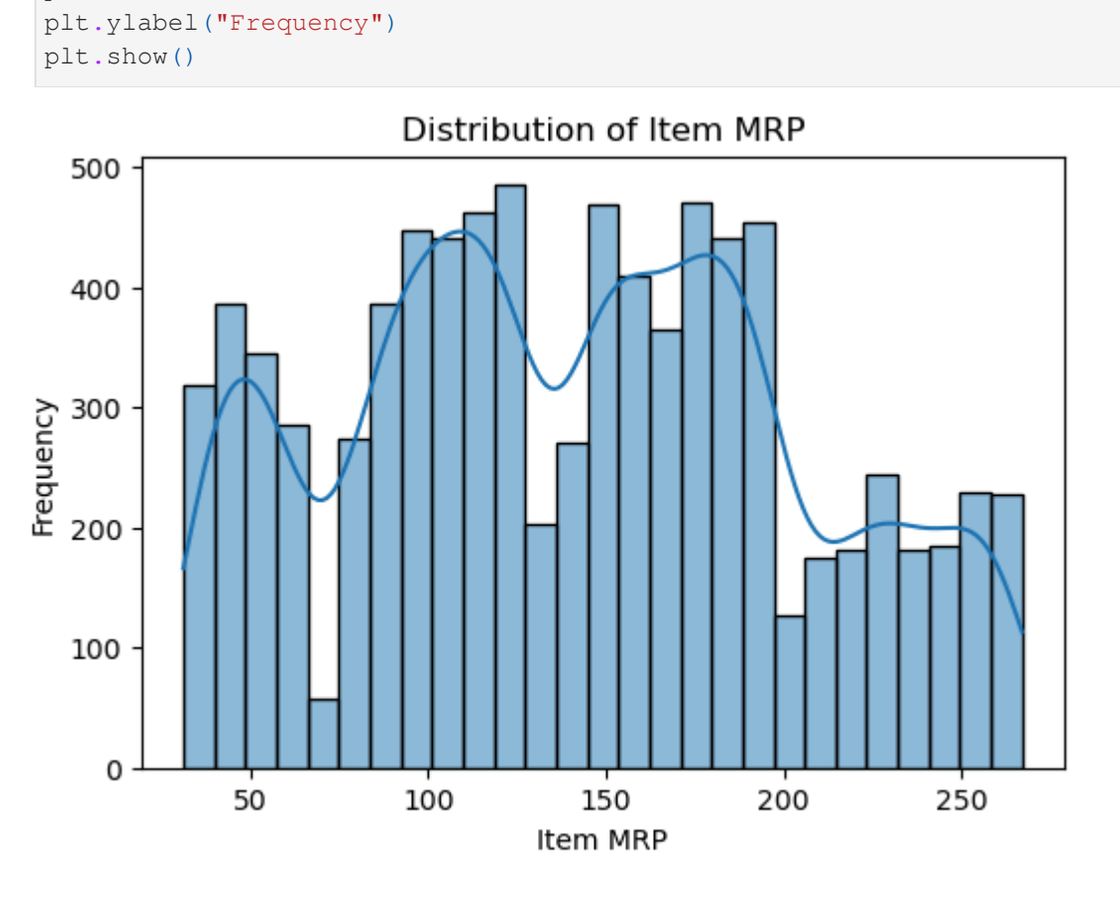
```python
# Item_Weight distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Weight'], kde=True)
plt.show()
```



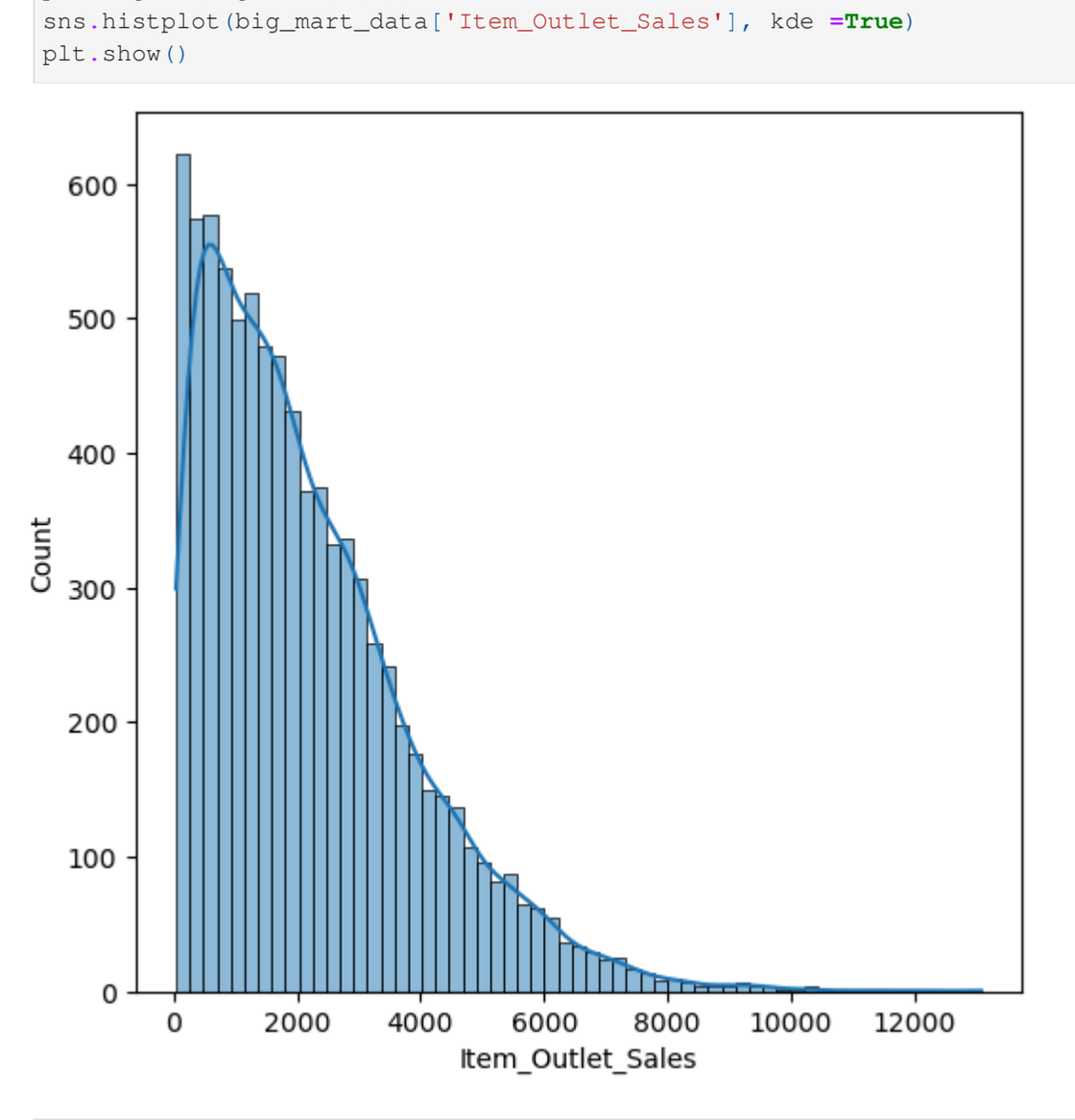

```python
# Item Visibility distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Visibility'], kde=True)
plt.show()
```



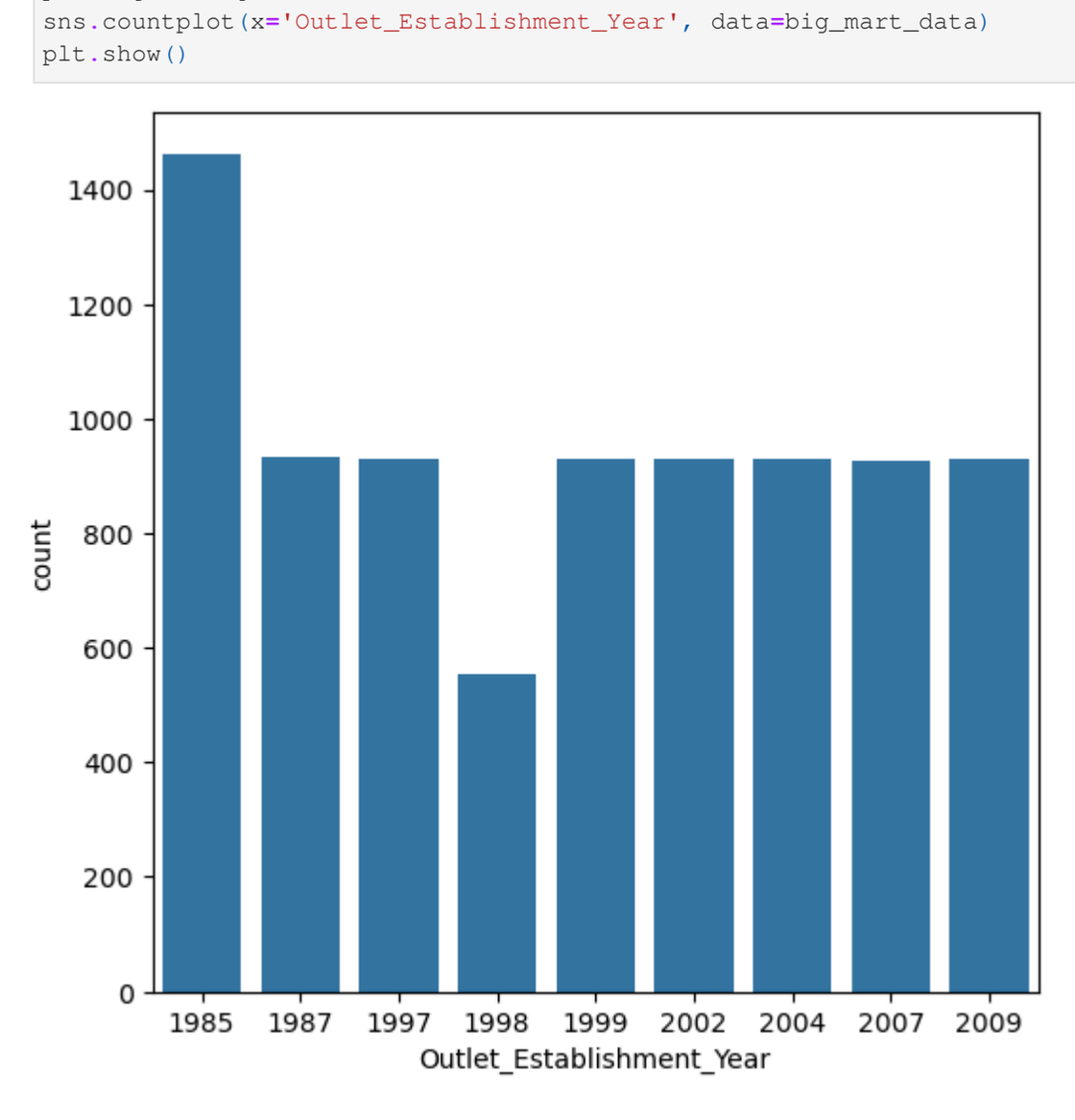

```python
# Item MRP distribution
plt.figure(figsize=(6,4))
sns.histplot(big_mart_data['Item_MRP'], kde=True)
plt.title("Distribution of Item MRP")
plt.xlabel("Item MRP")
plt.ylabel("Frequency")
plt.show()
```




```python
# Item_Outlet_Sales distribution
plt.figure(figsize=(6,6))
sns.histplot(big_mart_data['Item_Outlet_Sales'], kde =True)
plt.show()
```

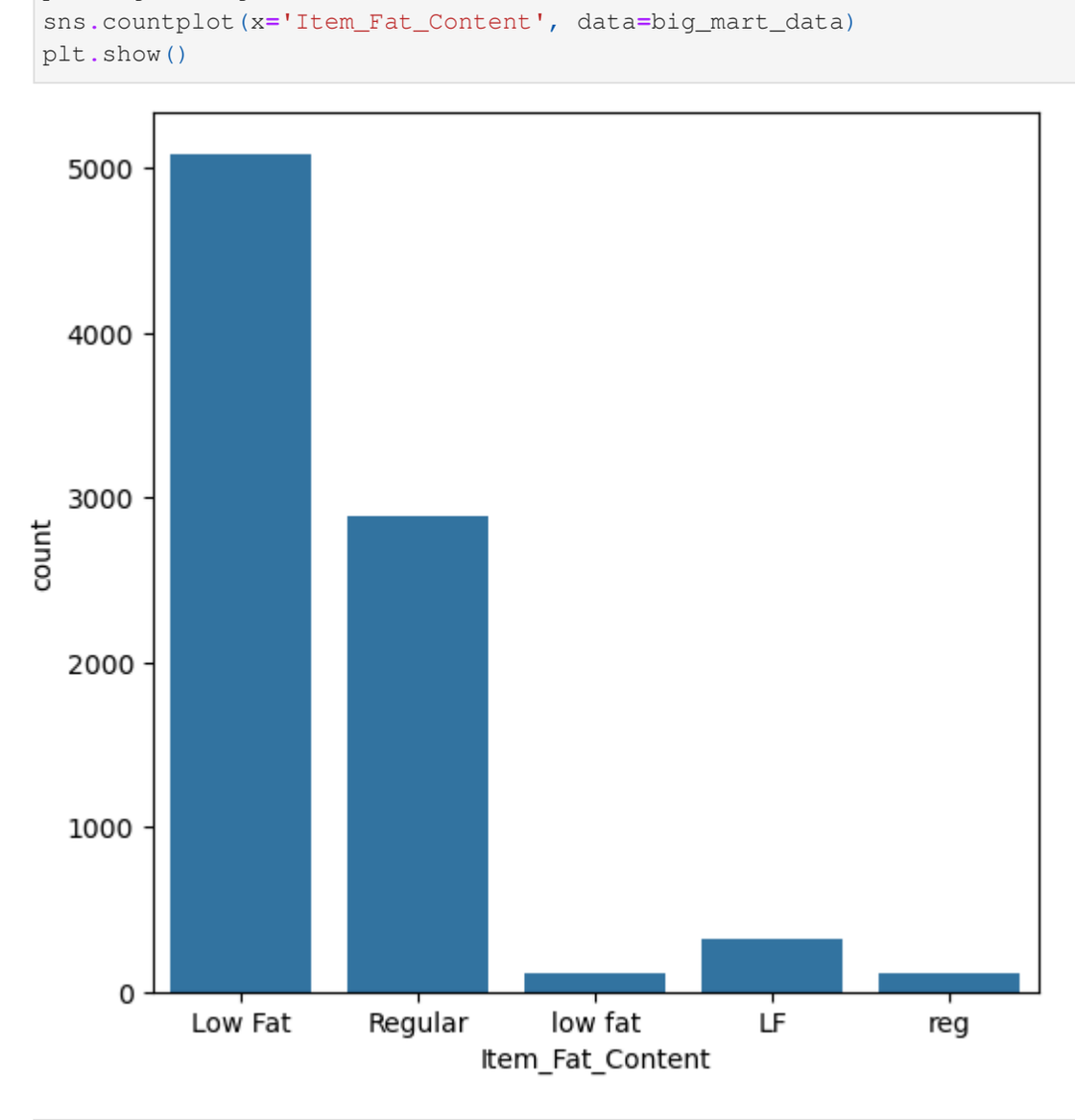



```python
# Outlet_Establishment_Year column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year', data=big_mart_data)
plt.show()
```

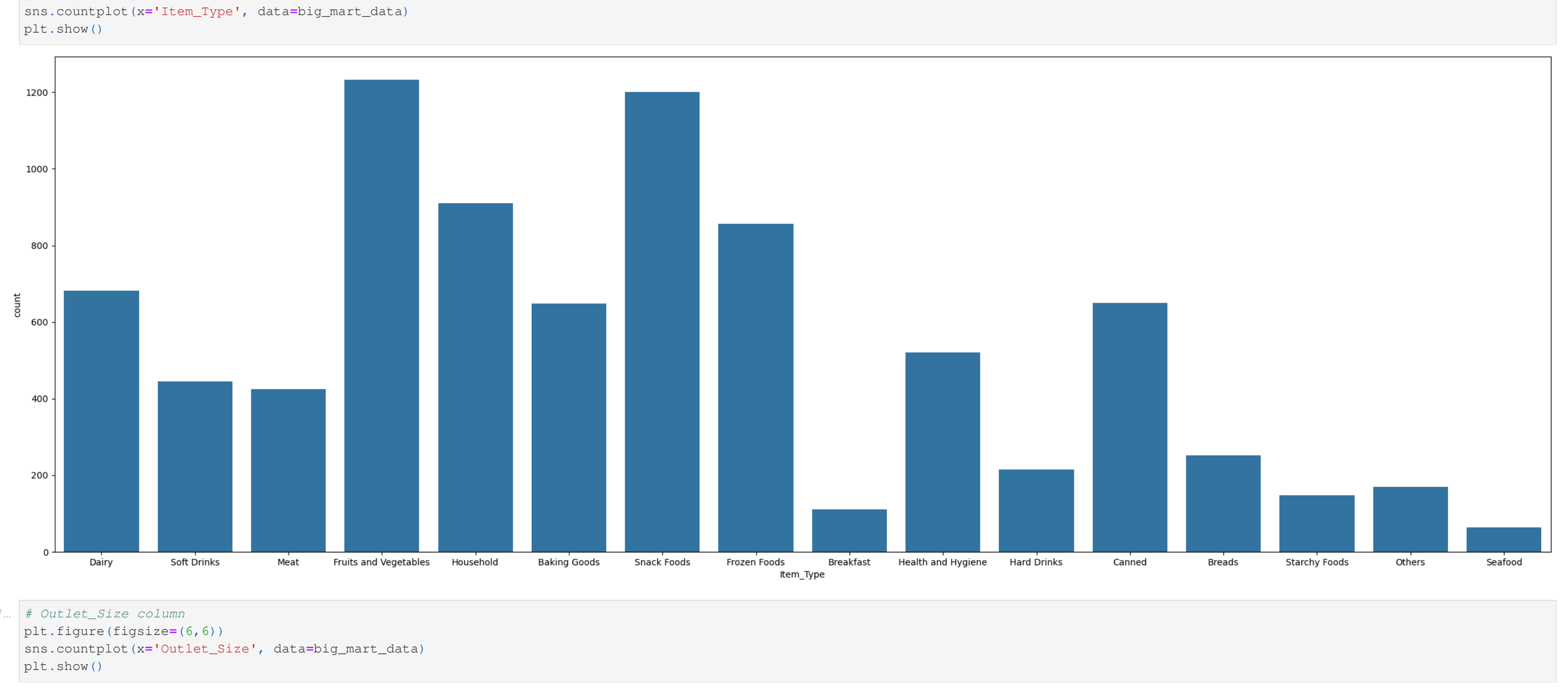


Categorical Features

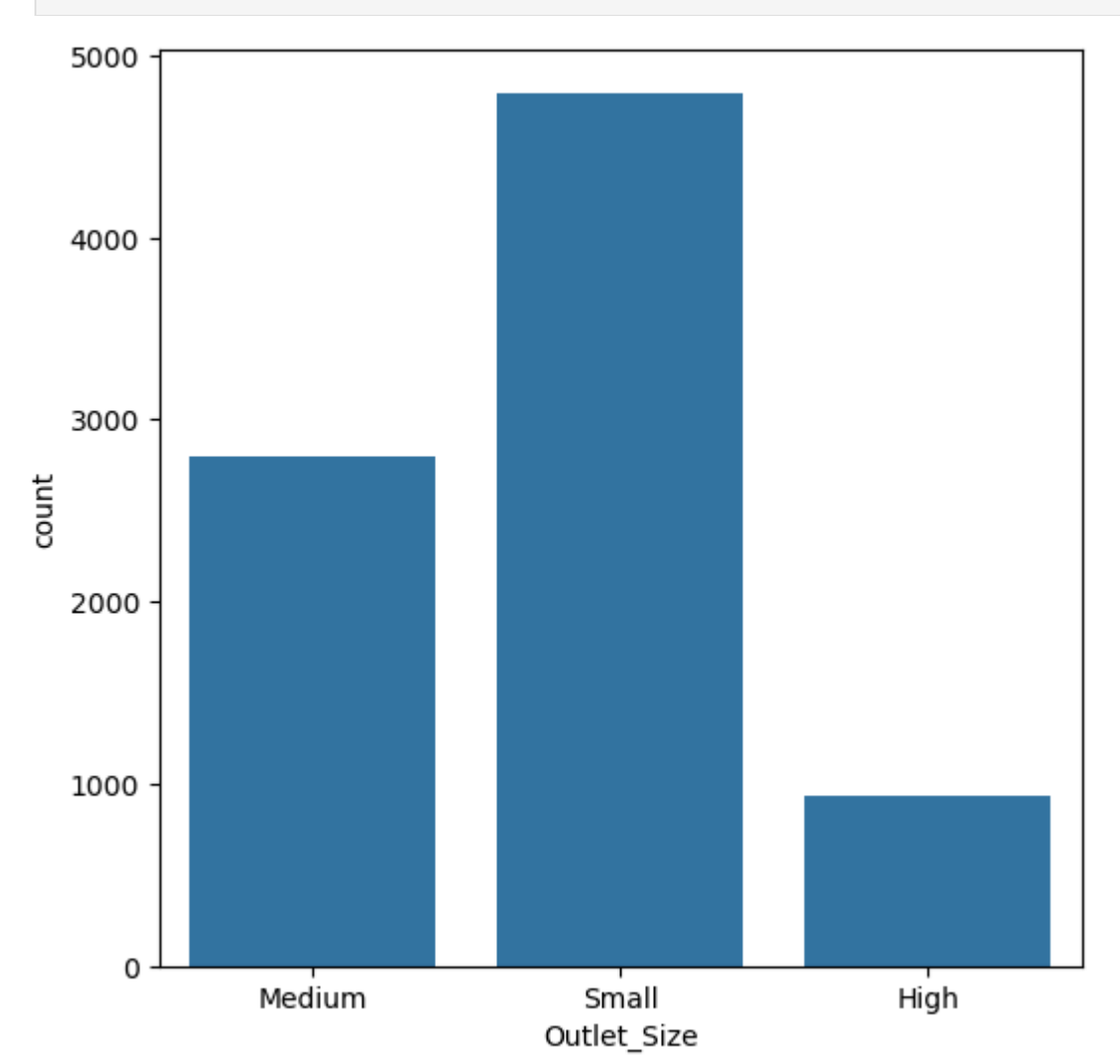
```python
# Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x='Item_Fat_Content', data=big_mart_data)
plt.show()
```




```python
# Item_Type column
plt.figure(figsize=(30,10))
sns.countplot(x='Item_Type', data=big_mart_data)
plt.show()
```




```python
# Outlet_Size column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Size', data=big_mart_data)
plt.show()
```



Data Pre-Processing

```python
big_mart_data.head()
```

	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
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	Tier 1	Supermarket Type1	3735.1380
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	Tier 3	Supermarket Type2	443.4228
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	Tier 1	Supermarket Type1	2097.2700
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	Small	Tier 3	Grocery Store	732.3800
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	Tier 3	Supermarket Type1	994.7052

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

```
Item_Fat_Content
Low Fat    5089
Regular    2889
LF          316
reg         117
low fat     112
Name: count, dtype: int64
```

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

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

```
Item_Fat_Content
Low Fat    5517
Regular    3006
Name: count, dtype: int64
```

Label Encoding

```python
encoder = LabelEncoder()
```

```python
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'])
```

```python
big_mart_data.head()
```

	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
0	156	9.30	0	0.016047	4	249.8092	9	1999	1	0	1	3735.1380
1	8	5.92	1	0.019278	14	48.2692	3	2009	1	2	2	443.4228
2	662	17.50	0	0.016760	10	141.6180	9	1999	1	0	1	2097.2700
3	1121	19.20	1	0.000000	6	182.0950	0	1998	2	2	0	732.3800
4	1297	8.93	0	0.000000	9	53.8614	1	1987	0	2	1	994.7052

Splitting features and Target

```python
X = big_mart_data.drop(columns='Item_Outlet_Sales', axis=1)
Y = big_mart_data['Item_Outlet_Sales']
```

```python
X
```

	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
0	156	9.300	0	0.016047	4	249.8092	9	1999	1	0	1
1	8	5.920	1	0.019278	14	48.2692	3	2009	1	2	2
2	662	17.500	0	0.016760	10	141.6180	9	1999	1	0	1
3	1121	19.200	1	0.000000	6	182.0950	0	1998	2	2	0
4	1297	8.930	0	0.000000	9	53.8614	1	1987	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...
8518	370	6.865	0	0.056783	13	214.5218	1	1987	0	2	1
8519	897	8.380	1	0.046982	0	108.1570	7	2002	2	1	1
8520	1357	10.600	0	0.035186	8	85.1224	6	2004	2	1	1
8521	681	7.210	1	0.145221	13	103.1332	3	2009	1	2	2
8522	50	14.800	0	0.044878	14	75.4670	8	1997	2	0	1

8523 rows × 11 columns

```python
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

```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

```python
X.shape, X_train.shape, X_test.shape
```

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

Machine Learning Model Training

XGBoost Regressor

```python
regressor = XGBRegressor()
```

```python
regressor.fit(X_train, Y_train)
```

```
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,
```

Evaluation

```python
# prediction on training data
training_data_prediction = regressor.predict(X_train)
```

```python
# R squared Value
r2_train = metrics.r2_score(Y_train, training_data_prediction)
```

```python
print('R Squared value = ', r2_train)
```

```
R Squared value =  0.8762174618111388
```

```python
# prediction on test data
test_data_prediction = regressor.predict(X_test)
```

```python
# R squared Value
r2_test = metrics.r2_score(Y_test, test_data_prediction)
```

```python
print('R Squared value = ', r2_test)
```

```
R Squared value =  0.5017253991620692
```

** END - PROJECT **