Importing the Dependencies

```
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

```
# loading the data from csv file to Pandas DataFrame
big_mart_data = pd.read_csv('/content/Train.csv')
```

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

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	

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

```
(8523, 12)
```

```
# 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

```
# 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

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

```
12.857645184136183
```

```
# 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)
```

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

```
0    Medium
dtype: object
```

```
# 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', aggfu
```

```
print(mode_of_Outlet_size)
```

```
Outlet_Type Grocery Store Supermarket Type1 Supermarket Type2 Supermarket Type3
Outlet_Size         Small             Small            Medium            Medium
```

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

```
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
```

```
big_mart_data.loc[miss_values, 'Outlet_Size'] = big_mart_data.loc[miss_values,'Outlet_Type'].apply
```

```
# 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

```
big_mart_data.describe()
```

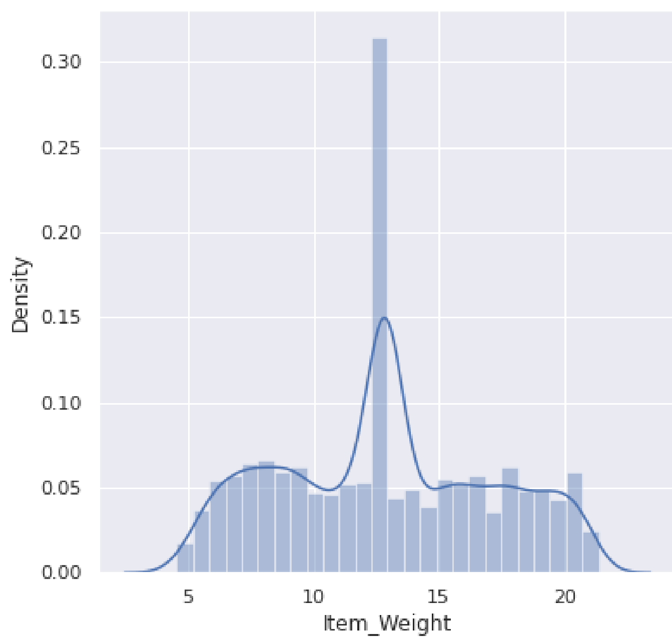
	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	8523.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.226124	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000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

```
sns.set()
```

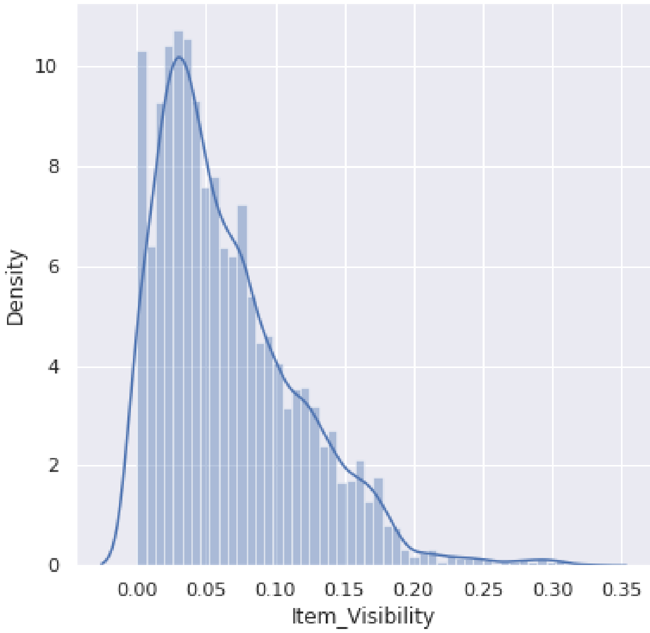
```
# Item_Weight distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Weight'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplot
  warnings.warn(msg, FutureWarning)
```



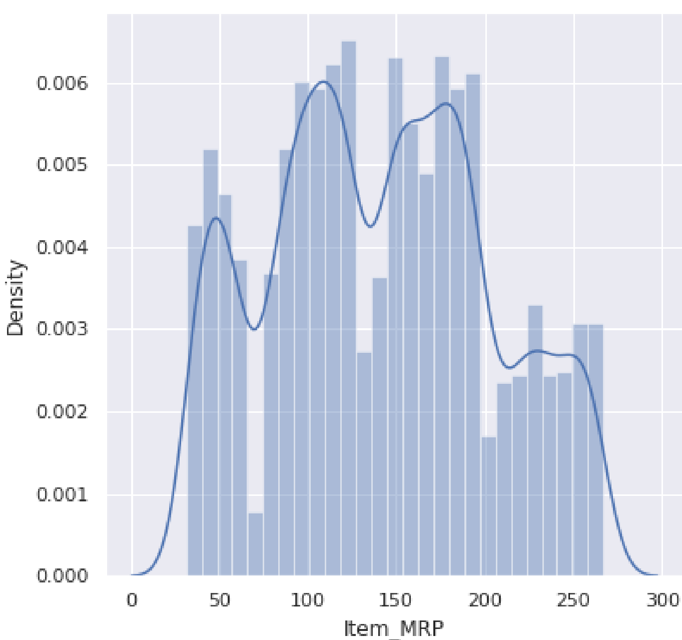

```
# Item Visibility distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Visibility'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplot
  warnings.warn(msg, FutureWarning)
```



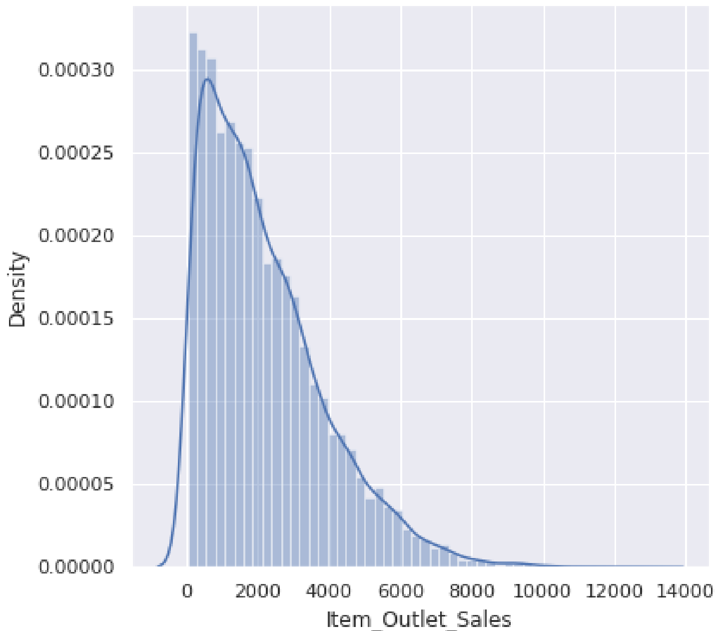

```
# Item MRP distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_MRP'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplot
  warnings.warn(msg, FutureWarning)
```

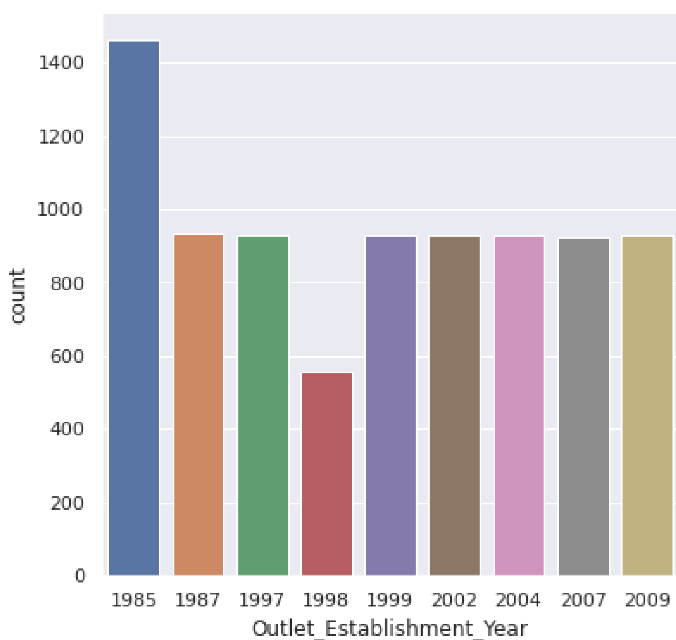


```
# Item_Outlet_Sales distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Outlet_Sales'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplot
  warnings.warn(msg, FutureWarning)
```

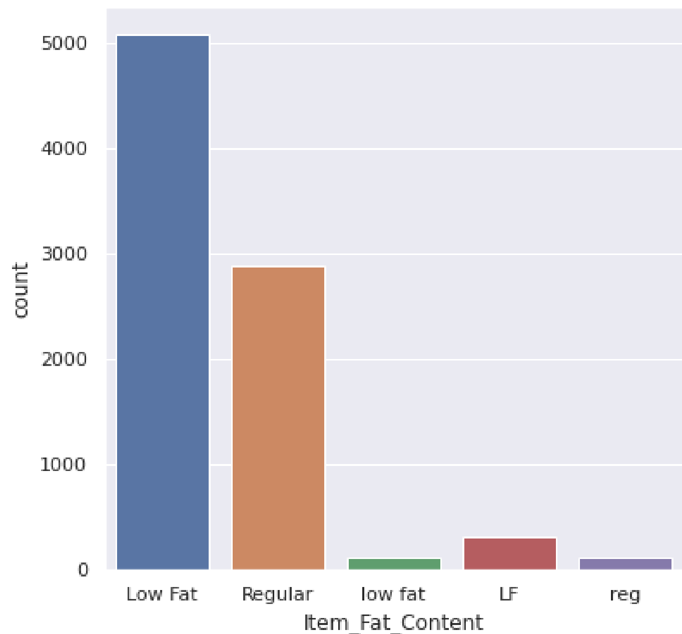



```
# Outlet_Establishment_Year column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year', data=big_mart_data)
plt.show()
```

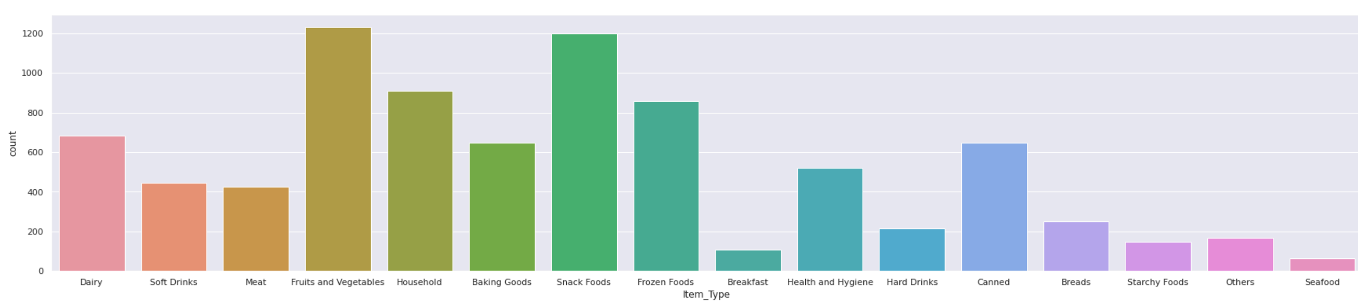


Categorical Features

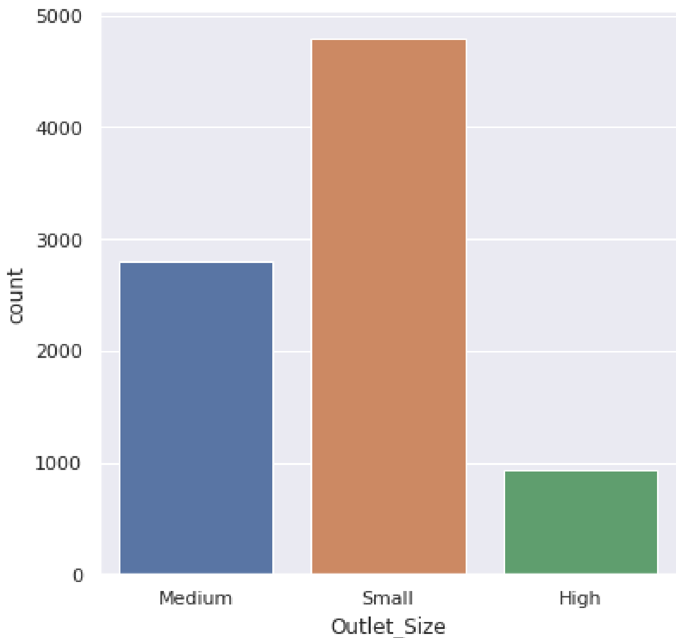
```
# Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x='Item_Fat_Content', data=big_mart_data)
plt.show()
```




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




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



Data Pre-Processing

```
big_mart_data.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	

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

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

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

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

```
Low Fat     5517
Regular     3006
```

```
Name: Item_Fat_Content, dtype: int64
```

Label Encoding

```
encoder = LabelEncoder()
```

```
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'])
```

```
big_mart_data.head()
```

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

Splitting features and Target

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

```
print(X)
```

```
      Item_Identifier  Item_Weight  ...  Outlet_Location_Type  Outlet_Type
0                 156        9.300  ...                     0            1
1                   8        5.920  ...                     2            2
2                 662       17.500  ...                     0            1
3                1121       19.200  ...                     2            0
4                1297        8.930  ...                     2            1
...               ...          ...  ...                   ...          ...
8518              370        6.865  ...                     2            1
8519              897        8.380  ...                     1            1
8520             1357       10.600  ...                     1            1
8521              681        7.210  ...                     2            2
8522               50       14.800  ...                     0            1

[8523 rows x 11 columns]
```

```
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

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

```
print(X.shape, X_train.shape, X_test.shape)
```

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

Machine Learning Model Training

XGBoost Regressor

```
regressor = XGBRegressor()
```

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

```
[02:56:53] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecat
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

Evaluation

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

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

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

```
R Squared value =  0.6364457030941357
```

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


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


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

```
R Squared value =  0.5867640914432671
```