Importing Libraries

In [17]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [18]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn import metrics
```

Data Preprocessing

In [19]:
```
#loading the data from csv to pandas dataframe

bigmart_data = pd.read_csv("train_v9rqX0R.csv")
bigmart_data.head()

#Label or Target variable --> Item_Outlet_Sales
```

Out[19]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outle
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	M
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	M
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	M
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 [20]:
```
bigmart_data.shape  #data points and features
```

Out[20]:
```
(8523, 12)
```

In [21]:
```
bigmart_data.dtypes  #Data types of the columns
```

Out[21]:
```
Item_Identifier               object
Item_Weight                  float64
Item_Fat_Content              object
Item_Visibility              float64
Item_Type                     object
Item_MRP                     float64
Outlet_Identifier             object
Outlet_Establishment_Year      int64
Outlet_Size                   object
Outlet_Location_Type          object
Outlet_Type                   object
Item_Outlet_Sales            float64
dtype: object
```

In [22]:
```
bigmart_data.isnull().sum()   #Missing value count in all the columns
```

Out[22]:
```
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

In [23]:
```
#Mean value imputation for numerical column Item_Weight

mean_weight = bigmart_data["Item_Weight"].mean()

bigmart_data["Item_Weight"].fillna(mean_weight,inplace = True)
```

In [24]:
```
bigmart_data.isnull().sum()
```

Out[24]:
```
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 [25]:
```
#Mode value imputation for categorical column Outlet_Size

mode_outlet_size = bigmart_data.pivot_table(values="Outlet_Size",columns="Outlet_Type",aggfunc=(lambda
x:x.mode()[0] ))
```

In [26]:
```
mode_outlet_size  #Mode value of Outlet_Size for each of the different Outlet_Type are shown as they ar
e correlated.
```

Out[26]:

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

In [27]:
```
missing_values = bigmart_data["Outlet_Size"].isnull() #gives a list of True or False
```

In [28]:
```
bigmart_data.loc[missing_values, 'Outlet_Size'] = bigmart_data.loc[missing_values, 'Outlet_Type'].apply
(lambda x: mode_outlet_size)
```

In [29]:
```
bigmart_data.isnull().sum()   #Missing values are handled
```

Out[29]:
```
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
```

Exploratory Data Analysis

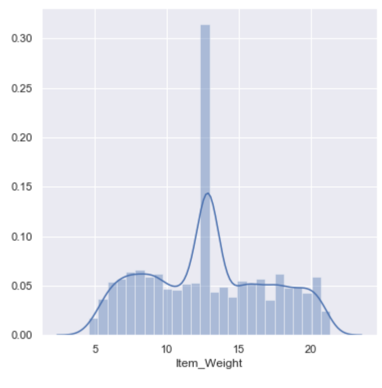
In [30]:
```
bigmart_data.describe()   #statistics on the numerical features of the data
```

Out[30]:

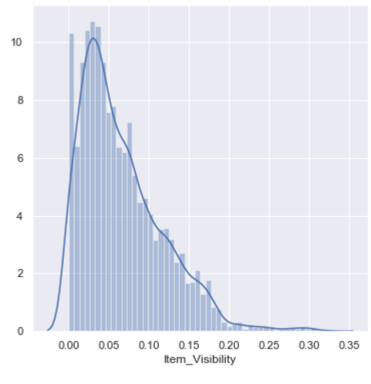
	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	8523.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.226124	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000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

In [31]:
```
 #Plots with numerical features

sns.set()   #creating theme for the plots
```

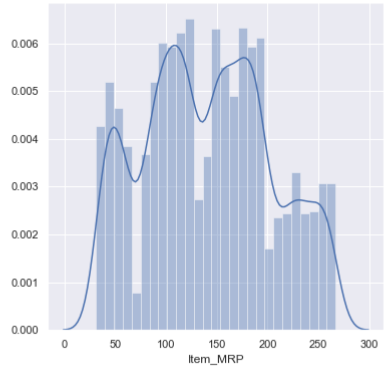
In [33]:
```
#Item weight distribution

plt.figure(figsize=(6,6))
sns.distplot(bigmart_data["Item_Weight"])
plt.show()
```



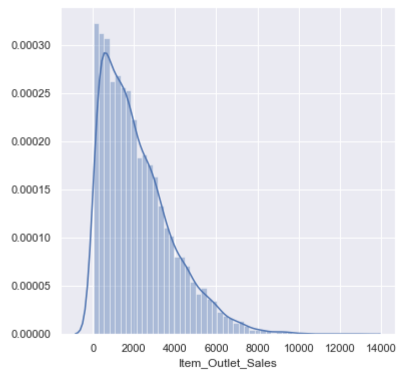
In [34]:
```
#Item visibility distribution
#the plot is skewed
plt.figure(figsize=(6,6))
sns.distplot(bigmart_data["Item_Visibility"])
plt.show()
```



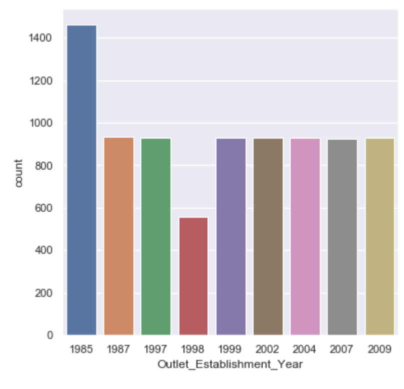
In [35]:
```
#Item MRP distribution --> Not a normal distribution

plt.figure(figsize=(6,6))
sns.distplot(bigmart_data["Item_MRP"])
plt.show()
```



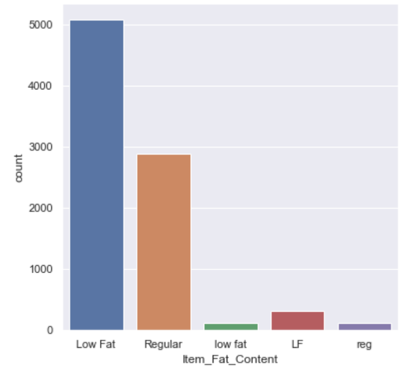
In [36]:
```
#Item outlet sales distribution

plt.figure(figsize=(6,6))
sns.distplot(bigmart_data["Item_Outlet_Sales"])
plt.show()
```



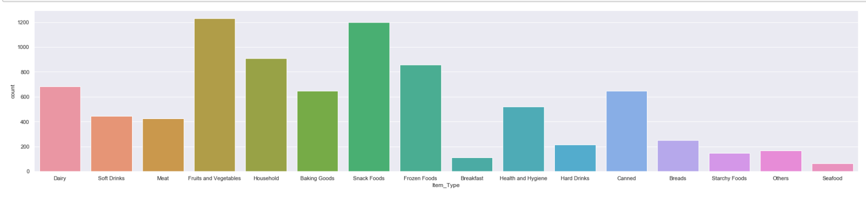
In [37]:
```
#count plot for outlet establishment year

plt.figure(figsize=(6,6))
sns.countplot(x = "Outlet_Establishment_Year",data=bigmart_data)
plt.show()
```



In [38]:
```
#Categorical features plots except ID columns

#fat content of Items
plt.figure(figsize=(6,6))
sns.countplot(x = "Item_Fat_Content",data=bigmart_data)
plt.show()
```

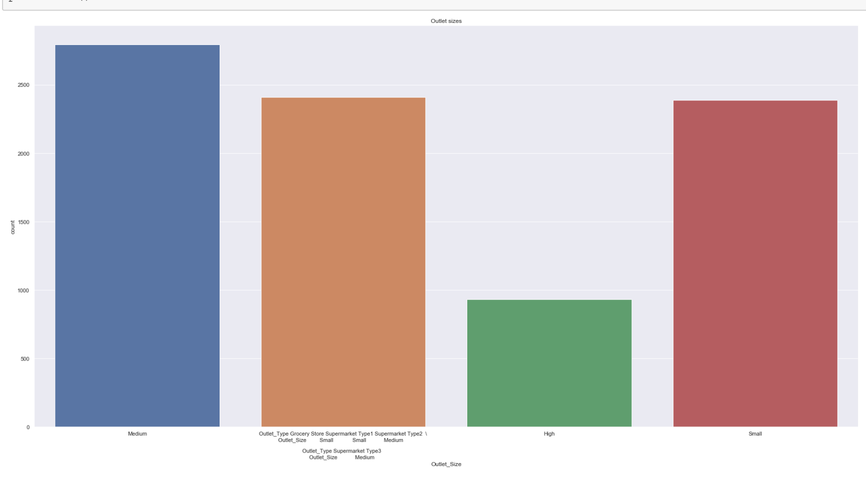


In [42]:
```
plt.figure(figsize=(30,6))
sns.countplot(x = "Item_Type",data=bigmart_data)
plt.show()
```



In [55]:
```
bigmart_data["Outlet_Size"]=bigmart_data["Outlet_Size"].apply(str)
```

In [59]:
```
plt.figure(figsize=(30,15))
sns.countplot(x='Outlet_Size',data=bigmart_data)

plt.title("Outlet sizes")
plt.show()
```



Data cleaning and pre processing

Encoding

In [48]:
```
#encode categorical features

#cleaning the data

bigmart_data["Item_Fat_Content"].value_counts()
```

Out[48]:
```
Low Fat    5089
Regular    2889
LF          316
reg         117
low fat     112
Name: Item_Fat_Content, dtype: int64
```

In [49]:
```
bigmart_data.replace({'Item_Fat_Content':{'low fat':'Low Fat','LF':'Low Fat','reg':'Regular'}},inplace=
True)
```

In [50]:
```
bigmart_data["Item_Fat_Content"].value_counts()
```

Out[50]:
```
Low Fat    5517
Regular    3006
Name: Item_Fat_Content, dtype: int64
```

In [51]:
```
#Categorical values encoding to numerical values

encoder = LabelEncoder()
```

In [60]:
```
bigmart_data['Item_Identifier'] = encoder.fit_transform(bigmart_data['Item_Identifier'])

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

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

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

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

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

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

In [61]:
```
bigmart_data.head()
```

Out[61]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outle
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	

Splitting Features and Target

In [62]:
```
X = bigmart_data.drop(columns='Item_Outlet_Sales',axis = 1)
```

In [63]:
```
Y = bigmart_data['Item_Outlet_Sales']
```

In [64]:
```
X
```

Out[64]:

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

8523 rows × 11 columns

In [65]:
```
Y
```

Out[65]:
```
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
```

Train Test split

In [81]:
```
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.2,random_state=100)
```

In [67]:
```
print(X_train.shape,X_test.shape)
```

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

Training the Machine learning Model - XGBoost Regressor

In [82]:
```
regressor = XGBRegressor()
```

In [83]:
```
regressor.fit(X_train,Y_train)
```

Out[83]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

Prediction

In [84]:
```
train_prediction = regressor.predict(X_train)
```

Evaluation

In [85]:
```
r2_train = metrics.r2_score(Y_train,train_prediction)
```

In [86]:
```
print('R squared value on train data : ',r2_train)
```

```
R squared value on train data :  0.8645959675073867
```

In [87]:
```
#Test data predictions

test_prediction = regressor.predict(X_test)
```

In [88]:

```python
r2_test = metrics.r2_score(Y_test,test_prediction)
print("R squared value for test data : ",r2_test)
```

```
R squared value for test data :  0.5152503359077216
```