Big_Mart_Sales_Prediction

August 17, 2025

Importing the Dependencies

[1]:
```
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

[2]:
```
# loading the data from csv file to Pandas DataFrame
big_mart_data = pd.read_csv('Train.csv')
```

[3]:
```
# first 5 rows of the dataframe
big_mart_data.head()
```

[3]:

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

```
         Outlet_Type  Item_Outlet_Sales
0  Supermarket Type1          3735.1380
1  Supermarket Type2           443.4228
2  Supermarket Type1          2097.2700
3      Grocery Store           732.3800
4  Supermarket Type1           994.7052
```

[4]:
```
# number of data points & number of features
big_mart_data.shape
```

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

[5]:
```
# 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

[6]:
```
# checking for missing values
big_mart_data.isnull().sum()
```

[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

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

[7]:
```
np.float64(12.857645184135977)
```

[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)
```

```
/tmp/ipykernel_7560/2509980927.py:2: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  big_mart_data['Item_Weight'].fillna(big_mart_data['Item_Weight'].mean(),
inplace=True)
```

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

[9]:
```
0    Medium
Name: Outlet_Size, dtype: object
```

[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]))
```

[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
```

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

[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
```

[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])
```

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

[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

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

[16]:
```
       Item_Weight  Item_Visibility     Item_MRP  Outlet_Establishment_Year  \
count  8523.000000      8523.000000  8523.000000                8523.000000
```

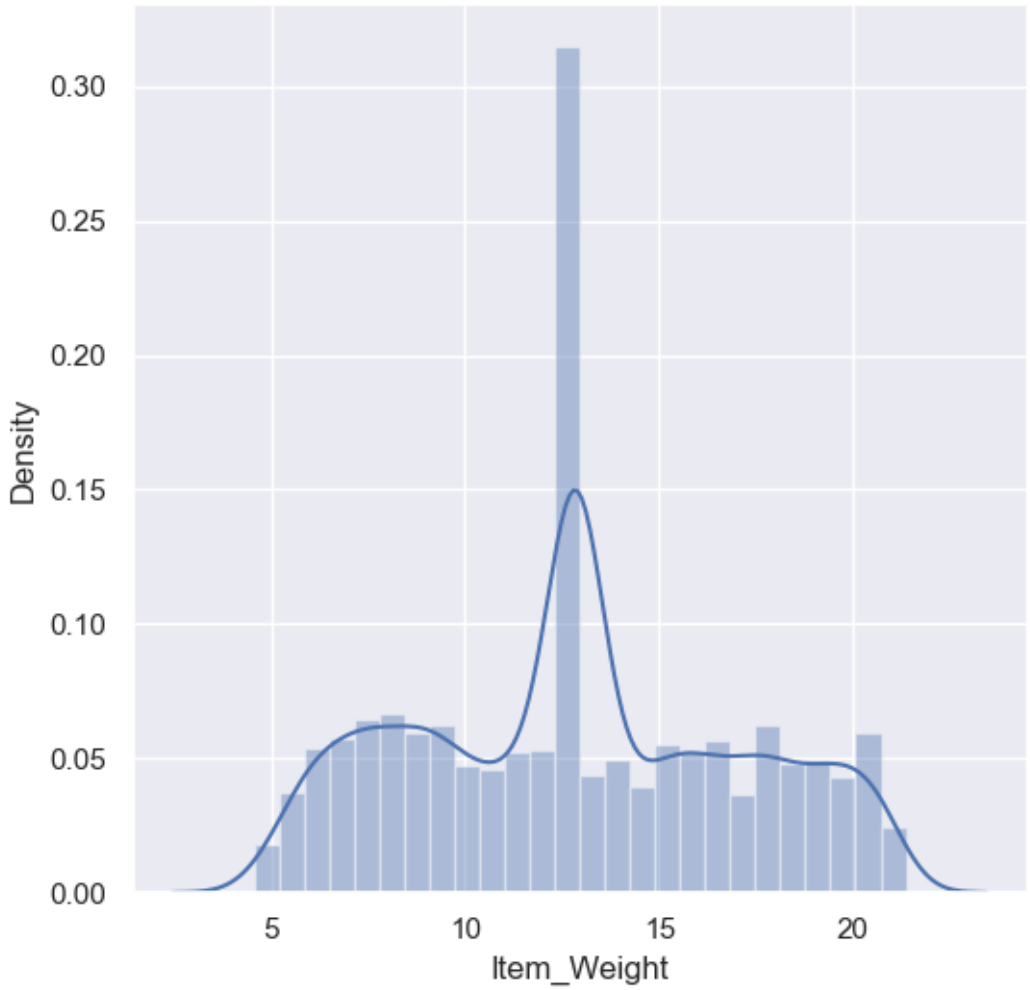
```
mean     12.857645         0.066132   140.992782                1997.831867
std       4.226124         0.051598    62.275067                   8.371760
min       4.555000         0.000000    31.290000                1985.000000
25%       9.310000         0.026989    93.826500                1987.000000
50%      12.857645         0.053931   143.012800                1999.000000
75%      16.000000         0.094585   185.643700                2004.000000
max      21.350000         0.328391   266.888400                2009.000000

       Item_Outlet_Sales
count        8523.000000
mean         2181.288914
std          1706.499616
min            33.290000
25%           834.247400
50%          1794.331000
75%          3101.296400
max         13086.964800
```

Numerical Features

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

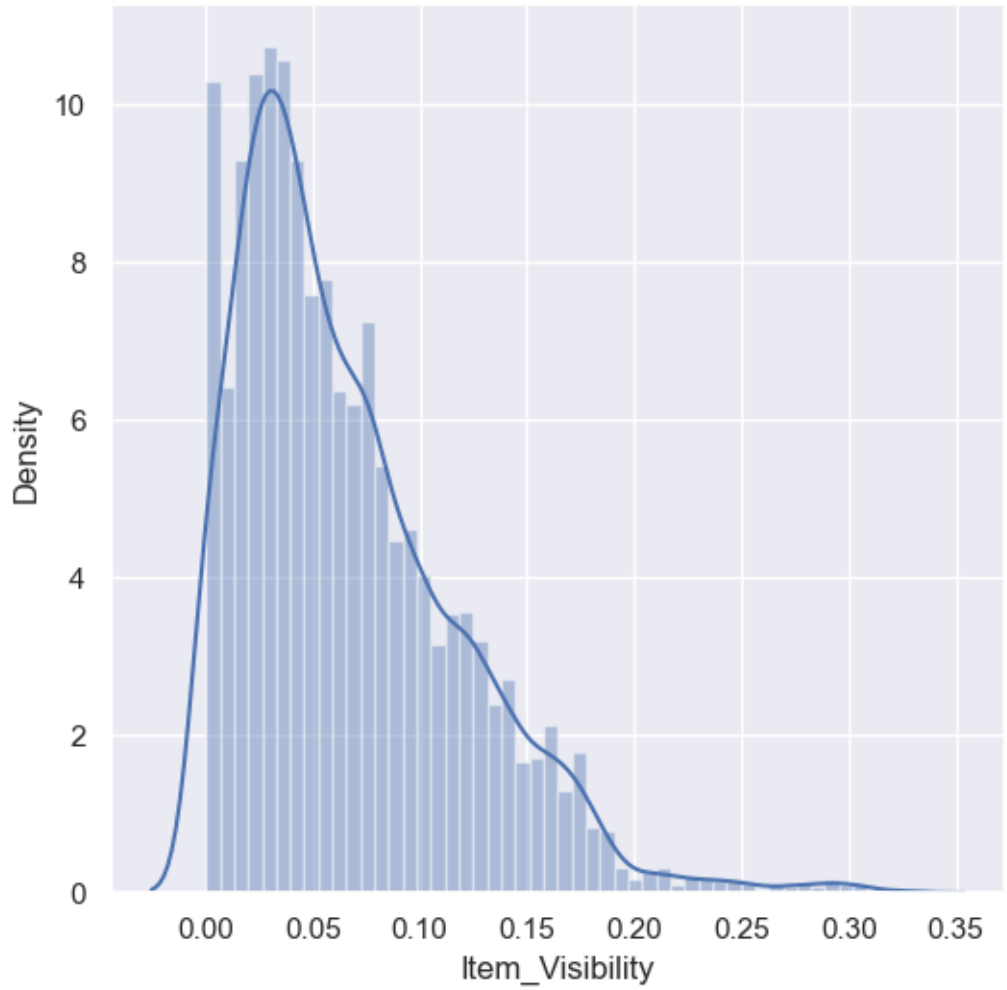
[18]:
```
# Item_Weight distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Weight'])
plt.show()
```

```
/tmp/ipykernel_7560/1330319193.py:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(big_mart_data['Item_Weight'])
```



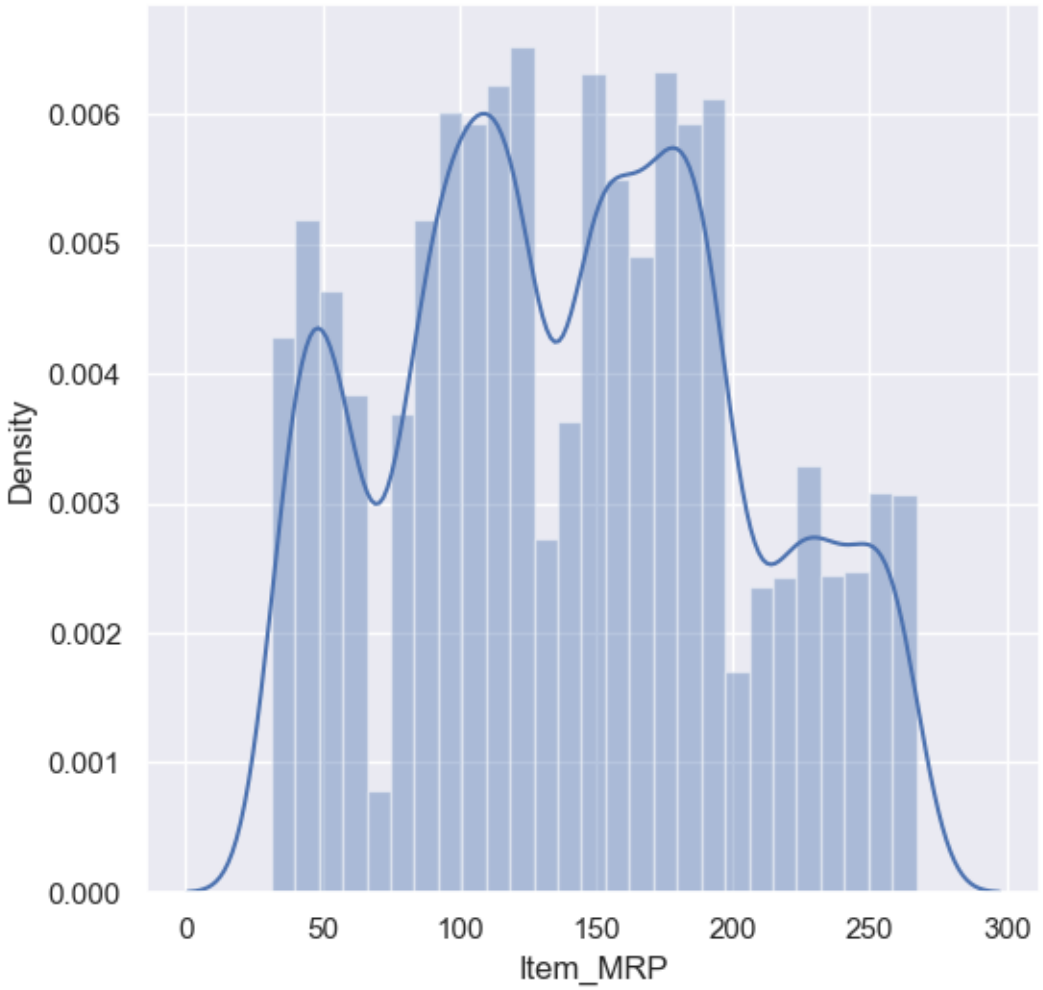
[19]:
```
# Item Visibility distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Visibility'])
plt.show()
```

```
/tmp/ipykernel_7560/193435663.py:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(big_mart_data['Item_Visibility'])
```



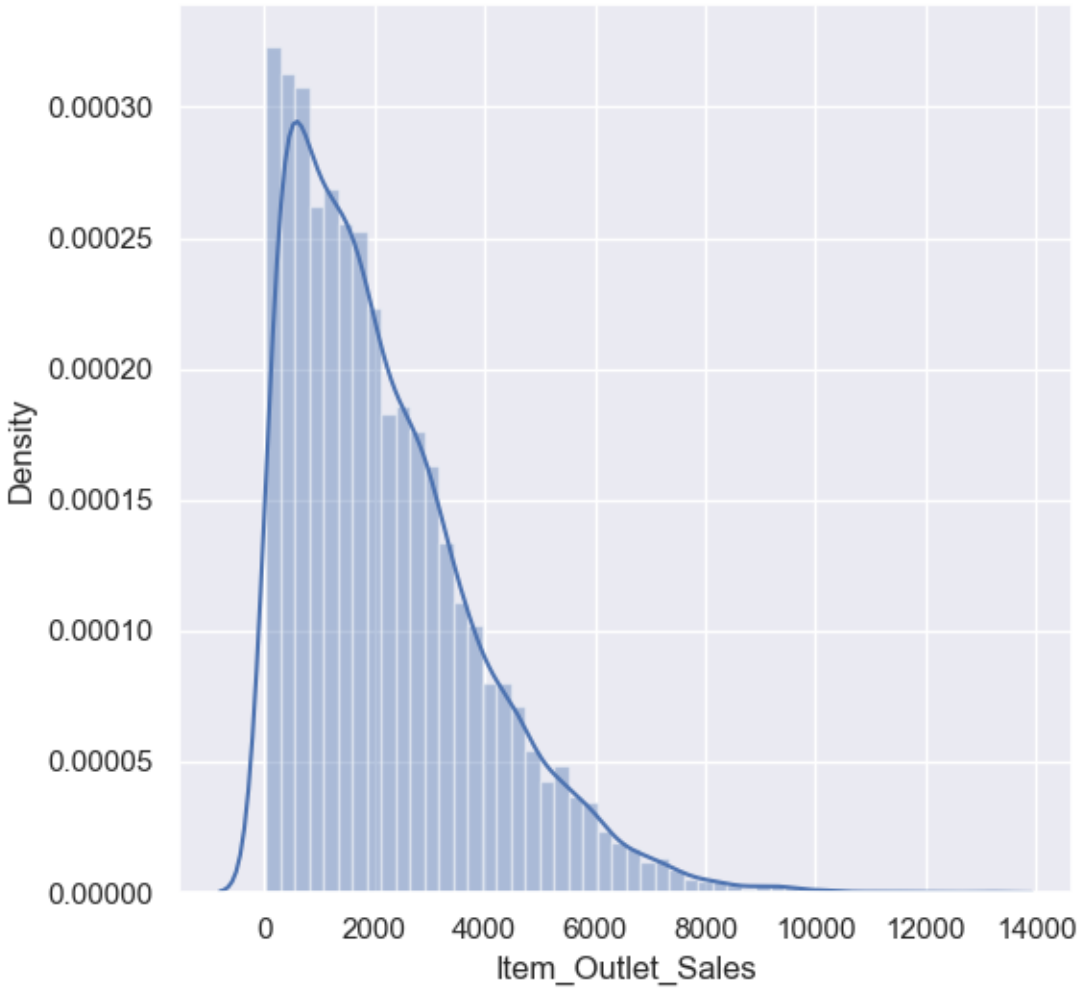
[20]:
```
# Item MRP distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_MRP'])
plt.show()
```

```
/tmp/ipykernel_7560/1610987680.py:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(big_mart_data['Item_MRP'])
```

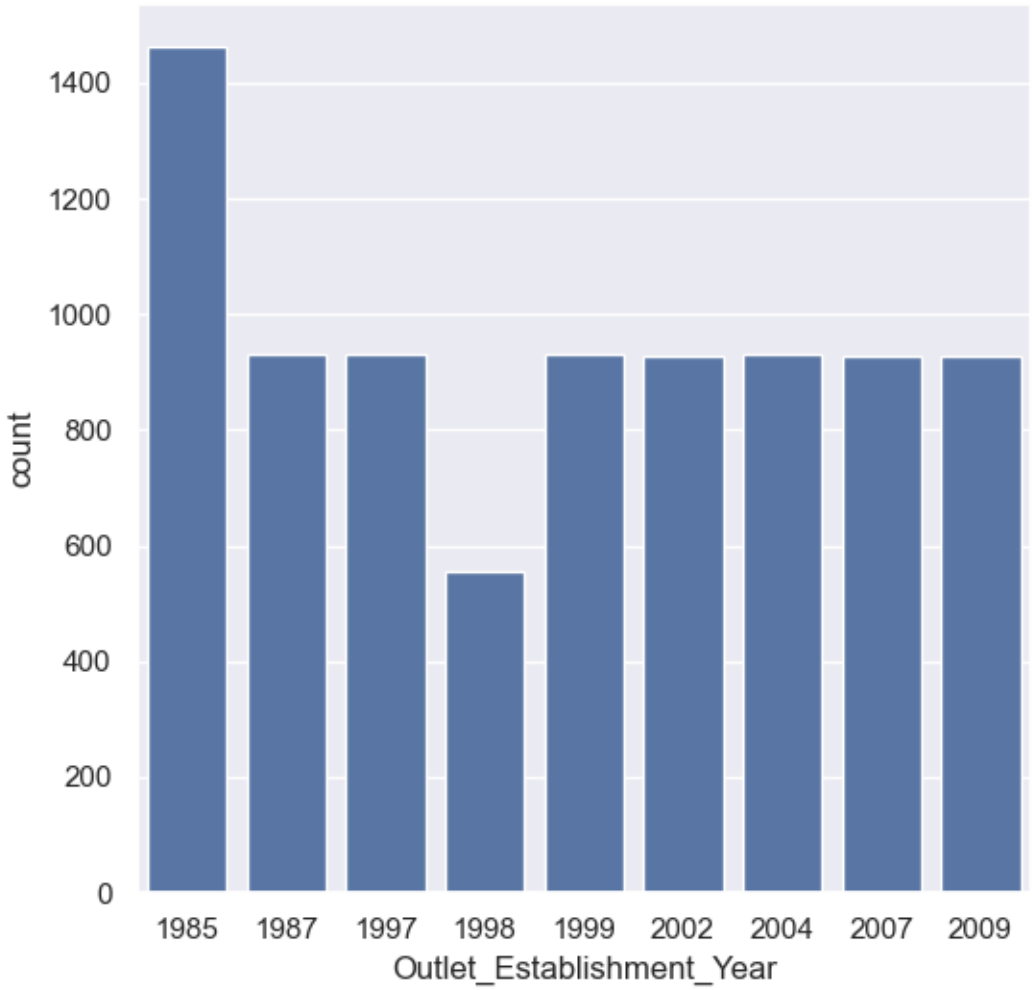


[21]:
```
# Item_Outlet_Sales distribution
plt.figure(figsize=(6,6))
sns.distplot(big_mart_data['Item_Outlet_Sales'])
plt.show()
```

```
/tmp/ipykernel_7560/1323853436.py:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(big_mart_data['Item_Outlet_Sales'])
```

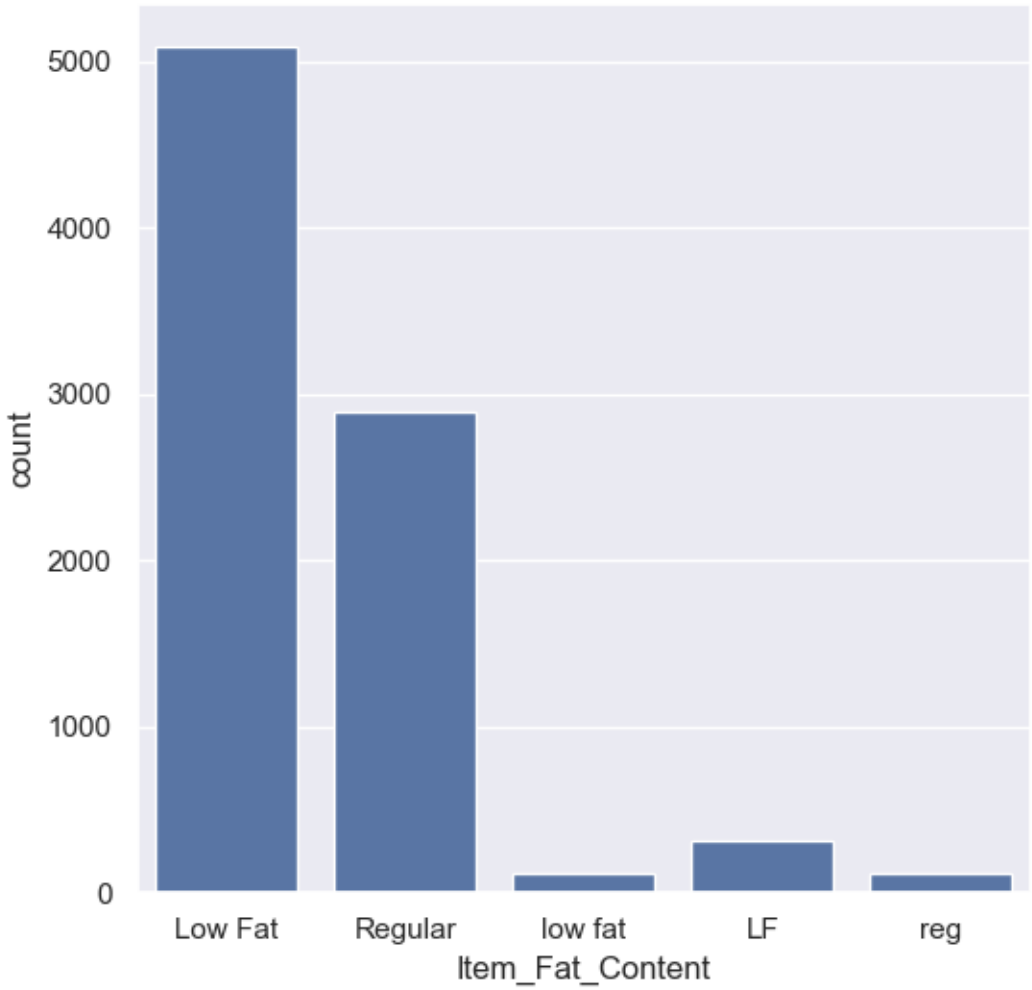


[22]:
```
# Outlet_Establishment_Year column
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year', data=big_mart_data)
plt.show()
```

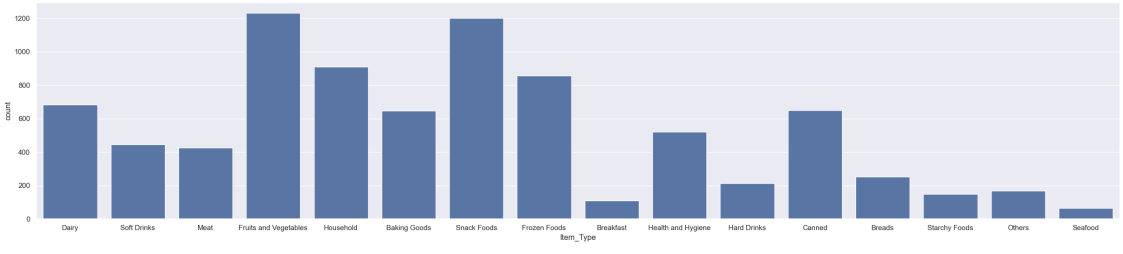


Categorical Features

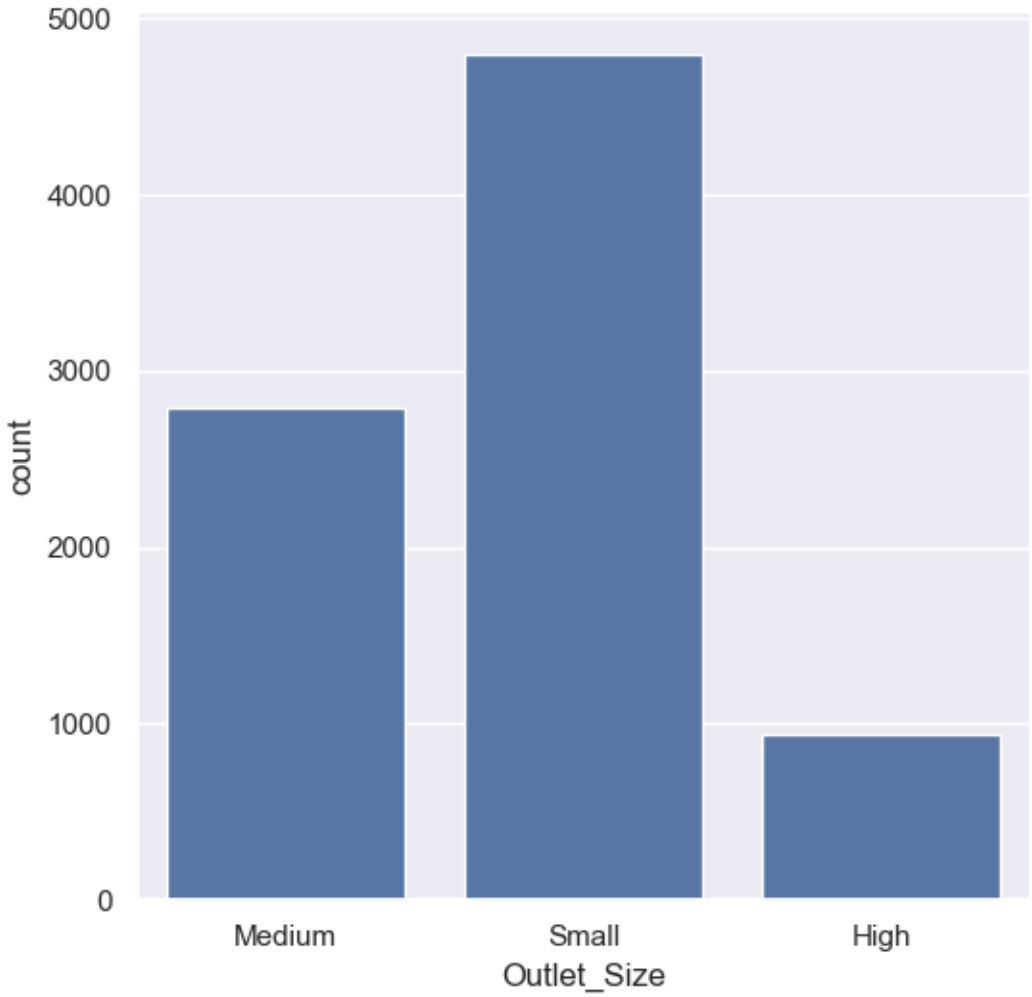
[23]:
```
# Item_Fat_Content column
plt.figure(figsize=(6,6))
sns.countplot(x='Item_Fat_Content', data=big_mart_data)
plt.show()
```



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



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



Data Pre-Processing

[26]:
```
big_mart_data.head()
```

[26]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	\
0	FDA15	9.30	Low Fat	0.016047	
1	DRC01	5.92	Regular	0.019278	
2	FDN15	17.50	Low Fat	0.016760	
3	FDX07	19.20	Regular	0.000000	
4	NCD19	8.93	Low Fat	0.000000	

```
              Item_Type  Item_MRP Outlet_Identifier  \
0                 Dairy  249.8092            OUT049
1           Soft Drinks   48.2692            OUT018
2                  Meat  141.6180            OUT049
3  Fruits and Vegetables  182.0950            OUT010
4             Household   53.8614            OUT013

   Outlet_Establishment_Year Outlet_Size Outlet_Location_Type  \
0                       1999      Medium               Tier 1
1                       2009      Medium               Tier 3
2                       1999      Medium               Tier 1
3                       1998       Small               Tier 3
4                       1987        High               Tier 3

        Outlet_Type  Item_Outlet_Sales
0  Supermarket Type1          3735.1380
1  Supermarket Type2           443.4228
2  Supermarket Type1          2097.2700
3      Grocery Store           732.3800
4  Supermarket Type1           994.7052
```

[27]:
```
big_mart_data['Item_Fat_Content'].value_counts()
```

[27]:
```
Item_Fat_Content
Low Fat    5089
Regular    2889
LF          316
reg         117
low fat     112
Name: count, dtype: int64
```

[28]:
```
big_mart_data.replace({'Item_Fat_Content': {'low fat':'Low Fat','LF':'Low Fat',␣
 ↪'reg':'Regular'}}, inplace=True)
```

[29]:
```
big_mart_data['Item_Fat_Content'].value_counts()
```

[29]:
```
Item_Fat_Content
Low Fat    5517
Regular    3006
Name: count, dtype: int64
```

Label Encoding

[30]:
```
encoder = LabelEncoder()
```

[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'])
```

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

[32]:
```
   Item_Identifier  Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  \
0              156         9.30                 0         0.016047          4
1                8         5.92                 1         0.019278         14
2              662        17.50                 0         0.016760         10
3             1121        19.20                 1         0.000000          6
4             1297         8.93                 0         0.000000          9

   Item_MRP  Outlet_Identifier  Outlet_Establishment_Year  Outlet_Size  \
0  249.8092                  9                       1999            1
1   48.2692                  3                       2009            1
2  141.6180                  9                       1999            1
3  182.0950                  0                       1998            2
4   53.8614                  1                       1987            0

   Outlet_Location_Type  Outlet_Type  Item_Outlet_Sales
0                     0            1          3735.1380
1                     2            2           443.4228
2                     0            1          2097.2700
3                     2            0           732.3800
4                     2            1           994.7052
```

Splitting features and Target

[33]:
```
X = big_mart_data.drop(columns='Item_Outlet_Sales', axis=1)
Y = big_mart_data['Item_Outlet_Sales']
```

[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]
```

[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

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

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

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

Machine Learning Model Training

XGBoost Regressor

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

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

[39]:
```
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,
             monotone_constraints=None, multi_strategy=None, n_estimators=None,
             n_jobs=None, num_parallel_tree=None, …)
```

Evaluation

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

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

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

```
R Squared value =  0.8762174618111388
```

[43]:
```
# prediction on test data
test_data_prediction = regressor.predict(X_test)
```

[44]:
```
# R squared Value
r2_test = metrics.r2_score(Y_test, test_data_prediction)
```

[45]:
```
print('R Squared value = ', r2_test)
```

```
R Squared value =  0.5017253991620692
```

[ ]:
```

```