Import modules

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

Loading the dataset

In [2]:
```
df = pd.read_csv('Train.csv')
df.head()
```

Out[2]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Ye
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	19
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	20
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	19
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	19
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	19

In [3]:
```
# statistical info
df.describe()
```

Out[3]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	7060.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.643456	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000	33.290000
25%	8.773750	0.026989	93.826500	1987.000000	834.247400
50%	12.600000	0.053931	143.012800	1999.000000	1794.331000
75%	16.850000	0.094585	185.643700	2004.000000	3101.296400
max	21.350000	0.328391	266.888400	2009.000000	13086.964800

In [4]:
```
# datatype of attributes
df.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
```

In [5]:
```
# check unique values in dataset
df.apply(lambda x: len(x.unique()))
```

Out[5]:
```
Item_Identifier              1559
Item_Weight                   416
Item_Fat_Content                5
Item_Visibility              7880
Item_Type                      16
Item_MRP                     5938
Outlet_Identifier              10
Outlet_Establishment_Year       9
Outlet_Size                     4
Outlet_Location_Type            3
Outlet_Type                     4
Item_Outlet_Sales            3493
dtype: int64
```

Preprocessing the dataset

Let us check for NULL values in the dataset.

In [6]:
```
# check for null values
df.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
```

In [7]:
```
# check for categorical attributes
cat_col = []
for x in df.dtypes.index:
    if df.dtypes[x] == 'object':
        cat_col.append(x)
cat_col
```

Out[7]:
```
['Item_Identifier',
 'Item_Fat_Content',
 'Item_Type',
 'Outlet_Identifier',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

Let us remove unnecessary columns.

In [8]:
```
cat_col.remove('Item_Identifier')
cat_col.remove('Outlet_Identifier')
cat_col
```

Out[8]:
```
['Item_Fat_Content',
 'Item_Type',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

Let's print the categorical columns.

In [9]:
```
# print the categorical columns
for col in cat_col:
    print(col)
    print(df[col].value_counts())
    print()
```

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

Item_Type
Fruits and Vegetables    1232
Snack Foods              1200
Household                 910
Frozen Foods              856
Dairy                     682
Canned                    649
Baking Goods              648
Health and Hygiene        520
Soft Drinks               445
Meat                      425
Breads                    251
Hard Drinks               214
Others                    169
Starchy Foods             148
Breakfast                 110
Seafood                    64
Name: Item_Type, dtype: int64

Outlet_Size
Medium    2793
Small     2388
High       932
Name: Outlet_Size, dtype: int64

Outlet_Location_Type
Tier 3    3350
Tier 2    2785
Tier 1    2388
Name: Outlet_Location_Type, dtype: int64

Outlet_Type
Supermarket Type1    5577
Grocery Store        1083
Supermarket Type3     935
Supermarket Type2     928
Name: Outlet_Type, dtype: int64
```

Let us now fill in the missing values.

In [10]:
```
# fill the missing values
item_weight_mean = df.pivot_table(values = "Item_Weight", index = 'Item_Identifier')
item_weight_mean
```

Out[10]:

Item_Identifier	Item_Weight
DRA12	11.600
DRA24	19.350
DRA59	8.270
DRB01	7.390
DRB13	6.115
...	...
NCZ30	6.590
NCZ41	19.850
NCZ42	10.500
NCZ53	9.600
NCZ54	14.650

1555 rows × 1 columns

Let's check for the missing values of Item_Weight.

In [11]:
```
miss_bool = df['Item_Weight'].isnull()
miss_bool
```

Out[11]:
```
0       False
1       False
2       False
3       False
4       False
        ...
8518    False
8519    False
8520    False
8521    False
8522    False
Name: Item_Weight, Length: 8523, dtype: bool
```

In [12]:
```
for i, item in enumerate(df['Item_Identifier']):
    if miss_bool[i]:
        if item in item_weight_mean:
            df['Item_Weight'][i] = item_weight_mean.loc[item]['Item_Weight']
        else:
            df['Item_Weight'][i] = np.mean(df['Item_Weight'])
```

In [13]:
```
df['Item_Weight'].isnull().sum()
```

Out[13]:
```
0
```

Let's check for the missing values of Outler_Type.

In [14]:
```
outlet_size_mode = df.pivot_table(values='Outlet_Size', columns='Outlet_Type', aggfunc=(lambda x: x.mode
outlet_size_mode
```

Out[14]:

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

Let's fill in the missing values for Outlet_Size.

In [15]:
```
miss_bool = df['Outlet_Size'].isnull()
df.loc[miss_bool, 'Outlet_Size'] = df.loc[miss_bool, 'Outlet_Type'].apply(lambda x: outlet_size_mode[x]
```

In [16]:
```
df['Outlet_Size'].isnull().sum()
```

Out[16]:
```
0
```

Similarly, we can check for Item_Visibility.

In [17]:
```
sum(df['Item_Visibility']==0)
```

Out[17]:
```
526
```

In [18]:
```
# replace zeros with mean
df.loc[:, 'Item_Visibility'].replace([0], [df['Item_Visibility'].mean()], inplace=True)
```

In [19]:
```
sum(df['Item_Visibility']==0)
```

Out[19]:
```
0
```

Let us combine the repeated Values of the categorical column.

In [20]:
```
# combine item fat contentdf['Item_Fat_Content'] = df['Item_Fat_Content'].replace({'LF':'Low Fat', 'reg
df['Item_Fat_Content'].value_counts()
```

Out[20]:
```
Low Fat    5089
Regular    2889
LF          316
reg         117
low fat     112
Name: Item_Fat_Content, dtype: int64
```

Creation of New Attributes

In [21]:
```
df['New_Item_Type'] = df['Item_Identifier'].apply(lambda x: x[:2])
df['New_Item_Type']
```

Out[21]:
```
0       FD
1       DR
2       FD
3       FD
4       NC
        ..
8518    FD
8519    FD
8520    NC
8521    FD
8522    DR
Name: New_Item_Type, Length: 8523, dtype: object
```

In [22]:
```
df['New_Item_Type'] = df['New_Item_Type'].map({'FD':'Food', 'NC':'Non-Consumable', 'DR':'Drinks'})
df['New_Item_Type'].value_counts()
```

Out[22]:
```
Food              6125
Non-Consumable    1599
Drinks             799
Name: New_Item_Type, dtype: int64
```

In [23]:
```
df.loc[df['New_Item_Type']=='Non-Consumable', 'Item_Fat_Content'] = 'Non-Edible'
df['Item_Fat_Content'].value_counts()
```

Out[23]:
```
Low Fat       3612
Regular       2889
Non-Edible    1599
LF             222
reg            117
low fat         84
Name: Item_Fat_Content, dtype: int64
```

Let us create a new attribute to show small values for the establishment year.

In [24]:
```
# create small values for establishment year
df['Outlet_Years'] = 2013 - df['Outlet_Establishment_Year']
df['Outlet_Years']
```

Out[24]:
```
0       14
1        4
2       14
3       15
4       26
        ..
8518    26
8519    11
8520     9
8521     4
8522    16
Name: Outlet_Years, Length: 8523, dtype: int64
```

Let's print the dataframe.

In [25]:
```
df.head()
```

Out[25]:

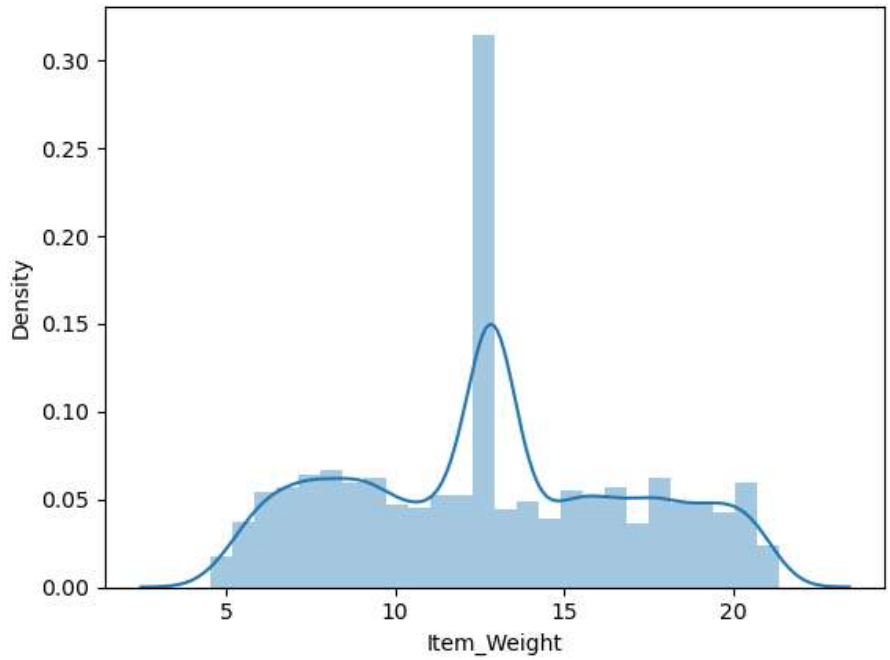
	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Ye
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	19
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	20
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	19
3	FDX07	19.20	Regular	0.066132	Fruits and Vegetables	182.0950	OUT010	19
4	NCD19	8.93	Non-Edible	0.066132	Household	53.8614	OUT013	19

Exploratory Data Analysis

Let us explore the numerical columns.

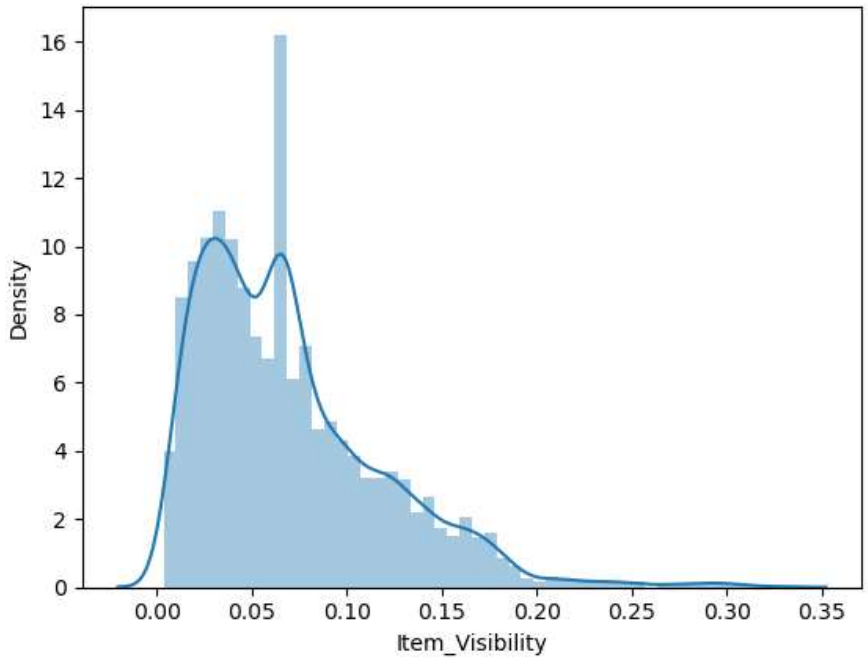
In [26]:
```
sns.distplot(df['Item_Weight'])
```

Out[26]: <AxesSubplot:xlabel='Item_Weight', ylabel='Density'>



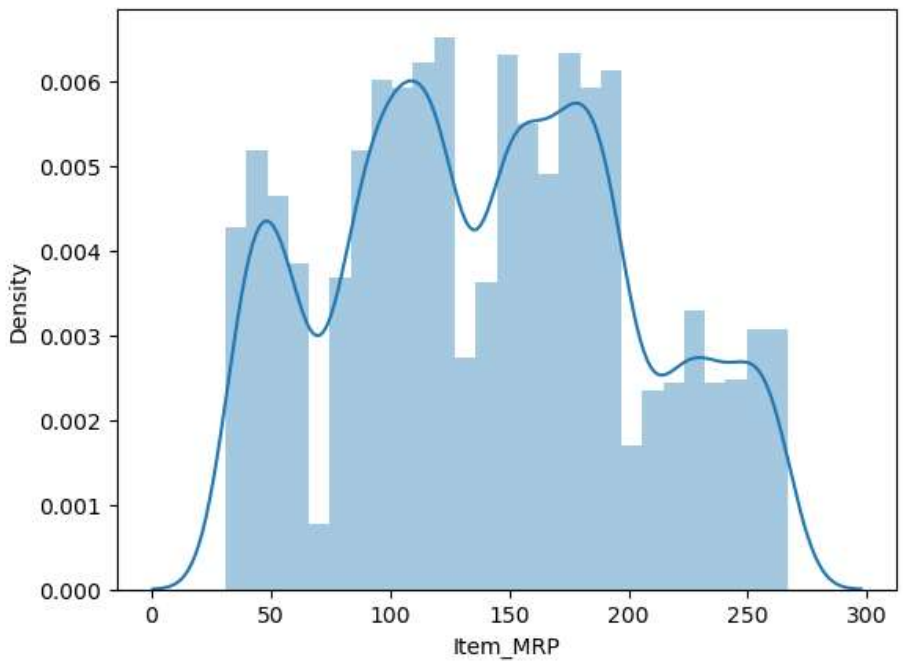
In [27]:
```
sns.distplot(df['Item_Visibility'])
```

Out[27]:
```
<AxesSubplot:xlabel='Item_Visibility', ylabel='Density'>
```



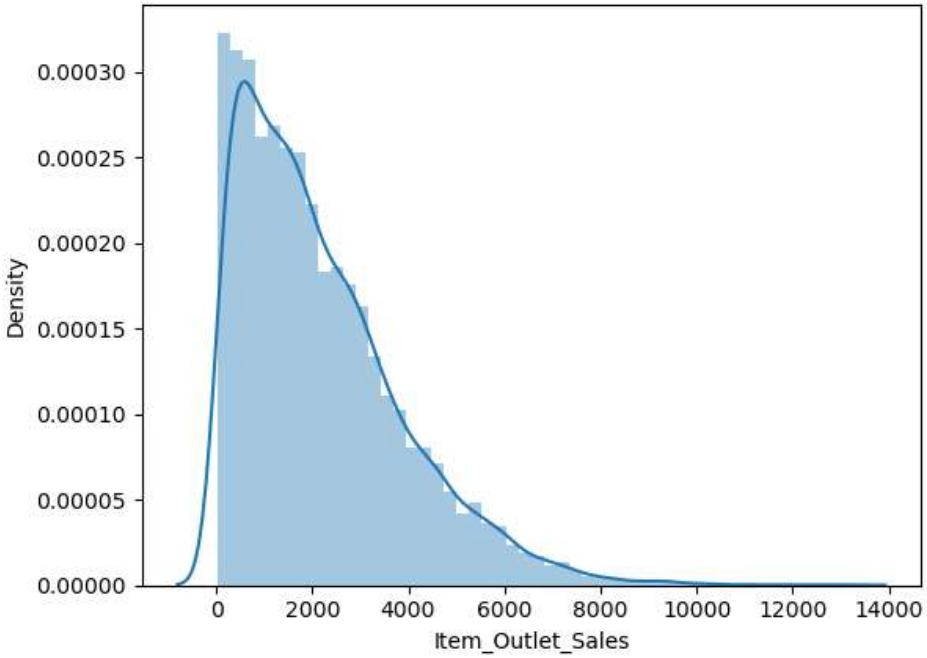
In [28]:
```
sns.distplot(df['Item_MRP'])
```

Out[28]:
```
<AxesSubplot:xlabel='Item_MRP', ylabel='Density'>
```



In [29]:
```
sns.distplot(df['Item_Outlet_Sales'])
```

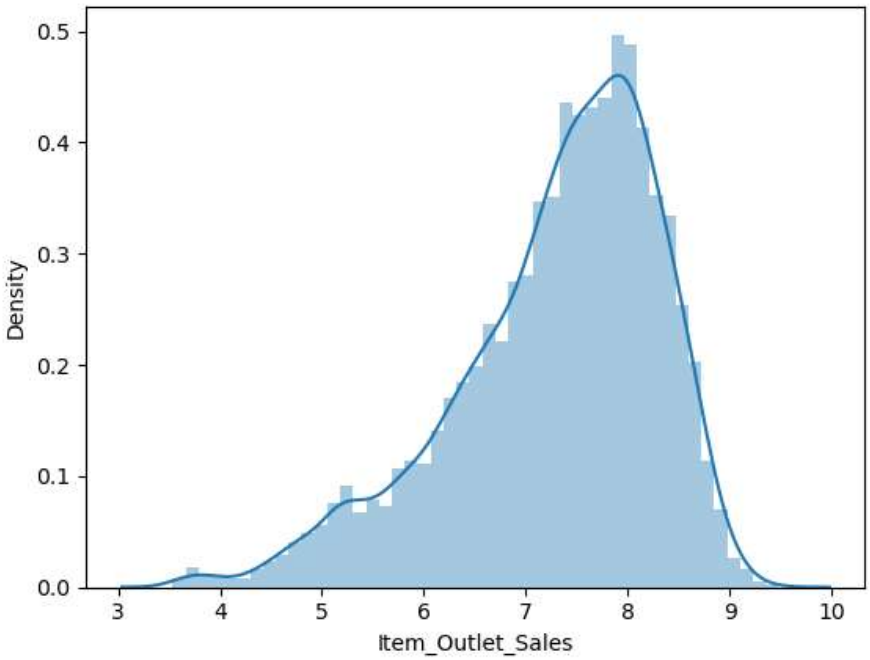
Out[29]: <AxesSubplot:xlabel='Item_Outlet_Sales', ylabel='Density'>



Log transformation helps to make the highly skewed distribution less skewed.

In [30]:
```
# log transformation
df['Item_Outlet_Sales'] = np.log(1+df['Item_Outlet_Sales'])
sns.distplot(df['Item_Outlet_Sales'])
```

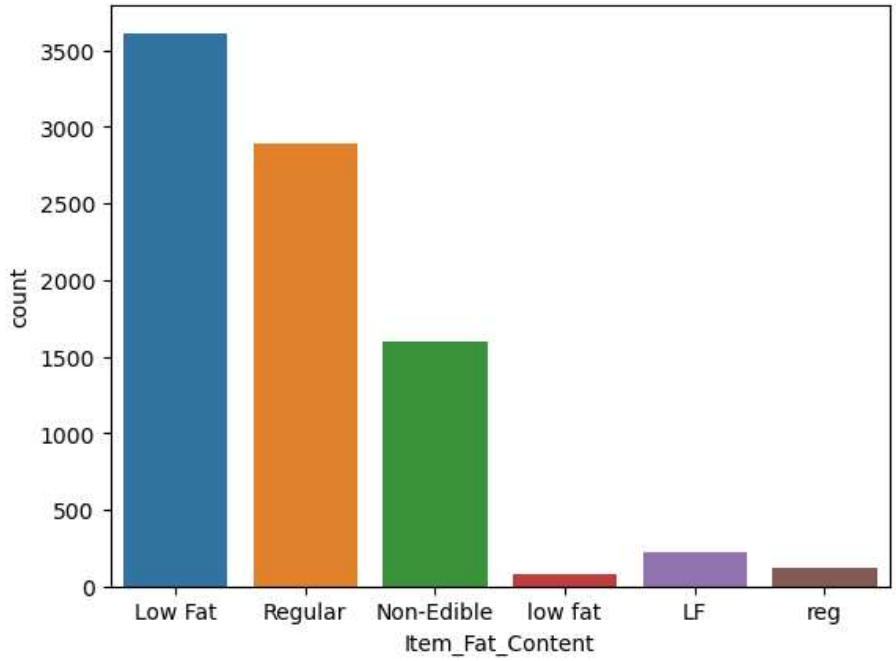
Out[30]: <AxesSubplot:xlabel='Item_Outlet_Sales', ylabel='Density'>



Let us explore the categorical columns.

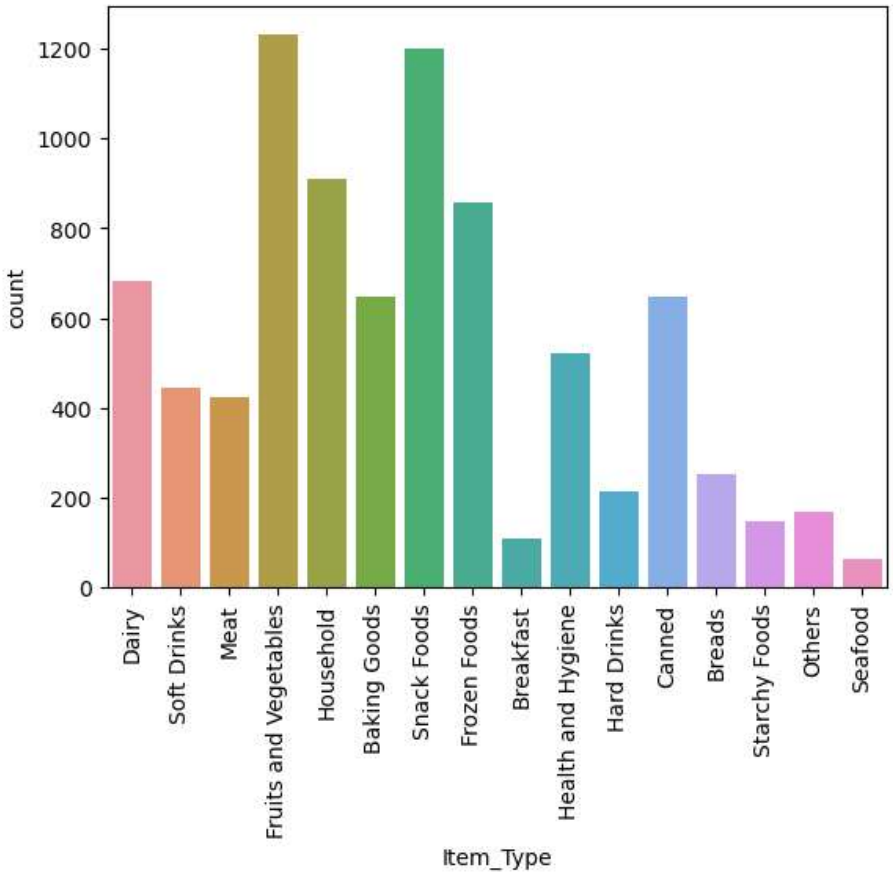
In [31]:
```
sns.countplot(df["Item_Fat_Content"])
```

Out[31]: <AxesSubplot:xlabel='Item_Fat_Content', ylabel='count'>



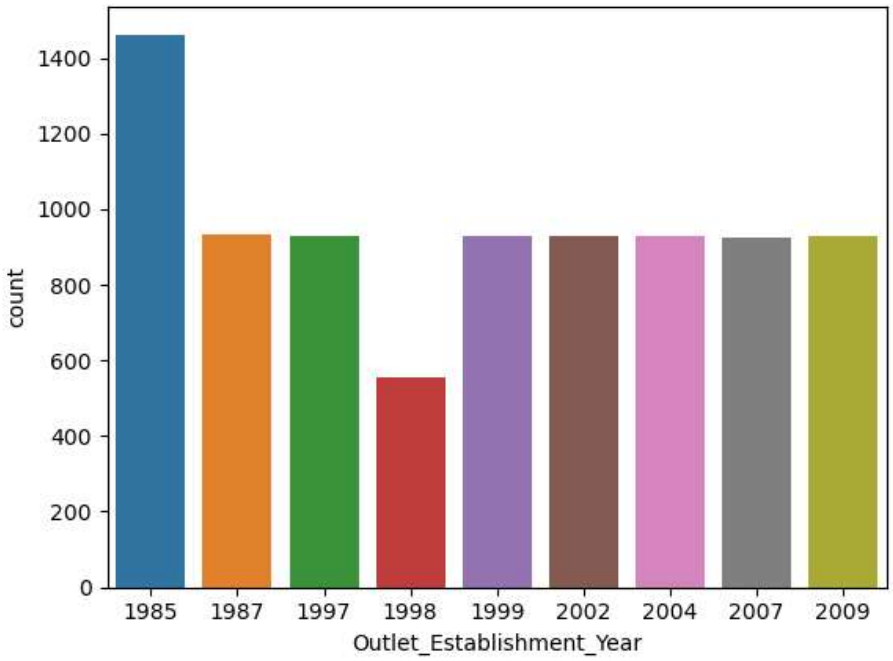
In [32]:
```
# plt.figure(figsize=(15,5))
l = list(df['Item_Type'].unique())
chart = sns.countplot(df["Item_Type"])
chart.set_xticklabels(labels=l, rotation=90)
```

Out[32]:
```
[Text(0, 0, 'Dairy'),
 Text(1, 0, 'Soft Drinks'),
 Text(2, 0, 'Meat'),
 Text(3, 0, 'Fruits and Vegetables'),
 Text(4, 0, 'Household'),
 Text(5, 0, 'Baking Goods'),
 Text(6, 0, 'Snack Foods'),
 Text(7, 0, 'Frozen Foods'),
 Text(8, 0, 'Breakfast'),
 Text(9, 0, 'Health and Hygiene'),
 Text(10, 0, 'Hard Drinks'),
 Text(11, 0, 'Canned'),
 Text(12, 0, 'Breads'),
 Text(13, 0, 'Starchy Foods'),
 Text(14, 0, 'Others'),
 Text(15, 0, 'Seafood')]
```



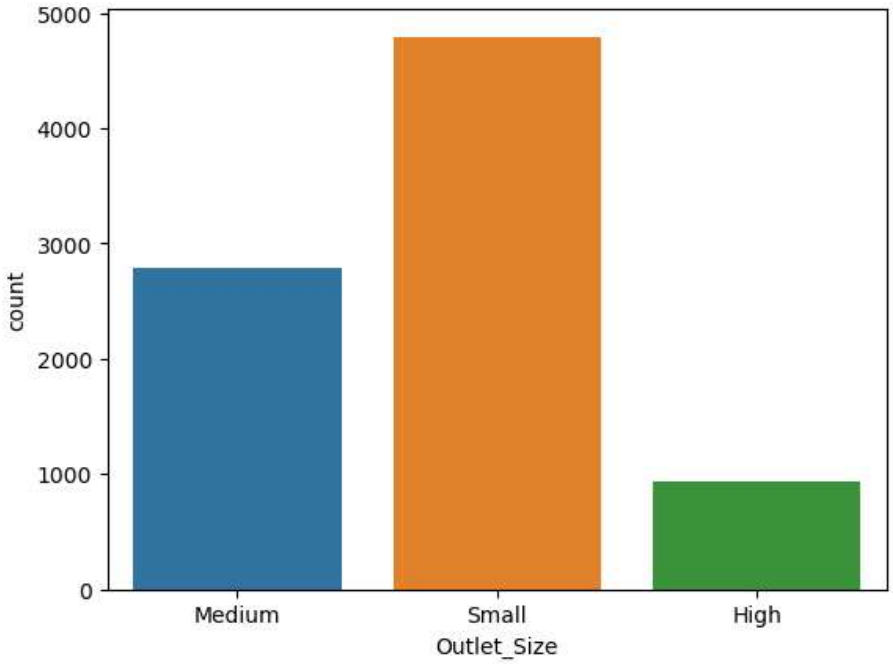
In [33]:
```
sns.countplot(df['Outlet_Establishment_Year'])
```

Out[33]: <AxesSubplot:xlabel='Outlet_Establishment_Year', ylabel='count'>



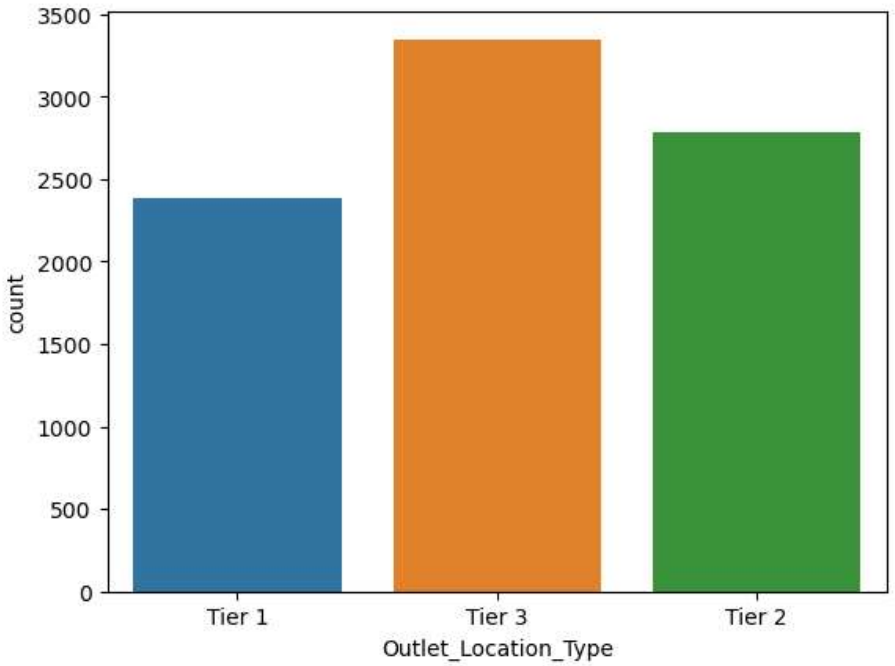
In [34]:
```
sns.countplot(df['Outlet_Size'])
```

Out[34]: <AxesSubplot:xlabel='Outlet_Size', ylabel='count'>



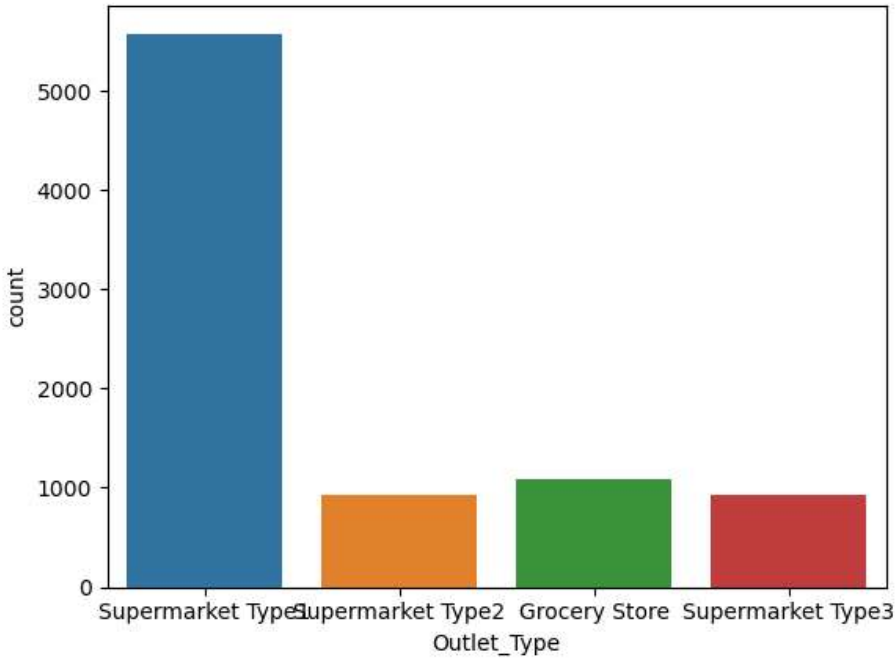
In [35]:
```
sns.countplot(df['Outlet_Location_Type'])
```

Out[35]: <AxesSubplot:xlabel='Outlet_Location_Type', ylabel='count'>



In [36]:
```
sns.countplot(df['Outlet_Type'])
```

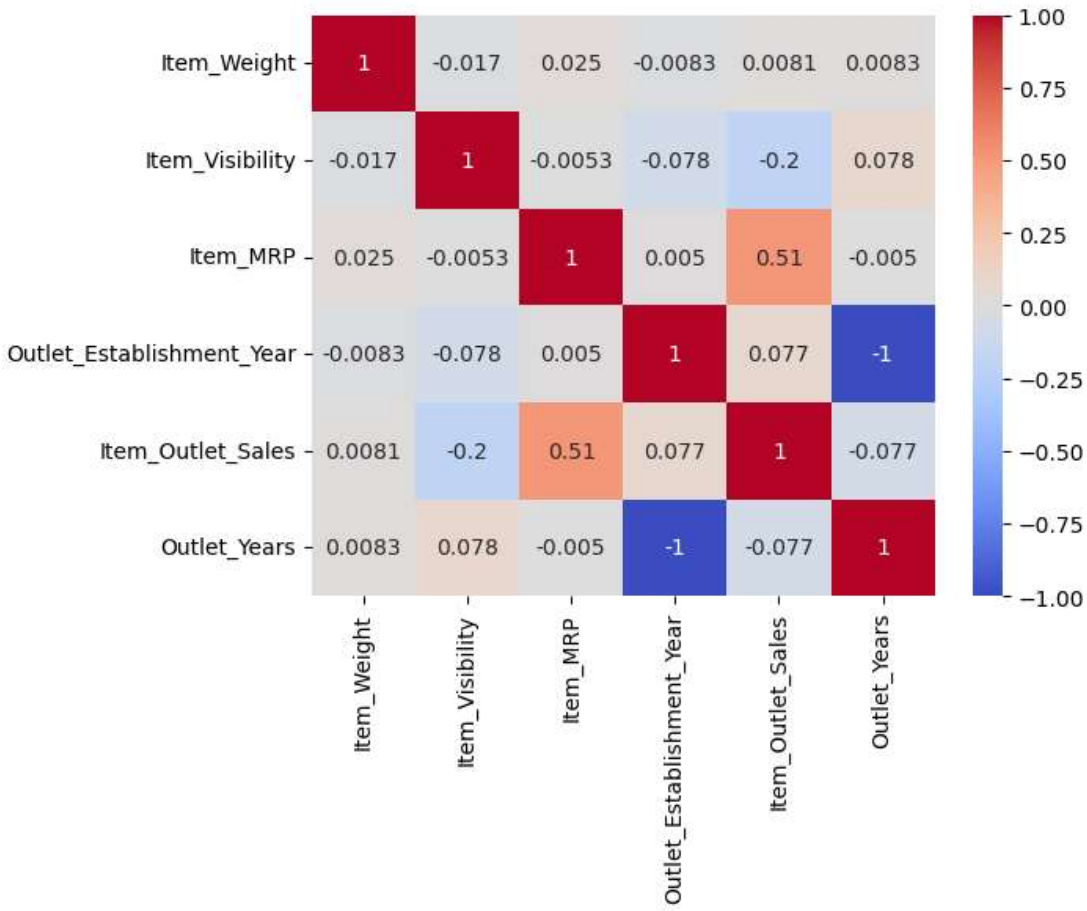
Out[36]: <AxesSubplot:xlabel='Outlet_Type', ylabel='count'>



Correlation Matrix

In [37]:
```
corr = df.corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

Out[37]: <AxesSubplot:>



Let's check the values of the dataset.

In [38]:
```
df.head()
```

Out[38]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Ye
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	19
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	20
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	19
3	FDX07	19.20	Regular	0.066132	Fruits and Vegetables	182.0950	OUT010	19
4	NCD19	8.93	Non-Edible	0.066132	Household	53.8614	OUT013	19

Label Encoding

In [39]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['Outlet'] = le.fit_transform(df['Outlet_Identifier'])
cat_col = ['Item_Fat_Content', 'Item_Type', 'Outlet_Size', 'Outlet_Location_Type', 'Outlet_Type', 'New_
for col in cat_col:
    df[col] = le.fit_transform(df[col])
```

One Hot Encoding

In [40]:
```
df = pd.get_dummies(df, columns=['Item_Fat_Content', 'Outlet_Size', 'Outlet_Location_Type', 'Outlet_Type
df.head()
```

Out[40]:

	Item_Identifier	Item_Weight	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Item_Outlet_Sal
0	FDA15	9.30	0.016047	4	249.8092	OUT049	1999	8.2258
1	DRC01	5.92	0.019278	14	48.2692	OUT018	2009	6.0967
2	FDN15	17.50	0.016760	10	141.6180	OUT049	1999	7.6488
3	FDX07	19.20	0.066132	6	182.0950	OUT010	1998	6.5976
4	NCD19	8.93	0.066132	9	53.8614	OUT013	1987	6.9034

5 rows × 29 columns

Splitting the data for Training and Testing

In [41]:
```
X = df.drop(columns=['Outlet_Establishment_Year', 'Item_Identifier', 'Outlet_Identifier', 'Item_Outlet_S
y = df['Item_Outlet_Sales']
```

Model Training

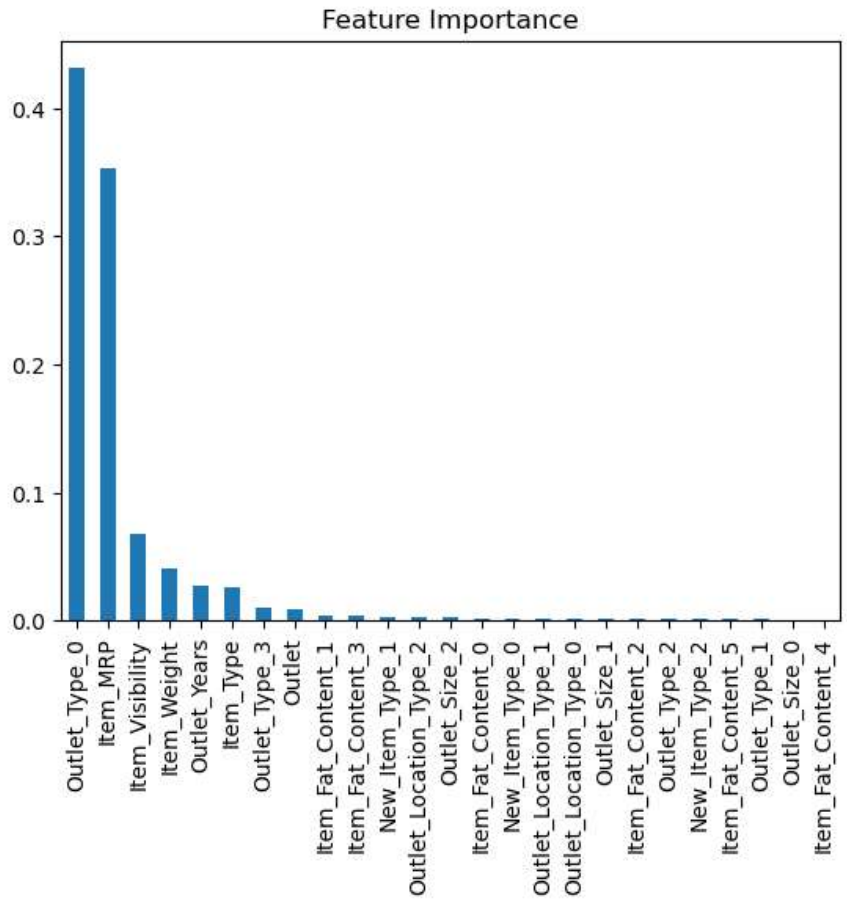
In [42]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
def train(model, X, y):
    # train the model
    model.fit(X, y)

    # predict the training set
    pred = model.predict(X)

    # perform cross-validation
    cv_score = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=5)
    cv_score = np.abs(np.mean(cv_score))

    print("Model Report")
    print("MSE:",mean_squared_error(y,pred))
    print("CV Score:", cv_score)
```

Random Forest:

In [43]:
```
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title="Feature Importance")
```

```
Model Report
MSE: 0.0421219320243586
CV Score: 0.30992860984420495
```

Out[43]: <AxesSubplot:title={'center':'Feature Importance'}>

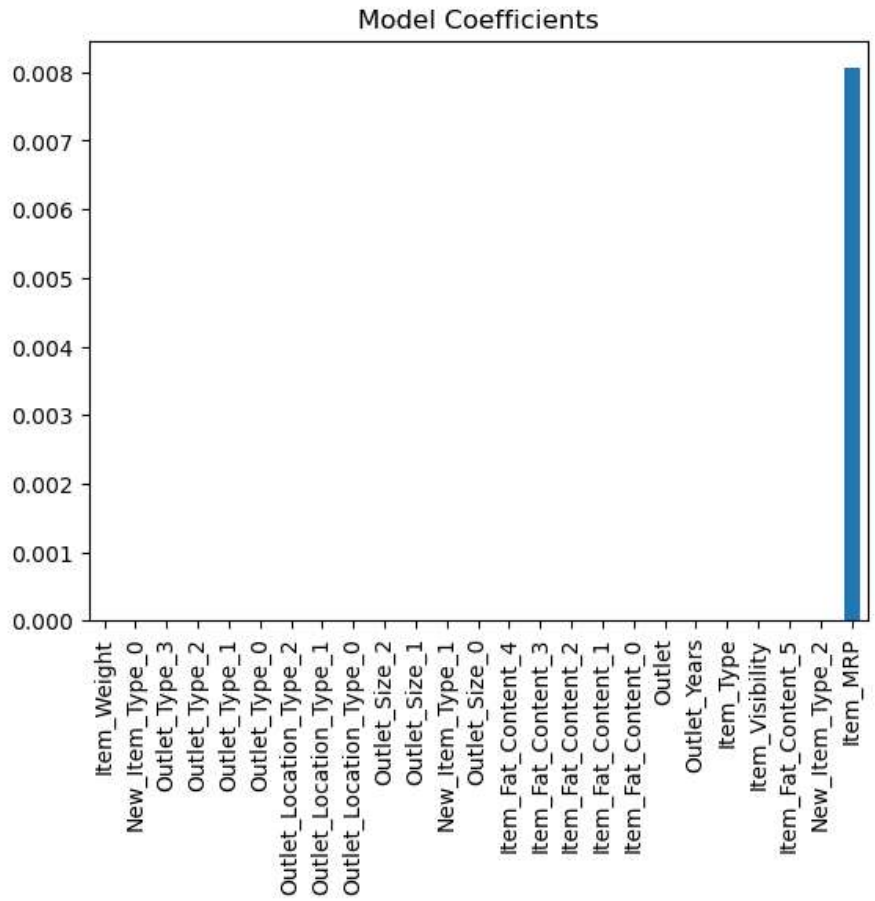


Lasso:

In [44]:
```
from sklearn.linear_model import Lasso
model = Lasso()
train(model, X, y)
coef = pd.Series(model.coef_, X.columns).sort_values()
coef.plot(kind='bar', title="Model Coefficients")
```

```
Model Report
MSE: 0.7628688679102086
CV Score: 0.7630789166281843
```

Out[44]: <AxesSubplot:title={'center':'Model Coefficients'}>

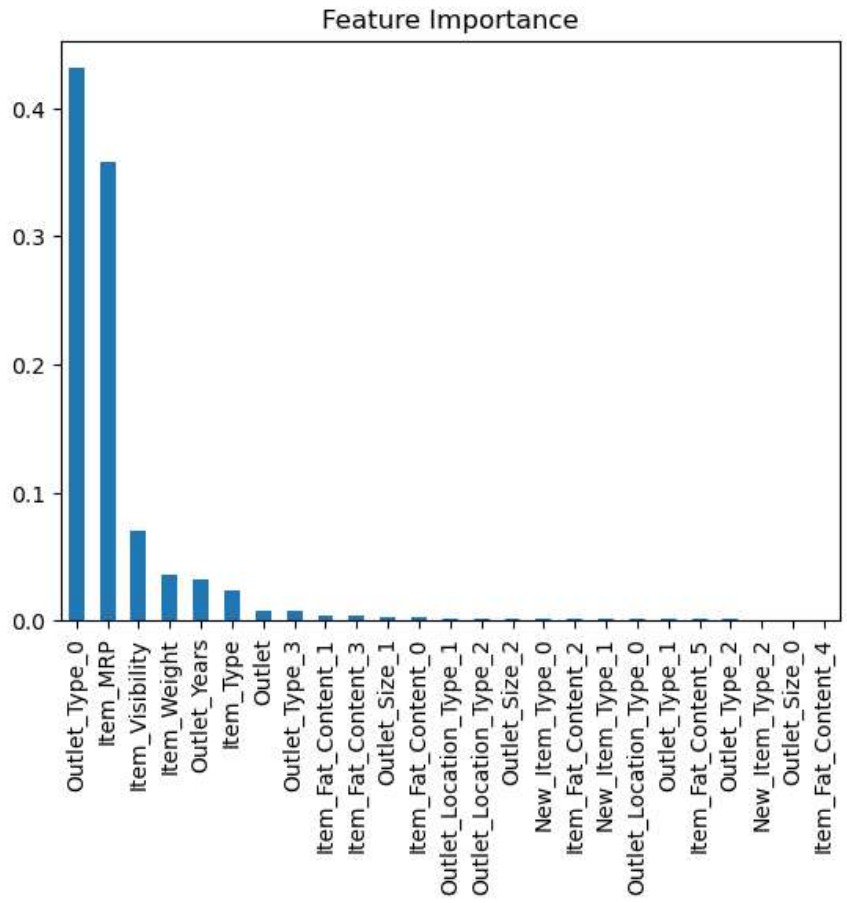


Decision Tree:

In [45]:
```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title="Feature Importance")
```

```
Model Report
MSE: 5.5534030638578795e-34
CV Score: 0.5712575735368502
```

Out[45]: <AxesSubplot:title={'center':'Feature Importance'}>

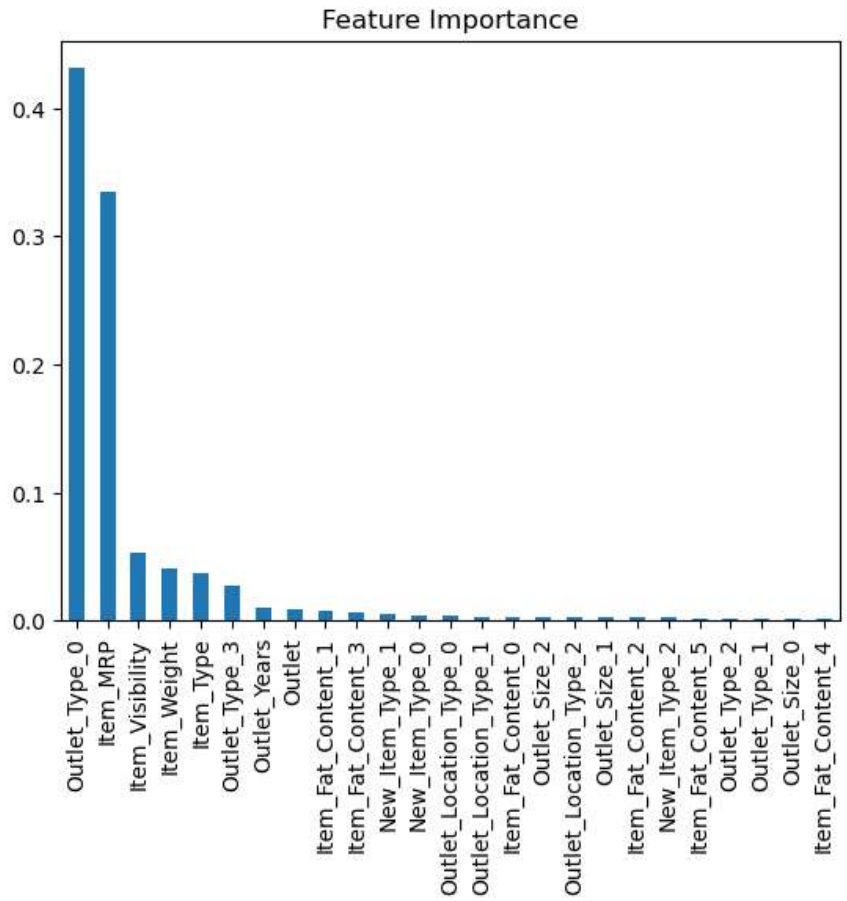


Extra Trees:

In [46]:
```
from sklearn.ensemble import ExtraTreesRegressor
model = ExtraTreesRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title="Feature Importance")
```

```
Model Report
MSE: 1.0418489584965893e-28
CV Score: 0.33339578580466656
```

Out[46]: <AxesSubplot:title={'center':'Feature Importance'}>



In [ ]: