# 🛒 BigMart Sales Prediction 📈

In [2]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [3]:
```python
df = pd.read_csv('train.csv')
```

In [4]:
```python
df.head()
```

Out[4]:

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

In [5]:
```python
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 [6]:
```
df.describe()
```

Out[6]:

| | 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 |

## Dealing with Null Values

In [7]:
```
df.shape
```

Out[7]:
```
(8523, 12)
```

In [8]:
```
df.isna().sum()
```

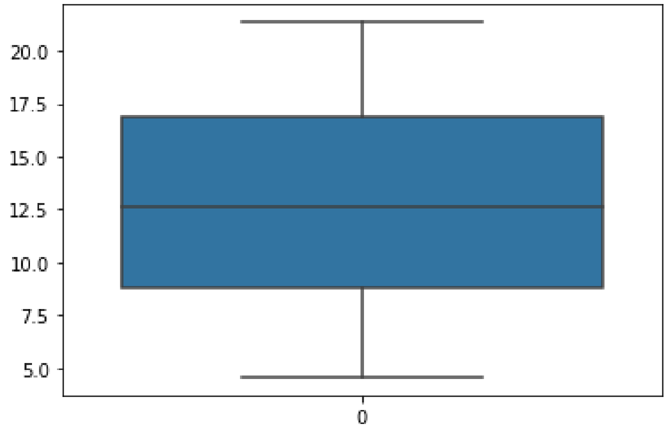
Out[8]:
```
Item_Identifier                 0
Item_Weight                  1463
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  2410
Outlet_Location_Type            0
Outlet_Type                     0
Item_Outlet_Sales               0
dtype: int64
```

In [9]:
```
df['Item_Weight'].describe()
```

Out[9]:
```
count    7060.000000
mean       12.857645
std         4.643456
min         4.555000
25%         8.773750
50%        12.600000
75%        16.850000
max        21.350000
Name: Item_Weight, dtype: float64
```

In [10]:
```
sns.boxplot(df.Item_Weight)
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1ed1e16ba08>
```




- It seems there are no outliers, hence it is safe to impute with the mean.

In [11]:
```
df.Item_Weight.fillna(df.Item_Weight.mean(),inplace=True)
```

In [12]:
```
# Imputing Outlet size with mode.
df.Outlet_Size.fillna(df.Outlet_Size.mode()[0],inplace=True)
```

In [13]:
```
df.info()
```

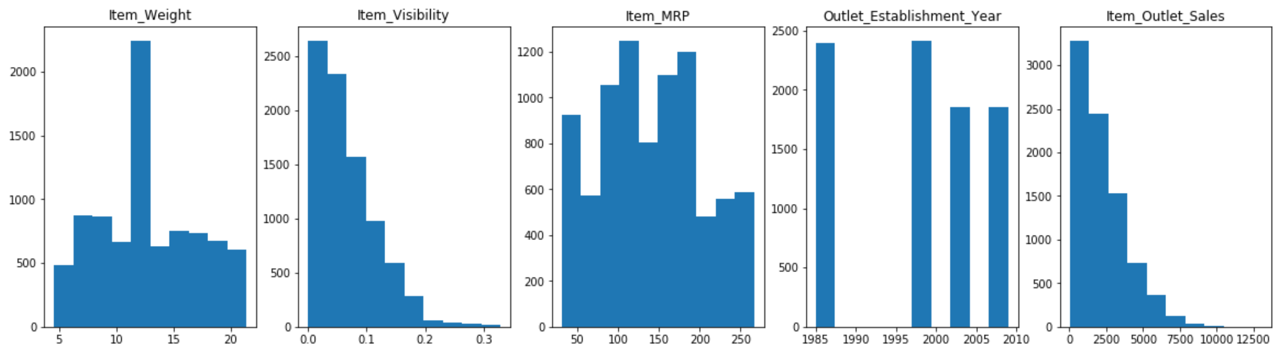
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                8523 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                8523 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
```

# Data Visualization of Numeric Columns

In [14]:
```
nums = df.select_dtypes(include=['float64', 'int64']).columns.to_numpy()
nums
```

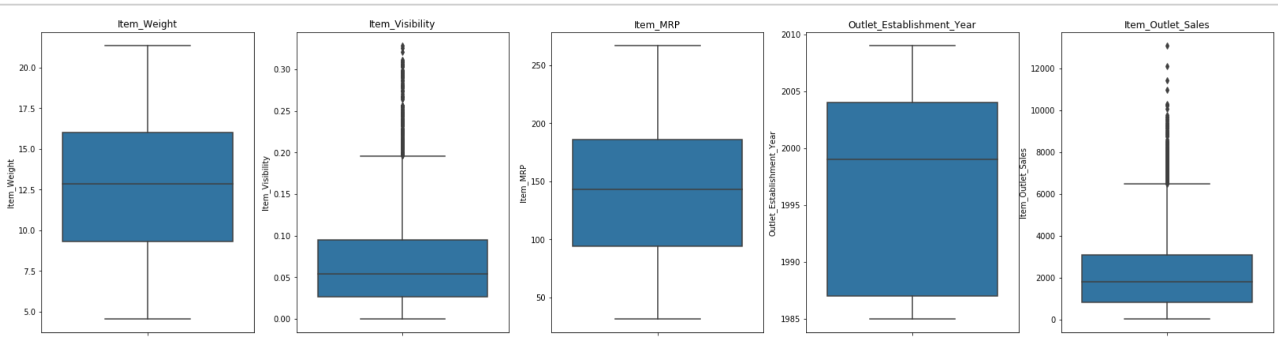
Out[14]:
```
array(['Item_Weight', 'Item_Visibility', 'Item_MRP',
       'Outlet_Establishment_Year', 'Item_Outlet_Sales'], dtype=object)
```

In [15]:
```
# Checking the distribution of the numeric Columns

fig, ax = plt.subplots(1, 5, figsize=(20, 5))

for i, col in enumerate(nums):
    ax[i].hist(df[col])
    ax[i].set_title(col)
```



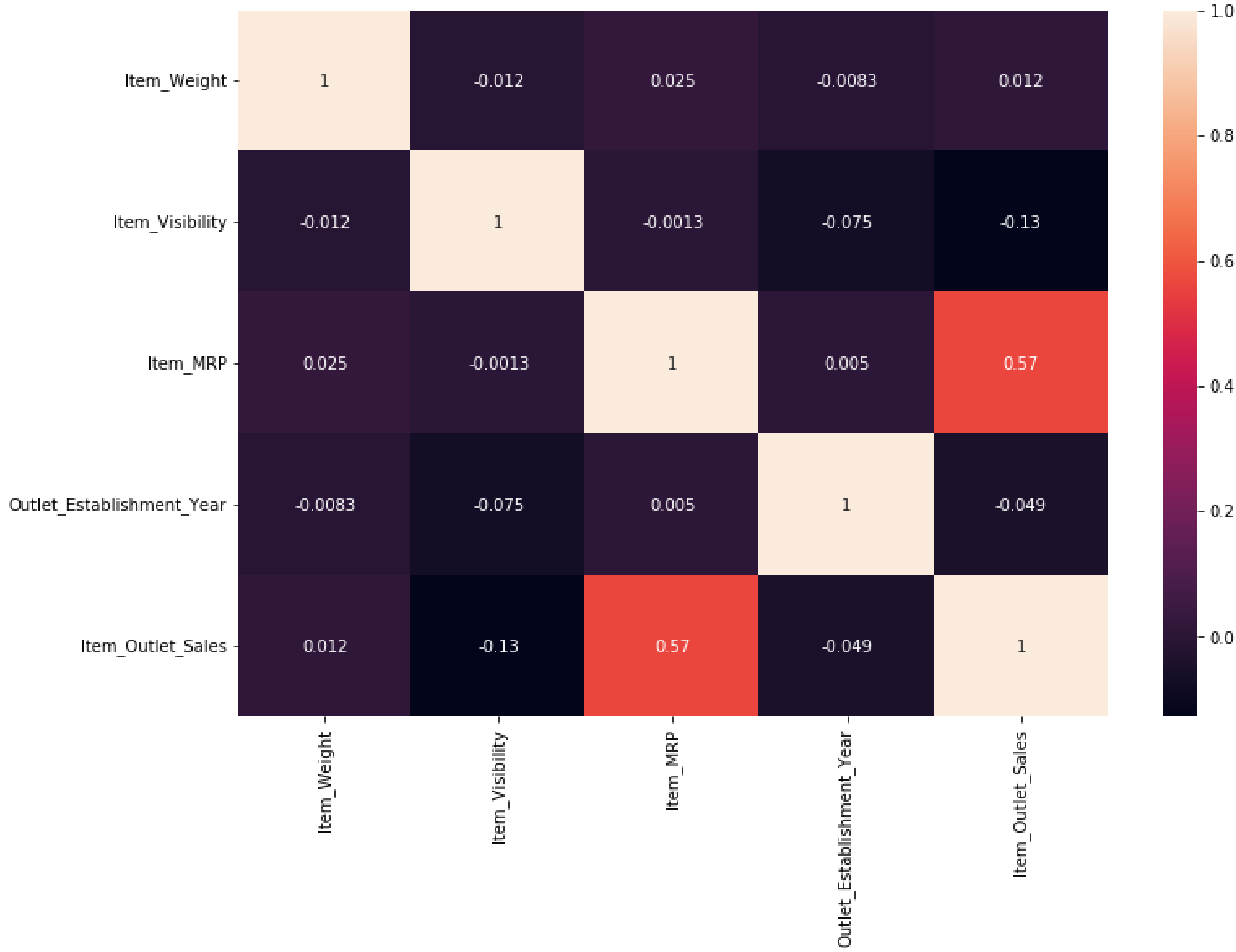

- It seems that the Item Visibility and Item outlet sales columns are right skewed!
- We can apply Data transformations to make them Normally distributed.

In [16]:
```
# Checking for outliers in the numeric columns

fig, ax = plt.subplots(1, 5, figsize=(28, 7))

for i, col in enumerate(nums):
    sns.boxplot(data=df, y=col, ax=ax[i])
    ax[i].set_title(col)
```




- It seems that the Item Visibility and Item outlet sales columns have some outliers which need to be handled!

In [17]:
```python
# Observing the relation between the numeric Columns

plt.figure(figsize=(12,8))
sns.heatmap(df[nums].corr(),annot=True)
plt.show()
```




## Feature Engineering of Numeric Columns

In [18]:
```python
def remove_outliers(col):
    q1 = df[col].quantile(0.25)
    q3 = df[col].quantile(0.75)
    iqr = q3 - q1

    upper_limit = q3 + 1.5*iqr
    count_outliers = df[df[col] > upper_limit].shape[0]

    print(f'{count_outliers} outliers out of {df.shape[0]}. i.e; {count_outliers/df.shape[0]*1

    return df[df[col] < upper_limit]
```

In [19]:
```python
df = remove_outliers('Item_Visibility')
```

```
144 outliers out of 8523. i.e; 1.69% of outliers.
```

In [20]:
```
df = remove_outliers('Item_Outlet_Sales')
```

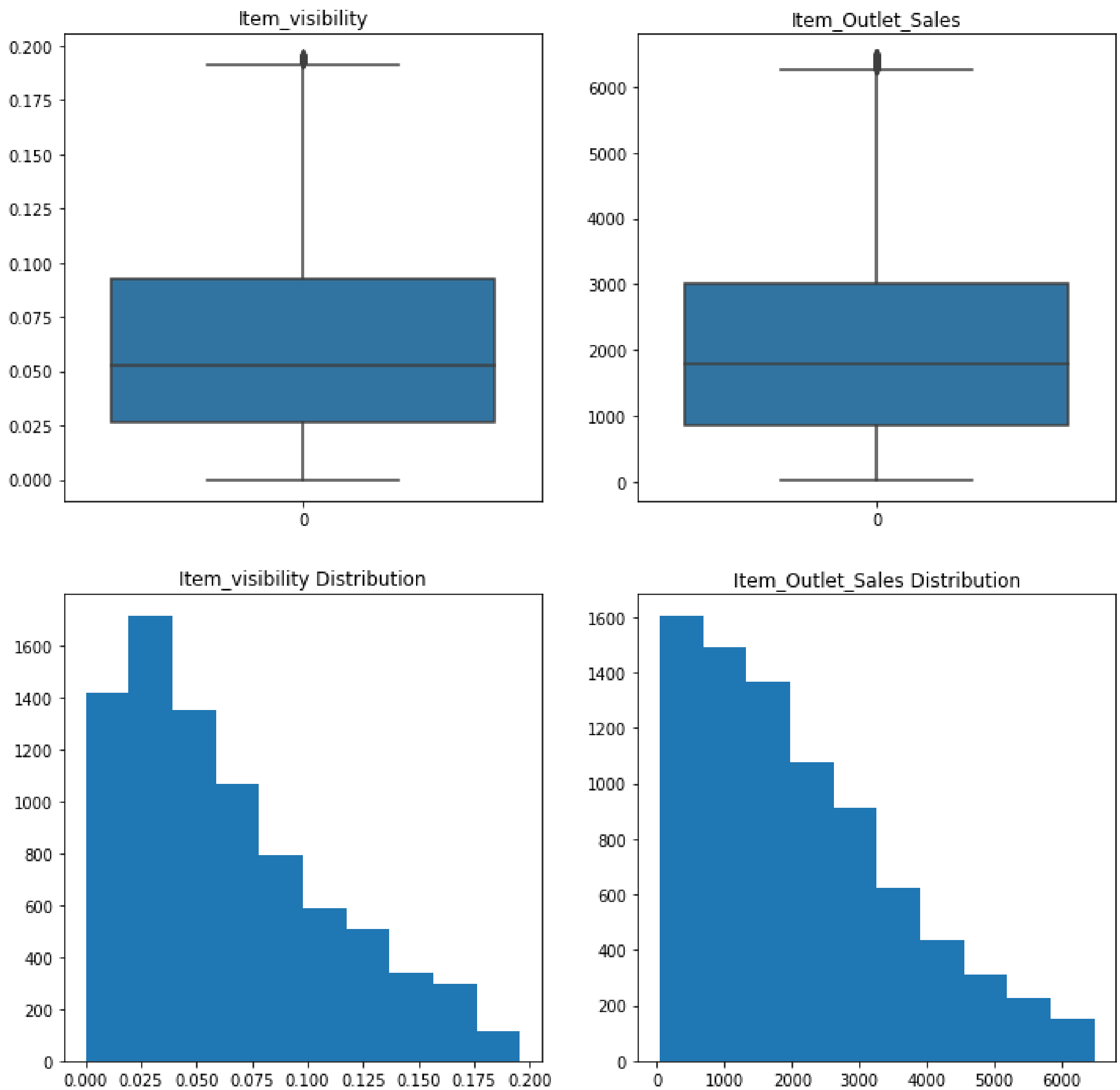
```
186 outliers out of 8379. i.e; 2.22% of outliers.
```

In [21]:
```
df.head()
```

Out[21]:

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

In [22]:
```
fig, ax = plt.subplots(2,2,figsize=(12,12))

sns.boxplot(df.Item_Visibility,ax=ax[0,0])
ax[0,0].set_title('Item_visibility')

sns.boxplot(df.Item_Outlet_Sales,ax=ax[0,1])
ax[0,1].set_title('Item_Outlet_Sales')

ax[1,0].hist(df.Item_Visibility)
ax[1,0].set_title('Item_visibility Distribution')

ax[1,1].hist(df.Item_Outlet_Sales)
ax[1,1].set_title('Item_Outlet_Sales Distribution')
plt.show()
```

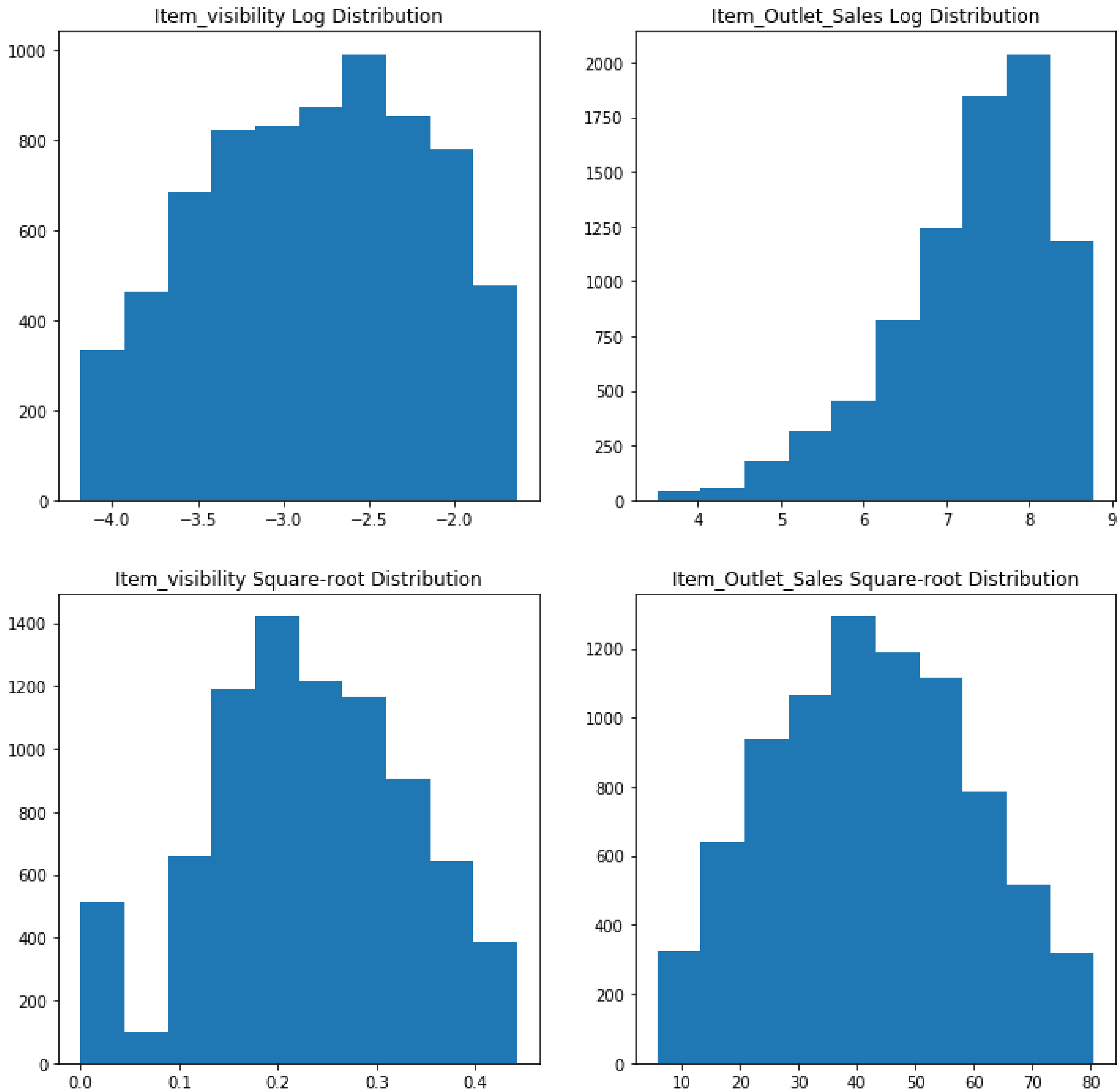


In [23]:
```
log_item = np.log(df.Item_Visibility)
```

In [24]:
```
# AFter log, it is having negative values, hence to check the distribution, removing outliers.
q1 = log_item.quantile(0.25)
q3 = log_item.quantile(0.75)
iqr = q3-q1

ll = iqr + 1.5*q1
```

In [25]:

```
fig, ax1 = plt.subplots(2,2,figsize=(12,12))

ax1[0,0].hist(log_item[log_item>ll])
ax1[0,0].set_title('Item_visibility Log Distribution')

ax1[0,1].hist(np.log(df.Item_Outlet_Sales))
ax1[0,1].set_title('Item_Outlet_Sales Log Distribution')

ax1[1,0].hist(np.sqrt(df.Item_Visibility))
ax1[1,0].set_title('Item_visibility Square-root Distribution')

ax1[1,1].hist(np.sqrt(df.Item_Outlet_Sales))
ax1[1,1].set_title('Item_Outlet_Sales Square-root Distribution')

plt.show()
```

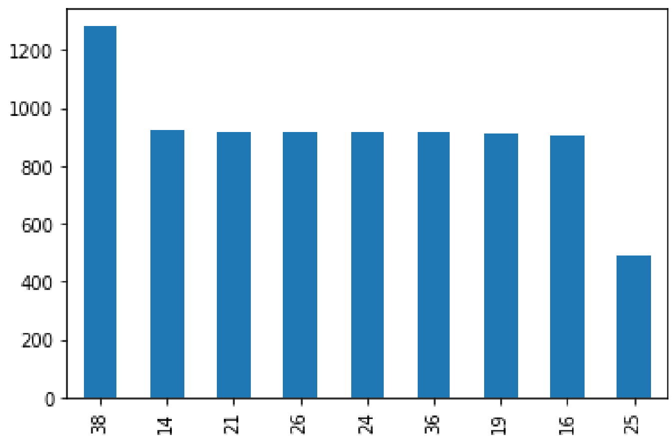


- Compartively, we can say that applying square root have made them normally distributed. And hence, we can transform them with square root.

In [26]:
```
df.Item_Visibility = np.sqrt(df.Item_Visibility)
df.Item_Outlet_Sales = np.sqrt(df.Item_Outlet_Sales)
```

In [27]:
```
# Outlet establishment year will be much useful, if we can convert that to the no of years sin
df['nof_years']=2023-df.Outlet_Establishment_Year
```

In [28]:
```
df.nof_years.value_counts().plot(kind='bar')
plt.show()
```




In [29]:
```
df.drop('Outlet_Establishment_Year',axis=1,inplace=True)
```

In [30]:
```
df.head()
```

Out[30]:

| | Item_Identifier | Item_Weight | Item_Fat_Content | Item_Visibility | Item_Type | Item_MRP | Outlet_Identifier | Outlet_Size |
|---|---|---|---|---|---|---|---|---|
| **0** | FDA15 | 9.30 | Low Fat | 0.126678 | Dairy | 249.8092 | OUT049 | Medium |
| **1** | DRC01 | 5.92 | Regular | 0.138846 | Soft Drinks | 48.2692 | OUT018 | Medium |
| **2** | FDN15 | 17.50 | Low Fat | 0.129461 | Meat | 141.6180 | OUT049 | Medium |
| **3** | FDX07 | 19.20 | Regular | 0.000000 | Fruits and Vegetables | 182.0950 | OUT010 | Medium |
| **4** | NCD19 | 8.93 | Low Fat | 0.000000 | Household | 53.8614 | OUT013 | High |

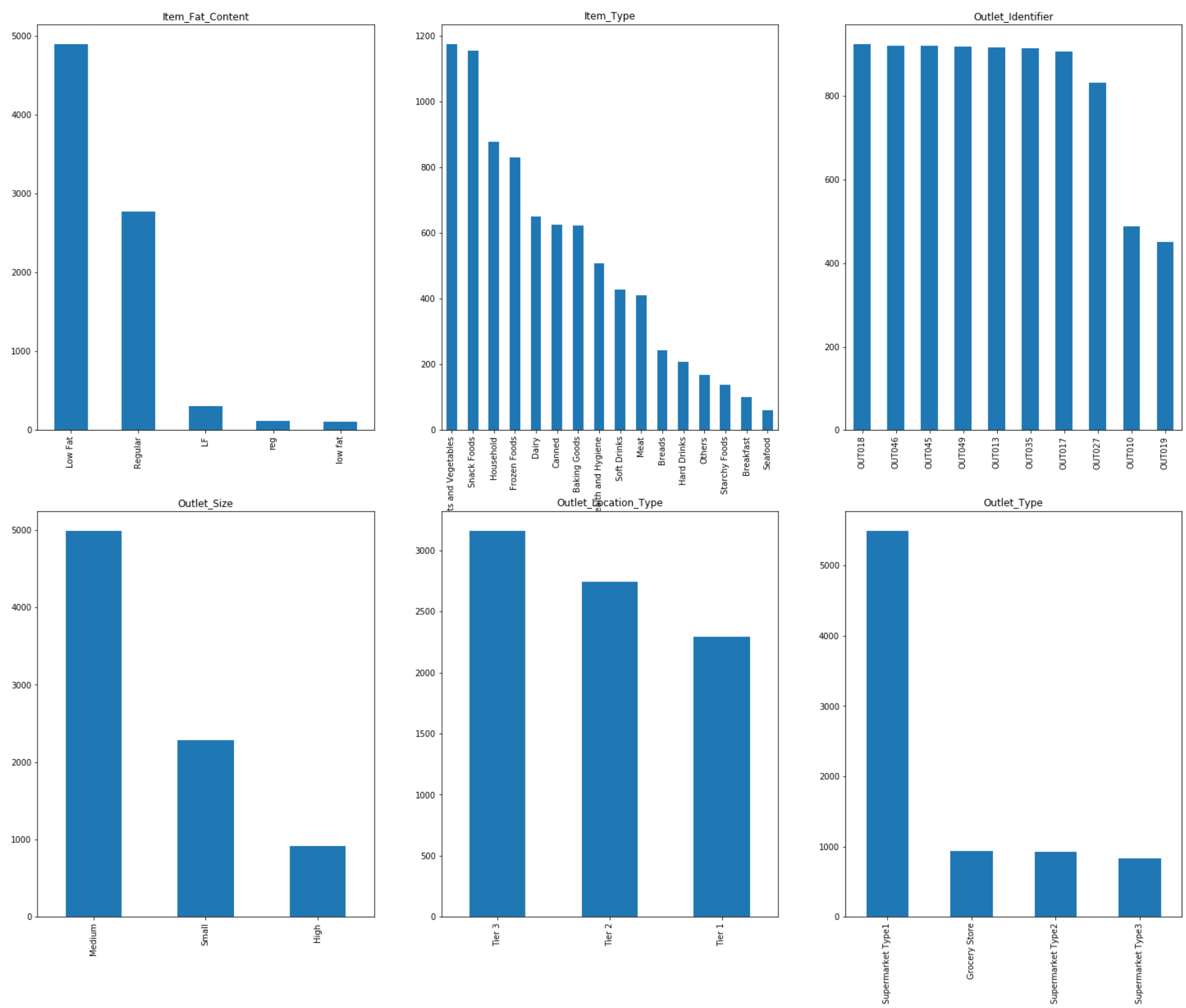
## Data Visualization of Categorical Columns

In [31]:
```
cat_cols = df.select_dtypes(include='object').columns.to_numpy()
```

In [32]:
```
cat_cols
```

Out[32]:
```
array(['Item_Identifier', 'Item_Fat_Content', 'Item_Type',
       'Outlet_Identifier', 'Outlet_Size', 'Outlet_Location_Type',
       'Outlet_Type'], dtype=object)
```

In [33]:
```
fig, ax = plt.subplots(2,3,figsize=(25,20))
a,b=0,0
for i,col in enumerate(cat_cols[1:]):
    if a!=1:
        df[col].value_counts().plot(kind='bar',ax=ax[a,b])
        ax[a,b].set_title(col)
        if b==2: a,b=1,0
        else: b+=1
    else:
        df[col].value_counts().plot(kind='bar',ax=ax[a,b])
        ax[a,b].set_title(col)
        b+=1
```




- So it seems, Low fat is recorded in 3 different names, and regular is recorded in two diff names.
- Outlet_Size, Item_Fat_Content, Outlet_Type, Outlet_Location_Type seems to be ordinal, and hence they can be label encoded.

- Item_Type, Outlet_Identifier can be one hot encoded.

## Feature Engineering Categorical Columns

In [34]:
```
df.select_dtypes(include='object').head()
```

Out[34]:

| | Item_Identifier | Item_Fat_Content | Item_Type | Outlet_Identifier | Outlet_Size | Outlet_Location_Type | Outlet_Type |
|---|---|---|---|---|---|---|---|
| **0** | FDA15 | Low Fat | Dairy | OUT049 | Medium | Tier 1 | Supermarket Type1 |
| **1** | DRC01 | Regular | Soft Drinks | OUT018 | Medium | Tier 3 | Supermarket Type2 |
| **2** | FDN15 | Low Fat | Meat | OUT049 | Medium | Tier 1 | Supermarket Type1 |
| **3** | FDX07 | Regular | Fruits and Vegetables | OUT010 | Medium | Tier 3 | Grocery Store |
| **4** | NCD19 | Low Fat | Household | OUT013 | High | Tier 3 | Supermarket Type1 |

- If we see the item identifier, the first characters of it are basically the categories, so we can categorize them in that way.

In [35]:
```
df['Item_Categories'] = df['Item_Identifier'].str[0:2]
df.drop('Item_Identifier',axis=1,inplace=True)
```

In [36]:
```
df.Item_Fat_Content.unique()
```

Out[36]:
```
array(['Low Fat', 'Regular', 'low fat', 'LF', 'reg'], dtype=object)
```

- Indeed they seem to repeated due to human error.

In [37]:
```
df['Item_Fat_Content'].replace(['low fat','LF'],'Low Fat',inplace=True)
df['Item_Fat_Content'].replace('reg','Regular',inplace=True)
```

In [38]:
```
df.Item_Fat_Content.value_counts(dropna=False)
```

Out[38]:
```
Low Fat     5309
Regular     2884
Name: Item_Fat_Content, dtype: int64
```

In [39]:
```
# Label Encoding outlet size column
df.Item_Fat_Content = df.Item_Fat_Content.map({'Regular': 0,'Low Fat': 1}).astype(int)
```

In [40]:
```
df.select_dtypes(include='object')['Item_Type'].unique()
```

Out[40]:
```
array(['Dairy', 'Soft Drinks', 'Meat', 'Fruits and Vegetables',
       'Household', 'Baking Goods', 'Snack Foods', 'Frozen Foods',
       'Breakfast', 'Health and Hygiene', 'Hard Drinks', 'Canned',
       'Breads', 'Starchy Foods', 'Others', 'Seafood'], dtype=object)
```

In [41]:
```
# Label Encoding outlet size column
df.Outlet_Size = df.Outlet_Size.map({'Small': 1,'Medium': 2,'High': 3}).astype(int)
```

In [42]:
```
df.head()
```

Out[42]:

| | Item_Weight | Item_Fat_Content | Item_Visibility | Item_Type | Item_MRP | Outlet_Identifier | Outlet_Size | Outlet_Locatio |
|---|---|---|---|---|---|---|---|---|
| **0** | 9.30 | 1 | 0.126678 | Dairy | 249.8092 | OUT049 | 2 | |
| **1** | 5.92 | 0 | 0.138846 | Soft Drinks | 48.2692 | OUT018 | 2 | |
| **2** | 17.50 | 1 | 0.129461 | Meat | 141.6180 | OUT049 | 2 | |
| **3** | 19.20 | 0 | 0.000000 | Fruits and Vegetables | 182.0950 | OUT010 | 2 | |
| **4** | 8.93 | 1 | 0.000000 | Household | 53.8614 | OUT013 | 3 | |

In [43]:
```
df.select_dtypes(include='object')
```

Out[43]:

| | Item_Type | Outlet_Identifier | Outlet_Location_Type | Outlet_Type | Item_Categories |
|---|---|---|---|---|---|
| **0** | Dairy | OUT049 | Tier 1 | Supermarket Type1 | FD |
| **1** | Soft Drinks | OUT018 | Tier 3 | Supermarket Type2 | DR |
| **2** | Meat | OUT049 | Tier 1 | Supermarket Type1 | FD |
| **3** | Fruits and Vegetables | OUT010 | Tier 3 | Grocery Store | FD |
| **4** | Household | OUT013 | Tier 3 | Supermarket Type1 | NC |
| **...** | ... | ... | ... | ... | ... |
| **8518** | Snack Foods | OUT013 | Tier 3 | Supermarket Type1 | FD |
| **8519** | Baking Goods | OUT045 | Tier 2 | Supermarket Type1 | FD |
| **8520** | Health and Hygiene | OUT035 | Tier 2 | Supermarket Type1 | NC |
| **8521** | Snack Foods | OUT018 | Tier 3 | Supermarket Type2 | FD |
| **8522** | Soft Drinks | OUT046 | Tier 1 | Supermarket Type1 | DR |

8193 rows × 5 columns

In [44]:
```
# Label Encoding Outlet Location type and outlet type
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df['Outlet_Type'] = encoder.fit_transform(df['Outlet_Type'])
df['Outlet_Location_Type'] = encoder.fit_transform(df['Outlet_Location_Type'])
```

In [45]:
```
df.head()
```

Out[45]:

| | Item_Weight | Item_Fat_Content | Item_Visibility | Item_Type | Item_MRP | Outlet_Identifier | Outlet_Size | Outlet_Locatio |
|---|---|---|---|---|---|---|---|---|
| **0** | 9.30 | 1 | 0.126678 | Dairy | 249.8092 | OUT049 | 2 | |
| **1** | 5.92 | 0 | 0.138846 | Soft Drinks | 48.2692 | OUT018 | 2 | |
| **2** | 17.50 | 1 | 0.129461 | Meat | 141.6180 | OUT049 | 2 | |
| **3** | 19.20 | 0 | 0.000000 | Fruits and Vegetables | 182.0950 | OUT010 | 2 | |
| **4** | 8.93 | 1 | 0.000000 | Household | 53.8614 | OUT013 | 3 | |

In [46]:
```
df.select_dtypes(include='object')
```

Out[46]:

| | Item_Type | Outlet_Identifier | Item_Categories |
|---|---|---|---|
| **0** | Dairy | OUT049 | FD |
| **1** | Soft Drinks | OUT018 | DR |
| **2** | Meat | OUT049 | FD |
| **3** | Fruits and Vegetables | OUT010 | FD |
| **4** | Household | OUT013 | NC |
| **...** | ... | ... | ... |
| **8518** | Snack Foods | OUT013 | FD |
| **8519** | Baking Goods | OUT045 | FD |
| **8520** | Health and Hygiene | OUT035 | NC |
| **8521** | Snack Foods | OUT018 | FD |
| **8522** | Soft Drinks | OUT046 | DR |

8193 rows × 3 columns

- Now we have to deal with other cat columns as Item_Type,Outlet_Identifier,Item_categories

In [47]:
```
# onehot encoding for the rest

df = pd.get_dummies(df, columns=['Item_Type', 'Item_Categories', 'Outlet_Identifier'])
```

In [48]:
```
df.head()
```

Out[48]:

| | Item_Weight | Item_Fat_Content | Item_Visibility | Item_MRP | Outlet_Size | Outlet_Location_Type | Outlet_Type | Item_O |
|---|---|---|---|---|---|---|---|---|
| **0** | 9.30 | 1 | 0.126678 | 249.8092 | 2 | 0 | 1 | |
| **1** | 5.92 | 0 | 0.138846 | 48.2692 | 2 | 2 | 2 | |
| **2** | 17.50 | 1 | 0.129461 | 141.6180 | 2 | 0 | 1 | |
| **3** | 19.20 | 0 | 0.000000 | 182.0950 | 2 | 2 | 0 | |
| **4** | 8.93 | 1 | 0.000000 | 53.8614 | 3 | 2 | 1 | |

5 rows × 38 columns

In [49]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8193 entries, 0 to 8522
Data columns (total 38 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Item_Weight                      8193 non-null   float64
 1   Item_Fat_Content                 8193 non-null   int32  
 2   Item_Visibility                  8193 non-null   float64
 3   Item_MRP                         8193 non-null   float64
 4   Outlet_Size                      8193 non-null   int32  
 5   Outlet_Location_Type             8193 non-null   int32  
 6   Outlet_Type                      8193 non-null   int32  
 7   Item_Outlet_Sales                8193 non-null   float64
 8   nof_years                        8193 non-null   int64  
 9   Item_Type_Baking Goods           8193 non-null   uint8  
 10  Item_Type_Breads                 8193 non-null   uint8  
 11  Item_Type_Breakfast              8193 non-null   uint8  
 12  Item_Type_Canned                 8193 non-null   uint8  
 13  Item_Type_Dairy                  8193 non-null   uint8  
 14  Item_Type_Frozen Foods           8193 non-null   uint8  
 15  Item_Type_Fruits and Vegetables  8193 non-null   uint8  
 16  Item_Type_Hard Drinks            8193 non-null   uint8  
 17  Item_Type_Health and Hygiene     8193 non-null   uint8  
 18  Item_Type_Household              8193 non-null   uint8  
 19  Item_Type_Meat                   8193 non-null   uint8  
 20  Item_Type_Others                 8193 non-null   uint8  
 21  Item_Type_Seafood                8193 non-null   uint8  
 22  Item_Type_Snack Foods            8193 non-null   uint8  
 23  Item_Type_Soft Drinks            8193 non-null   uint8  
 24  Item_Type_Starchy Foods          8193 non-null   uint8  
 25  Item_Categories_DR               8193 non-null   uint8  
 26  Item_Categories_FD               8193 non-null   uint8  
 27  Item_Categories_NC               8193 non-null   uint8  
 28  Outlet_Identifier_OUT010         8193 non-null   uint8  
 29  Outlet_Identifier_OUT013         8193 non-null   uint8  
 30  Outlet_Identifier_OUT017         8193 non-null   uint8  
 31  Outlet_Identifier_OUT018         8193 non-null   uint8  
 32  Outlet_Identifier_OUT019         8193 non-null   uint8  
 33  Outlet_Identifier_OUT027         8193 non-null   uint8  
 34  Outlet_Identifier_OUT035         8193 non-null   uint8  
 35  Outlet_Identifier_OUT045         8193 non-null   uint8  
 36  Outlet_Identifier_OUT046         8193 non-null   uint8  
 37  Outlet_Identifier_OUT049         8193 non-null   uint8  
dtypes: float64(4), int32(4), int64(1), uint8(29)
memory usage: 1.0 MB
```

## Model Building

In [50]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

In [51]:
```
X = df.drop('Item_Outlet_Sales', axis=1)
y = df['Item_Outlet_Sales']
```

In [52]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y)
```

In [53]:
```
def scores(model):
    train_pred = model.predict(X_train)
    print(f'Score on Training dataset = {r2_score(y_train,train_pred)}')
    test_pred = model.predict(X_test)
    print(f'Score on Training dataset = {r2_score(y_test,test_pred)}')
```

## Simple Linear Regression

In [54]:
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
scores(lin_reg)
```

```
Score on Training dataset = 0.6383938275642018
Score on Training dataset = 0.6214603498517137
```

## Applying Regularization Techniques

The key difference is in how they assign penalties to the coefficients:

**Ridge Regression:**

```
1. Performs L2 regularization, i.e., adds penalty equivalent to the square of the mag
nitude of coefficients
2. Minimization objective = LS Obj + α * (sum of square of coefficients)
```

**Lasso Regression:**

```
1. Performs L1 regularization, i.e., adds penalty equivalent to the absolute value of
the magnitude of coefficients
2. Minimization objective = LS Obj + α * (sum of the absolute value of coefficients)
```

- Here, LS Obj refers to the ‘least squares objective,’ i.e., the linear regression objective without regularization.

In [55]:
```
from sklearn.linear_model import Ridge

ridge = Ridge()
ridge.fit(X_train,y_train)
scores(ridge)
```

```
Score on Training dataset = 0.6383934083247518
Score on Training dataset = 0.6214350758753172
```

In [56]:
```
from sklearn.linear_model import Lasso

lasso = Lasso()
lasso.fit(X_train,y_train)
scores(lasso)
```

```
Score on Training dataset = 0.4981745084448651
Score on Training dataset = 0.46019129104610856
```

## Bossting Regressors

In [57]:
```
from sklearn.ensemble import RandomForestRegressor

rfg = RandomForestRegressor()
rfg.fit(X_train,y_train)
scores(rfg)
```

```
Score on Training dataset = 0.9470717118105295
Score on Training dataset = 0.6022049030452542
```

- The Difference between the training score and the test score is huge, which indicatest that it is overfitting the data.
- We can get the better scores for all these algorithms, by find the right suitable paramters through Hyperparameter Tuning.

## Hyperparameter Tuning the Models

### Hyperparameter Tuning Ridge

In [58]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

# Initialize the Ridge model
ridge = Ridge()

# Define the hyperparameters to tune
param_grid = {
    'alpha': [0.1, 1,3,5,7,9,10],
    'fit_intercept': [True]
}

# Perform Grid Search Cross-Validation
grid_search = GridSearchCV(ridge, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best parameters and the corresponding score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)
```

```
Best parameters:  {'alpha': 10, 'fit_intercept': True}
Best score:  0.6351441341336047
```

In [59]:
```
ridge_best = Ridge(alpha=10)
ridge_best.fit(X_train,y_train)
scores(ridge_best)
```

```
Score on Training dataset = 0.6383536983989735
Score on Training dataset = 0.6211808846712839
```

### Hyperparameter Tuning Lasso

In [60]:
```
# Create a Lasso regressor
lasso = Lasso()

# Define the hyperparameter grid
param_grid = {
    'alpha': [0.1, 1.0, 10.0, 100.0],
    'fit_intercept': [True, False],
    'normalize': [True, False],
    'max_iter': [1000, 2000, 3000]
}

# Perform Grid Search with cross-validation
grid_search = GridSearchCV(estimator=lasso, param_grid=param_grid, cv=5, verbose=2, n_jobs=-1

# Fit the model
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print("Best parameters:", best_params)
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
Best parameters: {'alpha': 0.1, 'fit_intercept': True, 'max_iter': 1000, 'normalize': False}
```

In [61]:
```
# Use the best parameters to create a new Lasso model
best_lasso = Lasso(**best_params)
best_lasso.fit(X_train,y_train)
scores(best_lasso)
```

```
Score on Training dataset = 0.6346292560442294
Score on Training dataset = 0.6184364337716537
```

## Hyperparameter Tuning Randomforest Regressor

In [62]:
```
# Create a RandomForestRegressor
rf = RandomForestRegressor()

# Define the hyperparameter grid with fewer parameters
param_grid = {
    'n_estimators': [100, 300, 500],
    'max_depth': [5, 10],
    'min_samples_split': [2, 5, 10],
}

# Perform Randomized Search with cross-validation
random_search = RandomizedSearchCV(estimator=rf, param_distributions=param_grid, n_iter=100, 

# Fit the model
random_search.fit(X_train, y_train)

# Get the best parameters
best_params = random_search.best_params_

# Use the best parameters to create a new RandomForestRegressor model
best_rf = RandomForestRegressor(**best_params)

# Fit the model with the best parameters
best_rf.fit(X_train, y_train)

scores(best_rf)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
Score on Training dataset = 0.6660287032459365
Score on Training dataset = 0.6426640021495466
```

In [63]:
```
best_params
```

Out[63]:
```
{'n_estimators': 500, 'min_samples_split': 2, 'max_depth': 5}
```

- Of All these, we can random forest gave the best score after hyperparameter tuning. So we take the random forest to be as best model Regressor to be as best model.

## Saving the model

In [64]:
```

import joblib

# Save the trained model
joblib.dump(best_rf, 'random_forest_regressor.pkl')
```

Out[64]:
```
['random_forest_regressor.pkl']
```