Problem Statement:

The data scientists at BigMart have collected 2013 sales data for 1559 products across 10 stores in different cities. Also, certain attributes of each product and store have been defined. The aim is to build a predictive model and find out the sales of each product at a particular store. Using this model, BigMart will try to understand the properties of products and stores which play a key role in increasing the sales of their products.

Importing Required Library

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import PowerTransformer
import statsmodels.formula.api as smf
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
import xgboost as xgb
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading Data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\Data Analysis With Python\ML File
df.head()
```

Out[2]:

n_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	Ou
Dairy	249.8092	OUT049	1999	Medium	Tier 1	Su
t Drinks	48.2692	OUT018	2009	Medium	Tier 3	Su
Meat	141.6180	OUT049	1999	Medium	Tier 1	Su
uits and jetables	182.0950	OUT010	1998	NaN	Tier 3	
usehold	53.8614	OUT013	1987	High	Tier 3	Su

Check no of row and column

In [3]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (8523, 12)
```

Checking for Null values

In [4]:
```
print('----------------------\n')
print(df.isnull().sum())
print('\n----------------------')
```

```
----------------------

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

----------------------
```

There is Item weight and Outlet size has Nan value

Removing Nan Value

In [5]:
```
df['Item_Weight'] = df['Item_Weight'].fillna(df['Item_Weight'].mean())
df['Outlet_Size'] = df['Outlet_Size'].fillna(df['Outlet_Size'].mode()[0])
```

We remove all nan on those features

Checking for Null values remove or not

In [6]:
```
print('----------------------\n')
print(df.isnull().sum())
print('\n----------------------')
```

```
----------------------

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

----------------------
```

In [7]:
```
print('No of Rows and Columns Left After Removing NaN ----->', df.shape )
```

```
No of Rows and Columns Left After Removing NaN -----> (8523, 12)
```

Information about dataset

In [8]:
```python
print('----------------------------------------------------\n')
print(df.info())
print('\n----------------------------------------------------')
```

```
----------------------------------------------------

<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
None

----------------------------------------------------
```

Some features are in float and some are in object

Droping Unwanted Column

In [9]:
```python
col = ['Item_Identifier','Outlet_Identifier']
```

In [10]:
```
df = df.drop(columns = col, axis = 1)
df.head()
```

Out[10]:

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Establishment_Year
0	9.30	Low Fat	0.016047	Dairy	249.8092	1999
1	5.92	Regular	0.019278	Soft Drinks	48.2692	2009
2	17.50	Low Fat	0.016760	Meat	141.6180	1999
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	1998
4	8.93	Low Fat	0.000000	Household	53.8614	1987

In [11]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (8523, 10)
```

Analysis of data

In [12]:
```
df['Item_Fat_Content'].value_counts()
```

Out[12]:
```
Low Fat     5089
Regular     2889
LF           316
reg          117
low fat      112
Name: Item_Fat_Content, dtype: int64
```

In [13]:
```
df['Item_Type'].value_counts()
```

Out[13]:
```
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
```

In [14]:
```python
df['Outlet_Size'].value_counts()
```

Out[14]:
```
Medium    5203
Small     2388
High       932
Name: Outlet_Size, dtype: int64
```

In [15]:
```python
df['Outlet_Location_Type'].value_counts()
```

Out[15]:
```
Tier 3    3350
Tier 2    2785
Tier 1    2388
Name: Outlet_Location_Type, dtype: int64
```

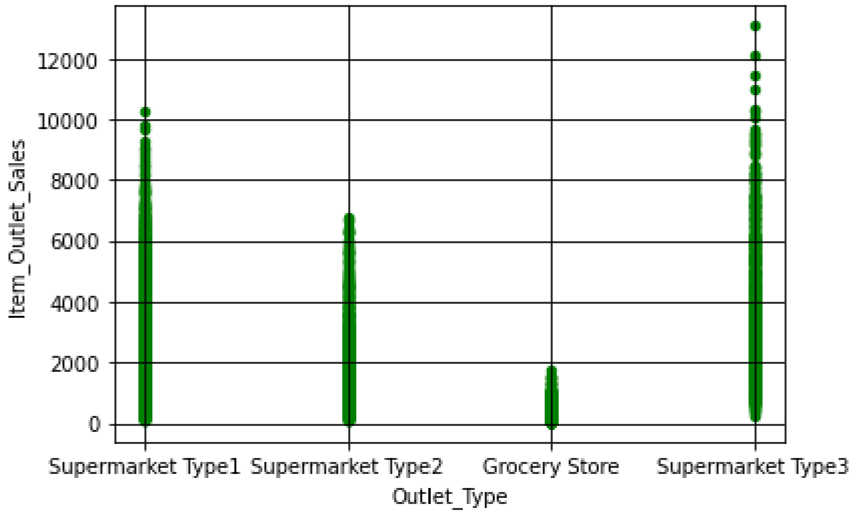
In [16]:
```python
df['Outlet_Type'].value_counts()
```

Out[16]:
```
Supermarket Type1    5577
Grocery Store        1083
Supermarket Type3     935
Supermarket Type2     928
Name: Outlet_Type, dtype: int64
```

In [17]:
```python
df['Outlet_Establishment_Year'].value_counts()
```

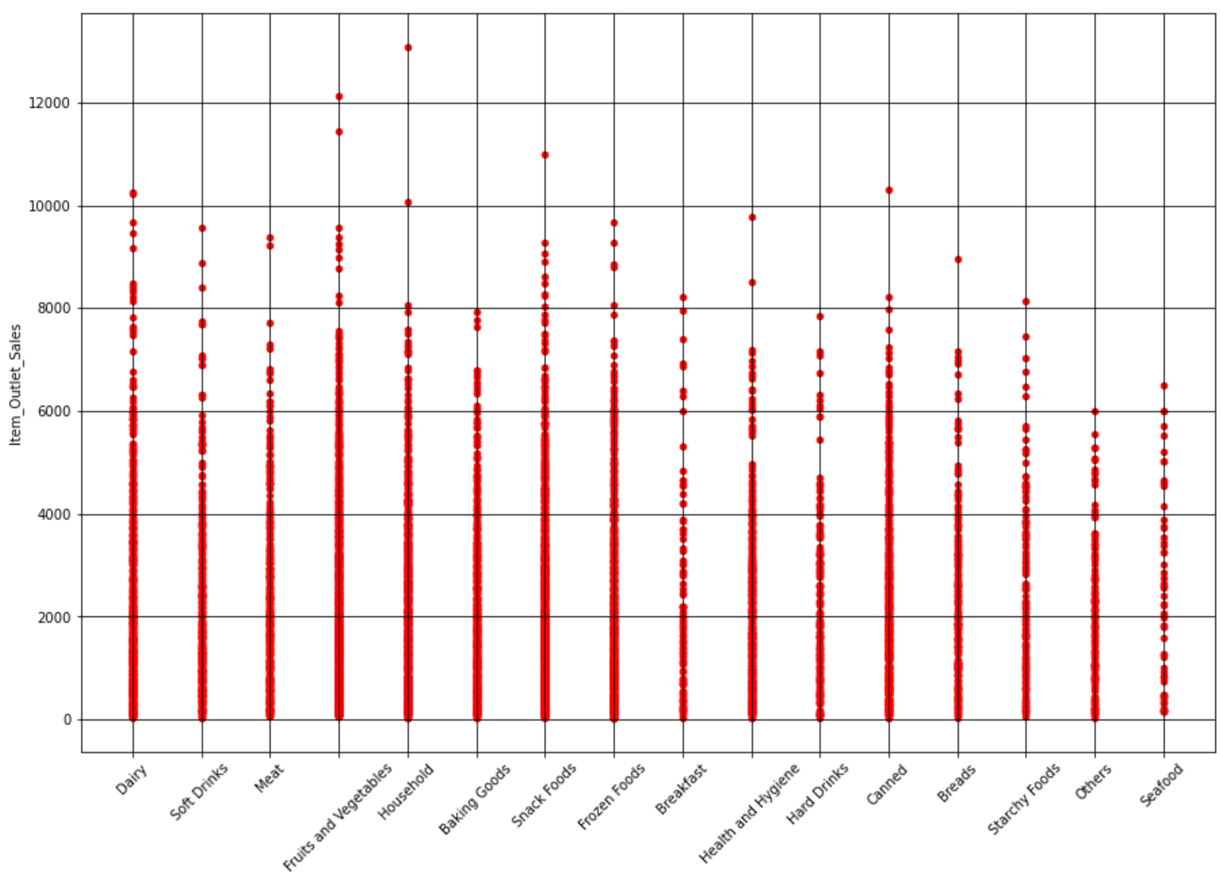
Out[17]:
```
1985    1463
1987     932
2004     930
1997     930
1999     930
2002     929
2009     928
2007     926
1998     555
Name: Outlet_Establishment_Year, dtype: int64
```

```
In [18]: df.plot.scatter('Outlet_Type','Item_Outlet_Sales', c = 'g')
         plt.grid(which = 'major', c = 'black')
         plt.show()
```



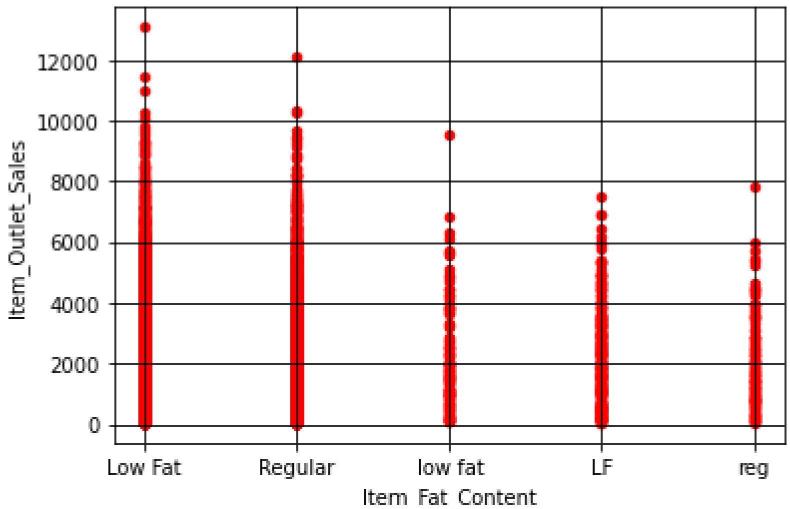
Supermarket Type3 highest sales

```
In [19]: df.plot.scatter('Item_Type','Item_Outlet_Sales', figsize = (15,10), rot = 45, c =
         plt.grid(which = 'major', c = 'black')
         plt.show()
```



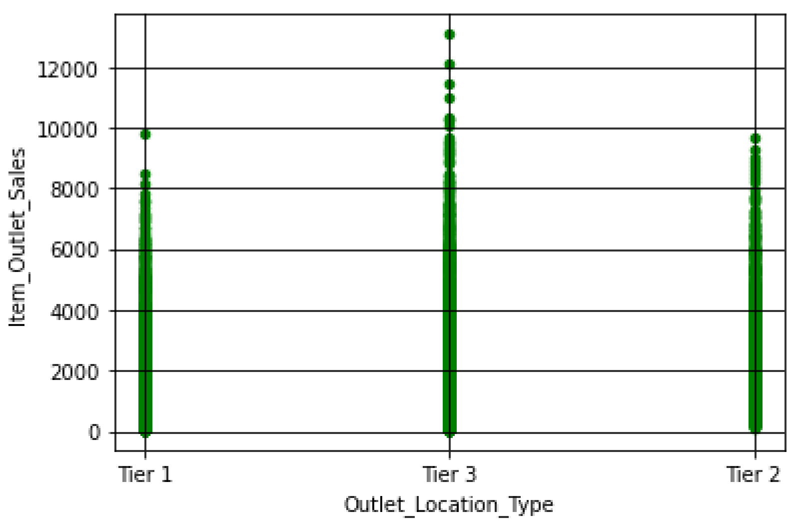
Household products sales higest and other products least sales

In [20]:
```
df.plot.scatter('Item_Fat_Content','Item_Outlet_Sales', c = 'r')
plt.grid(which = 'major', c = 'black')
plt.show()
```



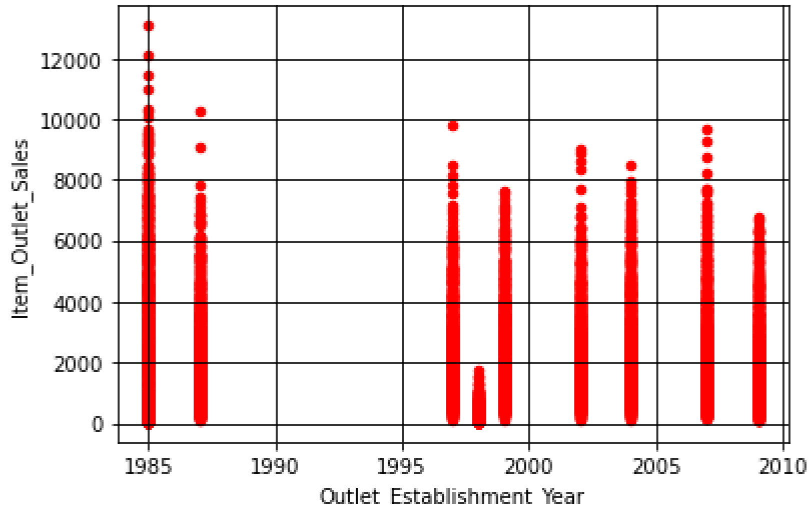
Low fat content sales higest among all and LF is least

In [21]:
```
df.plot.scatter('Outlet_Location_Type','Item_Outlet_Sales', c = 'g')
plt.grid(which = 'major', c = 'black')
plt.show()
```



Tier 3 cites sales highest and Tier 2 sales lowest.

In [22]:
```
df.plot.scatter('Outlet_Establishment_Year','Item_Outlet_Sales', c = 'r')
plt.grid(which = 'major', c = 'black')
plt.show()
```



Older oulets sales higher compare to newly open outlets

In [23]:
```
df.head()
```

Out[23]:

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Establishment_Year
0	9.30	Low Fat	0.016047	Dairy	249.8092	1999
1	5.92	Regular	0.019278	Soft Drinks	48.2692	2009
2	17.50	Low Fat	0.016760	Meat	141.6180	1999
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	1998
4	8.93	Low Fat	0.000000	Household	53.8614	1987

In [24]:
```
df['No_of_years_outlet_open'] = [2021] - df['Outlet_Establishment_Year']
df.head()
```

Out[24]:

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Establishment_Year
0	9.30	Low Fat	0.016047	Dairy	249.8092	1999
1	5.92	Regular	0.019278	Soft Drinks	48.2692	2009
2	17.50	Low Fat	0.016760	Meat	141.6180	1999
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	1998
4	8.93	Low Fat	0.000000	Household	53.8614	1987

Convert Outlet establishment year into No of years outlets open because it esaier to incode

In [25]:
```
print('----------------------------------------------------\n')
print(df.info())
print('\n----------------------------------------------------')
```

```
----------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 11 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Weight                8523 non-null   float64
 1   Item_Fat_Content           8523 non-null   object 
 2   Item_Visibility            8523 non-null   float64
 3   Item_Type                  8523 non-null   object 
 4   Item_MRP                   8523 non-null   float64
 5   Outlet_Establishment_Year  8523 non-null   int64  
 6   Outlet_Size                8523 non-null   object 
 7   Outlet_Location_Type       8523 non-null   object 
 8   Outlet_Type                8523 non-null   object 
 9   Item_Outlet_Sales          8523 non-null   float64
 10  No_of_years_outlet_open    8523 non-null   int64  
dtypes: float64(4), int64(2), object(5)
memory usage: 732.6+ KB
None

----------------------------------------------------
```

In [26]:
```python
df = df.drop('Outlet_Establishment_Year', axis = 1)
df.head()
```

Out[26]:

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Size	Outlet_Locatic
0	9.30	Low Fat	0.016047	Dairy	249.8092	Medium	
1	5.92	Regular	0.019278	Soft Drinks	48.2692	Medium	
2	17.50	Low Fat	0.016760	Meat	141.6180	Medium	
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	Medium	
4	8.93	Low Fat	0.000000	Household	53.8614	High	

Drop Outlet establishment year

Spliting data into features and label

In [27]:
```python
x = df.drop('Item_Outlet_Sales', axis = 1)
y = df['Item_Outlet_Sales']
print('Data has been splited')
```

```
Data has been splited
```

Filter Categorical features

In [28]:
```python
numerics = ['int64', 'float64']
categorical_col = []
features = x.columns.values.tolist()
for col in features:
    if x[col].dtype in numerics:
        continue
    categorical_col.append(col)
```

Encoding categorical columns using get dummies

In [29]:
```
x_dummies = pd.get_dummies(x[categorical_col], drop_first = True)
x_dummies.head()
```

Out[29]:

	Item_Fat_Content_Low Fat	Item_Fat_Content_Regular	Item_Fat_Content_low fat	Item_Fat_Content_reg	I
0	1	0	0	0	
1	0	1	0	0	
2	1	0	0	0	
3	0	1	0	0	
4	1	0	0	0	

5 rows × 26 columns

In [30]:
```
x_dummies.shape
```

Out[30]:
```
(8523, 26)
```

In [31]:
```
x = x.join(x_dummies)
```

In [32]:
```
x.head()
```

Out[32]:

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Size	Outlet_Locatic
0	9.30	Low Fat	0.016047	Dairy	249.8092	Medium	
1	5.92	Regular	0.019278	Soft Drinks	48.2692	Medium	
2	17.50	Low Fat	0.016760	Meat	141.6180	Medium	
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	Medium	
4	8.93	Low Fat	0.000000	Household	53.8614	High	

5 rows × 35 columns

In [33]:
```
x.drop(columns = categorical_col, axis = 1, inplace = True)
```

In [34]:
```
x.head()
```

Out[34]:

	Item_Weight	Item_Visibility	Item_MRP	No_of_years_outlet_open	Item_Fat_Content_Low Fat	Item_Fa
0	9.30	0.016047	249.8092	22	1	
1	5.92	0.019278	48.2692	12	0	
2	17.50	0.016760	141.6180	22	1	
3	19.20	0.000000	182.0950	23	0	
4	8.93	0.000000	53.8614	34	1	

5 rows × 30 columns

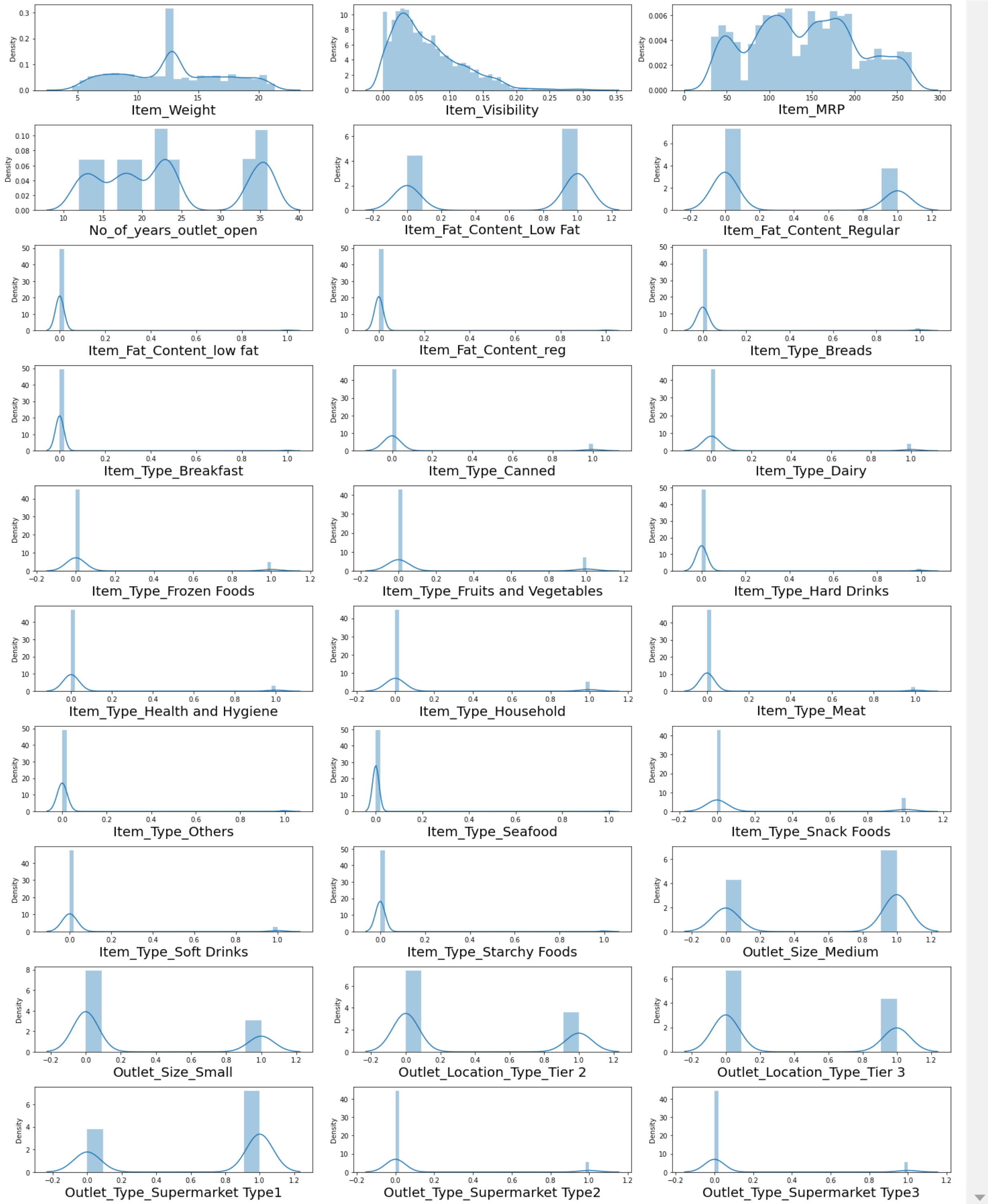
Checking Outliers

In [35]:
```
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in x:
    if plotnumber <=30:
        ax = plt.subplot(10,3, plotnumber)
        sns.distplot(x[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



Some outliers present in columns

Power Transformer to remove outliers

In [36]:
```
scaler = PowerTransformer(method = 'yeo-johnson')
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[36]:
```
array([[-0.82263635, -1.14688621,  1.62367023, ...,  0.72680189,
        -0.34955064, -0.35102831],
       [-1.73380133, -1.03709991, -1.59501643, ..., -1.37589075,
         2.86081583, -0.35102831],
       [ 1.08636176, -1.12237453,  0.08123678, ...,  0.72680189,
        -0.34955064, -0.35102831],
       ...,
       [-0.49655592, -0.54297932, -0.86792986, ...,  0.72680189,
        -0.34955064, -0.35102831],
       [-1.37344321,  1.45998957, -0.54899589, ..., -1.37589075,
         2.86081583, -0.35102831],
       [ 0.49178563, -0.27619496, -1.04722682, ...,  0.72680189,
        -0.34955064, -0.35102831]])
```

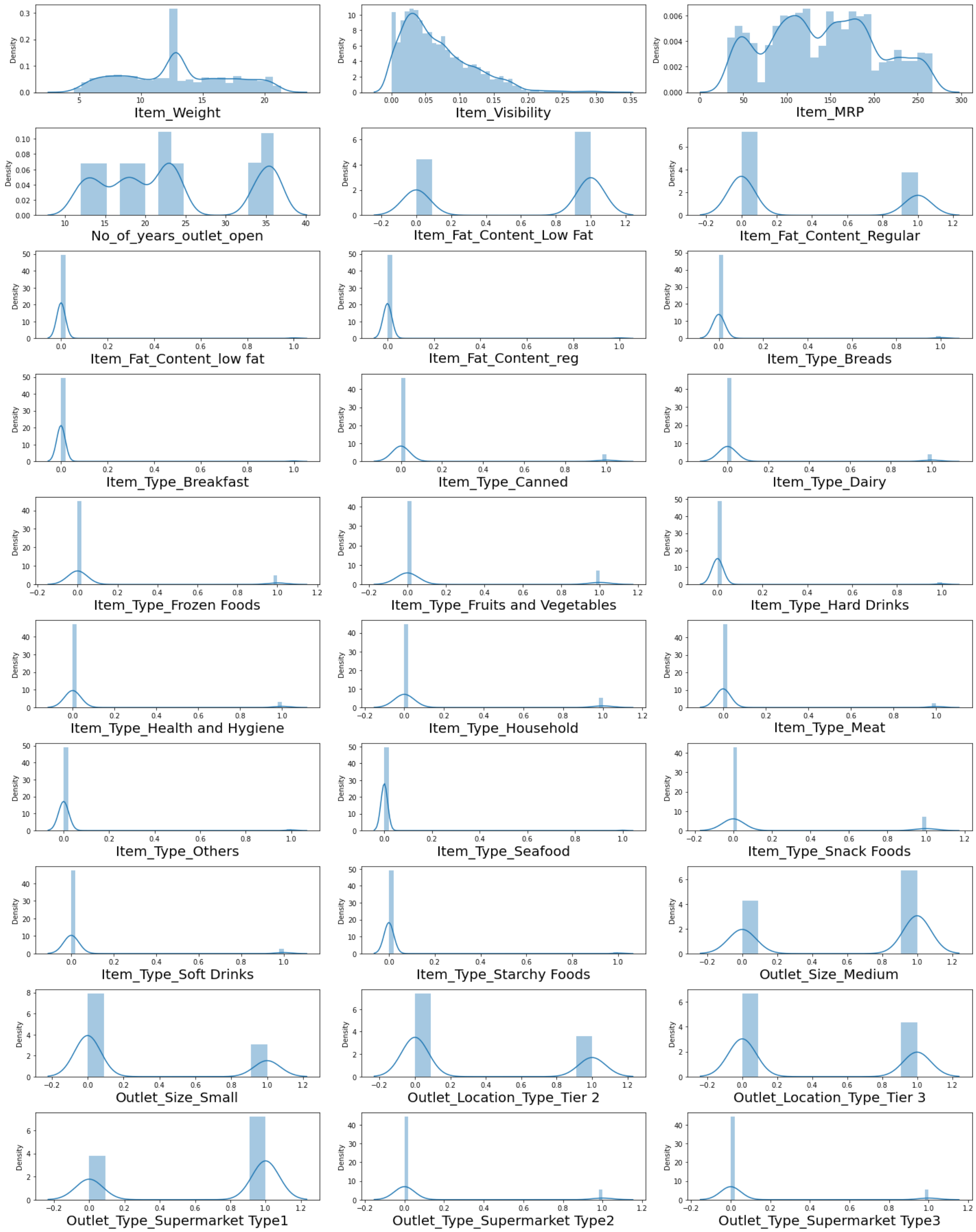
Checking Outlier remove or not

In [37]:
```
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in x:
    if plotnumber <=30:
        ax = plt.subplot(10,3, plotnumber)
        sns.distplot(x[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



Outliers are removed

Split data into train and test. Model will be bulit on training data and tested on test data

In [38]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, rando
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building

Xgboost model instantiaing, training and evaluating

In [39]:
```
xgb = xgb.XGBRegressor()
xgb.fit(x_train, y_train)
y_pred = xgb.predict(x_test)
```

In [40]:
```
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', xgb.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.5294371130690214
=========================================================
RMSE of Model -------> 1163.248310421678
=========================================================
MSE of Model -------> 1353146.631698889
=========================================================
Score of test data ----> 0.5294371130690214
=========================================================
```

Conclusion : XGBoost model has 52% score

Knn model instantiaing, training and evaluating

In [41]:
```
Knn = KNeighborsRegressor()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

```
In [42]: print('=========================================================')
         print('R2 Score ----->', r2_score(y_test, y_pred))
         print('=========================================================')
         print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
         print('=========================================================')
         print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
         print('=========================================================')
         print('Score of test data ---->', Knn.score(x_test, y_test))
         print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.42296758232174914
=========================================================
RMSE of Model -------> 1288.1418819087874
=========================================================
MSE of Model -------> 1659309.5079275125
=========================================================
Score of test data ----> 0.42296758232174914
=========================================================
```

Conclusion : Knn model has 42% score

Decision Tree model instantiaing, training and evaluating

```
In [43]: DT = DecisionTreeRegressor()
         DT.fit(x_train, y_train)
         y_pred = DT.predict(x_test)
```

```
In [44]: print('=========================================================')
         print('R2 Score ----->', r2_score(y_test, y_pred))
         print('=========================================================')
         print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
         print('=========================================================')
         print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
         print('=========================================================')
         print('Score of test data ---->', DT.score(x_test, y_test))
         print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.17620759508520245
=========================================================
RMSE of Model -------> 1539.1200169339468
=========================================================
MSE of Model -------> 2368890.4265267523
=========================================================
Score of test data ----> 0.17620759508520245
=========================================================
```

Conclusion : Decision Tree model has 19% score

Random Forest model instantiaing, training and evaluating

In [45]:
```
Rn = RandomForestRegressor()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [46]:
```
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Rn.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.5658710564717431
=========================================================
RMSE of Model -------> 1117.3081464916793
=========================================================
MSE of Model -------> 1248377.4942166717
=========================================================
Score of test data ----> 0.5658710564717431
=========================================================
```

Conclusion : Random Forest model has 56% score

SVM model instantiaing, training and evaluating

In [47]:
```
svr = SVR()
svr.fit(x_train, y_train)
y_pred = svr.predict(x_test)
```

In [48]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', svr.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.17505733672176238
=========================================================
RMSE of Model -------> 1540.1941759675528
=========================================================
MSE of Model -------> 2372198.0996843693
=========================================================
Score of test data ----> 0.17505733672176238
=========================================================
```

Conclusion : SVM model has 17% score

Linear Regression model instantiaing, training and evaluating

In [49]:
```python
Lr = LinearRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

In [50]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Lr.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.5761275930961476
=========================================================
RMSE of Model -------> 1104.0307445061003
=========================================================
MSE of Model -------> 1218883.884814694
=========================================================
Score of test data ----> 0.5761275930961476
=========================================================
```

Conclusion : Linear Regression model has 57% score

Looking R2 score we found Linear Regression has best model so we do Hyperparameter Tuning on it.

In [51]:
```
param_grid = {'fit_intercept' : [True, False],'normalize' : [True, False],'copy_X
             'positive':[True, False]}
```

In [52]:
```
grid_search = GridSearchCV(estimator = Lr, param_grid = param_grid, cv = 5,n_jobs
```

In [53]:
```
grid_search.fit(x_train, y_train)
```

Out[53]:
```
GridSearchCV(cv=5, estimator=LinearRegression(), n_jobs=-1,
             param_grid={'copy_X': [True, False],
                         'fit_intercept': [True, False],
                         'normalize': [True, False],
                         'positive': [True, False]})
```

In [54]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'copy_X': True, 'fit_intercept': False, 'normalize': True, 'positive': False}
```

In [55]:
```
hlr = LinearRegression(copy_X = True, fit_intercept = False, normalize = True, po
hlr.fit(x_train, y_train)
hlr.score(x_test, y_test)
```

Out[55]:
```
0.5761141582584479
```

In [56]:
```
y_pred = hlr.predict(x_test)
```

In [57]:
```
print('==========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('==========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('==========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('==========================================================')
print('Score of test data ---->', Lr.score(x_test, y_test))
print('==========================================================')
```

```
==========================================================
R2 Score -----> 0.5761141582584479
==========================================================
RMSE of Model -------> 1104.0482407574457
==========================================================
MSE of Model -------> 1218922.5179196107
==========================================================
Score of test data ----> 0.5761275930961476
==========================================================
```

After Hyperparameter Tuning model accuracy score 57%.

Saving The Model

In [58]:

```
# saving the model to the Local file system
filename = 'Big Data Mart Sales Train.pickle'
pickle.dump(hlr, open(filename, 'wb'))
```

Final Conclusion : LinearRegression is our best model.

In [ ]: