Problem Statement: The data scientists at BigMart have collected sales data for 1559 products across 10 stores in different cities for the year 2013. Now each product has certain attributes that sets it apart from other products.

Breakdown of the Problem Statement: Supervised machine learning problem. The target value will be Item_Outlet_Sales. Aim of the NoteBook: The objective is to create a model that can predict the sales per product for each store. Using this model, BigMart will try to understand the properties of products and stores which play a key role in increasing sales

The Big Mart Sales dataset contains information on sales of products in various stores of the Big Mart chain. The dataset contains 12 variables, including both categorical and numerical data. Here's a summary of the variables in the Big Mart Sales dataset

```
import pandas as pd
import numpy as np

filename='/content/Train.csv'
df = pd.read_csv(filename, index_col=0)

df.head()
```

```
                 Item_Weight Item_Fat_Content  Item_Visibility  \
Item_Identifier
FDA15                   9.30          Low Fat         0.016047
DRC01                   5.92          Regular         0.019278
FDN15                  17.50          Low Fat         0.016760
FDX07                  19.20          Regular         0.000000
NCD19                   8.93          Low Fat         0.000000

                             Item_Type  Item_MRP Outlet_Identifier  \
Item_Identifier
FDA15                            Dairy  249.8092            OUT049
DRC01                      Soft Drinks   48.2692            OUT018
FDN15                             Meat  141.6180            OUT049
FDX07            Fruits and Vegetables  182.0950            OUT010
NCD19                        Household   53.8614            OUT013

                 Outlet_Establishment_Year Outlet_Size
Outlet_Location_Type  \
Item_Identifier

FDA15                                 1999      Medium
Tier 1
DRC01                                 2009      Medium
Tier 3
FDN15                                 1999      Medium
Tier 1
FDX07                                 1998         NaN
Tier 3
NCD19                                 1987        High
```

```
Tier 3

                             Outlet_Type  Item_Outlet_Sales
Item_Identifier
FDA15            Supermarket Type1          3735.1380
DRC01            Supermarket Type2           443.4228
FDN15            Supermarket Type1          2097.2700
FDX07                 Grocery Store          732.3800
NCD19            Supermarket Type1           994.7052
```

Lets explore the DataFrame

```
df.shape
```

```
(8523, 11)
```

```
#finding NaN values
df.isnull().sum()
```

```
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
```

so we have some nulls, we should do to deal with them

```
df.describe()
```

```
       Item_Weight  Item_Visibility     Item_MRP
Outlet_Establishment_Year  \
count  7060.000000      8523.000000  8523.000000
8523.000000
mean     12.857645         0.066132   140.992782
1997.831867
std       4.643456         0.051598    62.275067
8.371760
min       4.555000         0.000000    31.290000
1985.000000
25%       8.773750         0.026989    93.826500
1987.000000
50%      12.600000         0.053931   143.012800
1999.000000
```

```
75%      16.850000         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
```

```
df.groupby('Item_Type').Item_Weight.agg([min, max, np.mean])
```

```
                         min    max       mean
Item_Type
Baking Goods           4.880  20.85  12.277108
Breads                 4.635  20.85  11.346936
Breakfast              6.425  21.10  12.768202
Canned                 4.615  21.35  12.305705
Dairy                  4.805  20.70  13.426069
Frozen Foods           4.555  20.85  12.867061
Fruits and Vegetables  5.460  21.35  13.224769
Hard Drinks            4.610  19.70  11.400328
Health and Hygiene     5.175  21.25  13.142314
Household              5.030  21.25  13.384736
Meat                   5.150  21.25  12.817344
Others                 5.500  20.50  13.853285
Seafood                5.365  20.75  12.552843
Snack Foods            5.095  21.25  12.987880
Soft Drinks            4.590  20.75  11.847460
Starchy Foods          6.695  21.20  13.690731
```

```
df.groupby(['Item_Type', 'Item_Fat_Content']).mean()
```

```
<ipython-input-192-c5a2ee088b20>:1: FutureWarning: The default value
of numeric_only in DataFrameGroupBy.mean is deprecated. In a future
version, numeric_only will default to False. Either specify
numeric_only or select only columns which should be valid for the
function.
  df.groupby(['Item_Type', 'Item_Fat_Content']).mean()

                                Item_Weight  Item_Visibility
Item_MRP  \
Item_Type     Item_Fat_Content

Baking Goods  LF                  12.052500         0.068426
115.641430
```

```
              Low Fat              12.633128        0.066465
121.286145
              Regular              11.976126        0.071573
133.311137
              low fat              10.060000        0.048614
104.131575
              reg                  12.825000        0.089004
111.424431
...                                      ...              ...          .
..
Starchy Foods LF                   14.375000        0.067391
156.902489
              Low Fat              13.669692        0.066966
158.575569
              Regular              13.757200        0.069425
133.824861
              low fat              14.150000        0.037877
124.004600
              reg                  12.375833        0.062482
147.256086

                                Outlet_Establishment_Year
Item_Outlet_Sales
Item_Type     Item_Fat_Content

Baking Goods  LF                              1995.500000
1670.791810
              Low Fat                         1997.491694
1781.871029
              Regular                         1998.117647
2192.281401
              low fat                         1995.000000
1345.581800
              reg                             1999.153846
1089.504877
...                                                   ...
...
Starchy Foods LF                              1998.111111
2466.419111
              Low Fat                         1998.986111
2582.980347
              Regular                         1998.694915
2141.867315
              low fat                         1987.000000
1618.559800
              reg                             1995.714286
2177.166000

[70 rows x 5 columns]
```

```
#filling the nan values.
group_means = df.groupby(['Item_Type', 'Item_Fat_Content'])
['Item_Weight'].mean()
df.loc[df['Item_Weight'].isnull(), 'Item_Weight'] =
df.loc[df['Item_Weight'].isnull(), ['Item_Type',
'Item_Fat_Content']].apply(lambda x: group_means[x['Item_Type'],
x['Item_Fat_Content']], axis=1)
```

```
df.isnull().sum()
```

```
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
```

```
(df['Item_Visibility']==0).sum()
```

```
526
```

```
df['Outlet_Size'].value_counts()
```

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

we fill NaN values of Outlet_Size with Mode Imputation

```
df['Outlet_Size'].mode()
```

```
0    Medium
Name: Outlet_Size, dtype: object
```

```
df['Outlet_Size'].fillna(df['Outlet_Size'].mode()[0], inplace=True)
```

```
df['Outlet_Size']
```

```
Item_Identifier
FDA15    Medium
DRC01    Medium
FDN15    Medium
FDX07    Medium
NCD19      High
```

```
          ...
FDF22      High
FDS36    Medium
NCJ29     Small
FDN46    Medium
DRG01     Small
Name: Outlet_Size, Length: 8523, dtype: object
```

```
df['Item_Fat_Content'].value_counts()
```

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

```
#replacing 2 identitical words into one word
df.replace({'LF':'Low Fat', 'reg':'Regular','low fat':'Low Fat'},
inplace=True)
```

```
df['Item_Fat_Content'].value_counts()
```

```
Low Fat    5517
Regular    3006
Name: Item_Fat_Content, dtype: int64
```

```
#use the correlation to find out which column affecting more
df.corrwith(df['Item_Outlet_Sales'])
```

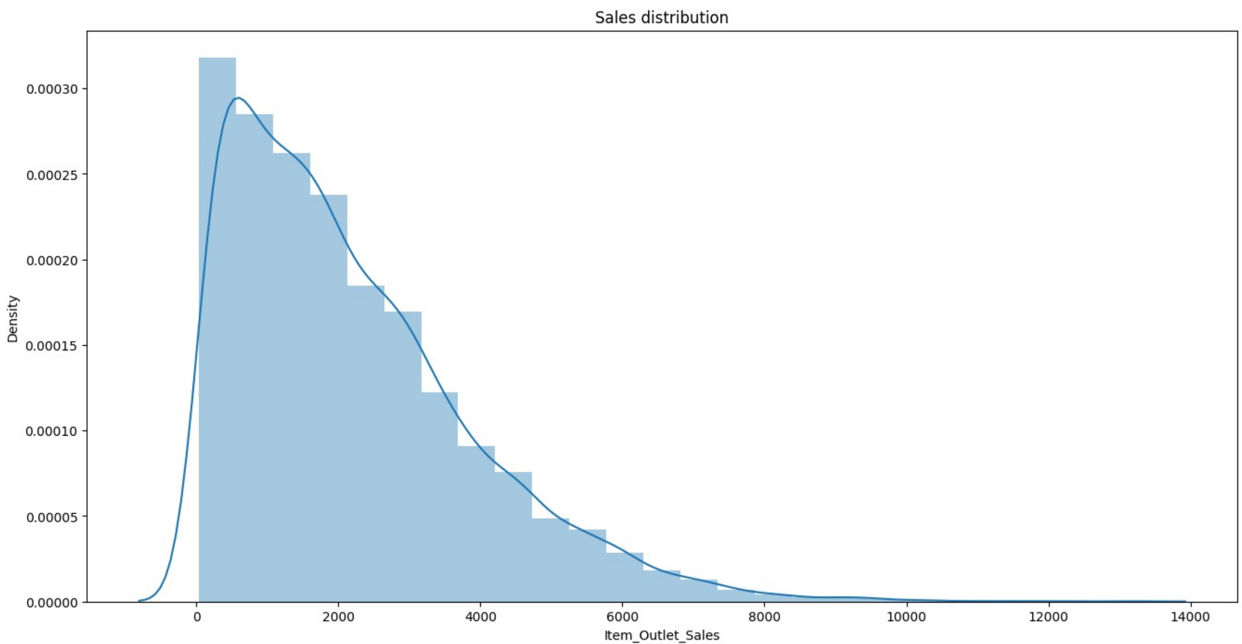
```
<ipython-input-203-84f42a0ed7ac>:2: FutureWarning: The default value
of numeric_only in DataFrame.corrwith is deprecated. In a future
version, it will default to False. Select only valid columns or
specify the value of numeric_only to silence this warning.
  df.corrwith(df['Item_Outlet_Sales'])
```

```
Item_Weight                   0.012432
Item_Visibility              -0.128625
Item_MRP                      0.567574
Outlet_Establishment_Year    -0.049135
Item_Outlet_Sales             1.000000
dtype: float64
```

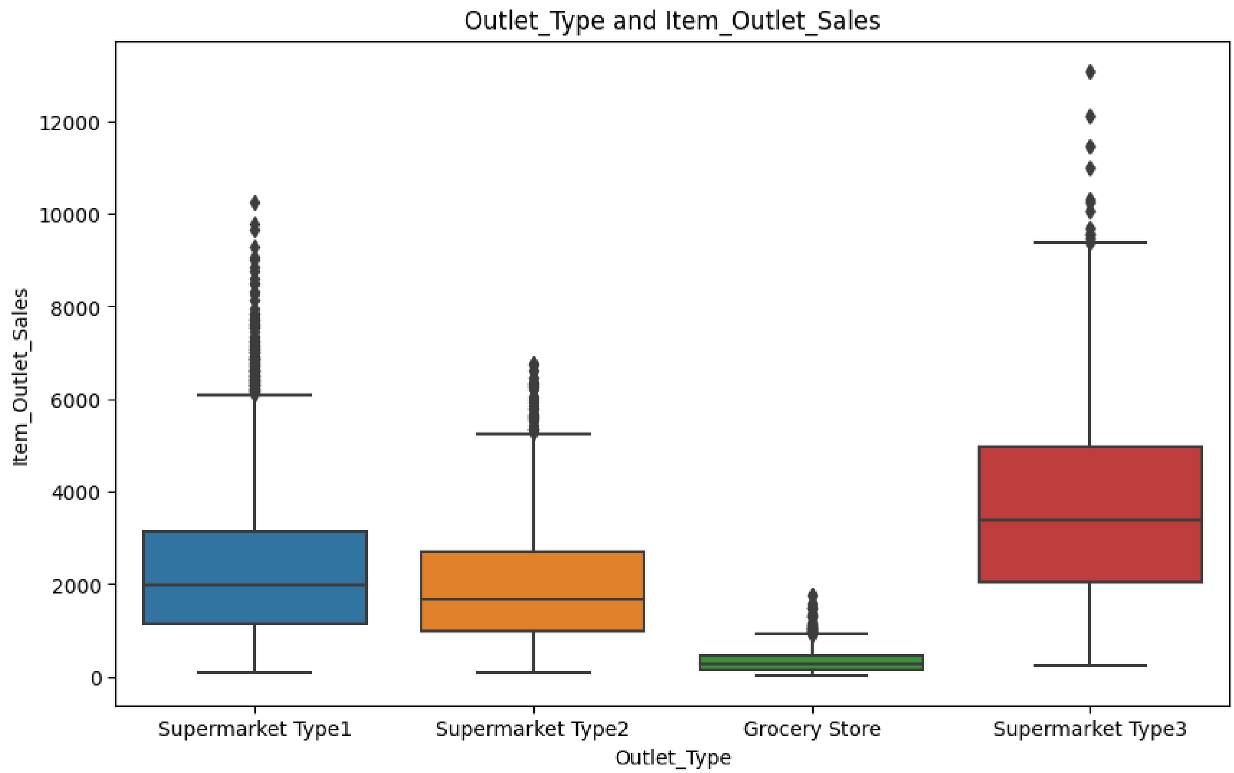
Now, lets draw some graphs to understand dataframe more clear

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(16,8))
sns.distplot(df['Item_Outlet_Sales'], bins=25)
plt.title("Sales distribution")
```

```
<ipython-input-204-187655669e16>:4: 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(df['Item_Outlet_Sales'], bins=25)

Text(0.5, 1.0, 'Sales distribution')
```




```
plt.figure(figsize=(10,6))
sns.boxplot(data=df, x='Outlet_Type', y='Item_Outlet_Sales')
plt.title("Outlet_Type and Item_Outlet_Sales")

Text(0.5, 1.0, 'Outlet_Type and Item_Outlet_Sales')
```



Using Label Encoder

```
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
columns=['Item_Fat_Content','Item_Type','Outlet_Identifier','Item_Type
','Outlet_Size','Outlet_Location_Type','Outlet_Type']
for y in columns:
     df[y] = labelencoder.fit_transform(df[y].values)


df.drop(['Outlet_Identifier'], axis=1)
```

```
                 Item_Weight  Item_Fat_Content  Item_Visibility
Item_Type  \
Item_Identifier

FDA15                  9.300                 0         0.016047
4
DRC01                  5.920                 1         0.019278
14
FDN15                 17.500                 0         0.016760
10
FDX07                 19.200                 1         0.000000
6
NCD19                  8.930                 0         0.000000
9
...                      ...               ...              ...
```

```
...
FDF22                  6.865                 0         0.056783
13
FDS36                  8.380                 1         0.046982
0
NCJ29                 10.600                 0         0.035186
8
FDN46                  7.210                 1         0.145221
13
DRG01                 14.800                 0         0.044878
14

                 Item_MRP  Outlet_Establishment_Year  Outlet_Size  \
Item_Identifier
FDA15            249.8092                       1999            1
DRC01             48.2692                       2009            1
FDN15            141.6180                       1999            1
FDX07            182.0950                       1998            1
NCD19             53.8614                       1987            0
...                   ...                        ...          ...
FDF22            214.5218                       1987            0
FDS36            108.1570                       2002            1
NCJ29             85.1224                       2004            2
FDN46            103.1332                       2009            1
DRG01             75.4670                       1997            2

                 Outlet_Location_Type  Outlet_Type  Item_Outlet_Sales

Item_Identifier

FDA15                               0            1          3735.1380

DRC01                               2            2           443.4228

FDN15                               0            1          2097.2700

FDX07                               2            0           732.3800

NCD19                               2            1           994.7052

...                               ...          ...                ...

FDF22                               2            1          2778.3834

FDS36                               1            1           549.2850

NCJ29                               1            1          1193.1136

FDN46                               2            2          1845.5976

DRG01                               0            1           765.6700
```

```
[8523 rows x 10 columns]

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

Scaling data

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X = scaler.fit_transform(X)
```

Splitting data

```
#Train/test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,
test_size=0.2, random_state=12)
```

Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
RF_model = RandomForestRegressor()
RF_model.fit(X_train, y_train)

RandomForestRegressor()

prediction = RF_model.predict(X_train)
prediction

array([ 520.768786, 1579.697054, 2437.633618, ..., 2535.273188,
       1242.502644, 2928.161768])
```

this is final our guess with comparison with the real price

```
pd.DataFrame({'Guess': prediction, 'Real Price':y_train})

                       Guess  Real Price
Item_Identifier
DRM37             520.768786    591.2304
NCQ42            1579.697054   1017.3424
NCE54            2437.633618   2332.2974
NCQ41            3693.771846   3901.5880
FDR19            2627.346670   2770.3938
...                      ...         ...
FDK21             507.119886    500.6816
FDS13            4962.713408   5299.7680
FDY19            2535.273188   2828.3184
```

```
FDX37              1242.502644    998.7000
NCN26              2928.161768   3866.9664

[6818 rows x 2 columns]
```

```
from sklearn.metrics import mean_squared_error
mse=mean_squared_error(prediction,y_train)
wrong=np.sqrt(mse)
print(wrong)
```

```
425.2745791230239
```

```
RF_accuracy = round(RF_model.score(X_train,y_train) * 100,2)
RF_accuracy
```

```
93.78
```

XGBRegressor

```
from xgboost import XGBRegressor

xgb = XGBRegressor(n_estimators=100, random_state=42)
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
```

```
from sklearn.metrics import mean_absolute_error
mean = mean_absolute_error(y_test,y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)


print(f"RMSE: {rmse}")
print(f'mean: {mean}')
```

```
RMSE: 1127.9347582596201
mean: 802.7026629318935
```

```
#Accuracy
accur = round(xgb.score(X_train,y_train) * 100,2)
accur
```

```
86.67
```

GradientBoostingRegressor

```
from sklearn.ensemble import GradientBoostingRegressor
gbr = GradientBoostingRegressor()
gbr.fit(X_train, y_train)
gbr_pred = gbr.predict(X_test)
gbr_score = np.sqrt(mean_squared_error(y_test, gbr_pred))

print("RMSE (Gradient Boosting Regressor): ", gbr_score)
```

```
RMSE (Gradient Boosting Regressor):  1056.3519352269534
```

```
#Accuracy
accur_gbr = round(gbr.score(X_train, y_train)*100,2)
accur_gbr
```

```
63.03
```

so the final thought of the dataframe, I used Random Forest Regressor(93.7%), XGBRegressor(86.7%), GradientBoostingRegressor (63.3%) accuracy.

Random Forest Regressor is more efficeint among the regressors i used above,

```
import joblib


# Save the trained model as a .pkl file
joblib.dump(RF_model, 'model.pkl')
```

```
['model.pkl']
```