Mini Project 5: Sales Prediction

Step 1: Import library

```
import pandas as pd
```

```
import numpy as np
```

```
import seaborn as sns
```

Step 2: Import Data

```
df=pd.read_csv('https://github.com/YBI-Foundation/Dataset/blob/main/Big%20Sales%20Data.csv?raw=true')
```

```
df
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establis
0	FDT36	12.3	Low Fat	0.111448	Baking Goods	33.4874	OUT049	
1	FDT36	12.3	Low Fat	0.111904	Baking Goods	33.9874	OUT017	
2	FDT36	12.3	LF	0.111728	Baking Goods	33.9874	OUT018	
3	FDT36	12.3	Low Fat	0.000000	Baking Goods	34.3874	OUT019	
4	FDP12	9.8	Regular	0.045523	Baking Goods	35.0874	OUT017	
...	...	...	...	...	...	...	...	
14199	FDG47	12.8	Low Fat	0.069606	Starchy Foods	261.9252	OUT035	
14200	FDG47	12.8	Low Fat	0.070013	Starchy Foods	262.8252	OUT017	

14204 rows × 12 columns

```
df.columns
```

```
Index(['Item_Identifier', 'Item_Weight', 'Item_Fat_Content', 'Item_Visibility',
       'Item_Type', 'Item_MRP', 'Outlet_Identifier',
       'Outlet_Establishment_Year', 'Outlet_Size', 'Outlet_Location_Type',
       'Outlet_Type', 'Item_Outlet_Sales'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14204 entries, 0 to 14203
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
```

```
 0   Item_Identifier            14204 non-null  object 
 1   Item_Weight                11815 non-null  float64
 2   Item_Fat_Content           14204 non-null  object 
 3   Item_Visibility            14204 non-null  float64
 4   Item_Type                  14204 non-null  object 
 5   Item_MRP                   14204 non-null  float64
 6   Outlet_Identifier          14204 non-null  object 
 7   Outlet_Establishment_Year  14204 non-null  int64  
 8   Outlet_Size                14204 non-null  object 
 9   Outlet_Location_Type       14204 non-null  object 
 10  Outlet_Type                14204 non-null  object 
 11  Item_Outlet_Sales          14204 non-null  float64
dtypes: float64(4), int64(1), object(7)
memory usage: 1.3+ MB
```

```
df.describe()
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	11815.000000	14204.000000	14204.000000	14204.000000	14204.000000
mean	12.788355	0.065953	141.004977	1997.830681	2185.836320
std	4.654126	0.051459	62.086938	8.371664	1827.479550
min	4.555000	0.000000	31.290000	1985.000000	33.290000
25%	8.710000	0.027036	94.012000	1987.000000	922.135101
50%	12.500000	0.054021	142.247000	1999.000000	1768.287680
75%	16.750000	0.094037	185.855600	2004.000000	2988.110400
max	30.000000	0.328391	266.888400	2009.000000	31224.726950

```
df.shape
```

```
(14204, 12)
```

Auxillary Step: Complete Missing Values

```
df['Item_Weight'].fillna(df.groupby(['Item_Type'])['Item_Weight'].transform('mean'), inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14204 entries, 0 to 14203
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            14204 non-null  object 
 1   Item_Weight                14204 non-null  float64
 2   Item_Fat_Content           14204 non-null  object 
 3   Item_Visibility            14204 non-null  float64
 4   Item_Type                  14204 non-null  object 
 5   Item_MRP                   14204 non-null  float64
 6   Outlet_Identifier          14204 non-null  object 
 7   Outlet_Establishment_Year  14204 non-null  int64  
 8   Outlet_Size                14204 non-null  object 
 9   Outlet_Location_Type       14204 non-null  object 
 10  Outlet_Type                14204 non-null  object 
 11  Item_Outlet_Sales          14204 non-null  float64
dtypes: float64(4), int64(1), object(7)
memory usage: 1.3+ MB
```

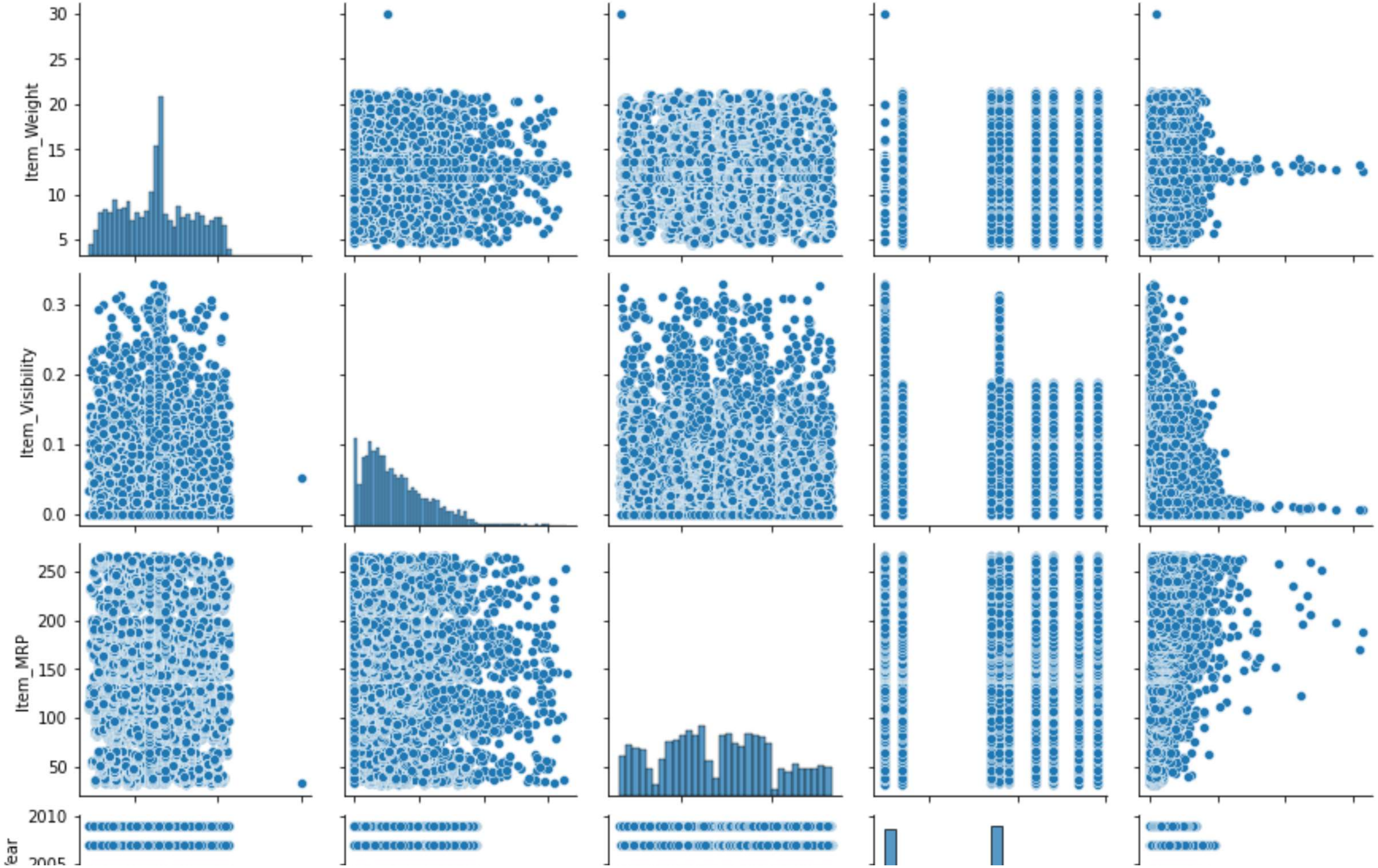
```
df.describe()
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	14204.000000	14204.000000	14204.000000	14204.000000	14204.000000
mean	12.790642	0.065953	141.004977	1997.830681	2185.836320
std	4.251186	0.051459	62.086938	8.371664	1827.479550
min	4.555000	0.000000	31.290000	1985.000000	33.290000

Step 3: Data Visualisation

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7f5ad2798350>
```



Step 4: Getting Categories and Counts of Categorical Variables


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

```
Item_Identifier
FDQ08            10
FDO24            10
FDQ19            10
```

```
FDQ28            10
FDQ31            10
                 ..
FDM52             7
FDM50             7
FDL50             7
FDM10             7
FDR51             7
Length: 1559, dtype: int64
```

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

```
Item_Fat_Content
Low Fat             8485
Regular             4824
LF                   522
reg                  195
low fat              178
dtype: int64
```

```
df.replace({'Item_Fat_Content':{'LF':'Low Fat','reg':'Regular','low fat':'Low Fat'}}, inplace=True)
```

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

```
Item_Fat_Content
Low Fat             9185
Regular             5019
dtype: int64
```

```
df.replace({'Item_Fat_Content':{'Low Fat':0,'Regular':1}},inplace=True)
```

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

```
Item_Type
Fruits and Vegetables    2013
Snack Foods              1989
```

```
Household                1548
Frozen Foods             1426
Dairy                    1136
Baking Goods             1086
Canned                   1084
Health and Hygiene        858
Meat                      736
Soft Drinks               726
Breads                    416
Hard Drinks               362
Others                    280
Starchy Foods             269
Breakfast                 186
Seafood                    89
dtype: int64
```

```
df.replace({'Item_Type':{'Fruits and Vegetables':0,'Snack Foods':0,'Household':1,
                         'Frozen Foods':0,'Dairy':0,'Baking Goods':0,
                         'Canned':0,'Health and Hygiene':1,
                         'Meat':0,'Soft Drinks':0,'Breads':0,'Hard Drinks':0,
                         'Others':2,'Starchy Foods':0,'Breakfast':0,'Seafood':0
                         }},inplace=True)
```

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

```
Item_Type
0            11518
1             2406
2              280
dtype: int64
```

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

```
Outlet_Identifier
OUT027               1559
OUT013               1553
OUT035               1550
```

```
OUT046             1550
OUT049             1550
OUT045             1548
OUT018             1546
OUT017             1543
OUT010              925
OUT019              880
dtype: int64
```

```
df.replace({'Outlet_Identifier':{'OUT027':0,'OUT013':1,'OUT049':2,'OUT046':3,'OUT035':4,'OUT045':5,'OUT018':6,'OUT017':7,'OUT010':8,'
```

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

```
Outlet_Identifier
0                    1559
1                    1553
2                    1550
3                    1550
4                    1550
5                    1548
6                    1546
7                    1543
8                     925
9                     880
dtype: int64
```

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

```
Outlet_Size
Medium         7122
Small          5529
High           1553
dtype: int64
```

```
df.replace({'Outlet_Size':{'Small':0,'Medium':1,'High':2}},inplace=True)
```

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

```
Outlet_Size
1              7122
0              5529
2              1553
dtype: int64
```

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

```
Outlet_Location_Type
Tier 3                  5583
Tier 2                  4641
Tier 1                  3980
dtype: int64
```

```
df.replace({'Outlet_Location_Type':{'Tier 1':0,'Tier 2':1,'Tier 3':2}},inplace=True)
```

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

```
Outlet_Location_Type
2                       5583
1                       4641
0                       3980
dtype: int64
```

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

```
Outlet_Type
Supermarket Type1    9294
Grocery Store        1805
Supermarket Type3    1559
Supermarket Type2    1546
dtype: int64
```

```
df.replace({'Outlet_Type':{'Grocery Store':0,'Supermarket Type1':1,'Supermarket Type2':2,'Supermarket Type3':3}},inplace=True)
```

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

```
Outlet_Type
1              9294
0              1805
3              1559
2              1546
dtype: int64
```

```
df.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identi
0	FDT36	12.3	0	0.111448	0	33.4874	
1	FDT36	12.3	0	0.111904	0	33.9874	
2	FDT36	12.3	0	0.111728	0	33.9874	
3	FDT36	12.3	0	0.000000	0	34.3874	
4	FDP12	9.8	1	0.045523	0	35.0874	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14204 entries, 0 to 14203
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Item_Identifier            14204 non-null  object
 1   Item_Weight                14204 non-null  float64
 2   Item_Fat_Content           14204 non-null  int64
 3   Item_Visibility            14204 non-null  float64
```

```
 4   Item_Type                  14204 non-null  int64
 5   Item_MRP                   14204 non-null  float64
 6   Outlet_Identifier          14204 non-null  int64
 7   Outlet_Establishment_Year  14204 non-null  int64
 8   Outlet_Size                14204 non-null  int64
 9   Outlet_Location_Type       14204 non-null  int64
 10  Outlet_Type                14204 non-null  int64
 11  Item_Outlet_Sales          14204 non-null  float64
dtypes: float64(4), int64(7), object(1)
memory usage: 1.3+ MB
```

```
df.shape
```

```
(14204, 12)
```

Step 5: Define X and y

```
y=df['Item_Outlet_Sales']
```

```
y.shape
```

```
(14204,)
```

```
y
```

```
0         436.608721
1         443.127721
2         564.598400
3        1719.370000
4         352.874000
            ...
14199    4984.178800
14200    2885.577200
14201    2885.577200
```

```
14202    3803.676434
14203    3644.354765
Name: Item_Outlet_Sales, Length: 14204, dtype: float64
```

```
#X=df[['Item_Weight', 'Item_Fat_Content', 'Item_Visibility','Item_Type', 'Item_MRP', 'Outlet_Identifier','Outlet_Establishment_Year',
X=df.drop(['Item_Identifier','Item_Outlet_Sales'],axis=1)
```

```
X.shape
```

```
(14204, 10)
```

```
X
```

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_
0	12.300000	0	0.111448	0	33.4874	2	
1	12.300000	0	0.111904	0	33.9874	7	
2	12.300000	0	0.111728	0	33.9874	6	
3	12.300000	0	0.000000	0	34.3874	9	
4	9.800000	1	0.045523	0	35.0874	7	
...	...	...	...	...	...	...	
14199	12.800000	0	0.069606	0	261.9252	4	
14200	12.800000	0	0.070013	0	262.8252	7	
14201	12.800000	0	0.069561	0	263.0252	1	
14202	13.659758	0	0.069282	0	263.5252	0	
14203	12.800000	0	0.069727	0	263.6252	2	

14204 rows × 10 columns

Step 6: Standardizing X

```
from sklearn.preprocessing import StandardScaler
```

```
sc=StandardScaler()
```

```
X_std=df[['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year']]
```

```
X_std=sc.fit_transform(X_std)
```

```
X_std
```

```
array([[-0.11541705,  0.88413635, -1.73178716,  0.13968068],
       [-0.11541705,  0.89300616, -1.72373366,  1.09531886],
       [-0.11541705,  0.88958331, -1.72373366,  1.3342284 ],
       ...,
       [ 0.00220132,  0.07011952,  1.96538148, -1.29377659],
       [ 0.20444792,  0.06469366,  1.97343499, -1.53268614],
       [ 0.00220132,  0.07334891,  1.97504569,  0.13968068]])
```

```
X[['Item_Weight', 'Item_Visibility', 'Item_MRP', 'Outlet_Establishment_Year' ]] = pd.DataFrame(X_std,columns=[['Item_Weight','Item_Vi
```

```
X
```

	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_
0	-0.115417	0	0.884136	0	-1.731787	2	
1	-0.115417	0	0.893006	0	-1.723734	7	
2	-0.115417	0	0.889583	0	-1.723734	6	
3	-0.115417	0	-1.281712	0	-1.717291	9	
4	-0.703509	1	-0.397031	0	-1.706016	7	
...	...	...	...	...	...	...	
14199	0.002201	0	0.070990	0	1.947664	4	
14200	0.002201	0	0.078898	0	1.962160	7	
14203	0.002201	0	0.073349	0	1.975046	2	

Step 7: Splitting Data

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.1,random_state=2529)
```

```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

```
((12783, 10), (1421, 10), (12783,), (1421,))
```

Step 8: Creating Model

```
from sklearn.ensemble import RandomForestRegressor
```

```
rfr = RandomForestRegressor(random_state=2529)
```

Step 9: Training Model

```
rfr.fit(X_train, y_train)
```

```
RandomForestRegressor(random_state=2529)
```

Step 10: Prediction of Model

```
y_pred=rfr.predict(X_test)
```

```
y_pred.shape
```

```
(1421,)
```

```
y_pred
```

```
array([1445.29507934,  669.51312572, 1883.54185796, ..., 2228.46101734,
       3251.93307564,  460.5156873 ])
```

Step 11: Evaluation of model

```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
```

```
mean_squared_error(y_test,y_pred)
```

```
1611177.5560500463
```

```
mean_absolute_error(y_test,y_pred)
```

```
828.3494726840753
```

```
r2_score(y_test,y_pred)
```

```
0.5806344037136959
```

Step 12: Visualisation of Actual v/s Predicted

```
import matplotlib.pyplot as plt
plt.scatter(y_test,y_pred)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price v/s Predicted Price")
plt.show()
```

Link of the same:

https://colab.research.google.com/drive/1QyEb4Hs8DUX0jI4Nr6gqxoMBPZWurgU7?usp=sharing