Importing the Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings

warnings.filterwarnings('ignore')

data=pd.read_csv("Sales.csv")
```

Getting info about Dataset

```
data.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
```

Checking Null Values in Dataset

```
data.isnull().sum()
```

```
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
```

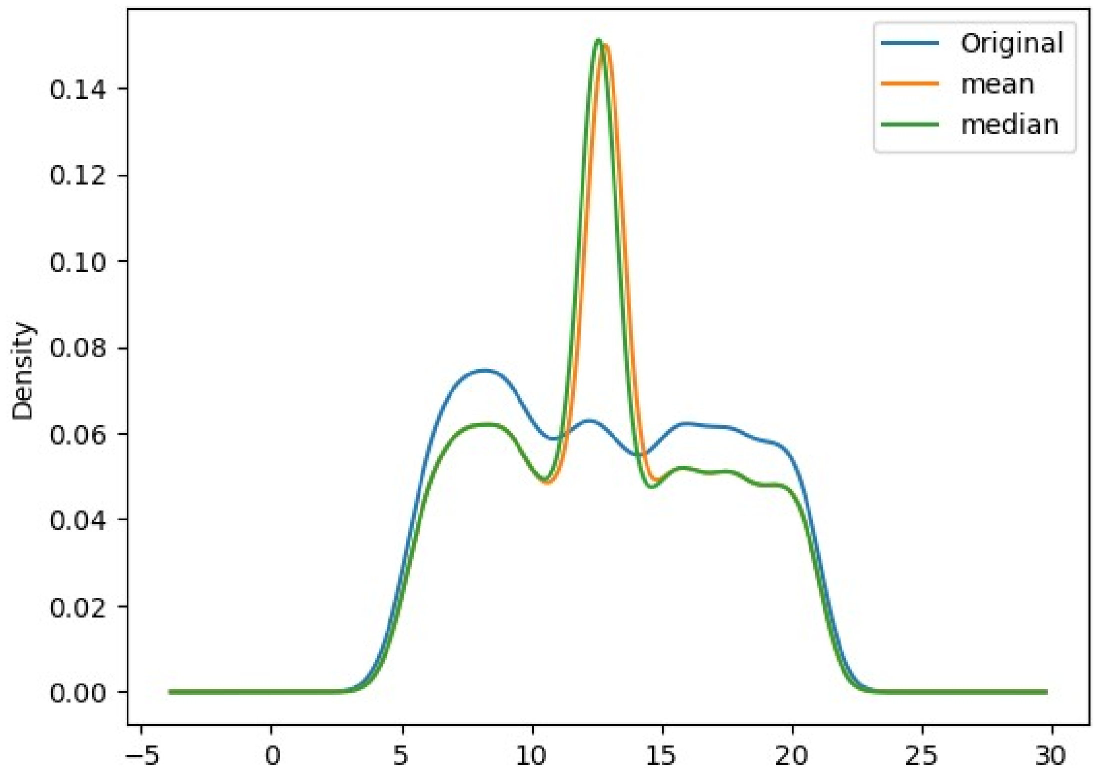
Taking care of Duplicate Values

```
data.duplicated().any()

False
```

Handling Missing Values

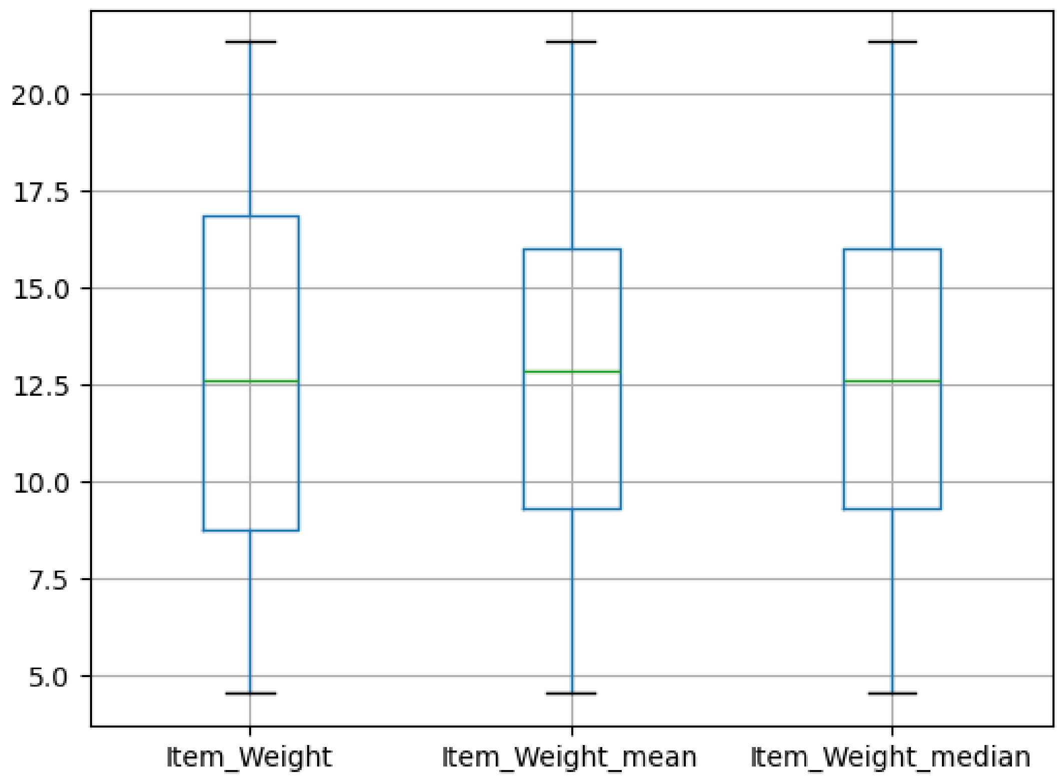
Item_Weight

```
mean_weight=data['Item_Weight'].mean()
median_weight=data['Item_Weight'].median()

data['Item_Weight_mean']=data['Item_Weight'].fillna(mean_weight)
data['Item_Weight_median']=data['Item_Weight'].fillna(median_weight)

print("Original weight variable variance",data['Item_Weight'].var())
print("Item weight variable variance after mean
imputation",data['Item_Weight_mean'].var())
print("Item weight variable variance after median
imputation",data['Item_Weight_median'].var())

Original weight variable variance 21.56168825983637
Item weight variable variance after mean imputation 17.860121735060453
Item weight variable variance after median imputation
17.869561454073366

data['Item_Weight'].plot(kind='kde',label="Original")

data['Item_Weight_mean'].plot(kind='kde',label="mean")

data['Item_Weight_median'].plot(kind='kde',label="median")

plt.legend()
plt.show()
```

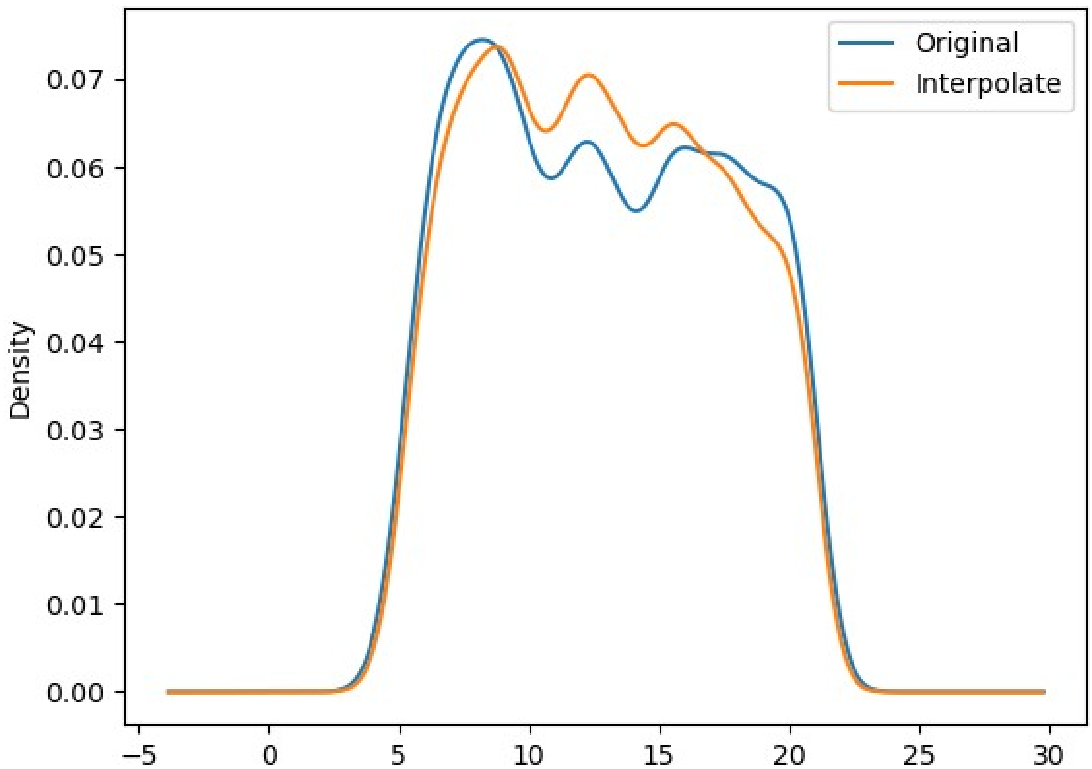



```
data[['Item_Weight','Item_Weight_mean','Item_Weight_median']].boxplot(
)
```

```
<Axes: >
```

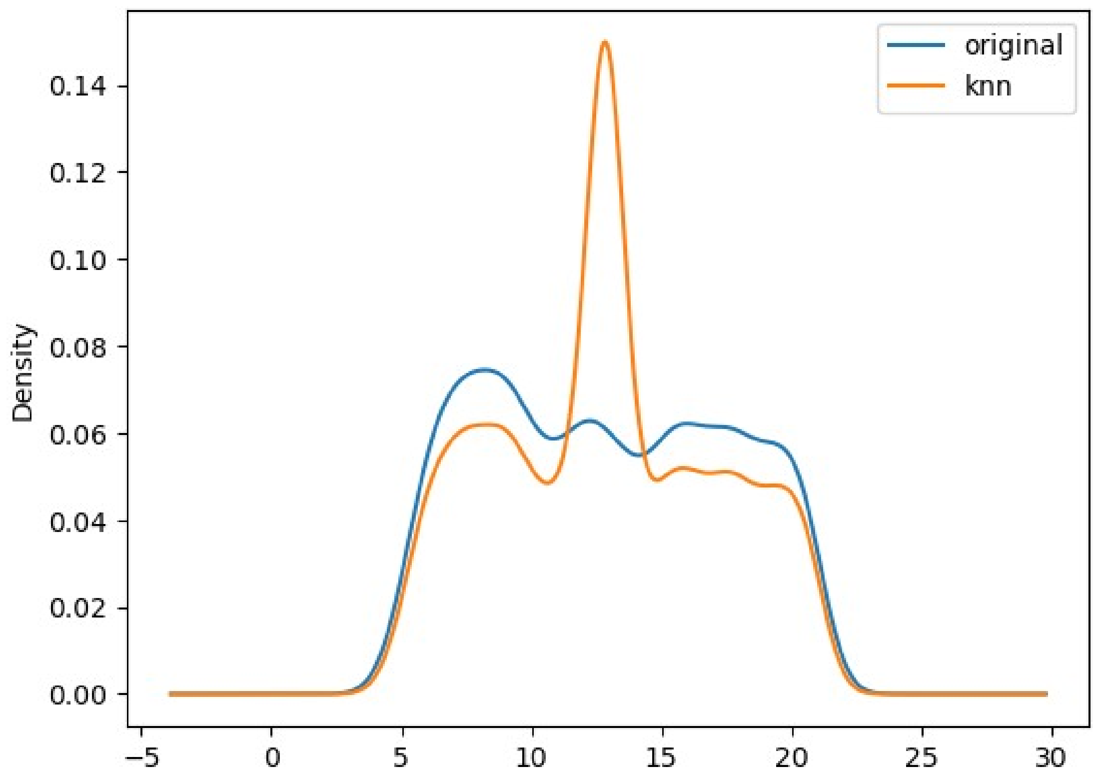



```
data['Item_Weight_Interpolate']=data['Item_Weight'].interpolate(method
='linear')

data['Item_Weight'].plot(kind='kde',label="Original")

data['Item_Weight_Interpolate'].plot(kind='kde',label="Interpolate")

plt.legend()
plt.show()
```



Multivariate Imputaion

```
from sklearn.impute import KNNImputer

knn=KNNImputer(n_neighbors=10,weights='distance')

data['knn_impute']=knn.fit_transform(data[['Item_Weight']]).ravel()

data['Item_Weight'].plot(kind='kde',label='original')
data['knn_impute'].plot(kind='kde',label='knn')
plt.legend()
plt.show()
```




```
data=data.drop(['Item_Weight','Item_Weight_mean','Item_Weight_median',
'knn_impute'],axis=1)

data.isnull().sum()

Item_Identifier                 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
Item_Weight_Interpolate         0
dtype: int64
```

Outlet_Size

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

Outlet_Size
Medium    2793
```

```
Small     2388
High       932
Name: count, dtype: int64
```

```
mode_outlet=data.pivot_table(values='Outlet_Size',columns='Outlet_Type
',aggfunc=(lambda x:x.mode()[0]))
```

```
mode_outlet
```

```
Outlet_Type Grocery Store Supermarket Type1 Supermarket Type2  \
Outlet_Size         Small             Small            Medium

Outlet_Type Supermarket Type3
Outlet_Size            Medium
```

```
missing_values=data['Outlet_Size'].isnull()
```

```
missing_values
```

```
0       False
1       False
2       False
3        True
4       False
        ...
8518    False
8519     True
8520    False
8521    False
8522    False
Name: Outlet_Size, Length: 8523, dtype: bool
```

```
data.loc[missing_values,'Outlet_Size']=data.loc[missing_values,'Outlet
_Type'].apply(lambda x:mode_outlet[x])
```

```
data.isnull().sum()
```

```
Item_Identifier              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
Item_Weight_Interpolate      0
dtype: int64
```

Item_Fat_Content

```
data.columns
```

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

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

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

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

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

```
Item_Fat_Content
LF         5517
Regular    3006
Name: count, dtype: int64
```

Item_Visibility

```
data['Item_Visibility'].value_counts()
```

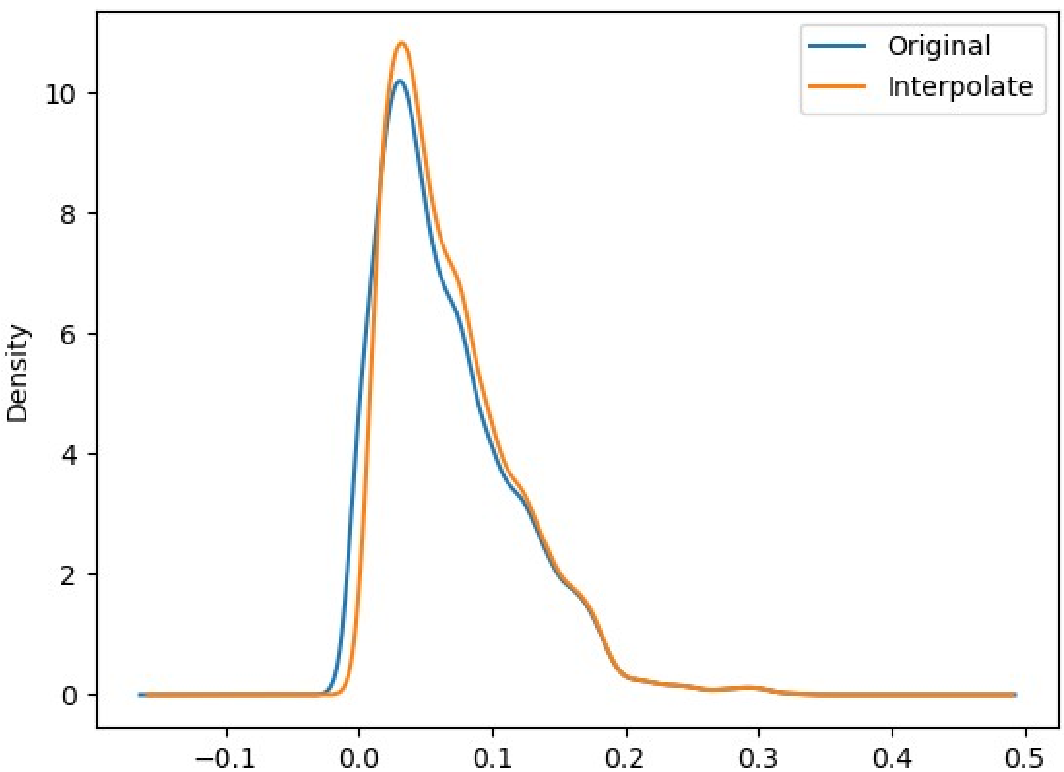
```
Item_Visibility
0.000000    526
0.076975      3
0.162462      2
0.076841      2
0.073562      2
           ...
0.013957      1
0.110460      1
0.124646      1
0.054142      1
0.044878      1
Name: count, Length: 7880, dtype: int64
```

```
data['Item_Visibility_Interpolate']=data['Item_Visibility'].replace(0,
np.nan).interpolate(method='linear')
```

```
data['Item_Visibility_Interpolate'].value_counts()
```

```
Item_Visibility_Interpolate
0.076975    3
0.044024    2
0.040912    2
0.076856    2
0.078759    2
           ..
0.021011    1
0.099189    1
0.076866    1
0.014116    1
0.044878    1
Name: count, Length: 8405, dtype: int64
```

```
data['Item_Visibility'].plot(kind='kde',label='Original')
data['Item_Visibility_Interpolate'].plot(kind='kde',label='Interpolate
')
plt.legend()
plt.show()
```




```
data=data.drop('Item_Visibility',axis=1)
```

Item_Type

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

```
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: count, dtype: int64
```

Item_Identifier

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

```
Item_Identifier
FDW13    10
FDG33    10
NCY18     9
FDD38     9
DRE49     9
         ..
FDY43     1
FDQ60     1
FDO33     1
DRF48     1
FDC23     1
Name: count, Length: 1559, dtype: int64
```

```
data['Item_Identifier']=data['Item_Identifier'].apply(lambda x:x[:2])
```

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

```
Item_Identifier
FD    6125
NC    1599
DR     799
Name: count, dtype: int64
```

Outlet_Establishment_Year

```
data['Outlet_Establishment_Year']
```

```
0       1999
1       2009
2       1999
3       1998
4       1987
        ...
8518    1987
8519    2002
8520    2004
8521    2009
8522    1997
Name: Outlet_Establishment_Year, Length: 8523, dtype: int64
```

```
import datetime as dt

current_year=dt.datetime.today().year

data['Outlet_Age']=current_year-data['Outlet_Establishment_Year']

data=data.drop('Outlet_Establishment_Year',axis=1)
```

Handling Categorical Columns

```
from sklearn.preprocessing import OrdinalEncoder

data_encoded=data.copy()

cat_cols=data.select_dtypes(include=['object']).columns

for col in cat_cols:
    oe=OrdinalEncoder()
    data_encoded[col]=oe.fit_transform(data_encoded[[col]])
    print(oe.categories_)
```

```
[array(['DR', 'FD', 'NC'], dtype=object)]
[array(['LF', 'Regular'], dtype=object)]
[array(['Baking Goods', 'Breads', 'Breakfast', 'Canned', 'Dairy',
       'Frozen Foods', 'Fruits and Vegetables', 'Hard Drinks',
       'Health and Hygiene', 'Household', 'Meat', 'Others', 'Seafood',
       'Snack Foods', 'Soft Drinks', 'Starchy Foods'], dtype=object)]
[array(['OUT010', 'OUT013', 'OUT017', 'OUT018', 'OUT019', 'OUT027',
       'OUT035', 'OUT045', 'OUT046', 'OUT049'], dtype=object)]
[array(['High', 'Medium', 'Small'], dtype=object)]
[array(['Tier 1', 'Tier 2', 'Tier 3'], dtype=object)]
[array(['Grocery Store', 'Supermarket Type1', 'Supermarket Type2',
       'Supermarket Type3'], dtype=object)]
```

```
data_encoded.head(3)
```

```
   Item_Identifier  Item_Fat_Content  Item_Type  Item_MRP
Outlet_Identifier  \
0               1.0               0.0        4.0  249.8092
9.0
1               0.0               1.0       14.0   48.2692
3.0
2               1.0               0.0       10.0  141.6180
9.0

   Outlet_Size  Outlet_Location_Type  Outlet_Type
Item_Outlet_Sales  \
0          1.0                   0.0          1.0          3735.1380

1          1.0                   2.0          2.0           443.4228

2          1.0                   0.0          1.0          2097.2700


   Item_Weight_Interpolate  Item_Visibility_Interpolate  Outlet_Age
0                     9.30                     0.016047          26
1                     5.92                     0.019278          16
2                    17.50                     0.016760          26

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

Random Forest Regressior

```
from sklearn.ensemble import RandomForestRegressor

from sklearn.model_selection import cross_val_score

rf=RandomForestRegressor(n_estimators=100,random_state=42)
scores=cross_val_score(rf,X,y,cv=5,scoring='r2')
print(scores.mean())

0.5549992903957147
```

XGBRFRegressior

```
from xgboost import XGBRFRegressor

xg=XGBRFRegressor(n_estimators=100,random_state=42)

scores=cross_val_score(xg,X,y,cv=5,scoring='r2')
print(scores.mean())

0.5954067732342189
```

XGBRFRegressor Feature Importances

```
xg=XGBRFRegressor(n_estimators=100,random_state=42)
xg1=xg.fit(X,y)
pd.DataFrame({
    'feature':X.columns,
    'XGBRF_importance':xg1.feature_importances_
}).sort_values(by='XGBRF_importance',ascending=False)
```

	feature	XGBRF_importance
7	Outlet_Type	0.349864
5	Outlet_Size	0.192658
10	Outlet_Age	0.175040
3	Item_MRP	0.131012
4	Outlet_Identifier	0.130735
6	Outlet_Location_Type	0.013184
9	Item_Visibility_Interpolate	0.002493
8	Item_Weight_Interpolate	0.001770
2	Item_Type	0.001566
0	Item_Identifier	0.000999
1	Item_Fat_Content	0.000680

```
['Outlet_Location_Type','Item_Visibility_Interpolate','Item_Weight_Int
erpolate','Item_Type','Item_Identifier','Item_Fat_Content']
```

```
['Outlet_Location_Type',
 'Item_Visibility_Interpolate',
 'Item_Weight_Interpolate',
 'Item_Type',
 'Item_Identifier',
 'Item_Fat_Content']
```

```
from xgboost import XGBRFRegressor
```

```
xg=XGBRFRegressor(n_estimators=100,random_state=42)
```

```
scores=cross_val_score(xg1,X.drop(['Outlet_Location_Type','Item_Visibi
lity_Interpolate','Item_Weight_Interpolate','Item_Type','Item_Identifi
er','Item_Fat_Content'],axis=1),y,cv=5,scoring='r2')
print(scores.mean())
```

```
0.5966037632320667
```

```
final_data=X.drop(['Outlet_Location_Type','Item_Visibility_Interpolate
','Item_Weight_Interpolate','Item_Type','Item_Identifier','Item_Fat_Co
ntent'],axis=1)
```

```
final_data
```

```
      Item_MRP  Outlet_Identifier  Outlet_Size  Outlet_Type  
Outlet_Age
0     249.8092                9.0          1.0          1.0  
26
```

```
1      48.2692                3.0          1.0          2.0
16
2     141.6180                9.0          1.0          1.0
26
3     182.0950                0.0          2.0          0.0
27
4      53.8614                1.0          0.0          1.0
38
...        ...                ...          ...          ...          ..
.
8518  214.5218                1.0          0.0          1.0
38
8519  108.1570                7.0          2.0          1.0
23
8520   85.1224                6.0          2.0          1.0
21
8521  103.1332                3.0          1.0          2.0
16
8522   75.4670                8.0          2.0          1.0
28

[8523 rows x 5 columns]
```

Best Model

```
from xgboost import XGBRFRegressor

xg_final=XGBRFRegressor()

xg_final.fit(final_data,y)

XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None,
device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=None,
               grow_policy=None, importance_type=None,
               interaction_constraints=None, max_bin=None,
               max_cat_threshold=None, max_cat_to_onehot=None,
               max_delta_step=None, max_depth=None, max_leaves=None,
               min_child_weight=None, missing=nan,
monotone_constraints=None,
               multi_strategy=None, n_estimators=None, n_jobs=None,
               num_parallel_tree=None, objective='reg:squarederror',
               random_state=None, reg_alpha=None, ...)

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
```

```
X_train,X_test,y_train,y_test=train_test_split(final_data,y,test_size=
0.2,random_state=42)
```

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

```
XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None,
device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=None,
               grow_policy=None, importance_type=None,
               interaction_constraints=None, max_bin=None,
               max_cat_threshold=None, max_cat_to_onehot=None,
               max_delta_step=None, max_depth=None, max_leaves=None,
               min_child_weight=None, missing=nan,
monotone_constraints=None,
               multi_strategy=None, n_estimators=None, n_jobs=None,
               num_parallel_tree=None, objective='reg:squarederror',
               random_state=None, reg_alpha=None, ...)
```

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

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

```
713.9516489619299
```

Prediction on Unseen Data

```
pred=xg_final.predict(np.array([[141.6180,9.0,1.0,1.0,24]]))[0]
print(pred)
```

```
2067.0864
```

```
print(f"Sales Value is between {pred-713.95} and {pred+713.95}")
```

```
Sales Value is between 1353.13642578125 and 2781.03642578125
```

Save Model Using Joblib

```
import joblib
```

```
joblib.dump(xg_final,'final_model')
```

```
['final_model']
```

```
model=joblib.load('final_model')
```

```
pred=model.predict(np.array([[141.6180,9.0,1.0,1.0,24]]))[0]
print(pred)
```

```
2067.0864
```