In [ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import matplotlib
matplotlib.rcParams['figure.figsize']=(5,5)
sns.set_theme(color_codes=True)
```

In [ ]:
```python
data=pd.read_csv("/content/Big Mart Sales Prediction.csv")
data.head()
```

Out[147]:

	ProductID	Weight	FatContent	ProductVisibility	ProductType	MRP	OutletID	EstablishmentYear	C
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	

In [ ]:
```python
data.shape
```

Out[148]: (8523, 12)

In [ ]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   ProductID          8523 non-null   object 
 1   Weight             7060 non-null   float64
 2   FatContent         8523 non-null   object 
 3   ProductVisibility  8523 non-null   float64
 4   ProductType        8523 non-null   object 
 5   MRP                8523 non-null   float64
 6   OutletID           8523 non-null   object 
 7   EstablishmentYear  8523 non-null   int64  
 8   OutletSize         6113 non-null   object 
 9   LocationType       8523 non-null   object 
 10  OutletType         8523 non-null   object 
 11  OutletSales        8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

In [ ]:
```
#DATA PRE-PROCESSING

#Checking the number of unique values
data.select_dtypes(include='object').nunique()
```

Out[150]:
```
ProductID       1559
FatContent         5
ProductType       16
OutletID          10
OutletSize         3
LocationType       3
OutletType         4
dtype: int64
```

In [ ]:
```
data.dtypes
```

Out[151]:
```
ProductID              object
Weight                float64
FatContent             object
ProductVisibility     float64
ProductType            object
MRP                   float64
OutletID               object
EstablishmentYear       int64
OutletSize             object
LocationType           object
OutletType             object
OutletSales           float64
dtype: object
```

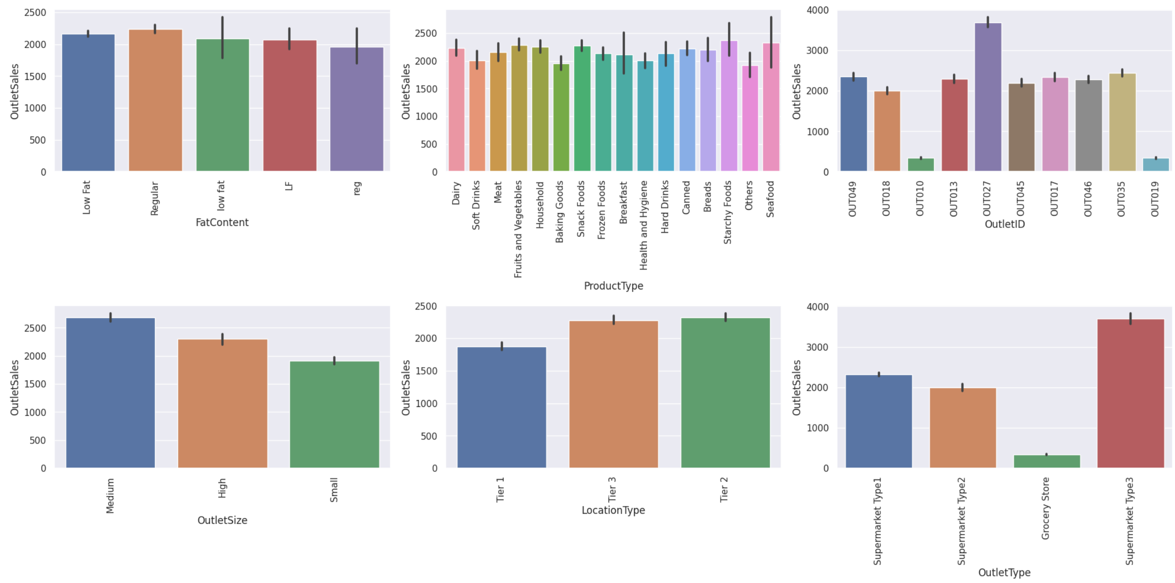
In [ ]:
```
#Drop product id column because it is unnecessary
data.drop(columns='ProductID',inplace=True)
data.head()
```

Out[152]:

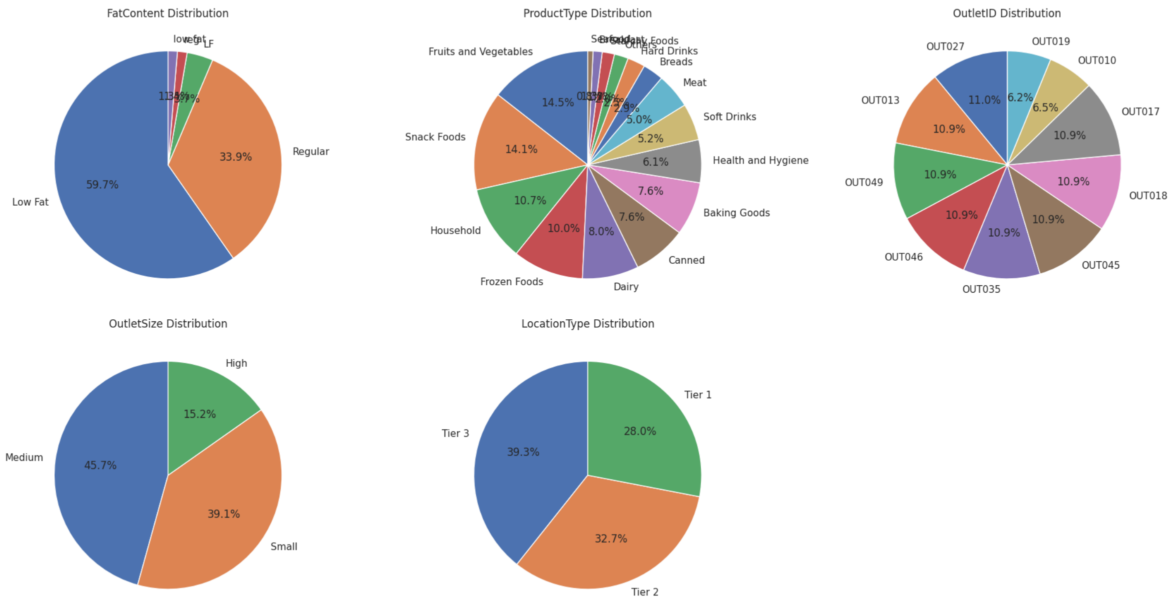
	Weight	FatContent	ProductVisibility	ProductType	MRP	OutletID	EstablishmentYear	OutletSize	L
0	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	
1	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	
2	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	
3	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	
4	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	

In [ ]:

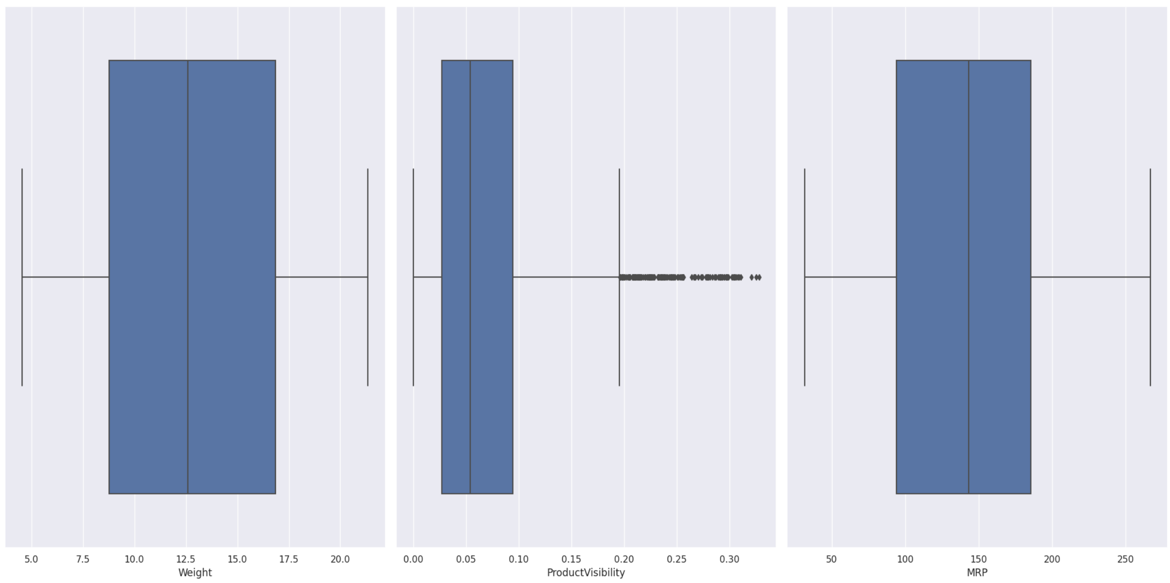
```
#EXPLORATORY DATA ANALYSIS

#Constructing bar sublpots on categorical features against outlet sales
#list of categorical variables

cat_vars=['FatContent','ProductType','OutletID','OutletSize','LocationType','OutletTyp
#create figure with subplots
fig,axs=plt.subplots(nrows=2,ncols=3,figsize=(20,10))
axs=axs.flatten()

#creating bar plot for each categorical variable
for i,var in enumerate(cat_vars):
  sns.barplot(x=var,y='OutletSales',data=data,ax=axs[i])
  axs[i].set_xticklabels(axs[i].get_xticklabels(),rotation=90)
fig.tight_layout()
```



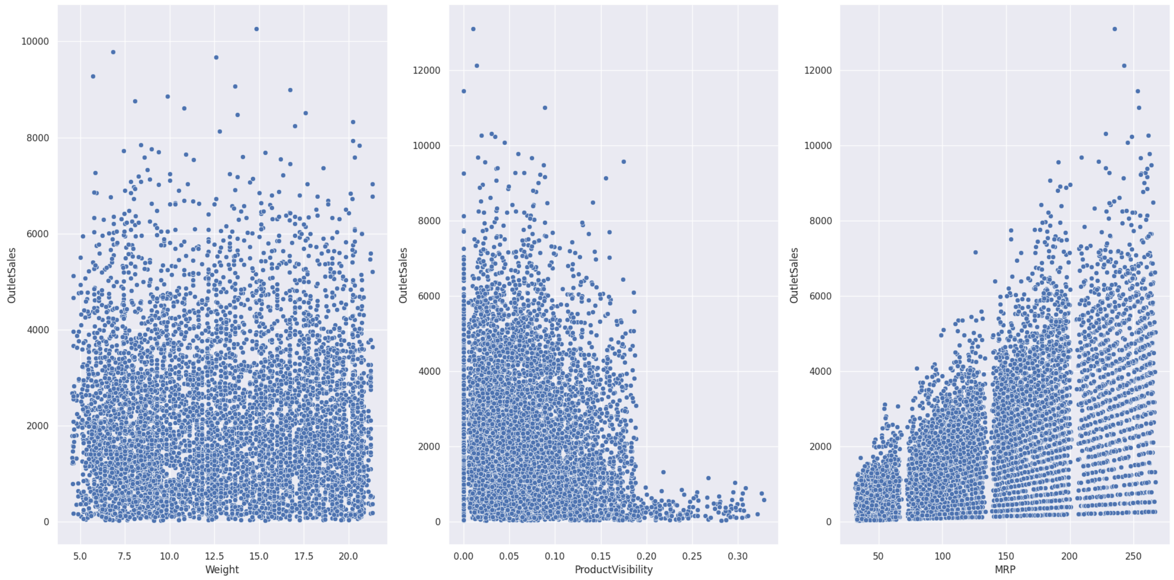
```
In [ ]: #Creating pie-charts for each categorical variable
        fig,axs=plt.subplots(nrows=2,ncols=3,figsize=(20,10))
        axs=axs.flatten()

        for i,var in enumerate(cat_vars):
          if i<len(axs):
            #count the number of occurences of each category
            cat_counts=data[var].value_counts()
            axs.flat[i].pie(cat_counts,labels=cat_counts.index,autopct='%1.1f%%',startangle=9
            axs.flat[i].set_title(f'{var} Distribution')
        fig.tight_layout()
        fig.delaxes(axs[5])
```



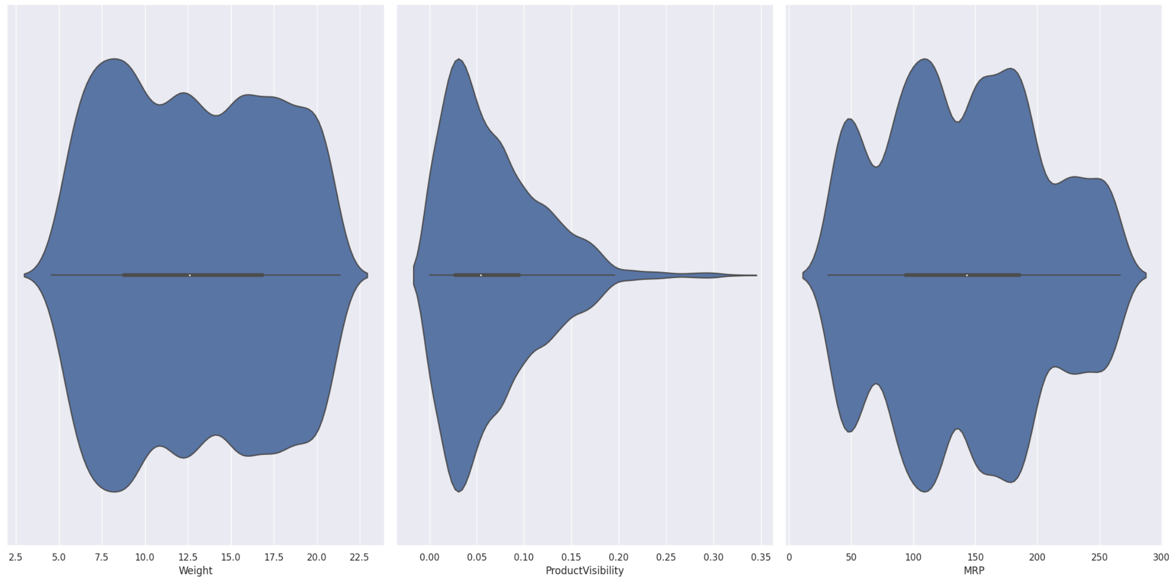

```
In [ ]: #Analysing Numerical Variables
        #Creating box plot for each numerical variable
        num_vars=['Weight','ProductVisibility','MRP']
        fig,axs=plt.subplots(nrows=1,ncols=3,figsize=(20,10))
        axs=axs.flatten()
        for i,var in enumerate(num_vars):
          sns.boxplot(x=var,data=data,ax=axs[i])
        fig.tight_layout()
```



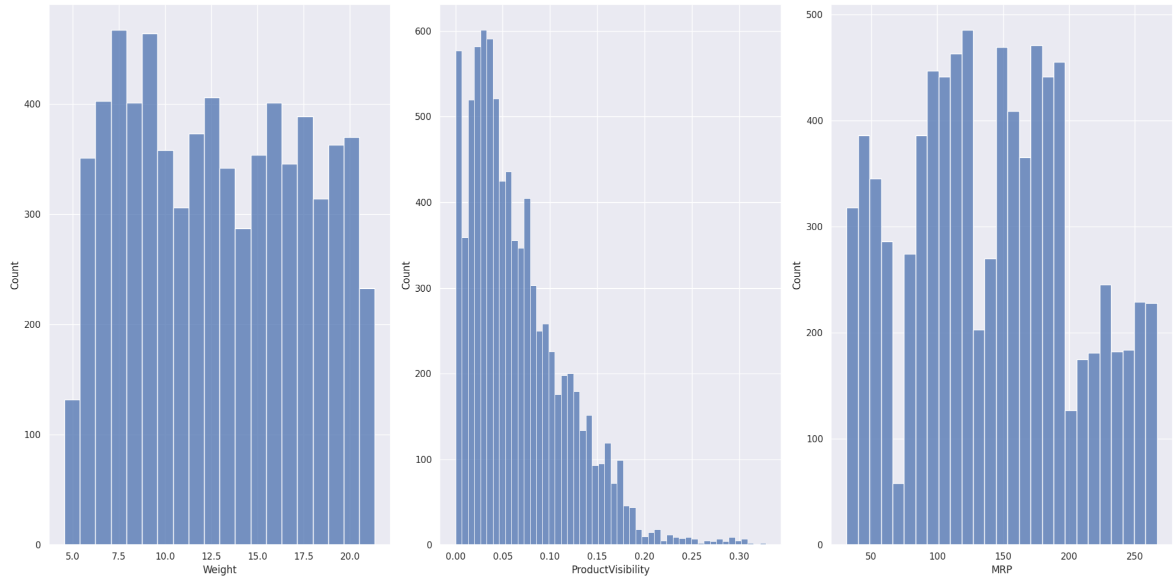
In [ ]:
```python
#Creating scatter plots
fig,axs=plt.subplots(nrows=1,ncols=3,figsize=(20,10))
axs=axs.flatten()
for i,var in enumerate(num_vars):
  sns.scatterplot(x=var,y='OutletSales',data=data,ax=axs[i])
fig.tight_layout()
```



In [ ]:
```python
#Making a violin plot for numerical variables
fig,axs=plt.subplots(nrows=1,ncols=3,figsize=(20,10))
axs=axs.flatten()
for i,var in enumerate(num_vars):
  sns.violinplot(x=var,data=data,ax=axs[i])
fig.tight_layout()
```

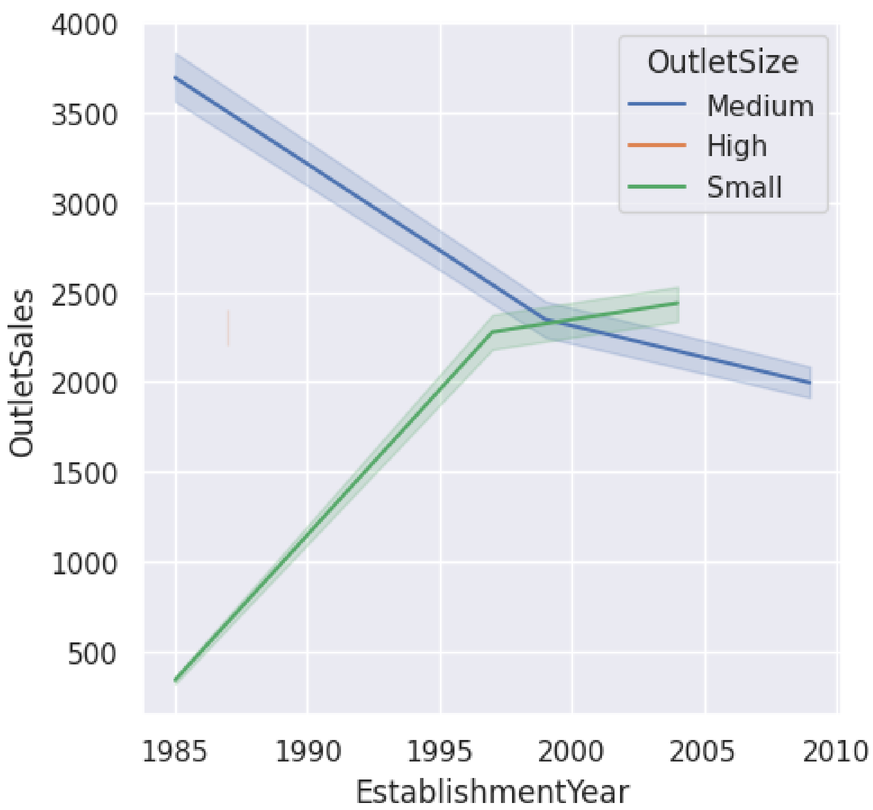


In [ ]:
```
#Creating histograms for numerical variables
fig,axs=plt.subplots(nrows=1,ncols=3,figsize=(20,10))
axs=axs.flatten()
for i,var in enumerate(num_vars):
  sns.histplot(x=var,data=data,ax=axs[i])
fig.tight_layout()
```



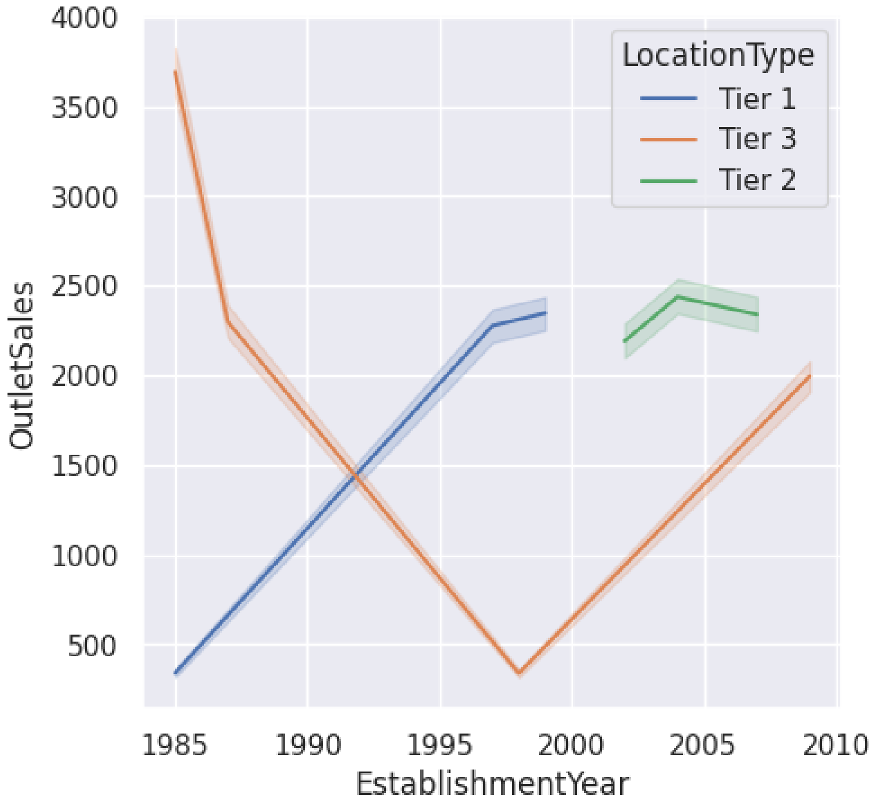
In [ ]:
```
#Making line plots of Establishment year and outlet sales against each categorical var
#Making a line plot of outlet sales against estabilishment year on the bases of outlet
sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='OutletSize')
```

Out[159]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



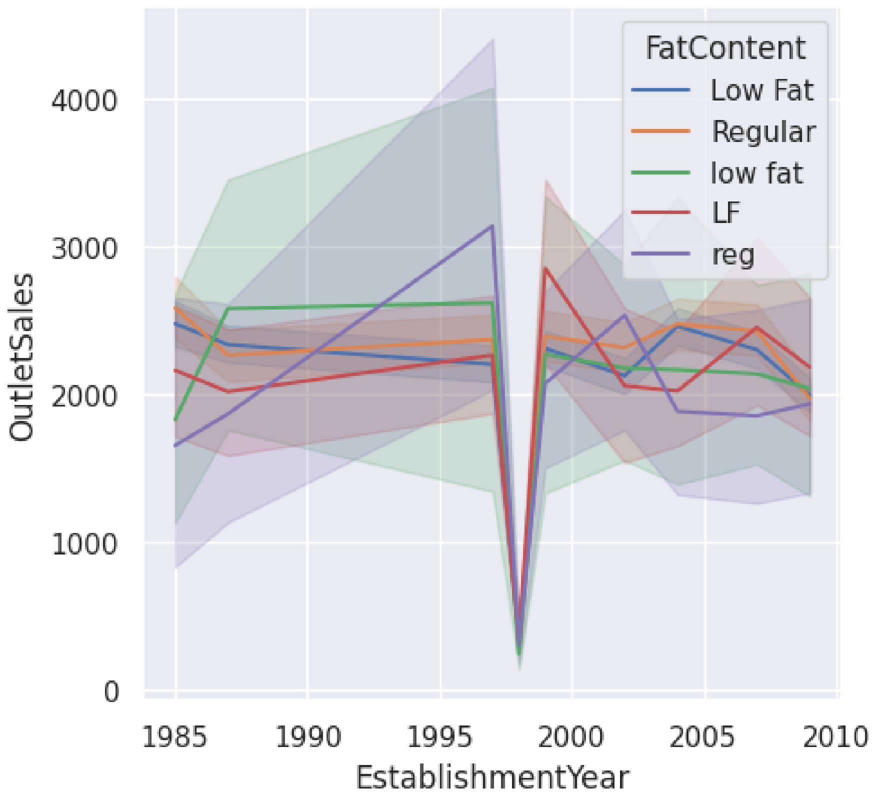
In [ ]:
```
#Making a line plot of outlet sales against estabilishment year on the bases of locati
sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='LocationType')
```

Out[160]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



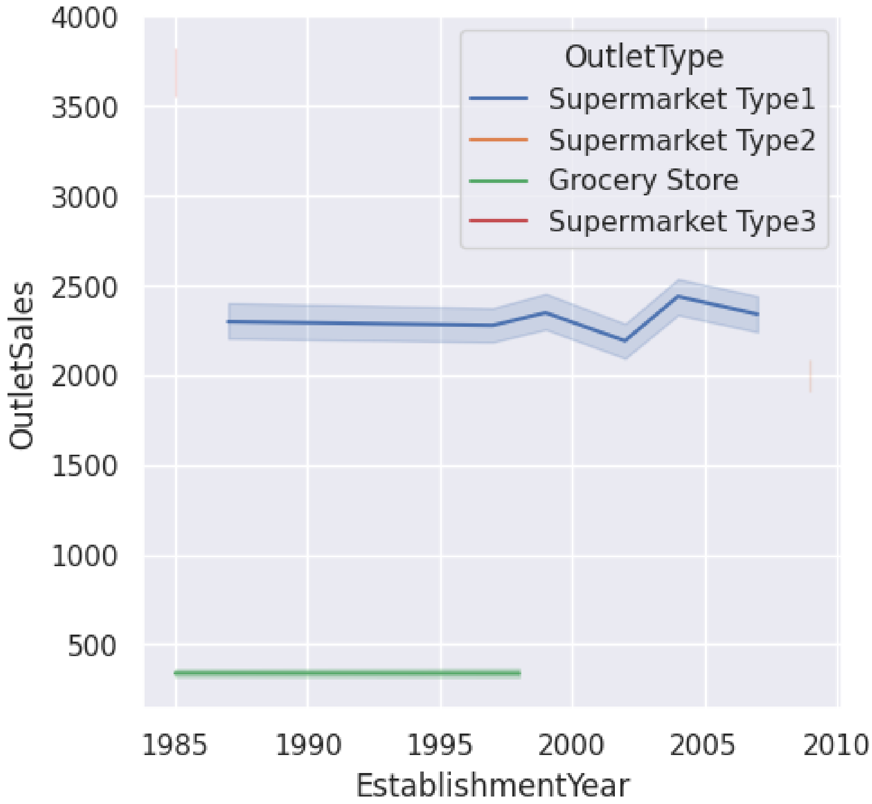
In [ ]:
```
#Making a line plot of outlet sales against estabilishment year on the bases of fat cc
sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='FatContent')
```

Out[161]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



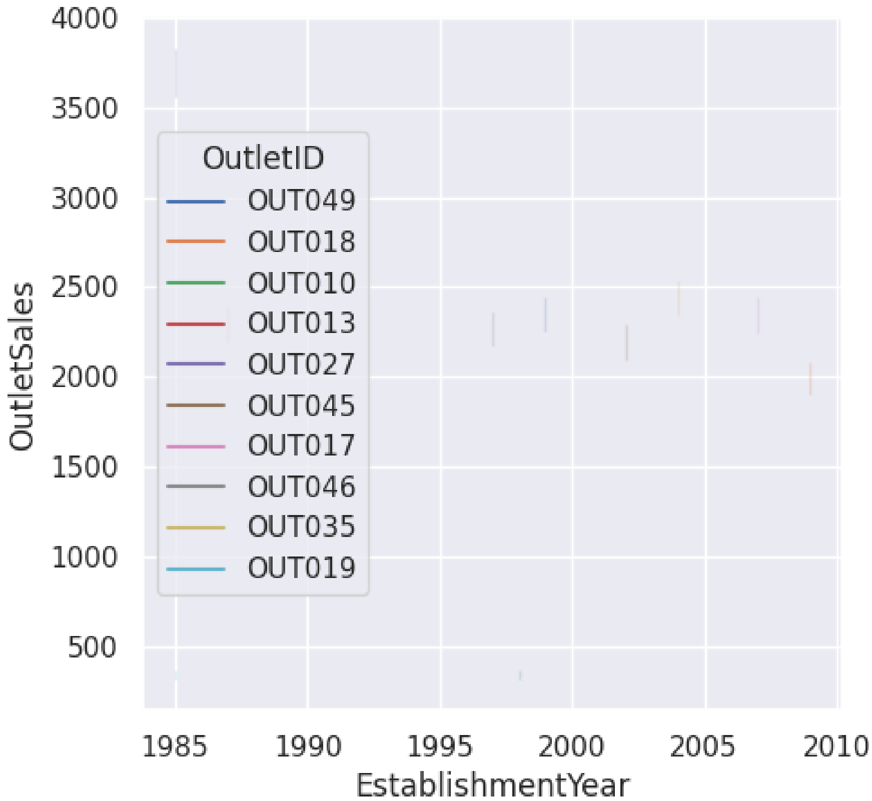
```
In [ ]: #Making a line plot of outlet sales against estabilishment year on the bases of outlet
        sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='OutletType')
```

Out[162]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



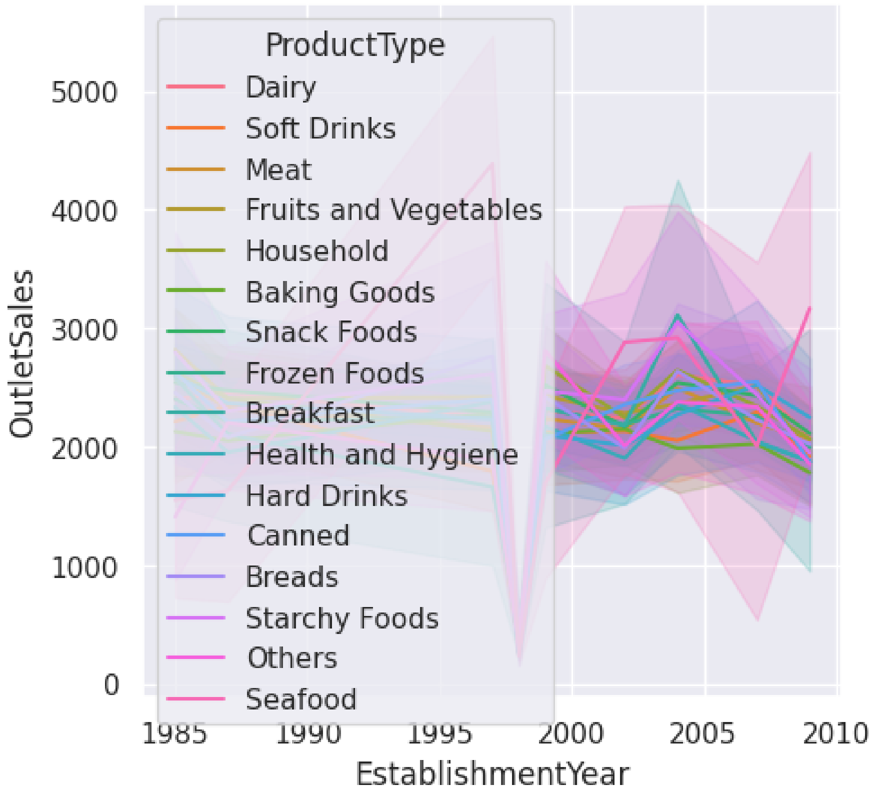

```
In [ ]: sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='OutletID')
```

Out[163]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



In [ ]:
```
sns.lineplot(data=data,x='EstablishmentYear',y='OutletSales',hue='ProductType')
```

Out[164]: <Axes: xlabel='EstablishmentYear', ylabel='OutletSales'>



In [ ]:
```
#DATA PRE-PROCESSING
```

In [ ]:
```
#Checking missing values
check_missing=data.isnull().sum()*100/data.shape[0]
check_missing
```

Out[166]:
```
Weight               17.165317
FatContent            0.000000
ProductVisibility     0.000000
ProductType           0.000000
MRP                   0.000000
OutletID              0.000000
EstablishmentYear     0.000000
OutletSize           28.276428
LocationType          0.000000
OutletType            0.000000
OutletSales           0.000000
dtype: float64
```

In [ ]:
```
data.isnull().sum()
```

Out[167]:
```
Weight               1463
FatContent              0
ProductVisibility       0
ProductType             0
MRP                     0
OutletID                0
EstablishmentYear       0
OutletSize           2410
LocationType            0
OutletType              0
OutletSales             0
dtype: int64
```

In [ ]:
```
data.isnull().sum()*100/data.shape[0]
```

Out[168]:
```
Weight               17.165317
FatContent            0.000000
ProductVisibility     0.000000
ProductType           0.000000
MRP                   0.000000
OutletID              0.000000
EstablishmentYear     0.000000
OutletSize           28.276428
LocationType          0.000000
OutletType            0.000000
OutletSales           0.000000
dtype: float64
```

In [ ]:
```
check_missing[check_missing>0].sort_values(ascending=False)
```

Out[169]:
```
OutletSize    28.276428
Weight        17.165317
dtype: float64
```

In [ ]:
```
#Filling the missing values
#Filling the missing values of weight with mean
data['Weight']=data['Weight'].fillna(data['Weight'].mean())
```

In [ ]:
```
data.OutletSize.unique()
```

Out[171]:
```
array(['Medium', nan, 'High', 'Small'], dtype=object)
```

In [ ]:
```
data.shape
```

Out[172]:
```
(8523, 11)
```

In [ ]:
```
#Finding in which outlet type we have nan values in outlet size using groupby() functi
unique_sizes_train3=data.groupby("OutletType")["OutletSize"].unique()
unique_sizes_train3
```

Out[173]:
```
OutletType
Grocery Store                        [nan, Small]
Supermarket Type1    [Medium, High, nan, Small]
Supermarket Type2                        [Medium]
Supermarket Type3                        [Medium]
Name: OutletSize, dtype: object
```

In [ ]:
```
#Filling the outlet size in Grocery store with Small value
data.loc[(data['OutletType']=='Grocery Store')&(data['OutletSize'].isna()),'OutletSize
# .loc() function is used to access a particular element using index and column names
#Dropping the nan values in OutletSize
data.dropna(subset=['OutletSize'],inplace=True)
print(data.shape)
```

```
(6668, 11)
```

In [ ]:
```
#Again checking missing values
data.isnull().sum()*100/data.shape[0]
```

Out[175]:
```
Weight              0.0
FatContent          0.0
ProductVisibility   0.0
ProductType         0.0
MRP                 0.0
OutletID            0.0
EstablishmentYear   0.0
OutletSize          0.0
LocationType        0.0
OutletType          0.0
OutletSales         0.0
dtype: float64
```

In [ ]:
```
#LABEL ENCODING FOR EACH OBJECT DATA TYPE
data.select_dtypes(include='object').nunique()
```

Out[176]:
```
FatContent       5
ProductType     16
OutletID         8
OutletSize       3
LocationType     3
OutletType       4
dtype: int64
```

In [ ]:
```
#Loop for each column in the DataFrame where dtype is 'object'
for col in data.select_dtypes(include='object').columns:
  print(f'{col}:{data[col].unique()}')
```

```
FatContent:['Low Fat' 'Regular' 'low fat' 'LF' 'reg']
ProductType:['Dairy' 'Soft Drinks' 'Meat' 'Fruits and Vegetables' 'Household'
 'Baking Goods' 'Snack Foods' 'Breakfast' 'Health and Hygiene'
 'Hard Drinks' 'Frozen Foods' 'Canned' 'Starchy Foods' 'Others' 'Breads'
 'Seafood']
OutletID:['OUT049' 'OUT018' 'OUT010' 'OUT013' 'OUT027' 'OUT046' 'OUT035' 'OUT019']
OutletSize:['Medium' 'Small' 'High']
LocationType:['Tier 1' 'Tier 3' 'Tier 2']
OutletType:['Supermarket Type1' 'Supermarket Type2' 'Grocery Store'
 'Supermarket Type3']
```

In [ ]:
```
#Label Encoding
from sklearn import preprocessing
for col in data.select_dtypes(include='object').columns:
  label_encoder=preprocessing.LabelEncoder()
  label_encoder.fit(data[col].unique())
  data[col]=label_encoder.transform(data[col])
  print(f"{col}:{data[col].unique()}")
```

```
FatContent:[1 2 3 0 4]
ProductType:[ 4 14 10  6  9  0 13  2  8  7  5  3 15 11  1 12]
OutletID:[7 2 0 1 4 6 5 3]
OutletSize:[1 2 0]
LocationType:[0 2 1]
OutletType:[1 2 0 3]
```

In [ ]:
```
#REMOVE OUTLIER USING IQR
data.shape
```

Out[179]:
```
(6668, 11)
```

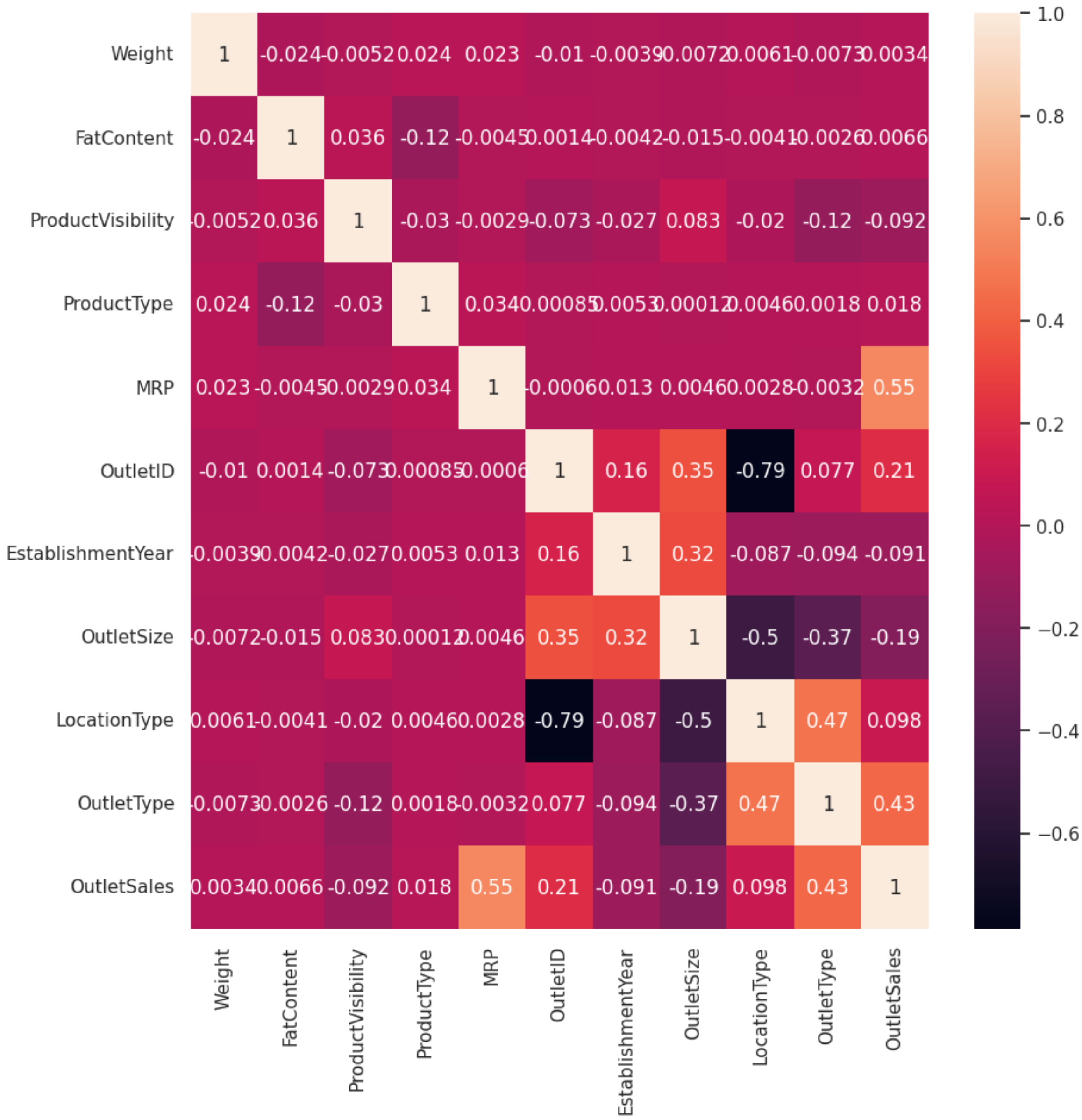
In [ ]:
```python
#Specifying the column name to remove outliers from data frame
column_names=['ProductVisibility']
#remove outliers for each selected column using IQR method
for column_name in column_names:
  q1=data[column_name].quantile(0.25)
  q3=data[column_name].quantile(0.75)
  IQR=q3-q1
  lower_bound=q1-1.5*IQR
  upper_bound=q3+1.5*IQR
  data=data[~((data[column_name]<lower_bound)|(data[column_name]>upper_bound))]
```

In [ ]:
```python
data.shape
```

Out[181]: (6535, 11)

In [ ]:
```python
#HEATMAP CORRELATION
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(),fmt='.2g',annot=True)
```

Out[182]: <Axes: >



In [ ]:
```
#TRAIN TEST SPLIT
x=data.drop("OutletSales",axis=1)
y=data["OutletSales"]
```

In [ ]:
```
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=0)
```

In [ ]:
```
#DECISION TREE REGRESSOR
import warnings
warnings.filterwarnings("ignore")
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
dtree=DecisionTreeRegressor()
param_grid={'max_depth':[2,4,6,8],'min_samples_split':[2,4,6,8],'min_samples_leaf':[1,
grid_search=GridSearchCV(dtree,param_grid,cv=5,scoring='neg_mean_squared_error')
grid_search.fit(x_train,y_train)
print(grid_search.best_params_)
```

```
{'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split':
4}
```

In [ ]:
```
dtree=DecisionTreeRegressor(max_depth=6,max_features='auto',min_samples_leaf=4,min_sam
```

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

Out[187]:
```
DecisionTreeRegressor(max_depth=6, max_features='auto', min_samples_leaf=4)
```

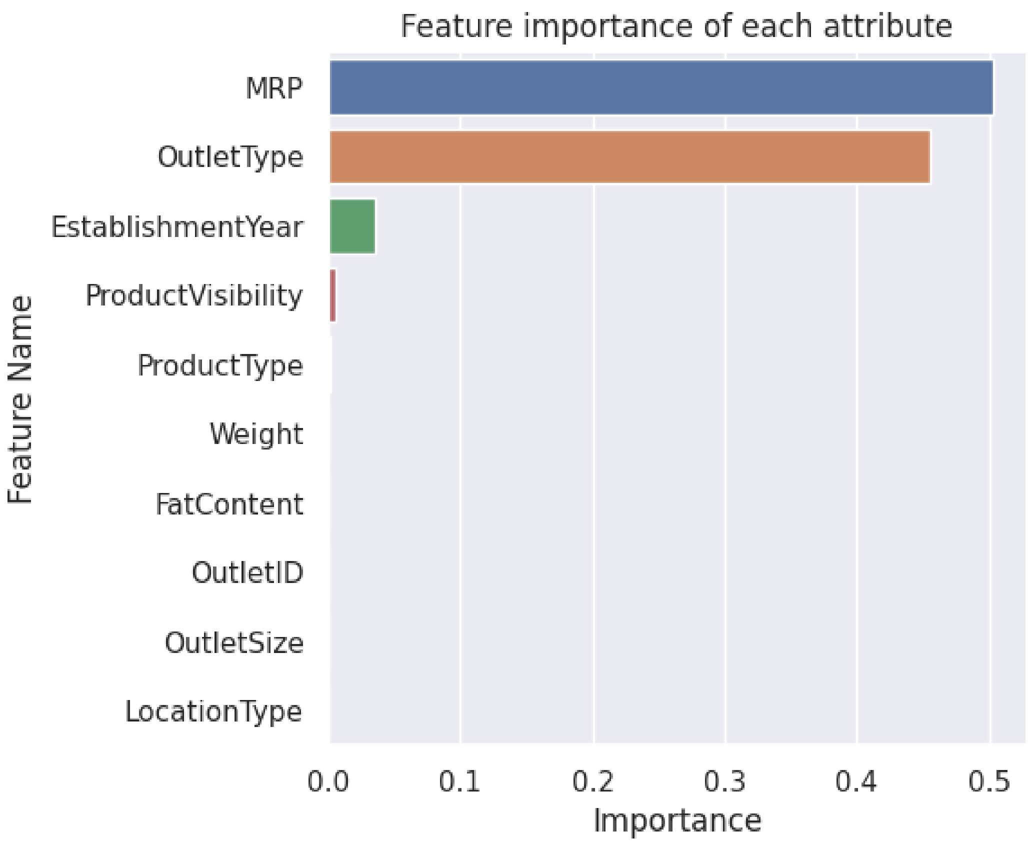
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred=dtree.predict(x_test)
mae=metrics.mean_absolute_error(y_test,y_pred)
mape=mean_absolute_percentage_error(y_test,y_pred)
mse=metrics.mean_squared_error(y_test,y_pred)
r2=metrics.r2_score(y_test,y_pred)
rmse=math.sqrt(mse)

print("MAE is {}".format(mae))
print("MAPE is {}".format(mape))
print("MSE is {}".format(mse))
print("R2 Score is {}".format(r2))
print("RMSE is {}".format(rmse))
```

```
MAE is 764.9872280051599
MAPE is 0.5784403446838259
MSE is 1245334.0275746458
R2 Score is 0.6233611975537985
RMSE is 1115.945351518006
```

```
In [ ]: imp_data=pd.DataFrame({"Feature Name":x_train.columns,"Importance":dtree.feature_impor
        fi=imp_data.sort_values(by='Importance',ascending=False)
        sns.barplot(data=fi,x="Importance",y="Feature Name")
        plt.title("Feature importance of each attribute")
        plt.xlabel("Importance")
        plt.ylabel("Feature Name")
```

```
Out[189]: Text(0, 0.5, 'Feature Name')
```




```
In [ ]: #RANDOM FOREST REGRESSOR
        from sklearn.ensemble import RandomForestRegressor
        rf=RandomForestRegressor()
        param_grid={'max_depth':[3,5,7,9],'min_samples_split':[2,5,10],'min_samples_leaf':[1,2
```

```
In [ ]: grid_search=GridSearchCV(rf,param_grid,cv=5,scoring='r2')
        grid_search.fit(x_train,y_train)
        print(grid_search.best_params_)
```

```
{'max_depth': 5, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split':
2}
```

```
In [ ]: rf=RandomForestRegressor(max_depth=5,max_features='auto',min_samples_leaf=4,min_sample
        rf.fit(x_train,y_train)
```

```
Out[193]: RandomForestRegressor(max_depth=5, max_features='auto', min_samples_leaf=4)
```

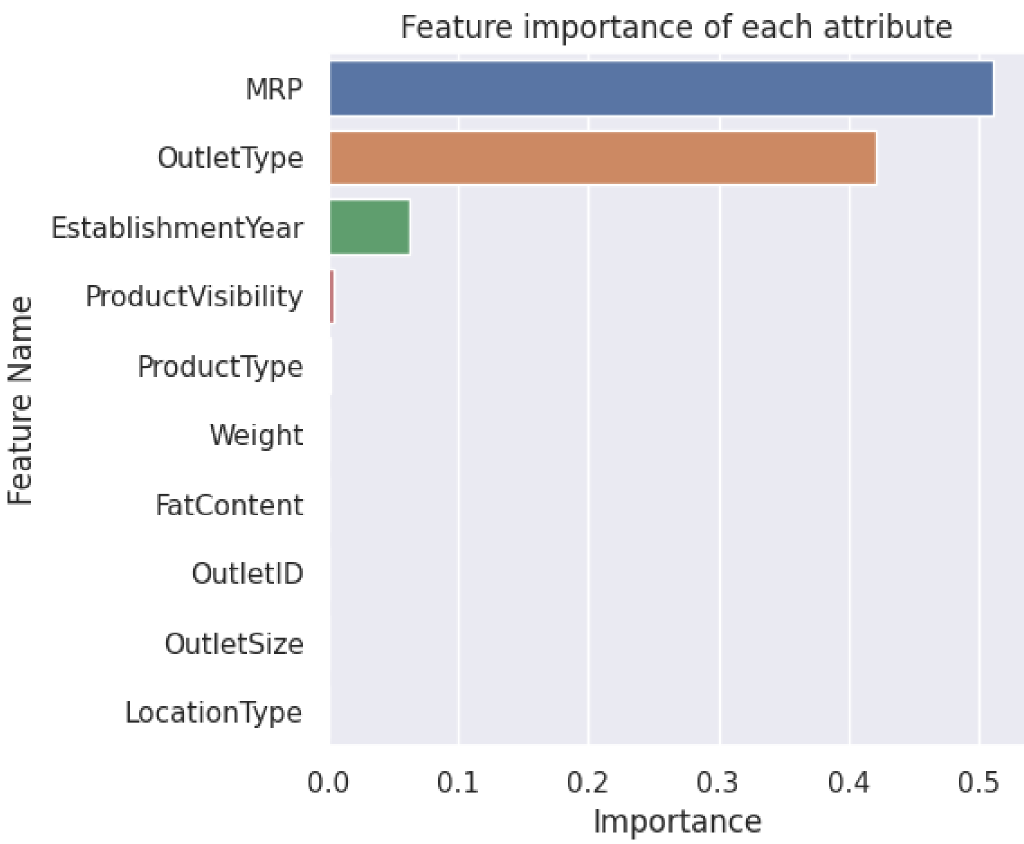
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
y_pred=rf.predict(x_test)
mae=metrics.mean_absolute_error(y_test,y_pred)
mape=mean_absolute_percentage_error(y_test,y_pred)
mse=metrics.mean_squared_error(y_test,y_pred)
r2=metrics.r2_score(y_test,y_pred)
rmse=math.sqrt(mse)

print("MAE is {}".format(mae))
print("MAPE is {}".format(mape))
print("MSE is {}".format(mse))
print("R2 Score is {}".format(r2))
print("RMSE is {}".format(rmse))
```

```
MAE is 754.7249110043322
MAPE is 0.580404147152516
MSE is 1199593.8867742838
R2 Score is 0.6371948449715281
RMSE is 1095.259734845705
```

In [ ]:
```
imp_data=pd.DataFrame({"Feature Name":x_train.columns,"Importance":rf.feature_importar
fi=imp_data.sort_values(by='Importance',ascending=False)
sns.barplot(data=fi,x="Importance",y="Feature Name")
plt.title("Feature importance of each attribute")
plt.xlabel("Importance")
plt.ylabel("Feature Name")
```

Out[195]: Text(0, 0.5, 'Feature Name')



In [ ]:
```
#XGBOOST REGRESSOR
from xgboost import XGBRegressor
xgb=XGBRegressor()
param_grid={'max_depth':[3,5,7,9],'min_child_weight':[1,3,5],'learning_rate':[0.1,0.01
grid_search=GridSearchCV(xgb,param_grid,cv=5,scoring='r2')
grid_search.fit(x_train,y_train)
print(grid_search.best_params_)
```

```
{'gamma': 0, 'learning_rate': 0.1, 'max_depth': 3, 'min_child_weight': 1}
```

In [ ]:
```
xgb=XGBRegressor(gamma=0,learning_rate=0.1,max_depth=3,min_child_weight=1)
xgb.fit(x_train,y_train)
```

Out[199]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=0, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=3, max_leaves=None,
             min_child_weight=1, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
y_pred=xgb.predict(x_test)
mae=metrics.mean_absolute_error(y_test,y_pred)
mape=mean_absolute_percentage_error(y_test,y_pred)
mse=metrics.mean_squared_error(y_test,y_pred)
r2=metrics.r2_score(y_test,y_pred)
rmse=math.sqrt(mse)

print("MAE is {}".format(mae))
print("MAPE is {}".format(mape))
print("MSE is {}".format(mse))
print("R2 Score is {}".format(r2))
print("RMSE is {}".format(rmse))
```

```
MAE is 754.4837491406836
MAPE is 0.5890650529183769
MSE is 1196676.6797329972
R2 Score is 0.6380771250202455
RMSE is 1093.9271820980578
```

In [ ]:
```
imp_data=pd.DataFrame({"Feature Name":x_train.columns,"Importance":xgb.feature_importa
fi=imp_data.sort_values(by='Importance',ascending=False)
sns.barplot(data=fi,x="Importance",y="Feature Name")
plt.title("Feature importance of each attribute")
plt.xlabel("Importance")
plt.ylabel("Feature Name")
```