MAHATMA EDUCATION SOCIETY'S

PILLAI COLLEGE OF ARTS, COMMERCE & SCIENCE
(Autonomous)

NEW PANVEL

PROJECT REPORT ON

"BIG MART SALE PREDICTION"

IN PARTIAL FULFILLMENT OF

MASTER OF **DATA ANALYTICS**

SEMESTER 1 – 2023-24

PROJECT GUIDE

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BIG MART SALES PREDICTION

Big Mart 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 of this data science project is to build a predictive model and find out the sales of each product at a particular store.
Using this model, Big Mart will try to understand the properties of products and stores which play a key role in increasing sales.
This dataset is taken from kaggle.com, the data may have missing values as some stores might not report all the data due to technical glitches. Hence, it will be required to treat them accordingly.

The Target Value is Item_Outlet_Sales.
The below table specifies the name of the columns, their data types, the feature is categorical or numerical and their description.
The dataset provides the product details and the outlet information of the products purchased with their sales value split into a train set (8523) and a test (5681) set.
Train file: CSV containing the item outlet information with sales value
Test file: CSV containing item outlet combinations for which sales need to be forecasted

Dataset link:
https://www.kaggle.com/code/mebiali01/bigmart-sales-prediction-analysis?scriptVersionId=114874761

Using the above dataset, will be performing all the Life Cycle phases of Data Science,i.e, Data Understanding, Data Preparation, Data Visualization (EDA), Data Modeling, Model Evaluation.
Business Understanding and Model Deployment are also the phases, but as this is not an industry-oriented project, hence it is not included above.

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Column Name	Data Types	Categorical/Numerical value	Description
Item_Identifier	string	Categorical	Unique product ID
Item_Weight	float	Numerical	Weight of product
Item_Fat_Content	string	Categorical	Checks the Concentration of fat in the product
Item_Visibility	float	Numerical	The % of total display area of all similar products in a store
Item_Type	string	Categorical	Category
Item_MRP	float	Numerical	Maximum Retail Price for a Product
Outlet_Identifier	string	Categorical	Store ID
Outlet_Establishment_Year	int	Numerical	The year in which store was established
Outlet_Size	string	Categorical	The size of the store (Area Size Category
Outlet_Location_Type	string	Categorical	In Terms of city Tiers (Size)
Outlet_Type	string	Categorical	Grocery store or a type of supermarket
Item_Outlet_Sales	float	Numerical	Sales of the product In the Specific outlet

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Code and Output:

Importing required in-built libraries/packages.

```
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'] = (20,10)
import warnings
warnings.filterwarnings('ignore')
```

```
mart_sales_train=pd.read_csv('/content/train.csv')
mart_sales_test=pd.read_csv('/content/test.csv')
mart_sales_train.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outlet_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	

```
mart_sales_train.tail()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outl
8518	FDF22	6.865	Low Fat	0.056783	Snack Foods	214.5218	OUT013	1987	High	
8519	FDS36	8.380	Regular	0.046982	Baking Goods	108.1570	OUT045	2002	NaN	
8520	NCJ29	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	OUT035	2004	Small	
8521	FDN46	7.210	Regular	0.145221	Snack Foods	103.1332	OUT018	2009	Medium	
8522	DRG01	14.800	Low Fat	0.044878	Soft Drinks	75.4670	OUT046	1997	Small	

```
mart_sales_train.shape, mart_sales_test.shape
```

```
((8523, 12), (5681, 11))
```

```
# test_df['Item_Outlet_Sales'] = np.nan
mart_sales_train['source'] = 'train'
mart_sales_test['source'] = 'test'
data = pd.concat([mart_sales_train, mart_sales_test],
ignore_index=True)
print('After Combining Datasets: ', data.shape)
```

```
After Combining Datasets:  (14204, 11)
```

```
mart_sales_train.info()
```

```
<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                7060 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                6113 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
```

```
mart_sales_train.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
```

```
mart_sales_train.isnull().sum()/mart_sales_train.shape[0]*100
```

```
Item_Identifier              0.000000
Item_Weight                 17.165317
Item_Fat_Content             0.000000
Item_Visibility              0.000000
Item_Type                    0.000000
Item_MRP                     0.000000
Outlet_Identifier            0.000000
Outlet_Establishment_Year    0.000000
Outlet_Size                 28.276428
Outlet_Location_Type         0.000000
Outlet_Type                  0.000000
Item_Outlet_Sales            0.000000
dtype: float64
```

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Explanation :

The output of the code will be a Series or DataFrame (depending on the structure of mart_sales_train) that shows the percentage of missing values in each column of the dataset. This information can help you identify columns with a high percentage of missing values that may require further investigation or handling, such as imputation or removal of those columns.

We have 17% and 28% null value in item_weight and outlet_size column in mar_sales_train

```
corr=mart_sales_train.corr()
sns.heatmap(corr,annot=True,cbar=False)
corr
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
Item_Weight	1.000000	-0.014048	0.027141	-0.011588	0.014123
Item_Visibility	-0.014048	1.000000	-0.001315	-0.074834	-0.128625
Item_MRP	0.027141	-0.001315	1.000000	0.005020	0.567574
Outlet_Establishment_Year	-0.011588	-0.074834	0.005020	1.000000	-0.049135
Item_Outlet_Sales	0.014123	-0.128625	0.567574	-0.049135	1.000000

Explanation :

The output of the code will be a heatmap plot that visually represents the correlation between the columns of the `mart_sales_train` dataset. This plot helps identify patterns and relationships between variables.

```
object=mart_sales_train.select_dtypes(include='object').columns
```

```
object
```

```
Index(['Item_Identifier', 'Item_Fat_Content', 'Item_Type',
'Outlet_Identifier', 'Outlet_Size', 'Outlet_Location_Type',
'Outlet_Type'], dtype='object')
```

Data Visualization

```
plt.figure(figsize=(10,20))
i=1
for col in ['Outlet_Size', 'Outlet_Location_Type','Item_Fat_Content']:
    plt.subplot(3,2,i)
    sns.countplot(x=col,data=mart_sales_train,palette='Set2')
    i+=1
    plt.subplot(3,2,i)

sns.countplot(x=col,hue='Outlet_Type',data=mart_sales_train,palette='Se
t2')
    i+=1
```

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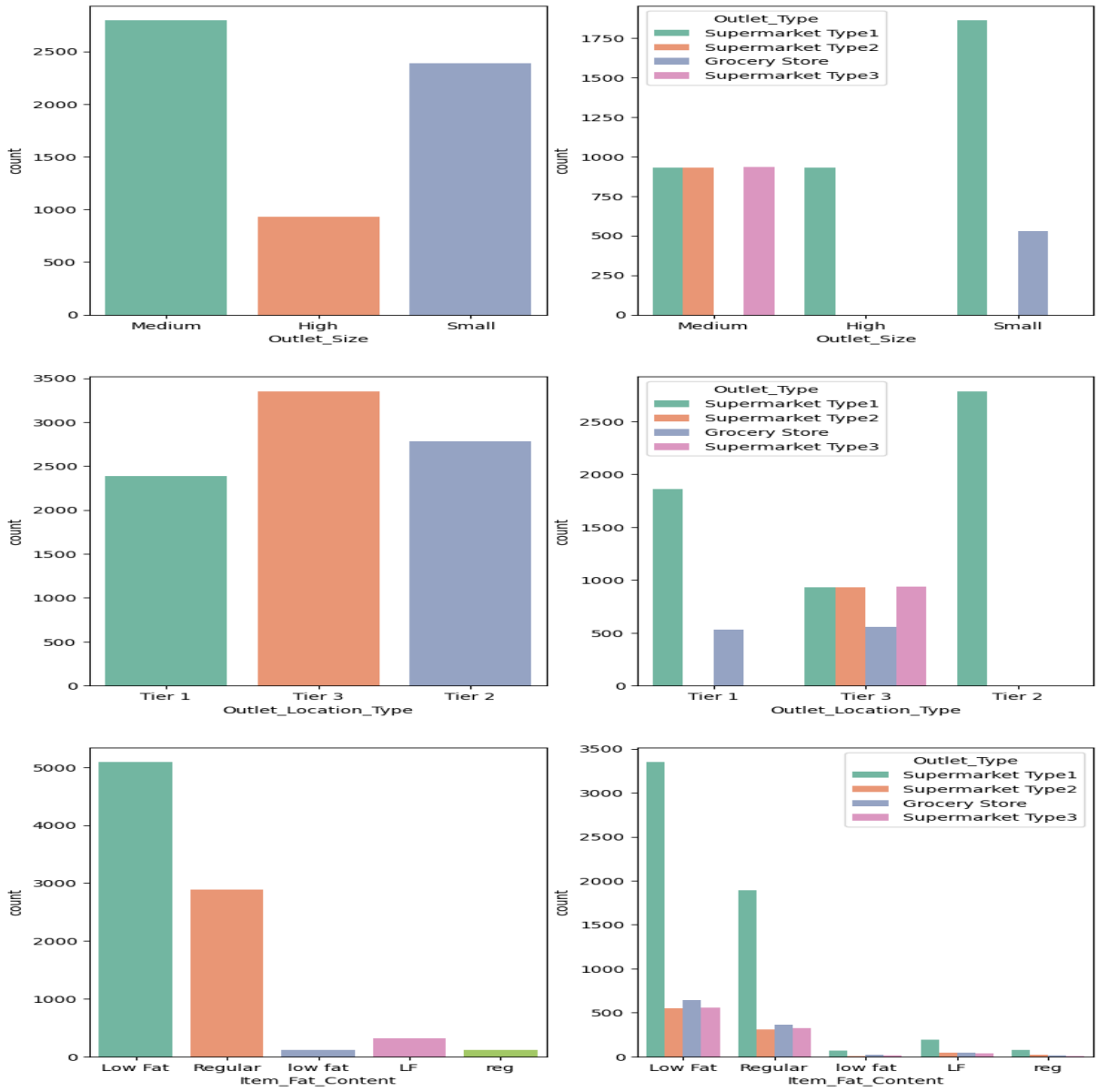
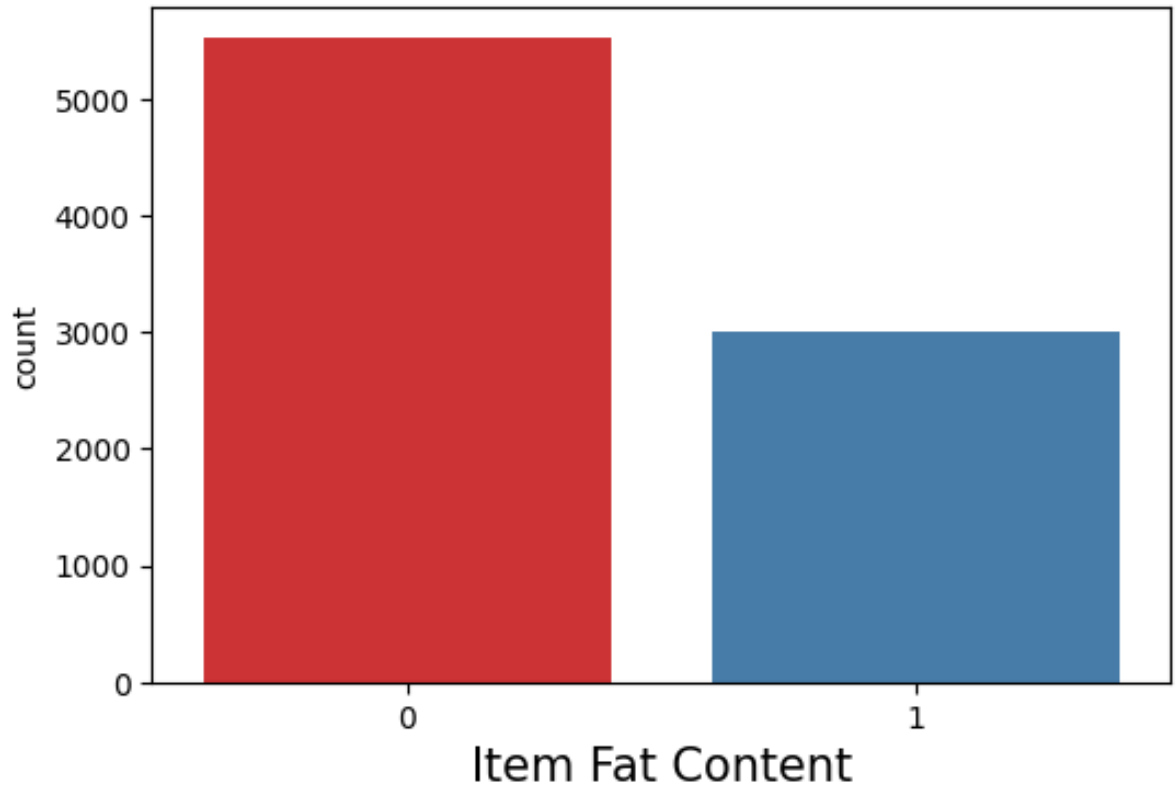


EXPLANATION

The first count plot shows the count of each unique value in the column, while the second count plot differentiates the counts based on the 'Outlet_Type' column. This visualization helps understand the distribution and relationships between the selected columns and the 'Outlet_Type' column.

```
# Categorial Data
['Item_Identifier', 'Item_Fat_Content', 'Outlet_Identifier',
'Outlet_Size',
'Outlet_Location_Type', 'Outlet_Type', 'Item_Type',
'Item_Type_Combined' ]
```

```
# CountPlot for Item_Fat_Content
plt.figure(figsize=(6,4))
sns.countplot(data=mart_sales_train,
x='Item_Fat_Content',palette='Set1')
plt.xlabel('Item Fat Content', fontsize=15)
plt.show()
```



EXPLANATION

code creates a countplot to visualize the frequency of different categories in the 'Item_Fat_Content' column of the 'mart_sales_train' dataframe.

```
# CountPlot for Individual Item Category
plt.figure(figsize=(24,6))
sns.countplot(data=mart_sales_train, x='Item_Type',  palette='Set1')
plt.xlabel('Individual Item Category ', fontsize=30)
plt.show()
```

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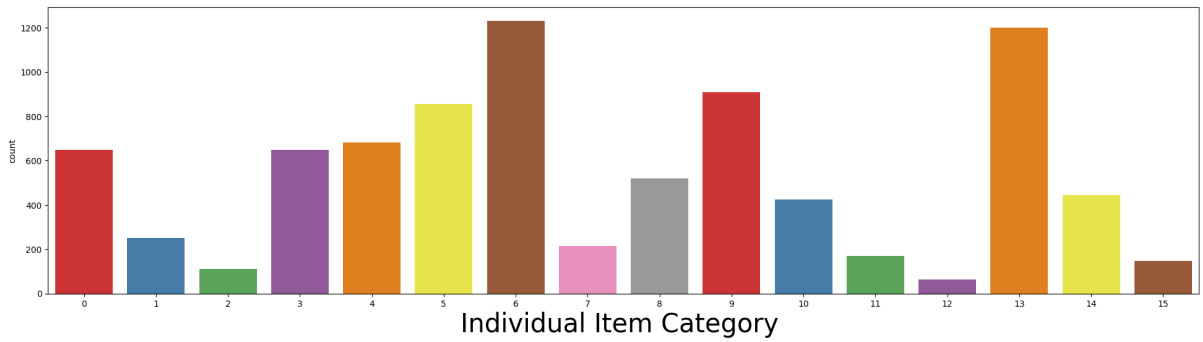
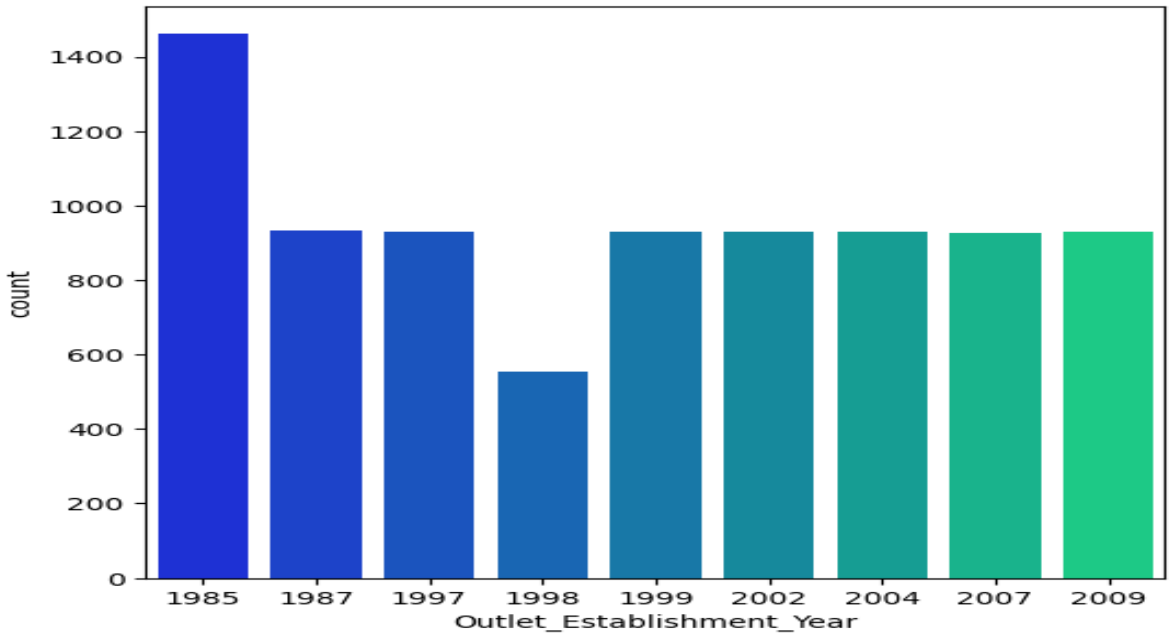


EXPLANATION

A countplot to visualize the frequency of different categories in the 'Item_Type' column of the 'mart_sales_train' dataframe. The figure size is adjusted to be larger, and the x-axis label is set to 'Individual Item Category'

```
plt.figure(figsize=(6,6))
sns.countplot(x='Outlet_Establishment_Year',
data=mart_sales_train,palette='winter')
```

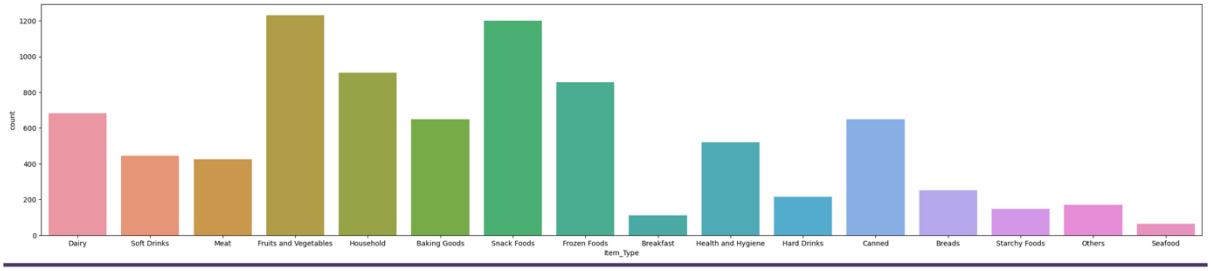


EXPLANATION

The x-axis represents the 'Outlet_Establishment_Year' column, which contains the years in which the outlets were established.

- The y-axis represents the count of occurrences for each unique value (i.e., each year) in the 'Outlet_Establishment_Year' column. This count plot helps analyze the frequency of outlet establishment years and provides insights into the distribution of sales outlets over time.

```
plt.figure(figsize=(30,6))
sns.countplot(x='Item_Type', data=mart_sales_train)
```



EXPLANATION

The x-axis represents the 'Item_Type' column, which contains the types of items sold in the sales mart. The y-axis represents the count of occurrences for each unique item type in the 'Item_Type' column. This count plot helps analyze the frequency of different item types and provides insights into the distribution of sales across various categories of products.

```
plt.figure(figsize=(15,10))
plt.subplot(3,2,1)
sns.kdeplot(x='Outlet_Establishment_Year',data=mart_sales_train,palette
='Set2')
plt.subplot(3,2,2)
sns.kdeplot(x='Item_Outlet_Sales',data=mart_sales_train,palette='Set2')
plt.subplot(3,2,3)
sns.kdeplot(x='Item_Weight',data=mart_sales_train,palette='Set2')
plt.subplot(3,2,4)
sns.kdeplot(x='Item_Visibility',data=mart_sales_train,palette='Set2')
plt.subplot(3,2,5)
sns.kdeplot(x='Item_MRP',data=mart_sales_train,palette='Set2')
```

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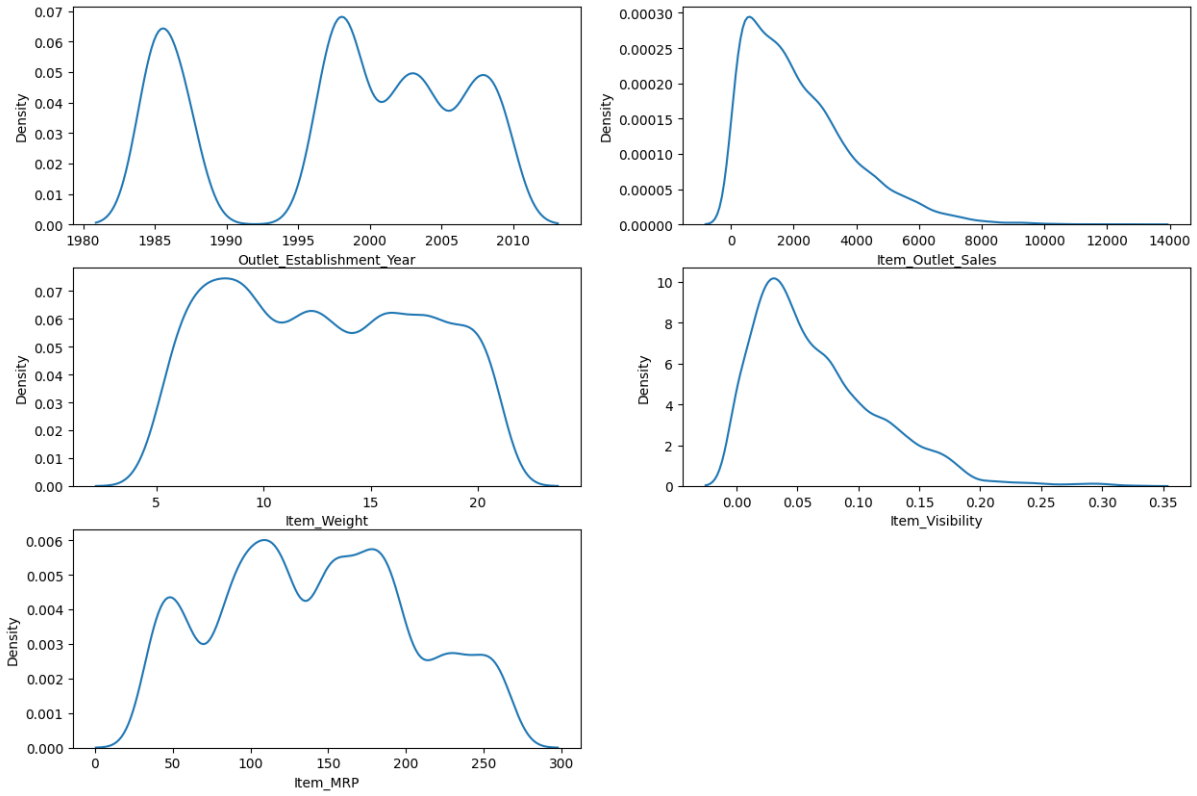

EXPLANATION

These KDE plots provide insights into the distribution and density of the selected numerical columns in the `mart_sales_train` dataset. They help identify patterns, peaks, and outliers, allowing for a better understanding of the data's characteristics.

```
mart_sales_test.isnull().sum()
```

```
Item_Identifier                 0
Item_Weight                   976
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  1606
Outlet_Location_Type            0
Outlet_Type                     0
dtype: int64
```

EXPLANATION

The output of `mart_sales_test.isnull().sum()` provides information about the presence of missing values in each column of the dataset. It helps identify columns with missing data, allowing for further investigation or appropriate handling of missing values during data preprocessing.

We have 11% and 18% null value in item_weight and outlet_size column in mar_sales_test

```
mart_sales_train.info()
```

```
<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                7060 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                6113 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
```

EXPLANATION

The output of `mart_sales_train.info()` provides a summary of the datase

The percentage of null in Item_weight column is less just 17% and 11% in train and test so we can impute the null value with mean

```
data_=pd.DataFrame(mart_sales_train.isnull().sum(),columns=['Number Of Null'])
data_['Precision']=data_['Number Of Null']/len(mart_sales_train)*100
data_
```

	Number Of Null	Precision
Item_Identifier	0	0.000000
Item_Weight	1463	17.165317
Item_Fat_Content	0	0.000000
Item_Visibility	0	0.000000
Item_Type	0	0.000000
Item_MRP	0	0.000000
Outlet_Identifier	0	0.000000
Outlet_Establishment_Year	0	0.000000
Outlet_Size	2410	28.276428
Outlet_Location_Type	0	0.000000
Outlet_Type	0	0.000000
Item_Outlet_Sales	0	0.000000

```
mart_sales_train['Item_Weight'] =
mart_sales_train['Item_Weight'].fillna(mart_sales_train['Item_Weight'].
mean())
mart_sales_test['Item_Weight'] =
mart_sales_test['Item_Weight'].fillna(mart_sales_test['Item_Weight'].me
an())
```

EXPLANATION

The percentage of null in Outlet_Size column is less just 28% and 18% in train and test and Since the outlet_size is a categorical column, we can impute the missing values by "Mode"(Most Repeated Value) from the column

```
mart_sales_train.isnull().sum()
```

```
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
```

```
mart_sales_test.isnull().sum()
```

```
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
dtype: int64
```

EXPLANATION

We have successfully removed null values from train and test

```
#Checking outliers

import seaborn as sns
plt.figure(figsize=(8,5))
sns.boxplot(x=mart_sales_train['Item_Weight'])
```

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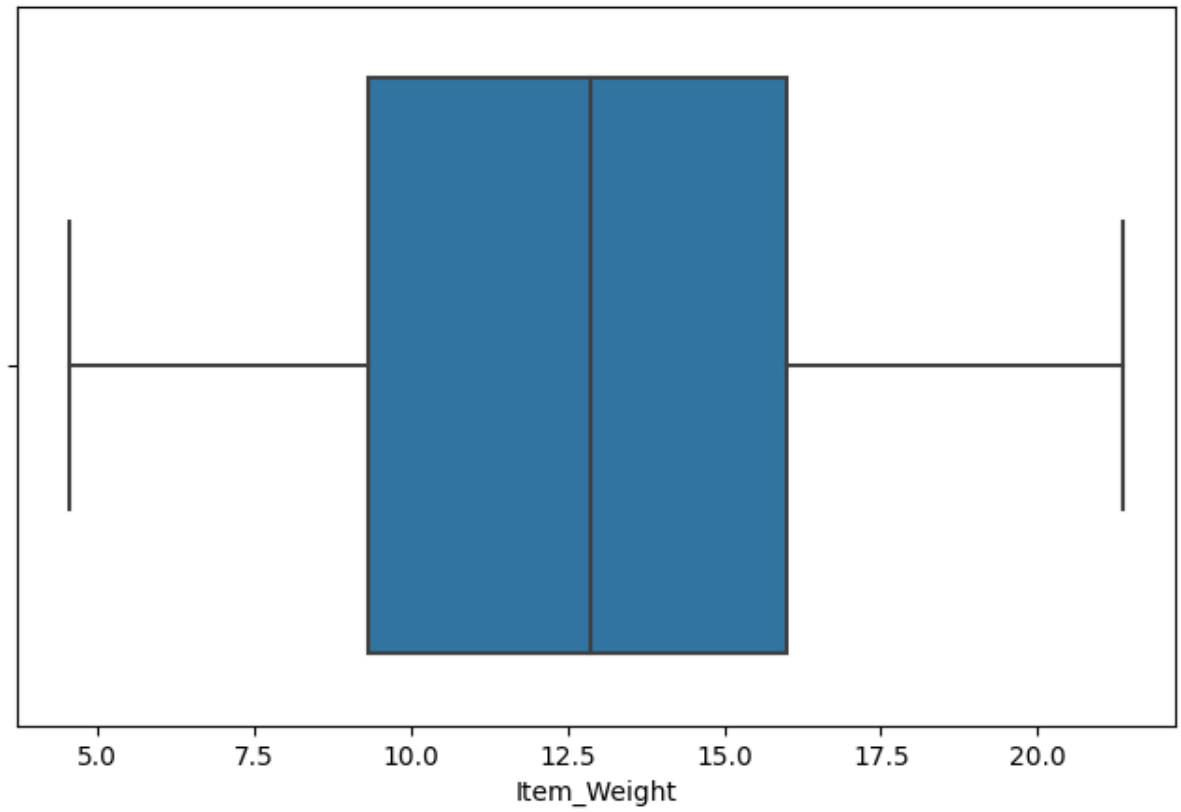

EXPLANATION

The resulting output is a boxplot visualization of the 'Item_Weight' column from the 'mart_sales_train' dataset.The box in the plot represents the interquartile range (IQR), which is the range between the 25th and 75th percentiles of the data. The line inside the box represents the median.

```
#Removing irregularities from Item_Fat_Content column
mart_sales_train['Item_Fat_Content'].unique()
```

```
array(['Low Fat', 'Regular', 'low fat', 'LF', 'reg'], dtype=object)
```

```
mart_sales_train['Item_Fat_Content'].replace(['low
fat','LF','reg'],['Low Fat','Low Fat','Regular'],inplace = True)
mart_sales_test['Item_Fat_Content'].replace(['low
fat','LF','reg'],['Low Fat','Low Fat','Regular'],inplace = True)
```

```
mart_sales_train.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
Item_Weight	8523.0	12.857645	4.226124	4.555	9.310000	12.857645	16.000000	21.350000
Item_Visibility	8523.0	0.066132	0.051598	0.000	0.026989	0.053931	0.094585	0.328391
Item_MRP	8523.0	140.992782	62.275067	31.290	93.826500	143.012800	185.643700	266.888400
Outlet_Establishment_Year	8523.0	1997.831867	8.371760	1985.000	1987.000000	1999.000000	2004.000000	2009.000000
Item_Outlet_Sales	8523.0	2181.288914	1706.499616	33.290	834.247400	1794.331000	3101.296400	13086.964800

```
#Encode Categorical Data in both test and train
# Encoding train

from sklearn.preprocessing import LabelEncoder
for col in mart_sales_train.columns:
    if mart_sales_train[col].dtype == 'object':
        lbl=LabelEncoder()
        lbl.fit(list(mart_sales_train[col].values))

mart_sales_train[col]=lbl.transform(mart_sales_train[col].values)

# Encoding test

for coll in mart_sales_test.columns:
    if mart_sales_test[coll].dtype == 'object':
        lbl=LabelEncoder()
        lbl.fit(list(mart_sales_test[coll].values))

mart_sales_test[coll]=lbl.transform(mart_sales_test[coll].values)
```

EXPLANATION

The output of this code is that the categorical variables in both the 'mart_sales_train' and 'mart_sales_test' datasets are encoded using the LabelEncoder. The categorical values are replaced with their corresponding numerical representations.

```
#Spliting data by train_test_split
x=mart_sales_train.drop('Item_Outlet_Sales',axis=1)
y=mart_sales_train['Item_Outlet_Sales']
```

EXPLANATION

The resulting output is that the data has been split into input features (x) and the target variable (y). The input features (x) will contain all the columns except for the 'Item_Outlet_Sales' column, while the target variable (y) will contain only the values from the 'Item_Outlet_Sales' column.

```
#Scaling Data

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.20,
random_state=0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

EXPLANATION

The resulting output is that the input features (x_train and x_test) are scaled using the StandardScaler.It helps to normalize the features and bring them to a similar scale, preventing certain features from dominating others based on their magnitude.

```
#Model Training and Testing
from sklearn.linear_model import LinearRegression #Linear regression is
a simple linear model that fits a line to the data.
from sklearn.ensemble import
AdaBoostRegressor,GradientBoostingRegressor,RandomForestRegressor#These
are ensemble methods that combine multiple weak models (e.g., decision
trees) to create a stronger regression model.
from sklearn.tree import DecisionTreeRegressor#Decision trees are non-
linear models that partition the feature space into regions to make
predictions.
from sklearn.neighbors import KNeighborsRegressor# K-nearest neighbors
is a non-parametric regression algorithm that predicts the target value
based on the average of the k nearest neighbors in the feature space
from xgboost import XGBRFRegressor#XGBoost is an optimized
implementation of gradient boosting, which is a powerful ensemble
method for regression tasks.
```

```
lr=LinearRegression()
```

```
knn = KNeighborsRegressor(n_neighbors=10)

dt = DecisionTreeRegressor(max_depth = 3)

rf = RandomForestRegressor(max_depth = 3, n_estimators=500)

ada = AdaBoostRegressor( n_estimators=50, learning_rate =.01)

gbr = GradientBoostingRegressor(max_depth=2, n_estimators=100,
learning_rate =.2)
```

EXPLANATION

The output of this code is that instances of the LinearRegression, KNeighborsRegressor, DecisionTreeRegressor, RandomForestRegressor, AdaBoostRegressor, and GradientBoostingRegressor models are created with specific hyperparameters. These instances can be used to train and test regression models on the data.

```
#Testing with linear regression

lr = LinearRegression()
lr.fit(x_train,y_train)

y_pred = lr.predict(x_test)
from sklearn.metrics import r2_score
r1 = r2_score(y_test,y_pred)
r1
```

```
0.5105951012871442
```

EXPLANATION

The output of this code is that the linear regression model is trained on the training data, and then used to predict the target variable on the testing data.

```
#Testing with KNeighborsRegressor

knn = KNeighborsRegressor(n_neighbors=10)
knn.fit(x_train,y_train)

y_pred = knn.predict(x_test)
from sklearn.metrics import r2_score,mean_absolute_error
r2 = r2_score(y_test,y_pred)
r2
```

```
0.5612992412263934
```

EXPLANATION

The output of this code is that the K-nearest neighbors regression model is trained on the training data, and then used to predict the target variable on the testing data. The R-squared score (`r2`) is calculated to evaluate the performance of the model.

```
#Testing with DecisionTreeRegressor

dt = DecisionTreeRegressor(max_depth = 3)
dt.fit(x_train,y_train)

y_pred = dt.predict(x_test)
from sklearn.metrics import r2_score
r3 = r2_score(y_test,y_pred)
r3
```

```
0.5373350141246751
```

EXPLANATION

The R-squared score ranges from 0 to 1, where a score of 1 indicates a perfect fit, and
a score of 0 indicates no linear relationship between the input features and the target variable. The Decision Tree regression model is trained on the training data, and then used to predict the target variable on the testing data. The R-squared score (`r3`) is calculated to evaluate the performance of the model

```
#Testing with RandomForestRegressor

rf = RandomForestRegressor(max_depth = 3, n_estimators=500)
rf.fit(x_train,y_train)

y_pred = rf.predict(x_test)
from sklearn.metrics import r2_score
r4 = r2_score(y_test,y_pred)
r4
```

```
0.5505118953347935
```

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EXPLANATION

The code provided is used to test a Random Forest regression model on the testing data and calculate the R-squared score, which is a measure of how well the model fits the data.

```
#Testing with AdaBoostRegressor

ada = AdaBoostRegressor( n_estimators=50, learning_rate =.01)
ada.fit(x_train,y_train)

y_pred = ada.predict(x_test)
from sklearn.metrics import r2_score
r5 = r2_score(y_test,y_pred)
r5
```

```
0.5344972153083329
```

EXPLANATION

The AdaBoostRegressor algorithm to build a regression model, trains it on the training data, makes predictions on the test data, and evaluates the model's performance using the R-squared (R2) score, which quantifies how well the model explains the variance in the target variable.

```
#Testing with GradientBoostingRegressor

gbr = GradientBoostingRegressor(max_depth=2, n_estimators=100,
learning_rate =.2)
gbr.fit(x_train,y_train)

y_pred = gbr.predict(x_test)
from sklearn.metrics import r2_score
r6 = r2_score(y_test,y_pred)
r6
```

```
0.5914711773741286
```

EXPLANATION

The GradientBoostingRegressor algorithm to build a regression model, trains it on the training data, makes predictions on the test data, and evaluates the model's performance.The resulting R2 score is stored in the variable r6.

```
#Model Results
```

```
metric_results= {'Model': ['linear Regression', 'KNeighbors', 'Decision
Tree','RandomForest','AdaBoost','GradientBoosting'],
                 'R Square': [r1, r2, r3,r4,r5,r6]}
metrics= pd.DataFrame(metric_results)
metrics
```

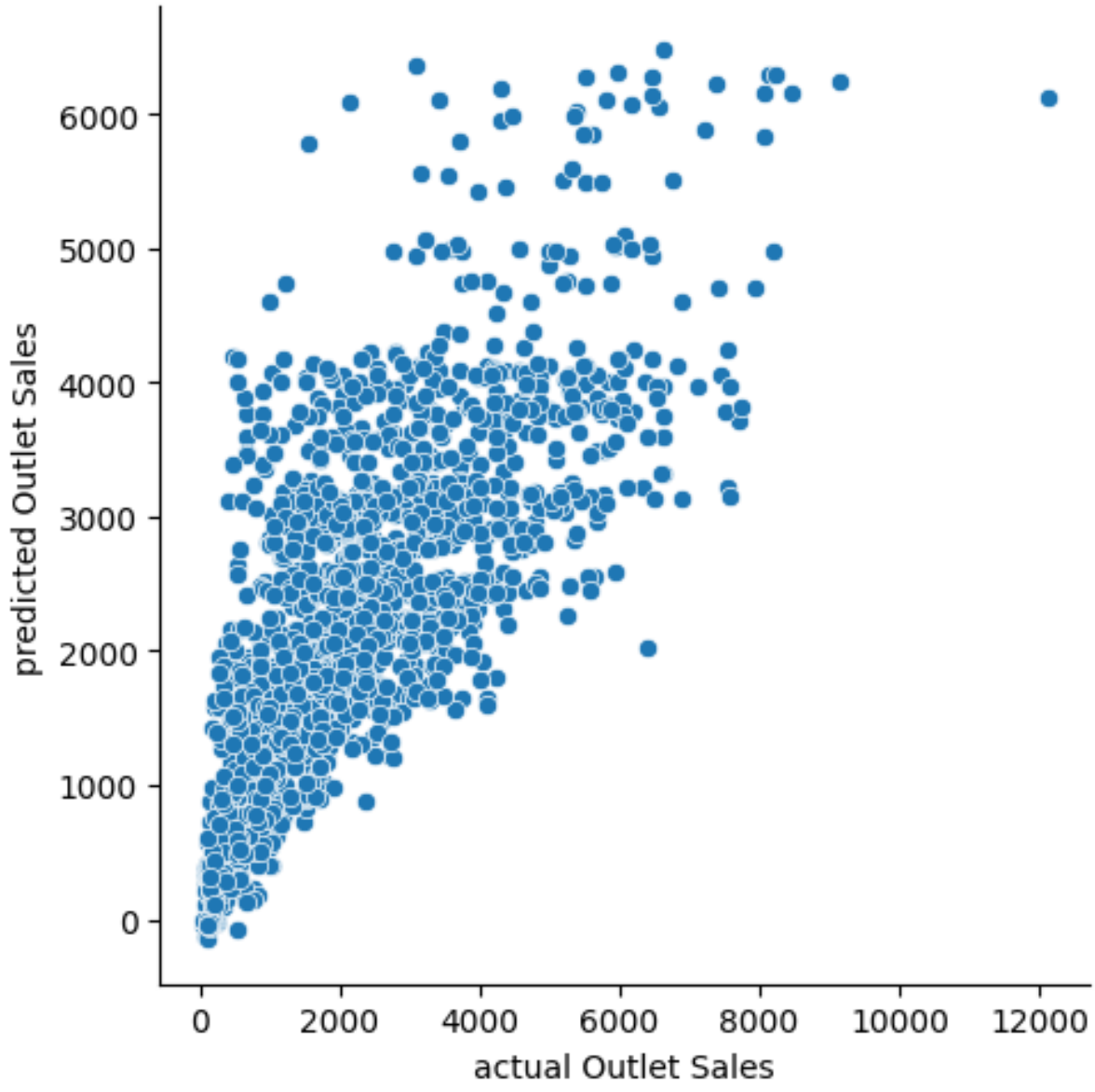
	Model	R Square
0	linear Regression	0.510595
1	KNeighbors	0.561299
2	Decision Tree	0.537335
3	RandomForest	0.550512
4	AdaBoost	0.534497
5	GradientBoosting	0.591471

EXPLANATION

These R2 values give you insights into how well each model is performing in explaining the variance in the target variable. A higher R2 value indicates that the model is better at capturing and explaining the variability in your data. In this case, the GradientBoosting model has the highest R2 value, suggesting that it provides the best fit among the models evaluated.

```
#plotting model
prediction= pd.DataFrame({'actual Outlet Sales': y_test, 'predicted
Outlet Sales': y_pred})#This column holds the actual (ground truth)
```

```
values of Outlet Sales from your test dataset. These are the real
values you want to predict using your regression model.
sns.relplot(data=prediction, x='actual Outlet Sales', y='predicted
Outlet Sales')#This column contains the predicted values of Outlet
Sales generated by your GradientBoosting regression model (y_pred) for
the same set of data points used in the test dataset.
```



EXPLANATION

The resulting scatter plot will show individual points where each point represents a data instance. The x-coordinate of each point corresponds to the actual outlet sales, and the y-coordinate corresponds to the predicted outlet sales

CONCLUSION

In this project the effectiveness In this case, the GradientBoosting model has the highest R2 value, suggesting that it provides the best fit among the models evaluated.

FUTURE SCOPE

In future the forecasting sales and building a sales plan can help to avoid unforeseen cash flow and manage production, staff and financing need more effectively. In future work we can also consider with the ARIMA model which shows the time series graph.