Technocolabs Softwares Internship Task I

BigMart Sales Prediction

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1. Problem Statement

The data scientists at BigMart 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.

Statement Analysis

- Supervised Machine Learning Problem.
- The Target Value is **Item_Outlet_Sales.**

Exploring business problem

BigMart, a supermarket with multiple store branches, aims to forecast the sales of any product at any branch in order to achieve financial benefits such as optimal inventory management, efficient resource allocation, effective marketing and promotions, and many other financial benifits.

Goal

Using this model, BigMart will try to understand the properties of products and stores which play a key role in increasing sales.

This dataset is named **BigMart Sales**. The dataset contains a set of 8,523 records under 12 attributes:

Column Name and their Description

- **Item_Identifier:** Unique product ID
- **Item_Weight :** Weight of product
- **Item_Fat_Content :** Checks the Concentration of fat in the product
- **Item_Visibility :** The % of total display area of all similar products in a store
- **Item_Type:** Category
- **Item_MRP :** Maximum Retail Price for a Product
- **Outlet_Identifier :** Store ID
- **Outlet_Establishment_Year :**The year in which store was established
- **Outlet_Size :**The size of the store (Area Size Category)
- **Outlet_Location_Type :**In Terms of city Tiers (Size)
- **Outlet_Type :**Grocery store or a type of supermarket
- **Item_Outlet_Sales :** Sales of the product In the Specific outlet

2. Hypothesis Generation Using Product, Store and City

1. **City Type:** Stores located in urban should have higher Sales.
2. **Store Location:** Store located in popular market place shoud have higher Sales
3. **Populted City:** City with high population should have higher Sales.
4. **Store Size**: Stores with large size should have higher Sales.
5. **Staff**: Stores with more staff should have higher Sales.
6. **Branded Products**: Branded Products will have higher Sales.
7. **Product Visbility**: Products with large space should have higher Sales.
8. **Product Frequency**: More frequnct products will have high Sales.
9. **Utilities**: Daily Basic Products should have higher Sales.
10. **Promotional Offers**: Promo Products should have higher Sales.

3. Loading Packages, Libraries and Dataset

```
import numpy as np # linear algebra
import pandas as pd # data processing
import warnings  # warning filter
import matplotlib.pyplot as plt # Data visulization
import matplotlib.colors # Data visulization
import seaborn as sns # Data visulization
%matplotlib inline

#train test split
from sklearn.model_selection import train_test_split

#feature engineering
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import RobustScaler

#metrics
from sklearn.metrics import mean_absolute_error as MAE
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import r2_score as R2

#ML models
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import RandomizedSearchCV

# Cross Validation
from sklearn.model_selection import cross_val_score as CVS

#warning hadle
warnings.filterwarnings("always")
warnings.filterwarnings("ignore")
```

```
#path for the training set
train_path = "/content/Train.csv"
#path for the testing set
test_path = "/content/Test.csv"
```

```
# Reading Dataset Train.csv
train = pd.read_csv(train_path)
train.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0
4	NCD19	8.93	Low Fat	0.000000	Household	53.8

```
# Reading Dataset Test.csv
test = pd.read_csv(test_path)
test.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDW58	20.750	Low Fat	0.007565	Snack Foods	107.8
1	FDW14	8.300	reg	0.038428	Dairy	87.3
2	NCN55	14.600	Low Fat	0.099575	Others	241.7

```
# Rows and columns
print(f'Training Dataset (row, col): {train.shape} \n\nTesting Dataset (row, col): {test.shape}')
```

```
Training Dataset (row, col): (8523, 12)

Testing Dataset (row, col): (5681, 11)
```

```
# Combine Both DataSets since both are Similiar
train['source'] = 'train'
test['source'] = 'test'
data = pd.concat([train, test], ignore_index=True)
print('After Combining Datasets: ', data.shape)
```

```
After Combining Datasets:  (14204, 13)
```

```
data.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14204 entries, 0 to 14203
Data columns (total 13 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Item_Identifier            14204 non-null  object
 1   Item_Weight                11765 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                10188 non-null  object
 9   Outlet_Location_Type       14204 non-null  object
 10  Outlet_Type                14204 non-null  object
 11  Item_Outlet_Sales          8523 non-null   float64
 12  source                     14204 non-null  object
dtypes: float64(4), int64(1), object(8)
memory usage: 1.4+ MB
```

```
# Summary of Dataset Train
data.describe(include=[object, np.number]).T
```

	count	unique	top	freq	mean	std
Item_Identifier	14204	1559	FDU15	10	NaN	NaN
Item_Weight	11765.0	NaN	NaN	NaN	12.792854	4.652502
Item_Fat_Content	14204	5	Low Fat	8485	NaN	NaN
Item_Visibility	14204.0	NaN	NaN	NaN	0.065953	0.051459
Item_Type	14204	16	Fruits and Vegetables	2013	NaN	NaN
Item_MRP	14204.0	NaN	NaN	NaN	141.004977	62.086938
Outlet_Identifier	14204	10	OUT027	1559	NaN	NaN
Outlet_Establishment_Year	14204.0	NaN	NaN	NaN	1997.830681	8.371664
Outlet_Size	10188	3	Medium	4655	NaN	NaN
Outlet_Location_Type	14204	3	Tier 3	5583	NaN	NaN
Outlet_Type	14204	4	Supermarket Type1	9294	NaN	NaN
Item_Outlet_Sales	8523.0	NaN	NaN	NaN	2181.288914	1706.499616
source	14204	2	train	8523	NaN	NaN

4. Data Exploration

The steps which are involved to understand, clean and prepare the data for building the predictive model:

- Missing values treatment
- Variable Identification
- Univariate Analysis
- Bi-variate Analysis
- Outlier treatment
- Variable transformation
- Variable creation

Missing Values

```
# Total number of missing values and percent of it.
total = data.isnull().sum().sort_values(ascending = False)
percent = (data.isnull().sum()/data.isnull().count()*100).sort_values(ascending = False)
missing_data  = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data
```

	Total	Percent
Item_Outlet_Sales	5681	39.995776
Outlet_Size	4016	28.273726
Item_Weight	2439	17.171219
Item_Identifier	0	0.000000
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_Location_Type	0	0.000000
Outlet_Type	0	0.000000
source	0	0.000000

```
# Check and imputate missing values
print('Missing Values in Outlet_Size :\n',data.Outlet_Size.value_counts())
print('\nMissing Values in Item_Weight :\n',data.Item_Weight.value_counts())
```

```
Missing Values in Outlet_Size :
 Medium    4655
Small     3980
High      1553
Name: Outlet_Size, dtype: int64

Missing Values in Item_Weight :
 17.600    135
12.150    127
10.500    123
13.650    115
11.800    113
         ...
7.640       7
5.905       7
7.850       6
4.615       6
9.035       6
Name: Item_Weight, Length: 415, dtype: int64
```

Outlet_Size is a catogerical column, **mode** can be used to fill the values.

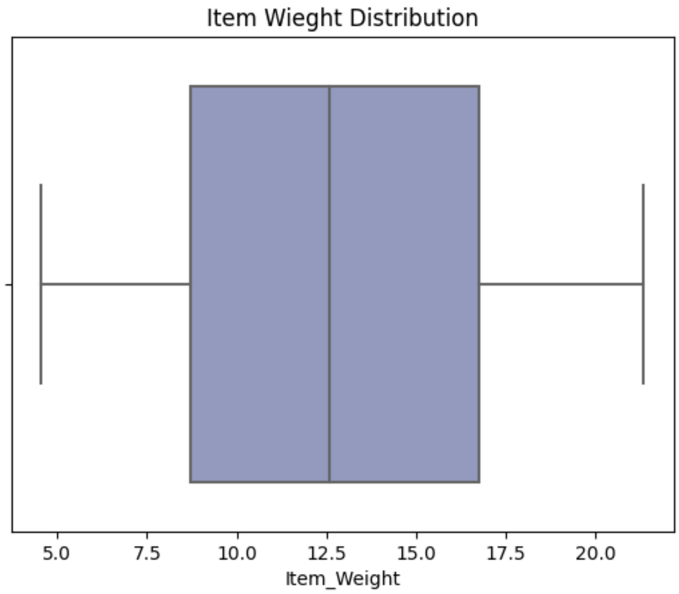
```
# Filling Outlet Size missing values
print('Missing Values in Outlet_Size: ', len(data[data.Outlet_Size.isnull()]))
miss_values = data.Outlet_Size.isnull()
O_Size_avg = data.pivot_table(values='Outlet_Size', index='Outlet_Type', aggfunc=(lambda x: x.mode()[0]))
data.loc[miss_values, 'Outlet_Size'] = data.loc[miss_values, 'Outlet_Type'].apply(lambda x:O_Size_avg.loc[x])

# Checking if all values are filled
print('Missing values after filling: ' , sum(data['Outlet_Size'].isnull()))
```

```
Missing Values in Outlet_Size:  4016
Missing values after filling:  0
```

Item_weight is a numeric column, we need to **visulize** the its values/distribution to see clearly.

```
sns.boxplot(x=data['Item_Weight'], palette='BuPu')
plt.title('Item Wieght Distribution')
```

```
Text(0.5, 1.0, 'Item Wieght Distribution')
```



No **Outliers** in **Item_wieght**, So **missing values** can be replaced with its mean

```
# Imputate missing values in item weight
print('Missing Values in Item_Weight: ', len(data[data.Item_Weight.isnull()]))
miss_values = data.Item_Weight.isnull()
item_wt_avg = data.pivot_table(values='Item_Weight', index ='Item_Identifier')
data.loc[miss_values, 'Item_Weight'] = data.loc[miss_values, 'Item_Identifier'].apply(lambda x:item_wt_avg.loc[x])

# Checking if all values are filled
print('Missing values after filling: ' , sum(data['Item_Weight'].isnull()))
```

```
Missing Values in Item_Weight:  2439
Missing values after filling:  0
```

```
# Check info for missing values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14204 entries, 0 to 14203
Data columns (total 13 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          8523 non-null   float64
 12  source                     14204 non-null  object 
dtypes: float64(4), int64(1), object(8)
memory usage: 1.4+ MB
```

Variable Identification

```
# Numerical
num_df = data.select_dtypes('number')
```

```
# Categorial
cat_df = data.select_dtypes('object')


# Dealing with catgorial data first
for col in cat_df.columns:
    if(col != 'Item_Identifier'):
        print('\nFrequency of Categories for varible %s'%col)
        print('\nTotal Categories: ', len(cat_df[col].value_counts()), '\n', cat_df[col].value_counts())
```

```
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
Name: Item_Type, dtype: int64

Frequency of Categories for varible Outlet_Identifier

Total Categories:  10
 OUT027    1559
OUT013    1553
OUT049    1550
OUT046    1550
OUT035    1550
OUT045    1548
OUT018    1546
OUT017    1543
OUT010     925
OUT019     880
Name: Outlet_Identifier, dtype: int64

Frequency of Categories for varible Outlet_Size

Total Categories:  3
 Small     7996
Medium    4655
High      1553
Name: Outlet_Size, dtype: int64

Frequency of Categories for varible Outlet_Location_Type

Total Categories:  3
 Tier 3    5583
Tier 2    4641
Tier 1    3980
Name: Outlet_Location_Type, dtype: int64

Frequency of Categories for varible Outlet_Type

Total Categories:  4
 Supermarket Type1    9294
Grocery Store        1805
Supermarket Type3    1559
Supermarket Type2    1546
Name: Outlet_Type, dtype: int64

Frequency of Categories for varible source

Total Categories:  2
 train    8523
test     5681
Name: source, dtype: int64
```

- **Item_Fat_Content**: Has **reapted values** in , replace them
- **Item_Type**: Has categories of **items**, that can be shrinked
- **Outlet_Type**: Has Store **type2**,and **type3**, that can be combined

```
# Replace reapted values in Item_Fat_Content
data['Item_Fat_Content'] = data.Item_Fat_Content.replace(['LF', 'low fat', 'reg'],
                                                          ['Low Fat','Low Fat', 'Regular'])
data.Item_Fat_Content.value_counts()
```

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

Combine Item_Type, as we have 16 catgories, but **Item_identifier ID** has first two charachters defining the item type, these are **FD**, **DR**, **NC** means food, Drinks, Non-Consumables.

Convert Item_Type into these 3 categories

```
# Combine Item_Type, and create new category
data['Item_Type_Combined'] = data.Item_Identifier.apply(lambda x:x[0:2])
data['Item_Type_Combined'] = data['Item_Type_Combined'].replace(['FD','DR','NC'],
                                                                 ['Food','Drinks', 'Non-Consumable'])

data.Item_Type_Combined.value_counts()
```

```
Food              10201
Non-Consumable     2686
Drinks             1317
Name: Item_Type_Combined, dtype: int64
```

Store has Types, **type2** and **Type3**, we can combine them, but it is to be first checked.

Check their sales, if both have approx. similier sales, we can combine them.

```
data.pivot_table(values='Item_Outlet_Sales', index='Outlet_Type')
```

Outlet_Type	Item_Outlet_Sales
Grocery Store	339.828500
Supermarket Type1	2316.181148
Supermarket Type2	1995.498739
Supermarket Type3	3694.038558

There is a huge difference in sales, so not good idea to combine them.

```
# Lets deal with Numerical Data
num_df.describe()
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_(
count	14204.000000	14204.000000	14204.000000	14204.000000	
mean	12.793380	0.065953	141.004977	1997.830681	
std	4.651716	0.051459	62.086938	8.371664	
min	4.555000	0.000000	31.290000	1985.000000	
25%	8.710000	0.027036	94.012000	1987.000000	
50%	12.600000	0.054021	142.247000	1999.000000	
75%	16.750000	0.094037	185.855600	2004.000000	
max	21.350000	0.328391	266.888400	2009.000000	

- **Item_Visibility**: It has min **0** value, which makes no sense
- **Outlet_Establishment_Year**: It's better to address how old store is

Outliers

```
# Box plot for Item_Outlet_Sales to see outliers
sns.boxplot(x=data['Item_Outlet_Sales'], palette='BuPu')
plt.title('Item Outlet Sales Distribution')
```

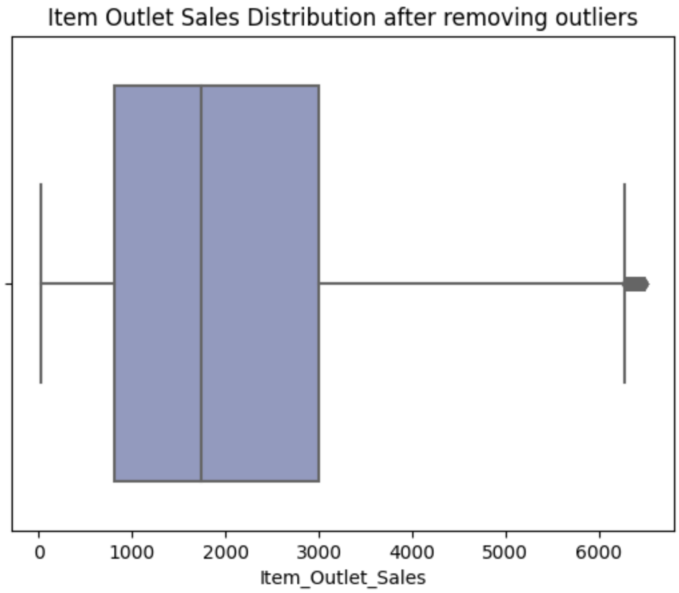
```
Text(0.5, 1.0, 'Item Outlet Sales Distribution')
```


```
# Removing Outliers
def outliers(df, feature):
    Q1= df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    upper_limit = Q3 + 1.5 * IQR
    lower_limit = Q1 - 1.5 * IQR
    return upper_limit, lower_limit

upper, lower = outliers(data, "Item_Outlet_Sales")
print("Upper whisker: ",upper)
print("Lower Whisker: ",lower)
data = data[(data['Item_Outlet_Sales'] > lower) & (data['Item_Outlet_Sales'] < upper)]
```

```
Upper whisker:  6501.8699
Lower Whisker:  -2566.3261
```

```
# Item_Outlet_Sales after removing Outliers
sns.boxplot(x=data['Item_Outlet_Sales'], palette='BuPu')
plt.title('Item Outlet Sales Distribution after removing outliers')
```

```
Text(0.5, 1.0, 'Item Outlet Sales Distribution after removing outliers')
```




```
# Change Establishment_Year to Outlet_Age
data['Oultet_Age'] = 2013 - data['Outlet_Establishment_Year']
```

```
# Consider 0 as missing value in Item_visibility
print('Missing Values in Item_Visibility: ', len(data[num_df['Item_Visibility'] == 0]))
miss_values = (data['Item_Visibility'] == 0)
item_vis_avg = data.pivot_table(values='Item_Visibility', index ='Item_Identifier')

data.loc[miss_values, 'Item_Visibility'] = data.loc[miss_values, 'Item_Identifier'].apply(lambda x:item_vis_avg.loc[x])
print('Missing values after filling: ' , sum(data['Item_Visibility'].isnull()))
```

```
Missing Values in Item_Visibility:  512
Missing values after filling:  0
```

```
data.head()
```

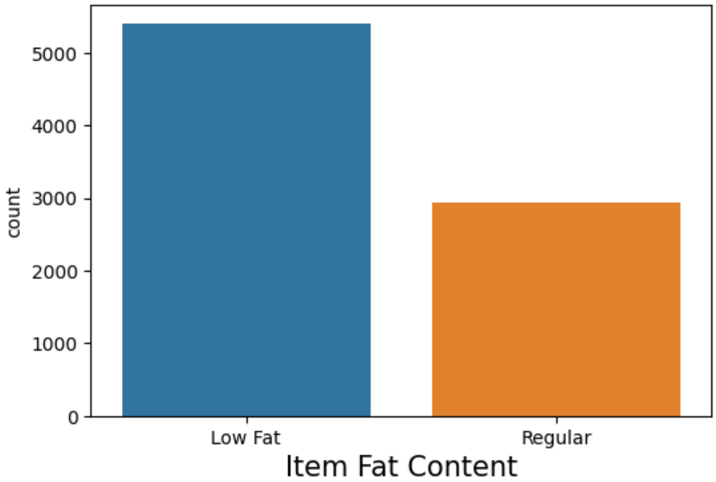
	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6
3	FDX07	19.20	Regular	0.015274	Fruits and Vegetables	182.0

5. Data Visualization

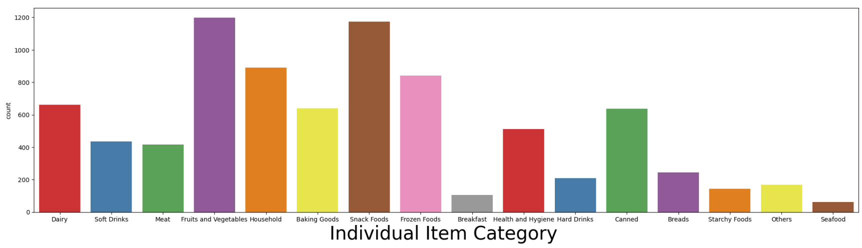
Univariate Plots

Countplots for categorial data

```
# 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=data, x='Item_Fat_Content')
plt.xlabel('Item Fat Content', fontsize=15)
plt.show()
```

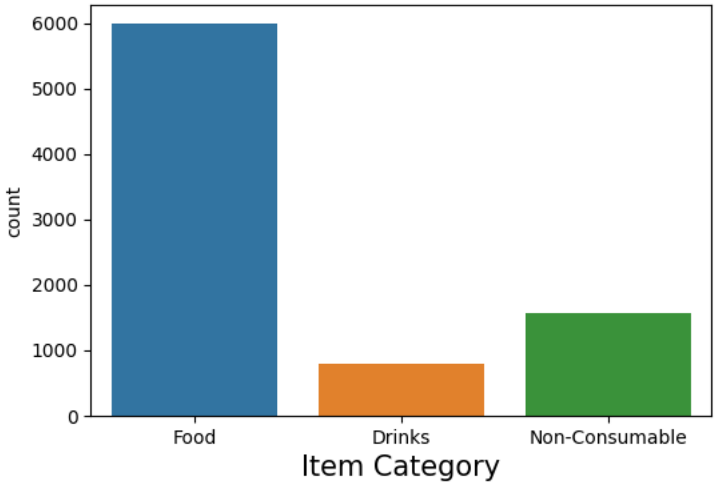



```
# CountPlot for Individual Item Category
plt.figure(figsize=(24,6))
sns.countplot(data=data, x='Item_Type',  palette='Set1')
plt.xlabel('Individual Item Category ', fontsize=30)
plt.show()
```

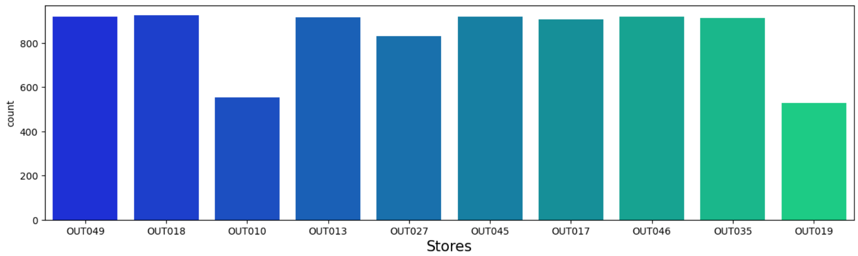



```
#  CountPlot for Item_Type_Combined
plt.figure(figsize=(6,4))
sns.countplot(data=data, x='Item_Type_Combined')
```

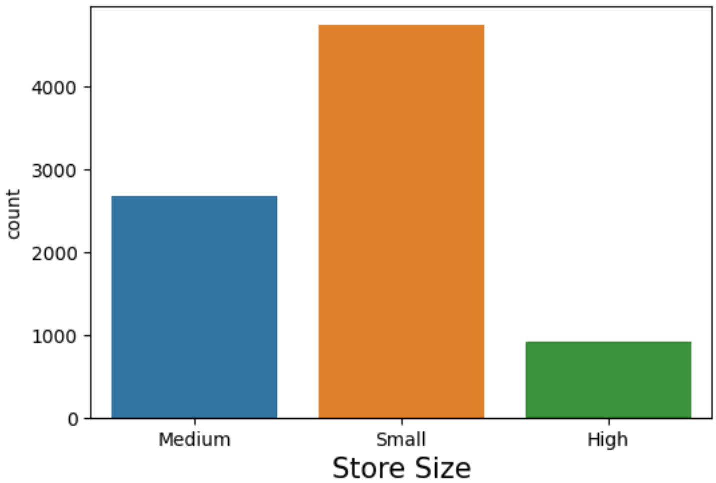
```
plt.xlabel('Item Category', fontsize=15)
plt.show()
```




```
# CountPlot for Outlet_Identifier
plt.figure(figsize=(15,4))
sns.countplot(data=data, x='Outlet_Identifier', palette='winter')
plt.xlabel('Stores', fontsize=15)
plt.show()
```

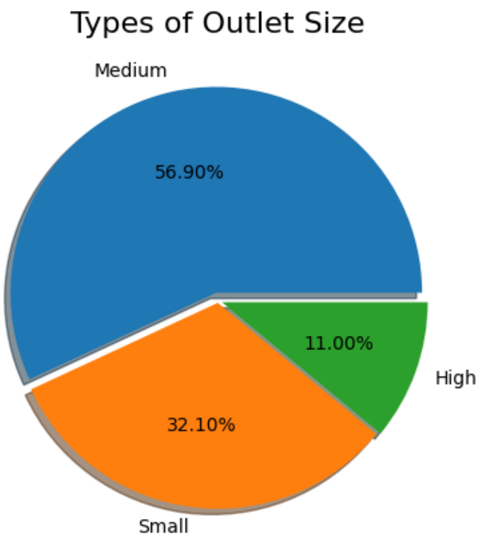



```
# CountPlot for Outlet_Size
plt.figure(figsize=(6,4))
sns.countplot(data=data, x='Outlet_Size')
plt.xlabel('Store Size', fontsize=15)
plt.show()
```




```
# Proportion of different types of Outlet Sizes
plt.figure(figsize=(5,5))
plt.pie(x=data['Outlet_Size'].value_counts(),
        labels=["Medium","Small",'High'],
        autopct='%1.2f%%',
```

```
        explode=[0.04,0.01,0.02],shadow=True,)

plt.title("Types of Outlet Size",fontsize=16)
plt.show()
```




```
# CountPlot for Outlet_Location_Type
plt.figure(figsize=(10,4))
sns.countplot(data=data, x='Outlet_Location_Type')
plt.xlabel('Store Location Type', fontsize=15)
plt.show()
```

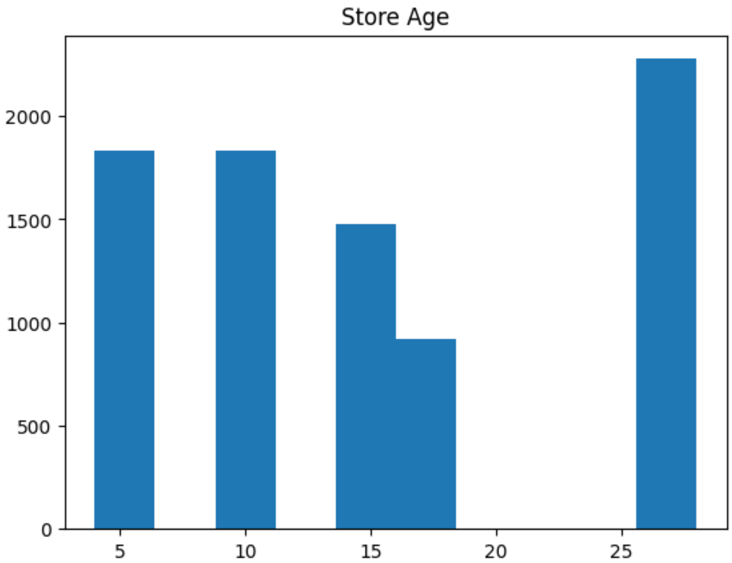

```
# CountPlot for Outlet_Type
plt.figure(figsize=(10,7))
sns.countplot(data=data, x='Outlet_Type')
plt.xlabel('Store Type', fontsize=15)
plt.show()
```

Realizations

- **Item_Fat_Content**: Most items sold are **low Fat**.
- **Item_Type**: Distictly **fruits & veg**, **food snacks** are popular.
- **Item_Type_Combined**: Most sold item cateogory is food.
- **Outlet_Identifier**: Sold items are ditributed evenly amoung all stores, execpt **OUT010** and **OUT019**.
- **Outlet_Size**: Bigmart Stores are mostly in **medium size** in this data.
- **Outlet_Location_Type**: Most common type of location is **Tier3**.
- **Outlet_Type**: By a wide mergin most Store Types are **SuperMarket Type1**.

For Numerical Data

```
# HistPlot for Outlet_Age
plt.hist(x=data['Oultet_Age'], )
plt.title('Store Age')
plt.show()
```




```
# Distribution of target values
sns.distplot(data['Item_Outlet_Sales'],bins=20,rug=True,hist=True)
plt.show()
```

Realizations

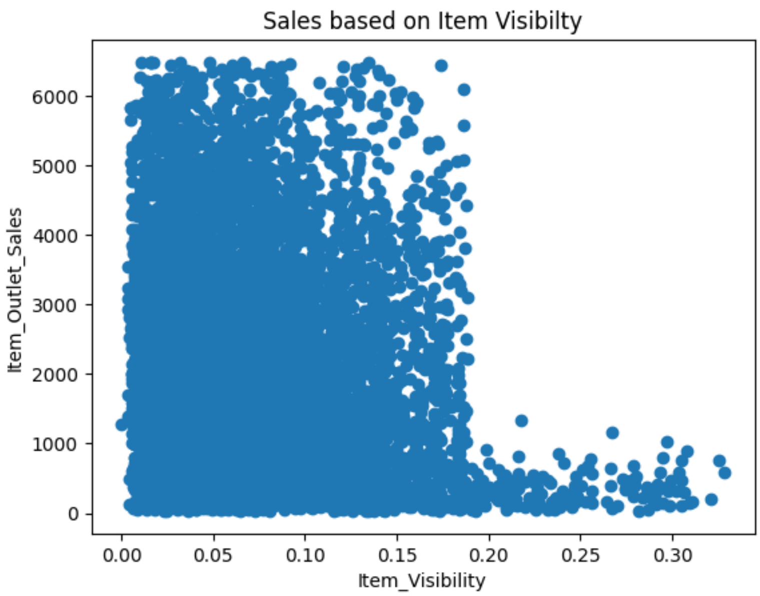
- **Outlet_Age**: Most Common **Outlets** are 35 year's old.

Bivariate plots

For Numeric Data

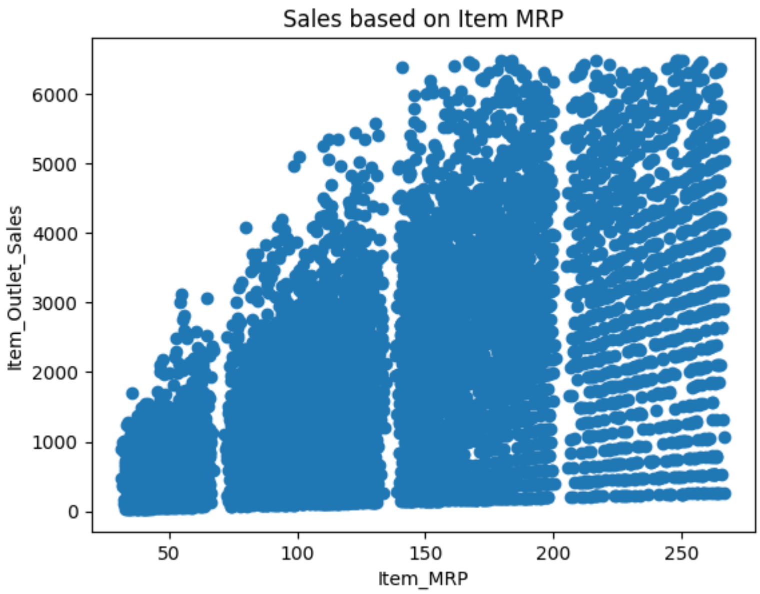
> Let's check following relationships
>
> - **Sales per Item_MRP**
> - **Sales per Item_Visibility**
> - **Sales per Item_Weight**

```
# ScatterPlot for Sales per Item_Visibilty
plt.scatter(data['Item_Visibility'], data['Item_Outlet_Sales'])
plt.title('Sales based on Item Visibilty')
plt.xlabel('Item_Visibility')
plt.ylabel('Item_Outlet_Sales')
plt.show()
```




```
# ScatterPlot for Sales per Item_Weight
plt.scatter(data['Item_Weight'], data['Item_Outlet_Sales'])
plt.title('Sales based on Item Weight')
plt.xlabel('Item_Weight')
plt.ylabel('Item_Outlet_Sales')
plt.show()
```


```
# ScatterPlot for Sales per Item_MRP
plt.scatter(data['Item_MRP'], data['Item_Outlet_Sales'])
plt.title('Sales based on Item MRP')
plt.xlabel('Item_MRP')
plt.ylabel('Item_Outlet_Sales')
plt.show()
```



Realizations

- **Item_Visibility**: Looks like it has **negative correlation**.
- **Item_Weight**: Not a particular Pattern, data is very spread.
- **Item_MRP**: Items with higer **MRP** Sales tends to sell better.

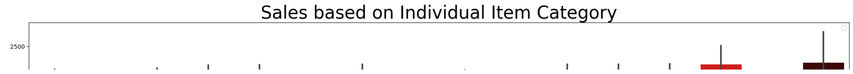
For Categorical Data

> Let's check following relationships

- **Sales per Item_Type_Combined**
- **Sales per Outlet_Identifier**
- **Sales per Outlet_Type**
- **Sales per Outlet_Size**
- **Sales per Outlet_Location_Type**

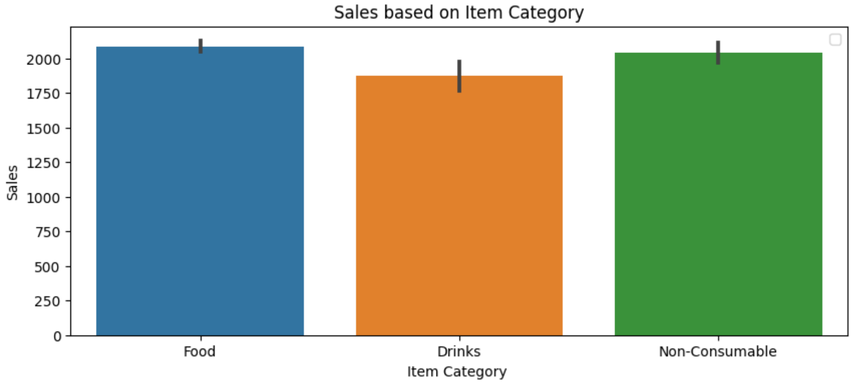
```
# BarPlot for Sales per Item_Type
plt.figure(figsize=(25,6))
sns.barplot(data=data,x='Item_Type', y='Item_Outlet_Sales', palette='flag')
plt.title('Sales based on Individual Item Category', fontsize=30)
plt.xlabel('Individual Item Category', fontsize=20)
plt.ylabel('Sales', fontsize=20)
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```




```
# BarPlot for Sales per Item_Type_Combined
plt.figure(figsize=(10,4))
sns.barplot(data=data,x='Item_Type_Combined', y='Item_Outlet_Sales')
plt.title('Sales based on Item Category')
plt.xlabel('Item Category ')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```

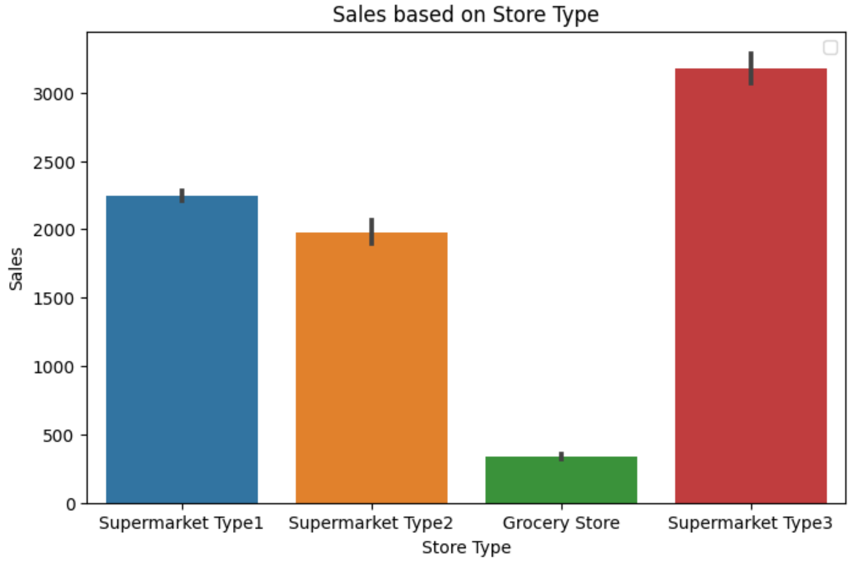



```
# BarPlot for Sales per Outlet_Identifier
plt.figure(figsize=(10,4))
sns.barplot(data=data,x='Outlet_Identifier', y='Item_Outlet_Sales')
plt.title('Sales based on Store')
plt.xlabel('Store')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```

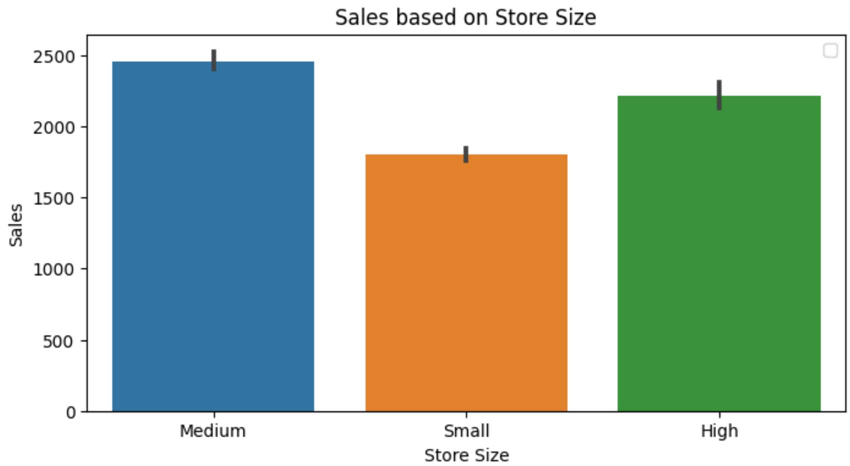

```
# BarPlot for Sales per Outlet_Type
plt.figure(figsize=(8,5))
sns.barplot(data=data,x='Outlet_Type', y='Item_Outlet_Sales')
plt.title('Sales based on Store Type')
plt.xlabel('Store Type')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```




```
# BarPlot for Sales per Outlet_Size
plt.figure(figsize=(8,4))
sns.barplot(data=data,x='Outlet_Size', y='Item_Outlet_Sales')
plt.title('Sales based on Store Size')
plt.xlabel('Store Size')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```




```
# BarPlot for Sales per Outlet_Location_Type
plt.figure(figsize=(10,4))
sns.barplot(data=data,x='Outlet_Location_Type', y='Item_Outlet_Sales')
plt.title('Sales based on Store location type ')
plt.xlabel('Store location type')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that
```

Realizations

- **Item_Type_Combined**: Based on Categories, **Food** has most Sells, but difference is very small.
- **Outlet_Identifier**: **Outlet027** has most profitable, and **Outlet019** and **Outlet010** has least Sells.
- **Outlet_Type**: Most Sells are through **SuperMarket Type3** surprisingly not **Type1**.
- **Outlet_Size**: Sells are mostly even in **Medium** and **High** size Stores.
- **Outlet_Location_Type**: Most sells are through **Tier3** and **Tier2**, **Tier2** is slightly higher.

Multivariate plots

Numerical vs. Numerical

1. Scatterplot
2. Line plot
3. Heatmap for correlation
4. Joint plot

Categorical vs. Numerical

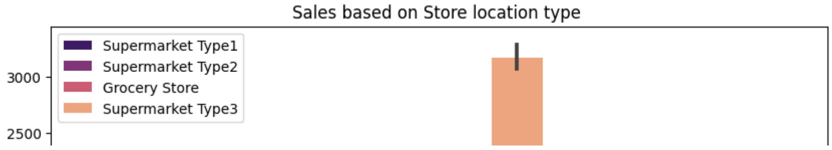
1. Bar chart
2. Voilin plot
3. Categorical box plot
4. Swarm plot

Two Categorcal Variables

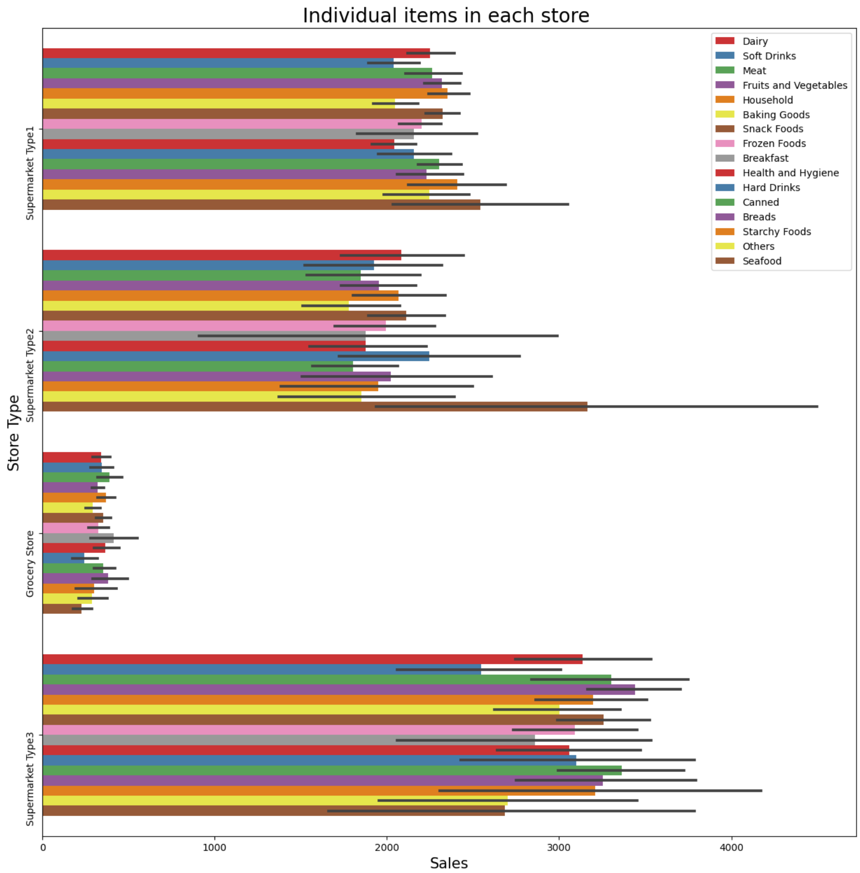
1. Bar chart
2. Grouped bar chart
3. Point plot

> Let's check following data
>
> - **Outlet Type in all Outlet location based on sales.**
> - **Sales of Item_Type based on Outlet_Type.**
> - **Outlet_Location_Type of Outlet_Type based on sales.**
> - **Sales of Outlet_Location_Type based on Item_Type_Combined.**

```
plt.figure(figsize=(10,5))
sns.barplot(data=data,x='Outlet_Location_Type', y='Item_Outlet_Sales',hue='Outlet_Type',palette='magma')
plt.title('Sales based on Store location type ')
plt.xlabel('Store location type')
plt.ylabel('Sales')
plt.legend()
plt.show()
```

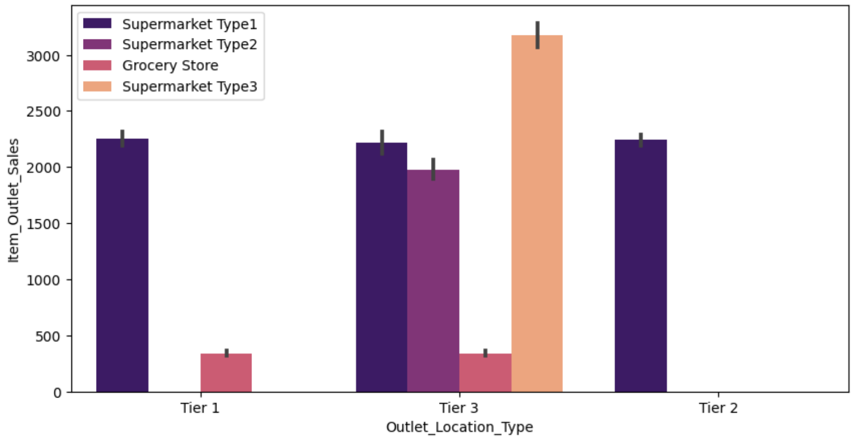



```
plt.figure(figsize=(15,15))
sns.barplot(data=data,x='Item_Outlet_Sales', y='Outlet_Type',hue='Item_Type',palette='Set1')
plt.title('Individual items in each store ', fontsize=20)
plt.xlabel('Sales', fontsize=15)
plt.ylabel('Store Type', fontsize=15)
plt.yticks(rotation=90)
plt.legend()
plt.show()
```

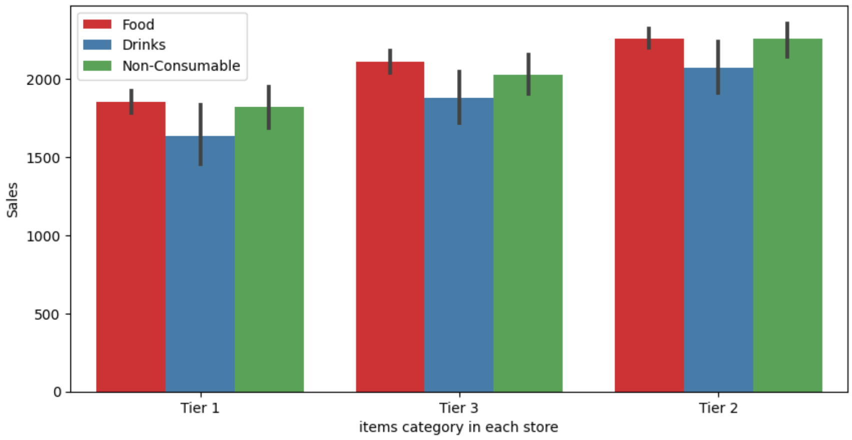



```
plt.figure(figsize=(10,5))
sns.barplot(x='Outlet_Location_Type',y='Item_Outlet_Sales',hue='Outlet_Type',data=data,palette='magma')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f4e73c4fee0>
```




```
plt.figure(figsize=(10,5))
sns.barplot(data=data,x='Outlet_Location_Type',y='Item_Outlet_Sales',hue='Item_Type_Combined',palette='Set1')
plt.xlabel('items category in each store', fontsize=10)
plt.ylabel('Sales', fontsize=10)
plt.legend()
plt.show()
```




```
plt.figure(figsize=(10,5))
sns.barplot(x='Outlet_Type',y='Item_Outlet_Sales',hue='Outlet_Location_Type',data=data,palette='magma')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f4e73acd7b0>
```

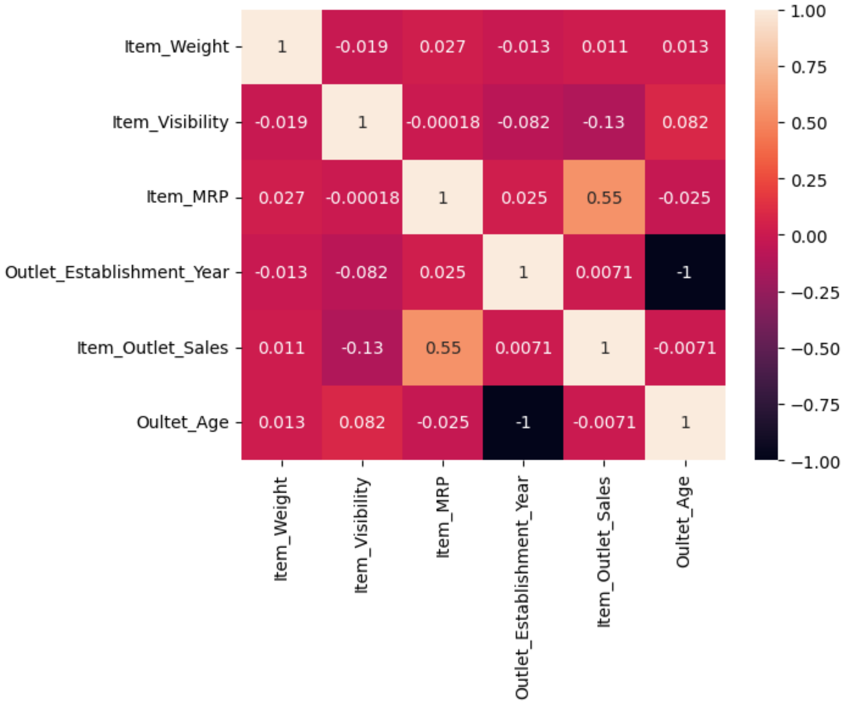
Realizations

- **Seafood** is the most **item_type** sold in **SuperMarket 1 and 2**, **Grocery store** has less **sales.**
- Only **Teir3** has **all Outlet_Type**, and **SuperMarket type3** has most **sales.**.
- **Outlet_Location_Type** has almost **equal sales** based on **Item_Type_combined.**

Correlation Matrix

```
# Correlation Matrix
plt.Figure(figsize=(20,5))
sns.heatmap(data.corr(), annot=True)
```

```
<Axes: >
```



- We can see **Item_Outlet_Sales** is highly correlated with **Item_MRP**.
- We can see **Outlet_Age** and **Item_Visibility** are negativaly correlated, we need to drop them.

6. Feature Engineering

The main feature engineering techniques are:

- Categorical encoding
- Variable transformation
- Outlier engineering
- Date and time engineering

There are 7 categorial columns

Ordinal Data:

- Item_Fat_Content
- Outlet_Size
- Outlet_Location_Type

Nominal Data:

- Item_Identifier
- Item_Type
- Outlet_Identifier

- Outlet_Type

Since **Item_Identifier**, **Outlet_Identifier** don't have significant values, we can drop them.

Label Encoding for Ordinal Data

```
# Label Encoding for Ordinal Data
le = LabelEncoder()
label = ['Item_Fat_Content', 'Outlet_Type', 'Outlet_Location_Type', 'Outlet_Size']
for i in label:
    data[i] = le.fit_transform(data[i])
data.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDA15	9.30	0	0.016047	Dairy	249.8
1	DRC01	5.92	1	0.019278	Soft Drinks	48.2
2	FDN15	17.50	0	0.016760	Meat	141.6
3	FDX07	19.20	1	0.015274	Fruits and Vegetables	182.0
4	NCD19	8.93	0	0.008082	Household	53.8

One-Hot encoding for Nominal Data

```
# One-Hot encoding for Nominal Data

# Columns for applying One-Hot encoding
cols = ['Item_Type_Combined']
# Apply one-hot encoder
OH_encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)
data_oh = pd.DataFrame(OH_encoder.fit_transform(data[cols])).astype('int64')

# get feature columns
data_oh.columns = OH_encoder.get_feature_names_out(cols)
# # # One-hot encoding removed index; put it back
data_oh.index = data.index

# # # Add one-hot encoded columns to our main df new name: tr_fe, te_fe (means feature engeenired)
data_fe = pd.concat([data, data_oh], axis=1)
data_fe.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDA15	9.30	0	0.016047	Dairy	249.8
1	DRC01	5.92	1	0.019278	Soft Drinks	48.2
2	FDN15	17.50	0	0.016760	Meat	141.6
3	FDX07	19.20	1	0.015274	Fruits and Vegetables	182.0
4	NCD19	8.93	0	0.008082	Household	53.8

```
data_fe.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_
0	FDA15	9.30	0	0.016047	Dairy	249.8

Normalization

2	FDN15	17.50	0	0.016760	Meat	141.6

```
scaler_Robust=RobustScaler()
scaler_minmax=MinMaxScaler()
scaler_standard=StandardScaler()
scaled_X_Robust=pd.DataFrame(scaler_Robust.fit_transform(data_fe[['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year'
                             ,columns=['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year'])
scaled_X_minmax=pd.DataFrame(scaler_minmax.fit_transform(data_fe[['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year'
                             ,columns=['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year'])
scaled_X_standard=pd.DataFrame(scaler_standard.fit_transform(data_fe[['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Y
                                columns=['Item_Weight','Item_Visibility','Item_MRP','Outlet_Establishment_Year'])
```

```
scaled_X_standard
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year
0	-0.768166	-1.075012	1.797705	0.124185
1	-1.495568	-1.010464	-1.476724	1.327635
2	0.996535	-1.060772	0.039918	0.124185
3	1.362388	-1.090468	0.697549	0.003840
4	-0.847793	-1.234141	-1.385868	-1.319955
...	...	...	...	...
8332	-1.292197	-0.261179	1.224389	-1.319955
8333	-0.966157	-0.456985	-0.503725	0.485220
8334	-0.488397	-0.692650	-0.877969	0.725910
8335	-1.217950	1.505636	-0.585347	1.327635
8336	0.415475	-0.499022	-1.034841	-0.116505

8337 rows × 4 columns

```
# Drop irrlevent Columns
data_fe = data_fe.drop(['Item_Identifier','Item_Type_Combined', 'Outlet_Identifier','Oultet_Age',
                     'Item_Fat_Content','Item_Visibility', 'Item_Type','Item_Type_Combined',
                     'Outlet_Establishment_Year','Item_Type'], axis=1)
data_fe.head()

# Divide Data into train and test
train = data_fe.loc[data_fe['source']=="train"]
test = data_fe.loc[data_fe['source']=="test"]

train = train.drop('source', axis=1)
test = test.drop(['source',  'Item_Outlet_Sales'], axis=1)

# Check Datasets
print('\nTrain Dataset for Model Buidling: \n')
print(train.info(verbose=True, show_counts=True))
print('\nTest Dataset for Model Buidling: \n')
print(test.info(verbose=True, show_counts=True))
train.head()
```

```
Train Dataset for Model Buidling:

<class 'pandas.core.frame.DataFrame'>
Int64Index: 8337 entries, 0 to 8522
Data columns (total 9 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Item_Weight                      8337 non-null   float64
 1   Item_MRP                         8337 non-null   float64
 2   Outlet_Size                      8337 non-null   int64  
 3   Outlet_Location_Type             8337 non-null   int64  
 4   Outlet_Type                      8337 non-null   int64  
 5   Item_Outlet_Sales                8337 non-null   float64
 6   Item_Type_Combined_Drinks        8337 non-null   int64  
 7   Item_Type_Combined_Food          8337 non-null   int64  
 8   Item_Type_Combined_Non-Consumable  8337 non-null   int64  
dtypes: float64(3), int64(6)
memory usage: 651.3 KB
None

Test Dataset for Model Buidling:

<class 'pandas.core.frame.DataFrame'>
Int64Index: 0 entries
Data columns (total 8 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Item_Weight                      0 non-null      float64
 1   Item_MRP                         0 non-null      float64
 2   Outlet_Size                      0 non-null      int64  
 3   Outlet_Location_Type             0 non-null      int64  
 4   Outlet_Type                      0 non-null      int64  
 5   Item_Type_Combined_Drinks        0 non-null      int64  
```

7. Machine Learning Models

Divide dataset into two variables.

- **X** as the features we defined earlier.
- **y** as the Item_Outlet_Sales the target value we want to predict.

Assumptions:

- This is a regression problem.
- Train test split 8:2 ratio respectively.

Regression Models

1. **Linear Regression**
2. **Lasso Regression**
3. **Ridge Regression**
4. **Random Forest Regressor**
5. **XGBoost Regressor**

```
# Extracting Dependent and Independent Variable
y = train['Item_Outlet_Sales']
X = train.drop('Item_Outlet_Sales', axis=1)

# Train and Test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 20)

# Cross Validation Score after model completion
def cross_val(model, X, y, cv):
    scores = CVS(model, X, y, cv=cv)
    print(f'{model} Scores:')
    for i in scores:
        print(round(i,2))
    print(f'Average {model} score: {round(scores.mean(),4)}')
```

Linear Regression

Equation of linear Regression

y = B0 + Bixi

- B0 = **Intercept**: means where linear line **intercept y when x = 0**
- xi = any indpendent veriable/ **feature**

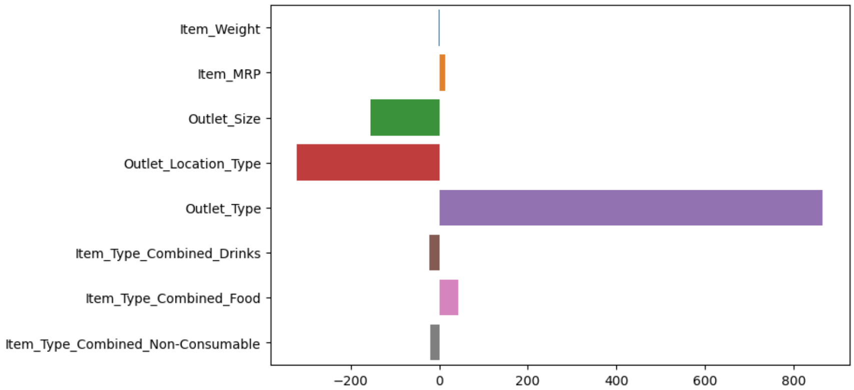
- Bi = How **impactfull** feature is greater the bi means more valuable the feature is.

```
# Model
linear_reg = LinearRegression()

# Fit
linear_reg.fit(X_train, y_train)

# Predict
y_predict = linear_reg.predict(X_test)

# Score Metrics for Regression:
LR_MAE = MAE(y_test, y_predict)
LR_MSE = MSE(y_test, y_predict)
LR_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {LR_MAE}\n")
print(f" Squared Mean Squared Error: {np.sqrt(LR_MSE)}\n")
print(f" R^2 Score: {LR_R_2}\n")

# Cross Validation Score check
cross_val(LinearRegression(),X,y,5)
```

```
 Mean Absolute Error: 841.7399321979832

 Squared Mean Squared Error: 1083.0083784825522

 R^2 Score: 0.4720668459427

LinearRegression() Scores:
0.48
0.49
0.46
0.48
0.48
Average LinearRegression() score: 0.4778
```

```
# Visualization of model's perfomance
LR_coef = pd.Series(linear_reg.coef_, linear_reg.feature_names_in_).sort_values()
print(LR_coef)
plt.figure(figsize=(8,5))
sns.barplot(x=linear_reg.coef_,y=linear_reg.feature_names_in_)
```

```
Outlet_Location_Type                 -322.671164
Outlet_Size                          -156.362962
Item_Type_Combined_Drinks             -23.091355
Item_Type_Combined_Non-Consumable     -20.672003
Item_Weight                            -0.839481
Item_MRP                               13.892046
Item_Type_Combined_Food                43.763358
Outlet_Type                           866.786806
dtype: float64
<Axes: >
```



Observations

- Outlet_Type_Supermarket Type3 has **highest impact** in model.
- R^2 is close to 1, but **it is in 0.5 range**, so predictor is good.

Regularization

When **indepdent veriables/ features** have large **coefficients/slope**, it can be **computationaly expensive**, so we do **regulariation technique** to reduce regression cefficients/slope and model complexity.

- Types of Regularization:

1. Lasso Regression
2. Ridge Regression

- Lasso regression **performs L1 regularization**, which adds a penalty equal to the absolute value of the **magnitude of coefficients**. This type of regularization can result in sparse models with few coefficients; **Some coefficients can become zero** and eliminated from the model. Larger penalties result in coefficient values closer to zero, which is the ideal for producing simpler models.

- On the other hand, **L2 regularization** (e.g. Ridge regression) doesn’t result in elimination of coefficients or sparse models. This makes the Lasso far easier to interpret than the Ridge.

```
# Lasso Regression
# Model
lasso_reg = Lasso(alpha=0.05)

# Fit
lasso_reg.fit(X_train, y_train)

# Predict
y_predict = lasso_reg.predict(X_test)

# Score Metrics for Regression:
LS_MAE = MAE(y_test, y_predict)
LS_MSE = MSE(y_test, y_predict)
LS_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {LS_MAE}\n")
print(f" Mean Squared Error: {LS_MSE}\n")
print(f" R^2 Score: {LS_R_2}\n")

# Cross Validation Score check
cross_val(Lasso(),X,y,5)
```

```
 Mean Absolute Error: 841.726353976078

 Mean Squared Error: 1172885.8412699758

 R^2 Score: 0.4720764361793124

Lasso() Scores:
0.48
0.49
0.46
0.48
0.48
Average Lasso() score: 0.4778
```

```
# Visuaization of model's perfomance
LS_coef = pd.Series(lasso_reg.coef_, lasso_reg.feature_names_in_).sort_values()
print(LS_coef)
plt.figure(figsize=(10,5))
sns.barplot(x=lasso_reg.coef_,y=lasso_reg.feature_names_in_)
```

```
Outlet_Location_Type                -322.485070
Outlet_Size                         -156.203738
Item_Type_Combined_Drinks             -1.882956
Item_Weight                           -0.835746
Item_Type_Combined_Non-Consumable     -0.000000
Item_MRP                              13.892099
Item_Type_Combined_Food               64.376063
Outlet_Type                          866.674132
dtype: float64
<Axes: >
```

```
# Ridge Regression
# Model
ridge_reg = Ridge()

# Fit
ridge_reg.fit(X_train, y_train)

# Predict
y_predict = ridge_reg.predict(X_test)

# Score Metrics for Regression:
R_MAE = MAE(y_test, y_predict)
R_MSE = MSE(y_test, y_predict)
R_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {R_MAE}\n")
print(f" Mean Squared Error: {R_MSE}\n")
print(f" R^2 Score: {R_R_2}\n")

# Cross Validation Score check
cross_val(Lasso(),X,y,5)
```

```
 Mean Absolute Error: 841.7250590873847

 Mean Squared Error: 1172883.1800144718

 R^2 Score: 0.4720776340277648

Lasso() Scores:
0.48
0.49
0.46
0.48
0.48
Average Lasso() score: 0.4778
```

```
# Visualization of model's perfomance
R_coef = pd.Series(ridge_reg.coef_, ridge_reg.feature_names_in_).sort_values(ascending=False)
print(R_coef)
sns.barplot(x=ridge_reg.coef_,y=ridge_reg.feature_names_in_)
```

Outlet_Type 866.458565

Random Forest Regressor

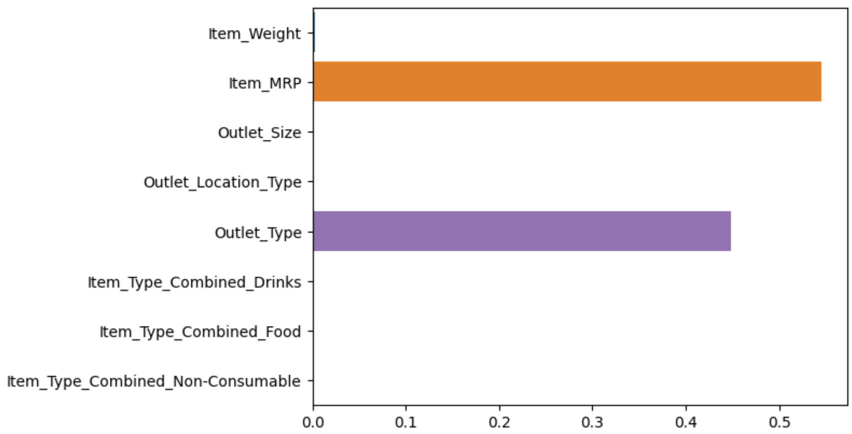
```
Item_Type_Combined_Non-Consumable    -20.673402
```

```
# Model
random_forest = RandomForestRegressor(n_estimators=400, max_depth=6, min_samples_leaf=100, n_jobs=4, random_state=101)

# Fit
random_forest.fit(X_train, y_train)

# Predict
y_predict = random_forest.predict(X_test)

# Score Metrics
RFR_MAE = MAE(y_test, y_predict)
RFR_MSE = MSE(y_test, y_predict)
RFR_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {RFR_MAE}\n")
print(f" Mean Squared Error: {RFR_MSE}\n")
print(f" R^2 Score: {RFR_R_2}\n")
cross_val(RandomForestRegressor(),X, y, 5)
```

```
 Mean Absolute Error: 718.1273348955266

 Mean Squared Error: 945500.1707830498

 R^2 Score: 0.5744242089133027

RandomForestRegressor() Scores:
0.52
0.51
0.48
0.53
0.53
Average RandomForestRegressor() score: 0.5131
```

```
# Visualization of model's perfomance
RFR_coef = pd.Series(random_forest.feature_importances_, random_forest.feature_names_in_).sort_values(ascending=False)
print(RFR_coef)
sns.barplot(x=random_forest.feature_importances_, y=random_forest.feature_names_in_)
```

```
Item_MRP                             0.545500
Outlet_Type                          0.448041
Item_Weight                          0.002964
Outlet_Location_Type                 0.001605
Outlet_Size                          0.001022
Item_Type_Combined_Food              0.000840
Item_Type_Combined_Non-Consumable    0.000027
Item_Type_Combined_Drinks            0.000000
dtype: float64
<Axes: >
```



Gradient Boosting Regressor

```
# Model
gbr = GradientBoostingRegressor()

# Fit
```

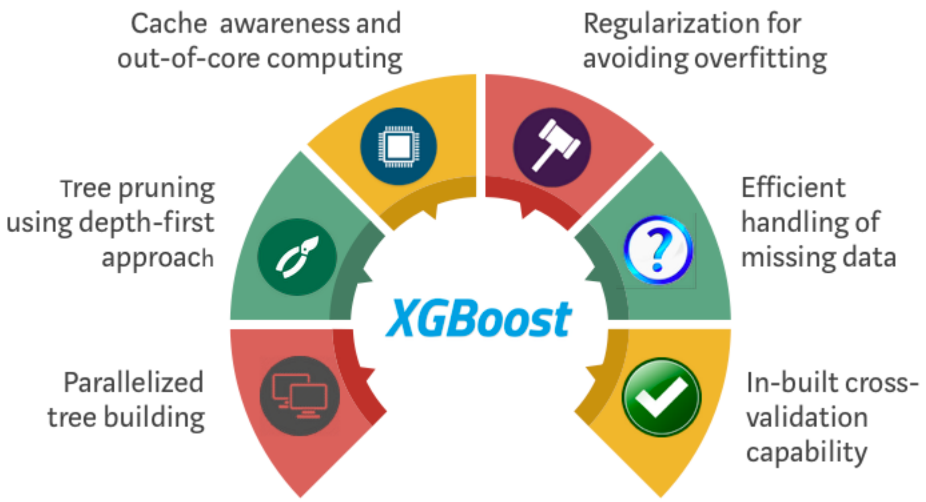
```
gbr.fit(X_train, y_train)

# Predict
y_predict = gbr.predict(X_test)

# Score Metrics
RGB_MAE = MAE(y_test, y_predict)
RGB_MSE = MSE(y_test, y_predict)
RGB_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {RGB_MAE}\n")
print(f" Mean Squared Error: {RGB_MSE}\n")
print(f" R^2 Score: {RGB_R_2}\n")
cross_val(GradientBoostingRegressor(),X, y, 5)
```

```
 Mean Absolute Error: 708.752939611297

 Mean Squared Error: 927244.9346567268

 R^2 Score: 0.5826410097093302

GradientBoostingRegressor() Scores:
0.59
0.58
0.58
0.59
0.59
Average GradientBoostingRegressor() score: 0.5859
```

XGBoost Regressor

XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable.

It implements Machine Learning algorithms under the Gradient Boosting framework. It provides a parallel tree boosting to solve many data science problems in a fast and accurate way.



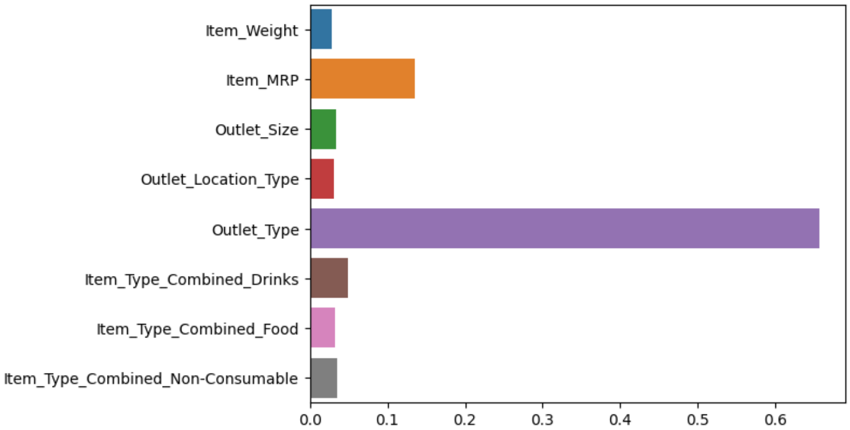

```
# Model
xgb = XGBRegressor()

# Fit
xgb.fit(X_train, y_train)

# Predict
y_predict = xgb.predict(X_test)

# Score Matrix
XG_MAE = MAE(y_test, y_predict)
XG_MSE = MSE(y_test, y_predict)
XG_R_2 = R2(y_test, y_predict)
print(f" Mean Absolute Error: {XG_MAE}\n")
print(f" Mean Squared Error: {XG_MSE}\n")
print(f" R^2 Score: {XG_R_2}\n")
cross_val(XGBRegressor(),X, y, 5)
```

```
 Mean Absolute Error: 761.9328402504542

 Mean Squared Error: 1071171.3149916385

 R^2 Score: 0.5178588075881532
```

```
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=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=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,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...) Scores:
0.54
0.52
0.48
0.53
0.53
Average 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=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=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,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...) score: 0.5212
```

```
# Visualization of model's perfomance
XG_coef = pd.Series(xgb.feature_importances_, xgb.feature_names_in_).sort_values(ascending=False)
print(XG_coef)
sns.barplot(x=xgb.feature_importances_,y=xgb.feature_names_in_)
```

```
Outlet_Type                      0.656383
Item_MRP                         0.135247
Item_Type_Combined_Drinks        0.048880
Item_Type_Combined_Non-Consumable    0.034884
Outlet_Size                      0.033279
Item_Type_Combined_Food          0.032013
Outlet_Location_Type             0.031630
Item_Weight                      0.027684
dtype: float32
<Axes: >
```



Hyperparameter tuning for XGB and GBR

```
from sklearn.model_selection import RandomizedSearchCV

xgb_param_dist = {
    'n_estimators': np.random.randint(100, 500, 5),
    'max_depth': np.random.randint(1, 10, 5),
    'learning_rate': np.random.uniform(0.01, 0.3, 5)
}

xgb_random_search = RandomizedSearchCV(
    xgb, xgb_param_dist, n_iter=20,scoring='neg_mean_absolute_error', random_state=42
)
xgb_random_search.fit(X_train, y_train)
xgb_best_model = xgb_random_search.best_estimator_
xgb_pred = xgb_best_model.predict(X_test)
```

```
# Score Matrix
XGB_MAE = MAE(y_test, xgb_pred)
XGB_MSE = MSE(y_test, xgb_pred)
XGB_R_2 = R2(y_test, xgb_pred)
print(f" Mean Absolute Error: {XGB_MAE}\n")
print(f" Mean Squared Error: {XGB_MSE}\n")
print(f" R^2 Score: {XGB_R_2}\n")

print("XGBoost Best Parameters:", xgb_random_search.best_params_)
```

```
 Mean Absolute Error: 707.5504532494707

 Mean Squared Error: 924000.3654689348

 R^2 Score: 0.5841014114538233

XGBoost Best Parameters: {'n_estimators': 335, 'max_depth': 4, 'learning_rate': 0.019611188844722204}
```

```
gbr_param_dist = {
    'n_estimators': np.random.randint(100, 500, 5),
    'max_depth': np.random.randint(1, 10, 5),
    'learning_rate': np.random.uniform(0.01, 0.3, 5)
}

gbr_random_search = RandomizedSearchCV(
    gbr, gbr_param_dist, n_iter=20,scoring='neg_mean_absolute_error', random_state=42
)
gbr_random_search.fit(X_train, y_train)
gbr_best_model = gbr_random_search.best_estimator_
gbr_pred = gbr_best_model.predict(X_test)

# Score Metrics
RGB1_MAE = MAE(y_test, gbr_pred)
RGB1_MSE = MSE(y_test, gbr_pred)
RGB1_R_2 = R2(y_test, gbr_pred)
print(f" Mean Absolute Error: {RGB1_MAE}\n")
print(f" Mean Squared Error: {RGB1_MSE}\n")
print(f" R^2 Score: {RGB1_R_2}\n")

print("Gradient Boosting Regressor Best Parameters:", gbr_random_search.best_params_)
```

```
 Mean Absolute Error: 707.8526975223238

 Mean Squared Error: 924314.0502176603

 R^2 Score: 0.5839602199033447

Gradient Boosting Regressor Best Parameters: {'n_estimators': 132, 'max_depth': 3, 'learning_rate': 0.05831366369506832}
```

8. Saving the final model

```
import pickle

pickle.dump(gbr_best_model, open('gbr_best_model.pkl', 'wb'))
```

9. Conclusion

Finally, from the comparison of evaluation metrics scores of all the models implemented with optimal paprameters, we have arrived to the conclusion that **Gradient Boosting Regressor** is the best performing model.