

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

```
mart=pd.read_csv("bigmart1.csv")
```

```
mart
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	\
0	FDA15	9.300	Low Fat	0.016047	
1	DRC01	5.920	Regular	0.019278	
2	FDN15	17.500	Low Fat	0.016760	
3	FDX07	19.200	Regular	0.000000	
4	NCD19	8.930	Low Fat	0.000000	
...	
8518	FDF22	6.865	Low Fat	0.056783	
8519	FDS36	8.380	Regular	0.046982	
8520	NCJ29	10.600	Low Fat	0.035186	
8521	FDN46	7.210	Regular	0.145221	
8522	DRG01	14.800	Low Fat	0.044878	

	Item_Type	Item_MRP	Outlet_Identifier	\
0	Dairy	249.8092	OUT049	
1	Soft Drinks	48.2692	OUT018	
2	Meat	141.6180	OUT049	
3	Fruits and Vegetables	182.0950	OUT010	
4	Household	53.8614	OUT013	
...	
8518	Snack Foods	214.5218	OUT013	
8519	Baking Goods	108.1570	OUT045	
8520	Health and Hygiene	85.1224	OUT035	
8521	Snack Foods	103.1332	OUT018	
8522	Soft Drinks	75.4670	OUT046	

	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	\
0	1999	Medium	Tier 1	
1	2009	Medium	Tier 3	
2	1999	Medium	Tier 1	
3	1998	NaN	Tier 3	
4	1987	High	Tier 3	
...	
8518	1987	High	Tier 3	
8519	2002	NaN	Tier 2	
8520	2004	Small	Tier 2	
8521	2009	Medium	Tier 3	
8522	1997	Small	Tier 1	

```
Outlet_Type Item_Outlet_Sales
```

0	Supermarket	Type1	3735.1380
1	Supermarket	Type2	443.4228
2	Supermarket	Type1	2097.2700
3	Grocery	Store	732.3800
4	Supermarket	Type1	994.7052
...			...
8518	Supermarket	Type1	2778.3834
8519	Supermarket	Type1	549.2850
8520	Supermarket	Type1	1193.1136
8521	Supermarket	Type2	1845.5976
8522	Supermarket	Type1	765.6700

[8523 rows x 12 columns]

mart.head(10)

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	\
0	FDA15	9.300	Low Fat	0.016047	
1	DRC01	5.920	Regular	0.019278	
2	FDN15	17.500	Low Fat	0.016760	
3	FDX07	19.200	Regular	0.000000	
4	NCD19	8.930	Low Fat	0.000000	
5	FDP36	10.395	Regular	0.000000	
6	FD010	13.650	Regular	0.012741	
7	FDP10	NaN	Low Fat	0.127470	
8	FDH17	16.200	Regular	0.016687	
9	FDU28	19.200	Regular	0.094450	

	Item_Type	Item_MRP	Outlet_Identifier	\
0	Dairy	249.8092	OUT049	
1	Soft Drinks	48.2692	OUT018	
2	Meat	141.6180	OUT049	
3	Fruits and Vegetables	182.0950	OUT010	
4	Household	53.8614	OUT013	
5	Baking Goods	51.4008	OUT018	
6	Snack Foods	57.6588	OUT013	
7	Snack Foods	107.7622	OUT027	
8	Frozen Foods	96.9726	OUT045	
9	Frozen Foods	187.8214	OUT017	

	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	\
0	1999	Medium	Tier 1	
1	2009	Medium	Tier 3	
2	1999	Medium	Tier 1	
3	1998	NaN	Tier 3	
4	1987	High	Tier 3	
5	2009	Medium	Tier 3	
6	1987	High	Tier 3	
7	1985	Medium	Tier 3	
8	2002	NaN	Tier 2	

	Outlet_Type	Item_Outlet_Sales
0	Supermarket Type1	3735.1380
1	Supermarket Type2	443.4228
2	Supermarket Type1	2097.2700
3	Grocery Store	732.3800
4	Supermarket Type1	994.7052
5	Supermarket Type2	556.6088
6	Supermarket Type1	343.5528
7	Supermarket Type3	4022.7636
8	Supermarket Type1	1076.5986
9	Supermarket Type1	4710.5350

checking the datatype of each columns

```
def datainfo():
```

```
    temp_ps = pd.DataFrame(index=mart.columns)
    temp_ps['DataType'] = mart.dtypes
    temp_ps["Non-null_Values"] = mart.count()
    temp_ps['Unique_Values'] = mart.nunique()
    temp_ps['NaN_Values'] = mart.isnull().sum()
    temp_ps['NaN_Values_Percentage'] =
    (temp_ps['NaN_Values']/len(mart))*100
    return temp_ps
```

```
datainfo()
```

	DataType	Non-null_Values	Unique_Values	\
Item_Identifier	object	8523	1559	
Item_Weight	float64	7060	415	
Item_Fat_Content	object	8523	5	
Item_Visibility	float64	8523	7880	
Item_Type	object	8523	16	
Item_MRP	float64	8523	5938	
Outlet_Identifier	object	8523	10	
Outlet_Establishment_Year	int64	8523	9	
Outlet_Size	object	6113	3	
Outlet_Location_Type	object	8523	3	
Outlet_Type	object	8523	4	
Item_Outlet_Sales	float64	8523	3493	

	NaN_Values	NaN_Values_Percentage
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

- from above datainfo we find that over data have some null value so we need to drop or fill them with fillna command
- in this datainfo over item_weight does not effect on the dataset
- and the otlet_size matter so we change the data

```
mart["Item_Weight"].fillna(mart["Item_Weight"].mean(), inplace=True)
mart.dropna(inplace=True)
```

```
datainfo()
```

	DataType	Non-null_Values	Unique_Values	\
Item_Identifier	object	6113	1555	
Item_Weight	float64	6113	410	
Item_Fat_Content	object	6113	5	
Item_Visibility	float64	6113	5641	
Item_Type	object	6113	16	
Item_MRP	float64	6113	4694	
Outlet_Identifier	object	6113	7	
Outlet_Establishment_Year	int64	6113	6	
Outlet_Size	object	6113	3	
Outlet_Location_Type	object	6113	3	
Outlet_Type	object	6113	4	
Item_Outlet_Sales	float64	6113	3056	

	NaN_Values	NaN_Values_Percentage
Item_Identifier	0	0.0
Item_Weight	0	0.0
Item_Fat_Content	0	0.0
Item_Visibility	0	0.0
Item_Type	0	0.0
Item_MRP	0	0.0
Outlet_Identifier	0	0.0
Outlet_Establishment_Year	0	0.0
Outlet_Size	0	0.0
Outlet_Location_Type	0	0.0
Outlet_Type	0	0.0
Item_Outlet_Sales	0	0.0

checking the shape type of data

```
mart.shape
```

```
(6113, 12)
```

```
mart.describe().T
```

	count	mean	std	min
\				
Item_Weight	6113.0	12.888856	4.073798	4.5550
Item_Visibility	6113.0	0.064505	0.050092	0.0000
Item_MRP	6113.0	141.256859	62.229701	31.2900
Outlet_Establishment_Year	6113.0	1995.794373	8.842615	1985.0000
Item_Outlet_Sales	6113.0	2322.688445	1741.592093	33.9558

	25%	50%	75%
max			
Item_Weight	9.800000	12.857645	15.700000
21.350000			
Item_Visibility	0.026681	0.052811	0.092834
0.328391			
Item_MRP	94.012000	143.178600	185.892400
266.888400			
Outlet_Establishment_Year	1987.000000	1997.000000	2004.000000
2009.000000			
Item_Outlet_Sales	974.731200	1928.156800	3271.075400
13086.964800			

EDA on that project

```
numerical_feature=mart.select_dtypes("number")
```

```
numerical_feature
```

	Item_Weight	Item_Visibility	Item_MRP
Outlet_Establishment_Year \			
0	9.300	0.016047	249.8092
1999			
1	5.920	0.019278	48.2692
2009			
2	17.500	0.016760	141.6180
1999			
4	8.930	0.000000	53.8614
1987			
5	10.395	0.000000	51.4008
2009			
...
.			
8517	20.750	0.083607	178.8318
1997			

8518	6.865	0.056783	214.5218
1987			
8520	10.600	0.035186	85.1224
2004			
8521	7.210	0.145221	103.1332
2009			
8522	14.800	0.044878	75.4670
1997			

	Item_Outlet_Sales
0	3735.1380
1	443.4228
2	2097.2700
4	994.7052
5	556.6088
...	...
8517	3608.6360
8518	2778.3834
8520	1193.1136
8521	1845.5976
8522	765.6700

[6113 rows x 5 columns]

catagorical_feature=mart.select_dtypes("object")

catagorical_feature

	Item_Identifier	Item_Fat_Content	Item_Type
Outlet_Identifier \			
0	FDA15	Low Fat	Dairy
OUT049			
1	DRC01	Regular	Soft Drinks
OUT018			
2	FDN15	Low Fat	Meat
OUT049			
4	NCD19	Low Fat	Household
OUT013			
5	FDP36	Regular	Baking Goods
OUT018			
...
...			
8517	FDF53	reg	Frozen Foods
OUT046			
8518	FDF22	Low Fat	Snack Foods
OUT013			
8520	NCJ29	Low Fat	Health and Hygiene
OUT035			
8521	FDN46	Regular	Snack Foods
OUT018			
8522	DRG01	Low Fat	Soft Drinks

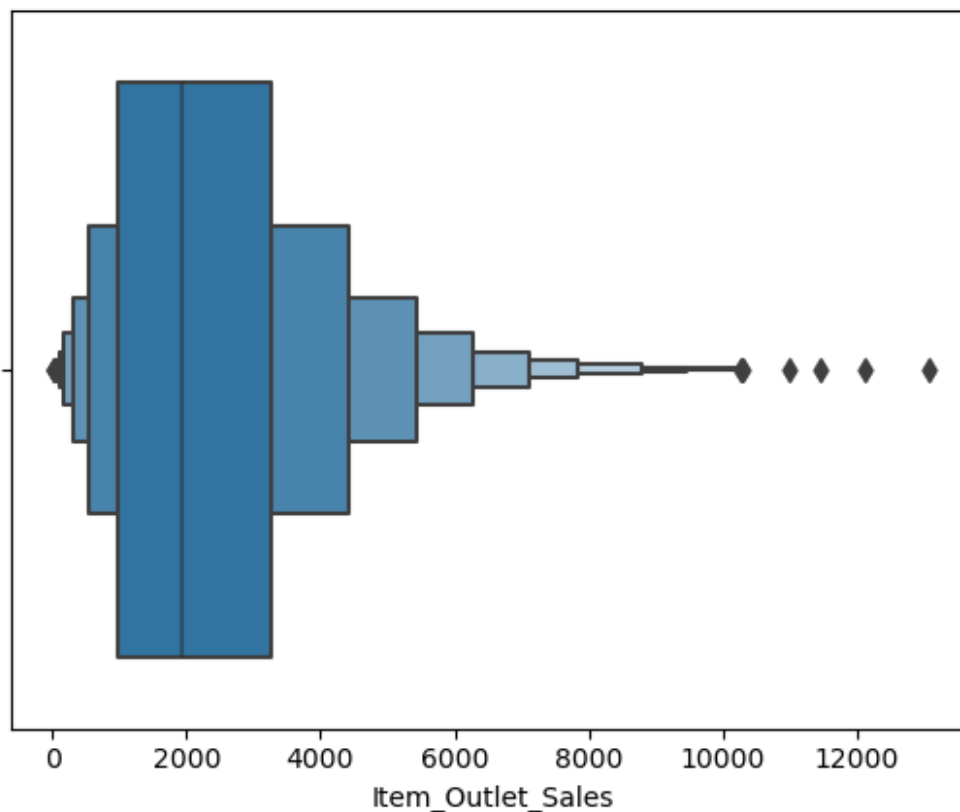
OUT046

	Outlet_Size	Outlet_Location_Type	Outlet_Type
0	Medium	Tier 1	Supermarket Type1
1	Medium	Tier 3	Supermarket Type2
2	Medium	Tier 1	Supermarket Type1
4	High	Tier 3	Supermarket Type1
5	Medium	Tier 3	Supermarket Type2
...
8517	Small	Tier 1	Supermarket Type1
8518	High	Tier 3	Supermarket Type1
8520	Small	Tier 2	Supermarket Type1
8521	Medium	Tier 3	Supermarket Type2
8522	Small	Tier 1	Supermarket Type1

[6113 rows x 7 columns]

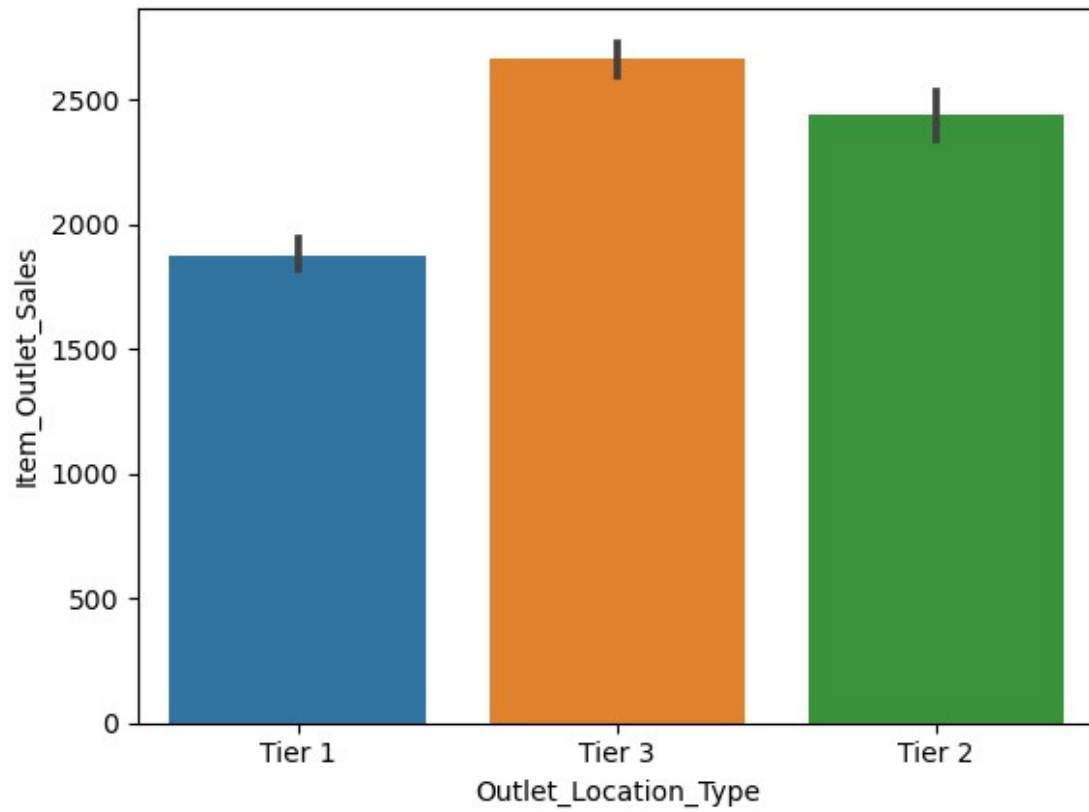
```
sns.boxenplot(data=mart,x="Item_Outlet_Sales")
```

```
<AxesSubplot:xlabel='Item_Outlet_Sales'>
```



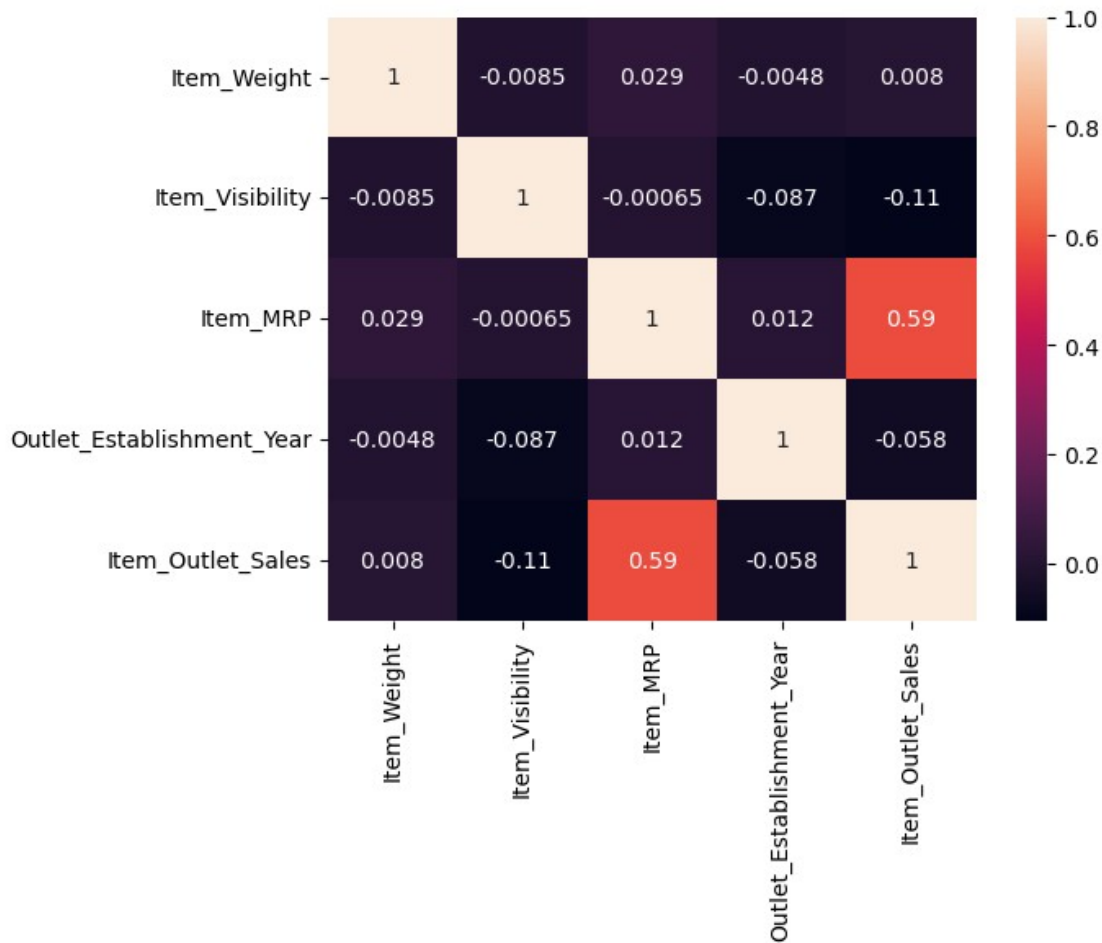
```
sns.barplot(x="Outlet_Location_Type",y='Item_Outlet_Sales',data=mart)
```

```
<AxesSubplot:xlabel='Outlet_Location_Type',  
ylabel='Item_Outlet_Sales'>
```



```
sns.heatmap(mart.corr(),annot=True)
```

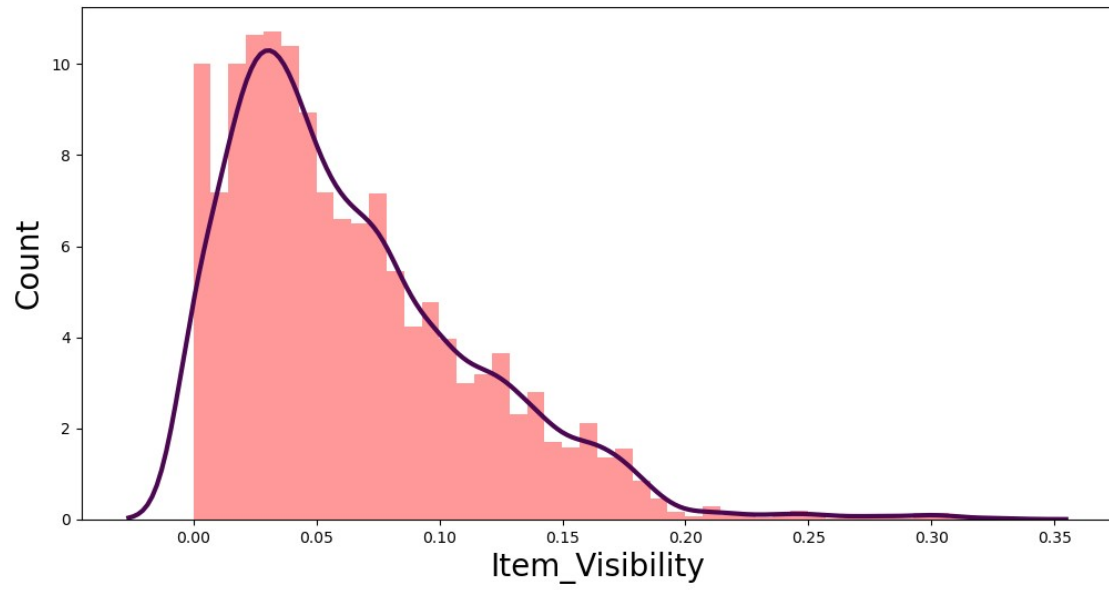
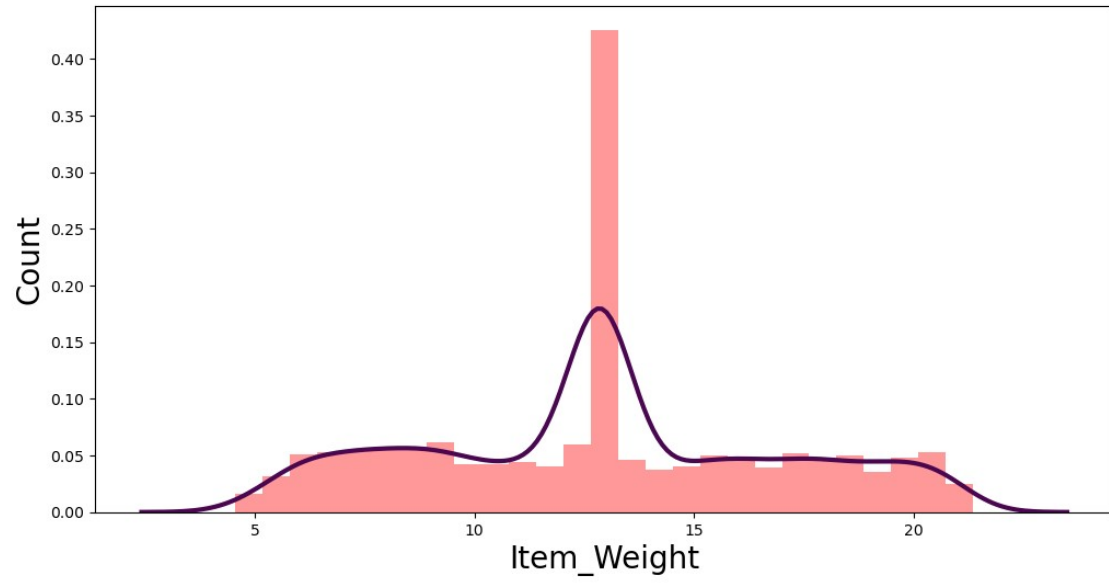
```
<AxesSubplot:>
```

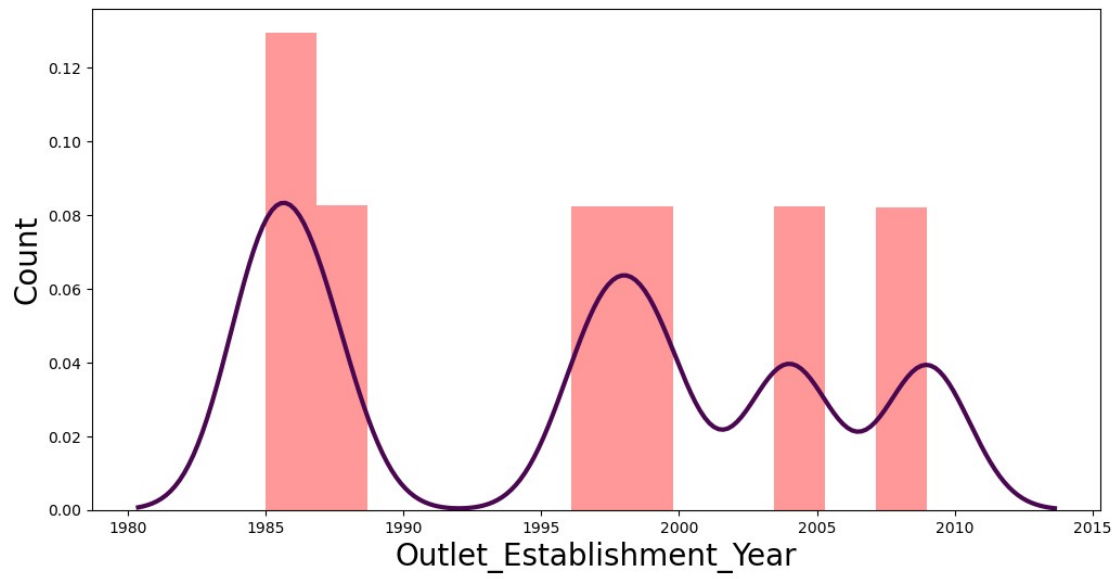
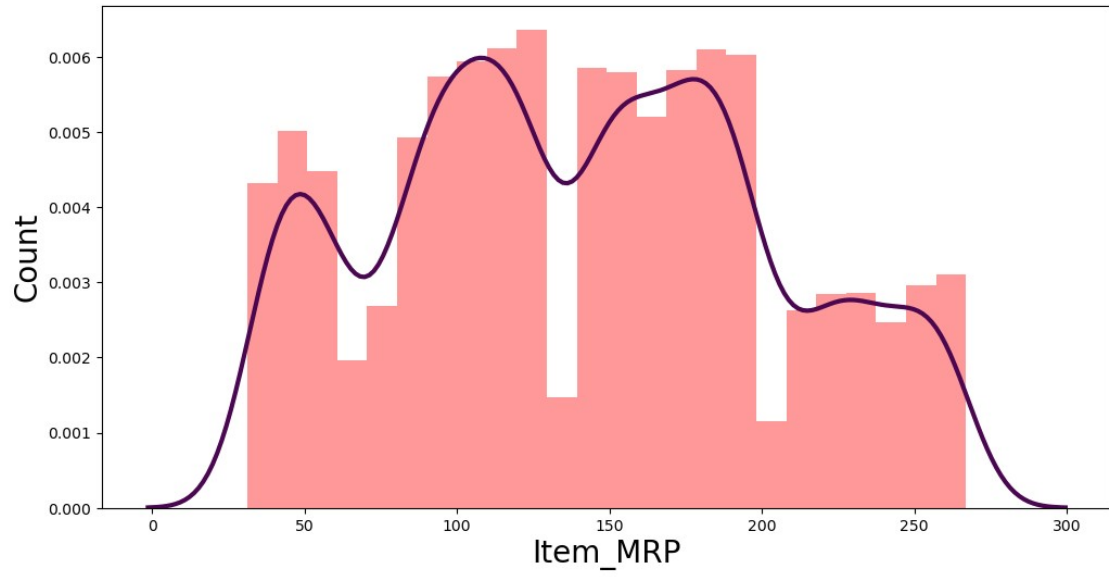



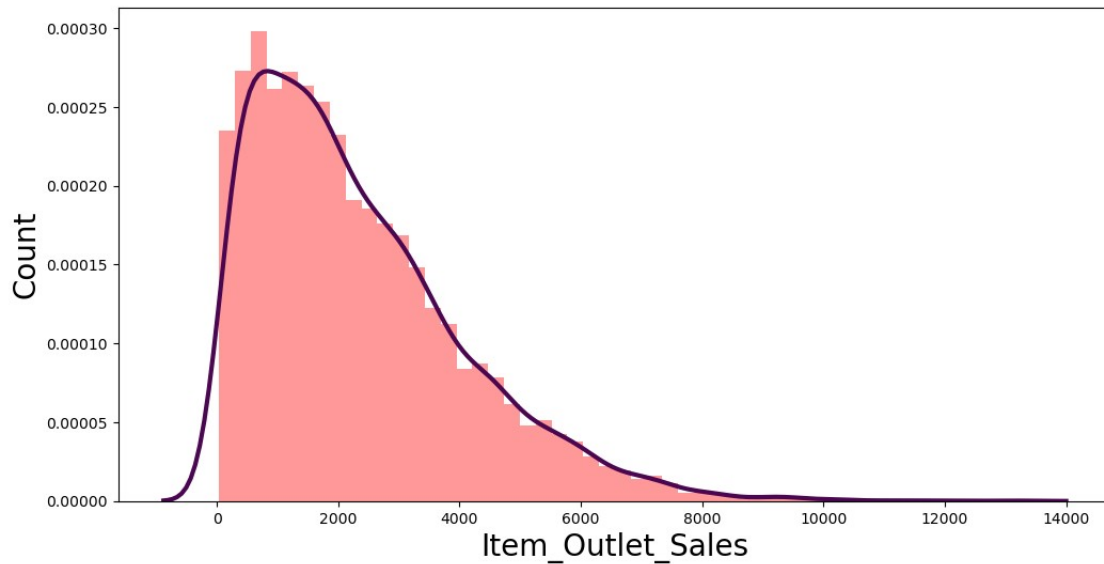
```
import warnings
warnings.filterwarnings("ignore")

for feature in numerical_feature:
    dataset=mart.copy()
    fig, ax = plt.subplots(figsize=(12,6))

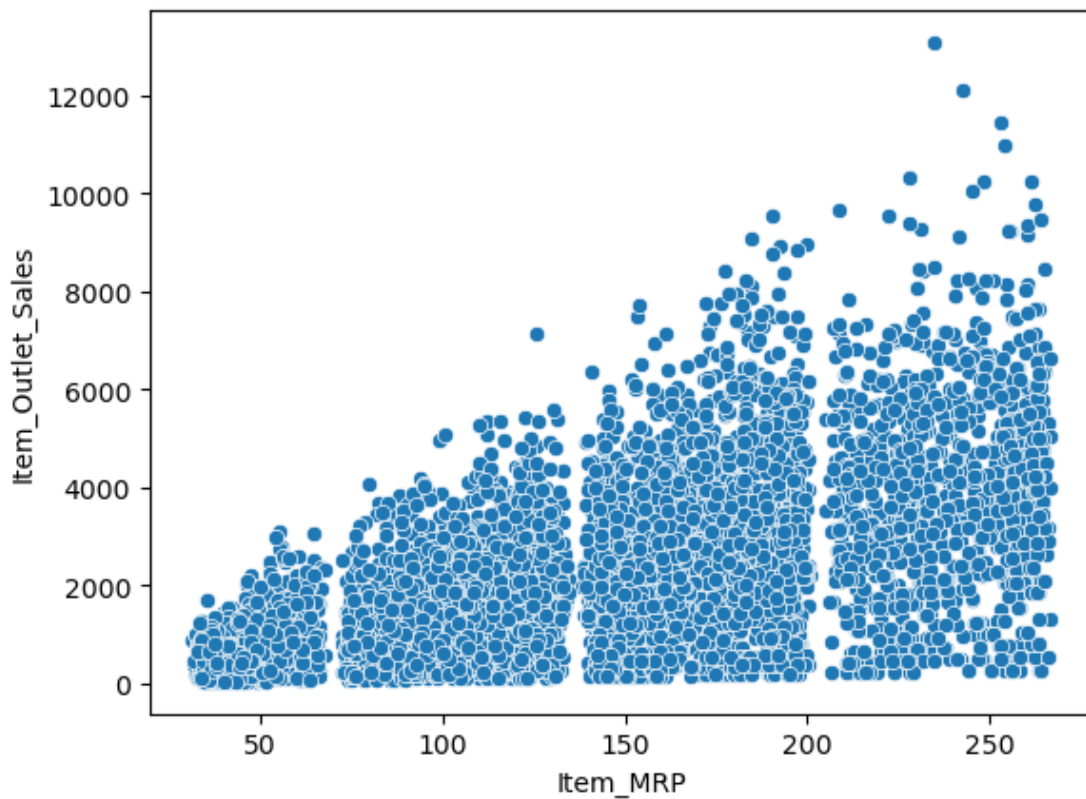
sns.distplot(dataset[feature],color='r',kde_kws={'linewidth':3,'color': '#4B0751'});
    ax.set_xlabel(feature, fontsize=20)
    ax.set_ylabel("Count", fontsize=20)
```



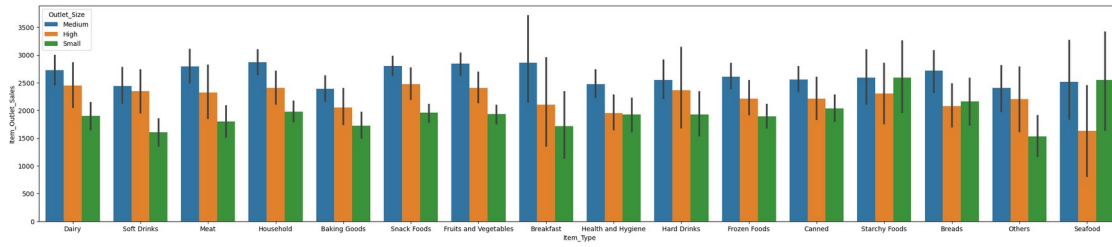




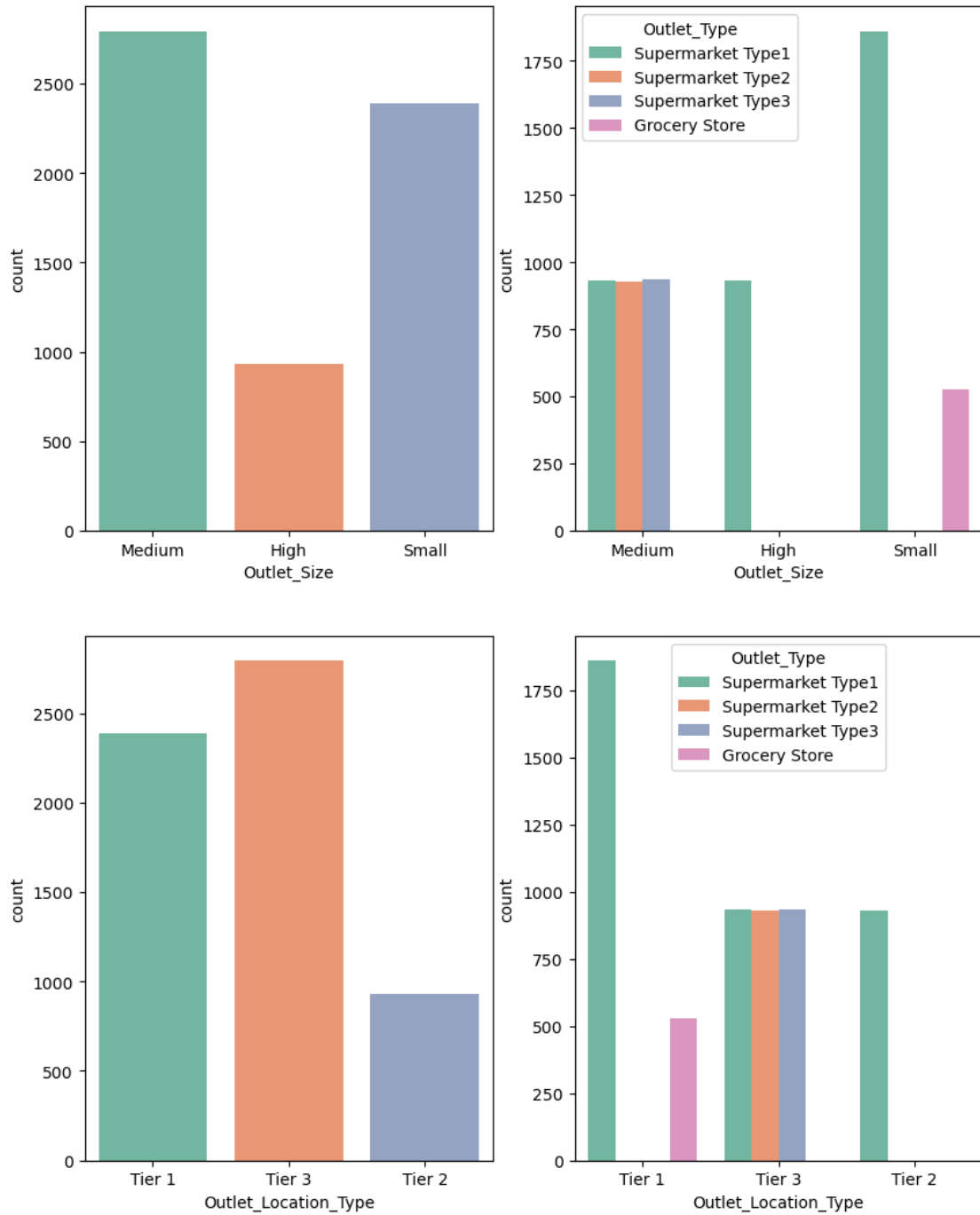
```
sns.scatterplot(x="Item_MRP",y='Item_Outlet_Sales',data=mart)
<AxesSubplot:xlabel='Item_MRP', ylabel='Item_Outlet_Sales'>
```



```
plt.figure(figsize=(30,6))
sns.barplot(x="Item_Type",y="Item_Outlet_Sales",data=mart,hue="Outlet_
Size")
plt.show()
```

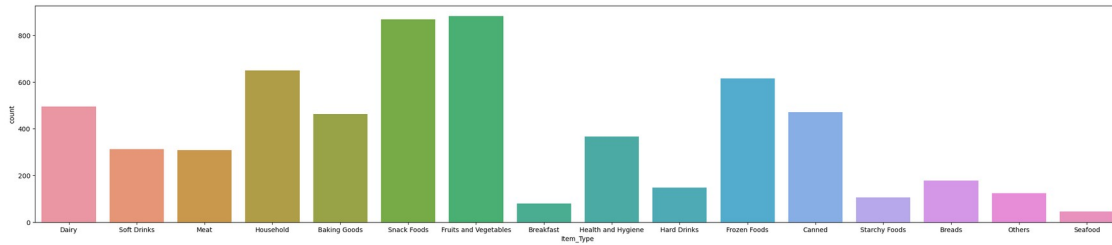


```
plt.figure(figsize=(10,20))
i=1
for col in ['Outlet_Size', 'Outlet_Location_Type']:
    plt.subplot(3,2,i)
    sns.countplot(x=col,data=mart,palette='Set2')
    i+=1
    plt.subplot(3,2,i)
    sns.countplot(x=col,hue='Outlet_Type',data=mart,palette='Set2')
    i+=1
```



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

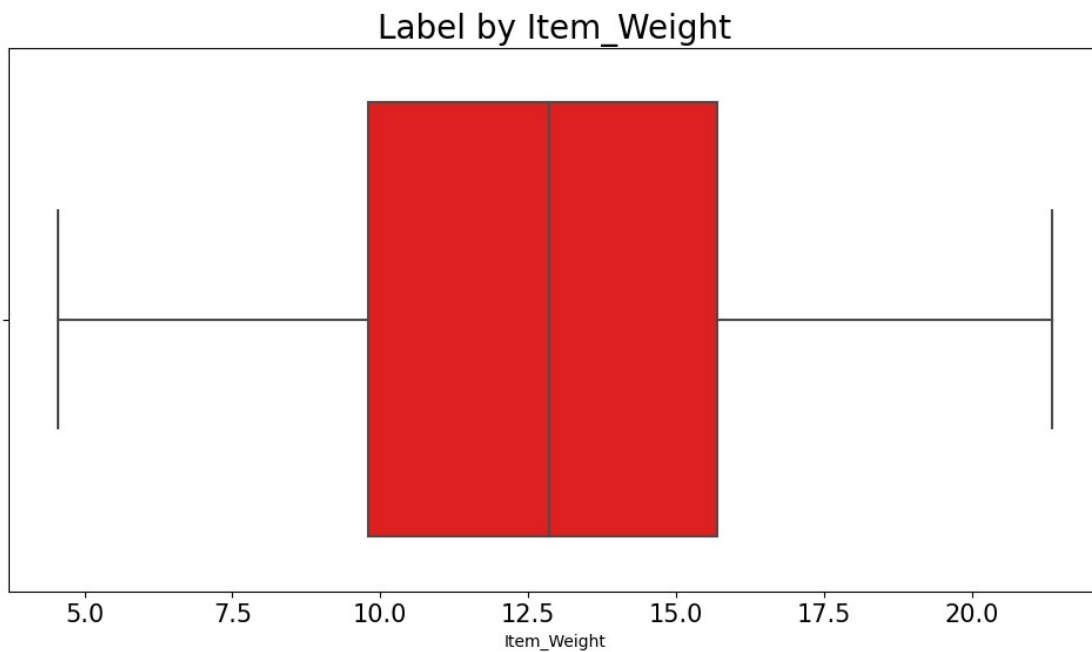
```
<AxesSubplot:xlabel='Item_Type', ylabel='count'>
```



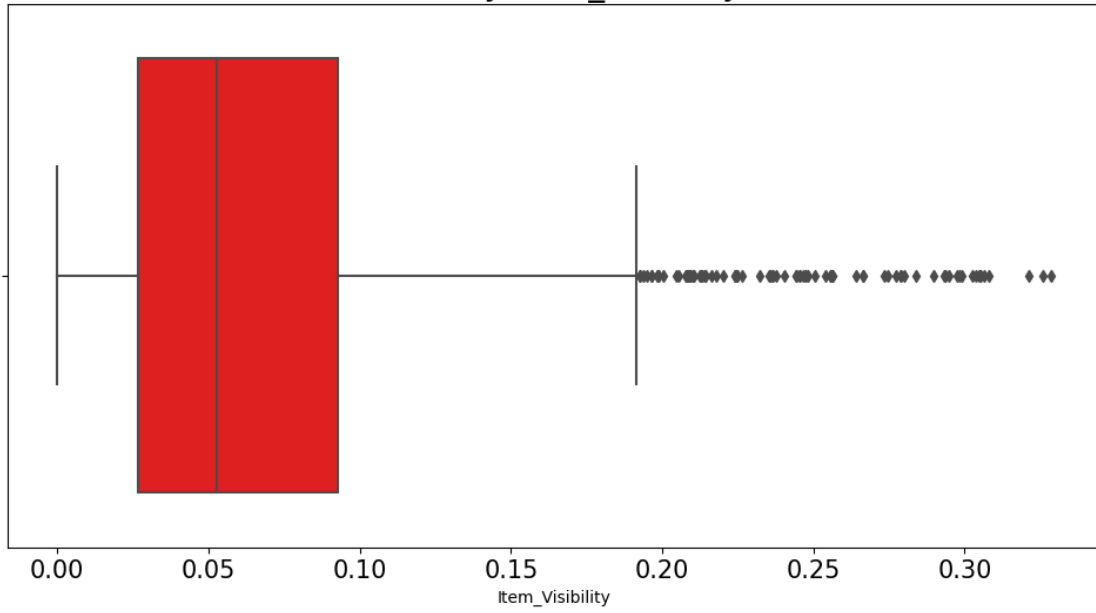
Outliers

“Outlier Analysis is a process that involves identifying the anomalous observation in the dataset.” Outliers are extreme values that deviates from the other observations in the dataset.

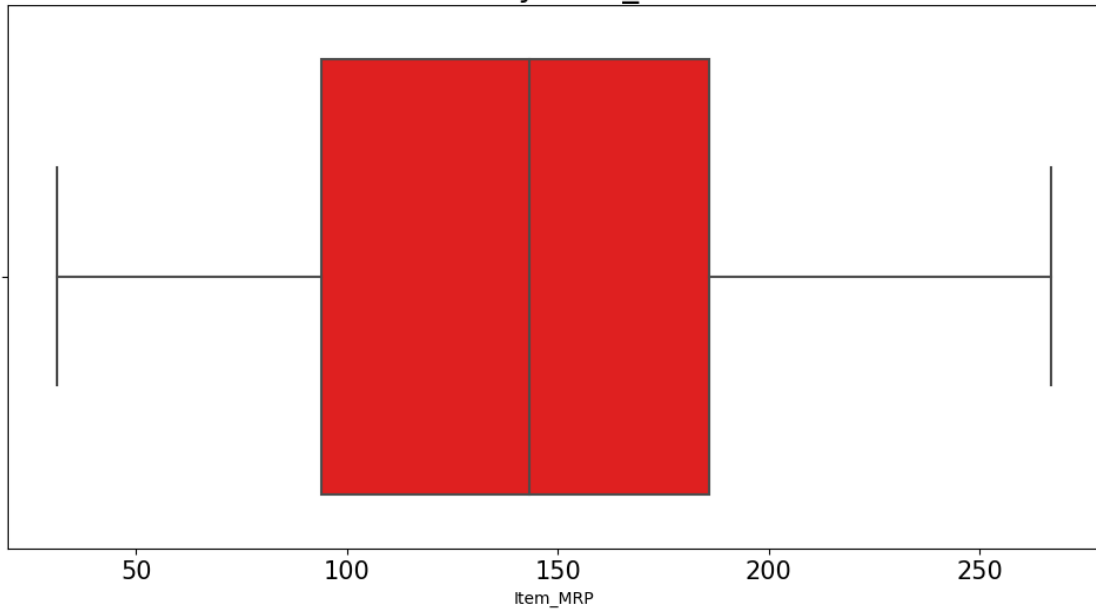
```
for col in dataset.describe().columns:
    fig, ax = plt.subplots(figsize=(12,6))
    sns.boxplot(dataset[col],color='red')
    ax.tick_params(axis='x',labelsize=15)
    ax.tick_params(axis='y',labelsize=15)
    ax.set_title('Label by ' + col, fontsize=20)
plt.show()
```

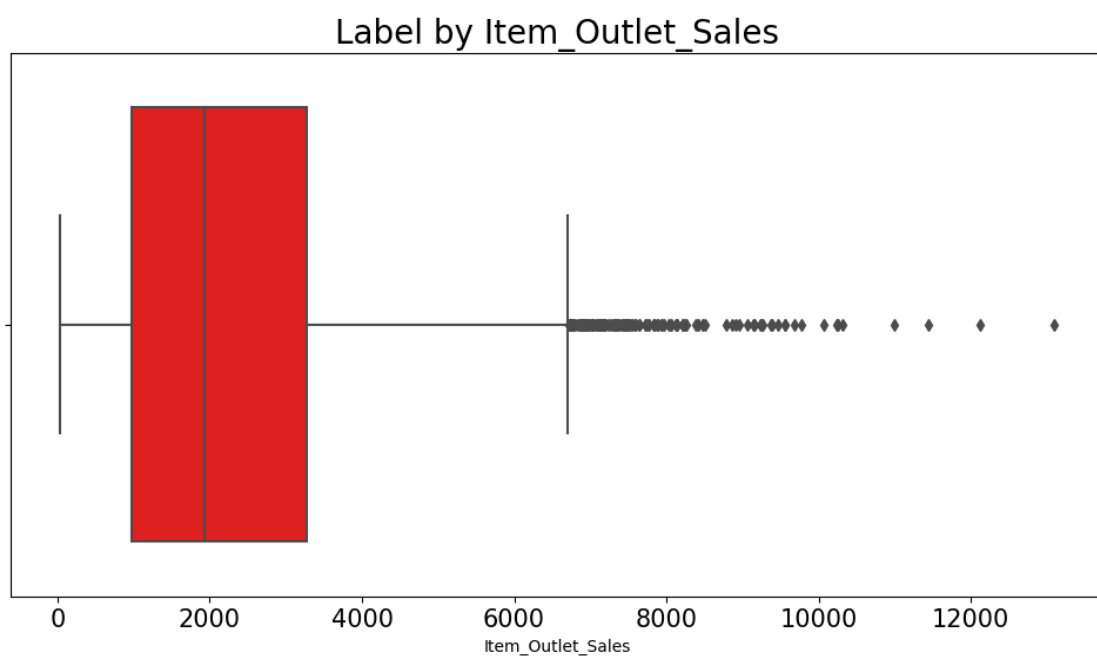
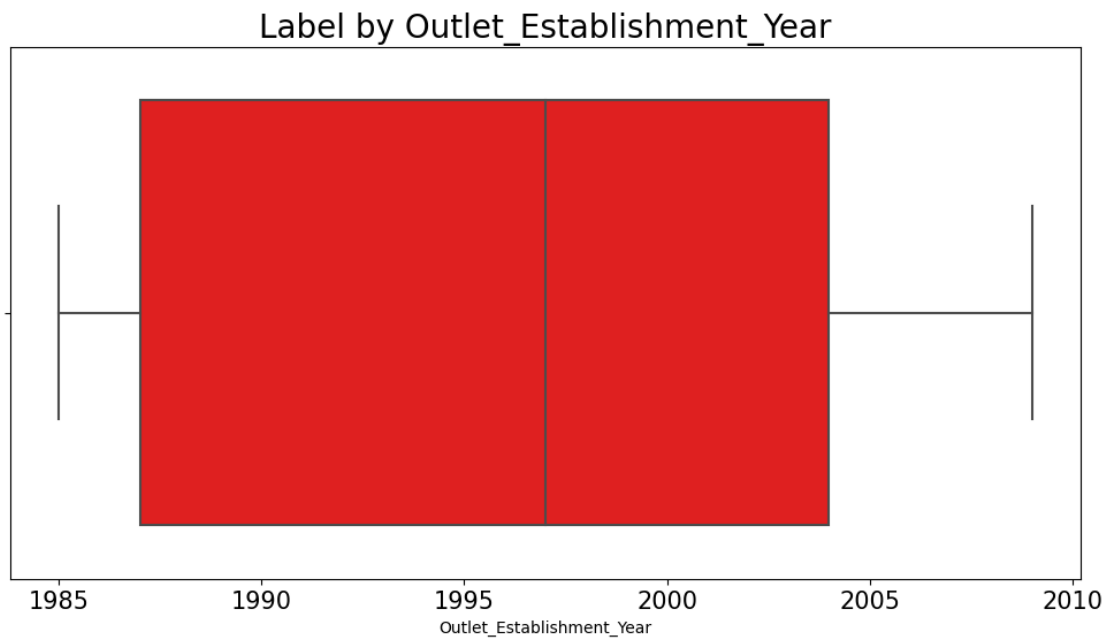


Label by Item_Visibility



Label by Item_MRP





```
mart.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

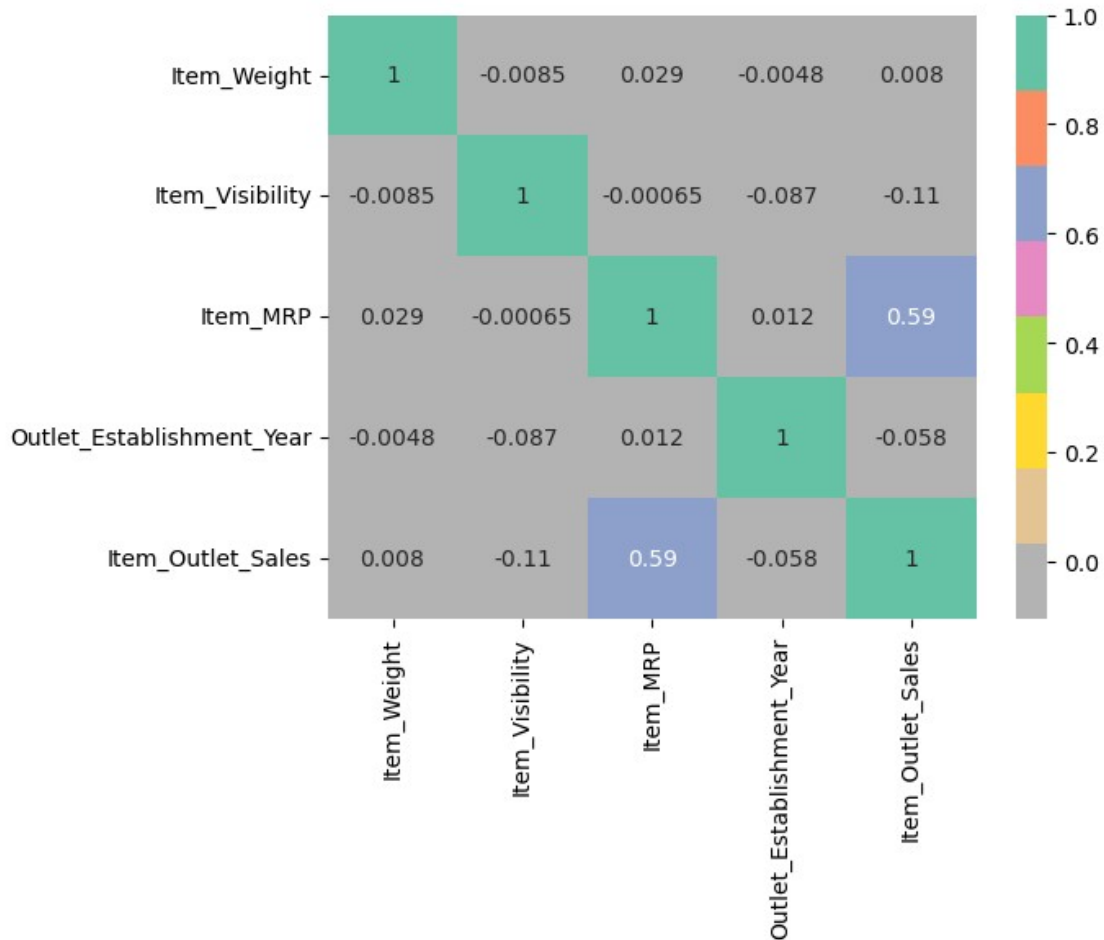
```

```

sns.heatmap(numerical_feature.corr(),annot=True,data=mart,cbar=True,xt
icklabels='auto',yticklabels='auto',linecolor='white',linewidths=0,cma
p="Set2_r")

```

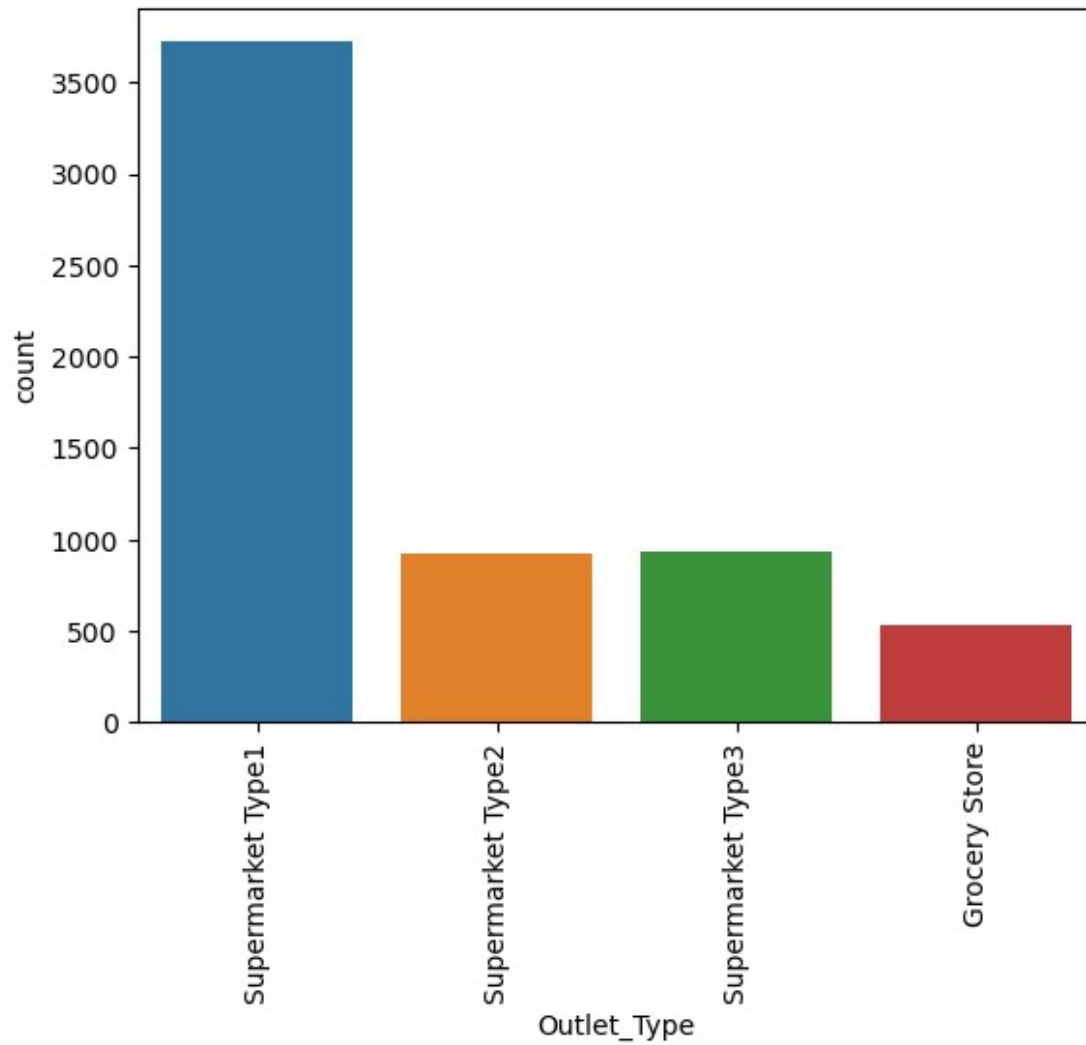
<AxesSubplot:>



```

sns.countplot(data=mart,x='Outlet_Type')
plt.xticks(rotation = 90)
plt.show()

```



grouping the data

```
mart[["Item_Weight", "Item_Outlet_Sales"]].groupby(["Item_Weight"]).agg(
    ("median")
```

Item_Weight	Item_Outlet_Sales
4.555	1565.9616
4.590	1358.2320
4.610	1831.6158
4.615	4893.6300
4.635	1927.4910
...	...
21.000	1356.2346
21.100	2015.3766
21.200	2954.1546
21.250	2470.1180
21.350	5206.5560

[410 rows x 1 columns]

```
mart[["Item_Fat_Content","Item_Outlet_Sales"]].groupby(["Item_Fat_Content"]).agg("median")
```

	Item_Outlet_Sales
Item_Fat_Content	
LF	2028.6926
Low Fat	1907.5170
Regular	1974.4299
low fat	1722.4246
reg	1598.5858

```
mart[["Item_Visibility","Item_Outlet_Sales"]].groupby(["Item_Visibility"]).agg("median")
```

	Item_Outlet_Sales
Item_Visibility	
0.000000	1844.2660
0.003575	3229.7958
0.003589	1691.7978
0.003598	2922.1962
0.003607	1384.1982
...	...
0.306543	291.6204
0.308145	889.5088
0.321115	199.7400
0.325781	761.0094
0.328391	588.5672

[5641 rows x 1 columns]

```
mart[["Item_Type","Item_Outlet_Sales"]].groupby(["Item_Type"]).agg("median")
```

	Item_Outlet_Sales
Item_Type	
Baking Goods	1701.7848
Breads	2055.9904
Breakfast	1561.9668
Canned	1901.5248
Dairy	1851.5898
Frozen Foods	1808.3128
Fruits and Vegetables	2022.7004
Hard Drinks	1940.1412
Health and Hygiene	1884.2140
Household	2125.2336
Meat	1964.7758
Others	1837.6080
Seafood	2154.1959

Snack Foods	2084.9527
Soft Drinks	1617.2282
Starchy Foods	2181.1608

```
mart[["Item_MRP", "Item_Outlet_Sales"]].groupby(["Item_MRP"]).agg("median")
```

Item_MRP	Item_Outlet_Sales
31.2900	898.8300
31.4900	466.0600
31.8900	366.1900
31.9558	679.1160
32.0558	1018.6740
...	...
266.1884	4239.8144
266.2884	2914.8724
266.5884	3974.8260
266.6884	3974.8260
266.8884	5034.7796

[4694 rows x 1 columns]

```
mart[["Outlet_Identifier", "Item_Outlet_Sales"]].groupby(["Outlet_Identifier"]).agg("median")
```

Outlet_Identifier	Item_Outlet_Sales
OUT013	2050.6640
OUT018	1655.1788
OUT019	265.3213
OUT027	3364.9532
OUT035	2109.2544
OUT046	1945.8005
OUT049	1966.1074

```
mart[["Outlet_Establishment_Year", "Item_Outlet_Sales"]].groupby(["Outlet_Establishment_Year"]).agg("median")
```

Outlet_Establishment_Year	Item_Outlet_Sales
1985	1845.5976
1987	2050.6640
1997	1945.8005
1999	1966.1074
2004	2109.2544
2009	1655.1788

```
mart[["Outlet_Size", "Item_Outlet_Sales"]].groupby(["Outlet_Size"]).agg("median")
```

Outlet_Size	Item_Outlet_Sales
High	2050.6640
Medium	2251.0698
Small	1544.6560

```
mart[["Outlet_Type", "Item_Outlet_Sales"]].groupby(["Outlet_Type"]).agg(
("median")
```

Outlet_Type	Item_Outlet_Sales
Grocery Store	265.3213
Supermarket Type1	2024.0320
Supermarket Type2	1655.1788
Supermarket Type3	3364.9532

```
mart.head()
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	\
0	FDA15	9.300	Low Fat	0.016047	
1	DRC01	5.920	Regular	0.019278	
2	FDN15	17.500	Low Fat	0.016760	
4	NCD19	8.930	Low Fat	0.000000	
5	FDP36	10.395	Regular	0.000000	

	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year
0	Dairy	249.8092	OUT049	1999
1	Soft Drinks	48.2692	OUT018	2009
2	Meat	141.6180	OUT049	1999
4	Household	53.8614	OUT013	1987
5	Baking Goods	51.4008	OUT018	2009

	Outlet_Size	Outlet_Location_Type	Outlet_Type
0	Medium	Tier 1	Supermarket Type1
1	Medium	Tier 3	Supermarket Type2
2	Medium	Tier 1	Supermarket Type1
4	High	Tier 3	Supermarket Type1
5	Medium	Tier 3	Supermarket Type2

```
sns.heatmap
```

```
<function seaborn.matrix.heatmap(data, *, vmin=None, vmax=None,
cmap=None, center=None, robust=False, annot=None, fmt='.2g',
annot_kws=None, linewidths=0, linecolor='white', cbar=True,
cbar_kws=None, cbar_ax=None, square=False, xticklabels='auto',
yticklabels='auto', mask=None, ax=None, **kwargs)>
```

labelencoding

```
from sklearn.preprocessing import LabelEncoder
```

```
Le=LabelEncoder()
```

```
mart["Item_Identifier"]=Le.fit_transform(mart["Item_Identifier"])
mart["Item_Fat_Content"]=mart["Item_Fat_Content"].replace({'LF':0,
'Low Fat':1, 'Regular':2, 'low fat':3, 'reg':4})
```

```
mart["Outlet_Identifier"]=mart["Outlet_Identifier"].replace({"OUT013":
0,"OUT018":1,"OUT019":2,"OUT027":3,"OUT035":4,"OUT046":5,"OUT049":6})
```

```
mart["Item_Type"]=mart["Item_Type"].replace({"Fruits and
Vegetables":0,"Snack Foods":1,"Household":2,"Frozen
Foods":3,"Dairy":4,"Canned":5,"Baking Goods":6,"Health and
Hygiene":7,"Soft Drinks":8,"Meat":8,"Breads":10,"Hard
Drinks":11,"Others":12,"Starchy
Foods":13,"Breakfast":14,"Seafood":15})
```

```
mart["Outlet_Size"]=mart["Outlet_Size"].replace({"Small":0,"Medium":1,
"High":2})
```

```
mart["Outlet_Location_Type"]=mart["Outlet_Location_Type"].replace({"Ti
er 1":0,"Tier 2":1,"Tier 3":2})
```

```
mart["Outlet_Type"]=mart["Outlet_Type"].replace({"Grocery
Store":0,"Supermarket Type1":1,"Supermarket Type2":2,"Supermarket
Type3":3})
```

```
mart
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility
0	155	9.300	1	0.016047
1	8	5.920	2	0.019278
2	661	17.500	1	0.016760
4	1294	8.930	1	0.000000
5	757	10.395	2	0.000000
...

8517	388	20.750	4	0.083607
8518	369	6.865	1	0.056783
8520	1354	10.600	1	0.035186
8521	680	7.210	2	0.145221
8522	49	14.800	1	0.044878

Item_Type	Item_MRP	Outlet_Identifier
Outlet_Establishment_Year		
0	4 249.8092	6
1999		
1	8 48.2692	1
2009		
2	8 141.6180	6
1999		
4	2 53.8614	0
1987		
5	6 51.4008	1
2009		
...
.		..
8517	3 178.8318	5
1997		
8518	1 214.5218	0
1987		
8520	7 85.1224	4
2004		
8521	1 103.1332	1
2009		
8522	8 75.4670	5
1997		

Outlet_Size	Outlet_Location_Type	Outlet_Type
Item_Outlet_Sales		
0	1	0 1
3735.1380		
1	1	2 2
443.4228		
2	1	0 1
2097.2700		
4	2	2 1
994.7052		
5	1	2 2
556.6088		


```

...
.
8517          0          0          1
3608.6360
8518          2          2          1
2778.3834
8520          0          1          1
1193.1136
8521          1          2          2
1845.5976
8522          0          0          1
765.6700

```

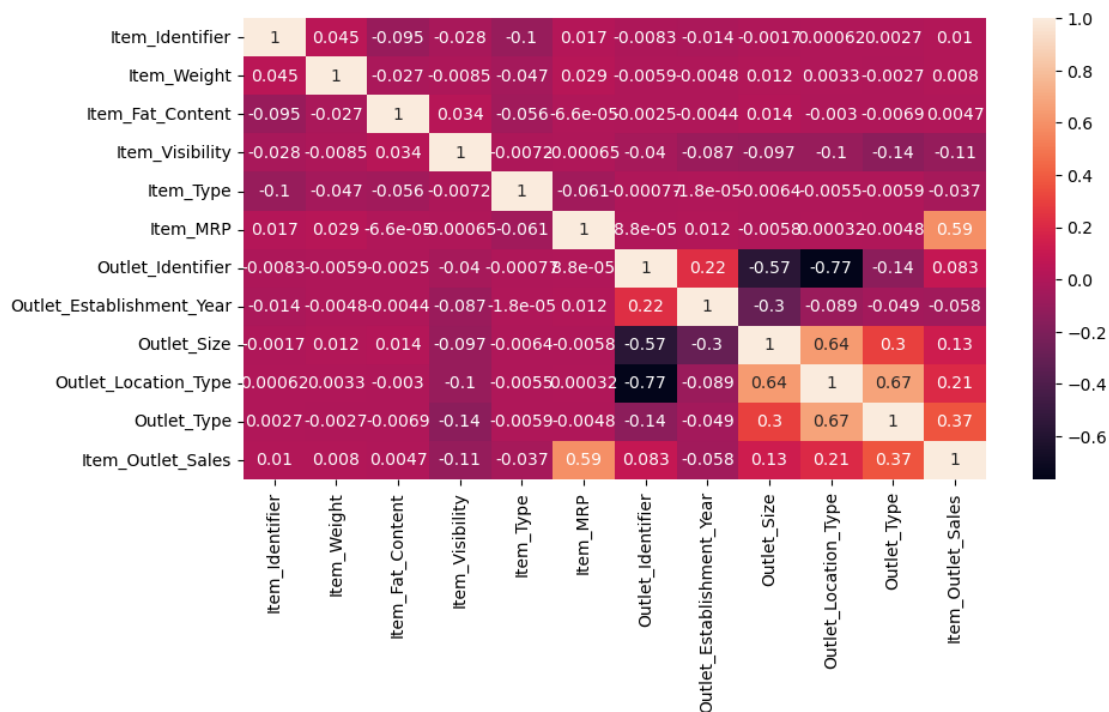
[6113 rows x 12 columns]

```

plt.figure(figsize=(10,5))
sns.heatmap(mart.corr(),annot=True)
plt.show

```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



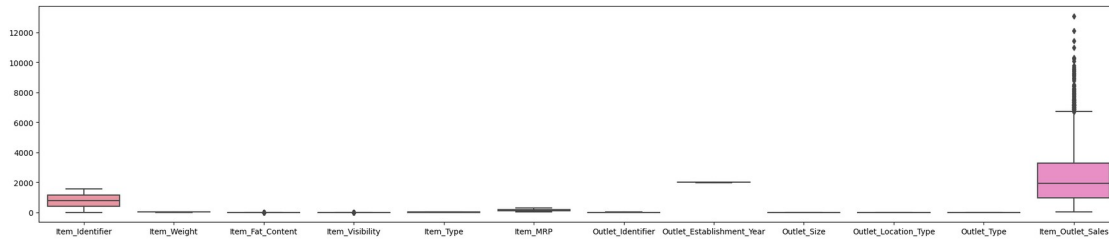
Checking Outlier !

```

plt.figure(figsize=(25,5))
sns.boxplot(data=mart)

```

```
<AxesSubplot:>
```



```
mart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 6113 entries, 0 to 8522
```

```
Data columns (total 12 columns):
```

#	Column	Non-Null Count	Dtype
0	Item_Identifier	6113 non-null	int32
1	Item_Weight	6113 non-null	float64
2	Item_Fat_Content	6113 non-null	int64
3	Item_Visibility	6113 non-null	float64
4	Item_Type	6113 non-null	int64
5	Item_MRP	6113 non-null	float64
6	Outlet_Identifier	6113 non-null	int64
7	Outlet_Establishment_Year	6113 non-null	int64
8	Outlet_Size	6113 non-null	int64
9	Outlet_Location_Type	6113 non-null	int64
10	Outlet_Type	6113 non-null	int64
11	Item_Outlet_Sales	6113 non-null	float64

```
dtypes: float64(4), int32(1), int64(7)
```

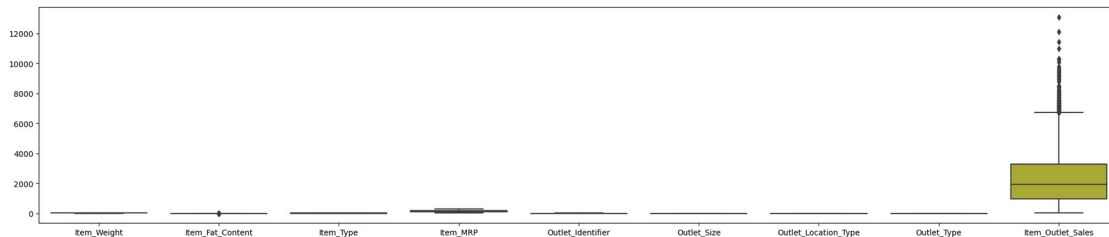
```
memory usage: 597.0 KB
```

```
mart.drop(["Item_Identifier","Item_Visibility","Outlet_Establishment_Year"],axis=1,inplace=True)
```

```
plt.figure(figsize=(25,5))
```

```
sns.boxplot(data=mart)
```

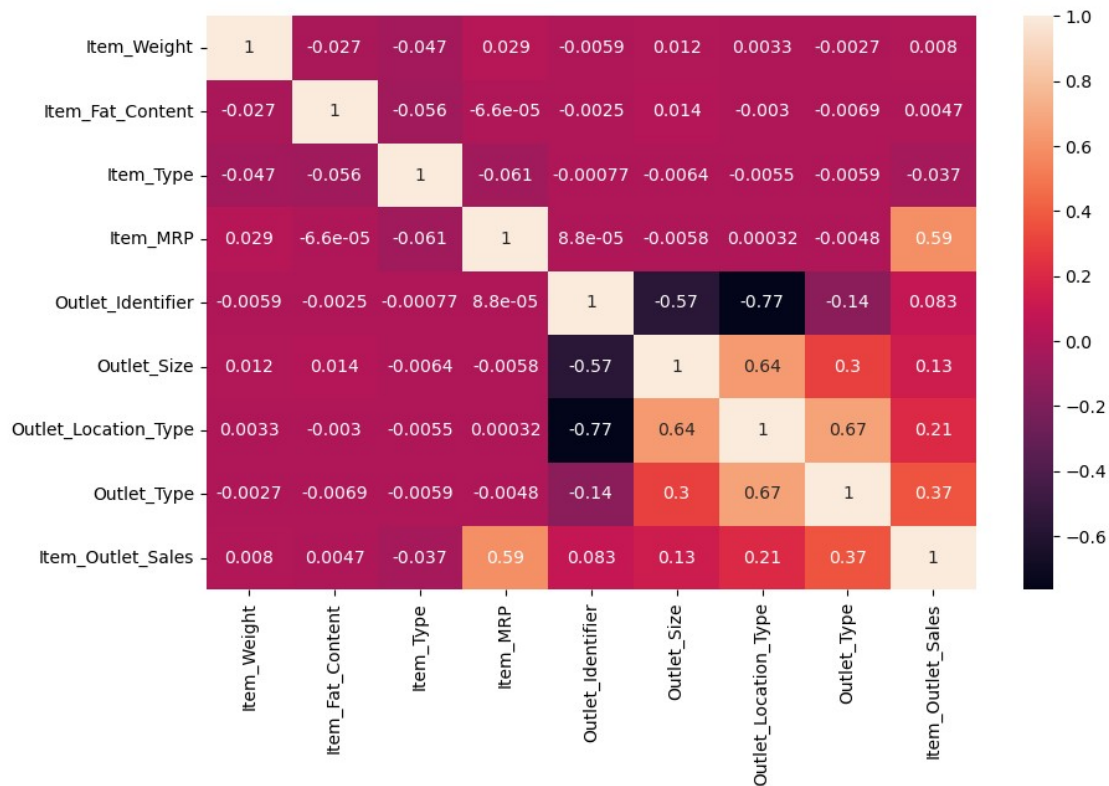
```
<AxesSubplot:>
```



```
plt.figure(figsize=(10,6))
```

```
sns.heatmap(mart.corr(),annot=True)
```

```
<AxesSubplot:>
```



```
X=mart.drop("Item_Outlet_Sales",axis=1)
Y=mart["Item_Outlet_Sales"]
```

```
test_X=X.iloc[0:500]
test_Y=Y.iloc[0:500]
#testing only first 500
```

```
from sklearn.metrics import r2_score

score={}
```

RANDOM FOREST REGRESSOR

```
from sklearn.ensemble import RandomForestRegressor

rf=RandomForestRegressor(n_estimators=500)

rf.fit(X,Y)

RandomForestRegressor(n_estimators=500)

rf_pred=rf.predict(test_X)

r2_score(test_Y,rf_pred)

0.939023238479339
```

XGBOOST

```
# pip install xgboost
```

```
import xgboost as xg
```

```
xgb=xg.XGBRegressor(n_estimators=500)
```

```
xgb.fit(X,Y)
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,  
             colsample_bylevel=None, colsample_bynode=None,  
             colsample_bytrees=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=500, n_jobs=None, num_parallel_tree=None,  
             predictor=None, random_state=None, ...)
```

```
xgb_pred=xgb.predict(test_X)
```

```
r2_score(test_Y,xgb_pred)
```

```
0.9774015892942607
```

```
import pickle
```

```
    pickle.dump(xgb,open(r"model.pkl","wb"))
```

```
import sklearn
```

```
import streamlit as st
```

```
# pip install streamlit
```

```
Requirement already satisfied: streamlit in c:\programdata\anaconda3\lib\site-packages (1.22.0)Note: you may need to restart the kernel to use updated packages.
```

```
WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)
```

```
WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)
```

```
WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)
```

```
WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)
```

WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\programdata\anaconda3\lib\site-packages)

Requirement already satisfied: pyarrow>=4.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (12.0.0)
Requirement already satisfied: gitpython!=3.1.19 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (3.1.31)
Requirement already satisfied: pympler>=0.9 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (1.0.1)
Requirement already satisfied: rich>=10.11.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (13.3.5)
Requirement already satisfied: validators>=0.2 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (0.20.0)
Requirement already satisfied: importlib-metadata>=1.4 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (4.11.3)
Requirement already satisfied: tzlocal>=1.1 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (5.0.1)
Requirement already satisfied: typing-extensions>=3.10.0.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (4.3.0)
Requirement already satisfied: tenacity<9,>=8.0.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (8.0.1)
Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (9.2.0)
Requirement already satisfied: protobuf<4,>=3.12 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (3.20.3)
Requirement already satisfied: cachetools>=4.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (5.3.0)
Requirement already satisfied: toml in c:\programdata\anaconda3\lib\site-packages (from streamlit) (0.10.2)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-packages (from streamlit) (1.23.5)
Requirement already satisfied: blinker>=1.0.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (1.6.2)
Requirement already satisfied: tornado>=6.0.3 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (6.1)
Requirement already satisfied: pandas<3,>=0.25 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (1.4.4)
Requirement already satisfied: click>=7.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (8.0.4)
Requirement already satisfied: python-dateutil in c:\programdata\anaconda3\lib\site-packages (from streamlit) (2.8.2)
Requirement already satisfied: requests>=2.4 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (2.28.1)
Requirement already satisfied: watchdog in c:\programdata\anaconda3\lib\site-packages (from streamlit) (2.1.6)
Requirement already satisfied: altair<5,>=3.2.0 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (4.2.2)

Requirement already satisfied: packaging>=14.1 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (21.3)

Requirement already satisfied: pydeck>=0.1.dev5 in c:\programdata\anaconda3\lib\site-packages (from streamlit) (0.8.1b0)

Requirement already satisfied: jinja2 in c:\programdata\anaconda3\lib\site-packages (from altair<5,>=3.2.0->streamlit) (2.11.3)

Requirement already satisfied: entrypoints in c:\programdata\anaconda3\lib\site-packages (from altair<5,>=3.2.0->streamlit) (0.4)

Requirement already satisfied: toolz in c:\programdata\anaconda3\lib\site-packages (from altair<5,>=3.2.0->streamlit) (0.11.2)

Requirement already satisfied: jsonschema>=3.0 in c:\programdata\anaconda3\lib\site-packages (from altair<5,>=3.2.0->streamlit) (4.16.0)

Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-packages (from click>=7.0->streamlit) (0.4.5)

Requirement already satisfied: gitdb<5,>=4.0.1 in c:\programdata\anaconda3\lib\site-packages (from gitpython!=3.1.19->streamlit) (4.0.10)

Requirement already satisfied: zipp>=0.5 in c:\programdata\anaconda3\lib\site-packages (from importlib-metadata>=1.4->streamlit) (3.8.0)

Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\programdata\anaconda3\lib\site-packages (from packaging>=14.1->streamlit) (3.0.9)

Requirement already satisfied: pytz>=2020.1 in c:\programdata\anaconda3\lib\site-packages (from pandas<3,>=0.25->streamlit) (2022.1)

Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-packages (from python-dateutil->streamlit) (1.16.0)

Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\programdata\anaconda3\lib\site-packages (from requests>=2.4->streamlit) (1.26.11)

Requirement already satisfied: charset-normalizer<3,>=2 in c:\programdata\anaconda3\lib\site-packages (from requests>=2.4->streamlit) (2.0.4)

Requirement already satisfied: idna<4,>=2.5 in c:\programdata\anaconda3\lib\site-packages (from requests>=2.4->streamlit) (3.3)

Requirement already satisfied: certifi>=2017.4.17 in c:\programdata\anaconda3\lib\site-packages (from requests>=2.4->streamlit) (2022.9.14)

Requirement already satisfied: pygments<3.0.0,>=2.13.0 in c:\programdata\anaconda3\lib\site-packages (from rich>=10.11.0->streamlit) (2.15.1)

Requirement already satisfied: markdown-it-py<3.0.0,>=2.2.0 in c:\programdata\anaconda3\lib\site-packages (from rich>=10.11.0->streamlit) (2.2.0)

Requirement already satisfied: tzdata in c:\programdata\anaconda3\lib\site-packages (from tzlocal>=1.1->streamlit) (2023.3)

Requirement already satisfied: decorator>=3.4.0 in c:\programdata\anaconda3\lib\site-packages (from validators>=0.2->streamlit) (5.1.1)

Requirement already satisfied: smmap<6,>=3.0.1 in c:\programdata\anaconda3\lib\site-packages (from gitdb<5,>=4.0.1->gitpython!=3.1.19-

```
>streamlit) (5.0.0)
Requirement already satisfied: MarkupSafe>=0.23 in c:\programdata\
anaconda3\lib\site-packages (from jinja2->altair<5,>=3.2.0->streamlit)
(2.0.1)
Requirement already satisfied: pyrsistent!=0.17.0,!0.17.1,!
=0.17.2,>=0.14.0 in c:\programdata\anaconda3\lib\site-packages (from
jsonschema>=3.0->altair<5,>=3.2.0->streamlit) (0.18.0)
Requirement already satisfied: attrs>=17.4.0 in c:\programdata\
anaconda3\lib\site-packages (from jsonschema>=3.0->altair<5,>=3.2.0-
>streamlit) (21.4.0)
Requirement already satisfied: mdurl~=0.1 in c:\programdata\anaconda3\
lib\site-packages (from markdown-it-py<3.0.0,>=2.2.0->rich>=10.11.0-
>streamlit) (0.1.2)
```