In [1]:

```
!pip install dmba
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) http
s://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pkg.de
v/colab-wheels/public/simple/)
Requirement already satisfied: dmba in /usr/local/lib/python3.8/dist-package
s (0.1.0)
```

In [1]:

```
%matplotlib inline
import math
from pathlib import Path
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import accuracy_score, roc_curve, auc
from sklearn.metrics import confusion_matrix
from dmba import regressionSummary, classificationSummary

from sklearn.metrics import r2_score,mean_squared_error
from sklearn.linear_model import BayesianRidge
import matplotlib.pylab as plt

custom_params = {"axes.spines.right": False, "axes.spines.top": False}
sns.set_theme(style="white", palette="Set2", rc=custom_params)
```

In [2]:

```
area_df=pd.read_csv("fulfilment_center_info.csv")
area_df.head()
```

Out[2]:

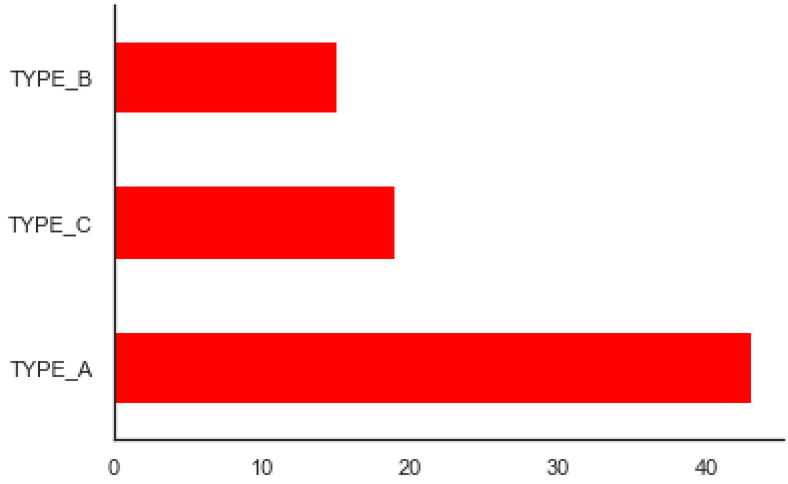
	center_id	city_code	region_code	center_type	op_area
0	11	679	56	TYPE_A	3.7
1	13	590	56	TYPE_B	6.7
2	124	590	56	TYPE_C	4.0
3	66	648	34	TYPE_A	4.1
4	94	632	34	TYPE_C	3.6

In [3]:

```
area_df['center_type'].value_counts().plot(kind='barh',color="red")
```

Out[3]:

```
<AxesSubplot:>
```



In [4]:

```
print("Number of different centers from where the order dispatched")
len(area_df['center_id'].unique())
```

```
Number of different centers from where the order dispatched
```

Out[4]:

```
77
```

In [5]:

```
meal_df=pd.read_csv("meal_info.csv")
meal_df.head(7)
```

Out[5]:

	meal_id	category	cuisine
0	1885	Beverages	Thai
1	1993	Beverages	Thai
2	2539	Beverages	Thai
3	1248	Beverages	Indian
4	2631	Beverages	Indian
5	1311	Extras	Thai
6	1062	Beverages	Italian

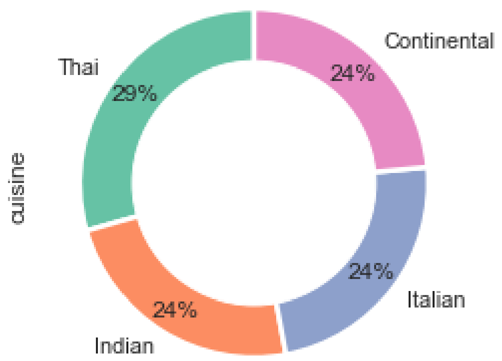
In [6]:

```
meal_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   meal_id   51 non-null     int64 
 1   category  51 non-null     object
 2   cuisine   51 non-null     object
dtypes: int64(1), object(2)
memory usage: 1.3+ KB
```

In [7]:

```
meal_df['cuisine'].value_counts().plot(kind='pie',autopct='%0.0f%%',startangle=90, wedgepro
my_circle=plt.Circle( (0,0), 0.70, color='white')
p=plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```

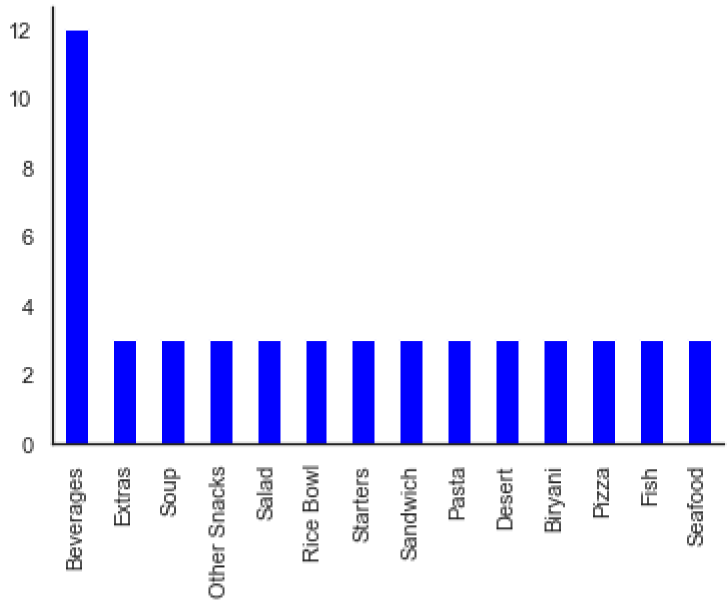


In [8]:

```
meal_df['category'].value_counts().plot(kind='bar',color="blue")
```

Out[8]:

```
<AxesSubplot:>
```



In [9]:

```
df=pd.read_csv("Food demand.csv")
df
```

Out[9]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	h
0	1000000	3	157	2760	233.83	231.83	0	
1	1000001	100	104	2956	486.03	583.03	0	
2	1000002	143	75	1971	328.86	327.86	0	
3	1000003	41	24	2539	145.53	145.53	0	
4	1000004	45	83	2539	95.06	120.34	0	
...	...	...	...	...	...	...	...	
1994	1002177	89	72	1311	130.04	177.51	0	
1995	1002178	24	50	2444	604.31	606.31	0	
1996	1002179	43	88	1971	291.06	291.06	0	
1997	1002180	107	58	1543	473.39	473.39	0	
1998	1002181	105	177	2322	284.27	284.27	0	

1999 rows × 9 columns

In [10]:

```
df.describe()
```

Out[10]:

	id	week	center_id	meal_id	checkout_price	base_price	ema
count	1.999000e+03	1999.000000	1999.000000	1999.000000	1999.000000	1999.000000	
mean	1.001093e+06	75.393197	81.649825	2010.123562	327.302596	347.972866	
std	6.323493e+02	41.743802	46.139173	554.686525	150.906902	158.625091	
min	1.000000e+06	1.000000	10.000000	1062.000000	65.020000	93.120000	
25%	1.000546e+06	40.000000	43.000000	1543.000000	222.645000	242.530000	
50%	1.001094e+06	78.000000	76.000000	1971.000000	292.030000	309.430000	
75%	1.001638e+06	111.500000	110.000000	2539.000000	435.530000	447.230000	
max	1.002181e+06	145.000000	186.000000	2956.000000	767.330000	767.330000	

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1999 entries, 0 to 1998
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     1999 non-null   int64  
 1   week                   1999 non-null   int64  
 2   center_id              1999 non-null   int64  
 3   meal_id                1999 non-null   int64  
 4   checkout_price         1999 non-null   float64
 5   base_price             1999 non-null   float64
 6   emailer_for_promotion  1999 non-null   int64  
 7   homepage_featured      1999 non-null   int64  
 8   num_orders             1999 non-null   int64  
dtypes: float64(2), int64(7)
memory usage: 140.7 KB
```

In [12]:

```
df.isnull().sum()
```

Out[12]:

```
id                       0
week                     0
center_id                0
meal_id                  0
checkout_price           0
base_price               0
emailer_for_promotion    0
homepage_featured        0
num_orders               0
dtype: int64
```

In [13]:

```
df=df.drop(columns=['emailer_for_promotion','homepage_featured'])
```

In [14]:

```
df.head()
```

Out[14]:

	id	week	center_id	meal_id	checkout_price	base_price	num_orders
0	1000000	3	157	2760	233.83	231.83	149
1	1000001	100	104	2956	486.03	583.03	161
2	1000002	143	75	1971	328.86	327.86	149
3	1000003	41	24	2539	145.53	145.53	540
4	1000004	45	83	2539	95.06	120.34	271

In [15]:

```
df=pd.merge(df,area_df,on='center_id')
```

In [16]:

```
df.head()
```

Out[16]:

	id	week	center_id	meal_id	checkout_price	base_price	num_orders	city_code	regi
0	1000000	3	157	2760	233.83	231.83	149	609	
1	1000251	126	157	2306	338.53	340.53	15	609	
2	1000336	16	157	2492	445.23	447.23	55	609	
3	1000406	103	157	1109	192.09	339.50	68	609	
4	1000520	128	157	1230	363.78	363.78	190	609	

In [17]:

```
df=pd.merge(df,meal_df,on='meal_id')
```

In [18]:

```
df.head()
```

Out[18]:

	id	week	center_id	meal_id	checkout_price	base_price	num_orders	city_code	regi
0	1000000	3	157	2760	233.83	231.83	149	609	
1	1001086	144	157	2760	184.36	261.93	96	609	
2	1001863	120	157	2760	219.28	241.53	27	609	
3	1000867	38	24	2760	242.53	242.53	204	614	
4	1001080	131	83	2760	260.93	260.93	107	659	

In [19]:

```
df.columns
```

Out[19]:

```
Index(['id', 'week', 'center_id', 'meal_id', 'checkout_price', 'base_price',
       'num_orders', 'city_code', 'region_code', 'center_type', 'op_area',
       'category', 'cuisine'],
      dtype='object')
```

In [20]:

```
df['category'].unique()
```

Out[20]:

```
array(['Other Snacks', 'Pasta', 'Desert', 'Rice Bowl', 'Beverages',
       'Sandwich', 'Pizza', 'Salad', 'Fish', 'Seafood', 'Biryani',
       'Extras', 'Starters', 'Soup'], dtype=object)
```

In [21]:

```
df["center_type"].unique()
```

Out[21]:

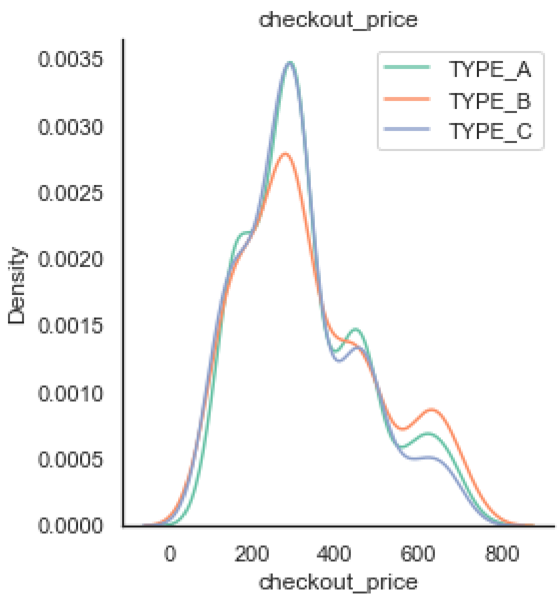
```
array(['TYPE_A', 'TYPE_B', 'TYPE_C'], dtype=object)
```

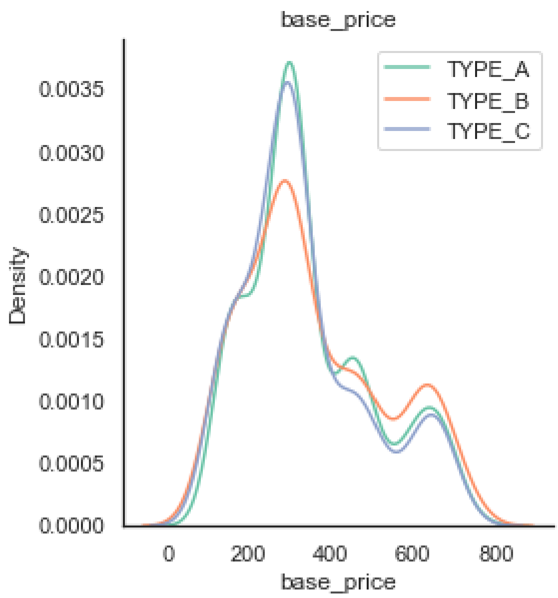
In [22]:

```
TYPE_A = df[df["center_type"] == "TYPE_A"]
TYPE_B = df[df["center_type"] == "TYPE_B"]
TYPE_C = df[df["center_type"] == "TYPE_C"]

plt.figure(figsize = (16,16))
for ax, col in enumerate(df.columns[4:6]):
    plt.subplot(4,4, ax + 1)# here 4,4 will result 4 graphs
    plt.title(col)
    sns.kdeplot(x = TYPE_A[col], label = "TYPE_A")
    sns.kdeplot(x = TYPE_B[col], label = "TYPE_B")
    sns.kdeplot(x = TYPE_C[col], label = "TYPE_C")

    plt.legend()
plt.tight_layout()
```





In [23]:

```
df["cuisine"].unique()
```

Out[23]:

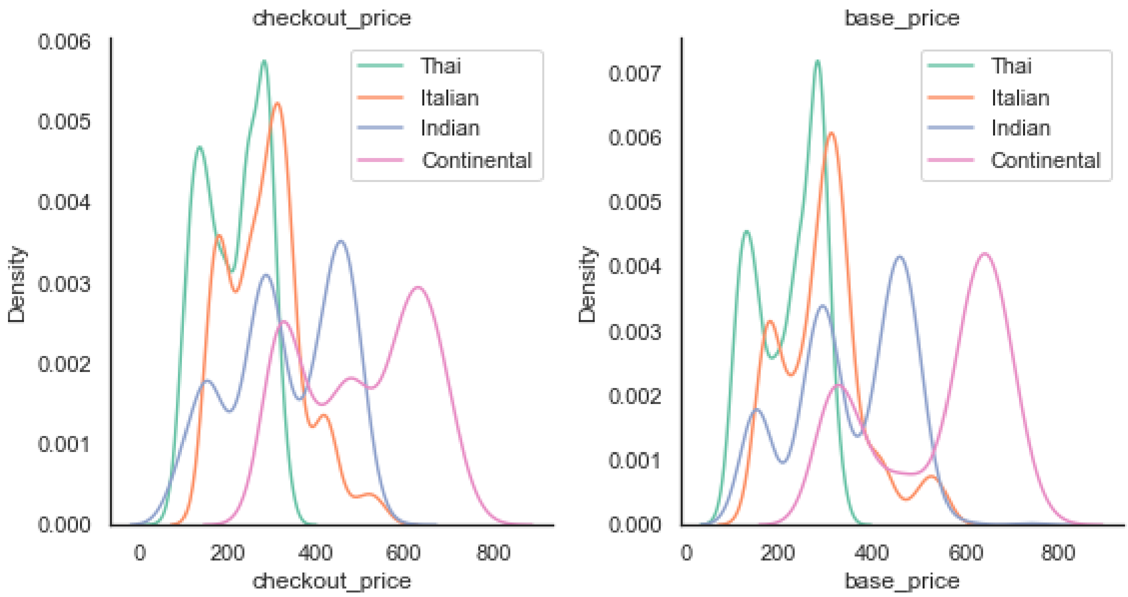
```
array(['Thai', 'Italian', 'Indian', 'Continental'], dtype=object)
```

In [24]:

```
A = df[df["cuisine"] == "Thai"]
B = df[df["cuisine"] == "Italian"]
C = df[df["cuisine"] == "Indian"]
D = df[df["cuisine"] == "Continental"]

plt.figure(figsize = (16,16))
for ax, col in enumerate(df.columns[4:6]):
    plt.subplot(4,4, ax + 1)# here 4,4 will result 4 graphs
    plt.title(col)
    sns.kdeplot(x = A[col], label = "Thai")
    sns.kdeplot(x = B[col], label = "Italian")
    sns.kdeplot(x = C[col], label = "Indian")
    sns.kdeplot(x = D[col], label = "Continental")


    plt.legend()
plt.tight_layout()
```



In [25]:

```
sns.pairplot(df)
```

Out[25]:

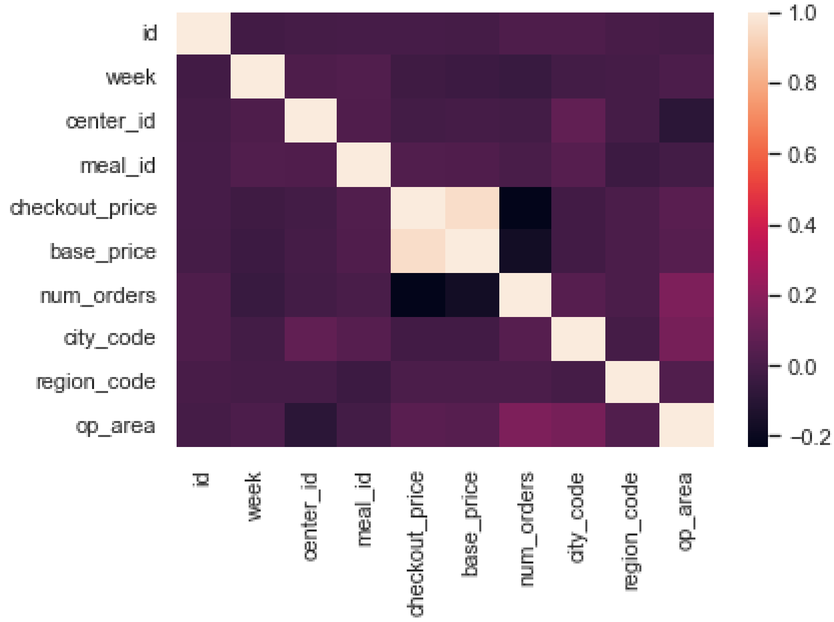
```
<seaborn.axisgrid.PairGrid at 0x2120f752ac0>
```

In [26]:

```
corr = df.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns)
```

Out[26]:

<AxesSubplot:>



In [28]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['cuisine']=le.fit_transform(df['cuisine'])
df['center_type']=le.fit_transform(df['center_type'])
df['category']=le.fit_transform(df['category'])
```

In [29]:

```
df
```

Out[29]:

	id	week	center_id	meal_id	checkout_price	base_price	num_orders	city_code
0	1000000	3	157	2760	233.83	231.83	149	609
1	1001086	144	157	2760	184.36	261.93	96	609
2	1001863	120	157	2760	219.28	241.53	27	609
3	1000867	38	24	2760	242.53	242.53	204	614
4	1001080	131	83	2760	260.93	260.93	107	659
...	...	...	...	...	...	...	...	...
1994	1001791	145	143	2104	582.03	581.03	69	562
1995	1001295	141	74	2104	582.03	581.03	14	702
1996	1000382	64	61	2104	629.53	631.53	41	473
1997	1001089	114	61	2104	588.79	590.79	82	473
1998	1002144	140	113	2104	484.03	630.53	28	680

1999 rows × 13 columns

In [30]:

```
df=df.drop(columns='id')
```

In [31]:

```
df
```

Out[31]:

	week	center_id	meal_id	checkout_price	base_price	num_orders	city_code	region_coc
0	3	157	2760	233.83	231.83	149	609	(
1	144	157	2760	184.36	261.93	96	609	(
2	120	157	2760	219.28	241.53	27	609	(
3	38	24	2760	242.53	242.53	204	614	{
4	131	83	2760	260.93	260.93	107	659	7
...	...	...	...	...	...	...	...	
1994	145	143	2104	582.03	581.03	69	562	7
1995	141	74	2104	582.03	581.03	14	702	:
1996	64	61	2104	629.53	631.53	41	473	7
1997	114	61	2104	588.79	590.79	82	473	7
1998	140	113	2104	484.03	630.53	28	680	7

1999 rows × 12 columns

In [32]:

```
predictors =[ 'week', 'center_id', 'meal_id', 'checkout_price', 'base_price', 'city_code',
outcome = 'num_orders'

X = df[predictors]
y = df[outcome]

# partition data
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [33]:

```
print(train_X.shape)
print(test_X.shape)
print(train_y.shape)
print(test_y.shape)
```

```
(1599, 11)
(400, 11)
(1599,)
(400,)
```

In [34]:

```
rf = RandomForestRegressor()
rf.fit(train_X,train_y)
```

Out[34]:

```
RandomForestRegressor()
```

In [35]:

```
# training
regressionSummary(train_y, rf.predict(train_X))
# validation
regressionSummary(test_y, rf.predict(test_X))
```

```
Regression statistics

                      Mean Error (ME) : -4.3113
       Root Mean Squared Error (RMSE) : 139.6324
            Mean Absolute Error (MAE) : 50.6919
          Mean Percentage Error (MPE) : -29.4344
Mean Absolute Percentage Error (MAPE) : 38.0004

Regression statistics

                      Mean Error (ME) : -32.0695
       Root Mean Squared Error (RMSE) : 234.1408
            Mean Absolute Error (MAE) : 135.8930
          Mean Percentage Error (MPE) : -95.6834
Mean Absolute Percentage Error (MAPE) : 116.0958
```

In [36]:

```
MSE=mean_squared_error(train_y,rf.predict(train_X))
MSE
```

Out[36]:

```
19497.2014395247
```

In [37]:

```
r2=r2_score(train_y,rf.predict(train_X))
r2
```

Out[37]:

```
0.8969755105214148
```

In [38]:

```
lr = LinearRegression()
lr.fit(train_X,train_y)
```

Out[38]:

```
LinearRegression()
```

In [39]:

```
# training
regressionSummary(train_y, lr.predict(train_X))
# validation
regressionSummary(test_y, lr.predict(test_X))
```

```
Regression statistics

                      Mean Error (ME) : 0.0000
       Root Mean Squared Error (RMSE) : 404.2196
            Mean Absolute Error (MAE) : 195.1953
          Mean Percentage Error (MPE) : -160.8192
Mean Absolute Percentage Error (MAPE) : 219.4809

Regression statistics

                      Mean Error (ME) : 3.1304
       Root Mean Squared Error (RMSE) : 280.7624
            Mean Absolute Error (MAE) : 185.3807
          Mean Percentage Error (MPE) : -142.7065
Mean Absolute Percentage Error (MAPE) : 214.3767
```

In [40]:

```
MSE=mean_squared_error(train_y,lr.predict(train_X))
MSE
```

Out[40]:

```
163393.50022405767
```

In [41]:

```
r2=r2_score(train_y,lr.predict(train_X))
r2
```

Out[41]:

```
0.13661804249620557
```

In [42]:

```
import xgboost as xgb
xgb=xgb.XGBRegressor(objective ='reg:linear', colsample_bytree = 0.3, learning_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 10)
xgb.fit(train_X,train_y)
```

```
[23:48:22] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:line
ar is now deprecated in favor of reg:squarederror.
```

Out[42]:

```
XGBRegressor(alpha=10, colsample_bytree=0.3, max_depth=5, n_estimators=10)
```

In [43]:

```
# training
regressionSummary(train_y, xgb.predict(train_X))
# validation
regressionSummary(test_y, xgb.predict(test_X))
```

```
Regression statistics

                      Mean Error (ME) : 93.3079
       Root Mean Squared Error (RMSE) : 359.5107
            Mean Absolute Error (MAE) : 156.0619
          Mean Percentage Error (MPE) : -74.4509
Mean Absolute Percentage Error (MAPE) : 117.1119

Regression statistics

                      Mean Error (ME) : 90.4496
       Root Mean Squared Error (RMSE) : 291.5579
            Mean Absolute Error (MAE) : 160.9225
          Mean Percentage Error (MPE) : -80.4611
Mean Absolute Percentage Error (MAPE) : 124.5857
```

In [44]:

```
MSE=mean_squared_error(train_y,xgb.predict(train_X))
MSE
```

Out[44]:

```
129247.90955415349
```

In [45]:

```
r2=r2_score(train_y,xgb.predict(train_X))
r2
```

Out[45]:

```
0.31704558014169937
```

In [46]:

```
svm = SVR()
svm.fit(train_X,train_y)
```

Out[46]:

```
SVR()
```

In [47]:

```
# training
regressionSummary(train_y, svm.predict(train_X))
# validation
regressionSummary(test_y, svm.predict(test_X))
```

```
Regression statistics

                      Mean Error (ME) : 115.6317
       Root Mean Squared Error (RMSE) : 448.8388
            Mean Absolute Error (MAE) : 193.9638
          Mean Percentage Error (MPE) : -106.4076
Mean Absolute Percentage Error (MAPE) : 158.1633

Regression statistics

                      Mean Error (ME) : 113.3291
       Root Mean Squared Error (RMSE) : 331.4003
            Mean Absolute Error (MAE) : 189.7209
          Mean Percentage Error (MPE) : -106.0646
Mean Absolute Percentage Error (MAPE) : 158.5903
```

In [48]:

```
MSE=mean_squared_error(train_y,svm.predict(train_X))
MSE
```

Out[48]:

```
201456.23876258524
```

In [49]:

```
r2=r2_score(train_y,svm.predict(train_X))
r2
```

Out[49]:

```
-0.06450796106137302
```

In [50]:

```
print(rf.get_params())
```

```
{'bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'squared_error', 'max_dep
th': None, 'max_features': 'auto', 'max_leaf_nodes': None, 'max_samples': No
ne, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_spli
t': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_jobs': None,
'oob_score': False, 'random_state': None, 'verbose': 0, 'warm_start': False}
```

In [62]:

```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
# Create a based model
rf = RandomForestRegressor()
# Instantiate the grid search model
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
                          cv = 3, n_jobs = -1, verbose = 2)
grid_search.fit(train_X, train_y)
grid_search.best_params_
{'bootstrap': True,
 'max_depth': 80,
 'max_features': 3,
 'min_samples_leaf': 5,
 'min_samples_split': 12,
 'n_estimators': 100}
best_grid = grid_search.best_estimator_
grid_accuracy = evaluate(best_grid, test_X, test_y)
print('Improvement of {:0.2f}%.'.format( 100 * (grid_accuracy - base_accuracy) / base_accur
```

```
Fitting 3 folds for each of 288 candidates, totalling 864 fits
Model Performance
Average Error: 131.8716 degrees.
Accuracy = 23.35%.
Improvement of 45.09%.
```