Importing required Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Download the dataset from the link available above.:

In [2]:

```
df=pd.read_csv(r"C:\Users\Irfan\Downloads\dataframe_.csv")
df.drop(df.filter(regex="Unnamed"),axis=1, inplace=True)
```

In [3]:

```
df
```

Out[3]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214
...	...	...
1692	25.410184	-76.380902
1693	29.537304	-82.796934
1694	31.633331	-87.000000
1695	29.091458	-104.943052
1696	17.145296	-101.726894

1697 rows × 2 columns

Basic Exploration::

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1697 entries, 0 to 1696
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   input   1696 non-null   float64
 1   output  1696 non-null   float64
dtypes: float64(2)
memory usage: 26.6 KB
```

In [5]:

```
df.describe()
```

Out[5]:

	input	output
count	1696.000000	1696.000000
mean	1.159933	-34.088017
std	79.005970	65.771112
min	-134.962839	-132.422167
25%	-63.386506	-80.026767
50%	10.195194	-50.470981
75%	70.264109	-11.000000
max	134.605775	134.425495

Drop duplicates

In [6]:

```
print(df.duplicated().sum())

df.drop_duplicates(inplace=True)
```

```
606
```

Missing values :

In [7]:

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

Out[7]:

```
input     1
output    1
dtype: int64
```

In [8]:

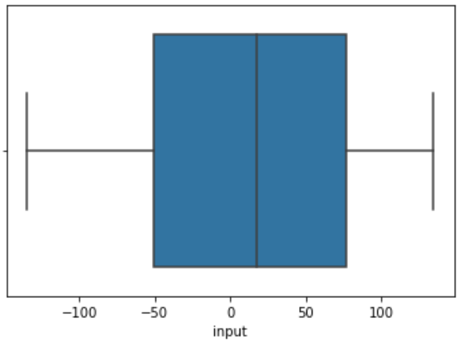
```
df.dropna(inplace=True)
```

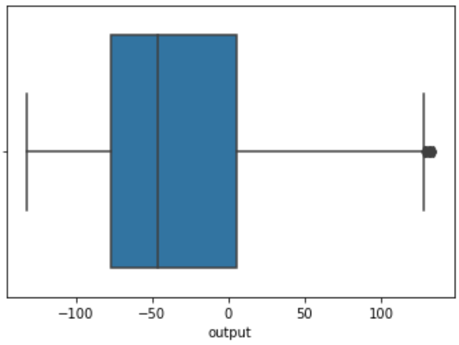
In [9]:

```
num=df.select_dtypes(include='number')
cat=df.select_dtypes(exclude='number')
```

In [10]:

```
for i in num:
    sns.boxplot(df[i])
    plt.show()
```





In [11]:

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

Out[11]:

```
input     0
output    0
dtype: int64
```

In [12]:

```
df
```

Out[12]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214
...	...	...
1105	-112.018496	121.096397
1107	-119.954237	123.609122
1108	-109.942155	127.197394
1109	-111.515368	128.170885
1110	-110.344221	123.087950

1090 rows × 2 columns

In [13]:

```
import os
os.getcwd()
df.to_csv('C:\\Users\\Irfan\\Machine Learning\\df.csv')
```

In [14]:

```
df=pd.read_csv("df.csv")
df.drop(df.filter(regex="Unnamed"),axis=1, inplace=True)
df
```

Out[14]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214
...	...	...
1085	-112.018496	121.096397
1086	-119.954237	123.609122
1087	-109.942155	127.197394
1088	-111.515368	128.170885
1089	-110.344221	123.087950

1090 rows × 2 columns

- Inputvariables:input

- Target variable:output

- Type:Supervised Learning(since target variable is given).

- Task:Regression

- Identify the Evaluation Metric.

- Regression task: Mean Absolute Error

In [15]:

```
X=df[["input"]]
y=df[['output']]
```

In [16]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1090 entries, 0 to 1089
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   input   1090 non-null   float64
 1   output  1090 non-null   float64
dtypes: float64(2)
memory usage: 17.2 KB
```

Split the dataset into Training and Testing (recommended 75:25 split).

In [17]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=42)
print(X_train.shape,y_train.shape)
print(X_test.shape,y_test.shape)
```

```
(817, 1) (817, 1)
(273, 1) (273, 1)
```

Train_data

In [18]:

```
# scaling the numerical features
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

# column names are (annoyingly) lost after Scaling
# (i.e. the dataframe is converted to a numpy ndarray)

X_train_num_rescaled = pd.DataFrame(scaler.fit_transform(X_train),
                                    columns = X_train.columns,
                                    index = X_train.index)

X_train_num_rescaled
```

Out[18]:

	input
92	-0.971544
695	-0.101785
1050	1.370721
759	-0.977240
294	0.907271
...	...
330	1.464943
466	1.345194
121	-0.748031
1044	1.604825
860	-1.746129

817 rows × 1 columns

Test data

In [20]:

```
X_test_num=X_test.select_dtypes(include=['float64'])
```

In [21]:

```
X_test_num_rescaled = pd.DataFrame(scaler.transform(X_test),
                                   columns = X_test.columns,
                                   index = X_test.index)

X_test_num_rescaled
```

Out[21]:

	input
834	-1.410798
940	0.248286
1084	-1.597815
1005	0.992130
760	-1.079884
...	...
566	0.703859
299	0.965640
939	0.432393
60	-1.588474
445	1.054469

273 rows × 1 columns

In [22]:

```
Algorithm=[]
mean_absolute_error=[]
```

Traning Linear Regression

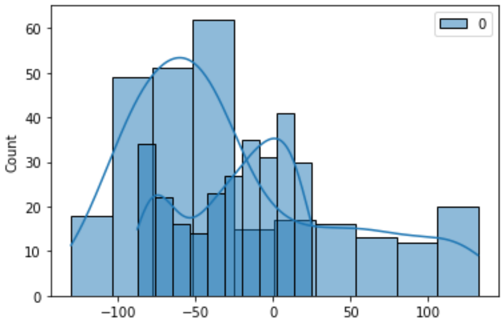
In [23]:

```
from sklearn.linear_model import LinearRegression
classifier = LinearRegression()
classifier.fit(X_train_num_rescaled, y_train)
y_test_pred = classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("LinearRegression")
mean_absolute_error.append(a)
print(a)
```

```
43.85740160235116
```

In [24]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Training-KNN Regression

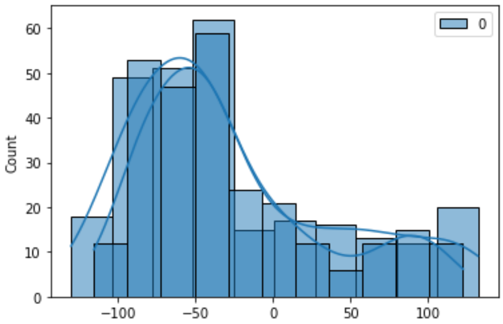
In [25]:

```
from sklearn.neighbors import KNeighborsRegressor
classifier=KNeighborsRegressor()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("KNeighborsRegressor")
mean_absolute_error.append(a)
print(a)
```

23.367927419547254

In [26]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Training-Support vector Regression

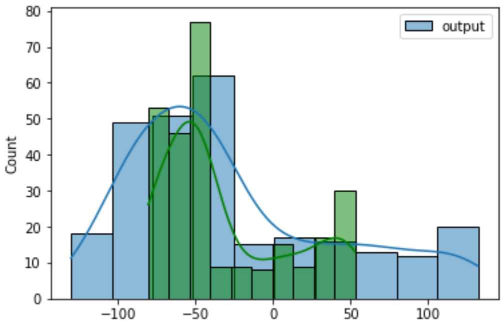
In [27]:

```
from sklearn.svm import SVR
classifier=SVR()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("SVR")
mean_absolute_error.append(a)
print(a)
```

24.9156375496118

In [28]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Training-Decision Tree Regression

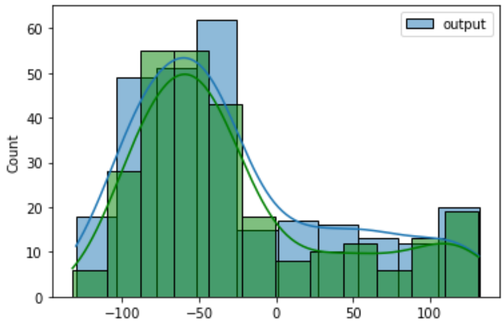
In [29]:

```
from sklearn.tree import DecisionTreeRegressor
classifier=DecisionTreeRegressor()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("DecisionTreeRegressor")
mean_absolute_error.append(a)
print(a)
```

```
29.161937218296703
```

In [30]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Ensemble

Training-Random Forest Regression

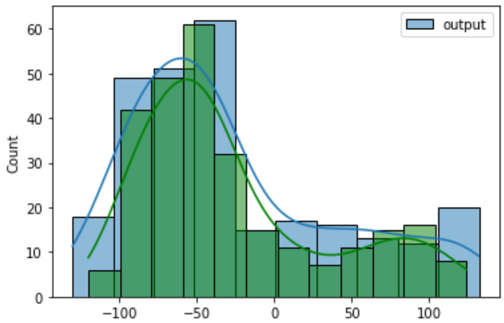
In [31]:

```
from sklearn.ensemble import RandomForestRegressor
classifier=RandomForestRegressor()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("RandomForestRegressor")
mean_absolute_error.append(a)
print(a)
```

```
25.131624863839875
```

In [32]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Training-Adaboost Regression

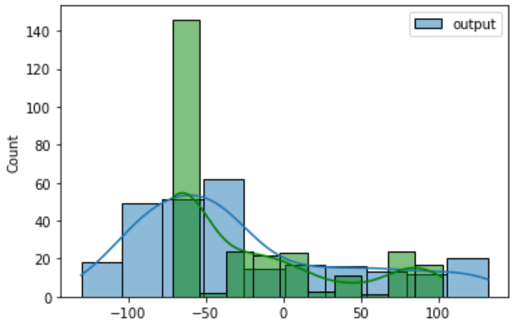
In [33]:

```
from sklearn.ensemble import AdaBoostRegressor
classifier=AdaBoostRegressor()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("AdaBoostRegressor")
mean_absolute_error.append(a)
print(a)
```

28.665753947303866

In [34]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



Training-Gradiant boost decision tree Regression

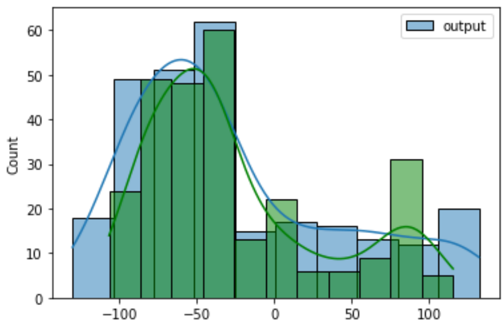
In [35]:

```
from sklearn.ensemble import GradientBoostingRegressor
classifier=GradientBoostingRegressor()
classifier.fit(X_train_num_rescaled,y_train)
y_test_pred=classifier.predict(X_test_num_rescaled)
from sklearn import metrics
a=metrics.mean_absolute_error(y_test,y_test_pred)
Algorithm.append("GradientBoostingRegressor")
mean_absolute_error.append(a)
print(a)
```

22.62282287088458

In [36]:

```
sns.histplot(y_test, color='pink',kde=True)
sns.histplot(y_test_pred, color='green',kde=True);
```



In [37]:

```
overview=pd.DataFrame({"mean_absolute_error":mean_absolute_error,},index=Algorithm)
```

In [38]:

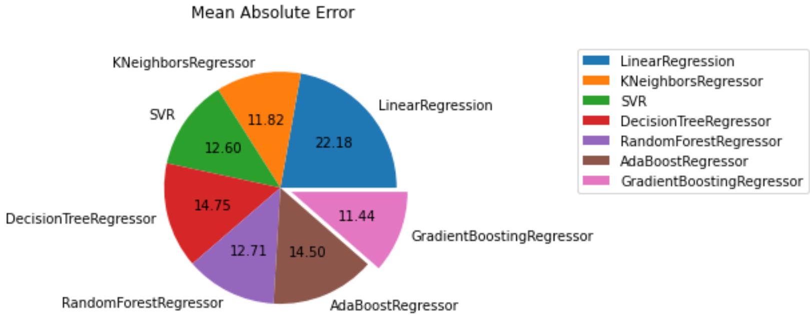
```
overview
```

Out[38]:

	mean_absolute_error
LinearRegression	43.857402
KNeighborsRegressor	23.367927
SVR	24.915638
DecisionTreeRegressor	29.161937
RandomForestRegressor	25.131625
AdaBoostRegressor	28.665754
GradientBoostingRegressor	22.622823

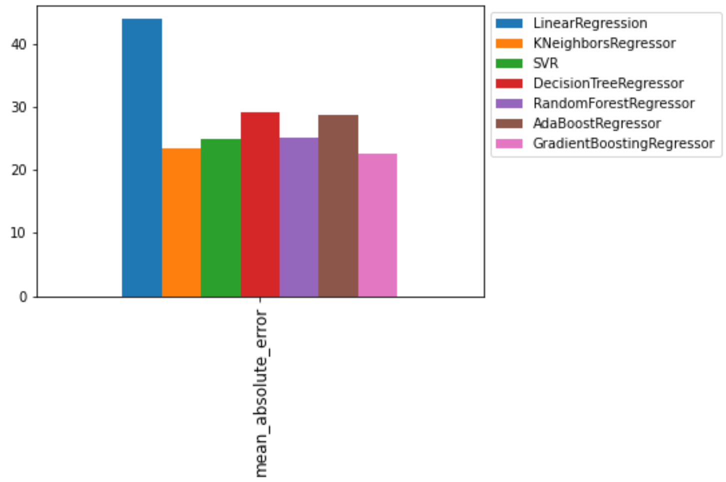
In [39]:

```
overview.plot(kind='pie',subplots=True,explode=[0,0,0,0,0,0,0.1],title='Mean Absolute Error',ylabel=' ',autopct='%.2f')
plt.legend(bbox_to_anchor=(1.5,1));
```



In [63]:

```
overview.T.plot(kind='bar',width=0.8,align='center')
plt.legend(bbox_to_anchor=(1,1))
plt.xticks(fontsize=12);
```



Conclusion:

- Gradiant boost decision tree Regression algorithm is the best model for Medical Cost Prediction
- Becuase Gradiant boost decision tree Regression mean absolute error is less compare to the other models .

Exploratory Data Analysis

Univariate Analysis

In [41]:

```
num
```

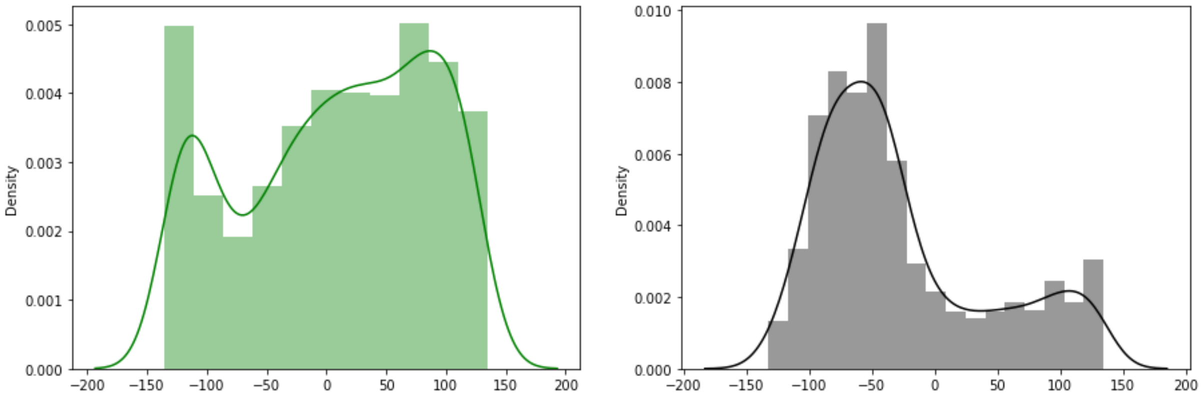
Out[41]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214
...	...	...
1105	-112.018496	121.096397
1107	-119.954237	123.609122
1108	-109.942155	127.197394
1109	-111.515368	128.170885
1110	-110.344221	123.087950

1090 rows × 2 columns

In [62]:

```
fig,axes=plt.subplots(1,2,figsize=(15,5))
sns.distplot(x=df['input'],ax=axes[0],color='green')
sns.distplot(x=df['output'],ax=axes[1],color='black')
plt.show()
```

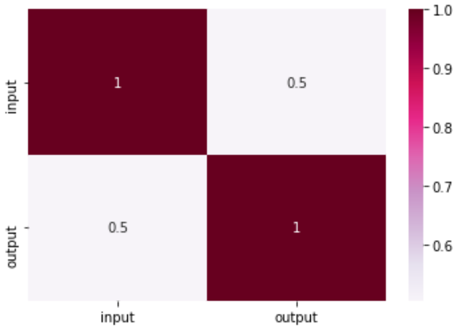


Observation:

- In input column the most of the values lies between -100 to 100.
- In output column the most of the values lies between -100 to 0.

In [67]:

```
sns.heatmap(df.corr(),annot=True,cmap="PuRd");
```



Observation:

- input and outut have postive correlation

In [59]:

```
sns.pairplot(data=df);
```