Problem statement: To Predict How Best the Data Fits and To Pridect the Insurance Based on the given Features

1)Data collection

#Importing Libraries

In [1]: #Importing Libraries import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns from sklearn import preprocessing,svm from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression

Out[2]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

2)Data cleaning and Preprocessing

#Exploratory data anlysis

In [3]: df.head()

Out[3]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

In [4]: df.tail()

Out[4]:

		age	sex	bmi	children	smoker	region	charges
1	333	50	male	30.97	3	no	northwest	10600.5483
1	334	18	female	31.92	0	no	northeast	2205.9808
1	335	18	female	36.85	0	no	southeast	1629.8335
1	336	21	female	25.80	0	no	southwest	2007.9450
1	337	61	female	29.07	0	yes	northwest	29141.3603

In [5]: df.shape

Out[5]: (1338, 7)

```
In [6]: df.describe
Out[6]: <bound method NDFrame.describe of</pre>
                                                                                          region
                                                                 bmi children smoker
                                                                                                      charges
                                                 age
                                                         sex
               19 female 27,900
                                           0
                                                ves southwest 16884.92400
                     male 33.770
                                          1
                                                                 1725,55230
        1
               18
                                                     southeast
                     male 33.000
        2
                                                     southeast
                                                                 4449.46200
               28
                     male 22.705
               33
                                           0
                                                     northwest 21984.47061
               32
                     male 28.880
                                           0
        4
                                                     northwest
                                                                 3866.85520
                                                 no
               . . .
                               . . .
                                         . . .
                                                           . . .
                                                                        . . .
        . . .
        1333
               50
                     male 30.970
                                           3
                                                     northwest 10600.54830
               18 female 31.920
        1334
                                                 no northeast
                                                                 2205.98080
        1335
                   female 36.850
                                                                 1629.83350
               18
                                                     southeast
        1336
               21
                   female 25.800
                                                     southwest
                                                                 2007.94500
                                                 no
               61 female 29.070
        1337
                                                ves northwest 29141.36030
        [1338 rows x 7 columns]>
In [7]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1338 entries, 0 to 1337
        Data columns (total 7 columns):
                       Non-Null Count Dtype
             Column
                        -----
         0
                       1338 non-null
                                        int64
             age
         1
             sex
                       1338 non-null
                                        object
          2
             bmi
                       1338 non-null
                                        float64
             children 1338 non-null
                                        int64
                       1338 non-null
                                       object
             smoker
             region
                                       object
                       1338 non-null
             charges
                       1338 non-null
                                       float64
        dtypes: float64(2), int64(2), object(3)
        memory usage: 73.3+ KB
```

```
In [8]: df.isnull().any()
Out[8]: age
                     False
                     False
         sex
         bmi
                     False
         children
                     False
         smoker
                     False
         region
                     False
         charges
                     False
         dtype: bool
 In [9]: df.isna().sum()
Out[9]: age
                     0
                     0
         sex
         bmi
                     0
         children
                     0
         smoker
                     0
         region
                     0
         charges
                     0
         dtype: int64
In [10]: df['region'].value_counts()
Out[10]: southeast
                      364
         southwest
                      325
         northwest
                      325
         northeast
                      324
         Name: region, dtype: int64
```

```
In [11]: convert={"sex":{"female":1,"male":0}}
    df=df.replace(convert)
    df
```

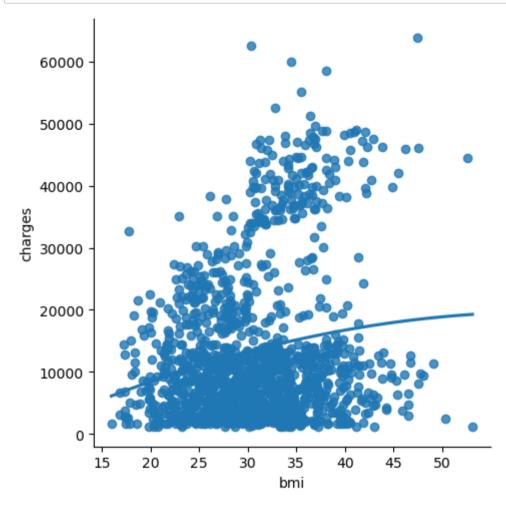
Out[11]:

	age	sex	bmi	children	smoker	region	charges
0	19	1	27.900	0	yes	southwest	16884.92400
1	18	0	33.770	1	no	southeast	1725.55230
2	28	0	33.000	3	no	southeast	4449.46200
3	33	0	22.705	0	no	northwest	21984.47061
4	32	0	28.880	0	no	northwest	3866.85520
1333	50	0	30.970	3	no	northwest	10600.54830
1334	18	1	31.920	0	no	northeast	2205.98080
1335	18	1	36.850	0	no	southeast	1629.83350
1336	21	1	25.800	0	no	southwest	2007.94500
1337	61	1	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

3)Data Visualization

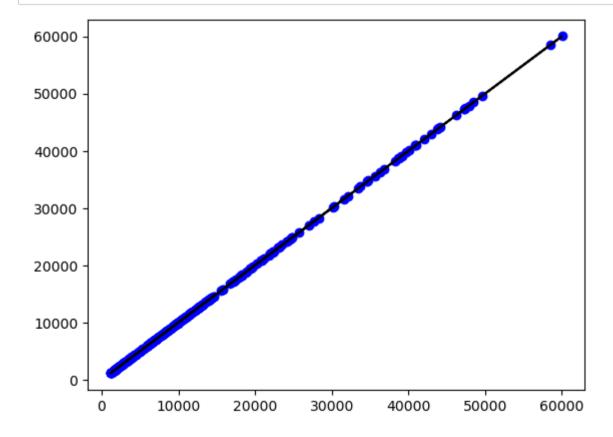
```
In [12]: sns.lmplot(x='bmi',y='charges',order=2,data=df,ci=None)
    plt.show()
```



```
In [13]: x=np.array(df['bmi']).reshape(-1,1)
y=x=np.array(df['charges']).reshape(-1,1)
```

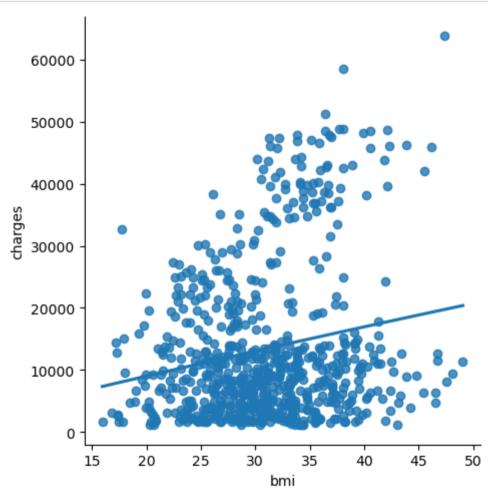
1.0

```
In [15]: y_pred=lr.predict(x_test)
   plt.scatter(x_test,y_test,color='b')
   plt.plot(x_test,y_pred,color='k')
   plt.show()
```



working with subset of data

```
In [16]: df700=df[:][:700]
sns.lmplot(x='bmi',y='charges',order=2,ci=None,data=df700)
plt.show()
```



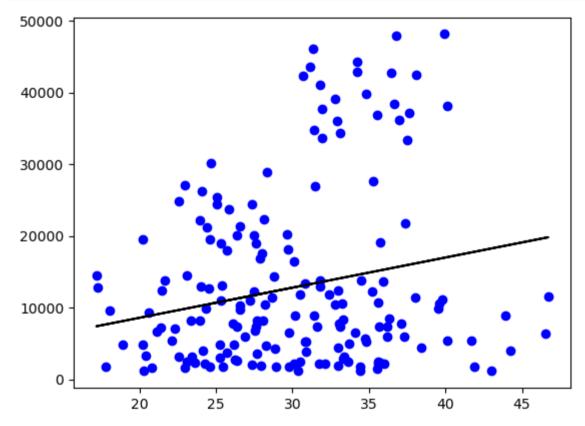
```
In [17]: df700.fillna(method='ffill',inplace=True)
In [18]: x=np.array(df700["bmi"]).reshape(-1,1)
y=np.array(df700['charges']).reshape(-1,1)
In [19]: df700.dropna(inplace=True)
```

4)Building the Model

```
In [20]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
lr=LinearRegression()
lr.fit(x_train,y_train)
print(lr.score(x_test,y_test))
```

0.022173472781516046

```
In [21]: y_pred=lr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



4) Evaluation of model (or) Predicting the Output

In [22]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

```
In [23]: lr=LinearRegression()
    lr.fit(x_train,y_train)
    y_pred=lr.predict(x_test)
    r2=r2_score(y_test,y_pred)
    print(r2)
```

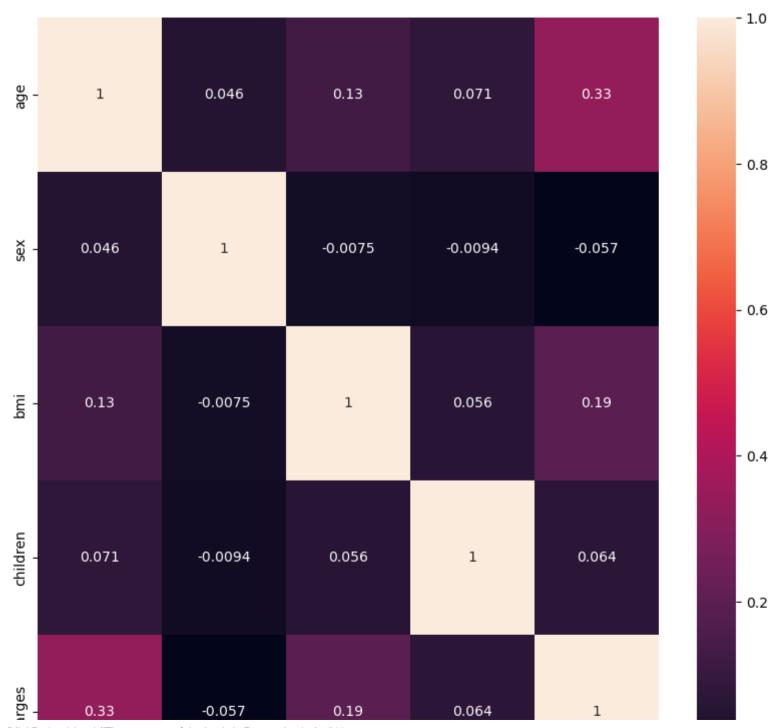
0.022173472781516046

The accuracy of the Linear Regression is 0.0221

Ridge Regression

```
In [24]: #Importing Libraries
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

```
In [25]: plt.figure(figsize=(10,10))
    sns.heatmap(df700.corr(),annot=True)
    plt.show()
```





```
In [26]: features=df.columns[0:1]
    target=df.columns[-1]
```

```
In [27]: x=df[features].values
    y=df[target].values
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=1)
    print("The dimension of X_train is {}".format(x_train.shape))
    print("The dimension of X_test is {}".format(x_test.shape))
```

The dimension of X_{train} is (936, 1) The dimension of X_{train} test is (402, 1)

```
In [28]: lr = LinearRegression()
#Fit model
lr.fit(x_train, y_train)
#predict
actual = y_test
train_score_lr = lr.score(x_train, y_train)
test_score_lr = lr.score(x_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".format(train_score_lr))
print("The test score for lr model is {}".format(test_score_lr))
```

Linear Regression Model:

The train score for lr model is 0.0910963973805714 The test score for lr model is 0.08490473916580776

```
In [29]: ridgeReg = Ridge(alpha=10)
    ridgeReg.fit(x_train,y_train)
    #train and test scorefor ridge regression
    train_score_ridge = ridgeReg.score(x_train, y_train)
    test_score_ridge = ridgeReg.score(x_test, y_test)
    print("NnRidge Model:\n")
    print("The train score for ridge model is {}".format(train_score_ridge))
    print("The test score for ridge model is {}".format(test_score_ridge))

Ridge Model:
    The train score for ridge model is 0.09109639711159623
    The test score for ridge model is 0.08490538609860176

In [30]: plt.figure(figsize=(10,10))

Out[30]: <Figure size 1000x1000 with 0 Axes>
```



The accuracy of the Ridge Model is 0.091096

Lasso Regression

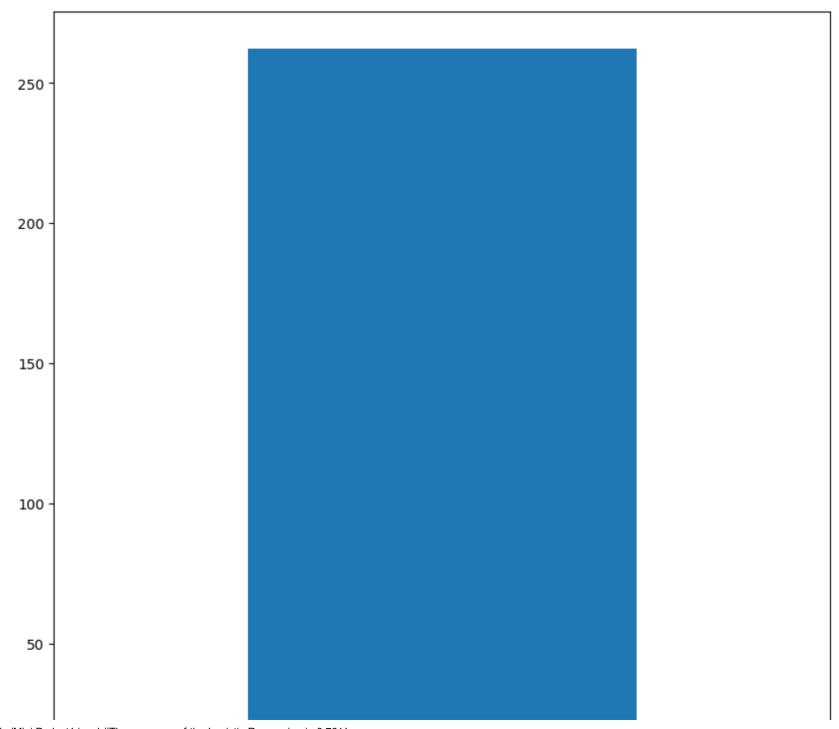
```
In [32]: #Importing Libraries
lasso= Lasso(alpha=10)
lasso.fit(x_train,y_train)
  #train and test scorefor ridge regression
  train_score_ls = lasso.score(x_train, y_train)
  test_score_ls= lasso.score(x_test, y_test)
  print("\nLasso Model:\n")
  print("The train score for lasso model is {}".format(train_score_ls))
  print("The test score for lasso model is {}".format(test_score_ls))

Lasso Model:
  The train score for lasso model is 0.09109639395809044
  The test score for lasso model is 0.08490704421828055

In [33]: plt.figure(figsize=(10,10))

Out[33]: <Figure size 1000x1000 with 0 Axes>
```

```
In [34]: pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar")
plt.show()
```

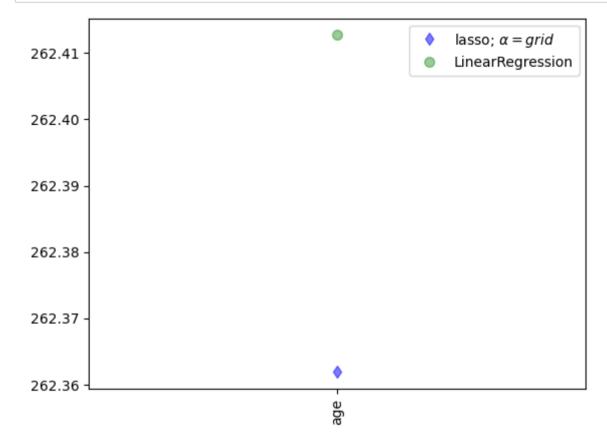


```
O Be
```

```
In [35]: from sklearn.linear model import LassoCV
In [36]: #using the linear cv model
         from sklearn.linear model import RidgeCV
         #cross validation
         ridge_cv=RidgeCV(alphas =[0.0001,0.001,0.01,0.1,1,10]).fit(x_train,y_train)
         #score
         print(ridge cv.score(x train,y train))
         print(ridge cv.score(x test,y test))
         0.09109639711159634
         0.08490538609865872
In [37]: #using the linear cv model
         from sklearn.linear model import LassoCV
         #cross validation
         lasso cv=LassoCV(alphas =[0.0001, 0.001, 0.01, 0.1, 1, 1, 10]).fit(x train,y train)
         #score
         print(lasso cv.score(x train,y train))
         print(lasso cv.score(x test,y test))
```

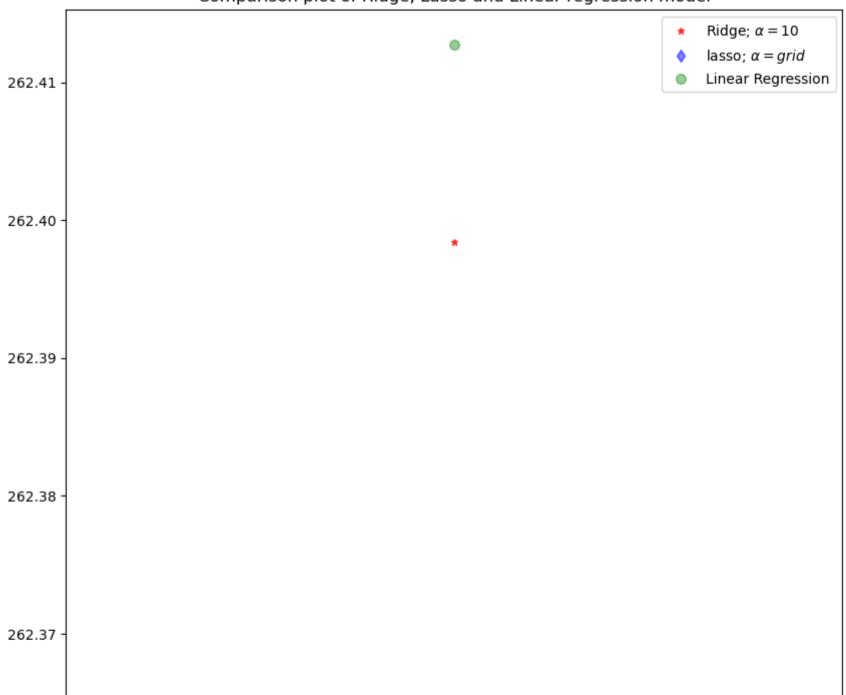
- 0.09109639395809044
- 0.08490704421828055

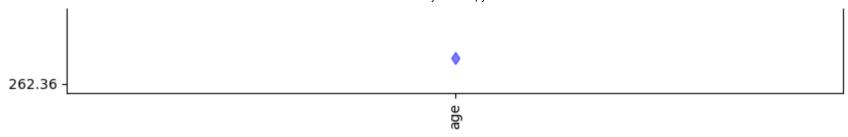
```
In [38]: plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso; $\alpha = grid$
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker="o",markersize=7,color='green',label='LinearRegression')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



```
In [39]: plt.figure(figsize = (10, 10))
    #add plot for ridge regression
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge; $\alpha #add plot for lasso regression
    plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso; $\alpha = grid$
    #add plot for linear model
    plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regression')
    #rotate axis
    plt.xticks(rotation = 90)
    plt.legend()
    plt.title("Comparison plot of Ridge, Lasso and Linear regression model")
    plt.show()
```

Comparison plot of Ridge, Lasso and Linear regression model





The accuracy of the Lasso Model is 0.091096

ElasticNet Regression

```
In [40]: from sklearn.linear model import ElasticNet
In [41]: el=ElasticNet()
         el.fit(x_train,y_train)
         print(el.coef )
         print(el.intercept )
         el.score(x,y)
         [261.74450967]
         3115.0831774262424
Out[41]: 0.08930616764094623
In [42]: y_pred_elastic=el.predict(x_train)
In [43]: mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
         print(mean_squared_error)
         135077142.70714515
```

The accuracy of the ElasticNet is 0.08930

Logistic Regression

```
In [44]: import numpy as np
    import pandas as pd
    from sklearn.linear_model import LogisticRegression
    from sklearn.preprocessing import StandardScaler
In [45]: df=pd.read_csv(r"C:\Users\Jayadeep\Downloads\insurance.csv")
```

Out[45]:

age	sex	bmi	children	smoker	region	charges
19	female	27.900	0	yes	southwest	16884.92400
18	male	33.770	1	no	southeast	1725.55230
28	male	33.000	3	no	southeast	4449.46200
33	male	22.705	0	no	northwest	21984.47061
32	male	28.880	0	no	northwest	3866.85520
50	male	30.970	3	no	northwest	10600.54830
18	female	31.920	0	no	northeast	2205.98080
18	female	36.850	0	no	southeast	1629.83350
21	female	25.800	0	no	southwest	2007.94500
61	female	29.070	0	yes	northwest	29141.36030
	19 18 28 33 32 50 18 18 21	19 female 18 male 28 male 33 male 32 male 50 male 18 female 18 female 21 female	19 female 27.900 18 male 33.770 28 male 33.000 33 male 22.705 32 male 28.880 50 male 30.970 18 female 31.920 18 female 36.850 21 female 25.800	19 female 27.900 0 18 male 33.770 1 28 male 33.000 3 33 male 22.705 0 32 male 28.880 0 50 male 30.970 3 18 female 31.920 0 18 female 36.850 0 21 female 25.800 0	19 female 27.900 0 yes 18 male 33.770 1 no 28 male 33.000 3 no 33 male 22.705 0 no 32 male 28.880 0 no 50 male 30.970 3 no 18 female 31.920 0 no 18 female 36.850 0 no 21 female 25.800 0 no	19 female 27.900 0 yes southwest 18 male 33.770 1 no southeast 28 male 33.000 3 no southeast 33 male 22.705 0 no northwest 32 male 28.880 0 no northwest 50 male 30.970 3 no northwest 18 female 31.920 0 no northeast 18 female 36.850 0 no southeast 21 female 25.800 0 no southwest

1338 rows × 7 columns

```
In [46]: df.shape
Out[46]: (1338, 7)
In [47]: pd.set_option('display.max_rows',10000000000)
         pd.set_option('display.max_columns',10000000000)
         pd.set option('display.width',95)
In [48]: print('This Dataset has %d rows and %d columns'%(df.shape))
         This Dataset has 1338 rows and 7 columns
In [49]: | df.head()
```

Out[49]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

```
In [50]:
        df.describe
         44
                38
                      maie 3/.050
                                                     nortneast
                                                                 60/9.6/1500
                                           0
         45
                55
                      male 37.300
                                                     southwest 20630.283510
                    female 38.665
         46
                18
                                           2
                                                     northeast
                                                                 3393.356350
                    female 34.770
                                           0
         47
                28
                                                     northwest
                                                                 3556.922300
                                                 no
                60
                    female 24.530
                                           0
                                                     southeast 12629.896700
         48
                      male 35.200
         49
                36
                                           1
                                                     southeast 38709.176000
                                                yes
                    female 35.625
                                           0
                                                     northeast
         50
                18
                                                                 2211.130750
                    female 33.630
                                           2
                                                     northwest
                                                                 3579.828700
         51
                21
                      male 28.000
                                           1
         52
                48
                                                     southwest 23568.272000
                                                ves
                      male 34.430
                                           0
         53
                36
                                                     southeast 37742.575700
                                                ves
         54
                40
                    female 28.690
                                           3
                                                     northwest
                                                                 8059.679100
                      male 36.955
         55
                58
                                           2
                                                     northwest 47496.494450
                                                ves
                    female 31.825
                                           2
         56
                58
                                                 no
                                                     northeast 13607.368750
                      male 31.680
                                           2
         57
                18
                                                     southeast 34303.167200
                                                ves
                    female 22.880
         58
                                           1
                                                     southeast 23244.790200
                53
                                                ves
                    female 37.335
                                           2
         59
                                                     northwest
                                                                 5989.523650
                      male 27.360
                                           3
         60
                43
                                                     northeast
                                                                 8606.217400
                      male 33.660
                                           4
         61
                25
                                                     southeast
                                                                 4504.662400
                      male 24.700
                                           1
         62
                64
                                                     northwest 30166.618170
                28 female 25.935
                                           1
         63
                                                     northwest
                                                                 4133.641650
```

In [51]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):

#	Column	Non-N	Null Count	Dtype
0	age	1338	non-null	int64
1	sex	1338	non-null	object
2	bmi	1338	non-null	float64
3	children	1338	non-null	int64
4	smoker	1338	non-null	object
5	region	1338	non-null	object
6	charges	1338	non-null	float64
dtyp	es: float6	4(2),	int64(2),	object(3)

memory usage: 73.3+ KB

```
In [52]: df.isnull().sum()
Out[52]: age
                        0
                        0
           sex
           bmi
                        0
          children
                        0
          smoker
                        0
          region
                        0
          charges
                        0
          dtype: int64
          convert={"smoker":{"yes":1,"no":0}}
          df=df.replace(convert)
          df
Out[53]:
                                                                   charges
                               bmi children smoker
                                                        region
                 age
                        sex
                      female 27.900
                                                               16884.924000
                  19
                                          0
                                                  1 southwest
              0
                       male 33.770
                  18
                                          1
                                                   0 southeast
                                                                1725.552300
              2
                  28
                       male 33.000
                                          3
                                                   0 southeast
                                                                4449.462000
                       male 22.705
                                          0
                                                   0 northwest 21984.470610
                  33
                                                  0 northwest
                                                                3866.855200
                       male 28.880
                  32
                                          0
                      female 25.740
                                          0
                                                    southeast
                                                                3756.621600
                      female 33.440
                                                                8240.589600
                  46
                                          1
                                                     southeast
                      female 27.740
                                          3
                                                   0 northwest
                                                                7281.505600
                       male 29.830
                                          2
                                                                6406.410700
                  37
                                                     northeast
                      female 25.840
                                                               28923.136920
                                          0
                                                     northwest
```

2721.320800

northeast

male 26.220

0

25

10

```
In [54]: convert={"sex":{"female":1,"male":0}}
    df=df.replace(convert)
    df
```

Out[54]:

	age	sex	bmi	children	smoker	region	charges
0	19	1	27.900	0	1	southwest	16884.924000
1	18	0	33.770	1	0	southeast	1725.552300
2	28	0	33.000	3	0	southeast	4449.462000
3	33	0	22.705	0	0	northwest	21984.470610
4	32	0	28.880	0	0	northwest	3866.855200
5	31	1	25.740	0	0	southeast	3756.621600
6	46	1	33.440	1	0	southeast	8240.589600
7	37	1	27.740	3	0	northwest	7281.505600
8	37	0	29.830	2	0	northeast	6406.410700
9	60	1	25.840	0	0	northwest	28923.136920
10	25	0	26.220	0	0	northeast	2721.320800

Out[55]:

	age	sex	bmi	children	smoker	region	charges
0	19	1	27.900	0	1	2	16884.924000
1	18	0	33.770	1	0	1	1725.552300
2	28	0	33.000	3	0	1	4449.462000
3	33	0	22.705	0	0	4	21984.470610
4	32	0	28.880	0	0	4	3866.855200
5	31	1	25.740	0	0	1	3756.621600
6	46	1	33.440	1	0	1	8240.589600
7	37	1	27.740	3	0	4	7281.505600
8	37	0	29.830	2	0	3	6406.410700
9	60	1	25.840	0	0	4	28923.136920
10	25	0	26.220	0	0	3	2721.320800

```
In [56]: features_matrix=df.iloc[:,0:4]
```

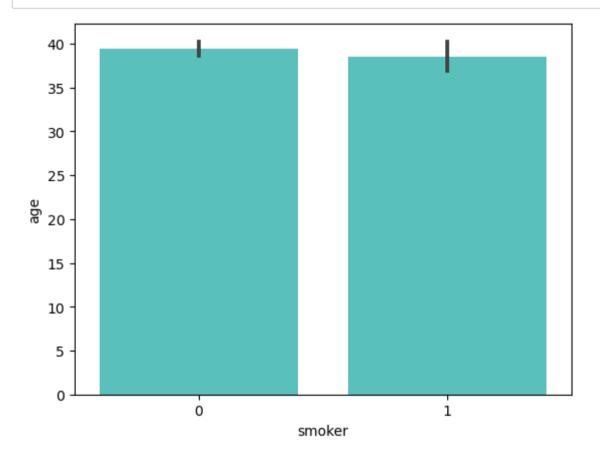
```
In [57]: target_vector=df.iloc[:,-3]
```

```
In [58]: print('The Feature Matrix has %d Rows and %d columns(s)'%(features_matrix.shape))
print('The Target Matrix has %d Rows and %d columns(s)'%(np.array(target_vector).reshape(-1,1).shape))
```

The Feature Matrix has 1338 Rows and 4 columns(s)
The Target Matrix has 1338 Rows and 1 columns(s)

```
In [59]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [60]: sns.barplot(x='smoker', y='age', data=df, color="mediumturquoise")
plt.show()
```



In [61]: features_matrix_standardized=StandardScaler().fit_transform(features_matrix)

```
In [62]: algorithm=LogisticRegression(max iter=10000)
In [63]: Logistic Regression Model=algorithm.fit(features matrix standardized,target vector)
In [64]: observation=[[1,0,0.99539,-0.0588]]
In [65]: predictions=Logistic Regression Model.predict(observation)
         print('The model predicted the observation to belong to class %s'%(predictions))
         The model predicted the observation to belong to class [0]
In [66]: print('The algorithm was trained to predict one of the two classes:%s'%(algorithm.classes ))
         The algoritham was trained to predict one of the two classes:[0 1]
In [67]: print(" " "The Model says the probability of the observation we passed belonging to class[0] %s" " "%(algorithm.prediction)
         print()
          The Model says the probability of the observation we passed belonging to class[0] 0.8057075871331396
In [68]: print(" " "The Model says the probability of the observation we passed belonging to class['1'] Is %s" " "%(algorithm.r
          The Model says the probability of the observation we passed belonging to class['1'] Is 0.19429241286686041
In [69]: | x=np.array(df['age']).reshape(-1,1)
         y=np.array(df['smoker']).reshape(-1,1)
```

```
In [70]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.05)
lo=LogisticRegression()
lo.fit(x_train,y_train)
print(lo.score(x_test,y_test))
```

0.746268656716418

```
C:\Users\Jayadeep\anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vecto
r y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel
().
    y = column_or_1d(y, warn=True)
```

The accuracy of the Logistic Regression is 0.7462

Decision Tree

```
In [71]: #Importing Libraries
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
```

```
In [72]: | df=pd.read_csv(r"C:\Users\Jayadeep\Downloads\insurance.csv")
                       male 42.130
                                                    southeast 39611.757700
              14
                  27
                                          0
                                                 ves
              15
                   19
                        male 24.600
                                          1
                                                     southwest
                                                                1837.237000
                      female 30.780
                                                               10797.336200
              16
                   52
                                          1
                                                      northeast
                       male 23.845
              17
                  23
                                          0
                                                      northeast
                                                                2395.171550
              18
                   56
                        male 40.300
                                          0
                                                     southwest
                                                              10602.385000
              19
                   30
                        male 35.300
                                          0
                                                     southwest
                                                               36837.467000
                  60 female 36.005
                                          0
                                                      northeast 13228.846950
              20
                   30
                     female 32.400
                                          1
                                                    southwest
                                                                4149.736000
              21
                   18
                        male 34.100
                                          0
                                                                1137.011000
              22
                                                     southeast
                                                      northeast 37701.876800
              23
                   34
                      female 31.920
                                          1
                                                 ves
                        male 28.025
                                          2
                                                     northwest
                                                                6203.901750
                      female 27.720
                                          3
                                                     southeast 14001.133800
                  63 female 23.085
                                          0
                                                      northeast 14451.835150
In [73]: df.shape
Out[73]: (1338, 7)
In [74]: df.isnull().any()
Out[74]: age
                        False
                        False
           sex
           bmi
                        False
           children
                        False
           smoker
                        False
                        False
          region
                        False
          charges
          dtype: bool
```

```
In [75]: df['region'].value_counts()
Out[75]: southeast
                         364
           southwest
                         325
           northwest
                         325
          northeast
                         324
          Name: region, dtype: int64
          convert={"sex":{"female":1,"male":0}}
In [76]:
          df=df.replace(convert)
          df
Out[76]:
                 age sex
                             bmi children smoker
                                                      region
                                                                 charges
                  19
                        1 27.900
                                        0
                                                             16884.924000
               0
                                               yes southwest
                        0 33.770
                   18
                                        1
                                                   southeast
                                                              1725.552300
                        0 33.000
                  28
                                        3
                                                   southeast
                                                              4449.462000
                   33
                        0 22.705
                                        0
                                                   northwest 21984.470610
                  32
                        0 28.880
                                        0
                                                   northwest
                                                              3866.855200
                  31
                        1 25.740
                                        0
                                                   southeast
                                                              3756.621600
                        1 33.440
                  46
                                        1
                                                   southeast
                                                              8240.589600
                                               no
                        1 27.740
                                        3
                  37
                                                   northwest
                                                              7281.505600
               8
                  37
                        0 29.830
                                        2
                                                   northeast
                                                              6406.410700
                                               no
                  60
                        1 25.840
                                        0
                                                   northwest
                                                             28923.136920
                  25
                        0 26.220
                                        0
              10
                                                   northeast
                                                              2721.320800
```

```
convert={"smoker":{"yes":1,"no":0}}
In [77]:
          df=df.replace(convert)
          df
Out[77]:
                            bmi children smoker
                                                    region
                                                                charges
                 age sex
              0
                  19
                       1 27.900
                                       0
                                               1 southwest
                                                           16884.924000
                       0 33.770
                                                            1725.552300
                  18
                                       1
                                                 southeast
              2
                  28
                       0 33.000
                                       3
                                                 southeast
                                                            4449.462000
                  33
                       0 22.705
                                       0
                                                  northwest 21984.470610
              3
                  32
                       0 28.880
                                                            3866.855200
                                                 northwest
                  31
                       1 25.740
                                       0
                                                 southeast
                                                            3756.621600
                  46
                       1 33.440
                                       1
                                                 southeast
                                                            8240.589600
                  37
                       1 27.740
                                       3
                                                            7281.505600
                                                 northwest
                                       2
              8
                  37
                       0 29.830
                                                  northeast
                                                            6406.410700
                       1 25.840
                                                           28923.136920
                  60
                                               0 northwest
             10
                  25
                       0 26.220
                                       0
                                                  northeast
                                                            2721.320800
         x=["bmi","children"]
In [78]:
          y=["Yes","No"]
          all inputs=df[x]
          all classes=df["sex"]
In [79]: (x train,x test,y train,y test)=train test split(all inputs,all classes,test size=0.03)
In [80]: clf=DecisionTreeClassifier(random state=0)
In [81]:
         clf.fit(x_train,y_train)
Out[81]: DecisionTreeClassifier(random_state=0)
```

```
In [82]: score=clf.score(x_test,y_test)
print(score)
```

0.3902439024390244

The accuracy of the Decision Tree is 0.39024

Random Forest

```
In [83]:
          import pandas as pd
           import numpy as np
           import matplotlib.pyplot as plt ,seaborn as sns
          df=pd.read csv(r"C:\Users\Jayadeep\Downloads\insurance.csv")
In [84]:
           df
                      female 25.840
                                                                28923.136920
               9
                   60
                                           0
                                                      northwest
                   25
                        male 26.220
                                           0
                                                       northeast
                                                                 2721.320800
                             26.290
              11
                      female
                                                      southeast
                                                                27808.725100
                   23
                             34.400
                                           0
                                                                 1826.843000
                        male
                                                      southwest
                      female 39.820
                   56
                                           0
                                                      southeast
                                                                11090.717800
                   27
                        male 42.130
                                                      southeast
                                                                39611.757700
                   19
                        male 24.600
                                                      southwest
                                                                 1837.237000
              16
                   52
                      female
                             30.780
                                                       northeast
                                                                10797.336200
              17
                   23
                        male 23.845
                                                       northeast
                                                                 2395.171550
                   56
                        male 40.300
                                                                10602.385000
              18
                                                      southwest
                        male 35.300
                                                      southwest
                                                                36837.467000
                      female 36.005
                                                       northeast
                                                                13228.846950
              20
                   60
              21
                   30 female 32.400
                                           1
                                                  no southwest 4149.736000
```

```
In [85]: df.shape
Out[85]: (1338, 7)
In [86]: df['region'].value_counts()
Out[86]: southeast
                      364
         southwest
                      325
         northwest
                      325
         northeast
                      324
         Name: region, dtype: int64
In [87]: df['bmi'].value_counts()
Out[87]: 32.300
                   13
         28.310
                    9
         30.495
                    8
         30.875
                    8
         31.350
                    8
         30.800
                    8
         34.100
                    8
         28.880
                    8
         33.330
                    7
         35.200
                    7
         25.800
                    7
         32.775
                    7
         27.645
                    7
         32.110
                    7
         38.060
                    7
         25.460
                    7
         30.590
                    7
         27.360
                    7
         24.320
                    7
         34 000
```

```
In [88]: | m={"sex":{"female":1,"male":0}}
         df=df.replace(m)
         print(df)
                             bmi
                                  children smoker
                                                       region
                                                                    charges
                     sex
                age
          0
                 19
                       1 27.900
                                         0
                                                    southwest
                                                               16884.924000
                                               ves
         1
                 18
                       0
                          33.770
                                         1
                                                    southeast
                                                                1725.552300
          2
                 28
                          33.000
                                          3
                                                    southeast
                                                                4449.462000
                                                no
          3
                 33
                       0 22.705
                                         0
                                                    northwest
                                                               21984.470610
                 32
                                                    northwest
                         28.880
          4
                                         0
                                                                3866.855200
                       1 25.740
                                                    southeast
          5
                 31
                                         0
                                                no
                                                                3756.621600
                 46
                       1 33.440
                                         1
                                                    southeast
                                                                8240.589600
          6
                       1 27.740
                                                                7281.505600
          7
                 37
                                          3
                                                    northwest
                                                no
                         29.830
                                                    northeast
          8
                 37
                       0
                                                                6406.410700
          9
                 60
                       1 25.840
                                          0
                                                    northwest
                                                               28923.136920
                 25
                          26.220
                                                    northeast
                                                                2721.320800
          10
                                         0
                 62
                       1 26.290
                                                    southeast
         11
                                         0
                                                               27808.725100
                                               yes
         12
                 23
                          34.400
                                         0
                                                    southwest
                                                                1826.843000
                                                no
          13
                 56
                       1 39.820
                                         0
                                                    southeast
                                                               11090.717800
                       0 42.130
                                                    southeast
                                                               39611.757700
          14
                 27
                                         0
                                               yes
         15
                 19
                          24.600
                                         1
                                                    southwest
                                                                1837.237000
                 52
                          30.780
                                         1
                                                    northeast
                                                               10797.336200
          16
                       1
                                                no
                 23
         17
                       0
                          23.845
                                         0
                                                    northeast
                                                                2395.171550
                                                no
```

40000 305000

40 300

40

```
In [89]: n={"smoker":{"yes":1,"no":0}}
         df=df.replace(n)
         print(df)
         49
                      0 35,200
                                                1 southeast 38709.176000
                36
                                        1
         50
                18
                      1 35.625
                                         0
                                                   northeast
                                                                2211.130750
         51
                21
                      1 33.630
                                                   northwest
                                                                3579.828700
         52
                48
                      0 28,000
                                        1
                                                   southwest 23568.272000
         53
                36
                      0 34.430
                                        0
                                                   southeast 37742.575700
                                                   northwest
         54
                40
                      1 28.690
                                                               8059.679100
         55
                58
                      0 36,955
                                         2
                                                   northwest 47496,494450
         56
                58
                                         2
                                                   northeast 13607.368750
                      1 31.825
         57
                18
                      0 31.680
                                                   southeast 34303.167200
         58
                53
                      1 22.880
                                        1
                                                   southeast 23244.790200
                                                   northwest
         59
                34
                      1 37.335
                                                                5989.523650
         60
                43
                      0 27.360
                                                   northeast
                                                               8606.217400
         61
                25
                      0 33.660
                                                   southeast
                                                                4504.662400
                                                   northwest 30166.618170
         62
                64
                      0 24,700
         63
                      1 25.935
                                        1
                                                   northwest
                                                                4133.641650
                28
         64
                20
                      1 22.420
                                                   northwest 14711.743800
         65
                19
                      1 28.900
                                                   southwest
                                                               1743.214000
         66
                61
                      1 39.100
                                                   southwest 14235.072000
         67
                40
                         26.315
                                                   northwest
                                                                6389.377850
         հՋ
                10
                         36 190
                                         а
                                                 a southeast
                                                                5920 10/100
In [90]:
         from sklearn.ensemble import RandomForestClassifier
         rfc=RandomForestClassifier()
         rfc.fit(x train,y train)
Out[90]: RandomForestClassifier()
In [91]: rf=RandomForestClassifier()
         params={'max_depth':[2,3,5,20],
                  'min samples leaf':[5,10,20,50,100,200],
                  'n estimators':[10,25,30,50,100,200]}
```

```
In [92]: from sklearn.model selection import GridSearchCV
         grid_search=GridSearchCV(estimator=rf,param_grid=params,cv=2,scoring="accuracy")
         grid search.fit(x train,y train)
Out[92]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                      param grid={'max depth': [2, 3, 5, 20],
                                   'min samples leaf': [5, 10, 20, 50, 100, 200],
                                  'n estimators': [10, 25, 30, 50, 100, 200]},
                      scoring='accuracy')
In [93]: grid search.best score
Out[93]: 0.5250718103825449
In [94]: import seaborn as sns
         import matplotlib.pyplot as plt
In [95]: rf_best=grid_search.best_estimator_
         print(rf best)
         RandomForestClassifier(max depth=2, min samples leaf=200, n estimators=25)
```

```
In [96]: from sklearn.tree import plot_tree
    plt.figure(figsize=(80,40))
    plot_tree(rf_best.estimators_[4],class_names=['1','0'],filled=True);
    plt.show()
```

 $X[0] \le 29.62$ gini = 0.5 samples = 808 value = [654, 643]class = 1

gini = 0.497 samples = 347 value = [260, 302] class = 0 X[0] <= 34.505 gini = 0.497 samples = 461 value = [394, 341] class = 1

gini = 0.493 samples = 249 value = [220, 174] class = 1 gini = 0.5 samples = 212 value = [174, 167] class = 1

```
In [97]: from sklearn.tree import plot tree
        plt.figure(figsize=(70,30))
        plot_tree(rf_best.estimators_[6],class_names=["1","0"],filled=True);
        plt.show()
                                                           X[0] \le 33.517
                                                              gini = 0.5
                                                            samples = 820
                                                          value = [630, 667]
                                                               class = 0
                                       X[0] \le 26.555
                                                                                 gini = 0.497
                                         gini = 0.497
                                                                                samples = 254
                                        samples = 566
                                                                              value = [216, 186]
                                      value = [414, 481]
                                                                                   class = 1
                                           class = 0
                      gini = 0.5
                                                             gini = 0.494
                    samples = 215
                                                            samples = 351
                                                          value = [249, 311]
                 value = [165, 170]
                                                               class = 0
                       class = 0
In [98]: rf best.feature importances
Out[98]: array([0.78503705, 0.21496295])
In [99]: rf=RandomForestClassifier(random state=0)
```

```
In [100]: rf.fit(x_train,y_train)
Out[100]: RandomForestClassifier(random_state=0)
In [101]: score=rf.score(x_test,y_test)
    print(score)
```

The accuracy of the Random Forest is 0.4146

CONCLUSION:

0.4146341463414634

The given dataset is "Insurance",we need to find the bestfit Model. As per the data set, we have used different types of models, that different models got different types of accuracyies. In this process Ridge and Lasso got same accuracy of 0.091 so, we should not consider that. For the ElasticNet model I got the accuracy of 0.089306. For the highest accuracy, I have done so many models among those ElasticNet got highest accuracy. I have done so many visuvalization graps as per the given Features.

Therefore ElasticNet Regression is the Bestfit for this Model.