Problem Statement: To predict how best the data fits and which model suits

```
In [2]: import numpy as np
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    from sklearn import preprocessing,svm
    from sklearn.model_selection import train_test_split
    from sklearn.linear_model import LinearRegression
    from sklearn.preprocessing import StandardScaler
```

Data collection

```
In [3]: df=pd.read_csv(r"C:\Users\rubin\Downloads\insurance.csv")
    df
```

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
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

Data Cleaning and Preprocessing

In [4]: df.head()

Out[4]:

	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 [5]: df.tail()

Out[5]:

	age	sex	bmi	children	smoker	region	charges
1333	50	male	30.97	3	no	northwest	10600.5483
1334	18	female	31.92	0	no	northeast	2205.9808
1335	18	female	36.85	0	no	southeast	1629.8335
1336	21	female	25.80	0	no	southwest	2007.9450
1337	61	female	29.07	0	yes	northwest	29141.3603

In [6]: df.shape

Out[6]: (1338, 7)

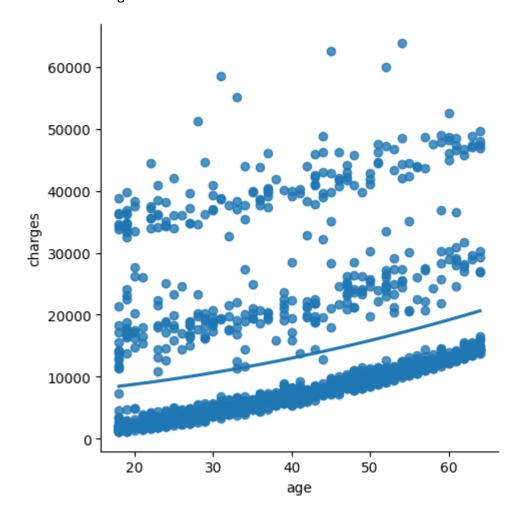
In [7]: df.describe()

Out[7]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

```
In [8]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1338 entries, 0 to 1337
        Data columns (total 7 columns):
             Column
                       Non-Null Count
                                        Dtype
         0
             age
                        1338 non-null
                                        int64
         1
             sex
                        1338 non-null
                                        object
         2
                       1338 non-null
                                        float64
             bmi
         3
             children 1338 non-null
                                        int64
         4
             smoker
                       1338 non-null
                                        object
         5
                                        object
             region
                       1338 non-null
                                        float64
         6
             charges
                       1338 non-null
        dtypes: float64(2), int64(2), object(3)
        memory usage: 73.3+ KB
In [9]: sns.lmplot(x="age",y="charges",data=df,order=2,ci=None)
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x243c7290850>



From the above scatter plot we can able to know that the aged people charges are low

```
In [10]: | df.fillna(method='ffill',inplace=True)
In [11]: x=np.array(df['age']).reshape(-1,1)
         y=np.array(df['charges']).reshape(-1,1)
In [12]: df.dropna(inplace=True)
In [13]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
         regr=LinearRegression()
         regr.fit(x_train,y_train)
         print(regr.score(x_test,y_test))
         0.1373952553426976
In [14]: y pred=regr.predict(x test)
         plt.scatter(x_test,y_test,color='g')
         plt.plot(x_test,y_pred,color='y')
         plt.show()
          60000
           50000
           40000
           30000
          20000
           10000
               0
```

20

30

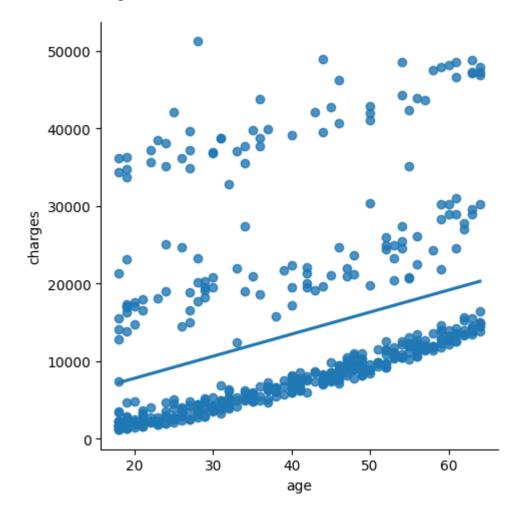
40

50

60

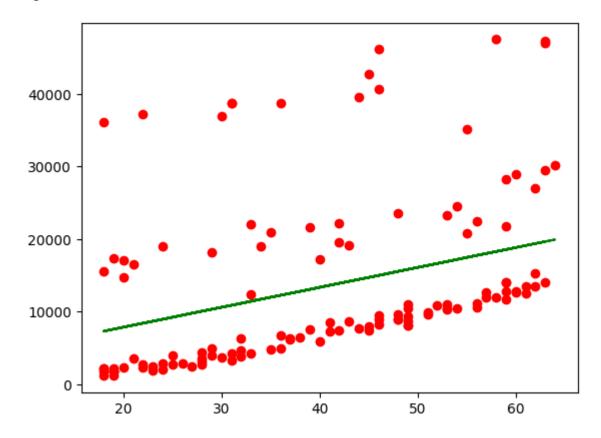
```
In [15]: df500=df[:][:500]
sns.lmplot(x="age",y="charges",data=df500,order=1,ci=None)
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x243a4f02530>



```
In [16]: df500.fillna(method='ffill',inplace=True)
    x=np.array(df500['age']).reshape(-1,1)
    y=np.array(df500['charges']).reshape(-1,1)
    df500.dropna(inplace=True)
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
    regr=LinearRegression()
    regr.fit(x_train,y_train)
    print("Regression:",regr.score(x_test,y_test))
    y_pred=regr.predict(x_test)
    plt.scatter(x_test,y_test,color='r')
    plt.plot(x_test,y_pred,color='g')
    plt.show()
```

Regression: 0.1392391637942142



```
In [17]: from sklearn.linear_model import LinearRegression
    from sklearn.metrics import r2_score
    model=LinearRegression()
    model.fit(x_train,y_train)
    y_pred=model.predict(x_test)
    r2=r2_score(y_test,y_pred)
    print("R2 Score:",r2)
```

R2 Score: 0.1392391637942142

There are no null values in the given data set

Implementing Ridge&Lasso Regression Model

```
In [19]: from sklearn.linear_model import Ridge,RidgeCV,Lasso
    from sklearn.preprocessing import StandardScaler

In [20]: convert={"sex":{"male":1,"female":2}}
    df=df.replace(convert)
    df
```

Out[20]:

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

1338 rows × 7 columns

```
In [21]: convert={"smoker":{"yes":1,"no":2}}
    df=df.replace(convert)
    df
```

Out[21]:

	age	sex	bmi	children	smoker	region	charges
0	19	2	27.900	0	1	southwest	16884.92400
1	18	1	33.770	1	2	southeast	1725.55230
2	28	1	33.000	3	2	southeast	4449.46200
3	33	1	22.705	0	2	northwest	21984.47061
4	32	1	28.880	0	2	northwest	3866.85520
1333	50	1	30.970	3	2	northwest	10600.54830
1334	18	2	31.920	0	2	northeast	2205.98080
1335	18	2	36.850	0	2	southeast	1629.83350
1336	21	2	25.800	0	2	southwest	2007.94500
1337	61	2	29.070	0	1	northwest	29141.36030

1338 rows × 7 columns

```
In [22]: convert={"region":{"southeast":3,"southwest":4,"northeast":5,"northwest":6}}
    df=df.replace(convert)
    df
```

Out[22]:

	age	sex	bmi	children	smoker	region	charges
0	19	2	27.900	0	1	4	16884.92400
1	18	1	33.770	1	2	3	1725.55230
2	28	1	33.000	3	2	3	4449.46200
3	33	1	22.705	0	2	6	21984.47061
4	32	1	28.880	0	2	6	3866.85520
1333	50	1	30.970	3	2	6	10600.54830
1334	18	2	31.920	0	2	5	2205.98080
1335	18	2	36.850	0	2	3	1629.83350
1336	21	2	25.800	0	2	4	2007.94500
1337	61	2	29.070	0	1	6	29141.36030

1338 rows × 7 columns

```
In [23]: features = df.columns[0:1]
    target = df.columns[-1]
    #X and y values
    X = df[features].values
    y = df[target].values
    #splot
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, randout print("The dimension of x_train is {}".format(X_train.shape))
    print("The dimension of x_test is {}".format(X_test.shape))
    #Scale features
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)
```

The dimension of x_{train} is (936, 1) The dimension of x_{tst} is (402, 1)

```
In [24]: ridgeReg=Ridge(alpha=10)
    ridgeReg.fit(X_train,y_train)
        train_score_ridge=ridgeReg.score(X_train,y_train)
        test_score_ridge=ridgeReg.score(X_test,y_test)
        print("\nRidge 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 0.1038565773808342 The test score for ridge model is 0.04500705629317203

```
In [25]: lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
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:

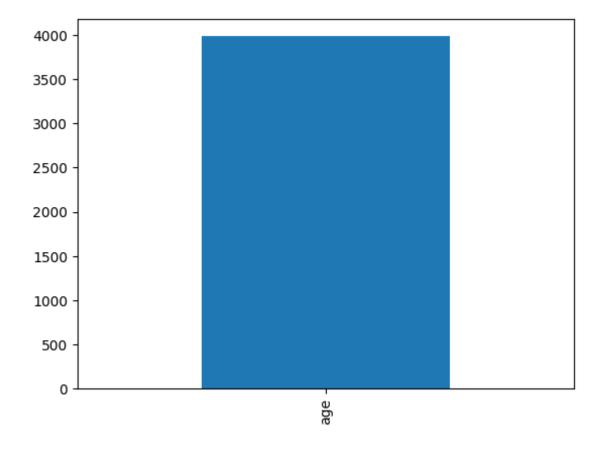
The train score for lr model is 0.10386818385382768 The test score for lr model is 0.04432028433481028

```
In [26]: plt.figure(figsize=(10,10))
         plt.plot(features, ridgeReg.coef_, alpha=0.7, linestyle='none', marker='*', markers
         #plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color
         plt.plot(features,lr.coef ,alpha=0.4,linestyle='none',marker='o',markersize=7,
         plt.xticks(rotation=90)
         plt.legend()
         #plt.title("comparison plot of Ridge, Lasso and Linear regression model")
         plt.show()
                                                                          Ridge; \alpha = 10
                                                                          Linear Regression
           3990
           3980
           3970
In [27]: print("\nLasso Model: \n")
         lasso = Lasso(alpha = 10)
         lasso.fit(X_train,y_train)
         train_score_ls =lasso.score(X_train,y_train)
         test score ls =lasso.score(X test,y test)
         print("The train score for ls model is {}".format(train_score_ls))
         print("The test score for ls model is {}".format(test_score_ls))
```

Lasso Model:

The train score for ls model is 0.1038675328268055 The test score for ls model is 0.04448522322607196 In [28]: pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "ba

Out[28]: <Axes: >

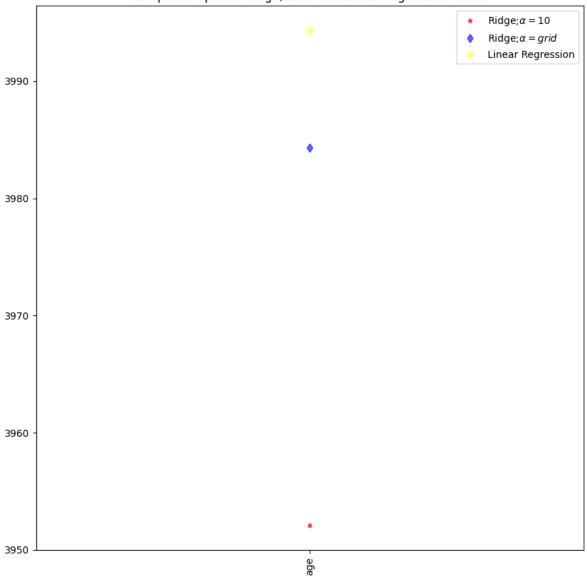


```
In [29]: from sklearn.linear_model import LassoCV
    lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,10],random_state=0).fit(X_traprint(lasso_cv.score(X_train,y_train))
    print(lasso_cv.score(X_test,y_test))
```

- 0.1038675328268055
- 0.04448522322607196

```
In [30]: plt.figure(figsize=(10,10))
   plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markers
   plt.plot(lasso_cv.coef_,alpha=0.6,linestyle='none',marker='d',markersize=6,col
   plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,
   plt.xticks(rotation=90)
   plt.legend()
   plt.title("comparison plot of Ridge,Lasso and Linear regression model")
   plt.show()
```





```
In [31]: from sklearn.linear_model import RidgeCV
#Ridge Cross validation
ridge_cv = RidgeCV(alphas = [0.0001, 0.001, 0.01, 1, 10]).fit(X_train, y_t
#score
print("The train score for ridge model is {}".format(ridge_cv.score(X_train, y_t))
print("The train score for ridge model is {}".format(ridge_cv.score(X_test, y_t))
```

The train score for ridge model is 0.10385657738083431 The train score for ridge model is 0.0450070562931667

```
In [ ]:
```

Elastic net regression

Mean Squared Error on test set 256816236.54565856

Logistic Regression

```
In [35]: import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
```

In [36]: df=pd.read_csv(r"C:\Users\rubin\Downloads\insurance.csv")
df

Out[36]:

	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

```
In [37]: pd.set_option('display.max_rows',10000000000)
   pd.set_option('display.max_columns',10000000000)
   pd.set_option('display.width',95)
```

```
In [38]: print('This DataFrame has %d Rows and %d columns'%(df.shape))
```

This DataFrame has 1338 Rows and 7 columns

```
convert={"smoker":{"yes":1,"no":2}}
           df=df.replace(convert)
           df
                                              0
              18
                    56
                         male 40.300
                                                      2
                                                         southwest 10602.385000
              19
                    30
                                              0
                                                                   36837.467000
                               35.300
                                                          southwest
                         male
              20
                    60
                       female
                               36.005
                                              0
                                                          northeast
                                                                    13228.846950
              21
                    30
                       female 32.400
                                              1
                                                      2
                                                          southwest
                                                                     4149.736000
              22
                    18
                         male 34.100
                                              0
                                                          southeast
                                                                     1137.011000
              23
                       female 31.920
                                              1
                                                          northeast 37701.876800
                                                                     6203.901750
                    37
                                              2
              24
                         male 28.025
                                                      2
                                                          northwest
              25
                    59
                       female 27.720
                                              3
                                                          southeast
                                                                    14001.133800
                       female 23.085
              26
                    63
                                              0
                                                      2
                                                          northeast
                                                                    14451.835150
              27
                    55
                                              2
                       female 32.775
                                                      2
                                                          northwest
                                                                   12268.632250
              28
                    23
                         male
                              17.385
                                                          northwest
                                                                     2775.192150
              29
                    31
                               36.300
                                              2
                                                                    38711.000000
                         male
                                                          southwest
              30
                    22
                         male 35.600
                                              0
                                                          southwest 35585.576000
           convert={"region":{"southeast":3,"southwest":4,"northeast":5,"northwest":6}}
In [43]:
           df=df.replace(convert)
           df
              40
                    Ö
                                     4 37.300
                                                 ၁၁
                             2
              46
                     9
                                        38.665
                                                 18
              47
                    9
                             2
                                        34.770
                                                 28
                                     6
              48
                    9
                             2
                                     3
                                        24.530
                                                 60
                    8
                                        35.200
              49
                                                 36
                                        35.625
              50
                    9
                             2
                                     5
                                                 18
                    9
                             2
                                        33.630
              51
                                     6
                                                 21
              52
                     8
                                     4
                                        28.000
                                                 48
                    8
                                        34.430
              53
                                     3
                                                 36
                     9
                             2
                                        28.690
              54
                                     6
                                                 40
              55
                     8
                              1
                                     6
                                        36.955
                                                 58
                     9
                             2
                                        31.825
              56
                                     5
                                                 58
              57
                    8
                                        31.680
                                                 18
```

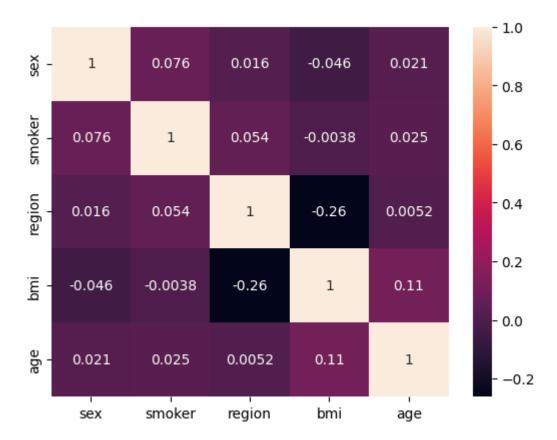
```
In [85]: convert={"sex":{"male":8,"female":9}}
    df=df.replace(convert)
    df
```

Out[85]:

	age	sex	bmi	children	smoker	region	charges
0	19	9	27.900	0	yes	2	16884.924000
1	18	8	33.770	1	no	1	1725.552300
2	28	8	33.000	3	no	1	4449.462000
3	33	8	22.705	0	no	4	21984.470610
4	32	8	28.880	0	no	4	3866.855200
5	31	9	25.740	0	no	1	3756.621600
6	46	9	33.440	1	no	1	8240.589600
7	37	9	27.740	3	no	4	7281.505600
8	37	8	29.830	2	no	3	6406.410700
9	60	9	25.840	0	no	4	28923.136920
10	25	8	26.220	0	no	3	2721.320800

```
In [44]: df=df[['sex','smoker','region','bmi','age']]
sns.heatmap(df.corr(),annot=True)
```

Out[44]: <Axes: >



In [45]: features matrix=df.iloc[:,0:4] In [46]: target vector=df.iloc[:,-3] In [47]: print('The Features Matrix Has %d Rows And %d Column(s)'%(features matrix.shap The Features Matrix Has 1338 Rows And 4 Column(s) In [48]: print('The Target Matrix Has %d Rows And %d Column(s)'%(np.array(target_vector The Target Matrix Has 1338 Rows And 1 Column(s) In [49]: | features matrix standardized=StandardScaler().fit transform(features matrix) In [50]: algorithm=LogisticRegression(penalty='12',dual=False,tol=1e-4,C=1.0,fit_interd In [51]: Logistic Regression Model=algorithm.fit(features matrix standardized, target ve In [52]: | observation=[[1,0,0.99539,-0.05889,]] predictions=Logistic Regression Model.predict(observation) In [53]: print('The Model Predicted The Observation To Belong To Class %s'%(predictions The Model Predicted The Observation To Belong To Class [6] In [54]: print('The Algorithm Was Trained To Predict One of The Two Classes: %s'%(algorithm) The Algorithm Was Trained To Predict One of The Two Classes: [3 4 5 6] In [55]: print("""The Model Says The Probability Of The Observation We Passed Belonging The Model Says The Probability Of The Observation We Passed Belonging To Clas s['0'] Is 8.73705876312762e-10 In [56]: print() In [57]: print("""The Model Says The Probabaility Of The Observation We Passed Belongin The Model Says The Probabaility Of The Observation We Passed Belonging To Cla ss['1'] Is 0.0006558137260463323

```
In [58]: x=np.array(df['age']).reshape(-1,1)
y=np.array(df['smoker']).reshape(-1,1)
```

```
In [59]: lerg=LogisticRegression()
    lerg.fit(x,y)
    print(lerg.score(x,y))
```

0.7952167414050823

C:\Users\rubin\AppData\Local\Programs\Python\Python310\lib\site-packages\skle
arn\utils\validation.py:1143: DataConversionWarning: A column-vector y was pa
ssed when a 1d array was expected. Please change the shape of y to (n_sample
s,), for example using ravel().
y = column_or_1d(y, warn=True)

Decision Tree Regression

```
In [60]: 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 [61]: df=pd.read_csv(r"C:\Users\rubin\Downloads\insurance.csv")
df
```

Out[61]:

	age	sex	bmi	children	smoker	region	charges	
0	19	female	27.900	0	yes	southwest	16884.924000	
1	18	male	33.770	1	no	southeast	1725.552300	
2	28	male	33.000	3	no	southeast	4449.462000	
3	33	male	22.705	0	no	northwest	21984.470610	
4	32	male	28.880	0	no	northwest	3866.855200	
5	31	female	25.740	0	no	southeast	3756.621600	
6	46	female	33.440	1	no	southeast	8240.589600	
7	37	female	27.740	3	no	northwest	7281.505600	
8	37	male	29.830	2	no	northeast	6406.410700	
9	60	female	25.840	0	no	northwest	28923.136920	
10	25	male	26.220	0	no	northeast	2721.320800	

```
In [62]: df['region'].value_counts()
Out[62]: region
           southeast
                          364
                          325
           southwest
           northwest
                          325
           northeast
                          324
           Name: count, dtype: int64
In [63]: df['bmi'].value counts()
Out[63]: bmi
           32.300
                       13
           28.310
                        9
           30.495
                        8
                        8
           30.875
           31.350
                        8
           30.800
                        8
           34.100
                        8
           28.880
                        8
                        7
           33.330
           35.200
                        7
           25.800
                        7
                        7
           32.775
           27.645
                        7
                        7
           32.110
           38.060
                        7
           25.460
                        7
                        7
           30.590
                        7
           27.360
           convert={"sex":{"male":1,"female":0}}
In [64]:
           df=df.replace(convert)
Out[64]:
                              bmi
                                  children smoker
                                                       region
                                                                   charges
                 age
                      sex
               0
                           27.900
                                         0
                                                               16884.924000
                   19
                         0
                                                yes
                                                    southwest
               1
                   18
                         1 33.770
                                         1
                                                 no
                                                     southeast
                                                                1725.552300
               2
                   28
                         1 33.000
                                         3
                                                                4449.462000
                                                     southeast
                                                 no
                   33
                                                              21984.470610
               3
                         1 22.705
                                         0
                                                     northwest
                   32
                         1 28.880
                                                     northwest
                                                                3866.855200
               4
                                         0
                                                 no
               5
                   31
                         0 25.740
                                         0
                                                                3756.621600
                                                 no
                                                     southeast
               6
                   46
                           33.440
                                         1
                                                     southeast
                                                                8240.589600
                                                 no
               7
                   37
                         0 27.740
                                         3
                                                     northwest
                                                                7281.505600
                                                 no
               8
                   37
                         1 29.830
                                         2
                                                     northeast
                                                                6406.410700
                   60
                           25.840
                                         0
                                                               28923.136920
               9
                         0
                                                     northwest
                                                 no
                                                                2721.320800
              10
                   25
                         1 26.220
                                         0
                                                 no
                                                     northeast
```

Random Forest

```
In [70]:
          import pandas as pd
          import numpy as ny
          import matplotlib.pyplot as plt,seaborn as sns
In [71]: df=pd.read csv(r"C:\Users\rubin\Downloads\insurance.csv")
Out[71]:
                               bmi children
                 age
                        sex
                                           smoker
                                                       region
                                                                   charges
              0
                  19
                     female 27.900
                                          0
                                                    southwest
                                                              16884.924000
                                                yes
              1
                  18
                       male
                             33.770
                                          1
                                                     southeast
                                                               1725.552300
                  28
              2
                       male
                             33.000
                                          3
                                                     southeast
                                                               4449.462000
                                                 no
```

no

no

no

no

no

no

no

nο

northwest

northwest

southeast

southeast

northwest

northeast

northwest

northeast

21984.470610

3866.855200

3756.621600

8240.589600

7281.505600

6406.410700

28923.136920

2721.320800

0

0

1

3

2

0

3

5

6

7

8

9

10

33

32

31

46

37

60

25

male 22.705

male 28.880

female 25.740

female 33.440

male 29.830

male 26.220

female 25.840

37 female 27.740

```
In [72]: df['charges'].value counts()
Out[72]: charges
                           2
          1639.563100
          16884.924000
                           1
          29330.983150
                           1
          2221.564450
                            1
          19798.054550
                           1
          13063.883000
                            1
                           1
          13555.004900
          44202.653600
                           1
          10422.916650
                           1
          7243.813600
                           1
          11945.132700
                            1
                            1
          6311.952000
          1682.597000
                            1
          5272.175800
                           1
          27218.437250
                           1
          19719.694700
                            1
          4877.981050
                            1
          46255.112500
                            1
         m={"region":{"southeast":1,"southwest":2,"northeast":3,"northwest":4}}
In [73]:
          df=df.replace(m)
          print(df)
          36
                  62
                      female
                              32.965
                                               3
                                                               4
                                                                   15612.193350
                                                      no
                              20.800
                                                                2
          37
                  26
                        male
                                               0
                                                      no
                                                                    2302.300000
          38
                  35
                        male
                              36.670
                                               1
                                                     yes
                                                                3
                                                                   39774.276300
          39
                  60
                        male
                               39.900
                                               0
                                                                2
                                                                   48173.361000
                                                     yes
          40
                  24
                      female
                              26.600
                                               0
                                                                3
                                                      no
                                                                    3046.062000
          41
                      female
                              36.630
                                               2
                                                                1
                                                                    4949.758700
                  31
                                                      no
          42
                  41
                        male
                              21.780
                                               1
                                                                1
                                                                    6272.477200
                                                      no
                                               2
          43
                  37
                      female
                              30.800
                                                      no
                                                                1
                                                                    6313.759000
          44
                  38
                        male
                               37.050
                                               1
                                                                3
                                                                    6079.671500
                                                      no
          45
                  55
                        male
                              37.300
                                               0
                                                                2
                                                                   20630.283510
                                                      no
          46
                  18
                      female
                              38.665
                                               2
                                                                3
                                                      no
                                                                    3393.356350
                                                                4
          47
                  28
                      female
                              34.770
                                               0
                                                                    3556.922300
                                                      no
          48
                  60
                      female
                              24.530
                                               0
                                                      no
                                                                1
                                                                   12629.896700
          49
                  36
                        male
                              35.200
                                               1
                                                                1
                                                                   38709.176000
                                                     yes
          50
                  18
                      female 35.625
                                               0
                                                                3
                                                                    2211.130750
                                                      no
                                               2
          51
                  21
                      female
                              33.630
                                                      no
                                                                4
                                                                    3579.828700
          52
                  48
                        male
                              28.000
                                               1
                                                                2
                                                                   23568.272000
                                                     yes
          53
                  36
                        male
                               34.430
                                               0
                                                                1
                                                                   37742.575700
                                                     yes
          54
                  40
                      female
                               28.690
                                               3
                                                                4
                                                                    8059.679100
                                                      no
          55
                  58
                        male
                               36.955
                                               2
                                                     VAS
                                                                   47496 494450
         df.shape
In [74]:
Out[74]: (1338, 7)
```

```
In [75]: from sklearn.ensemble import RandomForestClassifier
         rfc=RandomForestClassifier()
         rfc.fit(x_train,y_train)
Out[75]:
          ▼ RandomForestClassifier
          RandomForestClassifier()
In [76]: rf=RandomForestClassifier()
In [77]: params={'max_depth':[2,3,5,10,20],'min_samples_leaf':[5,10,20,50,100,200],'n_e
In [78]:
         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[78]:
                       GridSearchCV
           ▶ estimator: RandomForestClassifier
                ▶ RandomForestClassifier
In [79]: grid_search.best_score_
Out[79]: 0.5384112253580489
In [80]: rf_best=grid_search.best_estimator_
         print(rf_best)
         RandomForestClassifier(max_depth=10, min_samples_leaf=100, n_estimators=30)
```

```
In [81]:
          from sklearn.tree import plot tree
          plt.figure(figsize=(80,40))
          plot tree(rf best.estimators [4],class names=['1','0'],filled=True);
                                                                 x[1] <= 1.5
                                                                  gini = 0.5
                                                                samples = 623
                                                              value = [513, 490]
                                                                  class = 1
                                                  x[1] <= 0.5
                                                                                gini = 0.496
                                                   gini = 0.5
                                                                              samples = 192
                                                 samples = 431
                                                                             value = [178, 148]
                                               value = [335, 342]
                                                                                 class = 1
                                                   class = 0
                                  x[0] \le 30.182
                                                                 gini = 0.498
                                    gini = 0.5
                                                                samples = 166
                                  samples = 265
                                                              value = [128, 146]
                                value = [207, 196]
                                                                  class = 0
                                     class = 1
                    gini = 0.497
                                                   gini = 0.5
                   samples = 119
                                                 samples = 146
                   value = [94, 81]
                                               value = [113, 115]
                      class = 1
                                                   class = 0
In [82]: rf best.feature importances
Out[82]: array([0.81698821, 0.18301179])
          imp_df=pd.DataFrame({"Variance":x_train.columns,"Imp":rf_best.feature_importan
In [83]:
          imp df.sort values(by="Imp",ascending=False)
Out[83]:
              Variance
                            Imp
           0
                   bmi 0.816988
               children 0.183012
          score=rfc.score(x_test,y_test)
In [84]:
          print(score)
          0.48059701492537316
```

Conclusion:- For the given insurance data set have performed Linear, Logistic, Decision Tree and Random Forest models of Regressions, and have concluded that the most accuracy is occured in Logistic Regression i.e 79 percent when compare to other Regression models.

And concluded that "	OGISTIC	REGRESSION'
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