INSURANCE REPORT

By: Quan Le, Anirudh Chaudhary, Hao Nguyen

Columns

```
1. age : age of policyholder
2. sex: gender of policy holder (female=0, male=1)
3. bmi: Body mass index, providing an understanding of body, weights that are relatively high or low re
lative
        to height, objective index of body weight (kg / m^2) using the ratio of height to weight, ideal
ly
        18.5 to 25
4. children: number of children / dependents of policyholder
5. smoker: smoking state of policyholder (non-smoke=0;smoker=1)
6. region: the residential area of policyholder in the US (northeast=0, northwest=1, southeast=2, south
west=3)
7. charges: individual medical costs billed by health insurance
8. insuranceclaim:(yes=1, no=0)
```

Link: [https://www.kaggle.com/easonlai/sample-insurance-claim-prediction-dataset (https://www.kaggle.com/easonlai/sample-insurance-claim-prediction-dataset)](https://www.kaggle.com/easonlai/sample-insurance-claim-prediction-dataset)

1. Get Relevant Data Sets

In [1]:

```
#Import all packages needed for Data set
import numpy as np
import pandas as pd

#Parse csv file to a data frame
insurance_table = pd.io.parsers.read_csv("~/Desktop/Project/insurance_claim.csv")
df_table = pd.DataFrame(insurance_table)
```

2. Cleansing Data and Transformation

In [12]:
```
#Find number of record
count_record = len(df_table.index)
count_record
```

Out[12]: 1338

In [6]:
```
#remove duplication
df_table.drop_duplicates()
```

Out[6]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
0	19	0	27.900	0	1	3	16884.92400	1
1	18	1	33.770	1	0	2	1725.55230	1
2	28	1	33.000	3	0	2	4449.46200	0
3	33	1	22.705	0	0	1	21984.47061	0
4	32	1	28.880	0	0	1	3866.85520	1
5	31	0	25.740	0	0	2	3756.62160	0
6	46	0	33.440	1	0	2	8240.58960	1
7	37	0	27.740	3	0	1	7281.50560	0
8	37	1	29.830	2	0	0	6406.41070	0
9	60	0	25.840	0	0	1	28923.13692	0
10	25	1	26.220	0	0	0	2721.32080	1

In [7]:
```
#Check for missing data
df_table.isnull().sum()
```

Out[7]:
```
age               0
sex               0
bmi               0
children          0
smoker            0
region            0
charges           0
insuranceclaim    0
dtype: int64
```

In [8]:
```
#Transform Dummy Variable Region
df_table['isNorthEast'] = np.where(df_table['region'] == 0,1,0) #np.where(condition,x,y) for condition where tr
df_table['isNorthWest'] = np.where(df_table['region'] == 1,1,0)
df_table['isSouthEast'] = np.where(df_table['region'] == 2,1,0)
df_table['isSouthWest'] = np.where(df_table['region'] == 3,1,0)

#Drop the region column
df_table = df_table.drop('region', axis = 1)
```

In [9]:
```
#Repositioning columns for better view
df_table = df_table[['age', 'sex', 'bmi', 'children', 'smoker', 'charges','isNorthEast', 'isNorthWest', 'isSout
df_table
```

Out[9]:

	age	sex	bmi	children	smoker	charges	isNorthEast	isNorthWest	isSouthEast	isSouthWest	insuranceclaim
0	19	0	27.900	0	1	16884.92400	0	0	0	1	1
1	18	1	33.770	1	0	1725.55230	0	0	1	0	1
2	28	1	33.000	3	0	4449.46200	0	0	1	0	0
3	33	1	22.705	0	0	21984.47061	0	1	0	0	0
4	32	1	28.880	0	0	3866.85520	0	1	0	0	1
5	31	0	25.740	0	0	3756.62160	0	0	1	0	0
6	46	0	33.440	1	0	8240.58960	0	0	1	0	1
7	37	0	27.740	3	0	7281.50560	0	1	0	0	0
8	37	1	29.830	2	0	6406.41070	1	0	0	0	0
9	60	0	25.840	0	0	28923.13692	0	1	0	0	0
10	25	1	26.220	0	0	2721.32080	1	0	0	0	1

3. Pattern Discovery

Max, Min, Mean

In [10]:
```
print(df_table.loc[:,['age','bmi', 'children', 'charges']].describe())
```

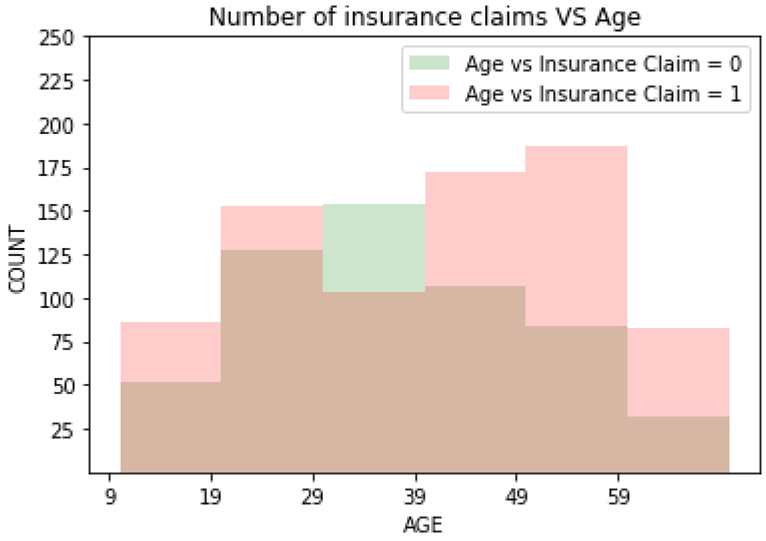
```
               age          bmi     children       charges
count  1338.000000  1338.000000  1338.000000   1338.000000
mean     39.207025    30.663397     1.094918  13270.422265
std      14.049960     6.098187     1.205493  12110.011237
min      18.000000    15.960000     0.000000   1121.873900
25%      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
```

Numbers of insurance claims vs Age

In [17]:
```
df_table['age_bins'] = pd.cut(x=df_table['age'], bins=[10, 19, 29, 39, 49, 59, 69])

df = df_table.groupby(['age_bins','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df) #need visualization to see the trend
```

```
    age_bins  insuranceclaim  Count
0   (10, 19]               0     51
1   (10, 19]               1     86
2   (19, 29]               0    127
3   (19, 29]               1    153
4   (29, 39]               0    154
5   (29, 39]               1    103
6   (39, 49]               0    107
7   (39, 49]               1    172
8   (49, 59]               0     84
9   (49, 59]               1    187
10  (59, 69]               0     32
11  (59, 69]               1     82
```

In [15]:
```
import matplotlib.pyplot as plt

df0 = df_table[df_table['insuranceclaim'] == 0]
df1 = df_table[df_table['insuranceclaim'] == 1]

plt.hist(df0['age'], bins=6, range=(10, 70), histtype='stepfilled',
         align='mid', color='g', label='Age vs Insurance Claim = 0', alpha=0.2)
plt.hist(df1['age'], bins=6, range=(10, 70), histtype='stepfilled',
         align='mid', color='r', label='Age vs Insurance Claim = 1', alpha=0.2)

plt.legend()
plt.xlabel('AGE')
plt.ylabel('COUNT')
plt.xticks(range(9,69,10))
plt.yticks(range(25,275,25))
plt.title('Number of insurance claims VS Age')
plt.show()
```



Only people around 29-39 are mostly not filing insurance claims.

Other age groups are likely filing insurance claims.

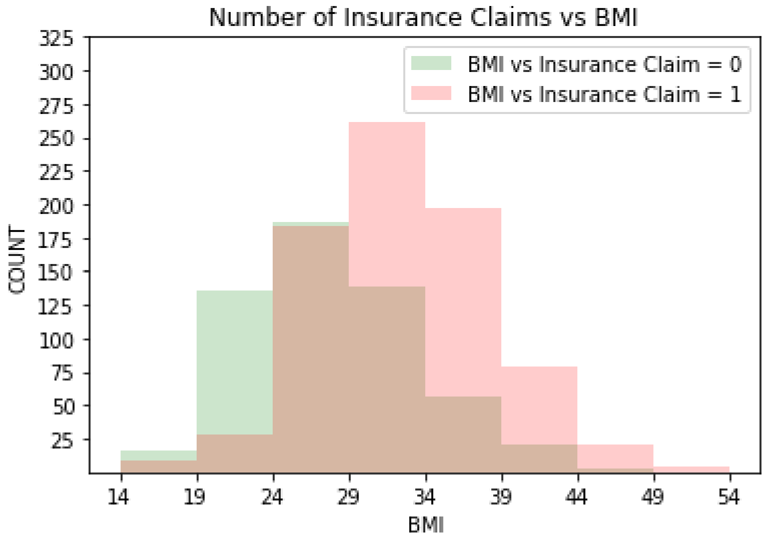
Numbers of insurance claims vs BMI

In [9]:
```
df_table['bmi_bins'] = pd.cut(x=df_table['bmi'], bins=[10, 14, 19, 24, 29, 34, 39, 44, 49, 54, 59])

df = df_table.groupby(['bmi_bins','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df) #need visualization to see the trend
```

```
     bmi_bins  insuranceclaim  Count
0    (14, 19]               0     17
1    (14, 19]               1      8
2    (19, 24]               0    135
3    (19, 24]               1     28
4    (24, 29]               0    187
5    (24, 29]               1    185
6    (29, 34]               0    137
7    (29, 34]               1    261
8    (34, 39]               0     57
9    (34, 39]               1    197
10   (39, 44]               0     20
11   (39, 44]               1     80
12   (44, 49]               0      2
13   (44, 49]               1     20
14   (49, 54]               1      4
```

In [18]:

```
import matplotlib.pyplot as plt1

plt1.hist(df0['bmi'], bins=8, range=(14, 54), histtype='stepfilled',
          align='mid', color='g', label='BMI vs Insurance Claim = 0', alpha=0.2)
plt1.hist(df1['bmi'], bins=8, range=(14, 54), histtype='stepfilled',
          align='mid', color='r', label='BMI vs Insurance Claim = 1', alpha=0.2)

plt1.legend()
plt1.xlabel('BMI')
plt1.ylabel('COUNT')
plt1.xticks(range(14,55,5))
plt1.yticks(range(25,350,25))
plt1.title('Number of Insurance Claims vs BMI')
plt1.show()
```



People who has BMI around 15-24 are less likely to file insurance claims.

People who has BMI around 25-29 are neutral.

People who has BMI above 29 are most likely to file insurace claims.

Numbers of insurance claims vs Age and BMI

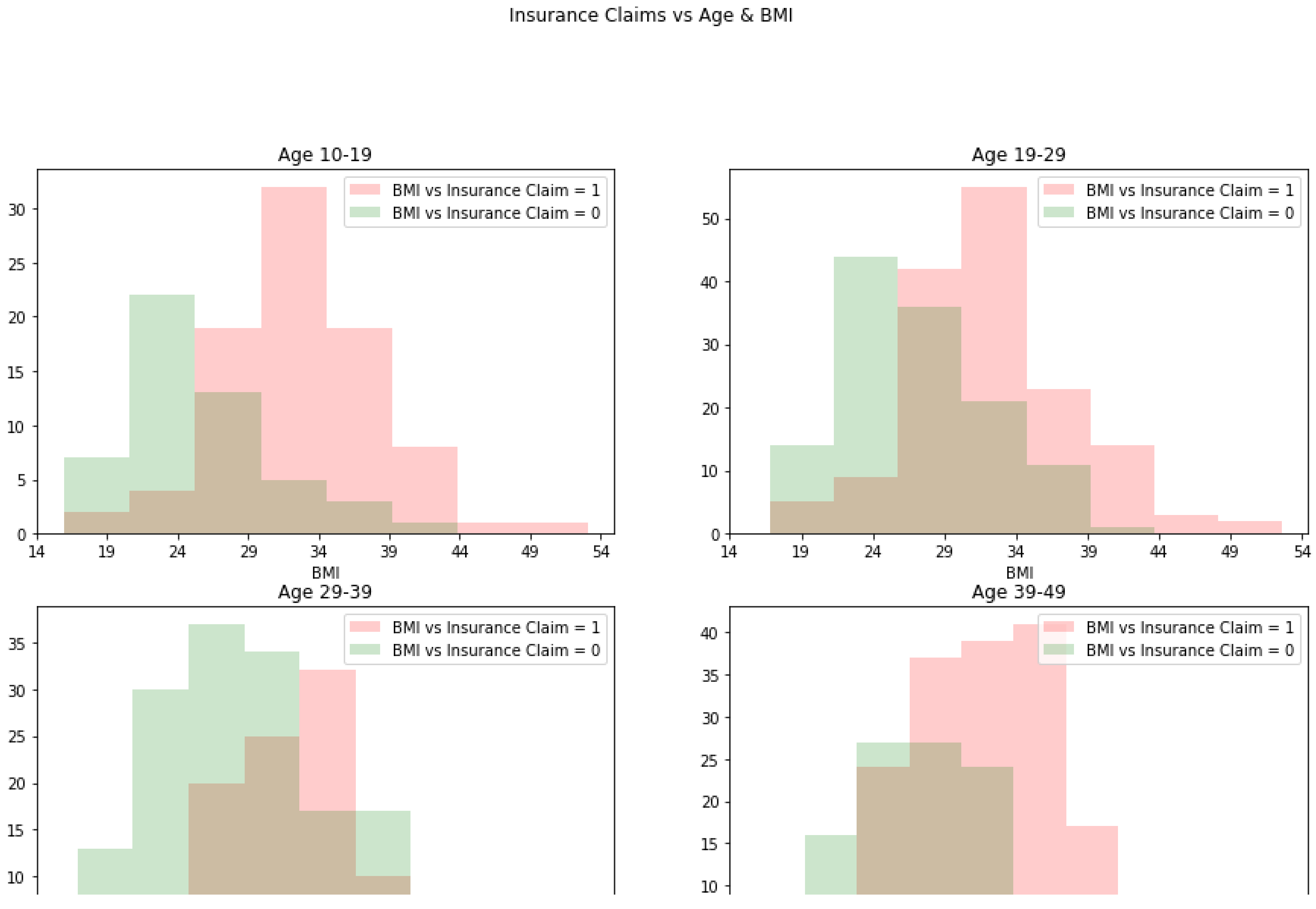
In [10]:

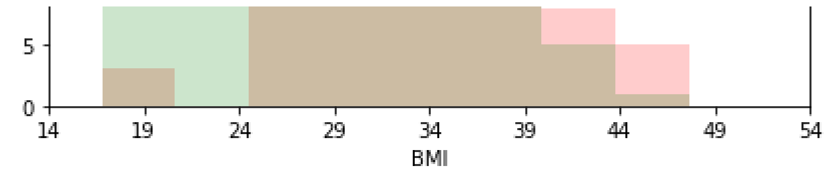
```
df = df_table.groupby(['age_bins','bmi_bins','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df) #need visualization to see the trend
```

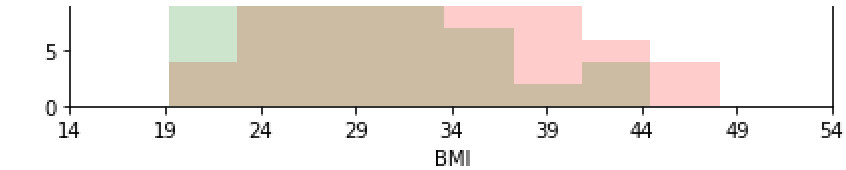
```
60  (49, 59]  (34, 39]              0      8
61  (49, 59]  (34, 39]              1     48
62  (49, 59]  (39, 44]              0      1
63  (49, 59]  (39, 44]              1     21
64  (49, 59]  (44, 49]              0      1
65  (49, 59]  (44, 49]              1      7
66  (49, 59]  (49, 54]              1      1
67  (59, 69]  (14, 19]              0      1
68  (59, 69]  (19, 24]              0      7
69  (59, 69]  (19, 24]              1      2
70  (59, 69]  (24, 29]              0     12
71  (59, 69]  (24, 29]              1     14
72  (59, 69]  (29, 34]              0      8
73  (59, 69]  (29, 34]              1     29
74  (59, 69]  (34, 39]              0      1
75  (59, 69]  (34, 39]              1     24
76  (59, 69]  (39, 44]              0      3
77  (59, 69]  (39, 44]              1     13

[78 rows x 4 columns]
```

In [20]:
```
import matplotlib.pyplot as plt2
fig, axs = plt2.subplots(3, 2, tight_layout=False, figsize=(15,15))
df2 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>10) & (df_table['age']<=19)]
df3 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>10) & (df_table['age']<=19)]
axs[0,0].hist([df2['bmi'],df3['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

df4 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>19) & (df_table['age']<=29)]
df5 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>19) & (df_table['age']<=29)]
axs[0,1].hist([df4['bmi'],df5['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

df6 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>29) & (df_table['age']<=39)]
df7 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>29) & (df_table['age']<=39)]
axs[1,0].hist([df6['bmi'],df7['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

df8 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>39) & (df_table['age']<=49)]
df9 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>39) & (df_table['age']<=49)]
axs[1,1].hist([df8['bmi'],df9['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

df10 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>49) & (df_table['age']<=59)]
df11 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>49) & (df_table['age']<=59)]
axs[2,0].hist([df10['bmi'],df11['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

df12 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['age']>59) & (df_table['age']<=69)]
df13 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['age']>59) & (df_table['age']<=69)]
axs[2,1].hist([df12['bmi'],df13['bmi']], bins=8, histtype='stepfilled',
         align='mid', color=['g','r'], label=['BMI vs Insurance Claim = 0','BMI vs Insurance Claim = 1'], alpha

for i in range(3):
    for j in range(2):
        axs[i,j].legend()
        axs[i,j].set(xlabel='BMI')
        plt2.sca(axs[i,j])
        plt2.xticks(range(14,55,5))

axs[0,0].set_title('Age 10-19')
axs[0,1].set_title('Age 19-29')
```

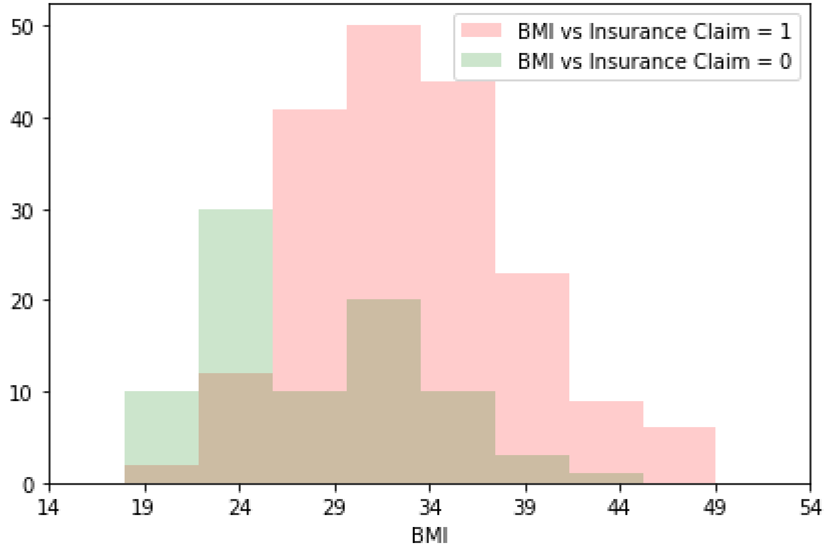
```
axs[1,0].set_title('Age 29-39')
axs[1,1].set_title('Age 39-49')
axs[2,0].set_title('Age 49-59')
axs[2,1].set_title('Age 59-69')

fig.suptitle('Insurance Claims vs Age & BMI')
plt2.show()
```



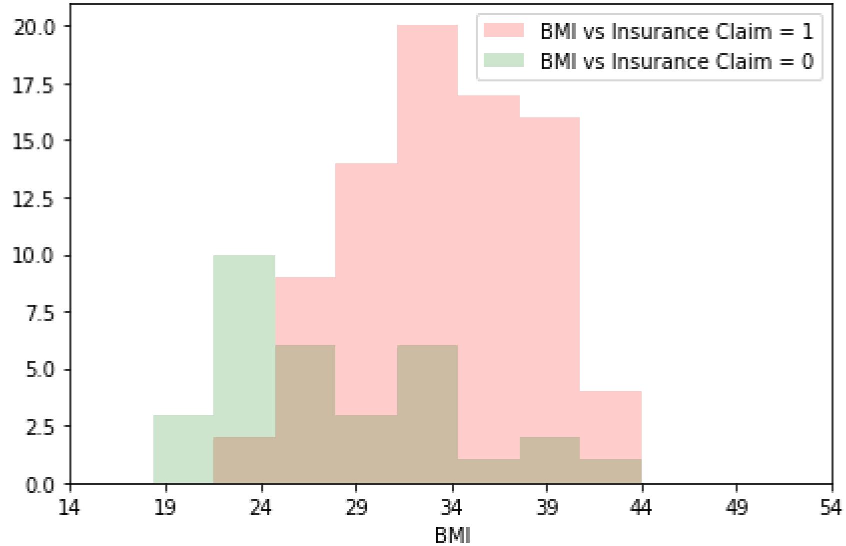




Age 49-59



Age 59-69



Number of insurance claims for smokers vs nonsmokers

In [21]:
```
df = df_table.groupby(['smoker','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df)
```

```
   smoker  insuranceclaim  Count
0       0               0    530
1       0               1    534
2       1               0     25
3       1               1    249
```

Nonsmokers are neutral regarding claims.

Smokers tends to file insurance claims.

Number of insurance claims vs amount getting charge

In [22]:
```
df_table['charges_bins'] = pd.cut(x=df_table['charges'], bins=[1000, 4999, 9999, 14999, 19999, 24999, 29999,349

df = df_table.groupby(['charges_bins','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df)
```

```
      charges_bins  insuranceclaim  Count
0     (1000, 4999]               0    182
1     (1000, 4999]               1    177
2     (4999, 9999]               0    199
3     (4999, 9999]               1    154
4    (9999, 14999]               0     99
5    (9999, 14999]               1    169
6   (14999, 19999]               0     34
7   (14999, 19999]               1     51
8   (19999, 24999]               0     20
9   (19999, 24999]               1     52
10  (24999, 29999]               0     14
11  (24999, 29999]               1     25
12  (29999, 34999]               0      4
13  (29999, 34999]               1     25
14  (34999, 39999]               0      3
15  (34999, 39999]               1     51
16  (39999, 44999]               1     41
17  (44999, 49999]               1     31
18  (49999, 54999]               1      2
19  (54999, 59999]               1      2
20  (59999, 64999]               1      3
```

People who have to pay around $1000 - $10,000 are less likely to file insurance claims.

People who have to pay $35,000+ are 100% will file insurance claim.

Number of insurance claims for each gender who is either smoker/non-smoker

In [23]:
```
df = df_table.groupby(['sex','smoker','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df)
```

```
   sex  smoker  insuranceclaim  Count
0    0       0               0    273
1    0       0               1    274
2    0       1               0     12
3    0       1               1    103
4    1       0               0    257
5    1       0               1    260
6    1       1               0     13
7    1       1               1    146
```

Female or Male who is not a smoker are neutral.

Female or Male who is a smoker are likely to claim.

Number of insurance claims based on age groups and smoker/non smoker

In [24]:
```python
df = df_table.groupby(['age_bins','smoker','insuranceclaim'], sort=True).size().reset_index(name='Count')
print (df)
```

```
    age_bins  smoker  insuranceclaim  Count
0   (10, 19]       0               0     49
1   (10, 19]       0               1     58
2   (10, 19]       1               0      2
3   (10, 19]       1               1     28
4   (19, 29]       0               0    121
5   (19, 29]       0               1    103
6   (19, 29]       1               0      6
7   (19, 29]       1               1     50
8   (29, 39]       0               0    140
9   (29, 39]       0               1     59
10  (29, 39]       1               0     14
11  (29, 39]       1               1     44
12  (39, 49]       0               0    104
13  (39, 49]       0               1    113
14  (39, 49]       1               0      3
15  (39, 49]       1               1     59
16  (49, 59]       0               0     84
17  (49, 59]       0               1    146
18  (49, 59]       1               1     41
19  (59, 69]       0               0     32
20  (59, 69]       0               1     55
21  (59, 69]       1               1     27
```

Based on the result, people between 30-49 and not a smoker are likely to not file claim (line8) while people between 50-59 and not a smoker are likely to file claim (line 17).

Seem like regarding smoking or not, they will likely to file claim. Therefore, the feature for smokers might not really determine the claim.

Number of insurance claims each region

```
In [25]: df = df_table.groupby(['isNorthEast', 'isNorthWest', 'isSouthEast','isSouthWest','insuranceclaim'], sort=True).
         print (df)
```

```
   isNorthEast  isNorthWest  isSouthEast  isSouthWest  insuranceclaim  Count
0            0            0            0            1               0    142
1            0            0            0            1               1    183
2            0            0            1            0               0    119
3            0            0            1            0               1    245
4            0            1            0            0               0    162
5            0            1            0            0               1    163
6            1            0            0            0               0    132
7            1            0            0            0               1    192
```

No much difference between claiming or not claiming in each region as they are around 50% that claims and 50% that don't.

Number of insurance claims vs the charged amounts in each region

In [26]:

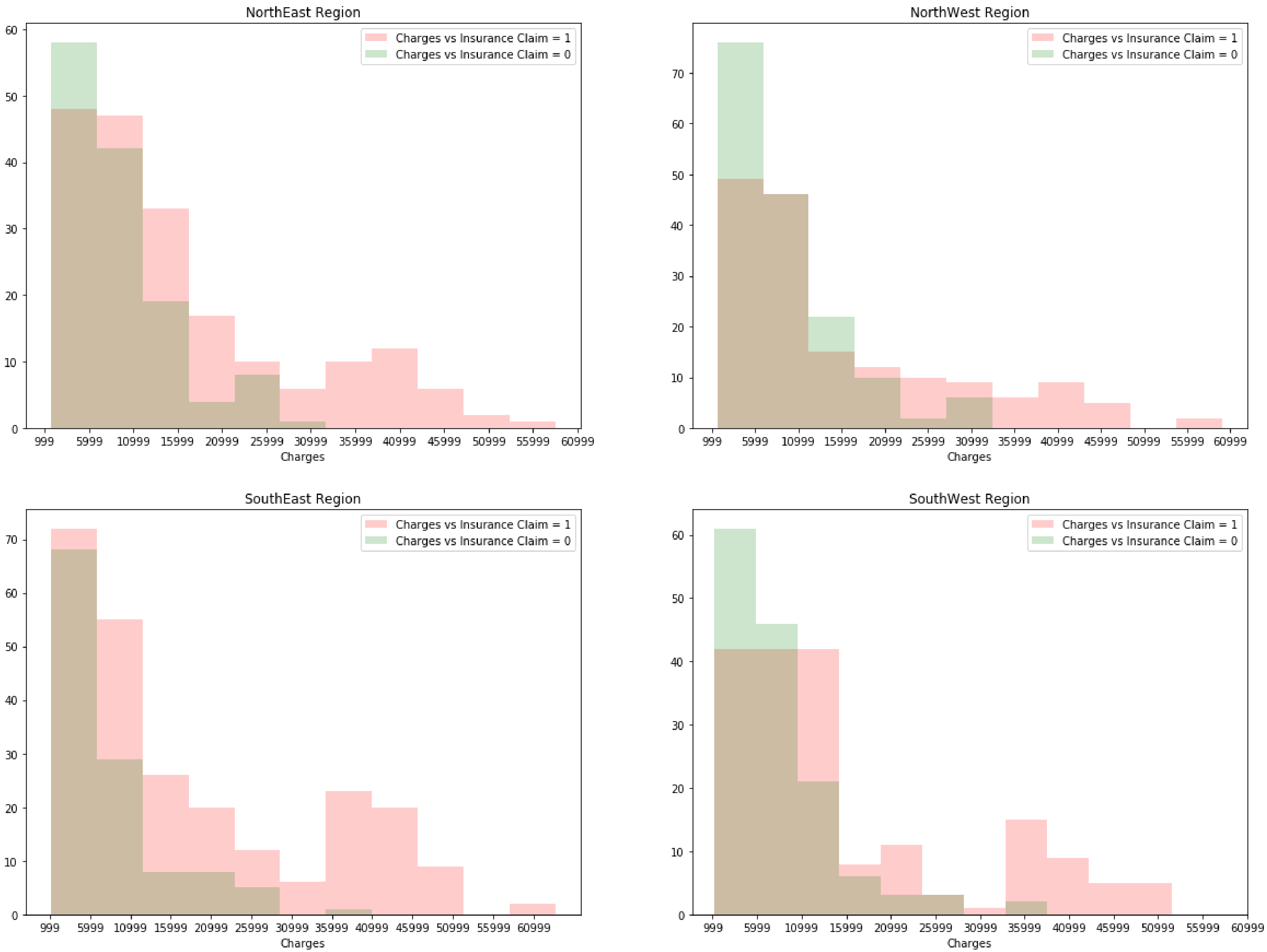
```
df_table['charges_bins'] = pd.cut(x=df_table['charges'], bins=[1000, 4999, 9999, 14999, 19999, 24999, 29999,349
df = df_table.groupby(['isNorthEast', 'isNorthWest', 'isSouthEast','isSouthWest','charges_bins','insuranceclaim
print (df) #need visualization to see the trend
```

```
    isNorthEast  isNorthWest  isSouthEast  isSouthWest    charges_bins  \
0             0            0            0            1    (1000, 4999]
1             0            0            0            1    (1000, 4999]
2             0            0            0            1    (4999, 9999]
3             0            0            0            1    (4999, 9999]
4             0            0            0            1   (9999, 14999]
5             0            0            0            1   (9999, 14999]
6             0            0            0            1  (14999, 19999]
7             0            0            0            1  (14999, 19999]
8             0            0            0            1  (19999, 24999]
9             0            0            0            1  (19999, 24999]
10            0            0            0            1  (24999, 29999]
11            0            0            0            1  (24999, 29999]
12            0            0            0            1  (29999, 34999]
13            0            0            0            1  (34999, 39999]
14            0            0            0            1  (34999, 39999]
15            0            0            0            1  (39999, 44999]
16            0            0            0            1  (44999, 49999]
17            0            0            0            1  (49999, 54999]
```

In [27]:

```
import matplotlib.pyplot as plt3
fig, axs = plt3.subplots(2, 2, tight_layout=False, figsize=(20,15))
df14 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['isNorthEast']==1)]
df15 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['isNorthEast']==1)]
axs[0,0].hist([df14['charges'],df15['charges']], bins=11, histtype='stepfilled',
         align='mid', color=['g','r'], label=['Charges vs Insurance Claim = 0','Charges vs Insurance Claim = 1'

df16 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['isNorthWest']==1)]
df17 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['isNorthWest']==1)]
axs[0,1].hist([df16['charges'],df17['charges']], bins=11, histtype='stepfilled',
         align='mid', color=['g','r'], label=['Charges vs Insurance Claim = 0','Charges vs Insurance Claim = 1'

df18 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['isSouthEast']==1)]
df19 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['isSouthEast']==1)]
axs[1,0].hist([df18['charges'],df19['charges']], bins=11, histtype='stepfilled',
         align='mid', color=['g','r'], label=['Charges vs Insurance Claim = 0','Charges vs Insurance Claim = 1'

df20 = df_table[(df_table['insuranceclaim'] == 0) & (df_table['isSouthWest']==1)]
df21 = df_table[(df_table['insuranceclaim'] == 1) & (df_table['isSouthWest']==1)]
axs[1,1].hist([df20['charges'],df21['charges']], bins=11, histtype='stepfilled',
         align='mid', color=['g','r'], label=['Charges vs Insurance Claim = 0','Charges vs Insurance Claim = 1'

for i in range(2):
    for j in range(2):
        axs[i,j].legend()
        axs[i,j].set(xlabel='Charges')
        plt2.sca(axs[i,j])
        plt2.xticks(range(999,64999,5000))

axs[0,0].set_title('NorthEast Region')
axs[0,1].set_title('NorthWest Region')
axs[1,0].set_title('SouthEast Region')
axs[1,1].set_title('SouthWest Region')

fig.suptitle('Insurance Claims vs Age & BMI')
plt3.show()
```

Insurance Claims vs Age & BMI


NorthEast Region
Charges vs Insurance Claim = 1
Charges vs Insurance Claim = 0
Charges
NorthWest Region
Charges vs Insurance Claim = 1
Charges vs Insurance Claim = 0
Charges
SouthEast Region
Charges vs Insurance Claim = 1
Charges vs Insurance Claim = 0
Charges
SouthWest Region
Charges vs Insurance Claim = 1
Charges vs Insurance Claim = 0
Charges
999 5999 10999 15999 20999 25999 30999 35999 40999 45999 50999 55999 60999

5. Predictive Models

WE DECIDED TO USE RANDOM FOREST AND MULTINOMIAL LOGISTIC REGRESSION TO CLASSIFY INSURANCE CLAIM

In [28]:
```
#Split data frame into two data frame for Random Forest and MULTINOMIAL LOGISTIC Regression
rf_df = df_table[:int(len(df_table.index)/2)]
mlg_df = df_table[int(len(df_table.index)/2):]
mlg_df = mlg_df[['age', 'sex', 'bmi', 'children', 'smoker', 'charges','isNorthEast', 'isNorthWest', 'isSouthEas
```

A. Multinomial Logistic Regression

Create Training Set and Testing Set

In [39]:
```
#Import packages for MULTINOMIAL Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
from pandas import Series, DataFrame

#Create Training set and Testing set for MULTINOMIAL logistic Regression
y_mlg = mlg_df['insuranceclaim']
x_train_mlg, x_test_mlg, y_train_mlg, y_test_mlg = train_test_split(mlg_df, y_mlg, test_size=0.20)
```

In [30]:
```
#Check Size
mlg_size = Series([len(x_train_mlg),len(y_train_mlg),len(x_test_mlg),len(y_test_mlg)], index = ['X Training','Y
mlg_size
```

Out[30]:
```
X Training    535
Y Training    535
X Test        134
Y Test        134
dtype: int64
```

Features Selection for Multinomial Logistic Regression with RFE

In [36]:
```
# Import package for feature selections
from __future__ import division  #will change the / operator to mean true division throughout the module.
from sklearn.metrics import confusion_matrix
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

#Get Series of reponse and variables
y = mlg_df['insuranceclaim']
x = mlg_df[['age', 'sex', 'bmi', 'children', 'smoker', 'charges','isNorthEast', 'isNorthWest', 'isSouthEast','i

#Create lists of metric and informational values
precision =[]
recall = []
currate = []
correct = []
total = []
findex = []
feature = []
K_Fold = []

#Declare type of model for RFE to evaluate
logreg = LogisticRegression()

#Loop through each number of variables to run RFE
for i in range(1, len(mlg_df.columns)):
    rfe = RFE(logreg, i, step = 1)
    rfe = rfe.fit(x, y)

    #Zip variables and choice indication of features
    choices = dict(zip(x,rfe.support_))
    cols = []

    #Save features chosen by RFE based on coefficient and feature important score
    for var in choices:
        if choices[var] == True:
            cols.append(var)
```

```
#Rebuild training and testing set based on number of chosen variables
x_ftrain_mlg = x_train_mlg[cols]
x_ftest_mlg = x_test_mlg[cols]
mlg_model = LogisticRegression()

#Find best cv for current amount of feature
meancv = {3:0,5:0,10:0,20:0,50:0}
maxdictindex = 0
maxdictvalue = 0
for j in (3,5,10,20,50):
    x_cv = x_ftrain_mlg.to_numpy()   ##instead of .as_matrix() using .to_numpy() to remove the future warni
    y_cv = y_train_mlg.to_numpy()    ##instead of .as_matrix() using .to_numpy() to remove the future warni
    cv_score = cross_val_score(mlg_model,x_cv,y_cv, cv = j)
    meancv[j] = np.mean(cv_score)
    if meancv[j] > maxdictvalue:
        maxdictindex = j
        maxdictvalue = meancv[j]

# Train Multinomial Logistic Regression with best cross validation to create a model
mlg_model_cv = LogisticRegressionCV(cv=maxdictindex, solver='lbfgs', random_state=0,multi_class='multinomia
mlg_fit = mlg_model_cv.fit(x_ftrain_mlg, y_train_mlg)

#Use Model to test the testing data set
y_pred_mlg= mlg_model_cv.predict(x_ftest_mlg)

#Calculate Classification Rate/Accuracy of MULTINOMIAL Logistic Regression
accurate = accuracy_score(y_test_mlg, y_pred_mlg, normalize=False)
rate = accurate / len(y_test_mlg)
p_score = precision_score(y_test_mlg, y_pred_mlg)
r_score = recall_score(y_test_mlg, y_pred_mlg)
#Add values for the result dataframe
currate.append(rate)
findex.append(i)
total.append(len(y_test_mlg))
correct.append(accurate)
feature.append(cols)
K_Fold.append(maxdictindex)
precision.append(p_score)
recall.append(r_score)
```

Choose Best Number of Features for Multinomial Logistic Regression

In [37]:
```
#Create DataFrame for RFE result
dictresult = {'Accurate Predict': correct, 'Total' : total, 'Rate' : currate,'Number of Features':findex, 'Feat
rferesult = DataFrame(dictresult, index = findex)

#Rearrange columns
rferesult = rferesult[['Number of Features','Precision','Recall','Rate','Accurate Predict','Total','Feature','K
```

In [38]:
```
#Sort by highest prediction accuracy
rferesult = rferesult.sort_values("Recall", ascending = False)
rferesult
```

Out[38]:

	Number of Features	Precision	Recall	Rate	Accurate Predict	Total	Feature	K-Fold
8	8	0.974026	0.961538	0.962687	129	134	[isSouthEast, isSouthWest, bmi, smoker, sex, i...	50
9	9	0.914634	0.961538	0.925373	124	134	[isSouthEast, isSouthWest, age, bmi, smoker, s...	50
10	10	0.860465	0.948718	0.880597	118	134	[isSouthEast, isSouthWest, charges, age, bmi, ...	5
3	3	0.784810	0.794872	0.753731	101	134	[isSouthEast, smoker, children]	3
4	4	0.784810	0.794872	0.753731	101	134	[isSouthEast, smoker, isNorthWest, children]	3
5	5	0.784810	0.794872	0.753731	101	134	[isSouthEast, smoker, sex, isNorthWest, children]	3
6	6	0.784810	0.794872	0.753731	101	134	[isSouthEast, smoker, sex, isNorthEast, isNort...	3
7	7	0.784810	0.794872	0.753731	101	134	[isSouthEast, isSouthWest, smoker, sex, isNort...	3
2	2	0.805556	0.743590	0.746269	100	134	[smoker, children]	50
1	1	0.931034	0.346154	0.604478	81	134	[smoker]	50

B. Random Forest Classifier

In [23]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [24]: rf_df = rf_df[['age', 'sex', 'bmi', 'children', 'smoker', 'charges','isNorthEast', 'isNorthWest', 'isSouthEast'
```

Split 70% Training and 30% Testing

```
In [25]: Features = rf_df[['age', 'sex', 'bmi', 'children', 'smoker', 'charges','isNorthEast', 'isNorthWest', 'isSouthEa
         Label = rf_df['insuranceclaim']

         X_train, X_test, y_train, y_test = train_test_split(Features, Label, test_size=0.3)

         print("Training features:", len(X_train))
         print("Training label:", len(y_train))
         print("Test features:", len(X_test))
         print("Test label:", len(y_test))
```

```
Training features: 468
Training label: 468
Test features: 201
Test label: 201
```

Generate Random Forest Classifier

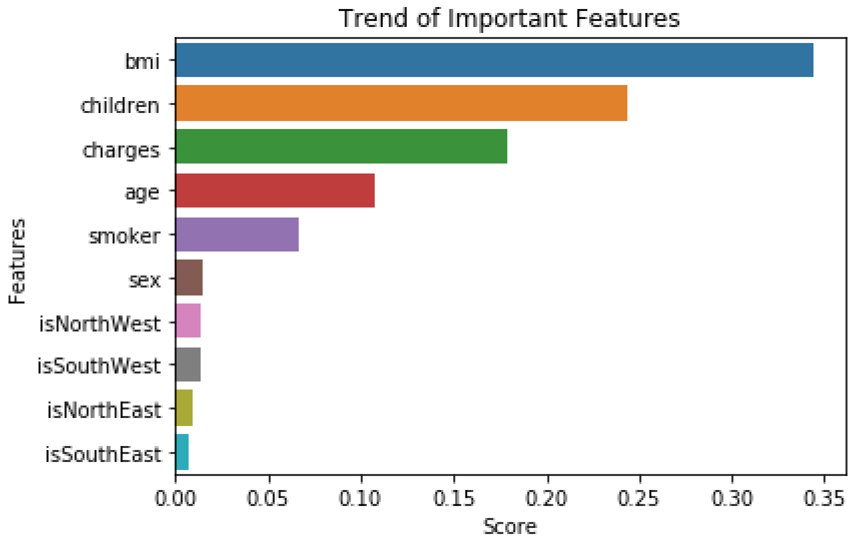
```
In [26]: clf=RandomForestClassifier(n_estimators=100, random_state = 0) #n_estimators = number of random decision trees

         #Train the model
         clf.fit(X_train,y_train)

         #Prediction on test set
         y_pred=clf.predict(X_test)
```

Display Important Features

In [27]:
```python
feature_imp = pd.Series(clf.feature_importances_,index=Features.columns).sort_values(ascending=False)
feature_imp
```

Out[27]:
```
bmi            0.344364
children       0.243374
charges        0.179374
age            0.107397
smoker         0.066553
sex            0.015230
isNorthWest    0.013771
isSouthWest    0.013669
isNorthEast    0.008929
isSouthEast    0.007339
dtype: float64
```

In [28]:
```python
sns.barplot(x=feature_imp, y=feature_imp.index)
plt.title("Trend of Important Features")
plt.xlabel('Score')
plt.ylabel('Features')
plt.show()
```



Confusion Matrix

In [29]:
```
pd.crosstab(y_test,y_pred, rownames = ['Actual Claims'], colnames = ['Predicted Claims'], margins=True, margins_
```

Out[29]:

Predicted Claims	0	1	Total
Actual Claims			
0	55	12	67
1	6	128	134
Total	61	140	201

In [30]:
```
cm = np.zeros((len(y_test), len(y_pred)))
for a, p in zip(y_test,y_pred):
    cm[a][p] += 1


truePositive = cm[0][0]
falsePositive = cm[0][1]
falseNegative = cm[1][0]
trueNegative = cm[1][1]
precision = truePositive / (truePositive + falsePositive)
recall = truePositive / (truePositive + falseNegative)
accuracy = (y_test == y_pred).sum() / float(len(y_test))

print("Precision =", precision)
print("Recall =", recall)
print("F1 score =", 2*precision*recall / (precision+recall))
print("Accuracy= ",accuracy)
```

```
Precision = 0.8208955223880597
Recall = 0.9016393442622951
F1 score = 0.8593750000000001
Accuracy=  0.9104477611940298
```

Select: 'bmi', 'children', 'charges', 'age', 'smoker', 'sex'

In [33]:
```python
new_Features2 = rf_df[['bmi', 'children', 'charges', 'age', 'smoker', 'sex']] #Getting BMI, Children, Charges, 

F_train, F_test, L_train, L_test = train_test_split(new_Features2, Label, test_size=0.3)

print("Training features:", len(F_train))
print("Training label:", len(L_train))
print("Test features:", len(F_test))
print("Test label:", len(L_test))

#Train the model
clf.fit(F_train,L_train)

#Prediction on test set
L_pred=clf.predict(F_test)

cm = np.zeros((len(L_test), len(L_pred)))
for a, p in zip(L_test,L_pred):
    cm[a][p] += 1

truePositive = cm[0][0]
falsePositive = cm[0][1]
falseNegative = cm[1][0]
trueNegative = cm[1][1]
precision = truePositive / (truePositive + falsePositive)
recall = truePositive / (truePositive + falseNegative)
accuracy = (L_test == L_pred).sum() / float(len(L_test))

print("Precision =", precision)
print("Recall =", recall)
print("F1 score =", 2*precision*recall / (precision+recall))
print("Accuracy= ",accuracy)

pd.crosstab(L_test,L_pred, rownames = ['Actual Claims'], colnames = ['Predicted Claims'], margins=True, margins
```

```
Training features: 468
Training label: 468
Test features: 201
Test label: 201
Precision = 0.925
```

```
Recall = 0.9367088607594937
F1 score = 0.9308176100628932
Accuracy=  0.945273631840796
```

Out[33]:

Predicted Claims	0	1	Total
Actual Claims			
0	74	6	80
1	5	116	121
Total	79	122	201

Select Important Features: 'bmi', 'children', 'charges', 'age', 'smoker'

Split 70% Training and 30% Testing

```
In [34]: new_Features = rf_df[['bmi', 'children', 'charges', 'age', 'smoker']] #Getting BMI, Children, Charges, Age, Smo

Features_train, Features_test, Label_train, Label_test = train_test_split(new_Features, Label, test_size=0.3)

print("Training features:", len(Features_train))
print("Training label:", len(Label_train))
print("Test features:", len(Features_test))
print("Test label:", len(Label_test))


#Train the model
clf.fit(Features_train,Label_train)

#Prediction on test set
Label_pred=clf.predict(Features_test)

cm = np.zeros((len(Label_test), len(Label_pred)))
for a, p in zip(Label_test,Label_pred):
    cm[a][p] += 1

truePositive = cm[0][0]
falsePositive = cm[0][1]
falseNegative = cm[1][0]
trueNegative = cm[1][1]
precision = truePositive / (truePositive + falsePositive)
recall = truePositive / (truePositive + falseNegative)
accuracy = (Label_test == Label_pred).sum() / float(len(Label_test))

print("Precision =", precision)
print("Recall =", recall)
print("F1 score =", 2*precision*recall / (precision+recall))
print("Accuracy= ",accuracy)

pd.crosstab(Label_test,Label_pred, rownames = ['Actual Claims'], colnames = ['Predicted Claims'], margins=True,
```

```
Training features: 468
Training label: 468
Test features: 201
Test label: 201
Precision = 0.9090909090909091
```

```
Recall = 0.958904109589041
F1 score = 0.9333333333333333
Accuracy=  0.9502487562189055
```

Out[34]:

Predicted Claims	0	1	Total
Actual Claims			
0	70	7	77
1	3	121	124
Total	73	128	201

In [ ]: