Insurance Claim Prediction using Machine Learning.

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1. Introduction

- Logistic regression is a techinque used for solving the **classification problem**.
- Insurance claim prediction is the process of using data analytics and machine learning techniques to forecast the likelihood and severity of future insurance claims. By analyzing historical data.

2. Problume statment

- Ultimately, insurance claim prediction contributes to more accurate risk assessment and more efficient allocation of resources within the insurance industry.
- Insurance companies can better anticipate potential risks and adjust their pricing, underwriting, and risk management strategies accordingly. This predictive modeling helps insurers optimize their operations, improve customer service, and mitigate financial losses by identifying high-risk policies or customers early on.

3. Installing & Importing Libraries

In [105]:
```python
#------------------------------------------------------------------------------------------------------------
import pandas as pd                                                             # Impor
from pandas_profiling import ProfileReport                                      # Impor
pd.set_option('display.max_columns', None)                                      # Unfol
pd.set_option('display.max_colwidth', None)                                     # Unfol
pd.set_option('display.max_rows', None)                                         # Unfol
pd.set_option('mode.chained_assignment', None)                                  # Remov
pd.set_option('display.float_format', lambda x: '%.5f' % x)                     # To su
#------------------------------------------------------------------------------------------------------------
import numpy as np                                                              # Impor
#------------------------------------------------------------------------------------------------------------
import matplotlib.pyplot as plt                                                 # Impor
from matplotlib.pylab import rcParams                                           # Backe
import seaborn as sns                                                           # Impor
%matplotlib inline
#------------------------------------------------------------------------------------------------------------
from sklearn.metrics import accuracy_score                                      # For c
from sklearn.metrics import precision_score                                     # For c
from sklearn.metrics import recall_score                                        # For c
from sklearn.metrics import precision_recall_curve                              # For p
from sklearn.metrics import confusion_matrix                                    # For v
from sklearn.metrics import f1_score                                            # For C
from sklearn.metrics import roc_curve                                           # For R
#------------------------------------------------------------------------------------------------------------
from sklearn.model_selection import train_test_split                            # To sp
from sklearn.linear_model import LogisticRegression                             # To cr
#------------------------------------------------------------------------------------------------------------
import warnings                                                                 # Impor
warnings.filterwarnings("ignore")                                               # Warni
```

4. Data Acquisition & Description

In [92]:
```python
data =pd.read_csv('C:/Users/Abhishek/Downloads/insurance.csv')
```

- The dataset consists of the information about people Insurance Claim . Various variables present in the dataset includes data of age, sex,BMI, etc.
- The dataset comprises of **1338 observations of 8 columns**. Below is a table showing names of all the columns and their description.

Column Name	Description
Age	Age of Person
Sex	Sex of Person(Male, Female)
BMI	Body mass index (BMI) of a person's
Children	Number of children
Smoker	A smoker is a person who smokes cigarettes
Region	Person belongs to particular region
Charges	Price of Insurance

5. Data Pre-Profiling

In [111]:
```
data.head(10)
```

Out[111]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
0	19	0	27.90000	0	1	3	16884.92400	1
1	18	1	33.77000	1	0	2	1725.55230	1
2	28	1	33.00000	3	0	2	4449.46200	0
3	33	1	22.70500	0	0	1	21984.47061	0
4	32	1	28.88000	0	0	1	3866.85520	1
5	31	0	25.74000	0	0	2	3756.62160	0
6	46	0	33.44000	1	0	2	8240.58960	1
7	37	0	27.74000	3	0	1	7281.50560	0
8	37	1	29.83000	2	0	0	6406.41070	0
9	60	0	25.84000	0	0	1	28923.13692	0

In [94]:
```
data.describe()
```

Out[94]:

	age	sex	bmi	children	smoker	region	charges
count	1338.00000	1338.00000	1338.00000	1338.00000	1338.00000	1338.00000	1338.00000
mean	39.20703	0.50523	30.66340	1.09492	0.20478	1.51570	13270.42227
std	14.04996	0.50016	6.09819	1.20549	0.40369	1.10488	12110.01124
min	18.00000	0.00000	15.96000	0.00000	0.00000	0.00000	1121.87390
25%	27.00000	0.00000	26.29625	0.00000	0.00000	1.00000	4740.28715
50%	39.00000	1.00000	30.40000	1.00000	0.00000	2.00000	9382.03300
75%	51.00000	1.00000	34.69375	2.00000	0.00000	2.00000	16639.91251
max	64.00000	1.00000	53.13000	5.00000	1.00000	3.00000	63770.42801

In [95]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             1338 non-null   int64  
 1   sex             1338 non-null   int64  
 2   bmi             1338 non-null   float64
 3   children        1338 non-null   int64  
 4   smoker          1338 non-null   int64  
 5   region          1338 non-null   int64  
 6   charges         1338 non-null   float64
 7   insuranceclaim  1338 non-null   int64  
dtypes: float64(2), int64(6)
memory usage: 83.8 KB
```

In [96]:
```
data.shape
```
Out[96]:
```
(1338, 8)
```

In [97]:
```
data.skew()
```
Out[97]:
```
age              0.05567
sex             -0.02095
bmi              0.28405
children         0.93838
smoker           1.46477
region          -0.03810
charges          1.51588
insuranceclaim  -0.34625
dtype: float64
```

Check Null Values

In [98]:
```
null_frame = pd.DataFrame(index=data.columns.values)
null_frame['Null Frequency']=data.isnull().sum().values
percent=data.isnull().sum().values/data.shape[0]
null_frame["Missing%"]=np.round(percent,decimals=4)*100
null_frame.transpose()
```
Out[98]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
Null Frequency	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Missing%	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Observation:

- This dataset contains 1338 rows and 8 columns
- There are ** No null values present**
- **Each feature** seems to have **correct data type**
- The **average** age of the people is about 39 years.
- **Minimum** age seems to be 18 years. Where, the **Max** age was 64.
- The **average Charges** was 13270
- **Minimum** charges seems to be 1338. Where, the **Max** charges is 63770 indicates its skewed.

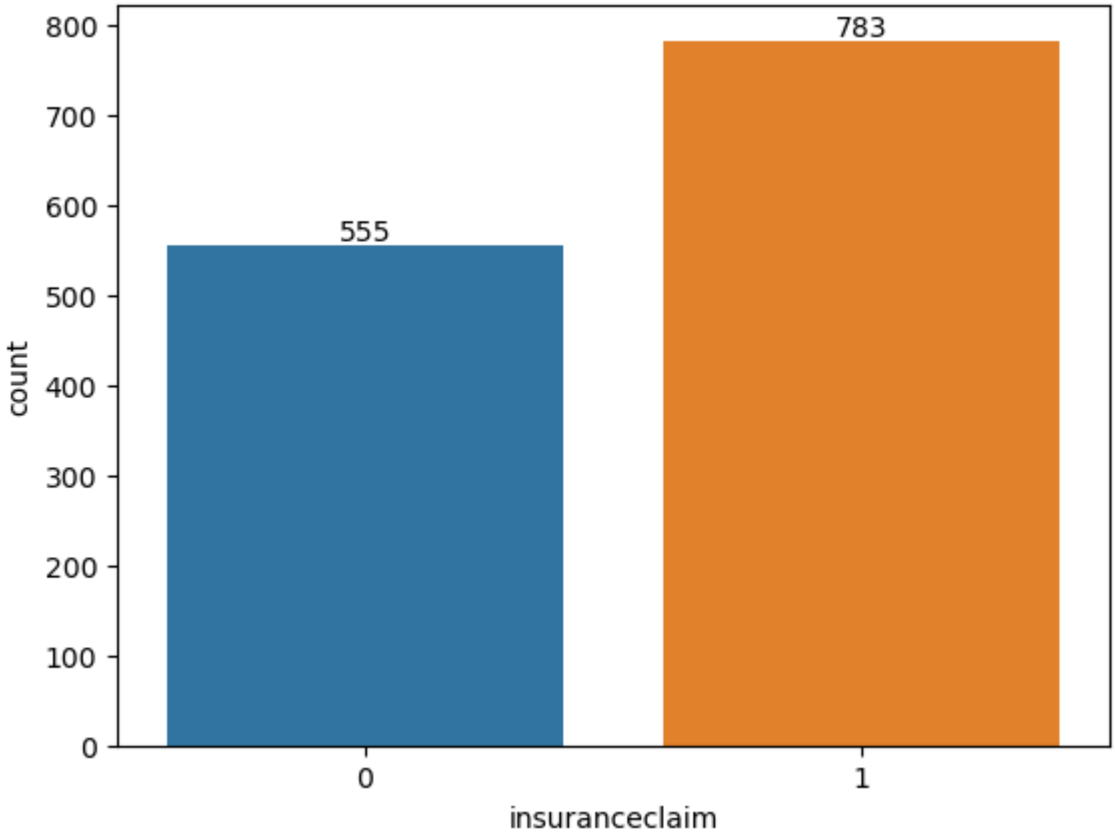
---

6. Exploratory Data Analysis

-By conducting thorough data analysis, one can observe patterns in insurance claims across different age groups, cultural backgrounds, and genders.

Analyzing the Frequency of Insurance Claims:

In [99]:
```python
insuranceclaim = sns.countplot(x = 'insuranceclaim',data = data)

for bars in insuranceclaim.containers:
    insuranceclaim.bar_label(bars)
```

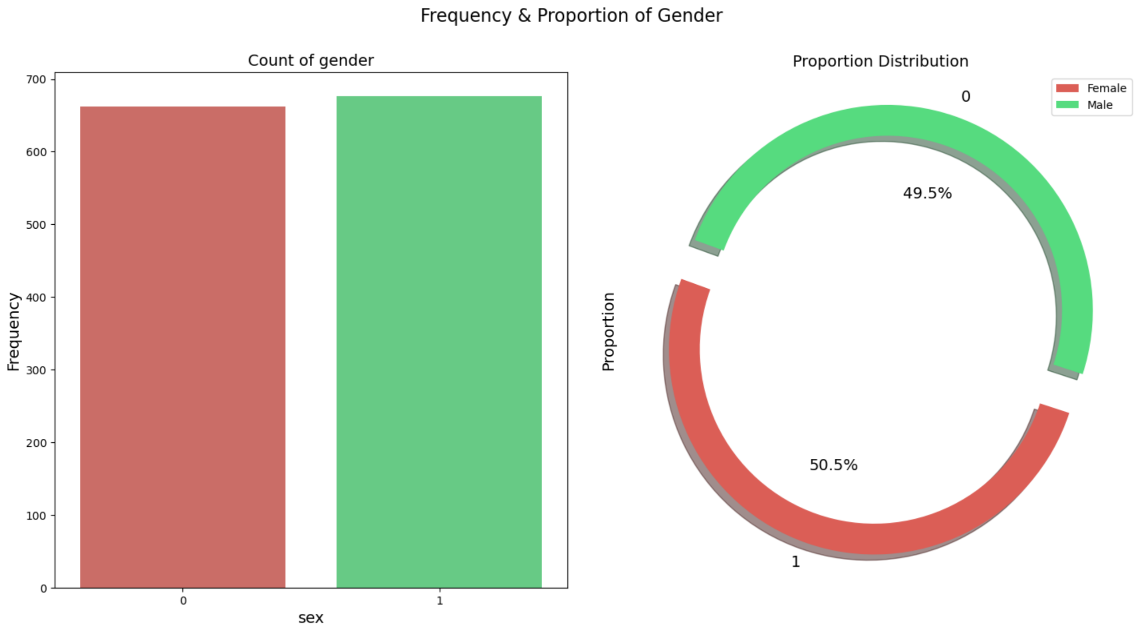


Observation:

- We can **observe** 778 people clamed.

Gender Distribution: Analyzing the Count of Genders

```
In [110]: fig = plt.figure(figsize = [15, 8])
plt.subplot(1, 2, 1)
sns.countplot(x = 'sex', data = data, palette = ['#DB5E56','#56DB7F'])
plt.xlabel(xlabel = 'sex', size = 14)
plt.ylabel(ylabel = 'Frequency', size = 14)
plt.title(label = 'Count of gender', size = 14)

plt.subplot(1, 2, 2)
space = np.ones(2)/10
data['sex'].value_counts().plot(kind = 'pie', explode = space, fontsize = 14
                                shadow = True, startangle = 160, fig
plt.legend(['Female', 'Male'])
plt.ylabel(ylabel = 'Proportion', size = 14)
plt.title(label = 'Proportion Distribution', size = 14)
plt.tight_layout(pad = 3.0)
plt.suptitle(t = 'Frequency & Proportion of Gender', y = 1.02, size = 16)
plt.show()
```

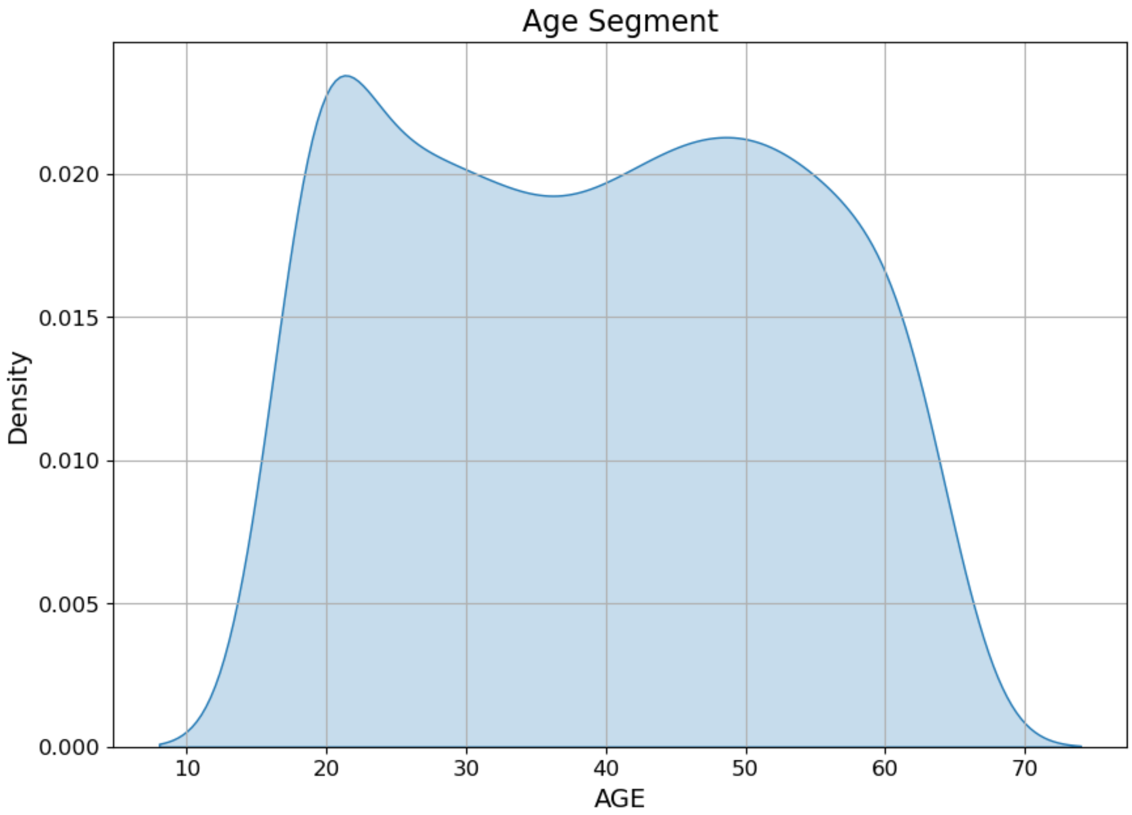


Observation:

- The count of males and females is nearly equal.

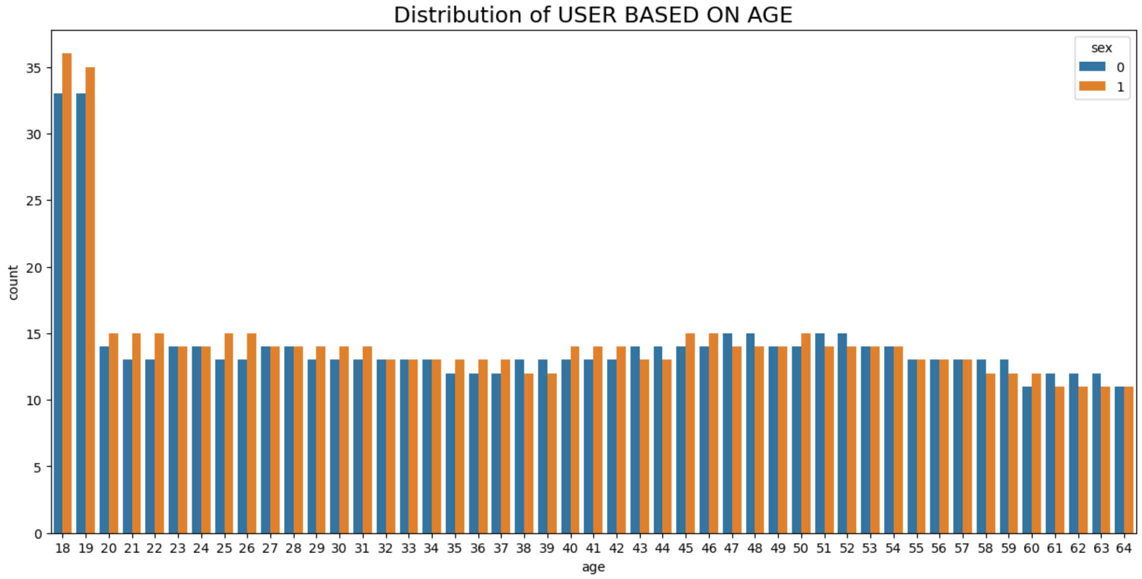
Count of Age Segments

In [11]:
```
fig = plt.figure(figsize=(10, 7))

sns.kdeplot(x = (data['age']), shade=True)

plt.xlabel(xlabel='AGE', size=14)
plt.ylabel(ylabel='Density', size=14)
plt.xticks(size=12)
plt.yticks(size=12)
plt.title(label='Age Segment', size=16)

# Put a grid
plt.grid(b=True)

# Display the plot
plt.show()
```



In [12]:

```
figure=plt.figure(figsize=[15,7])
sns.countplot(data=data, x="age", hue="sex")
plt.title("Distribution of USER BASED ON AGE",size=17)
plt.show()
```

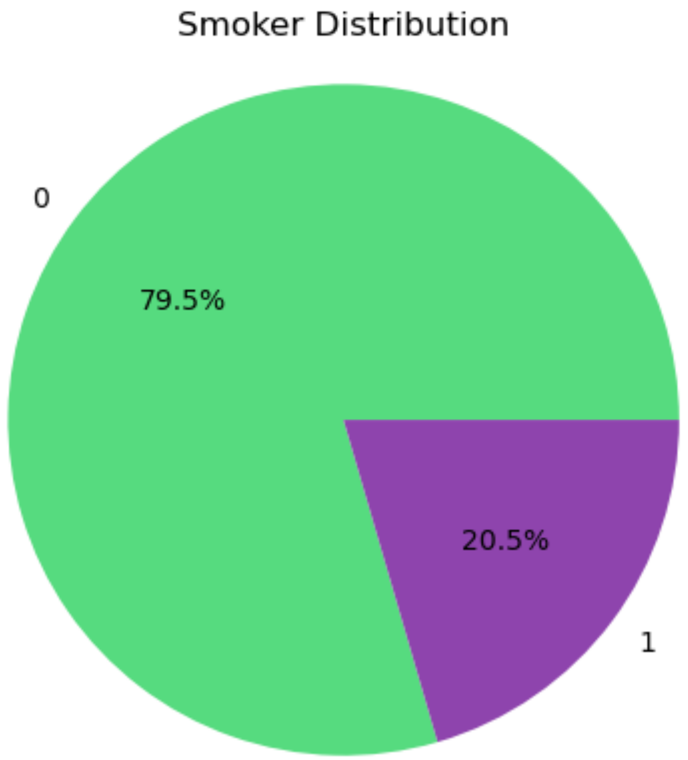


Observation:

- Minimum age seems to be 18 years. Where, the Max age was 64.

Analyzing the Count of Smokers

In [31]:
```
plt.title('Smoker Distribution')
smoker_count = data['smoker'].value_counts()
plt.pie(smoker_count, labels=smoker_count.index, autopct='%.1f%%',colors =
plt.axis('equal')
plt.show()
```

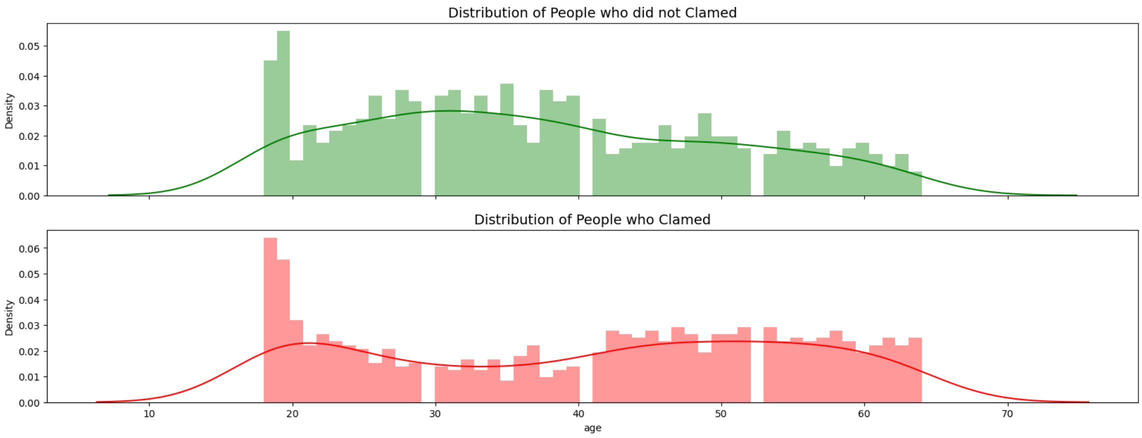


Observation:

- We can **observe** 20.5% people are smoker.

Is there any association between Age and Clame?
**

In [55]:
```python
# Slicing data with non-clamed
Not_clamed = data['age'][data['insuranceclaim'] == 0]

# Slicing data with clamed
clamed = data['age'][data['insuranceclaim'] == 1]

# Plotting the distribution of the sliced data
fig, (ax1, ax2) = plt.subplots(nrows = 2, ncols = 1, sharex = True, figsize
sns.distplot(a = Not_clamed, bins = 50, ax = ax1, color = 'green')
ax1.set_title(label = 'Distribution of People who did not Clamed', size = 14
ax1.set_xlabel(xlabel = '')
sns.distplot(a = clamed, bins = 50, ax = ax2, color = 'red')
ax2.set_title(label = 'Distribution of People who Clamed', size = 14)
plt.show()
```

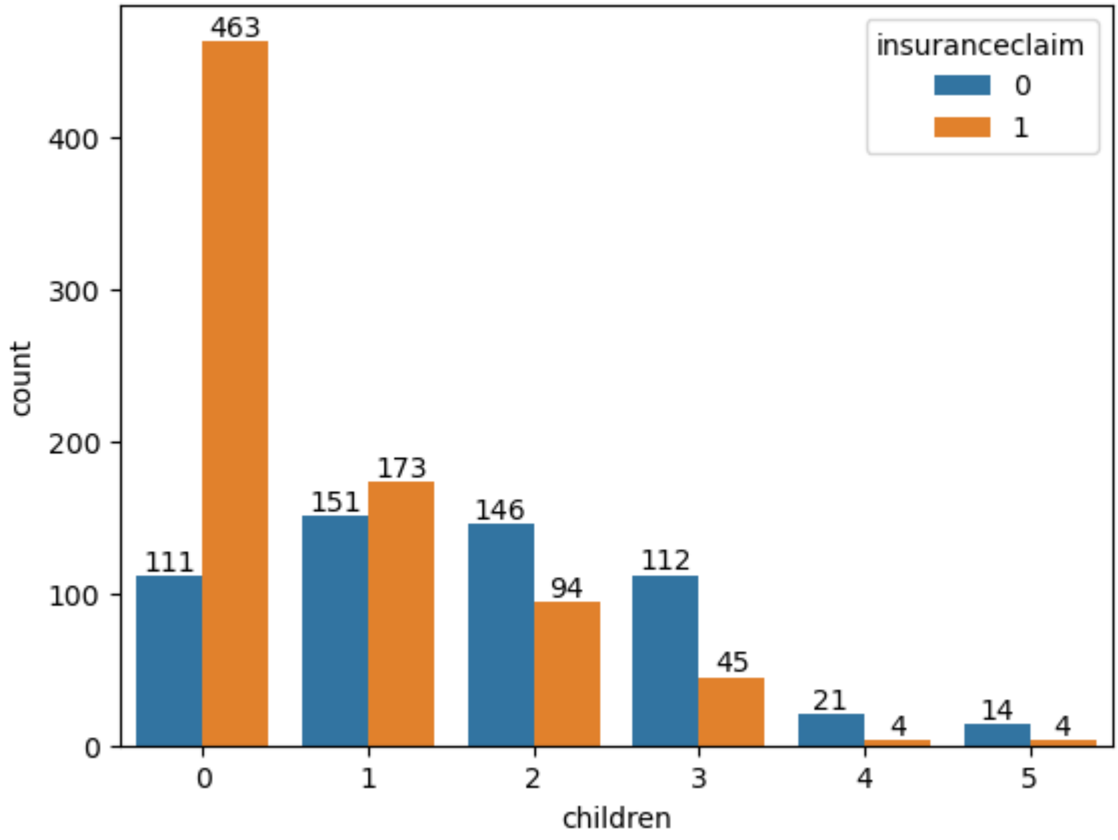


Observation:

- We can see that the distribution of both the cases are similar.
- If you notice the second graph you will see a little rise in the bar at the Age from 55-65 of the graphs.

Demonstrate an individual's insurance claim alongside the count of their dependents.

In [48]:
```
ax = sns.countplot(data = data, x = 'children', hue = 'insuranceclaim')

for bars in ax.containers:
    ax.bar_label(bars)
```

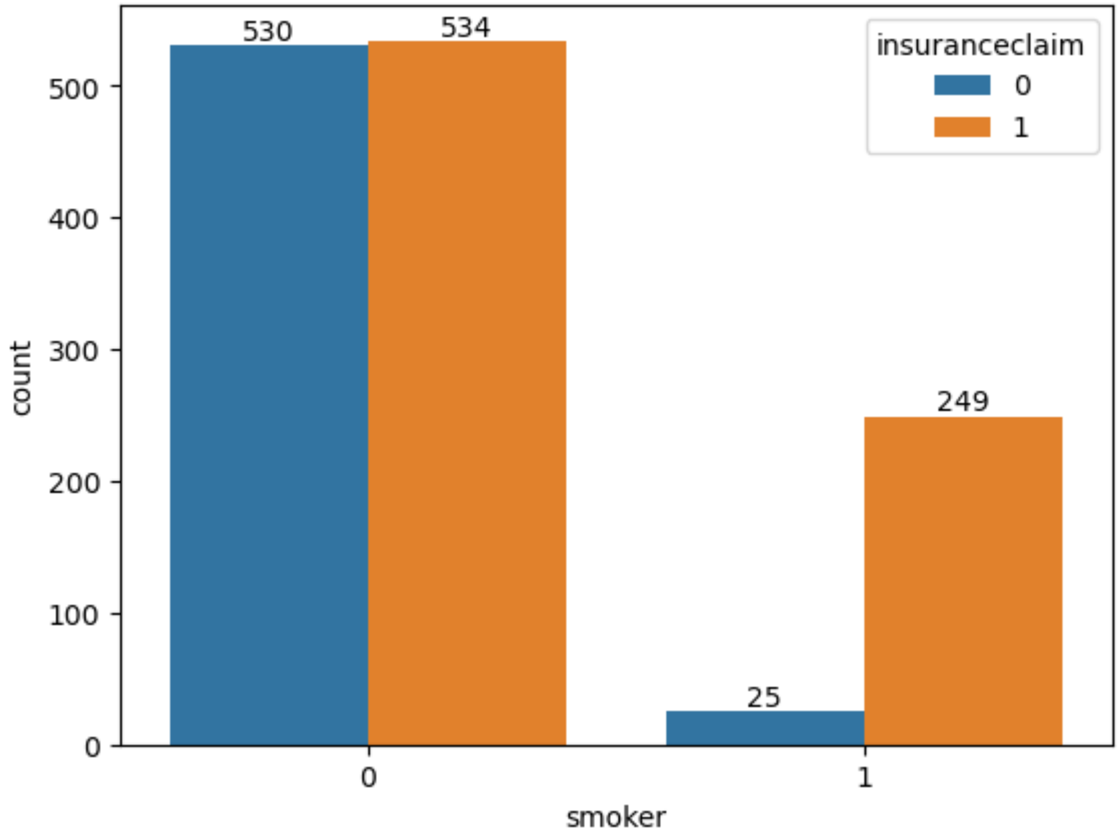


Observation:

- The distribution analysis uncovers a notable pattern wherein the dependent segment ranging from 0 to 1 shows a notably higher count compared to other dependent segments.

Display a claim for personal insurance from an individual who is a smoker.

In [51]:
```
ay = sns.countplot(data = data, x = 'smoker', hue = 'insuranceclaim')

for bars in ay.containers:
    ay.bar_label(bars)
```



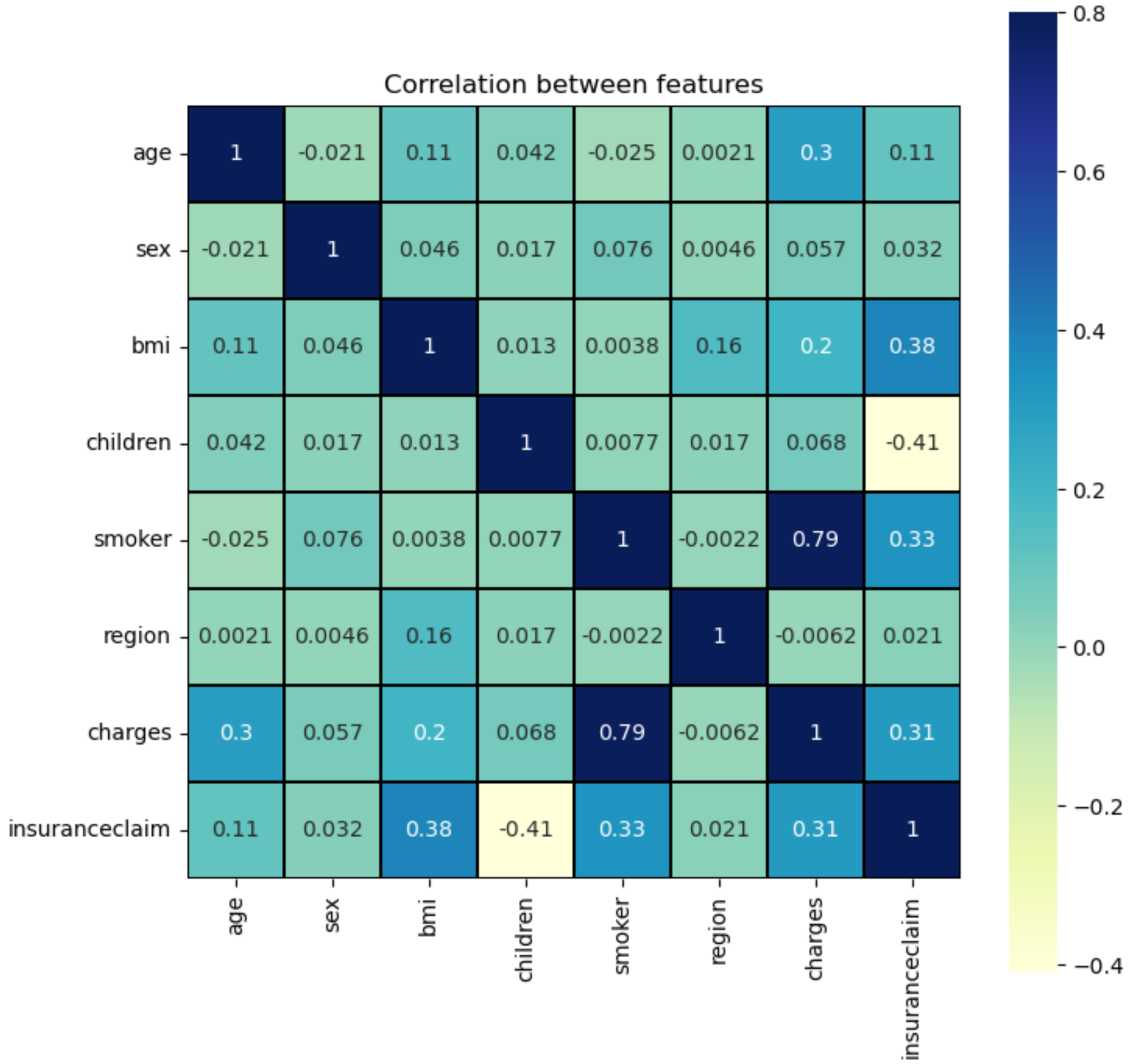
In [ ]:

Feature Selection**

- Here we will **visualize the correlation** of input features **using Heatmap**.
- If we see a case of correlation we will **remove the highly correlated feature**.

In [115]:
```
corr = data.corr()
plt.figure(figsize=(8,8))
sns.heatmap(corr,vmax=.8,linewidth=.01, square = True, annot = True,cmap='Y
plt.title('Correlation between features')
```

Out[115]: Text(0.5, 1.0, 'Correlation between features')



Observation:

- Children are Insuranceclame are negatively corelated with Clam.
- Smoker and Charges are positively coorelated with clam.

7. Data Preparation

- Now we will **split** our **data** in **training** and **testing** part for further development.

In [64]:
```
x = data.drop('insuranceclaim',axis = 1)
y = data['insuranceclaim']
```

In [65]:
```
x.shape
```
Out[65]:
```
(1338, 7)
```
In [66]:
```
y.shape
```
Out[66]:
```
(1338,)
```
In [67]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1, 

print('Training Data Shape:', x_train.shape, y_train.shape)
print('Testing Data Shape:', x_test.shape, y_test.shape)
```
```
Training Data Shape: (1204, 7) (1204,)
Testing Data Shape: (134, 7) (134,)
```

---

8. Model Development & Evaluation

- In this section we will **develop Logistic Regression using input features** and **tune** our **model if required**.
- Then we will **analyze the results** obtained and **make our observation**.
- For **evaluation purpose** we will **focus** on **Accuracy**, also we will check for **Precision**, **Recall**, **F1-Score**, **Roc-Auc-Curve** and **Precision-Recall Score**.

** Logistic Regression - Baseline Model**

In [68]:
```
logreg = LogisticRegression()
logreg.fit(x_train,y_train)
```
Out[68]:
```
LogisticRegression()
```
In [69]:
```
logreg.classes_
```
Out[69]:
```
array([0, 1], dtype=int64)
```
In [70]:
```
logreg.coef_
```
Out[70]:
```
array([[ 9.74104000e-04, -9.44094018e-01,  1.71763343e-01,
        -1.31637620e+00,  2.37777955e+00,  1.42494174e-01,
         4.91435315e-05]])
```
In [71]:
```
logreg.intercept_
```
Out[71]:
```
array([-4.00392273])
```

In [72]:
```
logreg.score(x_test,y_test)
```
Out[72]:
```
0.8432835820895522
```

Using Trained Model for Prediction

In [73]:
```
#predicting on train data
y_pred_train = logreg.predict(x_train)
```

In [74]:
```
#predicting on test data
y_pred_test = logreg.predict(x_test)
```

In [75]:
```
y_pred_train
```
Out[75]:
```
array([0, 1, 0, ..., 1, 0, 1], dtype=int64)
```

Model Evaluation On Test Data

In [78]:
```
confusion_matrix = pd.DataFrame(confusion_matrix(y_test,y_pred_test))
confusion_matrix.index = ['Positive','Negative']
confusion_matrix.columns = ['Positive','Negative']
print(confusion_matrix)
```
```
          Positive  Negative
Positive        42        14
Negative         7        71
```

Observations

- True Positive(TP) = 42
- True Negative(TN) = 71
- False Positive(FP) = 7
- False Negative(FN) = 14

Model Evaluation On Train Data

In [82]:
```
confusion_matrix = pd.DataFrame(confusion_matrix(y_train,y_pred_train))
confusion_matrix.index = ['Positive','Negative']
confusion_matrix.columns = ['Positive','Negative']
print(confusion_matrix)
```
```
          Positive  Negative
Positive       378       121
Negative        92       613
```

Checking Accuracy on test

In [83]:
```
logreg.score(x_test,y_test)
```
Out[83]:
```
0.8432835820895522
```

In [84]:
```
print('Accuracy score for test data is:', logreg.score(x_test,y_test))
```
```
Accuracy score for test data is: 0.8432835820895522
```

In [85]:
```
### Checking Accuracy on train
```

In [86]:
```
accuracy_score(y_train,y_pred_train)
```
Out[86]:
```
0.8230897009966778
```

Classification Report

In [90]:
```
from sklearn.metrics import classification_report
cr = classification_report(y_test,y_pred_test)
print(cr)
```
```
              precision    recall  f1-score   support

           0       0.86      0.75      0.80        56
           1       0.84      0.91      0.87        78

    accuracy                           0.84       134
   macro avg       0.85      0.83      0.84       134
weighted avg       0.84      0.84      0.84       134
```

---

9. Conclusion

- We **studied in breifly about the data**, its **characteristics** and its **distribution**.
- We **explored** some **questions related** to Clames.
- We **investigated in depth about the features** which to **retain** and which to **discard**.
- We **performed model training**.
- We **observed metrics for our prediction**.
- This **model With accuracy_score of 82%** now can **help us** in **identifying** who survived and who did not survive.

In [ ]: