HEALTHWELL ANALYSIS

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

df1=pd.read_excel("C:\\Users\\ajaya\\Downloads\\Assignment - Data
Analysis\\Healthwell Data\\Healthwell Customer
Data.xlsx",engine='openpyxl')
df2=pd.read_csv("C:\\Users\\ajaya\\Downloads\\Assignment - Data
Analysis\\Healthwell Data\\Healthwell Money claimed Data.csv")

df1.head()
```

	Policy no.	children	smoker	region
0	PLC157006	0	no	southwest
1	PLC157033	1	no	southwest
2	PLC157060	0	no	southwest
3	PLC157087	1	no	southwest
4	PLC157186	5	no	southwest

```
df2.head()
```

	Policy no.	age	sex	bmi	charges in INR
0	PLC156898	19	female	27.900	16884.92400
1	PLC156907	18	male	33.770	1725.55230
2	PLC156916	28	male	33.000	4449.46200
3	PLC156925	33	male	22.705	21984.47061
4	PLC156934	32	male	28.880	3866.85520

merging the two data set

```
df=pd.merge(df1,df2)
df
```

	Policy no.	children	smoker	region	age	sex	bmi	\
0	PLC157006	0	no	southwest	23	male	34.400	
1	PLC157033	1	no	southwest	19	male	24.600	
2	PLC157060	0	no	southwest	56	male	40.300	
3	PLC157087	1	no	southwest	30	female	32.400	
4	PLC157186	5	no	southwest	19	female	28.600	
...	...	...	...	...	...	...	...	
1333	PLC168400	1	yes	northeast	39	male	29.925	
1334	PLC168436	0	yes	northeast	18	female	21.660	
1335	PLC168634	2	yes	northeast	42	male	24.605	
1336	PLC168652	0	yes	northeast	29	female	21.850	
1337	PLC168787	0	yes	northeast	62	male	26.695	

```
      charges in INR
0          1826.84300
1          1837.23700
2         10602.38500
3          4149.73600
4          4687.79700
...               ...
1333      22462.04375
1334      14283.45940
1335      21259.37795
1336      16115.30450
1337      28101.33305

[1338 rows x 8 columns]
```

```
df.head()
```

```
  Policy no.  children smoker     region  age     sex   bmi  charges
in INR
0  PLC157006         0     no  southwest   23    male  34.4
1826.843
1  PLC157033         1     no  southwest   19    male  24.6
1837.237
2  PLC157060         0     no  southwest   56    male  40.3
10602.385
3  PLC157087         1     no  southwest   30  female  32.4
4149.736
4  PLC157186         5     no  southwest   19  female  28.6
4687.797
```

```
df.shape
```

```
(1338, 8)
```

This dataset contains 1330 rows and 7 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1338 entries, 0 to 1337
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Policy no.      1338 non-null   object
 1   children        1338 non-null   int64
 2   smoker          1338 non-null   object
 3   region          1338 non-null   object
 4   age             1338 non-null   int64
 5   sex             1338 non-null   object
 6   bmi             1338 non-null   float64
```

```
 7   charges in INR  1338 non-null   float64
dtypes: float64(2), int64(2), object(4)
memory usage: 94.1+ KB
```

Exploratory Data Analysis

```
df.columns
```

```
Index(['Policy no.', 'children', 'smoker', 'region', 'age', 'sex',
'bmi',
       'charges in INR'],
      dtype='object')
```

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

```
Policy no.         0
children           0
smoker             0
region             0
age                0
sex                0
bmi                0
charges in INR     0
dtype: int64
```

There are no null Values

Q1. Does the gender of the person matter for the company as a constraint for extending policies?

```
pd.get_dummies(df['sex'],prefix='Gender').head()
```

```
   Gender_female  Gender_male
0              0            1
1              0            1
2              0            1
3              1            0
4              1            0
```

```
df=pd.concat([df,pd.get_dummies(df['sex'],prefix='Gender')],axis=1)
```

```
df.head()
```

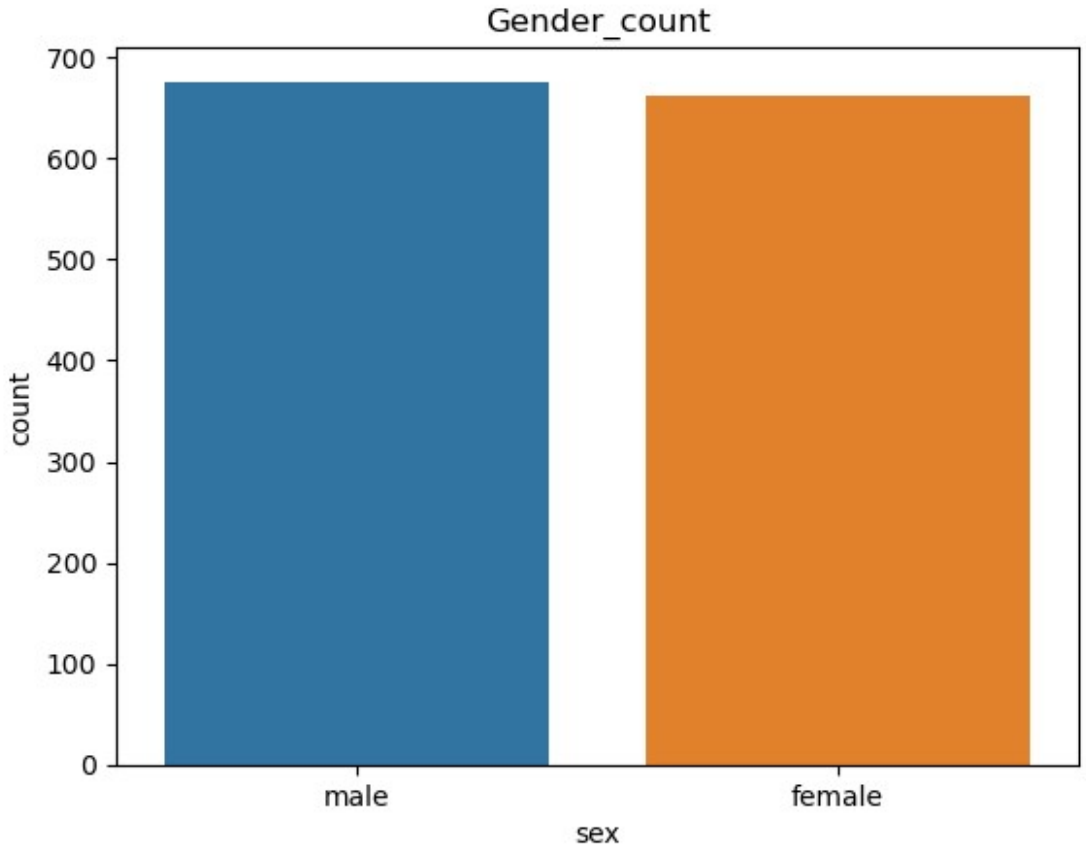
```
  Policy no.  children smoker     region  age     sex   bmi  charges
in INR  \
0  PLC157006         0     no  southwest   23    male  34.4
1826.843
1  PLC157033         1     no  southwest   19    male  24.6
1837.237
2  PLC157060         0     no  southwest   56    male  40.3
```

```
10602.385
3  PLC157087          1     no  southwest   30  female  32.4
4149.736
4  PLC157186          5     no  southwest   19  female  28.6
4687.797
```

```
   Gender_female  Gender_male
0              0            1
1              0            1
2              0            1
3              1            0
4              1            0
```

```
sns.countplot(data=df,x='sex',label='count')
M, F = df['sex'].value_counts()
plt.title('Gender_count')
print('Number of Male Who taken Policy: ',M)
print('Number of Female Who taken Policy: ',F)
```

```
Number of Male Who taken Policy:  676
Number of Female Who taken Policy:  662
```



From this Visualization we can understand the proportion of male and female is nearly equal.So the gender of the person doesnot matter for the company as a constraint for extending policies.

Q2. What is the average amount of money the company spent on each policy cover?

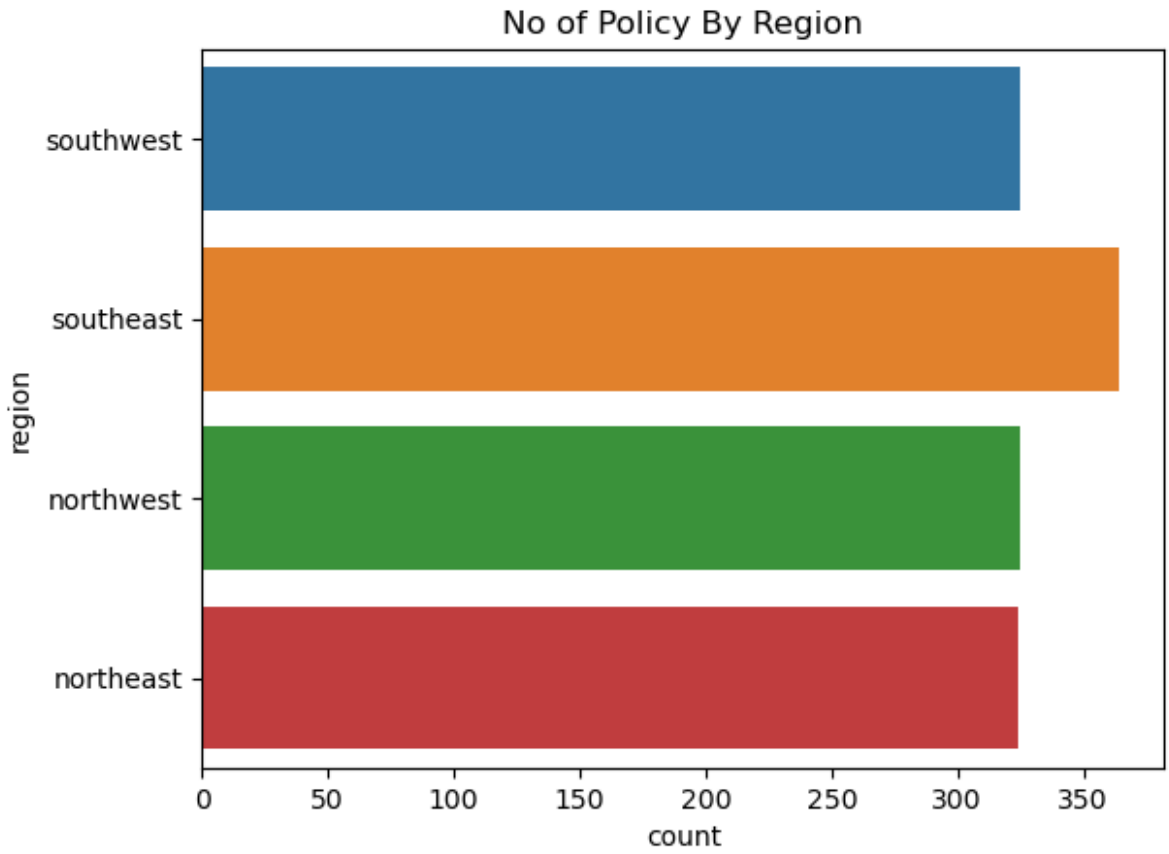
```
total_amount=df['charges in INR'].sum()
total_policies=df['Policy no.'].count()
average_amount=total_amount/total_policies

print('The Average amount Company Spent On Each Policy Cover
Is:',round(average_amount,2))
```

```
The Average amount Company Spent On Each Policy Cover Is: 13270.42
```

Q3. Could you advise if the company needs to offer separate policies based upon the geographic location of the person?

```
sns.countplot(data=df,y='region')
plt.title('No of Policy By Region')
se,sw,nw,ne=df['region'].value_counts()
print('No of Policies in SouthWest Region:',sw)
print('No of Policies in SouthEast Region:',se)
print('No of Policies in NorthWest Region:',nw)
print('No of Policies in NorthEast Region:',ne)
```

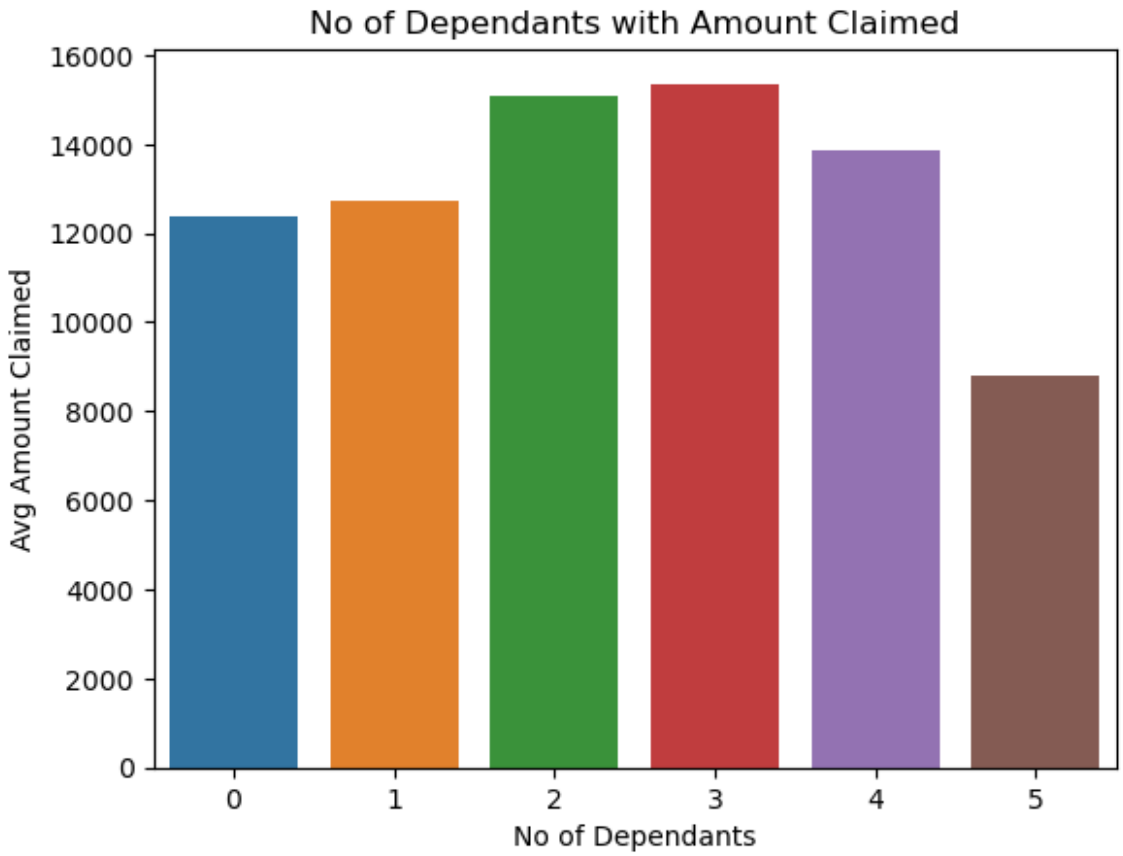
```
No of Policies in SouthWest Region: 325
No of Policies in SouthEast Region: 364
No of Policies in NorthWest Region: 325
No of Policies in NorthEast Region: 324
```



The company should implement seperate policies on the SouthWest,NorthWest,NorthEast Regions beacuse the no of policy holders is less compared to the south east region.

Q4. Does the no. of dependents make a difference in the amount claimed?

```
average_amount = df.groupby('children')['charges in
INR'].mean().reset_index()
sns.barplot(x='children',y='charges in INR',data=average_amount)
plt.title('No of Dependants with Amount Claimed')
plt.xlabel('No of Dependants')
plt.ylabel('Avg Amount Claimed')
plt.show()
```



From this Visualization we can understand that the No of dependants does affect the amount claimed.

1)The most amount claimed by customer having 3 dependants.

2)The least amount claimed by customer having 5 dependants.

Q5. Does a study of a person's BMI give the company any idea for the insurance claim that it would extend?

Yes studying a person's BMI give a vital role in extending the insurance claim.BMI index show the person is underweight or overweight. Underweight and Overweight is considered as a risk factor for extending policy claim.Value under 18.5 is considered as underweight,18.5-24.9 is considered as normal weight and above 24.9 is considered as overweight.

```
def weight(row):
    if row['bmi']>24.9:
        return 'Over Weight'
    elif row['bmi']<18.5:
        return 'Under Weight'
    else:
```

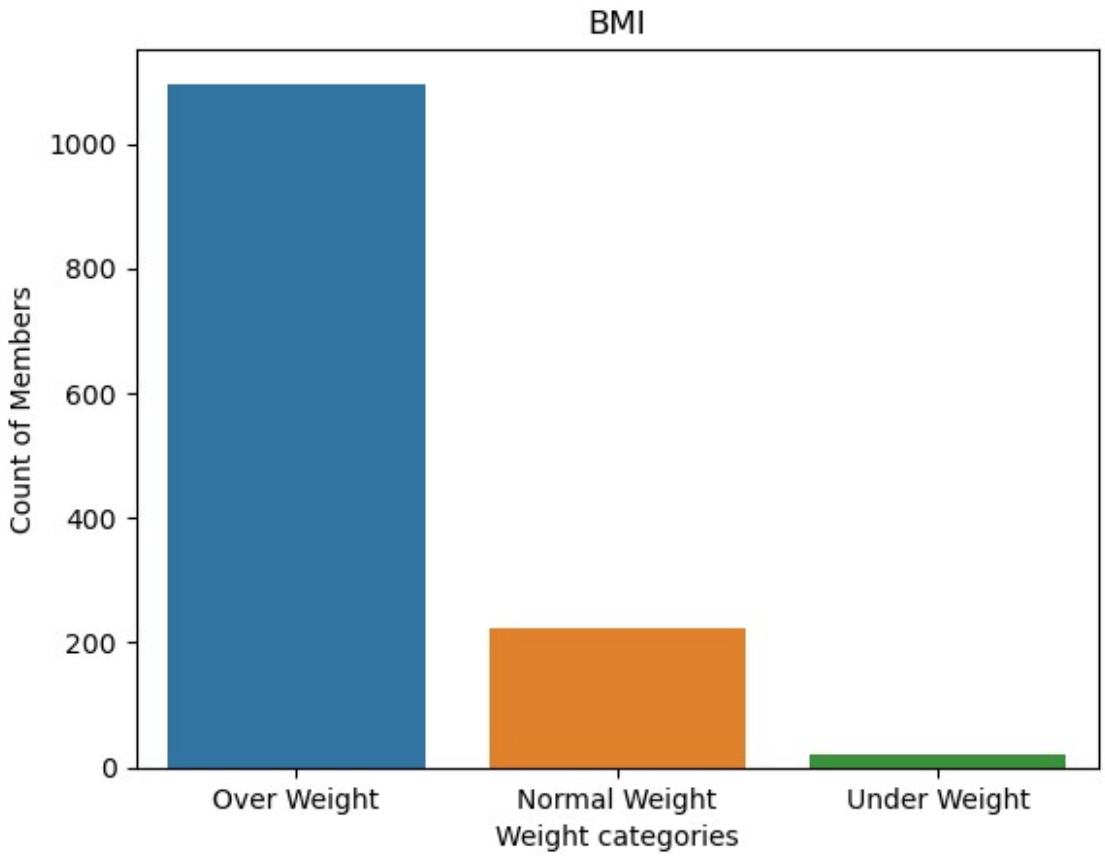
```
        return 'Normal Weight'
df['Weight']=df.apply(weight,axis=1)

df.head()
```

```
  Policy no.  children smoker     region  age     sex   bmi  charges
in INR  \
0  PLC157006         0     no  southwest   23    male  34.4
1826.843
1  PLC157033         1     no  southwest   19    male  24.6
1837.237
2  PLC157060         0     no  southwest   56    male  40.3
10602.385
3  PLC157087         1     no  southwest   30  female  32.4
4149.736
4  PLC157186         5     no  southwest   19  female  28.6
4687.797
```

```
   Gender_female  Gender_male         Weight
0              0            1    Over Weight
1              0            1  Normal Weight
2              0            1    Over Weight
3              1            0    Over Weight
4              1            0    Over Weight
```

```
sns.countplot(data=df,x='Weight')
plt.title('BMI')
plt.xlabel('Weight categories')
plt.ylabel('Count of Members')

o,n,u=df['Weight'].value_counts()
print('No of Policy Members With Over Weight:',o)
print('No of Policy Members With Normal Weight:',n)
print('No of Policy Members With Under Weight:',u)
```

```
No of Policy Members With Over Weight: 1096
No of Policy Members With Normal Weight: 222
No of Policy Members With Under Weight: 20
```



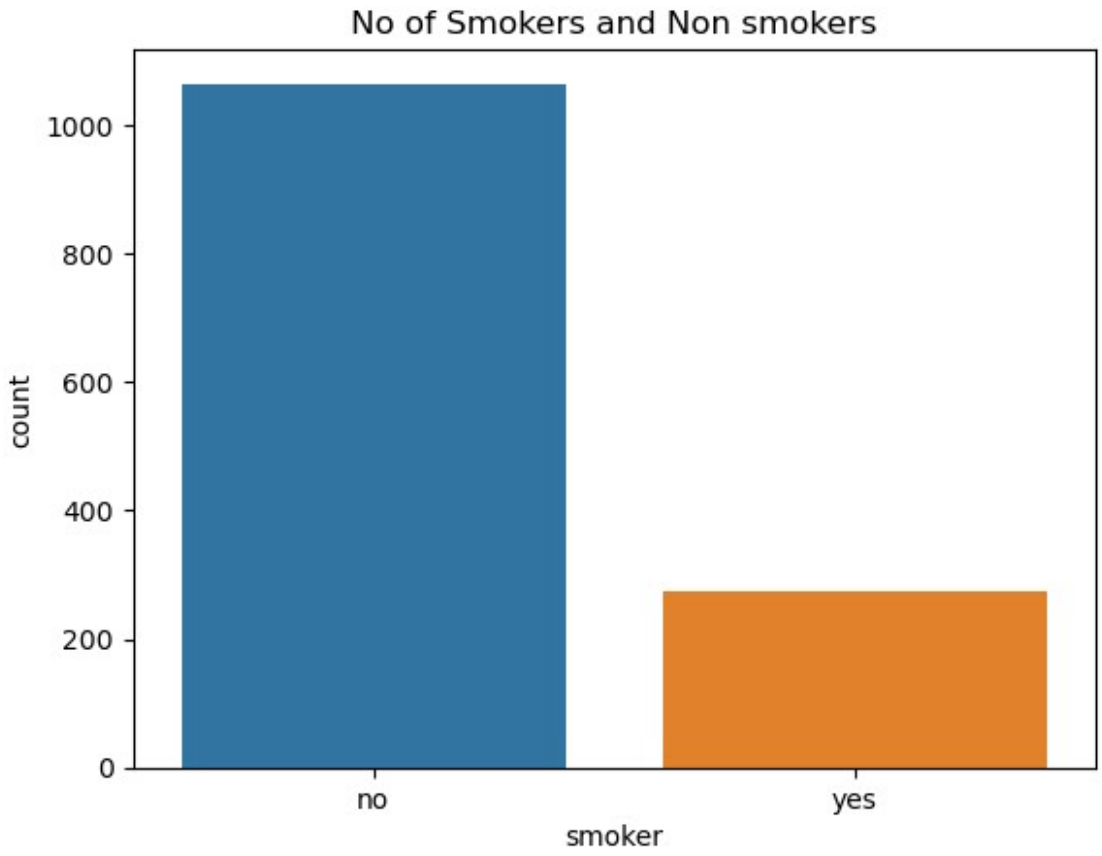
From This we can understand that most of the policy members are overweight acording to the BMI value So the company should consider before extending their policy. Or the company should Introduce new policy for the policy members to decrease the risk factor.

Q6. Is it needed for the company to understand whether the person covered is a smoker or a non-smoker?

smoking status is often a critical factor. Smokers are at a higher risk of various health conditions, including lung cancer, heart disease, and respiratory issues.

```
sns.countplot(data=df,x='smoker')
plt.title('No of Smokers and Non smokers')
n,y=df['smoker'].value_counts()
print('No of Policy Members Who Doesnot Smoke :',n)
print('No of Policy Members Who Smokes :',y)
```

```
No of Policy Members Who Doesnot Smoke : 1064
No of Policy Members Who Smokes : 274
```



From this visualisation we can understand that most of the policy members are non smokers.But a small amount of people are smokers the company should increase premium amounts for policy members who smokes.

Q7. Does age have any barrier on the insurance claimed?

Age can affect health insurance claims in several ways. Older individuals may require more frequent medical care and may be more susceptible to certain health conditions.

```
def age(row):
    if row['age']>64:
        return 'Senor category'
    elif row['age']<=25:
        return 'Youth category'
    else:
        return 'Adult Category'

df['Age_Category']=df.apply(age,axis=1)
df.head()
```

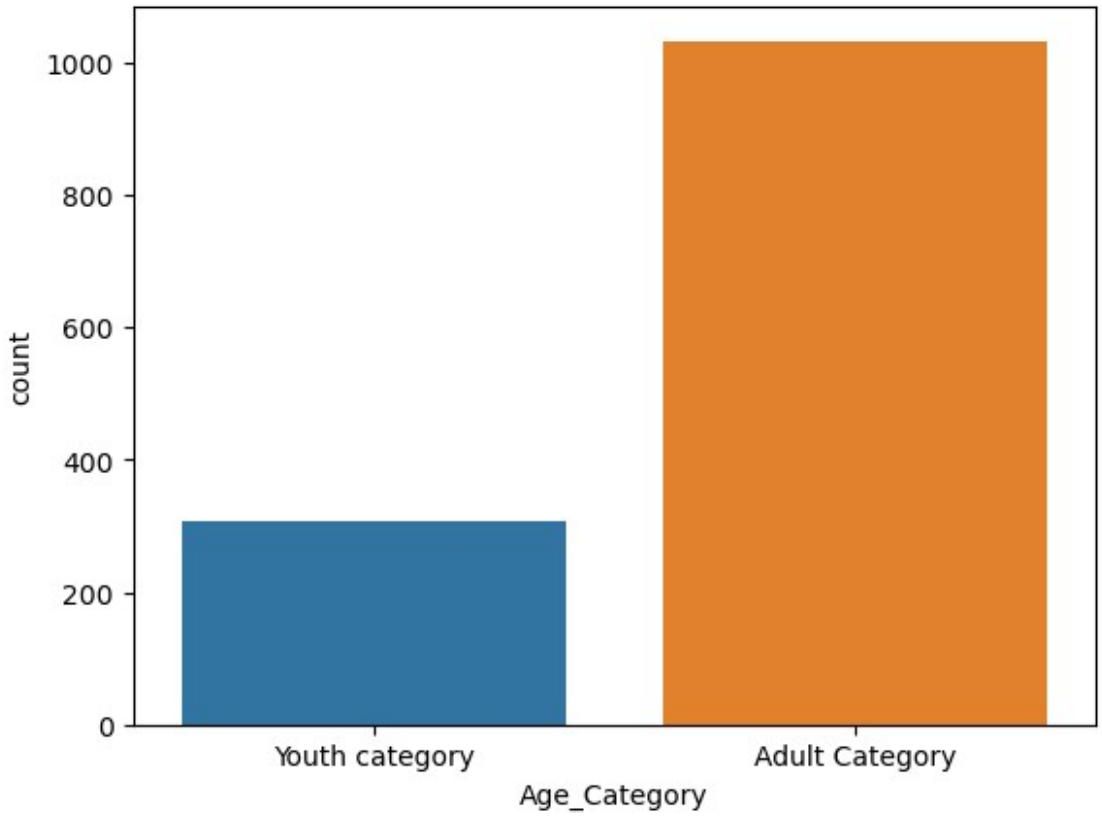
```
  Policy no.  children smoker     region  age     sex   bmi  charges
in INR  \
```

```
0  PLC157006          0     no  southwest   23    male  34.4
1826.843
1  PLC157033          1     no  southwest   19    male  24.6
1837.237
2  PLC157060          0     no  southwest   56    male  40.3
10602.385
3  PLC157087          1     no  southwest   30  female  32.4
4149.736
4  PLC157186          5     no  southwest   19  female  28.6
4687.797
```

	Gender_female	Gender_male	Weight	Age_Category
0	0	1	Over Weight	Youth category
1	0	1	Normal Weight	Youth category
2	0	1	Over Weight	Adult Category
3	1	0	Over Weight	Adult Category
4	1	0	Over Weight	Youth category

```
sns.countplot(data=df,x='Age_Category')

y,a=df['Age_Category'].value_counts()
print('No of policy members in Youth category :',y)
print('No of Policy Members in Adult category :',a)
```

```
No of policy members in Youth category : 1032
No of Policy Members in Adult category : 306
```

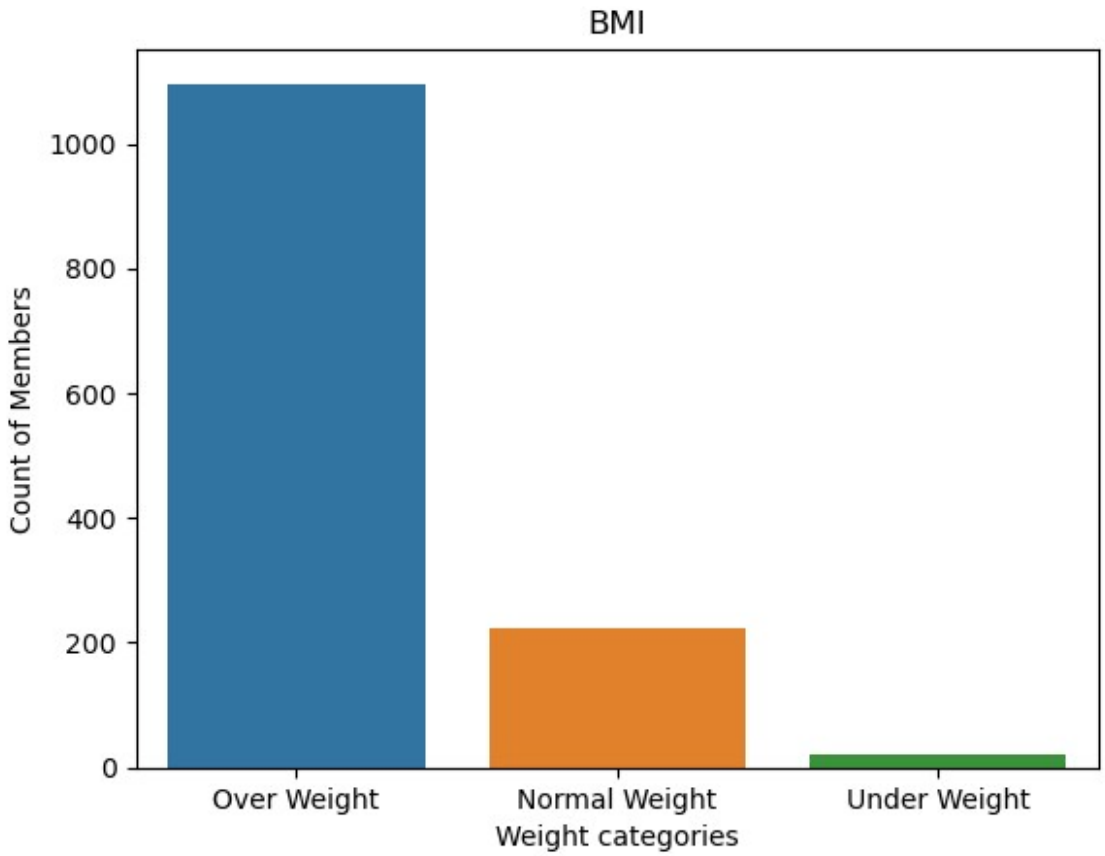


From this analysis we can see that there is no senior citizen thus company risk factor decreases.youth citizen and adult citizen are mostly healthy people with less chance of getting a health condition.thus the amount claimed by these category will be less.

Q8. Can the company extend certain discounts after checking the health status (BMI) in this case?

```
sns.countplot(data=df,x='Weight')
plt.title('BMI')
plt.xlabel('Weight categories')
plt.ylabel('Count of Members')

o,n,u=df['Weight'].value_counts()
print('No of Policy Members With Over Weight:',o)
print('No of Policy Members With Normal Weight:',n)
print('No of Policy Members With Under Weight:',u)
```

```
No of Policy Members With Over Weight: 1096
No of Policy Members With Normal Weight: 222
No of Policy Members With Under Weight: 20
```



Yes the company can extend certain discounts after checkin health status Using BMI . normal weight is considered as healthy hence the company can extend certains discount for this particular category of people.

from this analysis we understood that Age,BMI,Smoker,dependants are a important factor in health insurance.

Linear regression model

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score


def smok(row):
    if row['smoker']=='no':
```

```
        return 0
    else:
        return 1
df['smoker']=df.apply(smok,axis=1)

df
```

```
     Policy no.  children  smoker     region  age     sex     bmi  \
0     PLC157006         0       0  southwest   23    male  34.400
1     PLC157033         1       0  southwest   19    male  24.600
2     PLC157060         0       0  southwest   56    male  40.300
3     PLC157087         1       0  southwest   30  female  32.400
4     PLC157186         5       0  southwest   19  female  28.600
...         ...       ...     ...        ...  ...     ...     ...
1333  PLC168400         1       1  northeast   39    male  29.925
1334  PLC168436         0       1  northeast   18  female  21.660
1335  PLC168634         2       1  northeast   42    male  24.605
1336  PLC168652         0       1  northeast   29  female  21.850
1337  PLC168787         0       1  northeast   62    male  26.695

      charges in INR  Gender_female  Gender_male         Weight  \
0         1826.84300              0            1    Over Weight
1         1837.23700              0            1  Normal Weight
2        10602.38500              0            1    Over Weight
3         4149.73600              1            0    Over Weight
4         4687.79700              1            0    Over Weight
...              ...            ...          ...           ...
1333     22462.04375              0            1    Over Weight
1334     14283.45940              1            0  Normal Weight
1335     21259.37795              0            1  Normal Weight
1336     16115.30450              1            0  Normal Weight
1337     28101.33305              0            1    Over Weight

        Age_Category
0     Youth category
1     Youth category
2     Adult Category
3     Adult Category
4     Youth category
...              ...
1333  Adult Category
1334  Youth category
1335  Adult Category
1336  Adult Category
1337  Adult Category

[1338 rows x 12 columns]
```

Dropping unnecassery columns

```
df.drop('region',axis=1,inplace=True)

df.drop('sex',axis=1,inplace=True)

df.head()
```

```
  Policy no.  children  smoker  age   bmi  charges in INR
Gender_female  \
0  PLC157006         0       0   23  34.4        1826.843
0
1  PLC157033         1       0   19  24.6        1837.237
0
2  PLC157060         0       0   56  40.3       10602.385
0
3  PLC157087         1       0   30  32.4        4149.736
1
4  PLC157186         5       0   19  28.6        4687.797
1

   Gender_male         Weight    Age_Category
0            1    Over Weight  Youth category
1            1  Normal Weight  Youth category
2            1    Over Weight  Adult Category
3            0    Over Weight  Adult Category
4            0    Over Weight  Youth category
```

```
df.drop('Policy no.',axis=1,inplace=True)

df.drop('Weight',axis=1,inplace=True)

df.drop('Age_Category',axis=1,inplace=True)

df.head()
```

```
   children  smoker  age   bmi  charges in INR  Gender_female
Gender_male
0         0       0   23  34.4        1826.843              0
1
1         1       0   19  24.6        1837.237              0
1
2         0       0   56  40.3       10602.385              0
1
3         1       0   30  32.4        4149.736              1
0
4         5       0   19  28.6        4687.797              1
0
```

Finding Corelation of each columns

```
df.corr()
```

```
                  children    smoker       age       bmi  charges in INR
\
children          1.000000  0.007673  0.042469  0.012759        0.067998

smoker            0.007673  1.000000 -0.025019  0.003750        0.787251

age               0.042469 -0.025019  1.000000  0.109272        0.299008

bmi               0.012759  0.003750  0.109272  1.000000        0.198341

charges in INR    0.067998  0.787251  0.299008  0.198341        1.000000

Gender_female    -0.017163 -0.076185  0.020856 -0.046371       -0.057292

Gender_male       0.017163  0.076185 -0.020856  0.046371        0.057292


                  Gender_female  Gender_male
children              -0.017163     0.017163
smoker                -0.076185     0.076185
age                    0.020856    -0.020856
bmi                   -0.046371     0.046371
charges in INR        -0.057292     0.057292
Gender_female          1.000000    -1.000000
Gender_male           -1.000000     1.000000
```

From this We can Understand That Charges in INR are Mostly Corelated with Age and BMI

Split Data into Features (x) and Target (y)

```
x=df.drop('charges in INR',axis=1)
y=df['charges in INR']

x
```

```
      children  smoker  age     bmi  Gender_female  Gender_male
0            0       0   23  34.400              0            1
1            1       0   19  24.600              0            1
2            0       0   56  40.300              0            1
3            1       0   30  32.400              1            0
4            5       0   19  28.600              1            0
...        ...     ...  ...     ...            ...          ...
1333         1       1   39  29.925              0            1
1334         0       1   18  21.660              1            0
1335         2       1   42  24.605              0            1
1336         0       1   29  21.850              1            0
1337         0       1   62  26.695              0            1

[1338 rows x 6 columns]
```

```
y
```

```
0         1826.84300
1         1837.23700
2        10602.38500
3         4149.73600
4         4687.79700
             ...
1333     22462.04375
1334     14283.45940
1335     21259.37795
1336     16115.30450
1337     28101.33305
Name: charges in INR, Length: 1338, dtype: float64
```

Split Data into Training and Testing Sets

```
X_train, X_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)
```

Initialize and train a Linear Regression model

```
model = LinearRegression()
model.fit(X_train, y_train)
```

```
LinearRegression()
```

Make predictions on the test set

```
y_pred = model.predict(X_test)
```

Evaluating the model

mse=Mean squared error mae=Mean absolute error rmse=Root Mean Squared Error r2= R-squared Score

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

Printing the values

```
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("Mean Absolute Error (MAE):", mae)
print("R-squared (R2) Score:", r2)
```

```
Mean Squared Error (MSE): 38561491.17955518
Root Mean Squared Error (RMSE): 6209.789946492166
```

```
Mean Absolute Error (MAE): 4216.4212972131945
R-squared (R2) Score: 0.7286261479143632
```

```
print("Model Coefficients:", model.coef_)
print("Model Intercept:", model.intercept_)
```

```
Model Coefficients: [ 4.33984343e+02  2.40966455e+04  2.56685360e+02
3.07504184e+02
  2.10855199e+01 -2.10855199e+01]
Model Intercept: -11644.303266585008
```

Hyper parametrically tuning the model for getting best result

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Creating the GridSearchCV object with cross-validation and Fiting the grid search to the data

```
param_grid = {'fit_intercept': [True, False]}
grid_search = GridSearchCV(model, param_grid, cv=5,
scoring='neg_mean_squared_error', verbose=1)
grid_search.fit(X_train_scaled, y_train)
```

```
Fitting 5 folds for each of 2 candidates, totalling 10 fits
```

```
GridSearchCV(cv=5, estimator=LinearRegression(),
             param_grid={'fit_intercept': [True, False]},
             scoring='neg_mean_squared_error', verbose=1)
```

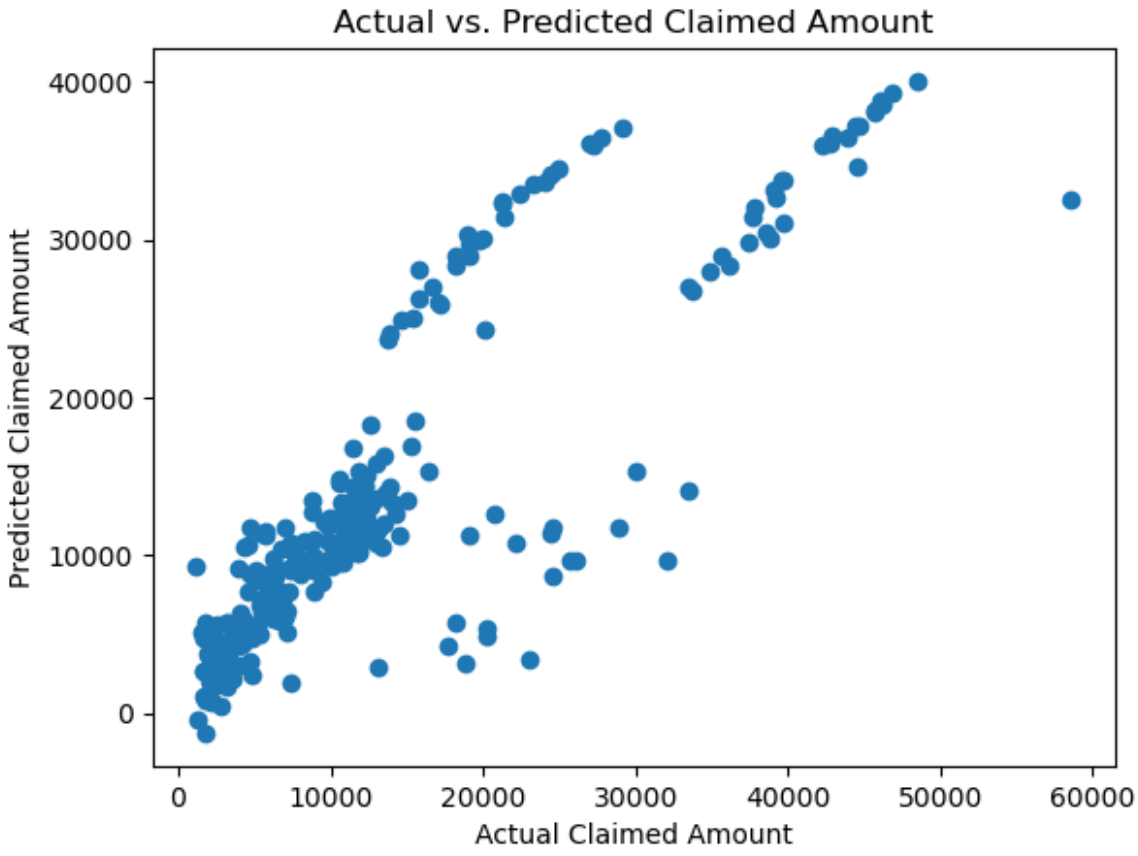
Getting the best hyperparameters and Model

```
best_model = grid_search.best_estimator_
best_params = grid_search.best_params_

mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r_squared = r2_score(y_test, y_pred)

print(f'Best Model - Mean Squared Error: {mse}')
print(f'rmse :{rmse}')
print(f'R-squared: {r_squared}')
```

```
Best Model - Mean Squared Error: 38561491.17955518
rmse :6209.789946492166
R-squared: 0.7286261479143632
```

Visualising the Actual and Predicted Claim Amount

```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Claimed Amount")
plt.ylabel("Predicted Claimed Amount")
plt.title("Actual vs. Predicted Claimed Amount")
plt.show()
```



From this linear regression Model we got About 0.72 accuracy which is nearly to one.About 72% of the variability in the claim amounts can be explained by the features included in the model. This suggests that the chosen features have some influence on the predicted claim amounts