In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
#load dataset
df=pd.read_csv('insurance.csv')
df.head()
```

Out[3]:

	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

In [4]:
```
#check the rows & columns of the dataset
df.shape
```

Out[4]:
```
(1338, 8)
```

In [5]:
```
# getting information of the dataset regarding null values, datatypes.
df.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 [6]:
```
#check the null values
df.isnull().sum()
```

Out[6]:
```
age               0
sex               0
bmi               0
children          0
smoker            0
region            0
charges           0
insuranceclaim    0
dtype: int64
```

In [7]:
```
# returns description of the data in the DataFrame.
df.describe()
```

Out[7]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
count	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	0.505232	30.663397	1.094918	0.204783	1.515695	13270.422265	0.585202
std	14.049960	0.500160	6.098187	1.205493	0.403694	1.104885	12110.011237	0.492871
min	18.000000	0.000000	15.960000	0.000000	0.000000	0.000000	1121.873900	0.000000
25%	27.000000	0.000000	26.296250	0.000000	0.000000	1.000000	4740.287150	0.000000
50%	39.000000	1.000000	30.400000	1.000000	0.000000	2.000000	9382.033000	1.000000
75%	51.000000	1.000000	34.693750	2.000000	0.000000	2.000000	16639.912515	1.000000
max	64.000000	1.000000	53.130000	5.000000	1.000000	3.000000	63770.428010	1.000000

In [8]:
```
#feature engineering with map function
df['sex']=df['sex'].map({0:'female', 1:'male'})
df.head()
```

Out[8]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
0	19	female	27.900	0	1	3	16884.92400	1
1	18	male	33.770	1	0	2	1725.55230	1
2	28	male	33.000	3	0	2	4449.46200	0
3	33	male	22.705	0	0	1	21984.47061	0
4	32	male	28.880	0	0	1	3866.85520	1

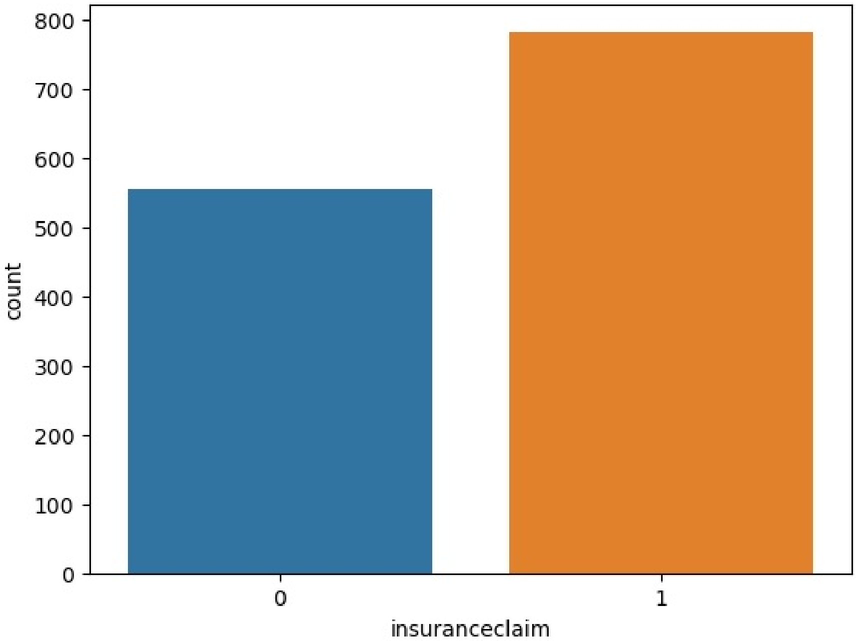
EDA

univarite analysis

In [9]:

```
sns.countplot(df['insuranceclaim'])
claim_percent=round((df['insuranceclaim'].value_counts().values[0]/1338)*100)
print('out of 1338 , {}% claim insurance'.format(claim_percent))
```

```
out of 1338 , 59% claim insurance
```

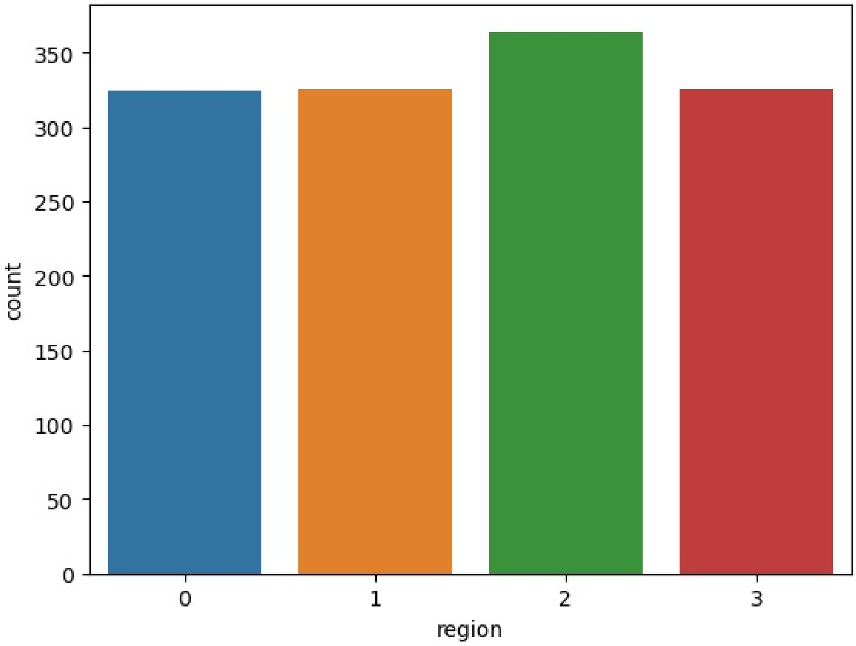


0: people not claim the insurance 1:people claim the insurance

In [10]:

```
# people from different region
sns.countplot(df['region'])
print((df['region'].value_counts()/1338)*100)
```

```
2    27.204783
3    24.289985
1    24.289985
0    24.215247
Name: region, dtype: float64
```



0 : Northeast

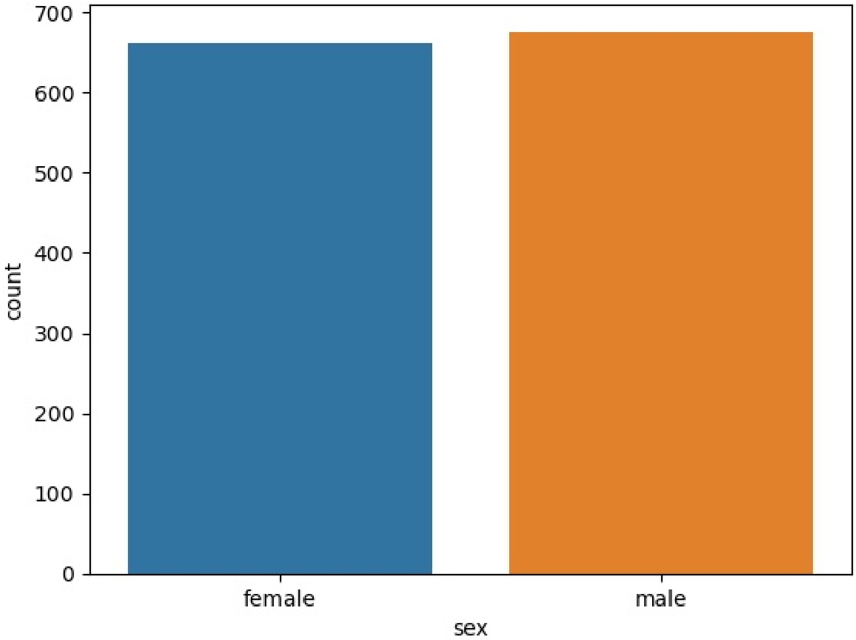
1 : Northwest

2 : Southeast

3 : Southwest

In [11]:
```
# gender
sns.countplot(df['sex'])
print((df['sex'].value_counts()/1338)*100)
```

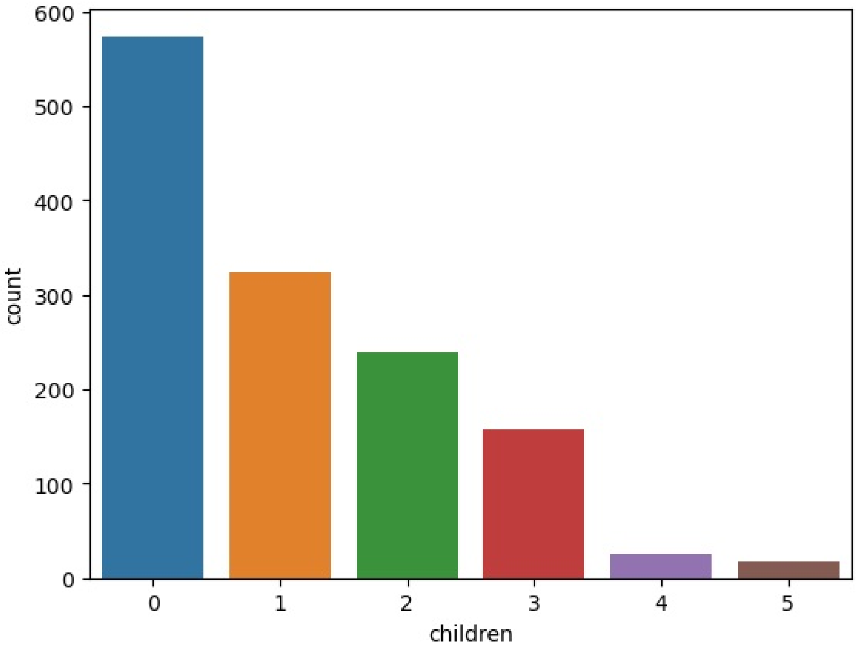
```
male      50.523169
female    49.476831
Name: sex, dtype: float64
```



in this graph we can see the number of female and male in this dataset

In [12]:
```
#childern column
sns.countplot(df['children'])
print((df['children'].value_counts()/1338)*100)
```

```
0    42.899851
1    24.215247
2    17.937220
3    11.733931
4     1.868460
5     1.345291
Name: children, dtype: float64
```



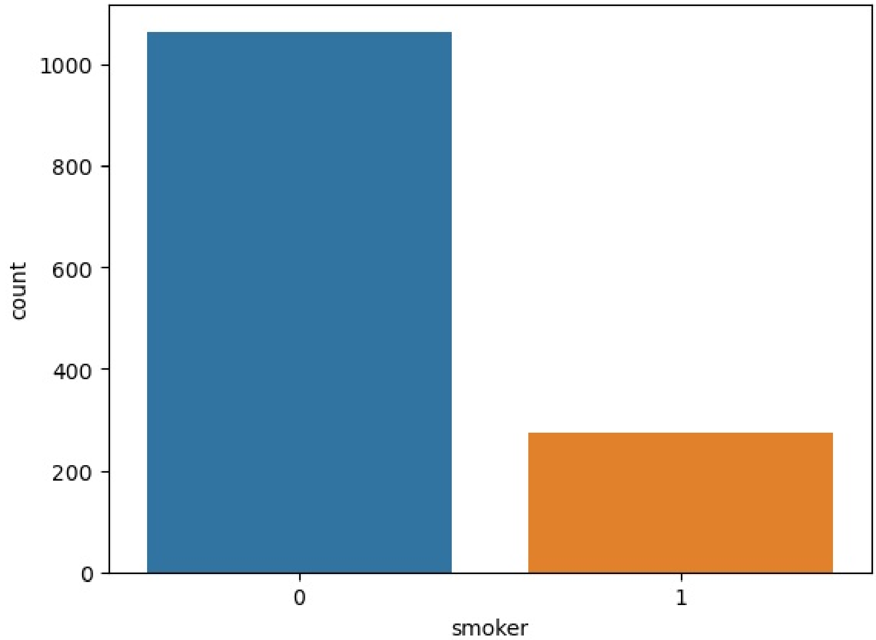
With the help of graph, we observe that how many children belongs to peoples who have insurance policy.

Maximum number of peoples hold policy who have no child.

And less policy holders who more number of child.

In [13]:
```
# counting how many peoples smoking
sns.countplot(df['smoker'])
print((df['smoker'].value_counts()/1338) *100)
```

```
0    79.521674
1    20.478326
Name: smoker, dtype: float64
```

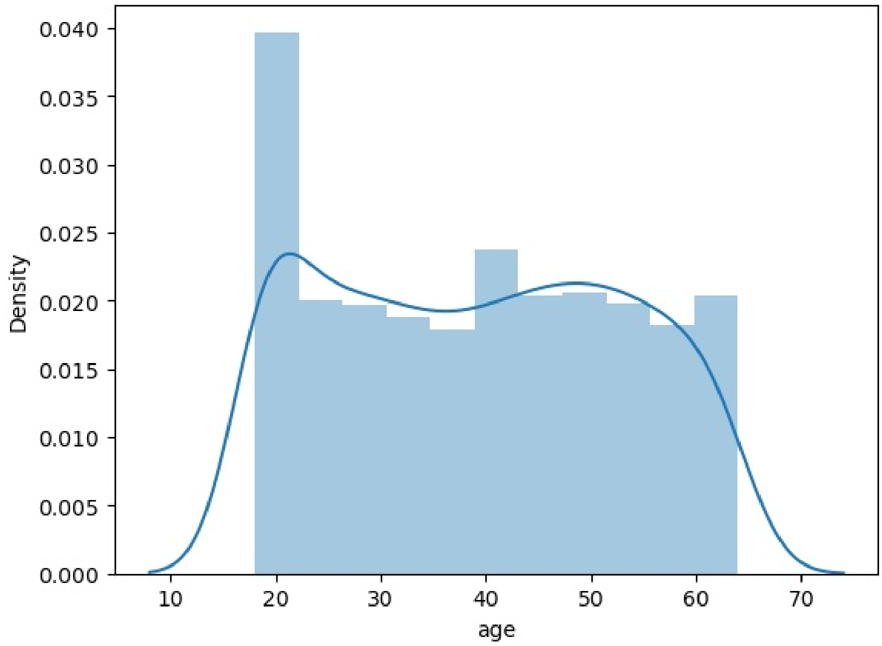


0: non-smoking

1: smoking

In [14]:
```
# age column
sns.distplot(df['age'])
print(df['age'].skew())
print(df['age'].kurt())
```

```
0.05567251565299186
-1.2450876526418673
```

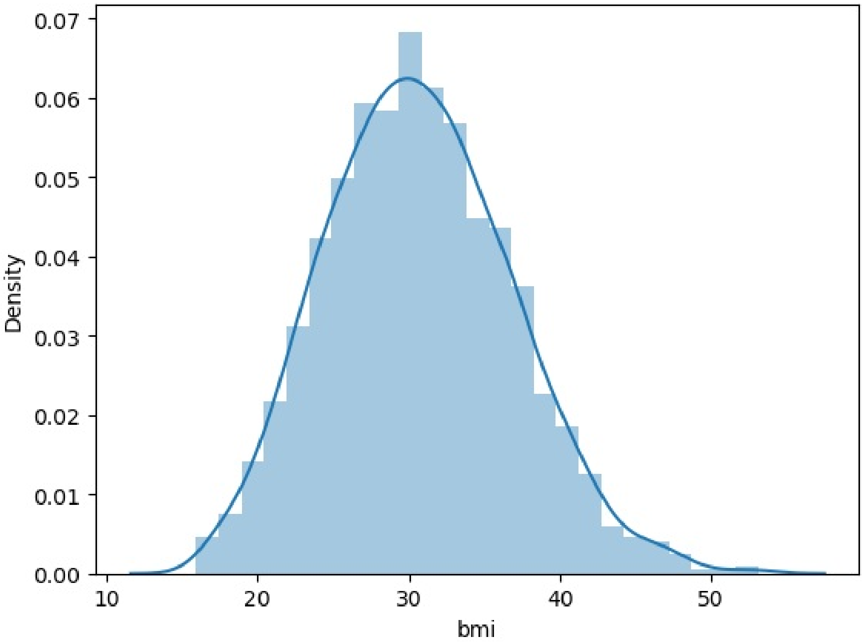


The value printed will indicate the skewness of the 'Age' column. If the skewness is close to 0, it suggests that the distribution is approximately symmetric. A negative skewness value indicates a longer left tail, while a positive skewness value indicates a longer right tail.

Kurtosis is a measure of the shape of the distribution of values in the column, specifically focusing on the tails and outliers. If the kurtosis is close to 0, it suggests a normal distribution. Positive kurtosis indicates a distribution with heavier tails and a sharper peak, while negative kurtosis indicates a distribution with lighter tails and a flatter peak.

In [15]:
```
sns.distplot(df['bmi'])
```

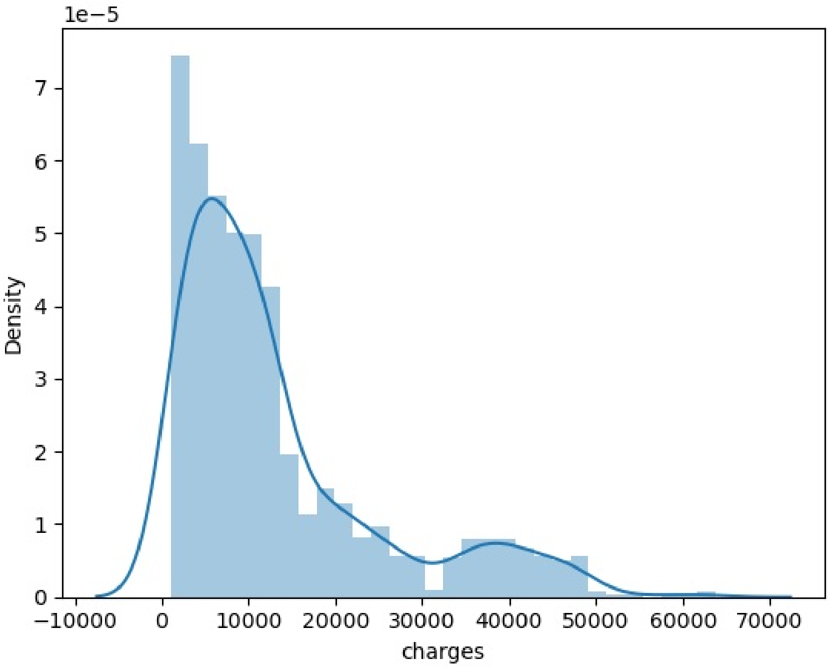
Out[15]:
```
<AxesSubplot:xlabel='bmi', ylabel='Density'>
```



Peoples who have insurance policy lies mostly in the range of BMI 20 to BMI 40.

In [16]:
```
sns.distplot(df['charges'])
```

Out[16]:
```
<AxesSubplot:xlabel='charges', ylabel='Density'>
```

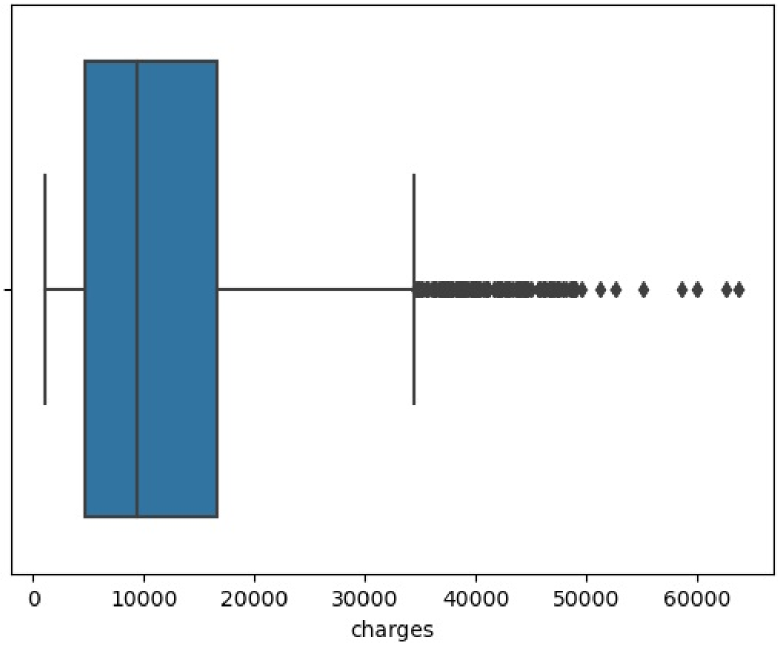


maximum number of people who claim the insurance for medical treatment lies between 1000 to 15000

cheking outliers with the help of boxplot.

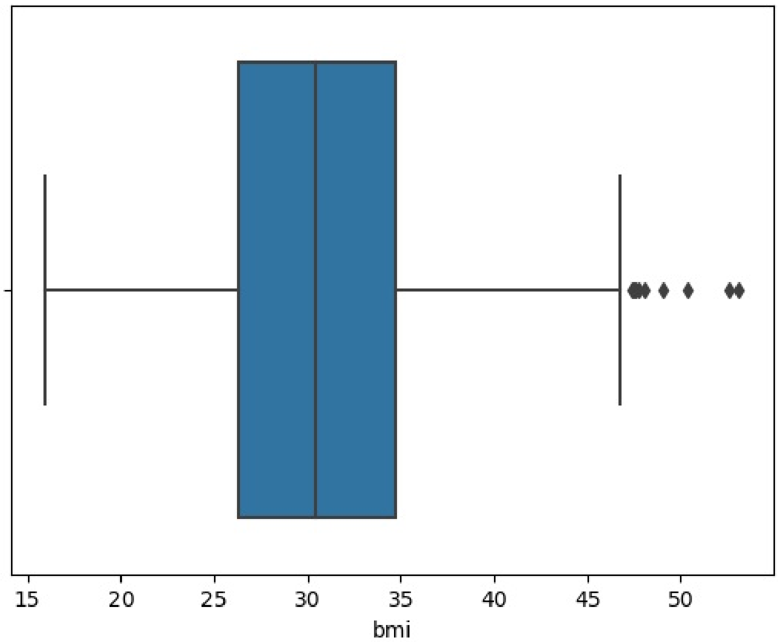
In [17]:
```
sns.boxplot(df['charges'])
```

Out[17]:
```
<AxesSubplot:xlabel='charges'>
```



In [18]:
```
sns.boxplot(df['bmi'])
```

Out[18]:
```
<AxesSubplot:xlabel='bmi'>
```

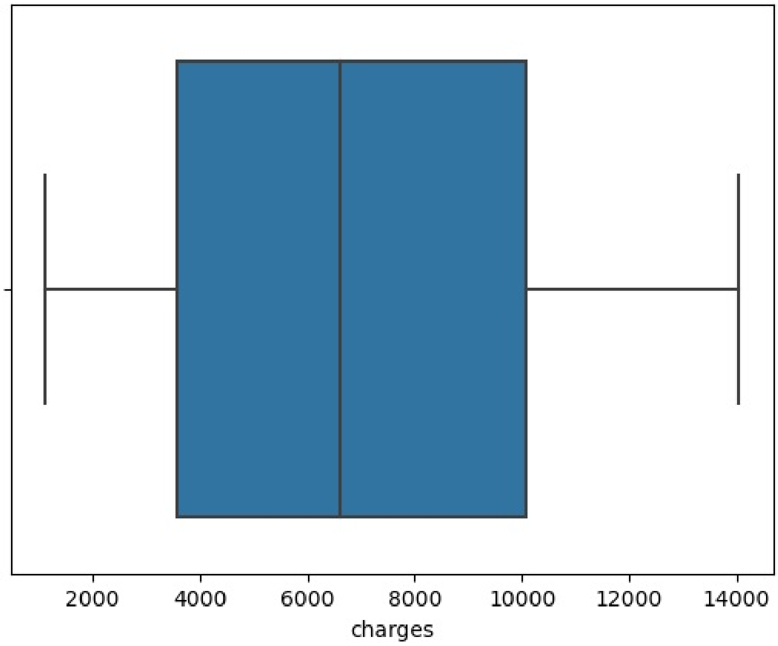


Treatment of Outlier

In [19]:
```
# handing outliers from the columns bmi and charges
# find IQR
Q1=np.percentile(df[['charges','bmi']],25)
Q3=np.percentile(df[['charges','bmi']],75)
outlier_low=Q1-1.5*(Q3-Q1)
outlier_high=Q1+1.5*(Q3-Q1)
df = df[(df['charges'] > outlier_low) & (df['charges'] < outlier_high) &
        (df['bmi'] > outlier_low) & (df['bmi'] < outlier_high)]
```

In [20]:
```
sns.boxplot(df['charges'])
```

Out[20]:
```
<AxesSubplot:xlabel='charges'>
```



After treatment of outliers with the help of IQR method, we can see the there is no outliers lies.

In [21]:
```
df.head()
```

Out[21]:

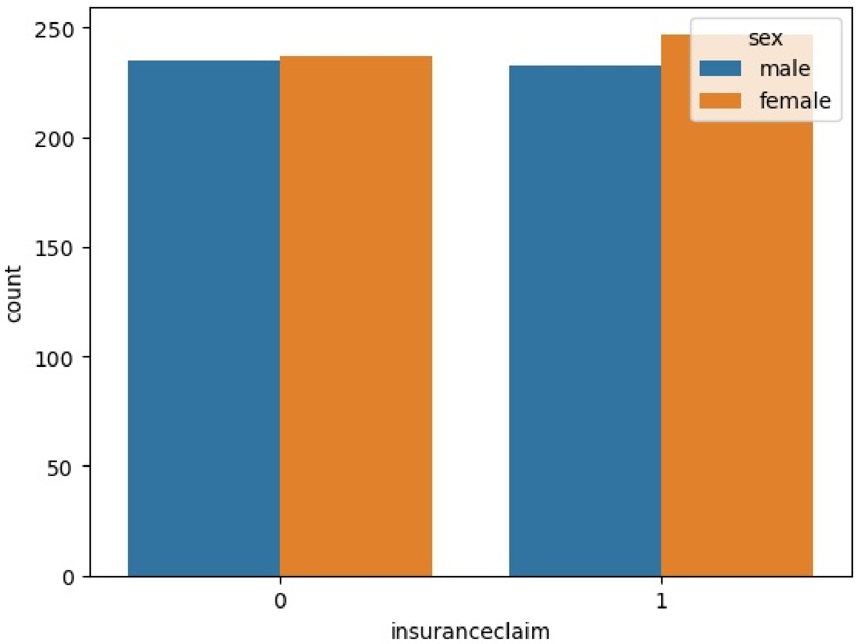
	age	sex	bmi	children	smoker	region	charges	insuranceclaim
1	18	male	33.77	1	0	2	1725.5523	1
2	28	male	33.00	3	0	2	4449.4620	0
4	32	male	28.88	0	0	1	3866.8552	1
5	31	female	25.74	0	0	2	3756.6216	0
6	46	female	33.44	1	0	2	8240.5896	1

Multivariate

In [22]:
```
# insuranceclaim with sex
sns.countplot(df['insuranceclaim'],hue=df['sex'])
pd.crosstab(df['sex'],df['insuranceclaim']).apply(lambda r: round((r/r.sum())*100,1), axis=1)
```

Out[22]:

insuranceclaim	0	1
sex		
female	49.0	51.0
male	50.2	49.8



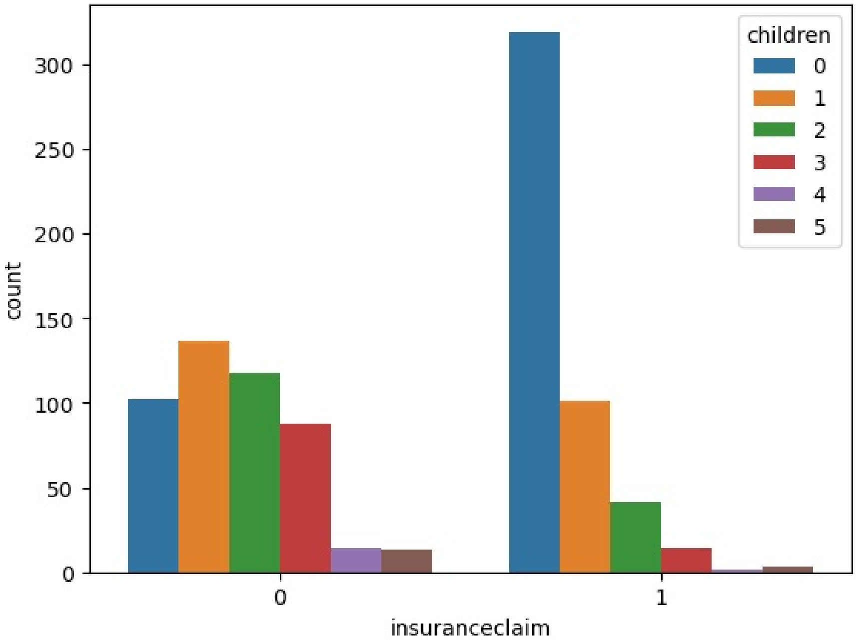
Above the table shows the percentage break with the gender who claimed insurance.

And graph shows the gender wise with the number of people who claimed or not claimed insurance policy.

In [23]:
```
#insurance eith childern
sns.countplot(df['insuranceclaim'],hue=df['children'])
pd.crosstab(df['children'],df['insuranceclaim']).apply(lambda r: round(r/r.sum()*100,1),axis=1)
```

Out[23]:

insuranceclaim	0	1
children		
0	24.2	75.8
1	57.6	42.4
2	74.2	25.8
3	86.3	13.7
4	87.5	12.5
5	81.2	18.8



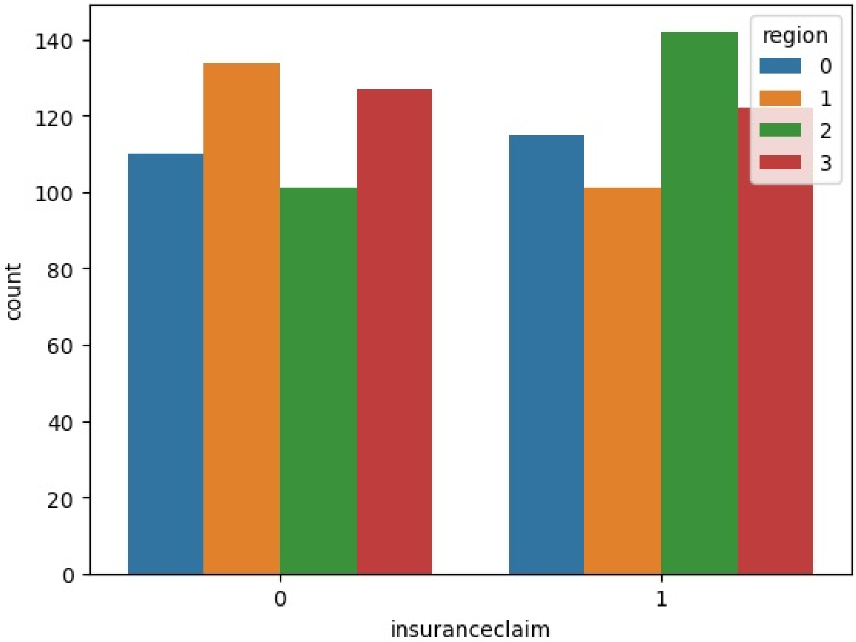
In this graph, we clearly see the the people who don't claim insurance section have maximum one child.

And people who claimed maximum times insurance have no child.

In [24]:
```
#insurance with region
sns.countplot(df['insuranceclaim'], hue=df['region'])
pd.crosstab(df['region'],df['insuranceclaim']).apply(lambda r: round(r/r.sum()*100,1),axis=1)
```

Out[24]:

insuranceclaim	0	1
region		
0	48.9	51.1
1	57.0	43.0
2	41.6	58.4
3	51.0	49.0



Above the table shows the percentage break with the region who claimed insurance.

0 : Northeast

1 : Northwest

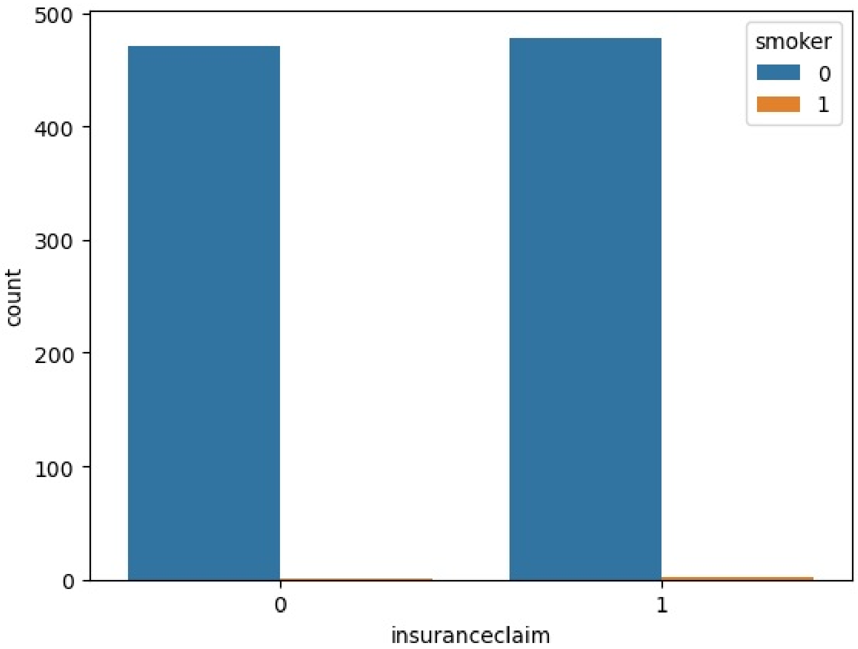
2 : Southeast

3 : Southwest

In [25]:
```
#insurance with smoker
sns.countplot(df['insuranceclaim'],hue=df['smoker'])
pd.crosstab(df['smoker'],df['insuranceclaim']).apply(lambda r: round(r/r.sum()*100,1),axis=1)
```

Out[25]:

insuranceclaim	0	1
smoker		
0	49.6	50.4
1	33.3	66.7

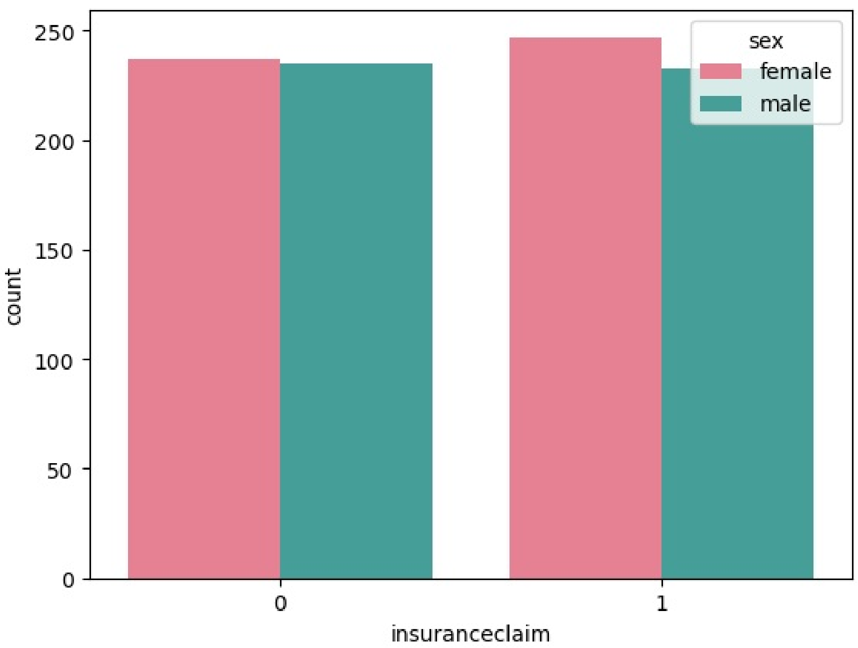


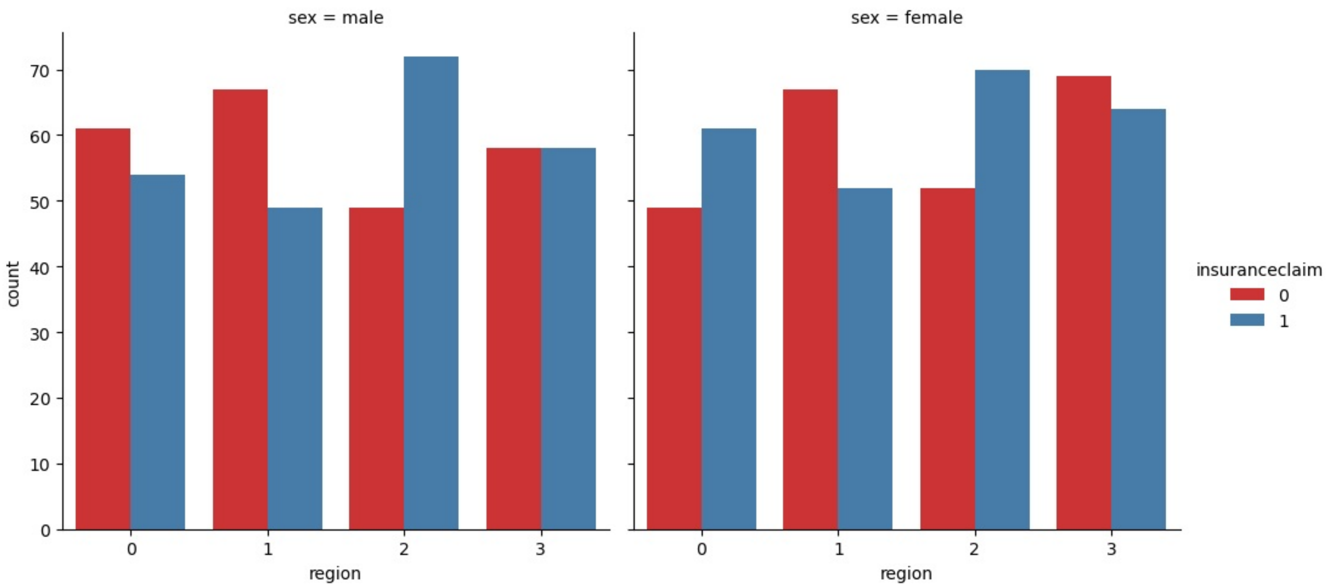
Above the table shows the percentage break with the smoker who claimed insurance.

And graph shows the smoker wise with the number of people who claimed or not claimed insurance policy.

In [26]:
```
#create countplot with insurance claim, sex and region
sns.countplot(x='insuranceclaim',hue='sex',data=df,palette='husl',hue_order=['female','male'])
sns.catplot(x='region', hue='insuranceclaim', col='sex', data=df, kind='count', palette='Set1')
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x26d2ac1d7f0>





In [27]:
```
# Create a pivot table with region, insurance claim, and sex
pivot_table=pd.pivot_table(df,values='insuranceclaim',index='region',columns=['sex'],aggfunc='count',fill_value
# Calculate the percentage of each row
percentage = pivot_table.apply(lambda r: round((r / r.sum()) * 100, 1), axis=1)
print(percentage)
```

```
sex     female  male
region
0         48.9  51.1
1         50.6  49.4
2         50.2  49.8
3         53.4  46.6
```

In [28]:
```
df1=df
```

In [29]:
```
# Map the values in the "sex" column to 0 and 1
df1['sex'] = df1['sex'].map({'female': 0, 'male': 1})
df1.head()
```

Out[29]:

	age	sex	bmi	children	smoker	region	charges	insuranceclaim
1	18	1	33.77	1	0	2	1725.5523	1
2	28	1	33.00	3	0	2	4449.4620	0
4	32	1	28.88	0	0	1	3866.8552	1
5	31	0	25.74	0	0	2	3756.6216	0
6	46	0	33.44	1	0	2	8240.5896	1

In [30]:
```
# importing libraries for prediction the model.

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

In [31]:
```
# Separate the features and target variable

X = df1.drop("insuranceclaim", axis=1)
y = df1["insuranceclaim"]
```

In [32]:
```
# Split the 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)
```

In [33]:
```
# Create an instance of the logistic regression model
model = LogisticRegression()

# Fit the model to the training data
model.fit(X_train, y_train)
```

Out[33]:
```
LogisticRegression()
```

In [34]:
```
# Make predictions on the testing data

y_pred = model.predict(X_test)
```

Testing

In [35]:
```
# Import confusion metrix
```

In [36]:
```
from sklearn.metrics import confusion_matrix
```

In [37]:
```
confusion_matrix(y_test, y_pred)
```

Out[37]:
```
array([[73, 30],
       [10, 78]], dtype=int64)
```

In [38]:
```
pd.DataFrame(confusion_matrix(y_test, y_pred), columns=['Predicted No', 'Predicted Yes'], index =['Actual No',
```

Out[38]:

	Predicted No	Predicted Yes
Actual No	73	30
Actual Yes	10	78

In the 'Predicted No' column, there are 73 peoples who actually not claiming and our model also predicted that they are not claiming insurance. whereas, 10 peoples who actually claimed insurance but our model predict that they don't claim.

In 'Predicted Yes' column, there are 78 peoples who actually claiming insurance and model also predict that they claimed. whereas, 30 peoples who actually not claiming insurance but model predicts that they claimed.

In [39]:
```
# Now  We import classification report
```

In [41]:
```
from sklearn.metrics import classification_report
```

In [42]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.71      0.78       103
           1       0.72      0.89      0.80        88

    accuracy                           0.79       191
   macro avg       0.80      0.80      0.79       191
weighted avg       0.81      0.79      0.79       191
```

In [43]:
```
# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7905759162303665
```

The accuracy is 0.79, meaning that the model correctly predicted 79% of the instances.

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js